Introduction to Machine Learning with Python

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Content Overview

- What is Machine Learning?
- Why Machine Learning is important?
- Examples
- Types of Machine Learning
- How does it work?

Available on github.com/Pikakshi/Advanced_NLP_with_ML

What is Machine Learning?

- Field of study that gives computers the ability to learn without being explicitly programmed -Arthur Samuel, 1959.
  - Wrote a checkers playing program
  - Program learned by observing board positions

- Study of algorithms that improve their performance P at some task T with experience E - Tom Mitchell, 1998.
  - A well-defined learning task is given by <*P, T, E*>.
  - ✓ T: Playing checkers
  - ✓ P: The number (or percentage) of games won
  - ✓ E: Playing against oneself.

Why is it important?

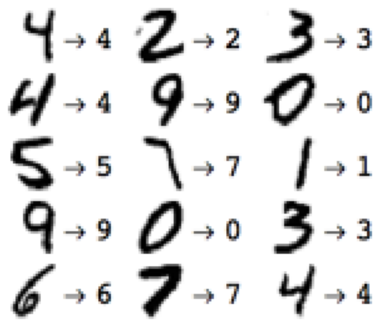
- **Machine learning is a subfield of artificial intelligence**.
- Its goal is to enable computers to learn on their own.
- Machine learning is at the core of AI → it will change every industry and have a massive impact on our day-to-day lives.
- A research report by McKinsey Global Institute(Sep-2018 report) suggests that ‘*Artificial intelligence has the potential to incrementally add 16% or around $13 trillion to the US economy by 2030*’.
- Growing volumes and varieties of data. More and more powerful computational processing. Extensive data storage capabilities. ➔ Better chances at building precise ML models capable of analysing complex and huge quantities of data.

Examples of Machine Learning

- Handwriting Recognition
- Speech Recognition
- Image Tagging
- Fraud Detection
- Virtual Assistants and Chatbots
- Self driving cars
- Stock Market Predictions
- Recommender Systems: Netflix, Spotify, Amazon, etc.
- Text Analysis: Sentiment Analysis, Cluster Analysis, Topic Detection, Entity Recognition, Spam Detection, Document Similarity, ..

Examples of Machine Learning

- Handwriting Recognition
  - Task T: recognizing and classifying handwritten words within images
  - Performance P: percent of words correctly classified
  - Training experience E: a database of written words with given classification
  - Use of algorithms like *Neural Networks, Support Vector Machines*.



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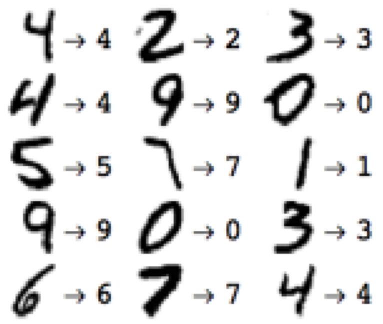

- Fraud Detection
  - Task T: Recognize presence of fraud among business transactions
  - Performance P: percent of fraudulent payments correctly detected
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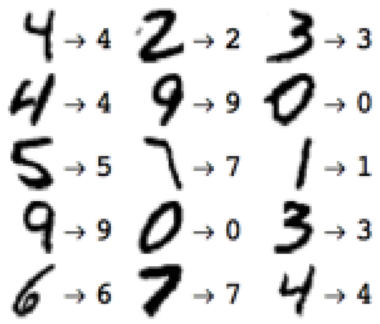

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- How about Facebook's Image Tagging?

- And Sentiment Analysis?

Types of Machine Learning

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

1. Supervised Learning

- Task Driven learning.
- Making predictions using data.

