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Use Blackboard's forum if a question may be relevant to other students, too.
Email always both joeran.beel@scss.tcd.ie and doug.leith@scss.tcd.ie. Give a meaningful subject, starting with "[ML1819]". No file attachments.

Week 01 (2): Introduction to Machine Learning

CS7CS4/CS4404 Machine Learning

v4 2018-09-22 16:06

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Any questions?



<https://kaiserhealthnews.files.wordpress.com/2017/02/khnoncall-2-2.jpg?w=1024>

Update

- **Have a look at slides from previous lecture for literature recommendation, and marks from previous year**
- **Begin to find your team already now**
 - 3 Members
 - Ideally same module code
 - Ideally 1 native English speaker

Outline

- 1. Machine Learning Examples**
- 2. Types of Machine Learning**
- 3. Definition**
- 4. Traditional Approaches to Problem Solving**
- 5. Overview of the Machine Learning Pipeline**
- 6. The Machine Learning Landscape**
- 7. Strength and Weaknesses of Machine Learning**



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Machine Learning Examples

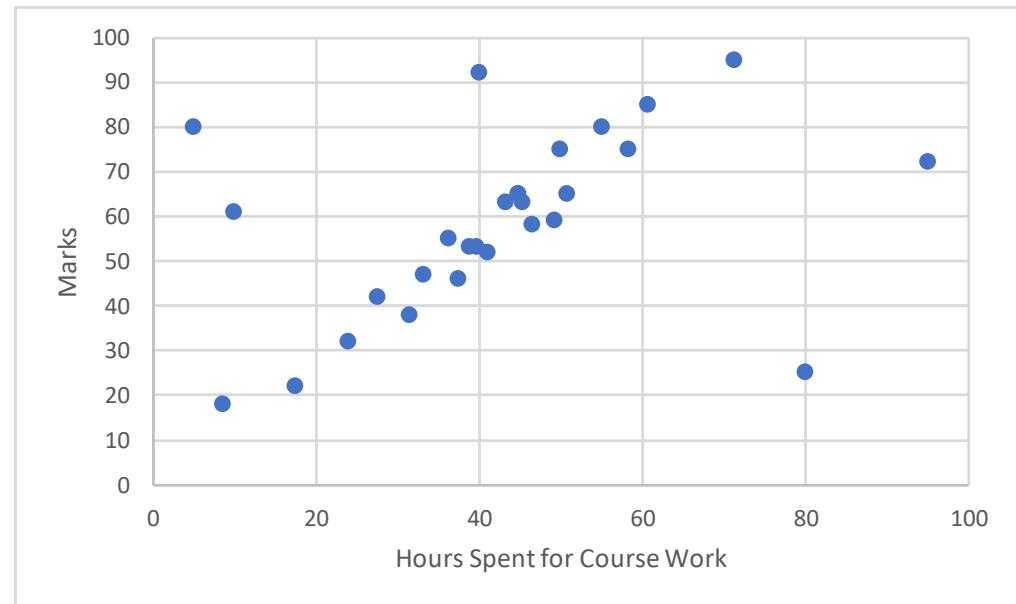


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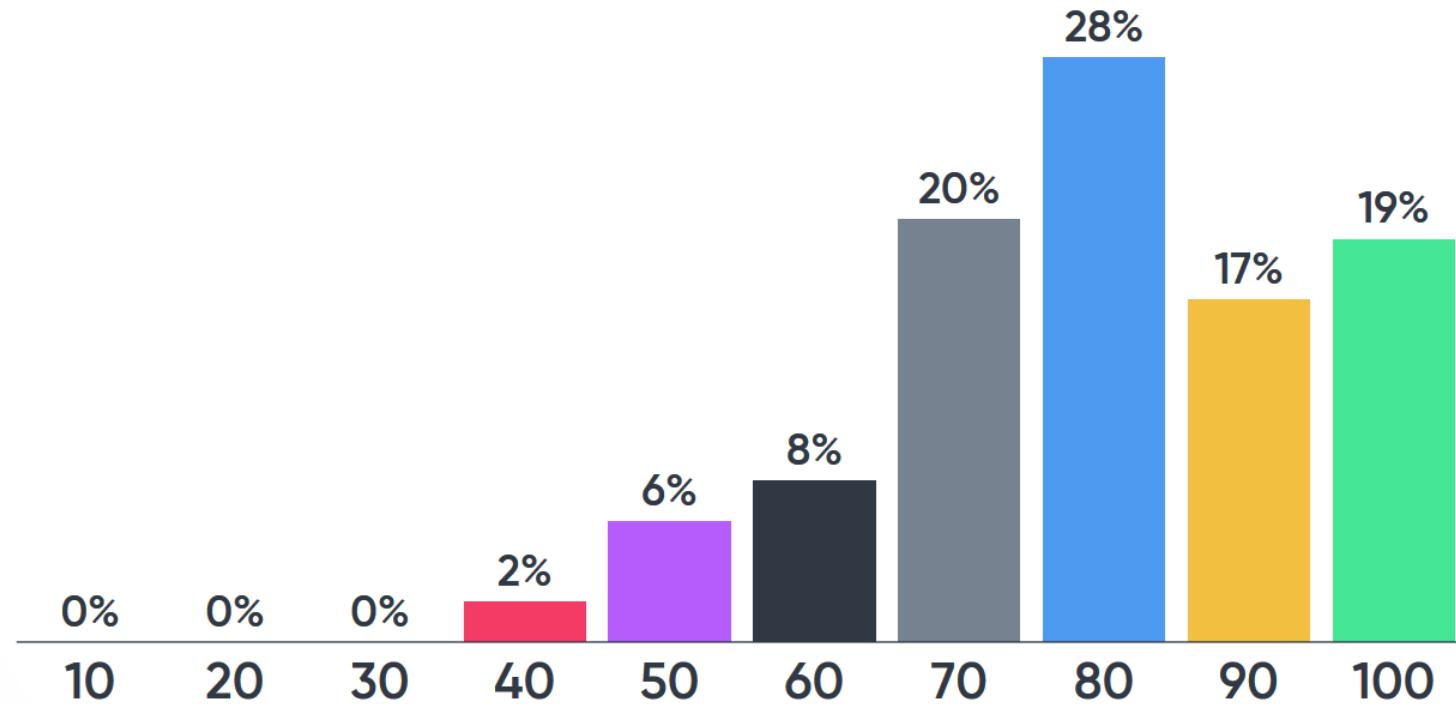
Example 1: Regression

Predict Marks for Students

- A student tells you that she spent 90 hours for the course work in the Machine Learning module. How many marks do you think she will receive?
- Without any other information difficult to answer
- Have a look at her fellow students
 - x = Time spent
 - y = Achieved marks
- Now, again: How many marks will she receive?
10, 20, 30 ... 90, 100?



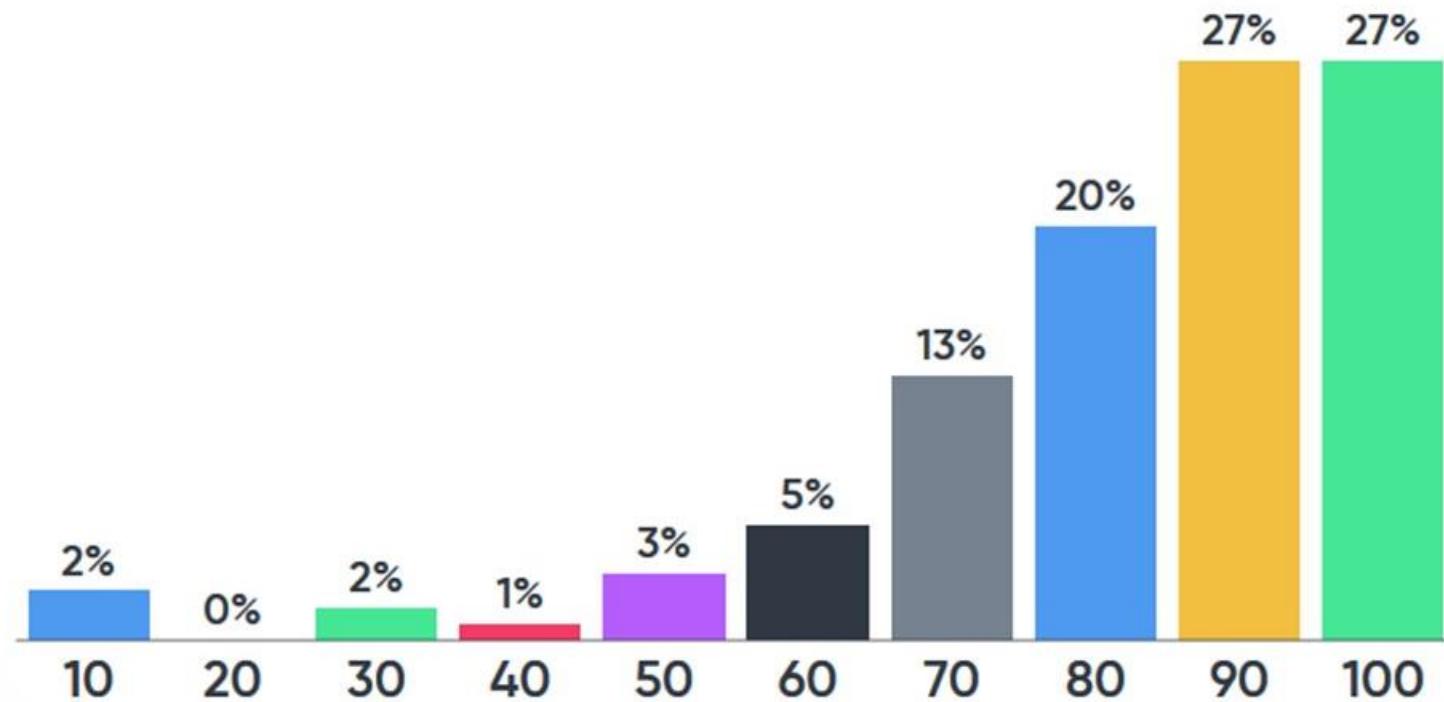
How many marks will a student receive who spends 90 hours?



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Activate

Last year's results



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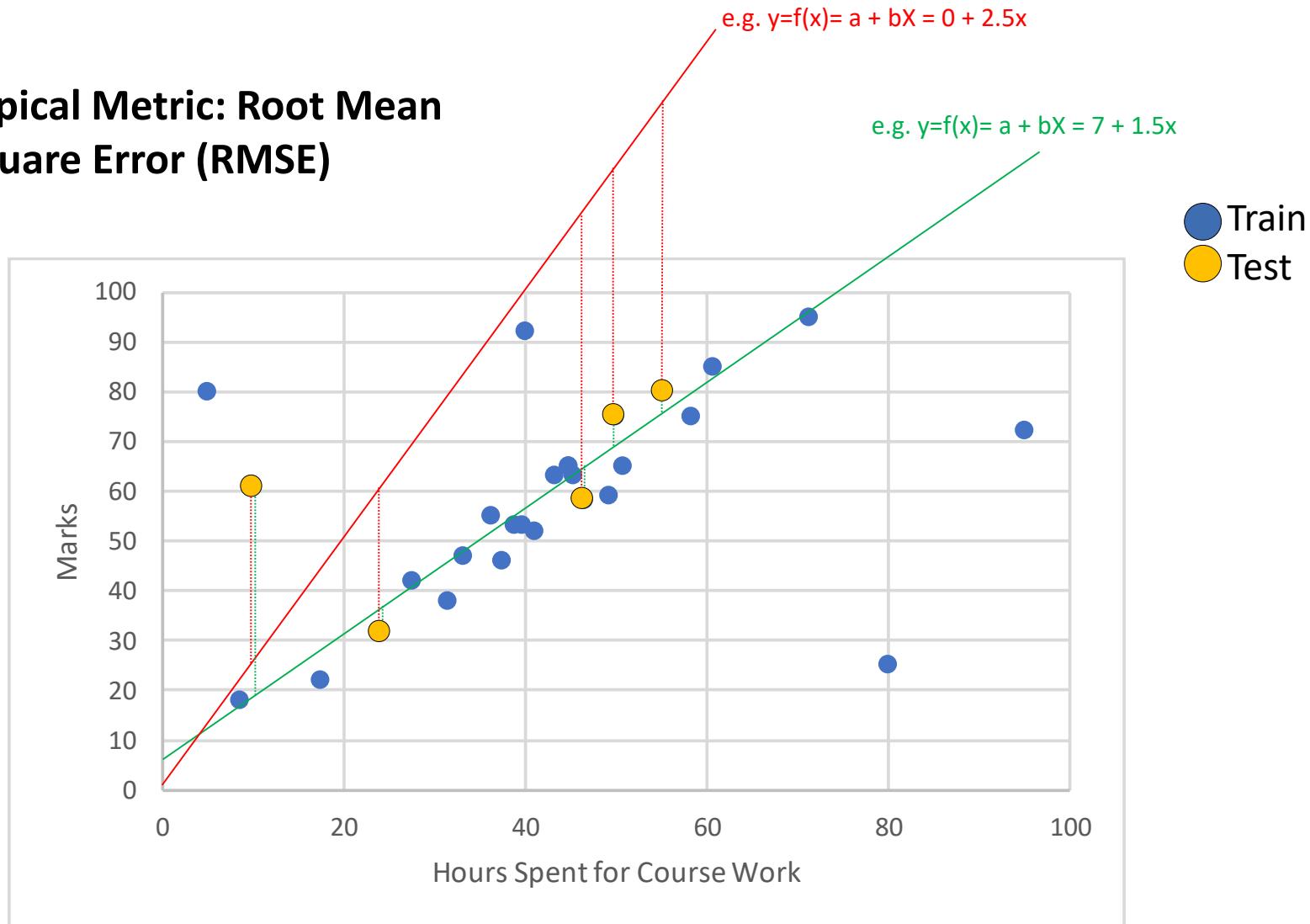
Example

