MINISTRY EDUCATION AND SCIENCES UKRAINE
NATIONAL TECHNICAL UNIVERSITY OF UKRAINE
"IGOR SIKORSKY KYIV
POLYTECHNIC INSTITUTE"

Gordienko Yu.G., Kochura Yu.P.

DEEP LEARNING METHODS

Lectures

Tutorial
for master's degree holders
according to the educational program "Software engineering of computer systems»
specialties 121 "Software engineering"
according to the educational program "Computer systems and networks»
specialty 123 "Computer engineering"
according to the educational program "Information management systems and technologies»
specialties 126 "Information systems and technologies»

Electronic educational publication

APPROVED
at the meeting of Computer Engineering department,
protocol No. 10 on 05/25/2022

2022

Deep Learning Methods

Lecture_01

****
Lecture Slides:
https://cloud.comsys.kpi.ua/s/SMkBSsxRTazoTD6

****

Lecture 01 - Introduction

The course includes materials proposed by NVIDIA Deep Learning Institute (DLI) in the framework of the common

NVIDIA Research Center
and
NVIDIA Education Center.

https://kpi.ua/nvidia-info

DEEP LEARNING METHODS

LECTURE 1: INTRODUCTION

Yuri Gordienko, DLI Certified Instructor

NVIDIA DEEP LEARNING INSTITUTE

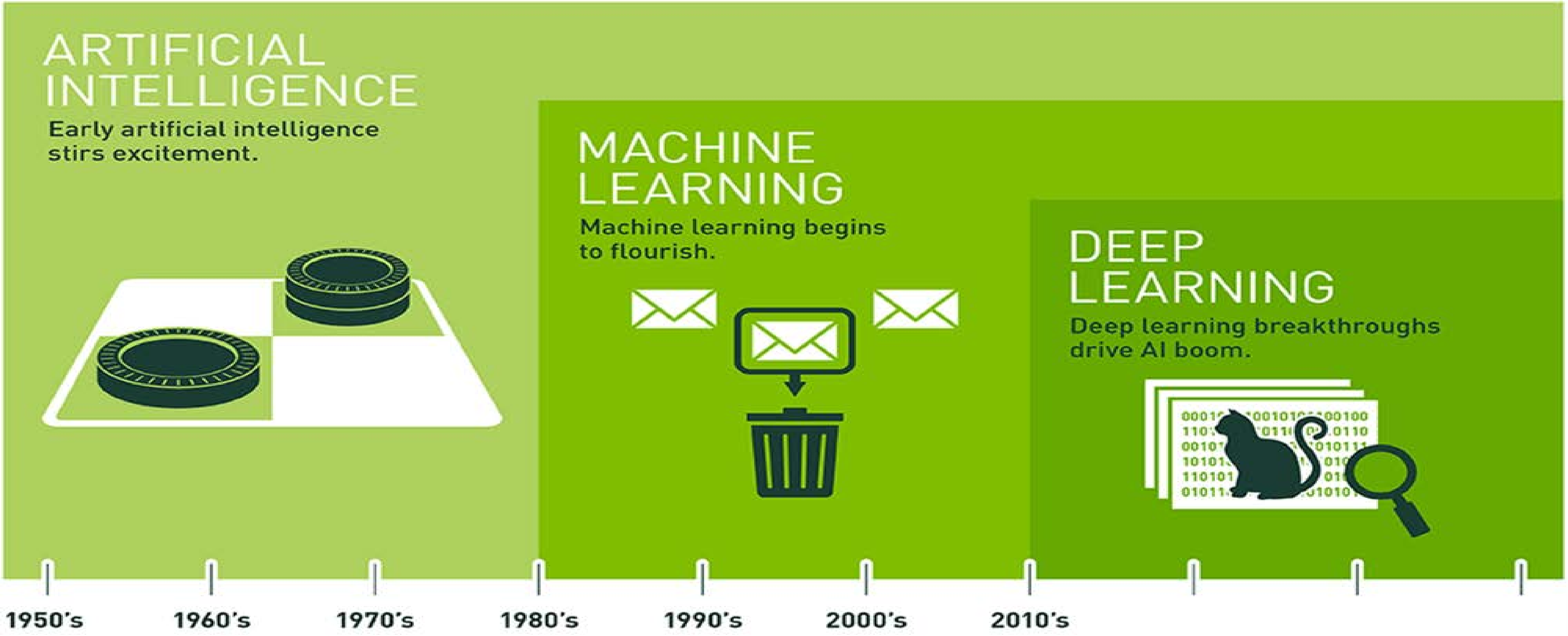
DEEP LEARNING INSTITUTE

DLI Mission

Training you to solve the world's most challenging problems.

- Developers, data scientists and engineers
- Self-driving cars, healthcare and robotics
- Training, optimizing, and deploying deep neural networks

DEFINITIONS

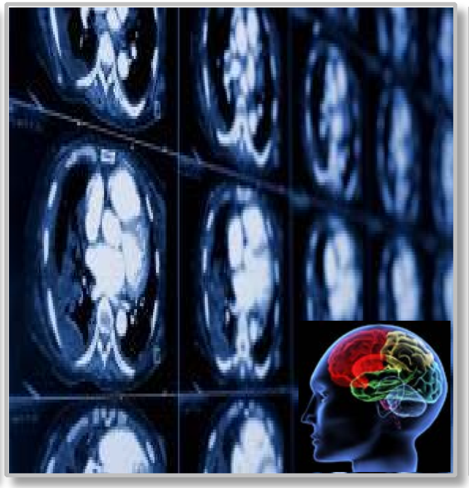


DEEP LEARNING IS SWEEPING ACROSS INDUSTRIES

Internet Services

- Image/Video classification
- Speech recognition
- Natural language processing

Medicine



- Cancer cell detection
- Diabetic grading
- Drug discovery

Media & Entertainment

- Video captioning
- Content based search
- Real time translation

Security & Defense

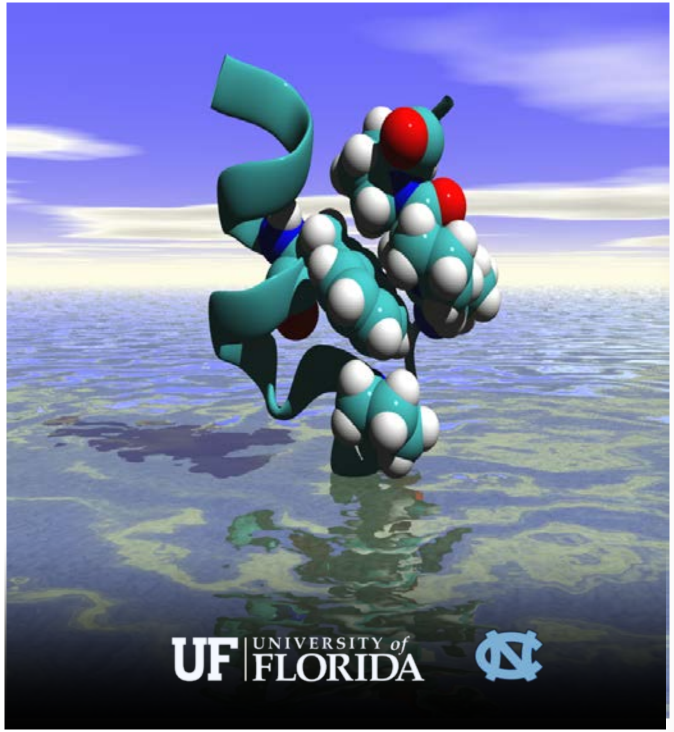
- Face recognition
- Video surveillance
- Cyber security

Autonomous Machines

- Pedestrian detection
- Lane tracking
- Recognize traffic signs

DEEP LEARNING IS TRANSFORMING HPC

"Seeing" Gravity In Real Time



Accelerating Drug Discovery

92%

believe AI will impact their work

93%

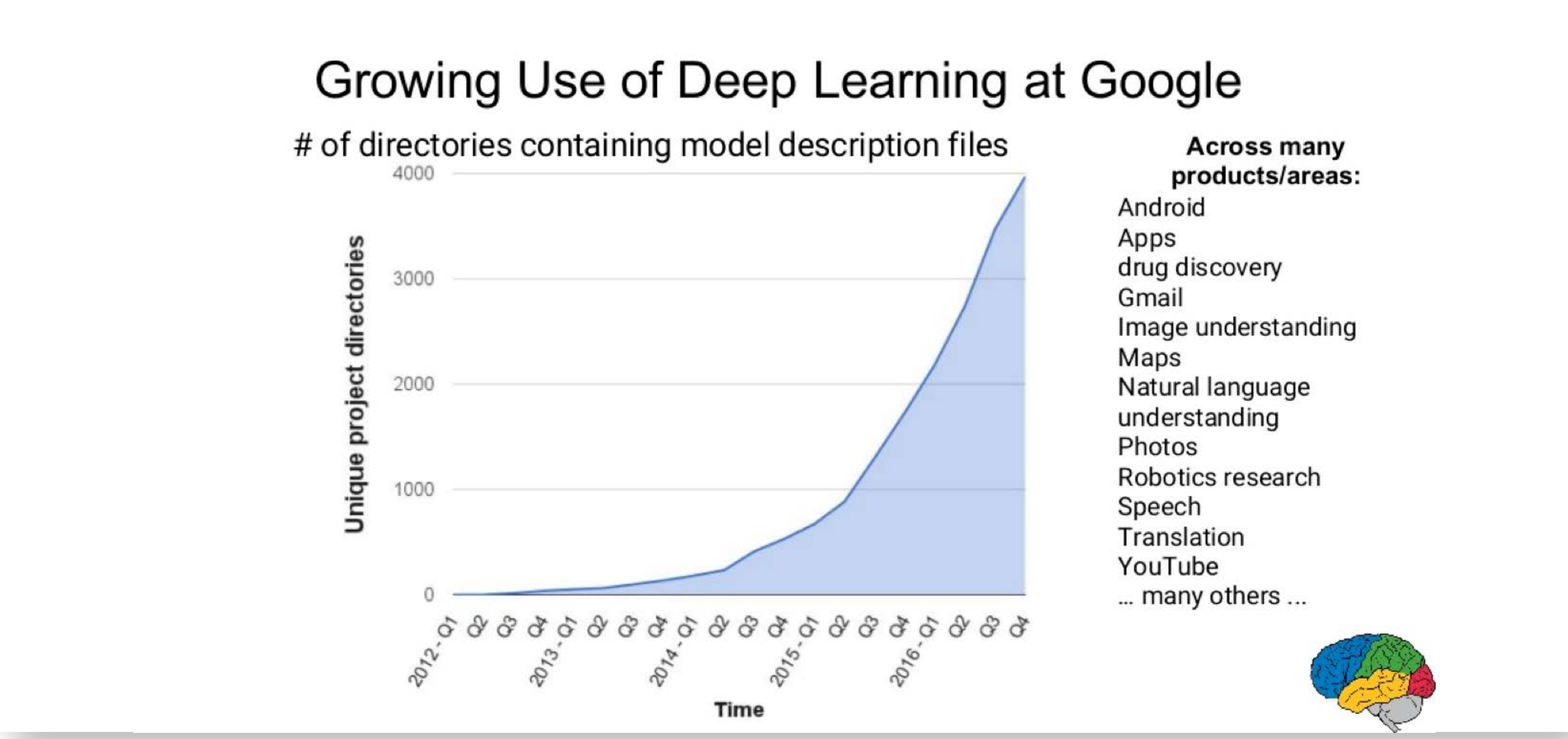
using deep learning seeing positive results

inside HPC

insideHPC.com Survey November 2016

AI IS CRITICAL FOR INTERNET APPLICATIONS

Users Expect Intelligence In Services



THE EXPANDING UNIVERSE OF MODERN AI

" THE BIG BANG "
Big Data
GPU
Algorithms

RESEARCH
Berkeley
Carnegie Mellon University
DEEPMIND
MIT
NYU
OpenAI
Université de Montréal
OXFORD
TORONTO

CORE TECHNOLOGY / FRAMEWORKS
Preferred Networks
Chainer
facebook
torch
Université de Montréal
theano
Google
TensorFlow
Berkeley
Caffe
Microsoft
CNTK
OXFORD
NVIDIA
cuDNN

AI-as-a-PLATFORM
amazon web services
IBM Watson
Google
Microsoft Azure

START-UPS
api.ai — Personal Assistants — conversational interface
BLUE RIVER TECHNOLOGY — Agriculture — crop-yield optimization
clarifai — Tech — visual recognition platform
deep genomics — Genomics — genetic interpretation
drive.ai — Automotive — computer vision
MetaMind — eCommerce & Medical — recommendation engines
Morpho — Tech — computer vision
Orbital Insight — Geospatial — predictions from images
nervana — Tech — AI-as-a-service
SADAKO — Waste Management — sorting robots
SocialEyes — Medical — diabetic retinopathy
Education — teaching robots

1,000+ AI START-UPS
$5B IN FUNDING
Source: Venture Scanner

INDUSTRY LEADERS
Alibaba.com
AstraZeneca
Audi
Baidu 百度
Bloomberg
charles SCHWAB
CISCO
ebay
FANUC ROBOTICS
Ford
gsk
MASSACHUSETTS GENERAL HOSPITAL
Mercedes-Benz
MERCK
Pinterest
Schlumberger

A NEW COMPUTING MODEL

Algorithms that Learn from Examples

Traditional Approach

- ➢ Requires domain experts
- ➢ Time consuming
- ➢ Error prone
- ➢ Not scalable to new problems

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Algorithms that Learn from Examples

Traditional Approach

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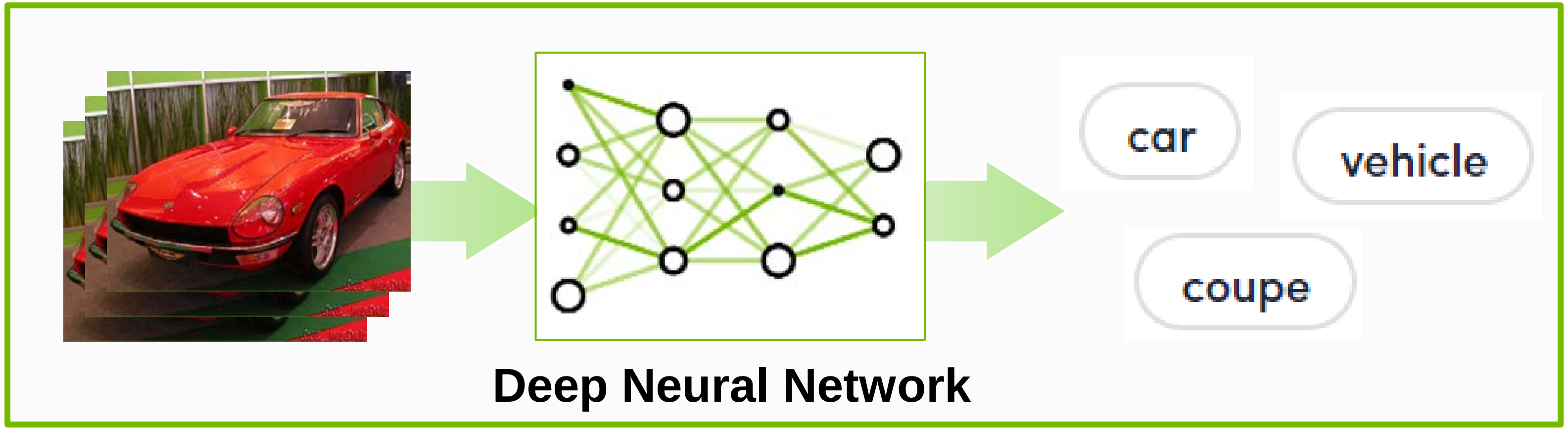
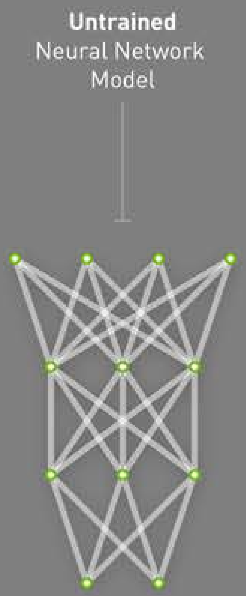


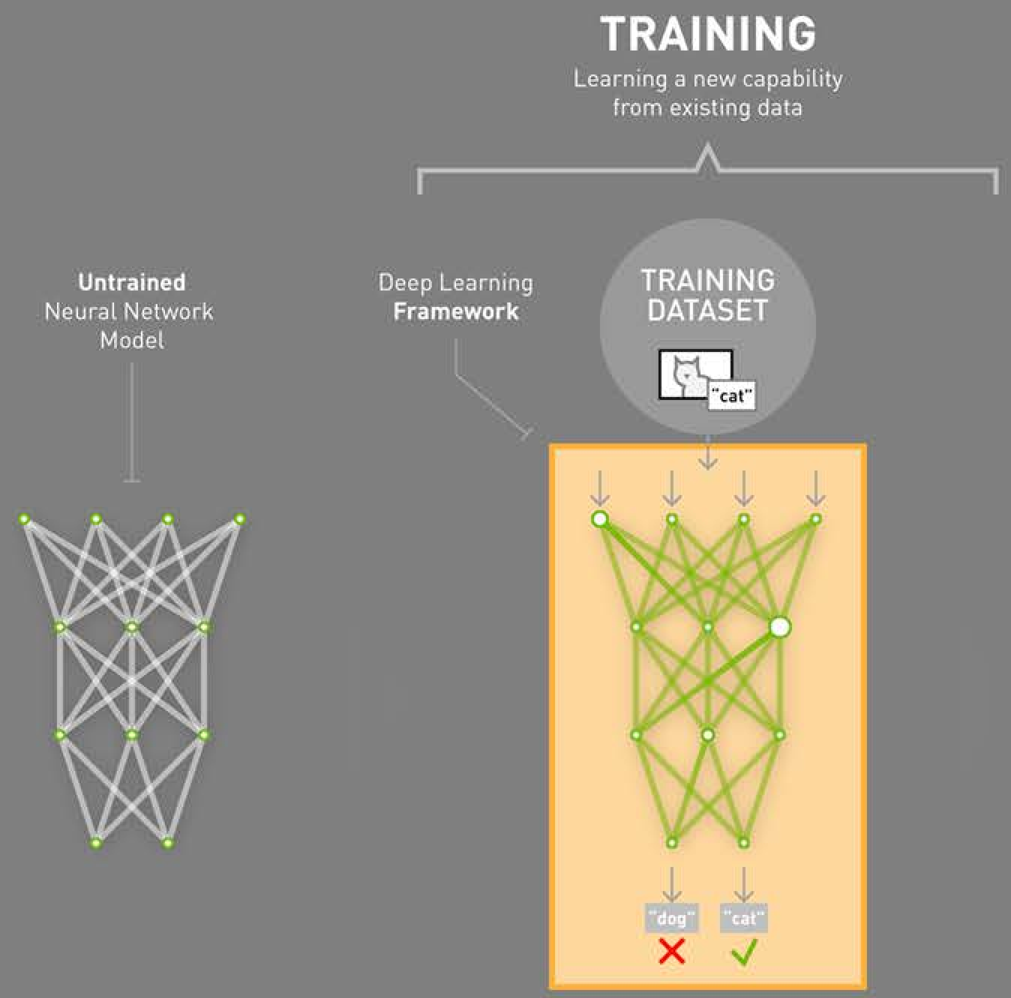
Deep Learning Approach

✓ Learn from data
✓ Easily to extend
✓ Speedup with GPUs

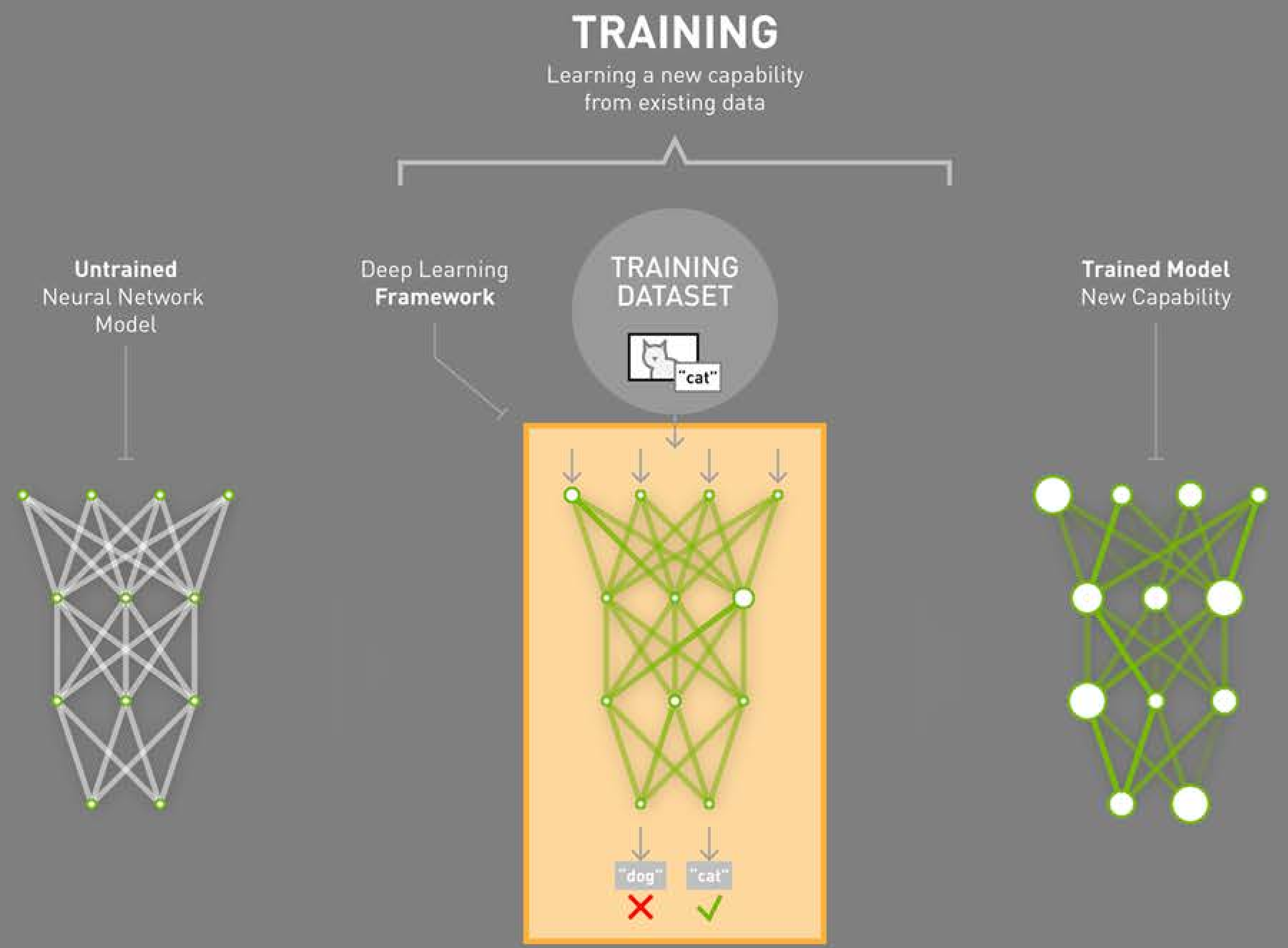
DEEP LEARNING

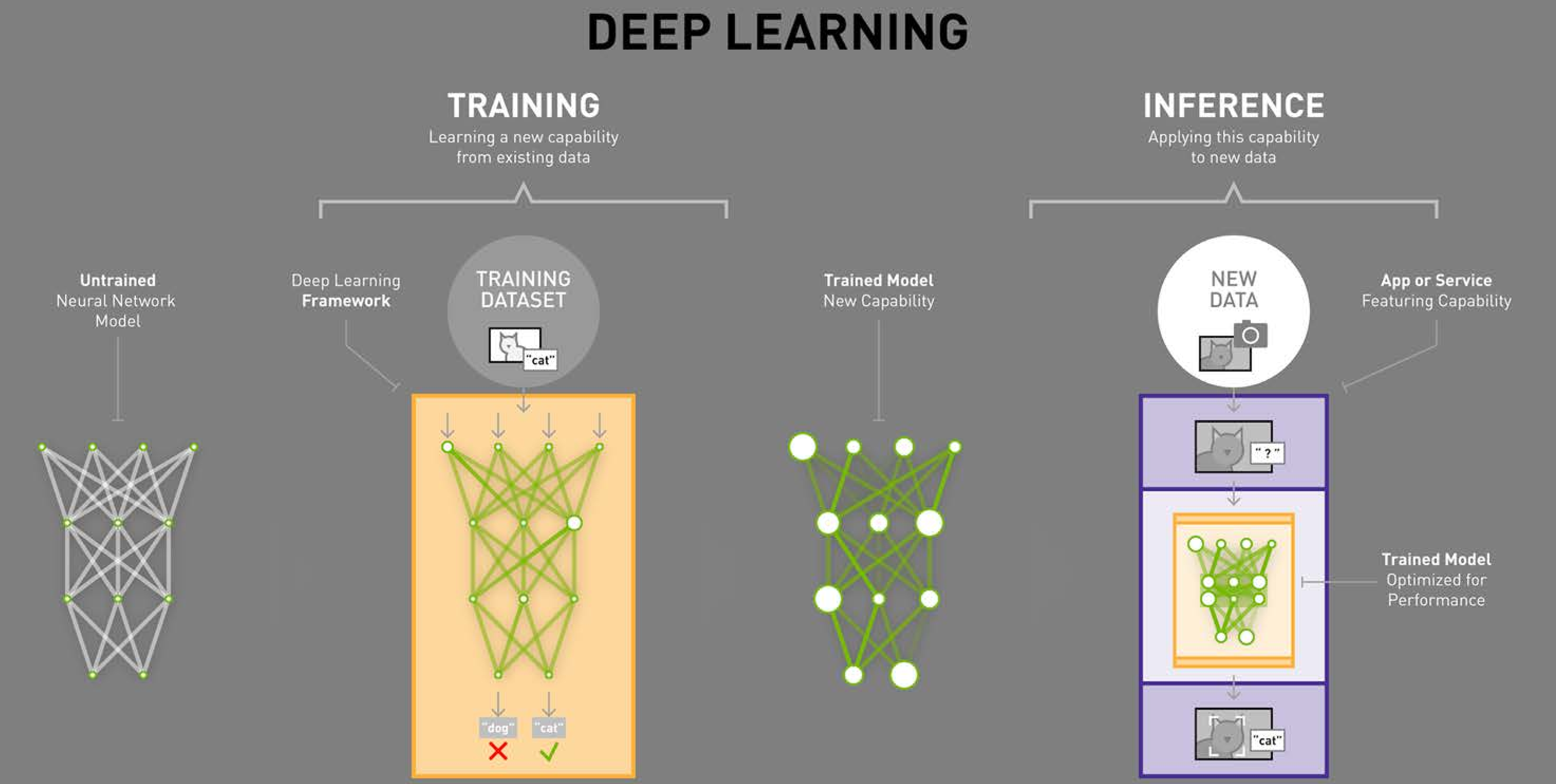


DEEP LEARNING



DEEP LEARNING




DEEP LEARNING
TRAINING
Learning a new capability from existing data
INFERENCE
Applying this capability to new data
Untrained Neural Network Model
Deep Learning Framework
TRAINING DATASET
"cat"
"dog"
"cat"
Trained Model New Capability
NEW DATA
App or Service Featuring Capability
" ? "
Trained Model Optimized for Performance
"cat"

CHALLENGES

Deep Learning Needs	Why
Data Scientists	New computing model
Latest Algorithms	Rapidly evolving
Fast Training	Impossible -> Practical
Deployment Platforms	Must be available everywhere

NVIDIA DEEP LEARNING INSTITUTE

Online self-paced labs and instructor-led workshops on deep learning and accelerated computing

Take self-paced labs at **www.nvidia.com/dlilabs**

View upcoming workshops and request a workshop onsite at **www.nvidia.com/dli**

Educators can join the University Ambassador Program to teach DLI courses on campus and access resources. Learn more at **www.nvidia.com/dli**

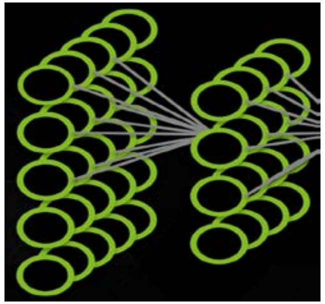
Caffe2

Microsoft Cognitive Toolkit

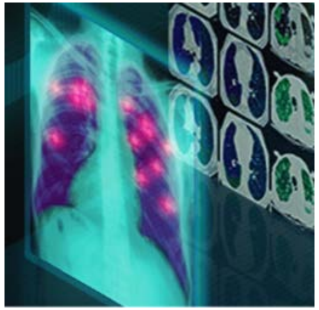
mxnet

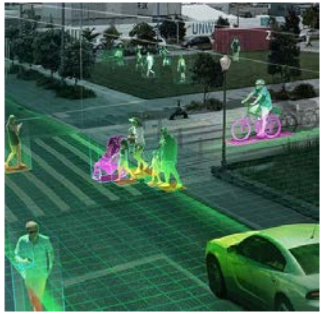
TensorFlow

PYTORCH


Fundamentals

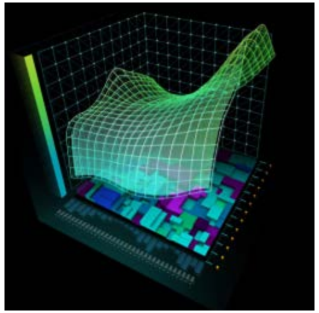

Autonomous Vehicles

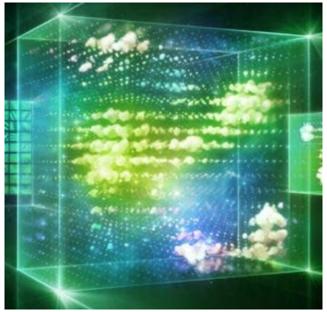

Healthcare


Intelligent Video Analytics


Robotics

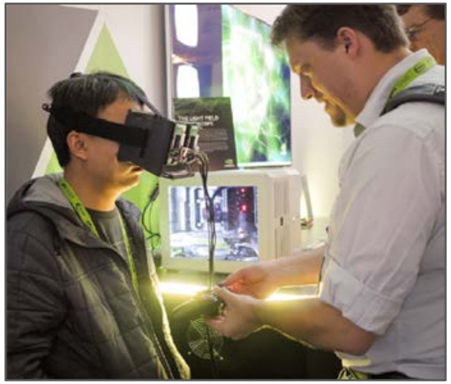

Game Development & Digital Content

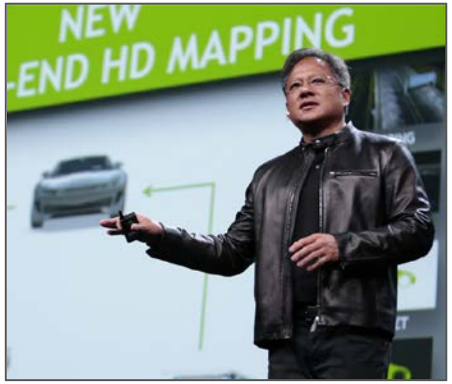

Finance


Accelerated Computing


Virtual Reality

GPU TECHNOLOGY CONFERENCE





ADVANCE YOUR DEEP LEARNING TRAINING AT GTC

Don't miss the world's most important event for GPU developers

CALL FOR SUBMISSIONS

Showcase your brilliant work **online** at GTC 2021 - **date TBD**

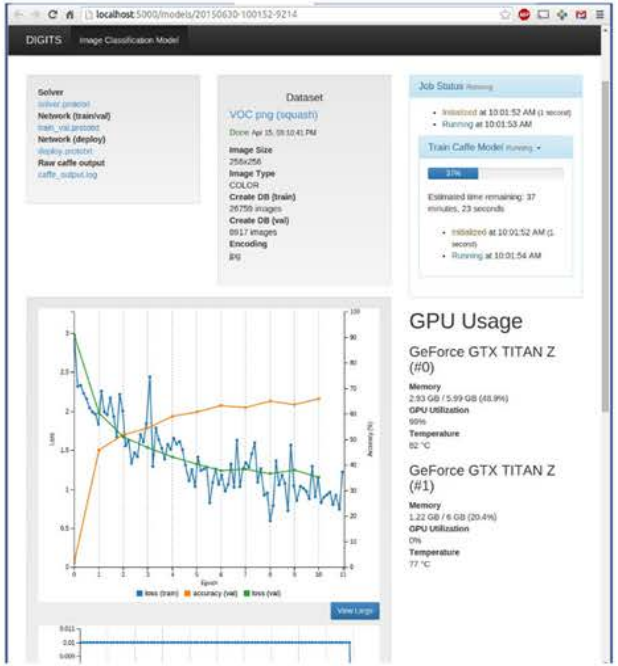
https://www.nvidia.com/en-us/gtc/call-for-submissions/

DEEP LEARNING SOFTWARE

NVIDIA DIGITS™

Interactively manage data and train deep learning models for image classification without the need to write code.

Learn more



Deep Learning Frameworks

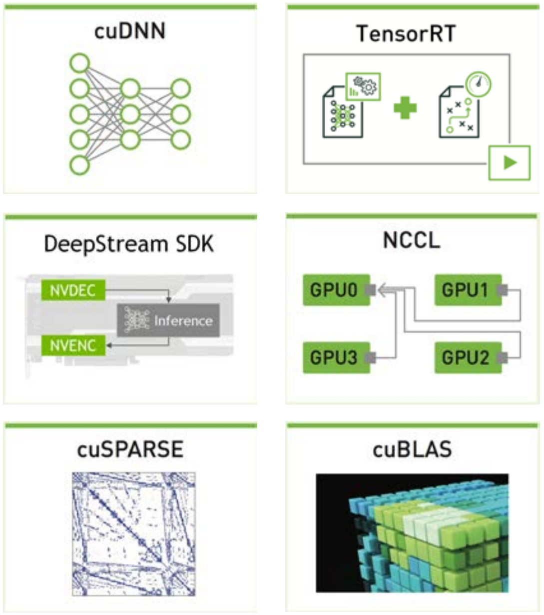
Design and train deep learning models using a high-level interface. Choose a deep learning framework that best suits your needs based on your choice of programming language, platform, and target application.

Learn more

Caffe2 Chainer DL4J Deeplearning4j
MINERVA mxnet Purine
KERAS Microsoft Cognitive Toolkit MatConvNet
TensorFlow theano torch

NVIDIA Deep Learning SDK

This SDK delivers high- performance multi-GPU acceleration and industry-vetted deep learning algorithms, and is designed for easy drop-in acceleration for deep learning frameworks.



developer.nvidia.com/deep-learning

END-TO-END PRODUCT FAMILY

TRAINING

FULLY INTERGRATED DL SUPERCOMPUTER

DGX-1 & DGX Station

DESKTOP

Titan X Pascal

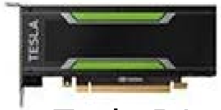
DATA CENTER

Tesla P100
Tesla V100

INFERENCE

DATA CENTER

Tesla P100/V100



Tesla P4

AUTOMOTIVE

Drive PX2

EMBEDDED

Jetson TX1

CHALLENGES

Deep Learning Needs	Why
Data Scientists	New computing model
Latest Algorithms	Rapidly evolving
Fast Training	Impossible -> Practical
Deployment Platforms	Must be available everywhere

CHALLENGES

Deep Learning Needs	NVIDIA Delivers
Data Scientists	Deep Learning Institute, GTC, DIGITS
Latest Algorithms	DL SDK, GPU-Accelerated Frameworks
Fast Training	DGX, V100, P100, TITAN X, **A100(!)**
Deployment Platforms	TensorRT, P100, P4, Drive PX, Jetson

READY TO GET STARTED?

Project Checklist

1. What problem are you solving, what are the DL tasks?
2. What data do you have/need, and how is it labeled?
3. Which deep learning framework & tools will you use?
4. On what platform(s) will you train and deploy?

WHAT PROBLEM ARE YOU SOLVING?

Defining the AI/DL Tasks

INPUTS	QUESTION	AI/DL TASK	EXAMPLE OUTPUTS
Text Data, Images, Video, Audio	Is "it" present or not?	Detection	Cancer Detection
	What type of thing is "it"?	Classification	Tumor Identification
	To what extent is "it" present?	Segmentation	Tumor Size/Shape Analysis
	What is the likely outcome?	Prediction	Survivability Prediction
	What will likely satisfy the objective?	Recommendation	Therapy Recommendation

SELECTING A DEEP LEARNING FRAMEWORK

Considerations

1. Type of problem
2. Training & deployment platforms
3. DNN models available, layer types supported
4. Latest algos & GPU acceleration: cuDNN, NCCL, etc.
5. Usage model/interfaces: GUI, command line, programming language, etc.
6. Easy to install and get started: containers, docs, code samples, tutorials, …
7. Enterprise integration, vendors, ecosystem

START SIMPLE, LEARN FAST

WHAT'S NEXT?

Learn More

Listen to the NVIDIA AI Podcast
Review examples of AI in action

Take a Self-Paced Lab

www.nvidia.com/dlilabs

Attend an Instructor-Led Workshop

Or request a workshop onsite
www.nvidia.com/dli

Join the Developer Program

https://developer.nvidia.com/join

Contact us at nvdli@nvidia.com

DEEP
LEARNING
INSTITUTE

www.nvidia.com/dli

Deep Learning Methods – Lecture 2 — Data, Datasets, Exploratory Data Analysis (EDA)

Yuri Gordienko, DLI Certified Instructor

DEEP LEARNING INSTITUTE

DLI Mission

Training you to solve the world's most challenging problems.

- Developers, data scientists and engineers
- Self-driving cars, healthcare and robotics
- Training, optimizing, and deploying deep neural networks

NVIDIA DEEP LEARNING INSTITUTE

This Lecture Overview

- Understand different types and formats of data
- Be able to soundly select appropriate data
- Have awareness of biases that exist
- Be able to refine questions to suite your true inquiry
- Understand how to parse text with regular expressions

Definitions

Definitions - Data

- Factual information (such as measurements or statistics) used as a basis for reasoning, discussion, or calculation

- Information in digital form that can be transmitted or processed

- Information output by a sensing device or organ that includes both useful and irrelevant or redundant information and must be processed to be meaningful

Definitions — Datum, Data, Dataset

- **Datum** - A single piece of information, which can be treated as an **observation**;

- **Data** - The **plural** of datum; multiple observations;

- **Dataset** - A homogenous **collection** of data (each datum must have the same focus)

Definitions — Data Sources

- Factual information (such as measurements or statistics) used as a basis for reasoning, discussion, or calculation

- Information in digital form that can be transmitted or processed

- Information from sensors or organs that includes both useful and irrelevant or redundant information and must be processed to be meaningful

Definitions — Data Sources - Use Cases

- Measurements from a thermometer every hour for a year
- Counts from a person who tracks the days that a particular hummingbird visits his birdfeeder across an entire year
- Tweets from Elon Musk
- Readouts from a mysterious sensor, for example, from wundergorund.com

Definitions — Data Sources - Use Cases

- Measurements from a thermometer every hour for a year
  - **Probably inaccurate data**
- Counts from a person who tracks the days that a particular hummingbird visits his birdfeeder across an entire year
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Definitions — Data Sources - Use Cases

- Measurements from a thermometer every hour for a year
  - **Probably inaccurate data**
- Counts from a person who tracks the days that a particular hummingbird visits his birdfeeder across an entire year
  - **Probably missing data**
- Tweets from Elon Musk

- Readouts from a mysterious sensor, for example, from wundergorund.com

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    - **Probably not 100% factually true**
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Data Processing

-

Workflow

-

Datasets

Recall -> Data Processing from Scientific Point of View

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Visualize the Results

Dataset — Important Questions!

- What data is necessary to **answer** our question?
- How **difficult** is it to analyze a dataset?
- Is the source **authoritative**? (.com, .net, .org, .gov, .name)
- **Comprehensive** data vs sampled data?
- **Biases**
- What is the allowed usage of data under its **license**?
- **Who** collected the data?
- **When** was the data collected?
- **How** was the data collected?
- **How** is the data **formatted**?
- **Ethical** issues?

Dataset — Examples

- Open access data

29 billion words in
55 million articles in 309 languages

- Collected and digitized as part of generalized procedures of an institution

~610 million tweets per day

https://www.internetlivestats.com/twitter-statistics/

Dataset — Important Questions!

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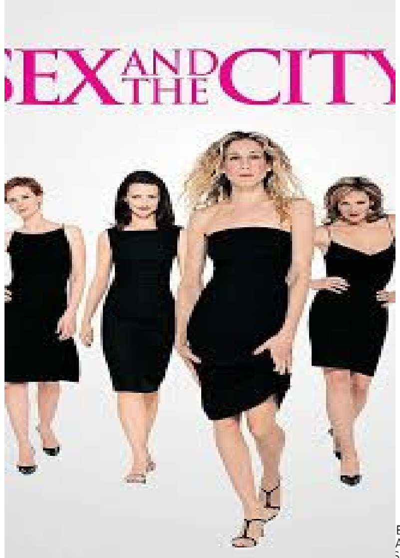
- **How** is the data **formatted**?
- **Ethical** issues?

Dataset — Common Problems!

- **Omission**: Using only arguments from one side
- **Source selection**: Include more sources or more authoritative sources for one side over the other
- **Story selection**: Regularly including stories that agree or reinforce the arguments of one side
- **Labelling**:
- Using only arguments from one side
- Labeling people on one side of the argument with labels and not the other
- **Spin**: Story provides only one interpretation of the events

Dataset —
Common Problems — IMDb Example

- Registered users rate films 1-10 stars; they are an **overrepresented subpopulation** relative to the **general population**.
- Registered users who rate movies in their free time **over represents** a specific segment of the **general population**.

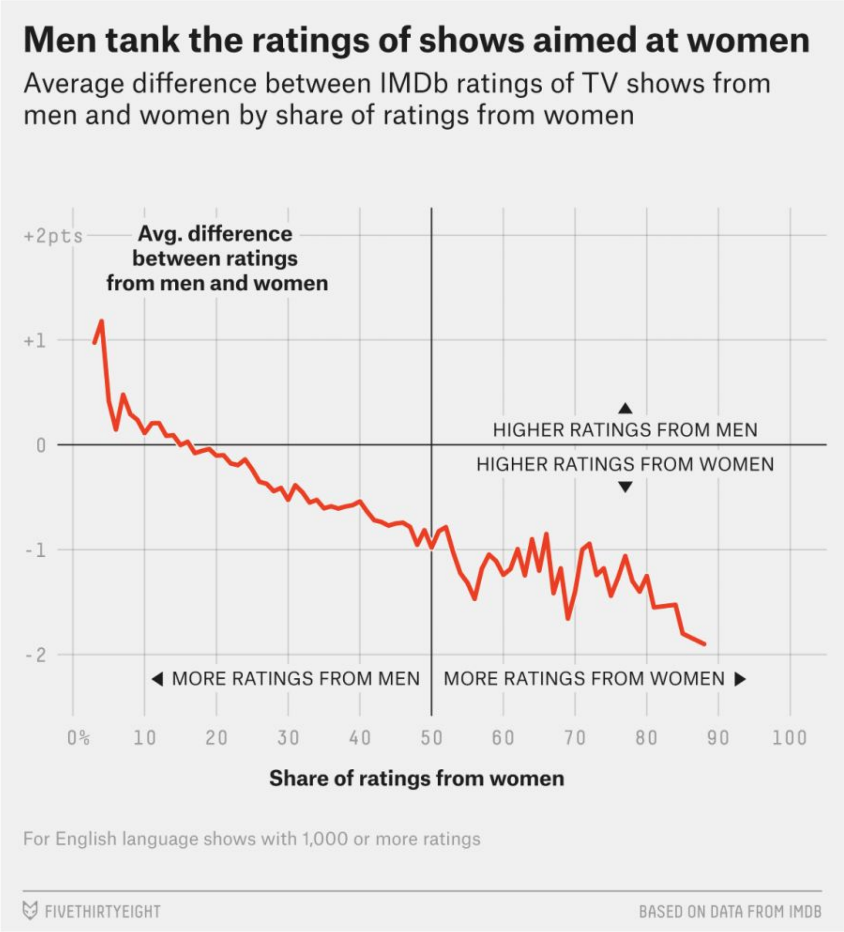


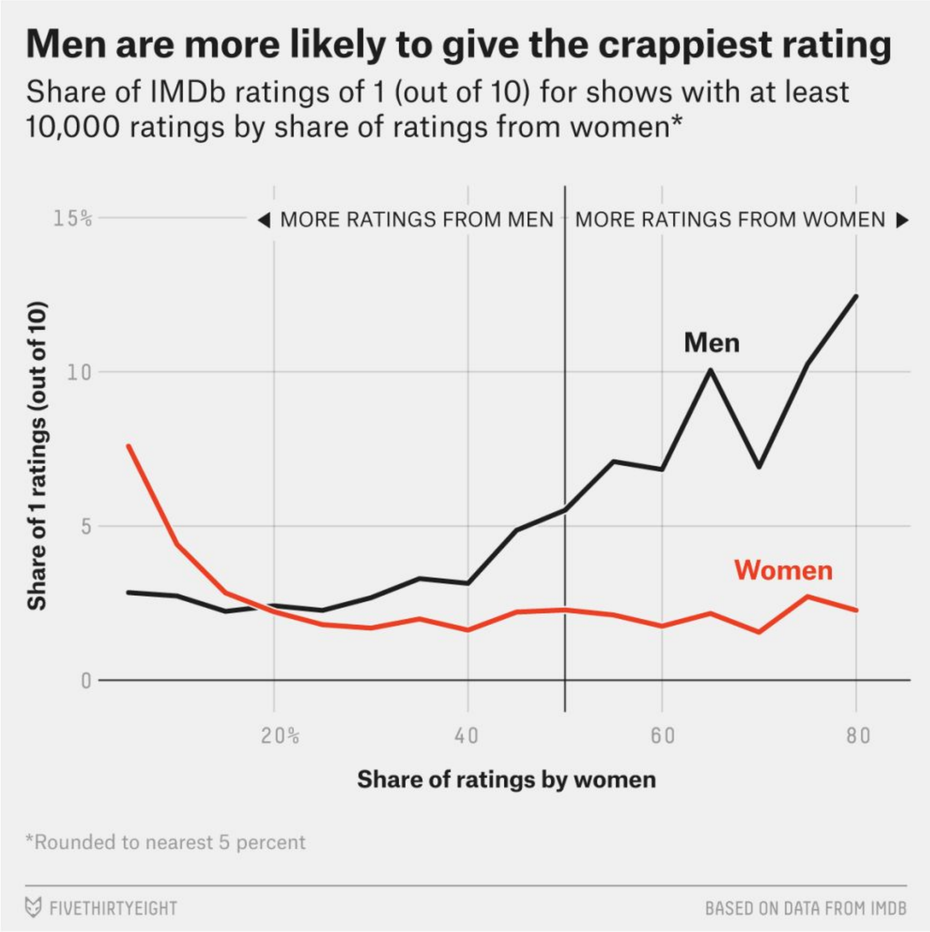
<u>**Example**</u>: “Men Are Sabotaging The Online Reviews Of TV Shows Aimed At Women”

60% who rated “*Sex in the City*” were women.

Women gave it a **8.1**, men gave it **5.8**.

Dataset — Common Problems — IMDb Example





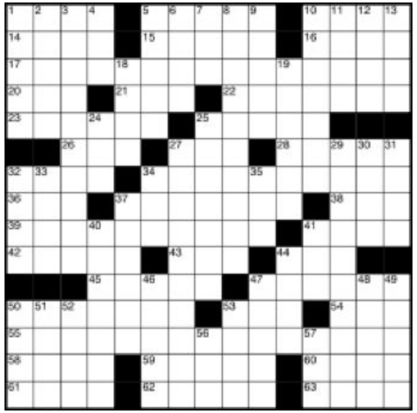
Dataset —
Common Problems — Resume

- Nearly all datasets **involve a human** in some way or another.
- This means that **nearly all** datasets probably has **bias**.
- Our goal: to **minimize the bias** as much as possible.
- For **models** (later), the **same** advice should be applied.

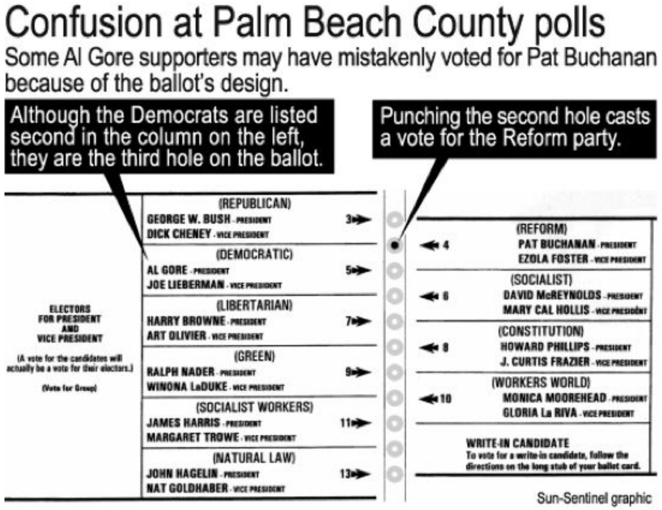
Datasets — Easy vs. Hard

hard for computers

easy for computers



	A	B	C
1	name	age	height
2	Michael	46	5'9"
3	Jim	31	6'0"
4	Pam	29	5'7"
5	Meredith	53	5'6"
6	Dwight	35	5'10"



easy for people ⟷ hard for people

Dataset — Easy vs. Hard

Computers are better at ‘understanding’ photos and videos, and text and numbers are much easier.

Why?

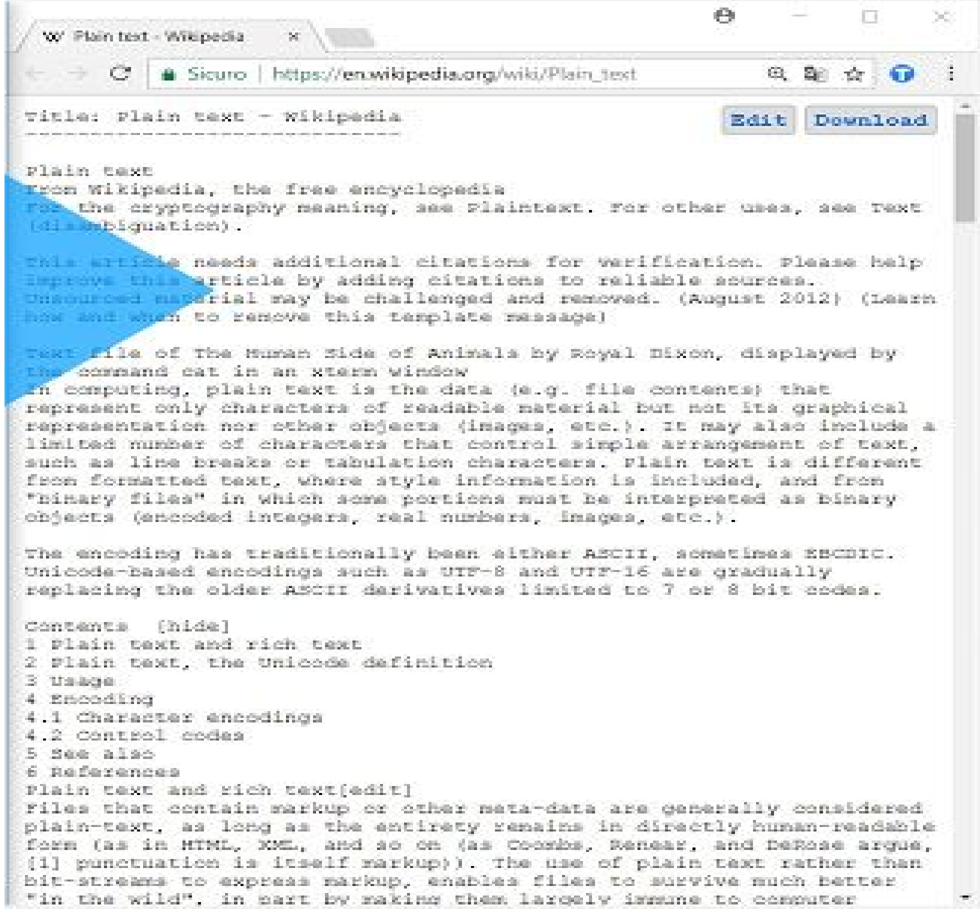
Structured data (e.g., spreadsheet formatted data)

is **much easier** than

unstructured data (e.g., free-flowing essays)

Dataset — Text Formats - Plain

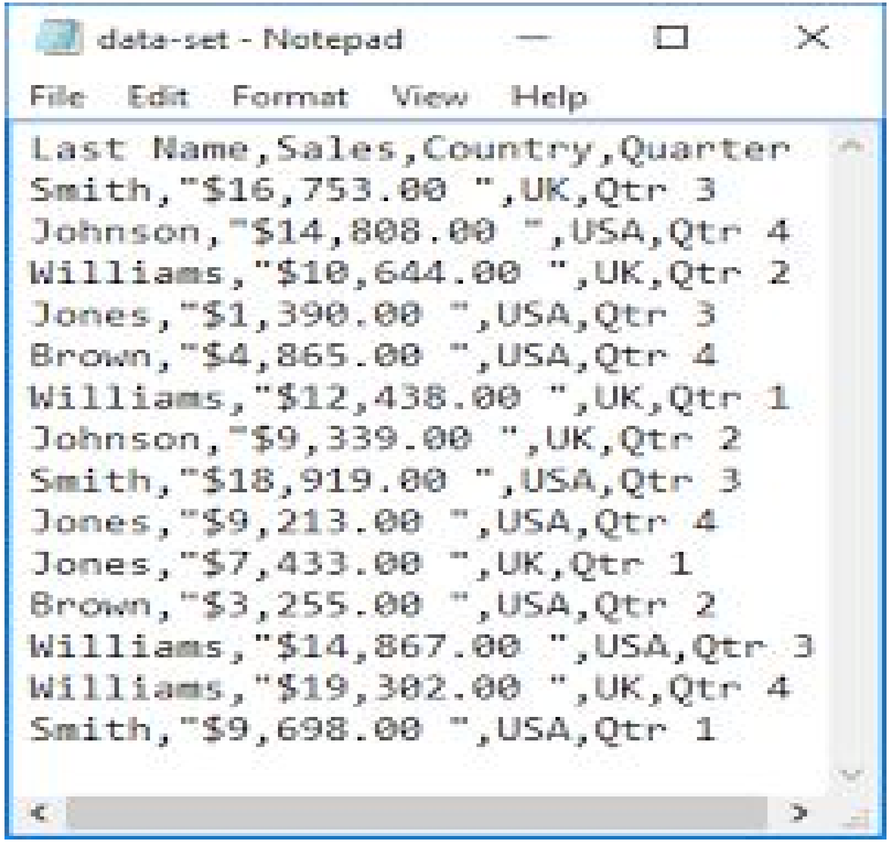
- File extension ends in .txt (generally)
- **No formatting:** font type, font size, color, etc.
- **Text** is **delimited** (position provided) by whitespace characters (space, tab, return)



Dataset — Text Formats - Plain

Delimiter: The character that separates each value

- Comma-separated (.csv)
- Tab-separated (.tsv)

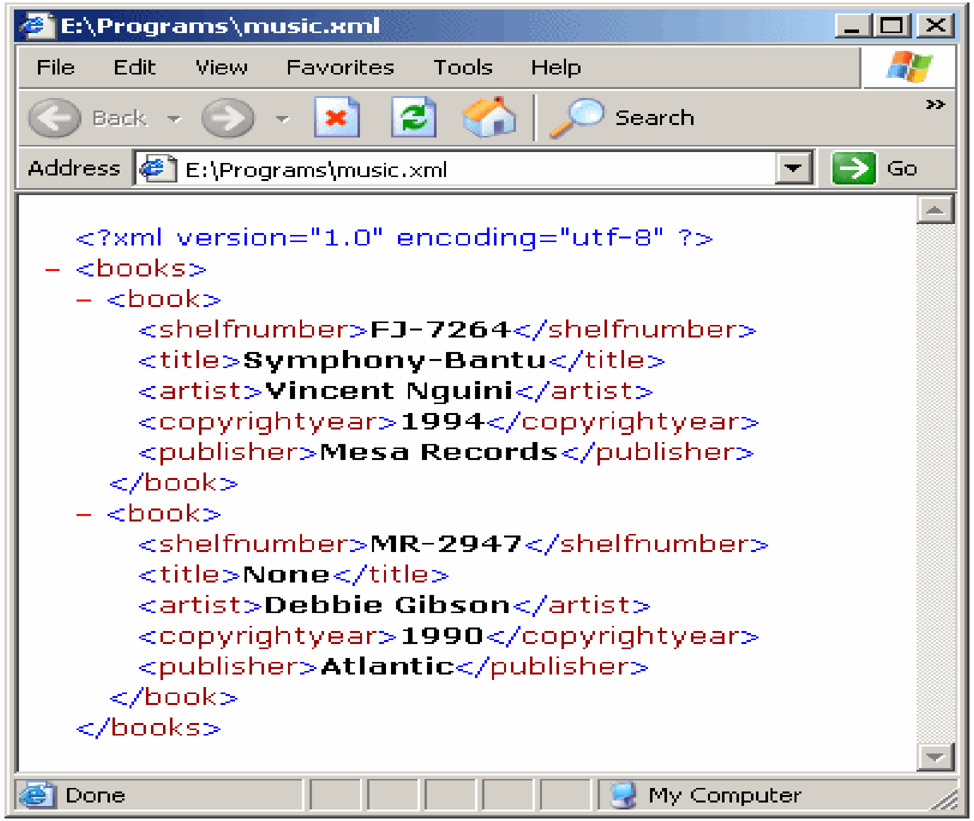


Dataset — Text Formats - XML

Extensible Markup Language (XML) is a markup language that defines a set of rules for encoding documents in a format that is both human-readable and machine-readable.

XML (.xml)

The colors aren’t actually stored in the file, the editor just adds them on your screen to help make it look prettier.



Dataset — Text Formats - JSON

JSON (JavaScript Object Notation) is an open standard file format, and data interchange format, that uses human-readable text to store and transmit data objects consisting of attribute–value pairs and array data types.


```
{
    hey: "guy",
    anumber: 243,
  - anobject: {
        whoa: "nuts",
      - anarray: [
            1,
            2,
            "thr<h1>ee"
        ],
        more: "stuff"
    },
    awesome: true,
    bogus: false,
    meaning: null,
    japanese: "明日がある。",
    link: http://jsonview.com,
    notLink: "http://jsonview.com is great"
}
```


- Like XML, data is annotated
- A nesting of key-value pairs
- Can be more space efficient than XML

Dataset — Text Formats - Resume

- They can all express the same content
- Plain Text doesn’t have structure, but is universally robust
- XML is the most verbose, harder to parse
- JSON doesn’t have </stuff_here> end tags
- JSON is more succinct than XML (easier to parse)

Data Processing
-
Workflow
-
Starting Question

Recall -> Data Processing from Scientific Point of View

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Visualize the Results

Starting Question — Concrete

- It’s crucial for your starting question (**assumption**) of data research to have **concrete defined terms that can be proven** true or false.

- **Assumption:** “Voting turnout is high”

- Where? Ukraine? World-wide?
- What type of voting? Presidential races, local elections?
- What is our metric? Number of total votes. Percentage of the population?
- What’s our actual time scale?

Starting Question — Resume

- The **more specific** your questions, the **more meaningful** your results can be.

- Aware of **biases** (both in your data and in your modelling) as much as you can. Doing so will ensure you are providing results that **accurately represent reality**, leading to more equitable interpretations and uses of your work.

- This is immensely important, … for Data Science will **only continue to play** an increasingly powerful and **influential role** in our society and world at large.

Data Processing

-

Workflow

-

Parsing Data

Where do data come from?

- **Internal sources:** already collected by or is part of the overall data collection of you organization.
  For example: business-centric data that is available in the organization data base to record day to day operations; scientific or experimental data.
- **Existing External Sources:** available in ready to read format from an outside source for free or for a fee.
  For example: public government databases, stock market data, Yelp reviews, [your favorite sport]-reference.
- **External Sources Requiring Collection Efforts**: available from external source but acquisition requires special processing.
  For example: data appearing only in print form, or data on websites.

Ways to gather online data

- How to get data generated, published or hosted online:
- **API (Application Programming Interface):** using a prebuilt set of functions developed by a company to access their services. Often pay to use. For example: Google Map API, Facebook API, Twitter API
- **RSS (Rich Site Summary):** summarizes frequently updated online content in standard format. Free to read if the site has one. For example: news-related sites, blogs
- **Web scraping:** using software, scripts or by-hand extracting data from what is displayed on a page or what is contained in the HTML file (often in tables).

Web scraping

- **Why do it?** Older government or smaller news sites might not have APIs for accessing data, or publish RSS feeds or have databases for download. Or, you don't want to pay to use the API or the database.
- You just want to explore: Are you violating their terms of service? Privacy concerns for website and their clients?
- You want to publish your analysis or product: Do they have an API or fee that you are bypassing? Are they willing to share this data? Are you violating their terms of service? Are there privacy concerns?

Types of data

- What kind of values are in your data (data types)?
-
- Simple or atomic:
- **Numeric:** integers, floats
- **Boolean:** binary or true false values
- **Strings:** sequence of symbols

Types of data - 2

- What kind of values are in your data (data types)? Compound, composed of a bunch of atomic types:
- **Date and time:** compound value with a specific structure
- **Lists:** a list is a sequence of values
- **Dictionaries:** A dictionary is a collection of key-value pairs, a pair of values *x* : *y* where *x* is usually a string called the key representing the “name” of the entry, and *y* is a value of any type.
- Example: Student record: what are *x* and *y*?
- First: Kevin
- Last: Rader
- Classes: [CS-109A, STAT139]

Data storage

- How is your data represented and stored (data format)?
- **Tabular Data:** a dataset that is a two-dimensional table, where each row typically represents a single data record, and each column represents one type of measurement (csv, dat, xlsx, etc.).
- **Structured Data:** each data record is presented in a form of a [possibly complex and multi-tiered] dictionary (json, xml, etc.)
- **Semistructured Data:** not all records are represented by the same set of keys or some data records are not represented using the key-value pair structure.

Tabular Data

- In tabular data, we expect each record or observation to represent a set of measurements of a single object or event.

First Look At The Data

In [27]:
```
hubway_data = pd.read_csv('hubway_trips.csv', low_memory=False)
hubway_data.head()
```

Out[27]:

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_da
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0
2	3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/2011 10:34:00	23.0	B00456	Registered	'02108	1943.0
3	4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/2011 10:36:00	23.0	B00554	Registered	'02116	1981.0
4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0

Tabular Data

- Each type of measurement is called a **variable** or an **attribute** of the data (e.g. `seq_id`, `status` and `duration` are variables or attributes). The number of attributes is called the **dimension**. These are often called **features**.
- We expect each table to contain a set of **records** or **observations** of the same kind of object or event (e.g. our table above contains observations of rides/checkouts).

In [27]:
```
hubway_data = pd.read_csv('hubway_trips.csv', low_memory=False)
hubway_data.head()
```

Out[27]:

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_da
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0
2	3	10	Closed	56	7/28/2011	23.0	7/28/2011	23.0	B00456	Registered	'02108	1943.0

Data Types

- We’ll see later that it’s important to distinguish between classes of variables or attributes based on the type of values they can take on.

- **Quantitative variable:** is numerical and can be either:
- **discrete -** a finite number of values are possible in any bounded interval. For example: “Number of siblings” is a discrete variable
- **continuous -** an infinite number of values are possible in any bounded interval. For example: “Height” is a continuous variable
- **Categorical variable:** no inherent order among the values For example: “What kind of pet you have” is a categorical variable

Data Processing

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Workflow

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Exploration Data Analysis: Common Issues

Common Issues

- Common issues with data:
- **Missing** values: how do we fill in?
- **Wrong** values: how can we detect and correct?
- **Messy** format
- **Not usable**: the data cannot answer the question posed

Messy Data

The following is a table accounting for the number of produce deliveries over a weekend.

What are the variables in this dataset?

What object or event are we measuring?

	Friday	Saturday	Sunday
Morning	15	158	10
Afternoon	2	90	20
Evening	55	12	45

What's the issue?

How do we fix it?

Messy Data

We’re measuring individual deliveries; the variables are Time, Day, Number of Produce.

	Friday	Saturday	Sunday
Morning	15	158	10
Afternoon	2	90	20
Evening	55	12	45

Problem: each column header represents a single value rather than a variable.

Row headers are “hiding” the Day variable. The values of the variable, “Number of Produce”, is not recorded in a single column.

Fixing Messy Data

We need to reorganize the information to make explicit the event we're observing and the variables associated to this event.

ID	Time	Day	Number
1	Morning	Friday	15
2	Morning	Saturday	158
3	Morning	Sunday	10
4	Afternoon	Friday	2
5	Afternoon	Saturday	9
6	Afternoon	Sunday	20
7	Evening	Friday	55
8	Evening	Saturday	12
9	Evening	Sunday	45

Common Causes of Messiness

- Column headers are values, not variable names
- Variables are stored in both rows and columns
- Multiple variables are stored in one column/entry
- Multiple types of experimental units stored in same table
- In general, we want each file to correspond to a dataset, each column to represent a single variable and each row to represent a single observation.
- We want to **tabularize** the data. This makes Python happy.

Data Processing
-
Workflow
-
Data Exploration:
Descriptive Statistics

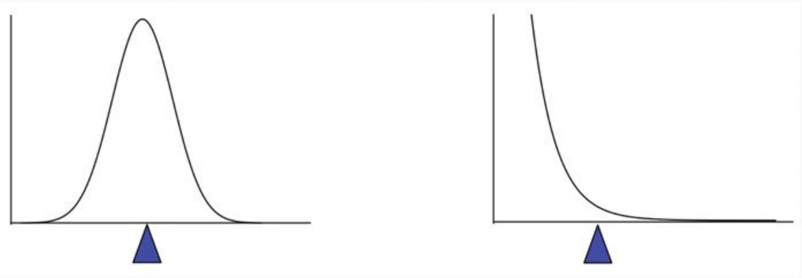
Basics of Sampling

- A **population** is the entire set of objects or events under study. Population can be hypothetical “all students” or all students in this class.
- A **sample** is a “representative” subset of the objects or events under study. Needed because it’s impossible or intractable to obtain or compute with population data.
  - Biases in samples:
- **Selection bias**: some subjects or records are more likely to be selected
- Volunteer/**nonresponse bias**: subjects or records who are not easily available are not represented

Sample - Mean

The **mean** of a set of *n* observations of a variable is denoted and is defined as:

$$\acute{x} = \frac{x_1 + x_2 + \ldots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$



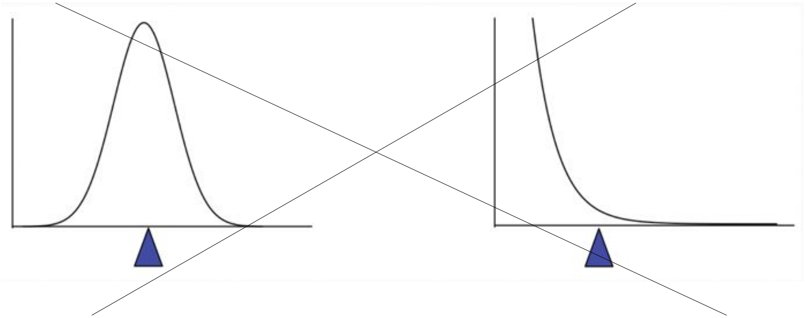
The **mean** describes what a “typical” sample value looks like, or where is the “center” of the distribution of the data.

<u>Note</u>: there is always uncertainty involved when calculating a sample mean to estimate a population mean.

Sample - Median

The **median** of a set of n number of observations in a sample, ordered by value, of a variable is is defined by

$$\text{Median} = \begin{cases} x_{(n+1)/2} & \text{if } n \text{ is odd} \\ \frac{x_{n/2} + x_{(n+1)/2}}{2} & \text{if } n \text{ is even} \end{cases}$$



Example (already in order):

Ages: 17, 19, 21, 22, 23, 23, 23, 38

Median = (22+23)/2 = 22.5

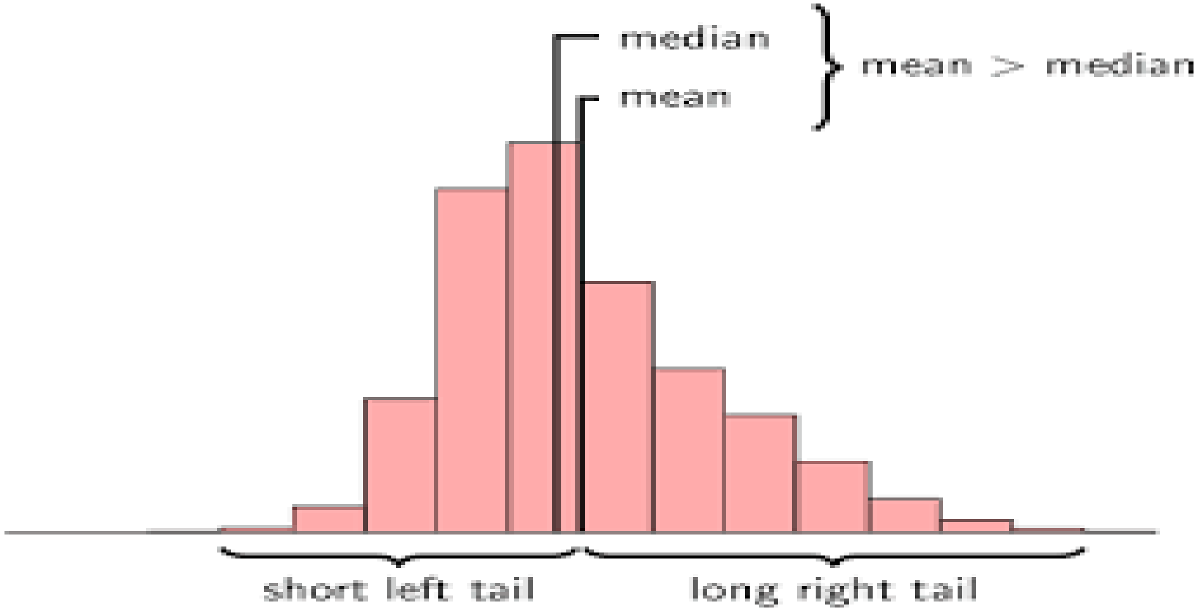
The median also describes what a typical observation looks like, or where is the center of the distribution of the sample of observations.

