Feature Engineering and Selection for Machine Learning

Soledad Galli, PhD

CorrelAid meetup

Berlin, 30th November 2019

Intro to the speaker

Soledad Galli, PhD

Lead Data Scientist

Finance

- Credit Risk
- Fraud Prevention

Insurance

- Fraud Prevention
- Motor Claim Liability
- Car repair / scrapping

Author, instructor

- Online Courses
- Tech Book
- Articles, talks, open-source

Machine Learning in Finance and Insurance

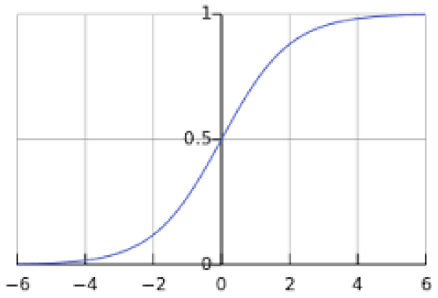
Credit Risk

Marketing

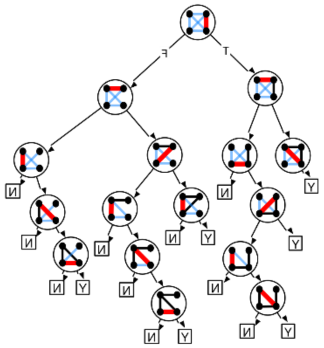
Pricing

Machine Learning Pipeline

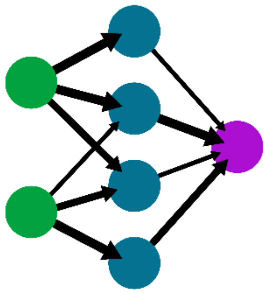
Data Sources



Linear Models
Logistic Regression
MARS



Tree Models
Random Forests
Gradient Boosted Trees



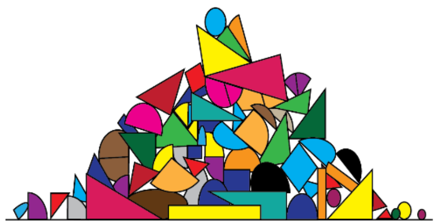
Neural Networks

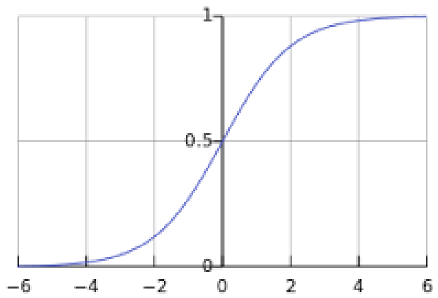
Average Probability

Continuous Output

Machine Learning Pipeline

Data Sources





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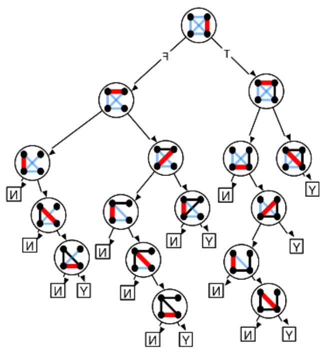
Logistic Regression
MARS



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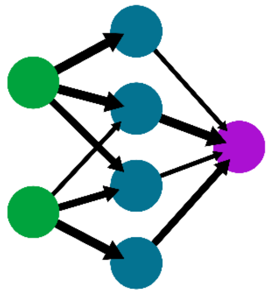

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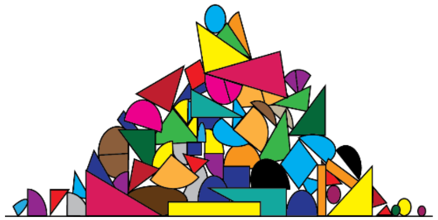
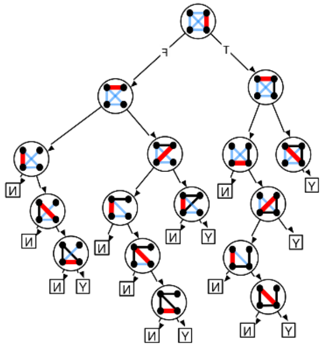
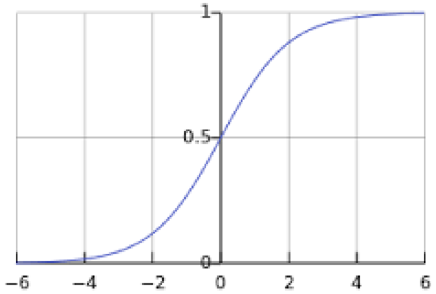


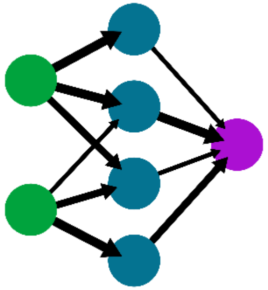
Feature Engineering

+

Feature Selection







Average Probability

Continuous Output

Data Preparation 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

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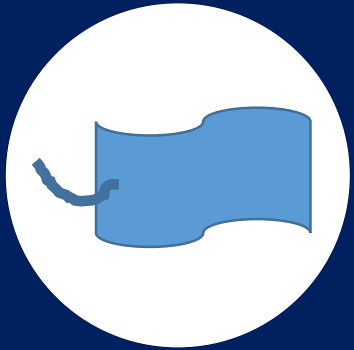
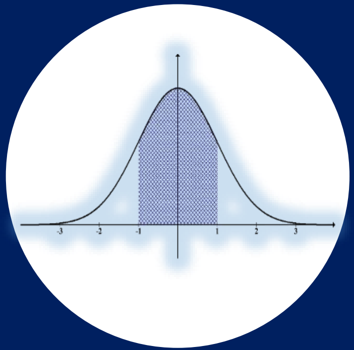
Problems in Variables

