Predictive Analytics: Application of Machine Learning

Lecture 1

Instructor : Pramod Gupta aka PG

What to expect

- About the course
  - About me, About you, your expectations
  - How this course has been put together
  - Rubric
- This course is not a regular course with a regular textbook. This is a course:
  - To familiarize you with the developing field of predictive analytics and machine learning
  - To equip you with useful knowledge and methods
  - To inspire your research interests
  - To connect your knowledge to real world problems
- This course is a fun class to enjoy

About me

- HELLO
  - My name is Pramod Gupta
- PhD in Electrical and Computer Engineering, from McMaster University, Canada
- Academics and corporate sector
- Independent data consultant

Philosophy

- Sharing what I’ve Learned
- Goal: “ Learning to self-Learn
- It can sometimes take time (hours, days) to figure out how to do something
- I would like this class to be as open and interactive
- Don’t be shy or hesitant
- Knowledge flow is bi-direction.
- Ideas are important than age. Just because someone is junior does not mean they don’t deserve respect and cooperation

We’re all exploring and figuring out. Just share what you’ve learned.

Your Turn

Quick Introductions

Name, Profession

Experience in data mining and modeling do you have?

Which analytics/ML tools have you used/familiar

What are your expectation and motivation from this course?

What are the areas where you would like to apply and analyze

Course Logistics

Who is this course for?

- Anyone who is interested in:
  - Helping companies make decisions aided by data
  - Refreshing some theory learned in school, but with a practical focus
  - Getting up to speed with new Open Source tools and libraries
  - Curious about the new technology
- What is missing:
  - Lack of real-world analysis experiment, outside of work domain
  - Balance between theory and practice
  - Toolkit with which to explore

Goals and objectives

- The overall goal of this class is to introduce you to the discipline of predictive analytics, a science of understanding and analyzing data and machine learning algorithms for various tasks such *as prediction, classification, regression, clustering* etc. This class is designed to provide you with the tools you need for solving real world problems using statistics and machine learning algorithms.
- *How to achieve above goal:* We plan to achieve these goals by introducing you to the relevant statistical knowledge, how to use statistical software R to perform these tasks and engage in solving problems, analysis through homework, discussion, class participation and project.

Cont'd

- At the end of the course:
  - Feel inspired to work on and learn more about Machine Learning
  - Understand how various machine learning algorithms work
  - Look at a real-world problem and see if machine learning is appropriate for the given problem at hand.
  - If so, identify what type of algorithm might be applicable
  - Implement them and hopefully their variants and improvements on your own

Course Structure

- The course has two parts
  - Lectures
  - Assignments and project (done in groups)
- Lecture slides will be available on the course web page

Homework and exams

- 3-4 homework assignments due in class
  - Permission for late submission should be obtained in advance
  - Throughout the course, you are encouraged to discuss issues in class including homework problems with your peers or me (but everyone should submit his/her own work and no cheating)
- No midterm; no final exam

Cont'd

- **Aim**: Turning machine learning techniques you learn in class to become your strength in dealing with real world problems

- The project involves analysis of the data, implementation of ML algorithm, preparation of a report and presentation of the results during the last week of the class. The project will be done in groups of 2~3 students. If you already working on a research project in the area of interest you are encouraged to use dataset/topic from your research provided you make some extra effort for the class.

- Detailed instructions for the project will be posted later

Grading

- Grading
  - Homework 40%
  - Project 60%

- Work Load
  - You are expected to put in 8-10 hrs. of work outside of class. A few of you will do well with less time than this, and a few of you will need more.

Course description

- Will introduce
  - Basic concepts of predictive analytics
  - Basic of various machine learning algorithms
  - Implementation of algorithms using R or Python and
  - How to use and write your own code
- Hands-on experience
- Report and presentation for final project

Textbooks

- Machine Learning, Tom M. Mitchell
- Pattern Recognition and Machine Learning, Christopher .M. Bishop
- Data Mining: Practical Machine Learning Tools and Techniques
- An Introduction to Statistical Learning with Applications in R, R.G. James, D.Witten, T. Hastie and R. Tibshiarni
- Machine Learning in Action, Peter Harrington
- Machine Learning with R , Brett Lantz

Topics to cover

- Introduction
- Data pre-processing
- Classification (supervised learning)
- Forecasting: regression methods
- Clustering (unsupervised learning)
- Evaluating and improving model performance
- Overfitting and regularization
- Applying machine learning: guidance and practical issues
- Dimensionality Reduction

Predictive Analytics

Motivation

- Lots of data is being collected and warehoused
  - Web data, social networking, e-commerce
  - Bank/credit card transactions
- Computers have become cheaper and more powerful
- Competitive Pressure is strong
- Data collected and stored at enormous speed (GB/hour)
- Traditional techniques infeasible for raw data
- There is often information “hidden” in the data that is not readily evident
- Human analysts may take weeks to discover useful information
- Much of the data is never analyzed at all.
  - Web data, social networking, e-commerce
  - Bank/credit card transactions

