

CONTEXT & VOCABULARY



WHAT REPRESENTS ARTIFICIAL INTELLIGENCE?



- The term Artificial Intelligence, as a research field, was coined at the conference on the campus of Dartmouth College in the summer of 1956, even though the idea was around since antiquity.
- For instance in the first manifesto of Artificial Intelligence, "Intelligent Machinery", in 1948 Alan Turing distinguished two different approaches to AI, which may be termed "top-down" or knowledge-driven AI and "bottom-up" or data-driven AI



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- The two different approaches to AI can be detailed:
 - "top-down" or knowledge-driven AI
 - cognition = high-level phenomenon, independent of low-level details of implementation mechanism, first neuron (1943), first neural network machine (1950), neucognitron (1975)
 - Evolutionary Algorithms (1954,1957, 1960), Reasoning (1959,1970), Expert Systems (1970), Logic, Intelligent Agent Systems (1990)...
 - "bottom-up" or data-driven AI
 - opposite approach, start from data to build incrementally and mathematically mechanisms taking decisions
 - Machine learning algorithms, Decision Trees (1983), Backpropagation (1984-1986), Random Forest (1995), Support Vector Machine (1995), Boosting (1995), Deep Learning (1998/2006)...



- AI is originally defined, by Marvin Lee Minsky, as "the construction of computer programs doing tasks, that are, for the moment, accomplished more satisfyingly by human beings because they require high level mental processes such as: learning. perceptual organization of memory and critical reasoning".
- There are so the "artificial" side with the usage of computers or sophisticated electronic processes and the side "intelligence" associated with its goal to imitate the (human) behavior.



- The concept of strong artificial intelligence makes reference to a machine capable not only of producing intelligent behavior, but also to experience a feeling of a real sense of itself, "real feelings" (whatever may be put behind these words), and "an understanding of its own arguments".
- The notion of **weak artificial intelligence** is a pragmatic approach of engineers: targeting to build more autonomous systems (to reduce the cost of their supervision), algorithms capable of solving problems of a certain class, etc. But this time, the machine *simulates* the intelligence, it seems to act as if it was smart.



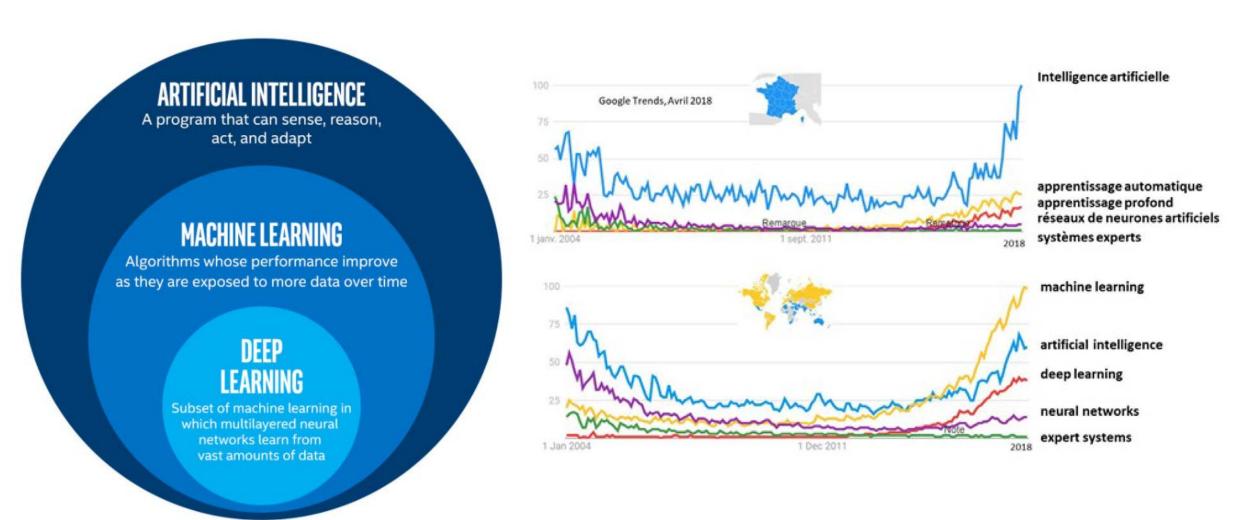
Why Artificial Intelligence is so difficult to grasp?