Missing data
Missing values within a variable



Labels
Strings in categorical variables



Distribution
Normal vs skewed
Scale / magnitude

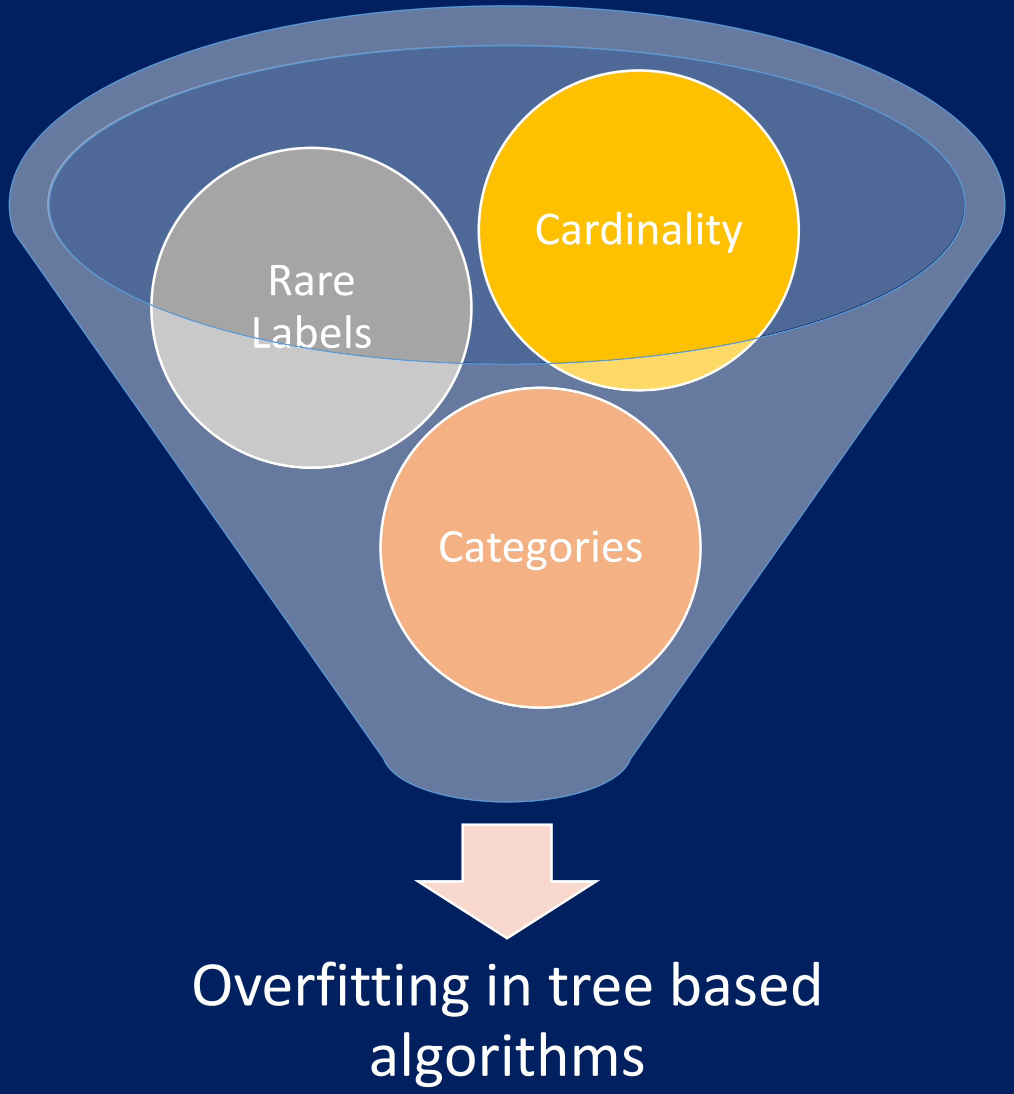
Outliers
Unusual or unexpected values

Missing Data

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

Labels in categorical variables

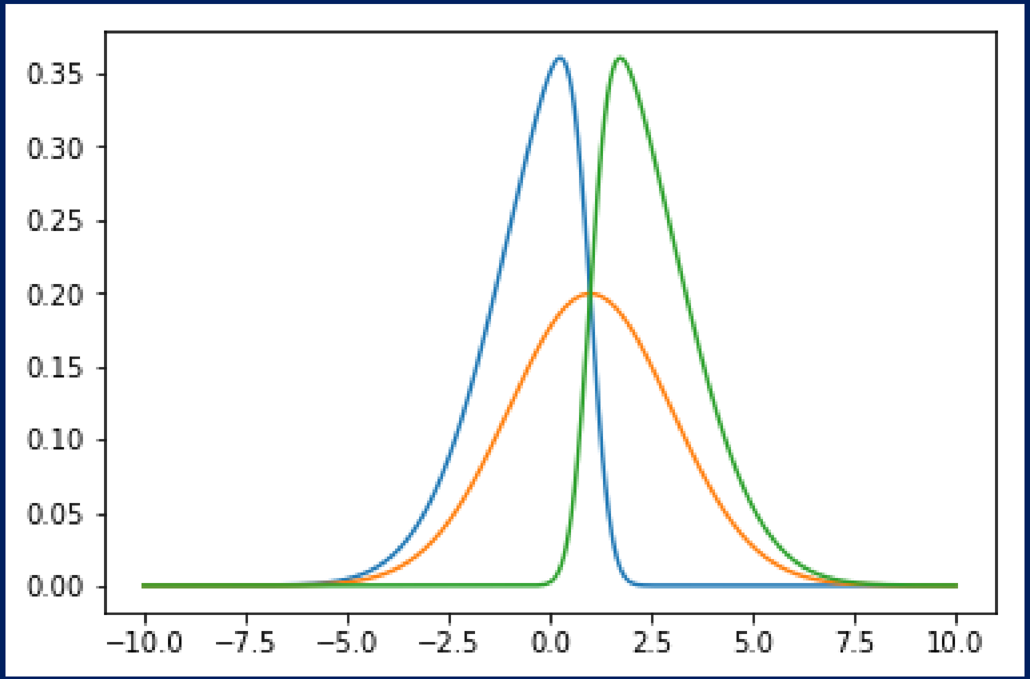
- Cardinality: high number of labels
- Rare Labels: infrequent categories
- Categories: strings
    - Scikit-learn