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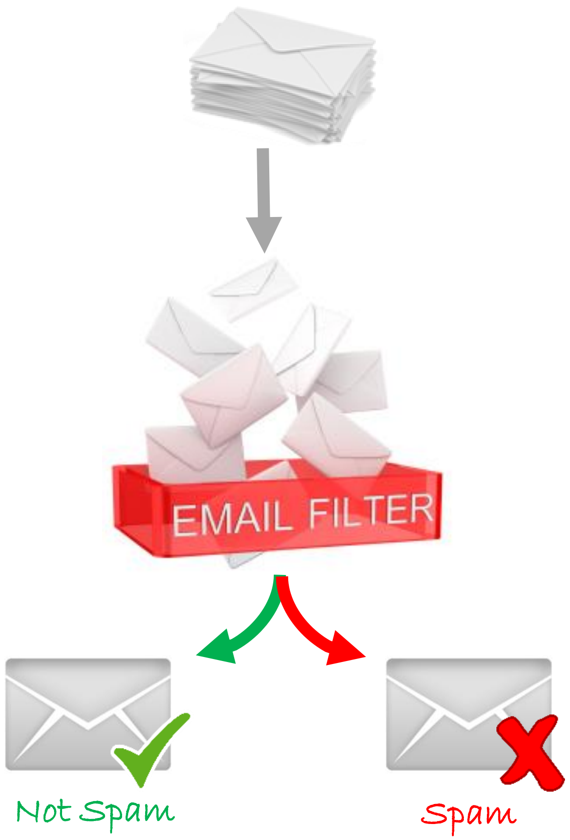
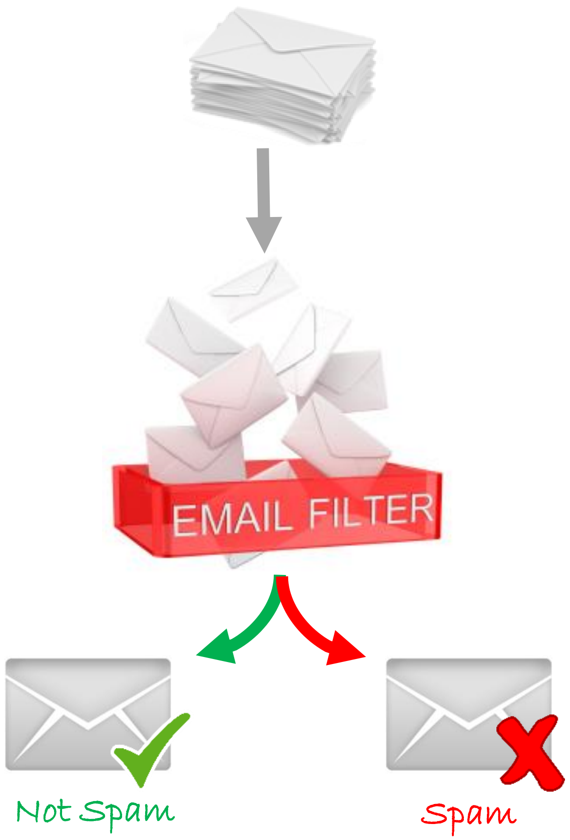
- Consider the problem of *email spam detection* -- predicting whether an incoming email is spam or not.



1. Supervised Learning

- Task Driven learning.
- Making predictions using data.
- Consider the problem of *email spam detection* -- predicting whether an incoming email is spam or not.
  - ✓ Task T: Categorize email messages as spam or legitimate.
  - ✓ Performance P: Percentage of email messages correctly classified.
  - ✓ Experience E: Database of emails, some with human-given labels.

➔ Given a dataset with 'right answers', an algorithm learns to produce predictions on never-before-seen data.



Terminology:

- *Label*: Variable we're predicting – usually represented by the variable **y**
- *Features*: Input variables describing data – usually represented by variables $\{x_1, x_2, \ldots, x_n\}$
- *Example*: particular instance of data, **x**
- *Labeled Example*: has **{features,label}**: **(x,y)** – used to train the model
  - Input data with labeled examples form the *training dataset*.
- *Unlabeled Example*: has **{features,?}**: **(x,?)** – used for making predictions on new data
  - Collection of unlabeled examples are the *test dataset* which are used to test the performance of the trained model.
- *Model*: maps examples to predicted labels **y'**

How does it work?

1. Training the Machine Learning Algorithm using **labelled data**.

- The model learns the relationship between attributes of input data and the outcome.
- The goal is to approximate a mapping function which can predict the output variable **(Y)** for a new input data **(x)**, i.e.,

$$Y = f(X)$$

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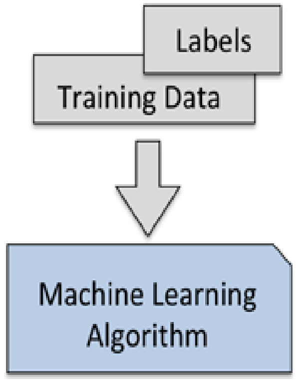

