# Demystifying ML, AI & Automation Part I

Spyros Gkezerlis

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# Intro

Spyros Gkezerlis - @sgez

About
BSc Automation Engineering – Telematic Applications
MSc Information Systems – Reinforcement Learning
Interests – Applied ML, RL especially in time domain

Experience
5 years Software Developer in Greece
8 years Engineer and Manager in OTE
3 years Program Manager in DTAG

Ariadni Gkezerli (8 y.o), © 2017

**Depiction accuracy: 100%!**

# Why Lectures?

- Get a better overview of the current landscape in ML, AI & Automation, because they can potentially can help us on:
  - Reducing complexity of network
  - Improving experience by Time-to-market, Time-to-repair
  - Repetitive caused costs can be targeted and reduced
  - Forecasting, Automating, Making predictions smarter

- Create a common understanding of what ML, AI & Automation

- "Start with the problem" philosophy

Pros cons, Tools, etc. should not dictate what we should use!

  - Identify what we want to solve
  - Work to the algorithms & models needed
  - Utilise best approach

- Start changing mindset and attitude…

> "AI is the New Electricity"
>
> Andrew Ng

# But, be aware of the dark side!

- Keep in mind it can solve particular types of problems!
- ML is not a tool to fix everything
- In some cases needs high degree of mathematics understanding and of course, you should know your problem.

# Simplistic Definitions

- Automation Comes from ancient compound greek word which means the thing that wishes on its own or the has a will or fury by itself
- Artificial Intelligence[1c] is Human Intelligence Exhibited by Machines
- Machine Learning[1a] is a field of computer science that gives computers the ability to learn without being explicitly programmed
- Deep learning[1b] is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms.

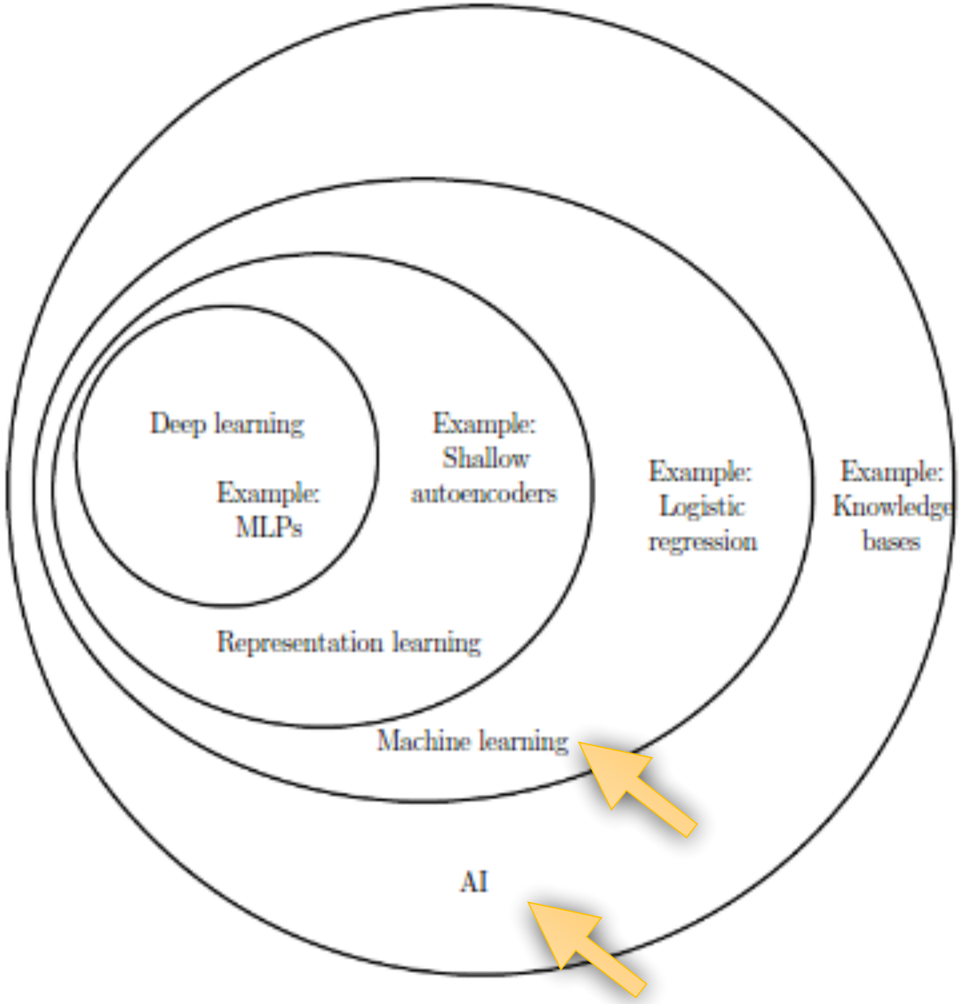
def·i·ni·tion
defəˈniSH(ə)n
noun
a statement of the exact meaning of a word, especially in a dictionary.

