Data Science & ML Course
Lesson #16 Fundamentals of ML

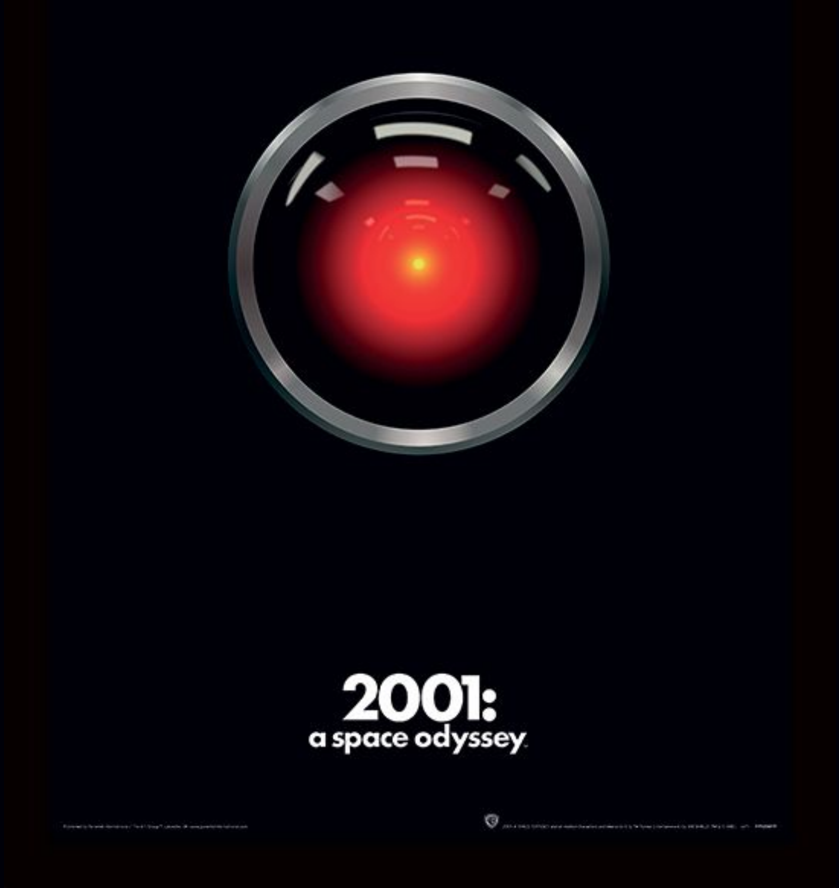
Ivanovitch Silva

November, 2018

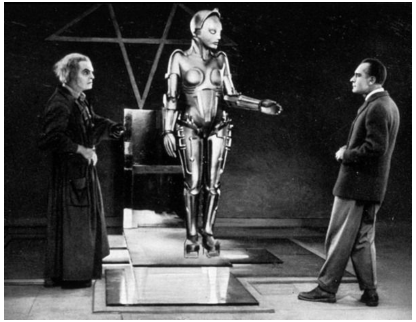
Agenda

1. A brief history of AI
2. Key definitions
3. Types of Machine Learning
4. Machine Learning Workflow
5. Main challenges
6. End-to-end ML project

Artificial Intelligence

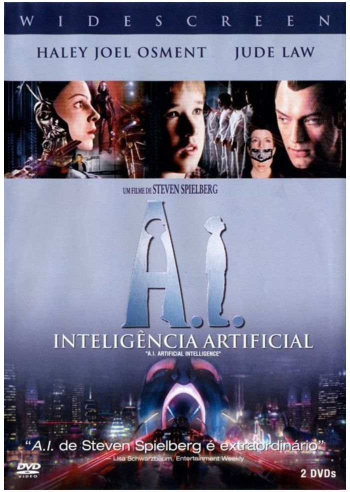


Metropolis (1927)

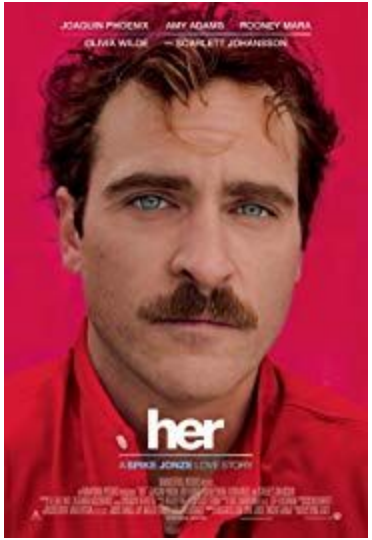


Blade Runner (1982)

AI (2001)



Her (2013)



2001 Space Odyssey' (1969)

The terminator (1984,1991, 2003,2009,20015, 2019)

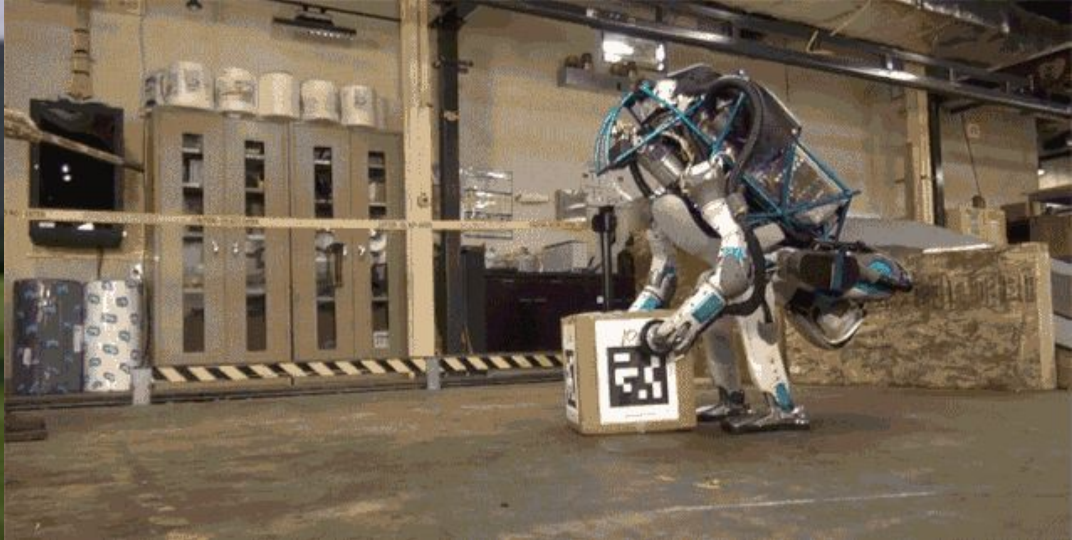
Matrix (1999)

I Robot (2004)

Ex Machina (2014)

Transcendence (2014)

Altered Carbon (2018)

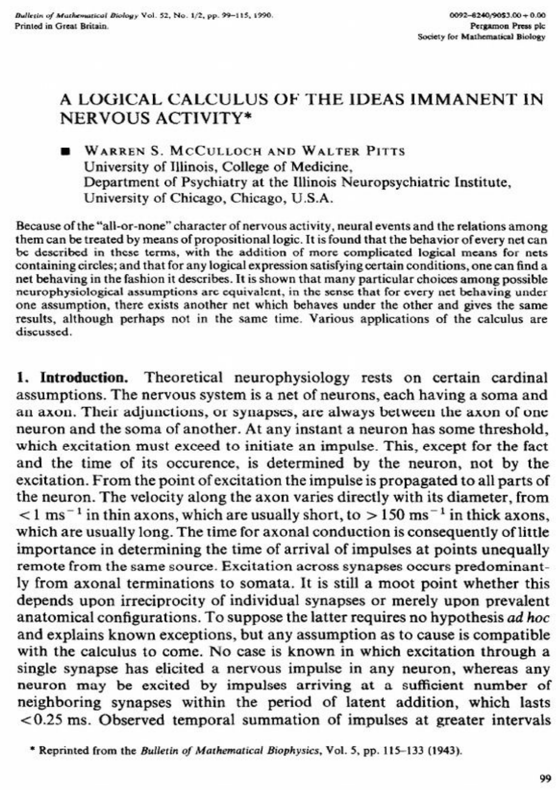



World War II (1939 - 1945)

1943

Walter Pitts

Warren McCulloch



Bulletin of Mathematical Biology Vol. 52, No. 1/2, pp. 99–115, 1990.
Printed in Great Britain.
0092–8240/90$3.00 + 0.00
Pergamon Press plc
Society for Mathematical Biology

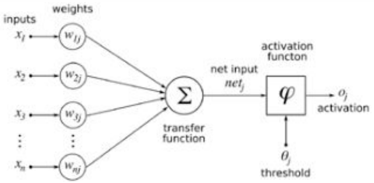
A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY*

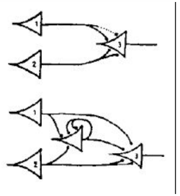
■ WARREN S. MCCULLOCH AND WALTER PITTS
University of Illinois, College of Medicine,
Department of Psychiatry at the Illinois Neuropsychiatric Institute,
University of Chicago, Chicago, U.S.A.

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

1. Introduction. Theoretical neurophysiology rests on certain cardinal assumptions. The nervous system is a net of neurons, each having a soma and an axon. Their adjunctions, or synapses, are always between the axon of one neuron and the soma of another. At any instant a neuron has some threshold, which excitation must exceed to initiate an impulse. This, except for the fact and the time of its occurence, is determined by the neuron, not by the excitation. From the point of excitation the impulse is propagated to all parts of the neuron. The velocity along the axon varies directly with its diameter, from $<1\ \mathrm{ms}^{-1}$ in thin axons, which are usually short, to $>150\ \mathrm{ms}^{-1}$ in thick axons, which are usually long. The time for axonal conduction is consequently of little importance in determining the time of arrival of impulses at points unequally remote from the same source. Excitation across synapses occurs predominantly from axonal terminations to somata. It is still a moot point whether this depends upon irreciprocity of individual synapses or merely upon prevalent anatomical configurations. To suppose the latter requires no hypothesis *ad hoc* and explains known exceptions, but any assumption as to cause is compatible with the calculus to come. No case is known in which excitation through a single synapse has elicited a nervous impulse in any neuron, whereas any neuron may be excited by impulses arriving at a sufficient number of neighboring synapses within the period of latent addition, which lasts <0.25 ms. Observed temporal summation of impulses at greater intervals

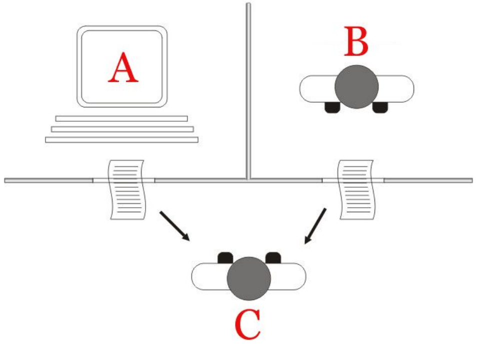
* Reprinted from the *Bulletin of Mathematical Biophysics*, Vol. 5, pp. 115–133 (1943).

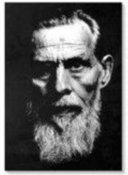


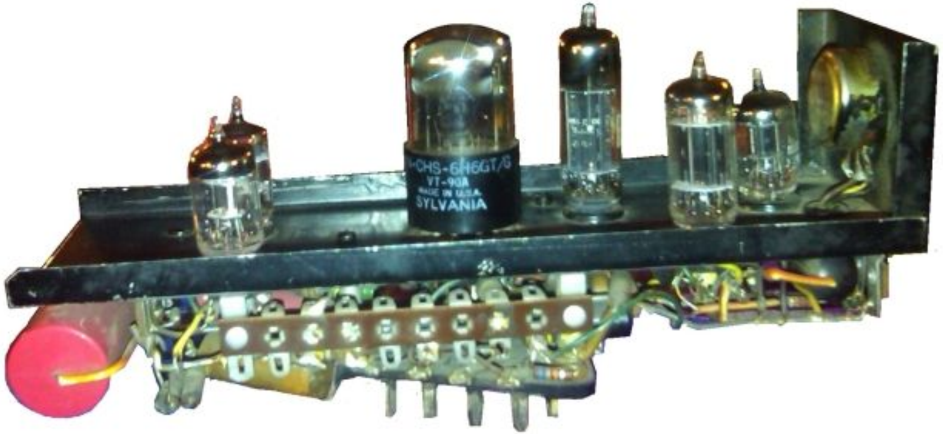


Claude Shannon (1950)
Chess machine

Alan Turing (1950)
Turing Test







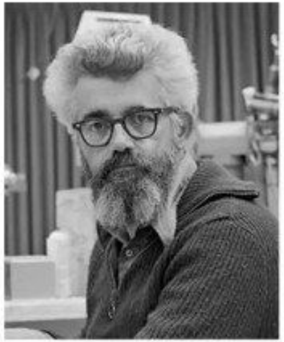
Stochastic Neural Analog Reinforcement Calculator (SNARC)

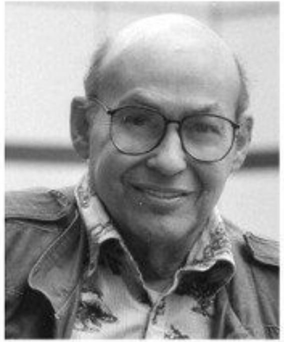
Marvin Minsky (1951)

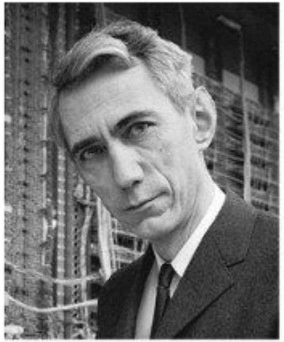
The Samuel Checkers-playing Program was among the world's first successful self-learning programs

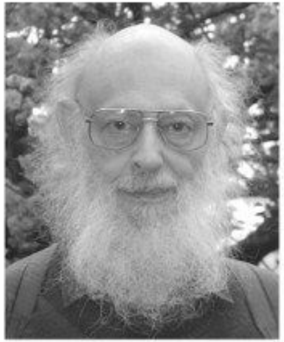
Arthur Samuel (1952)
IBM 701

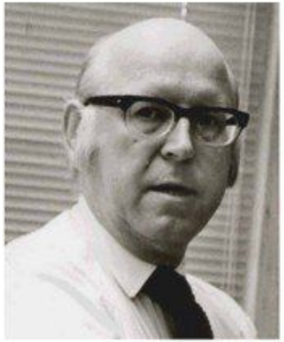
1956 Dartmouth Conference: The Founding Fathers of AI


John MacCarthy


Marvin Minsky

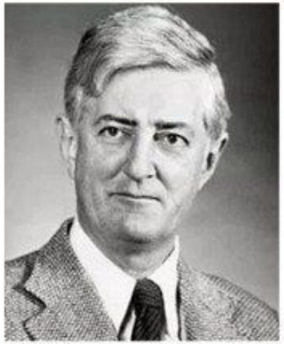

Claude Shannon


Ray Solomonoff


Alan Newell


Herbert Simon


Arthur Samuel


Oliver Selfridge


Nathaniel Rochester


Trenchard More

(2006) From left: Trenchard More, John McCarthy, Marvin Minsky, Oliver Selfridge, and Ray Solomonoff.

Dartmouth Conference, 1956


ARPA
ADVANCED RESEARCH PROJECTS AGENCY

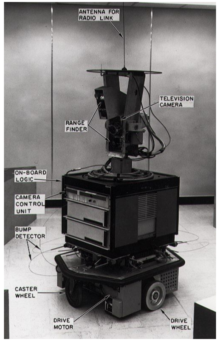
Frank Rosenblatt (1957)
Perceptron - one layer NN

```
(defun m-length (list)
  (if (null list)
    0
    (+ 1 (m-length (cdr list)))))

(defun print-list (list)
  (if (not (null list))
    (progn
      (princ (car list))
      (print-list (cdr list)))))

((((1 5 x) o 1) a) 7 2 3)

(defun sum-numbers (list)
  (if
```

LISP (1958)

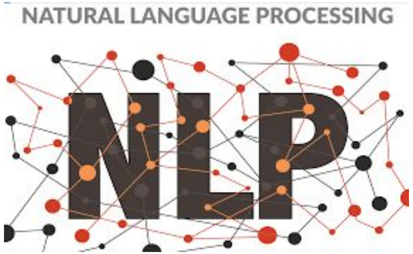
Machine Learning is coined by Arthur Samuel in 1959

Shakey (1969)



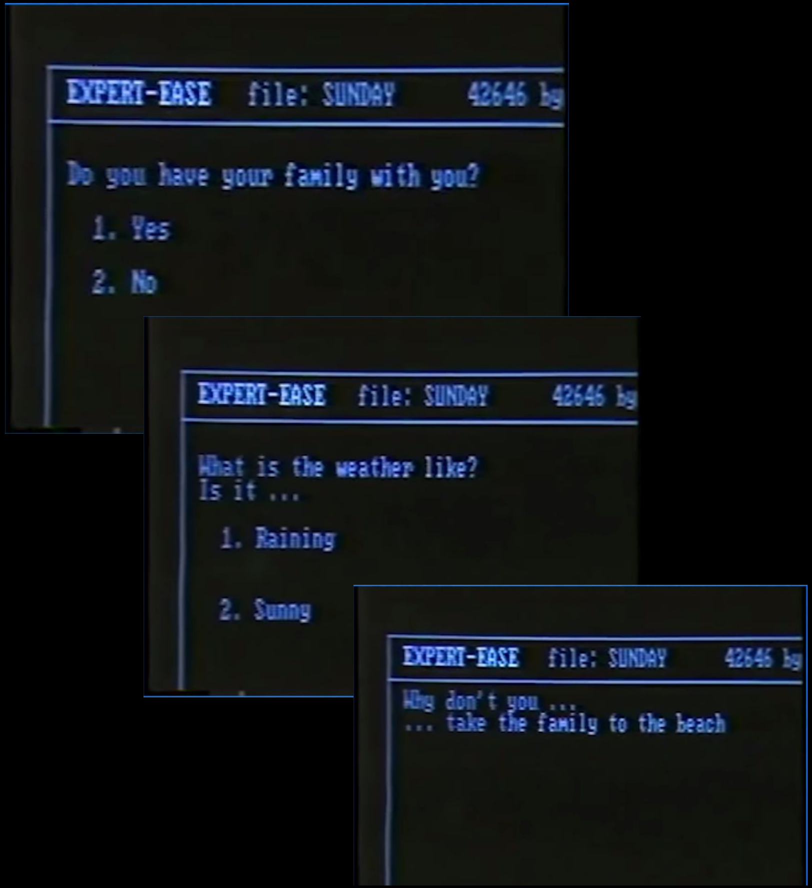

```
 Welcome to
                    EEEEEE  LL      IIII  ZZZZZZZ   AAAAA
                    EE      LL       II      ZZ   AA   AA
                    EEEEE   LL       II     ZZZ   AAAAAAA
                    EE      LL       II    ZZ     AA   AA
                    EEEEEE  LLLLLL  IIII  ZZZZZZZ AA   AA

 Eliza is a mock Rogerian psychotherapist.
 The original program was described by Joseph Weizenbaum in 1966.
 This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:
```

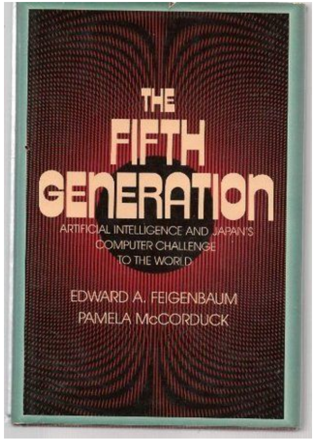
First chatbot - Eliza 1964

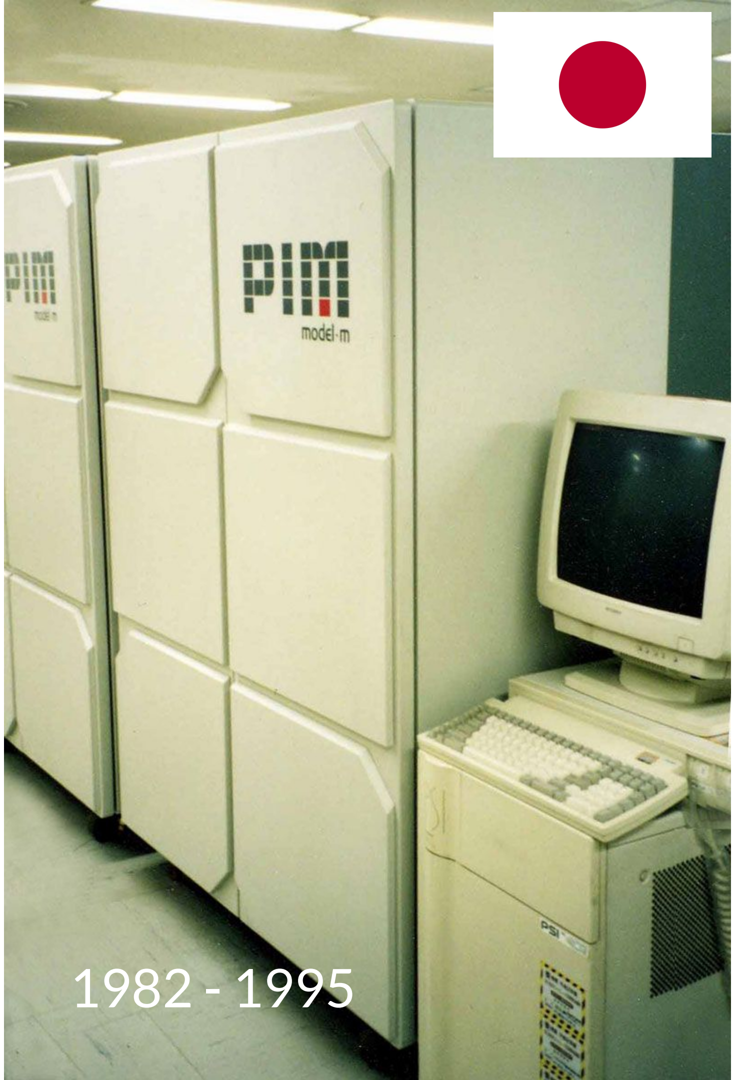



AI Winter
(1970-1980)

Edward Feigenbaum (1980's)
Expert Systems





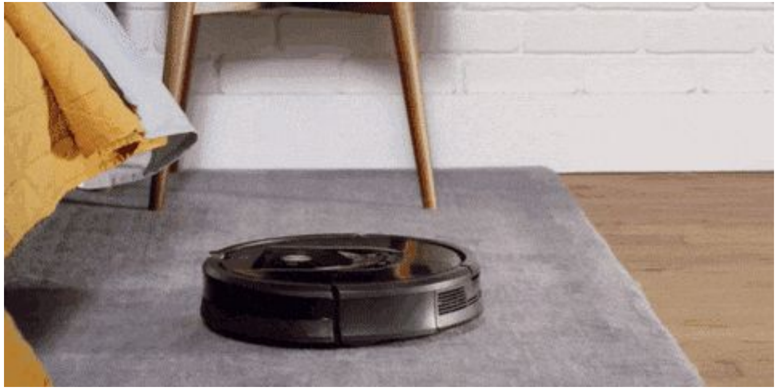


Prolog

The Fifth Generation Computer Systems was an initiative by Japan's Ministry of International Trade and Industry, began in 1982, to create a computer using massively parallel computing/processing.

