Machine learning

Presented by : Dr. Hanaa Bayomi

Lecture 1 : Introduction

REFERENCES

•T. Mitchell, *Machine Learning*, McGraw-Hill

• Peter Flach, Machine Learning. The Art and Science of Algorithms that Make Sense of Data.

• John D. Kelleher, *Fundamental of Machine Learning for predictive Data Analytic.*

Grading

Type	grades
▪ 3 Assignments	15
▪ Mid term Exam	15
▪ project	10
▪ Final exam	60
Total	100

What is machine learning?

➢ Definition:

Machine = computer, computer program (in this course)
Learning = improving performance on a given task, based on experience / examples

➢ In other words

▪ instead of the programmer writing explicit rules for how to solve a given problem, the programmer instructs the computer how to learn from examples

▪ in many cases the computer program can even become better at the task than the programmer is!

INTRODUCTION

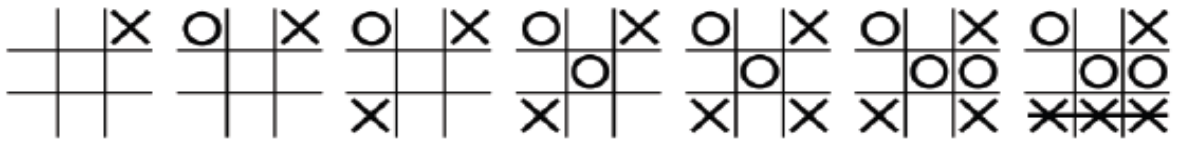
Traditional Programming

Machine Learning

EXAMPLES

Example 1 : Tic-Tac-Toe

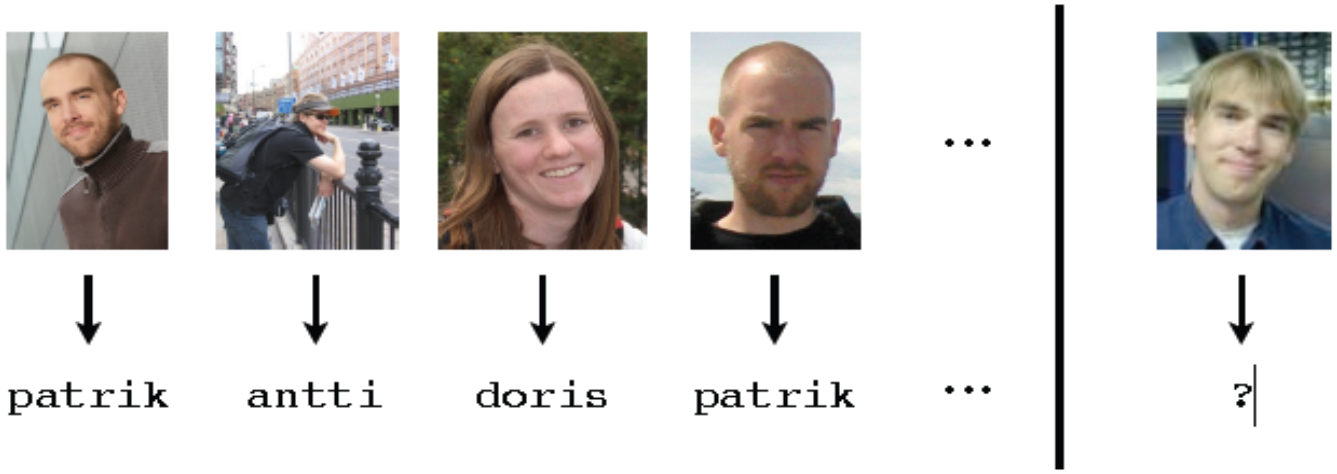
- How to program the computer to play tic-tac-toe?



- Option A: The programmer writes explicit rules, e.g. 'if the opponent has two in a row, and the third is free, stop it by placing your mark there', etc (lots of work, difficult, not at all scalable!)
- Option B: Go through the game tree, choose optimally (for non-trivial games, must be combined with some heuristics to restrict tree size)
- Option C: Let the computer try out various strategies by playing against itself and others, and noting which strategies lead to winning and which to losing (='machine learning')

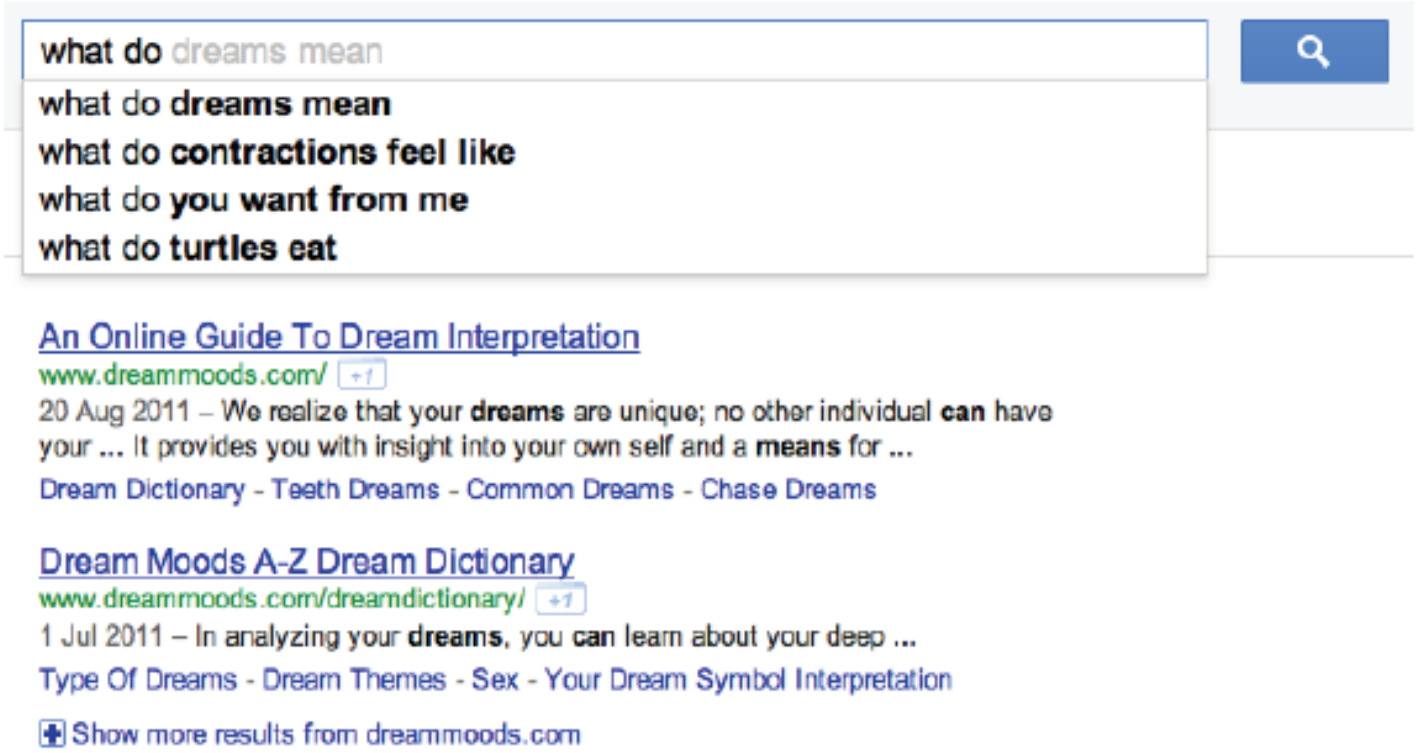
Example 2 : face recognition

- Face recognition is hot (facebook, apple; security; . . .)
- ~~Programmer writes rules: "If short dark hair, big nose, then it is Mikko"~~ (impossible! how do we judge the size of the nose?!)
- The computer is shown many (`image, name`) example pairs, and the computer learns which features of the images are predictive (difficult, but not impossible)



