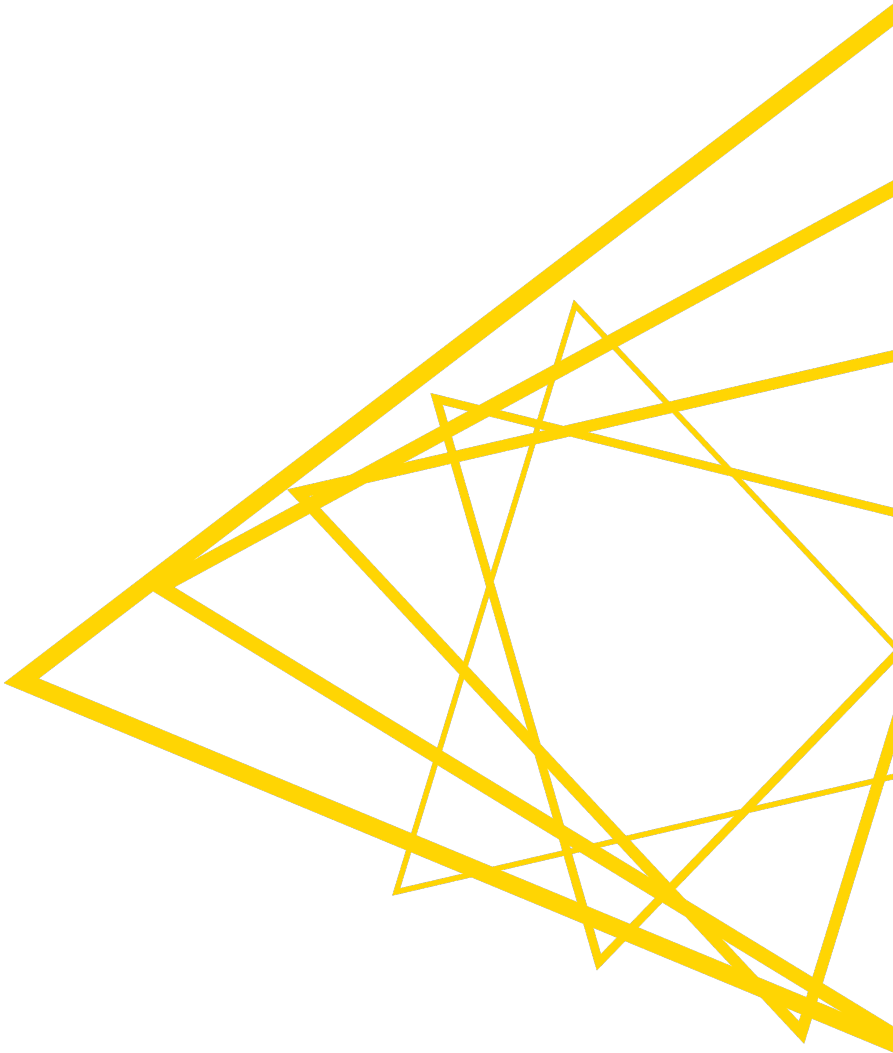
Open for Innovation
KNIME

[L4-ML] Introduction to Machine Learning Algorithms

KNIME AG



Structure of the Course

Session	Topic
Session 1	Introduction & Decision Tree Algorithm
Session 2	Regression Models, Ensemble Models, & Logistic Regression
Session 3	Neural Networks & Recommendation Engines
Session 4	Clustering & Data Preparation
Session 5	Last Exercise and Q&A

- Structure of each session
- Discussion of past exercises (10 minutes)
- Course (60 minutes)
- Introduction of next exercises (5 minutes)

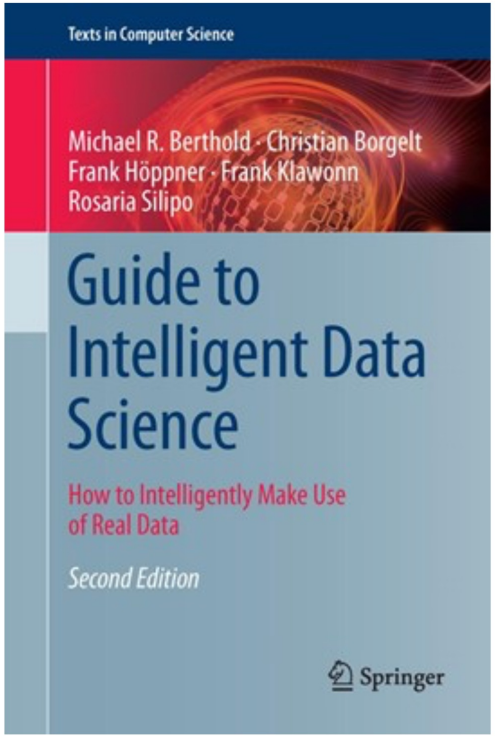
Material

- Michael Berthold, Christian Borgelt, Frank Höppner, Frank Klawonn:
  Guide to Intelligent Data Science
  Springer, 2010.

- Tom Mitchell:
  Machine Learning
  McGraw Hill, 1997.

- David Hand, Heikki Mannila, Padhraic Smyth:
  Principles of Data Mining
  MIT Press, 2001.

- Michael Berthold, David Hand (eds):
  Intelligent Data Analysis, An Introduction
  (2nd Edition) Springer Verlag, 2003.



What is Data Science?

[Wikipedia quoting Dhar 13, Leek 13]

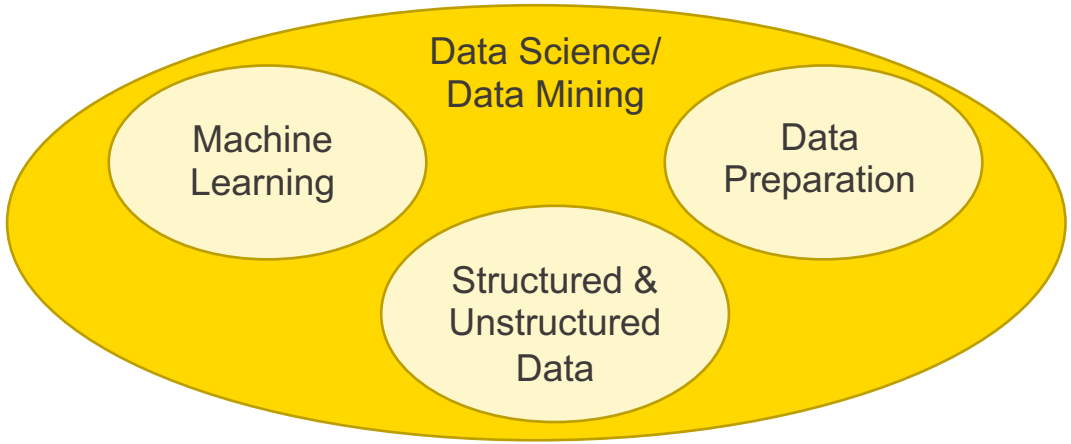
Data science is a multi-disciplinary field that uses scientific methods, processes, algorithms and systems to **extract knowledge and insights** from structured and unstructured data.

[Fayyad, Piatetsky-Shapiro & Smyth 96]

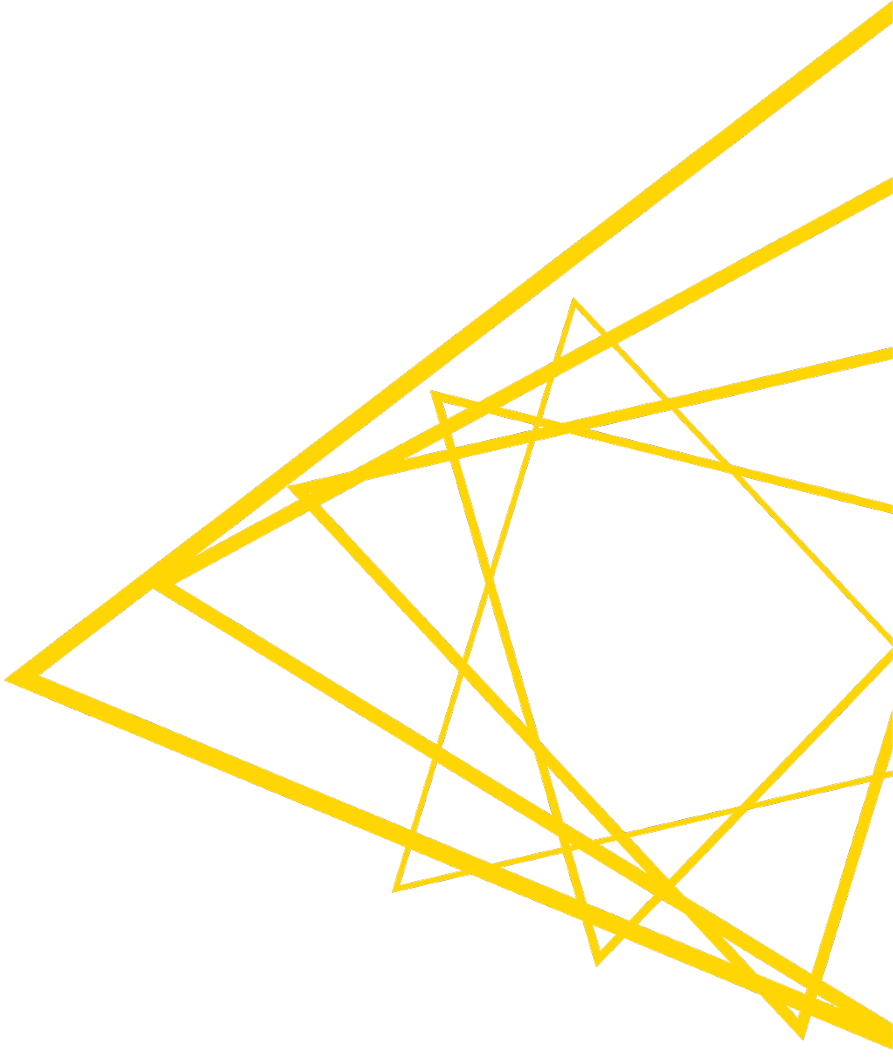
Knowledge discovery in databases (*KDD*) is the process of (semi-)automatic **extraction of knowledge** from databases which is *valid*, *previously unknown*, and *potentially useful.*

Some Clarity about Words

- *(semi)-automatic*: no manual analysis, though some user interaction required
- *valid*: in the statistical sense
- *previously unknown*: not explicit, no „common sense knowledge“
- *potentially useful*: for a given application
- *structured data*: numbers
- *unstructured data*: everything else (images, texts, networks, chem. compounds, …)



Use Case Collection



Churn Prediction

CRM System
Data about your customer

- Demographics
- Behavior
- Revenues

Model

- Churn Prediction
- Upselling Likelihood
- Product Propensity /NBO
- Campaign Management
- Customer Segmentation
- …

Customer Segmentation

CRM System
Data about your customer

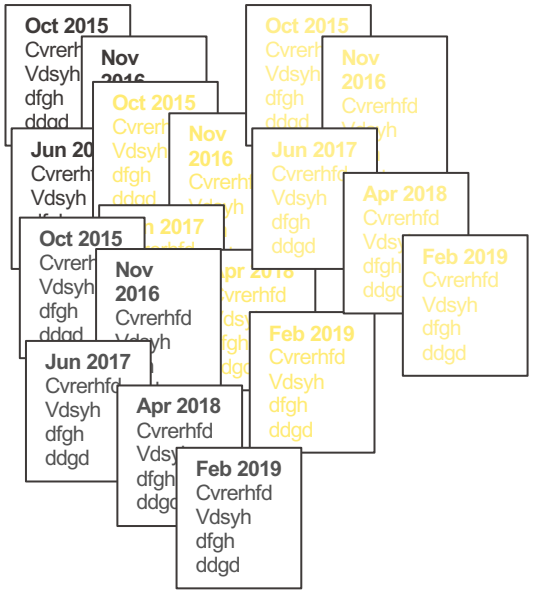
- Demographics
- Behavior
- Revenues

Model

- Churn Prediction
- Upselling Likelihood
- Product Propensity /NBO
- Campaign Management
- Customer Segmentation
- …

Risk Assessment

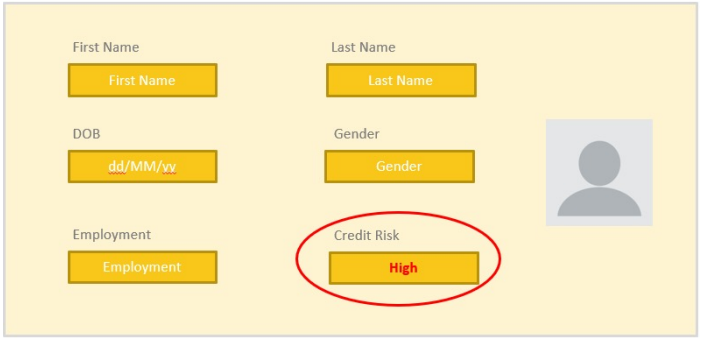
Customer History



Model

Risk Prognosis

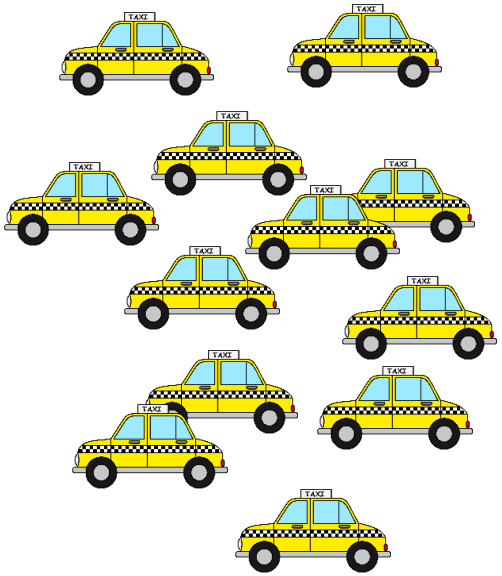
- High Risk
- Low Risk
- High Risk
- Very High Risk
- Very Low Risk
- Medium Risk
- …



Demand Prediction

- How many taxis do I need in NYC on Wednesday at noon?

Model



Recommendation Engines / Market Basket Analysis

Model

Recommendation

IF  ➔ 

Fraud Detection

Transactions

- Trx 1
- Trx 2
- Trx 3
- Trx 4
- Trx 5
- Trx 6
- …

Model

Sentiment Analysis

Samsung

Samsung Galaxy S7 Edge G935A 32GB Unlocked - Gold Platinum

★★★★☆ 125 customer reviews | 606 answered questions

★★★★★ **Beautiful phone from a wonderful seller!**

By on May 29, 2017

Color: Gold | **Verified Purchase**

This practically new beautiful phone well exceeded my expectations!

★☆☆☆☆ **One Star**

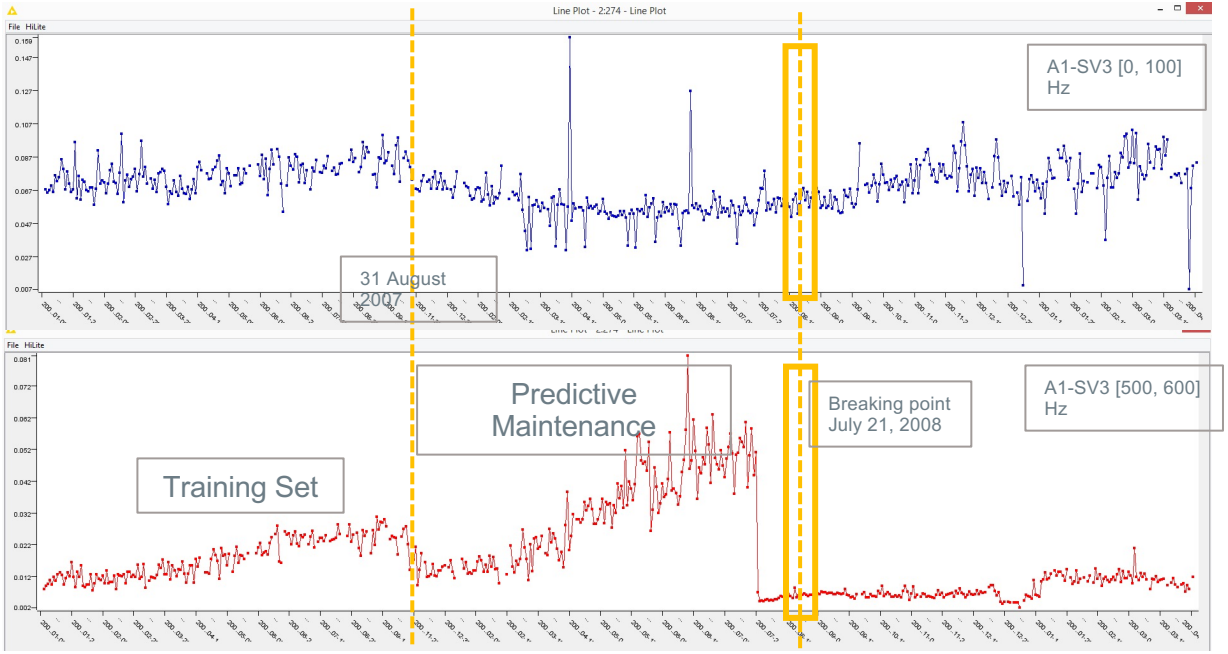
By on August 3, 2016

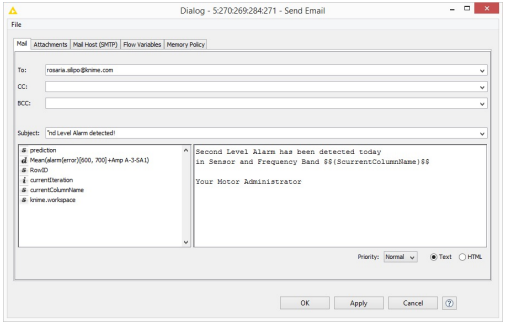
Color: Black Onyx | **Verified Purchase**

Very bad experience

Anomaly Detection

Predicting mechanical failure as late as possible but before it happens





via REST

Only some Spectral Time Series shows the break down

Basic Concepts in Data Science

What is a Learning Algorithm?

- Input features
- Input attributes
- Independent variables

$$\boldsymbol{X} = (x_1, x_2, \ldots, xm)$$

Model

y

- Class
- Label
- Target
- Output feature/attribute
- Dependent variable

Model parameters

$$y = f(\boldsymbol{\beta}, \boldsymbol{X}) \quad \text{with } \boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_m]$$

A learning algorithm adjusts (learns) the model parameters $\boldsymbol{\beta}$ throughout a number of iterations to maximize/minimize a likelihood/error function on y.

Algorithm Training / Learning

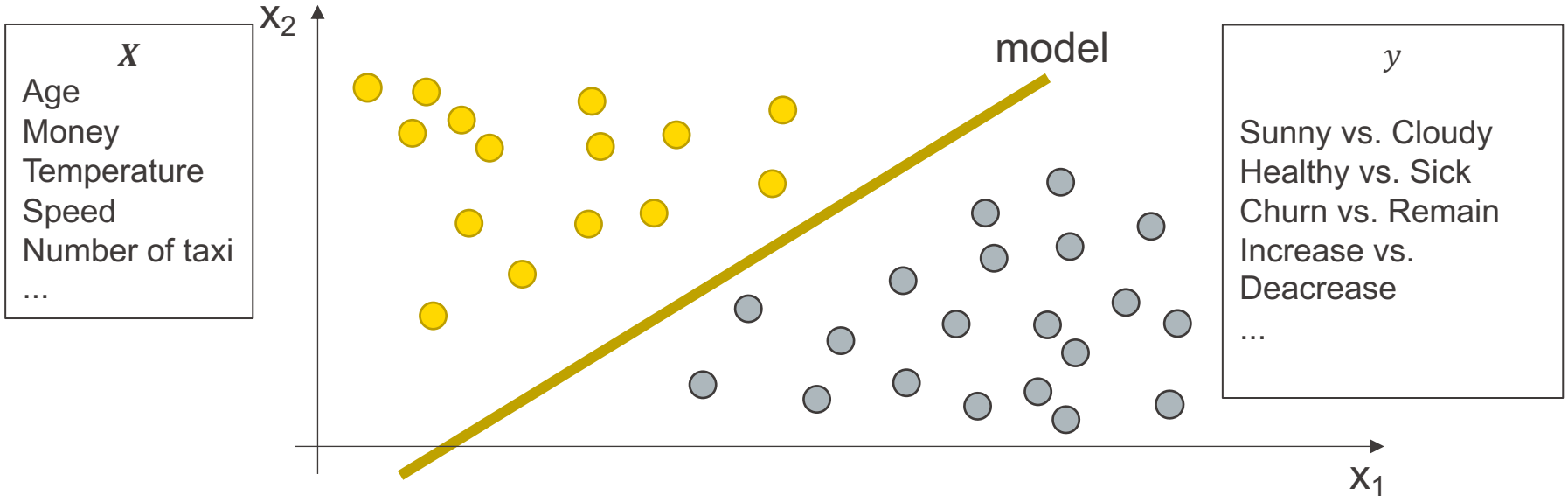
- The model ***learns*** / ***is trained*** during the ***learning / training*** phase to produce the right answer *y* (a.k.a., label)

- That is why ***machine learning*** ☺

- Many different algorithms for three ways of learning:
  - Supervised
  - Unsupervised
  - Semi-supervised

Supervised Learning

- $\boldsymbol{X} = (x_1, x_2)$ and $y = \{yellow, gray\}$
- A training set with many examples of $(\boldsymbol{X}, y)$
- The model learns on the examples of the training set to produce the right value of y for an input vector $\boldsymbol{X}$



Supervised Learning: Classification vs. Regression

- $\boldsymbol{X} = (x_1, x_2)$ and $y = \{label\ 1, \ldots, label\ n\}$ or $y \in \mathbb{R}$
- A training set with many examples of $(\boldsymbol{X}, y)$
- The model learns on the examples of the training set to produce the right value of y for an input vector $\boldsymbol{X}$

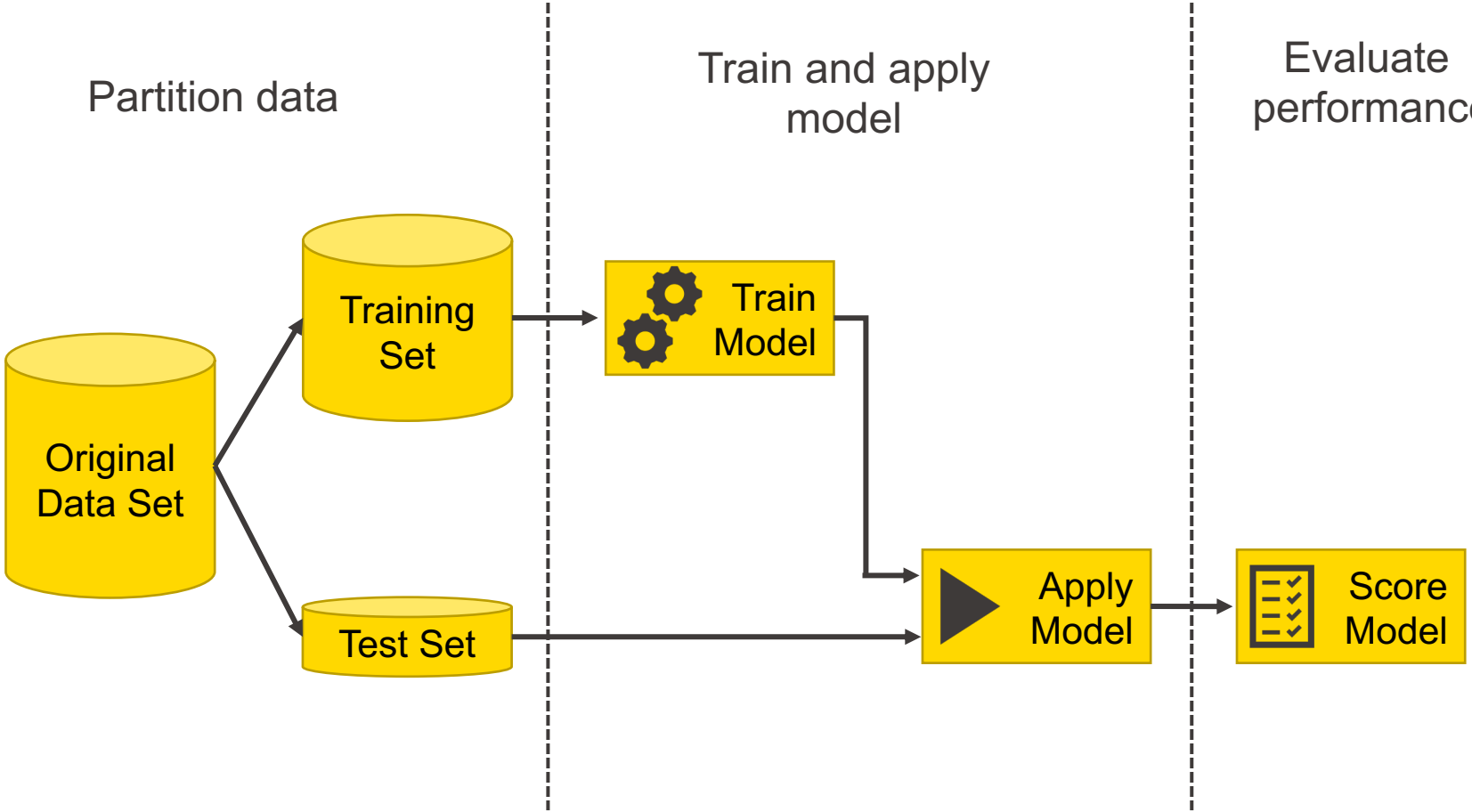
Classification

y = {yellow, gray}
y = {churn, no churn}
y = {increase, unchanged, decrease}
y = {blonde, gray, brown, red, black}
y = {job 1, job 2, ... , job n}

