Engineering and selecting features for machine learning

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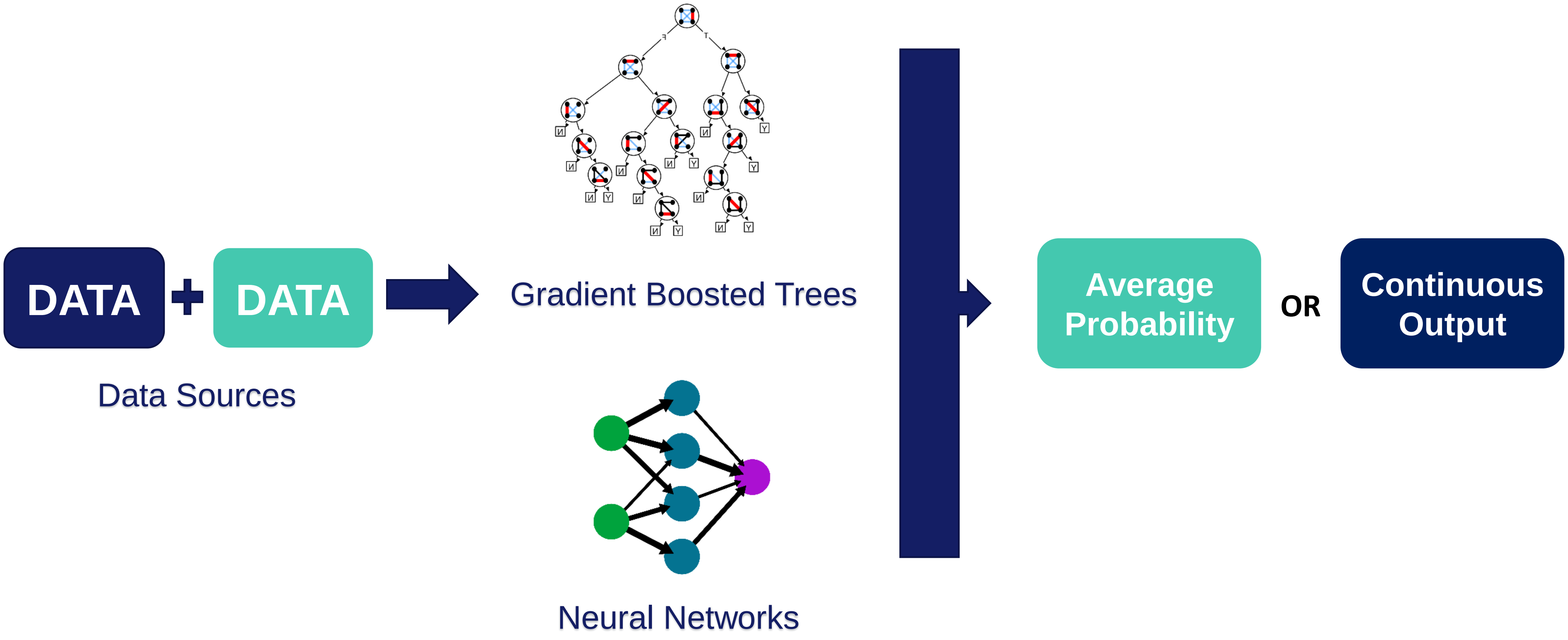
DSF meetup with Busuu

London, 16th October 2018

Machine Learning Pipeline



Machine Learning Finance and Insurance

Claims

Fraud

Credit Risk

Marketing

Pricing

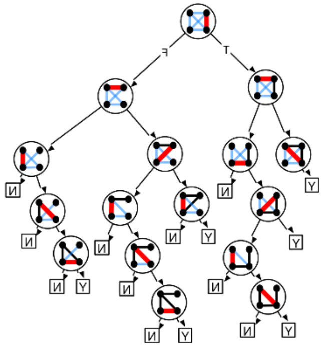
Machine Learning Pipeline

DATA

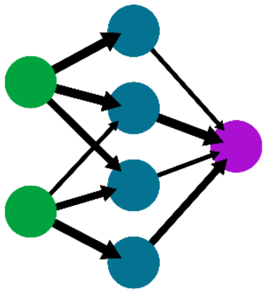
+

DATA

Data Sources



Gradient Boosted Trees



Neural Networks

Average Probability

Continuous Output

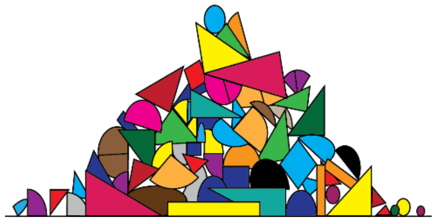
Machine Learning Pipeline

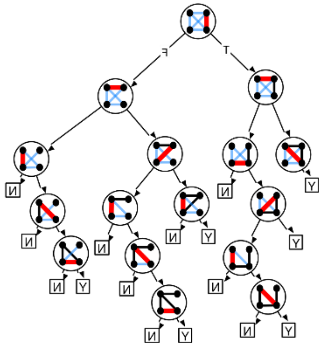
DATA

+

DATA

Data Sources





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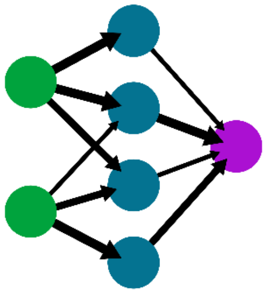

