Chapter 01

Machine Learning Basics

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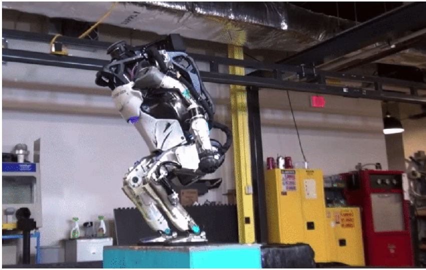
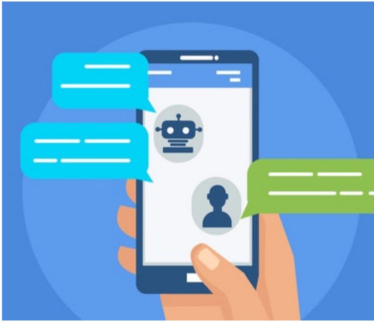
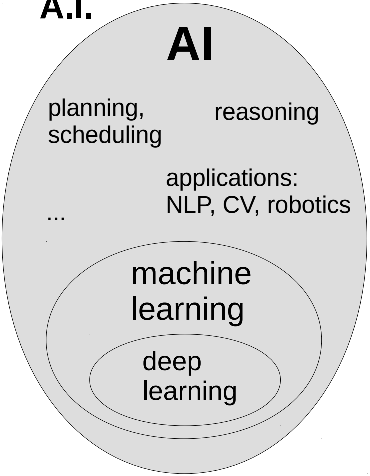
Machine Learning: Recent Successes images: [13] [14] [4] [12] [15]



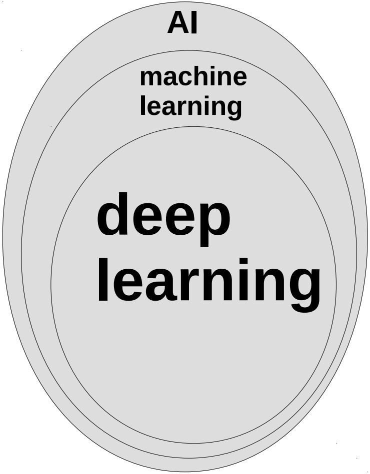


AI vs. Machine Learning vs. Deep Learning

Machine Learning is a sub-area of A.I.



public perception these days



Example Applications

Most common ML Applications

- object recognition, OCR+handwriting recognition
- search engines, recommender systems
- natural language processing, document categorization.

But there's a lot more! Check out kaggle.com...

- Flight Quest
  optimize flight routes based on wheather and traffic
- TFI Restaurant Revenue Prediction
  predict annual sales of restaurants to open
- Job Recommendation Challenge
  predict which jobs users will apply to
- Whale Detection Challenge
  detect whale calls from audio, prevent collision with ship traffic
- Discovering trolling in user comments
- ...

An ML Sample Application images: [3] [7]

- A computer system is to make a non-trivial decision.
- example: spam filtering
- Why not hard-code the decision logic?

Problems

- high effort to grasp problem's complexity.
- easy to code *something*, difficult to reach the optimal logic.
- feasibility checking: What accuracy can be reached by a decision?
- code is extremely difficult to maintain.
- keeping track of data changes (e.g., when spammers change strategies) is almost impossible.
- there is no way to take user feedback into account.

Outline

1. Basic Terminology

2. Benchmarking

Machine Learning: Definition

> *"Machine learning is a scientific discipline that explores the construction and study of* **algorithms that can learn from data**. *Such algorithms operate by building a* **model** *from* **example inputs** *and using that to make* **predictions or decisions**, *rather than following strictly static program instructions."*
>
> (en.wikipedia.org)

> *"The field of study that gives computers the ability to learn* **without being explicitly programmed.**"
>
> (Arthur Samuel (1959))

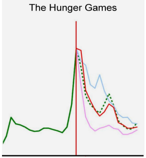
> *"A computer program is said to* **learn** *from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with Experience E."*
>
> (Tom Mitchell (1998))

Remark

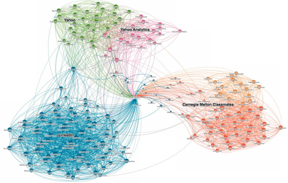
These definitions are entirely **non-operational**!