Sample - Mean vs. Median

The mean is sensitive to extreme values (**outliers**)

Mean, median, and skewness

The mean is sensitive to outliers:



The above distribution is called **right-skewed** since the mean is greater than the median. Note: **skewness** often

Computational time

How hard (in terms of algorithmic complexity) is it to calculate

the **mean**?

at most $O(n)$

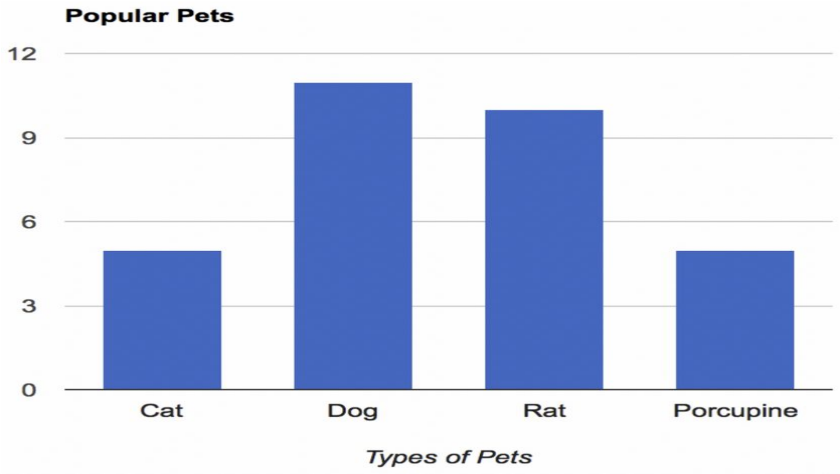
the **median**?

at most $O(n)$ or $O(n \log n)$

Note: Practicality of implementation should be considered!

Categorical Variables

For categorical variables, neither mean or median make sense. Why?



The mode might be a better way to find the most “representative” value.

Measures of Spread: Range

The spread of a sample of observations measures how well the mean or median describes the sample.

One way to measure spread of a sample of observations is via the **range**.

Range = Maximum Value - Minimum Value

Measures of Spread: Variance

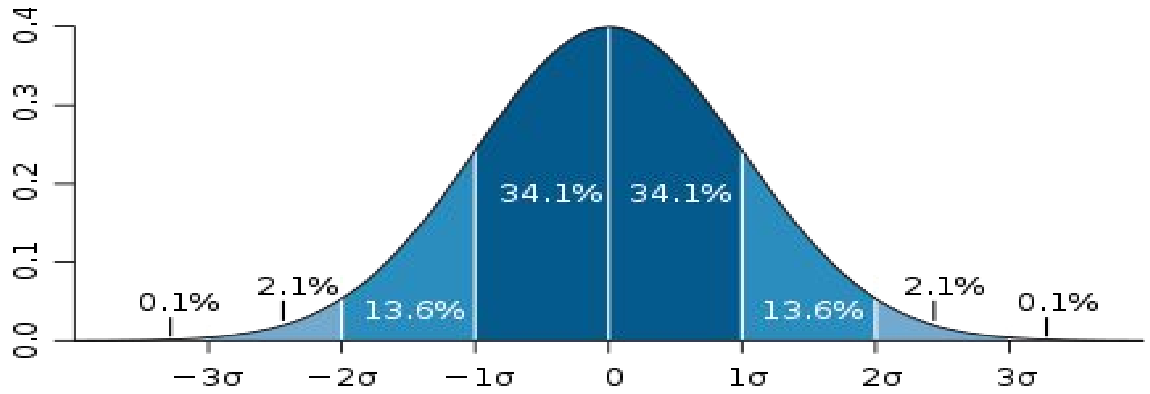
The (sample) **variance**, denoted σ^2, measures how much on average the sample values deviate from the mean:

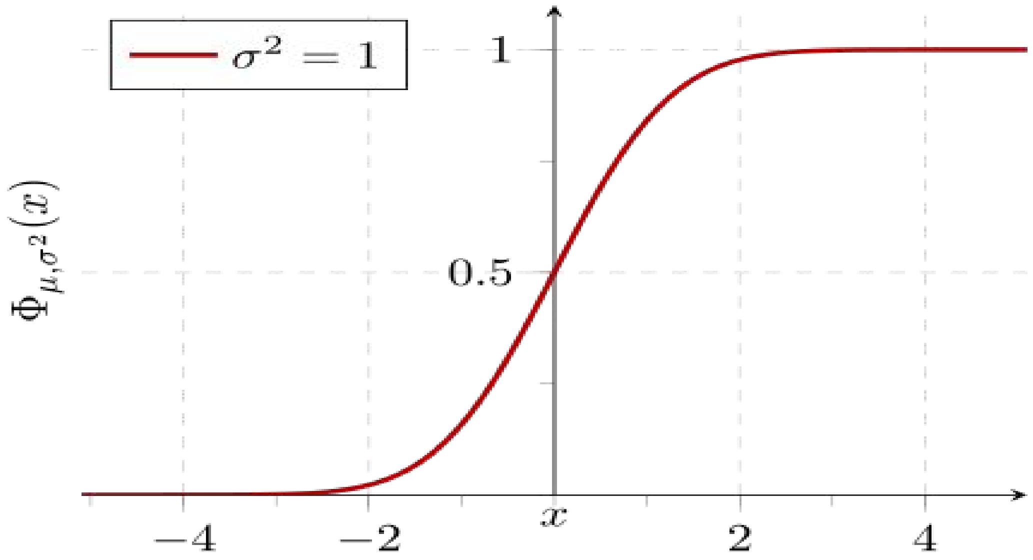
$$\sigma^2 \equiv \mathbf{D}(X) = \mathbf{E}[(X-\mu)^2] = \sum_x (x-\mu)^2 p(x)$$

Note: the difference measures the amount by which each *x* deviates from the mean.

Measures of Spread: Standard Deviation

The (sample) **standard deviation** is the square root of the variance





Data Processing

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Workflow

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Data Vizualization (for EDA)

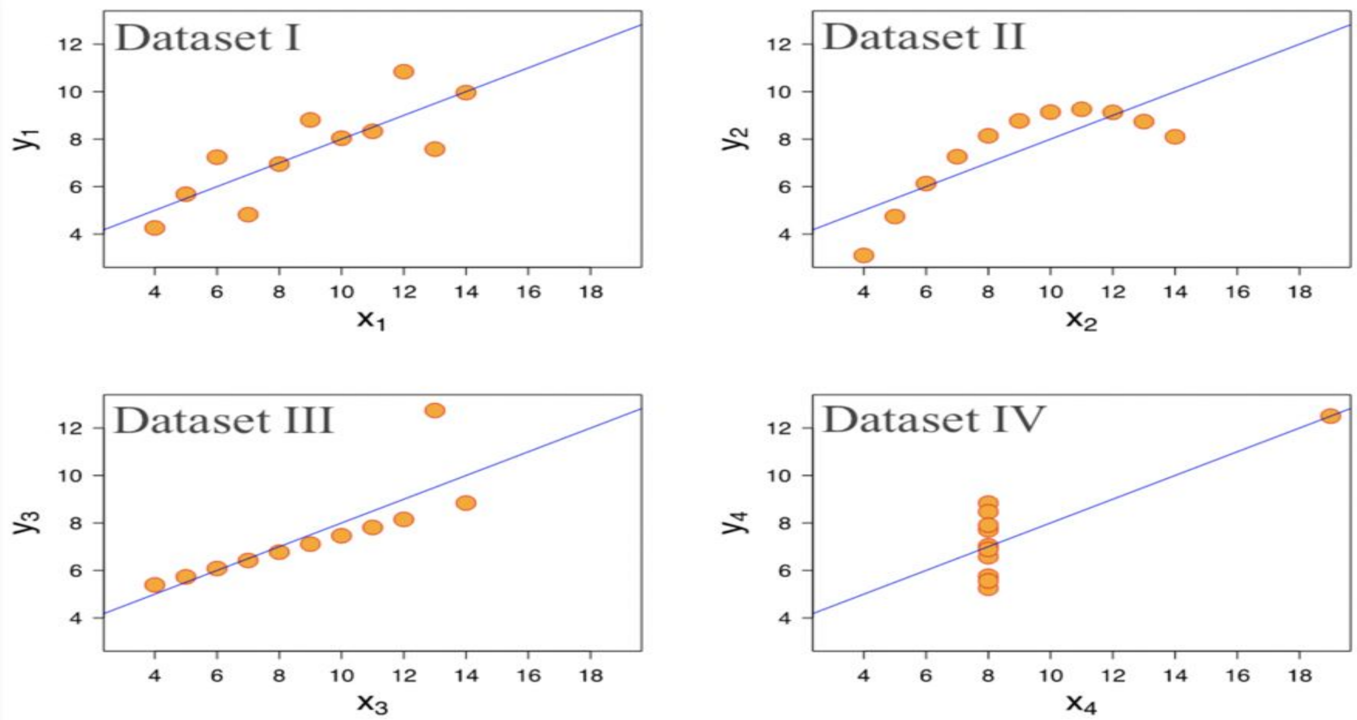
Anscombe's Quartet

- Anscombe's quartet comprises four data sets that have nearly identical simple descriptive statistics, yet have very different distributions and appear very different when graphed.

	Dataset I		Dataset II		Dataset III		Dataset IV	
	x	y	x	y	x	y	x	y
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.95	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.74	13	12.74	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.1	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.1	4	5.39	19	12.5
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Sum:	99.00	82.51	99.00	82.51	99.00	82.51	99.00	82.51
Avg:	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.50
Std:	3.32	2.03	3.32	2.03	3.32	2.03	3.32	2.03

Anscombe's Quartet

- They were constructed in 1973 by the statistician Francis Anscombe to demonstrate both the importance of graphing data before analyzing it and the effect of outliers and other influential observations on statistical properties.

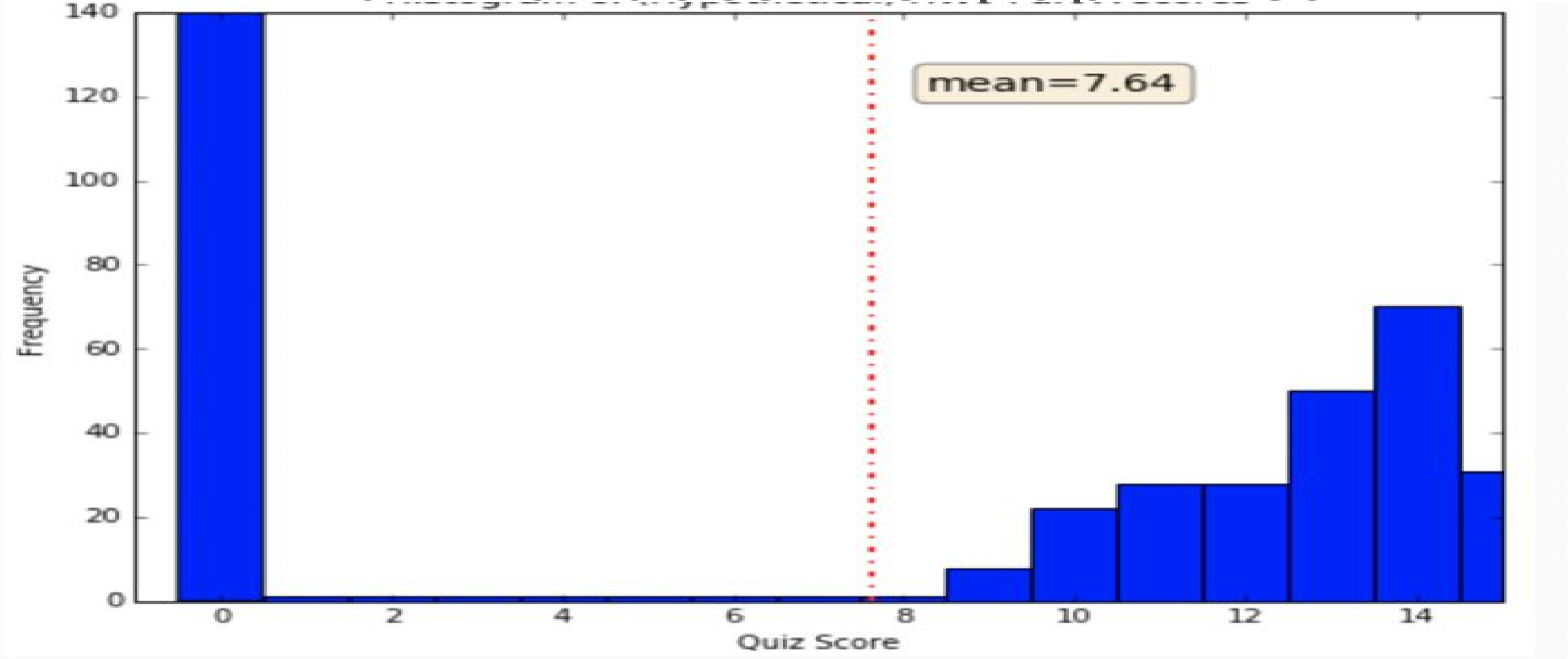


More Visualization Motivation

The average score for school class: 7.64

What does that mean?

And what does the graph mean?



More Visualization Motivation

Visualizations help us to analyze and explore the data:

- Identify hidden patterns and trends
- Formulate/test hypotheses
- Communicate any modeling results
- Present information and ideas succinctly
- Provide evidence and support
- Influence and persuade
- Determine the next step in analysis/modeling
-

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Other Types of Visualizations

What do you want your visualization to show about your data?

Distribution: how a variable or variables in the dataset distribute over a range of possible values.

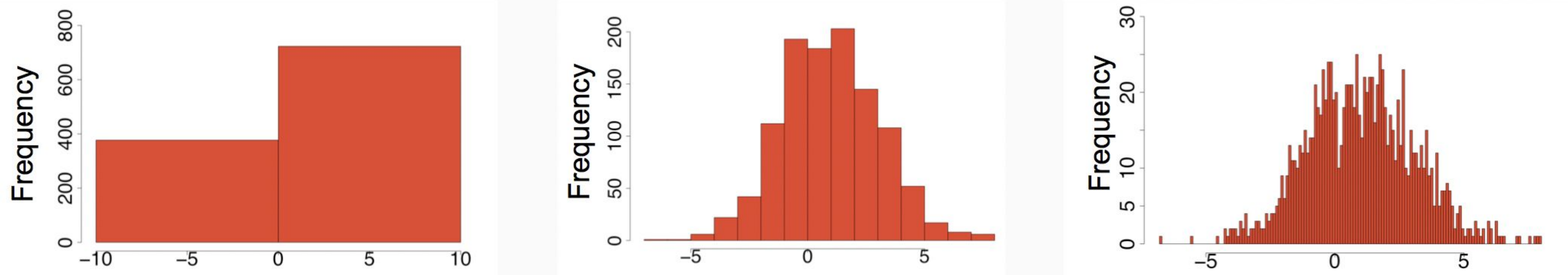
Relationship: how the values of multiple variables in the dataset relate

Composition: how the dataset breaks down into subgroups

Comparison: how trends in multiple variable or datasets compare

Histogram

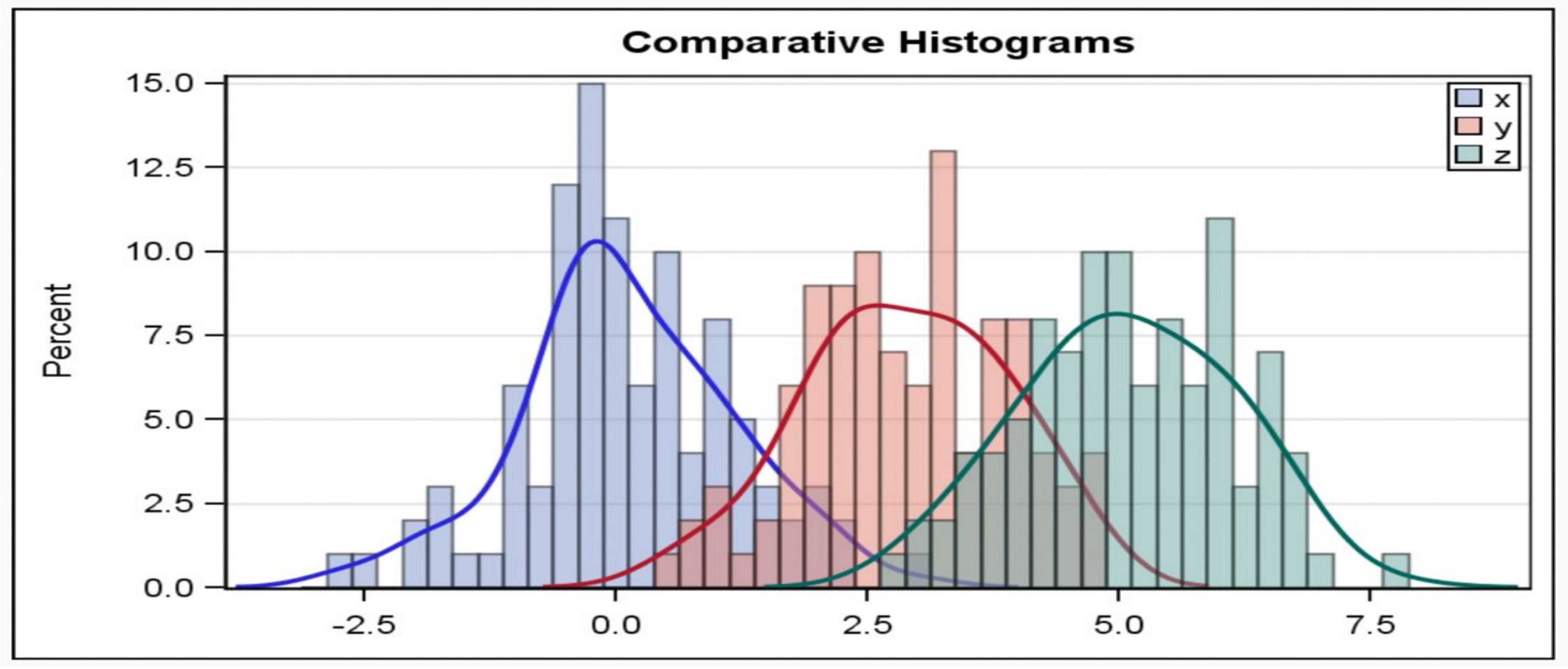
A **histogram** is a way to visualize how 1-dimensional data is distributed across certain values.



Note: Trends in histograms are sensitive to number of bins.

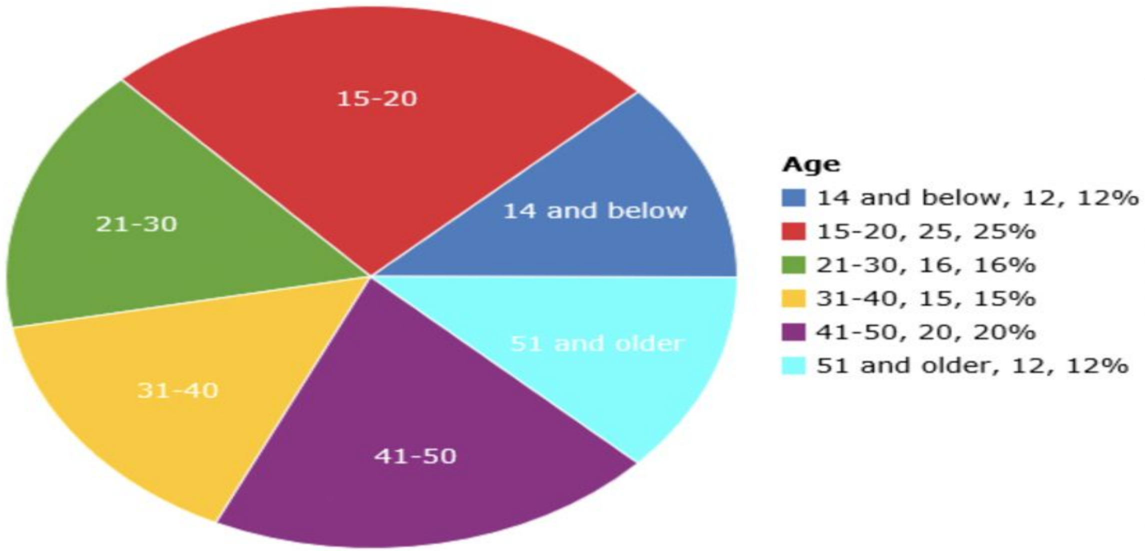
Multiple Histogram

Plotting **multiple histograms (**and **kernel density estimates** of the distribution, here) on the same axes is a way to visualize how different variables compare (or how a variable differs over specific groups).



Pie Chart

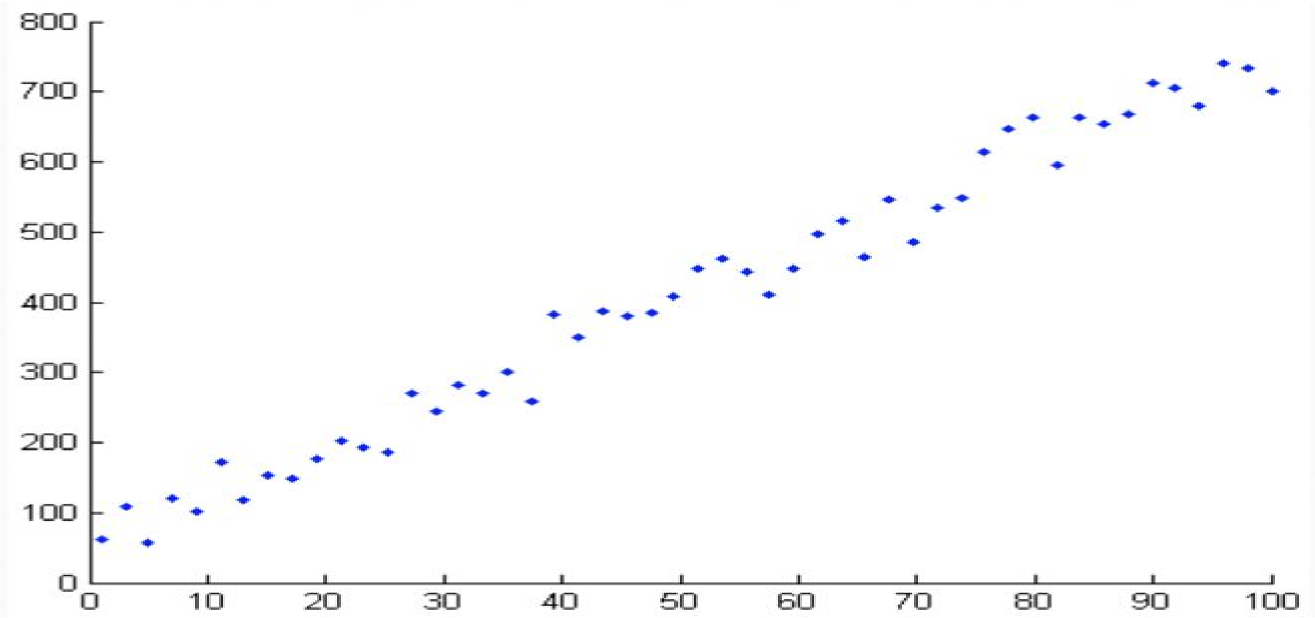
A **pie chart** is a way to visualize the static composition (aka, distribution) of a variable (or single group).



Pie charts are often frowned upon (and bar charts are used instead). Why?

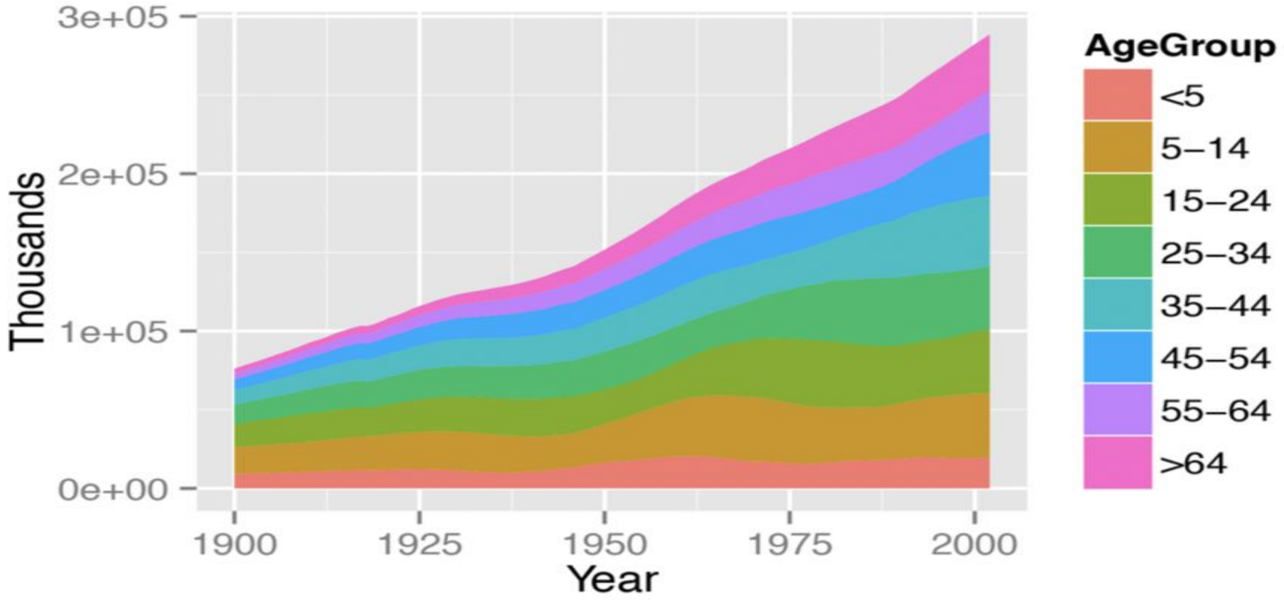
Scatter Plot

A **scatter plot** is a way to visualize the relationship between two different attributes of multi-dimensional data.



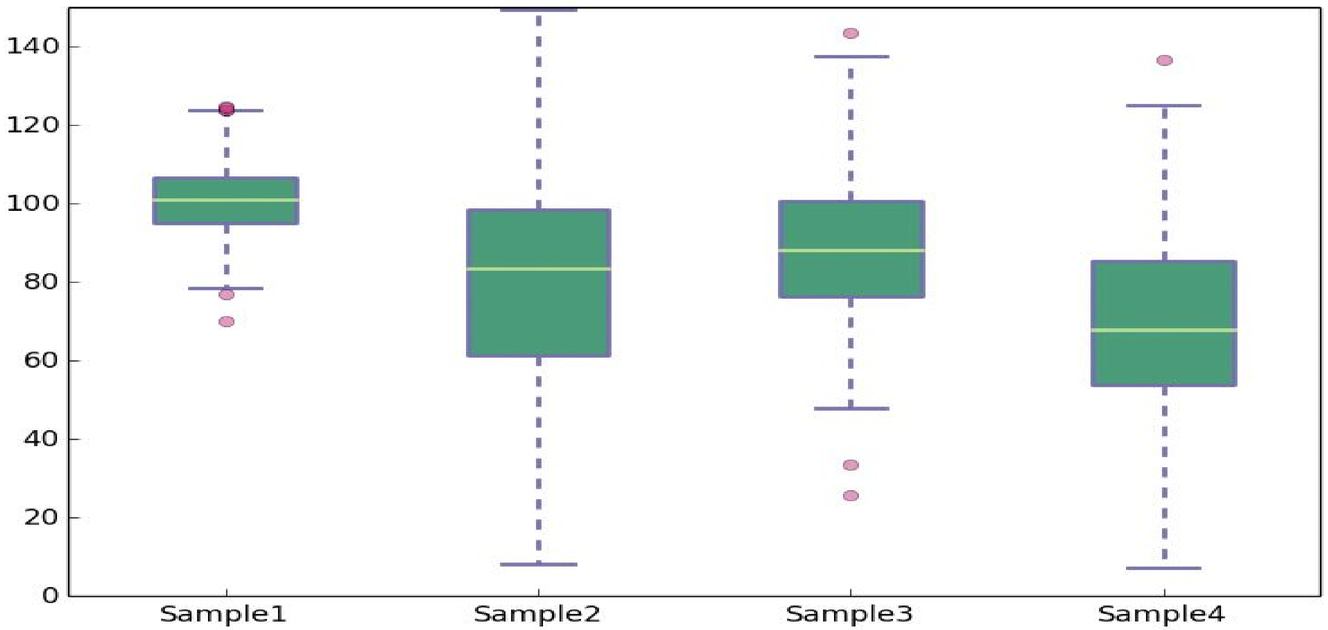
Stacked Area Plot

A **stacked area graph** is a way to visualize the composition of a group as it changes over time (or some other quantitative variable). This shows the relationship of a categorical variable (AgeGroup) to a quantitative variable (year).



Boxplot

A **boxplot** is a simplified visualization to compare a quantitative variable across groups. It highlights the range, quartiles, median and any outliers present in a data set.



Some Complex Cases

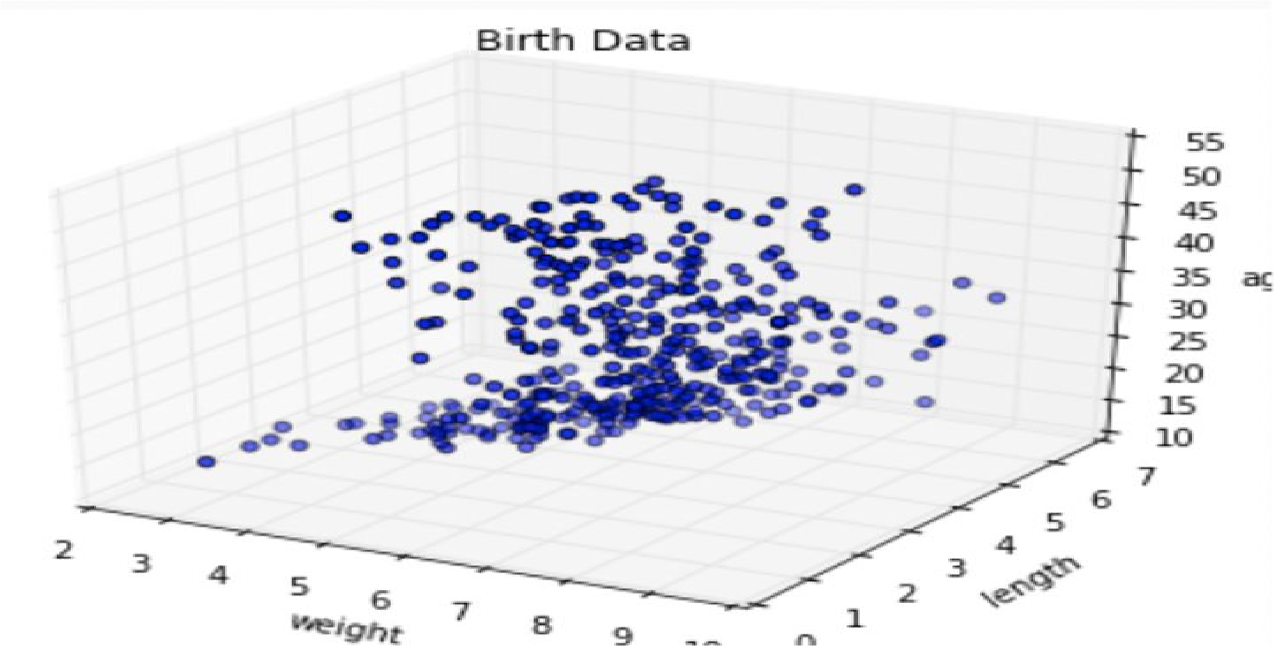
Often your dataset seem too complex to visualize:

Data is too **high dimensional** (how do you plot 100 variables on the same set of axes?)

Some variables are **categorical** (how do you plot values like Cat or No?)

Many Dimensions

When the data is high dimensional, a scatter plot of all data attributes can be impossible or unhelpful



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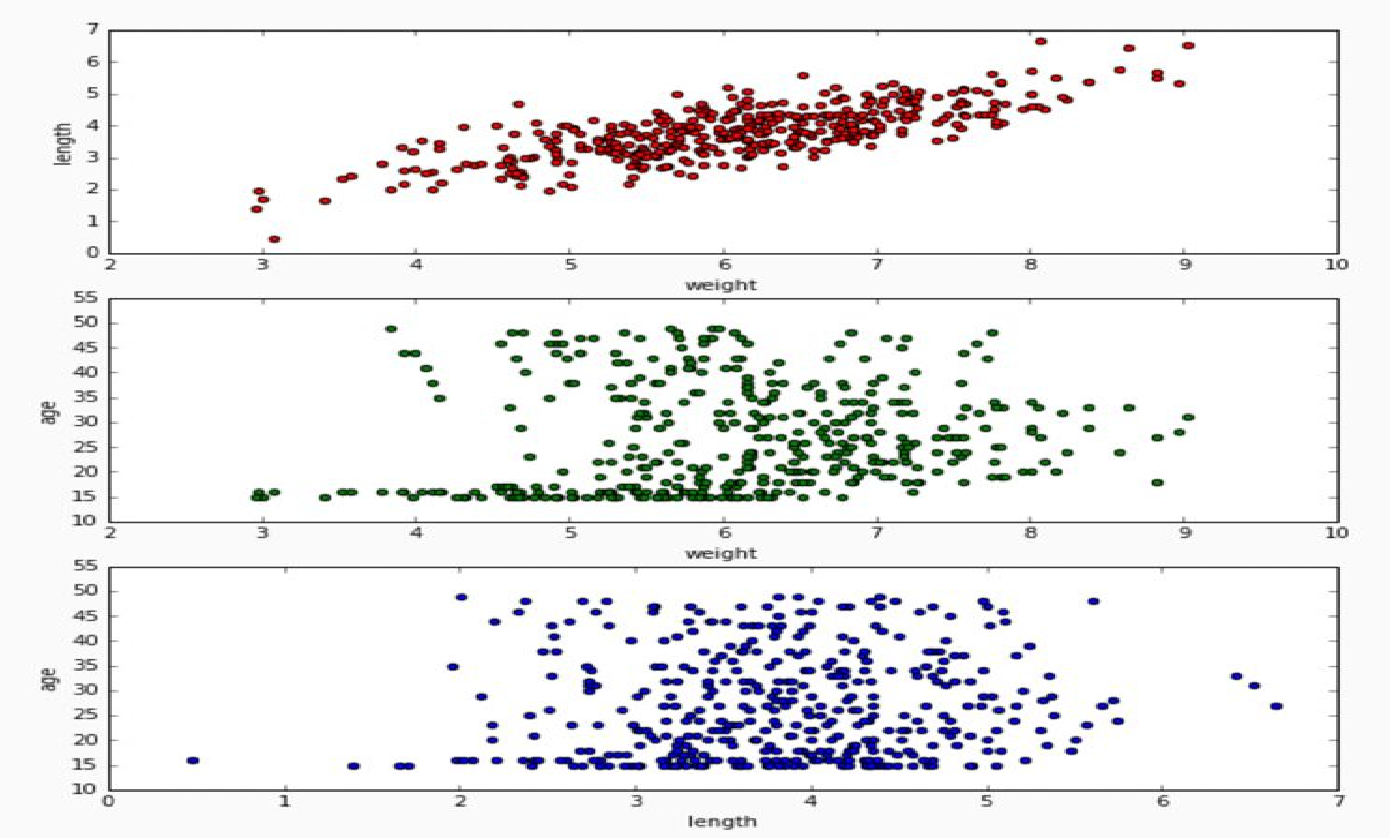
Reducing complexity

Relationships may be easier to spot by producing **multiple** plots of **lower** dimensionality.



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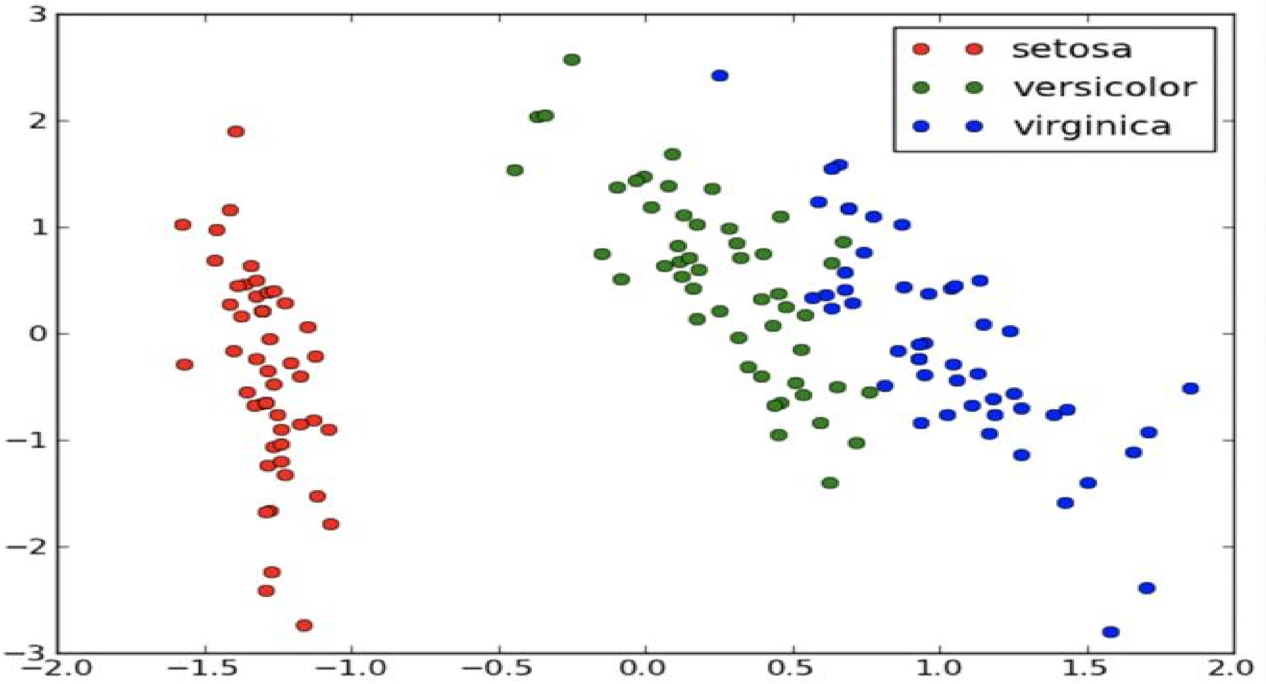
Reducing complexity

For 3D data, color coding a categorical attribute can be "effective"

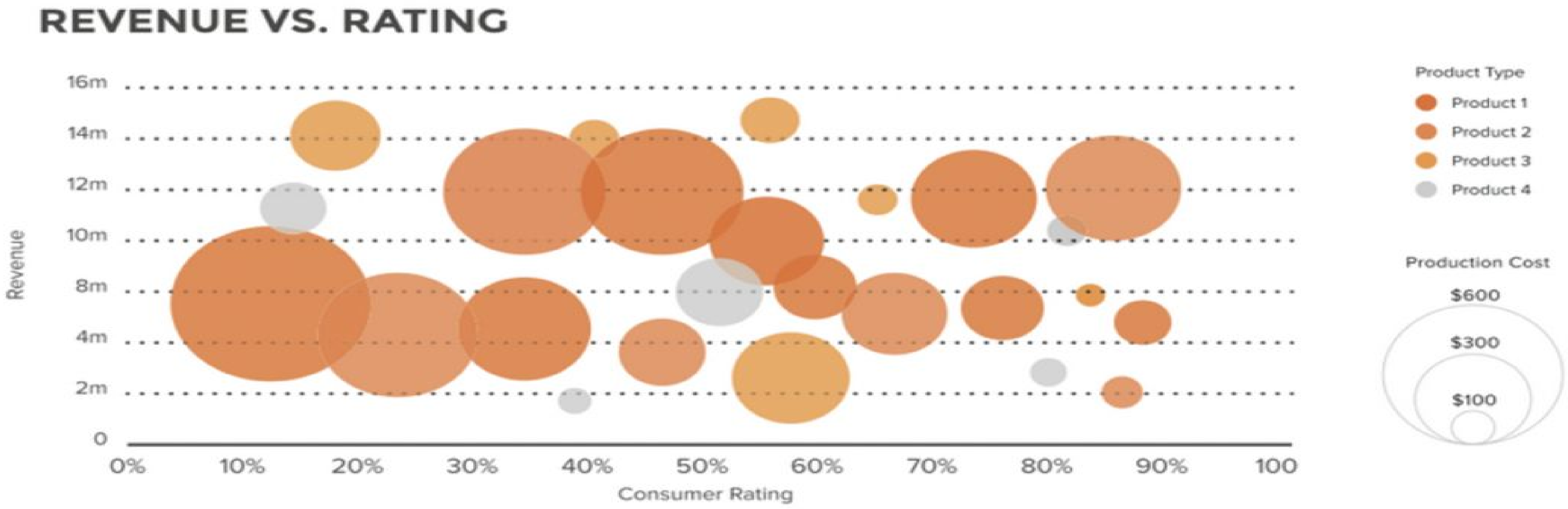


This visualizes a set of Iris measurements.
The variables are:
petal length,
sepal length,
Iris type (setosa, versicolor, virginica).

Except when it's not effective.

Reducing complexity — 3D Bubble Plot

For 3D data, a quantitative attribute can be encoded by size in a bubble chart.



The above visualizes a set of consumer products. The variables are: revenue, consumer rating, product type and product cost.

Data Processing

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Workflow

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EDA Example

Recall -> Data Processing -> EDA

Ask an interesting question

Get the Data — **EDA!**

Explore the Data

Model the Data

Visualize the Results

EDA for Hubway Data

Introduction: Hubway is metro-Boston's public bike share program, with more than 1600 bikes at 160+ stations across the Greater Boston area. Hubway is owned by four municipalities in the area.

By 2016, Hubway operated 185 stations and 1750 bicycles, with 5 million ride since launching in 2011.

The Data: In April 2017, Hubway held a Data Visualization Challenge at the Microsoft NERD Center in Cambridge, releasing 5 years of trip data.

The Question: What does the data tell us about the ride share

Customer Question -> Data Science Question

Original customer question:

'What does the data tell us about the ride share program?'

is not good for scientific investigation. Before we can improve the question, we should look at the data - **EDA!**

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_date	gender
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0	Male
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0	Male
2	3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/2011 10:34:00	23.0	B00456	Registered	'02108	1943.0	Male
3	4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/2011 10:36:00	23.0	B00554	Registered	'02116	1981.0	Female
4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0	Female

Based on the data, what kind of **concrete questions** can we ask?

The Data Exploration/Question Refinement Cycle - 1

Who? Who’s using the bikes?

Refine into specific hypotheses:

- More men or more women?
- Older or younger people?
- Subscribers or one time users?

The Data Exploration/Question Refinement Cycle - 2

Where? Where are bikes being checked out?

Refine into specific hypotheses:

- More in Boston than Cambridge?
- More in commercial or residential?
- More around tourist attractions?

Sometimes the data is given to you in pieces and must be merged!

The Data Exploration/Question Refinement Cycle - 3

When? When are the bikes being checked out?

Refine into specific hypotheses:

- More during the weekend than on the weekdays?
- More during rush hour?
- More during the summer than the fall?

Sometimes the feature you want to explore doesn't exist in the data, and must be engineered!

The Data Exploration/Question Refinement Cycle - 4

Why? For what reasons/activities are people checking out bikes?

Refine into specific hypotheses:

- More bikes are used for recreation than commute?
- More bikes are used for touristic purposes?
- Bikes are use to bypass traffic?

Do we have the data to answer these questions with reasonable certainty?

What data do we need to collect in order to answer these

The Data Exploration/Question Refinement Cycle - 5

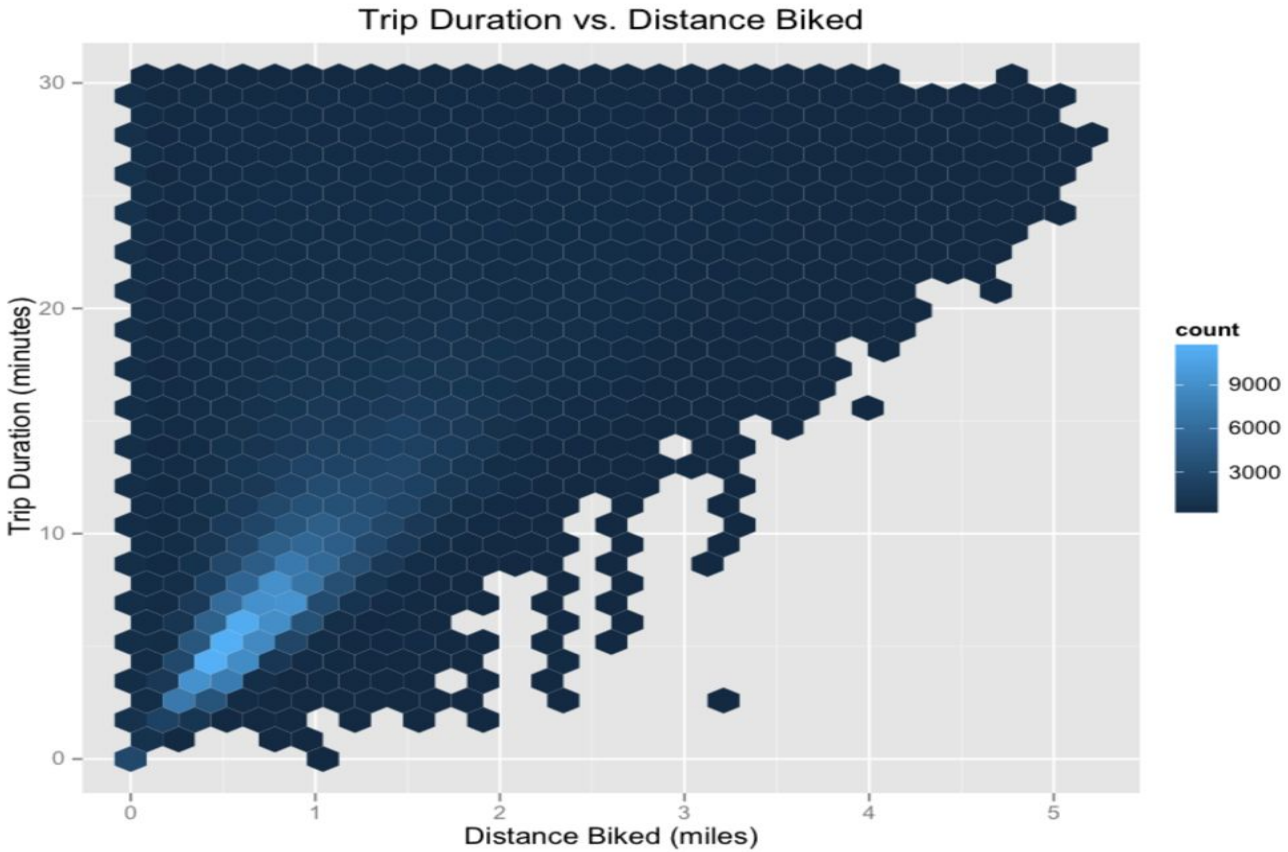
How? Questions that combine variables.

- How does user demographics impact the duration the bikes are being used? Or where they are being checked out?
- How does weather or traffic conditions impact bike usage?
- How do the characteristics of the station location affect the number of bikes being checked out?

How questions are about modeling relationships between different variables.

Reducing complexity

So how well did we do in formulating creative hypotheses and manipulating the data for answers?



https://www.bluebikes.com/blog/and-the-2017-hubway-data-challenge-winners-are

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www.nvidia.com/dli

```
## Lecture 1: Demo - Lab Work
```

Lecture 1: Demo - Lab Work

Download the data from

https://cloud.comsys.kpi.ua/s/7oW5GRWHpkKmAmC

unzip and put it in COLAB_DS directory (before create this directory!) at your Google Drive.

```
# Mount your Google drive for data input-output
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# Check the paths
! pwd
! ls /content/drive
! ls /content/drive/MyDrive
```

```
# Check directory for avaialbility of your HUBWAY-dataset
! mkdir /content/drive/MyDrive/COLAB_DS
```

```
! ls /content/drive/MyDrive/COLAB_DS
```

```
hubway_data  hubway_network_analysis.ipynb  Lab01_EDA_hubway_datasets.ipynb
```

```
import sys
import datetime
import numpy as np
import scipy as sp
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from math import radians, cos, sin, asin, sqrt
from sklearn.linear_model import LinearRegression

sns.set(style="ticks")
%matplotlib inline
```

```
import os

DATA_HOME = '/content/drive/MyDrive/COLAB_DS/hubway_data'
```

```
HUBWAY_STATIONS_FILE = os.path.join(DATA_HOME, 'hubway_stations.csv')
HUBWAY_TRIPS_FILE = os.path.join(DATA_HOME, 'hubway_trips.csv')
```

```
hubway_data = pd.read_csv(HUBWAY_TRIPS_FILE, index_col=0, low_memory=False)
hubway_data.head()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/arraysetops.py:580
  mask |= (ar1 == a)
```

	hubway_id	status	duration	start_date	strt_statn	end_dat
seq_id						
1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/201 10:12:0
2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/201 10:25:0
3	10	Closed	56	7/28/2011	23.0	7/28/201

Who? Who's using the bikes?

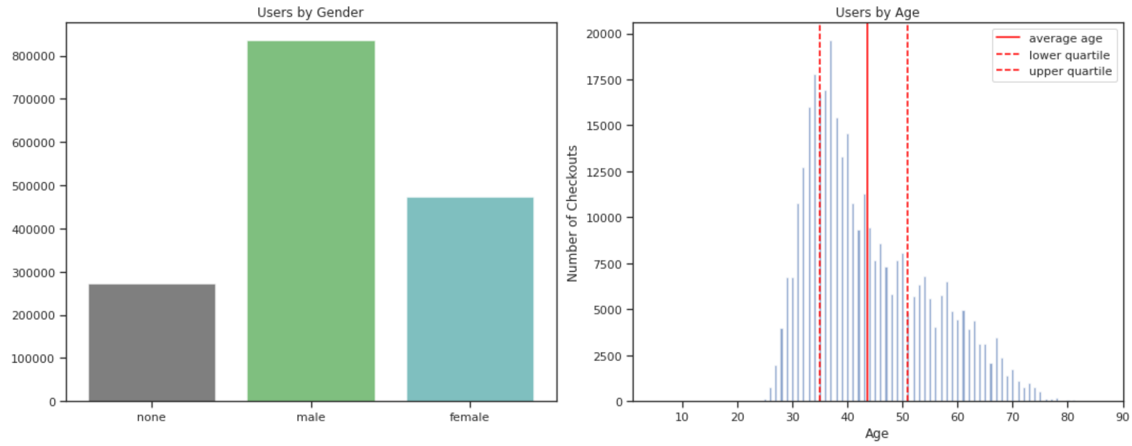
Refine into specific hypotheses:

- More men or more women?
- Older or younger people?
- Subscribers or one time users?

```
# Let's do some cleaning first by removing empty cells or replacing them with NaN.
# Pandas can do this.
# we will learn a lot about pandas
hubway_data['gender'] = hubway_data['gender'].replace(np.nan, 'NaN', regex=True).va


# we drop
hubway_data['birth_date'].dropna()
age_col = 2020.0 - hubway_data['birth_date'].values
```

```
# matplotlib can create a plot with two sub-plots.
# we will learn a lot about matplotlib
fig, ax = plt.subplots(1, 2, figsize=(15, 6))


# find all the unique value of the column gender
# numpy can do this
# we will learn a lot about numpy
gender_counts = np.unique(hubway_data['gender'].values, return_counts=True)
```

```
ax[0].bar(range(3), gender_counts[1], align='center', color=['black', 'green', 'tea
ax[0].set_xticks([0, 1, 2])
ax[0].set_xticklabels(['none', 'male', 'female'])
ax[0].set_title('Users by Gender')



age_col = 2020.0 - hubway_data['birth_date'].dropna().values
age_counts = np.unique(age_col, return_counts=True)
ax[1].bar(age_counts[0], age_counts[1], align='center', width=0.4, alpha=0.6)
ax[1].axvline(x=np.mean(age_col), color='red', label='average age')
ax[1].axvline(x=np.percentile(age_col, 25), color='red', linestyle='--', label='lo
ax[1].axvline(x=np.percentile(age_col, 75), color='red', linestyle='--', label='up
ax[1].set_xlim([1, 90])
ax[1].set_xlabel('Age')
ax[1].set_ylabel('Number of Checkouts')
ax[1].legend()
ax[1].set_title('Users by Age')

plt.tight_layout()
plt.savefig('who.png', dpi=300)
```



Challenge

There is actually a mistake in the code above. Can you find it?

Soon you will be skillful enough to answers many "who" questions

Where? Where are bikes being checked out?

Refine into specific hypotheses:

1. More in Boston than Cambridge?
2. More in commercial or residential?
3. More around tourist attractions?

```
# using pandas again to read the station locations
station_data = pd.read_csv(HUBWAY_STATIONS_FILE, low_memory=False)[['id', 'lat', '
station_data.head()
```

	id	lat	lng
0	3	42.340021	-71.100812
1	4	42.345392	-71.069616
2	5	42.341814	-71.090179
3	6	42.361285	-71.065140
4	7	42.353412	-71.044624

```
# Sometimes the data is given to you in pieces and must be merged!
# we want to combine the trips data with the station locations. pandas to the rescu

hubway_data_with_gps = hubway_data.join(station_data.set_index('id'), on='strt_sta
hubway_data_with_gps.head()
```

	hubway_id	status	duration	start_date	strt_statn	end_dat
seq_id						
1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/201 10:12:0
2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/201 10:25:0
3	10	Closed	56	7/28/2011	23.0	7/28/201

```
len(hubway_data_with_gps)
```

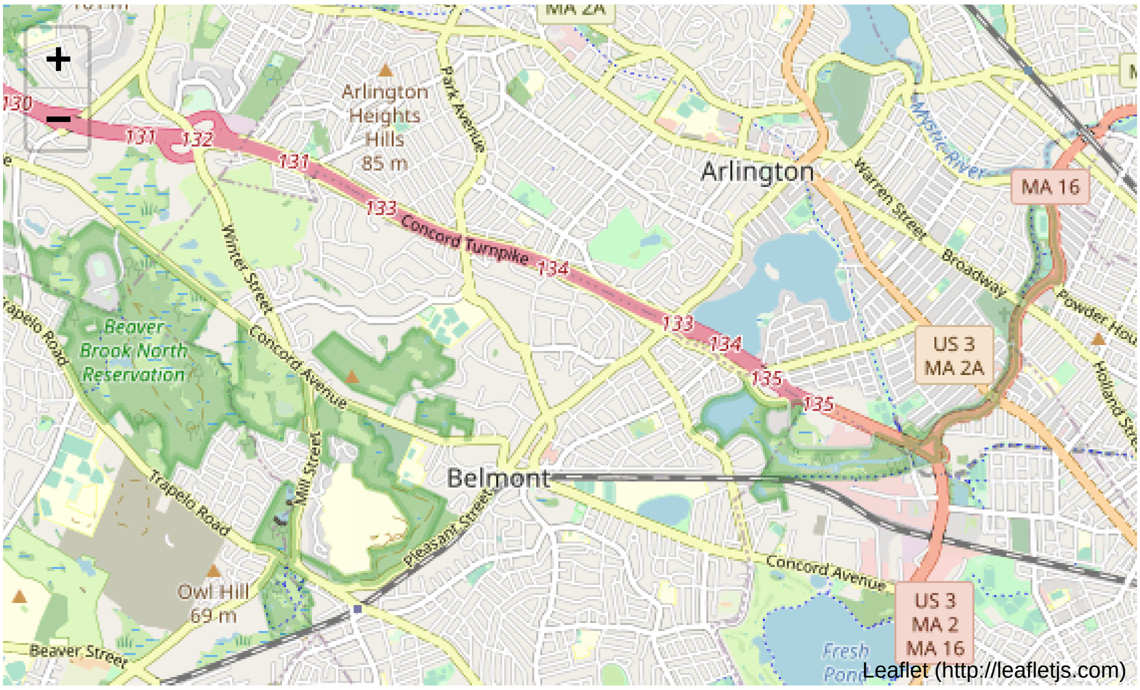
```
1579025
```

```
hubway_data_with_gps.head(-3)
```

seq_id	hubway_id	status	duration	start_date	strt_statn	end_da
1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/20 10:12:
2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/20 10:25:
3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/20 10:34:
4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/20 10:36:
5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/20 10:37:
...	...	...	...	...	...	
1579018	1748015	Closed	900	11/30/2013 23:17:00	76.0	11/30/20 23:32:

```
import pandas as pd
import folium
from folium.plugins import HeatMap
```

```
#for_map = pd.read_csv('campaign_contributions_for_map.tsv', sep='\t')
#for_map = hubway_data_with_gps.head(1000)
for_map = hubway_data_with_gps.head(200000)

#max_amount = float(for_map['Amount'].max())
max_amount = float(for_map['duration'].max())

hmap = folium.Map(location=[42.35, -71.05], zoom_start=13, )

hm_wide = HeatMap( list(zip(for_map.lat.values, for_map.lng.values, for_map.durati
                   min_opacity=0.2,
                   max_val=max_amount,
                   radius=27, blur=15,
                   max_zoom=1,
                 )

hmap.add_child(hm_wide)
```


MA 2A
Arlington Heights Hills
85 m
Park Avenue
Arlington
Mystic River
MA 16
Warren Street
Broadway
Powder Hou
130
131
132
131
133
Concord Turnpike
134
133
134
135
135
Winter Street
Beaver Brook North Reservation
Concord Avenue
US 3
MA 2A
Holland Stre
Mill Street
Belmont
Trapelo Road
Pleasant Street
Owl Hill
69 m
Concord Avenue
US 3
MA 2
MA 16
Beaver Street
Fresh Pond
Leaflet (http://leafletjs.com)

You should obtain something similar to the next image ...

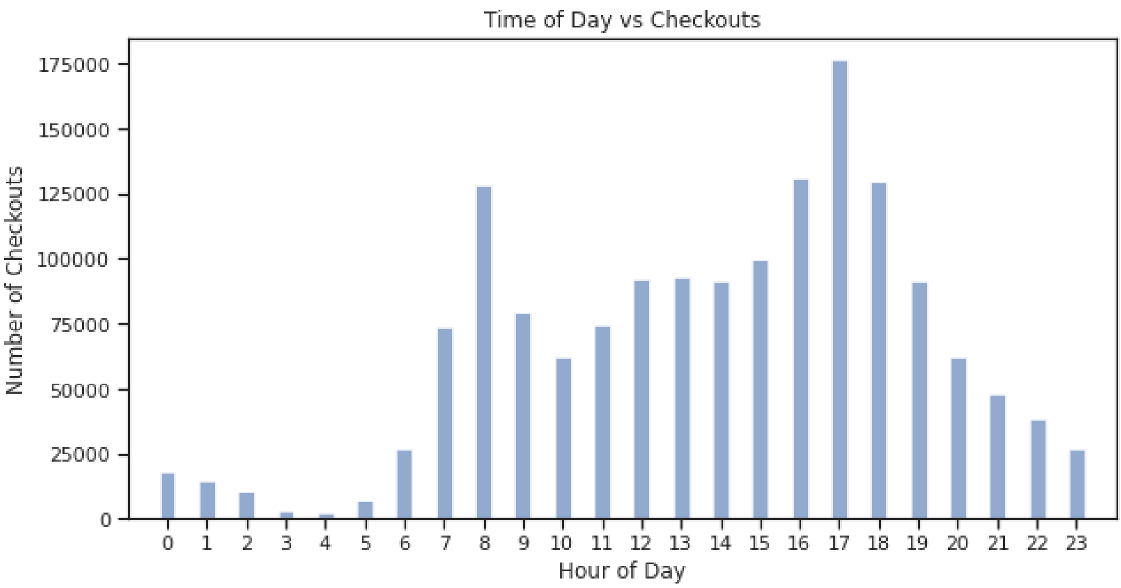
When? When are the bikes being checked out?

Refine into specific hypotheses:

1. More during the weekend than on the weekdays?
2. More during rush hour?
3. More during the summer than the fall?

```
# Sometimes the feature you want to explore doesn’t exist in the data, and must be


# to find the time of the day we will use the start_date column and extrat the hou
# we use list comprehension
```

```
# we will be doing a lot of those
check_out_hours = hubway_data['start_date'].apply(lambda s: int(s[-8:-6]))
fig, ax = plt.subplots(1, 1, figsize=(10, 5))

check_out_counts = np.unique(check_out_hours, return_counts=True)
ax.bar(check_out_counts[0], check_out_counts[1], align='center', width=0.4, alpha=
ax.set_xlim([-1, 24])
ax.set_xticks(range(24))
ax.set_xlabel('Hour of Day')
ax.set_ylabel('Number of Checkouts')
ax.set_title('Time of Day vs Checkouts')

plt.show()
```



Why? For what reasons/activities are people checking out bikes?

Refine into specific hypotheses:

1. More bikes are used for recreation than commute?
2. More bikes are used for touristic purposes?
3. Bikes are use to bypass traffic?

Do we have the data to answer these questions with reasonable certainty? What data do we need to collect in order to answer these questions?

How? Questions that combine variables.

1. How does user demographics impact the duration the bikes are being used? Or where they are being checked out?
2. How does weather or traffic conditions impact bike usage?
3. How do the characteristics of the station location affect the number of bikes being checked out?

How questions are about modeling relationships between different variables.

```
# Here we define the distance from a point as a python function.
# We set Boston city center long and lat to be the default value.
# you will become experts in building functions and using functions just like this

def haversine(pt, lat2=42.355589, lon2=-71.060175):
    """
    Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)
    """
    lon1 = pt[0]
    lat1 = pt[1]

    # convert decimal degrees to radians
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])

    # haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat/2)**2 + cos(lat1) * cos(lat2) * sin(dlon/2)**2
    c = 2 * asin(sqrt(a))
    r = 3956 # Radius of earth in miles
    return c * r
```

```
# use only the checkouts that we have gps location
station_counts = np.unique(hubway_data_with_gps['strt_statn'].dropna(), return_cou
counts_df = pd.DataFrame({'id':station_counts[0], 'checkouts':station_counts[1]})
counts_df = counts_df.join(station_data.set_index('id'), on='id')
counts_df.head()
```

	id	checkouts	lat	lng
0	3.0	9734	42.340021	-71.100812
1	4.0	18058	42.345392	-71.069616
2	5.0	10630	42.341814	-71.090179
3	6.0	23322	42.361285	-71.065140
4	7.0	9163	42.353412	-71.044624

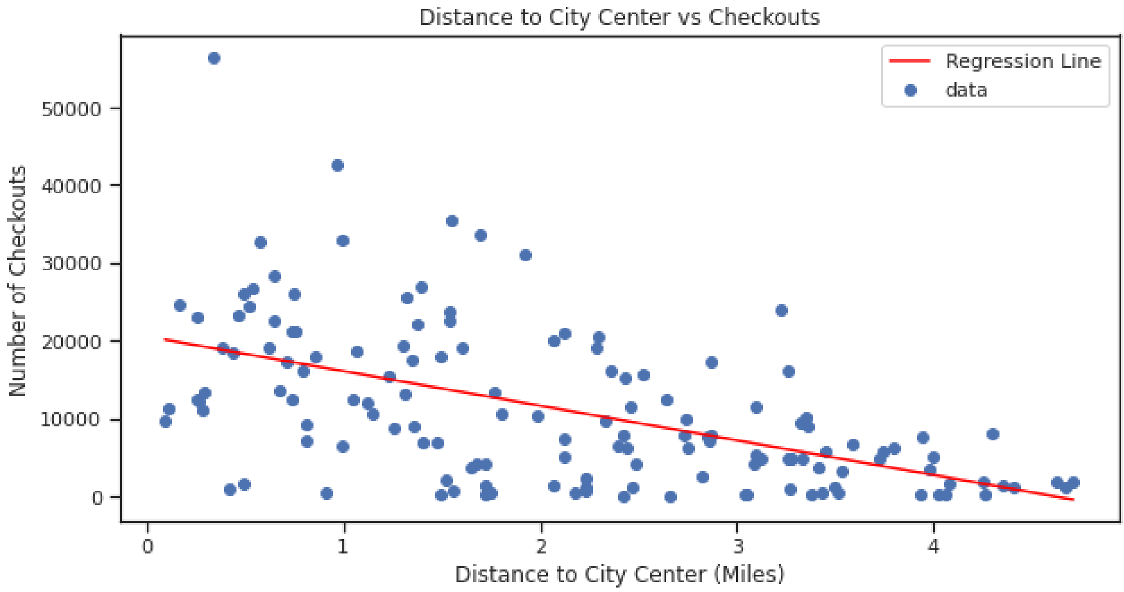
```
# add to the pandas dataframe the distance using the function we defined above and
counts_df.loc[:, 'dist_to_center'] = list(map(haversine, counts_df[['lng', 'lat']]
counts_df.head()
```

	id	checkouts	lat	lng	dist_to_center
0	3.0	9734	42.340021	-71.100812	2.335706
1	4.0	18058	42.345392	-71.069616	0.853095
2	5.0	10630	42.341814	-71.090179	1.802423
3	6.0	23322	42.361285	-71.065140	0.467803
4	7.0	9163	42.353412	-71.044624	0.807582

```
# we will use sklearn to fit a linear regression model
# we will learn a lot about modeling and using sklearn
reg_line = LinearRegression()
reg_line.fit(counts_df['dist_to_center'].values.reshape((len(counts_df['dist_to_cen

# use the fitted model to predict
distances = np.linspace(counts_df['dist_to_center'].min(), counts_df['dist_to_cent
```

```
fig, ax = plt.subplots(1, 1, figsize=(10, 5))

ax.scatter(counts_df['dist_to_center'].values, counts_df['checkouts'].values, labe

ax.plot(distances, reg_line.predict(distances.reshape((len(distances), 1))), color=

ax.set_xlabel('Distance to City Center (Miles)')
ax.set_ylabel('Number of Checkouts')
ax.set_title('Distance to City Center vs Checkouts')
ax.legend()
```

```
<matplotlib.legend.Legend at 0x7f01be5a0e48>
```



Deep Learning - Lecture 3 – Deep Learning Main Principles

Yuri Gordienko, DLI Certified Instructor

NVIDIA

DEEP
LEARNING
INSTITUTE

DEEP LEARNING INSTITUTE

DLI Mission

Training you to solve the world's most challenging problems.

- Developers, data scientists and engineers
- Self-driving cars, healthcare and robotics
- Training, optimizing, and deploying deep neural networks

Deck credit: Y. LeCun
MA Ranzato

Who is Y. LeCun?

Who is Yann LeCun?

He is a founding father of convolutional neural nets (CNNs).

He is also one of the main creators of the DjVu image compression technology (together with Léon Bottou and Patrick Haffner).

Chief AI Scientist at Facebook.

LeCun received the 2018 Turing Award, together with Yoshua Bengio and Geoffrey Hinton, for their work on deep learning.

LeCun - together with Geoffrey Hinton and Yoshua Bengio - are referred to by some as the "Godfathers of AI" and "Godfathers of Deep Learning" ... **BUT ... !!!**

2016 IEEE CIS Neural Networks Pioneer Award goes to Jürgen Schmidhuber

Jürgen Schmidhuber is recipient of the 2016 IEEE CIS Neural Networks Pioneer Award, for "pioneering contributions to deep learning and neural networks."

http://cis.ieee.org/award-recipients.html

Who is Schmidhuber?

Juergen Schmidhuber: Godel Machines, Meta-Learning, and LSTMs

https://www.youtube.com/watch?v=3FIo6evmweo

Who is Schmidhuber?

With his students Sepp Hochreiter, Felix Gers, Fred Cummins, Alex Graves, and others, Schmidhuber published increasingly sophisticated versions of a type of **recurrent neural network** called the **long short-term memory (LSTM)**.

First results were already reported in Hochreiter's **diploma thesis** (1991) which analyzed and overcame the famous vanishing gradient problem.

The name LSTM was introduced in a tech report (1995) leading to **the most cited LSTM publication** (1997).

Deep Learning since ...
https://people.idsia.ch/~juergen/deeplearning.html

2016 IEEE CIS Neural Networks Pioneer Award goes to Jürgen Schmidhuber

The award ceremony took place on the 27th of July 2016 in Vancouver at the Award Banquet of IJCNN 2016.

Transcript of the 3 min acceptance speech:

Dear IEEE,

it is a great honor to be listed among previous awardees such as K. Fukushima, who is present at this conference, the father of the deep convolutional neural architecture everybody is using now for computer vision.

The only thing that makes me a bit sad at this otherwise happy moment is that the Ukrainian mathematician A. G. Ivakhnenko, the father of deep learning himself, never got this award. His team had deep multilayer perceptrons with 8 layers or so back in the 1960s when I was a baby, at a time when others still focused on the limitations of shallow nets with a single layer. Apparently he was so far ahead of his time that even the not so young members of the award committees failed to appreciate the depth of his work.

Who is A. G. Ivakhnenko?