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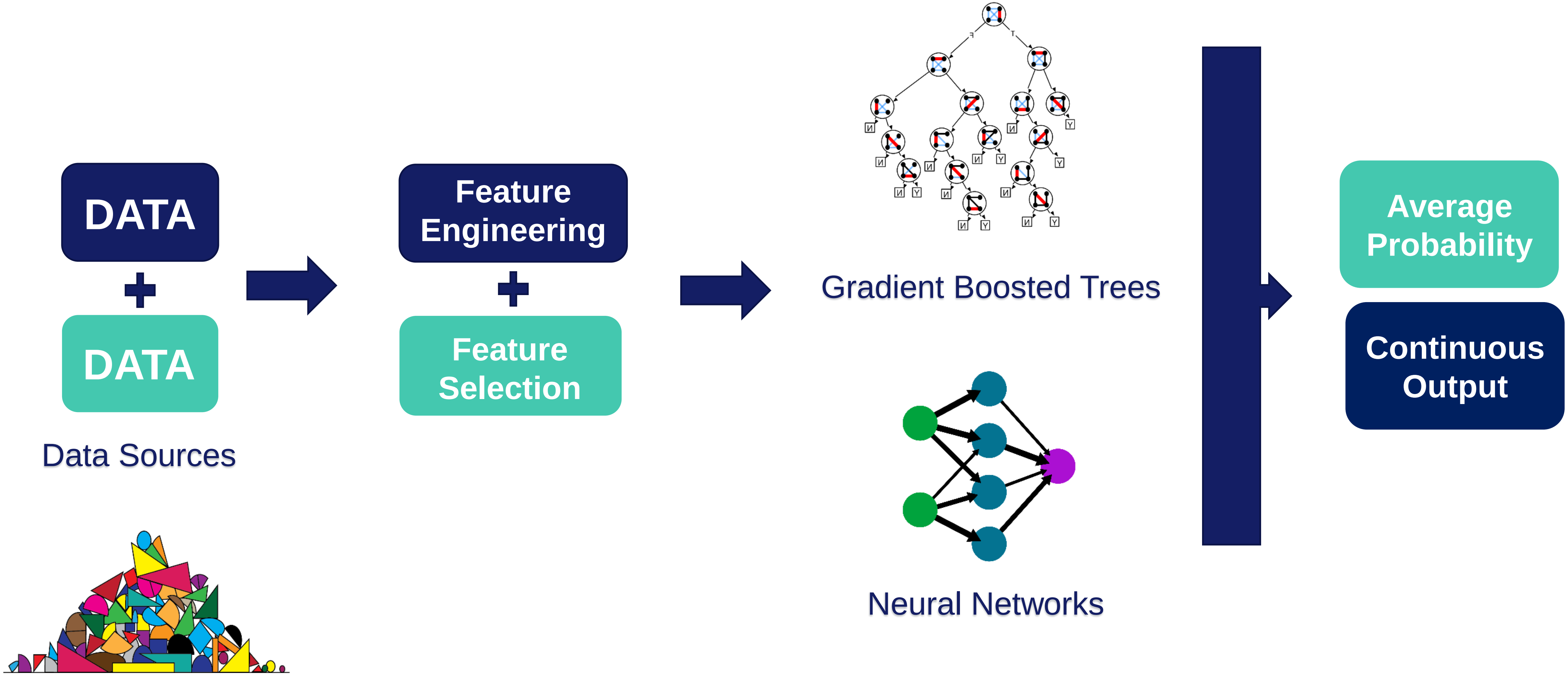

Data Pre-processing Journey

- Common issues found in variables
- Feature / Variable engineering: solutions to the data issues
- Feature selection: do we need to select features?
- Feature / Variable selection methods
- Overview and knowledge sources

Data Pre-processing Journey

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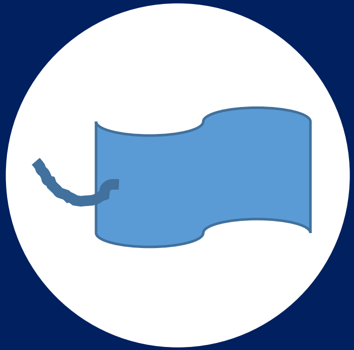
Problems in Variables

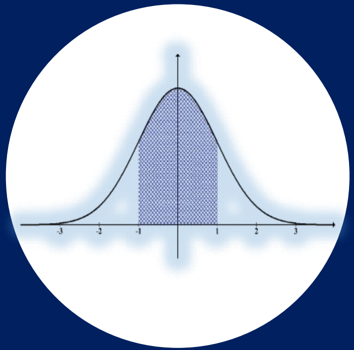
Missing data

Missing values within a variable



Labels

Strings in categorical variables



Distribution

Normal vs skewed

Outliers

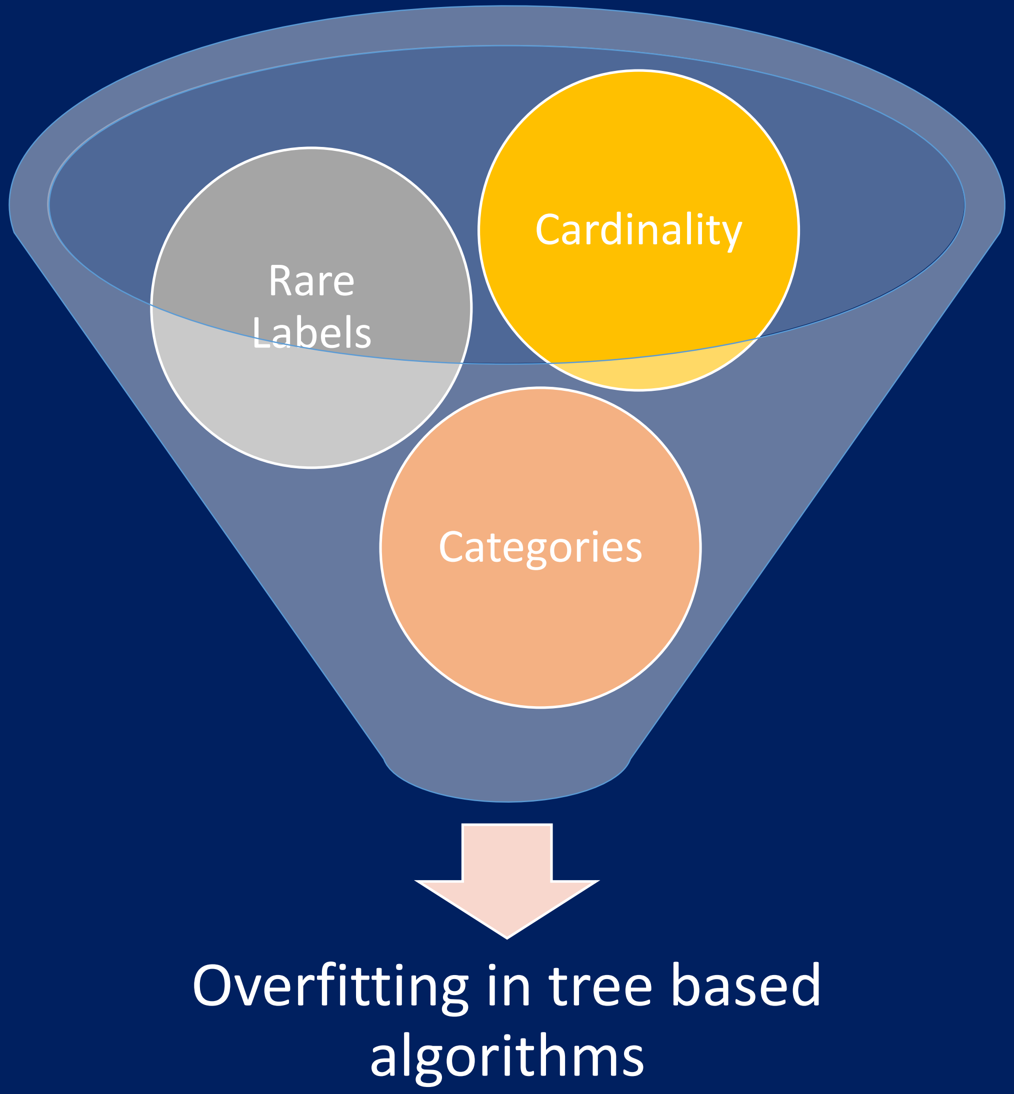
Unusual or unexpected values

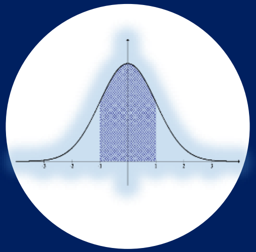
Missing Data

- Missing values for certain observations
- Affects all machine learning models
    - Scikit-learn

