Computational intelligence - first part

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Inteligenta Computationala

Computational intelligence (CI) usually refers to the ability of a computer to learn a specific task from data or experimental observation (wikipedia)

Computational Intelligence (CI) is the theory, design, application and development of biologically and linguistically motivated computational paradigms. Traditionally the three main pillars of CI have been Neural Networks, Fuzzy Systems and Evolutionary Computation. However, in time many nature inspired computing paradigms have evolved. (Computational Intelligence Society)

Computational intelligence is the study of the design of intelligent agents.
Similar to the concept of AI, there is no common accepted definition of CI.

Scurta istorie a Inteligentei Artificiale

- 1940-1950: Inceputurile
  - 1943: McCulloch si Pitts: circuit boolean ca model al creierului
  - 1950: Turing's article "Computing Machinery and Intelligence"
    Turing machine is a mathematical *model* of computation that defines an abstract machine, which manipulates symbols on a strip of tape according to a table of rules.
    Turing idea: Child programme:"Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulated the child's?

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  - 1956: intalnirea de la Dartmouth: a fost adoptat termenul de "Artificial Intelligence" John McCarthy
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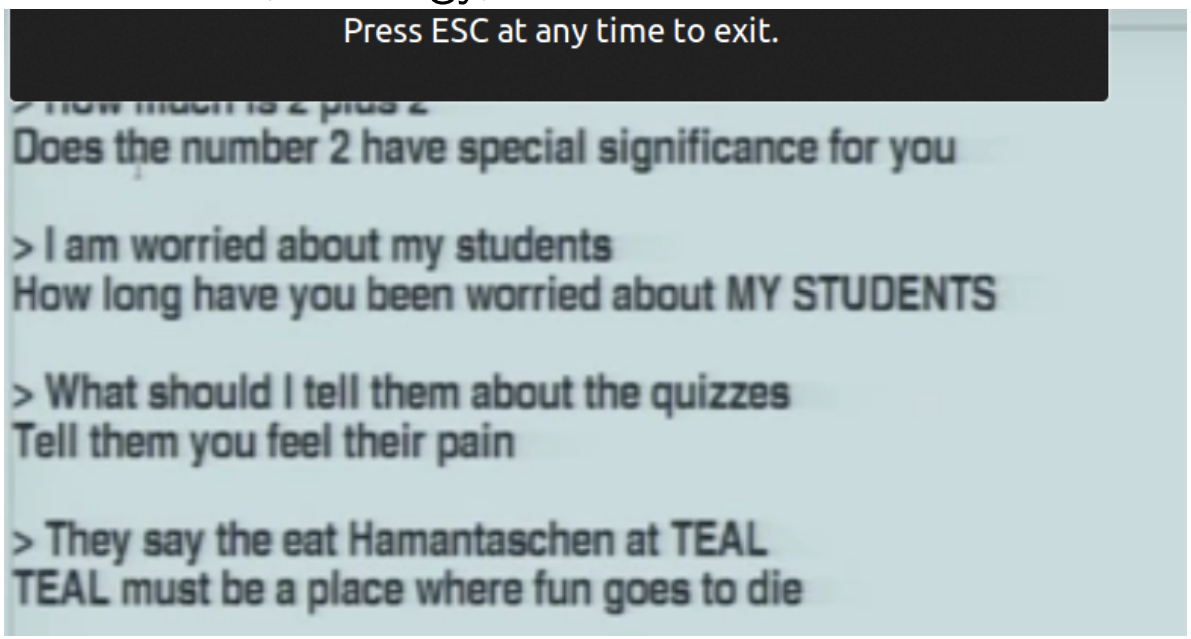

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  - 1965: Robinson's complete algorithm for logical reasoning
  - 1966: "the spirit is willing, but the flesh is weak" - "the vodka is good but the meat is rotten"

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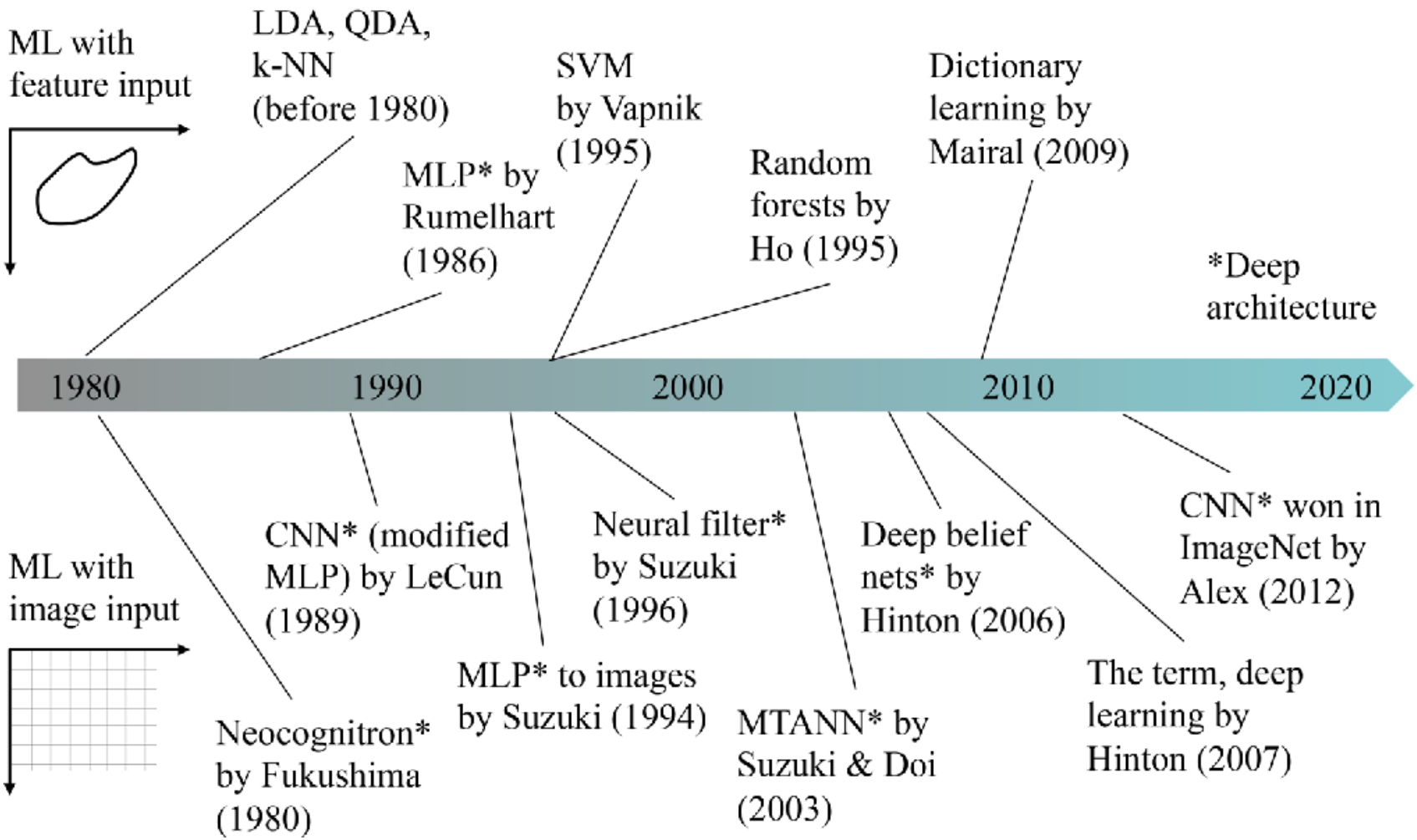
- 1970 - 90: Abordarea bazata pe cunostinte
  - 1969 - 79: Early development of knowledge-based systems
  - 1980 - 88: Expert systems industry booms
  - 1988 - 93: "AI Winter"
- 1990 -: Abordarea statistica
  - Resurgence of probability, focus on uncertainty
  - Deep Blue - 1997 chess Kasparov
  - General increase in technical depth
  - Agents and learning systems... "AI Spring"
- 2000 : Avant si omniprezenta
- 2013 - Deep learning

Hot topic - deep learning history (for medical images)



Organizare propusa

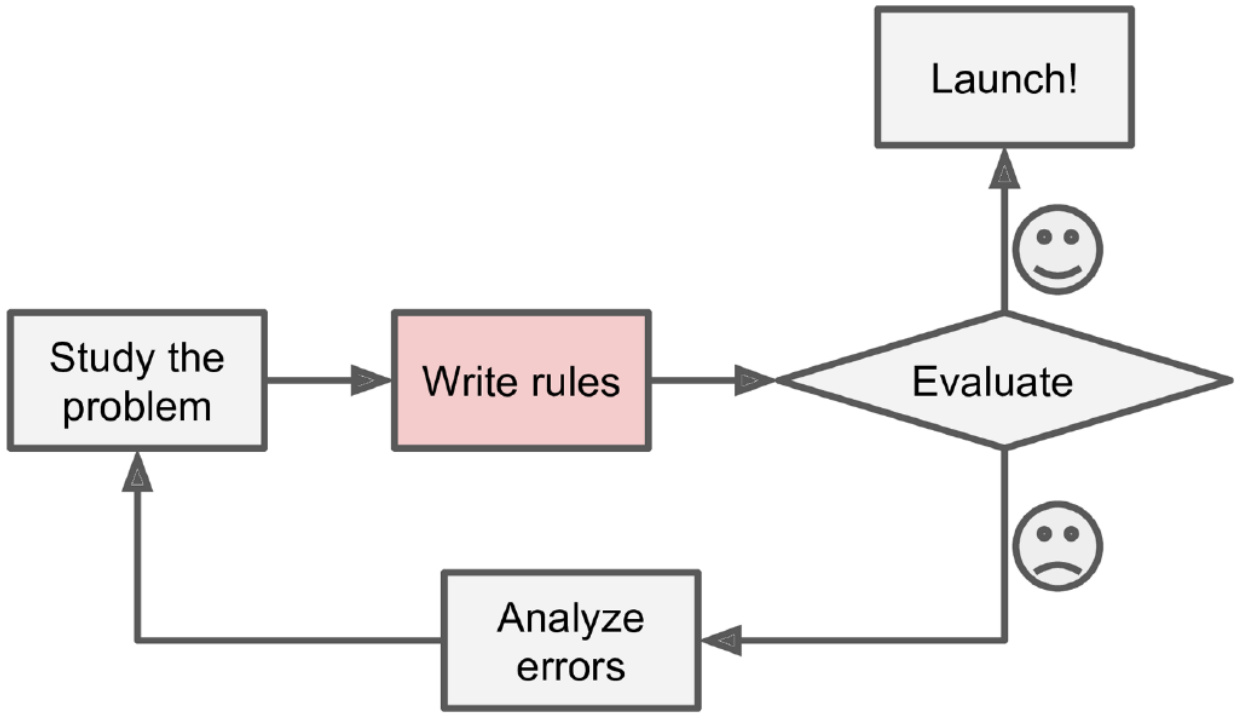
- Prima zi:
  - Machine learning clasic
  - Probleme generale ale ML,
  - Metrici de performanta
  - Diverse exemple in scikit si Matlab
- A doua zi:
  - Deep learning: retele neuronale, retele recurente, aplicatii
  - Exemple in tensorflow si Matlab
  - Exemplu Signal trading - comparatie
- A treia zi:
  - Deep learning in NLP - word embedding, text generation;
  - Vizualizarea retelelor pentru a intelege ce invata - exemplul OCT
  - Reinforcement Learning
  - Genetic Algorithm

Obiective generale ale cursului

- concepte generale ale paradigmelor CI prezentate
- explorare diverse probleme ML
- exemple de aplicare

Ce e Machine Learning?

- "Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed" (Arthur Samuel 1959)
  Clasic programming:



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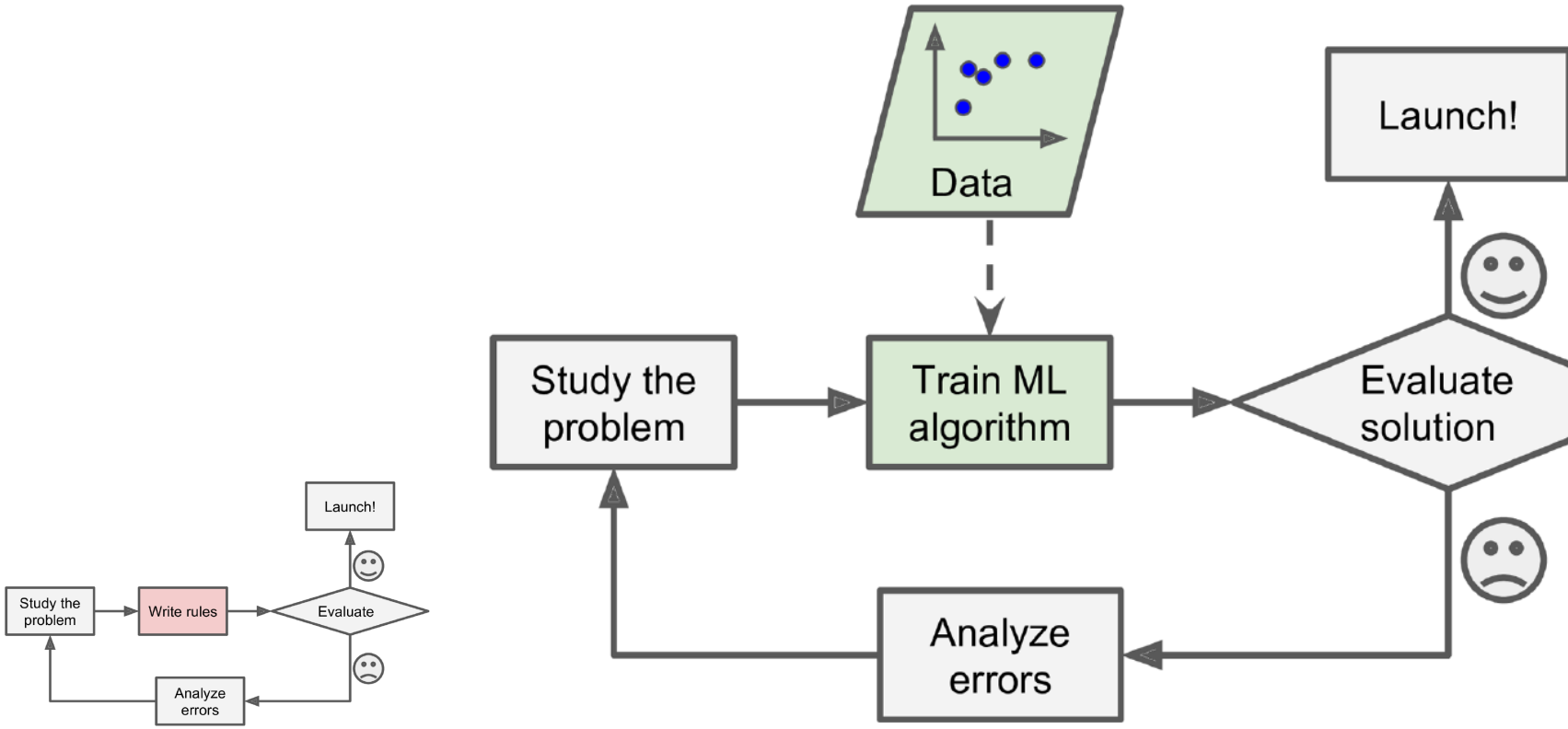
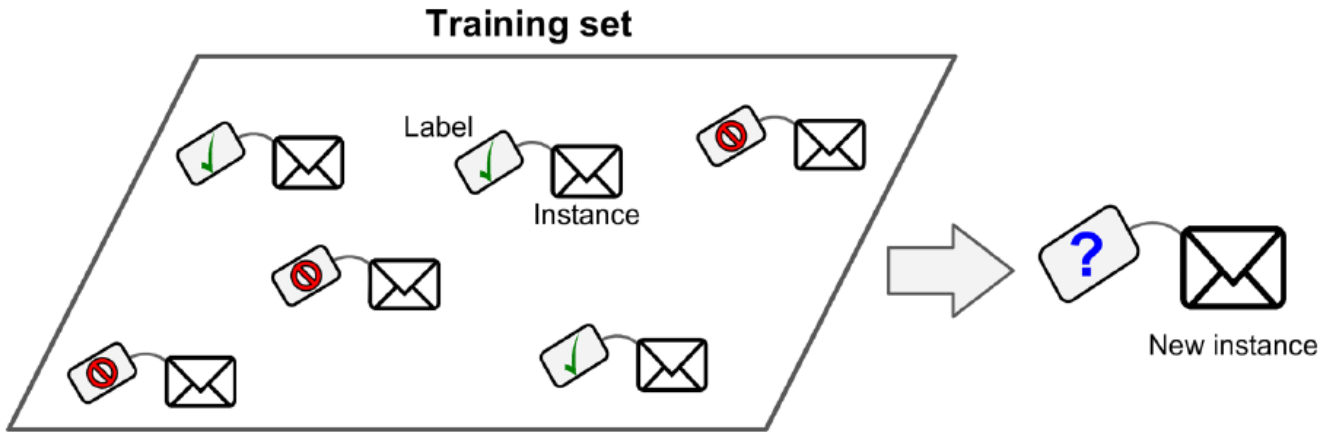


