MACHINE LEARNING FOR BUSINESS PROBLEM

MANB 2153

TOPIC

- **What is ML?**
- History of ML
- Why ML?
- ML challenges
- Steps in developing ML application
- The ML algorithm: How to choose the right algorithm for ML
- Type of ML: supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning
- ML with Python: Why?

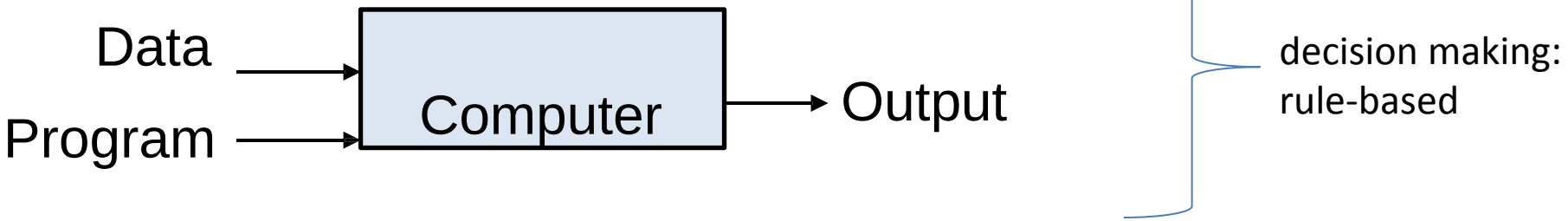
“A breakthrough in machine learning would be worth ten Microsoft.”
— Bill Gates, Former Chairman, Microsoft —

WHAT IS MACHINE LEARNING?

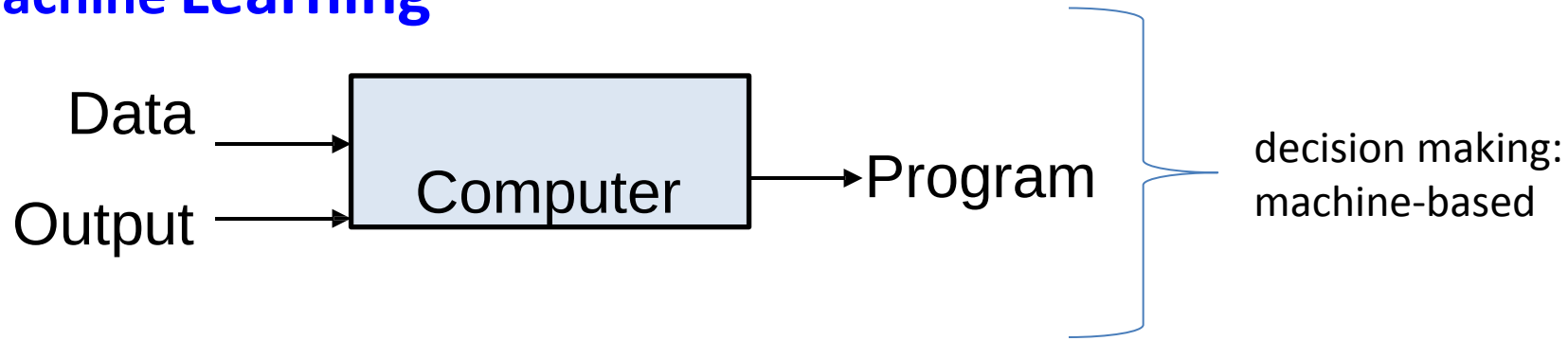
an automated process that extracts patterns from data.

algorithm ➔ search and “learn” the ‘features’ several times

Traditional Programming



Machine Learning

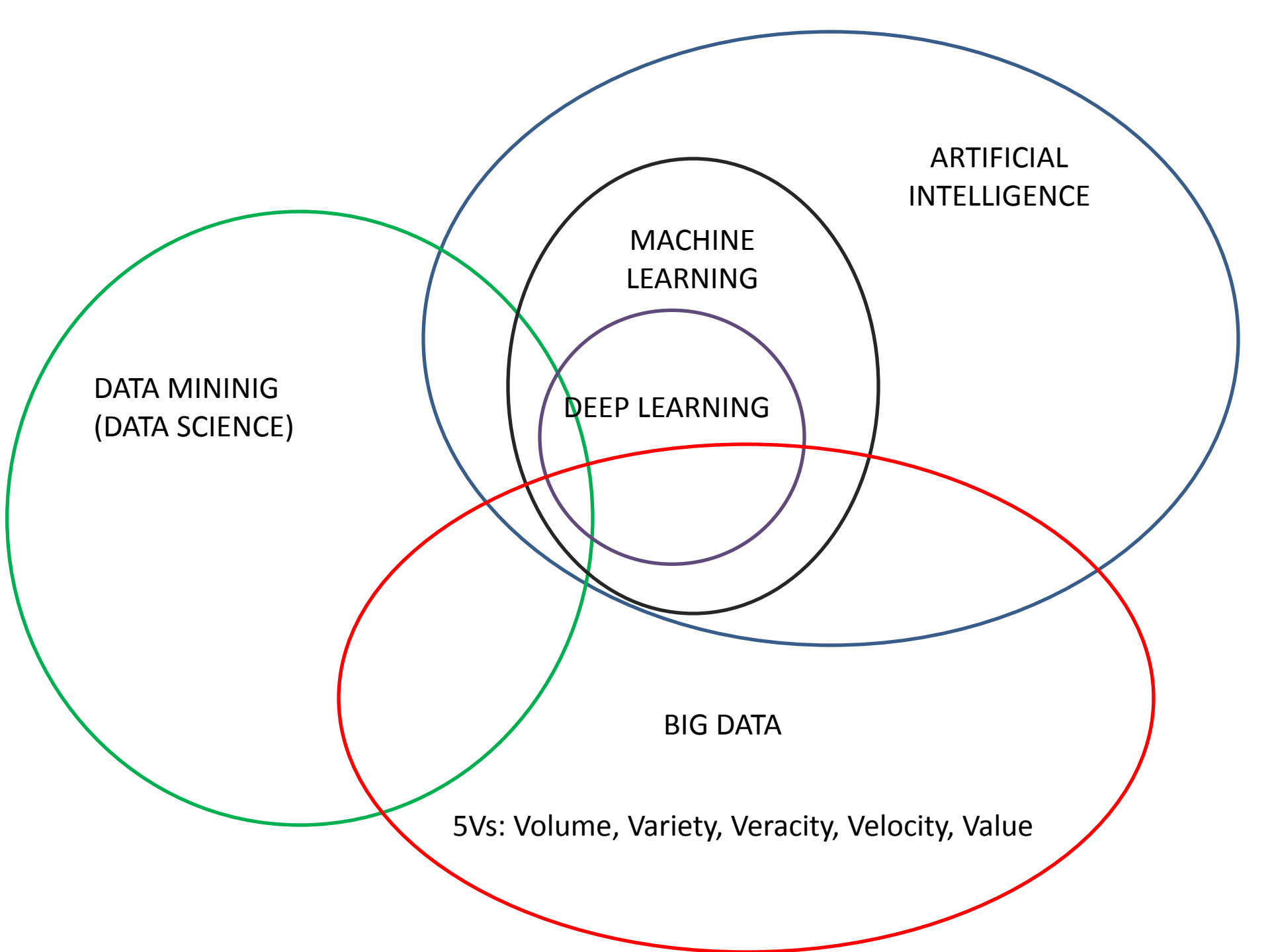


Machine learning is like farming or gardening

Seeds = Algorithms
Nutrients = Data
Gardener = You
Plants = Programs

ARTIFICIAL INTELLIGENCE + DATA MINING + MACHINE LEARNING = SIMILAR?

- Data Mining:
  - using Statistics as well as other methods to find patterns hidden in the data so that the phenomenon can be *explain* (builds intuition about what is really happening in data).
- Artificial Intelligence:
  - how to create intelligent agents, including its behavior to perform a task intelligently. This does not *have* to involve learning or induction at all, it can just be a way to 'build a better mousetrap'.
- Machine Learning:
  - computer algorithms that can extract information automatically (i.e., without on-line human guidance) accordingly to some performance measure

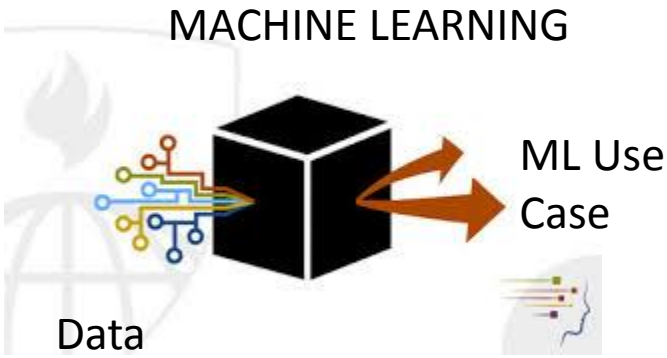

ARTIFICIAL
INTELLIGENCE
MACHINE
LEARNING
DEEP LEARNING
DATA MININIG
(DATA SCIENCE)
BIG DATA
5Vs: Volume, Variety, Veracity, Velocity, Value