Labels in categorical variables

- Cardinality: high number of labels
- Rare Labels: infrequent categories
- Categories: strings
  - Scikit-learn

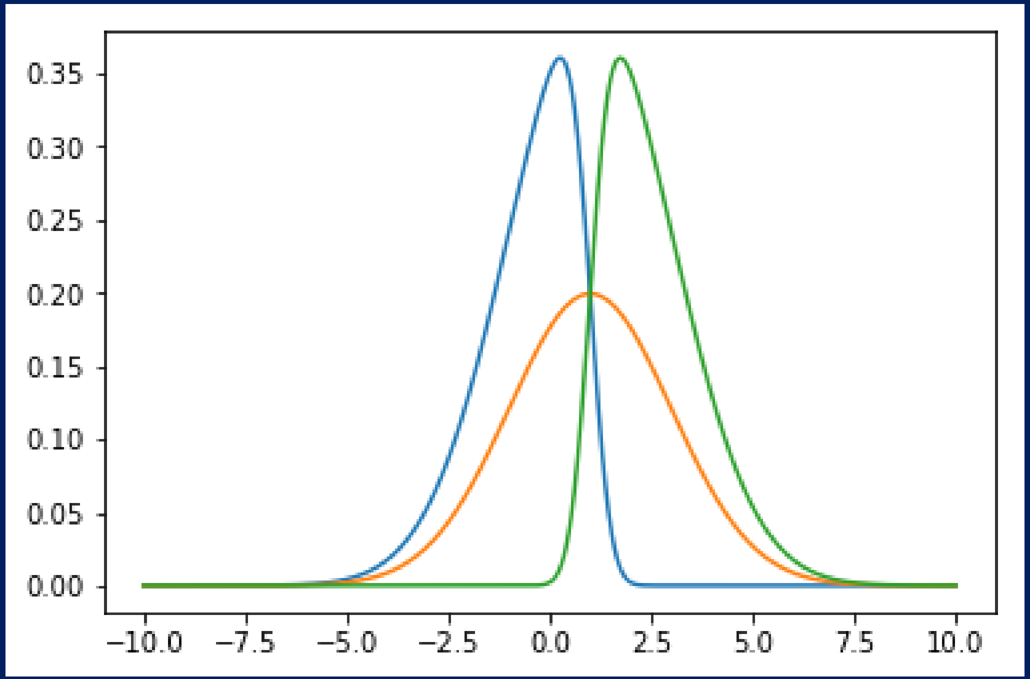




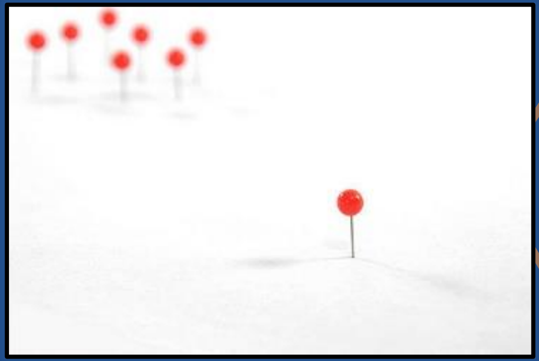
Distributions

- Linear model assumptions:
    - Variables follow a Gaussian distribution
- Other models: no assumption
    - Better spread of values may benefit performance

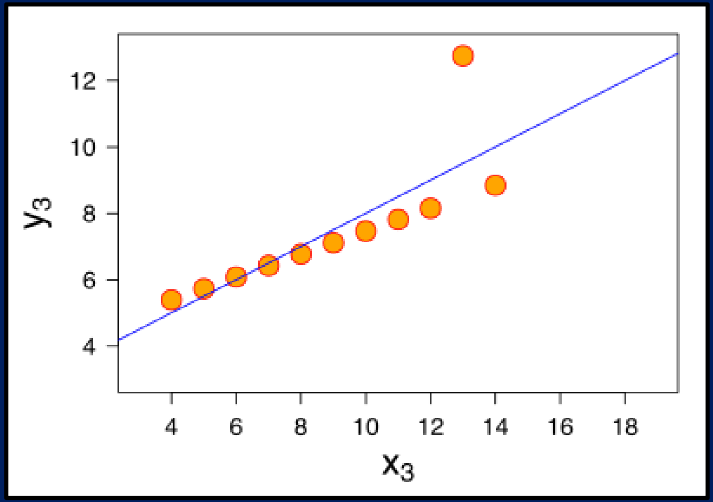
Gaussian vs Skewed



Outliers



Linear models

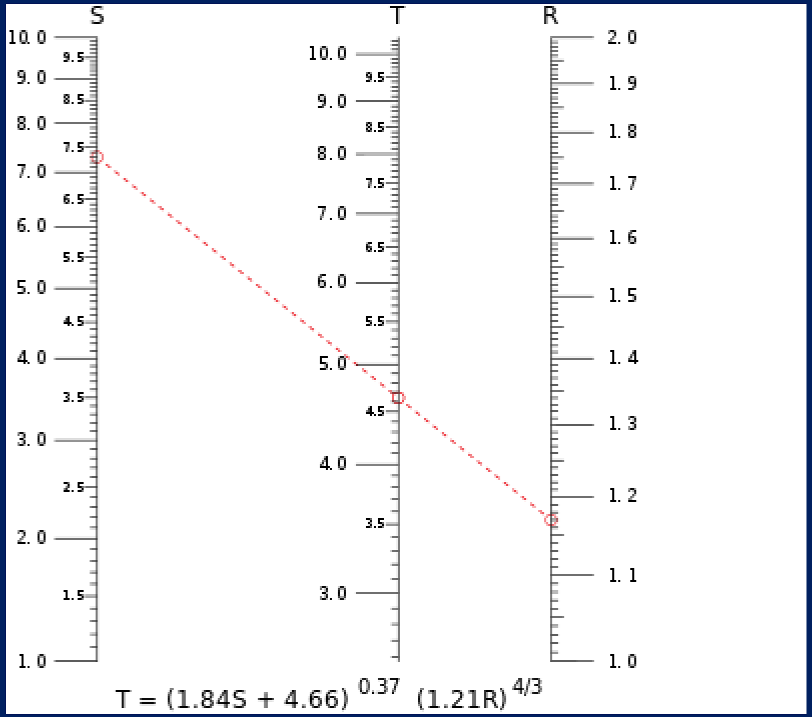


Adaboost

Tremendous weights

Bad generalisation

Feature Magnitude - Scale



Machine learning models sensitive to feature scale:

- Linear and Logistic Regression
- Neural Networks
- Support Vector Machines
- KNN
- K-means clustering
- Linear Discriminant Analysis (LDA)
- Principal Component Analysis (PCA)

Tree based ML models insensitive to feature scale:

- Classification and Regression Trees
- Random Forests
- Gradient Boosted Trees

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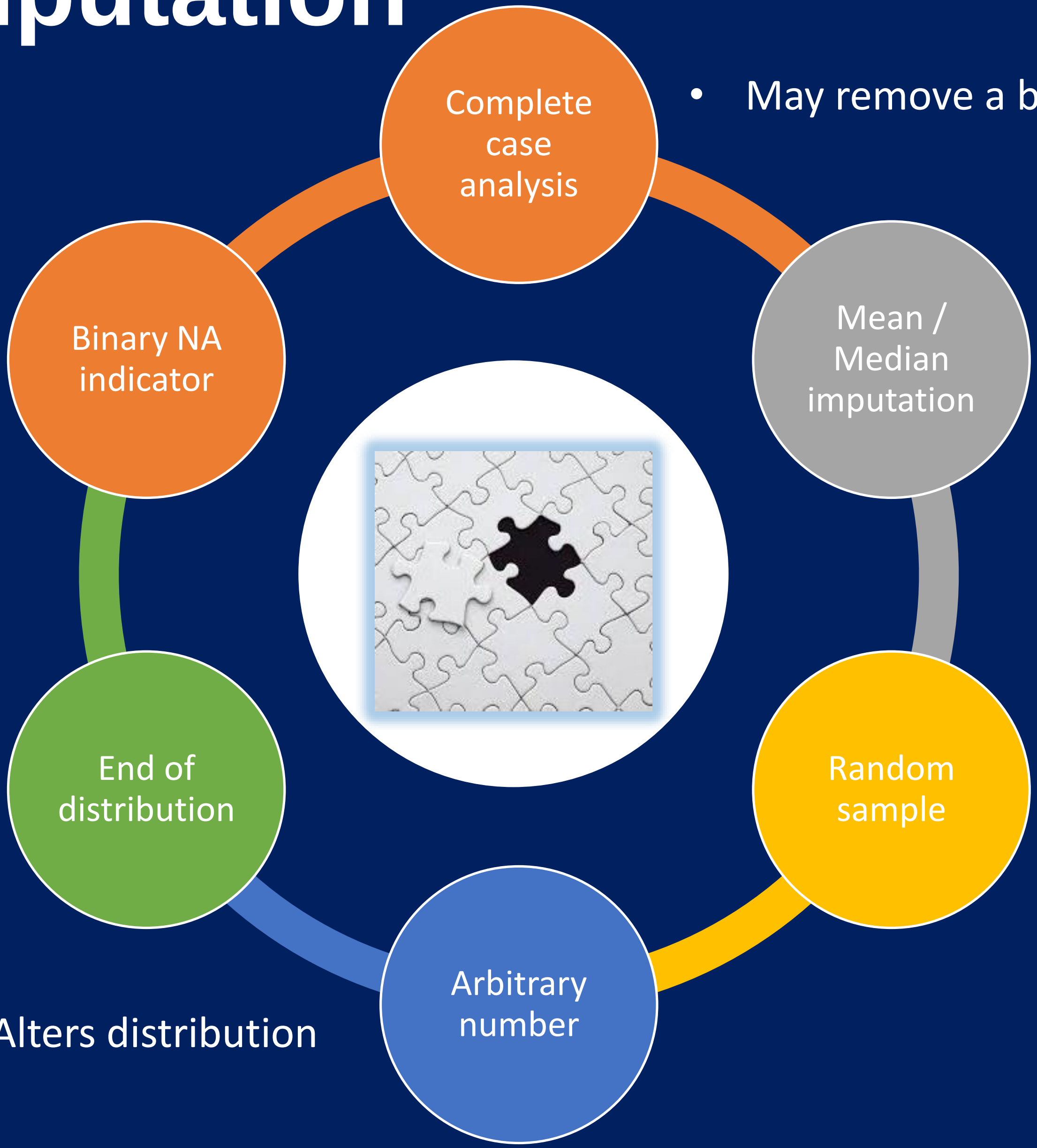
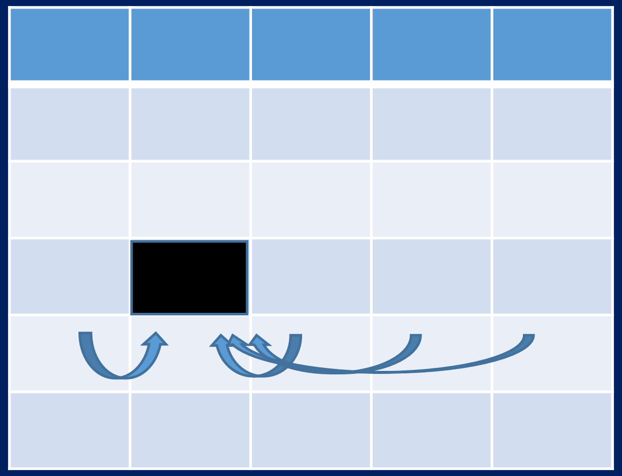
Missing Data Imputation



