Data Mining 2

Topic 01 : Module Introduction

Lecture 01 : Module Overview

Dr Kieran Murphy

Department of Computing and Mathematics, Waterford Institute of Technology.
(Kieran.Murphy@setu.ie)

Spring Semester, 2023

Outline

- Module motivation and aims.
- The three components of a Machine Learning Problem
- Data mining / Machine Learning workflow

Outline

What is Data Mining ?

We are drowning in data but starving for knowledge!

Necessity is the mother of invention $\Rightarrow$ Data Mining $\approx$ Automated analysis of massive data sets.

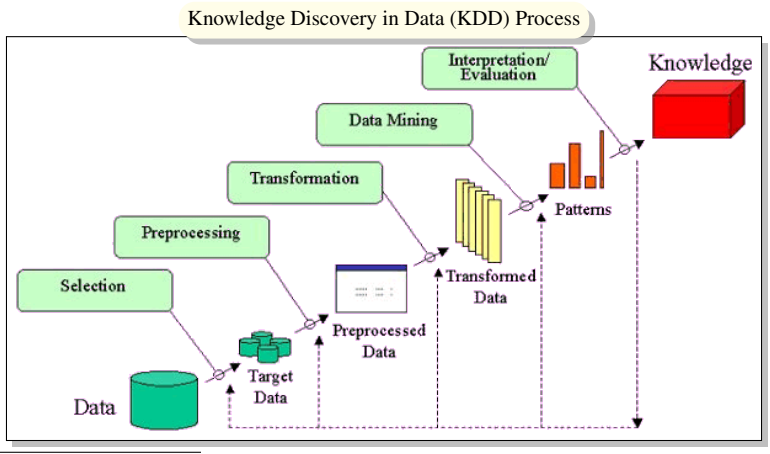
Definition 1 (Data Mining)

The non-trivial extraction of implicit, previously unknown and potentially useful knowledge from data in large data repositories

non trivial	— obvious knowledge is not useful (we already know it)
implicit	— hidden difficult to observe knowledge
previous unknown	— if known then, why go to this effort?
potentially useful	— actionable easy to understand

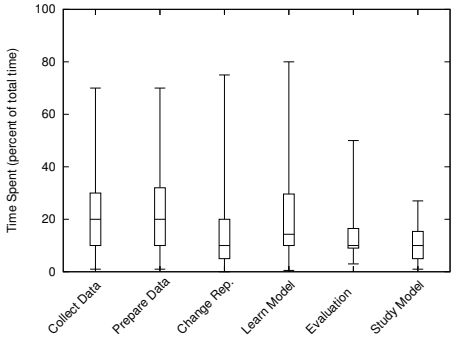
Data Mining vs Knowledge Discovery in Data (KDD)

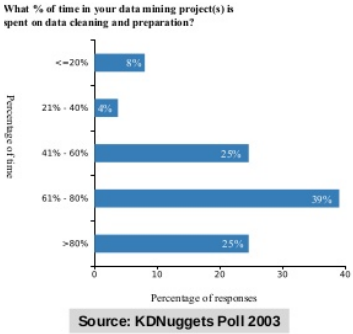
- Data mining and KDD are often used interchangeably.
- Actually data mining is only a part of the KDD process.



See A Comparative Study of Data Mining Process Models (KDD, CRISP-DM and SEMMA)

Data Mining (Model Building) is less than half of Data Mining

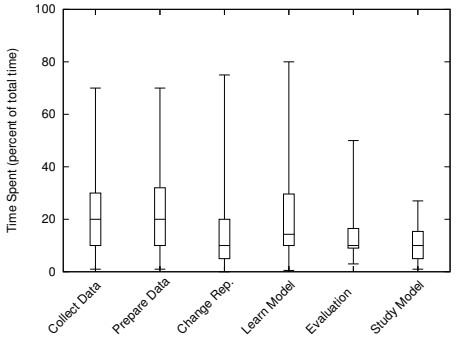


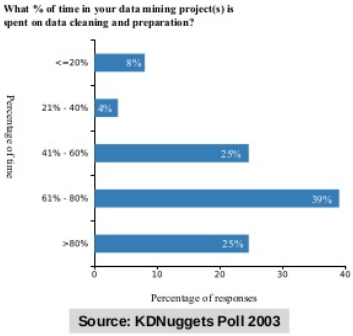


- Boxplots: median is 20% on collecting data, 20% on preparing data, and 10% on changing data representation — all before starting on model.
- Bar chart — data cleaning and preparation consumes at least 80% of project time for 25% of the participants, and 61% to 80% for another 39%.

See Study on the Importance of and Time Spent on Different Modeling Steps, 2012

Data Mining (Model Building) is less than half of Data Mining



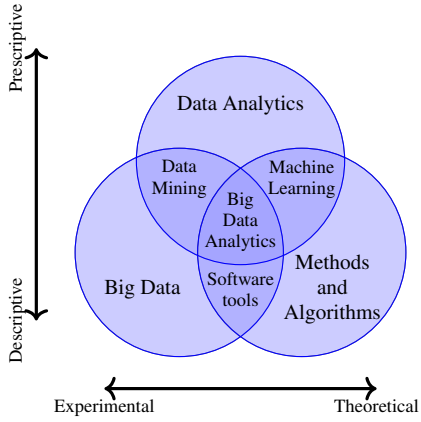


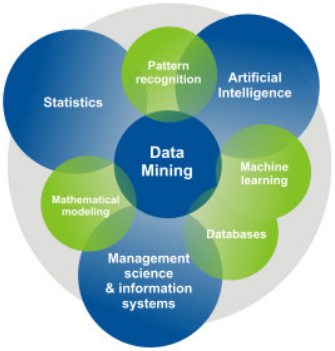
- Boxplots: median is 20% on collecting data, 20% on preparing data, and 10% on changing data representation — all before starting on model.
- Bar chart — data cleaning and preparation consumes at least 80% of project time for 25% of the participants, and 61% to 80% for another 39%.

