AI Toolkit Scikit Learn, TensorFlow and Keras

We will be starting soon

Day 1

Welcome to Day 1 AI Toolkit

Please perform PRE-WORK

1. Access the virtual Lab using link https://html.inspiredvlabs.com Use the username TEKBD142-XX (replace XX with your number) and password

TekBD142!23

https://tinyurl.com/bdtAIToolkit

We will be starting soon

Last Name	First Name	Login Id
AHMED	NAZEER	TEKBD142-01
AM	GANESH	TEKBD142-02
BISWAS	SOURAV	TEKBD142-03
CHACKO	THOMAS	TEKBD142-04
JAJOO	SANDESH	TEKBD142-05
MATTOX	CHRISTEL	TEKBD142-06
MAXSON	CRAIG	TEKBD142-07
MURPHY	MATTHEW	TEKBD142-08
PANDIAN	JEYARAJ	TEKBD142-09
PATURI	RAVIKIRAN	TEKBD142-10
RANI	AMITA	TEKBD142-11
SINGLA	SANJEEV	TEKBD142-12
VEERAMASU	BRAHMA RAO	TEKBD142-13

Logistics

- **Timing –** 8:30 AM – 4:30 PM CST
- **Lunch –** Approx. noon to 1 PM CST
- **Periodic Breaks –** At logical points

Virtual Class Tips

Audio

Please mute yourself if not speaking, unmute to ask questions

Notifications

✓ Give us green right check mark in participant panel when you are done

Notifications

🙂 Give a smiley when you are back from break

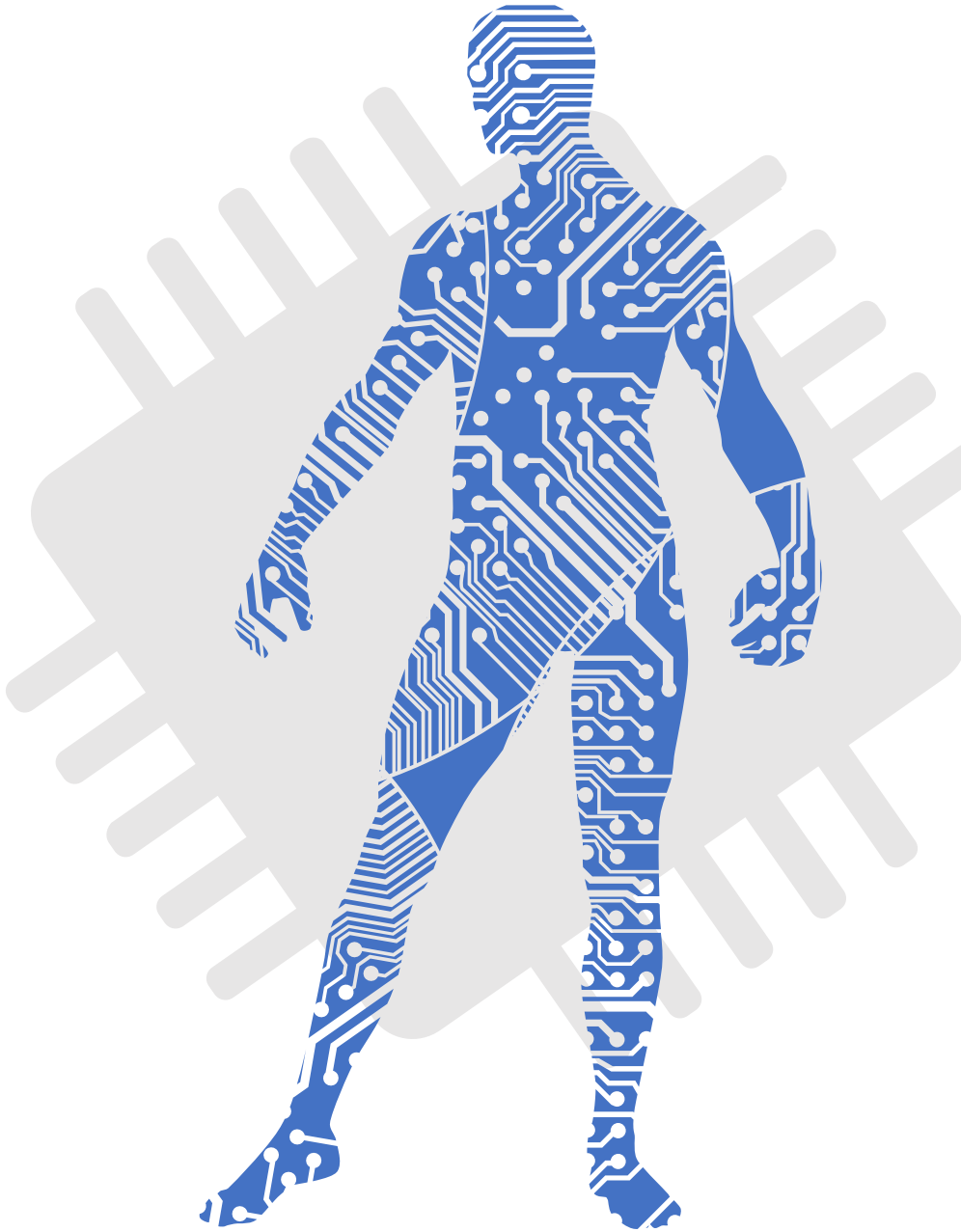
Notifications

 Please raise hand in participant panel or unmute and ask question

Let’s make it interactive !

Agenda – Day 1

1. Introductions
2. Machine Learning Introduction
3. Machine Learning Techniques
4. Machine Learning Development
5. Multiple Hands-on



Sanjay Oza

- 25+ years of experience in Software, Hardware and Data Engineering
- Multiple years of management experience in Networking and Insurance industries
- Provide training at multiple fortune 500 companies on wide variety of topics
- **Patents**
  - Detecting and mitigating a high-rate distributed denial of service - Approved
  - Individually assigned server alias address for contacting a server - Pending

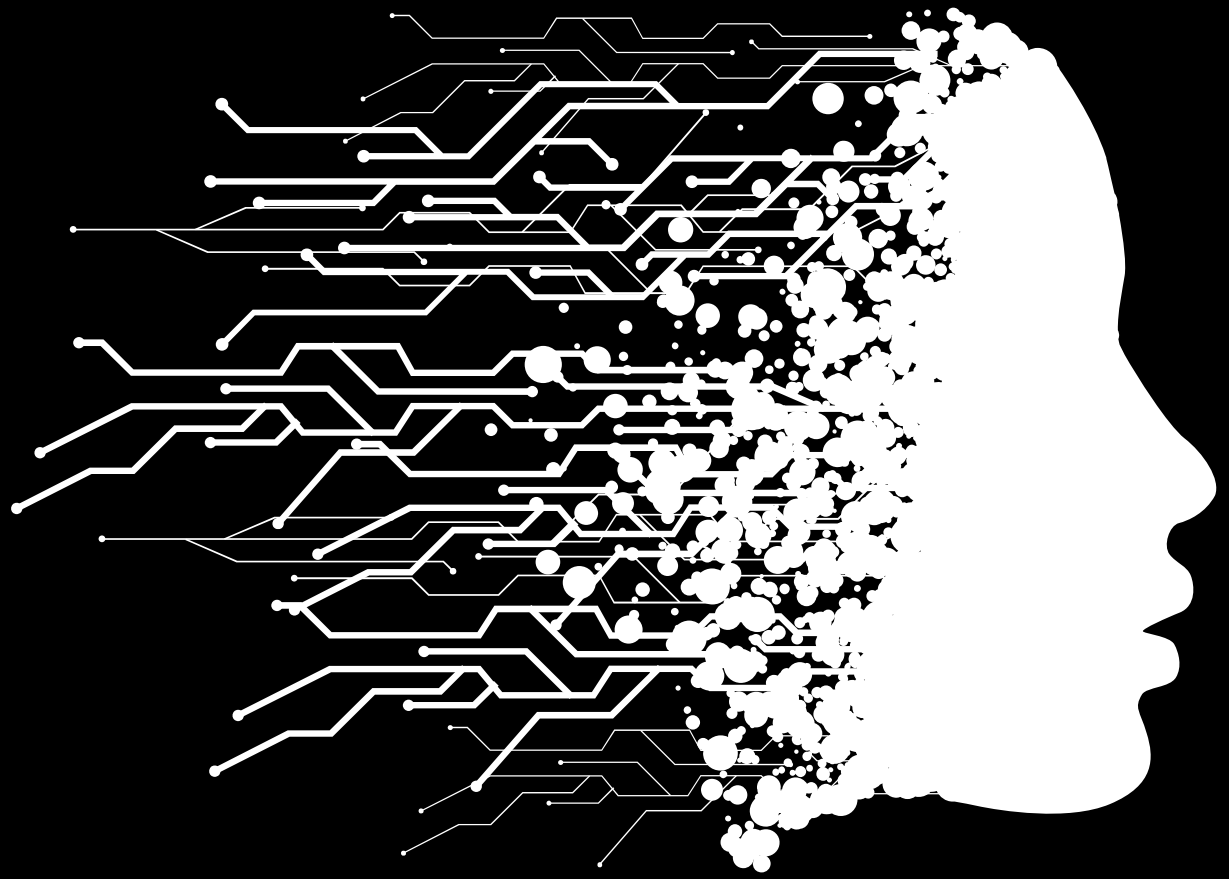
Your turn

Who? Name, Role & Group

What? Overall experience & Main Skill (Any Python, or ML Experience)

Why? Are you here (Key Motivations)

How? plan to use this (if already known)

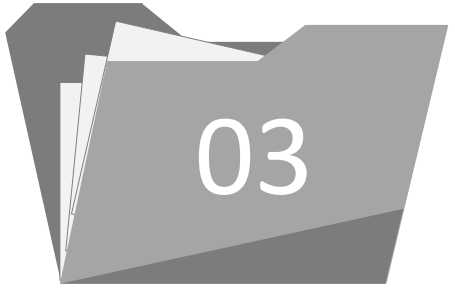


Hands-on Labs

Labs Folder Structure

Assignment

Contains notebooks:
instructions for assignment



Solution

Contains solution notebooks

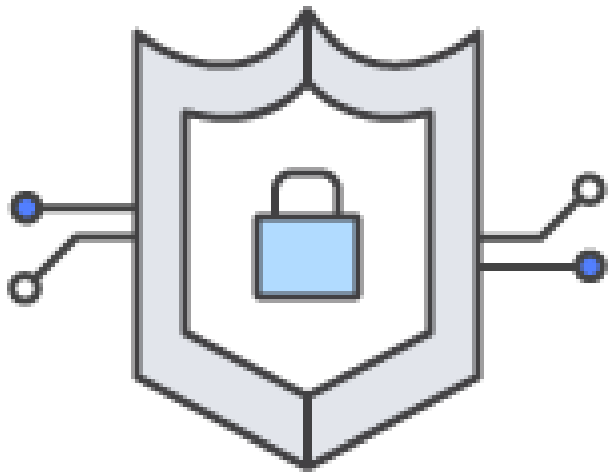
Code Samples

Contains code examples for
different topics.

Samples & Exercises

Folder	File Name	Dataset	Topic
CodeSamples	*Python Introduction*		Python Examples
CodeSamples	*Pandas Introduction*	*iris.csv*	Numpy and Pandas
CodeSamples	*Matplotlib Intro*	*iris.csv*	Matplotlib and Seaborn
CodeSamples	*Plotly Example*	*iris.csv*	Plotly - Interactive charts
CodeSamples	*Pandas-Profiling-Visualization*	*Telco-Customer-Churn.csv*	Autoviz, Pandas Profiling, Datasist
CodeSamples	*LinearRegression*	*50_Startups.csv*	Linear Regression
Assignment	*LinearRegression RealEstate*	*Boston dataset*	Implement Linear Regression
CodeSamples	*LogisticRegression*	*agent.csv*	Logistic Regression & Model Persistence
CodeSamples	*LoadModel-Predict*	*agent-new.csv*	Load pipeline, model, predict
CodeSamples	*PetFinder*	*pet-train.csv* *pet-test.csv*	Using wordcloud
CodeSamples	*Tensor Introduction*		TensorFlow (Tensors)
CodeSamples	*GradientDescent*		Gradient Descent
CodeSamples	*NeuralNetworks-Regression*	*auto-mpg (UCI)*	Neural Networks Regression
CodeSamples	*PredictPetFinder*	*pet-train.csv* *pet-test.csv*	Neural Networks Classification
CodeSamples	*ImageAugmentation*	*home-x.jpg*	Image Augmentation
CodeSamples	*NeuralNetworks*	*Keras MNIST Digits*	Neural Networks
CodeSamples	*CNN*	*Keras MNIST Digits*	Convolutional Neural Networks
Assignment	*CRM-CustomerChurn*	*CRM Dataset Shared.tsv* *CRM Churn Labels.tsv*	Classifier(s) and Neural Networks
Assignment	*CNN-Fashion*	*Keras MNIST Fashion*	Convolutional Neural Networks
CodeSamples	*SpacyExamples*		Using Spacy - text processing
CodeSamples	*SpacySentimentAnalysis*	*yelp_labelled.txt* *amazon_cells_labelled.txt* *imdb_labelled.txt*	Spacy -text processing & classification
CodeSamples	*TextClassification*	*IMDB Dataset.csv*	Recurrent Neural Networks

Lab Environment Verification



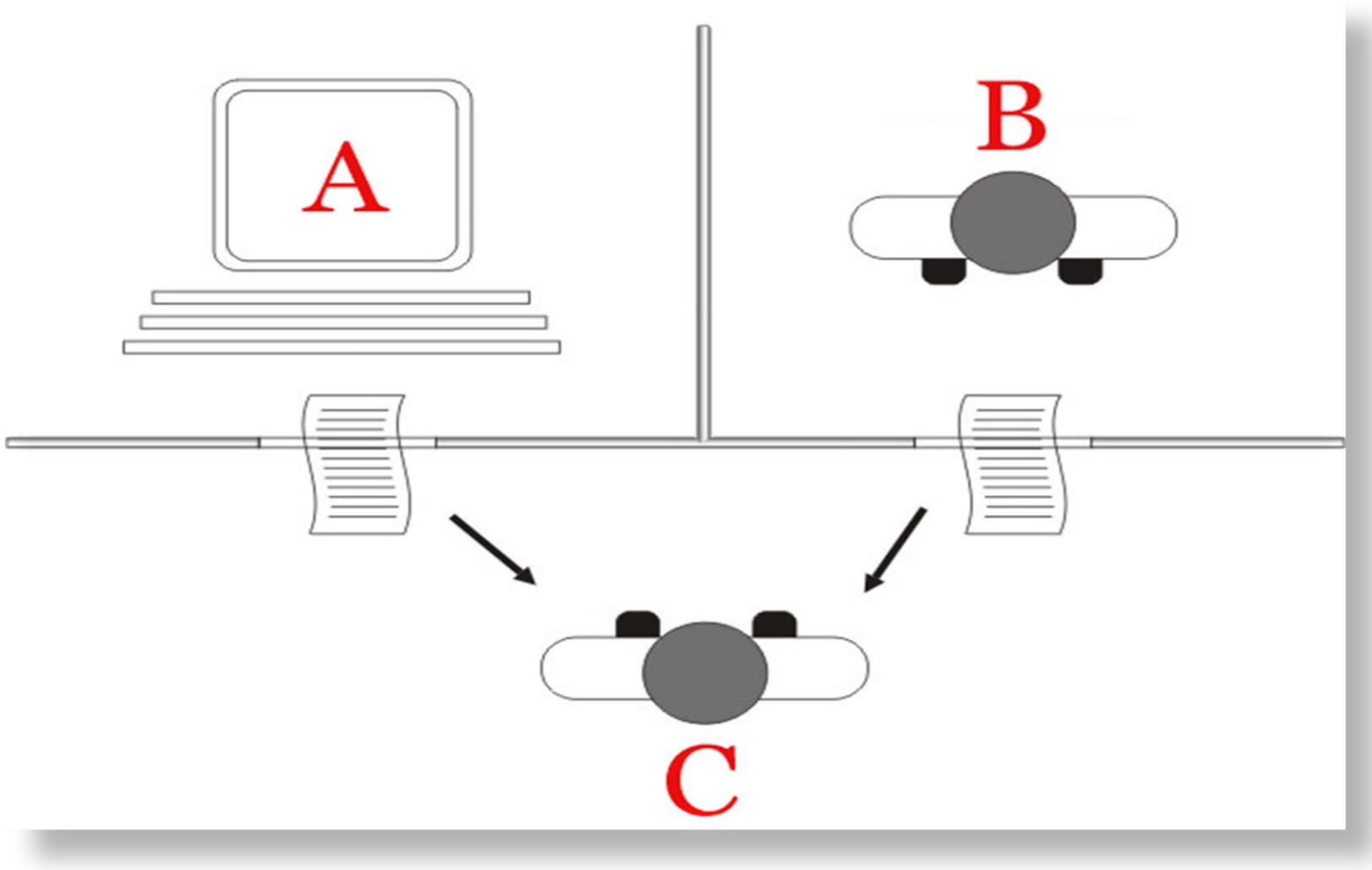
Notebooks

- Open notebook – “CodeSamples/Python Introduction”
- Demo of using Notebook
- Python refresher code – commonly used data structures, functions

When did Artificial Intelligence start?

Your thoughts?

Turing Test (1950)

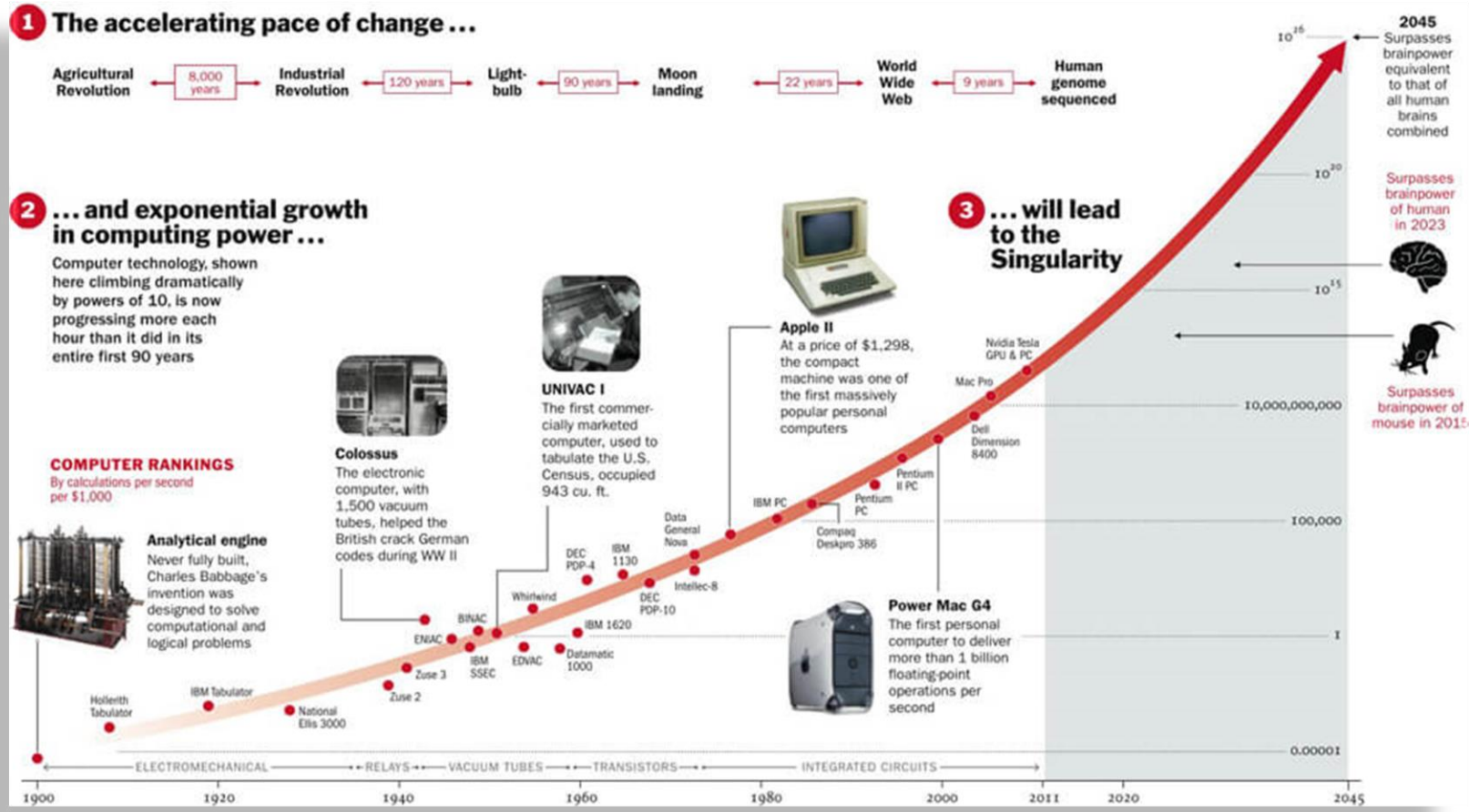


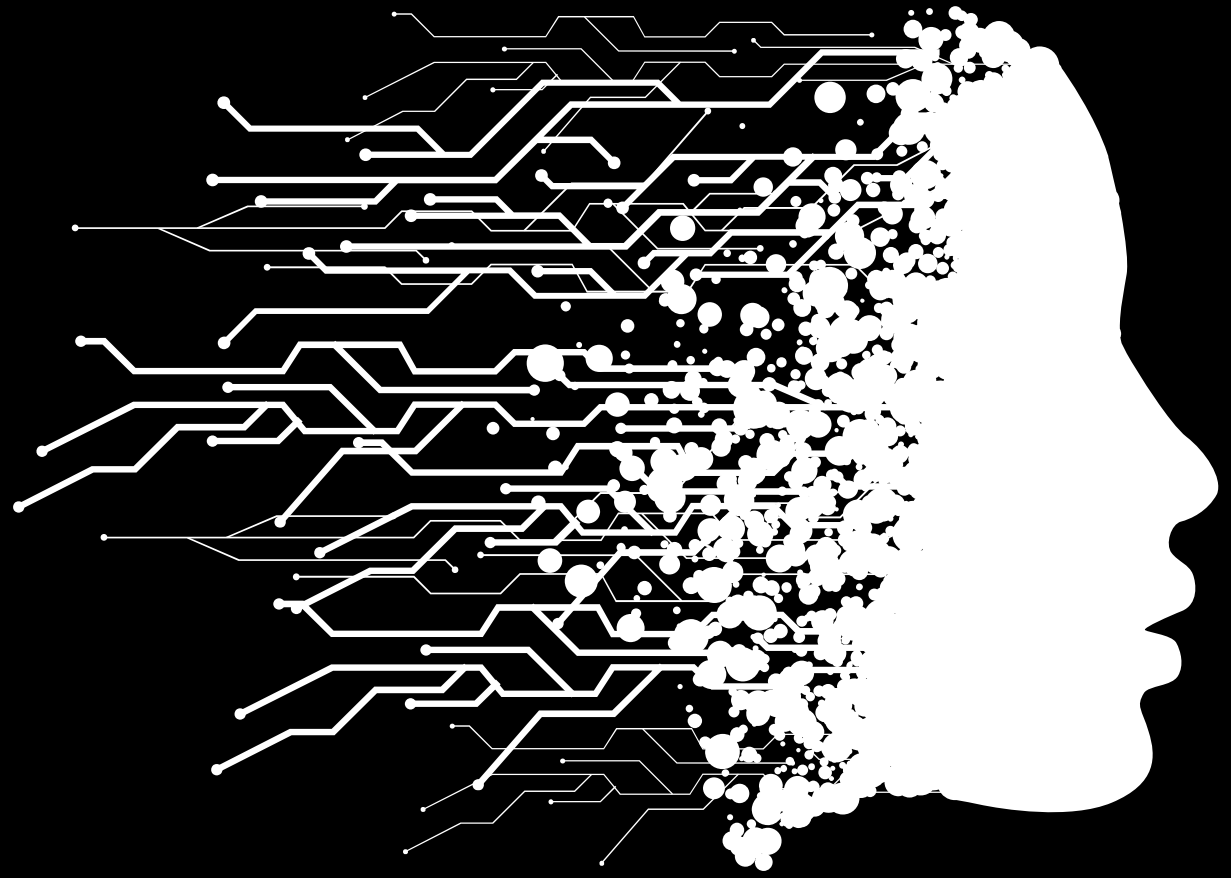
History of Artificial Intelligence

- 1950 – Turing Test
- 1951 – First Neural Network
- 1967 – “Nearest Neighbor” Algorithm is written
- 1974 – First AI winter
- 1979 – Stanford Cart
- 1997 – IBM Deep Blue beats Garry Kasparov
- 2006 - Geoffrey Hinton coins the term “deep learning”
- 2014 – Facebook develops Deep Face & Google Buys DeepMind
- 2015 – Amazon, Google & Microsoft ML offerings
- 2016 – AlphaGo beats Lee Sedol
- 2030 – Singularity?

Source https://www.bbc.com/timelines/zypd97h

Singularity 2045?





Artificial Intelligence, Machine Learning, Deep Learning

Concepts & Terminology

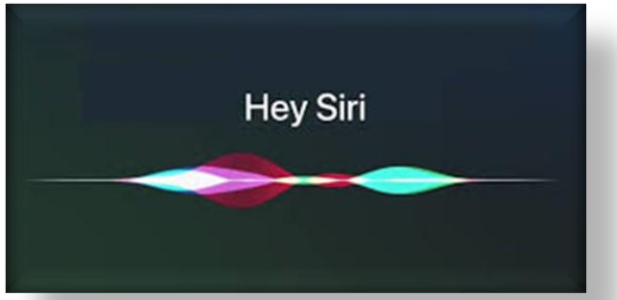
Artificial Intelligence

What is Artificial Intelligence?

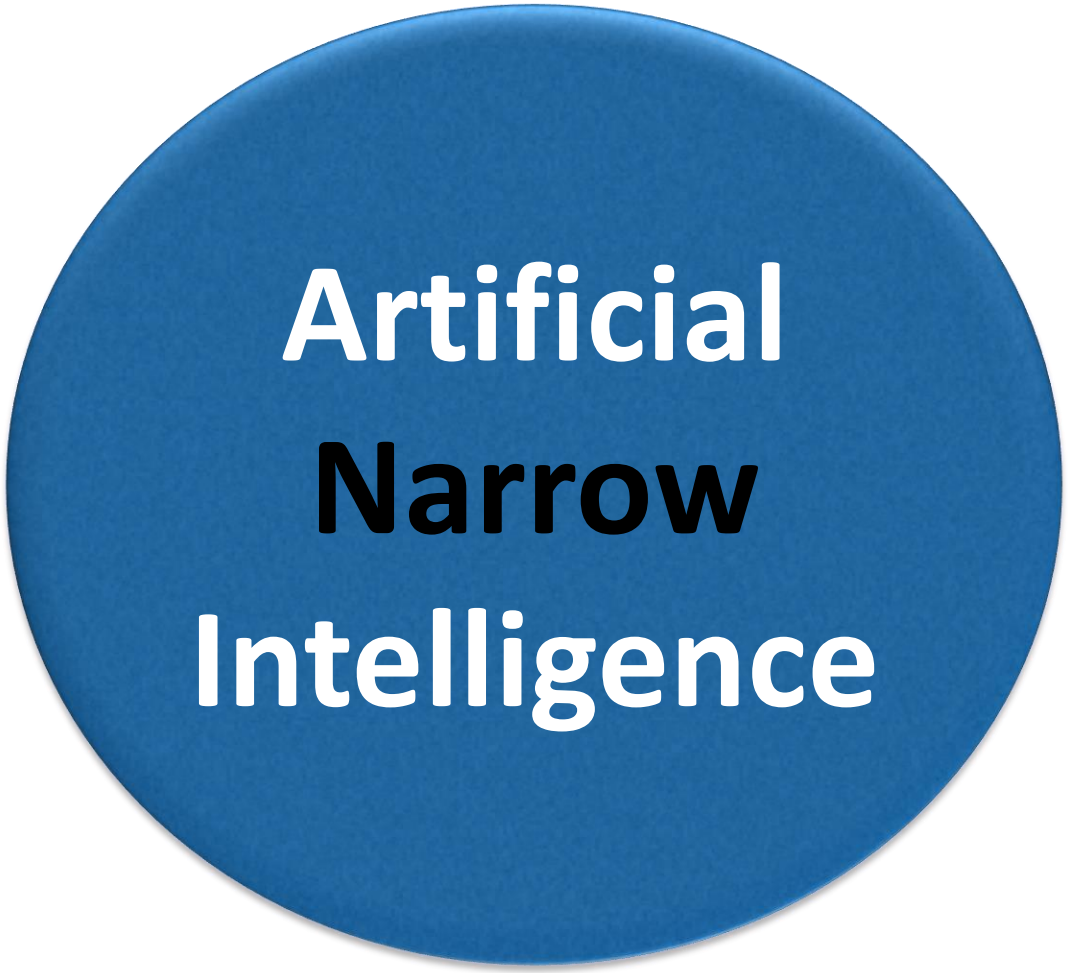
AI is the ability of a computer program or a machine to think and learn. It is also a field of study which tries to make computers "smart"

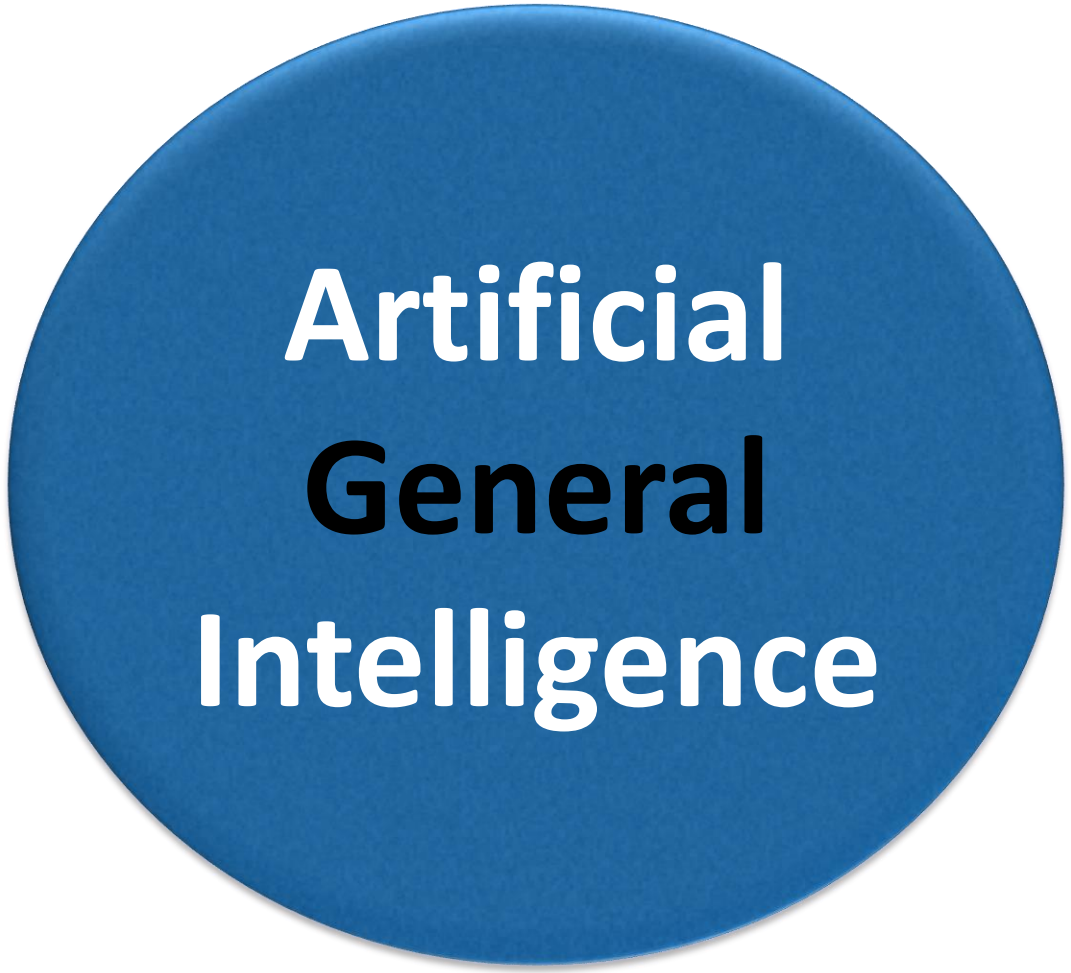
Applications include:

- Game playing
- Natural language processing
- Image Recognition



Artificial Intelligence - Types





Machine Learning

What is Machine Learning?

Humans learn from our past experiences

Machine follow instructions given by humans

What if we humans can train machines to learn from the historical data?

Instead of programming a computer you give a computer examples and it learns what you want

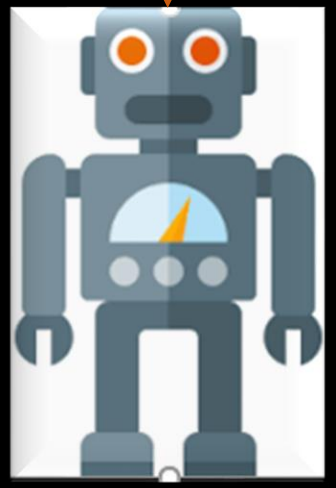
Machines Learn by Example

User ID	Gender	Age	Estimated Salary	Purchased
15624510	Male	19	19000	Yes
15810944	Male	35	20000	No
15668575	Female	26	43000	No
15804002	Male	19	76000	No
15728773	Male	27	58000	No
15598044	Female	27	84000	No
15694829	Female	32	150000	Yes
15600575	Male	25	33000	No

Learns from the data

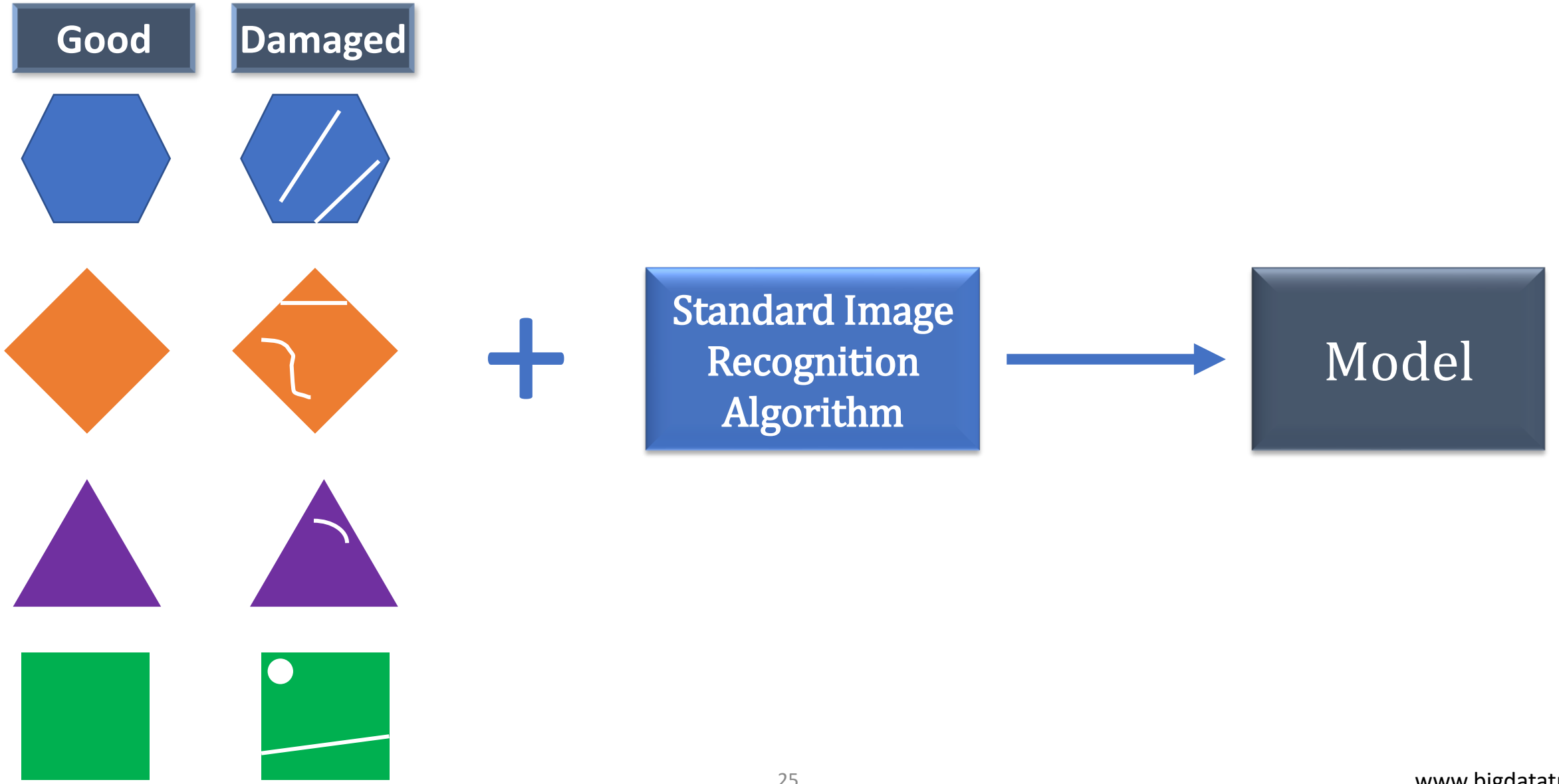
New Input Data

Gender, Age, Estimated Salary

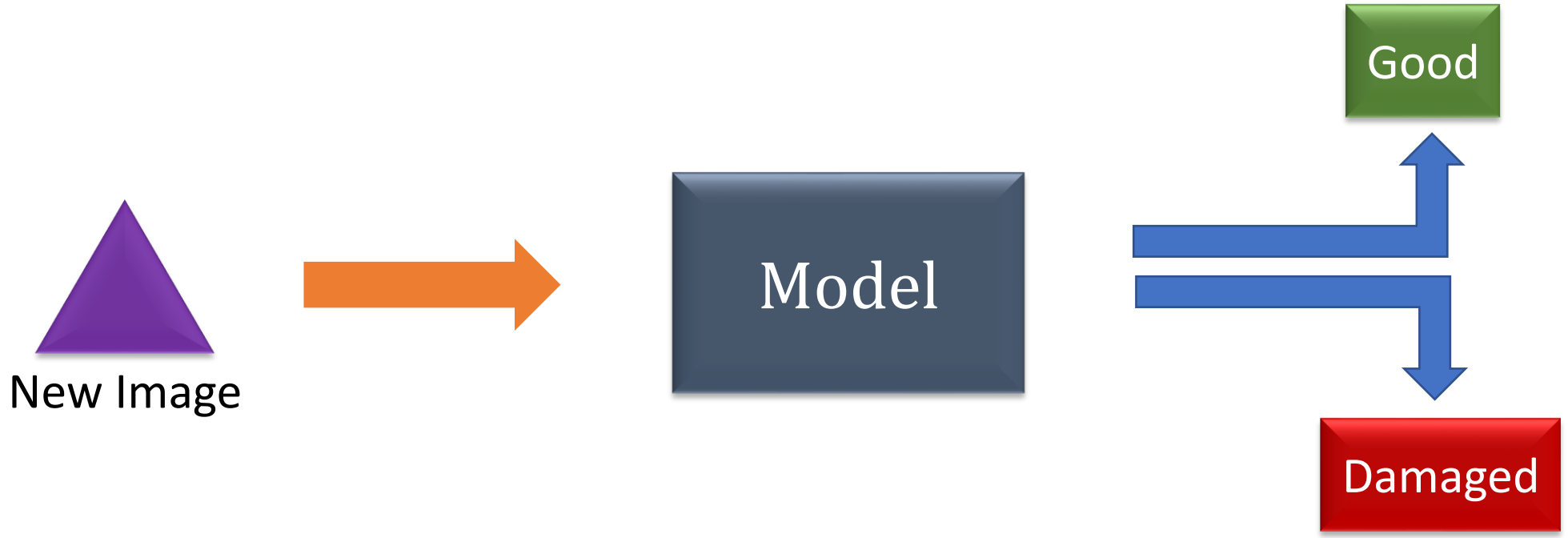


Purchase? Yes or No

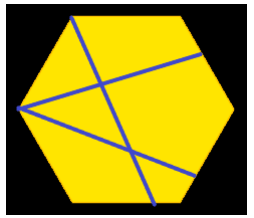
Machines Learn by Examples



Predict with Trained Model



Same Algorithm Different Trained Models



Flower Model (Trained)

≠

Parts Model (Trained)

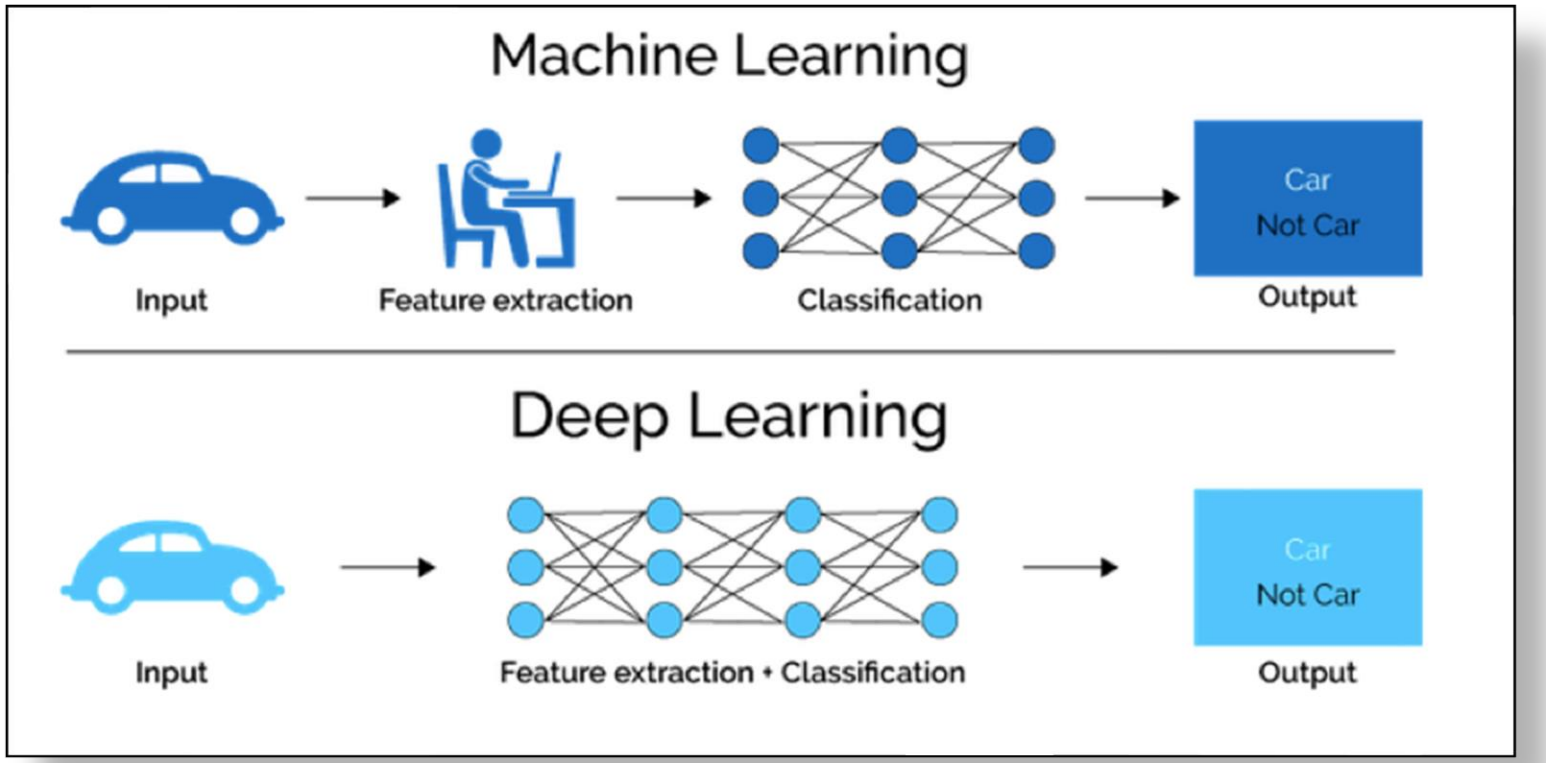
Iris Setosa

Damaged

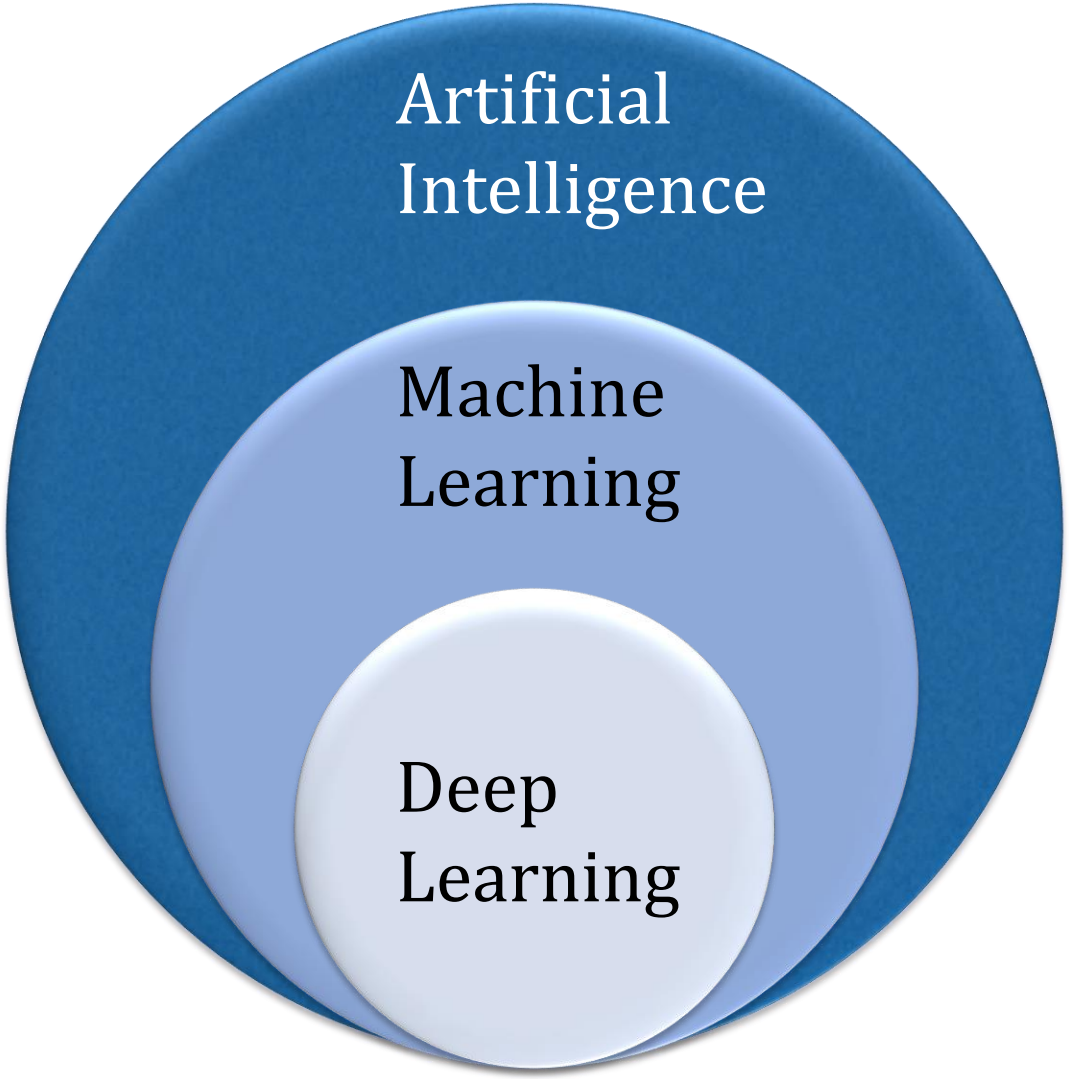
Deep Learning

What is Deep Learning?

Machine Learning v/s Deep Learning



Bringing Them Together



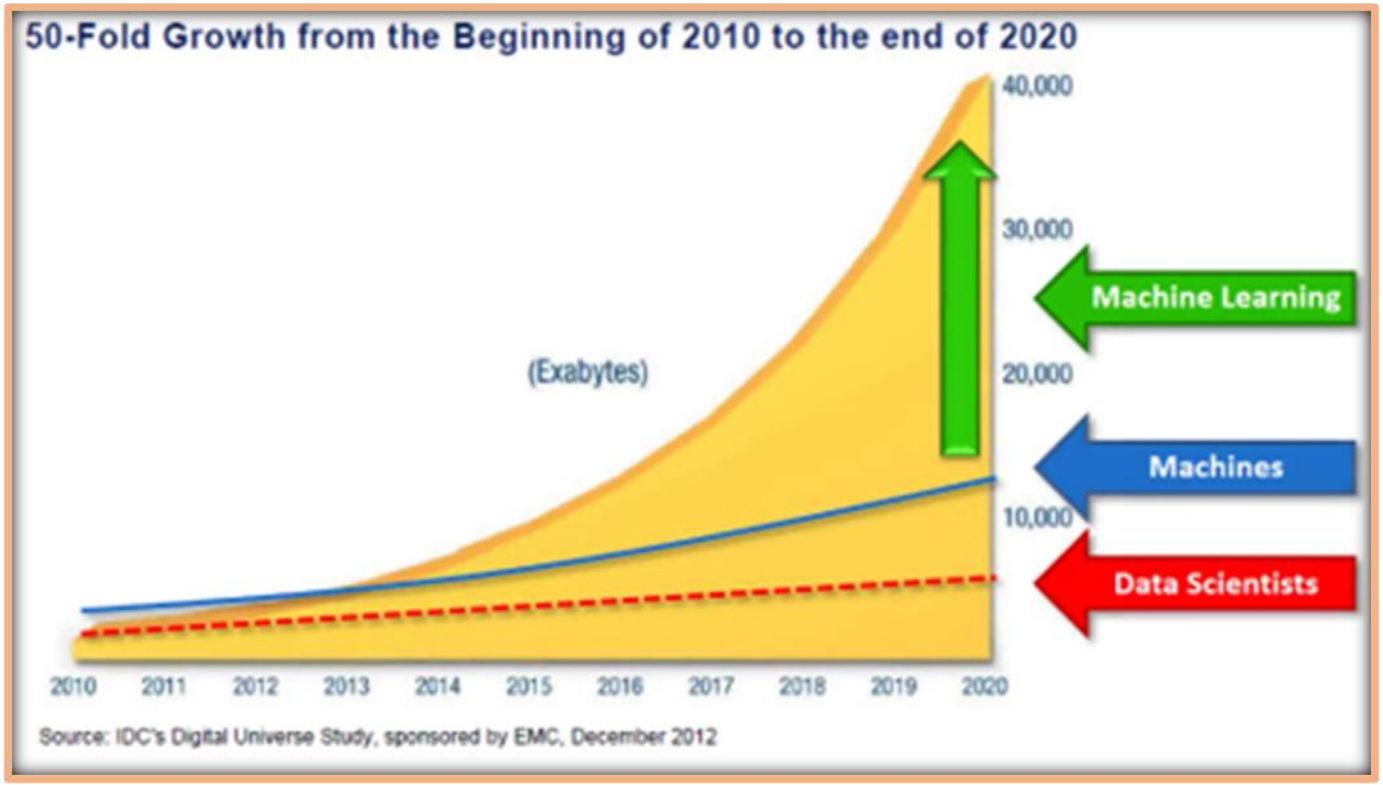
Intelligent Behavior

Learning from data to make predictions and gain insights

Learning using Artificial Neural Networks

Why is it popular in recent years?