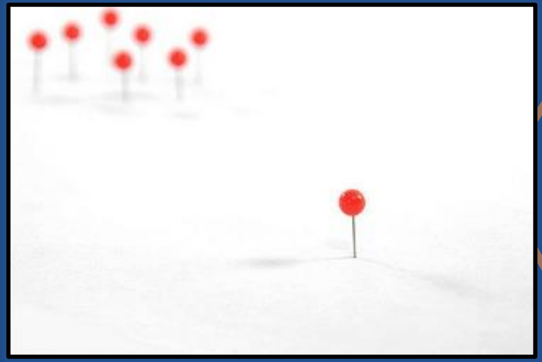
Distributions

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

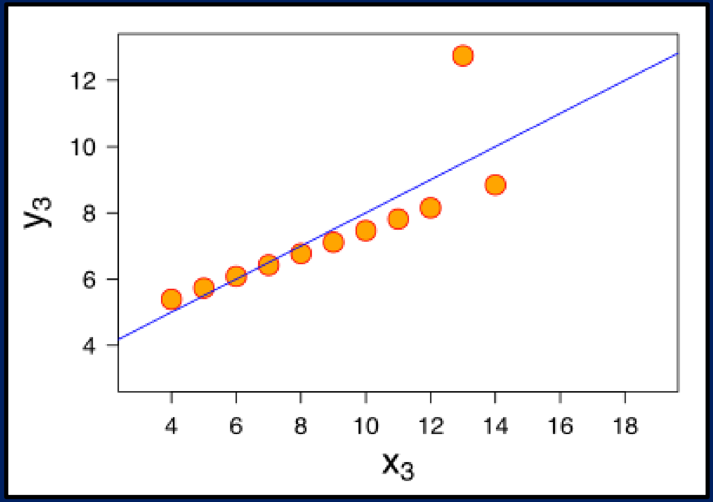
Gaussian vs Skewed



Outliers



Linear models

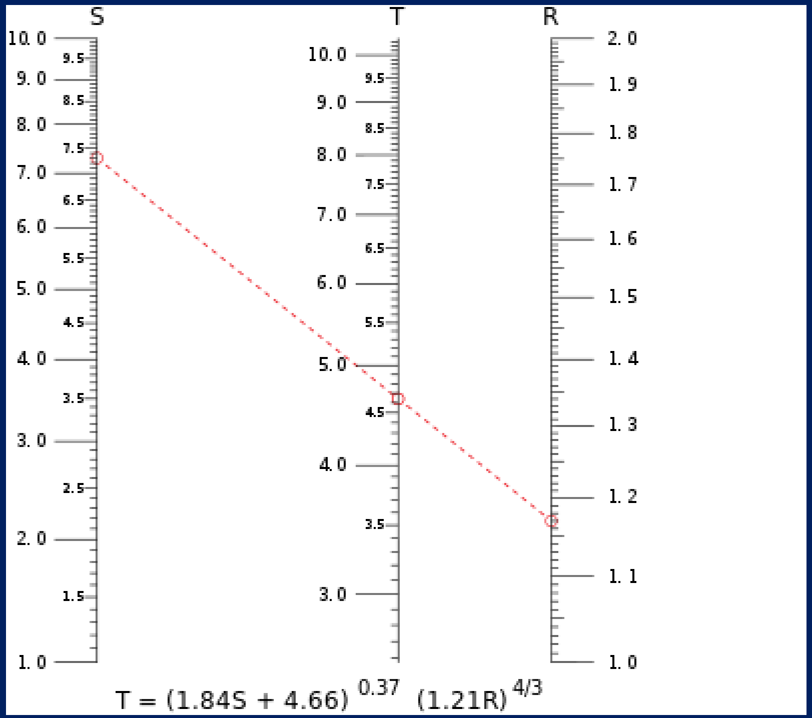


Adaboost

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

Complete case analysis

- May remove a big chunk of dataset

Mean / Median imputation

- Alters distribution