Tipuri de sisteme ML

Criteriu 1: sunt antrenate cu supervizare umana

- Supervizate: clasificare,



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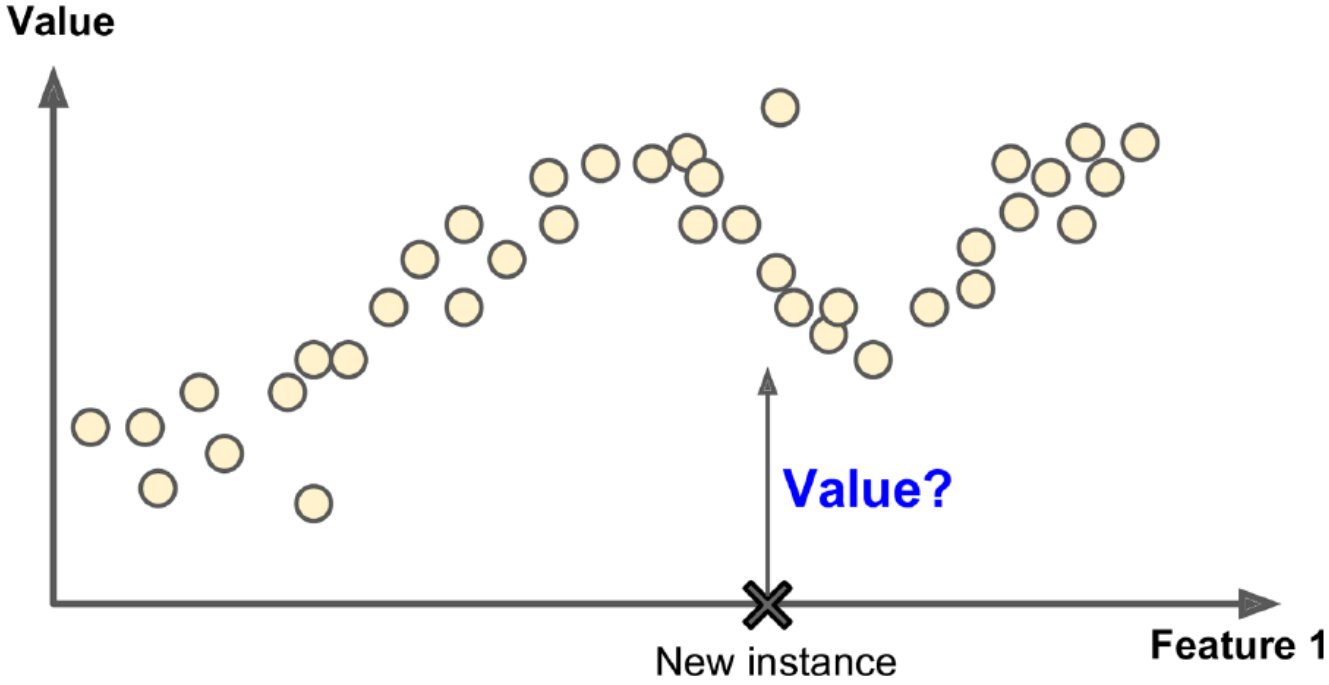

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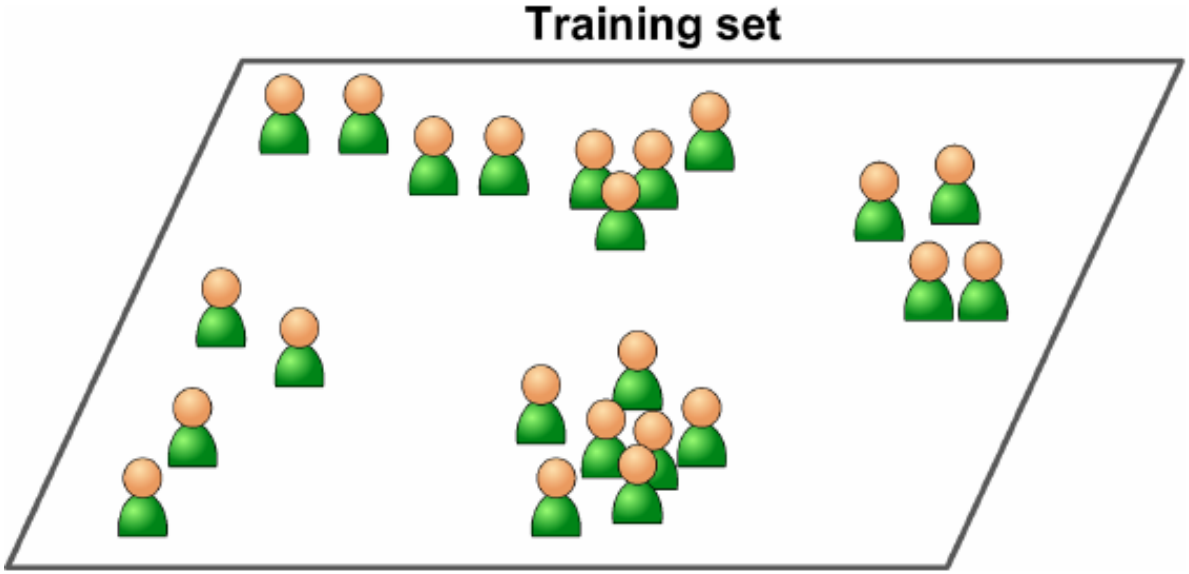
- Nesupervizate - datele de antrenare sunt ne-etichetate



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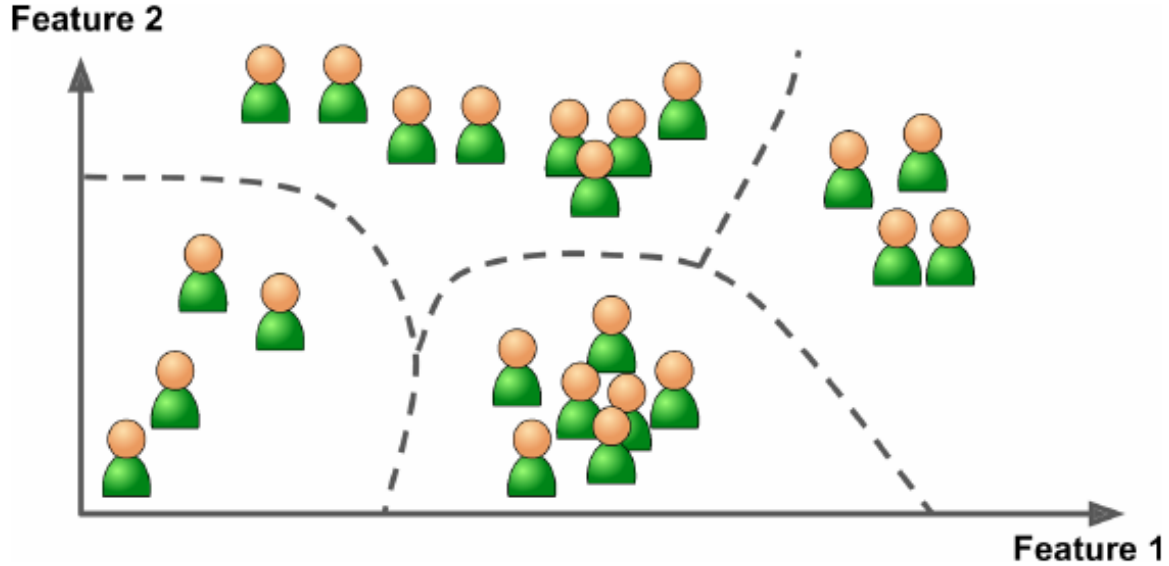

- Semi-supervizate

Tipuri de sisteme ML

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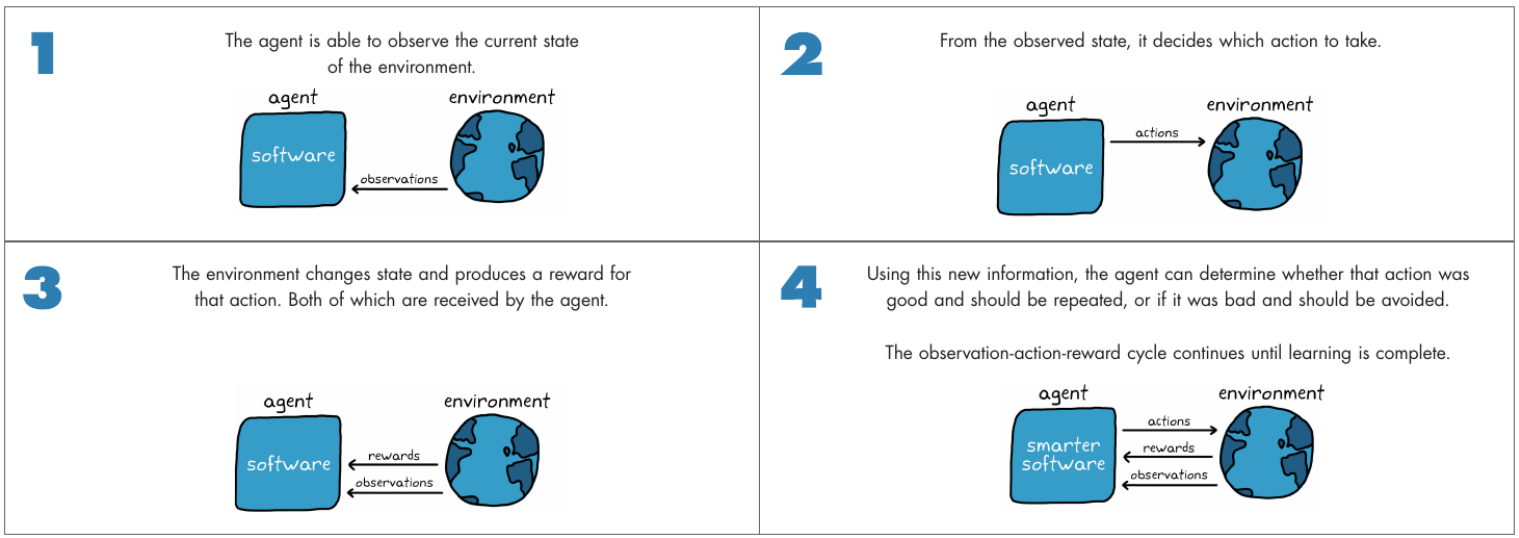
- Semi-supervizate
- Reinforcement Learning (invatare ranforsata)



Algoritmi invatare supervizata

- k-NN - k-nearest neighbors
- Linear Regression
- Logistic Regression
- Decision Trees, Random Forest
- Support Vector Machines (SVM)
- Retele neuronale

Algoritmi invatare nesupervizata

- Clustering: k-Means, Expectation Minimization
- Reducerea dimensionalitatii: Principal Component Analysis (PCA), t-distributed Stochastic Neighbor Embedding (t-SNE)
- Reguli de asociere(association rules): apriori, frequent item sets

Tipuri de sisteme ML

Criteriu 2: Sunt capabile sistemele sa invete din date primite continuu

- Batch learning: sistemele nu invata incremental
  - offline learning - sistemul este antrenatr si pe urma lansat - deci va aplica doar ce a invatat
- Online learning: sistemele se antreneaza incremental
  - mini-batch - impartirea datelor in grupuri mici - solutie si pentru date de dimensiune mare

Tipuri de sisteme ML

Criteriu 3: Cum generalizeaza sistemele? Dandu-se exemplele de antrenare, e necesar ca sistemul sa fie bun pe acestea, dar trebuie sa fie bun si pe date noi

- Instance-based learning - sistemul invata pe de rost datele si generalizeaza date noi prin diverse masuri de similaritate
- Model-based learning - sistemul invata un model pe care il poate aplica ulterior pentru a prezice (to predict) fara datele din care a invatat

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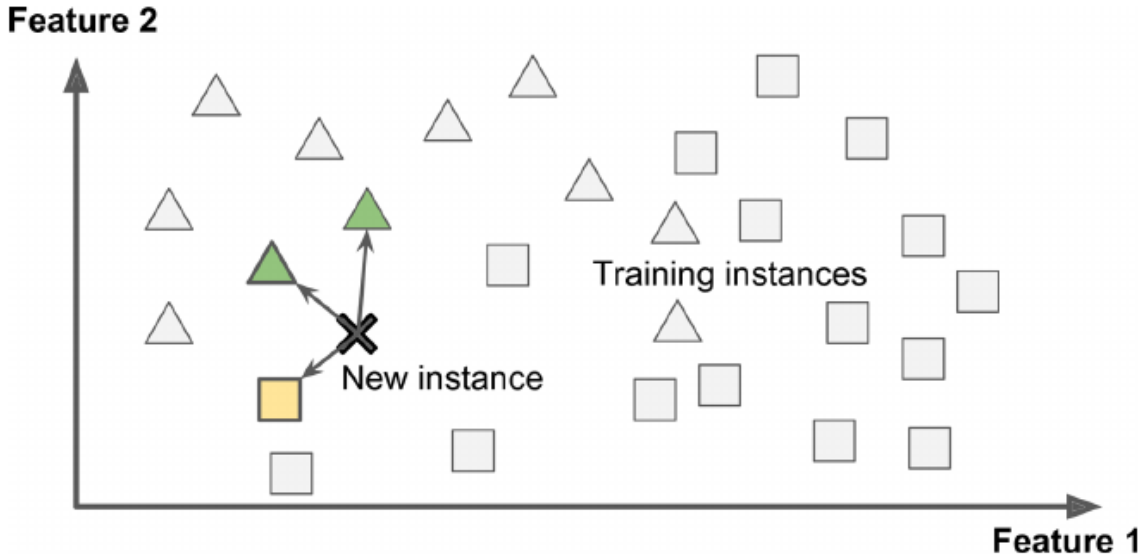

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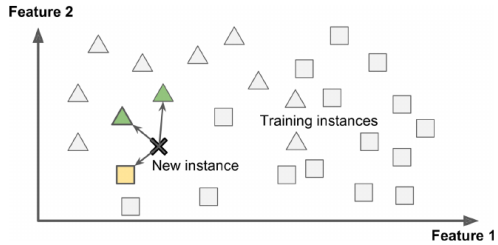

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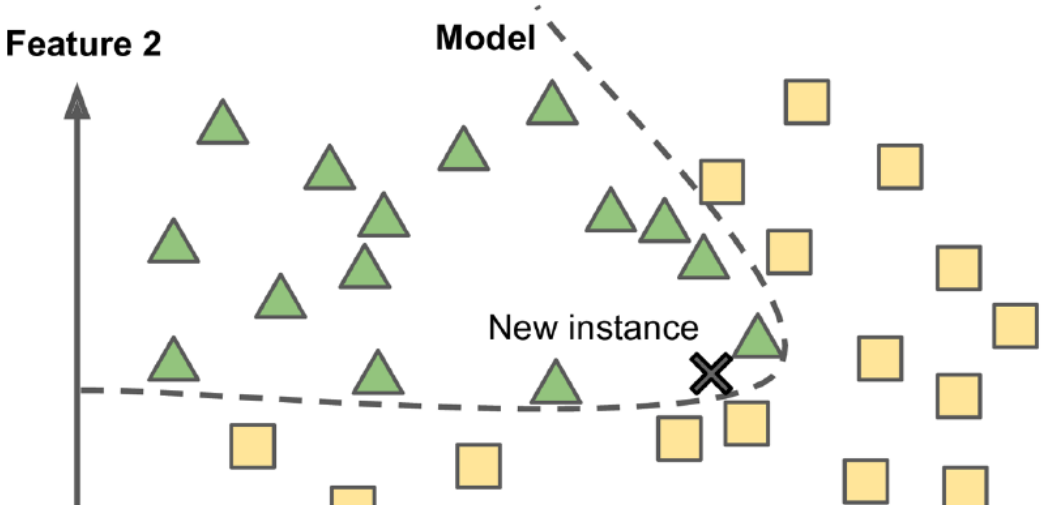
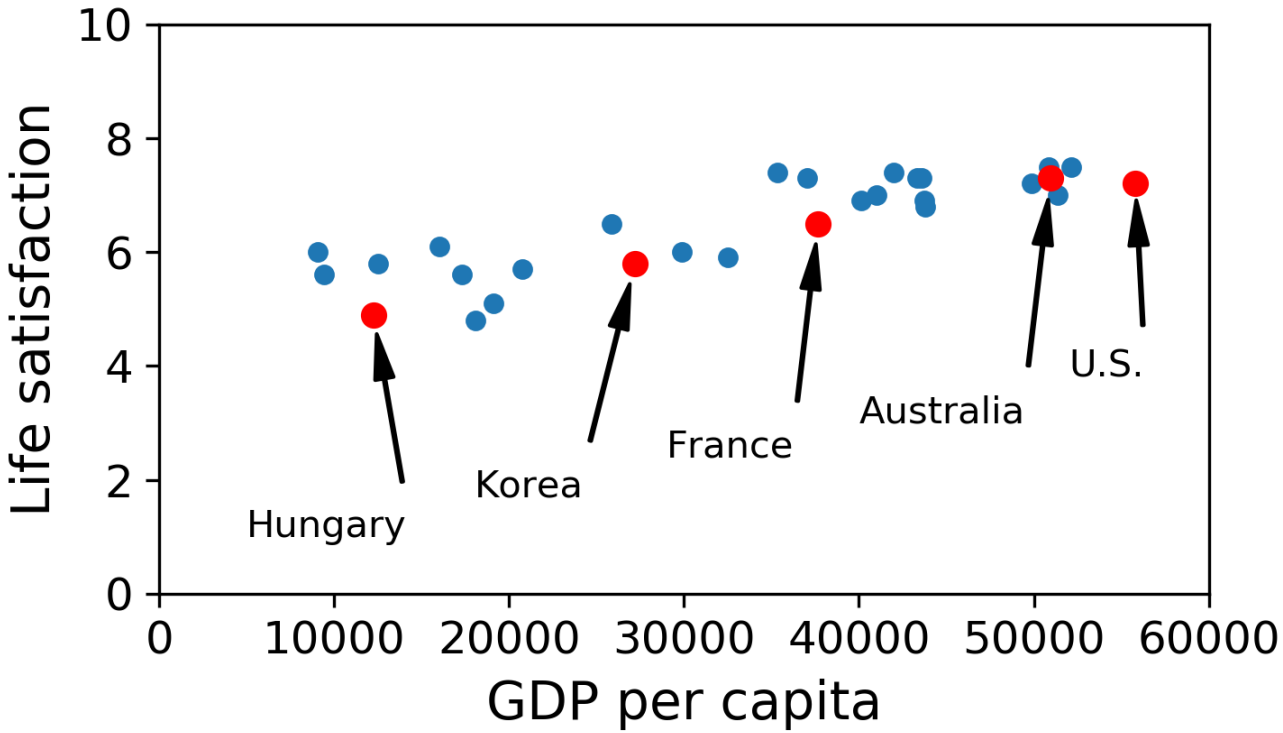


Exemplu de model

Can we say which is the life satisfaction of a country for which we know GDP per capita?