- **Instance based: What marks did other students receive who invested 90 hours?**
 - Find similar student(s)
 - Calculate value for new student
 - „K-Nearest Neighbour“ algorithm
 - Neighbourhood size k is a hyperparameter
- **Model based: What function can approximate the existing data best?**
 - Find a function $y=f(x)= a + bX$
 - E.g. $f(x)= 10 + 0.7x$
 - Calculate y , given x
 - E.g. $f(90)= 10 + 0.7*90 = 73$
 - Linear regression
 - a and b are hyperparameters



Loss Function / Optimization

- **Typical Metric: Root Mean Square Error (RMSE)**



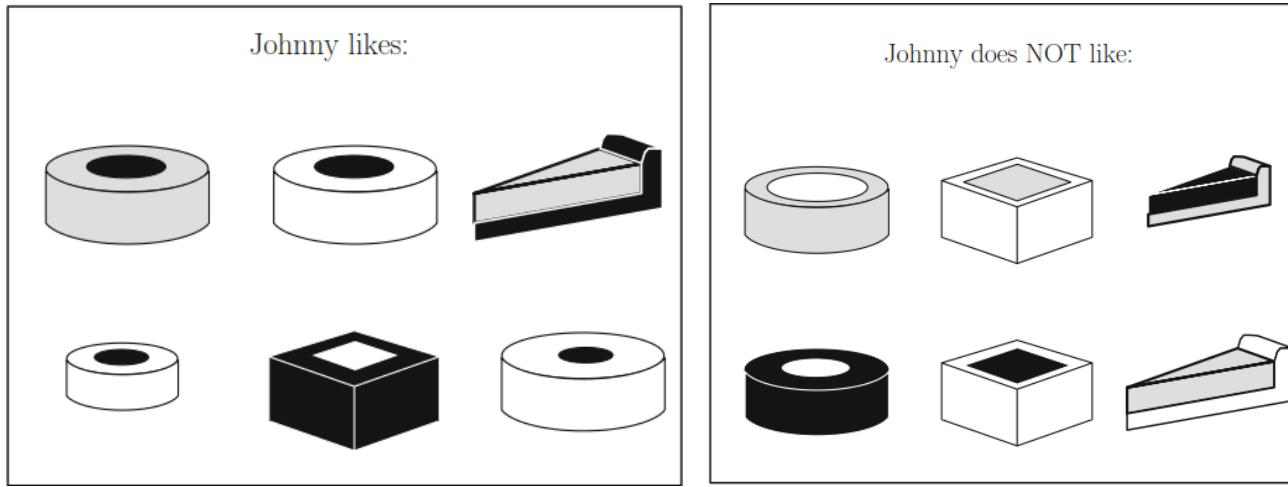


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Example 2: Classification

Example

Will Johnny like or dislike the pie?

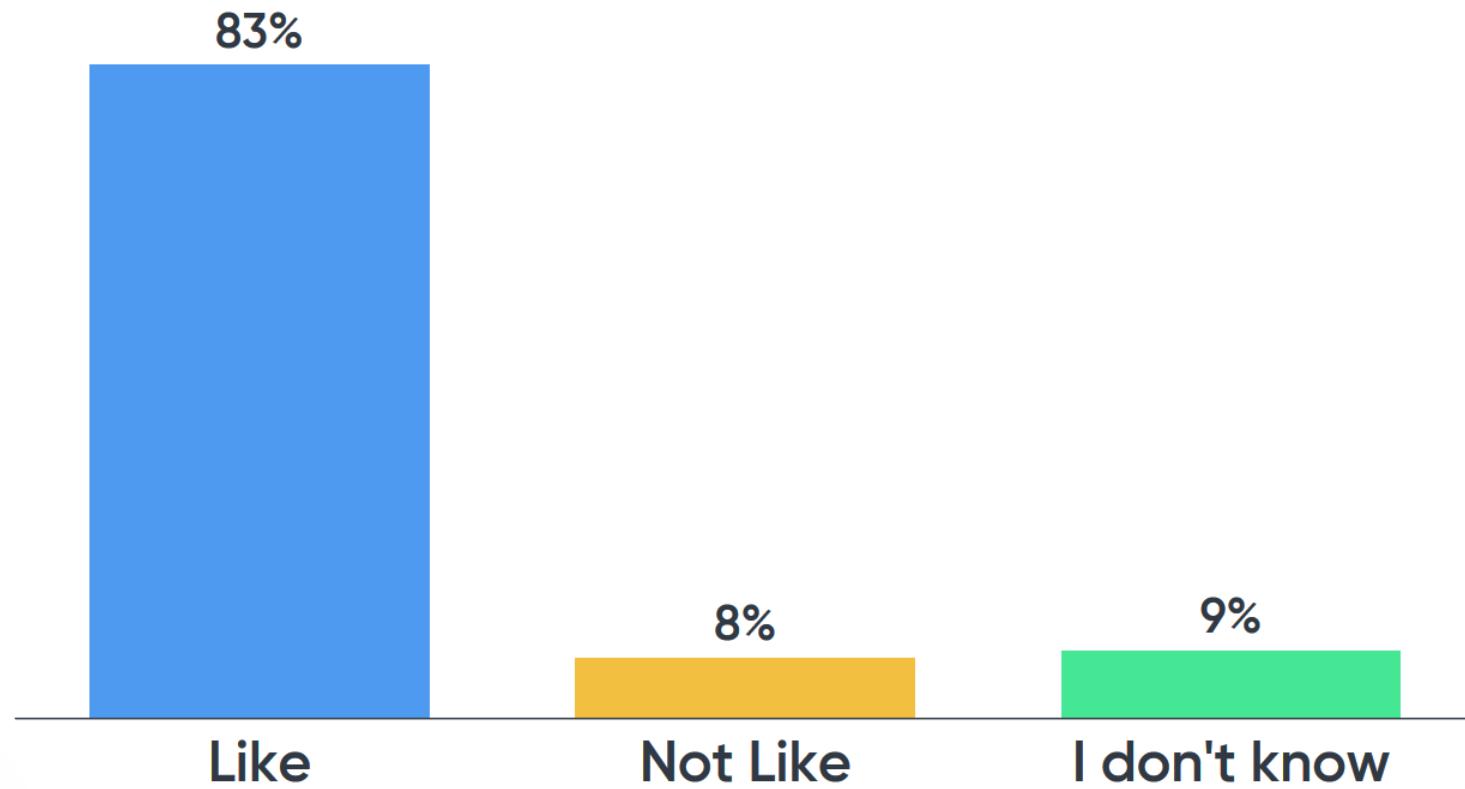


Miroslav Kubat, *An Introduction to Machine Learning* (Springer, 2015).

Go to www.menti.com and use the code 20 20 72

Will Johnny like or dislike the pie?

Mentimeter



Slide is not active

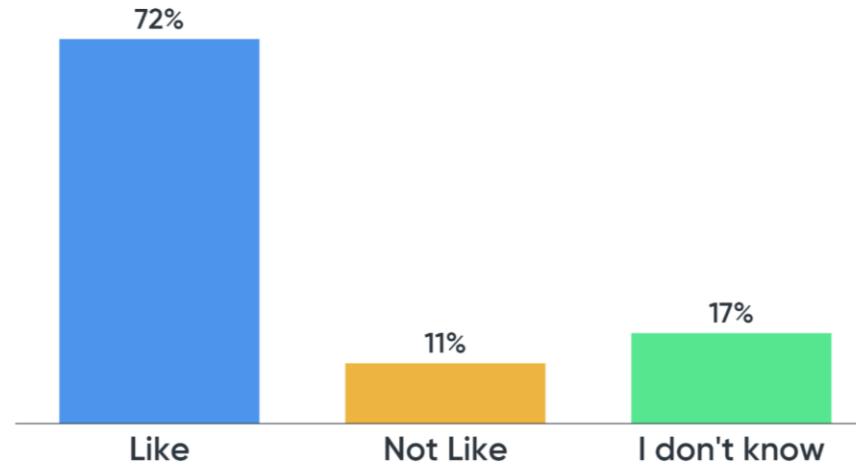
Activate

103

Last Year's Results

Will Johnny like or dislike the pie?

Mentimeter

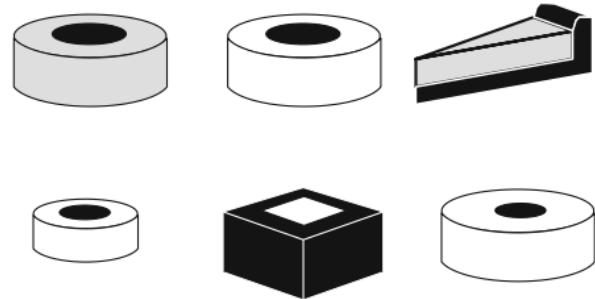


142

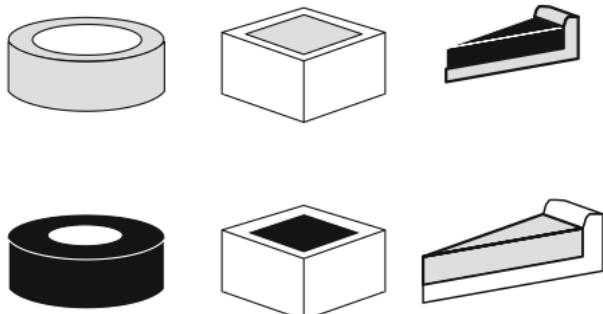
Features/Attributes

What are the features that distinguish the pies?

Johnny likes:



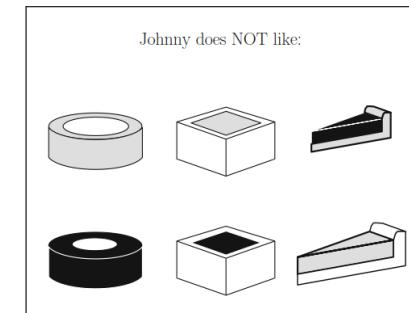
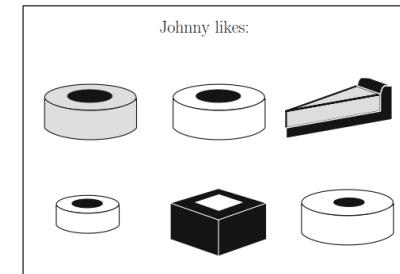
Johnny does NOT like:



Miroslav Kubat, *An Introduction to Machine Learning* (Springer, 2015).