Disruptive companies differentiated by

INTELLIGENT APPLICATIONS

using

Machine Learning

amazon
Retail

Google
PageRank
Search

livingsocial
Coupons

NETFLIX
Movie Distribution

LinkedIn
Networking

PANDORA
Music

Obama'08
Campaigning

Google
Adsense
Advertising

Zillow
Real Estate

glassdoor
Human Resources

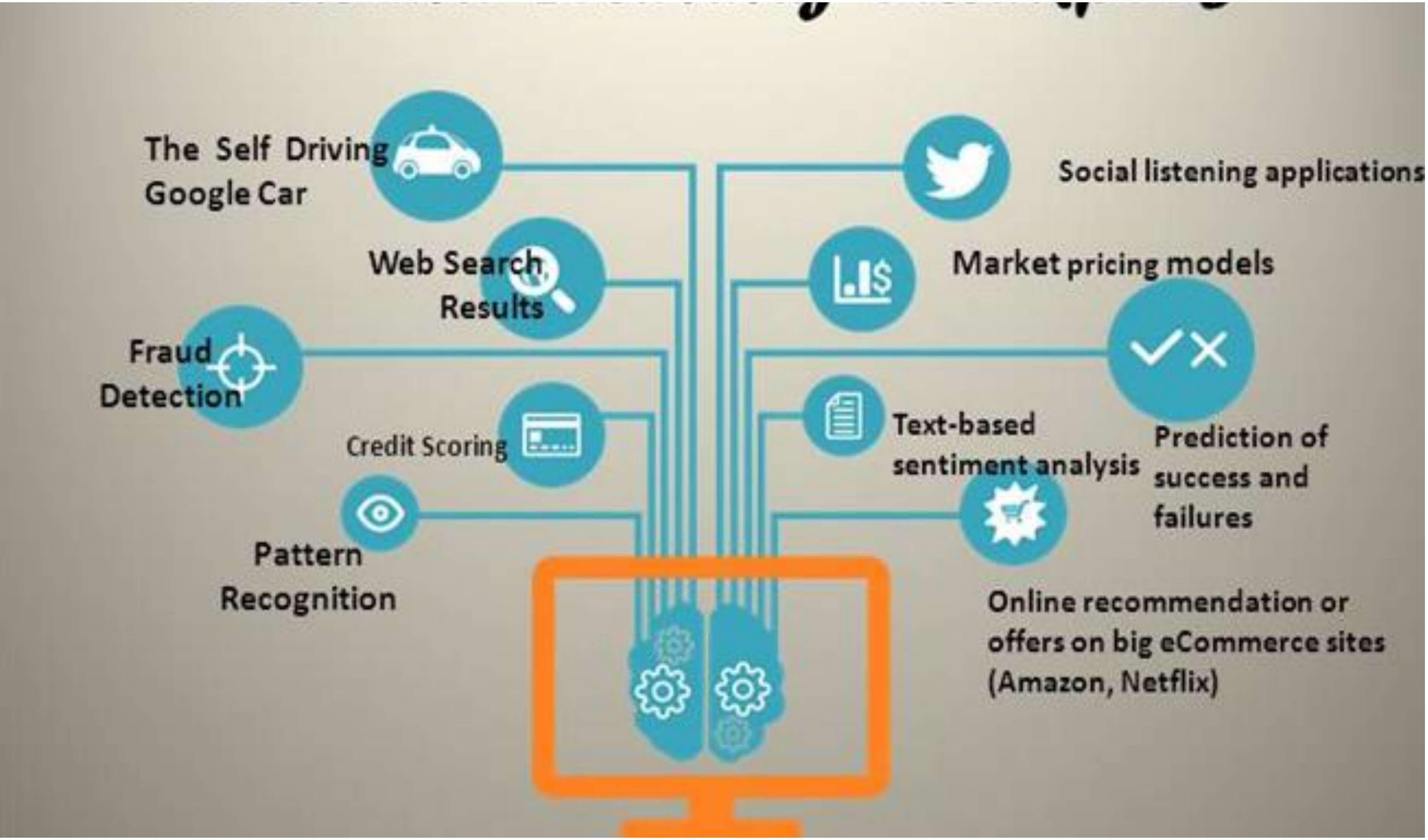
Avvo
Legal Advice

eHarmony
Dating

fitbit
Wearables

UBER
Taxis

RelateIQ
CRM

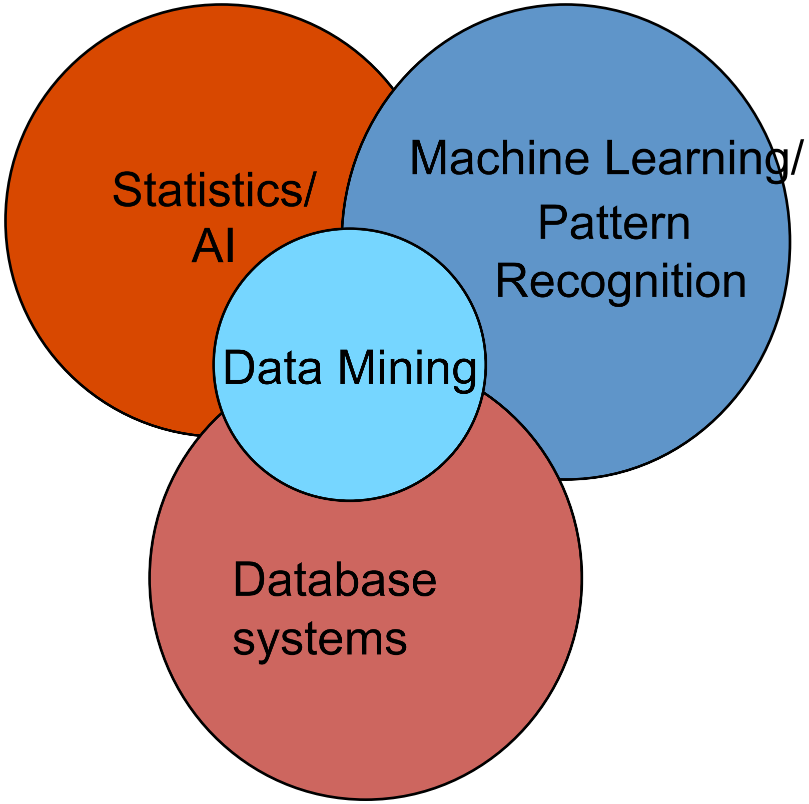

The Self Driving Google Car
Web Search Results
Fraud Detection
Credit Scoring
Pattern Recognition
Social listening applications
Market pricing models
Text-based sentiment analysis
Prediction of success and failures
Online recommendation or offers on big eCommerce sites (Amazon, Netflix)

- **What is Predictive Analytics**
  - Predictive analytics is an area of statistical analysis that deals with extracting information from data and uses it to predict future values and behavior patterns (Wikipedia)
  - The core predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting it to predict future outcomes.

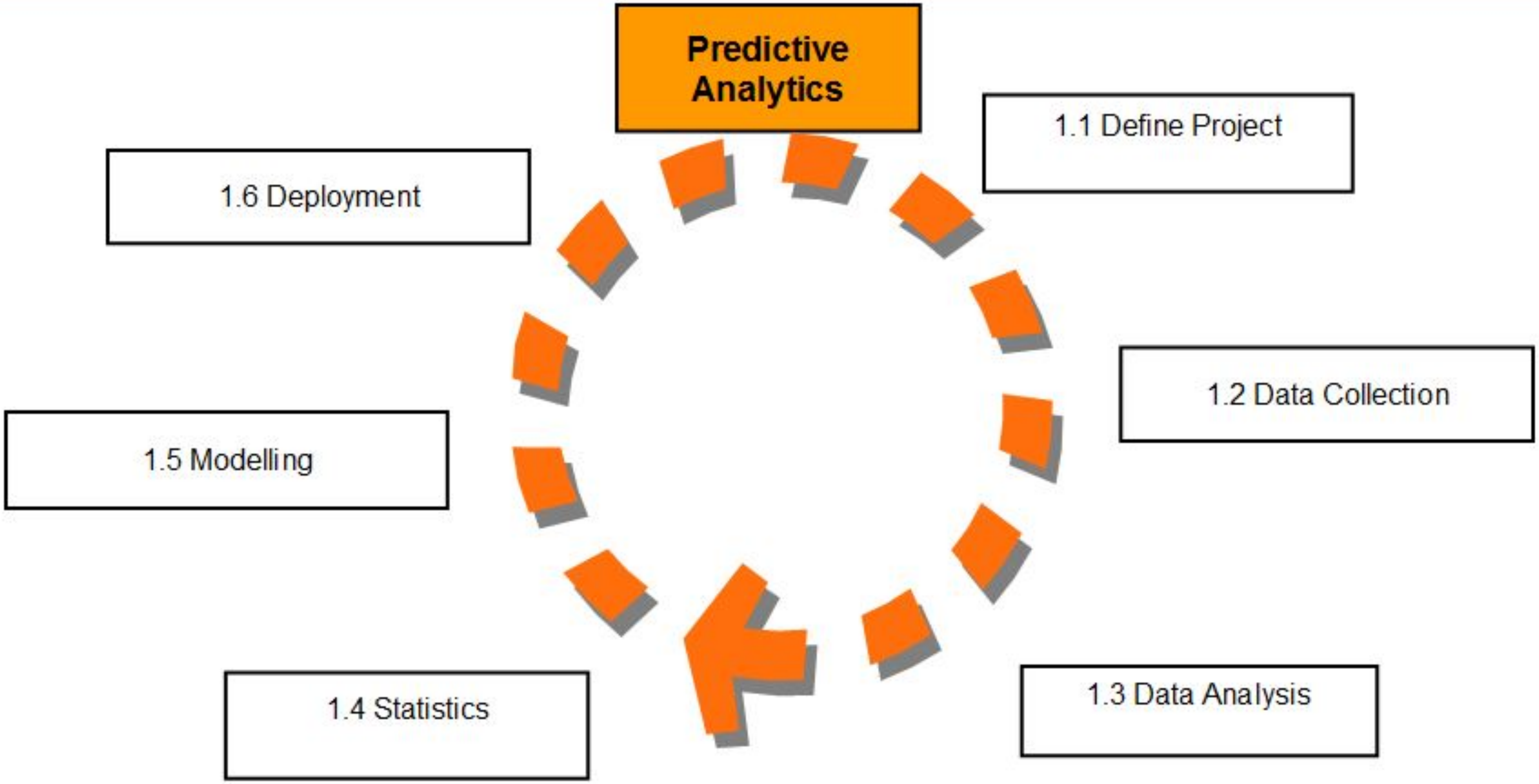
- **Other Definitions**
  - Predictive Analytics is emerging as a game-changer. Instead of looking backward to analyze " what happened?" predictive analytics help executives answer "what's next?" and "what should we do about it?" (Forbes Magazine, April 1, 2010)
  - Predictive analytics is the branch of data mining concerned with the prediction of future probabilities and trends (searchcrm.com)

Origins of predictive analytics

- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems
- Traditional Techniques may be unsuitable due to
  - Enormity of data
  - High dimensionality of data
  - Heterogeneous, distributed nature of data



What do predictive modelers do?