See Study on the Importance of and Time Spent on Different Modeling Steps, 2012

Related Disciplines — Data Mining vs Data Analytics vs Data Science†

- Data Mining is about finding the patterns in a data set, and using these patterns to make predictions.
- Data Science is a field of study which includes everything from Big Data Analytics, Data Mining, Predictive Modelling, Data Visualisation, Mathematics, and Statistics.





*In other words, have we titled this module correctly? Probably not, and it should be called Data Analytics 2 or Data Science 2

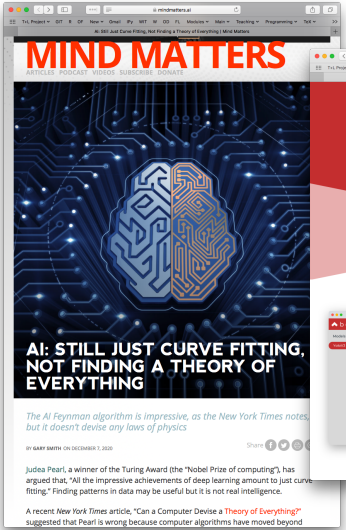
Data Science Mind Map

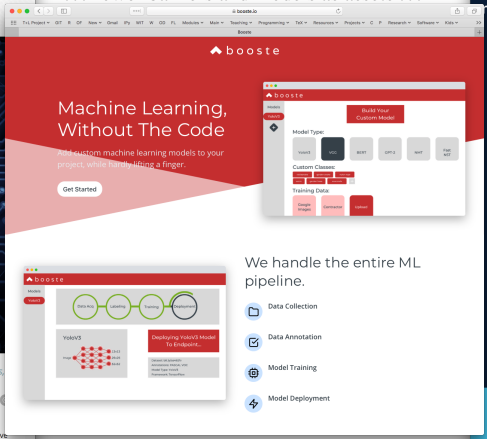
Data Science in 2021 — ML Models as assets, ML Deployment Services