Numerical Predictions (Regression)

y = temperature
y = number of visitors
y = number of kW
y = price
y = number of hours

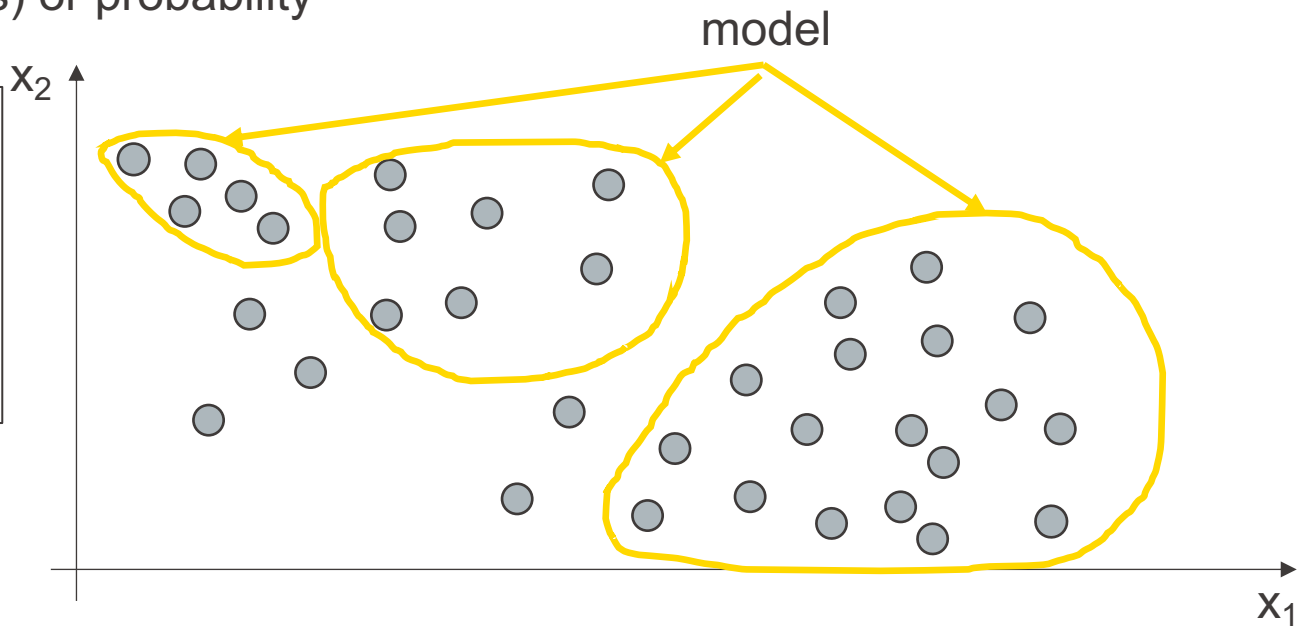
Process Overview for Supervised Learning



Unsupervised Learning

- $\boldsymbol{X} = (x_1, x_2)$ and ~~$y = \{yellow, gray\}$~~
- A training set with many examples of ($\boldsymbol{X}$, ~~y~~)
- The model learns to group the examples $\boldsymbol{X}$ of the training set based on similarity (closeness) or probability

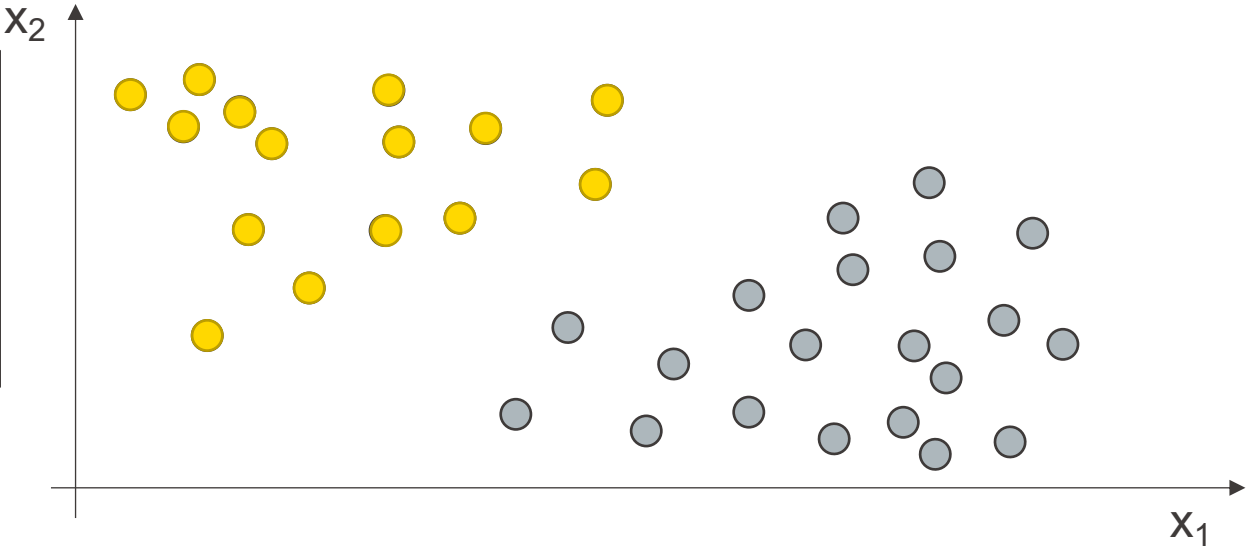
$\boldsymbol{X}$
Age
Money
Temperature
Speed
Number of taxi
...



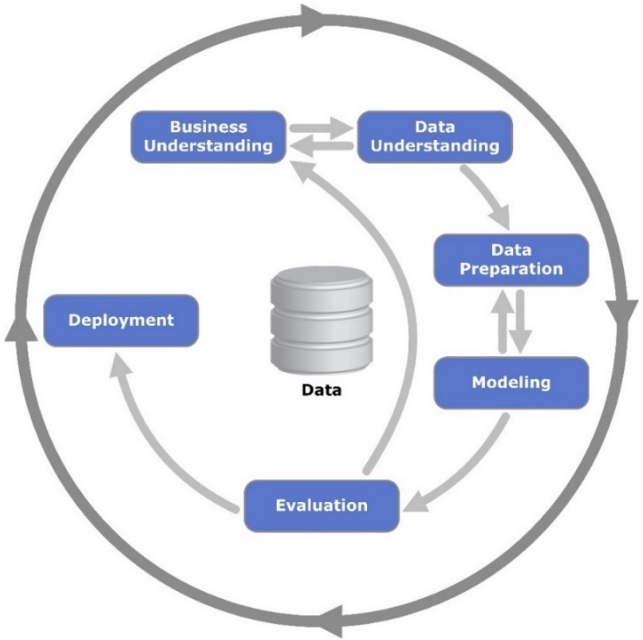
Semi-Supervised Learning

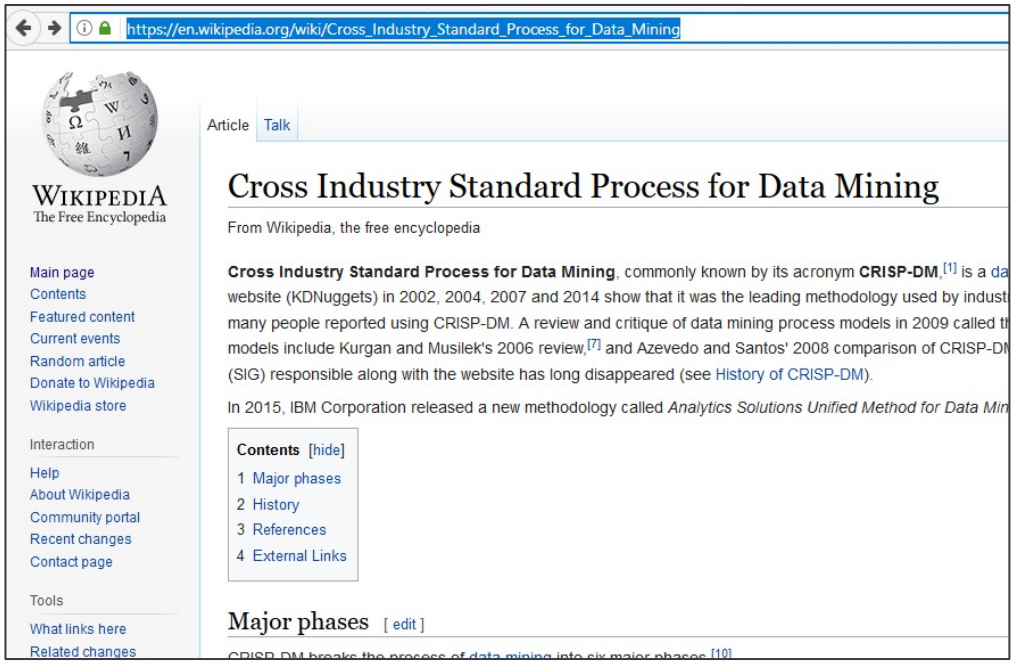
- $\boldsymbol{X} = (x_1, x_2)$ and $y = \{yellow, gray\}$
- A training set with many examples of ($\boldsymbol{X}$,~~y~~) and some samples $(\boldsymbol{X}, y)$
- The model labels the data in the training set using a modified unsupervised learning procedure

X
Age
Money
Temperature
Speed
Number of taxi
...



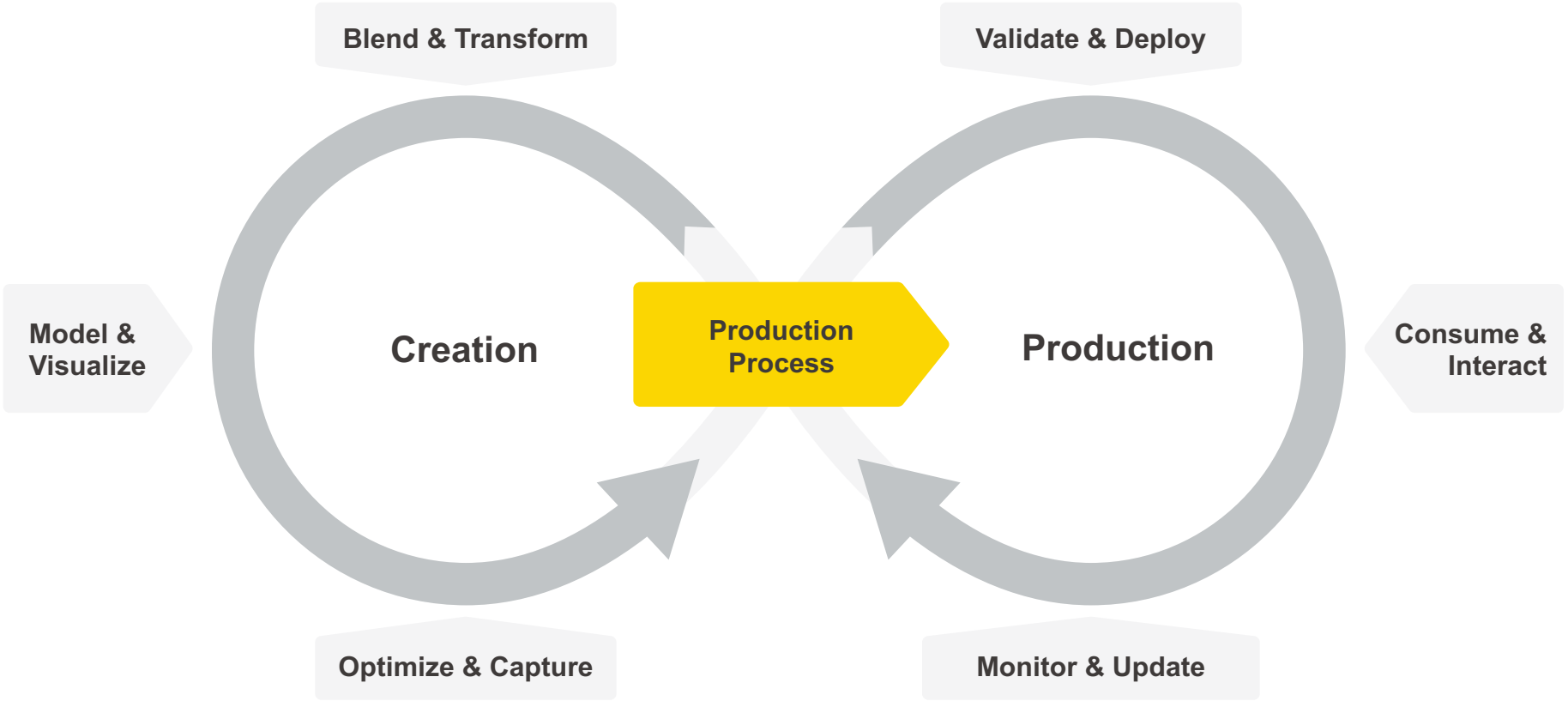
The CRISP-DM Cycle



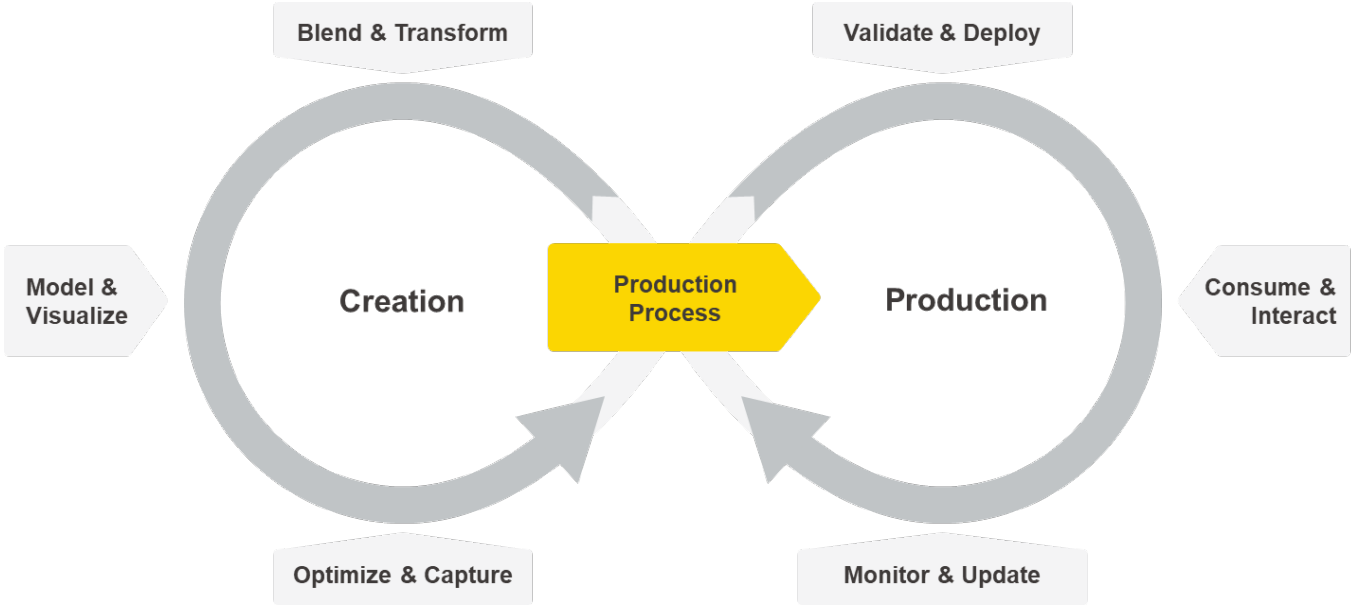


https://en.wikipedia.org/wiki/Cross_Industry_Standard_Process_for_Data_Mining

The Data Science Life Cycle



KNIME Software for the entire Data Science Life Cycle



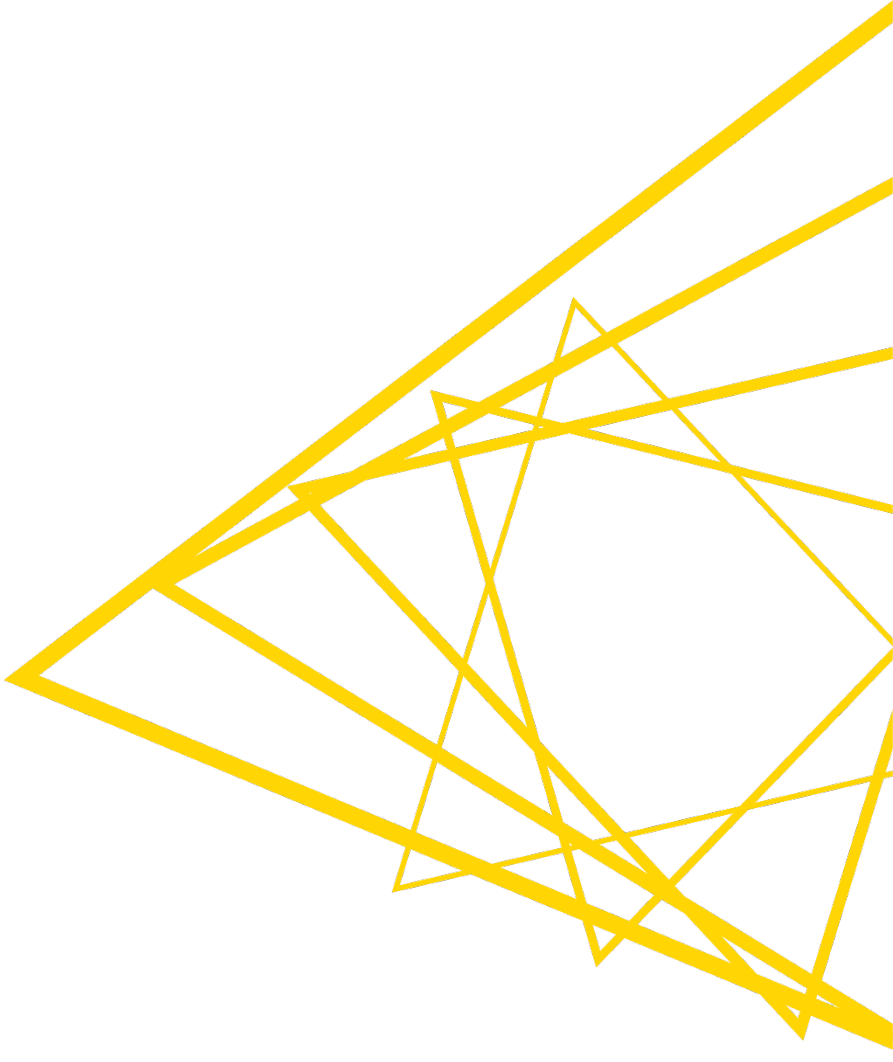
KNIME Analytics Platform

- KNIME Extensions
- KNIME Integrations
- Community Extensions
- Partner Extensions

KNIME Server

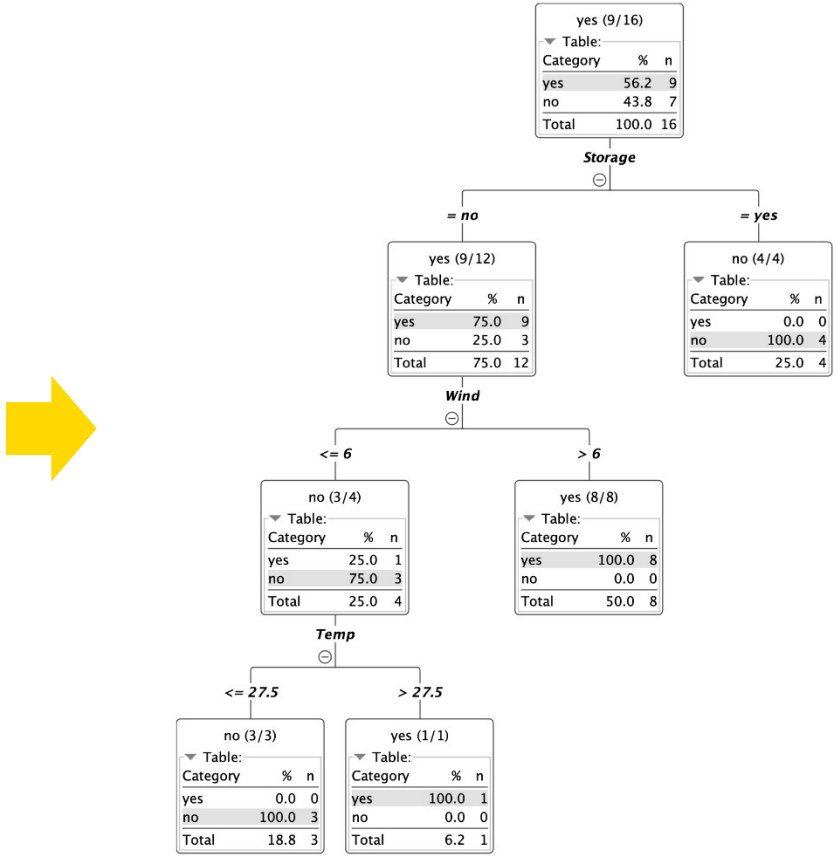
- Team Collaboration
- End User Applications
- API Services
- Managed Execution

Decision Tree Algorithm

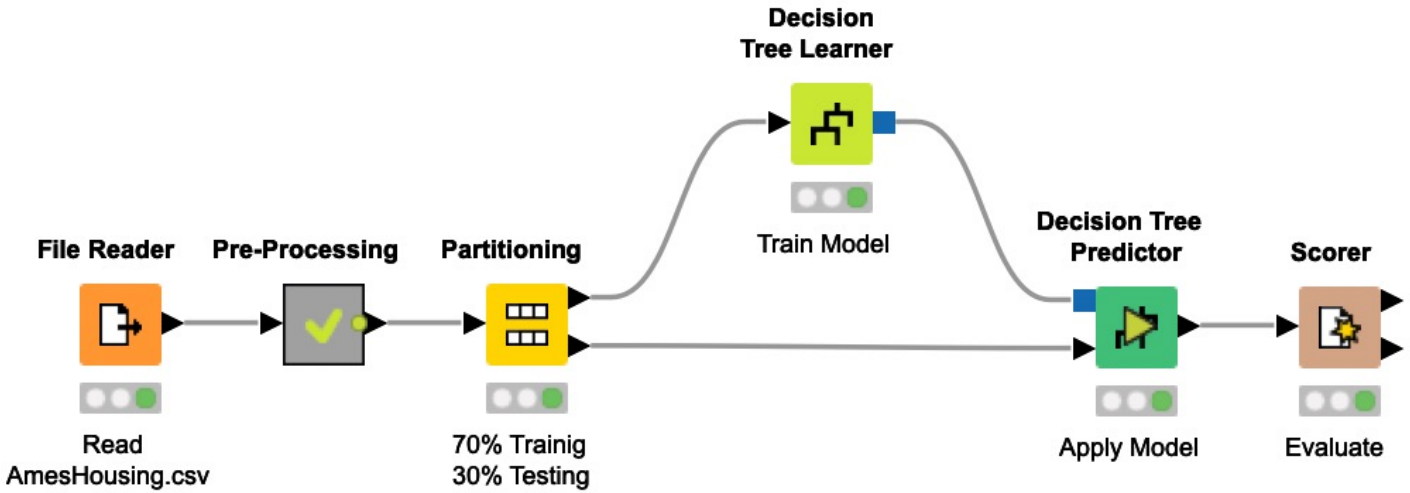


Goal: A Decision Tree

Outlook	Wind	Temp	(Winter) Storage	Sailing
sunny	3	30	no	yes
sunny	3	25	no	no
rain	12	15	no	yes
overcast	15	2	yes	no
rain	16	25	no	yes
sunny	14	18	no	yes
rain	3	5	yes	no
sunny	9	20	no	yes
overcast	14	5	yes	no
sunny	1	7	yes	no
rain	4	25	no	no
rain	14	24	no	yes
sunny	11	20	no	yes
sunny	2	18	no	no
overcast	8	22	no	yes
overcast	13	24	no	yes



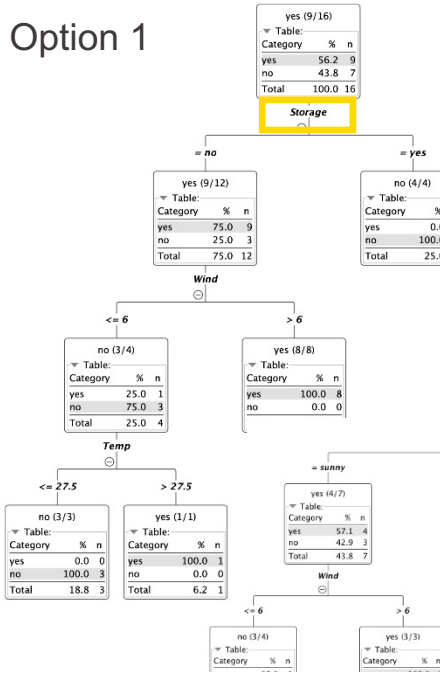
How can we Train a Decision Tree with KNIME Analytics Platform



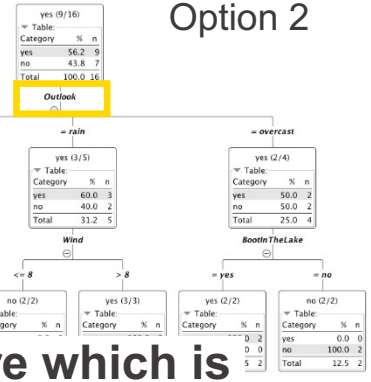
Goal: A Decision Tree

Outlook	Wind	Temp	Storage	Sailing
sunny	3	30	yes	yes
sunny	3	25	yes	no
rain	12	15	yes	yes
overcast	15	2	no	no
rain	16	25	yes	yes
sunny	14	18	yes	yes
rain	3	5	no	no
sunny	9	20	yes	yes
overcast	14	5	no	no
sunny	1	7	no	no
rain	4	25	yes	no
rain	14	24	yes	yes
sunny	11	20	yes	yes
sunny	2	18	yes	no
overcast	8	22	yes	yes
overcast	13	24	yes	yes

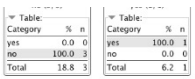
Option 1



Option 2



How can we measure which is the best feature for a split?