1a Machine Learning, Wikipedia Web page, 09 Nov 2017
https://en.wikipedia.org/wiki/Machine_learning
1b Deep Learning, Wikipedia Web page, 09 Nov 2017
https://en.wikipedia.org/wiki/Deep_learning#Definitions
1c What's the Difference Between Artificial Intelligence, Machine Learning, and Deep Learning?, Copeland, Nvidia Web page, 09 Nov 2017
https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

# Landscape overview

Landscape and focus[2] areas vary:

- Automation
- Statistics & Probability
- Data Mining
- Artificial Intelligence
- Machine Learning
    - Supervised Learning
    - Unsupervised Learning
    - Reinforcement Learning
- Deep Learning
- Other Areas
    - Deep Reinforcement Learning

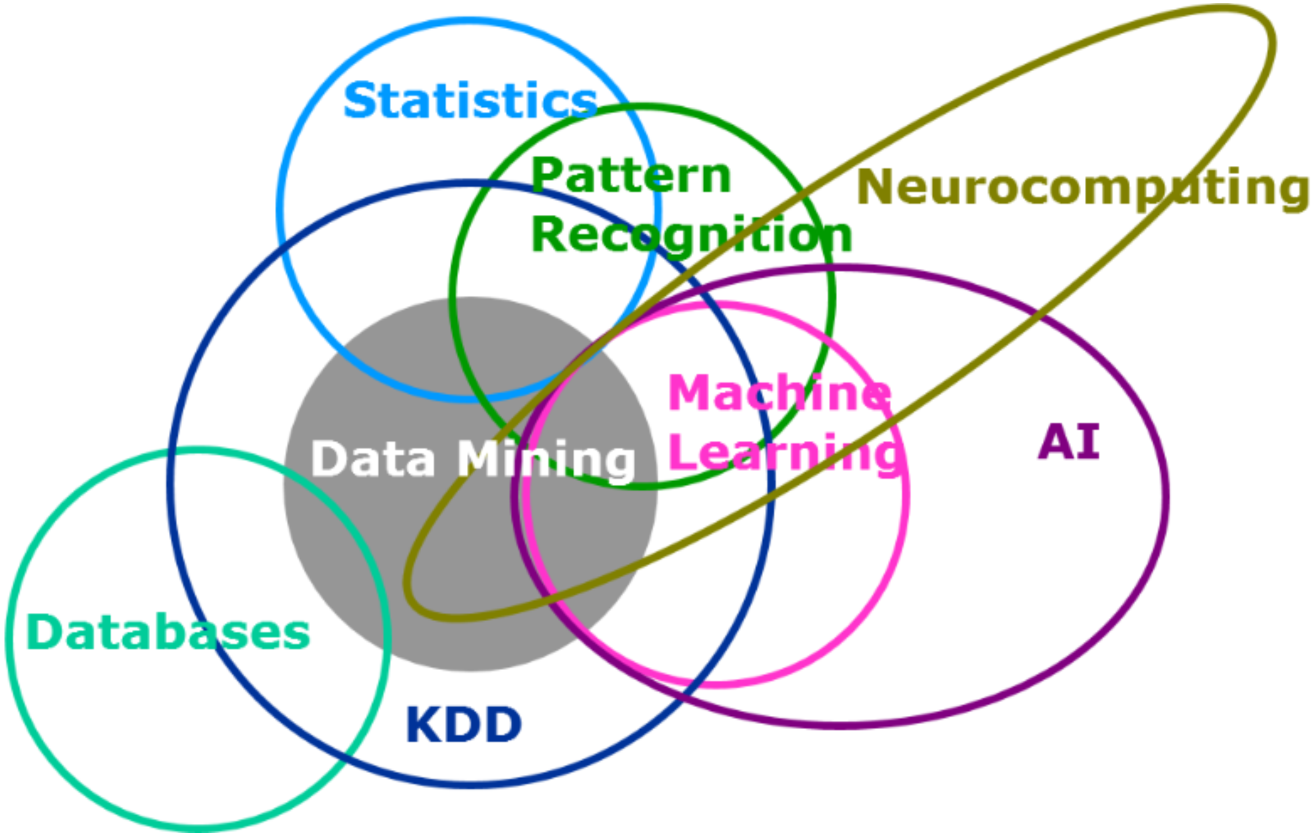



2 Deep Learning, Goodfellow; Bengio; Courville, 2016

[http://www.deeplearningbook.org](http://www.deeplearningbook.org)

# Landscape overview

Landscape and focus[3] areas of ML also could have overlaps with other scientific disciples such as Data Mining, AI, Big Data an other.




3 Look at Popular Data mining Algorithms and Deep learning, Sharma, 26 Feb 2015

http://https://www.linkedin.com/pulse/look-popular-data-mining-algorithms-deep-learning-sandeep-sharma-me-

# Bayes Theorem

- P(A|B) ==> Probability of A given that B

  - Exercise on Bayes[4]
    Out of 3000 emails received over a certain period, 2000 are spam and 1000 are not. The word "Rolex" appeared in 250 out of the 2000 which are spam and in 5 out of the 1000. So, if an email is received, i.e. $email_{3001}$, and contains the word "Rolex", what is the possibility that it is a spam?