Not all are believers…

… lower barriers and models as assets …

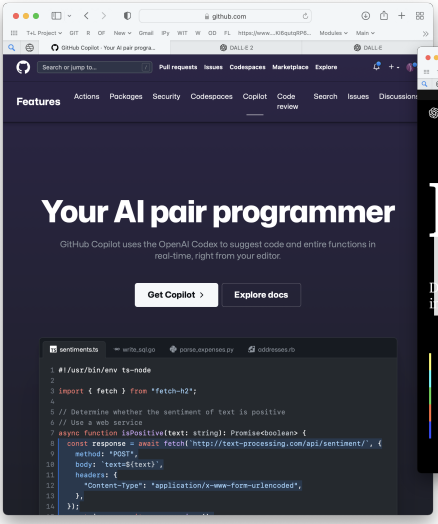
… MLOps



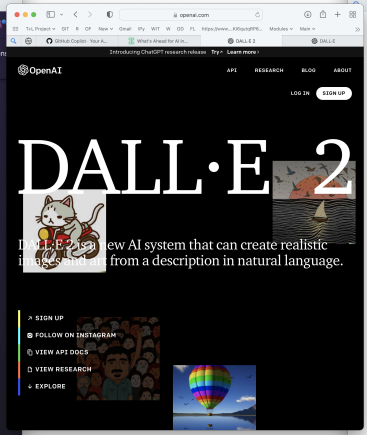


Data Science in 2022 — Generative AI and LLM

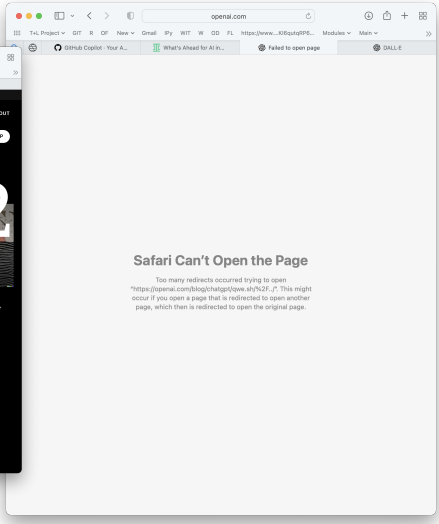
Generating code …



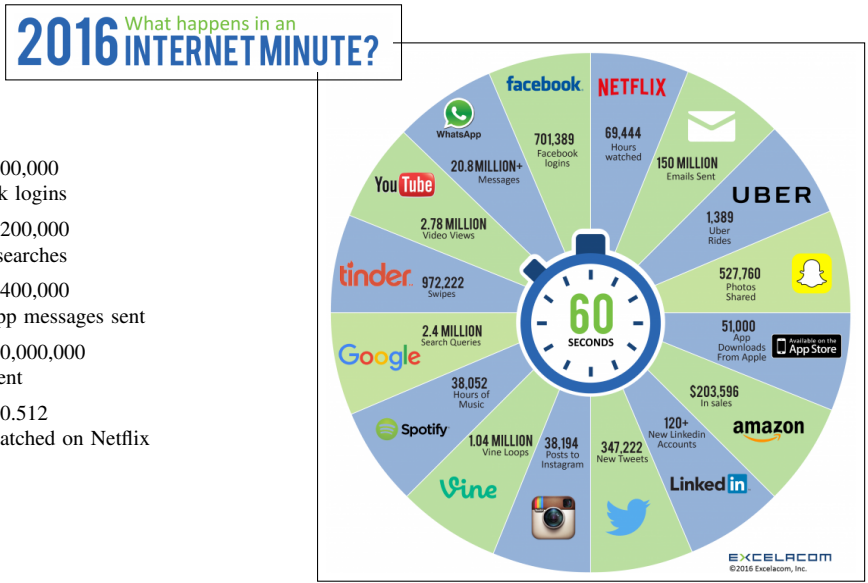
… images from text …



… any text (using chatGPT)



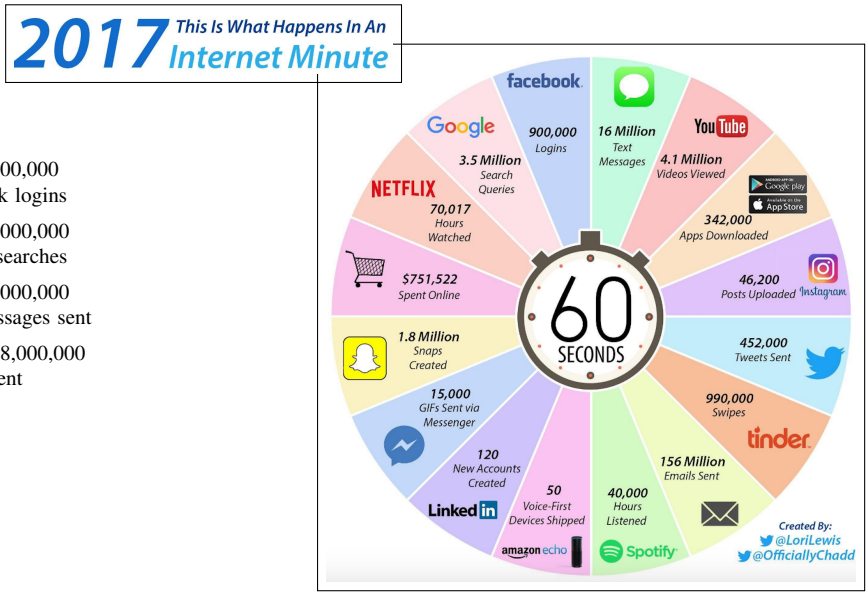
How Much Data?



By Month

- 30,754,000,000
  Facebook logins
- 105,235,200,000
  Google searches
- 912,038,400,000
  WhatsApp messages sent
- 6,577,200,000,000
  emails sent
- 3.044.980.512
  Hours watched on Netflix

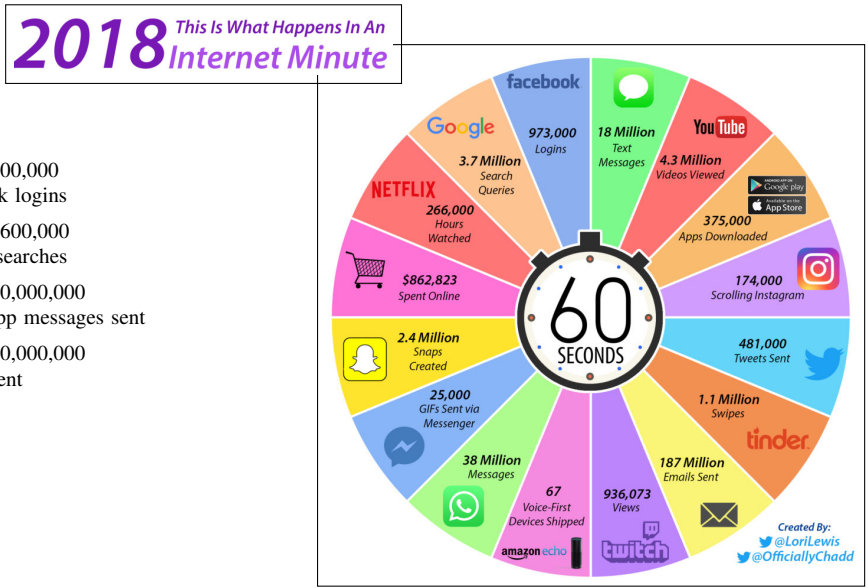
How Much Data?



By Month

- 39,463,200,000 Facebook logins
- 153,468,000,000 Google searches
- 701,568,000,000 Text messages sent
- 6,840,288,000,000 emails sent