- Frequently, when a technique reaches mainstream use, it is no longer considered as artificial intelligence; this phenomenon is described as the AI effect: "AI is whatever hasn't been done yet." (*Larry Tesler's Theorem*) -> e.g. Path Finding (GPS), Checkers game, Chess electronic game, Alpha Go...
- Consequently, AI domain is continuously evolving and so very difficult to grasp.



Al vs Machine Learning vs Deep Learning

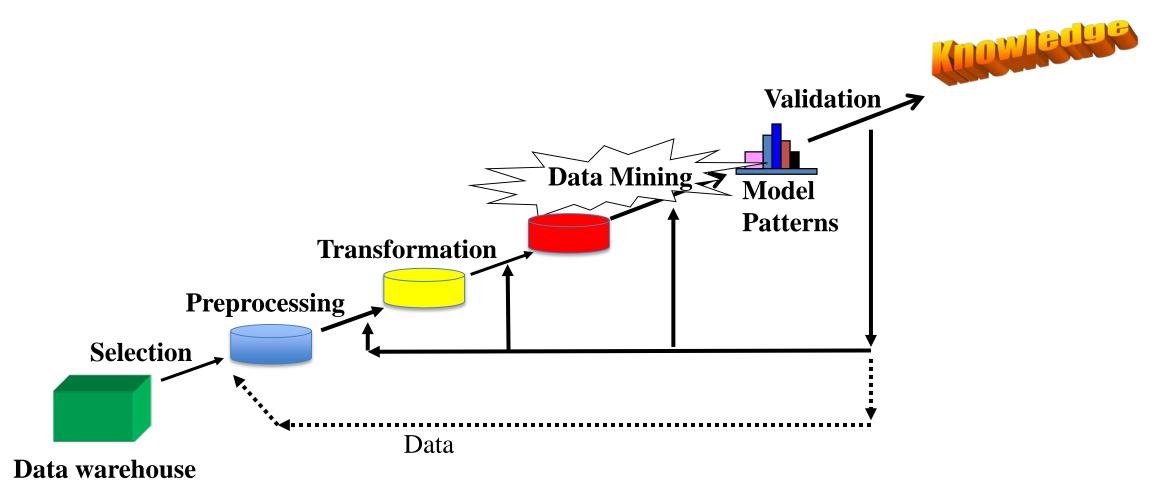
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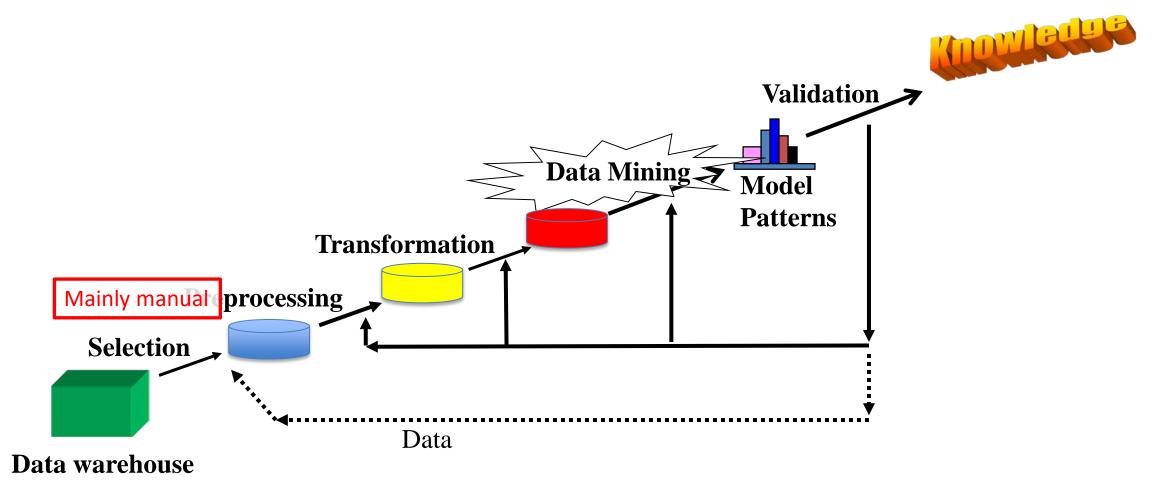


MACHINE LEARNING VS DATA MINING?