Let S be the event that the message is spam, and E be the event that the message contains the word w. Under our assumption from before, we have that:

$$P(S|E) = \frac{P(E|S)}{P(E|S) + P(E|\bar{S})}$$

4 CSE 240 Home Page, Sproull, Spring 2016

https://www.arl.wustl.edu/~todd/cse240/cse240_lecture17_3-24-16.pdf

# Bayes Theorem exercise

- Example – Solution:
  Out of 3000 emails received over a certain period, 2000 are spam and 1000 are not. The word “Rolex” appeared in 250 out of the 2000 which are spam and in 5 out of the 1000.

  So, if an email is received, and contains the word “Rolex”, what is the possibility that it is a spam?

$$P(S|E) = \frac{P(E|S)}{P(E|S) + P(E|\bar{S})}$$

$$P(S|E) = \frac{\frac{250}{2000}}{\frac{250}{2000} + \frac{5}{1000}} =$$

$$\frac{0.125}{0.125 + 0.005} \approx 0.962$$

# Markov Chains

- ## Statistics & Probability - Markov Chains[5]

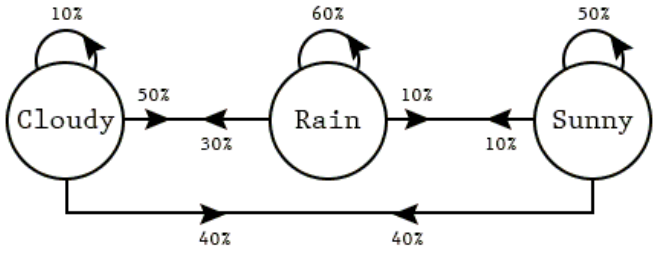
  Markov Chains is a probabilistic process, that relies on the current state to predict the next state. For Markov chains to be effective the current state has to be dependent on the previous state in some way;

  For instance, from experience we know that if it looks cloudy outside, the next state we expect is rain. We can also say that when the rain starts to subside into cloudiness, the next state will most likely be sunny.

