Do we know our data, as good as we know our tools?

DEVOXX
United Kingdom

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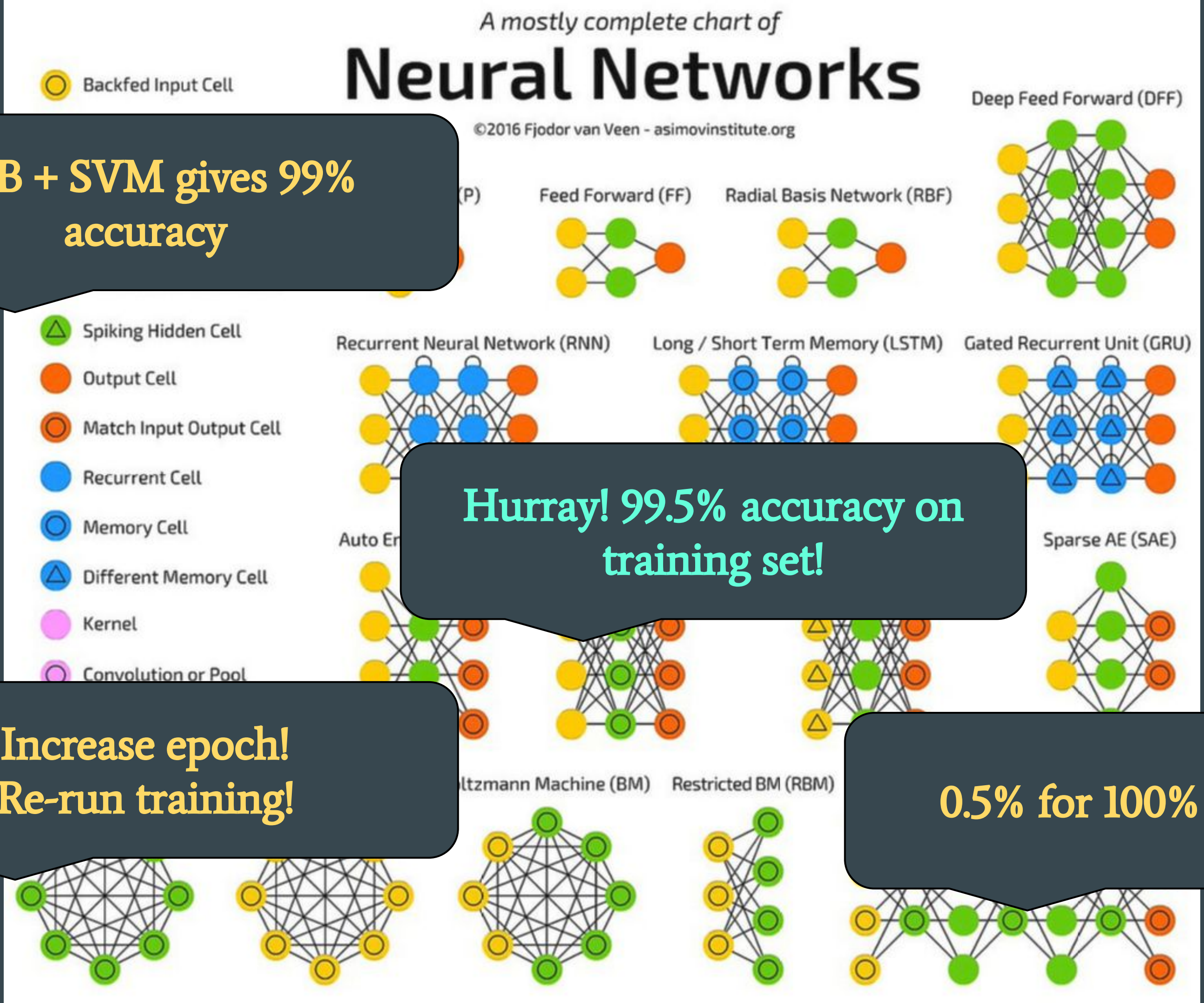
What you upto?
Busy!!! Training my model!

Tensorflow?
Pytorch? Keras?

Kubeflow?

XGBoost? Random Forest?

Dask for hyperparameter tuning



XGB + SVM gives 99% accuracy

Hurray! 99.5% accuracy on training set!

Increase epoch!
Re-run training!

0.5% for 100% accuracy

#DoWeKnowOurData

Wrong results on test set!

Model does not make sense at all!

Model is not generalising!

Training & Test set contain corrupt data, missing values


I HAVE NO
IDEA WHAT
I'M DOING

But, do we really know our data?

#DoWeKnowOurData

Do we know our data,

as good as we know our tools?

...

10th May 2019 * Devoxx UK 2019 * London, UK

About us

Freelance Software Developer

Java / JVM

Cloud/Infra/DevOps

Polyglot developer

LJC, Devoxx, dev. communities.

AI / ML / DL / DS

JCP member, F/OSS projects: @adoptopenjdk @graalvm

Mani Sarkar
@theNeomatrix369

Java Champion, Software Crafter, Blogger, Speaker, Conferences, Events

About us

Co founder & CTO
Trackener
(fitbit for horses)