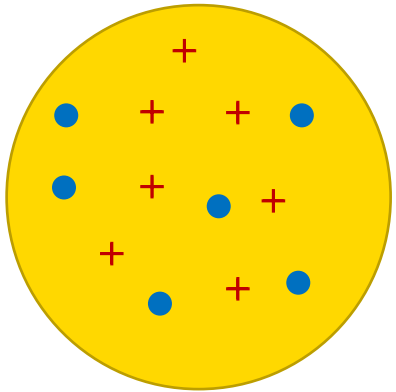
Possible Split Criterion: Gain Ratio

Based on entropy = measure for information / uncertainty

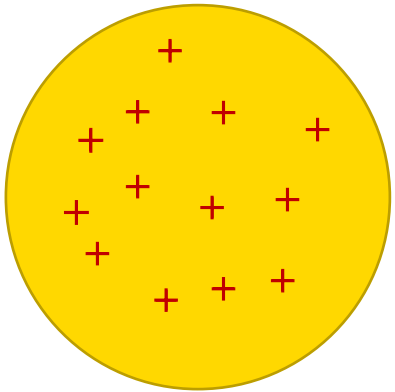
$$Entropy\ (p) = -\sum_{i=0}^{n} p_i\ \log_2 p_i \quad \text{for } p \in \mathbb{Q}^n$$

$p_1 = {}^{7}/_{13}$

$p_2 = {}^{6}/_{13}$



$$Entropy\ (p) = -\left({}^{7}/_{13} \log_2({}^{7}/_{13}) + {}^{6}/_{13} \log_2({}^{6}/_{13})\right)$$
$$= 0{,}995$$

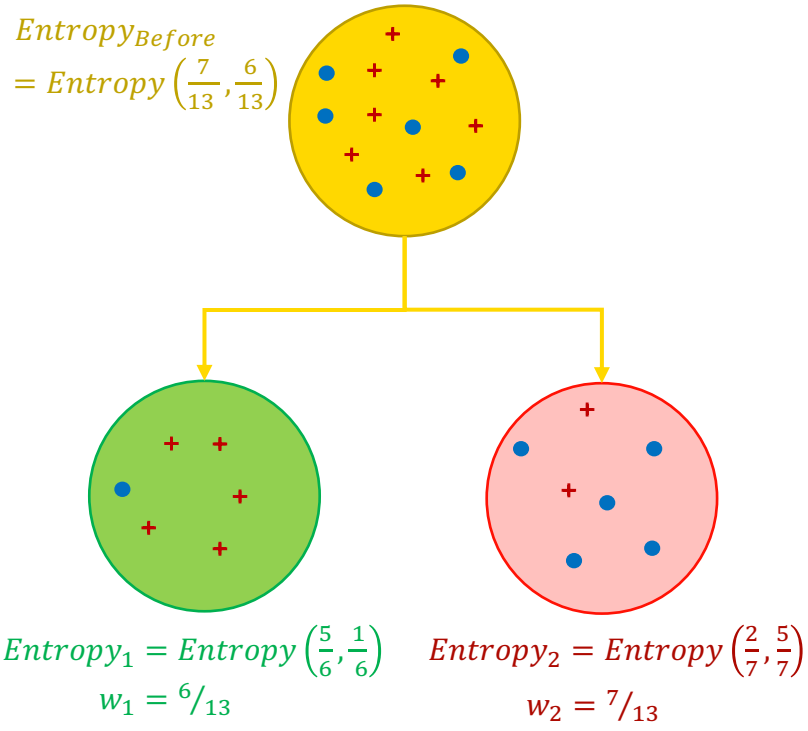


$p_1 = {}^{13}/_{13} = 1$

$p_2 = {}^{0}/_{13} = 0$

$$Entropy\ (p) = -\left({}^{13}/_{13} \log_2({}^{13}/_{13}) + {}^{0}/_{13} \log_2({}^{0}/_{13})\right)$$
$$= 0$$

Possible Split Criterion: Gain Ratio



Split criterion:

$$Gain = Entropy_{Before} - Entropy_{After}$$

$$Gain = Entropy_{Before} - \frac{6}{13} Entropy_1 - \frac{7}{13} Entropy_2$$

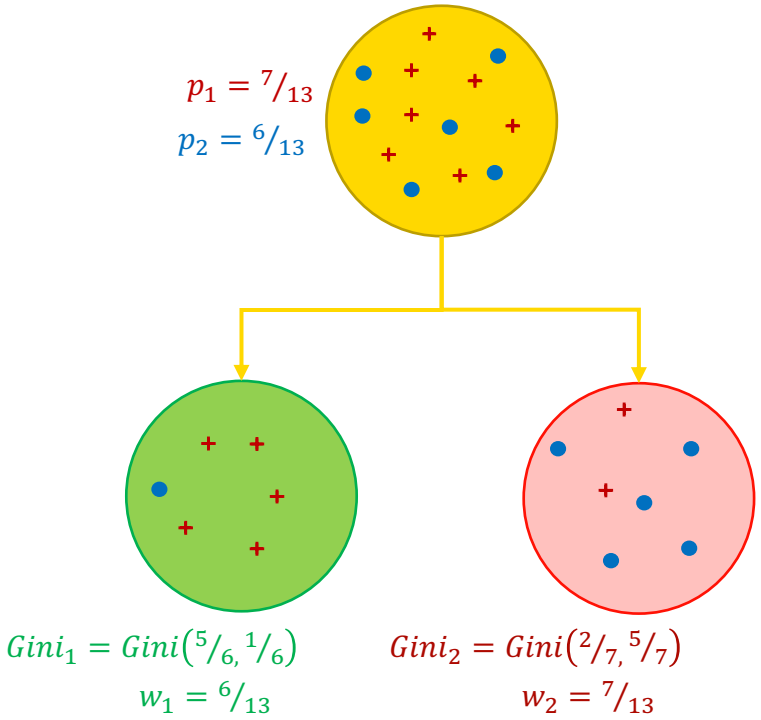
Next splitting feature: Feature with highest $Gain$

Problem: Favors features with many different values

Solution: *Gain Ratio*

$$GainRatio = \frac{Gain}{SplitInfo} = \frac{Entropy_{Before} - \sum_{i=1}^{k} w_i \, Entropy_i}{-\sum_{i=1}^{k} w_i \, log_2 \, w_i}$$

Possible Split Criterion: Gini Index



Gini index is based on Gini impurity:

$$Gini(p) = 1 - \sum_{i=1}^{n} p_i^2 \quad \text{for } p \in \mathbb{Q}^n$$

$$Gini(p) = 1 - \frac{7^2}{13^2} - \frac{6^2}{13^2}$$

Split criterion:

$$Gini_{Index} = \sum_{i=1}^{n} w_i Gini_i$$

$$Gini_{Index} = \frac{6}{13} Gini_1 + \frac{7}{13} Gini_2$$

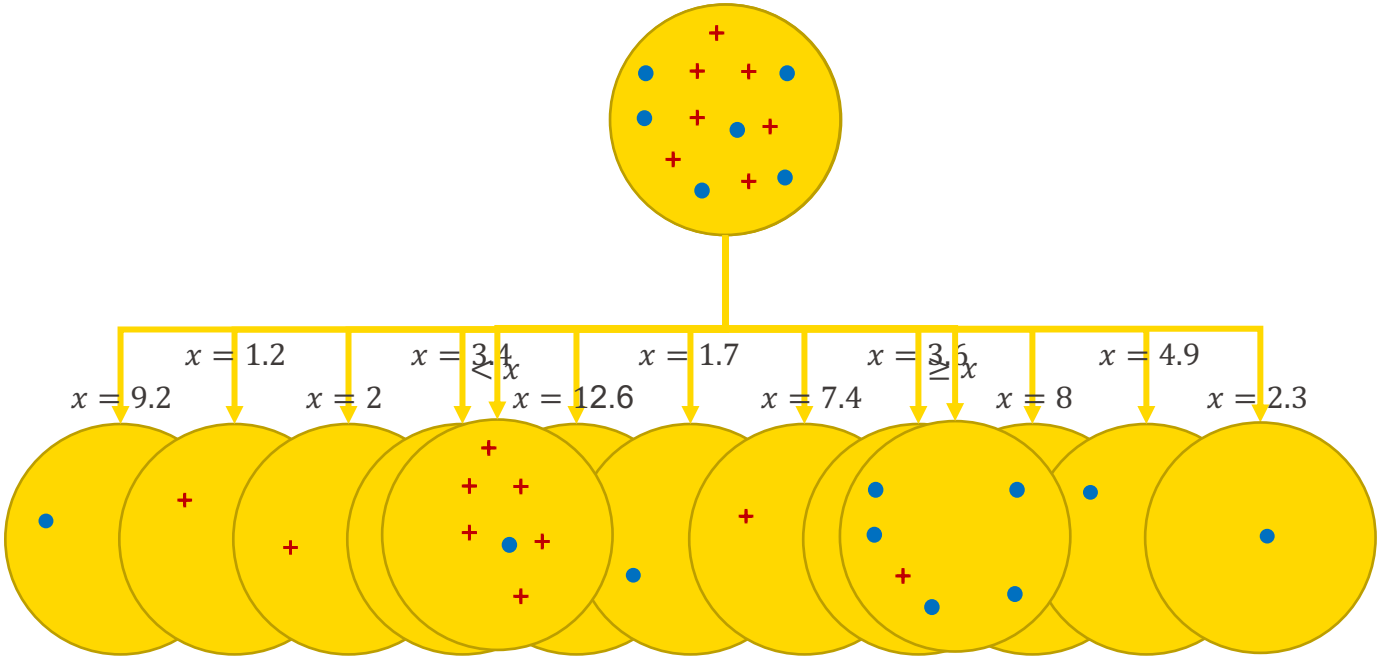
Next splitting feature:

Feature with lowest $Gini_{Index}$

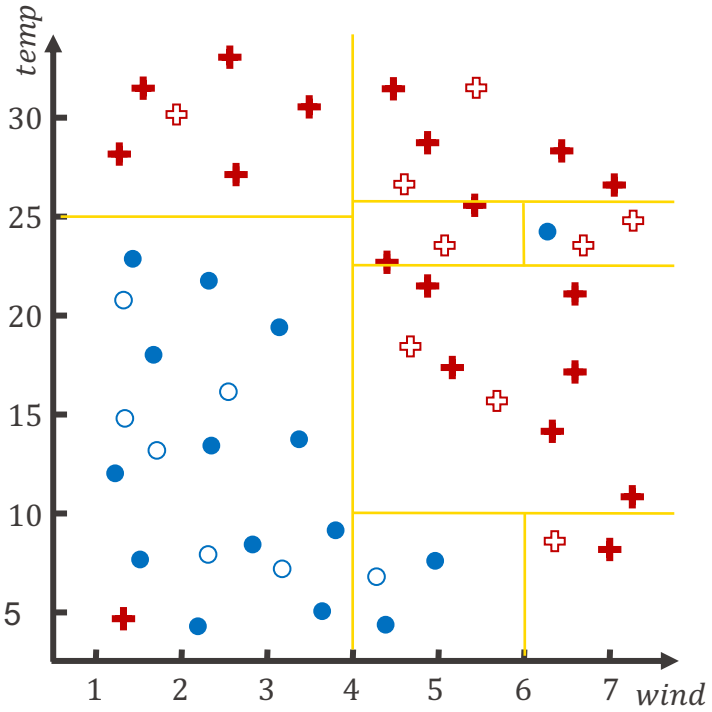
What happens for numerical Input Features?

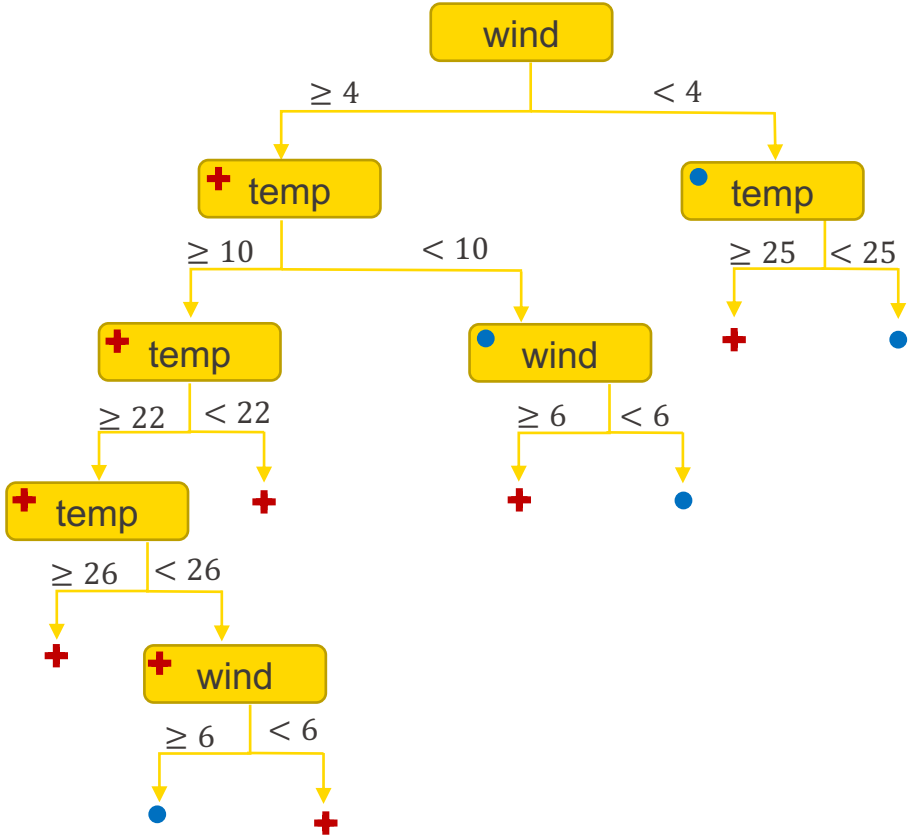
Subset for each value? – NO

Solution: Binary splits



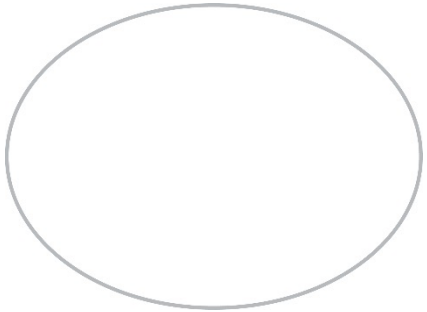
The Deeper the Better?!





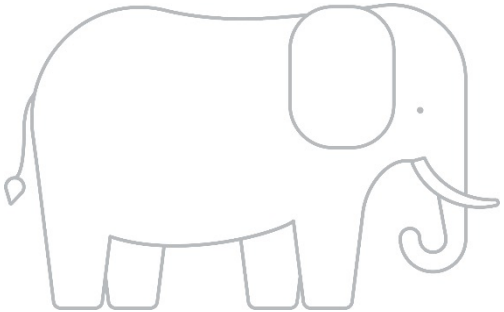
Overfitting vs Underfitting

Underfitted



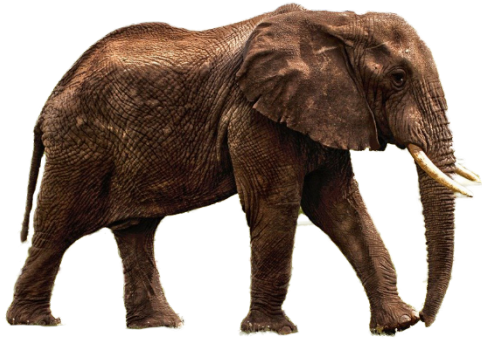
Model overlooks underlying patterns in the training set

Generalized



Model captures correlations in the training set

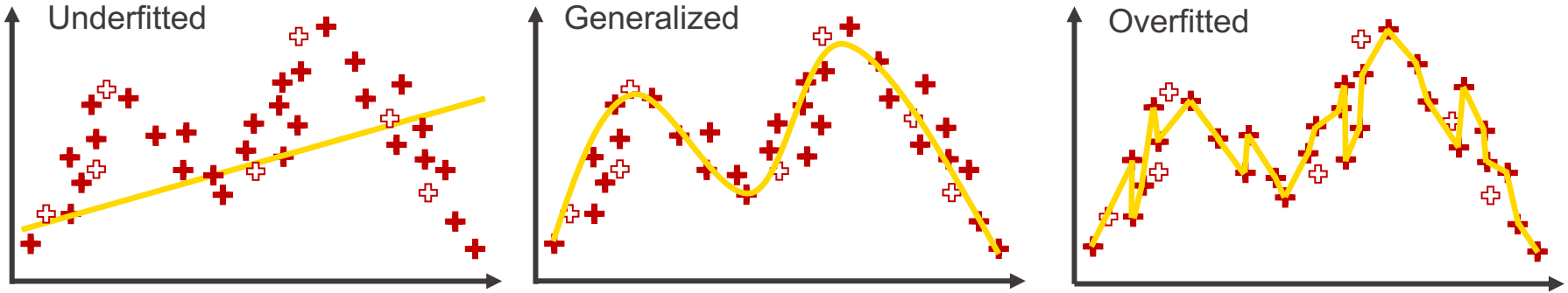
Overfitted



Model memorizes the training set rather then finding underlying patterns

Overfitting vs Underfitting

Underfitting	Overfitting
▪ A model that can neither model the training data nor generalize to new data	▪ Model that fits the training data too well, including details and noise ▪ Negative impact on the model's ability to generalize



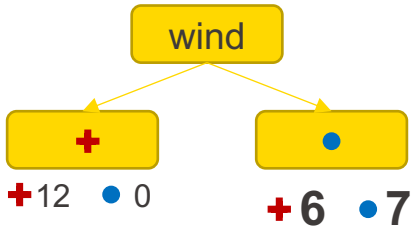
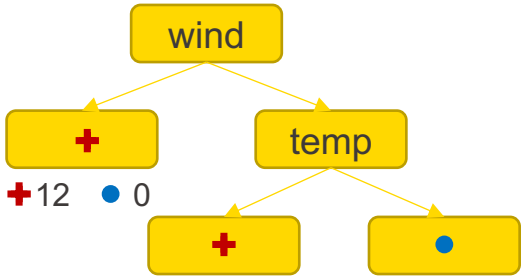
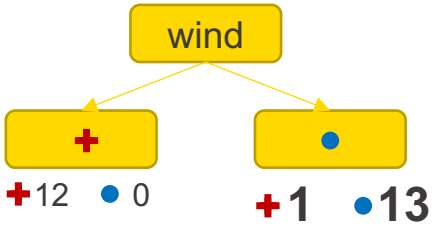
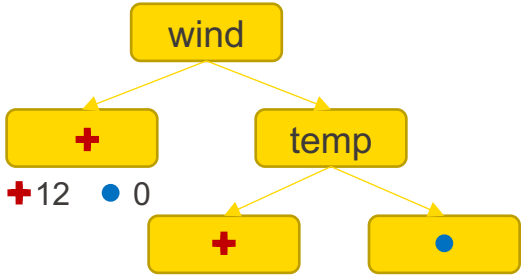
Controlling the Tree Depth

Goal: Tree that generalizes to new data and doesn't overfit

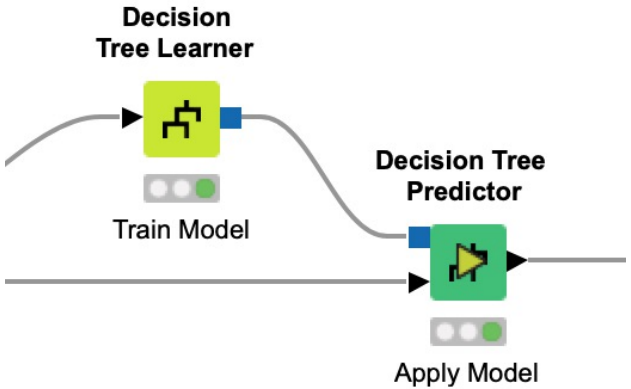
Pruning	Early stopping
Idea: Cut branches that seem as result from overfitting	**Idea:** Define a minimum size for the tree leaves
Techniques: • Reduced Error Pruning • Minimum description length	

Pruning - Minimum Description Length Pruning (MDL)

Definition: Description length = #bits(tree) + #bits(misclassified samples)

	Tree 1	Tree 2	Note
Example 1			Many misclassified samples in tree 1 => DL(Tree 1) > DL(Tree 2) => Select Tree 2
Example 2			Only 1 misclassified sample in tree 1 => DL(Tree 1) < DL(Tree 2) => Select Tree 1

Applying the Model – What are the Outputs?



Classified Data - 0:65 - Decision Tree Predictor (Apply Model)

File Hilite Navigation View

Table "default" – Rows: 879 | Spec – Columns: 82 | Properties | Flow Variables

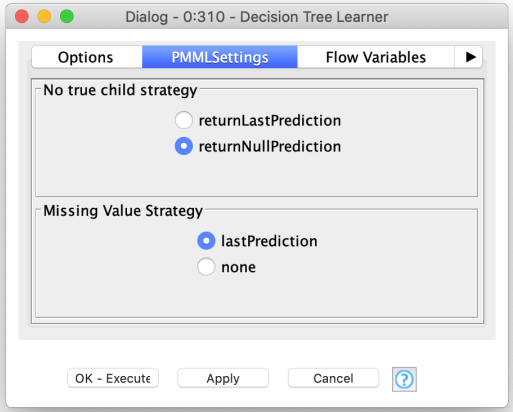
Row ID	SalePr...	rank	P (rank=Low)	P (rank=High)	Prediction (rank)
10	189000	Low	0.889	0.111	Low
11	175900	Low	1	0	Low
13	180400	Low	1	0	Low
15	212000	Low	0.946	0.054	Low
21	190000	High	0	1	High
22	170000	High	0.2	0.8	High
27	126000	Low	1	0	Low
28	115000	Low	1	0	Low
33	127500	Low	1	0	Low

No True Child Strategy

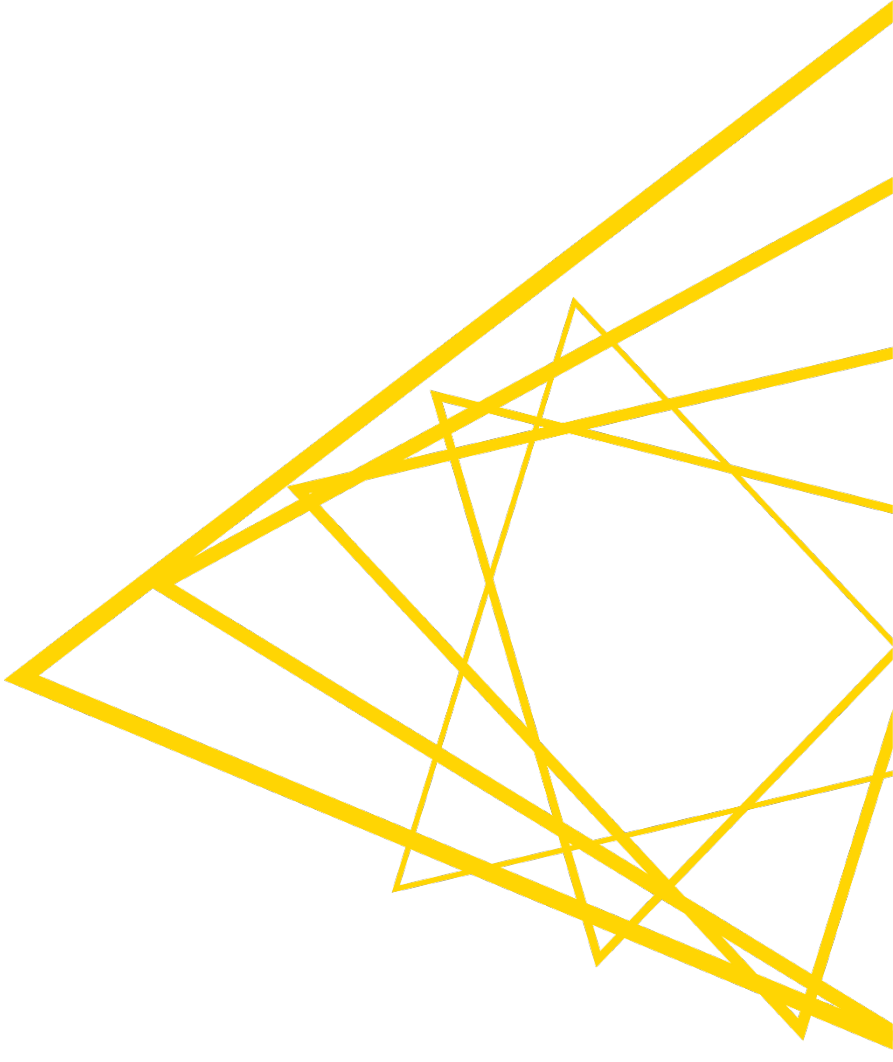
	Outlook	Wind	Temp	Storage	Sailing
Training	sunny	3	30	yes	yes
	sunny	3	25	yes	no
	rain	12	15	yes	yes
	rain	16	25	yes	yes
	sunny	14	18	yes	yes
	rain	3	5	no	no
	sunny	9	20	yes	yes
	sunny	1	7	no	no
Testing	rain	4	25	yes	no
	rain	14	24	yes	yes
	sunny	11	20	yes	yes
	sunny	2	18	yes	no
	overcast	8	22	yes	yes
	overcast	13	24	yes	yes

Training:

What happens with outlook = overcast?