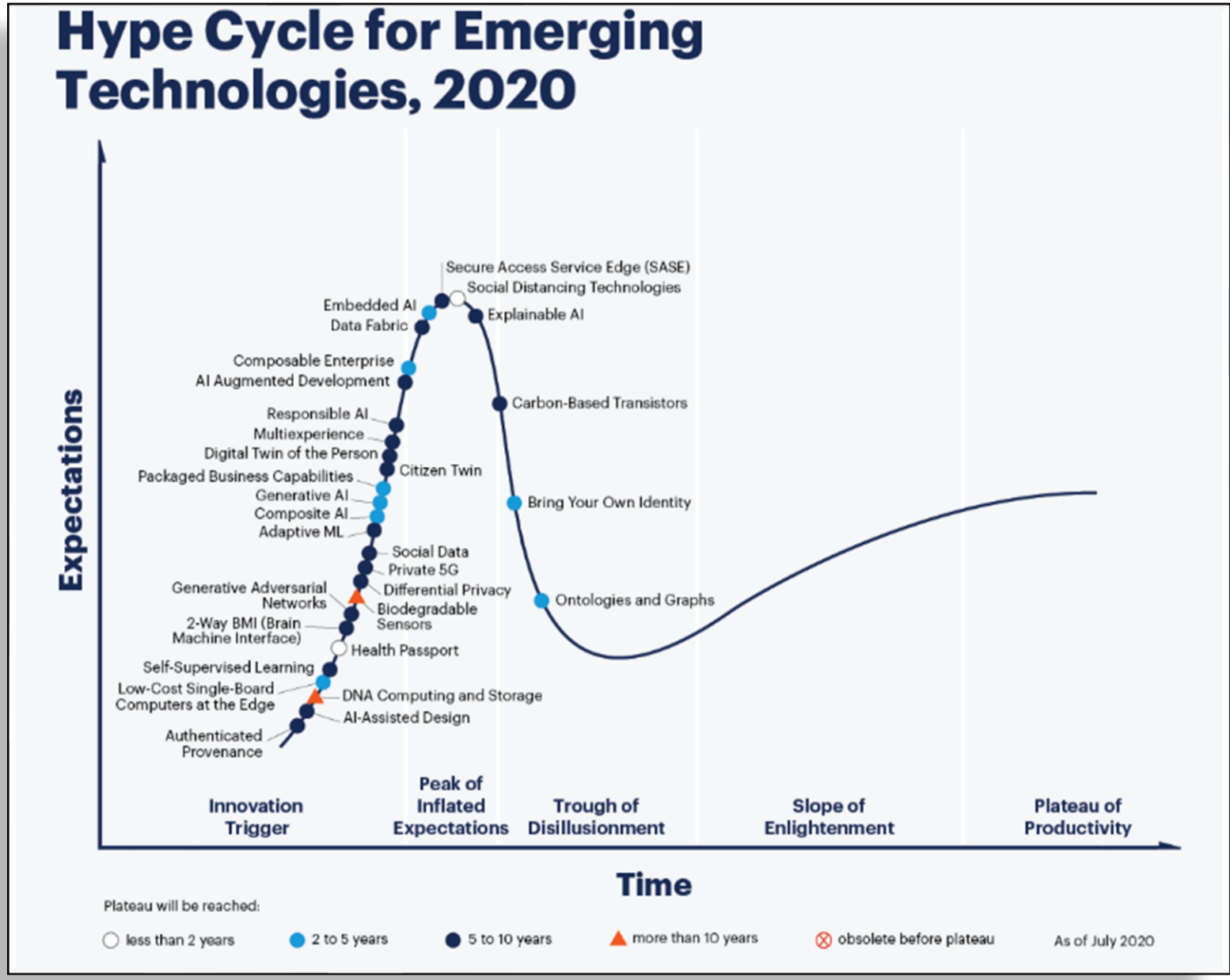
1 terabyte = 1,000 GB
1 petabyte = 1,000 terabytes
1 exabyte = 1,000 petabytes



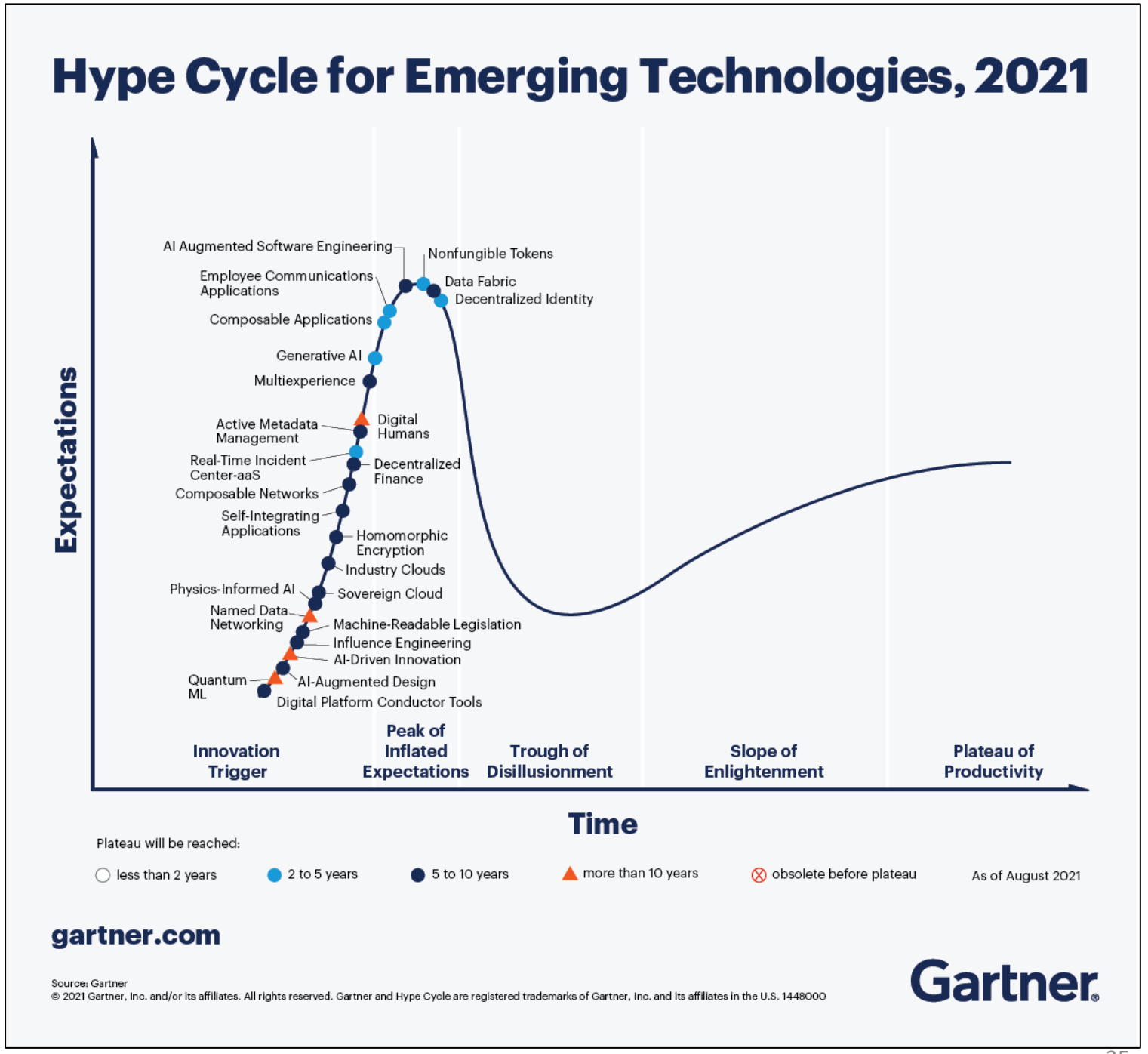
Industry Use Cases

Finance and risk	Sales and marketing	Customer and channel	Operations and workforce
$$$ Revenue Forecasting	Sales forecasting	User segmentation	Agent allocation
Portfolio optimization	Demand forecasting	Personalized offers	Warehouse efficiency
$$$ Investment modelling	Sales lead scoring	Product recommendation	Smart buildings
Fraud detection	Marketing mix optimization		Predictive maintenance
Risk management			Supply chain optimization

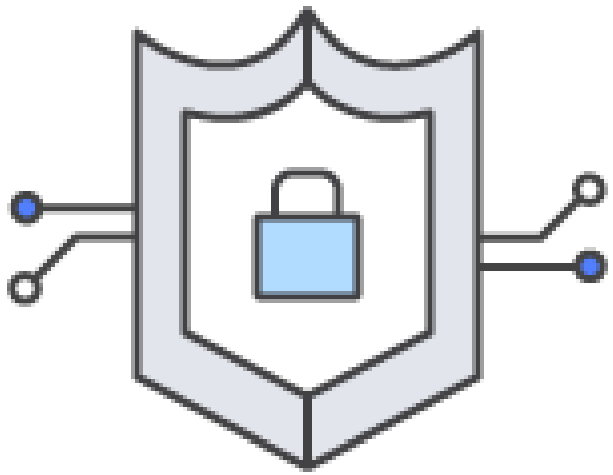
Gartner: 2020 Emerging Technologies



Gartner: 2021 Emerging Technologies

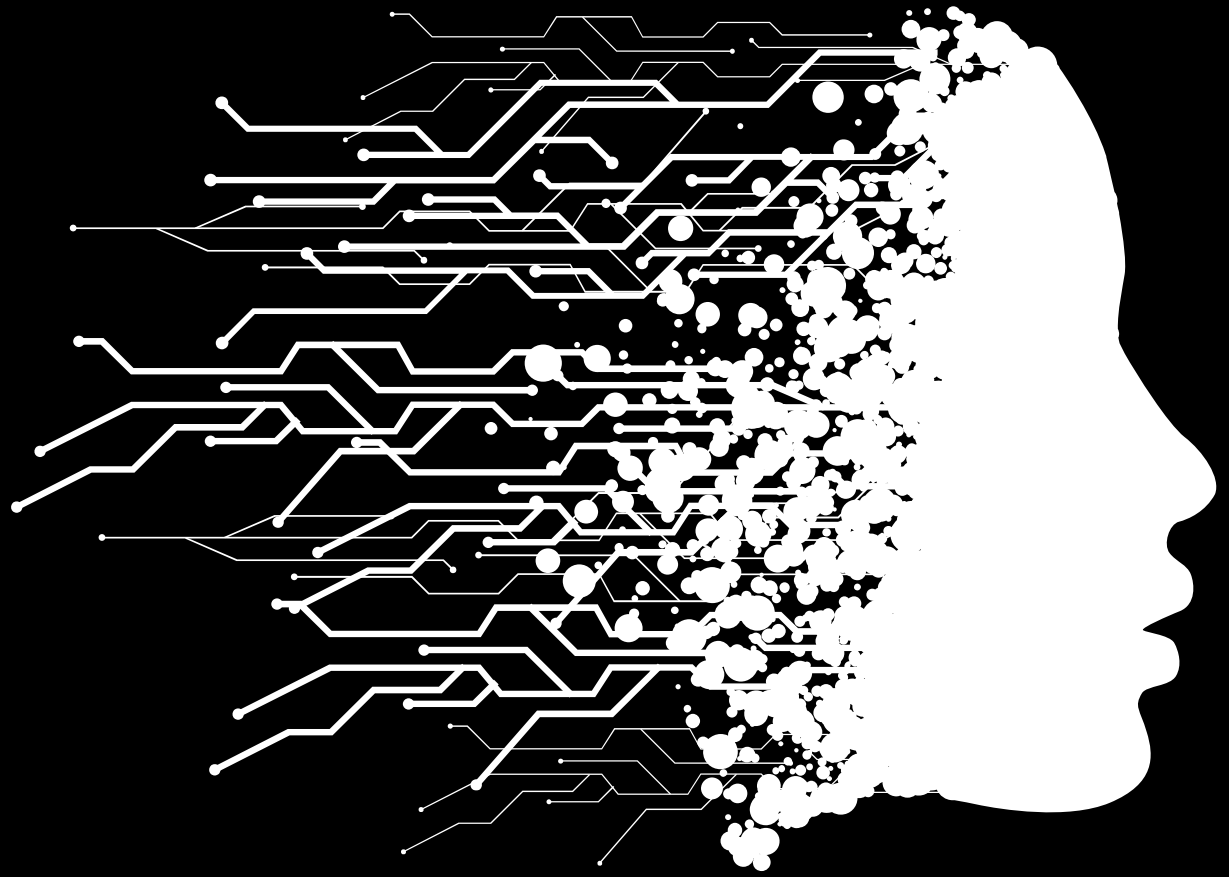


Hands-on

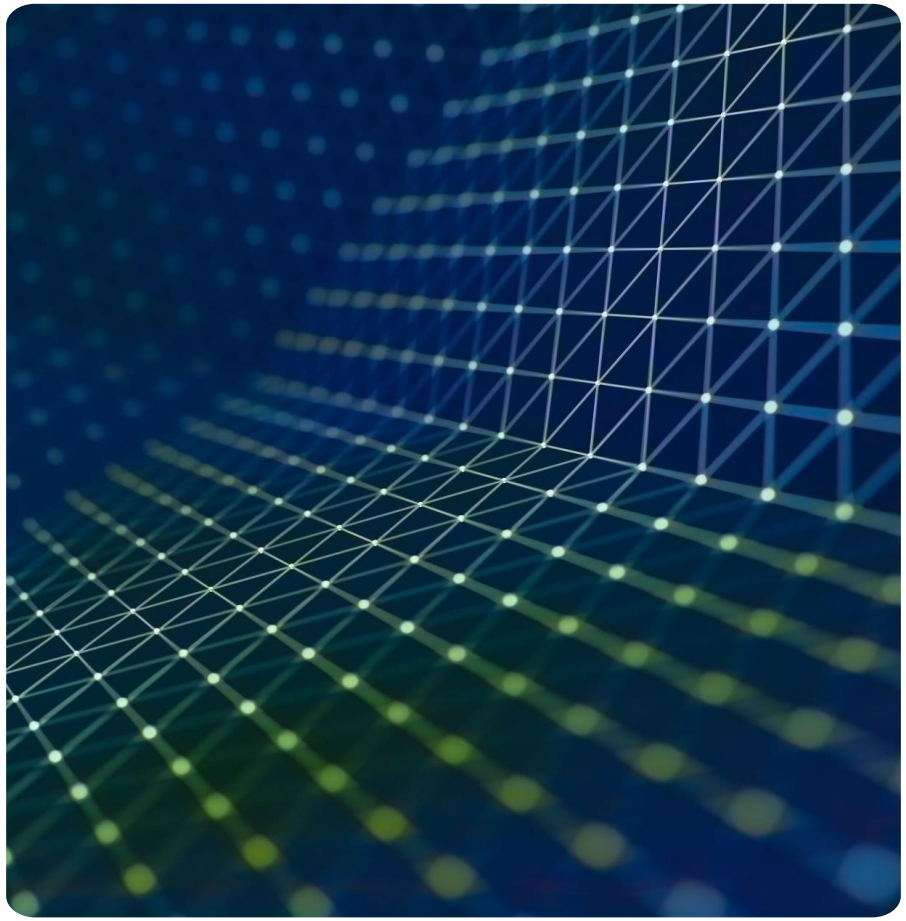


Pandas and Numpy

- Select “Jupyter Notebook” from start menu
- Open file Labs/CodeSamples folder ‘**Pandas Introduction**’ using Jupyter
- Numpy and Pandas examples



Data Exploration and Visualizations



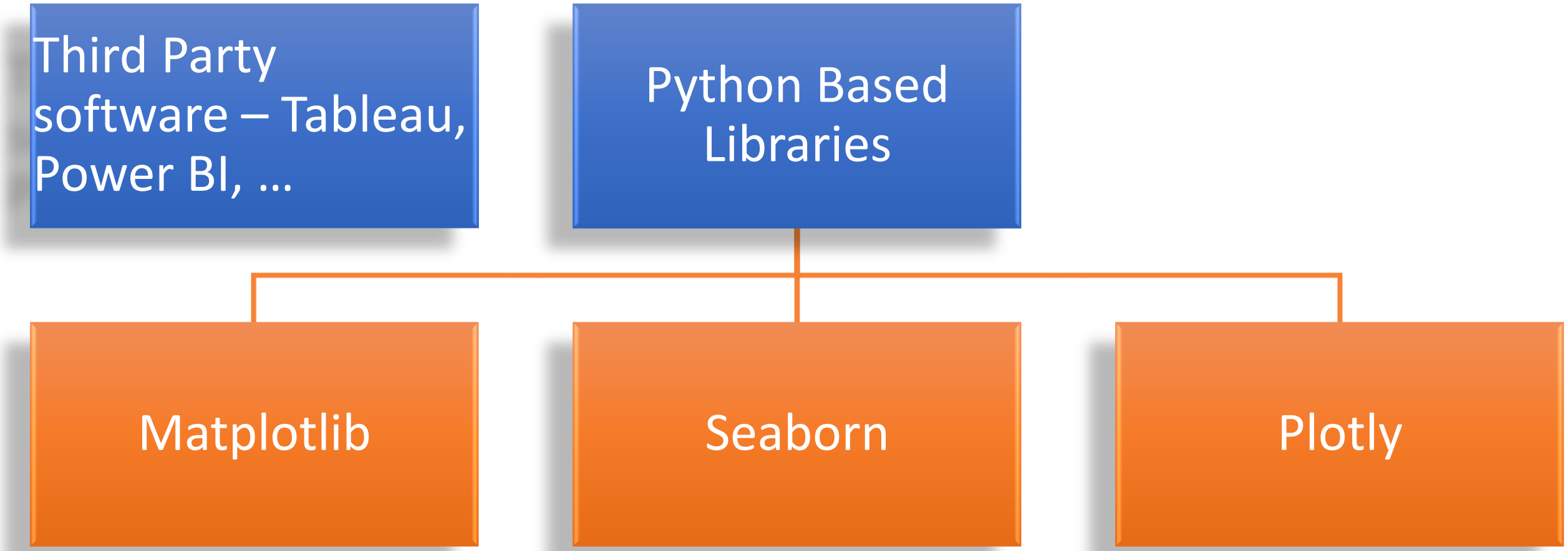
Data Visualization

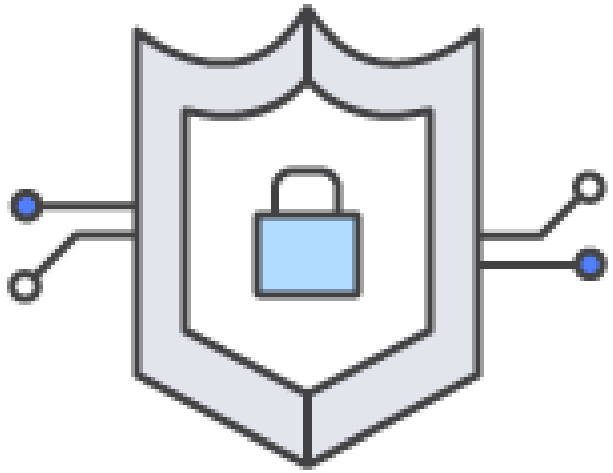
Picture is worth 1000 words …

Visualizing the data is heavily used during the data exploration phase

There are multiple libraries that **help visualize data**

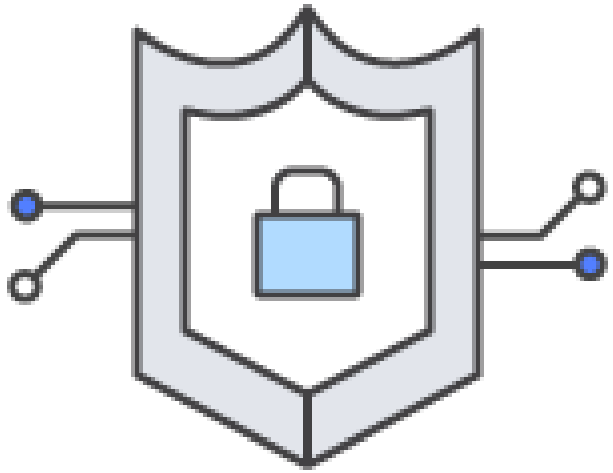
Data Visualization Tools





Matplotlib Examples

- Open file '**CodeSamples/Matplotlib Intro**' using Jupyter
- Creating line, scatter, histograms plots
- Use seaborn library
- Plot Time Series Data



Using Interactive Charts

- Open file '**CodeSamples/PlotlyExamples**' using Jupyter
- Using the Plotly library to create charts that we can zoom into, rotate it, etc.

Data Exploration

Data exploration is the initial step in data analysis

Want to explore any size of dataset to uncover patterns, characteristics

Objective is to get a broad view of the data

Methods include:

- Writing code and using utilities
- Performing data visualizations

Data Exploration

Data can be of various types

- Numbers – integers, float
- Textual

Software

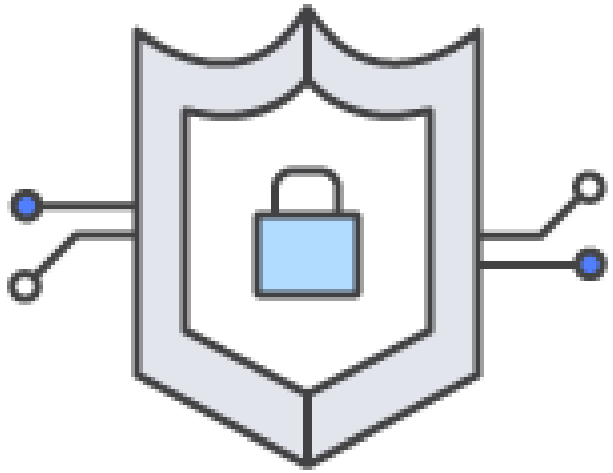
- Tableau, Power BI, ….
- Python based libraries
  - Pandas, Numpy
  - Number of text processing utilities like wordcloud, spacy, ….

Tools to Profile and Visualize Data

- Look at couple of tools to Profile and Visualize data by writing minimal code
- **AutoViz**
  - Load a dataframe and the plot continuous variables in them
  - Plot with or without the target variable
- **Pandas Profiling**
  - Generates HTML report based on Pandas Dataframe
  - Report contains information about:
    - Overall summary (rows, columns, categorical columns, numerical columns, etc.)
    - Variables: summary for each feature including a chart
    - Correlations: feature correlations
    - Missing Values: Display count of missing values (np.nan, null)

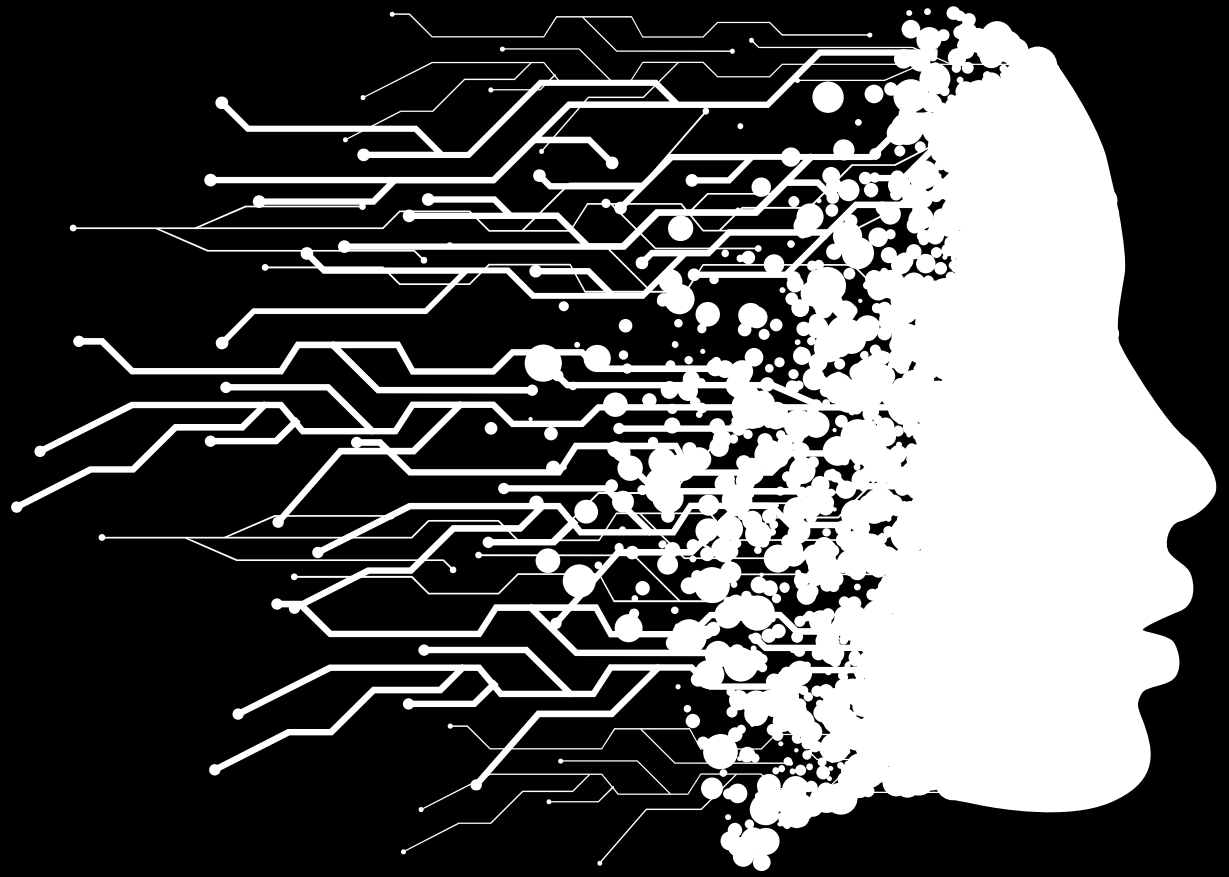
Tools to Profile and Visualize Data

- **Datasist**
  - Open-source python library for doing data analysis, visualizations, modelling, etc.
  - Has features such as:
    - Visualization
    - Model – classifiers, regressors, compare models, feature importance, etc.
  - Will look at visualizations



Profiling and Visualizing

- Open file '**CodeSamples/Pandas-Profiling-Visualizations**' using Jupyter
- Examples of using
  - AutoViz
  - Pandas Profiling
  - Datasist



Machine Learning

Data

If ML is a rocket engine, data is the fuel

Data

Structured Data

User ID	Gender	Age	Estimated Salary	Purchased
15624510	Male	19	19000	Yes
15810944	Male	35	20000	No
15668575	Female	26	43000	No
15603246	Female	27	57000	Yes
15804002	Male	19	76000	No
15728773	Male	27	58000	No
15598044	Female	27	84000	No
15694829	Female	32	150000	Yes
15600575	Male	25	33000	No
15727311	Female	35	65000	No
15570769	Female	26	80000	No
15606274	Female	26	52000	No

Structured Data Types

Numerical

- Exact numbers as data points
- Two types
  - ***Continuous***
    - Can assume any value within a range
    - Height, weight, salary, etc. e.g. 6.3, 40.32, 32.5
  - ***Discrete***
    - Data has distinct values
    - Number of students, units sold, etc. e.g. 15, 30, 10

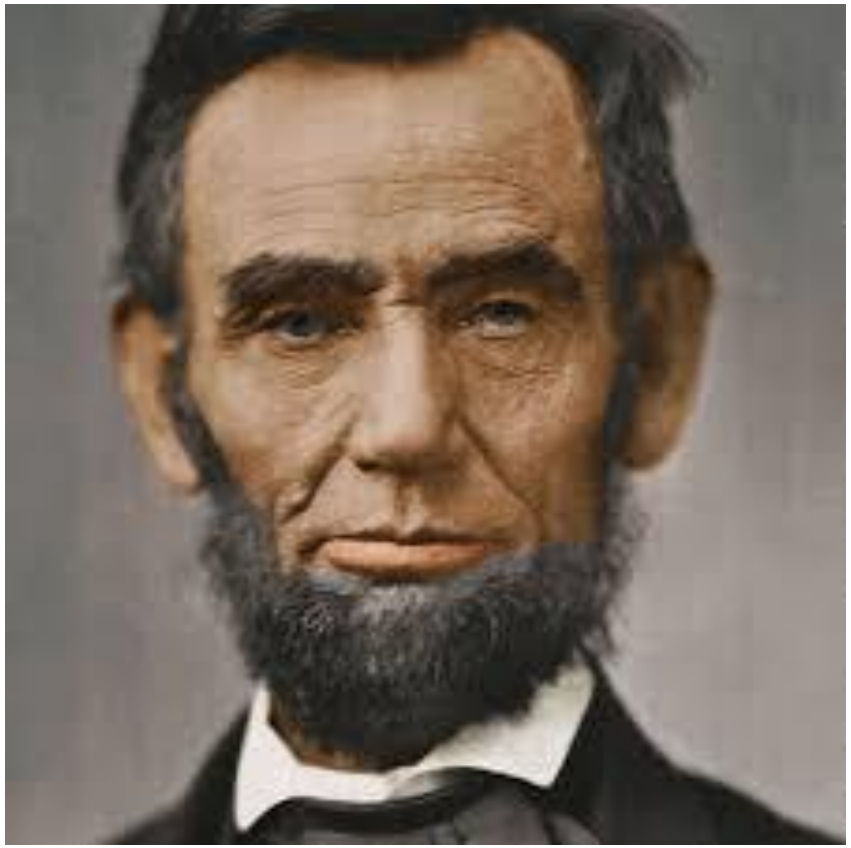
Categorical

- Qualitative data that has no inherent mathematical meaning
- Can assign numbers to categories in order to represent them, however the numbers have no mathematical meaning
- 1 for red, 2 for blue, 3 for green

Ordinal

- A mixture of numerical and categorical data
- Categorical data has the mathematical meaning
- Movie ratings in scale 1 to 5
  - Ratings can be 1, 2, 3, 4 or 5
  - 1 means worst rating, 5 being the best

Unstructured Data



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```

Best Data Qualities

Clean

Coverage

Complete

Otherwise, Garbage in Garbage out

Even for Images

Machine Learning Offerings

Cloud Based Offerings

Programming Languages

Python Based Libraries

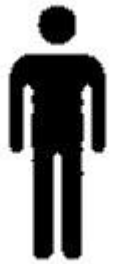
Machine Learning

Deep Learning

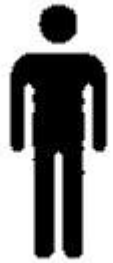
Traditional Software Development v/s Machine Learning

Traditional Software Development

Define an algorithm/logic to solve problem



Implement the algorithm/logic in code



Implemented algorithm

Apply

Input Parameters

Implemented algorithm

Results

Traditional Software Development

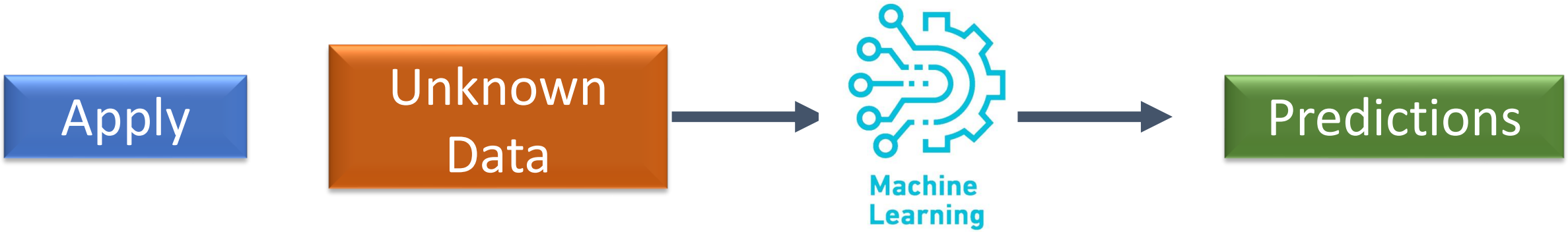
Convert inches to centimeters (cms)

Input: **inches**

Relationship: **cms** = **inches * 2.54**

Output: **cms**

Machine Learning Development



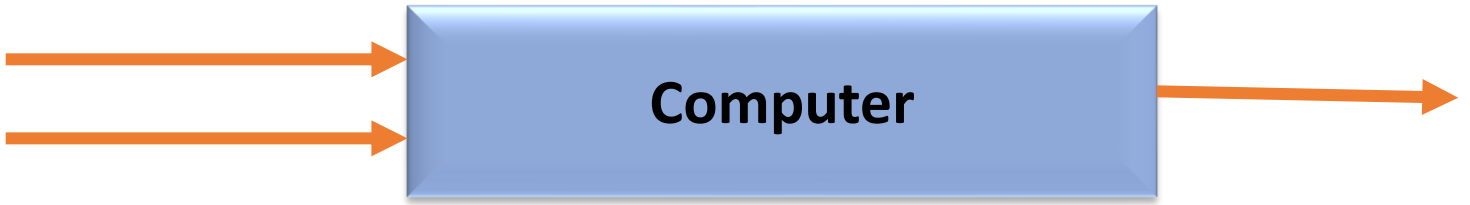
Programming v/s Machine Learning

Input Data

X= 1 , 2 , 3 , 4

Program

Square (X) = X * X



Output

1 , 4 , 9 , 16

Input Data

X= 1 , 2 , 3 , 4

Output

1 , 8 , 27, 64

5

125

y = Cube (X)

Machine Learning Techniques

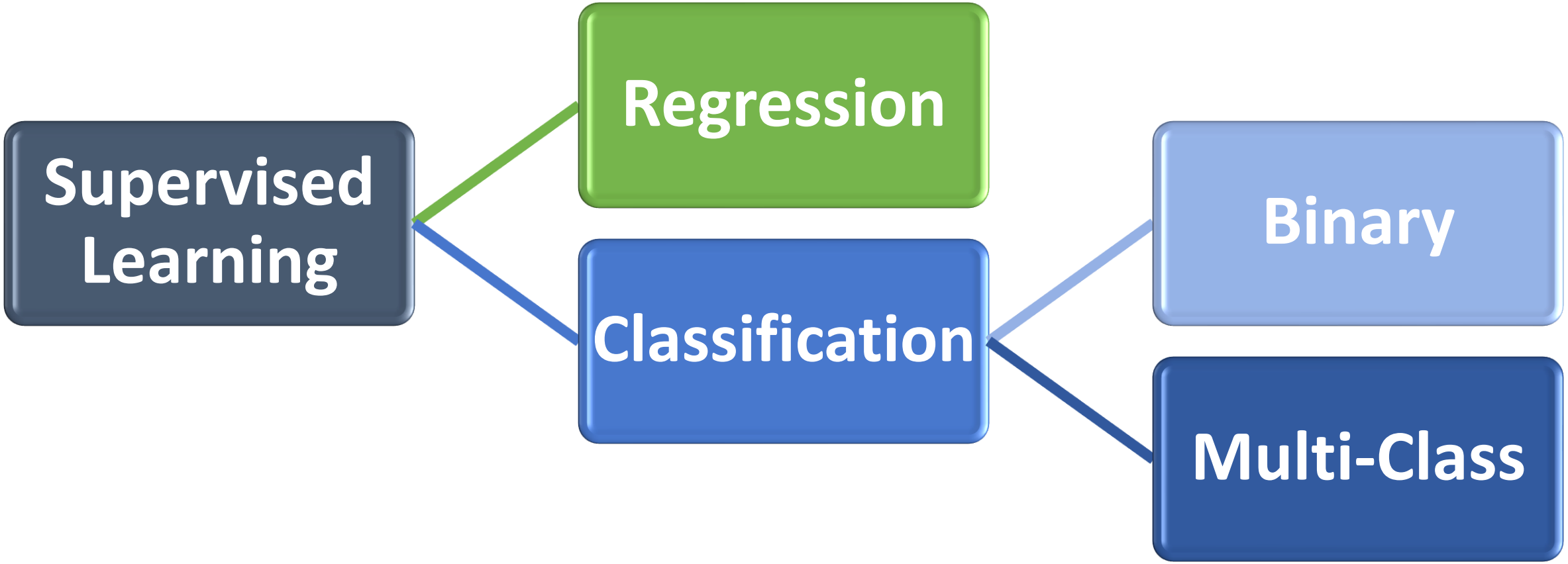
Machine Learning Techniques

Supervised Learning

Unsupervised Learning

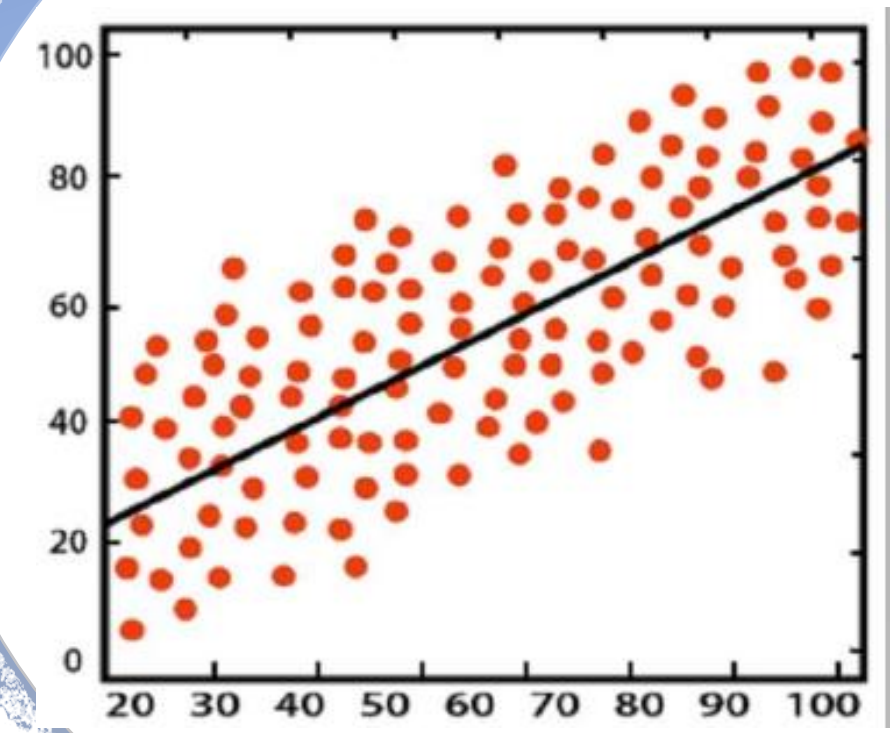
Supervised Learning

Supervised Learning – Predict a Label



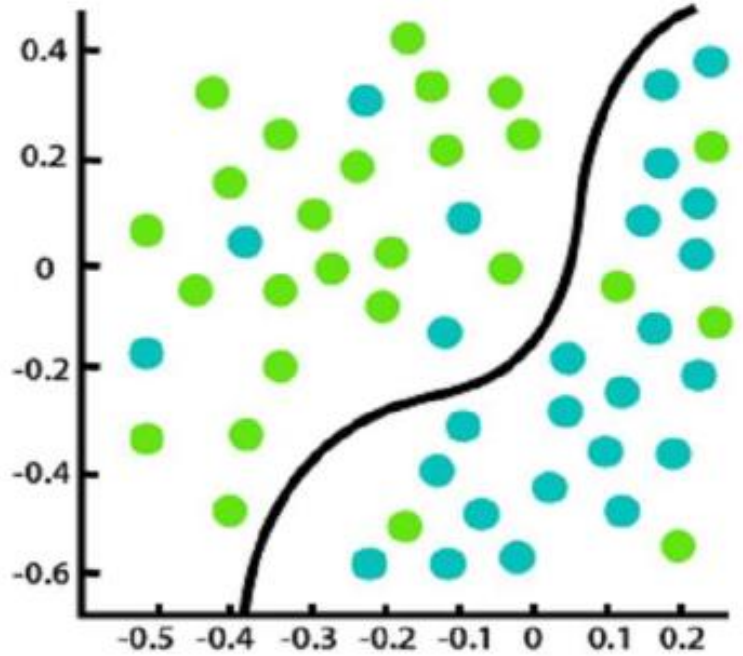
Regression

- **Use cases**
  - Forecasting Sales
  - Stock, Real Estate Prices
  - Auto/Home Insurance premiums
  - Customer support – number of issues over a time period, etc.
- **Algorithms**
  - Linear Regression
  - Decision Tree
  - Random Forest

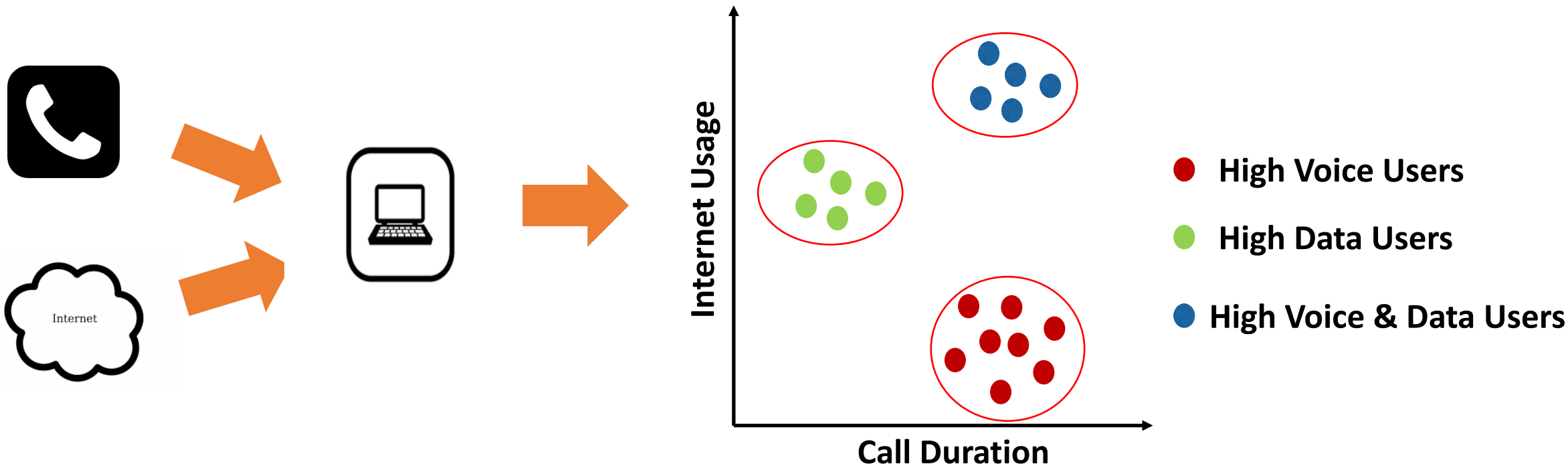


Classification

- **Use cases**
  - Patient is likely to have diabetes or not
  - Transaction is fraudulent or not
  - Which price quotes are likely to turn into orders
- **Machine Learning Algorithms**
  - Decision Tree
  - Logistic Regression
  - Random Forest
  - Support Vector Machine
  - Many more ….



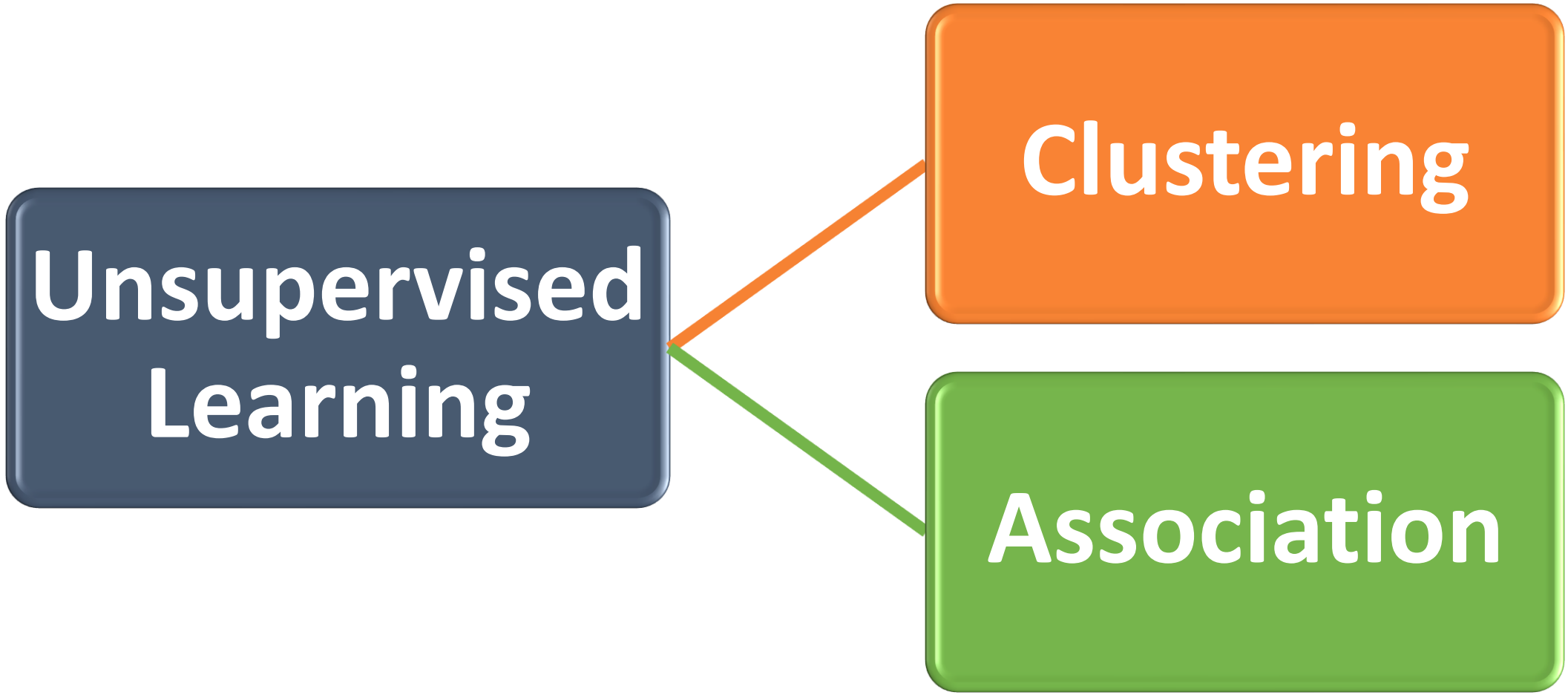
Unsupervised Learning



Unsupervised Learning – Creating grouping of data

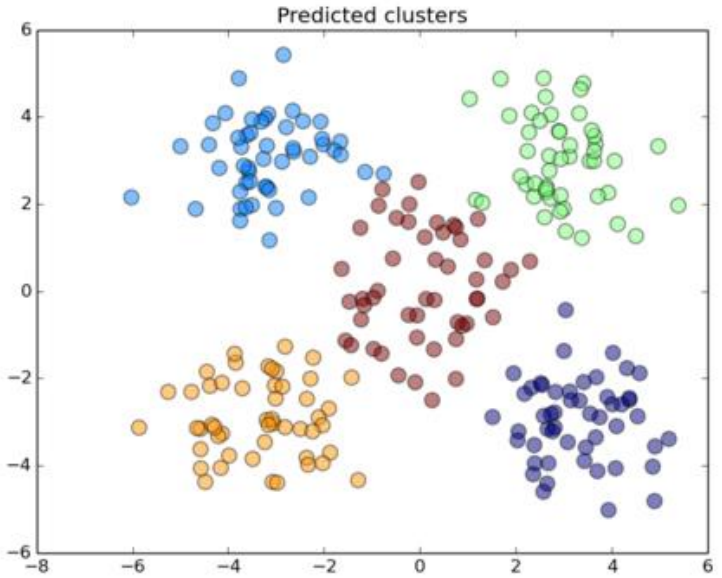
Not predicting a label

Unsupervised Learning- Types



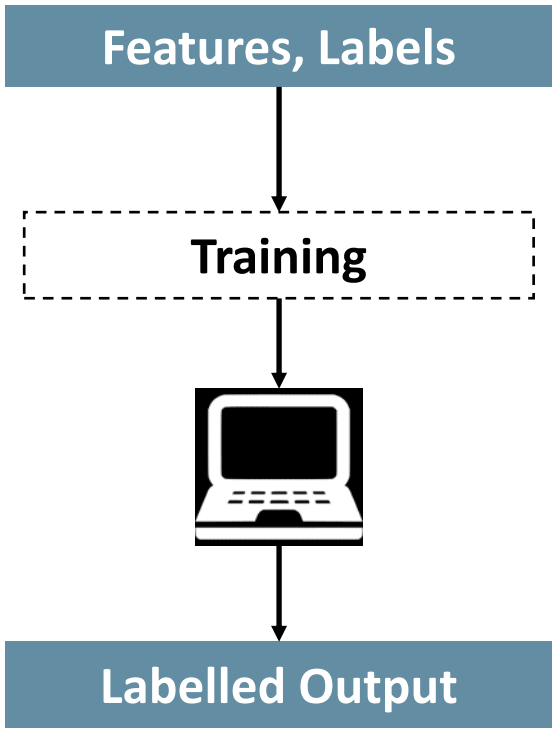
Clustering

- **Use cases**
  - Market segmentation
  - Pattern recognition
  - High Data, High Voice, High Data and Voice users – telecom company
- **Algorithms**
  - K-Means
  - Hierarchical Clustering



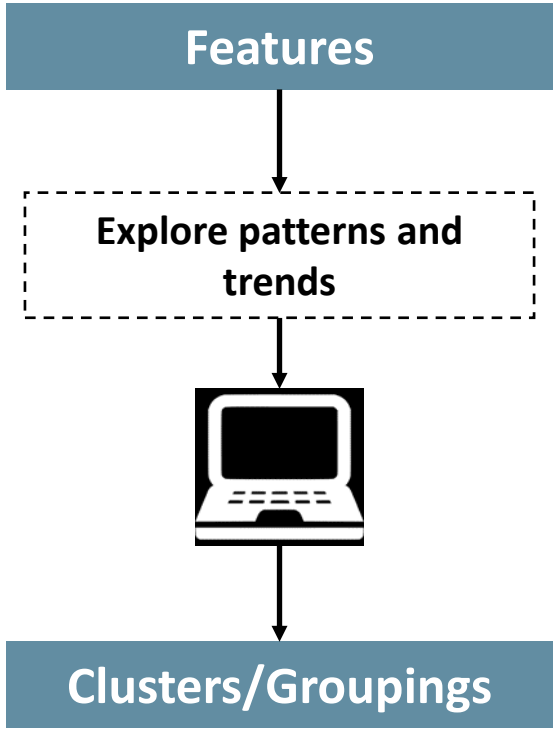
Learning Approaches

Map labelled input to known output



Supervised

Understand patterns and discover output



Unsupervised

Model Development

Define Problem

Collect Data

Data can come from various sources – social media, databases, etc.

Prepare Data

Clean data and prepare for machine learning

Analyze Data

Analyze data, perform feature selection.

Train Algorithm

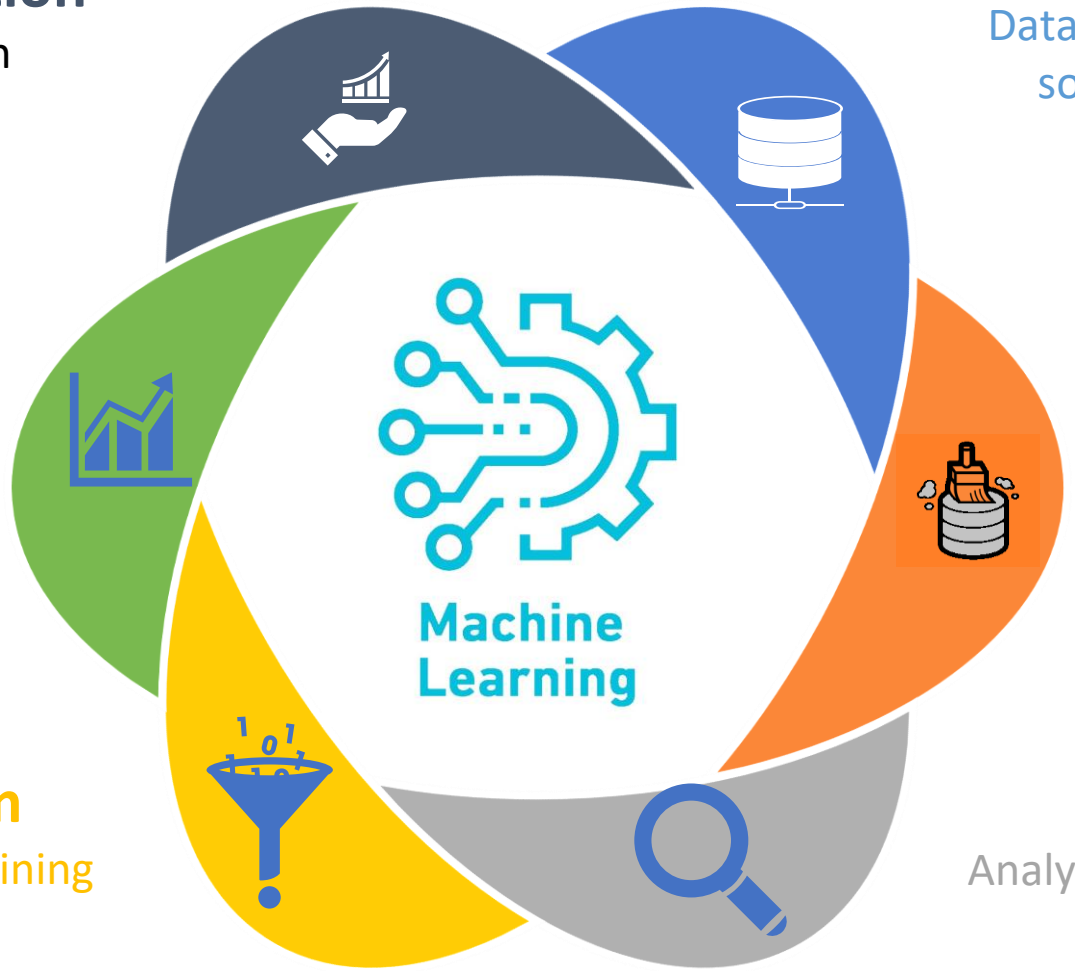
Train algorithm with training dataset

Evaluate Model

How does the model perform with unseen data?

