Data Mining 2

Topic 01 : Module Introduction

Lecture 01 : Module Overview

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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)

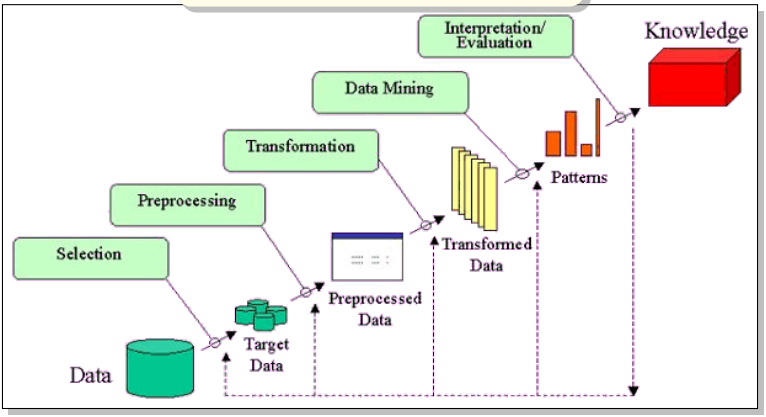
The non-trivial extraction of implicit, previously unknown and potentially useful knowledge from data in large data repositories

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)

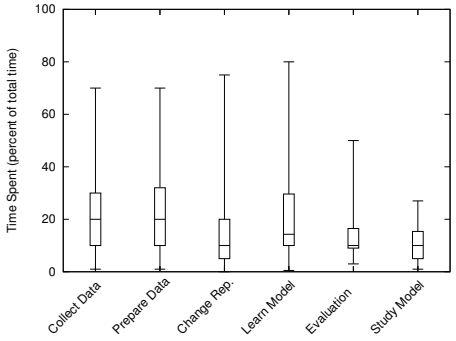
- Data mining and KDD are often used interchangeably.
- Actually data mining is only a part of the KDD process.

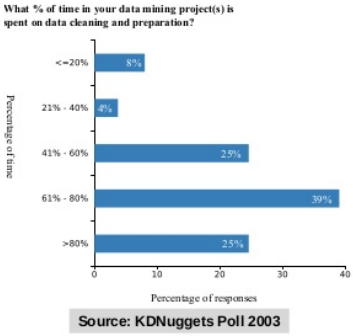
Knowledge Discovery in Data (KDD) Process



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

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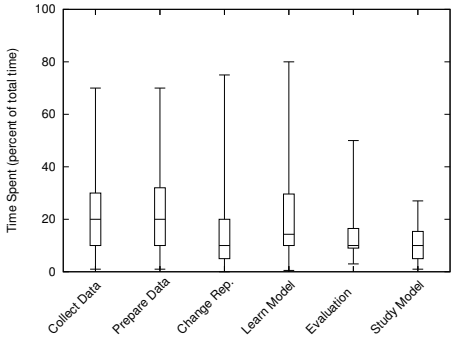

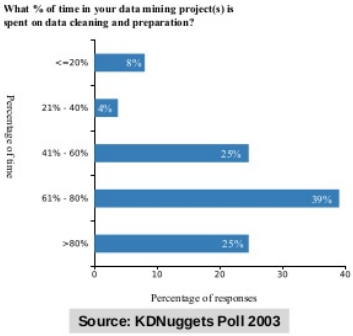

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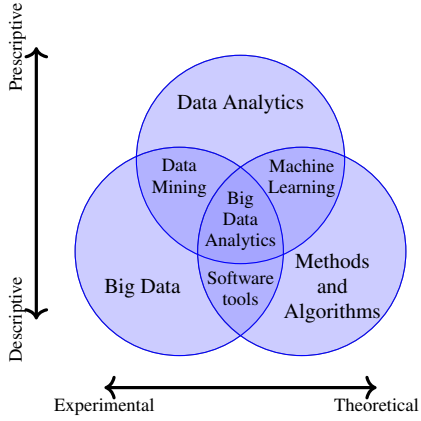
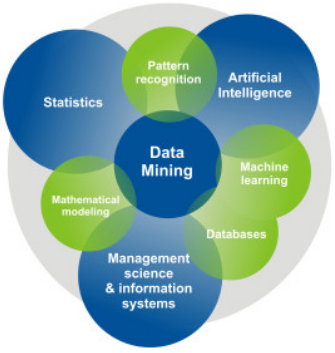
Related Disciplines — Data Mining vs Data Analytics vs Data Science†