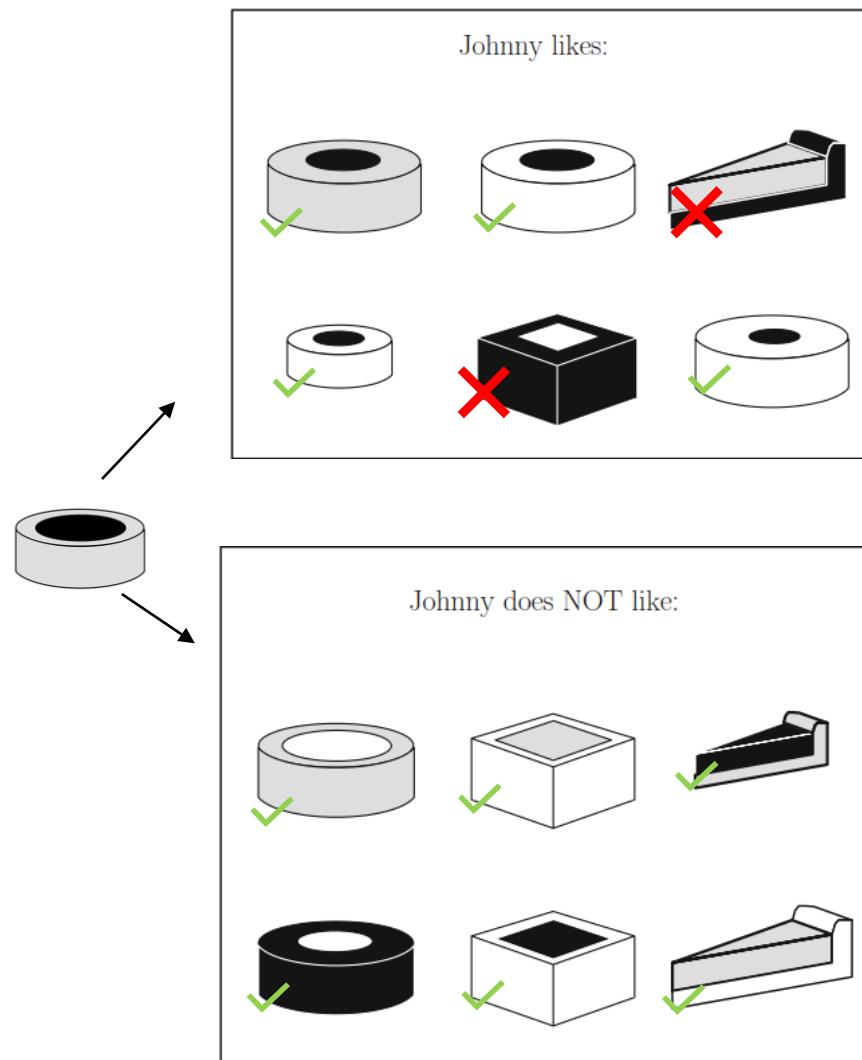
Representation

example	shape	crust		filling		class
		size	shade	size	shade	
ex1	circle	thick	gray	thick	dark	pos
ex2	circle	thick	white	thick	dark	pos
ex3	triangle	thick	dark	thick	gray	pos
ex4	circle	thin	white	thin	dark	pos
ex5	square	thick	dark	thin	white	pos
ex6	circle	thick	white	thin	dark	pos
ex7	circle	thick	gray	thick	white	neg
ex8	square	thick	white	thick	gray	neg
ex9	triangle	thin	gray	thin	dark	neg
ex10	circle	thick	dark	thick	white	neg
ex11	square	thick	white	thick	dark	neg
ex12	triangle	thick	white	thick	gray	neg



Rule Solution

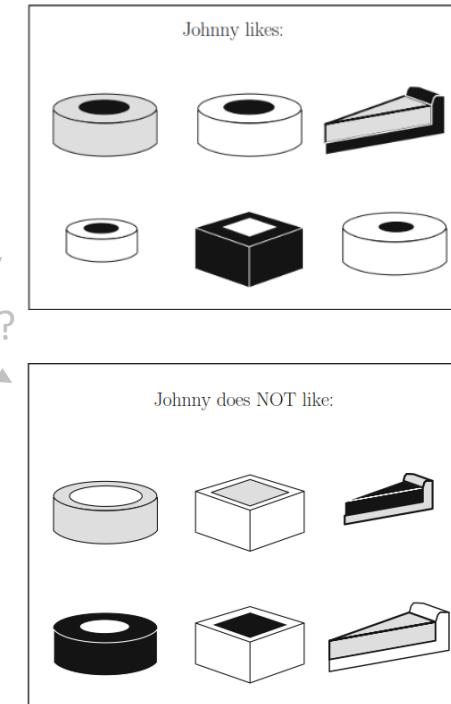
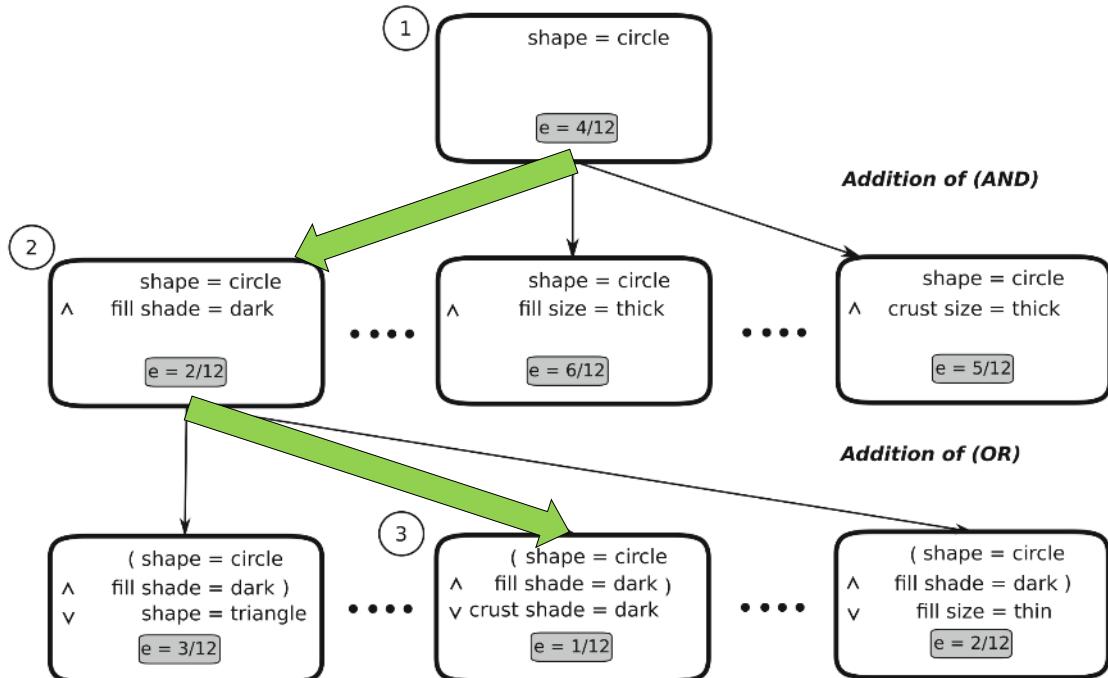
- **If [(shape=circle) AND (filling-shade=dark)] THEN “Like”
ELSE “Not Like”**
 - Classifies all „Not Like“ correctly
 - Classifies 4 out of 6 „Like“ correctly
- Accuracy: 10 of 12 (83%)
- **What would you do for thousands of users (and new pies)?**



Miroslav Kubat, *An Introduction to Machine Learning* (Springer, 2015).

Machine Learning Solution (Hill Climbing)

- Iterative algorithm
- Start with arbitrary solution
- Incremental improvements
- Repeat until no improvement is achieved
- Disadvantage: Finds only local optima & computing intensive



Miroslav Kubat, *An Introduction to Machine Learning* (Springer, 2015).



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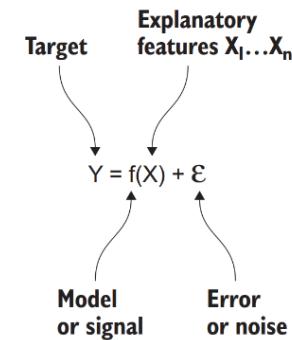
Machine Learning Classifications



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Supervised and Unsupervised Learning...

Supervised Learning



- **Typical Tasks**

- Prediction/Regression (predict a number: the price of a house, income of a person, ...)
- Classification (predict a class: *Spam* or *Not Spam*?)

- **Typical Algorithms**

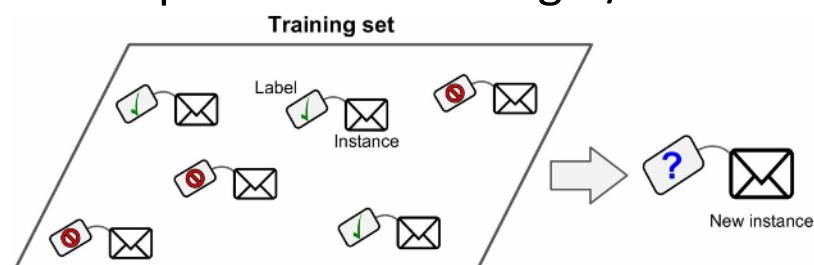
- K-Nearest Neighbours
- Regression
- Support Vector Machines
- Decision Trees and Random Forests

- **Training Input:**

- Labelled data / training data
- Instances/data points with known values for (independent) variables/features/attributes and known dependent variable/response/target/label

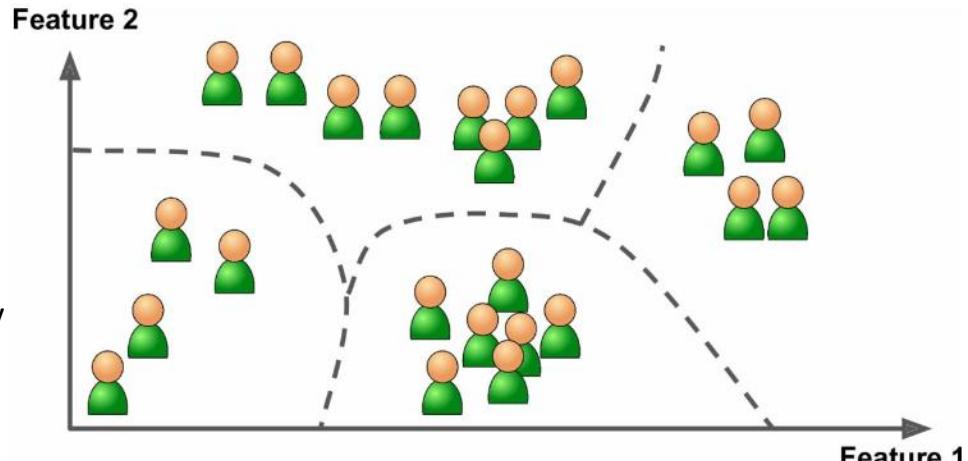
- **Production**

- Input: new instance with known independent variables
- Output: Predicted target/label

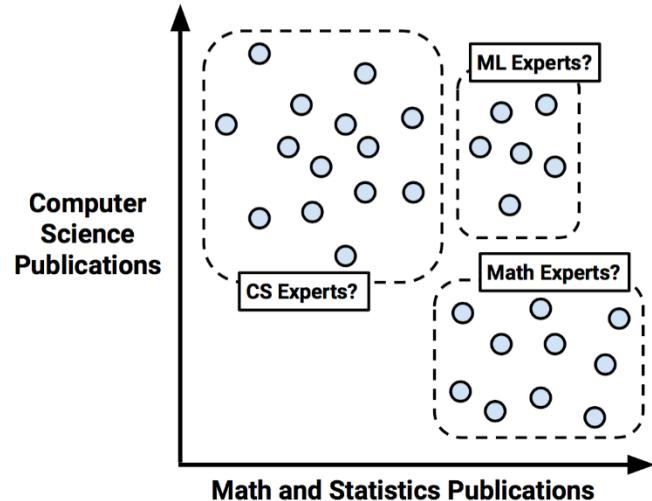


Unsupervised Learning

- **Unlabelled data**
- Work on the current data instead of predicting for future unknown instances
- **Typical task(s)**
- Clustering (group instances into previously unknown groups)
- Dimensionality Reduction
- **Algorithms**
- Clustering
 - K-means
 - Hierarchical Cluster Analysis (HCA)
 - Expected Maximization
- Dimensionality Reduction
 - Principal Component Analysis
 - Kernel PCA



A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.



<https://hub.packtpub.com/introduction-clustering-and-unsupervised-learning/>



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... and Semi Supervised and Reinforcement
Learning...

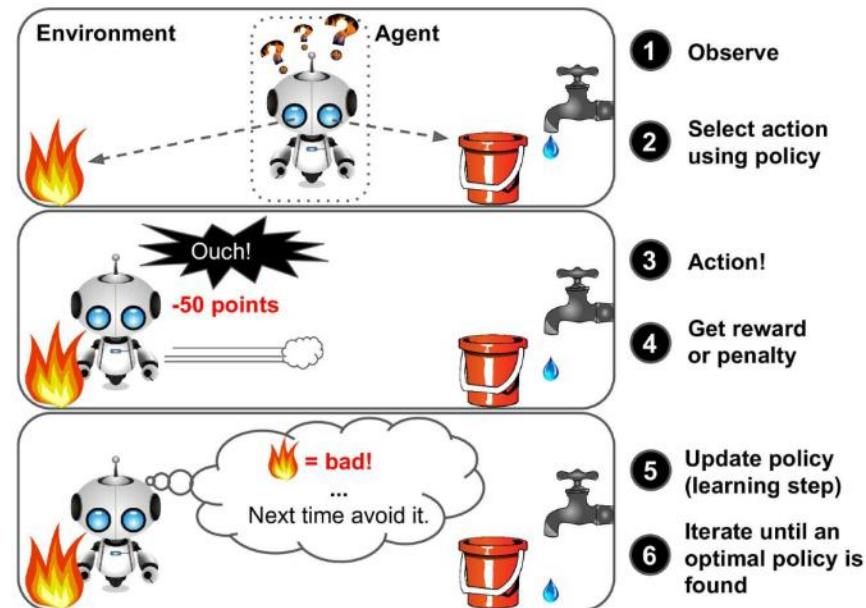
Semi-Supervised Learning

- **Some labelled but mostly unlabelled data**
- **For instance, Google Photos:**
 - Identification of the same persons (unsupervised)
 - Manually adding labels to clusters/persons (supervised)
- **Often based on Deep Belief Networks (DBN) / Restricted Boltzmann Machines (RBM)**

A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.