Model in production

Deploy the model in production



Data Split (Randomly)

Training Data

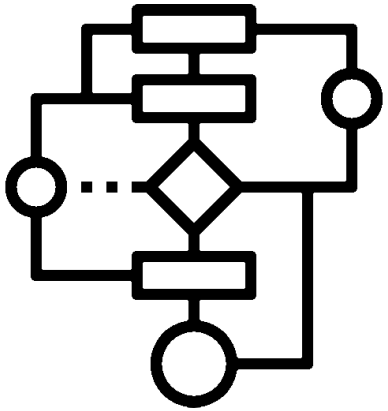
70 %

Test Data

30 %

Training Model

Training Data

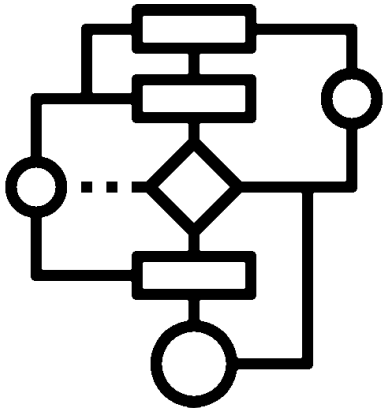


Algorithm

Prediction	Label
0	1
1	1
0	0
0	1
1	0
0	0

Training Model

Training Data

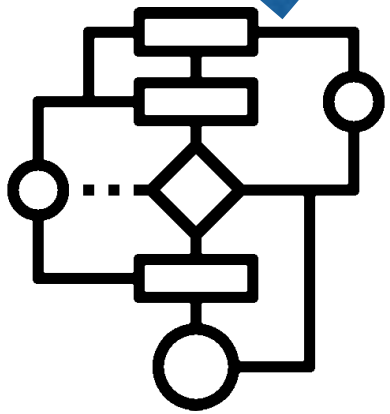


Initial Model

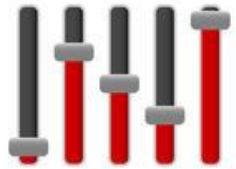
Prediction	Label
0	1
1	1
0	0
0	1
1	0
0	0

Training Model

Training Data



Initial Model

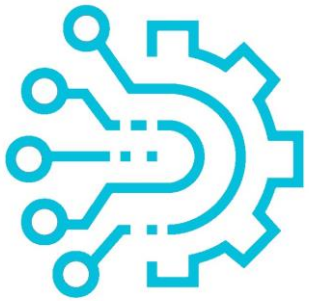


Adjust Parameters

Prediction	Label
0	1
1	1
0	0
0	1
1	0
0	0

Training Model

Training Data

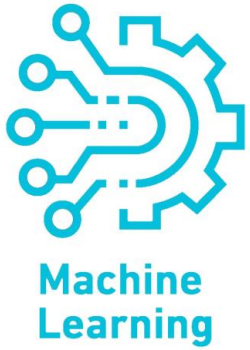


Model Ready

Prediction	Label
1	1
1	1
0	0
1	1
0	0
0	0

Model Evaluation

Test Data



Model

Prediction	Label
0	1
1	1
0	0
1	1
1	0
0	0

Machine Learning - Code

Training

algorithm.fit(training dataset)

Evaluate with Test Data

model.predict(test dataset)

Evaluation the Model

model.score(test dataset, predictions)

Algorithms

Machine Learning - Predictions

$y = f(X)$

$\hat{y} = \hat{f}(X)$ Prediction

$\hat{y} = 22.5$ Regression – continuous value

$\hat{y} = 0.89$ Classification – probability

$\hat{y} = 1$ Classification – prediction

Algorithms

Linear Regression

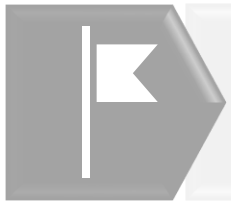
- Predicting real numbers – home prices, expected sales, etc.
- Drawing a best fit line to describe the relationship between the features

Logistic Regression

- Used in classification – buy a product or not
- Predicts probability of an event occurring

Support Vector Machines

- Can be used for either classification or regression – but mostly in classification
- Algorithm looks at data from non probabilistic view & uses linear separation of data



K-Nearest Neighbors

- Assumes that similar things exist in close proximity to each other
- Used for both classification and regression

Decision Trees

- Builds binary tree based on the data points
- Used for both classification and regression – mostly for classification

Algorithms

Random Forest

- Uses multiple decision trees to make predictions
- Majority prediction wins, can be used for both classification and regression

K-Means Clustering

- Partitions the data into K clusters (or grouping)
- Have to define how many clusters are required

Hierarchical Clustering

- Builds hierarchy of clusters by grouping data points (builds something called Dendrograms)
- Two types
  - Agglomerative – bottom up approach, every point starts as its own cluster and pairs of points are merged as one moves up the hierarchy
  - Divisive – top down approach, all points start as one cluster and they are split recursively as one moves down the hierarchy

Regression

Multiple Linear Regression - Multivariate

$$y = b_0 + b_1 x_1 + b_2 x_2 \ \ldots\ldots + b_n x_n$$

- *y* is the dependent variable
- x_i are the independent variables

Multiple Linear Regression

R&D Spend	Administration	Marketing Spend	State	Profit
165349.2	136897.8	471784.1	0	192261.83
162597.7	151377.59	443898.53	1	191792.06
153441.51	101145.55	407934.54	0	191050.39
144372.41	118671.85	383199.62	0	182901.99
142107.34	91391.77	366168.42	0	166187.94
131876.9	99814.71	362861.36	0	156991.12
134615.46	147198.87	127716.82	1	156122.51
130298.13	145530.06	323876.68	0	155752.6

$$profit = 1.63 + 7.91x_1 + 3.8x_2 + 6.88x_3 - 0.12x_4$$

x_1 = R&D Spend

x_2 = Administration

x_3 = Marketing Spending

x_4 = State (0 = California, 1 = New York)

Model Metrics

Model Evaluations

Loss Function

- A method to evaluate how well our algorithm is modeling our dataset
- If predictions are way off then the loss function will have higher value
- Absolute value of (prediction – actual value)

Loss Function – Mean Squared Error

Mean Square Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y} - y)^2$$

Root Mean Square Error (RMSE)

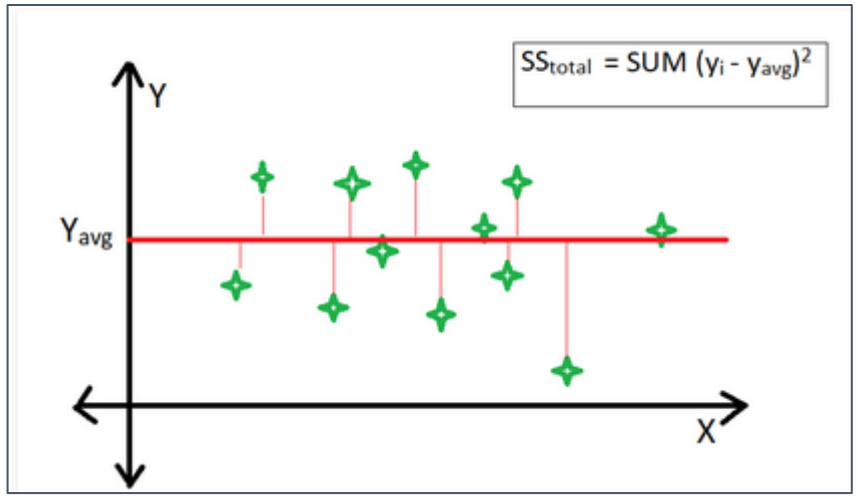
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y} - y)^2}$$

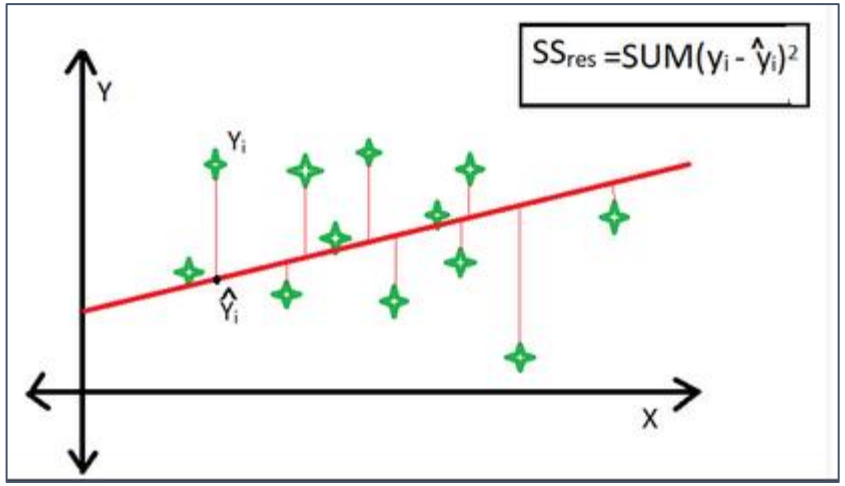
R-Squared (R^2)

Statistical measure of how close the data are to the fitted line

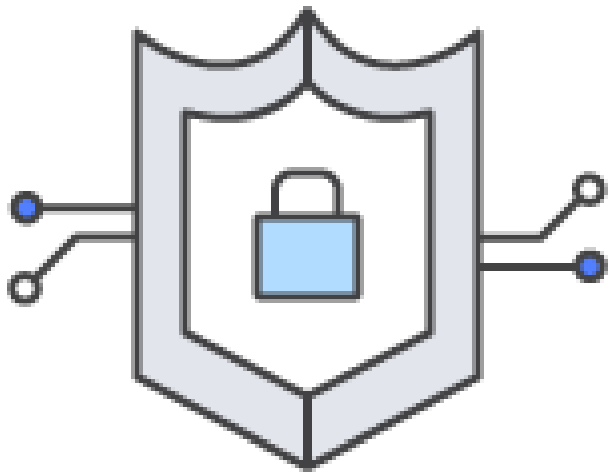
Usually, values are between 0.0 and 1.0

Higher the R^2 value, the better the model fits the data





$$R^2 = 1 - \frac{SSres}{SStot}$$



Linear Regression Demo

- Open file ‘CodeSamples/LinearRegression’ using Jupyter
- Start up dataset with 50 samples.
- Want to build a Linear Regression Model to predict a new start up will be profitable

Assignment – Linear Regression

- Open file '**Assignment/LinearRegression RealEstate**' using Jupyter
- Implementation requirements are defined in the notebook in red

Day 2

Welcome to Day 2 AI Toolkit

Please perform PRE-WORK

1. Access the virtual Lab using link https://html.inspiredvlabs.com Use the username TEKBD142-XX (replace XX with your number) and password

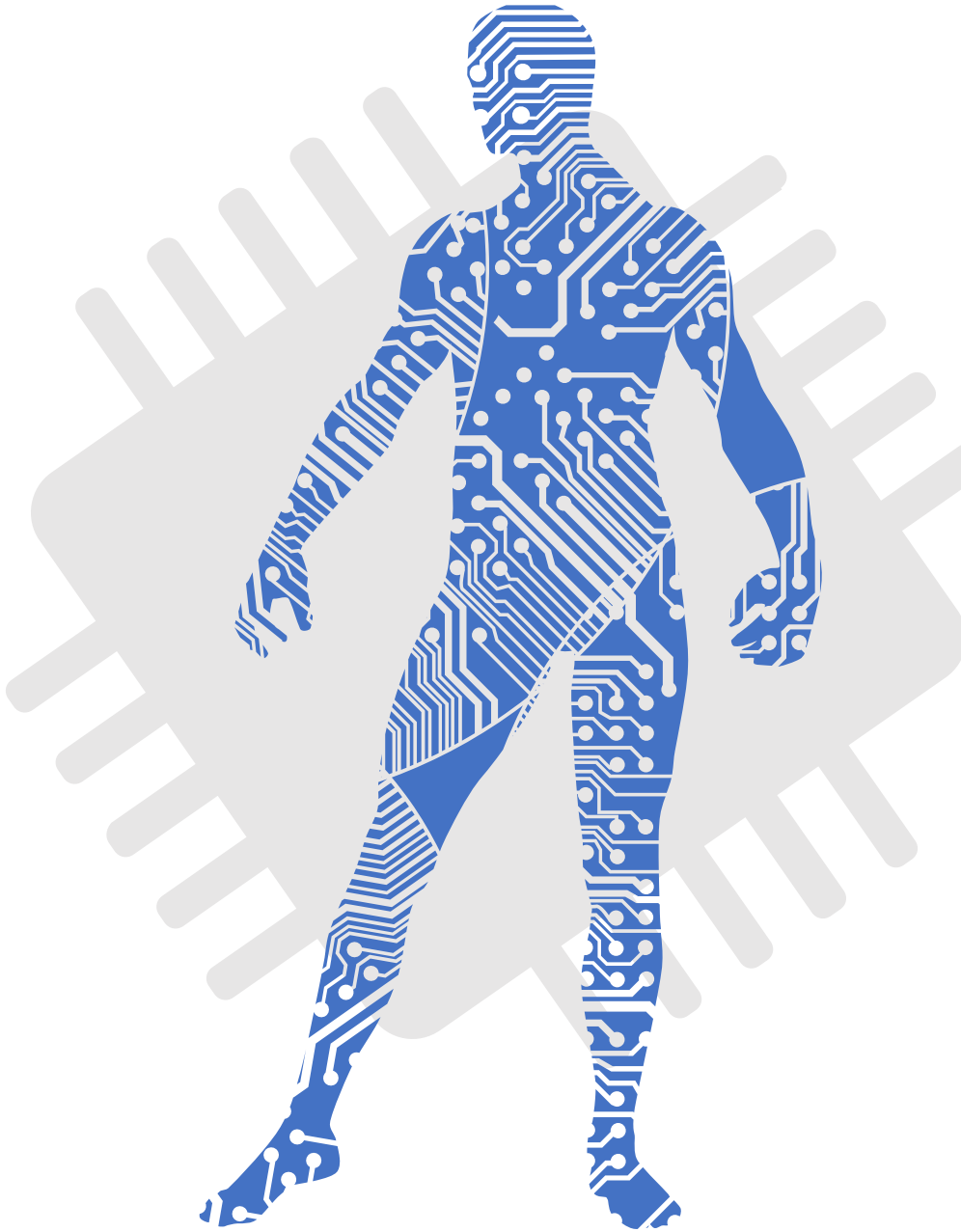
TekBD142!23

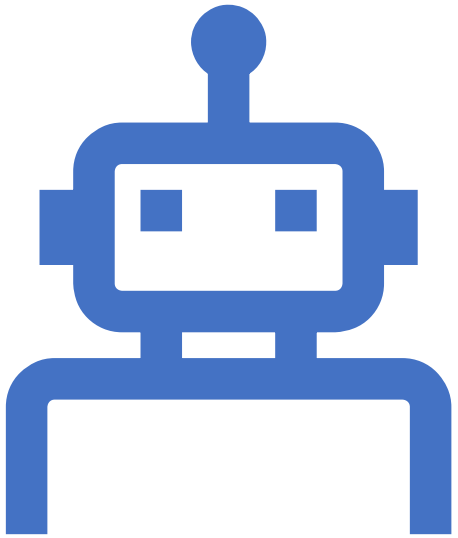
We will be starting soon

Last Name	First Name	Login Id
AHMED	NAZEER	TEKBD142-01
AM	GANESH	TEKBD142-02
BISWAS	SOURAV	TEKBD142-03
CHACKO	THOMAS	TEKBD142-04
JAJOO	SANDESH	TEKBD142-05
MATTOX	CHRISTEL	TEKBD142-06
MAXSON	CRAIG	TEKBD142-07
MURPHY	MATTHEW	TEKBD142-08
PANDIAN	JEYARAJ	TEKBD142-09
PATURI	RAVIKIRAN	TEKBD142-10
RANI	AMITA	TEKBD142-11
SINGLA	SANJEEV	TEKBD142-12
VEERAMASU	BRAHMA RAO	TEKBD142-13

Agenda – Day 2

1. Recap of Day 1
2. Classification
3. Pipeline and Model Persistence
4. Word Cloud
5. TensorFlow
6. Artificial Neural Networks (ANN)
7. Multiple Hands-on





Recap Day - 1

- AI – Machine Learning – Deep Learning
- Machine Learning Introduction
- Machine Learning Techniques
- Machine Learning Development
- Linear Regression
- Model Metrics
- Multiple Hands-on

Categorical Data Handling

DataFrame (some of the columns)

Age	Sex	Race	Income
39	Male	White	<=50K
50	Female	Black	>50K
38	Female	Asian	<=50K
53	Male	Other	>50K

Label Encoder / Imputer

Age	Sex	Race	Income
39	0	0	0
50	1	1	1
38	1	2	0
53	0	3	1

One-Hot Encoding

Age	Sex	Race	Race_ White	Race_ Black	Race_ Asian	Race_ Other	Income
39	0	0	1	0	0	0	0
50	1	1	0	1	0	0	1
38	1	2	0	0	1	0	0
53	0	3	0	0	0	1	1

Column Transformer

Age	Sex	Race	Race_ White	Race_ Black	Race_ Asian	Race_ Other	Income
39	0	0	1	0	0	0	0
50	1	1	0	1	0	0	1
38	1	2	0	0	1	0	0
53	0	3	0	0	0	1	1

Column Transformer:

Age	Sex	Race	Race_ White	Race_ Black	Race_ Asian	Race_ Other	Income
39	0	0	1	0	0	0	0
50	1	1	0	1	0	0	1
38	1	2	0	0	1	0	0
53	0	3	0	0	0	1	1

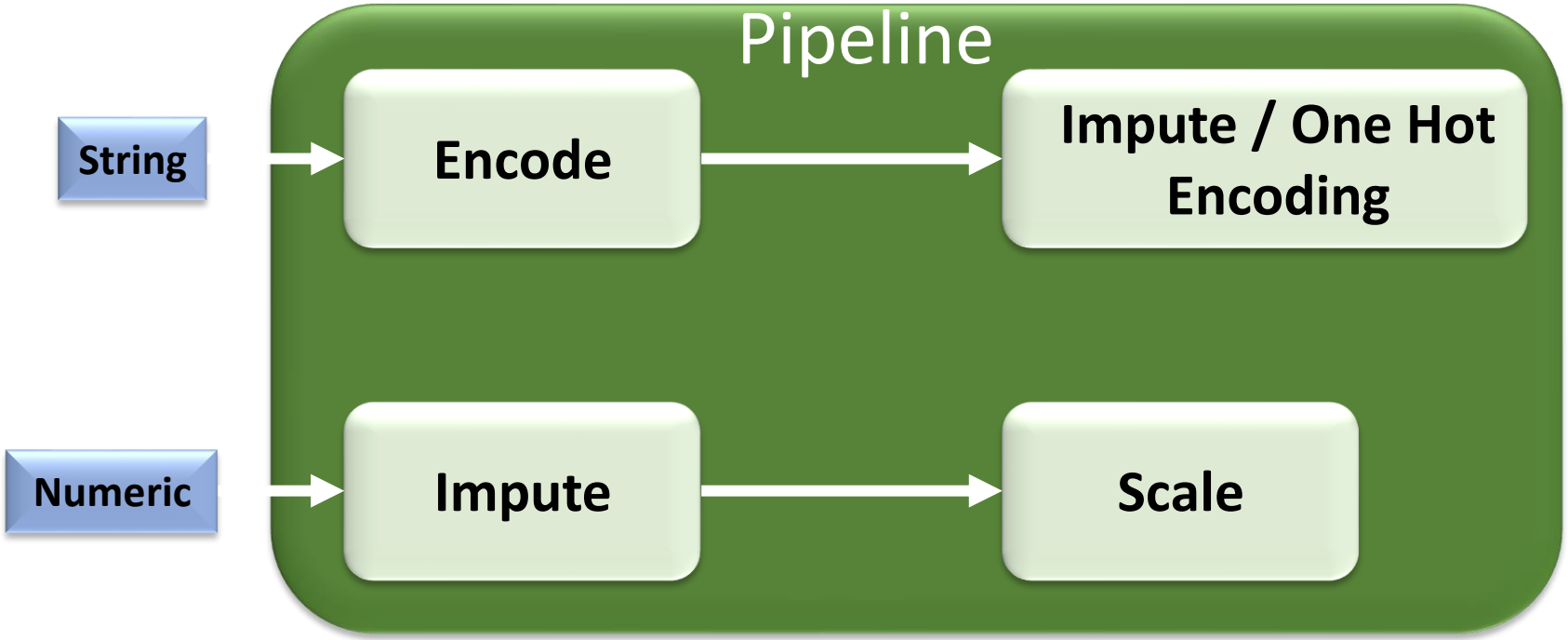
Column Transformer

Age	Sex	Race	Race_ White	Race_ Black	Race_ Asian	Race_ Other	Income
39	0	0	1	0	0	0	0
50	1	1	0	1	0	0	1
38	1	2	0	0	1	0	0
53	0	3	0	0	0	1	1

Column Transformer:

Age	Sex	Race	Race_ White	Race_ Black	Race_ Asian	Race_ Other	Income
39	0	0	1	0	0	0	0
50	1	1	0	1	0	0	1
38	1	2	0	0	1	0	0
53	0	3	0	0	0	1	1

Pipeline



- A machine learning work-flow
- Made up of number of stages
- Can be persisted

Logistic Regression

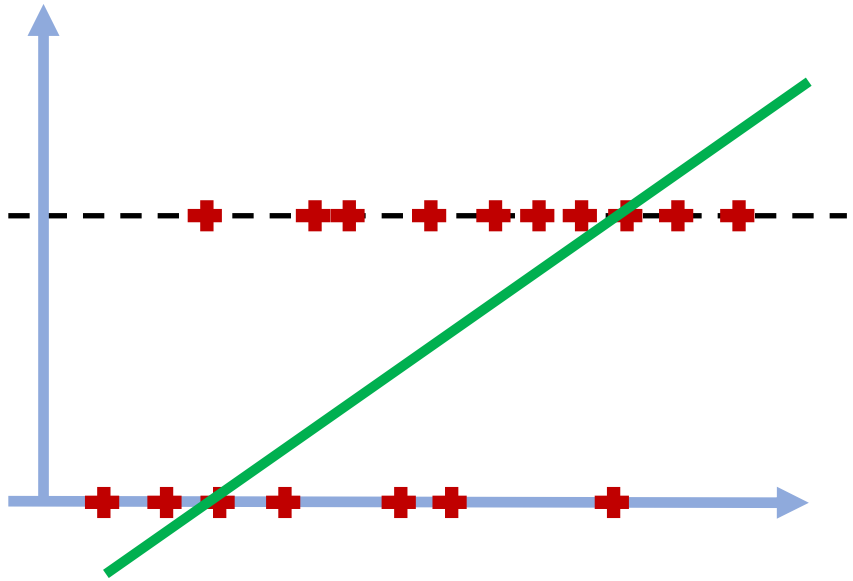
Logistic Regression

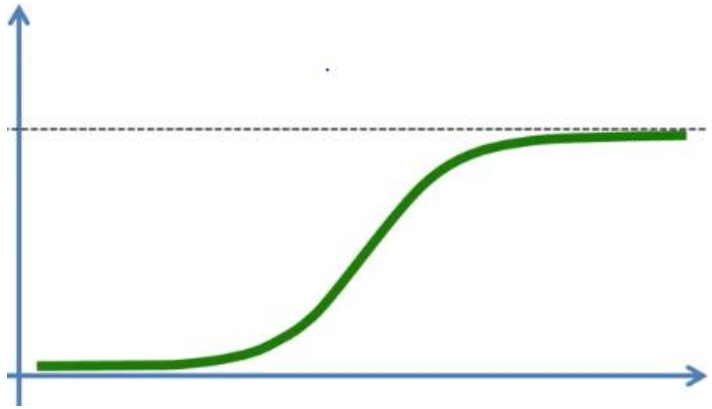
$$y = b_0 + b_1 * x_1$$

Sigmoid Function

$$p = \frac{1}{1 + e^{-y}}$$

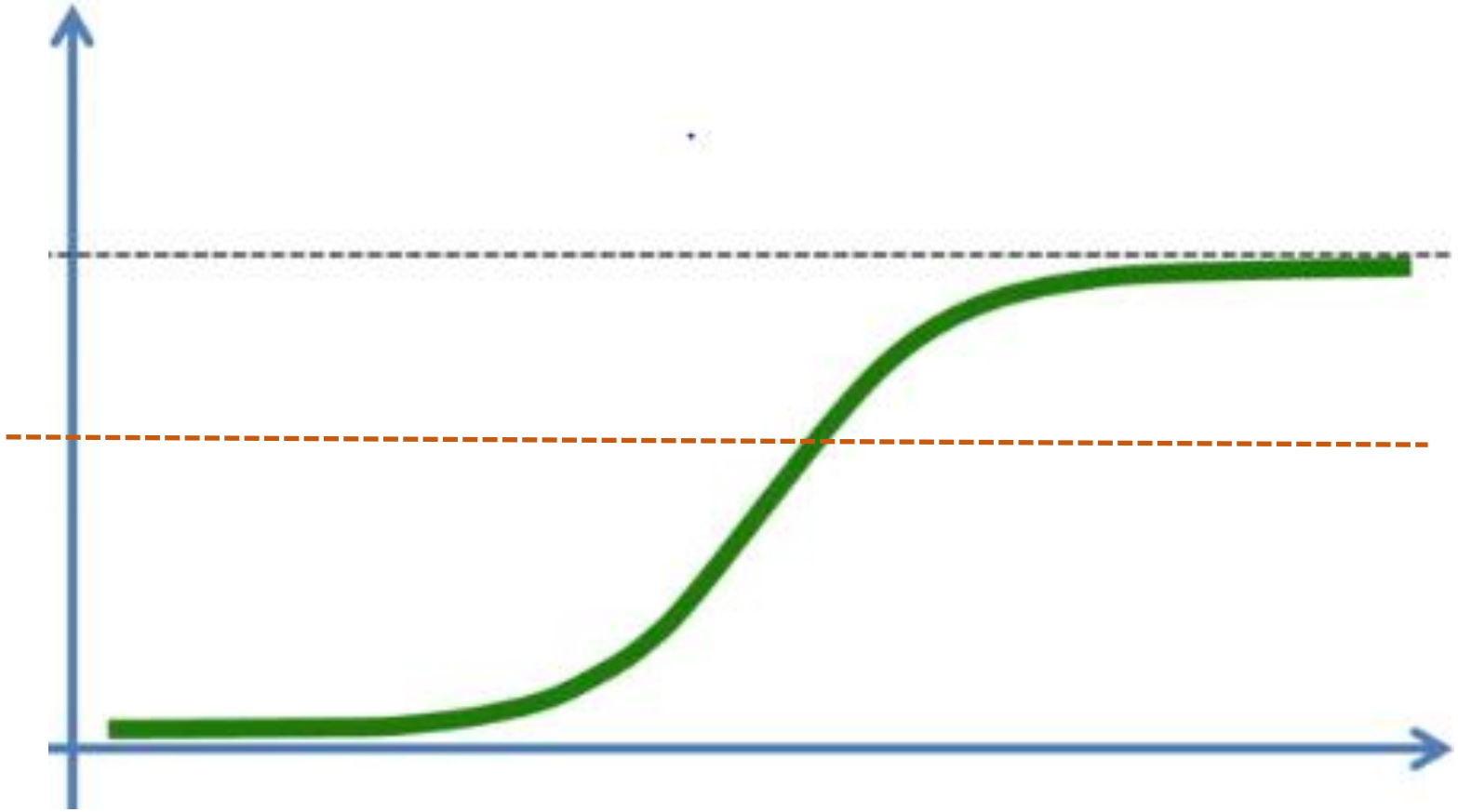
$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1 * x$$





This is the formula for logistic regression

Logistic Regression



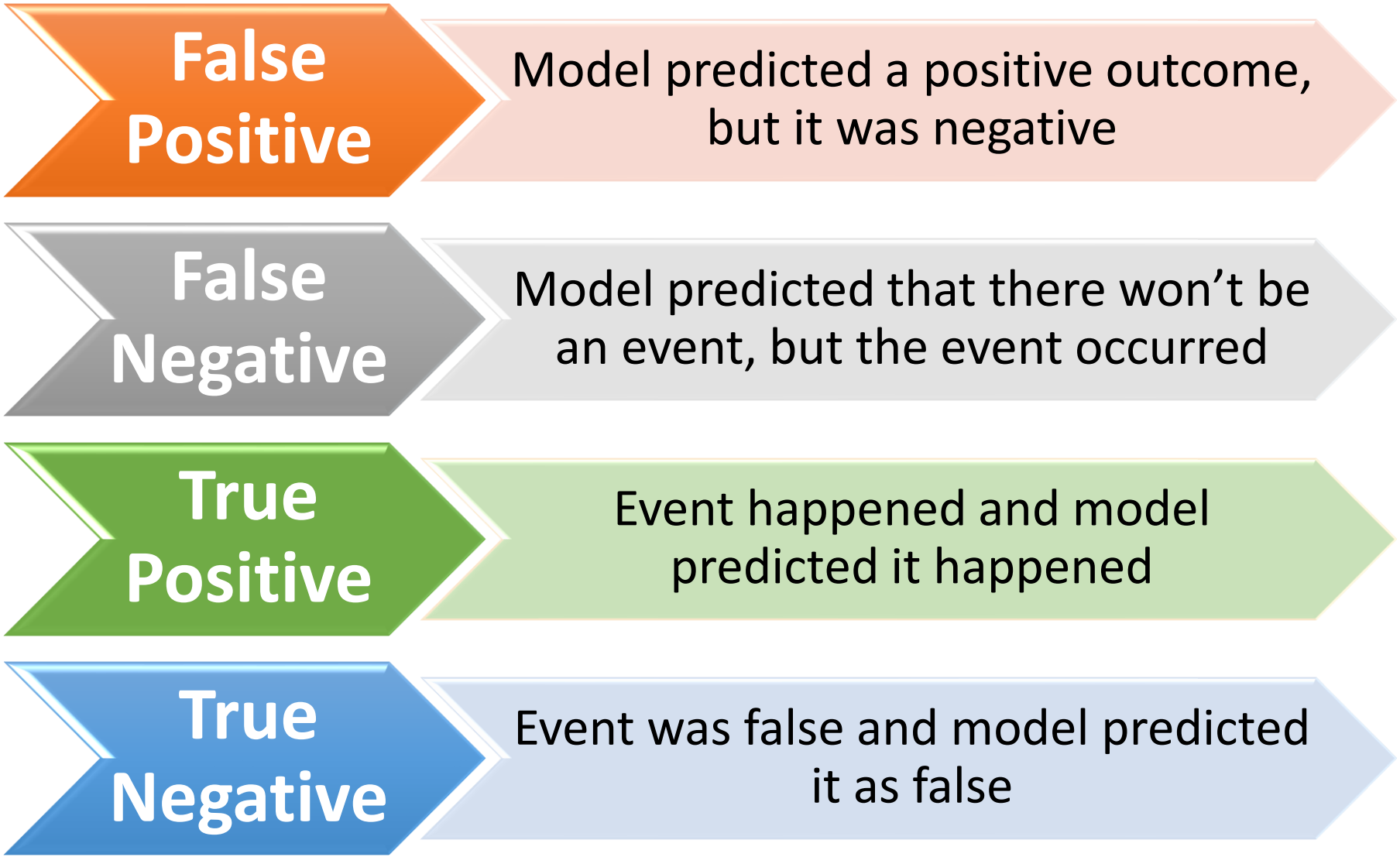
positive class = 1

negative class = 0

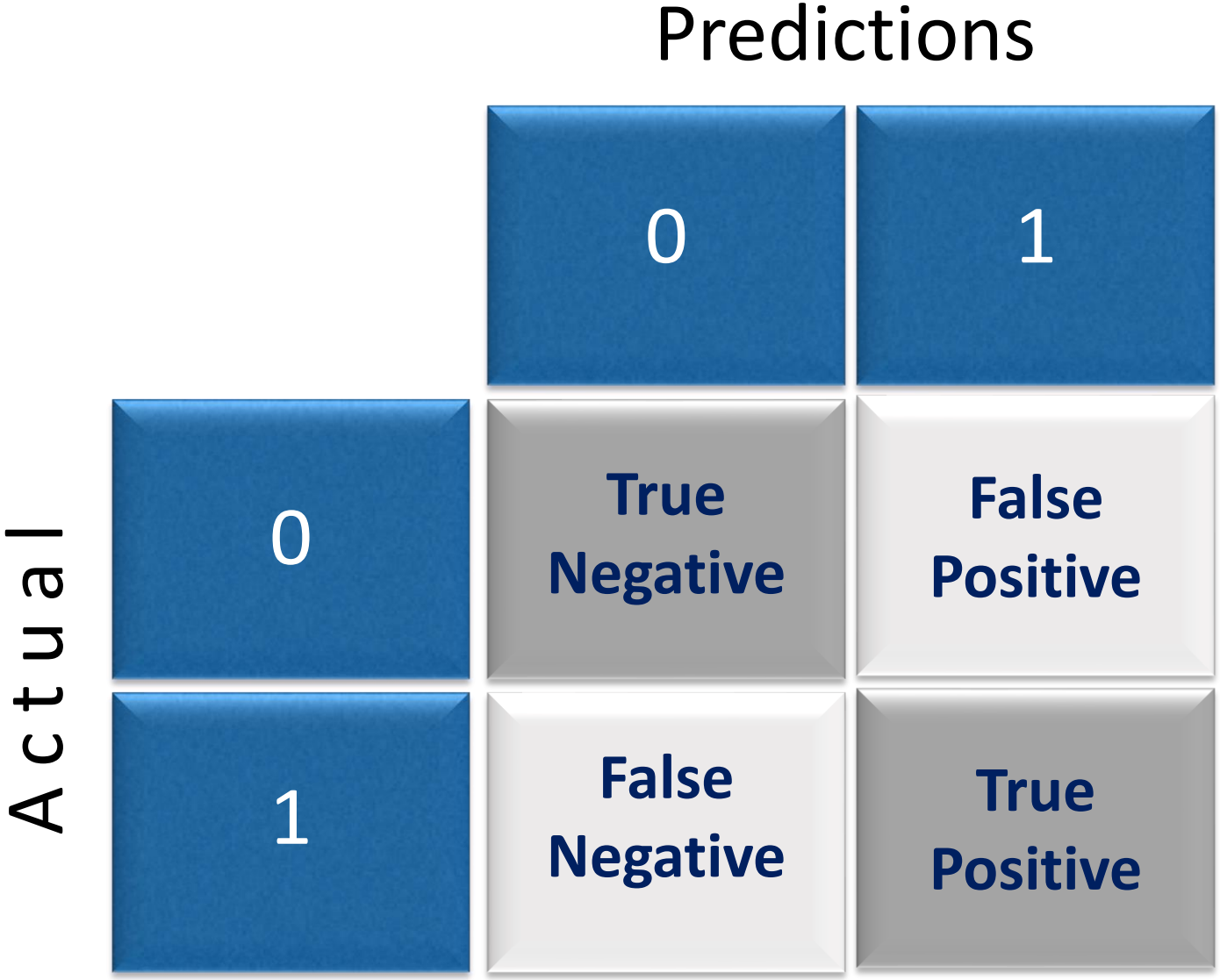
For every class, the model gives probability

Model Metrics

Model Evaluation



Confusion Matrix



$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Classification Report

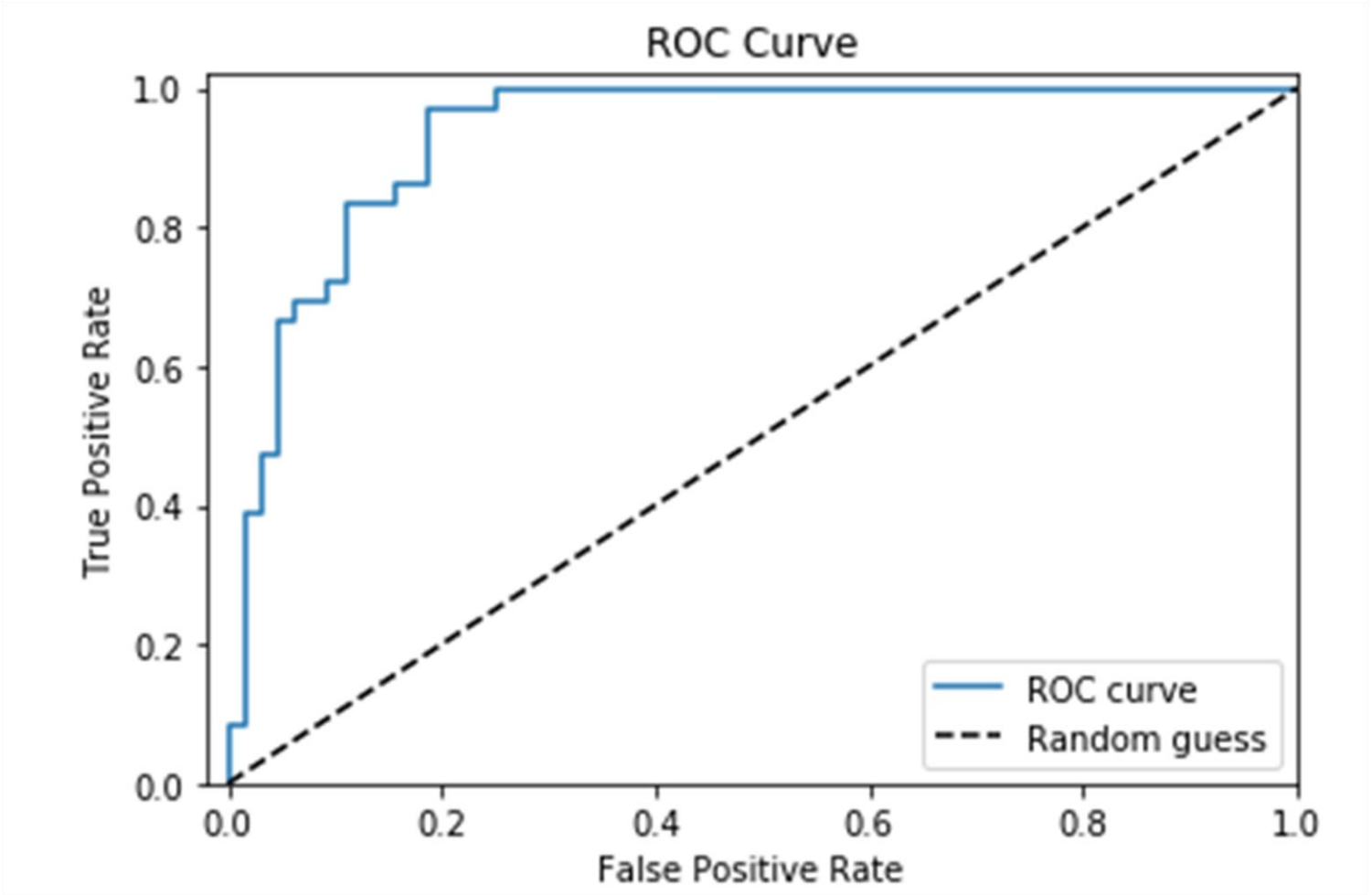
	precision	recall	f1-score	support
0	0.85	0.94	0.89	64
1	0.86	0.69	0.77	36

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$f1score = 2 \times \frac{precision \times recall}{precision + recall}$$

ROC Curve (Receiver Operating Characteristic)



Model Persistence

Model Persistence

Once the model is built, want to persist it so that the model can be used to make predictions for "new" data

Such persisted model is loaded by another script that uses it to make predictions

Not only the model needs to be persisted but also any scalers or pipelines used on data pre-processing

Persistence

Persistence can be applied to Models, Pipelines, Scalers

Pickle

```
from pickle import dump
# save model (in script 1)
dump(model, open('filename.pkl', 'wb')

# load model (in script 2)
from pickle import load
aModel = load(open('filename.pkl', 'rb'))
aModel.predict(data)
```

Joblib

```
from joblib import dump
# save model (in script 1)
dump(model, open('filename.joblib'))

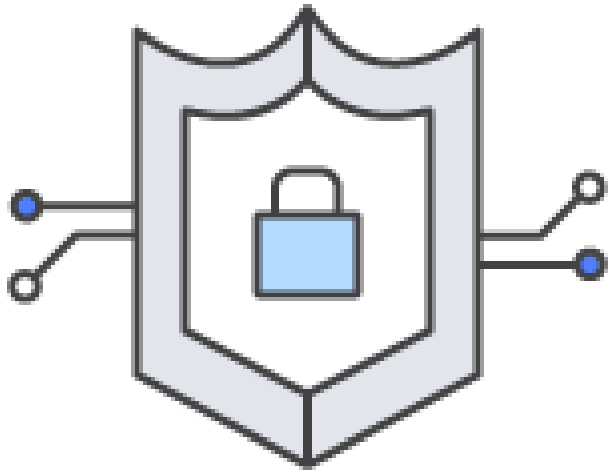
# load model (in script 2)
from joblib import load
aModel = load(open('filename.joblib'))
aModel.predict(data)
```

https://scikit-learn.org/stable/modules/model_persistence.html

Census Income Dataset (UCI)

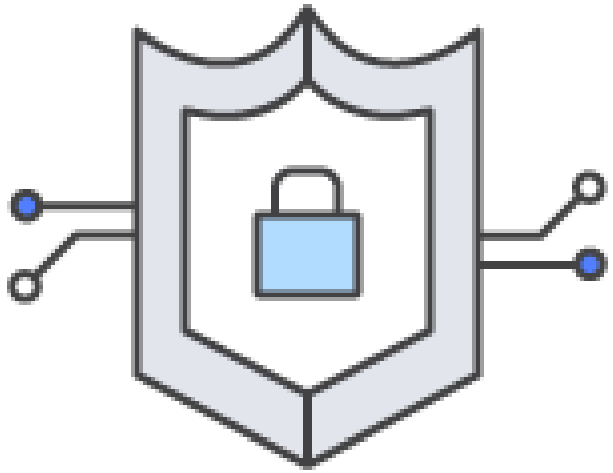
- Continuous – numerical values, rest are all categorical values

- **>50K, <=50K.**
- **age:** continuous.
- **workclass:** Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- **fnlwgt:** continuous.
- **education:** Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- **education-num:** continuous.
- **marital-status:** Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
- **occupation:** Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- **relationship**: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- **race:** White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- **sex:** Female, Male.
- **capital-gain:** continuous.
- **capital-loss:** continuous.
- **hours-per-week:** continuous.
- **native-country:** United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.



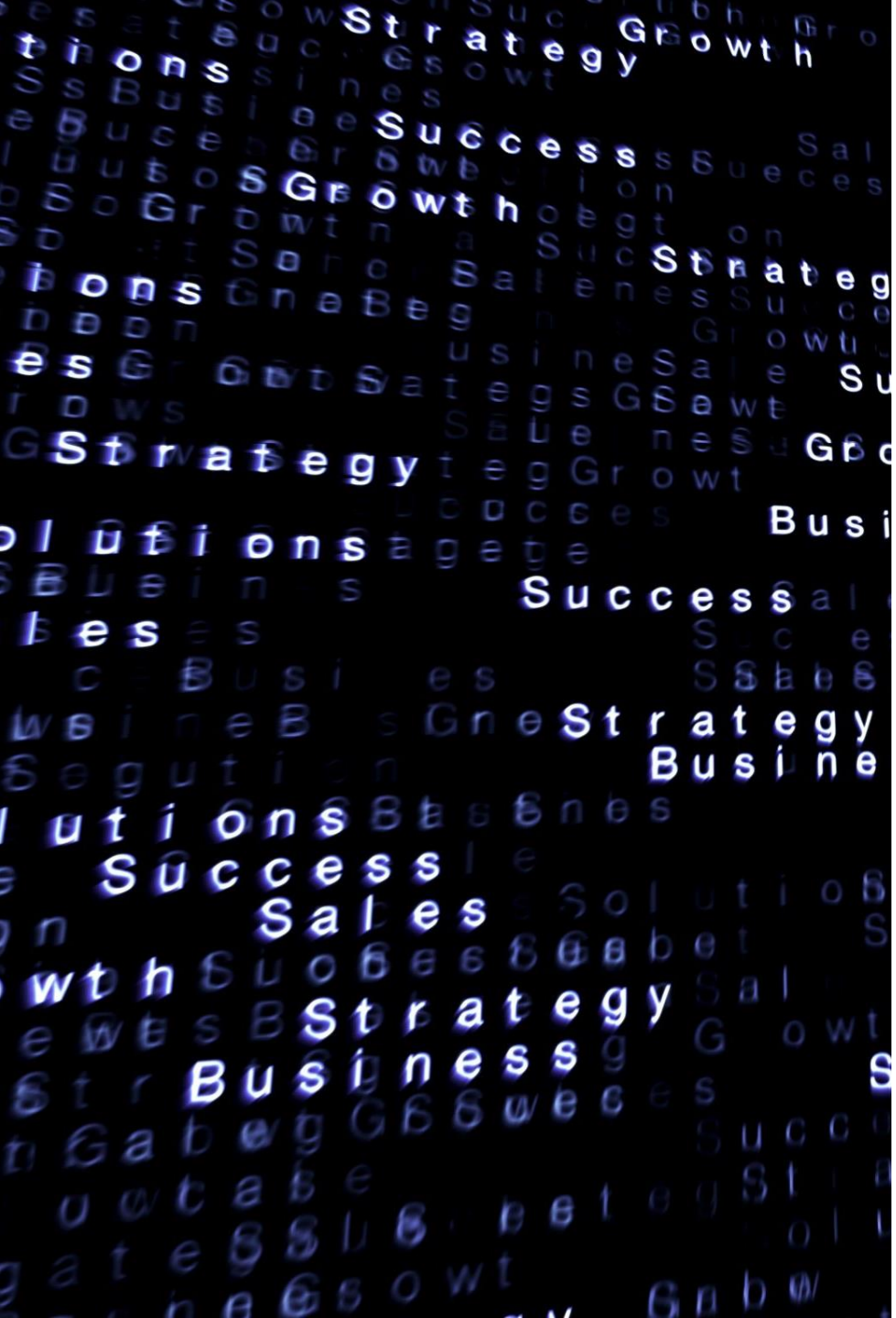
Logistic Regression

- Open file '**CodeSamples/Logistic Regression**' using Jupyter
- Load agent.csv into DataFrame
- Build a pipeline to handle categorical and numeric data
- Build a Logistic Regression model
- Check performance of model on training dataset
- Make predictions
- Compare predications v/s the actual values
- Persist the pipeline and the model



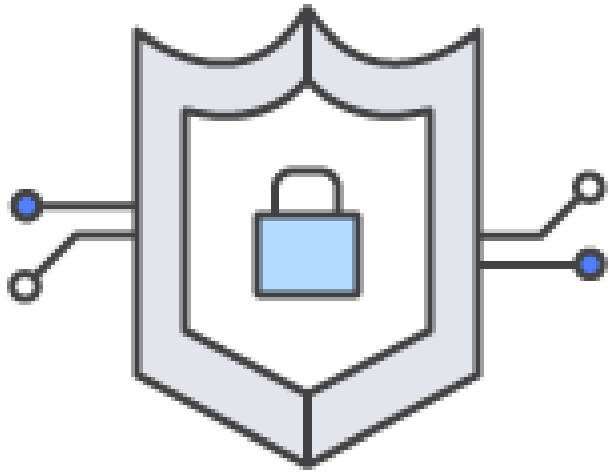
Load and Predict

- Open file '**CodeSamples/LoadModel-Predict**' using Jupyter
- Load agent-new.csv into DataFrame (note: no target variable – predicting it)
- Use the pipeline and model persisted in the previous example to apply to new data
- Apply them to new dataframe
- Make predictions and write the predictions to a .csv file



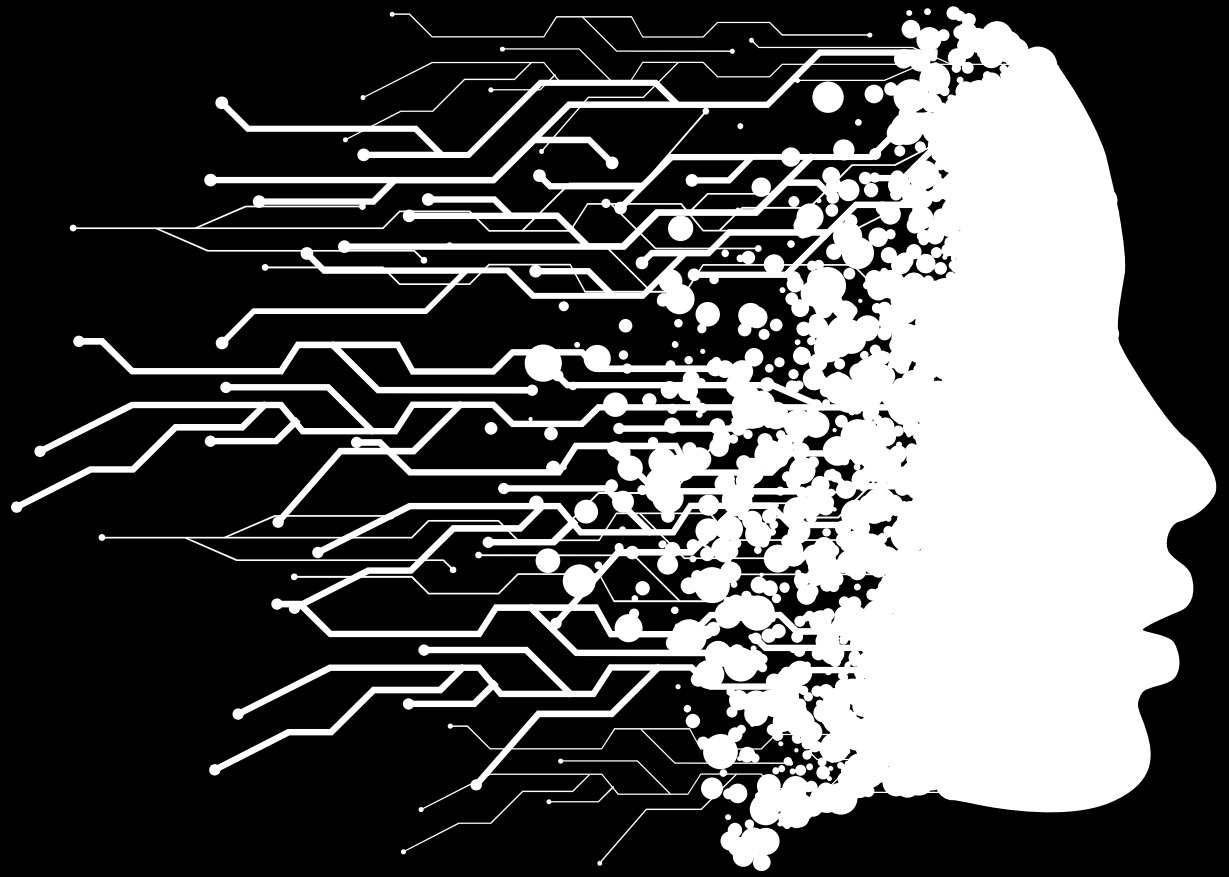
Word Cloud

- Datasets often have many text fields e.g. names, cities, states, descriptions, etc.
- Want to most prominent words
- Word Cloud (python-based library)
  - Get visual representation of the text – most frequent words
  - These are represented in big fonts and in different colors
  - Words in small fonts indicate that the words are not important



Word Cloud

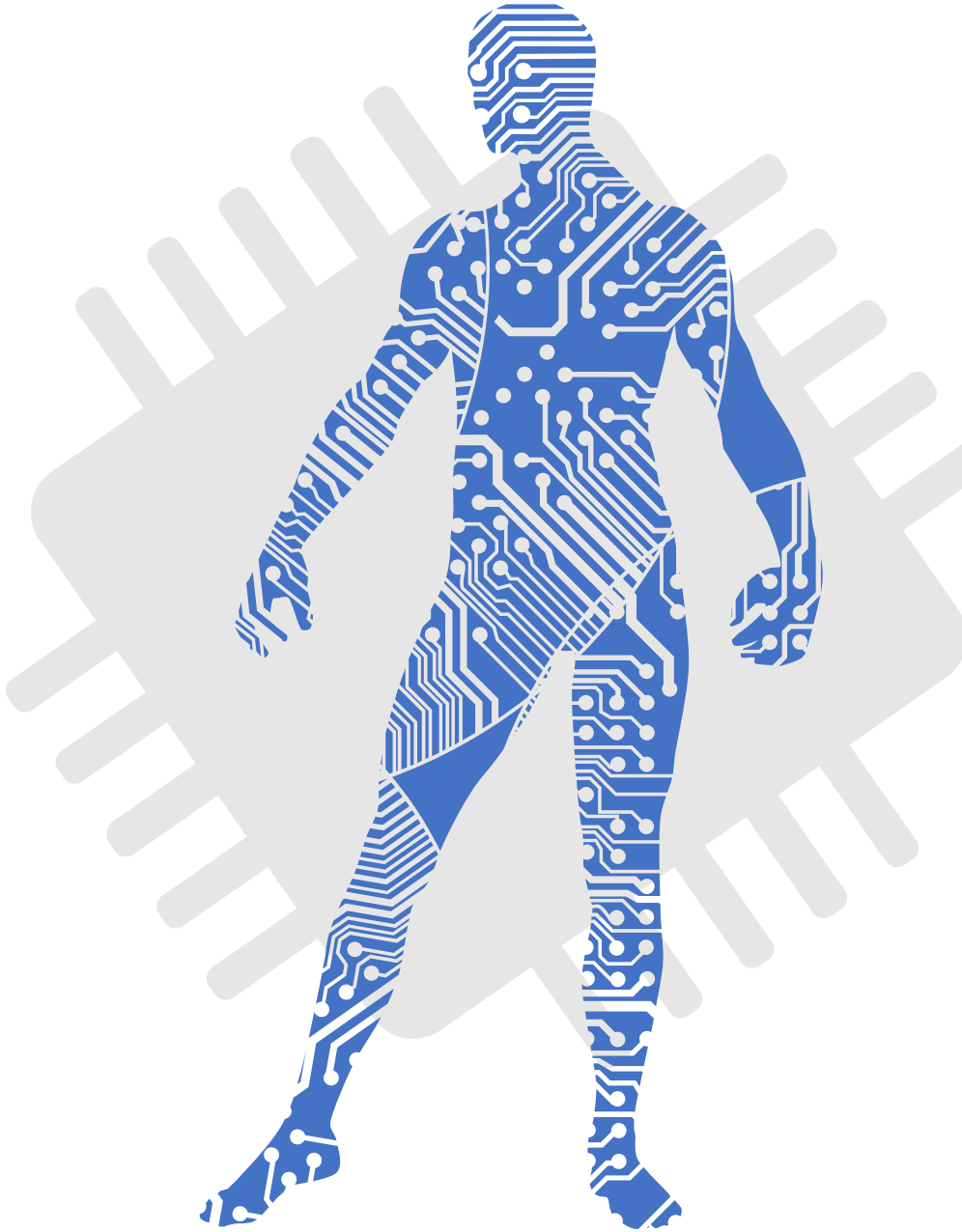
- Open file '**CodeSamples/PetFinder**' using Jupyter
- Dataset consists information about pets (cats, dogs) that are up for adoption
- Use wordcloud to explore the dataset



Deep Learning

Deep Learning

1. Deep Learning Packages
2. Understanding TensorFlow
3. Artificial Neural Networks



Deep Learning Packages

Deep Learning Package Zoo

Understanding TensorFlow

TensorFlow

- Open-source library developed by Google
- Developed to run large numerical calculations
- Data is provided as multi-dimensional arrays of high dimensions called Tensors
- Uses Data Flow Graphs to define and execute the computations

Tensors

Dimension [5,]