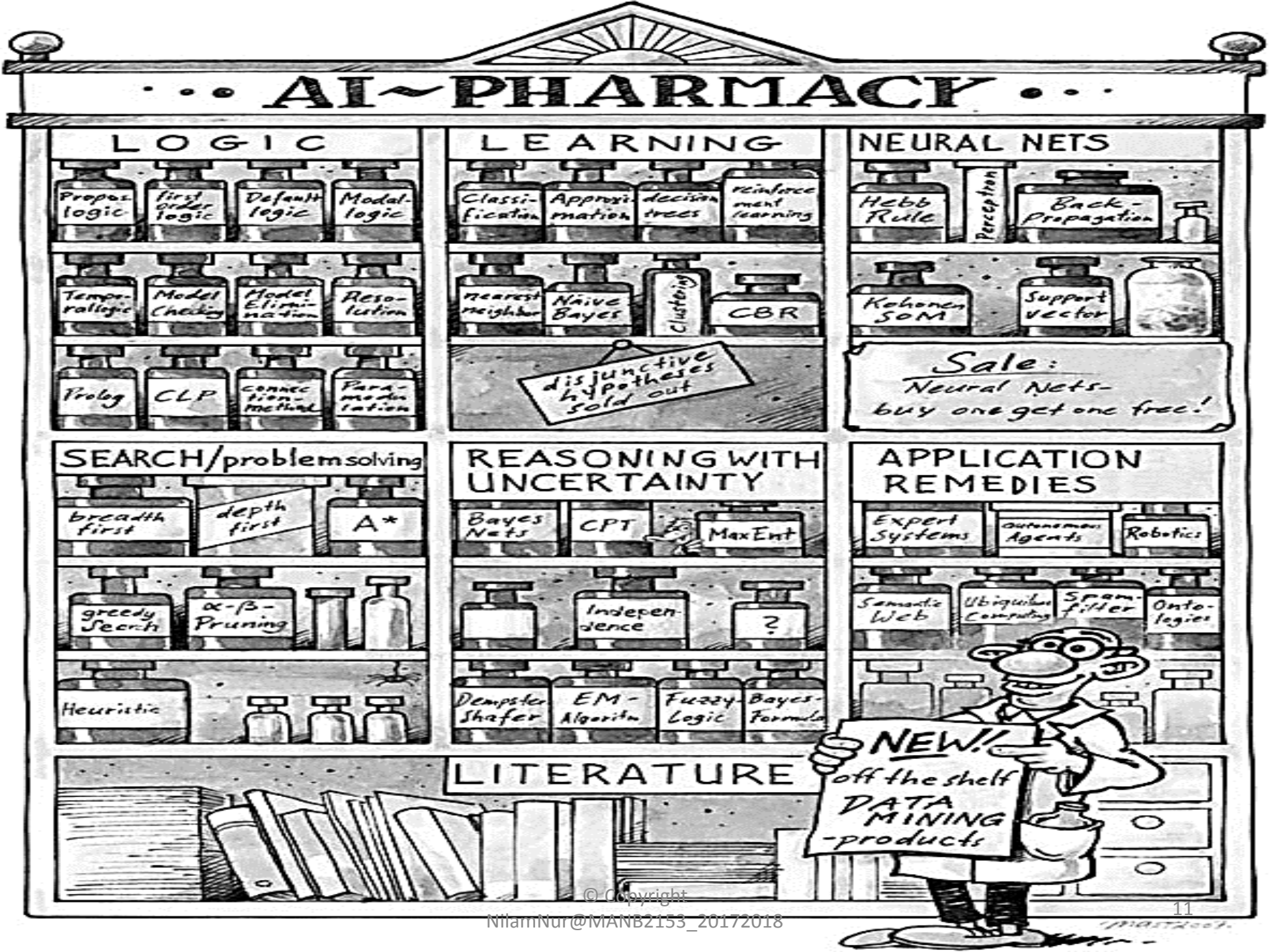
DATA MINING

- Discovery of (previously) unknown properties in the data

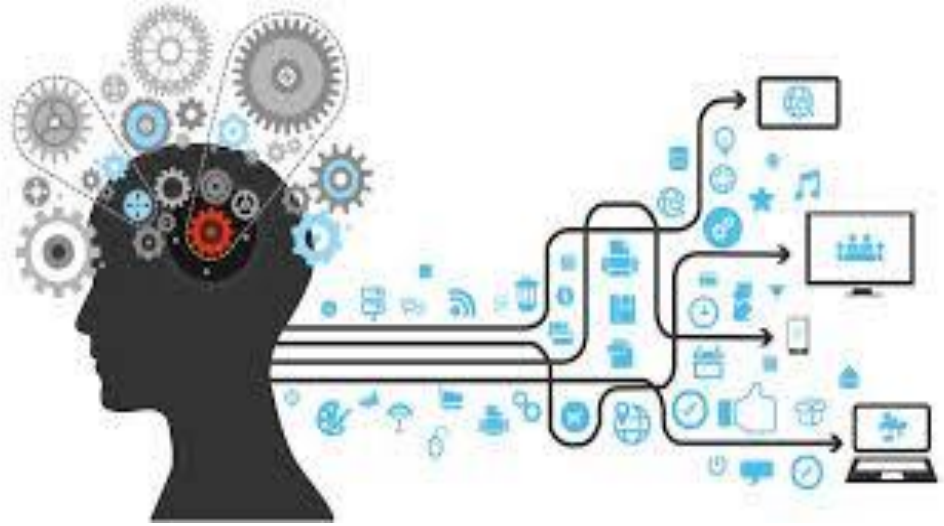
MACHINE LEARNING

- Prediction learn from the training data

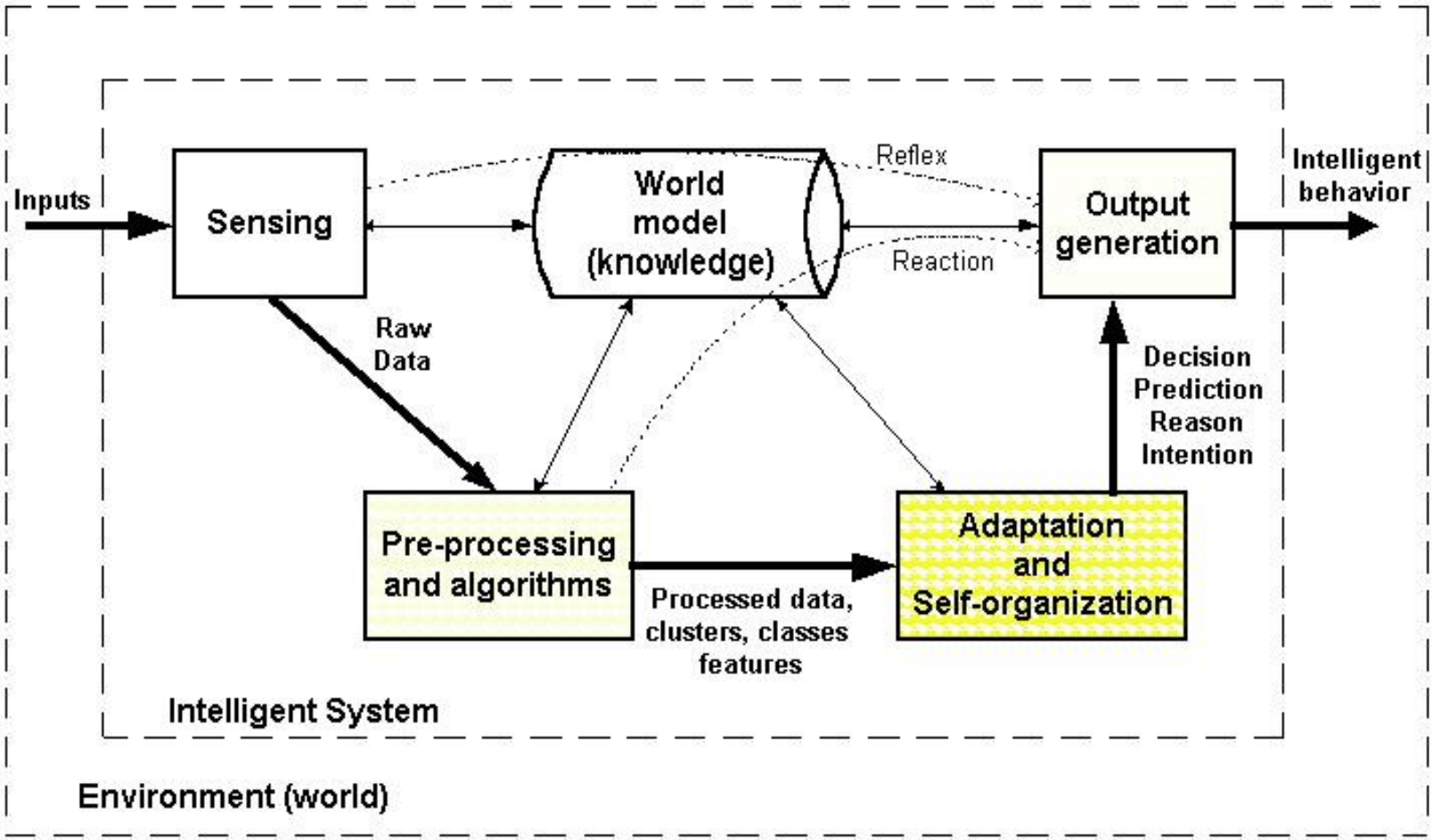




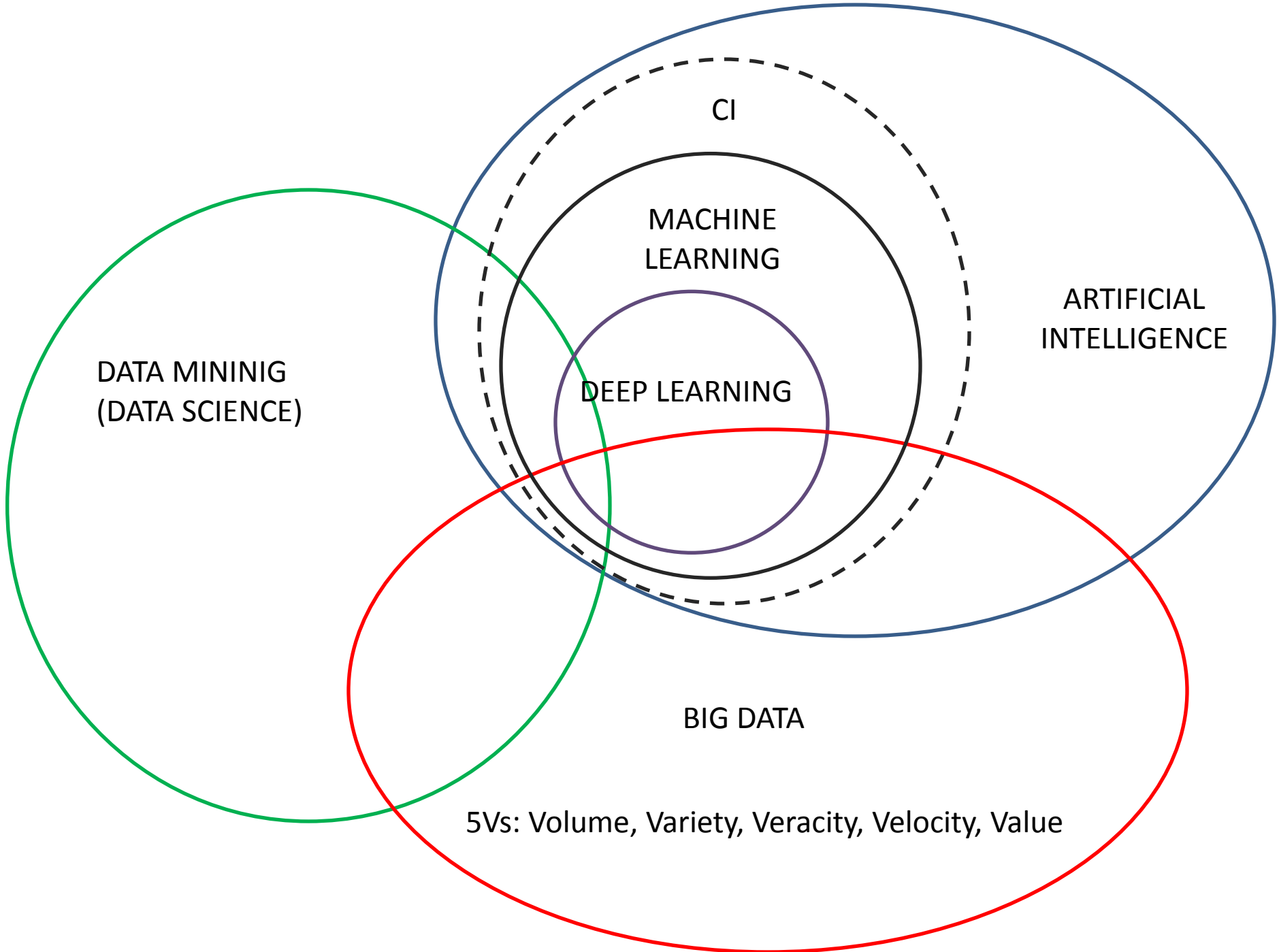
COMPUTATIONAL INTELLIGENCE?