MARKOV TABLE OF PROBABILITIES

| STATE | NEXT STATE | PROBABILITY | % |
|---|---|---|---|
| CLOUDY | CLOUDY | 0.1 | 10% |
| CLOUDY | RAIN | 0.5 | 50% |
| CLOUDY | SUNNY | 0.4 | 40% |
| RAIN | CLOUDY | 0.3 | 30% |
| RAIN | RAIN | 0.6 | 60% |
| RAIN | SUNNY | 0.1 | 10% |
| SUNNY | CLOUDY | 0.4 | 40% |
| SUNNY | RAIN | 0.1 | 10% |
| SUNNY | SUNNY | 0.5 | 50% |

Markov State Diagram




Current State Vector

| C | R | S |
|---|---|---|
| 1 | 0 | 0 |

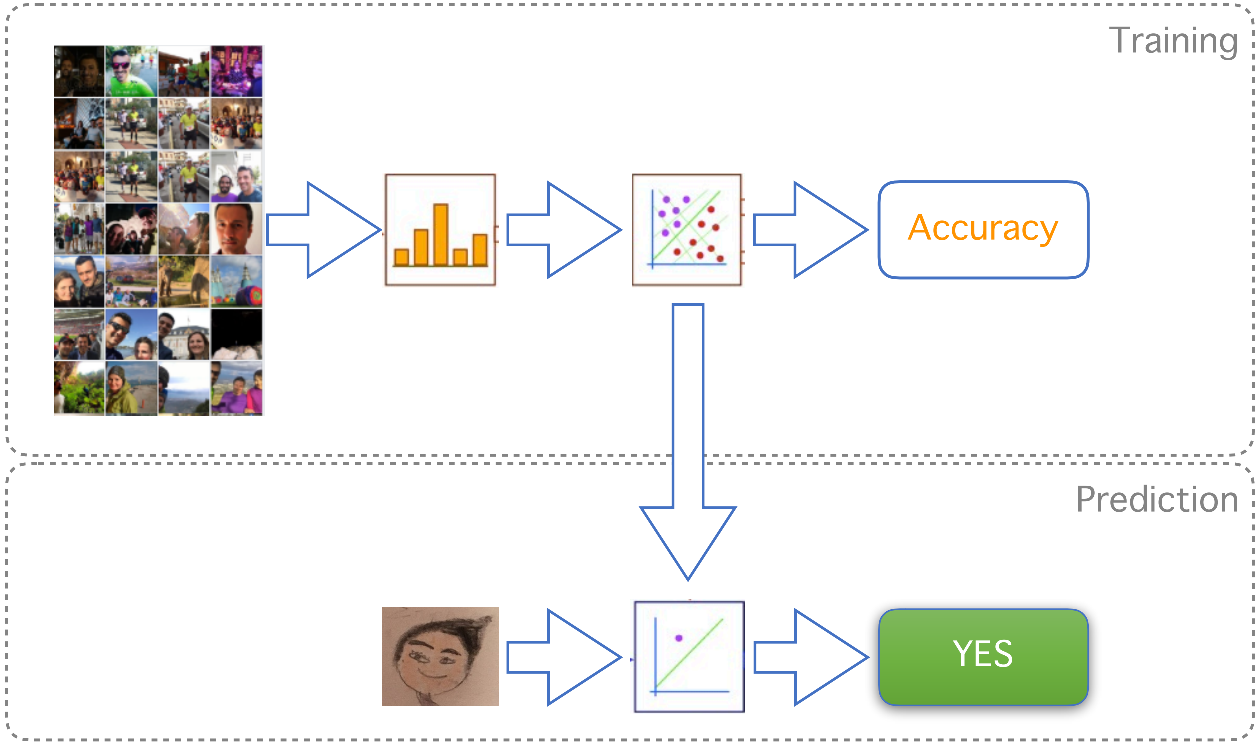
Figure 4

5 Markov Chains Explained, Armstrong, 2015

http://techeffigytutorials.blogspot.com/2015/01/markov-chains-explained.html

# Statistical Classification[6]

- Examples of Classifiers
  - Linear classifiers
  - Support vector machines
  - Quadratic classifiers
  - Kernel estimation
  - Boosting (meta-algorithm)
  - Decision trees
  - Neural networks
  - Learning vector quantisation
- Problems that classifiers help tackle:
  - Supervised Learning
  - Clustering
  - Dimensionality reduction
  - Anomaly prediction
  - Neural Nets
  - RL/DRL