Reinforcement Learning

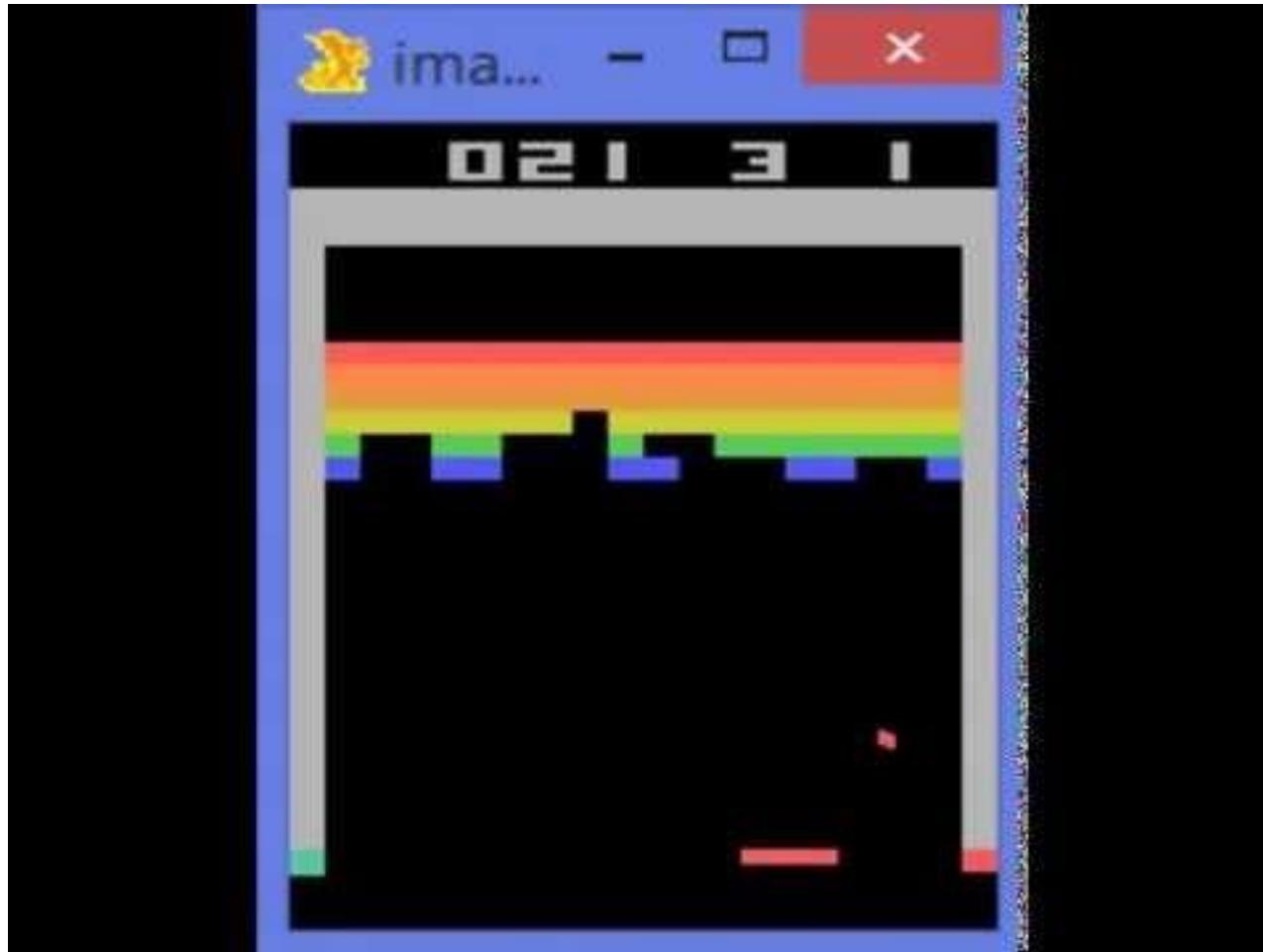
- An agent observes an environment, chooses between actions and gets rewards (or penalties) in return. The agent learns the best strategy („policy“) for what to do in a given situation.
- Often used for making robots to learn how to walk; also for DeepMind’s AlphaGo



A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.

Example (Reinforcement learning)

- <https://www.youtube.com/watch?v=V1eYniJ0Rnk>





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... and other views

Instance Based vs. Model Based

- **Instance**
 - No training
 - Algorithms
 - k-nearest neighbour
 - kernel machines
 - RBF networks
- **Model**
 - Model is learned through training data

Parametric vs. Nonparametric Models

- **Parametric**
 - Based on the features (and certain weights), Y can be calculated
 - E.g. (linear) regression

$$f(\mathbf{X}) = \beta_0 + X_1 \times \beta_1 + X_2 \times \beta_2 + \dots$$

- **Nonparametric**

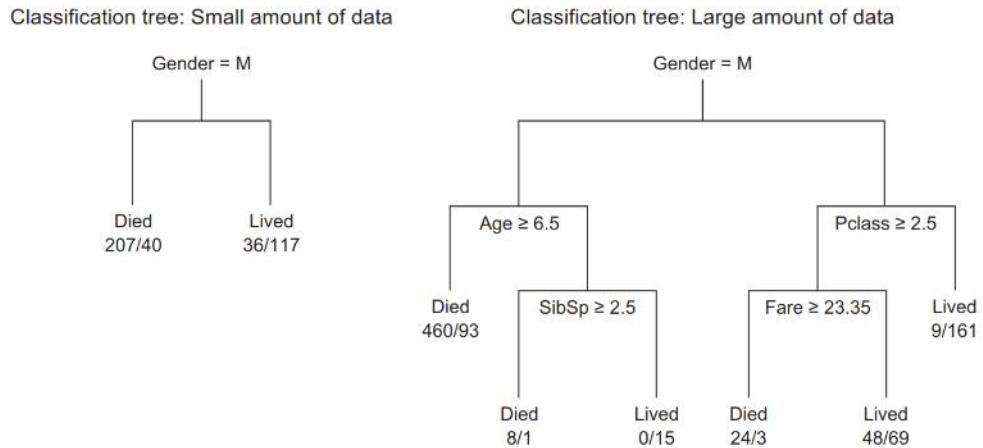


Figure 3.2 A decision tree is an example of a nonparametric ML algorithm, because its functional form isn't fixed. The tree model can grow in complexity with larger amounts of data to capture more complicated patterns. In each terminal node of the tree, the ratio represents the number of training instances in that node that died versus lived.

The five tribes of machine learning

- The five tribes of machine learning, Webinar by Pedro Domingos
https://learning.acm.org/webinar_pdfs/PedroDomingos_FTFML_WebinarSlides.pdf
- Pedro Domingos, *The master algorithm: How the quest for the ultimate learning machine will remake our world* (Basic Books, 2015), <http://www.idi.ntnu.no/emner/tdt4173/papers/Domingos-SVM-NN-CBR.pdf>.
- See also John Paul Mueller and Luca Massaron, Machine Learning for Dummies (John Wiley & Sons, 2016).

Tribe	Origins	Problem	Solution / Master Algorithm
Symbolists	Logic, Philosophy	Knowledge composition	Inverse deduction
Connectionists	Neuroscience	Credit Assignment	Backpropagation
Evolutionaries	Evolutionary Biology	Structure Discovery	Genetic programming
Bayesians	Statistics	Uncertainty	Probabilistic Inference
Analogizers	Psychology	Similarity	Kernel Machines



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Definition

Machine Learning Definitions

- „Machine Learning is the science (and art) of programming computers so they can *learn from data*.“
A. Géron, Hands on Machine Learning with scikit-learn and Tensorflow. O'Reilly Media, 2017.
- „[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed“
Arthur Samuel, 1959 in A. Géron
- „A computer program is said to learn from experience E with respect to some task T and some performance measure P if its performance on T, as measured by P, improves with experience E.“ Tom Mitchell, 1997 in A. Géron

Ignores the eventual goal, i.e. solving a task.

Experience = data

Typical Tasks (from an application point of view)

1. Prediction

1. House Prices
2. Diseases
3. Products a customer will like
4. ...

2. Recognition

1. Faces
2. Voices
3. Gestures
4. ...

3. Creation / Modification

1. Art (Paintings, Music, ...)
2. Videos (DeepFakes, ...)
3. Augmented Reality
4. ...

4. Anything else?

Typical Tasks (2)

Input A → Output B

What Machine Learning Can Do

A simple way to think about supervised learning.

INPUT A	RESPONSE B	APPLICATION
Picture	Are there human faces? (0 or 1)	Photo tagging
Loan application	Will they repay the loan? (0 or 1)	Loan approvals
Ad plus user information	Will user click on ad? (0 or 1)	Targeted online ads
Audio clip	Transcript of audio clip	Speech recognition
English sentence	French sentence	Language translation
Sensors from hard disk, plane engine, etc.	Is it about to fail?	Preventive maintenance
Car camera and other sensors	Position of other cars	Self-driving cars