- 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

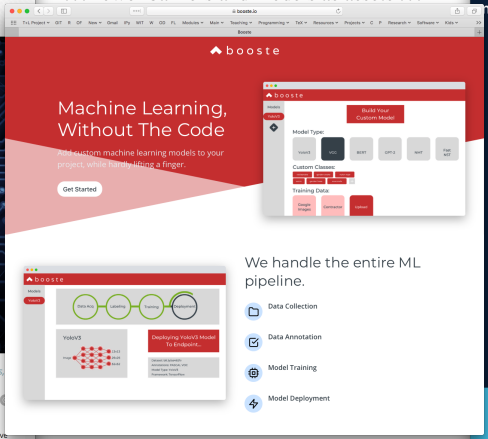
Data Science Mind Map

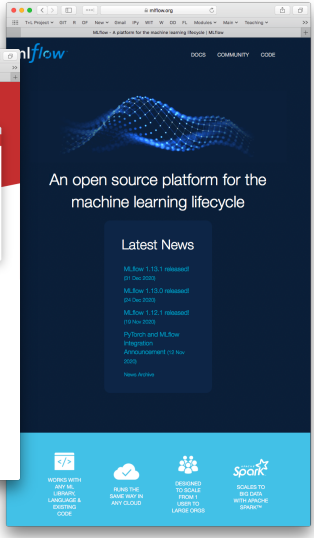
Data Science in 2021

There are still some skeptics …

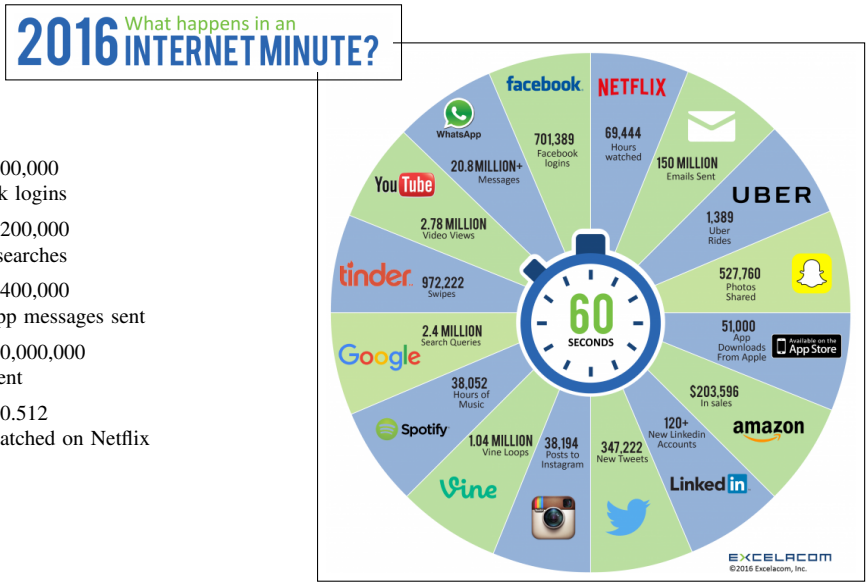
… lower barriers and models as assets …