OECD: Better life Index - Life satisfaction

PIB (GDB per capita) de pe site-ul IMF



Time for notebook: 1. GDP - Model based learning

Principalele provocari ale ML

- Date insuficiente
- Date nereprezentative
- Calitate slaba a datelor - (ex. date lipsa)
- Caracteristici (features) irelevante
- Probleme ale invatarii: overfitting, underfitting

No free lunch theorem

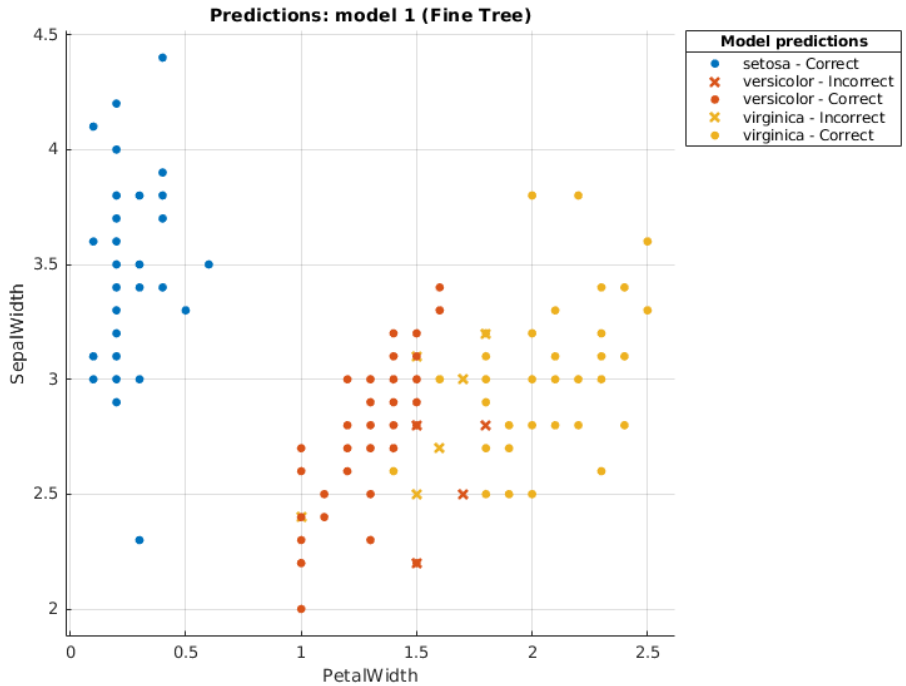
Ce e un model? este o versiune simplificata a observatiilor $\Rightarrow$ asumptii

- (NFL)In absenta oricarei asumptii, nu exista niciun motiv pentru a prefera un model in defavoarea altuia (1996).

Pentru unele date, modelul liniar este bun, pentru altele cel neuronal. Nu exista niciun model care este garantat apriori ca va functiona mai bine.

Exemplu in matlab - Clasificarea florilor de iris

- incarcare date
- vizualizare
- alegere model
- train
- vizualizare rezultate
- schimbare model/train
- schimbare features (caracteristici), alegere model, train
- exportare model
- utilizare model pentru a prezice

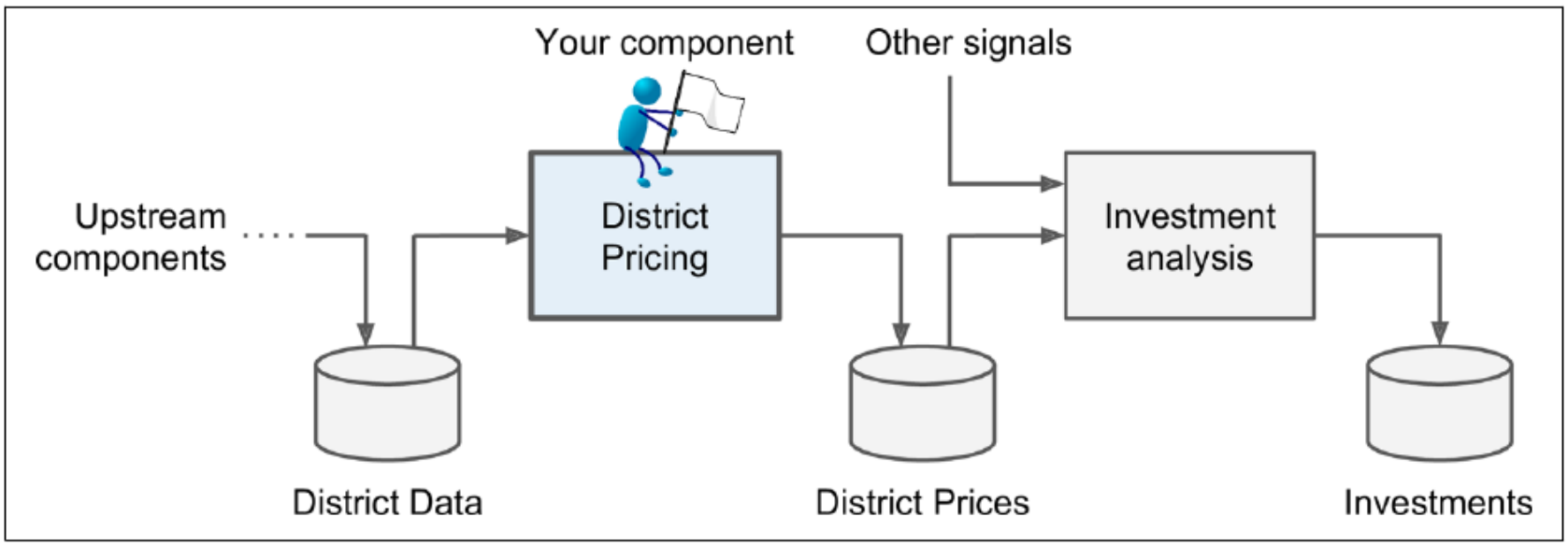


Pauza

End-to-End ML project

1. Look at the big picture :)
2. Obtinerea datelor
3. Descoperirea si vizualizarea datelor
4. Pregatirea datelor pentru algoritmii ML
5. Selectarea modelului si antrenarea lui
6. Fine-tuning al modelului

Look at the big picture

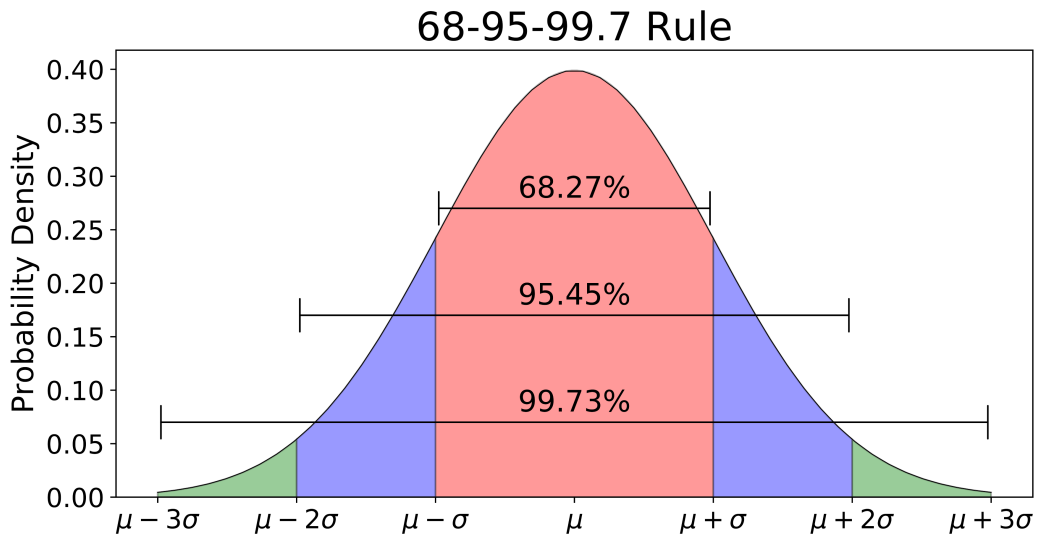


Alegerea unei masuri a performantei

Tipic pentru regresii: Root Mean Square Error (RMSE)

$$RMSE(X, h) = \sqrt{\frac{1}{m} \sum (h(x^{(i)}) - y^{(i)})^2}$$

- masoara deviatia standards a erorii in predictie



- 68% din predictii vor fi la *distanta* $= 1$ *deviatia standard* de valoarea reala, 95% la *distanta* $= 2 *$ *deviatia standard*, 99.7% la *distanta* $= 3 *$ *deviatia standard*

Alegerea unei masuri a performantei - MAE

Alternativa la

$$RMSE(X, h) = \sqrt{\frac{1}{m} \sum (h(x^{(i)}) - y^{(i)})^2}$$

Mean absolute error (MAE) - mai buna in cazul existentei valorilor outlier

$$MAE(X, h) = \frac{1}{m} \sum |h(x^{(i)} - y^{(i)})|$$

Time for Notebook

2. End-to-end Process Californian houses
   - Obiective: Pasii principali in cadrul unui proces care implica ML

Matlab: aplicarea invatarii pe aceleasi date in Matlab (cu/fara noile caracteristici, cu cross-validation) *original_housing.csv*, *processed_californian_houses.csv*

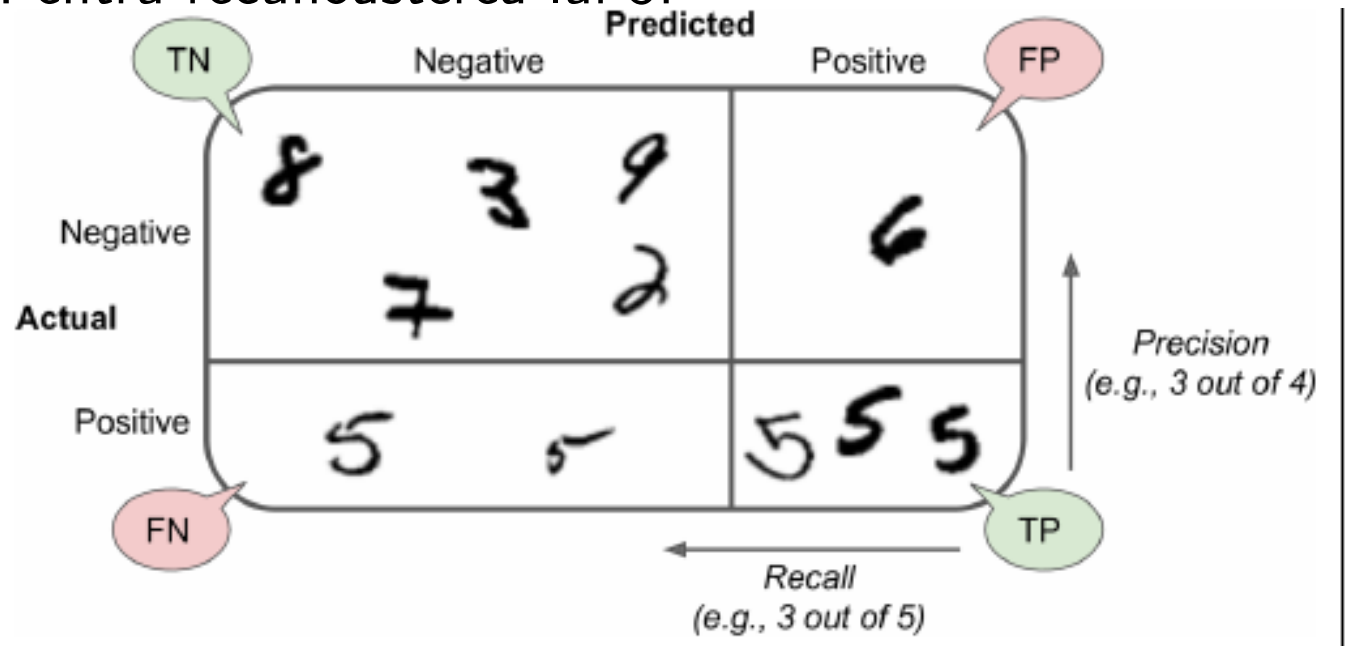
Clasificare - Classification

- Clasificare = predictia unei clase
- Exemplu = recunoasterea unei cifre scrise de mana MNIST

- Obiective:
  - Metrici de performanta pentru evaluare
    Observatie: De obicei, evaluarea e mai greu de facut decat la regresie
  - Seturi de date nebalansate

Tehnici folosite in evaluare

- Acuratete: de ce nu e suficienta acuratetea?
- Cross-validation
- Matricea de confuzie (confusion matrix)
  Pentru recunoasterea lui 5:



- Precision/recall

$$Precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

Precision vs Recall

- F-measure - media armonica intre precizie si recall

$$F_1 = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} = 2 \times \frac{precision \times recall}{precision + recall}$$

- care sunt cazurile extreme pt precision/recall?
- Exemplu 1: sistem care prezice video-uri safe pentru copii: precizie mare? sau recall mare?
- Exemplu 2: sistem care prezice daca cineva e hot de pe camera de supraveghere

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- Exemplu 1: sistem care prezice video-uri safe pentru copii: precizie mare? sau recall mare?
  Sistem care respinge multe video-uri chiar daca sunt safe, dar ce pastreaza sigur e safe $\Rightarrow$ precizie mare si recall mic
- Exemplu 2: sistem care prezice daca cineva e hot de pe camera de supraveghere

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  Sistem care identifica toate cazurile de furt, chiar daca incadreaza si situatii de nefurt: adica 30% precis, dar cu 99% recall de ex.

  De obicei, cresterea preciziei duce la scaderea recall-ului si invers $\Rightarrow$ compromis intre cele doua

Curba precizie vs recall

If someone says "let's reach 99%" precision", you should ask "at what recall?"