- What it is?
  - comprises practical **adaptation and self-organization** concepts, paradigms, algorithms and implementations that enable or facilitate appropriate actions (intelligent behavior) in complex and changing environments.
- How it works?
  - involving computing that exhibits an ability to learn and/or to deal with new situations, such that the system is perceived to possess one or more attributes of *reason*, such as generalization, discovery, association and abstraction.



Relationships among components of intelligent systems


CI
MACHINE
LEARNING
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NEXT…

- What is ML?
- **History of ML**
- Why ML?
- ML challenges
- Steps in developing ML application
- The ML algorithm: How to choose the right algorithm for ML
- Type of ML: supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning
- ML with Python: Why?

HISTORY OF MACHINE LEARNING

In 1959, an IBM computer scientist named Arthur Samuel wrote a computer program to play checkers. Each board position was assigned a score based on its likelihood of leading to a win. At first, scores were based on a formula using factors such as the number of pieces on each side and the number of kings. It worked, but Samuel had an idea about how to improve its performance. He had the program play thousands of games against itself and used the results to refine the positional scoring. By the mid 1970s, the program had achieved the proficiency of a respectable amateur player Samuel had written a computer program that was able to improve its own performance through experience.

It learned—and machine learning (ML) was born.

Schaeffer, Jonathan. One jump ahead: computer perfection at checkers. Springer Science & Business Media, 2008.

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WHY MACHINE LEARNING?

- Can ML being applied in business problem?

  – an example of business problem:

    fraud detection, to customer targeting and product recommendation, to real-time industrial monitoring, sentiment analysis, and medical diagnosis.

Any other else you want to add?

WHY MACHINE LEARNING?

- Why need ML (looking into business problem)?
  - dealing with huge amount of data that must be processed.
  - manually finding effective filters becomes harder and harder—if not impossible—as the filtering system grows in complexity.
  - The business rules may become so complicated and irrelevant rules may becomes virtually impossible.

USE CASES FOR MACHINE LEARNING ORGANIZED BY TYPE OF PROBLEM

Problem	Description	Example use cases
Classification	Determine the discrete class to which each individual belongs, based on input data	Spam filtering, sentiment analysis, fraud detection, customer ad targeting, churn prediction, support case flagging, content personalization, detection of manufacturing defects, customer segmentation, event discovery, genomics, drug efficacy
Regression	Predict the real-valued output for each individual, based on input data	Stock-market prediction, demand forecasting, price estimation, ad bid optimization, risk management, asset management, weather forecasting, sports prediction
Recommendation	Predict which alternatives a user would prefer	Product recommendation, job recruiting, Netflix Prize, online dating, content recommendation
Imputation	Infer the values of missing input data	Incomplete patient medical records, missing customer data, census data

BIZ INSIGHT

Elevating online shopping experiences through machine learning

PANAWAT INNURAK
SPECIAL TO THE NATION *September 5, 2016 1:00 am*

TO SERVE today's customers, accessibility and convenience through online channels are simply not enough.

Customer experiences have become indispensable for every successful business. According to IBM research, 70 per cent of the customers have stopped doing business with brands with which they have had poor experiences. Some 74 per cent even felt frustrated when they were not offered products related to their interests.

On top of these concerns, speed to fulfil customers' needs is paramount, as they are prone to instant gratification and impulse purchases. Hence e-commerce needs a swift personalisation engine to improve customer experiences.

Each proposition to customers should be dynamic and personalised.

Machine learning has been used by e-commerce giants like Amazon to provide customised product recommendations and best-seller lists. Not only does this save time for customers, it also helps segment them, taking into account their associations and existing contracts in a more seamless and instantaneous way.

Most conventional algorithms utilise previous keyword searches, the customer's characteristics, historical clicks etc, to rank the most related items on the first priority.

Microsoft is putting Cortana machine learning in a fridge

Posted Sep 2, 2016 by Darrell Etherington (@etherington)

Microsoft is working with Liebherr's appliance division to rebuild the refrigerator and make it smarter, faster, strong; well, maybe just smarter. The new collaboration between the two will see Microsoft provide computer vision technology, via its Microsoft Cognitive Services Computer Vision API, to let the fridge identify objects contained within.

Why would you want a fridge that knows what it's holding? It'll save you those extra return trips to the grocery store for things you forgot, for one. The deep learning algorithms in use will be able to learn new food types based on its experience from processing millions of generic food packaging images, and it should be able to get smarter very quickly while in use when and if it eventually comes to market, using data gathered from a wide pool of real-world users.

CrunchBase

Microsoft –

FOUNDED
1974

OVERVIEW
Microsoft is an American multinational corporation that develops, manufactures, licenses, supports and sells computer software, consumer electronics and personal computers and services. Its best known software products are the [Microsoft Windows line of operating systems](/product/windows), [Microsoft Office office suite](/product/microsoft-office), and [Internet Explorer](http://windows.microsoft.com/en-us/internet-explorer/download-ie) ....

LOCATION

Google DeepMind wants to use machine learning to help treat certain cancers

By Alex Brokaw on August 30, 2016 02:33 pm

Google DeepMind is launching a project to reduce the time it takes doctors to prepare treatment for head and neck cancers. Alphabet's London-based artificial intelligence division has partnered with the UK's National Health Service and will be conducting the research in coordination with the University College London Hospital.

Head and neck cancers are hard to plan treatment for because of their close proximity to important parts of the body. Before any kind of radiation treatment, clinicians will prepare a detailed map of where radiation will be administered on a patient in order to avoid damaging surrounding tissue. DeepMind says planning can take doctors up to four hours for head and neck cancers, and it hopes that by applying machine learning it will be able to automate parts of the process and reduce that planning time down to an hour.

DEEPMIND IS FOCUSED ON HEALTH CARE

Dr. Yen-Ching Chang, who heads radiotherapy at UCLH, said the technology has the potential to free up doctors, giving them more time to focus on patient care, research, and teaching.

Amazon poaches eBay A.I. chief, continues ramping up machine learning operations

BY MONICA NICKELSBURG on September 2, 2016 at 1:39 pm

Hassan Sawaf. (Photo via LinkedIn).

Amazon is getting serious about machine learning.

The Seattle tech titan hired eBay's head of artificial intelligence, Hassan Sawaf, to lead its own A.I. operation in Palo Alto, Calif.

Sawaf is now Director of Artificial Intelligence at Amazon-owned A9 Labs, the Wall Street Journal reports.

Poaching Sawaf from rival eBay is the latest in a series of moves this week that indicate Amazon is doubling down on A.I. The company just acquired a machine learning team in Cambridge, UK and used some of the $100 million Amazon Alexa fund to invest in natural language processing startup DefinedCrowd.

In 2012, Jeff Bezos provided $2 million to fund machine learning professorships for Turi CEO Carlos Guestrin and his wife, Emily Fox at the University of Washington. An open source project that Guestrin developed at UW later became Turi.

Though Apple won the $200 million Turi acquisition last month, Amazon was interested in buying the machine learning platform at one point, sources tell GeekWire. Apple is using the Turi acquisition to go much deeper into machine learning, perhaps setting up an epic battle between the two tech titans.

Roundup Of **Machine Learning** Forecasts And Market Estimates, 2018

Forbes - 18 Feb 2018

Deloitte Global is predicting up to 800K **machine learning** chips will be in **use** across global data centers this year. Enterprises are increasing their ... IBM, Microsoft, Google, LinkedIn, **Facebook**, Intel, and Fujitsu were the seven biggest ML patent producers in 2017. Source: IFI Claims Patent Services (Patent ...

Facebook to **use** snail mail to thwart election meddling

The Mercury News - 19 hours ago

MENLO PARK — **Facebook** will soon rely on centuries-old technology to try to prevent foreign meddling in U.S. elections: the post office. ... and remove “tens of thousands” of fake **Facebook** pages in advance of French, German and British elections last year **using** improved **machine learning** techniques.

Facebook to verify ads with postcards after Russian meddling

CNBC - 19 Feb 2018

Large-Scale Solar

Solar Markets & Finance

AI, machine learning can ‘make a difference’ in solar asset management

Published: 20 Feb 2018, 09:46

By:

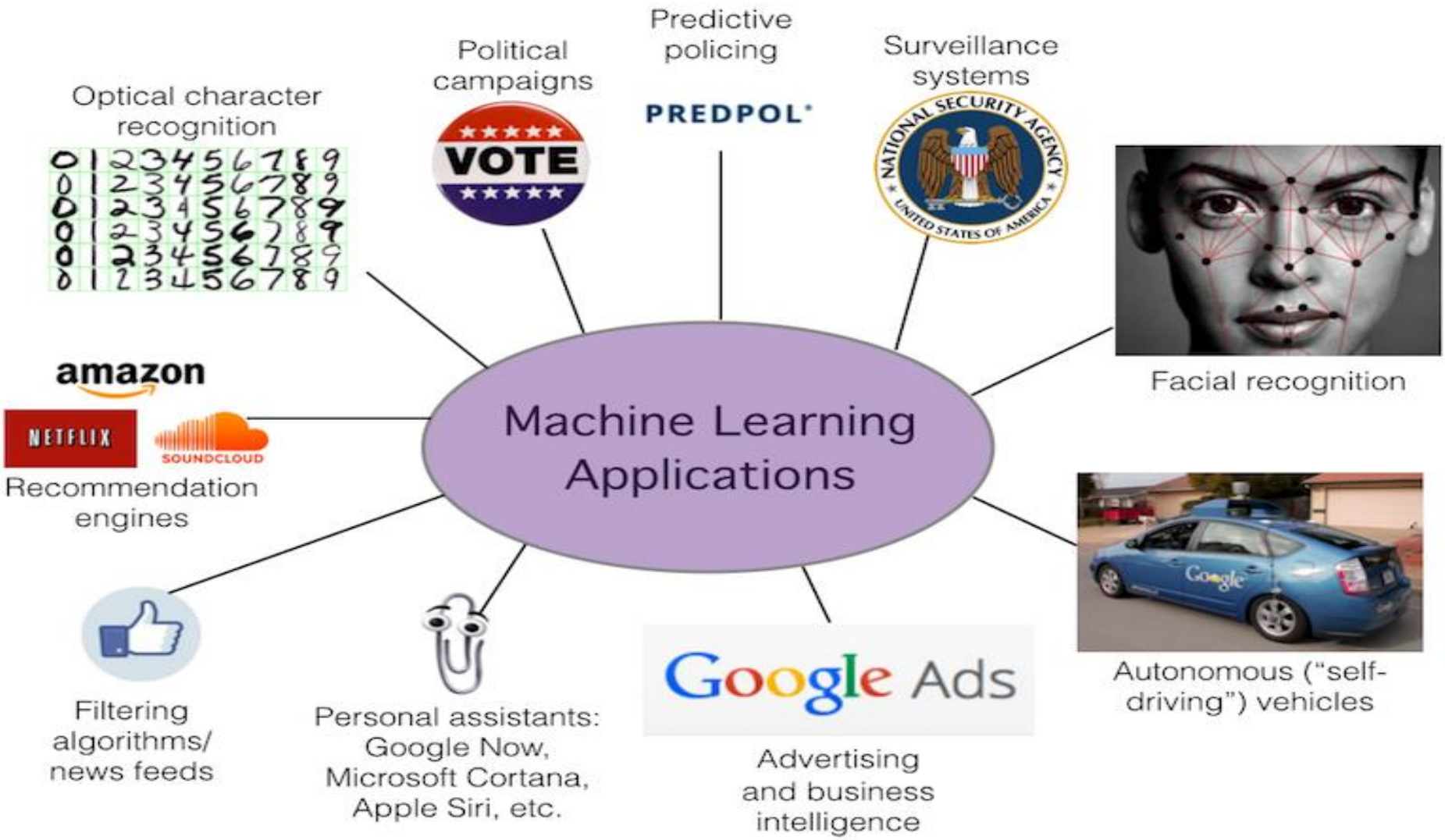
Liam Stoker

Editor, Solar Power Portal

The World's First Robot Citizen – Sophia-Bot

Hanson Robotics,
Lead by AI developer David Hanson

Many domains & applications



THE ADVANTAGES OF USING ML

Accurate

- ML uses data to discover the optimal decision-making engine for your problem. As you collect more data, the accuracy can increase automatically.