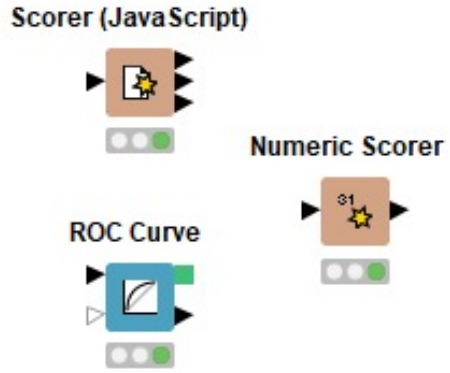


Evaluation of Classification Models



Evaluation Metrics

- Why evaluation metrics?
  - Quantify the power of a model
  - Compare model configurations and/or models, and select the best performing one
  - Obtain the expected performance of the model for new data
- Different model evaluation techniques are available for
  - Classification/regression models
  - Imbalanced/balanced target class distributions



Overall Accuracy

- Definition:

$$\boldsymbol{Overall\ accuracy} = \frac{\boldsymbol{\#\ Correct\ classifications\ (test\ set)}}{\boldsymbol{\#\ All\ events\ (test\ set)}}$$

- The proportion of correct classifications

- Downsides:
  - Only considers the performance in general and not for the different classes
  - Therefore, not informative when the class distribution is unbalanced

Confusion Matrix for Sailing Example

Sailing yes / no	Predicted class: yes	Predicted class: no
True class: yes	22	3
True class: no	12	328

$$Accuracy = \frac{350}{365} = 0{,}96$$

Sailing yes / no	Predicted class: yes	Predicted class: no
True class: yes	0	25
True class: no	0	340

$$Accuracy = \frac{340}{365} = 0{,}93$$

- Rows – true class values
- Columns – predicted class values
- Numbers on main diagonal – correctly classified samples
- Numbers off the main diagonal – misclassified samples

Confusion Matrix

Arbitrarily define one class value as POSITIVE and the remaining class as NEGATIVE

	Predicted class positive	Predicted class negative
True class positive	TRUE POSITIVE	FALSE NEGATIVE
True class negative	FALSE POSITIVE	TRUE NEGATIVE

TRUE POSITIVE (**TP**): Actual and predicted class is positive

TRUE NEGATIVE (**TN**): Actual and predicted class is negative

FALSE NEGATIVE (**FN**): Actual class is positive and predicted negative

FALSE POSITIVE (**FP**): Actual class is negative and predicted positive

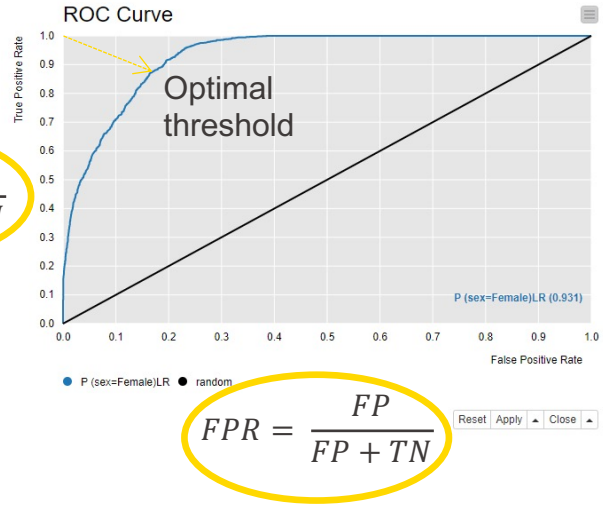
Use these four statistics to calculate other evaluation metrics, such as overall accuracy, true positive rate, and false positive rate

ROC Curve

- The ROC Curve shows the false positive rate and true positive rate for different threshold values
  - False positive rate (FPR)
    - negative events **in**correctly classified as positive
  - True positive rate (TPR)
    - positive events correctly classified as positive

	Predicted class positive	Predicted class negative
True class positive	True Positive (TP)	False Negative (FN)
True class negative	False Positive (FP)	True Negative (TN)

$$TPR = \frac{TP}{TP + FN}$$



$$FPR = \frac{FP}{FP + TN}$$

Cohen‘s Kappa (κ) vs. Overall accuracy

	Positive	Negative
Positive	14	6
Negative	5	75

Switch TP and FP

	Positive	Negative
Positive	6	14
Negative	5	75

$$p_{e1} = \frac{19}{100} \times \frac{20}{100}$$

$$p_{e2} = \frac{81}{100} \times \frac{80}{100}$$

$$p_e = p_{e1} + p_{e2} = 0.686$$

$$p_0 = \frac{89}{100} = 0.89$$

$$\kappa = \frac{p_0 - p_e}{1 - p_e} = \frac{0.204}{0.314} \approx 0.65$$

Overall accuracy

κ = 1: perfect model performance
κ = 0: the model performance is equal to a random classifier

$$p_{e1} = \frac{11}{100} \times \frac{20}{100}$$

$$p_{e2} = \frac{89}{100} \times \frac{80}{100}$$

$$p_e = p_{e1} + p_{e2} = 0.734$$

$$p_0 = \frac{81}{100} = 0.81$$

$$\kappa = \frac{p_0 - p_e}{1 - p_e} = \frac{0.076}{0.266} = 0.29$$

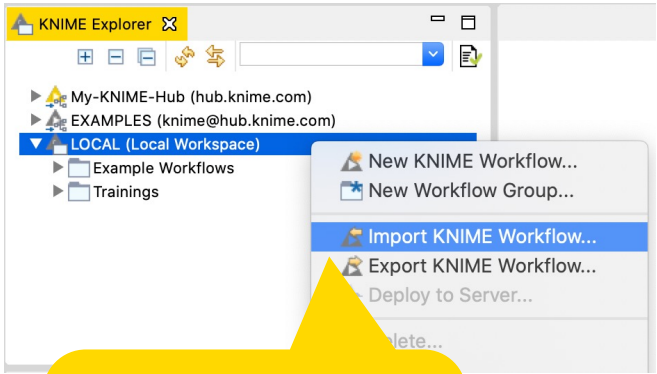
Exercise: 01_Training_a_Decision_Tree_Model

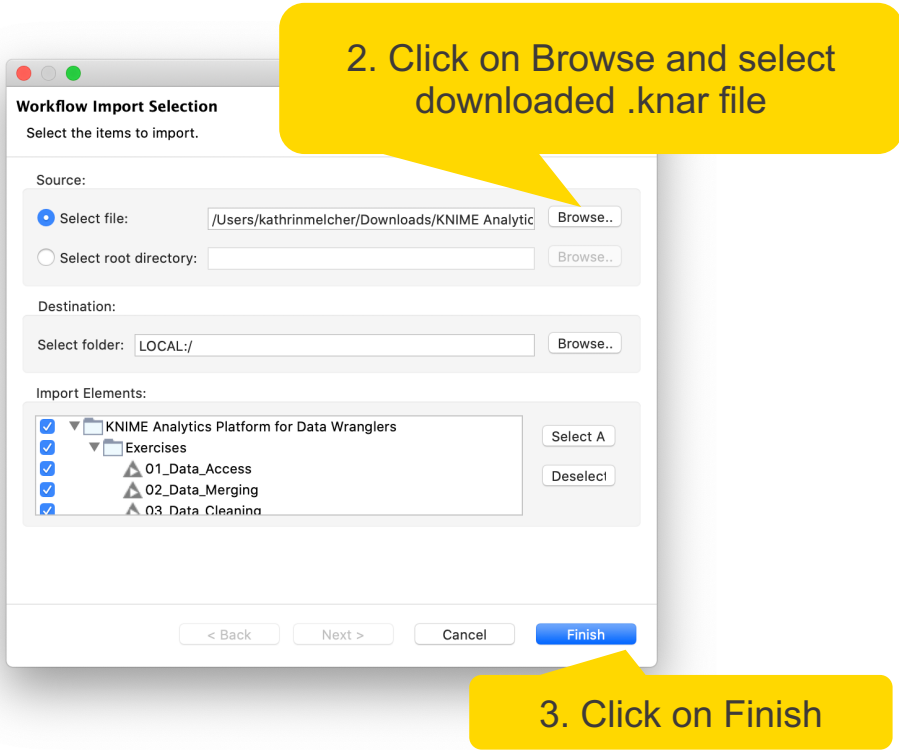
- Dataset: Sales data of individual residential properties in Ames, Iowa from 2006 to 2010.
- One of the columns is the overall condition ranking, with values between 1 and 10.
- Goal: train a binary classification model, which can predict whether the overall condition is high or low.

You can download the training workflows from the KNIME Hub:
https://hub.knime.com/knime/spaces/Education/latest/Courses/

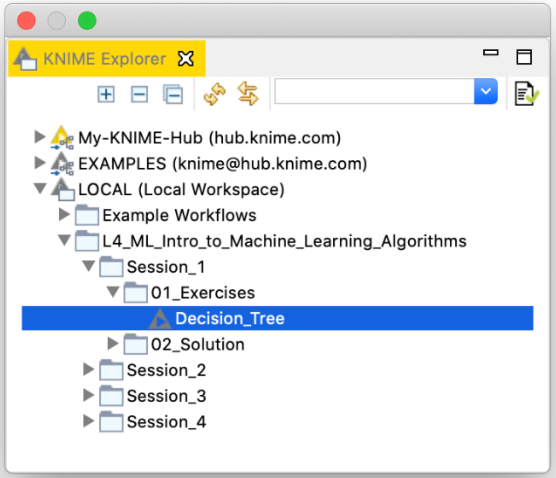
Exercise Session 1

- Import the course material to KNIME Analytics Platform





Exercise: Decision_Tree



Use Case Description

The dataset we use in this exercise describes the sale of individual residential properties in Ames, Iowa from 2006 to 2010. One of the columns is the overall condition ranking, with values between 1 and 10.
The goal of this exercise is to train a binary classification model, which can predict whether the overall condition is high or low. To do so, the workflow below reads the data set and creates the class column based on overall condition ranking, which is called rank and has the values low if the overall condition is smaller or equal to 5, otherwise high.
It is now on you continue this workflow!

Exercise: Decision Tree

1) Use a Partitioning node to split data into training (70%) e test set (30%)
- use stratified sampling based on the column rank, to retain the distribution of the class values in both output tabes.

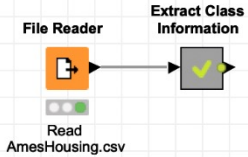
2) Train a Decision Tree model to predict the overall condition of a house (high/low) (Decision Tree Learner node)
- Select the "rank" column as the class column

2) Use the trained model to predict the rank of the houses in the test set (Decision Tree Predictor node)

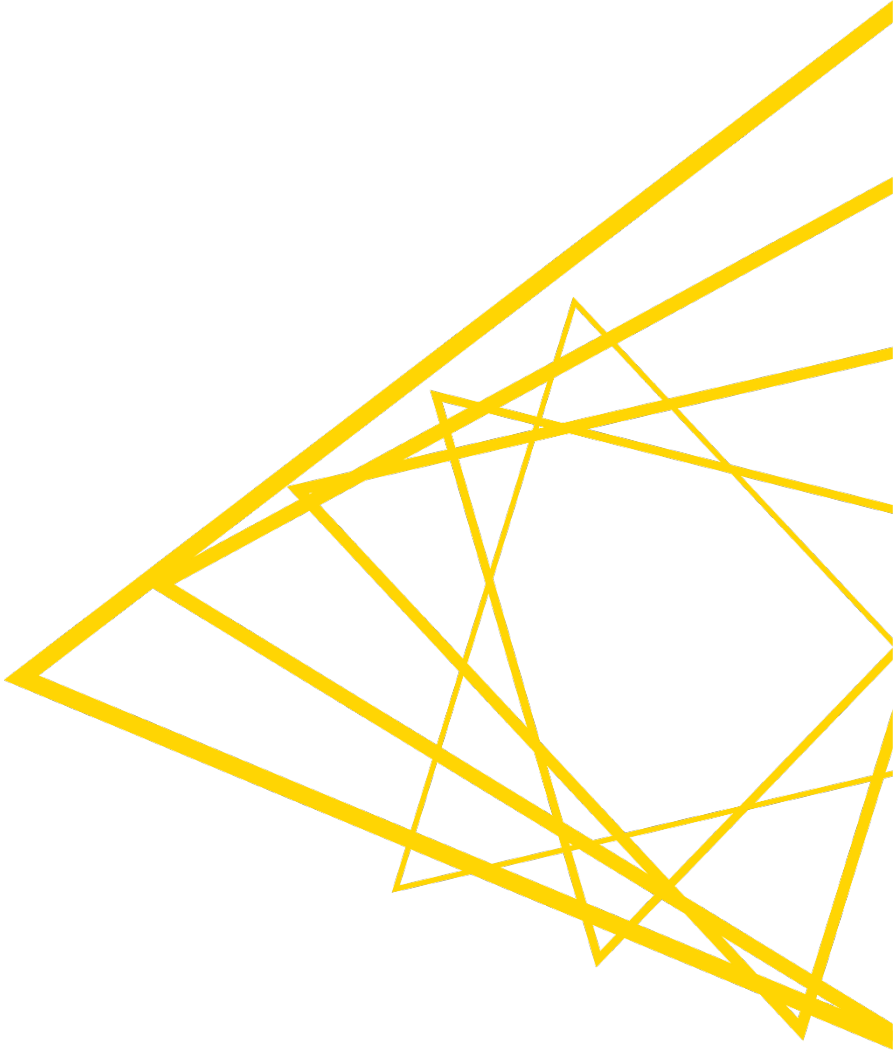
3) Evaluate the accuracy of the decision tree model (Scorer (Java Script) node)
- Select "rank" as the actual column and "Prediction (rank)" as the predicted column
- What is the accuracy of the model?

4) Visualize the ROC curve (ROC Curve node)
- Make sure that checkbox "append columns with normalized class distribution" in the Decision Tree Predictor node is activated
- Select "rank" as Class column and "High" as Positive class value. Include only the "P (rank=High)" column

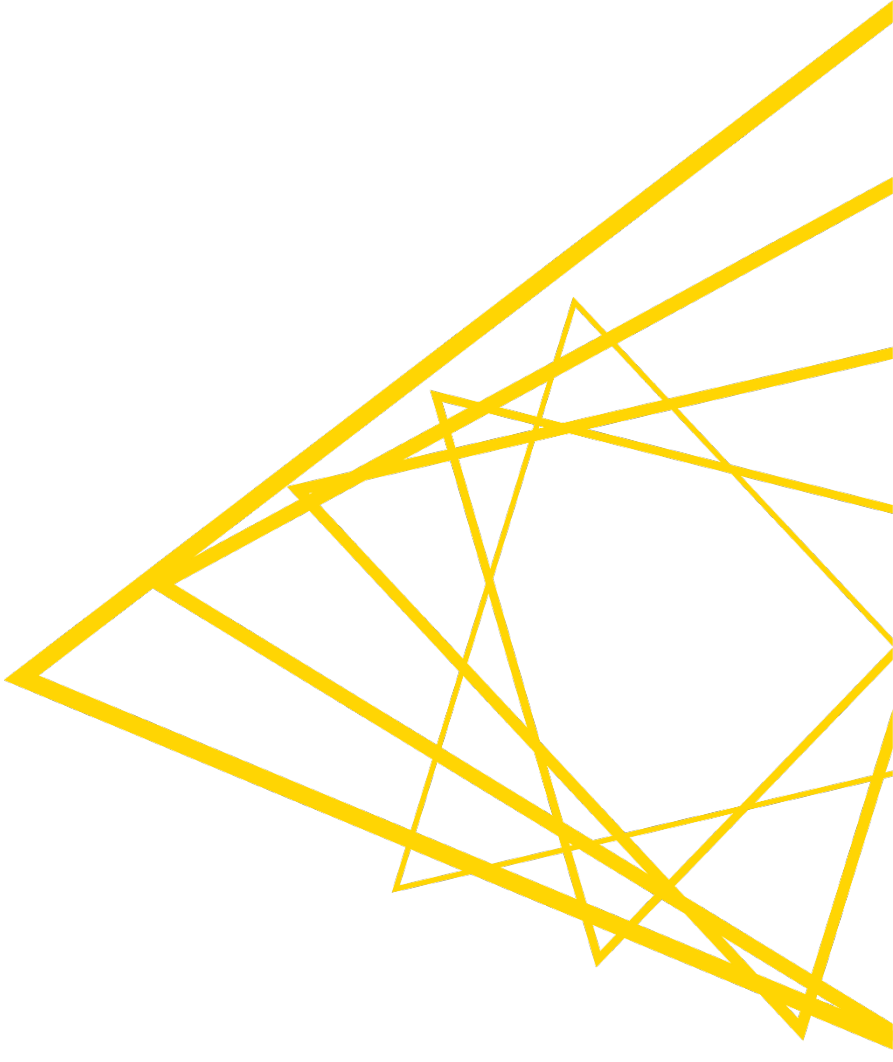
5) Optional: Try different setting options for the decision tree algorithm. Can you improve the model performance?



Session II: Regression Models, Ensemble Models & Logistic Regression



Regression Problems



Regression Analysis

- Prediction of numerical target values

- Commonality with models for classification
  - First, construct a model
  - Second, use model to predict unknown value
    - Major method for prediction is regression in all its flavors
      - Simple and multiple regression
      - Linear and non-linear regression

- Difference from classification
  - Classification aims at predicting categorical class label
  - Regression models aim at predicting values from continuous-valued functions

Regression

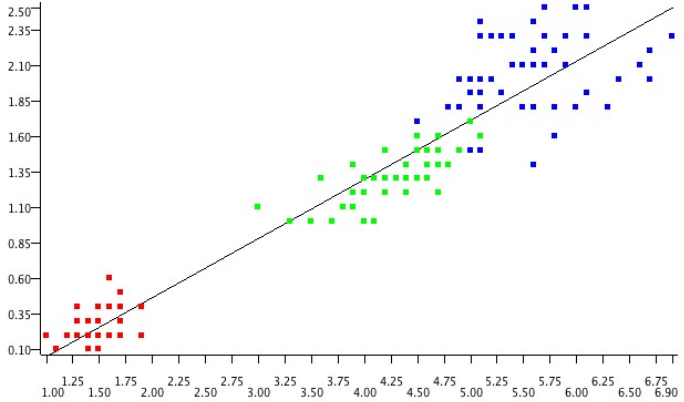
Predict *numeric* outcomes on existing data (supervised)

Applications

- Forecasting
- Quantitative Analysis

Methods

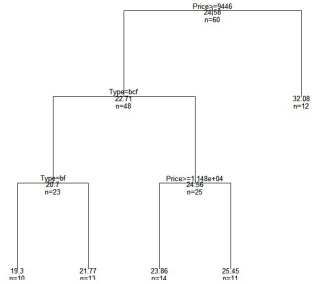
- Linear
- Polynomial
- Regression Trees
- Partial Least Squares



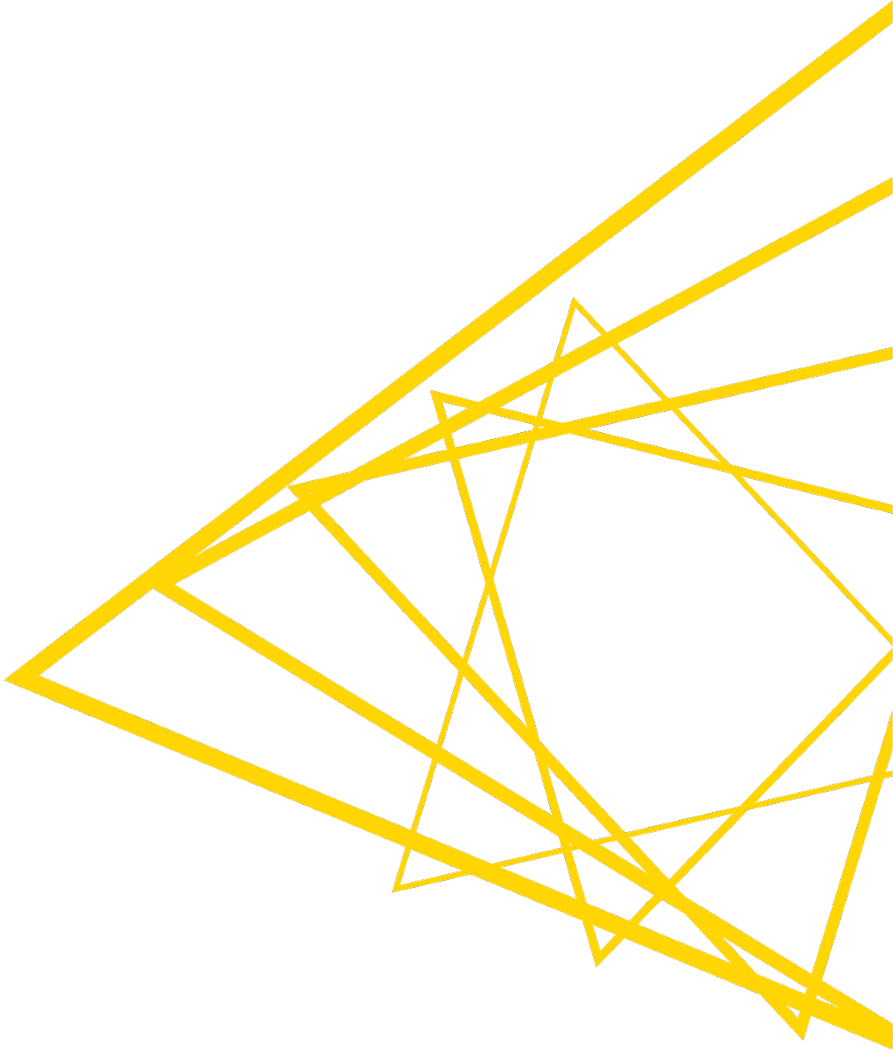
Statistics on Linear Regression

Variable	Coeff.	Std. Err.	t-value	P>|t|
Petal.Length	0.4158	0.0096	43.3872	0.0
Intercept	-0.3631	0.0398	-9.1312	4.44E-16

Multiple R-Squared: 0.9271
Adjusted R-Squared: 0.9266



Linear Regression Algorithm



Linear Regression

Predicts the values of the target variable y
based on a linear combination of
the values of the input feature(s) x_j

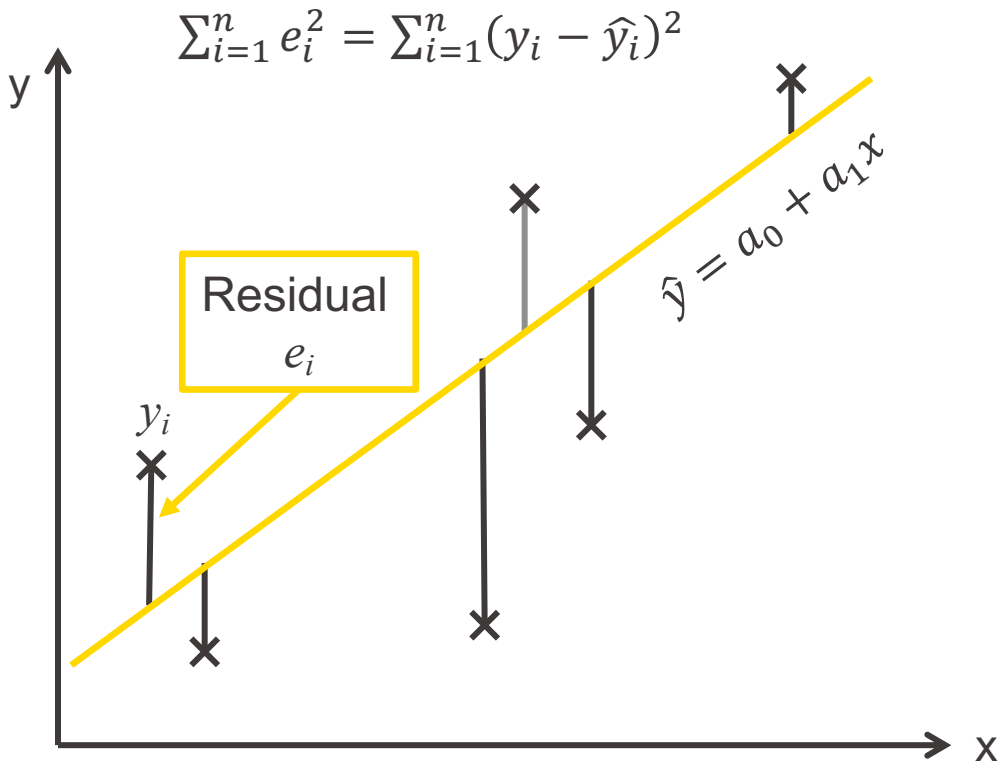
Two input features: $\hat{y} = a_0 + a_1 x_1 + a_2 x_2$

p input features: $\hat{y} = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_p x_p$