Time for start the notebook and come back for formulas
3. Performance Measures - MNIST

ROC curve si AUC (area under the curve

AUC-ROC curve - metrica de performanta pentru pb de clasificare la diverse praguri True positive rate = recall (sensitivity)

$$TPR/Recall/Sensitivity = \frac{TP}{TP + FN}$$

TNR = specificity

$$Specificity = \frac{TN}{TN + FP}$$

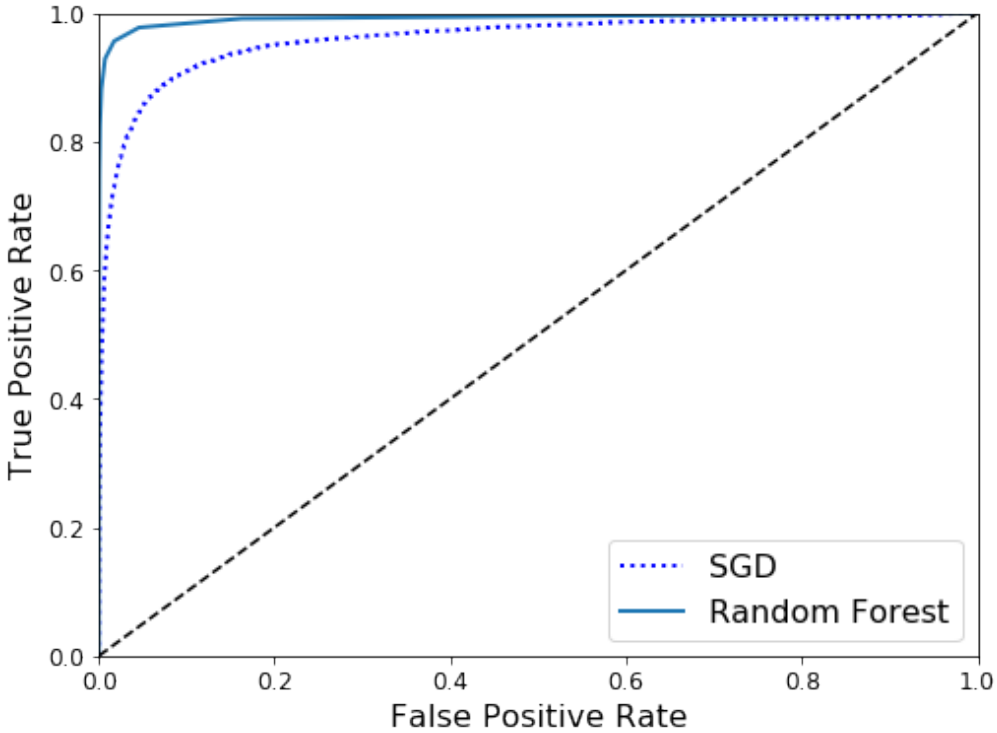
False positive rate - rata instantelor negative clasificate incorect ca positive TNR = specificity

$$FPR = 1 - Specificity = \frac{FP}{TN + FP}$$

ROC curve - sensitivity vs 1 - specificity
AUC = 0.7 - sanse 70% ca modelul sa distinga intre clasa pozitiva si cea negativa

Compararea algoritmilor cu AUC

Un clasificator perfect ar avea ROC AUC $= 1$ Un clasificator random pur are ROC AUC $= 0.5$



return to notebook

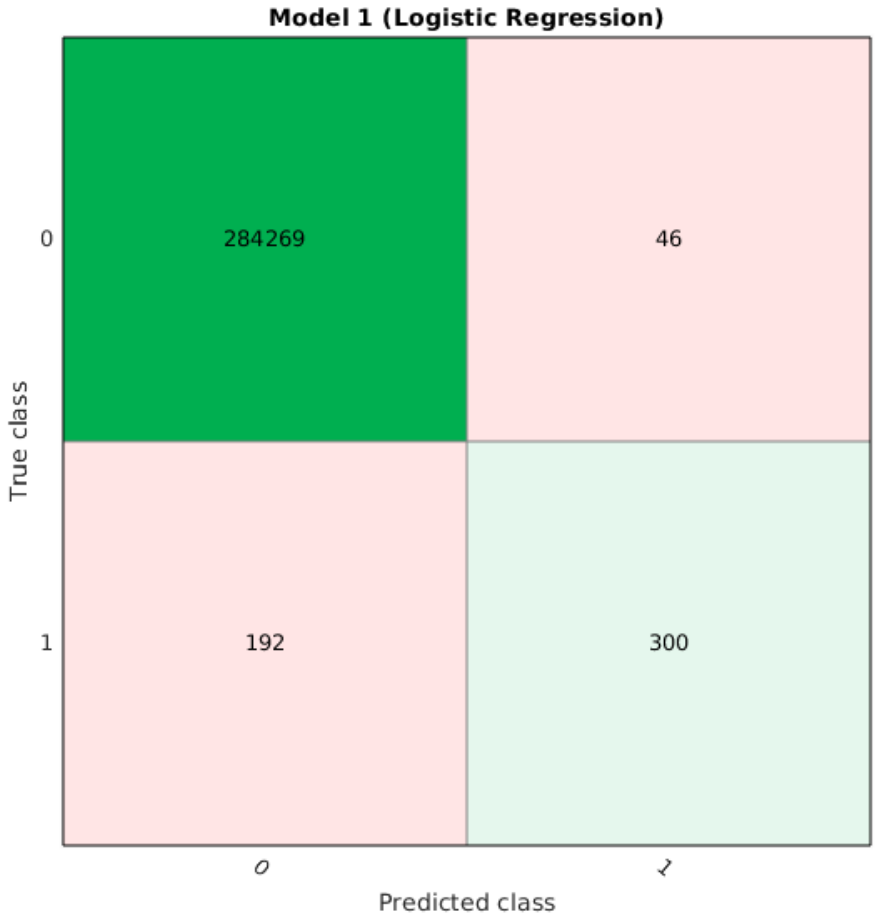
Fraud detection - matlab

Set de date: Wordline si Université Libre de Bruxelles

- Detect a 492 fraudulent transactions from 284,807 transactions in total
- Set de date de pe Kaggle
- Deep Learning Version - tensorflow
- readtable('examples/creditcard.csv')

Acuratete? - Logistic regression

acuratete=99% (52sec GPU Quadro Pro 6000)



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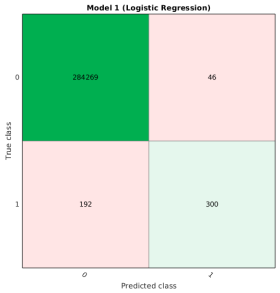

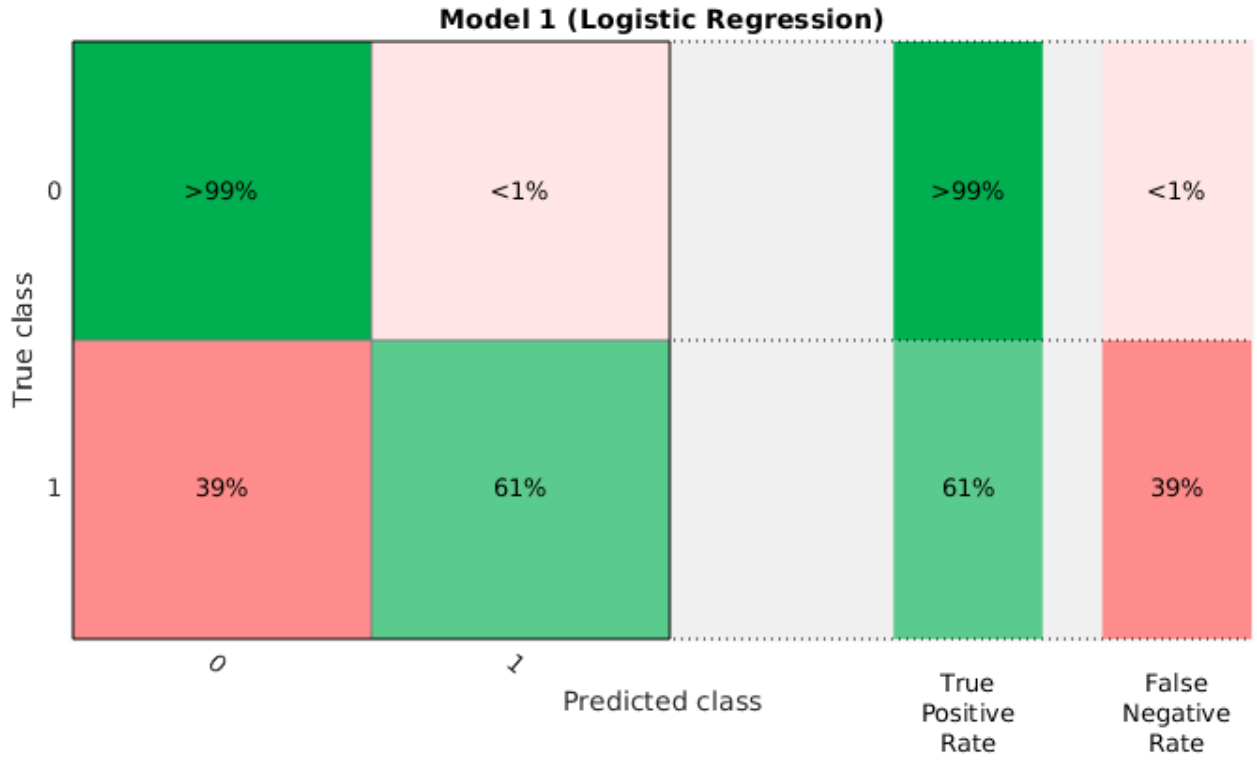

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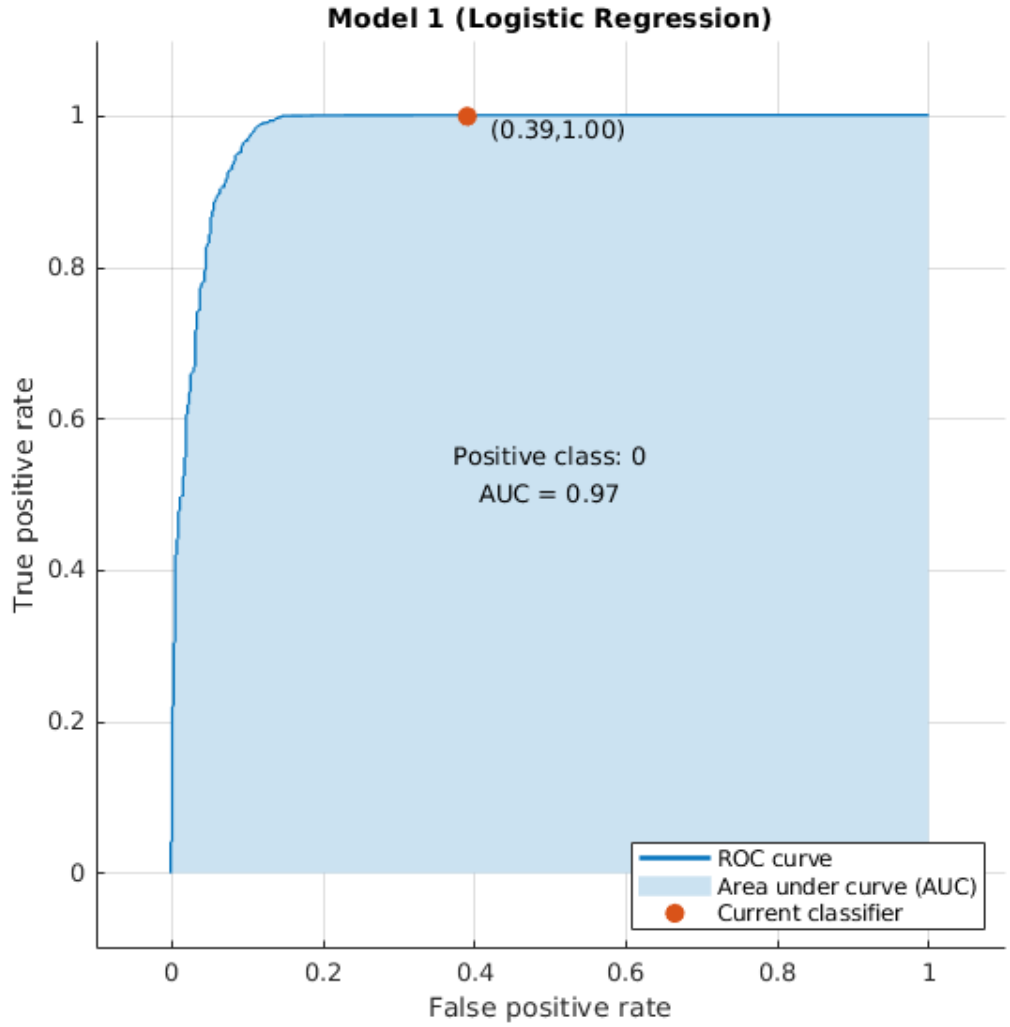
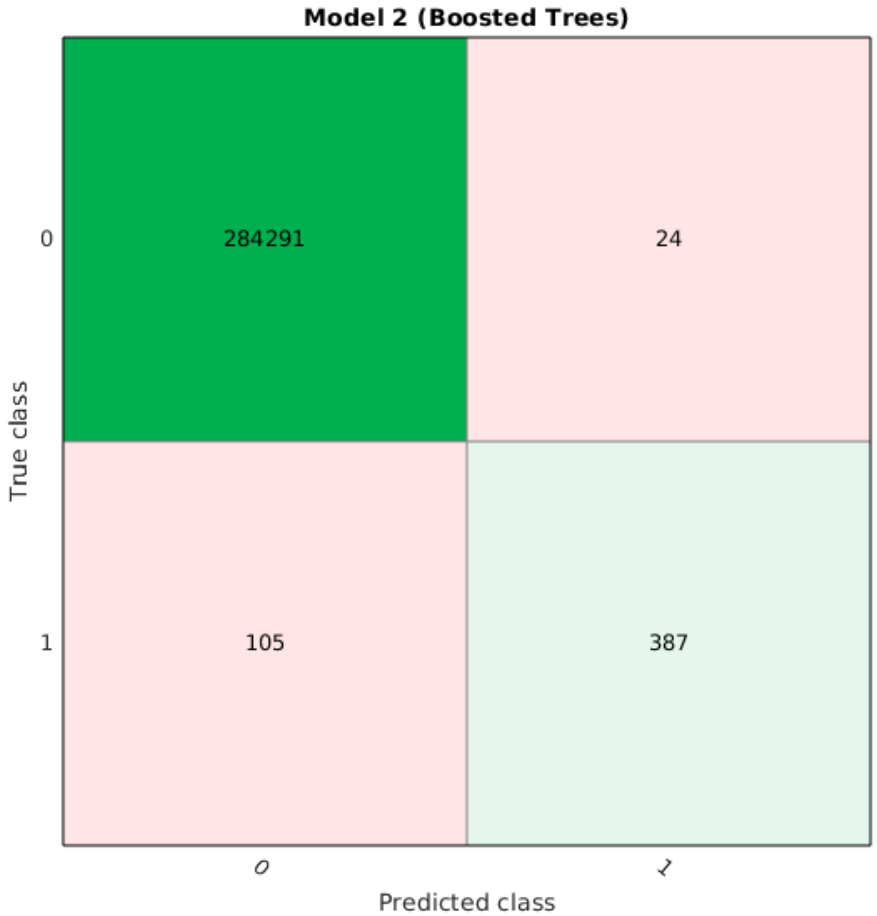


Acuratete? Boosted Decision Tree

acuratete=100% (700sec GPU Quadro Pro 6000)



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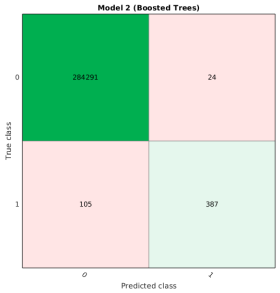
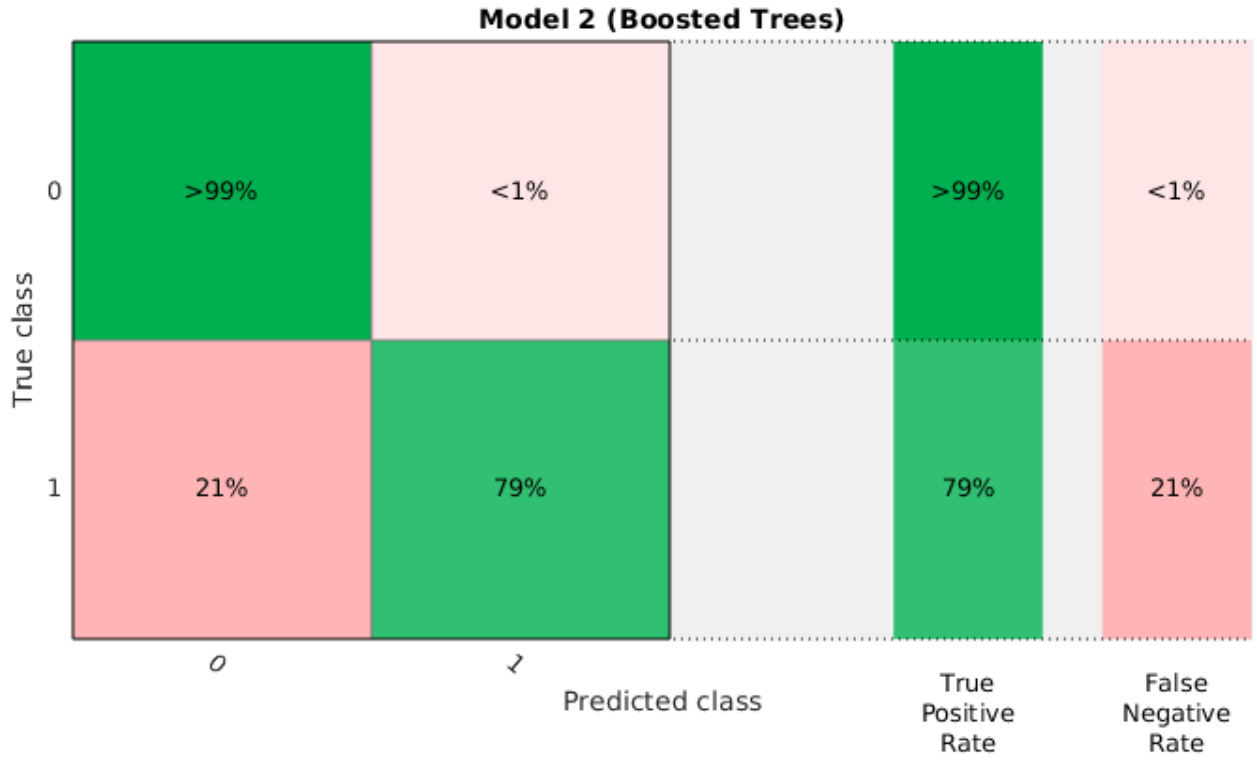
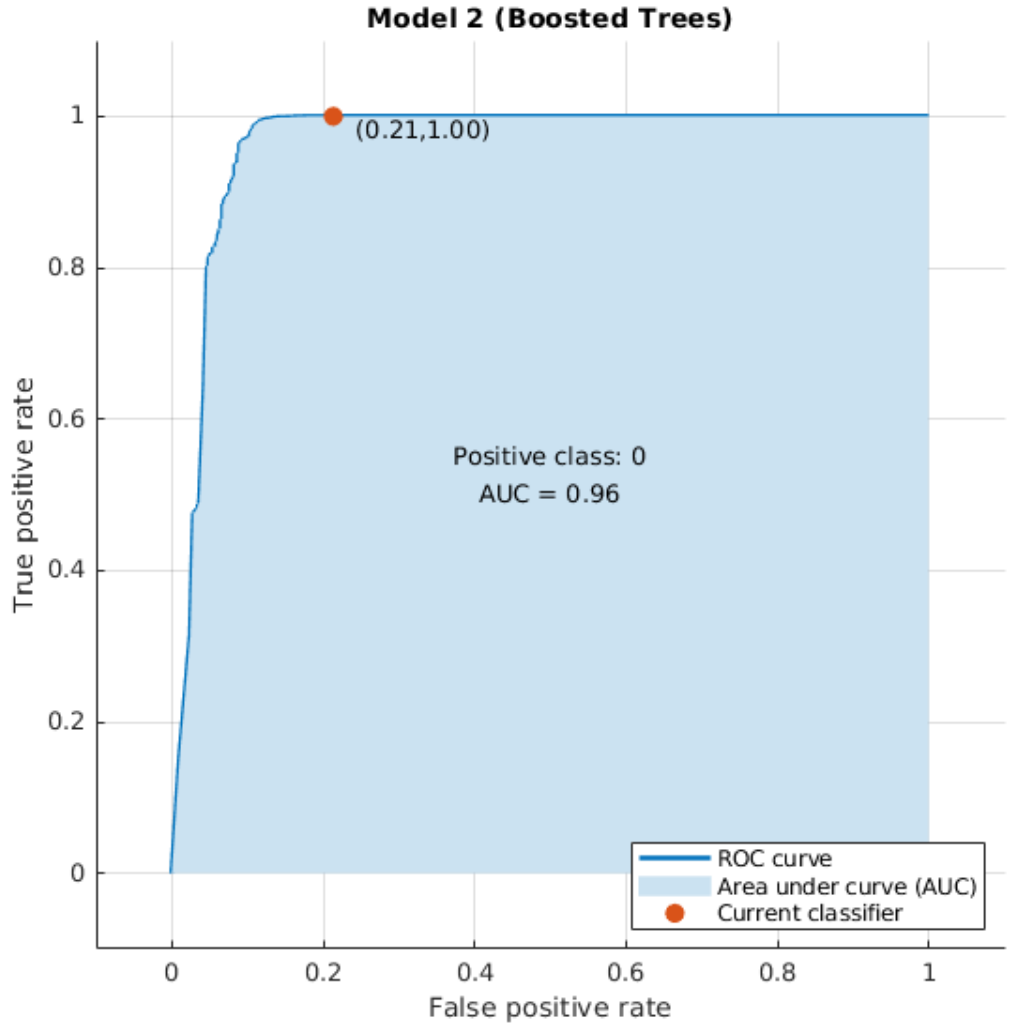
acuratete=100% (700sec GPU Quadro Pro 6000)