Automated

- As answers are validated or discarded, the ML model can learn new patterns automatically. This allows users to embed ML directly into an automated workflow.

Fast

- ML can generate answers in a matter of milliseconds as new data streams in allowing systems to react in real time.

Customizable

- Many data-driven problems can be addressed with ML. ML models are custom built from your own data, and can be configured to optimize whatever metric drives your business.

Scalable

- As your business grows, ML easily scales to handle increased data rates. Some ML algorithms can scale to handle large amounts of data on many machines in the cloud.

“At the highest level, machine learning is about understanding the world through data. Anything you can think of – public, policy, finance, automobiles , robotic for example– there’s a role for machine learning”

Geofrey Gordon
Carnegie Mellon Univeristy
Machine Learning Department

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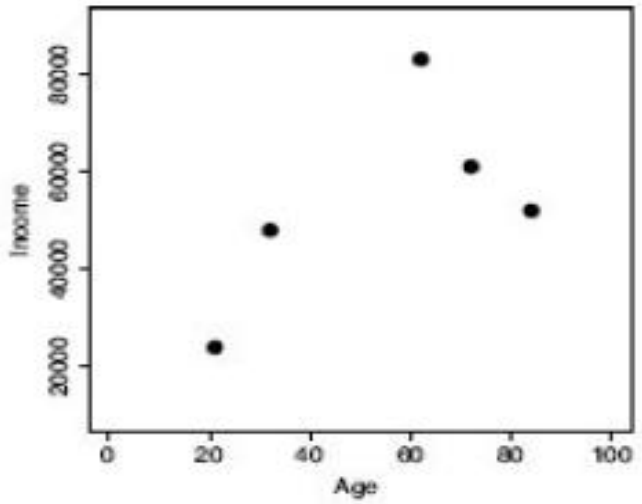
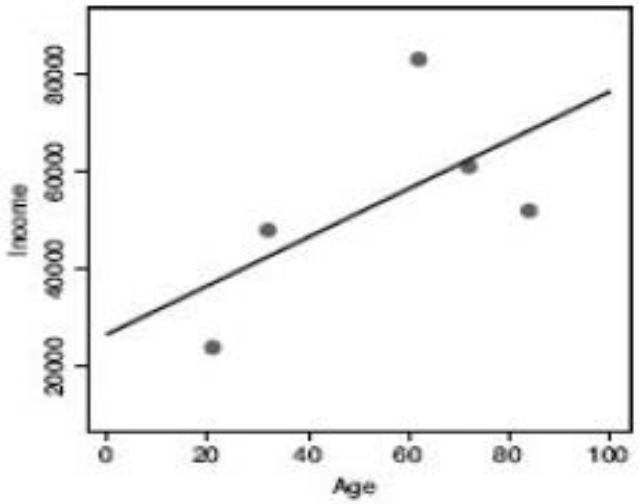
CHALLENGES IN MACHINE LEARNING

THE ML CHALLENGES

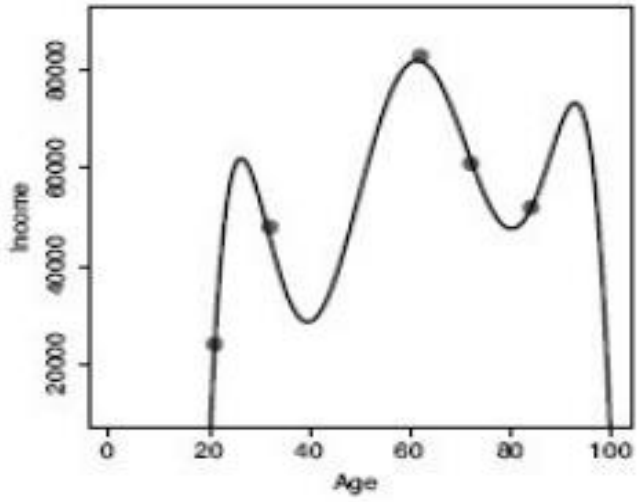
- Data Preparation
  - identifying and formulating problems to which ML can be applied, acquiring and transforming data to make it usable ➔ 'exhaust' in business process
  - finding the right algorithms for the problem
- Overfitting
  - the prediction model selected by the algorithm is so complex that the model fits to the dataset too closely and becomes sensitive to noise in the data.
- Under fitting
  - the prediction model selected by the algorithm is too simplistic to represent the underlying relationship in the dataset between the descriptive features and the target feature.

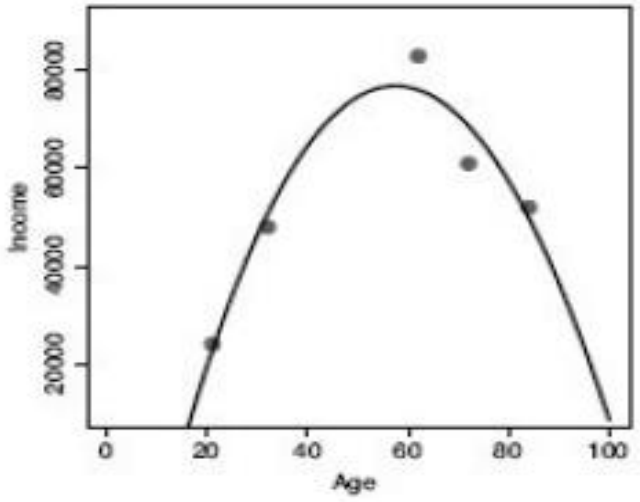


(a) Dataset



(b) Underfitting





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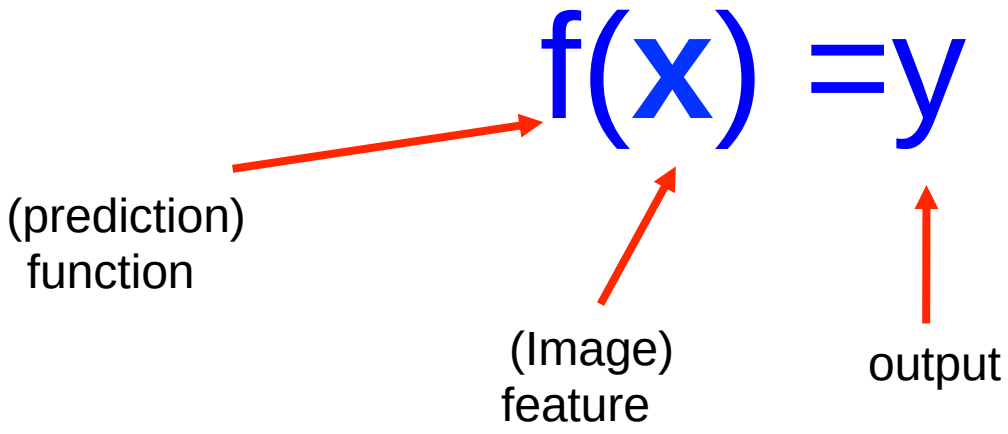
Know the Machine Learning Framework

The Machine Learning Framework
example: image classification



- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the (prediction) function f by minimizing the (prediction error) on the training set
- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

How it is done?
The Machine Learning Framework

- Example: Apply a prediction function to a feature representation of the image to get the desired output

f() = “apple”

f() = “tomato”

f() = “cow”

What are the key elements of Machine Learning?

Key Elements of Machine Learning

Machine learning algorithm has three components:

How to represent knowledge

Examples:
include decision trees, sets of rules, instances (features/attribute), graphical models, neural networks, support vector machines, model ensembles and others

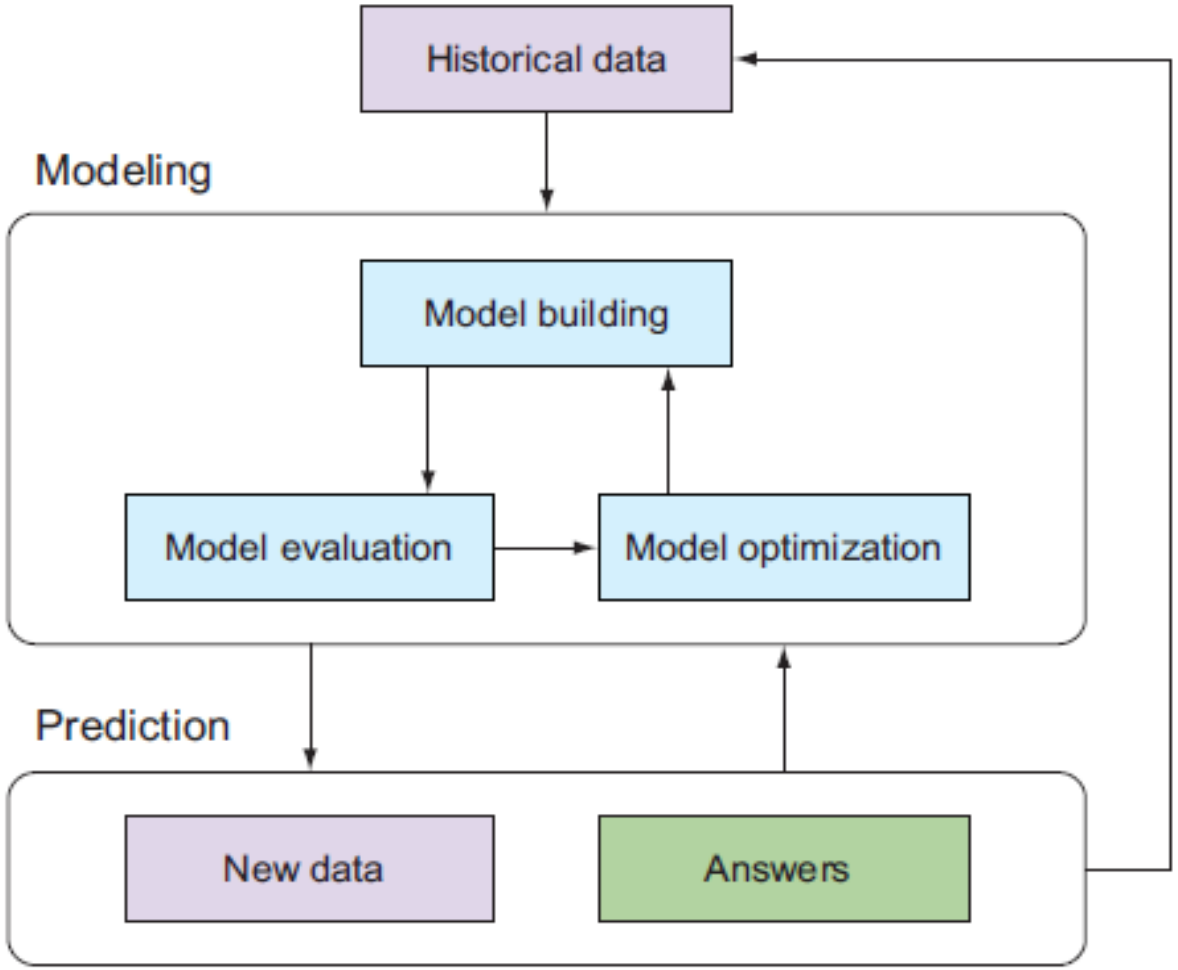
The way to evaluate candidate programs (hypotheses).