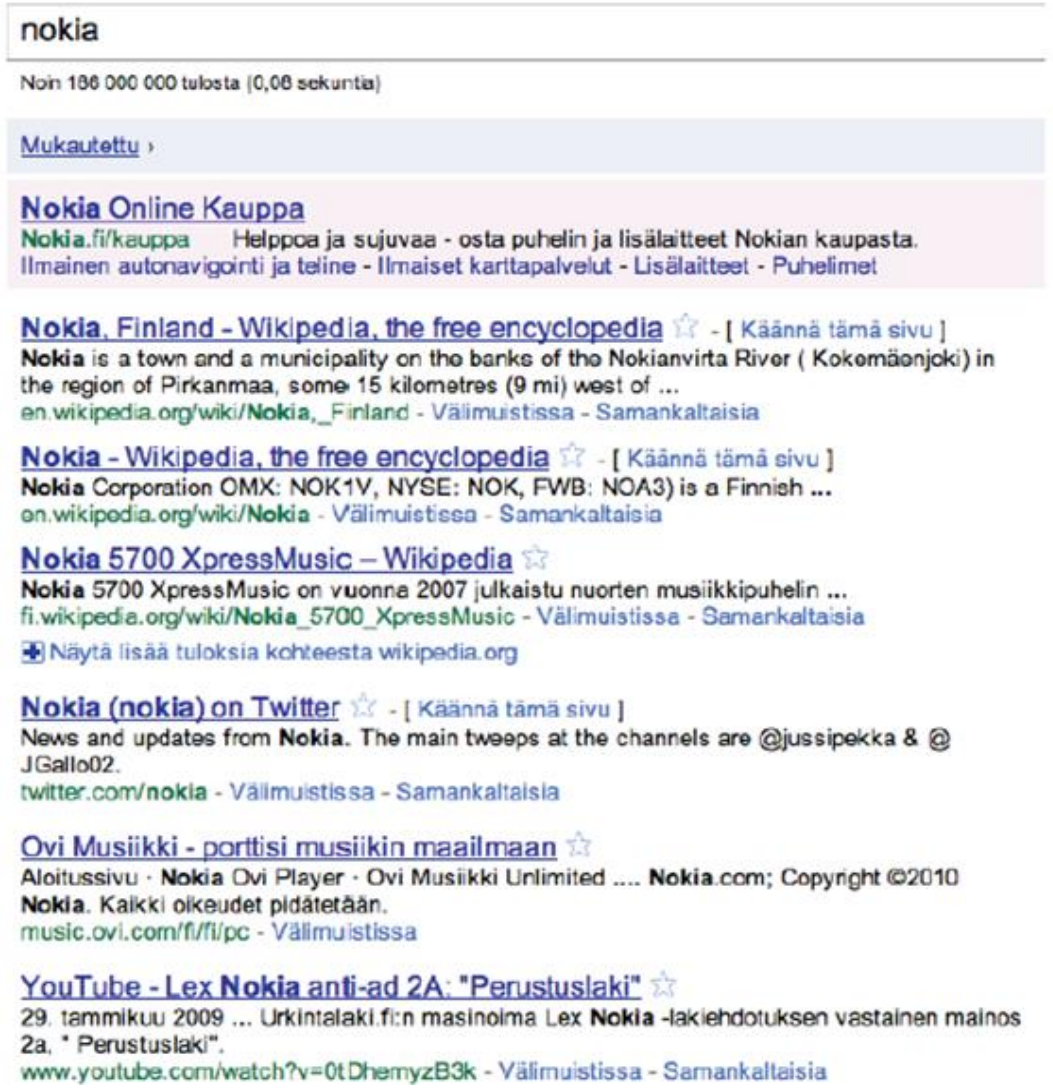
Example 3: Prediction of search queries

- ~~The programmer provides a standard dictionary~~ (words and expressions change!)
- Previous search queries are used as examples!



Example 4: Ranking search results

- Various criteria for ranking results
- What do users click on after a given search? Search engines can learn what users are looking for by collecting queries and the resulting clicks.



Example 5

- Self-driving cars:
  - Sensors (radars, cameras) superior to humans
  - How to make the computer react appropriately to the sensor data?

SMARTER THAN YOU THINK

Google Cars Drive Themselves, in Traffic

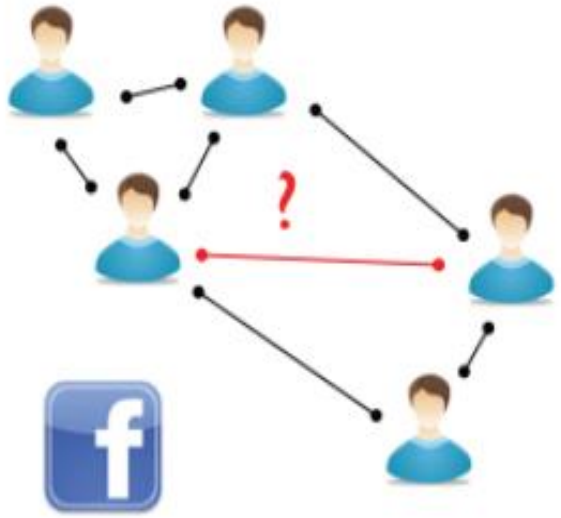
Ramin Rahimian for The New York Times

Example 6

- Machine translation:
  - Traditional approach: Dictionary and explicit grammar
  - More recently, *statistical* machine translation based on example data is increasingly being used

Example 7

- Prediction of friends in Facebook, or prediction of who you'd like to follow on Twitter.



Problem setup

- One definition of machine learning: A computer program improves its performance on a given task with experience (i.e. examples, data).

1- Task

- Task: What is the problem that the program is solving?

•Machine learning allows us to tackle tasks that are too difficult to solve with ***fixed programs written and designed by human beings***.

• Machine learning is interesting because developing our understanding of machine learning entails developing our understanding of the principles that underlie intelligence.

1- Task (Cont.)

Some of the most common machine learning tasks include the following:

1- Classification : In his type of task, the computer program is asked to specify which of k categories some input belongs to.

-Classification Algorithms attempt to map inputs into one of a set of classes (Colors, Good and Bad Credit Risks)

2- Regression : In this type of task, the computer program is asked to predict a numerical value given some input.

-Regression Algorithms attempt to mapinputs into continuous output (Integers,Real Numbers, Vectors, etc.)

1- Task (Cont.)

Some of the most common machine learning tasks include the following:

3- Transcription: In this type of task, the machine learning system is asked to observe a relatively unstructured representation of some kind of data and transcribe it into discrete, textual form.

E.g.: optical character recognition (OCR), where the computer program is shown a photograph containing an image of text and is asked to return this text in the form of a sequence of characters.

4- Machine translation: In a machine translation task, the input already consists of a sequence of symbols in some language, and the computer program must convert this into a sequence of symbols in another language.

2- Experience

- Experience: What is the data (examples) that the program is using to improve its performance?

• **Experience** is a dataset.

•**A dataset** is a collection of many examples.

• **An example** is a collection of **features** that have been quantitatively measured from some object or event that we want the machine learning system to process.

3- performance level

- Performance measure: How is the performance of the program (when solving the given task) evaluated?

In order to evaluate the abilities of a machine learning algorithm, we must design a quantitative measure of its performance. Usually this performance measure P is specific to the task T being carried out by the system.

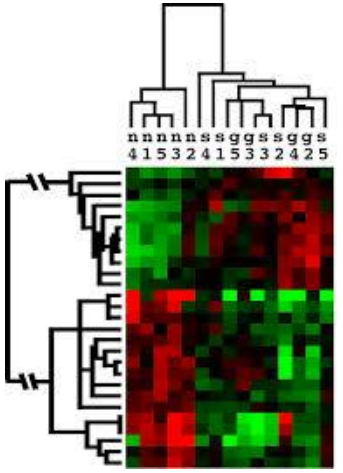
- Accuracy : Accuracy is just the proportion of examples for which the model ***produces the correct output***.

- Error Rate : the proportion of examples for which the model ***produces an incorrect output***.

WHEN DO WE USE MACHINE LEARNING?

ML is used when:

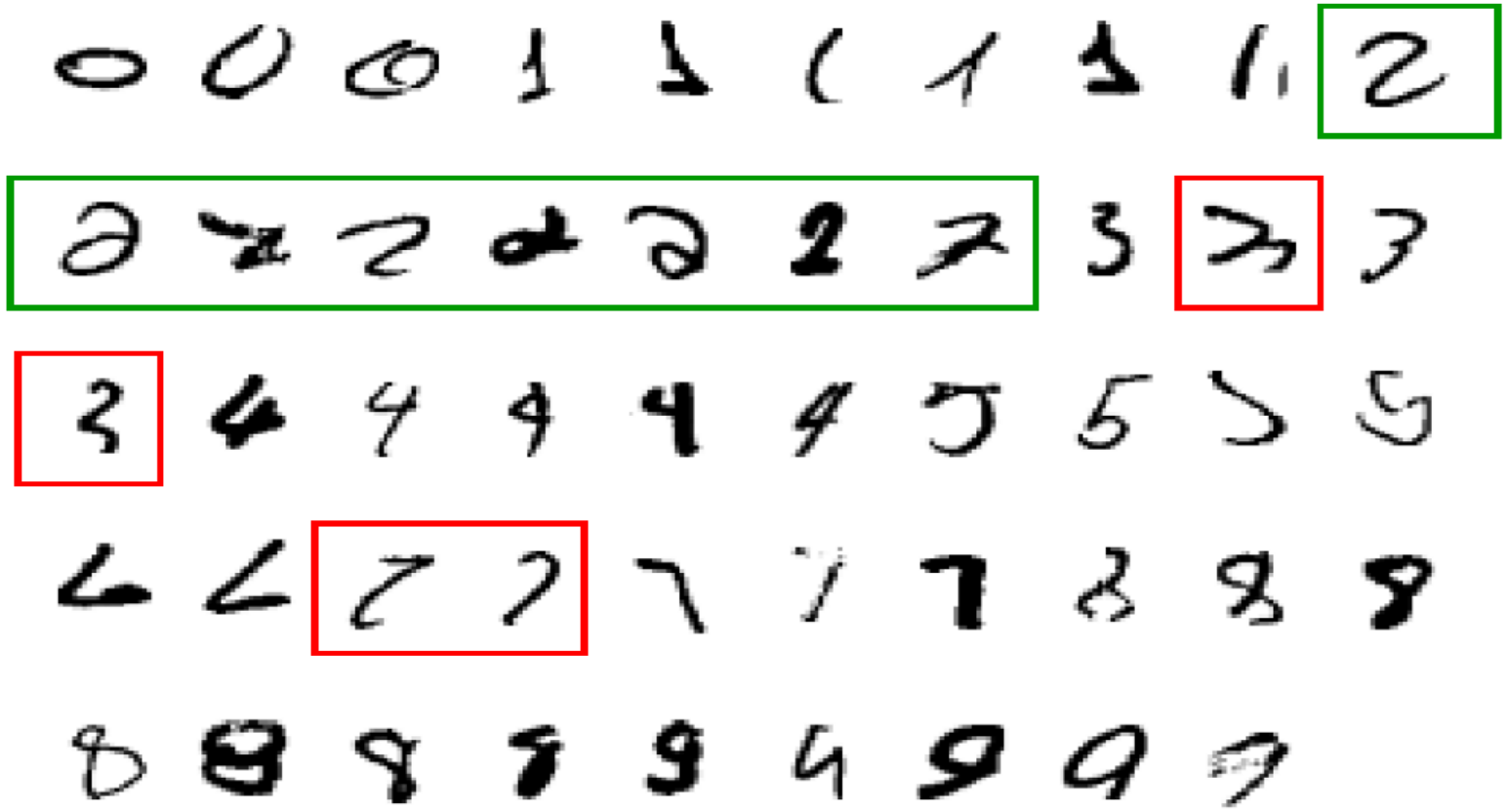
- ❑• Human expertise does not exist (navigating on Mars)
- ❑• Humans can’t explain their expertise (speech recognition)
- ❑• Models must be customized (personalized medicine)
- ❑• Models are based on huge amounts of data (genomics)



WHEN DO WE USE MACHINE LEARNING?

A classic example of a task that requires machine learning:

It is very hard to say what makes a 2

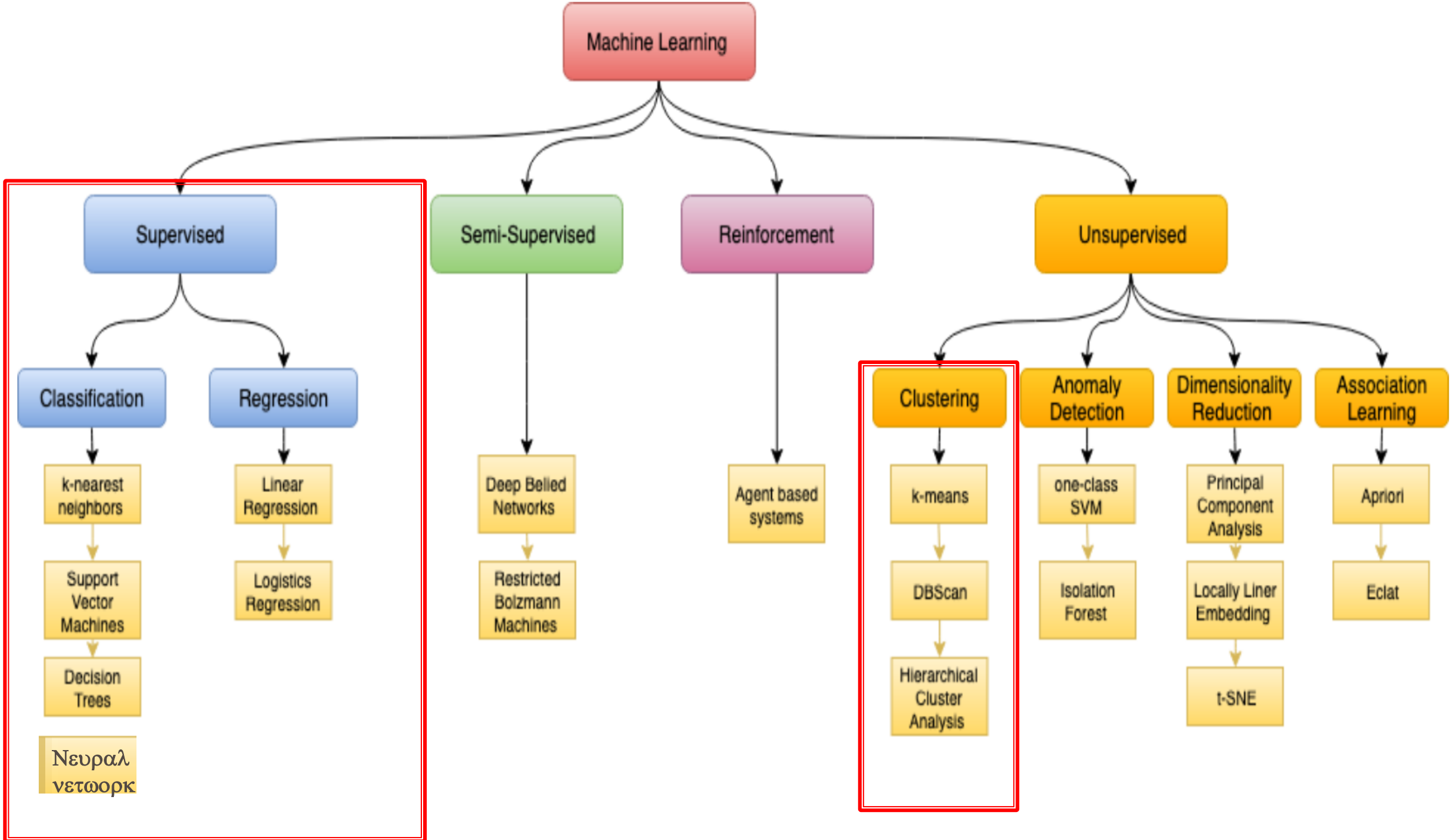


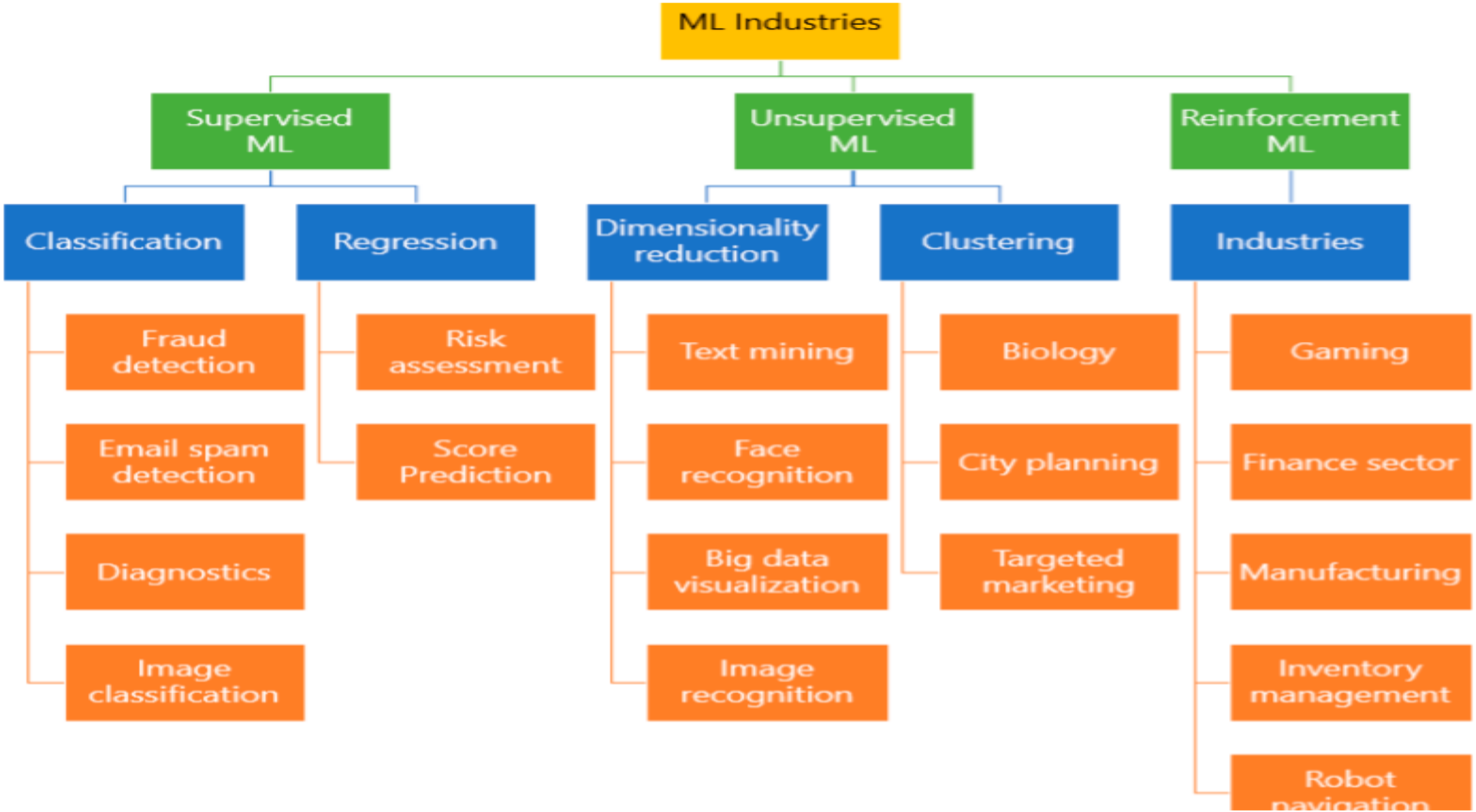
Slide credit: Geoffrey Hinton

Some more examples of tasks that are best solved by using a learning algorithm

- Recognizing patterns:
  - Facial identities or facial expressions
  - Handwritten or spoken words
  - Medical images
- Generating patterns:
  - Generating images or motion sequences
- Recognizing anomalies:
  - Unusual credit card transactions
  - Unusual patterns of sensor readings in a nuclear power plant
- Prediction:
  - Future stock prices or currency exchange rates

Slide credit: Geoffrey Hinton

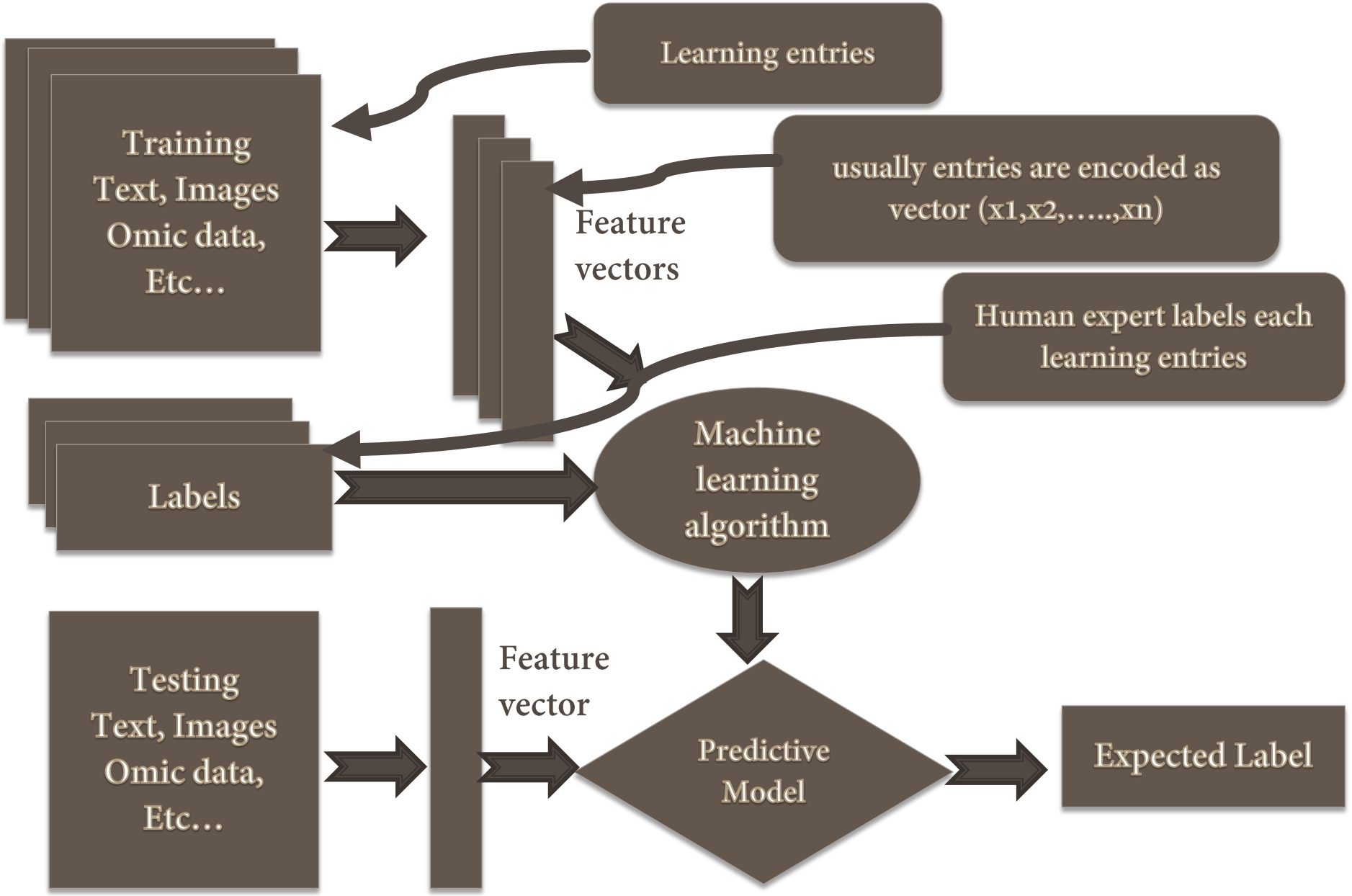

Machine Learning
Supervised
Semi-Supervised
Reinforcement
Unsupervised
Classification
Regression
k-nearest neighbors
Support Vector Machines
Decision Trees
Linear Regression
Logistics Regression
Deep Belied Networks
Restricted Bolzmann Machines
Agent based systems
Clustering
Anomaly Detection
Dimensionality Reduction
Association Learning
k-means
DBScan
Hierarchical Cluster Analysis
one-class SVM
Isolation Forest
Principal Component Analysis
Locally Liner Embedding
t-SNE
Apriori
Eclat
Νευραλ νετωορκ


ML Industries
Supervised ML
Unsupervised ML
Reinforcement ML
Classification
Regression
Dimensionality reduction
Clustering
Industries
Fraud detection
Email spam detection
Diagnostics
Image classification
Risk assessment
Score Prediction
Text mining
Face recognition
Big data visualization
Image recognition
Biology
City planning
Targeted marketing
Gaming
Finance sector
Manufacturing
Inventory management
Robot