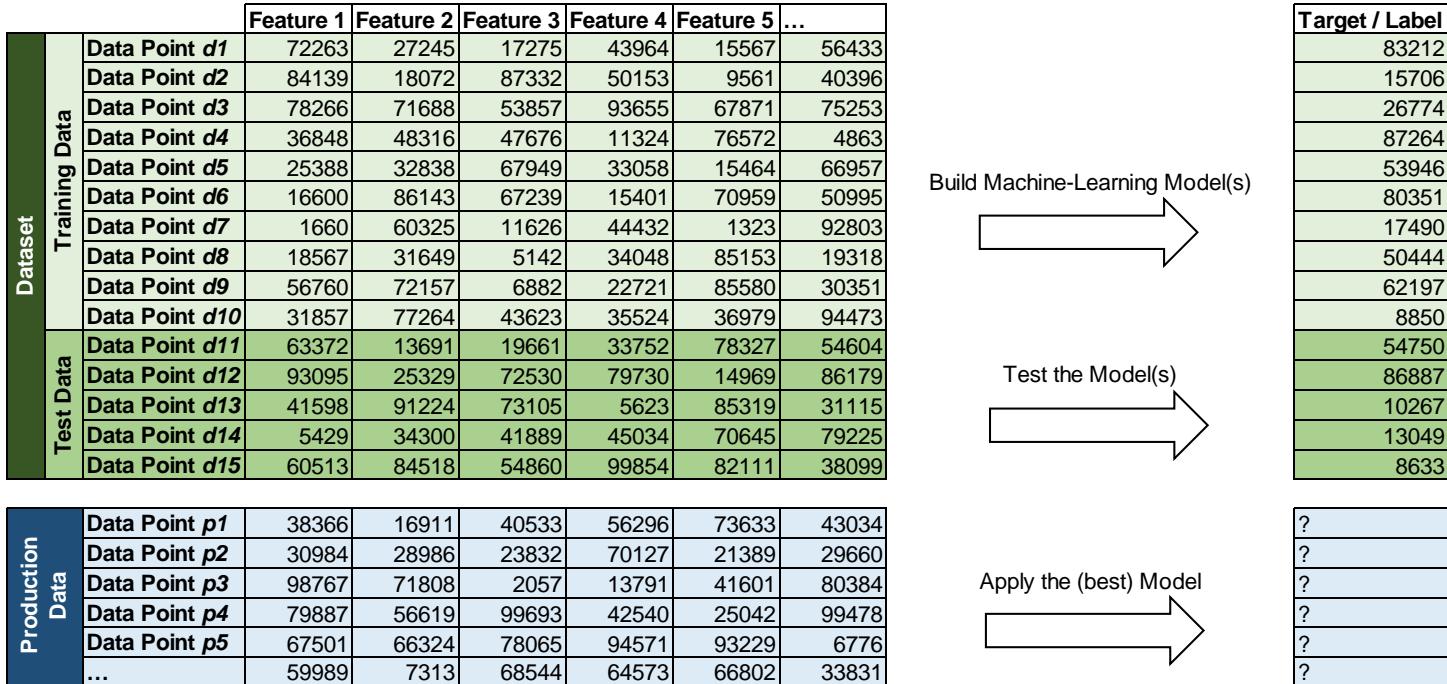
SOURCE ANDREW NG

© HBR.ORG

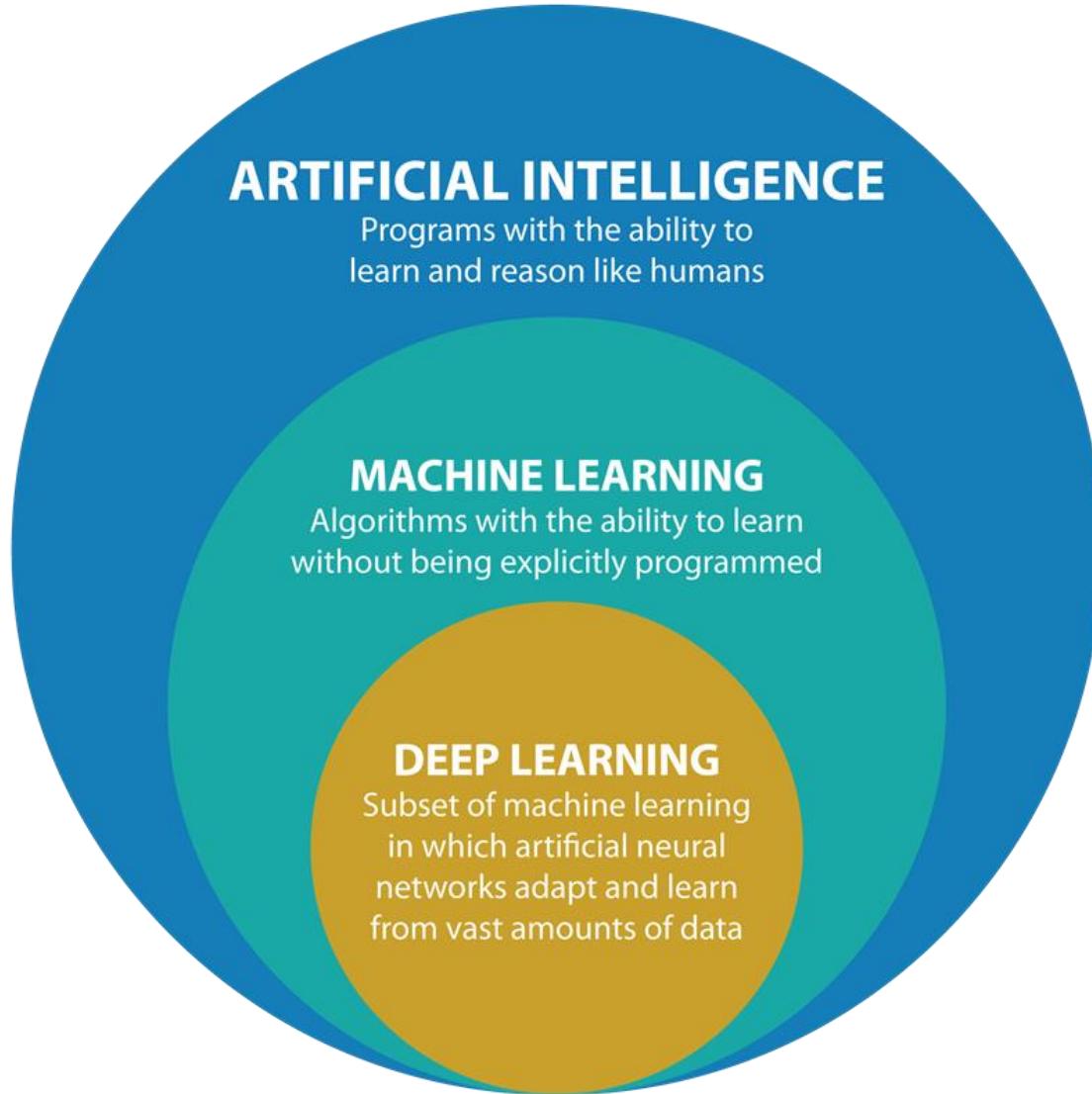
<https://hbr.org/2016/11/what-artificial-intelligence-can-and-cant-do-right-now>

Typical Experiences

- **Data with features from which the task can be inferred**
 - Instance/Data Point
 - Attribute/Feature/(Independent)Variable
 - Target/Label/(Dependent) Variable



ML vs. AI vs. DL (vs. Data Science)



<https://www.argility.com/wp-content/uploads/2018/04/image10.png>



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Traditional approaches to problem solving

Human Labour



Home Documentation Register Sign In

CAPTCHA solving service

✓ Cheapest price on the market
Starting from 0.7USD per 1000 images, depending on your daily upload volume

✓ Pay as you go
Pay-per-captcha payment basis. Minimum refill is 1 USD, no recurring charges

✓ 99.99% uptime since 2007
Vast amount of workers and premium infrastructure allows us to provide highly reliable 24/7/365 service

[registration](#) [Client area](#)

overlooks inquiry

Type the two words:



Discover, preview and complete HITs on the new Worker website. Try It out Today!

Sign In

amazon mechanical turk Artificial Artificial Intelligence

Your Account HITs Qualifications 258,645 HITs available now

All HITs | HITs Available To You | HITs Assigned To You

Find HITs containing that pay at least \$ 0.00 for which you are qualified require Master Qualification 60

Complete Profile Tasks to qualify for more HITs

Click here to add or update your profile information. By providing this information, you may qualify for HITs from Requesters looking for Workers like you.

All HITs 1-10 of 2323 Results

Sort by: HITs Available (most first) 601 Show all details | Hide all details

1 2 3 4 5 > Next >> Last Items per Page: 10 View a HIT in this group

Classify the building/property type based on address

Requester: James HIT Expiration Date: Sep 27, 2017 (6 days) Reward: \$0.03

Description: Search an address and look at results to determine what the property type might be

Keywords: properties, demographics, classification, classify, search

Qualifications Required: Location IS US

Find the website of a company from Google searches

Requester: Andres Riposati HIT Expiration Date: Sep 25, 2017 (4 days 2 hours) Reward: \$0.02

Description: Find the website of a company from Google searches

Time Allotted: 5 minutes

Time Allotted: 60 minutes

View a HIT in this group

Actions: View Details | Edit | Delete | Settings to activate Windows



<http://www.recaptcha.net/images/recaptcha-example.gif>

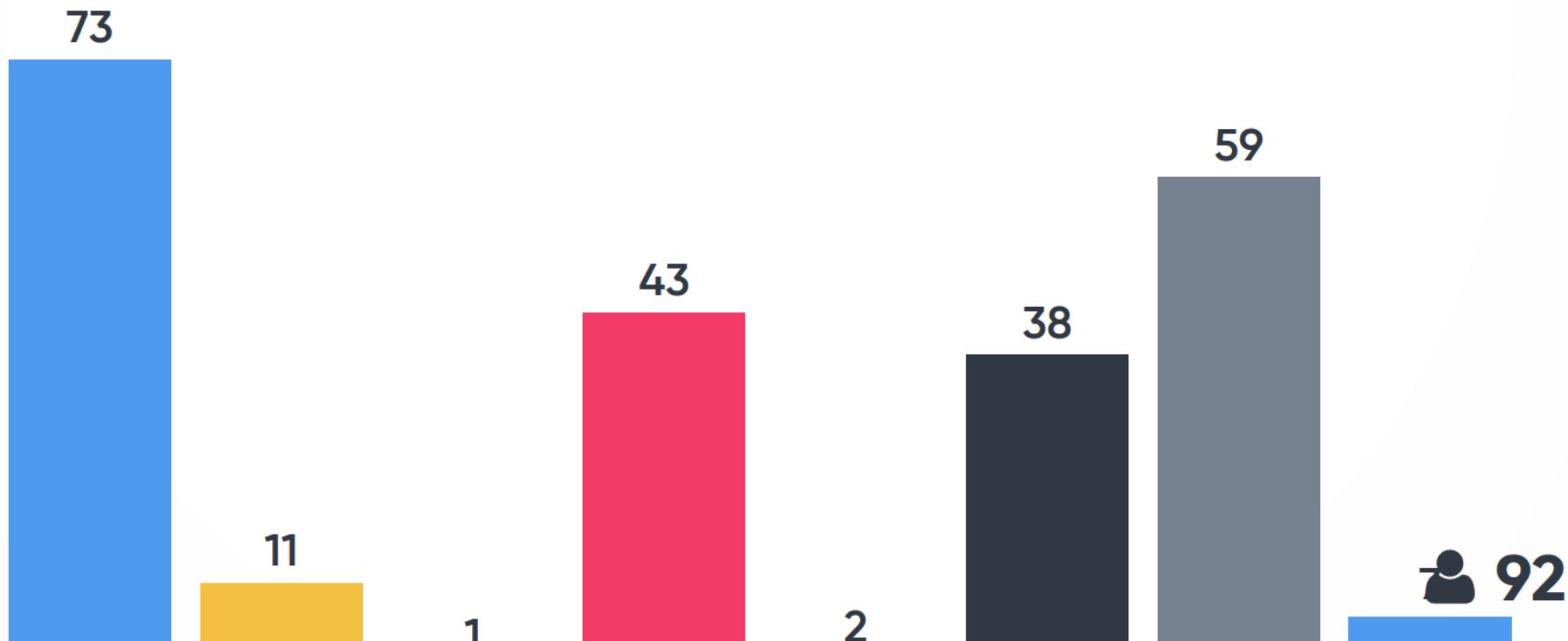
http://motorcitymuckraker.com/wp-content/uploads/2014/04/Shinola_2315-701x468.jpg

<https://anti-captcha.com/>

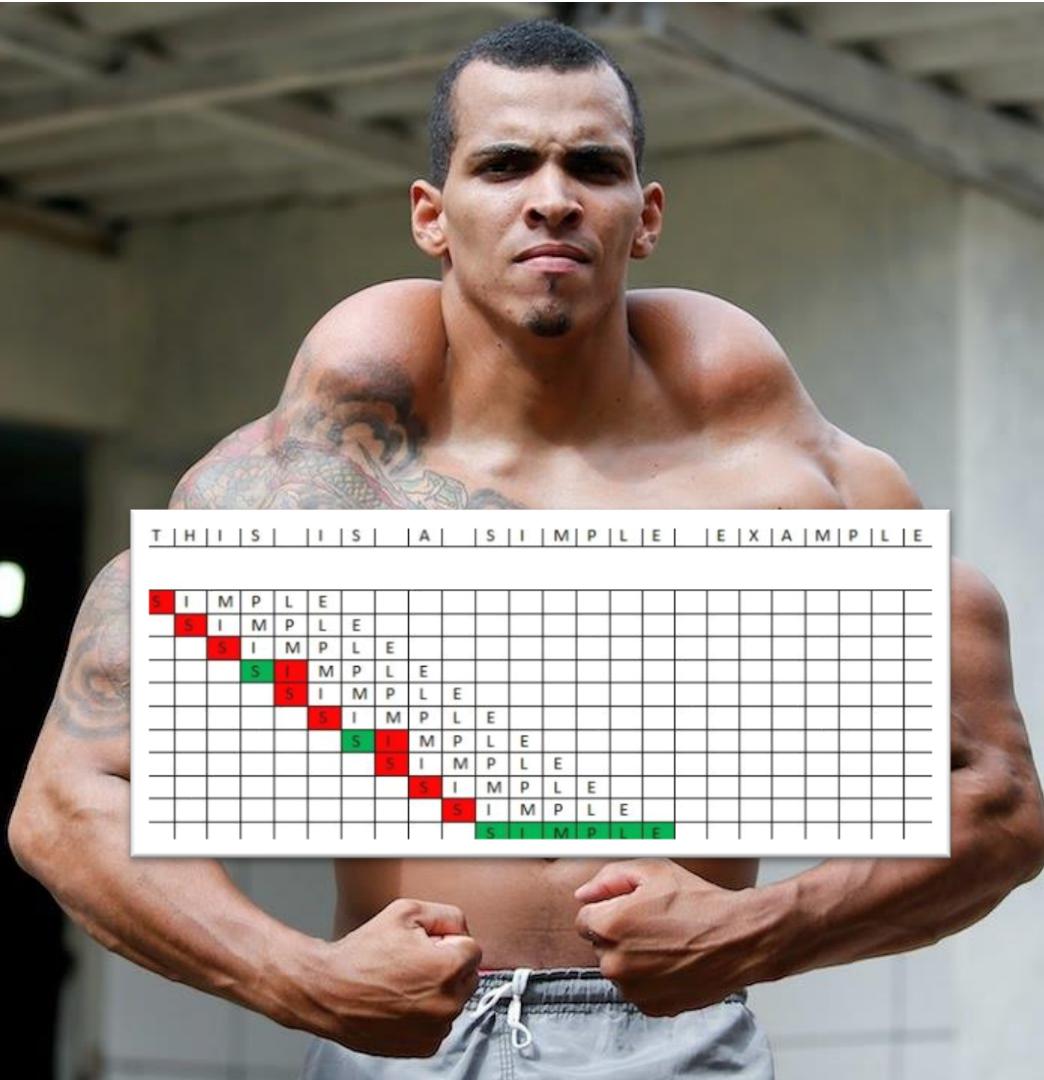
Go to www.menti.com and use the code 20 20 72

Lecture Evaluation

Mentimeter



Bruteforce



<https://i.ytimg.com/vi/SobAPTAAX1s/maxresdefault.jpg>

http://1.bp.blogspot.com/-YJDalyxz6XY/UFCYnd2_nBI/AAAAAAAAB4/uewJpXgs9Mc/s1600/Brute+Force.jpg