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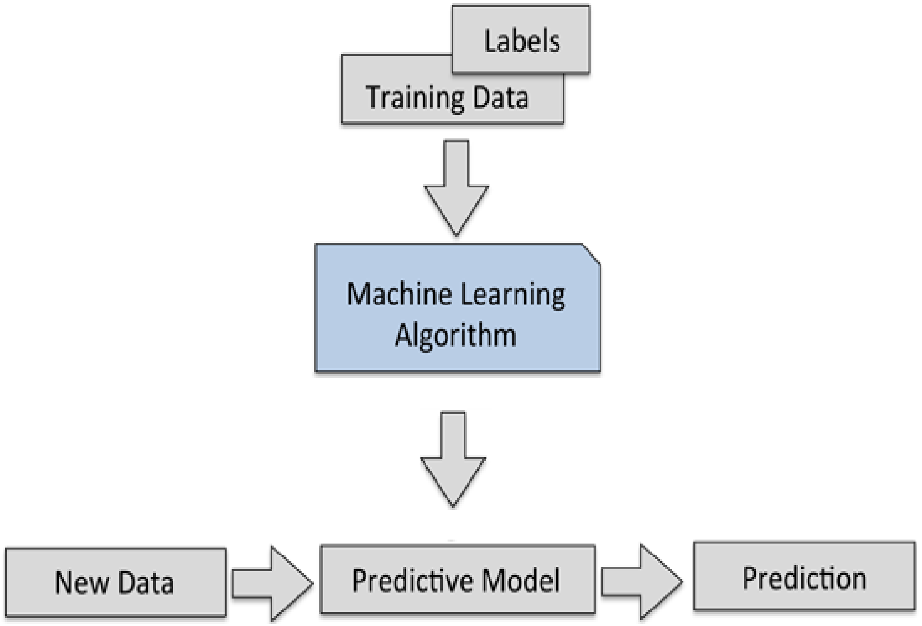
2. **Predictions** on **new (future) data** for which label is unknown using the trained model to predict **future outputs**.

➔ Predictive Modeling.



Types of Supervised Learning

REGRESSION

- Learn a function ***f(x)*** to predict ***y*** given ***x***, where y is a real-valued continuous output (eg: housing prices, monthly income)
- Continuous means there aren't gaps (discontinuities) in the value that Y can take on.
- Popular algorithms:
  - Linear Regression (simple/MLR)
  - Support Vector Machines
  - Random Forest
  - Neural Network
  - Decision Trees

CLASSIFICATION

- Learn a function ***f(x)*** to predict ***y*** given ***x***, where y is a discrete categorical output (eg: spam/not spam, male/female).
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Regression

- ➢ Consider the problem of predicting housing prices.
- ➢ Features: Input variables that can be used to predict housing prices such as: size ($feet^2$), number of bedrooms, number of floors, age of house (years)
  - Lets consider one input variable (size in sq. ft) → Univariate/Simple Linear Regression
- ➢ **Simple LR**: Finds a linear function (a straight line) that predicts the target variable (y) as a function of the independent variable (x).

Estimated Price

Slide credit: Andrew Ng

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Size in feet^2 (x)	Price ($) in 1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

Features/Independent Variables

Target Variable

Slide credit: Andrew Ng

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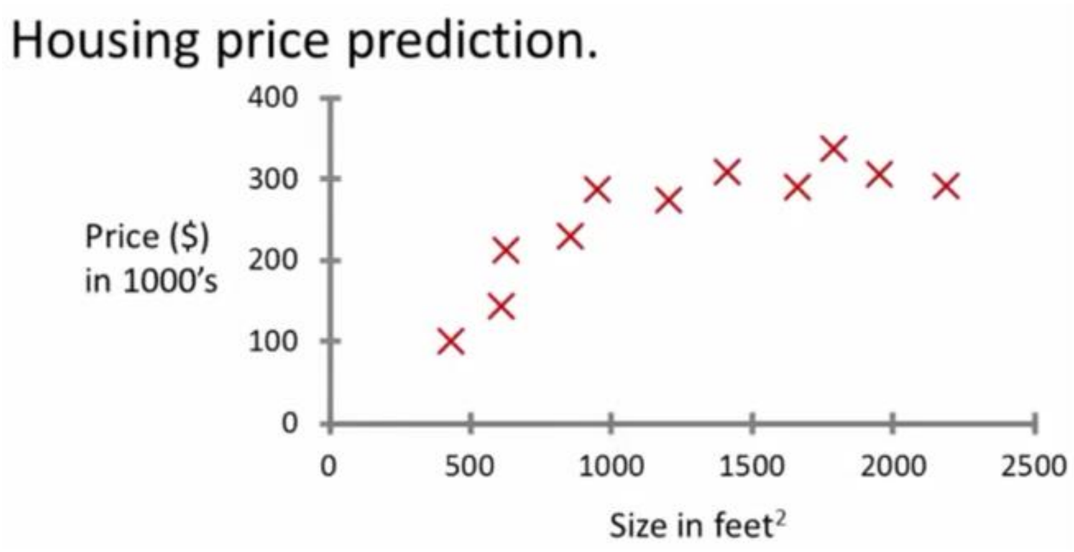