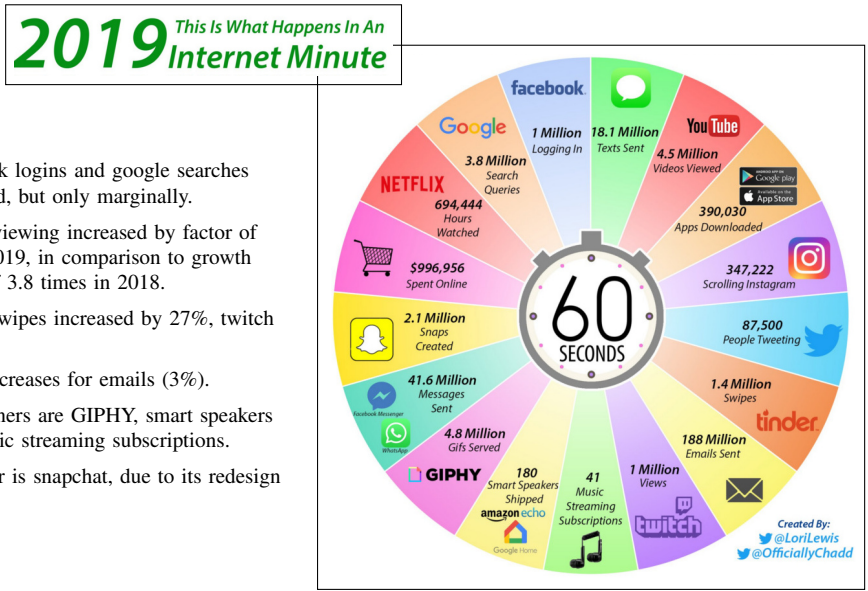
How Much Data?



By Month

- 42,033,600,000
  Facebook logins
- 162,237,600,000
  Google searches
- 1,641,600,000,000
  WhatsApp messages sent
- 8,078,400,000,000
  emails sent

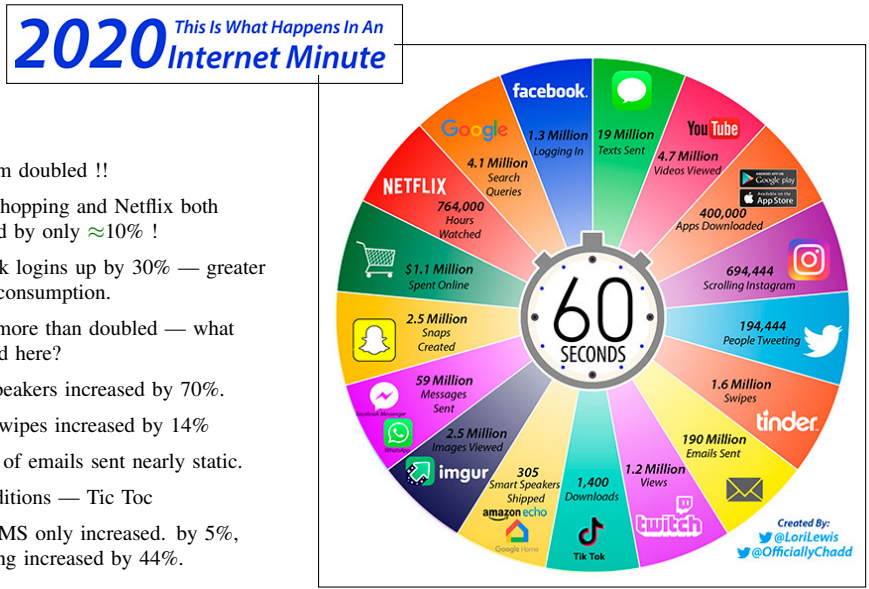
How Much Data?



By Month

- Facebook logins and google searches increased, but only marginally.
- Netflix viewing increased by factor of 2.6 in 2019, in comparison to growth factor of 3.8 times in 2018.
- Tinder swipes increased by 27%, twitch by 20%.
- Small increases for emails (3%).
- Big winners are GIPHY, smart speakers and music streaming subscriptions.
- Big loser is snapchat, due to its redesign issues.

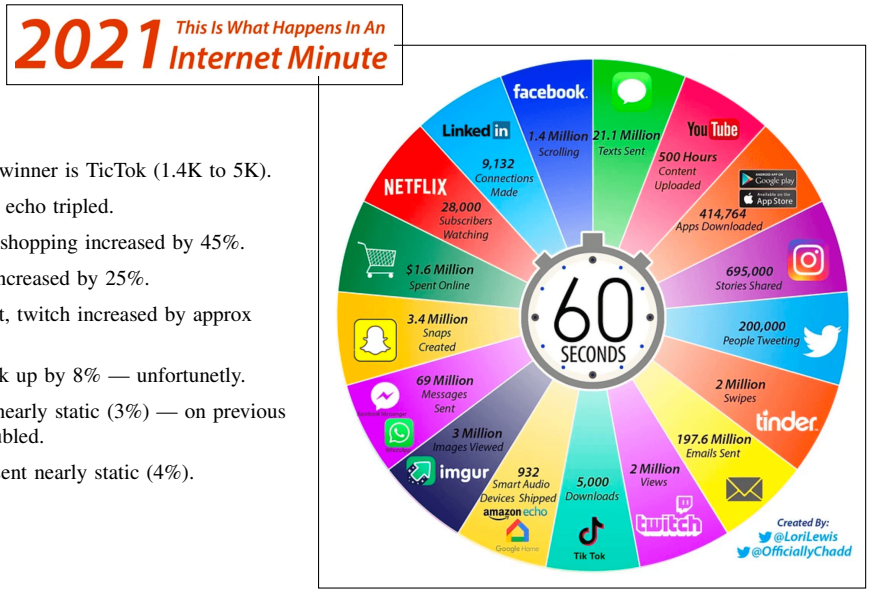
How Much Data?