Random sample

- Element of randomness

Arbitrary number

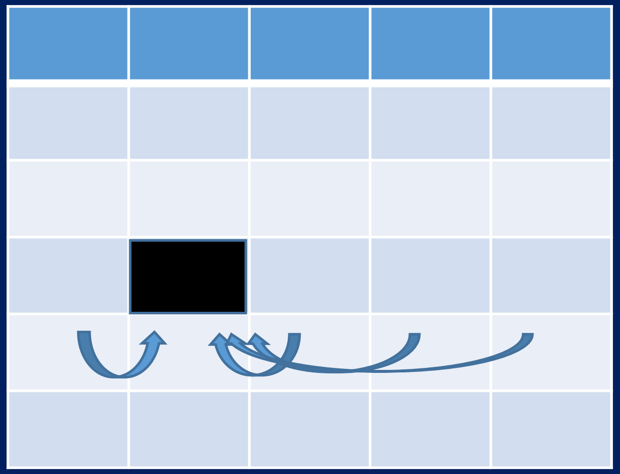
- Alters distribution

End of distribution

Binary NA indicator

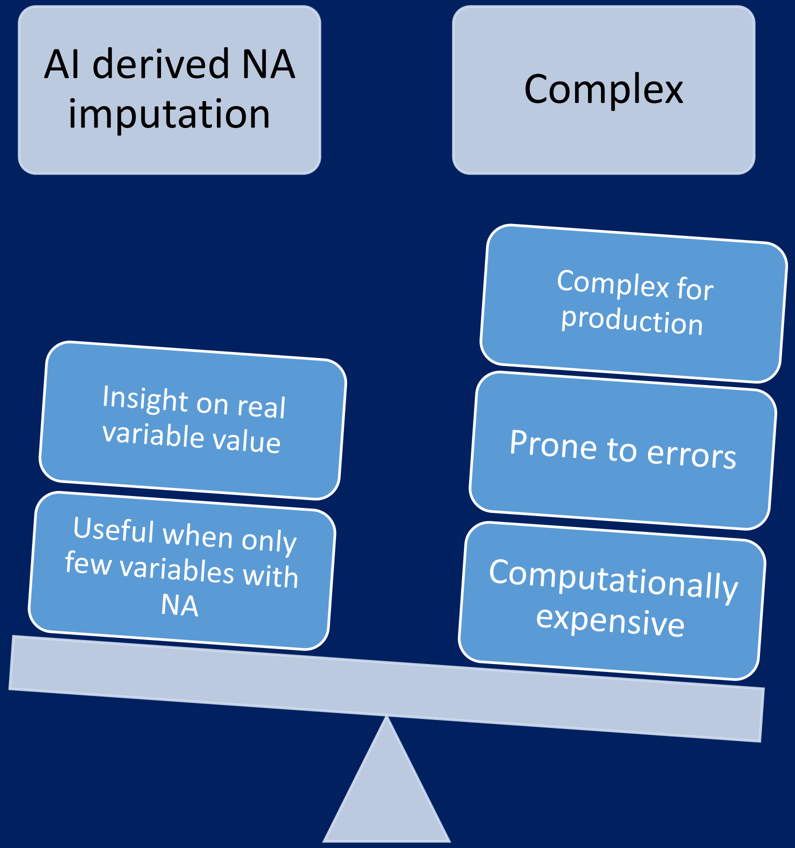
- Still need to fill in the NA

More on Missing Data Imputation

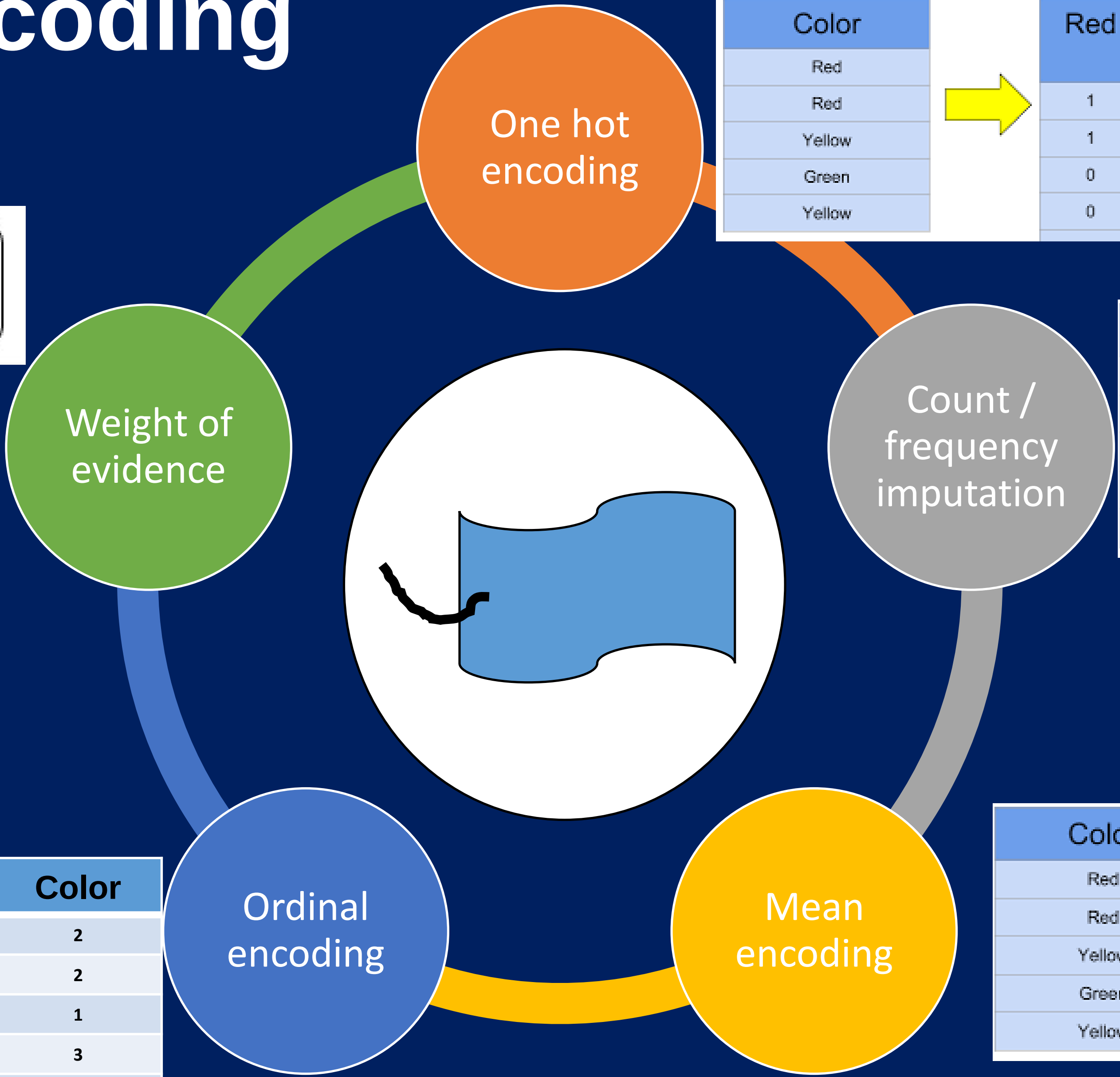


Use neighbouring variables to predict the missing value