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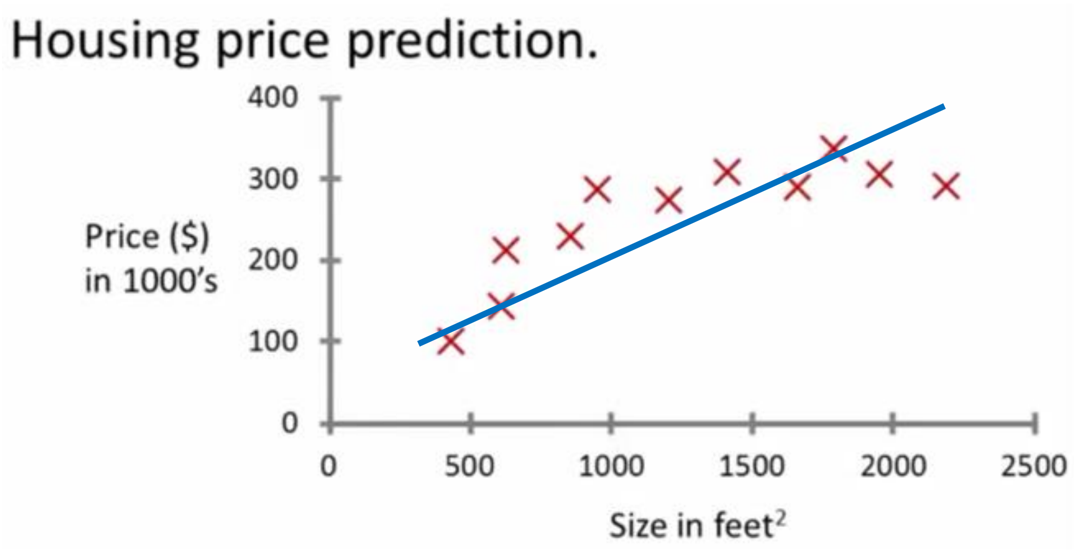

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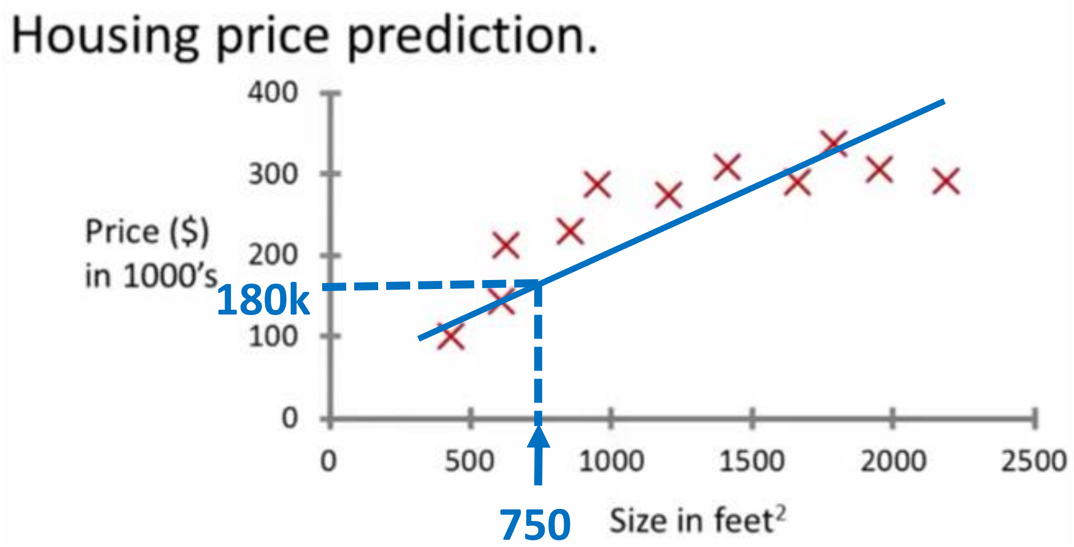