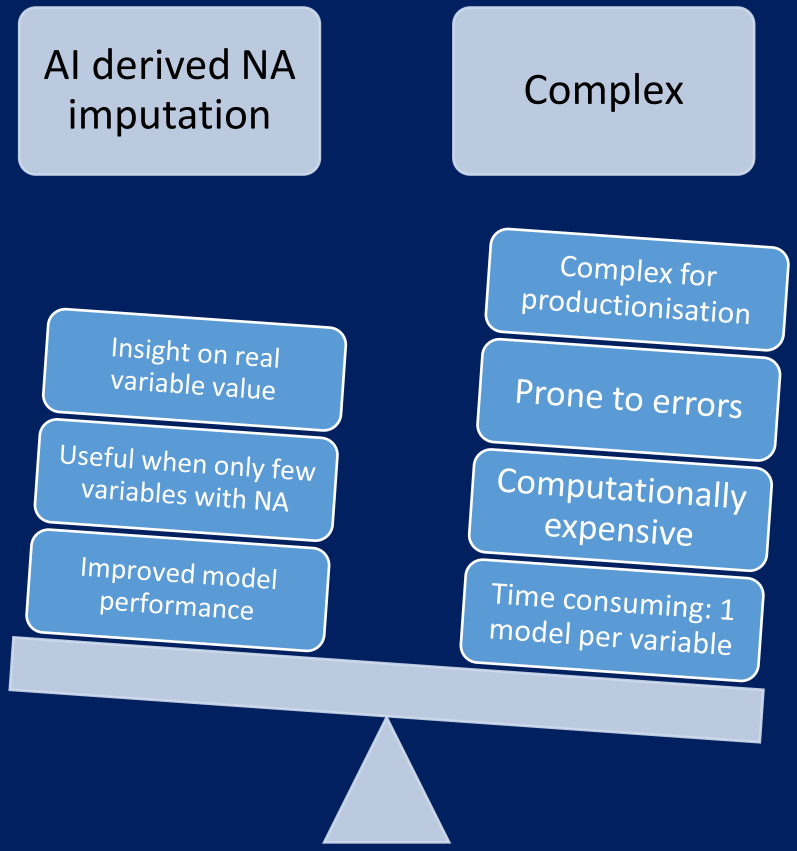
- May remove a big chunk of dataset
- Alters distribution
- Element of randomness
- Alters distribution
- Still need to fill in the NA

More on Missing Data Imputation



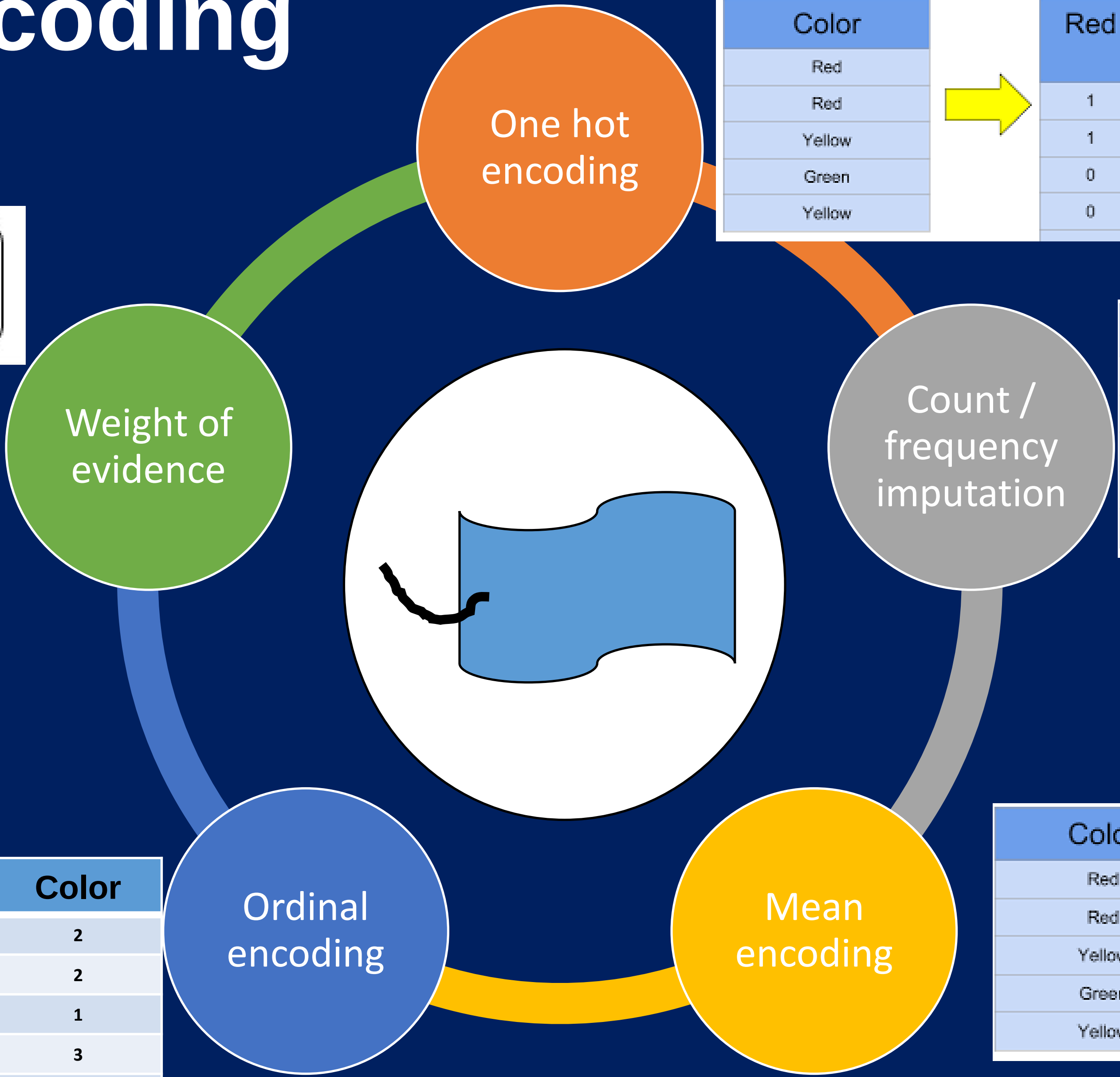
Use neighbouring variables to predict the missing value

- KNN
- Regression



Label Encoding

$$\text{WOE} = \ln\left(\frac{\%\text{ of non-events}}{\%\text{ of events}}\right)$$