Machine Learning: Tasks images: [8] [5] [2] [1]

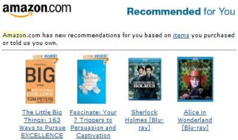
Regression



Clustering / Segmentation



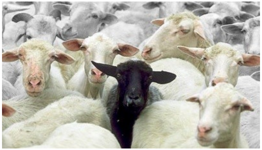
Recommendation



Classification

Data Reduction

Anomaly Detection



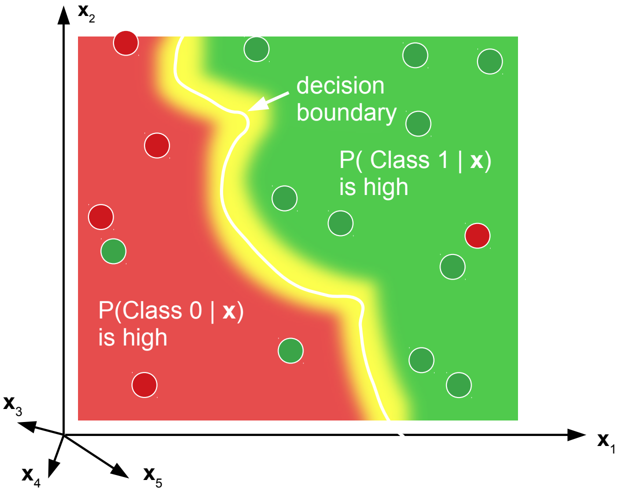
Machine Learning: Features+Labels image: [9]

- Machine learning makes predictions about real-world objects.
- We describe an object by a **feature vector** $\mathbf{x}$ *(bold=vectors!)*.
- Our goal is to predict a **label** y for the object.

	A	B	C	D	E	F	G	H	I	J	K	L
1	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
2	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
3	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
4	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7925		S
5	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
6	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
7	6	0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
8	7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
9	8	0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21075		S
10	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
11	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)								
12	11	1	3	Sandstrom, Miss. Marguerite Rut								
13	12	1	1	Bonnell, Miss. Elizabeth								
14	13	0	3	Saundercock, Mr. William Henry								
15	14	0	3	Andersson, Mr. Anders Johan								
16	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina								
17	16	1	2	Hewlett, Mrs. (Mary D Kingcome)								
18	17	0	3	Rice, Master. Eugene								
19	18	1	2	Williams, Mr. Charles Eugene								
20	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Van								
21	20	1	3	Masselmani, Mrs. Fatima								
22	21	0	2	Fynney, Mr. Joseph J								
23	22	1	2	Beesley, Mr. Lawrence								
24	23	1	3	McGowan, Miss. Anna "Annie"								
25	24	1	1	Sloper, Mr. William Thompson								
26	25	0	3	Palsson, Miss. Torborg Danira								
27	26	1	3	Asplund, Mrs. Carl Oscar (Selma Augusta Emi								
28	27	0	3	Emir, Mr. Farred Chehab								
29	28	0	1	Fortune, Mr. Charles Alexander								
30	29	1	3	O'Dwyer, Miss. Ellen "Nellie"								
31	30	0	3	Todoroff, Mr. Lalio								
32	31	0	1	Uruchurtu, Don. Manuel E								
33	32	1	1	Spencer, Mrs. William Augustus (Marie Eugen								
34	33	1	3	Glynn, Miss. Mary Agatha								
35	34	0	2	Wheadon, Mr. Edward H								
36	35	0	1	Meyer, Mr. Edgar Joseph								
37	36	0	1	Holverson, Mr. Alexander Oskar								
38	37	1	3	Mamee, Mr. Hanna								
39	38	0	3	Cann, Mr. Ernest Charles								
40	39	0	3	Vander Planke, Miss. Augusta Maria								
41	40	1	3	Nicola-Yarred, Miss. Jamila								
42	41	0	3	Ahlin, Mrs. Johan (Johanna Persdotter Larsso								
43	42	0	2	Turpin, Mrs. William John Robert (Dorothy Ann								
44	43	0	3	Kraeff, Mr. Theodor								

Machine Learning: Geometric View

- Feature vectors x are points in feature space.
- The ML model estimates decision boundaries between classes.



ML: Feature Engineering / Feature Extraction

Often, we preprocess features before applying machine learning.