Deep Blue versus Garry Kasparov (1997)

DARPA Grand Challenge (>2005)



iRobot Roomba (2002)

Bigdog (2005)

Sebastian Thrun

2005 First-Place

Google - voice recognition iPhone (2008)

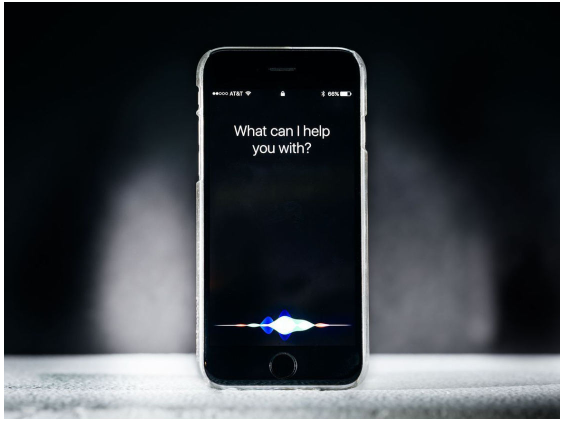
John Markoff / New York Times:

Google Is Taking Questions (Spoken, via iPhone) — SAN FRANCISCO — Pushing ahead in the decades-long effort to get computers to understand human speech, Google researchers have added sophisticated voice recognition technology to the company's search software for the Apple iPhone.

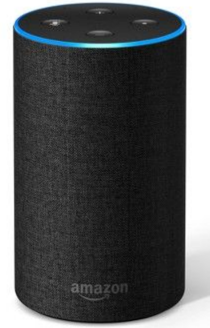
Discussion:

David Chartier / Infinite Loop: Google to bring Skynet to iPhone in voice recognition update
Google Watch: Google Voice Search Comes to Apple's iPhone, Not Android G1 First
Seth Weintraub / 9 to 5 Mac: Google Search now does speech recognition on iPhone (Updated Video)
Nathania Johnson / Search Engine Watch: Google Adds Voice Search to iPhone Search Application
Katie Marsal / AppleInsider: Google voice search app for iPhone arriving shortly
Nicholas Carlson / Silicon Alley Insider: Google iPhone App Gets Voice Recognition
Daniel Ionescu / PC World: iPhone Gets Google Search By Voice
Svetlana Gladkova / Profy: Google To Introduce Voice Search on iPhone, Hopefully It Will Work
Greg Sterling / Screenwerk: Google's New Voice-Search App for iPhone
Brian Lam / Gizmodo: Breaking: Google Adding Free Voice Search to the iPhone
Darrell Etherington / TheAppleBlog: Google Search Will Hear You, If You Have an iPhone
Longofest / MacRumors iPhone Blog: Google Bringing Voice Search To iPhone
Kevin Purdy / Lifehacker: Google iPhone App to Offer Search by Voice Google is expected ...
C.K. Sample III / Obsessable: Google iPhone app will add advanced voice recognition
David Gonzales / Unwired View: Google to introduce "Searching by Voice" feature for iPhone
Loren Baker / Search Engine Journal: Google Launches Voice Recognition Search for Apple iPhone
Luigi Lugmayr / I4U News: Google Search by Voice coming to Apple iPhone
Stan Schroeder / Mashable!: Now You, Too, Can Look Silly Talking to Your iPhone
Eric Zeman / InformationWeek: iPhone Gets Voice-Powered Search From Google
HarperStudio / The 26th Story: 4 Questions I'd like to ask Google on the iPhone
Rex Hammock / RexBlog.com: My first voice-recognition question for Google's new iPhone App
Rene Ritchie / The iPhone Blog: Google Advanced Voice Search for the iPhone!
Dusan Belic / IntoMobile: Google to make its iPhone app voice enabled
Warner Crocker / GottaBeMobile.com: Google to Release Voice Search for iPhone: iPhone Still Hands Free Crippled
MG Siegler / VentureBeat: Google. iPhone. Voice search. Awesome. (If it works.)
Boris Veldhuijzen van Zanten / TheNextWeb.com: Google launches Voice Search for the iPhone
Matt Burns / CrunchGear: Google to release speech-to-search iPhone app
Dave Jeyes / TECH.BLORGE.com: Can Google voice search for iPhone spur adoption?
Sam Kieldsen / Electricpig.co.uk: iPhone gets Google voice search
Brian Heater / AppScout: Google Intros Voice Search for iPhone
Matt McGee / Search Engine Land: Google Brings Voice Search To The iPhone
Marshall / Webmetricsguru: Google iPhone Voice (over); Google Is Taking Questions (Spoken, via iPhone)
Charles Starrett / iLounge: News: Google bringing voice search to iPhone
Eric M. Zeman / Phone Scoop: Google Brings Voice-Enabled Search to the iPhone
Emily / textually.org: GOOGLE ADDS SEARCHING BY VOICE TO IPHONE SOFTWARE
MacNN: Apple looking to develop new search tech?
Benwilson / iPhone Atlas: Google iPhone App Already Lists Voice Function, but It's Not There

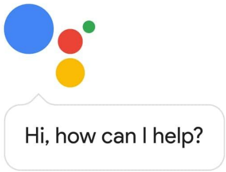
Apple - Siri (2011)



Amazon - Alexa (2014)

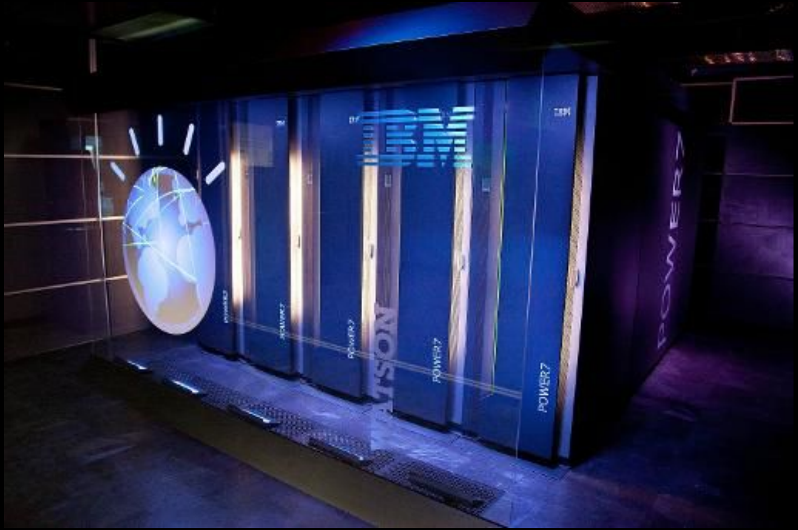


Google Assistant - 2016



Microsoft - Cortana (2014)

2011


IBM
POWER7


THINK
$24,000
$77,147
$21,600
Who is Stoker?
(I FOR ONE WELCOME OUR NEW COMPUTER OVERLORDS)
$1,000
Who is Bram Stoker?
$ 17,973
WHO IS BRAM STOKER?
$5600

English transcription by Joseph Geni. Reviewed by Morton Bast.

Details About the talk | **Transcript** 38 languages | **Comments (104)** Join the conversation

In the fall of 2011 Peter Norvig taught a class with Sebastian Thrun on artificial intelligence at Stanford attended by 175 students in situ -- and over 100,000 via an interactive webcast. He shares what he learned about teaching to a global classroom.

1,115,344 views

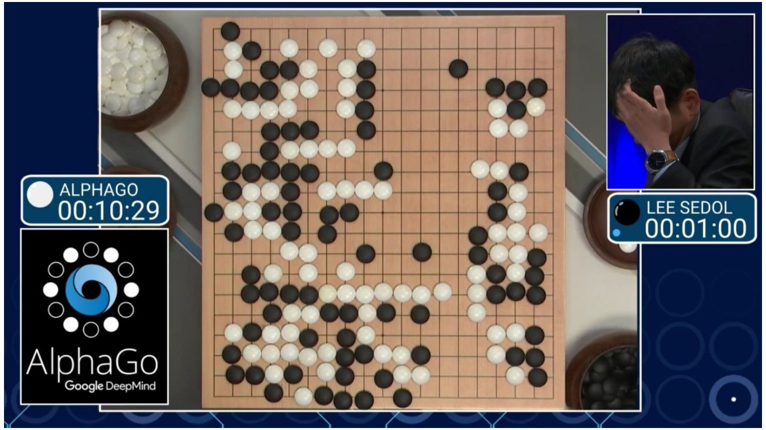
TED2012 | February 2012

UDACITY

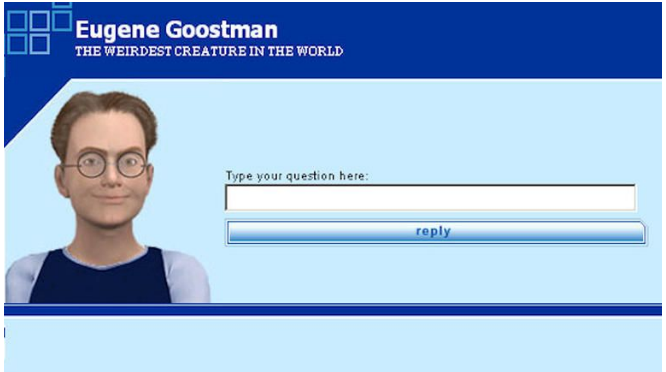
Practical, inexpensive, affordable and highly effective university.

Andrew Ng - Deep Learning (2012)

- 16k computer processors
- 10 million digital images found in YouTube videos
- 20,000 distinct items

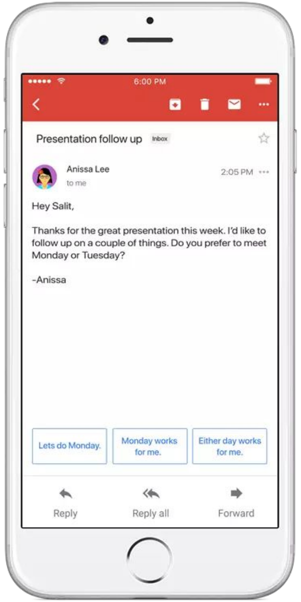


AlphaGo (2016)



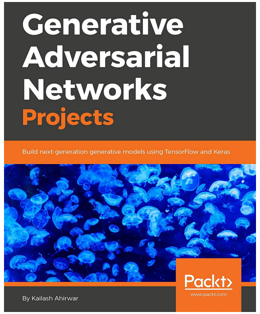
Pass in Turing Test (2014)

2018

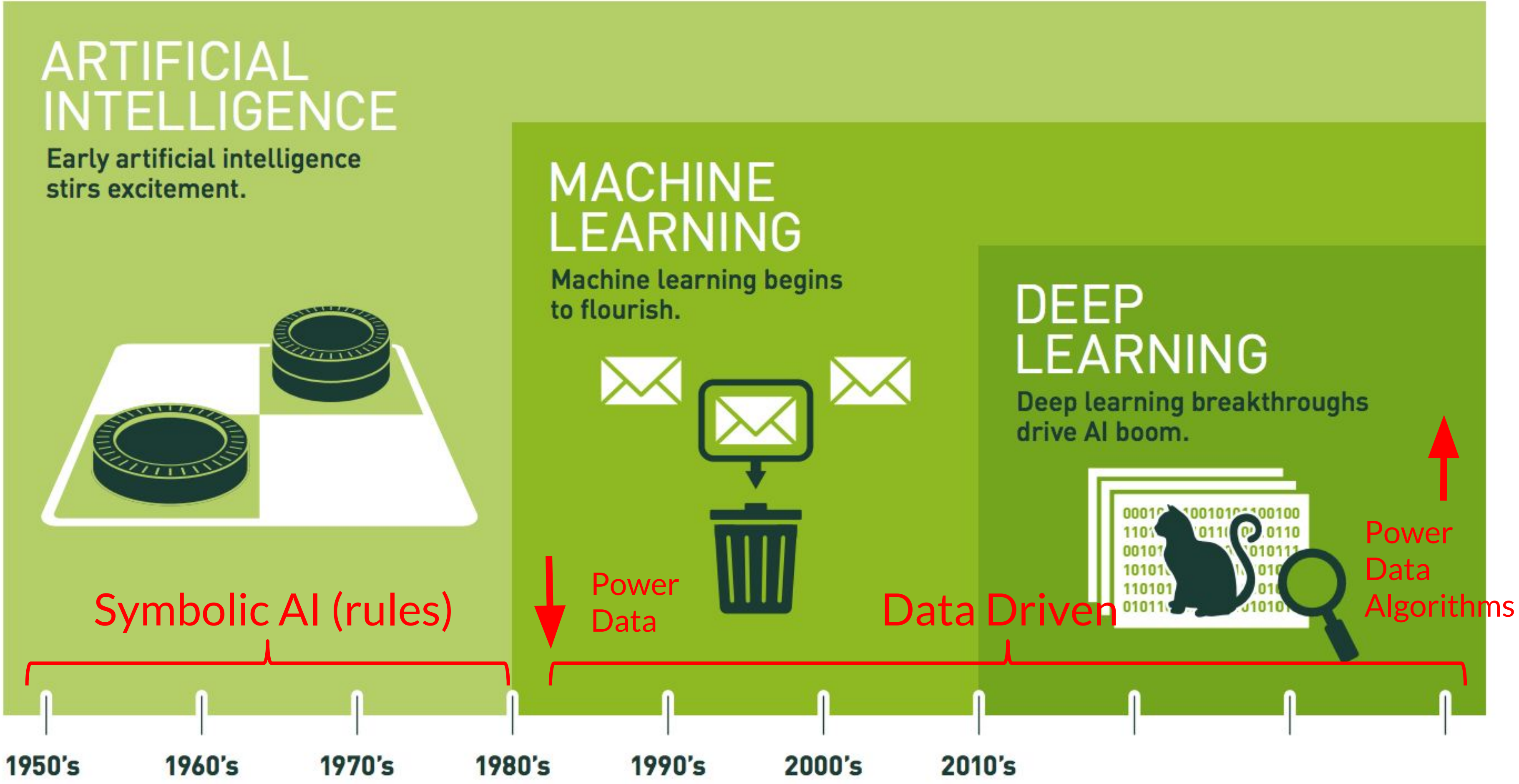


Google AI

Google Duplex



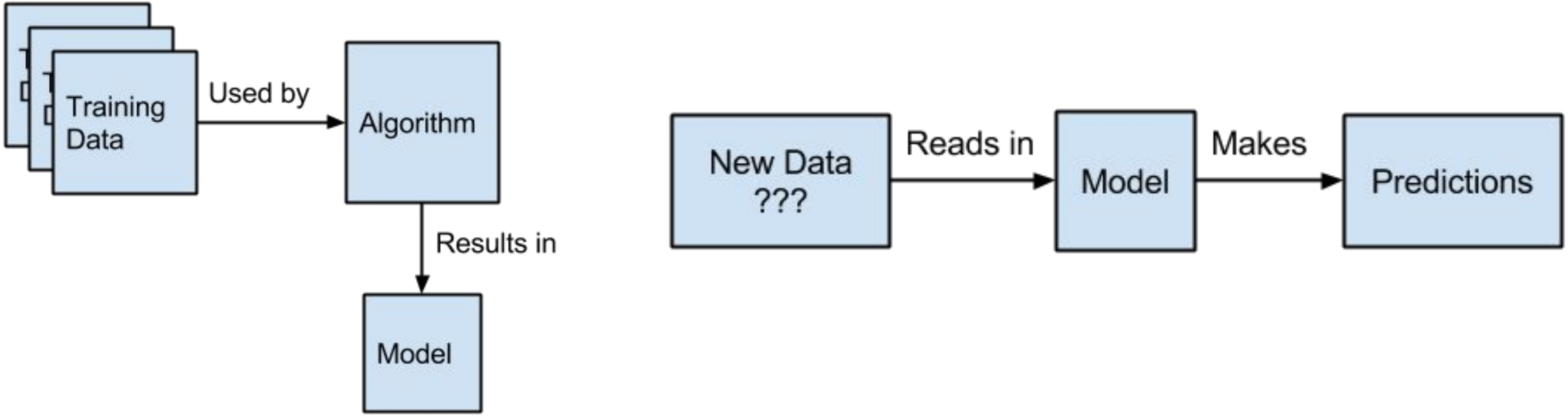
How do they related to each other?



NVIDIA


NVIDIA Corporation, United States, M, NA...
Market Closed
O 210.83 H 221.56 L 133.86 C 144.71
325.00
300.00
275.00
250.00
225.00
200.00
175.00
144.71
125.00
100.00
75.00
50.00
25.00
0.00
Investing.com
Volume (20)
0 299.03M
750M
500M
299.03M
0
2013
2015
2017
2019

Machine Learning a new programming paradigm

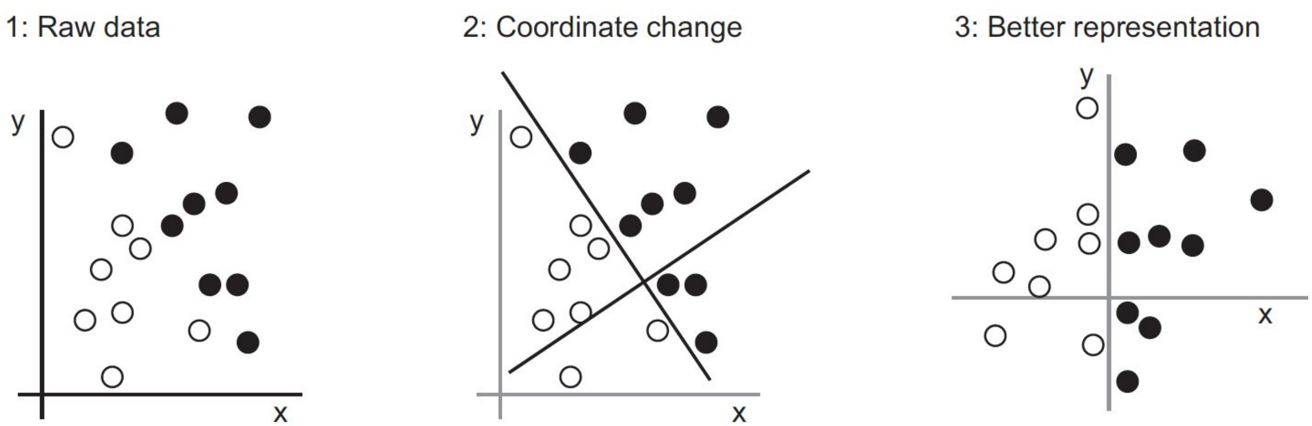


Machine Learning Definition

Arthur Samuel (1959)
Machine Learning: field of study that gives computers the ability to learn without being explicitly programmed.