Color
Red
Red
Yellow
Green
Yellow

Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1

Color
Red
Red
Yellow
Green
Yellow

Color
2
2
2
1
2

Color
Red
Red
Yellow
Green
Yellow

Target	Color
0	0.5
1	0.5
1	1
0	0
1	1

Color
Red
Red
Yellow
Green
Yellow

Target	Color
0	2
1	2
1	1
0	3
1	1

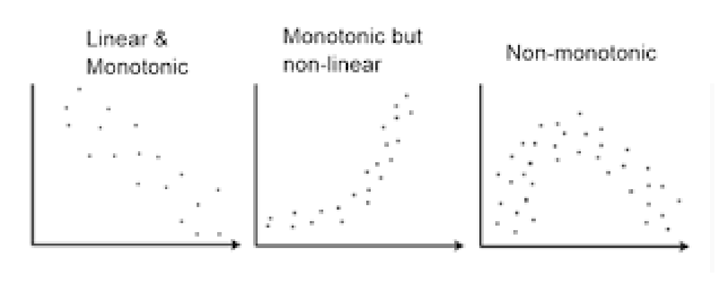
Label Encoding

One hot encoding

- Expands the feature space

Count / frequency imputation

- No monotonic relationship



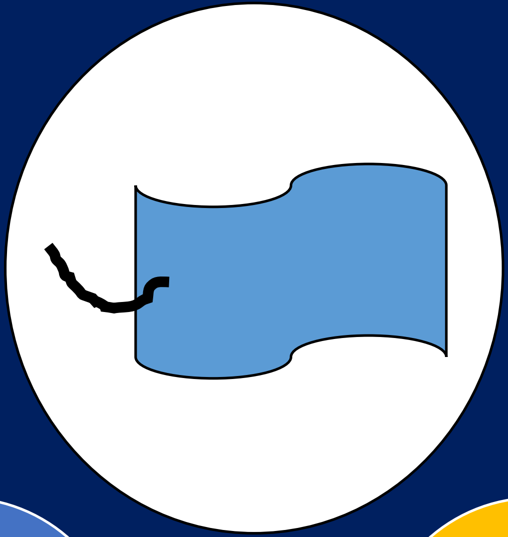
Mean encoding

Ordinal encoding

- Prone to overfitting

Weight of evidence

- Account for zero values as it uses logarithm



Rare Labels

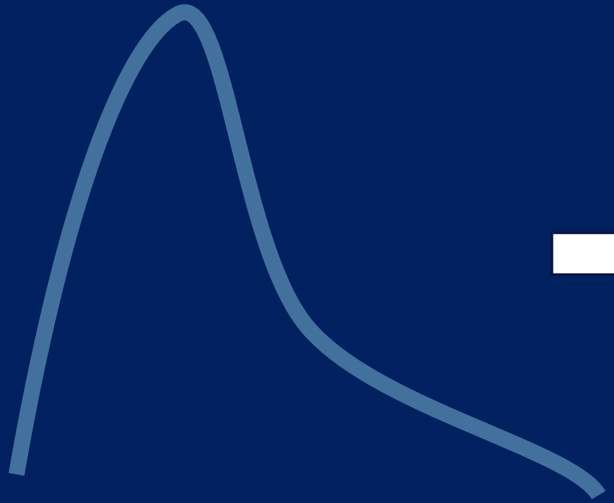
Distribution: Gaussian Transformation

Skewed Gaussian

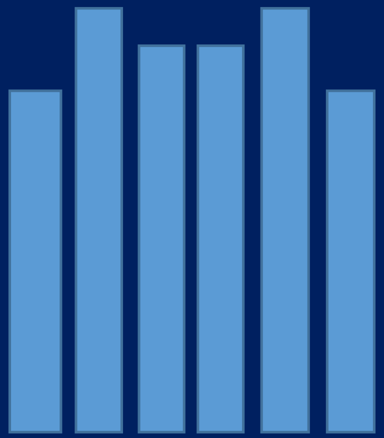
Variable transformation

- Logarithmic → ln(x)
- Exponential → x Exp (any power)
- Reciprocal → (1 / x)
- Box-Cox → (x Exp (λ) – 1) / λ
    - λ varies from -5 to 5

Distribution: Discretisation



Skewed



Improved value spread

Discretisation

- Equal width bins
  - Bins ➔ (max – min) / n bins
  - Generally does not improve the spread
- Equal frequency bins
  - Bins determined by quantiles
  - Equal number of observations per bin
  - Generally improves spread

Outliers

Trimming	• Remove the observations from dataset
Top | bottom coding	• Cap top and bottom values
Discretisation	• Equal bin / equal width

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Why Do We Select Features?

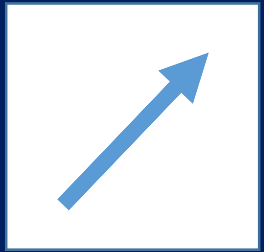
- Simple models are easier to interpret
- Shorter training times
- Enhanced generalisation by reducing overfitting
- Easier to implement by software developers → Model production
- Reduced risk of data errors during model use
- Data redundancy

Variable Redundancy

Constant variables
Only 1 value per variable

Quasi – constant Variables
> 99% of observations show same value

Duplication
Same variable multiple times in the dataset



Correlation
Correlated variables provide the same information

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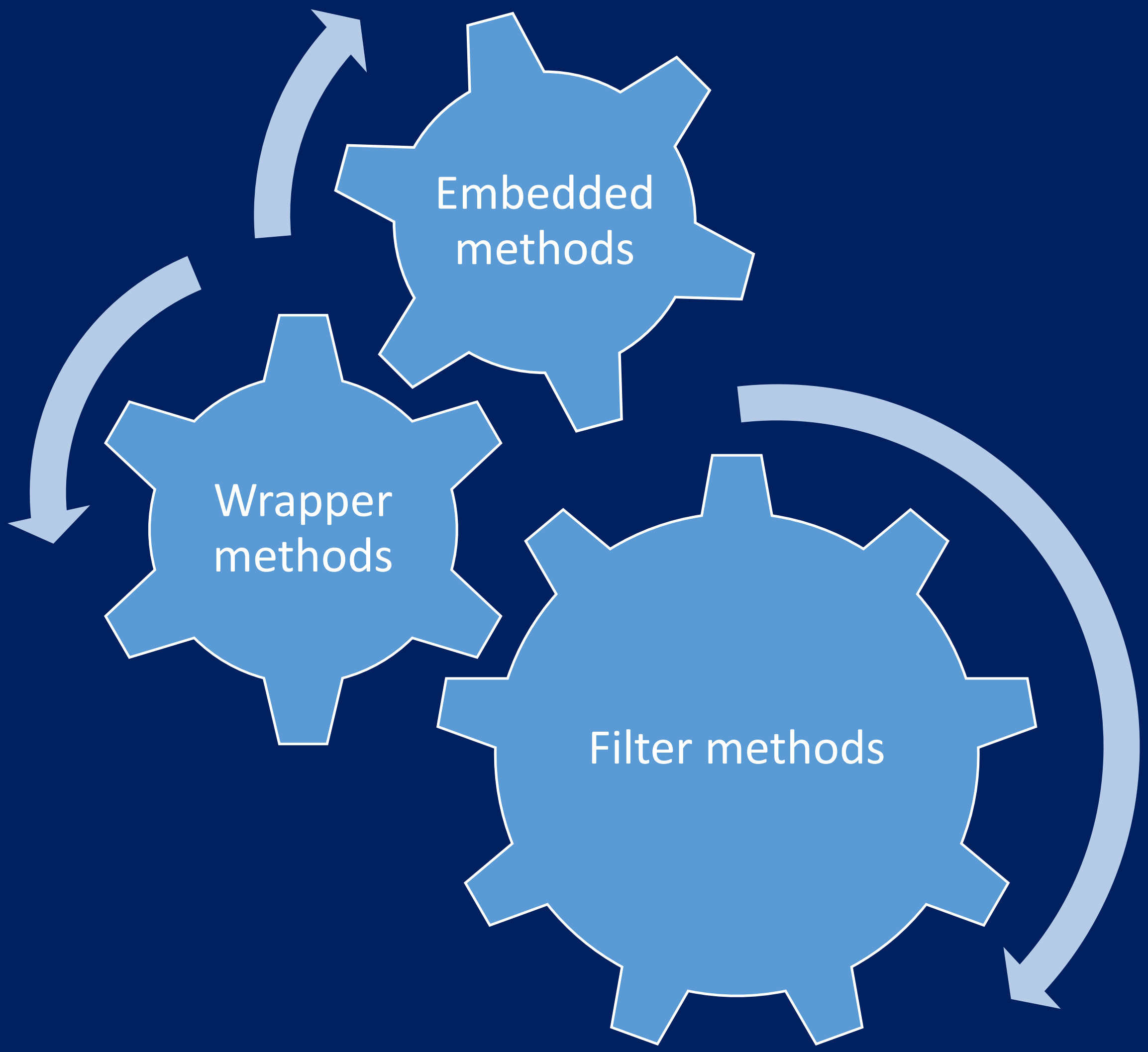
Feature Selection Methods