Co-Host
MaM ML Study group

Polyglot developer

Personal Dev /
Learning Addict

Datascience ML/DL

Mentor/Mentee
MeetAMentor.co.uk

JAVA Spring Boot <3

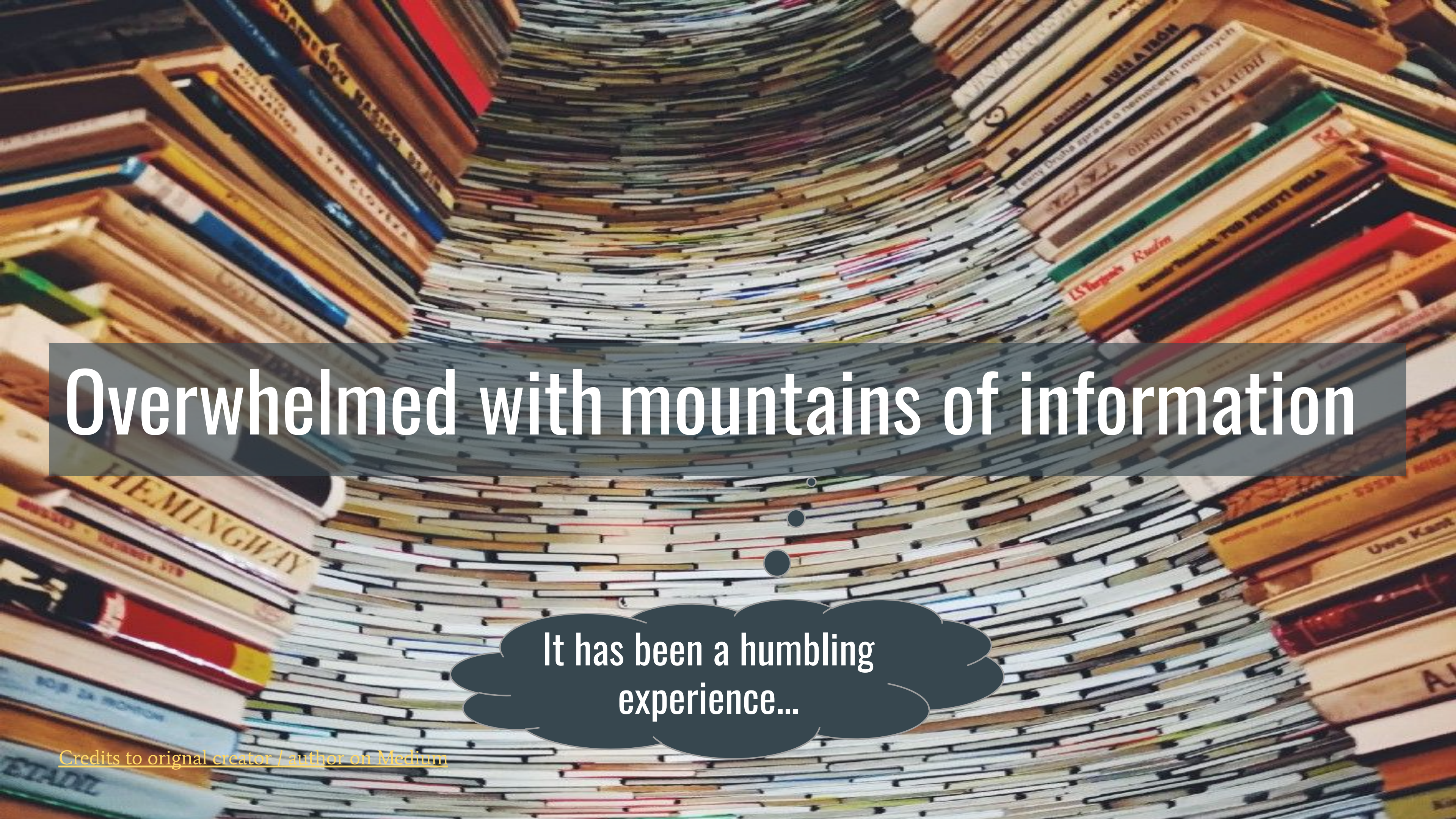
Jeremie Charlet
@jeremiecharlet

Presentation: live slides

http://bit.ly/do-we-know-our-data

Look inside folder
02-devoxx-uk-2019

https://github.com/neomatrix369/awesome-ai-ml-dl/tree/master/presentations/data


Overwhelmed with mountains of information
It has been a humbling experience...
Credits to orignal creator / author on Medium

Thank you

- All our data science mentors who helped
    - Ovidiu Serban (Imperial College)
    - Mark Bell (TNA Gov. UK)
    - Daniel Hulme (Satalia, UCL lecturer) and Joshua Cooper (Satalia)
    - Miguel Martinez (Nvidia, Deep Learning Solutions Architect),
    - Kerry O’Neill
    - Ole Moeller-Nilsson (Pivigo)
    - Antoine Paré (geophysicist at baker hughes)
    - And everyone else who has helped with our talk...

About us

PhD in Everything

I wish I knew everything

Mani Sarkar
@theNeomatrix369

Chief fool stack DevOps scientist (self inflicted)

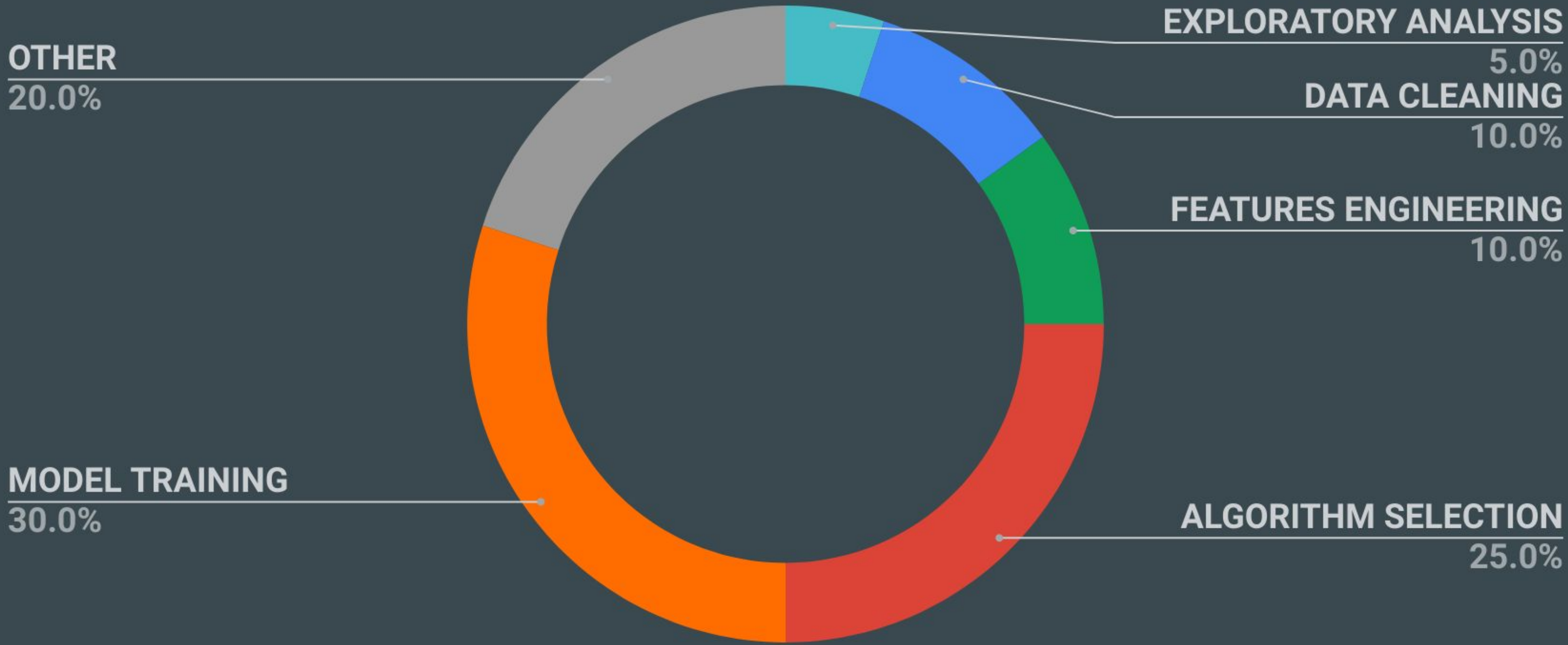
I know, I know nutthing!