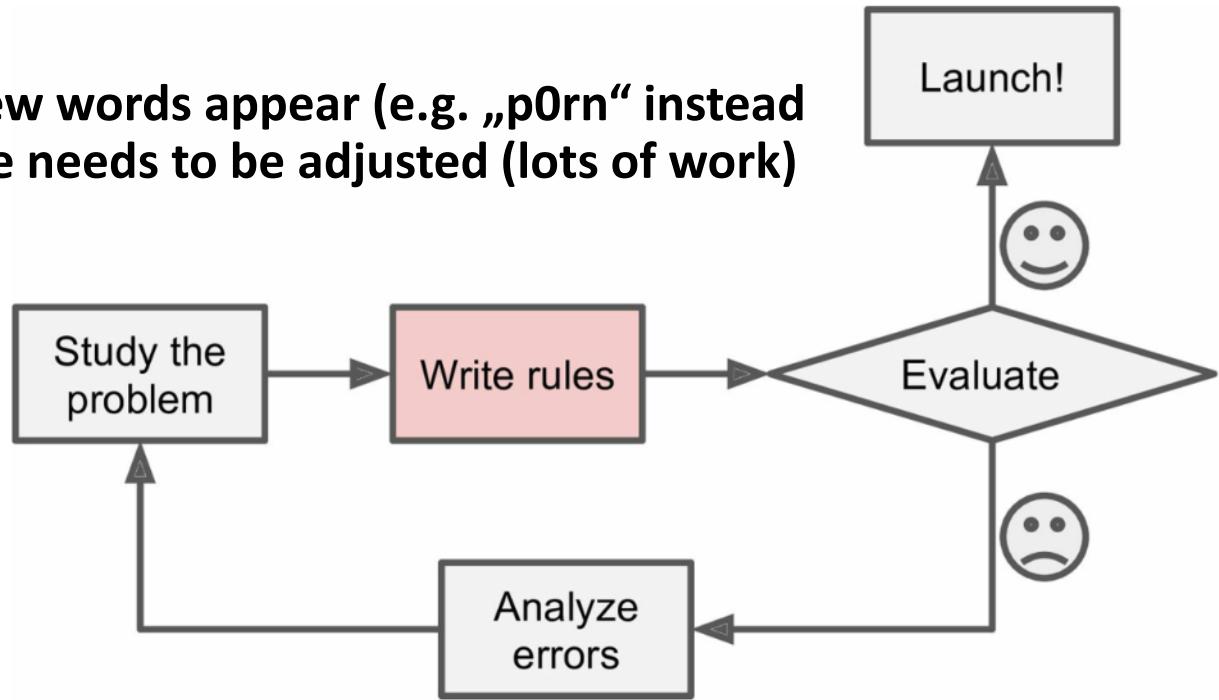
Rules / Heuristics / Algorithms



<https://mensconferenceuk.files.wordpress.com/2013/08/the-rule-book.jpg>

Example for Rules: Spam Detection

- **Goal:** Decide if an email is spam or not? (classification problem)
- **Potential Rule:** If an email contains the terms „porn, sex, viagra, ...“ then it is spam. Maybe with wildcards, e.g. p?rn, or sex*
- **Problem:** When new words appear (e.g. „p0rn“ instead of „porn“), the rule needs to be adjusted (lots of work)



A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.

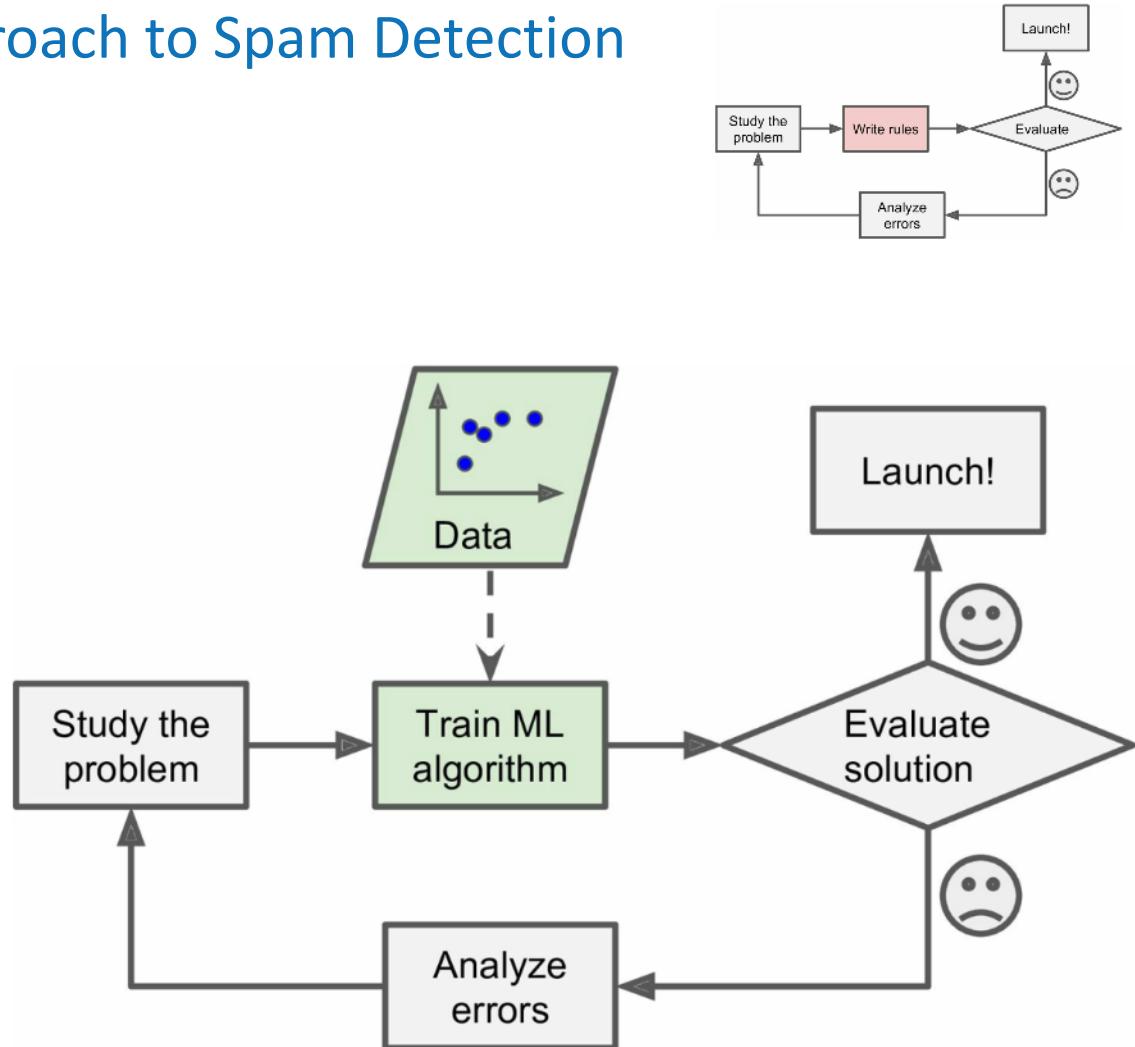


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The Machine Learning Approach to Problem Solving

Machine-Learning Approach to Spam Detection

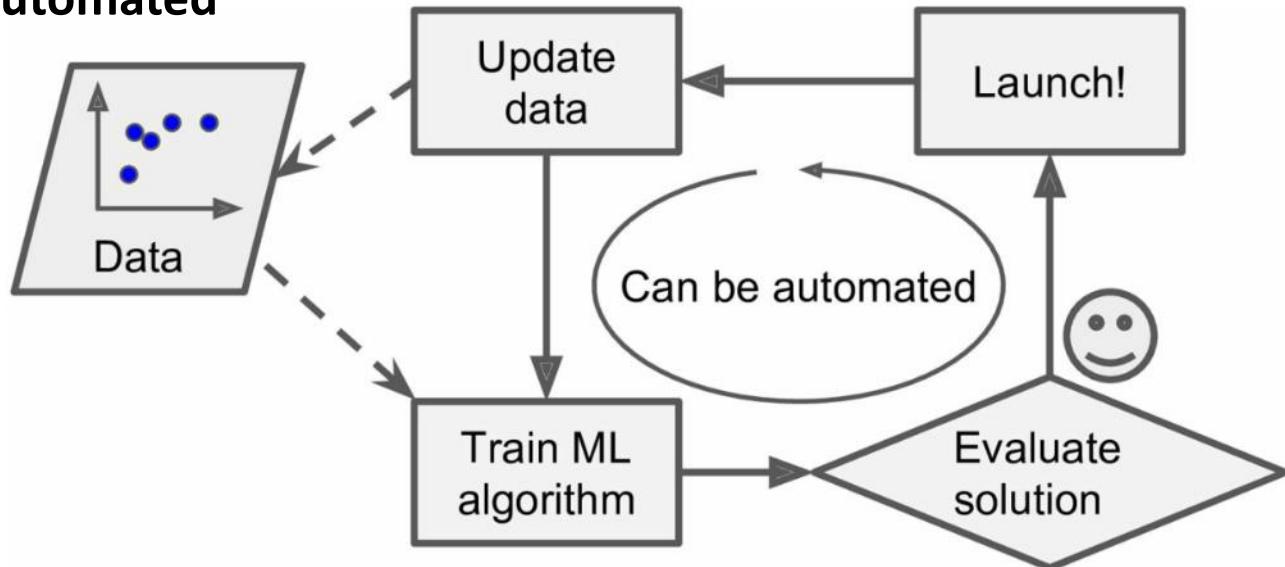
- „A computer program is said to learn from experience E with respect to some task T and some performance measure P if its performance on T, as measured by P, improves with experience E.“
- **T = Detect Spam Emails (flag new emails as spam/not-spam)**
- **P = Number of correctly classified (not-) spam emails**
- **E = Dataset with emails being classified as spam/not-spam** ← the more data, the better P becomes



A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.

Updating Machine-Learning

- You update the data, not the algorithm
- For instance, once there is an updated email dataset (with emails that contain e.g. the term „p0rn“ and are flagged as spam), the algorithm learns that emails containing the term „p0rn“ are also spam.
- Can be automated



A. Géron, *Hands on Machine Learning with scikit-learn and Tensorflow*. O'Reilly Media, 2017.

Spam Detection in Gmail

The image displays two side-by-side screenshots of the Gmail web interface, illustrating the process of marking a message as not spam.

Left Screenshot (Inbox View):

- The title bar shows "All Mail - j@beel.org - Bee".
- The address bar shows "Secure https://mail.google.com/mail/u/0/#all".
- The top navigation bar includes "Archive", "Spam" (which is highlighted with a red box), "Delete", "Mark as read", "Move to Inbox", and "Labels".
- The main area shows an email from "Takeaki Uno" with the subject "子供向けプログラミング教材: 情報共有".
- The message content is:

子供向けプログラミング教材: 情報共有

Takeaki Uno <uno@nii.jp> 11:29 AM (23 hours ago) [Reply to all](#)

NIIの皆様:

宁々です。

回答をいただいた背景、丁寧に、迅速に、いい情報をありがとうございました。個別にお返事、大変ですので、まとめてお礼申し上げさせていただきます。

意外とたくさん情報がありましたので、この機会に、下記に共有させていただきます。

こういう情報がレポジトリになってるといいかもですねえ。

- The sidebar on the left lists the following categories: Inbox, Starred, Sent Mail, Drafts, All Mail (highlighted with a red box), Spam, Trash, best_of-students, e-Commerce II, job application, nii_internship, Priority, tesento, x_old, and Google Calendar.

Right Screenshot (Spam Folder View):

- The title bar shows "Spam - j@beel.org - Bee".
- The address bar shows "Secure https://mail.google.com/mail/u/0/#spam".
- The top navigation bar includes "Delete forever", "Not spam" (which is highlighted with a red box), "Mark as read", "Move to", "Labels", and "More".
- The main area shows a list of spam messages:

 - IT Media
 - Computing Conference
 - Neues aus dem Königreich
 - John Graves
 - Herrmann Kober
 - Anja Dreßler
 - National Sustainability

- A message from "Herrmann Kober" is selected, showing the following details:

Herrmann Kober <herrmannkober@...> 8:23 AM (2 hours ago) [Reply](#)

Domainname propertysource.de

Why is this message in Spam? You clicked "Report spam" for this message. [Learn more](#)

Sehr geehrte Damen und Herren!

Der Domainname [propertysource.de](#) steht zur Disposition und könnte für Sie von Interesse sein.

Falls Sie nähere Informationen wünschen, würde ich mich über eine kurze Email freuen.

Hochachtungsvoll

Click here to [Reply](#) or [Forward](#)

- The sidebar on the left lists the same categories as the inbox view: Inbox, Starred, Sent Mail, Drafts, All Mail, Spam, Trash, best_of-students, e-Commerce II, job application, nii_internship, Priority, tesento, x_old, and Google Calendar.