Acuratete? Boosted Decision Tree

acuratete=100% (700sec GPU Quadro Pro 6000)



Matlab: play with the saved model

- Load the saved model
- Load the data
- Get prediction probabilties
- Set different threshold and compute TPR, FPR
- see *different_threshold.m*

Exemplul va fi reluat in Tensorflow cu diverse variante de rezolvare a caracterului nebalansat al datelor

Bias vs variance

Time for notebook: 4. Linear Regression- Bias - Variance

- Cum alegem complexitatea unui model?
- Ce inseamna Regresie Liniara?
- Curba de invatare
- Care sunt sursele de eroare ale modelelor in generalizare?

ML frameworks

- Micorosft Azure
- Matlab toolboxes
- scikit-learn, weka, Apache Spark, R
- Tensorflow, Keras, Pytorch, MXNet, Gluon, DL4j

Utilizare AI

- Microsoft AI Demos
  - Language understanding
  - Text analytics
  - Computer vision
  - Face and emotion recognition
- Microsoft Azure Cognitive services :
  - Demo, LUIS Home
  - Vision
- IBM Watson
  - Discovery

NLP

- Allen Institute applications
- Aristo news
- Aristo demo

Credit rating Demo

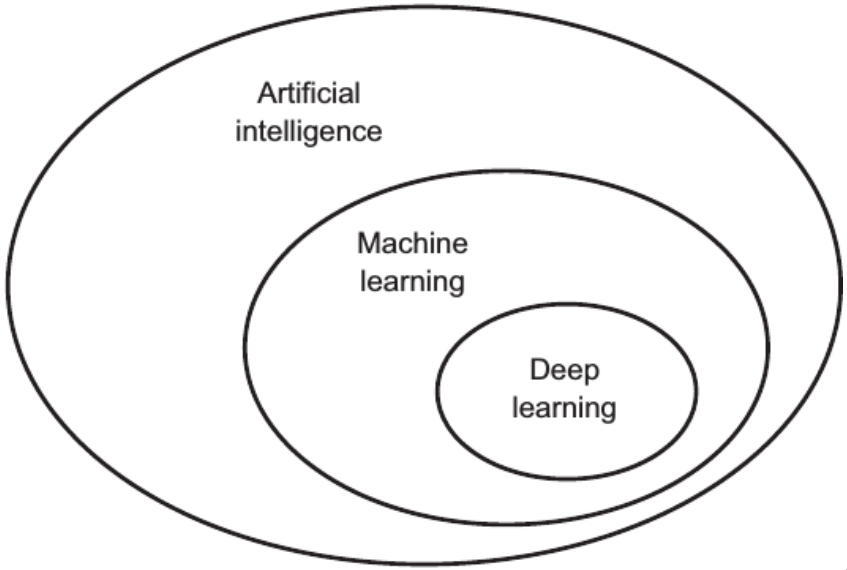
```
openExample('stats/creditratingdemo')
```

Open it as a Live Script
The data: "*CreditRating_Historical.dat*"
/home/nico/install_matlab/toolbox/stats/statsdemos

More matlab

Use Latlab_ex2.pdf

Ce e deep learning?

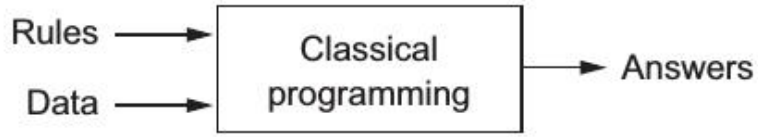


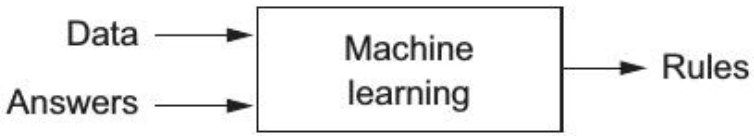
AI (anii 1950)

- automatizarea taskurilor intelectuale realizate in mod normal de oameni

... recomandari (youtube, carti, destinatii turistice), masina autonoma, rationare, identificarea automata a emailurilor spam, a fraudelor financiare

Sistemele de machine learning





- antrenat (trained), nu programat in mod explicit
- **invata**
  - cum sa combine input
  - pentru a produce predictii utile
  - pe data noi
- Ex: automatizarea taskului de descriere a unei poze
  - set de poze insotite de descriere
  - antrenare

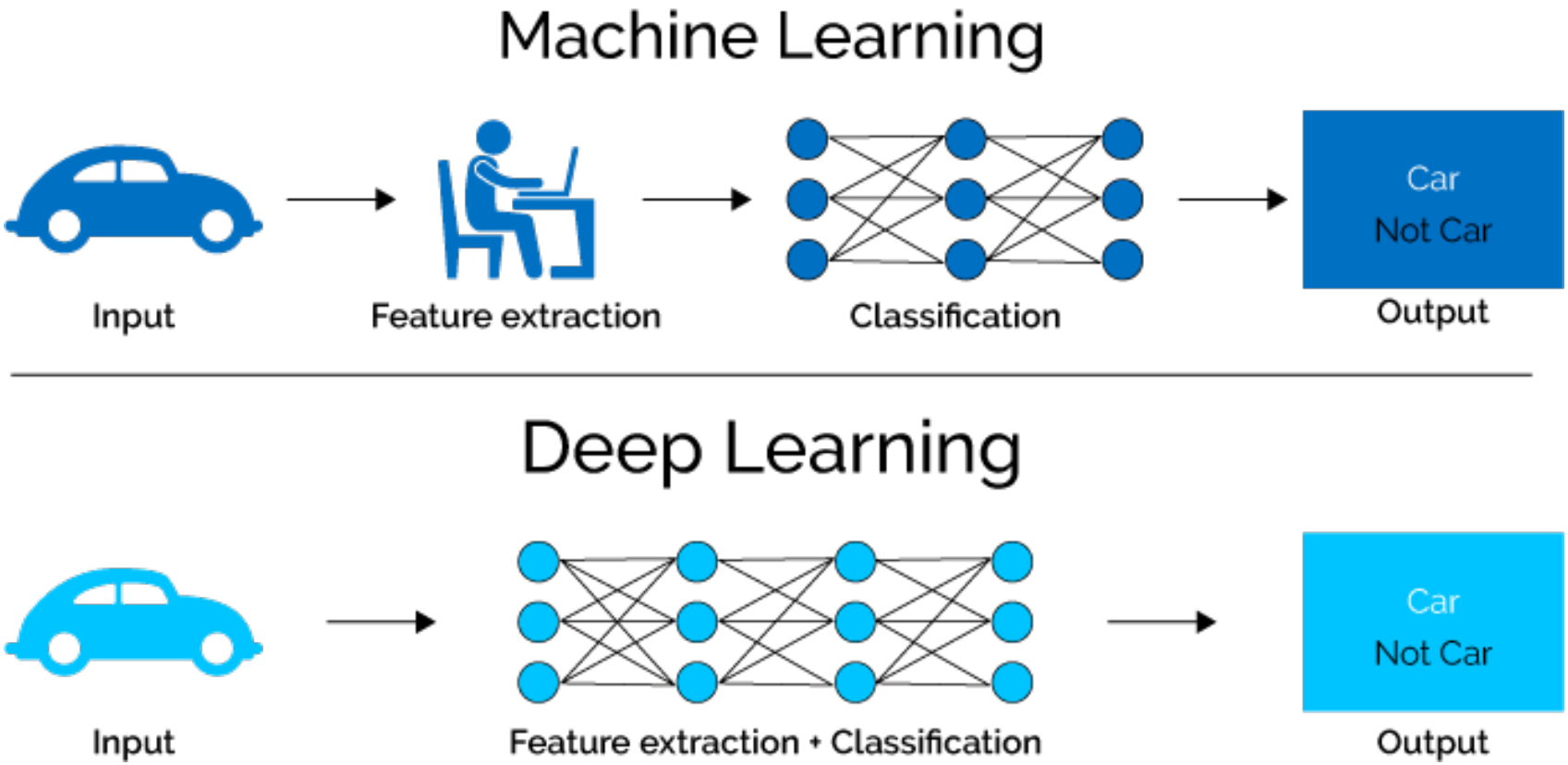
Deep learning (anii 2010)

Invatarea unor reprezentari din date care pune accentul pe

- invatarea unor nivele succesive de reprezentari
- layered representation learning

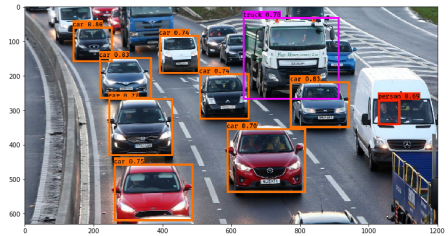
- retele neuronale (neural network)

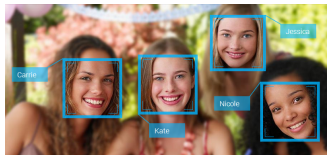
Deep Learning vs Classical Learning



Rezultate deep learning

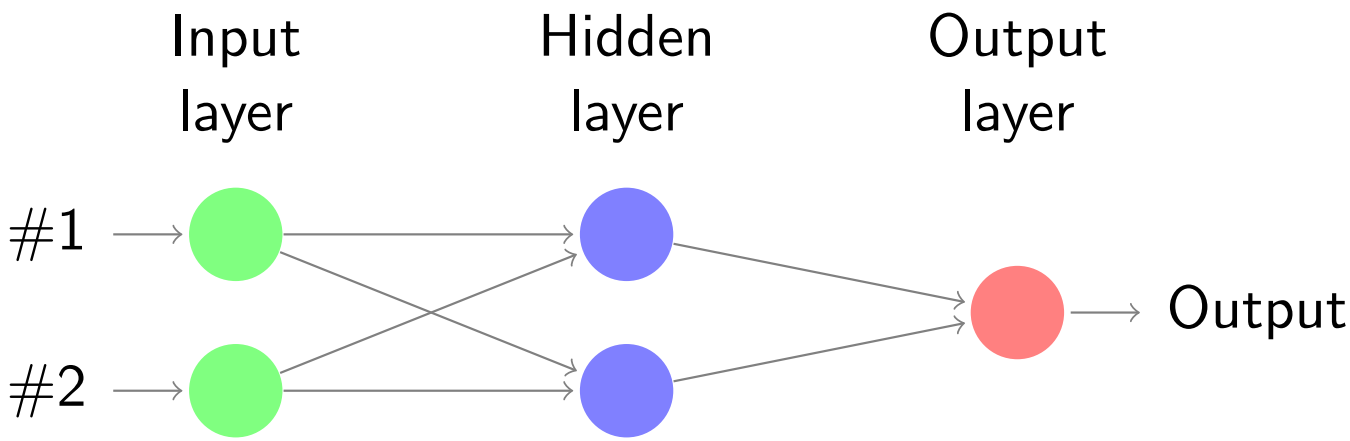
- clasificarea imaginilor (image classification) (near human-level)
- recunoasterea vorbii (speech recognition)
- recunoasterea scrisului de mana
- asistenti digitali Google Now, Amazon Alexa
- traduceri (imbunatatire)
- masina autonoma
- intelegerea textului
- Go (Alpha Go) (2016) (superhuman)



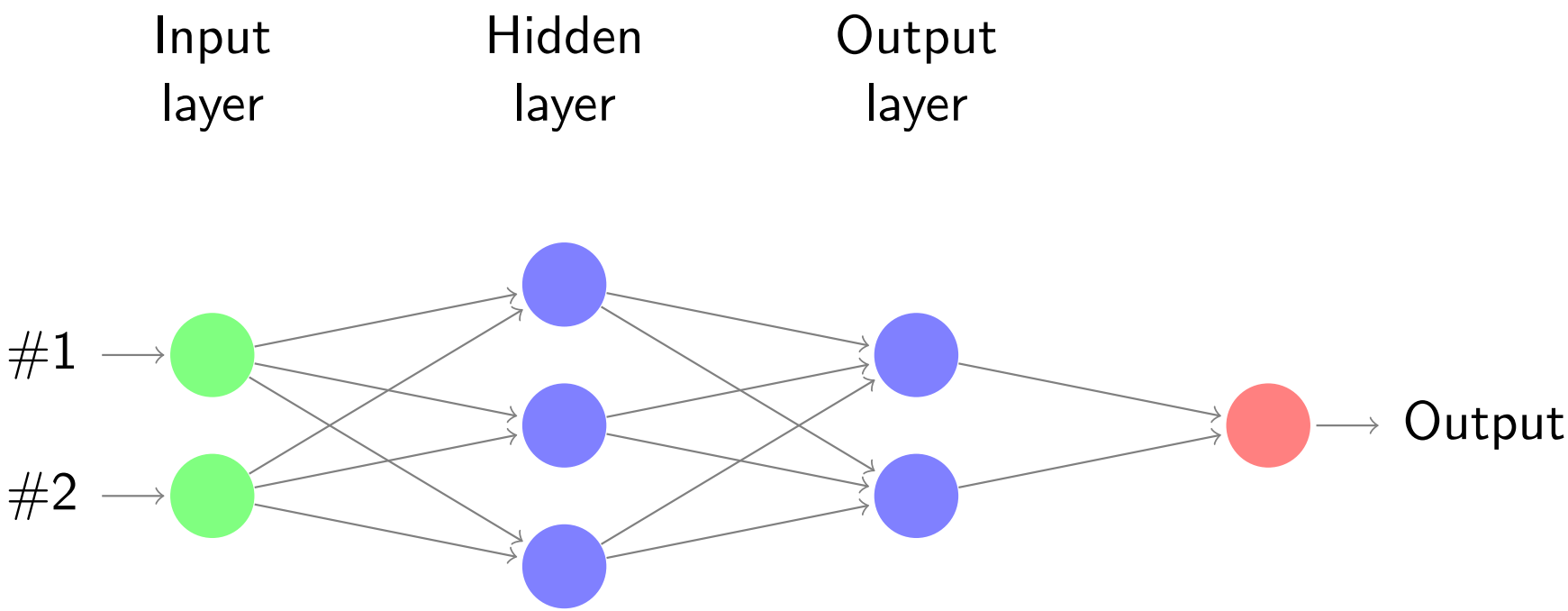


When I told John PER that I wanted to move to Alaska LOC , he warned me that I 'd have trouble finding a Starbucks MISC there .