Jeremie Charlet
@jeremiecharlet


Take it with a pinch of salt
Credits to Shutterstock / orignal creator / author

Disclaimer

- *YMMV*
- our first attempt at a Devoxx UK event
- might have rough edges and inaccuracies
- sharing our learnings over the past year
- gathered thoughts and ideas from various sources
- *sharing guidelines*, ***not*** a *silver-bullet*
- if it's not clear, tell us!



Are these figures correct?

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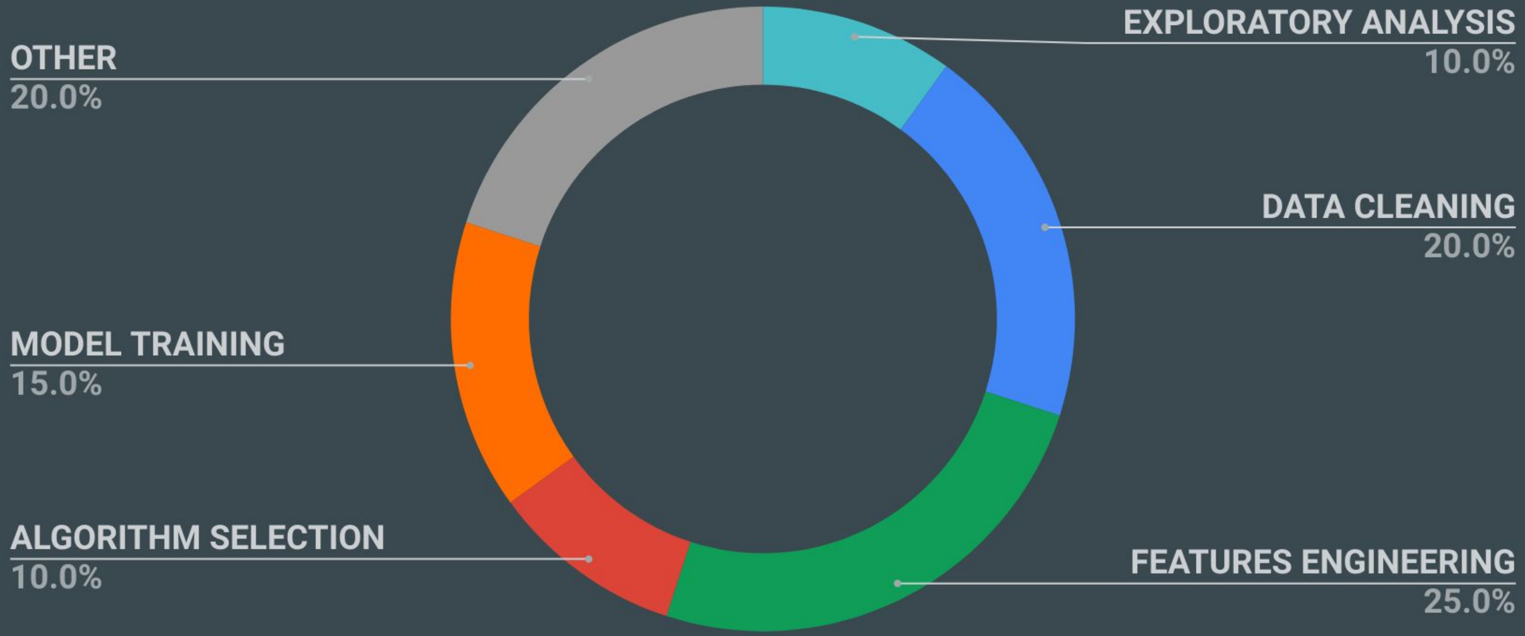
EliteDataScience

elitedatascience.com/birds-eye-view



Estimated figures, a mere guideline, NOT a canonical source!

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What we won’t cover

- Time series (resampling)
- Computer vision, Unstructured data (NLP)
- Generating synthetic data

For the sake of simplicity, we will focus on *tabular data !*

Agenda

- Introduction
  - Data collection
  - Exploratory Data Analysis
  - Data Preparation
  - Feature Engineering
  - Periphery
- Conclusion: what others do?

- Resources
- Thank you, feedback, stay in touch!
- Appendix

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Data visualisation driven presentation, instilling critical thinking

seaborn.pydata.org

Data Collection

Data Collection

Data Collection

Data Collection - questions to ask

- Requirements?
- Good enough details
- How much data is enough?
- Reflect reality ? Bias ?

Iterative process

See Appendix for further details

Exploratory Data Analysis

Exploratory Data Analysis

- Know the domain knowledge
- Check basic characteristics of dataset
- Check descriptive statistics
- Plot distribution of features
- Check correlations between features, with target column

Exploratory Data Analysis - why?