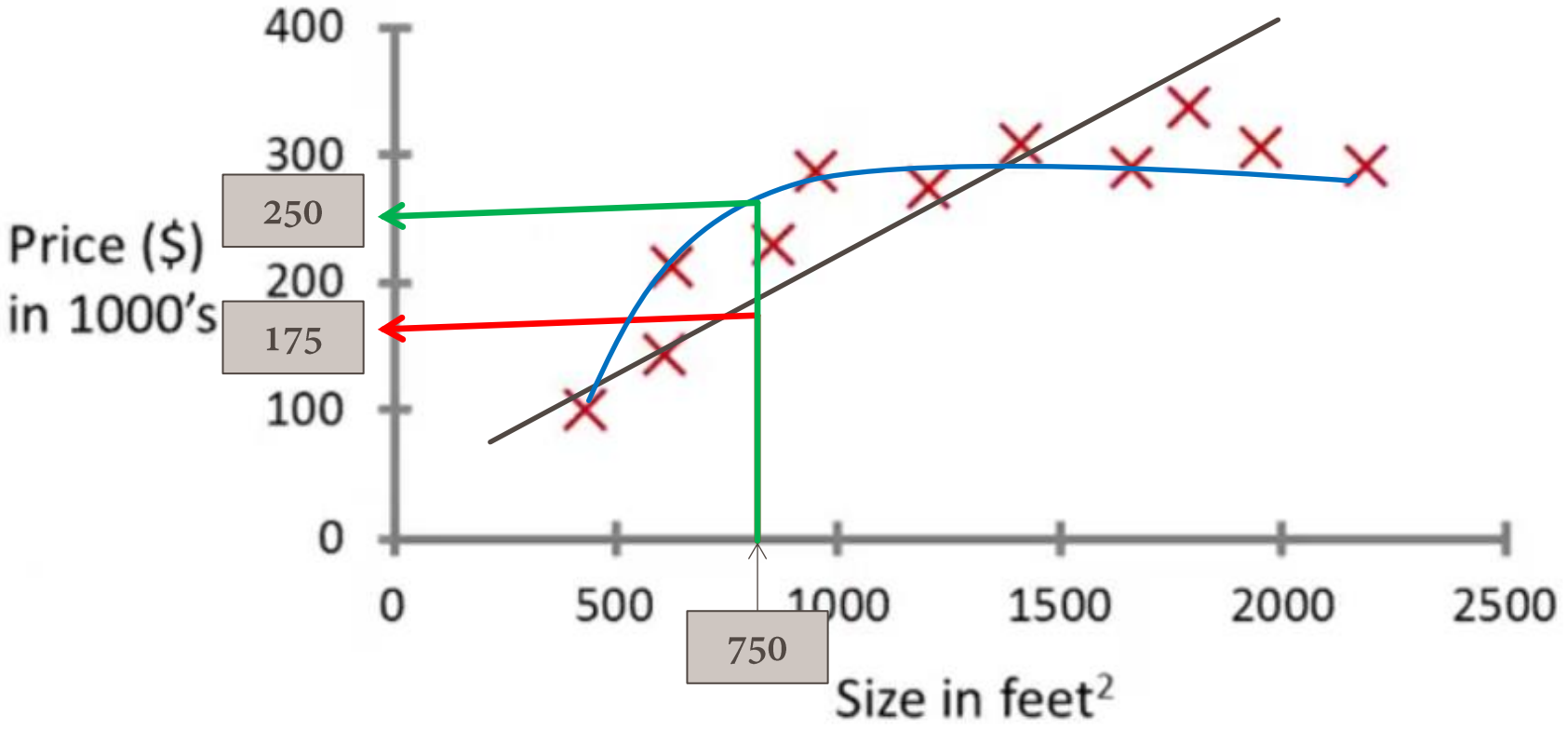
Supervised Learning

- In supervised learning, we are given a data set and already know what our correct output should look like, having the idea that there is a relationship between the input and the output.
- Supervised learning problems are categorized into "regression" and "classification" problems.
- In a regression problem, we are trying to predict results within a continuous output, meaning that we are trying to map input variables to some continuous function.
- In a classification problem, we are instead trying to predict results in a discrete output. In other words, we are trying to map input variables into discrete categories.

SUPERVISED LEARNING PARADIGM



Housing price prediction



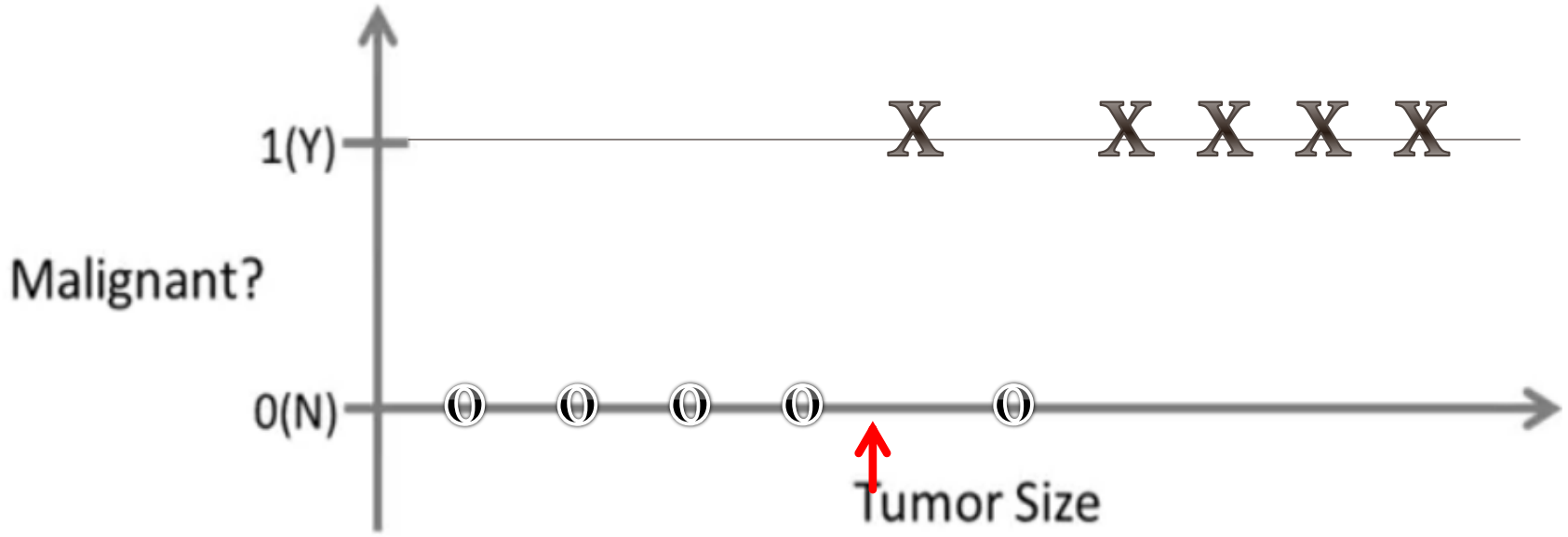
Supervised Learning

"right answers" or "Labeled data" given

Regression:

Predict continuous valued output (price)

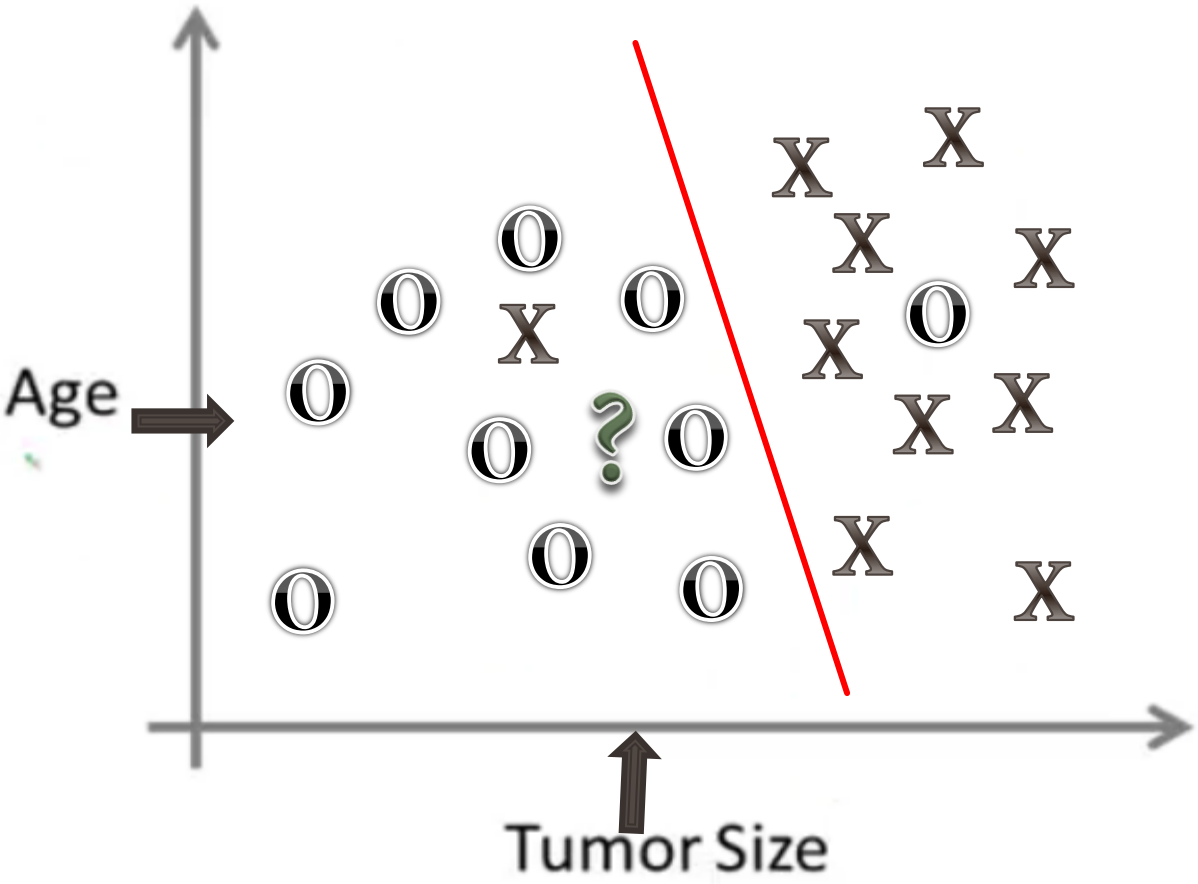
Lung Cancer
(Malignant or benign)