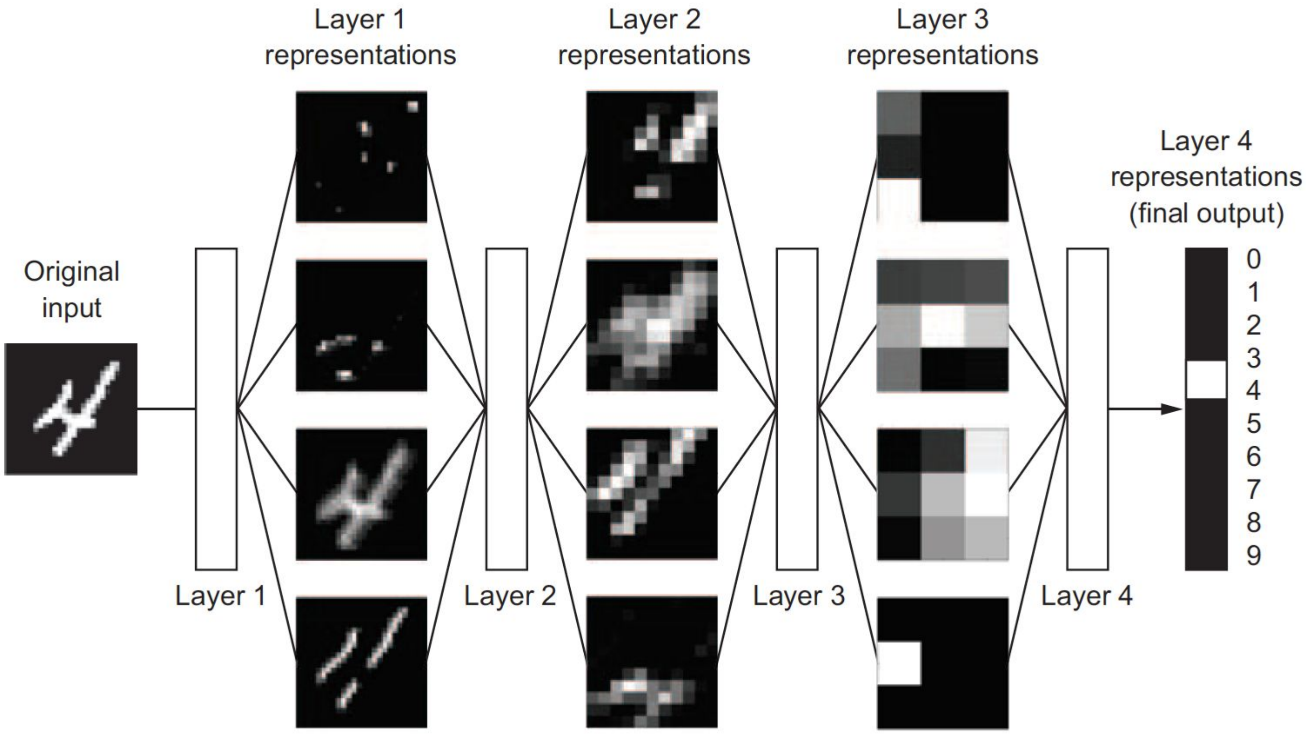
https://en.wikipedia.org/wiki/Arthur_Samuel

Machine Learning Definition



An automatic search process for better data representations

What is Deep Learning?

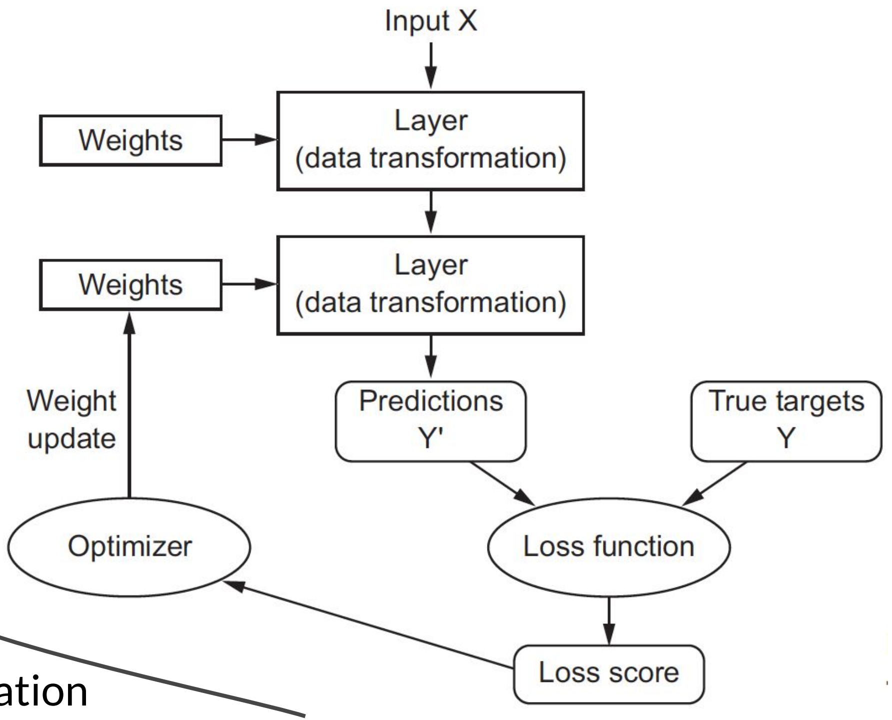


“Deep learning methods are representation-learning methods with multiple levels of representation, obtained by composing simple but nonlinear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level. [. . .] The key aspect of deep learning is that these layers are not designed by human engineers: they are learned from data using a general-purpose learning procedure”

[Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, Nature 2015]

Understanding how DL works

Finding the right values of weights which minimize the error



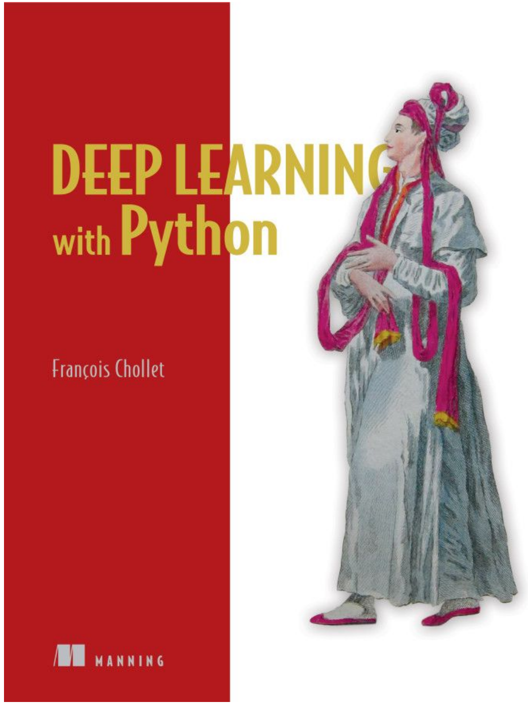
Backpropagation

What DL has archieved so far

Problems involving skills that seem natural and intuitive to humans but have long been elusive for machines.

- Near-human-level image classification
- Near-human-level speech recognition
- Near-human-level handwriting transcription
- Improved machine translation
- Improved text-to-speech conversion
- Digital assistants such as Google Now and Amazon Alexa
- Near-human-level autonomous driving
- Improved ad targeting, as used by Google, Baidu, and Bing
- Improved search results on the web
- Ability to answer natural-language questions
- Superhuman Go playing

A brief history of Machine Learning

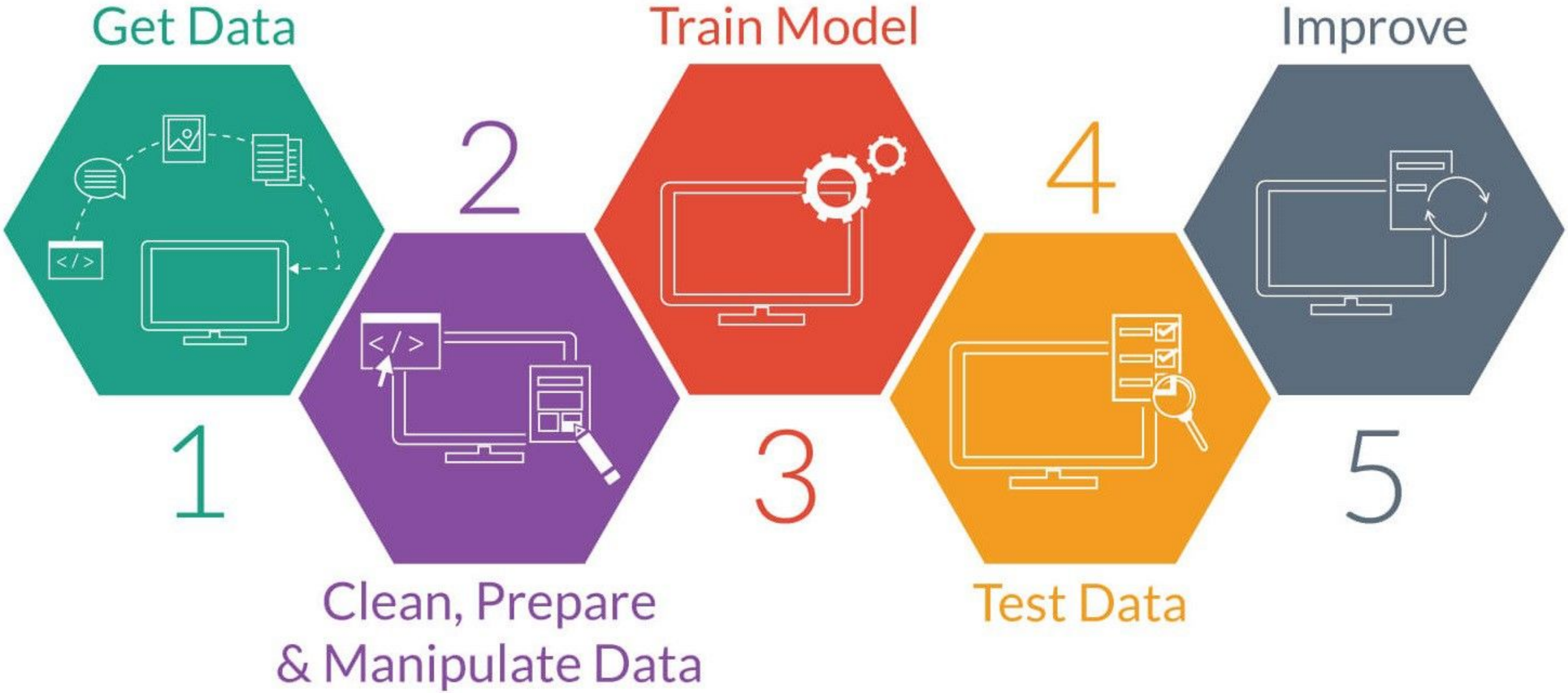


https://www.manning.com/books/deep-learning-with-python

Chapter 1, 2 and 3 are available for free!!!
Read the Chapter. 1, Section 1.2 !!!!!


It's time to
move on...

A general ML workflow



Types of Machine Learning Systems

- Whether or not they are trained with human supervision
  - Supervised
  - Unsupervised
  - Semisupervised
  - Reinforcement learning
- Whether or not they can learn incrementally on the fly
  - Online
  - Batch learning
- Whether they work by simply comparing new data points to known data points, or instead detect patterns in the training data and build a predictive model
  - Instance-based learning
  - Model-based learning

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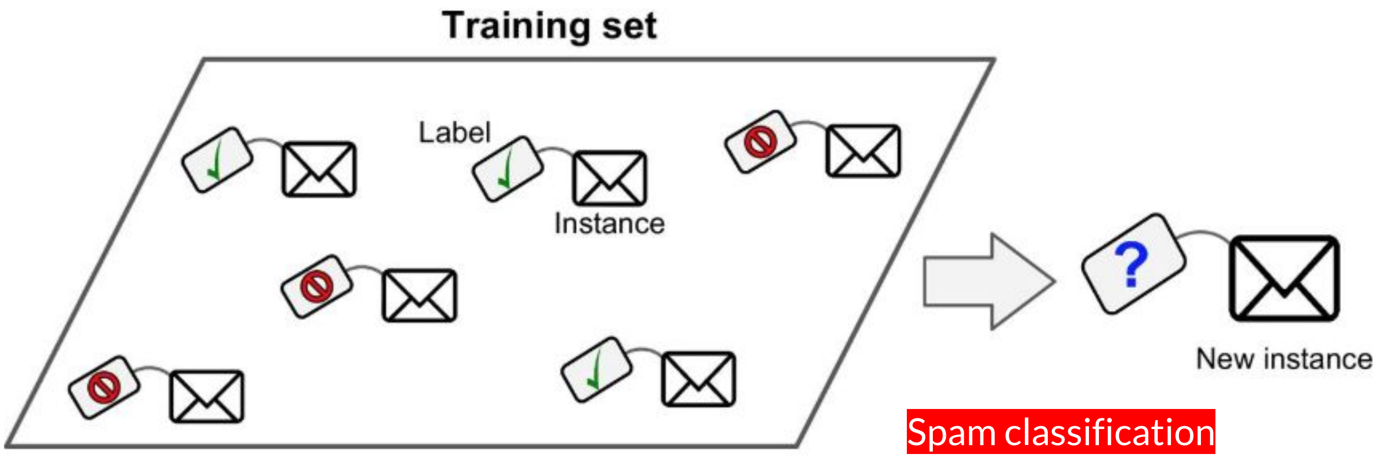
Supervised Learning

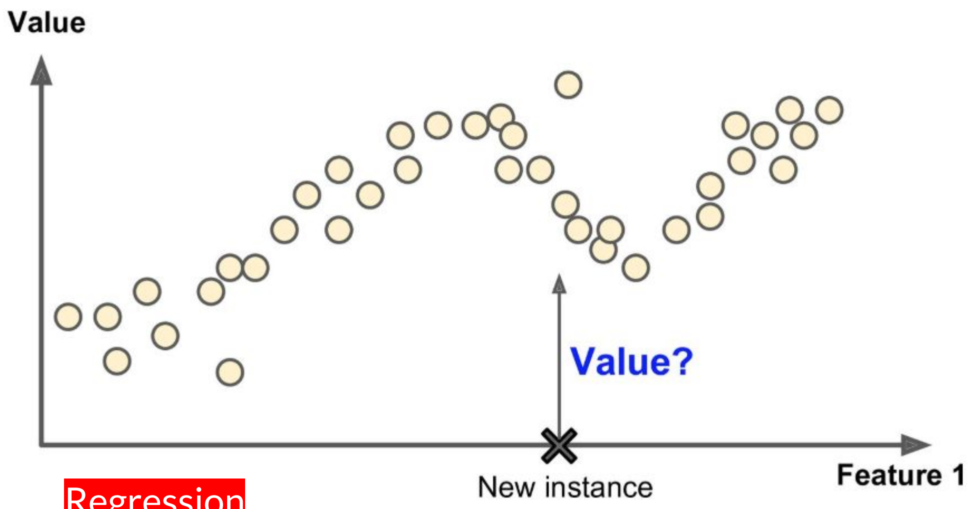
In supervised learning, the training data you feed to the algorithm includes the desired solutions, called labels.



Spam classification

Supervised Learning

Another typical task is to predict a target numeric value, such as the price of a car, given a set of features (mileage, age, brand, etc) called predictors.



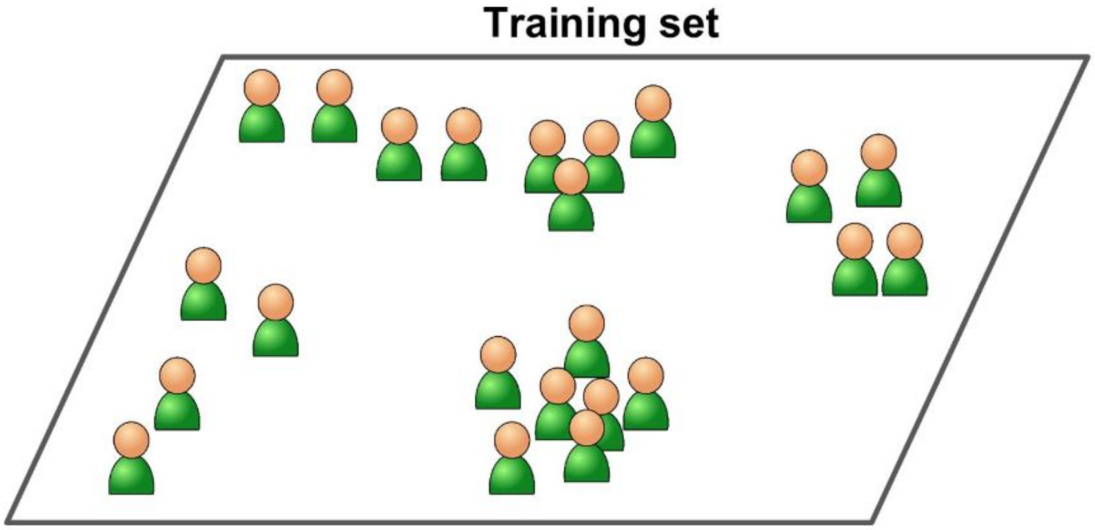
Regression

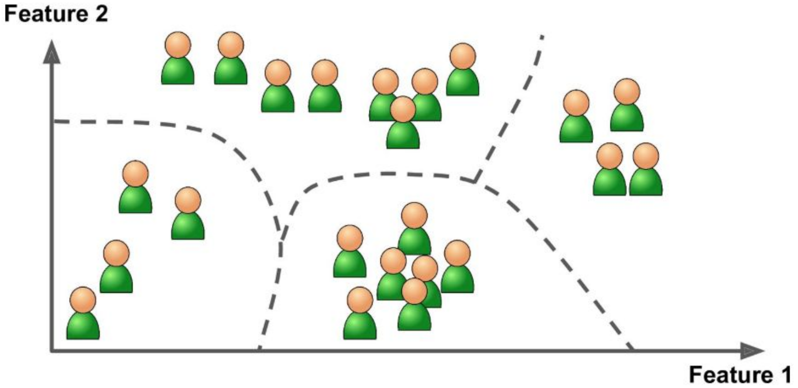
Supervised Learning

- K-Nearest Neighbors (KNN)
- Linear Regression
- Logistic Regression
- Support Vector Machines (SVM)
- Decision Trees and Random Forests
- Neural Networks
- Deep Learning
- XGBoost

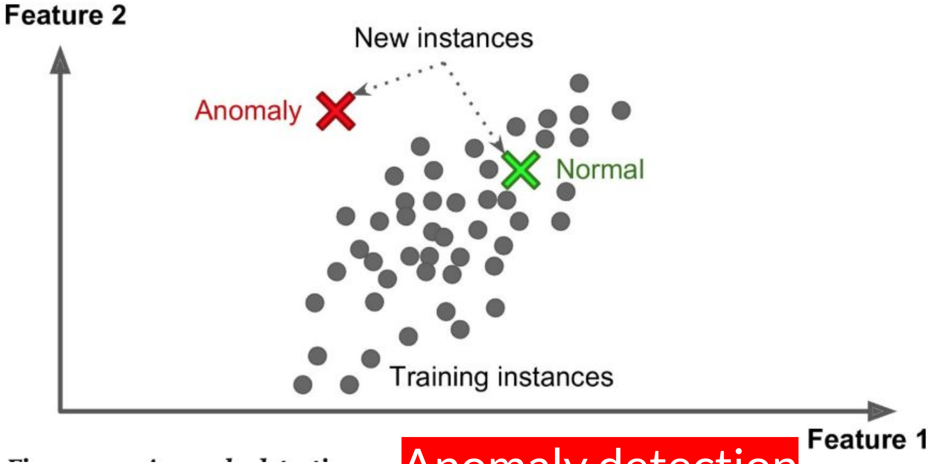
Unsupervised Learning

In unsupervised learning, as you might guess, the training data is unlabeled. The system tries to learn without a teacher.