- Black box
- Feeling lost
- Be better prepared
- Prevent wasting time
- To achieve the goal

See Appendix for further details

Exploratory Data Analysis

Go to the

Exploratory Data Analysis - Jupyter Notebook

See Appendix for further details

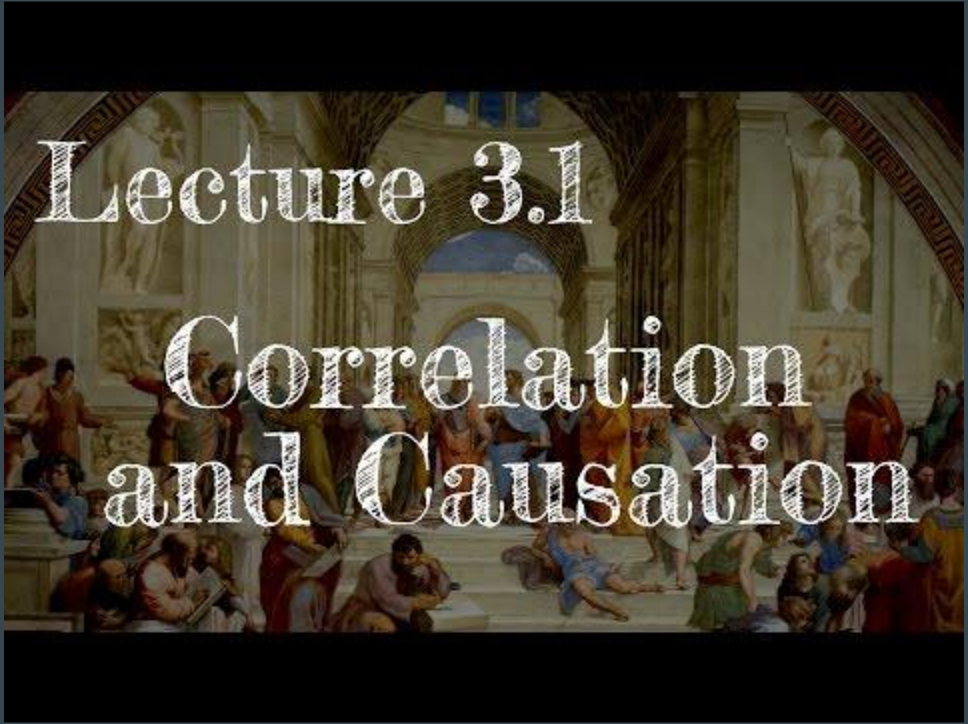
Exploratory Data Analysis - questions to ask

- Domain knowledge
- Source of data
- Nature of data accumulation
- Bias
- Dirty data
- What to fix ?

See Appendix for further details

Exploratory Data Analysis

Correlation not equal to causality (or does not mean they are related)



callingbullshit.org

#DoWeKnowOurData

Comedians really know their data!

55 seconds of fun

[Link to the video]

#DoWeKnowOurData

Comedians really know their data!

Ellen D. knew her time-series

Ellen D. knew her graphs

She made us laugh, so she must know something...

Data Preparation

Data Preparation

- Data cleaning
  - Deal with errors
  - Deal with duplicates
  - Deal with outliers
  - Deal with missing data
- Deal with too much data

Data Preparation - why?

- Garbage in, garbage out
- Clean dataset
- Replicate nature's model

Prof. Chris Holmes explains about Nature's model in Bayesian nonparametric machine learning through randomized loss functions & posterior bootstraps

See Appendix for further details

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Data Preparation

Go to the

[Data Preparation - Jupyter Notebook]

See Appendix for further details

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Data Preparation - questions to ask

- Outliers
- Missing data
- Class overload
- Too many features
- Unbalanced dataset
- Bias
- More data?

See Appendix for further details

Feature engineering

Feature Engineering

- Find hidden information
  - Feature extraction
  - Applying math / statistical functions
  - Apply physics functions
- Deal with too many features / too much data
  - Dimensionality reduction
  - Feature selection
- Statistical Inference
- Improve training efficiency: accuracy, speed, save resources

Too many features: revisiting this topic to extract relevant data after cleaning and preparation

Feature Engineering - why?

- Hidden information
- Extract the essence of the data
- Improve training

See Appendix for further details

Feature Engineering

Go to the

Feature Engineering - Jupyter Notebook

See Appendix for further details

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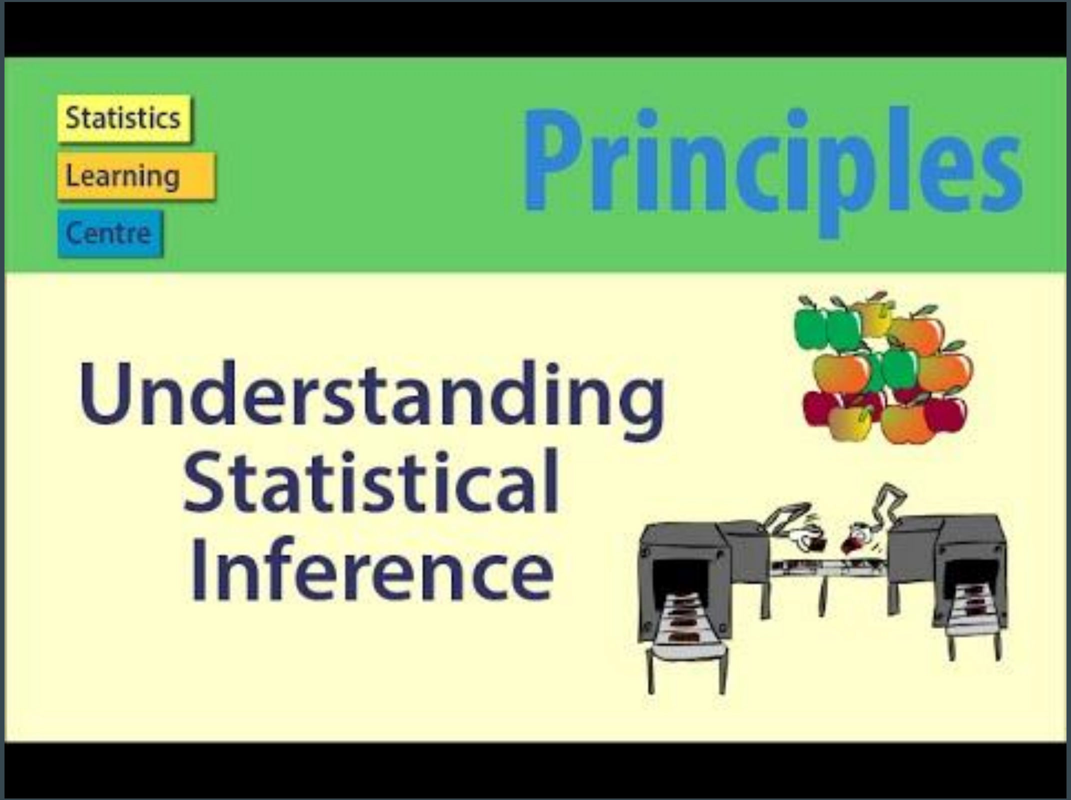
Feature Engineering - statistical inference