By Month

- Instagram doubled !!
- Online shopping and Netflix both increased by only ≈10% !
- Facebook logins up by 30% — greater “news” consumption.
- Twitter more than doubled — what happened here?
- Smart speakers increased by 70%.
- Tinder swipes increased by 14%
- Number of emails sent nearly static.
- New additions — Tic Toc
- While SMS only increased. by 5%, messaging increased by 44%.

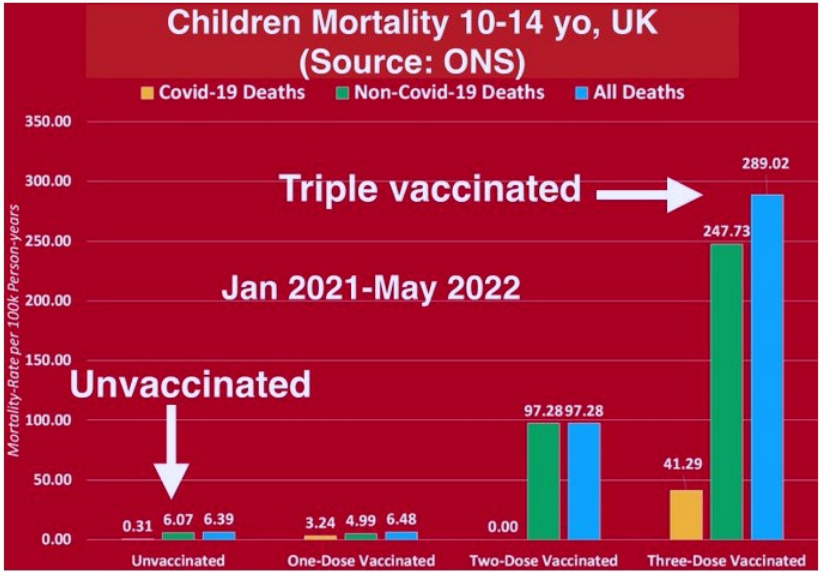
How Much Data?



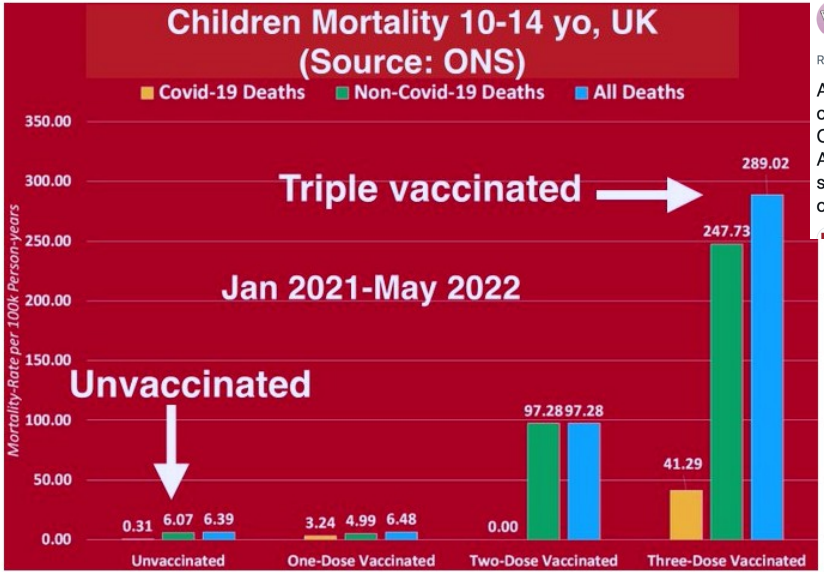
By Month

- Biggest winner is TicTok (1.4K to 5K).
- Amazon echo tripled.
- Internet shopping increased by 45%.
- Tinder increased by 25%.
- Snapchat, twitch increased by approx 20%.
- Facebook up by 8% — unfortunetly.
- Twitter nearly static (3%) — on previous year doubled.
- Emails sent nearly static (4%).

Lies, Dammed Lies and Statistics



Lies, Dammed Lies and Statistics



Honest Doreman
@Detrieman

Replying to @DrWigley

Actually, to understand all this, you only need to have access to the ONS and know primer school math. An understanding of big numbers vs smaller numbers. Zero knowledge of chem or biology is required...

— Jan 13, 2023

Hype ? Again ?

This article is more than **6 years old**

Two years until self-driving cars are on the road – is Elon Musk right?

The Tesla CEO has proclaimed that autonomous driving is a 'solved problem' but tech and executives in recent years have tempered their expectations

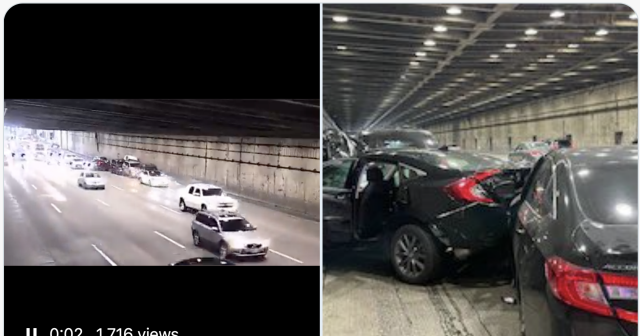
Hype ? Again ?

This article is more than **6 years old**

Two years until self-driving cars are on the road – is Elon Musk right?

The Tesla CEO has proclaimed that autono problem' but tech and executives in recen their expectations

#Tesla in 'self-driving mode' slams on brakes in tunnel for no reason. The car caused an eight-vehicle crash that injured nine people. Just hours before the crash #Musk had triumphantly announced that Tesla's "Full Self-Driving" capability was available in North America.