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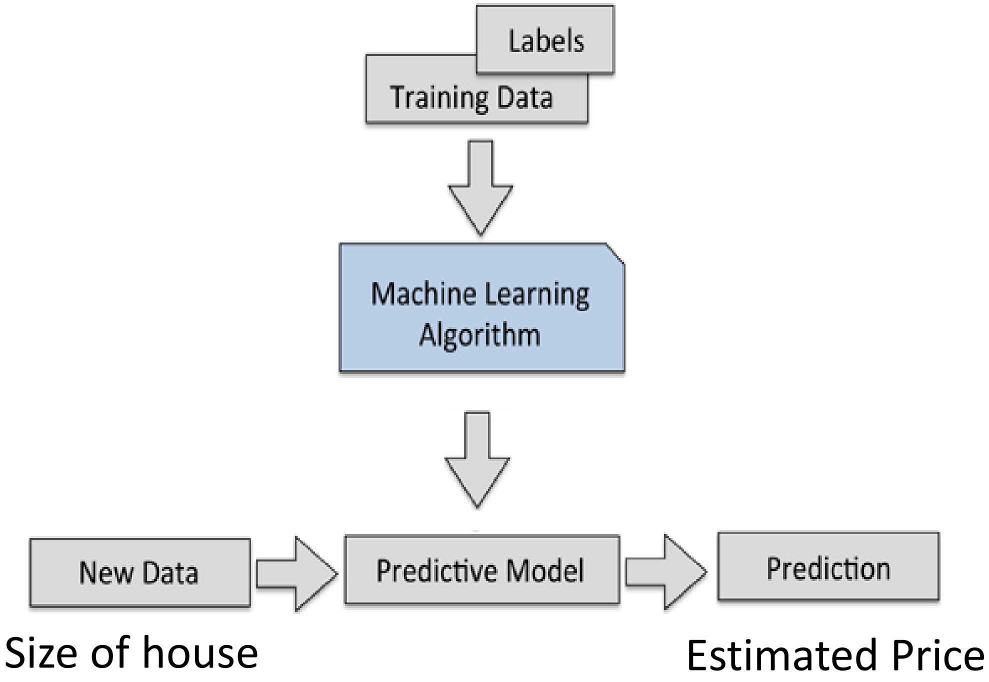

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- **MLR**: Model a linear function that predicts the target variable as a function of the independent variables.

Size (feet^2)	Number of bedrooms	Number of floors	... Age of home (years)	Price ($1000)
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178
...	...	...	...	...

Features/Independent Variables

Target Variable

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n features

Size (feet^2) x_1	Number of bedrooms x_2	Number of floors x_3	... Age of home (years) x_n	Price ($1000)
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m training examples

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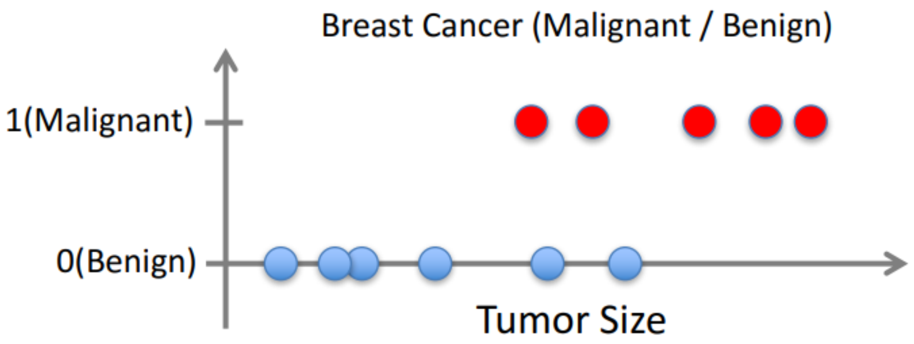
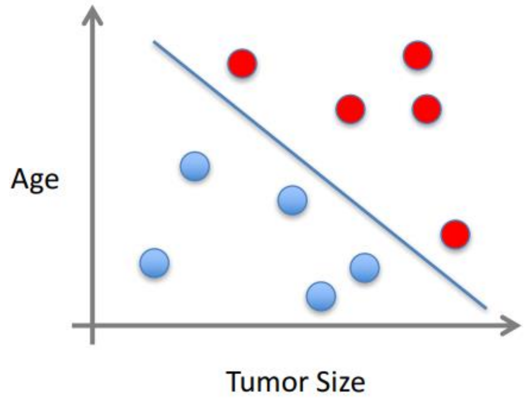
Classification

- ➢ Binary Classification: Spam/no spam, cancer/no cancer
  - ▪ Using one input variable
  - ▪ Using more than one input variable





- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

…

- ➢ Multi-class Classification: Handwritten Digit Recognition (0 to 9), Cancer stage (0, 1, 2, 3)

