Machine Learning and Data Mining

Machine Learning, lecture

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Before we start

Thank you for participating in the survey!

Deep Learning by Alexander Panin (Fedor Ratnikov)?

Machine Learning

What for?

Machine Learning - approximation of algorithms:

- to solve hard problems:
  - complex distributions:
    - physics, chemistry, ...;
  - unknown distributions:
    - cat images;
- to speed up algorithms:
  - also physics, chemistry;
  - games (AlphaGO).

What for?

How it is different from statistics or Computer Science?

Unlike statistics:

- we usually don't care much about underlying distributions,
- only about solution.

Unlike Computer Science:

- we usually learn from real data;
- all improvements and speeding up comes from adjusting to data.

Machine Learning problems

Machine Learning problem consists of:

- set of samples: $x \in X$:
    - for benchmark problems it is usually split into *training* and *test* sets;
- targets: $y \in Y$;
- quality metric: $Q : \mathcal{A} \times X \times Y \to \mathbb{R}$
- restrictions:
    - by speed,
    - by scalability,
    - invariance to some parameters,
    - etc.

Machine Learning algorithms generic recipe

Machine Learning algorithm:

- model - a set of algorithms:

$$\mathcal{A} \subseteq \{A : X \to Y\}$$

- learning procedure:

$$P : X \times Y \to A$$

usually:

$$P = \arg\min_{A \in \mathcal{A}} \mathcal{L}(X, Y, A)$$

where: $\mathcal{L} : \mathcal{A} \times X \times Y \to \mathbb{R}$ - a loss unction.

Model

Model is a set of <u>algorithms</u>.

Usually, algorithms are parametrized by some vector $\theta \in \mathbb{R}^n$. But nothing stops you from considering simply a bunch of algorithms.

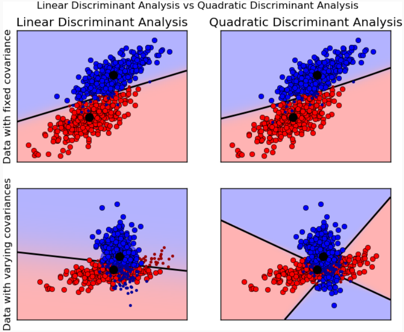


Figure 1: Separating hyperplane is a model too...

Hyper-parameters

Model can be parametrized itself, e.g. maximal depth of trees, regularization coefficients. These parameters are called **hyper-parameters** since they are not selected in learning procedure.

Learning procedures:

- brute force;
- random guessing;
- greedy methods
- continuous optimization:
  - gradient descent and Co.;
  - second order methods, e.g. Newton-Raphson method;
  - gradient-free optimization, e.g. genetics;
- discrete optimization.

Machine Learning = Model + Optimization.

No free lunch

Settings

- binary classification (for simplicity);
- Loss: accuracy:

$$L(A, X, y) = \frac{1}{|y|} \sum_i \mathbb{I}[A(x_i) = y_i]$$

- classifier (hypothesis) A, true relation $y = F(x)$:
- dataset D with $n = |D|$ and learning procedure $P_k(A \mid D)$;
- error for learning algorithm k:

$$E_k(F, n) = \sum_{x \notin D} P(x) L(A, x, y) P_k(A \mid D)$$

No free lunch

No free lunch theorem

1. Uniformly averaged over all target functions F:

$$E_1(F, n) - E_2(F, n) = 0$$

2. For any fixed trainingset D, uniformly averaged over F:

$$E_1(F, D) - E_2(F, D) = 0$$

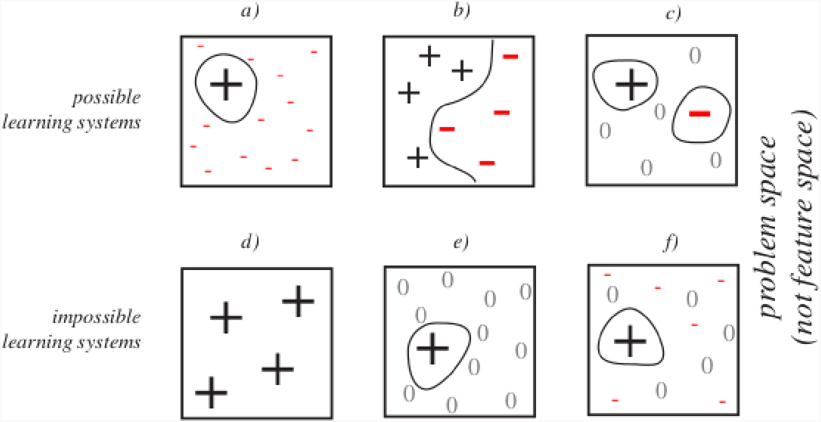
3. Uniformly averaged over all priors P(F):

$$E_1(n) - E_2(n) = 0$$

4. For any fixed trainingset D, uniformly averaged over P(F):

$$E_1(D) - E_2(D) = 0$$

No free lunch



Interpretation

> *The theorem tells that there is no universal learning algorithm. To successfully learn one type of problems you need to sacrifice generalization ability on the rest.*

Caveats:

- problems in the real world are not uniformly distributed;
- solving problem you have some prior knowledge about it;

Machine Learning algorithms generic recipe

Machine Learning algorithm:

- implicit or explicit assumptions about data;
- model;
- learning procedure.

Examples

Vanilla classification/regression:

- usually, assumptions on 'smoothness' of the functions;
- restrictions on number of interactions between variables.

Reinforcement learning:

- depends on sensor type;
- Markov properties;
- we can estimate 'goodness' of current state;
- assumptions on opponent/environment.

Examples

Vision:

- objects on image are connected region;
- strong correlation between neighbor pixels;
- position (or angle) of an object are not relevant.

Speech recognition:

- signal can be split into short samples;
- underlying language model;
- tone does not make any difference;
- a lot of samples correspond to the same class.

Examples

Recommendation systems:

- users with similar interest like similar items;
- latent variable models

Natural Language Processing:

- there is a lot of synonyms;
- words are highly correlated in a short term;
- almost uncorrelated in a long term;
- texts from the same author have similar statistical properties.