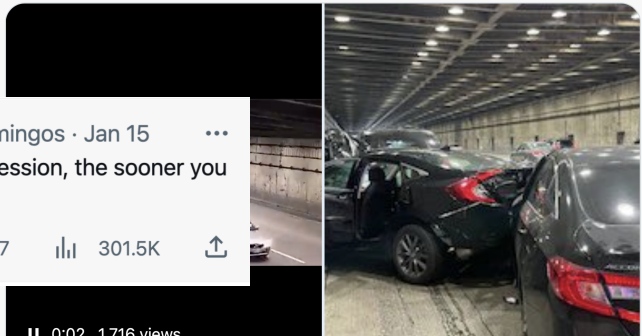
Hype ? Again ?

This article is more than **6 years old**

Two years until self-driving cars are on the road – is Elon Musk right?

The Tesla CEO has proclaimed that autono problem' but tech and executives in recen their expectations

#Tesla in 'self-driving mode' slams on brakes in tunnel for no reason. The car caused an eight-vehicle crash that injured nine people. Just hours before the crash #Musk had triumphantly announced that Tesla's "Full Self-Driving" capability was available in North America.



Pedro Domingos @pmddomingos · Jan 15

The less you know about a profession, the sooner you think it'll be replaced by AI.

70 421 2,357 301.5K

But chatGPT can do . . .

Mike's mum had 4 kids; 3 of them are Luis, Drake and Matilda. What is the name of 4th kid?

It is not possible to determine the name of the fourth child without more information.

The answer is in the question

I apologize for the confusion. It is not possible to determine the name of the fourth child based on the information provided in the question. The question states that Mike's mother had four children and that three of them are named Luis, Drake, and Matilda, but it does not

Chris Staudinger @ChrisStaud

ChatGPT has changed the game.

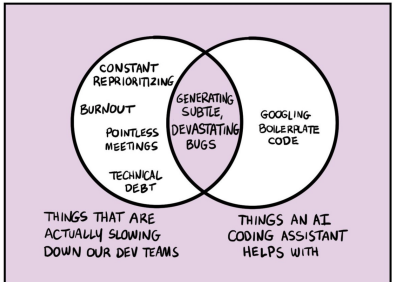
7 ways ChatGPT can 10x your programming productivity:

7:48 AM · Jan 14, 2023 · **1M** Views

Grady Booch @Grady_Booch · Jan 5

He's right, you know.

> **Forrest Brazeal** @forrestbrazeal · Dec 6, 2022
> Just saying.
> Show this thread



Delivery

Resources

- All lecture slides, handouts and datasets: GitHub — datamining2-202122.github.io/live
- All activities: quizzes and assignments: Moodle — moodle.wit.ie/course/view.php?id=192024

Delivery

- Two 1-hour lectures and one 2-practical session.
  - Lecture sessions can tend to get very non-interactive so to help avoid this please ask questions.
  - Lectures and practical sessions may be recorded — in the sessions that I record I will post links in slack.
- Slack
  - Will use this for all last minute posts and individual/group Q+A, particularly for assignments.

Strategy to handle module

- Prepare — review material in advance of the sessions, install/download the software/datasets.
- Interact — yes, this is rich coming for an introvert mathematician, but we live in strange times.
- Time management — give tasks a serious/focused effort, but when stuck ask for help.

Assessment Structure — 100% Continuous Assessment

Covering skills

- Data Wrangling + Feature Engineering (pandas and friends)
- NLP, Text processing (regex)
- Model building and optimisation (skilearn, tensorflow, . . .)

Breakdown

- Metric:
  - 20% Student engagement + 80% Demonstration of skills/understanding
- Activities:
  - Moodle quizzes based on analysing datasets / model building / etc.
  - Data science problems with mixture of Kaggle style grading and traditional grading.

Calandar

- Week 14/15 end of semester individual review interview (zoom).
- $\underbrace{\text{5 weeks} + \text{reading week} + \text{5 weeks} + \text{Easter break (2 weeks)} + \text{2 weeks}}_{\text{12 teaching weeks}} + \text{3 weeks for CA}$

Outline

Three Components of a Machine Learning Problem

It is easy to get lost among the multitude of choices one needs to make when given data mining problem. A good decomposition is the following:

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K-nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search
Hyperplanes	Likelihood	Branch-and-bound
Naive Bayes	Posterior probability	Continuous optimization
Logistic regression	Information gain	Unconstrained
Decision trees	K-L divergence	Gradient descent
Sets of rules	Cost/Utility	Conjugate gradient
Propositional rules	Margin	Quasi-Newton methods
Logic programs		Constrained
Neural networks		Linear programming
Graphical models		Quadratic programming
Bayesian networks		
Conditional random fields		

[†] A Few Useful Things to Know about Machine Learning, Domingos, 2012.

3 Components — Representation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K-nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

Representation refers to formulating the problem as a machine learning problem — typically a classification problem, a regression problem or a clustering problem.

- How do we represent the input?
- What features to use?
- How do we learn additional features?
- With each type of problem, we have multiple subtypes.
  For example which classifier? a decision tree, a neural network, a support vector machine, a hyperplane that separates the two classes etc.

3 Components — Evaluation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K-nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

Evaluation refers to an objective function or a scoring function, to distinguish good models from a bad model.