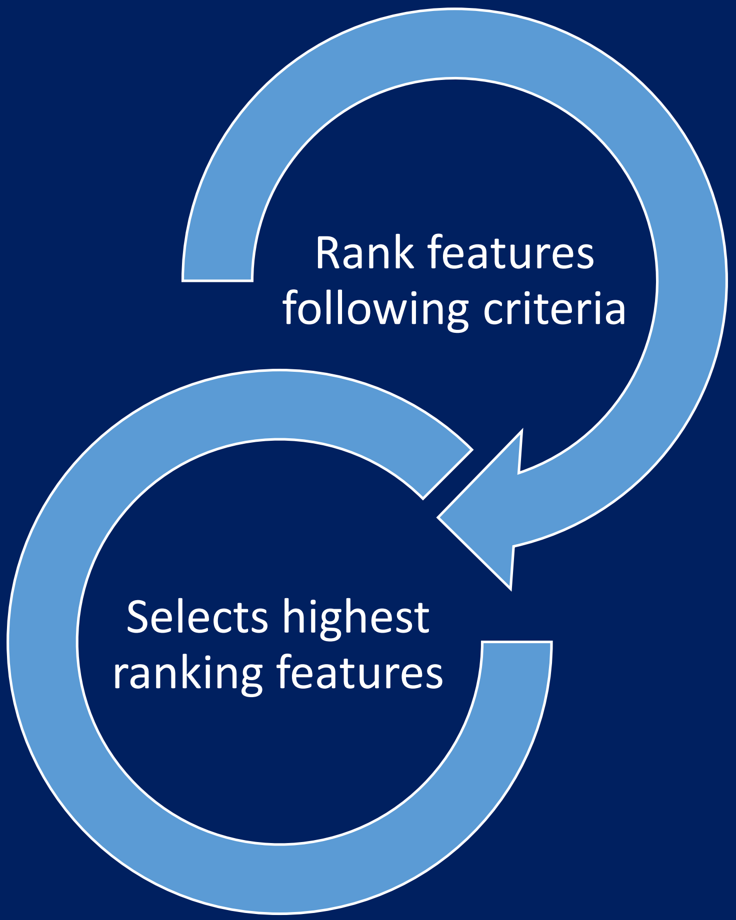


Filter methods

- Independent of ML algorithm
- Based only on variable characteristics

Pros	Cons
Quick feature removal	Does not capture redundancy
Model agnostic	Does not capture feature interaction
Fast computation	Poor model performance

Filter methods



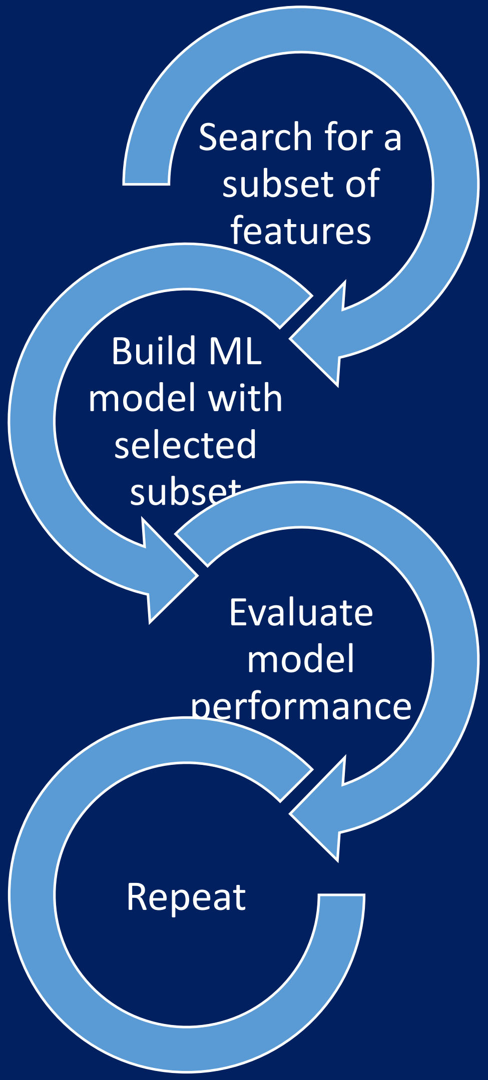
- Chi-square | Fisher Score
- Univariate parametric tests (anova)
- Mutual information
- Variance

Wrapper methods

- Considers ML algorithm
- Evaluates subsets of features

Pros	Cons
Considers feature interaction	Not model agnostic
Best performance	Computation expensive
Best feature subset for a given algorithm	Often impracticable