- Simple regression: one input feature → regression line
- Multiple regression: several input features → regression hyper-plane
- Residuals: differences between observed and predicted values (errors)
  Use the residuals to measure the model fit

Simple Linear Regression

Optimization goal: minimize sum of squared residuals



Simple Linear Regression

- Think of a straight line $\hat{y} = f(x) = a + bx$
- Find a and b to model all observations (x_i, y_i) as close as possible
- ➔ SSE $F(a,b) = \sum_{i=1}^{n}(f(x) - y_i)^2 = \sum_{i=1}^{n}(a + bx_i - y_i)^2$ should be minimal
- That is:

$$\frac{\partial F}{\partial a} = \sum_{i=1}^{n} 2(a + bx_i - y_i) = 0$$

$$\frac{\partial F}{\partial b} = \sum_{i=1}^{n} 2(a + bx_i - y_i)\, x_i = 0$$

- ➔ A unique solution exists for a and b

Linear Regression

- Optimization goal: minimize the squared residuals

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left(y_i - \sum_{j=0}^{n} a_j x_{j,i}\right)^2 = (y - aX)^T (y - aX)$$

- Solution:

$$\hat{a} = (X^T X)^{-1} X^T y$$

- Computational issues:
  - $X^T X$ must have full rank, and thus be invertible
    (Problems arise if linear dependencies between input features exist)
  - Solution may be unstable, if input features are almost linearly dependent

Linear Regression: Summary

- Positive:
  - Strong mathematical foundation
  - Simple to calculate and to understand
    (For moderate number of dimensions)
  - High predictive accuracy
    (In many applications)

- Negative:
  - Many dependencies are non-linear
    (Can be generalized)
  - Model is global and cannot adapt well to locally different data distributions
    But: Locally weighted regression, CART

Polynomial Regression

Predicts the values of the target variable y
based on a polynomial combination of degree d of
the values of the input feature(s) x_j

$$\tilde{y} = a_0 + \sum_{j=1}^{p} a_{j,1} x_j + \sum_{j=1}^{p} a_{j,2} x_j^2 + \cdots + \sum_{j=1}^{p} a_{j,d} x_j^d$$

- Simple regression: one input feature → regression curve
- Multiple regression: several input features → regression hypersurface
- Residuals: differences between observed and predicted values (errors)
  Use the residuals to measure the model fit

Evaluation of Regression Models

Numeric Errors: Formulas

Error Metric	Formula	Notes
R-squared	$1 - \frac{\sum_{i=1}^{n}(y_i - f(x_i))^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}$	Universal range: the closer to 1 the better
Mean absolute error (MAE)	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - f(x_i)\rvert$	Equal weights to all distances Same unit as the target column
Mean squared error (MSE)	$\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2$	Common loss function
Root mean squared error (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2}$	Weights big differences more Same unit as the target column
Mean signed difference	$\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))$	Only informative about the direction of the error
Mean absolute percentage error (MAPE)	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i - f(x_i)\rvert}{\lvert y_i\rvert}$	Requires non-zero target column values

MAE (Mean Absolute Error) vs. RMSE (Root Mean Squared Error)

MAE	RMSE
Easy to interpret – mean absolute error	Cannot be directly interpreted as the average error
All errors are equally weighted	Larger errors are weighted more
Generally smaller than RMSE	Ideal when large deviations need to be avoided

Example:

Actual values = [2,4,5,8],

Case 1: Predicted Values = [4, 6, 8, 10]

Case 2: Predicted Values = [4, 6, 8, 14]

	MAE	RMSE
Case 1	2.25	2.29
Case 2	3.25	3.64

R-squared vs. RMSE

R-squared	RMSE
Relative measure: Proportion of variability explained by the model	**Absolute measure**: How much deviation at each point
Range: Usually between 0 and 1. 0 = no variability explained 1 = all variability explained	Same scale as the target

Example:

Actual values = [2,4,5,8],

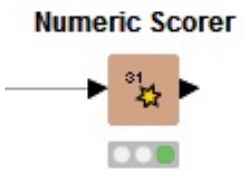
Case 1: Predicted Values = [3, 4, 5, 6]

Case 2: Predicted Values = [3, 3, 7, 7]

	R-sq	RMSE
Case 1	0.96	1.12
Case 2	0.65	1.32

Numeric Scorer

- Similar to scorer node, but for nodes with *numeric* predictions
- Compare dependent variable values to predicted values to evaluate model quality.
- Report R^2, RMSE, MAPE, etc.



Statistics - 0:393 - Numeric Scorer

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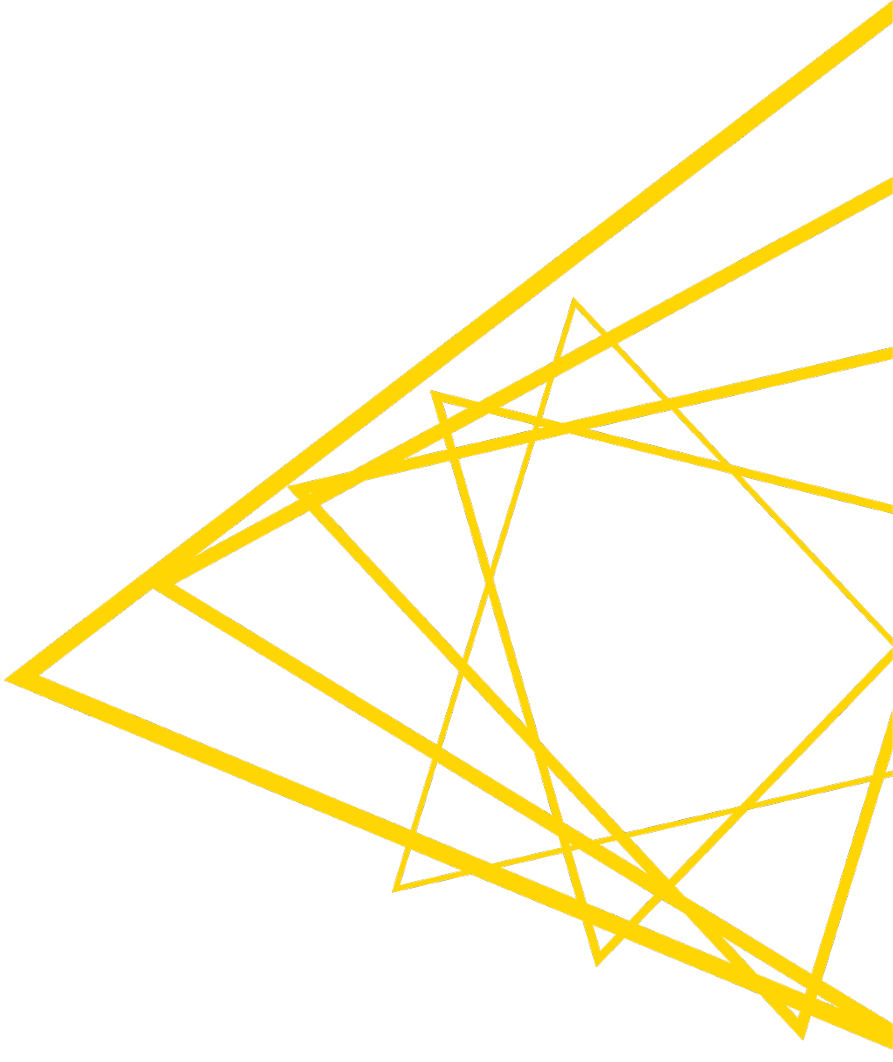
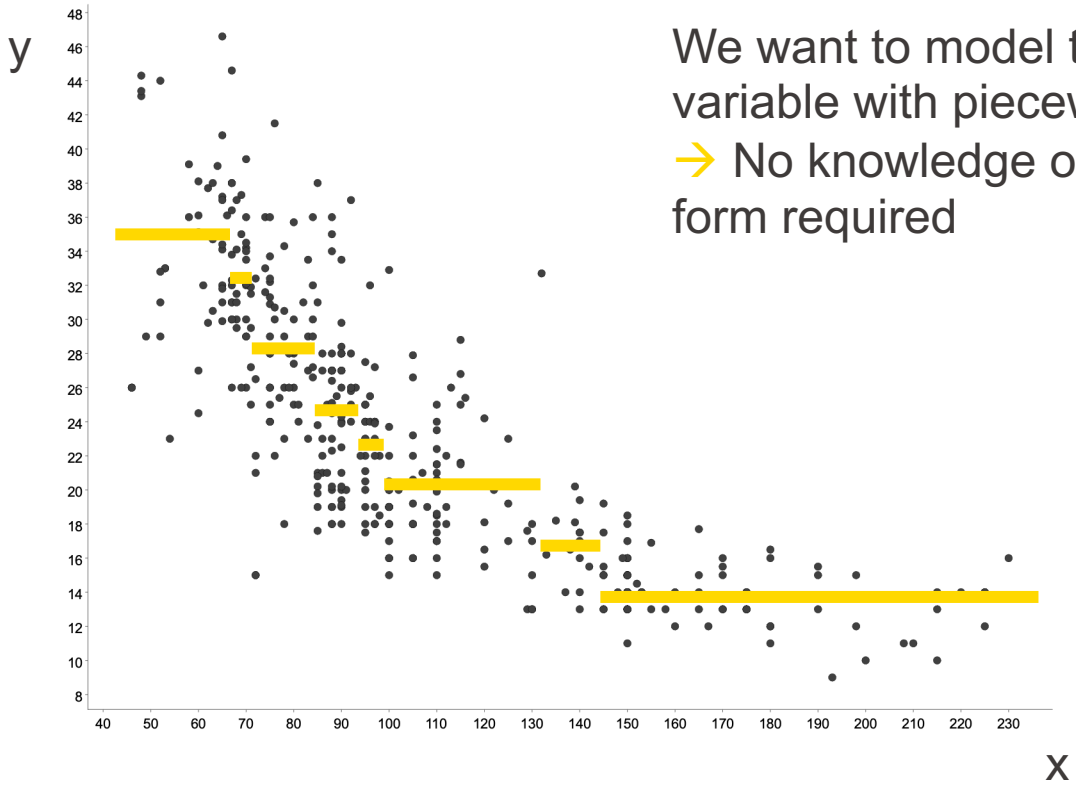
Table "Scores" - Rows: 6 | Spec - Column: 1 | Properties | Flow Variables

Row ID	D MA(Irregular Component)
R^2	0.343
mean absolute error	0.773
mean squared error	2.413
root mean squared error	1.553
mean signed difference	-0.003
mean absolute percentage error	7.064

Regression Tree



Regression Tree: Goal



We want to model the target variable with piecewise lines

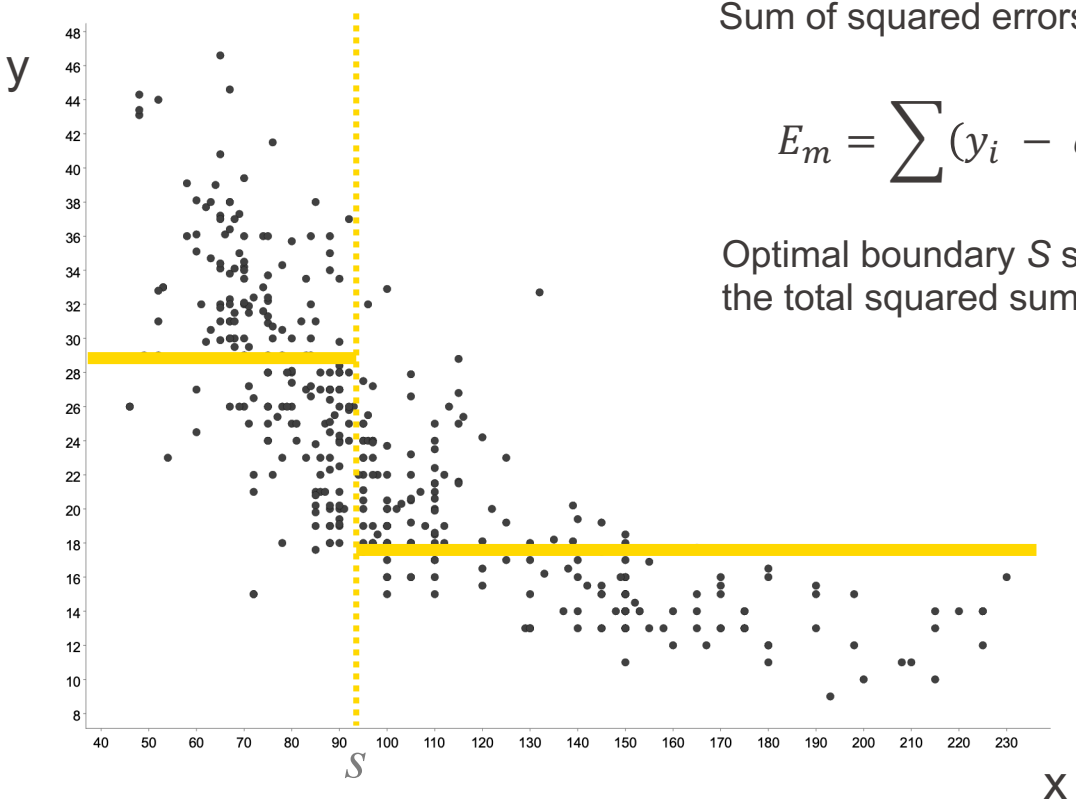
→ No knowledge of functional form required

Regression Tree: Initial Split

Local mean:

$$c_m = \frac{1}{n}\sum y_i$$

For observations in segment *m*



Sum of squared errors:

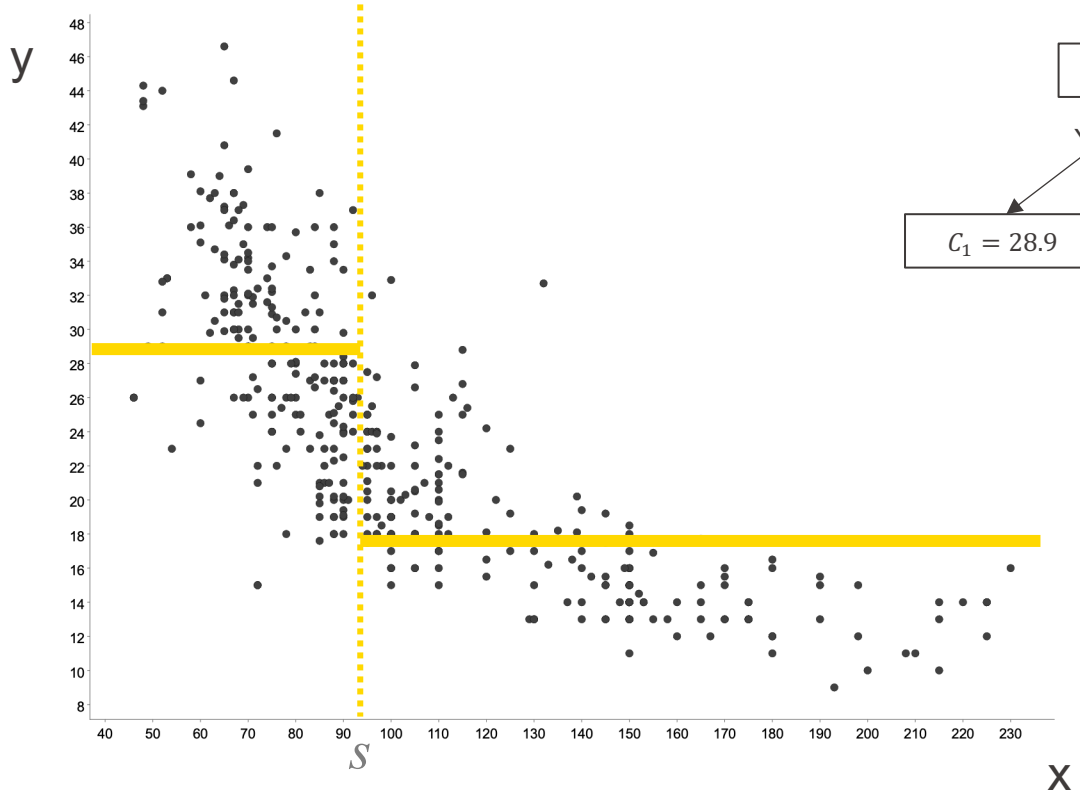
$$E_m = \sum (y_i - c_m)^2$$

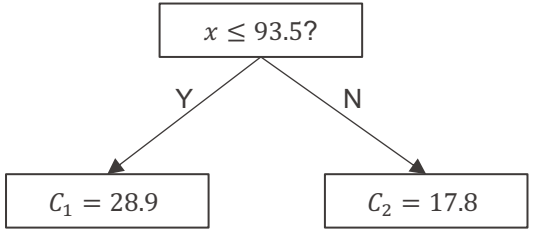
Optimal boundary *S* should minimize the total squared sum:

$$\sum E_m$$

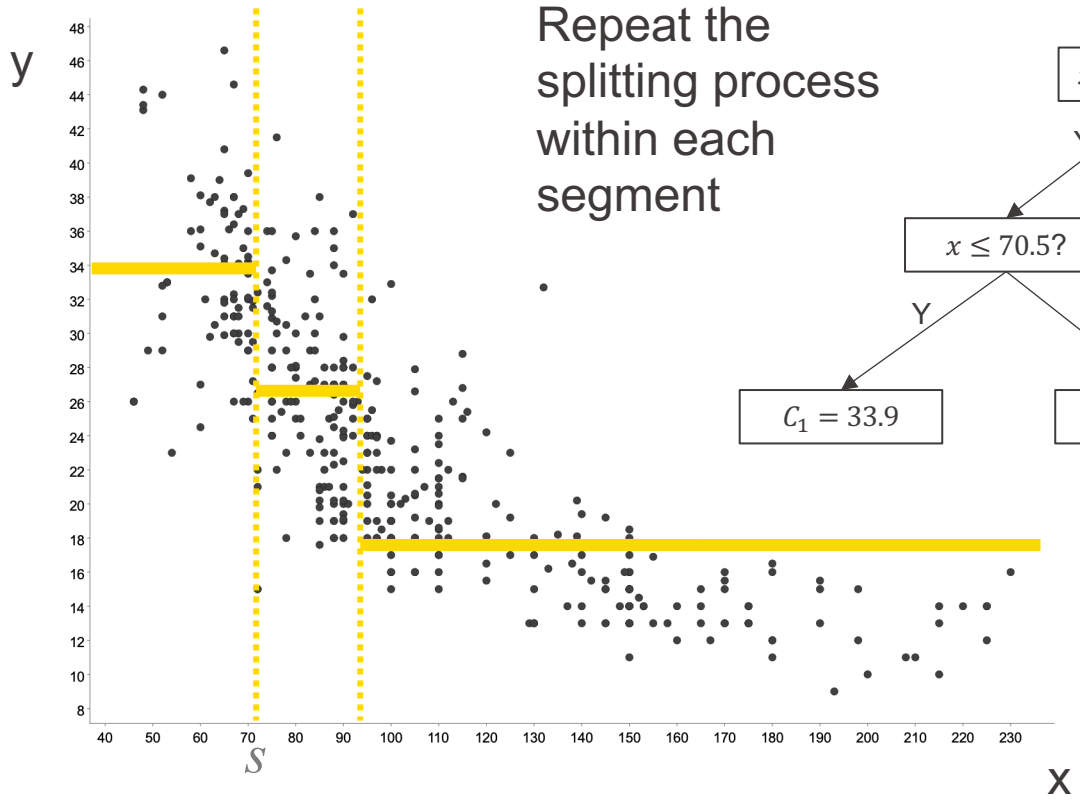
For all segments *m*

Regression Tree: Initial Split

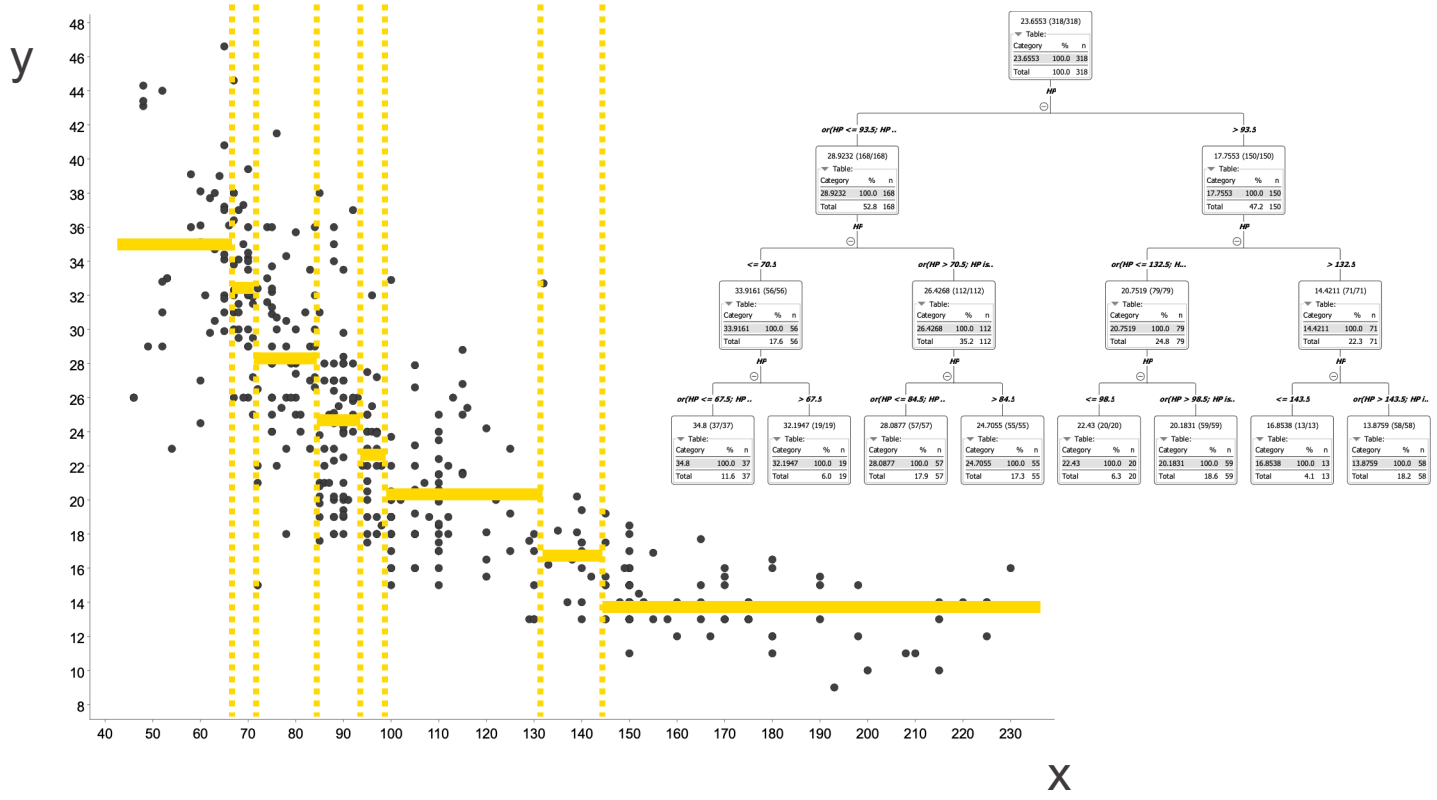




Regression Tree: Growing the Tree

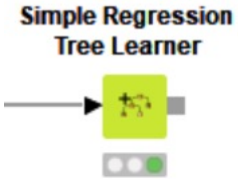


Regression Tree: Final Model



Regression Tree: Algorithm

Start with a single node containing all points.



1. Calculate c_i and E_i.
2. If all points have the same value for feature x_j, stop.
3. Otherwise, find the best binary splits that reduces $E_{j,s}$ as much as possible.
   - $E_{j,s}$ doesn't reduce as much → stop
   - A node contains less than the minimum node size → stop
   - Otherwise, take that split, creating two new nodes.
   - In each new node, go back to step 1.