Decision Trees for Classification

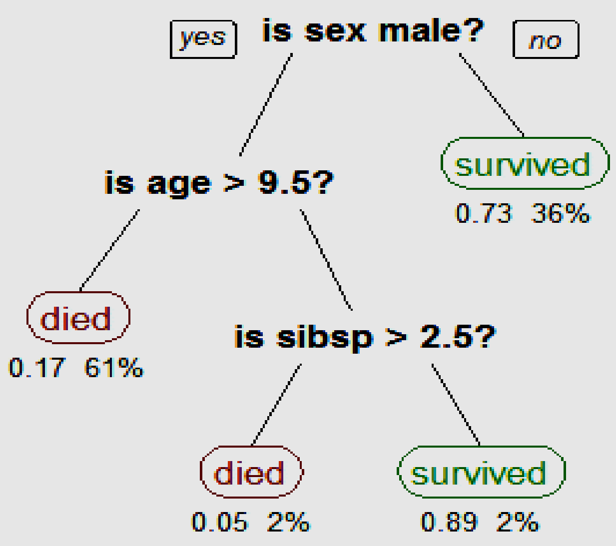


Image taken from wikipedia

- Uses a tree-like model for decisions.
- Visually and explicitly represents decisions and decision-making.
- Drawn upside down with the root at the top.
- Consider an example of the titanic dataset for predicting whether a passenger will survive or not (y).
  - Features (x_1, x_2, .., x_n): gender, age, and number of spouses or children aboard
  - Condition/**internal node** based on which the tree splits into branches/ **edges**.
  - End of the branch that doesn't split anymore is the decision/**leaf**, in this case, whether the passenger died or survived, represented as red and green text respectively.
  - From the tree it is seen that if you were (*i*) a female or (*ii*) a male younger than 9.5 years with less than 2.5 siblings, your survival chances were good.
  - The figures under the leaves show the probability of survival and the percentage of observations in the leaf.

Making it work

A Machine Learning project has a series of well known steps:

- Define the problem
- Load data
- Evaluate Algorithms
- Make Predictions

Machine Learning in Python

Installing the libraries

- *pandas:* Library for pre-processing data and convert data into Data Frames (similar to database tables).
- *SciPy:* Library used for scientific and technical computing.
- *NumPy:* Library for mathematical and scientific computing library for Python
- *matplotlib:* Library for visualising data and results.
- *Scikit-learn:* provides a consistent interface to ML models and covers libraries like *NumPy, SciPy* and *matplotlib*
- *Keras:* Library that encapsulates complex Deep Learning frameworks.

Installing scikit-learn: 2 options:

1. Install the library with the dependencies (NumPy and SciPy)
   - `pip install scikit-learn`
   - `pip install numpy`
   - `pip install scipy`
2. Install the Anaconda Distribution of Python
   - Getting started manual available here for Windows/Linux/macOS.
   - `conda install scikit-learn`

Supervised Learning (Classification) in Python

✓ Lets consider a *multi-class classification problem* – classification of iris flowers using the famous iris dataset. The dataset has:

- 4 attributes/input variables: sepal length, sepal width, petal length, petal width (in cm) ➔ n= 4
- 150 rows/training examples ➔ m = 150
- Target classes (3 species of 3 different types of Iris flowers): Iris Setosa, Iris Versicolour, Iris Virginica

- Problem definition: Predict the species of an iris flower given its sepal and petal measurements.

- Step-by-step tutorial provided here.

Supervised Learning (Regression) in Python

Problem Definition: Regression problem for *Product Sales Prediction* using an advertising dataset. The dataset has the following features:

- TV: advertising dollars spent on TV for a single product in a given market (in thousands of dollars)
- Radio: advertising dollars spent on Radio
- Newspaper: advertising dollars spent on Newspaper

$\rightarrow$ n = 3

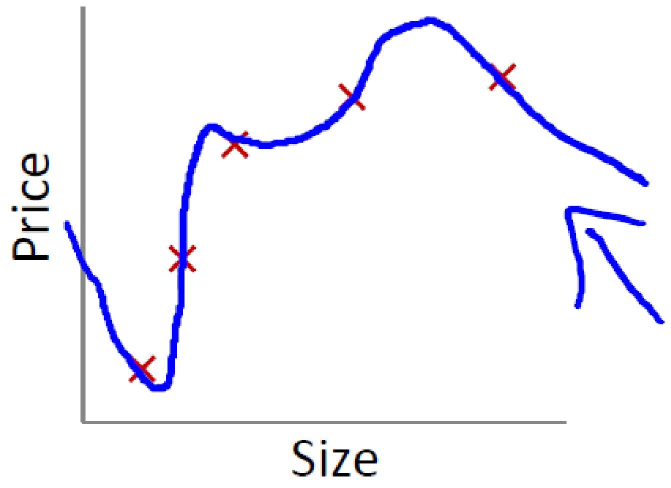
- m = 200 training examples
- Target variable is continuous valued which is why this is a **regression problem**.

- Step-by-step tutorial provided here.

Problems faced

1. **Overfitting**: Learning a function that perfectly explains the training data that the model learned from, but doesn't generalize well to unseen data.