...

the father of deep learning himself

and

перший виконуючий обов'язки декана ФІОТ

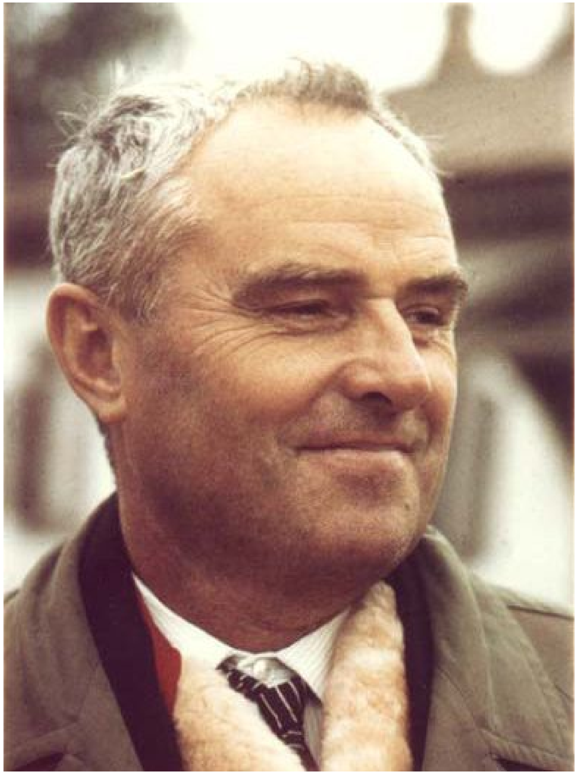
- перший "неофіційний" декан нашого факультету

Who is A. G. Ivakhnenko?

Ukrainian mathematician
most famous for developing the Group Method of Data Handling (GMDH), a method of inductive statistical learning, for which he is sometimes referred to as the "**Father of Deep Learning**".

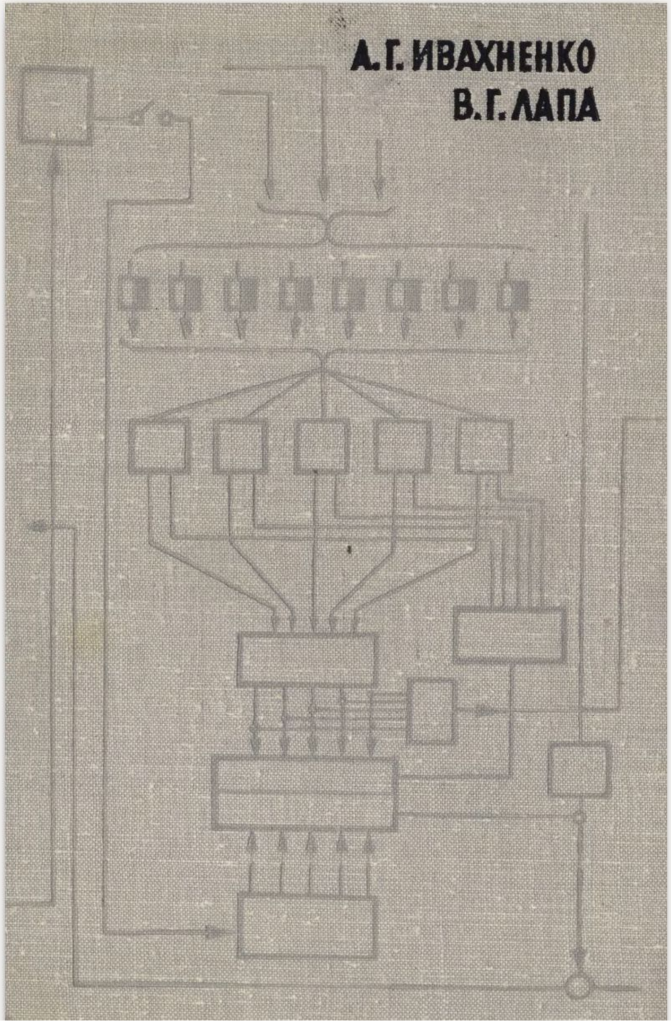
<u>Main results in the context of DL:</u>

- Principle of construction of self-organizing deep learning networks,
- Design of multilayered neural networks with active neurons, where each neuron is an algorithm,
- Principle of self-learning pattern recognition. It was demonstrated at first in the cognitive system "Alpha", created under his leadership.



Alexey Ivakhnenko
(Олексíй Григóрович Івáхненко)
(30 March 1913 – 16 October 2007)

https://en.wikipedia.org/wiki/Alexey_Ivakhnenko



АКАДЕМИЯ НАУК УКРАИНСКОЙ ССР

А. Г. ИВАХНЕНКО
В. Г. ЛАПА

КИБЕРНЕТИЧЕСКИЕ ПРЕДСКАЗЫВАЮЩИЕ УСТРОЙСТВА

НАУКОВА ДУМКА

Киев — 1965

Перша книжка А.Г.Івахненка про його систему "Альфа" - **першу 8-шарову глибинну мережу**.

Система "Альфа" -
перша 8-шарова глибинна мережа

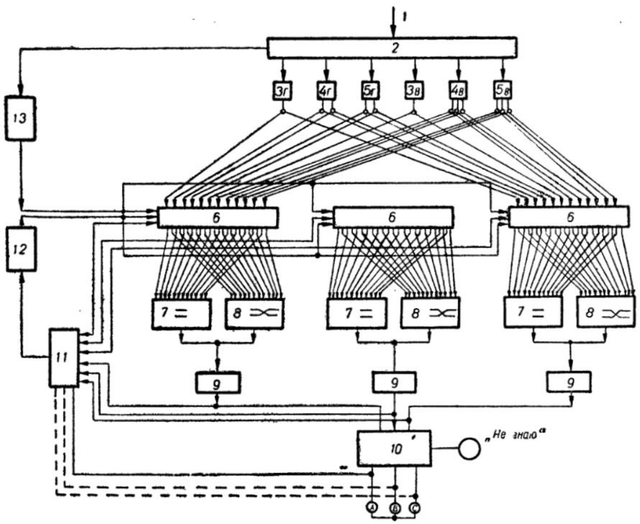


Рис. 49. Структурная схема распознающей системы с положительной обратной связью.

1 — различаемый образ; *2* — входное устройство; *3—5* — датчики; *6* — группы ассоциирующих элементов; *7* — прямые усилители; *8* — реверсирующие усилители; *9* —сумматоры; *10* —индикатор большого напряжения; *11* — управление порядком самообучения; *12* — положительная связь самообучения; *13* — разомкнутая связь обучения.

О.Г. Івахненко (справа) та Норберт Вінер (зліва) під час конференції ІФАК у Києві (1960 р.)

Насправді вона була розроблена ще раніше, не у 1965-1971, як пише Шмідхубер, а у 1962 році.

21. Івахненко О.Г., Системи, що саморганізуються, з додатними зворотними зв'язками. "Автоматика", №3, 1962.

Deep learning =
Learning representations/features

- The traditional model of pattern recognition (since the late 50's)
  - Fixed/engineered features (or fixed kernel) + trainable classifier

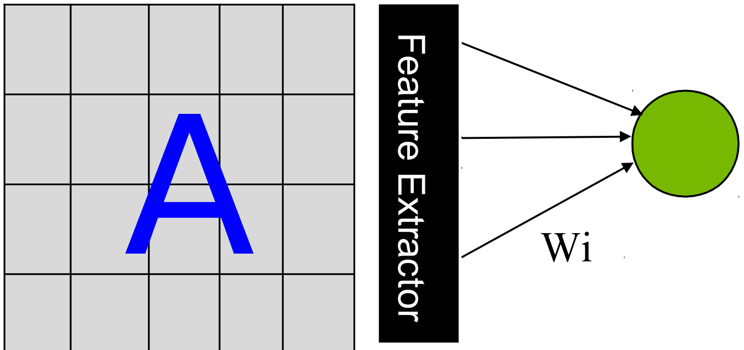
→ Hand-crafted Feature Extractor → "Simple" Trainable Classifier →

- End-to-end learning / Feature learning / Deep learning

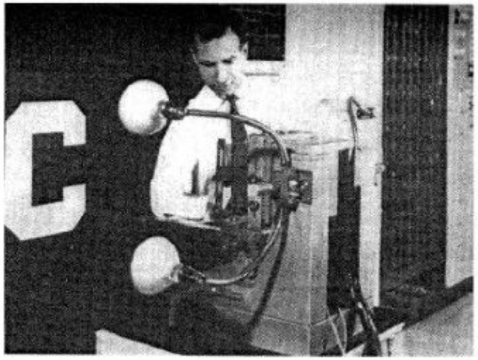
→ Trainable Feature Extractor → Trainable Classifier →

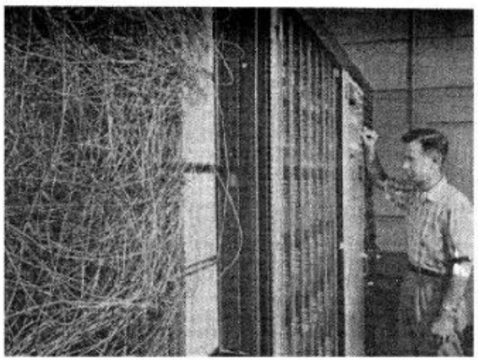
This basic model has not evolved much since the 50's

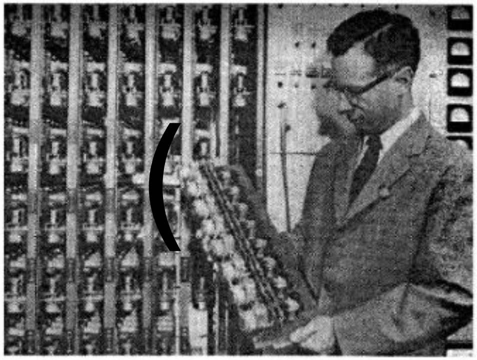
- The first learning machine: the Perceptron
  - Built at Cornell in 1960
- The Perceptron was a linear classifier on top of a simple feature extractor
- The vast majority of practical applications of ML today use glorified linear classifiers or glorified template matching.
- Designing a feature extractor requires considerable efforts by experts.



$$y = sign\left(\sum_{i=1}^{N} W_i F_i(X) + b\right)$$







Linear machines and their limitations

Linear machines: regression with mean square

Linear regression, mean square loss:

– Decision rule:

– Loss function:

– Gradient of loss:

– Update rule:

– Direct solution: solve linear system

Linear machines
Perception

- Decision rule: (F is the threshold function)
- Loss function:
- Gradient of loss:
- Update rule:
- Direct solution: fine W such that

Linear machines: logistic regression

Logistic regression, negative log-likelihood loss function:

- Decision rule:
- Loss function:
- Gradient of loss:
- Update rule:

General gradient-based supervised learning machine

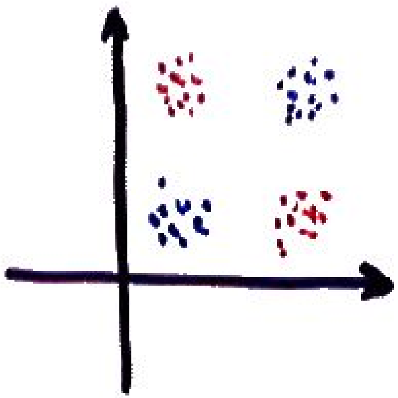
Neural nets, and many other models:

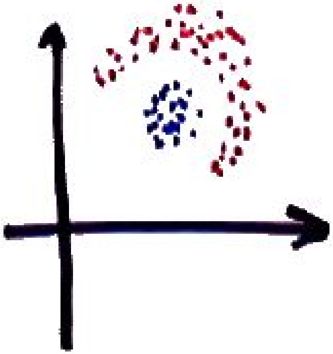
- Decision rule: $y = F(W,X)$, where F is some function, and W some parameter vector.
- Loss function: where $D(y, f)$ measures the "discrepancy" between A and B.
- Gradient loss:
- Update rule:

Three questions:

- What architecture $F(W,X)$.
- What loss function $L(W, y^i, X^i)$.
- What optimization method.

Limitations of Linear Machines

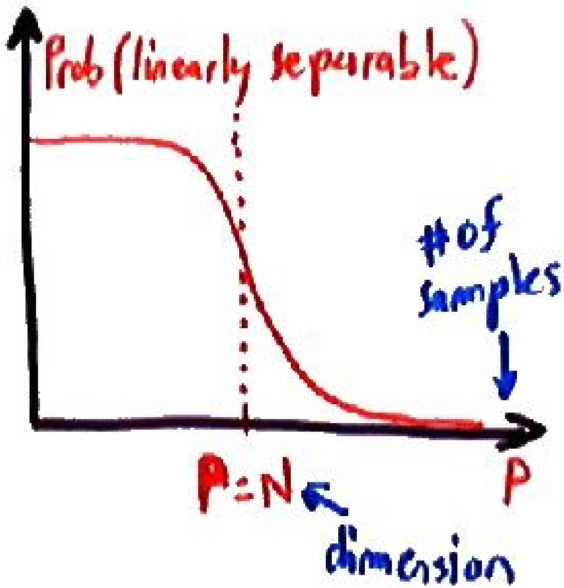




The *Linearly separable* dichotomies are the partitions that are realizable by a linear classifier (the boundary between the classes is a hyperplane).

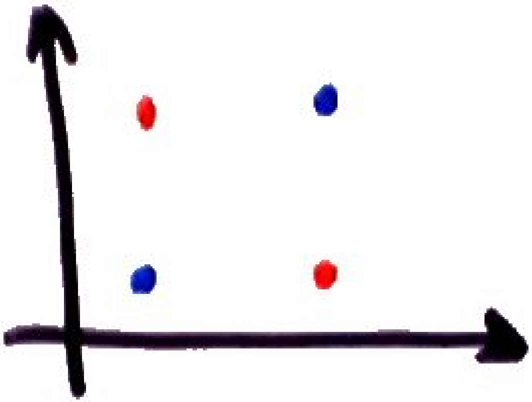
Number of Linearly Separable Dichotomies

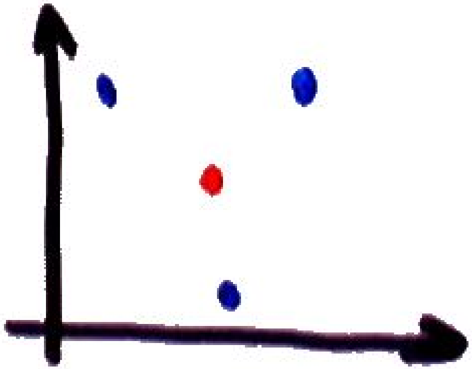
The probability that P samples of dimension N are linearly separable goes to zero very quickly as P grows larger than N (Cover's theorem, 1966).



- Problem: there are 2^P possible dichotomies of P points.
- Only about N are linearly separable.
- If P is larger than N, the probability that a random dichotomy is linearly separable is very, very small.

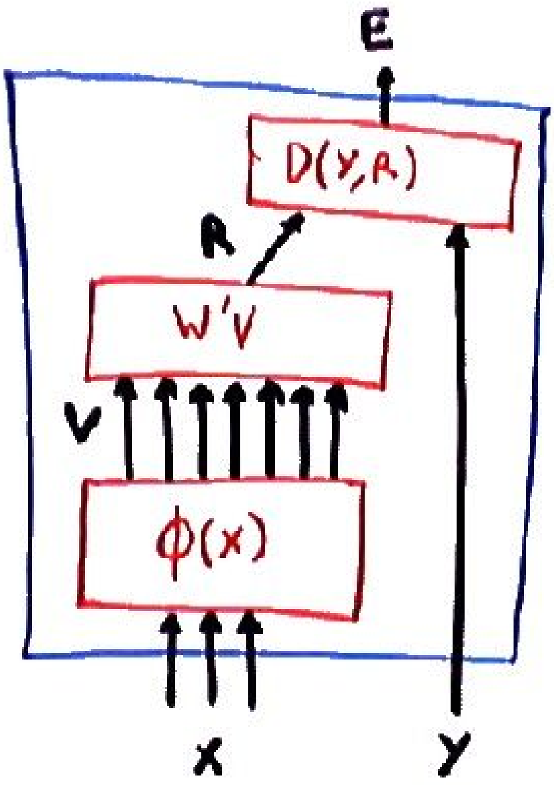
Example of Non-Linearly Separable Dichotomies





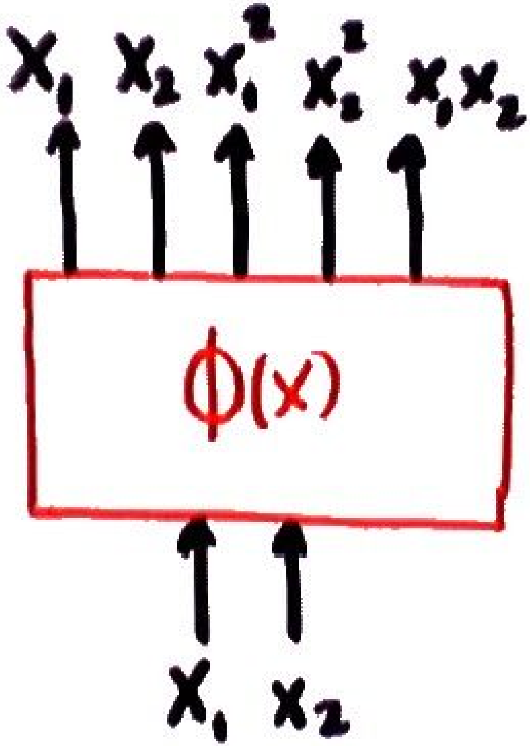
- Some seemingly simple dichotomies are not linearly separable
- Question: How do we make a given problem linearly separable?

Making N Larger: Preprocessing



- Answer 1: we make N larger by augmenting the input variables with new "features".
- we map/project X from its original N-dimensional space into a higher dimensional space where things are more likely to be linearly separable, using a vector function $\Phi(X)$.
- $E(Y, X, W) = D(Y, R)$
- $R = f(W'V)$
- $V = \Phi(X)$

Adding Cross-Product Terms

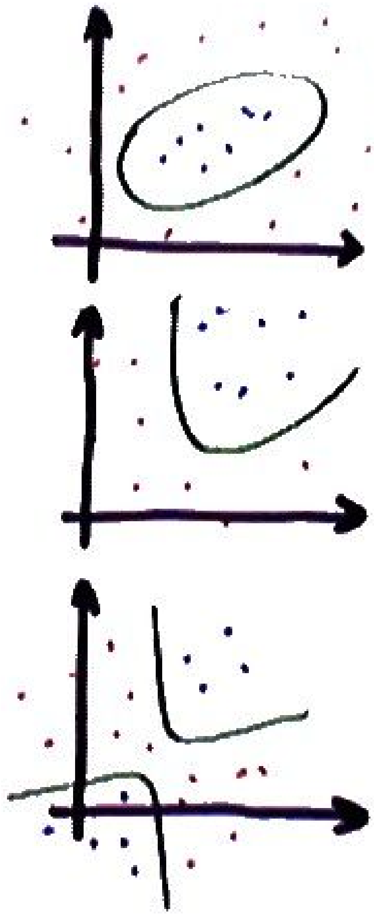


- Polynomial Expansion.
- If our original input variables are $(1, x_1, x_2)$, we construct a new *feature vector* with the following components:

$$\Phi(1, x_1, x_2) = (1, x_1, x_2, x_1^2, x_2^2, x_1 x_2)$$

  i.e. we add all the cross-products of the original variables.
- we map/project X from its original N-dimensional space into a higher dimensional space with $N(N+1)/2$ dimensions.

Polynomial Mapping



o

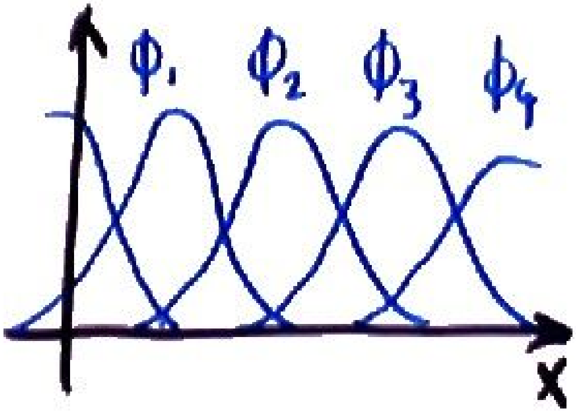
- Many new functions are now separable with the new architecture.
- With cross-product features, the family of class boundaries in the original space is the conic sections (ellipse, parabola, hyperbola).
- to each possible boundary in the original space corresponds a linear boundary in the transformed space.
- Because this is essentially a linear classifier with a preprocessing, we can use standard linear learning algorithms (perceptron, linear regression, logistic regression...).

Problems with polynomial mapping

- We can generalize this idea to higher degree polynomials, adding cross-product terms with 3, 4 or more variables
- Unfortunately, the number of terms is the number of combinations d choose N, which grows like N^d, where d is the degree, and N the number of original variables
- In particular, the number of free parameters that must be learned is also of order N^d.
- This is impractical for large N and for $d > 2$
- Example: handwritten digit recognition (16x16 pixel images). Number of variables: 256. degree 2: 32,896 variables. Degree 3: 2,796,160. degree 4: 247,460,160…

Next Idea: Tile the Space

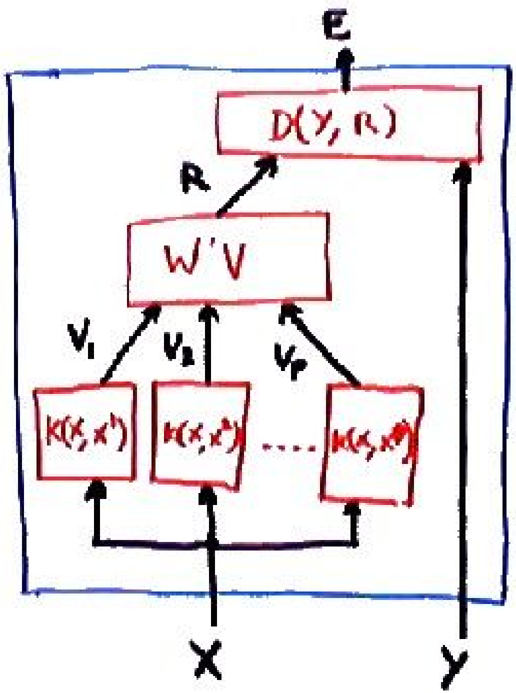
place a number of equally-spaced "bumps" that cover the entire input space.



- For classification, the bumps can be Gaussians
- For regression, the basis functions can be wavelets, sine/cosine, splines (pieces of polynomials)....
- problem: this does not work with more than a few dimensions.
- The number of bumps necessary to cover an N dimensional space grows exponentially with N.

Sample-Centered Basis Functions (Kernels)

Place the center of a basis function around each training sample. That way, we only spend resources on regions of the space where we actually have training samples.

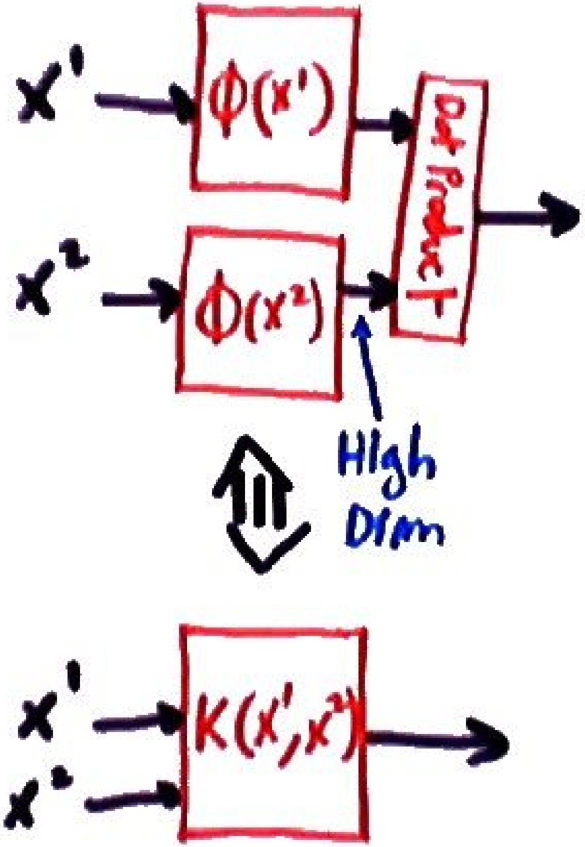


- Discriminant function:

$$f(X, W) = \sum_{k=1}^{k=P} W_k K(X, X^k)$$

- $K(X, X')$ often takes the form of a *radial basis function*: $K(X, X') = \exp(b||X - X'||^2)$ or a polynomial $K(X, X') = (X.X' + 1)^m$
- This is a very common architecture, which can be used with a number of energy functions.
- In particular, this is the architecture of the so-called Support Vector Machine (SVM), but the energy function of the SVM is a bit special. We will study it later in the course.

The Kernel Trick



- If the kernel function $K(X, X')$ verifies the *Mercer conditions*, then there exist a mapping Φ, such that $\Phi(X).\Phi(X') = K(X, X')$.
- The Mercer conditions are that K must be symmetric, and must be positive definite (i.e $K(X, X)$ must be positive for all X).
- In other words, if we want to map our X into a high-dimensional space (so as to make them linearly separable), and all we have to do in that space is compute dot products, we can take a shortcut and simply compute $K(X^1, X^2)$ without going through the high-dimensional space.
- This is called the "kernel trick". It is used in many so-called Kernel-based methods, including Support Vector Machines.

Examples of Kernels

- Quadratic kernel: $\Phi(X) = (1, \sqrt{2}x_1, \sqrt{2}x_2, \sqrt{2}x_1x2, x_1^2, x_2^2)$ then

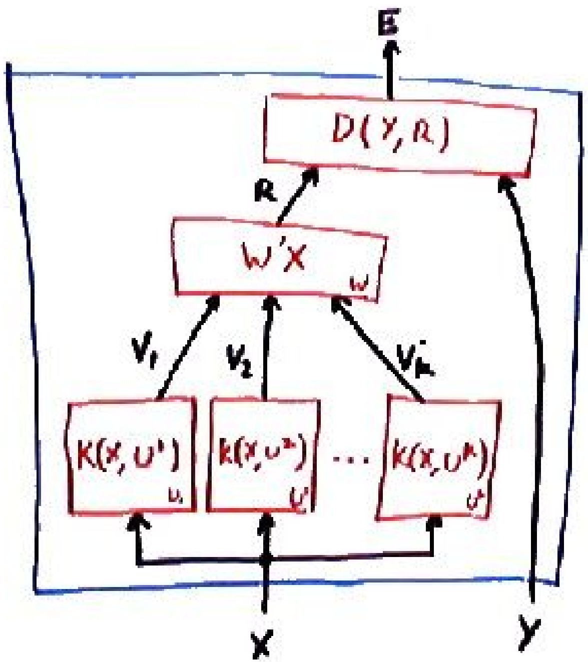
$$K(X, X') = \Phi(X).\Phi(X') = (X.X' + 1)^2$$

- Polynomial kernel: this generalizes to any degree d. The kernel that corresponds to $\Phi(X)$ bieng a polynomial of degree d is $K(X, X') = \Phi(X).\Phi(X') = (X.X' + 1)^d$.
- Gaussian Kernel:

$$K(X, X') = \exp(-b||X - X'||^2)$$

  This kernel, sometimes called the Gaussian Radial Basis Function, is very commonly used.

Sparse Basis Functions

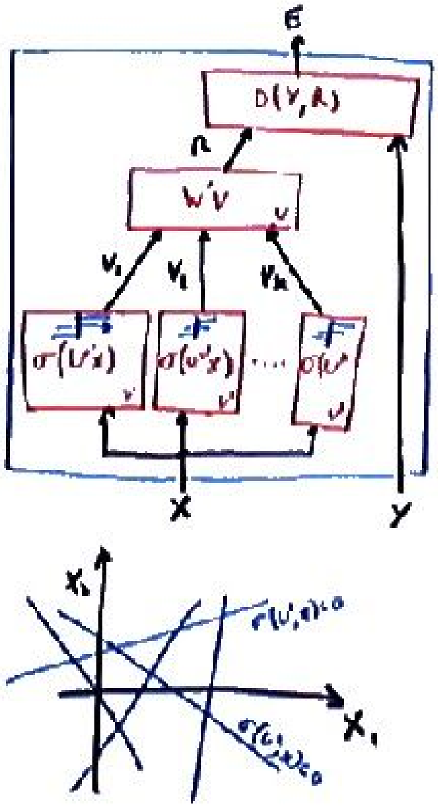


- Place the center of a basis function around areas containing training samples.
- Idea 1: use an unsupervised clustering algorithm (such as K-means or mixture of Gaussians) to place the centers of the basis functions in areas of high sample density.
- Idea 2: adjust the basis function centers through gradient descent in the loss function.

The discriminant function F is:

$$F(X, W, U^1, \ldots, U^K) = \sum_{k=1}^{k=K} W_k K(X, U^k)$$

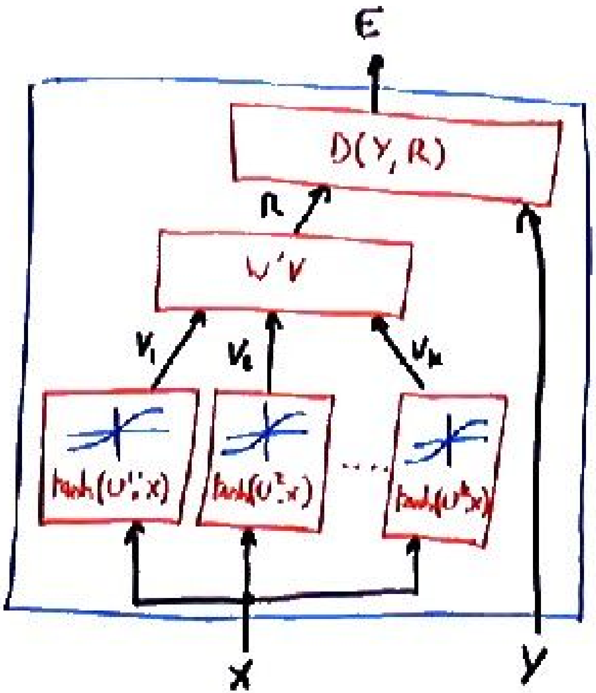
Other Idea: Random Directions



- Partition the space in lots of little domains by randomly placing lits of hyperplanes.
- Use many variables of the type $q(W^k X)$, where q is the threshold function (or some other squashing function) and W_k is a randomly picked vector.
- This is the original Perceptron.
- Without the non-linearity, the whole system would be linear (product of linear operations), and therefore would be no more powerful than a linear classifier.
- problem: a bit of a wishful thinking, but it works occasionally.

Neural Net with a Single Hidden Layer

A particularly interesting type of basis function is the sigmoid unit: $V_k = \tanh(U'^k X)$



- a network using these basis functions, whose output is $R = \sum_{k=1}^{k=K} W_k V_k$ is called a *single hidden-layer neural network*.
- Similarly to the RBF network, we can compute the gradient of the loss function with respect to the U^k:

$$\frac{\partial L(W)}{\partial U^j} = \frac{\partial L(W)}{\partial R} W_j \frac{\partial tanh(U_j' X)}{\partial U_j}$$

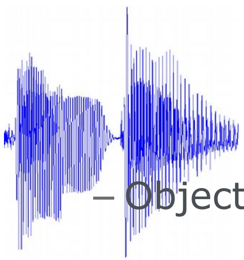
$$= \frac{\partial L(W)}{\partial R} W_j tanh'(U_j' X) X'$$

Any well-behaved function can be approximated as close as we wish by such networks (but K might be very large).

Architecture of “mainstream” pattern recognition systems

– Modern architecture for pattern recognition

  – Speech recognition: early 90's – 2011



MFCC → Mix of Gaussians → Classifier →

fixed | unsupervised | supervised

  – Object Recognition: 2006 - 2012

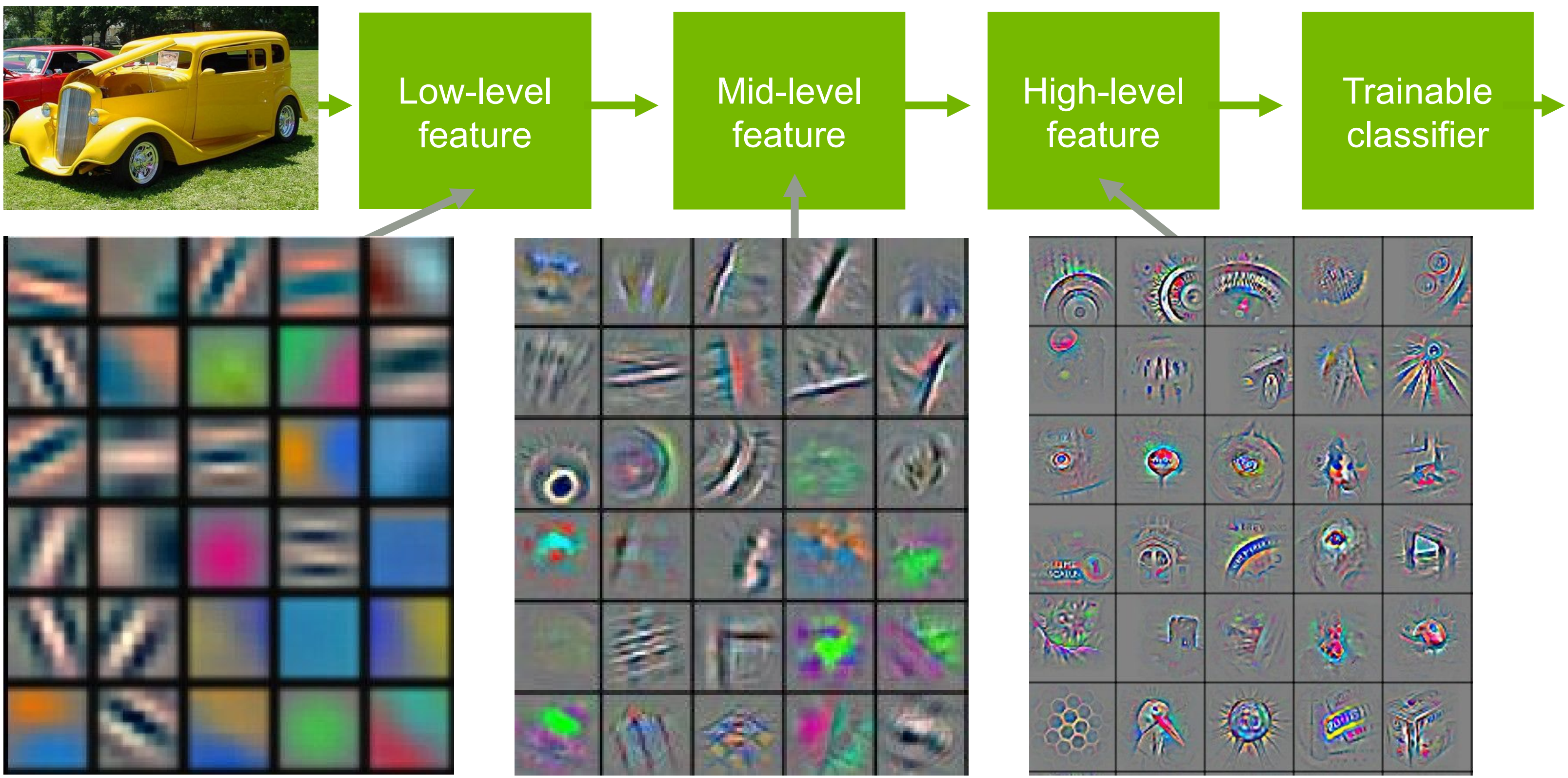
SIFT HoG → K-means Sparse Coding → Pooling → Classifier →

fixed | unsupervised | supervised

Low-level Features | Mid-level Features

Deep learning = learning hierarchical representations

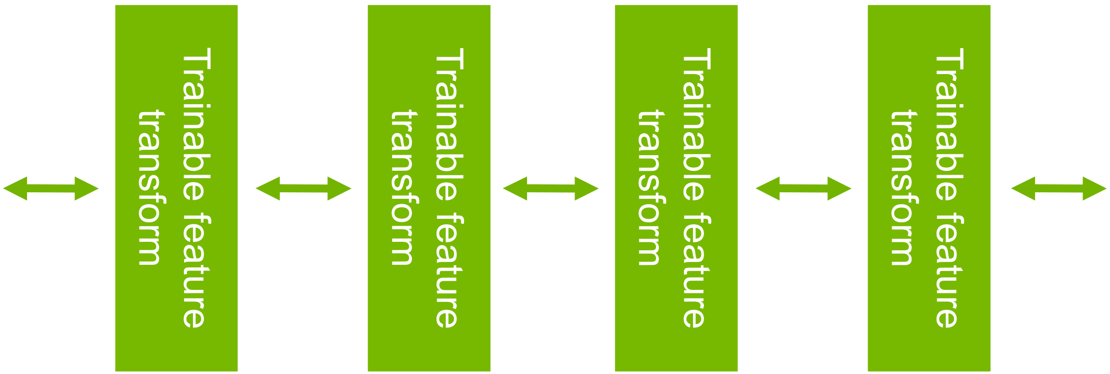
It's deep if it has more than one stage of non-linear feature transformation



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

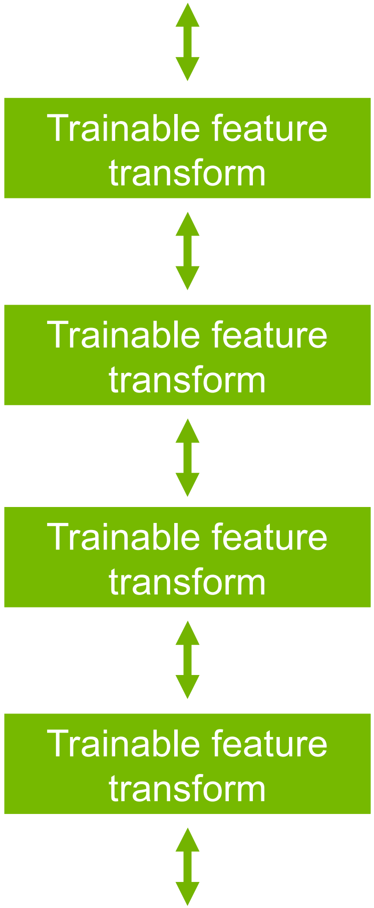
Trainable feature hierarchy

- Hierarchy of representations with increasing level of abstraction Each stage is a kind of trainable feature transform
- Image recognition
  - Pixel → edge → texton → motif → part → object
- Text
  - Character → word → word group → clause → sentence → story
- Speech
  - Sample → spectral band → sound → … → phone → phoneme → word



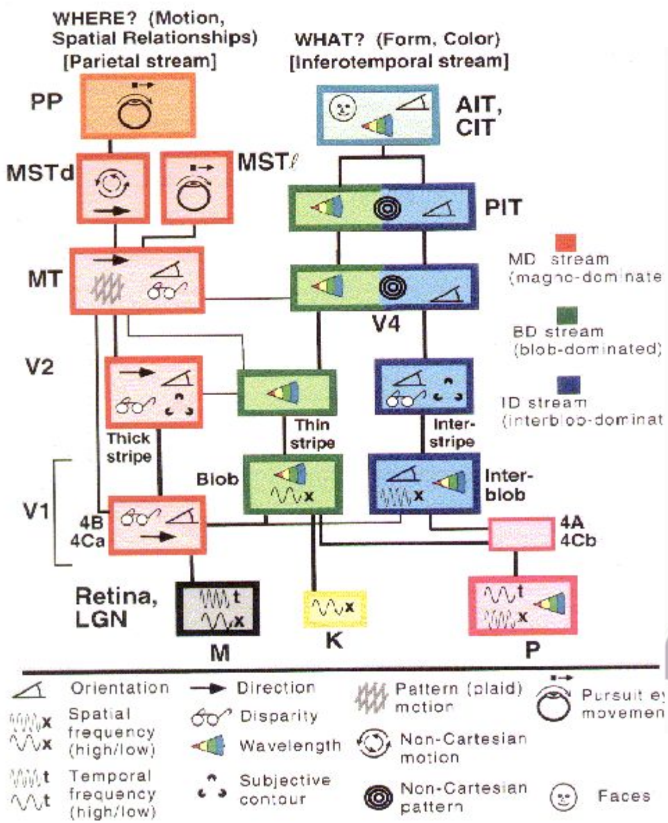
Learning representations: a challenge for ML, CV, AI, neuroscience, cognitive science...

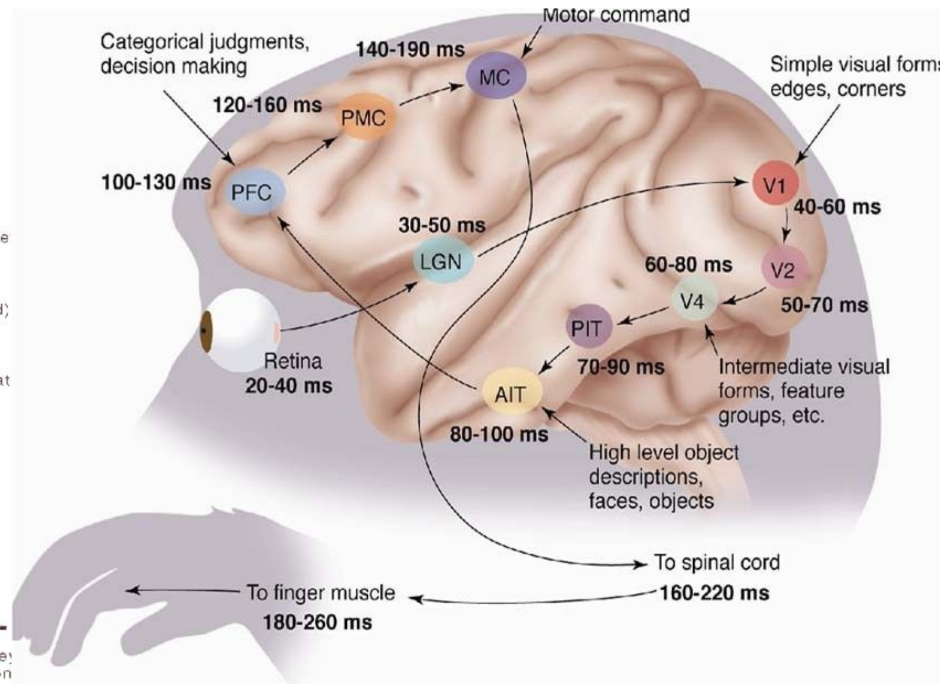
- How do we learn representations of the perceptual world?
  - How can a perceptual system build itself by looking at the world?
  - How much prior structure is necessary
- ML/AI: how do we learn features or feature hierarchies?
  - What is the fundamental principle? What is the learning algorithm? What is the architecture?
- Neuroscience: how does the cortex learn perception?
  - Does the cortex “run” a single, general learning algorithm? (or a small number of them)
- CogSci: how does the mind learn abstract concepts on top of less abstract ones?
- Deep Learning addresses the problem of learning hierarchical representations with a single algorithm
  - Or perhaps with a few algorithms



The mammalian visual cortex is hierarchical

- The ventral (recognition) pathway in the visual cortex has multiple stages Retina - LGN - V1 - V2 - V4 - PIT - AIT ....
- Lots of intermediate representations





[picture from Simon Thorpe]

[Gallant & Van Essen]

Let's be inspired by nature, but not too much

- It's nice imitate Nature,
- But we also need to understand
  - How do we know which details are important?
  - Which details are merely the result of evolution, and the constraints of biochemistry?
- For airplanes, we developed aerodynamics and compressible fluid dynamics.
  - We figured that feathers and wing flapping weren't crucial
- QUESTION: What is the equivalent of aerodynamics for understanding intelligence?

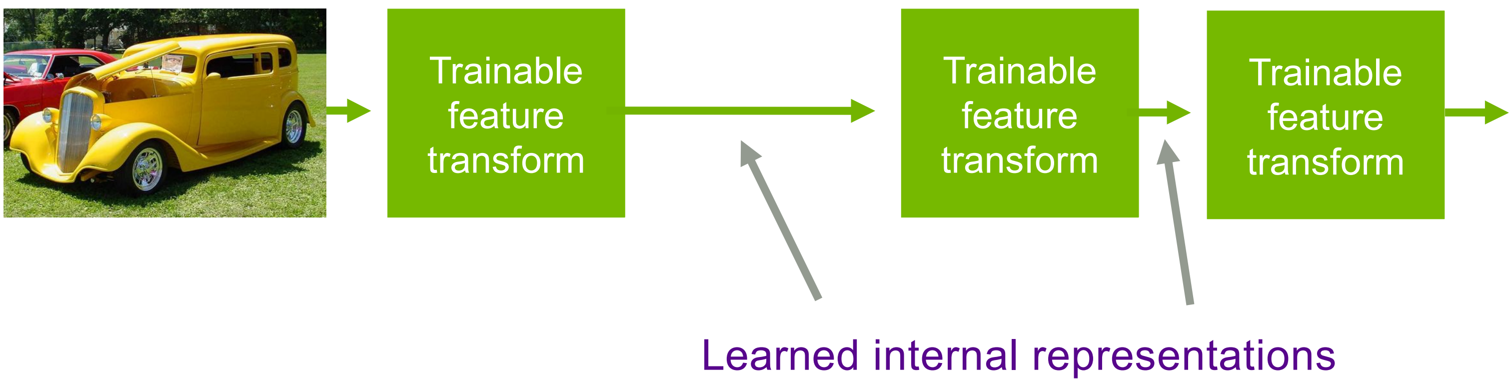
L'Avion III de Clément Ader, 1897

(Musée du CNAM, Paris)

His Eole took off from the ground in 1890, 13 years before the Wright Brothers, but you probably never heard of it.

Trainable feature hierarchies: end-to-end learning

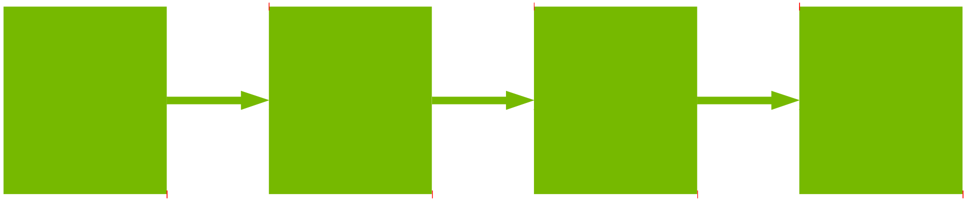
– A hierarchy of trainable feature transforms
  – Each module transforms its input representation into a higher-level one.
  – High-level features are more global and more invariant
  – Low-level features are shared among categories



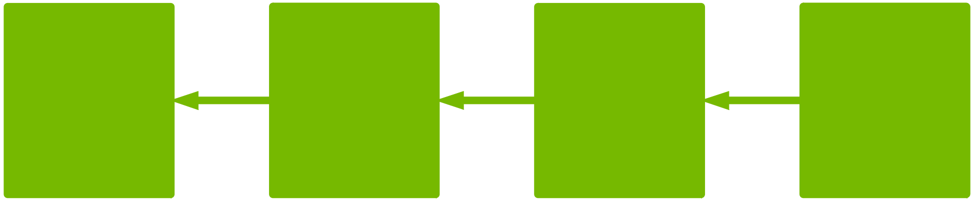
– How can we make all the modules trainable and get them to learn appropriate representations?

Three types of deep architectures

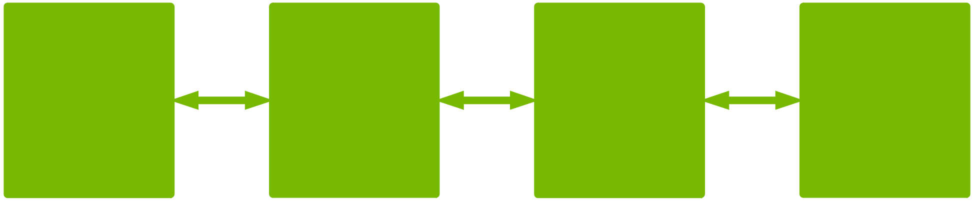
– Feed-forward: multilayer neural nets, convolutional nets



– Feed-back: stacked sparse coding, deconvolutional nets



– Bi-directional: Deep Boltzmann Machines, stacked auto-encoders



Three types of training protocols

- Purely Supervised
  - Initialize parameters randomly Train in supervised mode
    - Typically with SGD, using backprop to compute gradients
  - Used in most practical systems for speech and image recognition
- Unsupervised, layerwise + supervised classifier on top
  - Train each layer unsupervised, one after the other
  - Train a supervised classifier on top, keeping the other layers fixed
  - Good when very few labeled samples are available
- Unsupervised, layerwise + global supervised fine-tuning
  - Train each layer unsupervised, one after the other
  - Add a classifier layer, and retrain the whole thing supervised
  - Good when label set is poor (e.g. pedestrian detection)
- Unsupervised pre-training often uses regularized auto-encoders

Do we really need deep architectures?

– Theoretician's dilemma: "We can approximate any function as close as we want with shallow architecture. Why would we need deep ones?"

$$y = \sum_{i=1}^{P} \alpha_i K(X, X^i) \qquad y = F(W^1.F(W^0.X))$$

  – kernel machines (and 2-layer neural nets) are "universal".

– Deep learning machines

$$y = F(W^K.F(W^{K-1}.F(....F(W^0.X)...)))$$

– Deep machines are more efficient for representing certain classes of functions, particularly those involved in visual recognition

  – They can represent more complex functions with less "hardware"

– We need an efficient parameterization of the class of functions that are useful for "AI" tasks (vision, audition, NLP...)

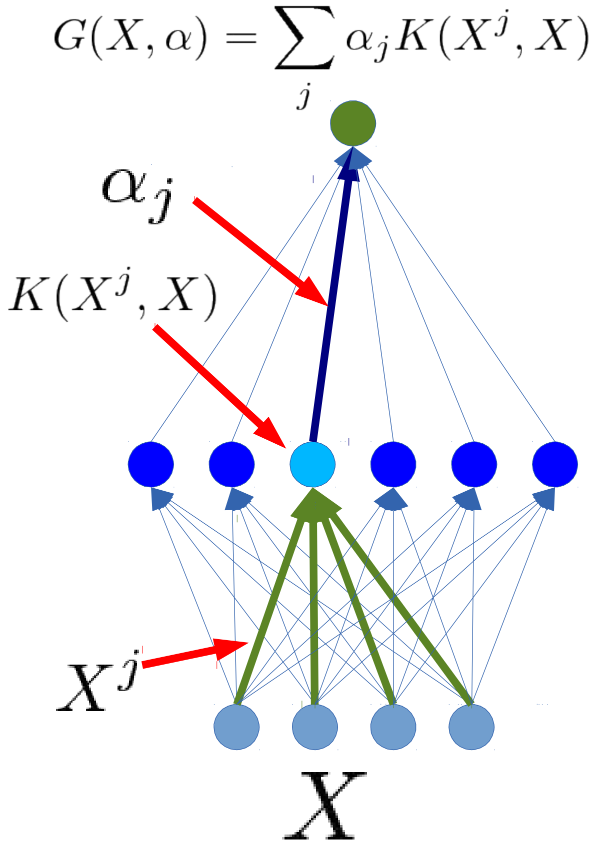
Why would deep architectures be more efficient?

[Bengio & LeCun 2007 “Scaling Learning Algorithms Towards AI”]

- A deep architecture trades space for time (or breadth for depth)
  - More layers (more sequential computation),
  - But less hardware (less parallel computation).
- Example1: N-bit parity
  - requires N-1 XOR gates in a tree of depth log(N).
  - Even easier if we use threshold gates
  - requires an exponential number of gates of we restrict ourselves to 2 layers (DNF formula with exponential number of minterms).
- Example2: circuit for addition of 2 N-bit binary numbers
  - Requires O(N) gates, and O(N) layers using N one-bit adders with ripple carry propagation.
  - Requires lots of gates (some polynomial in N) if we restrict ourselves to two layers (e.g. Disjunctive Normal Form).
  - Bad news: almost all boolean functions have a DNF formula with an exponential number of minterms O(2^N).....

Which models are deep?

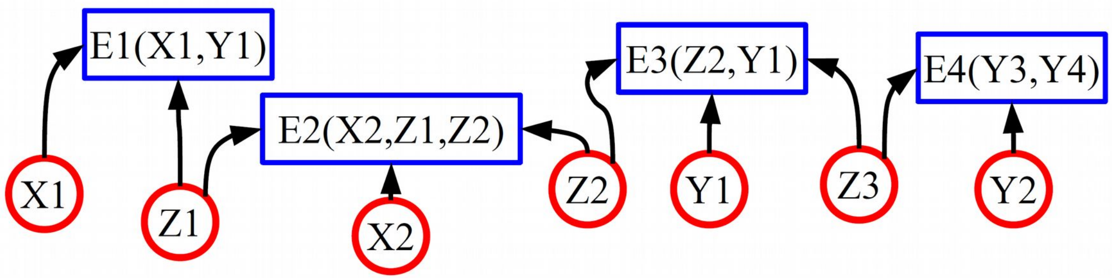
- 2-layer models are not deep (even if you train the first layer)
  - Because there is no feature hierarchy
- Neural nets with 1 hidden layer are not deep
- SVMs and Kernel methods are not deep
  - Layer1: kernels; layer2: linear
  - The first layer is “trained” in with the simplest unsupervised method ever devised: using the samples as templates for the kernel functions.
- Classification trees are not deep
  - No hierarchy of features. All decisions are made in the input space



Are graphical models deep?

– There is no opposition between graphical models and deep learning.
  – Many deep learning models are formulated as factor graphs
  – Some graphical models use deep architectures inside their factors
– Graphical models can be deep (but most are not). Factor graph: sum of energy functions
  – Over inputs X, outputs Y and latent variables Z. Trainable parameters: W

$$-\log P(X,Y,Z/W) \propto E(X,Y,Z,W) = \sum_i E_i(X,Y,Z,W_i)$$



– Each energy function can contain a deep network
– The whole factor graph can be seen as a deep network

Deep learning: A theoretician's nightmare?

- Deep Learning involves non-convex loss functions
  - With non-convex losses, all bets are off
  - Then again, every speech recognition system ever deployed has used non-convex optimization (GMMs are non convex).
- But to some of us all “interesting” learning is non convex
  - Convex learning is invariant to the order in which sample are presented (only depends on asymptotic sample frequencies).
  - Human learning isn't like that: we learn simple concepts before complex ones. The order in which we learn things matter.

Deep learning: A theoretician's nightmare?

- No generalization bounds?
  - Actually, the usual VC bounds apply: most deep learning systems have a finite VC dimension
  - We don't have tighter bounds than that.
  - But then again, how many bounds are tight enough to be useful for model selection?
- It's hard to prove anything about deep learning systems
  - Then again, if we only study models for which we can prove things, we wouldn't have speech, handwriting, and visual object recognition systems today.

Deep learning: A theoretician's paradise?

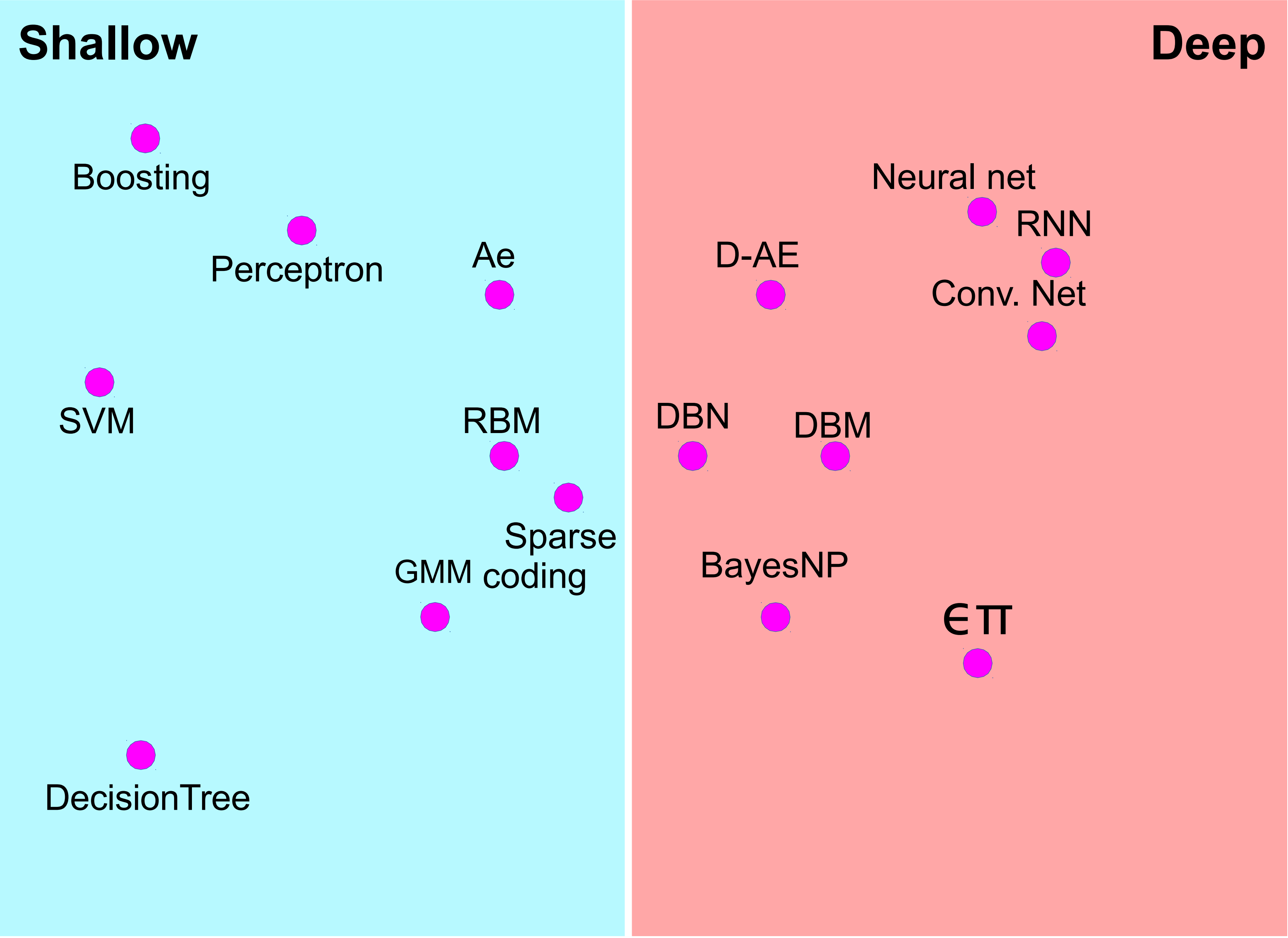
- Deep learning is about representing high-dimensional data
  - There has to be interesting theoretical questions there what is the geometry of natural signals?
  - Is there an equivalent of statistical learning theory for unsupervised learning?
  - What are good criteria on which to base unsupervised learning?
- Deep learning systems are a form of latent variable factor graph
  - Internal representations can be viewed as latent variables to be inferred, and deep belief networks are a particular type of latent variable models.
  - The most interesting deep belief nets have intractable loss functions: how do we get around that problem?
- Lots of theory at the 2012 IPAM summer school on deep learning
  - Wright's parallel SGD methods, Mallat's “scattering transform”, Osher's “split Bregman” methods for sparse modeling, Morton's “algebraic geometry of DBN”,....

Deep learning and feature learning today

- Deep learning has been the hottest topic in speech recognition in the last 2 years
  - A few long-standing performance records were broken with deep learning methods
  - Microsoft and google have both deployed dl-based speech recognition system in their products
  - Microsoft, google, IBM, nuance, AT&T, and all the major academic and industrial players in speech recognition have projects on deep learning
- Deep learning is the hottest topic in computer vision
  - Feature engineering is the bread-and-butter of a large portion of the CV community, which creates some resistance to feature learning
  - But the record holders on ImageNet and semantic segmentation are convolutional nets
- Deep learning is becoming hot in natural language processing
- Deep learning/feature learning in applied mathematics
  - The connection with applied math is through sparse coding, non-convex optimization, stochastic gradient algorithms, etc...

In many fields, feature learning has caused a revolution (methods used in commercially deployed systems)

- Speech Recognition I (late 1980s)
  - Trained mid-level features with Gaussian mixtures (2-layer classifier)
- Handwriting Recognition and OCR (late 1980s to mid 1990s)
  - Supervised convolutional nets operating on pixels
- Face & People Detection (early 1990s to mid 2000s)
  - Supervised convolutional nets operating on pixels (YLC 1994, 2004, Garcia 2004)
  - Haar features generation/selection (Viola-Jones 2001)
- Object Recognition I (mid-to-late 2000s: Ponce, Schmid, Yu, YLC....)
  - Trainable mid-level features (K-means or sparse coding)
- Low-Res Object Recognition: road signs, house numbers (early 2010's)
  - Supervised convolutional net operating on pixels
- Speech Recognition II (circa 2011)
  - Deep neural nets for acoustic modeling
- Object Recognition III, Semantic Labeling (2012, Hinton, YLC,...)
  - Supervised convolutional nets operating on pixels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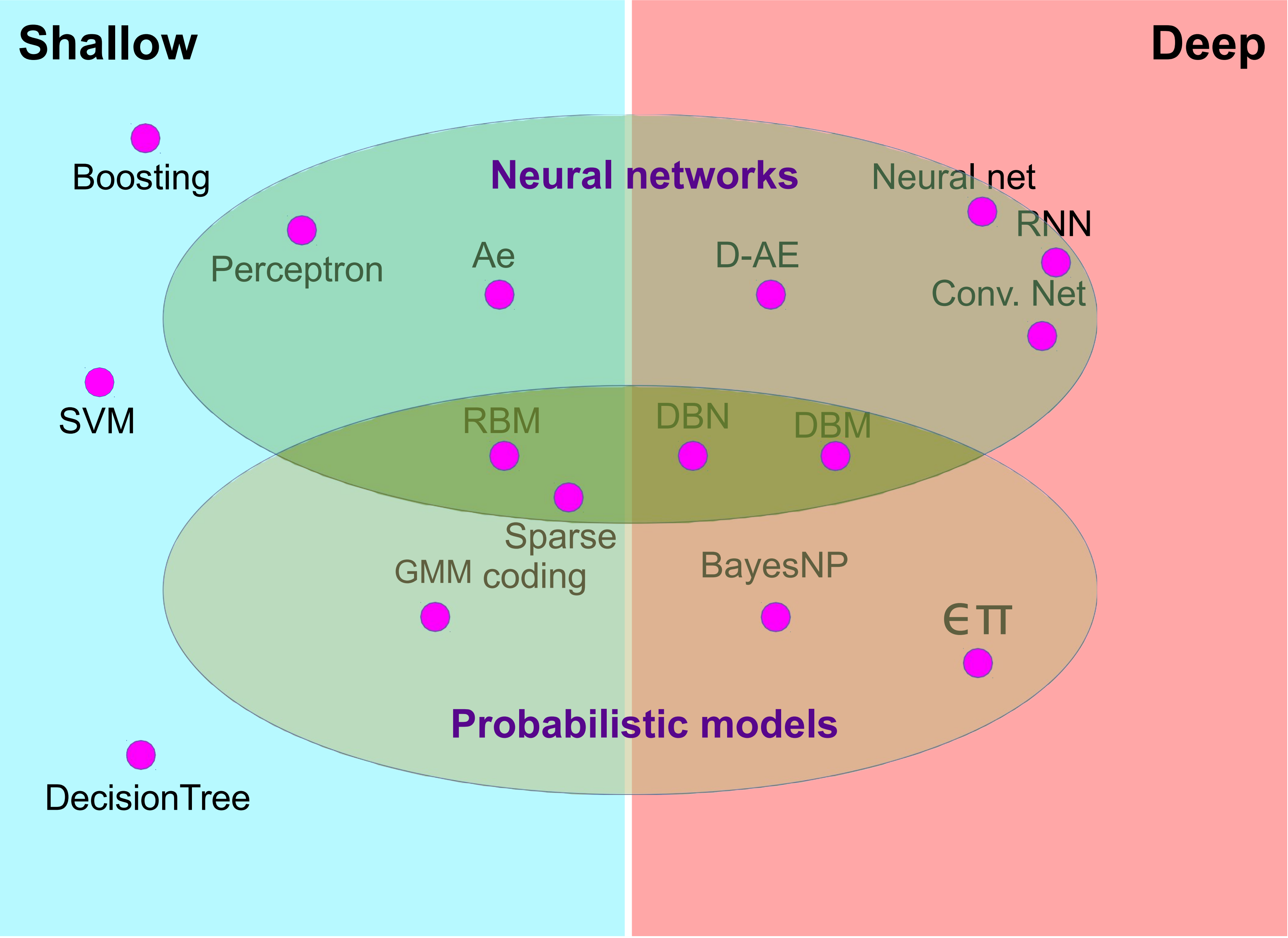
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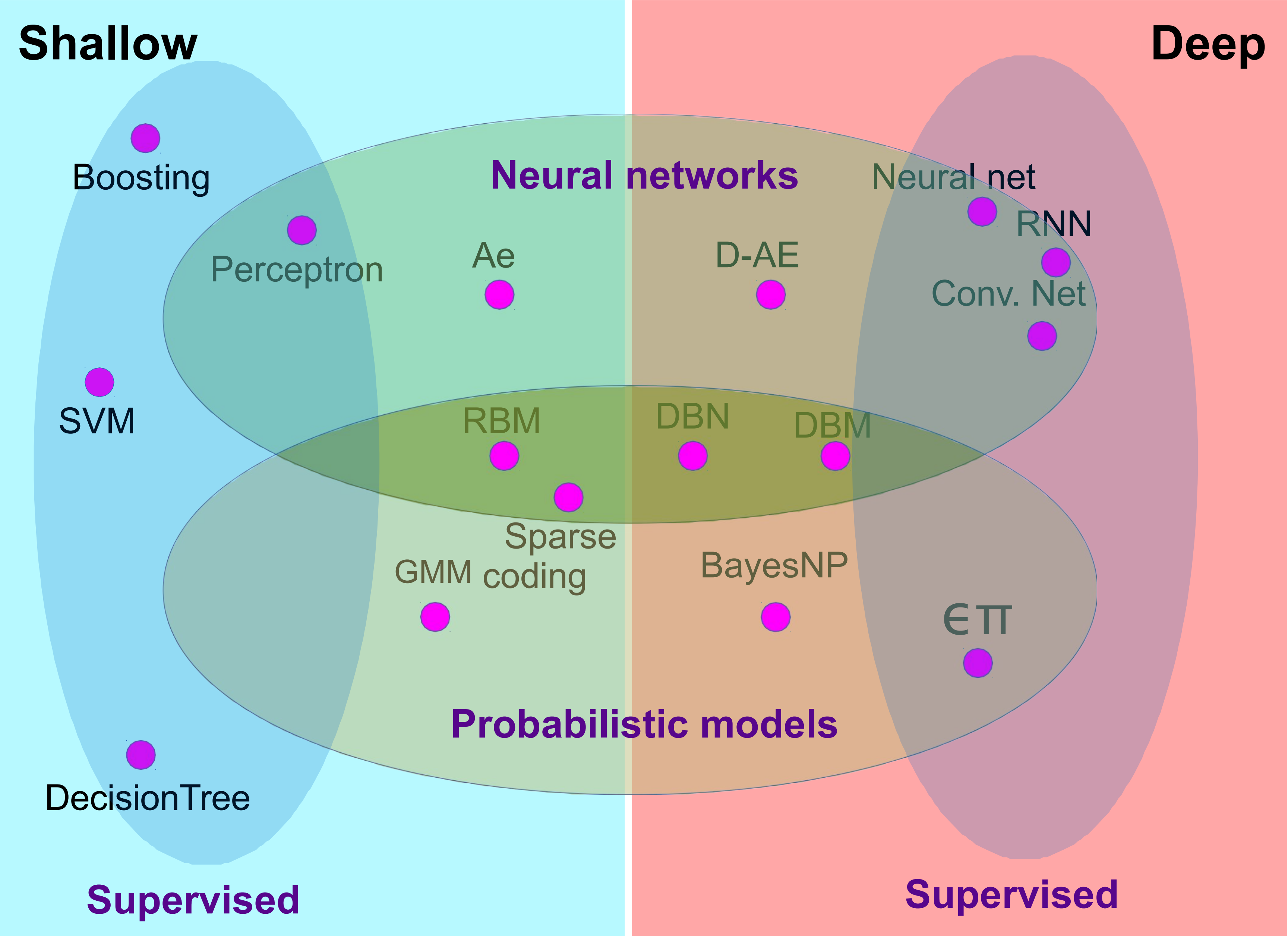
Probabilistic models
DecisionTree



Shallow
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Neural net

RNN

D-AE

Conv. Net

DBN

DBM

BayesNP

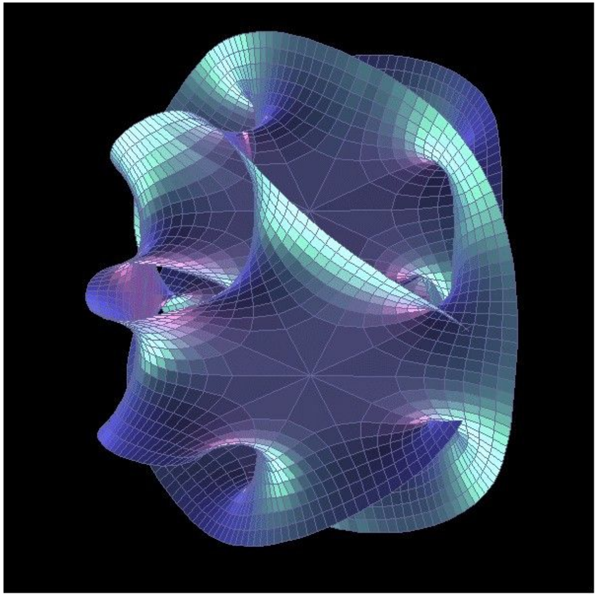
$\epsilon\pi$

In this talk, we'll focus on **the simplest and typically most effective methods**

What are good features?