Regression Trees: Summary

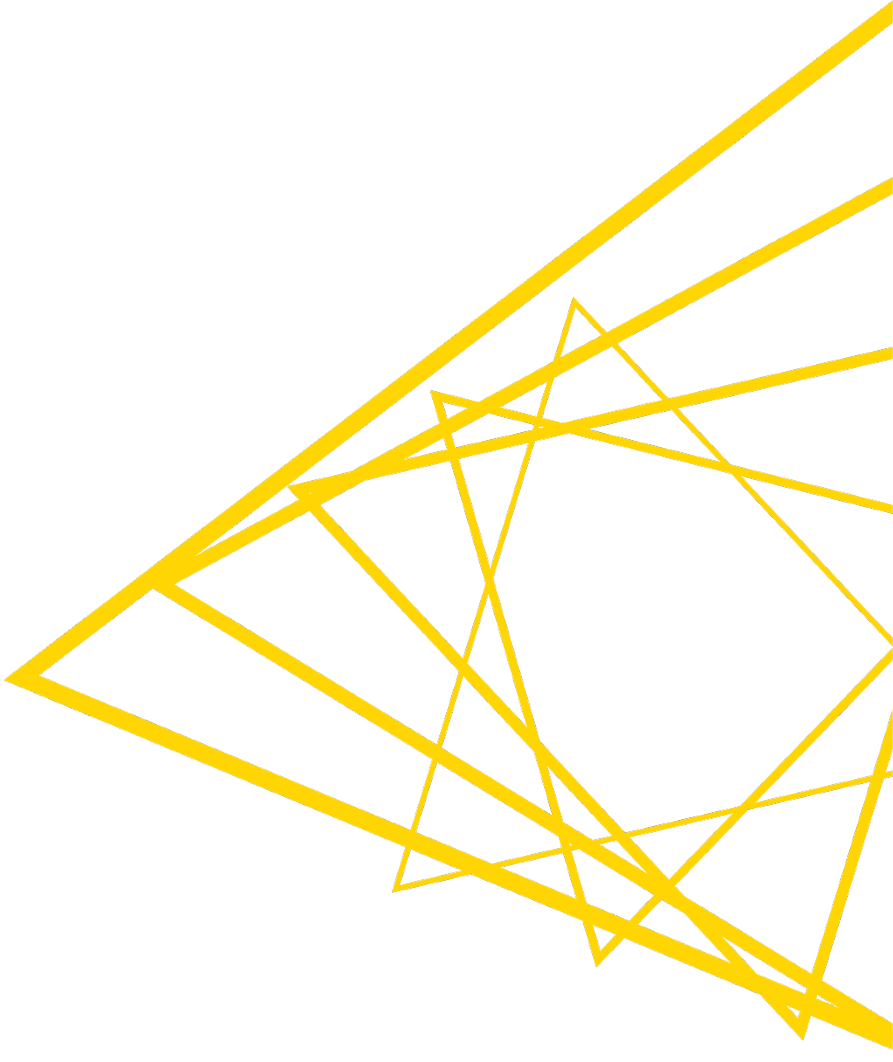
- Differences to decision trees:
  - Splitting criterion: minimizing intra-subset variation (error)
  - Pruning criterion: based on numeric error measure
  - Leaf node predicts average target values of training instances reaching that node
- Can approximate piecewise constant functions
- Easy to interpret

Regression Trees: Pros & Cons

- Finding of (local) regression values (average)
- Problems:
  - No interpolation across borders
  - Heuristic algorithm: unstable and not optimal.

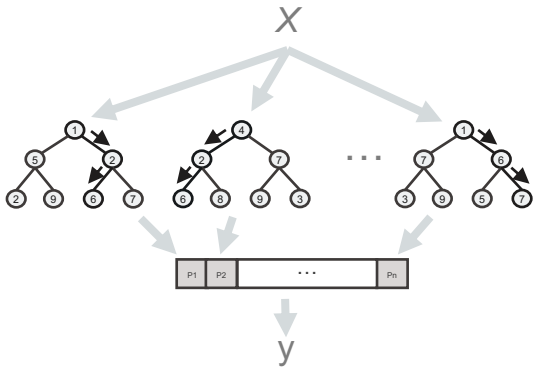
- Extensions:
  - Fuzzy trees (better interpolation)
  - Local models for each leaf (linear, quadratic)

Ensemble Models



Tree Ensemble Models

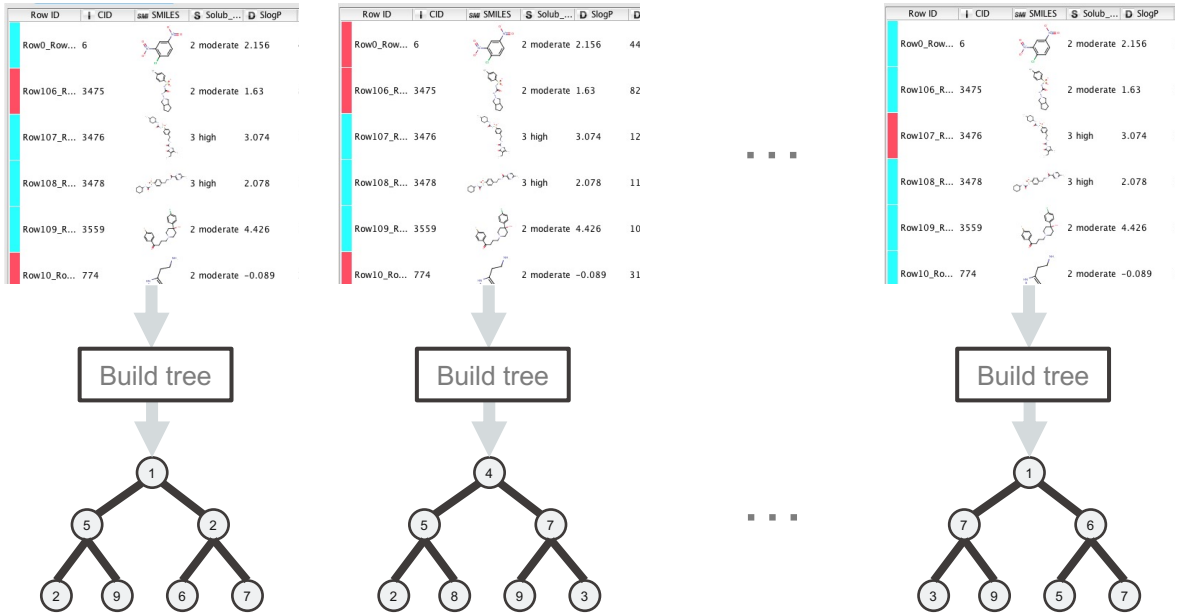
- General idea: take advantage of the “wisdom of the crowd”
- Ensemble models: Combining predictions from many predictors, e.g. decision trees
- Leads to a more accurate and robust model
- Model is difficult to interpret
  - There are multiple trees in the model



Typically for classification, the individual models vote and the majority wins; for regression, the individual predictions are averaged

Bagging - Idea

- One option is ”bagging” (Bootstrap AGGregatING)
- For each tree / model a training set is generated by sampling uniformly with replacement from the standard training set



Example for Bagging

Full training set

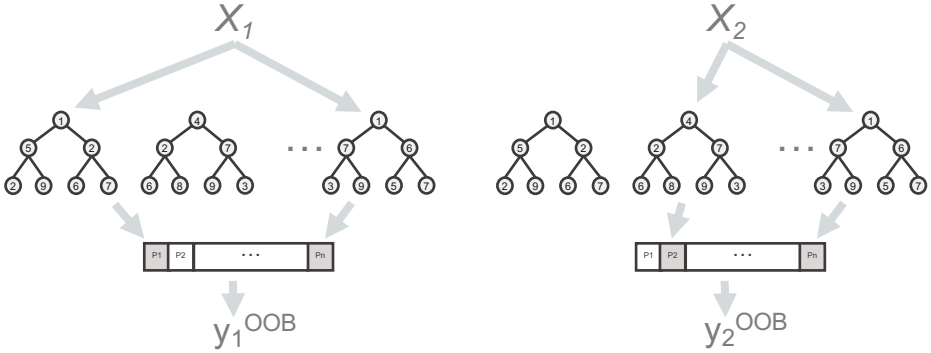
RowID	x_1	x_2	y
Row_1	2	6	Class 1
Row_2	4	1	Class 2
Row_3	9	3	Class 2
Row_4	2	7	Class 1
Row_5	8	1	Class 2
Row_6	2	6	Class 1
Row_7	5	2	Class 2

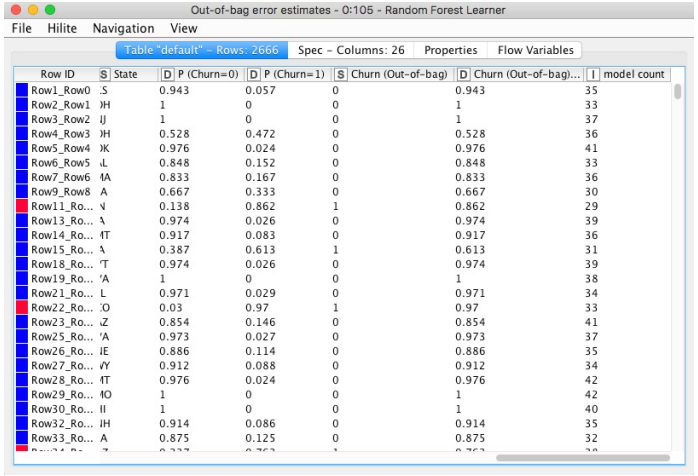
Sampled training set

RowID	x_1	x_2	y
Row_3	9	3	Class 2
Row_6	2	6	Class 1
Row_1	2	6	Class 1
Row_3	9	3	Class 2
Row_5	8	1	Class 2
Row_6	2	6	Class 1
Row_1	2	6	Class 1

An Extra Benefit of Bagging: Out of Bag Estimation

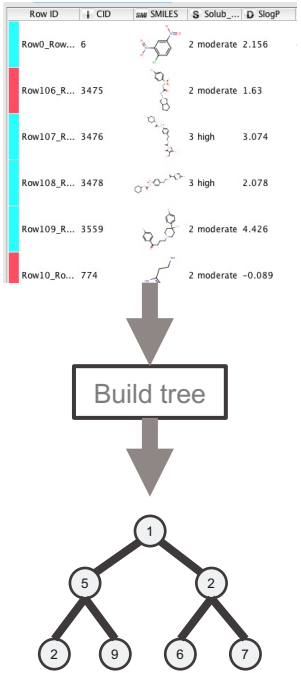
- Able to evaluate the model using the training data
- Apply trees to samples that haven't been used for training





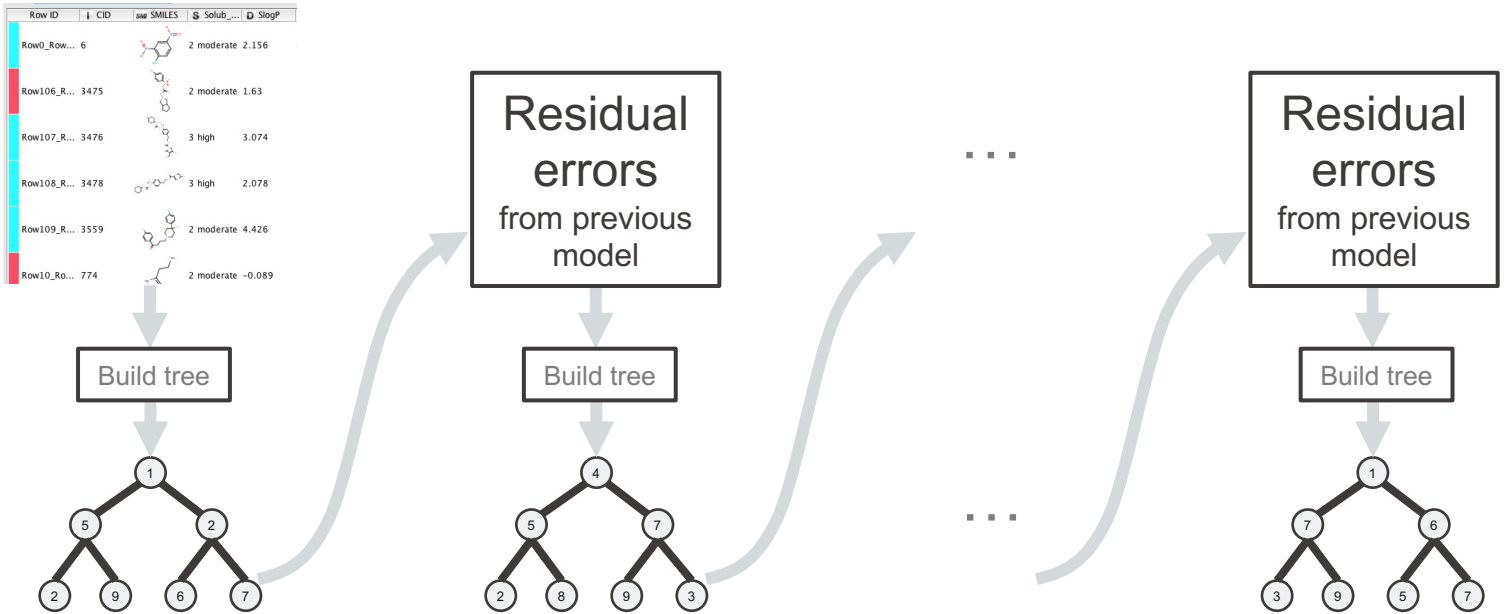
Random Forest

- Bag of decision trees, with an extra element of randomization
- **Each node** in the decision tree only “sees” **a subset of the input features**, typically $\sqrt{N}$ to pick from
- Random forests tend to be very robust w.r.t. overfitting



Boosting - Idea

- Starts with a single tree built from the data
- Fits a tree to residual errors from the previous model to refine the model sequentially



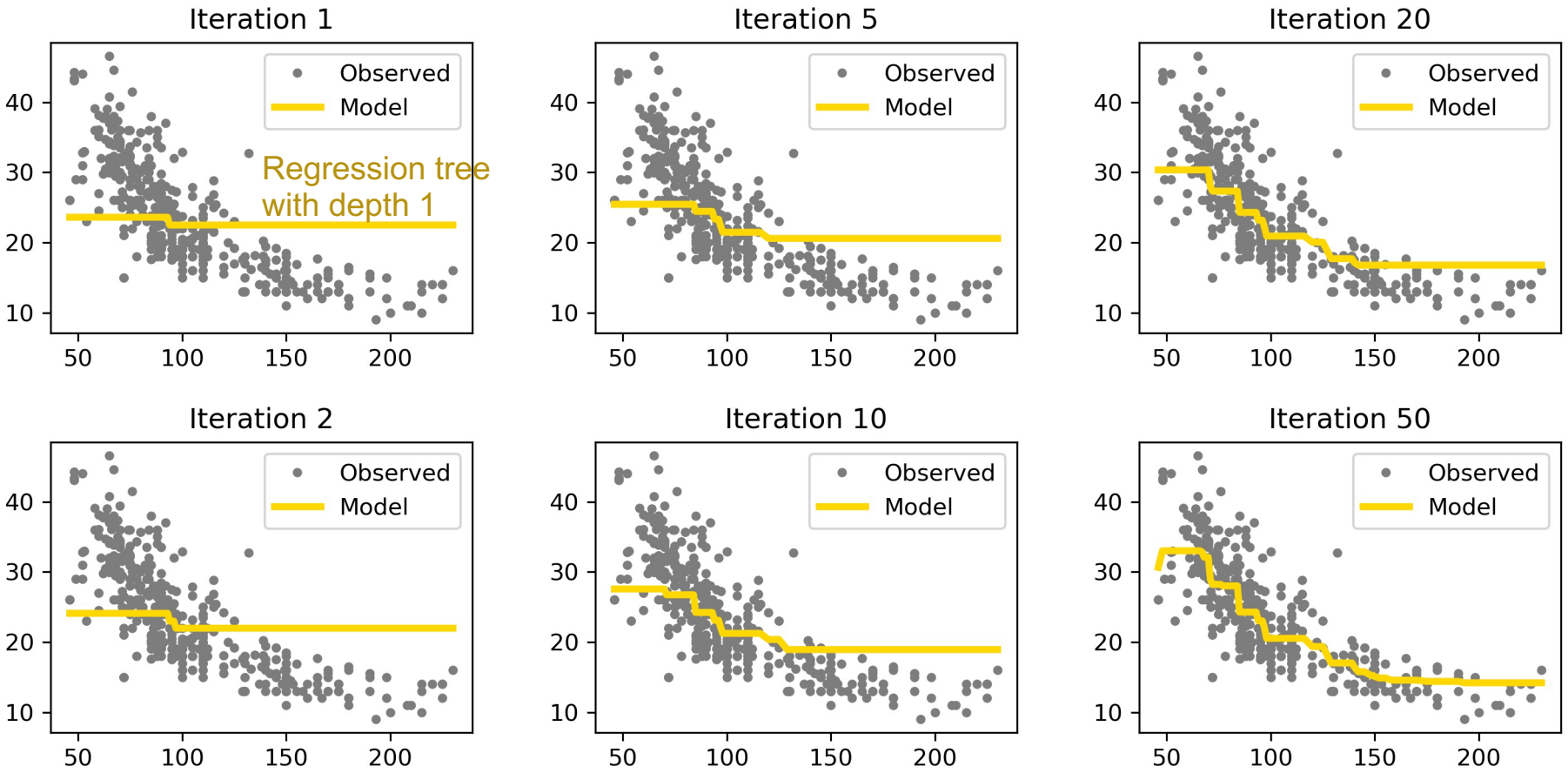
Boosting - Idea

- **Gradient boosting** method
- A shallow tree (depth 4 or less) is built at each step
  - To fit residual errors from the previous step
  - Resulting in a tree $h_m(x)$
- The resulting tree is added to the latest model to update

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

  - Where $F_{m-1}(x)$ is the model from the previous step
  - The weight γ_m is chosen to minimize the loss function
    - Loss function: quantifies the difference between model predictions and data

Gradient Boosting Example – Regression

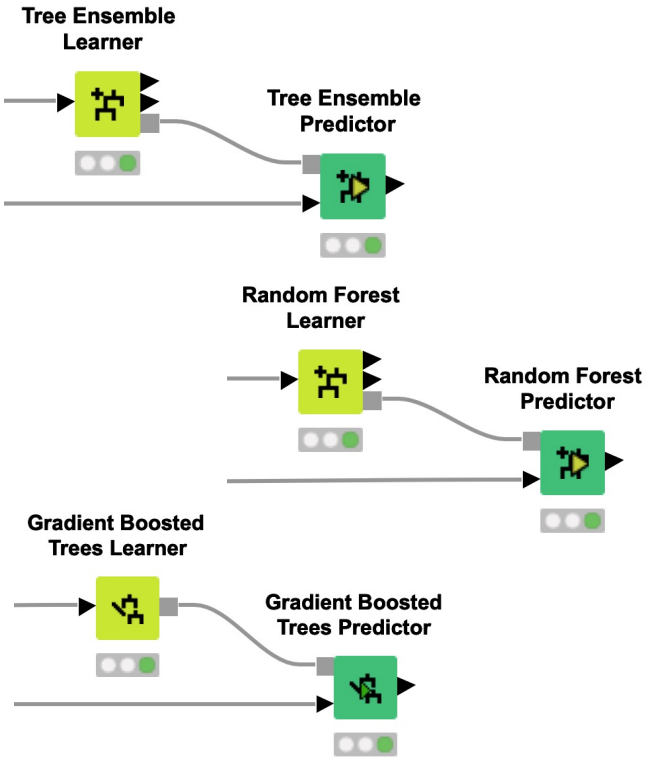


Gradient Boosted Trees

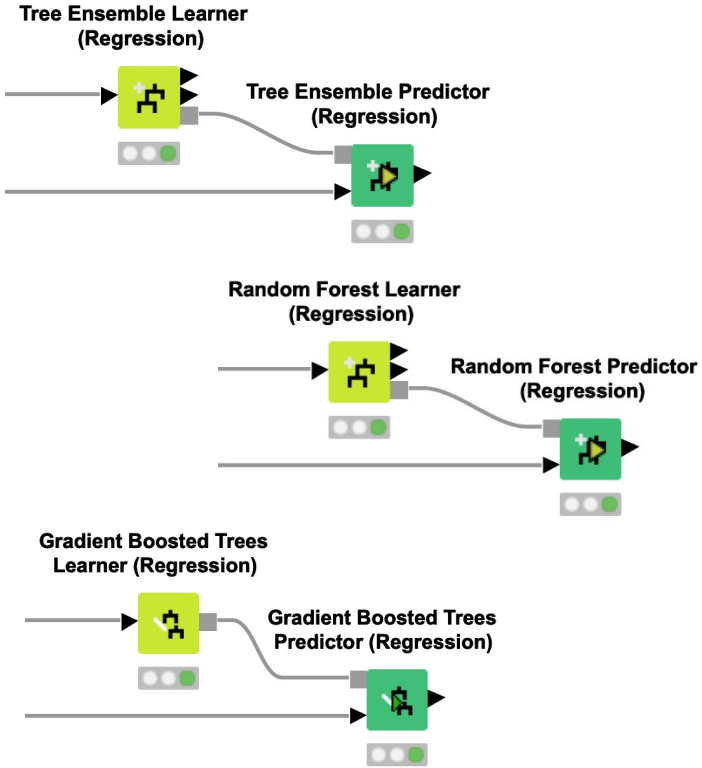
- Can be used for classification and regression
- Large number of iterations – prone to overfitting
  - ~100 iterations are sufficient
- Can introduce randomness in choice of data subsets (“stochastic gradient boosting”) and choice of input features