Examples:
include accuracy,
prediction and recall, squared error, likelihood, posterior probability, cost,

The way candidate programs are generated known as the search process

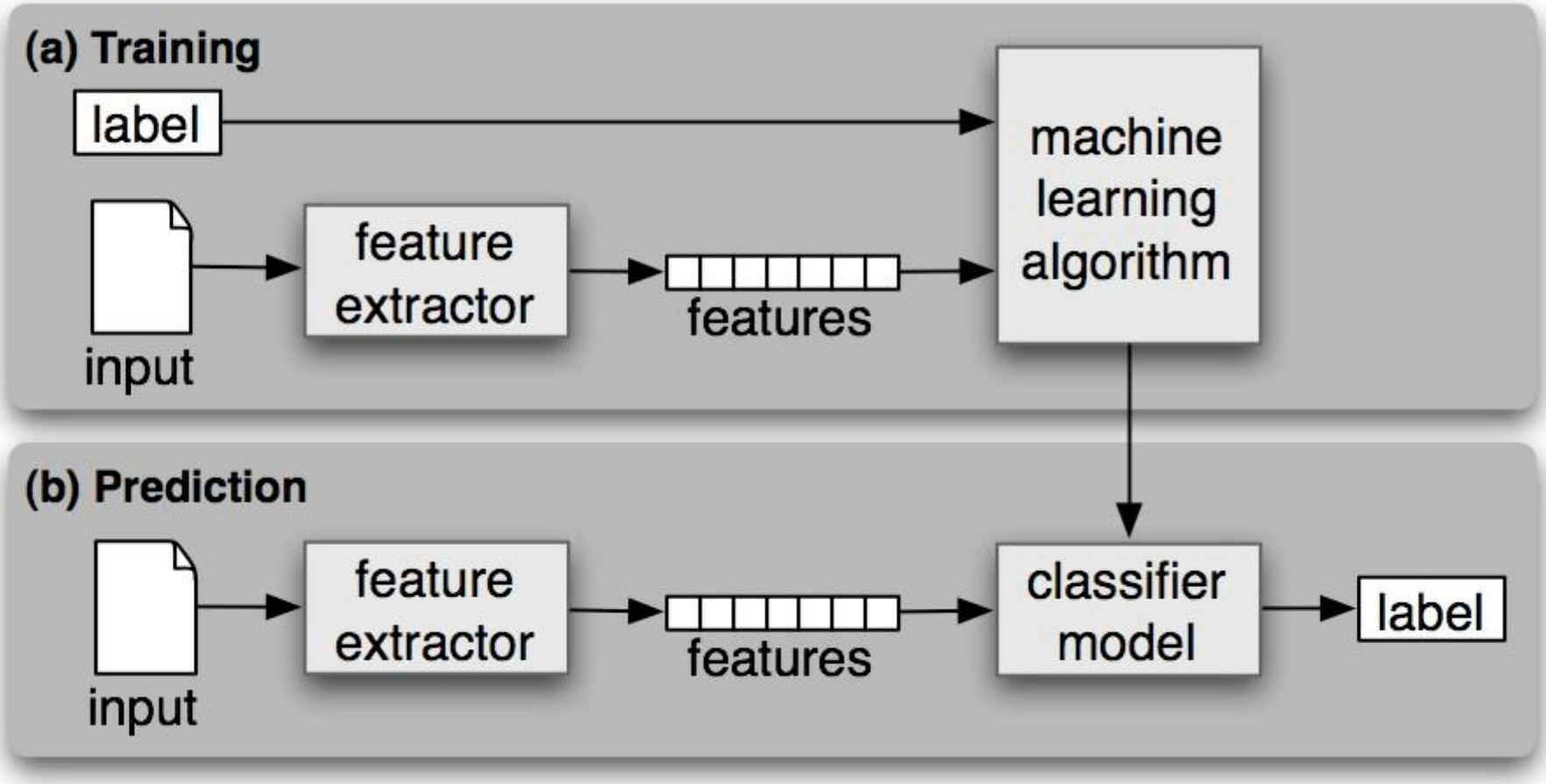
Example:
combinatorial optimization, convex optimization, constrained optimization.

ML WORKFLOW



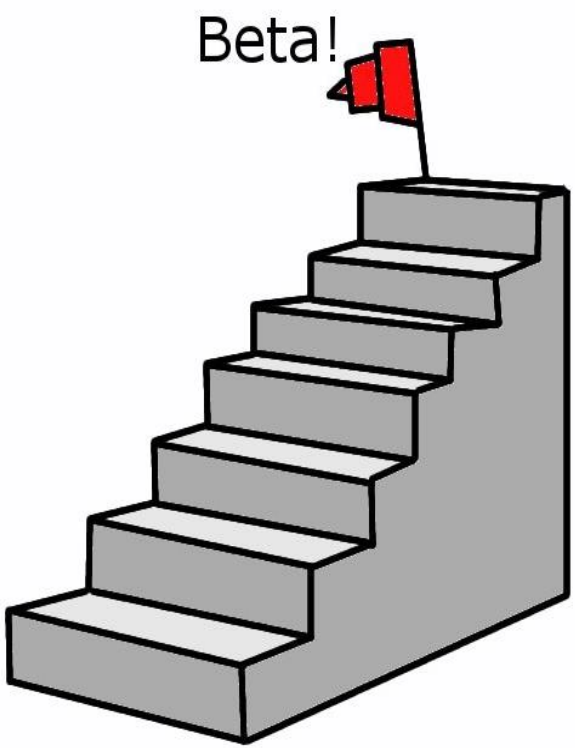
In this flow of an online ML system, predictions are fed back to the model for iterative improvements.

Typical Learning Process for ML



What are the steps involve in applying ML?

Steps of applying ML:-



1. Data Collection
2. Data Preprocessing
   - Data Cleaning
   - Data Transformation
   - Divide data into training and testing sets
3. Built a model learning (use training data)
4. Model Evaluation (use test data)
5. If the performance is satisfied, deploy the model to the real system.

- Feature Extraction
- Feature Selection

The ML Steps: Example of Image Prediction

Training

Training Images

Training Labels

Image Features

Training

Learned model

Testing

Test Image

Image Features

Learned model

Prediction

CHILL OUT & WATCH THIS

https://youtu.be/3bJ7RChxMWQ

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

ML NUTSHELL

Start with a general question

Can I automatically detect emails that are SPAM that are not?

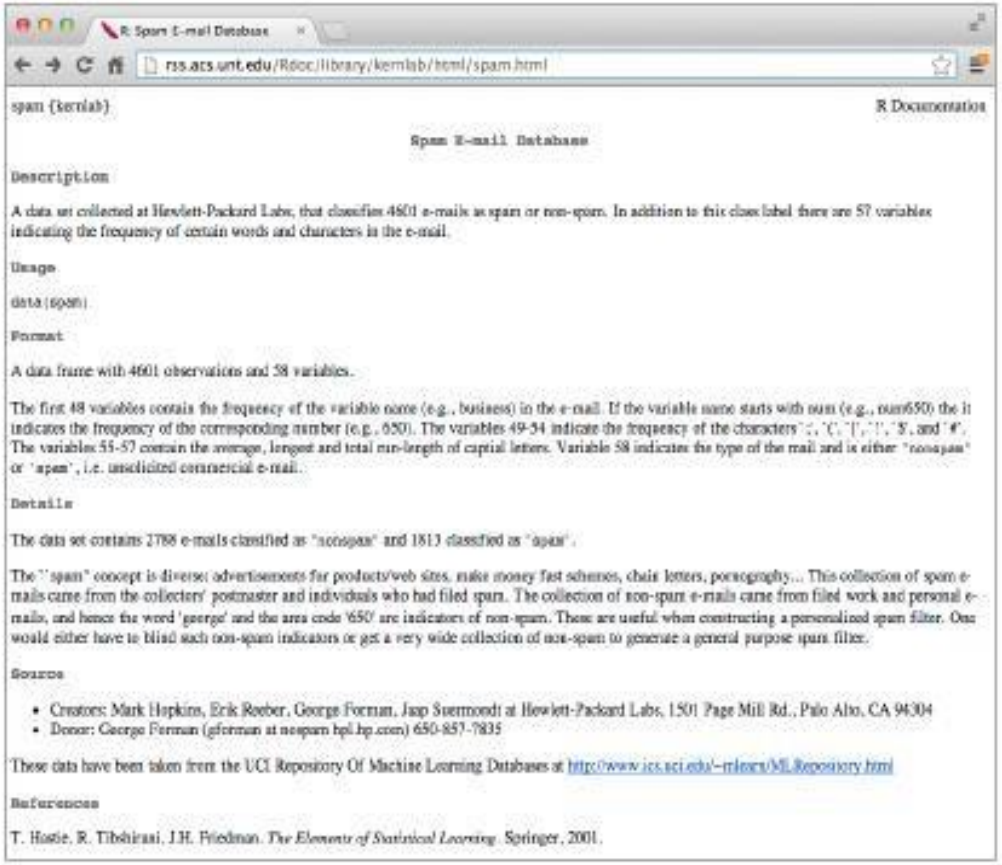
Make it concrete

Can I use quantitative characteristics of the emails to classify them as SPAM/HAM?