Wrapper methods



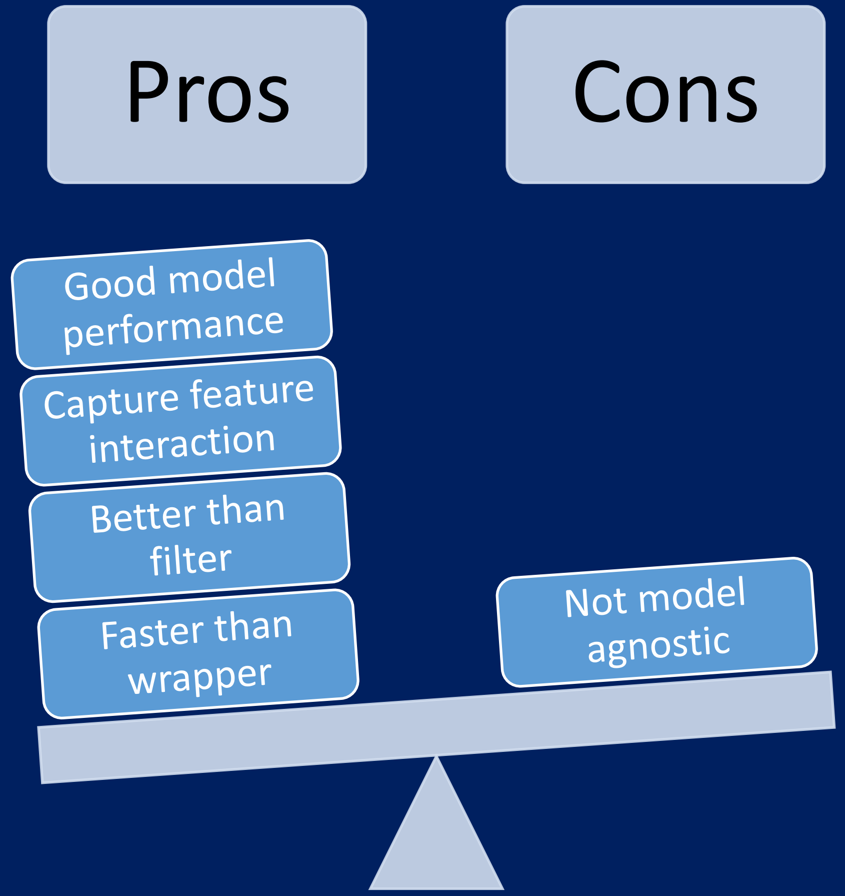
Forward feature selection
- Adds 1 feature at a time

Backward feature elimination
- Removes 1 feature at a time

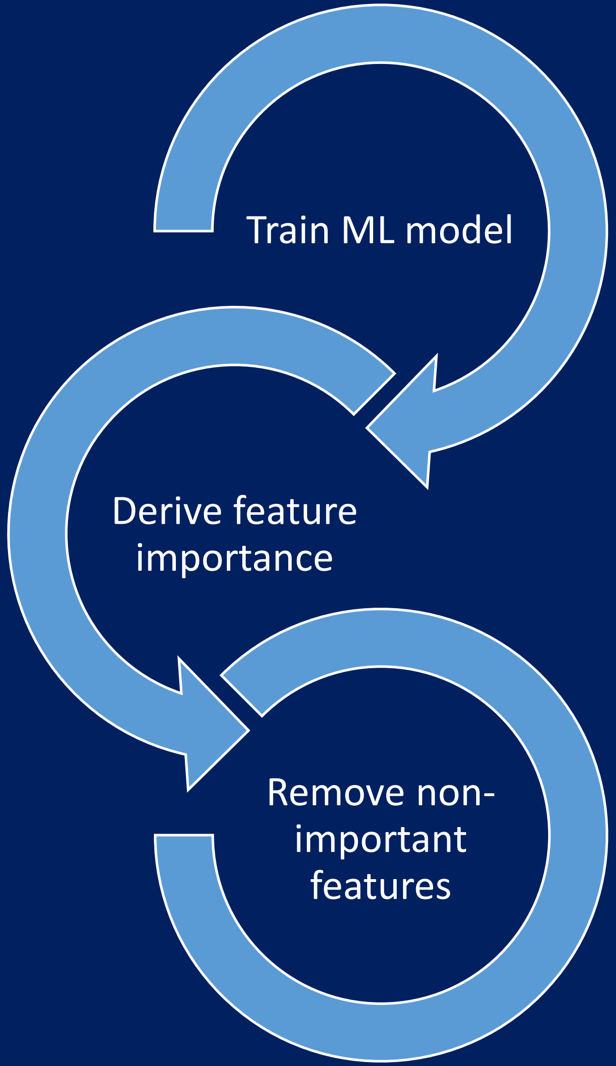
Exhaustive feature search
- Searches across all possible feature combinations

Embedded methods

Feature selection during training of ML algorithm



Embedded methods



- LASSO
- Tree derived feature importance
- Regression coefficients

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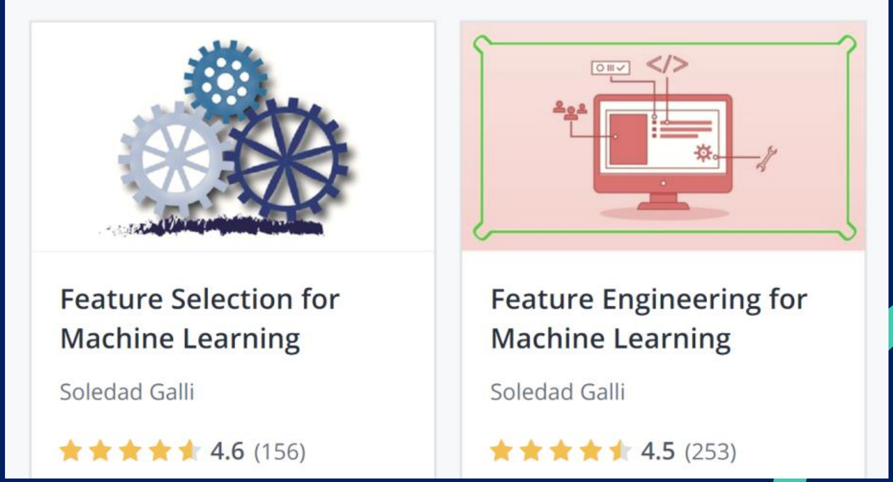
Knowledge Resources



Udemy.com, includes code

The 2009 Knowledge Discovery in Data Competition (KDD Cup 2009)
Challenges in Machine Learning, Volume 3

Gideon Dror, Marc Boullé, Isabelle Guyon,
Vincent Lemaire, and David Vogel, editors

Summary of learnings from the winners

Feature Engineering + Selection

scikit learn

Feature Engine

Python package for feature engineering
Work in progress

MLXTEND