Ensemble Tree Nodes in KNIME Analytics Platform

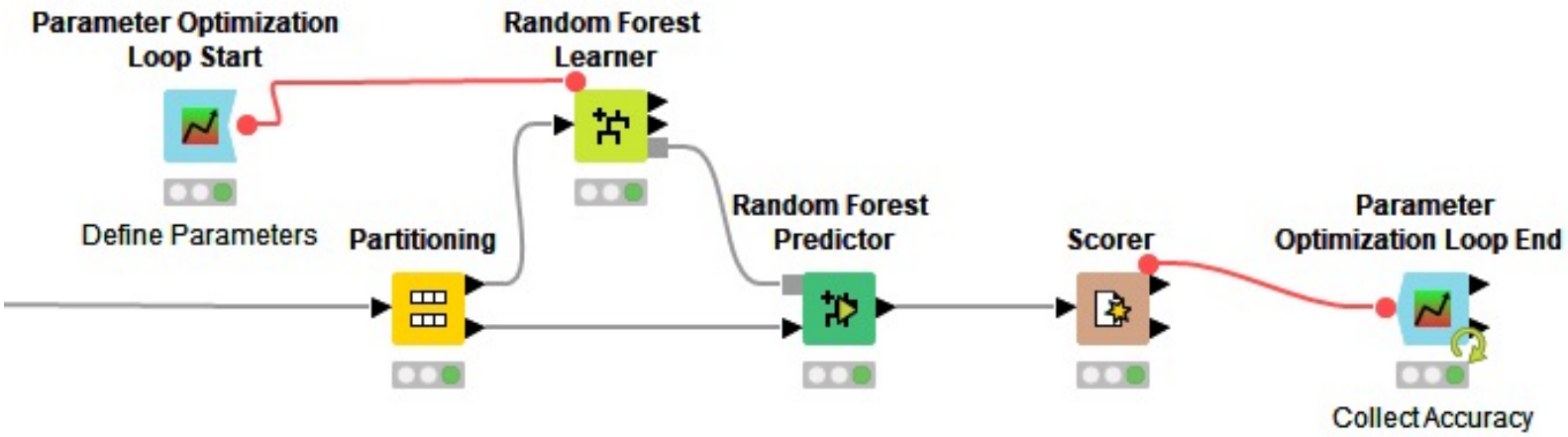
Classification Problems



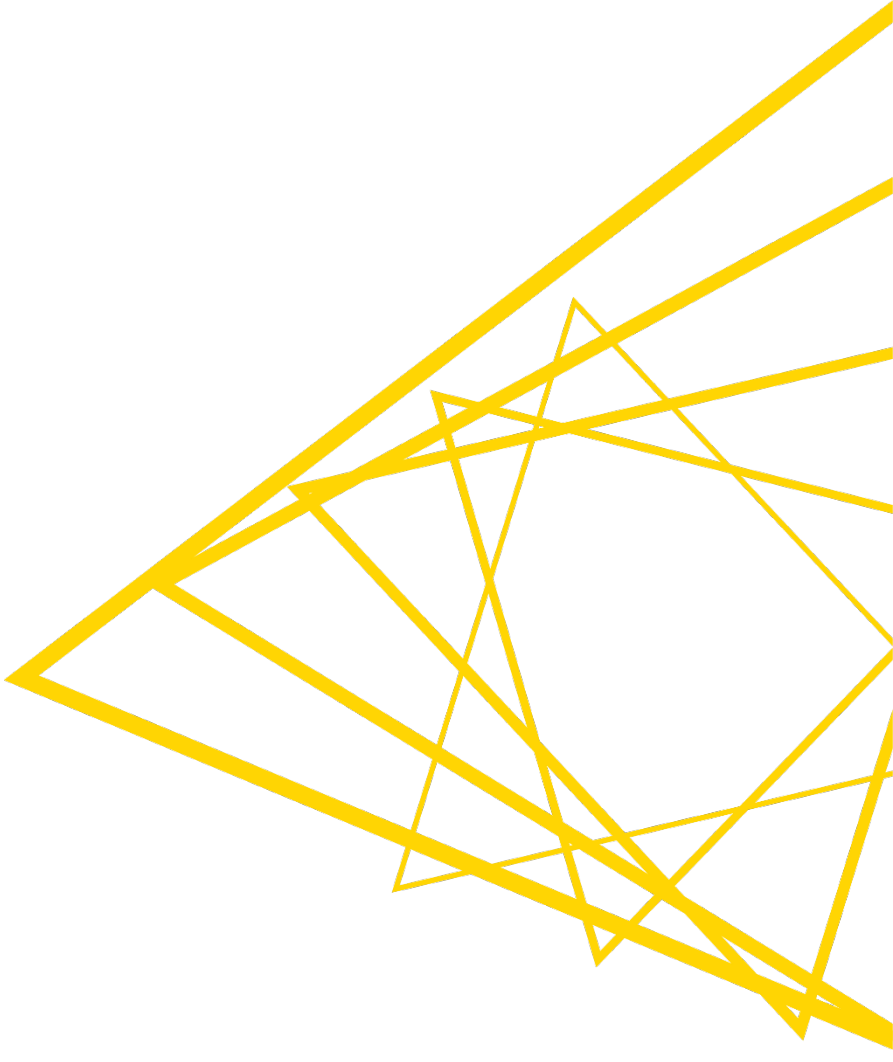
Regression Problems



Parameter Optimization



Logistic Regression

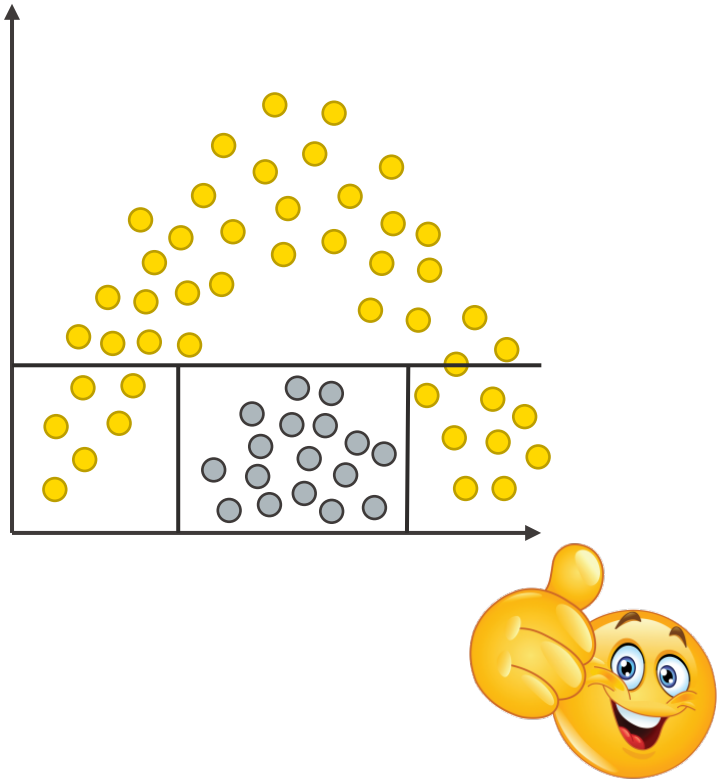


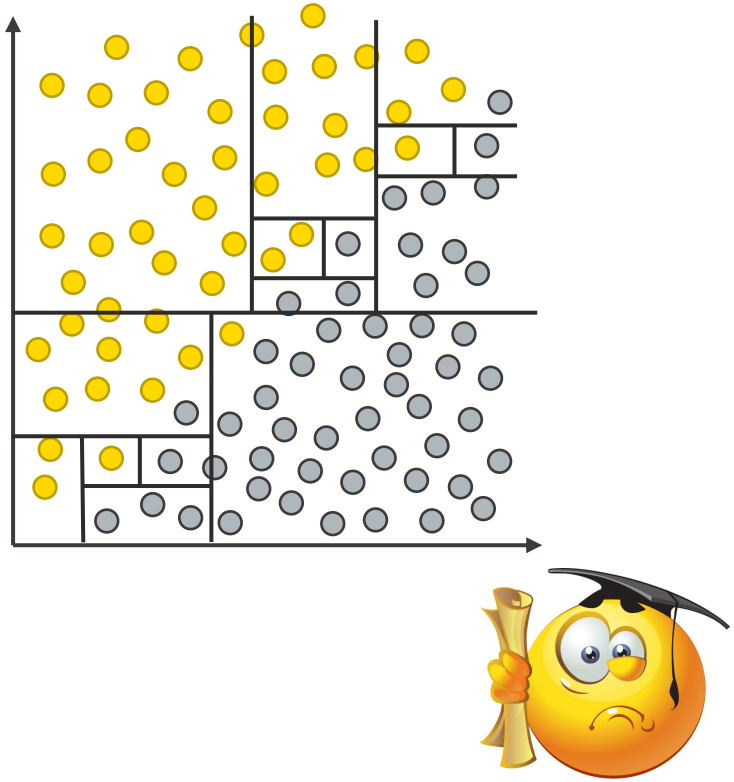
What is a Logistic Regression (algorithm)?

- Another algorithm to train a classification model

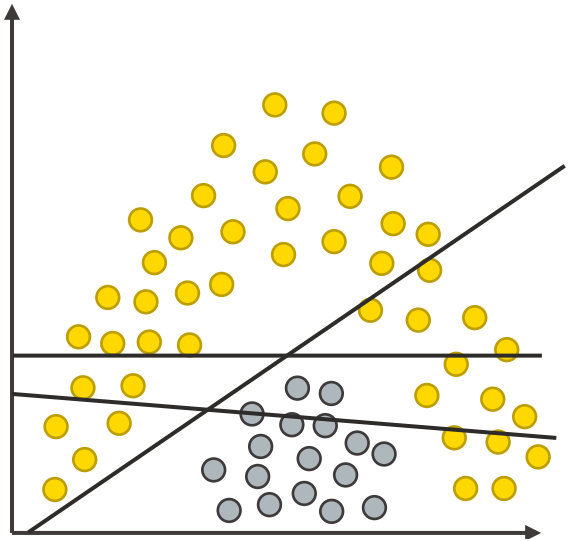
I know already the decision tree algorithm and tree ensembles. Why do I need another one?

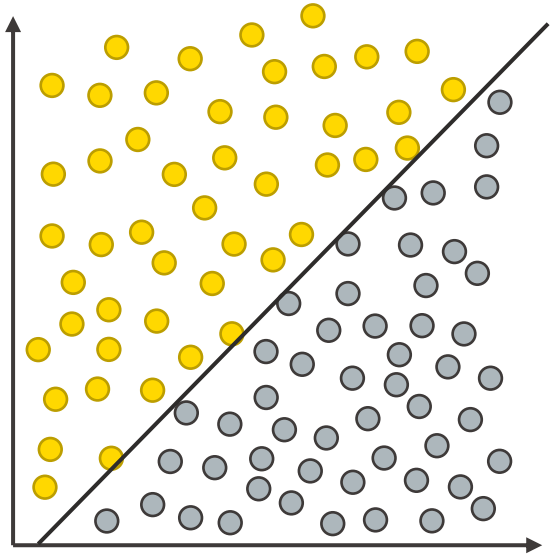
Why Shouldn’t we Always use the Decision Tree?

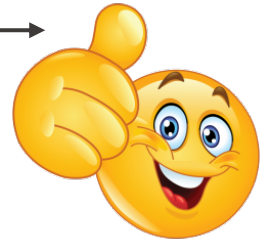




Decision Boundary of a Logistic Regression







Linear Regression vs. Logistic Regression

	Linear Regression	Logistic Regression
Target variable y	Numeric $y \in (-\infty, \infty)/[a, b]$	***Nominal*** $y \in \{0, 1, 2, 3\}/\{red, white\}$
Functional relationship between features and…	… target value y $y = f(x_1, \dots, x_n, \beta_0, \dots, \beta_n)$ $y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$	… ***class probability P (y = class i)*** $P(y = c_i) = f(x_1, \dots, x_n, \beta_0, \dots, \beta_n)$

Goal: Find the regression coefficients $\beta_0, \dots, \beta_n$

Let’s find out how Binary Logistic Regression works!

- Idea: Train a function, which gives us the probability for each class (0 and 1) based on the input features

- Recap on probabilities
  - Probabilities are always between 0 and 1
  - The probability of all classes sum up to 1

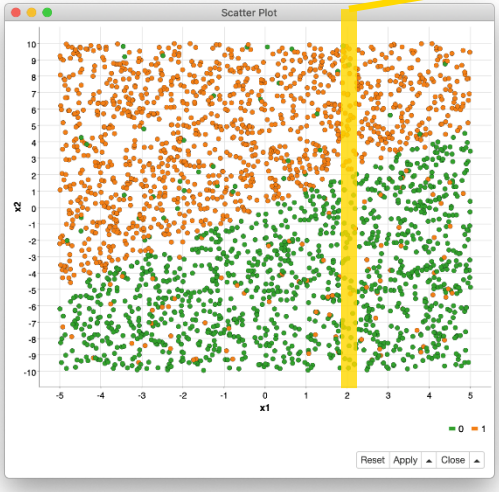
$$P(y = 1) = p_1 \Rightarrow P(y = 0) = 1 - p_1$$

➔ It’s sufficient to model the probability for one class

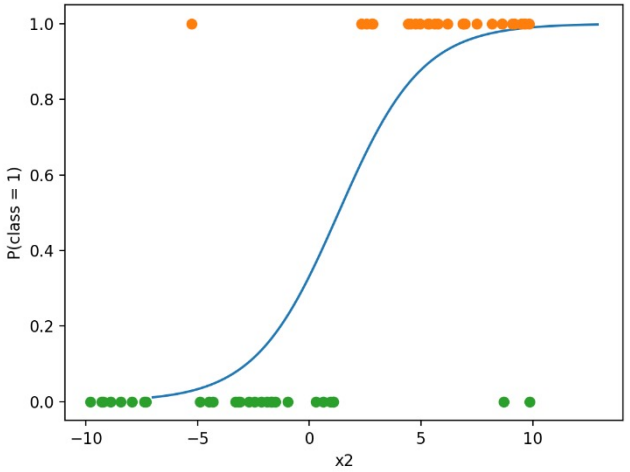
Let’s Find Out How Binary Logistic Regression Works!

$$P(y=1) = f(x_1, x_2; \beta_0, \beta_1, \beta_2) := \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2)}}$$

Feature space



Probability function given $x_1 = 2$



More General: Binary Logistic Regression

- Model:

$$\pi = P(y = 1) = \frac{1}{1+\exp(-z)}$$

With $z = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n = \boldsymbol{X}\boldsymbol{\beta}$.

- Goal: Find the regression coefficients $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_n)$
- Notation:
  - y_i is the class value for sample i
  - $x_1, \ldots, x_n$ is the set of input features, $\boldsymbol{X} = (1, x_1, \ldots, x_n)$
  - The training data set has m observations $(y_i, x_1^i, \ldots, x_n^i)$

How can we Find the Best Coefficients β?

Maximize the product of the probabilities ➔ Likelihood function

$$L(\beta; y, X) = \prod_{i=1}^{m} P(y = y_i) = \prod_{i=1}^{m} \pi_i^{y_i}(1 - \pi_i)^{1-y_i}$$

Why does it make sense to maximize this function?

$$P(y = y_i) = \begin{cases} \pi_i & if\ y_i = 1 \\ 1 - \pi_i & if\ y_i = 0 \end{cases}$$

$$= \pi_i^{y_i}(1 - \pi_i)^{1-y_i}$$

Remember:
$\pi_i = \mathrm{P}(y = 1)$
$u^0 = 1$ for $u \in \mathbb{R}$
$u^1 = u$ for $u \in \mathbb{R}$

Max Likelihood and Log Likelihood Functions

- Maximize the Likelihood function $L(\boldsymbol{\beta}; \boldsymbol{y}, \boldsymbol{X})$

$$\max_{\beta} L(\beta; y, X) = \max_{\beta} \prod_{i=1}^{m} \pi_i^{y_i} (1 - \pi_i)^{1-y_i}$$

- Equivalent to maximizing the Log Likelihood function $LL(\boldsymbol{\beta}; \boldsymbol{y}, \boldsymbol{X})$

$$\max_{\beta} LL(\boldsymbol{\beta}; \boldsymbol{y}, \boldsymbol{X}) = \max_{\beta} \sum_{i=1}^{n} y_i \ln(\pi_i) + (1 - y_i) \ln(1 - \pi_i)$$

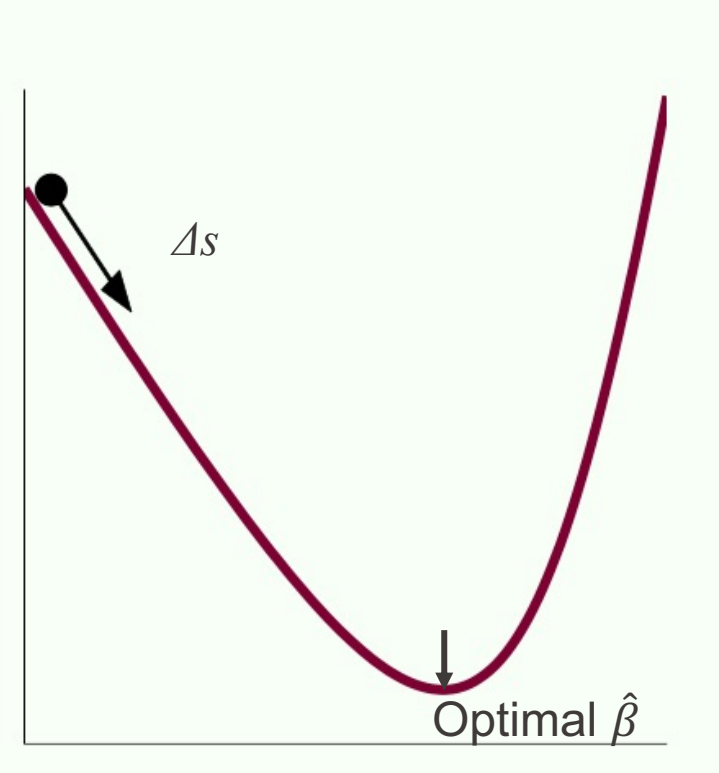
How can we find this Coefficients?

- To find the coefficients of our model we want to find $\boldsymbol{\beta}$ so that the value of the function $LL(\boldsymbol{\beta}; \boldsymbol{y}, \boldsymbol{X})$ is maximal

- KNIME Analytics Platform provides two algorithms
  - Iteratively re-weighted least squares
    - Uses the idea of the newton method
  - Stochastic average gradient descent

Idea: Gradient Descent Method

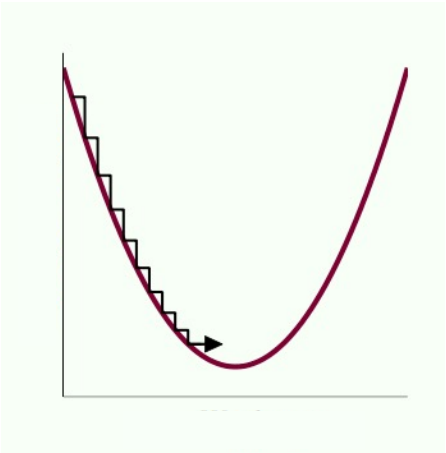
$$\max LL(\boldsymbol{\beta}; \boldsymbol{X}, \boldsymbol{y}) \Leftrightarrow \min -LL(\boldsymbol{\beta}; \boldsymbol{X}, \boldsymbol{y})$$



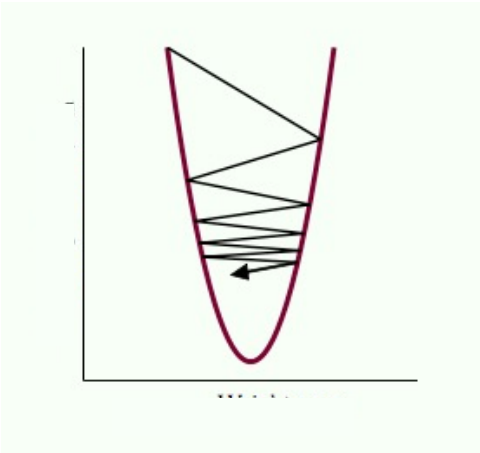
- Example: $\min\ -LL(\beta) \coloneqq f(\beta)$
- Start from an arbitrary point
- Move towards the minimum
- With step size Δs
- If $f(\beta)$ is strictly convex
  ➔ Only one global minimum exists
- Z normalization of the input data lead to better convergence

Learning Rate / Step Length Δs

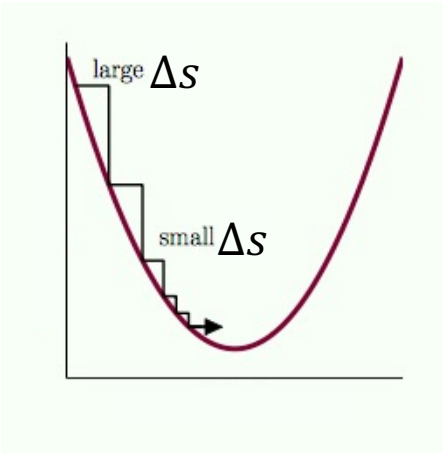
Δs too small



Δs too large



Just right



Learning Rate Δs

- Fixed:

$$\Delta s_k = \Delta s_0$$

- Annealing:

$$\Delta s_k = \frac{\Delta s_0}{1 + \frac{\alpha}{k}}$$

with iteration number k and decay rate α

- Line Search: Learning rate strategy that tries to find the optimal learning rate

Is there a way to handle Overfitting as well? (optional)

- To avoid overfitting: add regularization by penalizing large weights
  - L_2 regularizations = Coefficients are Gauss distributed with $\sigma = \frac{1}{\lambda}$

$$l(\hat{\beta}; y, X) := -LL(\hat{\beta}; y, X) + \frac{\lambda}{2}||\hat{\beta}||_2^2$$

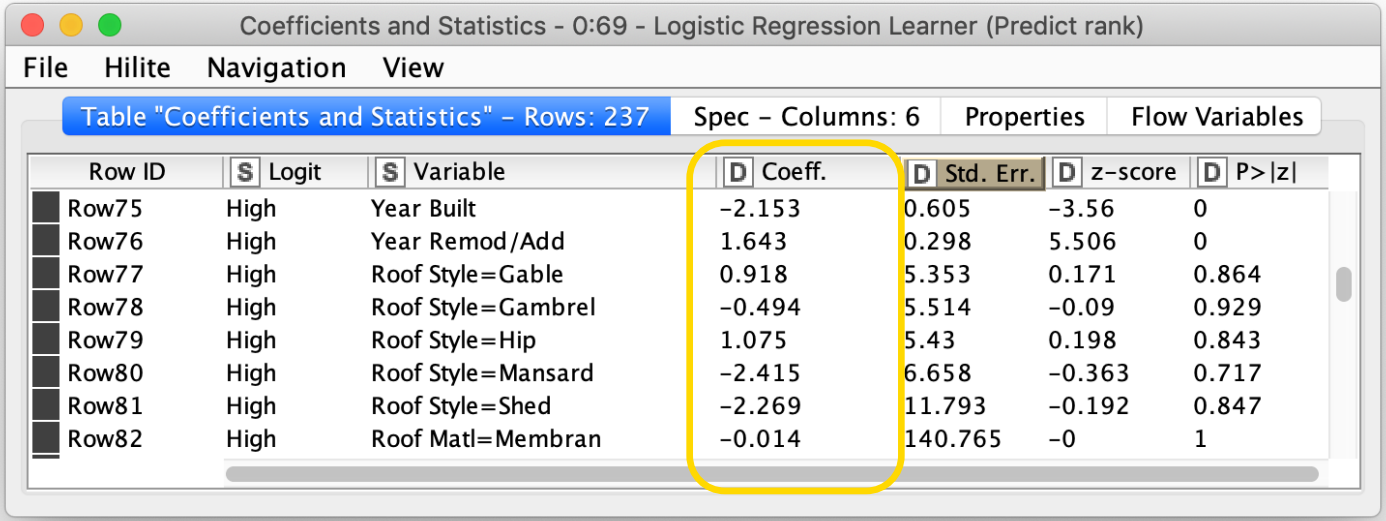
  - L_1 regularizations = Coefficients are Laplace distributed with $\sigma = \frac{\sqrt{2}}{\lambda}$

$$l(\hat{\beta}; y, X) := -LL(\hat{\beta}; y, X) + \lambda||\hat{\beta}||_1$$

=> The smaller σ, the smaller the coefficients $\hat{\beta}$

Impact of Regularization

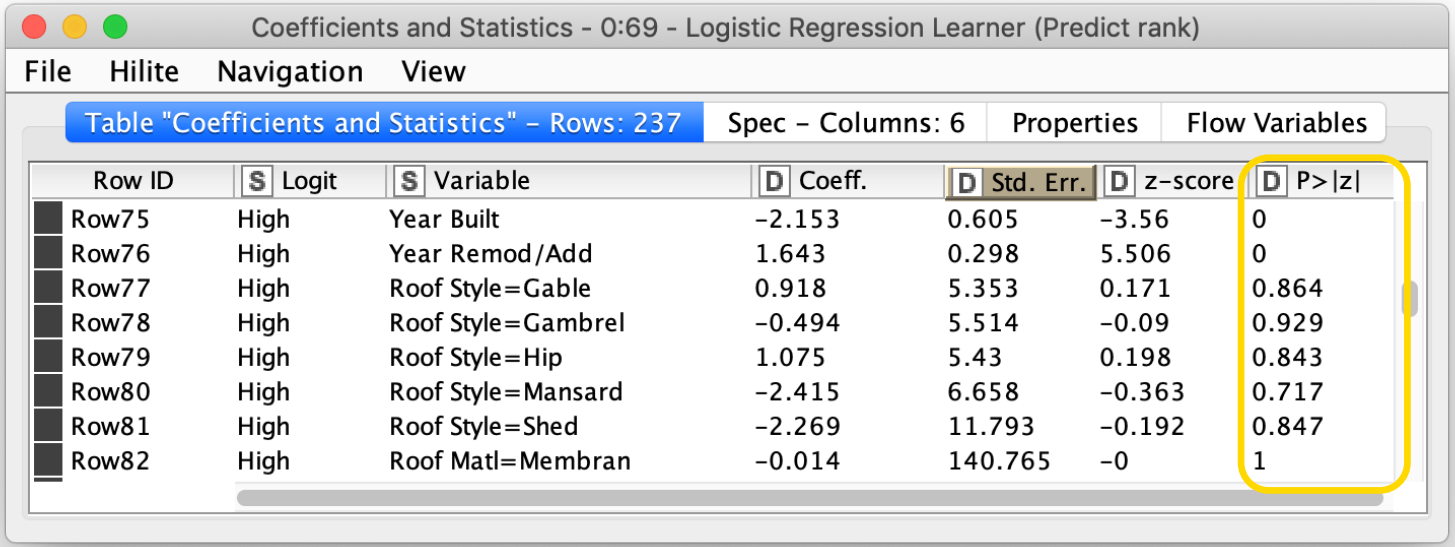
Interpretation of the Coefficients



Row ID	Logit	Variable	Coeff.	Std. Err.	z-score	P>|z|
Row75	High	Year Built	-2.153	0.605	-3.56	0
Row76	High	Year Remod/Add	1.643	0.298	5.506	0
Row77	High	Roof Style=Gable	0.918	5.353	0.171	0.864
Row78	High	Roof Style=Gambrel	-0.494	5.514	-0.09	0.929
Row79	High	Roof Style=Hip	1.075	5.43	0.198	0.843
Row80	High	Roof Style=Mansard	-2.415	6.658	-0.363	0.717
Row81	High	Roof Style=Shed	-2.269	11.793	-0.192	0.847
Row82	High	Roof Matl=Membran	-0.014	140.765	-0	1

- Interpretation of the sign
  - $\beta_i > 0$: Bigger x_i lead to higher probability
  - $\beta_i < 0$: Bigger x_i lead to smaller probability

Interpretation of the p Value



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Row82	High	Roof Matl=Membran	-0.014	140.765	-0	1

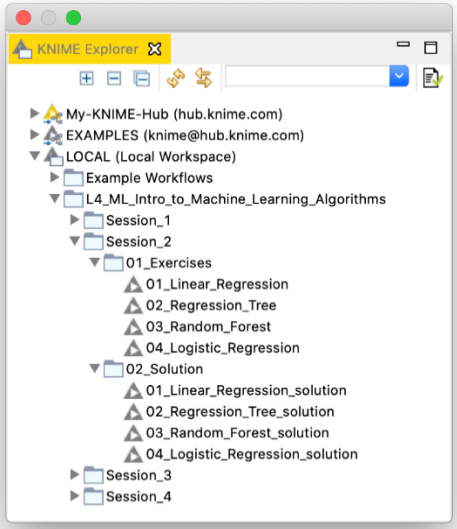
- p- value < α: input feature has a significant impact on the dependent variable.