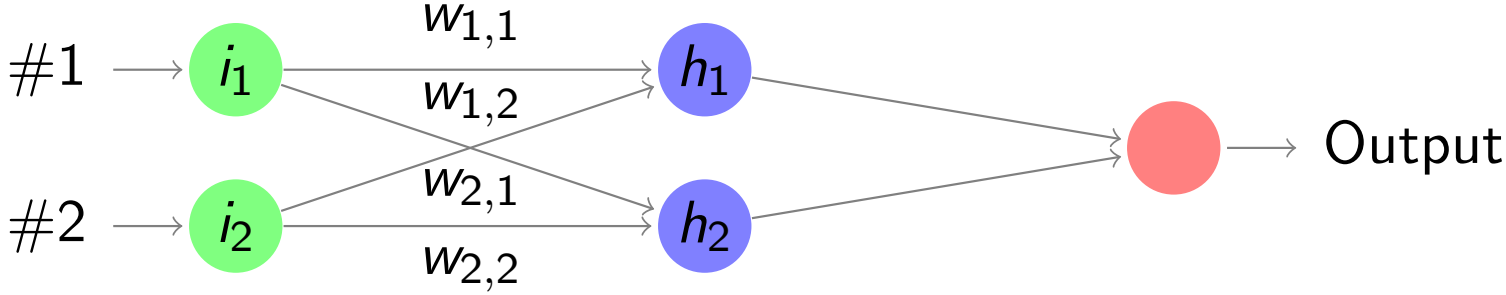
Retele neuronale



Retele neuronale



Retele neuronale



$$a_j = g(in_j)$$

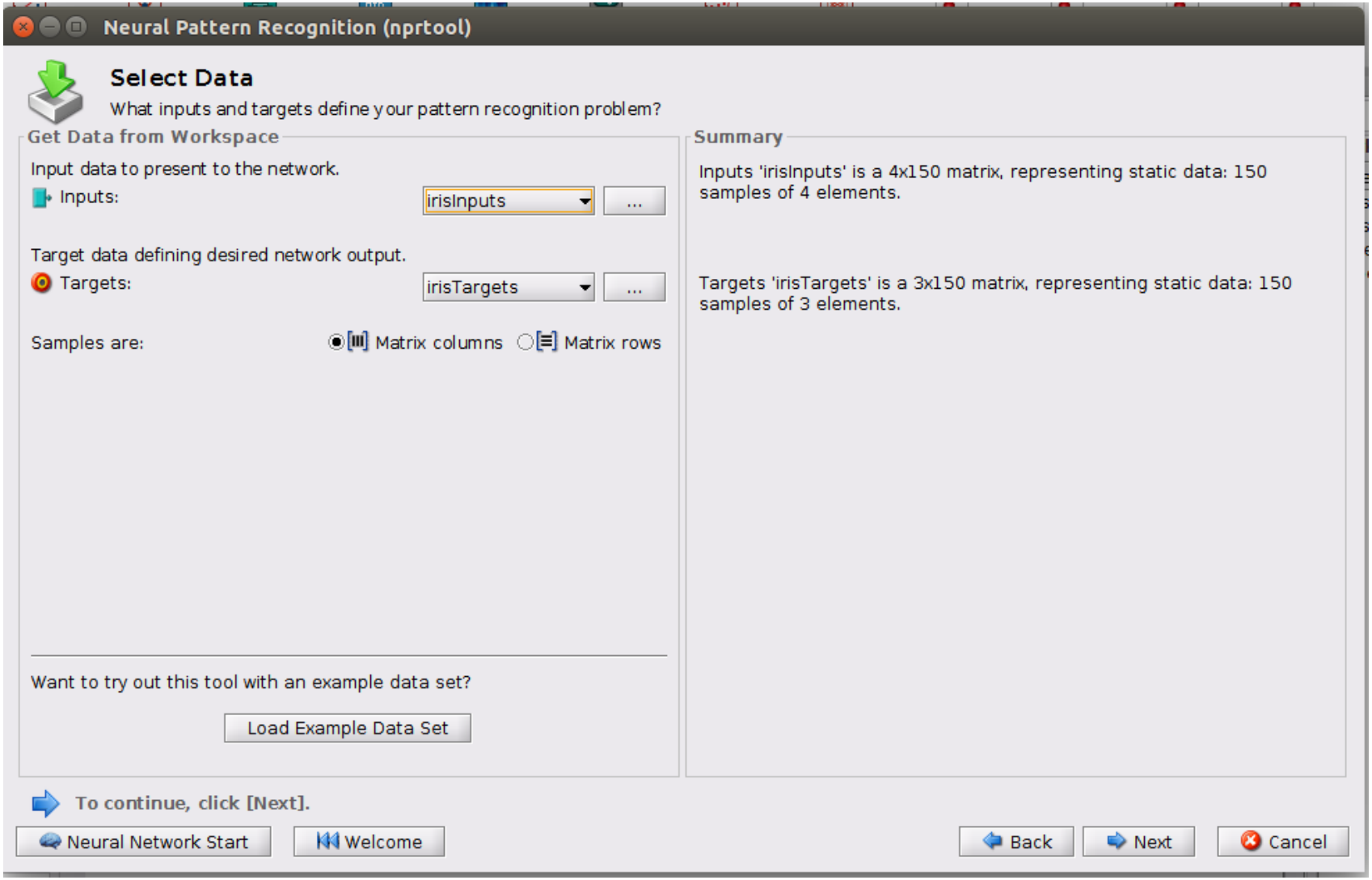
$$a_j = g(\sum_i (w_{i,j} * a_i))$$

- a_i outputul neuronului i,
- $a_0 = 1$ bias
- $W_{i,j}$ ponderea legaturii dintre neuronul i (de pe nivelul anterior) si neuronul j (de pe nivelul curent)
- g functie de activare

exemplu: $a_{h_1} = g(w_{1,1} * a_i + w_{2,1} * a_2 + w_{0,1})$

Matlab: Neural Net Pattern Recognition

Limited to a certain structure for the network



Matlab: neural net fit

Predict MPG for cars: *auto_mpg.csv*

1. Import the data with GUI
2. Create X and y

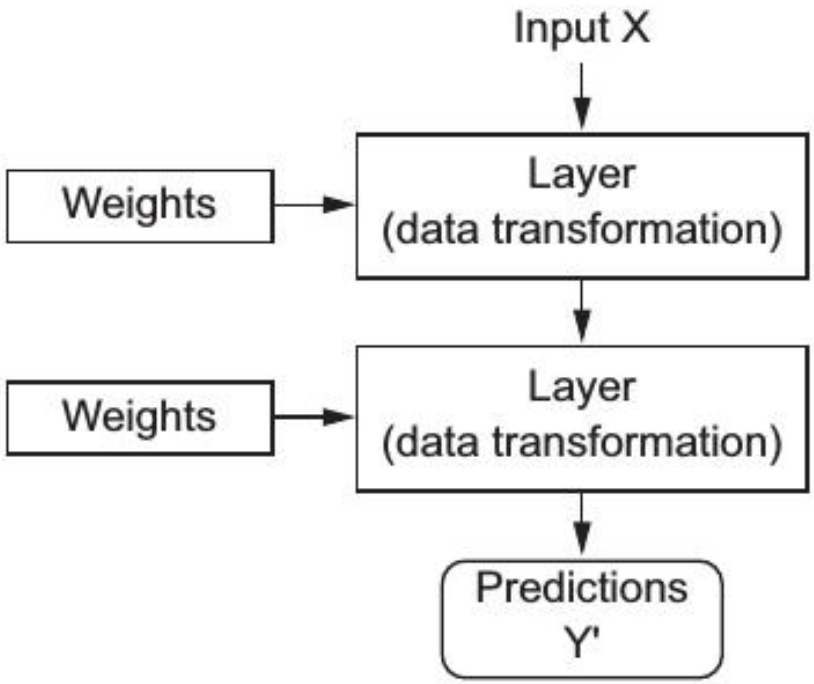
```
X = autompg(:,2:end)
y=autompg(:,1)

x=table2array(x)
y=table2array(y)
```

3. Start NeuralNet Fit

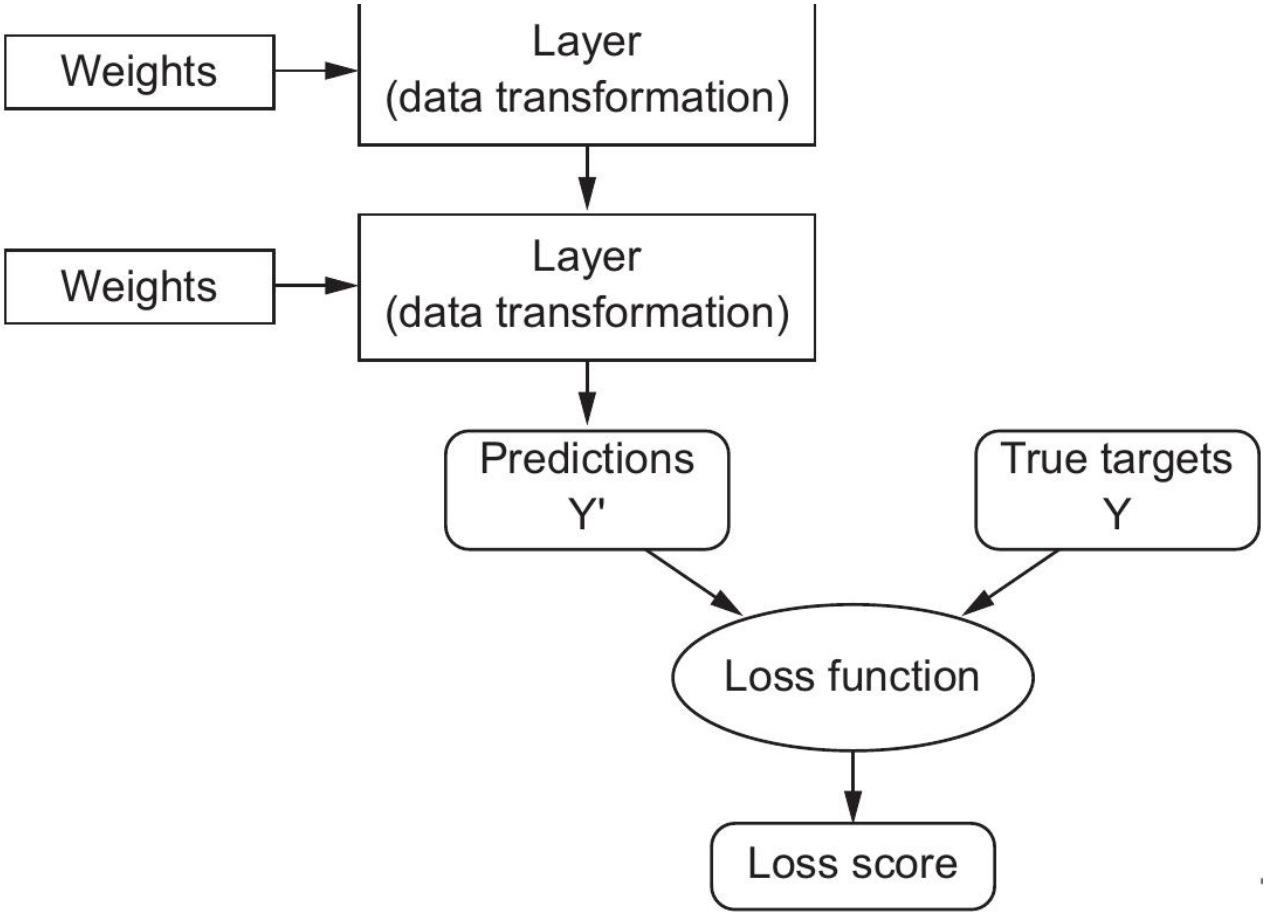
time for notebook

- activation functions and their derivatives
- why neural network can learn non linear functions?
- XOR with Tensorflow

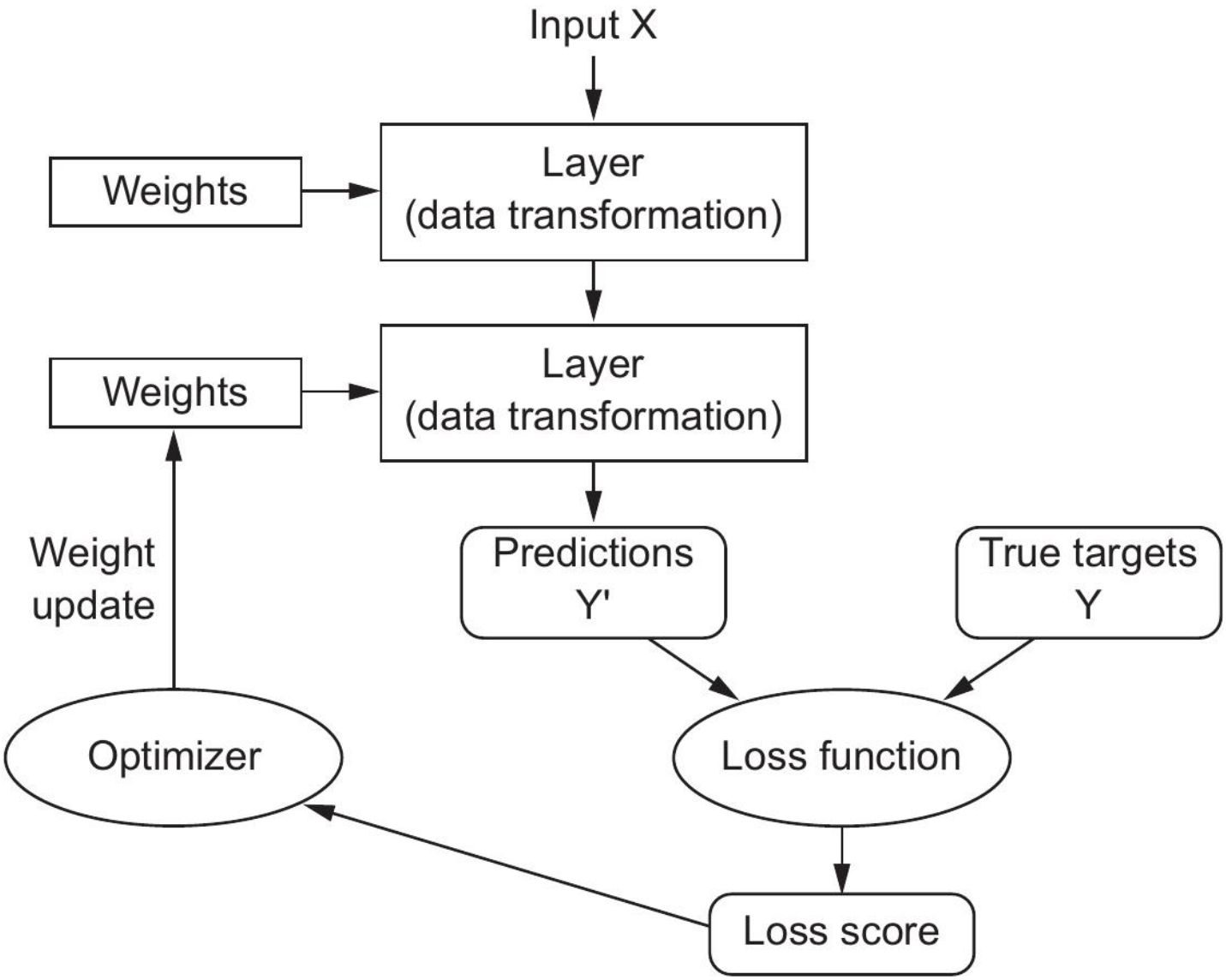
Cum functioneaza deep learning?



Cum functioneaza deep learning?



Cum functioneaza deep learning?