Predictive Analytics

1.1 Define Project

1.2 Data Collection

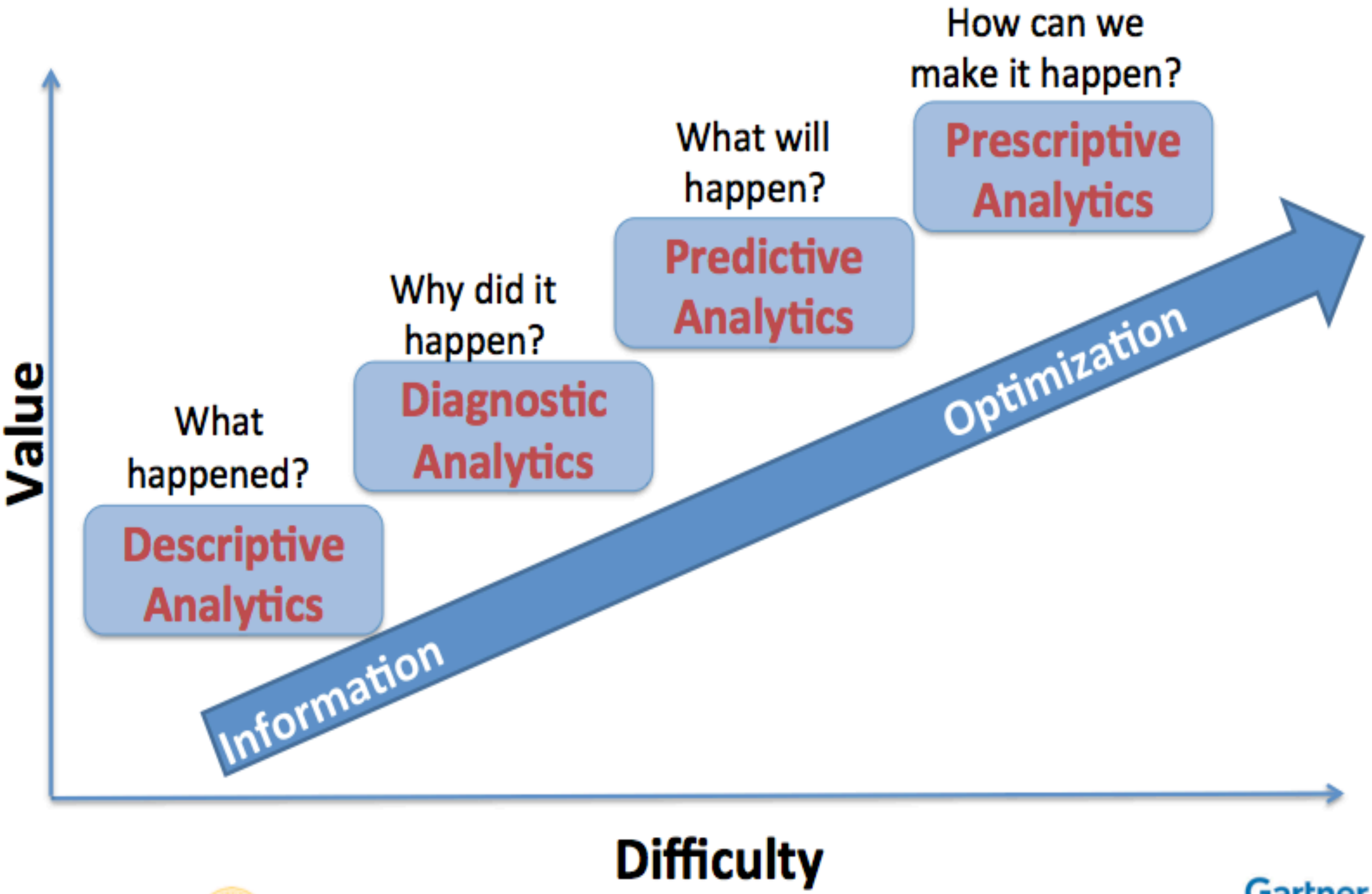
1.3 Data Analysis

1.4 Statistics

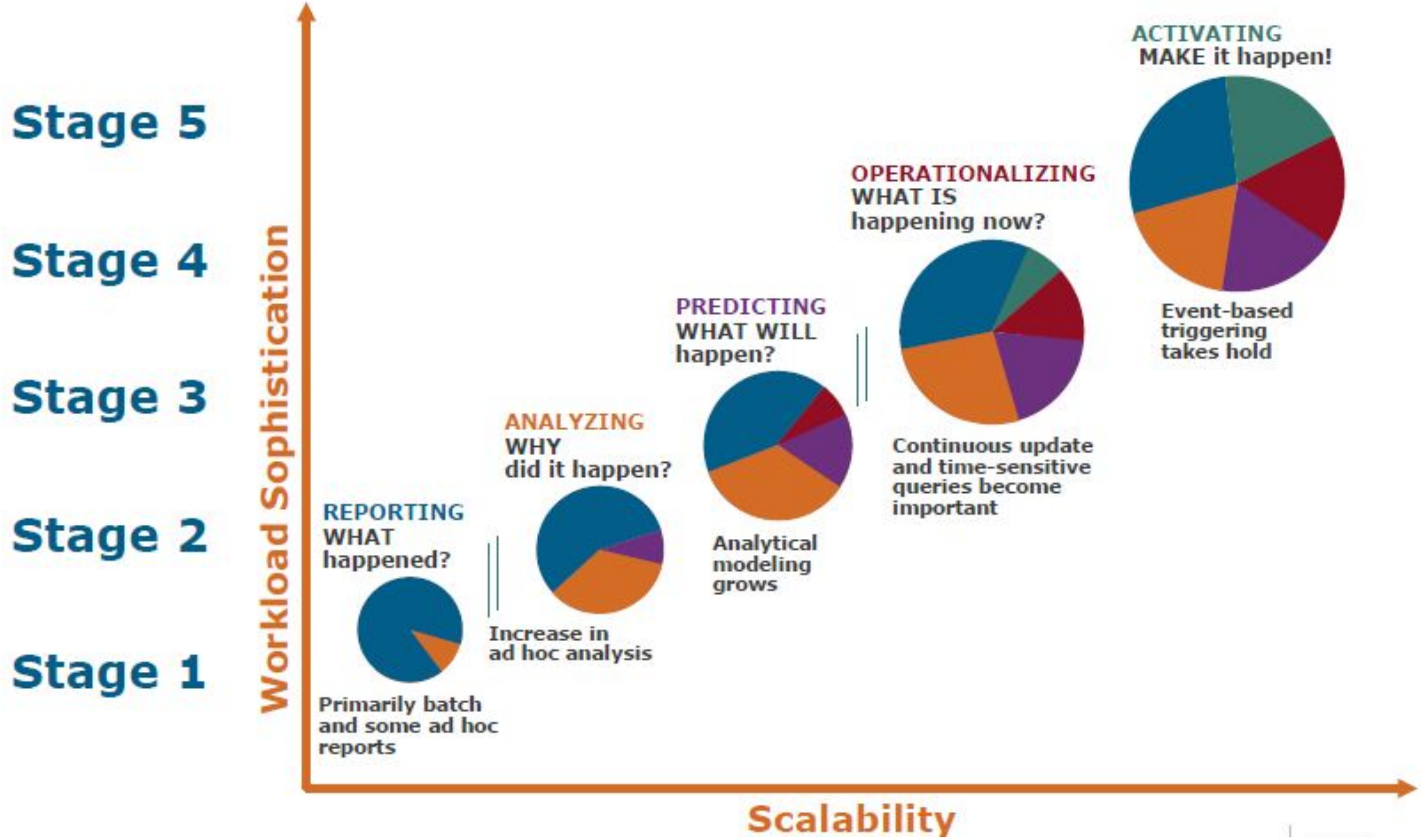
1.5 Modelling

1.6 Deployment

Analytics Capabilities Framework



Analytics Capabilities Framework



Quick Question?

- How many people have heard about machine learning
- How many people know about machine learning
- How many people are using machine learning

What is Machine Learning

- It is very hard to write programs that solve problems like recognizing a face.
  - We don’t know what program to write because we don’t know how our brain does it.
  - Even if we had a good idea about how to do it, the program might be horrendously complicated.
- Instead of writing a program by hand, we collect lots of examples that specify the correct output for a given input.

What is Machine Learning

- A machine learning algorithm then takes these examples and produces a program that does the job.
    - The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
    - If we do it right, the program works for new cases as well as the ones we trained it on.

What is Machine Learning

- Machine Learning
  - □Study of algorithms that
  - □improve their performance
  - □at some task
  - □with experience

- Optimize a performance criterion using example data or past experience.

- Role of Statistics: Inference from a sample

- Role of Computer science: Efficient algorithms to
  - □Solve the optimization problem
  - □Representing and evaluating the model for inference

What is Machine Learning

- Machine Learning:
  - Designing algorithms that can learn patterns from historical data, in other words, ML is the field of development of computer algorithms for transforming data into intelligent action
  - Approach: human supplies training examples, the machine learn
  - Example: Show the machine with the data having two classes (C1 and C2) and let it learn to predict if the new data belong to C1 or C2.
- Machine Learning primarily uses the statistically based approach.
  - The statistical model helps to uncover the process which generated the data
- Most desirable property is the *generalization*, i.e., model should generalize well on the new/unseen data

Generalization

- The real aim of supervised learning is to do well on test data that is not known during learning.
- Choosing the values for the parameters that minimize the loss function on the training data is not necessarily the best policy.
- We want the learning machine to model the true regularities in the data and to ignore the noise in the data.
  - But the learning machine does not know which regularities are real and which are accidental quirks of the particular set of training examples we happen to pick.
- So how can we be sure that the machine will generalize correctly to new data?

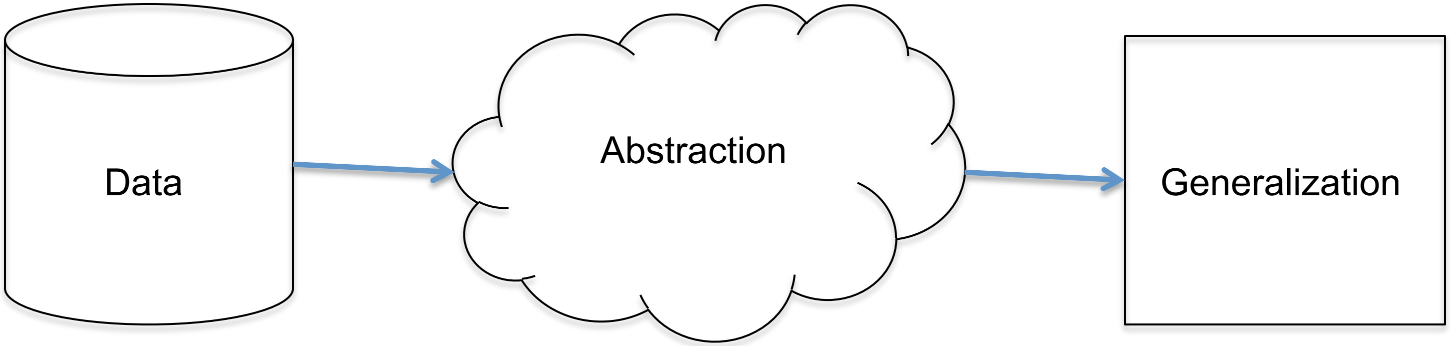
Classical Tasks for ML

- Classification:
  - Mining patterns that can classify future (new) data into known classes
- Clustering/grouping:
  - Identify a set of similar groups in the data
- Prediction/Regression
  - Predict the future value/behavior based on the past history
- Association rule mining:
  - Mining any rule of the form X → Y, where X and Y are sets of data items, e.g., apple, orange -> fruits
- Anomaly detection:
  - Discover the outliers/most significant changes in data

