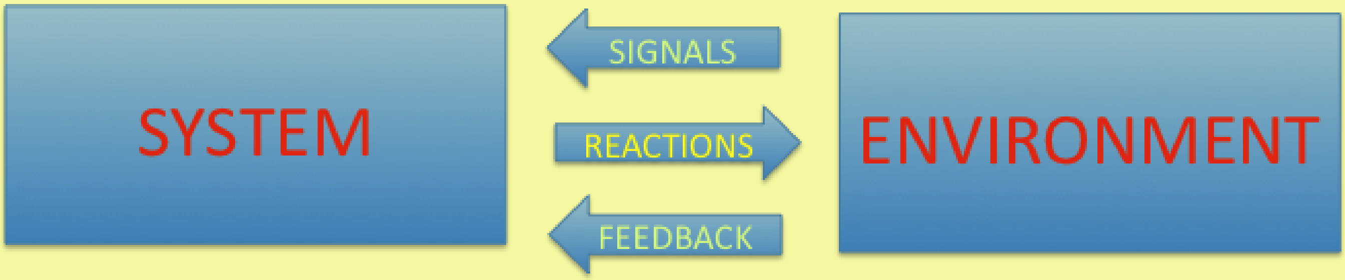
Site Map

TakeTechEase
Math, Physics and Numerics

Mathematical Software - Machine Learning - Tutorial

Machine Learning - Introduction

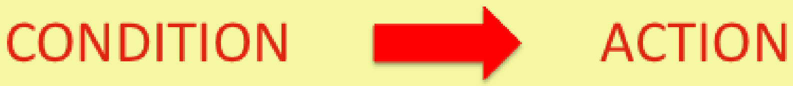
Machine Learning is aimed at configuring system to maximize feedback from environment. The general idea is presented below



System obtains some signals from the environment. Next system answers (reactions) to the incoming messages are sent back to it. As a next step system reactions are judged by the outer system. When system outputs are correct environment pays profits to it (positive feedback) otherwise system is punished by the signals sender and gets its negative feedback. This is a sign that something works wrongly and needs to be correct.

Machine Learning - System

System is completely defined by set of classifiers (rules). Each rule contains a pair of condition and corresponding system answer when this condition is satisfied.



CONDITION

ACTION

Conditions are written as strings built with signs from the set of {0, 1, #}. The first two symbols has clear meaning whereas the last one denotes an undefined sign that can be interpreted either as 0 or 1.
Answers are written as strings with signs from the set of {0, 1}. It means that there is no place for free translation. The system answer causes a well-defined action detected by the outer system.
Note. In the OptFinderML, classifiers (rules) must be set by an user. It can be done:

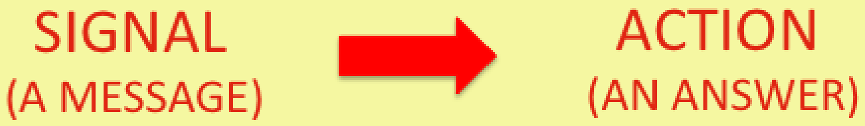
- manually
- randomly, program will print random sequences
- from a file (two columns separated by white sign(s))

Machine Learning - Surroundings

Surroundings (environment) is an outer structure that teaches our system how to react correctly to signals acting as stimuli. Therefore this structure must

- have
- be able to generate

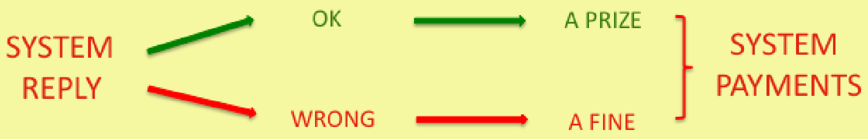
a set of inducements (signals) and expected answers (actions).



SIGNAL
(A MESSAGE)

ACTION
(AN ANSWER)

Signals are sent to the system that generates answers. When obtained reply to given stimuli is correct environment pays a prize to the system otherwise the system pays a fine.