Discovering the hidden structure in high-dimensional data the manifold hypothesis

- Learning representations of data:
  - Discovering & disentangling the independent explanatory factors
- The manifold hypothesis:
  - Natural data lives in a low-dimensional (non-linear) manifold
  - Because variables in natural data are mutually dependent



Discovering the hidden structure in high-dimensional data

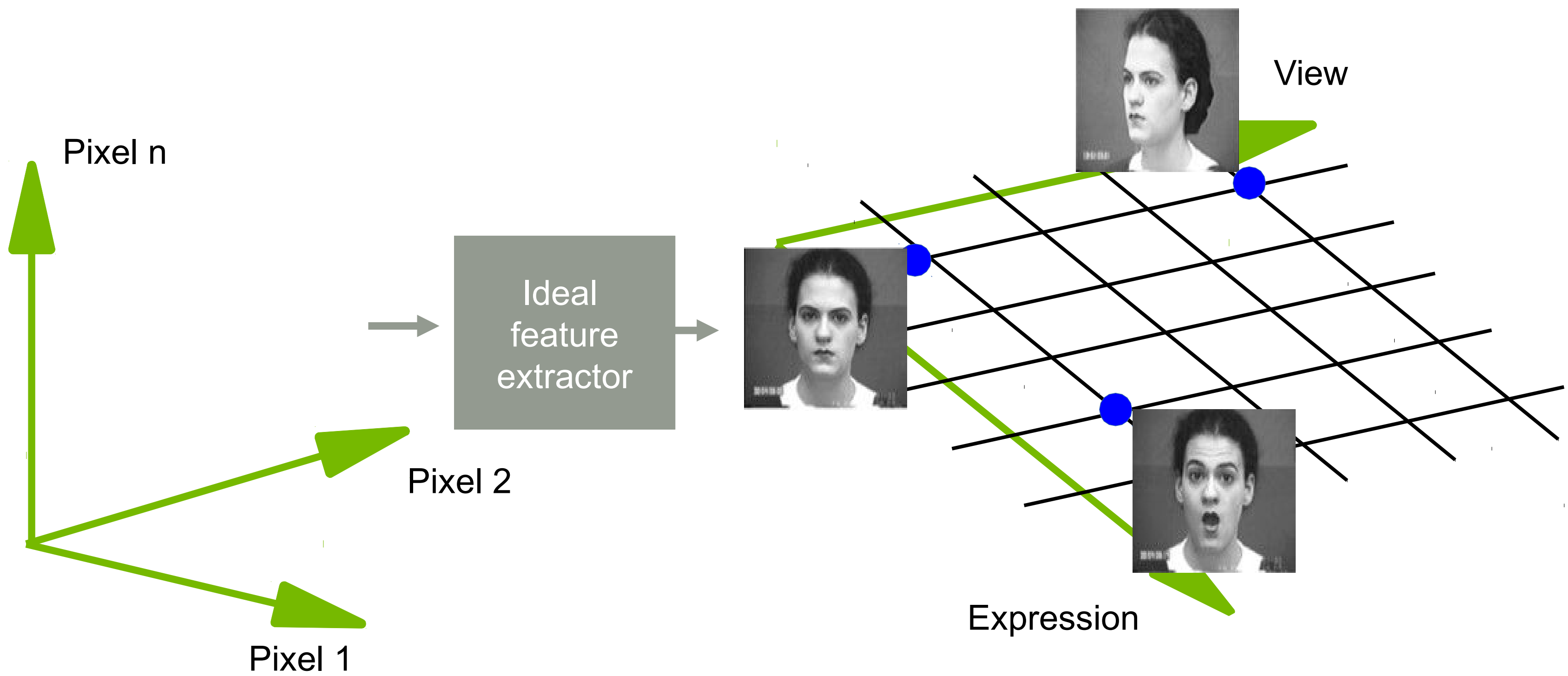
- Example: all face images of a person
  - 1000x1000 pixels = 1,000,000 dimensions
  - But the face has 3 Cartesian coordinates and 3 Euler angles and humans have less than about 50 muscles in the face
  - Hence the manifold of face images for a person has <56 dimensions
- The perfect representations of a face image:
  - Its coordinates on the face manifold
  - Its coordinates away from the manifold
- We do not have good and general methods to learn functions that turns an image into this kind of representation

Ideal feature extractor

1.2	Face/not face
-3	Pose
0.2	Lighting
-2…	Expression

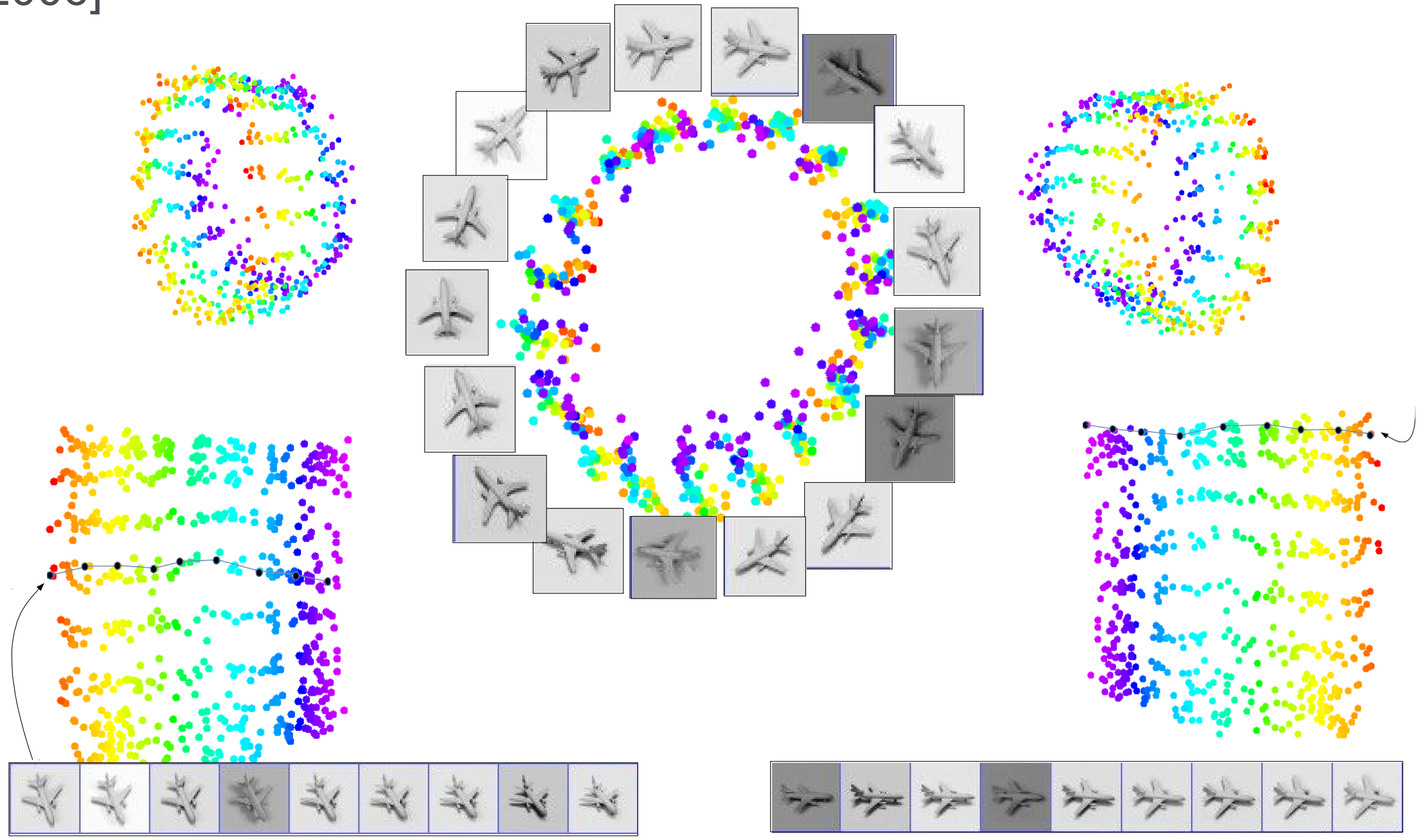
Disentangling factors of variation

The ideal disentangling feature extractor



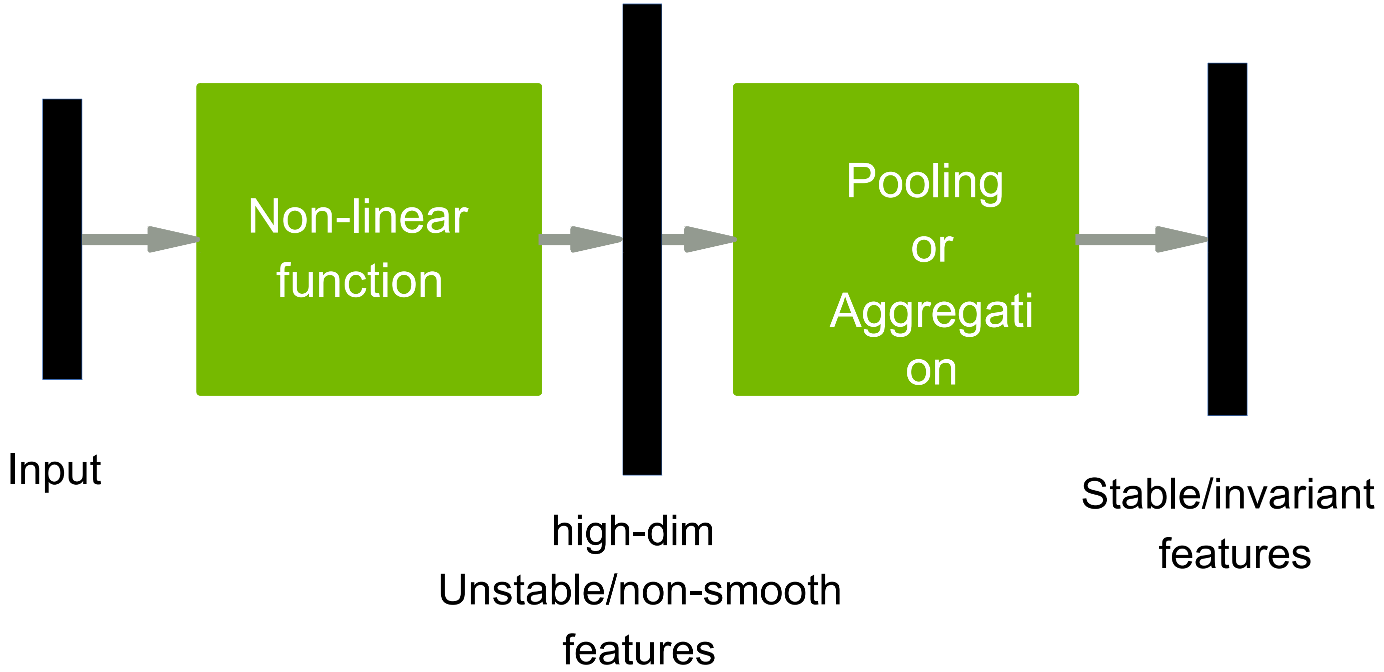
Data manifold & invariance: Some variations must be eliminated

– Azimuth-Elevation manifold. Ignores lighting. [Hadsell et al. CVPR 2006]



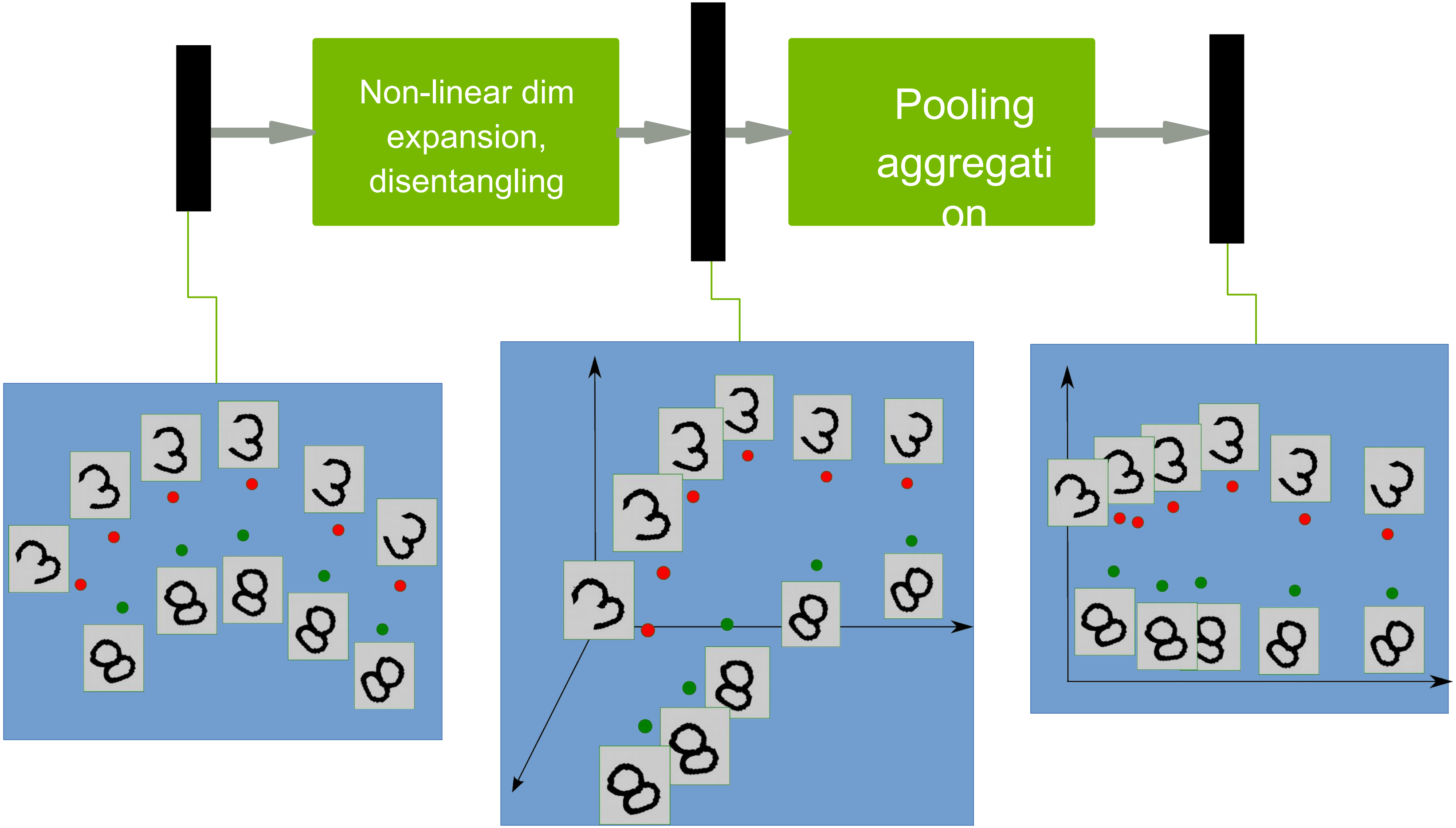
Basic idea for invariant feature learning

- Embed the input non-linearly into a high(er) dimensional space
  - In the new space, things that were non separable may become separable
- Pool regions of the new space together
  - Bringing together things that are semantically similar. Like pooling.



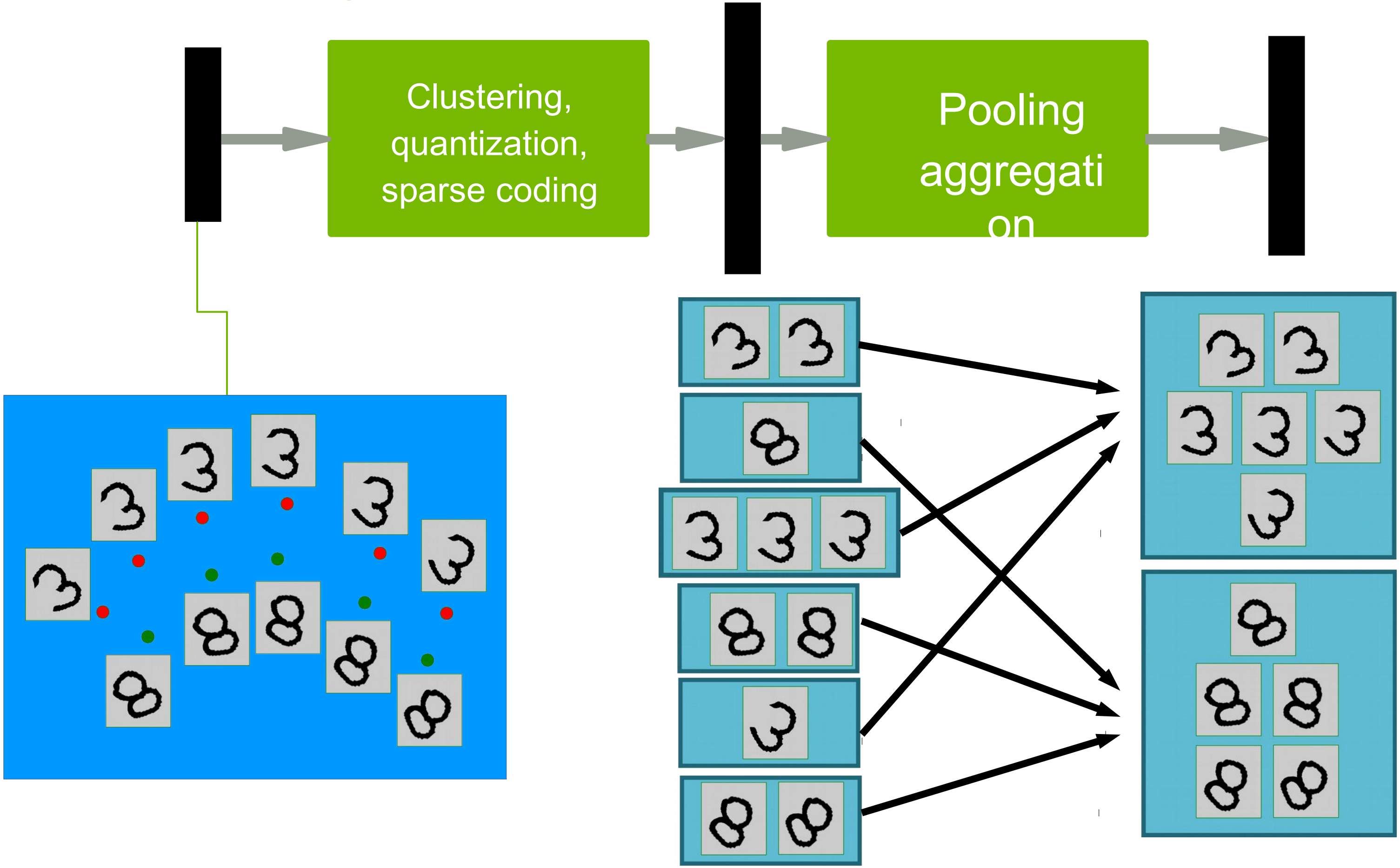
Non-linear expansion → pooling

Entangled data manifolds

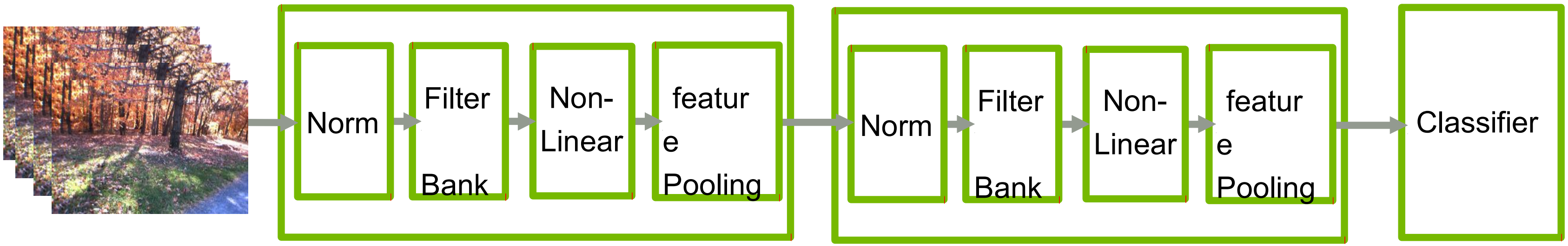


Sparse non-linear expansion → pooling

Use clustering to break things apart, pool together similar things



Overall architecture:
Normalization → filter bank → non-linearity → pooling



- Stacking multiple stages of
  - [Normalization → filter bank → non-linearity → pooling].
- Normalization: variations on whitening
  - Subtractive: average removal, high pass filtering
  - Divisive: local contrast normalization, variance normalization
- Filter bank: dimension expansion, projection on overcomplete basis
- Non-linearity: sparsification, saturation, lateral inhibition....
  - Rectification (relu), component-wise shrinkage, tanh, winner-takes-all
- Pooling: aggregation over space or feature type
  - $X_i;\quad L_p: \sqrt[p]{X_i^p};\quad PROB: \frac{1}{b}\log\left(\sum_i e^{bX_i}\right)$

Software

- Torch7: learning library that supports neural net training
  - http://www.torch.ch
  - http://code.cogbits.com/wiki/doku.php (tutorial with demos by C. Farabet)
  - http://eblearn.sf.net (C++ Library with convent support by P. Sermanet)
- Python-based learning library (U. Montreal)
  - http://deeplearning.net/software/theano/ (does automatic differentiation)
- RNN
  - www.fit.vutbr.cz/~imikolov/rnnlm (language modeling)
  - http://sourceforge.net/apps/mediawiki/index.php (LSTM)
- CUDAMat & GNumpy
  - code.google.com/p/cudamat
  - www.cs.toronto.edu/~tijmen/gnumpy.htm
- Misc
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NEW YORK UNIVERSITY

Deep Learning Teaching Kit

Thank you

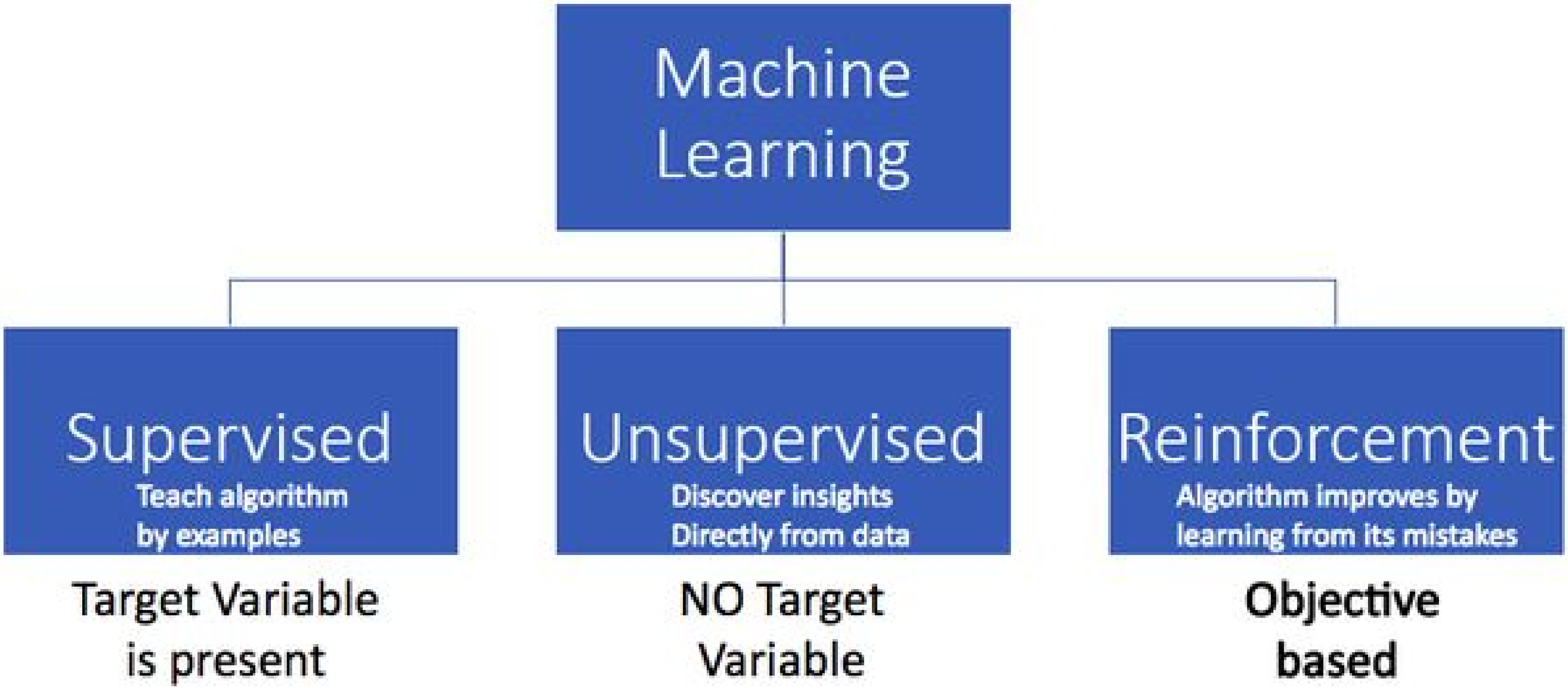
DEEP LEARNING METHODS

LECTURE 4: CATEGORIES, TYPES, ORIGIN, DEVELOPMENT

Yuri Gordienko, DLI Certified Instructor

TYPES OF LEARNING ALGORITHMS

Types of Learning Algorithms



Types of Learning Algorithms

Supervised
Teach algorithm by examples

Target Variable is present

Supervised Learning — Neural Networks (NN):

- Feed-Forward NN (FNN)
- Convolutional NN (CNN)
- Recurrent NN (RNN)
- Encoder-Decoder Architectures (EDA)

Unsupervised
Discover insights Directly from data

NO Target Variable

Unsupervised Learning — Neural Networks (NN):

- Autoencoder
- Generative Adversarial Networks

Reinforcement
Algorithm improves by learning from its mistakes

Objective based

Reinforcement Learning

- Networks for Learning Actions, Values, and Policies

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TYPES OF LEARNING ALGORITHMS

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NEURAL NETWORK ARCHITECTURES

-

SUPERVISED

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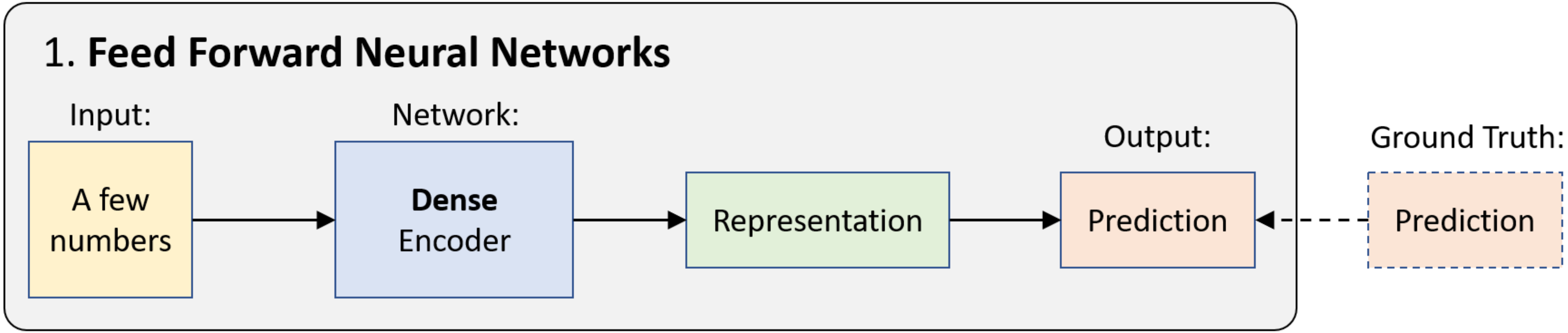

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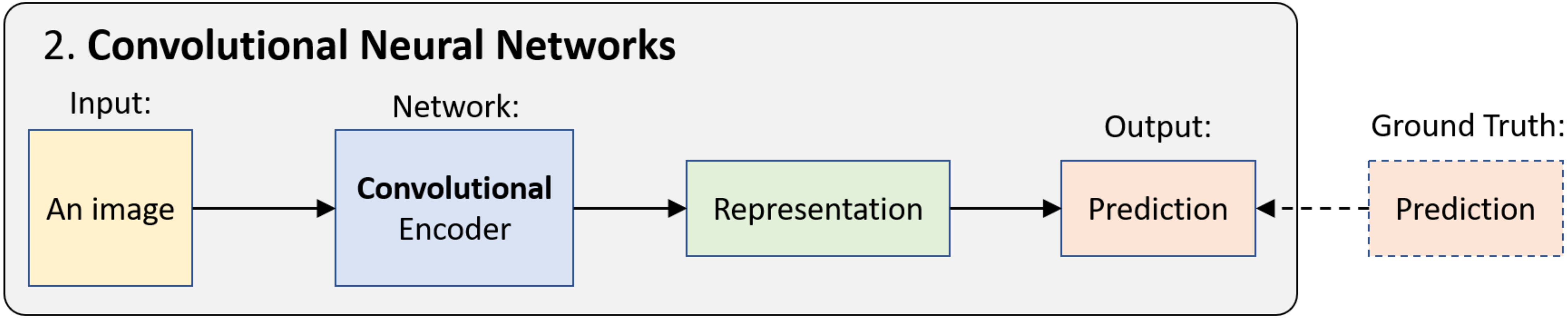

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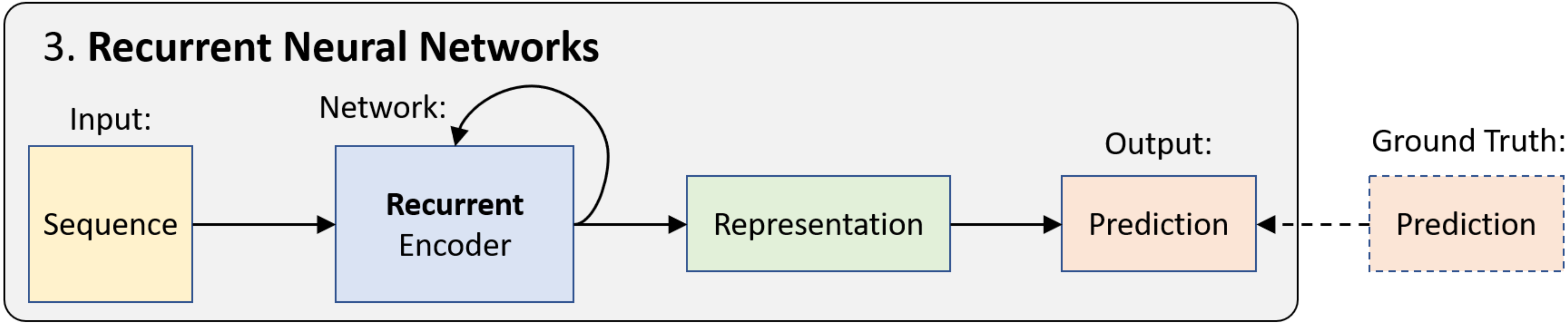

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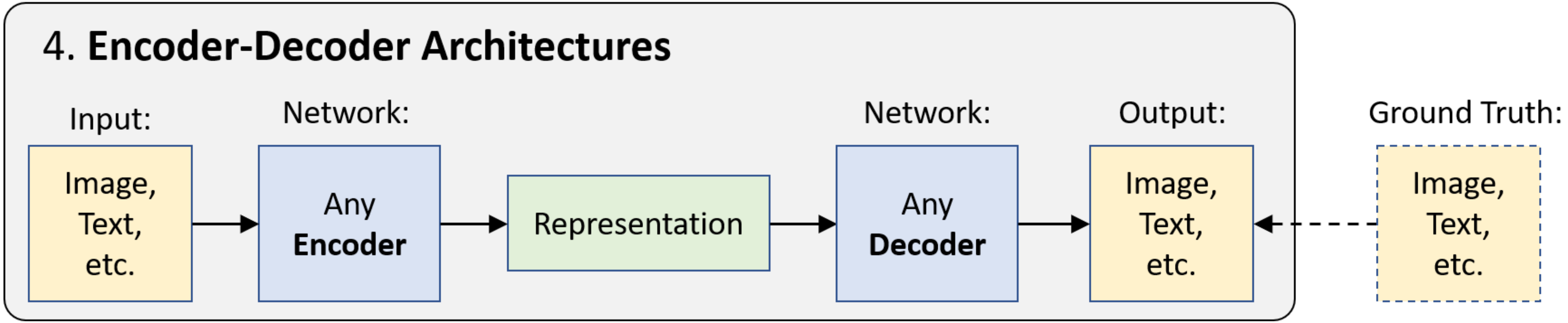
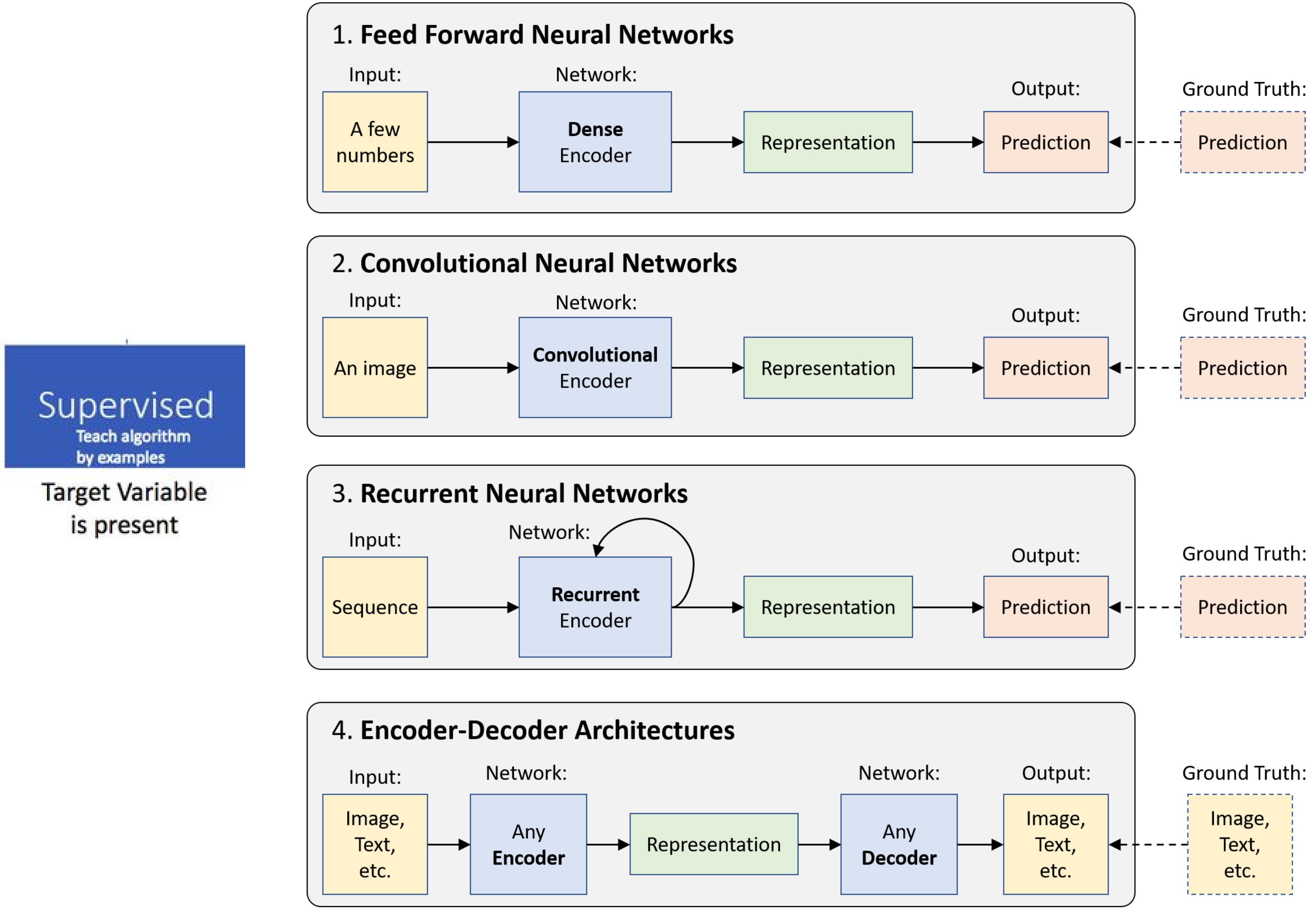



Supervised
Teach algorithm by examples
Target Variable is present
1. Feed Forward Neural Networks
Input:
A few numbers
Network:
Dense Encoder
Representation
Output:
Prediction
Ground Truth:
Prediction
2. Convolutional Neural Networks
Input:
An image
Network:
Convolutional Encoder
Representation
Output:
Prediction
Ground Truth:
Prediction
3. Recurrent Neural Networks
Input:
Sequence
Network:
Recurrent Encoder
Representation
Output:
Prediction
Ground Truth:
Prediction
4. Encoder-Decoder Architectures
Input:
Image, Text, etc.
Network:
Any Encoder
Representation
Network:
Any Decoder
Output:
Image, Text, etc.
Ground Truth:
Image, Text, etc.

TYPES OF LEARNING ALGORITHMS
-
NEURAL NETWORK ARCHITECTURES
-
UNSUPERVISED

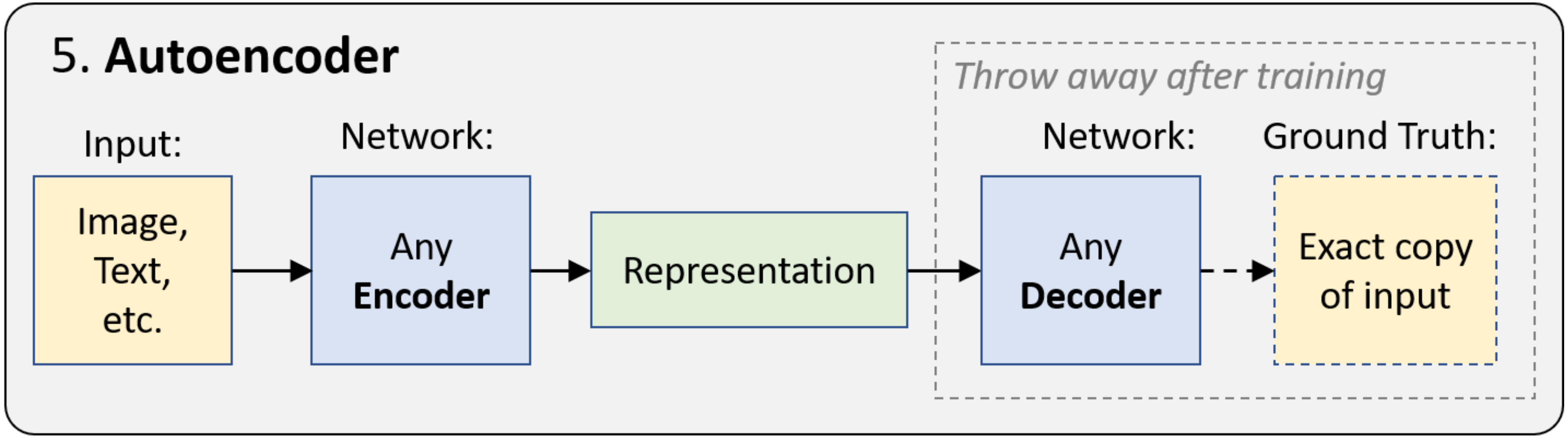
Types of Learning Algorithms

Unsupervised
Discover insights
Directly from data

NO Target
Variable

Unsupervised Learning — Neural Networks (NN):

- Autoencoder
- Generative Adversarial Networks

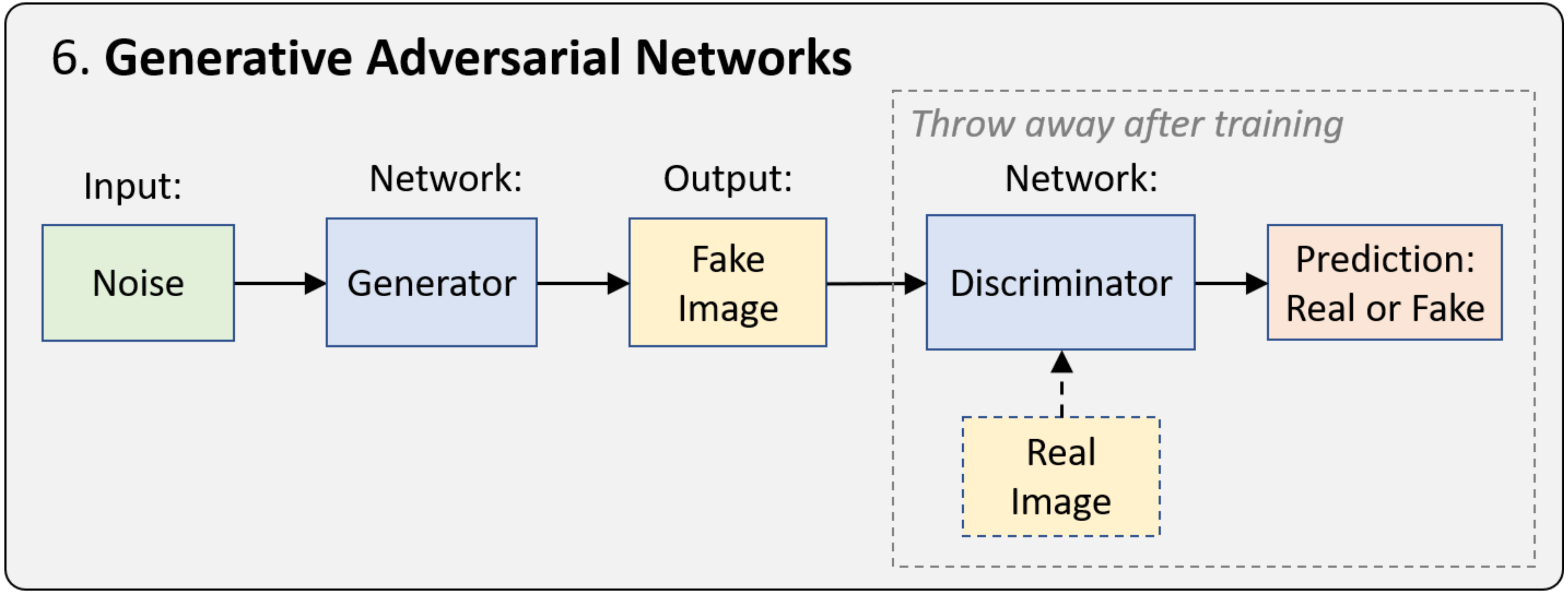


Types of Learning Algorithms

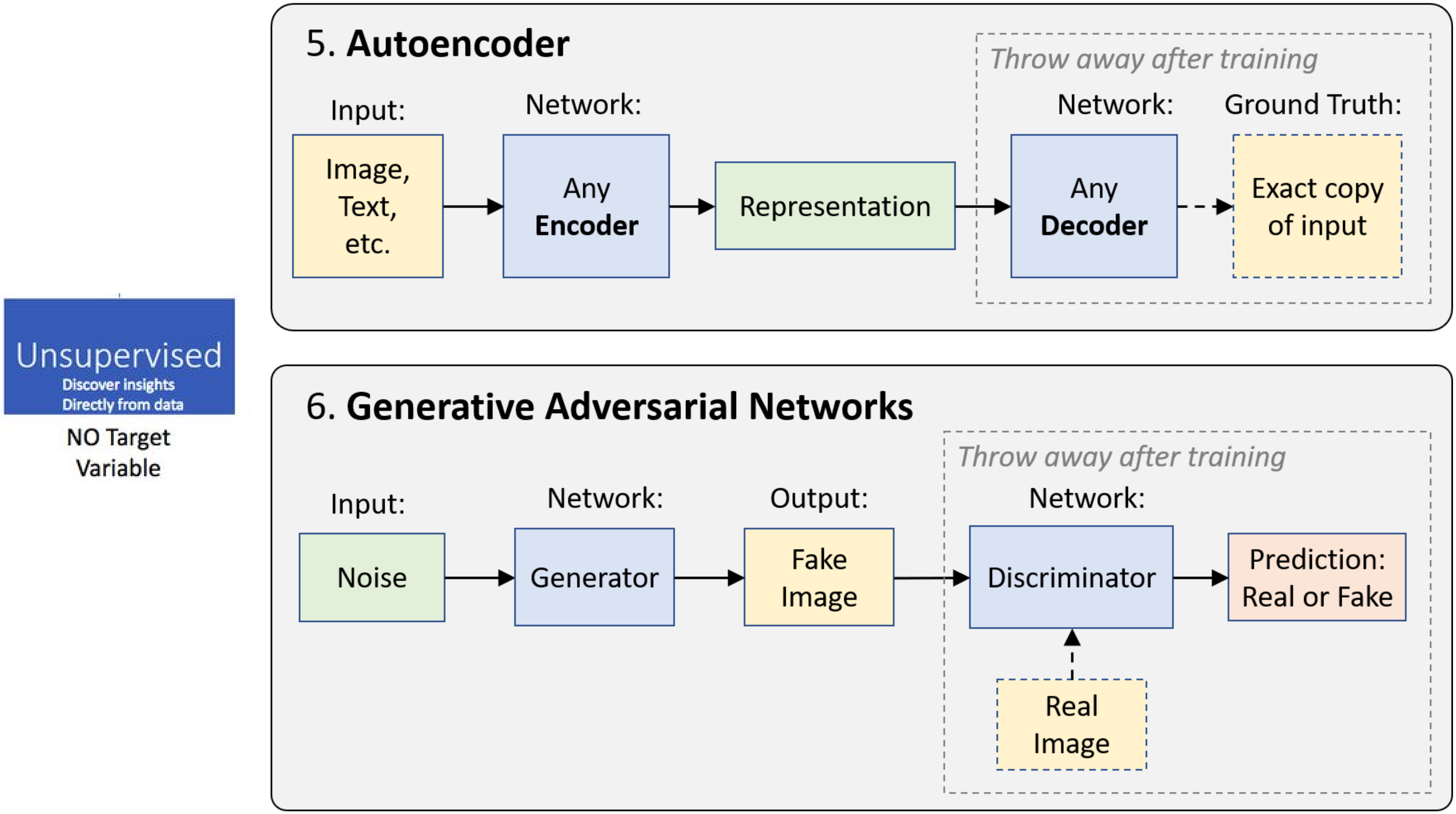
NO Target Variable

Unsupervised Learning — Neural Networks (NN):

- Autoencoder
- Generative Adversarial Networks



(C) Lex Fridman


Unsupervised
Discover insights
Directly from data
NO Target
Variable
5. Autoencoder
Throw away after training
Input:
Network:
Network:
Ground Truth:
Image,
Text,
etc.
Any
Encoder
Representation
Any
Decoder
Exact copy
of input
6. Generative Adversarial Networks
Throw away after training
Input:
Network:
Output:
Network:
Noise
Generator
Fake
Image
Discriminator
Prediction:
Real or Fake
Real
Image

TYPES OF LEARNING ALGORITHMS

-

NEURAL NETWORK ARCHITECTURES

-

REINFORCEMENT

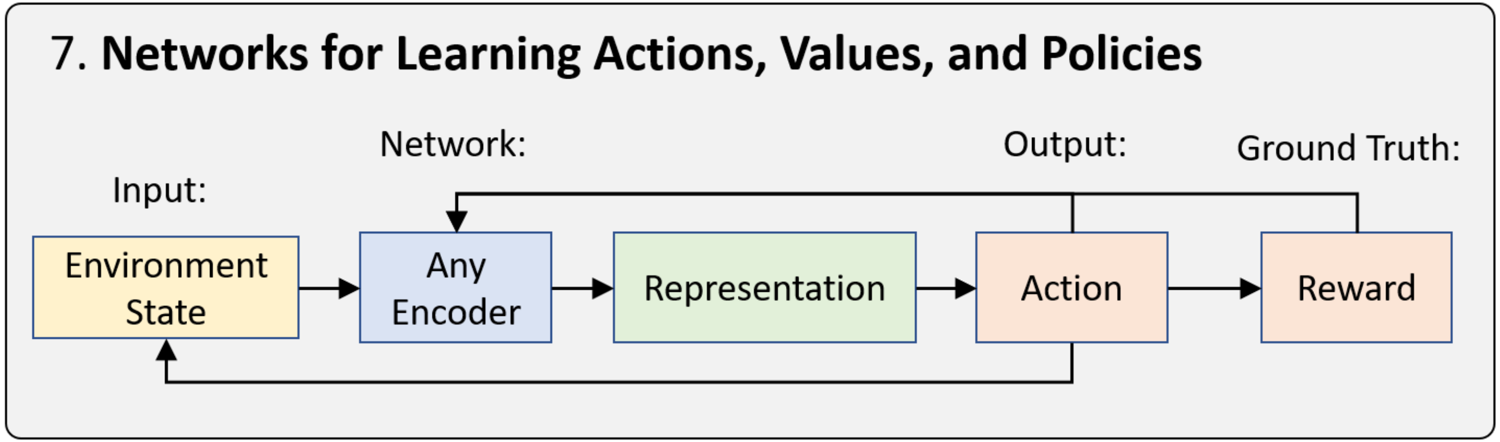
Types of Learning Algorithms

Reinforcement
Algorithm improves by learning from its mistakes

Objective based

Reinforcement Learning

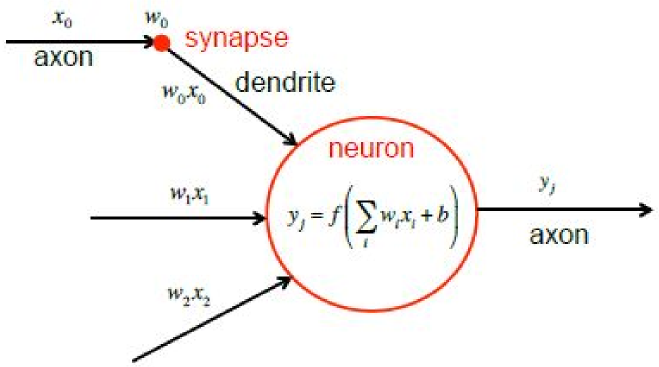
- Networks for Learning Actions, Values, and Policies

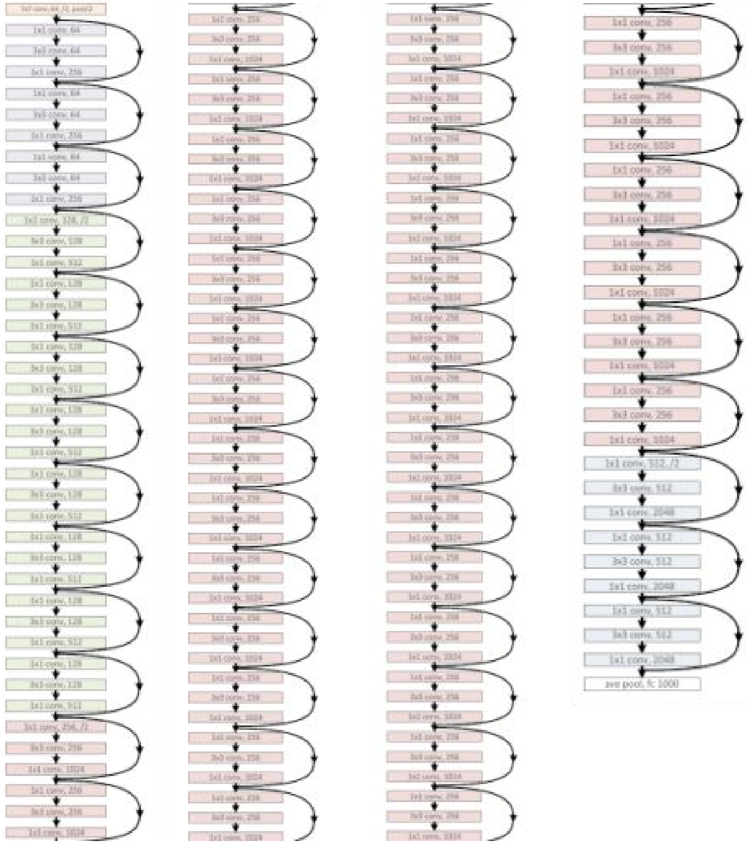


HOW THEY APPEARED
-
MOTIVATION

NEURAL NETWORKS ARE NOT NEW

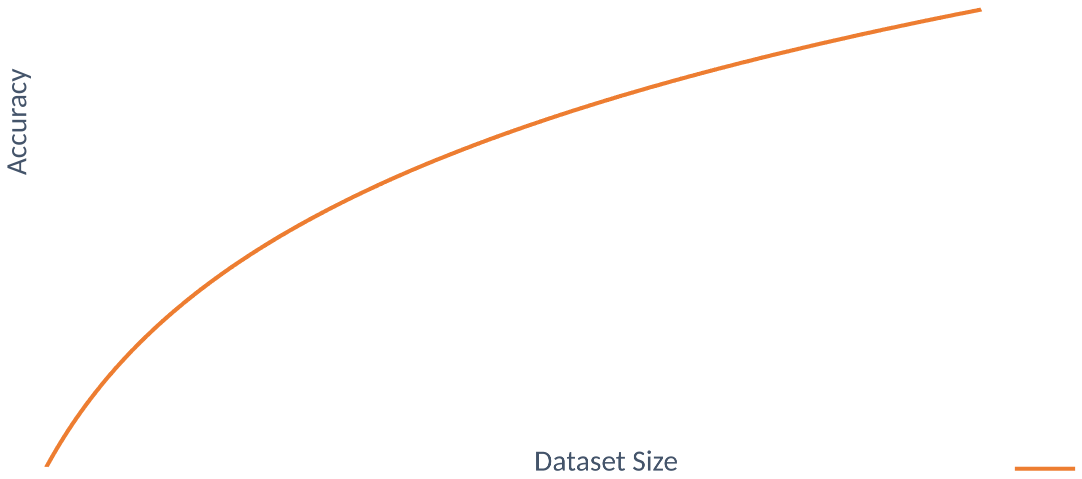
And are surprisingly simple as an algorithm





NEURAL NETWORKS ARE NOT NEW

They just historically never worked well



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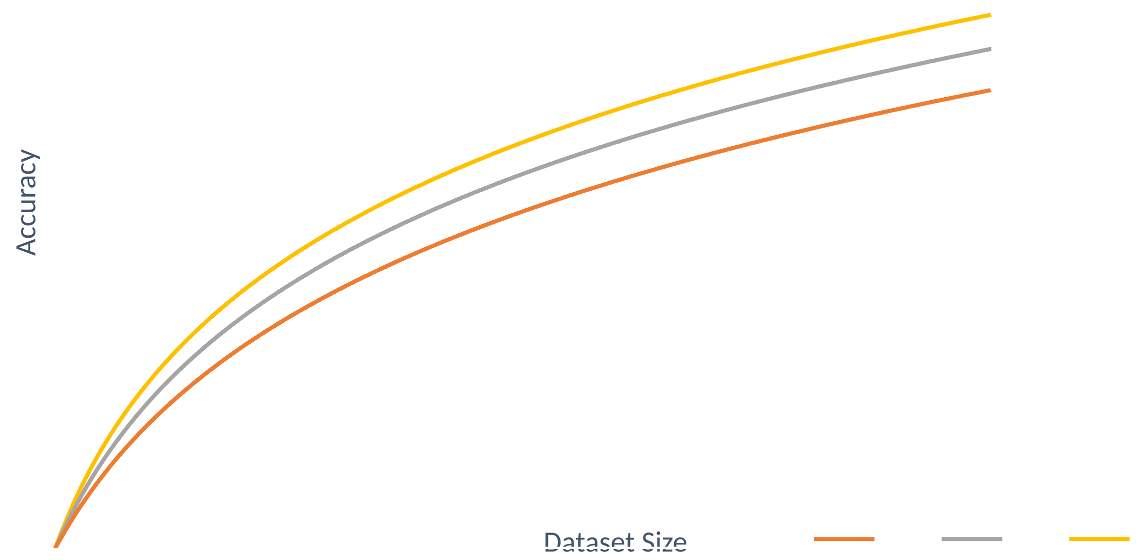

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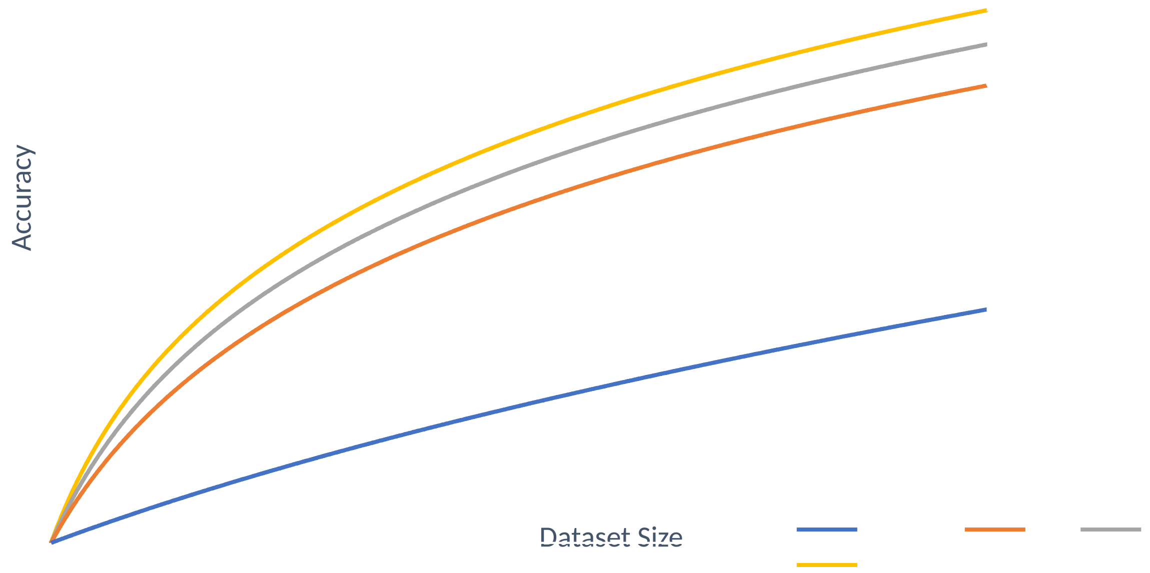

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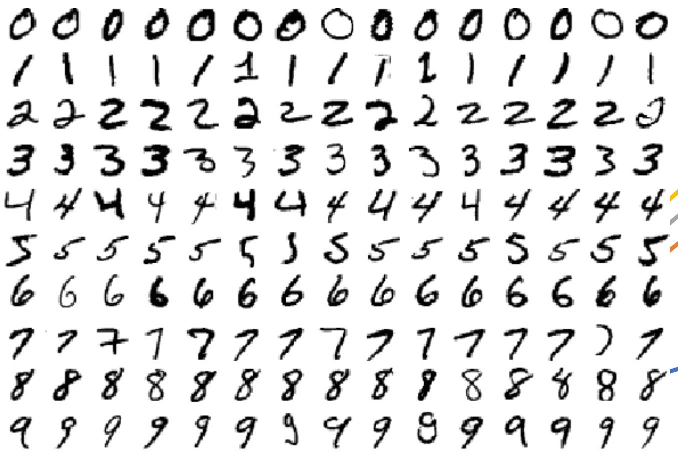
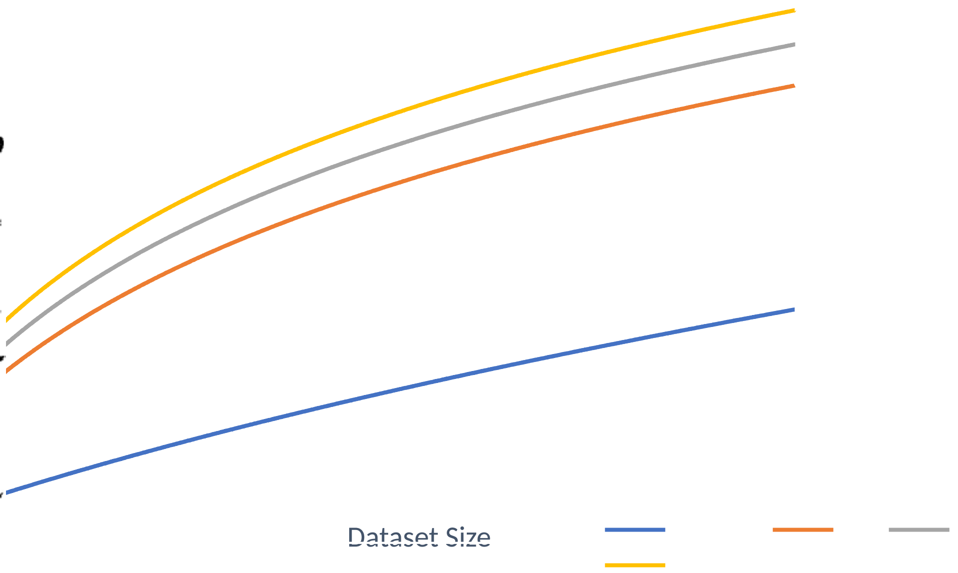
NEURAL NETWORKS ARE NOT NEW

Historically we never had large datasets or computers

The MNIST (1999) database contains 60,000 training images and 10,000 testing images.





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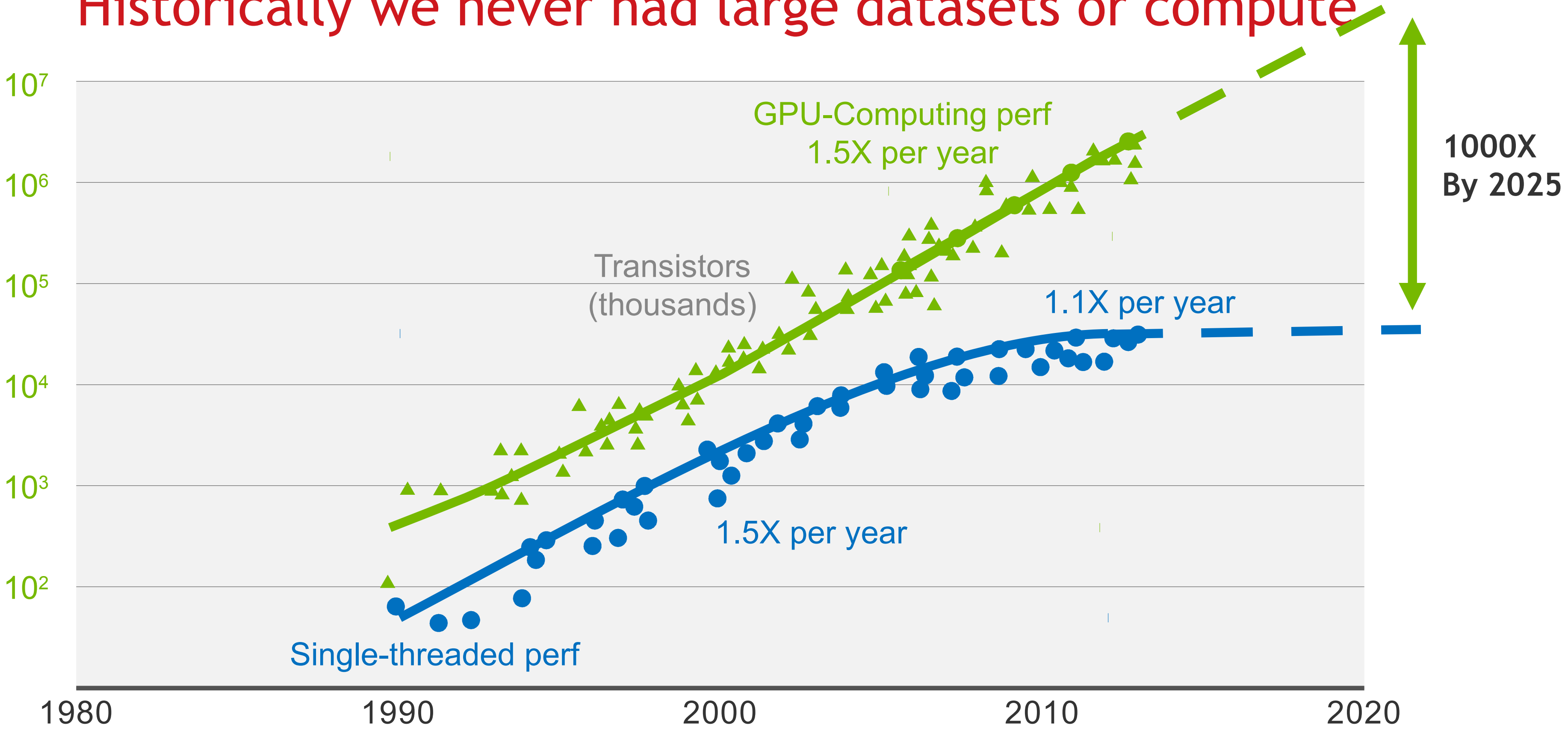
COMPUTE

Historically we never had large datasets or compute



AI BIG BANG PILLARS:

- HIGH-PERFORMANCE COMPUTING
- BIG DATA
- DEEP MODELS

AI BIG BANG PILLARS:

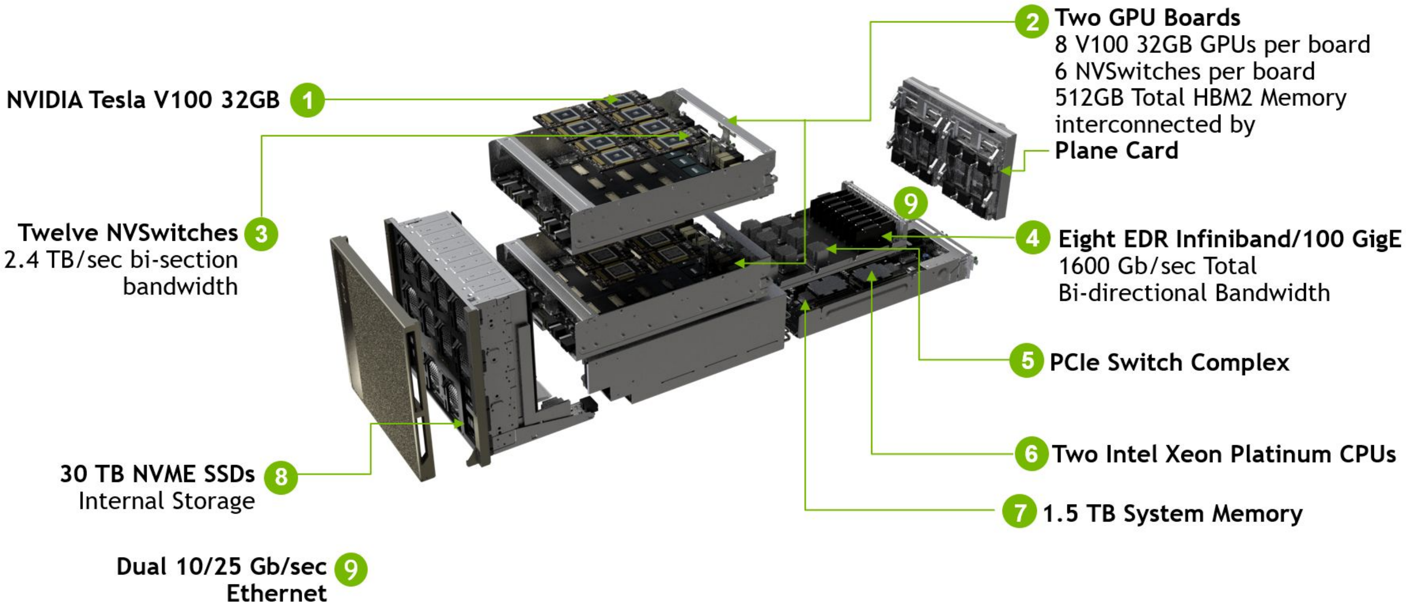
- HIGH-PERFORMANCE COMPUTING
- BIG DATA
- DEEP MODELS

CONTEXT

1.759 petaFLOPs in November 2009

CONTEXT

2 petaFLOPs - today



100 EXAFLOPS

=

2 YEARS ON A DUAL CPU SERVER

AI BIG BANG PILLARS:

- HIGH-PERFORMANCE COMPUTING
- BIG DATA
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EXPLODING DATASETS

Logarithmic relationship between the dataset size and accuracy

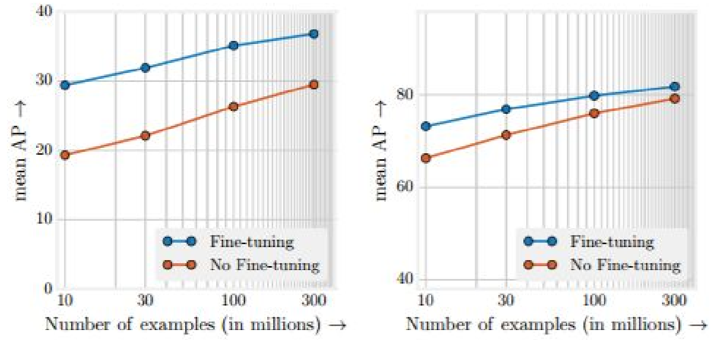


Figure 4. Object detection performance when initial checkpoints are pre-trained on different subsets of JFT-300M from scratch. x-axis is the data size in log-scale, y-axis is the detection performance in mAP@[.5,.95] on COCO minival* (left), and in mAP@.5 on PASCAL VOC 2007 test (right).

Initialization	mIOU
ImageNet	73.6
300M	75.3
ImageNet+300M	**76.5**

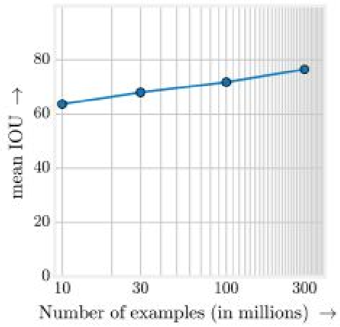
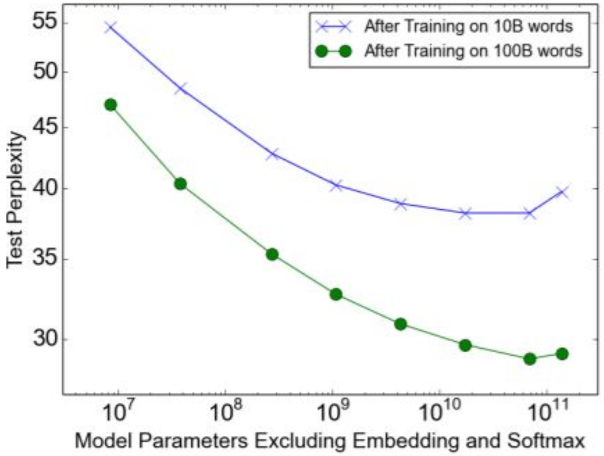


Figure 6. Semantic segmentation performance on Pascal VOC 2012 val set. (left) Quantitative performance of different initializations; (right) Impact of data size on performance.