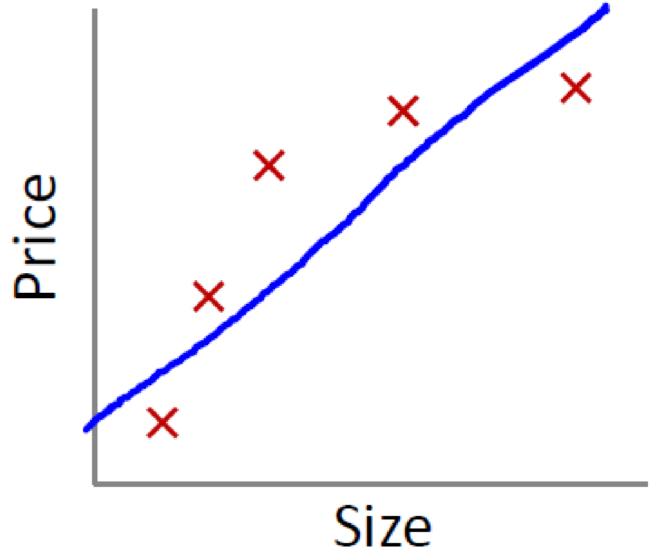
- Happens when a model overlearns from the training data to the point that it starts picking up idiosyncrasies that aren't representative of patterns in the real world.
- Leads to **high variance**.
- **Variance**: how much your model's test error changes on variation in training data. Reflects the model's sensitivity to the idiosyncrasies of the data set it was trained on.



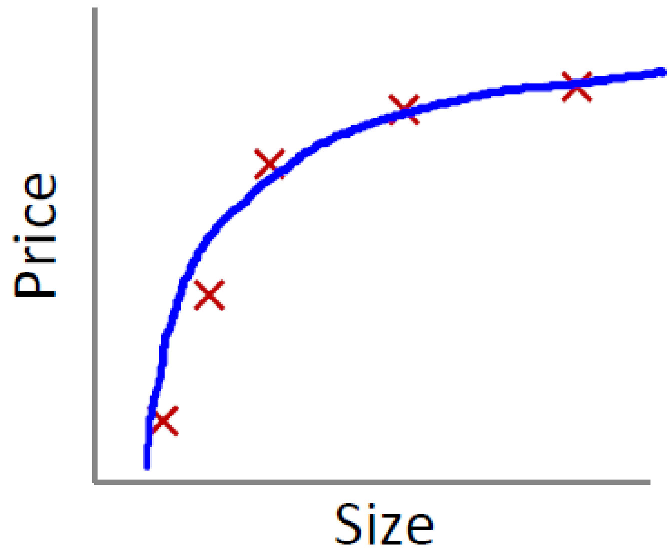
2. Underfitting: Model is not complex enough to capture the underlying trend in the data.

- Leads to **high bias**.
- Bias: Amount of error introduced by approximating real-world phenomena with a simplified model.

- For a good ML model → low bias, low variance.



Underfit → High bias

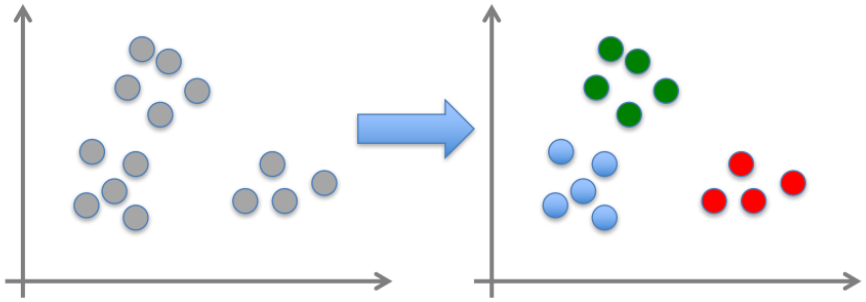


Just Right

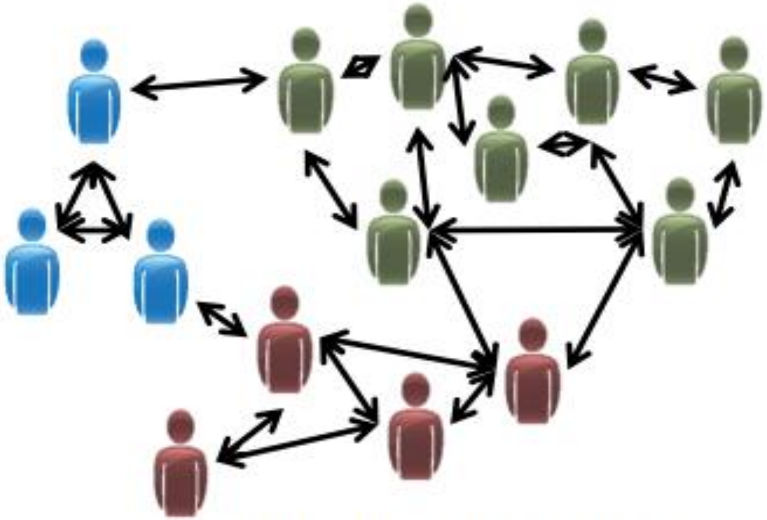
2. Unsupervised Learning

- Data driven learning.
- Extracting structure from data.
- Consider the problem of *market segmentation*.
  - Given a dataset of characteristics and purchasing behaviour of shoppers
  - Unsupervised Learning Task: Segment shoppers into groups or clusters exhibiting similar behaviour
  - No right or wrongs about number of clusters that can be found, which shopper belongs to which cluster or how to describe a cluster.