* Adapted from Jeff Leek

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation



R Spam E-mail Database

rss.acs.unt.edu/Rdoc/library/kernlab/html/spam.html

spam {kernlab} R Documentation

Spam E-mail Database

Description

A data set collected at Hewlett-Packard Labs, that classifies 4601 e-mails as spam or non-spam. In addition to this class label there are 57 variables indicating the frequency of certain words and characters in the e-mail.

Usage

data(spam)

Format

A data frame with 4601 observations and 58 variables.

The first 48 variables contain the frequency of the variable name (e.g., business) in the e-mail. If the variable name starts with num (e.g., num650) the it indicates the frequency of the corresponding number (e.g., 650). The variables 49-54 indicate the frequency of the characters ';', '(', '[', '!', '$', and '#'. The variables 55-57 contain the average, longest and total run-length of capital letters. Variable 58 indicates the type of the mail and is either "nonspam" or "spam", i.e. unsolicited commercial e-mail.

Details

The data set contains 2788 e-mails classified as "nonspam" and 1813 classified as "spam".

The "spam" concept is diverse: advertisements for products/web sites, make money fast schemes, chain letters, pornography... This collection of spam e-mails came from the collectors' postmaster and individuals who had filed spam. The collection of non-spam e-mails came from filed work and personal e-mails, and hence the word 'george' and the area code '650' are indicators of non-spam. These are useful when constructing a personalized spam filter. One would either have to blind such non-spam indicators or get a very wide collection of non-spam to generate a general purpose spam filter.

Source

- Creators: Mark Hopkins, Erik Reeber, George Forman, Jaap Suermondt at Hewlett-Packard Labs, 1501 Page Mill Rd., Palo Alto, CA 94304
- Donor: George Forman (gforman at nospam hpl.hp.com) 650-857-7835

These data have been taken from the UCI Repository Of Machine Learning Databases at http://www.ics.uci.edu/~mlearn/MLRepository.html

References

T. Hastie, R. Tibshirani, J.H. Friedman. *The Elements of Statistical Learning*. Springer, 2001.

http://rss.acs.unt.edu/Rdoc/library/kernlab/html/spam.html

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

Dear Jeff,

Can you

send me your address so I can send you the invitation?

Thanks,

Ben

Frequency of you = 2/17 = 0.118

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

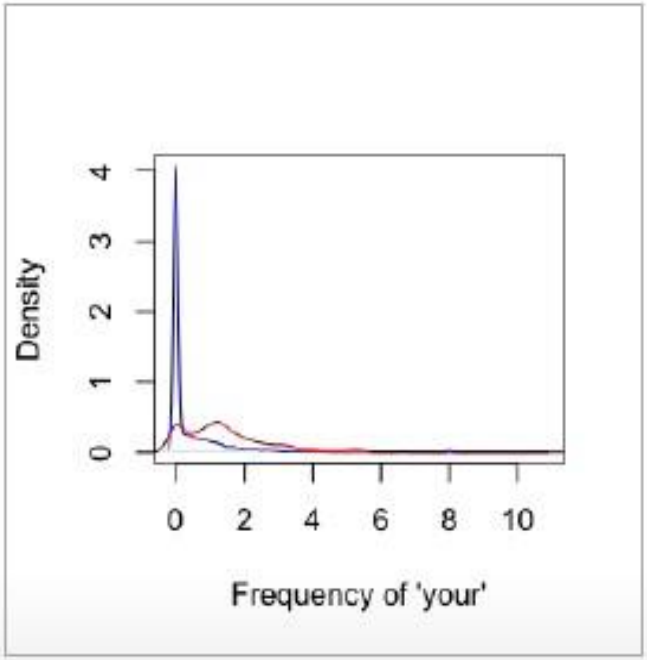
	make	address	all	num3d	our	over	remove	internet	order	mail	receive	will	people	report	addresses
1	0.00	0.64	0.64	0	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.00
2	0.21	0.28	0.50	0	0.14	0.28	0.21	0.07	0.00	0.94	0.21	0.79	0.65	0.21	0.14
3	0.06	0.00	0.71	0	1.23	0.19	0.19	0.12	0.64	0.25	0.38	0.45	0.12	0.00	1.75
4	0.00	0.00	0.00	0	0.63	0.00	0.31	0.63	0.31	0.63	0.31	0.31	0.31	0.00	0.00
5	0.00	0.00	0.00	0	0.63	0.00	0.31	0.63	0.31	0.63	0.31	0.31	0.31	0.00	0.00
6	0.00	0.00	0.00	0	1.85	0.00	0.00	1.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	free	business	email	you	credit	your	font	num000	money	hp	hpl	george	num650	lab	labs	telnet
1	0.32	0.00	1.29	1.93	0.00	0.96	0	0.00	0.00	0	0	0	0	0	0	0
2	0.14	0.07	0.28	3.47	0.00	1.59	0	0.43	0.43	0	0	0	0	0	0	0

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

```
plot(density(spam$your[spam$type=="nonspam"]),
     col="blue",main="",xlab="Frequency of 'your'")
lines(density(spam$your[spam$type=="spam"]),col="red")
```



Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

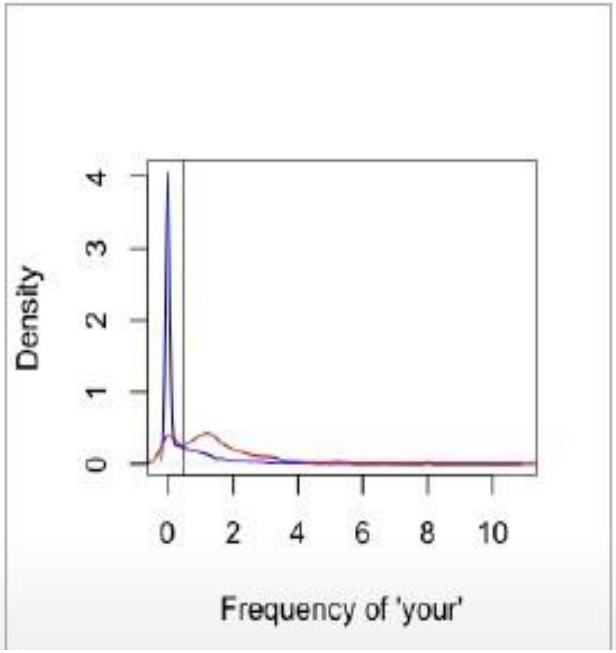
Our algorithm

- Find a value C.
- **frequency of 'your' > C** predict "spam"

Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

```
plot(density(spam$your[spam$type=="nonspam"]),
     col="blue",main="",xlab="Frequency of 'your'")
lines(density(spam$your[spam$type=="spam"]),col="red")
abline(v=0.5,col="black")
```



Example: SPAM detection

question -> input data -> features -> algorithm -> parameters -> evaluation

```
prediction <- ifelse(spam$your > 0.5,"spam","nonspam")
table(prediction,spam$type)/length(spam$type)
```

```
prediction nonspam   spam
   nonspam  0.4590 0.1017
   spam     0.1469 0.2923
```

Accuracy≈ 0.459 + 0.292 = 0.751

NEXT…

- What is ML?
- History of ML
- Why ML?
- ML Challenges
- Steps in developing ML application
- **The ML algorithm: How to choose the right algorithm for ML**
- Type of ML: supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning
- ML with Python: Why?