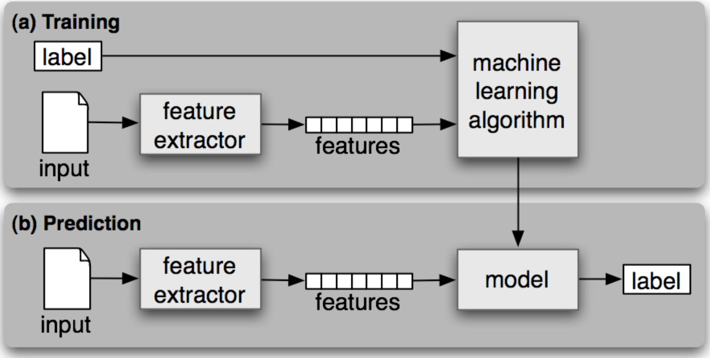
1. Features may be missing, i.e. x is *incomplete*.
   Approach: estimate missing values (*imputation*)
2. Categorical features may have to be transformed into numerical ones, typically by introducing dummy variables *(one-hot encoding)*.

one-hot encoding

	PS	color	PS	is_green	is_silver	is_red
Prof. Ulges' car	70	white	73	0	0	0
Prof. Ulges' wives' car	690	red	690	0	0	1

3. We may want to discard outliers.
4. We may want to discard uninformative features.
5. Often, we normalize features, for example by standardizing them to mean 0 and standard deviation 1 ($x := (x - \bar{x})/s$).

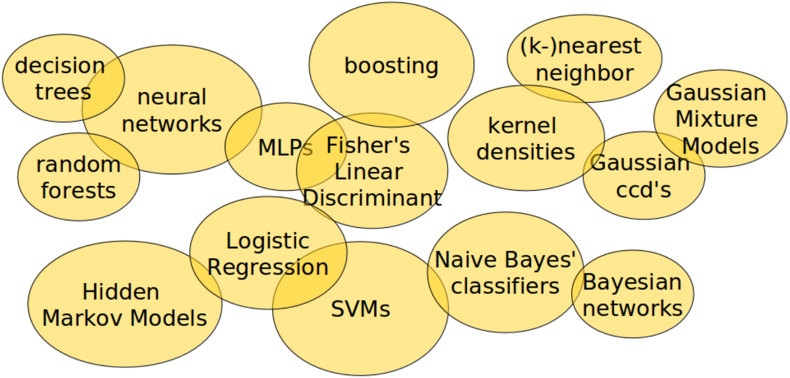
ML: System Pipeline image: [11]



Here: Batch Learning / Offline Learning

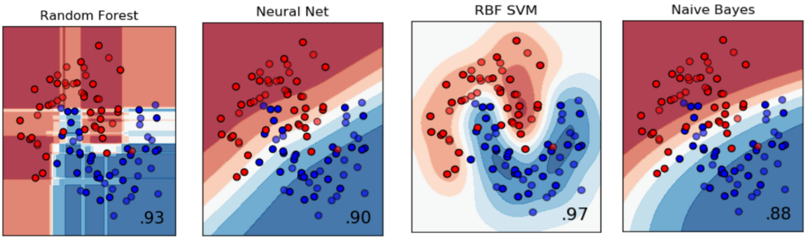
1. We train the system on training data $x_1, x_2, \ldots, x_n$ with labels $y_1, y_2, \ldots, y_n$, obtaining a model ϕ.
2. Given a new object x', the model predicts the label $\phi(x')$.
3. Training happens offline, the application of the model online.

ML: Approaches image: [6]



- There are many different methods in machine learning to solve the classification problem *(and also other problems)*.
- There is no universally best classifier *("no-free-lunch theorem")*.

ML: Sample Approaches



Different Approaches

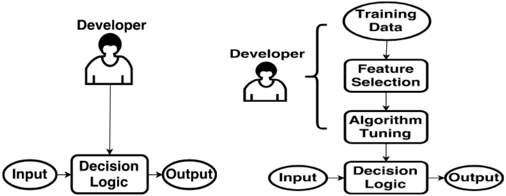
- **Random Forests**: Recursive Splitting of feature space.
- **Neural Networks**: Stacking of linear decision units.
- **SVMs**: Similarity comparison of objects.
- **Probabilistic Models (e.g., Naive Bayes)**: Use probabilities.

Types of Machine Learning

- **classification vs. regression**
  in classification, the labels $y_1, ..., y_n$ are categorical. In regression, they are real-valued.
- **supervised learning**
  learning from samples $x_1, ..., x_n$ with labels $y_1, ..., y_n$.
- **unsupervised learning**
  learning only from samples $x_1, ..., x_n$, no labels.
- **semi-supervised learning**
  learning from samples $x_1, ..., x_n$, some with labels.
- **active learning**
  ... where the system can pick which samples to label.
- **ensemble learning**
  ... is about combining learners for a more robust decision.
- **reinforcement learning**
  ... is about learning from feedback instead of labels.
- **transfer learning**
  ... is about applying models trained on Task X to Task Y.