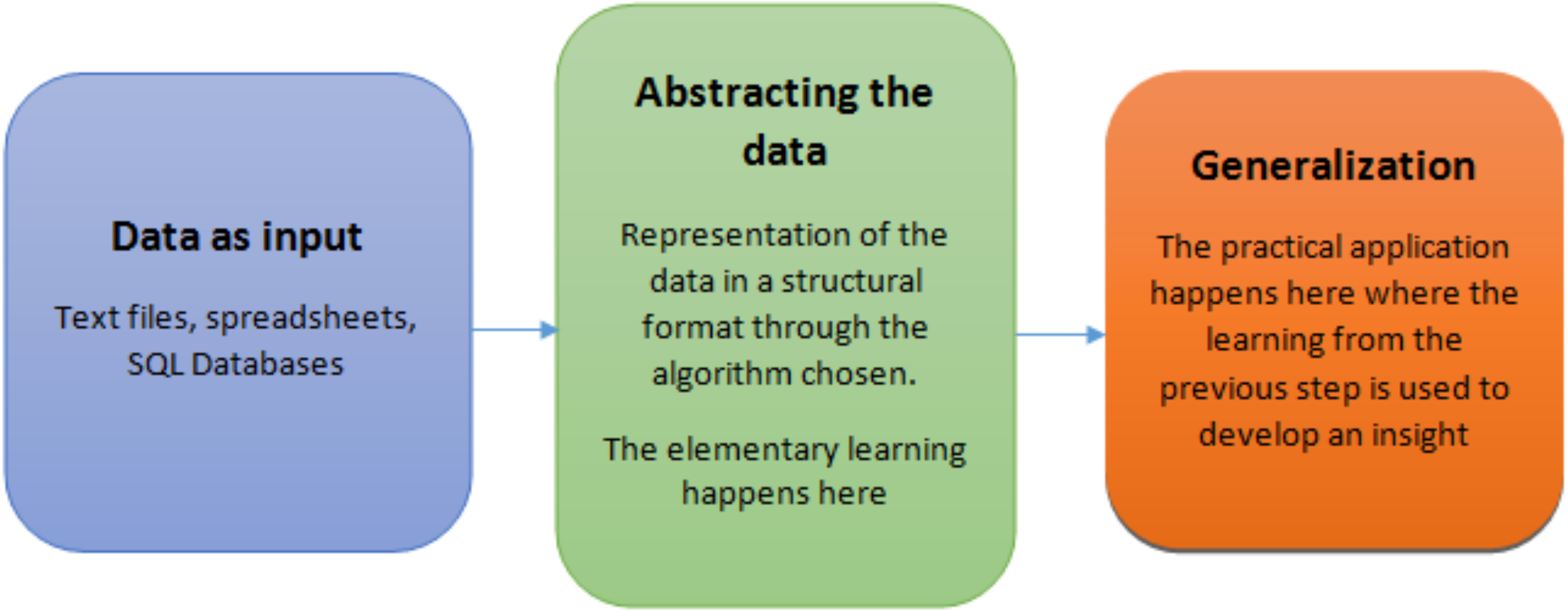
How do machines learn?

- A commonly cited formal definition of machine learning, proposed by computer scientist *Tom M. Mitchell*, says that a machine is said to learn if it is able to take experience and utilize it such that its performance improves up on similar experiences in the future. His definition is fairly exact, yet says little about how machine learning techniques actually learn to transform data into actionable knowledge.
- Regardless of whether the learner is a human or a machine, the basic learning process is similar. It can be divided into three components as follows:
  - **Data input**: It utilizes observation, memory storage, and recall to provide a factual basis for further reasoning.
  - **Abstraction**: It involves the translation of data into broader representations.
  - **Generalization**: It uses abstracted data to form a basis for action.

How do machines learn?



How do machines learn?



Data as input

Text files, spreadsheets, SQL Databases

Abstracting the data

Representation of the data in a structural format through the algorithm chosen.

The elementary learning happens here

Generalization

The practical application happens here where the learning from the previous step is used to develop an insight

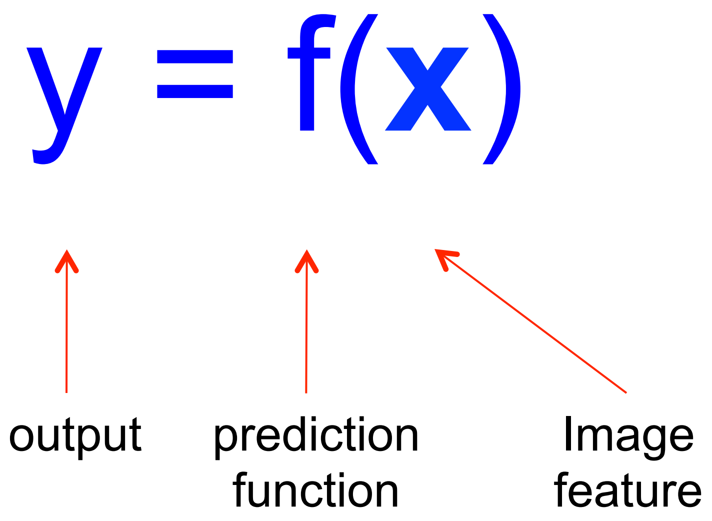
What We Talk About When We Talk About “Learning”

- Learning general models from a data of particular examples
- Data is cheap and abundant (data warehouses, data marts); knowledge is expensive and scarce.
- Example in retail: Customer transactions to consumer behavior:

  People who bought “Milk” also bought “Bread”

- Build a model that is *a good and useful approximation* to the data.