Want to know more? See Appendix.

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Feature Engineering - questions to ask

- Achievable
- Rinse-and-repeat
- Iterate and retrospect
- Viability of model
- Simplify
- Essence

See Appendix for further details

Conclusion

What others do? Why?

- Consistency
- Do not reinvent the wheel
- Learn from others

See Appendix for further details

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What others do?

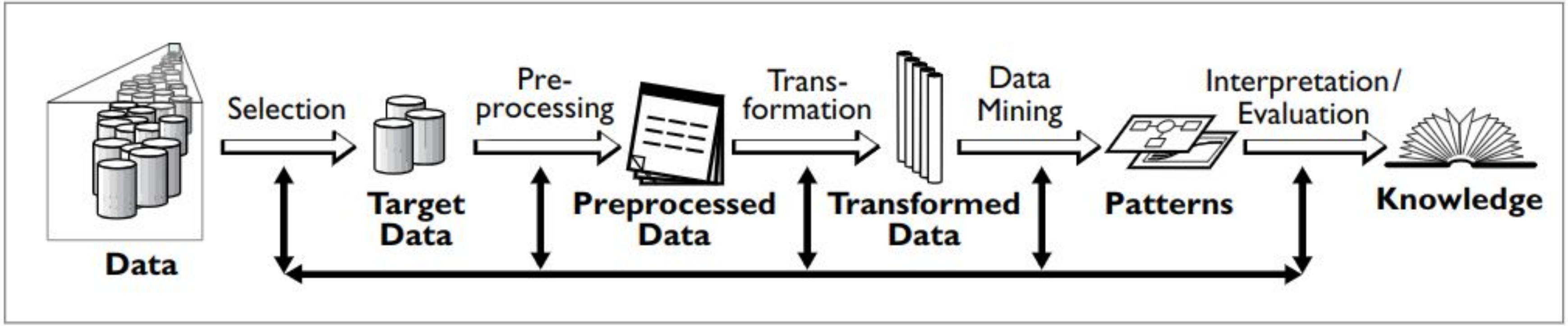
Our presentation so far is an example of the methodologies out there

What others do?

- Frameworks and resources you can learn from, see links: [1] [2]
  - Some call it methodology
  - Others call it rules or best practices
- KDD - knowledge discovery from data
- Data Mining book
  - It has been done for the last 20 years
  - We didn’t reinvent the wheel

What others do?

Figure 1. Overview of the steps constituting the KDD process



What others do?

- Motto and purpose: knowing our data is the most important
  - Model is dependent on the quality of the data
  - Garbage in, garbage out!!!

Overall - questions to ask

- Data Collection - questions to ask
- Exploratory data analysis - questions to ask
- Data Preparation - questions to ask
- Features engineering - questions to ask
- What others do? - questions to ask

- Ours is just a guideline
- Ask right questions (and come up with your own)

Periphery

- Data generation
- Unsupervised learning - clustering
- Data Science Ethics Checklist
- Know your data at Company Level
- AI Transformation Playbook. from Andrew NG
- Making your Neural Network say “I don’t know”

Additional resources

- Treasure trove of links and resources: http://github.com/neomatrix369/awesome-ai-ml-dl
- Everything you wanted to know about data: https://github.com/neomatrix369/awesome-ai-ml-dl/tree/master/data
- Notebooks: https://github.com/neomatrix369/awesome-ai-ml-dl/blob/master/data/README.md#notebooks
  - Data Exploratory Analysis
  - Data Preparation
    - Data Cleaning
    - Data Preprocessing / wrangling
  - Data Generation
  - Feature engineering
  - Statistics
  - Common mistakes

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Additional resources

- Everything you wanted to know about data (2 / 2): https://github.com/neomatrix369/awesome-ai-ml-dl/tree/master/data
  - Cheatsheets
  - Courses and books
  - Best practices
  - Frameworks
  - Notebooks
- Understanding Data Science Problems - template of questions to ask

Shout out!

Join the Meet-a-Mentor
ML Study Group based in **London, UK**

We meet weekly!

Meetamentor.co.uk
meetup.com/MaM-Machine-Learning-Study-Group
@RWmeetamentor

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Thank you, feedback, stay in touch!

Please share your feedback, to be applied to the live slides and other resources for everyone's benefit

[@theNeomatrix369]()
[@jeremiecharlet]()

Citations

The images used in this presentation are owned by the respective authors, and many of them come from the https://thenounproject.com.

Appendix

Data Collection - questions to ask

- What are you going to need ?
- What level of details would be good enough ?
- How much data do you need to start ?
- Do your data will reflect reality ? What are the biases ?

Be ready to repeat the process

Exploratory Data Analysis - why?