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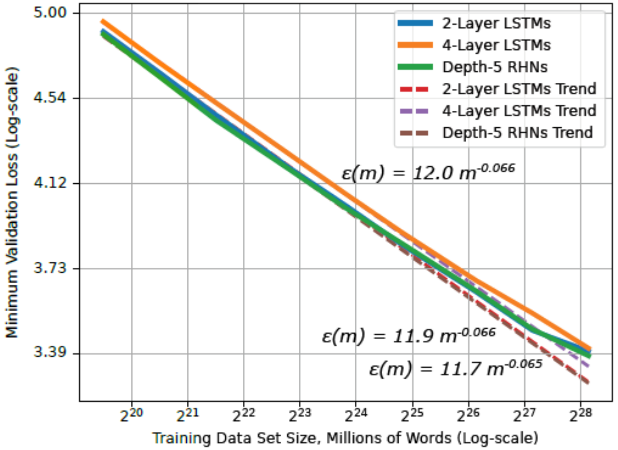
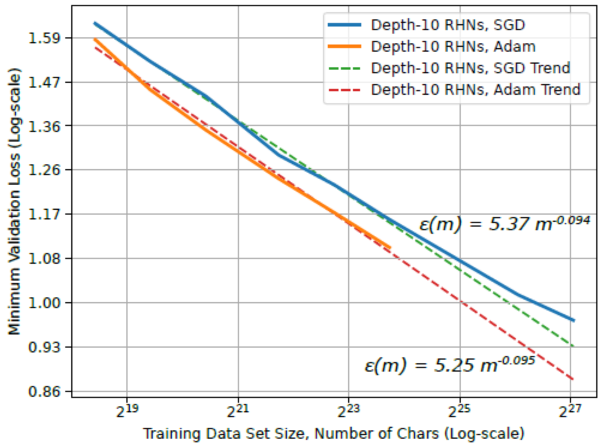
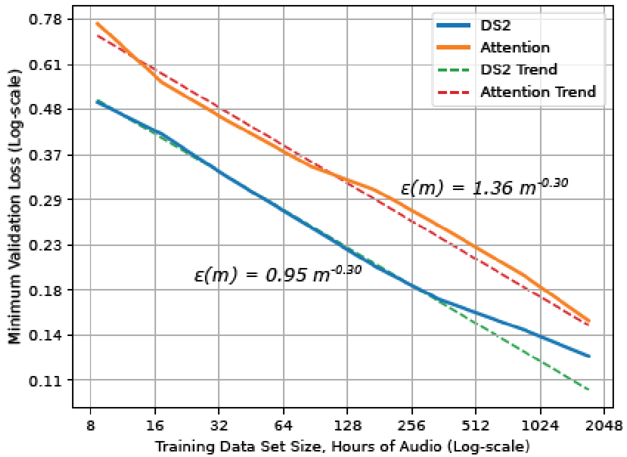
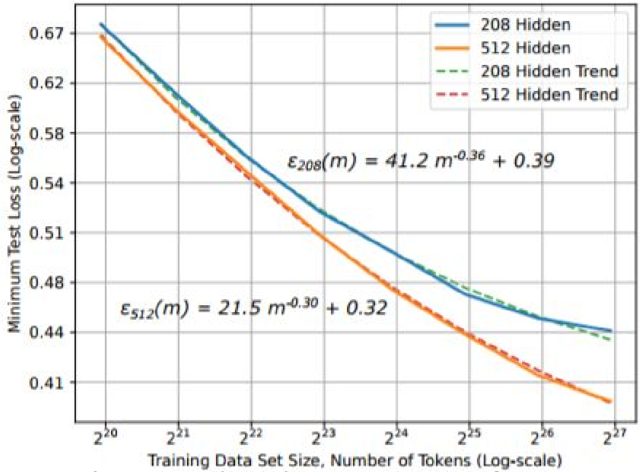
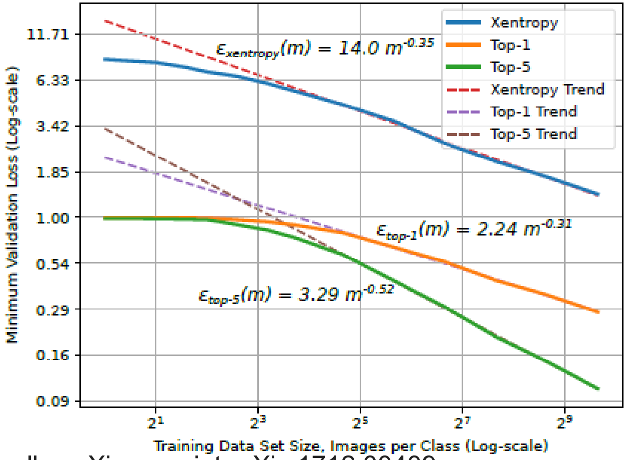


- Translation
- Language Models
- Character Language Models
- Image Classification
- Attention Speech Models









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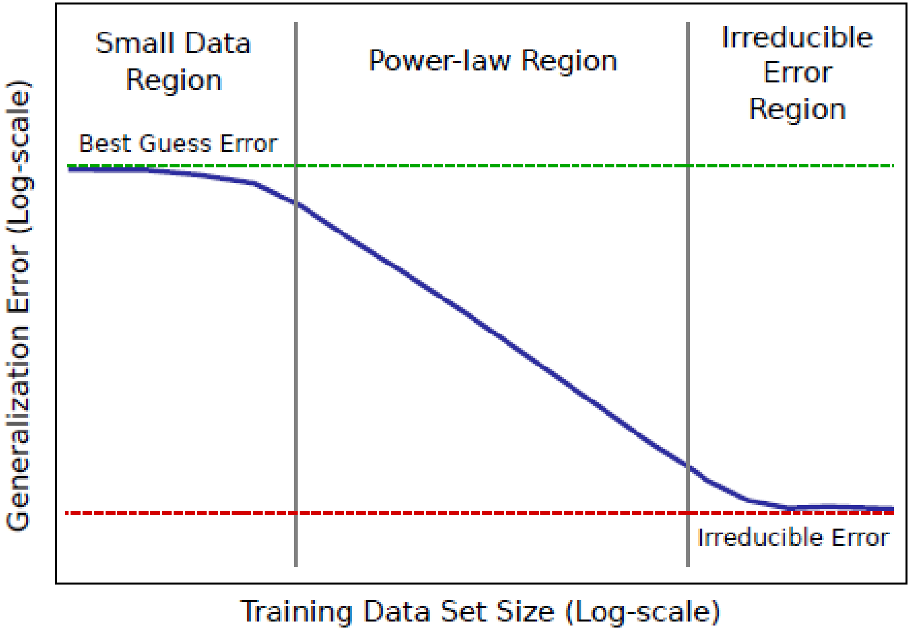

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AI BIG BANG PILLARS:

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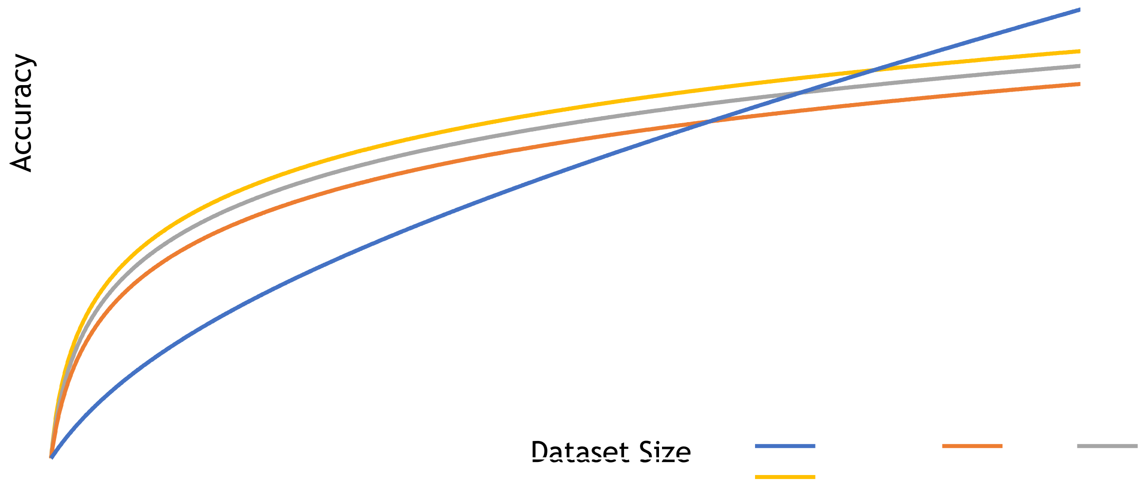
To Tackle Increasingly Complex Challenges

NEURAL NETWORKS ARE NOT NEW

But that changed and transformed the way we do machine learning



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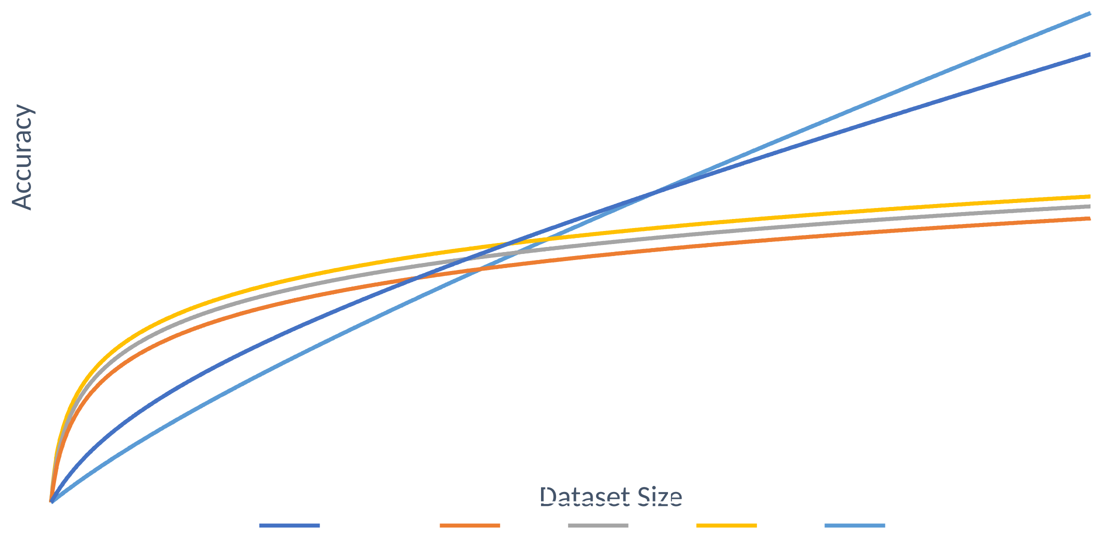
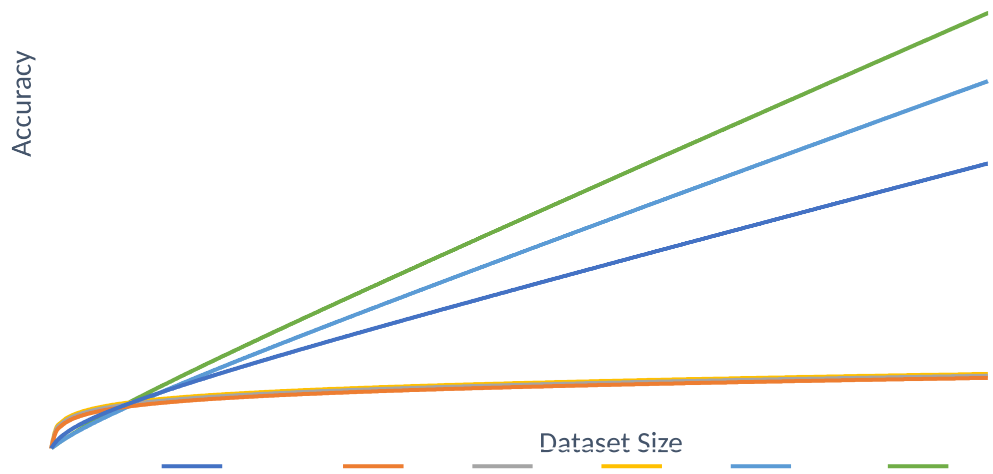
NEURAL NETWORKS ARE NOT NEW

Data and model size the key to accuracy



NEURAL NETWORKS ARE NOT NEW

Exceeding human level performance



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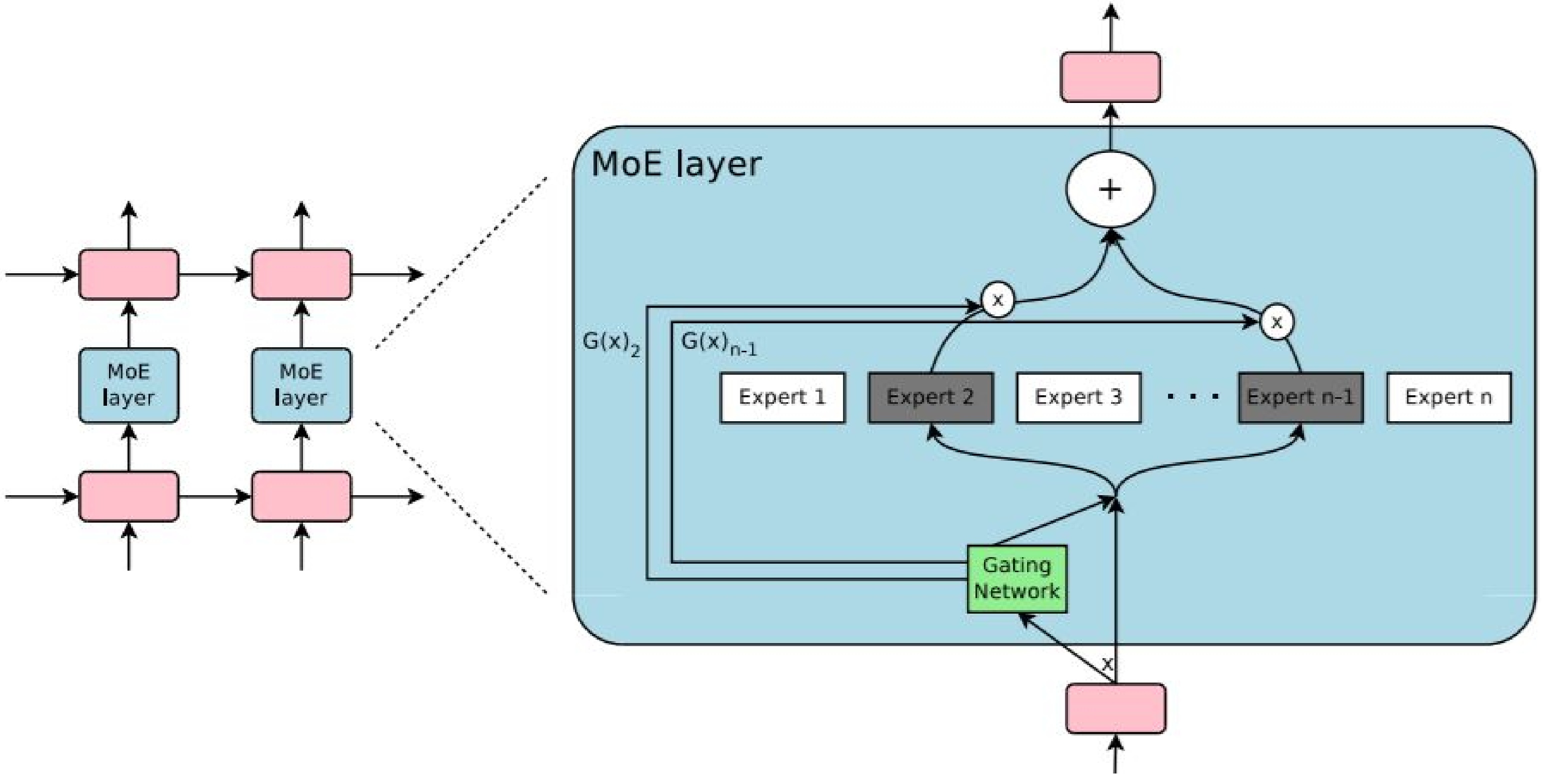
To Tackle Increasingly Complex Challenges

EXPLODING MODEL COMPLEXITY

Larger models are made possible



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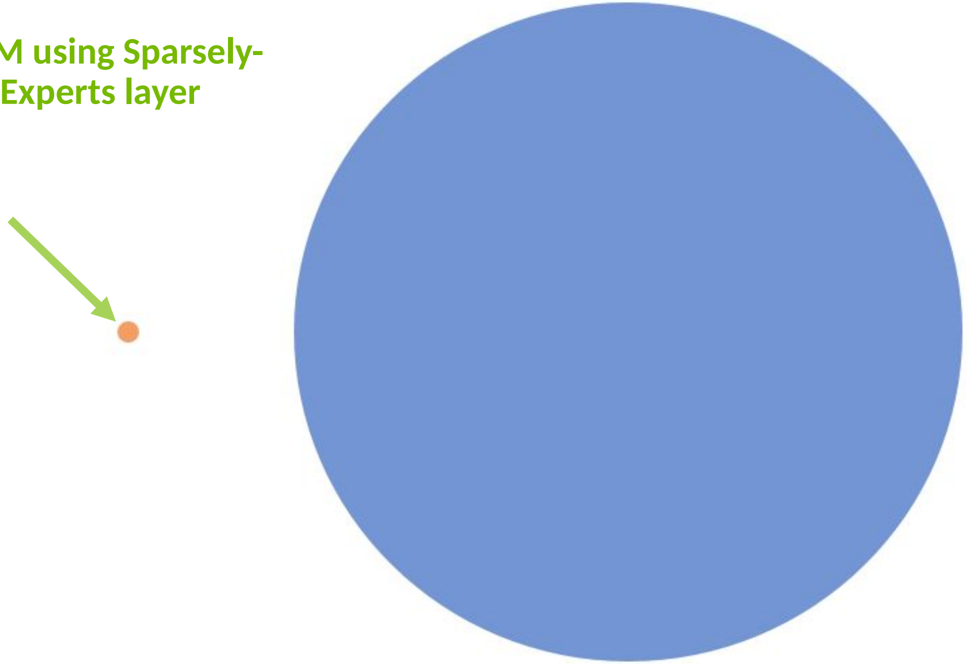
EXPLODING MODEL COMPLEXITY

„Outrageously large neural networks“ – size does matter

VGG 19 vs Google LSTM using Sparsely-Gated Mixture-of-Experts layer



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EXPLODING MODEL COMPLEXITY

Good news – model size scales sublinearly

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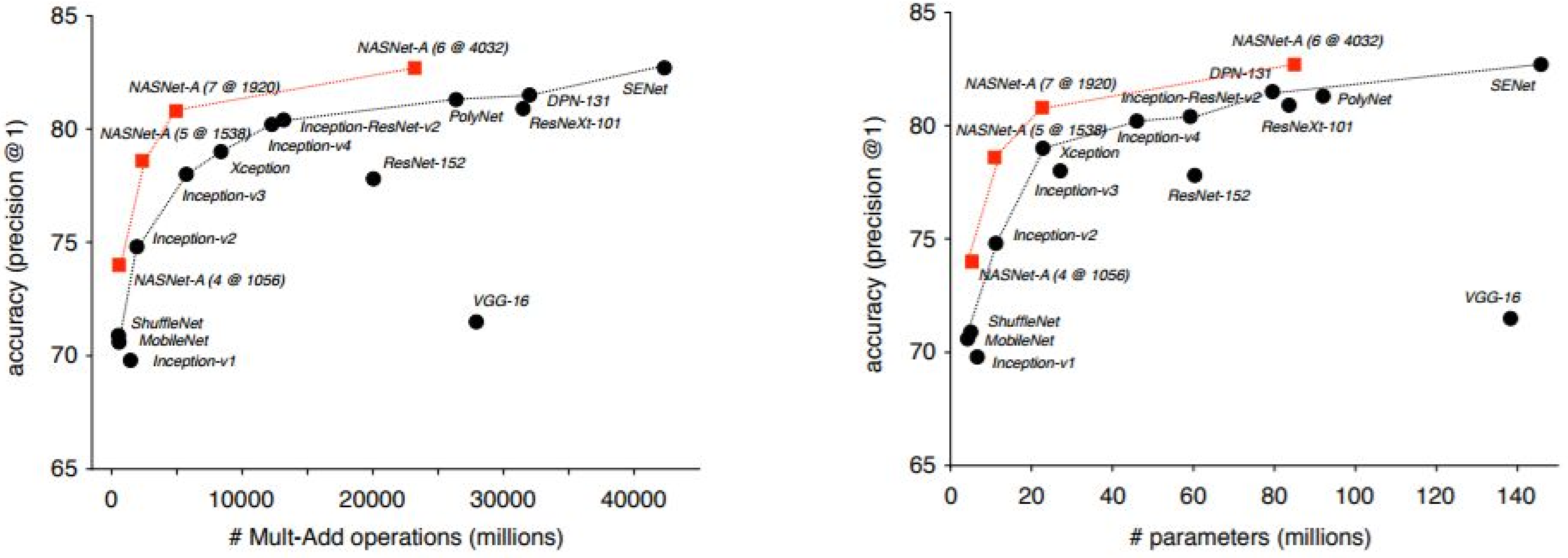
EVIDENCE FROM IMAGE PROCESSING

Good news – model size scales sublinearly



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IMPLICATIONS

Making complex problems easy

Making unsolvable problems expensive

“For any size of the data it’s a good idea to always make the data look small by using a huge model.”

Geoffrey Hinton

FUNDAMENTAL CHANGE TO THE ECONOMY

Impact

China's Got a Huge Artificial Intelligence Plan

Bloomberg News
July 21, 2017, 4:04 AM GMT+1 *Updated on* July 21, 2017, 8:12 AM GMT+1

→ Priorities are intelligent robotics, vehicles, virtual reality
→ AI seen contributing up to $15.7 trillion worldwide by 2030

Microsoft just officially listed AI as one of its top priorities, replacing mobile

- Satya Nadella's "mobile-first and cloud-first world" line is out.
- The change comes after Microsoft formed the Artificial Intelligence and Research group.

Jordan Novet | @jordannovet
Published 5:48 PM ET Wed, 2 Aug 2017 | Updated 7:00 PM ET Fri, 4 Aug 2017
CNBC

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UAE: First minister of artificial intelligence don land

19 October 2017

REUTERS World Business Markets Politics TV

SCIENCE NEWS MARCH 29, 2018 / 2:36 PM / 10 DAYS AGO

France to spend $1.8 billion on AI to compete with U.S., China

Mathieu Rosemain, Michel Rose

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European Commission - Press release

Commission proposes to invest EUR 1 billion in world-class European supercomputers

Brussels, 11 January 2018

Andrus **Ansip**, European Commission Vice-President for the Digital Single Market, said: *"Supercomputers are the engine to power the digital economy. It is a tough race and today the EU is lagging behind: we do not have any supercomputers in the world's top-ten. With the EuroHPC initiative we want to give European researchers and companies world-leading supercomputer capacity by 2020 – to develop technologies such as artificial intelligence and build the future's everyday applications in areas like health, security or engineering."*

TechRepublic

INNOVATION

The 10 tech companies that have invested the most money in AI

Of the tech giants, Google is the biggest investor in AI by billions.

By Olivia Krauth | January 12, 2018, 1:12 PM PST

1. Google - $3.9 billion
2. Amazon - $871 million
3. Apple - $786 million
4. Intel - $776 million
5. Microsoft - $690 million
6. Uber - $680 million
7. Twitter - $629 million
8. AOL - $191.7 million
9. Facebook - $60 million
10. Salesforce - $32.8 million

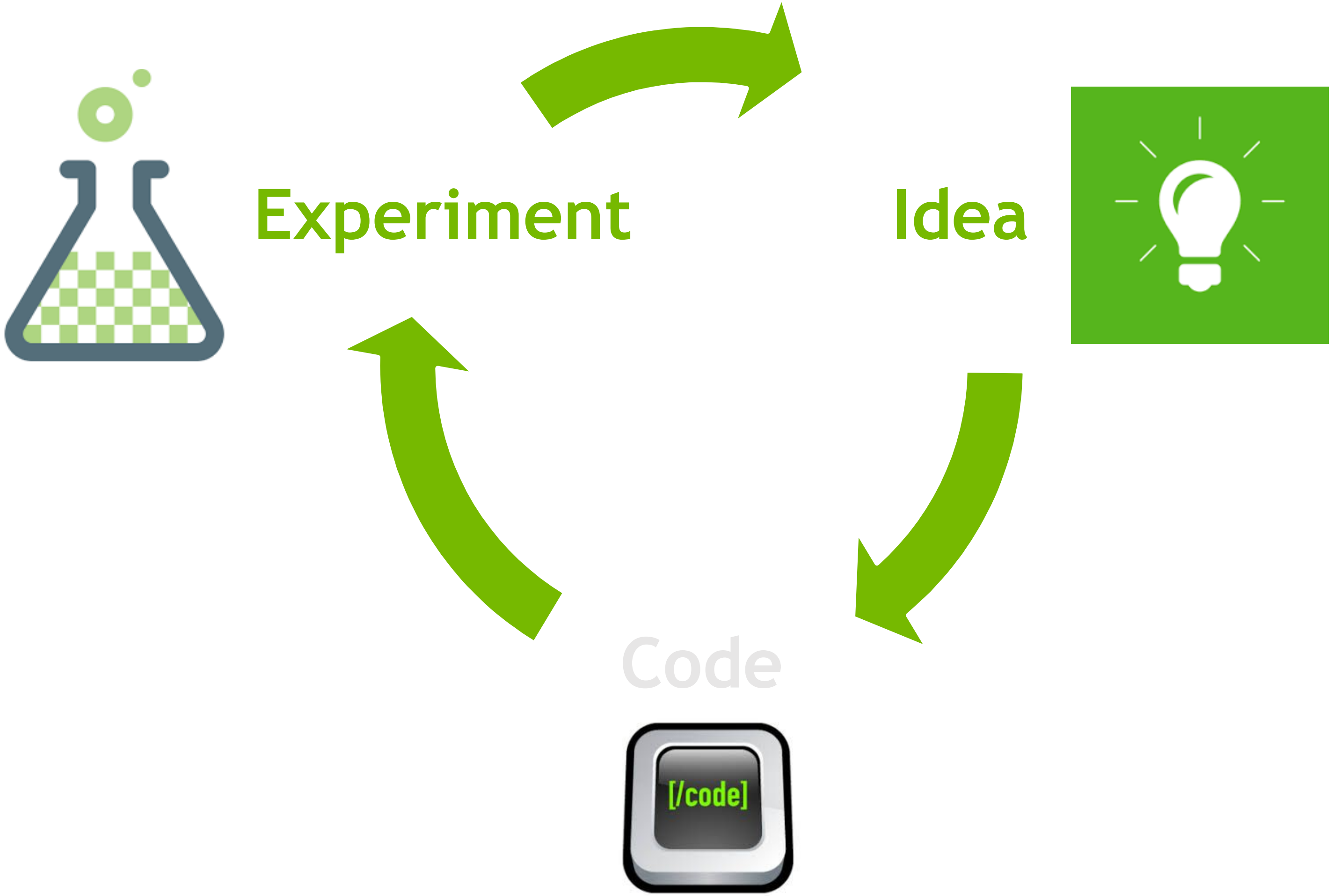
IMPLICATIONS

Good and bad news

- The good news: Requirements are predictable.
  - We can predict how much data we will need
  - We can predict how much computing power we will need
- The **bad** news: The values can be significant.

IMPLICATIONS

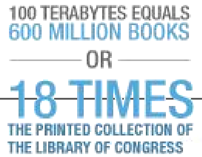
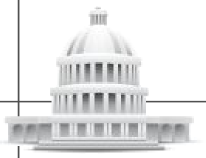
Experimental Nature of Deep Learning - Unacceptable training time



IMPLICATIONS

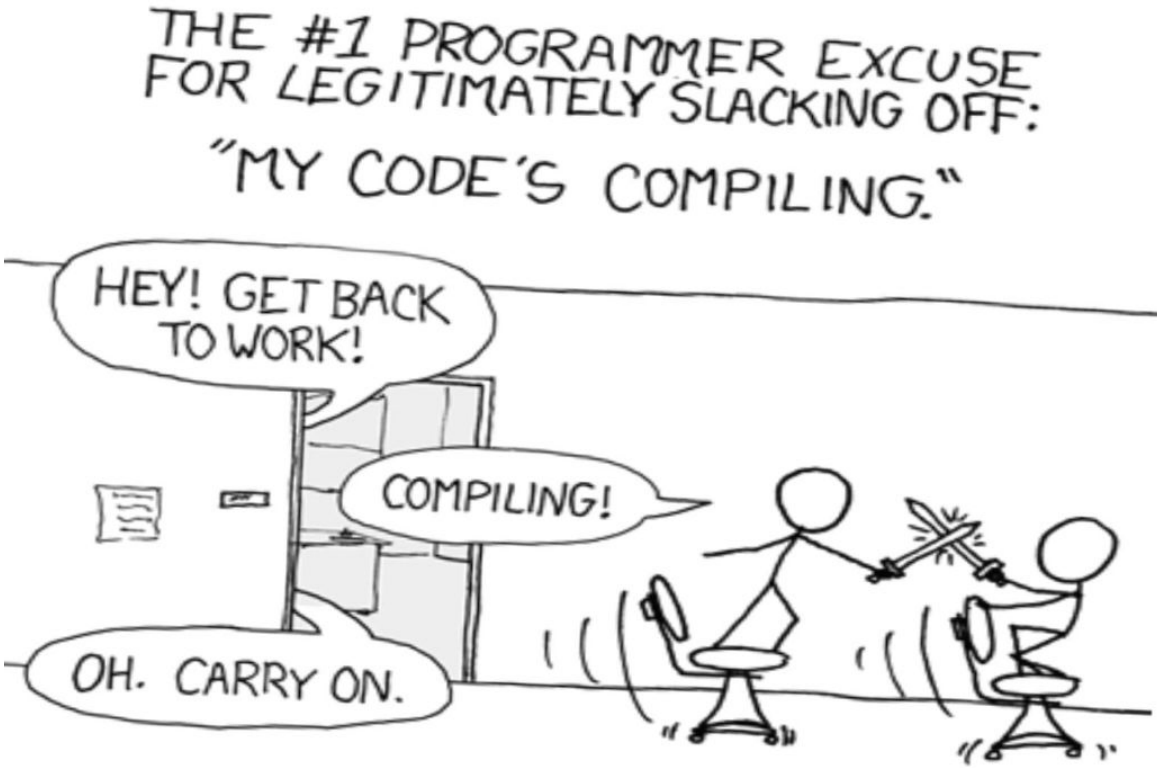
Automotive example

Majority of useful problems are too complex for a single GPU training

	VERY CONSERVATIVE	CONSERVATIVE
Fleet size (data capture per hour)	100 cars / 1TB/hour	125 cars / 1.5TB/hour
Duration of data collection	260 days * 8 hours	325 days * 10 hours
Data Compression factor	0.0005	0.0008
Total training set	104 TB 	 437.5 TB
InceptionV3 training time (with 1 Pascal GPU)	9.1 years	42.6 years 
AlexNet training time (with 1 Pascal GPU)	 1.1 years 	 5.4 years 

CONCLUSIONS

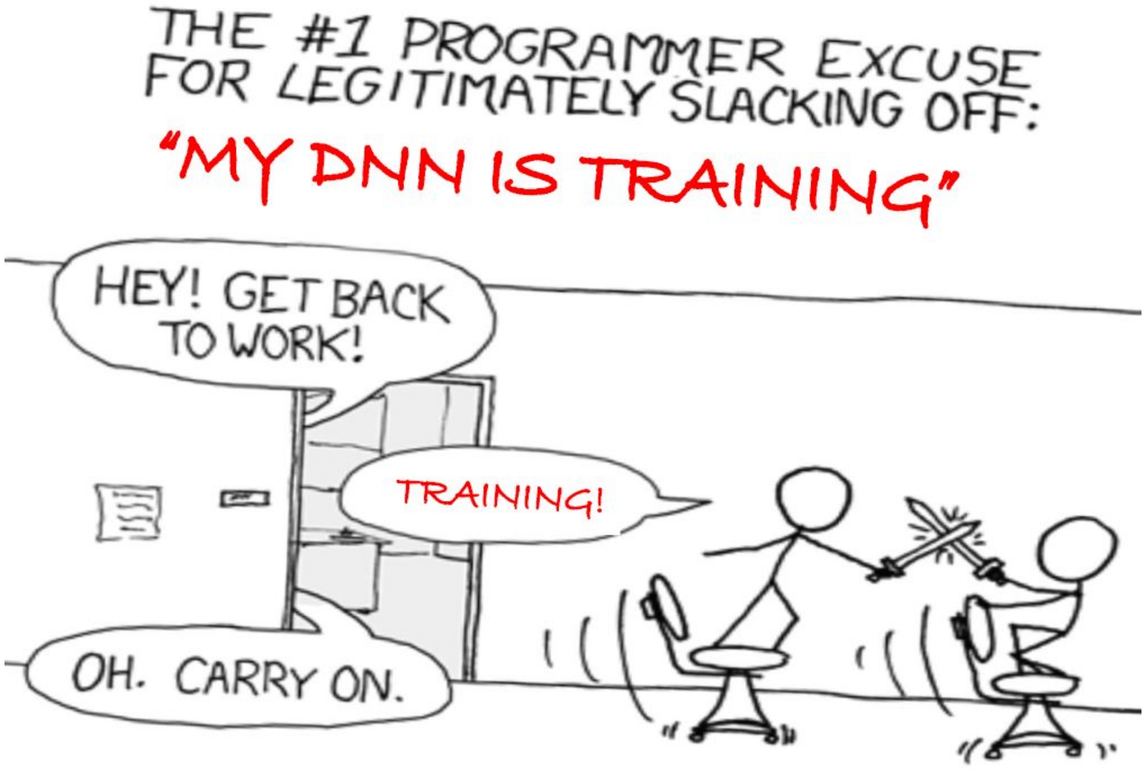
What does your team do in the mean time



Xkcd.com

CONCLUSIONS

What does your team do in the mean time



Xkcd.com

CONCLUSIONS

Need to scale the training process for a single job

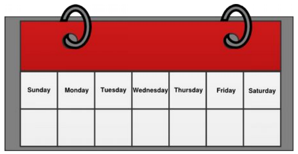
1 NVIDIA DGX-1

10 NVIDIA DGX-1's

	VERY CONSERVATIVE	CONSERVATIVE
Total training set	104 TB	487.5 TB
InceptionV3 (one DGX-1V)	166 days (5+ **months**)	778 days (2+ **years**)
AlexNet (one DGX-1V)	21 days (3 **weeks**)	98 days (3 **months**)
InceptionV3 (10 DGX-1V's)	16 days (2+ **weeks**)	77 days (11 **weeks**)
AlexNet (10 DGX-1V's)	2.1 days	9.8 days

Training
From
Months or Years

To
Weeks or Days

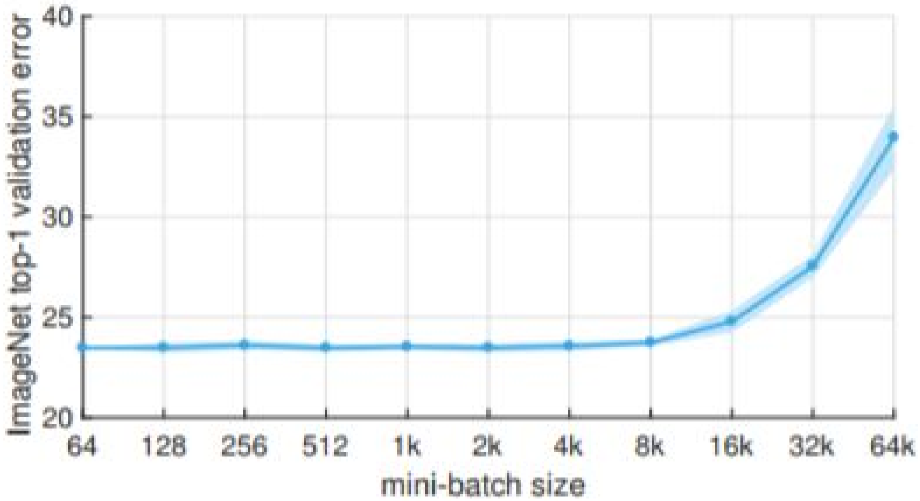


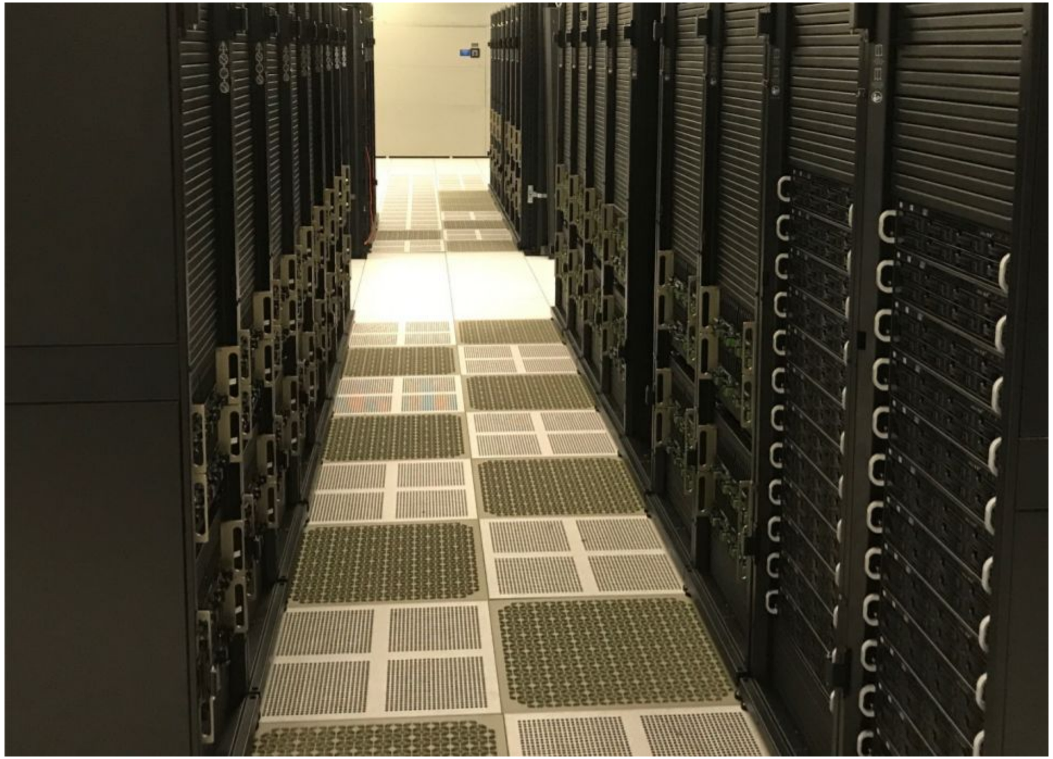
PRACTICAL EXAMPLES OF LARGE SCALE TRAINING

FACEBOOK

Training ImageNet with ResNet 50 in 1 hour

- 128 * DGX-1
- 10.5 PFLOPS total FP32
- 21 PFLOPS total FP16
- Non-blocking IB fabric



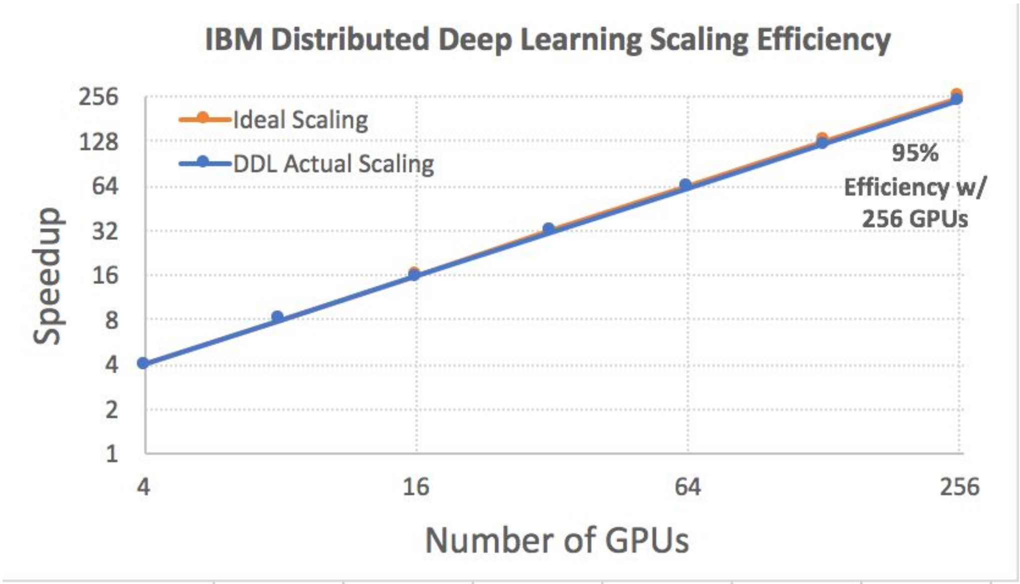


Goyal, P., Dollár, P., Girshick, R., Noordhuis, P., Wesolowski, L., Kyrola, A., ... & He, K. (2017). Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour. *arXiv preprint arXiv:1706.02677*.

IBM

Training ImageNet with ResNet 101 in 7 hours

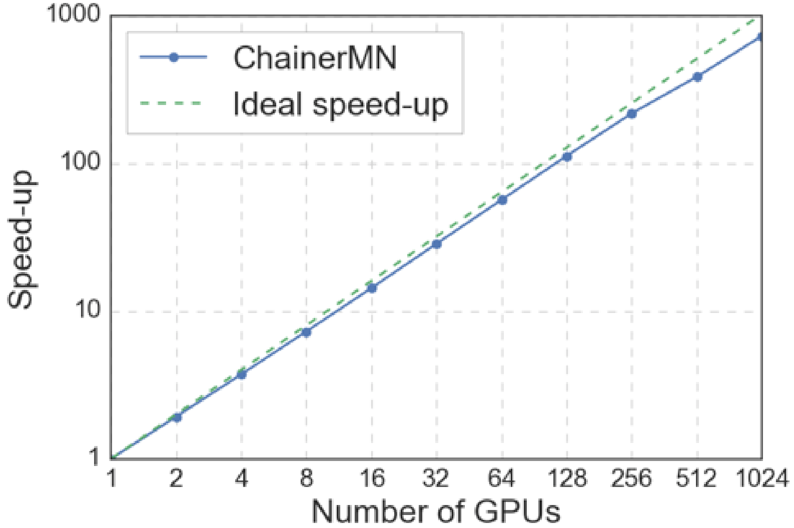
- 64 IBM Power Systems



PREFERRED NETWORKS

Training ImageNet in 15 minutes

- It consists of 128 nodes with 8 NVIDIA P100 GPUs each, for **1024 GPUs in total**.
- The nodes are connected with two FDR Infiniband links (56Gbps x 2).

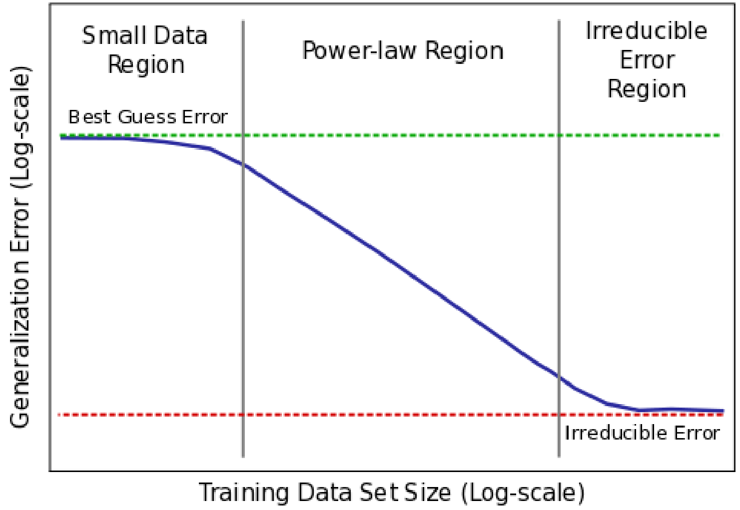


Akiba, T., Suzuki, S., & Fukuda, K. (2017). Extremely large minibatch sgd: Training resnet-50 on imagenet in 15 minutes. *arXiv preprint arXiv:1711.04325*.

BAIDU SVAIL

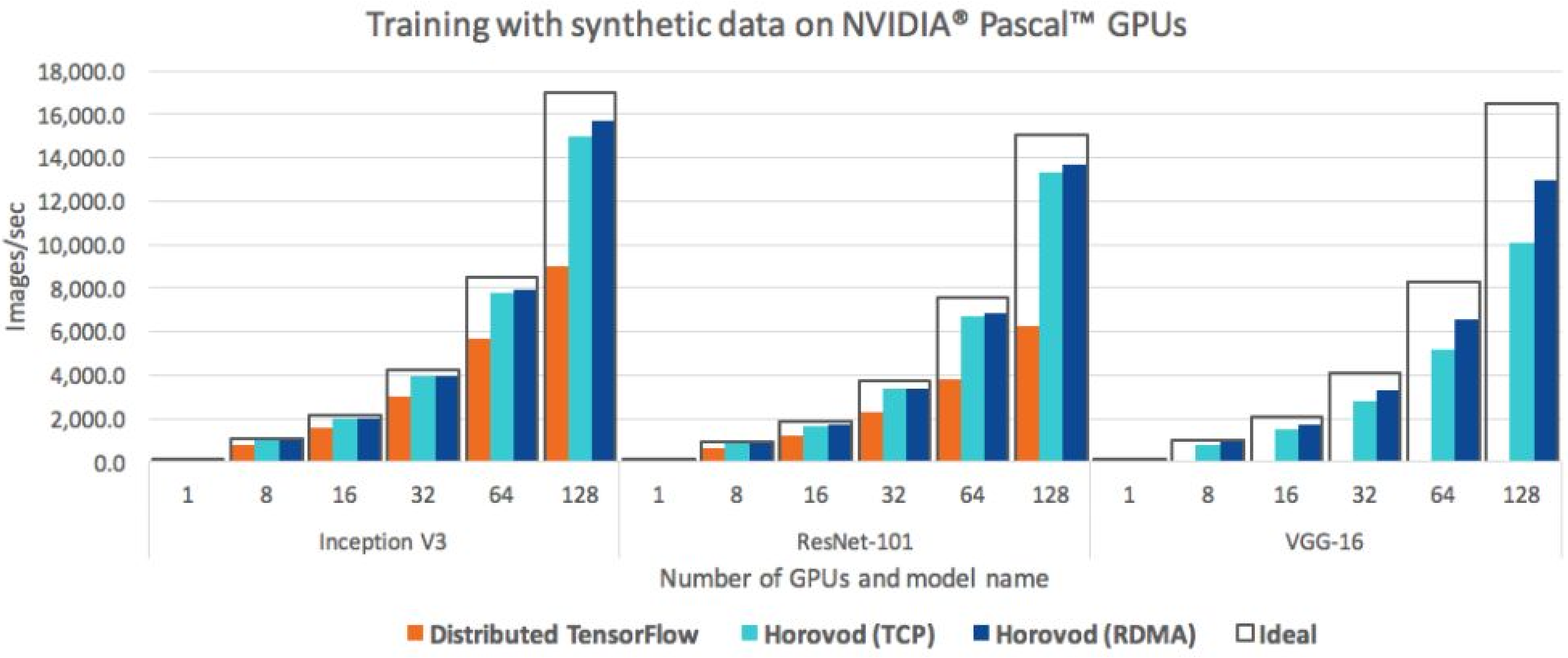
Investigating the log linear nature of the relationship between dataset size and generalization accuracy

- 11 PFLOPS across 1500 GPUs



UBER

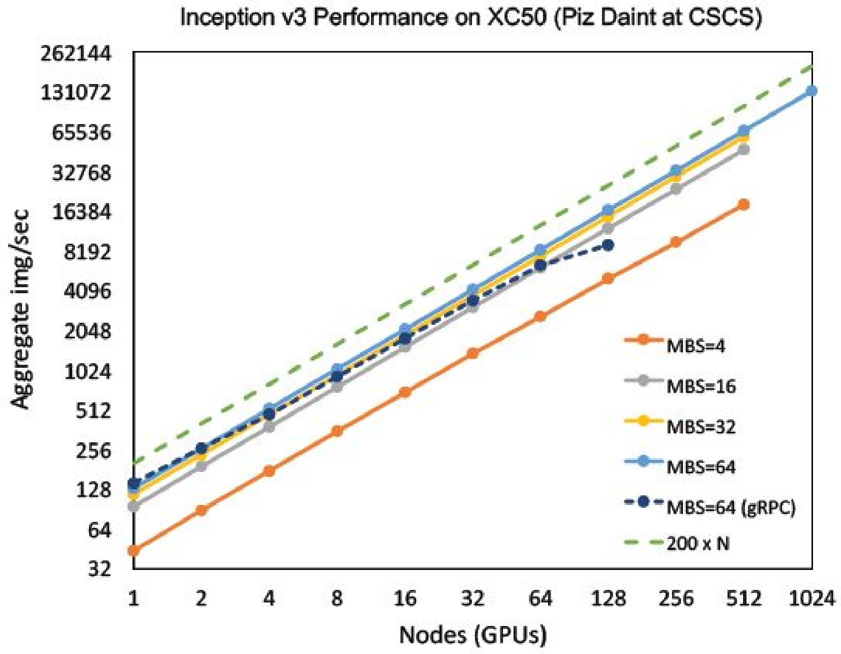
Investing heavily in Deep Learning scalability

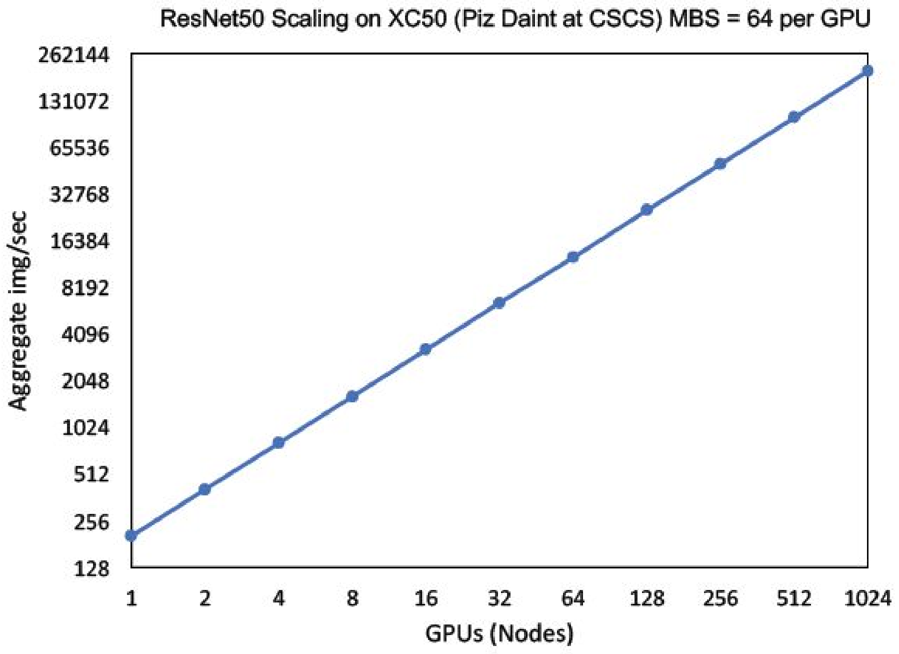


https://github.com/uber/horovod

CRAY

Piz Daint at CSCS





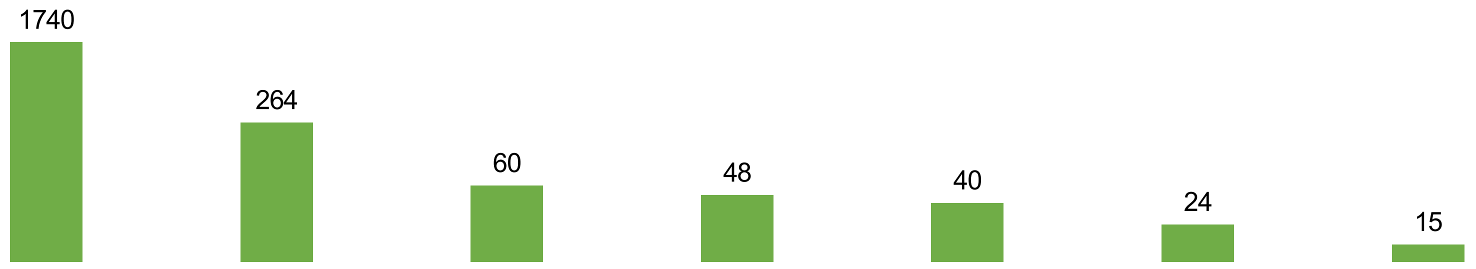
SATURN V

660 DGX-1 Volta Nodes

- 660 Nodes with a total of 5280 Volta GPUs
- 660 PFLOPs for AI training

ITERATION TIME

Short iteration time is fundamental for success



DESPITE
‘BLACK BOX’
INTERNALS
-
COMPLEX THEORY
BEHIND
IS
UNDER
RESEARCH NOW

Stochastic Gradient Descent

More Data and Model Parallelism

Adaptation for Edge Computing

Multi-GPU Scaling

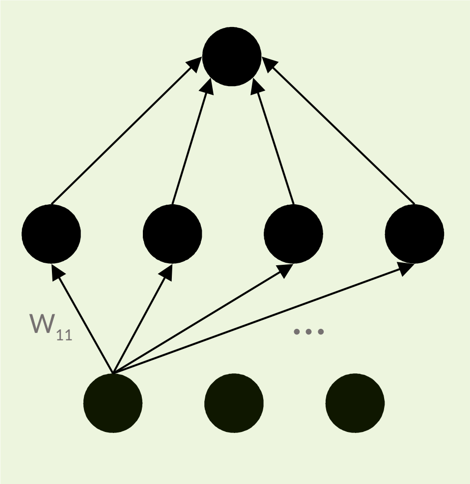
…

GRADIENT BASED OPTIMIZATION

STOCHASTIC GRADIENT DESCENT
(AND ITS VARIANTS)

OPTIMIZATION

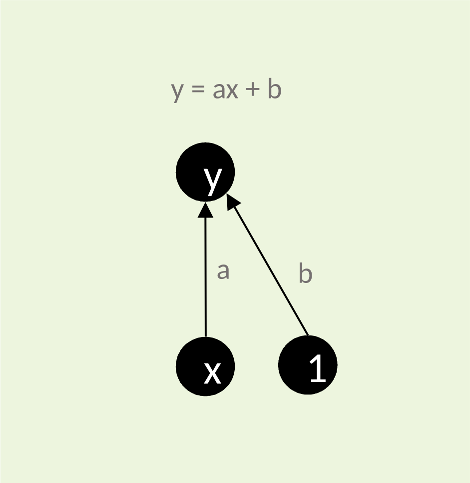
How do we find the parameters of the neural network in the first place?

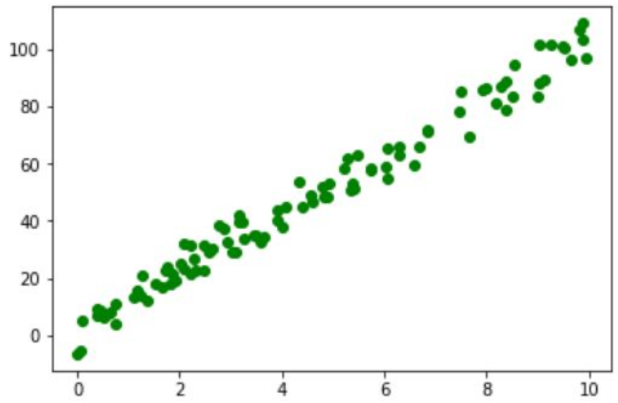


OPTIMIZATION

Lets start with the simplest of problems - linear neuron

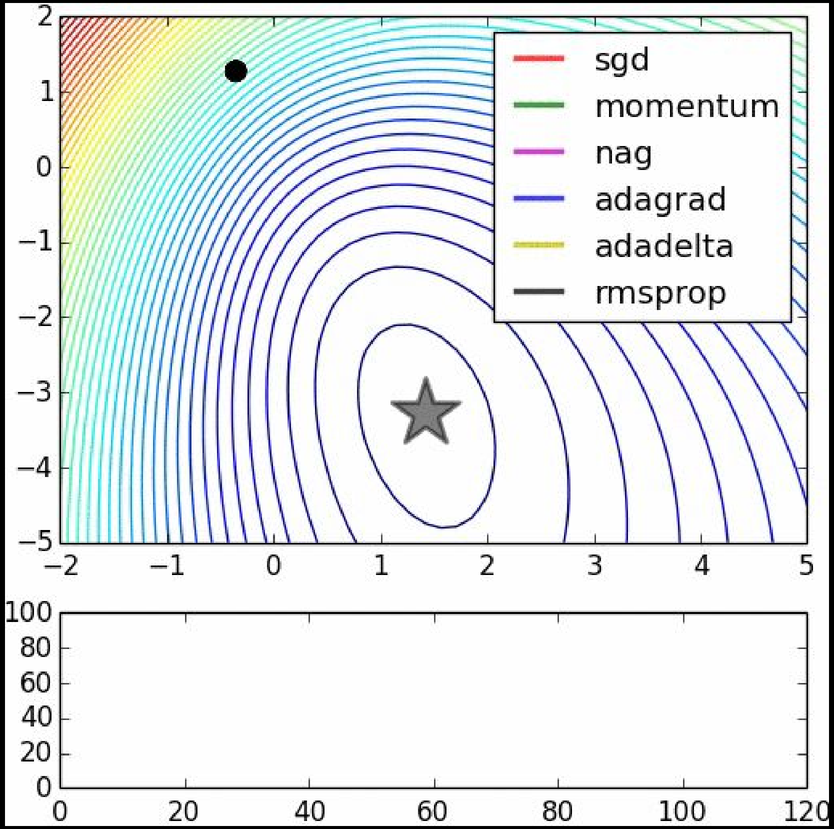
Our goal is to find best model parameters (combination of a and b) to fit the data





MORE THAN JUST SGD

There exists a wide range of optimization algorithms



SGD FOR MORE COMPLEX NEURAL NETWORKS

MODERN NEURAL NETWORKS

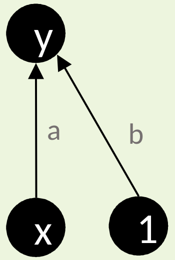
How do they differ from our trivial example?

Not significantly!

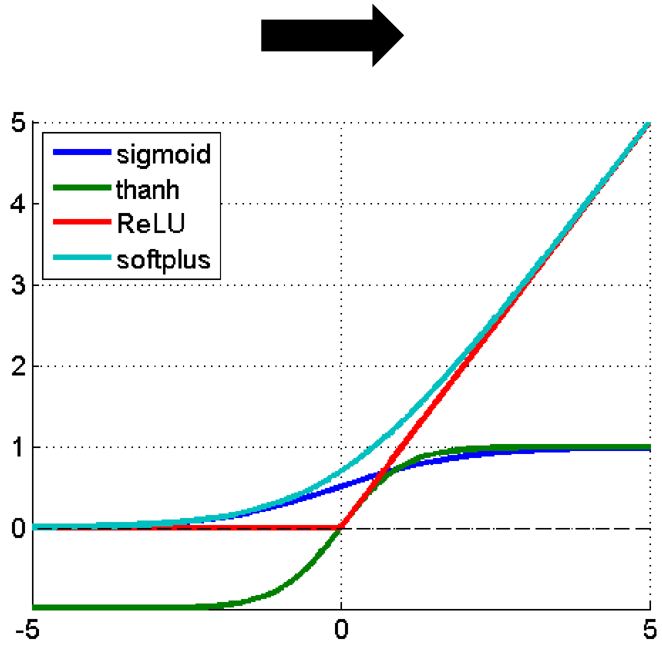
MODERN NEURAL NETWORKS

How do they differ from our trivial example?

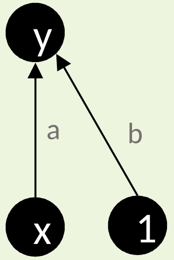
$y = ax + b$



Nonlinearity



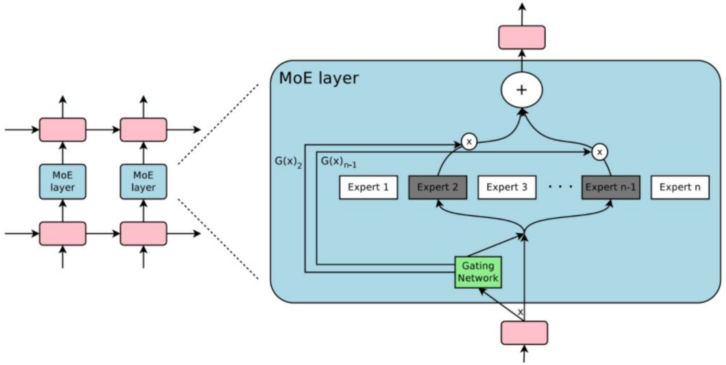
$y = f(ax + b)$

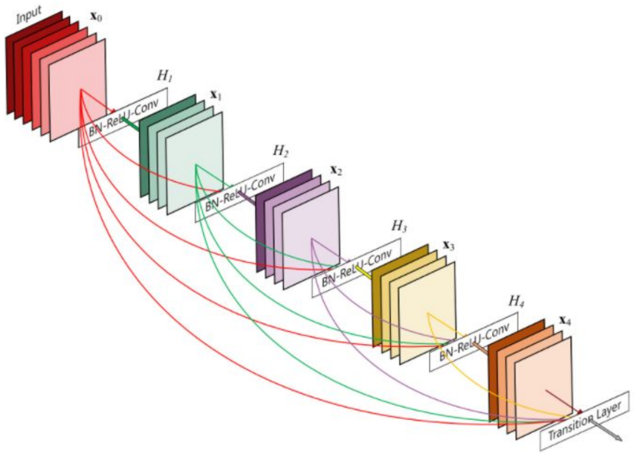


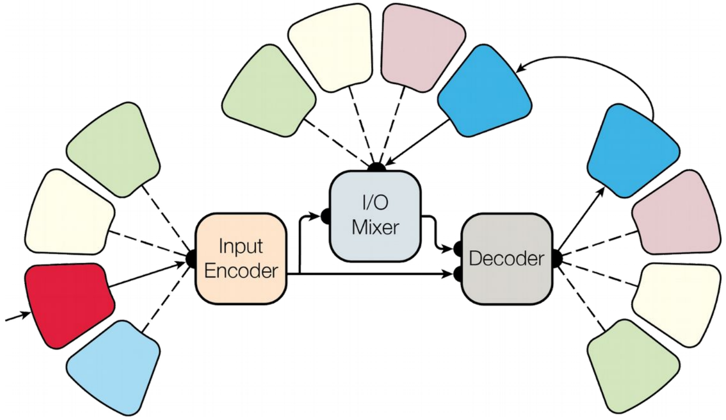
MODERN NEURAL NETWORKS

How do they differ from our trivial example?

More complex interconnection and many more parameters



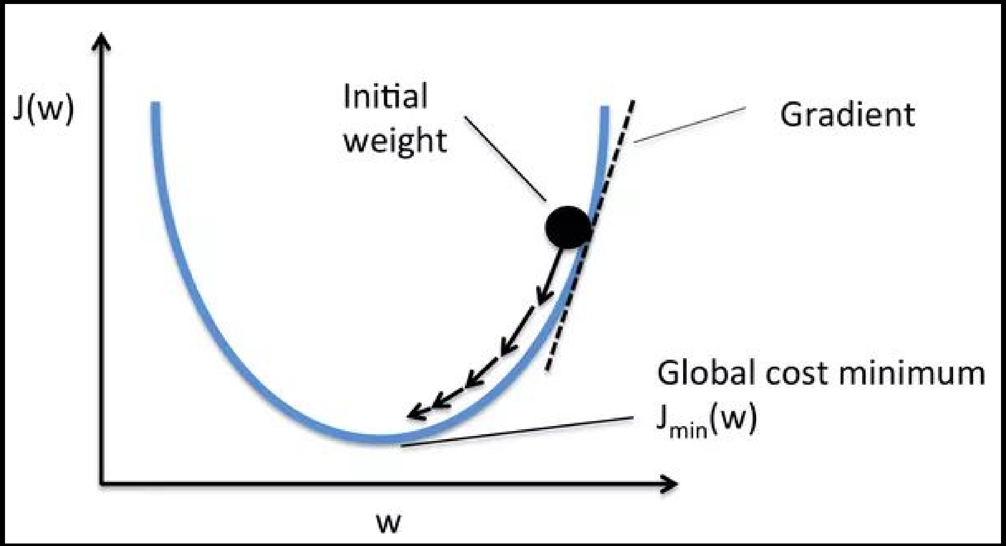


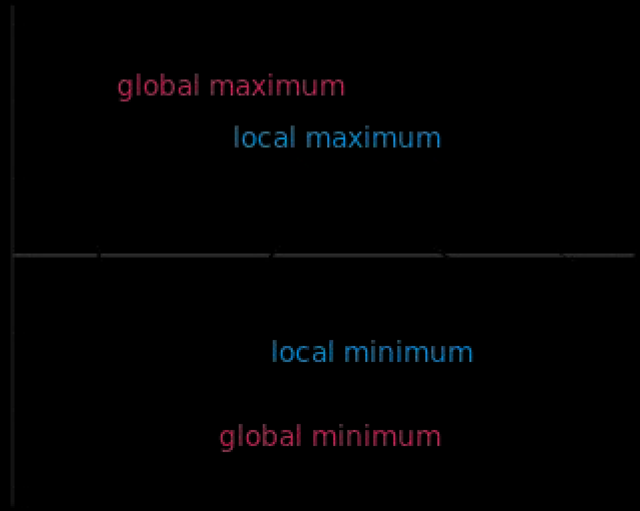


Kaiser, L., Gomez, A. N., Shazeer, N., Vaswani, A., Parmar, N., Jones, L., & Uszkoreit, J. (2017). One model to learn them all. *arXiv preprint arXiv:1706.05137*.
Iandola, F., Moskewicz, M., Karayev, S., Girshick, R., Darrell, T., & Keutzer, K. (2014). Densenet: Implementing efficient convnet descriptor pyramids. arXiv preprint arXiv:1404.1869.
Shazeer, N., Mirhoseini, A., Maziarz, K., Davis, A., Le, Q., Hinton, G., & Dean, J. (2017). Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *arXiv preprint arXiv:1701.06538*.