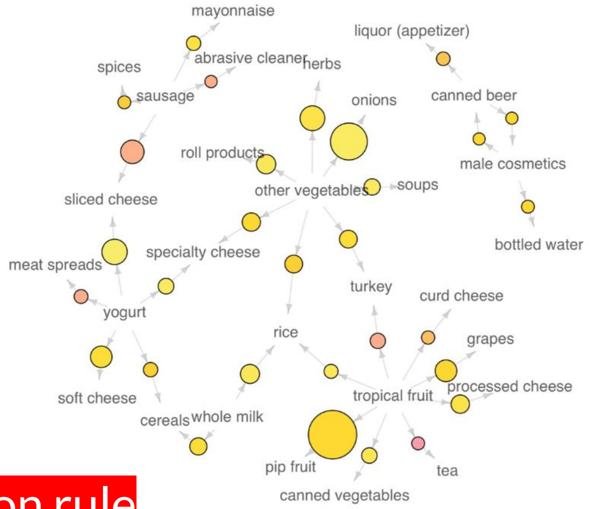




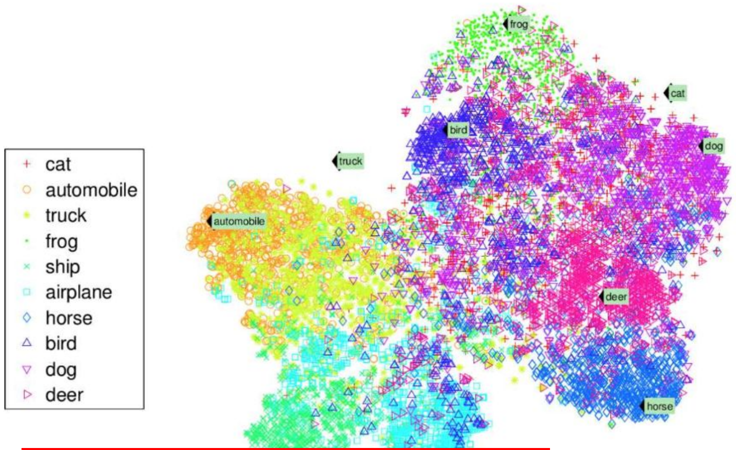
Clustering



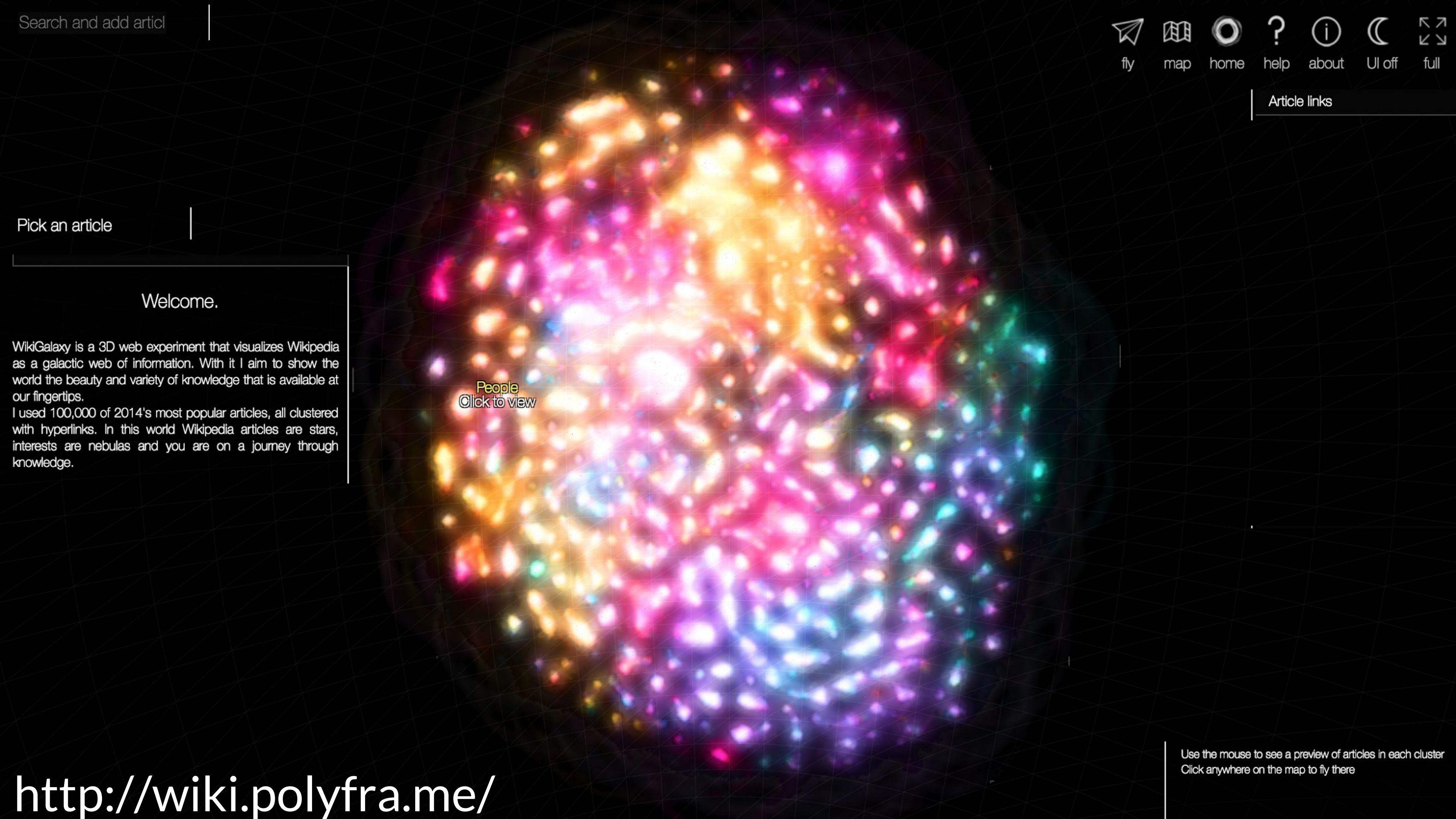
Anomaly detection



Association rule



Visualization highlighting



http://wiki.polyfra.me/

Unsupervised Learning

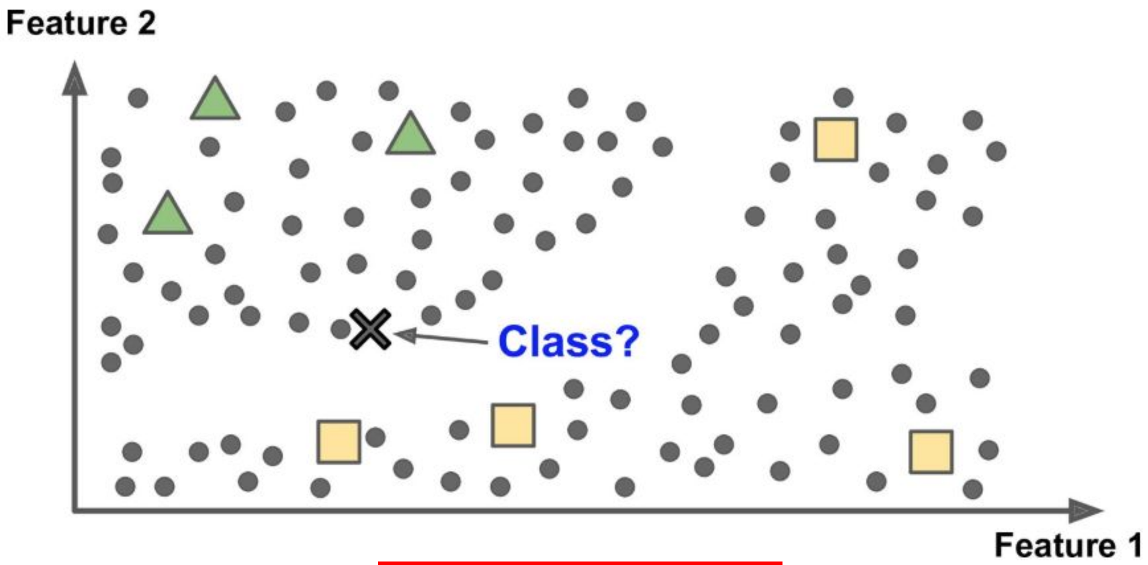
- Clustering
  - K-Means
  - Hierarchical Cluster Analysis (HCA)
  - Expectation Maximization
- Visualization and dimensionality reduction
  - Principal Component Analysis (PCA)
  - Kernel PCA
  - Locally-Linear Embedding (LLE)
  - T-distributed Stochastic Neighbor Embedding (t-SNE)
- Association rule learning
  - Apriori
  - Eclat

Semisupervised Learning

Semi-supervised learning algorithms are trained on a combination of labeled and unlabeled data.

- The process of labeling massive amounts of data for supervised learning is often prohibitively time-consuming and expensive.
- What's more, too much labeling can impose human biases on the model.
- That means including lots of unlabeled data during the training process actually tends to improve the accuracy of the final model while reducing the time and cost spent building it

Semisupervised Learning

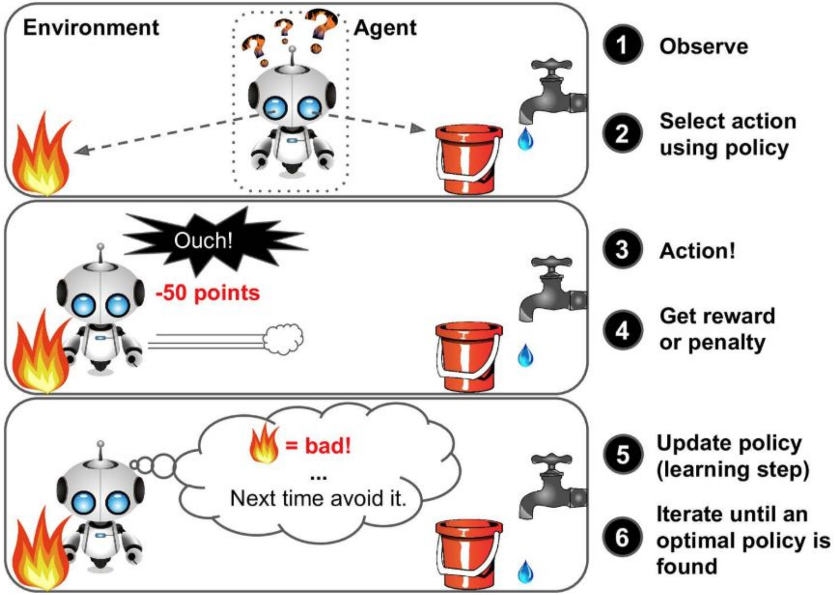


Web Page Classification
Google Photos

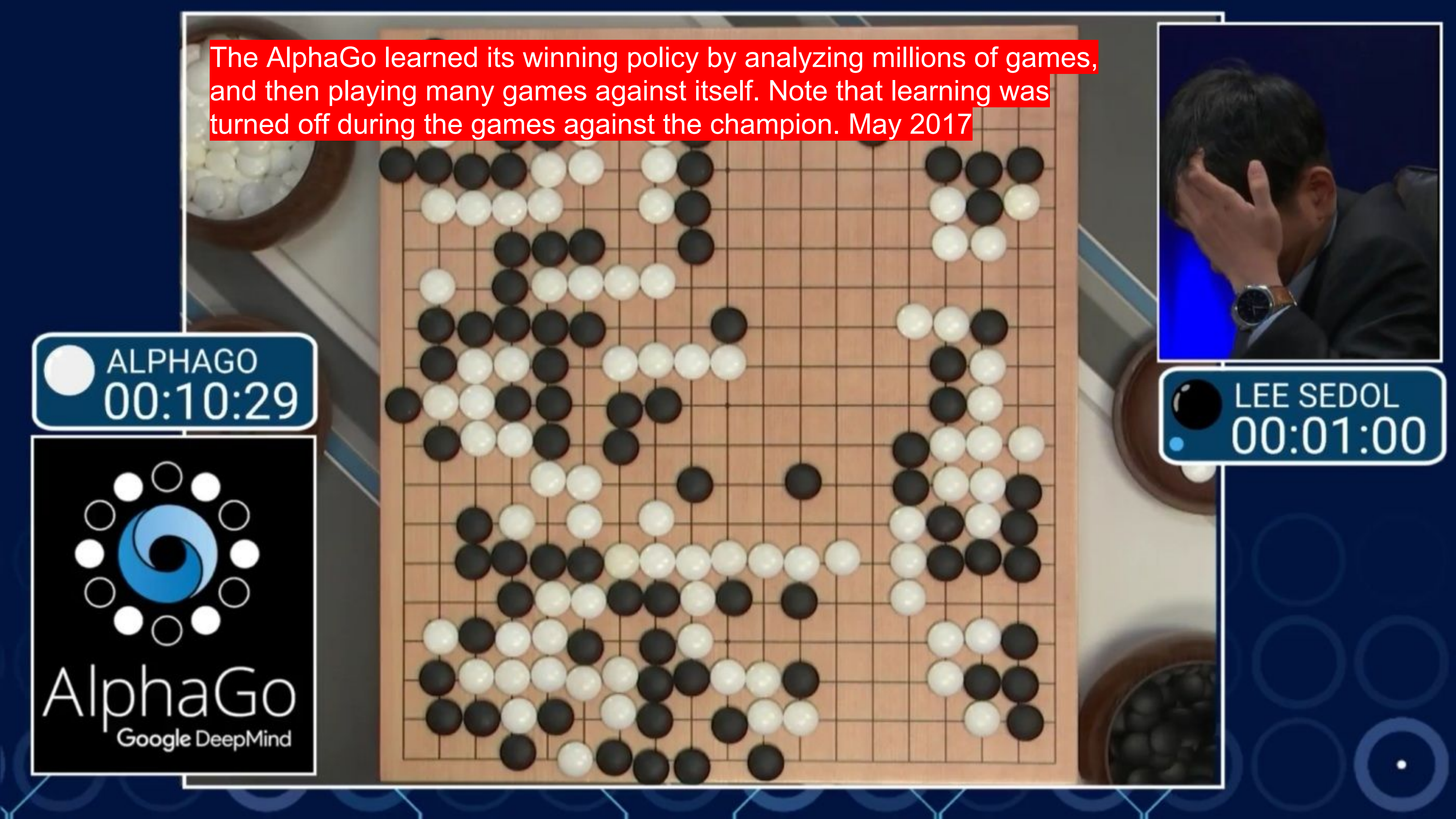
Reinforcement Learning

The learning system, called an agent in this context, can :

- Observe the environment
- Select and perform actions
- Get rewards in return (positive or negative)
- Learn by self what is the best strategy, called a policy



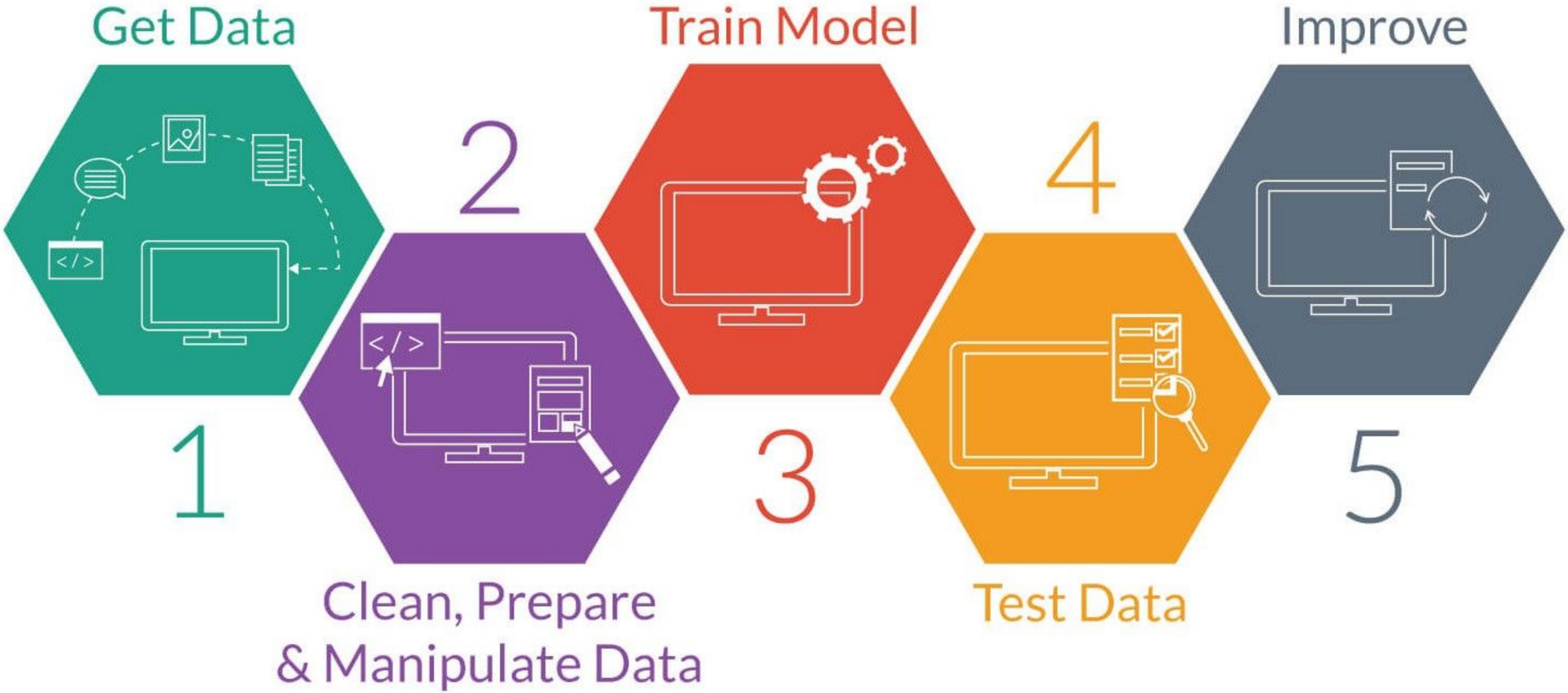
The AlphaGo learned its winning policy by analyzing millions of games, and then playing many games against itself. Note that learning was turned off during the games against the champion. May 2017



Reinforcement Learning

- Q-Learning
- State-Action-Reward-State-Action (SARSA)
- Deep Q Network (DQN)
- Deep Deterministic Policy Gradient (DDPG)
- A Brief Survey of Deep Reinforcement Learning (Dec, 2017)
  - https://arxiv.org/pdf/1708.05866.pdf

A general ML workflow

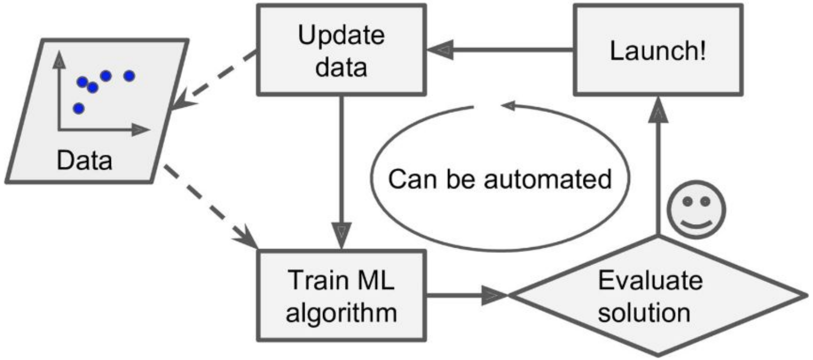


Types of Machine Learning Systems

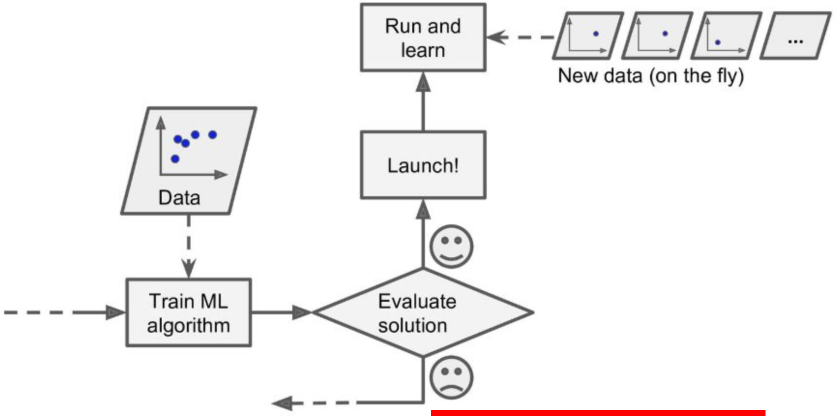
- Whether or not they are trained with human supervision
  - Supervised
  - Unsupervised
  - Semisupervised
  - Reinforcement learning
- Whether or not they can learn incrementally on the fly
  - Online
  - Batch learning
- Whether they work by simply comparing new data points to known data points, or instead detect patterns in the training data and build a predictive model
  - Instance-based learning
  - Model-based learning

Batch and Online Learning

Another criterion used to classify Machine Learning systems is whether or not the system can learn incrementally from a stream of incoming data.



Batch Learning



Online Learning

Types of Machine Learning Systems

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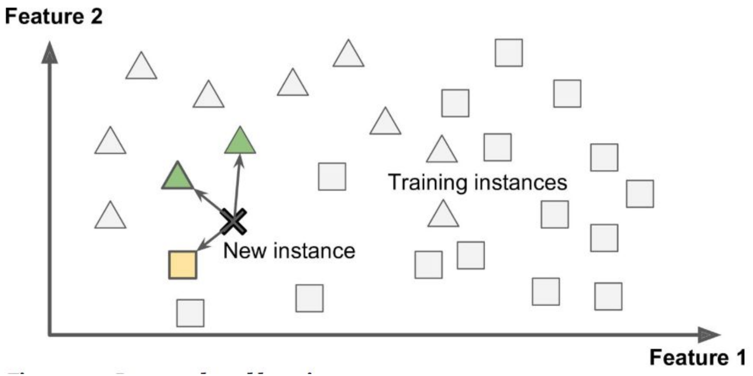
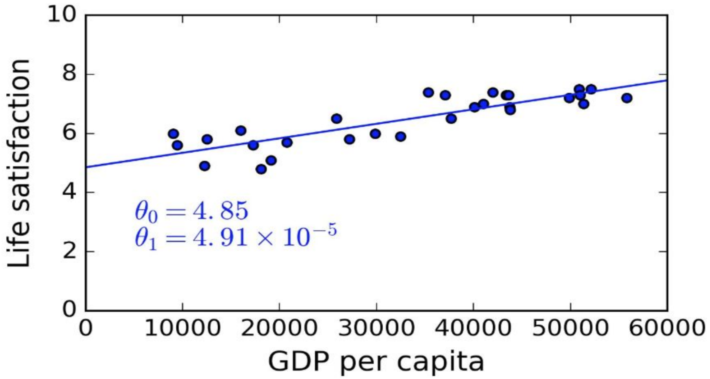
  - Model-based learning

Instance-Based or Model-Based Learning

One more way to categorize ML is by how they generalize (classify or predict to examples it has never seen before).