… MLOps





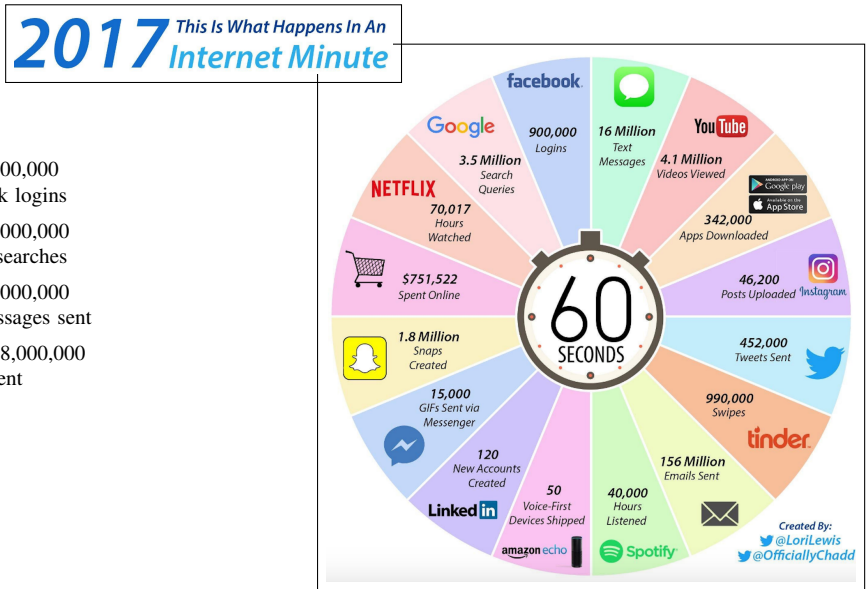
How Much Data?



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

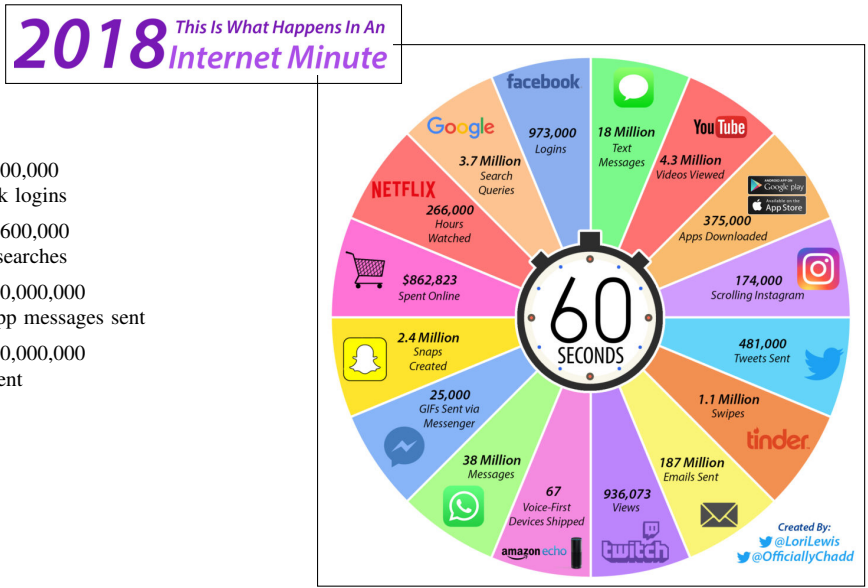
How Much Data?



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

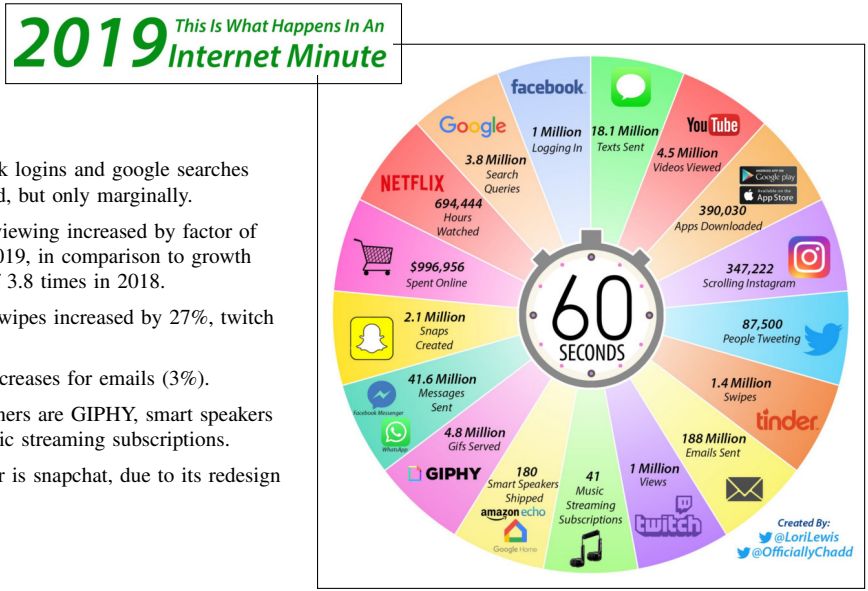
How Much Data?