- Black box: if anything wrong, if we don't understand our data, we won't be able to correct it
- We want to solve a problem in the end, with ML, and have good results. If we don't understand our data, we might not be able to train a model because of incoherent or missing data, or have poor results because we have misleading (unbalanced, highly correlated, too many useless features) data. Thus we need to find out if there are incoherent/missing/misleading data
- Know the nature / boundaries / source of the data
- When I work with someone, I want to get to know that person to get the best out of your relationship
- If you don't have domain knowledge, you risk wasting time on finding the root causes of issues, and might never manage to solve the problem

Exploratory Data Analysis

- Basic characteristics of dataset: get a feeling

```
[4]: df.columns

[4]: Index(['Movement', 'Gait', 'Rein', 'Comment', 'Date', 'ACCX', 'ACCY', 'ACCZ',
            'GX', 'GY', 'GZ', 'PITCH', 'ROLL', 'YAW', 'HEIGHT', 'GAIT', 'name',
            'height'],
           dtype='object')

[5]: df.head(3)
```

[5]:

	Movement	Gait	Rein	Comment	Date	ACCX	ACCY	ACCZ	GX	GY	GZ	PITC
0	NOT_ON_HORSE	NOT_ON_HORSE	NOT_ON_HORSE	None	2018-08-22 08:48:08.600	-0.00	-0.41	0.29	66.11	-78.55	-5.11	-20.11
1	NOT_ON_HORSE	NOT_ON_HORSE	NOT_ON_HORSE	None	2018-08-22 08:48:08.700	-0.01	-0.83	0.59	15.08	-18.35	0.00	-19.38
2	NOT_ON_HORSE	NOT_ON_HORSE	NOT_ON_HORSE	None	2018-08-22 08:48:08.800	-0.01	-0.83	0.59	0.00	0.00	0.00	-19.92

What fields have we collected for our dataset? What do they mean ? Are they gonna help?

You can go a bit further, like check the shape of your dataset (enough data? Too much?), data types (only float in that column or more stuff?) class values (what's in Gait?)

Get a global idea and finer details of what exactly your data looks like

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Exploratory Data Analysis

- Check descriptive statistics: explore a bit more, take some notes, raise questions

Summary details of datasets always helps spot Garbage or incorrect data? Start raising questions about your data

Mmh a horse gallopping towards the sky? On a rocket maybe? Some weird outliers we'll need to check / clean

Yaw always equals to 0. The data are useless. Is it gonna be a problem? Is there something wrong with the data collection? Can we simply ignore that column?

```
[8]: df.describe()
```

[8]:

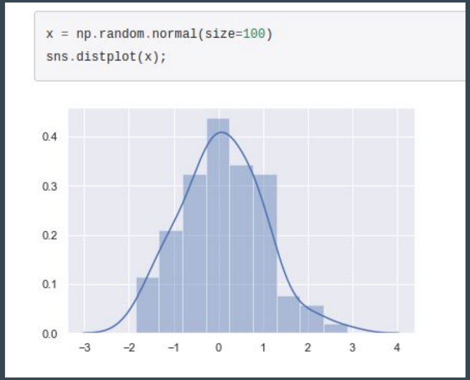
	ACCX	ACCY	ACCZ	GX	GY	GZ	PITCH	ROLL	YAW	HEIGHT	GAIT	height
count	680859.000000	680859.000000	680859.000000	680859.000000	680859.000000	680859.000000	680859.000000	680859.000000	680859.0	680859.0	680859.000000	680859.000000
mean	0.017209	-0.019569	0.954397	-0.058867	-0.404106	-0.104934	-1.725721	-1.549733	0.0	0.0	7.823378	15.649734
std	0.200833	0.250091	0.195043	13.572398	[illegible]	13.536762	11.981994	19.926747	0.0	0.0	22.704810	0.788629
min	-1.460000	-1.610000	-1.450000	-1082.390000	-501.250000	-1061.130000	-89.429000	-179.981000	0.0	0.0	0.000000	14.100000
25%	-0.150000	-0.160000	0.960000	-0.640000	-1.710000	-0.540000	-9.790000	-8.550000	0.0	0.0	3.000000	15.000000
50%	0.050000	-0.050000	0.990000	0.000000	-0.540000	0.000000	-3.356000	-3.188000	0.0	0.0	3.000000	16.100000
75%	0.150000	0.100000	1.010000	0.520000	0.580000	0.000000	7.437500	5.641000	0.0	0.0	3.000000	16.200000
max	2.580000	1.390000	2.730000	869.980000	438.640000	358.260000	89.652000	179.904000	0.0	0.0	155.000000	16.200000

Most ACCZ data around 1. We need to remove gravity on the acceleration

Exploratory Data Analysis

- Plot distribution of features: check overall distribution
    - Histogram for numeric data
    - Bar chart for categories

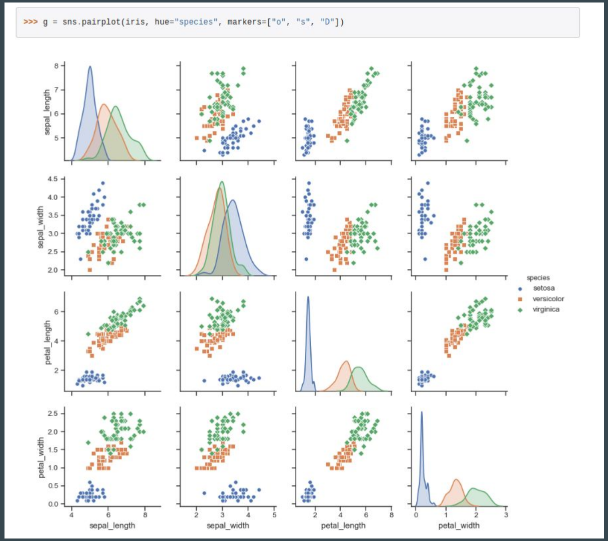
Are the category classes unbalanced? Are there sparse categories that we will need to group together?