SYSTEM REPLY

OK

WRONG

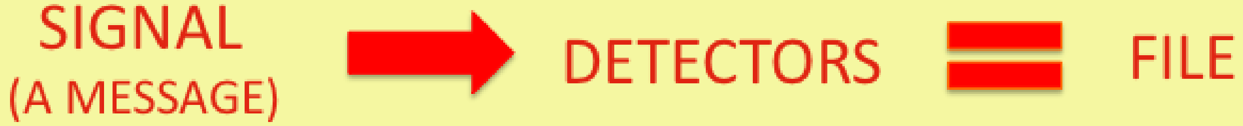
A PRIZE

A FINE

SYSTEM PAYMENTS

Machine Learning - Signals

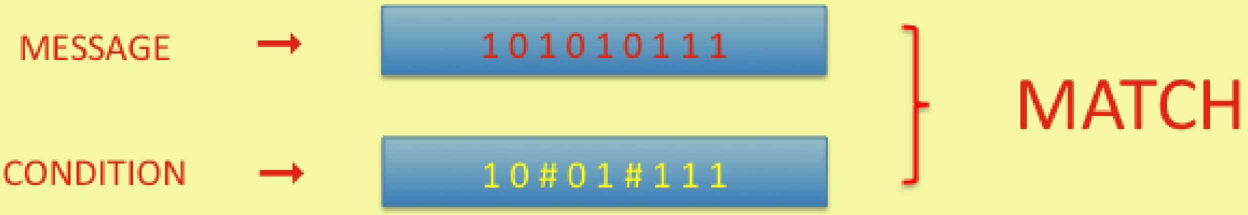
Signals are written as strings built with signs from the set of {0, 1} and are sent to the system each **dt** - a time step used in further calculations. System detectors register messages and write them to a file or environmental messages can be written to a file directly and then picked up by the system.



SIGNAL
(A MESSAGE)
DETECTORS
FILE

Machine Learning - Matching Auction

All classifiers are matched against detected signals. Each single signal is checked with each condition in the set of all system rules.



MESSAGE
101010111
CONDITION
10#01#111
MATCH

If a message matches a condition pattern it is allowed to attend an auction. By the auction the right to possess this signal can be sold according to one of the schemes:

- the best price - the single auction winner
- each offer greater than zero is a winner

The first auction plan is clear. The winner will activate the appropriate action being its (and system) answer to that message. The second method can be associated with the internal flow of information as a cascade: message - action(s) - message - ... - a single winner (final ACTION). This internal flow of inputs and outputs lasts as long as a single winner will be reached.

Machine Learning - Payments

Machine Learning - Classifiers - Strength

Strength of a rule reflects its quality. The higher strength value the better rule. A classifier's strength value is not constant but varies in time according to the auction results and can be represented by equations

- for the *j*-th classifier's merchant

$$s_i^j = s_{i-1}^j + \Delta s^m = s_{i-1}^j + \sum_k bid(s_i^k)$$

- for the *j*-th classifier's purchaser

$$s_i^j = s_{i-1}^j + \Delta s^p = s_{i-1}^j - \sum_k bid(s_i^k)$$

where $\mathbf{s_{i-1}^j}$ and $\mathbf{s_i^j}$ are strength values for the *j*-th classifier at *(i-1)*-th and *i*-th moments in time, respectively. Initial values of $\mathbf{s_{i=0}^j}$ for each *j* must be set.

Machine Learning - System Payment

Auctions are run with prices offered by selected classifiers. A classifier's bid is not any price that could be thought but depends on a variable **s** (strength) reflecting rule's quality. The higher **s** value the richer rule. It means that its ability to buy goods (signals) is high.

$$bid(s_i) = a_0 s_i dt$$

where $\mathbf{s_i}$ is the strength of i-th classifier, $\mathbf{a_0}$ is a constant and **dt** is a time step.

Bids are calculated in such a simple way since a purely deterministic mechanism is assumed as a governing law. However, classifier's offer can be additionally modified by some random fluctuations. Then the total bid value is computed according to the following equation:

$$\mathrm{bid}(s_i) = a_0 s_i dt + \mathrm{random}(\mu,\sigma,\lambda,\alpha,\mu_L,\sigma_L,\beta)$$

where **s_i** is the strength of *i*-th classifier and **random()** function can be built from the following types of noise

$$\mathrm{random}(\mu,\sigma,\lambda,\alpha,\mu_L,\sigma_L,\beta) = a_1 \mathrm{Gauss}(\mu,\sigma)\, dt^{1/2} + a_2 \mathrm{Poisson}(\lambda) - a_2 \lambda dt + a_3\, \mathrm{Levy}_\alpha(\mu_L,\sigma_L,\beta)\, dt^{1/\alpha}$$

where a_i coefficients are constants and

- Gauss(μ, σ) - a random value taken from the Gaussian distribution of average value μ and standard deviation σ

- Poisson(λ) - a random value denoting number of Poissonian jumps of intensity λ in the time range $[t_i,t_{i+1})$

- Levy$_\alpha$(μ_L, σ_L, β) - a random value from the α - stable distribution of average value μ_L, standard deviation σ_L and parameter of asymmetry β

- On the basis of above-presented stochastic processes another ones can be constructed. Among stochastic processes of significant importance one can find a Gaussian Ornstein-Uhlenbeck process and an α-stable Ornstein-Uhlenbeck process. The construction of these examples is shown.

- **dt** is a time between successive environmental messages; in the case of the cascade model, it is assumed that the cascade inner time step is much shorter than **dt** and is neglected.