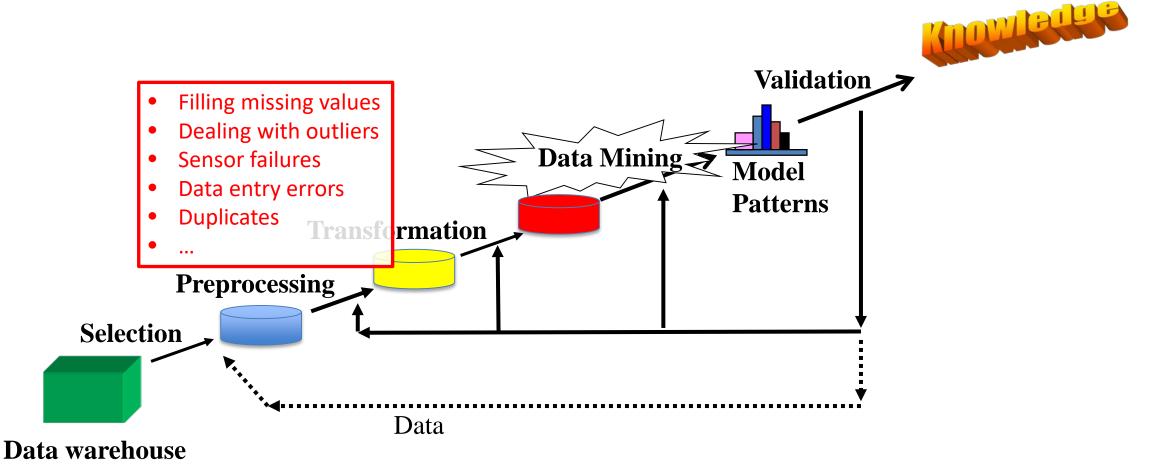




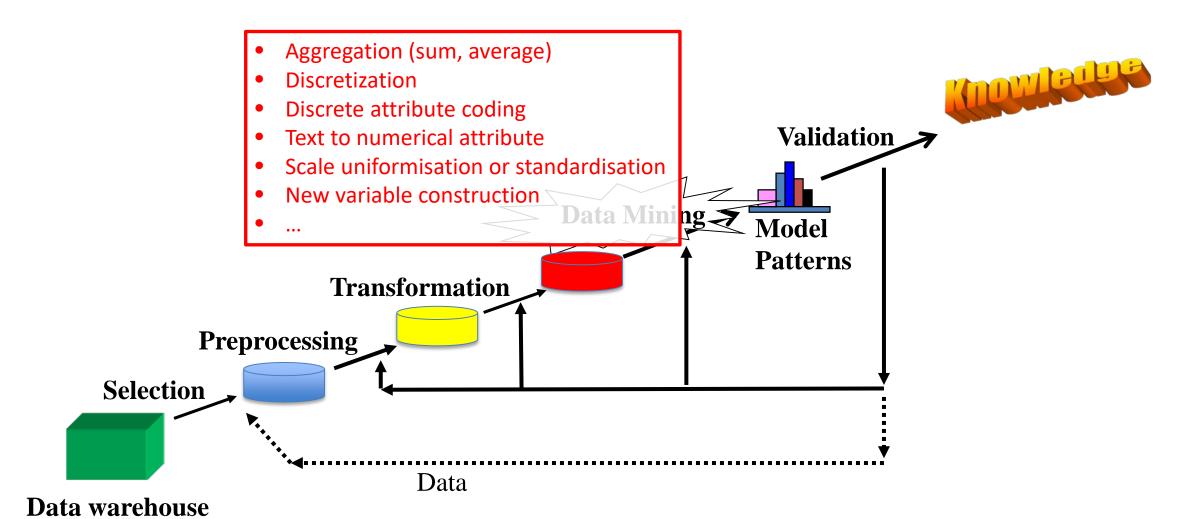














Selection

Data warehouse

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Data Mining Workflow

Validation ___

- Regression
- (Supervised) Classification
- Clustering (Unsupervised Classification)
- Feature Selection
- Association analysis
- Novelty/Drift