Classification

Discrete valued output (0 or 1)

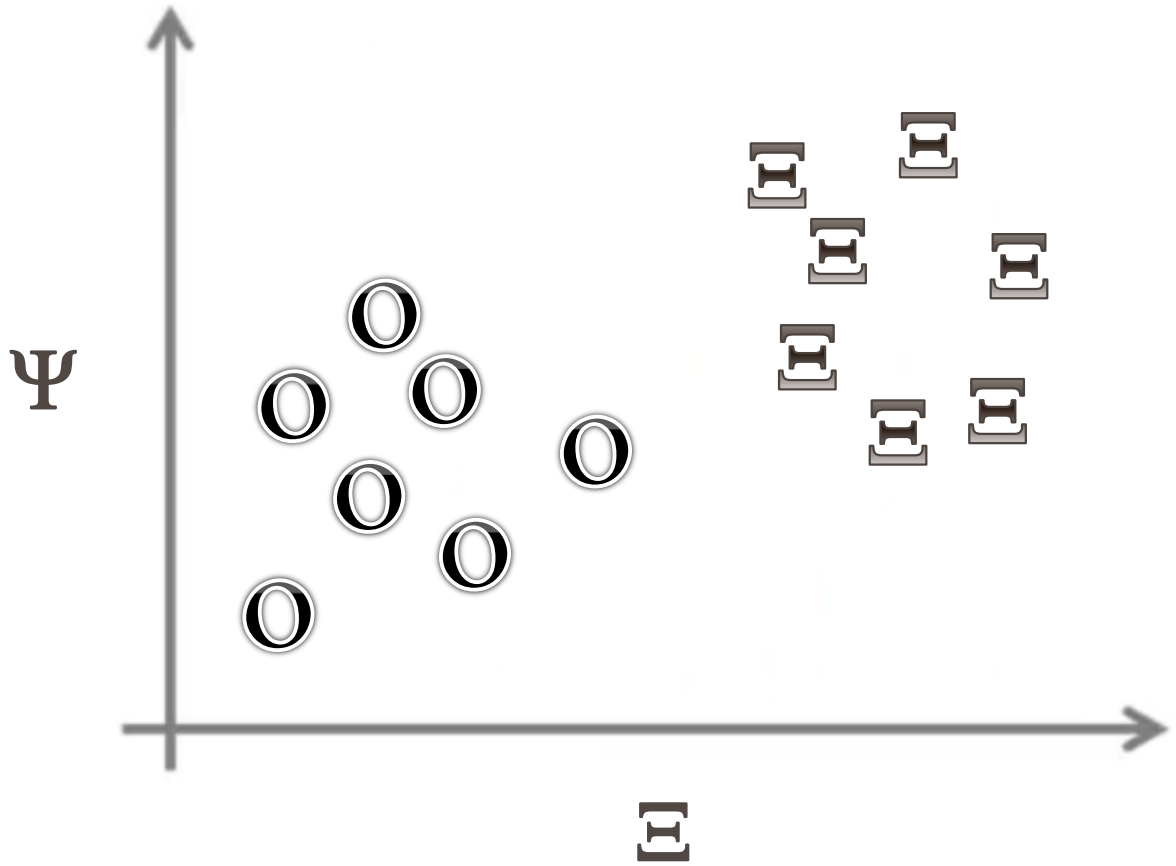
Lung Cancer
(Malignant or benign)



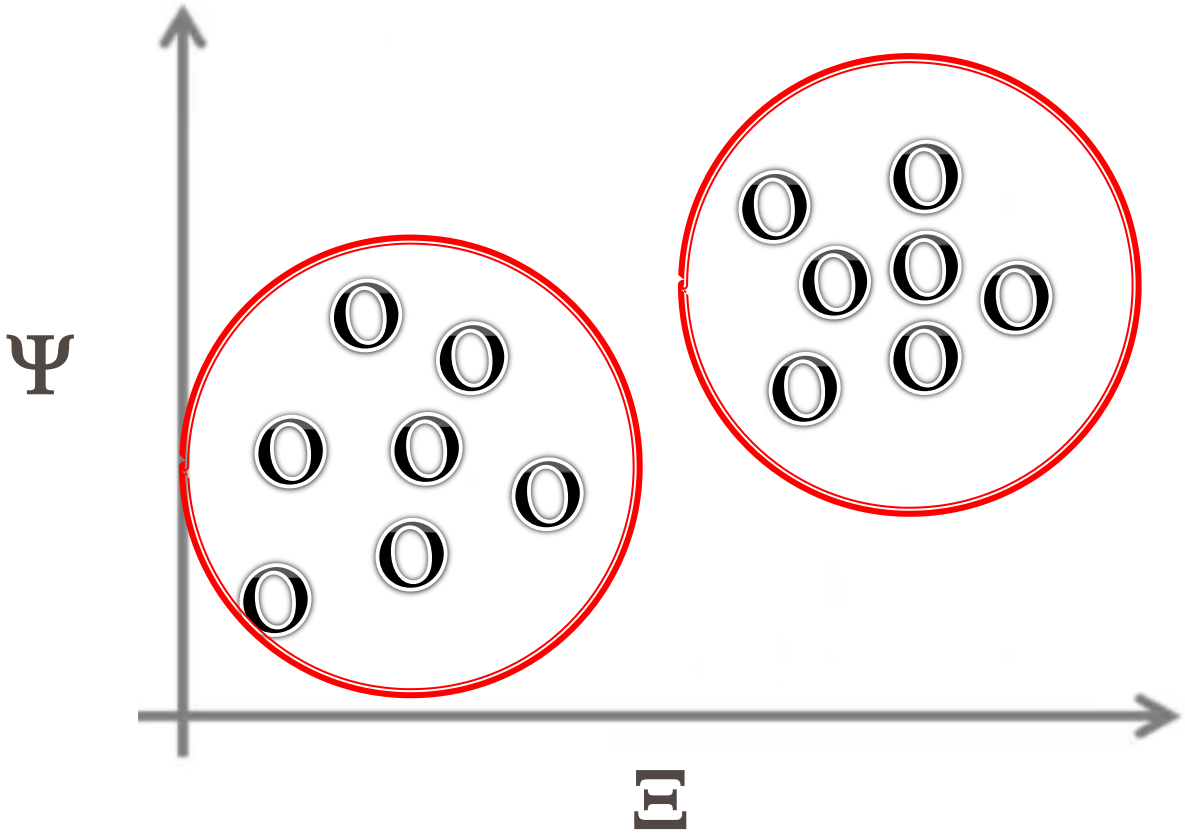
UNSUPERVISED LEARNING

- Unsupervised learning, on the other hand, allows us to approach problems with little or no idea what our results should look like.
- We can derive structure from data where we don't necessarily know the effect of the variables.
- We can derive this structure by clustering the data based on relationships among the variables in the data.
- With unsupervised learning there is no feedback based on the prediction results, i.e., there is no teacher to correct you.