NON CONVEX COST FUNCTIONS

Those differences make the optimization problem much more difficult

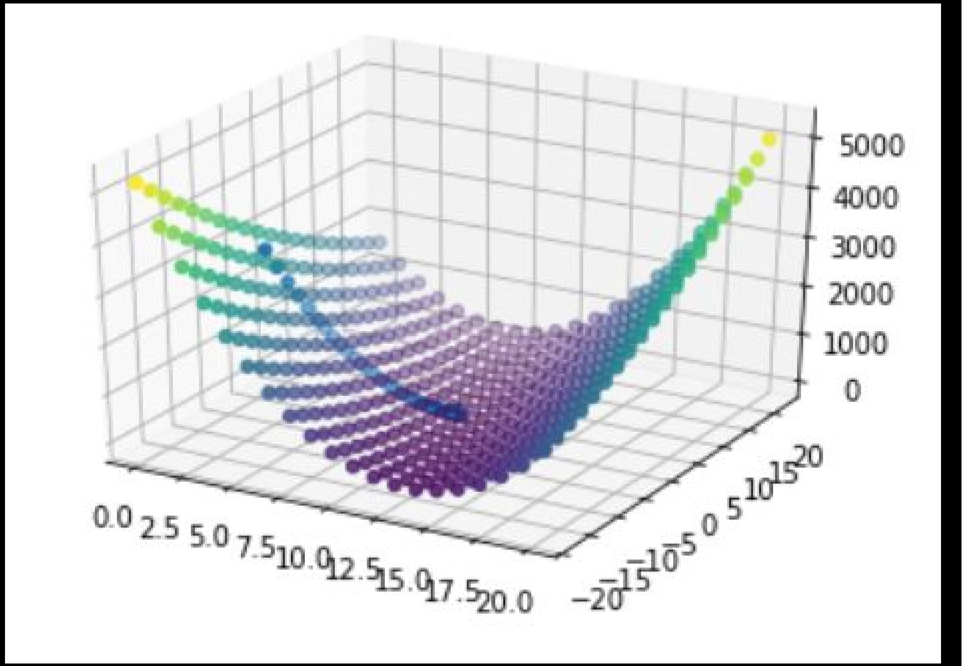




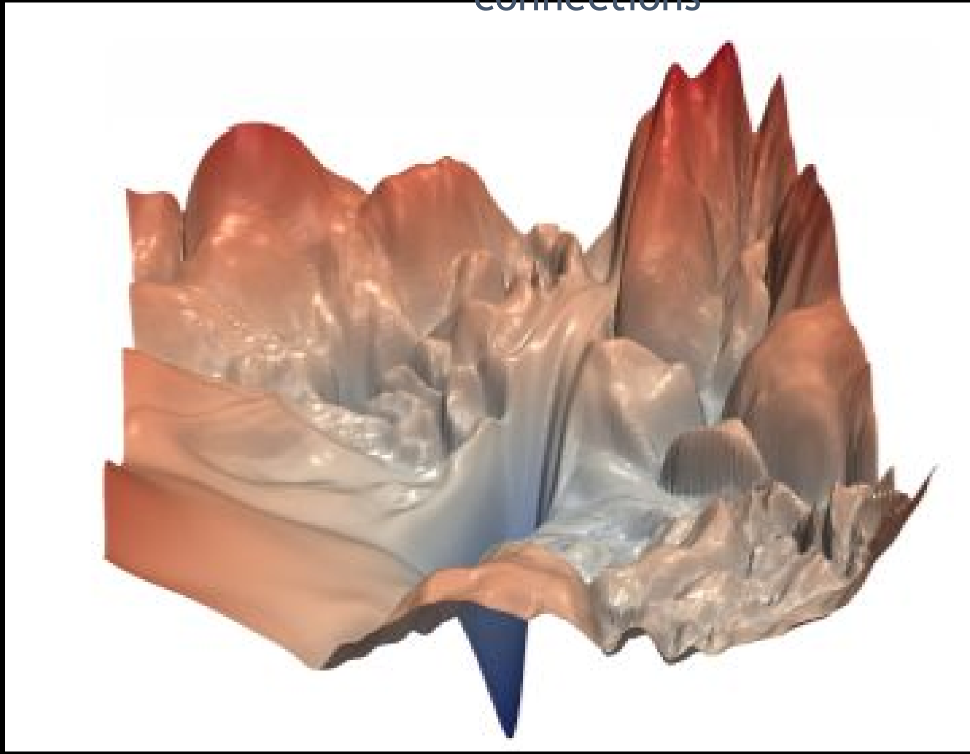
NON CONVEX COST FUNCTIONS

Those differences make the optimization problem much more difficult

Linear Neuron cost function



ResNet 56 cost function projection to 3D – no skip connections



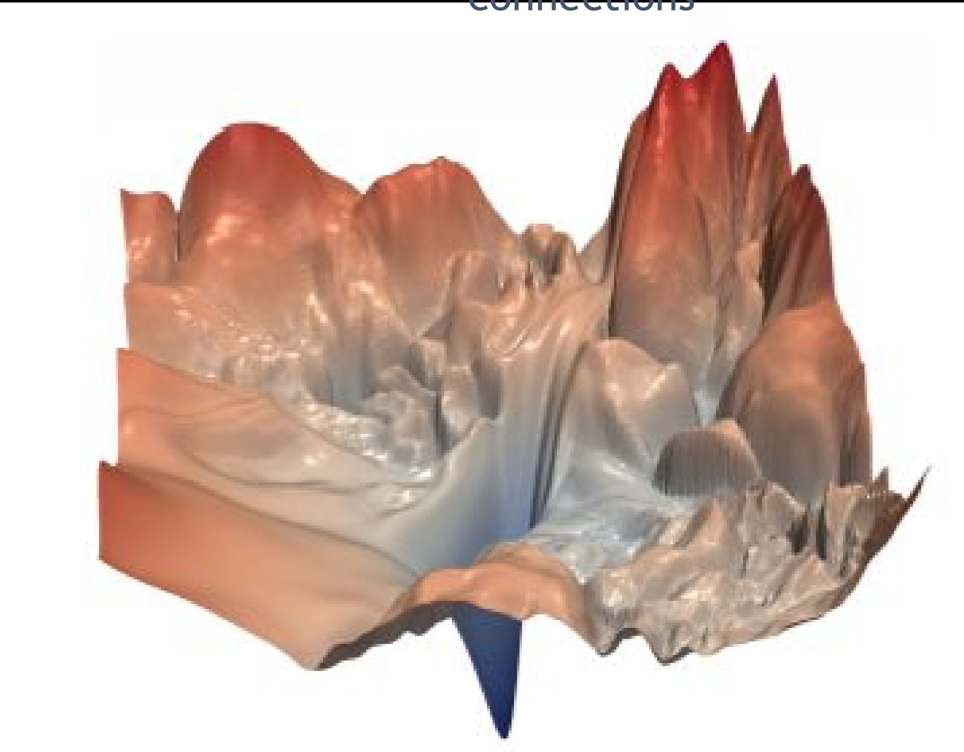
Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. *arXiv preprint arXiv:1712.09913.*

NON CONVEX COST FUNCTIONS

Those differences make the optimization problem much more difficult

Why do we succeed in finding good local minima?

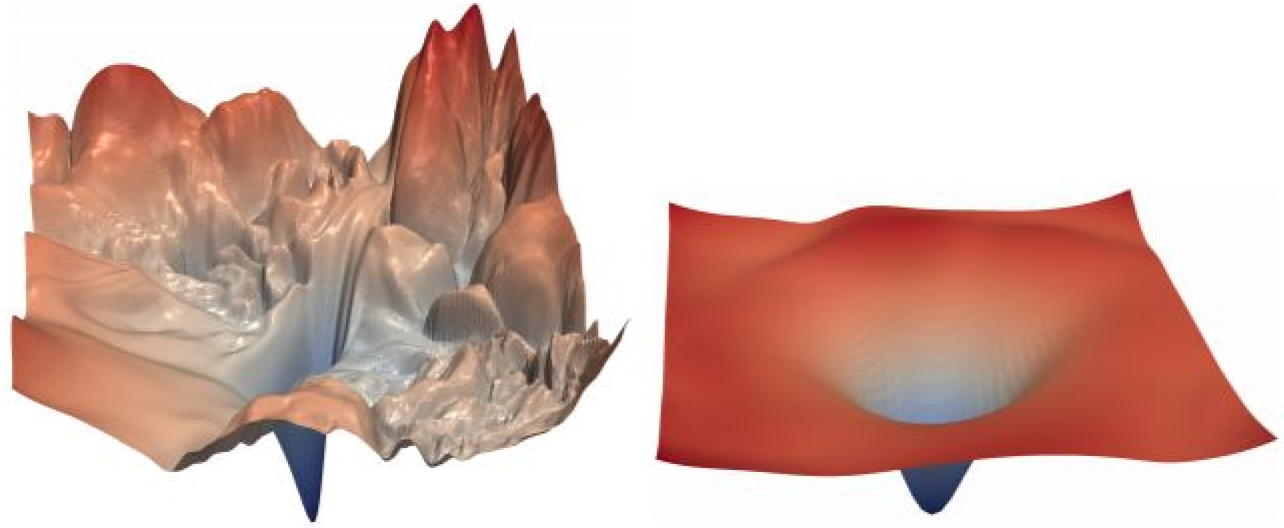
ResNet 56 cost function projection to 3D – no skip connections



Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. *arXiv preprint arXiv:1712.09913.*

NON CONVEX COST FUNCTIONS

Recent advances such as Residual Connections simplify the optimization problem



(a) without skip connections (b) with skip connections

Li, H., Xu, Z., Taylor, G., & Goldstein, T. (2017). Visualizing the Loss Landscape of Neural Nets. *arXiv preprint arXiv:1712.09913*.

OPTIMISATION

The approach is the same though

- Define a model (multilayer neural network)
- Define a cost function (problem specific)
- Iteratively:
    - Calculate the gradient of the cost function (the algorithm used to obtain the gradient is called backpropagation)
    - Update the model parameters (again using one of many optimisation algorithms)

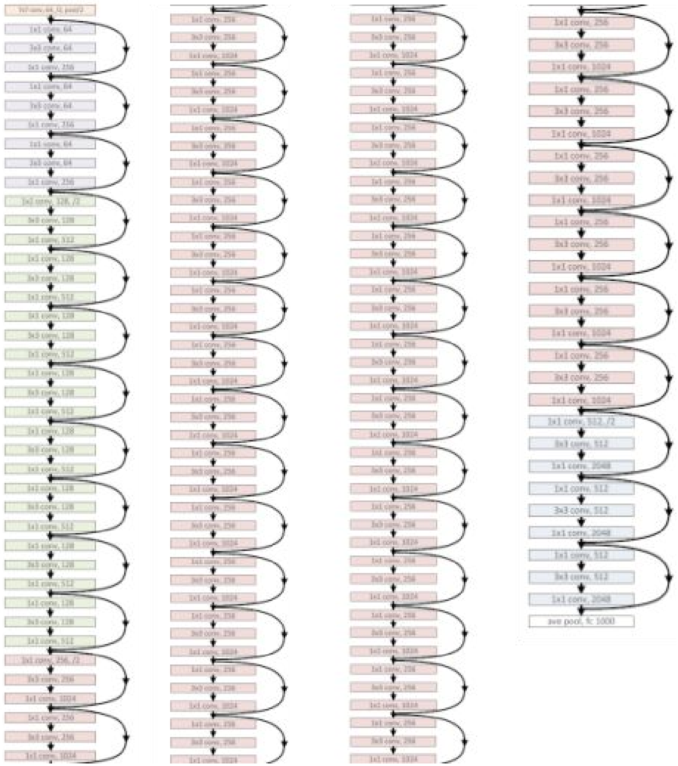
BACKPROPAGATION

How do we compute the gradient of such a complex function?

$$y = f(u),\ u = g(x)$$

Therefore, $y = (f \circ g)(x)$

$$\frac{dy}{dx} = \frac{dy}{du} \cdot \frac{du}{dx}$$



BACKPROPAGATION

Automatic differentiation

- In practice this is rarely if ever done manually as all of the deep learning frameworks come with:
  - A suite of prebuild optimisation algorithms
  - An automatic differentiation functionality
- A very useful side effect is a fact that you can embed ANY DIFFERENTIABLE code into your neural network!

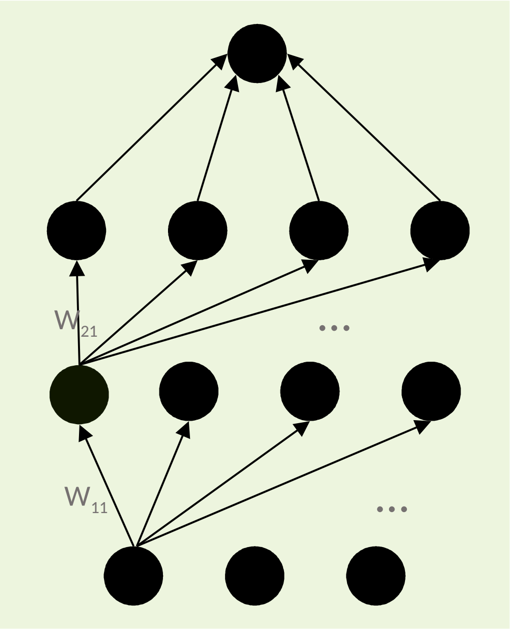
OPTIMIZATION

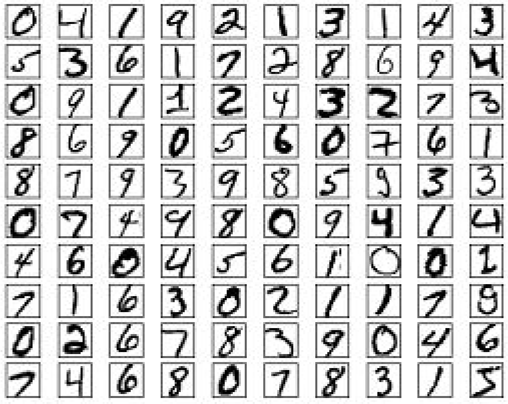
Let's start with a simplest neural network – multilayer perceptron

- We will build a simple (2 hidden layers) neural network – multilayer perceptron (no nonlinearity)

- We will work with the MNIST dataset

- Our goal is to find best model parameters to fit the data





DEEP
LEARNING
INSTITUTE

www.nvidia.com/dli

Deep Learning Methods

Lecture 04

****

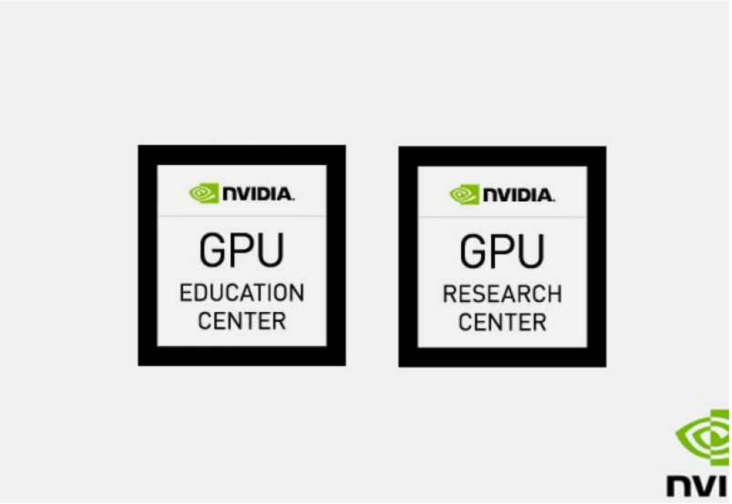
Lecture Slides + interactive Jupyter-notebooks for Google Colaboratory CPU/GPU/TPU cloud: https://cloud.comsys.kpi.ua/s/SMkBSsxRTazoTD6

****

Lecture 04 - CATEGORIES, TYPES, ORIGIN, DEVELOPMENT

The course includes materials proposed by NVIDIA Deep Learning Institute (DLI) in the framework of the common

NVIDIA Research Center
and
NVIDIA Education Center.



https://kpi.ua/nvidia-info

DEMO 1
CPU version - MNIST digit classification in TensorFlow 2.0
https://drive.google.com/file/d/1XeEckTs4qIFYFa56bYCoSeH_8YA0Q7No/view?usp=sharing

DEMO 2
GPU version - MNIST digit classification in TensorFlow 2.0
https://drive.google.com/file/d/1_whW7Q-gi7TN-NLWIH2AL6CxnkBfvwua/view?usp=sharing

DEMO 3
TPU version - MNIST digit classification in TensorFlow 2.0
https://drive.google.com/file/d/1vESaa6yes2VOdW99vJ0_saM_r2opzmpz/view?usp=sharing

DEMO 4
Main Types of Deep Neural Networks
https://drive.google.com/file/d/1PvGNAgGbC_LB3ytw_vgB8xLsIe-t74Dh/view?usp=sharing

CPU version - MNIST digit classification in TensorFlow 2.0

IMPORTANT: Runtime -> Change runtime -> None

Now, we will see how can we perform the MNIST handwritten digits classification using tensorflow 2.0. It hardly a few lines of code compared to the tensorflow 1.x. As we learned, tensorflow 2.0 uses as keras as its high-level API, we just need to add tf.keras to the keras code.

Enabling and testing the environment

```
! cat /sys/class/dmi/id/product_name
```

```
Google Compute Engine
```

```
! cat  /sys/class/dmi/id/sys_vendor
```

```
Google
```

```
! lscpu
```

```
Architecture:        x86_64
CPU op-mode(s):      32-bit, 64-bit
Byte Order:          Little Endian
CPU(s):              2
On-line CPU(s) list: 0,1
Thread(s) per core:  2
Core(s) per socket:  1
Socket(s):           1
NUMA node(s):        1
Vendor ID:           AuthenticAMD
CPU family:          23
Model:               49
Model name:          AMD EPYC 7B12
Stepping:            0
CPU MHz:             2249.998
BogoMIPS:            4499.99
Hypervisor vendor:   KVM
Virtualization type: full
L1d cache:           32K
L1i cache:           32K
L2 cache:            512K
L3 cache:            16384K
NUMA node0 CPU(s):   0,1
Flags:               fpu vme de pse tsc msr pae mce cx8 apic sep mtrr pge mca
```

```
! grep MemTotal /proc/meminfo
```

```
MemTotal:       13333596 kB
```

```
! df -h
```

```
Filesystem      Size  Used Avail Use% Mounted on
overlay         108G   31G   78G  28% /
tmpfs            64M     0   64M   0% /dev
tmpfs           6.4G     0  6.4G   0% /sys/fs/cgroup
shm             5.9G     0  5.9G   0% /dev/shm
tmpfs           6.4G   28K  6.4G   1% /var/colab
/dev/sda1       114G   32G   83G  28% /etc/hosts
tmpfs           6.4G     0  6.4G   0% /proc/acpi
tmpfs           6.4G     0  6.4G   0% /proc/scsi
tmpfs           6.4G     0  6.4G   0% /sys/firmware
```

```
! nvidia-smi
```

```
NVIDIA-SMI has failed because it couldn't communicate with the NVIDIA driver.
```

```
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
---------------------------------------------------------------------------
SystemError                               Traceback (most recent
call last)
<ipython-input-7-d1680108c58e> in <module>()
      2 device_name = tf.test.gpu_device_name()
      3 if device_name != '/device:GPU:0':
----> 4   raise SystemError('GPU device not found')
      5 print('Found GPU at: {}'.format(device_name))

SystemError: GPU device not found
```

Import the libraries:

```
import warnings
warnings.filterwarnings('ignore')

import tensorflow as tf
```

Check Tensorflow version

```
print(tf.__version__)
```

```
2.4.1
```

Load the dataset:

```
mnist =  tf.keras.datasets.mnist
```

Create a train and test set:

```
(x_train,y_train), (x_test, y_test) = mnist.load_data()
```

Normalize data ...

... the x values by diving with maximum value of x which is 255 and convert them to float:

```
x_train, x_test = tf.cast(x_train/255.0, tf.float32), tf.cast(x_test/255.0, tf.flo
```

convert y values to int:

```
y_train, y_test = tf.cast(y_train,tf.int64),tf.cast(y_test,tf.int64)
```

Create the model

Define the sequential model:

Define the sequential model:

```
model = tf.keras.models.Sequential()
```

Add the layers - We use a three-layered network. We apply ReLU activation at the first two layers and in the final output layer we apply softmax function:

```
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(256, activation="relu"))
model.add(tf.keras.layers.Dense(128, activation="relu"))
model.add(tf.keras.layers.Dense(10, activation="softmax"))
```

Compile the model with Stochastic Gradient Descent, that is 'sgd' (we will learn about this in the next chapter) as optimizer and sparse_categorical_crossentropy as loss function and with accuracy as a metric:

```
model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy', metrics=['a
```

- List item
- List item

Train

Train the model for 10 epochs with batch_size as 32:

```
history = model.fit(x_train, y_train, batch_size=32, epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 5s 2ms/step - loss: 1.0382 - acc
Epoch 2/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.3054 - acc
Epoch 3/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2385 - acc
Epoch 4/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.2010 - acc
Epoch 5/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.1730 - acc
Epoch 6/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.1538 - acc
Epoch 7/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.1348 - acc
Epoch 8/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.1239 - acc
Epoch 9/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.1116 - acc
Epoch 10/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.1017 - acc
```

Show the structure of the model

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
flatten (Flatten)           (32, 784)                 0

_________________________________________________________________
dense (Dense)               (32, 256)                 200960

_________________________________________________________________
dense_1 (Dense)             (32, 128)                 32896

_________________________________________________________________
dense_2 (Dense)             (32, 10)                  1290
=================================================================
Total params: 235,146
```

```
Trainable params: 235,146
Non-trainable params: 0
```

Evaluate

Evaluate the model on test sets:

```
model.evaluate(x_test, y_test)
```

```
313/313 [==============================] - 1s 1ms/step - loss: 0.1082 - accur
[0.10815522819757462, 0.9682999849319458]
```

GPU version - MNIST digit classification in TensorFlow 2.0

IMPORTANT: Runtime -> Change runtime -> GPU

Now, we will see how can we perform the MNIST handwritten digits classification using tensorflow 2.0. It hardly a few lines of code compared to the tensorflow 1.x. As we learned, tensorflow 2.0 uses as keras as its high-level API, we just need to add tf.keras to the keras code.

Enabling and testing the GPU

```
! nvidia-smi
```

```
Tue Feb 23 13:03:10 2021
+-----------------------------------------------------------------------------
| NVIDIA-SMI 460.39       Driver Version: 460.32.03    CUDA Version: 11.2
|-------------------------------+----------------------+----------------------
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M.
|                               |                      |               MIG M.
|===============================+======================+======================
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0
| N/A   37C    P8    10W /  70W |      0MiB / 15109MiB |      0%      Default
|                               |                      |                  N/A
+-------------------------------+----------------------+----------------------

+-----------------------------------------------------------------------------
| Processes:
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory
|        ID   ID                                                   Usage
|=============================================================================
|  No running processes found
+-----------------------------------------------------------------------------
```

```
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
Found GPU at: /device:GPU:0
```

Import the libraries:

```
import warnings
warnings.filterwarnings('ignore')
```

```
import tensorflow as tf
```

Check Tensorflow version

```
print(tf.__version__)
```

```
2.4.1
```

Load the dataset:

```
mnist =  tf.keras.datasets.mnist
```

Create a train and test set:

```
(x_train,y_train), (x_test, y_test) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
11493376/11490434 [==============================] - 0s 0us/step
```

Normalize data ...

... the x values by diving with maximum value of x which is 255 and convert them to float:

```
x_train, x_test = tf.cast(x_train/255.0, tf.float32), tf.cast(x_test/255.0, tf.flo
```

convert y values to int:

```
y_train, y_test = tf.cast(y_train,tf.int64),tf.cast(y_test,tf.int64)
```

Create the model

Define the sequential model:

Define the sequential model:

```
model = tf.keras.models.Sequential()
```

Add the layers - We use a three-layered network. We apply ReLU activation at the first two layers

```
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(256, activation="relu"))
model.add(tf.keras.layers.Dense(128, activation="relu"))
model.add(tf.keras.layers.Dense(10, activation="softmax"))
```

Compile the model with Stochastic Gradient Descent, that is 'sgd' (we will learn about this in the next chapter) as optimizer and sparse_categorical_crossentropy as loss function and with accuracy as a metric:

```
model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy', metrics=['a
```

Show the structure of the model

Train

Train the model for 10 epochs with batch_size as 32:

```
history = model.fit(x_train, y_train, batch_size=32, epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 5s 2ms/step - loss: 1.0041 - acc
Epoch 2/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2966 - acc
Epoch 3/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2382 - acc
Epoch 4/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2003 - acc
Epoch 5/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1774 - acc
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1537 - acc
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1370 - acc
Epoch 8/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1232 - acc
Epoch 9/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1089 - acc
Epoch 10/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1030 - acc
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (32, 784)                 0
```

```
dense (Dense)                (32, 256)                 200960

dense_1 (Dense)              (32, 128)                 32896

dense_2 (Dense)              (32, 10)                  1290
=================================================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
_________________________________________________________________
```

Evaluate

Evaluate the model on test sets:

```
model.evaluate(x_test, y_test)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.1084 - accur
[0.10837740451097488, 0.96670001745224]
```

TPU version - MNIST digit classification in TensorFlow 2.0

IMPORTANT: Runtime -> Change runtime -> TPU

Now, we will see how can we perform the MNIST handwritten digits classification using tensorflow 2.0. It hardly a few lines of code compared to the tensorflow 1.x. As we learned, tensorflow 2.0 uses as keras as its high-level API, we just need to add tf.keras to the keras code.

Enabling and testing the TPU

First, you'll need to enable TPUs for the notebook:

- Navigate to Edit→Notebook Settings
- select TPU from the Hardware Accelerator drop-down

Next, we'll check that we can connect to the TPU:

```
%tensorflow_version 2.x
import tensorflow as tf
print("Tensorflow version " + tf.__version__)

try:
  tpu = tf.distribute.cluster_resolver.TPUClusterResolver()  # TPU detection
  print('Running on TPU ', tpu.cluster_spec().as_dict()['worker'])
except ValueError:
  raise BaseException('ERROR: Not connected to a TPU runtime; please see the previ

tf.config.experimental_connect_to_cluster(tpu)
tf.tpu.experimental.initialize_tpu_system(tpu)
tpu_strategy = tf.distribute.experimental.TPUStrategy(tpu)
```

```
Tensorflow version 2.4.1
Running on TPU  ['10.15.163.122:8470']
INFO:tensorflow:Initializing the TPU system: grpc://10.15.163.122:8470
INFO:tensorflow:Initializing the TPU system: grpc://10.15.163.122:8470
INFO:tensorflow:Clearing out eager caches
INFO:tensorflow:Clearing out eager caches
INFO:tensorflow:Finished initializing TPU system.
INFO:tensorflow:Finished initializing TPU system.
WARNING:absl:`tf.distribute.experimental.TPUStrategy` is deprecated, please u
INFO:tensorflow:Found TPU system:
INFO:tensorflow:Found TPU system:
INFO:tensorflow:*** Num TPU Cores: 8
INFO:tensorflow:*** Num TPU Cores: 8
INFO:tensorflow:*** Num TPU Workers: 1
INFO:tensorflow:*** Num TPU Workers: 1
INFO:tensorflow:*** Num TPU Cores Per Worker: 8
INFO:tensorflow:*** Num TPU Cores Per Worker: 8
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:localhost/replic
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:localhost/replic
```

```
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
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INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
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INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
INFO:tensorflow:*** Available Device: _DeviceAttributes(/job:worker/replica:0
```

Import the libraries:

```
import warnings
warnings.filterwarnings('ignore')

import tensorflow as tf
```

Check Tensorflow version

```
print(tf.__version__)
```

```
2.4.1
```

Load the dataset:

```
mnist =  tf.keras.datasets.mnist
```

Create a train and test set:

```
(x_train,y_train), (x_test, y_test) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
11493376/11490434 [==============================] - 0s 0us/step
```

Normalize data ...

... the x values by diving with maximum value of x which is 255 and convert them to float:

```
x_train, x_test = tf.cast(x_train/255.0, tf.float32), tf.cast(x_test/255.0, tf.flo
```

convert y values to int:

```
y_train, y_test = tf.cast(y_train,tf.int64),tf.cast(y_test,tf.int64)
```

Create the model

Define the sequential model:

```
model = tf.keras.models.Sequential()
```

Add the layers - We use a three-layered network. We apply ReLU activation at the first two layers and in the final output layer we apply softmax function:

```
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(256, activation="relu"))
model.add(tf.keras.layers.Dense(128, activation="relu"))
model.add(tf.keras.layers.Dense(10, activation="softmax"))
```

Compile the model with Stochastic Gradient Descent, that is 'sgd' (we will learn about this in the next chapter) as optimizer and sparse_categorical_crossentropy as loss function and with accuracy as a metric:

```
model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy', metrics=['a
```

Train

Train the model for 10 epochs with batch_size as 32:

```
history = model.fit(x_train, y_train, batch_size=32, epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 21s 11ms/step - loss: 0.9990 - a
Epoch 2/10
1875/1875 [==============================] - 20s 11ms/step - loss: 0.2995 - a
Epoch 3/10
```

```
1875/1875 [==============================] - 20s 11ms/step - loss: 0.2413 - a
Epoch 4/10
1875/1875 [==============================] - 20s 11ms/step - loss: 0.2023 - a
Epoch 5/10
1875/1875 [==============================] - 20s 11ms/step - loss: 0.1679 - a
Epoch 6/10
1875/1875 [==============================] - 22s 12ms/step - loss: 0.1526 - a
Epoch 7/10
1875/1875 [==============================] - 21s 11ms/step - loss: 0.1340 - a
Epoch 8/10
1875/1875 [==============================] - 21s 11ms/step - loss: 0.1230 - a
Epoch 9/10
1875/1875 [==============================] - 21s 11ms/step - loss: 0.1105 - a
Epoch 10/10
1875/1875 [==============================] - 21s 11ms/step - loss: 0.1019 - a
```

Show the structure of the model

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (32, 784)                 0
_________________________________________________________________
dense (Dense)                (32, 256)                 200960
_________________________________________________________________
dense_1 (Dense)              (32, 128)                 32896
_________________________________________________________________
dense_2 (Dense)              (32, 10)                  1290
=================================================================
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0
_________________________________________________________________
```

Compare with training results on GPU

Epoch 1/10 1875/1875 [==============================] - 6s 2ms/step - loss: 0.9975 - accuracy: 0.7304

Epoch 2/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.3008 - accuracy: 0.9134

Epoch 3/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.2401 - accuracy: 0.9320

Epoch 4/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.2071 - accuracy: 0.9423

Epoch 5/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1794 - accuracy: 0.9492

Epoch 6/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1576 - accuracy: 0.9548

Epoch 7/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1393 - accuracy: 0.9613

Epoch 8/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1309 - accuracy: 0.9628

Epoch 9/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1119 - accuracy: 0.9680

Epoch 10/10 1875/1875 [==============================] - 4s 2ms/step - loss: 0.1042 -

Evaluate

Evaluate the model on test sets:

```
model.evaluate(x_test, y_test)
```

```
313/313 [==============================] - 3s 9ms/step - loss: 0.1062 - accur
[0.10615649074316025, 0.968500018119812]
```

Compare with training results on GPU

313/313 [==============================] - 1s 2ms/step - loss: 0.1077 - accuracy: 0.9671

[0.10774651169776917, 0.9671000242233276]

The results are nearly the same up to 3rd (loss) and 4th (accuracy) significant number after the decimal point.

```
```

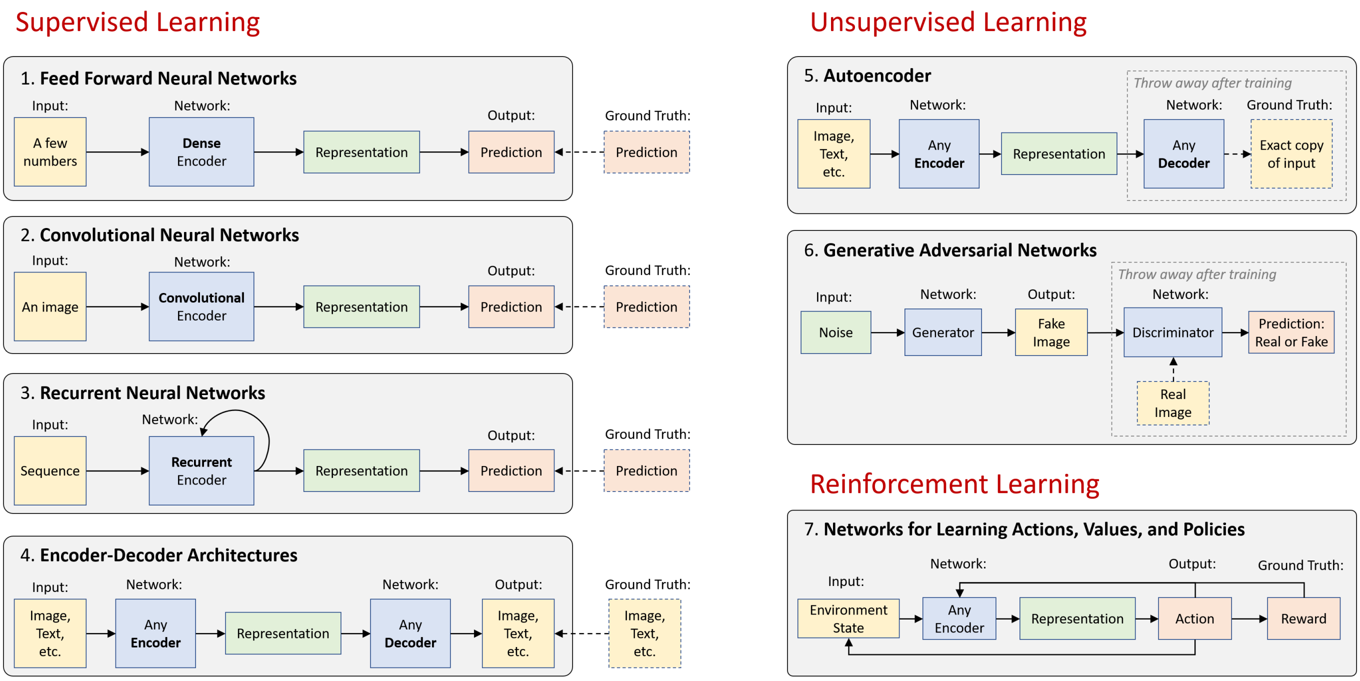
Deep Learning Basics

Main Types of Deep Neural Networks

based on (C) MIT Deep Learning course

This tutorial accompanies the lecture on Deep Learning Basics given as part of MIT Deep Learning. Acknowledgement to amazing people involved is provided throughout the tutorial and at the end. You can watch the video on YouTube:

In this tutorial, we mention seven important types/concepts/approaches in deep learning, introducing the first 2 and providing pointers to tutorials on the others. Here is a visual representation of the seven:



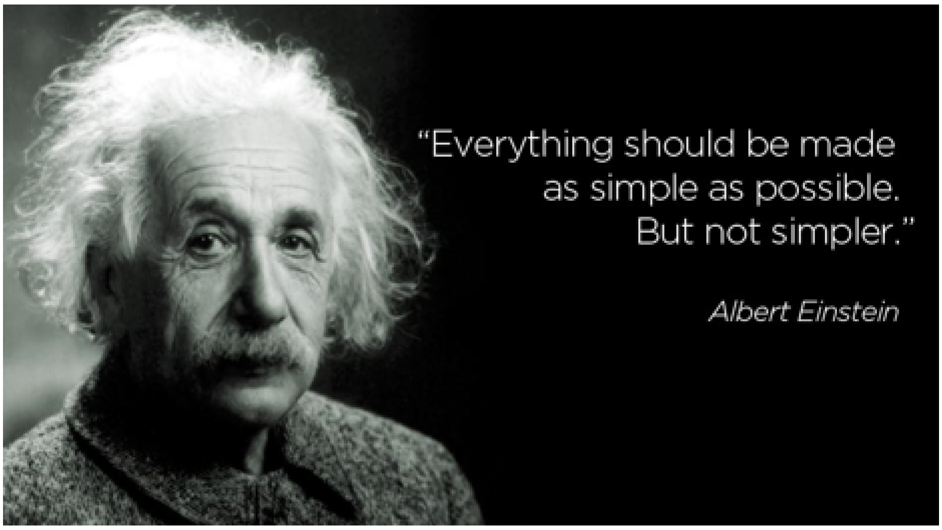
At a high-level, neural networks are either encoders, decoders, or a combination of both. Encoders find patterns in raw data to form compact, useful representations. Decoders generate new data or high-resolution useful infomation from those representations. As the lecture describes, deep learning discovers ways to **represent** the world so that we can reason about it. The rest is clever methods that help use deal effectively with visual information, language, sound (#1-6) and even act in a world based on this information and occasional rewards (#7).

1. **Feed Forward Neural Networks (FFNNs)** - classification and regression based on features. See Part 1 of this tutorial for an example.
2. **Convolutional Neural Networks (CNNs)** - image classification, object detection, video action recognition, etc. See Part 2 of this tutorial for an example.
3. **Recurrent Neural Networks (RNNs)** - language modeling, speech recognition/generation, etc. See this TF tutorial on text generation for an example.
4. **Encoder Decoder Architectures** - semantic segmentation, machine translation, etc. See our tutorial on semantic segmentation for an example.
5. **Autoencoder** - unsupervised embeddings, denoising, etc.
6. **Generative Adversarial Networks (GANs)** - unsupervised generation of realistic images, etc. See this TF tutorial on DCGANs for an example.
7. **Deep Reinforcement Learning** - game playing, robotics in simulation, self-play, neural arhitecture search, etc. We'll be releasing notebooks on this soon and will link them here.

There are selective omissions and simplifications throughout these tutorials, hopefully without losing the essence of the underlying ideas. See Einstein quote...

Part 0: Prerequisites:

We recommend that you run this this notebook in the cloud on Google Colab (see link with icon at the top) if you're not already doing so. It's the simplest way to get started. You can also install TensorFlow locally. But, again, simple is best (with caveats):



tf.keras is the simplest way to build and train neural network models in TensorFlow. So, that's what we'll stick with in this tutorial, unless the models neccessitate a lower-level API.

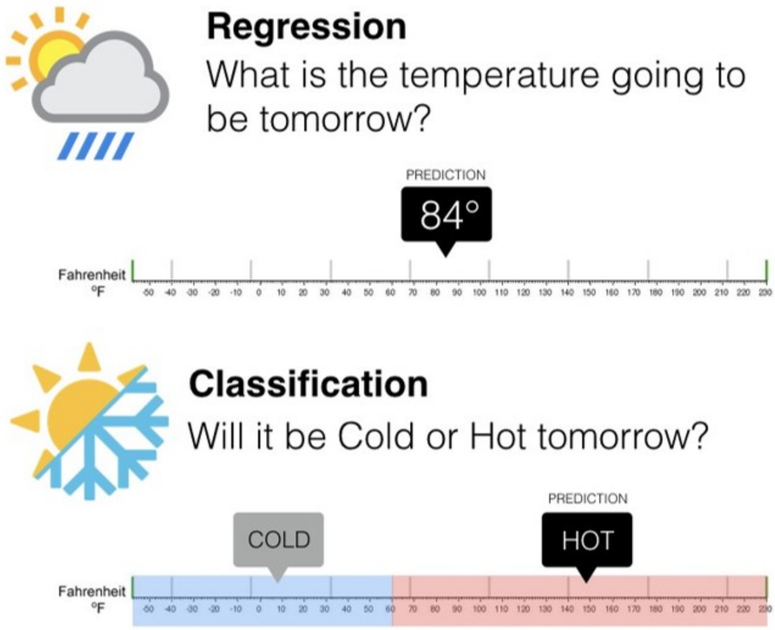
Note that there's tf.keras (comes with TensorFlow) and there's Keras (standalone). You should be using tf.keras because (1) it comes with TensorFlow so you don't need to install anything extra and (2) it comes with powerful TensorFlow-specific features.

```
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense

# Commonly used modules
import numpy as np
import os
import sys

# Images, plots, display, and visualization
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import cv2
import IPython
from six.moves import urllib

print(tf.__version__)
```

```
2.4.1
```

Part 1: Boston Housing Price Prediction with Feed Forward Neural Networks

Let's start with using a fully-connected neural network to do predict housing prices. The following image highlights the difference between regression and classification (see part 2). Given an observation as input, **regression** outputs a continuous value (e.g., exact temperature) and classificaiton outputs a class/category that the observation belongs to.



For the Boston housing dataset, we get 506 rows of data, with 13 features in each. Our task is to build a regression model that takes these 13 features as input and output a single value prediction of the "median value of owner-occupied homes (in $1000)."

Now, we load the dataset. Loading the dataset returns four NumPy arrays:

- The `train_images` and `train_labels` arrays are the *training set*—the data the model uses to learn.
- The model is tested against the *test set*, the `test_images`, and `test_labels` arrays.

```
(train_features, train_labels), (test_features, test_labels) = keras.datasets.bost

# get per-feature statistics (mean, standard deviation) from the training set to n
train_mean = np.mean(train_features, axis=0)
train_std = np.std(train_features, axis=0)
train_features = (train_features - train_mean) / train_std
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
57344/57026 [==============================] - 0s 0us/step
```

Build the model

Building the neural network requires configuring the layers of the model, then compiling the model. First we stack a few layers together using `keras.Sequential`. Next we configure the loss function, optimizer, and metrics to monitor. These are added during the model's compile step:

- *Loss function* - measures how accurate the model is during training, we want to minimize this with the optimizer.
- *Optimizer* - how the model is updated based on the data it sees and its loss function.
- *Metrics* - used to monitor the training and testing steps.

Let's build a network with 1 hidden layer of 20 neurons, and use mean squared error (MSE) as the loss function (most common one for regression problems):

```
def build_model():
    model = keras.Sequential([
        Dense(20, activation=tf.nn.relu, input_shape=[len(train_features[0])]),
        Dense(1)
    ])

    # for TF1
    #model.compile(optimizer=tf.train.AdamOptimizer(),
    # for TF2: tf.train.AdamOptimizer() => tf.optimizers.Adam()
    model.compile(optimizer=tf.optimizers.Adam(),
                  loss='mse',
                  metrics=['mae', 'mse'])
    return model
```

```
# this helps makes our output less verbose but still shows progress
class PrintDot(keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs):
        if epoch % 100 == 0: print('')
```

```
        print('.', end='')

model = build_model()
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense (Dense)                (None, 20)                280       
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 21        
=================================================================
Total params: 301
Trainable params: 301
Non-trainable params: 0
_________________________________________________________________
```

Train the model

Training the neural network model requires the following steps:

1. Feed the training data to the model—in this example, the `train_features` and `train_labels` arrays.
2. The model learns to associate features and labels.
3. We ask the model to make predictions about a test set—in this example, the `test_features` array. We verify that the predictions match the labels from the `test_labels` array.

To start training, call the `model.fit` method—the model is "fit" to the training data:

```
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=50)
history = model.fit(train_features, train_labels, epochs=1000, verbose=0, validati
                    callbacks=[early_stop, PrintDot()])

hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
```

```
.............................................................................
.............................................................................
.............................................................................
.............................................................................
.............................................................................
.............................................................................
```

```
hist.head()
```

	loss	mae	mse	val_loss	val_mae	val_mse	epc
0	587.850525	22.342070	587.850525	497.338501	21.296099	497.338501	
1	578.270081	22.107761	578.270081	488.346130	21.056395	488.346130	
2	568.495544	21.872797	568.495544	479.016754	20.807596	479.016754	
3	558.563049	21.626896	558.563049	469.127014	20.536999	469.127014	

```
# show RMSE measure to compare to Kaggle leaderboard on https://www.kaggle.com/c/b
rmse_final = np.sqrt(float(hist['val_mse'].tail(1)))
print()
print('Final Root Mean Square Error on validation set: {}'.format(round(rmse_final
```

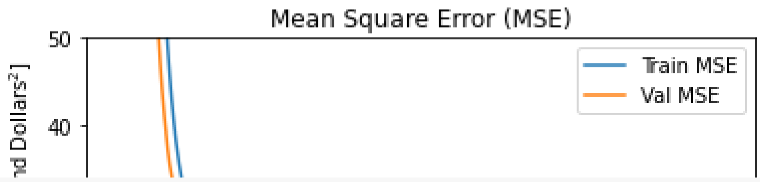
```
Final Root Mean Square Error on validation set: 2.383
```

```
# show RMSE measure to compare to Kaggle leaderboard on https://www.kaggle.com/c/b
rmse_final = np.sqrt(float(hist['val_mae'].tail(1)))
print()
print('Final Root Mean Average Error on validation set: {}'.format(round(rmse_fina
```

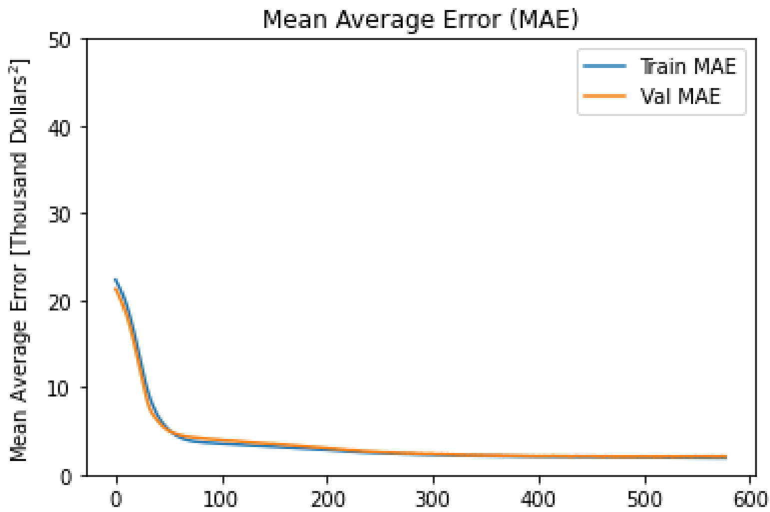
```
Final Root Mean Average Error on validation set: 1.441
```

Now, let's plot the loss function measure on the training and validation sets. The validation set is used to prevent overfitting (learn more about it here). However, because our network is small, the training convergence without noticeably overfitting the data as the plot shows.

```
def plot_history():
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Mean Square Error [Thousand Dollars$^2$]')
    plt.plot(hist['epoch'], hist['mse'], label='Train MSE')
    plt.plot(hist['epoch'], hist['val_mse'], label = 'Val MSE')
    plt.legend()
    plt.title("Mean Square Error (MSE)")
    plt.ylim([0,50])

plot_history()
```




```
def plot_history():
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Mean Average Error [Thousand Dollars$^2$]')
    plt.plot(hist['epoch'], hist['mae'], label='Train MAE')
    plt.plot(hist['epoch'], hist['val_mae'], label = 'Val MAE')
    plt.legend()
    plt.title("Mean Average Error (MAE)")
    plt.ylim([0,50])

plot_history()
```



Next, compare how the model performs on the test dataset:

```
print(model.metrics_names)
```

```
['loss', 'mae', 'mse']
```

```
test_features_norm = (test_features - train_mean) / train_std
loss, mae, mse = model.evaluate(test_features_norm, test_labels)
print('Loss on test set: {}'.format(round(loss, 3)))
print('Mean Average Error on test set: {}'.format(round(mae, 3)))
print('Mean Square Error on test set: {}'.format(round(mse, 3)))
rmse = np.sqrt(mse)
print('Root Mean Square Error on test set: {}'.format(round(rmse, 3)))
```

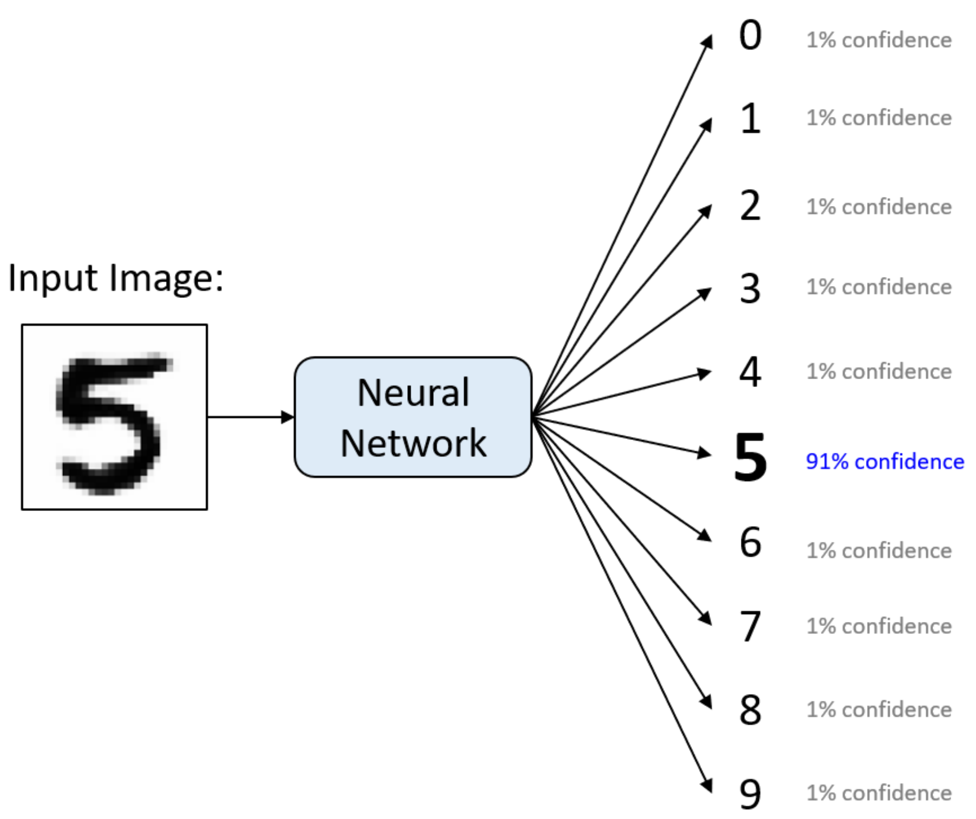
```
4/4 [==============================] - 0s 4ms/step - loss: 18.3065 - mae: 2.6
Loss on test set: 18.306
Mean Average Error on test set: 2.686
Mean Square Error on test set: 18.306
Root Mean Square Error on test set: 4.279
```

Compare the RMSE measure you get to the [Kaggle leaderboard](). An RMSE of 4.105 puts us in 24th place.

Part 2: Classification of MNIST Dreams with Convolutional Neural Networks

Next, let's build a convolutional neural network (CNN) classifier to classify images of handwritten digits in the MNIST dataset with a twist where we test our classifier on high-resolution hand-written digits from outside the dataset.

The MNIST dataset containss 70,000 grayscale images of handwritten digits at a resolution of 28 by 28 pixels. The task is to take one of these images as input and predict the most likely digit contained in the image (along with a relative confidence in this prediction):



Now, we load the dataset. The images are 28x28 NumPy arrays, with pixel values ranging between 0 and 255. The *labels* are an array of integers, ranging from 0 to 9.

```
(train_images, train_labels), (test_images, test_labels) = keras.datasets.mnist.lo

# reshape images to specify that it's a single channel
train_images = train_images.reshape(train_images.shape[0], 28, 28, 1)
test_images = test_images.reshape(test_images.shape[0], 28, 28, 1)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-data
```

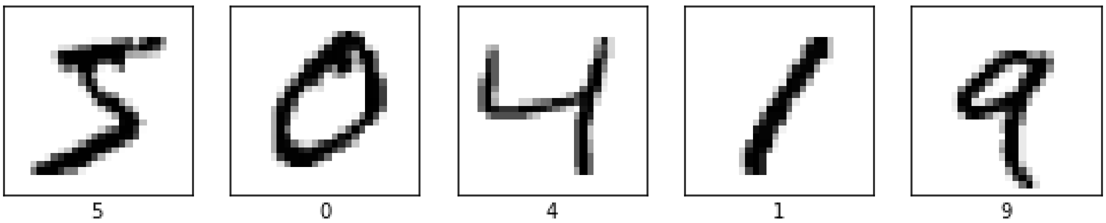
```
11493376/11490434 [==============================] - 0s 0us/step
```

We scale these values to a range of 0 to 1 before feeding to the neural network model. For this, we divide the values by 255. It's important that the *training set* and the *testing set* are preprocessed in the same way:

```
def preprocess_images(imgs): # should work for both a single image and multiple im
    sample_img = imgs if len(imgs.shape) == 2 else imgs[0]
    assert sample_img.shape in [(28, 28, 1), (28, 28)], sample_img.shape # make su
    return imgs / 255.0

train_images = preprocess_images(train_images)
test_images = preprocess_images(test_images)
```

Display the first 5 images from the *training set* and display the class name below each image. Verify that the data is in the correct format and we're ready to build and train the network.

```
plt.figure(figsize=(10,2))
for i in range(5):
    plt.subplot(1,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i].reshape(28, 28), cmap=plt.cm.binary)
    plt.xlabel(train_labels[i])
```



Build the model

Building the neural network requires configuring the layers of the model, then compiling the model. In many cases, this can be reduced to simply stacking together layers:

```
model = keras.Sequential()
# 32 convolution filters used each of size 3x3
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1
# 64 convolution filters used each of size 3x3
model.add(Conv2D(64, (3, 3), activation='relu'))
# choose the best features via pooling
model.add(MaxPooling2D(pool_size=(2, 2)))
# randomly turn neurons on and off to improve convergence
model.add(Dropout(0.25))
```

```
# flatten since too many dimensions, we only want a classification output
model.add(Flatten())
# fully connected to get all relevant data
model.add(Dense(128, activation='relu'))
# one more dropout
model.add(Dropout(0.5))
# output a softmax to squash the matrix into output probabilities
model.add(Dense(10, activation='softmax'))
```

Before the model is ready for training, it needs a few more settings. These are added during the model's *compile* step:

- *Loss function* - measures how accurate the model is during training, we want to minimize this with the optimizer.
- *Optimizer* - how the model is updated based on the data it sees and its loss function.
- *Metrics* - used to monitor the training and testing steps. "accuracy" is the fraction of images that are correctly classified.

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 12, 12, 64)        0
_________________________________________________________________
dropout (Dropout)            (None, 12, 12, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 9216)              0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               1179776
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 10)                1290
=================================================================
Total params: 1,199,882
Trainable params: 1,199,882
Non-trainable params: 0
_________________________________________________________________
```

```
model.compile(optimizer=tf.optimizers.Adam(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Train the model

Training the neural network model requires the following steps:

1. Feed the training data to the model—in this example, the `train_images` and `train_labels` arrays.
2. The model learns to associate images and labels.
3. We ask the model to make predictions about a test set—in this example, the `test_images` array. We verify that the predictions match the labels from the `test_labels` array.

To start training, call the `model.fit` method—the model is "fit" to the training data:

```
history = model.fit(train_images, train_labels, epochs=5, validation_split = 0.1)
```

```
Epoch 1/5
1688/1688 [==============================] - 11s 3ms/step - loss: 0.3720 - ac
Epoch 2/5
1688/1688 [==============================] - 6s 3ms/step - loss: 0.0842 - acc
Epoch 3/5
1688/1688 [==============================] - 5s 3ms/step - loss: 0.0678 - acc
Epoch 4/5
1688/1688 [==============================] - 5s 3ms/step - loss: 0.0535 - acc
Epoch 5/5
1688/1688 [==============================] - 6s 3ms/step - loss: 0.0418 - acc
```

```
print(model.metrics_names)
```

```
['loss', 'accuracy']
```

As the model trains, the loss and accuracy metrics are displayed. This model reaches an accuracy of about 98.68% on the training data.

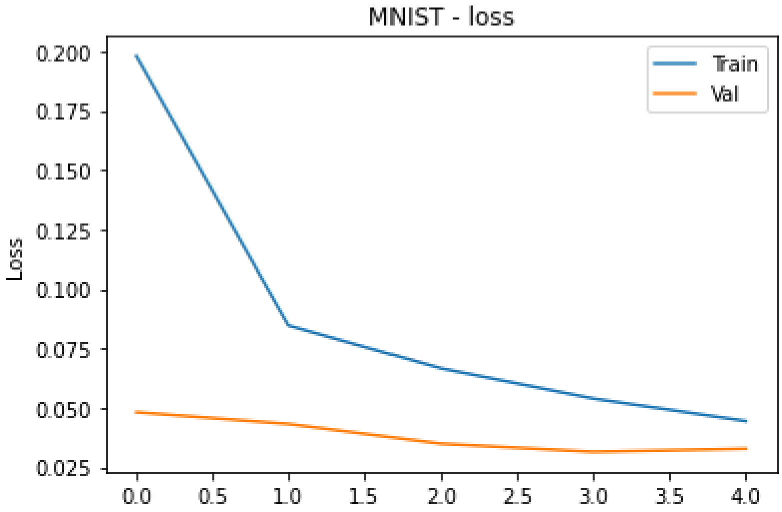
```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
```

```
hist.head()
```

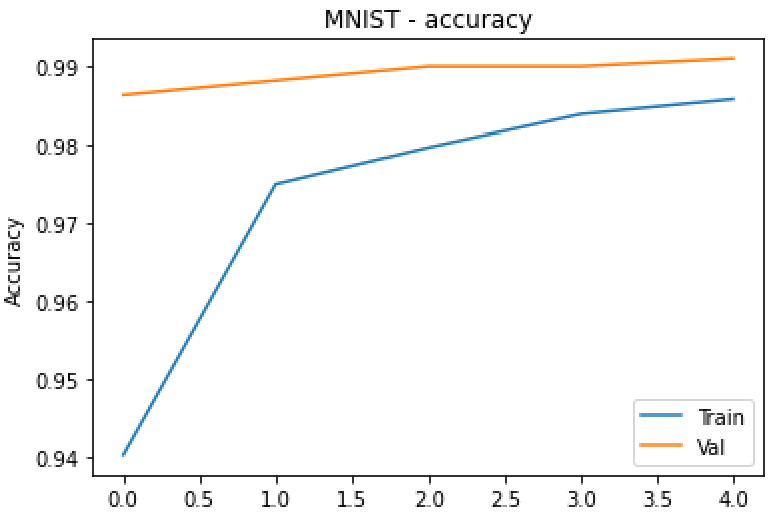
	loss	accuracy	val_loss	val_accuracy	epoch
0	0.198095	0.940278	0.048189	0.986333	0
1	0.084753	0.975000	0.043236	0.988167	1
2	0.066670	0.979667	0.034934	0.990000	2
3	0.053950	0.983907	0.031506	0.990000	3
4	0.044473	0.985796	0.032814	0.991000	4

```
def plot_history():
```

```
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.plot(hist['epoch'], hist['loss'], label='Train')
    plt.plot(hist['epoch'], hist['val_loss'], label = 'Val')
    plt.legend()
    plt.title("MNIST - loss")
    #plt.ylim([0,50])

plot_history()
```




```
def plot_history():
    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.plot(hist['epoch'], hist['accuracy'], label='Train')
    plt.plot(hist['epoch'], hist['val_accuracy'], label = 'Val')
    plt.legend()
    plt.title("MNIST - accuracy")
    #plt.ylim([0,50])

plot_history()
```



Evaluate accuracy

Next, compare how the model performs on the test dataset:

```
print(test_images.shape)
test_loss, test_acc = model.evaluate(test_images, test_labels)

print('MNIST - Test accuracy:', test_acc)
```

```
(10000, 28, 28, 1)
313/313 [==============================] - 1s 2ms/step - loss: 0.0291 - accur
MNIST - Test accuracy: 0.9905999898910522
```

Compare with ... after 5 epochs

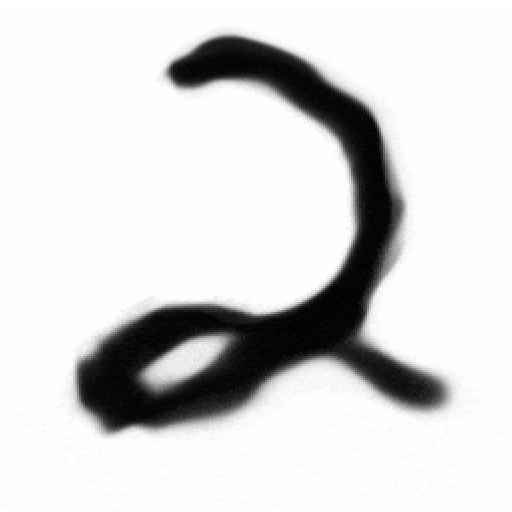
(10000, 28, 28, 1) 313/313 [==============================] - 1s 2ms/step - loss: 0.0302 - accuracy: 0.9910

Test accuracy: 0.9909999966621399

Often times, the accuracy on the test dataset is a little less than the accuracy on the training dataset. This gap between training accuracy and test accuracy is an example of *overfitting*. In our case, the accuracy is better at 99.19%! This is, in part, due to successful regularization accomplished with the Dropout layers.

Make predictions

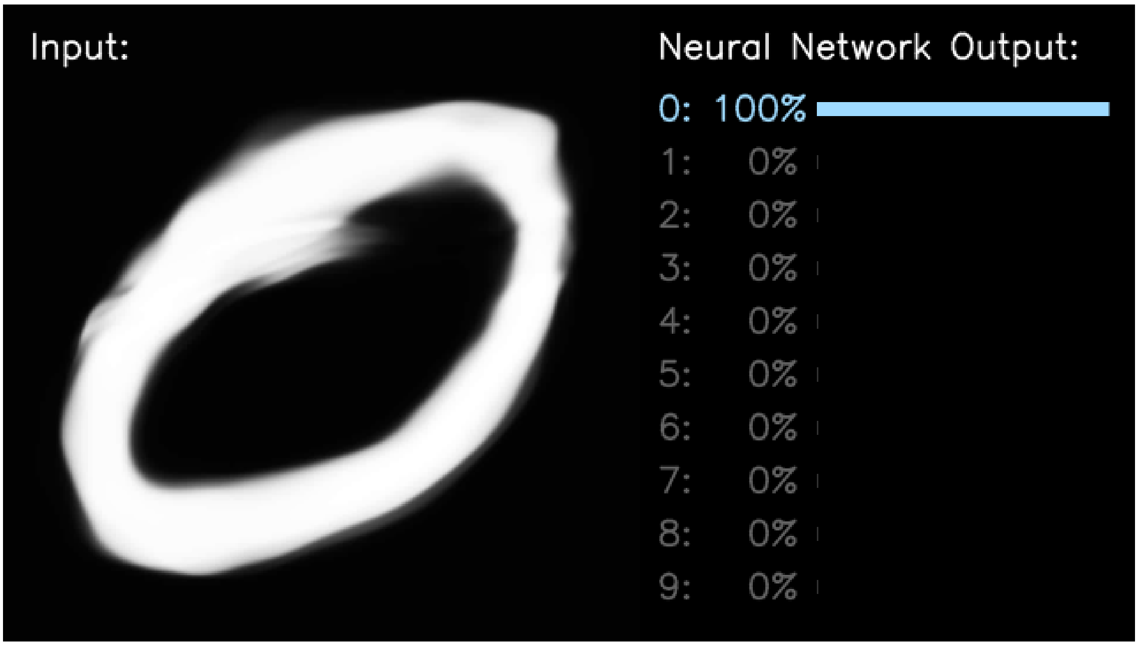
With the model trained, we can use it to make predictions about some images. Let's step outside the MNIST dataset for that and go with the beautiful high-resolution images generated by a mixture of CPPN, GAN, VAE. See [great blog post by hardmaru]() for the source data and a description of how these morphed animations are generated:



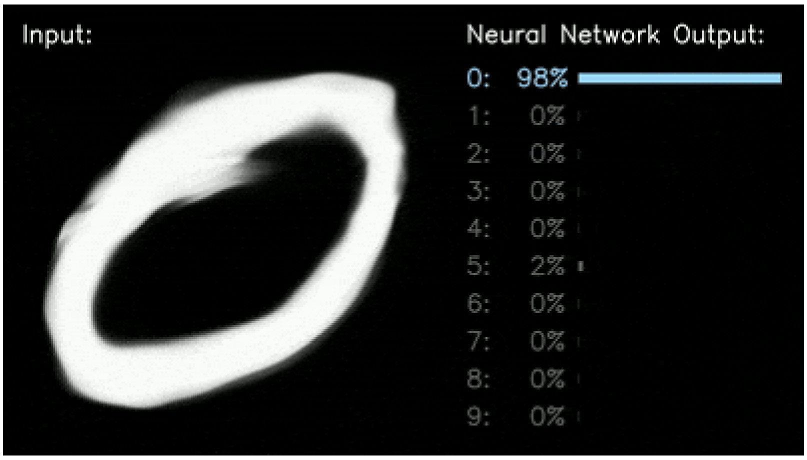
```python
# Set common constants
this_repo_url = 'https://github.com/lexfridman/mit-deep-learning/raw/master/'
this_tutorial_url = this_repo_url + 'tutorial_deep_learning_basics'
```

```python
mnist_dream_path = 'images/mnist_dream.mp4'
mnist_prediction_path = 'images/mnist_dream_predicted.mp4'

# download the video if running in Colab
if not os.path.isfile(mnist_dream_path):
    print('downloading the sample video...')
    vid_url = this_tutorial_url + '/' + mnist_dream_path

    mnist_dream_path = urllib.request.urlretrieve(vid_url)[0]

def cv2_imshow(img):
    ret = cv2.imencode('.png', img)[1].tobytes()
    img_ip = IPython.display.Image(data=ret)
    IPython.display.display(img_ip)

cap = cv2.VideoCapture(mnist_dream_path)
vw = None
frame = -1 # counter for debugging (mostly), 0-indexed

# go through all the frames and run our classifier on the high res MNIST images as
while True: # should 481 frames
    frame += 1
    ret, img = cap.read()
    if not ret: break

    assert img.shape[0] == img.shape[1] # should be a square
    if img.shape[0] != 720:
        img = cv2.resize(img, (720, 720))

    #preprocess the image for prediction
    img_proc = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    img_proc = cv2.resize(img_proc, (28, 28))
    img_proc = preprocess_images(img_proc)
    img_proc = 1 - img_proc # inverse since training dataset is white text with bl

    net_in = np.expand_dims(img_proc, axis=0) # expand dimension to specify batch
    net_in = np.expand_dims(net_in, axis=3) # expand dimension to specify number o

    preds = model.predict(net_in)[0]
    guess = np.argmax(preds)
    perc = np.rint(preds * 100).astype(int)

    img = 255 - img
    pad_color = 0
    img = np.pad(img, ((0,0), (0,1280-720), (0,0)), mode='constant', constant_valu
```

```
    line_type = cv2.LINE_AA
    font_face = cv2.FONT_HERSHEY_SIMPLEX
    font_scale = 1.3
    thickness = 2
    x, y = 740, 60
    color = (255, 255, 255)

    text = "Neural Network Output:"
    cv2.putText(img, text=text, org=(x, y), fontScale=font_scale, fontFace=font_fa
                    color=color, lineType=line_type)

    text = "Input:"
    cv2.putText(img, text=text, org=(30, y), fontScale=font_scale, fontFace=font_f
                    color=color, lineType=line_type)

    y = 130
    for i, p in enumerate(perc):
        if i == guess: color = (255, 218, 158)
        else: color = (100, 100, 100)

        rect_width = 0
        if p > 0: rect_width = int(p * 3.3)

        rect_start = 180
        cv2.rectangle(img, (x+rect_start, y-5), (x+rect_start+rect_width, y-20), c

        text = '{}: {:>3}%'.format(i, int(p))
        cv2.putText(img, text=text, org=(x, y), fontScale=font_scale, fontFace=fon
                    color=color, lineType=line_type)
        y += 60

    # if you don't want to save the output as a video, set this to False
    save_video = True

    if save_video:
        if vw is None:
            codec = cv2.VideoWriter_fourcc(*'DIVX')
            vid_width_height = img.shape[1], img.shape[0]
            vw = cv2.VideoWriter(mnist_prediction_path, codec, 30, vid_width_heigh
        # 15 fps above doesn't work robustly so we right frame twice at 30 fps
        vw.write(img)
        vw.write(img)

    # scale down image for display
    img_disp = cv2.resize(img, (0,0), fx=0.5, fy=0.5)
    cv2_imshow(img_disp)
    IPython.display.clear_output(wait=True)

cap.release()
if vw is not None:
    vw.release()
```



The above shows the prediction of the network by choosing the neuron with the highest output. While the output layer values add 1 to one, these do not reflect well-calibrated measures of "uncertainty". Often, the network is overly confident about the top choice that does not reflect a learned measure of probability. If everything ran correctly you should get an animation like this:



Acknowledgements

The contents of this tutorial is based on and inspired by the work of [TensorFlow team](), our [MIT Human-Centered AI team](), and individual pieces referenced in the [MIT Deep Learning]() course slides.

Методи Deep Learning
-
Deep Learning Methods
-
Lecture 05. Deep Neural Networks in TensorFlow

(based on (C) F.Colliet, Lex Fridman, ... and others works)

Content

- Recommended Sources
- DL Frameworks — Basics
- DL Frameworks — Workflow
  - DEMO 1: Workflow in TF2
  - DEMO 2: How to Monitor Workflow in TF2
- DL Workflow - Transfer Learning
  - DEMO 3A: Learning from Scratch in TF2
  - DEMO 3B: Transfer Learning in TF2

Recommended Sources — Books

Books (scientific):
Goodfellow, I., Bengio, Y., Courville, A. (2016). *Deep learning*. Cambridge: MIT press
Цитовано в 23692 джерелах.

Books (with codes at github):
Alan Fontaine (2018) *Mastering Predictive Analytics with scikit-learn and TensorFlow*. Packt Publishing.

Tanay Agrawal (2021). *Hyperparameter Optimization in Machine Learning: Make Your Machine Learning and Deep Learning Models More Efficient*, Apress

Recommended Sources — Papers

Imagenet

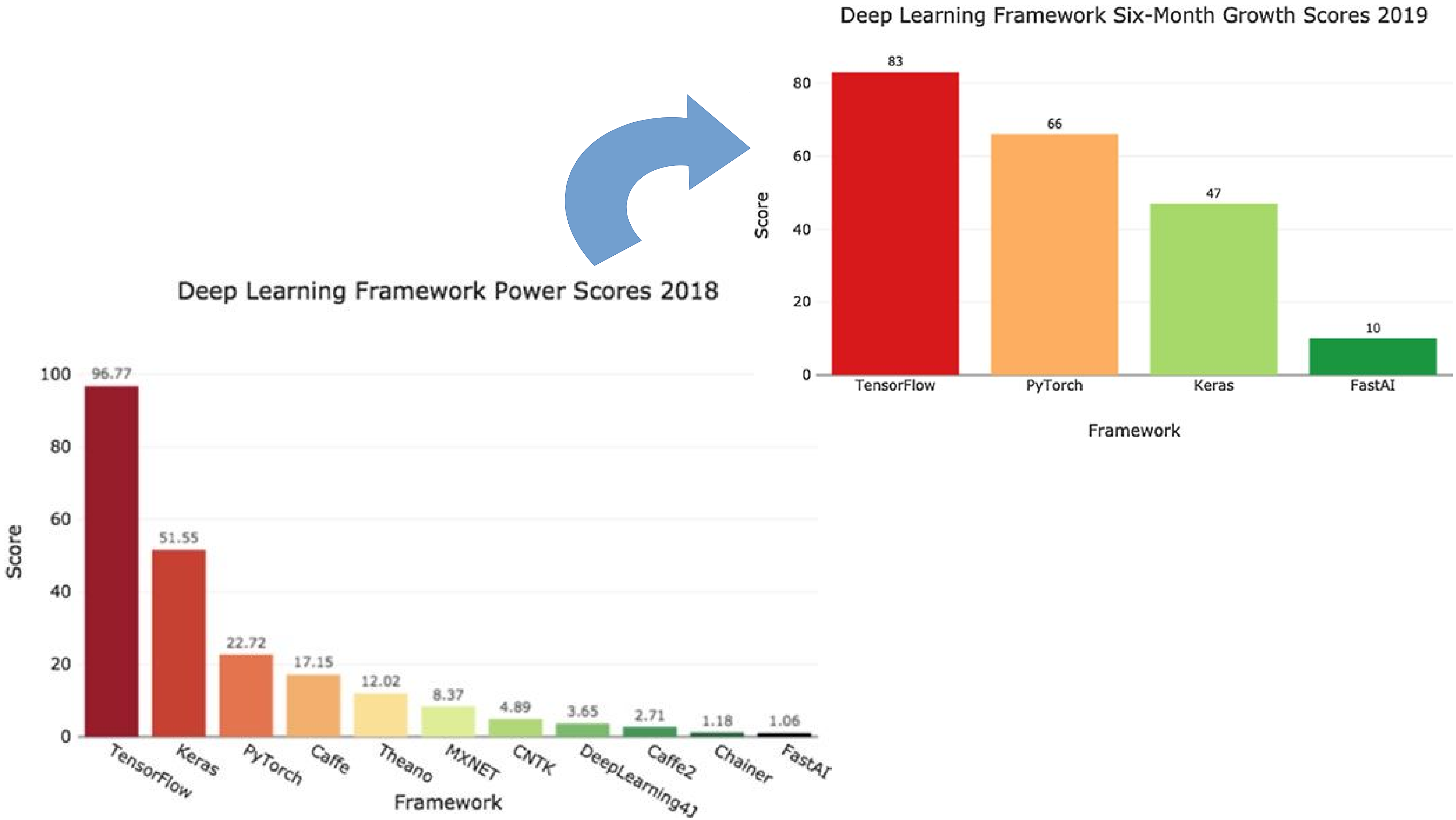
Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359.