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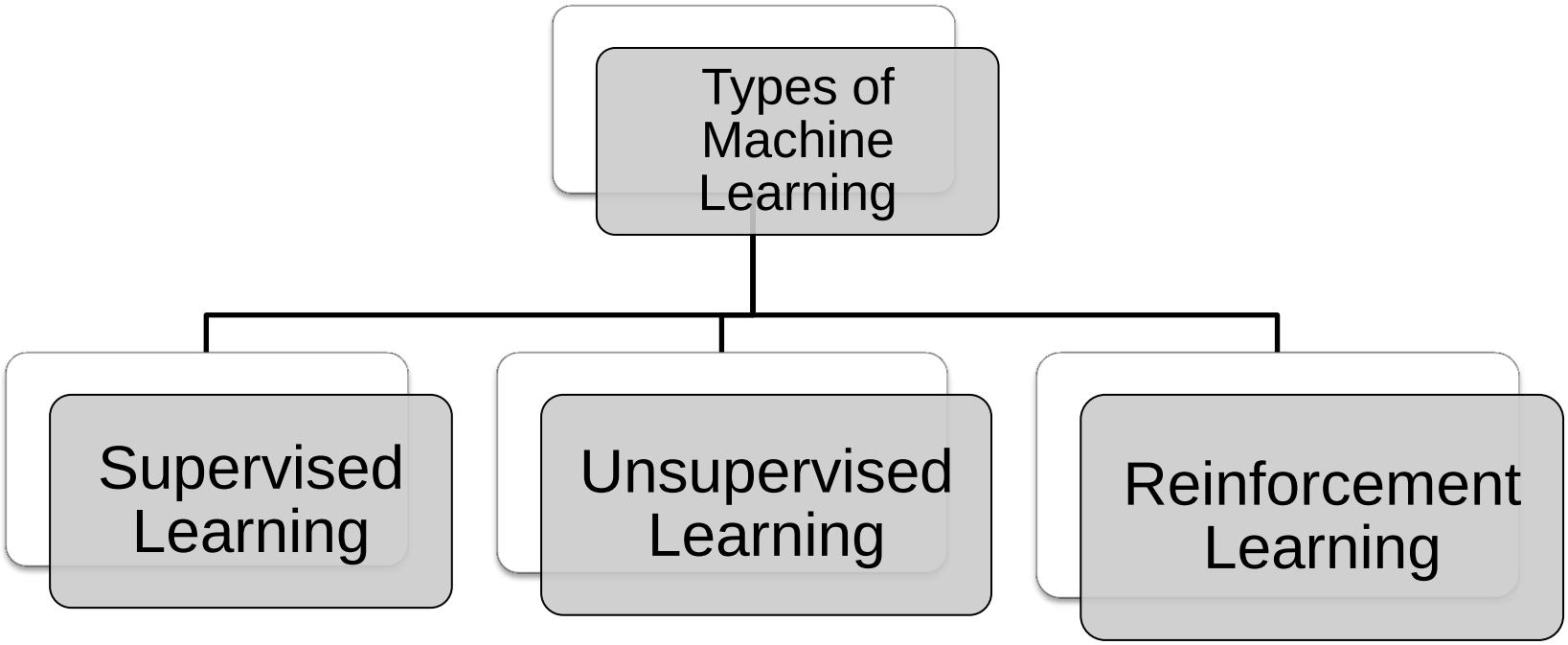
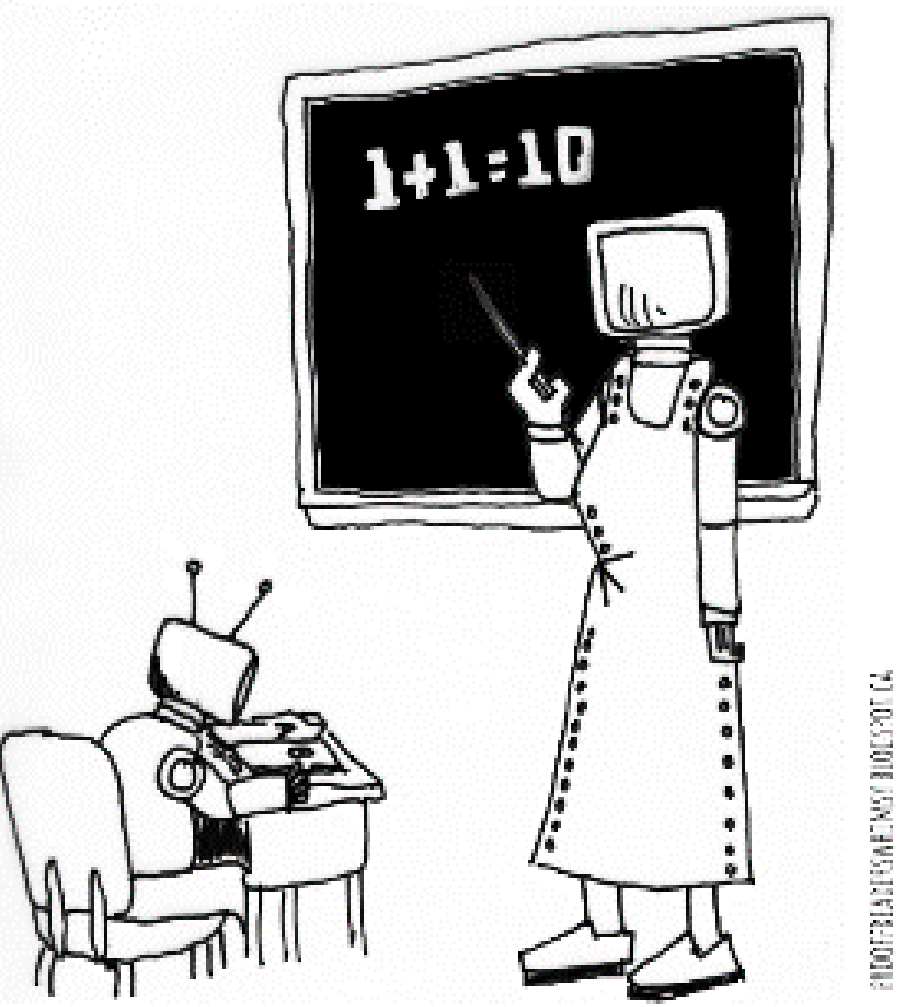
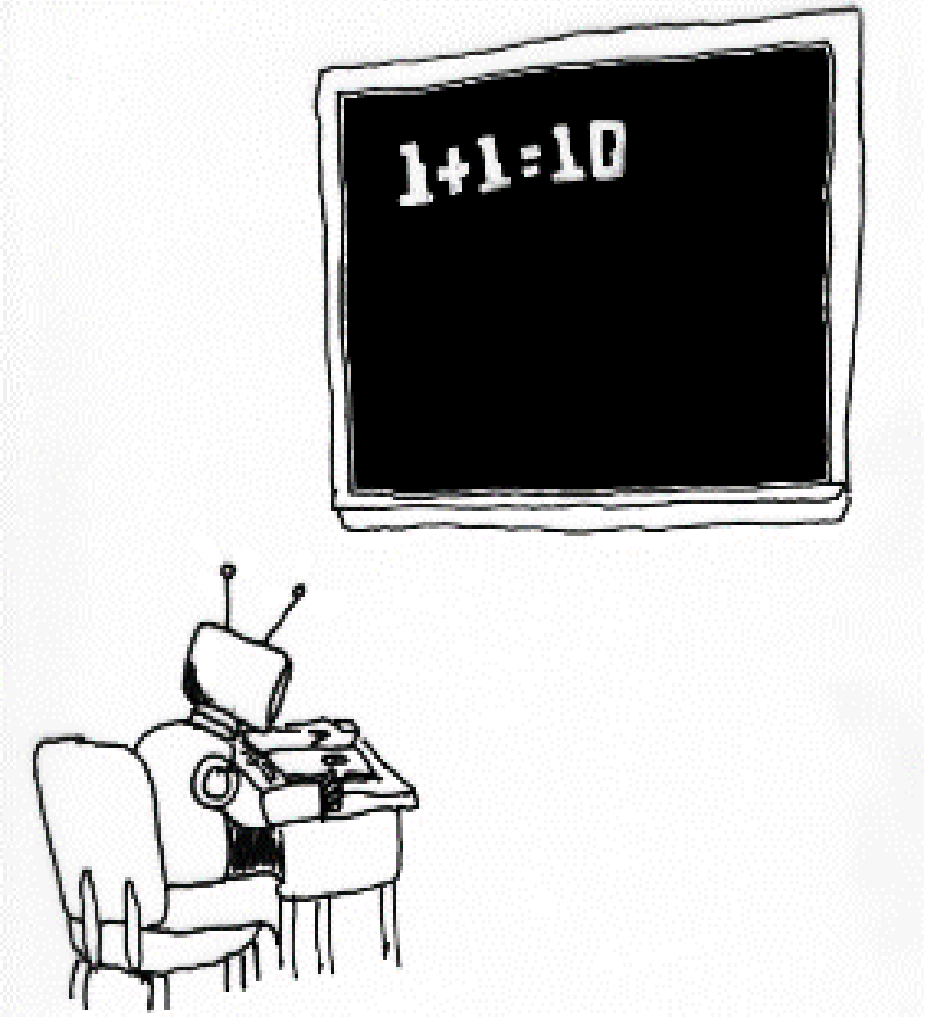
Types of Machine Learning



SUPERVISED MACHINE LEARNING



UNSUPERVISED MACHINE LEARNING

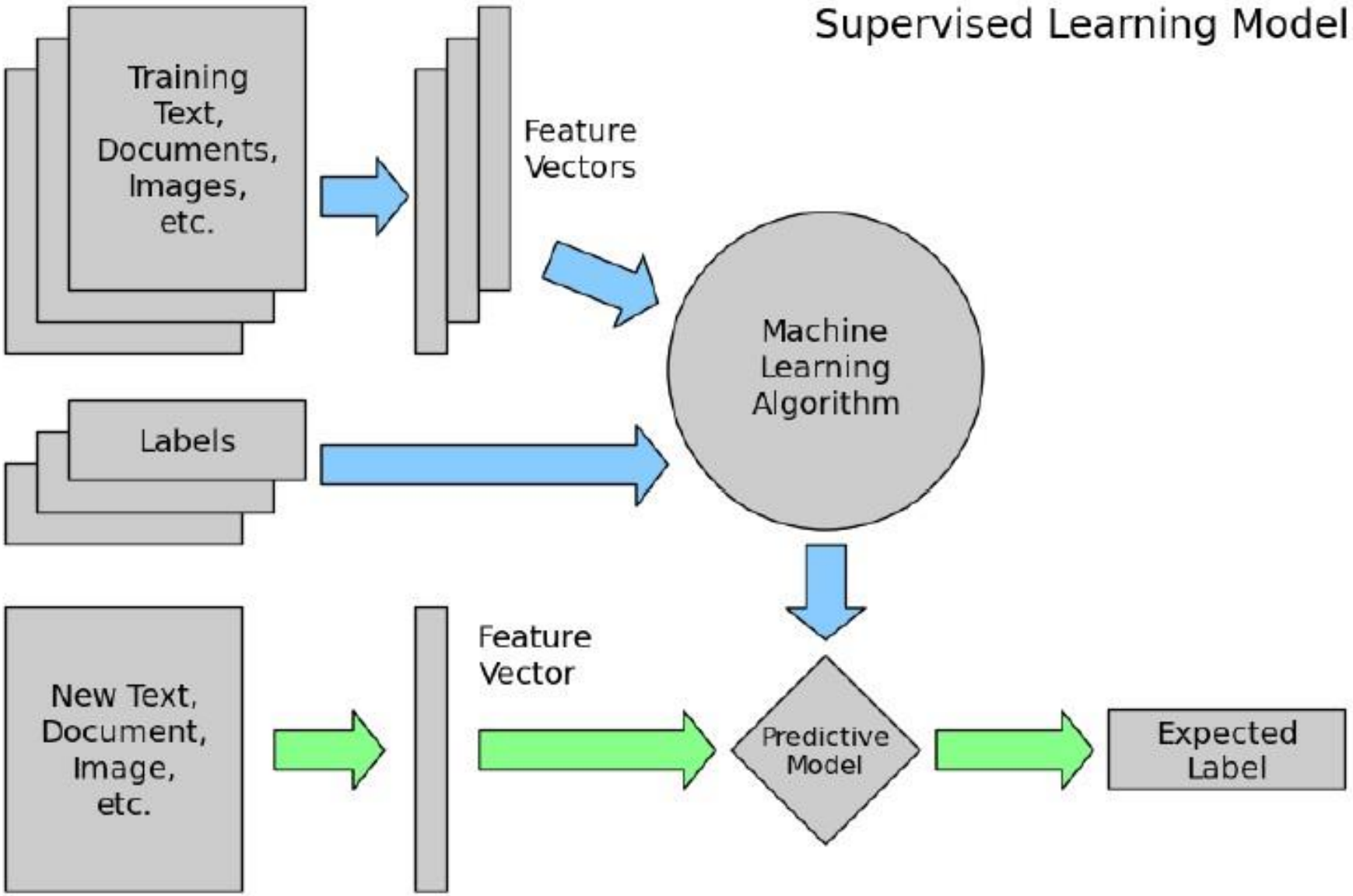


Supervised Learning

- Supervised learning is where you have input variables (x) and an output variable (y) and you use an algorithm to learn the mapping function from the input to the output.