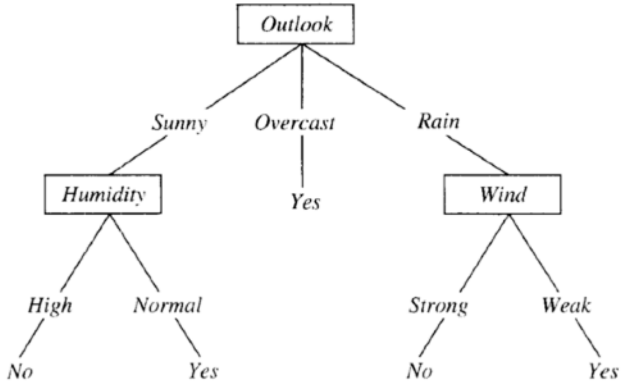



6 Statistical Classification, Wikipedia Web page, 09 Nov 2017
https://en.wikipedia.org/wiki/Statistical_classification

# Supervised Learning - DTL

- Decision Tree Learning
  DTL is method for approximating discrete valued target functions, in which the learned function is represented by a decision tree. (Weka example will follow)
- Example[7a] dataset converted via algorithm to Decision tree
- Methodology[7b] of is whenever a feature is able to tell us more about our class, it is selected as a node

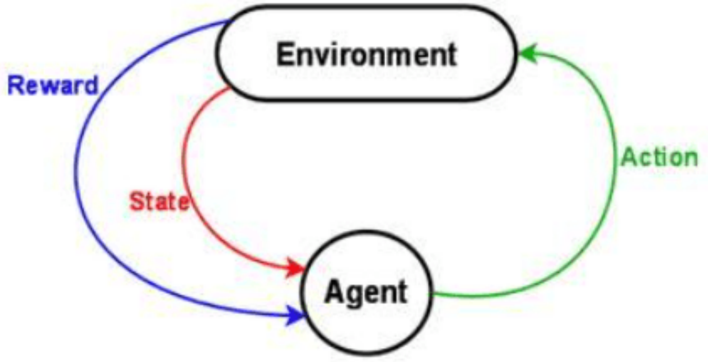
| No. | 1: outlook Nominal | 2: temperature Numeric | 3: humidity Numeric | 4: windy Nominal | 5: play Nominal |
|---|---|---|---|---|---|
| 1 | sunny | 85.0 | 85.0 | FALSE | no |
| 2 | sunny | 80.0 | 90.0 | TRUE | no |
| 3 | overcast | 83.0 | 86.0 | FALSE | yes |
| 4 | rainy | 70.0 | 96.0 | FALSE | yes |
| 5 | rainy | 68.0 | 80.0 | FALSE | yes |
| 6 | rainy | 65.0 | 70.0 | TRUE | no |
| 7 | overcast | 64.0 | 65.0 | TRUE | yes |
| 8 | sunny | 72.0 | 95.0 | FALSE | no |
| 9 | sunny | 69.0 | 70.0 | FALSE | yes |
| ... | rainy | 75.0 | 80.0 | FALSE | yes |
| ... | sunny | 75.0 | 70.0 | TRUE | yes |
| ... | overcast | 72.0 | 90.0 | TRUE | yes |
| ... | overcast | 81.0 | 75.0 | FALSE | yes |
| ... | rainy | 71.0 | 91.0 | TRUE | no |

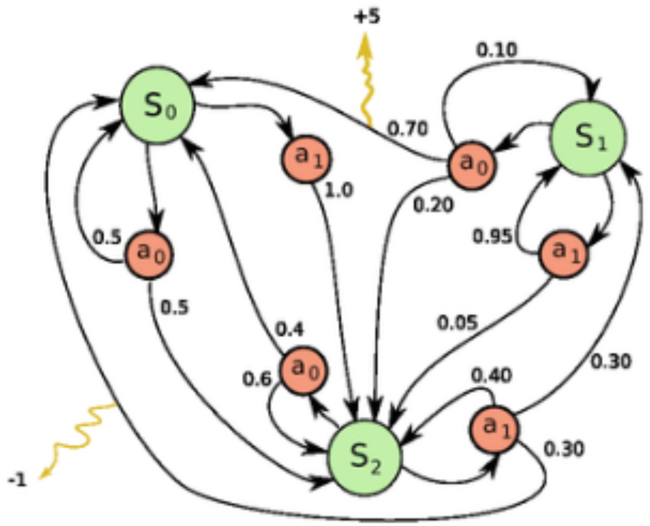



7a Machine Learning, Mitchell, McGraw, 1997.
http://www.cs.princeton.edu/courses/archive/spr07/cos424/papers/mitchell-dectrees.pdf
7b Classification Methods, Padhye, 2017.
http://www.d.umn.edu/~padhy005/Chapter5.html

# Reinforcement Learning (RL)

- Reinforcement Learning[8] is learning what to do--how to map situations to actions--so as to maximise a numerical reward signal.
- Reinforcement learning is defined not by characterising learning methods, but by characterising a learning problem.