The machine learning framework



$$y = f(\mathbf{x})$$

output

prediction function

Image feature

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

Slide credit: L. Lazebnik

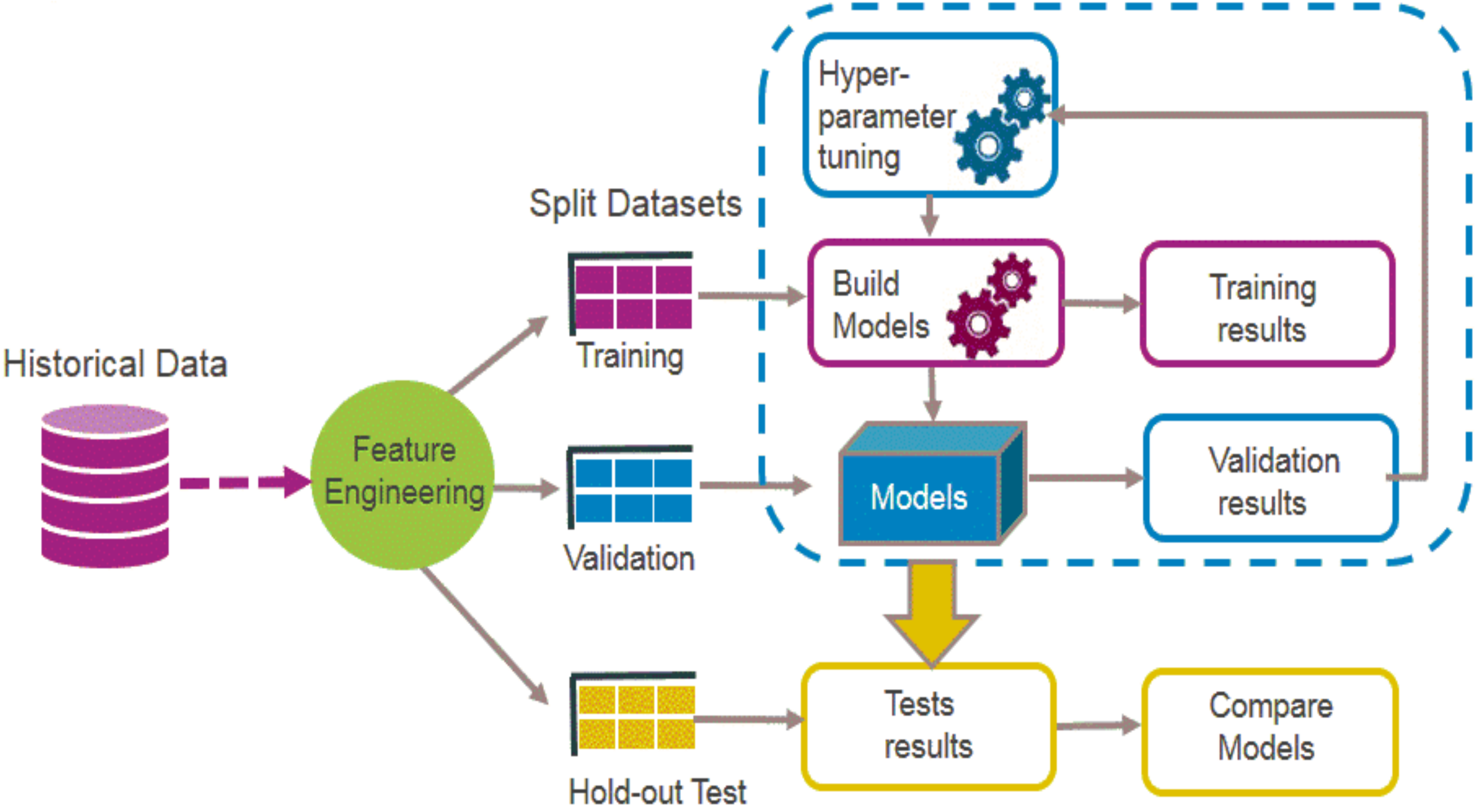
Steps to apply Machine Learning

- **Training a model on the data**: By the time the data has been prepared for analysis, you are likely to have a sense of what you are hoping to learn from the data. The specific machine learning task will inform the selection of an appropriate algorithm, and the algorithm will represent the data in the form of a model.
- **Evaluating model performance**: Because each machine learning model results in a biased solution to the learning problem, it is important to evaluate how well the algorithm learned from its experience. Depending on the type of model used, you might be able to evaluate the accuracy of the model using a test dataset, or you may need to develop measures of performance specific to the intended application.
- **Improving model performance**: If better performance is needed, it becomes necessary to utilize more advanced strategies to augment the performance of the model. Sometimes, it may be necessary to switch to a different type of model altogether. You may need to supplement your data with additional data, or perform additional preparatory work as in step two of this process.

Steps to apply Machine Learning

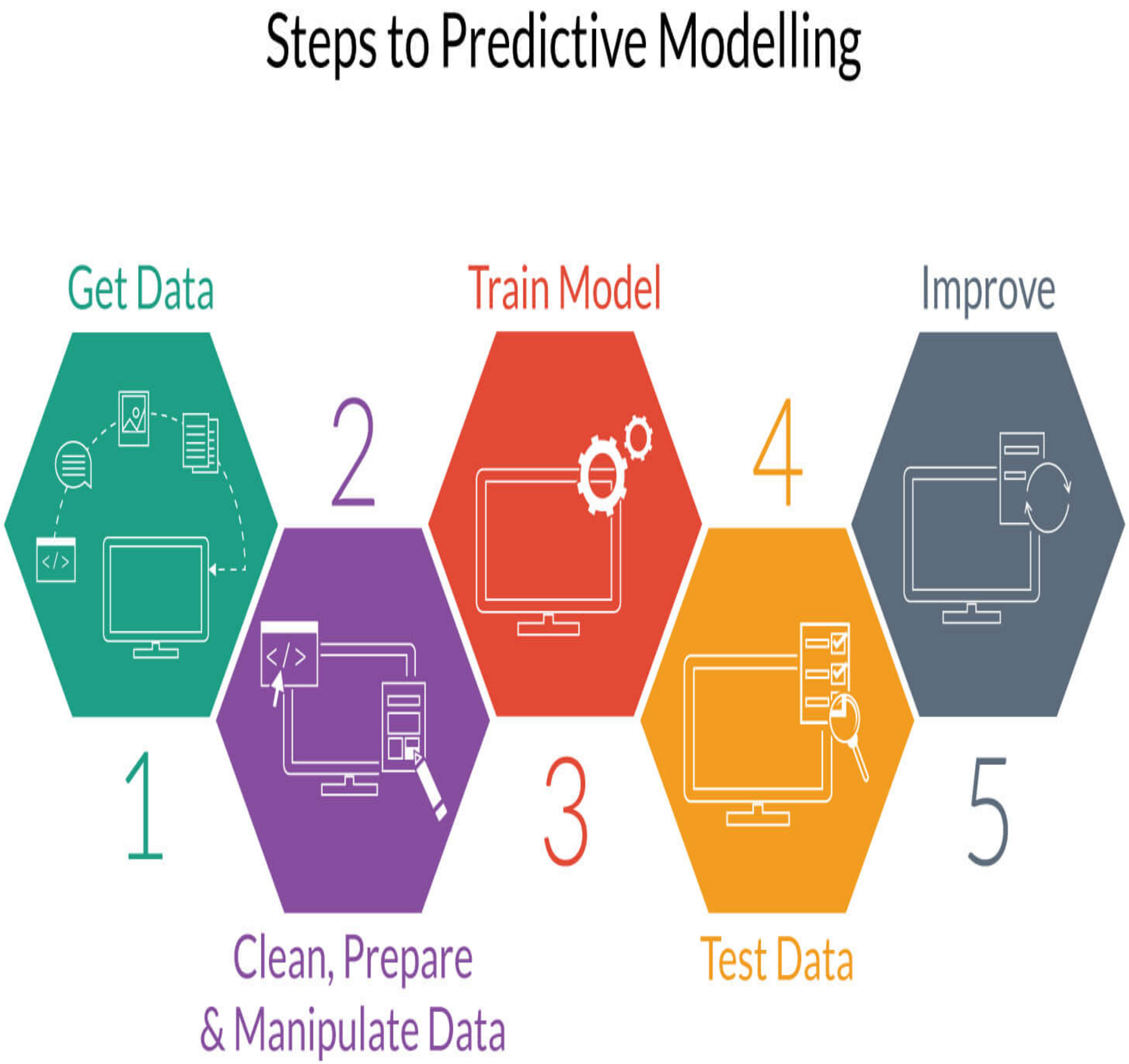
- **Deployment:** After the above steps are completed and if the model appears to be performing satisfactorily, it can be deployed for its intended task. The successes and failures of the deployed model might even provide additional data to tarrn the next generation of your model.

Steps to apply Machine Learning

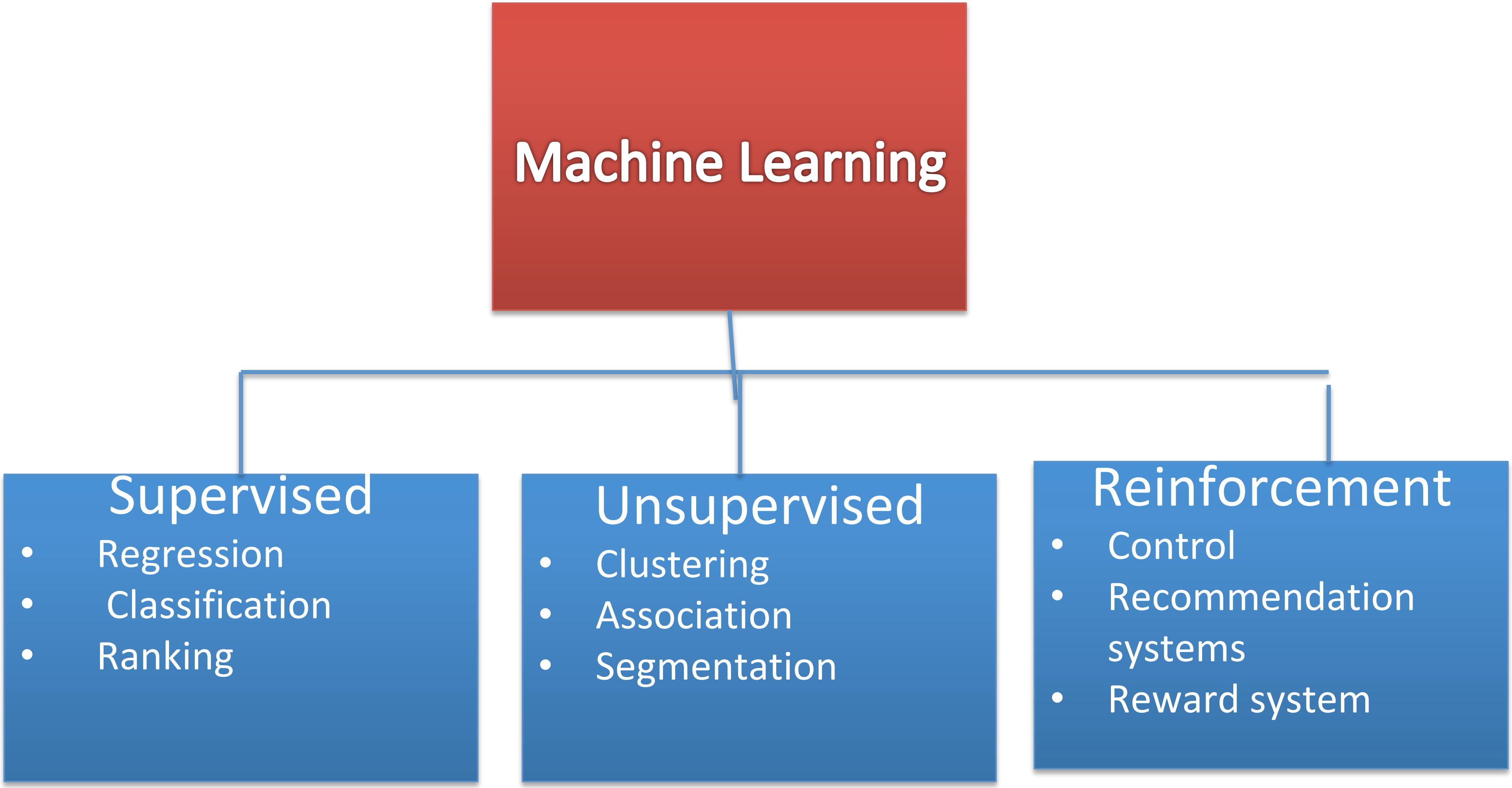


Steps in developing ML application

- Collect data
- Prepare the input data
- Train the algorithm
- Test the algorithm
- Use it and improve