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.

Konečný, J., McMahan, H. B., Yu, F. X., Richtárik, P., Suresh, A. T., & Bacon, D. (2016). Federated learning: Strategies for improving communication efficiency. arXiv preprint arXiv:1610.05492.

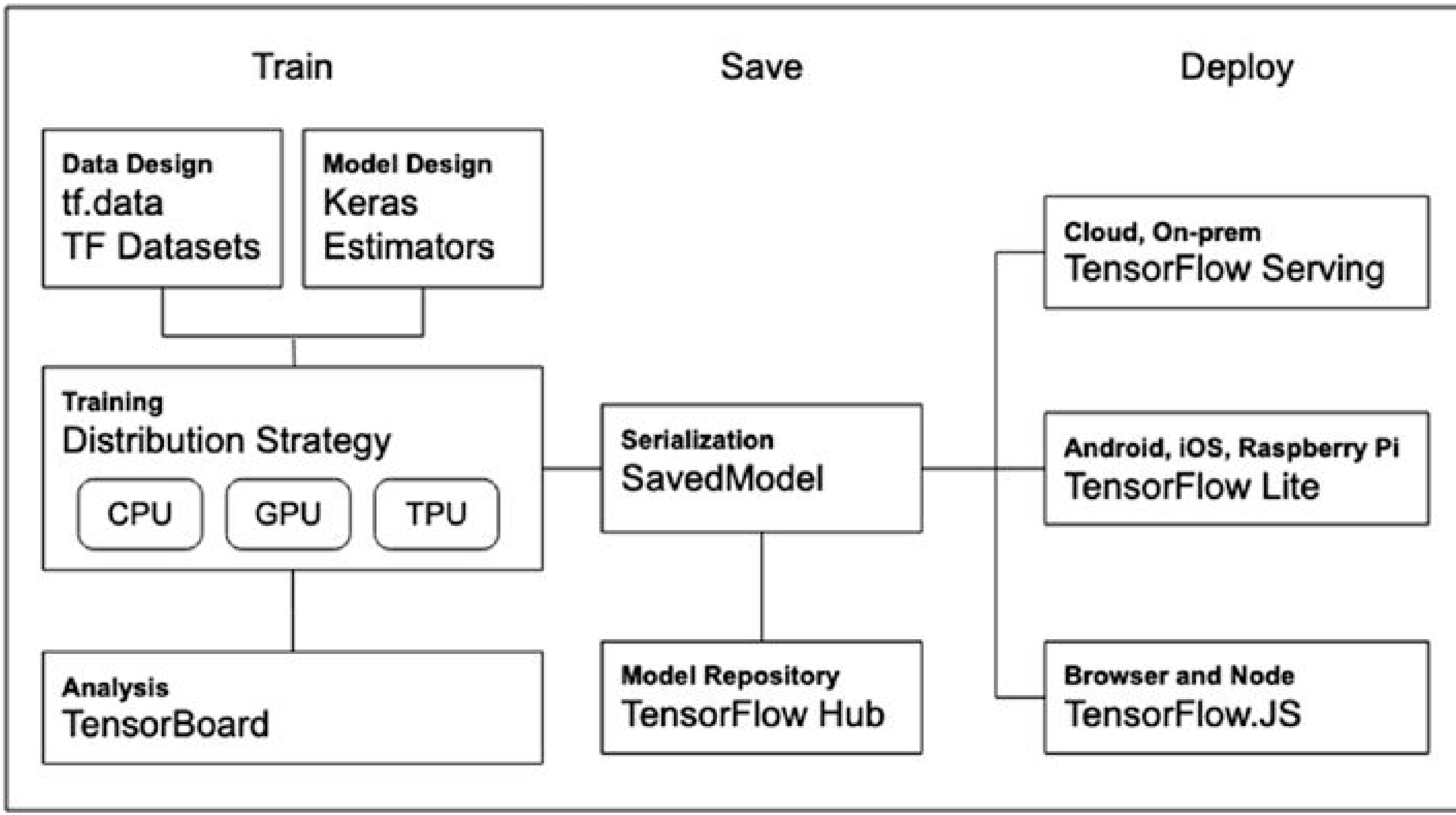
DL Frameworks
-
Basics

DL Frameworks — Evolution



https://www.kdnuggets.com/2019/05/which-deep-learning-framework-growing-fastest.html

DL Framework — Ecosystem (Tensorflow Example)



DL Framework — Components (Tensorflow Example)

Hardware Environment (local, cloud, Edge Computing, ...):

- CPU
- GPU
- TPU
- Edge Computing Devices ...

Software Environment (local, cloud, Edge Computing, ...):

Operational System: macOS (>=10.12.6), Ubuntu (>=16.04), Windows (>=7), Raspbian (>=9.0), ...

Programming Language: C, C++, C#, Java, Go, Julia, Ruby, Scala, but ... Python 3

Libraries: ... numerous ...

DL Frameworks
-
Workflow

DL Workflow
(Tensorflow at Google Cloud Example)

◆**Setup Hardware Environment (**at Google VM**)**:
◆select **Runtime Type**: CPU, GPU, TPU — **DEMO 1**.

Setup Software Environment:
Operational System: Ubuntu (pre-installed already).
Programming Language: Python 3 (pre-installed already)
Libraries: Python-libs (many pre-installed already)

Set up (get) dataset: local, cloud (AWS, GC, ... Kaggle, ...)

Get (define or load) model: local, TF Hub, cloud, ...

Compile (configure hyperparameters) model: loss function, optimization method, metrics, duration, callbacks, ...

Train and **validate** model -> **Prediction** -> **Production**? **Not yet!** :)

DEMO 1: Workflow in TF2

DEMO_1_Workflow_Example_CPU.ipynb
DEMO_1_Workflow_Example_GPU.ipynb
DEMO_1_Workflow_Example_TPU.ipynb

DEMO 2:
How to Monitor Workflow in TF2

DEMO_2_External_Data_Tensorboard_Binary_Classification_Example.ipynb

DL Workflow — Learning/Training Types

- **Learning from scratch**:
  - from **random initial** parameters (weights, ...)
  - from **previously trained** attempts.

- **Transfer learning** — is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.

- **Knowledge distillation** — learning is the process of transferring knowledge from a large model to a smaller one.

- **Federated learning** (also known as collaborative learning) is a machine learning technique that trains an algorithm across multiple decentralized edge devices or servers holding local data samples, without exchanging them.

DL Workflow — Learning/Training Types — from scratch ... on datasets

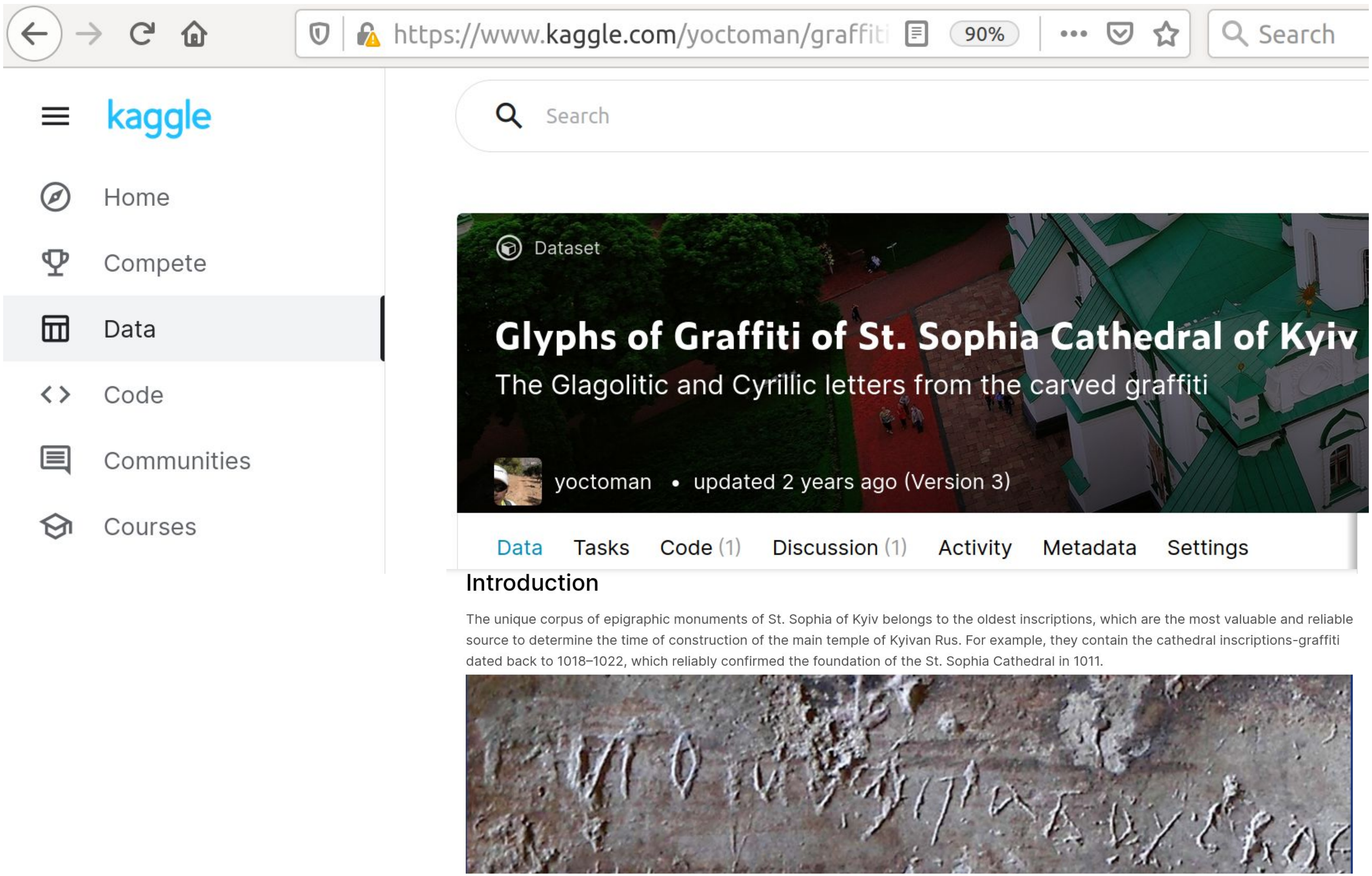
Learning from scratch from **random initial** parameters (weights, ...) is very resource-demanding task.

Even for MNIST (**60K** images), it took a time to train the model up to the accuracy 80-90%. For a higher accuracy, more images would be required.
DNN **learns better** with a **higher volume** of data.

notMNIST, FashionMNIST, ...
https://www.kaggle.com/yoctoman/graffiti-st-sophia-cathedral-kyiv
CIFAR10, CIFAR100, ...
Microsoft Common Objects in Context (COCO),
PASCAL Visual Object Classes (PASCAL VOC),
...
ImageNet !!!

DL Workflow — Learning/Training Types — from scratch ... on datasets

One more dataset with ancient Cyrillic letters ... from Kyiv

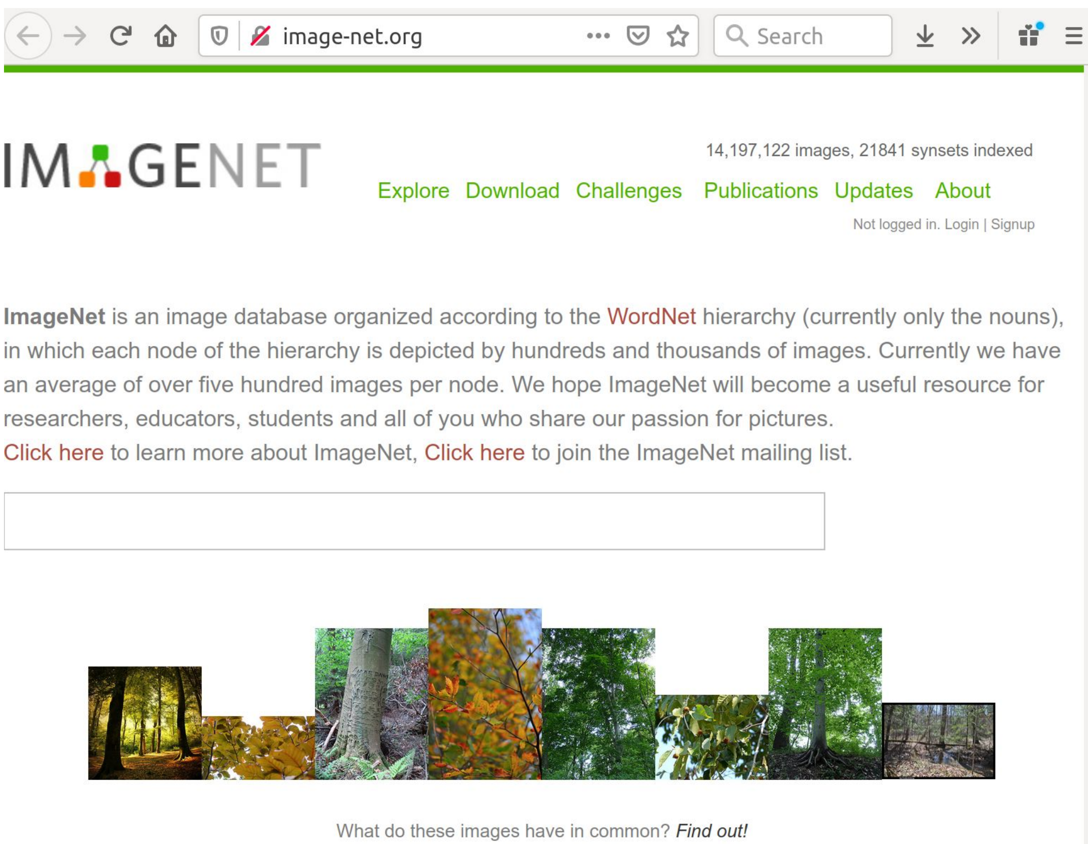


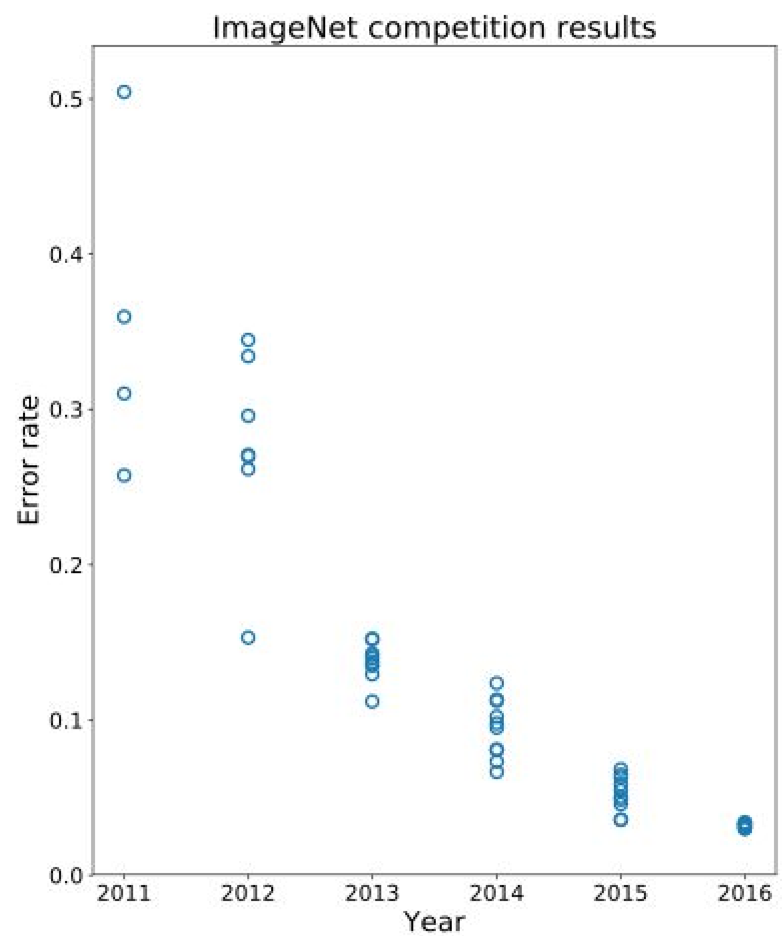
https://www.kaggle.com/yoctoman/graffiti-st-sophia-cathedral-kyiv

DL Workflow — Learning/Training Types — from scratch ... on Imagenet

ImageNet (http://image-net.org): **14,197,122** images into **21,841** subcategories into **27** subtrees.

To classify the images in ImageNet, many ML/DL models were developed. In 2017, one model achieved an error rate of 2.3%.





DL Workflow — Learning/Training Types — Transfer Learning

Transfer learning — is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.

1. Using a Pre-Trained Model

2. Training a Model to Reuse it

To solve task A you have limited data to train a DNN.
One way: to find a related task B with an abundance of data.
Train the DNN on task B and use the model as a starting point for solving task A.

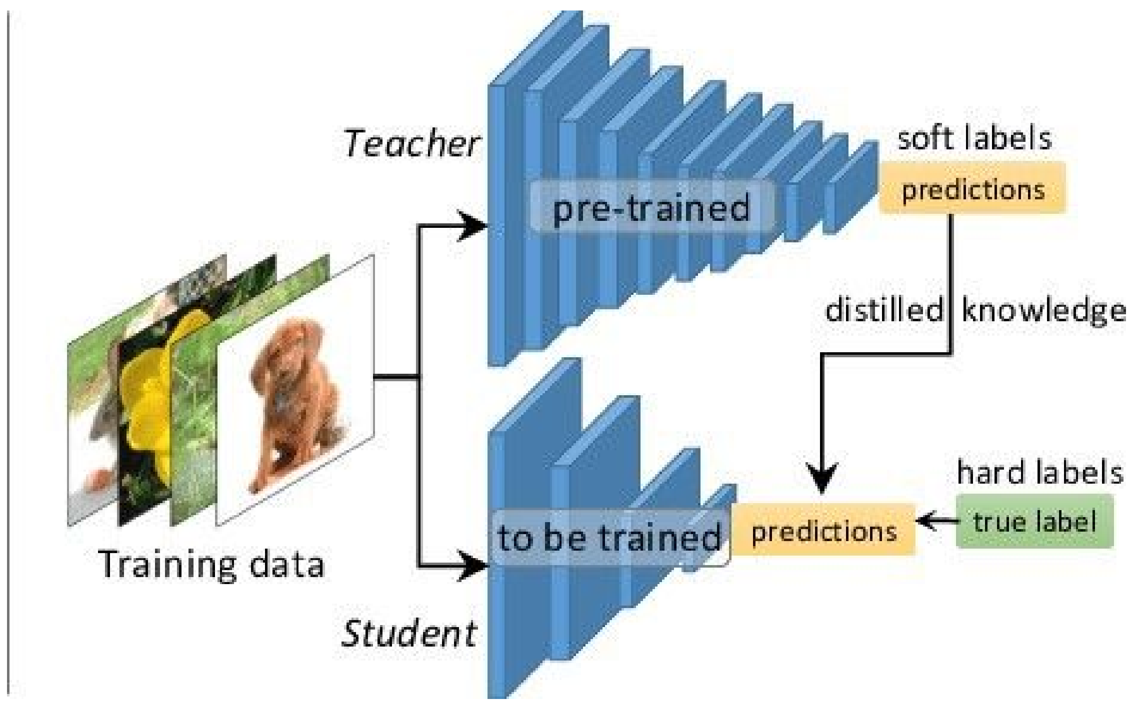
3. Feature Extraction

Another approach is to use DNN to find the best **representation** (most important features) of your problem, and use them.

DL Workflow — Learning/Training Types - Knowledge Distillation

A small model is trained to mimic a pre-trained, larger model (or ensemble of models). This training setting is sometimes referred to as “teacher-student”, where the **large** model is the **teacher** and the **small** model is the **student**.

It has even been observed that classifiers **learn** much **faster** and more **reliably** if trained with the **outputs** of another classifier as **soft** labels, instead of from hard labels (ground truth data).

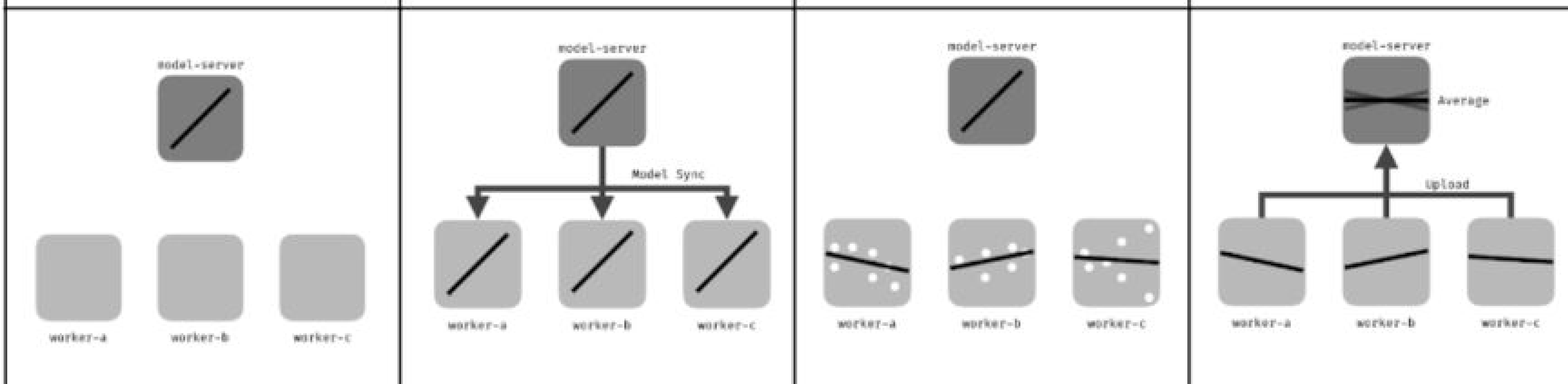


DL Workflow — Learning/Training Types — Federated Learning

... is **in contrast** to

- traditional **centralized** learning techniques where all the **local** datasets are **uploaded to one server**,
- and some **classical decentralized** learning techniques where local data samples are identically distributed.

Step 1	Step 2	Step 3	Step 4
Central server chooses a statistical model to be trained	Central server transmits the initial model to several nodes	Nodes train the model locally with their own data	Central server pools model results and generate one global mode without accessing any data



DL Workflow
-
Transfer Learning

DEMO 3A:
Learning from Scratch in TF2

DEMO_3A_Model_from_TF2_Keras_CNN_2_4_6_cifar10_imageClassification.ipynb

DL Workflow — Transfer Learning

Transfer learning

— in general sense: is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned,

— in ML/DL context: it is an important technique of **knowledge transfer** from one to another **ML/DL task**.

Examples:

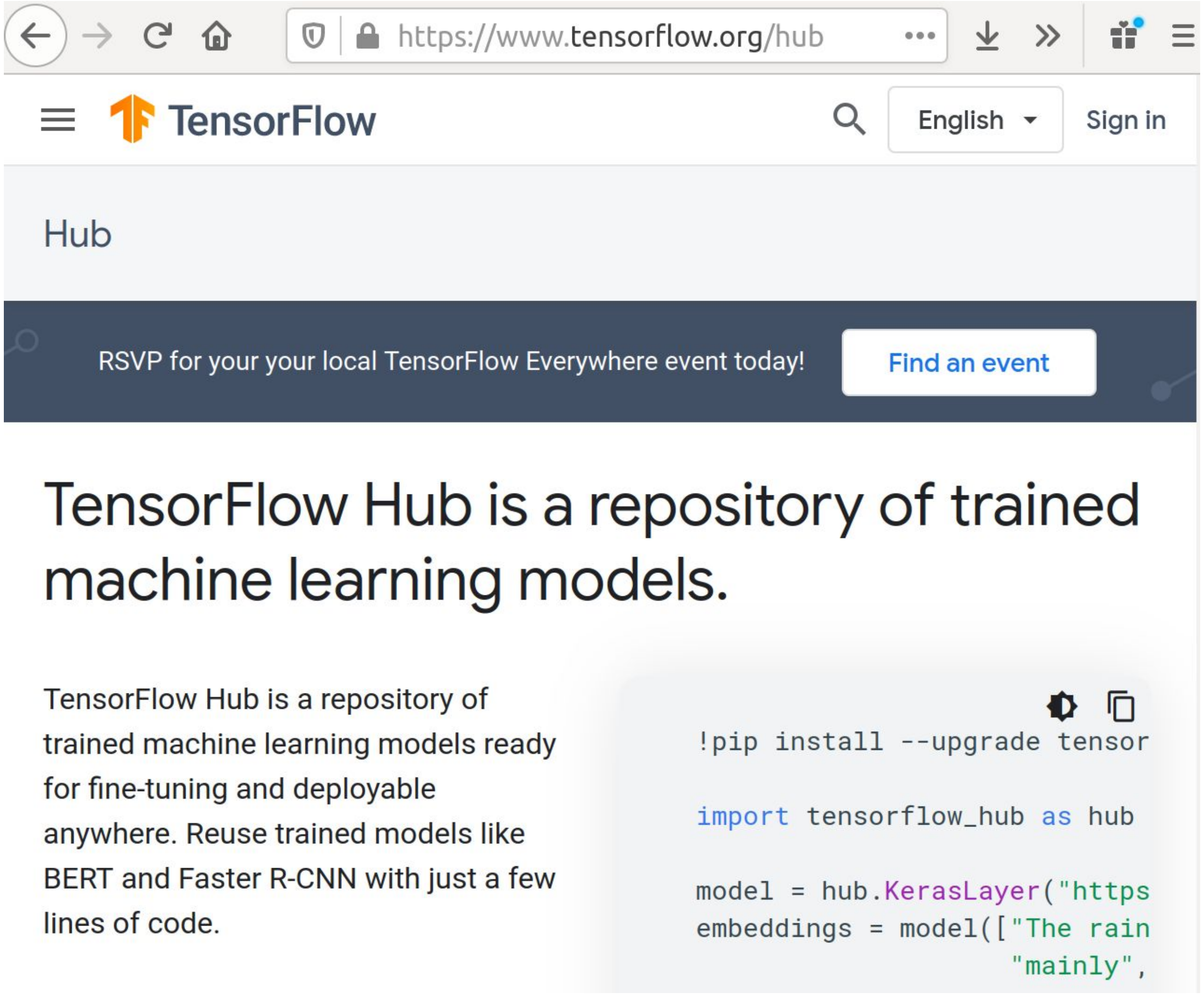
- In software engineering: people use binary libraries to reuse the code.
- In ML/DL: the trained models contain the **algorithms**, the **data**, the **processing power**, and the **expert's domain knowledge**. All these need to be **transferred** to the **new** model. That's what the transfer learning provides.

Transfer Learning — Model Sources

Pre-trained models can be found everywhere:
- from your **collegues**,
- **github**,
- **Kaggle**,

...

but **Tensorflow Hub** is a the widest and easiest source of pre-trained and trustable DNN models.



https://www.tensorflow.org/hub

DEMO 3B:
Transfer Learning in TF2

DEMO_3B_Model_from_TF2_Hub_MobileNetV2_ImageNet_imageClassification.ipynb

Deep Learning Methods

Lecture 07

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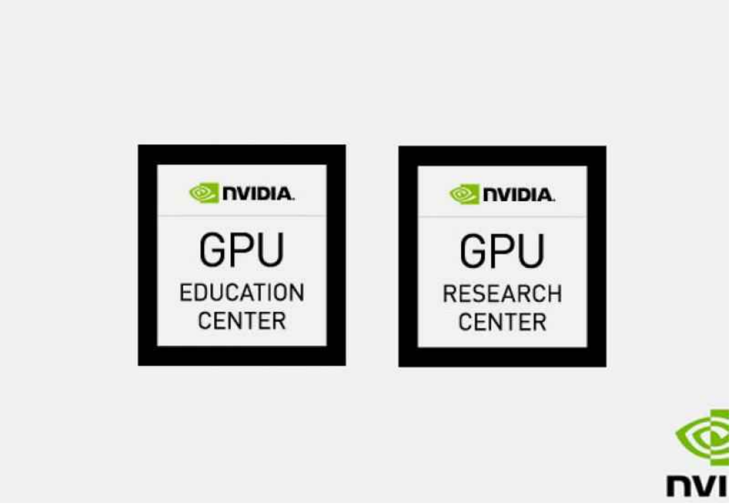
Lecture Slides + interactive Jupyter-notebooks for Google Colaboratory CPU/GPU/TPU cloud:
https://cloud.comsys.kpi.ua/s/SMkBSsxRTazoTD6

****

Lecture 07 – Deep Learning Workflow - Estimators

The course includes materials proposed by NVIDIA Deep Learning Institute (DLI) in the framework of the common

NVIDIA Research Center
and
NVIDIA Education Center.



https://kpi.ua/nvidia-info

Interactive Demonstrations

DEMO A
Introduction to TF Estimators
https://drive.google.com/file/d/10C-ypmitQmGkPQt-0oStL3OJGgSSvvvv/view?usp=sharing

DEMO B
Create DNN Model by TF Estimators
https://drive.google.com/file/d/1fro49geaFUoQJ4frgLJy04FRuzNeNA7T/view?usp=sharing

DEMO C
TF Datasets Benchmark by TF Estimators
https://drive.google.com/file/d/1dALe-tX9pyMjNKXbBikM9L6sEv34ulI4/view?usp=sharing

DEMO D
Transfer Learning - Rock Paper Scissors (using NASNetMobile)
https://drive.google.com/file/d/1XvXxDE5OSArPgwZ_bcn3ACfFRWu5rBuV/view?usp=sharing

DEMO A - Introduction to TF Estimators

based on (C) Velayudham, Sakranha, TF Authors works

```
import tensorflow as tf
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Connect to Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
! cp /content/drive/MyDrive/2022_COLAB_NN/Lecture_06_TF2_Estimators_CNN_RockPaperS
! ls
```

```
drive  sample_data  winequality-white.csv
```

Loading Data

```
data_url='winequality-white.csv'
data=pd.read_csv(data_url,delimiter=';')
data.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956

Selecting Features/Labels

```
x = data.iloc[:,:-1]
y = data.iloc[:,-1]
```

```
sc = StandardScaler()
x = sc.fit_transform(x)
```

Creating datasets

```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size = 0.3,random_state
```

```
input_shape = xtrain.shape[1]
```

Defining simple FCN Keras model

```
small_model = tf.keras.models.Sequential([
              tf.keras.layers.Dense(64,activation = 'relu',
                                    input_shape = (input_shape,)),
              tf.keras.layers.Dense(1)
])

small_model.compile(loss = 'mse', optimizer = 'adam')
```

```
def input_fn(features, labels, training = True, batch_size = 32):
  #converts inputs to a dataset
  dataset = tf.data.Dataset.from_tensor_slices(({'dense_input':features},labels))

  #shuffle and repeat in a training mode
  if training:
    dataset = dataset.shuffle(1000).repeat()

  #giving inputs in batch for training
  return dataset.batch(batch_size)
```

Convert Keras model to Estimator

```
keras_small_estimator = tf.keras.estimator.model_to_estimator(
    keras_model = small_model, model_dir = 'keras_small_classifier')
```

```
/usr/local/lib/python3.7/dist-packages/keras/backend.py:450: UserWarning: `tf
  warnings.warn('`tf.keras.backend.set_learning_phase` is deprecated and '
```

Train

```
keras_small_estimator.train(input_fn = lambda:input_fn(xtrain, ytrain), steps = 20
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/pyt
Instructions for updating:
Use Variable.read_value. Variables in 2.X are initialized automatically both
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has r
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has r
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has r
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has r
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has r
<tensorflow_estimator.python.estimator.estimator.EstimatorV2 at
0x7f96901753d0>
```

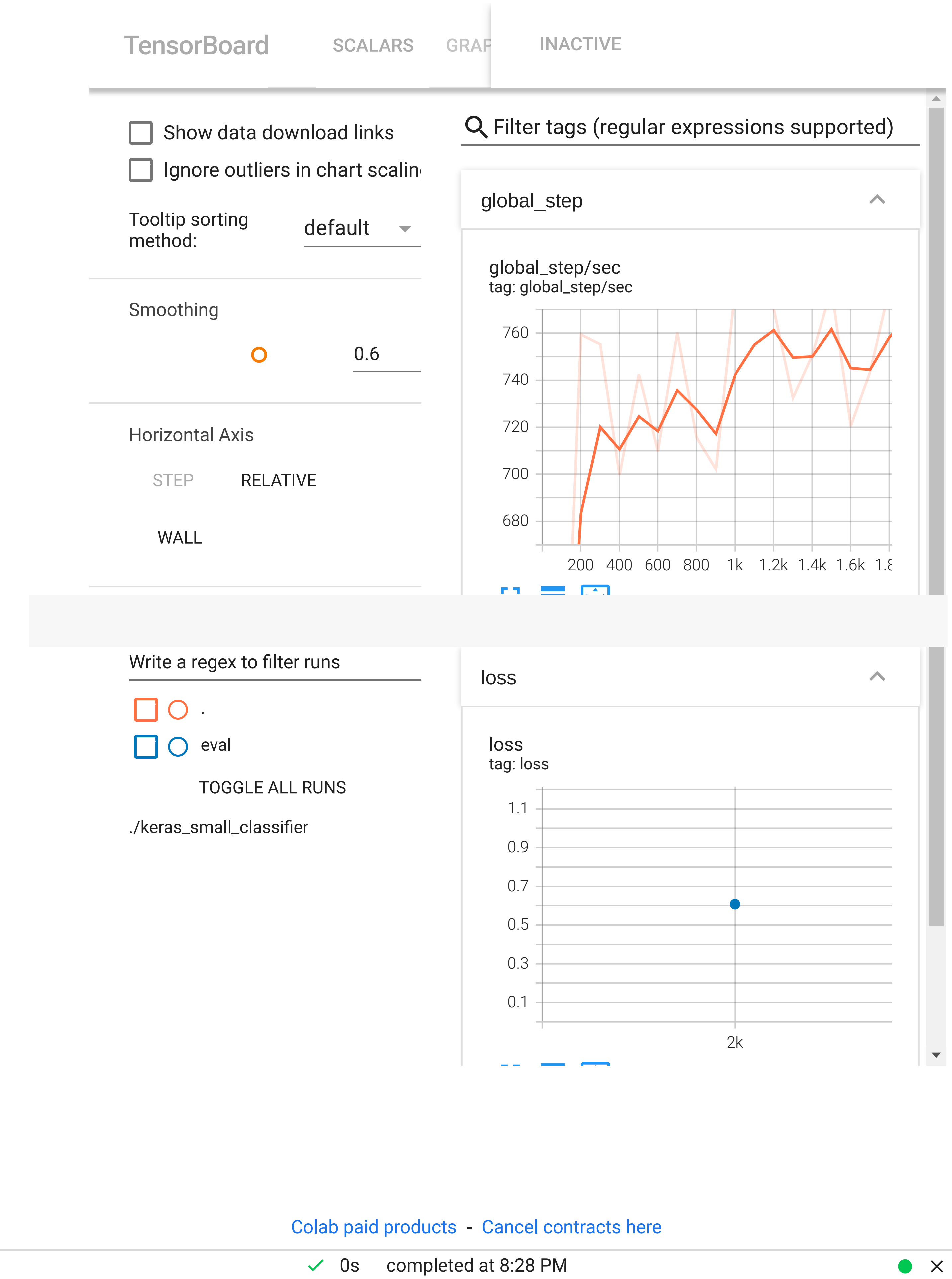
Evaluate

```
eval_small_result = keras_small_estimator.evaluate(
    input_fn = lambda:input_fn(xtest, ytest, training = False), steps=1000)
print('Eval result: {}'.format(eval_small_result))
```

```
/usr/local/lib/python3.7/dist-packages/keras/engine/training_v1.py:2057: User
  updates = self.state_updates
Eval result: {'loss': 0.6073161, 'global_step': 2000}
```

Analyze history and metrics

```
%load_ext tensorboard
%tensorboard --logdir ./keras_small_classifier
```


TensorBoard
SCALARS
GRAP
INACTIVE
Show data download links
Ignore outliers in chart scalin
Tooltip sorting method:
default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Write a regex to filter runs
.
eval
TOGGLE ALL RUNS
./keras_small_classifier
Filter tags (regular expressions supported)
global_step
global_step/sec
tag: global_step/sec
760
740
720
700
680
200
400
600
800
1k
1.2k
1.4k
1.6k
loss
loss
tag: loss
1.1
0.9
0.7
0.5
0.3
0.1
2k
Colab paid products - Cancel contracts here
0s completed at 8:28 PM

DEMO B - Create DNN Model by TF Estimators

based on (C) Velayudham, Sakranha, TF Authors works

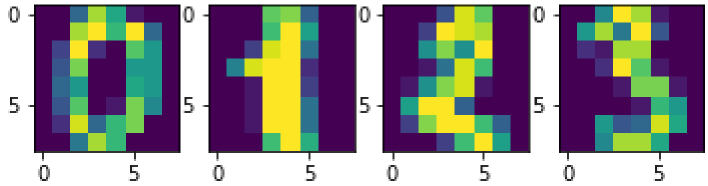
```
import tensorflow as tf
```

Loading Data

```
from sklearn import datasets
digits = datasets.load_digits()
```

```
#plotting sample image
import matplotlib.pyplot as plt
plt.figure(figsize=(1,1))
fig, ax = plt.subplots(1,4)
ax[0].imshow(digits.images[0])
ax[1].imshow(digits.images[1])
ax[2].imshow(digits.images[2])
ax[3].imshow(digits.images[3])
plt.show()
```

```
<Figure size 72x72 with 0 Axes>
```



Preprocessing Data

```
# reshape the data to two dimensions
n_samples = len(digits.images)
data = digits.images.reshape((n_samples, -1))
data.shape
```

```
(1797, 64)
```

```
# split into training/testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    data, digits.target, test_size=0.05, shuffle=False)
```

Defining Input Function

```
# create column names for our model input function
columns = ['p_'+ str(i) for i in range(1,65)]
```

```
feature_columns = []
for col in columns:
  feature_columns.append(tf.feature_column.numeric_column(key = col))
```

```
def input_fn(features, labels, training = True, batch_size = 32):
  #converts inputs to a dataset
  dataset = tf.data.Dataset.from_tensor_slices((dict(features),labels))
  #shuffle and repeat in a training mode
  if training:
    dataset=dataset.shuffle(1000).repeat()

  #giving inputs in batches for training
  return dataset.batch(batch_size)
```

Create DNNClassifier Estimator instance

```
classifier = tf.estimator.DNNClassifier(hidden_units = [256, 128, 64],
                                        feature_columns = feature_columns,
                                        optimizer = 'Adagrad',
                                        n_classes = 10,
                                        model_dir = 'classifier')
```

Adding extra hidden layer

without Dropout

```
classifier = tf.estimator.DNNClassifier(hidden_units = [256, 128, 64, 32],
                                        feature_columns = feature_columns,
                                        optimizer = 'Adagrad',
                                        n_classes = 10,
                                        model_dir = 'classifier')
```

with Dropout

```
'''
classifier = tf.estimator.DNNClassifier(hidden_units = [256, 128, 64, 32],
                                        feature_columns = feature_columns,
                                        optimizer = 'Adagrad',
                                        n_classes = 10,
                                        dropout = 0.2,
                                        model_dir = 'classifier')
'''
```

```
'\nclassifier = tf.estimator.DNNClassifier(hidden_units = [256, 12
8, 64, 32],\n                                        feature_column
s = feature_columns,\n                                              optim
```

Model Training

```
# create dataframes for training
import pandas as pd
dftrain = pd.DataFrame(X_train, columns = columns)


classifier.train(input_fn = lambda:input_fn(dftrain,
                                            y_train,
                                            training = True),
                                            steps = 2000)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/pyt
Instructions for updating:
Use Variable.read_value. Variables in 2.X are initialized automatically both
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/keras/optimize
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to th
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has n
WARNING:tensorflow:It seems that global step (tf.train.get_global_step) has n
<tensorflow_estimator.python.estimator.canned.dnn.DNNClassifierV2 at
0x7f988f1726d0>
```

Model Evaluation

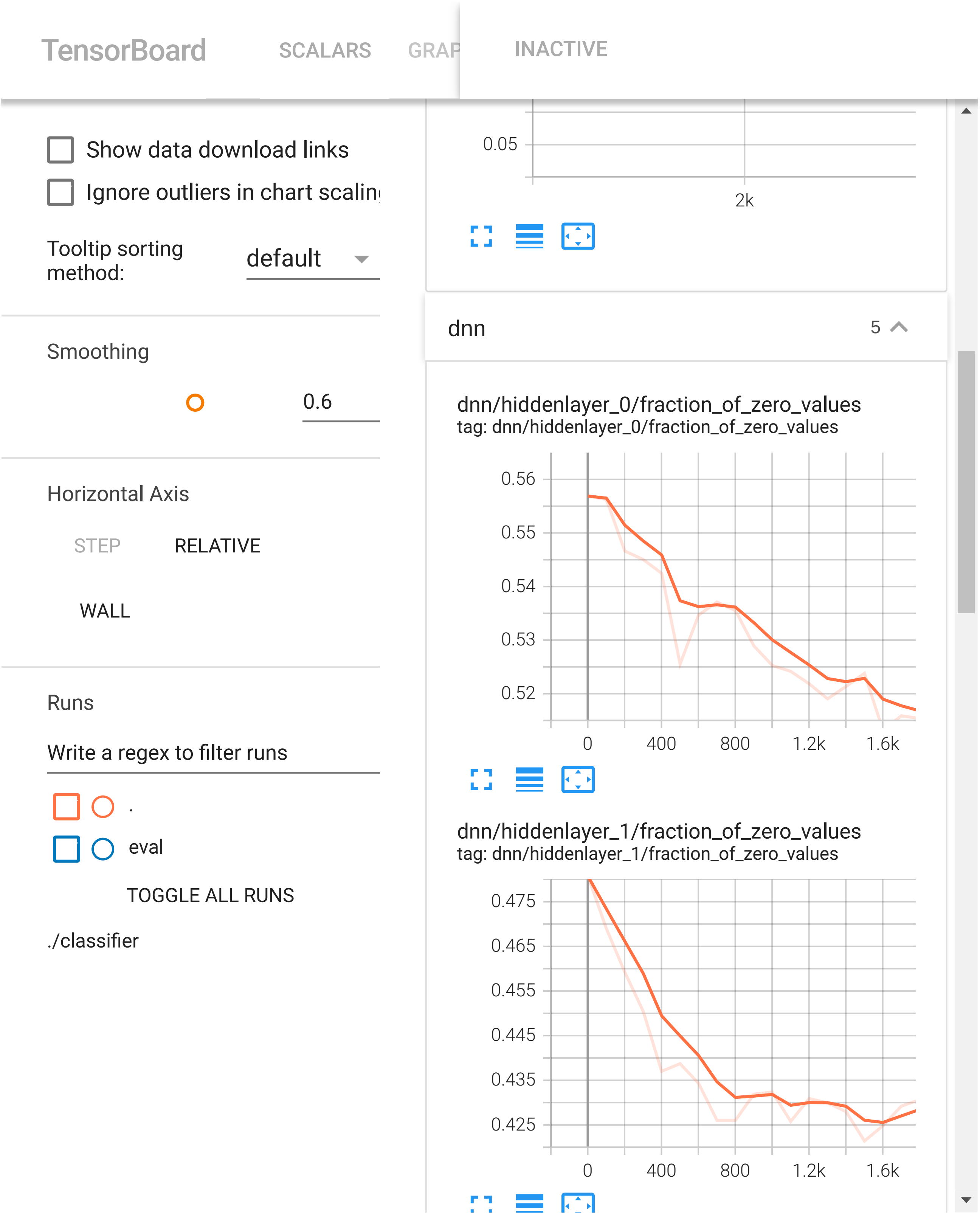
```
# create dataframe for evaluation
dftest = pd.DataFrame(X_test, columns = columns)

eval_result = classifier.evaluate(
    input_fn = lambda:input_fn(dftest, y_test, training = False)
)

eval_result
```

```
{'accuracy': 0.95555556,
 'average_loss': 0.2061766,
```

```
'loss': 0.19756849,
'global_step': 2000}
```

Resume at Tensorboard

```
%load_ext tensorboard
%tensorboard --logdir ./classifier
```



Predicting unseen data

```
# An input function for prediction
def pred_input_fn(features, batch_size = 32):
    # Convert the inputs to a Dataset without labels.
    return tf.data.Dataset.from_tensor_slices(dict(features)).batch(batch_size)

test = dftest.iloc[:2,:] #1st two data points for predictions

expected = y_test[:2].tolist() #expected labels

pred = list(classifier.predict(
    input_fn =  lambda:pred_input_fn(test))
)

for pred_dict, expec in zip(pred, expected):
    class_id = pred_dict['class_ids'][0]
    probability = pred_dict['probabilities'][class_id]
    print('predicted class {} , probability of prediction {} , expected label {}'.
```

```
predicted class 8 , probability of prediction 0.9750990867614746 , expected l
predicted class 4 , probability of prediction 0.95527184009552 , expected lab
```

DEMO C - TF Datasets Benchmark by TF Estimators

based on (C) Velayudham, Sakranha, TF Authors works

```
# To avoid the compatibility issue with Tensorflow, cuda and models repo code.
# Try installing the below TensorFlow version and cuda version at the start of col
!pip install tensorflow==2.8
!apt install --allow-change-held-packages libcudnn8=8.1.0.77-1+cuda11.2
```

```
Requirement already satisfied: flatbuffers>=1.12 in /usr/local/lib/python3.
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.7/dist
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.7/di
Requirement already satisfied: absl-py>=0.4.0 in /usr/local/lib/python3.7/d
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python
Requirement already satisfied: libclang>=9.0.1 in /usr/local/lib/python3.7/
Requirement already satisfied: keras-preprocessing>=1.1.1 in /usr/local/lib
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr
Requirement already satisfied: protobuf>=3.9.2 in /usr/local/lib/python3.7/
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.7
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/pyth
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in /us
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/loc
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/pyt
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/di
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/pyth
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/p
Requirement already satisfied: importlib-metadata>=4.4 in /usr/local/lib/py
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-p

Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/pytho
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.7/dis
Requirement already satisfied: charset-normalizer<3,>=2 in /usr/local/lib/p
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/pyth
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/
Installing collected packages: tf-estimator-nightly, tensorboard, keras, te
  Attempting uninstall: tensorboard
    Found existing installation: tensorboard 2.10.1
    Uninstalling tensorboard-2.10.1:
      Successfully uninstalled tensorboard-2.10.1
  Attempting uninstall: keras
    Found existing installation: keras 2.10.0
    Uninstalling keras-2.10.0:
      Successfully uninstalled keras-2.10.0
  Attempting uninstall: tensorflow
    Found existing installation: tensorflow 2.10.0
    Uninstalling tensorflow-2.10.0:
      Successfully uninstalled tensorflow-2.10.0
```

```
ERROR: pip's dependency resolver does not currently take into account all t
tfx-bsl 1.10.1 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.*,!=2.3.*,!=2.4.*,!
tensorflow-serving-api 2.10.0 requires tensorflow<3,>=2.10.0, but you have
tensorflow-data-validation 1.10.0 requires tensorflow!=2.0.*,!=2.1.*,!=2.2.
Successfully installed keras-2.8.0 tensorboard-2.8.0 tensorflow-2.8.0+zzzco
Reading package lists... Done
Building dependency tree
Reading state information... Done
libcudnn8 is already the newest version (8.1.0.77-1+cuda11.2).
The following package was automatically installed and is no longer required
  libnvidia-common-460
```

```
import tensorflow as tf
import tensorflow_datasets as tfds
```

TensorFlow Datasets

```
#To get the list of available
tfds.list_builders()
```

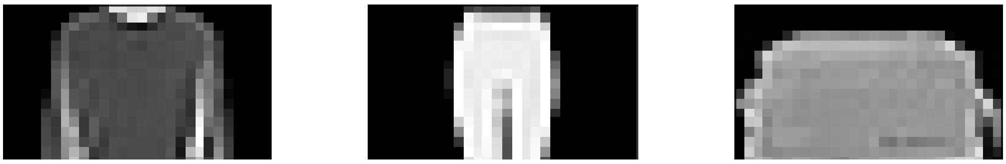
```
 'huggingface:psc',
 'huggingface:ptb_text_only',
 'huggingface:pubmed',
 'huggingface:pubmed_qa',
 'huggingface:py_ast',
 'huggingface:qa4mre',
 'huggingface:qa_srl',
 'huggingface:qa_zre',
 'huggingface:qangaroo',
 'huggingface:qanta',
 'huggingface:qasc',
 'huggingface:qasper',
 'huggingface:qed',
 'huggingface:qed_amara',
 'huggingface:quac',
 'huggingface:quail',
 'huggingface:quarel',
 'huggingface:quartz',
 'huggingface:quickdraw',
 'huggingface:quora',
 'huggingface:quoref',
 'huggingface:race',
 'huggingface:re_dial',
 'huggingface:reasoning_bg',
 'huggingface:recipe_nlg',
 'huggingface:reclor',
 'huggingface:red_caps',
 'huggingface:reddit',
 'huggingface:reddit_tifu',
 'huggingface:refresd',
 'huggingface:reuters21578',
 'huggingface:riddle_sense',
 'huggingface:ro_sent',
 'huggingface:ro_sts',
 'huggingface:ro_sts_parallel',
 'huggingface:roman_urdu',
```

```
 'huggingface:roman_urdu',
 'huggingface:roman_urdu_hate_speech',
 'huggingface:ronec',
 'huggingface:ropes',
 'huggingface:rotten_tomatoes',
 'huggingface:russian_super_glue',
 'huggingface:rvl_cdip',
 'huggingface:s2orc',
 'huggingface:samsum',
 'huggingface:sanskrit_classic',
 'huggingface:saudinewsnet',
 'huggingface:sberquad',
 'huggingface:sbu_captions',
 'huggingface:scan',
 'huggingface:scb_mt_enth_2020',
 'huggingface:scene_parse_150',
 'huggingface:schema_guided_dstc8',
 'huggingface:scicite',
 'huggingface:scielo',
 'huggingface:scientific_papers',
 'huggingface:scifact',
 'huggingface:sciq',
 'huggingface:scitail',
 'huggingface:scitldr',
```

```
len(tfds.list_builders())
```

```
1122
```

```
#ds, ds_info = tfds.load('cifar10', split='train', with_info=True)
ds, ds_info = tfds.load('fashion_mnist', split='train', with_info=True)
fig = tfds.show_examples(ds, ds_info)
```



Benchmark your datasets

Note: This API is new and only available via

! pip install tfds-nightly

```
#! pip install tfds-nightly
```

```
! nvidia-smi
```

```
Mon Oct  3 18:41:21 2022
+-----------------------------------------------------------------------------
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2
|-------------------------------+----------------------+----------------------
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M.
|                               |                      |               MIG M.
|===============================+======================+=====================
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0
| N/A   61C    P0    30W /  70W |    286MiB / 15109MiB |      0%      Default
|                               |                      |                  N/A
+-------------------------------+----------------------+---------------------

+-----------------------------------------------------------------------------
| Processes:
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory
|        ID   ID                                                   Usage
|=============================================================================
+-----------------------------------------------------------------------------
```

```
# Benchmark your datasets - GPU
ds = ds.batch(32).prefetch(1)

tfds.benchmark(ds, batch_size=32)
tfds.benchmark(ds, batch_size=32)  # Second epoch much faster due to auto-caching
```

```
************ Summary ************
```

100% 1875/1875 [00:04<00:00, 257.26it/s]

```
Examples/sec (First included) 12025.68 ex/sec (total: 60032 ex, 4.9
Examples/sec (First only) 364.56 ex/sec (total: 32 ex, 0.09 sec)
Examples/sec (First excluded) 12234.40 ex/sec (total: 60000 ex, 4.9

************ Summary ************
```

100% 1875/1875 [00:00<00:00, 2256.08it/s]

```
# Benchmark your datasets - TPU
ds = ds.batch(32).prefetch(1)

tfds.benchmark(ds, batch_size=32)
tfds.benchmark(ds, batch_size=32)  # Second epoch much faster due to auto-caching
```

```
************ Summary ************
```

100% 59/59 [00:00<00:00, 125.63it/s]

```
Examples/sec (First included) 3414.61 ex/sec (total: 1920 ex, 0.56
Examples/sec (First only) 249.06 ex/sec (total: 32 ex, 0.13 sec)
Examples/sec (First excluded) 4352.14 ex/sec (total: 1888 ex, 0.43

************ Summary ************
```

100% 59/59 [00:00<00:00, 174.71it/s]

```
Examples/sec (First included) 4876.42 ex/sec (total: 1920 ex, 0.39
Examples/sec (First only) 269.12 ex/sec (total: 32 ex, 0.12 sec)
Examples/sec (First excluded) 6869.81 ex/sec (total: 1888 ex, 0.27
```

BenchmarkResult:

	duration	num_examples	avg
first+lasts	0.393731	1920	4876.422340
first	0.118906	32	269.121261

```
#! pip install tensorflow_data_validation
```

```
# Display the datasets statistics on a Colab/Jupyter notebook
tfds.show_statistics(ds_info)
```

Sort by

Feature order | Reverse order | Feature search (regex enab…

Features: fixed-length ints(2)

Numeric Features (2)	count	missing	mean	std dev	zeros	min	med
image	60.0k	0%	0	0	0%	0	
label							

Import VGG16 module

```
keras_Vgg16 = tf.keras.applications.VGG16(
    input_shape=(160, 160, 3), include_top=False)
keras_Vgg16.trainable = False
```

Create Keras model by adding layers to VGG16 model

```
estimator_model = tf.keras.Sequential([
    keras_Vgg16,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(256),
    tf.keras.layers.Dense(1)
])
```

```
keras_Vgg16.summary()
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 160, 160, 3)]     0

 block1_conv1 (Conv2D)       (None, 160, 160, 64)      1792

 block1_conv2 (Conv2D)       (None, 160, 160, 64)      36928

 block1_pool (MaxPooling2D)  (None, 80, 80, 64)        0

 block2_conv1 (Conv2D)       (None, 80, 80, 128)       73856

 block2_conv2 (Conv2D)       (None, 80, 80, 128)       147584
```

```
 block2_pool (MaxPooling2D)  (None, 40, 40, 128)       0

 block3_conv1 (Conv2D)       (None, 40, 40, 256)       295168

 block3_conv2 (Conv2D)       (None, 40, 40, 256)       590080

 block3_conv3 (Conv2D)       (None, 40, 40, 256)       590080

 block3_pool (MaxPooling2D)  (None, 20, 20, 256)       0

 block4_conv1 (Conv2D)       (None, 20, 20, 512)       1180160

 block4_conv2 (Conv2D)       (None, 20, 20, 512)       2359808

 block4_conv3 (Conv2D)       (None, 20, 20, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 10, 10, 512)       0

 block5_conv1 (Conv2D)       (None, 10, 10, 512)       2359808

 block5_conv2 (Conv2D)       (None, 10, 10, 512)       2359808

 block5_conv3 (Conv2D)       (None, 10, 10, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 5, 5, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

```
estimator_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 5, 5, 512)         14714688

 global_average_pooling2d (G  (None, 512)              0
 lobalAveragePooling2D)

 dense (Dense)               (None, 256)               131328

 dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 14,846,273
Trainable params: 131,585
Non-trainable params: 14,714,688
_________________________________________________________________
```

Compile

```
# Compile the model
estimator_model.compile(
    optimizer = 'adam',
    loss=tf.keras.losses.BinaryCrossentropy(from_logits = True),
    metrics = ['accuracy'])
```

Create Estimator

```
est_vgg16 = tf.keras.estimator.model_to_estimator(keras_model = estimator_model,
                                                  model_dir = 'classifier')
```

Data preprocessing

```
IMG_SIZE = 160
import tensorflow_datasets as tfds
def preprocess(image, label):
  image = tf.cast(image, tf.float32)
  #image = (image/127.5) - 1
  image = tf.image.resize(image, (IMG_SIZE, IMG_SIZE))
  return image, label
```

Input function

```
def train_input_fn(batch_size):
  data = tfds.load('cats_vs_dogs', as_supervised=True)
  train_data = data['train']
  train_data = train_data.map(preprocess).shuffle(500).batch(batch_size)
  return train_data
```

Training

```
#%%time
est_vgg16.train(input_fn = lambda: train_input_fn(32), steps = 500)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/pyt
Instructions for updating:
Use Variable.read_value. Variables in 2.X are initialized automatically both
/usr/local/lib/python3.7/dist-packages/keras/backend.py:450: UserWarning: `tf
  warnings.warn('`tf.keras.backend.set_learning_phase` is deprecated and '
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/pyt
Instructions for updating:
Use standard file utilities to get mtimes.
<tensorflow_estimator.python.estimator.estimator.EstimatorV2 at
0x7fba65713650>
```

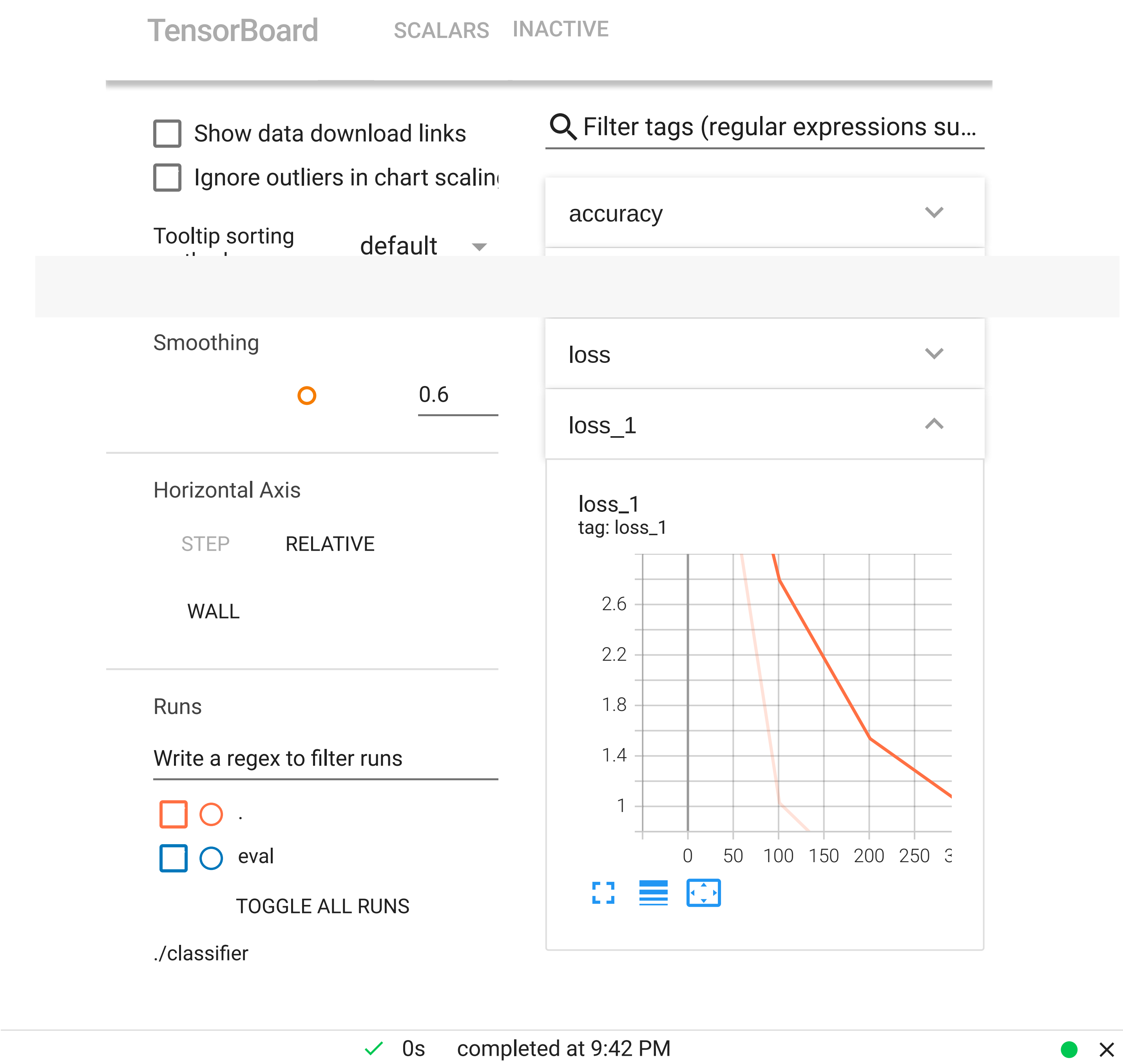
Evaluation

```
est_vgg16.evaluate(input_fn = lambda: train_input_fn(32), steps=10)
```

```
/usr/local/lib/python3.7/dist-packages/keras/engine/training_v1.py:2057: User
  updates = self.state_updates
{'accuracy': 0.934375, 'loss': 0.3812843, 'global_step': 500}
```

Monitoring

```
%load_ext tensorboard
%tensorboard --logdir ./classifier
```


TensorBoard
SCALARS
INACTIVE
Show data download links
Ignore outliers in chart scalin
Tooltip sorting
default
Filter tags (regular expressions su...
accuracy
Smoothing
0.6
loss
loss_1
Horizontal Axis
STEP
RELATIVE
WALL
loss_1
tag: loss_1
2.6
2.2
1.8
1.4
1
0
50
100
150
200
250
Runs
Write a regex to filter runs
.
eval
TOGGLE ALL RUNS
./classifier
0s
completed at 9:42 PM

DEMO D - Transfer Learning - Rock Paper Scissors (using NASNetMobile)

based on (C) Ng, Moroney, Mingxing Tan, Quoc V. Le, Rawlani, and **Oleksii Trekhleb** ("Our Man in Uber" :))

Experiment overview

In this experiment we will build a [Convolutional Neural Network](https://en.wikipedia.org/wiki/Convolutional_neural_network) (CNN) model using [Tensorflow](https://www.tensorflow.org/) to recognize Rock-Paper-Scissors signs (gestures) on the photo.

Instead of training the model from scratch we will use **transfer learning** method (look at DEMOs in previous lectures) a family of [TF2-Keras-Applications](https://www.tensorflow.org/api_docs/python/tf/keras/applications) models. Here we will actually use NASNetMobile and other models which are pre-trained on the [ImageNet](http://image-net.org/) dataset, a large dataset of 1.4M images and 1000 classes of web images.

Importing dependencies

```
import tensorflow as tf
import tensorflow_datasets as tfds
import matplotlib.pyplot as plt
import numpy as np
import platform
import datetime
import os
import math
import random

print('Python version:', platform.python_version())
print('Tensorflow version:', tf.__version__)
print('Keras version:', tf.keras.__version__)
```

```
Python version: 3.7.14
Tensorflow version: 2.8.2
Keras version: 2.8.0
```

Configuring TensorBoard

We will use TensorBoard as a helper to debug the model training process.

```
# Load the TensorBoard notebook extension.
```

```
# %reload_ext tensorboard
%load_ext tensorboard

# Clear any logs from previous runs.
!rm -rf ./logs/
```

Dataset - Example

We will download Rock-Paper-Scissors dataset from TensorFlow Datasets collection. To do that we loaded a `tensorflow_datasets` module.

`tensorflow_datasets` defines a collection of datasets ready-to-use with TensorFlow.