- 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

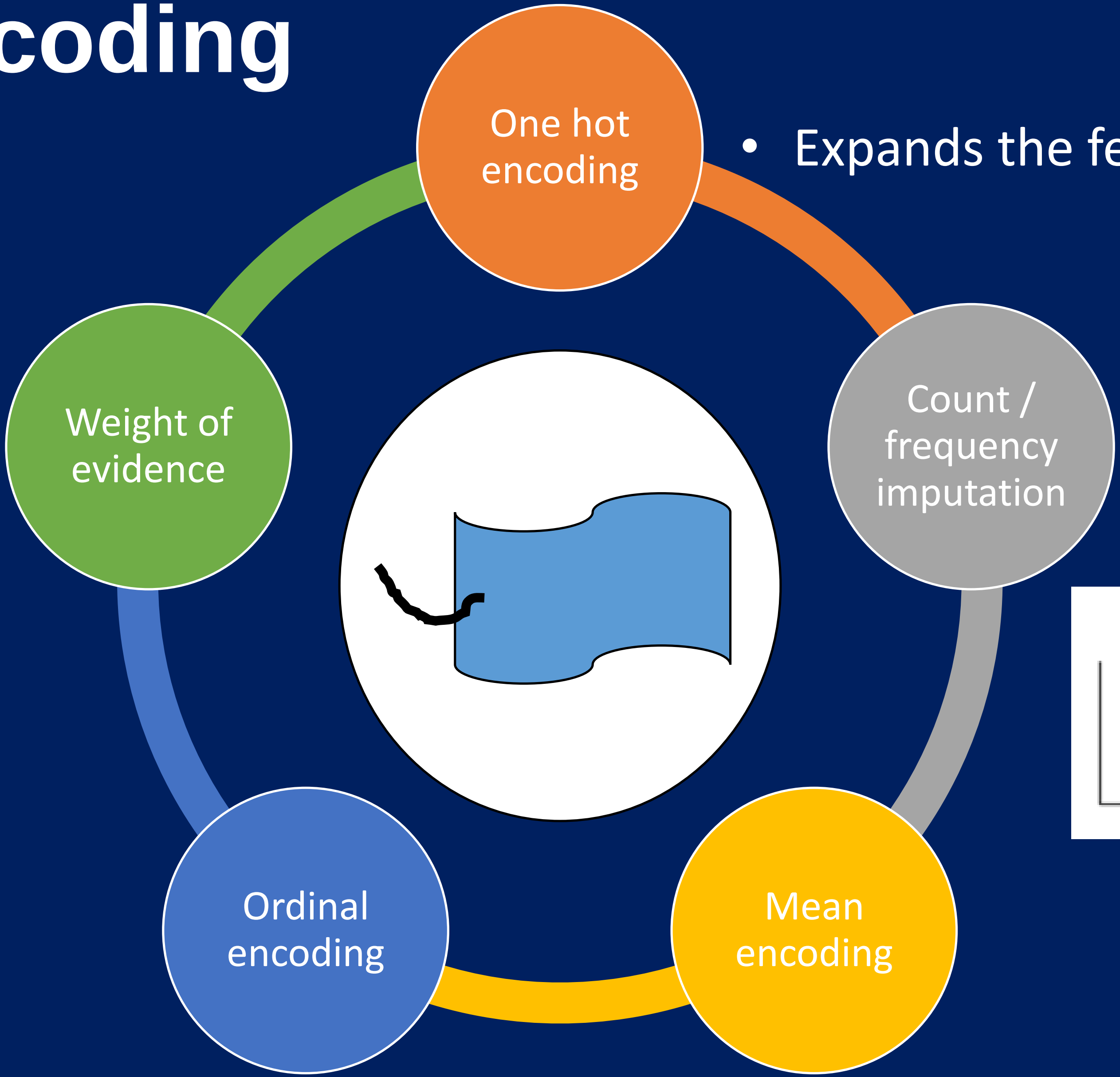
Color
Red
Red
Yellow
Green
Yellow

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

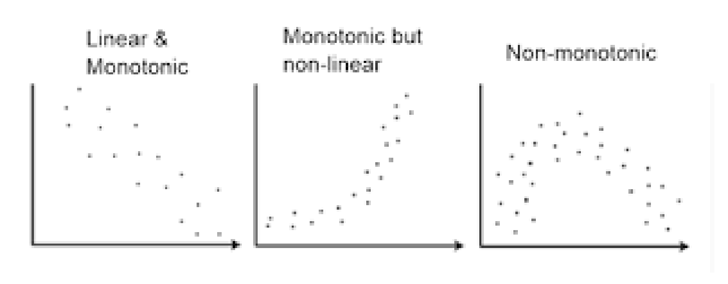
Color
Red
Red
Yellow
Green
Yellow

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

Label Encoding



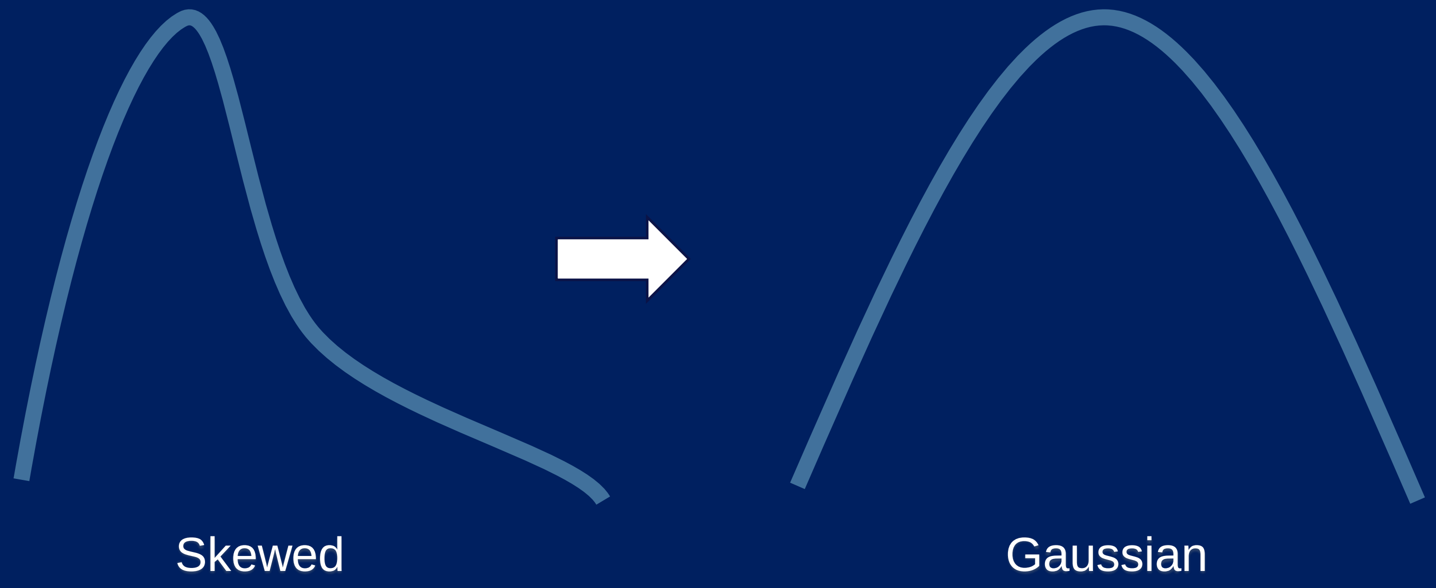
- Expands the feature space
- No monotonic relationship