Steps to Predictive Modelling
Get Data
1
2
Clean, Prepare & Manipulate Data
Train Model
3
4
Test Data
Improve
5

Types of Machine Learning



Machine Learning

Supervised

- Regression
- Classification
- Ranking

Unsupervised

- Clustering
- Association
- Segmentation

Reinforcement

- Control
- Recommendation systems
- Reward system

ML Cheat Sheet

A step-by-step guide for this sheet:

Learning Styles
Regressions
Classification
Clustering
The Curse of Dimensionality
Our * Wildcard * Section

https://www.datasciencecentral.com/profiles/blogs/the-making-of-a-cheatsheet-emoji-edition

MACHINE LEARNING IN EMOJI

🟣 SUPERVISED 🟢 UNSUPERVISED 🔴 REINFORCEMENT

🟣 SUPERVISED	human builds model based on input / output
🟢 UNSUPERVISED	human input, machine output human utilizes if satisfactory
🔴 REINFORCEMENT	human input, machine output human reward/punish, cycle continues

BASIC REGRESSION

🟣 LINEAR

linear_model.LinearRegression()

Lots of numerical data 💰 🚄 💱

🟣 LOGISTIC

linear_model.LogisticRegression()

Target variable is categorical 🍕 or 🍔

CLASSIFICATION

🟣🟢🔴 NEURAL NET

neural_network.MLPClassifier()

Complex relationships. Prone to overfitting
Basically magic. 🔮

🟣 K-NN

neighbors.KNeighborsClassifier()

Group membership based on proximity 🏘️

🟣 DECISION TREE

tree.DecisionTreeClassifier()

If/then/else. Non-contiguous data
Can also be regression 🚺 🚹

🟣🟢 RANDOM FOREST

ensemble.RandomForestClassifier()

Find best split randomly
Can also be regression 🌳 🎄 🌵 🌲

🟣🟢 SVM

svm.SVC() svm.LinearSVC()

Maximum margin classifier. Fundamental
Data Science algorithm 🦄

🟣 NAIVE BAYES

GaussianNB() MultinomialNB() BernoulliNB()

Updating knowledge step by step with new info 🎲

CLUSTER ANALYSIS

🟣🟢 K-MEANS

cluster.KMeans()

Similar datum into groups
based on centroids ☀️

🟣🟢 ANOMALY DETECTION

covariance.
EllipticalEnvelope()

Finding outliers
through grouping 🐼 🐼 🐻 🐼

FEATURE REDUCTION

T-DISTRIB STOCHASTIC NEIB EMBEDDING

manifold.TSNE()

Visualize high dimensional data. Convert
similarity to joint probabilities 🎨

PRINCIPLE COMPONENT ANALYSIS

decomposition.PCA()

Distill feature space into components that
describe greatest variance 🎠

CANONICAL CORRELATION ANALYSIS

decomposition.CCA()

Making sense of cross-correlation
matrices 🎭

LINEAR DISCRIMINANT ANALYSIS

lda.LDA()

Linear combination of features that
separates classes 💧 🔥

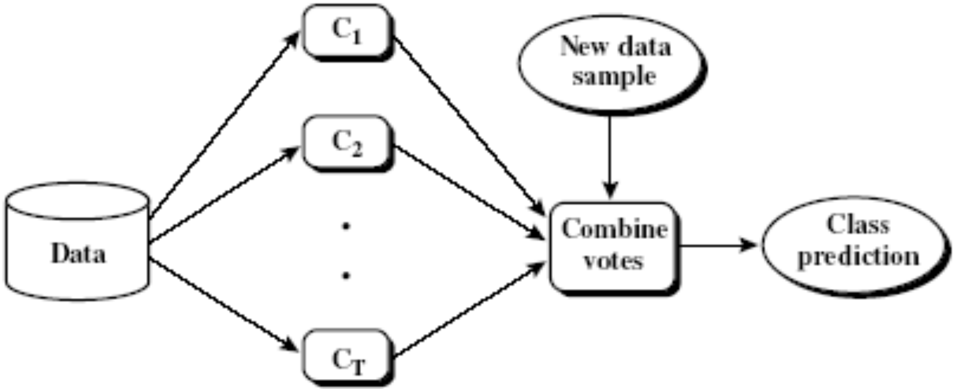
OTHER IMPORTANT CONCEPTS

BIAS VARIANCE TRADEOFF		🌦️
UNDERFITTING / OVERFITTING		⛅
INERTIA		🌈
ACCURACY FUNCTION	*(TP + TN) / (P + N)*	🌩️
PRECISION FUNCTION	*TP / (TP + FP)*	🌨️
SPECIFICITY FUNCTION	*TN / (FP + TN)*	❄️
SENSITIVITY FUNCTION	*TP / (TP + FN)*	🌪️

@emilyinamillion made this

Ensemble Methods: Increasing the Accuracy

- Ensemble methods
  - Use a combination of models to increase accuracy
  - Combine a series of k learned models, M_1, M_2, …, M_k, with the aim of creating an improved model M*
- Popular ensemble methods
  - Bagging: averaging the prediction over a collection of classifiers
  - Boosting: weighted vote with a collection of classifiers
  - Ensemble: combining a set of heterogeneous classifiers



Ensemble

- One of the benefits of using ensembles is that they may allow you to spend less time in pursuit of a single best model. Instead, you can train a number of reasonably strong candidates and combine them. Yet convenience isn't the only reason why ensemble-based methods continue to rack up wins in machine learning competitions; ensembles also offer a number of performance advantages over single models:
- B**etter generalizability to future problems**: Because the opinions of several learners are incorporated into a single final prediction, no single bias is able to dominate. This reduces the chance of overfitting to a learning task.

Ensemble

- **Improved performance on massive or miniscule datasets**: Many models run into memory or complexity limits when an extremely large set of features or examples are used, making it more efficient to train several small models than a single full model. Additionally, it is often trivial to parallelize an ensemble using distributed computing methods. Conversely, ensembles also do well on the smallest datasets because resampling methods like bootstrapping are inherently part of many ensemble designs.

- **The ability to synthesize of data from distinct domains**: Since there is no one-size-fits-all learning algorithm—recall the No Free Lunch theorem—the ensemble's ability to incorporate evidence from multiple types of learners is increasingly important as Big Data continues to draw from disparate domains.

Ensemble

- **A more nuanced understanding of difficult learning tasks**: Real-world phenomena are often extremely complex with many interacting intricacies. Models that divide the task into smaller portions are likely to more accurately capture subtle patterns that a single global model might miss.

Deep Learning

- Deep learning (such as deep neural networks (DNN), recurrent neural networks (RNN) or convolution neural networks CNN) is a part of a broader class of ML methods. Learning can be supervised, semi-supervised or unsupervised.

- They have been applied to fields such as computer vision, speech recognition, natural language processing machine translation, bio-informatics, drug design and self-driving cars where they have produced results comparable to human experts.

- Deep learning uses a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.

- Learn multiple levels of representations that correspond to different levels if abstraction; the levels form a hierarchy of concepts.

Evaluating Performance

- After doing the usual Feature engineering, selection, implementing a model and getting some output, the next step is to find out how effective is the model based on some metric using test dataset. Different performance metrics are used to evaluate Machine Learning Algorithms.

- The metrics that you choose to evaluate your machine learning model is very important. Choice of metrics influences how the performance of machine learning algorithms is measures and compared.

Machine Learning in Practice

- Machine learning algorithms are only a very small part of using machine learning in practice as a data analyst or data scientist. In practice, the process often looks like:

- Start Loop

1. **Understand the domain, prior knowledge and goals**. Talk to domain experts. Often the goals are very unclear. You often have more things to try then you can possibly implement.
2. **Data integration, selection, cleaning and pre-processing**. This is often the most time consuming part. It is important to have high quality data. The more data you have, the more it sucks because the data is dirty. Garbage in, garbage out.
3. **Learning models**. The fun part. This part is very mature. The tools are general.

Machine Learning in Practice

4. **Interpreting results**. Sometimes it does not matter how the model works as long it delivers results. Other domains require that the model is understandable. You will be challenged by human experts.

5. **Consolidating and deploying discovered knowledge.** The majority of projects that are successful in the lab are not used in practice. It is very hard to get something used.

- End Loop
- It is not a one-shot process, it is a cycle. You need to run the loop until you get a result that you can use in practice. Also, the data can change, requiring a new loop.

Why Use Machine Learning

It is important to remember that Machine learning (ML) is not solution to every type of problem in hand. There are cases where solutions can be developed without using ML techniques. For example, you don’t need ML if you can determine a target value by using simple rules, computations, or predetermined steps that can be programmed without needing any data driven learning.