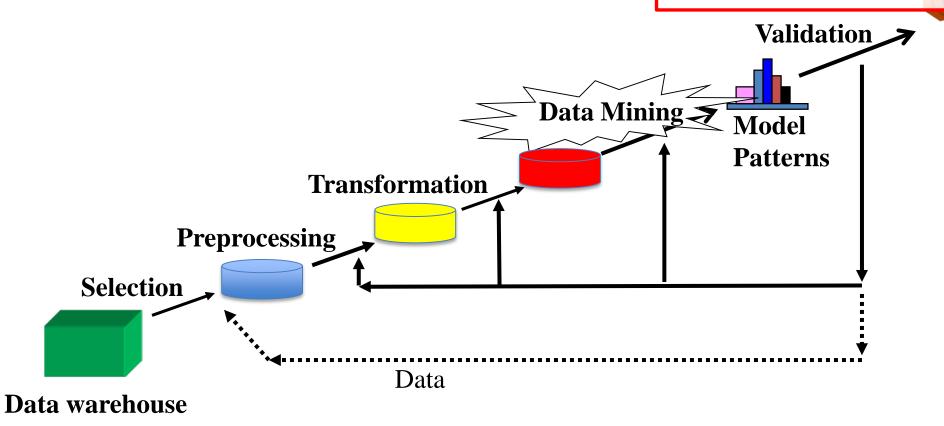
Data

Data Mining Model
Patterns

Preprocessing

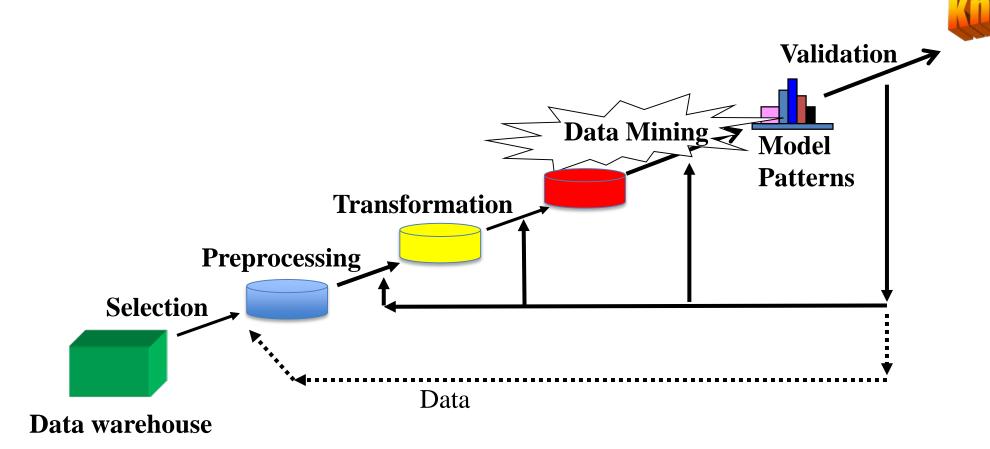


- Evaluation on Validation Set
- Evaluation Measures
- Visualization
- ..





- Visualization
- Reporting
- Knowledge
- •





Data Mining Workflow

Problems

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- Regression
- (Supervised) Classification
- Density Estimation / Clustering (Unsupervised Classification)
- Feature Selection
- Association analysis
- Anomality/Novelty/Drift
- ..

Possible Solutions

- Machine Learning
 - Support Vector Machine
 - Artificial Neural Network
 - Boosting
 - Decision Tree
 - Random Forest
 - •
- Statistical Learning
 - Gaussian Models (GMM)
 - Naïve Bayes
 - Gaussian processes
 - ...
- Other techniques
 - Galois Lattice
 - ...



MACHINE LEARNING VS DATA SCIENCE?



Data Science Stack

Visualization / Reporting / Knowledge

- Dashboard (Kibana / Datameer)
- Maps (InstantAtlas, Leaflet, CartoDB...)
- Charts (GoogleCharts, Charts.js...)
- D3.js / Tableau / Flame

Analysis / Statistics / Artificial Intelligence

- Machine Learning (Scikit Learn, Mahout, Spark)
- Search / retrieval (ElasticSearch, Solr)

Storage / Access / Exploitation

- File System (HDFS, GGFS, Cassandra ...)
- Access (Hadoop / Spark / Both, Sqoop...)
- Databases / Indexing (SQL / NoSQL / Both..., MongoDB, HBase, Infinispan)
- Exploit (LogStash, Flume...)