- For a classification problem, we need this function to know if a given classifier is good or bad. A typical function can be based on the number of errors made by the classifier on a test set, using precision and recall.
- For a regression problem, it could be the squared error, or likelihood. Do we include regularisation? etc

3 Components — Optimisation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K-nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

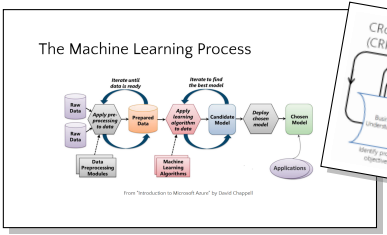
Optimisation is concerned with searching among the models in the language for the highest scoring model.

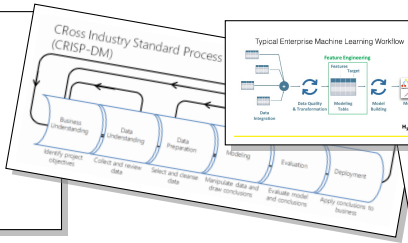
- How do we search among all the alternatives?
- Can we use some greedy approaches, branch and bound approaches, gradient descent, linear programming or quadratic programming methods.

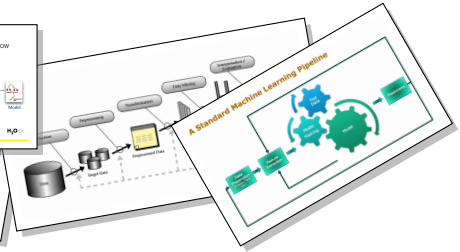
Outline

Data Mining Workflow

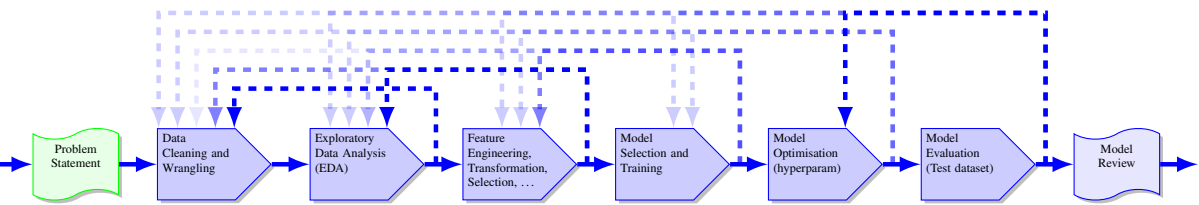
There are many, many . . .

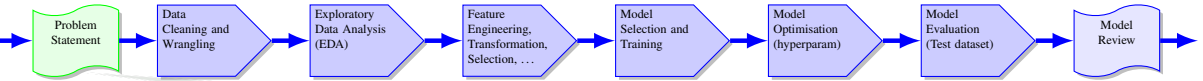






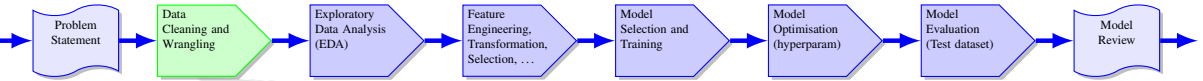
So why not make YADMW (Yet Another Data Mining Workflow)?





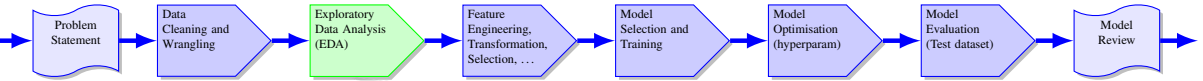
What type of problem is it?

- Exploratory data analysis
  Do we just want to see what the data says?
- Association / Rule finding
  Are we searching for relations/patterns?
- Hypothesis testing (Statistical)
  Do we have a theory we wish to test?
- Model building
  Do we wish to build a representation of some pattern within the data?
  - Supervised ⇐ data spilt into input variables (features) and output variable(s) (target(s))
    - Classification (target is categorical) vs regression (target is continuous)
  - Unsupervised ⇐ no target
    - Clustering — grouping similar cases

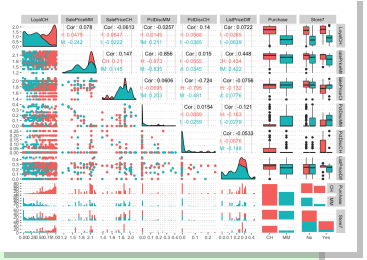


How to import and prepare data for subsequent analysis/processing?

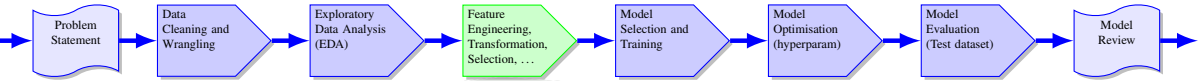
- Multiple file formats
  - Pandas supports a wide collection of file formats but default options often need to be changed to suit data.
  - Main file format (Comma Separated Values (csv)) does not support meta-data, is slow, and results in large files $\Longrightarrow$ use other formats (pickle, feather) to store datasets between steps in the workflow.
- Assumptions made by input parser can be important (i.e., bite you when you least expect)
  - Scientists rename human genes to stop Microsoft Excel from misreading them as dates
  - Pandas vs excel use different heuristics to decide on data type of each variable.
- Sub-tasks
  - Check dimension (number of rows/cases, number of columns/variables).
  - Check data types (categorical, ordinal, or numerical (discrete/continous)) of each variable.
  - Check for missing values, encoding errors, etc.
  - Merge tables, apply filters, and general data wrangling to generate (tabular) dataset suitable for EDA.