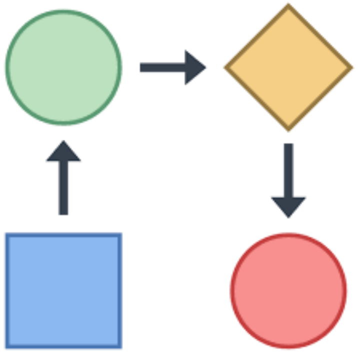



8 Reinforcement Learning: An Introduction, Sutton; Barto, 1998
https://mitpress.mit.edu/0262193981

# Workflow – The ML Pipeline[9]

- Start with the question or problem we want to solve
- Find proper data and sources, prepare data set (train/dev/test)
- Choose a model e.g. Decision Tree C4.5 Algorithm
- Train system & classify, Test
- Evaluate the system and fine-tune
- Predict / Forecast
- Apply to workflow
- Automate into workflow



9 ML Workflow - Loosely based on Yufeng G instructional series

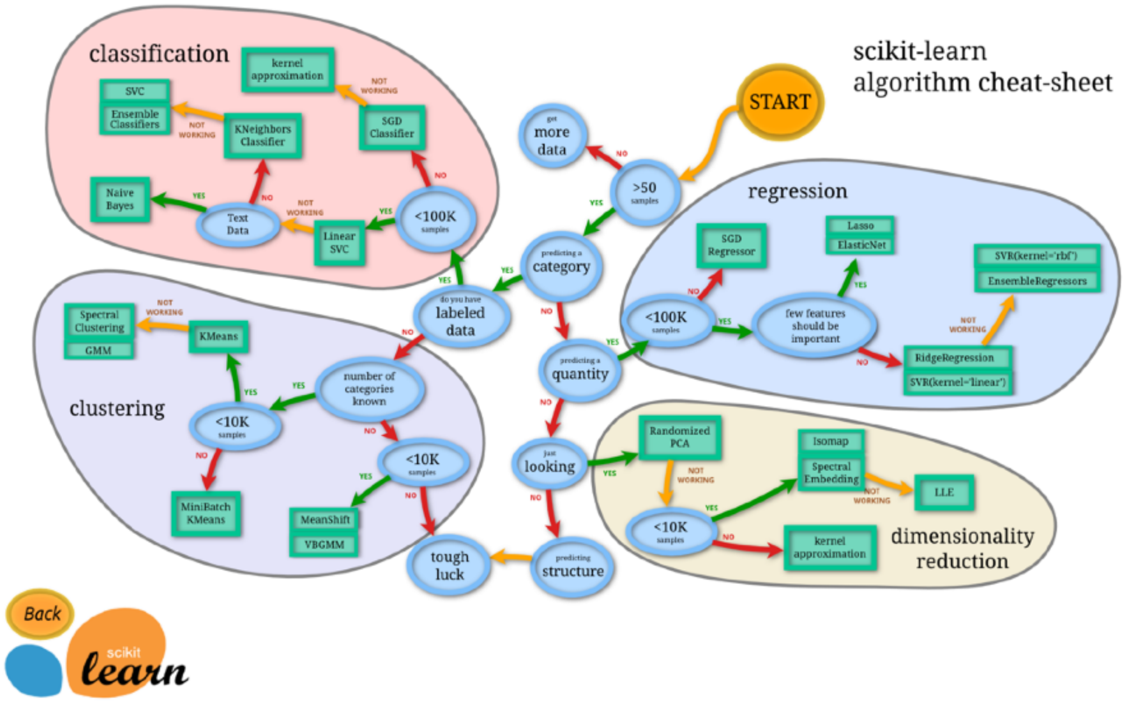
https://medium.com/towards-data-science/the-7-steps-of-machine-learning-2877d7e5548e