Each dataset is defined as a tfds.core.DatasetBuilder, which encapsulates the logic to download the dataset and construct an input pipeline, as well as contains the dataset documentation (version, splits, number of examples, etc.).

```
# See available datasets
tfds.list_builders()
```

```
 'huggingface:quac',
 'huggingface:quail',
 'huggingface:quarel',
 'huggingface:quartz',
 'huggingface:quickdraw',
 'huggingface:quora',
 'huggingface:quoref',
 'huggingface:race',
 'huggingface:re_dial',
 'huggingface:reasoning_bg',
 'huggingface:recipe_nlg',
 'huggingface:reclor',
 'huggingface:red_caps',
 'huggingface:reddit',
 'huggingface:reddit_tifu',
 'huggingface:refresd',
 'huggingface:reuters21578',
 'huggingface:riddle_sense',
 'huggingface:ro_sent',
 'huggingface:ro_sts',
 'huggingface:ro_sts_parallel',
 'huggingface:roman_urdu',
 'huggingface:roman_urdu_hate_speech',
 'huggingface:ronec',
 'huggingface:ropes',
 'huggingface:rotten_tomatoes',
 'huggingface:russian_super_glue',
 'huggingface:rvl_cdip',
 'huggingface:s2orc',
 'huggingface:samsum',
 'huggingface:sanskrit_classic',
 'huggingface:saudinewsnet',
 'huggingface:sberquad',
 'huggingface:sbu_captions',
 'huggingface:scan',
 'huggingface:scb_mt_enth_2020',
```

```
 'huggingface:scene_parse_150',
 'huggingface:schema_guided_dstc8',
 'huggingface:scicite',
 'huggingface:scielo',
 'huggingface:scientific_papers',
 'huggingface:scifact',
 'huggingface:sciq',
 'huggingface:scitail',
 'huggingface:scitldr',
 'huggingface:search_qa',
 'huggingface:sede',
 'huggingface:selqa',
 'huggingface:sem_eval_2010_task_8',
 'huggingface:sem_eval_2014_task_1',
 'huggingface:sem_eval_2018_task_1',
 'huggingface:sem_eval_2020_task_11',
 'huggingface:sent_comp',
 'huggingface:senti_lex',
 'huggingface:senti_ws',
 'huggingface:sentiment140',
 'huggingface:sepedi_ner',
 'huggingface:sesotho_ner_corpus',
```

We will use the classic dataset by Moroney:

- Title: rock_paper_scissors
- Description: Images of hands playing rock, paper, scissor game.
- Homepage: http://laurencemoroney.com/rock-paper-scissors-dataset
- Source code: `tfds.image_classification.RockPaperScissors`
- Versions: 3.0.0 (default): New split API (https://tensorflow.org/datasets/splits)
- Download size: 219.53 MiB
- Image Examples:

Rock 

Paper 

Scissors 

Loading the dataset

```
DATASET_NAME = 'rock_paper_scissors'

(dataset_train_raw, dataset_test_raw), dataset_info = tfds.load(
    name=DATASET_NAME,
    data_dir='tmp',
    with_info=True,
    as_supervised=True,
    split=[tfds.Split.TRAIN, tfds.Split.TEST],
)
```

Downloading and preparing dataset 219.53 MiB (download: 219.53 MiB, generatec

Dl Completed...: 100% 2/2 [00:05<00:00, 2.84s/ url]

Dl Size...: 100% 219/219 [00:05<00:00, 46.67 MiB/s]

Dataset rock paper scissors downloaded and prepared to tmp/rock paper scissor

```
print('Raw train dataset:', dataset_train_raw)
print('Raw train dataset size:', len(list(dataset_train_raw)), '\n')

print('Raw test dataset:', dataset_test_raw)
print('Raw test dataset size:', len(list(dataset_test_raw)), '\n')
```

```
Raw train dataset: <PrefetchDataset element_spec=(TensorSpec(shape=(300, 300,
Raw train dataset size: 2520

Raw test dataset: <PrefetchDataset element_spec=(TensorSpec(shape=(300, 300,
Raw test dataset size: 372
```

```
dataset_info
```

```
tfds.core.DatasetInfo(
    name='rock_paper_scissors',
    full_name='rock_paper_scissors/3.0.0',
    description="""
    Images of hands playing rock, paper, scissor game.
    """,
    homepage='http://laurencemoroney.com/rock-paper-scissors-dataset',
    data_path='tmp/rock_paper_scissors/3.0.0',
    file_format=tfrecord,
    download_size=219.53 MiB,
    dataset_size=219.23 MiB,
    features=FeaturesDict({
        'image': Image(shape=(300, 300, 3), dtype=tf.uint8),
        'label': ClassLabel(shape=(), dtype=tf.int64, num_classes=3),
    }),
    supervised_keys=('image', 'label'),
    disable_shuffling=False,
    splits={
        'test': <SplitInfo num_examples=372, num_shards=1>,
        'train': <SplitInfo num_examples=2520, num_shards=2>,
    },
    citation="""@ONLINE {rps,
    author = "Laurence Moroney",
    title = "Rock, Paper, Scissors Dataset",
    month = "feb",
    year = "2019",
    url = "http://laurencemoroney.com/rock-paper-scissors-dataset"
    }""",
)
```

```
NUM_TRAIN_EXAMPLES = dataset_info.splits['train'].num_examples
NUM_TEST_EXAMPLES = dataset_info.splits['test'].num_examples
NUM_CLASSES = dataset_info.features['label'].num_classes

print('Number of TRAIN examples:', NUM_TRAIN_EXAMPLES)
print('Number of TEST examples:', NUM_TEST_EXAMPLES)
print('Number of label classes:', NUM_CLASSES)
```

```
Number of TRAIN examples: 2520
Number of TEST examples: 372
```

```
Number of label classes: 3
```

```
INPUT_IMG_SIZE_ORIGINAL = dataset_info.features['image'].shape[0]
INPUT_IMG_SHAPE_ORIGINAL = dataset_info.features['image'].shape

# For some models only some sizes are possible, for example:
# for NASNetMobile - 224, ...
INPUT_IMG_SIZE_REDUCED = 224
INPUT_IMG_SHAPE_REDUCED = (
    INPUT_IMG_SIZE_REDUCED,
    INPUT_IMG_SIZE_REDUCED,
    INPUT_IMG_SHAPE_ORIGINAL[2]
)

# Here we may switch between bigger or smaller image sized that we will train our
INPUT_IMG_SIZE = INPUT_IMG_SIZE_REDUCED
INPUT_IMG_SHAPE = INPUT_IMG_SHAPE_REDUCED

print('Input image size (original):', INPUT_IMG_SIZE_ORIGINAL)
print('Input image shape (original):', INPUT_IMG_SHAPE_ORIGINAL)
print('\n')
print('Input image size (reduced):', INPUT_IMG_SIZE_REDUCED)
print('Input image shape (reduced):', INPUT_IMG_SHAPE_REDUCED)
print('\n')
print('Input image size:', INPUT_IMG_SIZE)
print('Input image shape:', INPUT_IMG_SHAPE)
```

```
Input image size (original): 300
Input image shape (original): (300, 300, 3)


Input image size (reduced): 224
Input image shape (reduced): (224, 224, 3)


Input image size: 224
Input image shape: (224, 224, 3)
```

```
# Function to convert label ID to labels string.
get_label_name = dataset_info.features['label'].int2str
```

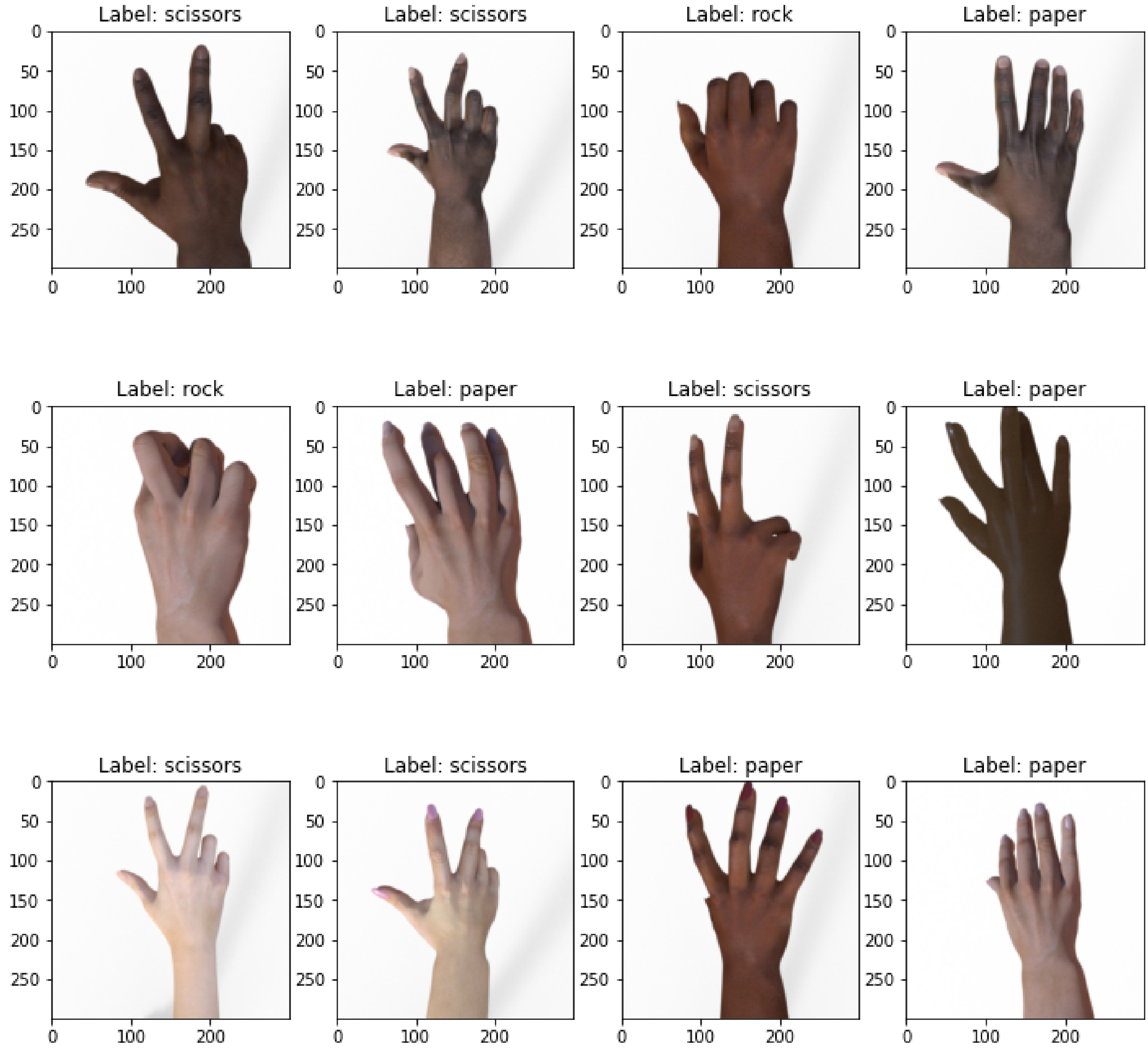
```
print(get_label_name(0));
print(get_label_name(1));
print(get_label_name(2));
```

```
rock
paper
scissors
```

Exploring the dataset

```
def preview_dataset(dataset):
    plt.figure(figsize=(12, 12))
    plot_index = 0
    for features in dataset.take(12):
        (image, label) = features
        plot_index += 1
        plt.subplot(3, 4, plot_index)
        # plt.axis('Off')
        label = get_label_name(label.numpy())
        plt.title('Label: %s' % label)
        plt.imshow(image.numpy())
```

```
# Explore raw training dataset images.
preview_dataset(dataset_train_raw)
```




```
# Explore what values are used to represent the image.
(first_image, first_lable) = list(dataset_train_raw.take(1))[0]
print('Label:', first_lable.numpy(), '\n')
```

```
print('Image shape:', first_image.numpy().shape, '\n')
print(first_image.numpy())
```

```
Label: 2

Image shape: (300, 300, 3)

[[[254 254 254]
  [253 253 253]
  [254 254 254]
  ...
  [251 251 251]
  [250 250 250]
  [250 250 250]]

 [[254 254 254]
  [254 254 254]
  [253 253 253]
  ...
  [250 250 250]
  [251 251 251]
  [249 249 249]]

 [[254 254 254]
  [254 254 254]
  [254 254 254]
  ...
  [251 251 251]
  [250 250 250]
  [252 252 252]]

 ...

 [[252 252 252]
  [251 251 251]
  [252 252 252]
  ...
  [247 247 247]
  [249 249 249]
  [248 248 248]]

 [[253 253 253]
  [253 253 253]
  [251 251 251]
  ...
  [248 248 248]
  [248 248 248]
  [248 248 248]]

 [[252 252 252]
  [253 253 253]
  [252 252 252]
  ...
  [248 248 248]
  [247 247 247]
  [250 250 250]]]
```

Pre-processing the dataset

```
def format_example(image, label):
    # Make image color values to be float.
    image = tf.cast(image, tf.float32)
    # Make image color values to be in [0..1] range.
    image = image / 255.
    # Make sure that image has a right size
    image = tf.image.resize(image, [INPUT_IMG_SIZE, INPUT_IMG_SIZE])
    return image, label
```

```
dataset_train = dataset_train_raw.map(format_example)
dataset_test = dataset_test_raw.map(format_example)
```

```
# Explore what values are used to represent the image.
(first_image, first_lable) = list(dataset_train.take(1))[0]
print('Label:', first_lable.numpy(), '\n')
print('Image shape:', first_image.numpy().shape, '\n')
print(first_image.numpy())
```

```
Label: 2

Image shape: (224, 224, 3)

[[[0.995526   0.995526   0.995526  ]
  [0.9941408  0.9941408  0.9941408 ]
  [0.99597746 0.99597746 0.99597746]
  ...
  [0.9869748  0.9869748  0.9869748 ]
  [0.98237604 0.98237604 0.98237604]
  [0.97995263 0.97995263 0.97995263]]

 [[0.99607843 0.99607843 0.99607843]
  [0.99509835 0.99509835 0.99509835]
  [0.99578613 0.99578613 0.99578613]
  ...
  [0.98232853 0.98232853 0.98232853]
  [0.98235357 0.98235357 0.98235357]
  [0.9824342  0.9824342  0.9824342 ]]

 [[0.99607843 0.99607843 0.99607843]
  [0.99438554 0.99438554 0.99438554]
  [0.9955736  0.9955736  0.9955736 ]
  ...
  [0.982799   0.982799   0.982799  ]
  [0.97900224 0.97900224 0.97900224]
  [0.98414266 0.98414266 0.98414266]]

 ...

 [[0.9886986  0.9886986  0.9886986 ]
  [0.98788357 0.98788357 0.98788357]
  [0.98773044 0.98773044 0.98773044]
  ...
```

```
  [0.97477514 0.97477514 0.97477514]
  [0.9725384  0.9725384  0.9725384 ]
  [0.96988803 0.96988803 0.96988803]]

 [[0.98982257 0.98982257 0.98982257]
  [0.9872209  0.9872209  0.9872209 ]
  [0.98630947 0.98630947 0.98630947]
  ...
  [0.9689198  0.9689198  0.9689198 ]
  [0.97251344 0.97251344 0.97251344]
  [0.9728876  0.9728876  0.9728876 ]]

 [[0.98945296 0.98945296 0.98945296]
  [0.9898225  0.9898225  0.9898225 ]
  [0.98757    0.98757    0.98757   ]
  ...
  [0.9692227  0.9692227  0.9692227 ]
  [0.9709499  0.9709499  0.9709499 ]
  [0.9774043  0.9774043  0.9774043 ]]]
```

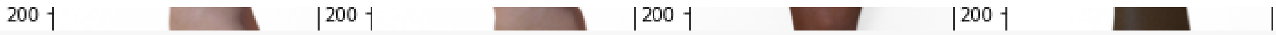
```
# Explore preprocessed training dataset images.
preview_dataset(dataset_train)
```

Data augmentation

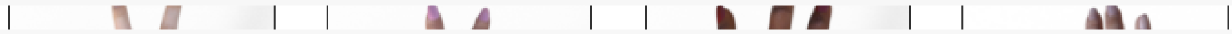
One of the way to fight the model overfitting and to generalize the model to a broader set of examples is to augment the training data.

As you saw from the previous section all training examples have a white background and vertically positioned right hands. But what if the image with the hand will be horizontally positioned or what if the background will not be that bright. What if instead of a right hand the model will see a left hand. To make our model a little bit more universal we're going to flip and rotate images and also to adjust background colors.

You may read more about a Simple and efficient data augmentations using the Tensorfow tf.Data and Dataset API.



```
def augment_flip(image: tf.Tensor) -> tf.Tensor:
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_flip_up_down(image)
    return image
```



```
def augment_color(image: tf.Tensor) -> tf.Tensor:
    image = tf.image.random_hue(image, max_delta=0.08)
    image = tf.image.random_saturation(image, lower=0.7, upper=1.3)
    image = tf.image.random_brightness(image, 0.05)
    image = tf.image.random_contrast(image, lower=0.8, upper=1)
    image = tf.clip_by_value(image, clip_value_min=0, clip_value_max=1)
    return image
```

```
def augment_rotation(image: tf.Tensor) -> tf.Tensor:
    # Rotate 0, 90, 180, 270 degrees
    return tf.image.rot90(
        image,
        tf.random.uniform(shape=[], minval=0, maxval=4, dtype=tf.int32)
    )
```

```
def augment_inversion(image: tf.Tensor) -> tf.Tensor:
    random = tf.random.uniform(shape=[], minval=0, maxval=1)
    if random > 0.5:
        image = tf.math.multiply(image, -1)
        image = tf.math.add(image, 1)
    return image
```

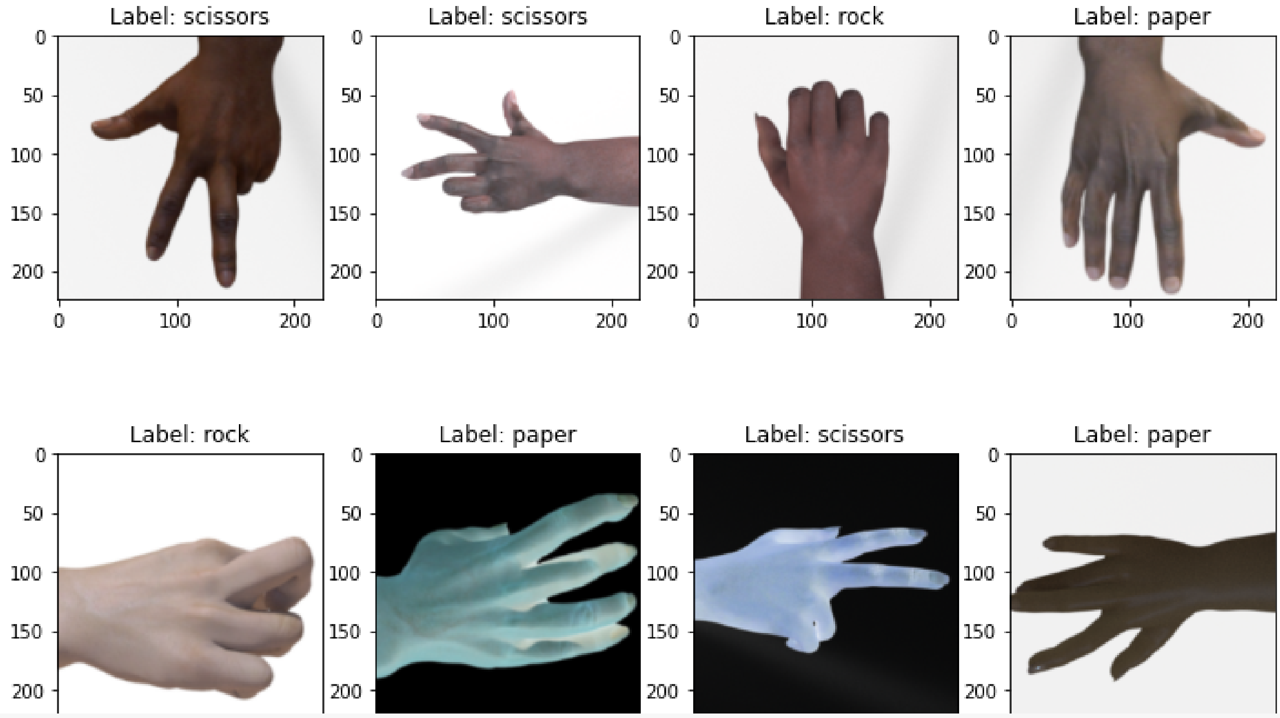
```
def augment_zoom(image: tf.Tensor, min_zoom=0.8, max_zoom=1.0) -> tf.Tensor:
    image_width, image_height, image_colors = image.shape
    crop_size = (image_width, image_height)

    # Generate crop settings, ranging from a 1% to 20% crop.
```

```
    scales = list(np.arange(min_zoom, max_zoom, 0.01))
    boxes = np.zeros((len(scales), 4))

    for i, scale in enumerate(scales):
        x1 = y1 = 0.5 - (0.5 * scale)
        x2 = y2 = 0.5 + (0.5 * scale)
        boxes[i] = [x1, y1, x2, y2]

    def random_crop(img):
        # Create different crops for an image
        crops = tf.image.crop_and_resize(
            [img],
            boxes=boxes,
            box_indices=np.zeros(len(scales)),
            crop_size=crop_size
        )
        # Return a random crop
        return crops[tf.random.uniform(shape=[], minval=0, maxval=len(scales), dty

    choice = tf.random.uniform(shape=[], minval=0., maxval=1., dtype=tf.float32)

    # Only apply cropping 50% of the time
    return tf.cond(choice < 0.5, lambda: image, lambda: random_crop(image))
```

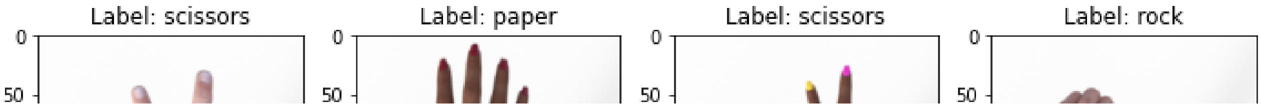
```
def augment_data(image, label):
    image = augment_flip(image)
    image = augment_color(image)
    image = augment_rotation(image)
    image = augment_zoom(image)
    image = augment_inversion(image)
    return image, label
```

```
dataset_train_augmented = dataset_train.map(augment_data)
```

```
# Explore augmented training dataset.
preview_dataset(dataset_train_augmented)
```



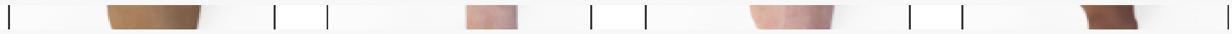

```
# Explore test dataset.
preview_dataset(dataset_test)
```



Data shuffling and batching

We don't want our model to learn anything from the order or grouping of the images in the dataset. To avoid that we will shuffle the training examples. Also we're going to split the training set by batches to speed up training process and make it less memory consuming.

```
BATCH_SIZE = 800

dataset_train_augmented_shuffled = dataset_train_augmented.shuffle(
    buffer_size=NUM_TRAIN_EXAMPLES
)

dataset_train_augmented_shuffled = dataset_train_augmented.batch(
    batch_size=BATCH_SIZE
)

# Prefetch will enable the input pipeline to asynchronously fetch batches while yo
dataset_train_augmented_shuffled = dataset_train_augmented_shuffled.prefetch(
    buffer_size=tf.data.experimental.AUTOTUNE
)

dataset_test_shuffled = dataset_test.batch(BATCH_SIZE)
```



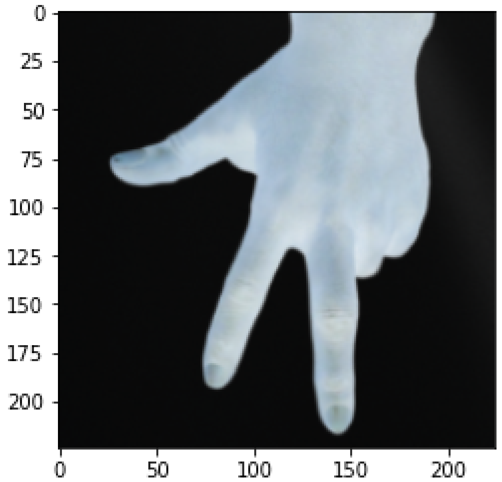
```
print(dataset_train_augmented_shuffled)
print(dataset_test_shuffled)
```

```
<PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=tf
<BatchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=tf.fl
```

```
# Debugging the batches using conversion to Numpy arrays.
batches = tfds.as_numpy(dataset_train_augmented_shuffled)
for batch in batches:
    image_batch, label_batch = batch
    print('Label batch shape:', label_batch.shape, '\n')
    print('Image batch shape:', image_batch.shape, '\n')
    print('Label batch:', label_batch, '\n')

    for batch_item_index in range(len(image_batch)):
        print('First batch image:', image_batch[batch_item_index], '\n')
        plt.imshow(image_batch[batch_item_index])
        plt.show()
        # Break to shorten the output.
        break
    # Break to shorten the output.
    break
```

```
Label batch shape: (800,)

Image batch shape: (800, 224, 224, 3)

Label batch: [2 2 0 1 0 1 2 1 2 2 1 1 2 1 1 1 1 1 1 1 0 0 0 0 1 1 2 2 2 0 0
 2 1 0 0 0 0 0 1 1 2 2 0 0 2 1 1 0 0 1 2 1 0 0 0 0 1 2 1 1 2 2 1 1 1 1 1 2
 0 0 2 1 0 1 0 0 1 1 1 1 2 1 1 0 0 2 2 1 0 0 1 1 2 1 1 0 0 0 2 0 0 1 1 2 0
 2 0 1 1 1 2 0 1 0 1 2 1 0 1 2 2 0 2 1 0 0 1 0 1 0 1 2 1 2 2 1 0 2 0 1 1 2
 0 2 2 1 0 1 2 2 1 1 0 2 0 0 1 1 0 1 2 2 0 0 2 1 1 0 1 2 0 1 1 1 2 0 2 1 2
 1 1 1 2 2 2 1 0 2 0 1 0 1 2 0 0 2 0 1 1 0 2 2 2 1 1 1 0 1 0 2 0 0 1 1 1 2
 1 2 1 2 2 0 2 1 0 1 0 0 2 1 1 0 2 2 2 0 1 1 1 2 0 1 0 2 1 1 2 1 2 2 0 1 2
 2 0 2 1 0 2 0 0 1 0 2 2 0 0 2 2 0 0 2 2 1 0 0 0 2 1 1 0 2 0 1 1 1 2 1 1 0
 1 1 2 2 2 1 2 0 0 0 2 0 2 0 0 0 0 2 2 0 1 0 0 1 1 0 1 1 0 2 1 0 2 0 1 1 0
 2 1 0 0 1 2 2 0 1 1 2 2 2 0 2 2 2 0 2 1 2 0 2 1 0 1 1 1 0 2 0 1 0 1 0 0 0
 0 1 2 1 0 2 2 0 2 2 2 1 2 1 2 0 1 0 0 0 1 1 1 1 1 2 1 1 1 0 1 0 2 0 0 1 0
 0 2 0 0 1 1 1 1 2 2 2 1 1 0 1 2 0 1 2 0 0 1 1 0 2 2 1 2 2 1 1 0 2 1 2 2 0
 1 0 0 1 2 0 2 1 1 2 1 1 2 0 2 1 1 1 1 1 2 0 0 0 0 1 1 0 0 2 2 2 1 0 2 1 2
 0 1 2 0 1 2 0 2 1 0 0 1 1 2 0 2 2 0 1 1 2 0 1 2 2 0 1 1 2 1 2 1 0 1 2 1 1
 1 0 1 1 1 2 0 0 1 0 1 2 2 0 0 0 0 2 0 0 0 2 2 2 0 2 2 2 1 2 1 1 1 0 0 1 2
 0 2 0 1 1 0 0 2 1 0 0 1 2 0 0 0 1 1 2 1 1 0 2 0 0 1 2 1 1 0 0 0 1 2 1 1 0
 2 0 1 1 0 2 0 2 0 2 2 1 0 1 1 1 2 1 0 0 2 0 0 2 0 1 0 2 2 2 1 1 0 2 1 0 0
 2 0 1 1 0 2 2 0 1 2 0 2 2 1 2 0 2 2 2 2 2 0 0 2 2 1 2 0 2 0 1 2 0 2 0 0 2
 0 2 2 0 1 1 0 0 2 0 1 1 1 1 0 2 1 0 1 1 2 2 1 0 0 1 1 0 2 2 1 1 2 2 2 1 2
 1 2 1 2 1 2 1 2 0 1 1 1 1 2 0 1 2 2 1 2 1 2 1 2 1 2 0 0 1 0 0 1 0 2 1 1 2
 0 1 1 2 1 0 1 2 0 0 0 2 0 0 2 2 2 0 0 0 1 1 0 1 1 1 1 1 1 0 1 2 1 1 2 2 1
 0 0 0 0 1 1 1 2 2 0 2 0 0 2 2 1 1 2 2 2 2 1 1]

First batch image: [[[0.03961003 0.04078156 0.04158181]
  [0.03945327 0.0406248  0.04142505]
  [0.03937632 0.04054785 0.0413481 ]
  ...
  [0.05511546 0.05628705 0.05708724]
  [0.05506533 0.05623692 0.05703712]
  [0.05474198 0.05591357 0.05671376]]

 [[0.03894454 0.04011607 0.04091632]
  [0.03992707 0.04109859 0.04189885]
  [0.04030651 0.04147804 0.04227829]
  ...
  [0.05373991 0.05491149 0.05571169]
  [0.05399573 0.05516732 0.05596751]
  [0.05498832 0.05615991 0.05696011]]

 [[0.03742933 0.03860086 0.03940111]
  [0.04090953 0.04208106 0.04288131]
  [0.04145235 0.04262388 0.04342413]
  ...
  [0.05520302 0.05637455 0.0571748 ]
  [0.05519873 0.05637026 0.05717051]
  [0.05594653 0.05711806 0.05791831]]

 ...

 [[0.03455669 0.03572822 0.03652847]
  [0.03422618 0.03539771 0.03619796]
  [0.03446275 0.03563428 0.03643453]
  ...
  [0.0422284  0.04339993 0.04420018]
  [0.04246092 0.04363251 0.0444327 ]
  [0.0427838  0.04395533 0.04475558]]
```

```
[[0.03543866 0.03661019 0.03741044]
 [0.03501242 0.03618395 0.03698421]
 [0.03423661 0.03540814 0.03620839]
 ...
 [0.04182118 0.04299271 0.04379296]
 [0.04188967 0.04306126 0.04386145]
 [0.04121393 0.04238546 0.04318571]]

[[0.0322209  0.03339243 0.03419268]
 [0.03201157 0.0331831  0.03398335]
 [0.03320897 0.0343805  0.03518075]
 ...
 [0.04205447 0.043226   0.04402626]
 [0.04196447 0.043136   0.04393625]
 [0.04137576 0.04254729 0.04334754]]]
```



Creating the model

Loading model

We don't want to use the top classification layer of the pre-trained model as it contains 1000 classes when we need only 3 (`rock`, `paper` and `scissors`). We will specify that by setting a `include_top` parameter to `False`.

You may read more about Keras models on [Keras Documentation]

```
base_model = tf.keras.applications.NASNetMobile(
  input_shape=INPUT_IMG_SHAPE,
  include_top=False,
  weights='imagenet',
  pooling='avg'
)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
19996672/19993432 [==============================] - 1s 0us/step
20004864/19993432 [==============================] - 1s 0us/step
```

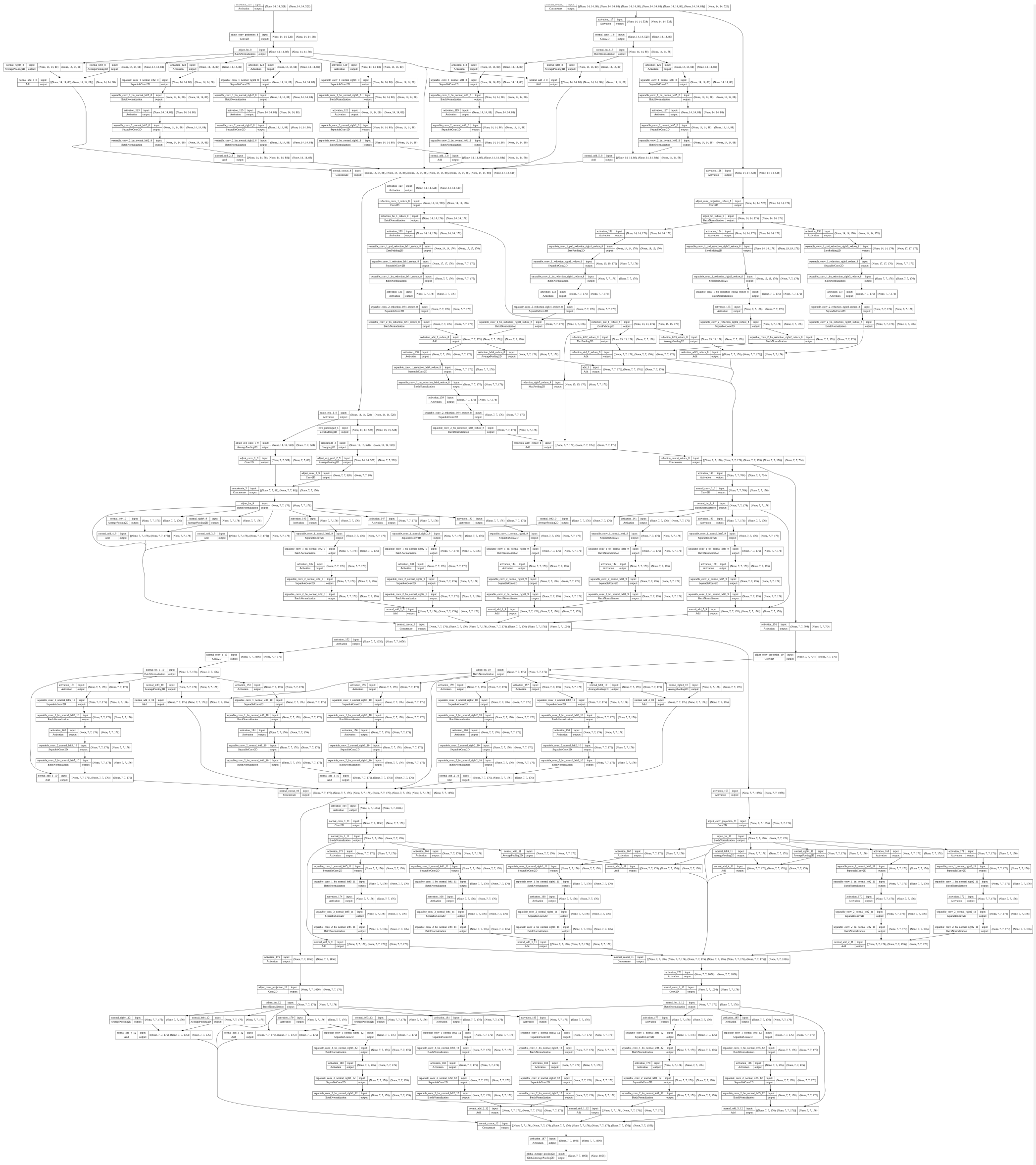
```
# Freezing the base model since we don't want to re-train it.
# We're only interesting in its feature extraction.
base_model.trainable = False
```

```
base_model.summary()
```

```
                                                                        'separabl
                                                                       t2_10[0][0

 normal_add_3_10 (Add)          (None, 7, 7, 176)    0                 ['normal_l
                                                                        'adjust_b

 normal_add_4_10 (Add)          (None, 7, 7, 176)    0                 ['normal_l
                                                                        'normal_r

 normal_add_5_10 (Add)          (None, 7, 7, 176)    0                 ['separabl
                                                                       5_10[0][0]
                                                                        'normal_b

 normal_concat_10 (Concatenate)  (None, 7, 7, 1056)  0                 ['adjust_b
                                                                        'normal_a
                                                                        'normal_a
                                                                        'normal_a
                                                                        'normal_a
                                                                        'normal_a

 activation_163 (Activation)    (None, 7, 7, 1056)   0                 ['normal_c

 activation_164 (Activation)    (None, 7, 7, 1056)   0                 ['normal_c

 adjust_conv_projection_11 (Con  (None, 7, 7, 176)   185856            ['activati
 v2D)

 normal_conv_1_11 (Conv2D)      (None, 7, 7, 176)    185856            ['activati

 adjust_bn_11 (BatchNormalizati  (None, 7, 7, 176)   704               ['adjust_c
 on)                                                                   ']

 normal_bn_1_11 (BatchNormaliza  (None, 7, 7, 176)   704               ['normal_c
 tion)

 activation_165 (Activation)    (None, 7, 7, 176)    0                 ['normal_b

 activation_167 (Activation)    (None, 7, 7, 176)    0                 ['adjust_b

 activation_169 (Activation)    (None, 7, 7, 176)    0                 ['adjust_b

 activation_171 (Activation)    (None, 7, 7, 176)    0                 ['adjust_b

 activation_173 (Activation)    (None, 7, 7, 176)    0                 ['normal_b

 separable_conv_1_normal_left1_  (None, 7, 7, 176)   35376             ['activati
 11 (SeparableConv2D)
```

```
separable_conv_1_normal_right1  (None, 7, 7, 176)   32560       ['activati
_11 (SeparableConv2D)

separable_conv_1_normal_left2_  (None, 7, 7, 176)   35376       ['activati
11 (SeparableConv2D)

separable_conv_1_normal_right2  (None, 7, 7, 176)   32560       ['activati
_11 (SeparableConv2D)

separable_conv_1_normal_left5_  (None, 7, 7, 176)   32560       ['activati
```

```
tf.keras.utils.plot_model(
    base_model,
    show_shapes=True,
    show_layer_names=True,
)
```



Adding a classification head

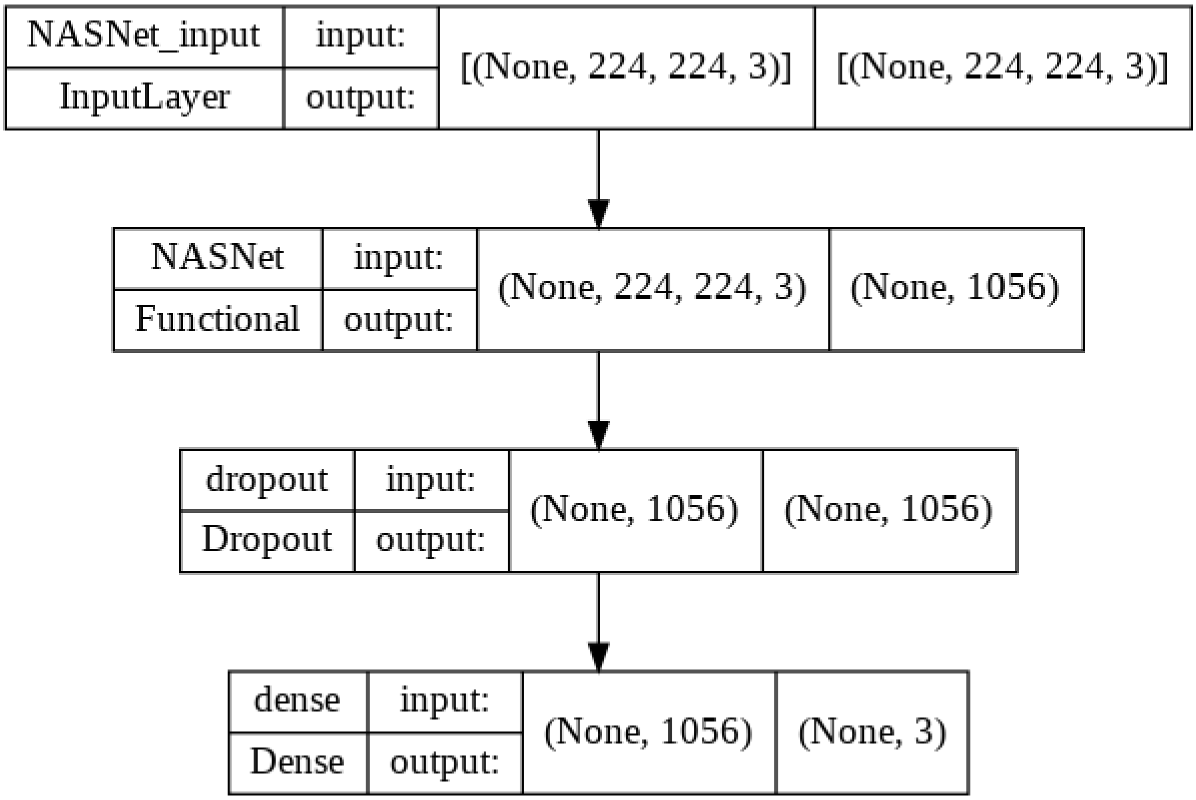
```
model = tf.keras.models.Sequential()

model.add(base_model)

# model.add(tf.keras.layers.GlobalAveragePooling2D())

model.add(tf.keras.layers.Dropout(0.5))

model.add(tf.keras.layers.Dense(
    units=NUM_CLASSES,
    activation=tf.keras.activations.softmax,
    kernel_regularizer=tf.keras.regularizers.l2(l=0.01)
))
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 NASNet (Functional)         (None, 1056)              4269716

 dropout (Dropout)           (None, 1056)              0

 dense (Dense)               (None, 3)                 3171

=================================================================
Total params: 4,272,887
Trainable params: 3,171
```

```
Non-trainable params: 4,269,716
```

```
tf.keras.utils.plot_model(
    model,
    show_shapes=True,
    show_layer_names=True,
)
```



Compiling the model

```
# adam_optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
rmsprop_optimizer = tf.keras.optimizers.RMSprop(learning_rate=0.001)

model.compile(
    optimizer=rmsprop_optimizer,
    loss=tf.keras.losses.sparse_categorical_crossentropy,
    metrics=['accuracy']
)
```

Training the model

```
steps_per_epoch = NUM_TRAIN_EXAMPLES // BATCH_SIZE
validation_steps = NUM_TEST_EXAMPLES // BATCH_SIZE if NUM_TEST_EXAMPLES // BATCH_S

print('steps_per_epoch:', steps_per_epoch)
print('validation_steps:', validation_steps)
```

```
steps_per_epoch: 3
validation_steps: 1
```

```
!rm -rf tmp/checkpoints
!rm -rf logs
```

```
# Preparing callbacks.
os.makedirs('logs/fit', exist_ok=True)
tensorboard_log_dir = 'logs/fit/' + datetime.datetime.now().strftime('%Y%m%d-%H%M%
tensorboard_callback = tf.keras.callbacks.TensorBoard(
    log_dir=tensorboard_log_dir,
    histogram_freq=1
)

os.makedirs('tmp/checkpoints', exist_ok=True)
model_checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(
    filepath='tmp/checkpoints/weights.{epoch:02d}-{val_loss:.2f}.hdf5'
)

early_stopping_callback = tf.keras.callbacks.EarlyStopping(
    patience=10,
    monitor='val_accuracy'
    # monitor='val_loss'
)
```

```
initial_epochs = 20
```

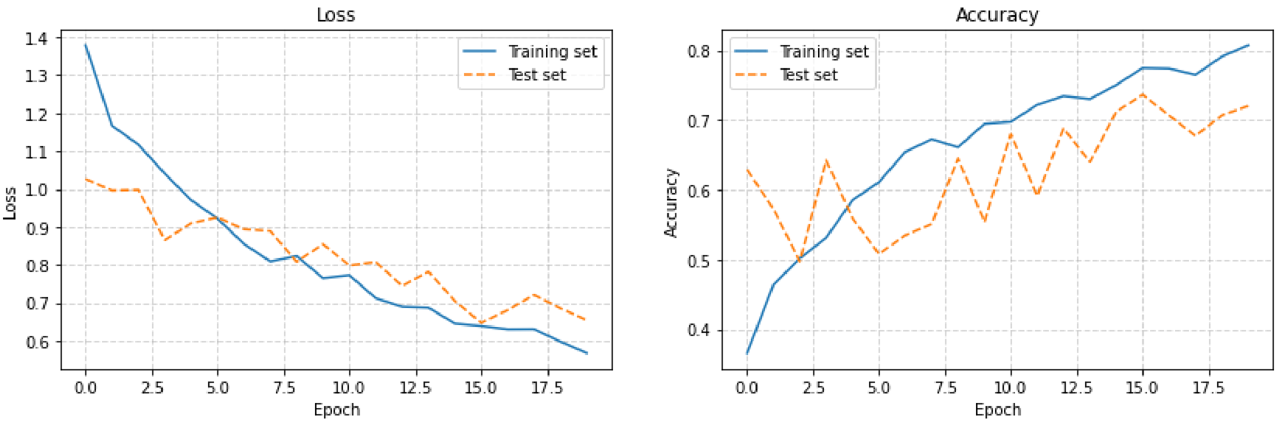
```
training_history = model.fit(
    x=dataset_train_augmented_shuffled.repeat(),
    validation_data=dataset_test_shuffled.repeat(),
    epochs=initial_epochs,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[
        # model_checkpoint_callback,
        # early_stopping_callback,
        tensorboard_callback
    ],
    verbose=2
)
```

```
Epoch 1/20
3/3 - 49s - loss: 1.3788 - accuracy: 0.3658 - val_loss: 1.0261 - val_accuracy
Epoch 2/20
3/3 - 25s - loss: 1.1668 - accuracy: 0.4640 - val_loss: 0.9962 - val_accuracy
Epoch 3/20
3/3 - 23s - loss: 1.1169 - accuracy: 0.5017 - val_loss: 0.9978 - val_accuracy
Epoch 4/20
3/3 - 17s - loss: 1.0405 - accuracy: 0.5314 - val_loss: 0.8654 - val_accuracy
Epoch 5/20
3/3 - 31s - loss: 0.9708 - accuracy: 0.5854 - val_loss: 0.9098 - val_accuracy
Epoch 6/20
3/3 - 25s - loss: 0.9220 - accuracy: 0.6110 - val_loss: 0.9252 - val_accuracy
```

```
Epoch 7/20
3/3 - 20s - loss: 0.8553 - accuracy: 0.6547 - val_loss: 0.8942 - val_accuracy
Epoch 8/20
3/3 - 18s - loss: 0.8091 - accuracy: 0.6727 - val_loss: 0.8893 - val_accuracy
Epoch 9/20
3/3 - 30s - loss: 0.8235 - accuracy: 0.6612 - val_loss: 0.8085 - val_accuracy
Epoch 10/20
3/3 - 25s - loss: 0.7650 - accuracy: 0.6948 - val_loss: 0.8547 - val_accuracy
Epoch 11/20
3/3 - 20s - loss: 0.7729 - accuracy: 0.6977 - val_loss: 0.7985 - val_accuracy
Epoch 12/20
3/3 - 17s - loss: 0.7122 - accuracy: 0.7221 - val_loss: 0.8077 - val_accuracy
Epoch 13/20
3/3 - 31s - loss: 0.6899 - accuracy: 0.7346 - val_loss: 0.7447 - val_accuracy
Epoch 14/20
3/3 - 25s - loss: 0.6873 - accuracy: 0.7302 - val_loss: 0.7823 - val_accuracy
Epoch 15/20
3/3 - 20s - loss: 0.6455 - accuracy: 0.7506 - val_loss: 0.7048 - val_accuracy
Epoch 16/20
3/3 - 17s - loss: 0.6388 - accuracy: 0.7750 - val_loss: 0.6474 - val_accuracy
Epoch 17/20
3/3 - 31s - loss: 0.6303 - accuracy: 0.7742 - val_loss: 0.6810 - val_accuracy
Epoch 18/20
3/3 - 26s - loss: 0.6307 - accuracy: 0.7651 - val_loss: 0.7209 - val_accuracy
Epoch 19/20
3/3 - 20s - loss: 0.5980 - accuracy: 0.7913 - val_loss: 0.6859 - val_accuracy
Epoch 20/20
3/3 - 17s - loss: 0.5676 - accuracy: 0.8076 - val_loss: 0.6541 - val_accuracy
```

```
def render_training_history(training_history):
    loss = training_history.history['loss']
    val_loss = training_history.history['val_loss']

    accuracy = training_history.history['accuracy']
    val_accuracy = training_history.history['val_accuracy']

    plt.figure(figsize=(14, 4))

    plt.subplot(1, 2, 1)
    plt.title('Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.plot(loss, label='Training set')
    plt.plot(val_loss, label='Test set', linestyle='--')
    plt.legend()
    plt.grid(linestyle='--', linewidth=1, alpha=0.5)

    plt.subplot(1, 2, 2)
    plt.title('Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.plot(accuracy, label='Training set')
    plt.plot(val_accuracy, label='Test set', linestyle='--')
    plt.legend()
    plt.grid(linestyle='--', linewidth=1, alpha=0.5)
```

```
    plt.show()
render_training_history(training_history)
```



Model fine tuning

We may try to unfreeze some of the top layers of the `base_model` and to train it a little bit more so to adjust top layers to our Rock-Paper-Scissors dataset.

```
# Un-freeze the top layers of the model
base_model.trainable = True

print("Number of layers in the base model: ", len(base_model.layers))
```

```
    Number of layers in the base model:  770
```

```
# Fine tune from this layer onwards.
# fine_tune_at = 149  # MobileNetV2
fine_tune_at = 752

# Freeze all the layers before the `fine_tune_at` layer
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable =  False

# Compile the model using a much-lower training rate.
adam_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)
rmsprop_optimizer = tf.keras.optimizers.RMSprop(learning_rate=0.0001)
model.compile(
    optimizer = rmsprop_optimizer,
    loss=tf.keras.losses.sparse_categorical_crossentropy,
    metrics=['accuracy']
)

model.summary()
```

```
    Model: "sequential"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 NASNet (Functional)         (None, 1056)              4269716

 dropout (Dropout)           (None, 1056)              0

 dense (Dense)               (None, 3)                 3171

=================================================================
Total params: 4,272,887
Trainable params: 70,051
Non-trainable params: 4,202,836
_________________________________________________________________
```

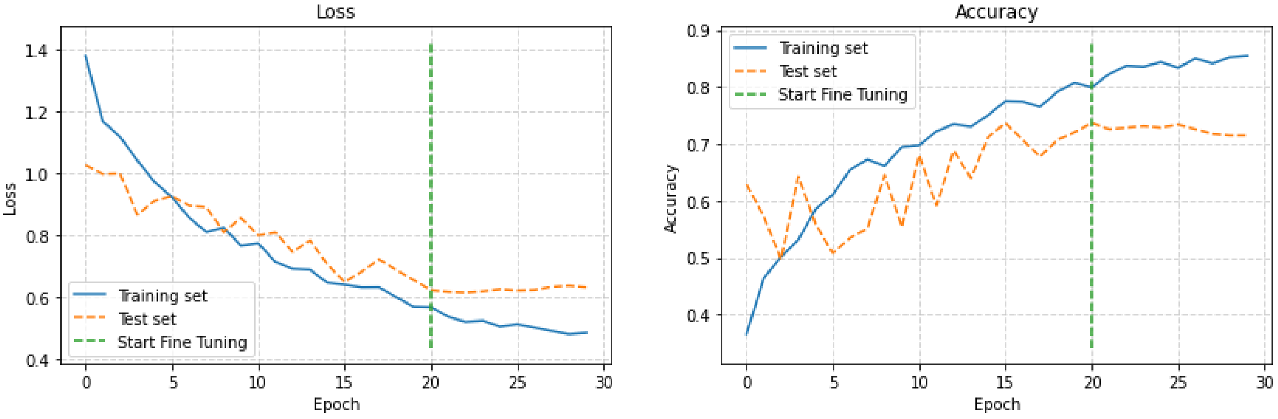
```
# The number of additional epochs during which we're going to fine tune the model.
fine_tuning_epochs = 10
```

```
training_history_fine = model.fit(
    x=dataset_train_augmented_shuffled.repeat(),
    validation_data=dataset_test_shuffled.repeat(),
    epochs=initial_epochs + fine_tuning_epochs,
    initial_epoch=initial_epochs,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[tensorboard_callback],
    verbose=1
)
```

```
Epoch 21/30
3/3 [==============================] - 46s 12s/step - loss: 0.5662 - accuracy
Epoch 22/30
3/3 [==============================] - 25s 12s/step - loss: 0.5352 - accuracy
Epoch 23/30
3/3 [==============================] - 21s 9s/step - loss: 0.5184 - accuracy:
Epoch 24/30
3/3 [==============================] - 17s 7s/step - loss: 0.5224 - accuracy:
Epoch 25/30
3/3 [==============================] - 31s 11s/step - loss: 0.5036 - accuracy
Epoch 26/30
3/3 [==============================] - 24s 12s/step - loss: 0.5107 - accuracy
Epoch 27/30
3/3 [==============================] - 20s 9s/step - loss: 0.5002 - accuracy:
Epoch 28/30
3/3 [==============================] - 17s 7s/step - loss: 0.4890 - accuracy:
Epoch 29/30
3/3 [==============================] - 31s 11s/step - loss: 0.4789 - accuracy
Epoch 30/30
3/3 [==============================] - 25s 12s/step - loss: 0.4831 - accuracy
```

```
loss = training_history.history['loss'] + training_history_fine.history['loss']
val_loss = training_history.history['val_loss'] + training_history_fine.history['v

accuracy = training_history.history['accuracy'] + training_history_fine.history['a
val_accuracy = training_history.history['val_accuracy'] + training_history_fine.hi
```

```
plt.figure(figsize=(14, 4))

plt.subplot(1, 2, 1)
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.plot(loss, label='Training set')
plt.plot(val_loss, label='Test set', linestyle='--')
plt.plot(
[initial_epochs, initial_epochs],
plt.ylim(),
label='Start Fine Tuning',
linestyle='--'
)
plt.legend()
plt.grid(linestyle='--', linewidth=1, alpha=0.5)

plt.subplot(1, 2, 2)
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.plot(accuracy, label='Training set')
plt.plot(val_accuracy, label='Test set', linestyle='--')
plt.plot(
[initial_epochs, initial_epochs],
plt.ylim(),
label='Start Fine Tuning',
linestyle='--'
)
plt.legend()
plt.grid(linestyle='--', linewidth=1, alpha=0.5)

plt.show()
```



Debugging the training with TensorBoard

Deep Learning Methods

Lecture 08

****
Lecture Slides + interactive Jupyter-notebooks for Google Colaboratory CPU/GPU/TPU cloud:
https://cloud.comsys.kpi.ua/s/SMkBSsxRTazoTD6

****

Lecture 08 - Deep Learning Methods - Model Deployment

The course includes materials proposed by NVIDIA Deep Learning Institute (DLI) in the framework of the common

NVIDIA Research Center
and
NVIDIA Education Center.

https://kpi.ua/nvidia-info

Interactive Demonstrations

DEMO A - CPU
Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)
https://drive.google.com/file/d/1ywWNaf8Y2MUG526p1tiKi6lHyDkcmz3C/view?usp=sharing

DEMO B - GPU
Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)
https://drive.google.com/file/d/11eReb0X2kJ3KScPHNM5I1XpLq2R560V0/view?usp=sharing

DEMO C - TPU
Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)
https://drive.google.com/file/d/1X8soRab064l5ROqCv1z8JSDr3JJUBohK/view?usp=sharing

Lecture 7 - DEMO A - CPU - Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)

based on (C) Tensorflow Authors Team, Parsaniya, Heaton, Jadhav and other works

Connect to Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Go to Project Folder at Google Drive and Check It

```
%cd 'drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app'
! ls
```

```
/content/drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app
generated_image                                  MNIST_test_images
Lecture_07_DL_Web-app.zip                        model
Lecture_07_MNIST_DEMO_A_web_app_CPU_EMPTY.ipynb  static
Lecture_07_MNIST_DEMO_B_web_app_GPU_EMPTY.ipynb  templates
Lecture_07_MNIST_DEMO_C_web_app_TPU_EMPTY.ipynb  uploads
```

Install Flask

```
!pip install flask-ngrok
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Collecting flask-ngrok
  Downloading flask_ngrok-0.0.25-py3-none-any.whl (3.1 kB)
Requirement already satisfied: Flask>=0.8 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: itsdangerous<2.0,>=0.24 in /usr/local/lib/pyth
Requirement already satisfied: Jinja2<3.0,>=2.10.1 in /usr/local/lib/python3.
Requirement already satisfied: click<8.0,>=5.1 in /usr/local/lib/python3.7/di
Requirement already satisfied: Werkzeug<2.0,>=0.15 in /usr/local/lib/python3.
ed: MarkupSafe>=0.23 in /usr/local/lib/python3.7/c
ed: certifi>=2017.4.17 in /usr/local/lib/python3.7
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
```

Saved successfully!

```
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
Installing collected packages: flask-ngrok
Successfully installed flask-ngrok-0.0.25
```

Import Libraries

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from flask import Flask, flash, redirect, render_template, request, url_for, send_
from flask_ngrok import run_with_ngrok
from tensorflow.keras.models import load_model
```

Load Trained Model

```
mnist_model = load_model('model/mnist.h5')
```

Configure Web-app

```
app = Flask(__name__)
run_with_ngrok(app)
app.secret_key = 'Putin_Huylo'

app.config["MNIST_BAR"] = "generated_image/mnist_vis"
app.config["IMAGES"] = "upload"

@app.route('/')
def home():
    flash("Try CNN Model Trained on MNIST-dataset for Single Digit Prediction...")
    return render_template('index.html')

@app.route('/mnist/')
def mnist_home():
    return render_template('mnist.html')

@app.route('/mnistprediction/', methods=['GET', 'POST'])
def mnist_prediction():
    if request.method == "POST":
        if not request.files['file'].filename:
            flash("No File Found")
        else:
                      file']
                      filename)
            image_gray  = cv2.imread("uploads/"+f.filename, cv2.IMREAD_GRAYSCALE)
            img_resize = cv2.resize(image_gray,(28,28))
```

```
            image_bw = cv2.threshold(img_resize, 75, 255, cv2.THRESH_BINARY)[1]
            bitwise_not_image = cv2.bitwise_not(image_bw, mask=None)
            pred_img = np.reshape(bitwise_not_image,(1,28,28,1))/255.0

            predictions = mnist_model.predict(pred_img)
            number = int(np.argmax(predictions))
            print(number)

            plt.figure()
            y_pos = np.arange(10)
            plt.bar(y_pos, predictions[0])
            plt.savefig('generated_image/mnist_vis/'+f.filename)

            return str(number)

@app.route("/get-mnist-image/<image_name>")
def get_mnist_image(image_name):
    try:
        return send_from_directory(app.config["MNIST_BAR"], filename=image_name)
    except FileNotFoundError:
        abort(404)
```

```
# Install pyngrok
!pip install pyngrok==4.1.1

# Register, get 'your authtoken', and replace my token below:
# !ngrok authtoken 'your authtoken'
!ngrok authtoken '2FdbDL8Rak9en9IT4S3pSeMjq0I_6Ntx7LfKFyeS9qLSFAoks'
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Collecting pyngrok==4.1.1
  Downloading pyngrok-4.1.1.tar.gz (18 kB)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: PyYAML in /usr/local/lib/python3.7/dist-packag
Building wheels for collected packages: pyngrok
  Building wheel for pyngrok (setup.py) ... done
  Created wheel for pyngrok: filename=pyngrok-4.1.1-py3-none-any.whl size=15
  Stored in directory: /root/.cache/pip/wheels/b1/d9/12/045a042fee3127dc40ba
Successfully built pyngrok
Installing collected packages: pyngrok
Successfully installed pyngrok-4.1.1
Authtoken saved to configuration file: /root/.ngrok2/ngrok.yml
```

Start Web-app

After start ...

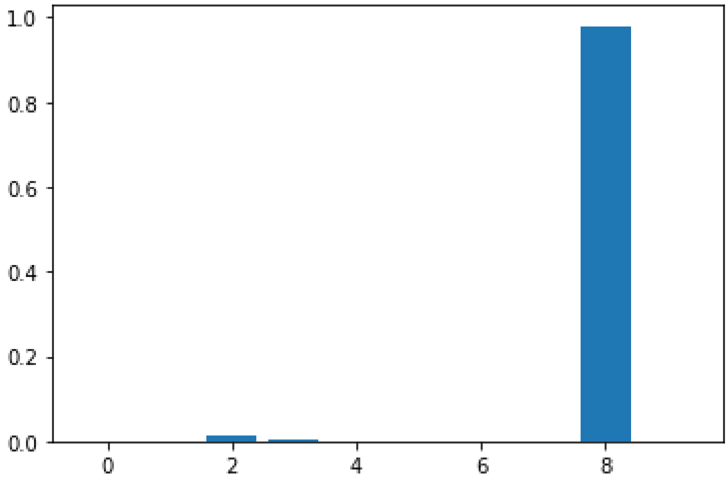
- click on the link in the row like:

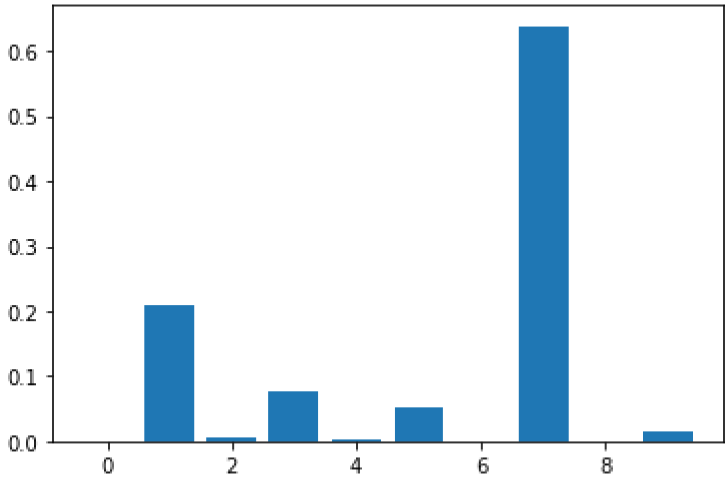
- load the local images of single digit numbers and obtain predictions;
- try images of different quality.

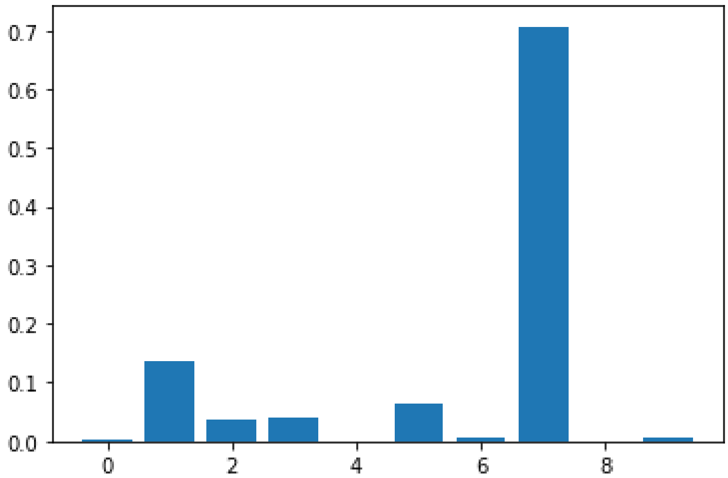
IMPORTANT: this Web-app is cloud-based and ... **some delay can be observed!**

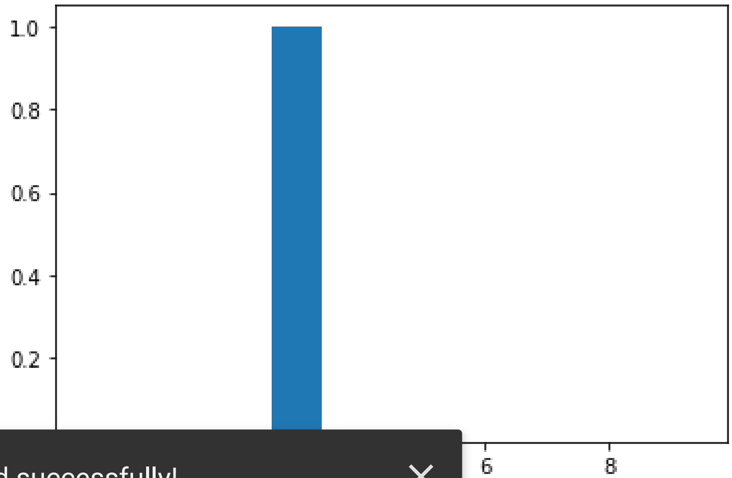
```
app.run()
```

Saved successfully!









Saved successfully!

Lecture 7 - DEMO B - GPU - Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)

based on (C) Tensorflow Authors Team, Parsaniya, Heaton, Jadhav and other works

```
! nvidia-smi
```

```
Mon Oct  3 19:43:07 2022
+-----------------------------------------------------------------------------
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2
|-------------------------------+----------------------+----------------------
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M.
|                               |                      |               MIG M.
|===============================+======================+======================
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0
| N/A   43C    P8     9W /  70W |      0MiB / 15109MiB |      0%      Default
|                               |                      |                  N/A
+-------------------------------+----------------------+----------------------

+-----------------------------------------------------------------------------
| Processes:
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory
|        ID   ID                                                   Usage
|=============================================================================
|  No running processes found
+-----------------------------------------------------------------------------
```

Connect to Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Go to Project Folder at Google Drive and Check It

```
%cd 'drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app'
! ls
```

```
/content/drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app
generated_image                                    MNIST_test_images
                                                   model
```

Saved successfully!

```
app_CPU_EMPTY.ipynb   static
app_GPU_EMPTY.ipynb   templates
Lecture_07_MNIST_DEMO_C_web_app_TPU_EMPTY.ipynb   uploads
```

Install Flask

```
!pip install flask-ngrok
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Collecting flask-ngrok
  Downloading flask_ngrok-0.0.25-py3-none-any.whl (3.1 kB)
Requirement already satisfied: Flask>=0.8 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: itsdangerous<2.0,>=0.24 in /usr/local/lib/pyth
Requirement already satisfied: Jinja2<3.0,>=2.10.1 in /usr/local/lib/python3.
Requirement already satisfied: Werkzeug<2.0,>=0.15 in /usr/local/lib/python3.
Requirement already satisfied: click<8.0,>=5.1 in /usr/local/lib/python3.7/di
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/c
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
Installing collected packages: flask-ngrok
Successfully installed flask-ngrok-0.0.25
```

Import Libraries

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from flask import Flask, flash, redirect, render_template, request, url_for, send_
from flask_ngrok import run_with_ngrok
from tensorflow.keras.models import load_model
```

Load Trained Model

```
mnist_model = load_model('model/mnist.h5')
```

```
mnist_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320
```

Saved successfully!

```
                            (None, 24, 24, 32)        9248

 max_pooling2d (MaxPooling2D  (None, 12, 12, 32)      0
 )

 dropout (Dropout)          (None, 12, 12, 32)        0

 conv2d_2 (Conv2D)          (None, 12, 12, 64)        18496

 conv2d_3 (Conv2D)          (None, 12, 12, 64)        36928

 max_pooling2d_1 (MaxPooling  (None, 6, 6, 64)        0
 2D)

 dropout_1 (Dropout)        (None, 6, 6, 64)          0

 conv2d_4 (Conv2D)          (None, 6, 6, 128)         73856

 dropout_2 (Dropout)        (None, 6, 6, 128)         0

 flatten (Flatten)          (None, 4608)              0

 dense (Dense)              (None, 128)               589952

 batch_normalization (BatchN  (None, 128)             512
 ormalization)

 dropout_3 (Dropout)        (None, 128)               0

 dense_1 (Dense)            (None, 10)                1290

=================================================================
Total params: 730,602
Trainable params: 730,346
Non-trainable params: 256
_________________________________________________________________
```

Configure Web-app

```
app = Flask(__name__)
run_with_ngrok(app)
app.secret_key = 'ACAB_таки_да_ACAB'

app.config["MNIST_BAR"] = "generated_image/mnist_vis"
app.config["IMAGES"] = "upload"

@app.route('/')
def home():
    flash("Try CNN Model Trained on MNIST-dataset for Single Digit Prediction...")
    return render_template('index.html')

@app.route('/mnist/')
def mnist_home():
    return render_template('mnist.html')
```

```
methods=['GET', 'POST'])
def mnist_prediction():
    if request.method == "POST":
        if not request.files['file'].filename:
            flash("No File Found")
        else:
            f =  request.files['file']
            f.save("uploads/"+f.filename)
            image_gray  = cv2.imread("uploads/"+f.filename, cv2.IMREAD_GRAYSCALE)
            img_resize = cv2.resize(image_gray,(28,28))
            image_bw = cv2.threshold(img_resize, 75, 255, cv2.THRESH_BINARY)[1]
            bitwise_not_image = cv2.bitwise_not(image_bw, mask=None)
            pred_img = np.reshape(bitwise_not_image,(1,28,28,1))/255.0

            predictions = mnist_model.predict(pred_img)
            number = int(np.argmax(predictions))
            print(number)

            plt.figure()
            y_pos = np.arange(10)
            plt.bar(y_pos, predictions[0])
            plt.savefig('generated_image/mnist_vis/'+f.filename)

            return str(number)

@app.route("/get-mnist-image/<image_name>")
def get_mnist_image(image_name):
    try:
        return send_from_directory(app.config["MNIST_BAR"], filename=image_name)
    except FileNotFoundError:
        abort(404)
```

```
# Install pyngrok
!pip install pyngrok==4.1.1

# Register, get 'your authtoken', and replace my token below:
# !ngrok authtoken 'your authtoken'
!ngrok authtoken '2FdbDL8Rak9en9IT4S3pSeMjq0I_6Ntx7LfKFyeS9qLSFAoks'
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Collecting pyngrok==4.1.1
  Downloading pyngrok-4.1.1.tar.gz (18 kB)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: PyYAML in /usr/local/lib/python3.7/dist-packag
Building wheels for collected packages: pyngrok
  Building wheel for pyngrok (setup.py) ... done
  Created wheel for pyngrok: filename=pyngrok-4.1.1-py3-none-any.whl size=15
  Stored in directory: /root/.cache/pip/wheels/b1/d9/12/045a042fee3127dc40ba
Successfully built pyngrok
Installing collected packages: pyngrok
Successfully installed pyngrok-4.1.1
Authtoken saved to configuration file: /root/.ngrok2/ngrok.yml
```

Saved successfully!

After start ...

- click on the link in the row like:

Running on [your_website_at_ngrok.io]

- follow the web-user interface:
  - load the local images of single digit numbers and obtain predictions;
  - try images of different quality.

IMPORTANT: this Web-app is cloud-based and ... **some delay can be observed!**

```
app.run()
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deplo
   Use a production WSGI server instead.
 * Debug mode: off
INFO:werkzeug: * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
 * Running on http://dbd3-34-72-230-125.ngrok.io
 * Traffic stats available on http://127.0.0.1:4040
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:44:12] "GET / HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:44:12] "GET /static/css/main.css
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:44:12] "GET /static/css/header_fi
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:44:13] "GET /static/image/mnist-s
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:44:13] "GET /favicon.ico HTTP/1.1
```

Saved successfully!

…r Self-Guided Experiments:

- try to train, save and use other *.h5 model (like it was described in the previous DEMOs),
- try to use other datasets and related models,
- try to port the web-app to your local environment,
- ...

Executing (2s) Cell > new_run() > run() > run_simple() > inner() > serve_forever() > serve_forever() > select()

Lecture 8 - DEMO C - TPU - Deep Learning Model Deployment Example - MNIST WebApp (Flask + Google Colab)

based on (C) Tensorflow Authors Team, Parsaniya, Heaton, Jadhav and other works

Connect to Google Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Go to Project Folder at Google Drive and Check It

```
%cd 'drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app'
! ls
```

```
/content/drive/MyDrive/2022_COLAB_NN/Lecture_07_DL_Web-app
generated_image                                  MNIST_test_images
Lecture_07_DL_Web-app.zip                        model
Lecture_07_MNIST_DEMO_A_web_app_CPU_EMPTY.ipynb  static
Lecture_07_MNIST_DEMO_B_web_app_GPU_EMPTY.ipynb  templates
Lecture_07_MNIST_DEMO_C_web_app_TPU_EMPTY.ipynb  uploads
```

Install Flask

```
!pip install flask-ngrok
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Requirement already satisfied: flask-ngrok in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: Flask>=0.8 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: itsdangerous<2.0,>=0.24 in /usr/local/lib/pyth
Requirement already satisfied: click<8.0,>=5.1 in /usr/local/lib/python3.7/di
Requirement already satisfied: Werkzeug<2.0,>=0.15 in /usr/local/lib/python3.
Requirement already satisfied: Jinja2<3.0,>=2.10.1 in /usr/local/lib/python3.
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/d
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
```

Import Libraries

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from flask import Flask, flash, redirect, render_template, request, url_for, send_
from flask_ngrok import run_with_ngrok
from tensorflow.keras.models import load_model
```

Load Trained Model

```
mnist_model = load_model('model/mnist.h5')
```

Configure Web-app

```
app = Flask(__name__)
run_with_ngrok(app)
app.secret_key = 'ACAB_таки_да_ACAB'

app.config["MNIST_BAR"] = "generated_image/mnist_vis"
app.config["IMAGES"] = "upload"

@app.route('/')
def home():
    flash("Try CNN Model Trained on MNIST-dataset for Single Digit Prediction...")
    return render_template('index.html')

@app.route('/mnist/')
def mnist_home():
    return render_template('mnist.html')

@app.route('/mnistprediction/', methods=['GET', 'POST'])
def mnist_prediction():
    if request.method == "POST":
        if not request.files['file'].filename:
            flash("No File Found")
        else:
            f =  request.files['file']
            f.save("uploads/"+f.filename)
            image_gray  = cv2.imread("uploads/"+f.filename, cv2.IMREAD_GRAYSCALE)
            img_resize = cv2.resize(image_gray,(28,28))
            image_bw = cv2.threshold(img_resize, 75, 255, cv2.THRESH_BINARY)[1]
            bitwise_not_image = cv2.bitwise_not(image_bw, mask=None)
            pred_img = np.reshape(bitwise_not_image,(1,28,28,1))/255.0
```

```
            predictions = mnist_model.predict(pred_img)
            number = int(np.argmax(predictions))
            print(number)

            plt.figure()
            y_pos = np.arange(10)
            plt.bar(y_pos, predictions[0])
            plt.savefig('generated_image/mnist_vis/'+f.filename)

            return str(number)

@app.route("/get-mnist-image/<image_name>")
def get_mnist_image(image_name):
    try:
        return send_from_directory(app.config["MNIST_BAR"], filename=image_name)
    except FileNotFoundError:
        abort(404)
```

```
# Install pyngrok
!pip install pyngrok==4.1.1

# Register, get 'your authtoken', and replace my token below:
# !ngrok authtoken 'your authtoken'
!ngrok authtoken '2FdbDL8Rak9en9IT4S3pSeMjq0I_6Ntx7LfKFyeS9qLSFAoks'
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
Collecting pyngrok==4.1.1
  Downloading pyngrok-4.1.1.tar.gz (18 kB)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: PyYAML in /usr/local/lib/python3.7/dist-packag
Building wheels for collected packages: pyngrok
  Building wheel for pyngrok (setup.py) ... done
  Created wheel for pyngrok: filename=pyngrok-4.1.1-py3-none-any.whl size=15
  Stored in directory: /root/.cache/pip/wheels/b1/d9/12/045a042fee3127dc40ba
Successfully built pyngrok
Installing collected packages: pyngrok
Successfully installed pyngrok-4.1.1
Authtoken saved to configuration file: /root/.ngrok2/ngrok.yml
```

Start Web-app

After start ...

- click on the link in the row like:

Running on [your_website_at_ngrok.io]

- follow the web-user interface:
  - load the local images of single digit numbers and obtain predictions;
  - try images of different quality.

IMPORTANT: this Web-app is cloud-based and ... **some delay can be observed!**

```
app.run()
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deplo
   Use a production WSGI server instead.
 * Debug mode: off
INFO:werkzeug: * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
 * Running on http://3a76-35-222-189-46.ngrok.io
 * Traffic stats available on http://127.0.0.1:4040
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:48:01] "GET / HTTP/1.1" 200 -
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:48:02] "GET /static/css/main.css
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:48:02] "GET /static/css/header_fi
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:48:02] "GET /static/image/mnist-s
INFO:werkzeug:127.0.0.1 - - [03/Oct/2022 19:48:02] "GET /favicon.ico HTTP/1.1
```

Some Possible Tasks for Self-Guided Experiments:

- try to train, save and use other *.h5 model (like it was described in the previous DEMOs),
- try to use other datasets and related models,
- try to port the web-app to your local environment,
- ...