Machine Learning - Tax Payment

When a bid value is calculated then both an elementary tax and a bidding tax are collected. They values depend on a variable **s** (strength). The elementary tax is gathered from all rules in the system

$$\mathrm{tax}_{el}(s_i^j) = -a_{el}\, s_i^j dt$$

while the bidding tax is charged to those classifiers which sold signals

$$tax_{bid}(s_i^j) = -a_{bid}\ s_i^j dt$$

where $\mathbf{s_i^j}$ is a strength of *j*-th classifier at *i*-th moment in time a_{el} is a tax coefficient for the elementary tax, a_{bid} is a tax coefficient for the bidding tax and **dt** is a time between successive outer (environmental) messages.

Machine Learning - Outer Payment

System answer to incoming signals must be judged by the sender. It means that there is a map of signals and corresponding proper answers. If environment obtains answers it must take an action. A correct answer causes payment leading to increase a value of a correct classifier whereas a wrong one causes a financial punishment decreasing rating of a bad one. Either a prize or a fine can be set as constant value or calculated from a receipt similar to that in the System Payments including both deterministic and **random** parts in the total payment (+) and charge (-) value:

$$OP(d_i^j) =\pm(b_0 + d_i^j)\ d\tau+ random(\mu,\sigma,\lambda,\alpha,\mu_L,\sigma_L,\beta)$$

where $\mathbf{d_i^j}$ is a deviation from the correct answer for *j*-th classifier at *i*-th moment in time, $\mathbf{b_0}$ is a constant and **random()** function is built from the following types of noise

$$random(\mu,\sigma,\lambda,\alpha,\mu_L,\sigma_L,\beta) = b_1 Gauss(\mu,\sigma)\ d\tau^{1/2} + b_2 Poisson(\lambda) - b_2\lambda d\tau + b_3\ Levy_\alpha(\mu_L,\sigma_L,\beta)\ d\tau^{1/\alpha}$$

where b_i coefficients are constants and

●Gauss(μ, σ) - a random number from the Gaussian distribution of average value μ and standard deviation σ

●Poisson(λ) - a random value denoting number of Poissonian jumps of intensity λ in the time range $[t_i,t_{i+1})$

- $Levy_{\alpha}(\mu_L, \sigma_L, \beta)$ - a random number from the α - stable distribution of average value μ_L, standard deviation σ_L and parameter of asymmetry β
- how to construct a Gaussian Ornstein-Uhlenbeck process and an α-stable Ornstein-Uhlenbeck process is also presented
- **d**τ is a time distance between successive environmental payments or/and charges.

Machine Learning - Internet Configuration

For a proper work of a machine learning system **synchronized communication** between **the system** and **the outer environment** is crucial. The **optfinderML** provides users with internet services available in two modes:

- as a http server
- as a http client

Machine Learning - Tools - Time Series Analysis

Time Series Analysis can be performed via three main approaches depending on time series origin:

- trend finding - means extracting the deterministic part of time series
- stochastic analysis - means a set of tools designed for examining time series of random sources
- chaotic systems analysis including
  - Poincare map -a tool for simplifying phase portraits invented for chaotic processes (and frequency calculator)
  - embed and correlation dimension finding
  - the largest positive Lyapunov exponent calculation

Machine Learning - Genetic Algorithms

Genetic algorithms (GA) approach is applied for performing a selection among a set of rules as well as introducing a certain level of rule's diversity in order to tend towards the maximum of environmental feedback. Genetic algorithms can be divided into two main groups of haploid and diploid type. Both genetic models deal with populations of sequences of ternary digits {0, 1, #} (rules conditions). Each sequence represents a condition written as

- a single string (constituting an artificial chromosome) in haploid GA
- a pair of strings (a pair of chromosomes) in diploid GA.

Information from the genotype (=condition) is used in the matching procedure. To every genotype is assigned a numeric value being the genotype's strength. It can be modified by auctions. The genotype's strength (=classifier's strength) is equivalent to the fitness function in genetic algorithms. The fitness function is the essential measure of chromosome strength to occur in the next generation. The higher fitness of chromosome the greater chance to reproduce. Reproduction in population is thought as a randomized process based on the fitness function. Only these chromosomes that are selected can take part in producing the next generation. The reproduction algorithm is based on the de Jong's crowd model.

In haploid models, a pair of chromosomes is a pair of parents that exchange their genetic information through the crossover process whereas, in diploid models, the process of gametogenesis uses the crossover mechanism to exchange genetic information between gametes. The crossover point on two parent chromosomes is chosen with assumed crossover probability. Apart from that random process genetic information can be modified through mutations. They also are random and occur with prescribed mutation probability.

Machine Learning - OptFinderML

Package for machine learning - OptFinderML.

Machine Learning - References

1.^ David E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley Publishing Company, Inc. 1989

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