SUPERVISED

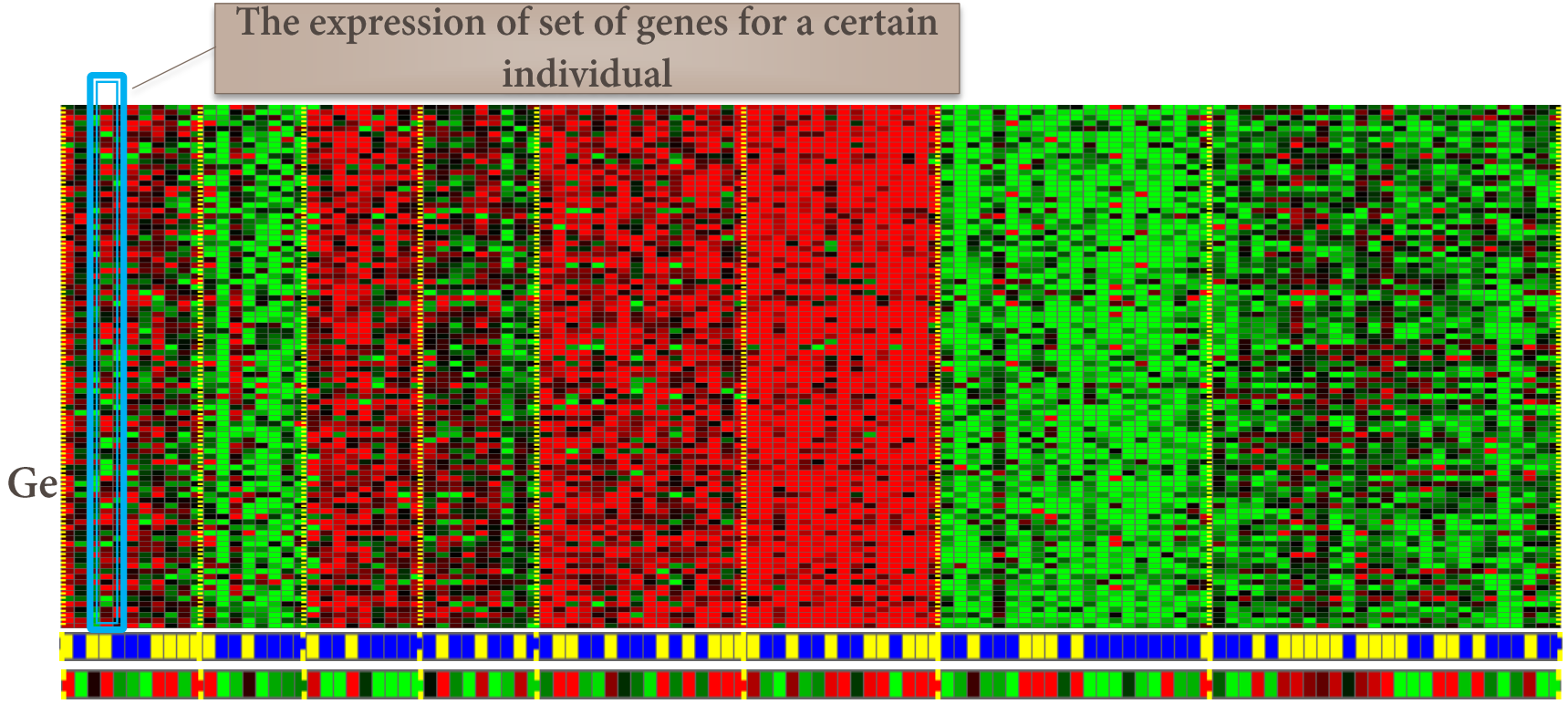


Unsupervised



Unsupervised learning is where you only have input data and no corresponding output variables.

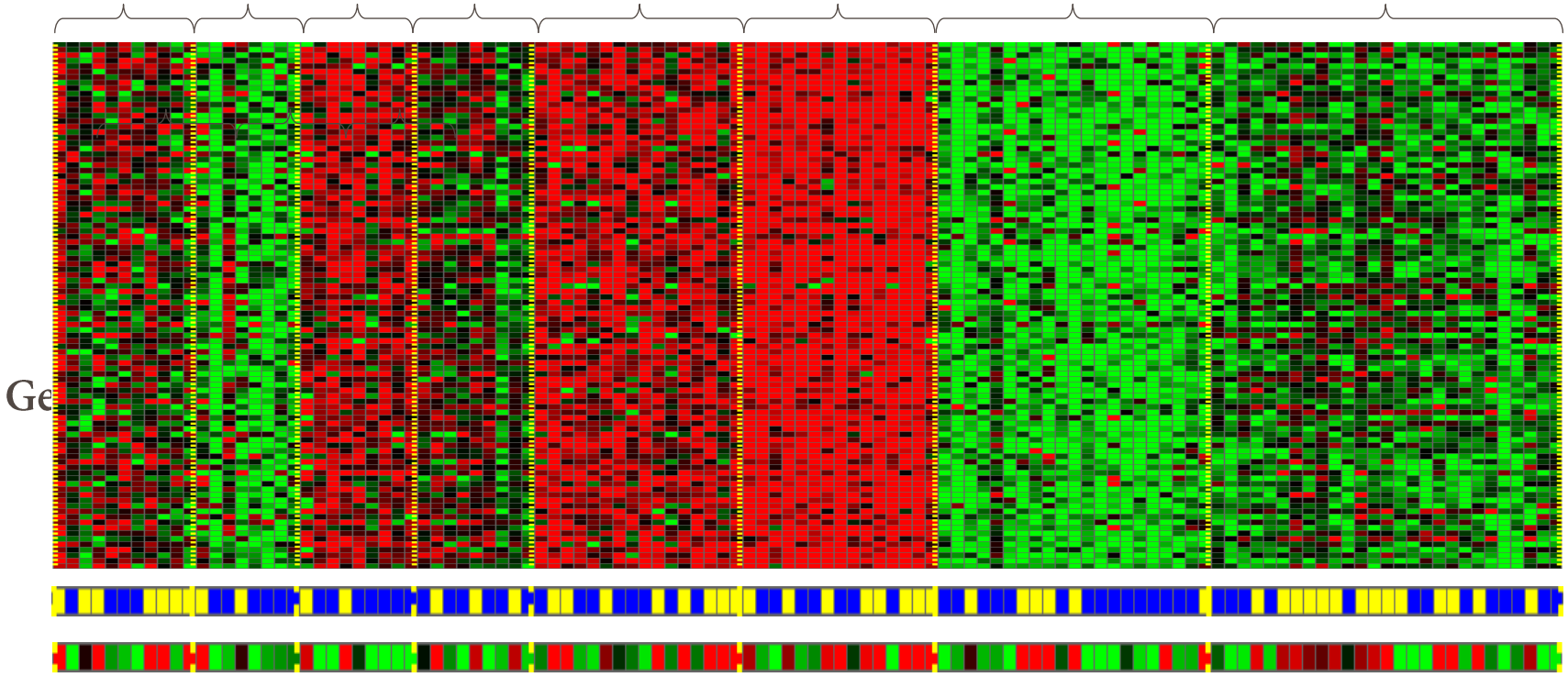
Unsupervised Learning applications



We need to cluster the individuals based of the similarity of their genes.

[Source: Daphne Koller]