Machine Learning as General Problem Solver

- **One algorithm can solve different problems. For instance, Support Vector Machines can solve:**
 - Spam Detection
 - Hand Written Character Recognition
 - Image Classification
 - ...
- **However, there is not „the one“ machine-learning algorithm that can do everything**

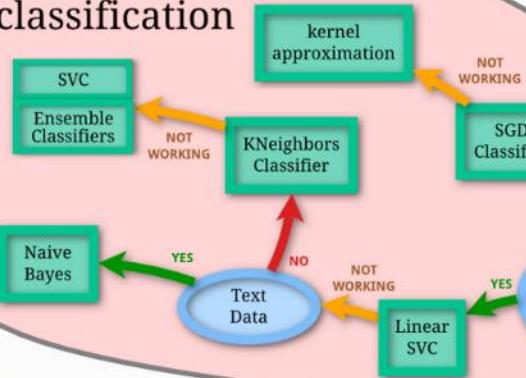


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The Machine Learning Landscape(s)

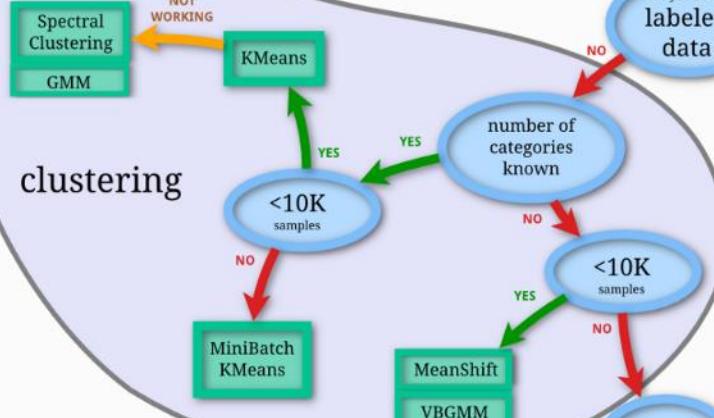
Scikit-learn

classification

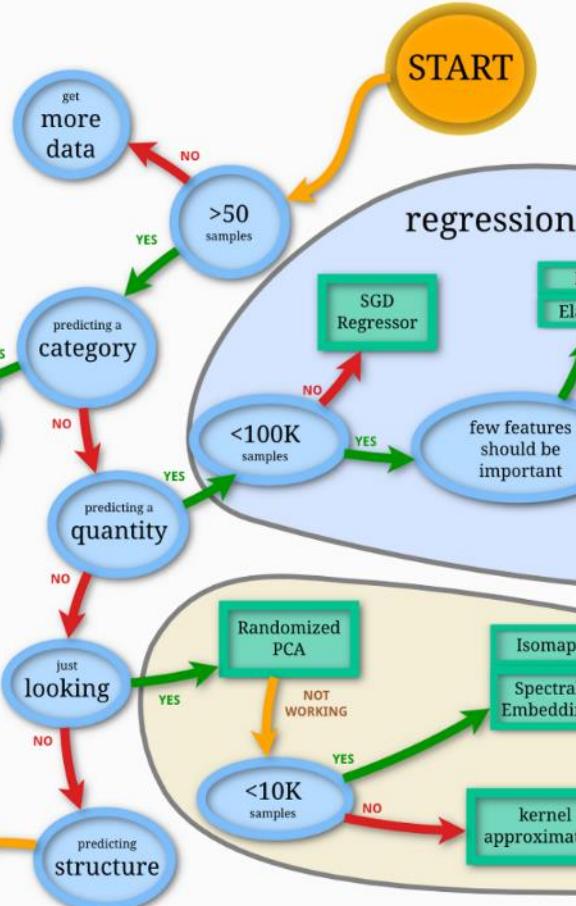


scikit-learn algorithm cheat-sheet

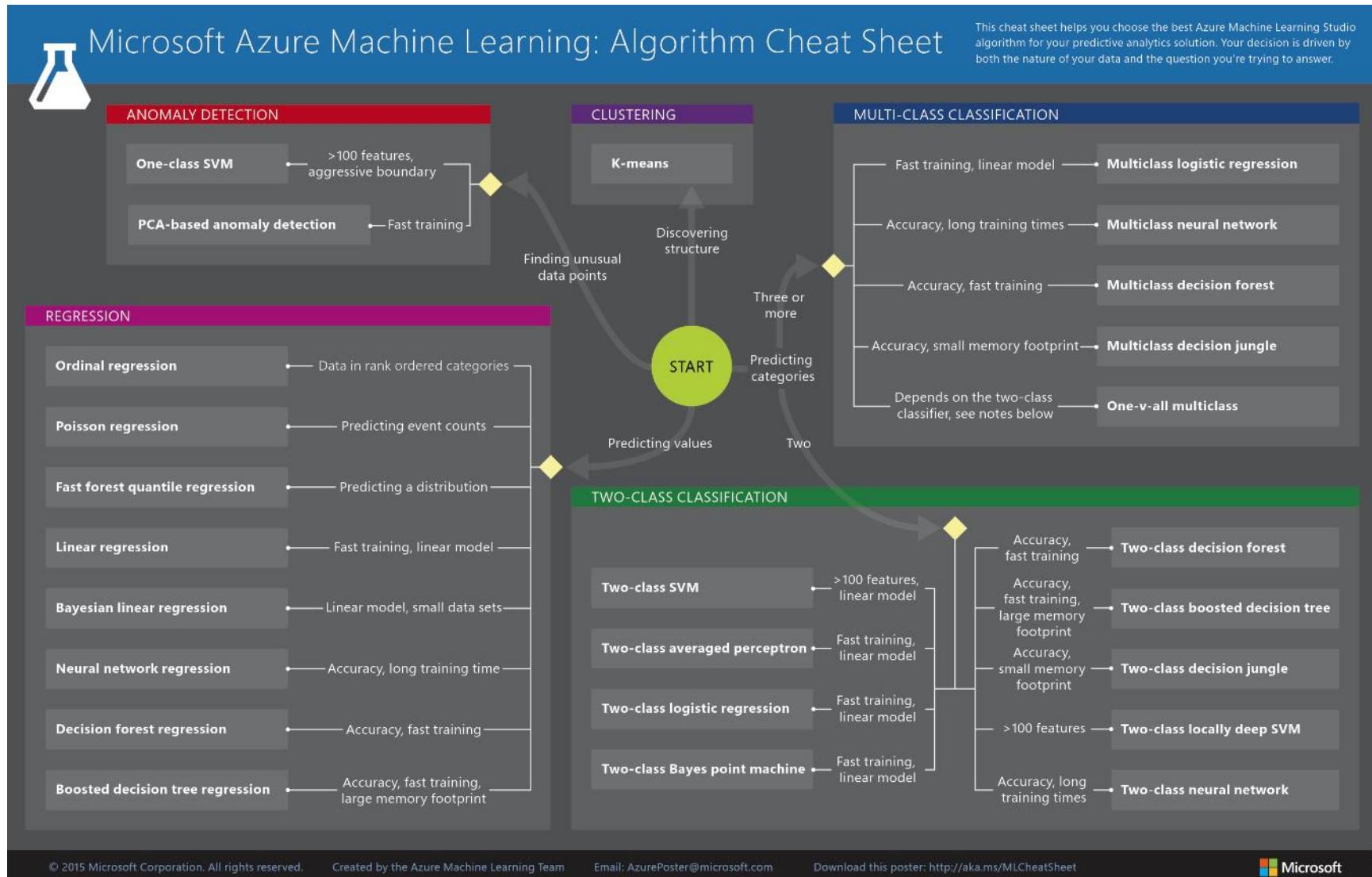
clustering



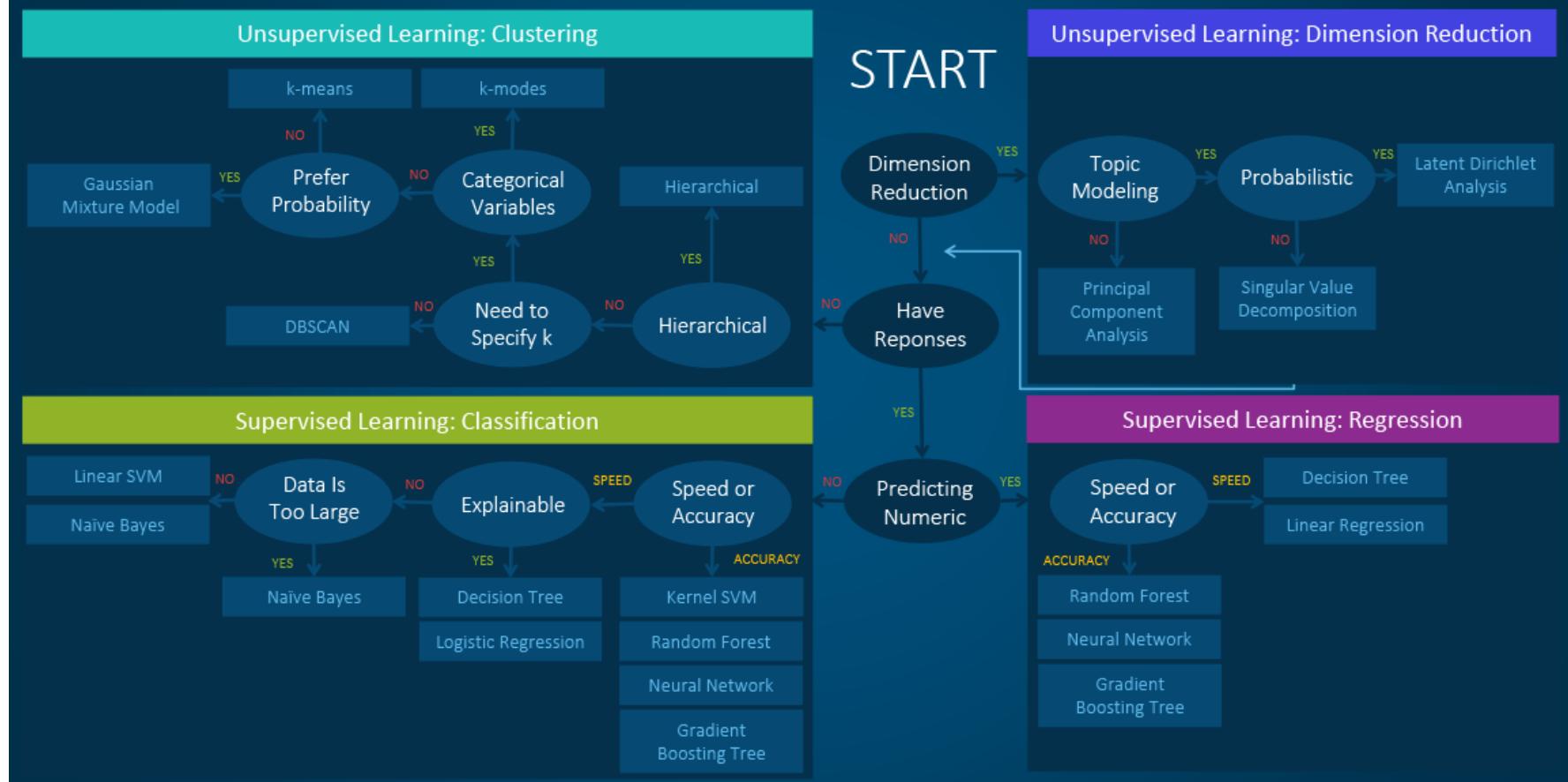
dimensionality reduction



Microsoft Azure



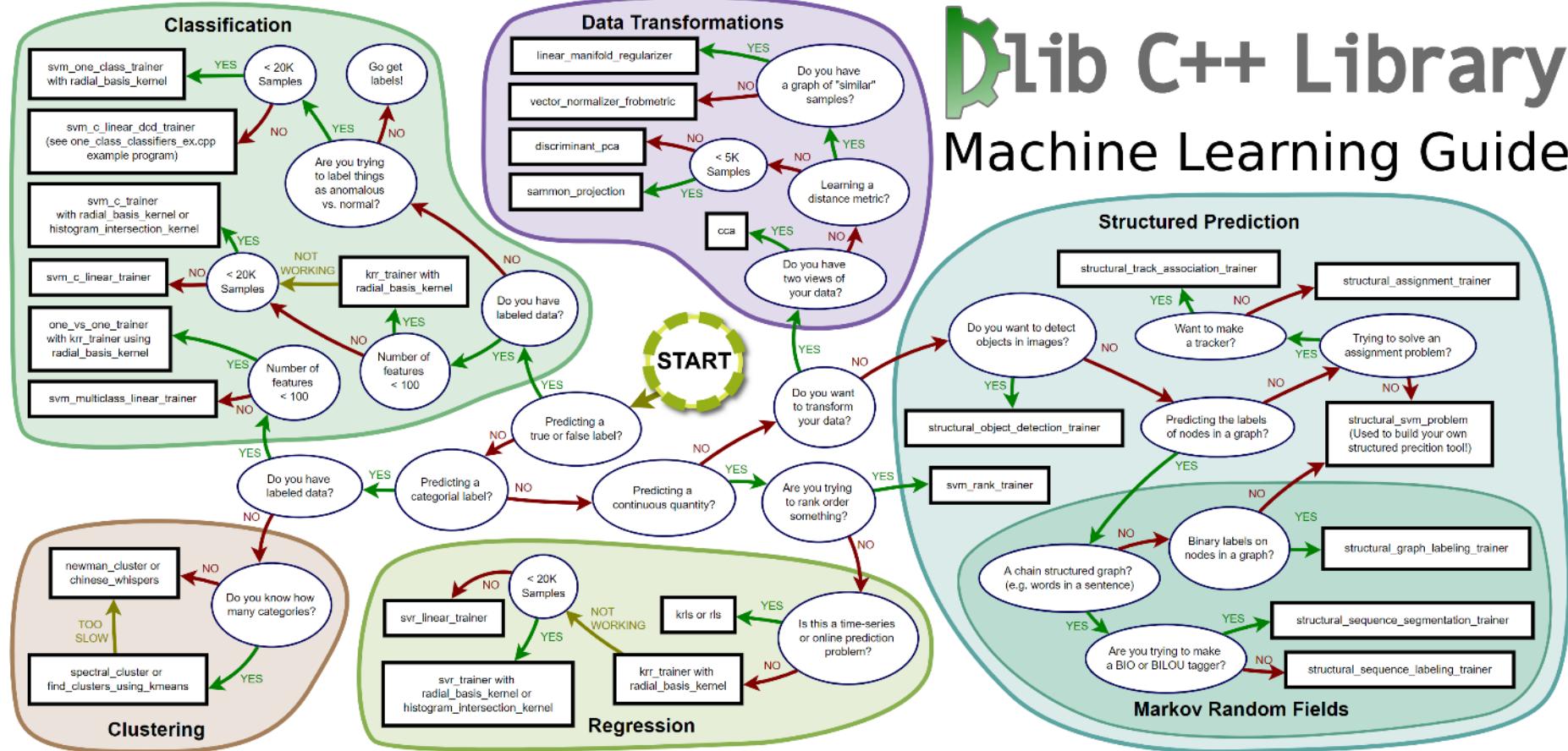
Machine Learning Algorithms Cheat Sheet



<http://blogs.sas.com/content/subconsciousmusings/2017/04/12/machine-learning-algorithm-use/>

dlib C++ Library

Machine Learning Guide



Facebook

the world of machine learning algorithms – a summary

regression

Ordinary Least Squares Regression (OLSR)
Linear Regression
Logistic Regression
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Jackknife Regression

regularization

Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least-Angle Regression (LARS)

instance based

also called **case-based, memory-based**

k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)

dimensionality reduction

Principal Component Analysis (PCA)
Principal Component Regression (PCR)
Partial Least Squares Regression (PLSR)
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Discriminant Analysis (LDA, MDA, QDA, FDA)

think big data

bayesian

Naive Bayes
Gaussian Naive Bayes
Multinomial Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Bayesian Network (BN)
Hidden Markov Models
Conditional random fields (CRFs)

decision tree

Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5 and C5.0 (different versions of a powerful approach)
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
M5
Random Forests
Conditional Decision Trees

clustering

Single-linkage clustering
k-Means
K-Medians
Expectation Maximisation (EM)
Hierarchical Clustering
Fuzzy clustering
DBSCAN
OPTICS algorithm
Non Negative Matrix Factorization
Latent Dirichlet allocation (LDA)

deep learning

Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders

associated rule

Apriori
Eclat
FP-Growth

ensemble

Logit Boost (Boosting)
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (blending)
Gradient Boosting Machines (GBM)
Gradient Boosted Regression Trees (GBRT)
Random Forest

neural networks

Self Organizing Map
Perceptron
Back-Propagation
Hopfield Network
Radial Basis Function Network (RBFN)
Backpropagation
Autoencoders
Hopfield networks
Boltzmann machines
Restricted Boltzmann Machines
Spiking Neural Networks
Learning Vector quantization (LVQ)

...and others

Support Vector Machines (SVM)
Evolutionary Algorithms
Inductive Logic Programming (ILP)
Reinforcement Learning (Q-Learning, Temporal Difference, State-Action-Reward-State-Action (SARSA))
ANOVA
Information Fuzzy Network (IFN)
Page Rank
Conditional Random Fields (CRF)

http://thinkbigdata.in/wp-content/uploads/2016/04/Best_Machine_Learning_Algorithms.jpg



Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

Strengths and Weaknesses of Machine Learning