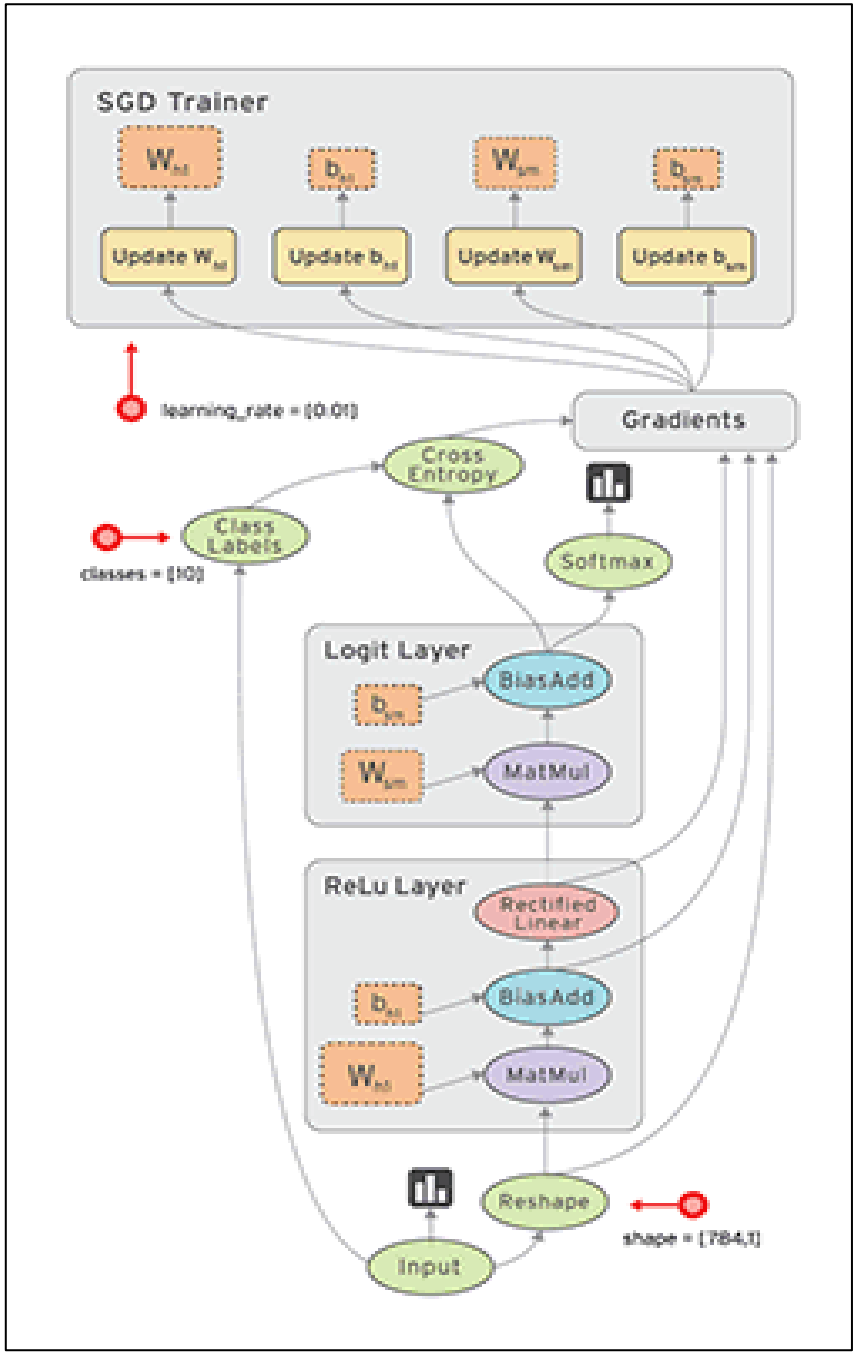
a
d
k
m
q

Dimension [5, 4]

1	3	4	7
9	7	3	2
8	4	1	6
6	3	9	1
3	1	5	9

Dimension [3,3,3]

Data Flow Graph ("Flow" in TensorFlow)



Two Basic Steps in TensorFlow

Build Computational Graph

Execute the Computational Graph

Keras - Backends

theano

Microsoft Cognitive Toolkit

aka.ms/CognitiveToolkit

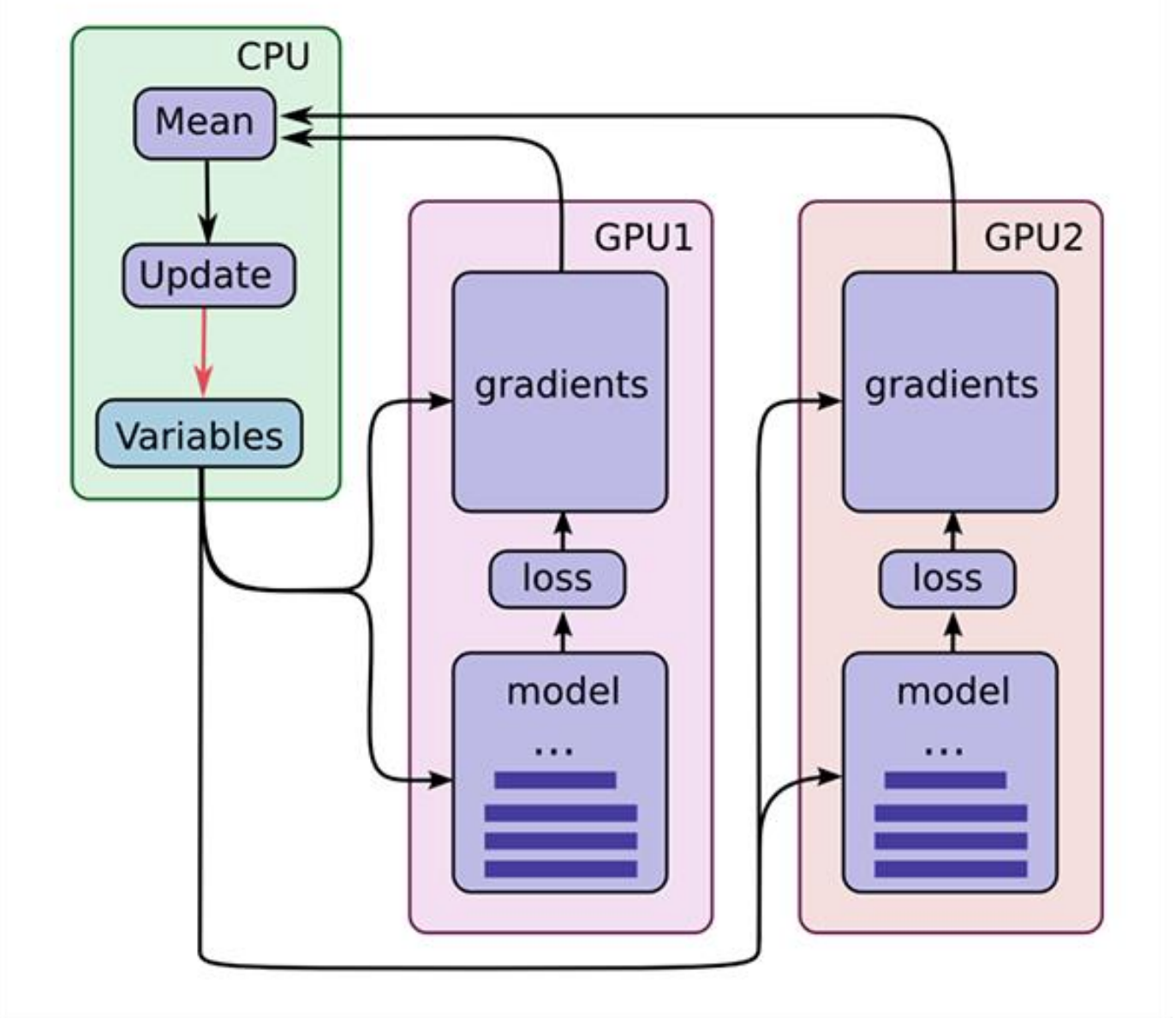
Microsoft

mxnet

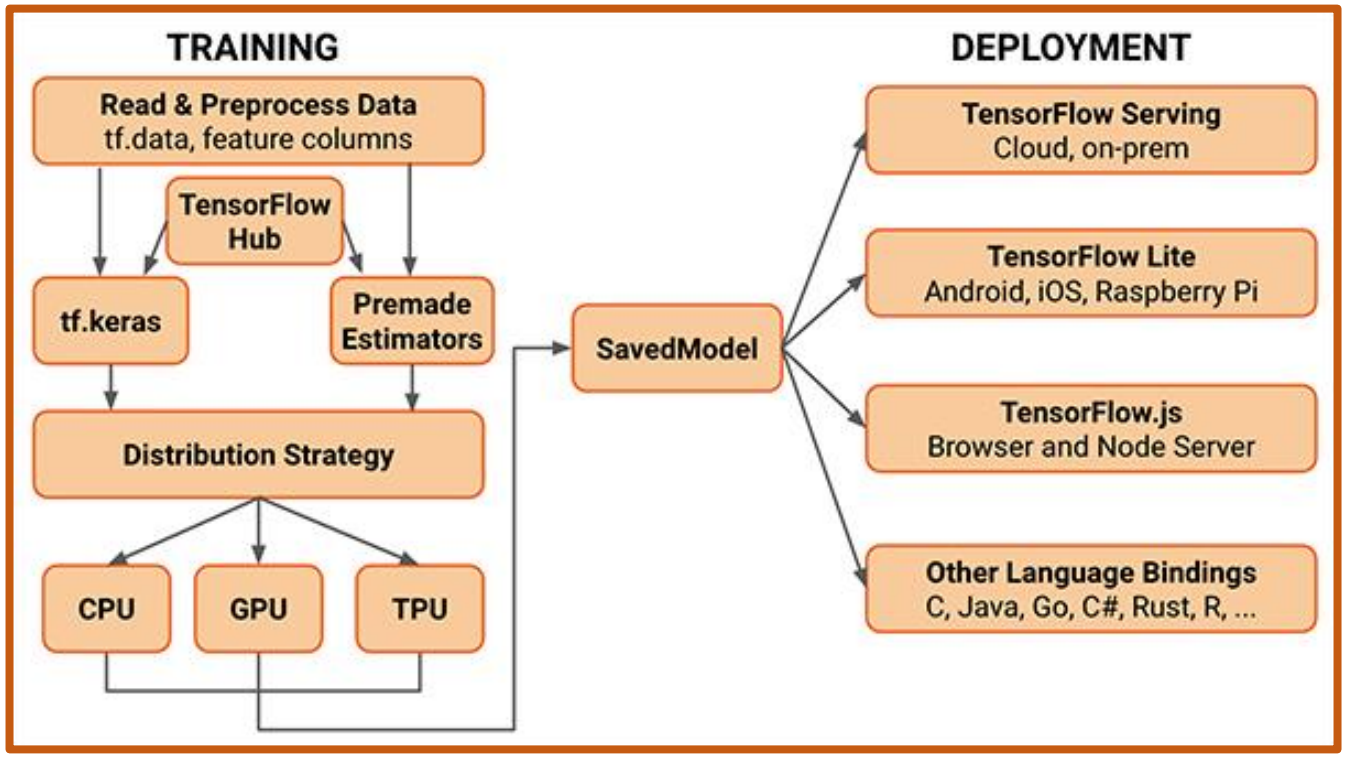
TensorFlow

TensorFlow: Multi GPU

https://www.tensorflow.org/guide/distributed_training#mirroredstrategy



TensorFlow Ecosystem



Google's Colaboratory (Colab)

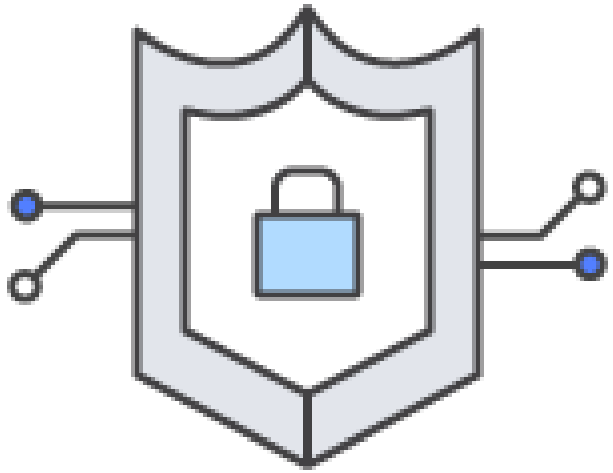
Colaboratory allows to write Python code in browser in a notebook format (Juypter notebooks or Labs)

Free access to GPU

Zero configuration

Easy Sharing

https://www.youtube.com/watch?v=inN8seMm7UI

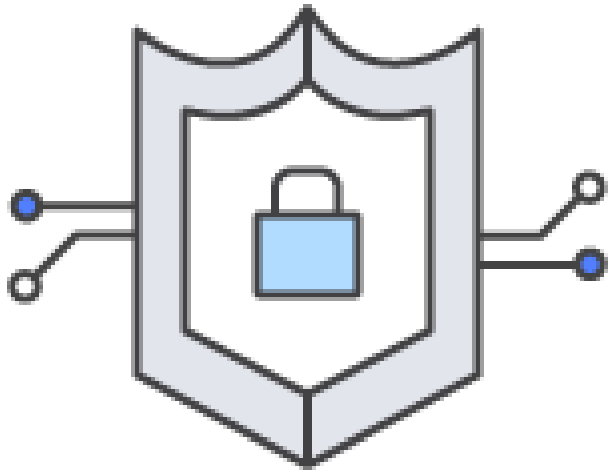


Tensors – Colab

- Will be using the Google's Colaboratory
- "Notebook" is used as an IDE
- Looking at basic code for

https://colab.research.google.com/

- Make sure to sign in with your gmail
- From the File menu, select "Upload notebook"
- Select the from the Labs folder, "Tensor Introduction.ipynb"

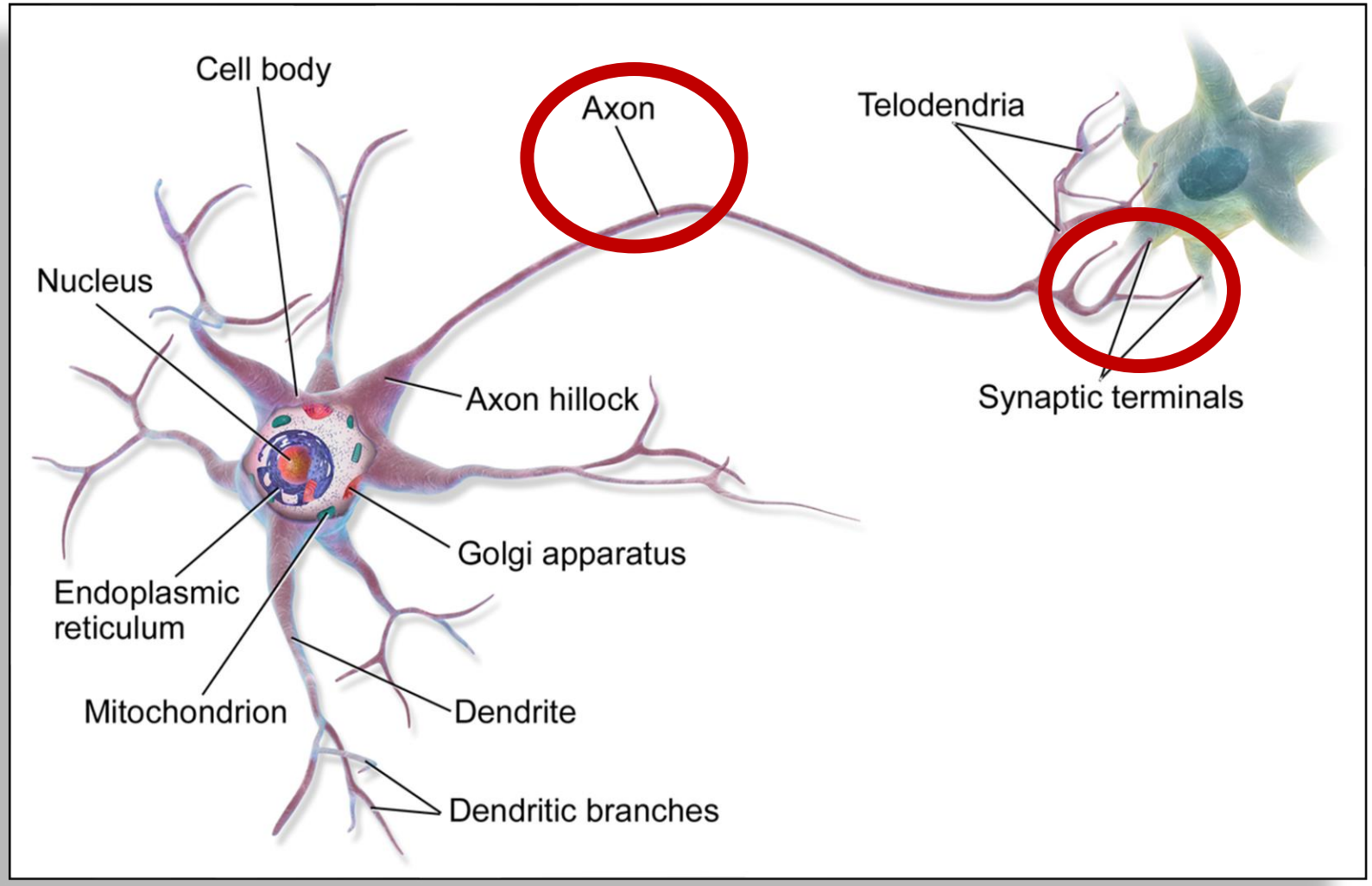


TensorFlow – Tensor Examples

- Open "**CodeSamples/Tensor Introduction**"
- Examples of properties of Tensor such as:
  - Different ranks
  - Different shape
  - Indexing
  - Reshaping

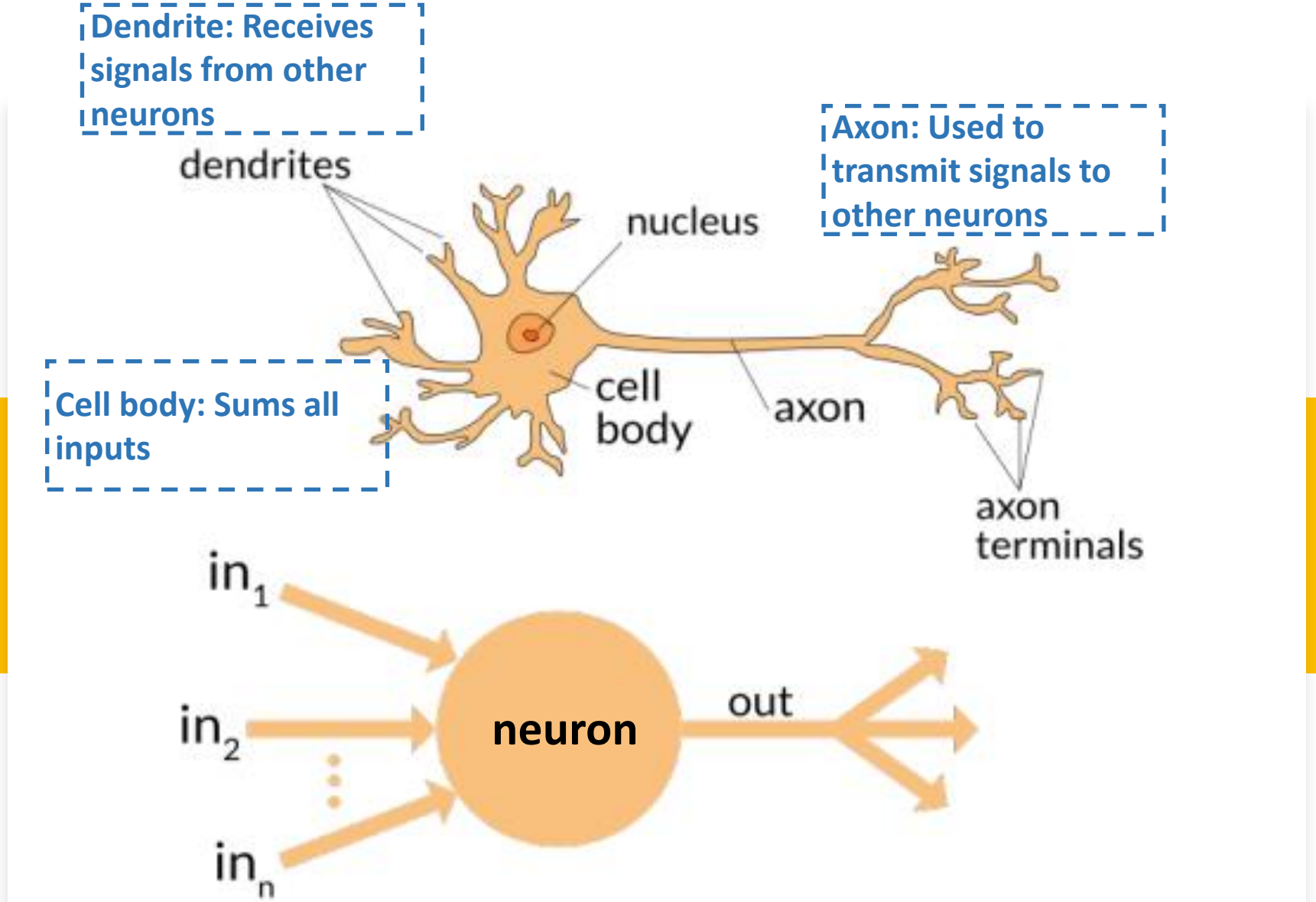
Artificial Neural Networks (ANN)

Neuron

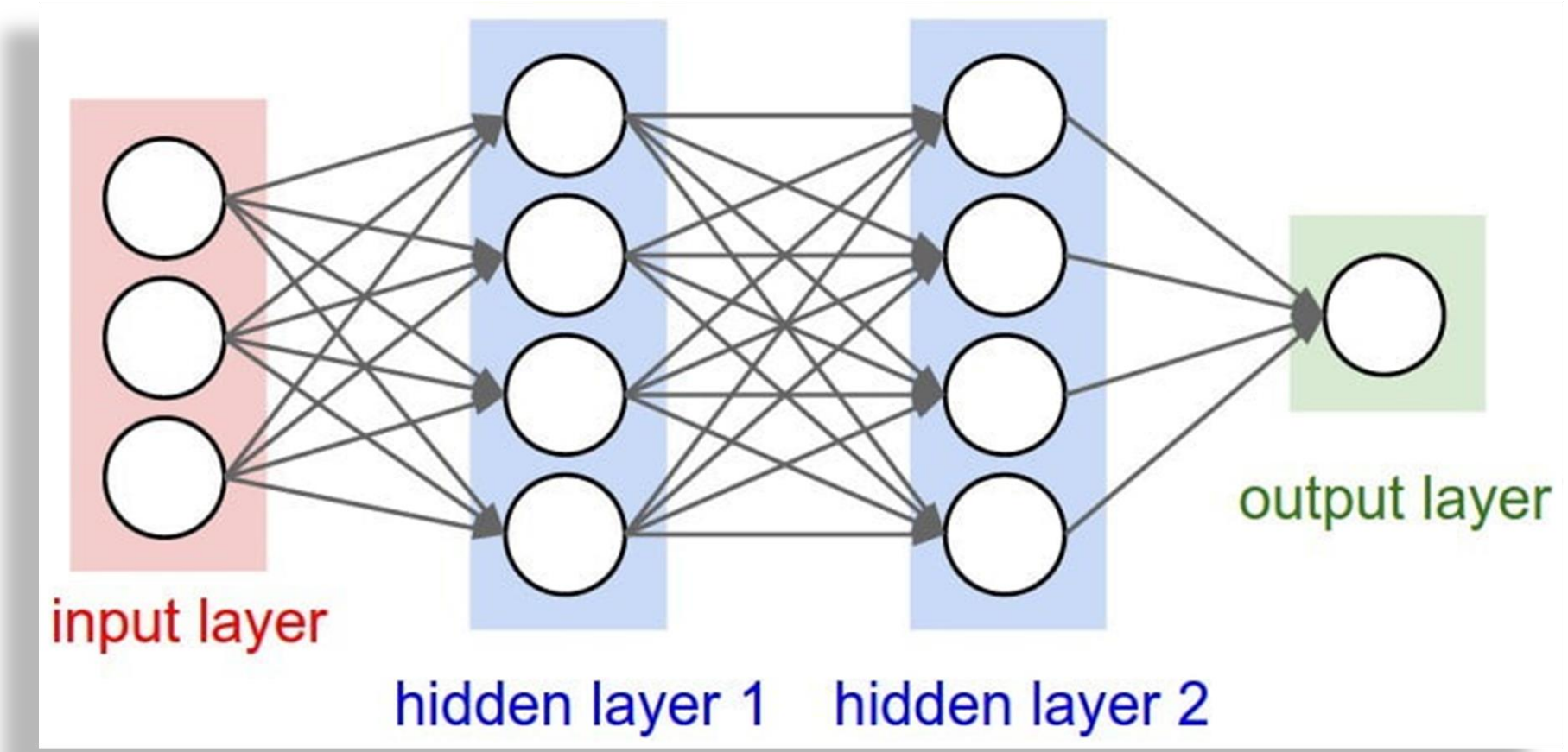


From Wikipedia

Neuron in Artificial Neural Networks



Artificial Neural Network (ANN)



Artificial Neural Networks - Layers

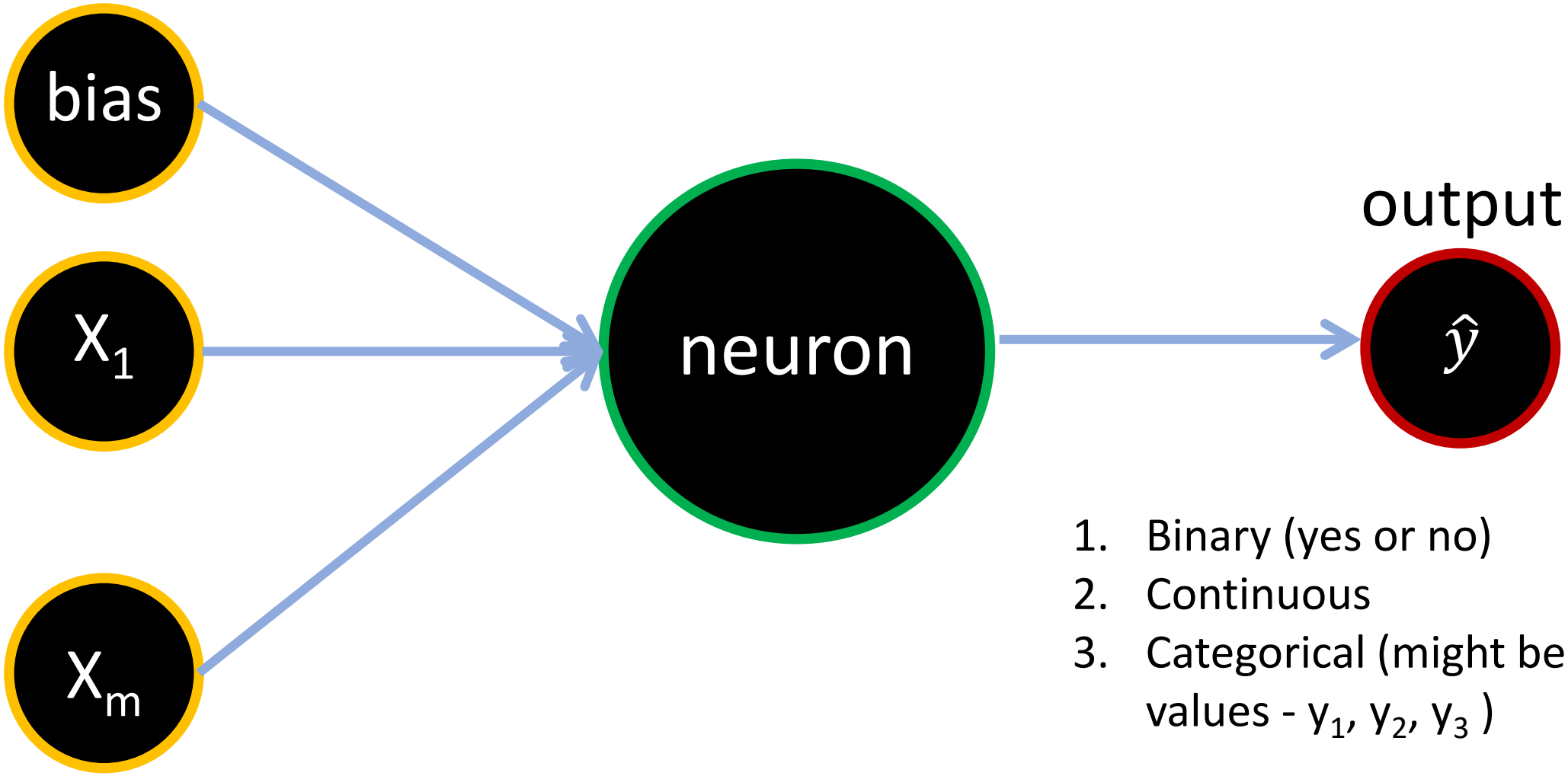
- Each of the layers in ANN perform different tasks
- Some are better suited for certain tasks compared to others

- Types of Layers
  - Dense (or fully connected layers)
  - Convolutional (Image processing)
  - Recurrent (Time series processing)
  - Pooling (Image processing)
  - Many more ….

```
# Create Neural Network

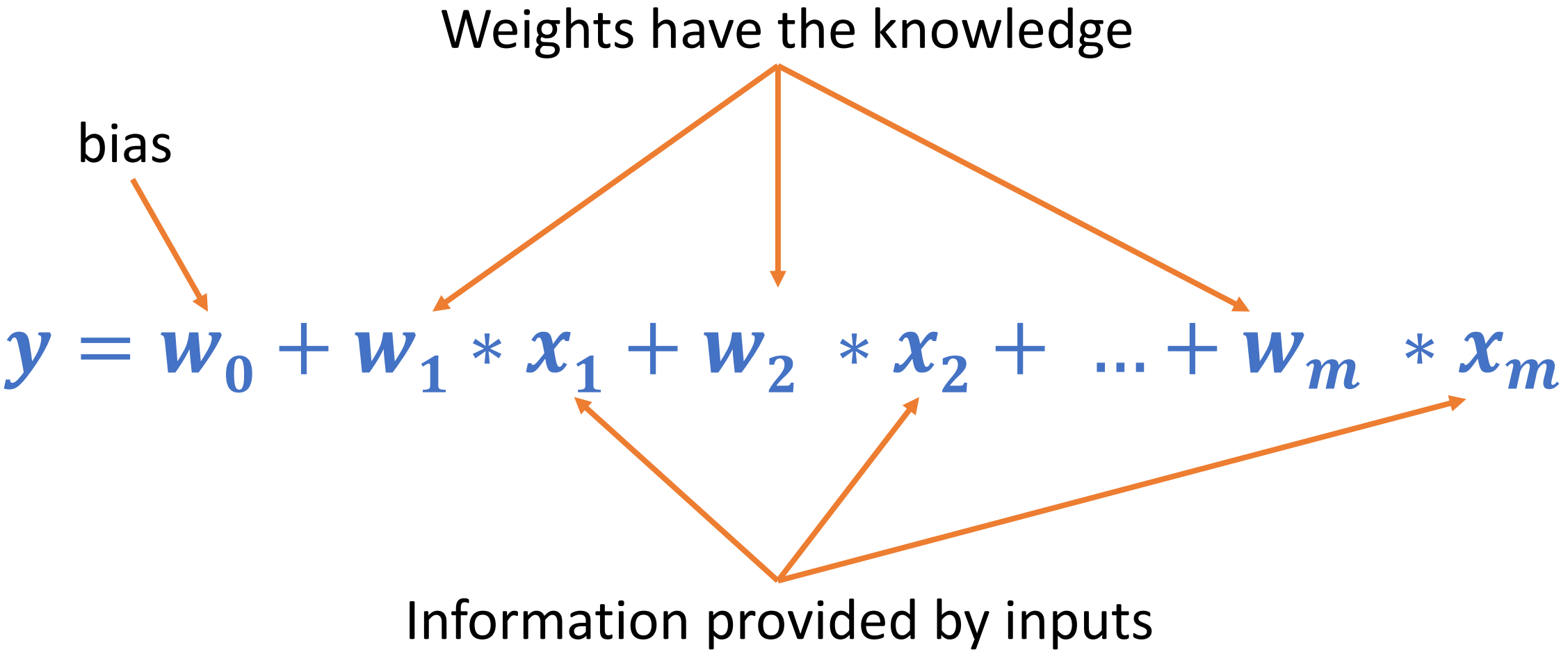
model = keras.models.Sequential()
model.add(keras.layers.Flatten(input_shape=[28, 28]))
model.add(keras.layers.Dense(128, activation="relu"))
model.add(keras.layers.Dense(10, activation="softmax"))
```

Artificial Neural Networks - Perceptron

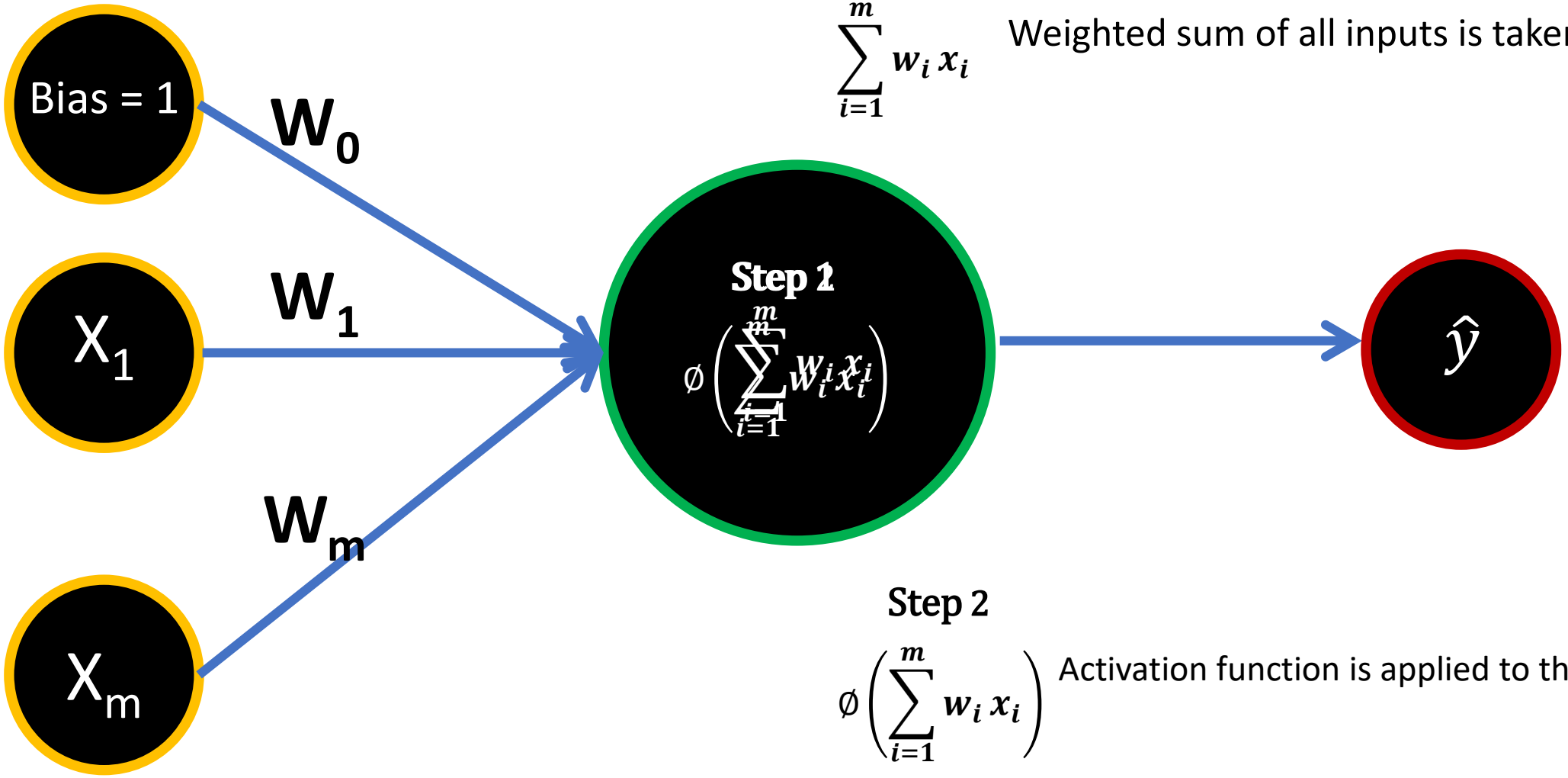


1. Binary (yes or no)
2. Continuous
3. Categorical (might be multiple values - y_1, y_2, y_3)

Weighted Combination of Features



Neural Networks – Weighted Sum



Step 1

$$\sum_{i=1}^{m} w_i x_i$$

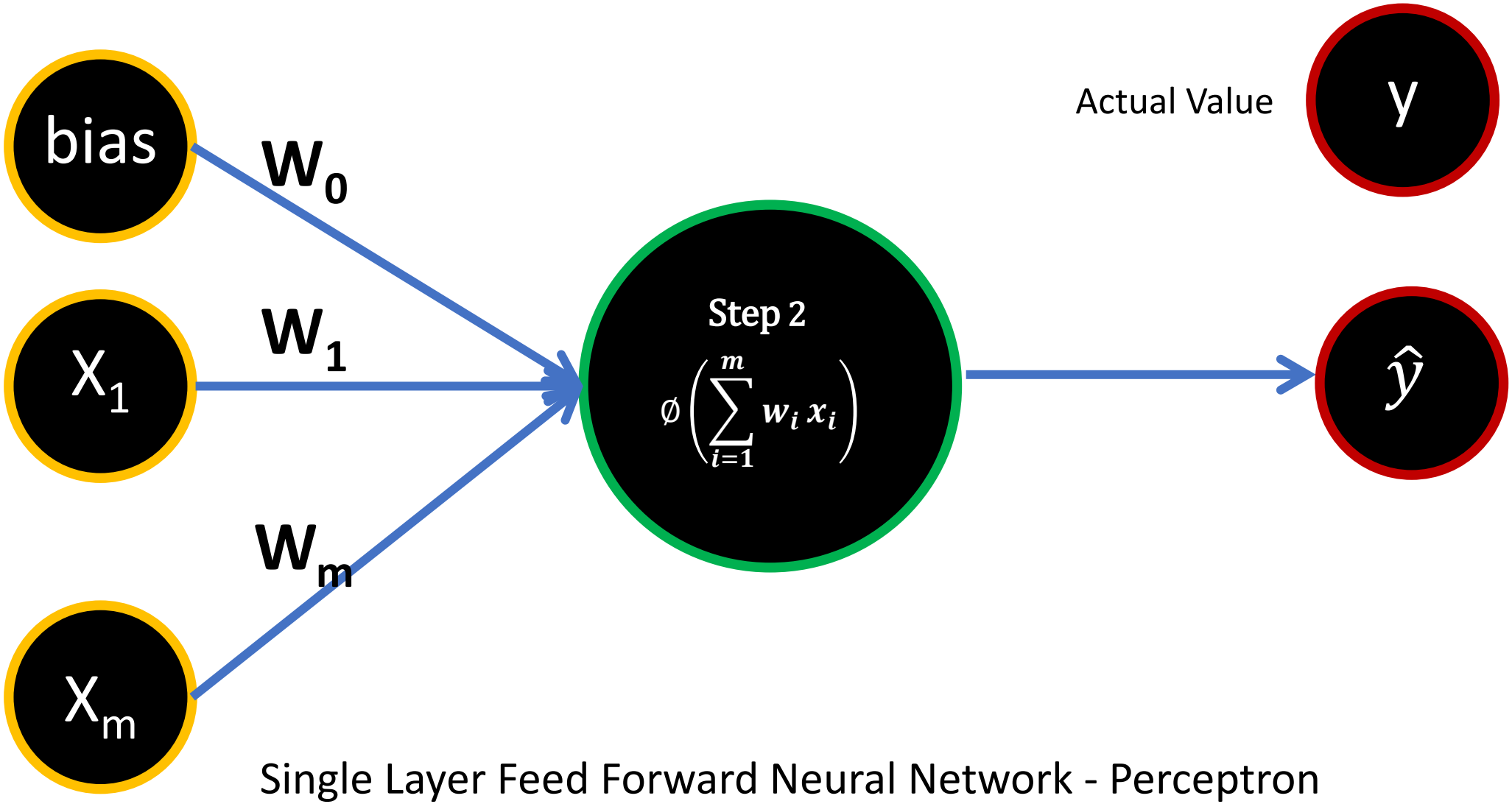
Weighted sum of all inputs is taken

Step 2

$$\emptyset\left(\sum_{i=1}^{m} w_i x_i\right)$$

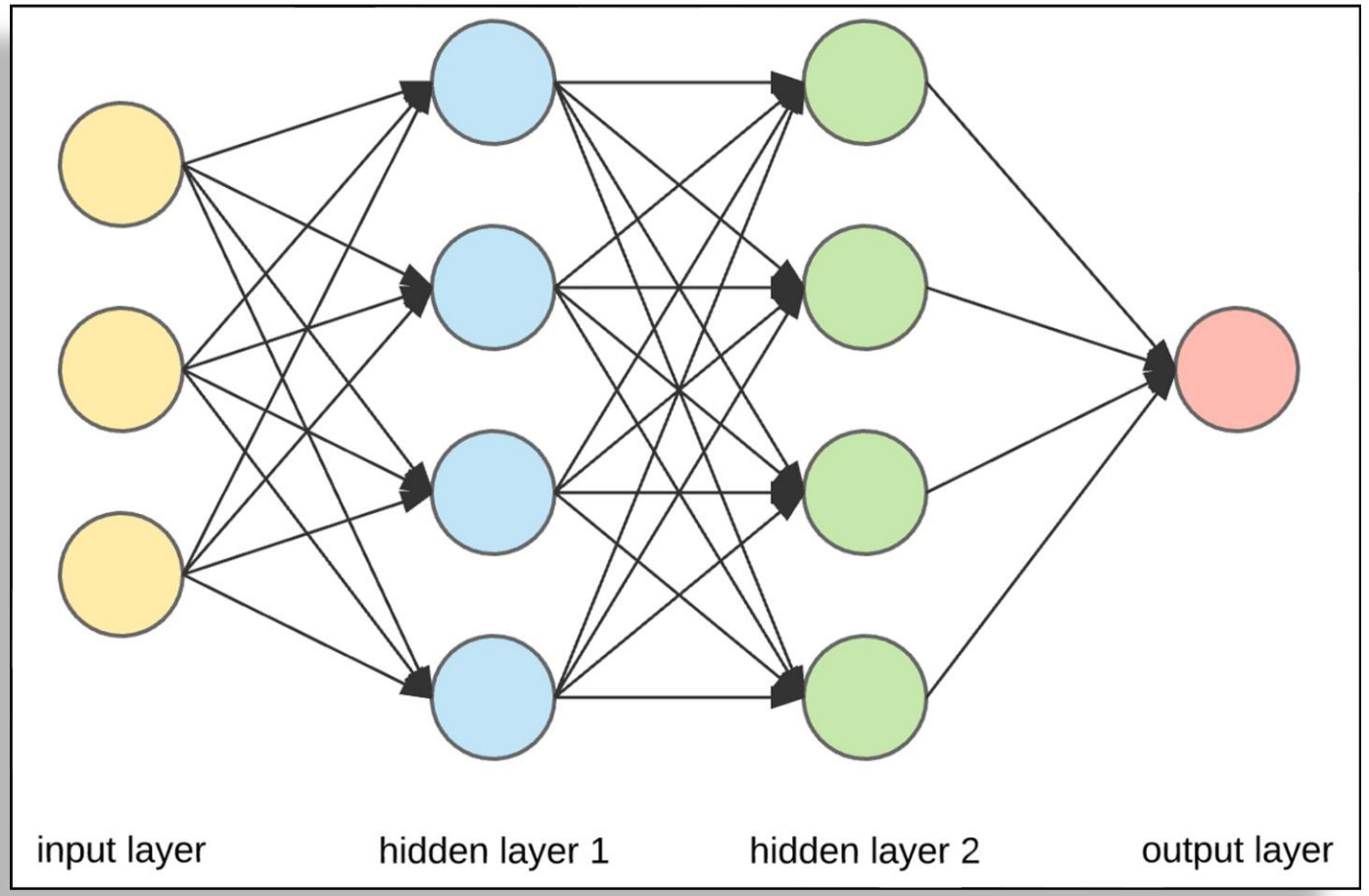
Activation function is applied to the sum

Single Layer Perceptron

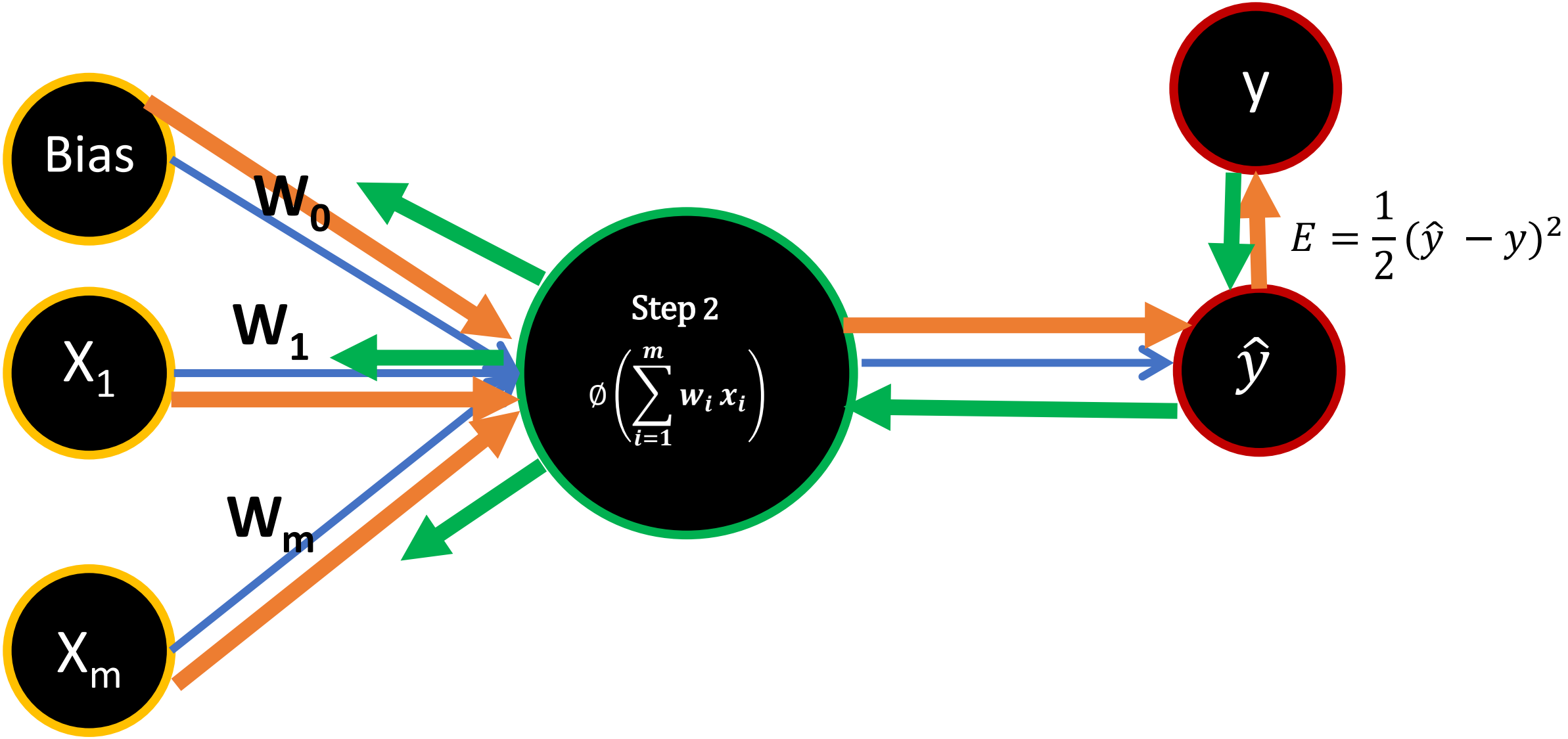


Single Layer Feed Forward Neural Network - Perceptron

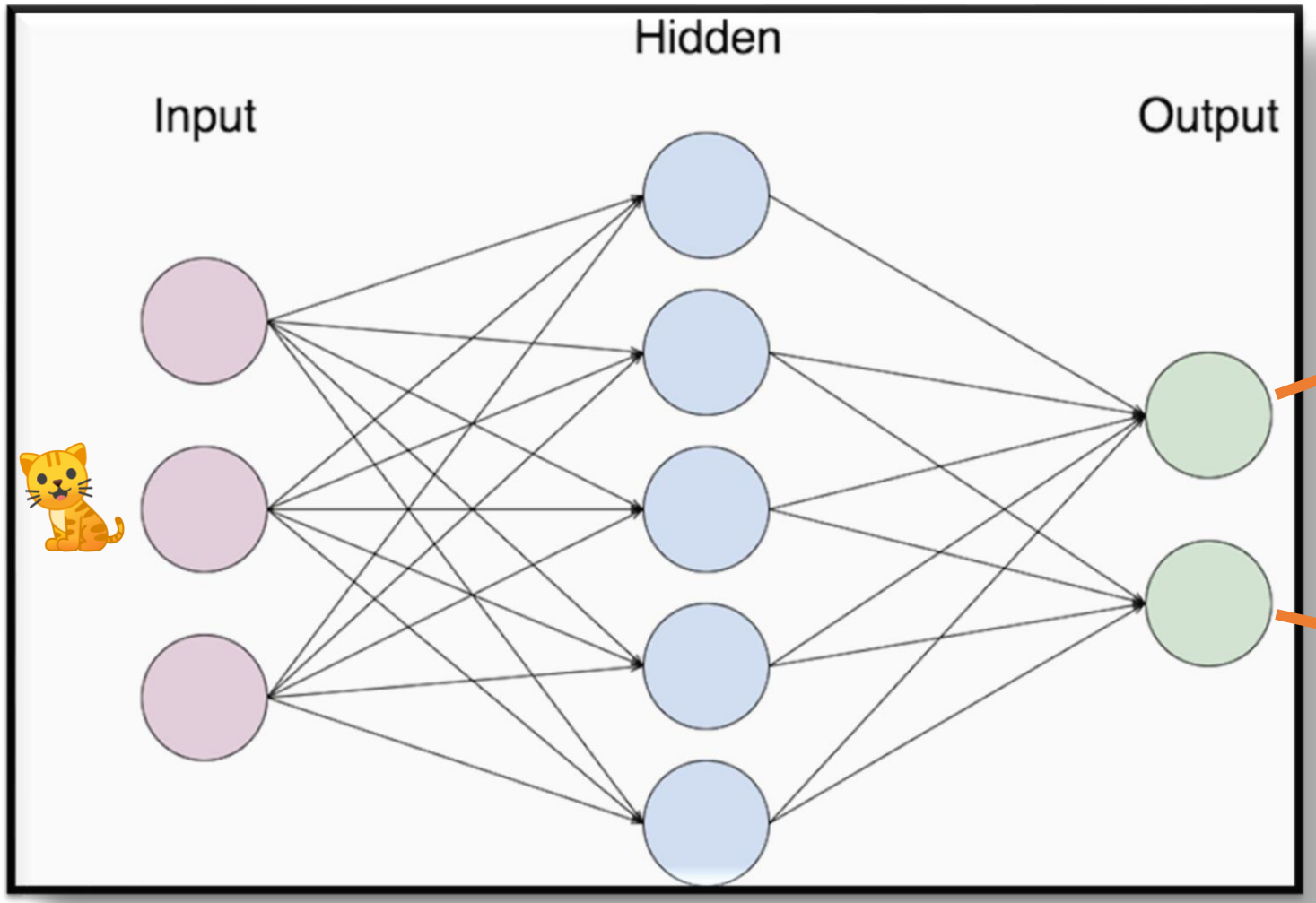
Multi Layer Perceptron



Neural Networks – Learning (Training)



ANN Learning – Minimizing Loss



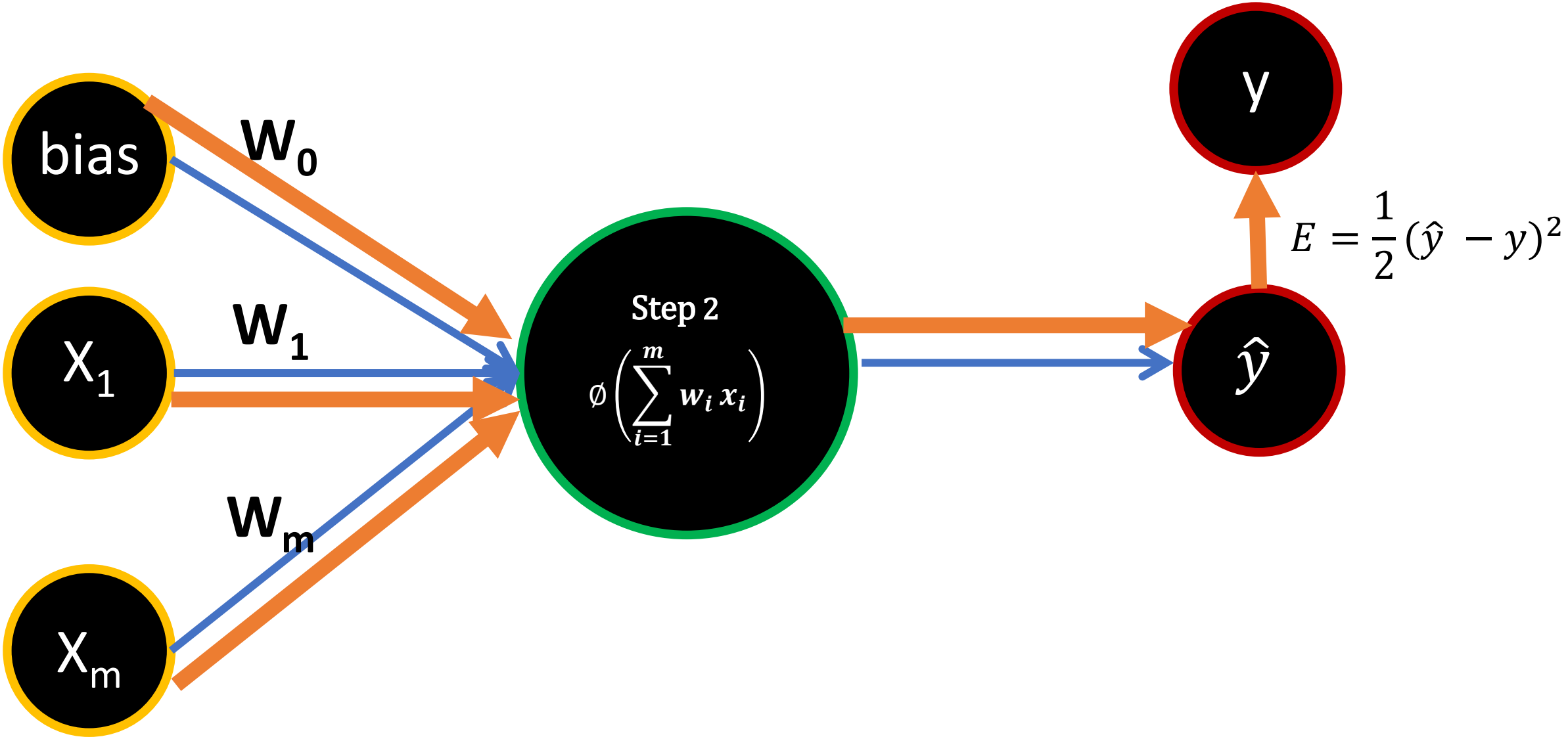
$$\frac{\partial loss}{\partial weight} * learning\ rate$$