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

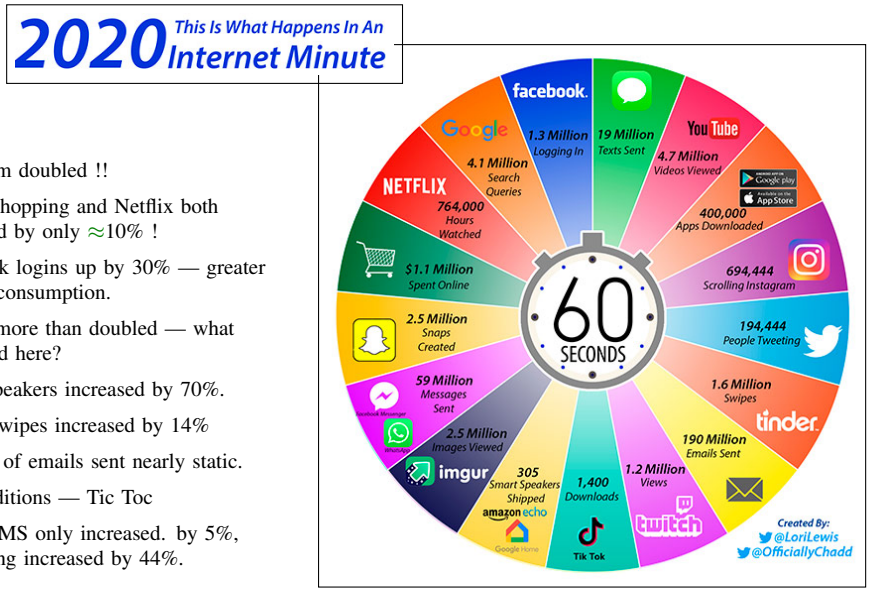
How Much Data?



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.

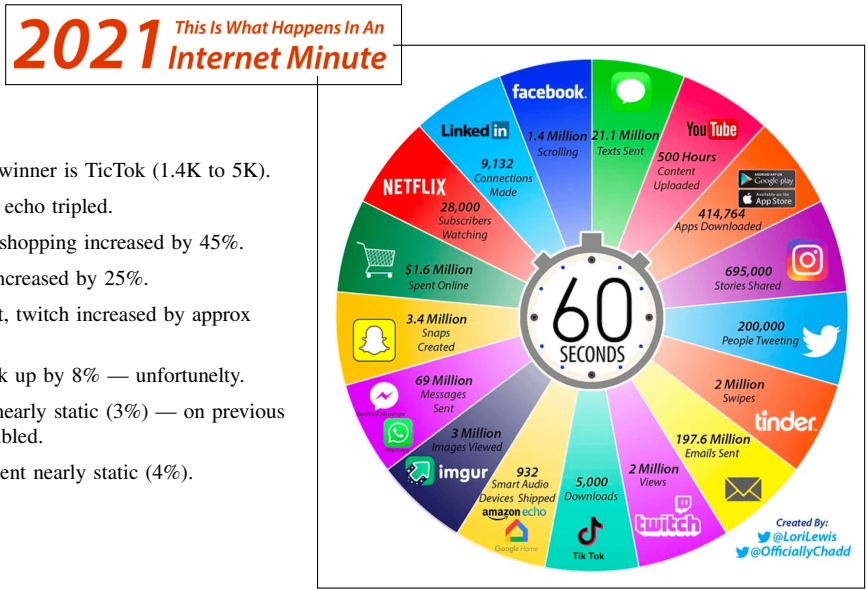
How Much Data?