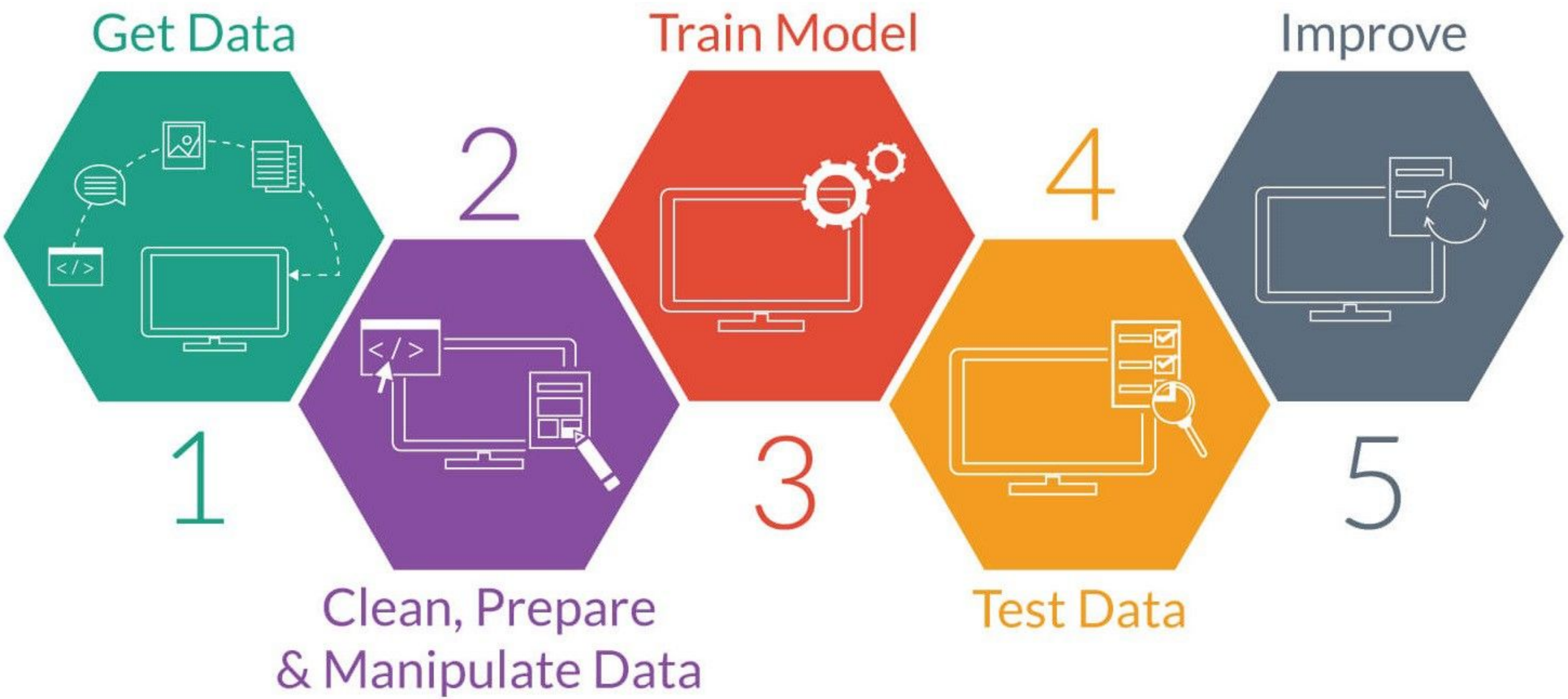
Instance-Based



Model-Based

main challenges of Machine Learning

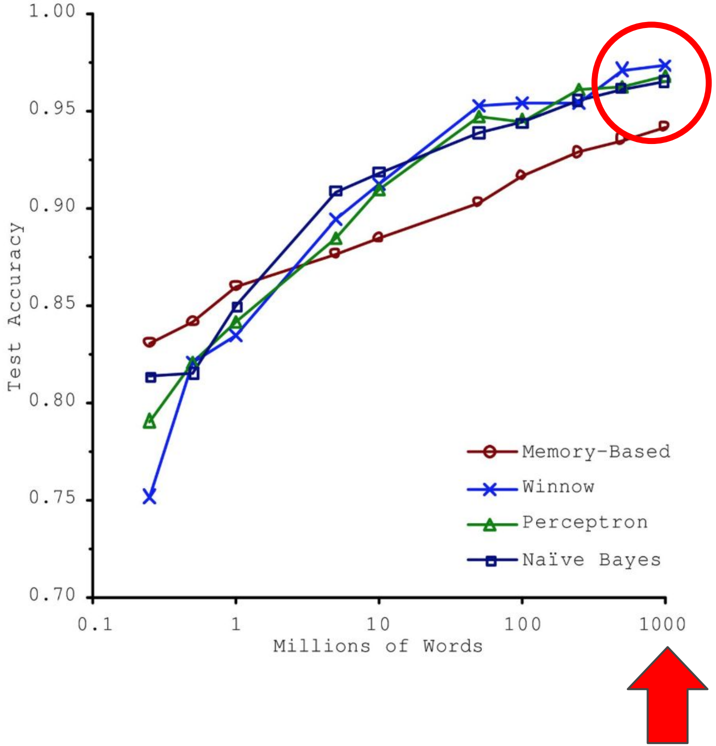
A general ML workflow



Main Challenges of Machine Learning

- Insufficient quantity of training data
- Nonrepresentative training data
- Poor quality-data
- Irrelevant features
- Overfitting the training data
- Underfitting the training data

Insufficient quantity of training data



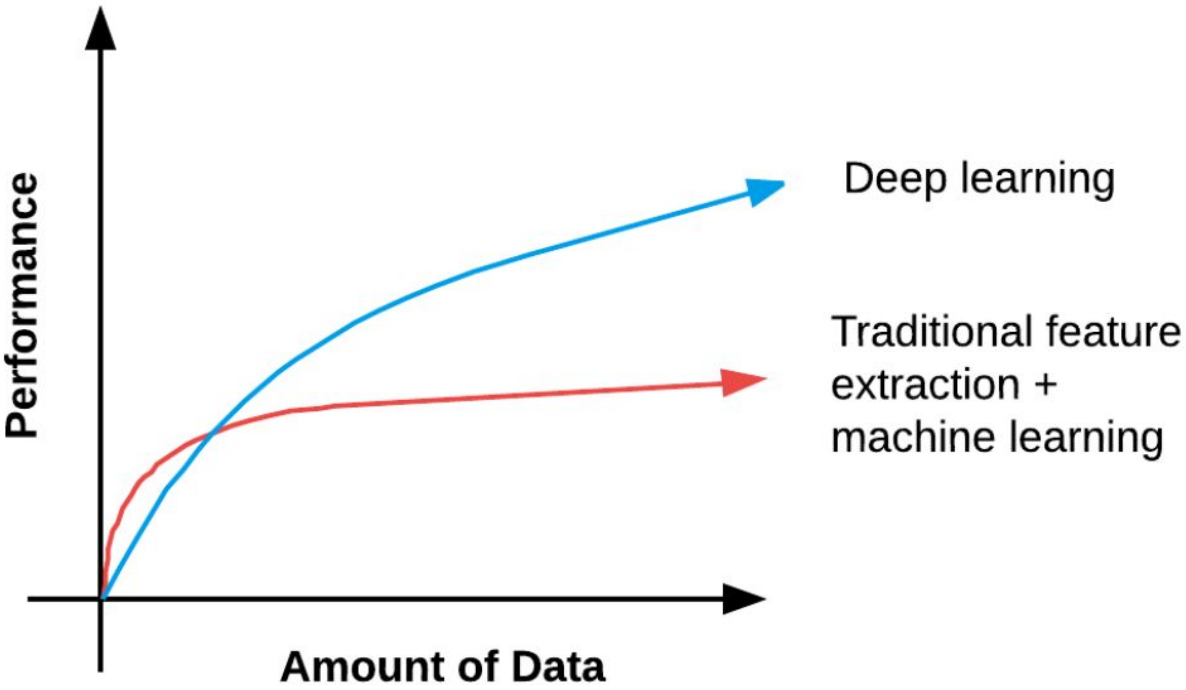
In a [famous paper] published in 2001, Microsoft researchers Michele Banko and Eric Brill showed that very differente ML algorithms, including fairly simples ones, performed almost identically well on a complex problem of natural language disambiguation once they were given enough data

Insufficient quantity of training data

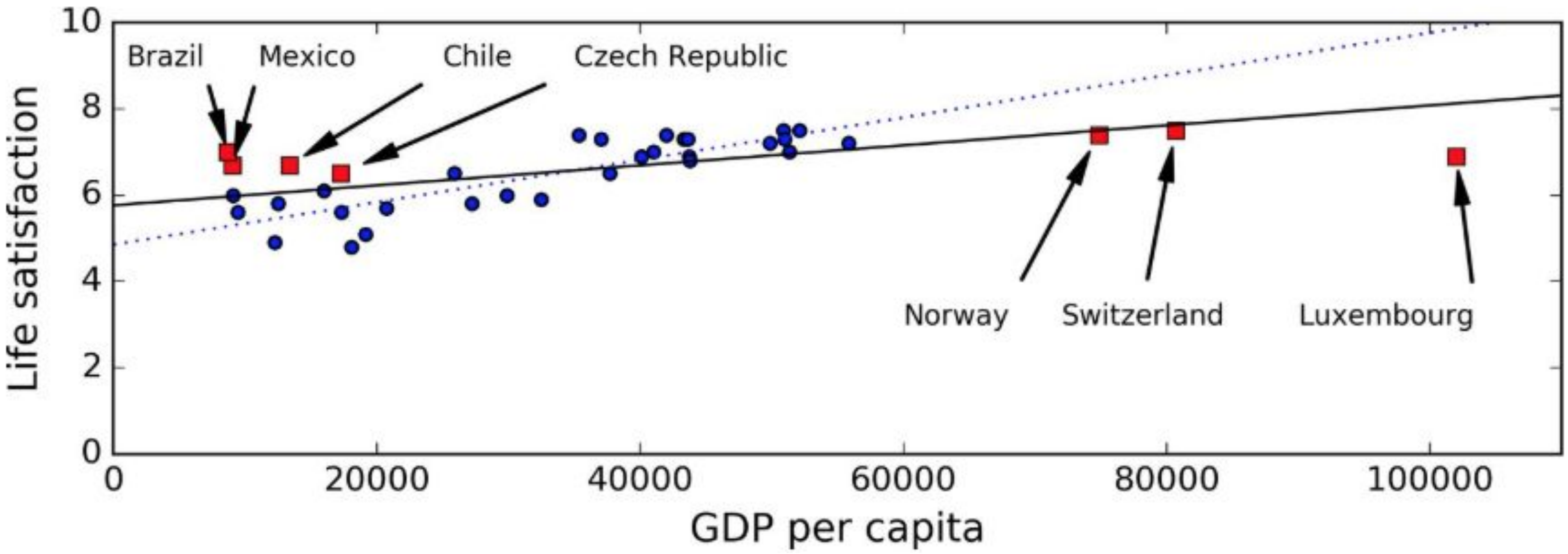
The idea that data matters more than algorithms for complex problems was further popularized by Peter Norvig et al. in a paper titled "The Unreasonable Effectiveness of Data" published in 2009.

Researchers from Google and Carnegie Mellon (2017) took a step towards clearing the clouds of mystery surrounding the relationship between "enormous data" and visual deep learning. we find that the performance on vision tasks increases logarithmically based on volume of training data size (300M images were labeled with 18291 categories resulting in more than 1 billion of labels)

Insufficient quantity of training data



Nonrepresentative Training Data



By using a nonrepresentative training set, we trained a model that is unlikely to make accurate predictions (sampling bias), especially for very poor and very rich countries

Poor-Quality Data

Obviously, if your training data is full of:

- Erros
- Outliers
- Noise
- Missing data

It will make it harder for the system to detect underlying patterns.

The truth is, most data scientist spend a significant part of their time doing cleaning up your training data.

Irrelevant Features

A critical part of the success of a ML project is coming up with a good set of features to train on. This process, called feature engineering involves:

- Feature selection
  - Selecting the most useful features to train on among existing features.
- Feature extraction
  - Combining existing features to produce a more useful one
- Creating new features by gathering new data.

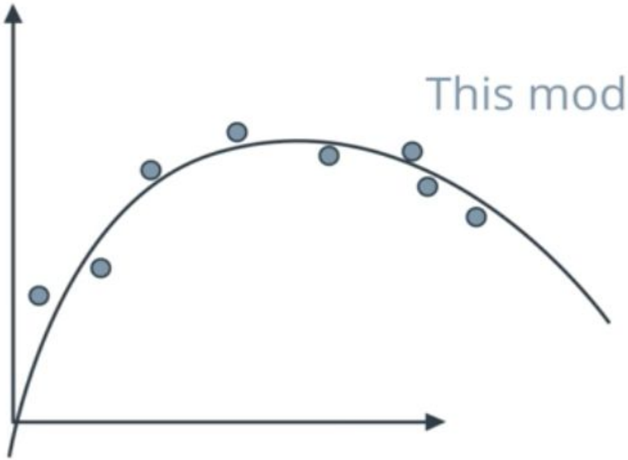
UNDERFITTING

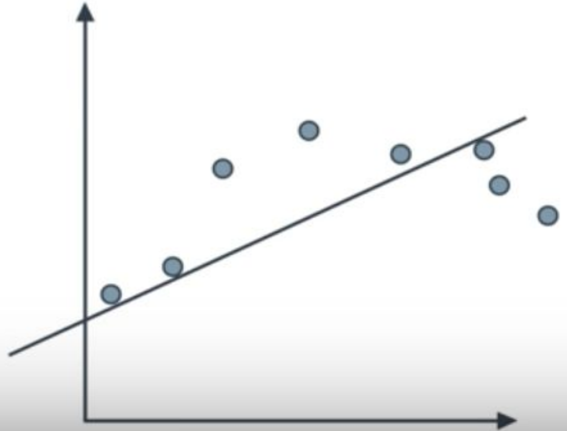
OVERFITTING

UNDERFITTING

Error due to bias

This model will not do well in the training set

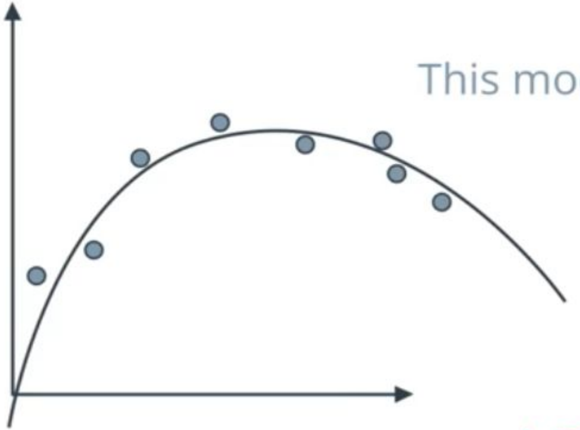


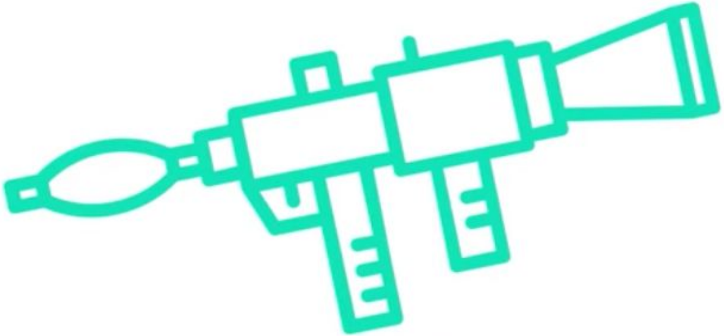


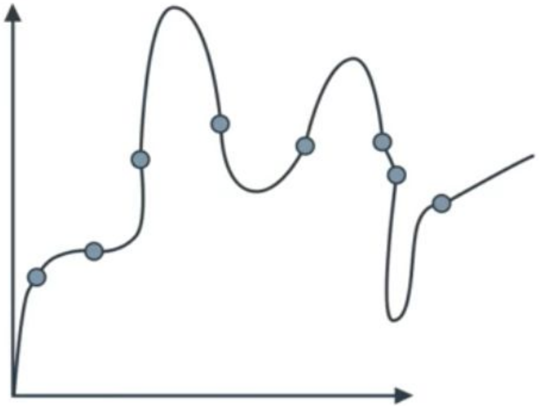
OVERFITTING

Error due to variance

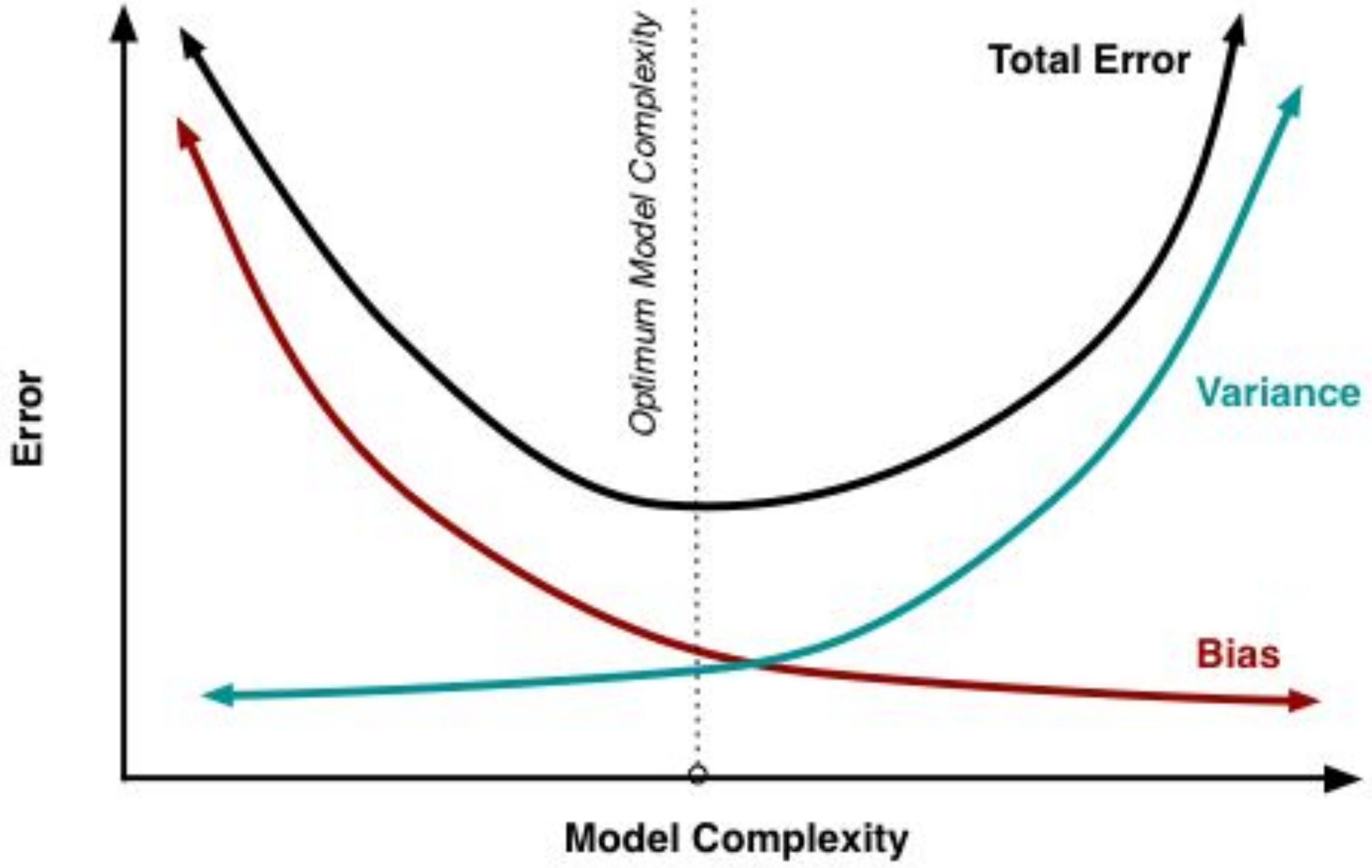
This model performs poorly in the testing set