- Prone to overfitting
- Account for zero values as it uses logarithm

Rare Labels

Distribution: Gaussian Transformation



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
- Yeo-Johnson

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
- KBins and Decision Trees

Outliers

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

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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

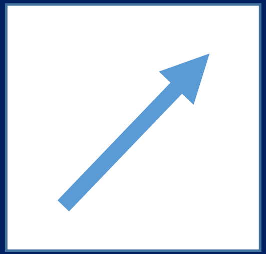
Only 1 value per variable

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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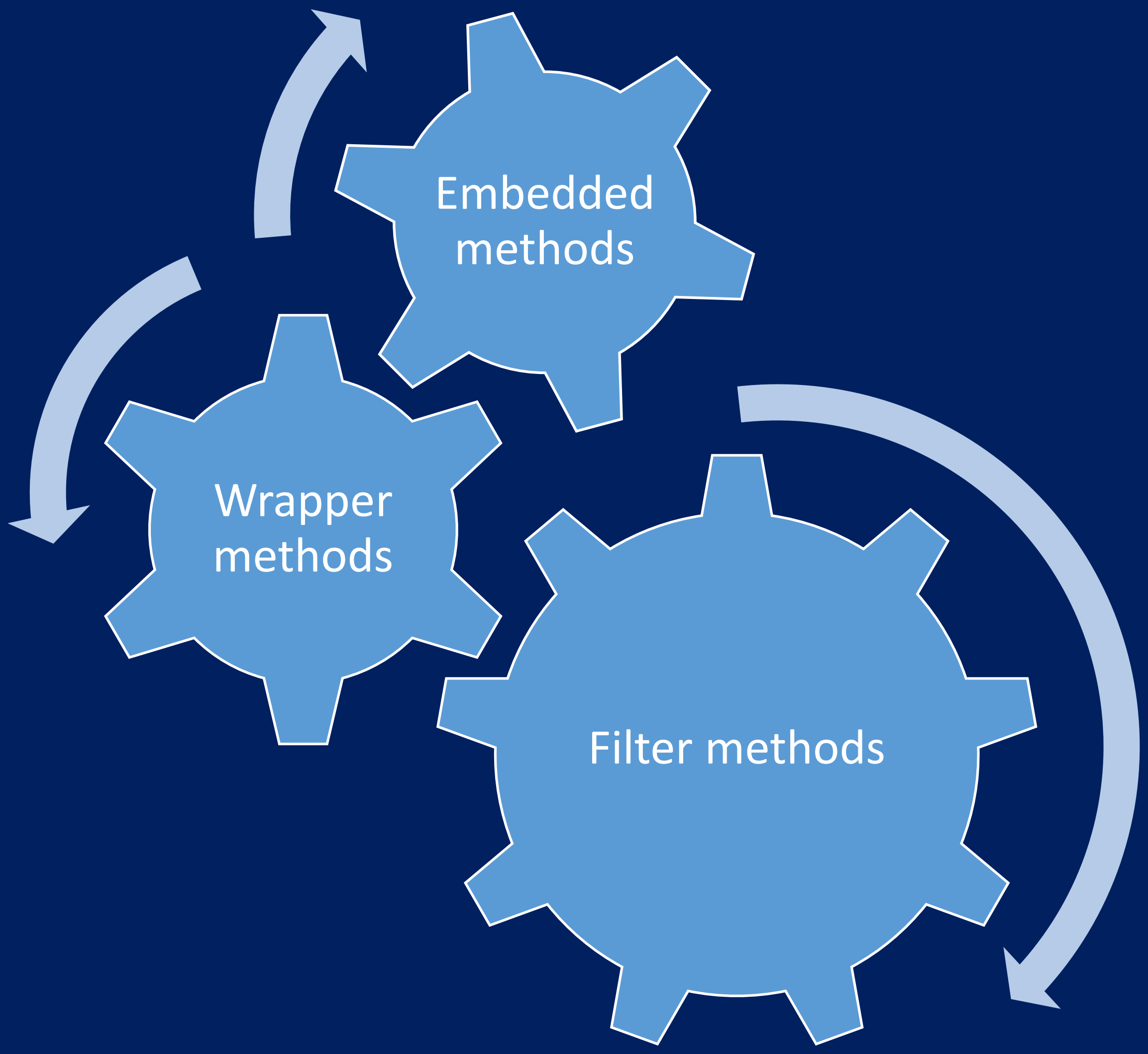
Feature Selection Methods