Machine Learning is good for

1. Problems that would require many rules to solve
2. Problems that are too complex to be solved by rules (e.g. handwriting or speech recognition)
3. Problems that have changing environments/data (e.g. spammers who try to cheat the system)
4. Problems where (lots of) data is already available (e.g. a corpus of labelled emails)

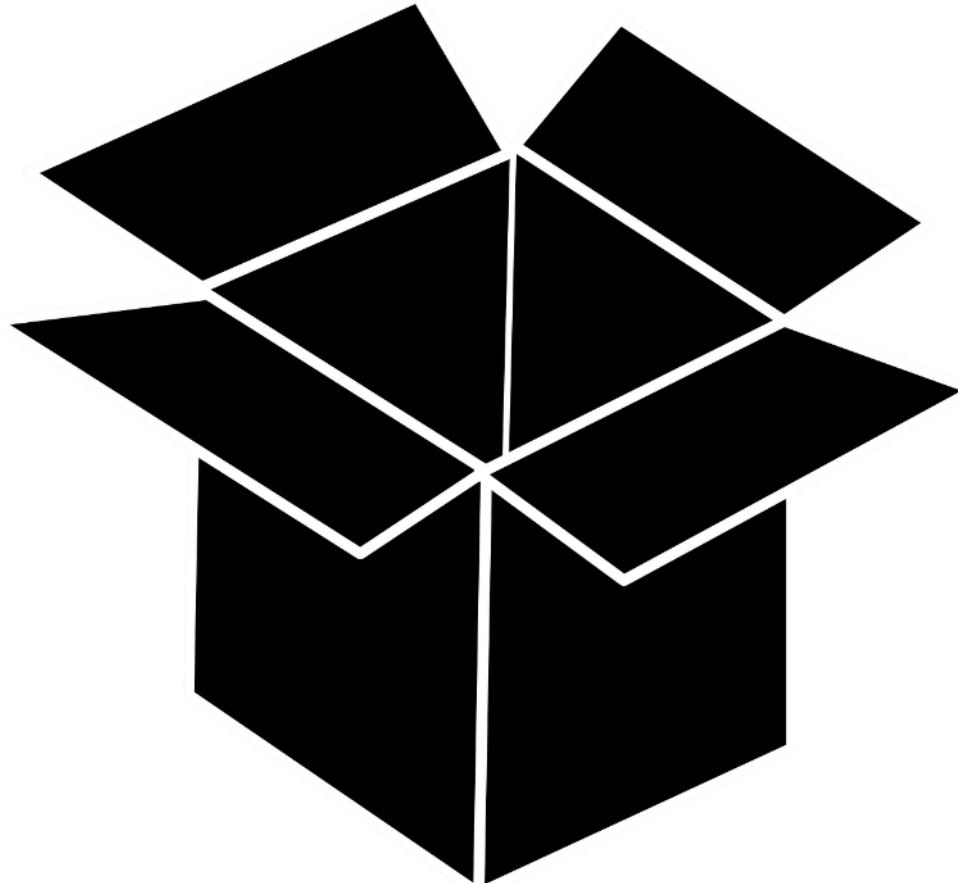


Machine Learning is not good for

- **Random number generation**
- **En/Decryption**
- **Simple operations such as copying data**
- **Executing programs (following algorithms)**

Blackbox

- It is often not immediately clear why a machine learning system creates the outputs it creates
- Understanding the reasoning behind the output, requires additional analyses; sometimes it's very difficult or impossible to fully understand the reasoning
- Legal implications



https://s3-us-west-2.amazonaws.com/courses-images-archive-read-only/wp-content/uploads/sites/903/2016/01/23225801/black-box-310220_1280.png

Legal Implications

European Commission - Press release

Antitrust: Commission fines Google €2.42 billion for abusing dominance as search engine by giving illegal advantage to own comparison shopping service

Brussels, 27 June 2017

The European Commission has fined Google €2.42 billion for breaching EU antitrust rules. Google has abused its market dominance as a search engine by giving an illegal advantage to another Google product, its comparison shopping service.

The company must now end the conduct within 90 days or face penalty payments of up to 5% of the average daily worldwide turnover of Alphabet, Google's parent company.

Commissioner Margrethe Vestager, in charge of competition policy, said: "Google has come up with many innovative products and services that have made a difference to our lives. That's a good thing. But Google's strategy for its comparison shopping service wasn't just about attracting customers by making its product better than those of its rivals. Instead, Google abused its market dominance as a search engine by promoting its own comparison shopping service in its search results, and demoting those of competitors.

AARON MARSHALL TRANSPORTATION 08.13.17 07:00 AM

TESLA BEARS SOME BLAME FOR SELF-DRIVING CRASH DEATH, FEDS SAY



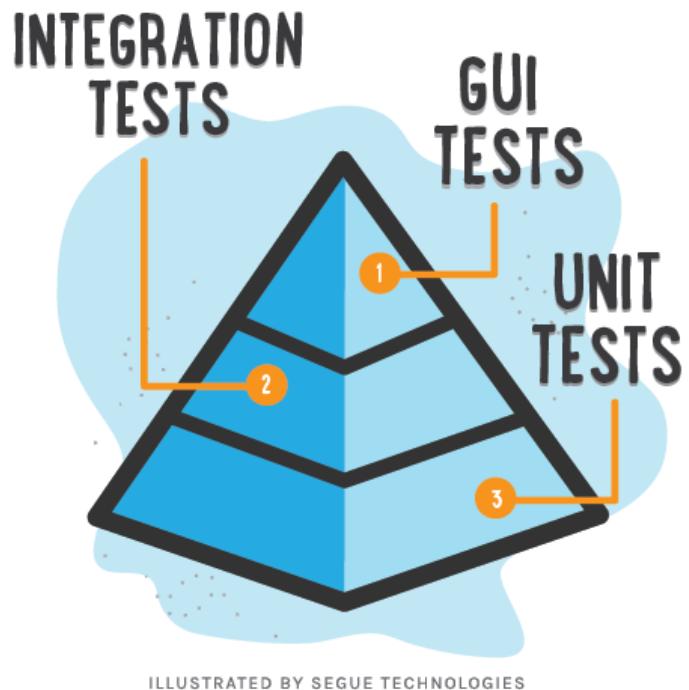
TESLA

IT'S BEEN NEARLY a year and a half since Joshua Brown became the first person to die in a car driving itself. In May 2016, Brown was on a Florida highway in his Tesla Model S using Autopilot, the semi-autonomous driver assist feature that handles steering and speed during highway driving.

Tesla has always warned drivers that Autopilot isn't perfect. According to car's driving manual and the disclaimer drivers accept before they can engage it, the system should only

No/Difficult Testing

- With traditional approaches, unit testing is easy
- For instance, title detection – detected title for a specific document will not change when e.g. new documents are added to the corpus.

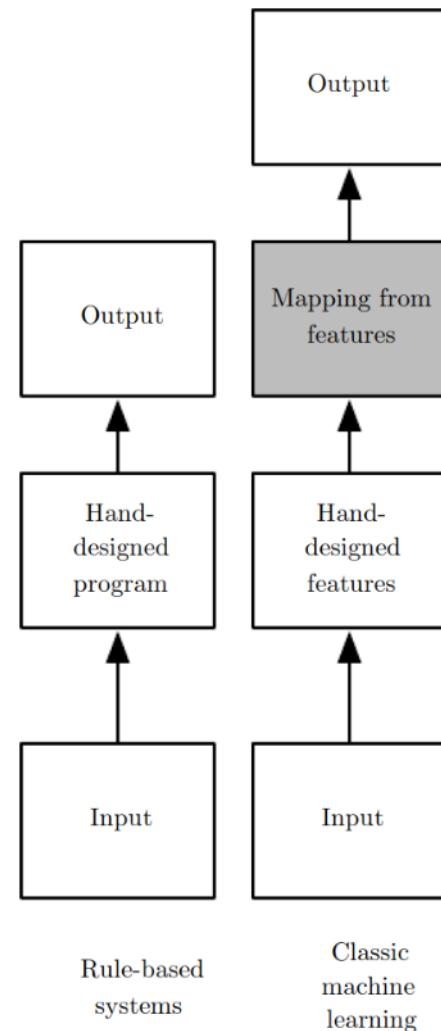


<https://eki5aot90-flywheel.netdna-ssl.com/wp-content/uploads/2014/10/segue-blog-benefits-unit-testing.png>



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Thank you



Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep learning* (MIT press, 2016).