Infrastructures

- Grid Computing / HPC
- Cloud / Virtualization

USER

HARD



MACHINE LEARNING VS STATISTICS?



What breed is that Dogmatix (Idéfix)?



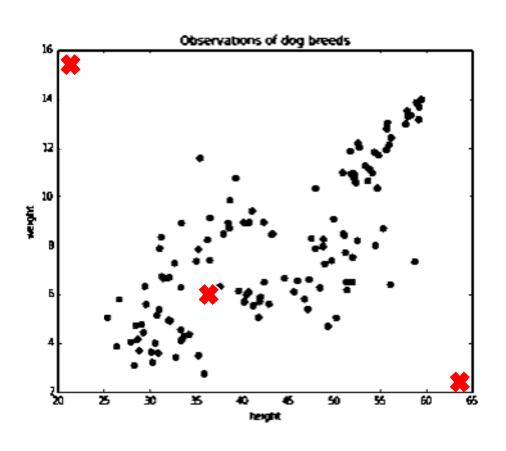


The illustrations of the slides in this section come from the blog "Bayesian Vitalstatistix: What Breed of Dog was Dogmatix?"



Does any real dog get this height and weight?



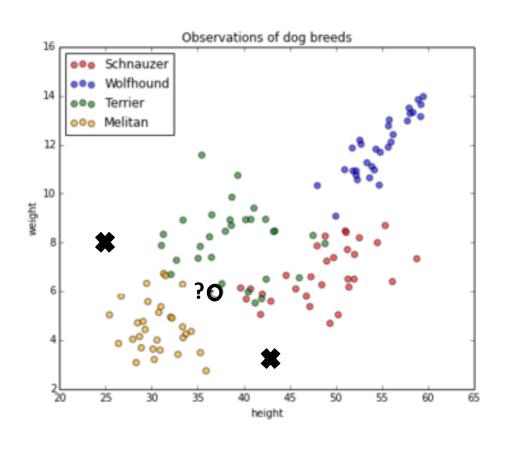


Let us consider x, vectors independently generated in R^d (here R²), following a probability distribution fixed but unknown P(x).



What should be the breed of these dogs?

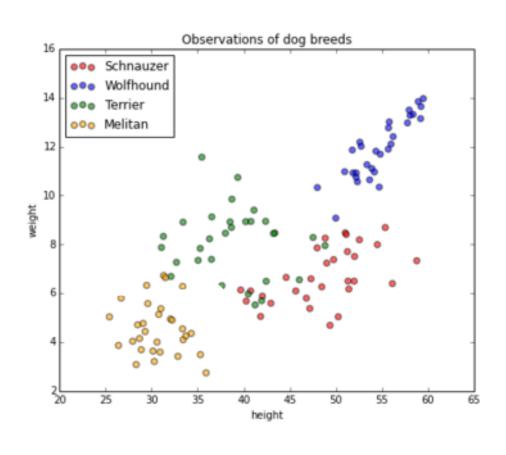




 An Oracle assignes a value y to each vector x following a probability distribution P(y/x) also fixed but unknown.



An oracle provides me with examples?

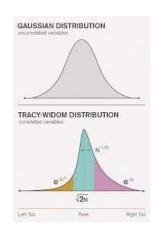


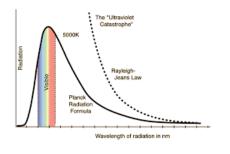
• Let S be a training set $S = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ..., (\mathbf{x}_m, \mathbf{y}_m)\},$ with m training samples i.i.d. which follow the joint probability $P(\mathbf{x}, y) = P(\mathbf{x})P(y|\mathbf{x}).$

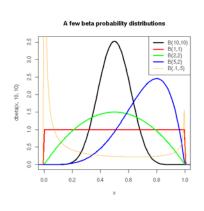


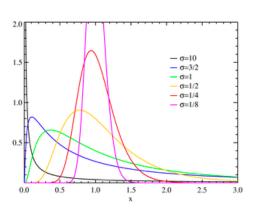
Statistical solution: Models, Hypotheses...