$$y = f(x)$$

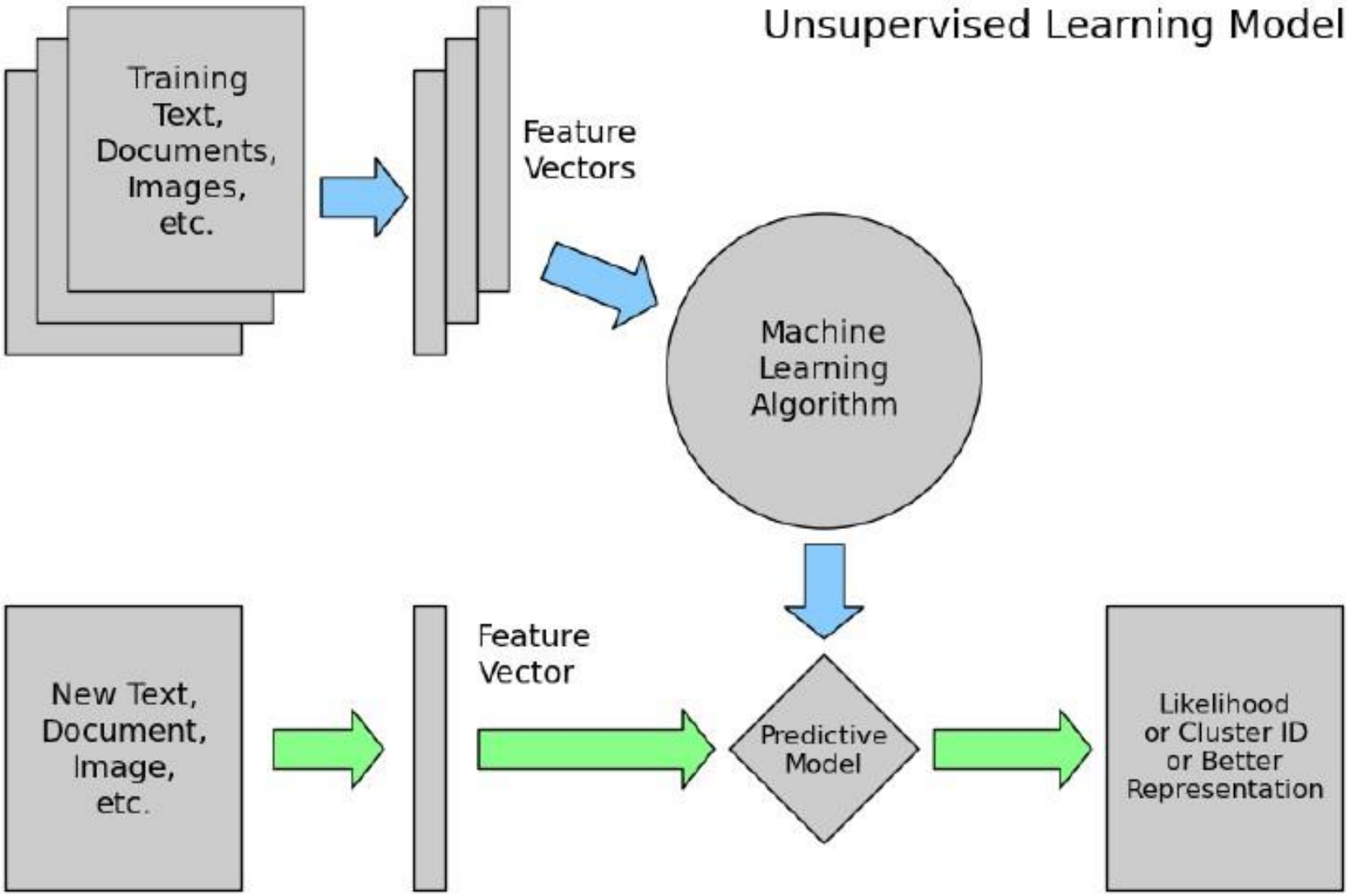
- The **goal** is to approximate the mapping function so well that when you have new input data (x) that you can predict the output variables (y) for that data.


Supervised Learning Model
Training Text, Documents, Images, etc.
Feature Vectors
Machine Learning Algorithm
Labels
New Text, Document, Image, etc.
Feature Vector
Predictive Model
Expected Label

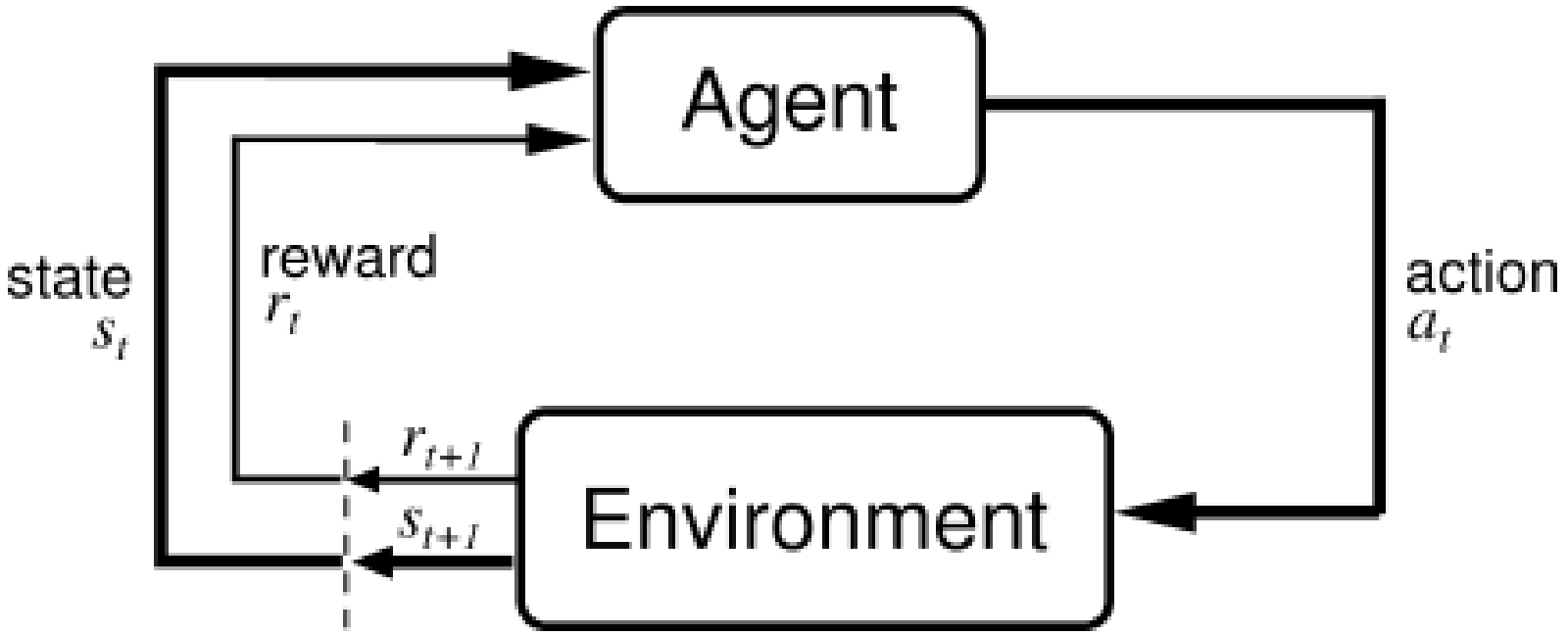
Unsupervised Learning

- Unsupervised learning is where you only have input data (X) and no corresponding output variables.
- Doesn't involve labels (the program is blindly thrown into the task)

- The **goal** for unsupervised learning is to model the underlying structure or distribution in the data in order to learn more about the data


Unsupervised Learning Model
Training
Text,
Documents,
Images,
etc.
Feature
Vectors
Machine
Learning
Algorithm
New Text,
Document,
Image,
etc.
Feature
Vector
Predictive
Model
Likelihood
or Cluster ID
or Better
Representation

Reinforcement Learning



- Close to human learning
- Algorithm learn the policy of how to act in a given environment
- Every action have some impact in the environment, and the environment provide rewards that guides the learning algorithm

Example: Reinforcement Learning

Chess would be an excellent example of this type of algorithm. The program knows the rules of the game and how to play, and goes through the steps to complete the round. The only information provided to the program is whether it won or lost the match. It continues to replay the game, keeping track of its successful moves, until it finally wins a match.

CHILL OUT !! ITS QUIZ TIME

**Please answer all the given question. Your answer should be discuss via Padlet.

https://padlet.com/nurulhuda_firdaus/buzz_MLapplication

QUIZ : Discuss Using Padlet

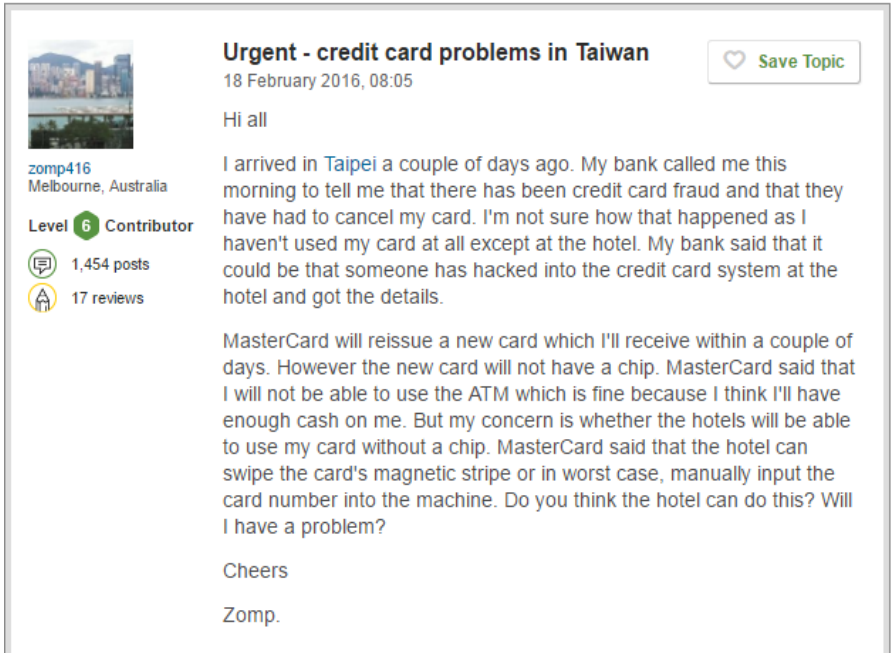


Figure 1. Credit card problem in Taiwan (https://www.tripadvisor.com.my/ShowTopic-g293910-i9303-k9274267-urgent_credit_card_problems_in_Taiwan-Taiwan.html)

Figures 1 shows an example of the credit card fraud issue happen in Taiwan. In well-developed financial system, crisis management is on downstream and risk prediction is on the upstream. In recent years, the credit cards issuers in Taiwan face the debt and credit card crisis. The crisis caused the blow to consumer finance confidence and big challenge for both bank and card holder. A full description is available at the site where the data was obtained from:

http://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients

Here are the data for the project:

http://archive.ics.uci.edu/ml/machine-learning-databases/00350/

QUESTION:

1. What problem can you solve with these data?
2. Is this a machine learning problem?
3. What is the x and the y?
4. Do you think this problem falls under which category? (supervised, unsupervised, semi-supervised or reinforcement learning)? Discuss.

**Please answer all the given question. Your answer should be discuss via Padlet.

ASSIGNMENT 1

- Instruction:
  - Answer this in TWO (2) Page. Do it in pairs.
  - Submit it on 4th May (FRIDAY) by 6 pm via GD. Chief of MANB 2153 please create GD for MANB2153_2_1718/Quiz
- Questions:

  Q1: For these use cases, identify how these use cases can be implemented as supervised learning. What are the inputs, label and the output?
  - Identifying the zip code from handwritten digits on an envelope
  - Determining whether a tumor is benign based on a medical image
  - Detecting medical insurance fraud
  - Predicting a tipping behavior for New York Taxi.

  Q2: For these use cases, explain how does the unsupervised learning can be implemented.
  - Identifying topics in a set of a blog post
  - Segmenting customers into a group with similar preferences
  - Detecting abnormal access pattern to a website.

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- History of ML
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- Knowing Your Task and knowing your Data: Problems ML can solve and cannot solve
- Steps in developing ML application
- The ML algorithm: How to choose the right algorithm for ML
- Type of ML: supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning
- **ML with Python: Why?**