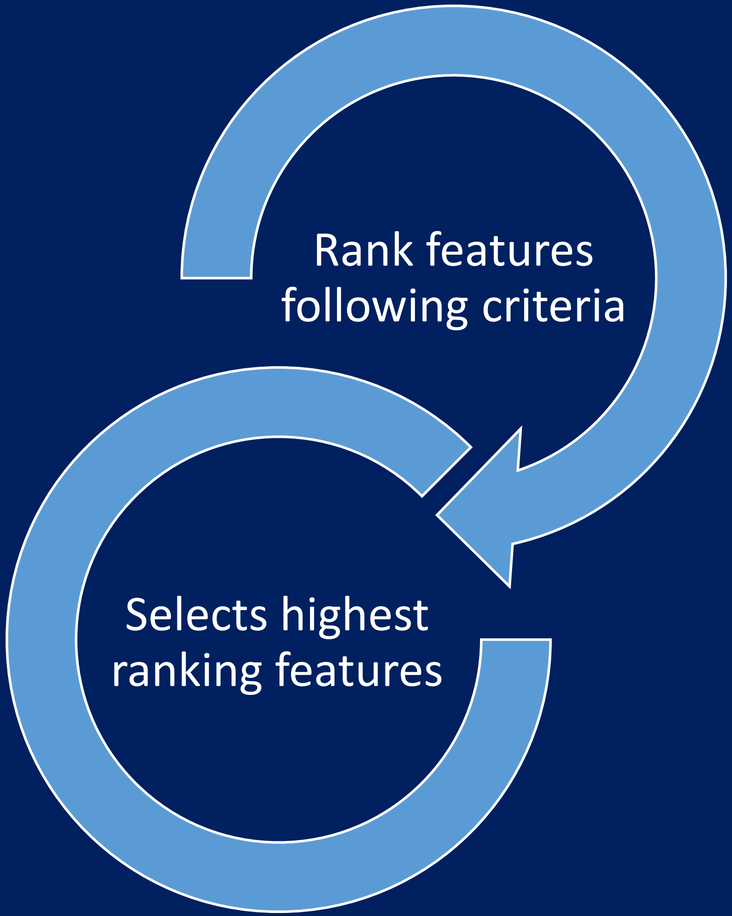


Filter methods

- Independent of ML algorithm
- Based only on variable characteristics

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

Filter methods



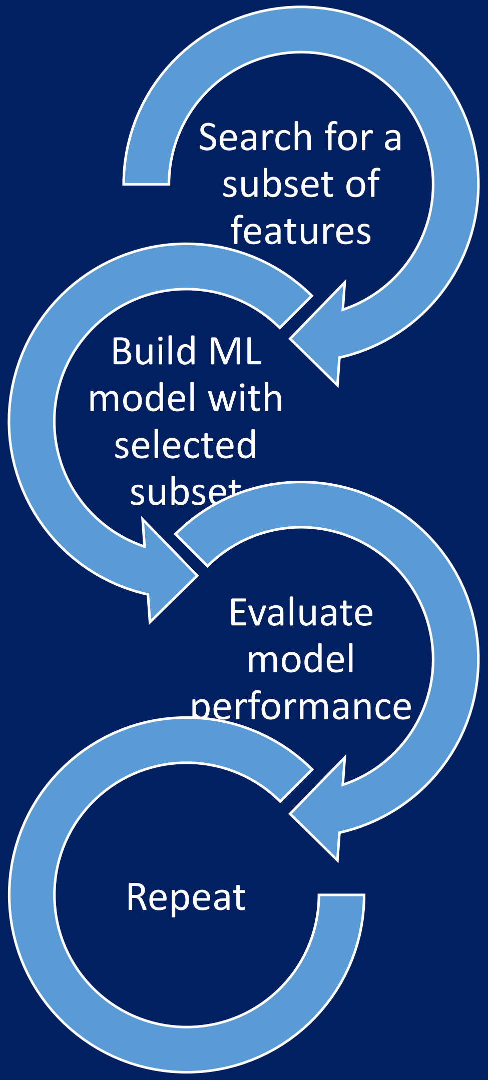
- Chi-square | Fisher Score
- Univariate parametric tests (anova)
- Mutual information
- Variance

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



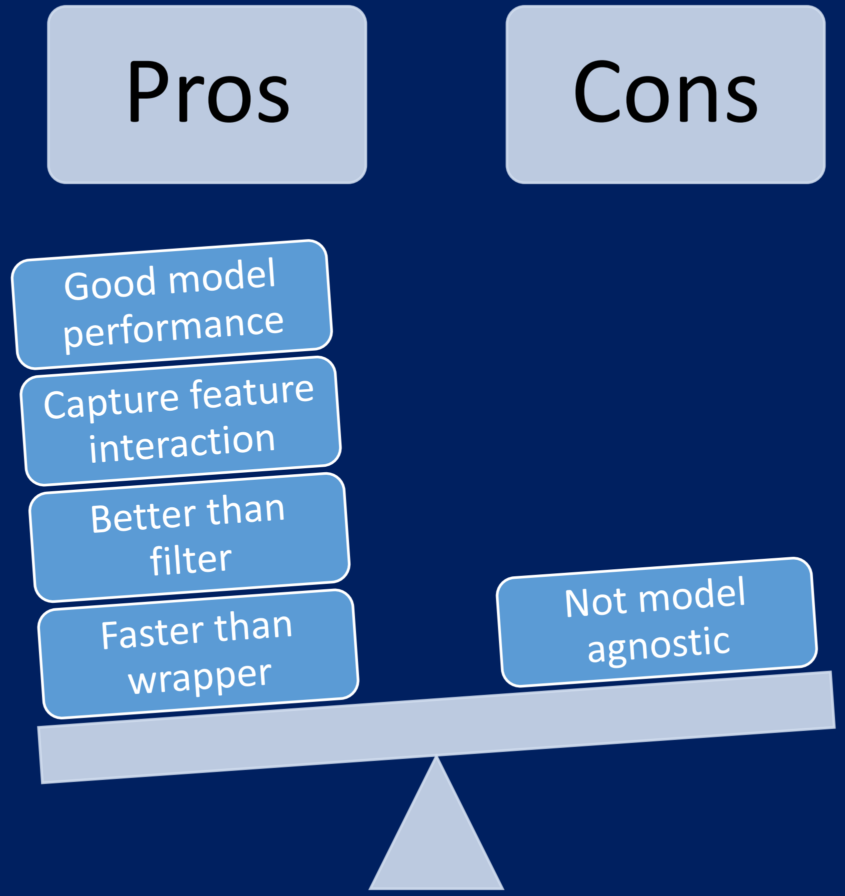
Forward feature selection
- Adds 1 feature at a time