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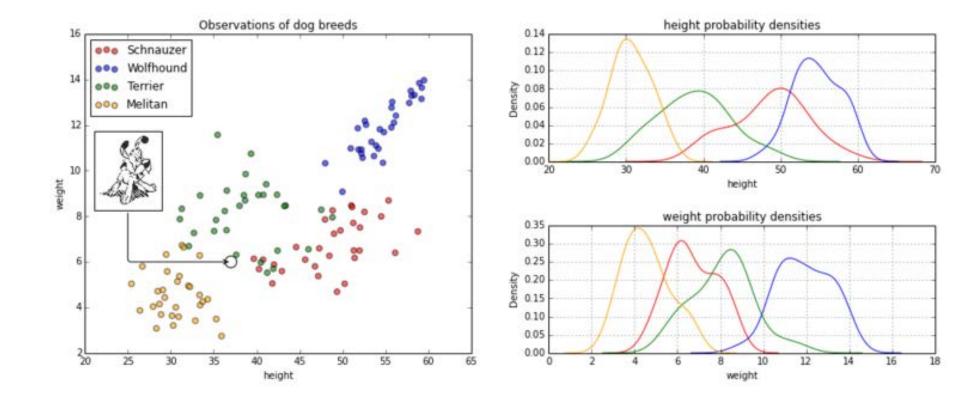








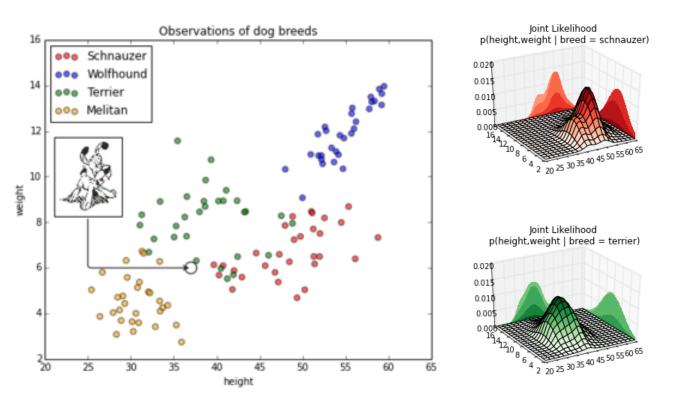
Statistical solution P(height, weight|breed)...

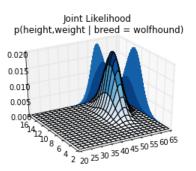


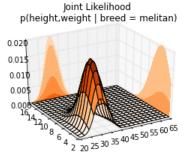


Statistical solution P(height, weight|breed)...