0.70

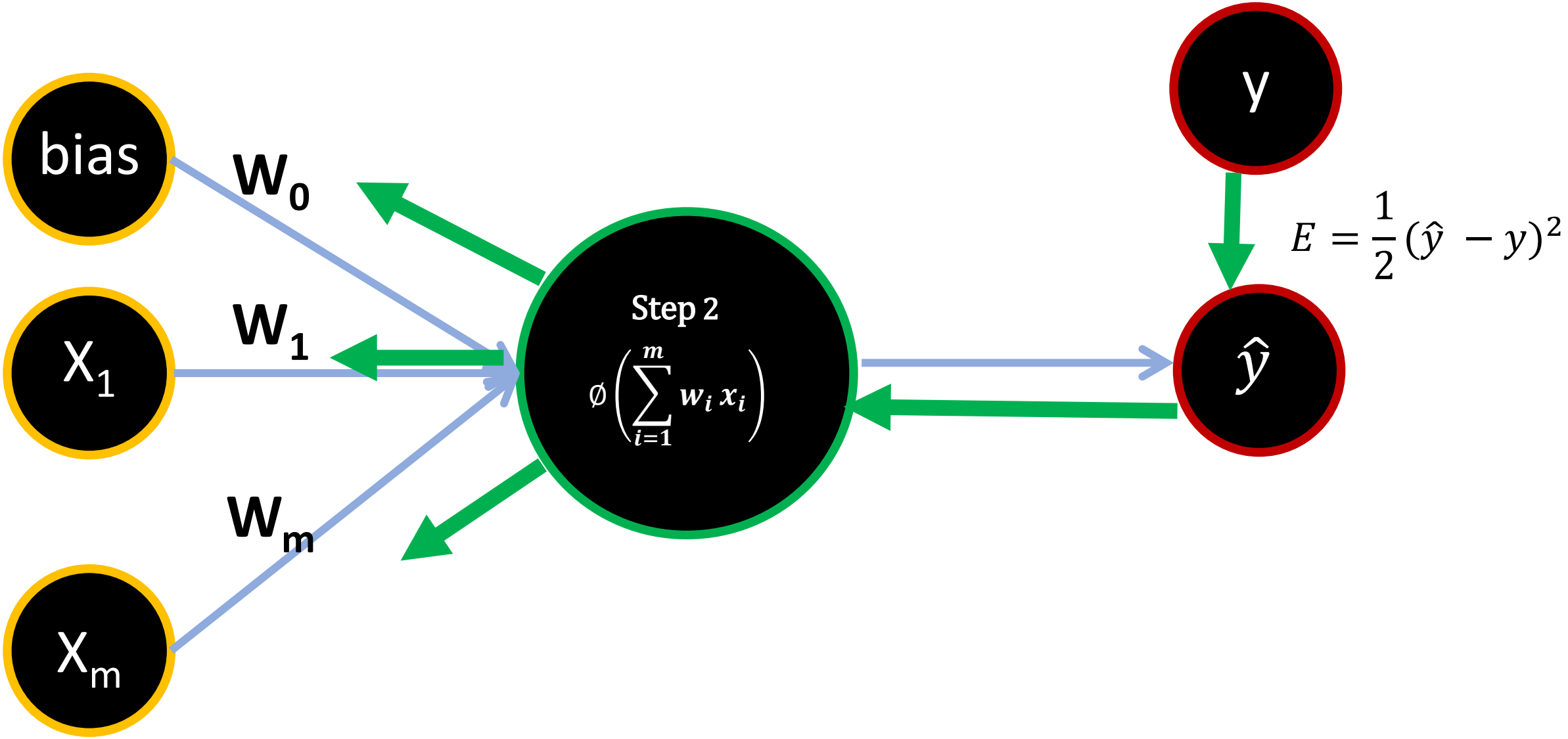
0.30

Range(0.01, 0.0001)

Neural Networks – Feed Forward

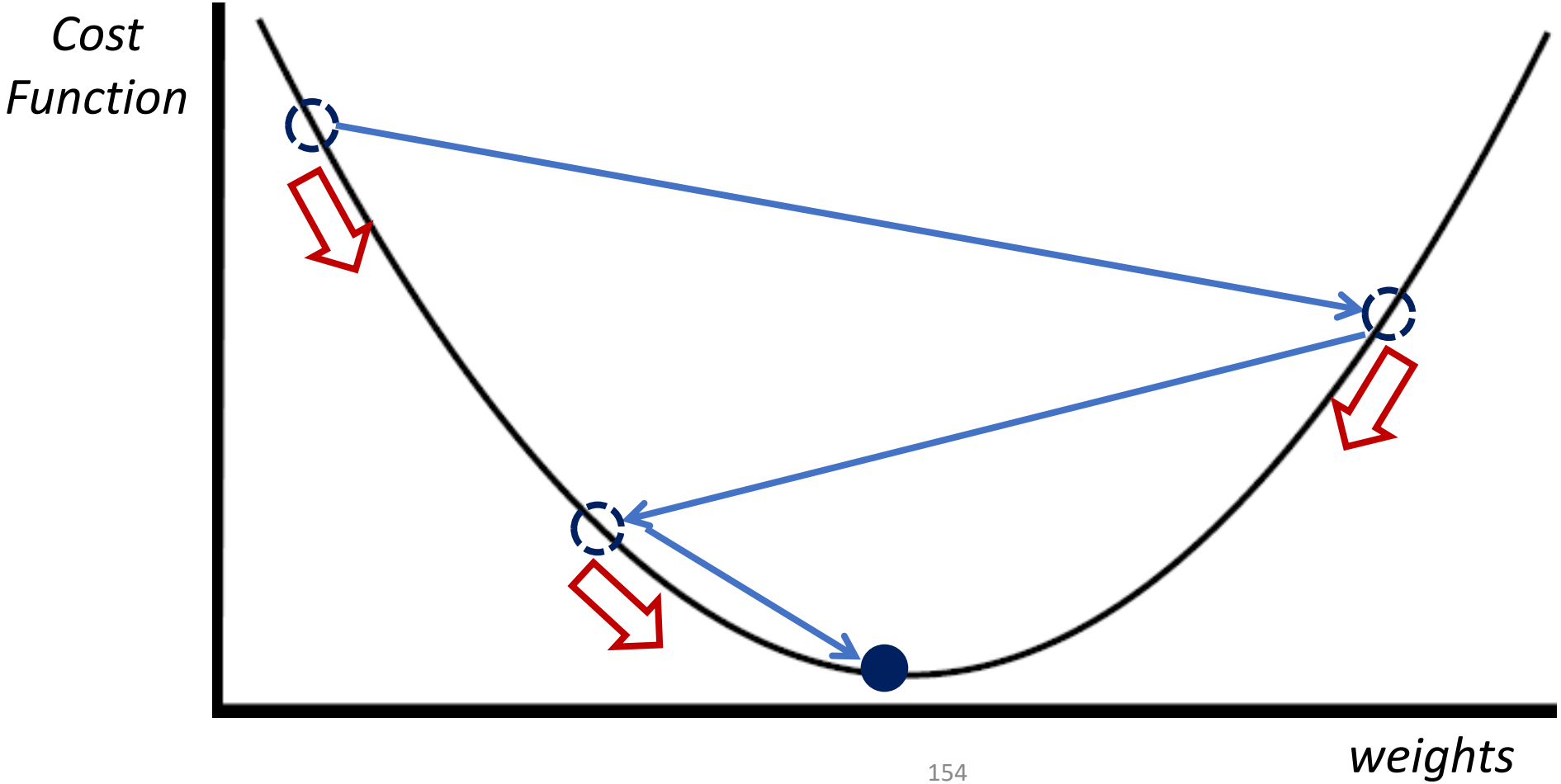


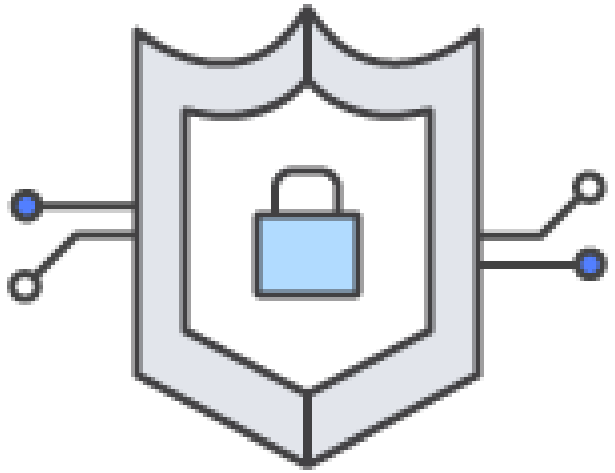
Neural Networks – Back Propagation



Gradient Descent

Used to learn the weights from the training dataset so that error can be minimized

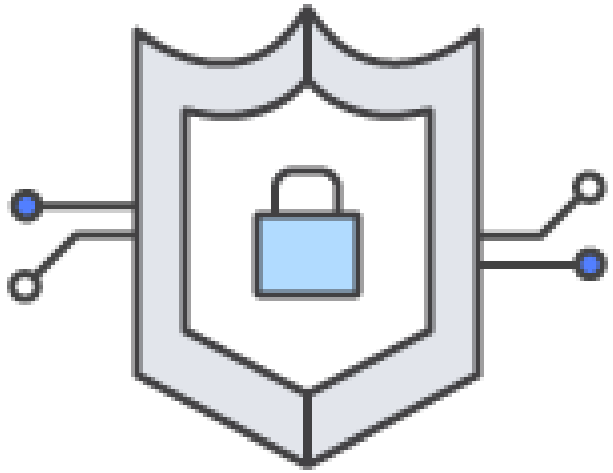




Neural Networks – Gradient Descent

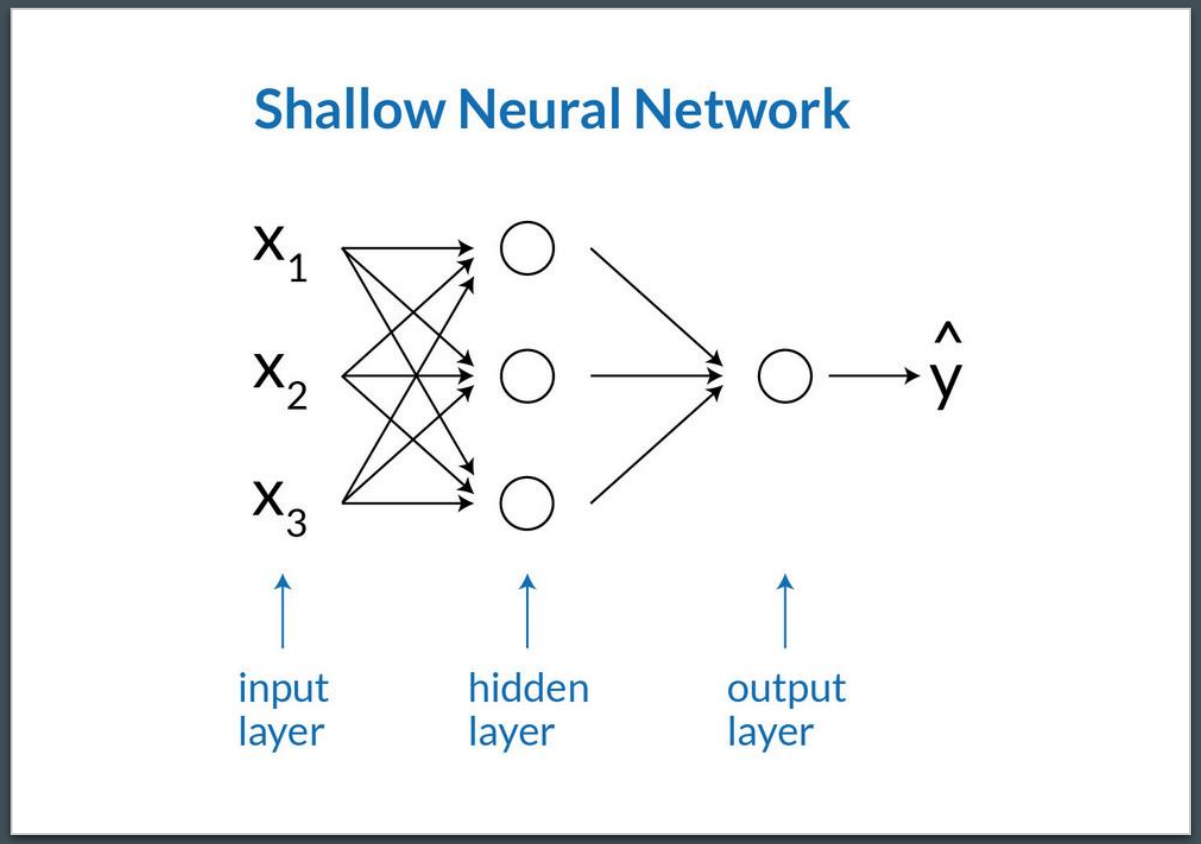
- Open file ‘CodeSamples/GradientDescent’ using Jupyter
- Examples of weight, loss, bias and epochs
- Plotting the values

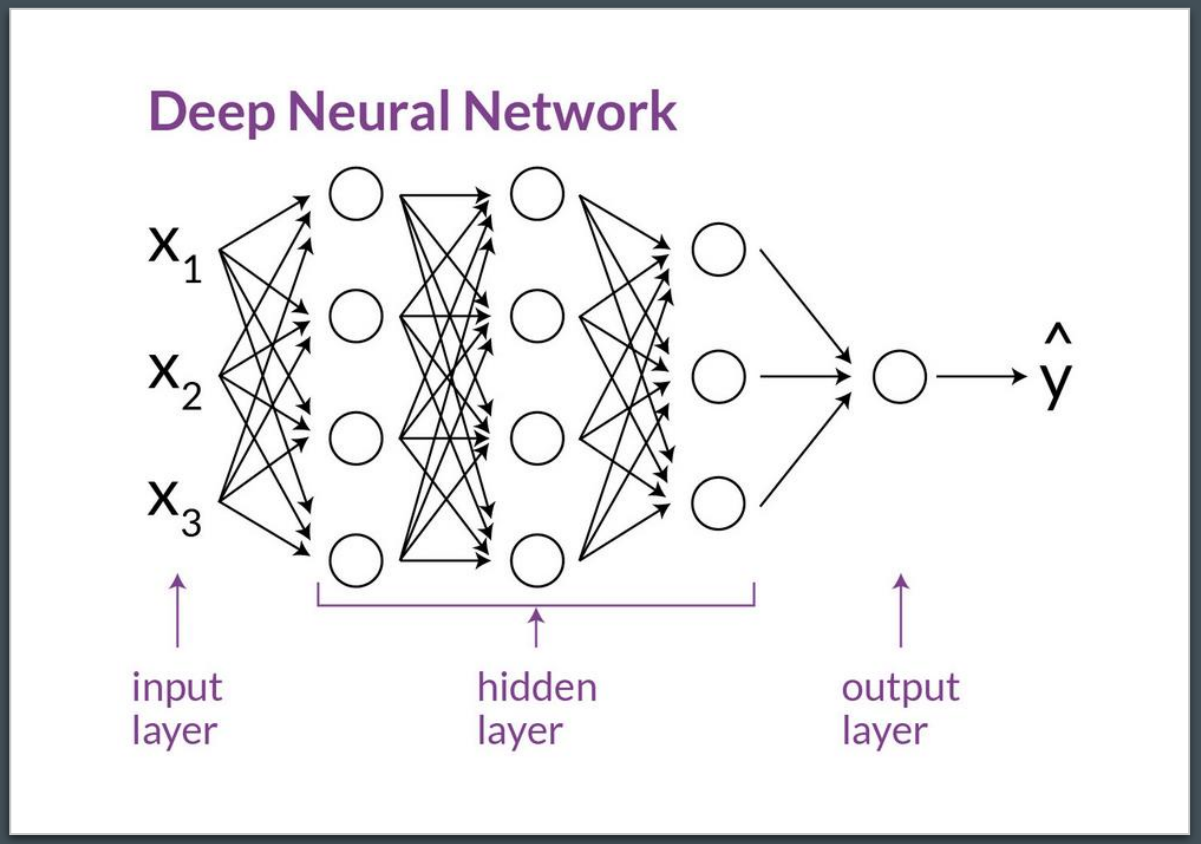
TensorFlow, Keras – Basic Model



- Open file '**CodeSamples/TensorFlow-BasicModel**' using Jupyter
- Basic model to illustrate the use of TensorFlow, Keras
- View loss function and the optimizer

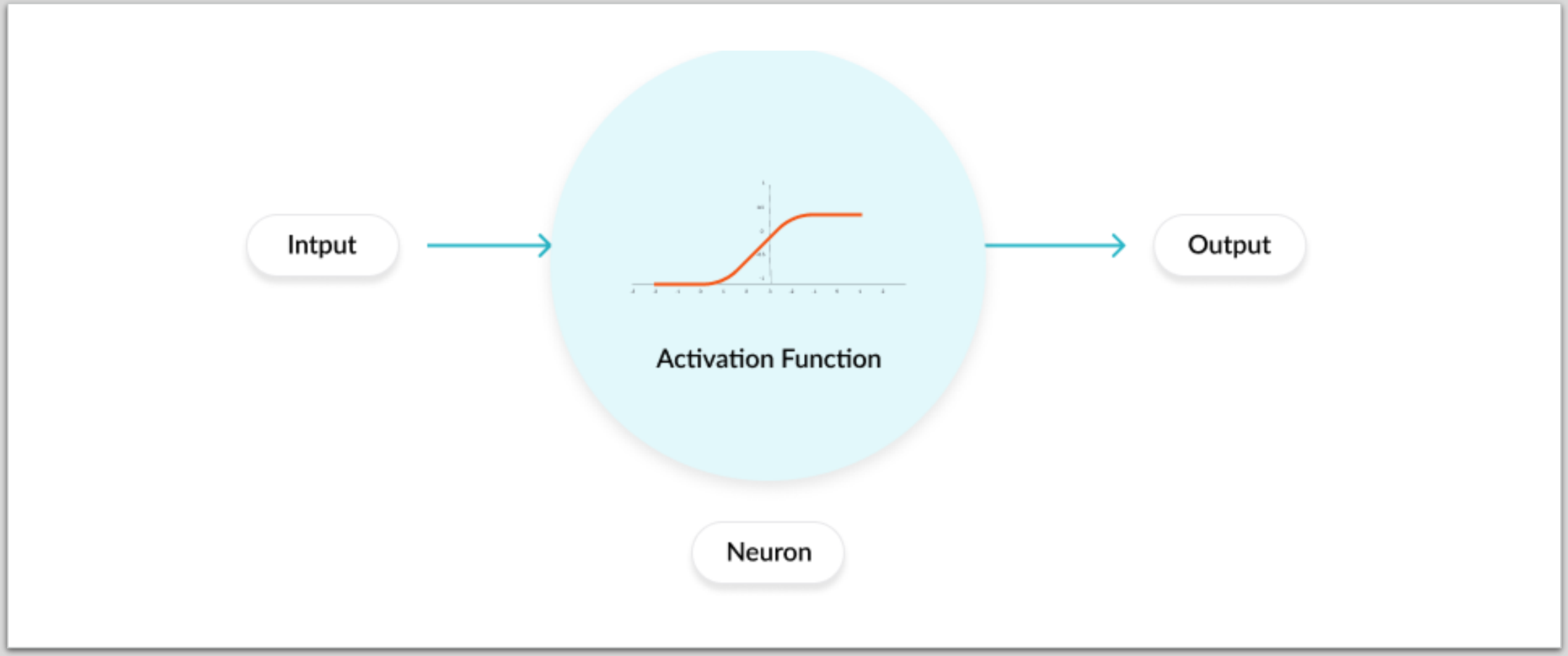
Shallow v/s Deep Neural Networks



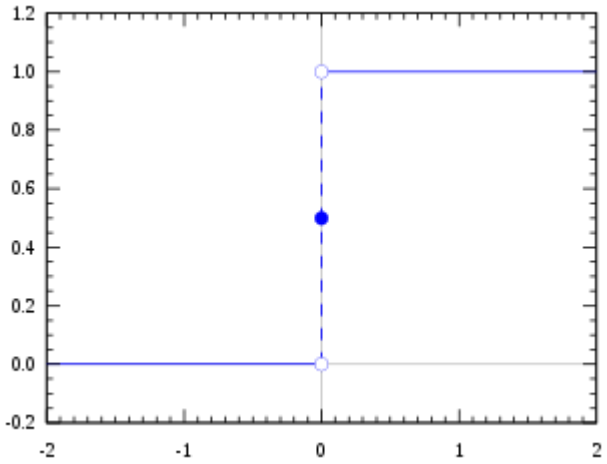


Activation Functions

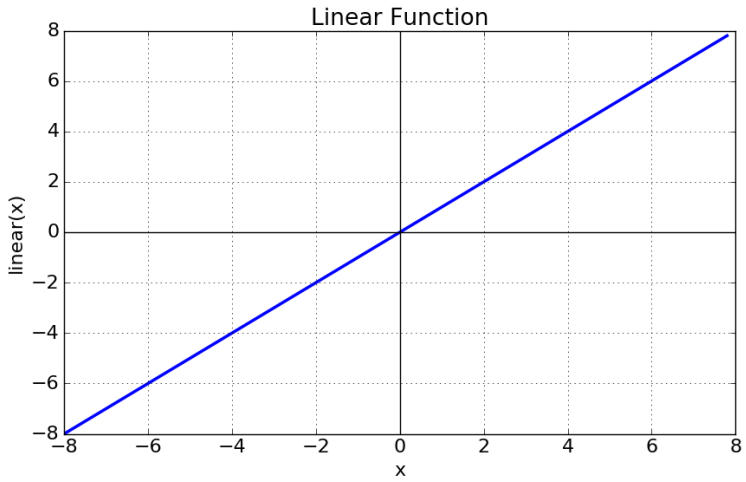
Activation Function



Step Functions

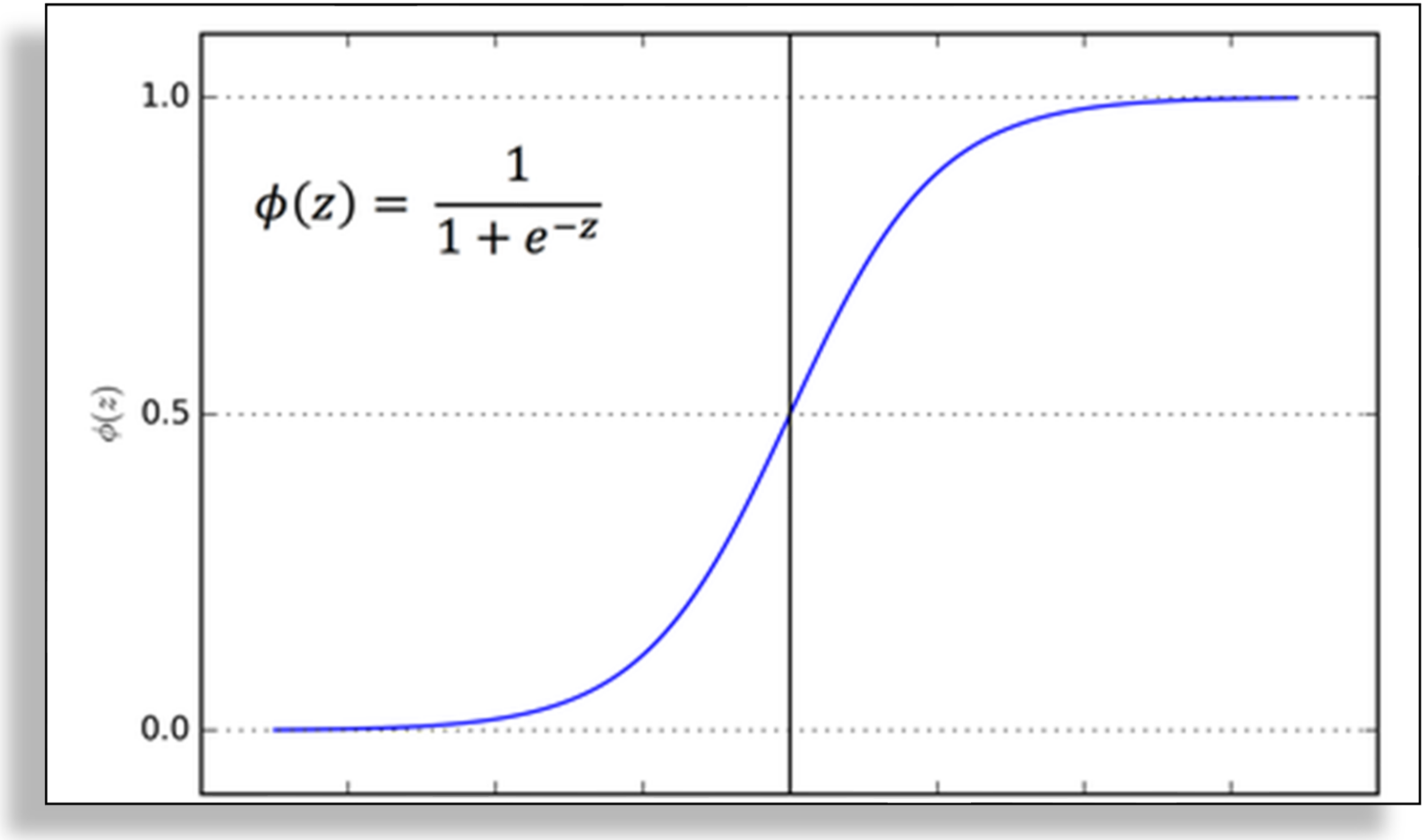


Binary Step Function

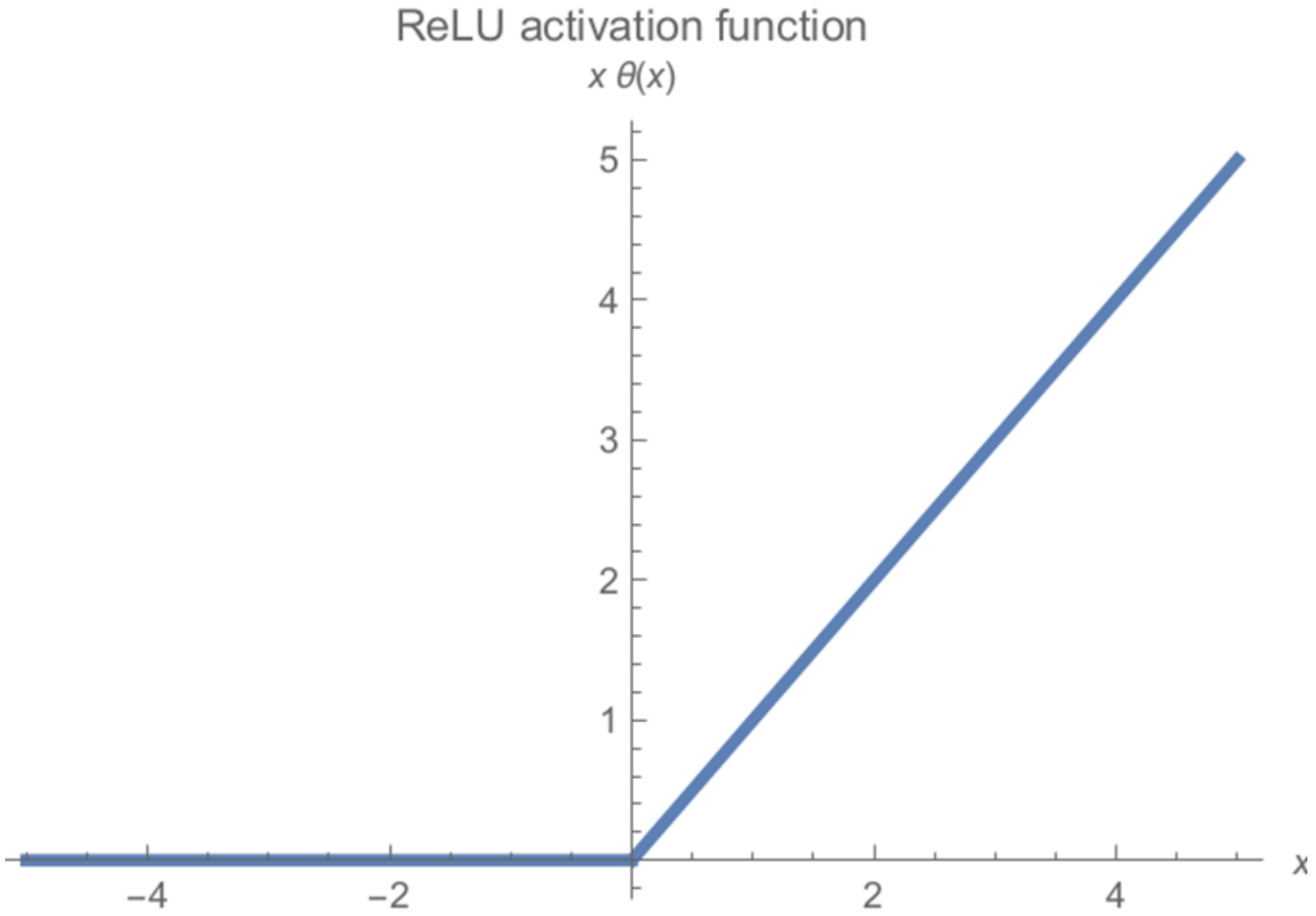


Linear Activation Step Function

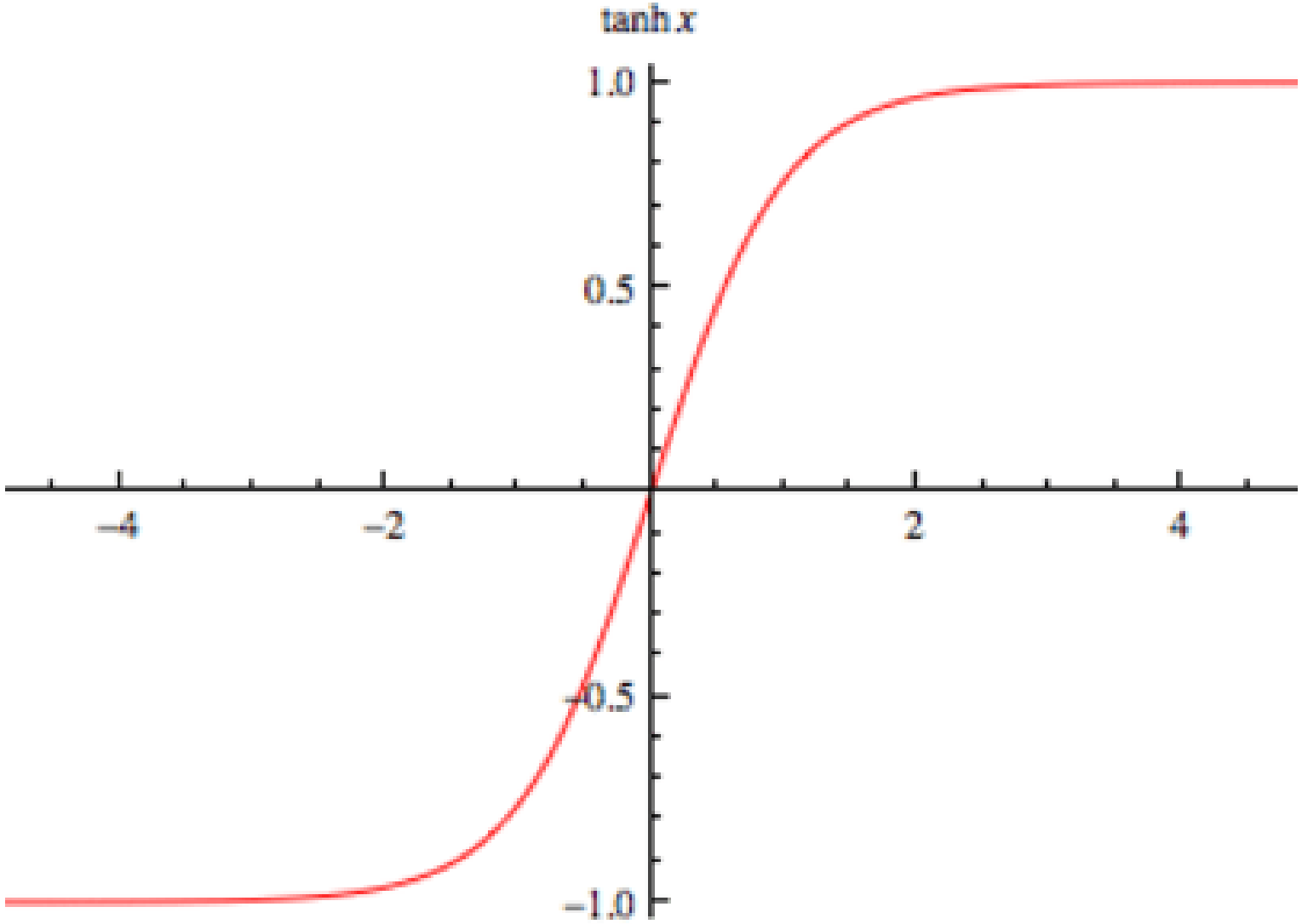
Sigmoid Function (Logistic)



Rectified Linear Unit (ReLU)



Hyperbolic Tangent (Tanh)

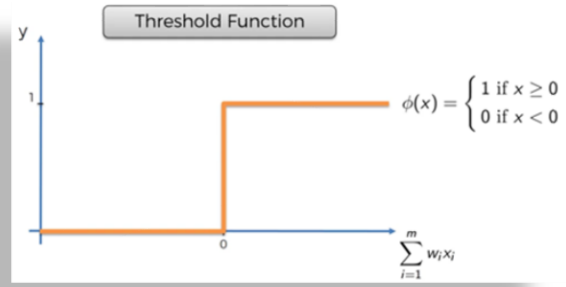


Softmax

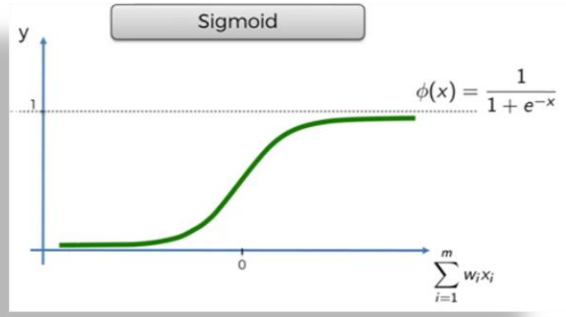
When handling multiple classes of output, Softmax function will give probability distribution for each class

Useful for finding class which has maximum probability

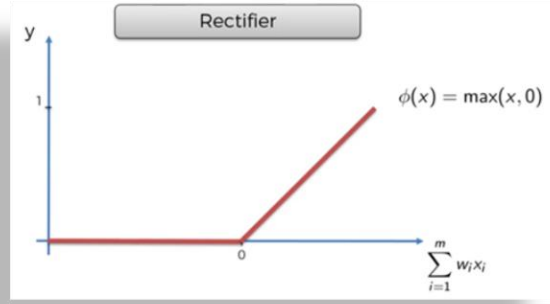
Often used in the output layer of multi-class classification



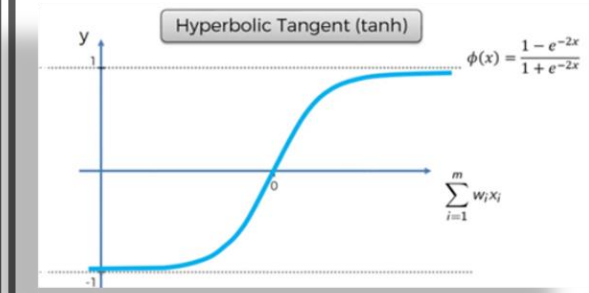
Binary Output Layer



Binary Output Layer



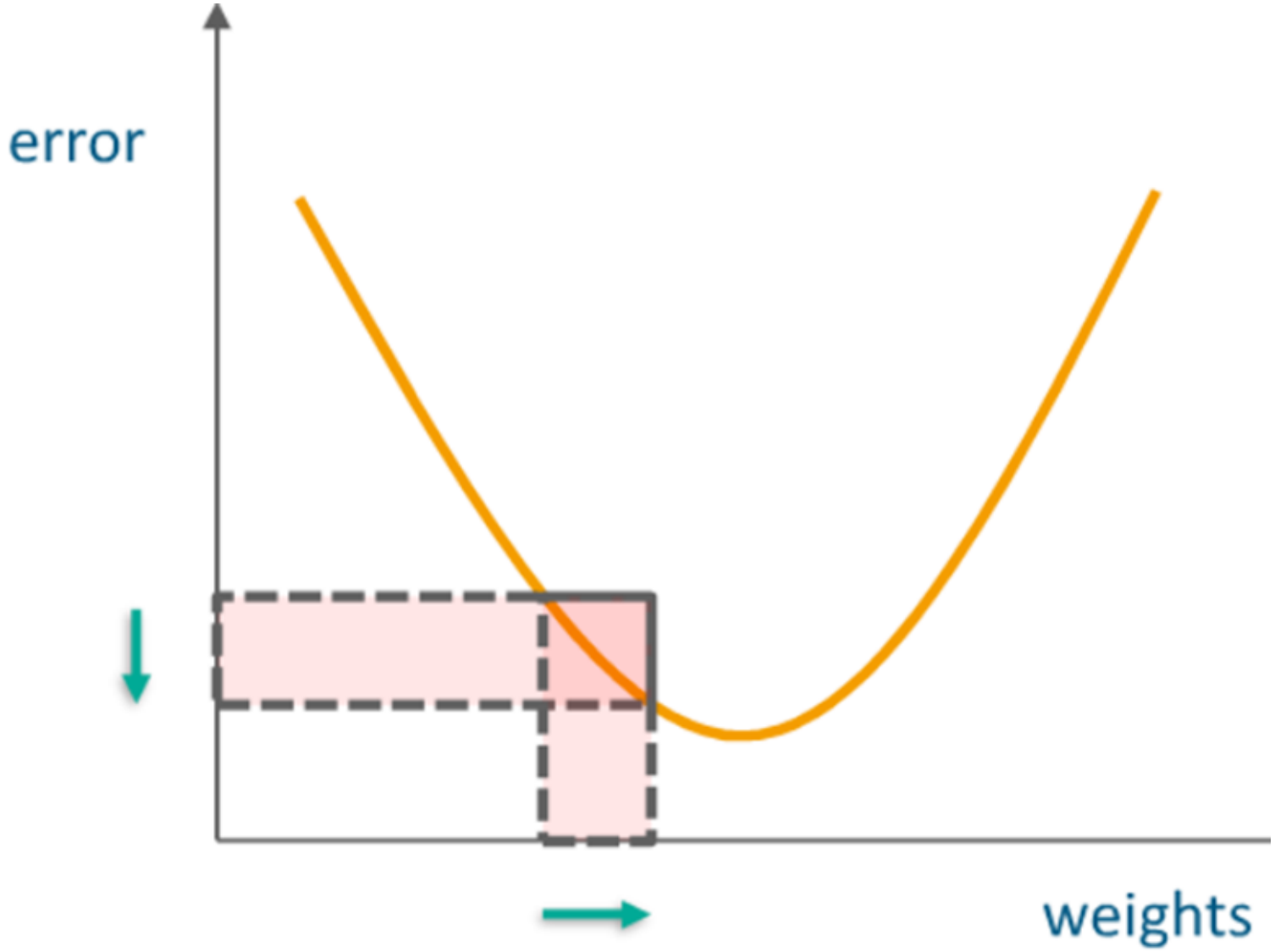
Hidden Layer: CNN



Hidden Layer: RNN

Neural Networks – Activation Functions

Learning Rate



Extra Credits

Extra Credits

- There are 4 datasets:
  1. Credit Card Application
  2. Churn Modelling
  3. Heart Disease
  4. Breast Cancer
- Your Work
  - Pick anyone of these datasets
  - Apply the techniques that you have learnt related to Feature Cleaning, Feature selection, etc.
  - Choose 1 or more algorithms and make predictions
  - Tomorrow afternoon we will review it with the class
- Description of datasets in following slides

Financial Customer Churn Data

- Dataset – Customer information with a financial institution
- Can use any algorithm to do classification (binary)
- Dataset has following features:

RowNumber: Dataset row number
CustomerId: Customer Id
Surname: Last name of the person
CreditScore: Credit Score of the person
Geography: Country of residence
Gender: Person's Gender
AGE: Age of the person
Tenure: How long has the person owned the card
Balance: Outstanding balance
NumOfProducts: Number of products owned by the person with company
HasCrCard: Person has credit card
IsActiveMember: Is the person active member of the company
EstimatedSalary: Estimated salary of the person
Exited: Did the person stay or leave

Dataset - Churn_Modelling.csv

Credit Card Application

- Based on 15 features (not named), predict whether a new customer's credit card application should be approved
- Predicting a "class" – 1 or 0

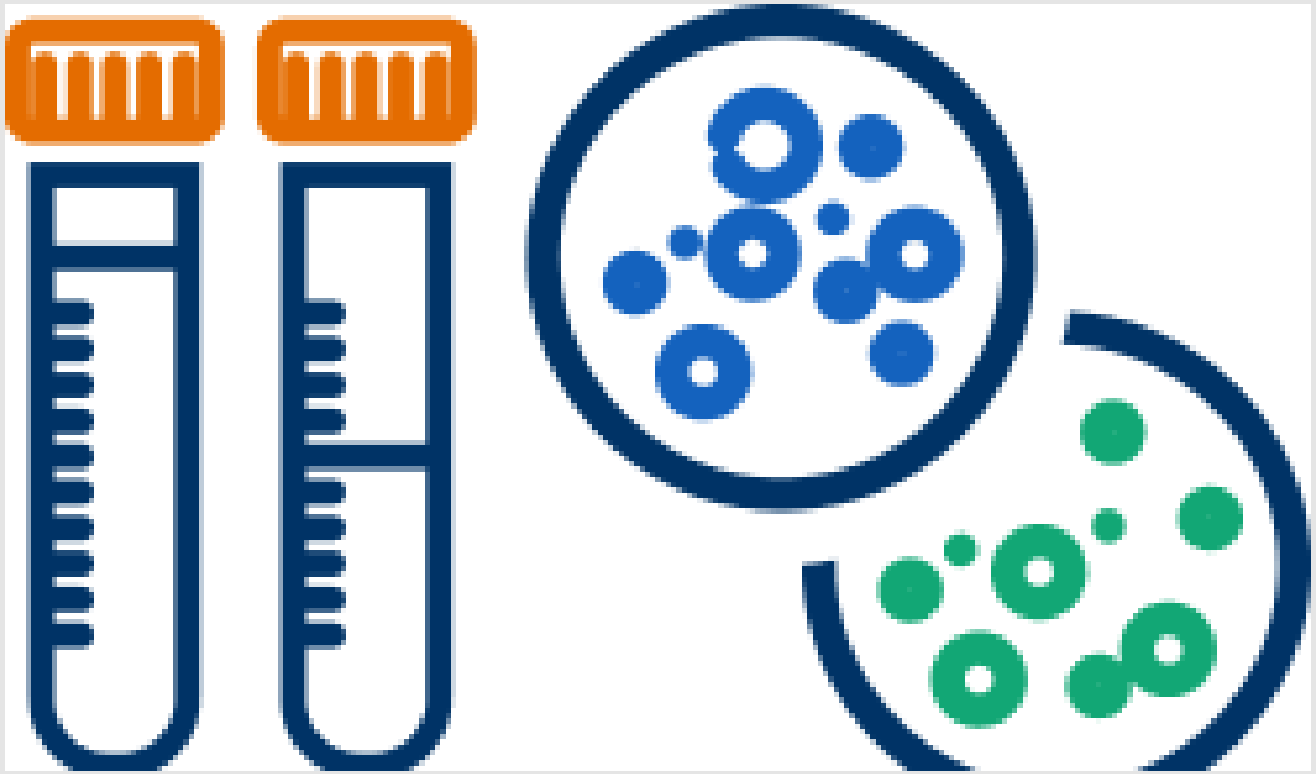
Dataset – Credit_Card_Applications.csv

Heart Disease

Dataset – Heart.csv

- Based on 13 features predict if a patient will have heart disease
- Features include age, gender, chest pain, resting blood pressure, cholesterol, fasting blood sugar, resting ECG, max heart rate, exercise induced angina, etc.
- Predicting a “target” – 1 or 0

Breast Cancer

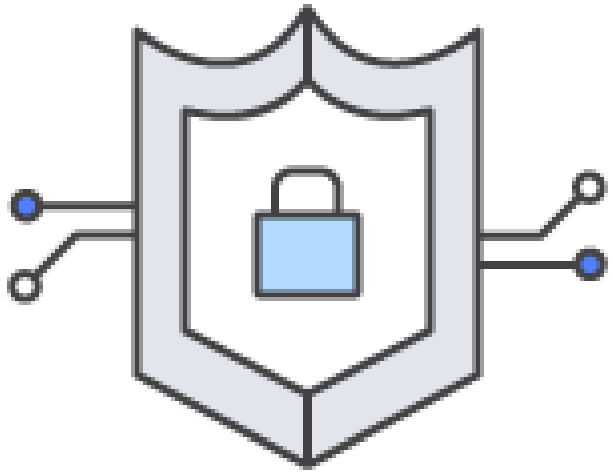


- Dataset includes a number of features related to tissue samples collected
- 2 Classes: benign and malignant (values 2 and 4 respectively)
- Attributes:
  - Sample code number
  - Clump Thickness,
  - Uniformity of Cell Size,
  - Uniformity of Cell Shape,
  - Marginal Adhesion,
  - Single Epithelial Cell Size,
  - Bare Nuclei,
  - Bland Chromatin,
  - Normal Nucleoli
  - Mitoses

Dataset:

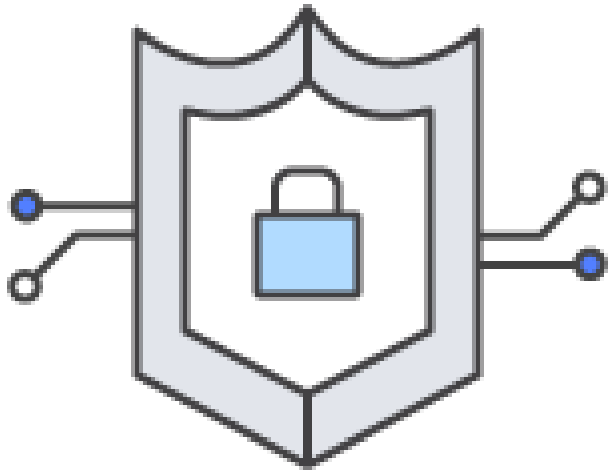
breast-cancer-wisconsin.csv

Neural Networks - Visual



- Use the link provided in the chat session to understand neural networks
- Tinker with number of hidden layers, number of neurons in each hidden layer, activation functions, etc.