Why Use Machine Learning

Consider using machine learning when you have a complex task or problem involving a large amount of data and lots of features, but no existing formula or equation. For example, machine learning is a good option if you need to handle situations like:

- Hand written rules and equations are too complex (face recognition)
- We can not write the program ourselves
- We cannot explain how (speech recognition)
- Need customized solutions (spam or not)
- Rules are constantly changing (Fraud detection)
- You cannot scale: ML solutions are effective at handling large-scale problems

Why Use Machine Learning

- Develop systems that can automatically adapt and customize themselves to individual users (personalized news or mail filter)
- Discover new knowledge from large databases (Market Basket analysis)

Why now?

- Lots of available data (especially with the advent of internet, soicla networking and e-commerce)
- Increasing computational power
- Growing progress in available algorithms and theory
- Increased support from industries

Growth of Machine Learning

- Machine learning is preferred approach to
  - Speech recognition, Natural language processing
  - Computer vision
  - Medical outcomes analysis
  - Robot control
  - Computational biology
  - Self driving cars
- This trend is accelerating

  Improved machine learning algorithms

  Improved data capture, networking, faster computers

  Software too complex to write by hand

  New sensors / IO devices

  Demand for self-customization to user, environment

Application of Machine Learning

- Broadly applicable in many domains (e.g., pattern recognition, finance, natural language, computer vision, robotics, manufacturing etc.). Some applications:
- Identify and filter spam messages from e-mail
- Speech/handwriting recognition
- Object detection/recognition
- Predict the outcomes of elections
- Stock market analysis
- Search engines (e.g, Google)
- Credit-card fraud detection
- Webpage clustering (e.g., Google News)
- Recommendation systems (e.g., pandora, amazon, Netflix)

Application from Day to Day Life

Artificial Intelligence is everywhere. Possibility is that you are using it I one way or the other and you don’t even realize.

1. Virtual Personal Assistants ; Siri, Alexa, and Google are some of the popular examples of virtual personal assistants.
2. Predictions while Commuting: Traffic predictions, online transportation Networks (when booking a cab, the app estimates the price of the ride. While sharing these services, how do they minimize the detours?
3. Video Surveillance: Monitoring multiple video cameras
4. Social Media Services: people you may know, Face Recognition etc.
5. Email Spam and Malware Filtering
6. Product Recommendation , online fraud detection

Application from Day to Day Life

Finance and Banking

- Credit scoring
- Fraud detection
- Risk analysis
- Client analysis
- Trading exchange forecasting

Retail and E-commerce

- Demand forecasting
- Price optimization
- Recommendations
- Fraud detection
- Customer segmentation

Marketing and Sales

- Market and customer segmentation
- Price optimization
- Churn rate analysis
- Customer lifetime value prediction
- Upsell opportunity analysis
- Sentiment analysis in social networks

Travel and Booking

- Demand forecasting
- Price optimization
- Price forecasting (for dynamically changing prices)

Healthcare and Life Sciences

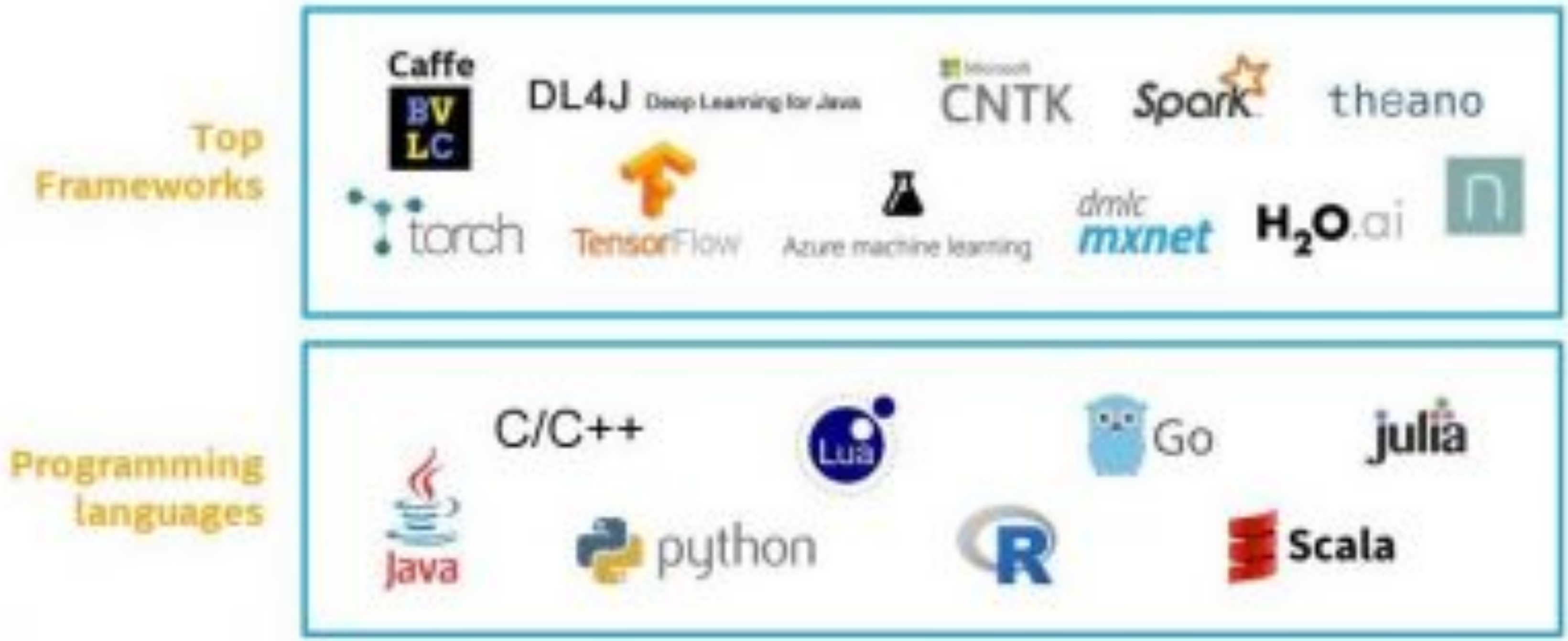
- Increase in diagnostic accuracy
- Identifying at-risk patients
- Insurance product cost optimization

Other

- Object recognition (photo and video)
- Content recommendations (movies, music, articles and news)
- And more

altexsoft

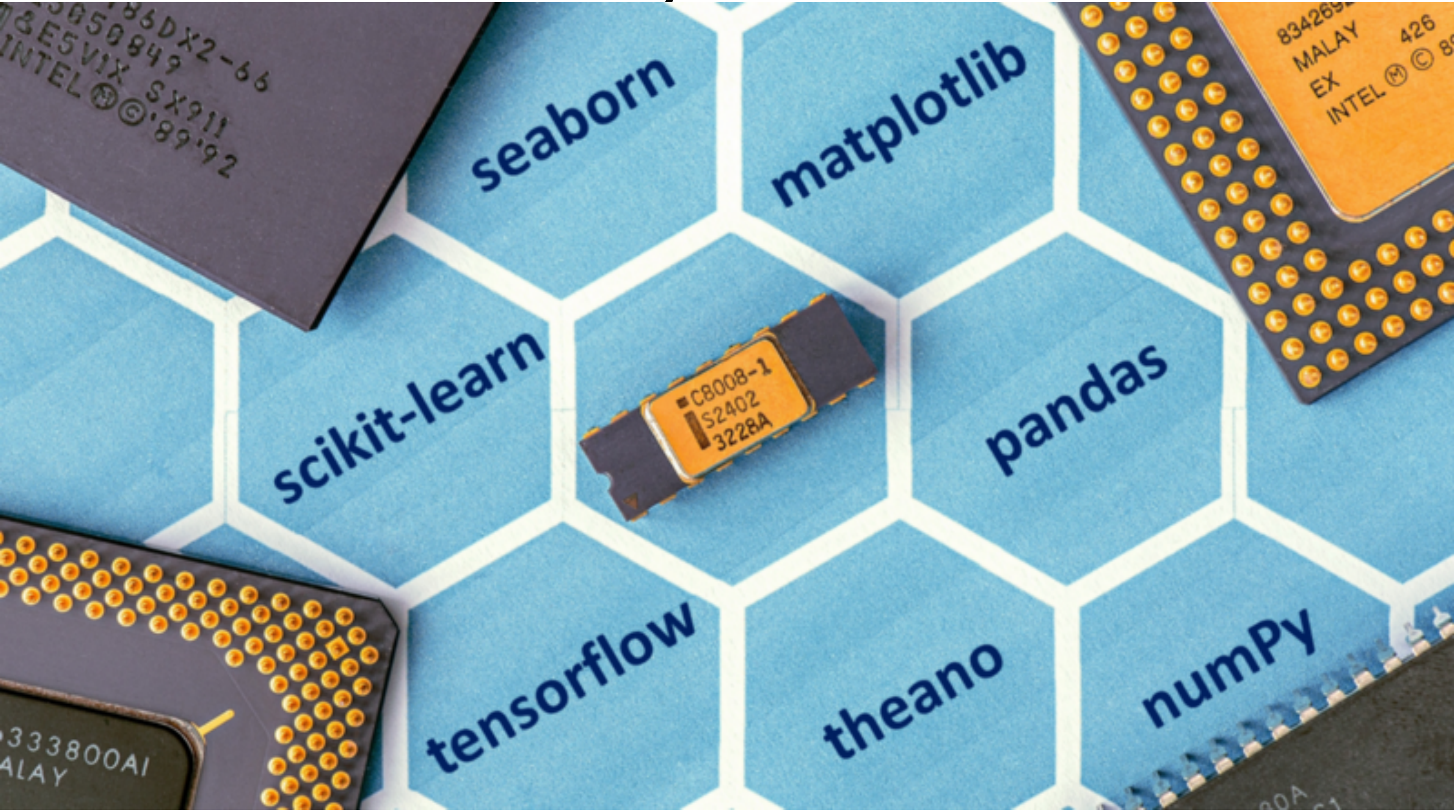
Software paradigm



Data Scientist’s Toolbox

Predictive Analytics Tools in Market
python
sas
MATLAB
WEKA
KNIME
rapidminer
mahout
IBM SPSS
R
Minitab
SAP
StatSoft STATISTICA

Essential Libraries for Machine Learning in Python



Python is often the language of choice for developers who need to apply statistical techniques or data analysis in their work. It is also used by data scientists whose tasks need to be integrated with web apps or production environments.