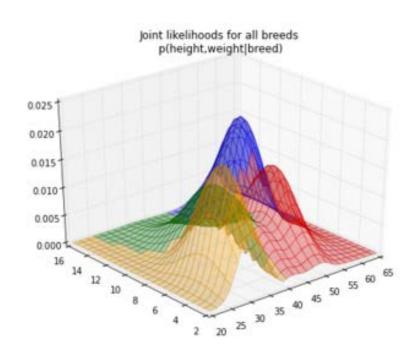


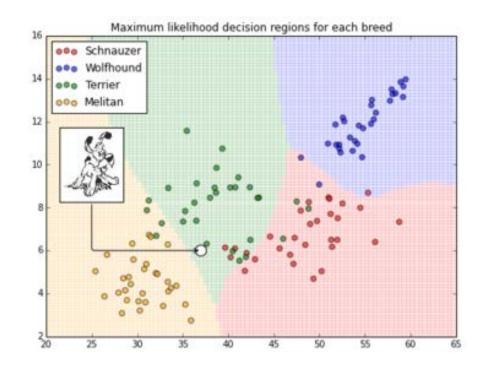






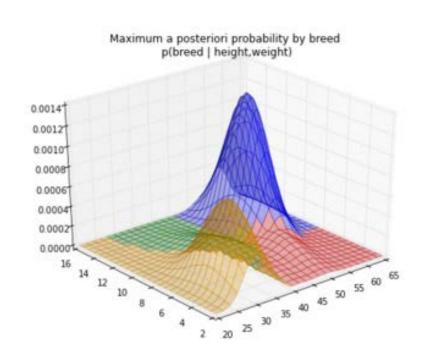
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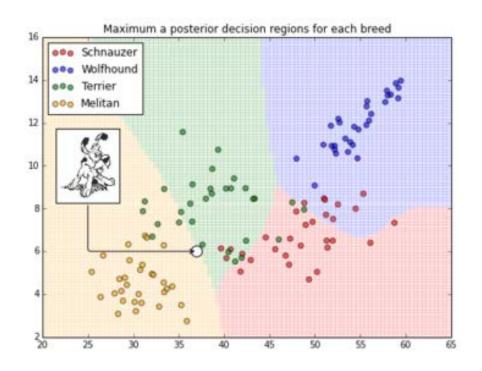






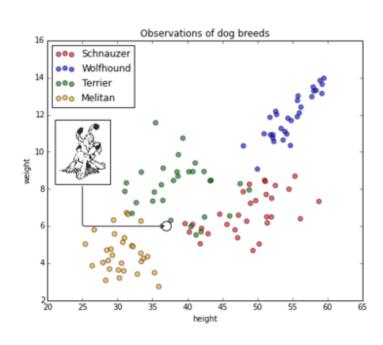
Statistical solution: Bayes, P(breed | height, weight)...







Machine Learning

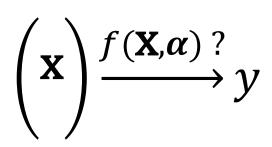


• we have a learning machine which can provide a family of functions $\{f(\mathbf{x};\alpha)\}$, where α is a set of parameters.

$$\left(\mathbf{x}\right) \xrightarrow{f(\mathbf{X},\alpha)} ?$$



The problem in Machine Learning



- The problem of learning consists in finding the function (among the $\{f \ (x;\alpha)\}\)$ which provides the best approximation \hat{y} of the true label y given by the Oracle.
- best is defined in terms of minimizing a specific (error) cost related to your problem/objectives

$$Q((\mathbf{x}, \mathbf{y}), \alpha) \in [a; b].$$

- Examples of cost functions Q:
 - Hinge Loss: error 0/1 cost, 0 if predicted and expected labels match, 1 otherwise (used in classification)
 - Quadratic Loss: $(f(x)-y)^2$ (used in regression)
 - Cross-Entropy Loss, Logistic Loss...



The problem in Machine Learning

For Clarity sake, let us note z = (x, y).

Thus, the objective is to minimize the *Risk*, i.e. the expectation of the error cost:

$$R(\alpha) = \int Q(z, \alpha) dP(z)$$

where P(z) is unknown.

The training set $S = \{z_i\}_{i=1,...,m}$ is built through an *i.i.d.* sampling according to P(z). Since we cannot compute $R(\alpha)$, we look for minimizing the **Empirical Risk** instead:

$$R_{emp}(\alpha) = \frac{1}{m} \sum_{i} Q(z_i, \alpha)$$



Machine Learning fundamental Hypothesis

For Clarity sake, let us note z = (x, y).

 $S = \{z_i\}_{i=1,...,m}$ is built through an *i.i.d.* sampling according to P(z).



Train through Cross-Validation



Training set & Test set have to be distributed according to the same law (i.e. P(z)).



Vapnik learning theory (1995)

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Vapnik had proven the following equation $\forall m$ with a probability at least equal to $1 - \eta$:

$$R(\alpha_m) \le R_{emp}(\alpha_m) + (b-a)\sqrt{\frac{d_{VC}(ln(2m/d_{VC})+1) - ln(\eta/4)}{m}}$$

Training Error

Generalization Error

Thus minimizing the **Risk** depends on minimizing the **Empirical Risk** and the **confidence interval** which is linked to the term d_{VC} corresponding to the complexity of the model family chosen, i.e. the Vapnik-Chervonenkis dimension



Vapnik learning theory (1995)

In his learning theory [Vapnik, 1995], Vapnik defines 4 fundamental steps:

- Study the theory of consistence of learning processes
- Define bounds on convergence speed of learning processes
- Handle the generalization power of learning processes
- Design a theory to build learning algorithms in order to find a tradeoff between minimizing the *Empirical Risk* and the confidence interval ⇒ minimization of the Structural Risk.



Machine Learning vs Statistics

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