Loss

- Mean square error MSE

$$MSE = \frac{1}{N} \sum_{(x,y) \in D} (y - prediction(x))^2$$

- Log Loss

$$LogLoss = \sum_{(x,y) \in D} -ylog(y') - (1 - y)log(1 - y')$$

- $(x, y) \in D$ - setul de date etichetate
- y - labelul exemplului x, unde x e un vector de caracteristici (features). Fiind clasificare, y e fie 0 fie 1
- y' - valoarea prezisa dat fiind x

Invatarea prin Gradient Descent

Regula de actualizare pentru perceptron:

$$w_j = w_j + \alpha * Loss * g'(in) * x_j$$

Back-propagation

- Nivelul de output

$$w_{j,i} = w_{j,i} + \alpha * a_j * \Delta_i$$

, unde $\Delta_i = Loss_i * g'(in_i)$

- Nivel ascuns Propagam eroarea:

$$\Delta_j = g'(in_j) \sum_i w_{j,i} \Delta_i$$

Actualizam ponderile

$$w_{k,j} = w_{k,j} + \alpha * a_k * \Delta_j$$

Neural Network Playground

https://playground.tensorflow.org/

Time for some examples in Tensorflow - MNIST with 10 classes

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(512, activation=tf.nn.relu),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation=tf.nn.softmax)
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

Run it in COLAB: observe the output layer, change the dim of layers, observe the accuracy

Examples in Tensorflow

Retele neuronale adanci Feed Forward

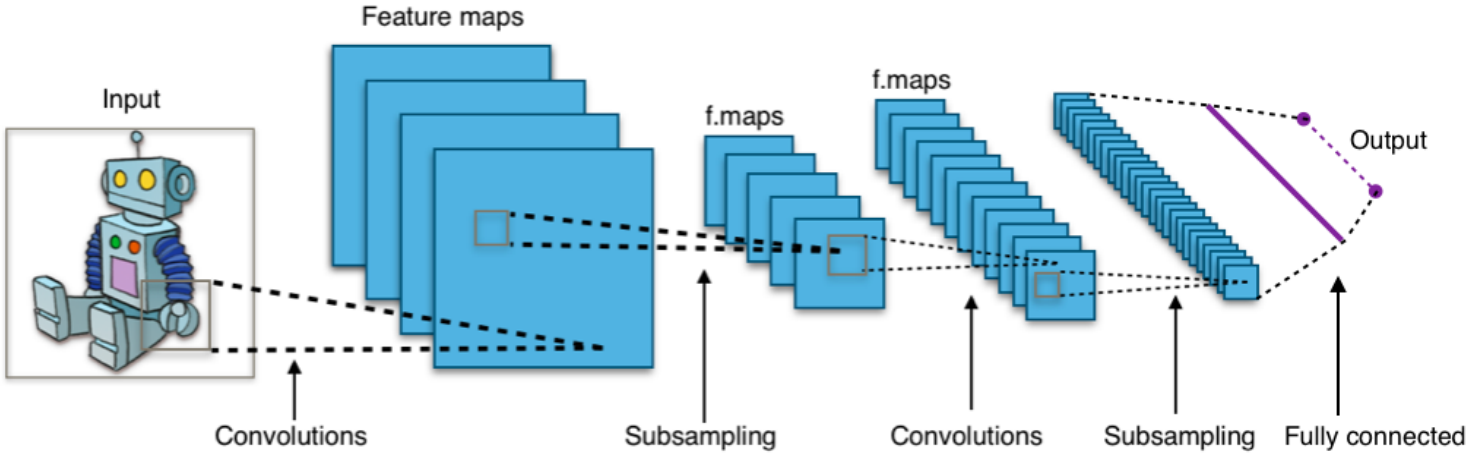
- More detailed Fashion MNIST - run it in **Colab**
- Basic text classification - with details about Text classification with Word embedding - vineri
- Iris example Good for Optimizers comparison

Main take aways for Deep FeedForward Networks

- Se pot aplica atat pentru regresie cat si pentru clasificare
- Au o structura bazata de layere
- Conteaza optimizatorul folosit

Procesare de imagini

Detalii sambata



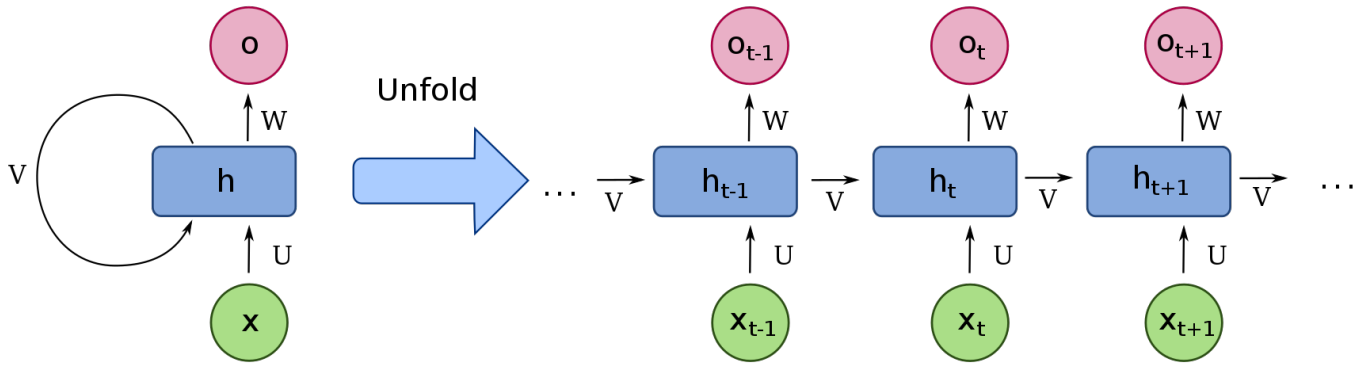
- Retele de convolutie (Convolutional neural network- CNN):
  - Image classification
  - Object detection
  - Image segmentation

https://aidemos.microsoft.com/face-recognition

```
./darknet detect cfg/yolov3.cfg yolov3.weights data/dog
    .jpg
```

Procesare de text - more details on Friday

- Word embeddings
- Retele neuronale recurente - RNN

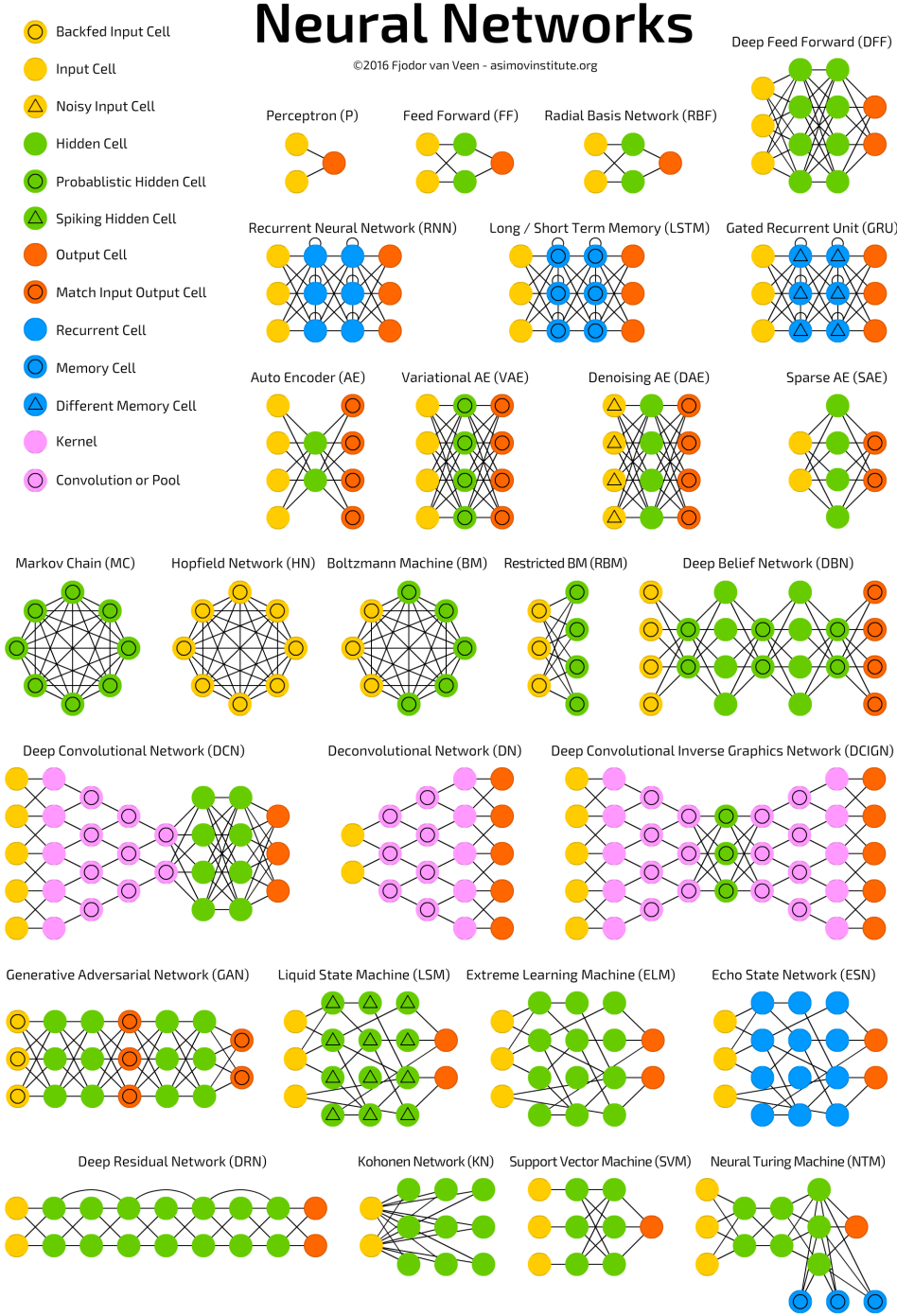


- Allen nlp (https://demo.allennlp.org/reading-comprehension/NzQwMTEy)
- Generare de text https://openai.com/blog/better-language-models/

```
./darknet rnn generate cfg/rnn.cfg shakespeare.weights
```

A mostly complete chart of

Neural Networks



reluare Fraud detection

Solutions for imbalanced data on credit card fraud detection

- Use the correct Metric for Evaluation
- Use class weights
- Oversampling the minority class

MatLab DeepNetwork Toolbox

1. Create Simple NN for MNIST - with CNN, but focus on layers, optimizers

```
openExample('nnet/
    TrainABasicConvolutionalNeuralNetworkForClassificationExam
    ')}
```

2. RNN
   - Sequence-to-sequence regression: Time series with RNN - chickenpox prediction

```
openExample('nnet/
    TimeSeriesForecastingUsingDeepLearningExample')
```

   - Sequence classification - Vowels classification, small example on syntetic data

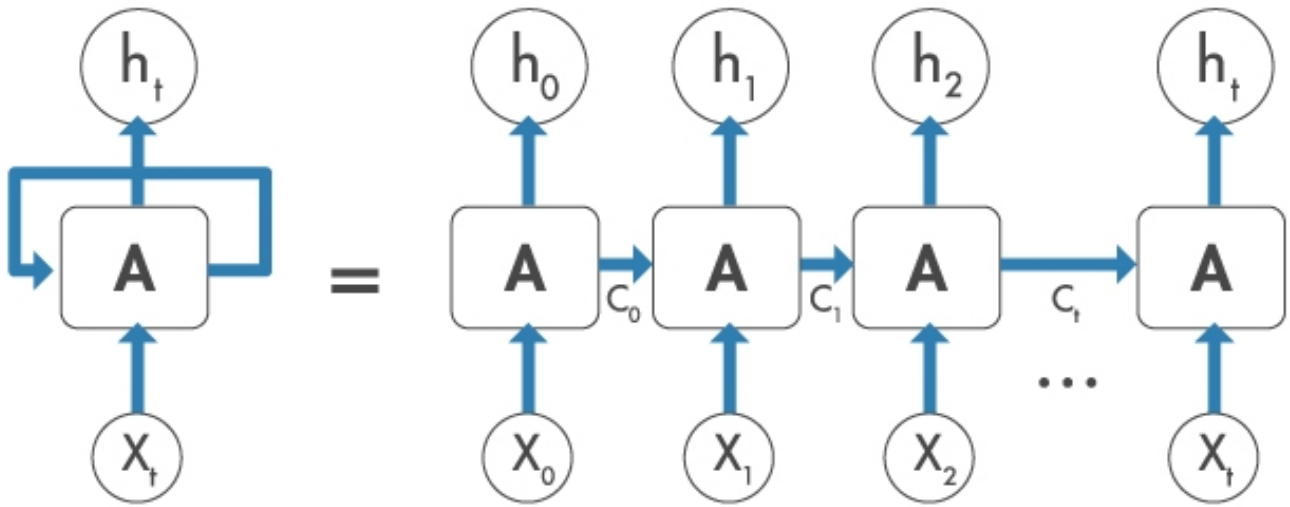
```
openExample('nnet/
    ClassifySequenceDataUsingLSTMNetworksExample')
or
run lstm.m
```

   - Sequence-to-Sequence Regression - human activities

```
openExample('nnet/
    SequencetoSequenceRegressionUsingDeepLearningExample
    ')
```

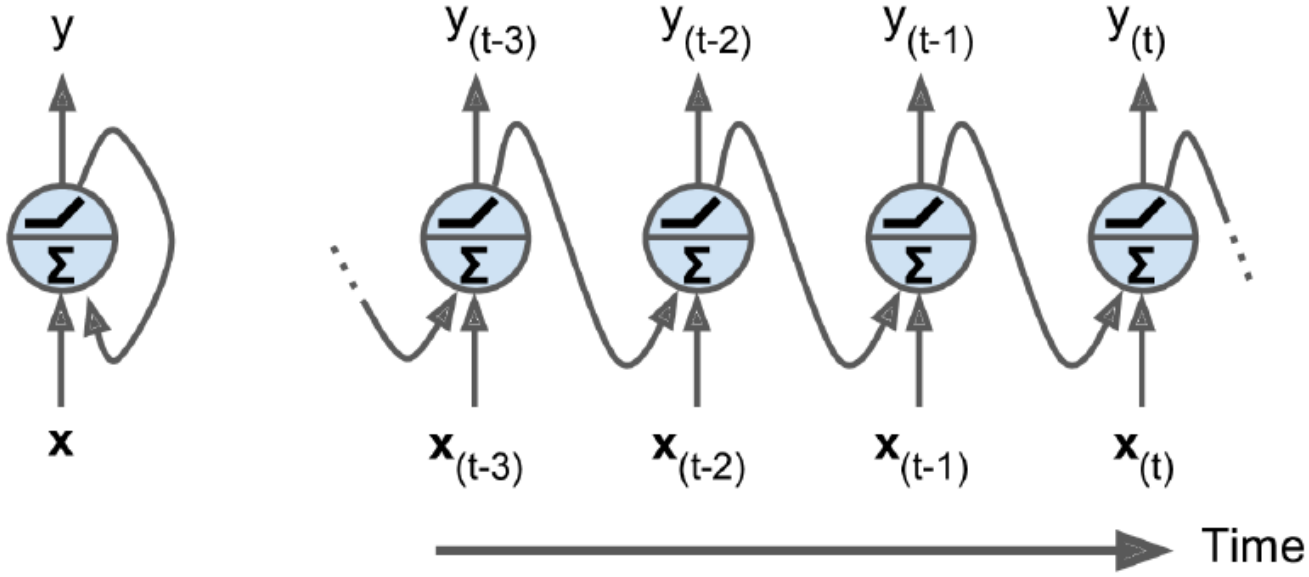
Tipuri de layere

- Dense Layer
- Dropout Layer
- Embedding Layer
- RNN layer: SimpleRNN, GRU, LSTM