Python really shines in the field of machine learning. Its combination of consistent syntax, shorter development time and flexibility makes it well-suited to developing sophisticated models and prediction engines that can plug directly into production systems.

One of Python’s greatest assets is its extensive set of libraries.

Machine Learning is largely based upon mathematics. Specifically, mathematical optimization, statistics and probability. Python libraries help researchers/developers who are less equipped with developer knowledge to easily “do machine learning”.

Pandas for data extraction preparation

Pandas is a very popular library that provides high-level data structures which are simple to use as well as intuitive. It is not directly related to Machine Learning. As we know that the dataset must be prepared before training. In this case, Pandas comes handy as it was developed specifically for data extraction and preparation

It has many inbuilt methods for grouping, combining data and filtering as well as performing time series analysis.

Pandas can easily fetch data from different sources like SQL databases, CSV, Excel, JSON files and manipulate the data to perform operations on it.

Numpy and Scipy

NumPy is a very popular python library for large multi-dimensional array and matrix processing, with the help of a large collection of high-level mathematical functions. It is very useful for fundamental scientific computations in Machine Learning. It is particularly useful for linear algebra, Fourier transform, and random number capabilities.

SciPy is a very popular library among Machine Learning enthusiasts as it contains different modules for optimization, linear algebra, integration and statistics.

Most commonly used libraries in ML

Scikit-learn for working with classical ML algorithms

Scikit-learn is one the most popular ML libraries. It supports many supervised and unsupervised learning algorithms. Examples include linear and logistic regressions, decision trees, clustering, k-means and so on.

It is built on tow basic libraries of Python, Numpy and SciPy. It adds a set of algorithms for common machine learning and data mining tasks, including clustering, regression and classification. Even tasks involve in pre-processing of data like transforming data, feature selection and ensemble methods can be implemented in a few lines and with ease.

Matplotlib for data visualization

The best and most sophisticated ML is meaningless if you can’t communicate it to other people. So how do you actually turn around value from all this data that you have? How do you inspire your business analysts and tell them “stories” full of “insights”? It is through visualization.

This is where Matplotlib comes to the rescue. It is a standard Python library used by every data scientist for creating plots and graphs.

With enough commands, you can make just about any kind of graph you want with Matplotlib. You can build diverse charts, from histograms and scatterplots to non-Cartesian coordinates graphs. A module named pyplot makes it easy for programmers for plotting as it provides features to control line styles, font properties, formatting axes, etc.

It supports different GUI backends on all operating systems, and can

Seaborn is another data visualization library

Seaborn is a popular visualization library that builds on Matplotlib’s foundations. It is a higher-level library, meaning it’s easier to generate certain kinds of plots, including heat maps, time series, and violin plots.

Theano

Theano is another good Python library for numerical computation, and is similar to NumPy. Theano allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently.

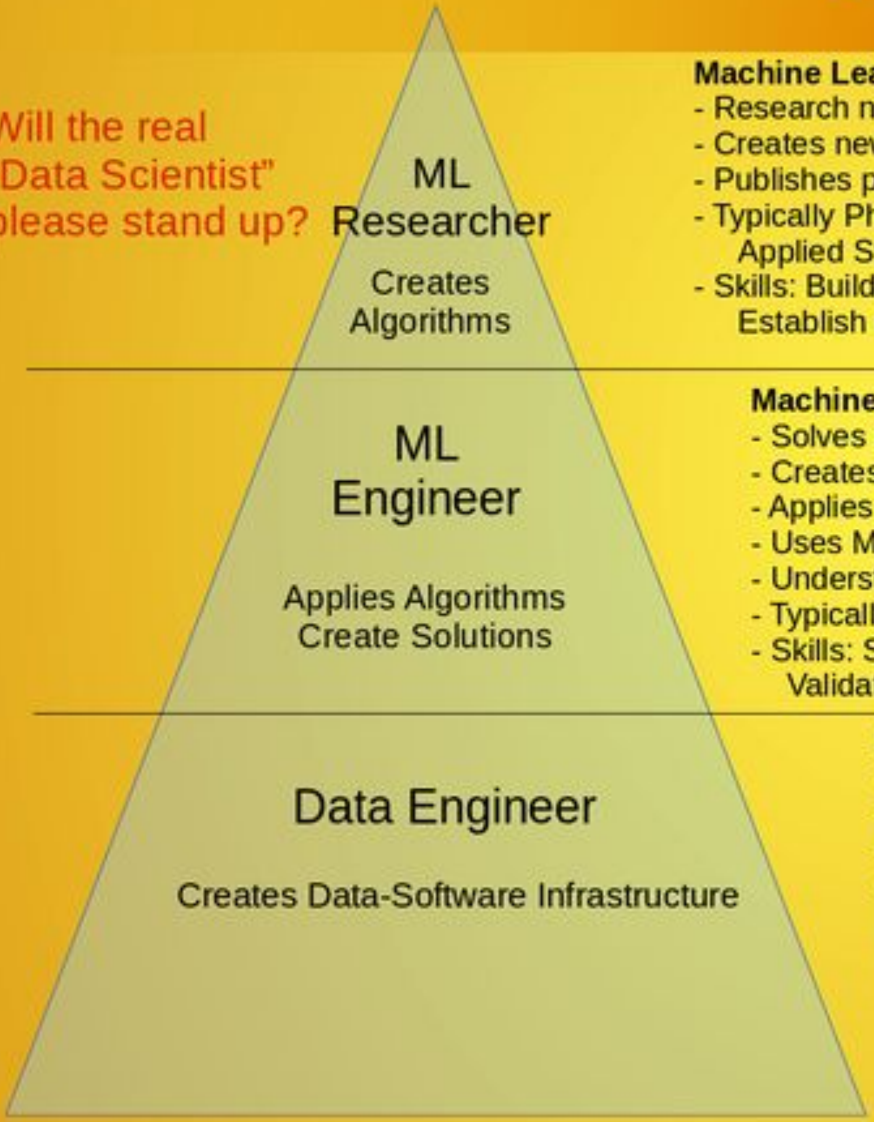
It is achieved by optimizing the utilization of CPU and GPU. It is extensively used for unit-testing and self-verification to detect and diagnose different types of errors. Theano is a very powerful library that has been used in large-scale computationally intensive scientific projects for a long time but is simple and approachable enough to be used by individuals for their own projects.

Challenges

- Scalability
- Dimensionality
- Complex and Heterogeneous Data
- Data Quality
- Data ownership and distribution
- Privacy preservation
- Streaming Data

Machine Learning Skills Pyramid v1.0

Will the real "Data Scientist" please stand up?



ML Researcher

Creates Algorithms

ML Engineer

Applies Algorithms Create Solutions

Data Engineer

Creates Data-Software Infrastructure

Machine Learning Researcher/Scientist:

- Research novel machine learning problems
- Creates new mathematical models and algorithms
- Publishes papers on research results
- Typically PhD/MA Level: Robotics, Machine Learning, Cognitive Science, Applied Statistics, Engineering, Operations Research, Math, etc.
- Skills: Builds mathematical models, Breaks ground in research, Establish new paradigms, Scientific Formalism, Experiment design

Machine Learning Engineer:

- Solves business/data learning problems
- Creates ML solutions to achieve an organization's objective
- Applies established algorithms
- Uses ML algorithm libraries
- Understands strengths and weaknesses of different algorithms
- Typically BS/MA Level: Computer Science, Math, Other Technical
- Skills: Software Eng. PLUS Data Analysis, ML Algorithm Selection, Cross Validation, Metrics/Scoring, Feature Engineering

Data Engineer:

- Develops code in support of Machine Learning Solutions
- Data extraction, transformation, scraping, joining, cleaning
- Summary Statistics, counting, sampling on request
- Skills: Platform/DB/Language specific expertise, Performance, Parallel and Distributed Computing, Quality, Reliability, Map/Reduce-Hadoop, VMs/Cloud, SQL/noSQL, Production Scaling etc.

- Some of the material and images have been taken from internet and Google images.