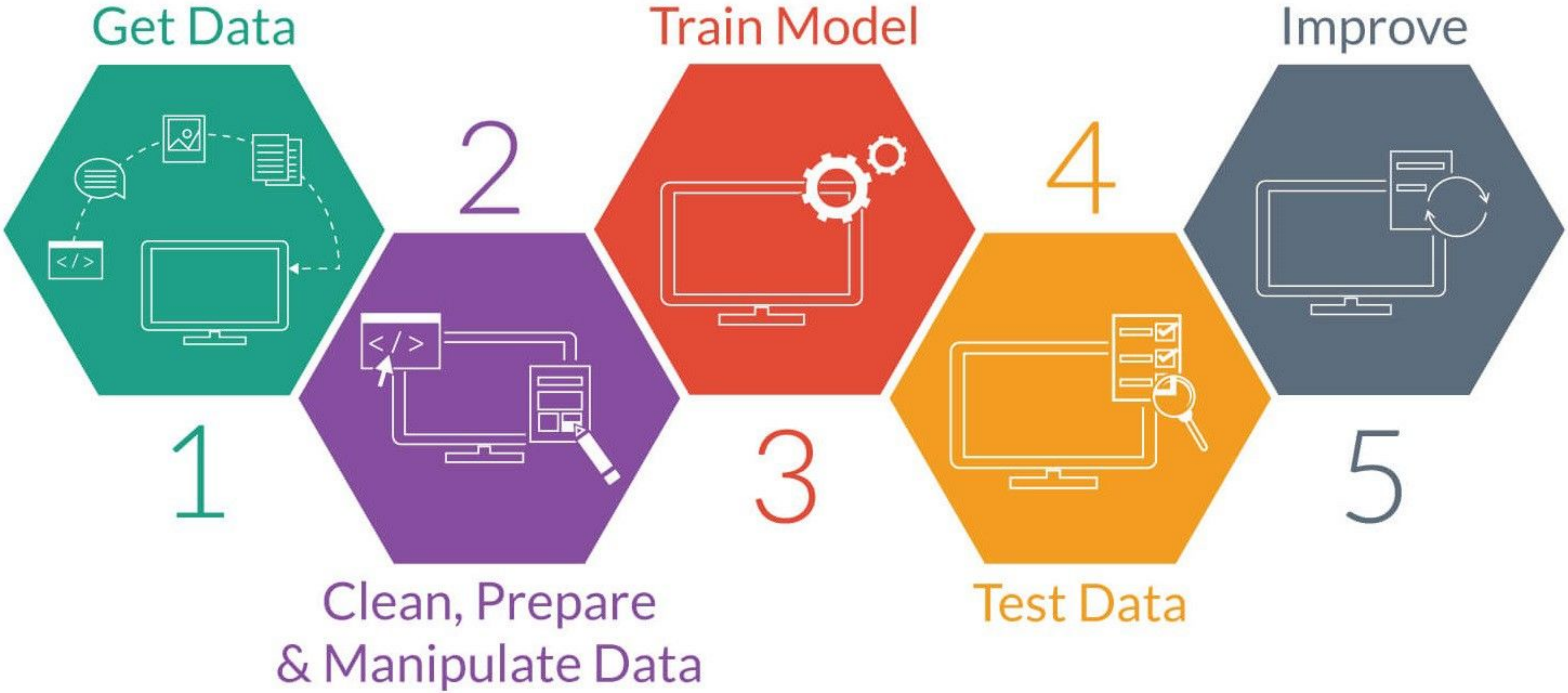


Underfitting Overfitting



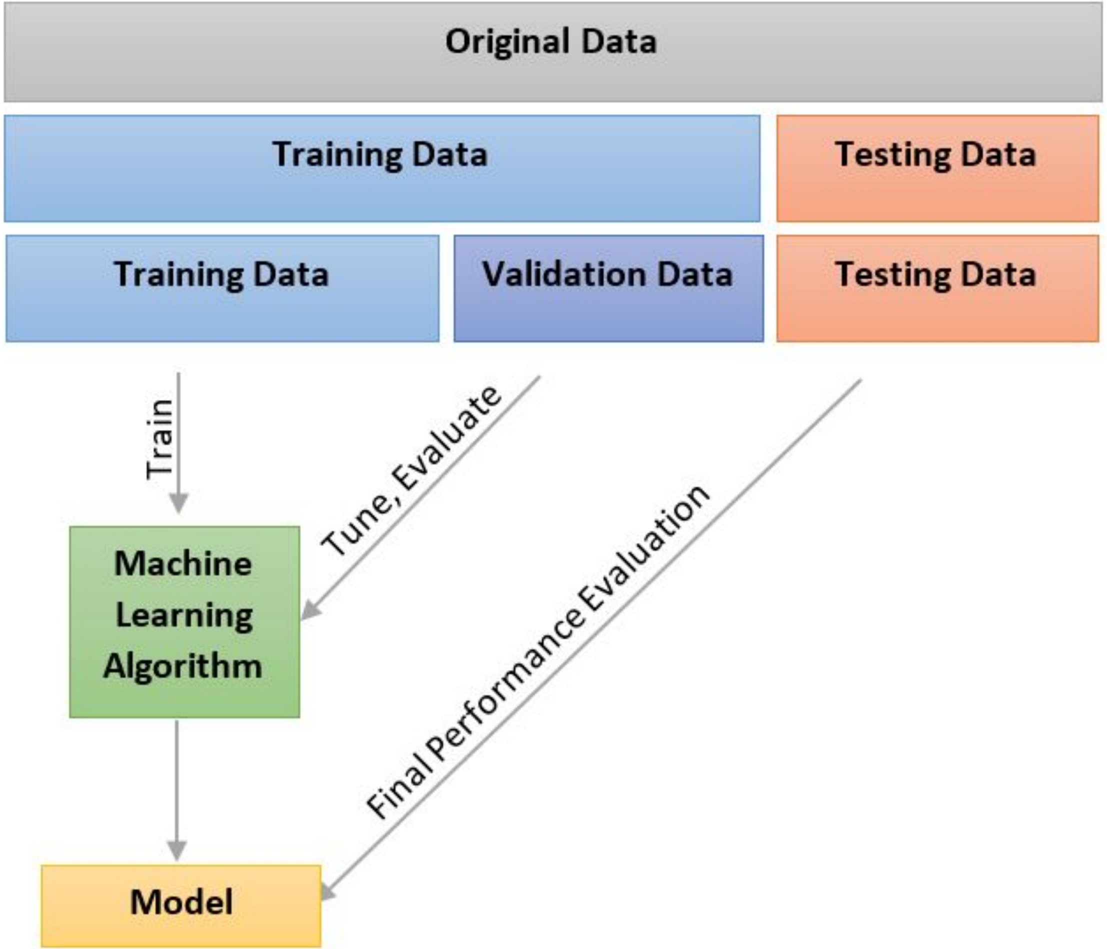
Testing
&
Validating

A general ML workflow

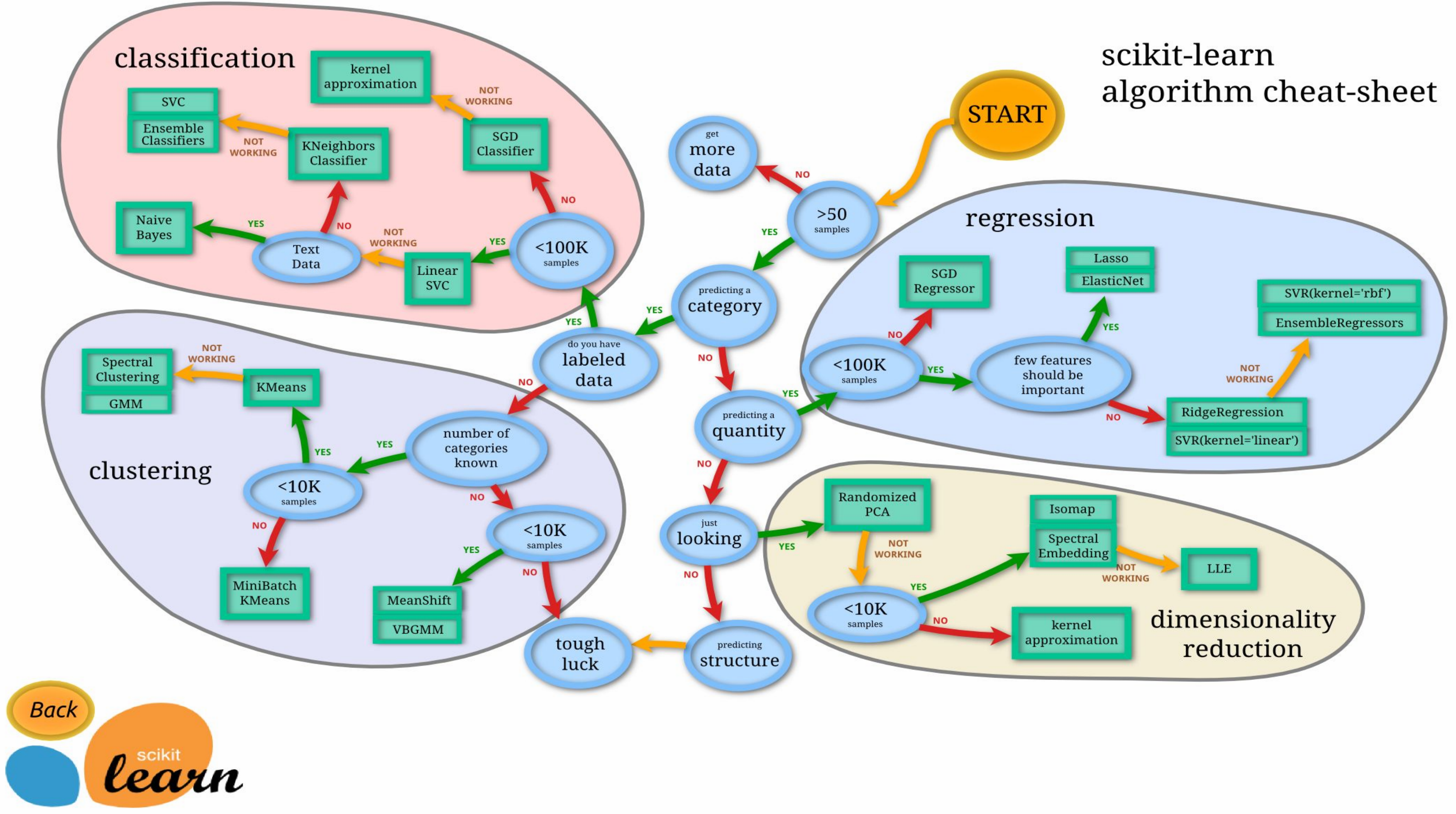


The only way to know how well a model will generalize to new cases is to actually try it out on new cases.

One way to do that is to put your model in production and monitor how well it performs!!!


Original Data
Training Data
Testing Data
Training Data
Validation Data
Testing Data
Train
Tune, Evaluate
Final Performance Evaluation
Machine Learning Algorithm
Model

End-to-end Machine Learning Project


scikit-learn
algorithm cheat-sheet
START
>50 samples
get more data
predicting a category
do you have labeled data
predicting a quantity
just looking
predicting structure
tough luck
classification
kernel approximation
SVC
Ensemble Classifiers
KNeighbors Classifier
SGD Classifier
Naive Bayes
Text Data
Linear SVC
<100K samples
clustering
Spectral Clustering
GMM
KMeans
number of categories known
<10K samples
MiniBatch KMeans
MeanShift
VBGMM
regression
SGD Regressor
Lasso
ElasticNet
SVR(kernel='rbf')
EnsembleRegressors
few features should be important
RidgeRegression
SVR(kernel='linear')
dimensionality reduction
Randomized PCA
Isomap
Spectral Embedding
LLE
kernel approximation
YES
NO
NOT WORKING
Back
scikit learn

Python For Data Science *Cheat Sheet*

Scikit-Learn

Learn Python for data science Interactively at www

LINK

Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> y = np.array(['M','M','F','F','M','F','M','M','F','F','F'])
>>> X[X < 0.7] = 0
```

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        random_state=0)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Model Fitting

Supervised learning

```
>>> lr.fit(X, y)
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

Fit the model to the data

Unsupervised Learning

```
>>> k_means.fit(X_train)
>>> pca_model = pca.fit_transform(X_train)
```

Fit the model to the data

Fit to data, then transform it

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.random((2,5)))
>>> y_pred = lr.predict(X_test)
>>> y_pred = knn.predict_proba(X_test)
```

Predict labels

Predict labels

Estimate probability of a label

Unsupervised Estimators

```
>>> y_pred = k_means.predict(X_test)
```

Predict labels in clustering algos

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>> imp = Imputer(missing_values=0, strategy='mean', axis=0)
>>> imp.fit_transform(X_train)
```

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)
>>> from sklearn.metrics import accuracy_score
>>> accuracy_score(y_test, y_pred)
```

Estimator score method

Metric scoring functions

Classification Report

```
>>> from sklearn.metrics import classification_report
>>> print(classification_report(y_test, y_pred))
```

Precision, recall, f1-score and support

Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test, y_pred))
```

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared_error(y_test, y_pred)
```

R^2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

Tune Your Model

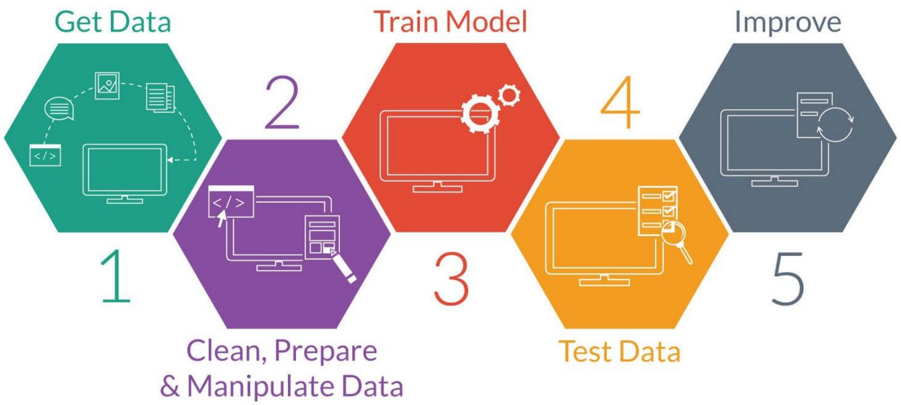
Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors": np.arange(1,3),
              "metric": ["euclidean", "cityblock"]}
>>> grid = GridSearchCV(estimator=knn,
                        param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5),
              "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn,
                                 param_distributions=params,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

End-to-end ML Project



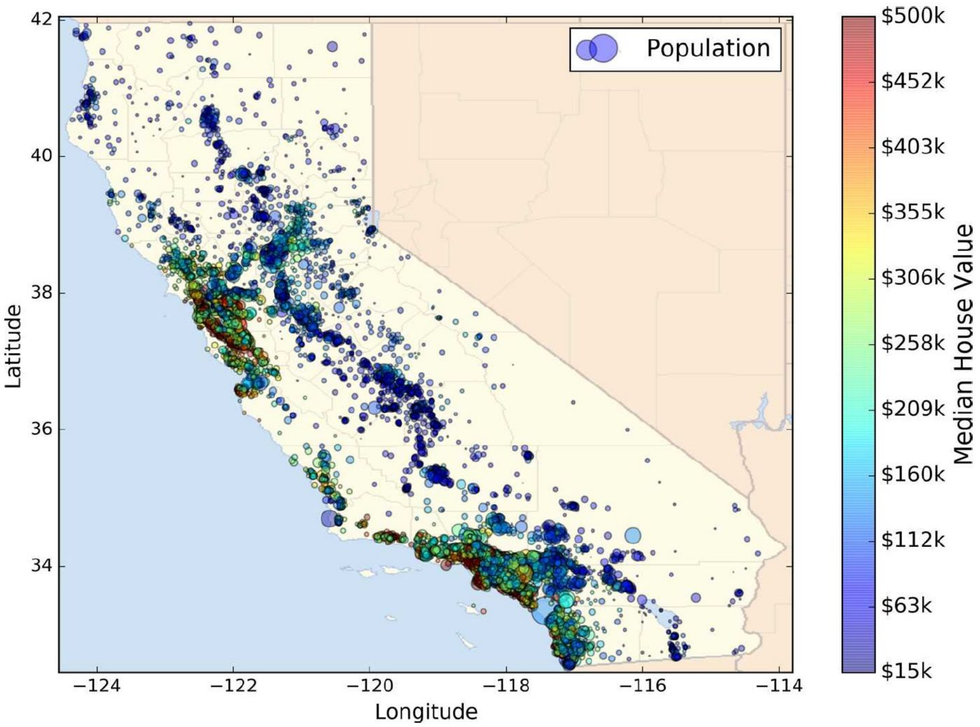
1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data. to gain insights.
4. Prepare the data for Machine Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.

#1 Look at the Big Picture

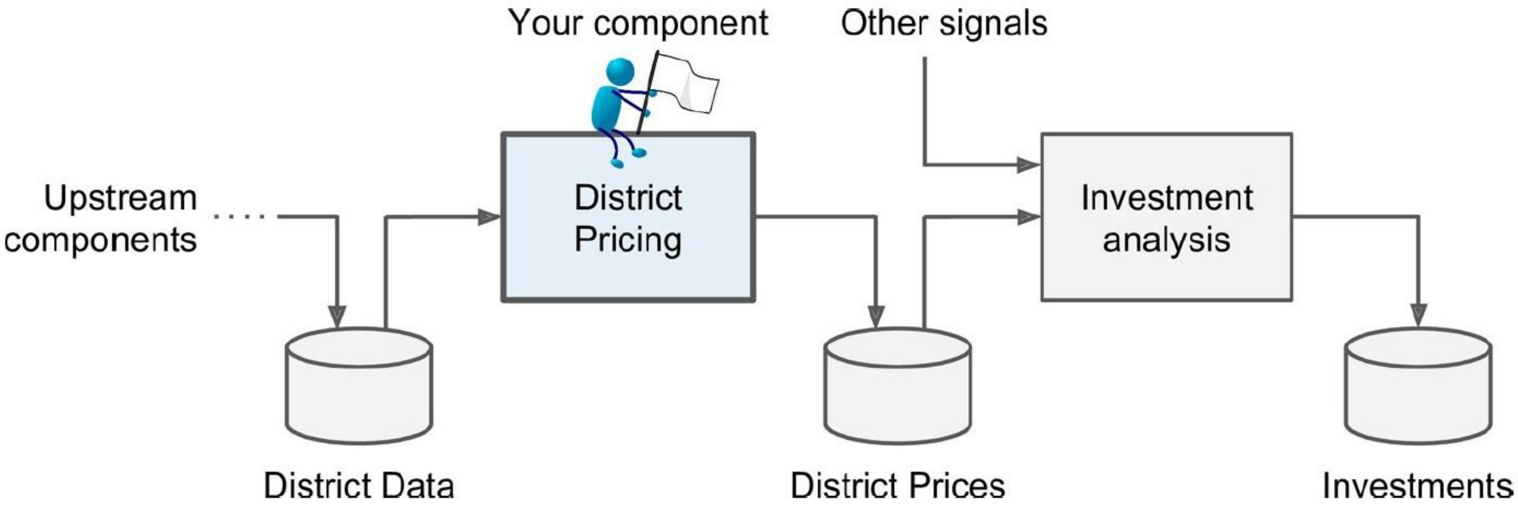
California Housing Prices dataset (90s)
https://www.kaggle.com/datasets

The first task you are asked to perform is to build a model of housing prices (block groups or districts) in California using the California census data

- Population
- Median income
- Median housing price
- and so on



Frame the problem



Building a model is probably not the end goal

Frame the problem

1. Is it supervised, unsupervised, or reinforcement learning?
2. Is it a classification task, a regression task, or something else?
3. Should you use batch learning or online learning techniques?
4. What algorithms you will select
5. What performance measure you will use to evaluate your model

Select a performance measure

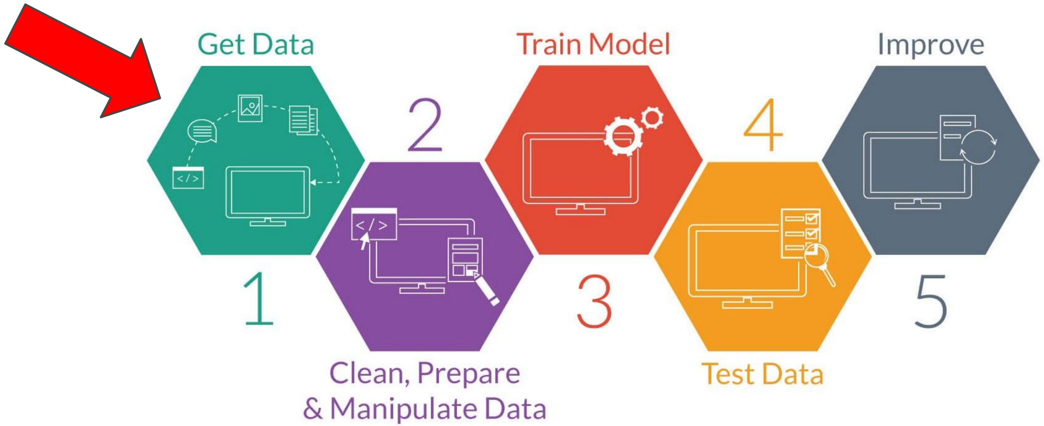
$$RMSE(X,h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(h(x^{(i)}) - y^{(i)})^2}$$

$$x^{(1)} = \begin{bmatrix} -118.29 \\ 33.91 \\ 1.416 \\ 38.372 \end{bmatrix}$$

$$y^{(1)} = 156.400$$

$$X = \begin{bmatrix} (x^{(1)})^T \\ (x^{(2)})^T \\ \vdots \\ (x^{(1999)})^T \\ (x^{(2000)})^T \end{bmatrix} = \begin{bmatrix} -118.29 & 33.91 & 1.416 & 38.372 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

End-to-end ML Project



1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data to gain insights.
4. Prepare the data for Machine Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.

#2. Get the data

```
import pandas as pd

# read the dataset to a Pandas' dataframe
data = pd.read_csv("housing.csv")
data.head()
```

- **longitude**: computed distances among the centroids of each district as measured in longitude.
- **latitude**: computed distances among the centroids of each district as measured in latitude.
- **housing_median_age**: median age of district housing at location
- **total_rooms**: total rooms in the district
- **total_bedrooms**: total bedrooms in the district
- **population**: total population in the district
- **households**: total households in the district
- **median_income**: median income of households in the district
- **median_house_value**: median value of housing in the district
- **ocean_proximity**: distance to the ocean

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

#2. Get the data