Outline

ML in Practice

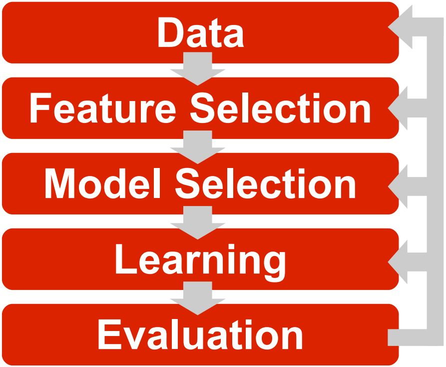


Verification in ML Practice ...

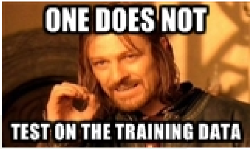
- is done by measuring accuracy on sample data: Benchmarking.

The Machine Learning Development Cycle

- We conduct an iterative search for good features, models, and input data.



Benchmarking: Ground Rule image: [10]

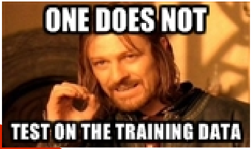


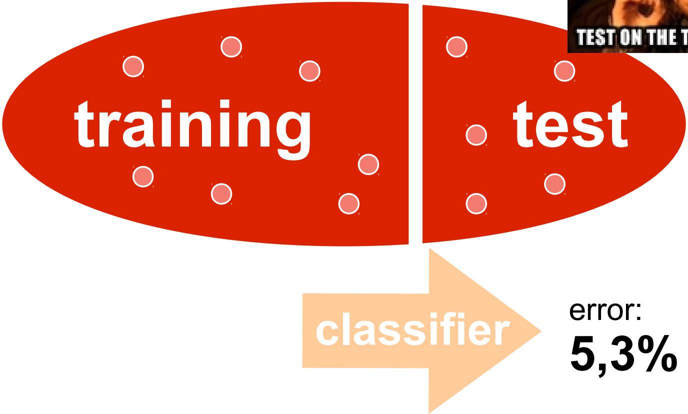
> *"The most common mistake among machine learning beginners is to test on the training data and have the illusion of success."*
>
> (P. Domingos, *A few Useful Things to Know about Machine Learning*)

Why?

- All classifiers are prone to overfitting.
- Achieving perfect accuracy on the training samples is simple *(e.g., nearest neighbor classifiers simply memorize them)*.
- It is the generalization to new data that matters.
- When building classifiers, always set some test data aside!
- Use the test data as rarely as possible!

Machine Learning: Benchmarking

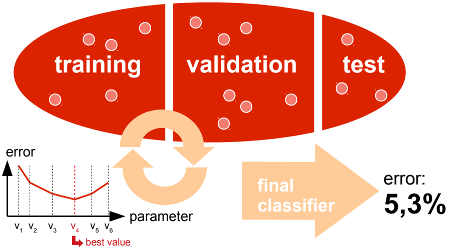




We separate our dataset into **training and testing data**:

- **Tip 1**: choose 'just enough' test data, use the rest for training.
- **Tip 2**: use a roughly balanced class distribution for training.

Machine Learning: Benchmarking

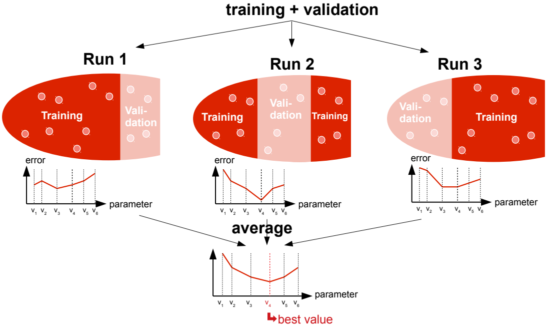


Some of a classifiers' parameters are **learned**, others (also called *hyperparameters*) must be **chosen**.

Common Approach: Grid Search

- For each parameter Θ_i, test a few values $\mathcal{R}_i := \{v_i^1, ..., v_i^{n_i}\}$.
- Train the classifier for each parameter combination in $\mathcal{R}_1 \times \mathcal{R}_2 \times ... \times \mathcal{R}_m$.
- Evaluate the resulting classifier on a separate **validation set**.

Machine Learning: Benchmarking



If there is **little data**, we apply **cross-validation**:

- Split the data into subsets ("*folds*"), train/validate **multiple times**, and average the results.
- Above: **3-fold cross-validation**.

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