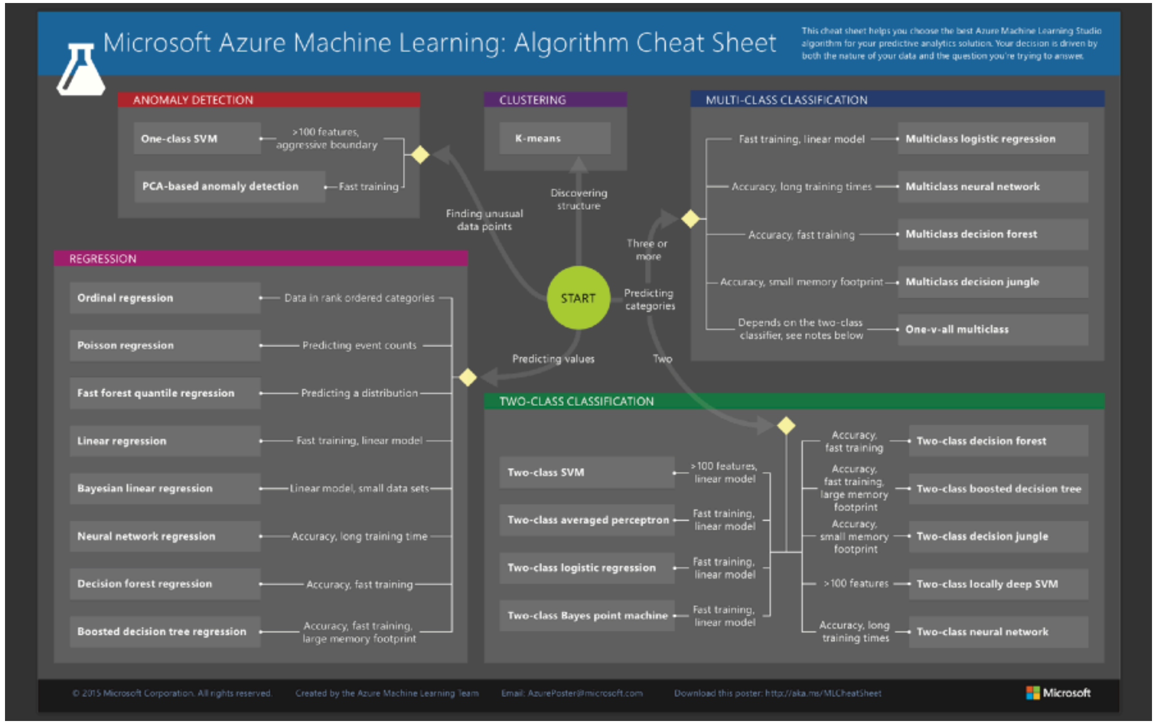
# Dataset semantics

- Dataset
  - Features or Attributes
  - Labels or Classes
  - Instances or Observations

| Age | Nationality | Education | Job |
|---|---|---|---|
| 25 | Greek | MSc | Engineer |
| 38 | American | MSc | Analyst |
| 35 | Japanese | PhD | Assistant |
| … | … | … | … |

# Choose an algorithm[10a, 10b]




10a Microsoft Azure Machine Learning: Algorithm Cheat Sheet, Microsoft website, 09 Nov 2017

http://download.microsoft.com/download/A/6/1/A613E11E-8F9C-424A-B99D-65344785C288/microsoft-machine-learning-algorithm-cheat-sheet-v6.pdf

10b Scikit-Learn Algorithm selection Procedure, Scikit-learn website, 23 Oct 2017