```
data.info()
```

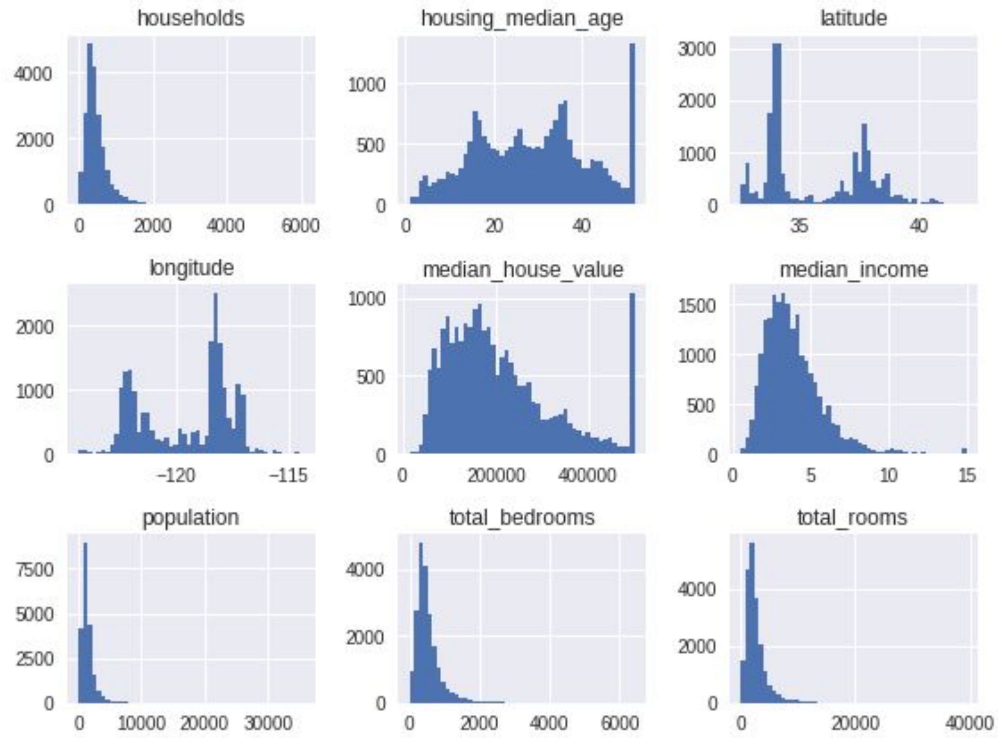
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

```
# You can find out what categories exist and
# how many districts belong to each category
# by using the value_counts()

data.ocean_proximity.value_counts()
```

```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

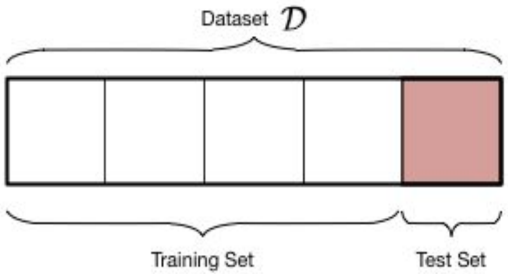
Histogram as an EDA tool




```python
import matplotlib.pyplot as plt
data.hist(bins=50, figsize=(8,6))
plt.tight_layout()
plt.show()
```

1. The median income attribute does not look like it is expressed in US dollars (USD)
2. The housing median age and the median house value were also capped
3. Different scales
4. Many histograms are tail heavy

Create a Train and Test sets



Train and Tune your models

Don't touch this until the very end

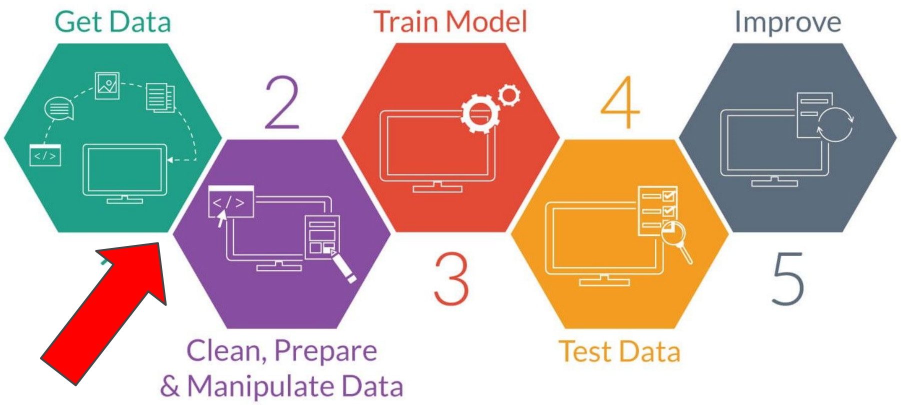
```python
from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(data,
                                       test_size=0.2,
                                       random_state=35)

print("data has {} atributes\n {} train instances\n {} test intances".
      format(len(data),len(train_set),len(test_set)))
```

```
data has 20640 atributes
 16512 train instances
 4128 test intances
```

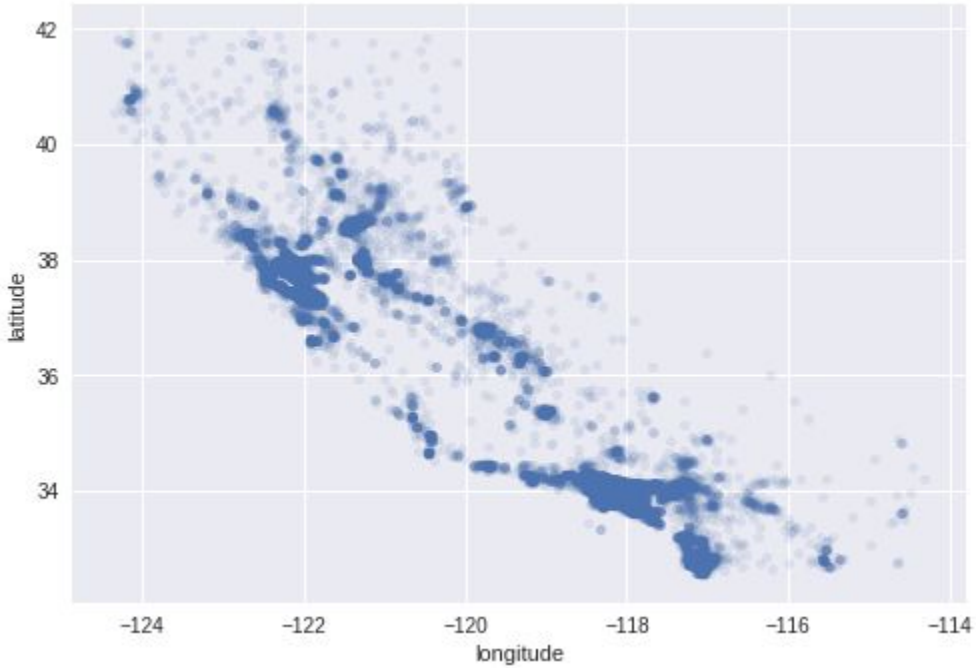
End-to-end ML Project



1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data. to gain insights.
4. Prepare the data for Machine. Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.

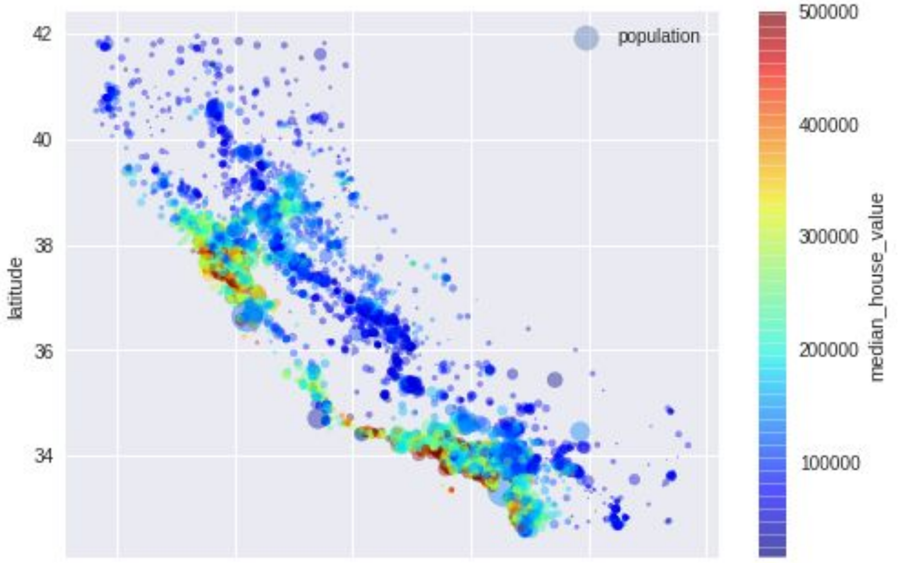
#3 Discovery and visualize the Data to Gain Insight

```
train.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

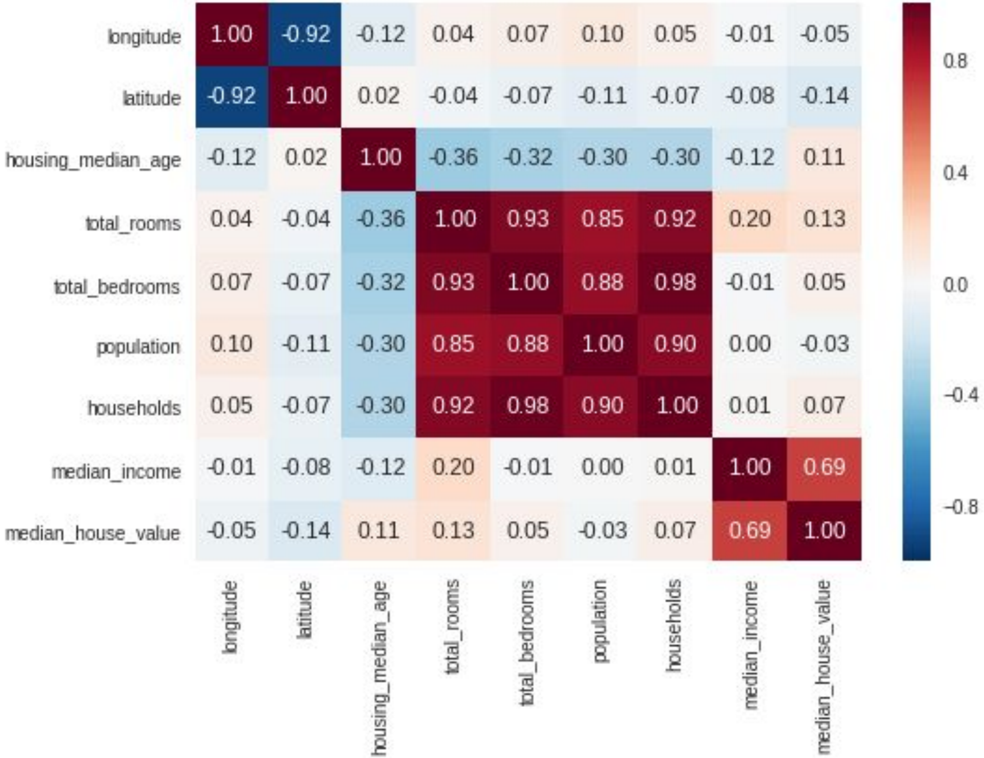


Visualizing geographical data (plus)

```
train.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
           s=train["population"]/100, label="population",
           c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True)
plt.legend()
```



Looking for correlations




```python
import seaborn as sns
sns.heatmap(train.corr(),
                annot=True, fmt=".2f")
```

```python
corr_matrix = train.corr()
corr_matrix["median_house_value"].\
  sort_values(ascending=False)
```

```
median_house_value          1.000000
median_income               0.687109
rooms_per_household         0.145460
total_rooms                 0.132943
housing_median_age          0.106175
households                  0.066714
total_bedrooms              0.051019
population                 -0.026685
population_per_household   -0.027255
longitude                  -0.047650
latitude                   -0.142797
bedrooms_per_room          -0.249959
Name: median_house_value, dtype: float64
```

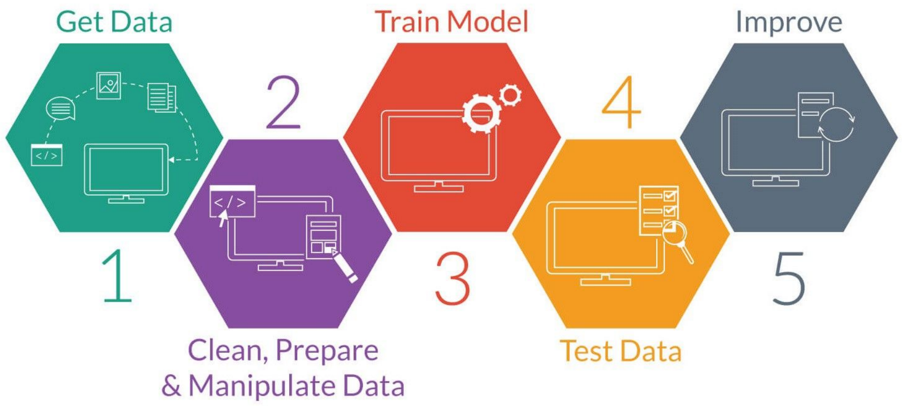
Experimenting with attributes combinations

```python
# attribute combinations
train["rooms_per_household"] = train["total_rooms"]/train["households"]
train["bedrooms_per_room"] = train["total_bedrooms"]/train["total_rooms"]
train["population_per_household"]=train["population"]/train["households"]
```

```python
train_correlation_matrix = train.corr()
train_correlation_matrix["median_house_value"].sort_values(ascending=False)
```

```
median_house_value          1.000000
median_income               0.687109
rooms_per_household         0.145460
total_rooms                 0.132943
housing_median_age          0.106175
households                  0.066714
total_bedrooms              0.051019
population                 -0.026685
population_per_household   -0.027255
longitude                  -0.047650
latitude                   -0.142797
bedrooms_per_room          -0.249959
Name: median_house_value, dtype: float64
```

End-to-end ML Project



1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data to gain insights.
4. Prepare the data for Machine. Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.

#4 Prepare the data for ML Algorithms

```python
# drop creates a copy of the remain data and does not affect train_set
train_X = train_set.drop("median_house_value", axis=1)

# copy the label (y) from train_set
train_y = train_set.median_house_value.copy()
```

train_y

train_X

Categorical

Numerical

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

Data Cleaning

```
# count the number of missing values
train_X.isnull().sum()
```

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        166
population              0
households              0
median_income           0
ocean_proximity         0
dtype: int64
```

You have three options:

1. Get rid of the corresponding districts.
2. Get rid of the whole attribute.
3. Set the values to some value (zero, the mean, the median, etc.).

You can accomplish these easily using DataFrame's **dropna()**, **drop()**, and **fillna()** methods:

```
train_X.dropna(subset=["total_bedrooms"]) # option 1
train_X.drop("total_bedrooms", axis=1) # option 2
median = train_X["total_bedrooms"].median()
train_X["total_bedrooms"].fillna(median) # option 3
```

Handling with missing values

Step #1 - Fit

```
# First, you need to create an Imputer instance, specifying that you want
# to replace each attribute's missing values with the median of that attribute:
from sklearn.preprocessing import Imputer
imputer = Imputer(strategy="median")

# Since the median can only be computed on numerical attributes, we need to
# create a copy of the data without the text attribute ocean_proximity:
train_X_num = train_X.drop("ocean_proximity", axis=1)

# Now you can fit the imputer instance to the training data using
# the fit() method:
imputer.fit(train_X_num)
```

#2 - Transforme

```
# Now you can use this "trained" imputer to transform the training set by
# replacing missing values by the learned medians:
train_X_num_array = imputer.transform(train_X_num)
```

Handling with missing values

Before

```
# count the number of missing values
train_X.isnull().sum()
```

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        166
population              0
households              0
median_income           0
ocean_proximity         0
dtype: int64
```

After

```
train_X_num_df.isnull().sum()
```

```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
dtype: int64
```

Handling Text and Categorical Attributes

```
train_X.ocean_proximity.head(10)
```

```
1380        NEAR BAY
12294         INLAND
7387       <1H OCEAN
14454     NEAR OCEAN
2927          INLAND
12462         INLAND
19813         INLAND
11229      <1H OCEAN
16696      <1H OCEAN
13564         INLAND
Name: ocean_proximity, dtype: object
```

```
# For this, we can use Pandas' factorize() method which maps each
# category to a different integer:

train_X_cat_encoded, train_X_categories = train_X.ocean_proximity.factorize()

# train_X_cat_encoded is now purely numerical
train_X_cat_encoded[0:10]
```

```
array([0, 1, 2, 3, 1, 1, 1, 2, 2, 1])
```

One issue with this representation is that ML algorithms will assume higher the categorical value, better the category. “Wait, What!?”.

Handling Text and Categorical Attributes

Solutions

```
train_X.ocean_proximity.head(10)
```

```
1380          NEAR BAY
12294           INLAND
7387         <1H OCEAN
14454       NEAR OCEAN
2927            INLAND
12462           INLAND
19813           INLAND
11229        <1H OCEAN
16696        <1H OCEAN
13564           INLAND
Name: ocean_proximity, dtype: object
```

maps each category to a different integer

```
array([0, 1, 2, 3, 1, 1, 1, 2, 2, 1])
```

Create a binary attribute per category

```
array([[1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

OneHotEnconder

Handling Text and Categorical Attributes

Solutions

```
# Scikit-Learn provides a OneHotEncoder encoder to convert
# integer categorical values into one-hot vectors.

from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder()

# Numpy's reshape() allows one dimension to be -1, which means "unspecified":
# the value is inferred from the lenght of the array and the remaining
# dimensions
train_X_cat_1hot = encoder.fit_transform(train_X_cat_encoded.reshape(-1,1))

# it is a column vector
train_X_cat_1hot
```

```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
	with 16512 stored elements in Compressed Sparse Row format>
```

```
Using a sparse matrix: 660592 bytes
Using a dense numpy array: 56 bytes
```

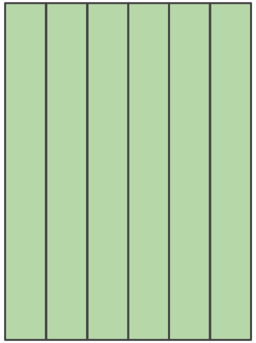
Custom Transformers

Although Scikit-Learn provides many useful transformers, **you will need to write your own for tasks such as custom cleanup operations or combining specific attributes**.

You will want your transformer to work seamlessly with Scikit-Learn functionalities. All you need is to create a class and implement three methods:

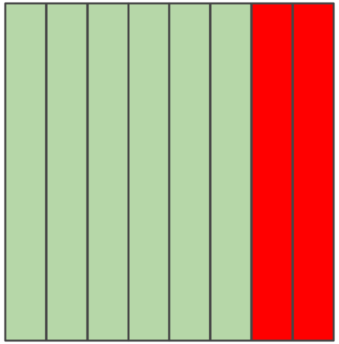
- fit()
- transform()
- fit_transform()

Train data

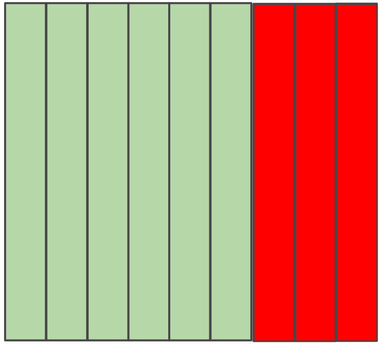


Custom Transformer for combine attribute

Train data



Train data



```python
import numpy as np

# these classes will be useful later for automatic hyperparameter tuning
from sklearn.base import BaseEstimator, TransformerMixin

# indices for the columns
rooms_ix, bedrooms_ix, population_ix, household_ix = 3, 4, 5, 6


class CombinedAttributesAdder(BaseEstimator, TransformerMixin):

  def __init__(self, add_bedrooms_per_room = True): # no *args or **kargs
    self.add_bedrooms_per_room = add_bedrooms_per_room

  def fit(self, X, y=None):
    return self # nothing else to do

  def transform(self, X, y=None):
    rooms_per_household = X[:, rooms_ix] / X[:, household_ix]
    population_per_household = X[:, population_ix] / X[:, household_ix]
    if self.add_bedrooms_per_room:
      bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
      # Translates slice objects to concatenation along the second axis.
      return np.c_[X, rooms_per_household,
                   population_per_household,
                   bedrooms_per_room]
    else:
      return np.c_[X, rooms_per_household, population_per_household]
```

```
attr_adder = CombinedAttributesAdder(add_bedrooms_per_room=False)
train_X_extra_attribs = attr_adder.transform(train_X.values)
```

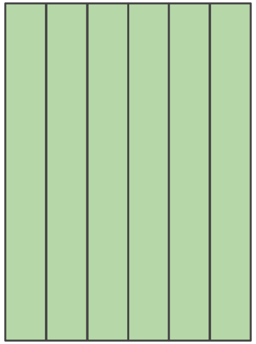
```
train_X.columns
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity'],
      dtype='object')
```

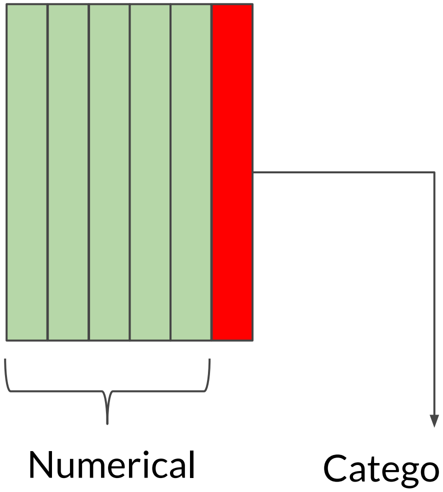
```
train_X_extra_attribs_df.columns
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity', 'rooms_per_household', 'population_per_household'],
      dtype='object')
```

Numerical Attributes

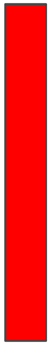


Train data



Custom Transformer for select attributes

Categorical Attribute



There is nothing in Scikit-Learn to handle Pandas DataFrames, but we can write a custom transformer for this task