Neural Networks - Regression



- Open file '**CodeSamples/NeuralNetworks-Regression**' using Jupyter
- Uses Auto MPG dataset from the UCI repository
- Predict fuel efficiency of late-1970s and early 1980s car models
- Dataset includes Cylinders, Displacement, Horsepower, Weight, Acceleration, Model Year, Country (US, Japan, Europe)

Assignment

- Open file '**Assignment/CRM-CustomerChurn**' using Jupyter
- Implementation requirements are defined in the notebook

Day 3

Welcome to Day 3 AI Toolkit

Please perform PRE-WORK

1. Access the virtual Lab using link https://html.inspiredvlabs.com Use the username TEKBD142-XX (replace XX with your number) and password

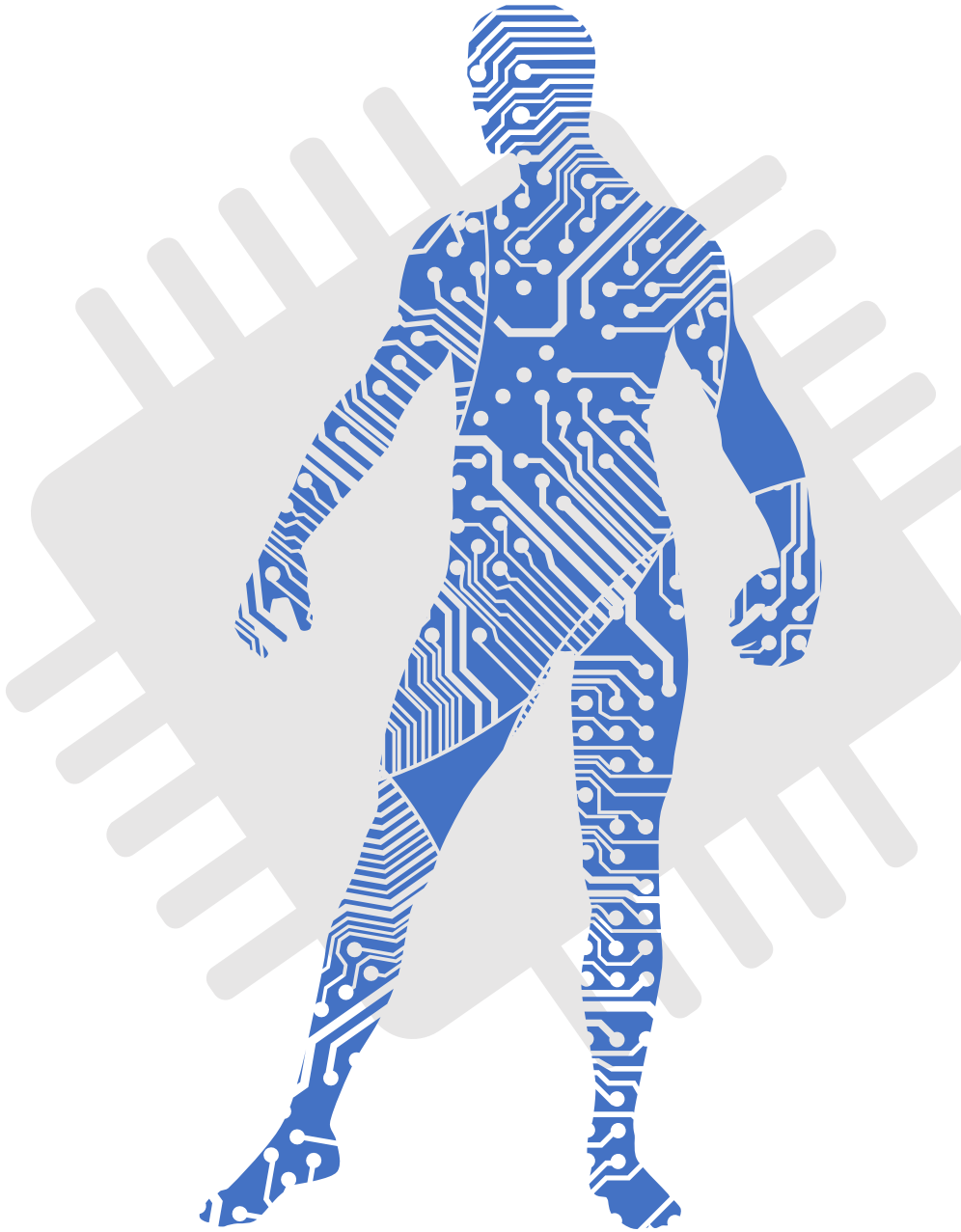
TekBD142!23

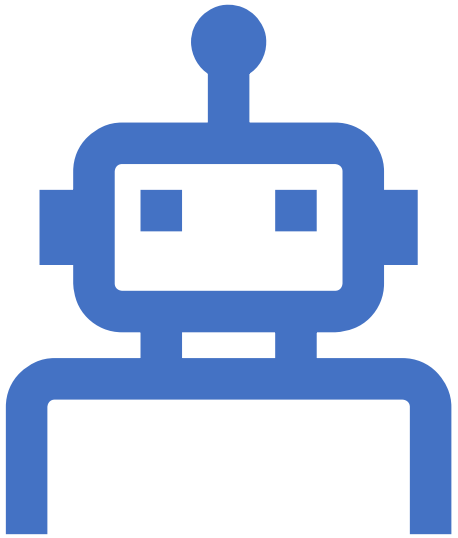
We will be starting soon

Last Name	First Name	Login Id
AHMED	NAZEER	TEKBD142-01
AM	GANESH	TEKBD142-02
BISWAS	SOURAV	TEKBD142-03
CHACKO	THOMAS	TEKBD142-04
JAJOO	SANDESH	TEKBD142-05
MATTOX	CHRISTEL	TEKBD142-06
MAXSON	CRAIG	TEKBD142-07
MURPHY	MATTHEW	TEKBD142-08
PANDIAN	JEYARAJ	TEKBD142-09
PATURI	RAVIKIRAN	TEKBD142-10
RANI	AMITA	TEKBD142-11
SINGLA	SANJEEV	TEKBD142-12
VEERAMASU	BRAHMA RAO	TEKBD142-13

Agenda – Day 3

1. Recap of Day 2
2. Neural Networks – Classification
3. Image Processing (CNN)
4. Recurrent Neural Networks (RNN)
5. Extra Credits
6. Natural Language Processing (NLP)
7. Assignment Solutions
8. Next Steps

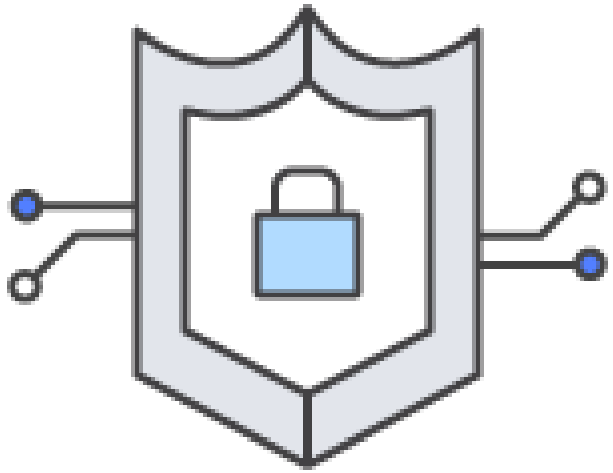




Recap Day - 2

- Logistic Regression
- Model and Pipeline Persistence
- Word Cloud
- TensorFlow
- Google’s Colab
- Artificial Neural Networks
- Multiple Hands-on

Neural Networks - Classification



- Open file '**CodeSamples/PredictPetFinder**' using Jupyter
- Pet adoption dataset that we used with Word Cloud
- Want to take our Adoption Speed and use it to do binary classification
- If the value is 4 then the pet does not get adopted
- Any other value the pet gets adopted
- Build a neural network to classify

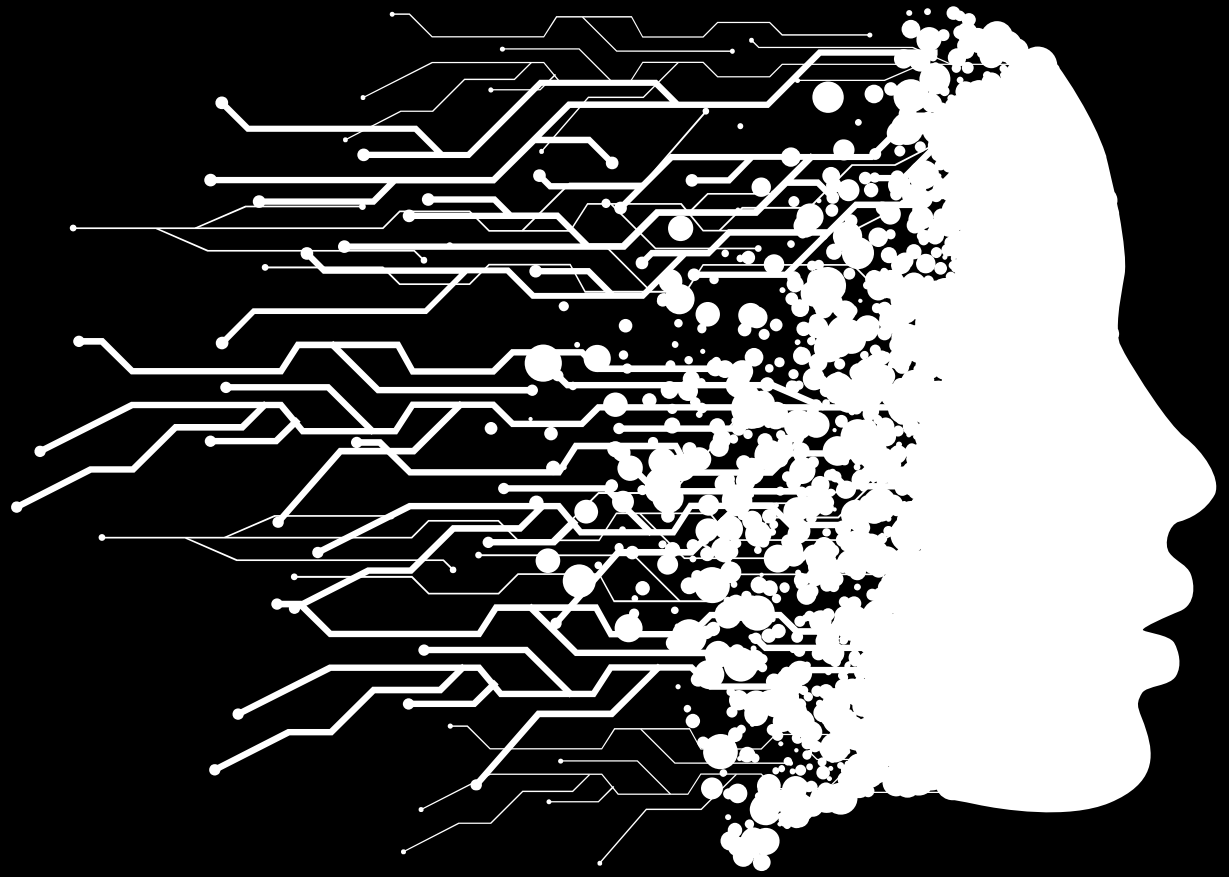


Image Processing

Image – Bunch of Bytes

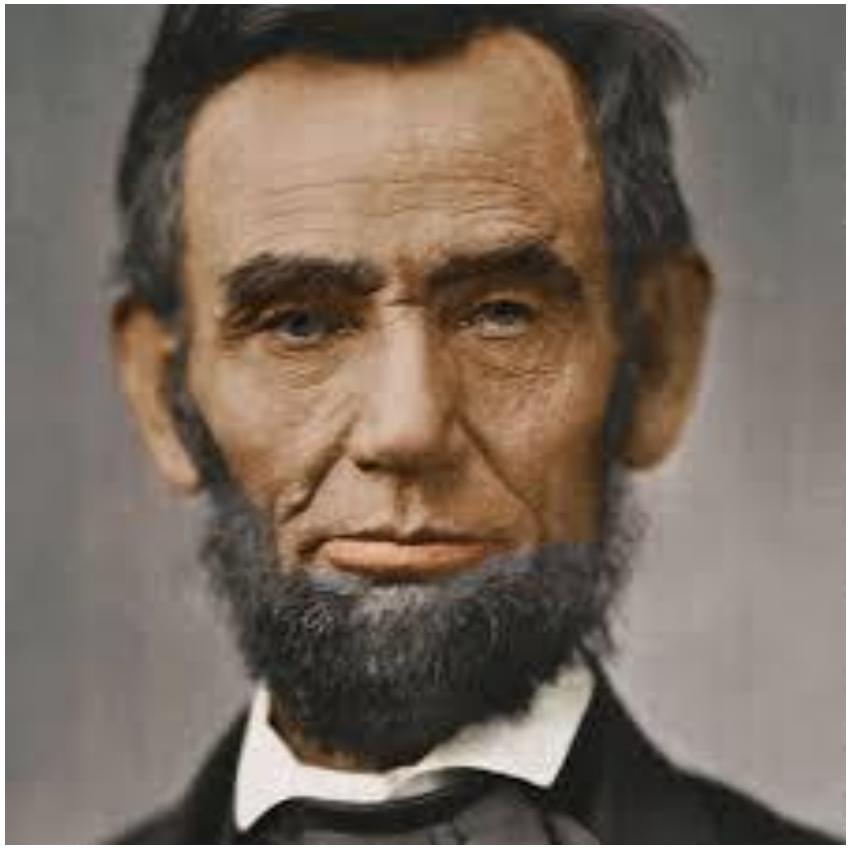


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Image - Resizing

720 x 960

33 %

216 x 288

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0	0	4	0	163	225	251	255	229	120	0	0	0	0	0	11	0	0
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Pixel Values (grayscale)

Image Augmentation

- Quite often there might not many images in the dataset
- Doing augmentation helps in adding new images to the data - add variety
- Some of augmentations that can be done on images:
  - Rotate the image by certain angle
  - Width or Height shifting
  - Change image brightness
  - Sheer or Zoom images
  - Convert to grayscale

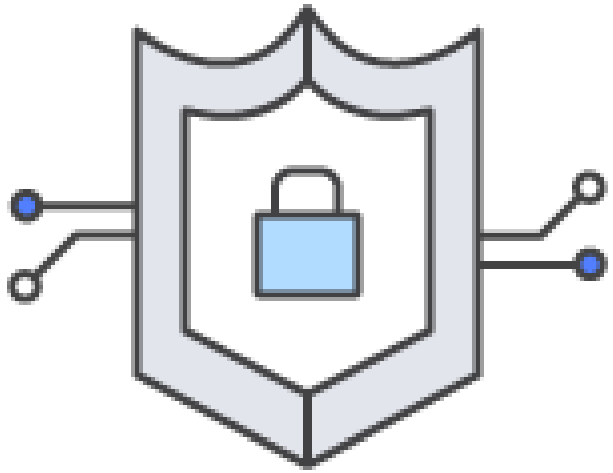


Image Augmentation

- Open file ‘**CodeSamples/ImageAugmentation**’ using Jupyter
- Example of doing image augmentation such as rotating images, changing width and height
- Converting to Gray Scale

Pixel Normalization: Min - Max

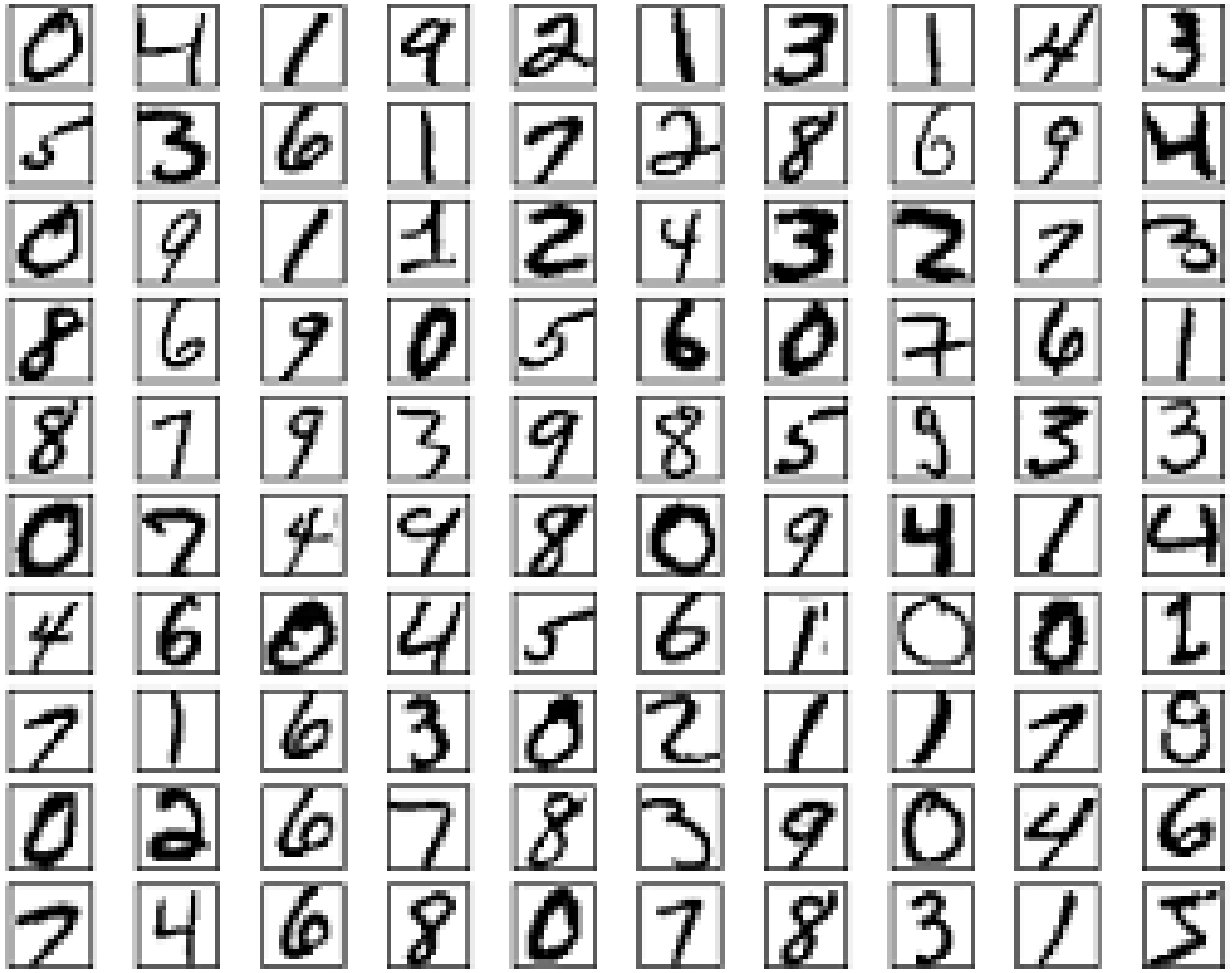
$$\frac{X - min}{\max - min}$$

Pixel values (gray scale) are between 0 (min) and 255 (max)

Want values between 0 and 1

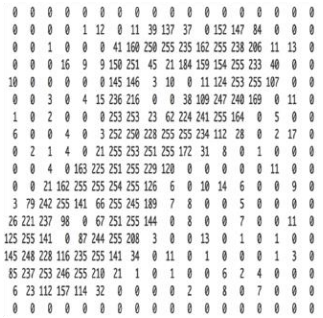
$$\frac{X}{255}$$

Hand-Written Digits Recognition



Digit Recognition

28 x 28



Flatten

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, 0, 11, 0, 1, 0, 0, 0, 1, 3, 0, 85, 237, 253, 246, 255, 210, 21, 1, 0, 1, 0, 0, 6, 2, 4, 0, 0, 0, 6, 23, 112, 157, 114, 32
, 0, 0, 0, 0, 2, 0, 8, 0, 7, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```
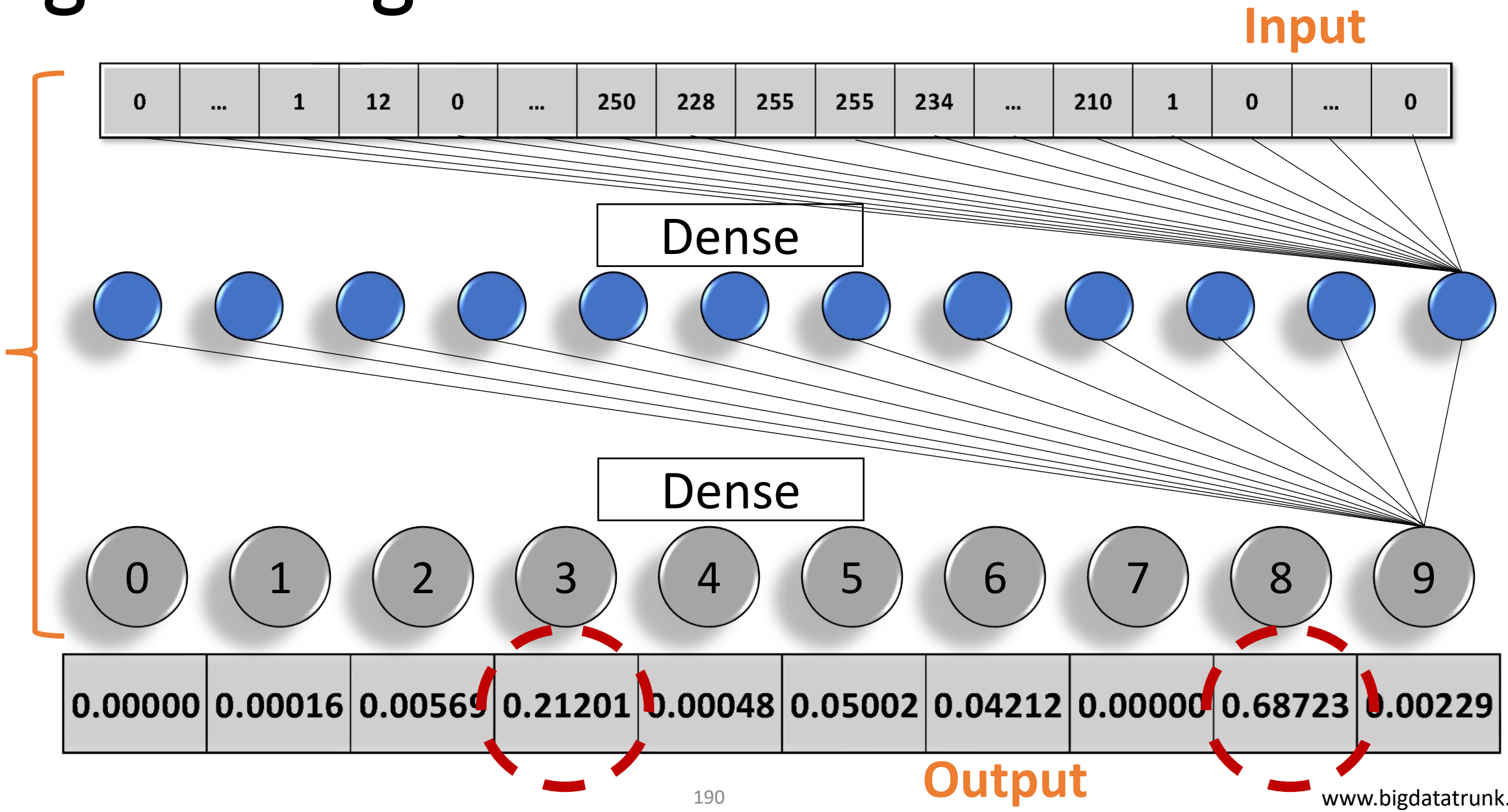

Digits Recognition



Keras and TensorFlow

```
model = keras.models.Sequential()
model.add(keras.layers.Flatten(input_shape=[28, 28]))
model.add(keras.layers.Dense(128, activation="relu"))
model.add(keras.layers.Dense(10, activation="softmax"))
```

Train model using the training data

```
model.fit(trainingImages, trainingLabels, epoch = 10)
```

Evaluate the performance of the trained model

```
model.evaluate(testImages, testLabels)
```

Make predictions on the test data

```
model.predict(testImages)
```

Hyper-Parameters

Hidden Layers

- Choose 1 or 2 layers

Neurons Per Hidden Layer

- Make first layer large
- Or make all layers with same number of neurons

Learning Rate

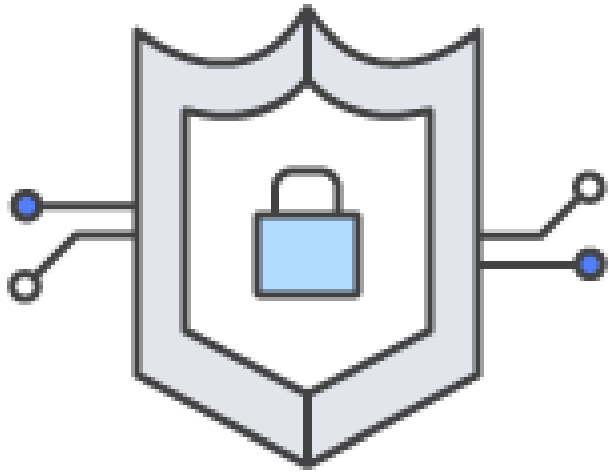
- Start at low rate (0.0001)
- Gradually increase

Activation

- Hidden layers: ReLU
- Multi-Class: Softmax
- Binary Class: Sigmoid
- Regression: None

Hyper-Parameters

	Classification	Regression
Optimizer	'adam': keras.optimizers.Adam(lr = 0.001) 'rmsprop': keras.optimizers.RMSProp(lr = 0.001)	'sgd': keras.optimizers.SGD(lr = 0.001) 'rmsprop': keras.optimizers.RMSProp(lr = 0.001)
Loss	Binary: 'binary_crossentropy' Multi-Class: 'categorical_crossentropy' Discrete: 'sparse_categorical_crossentropy'	'mse'
Metrics	'accuracy'	'mse', 'mae'



Neural Networks

- Open file ‘**CodeSamples/NeuralNetworks**’ using Jupyter
- Classify handwritten digits using MNIST Digits Data
- Recognize digits between 0 and 9

Challenges with Image Handling

Image 28 x28

Input Layer: 28 * 28 = 784 Features

Image 1000 x 1000

Input Layer: 1000 * 1000 = 1 million Features

Challenges with Image Handling

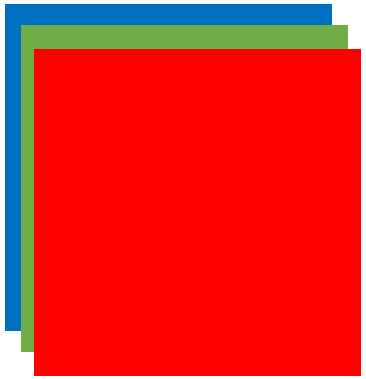


Image 1000 x 1000

Input Layer: 3 * 1000 * 1000 = 3 million Features

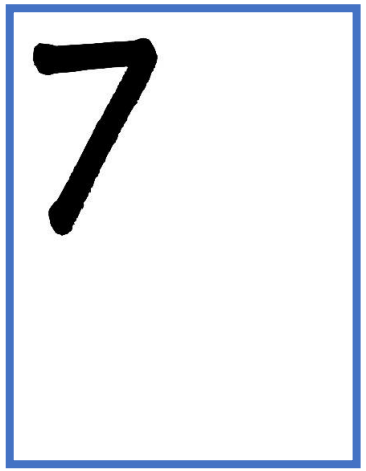
THAT IS HUGE - COMPUTATIONALLY

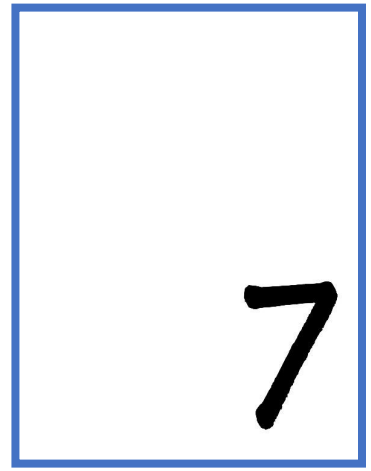
1 Hidden layer and 1000 Neurons in it:

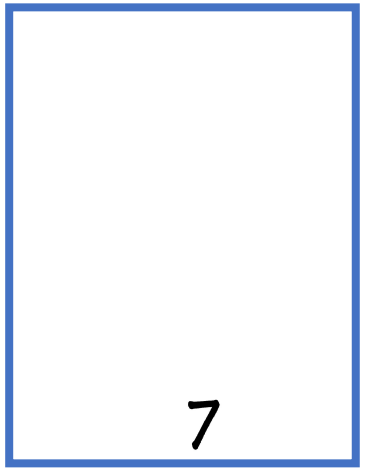
3 million * 1000 = **3 billion weights**

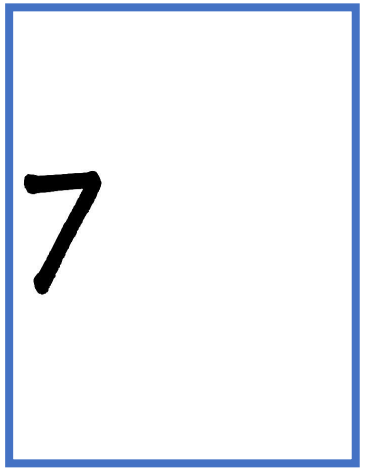
Challenges with Image Processing

How can neural network recognize the digits?









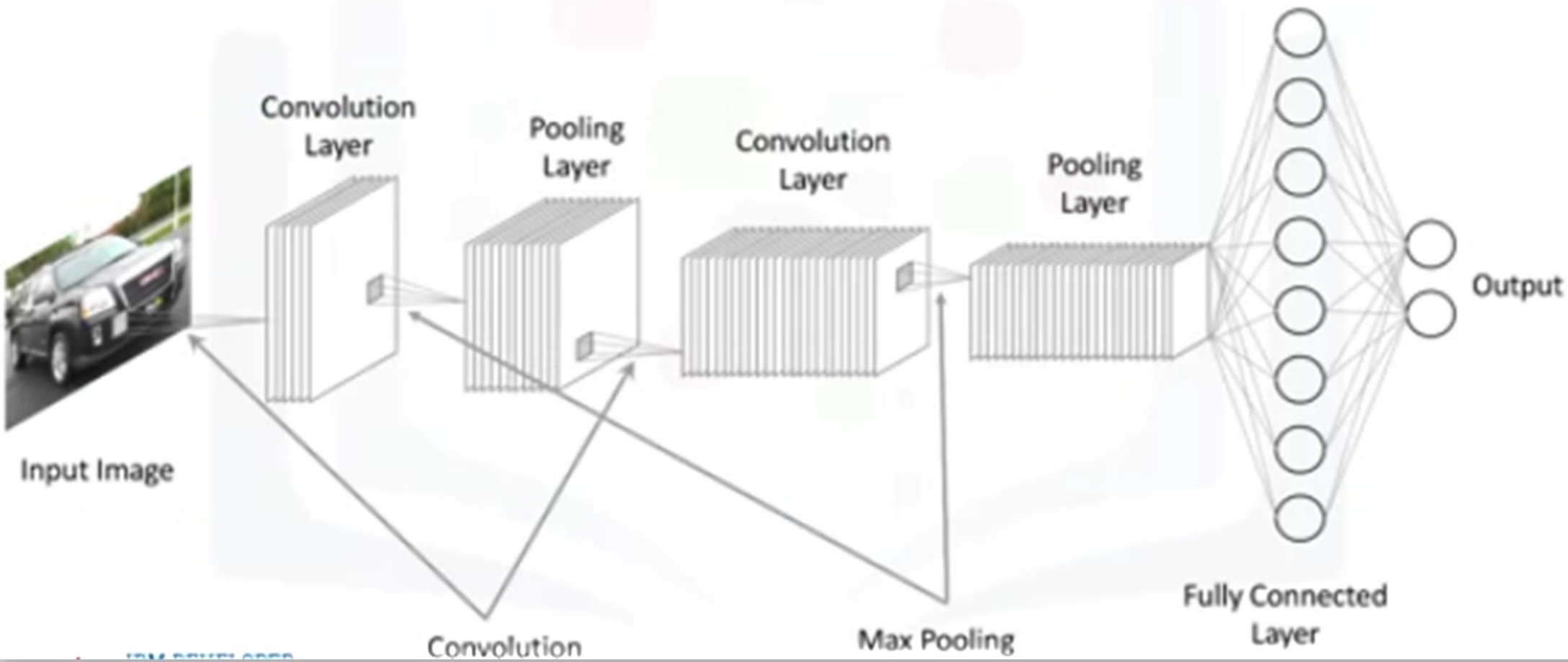
Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN)

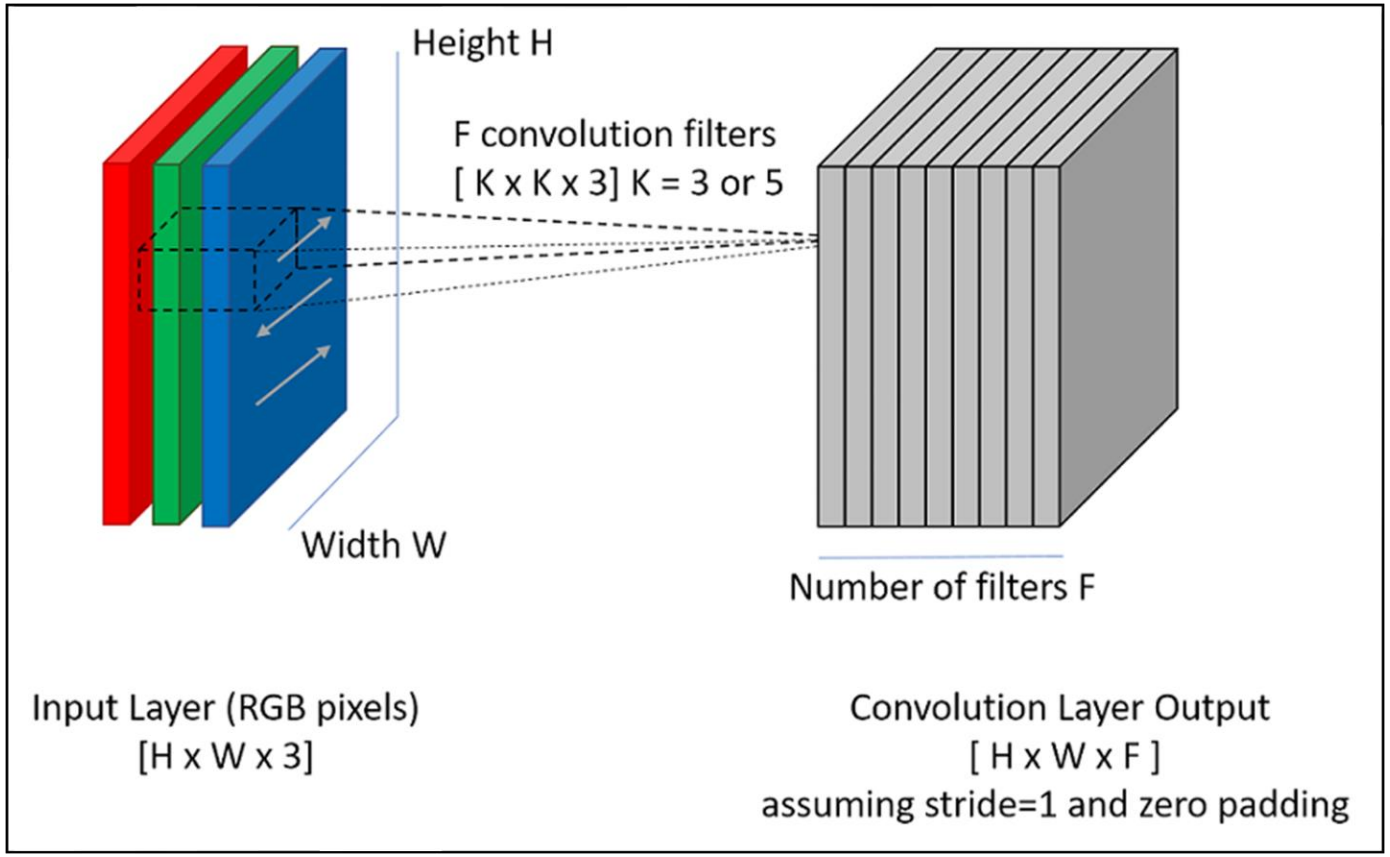
199

- Type of Supervised Deep Learning technique
- Takes images as inputs
- Provides methods to make the training of images efficient
- Helps make the forward propagation step efficient
- Reduces number of features in the images
- Useful in image recognition, object detection and other computer vision applications

CNN Architecture



Filter Maps


Height H
F convolution filters
[K x K x 3] K = 3 or 5
Width W
Number of filters F
Input Layer (RGB pixels)
[H x W x 3]
Convolution Layer Output
[H x W x F]
assuming stride=1 and zero padding

Convolutional Layer – Feature Maps

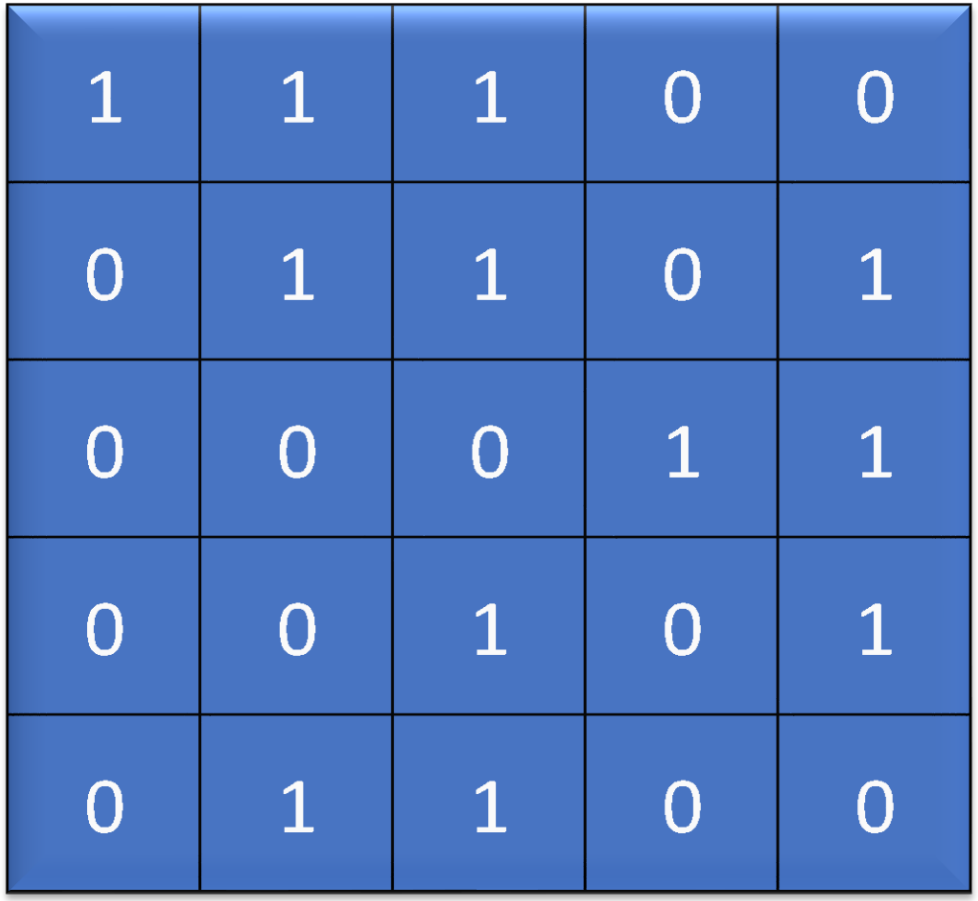
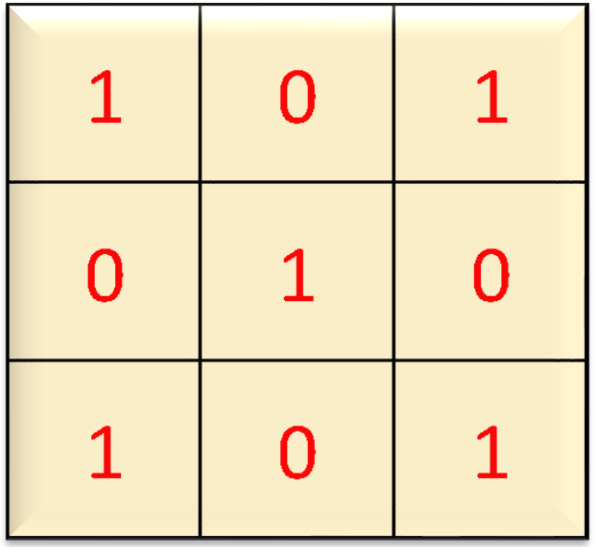
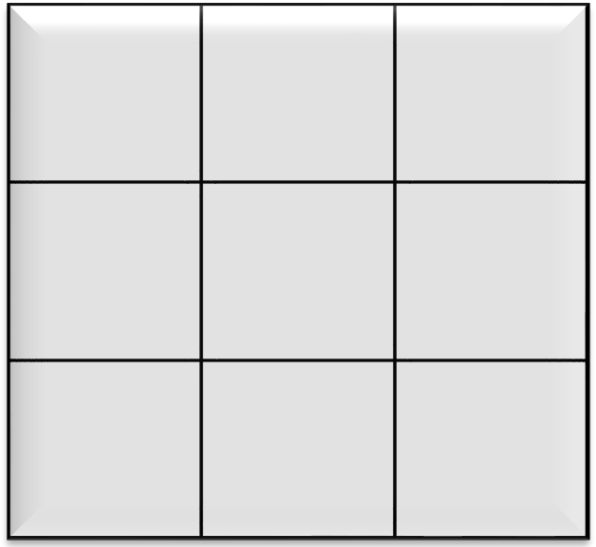


Image (5 x 5)

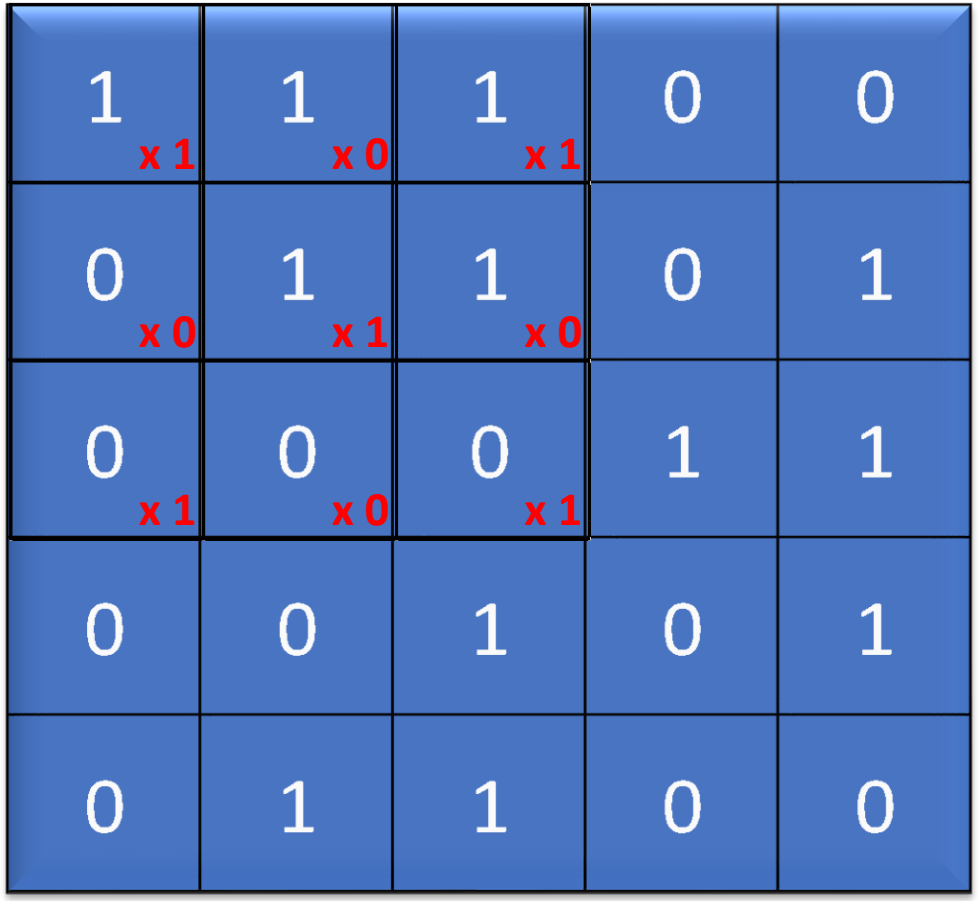


Filter (3 x 3)