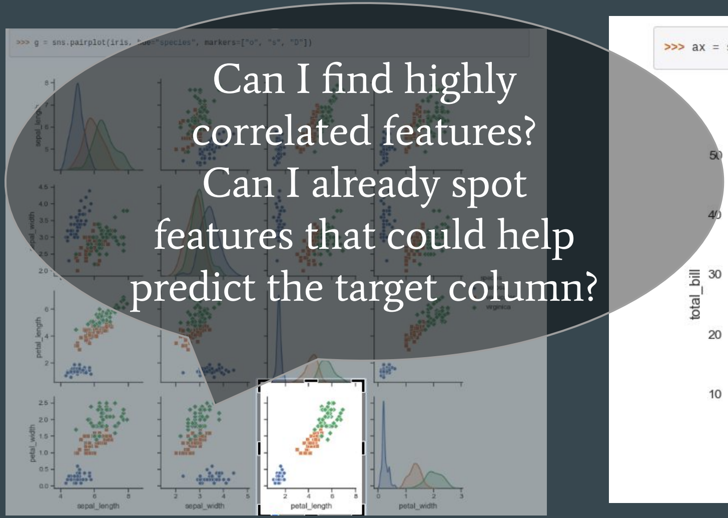


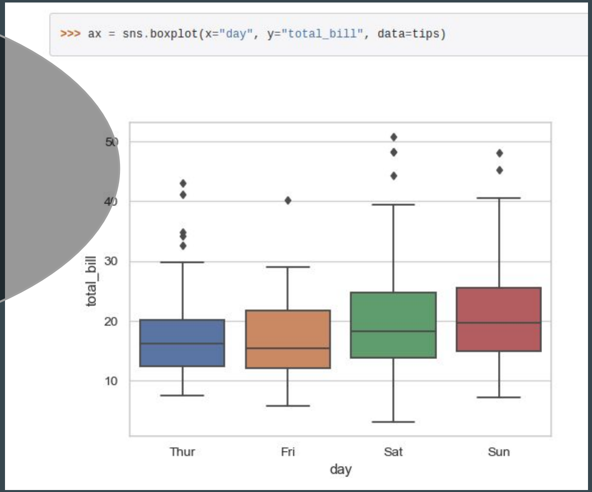
Are there outliers ?
Are the features following gaussian distribution ?

Exploratory Data Analysis

- Find correlations between features, with target column
  - Scatter charts for numeric data
  - Box whisker / violin plots for category data vs numeric







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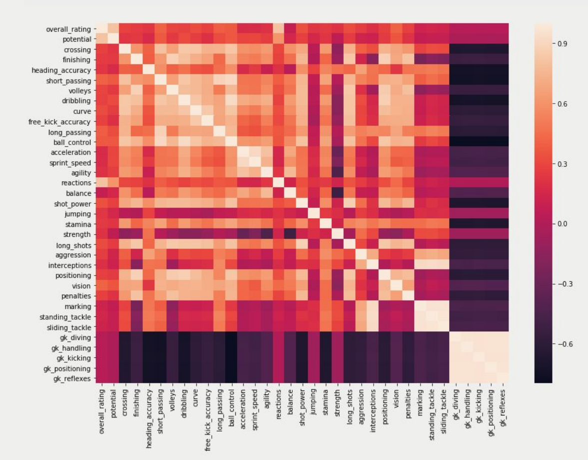
Exploratory Data Analysis

- Study correlations between features
  - Correlation matrix

Change in the value of one field / variable impacting the other...



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Exploratory Data Analysis - questions to ask

Do you know:

- The domain knowledge needed to understand the data. Have you done your research ?
- Where it comes from
  - Is it manually/automatically generated data or mix of both?
  - Process used to create the data
- Do you know the nature of the bias in the data ? Does it need to be reduced and can it be ?
- Do we know the strengths and weaknesses of the data ? Is the data trustworthy, dirty -> do we need to fix it ?
  - Are there outliers ? should we keep them ?
  - Are there missing data ? what should we do about them ?
- Are the data representative of the domain ?

#DoWeKnowOurData

Data Preparation - why?

- Garbage in, garbage out. If you work with dirty data, even the most sophisticated models won't be able to get satisfying results. Better data beats fancier algorithms
- To create a clean dataset (so that it has good enough accuracy and correctness)
- So that we can create models that are closer to nature's model

Data Preparation - data cleaning

Deal with errors (structural)

Type of error (problem)	Technique to use
mislabeled	relabel data automatically or manually
dataset standardisation issue	uniformly replace them
sync issues between sources of data	standardise the data

Data Preparation - data cleaning

Deal with duplicate data

Type of problem	Technique to use
duplicates	group values with frequencies

Link to Pandas data wrangling cheat sheet from DataCamp

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Data Preparation - data cleaning

Deal with duplicate data

`>>> s3.unique()`	Return unique values
`>>> df2.duplicated('Type')`	Check duplicates
`>>> df2.drop_duplicates('Type', keep='last')`	Drop duplicates
`>>> df.index.duplicated()`	Check index duplicates

Data Preparation - data cleaning

Deal with outliers

We tend to just ignore them while they can be very important in some cases (like anomaly detection) - expand on it!

Type of problem	Technique to use
outliers	- distribution graphs and/or pair plots - use of mean and std dev - filter out the outliers - apply filter to smoothen out a curve - to decide: to keep the outliers or try to remove them

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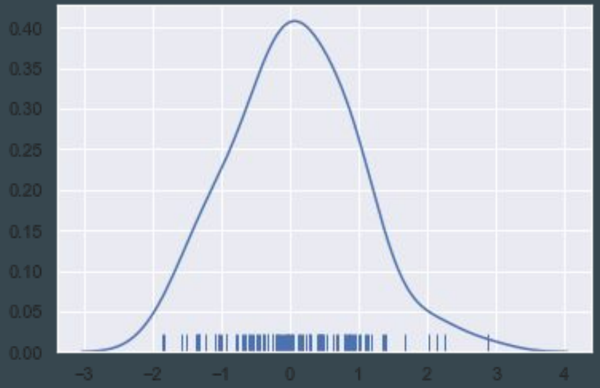
Data Preparation - data cleaning

Deal with outliers



std

Ignore everything after 2 stds

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Data Preparation - data cleaning

Deal with missing data

Type of problem	Technique to use
missing data	the best way to handle missing data is to first flag them as missing and fill with default values: median, mean, weighted mean, predicted, zero
	- fill based on observations or correlations - to generate synthetic data to fill missing values Using sklearn Imputer or KNN
	- decide whether to drop rows with missing values

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Data Preparation

Deal with too much data (information overload) [1 / 2]

<table>
<tr><th>Type of problem</th><th>Technique to use</th></tr>
<tr><td rowspan="2">needle in a haystack problems

(huge dataset with disproportionate class distribution: e.g. we try to detect a class which occurs in 0.5% of the data (horse rolling which is a rare event vs simply standing or lying)</td><td>Step1: group data + histogram
- to identify the disproportion

Step 2: Undersampling the classes to remove data

Step 3: Oversampling by adding more data</td></tr>
<tr><td>Step 1: Manage at the training stage (adjust hyperparameter)
(check ML Mastery for more techniques in the google docs)</td></tr>
</table>

Data Preparation

Deal with too much data (information overload) [2 / 2]

Type of problem	Technique to use
dataset with class overload problems (column with astronomical number of categories. e.g. city in house prices)	- Group together sparse categories - Remove sparse categories - Summarising categories into higher levels of abstractions

#DoWeKnowOurData

Data Preparation - questions to ask

Do we have those problems to fix and have we ?