http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

# Tools – Landscape[11]

| Category | Sub-category | Description | Examples |
|---|---|---|---|
| Packages of ML Implementations | **Statistical Software Packages** | Software toolkits with a large set of implementations of ML algorithms, typically with visualization support | SAS, **R**, Matlab, SPSS |
| | **Data Mining Toolkits** | Software toolkits with a relatively limited set of ML algorithms, typically over a data platform, possibly with incremental maintenance | **Weka**, AzureML, ODM, MADlib, Mahout, Hazy-Classify |
| | **Developability-oriented Frameworks** | Software frameworks and systems that aim to improve developability, typically from academic research | GraphLab, Bismarck, MLBase |
| | **SRL Frameworks** | Implementations of statistical relational learning (SRL) | DeepDive |
| | **Deep Learning Systems** | Implementations of deep neural networks | Google Brain, Microsoft Adam |
| | **Bayesian Inference Systems** | Systems providing scalable inference for Bayesian ML models | SimSQL, Elementary, Tuffy |
| Linear Algebra-based Systems | **Statistical Software Packages** | Systems offering an interactive statistical programming environment | SAS, **R**, Matlab |
| | **R-based Analytics Systems** | Systems that provide R or an R-like language for analytics, typically over a data platform, possibly with incremental maintenance | RIOT, ORE, SystemML, LINVIEW |
| **Model Management Systems** | | Systems that provide querying, versioning, and deployment support | SAS, LongView, Velox |
| **Systems for Feature Engineering** | | Systems that provide abstractions to make feature engineering easier | Columbus , DeepDive |
| **Systems for Algorithm Selection** | | Systems that provide abstractions to make algorithm selection easier | MLBase, AzureML |
| **Systems for Parameter Tuning** | | Systems that provide abstractions to make parameter tuning easier | SAS, R, MLBase, AzureML |

11 A Survey of the Existing Landscape of ML Systems, Kumar; McCann; Naughton; Patel, 27 Nov 2015
https://minds.wisconsin.edu/handle/1793/73834

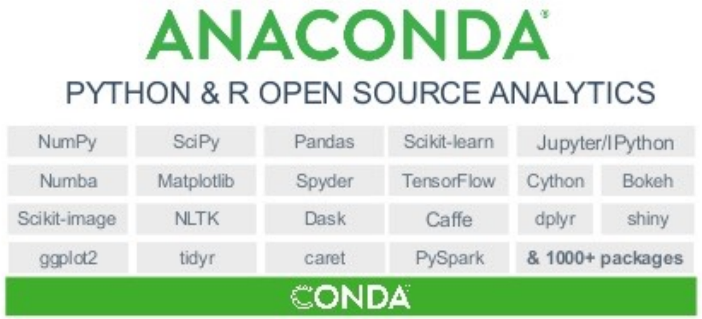
# Deep Learning Toolkits comparison[12]

| Toolkit | GPU Support | Other |
|---|---|---|
| Caffe | Yes | JSON-like text file to describe the network architecture |
| Deeplearning4j | Yes | Java on Scala API |
| Tensorflow | Yes | Google backing, high adoption - Python |
| Theano | | Python |
| Keras | | Python - uses Theano or Tensorflow as backend |
| MXNet | Yes | C++ |
| Lasagne | | Python - uses Then |
| CNTK | | VS for ML - developed by Microsoft |
| DIGITS | | Nvidia - web based tool |
| Torch | | Written in C |
| PyTorch | Yes | Python frontend |
| Pylearn2 | | Python |
| Chainer | | |

12 Toolkits and Libraries for Deep Learning, Erickson; Korfiatis; Akkus; J Digit Imaging 30: 400., 2017
https://doi.org/10.1007/s10278-017-9965-6

# Before-Selecting-a-Tool Checklist

- Things to consider for a toolkit/tool/ecosystem
  - Environment ease of use
  - Dev & Exec speed
  - Training Speed
  - GPU Support
  - Community support & contributors
  - License contamination
  - Language to be used




# Practice (fun part :-)

- R Studio - Basic Statistics on Large Files
- Anaconda Python - Statistics - Parallel Processing
- Weka - Supervised Learning - Decision Trees
- Orange Data Mining - SL Example - Predictions
- Elasticsearch (ELK) - Visual Analytics on Large Sets

on:

  - bitcoin (prices, open/close in time)
  - cars (values based on various features)
  - flights (features for flights in US 1989-2004)
  - milano_cells (Telecom Italia Milano area cell traffic)
  - predictive_maintenance (machine break down prediction)

Lectures & Data Sources Page
[https://github.com/sgez/MLAI](https://github.com/sgez/MLAI)

# Thank you!


mindset
positive
optimism
attitude
thinking
possible
optimists
health
people
research
think
style
success
philosophy
life
logic
mind
psychology
best
target