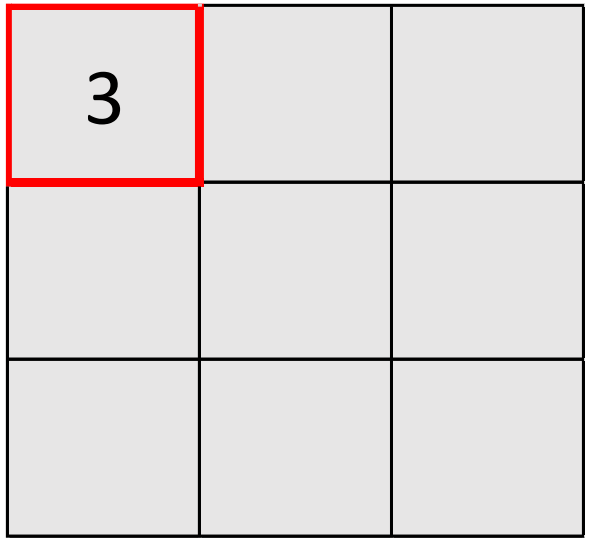


Output
Feature Map

Convolutional Layer – Feature Maps

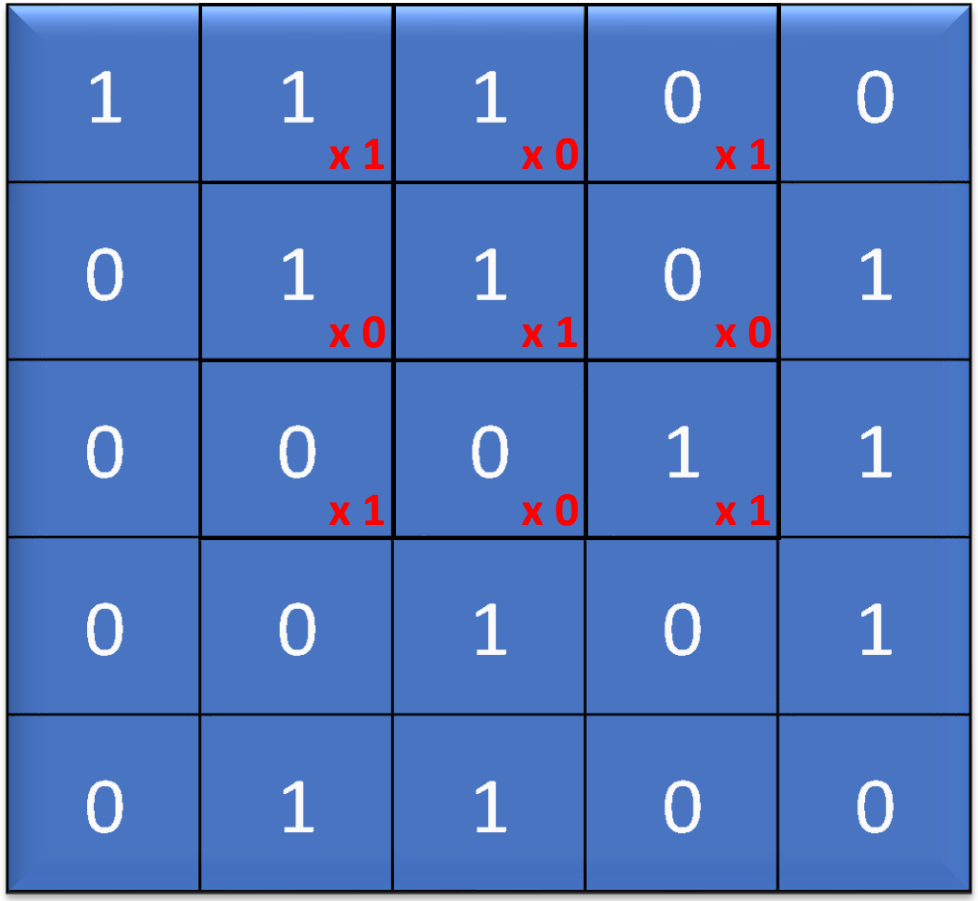


Image

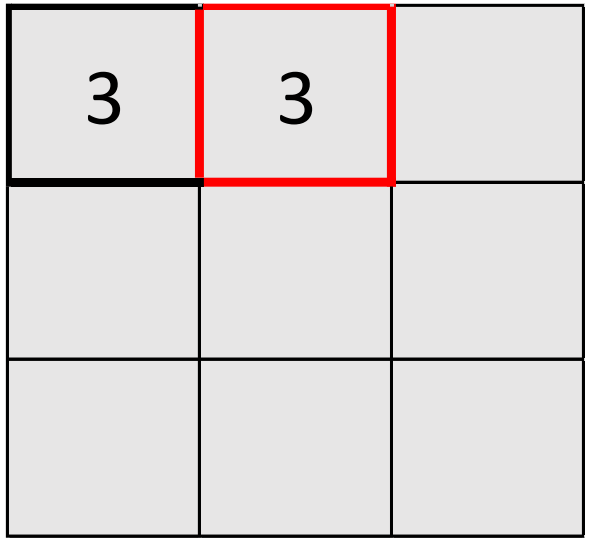


Output
Feature Map

Convolutional Layer- Feature Maps

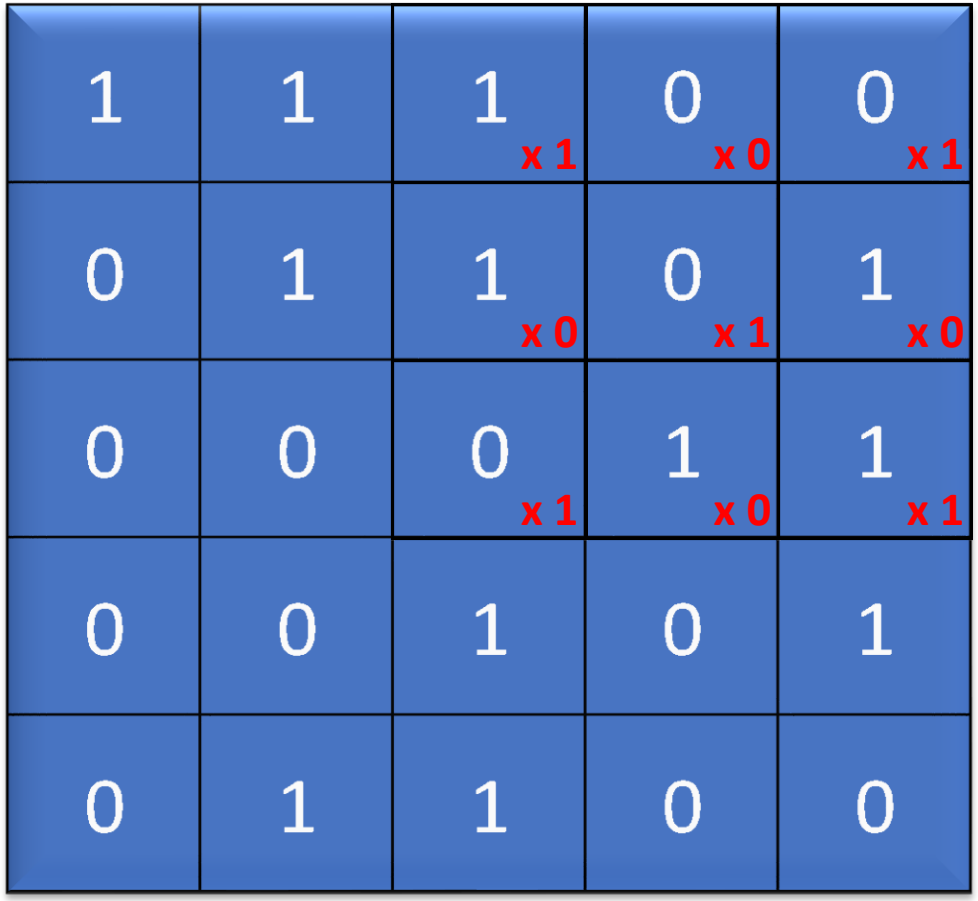


Image

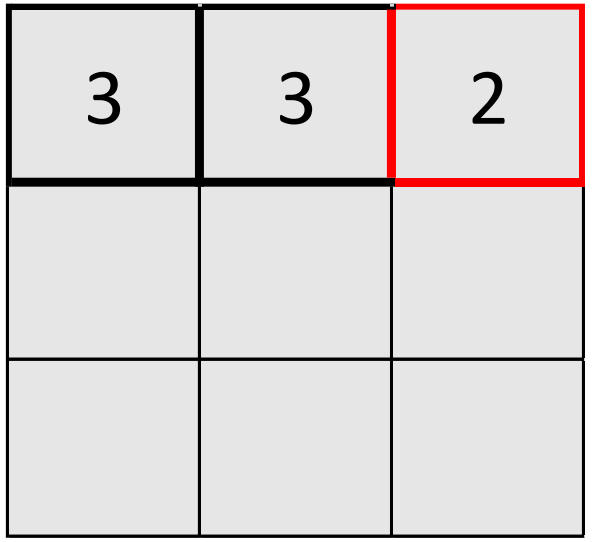


Output
Feature Map

Convolutional Layer – Feature Maps

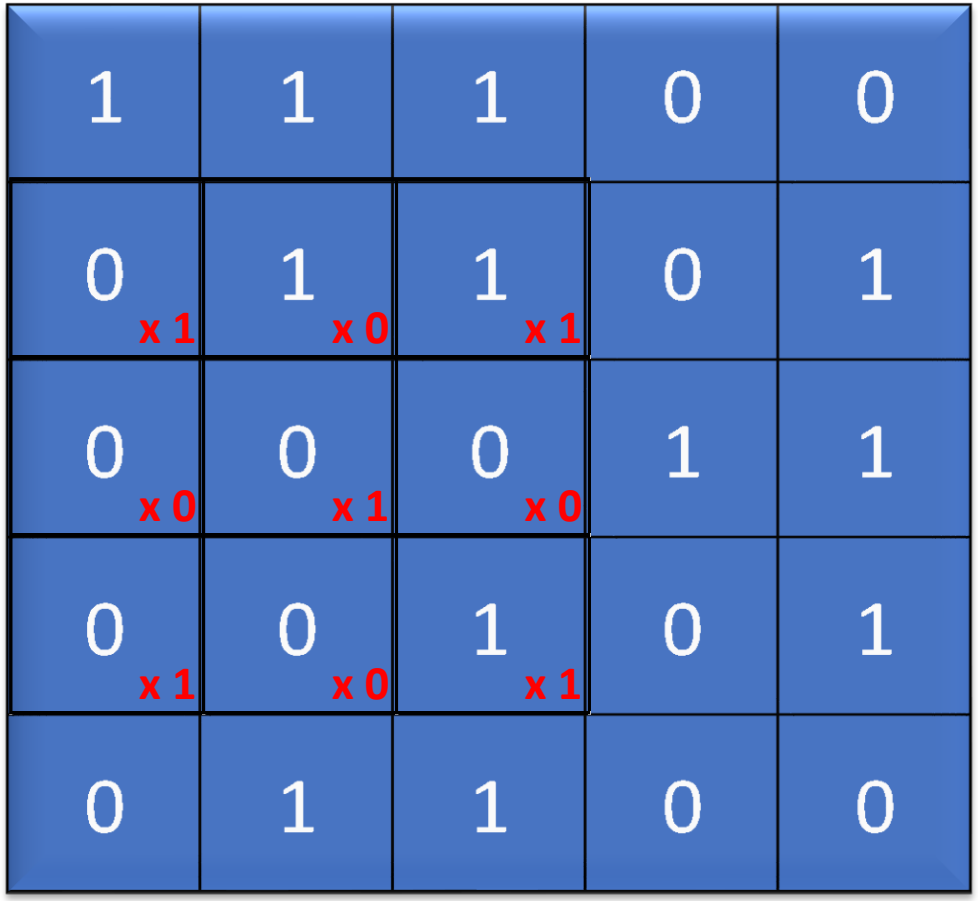


Image

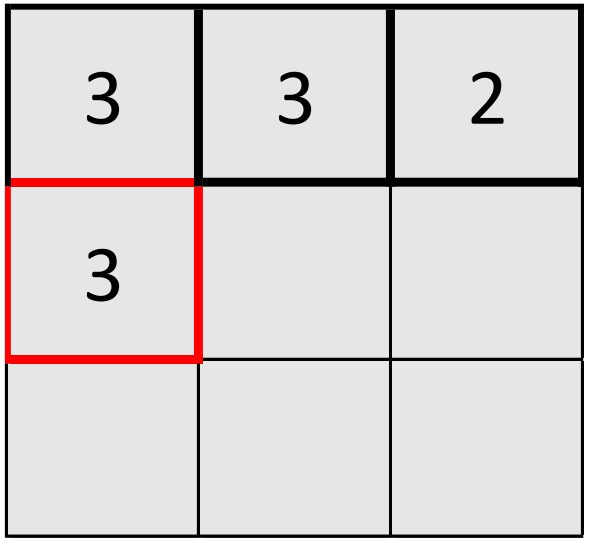


Output
Feature Map

Convolutional Layer – Feature Maps

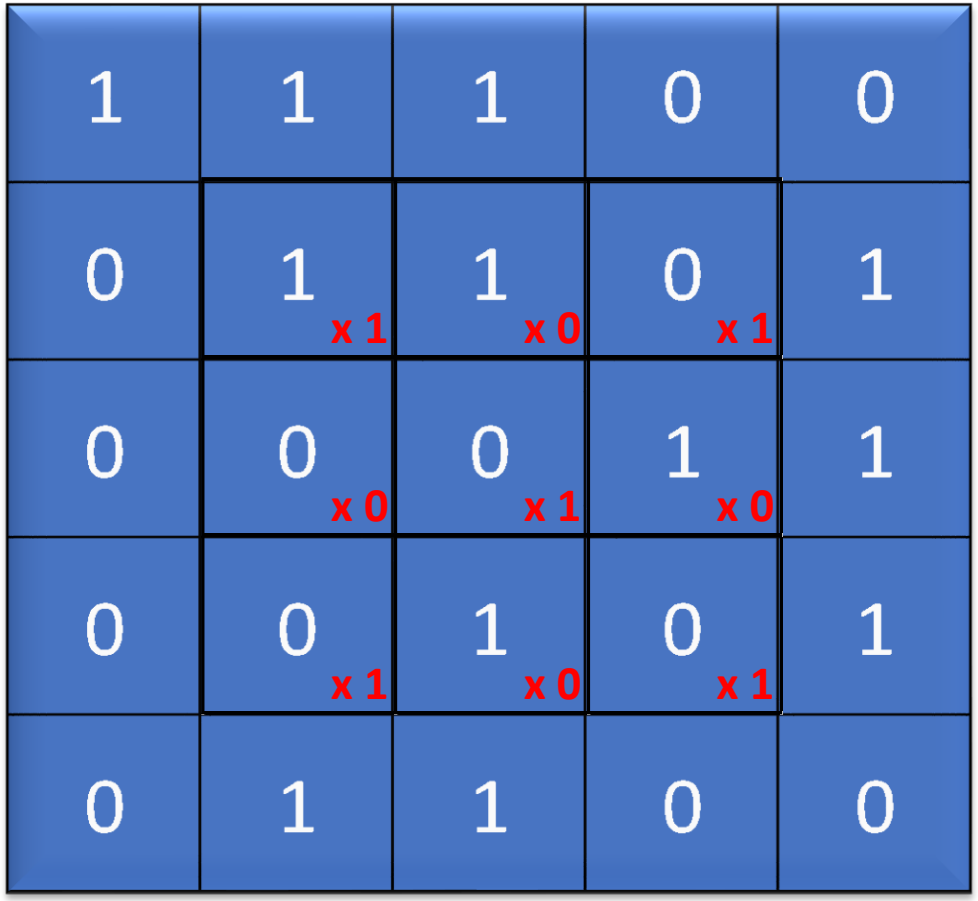


Image

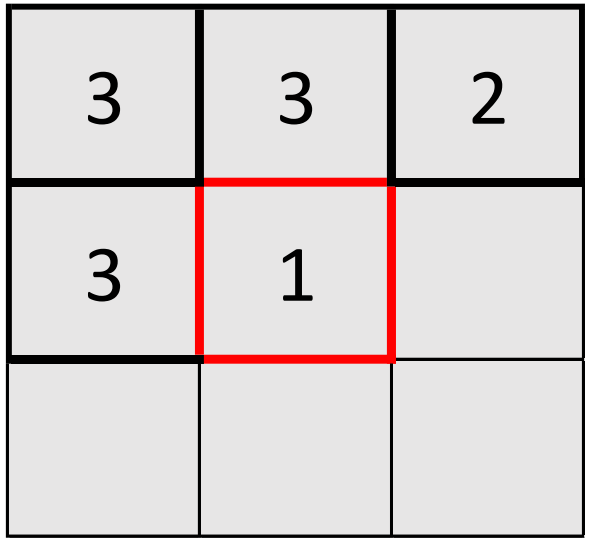


Output
Feature Map

Convolutional Layer – Feature Maps

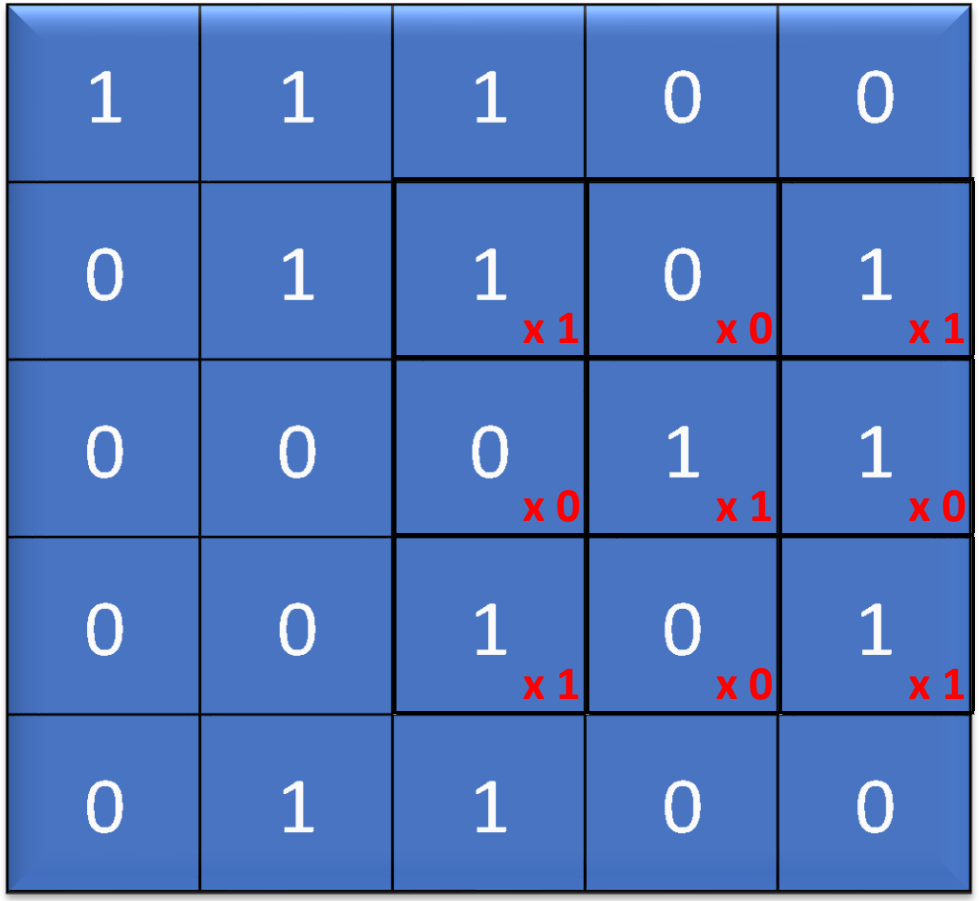


Image

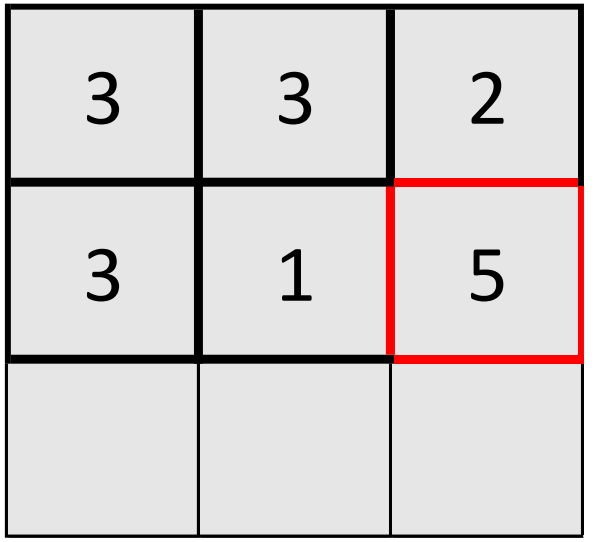


Output
Feature Map

Convolutional Layer – Feature Maps

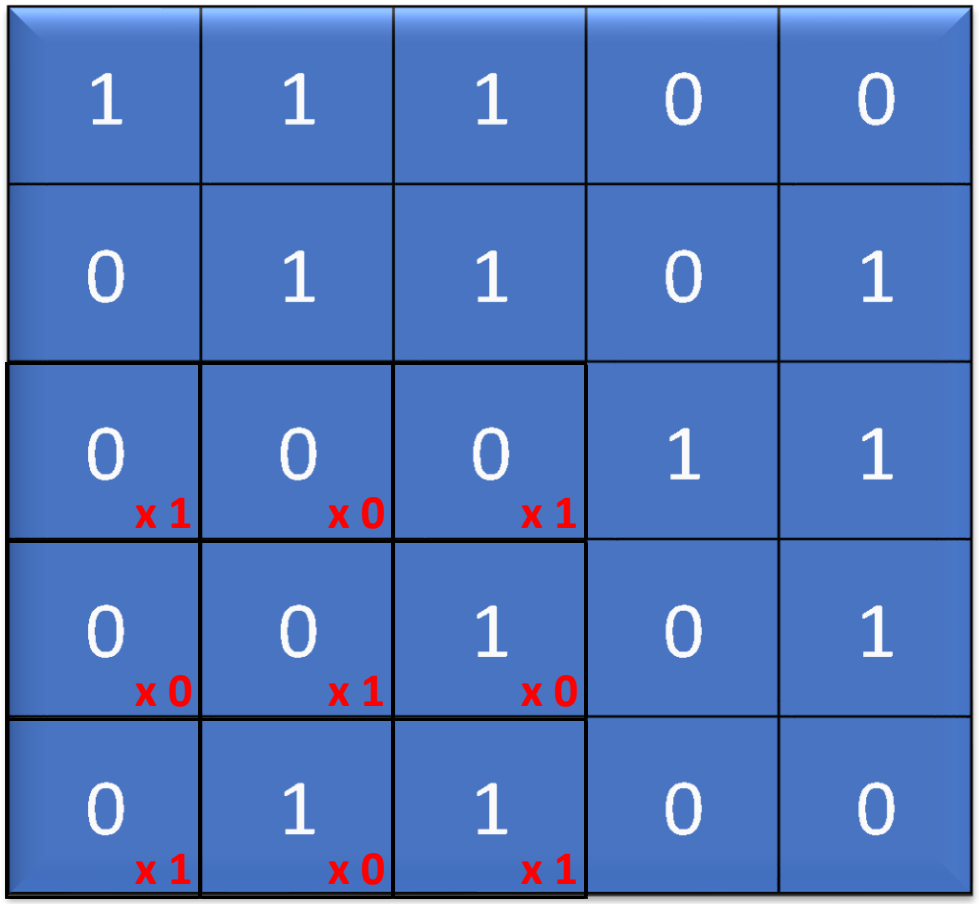


Image

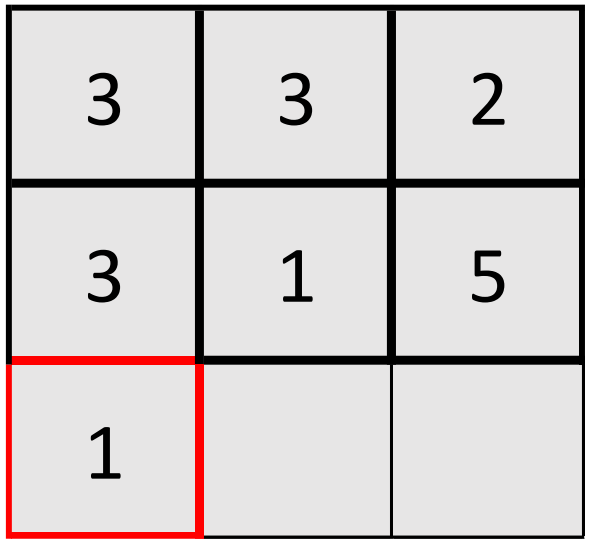


Output
Feature Map

Convolutional Layer – Feature Maps

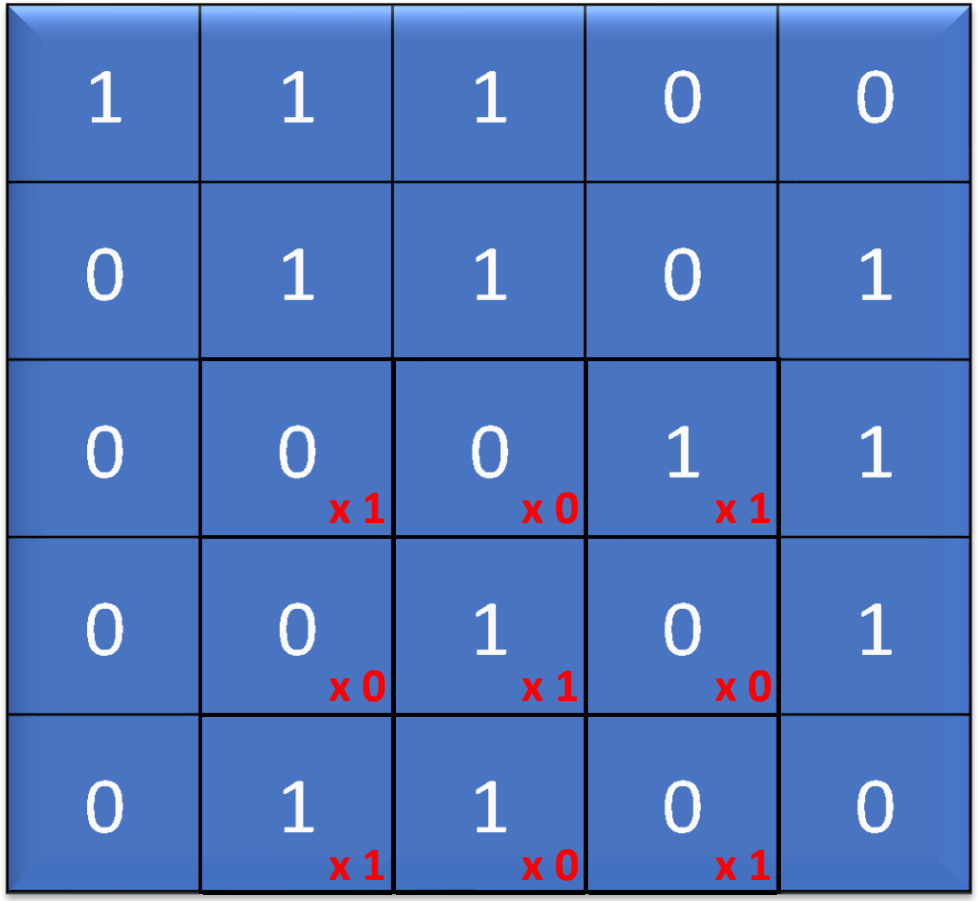


Image

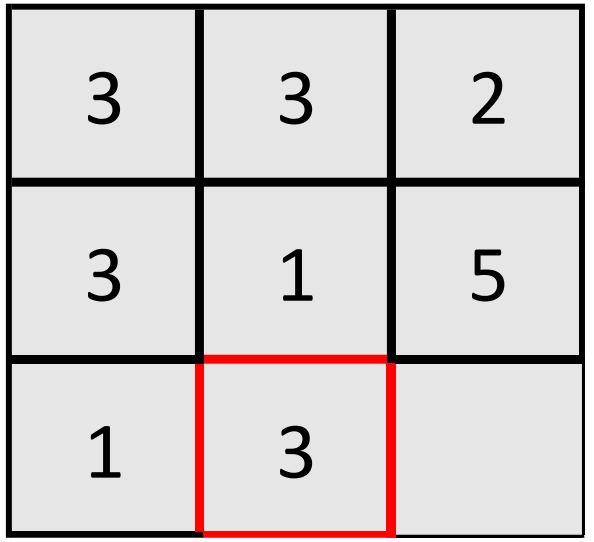


Output
Feature Map

Convolutional Layer – Feature Maps

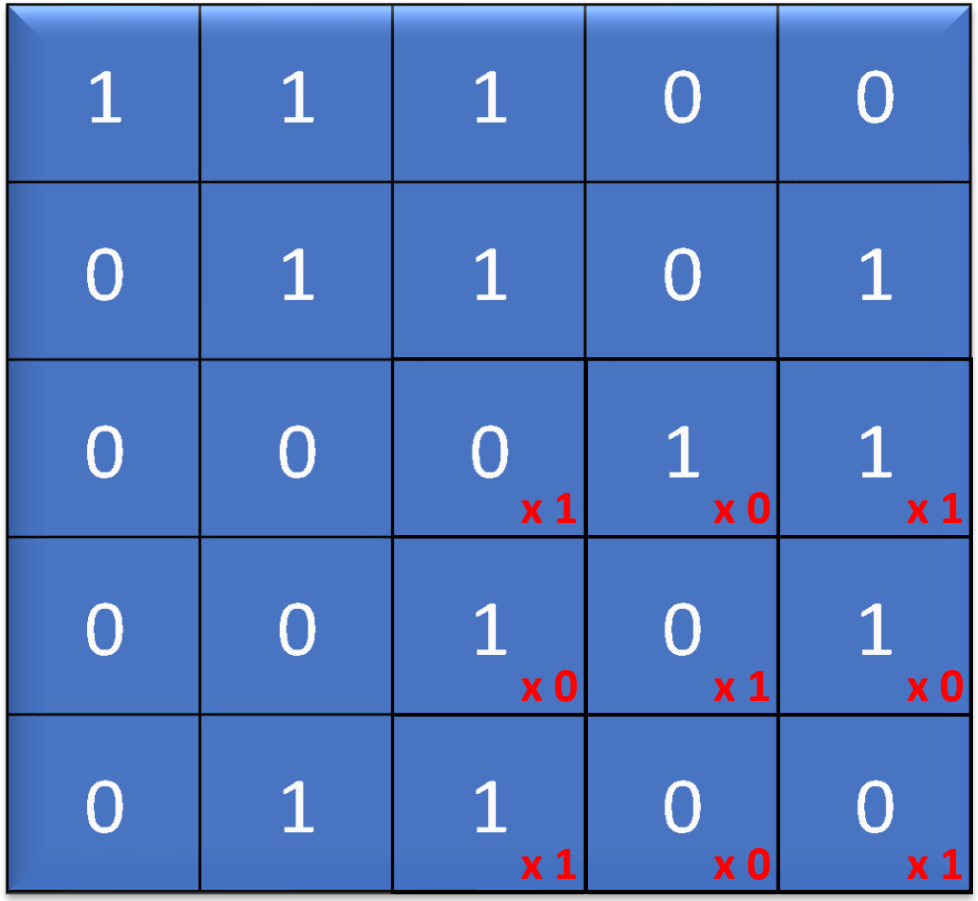


Image

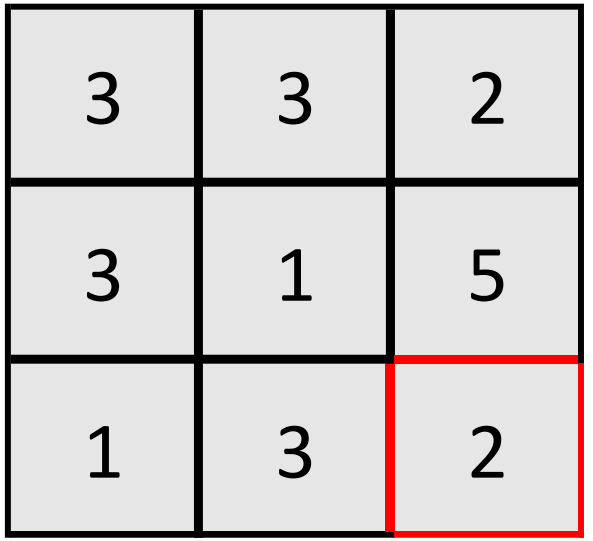


Output
Feature Map

Convolutional Layer – Feature Maps



Image



Output
Feature Map

Convolution

Filters

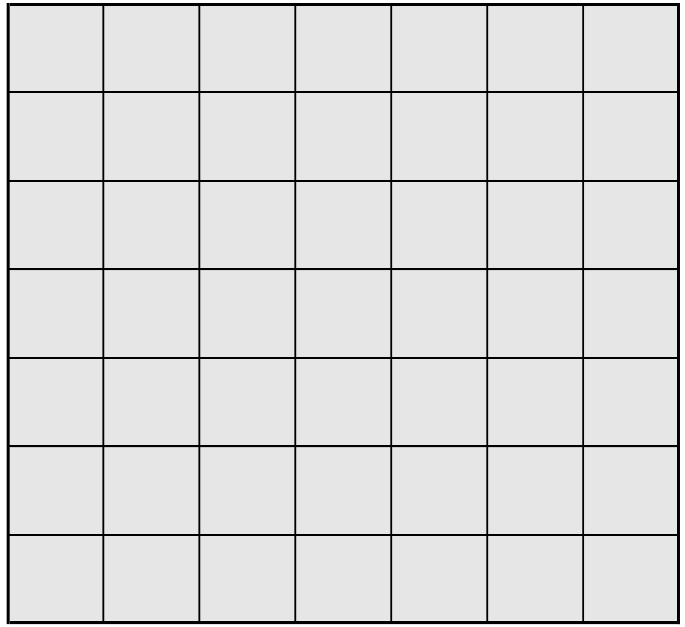
1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map



Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7						

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
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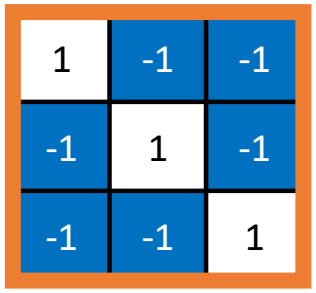
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

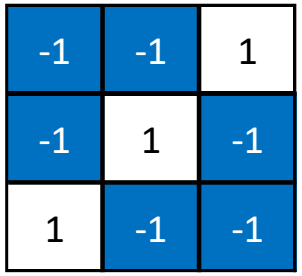
Feature Map

7						
	9					

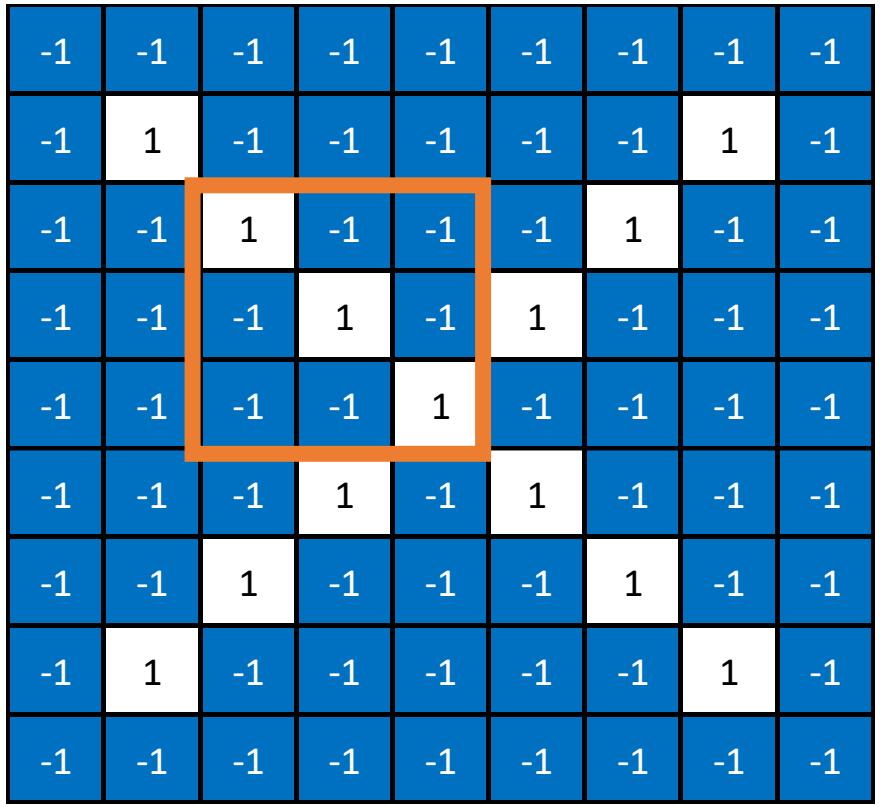
Convolution

Filters

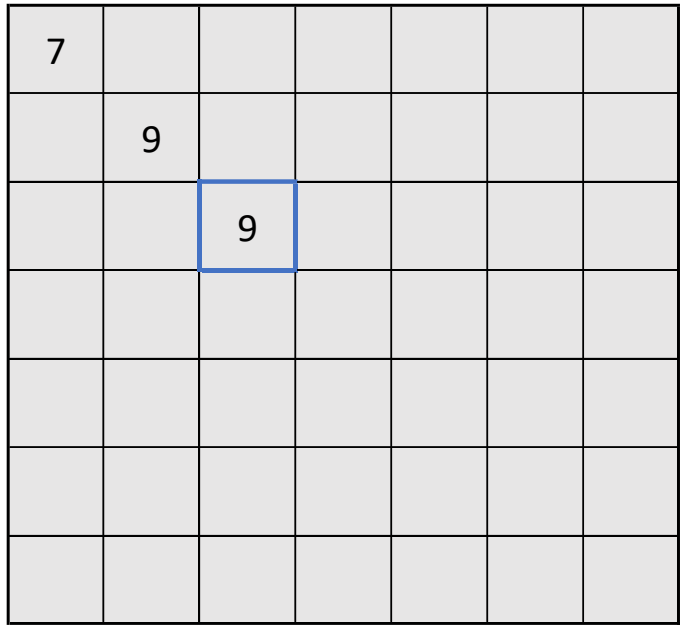




Image



Feature Map



Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
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-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7						
	9					
		9				
			5			

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7						
	9					
		9				
			5			
				9		

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7						
	9					
		9				
			5			
				9		
					9	

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

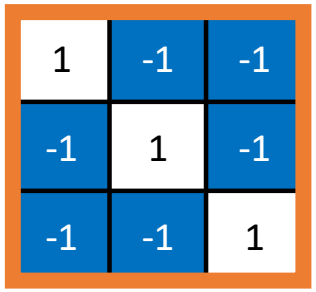
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7						
	9					
		9				
			5			
				9		
					9	
						7

Convolution

Filters



1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

						7

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

						7
					9	

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

						7
					9	
				9		
			5			
		9				
	9					
7						

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Convolution

Filters

1	-1	-1
-1	1	-1
-1	-1	1

-1	-1	1
-1	1	-1
1	-1	-1

Image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Feature Map

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

Pooling

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- Pooling layer is used to reduce the spatial dimensions of the data propagating through the network
- There are 2 types of pooling options:
  1. Max Pooling – keep the maximum value in the filter matrix
  2. Average Pooling – take an average value in the filter matrix
- Max pooling provides mechanism that helps in recognizing objects in the image even if the object does not resemble the original object

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9		

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5
3		

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5
3	9	

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5
3	9	3

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5
3	9	3
5		

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

9	3	5
3	9	3
5	3	

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

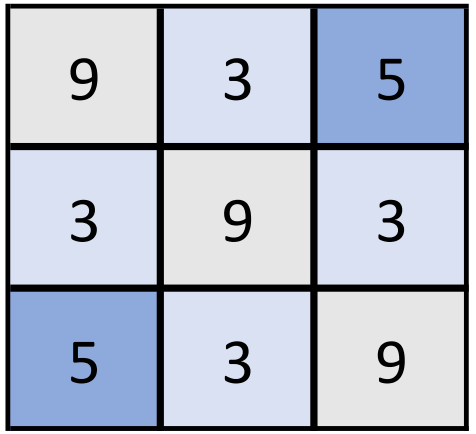
3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

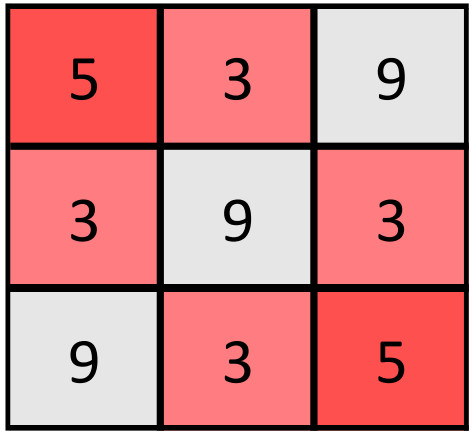
9	3	5
3	9	3
5	3	9

Pooling

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	3	1	1	-1	7

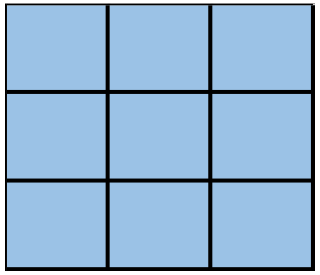
3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	-3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	1	-1	3

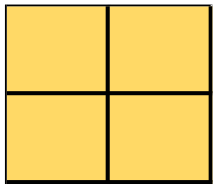




Zero Padding

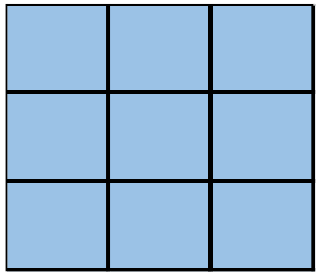
0.3	0.5	0.9	1.0
0.2	0.5	0.2	0.8
0.1	0.7	0.9	1.0
0.6	0.3	0.5	0.2

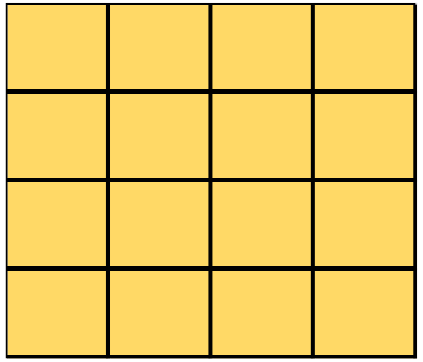




Input: 4 x 4
Filter: 3 x 3
Output: (In – Flt + 1) x (In – Flt + 1)
(4 – 3 + 1) x (4 – 3 + 1)
2 x 2

0	0	0	0	0	0
0	0.3	0.5	0.9	1.0	0
0	0.2	0.5	0.2	0.8	0
0	0.1	0.7	0.9	1.0	0
0	0.6	0.3	0.5	0.2	0
0	0	0	0	0	0

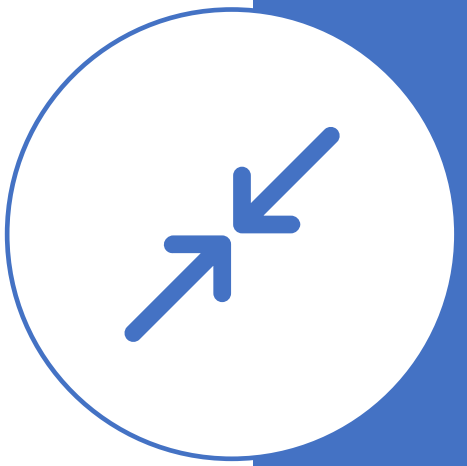




Input: 4 x 4
Filter: 3 x 3
Output: 4 x 4

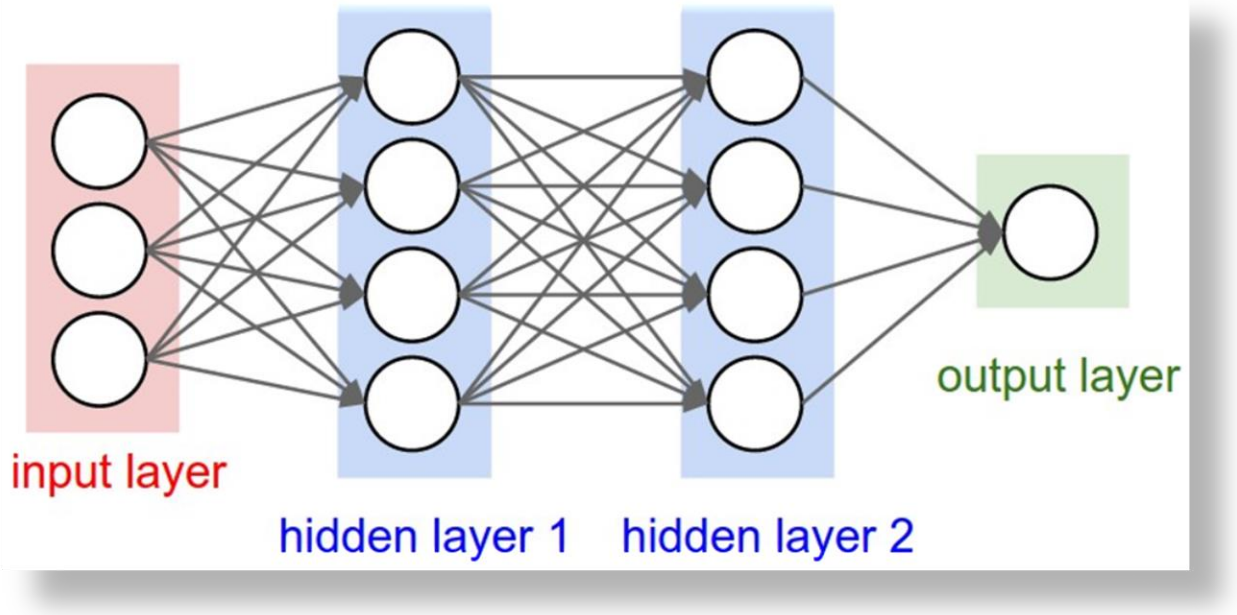
Zero Padding

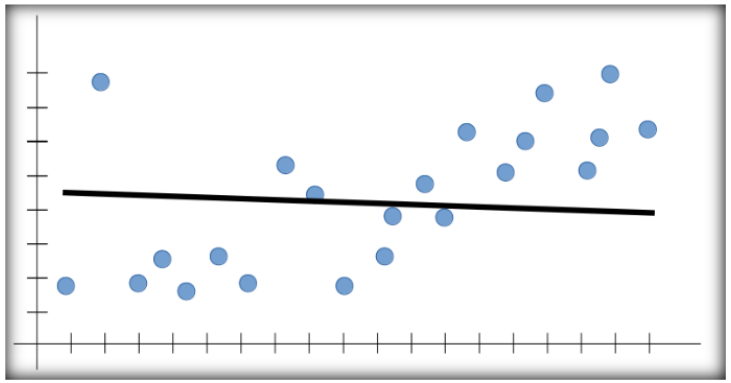
- Zero padding allows to preserve the original input size
- Can be specified per convolutional layer – need one or not
- Adds a vector of zeros around the image – not mandatory that there is only one layer, can be 2-3 determined by the library
- Specifying zero padding in Keras Layer (e.g. Conv2D):
  - **padding = “valid”** – means apply no zero padding
  - **padding = “same”** – means apply padding to make the output size of the image same as the input



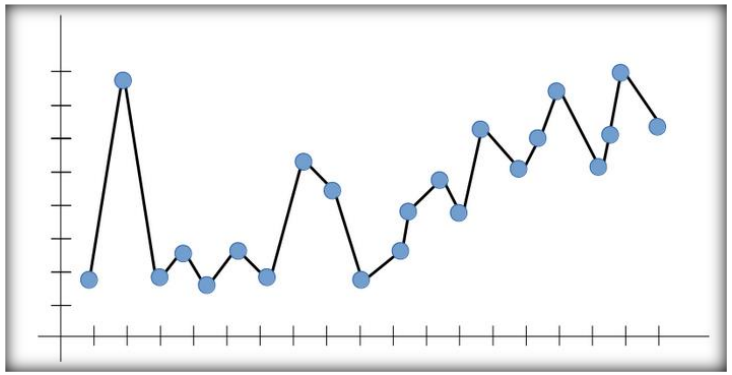
Fully Connected Layer

- Here output from the last Convolutional or Pooling layer are flattened
- Every node in the current layer is connected to every node in the next layer
- The last layer (output layer) consists on n nodes (depends on number of outcomes – in the digit recognition it is 10 representing digits 0 to 9)

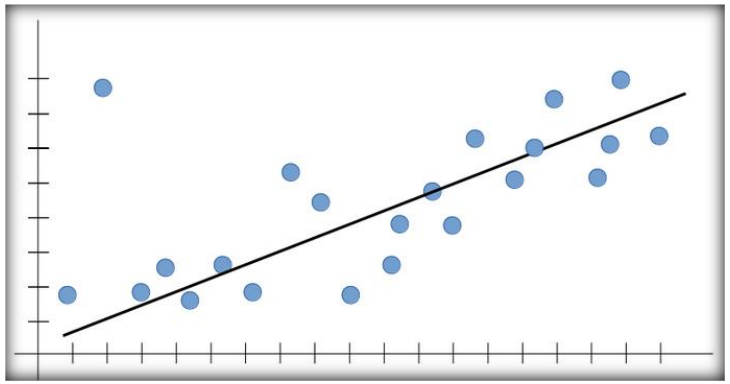




Under fitting (High Bias)

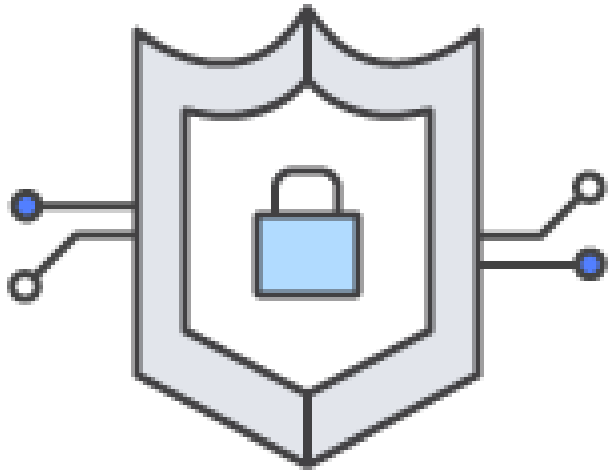


Over fitting (High Variance)



Bias-Variance Trade off

Under and Over Fitting



Convolutional Neural Networks

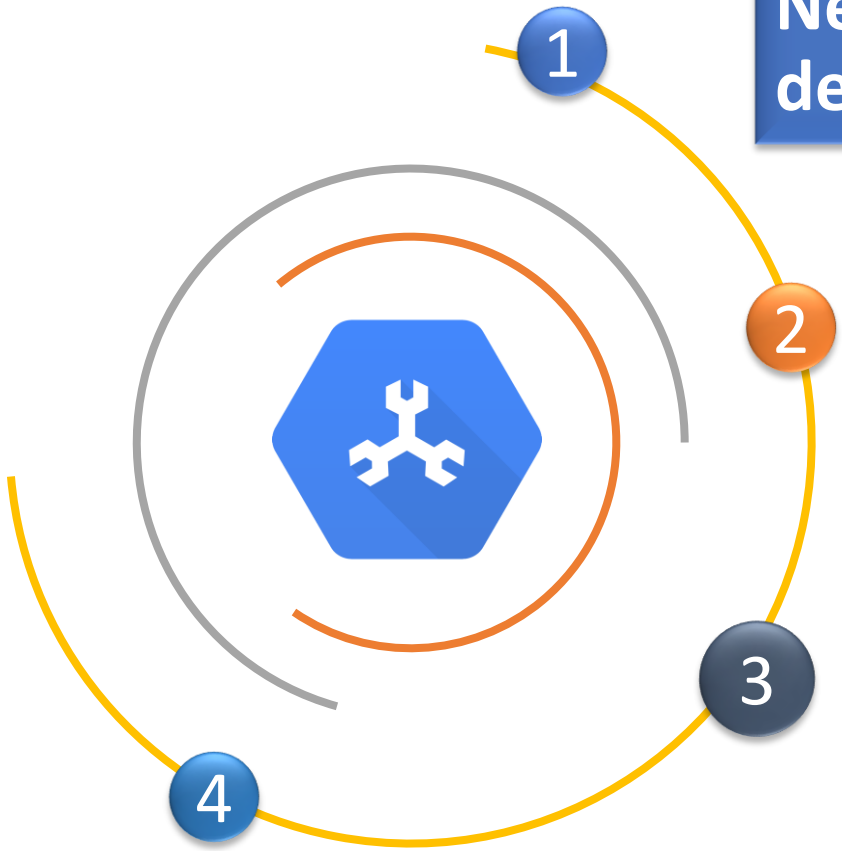
- Open file '**CodeSamples/CNN**' using Jupyter
- Classify handwritten digits using MNIST Digits Data
- Recognize digits between 0 and 9

Recurrent Neural Networks

Short Comings of Artificial Neural Networks

- Traditional Neural Networks assume that each data point is independent of other data points (inputs are analyzed in isolation)
- Does not handle sequential or “temporal” data
  - Sentences
  - Stock Prices trend
  - Time Series
  - Gene Sequences
- In sequential data the length of the input sequence can vary from sample to sample
- In sentences, need to understand the dependencies between words to get the full context of the sentence

Recurrent Neural Networks



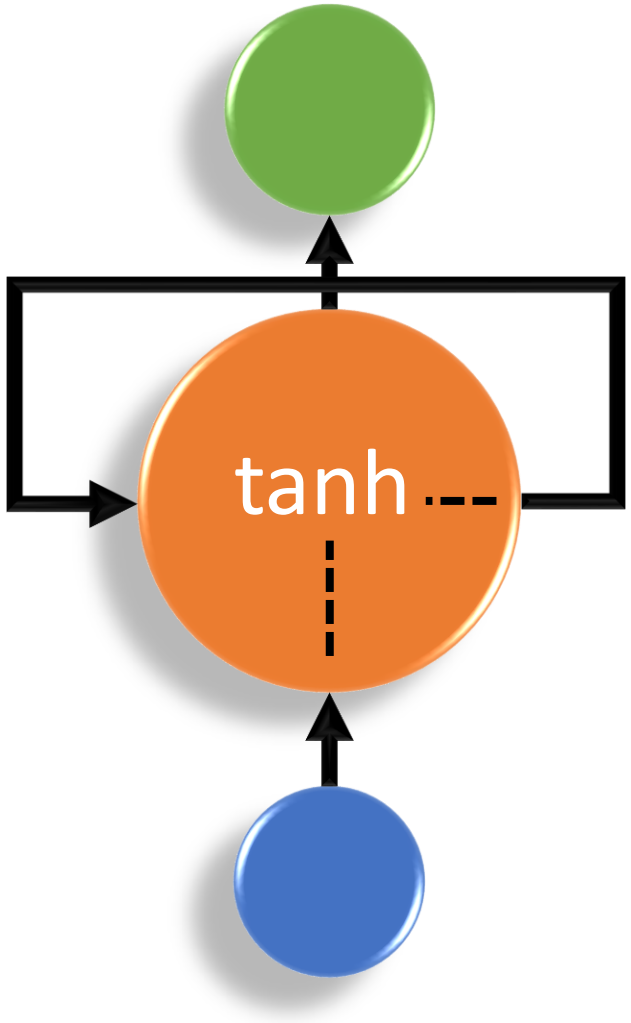
Neural Networks capture the temporal dependencies in data

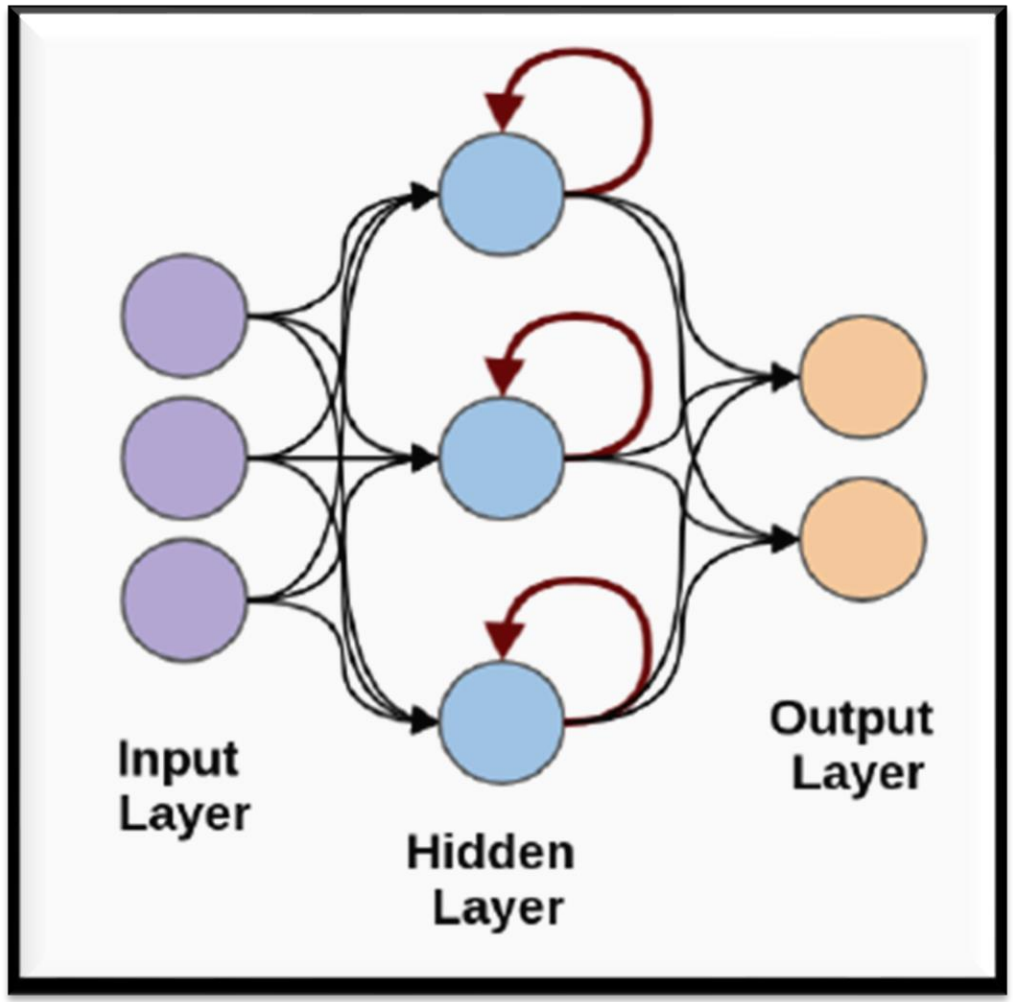
Each neuron in RNN uses its internal memory to maintain information about the previous input

Maintaining such state information is critical during language processing because in order to predict the next word, need to know which words came before it

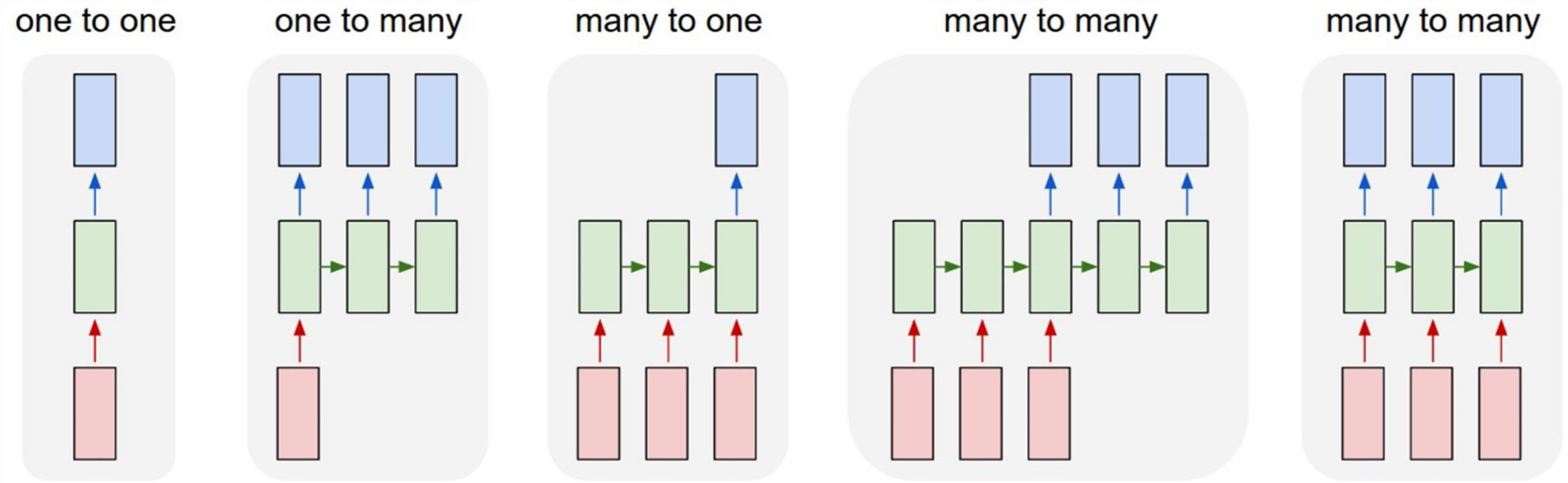
When reading a sentence, we pick up the context of the word based on the words that preceded it

Recurrent Neural Network





Types of RNNs



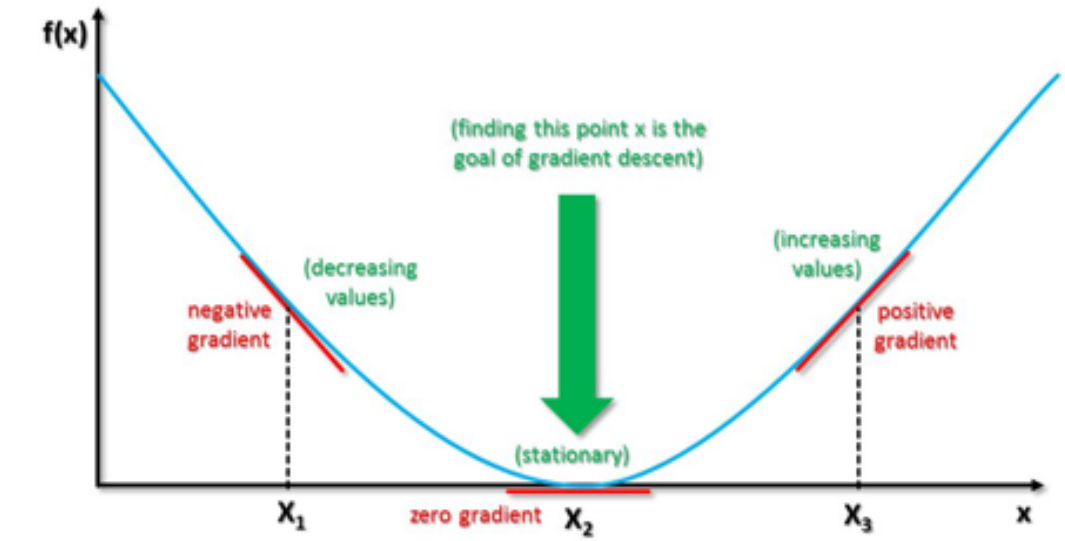
Gradient Problems

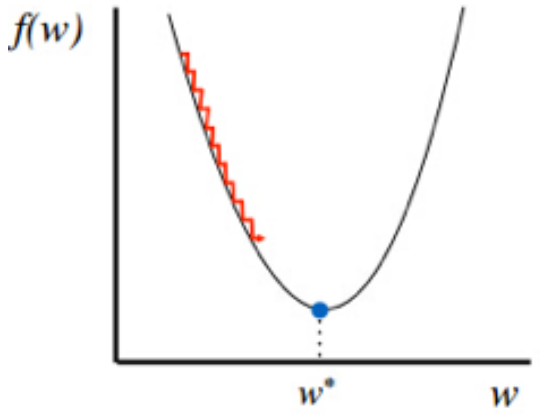
Gradient of the loss with respect to weights

- Calculated during the back-propagation phase of learning

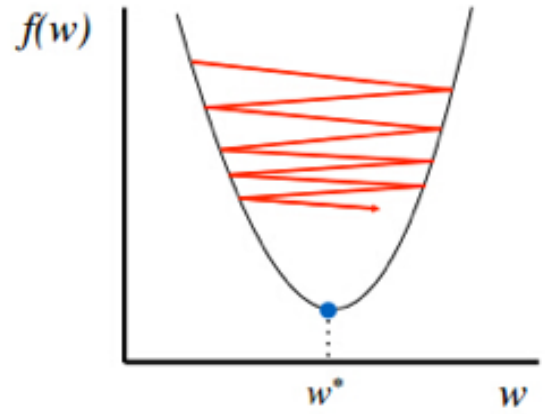
- Objective is to update the weights for each neuron in the network

Backward propagation issues



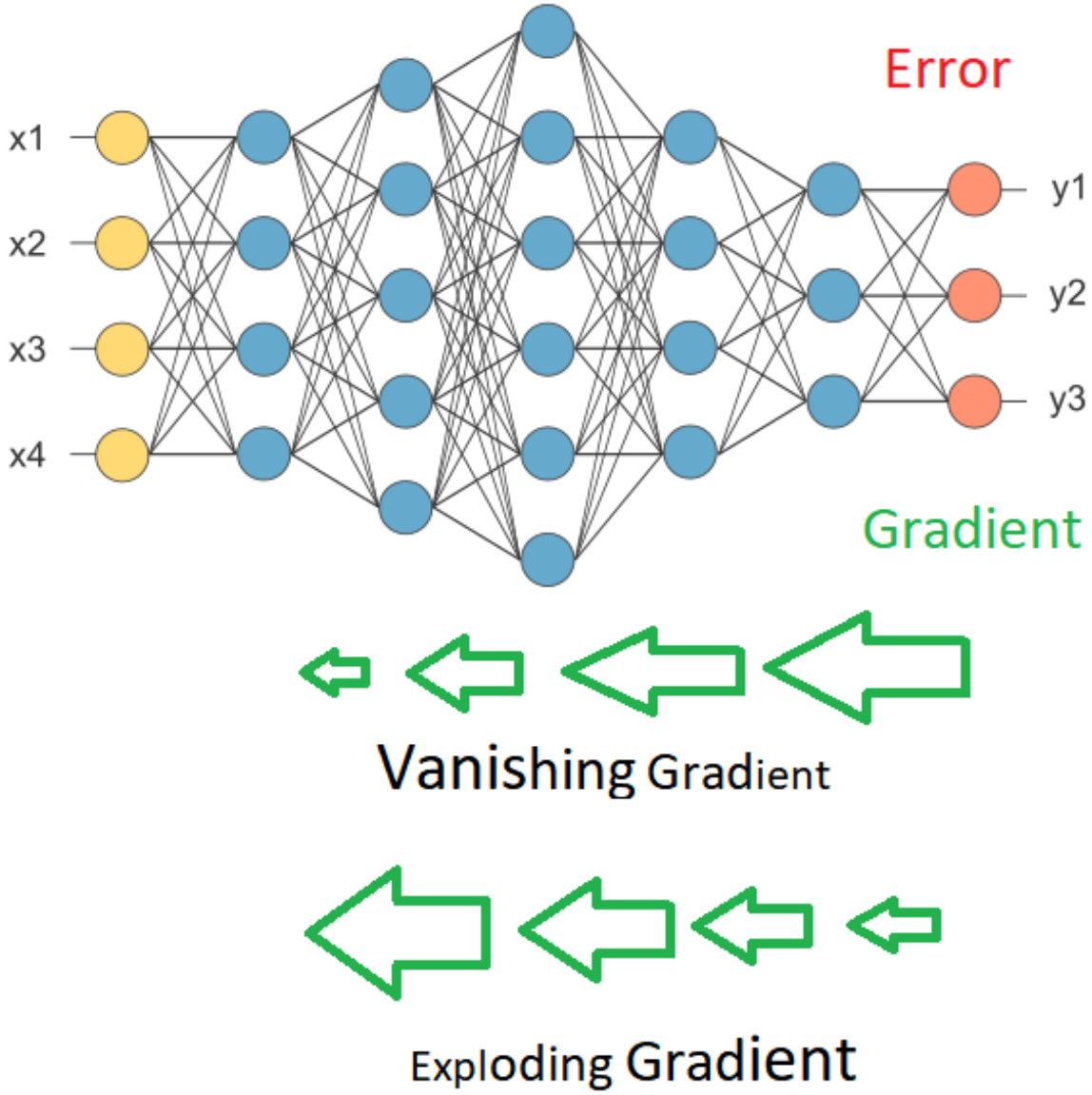


Too small: converge very slowly

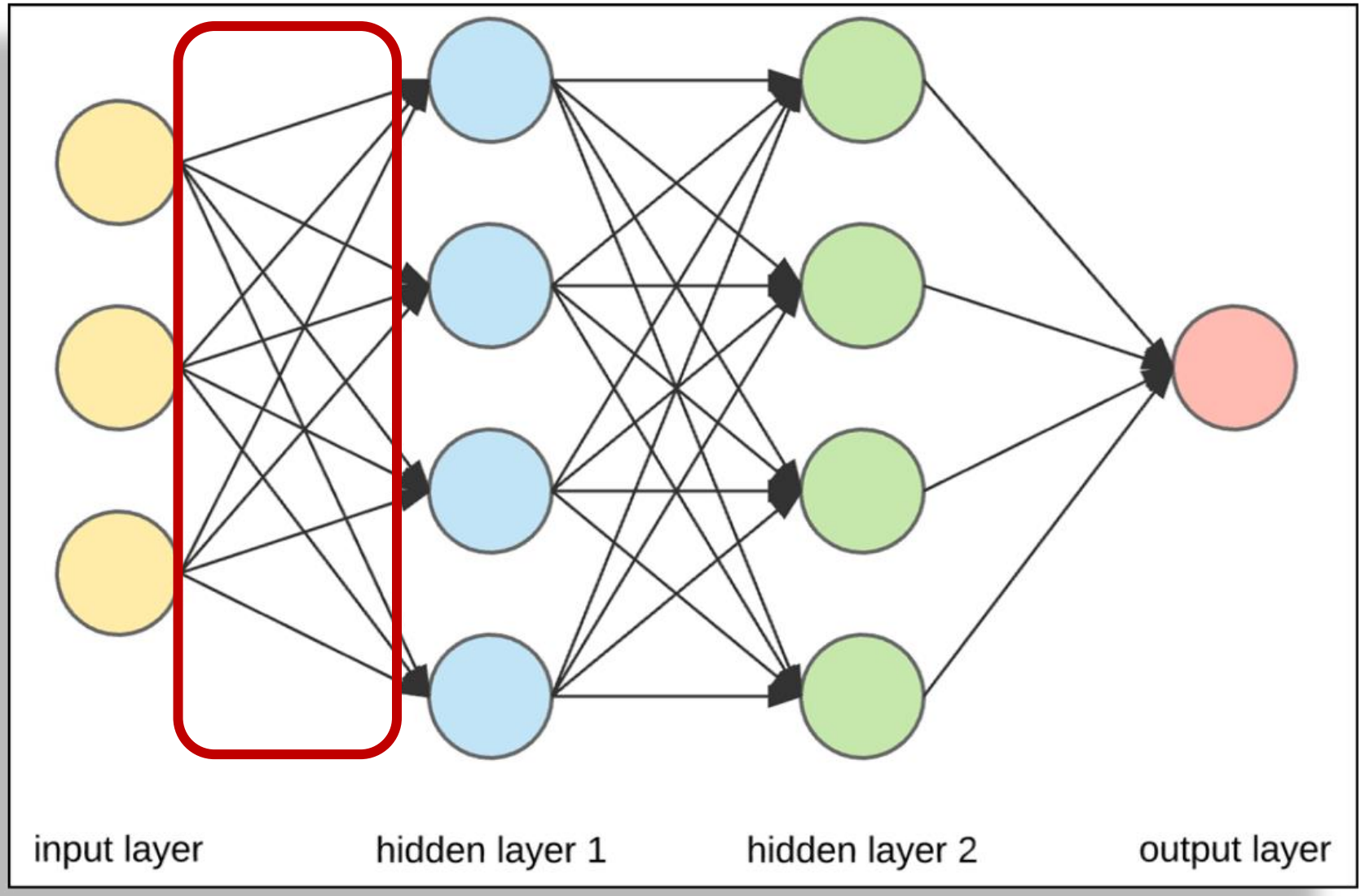


Too big: overshoot and even diverge

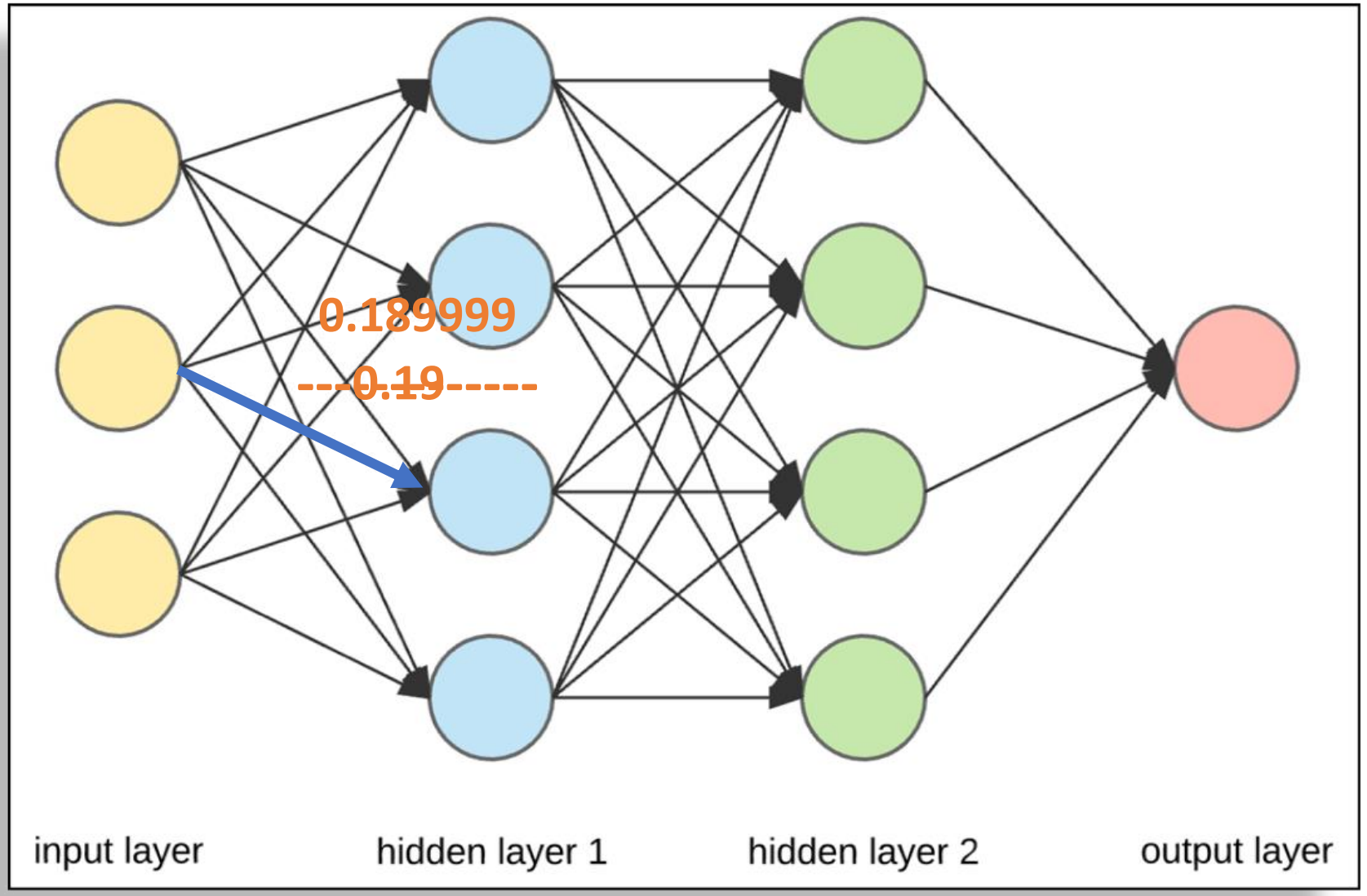
Vanishing and Exploding Gradients



Vanishing Gradient Problem



Vanishing Gradient Problem



Exploding Gradient Problem

- Exploding Gradient Problem in the opposite of the Vanishing Gradient Problem – rather than the gradient that vanishes it explodes
- What if the initial layers had bigger input number (greater than 1)
- So when such input is multiplied by number > 1, this will result in a number much greater than 1
- Resulting in larger gradient – thus exploding in size
- The updated weights will also be larger (0.19 → 1.8765)

How to fix the Gradient Issues?