Backward feature elimination
- Removes 1 feature at a time

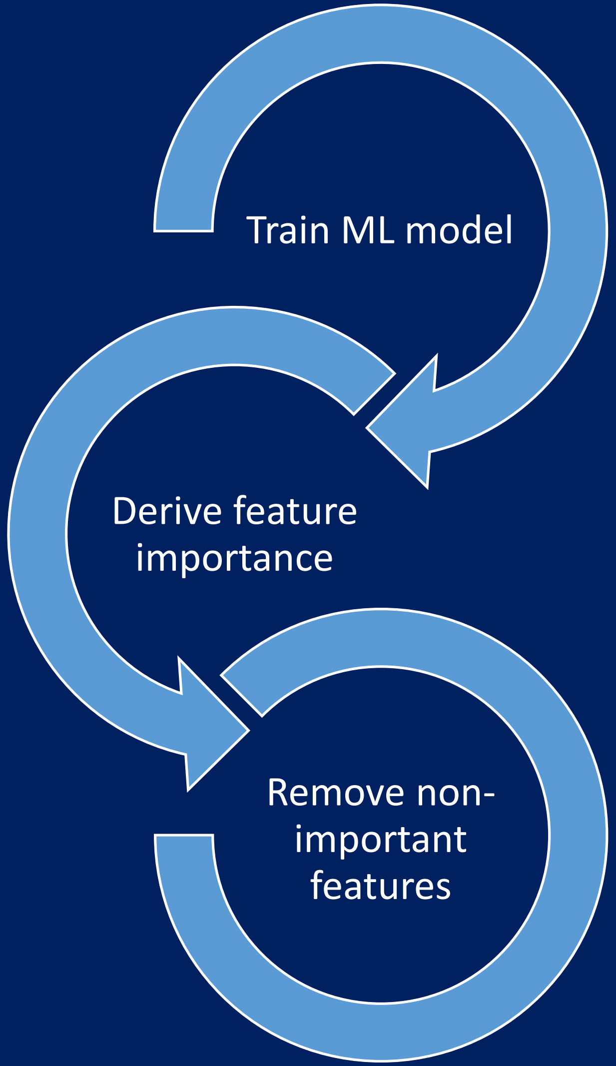
Exhaustive feature search
- Searches across all possible feature combinations

Embedded methods

Feature selection during training of ML algorithm



Embedded methods



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How can we engineer features?

scikit learn

+ Fast computation
+ Cross-validation

- Little versatility to select features

Category Encoders

+ Alternative encoding procedures

- Bad for interpretability

Feature-Engine

+ More engineering steps
+ Can apply to subset of features

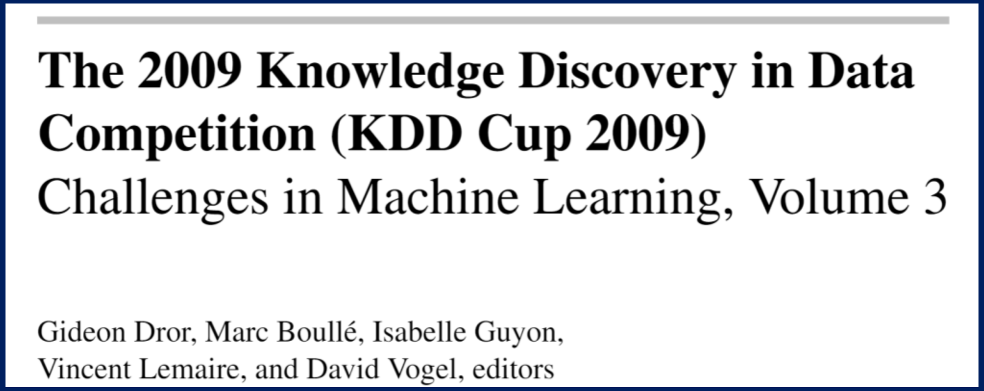
- Need to decide step a priori

How can we select features?

+ Filter and embedded methods

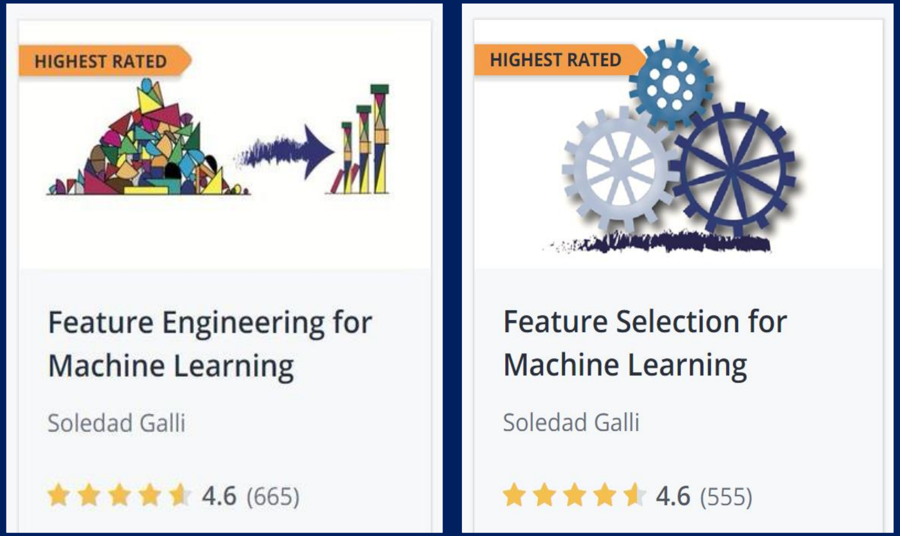
+ Wrapper methods
- Slow

How can we learn more?


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



Udemy.com, includes code

Documentation

How to Win a Data Science Competition: Learn from Top Kagglers