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% — unfortunelty.
- Twitter nearly static (3%) — on previous year doubled.
- Emails sent nearly static (4%).

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=182862

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 mathication, 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).
- $\underbrace{\text{4 weeks} + \text{reading week} + \text{4 weeks} + \text{Easter break (2 weeks)} + \text{3 weeks}}_{\text{12 teaching weeks}} + \text{3 weeks for CA}$

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

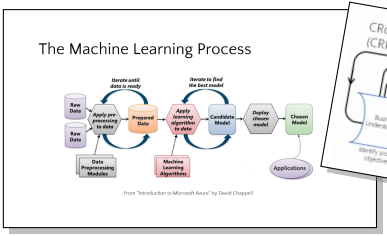
Optimisation is concerned with searching among the models in the language for the highest scoring model.

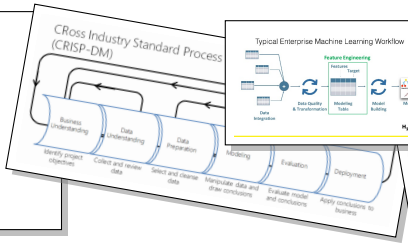
- How do we search among all the alternatives?
- Can we use some greedy approaches, branch and bound approaches, gradient descent, linear programming or quadratic programming methods.

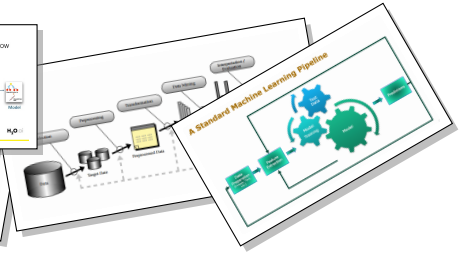
Outline

Data Mining Workflow

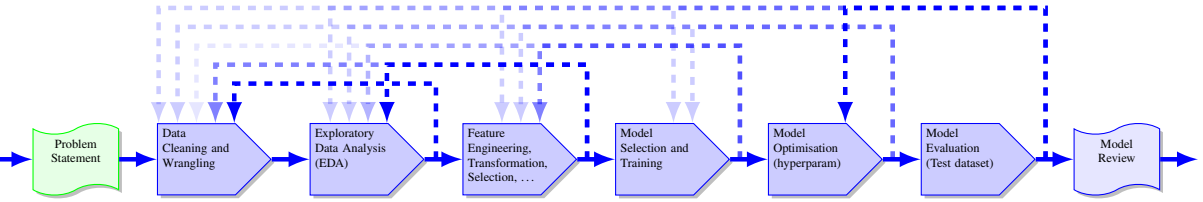
There are many, many . . .

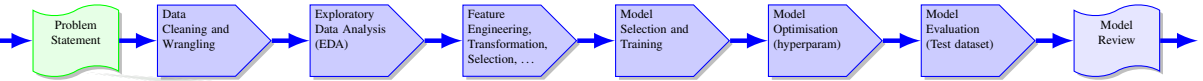






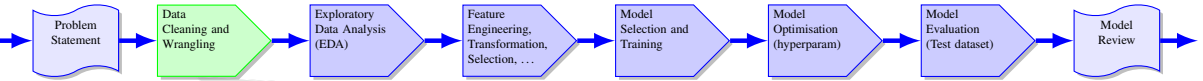
So why not make YADMW (Yet Another Data Mining Workflow)?





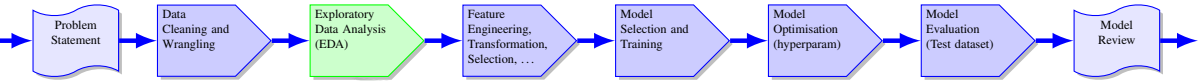
What type of problem is it?