What is the data telling us?



- Univariate descriptive statistics — examine each variable
  - What are typical values?
  - What is the variation / spread / range?
  - What does the data look like …bell curve, bath tub curve, etc. ?
- Bi- / multi- variable descriptive statistics
  - Identifying relationships between variables.
- All descriptive statistics methods summarise data:
  - ✔ A summary is good since it helps to focus on simpler and important aspects.
  - ✘ A summary is bad if it focuses on irrelevant or the wrong aspects.
  - ⇒ Need to use multiple methods, be aware of their strengths/deficiencies.

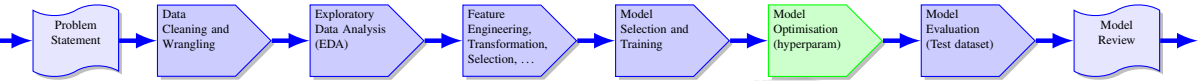


Can we transform, encode/bin, select, ..., the given features to improve model training?

- Better features can mean:
  - Better model performance and reduce training times.
  - Simpler models become applicable — think linear/logistic regression.
  - More explainable models — the future of machine learning (hopefully).
  - Cheaper and easier models to deploy.
- Feature selection reduces the number of features used in the model:
  - Drop features that have low variability.
  - Drop features that have no relation to target.
  - Drop features that are highly related to other features — multicollinearity.
  - Keep features whose addition to model have the largest improvement in model score.
- Feature extraction merges existing features to generate (hopefully) fewer features with essentially all the variation.

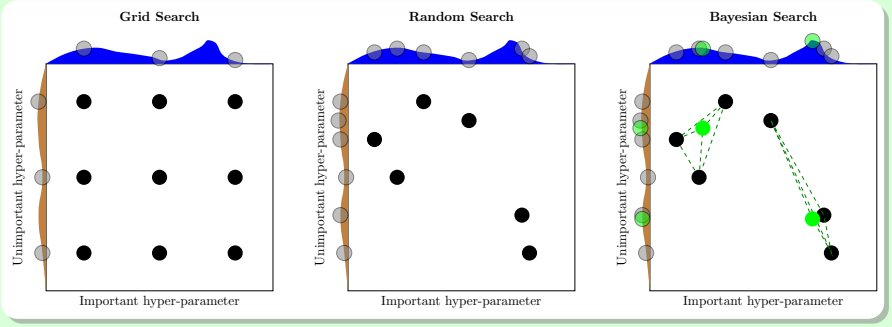
Which models are suitable?

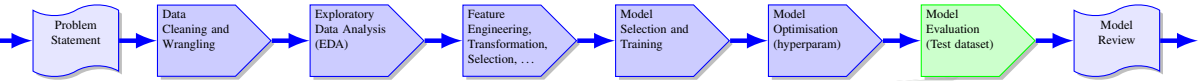
- Models vary greatly in terms of capabilities/deficiencies — usually aim to build a short list of candidate models, which are subsequently optimised in the next step.
- Select models based on different algorithms/approaches.
- Select (loss function and) evaluation metric.
  - Loss function is used to train model, evaluation metric is used to evaluate model (post training).
- Relative model performance can help identify issues with data.
  - Outliers can negatively affect linear regression but have smaller impact on decision tree based models.



How do we determine optimal values of the hyper-parameters?

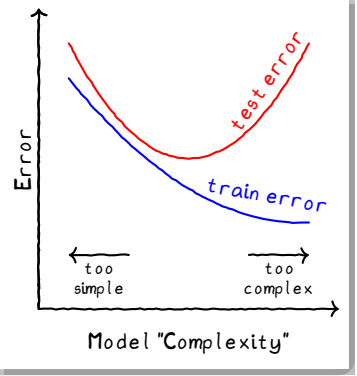
- Most models have options which control how a model "learns" from the training data.
- Three search stratagies: Grid search $<$ Random search $\ll$ Bayesian search

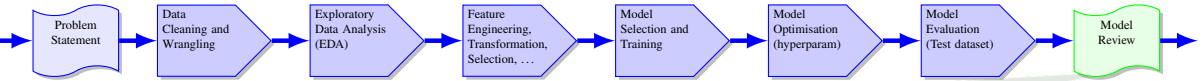




How well does the model generalise (to unseen data)?

- In the machine learning approach (vs statistical approach) we rely on model performance on **unseen data** to evaluate models.
  - Split data into train/test, only use train dataset for all modelling decisions.
  - Data leakage (MachineLearningMastery article), where information outside the train dataset is used in model building.
- Is there evidence for overfitting?
  - Does the model perform much better on training dataset than on the test dataset?
- Multiple techniques to address overfitting:
  - Regularisation (linear / logistic regression).
  - Trimming (decision trees).
  - Dropout (neural networks), Batch normalisation (CNN).





How well have we addressed the problem statement?

- A what level of accuracy (or other metrics) does a model become useful?
  - This is a business, medical, … decision
  - The larger the relative payoff the weaker the model can be and still be useful.
- OK, finally ready to implement/deploy model …
  - Separate skillset / concerns
  - MLOps = ML + DevOps
  - Monitoring of model drift needed.
- towards data science What is MLOps — Everything You Must Know to Get Started

Q: Why don't we automate all of this shtuff?
Tools are getting better and easier to use, but need intervention/direction (data can be weird in weird ways)

– xkcd.com/2054