➔ Given an unlabeled dataset $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$: an algorithm finds hidden structures in the data.



Organize computing clusters



Social network analysis

Market segmentation

Astronomical data analysis

Types of Unsupervised Learning

CLUSTERING

- Discovering inherent groupings or clusters in data. For instance, market segmentation.
- Popular clustering algorithms:
  - K-means
  - Hierarchical clustering
  - KNN (K Nearest Neighbour)
  - Principle Component Analysis

ASSOCIATION

- Association rules establish associations amongst data objects, for instance, in large databases.
- These rules can be used where you want to describe large portions of your data, such as people that buy X also tend to buy Y.
- For instance, people that buy a new home most likely buy new furniture → Market Basket Analysis.
- Popular algorithms for extracting association rules:
  - Apriori algorithm
  - FP-Growth algorithm

Questions

Which learning algorithm (supervised or unsupervised) should be applied for the following problems?

- Given a set of news articles on the web, group them into set of articles about the same story.
- Given a database of customer data, automatically discover market segments and group customers into different market segments.
- Given a dataset of patients diagnosed as either having diabetes or not, learn to classify new patients as having diabetes or not.
- Given an inventory of identical items, predict how many of items will sell over next 3 months.

Slide credit: [Andrew Ng]

3. Reinforcement Learning

- Learning what to do and how to map **situations** to **actions**.
- The **agent** is not told which action to take, but instead must discover which action will yield the maximum **reward (goal)**. The end result is to maximize the numerical reward signal.
- Algorithm learns to react to an **environment**.
- For instance: a toddler learning to walk, self driving cars,..

Slide credit: [Sutton & Barto]

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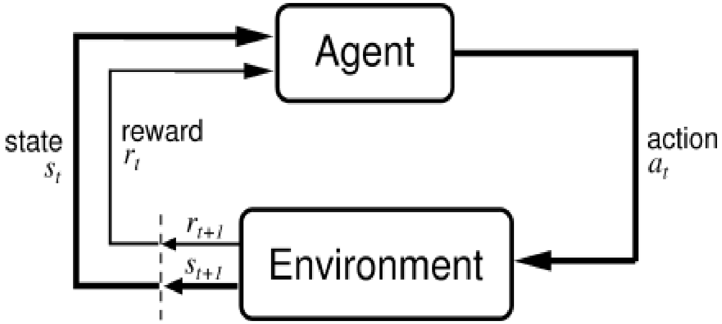


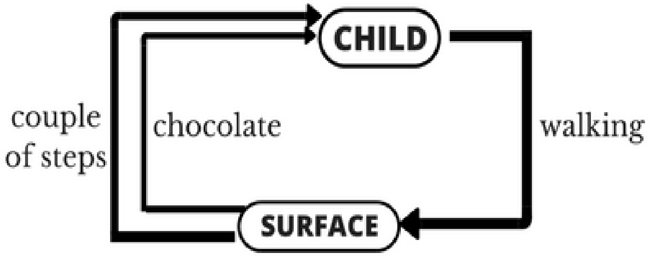
Agent and environment interact at discrete time steps : $t = 0, 1, 2, K$

Agent observes state at step t: $s_t \in S$

produces action at step t: $a_t \in A(s_t)$

gets resulting reward : $r_{t+1} \in \Re$

and resulting next state : s_{t+1}



Slide credit: Sutton & Barto

Semi-supervised Learning

- Represent a middle ground between supervised and unsupervised ML algorithms.
- Huge amount of input data and only some of it is labeled.
- Many real-world ML problems fall in this category since it can be expensive and time-consuming to label all data.

Reading Material

Books:

- Machine Learning Yearning by Andrew Ng --- a book in progress
- Machine Learning by Tom Mitchell
- The Elements of Statistical Learning by Trevor Hastie, Robert Tibshirani and Jerome Friedman

Online courses/articles:

- Machine Learning – Stanford University (online course) at Coursera.
- Tutorials available on DataCamp.
- Practical Machine Learning Video Series by PythonProgramming.net
- Machine Learning Mastery by Jason Brownlee – online reading material/crash course.