- Outliers
- Missing data
- Class overload
- Too many features
- Unbalanced dataset
- Have we removed or balanced any existing bias in the dataset?

Feature Engineering - why?

- To find hidden information
- To extract the essence of the data which is representative of the rest of the data
- Improve training efficiency: accuracy, speed, good use of resources

Feature Engineering

- Feature extraction

Type of problem	Technique to use
find hidden information	- group together sparse classes - create new calculated columns, for e.g. extracting weekday from date - generate relevant labels with the help of results from clustering

Feature Engineering

- Applying math / statistical functions

Type of problem	Technique to use
find hidden information Improve distribution, remove skewness	- convert to absolute values - apply root mean square - use logarithmic functions - applying rolling mean / stddev / min / max And manage precision of the data!

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Feature Engineering

- Applying physics related functions

Type of problem	Technique to use
find hidden information	- Energy - Energy rate - Short Term Average / Long term Avg - Kurtosis - FFT (Fast Fourier Transform)

Feature Engineering

- Feature scaling

Type of problem	Technique to use
Improve distribution, remove skewness. Required for some models	- Standardization - Normalization - Map to uniform or gaussian distribution

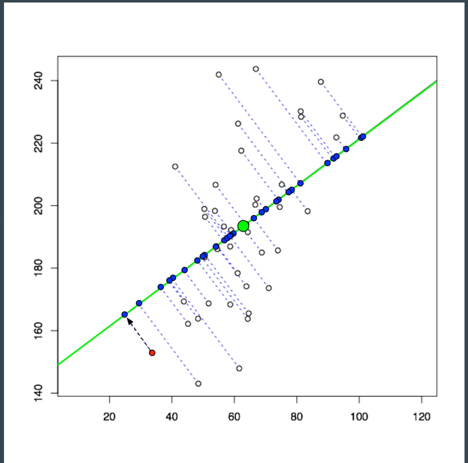
Feature Engineering

- Dimensionality Reduction [1 / 2]

Type of problem	Technique to use
too many features	Factorisation (PCA) ICA Independent Component Analysis t-SNE t-Distributed Stochastic Neighbour Embedding UMAP Uniform Manifold Approximation and Projection

Feature Engineering

- Dimensionality Reduction [2 / 2]

Type of problem	Technique to use
too many features	Principal Component Analysis (PCA) 

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Feature Engineering

- Feature selection [1 / 3]

Type of problem	Technique to use
too many features (dataset on house prices has 50 features. where to start, what does really affect the prices? Should I train on everything, just a subset of the features, how to choose them, etc?)	Manual feature selection Programmatically > Tree-based, during training Genetic process of selecting potent features

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Feature Engineering

- Feature selection [2 / 3]

Type of problem	Technique to use
too many features	(Manual) Filter out features which are highly correlated. Plot multi scatter chart Use correlation table (might need to remove features which were used for extraction)

Feature Engineering

- Feature selection [3 / 3]

Type of problem	Technique to use
too many features	(Programmatically) - Tree based feature selection Use feature importance from XGBoost or RandomForest - During training Recursive feature elimination (select features by recursively considering smaller and smaller sets of features)

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Feature Engineering

- Feature selection:

Type of problem	Technique to use
too many features	H2O driverless AI: Genetic algorithmic process of selecting potent features (automated)

Statistical inference

- Understanding statistical inference [video]
- Four ideas of Statistical Inference
- An Introduction to Statistical Learning [book]
- Statistical Inference [course]

Create a baseline first!

Feature engineering is an art!

Improve over training iterations!

Feature Engineering

Apply the same techniques on train, validation and test sets <u>separately</u>

Feature Engineering

Check the distribution of your data (descriptive analytics)

Repeat steps in the Data Exploratory section, again

Verify your data

Question your results !!!

Visualise feature engineered dataset

Feature Engineering

See Dummy Classifier or Dummy Regressor

Is your baseline model results better than those of a Dummy Classifier / Regressor?

Feature Engineering - questions to ask

- Can I create a model from my dataset efficiently given my resources?
- How do we make best use of the trial-error process yet get the best out of the dataset / model?
- How can I make informed decisions and record them and reuse them in my next iteration?
- How can I make sure that the end model is useful to solve my business problem after going through the tedious process?
- From the trends we identified previously can we make it simpler for the model to pick and use such information from the dataset?
- How can I get the essence out of my original dataset ? Can I express the intuitions I got during the analysis in a more obvious way ?

What others do? Why?

- Consistency
- Do not reinvent the wheel
- Learning from the good work of others from the past and current times
- Learning and applying from the lessons learnt from tried and tested empirical experiments from the past

Tips from Mark Bell (TNA, Data Scientist / Research)

- Data is rarely clean
- Tidy your data
- Visualise your data
- Know your numbers
  - High values; Low values; Missing values
  - Quartiles
  - Mean; Medians
  - Correlations
- Create your own features
- Go to Kaggle!

#DoWeKnowOurData

It's harder than it looks!

Slides to talk

- Keep your data & labels separate!
    - "How to Prevent Catastrophic Failure in Production ML Systems, Martin Goodson", QCon London 2019
- Need a methodology - or can get overwhelmed by all the possibilities
- If it looks too good to be true...

callingbullshit.org

Thanks Dave Snowdon & Jeremie Charlet

#DoWeKnowOurData