Exploding Gradients

- ✓ Instead of taking the data from first timestamp, use few timestamps to get the training going
- ✓ Use RMSprop optimizer to adjust the learning rate
- ✓ Set a threshold for the gradient if it goes above certain value

Vanishing Gradients

- ✓ Use different network architectures such as LSTM, GRU that are designed to handle such problems
- ✓ Use ReLU activation which takes negative values as zero and positive as one or greater, thereby helping in calculating gradient
- ✓ Use RMSprop to clip the gradient if it is going above certain threshold

Extra Credits

Extra Credits

- There are 4 datasets:
  1. Credit Card Application
  2. Churn Modelling
  3. Heart Disease
  4. Breast Cancer
- Your Work
  - Pick anyone of these datasets
  - Apply the techniques that you have learnt related to Feature Cleaning, Feature selection, etc.
  - Choose 1 or more algorithms and make predictions
  - Tomorrow afternoon we will review it with the class
- Description of datasets in following slides

Financial Customer Churn Data

- Dataset – Customer information with a financial institution
- If doing classification with SVM then it can be applied to most of the datasets where logistic regression is used
- Dataset has following features:

Dataset - Churn_Modelling.csv

RowNumber: Dataset row number
CustomerId: Customer Id
Surname: Last name of the person
CreditScore: Credit Score of the person
Geography: Country of residence
Gender: Person's Gender
AGE: Age of the person
Tenure: How long has the person owned the card
Balance: Outstanding balance
NumOfProducts: Number of products owned by the person with company
HasCrCard: Person has credit card
IsActiveMember: Is the person active member of the company
EstimatedSalary: Estimated salary of the person
Exited: Did the person stay or leave

Credit Card Application

- Based on 15 features (not named), predict whether a new customer's credit card application should be approved
- Predicting a "class" – 1 or 0

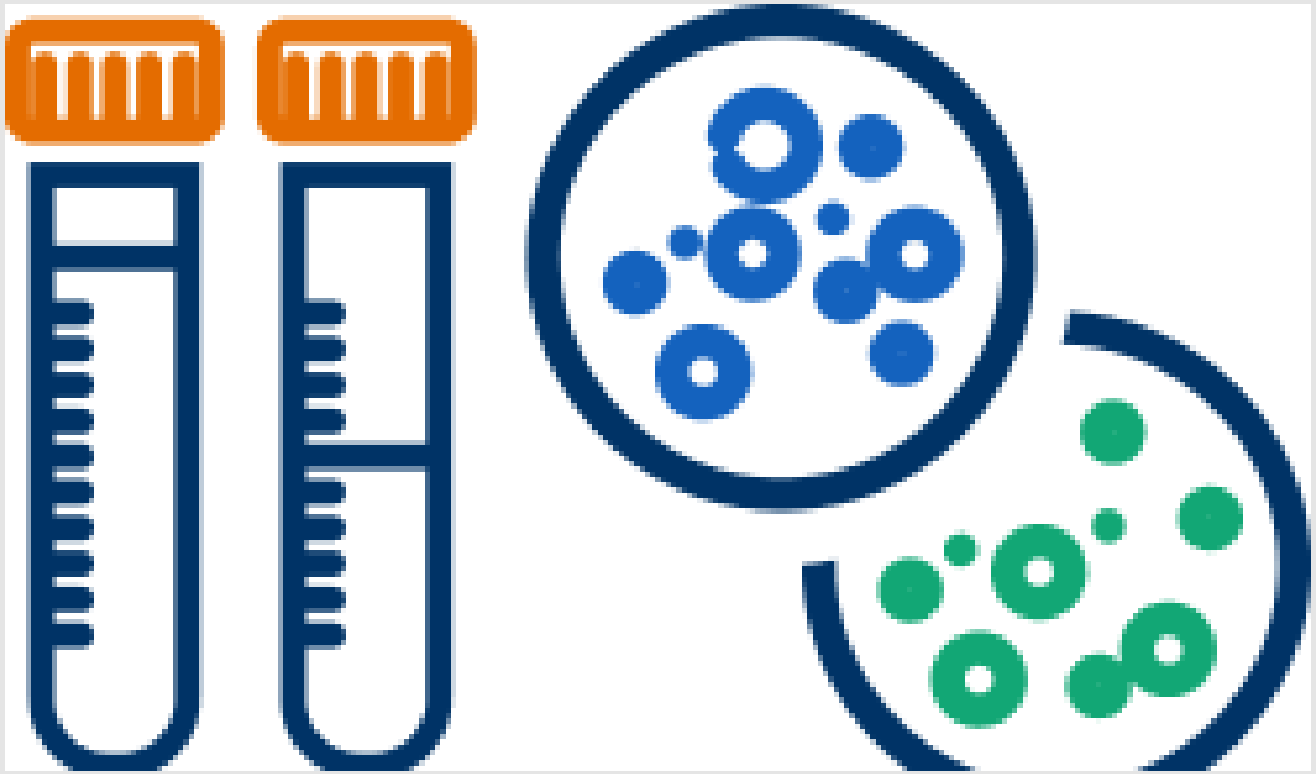
Dataset – Credit_Card_Applications.csv

Heart Disease

Dataset – Heart.csv

- Based on 13 features predict if a patient will have heart disease
- Features include age, gender, chest pain, resting blood pressure, cholesterol, fasting blood sugar, resting ECG, max heart rate, exercise induced angina, etc.
- Predicting a “target” – 1 or 0

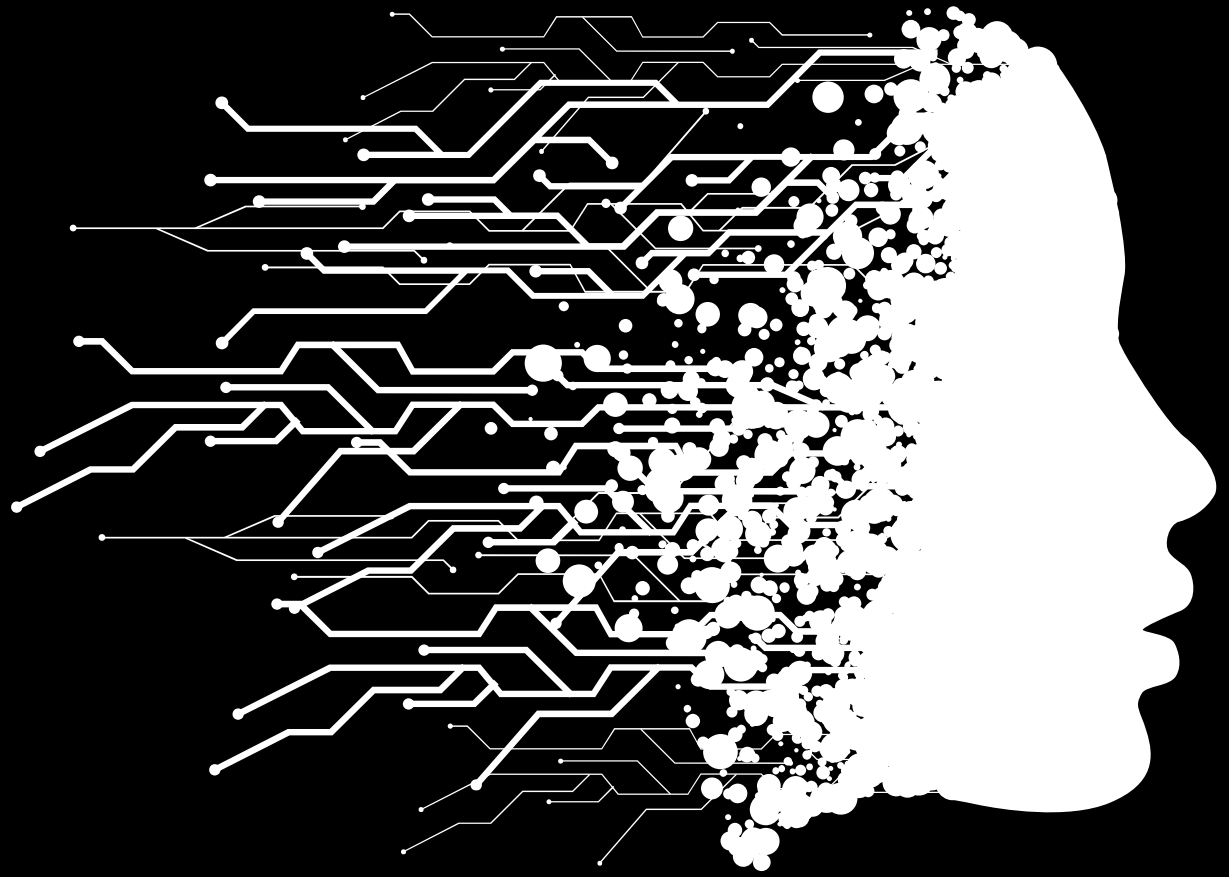
Breast Cancer



- Dataset includes a number of features related to tissue samples collected
- 2 Classes: benign and malignant (values 2 and 4 respectively)
- Attributes:
  - Sample code number
  - Clump Thickness,
  - Uniformity of Cell Size,
  - Uniformity of Cell Shape,
  - Marginal Adhesion,
  - Single Epithelial Cell Size,
  - Bare Nuclei,
  - Bland Chromatin,
  - Normal Nucleoli
  - Mitoses

Dataset:

breast-cancer-wisconsin.csv



Natural Language Processing (NLP)

NLP Use cases

Sentiment Recognition

We enjoyed the food and the service was great.

We had to wait for an excessive amount of time and our order was wrong.

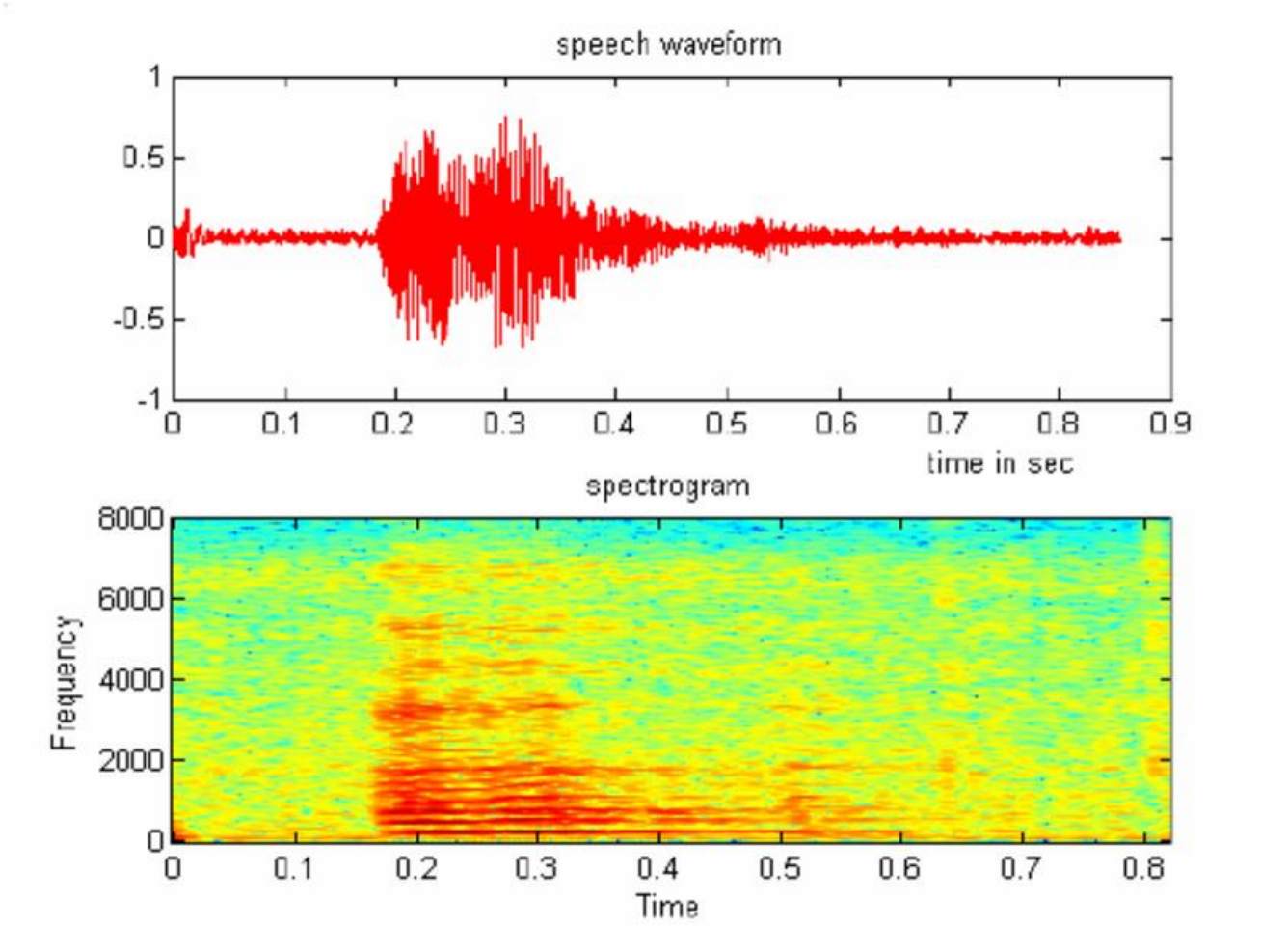
Machine Translation

A bird flies over the water

Machine Learning

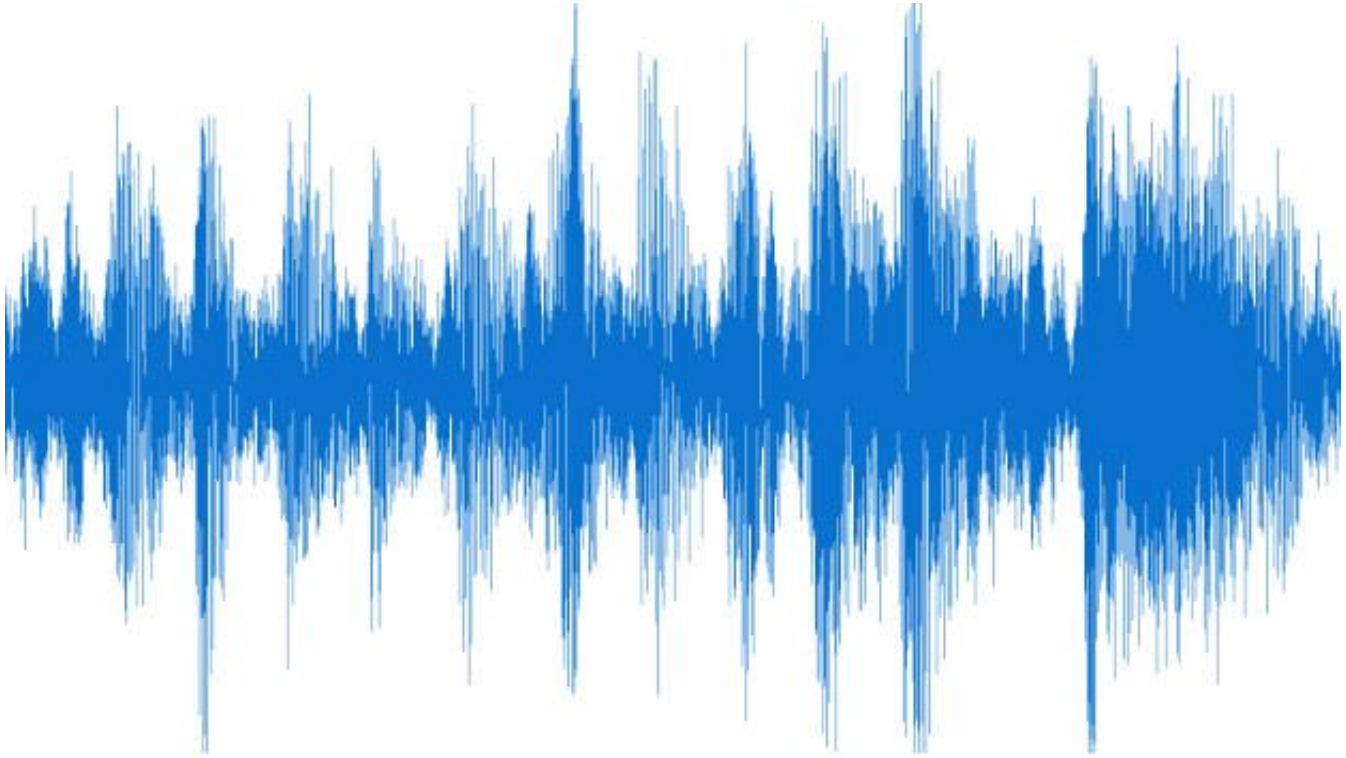
Un oiseau vole au-dessus de l'eau

Speech Recognition (Speech to Text)



Speech Synthesis (Text to Speech)

Becoming Human



NLP Processing

Encoding Words

Sentiment Classification

"A touching movie full of emotions with wonderful acting. Worth seeing a second time!"

Pre-Process

A touching movie full of emotions with wonderful acting
Worth seeing a second time

Encoding Words

Pre-Processed

A touching movie full of emotions with wonderful acting
Worth seeing a second time

Lowercase

a touching movie full of emotions with wonderful acting
worth seeing a second time

Encoding Words

Lowercase

a touching movie full of emotions with wonderful acting worth seeing a second time

Tokenization

[‘a’, ‘touching’, ‘movie’, ‘full’, ‘of’, ‘emotions’, ‘with’, ‘wonderful’, ‘acting’, ‘worth’, ‘seeing’, ‘a’, ‘second’, ‘time’]

Encoding Words

Tokenized

['a', 'touching', 'movie', 'full', 'of', 'emotions', 'with', 'wonderful', 'acting', 'worth', 'seeing', 'a', 'second', 'time']

Stop words removal

['touching', 'movie', 'full', 'emotions', 'wonderful', 'acting', 'worth', 'seeing', 'second', 'time']

Encoding Words

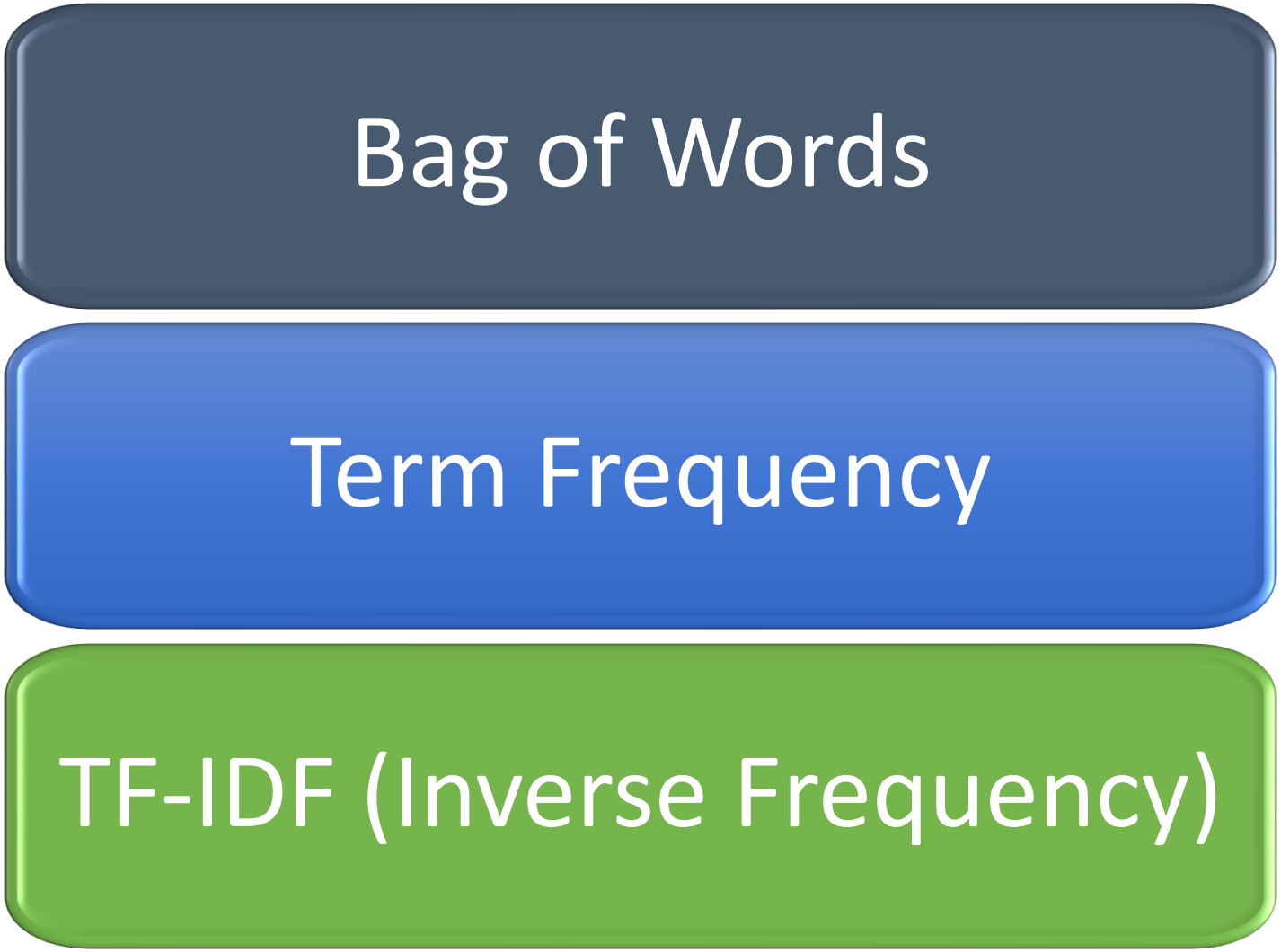
Stop words removed

['touching', 'movie', 'full', 'emotions', 'wonderful', 'acting', 'worth', 'seeing', 'second', 'time']

Lemmatization

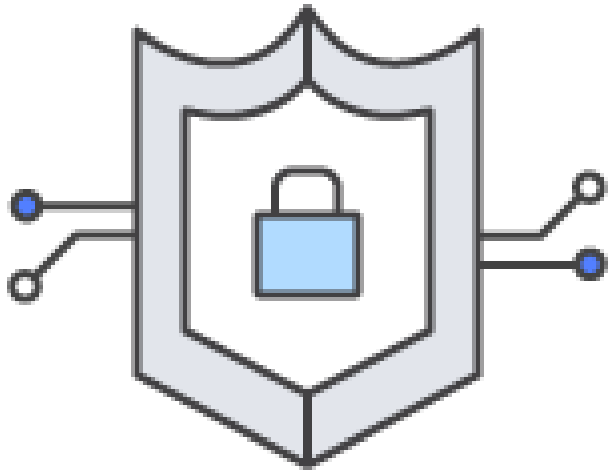
['touch', 'movie', 'full', 'emotion', 'wonder', 'act', 'worth', 'see', 'second', 'time']

Vectorization



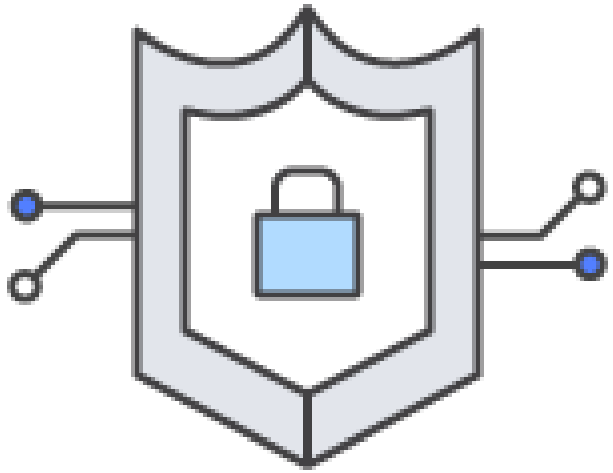
Text Classification – Movie Review

- Build a Neural Network for training (build layers)
  - Embedding layer: Takes the integer-encoded reviews and looks up embedding vector for each word-index
  - GlobalAveragePooling layer: Take average of each sequence dimension
  - Add couple of ReLU activation layers
  - Finally add a sigmoid layer (that will output probability of the sentiment – positive or negative)
- Explore the embedding – check weights, write files to visualize the embeddings
- Plot trained model performance
- Evaluate the model with the test dataset
- Write couple of reviews and make predictions



Text Processing: Neural Networks

- Open file '**CodeSamples/TextClassification**' using Jupyter
- Take Movies Dataset and build model to predict positive or negative review



TensorFlow Projector

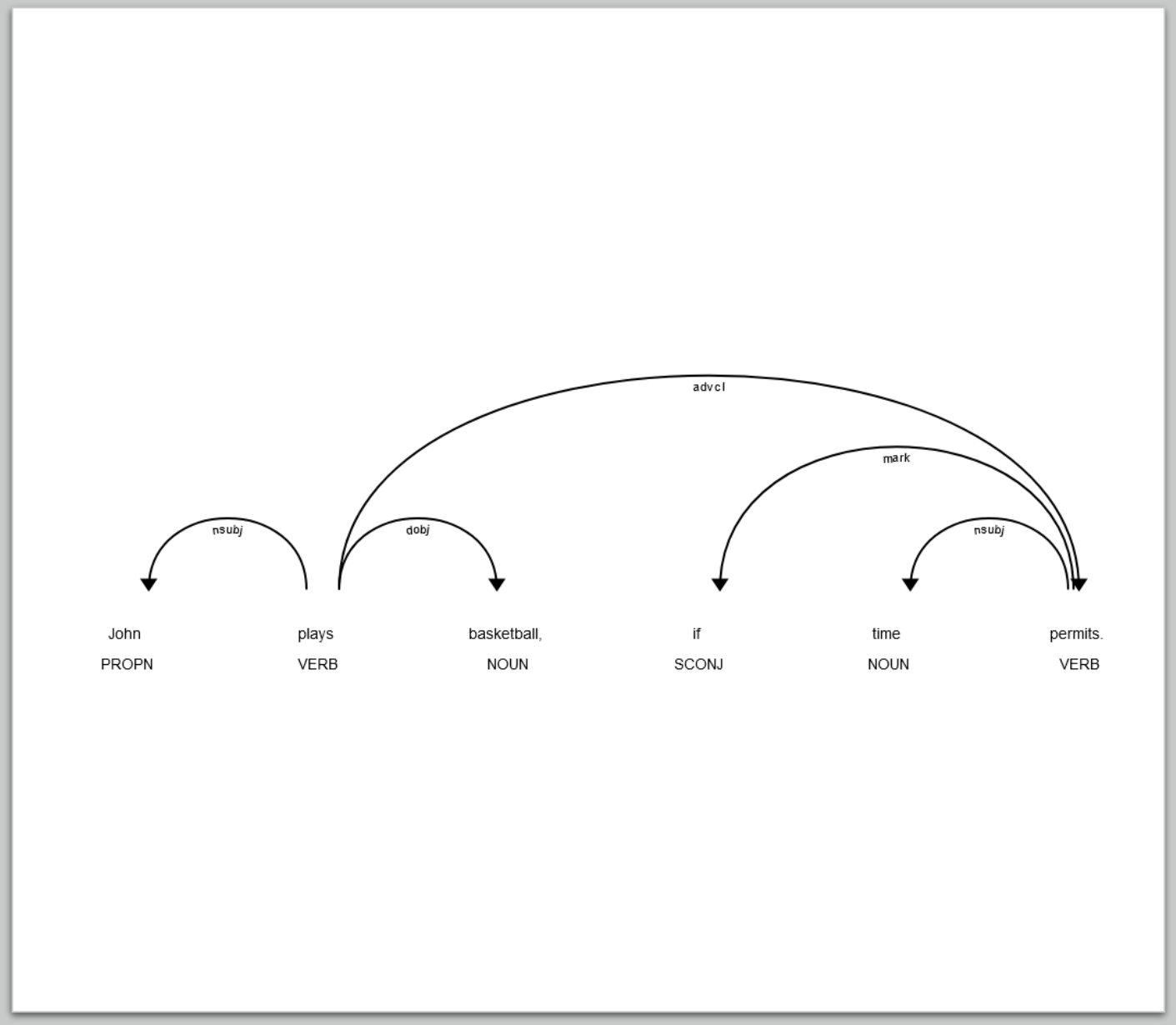
- Open link ‘https://projector.tensorflow.org/’
- Iris dataset
- MNIST with images
- Generated by Text Classification

Popular NLP Tools and Libraries

Name	Spark NLP	spaCy	NLTK	CoreNLP
Sentence detection	Yes	Yes	Yes	Yes
Tokenization	Yes	Yes	Yes	Yes
Stemming	Yes	Yes	Yes	Yes
Lemmatization	Yes	Yes	Yes	Yes
POS tagger	Yes	Yes	Yes	Yes
NER	Yes	Yes	Yes	Yes
Dependency parse	Yes	Yes	Yes	Yes
Text matcher	Yes	Yes	No	Yes
Date matcher	Yes	No	No	Yes
Chunking	Yes	Yes	Yes	Yes
Spell checker	Yes	No	No	No
Sentiment detector	Yes	No	No	Yes
Pretrained models	Yes	Yes	Yes	Yes
Training models	Yes	Yes	Yes	Yes

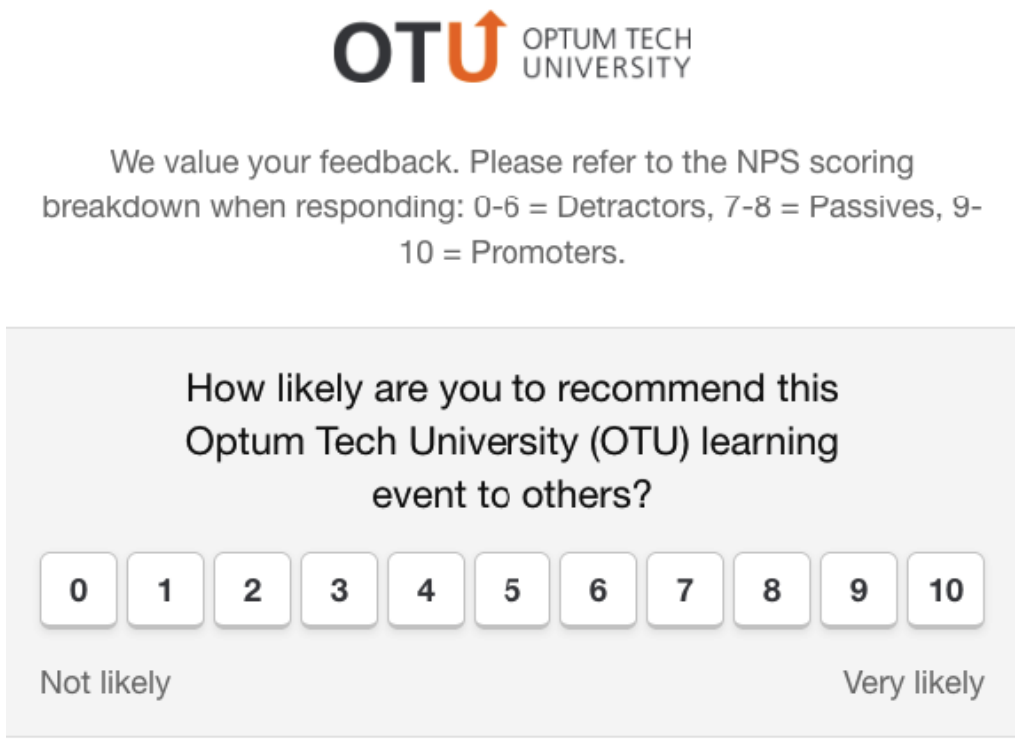
spaCy

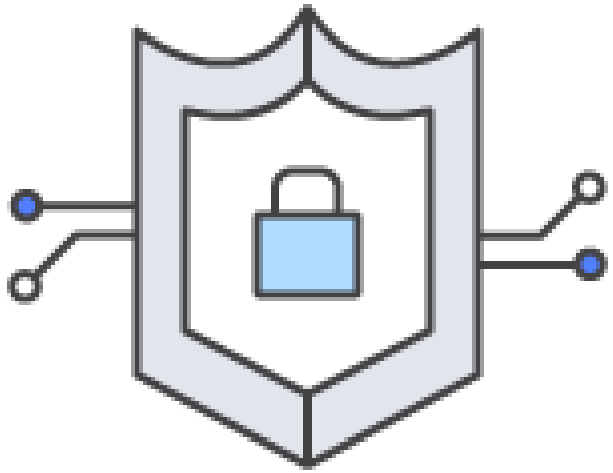
- Natural language processing library
- Fast – written using Cython
  - Cython is a superset of python that compiles to C code, thus providing better performance
  - Numpy is a wrapper around C libraries
- spaCy supports following functionality:
  - Tokenizer
  - Creating word vectors
  - Syntactic Parser
  - Named Entity Recognition



Survey

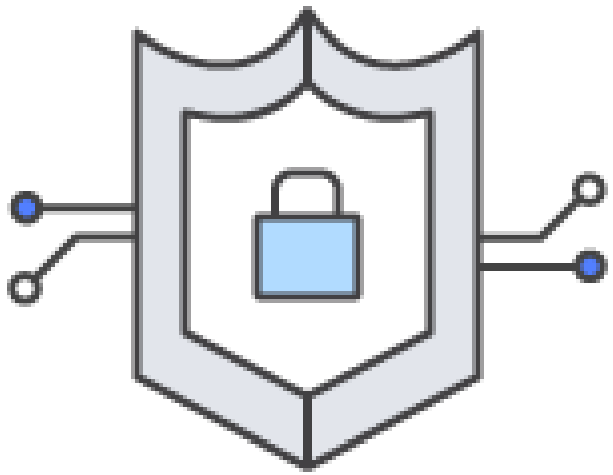
- The Optum Tech University (OTU) team would like your feedback regarding your learning experience in this class. Input from participants about their experience helps to continually enhance the value and effectiveness of courses like this.
- Thank you!





spaCy Examples

- Open file '**CodeSamples/SpacyExamples**' using Jupyter
- Different examples of using the spaCy library



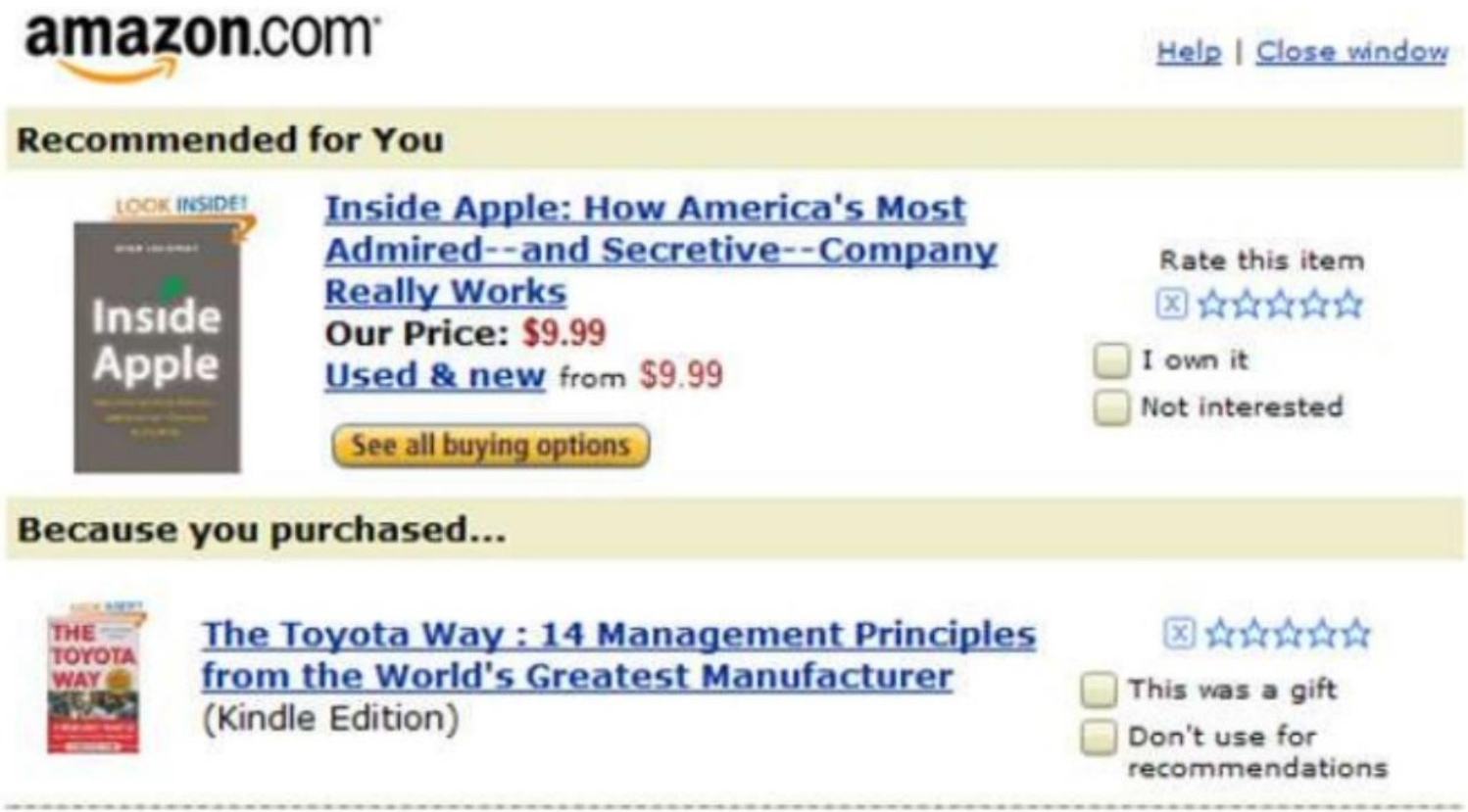
spaCy Examples

- Open file '**CodeSamples/Spacy-SentimentAnalysis**' using Jupyter
- Will use spaCy to preprocess the text
- Build a pipeline to clean the text, vectorize it
- Apply logistic regression to classify the text (positive or negative)

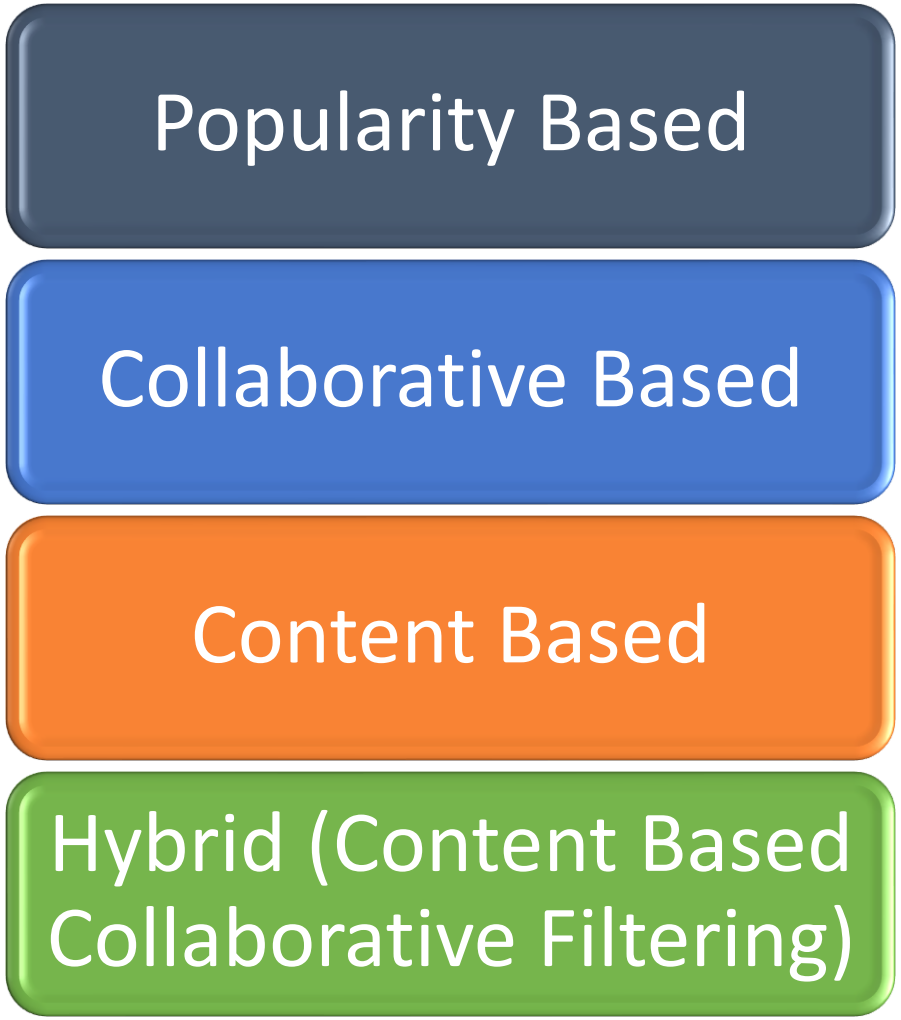
Recommendation Systems

Recommendation System

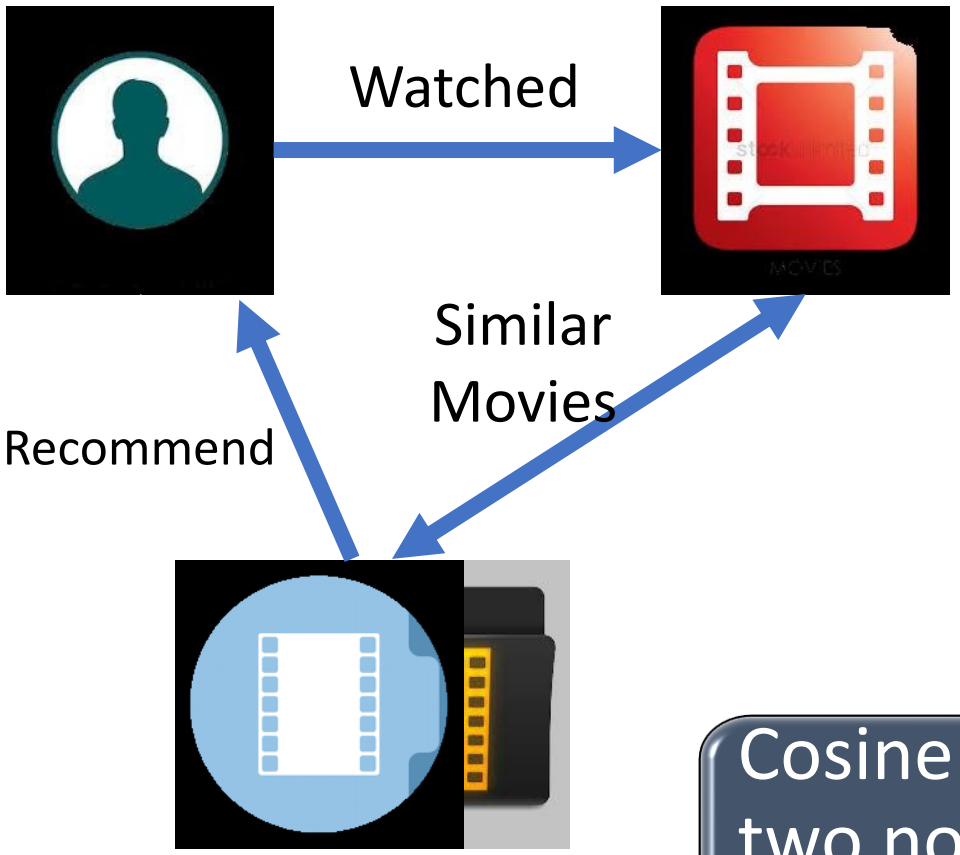
Example


amazon.com
Help | Close window
Recommended for You
LOOK INSIDE!
Inside Apple
Inside Apple: How America's Most Admired--and Secretive--Company Really Works
Our Price: $9.99
Used & new from $9.99
See all buying options
Rate this item
I own it
Not interested
Because you purchased...
THE TOYOTA WAY
The Toyota Way : 14 Management Principles from the World's Greatest Manufacturer
(Kindle Edition)
This was a gift
Don't use for recommendations

Types of Recommendation Systems



Content based filtering

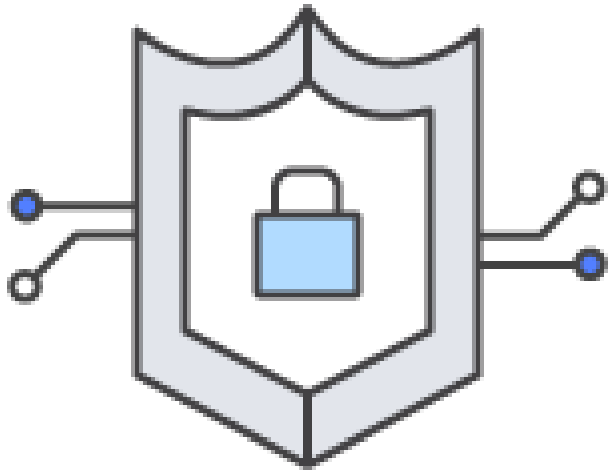


User ratings – movies liked and dis-liked (Profile Vector – X)

Item information – movie genre, cast, length, etc. (Item Vector – Y)

$$\cos(\theta) = \frac{\sum_i X_i Y_i}{\sqrt{\sum_i X_i^2}\sqrt{\sum_i Y_i^2}}$$

Cosine Similarity – measure of similarity between two non-zero vectors, movies are sorted in descending order based on these cosine values



Content Based

- Open file '**CodeSamples/CosineSimilarity**' using Jupyter
- Movie recommendation using keywords, cast, director and genres

Assignment

- Open file ‘Assignment/CRM-CustomerChurn’ using Jupyter
- Implementation requirements are defined in the notebook

Assignment

- Open file ‘Assignment/CNN-Fashion’ using Jupyter
- Implementation requirements are defined in the notebook

Dataset Sources

- UCI – Machine Learning Repository https://archive.ics.uci.edu/ml/index.php
- Kaggle - https://www.kaggle.com/
- Google - https://toolbox.google.com/datasetsearch
- Amazon – https://aws.amazon.com/opendata/public-datasets/
- US Government - https://www.data.gov/

Next steps

- Make a custom plan for yourself to continue this journey
- Improve some of your skills (Stats, Python, ML, Domain, etc.)
- Take some additional courses
- Try a Kaggle.com competition
- Work on a personal project to improve understanding

Glossary

Machine Learning Glossary

https://developers.google.com/machine-learning/glossary

Thank You