- 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



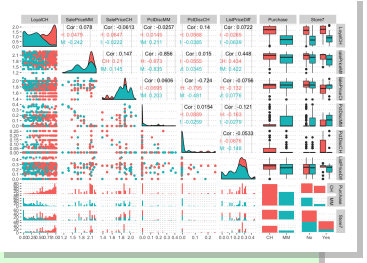
How to import and prepare data for subsequent analysis/processing?

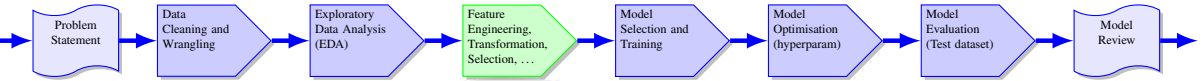
- Multiple file formats
  - Pandas supports a wide collection of file formats but default options often need to be changed to suit data.
  - Main file format (Comma Separated Values (csv)) does not support meta-data, is slow, and results in large files $\Longrightarrow$ use other formats (pickle, feather) 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.



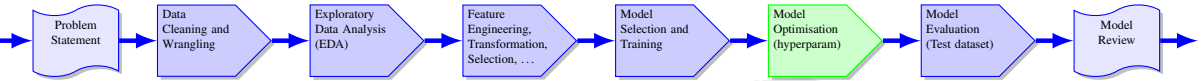


Can we transform, encode/bin, select, ..., the given features to improve model training?

- 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.

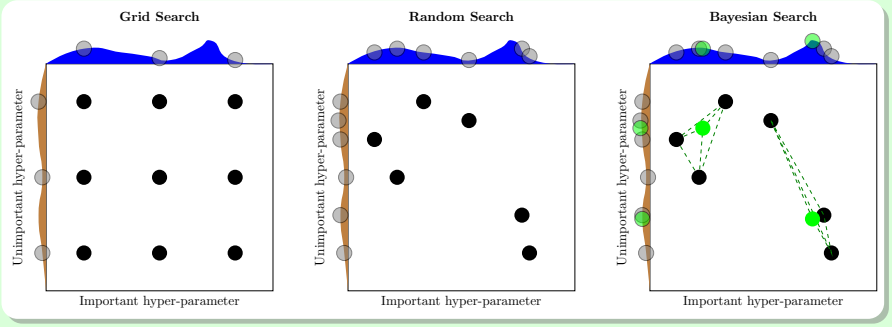
Which models are suitable?

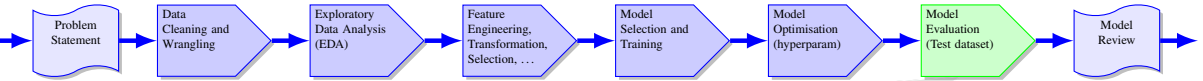
- Models vary greatly in terms of capabilities/deficiencies — usually aim to build a short list of candidate models, which are subsequently optimised in the next step.
- Select models based on different algorithms/approaches.
- Select (loss function and) evaluation metric.
  - Loss function is used to 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?

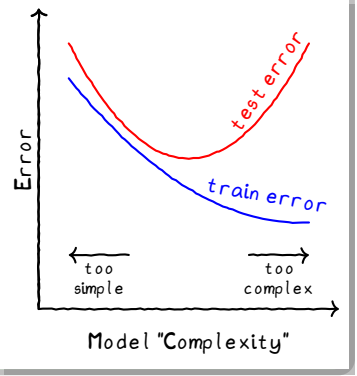
- Most models have options which control how a model "learns" from the training data.
- Three search stratagies: Grid search $<$ Random search $\ll$ Bayesian search

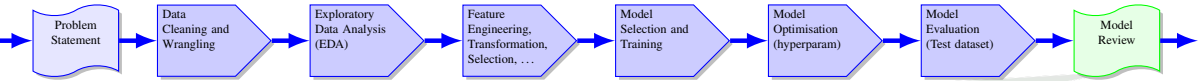




How well does the model generalise (to unseen data)?

- 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