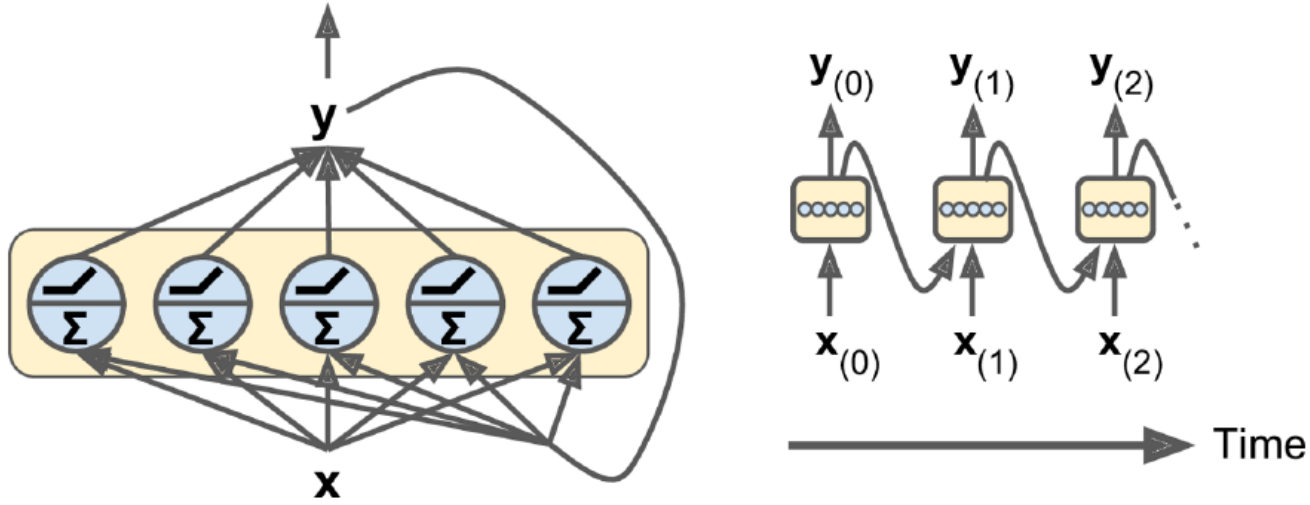


RNN details

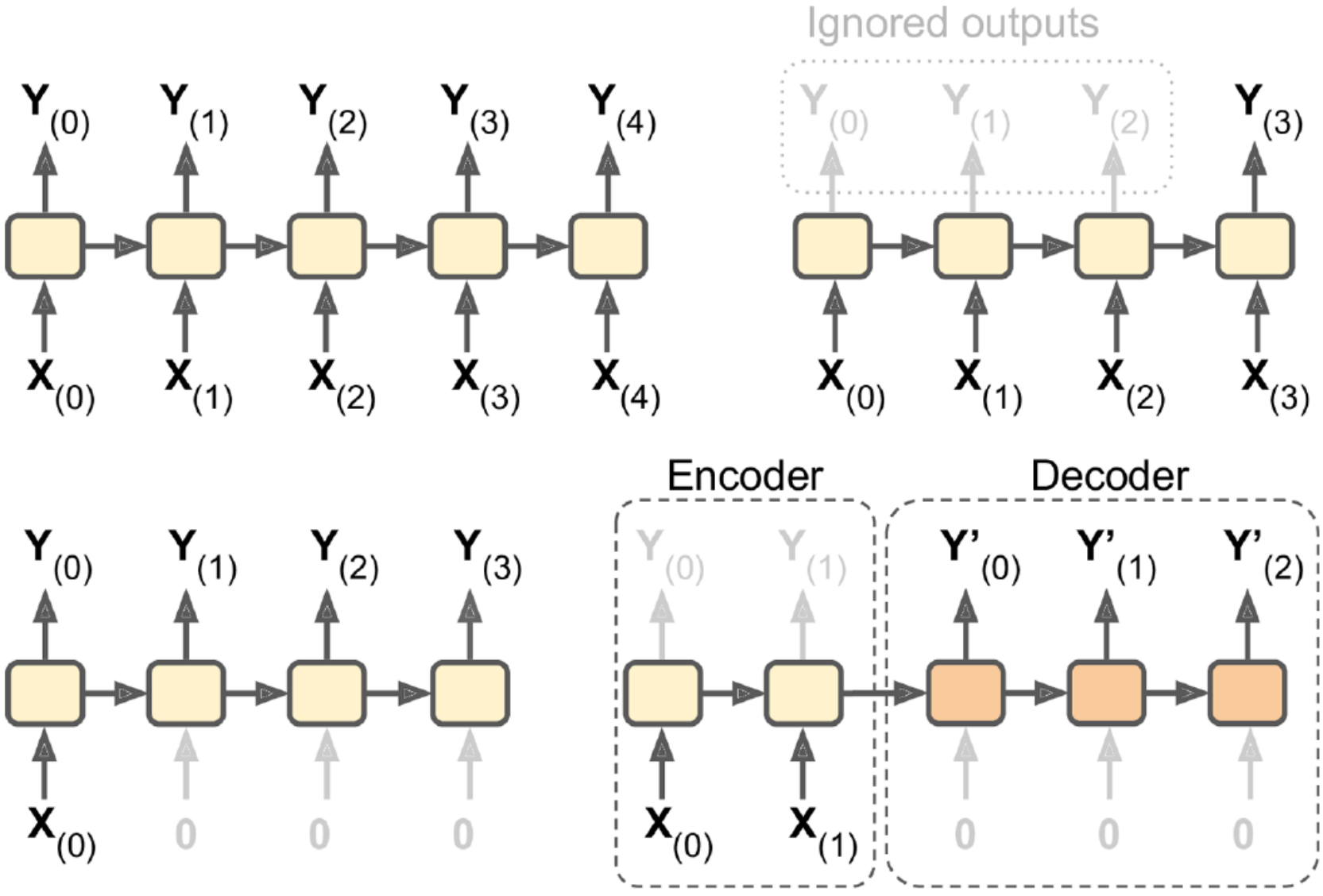
- Recurrent neuron



- Recurrent layer



Working with sequences



Representation of X for sequences

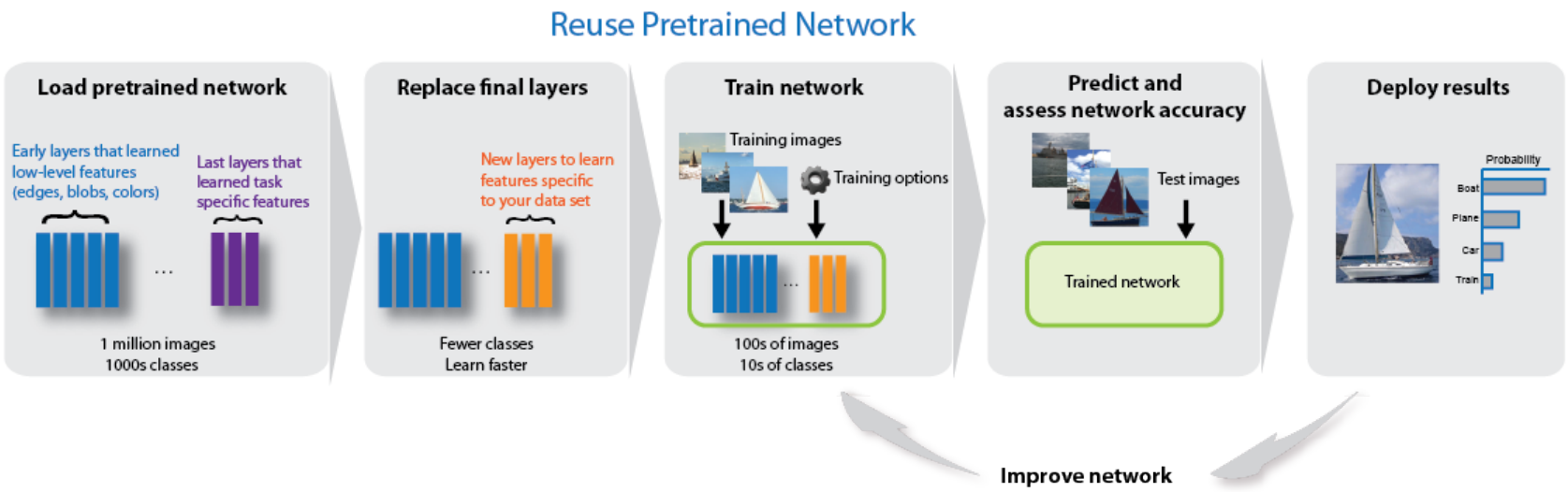
	time 0	time 1	...	time m
feature 1	$value_1^0$	$value_1^1$	...	$value_1^m$
feature 2	$value_2^0$	$value_2^1$	...	$value_2^m$
...				
feature n	$value_n^0$	$value_n^1$	...	$value_n^m$

Structura retelelor + Transfer learning

1. Import pretrained network

```
net = googlenet
deepNetworkDesigner
```

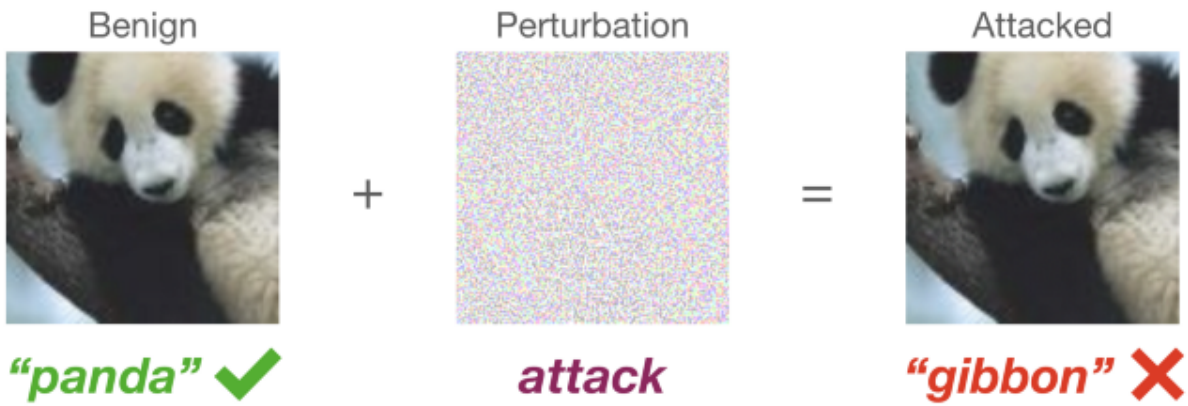
2. Change the network last layers
3. Export network for training
4. Train network



Clasificare de secvente cu retele neuronale

Quick draw https://quickdraw.withgoogle.com/

Don't believe the short-term hype

- Istoria se repeta:
  - 1960s: symbolic AI "Within a generation... the problem of creating 'artificial intelligence' will substantially be solved"
  - AI winter
  - 1980s: expert systems
  - AI winter
- 

Don't believe the short-term hype, but do believe in the long-term vision.

Materiale recomandate

- Machine learning Crash Course (Google)
- cursuri Andrew NG de pe Coursera
- Tutoriale Tensorflow
- Francois Chollet - Deep Learning with Python-Manning Publications (2017) - cu observatia ca exemplele din Tensorflow se pot face mai usor cu Keras (vezi Tensorflow 2.0)
- Observatii generale: Tensorflow are High level API si eager execution, dar si Low Level API (e mai simplu de inceput in Hogh Level API cu eager execution)

Exemplu de stire generata automat de OpenAI language model

- S-a furnizat ca intrare textul:
  A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.
- S-a generat automat continutul:

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.
In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.
"The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation," said Tom Hicks, the U.S. Energy Secretary, in a statement. "Our top priority is to secure the theft and ensure it doesn't happen again."
The stolen material was taken from the University of Cincinnati's Research Triangle Park nuclear research site, according to a news release from Department officials.
The Nuclear Regulatory Commission did not immediately release any information.
According to the release, the U.S. Department of Energy's Office of Nuclear Material Safety and Security is leading that team's investigation.
"The safety of people, the environment and the nation's nuclear stockpile is our highest priority," Hicks said. "We will get to the bottom of this and make no excuses.

Friday Objectives

1. Trading signal Classification - Demo in matlab - comparatie 3 abordari
2. NLP and word embeddings
3. Explainability - NN visualization - what are they learning? (1 and 2 - 2h)
4. Intro to Reinforcement learning (2h)
5. Genetic Algorithm
6. Frequent item sets (2h)

NLP with Deep Learning

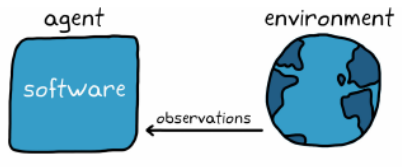
- Word Embeddings - time for Notebook - What are the embeddings?
- See word2Vec - file and projector
- Briefly revise Text classification example - accent on Embedding Layer
- RNN for text generation - text generation with RNN
- Examples from AllenNLP

Network visualization

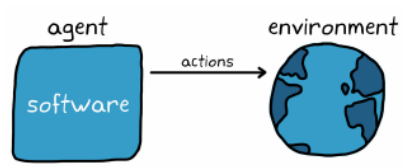
Class Activation Maps OCT example

Reinforcement Learning

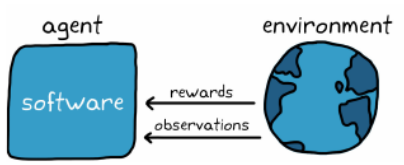
1 The agent is able to observe the current state of the environment.



2 From the observed state, it decides which action to take.

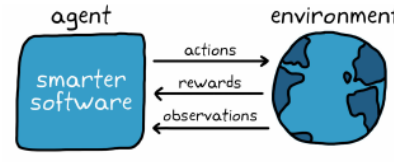


3 The environment changes state and produces a reward for that action. Both of which are received by the agent.



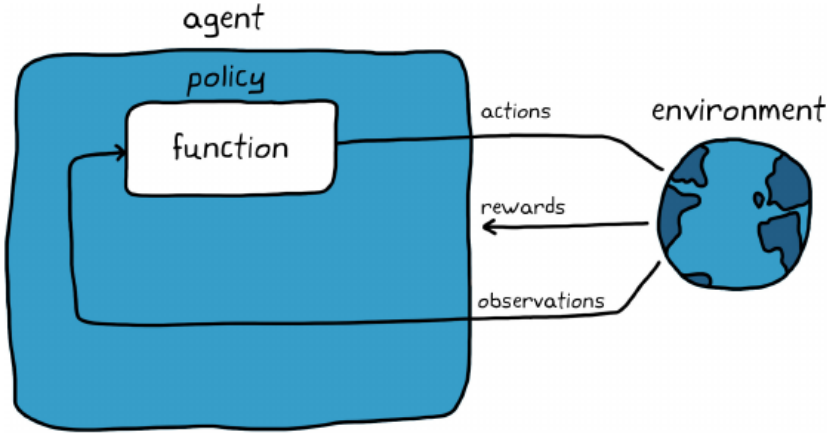
4 Using this new information, the agent can determine whether that action was good and should be repeated, or if it was bad and should be avoided.

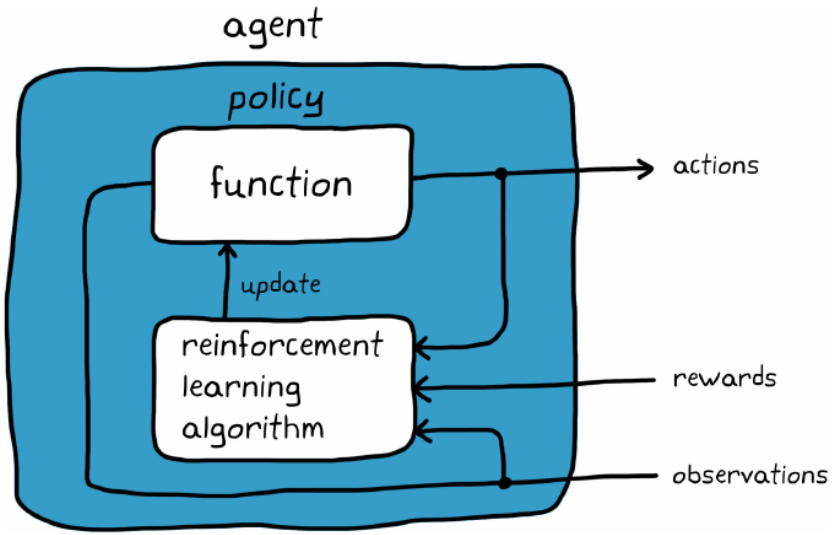
The observation-action-reward cycle continues until learning is complete.



Policy function

Given an observation, the policy decides what action to take





Main terms in reinforcement

- Action(A): possible moves the agent can take
- State(S): situations returned by the environment
- Reward(R): immediate feedback from the environment to evaluate ????
- Policy(π): strategy that the agent employs to determine next action based on the current state
- Value(V): the expected long-term return with discount. $V\pi(s)$ - expected long-term return of the current state under the policy π
- Q-value: long-term return of the current state s and action a

Policy and value function representation

Policy - mapping that selects an action to take based on observations from the environment

- Depending on the type of RL agent: actor and critic function approximators -
- The actor - represents the policy that selects the best action to take.
- The critic - represents the value function that estimates the long-term reward for the current policy.
- Depending on the application and selected agent: policy and value functions can be defined using
  - deep neural networks,
  - linear basis functions,
  - look-up tables.

Table representations

- value tables - stores rewards for corresponding observations
- Q-tables - stores reqards fro corresponding observation-action pairs

1. Create a value table: *rlTable*
2. Create a representation for the table: *rlRepresentation*
3. Configure the learning rate and optimization *rlRepresentationOptions*

Deep neural network representations

- Network Input and Output Dimensions
  - Critic network with only observations as input: dimensions of the input layers must match the dimensions of the environment observation specifications
  - Critic network with observations and actions as input: dimensions of the input layers must match the dimensions of the environment observation specifications and action specification
  - Actor network
    - input layers: dimensions of the environment observation specification
    - output layers: discrete action space: output size equal to the number of discrete actions continuous action space - output size must be a scalar or vector value

```
actInfo = getActionInfo(env);
actDimensions = actionInfo.Dimensions;

obsInfo = getObservationInfo(env);
obsDimensions = observatonInfo.Dimensions;
```

- Create deep Neural Network
- Create and Configure representation

Sarsa learning algorithm

model-free, online, on-policy reinforcement learning method

1. Initialize the critic Q(S,A) with random values.
2. For each training episode:
   - 2.1 Set the initial observation S.
   - 2.2 For the current observation S, select a random action A with probability ε. Otherwise, select the action for which the critic value function is greatest.

     $$A = maxQ(S, A)$$

     To specify *varepsilon* and its decay rate, use the *EpsilonGreedyExploration* option.
   - 2.3 Repeat the following for each step of the episode until S is a terminal state:
     - 2.3.1 Execute action A. Observe the reward R and next observation S'.
     - 2.3.2 Select an action A' by following the policy from state S'.

       $$A = maxQ(S', A')$$

     - 2.3.3 If S' is a terminal state, set the value function target y to R. Otherwise set it to:

       $$y = R + \gamma Q(S, A)$$

Q-Learning

model-free, online, off-policy

- Initialize the critic Q(S,A) with random values.
- For each training episode:
  1. Set the initial observation S.
  2. Repeat the following for each step of the episode until S is a terminal state:
     - 2.1 For the current observation S, select a random action A with probability . Otherwise, select the action for which the critic value function is greatest. here

       $$A = maxAQ(S, A)$$

       To specify and its decay rate, use the EpsilonGreedyExploration option.
     - 2.2 Execute action A. Observe the reward R and next observation S'.
     - 2.3 If S' is a terminal state, set the value function target y to R. Otherwise set it to:

       $$y = R + \gamma maxAQ(S, A)$$

       here

       To set the discount factor , use the DiscountFactor option.
     - 2.4 Compute the critic parameter update.

Simple example

```
openExample('rl/RLGenericMDPExample')
```

RL in Grid world

RL small example

```
openExample('rl/BasicGridWorldExample')
```

Simulation

https://www.mladdict.com/q-learning-simulator

DQN, Actor Critic

- Cart pole balancing with DQN

```
openExample('rl/MATLABCartPoleDQNExample')
```

- Actor Critic

```
openExample('rl/MATLABCartPoleACExample')
```

Genetic Algorithm

Knapsack problem: Given a set of n items numbered from 1 up to n, each with a weight w_i and a value v_i, along with a maximum weight capacity W...:

- find which items must be included in order to maximize the sum of the value, while keeping the weight under the maximum weight

$$fitness = \begin{cases} 0 & \text{if } \sum_{i \text{ selected}} w_i > W \\ \sum_{i \text{ selected}} v_i & \text{if } \sum_{i \text{ selected}} w_i \leq W \end{cases}$$

Matlab demo