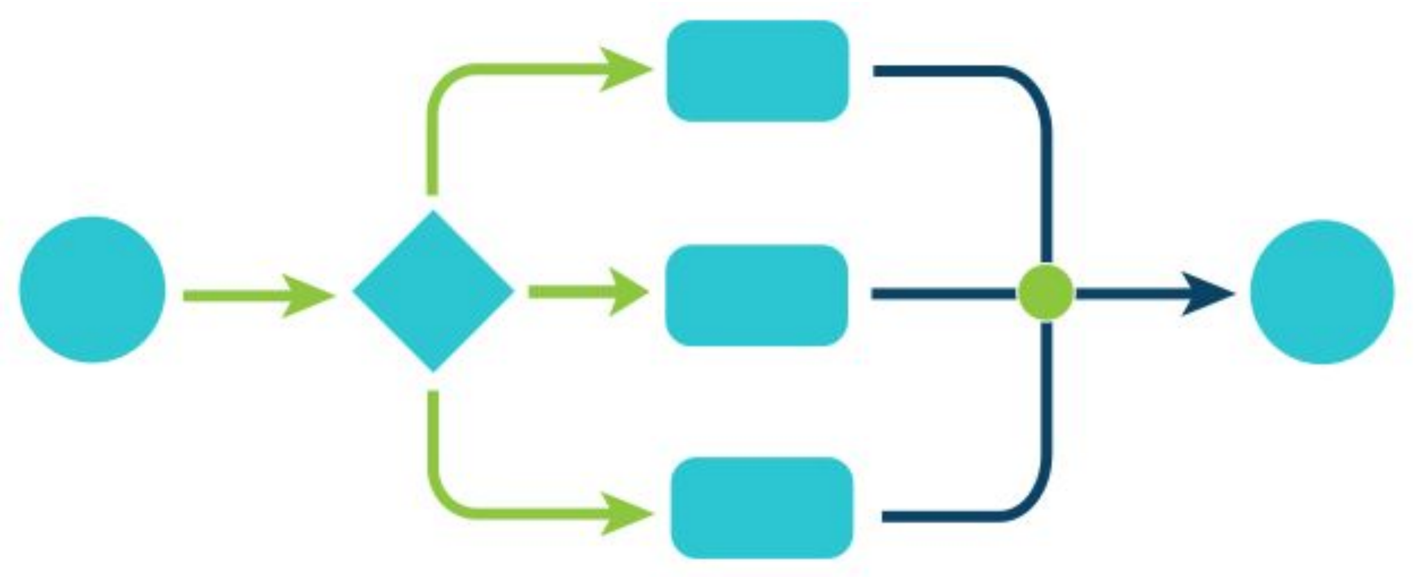
```
from sklearn.base import BaseEstimator, TransformerMixin

# This class will transform the data by selecting the desired attributes,
# dropping the rest, and converting the resulting DataFrame to a NumPy array.
class DataFrameSelector(BaseEstimator, TransformerMixin):
  def __init__(self, attribute_names):
    self.attribute_names = attribute_names

  def fit(self, X, y=None):
    return self

  def transform(self, X):
    return X[self.attribute_names].values
```

Transformation Pipelines



Transformation Pipelines

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler


num_pipeline = Pipeline([('imputer', Imputer(strategy="median")),
                         ('attribs_adder', CombinedAttributesAdder()),
                         ('std_scaler', StandardScaler())
                        ])
train_X_num_pipeline = num_pipeline.fit_transform(train_X_num)
```

```python
# Used to join two or more pipelines into a single pipeline
from sklearn.pipeline import FeatureUnion

# https://github.com/scikit-learn/scikit-learn/issues/10521
from future_encoders import OneHotEncoder

# numerical columns
num_attribs = list(train_X_num.columns)

# categorical columns
cat_attribs = ["ocean_proximity"]

# pipeline for numerical columns
num_pipeline = Pipeline([('selector', DataFrameSelector(num_attribs)),
                        ('imputer', Imputer(strategy="median")),
                        ('attribs_adder', CombinedAttributesAdder()),
                        ('std_scaler', StandardScaler())
                       ])

# pipeline for categorical column
cat_pipeline = Pipeline([('selector', DataFrameSelector(cat_attribs)),
                        ('cat_encoder', OneHotEncoder(sparse=False))
                       ])

# a full pipeline handling both numerical and categorical attributes
full_pipeline = FeatureUnion(transformer_list=[("num_pipeline", num_pipeline),
                                               ("cat_pipeline", cat_pipeline)
                                              ])
```

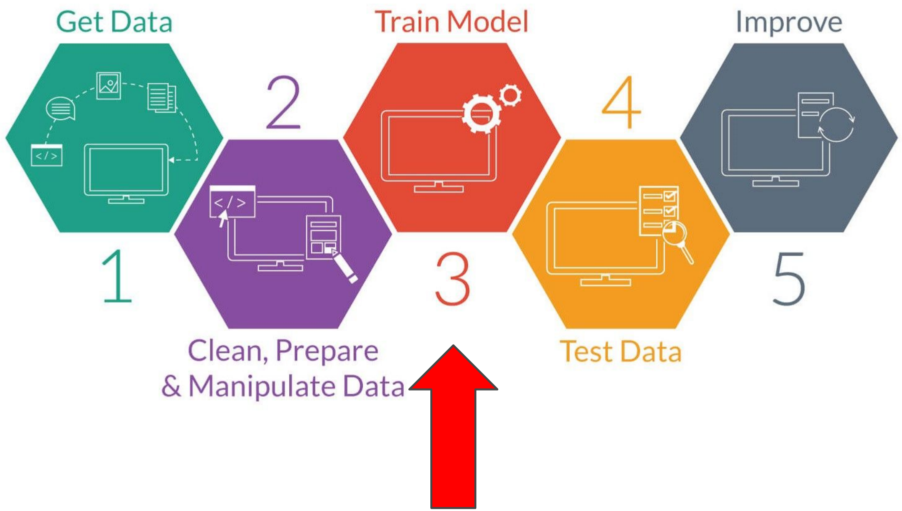
```
# you can run the whole pipeline simply
train_X_prepared = full_pipeline.fit_transform(train_X)
train_X_prepared
```

```
array([[-1.25390838,  1.10757958, -1.79230424, ...,  0.        ,
         1.        ,  0.        ],
       [ 1.31649014, -0.79863258, -1.2367069 , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.65894633, -0.77989831,  0.66819829, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [ 0.80340671, -0.54103634,  0.27134305, ...,  0.        ,
         0.        ,  0.        ],
       [-1.12937357,  0.78909696, -0.52236745, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.62407658, -0.67217624,  0.58882724, ...,  0.        ,
         0.        ,  0.        ]])
```

```
train_X_prepared.shape
```

```
(16512, 16)
```

End-to-end ML Project



1. Look at the big picture.
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Select a model and train it

```python
from sklearn.linear_model import LinearRegression

# create a LinearRegression model
lin_reg = LinearRegression()

# fit it
lin_reg.fit(train_X_prepared, train_y)
```

```python
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor()
tree_reg.fit(train_X_prepared, train_y)
```

```python
from sklearn.ensemble import RandomForestRegressor

# create a RandomForestRegressor model
forest_reg = RandomForestRegressor()

# fit it
forest_reg.fit(train_X_prepared, train_y)
```

Evaluate the training

Select data

```
# Done!! You now have a working Linear Regression Model.
# Let's try it out on a few instances from the trainning set.

# prepare the data
some_data = train_X.iloc[:5]
some_labels = train_y.iloc[:5]
some_data_prepared = full_pipeline.transform(some_data)

# make predictions
print("Predictions:", lin_reg.predict(some_data_prepared))
```

```
Predictions: [296903.77937561 117785.90822548 162198.49440035 256500.66710587
  58859.67211795]
```

```
# Compare against the actual values:
print("Labels:", list(some_labels))
```

```
Labels: [204200.0, 95600.0, 112000.0, 410000.0, 51600.0]
```

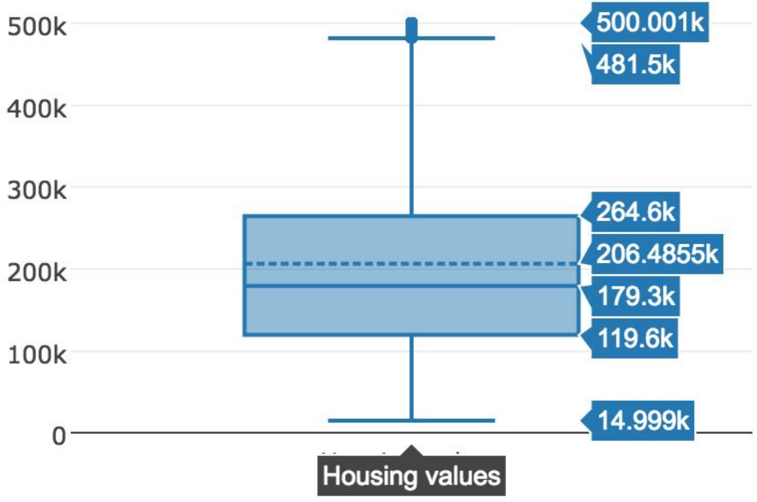
Using RMSE to evaluate your model

Linear Regression

```
from sklearn.metrics import mean_squared_error

housing_predictions = lin_reg.predict(train_X_prepared)
lin_mse = mean_squared_error(train_y, housing_predictions)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

```
68089.48048082175
```



Using RMSE to evaluate your model

Decision Tree Regressor

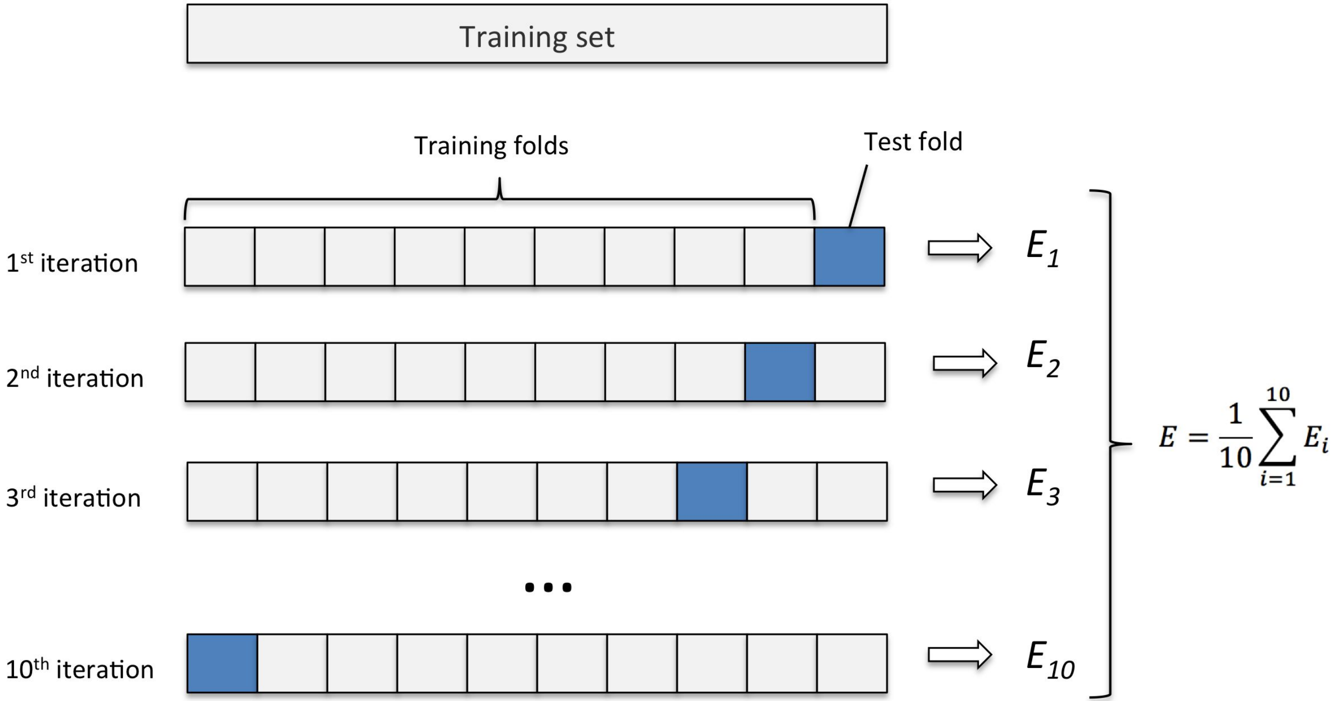
```
# now that the model is trained, let's evaluate it on the training set

housing_predictions = tree_reg.predict(some_data_prepared)
tree_mse = mean_squared_error(some_labels, housing_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

```
0.0
```

OVERFITTING

Better Evaluation using Cross-Validation



```
lin_reg = LinearRegression()

lin_scores = cross_val_score(lin_reg,
                             train_X_prepared,
                             train_y,
                             scoring="neg_mean_squared_error",
                             cv=10)
lin_rmse_scores = np.sqrt(-lin_scores)
```

```
forest_reg = RandomForestRegressor()

forest_scores = cross_val_score(forest_reg,
                                train_X_prepared,
                                train_y,
                                scoring="neg_mean_squared_error",
                                cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
```

```
tree_reg = DecisionTreeRegressor()

scores = cross_val_score(tree_reg,
                         train_X_prepared,
                         train_y,
                         scoring="neg_mean_squared_error",
                         cv=10)
rmse_scores = np.sqrt(-scores)
```

Linear Regressor

```
Scores: [70715.10105097 67073.39881848 70838.04099604 67554.17889268
 66899.49055729 65194.36521007 70433.39627599 71899.00507697
 65779.96671776 67532.51453746]
Mean: 68391.94581337104
Standard deviation: 2242.784819848661
```

Decision Tree Regressor

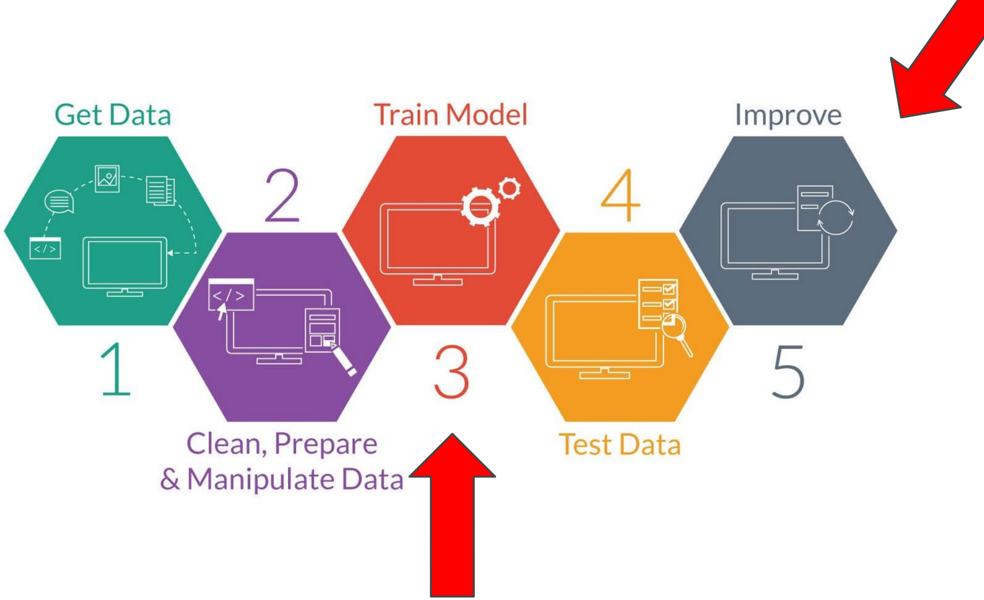
```
Scores: [71300.9897682  72182.25329239 71729.47336888 68647.09566751
 66740.35856553 66433.14534197 72121.22641768 68921.44236274
 69672.01490628 70304.96502729]
Mean: 69805.29647184593
Standard deviation: 2002.7061155158112
```

Random Forest Regressor

```
Scores: [52545.50217667 52216.87963698 54502.66476615 52140.38783264
 49866.0822568  52189.88358181 53031.70342465 54294.35976526
 50748.84852618 51886.28180741]
Mean: 52342.25937745378
Standard deviation: 1339.8770651999557
```

End-to-end ML Project

1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data to gain insights.
4. Prepare the data for Machine Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.



Grid Search with Cross Validation

```
from sklearn.model_selection import GridSearchCV

# hyperparameters values
# param_grid[0] - 12 combinations
# param_grid[1] - 6 combinations
param_grid = [{'n_estimators': [3, 10, 30],
               'max_features': [2, 4, 6, 8]
              },
              {'bootstrap': [False],
               'n_estimators': [3, 10],
               'max_features': [2, 3, 4]
              }
             ]

# create a randomforeestregressor model
forest_reg = RandomForestRegressor()

# run the grid search with cross validation
# (12 + 6) x 5 = 90 combinations
grid_search = GridSearchCV(forest_reg,
                           param_grid,
                           cv=5,
                           scoring='neg_mean_squared_error')

# see 90 combinations!!!
# it may take quite a long time
grid_search.fit(train_X_prepared, train_y)
```

Best combination of parameters

```
# when gridsearch is done you can get the best combination of parameters
grid_search.best_params_
```

```
{'max_features': 6, 'n_estimators': 30}
```

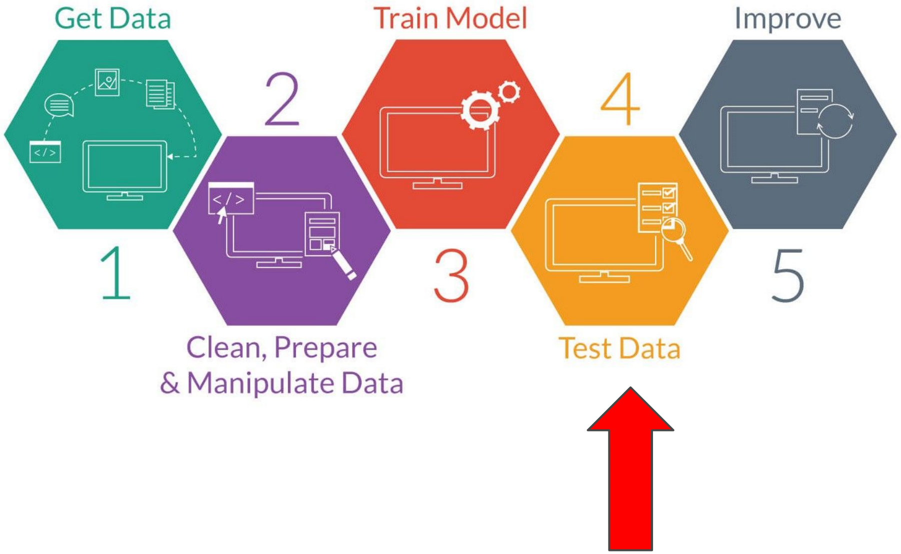
```
64252.163256566375 {'max_features': 2, 'n_estimators': 3}
55086.57916703393 {'max_features': 2, 'n_estimators': 10}
52260.28249700651 {'max_features': 2, 'n_estimators': 30}
59511.89329239456 {'max_features': 4, 'n_estimators': 3}
52226.15721344689 {'max_features': 4, 'n_estimators': 10}
49896.473307367676 {'max_features': 4, 'n_estimators': 30}
58786.81347625304 {'max_features': 6, 'n_estimators': 3}
51740.43037878579 {'max_features': 6, 'n_estimators': 10}
49404.62639980429 {'max_features': 6, 'n_estimators': 30}
58704.30259452863 {'max_features': 8, 'n_estimators': 3}
51854.336241117635 {'max_features': 8, 'n_estimators': 10}
49667.66166853269 {'max_features': 8, 'n_estimators': 30}
61834.61250169976 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54011.37659626647 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59803.93142565374 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52357.09768508134 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57407.46795177193 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51393.59047933123 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

Understanding the importance of features

```
# can indicate the relative importance of each attribute
# for making accurate predictions
feature_importances = grid_search.best_estimator_.feature_importances_
```

```
[(0.2932240517215898, 'median_income'),
 (0.16849927912474488, 'INLAND'),
 (0.1129734422811391, 'pop_per_hhold'),
 (0.08350531964855805, 'bedrooms_per_room'),
 (0.0729308899867341, 'longitude'),
 (0.07283949940912572, 'rooms_per_hhold'),
 (0.0688202085531236l, 'latitude'),
 (0.04330022841532853, 'housing_median_age'),
 (0.018220886556910475, 'population'),
 (0.017270129640924746, 'total_rooms'),
 (0.016563758506314884, 'total_bedrooms'),
 (0.0160184070566077 9, 'households'),
 (0.008515031117812108, '<1H OCEAN'),
 (0.004777746659219996, 'NEAR OCEAN'),
 (0.0024000797226816526, 'NEAR BAY'),
 (0.00014104159918470 45, 'ISLAND')]
```

End-to-end ML Project



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Evaluate the final model on the Test Set

```
# best model found in gridsearch step
final_model = grid_search.best_estimator_

# predictors and label
test_X = test_set.drop("median_house_value", axis=1)
test_y = test_set["median_house_value"].copy()

# prepared test's predictors
test_X_prepared = full_pipeline.transform(test_X)


final_predictions = final_model.predict(test_X_prepared)
final_mse = mean_squared_error(test_y, final_predictions)
final_rmse = np.sqrt(final_mse)
print(final_rmse)
```

```
49964.127058988925
```

Week Assignments

1. Lessons 3, 4 and 5
    a. https://github.com/ivanovitchm/EEC2006
2. Choose a regression problem and try to reproduce the same steps as described earlier.
    a. https://github.com/ShuaiW/kaggle-regression
    b. https://www.kaggle.com/rtatman/datasets-for-regression-analysis
3. Read Chapter #1
    a. https://www.manning.com/books/deep-learning-with-python