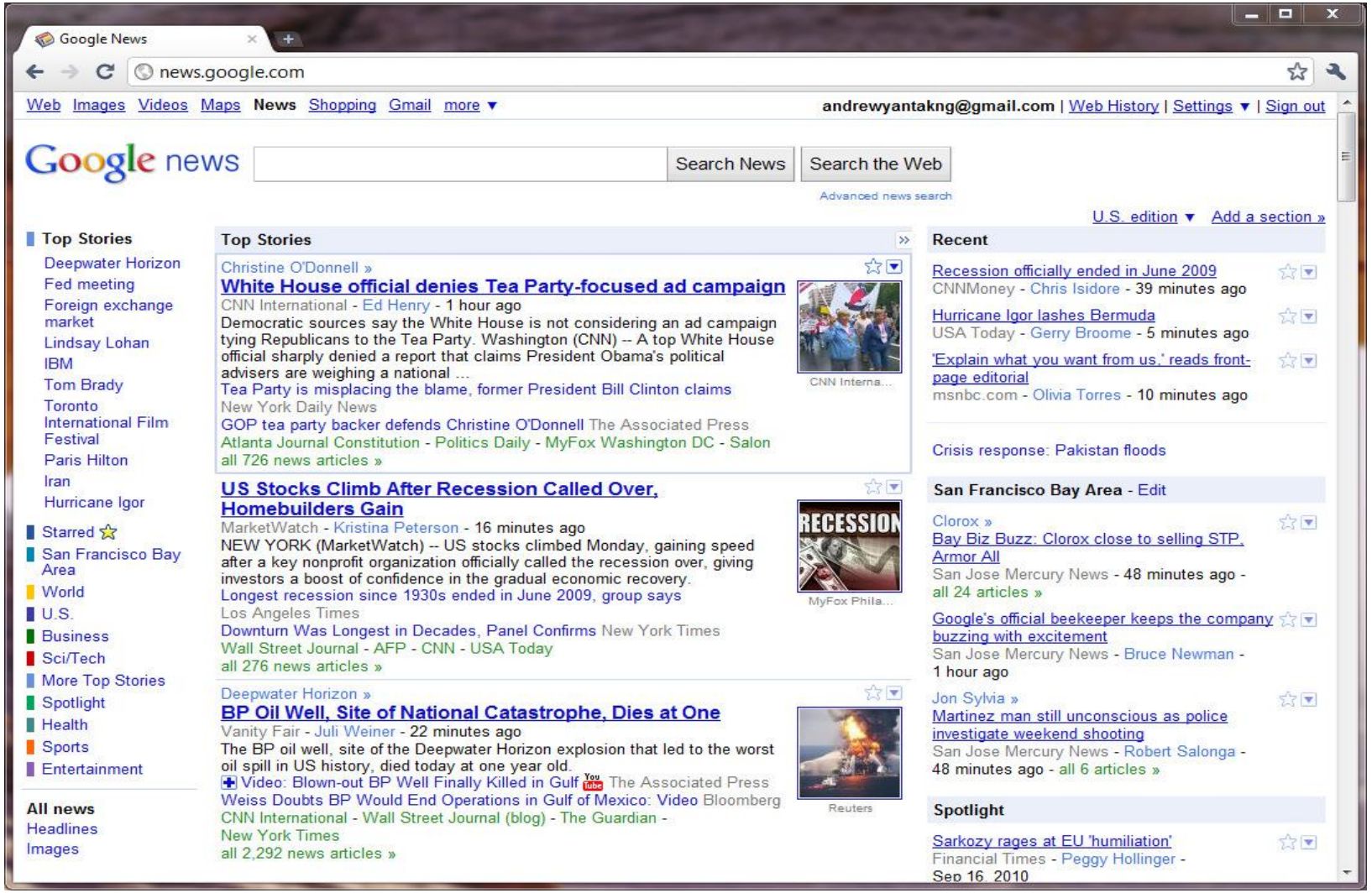
Unsupervised Learning applications

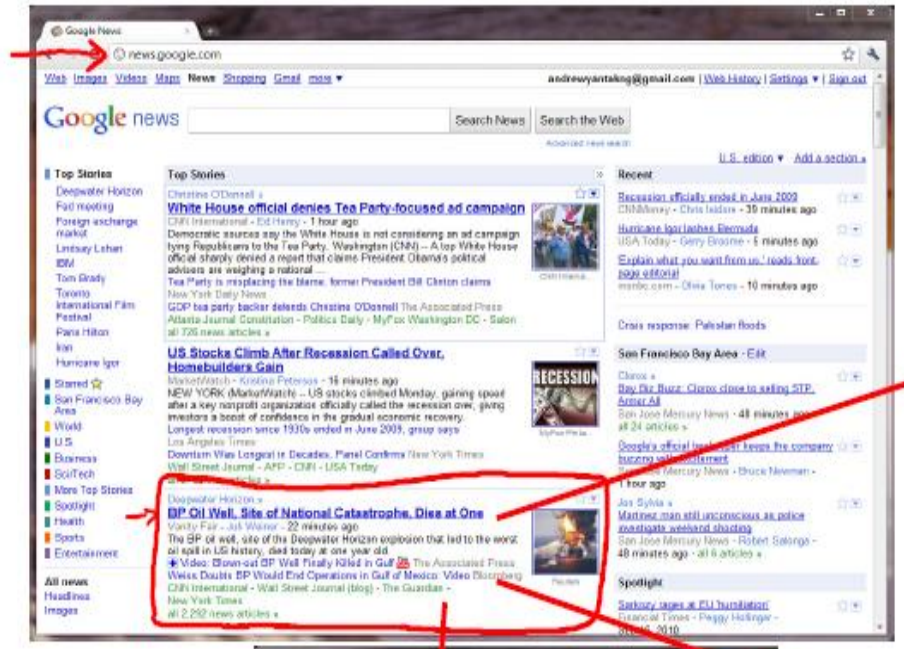


Microarray data

- Have a group of individuals
- On each measure expression of a gene
- Run algorithm to cluster individuals into types of people

UNSUPERVISED

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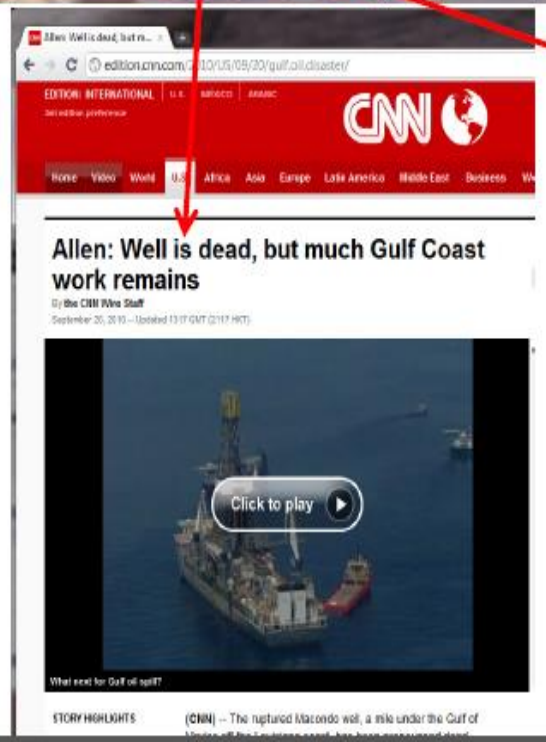
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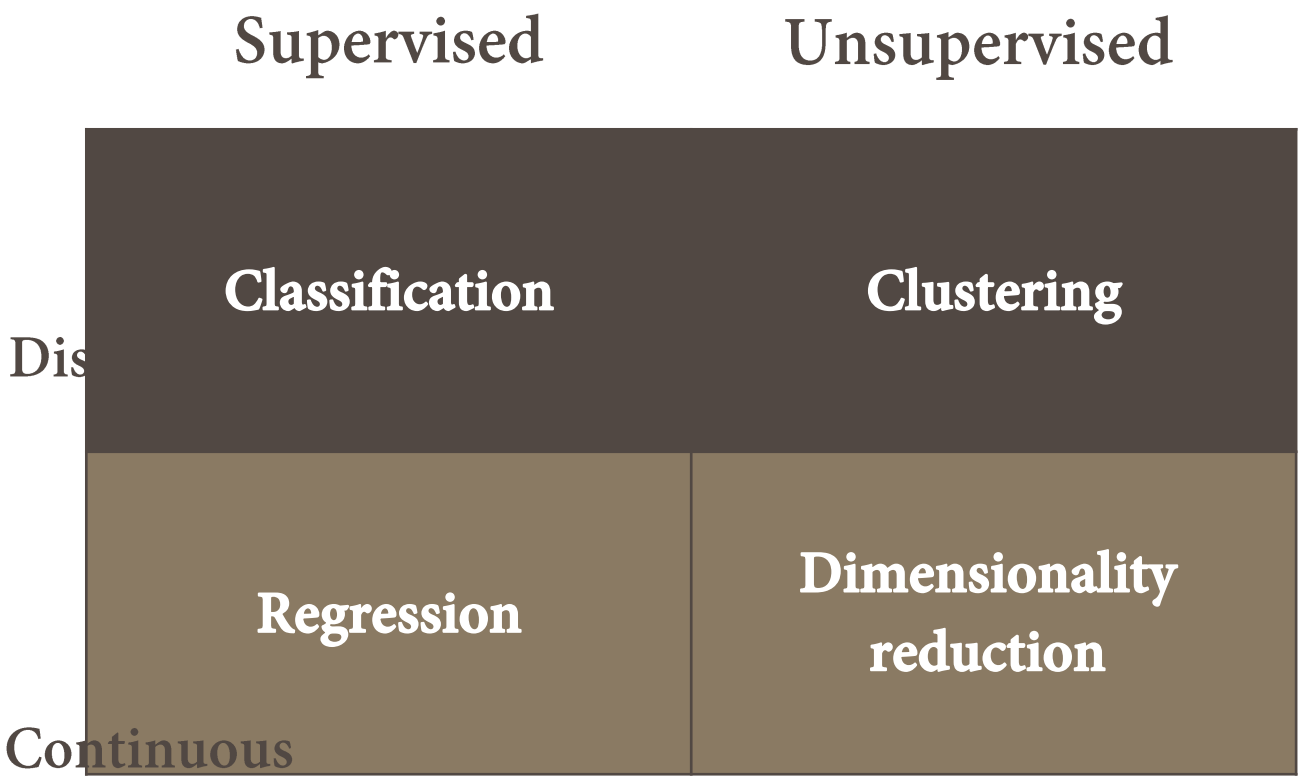
Learning Types



Machine Learning types

- Semi-supervised learning
  - mix of Supervised and Unsupervised learning
  - usually small part of data is labelled
- Reinforcement learning Leaning by interaction
  - Model learns from a series of actions by maximizing a reward function
  - The reward function can either be maximized by penalizing bad actions and/or rewarding good actions
  - Example - training of self-driving car using feedback from the environment