Summary Logistic Regression

- Logistic regression is used for classification problems
- The regression coefficients are calculated by maximizing the likelihood function, which has no closed form solution, hence iterative methods are used.
- Regularization can be used to avoid overfitting.
- The p-value shows us whether an independent variable is significant

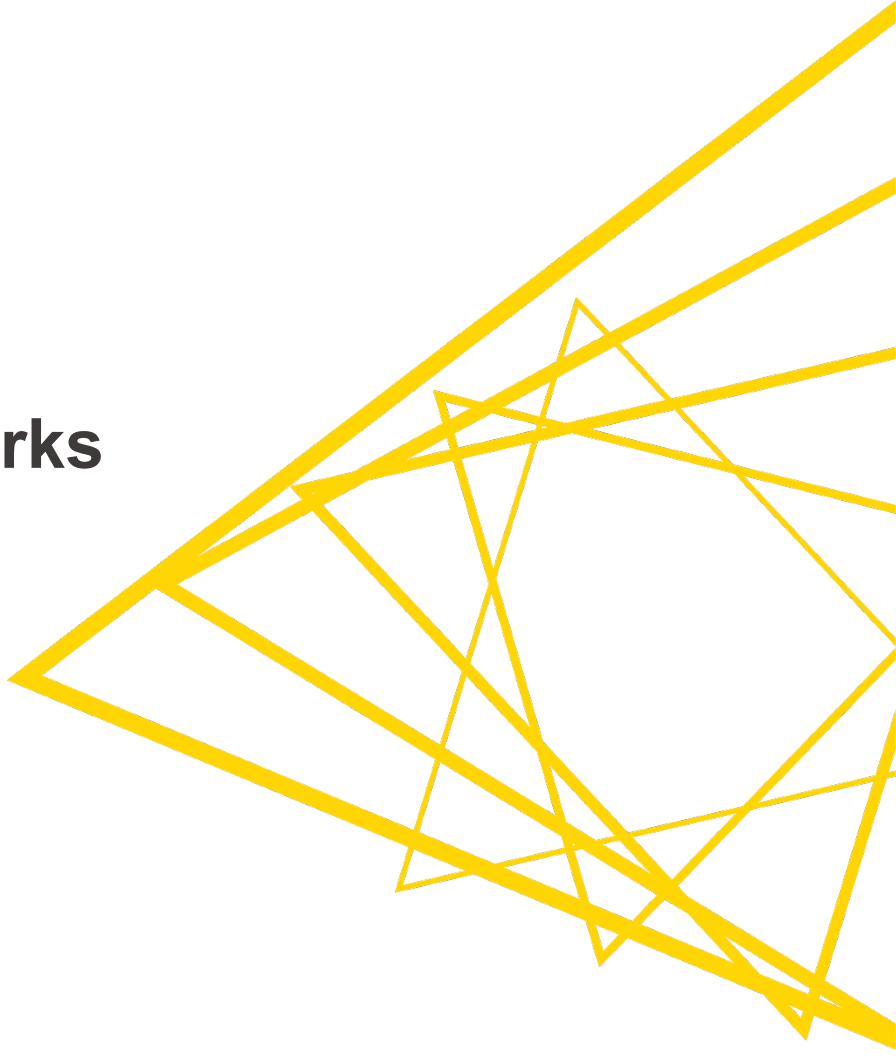
Exercises

- Regression Exercises:
  - Goal: Predicting the house price
  - 01_Linear_Regression
  - 02_Regression_Tree
- Classification Exercises:
  - Goal: Predicting the house condition (high /low)
  - 03_Radom_Forest (with optional exercise to build a parameter optimization loop)
  - 04_Logistic_Regression



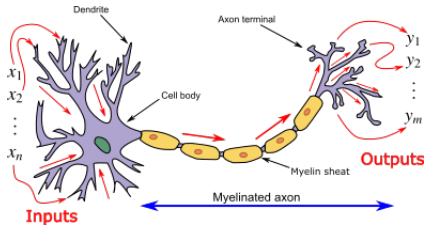
Session 3: Neural Networks and Recommendation Engines

Artificial Neurons and Networks

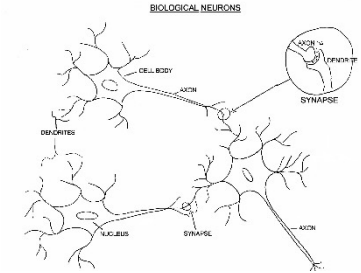


Biological vs. Artificial

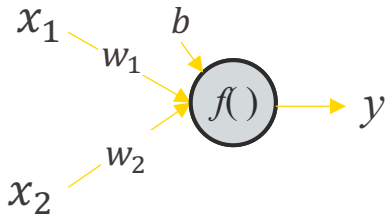
Biological Neuron



Biological Neural Networks



Artificial Neuron (Perceptron)



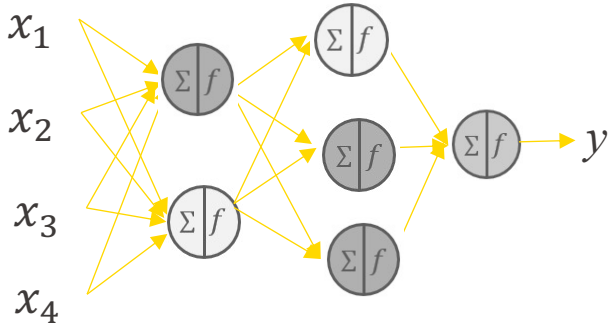
$$y = f(x_1 w_1 + x_2 w_2 + b)$$

$$b = w_0$$

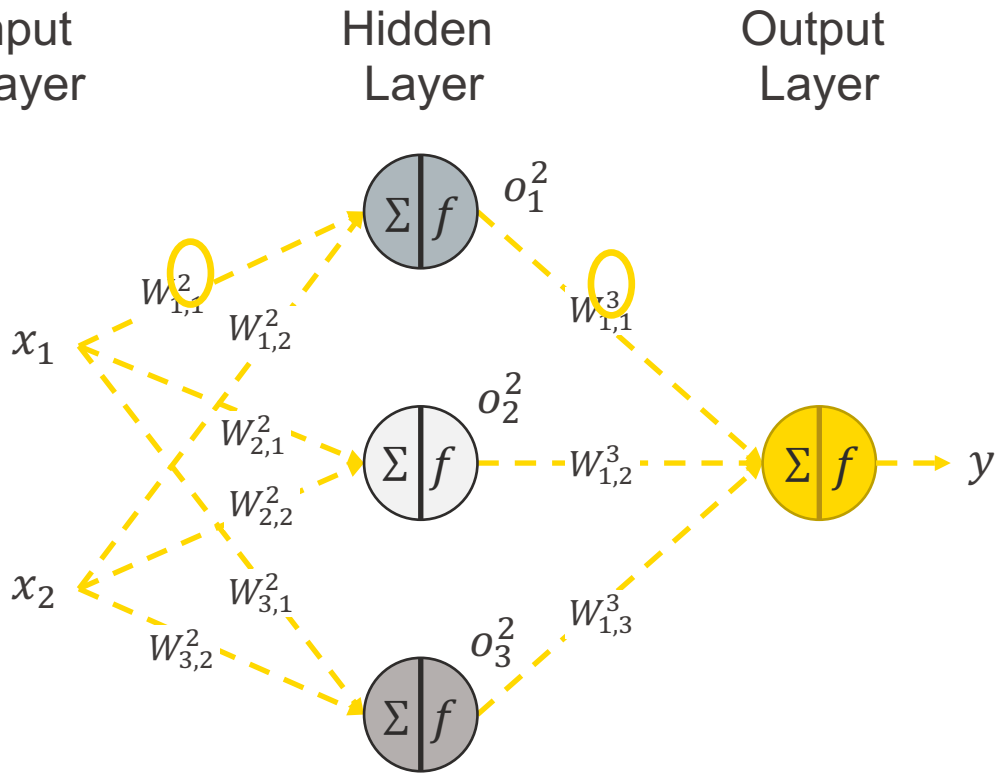
$$y = f(\sum_{i=0}^{n} x_i w_i)$$

Artificial Neural Networks

(Multilayer Perceptron, MLP)



Architecture / Topology



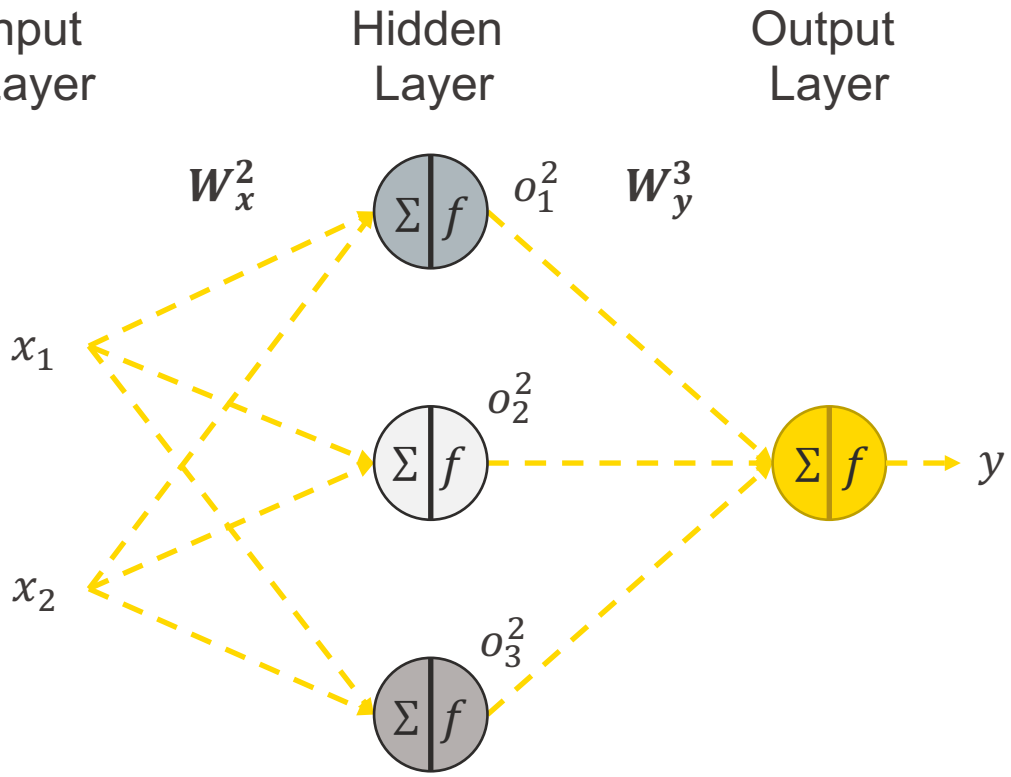
Forward pass:

$$\boldsymbol{o} = f(W_x^2 \boldsymbol{x})$$

$$y = f(W_y^3 \boldsymbol{o})$$

fully connected feed forward

Same with Matrix Notations



Forward pass:

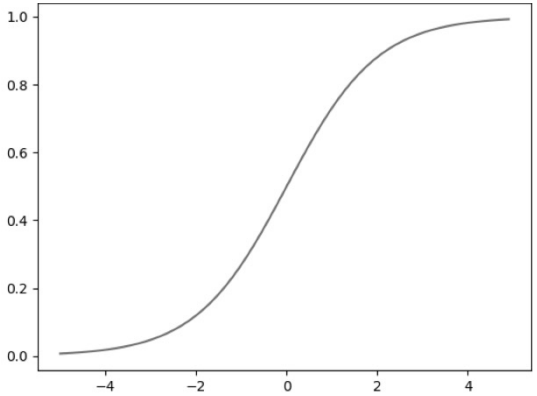
$$\boldsymbol{o} = f(W_x^2 \boldsymbol{x})$$

$$y = f(W_y^3 \boldsymbol{o})$$

$f(\ )$ = activation function

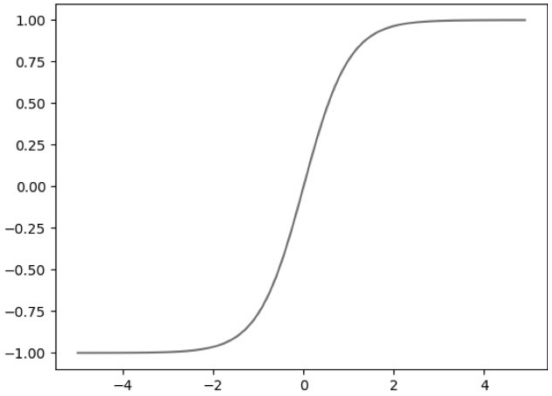
Frequently used activation functions

Sigmoid



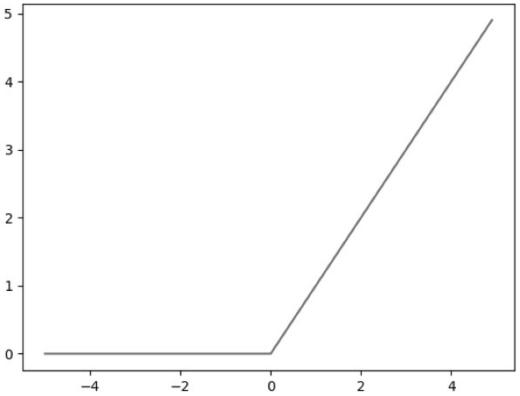
$$f(a) = \frac{1}{1 + e^{-ha}}$$

Tanh



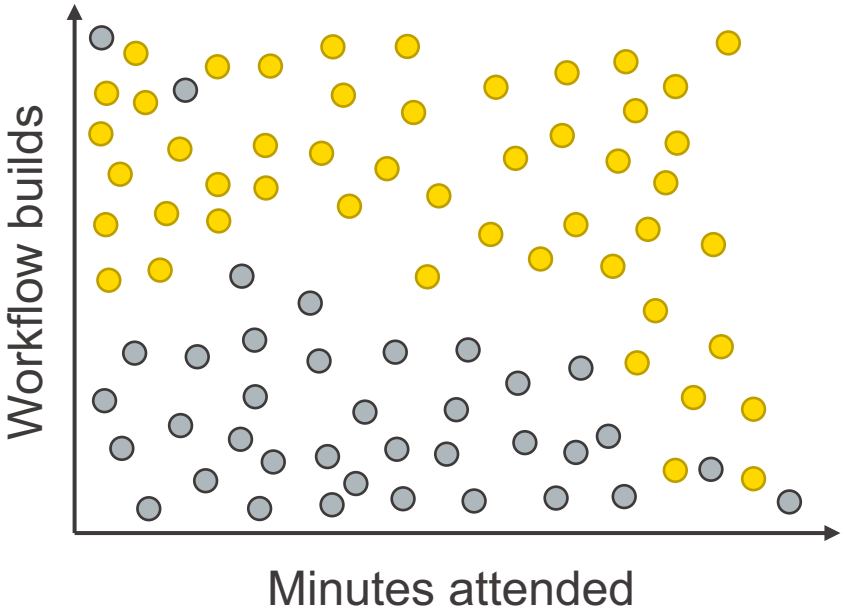
$$f(a) = \frac{e^{2ha} - 1}{e^{2ha} + 1}$$

Rectified Linear Unit (ReLU)



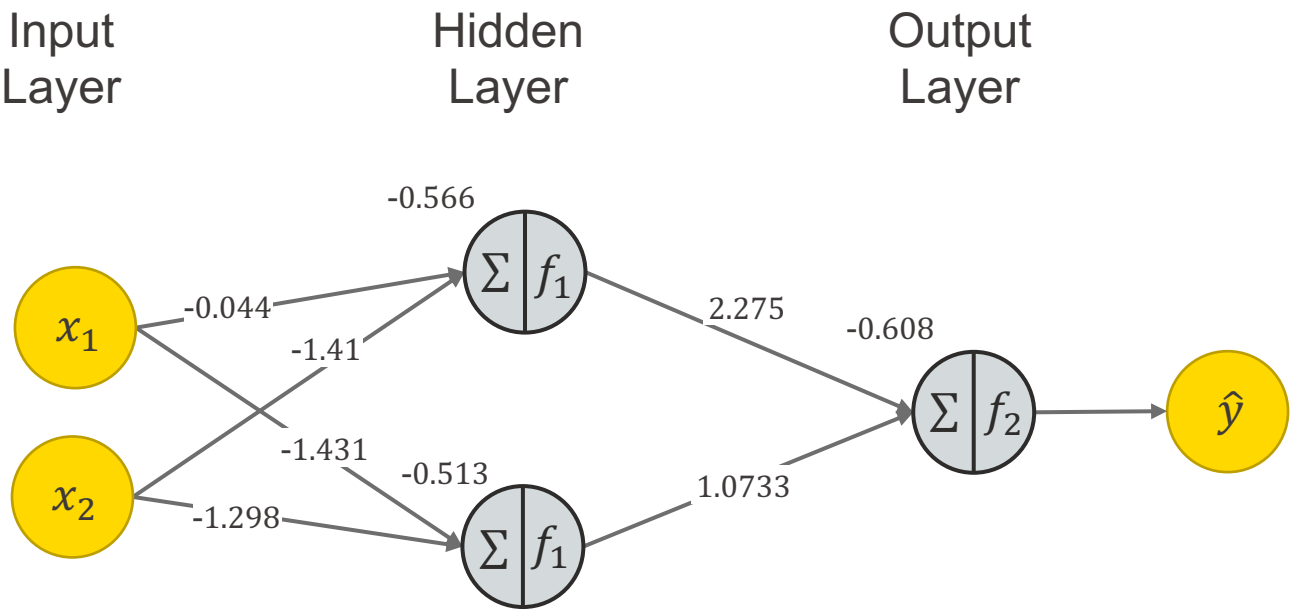
$$f(a) = max\{0, ha\}$$

Example: Passing the KNIME L1-Certification



- Passed certification
- Didn’t pass certification

Example: Passing the KNIME L1-Certification

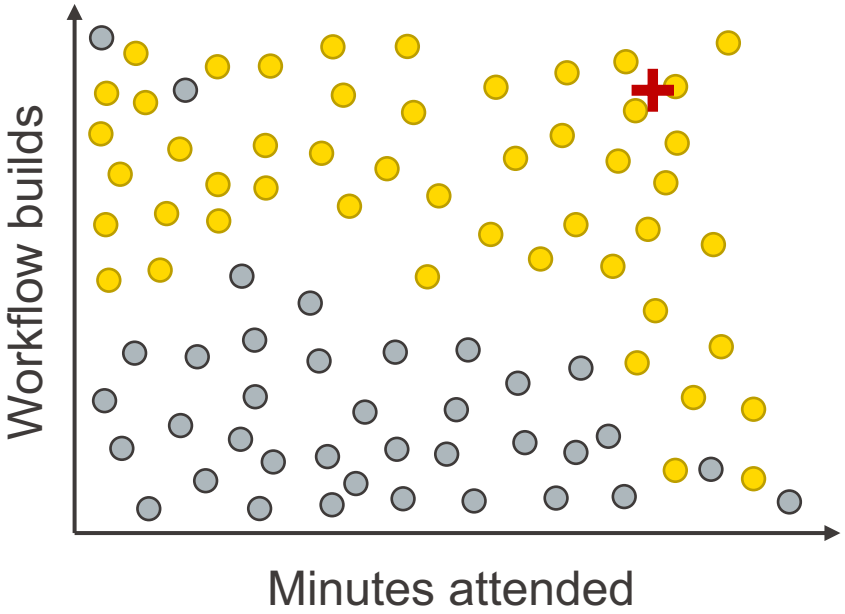


$f_1 = tanh$ $f_2 = sigmoid$

Input features:
x_1= minutes attended
x_2= workflows build

Output:
$\hat{y}$ =Probability that a person passed
$\hat{y} \geq 0.5 \Rightarrow Passed$ and $\hat{y} < 0.5 \Rightarrow Failed$

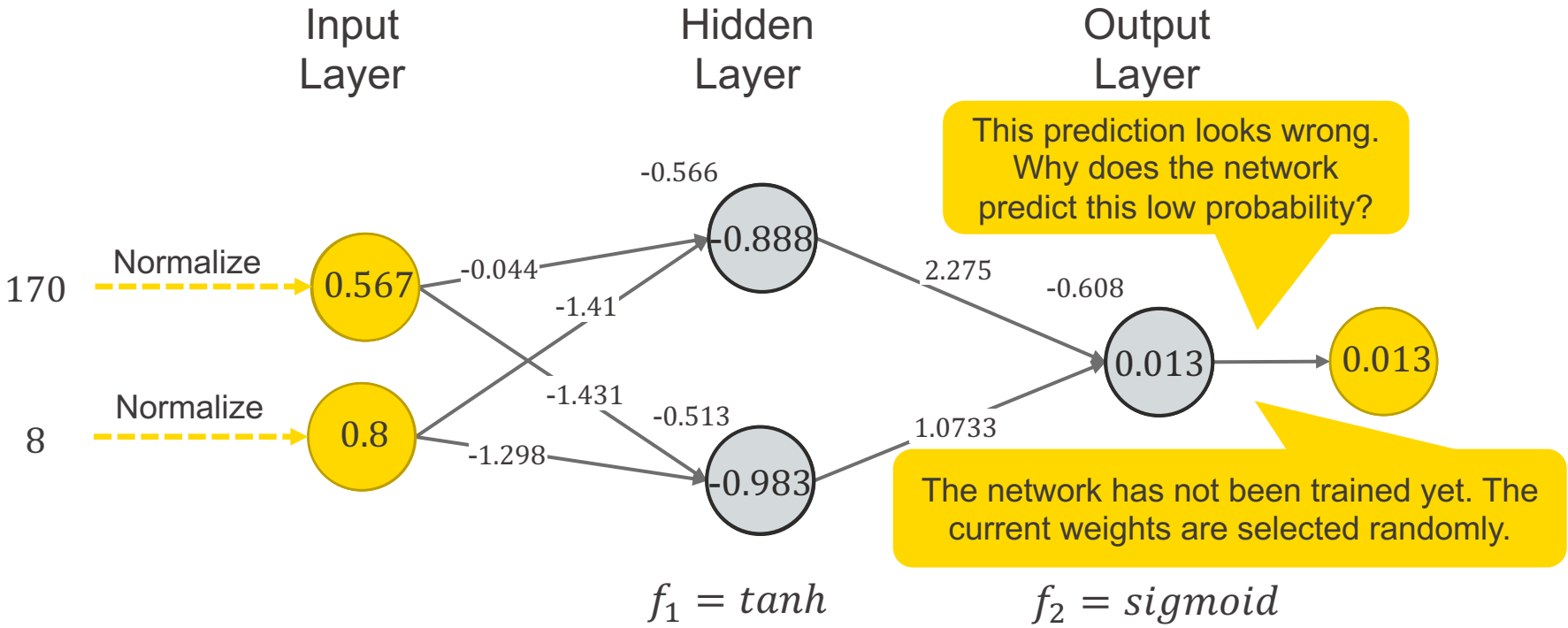
Example: Passing the KNIME L1-Certification



- Passed certification
- Didn't pass certification
- New sample

x_1 = minutes attended = 170
x_2 = workflows build = 8

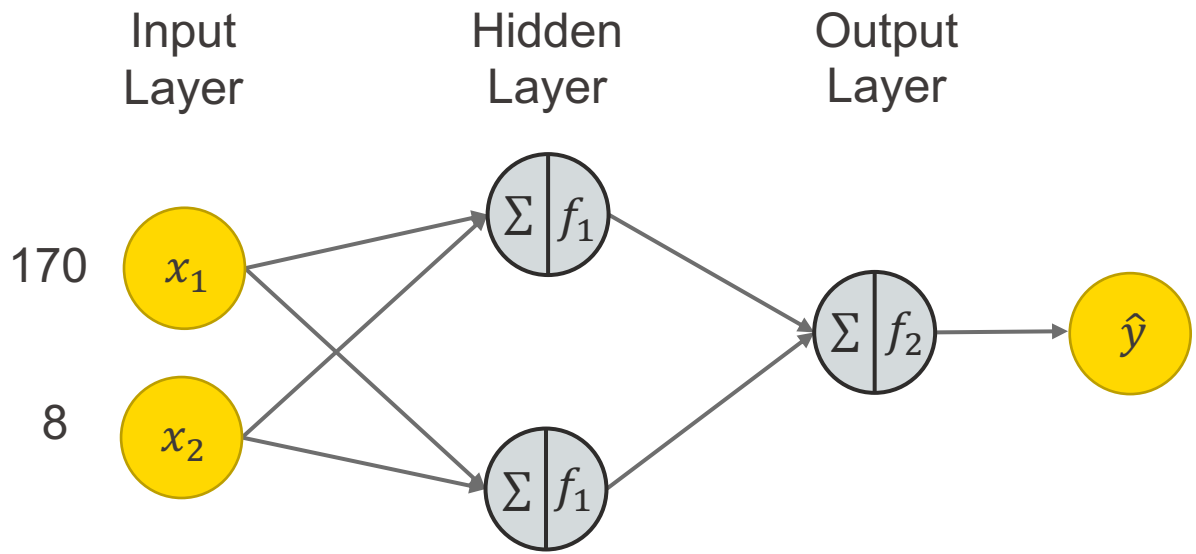
Example: Passing the KNIME L1-Certification



Input features:
x_1= minutes attended
x_2= workflows build

Output:
$\hat{y}$ =Probability that a person passed
$\hat{y} \geq 0.5 \Rightarrow Passed$ and $\hat{y} < 0.5 \Rightarrow Failed$

Training a Neural Network = Finding Good Weights



Predicted $\hat{y}$ = 0.013
True y = 1

Binary cross entropy

$$\mathcal{L} = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$

$$J(W) = \sum \mathcal{L}\left(\hat{y}(x_1, x_2, W), y\right)$$

Learning Rule from Gradient Descent

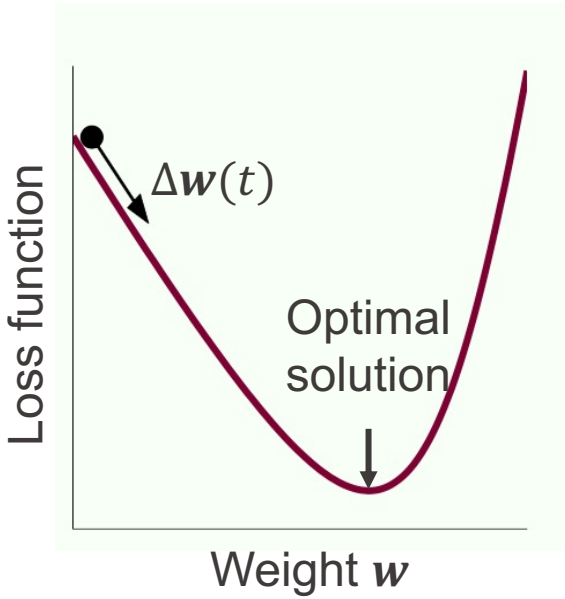
- Adjust the weight for the next step by the adjustment term $\Delta \boldsymbol{w}(t)$

$$\boldsymbol{w}(t+1) = \boldsymbol{w}(t) + \eta\, \Delta \boldsymbol{w}(t)$$

Updated weight in next step $t+1$

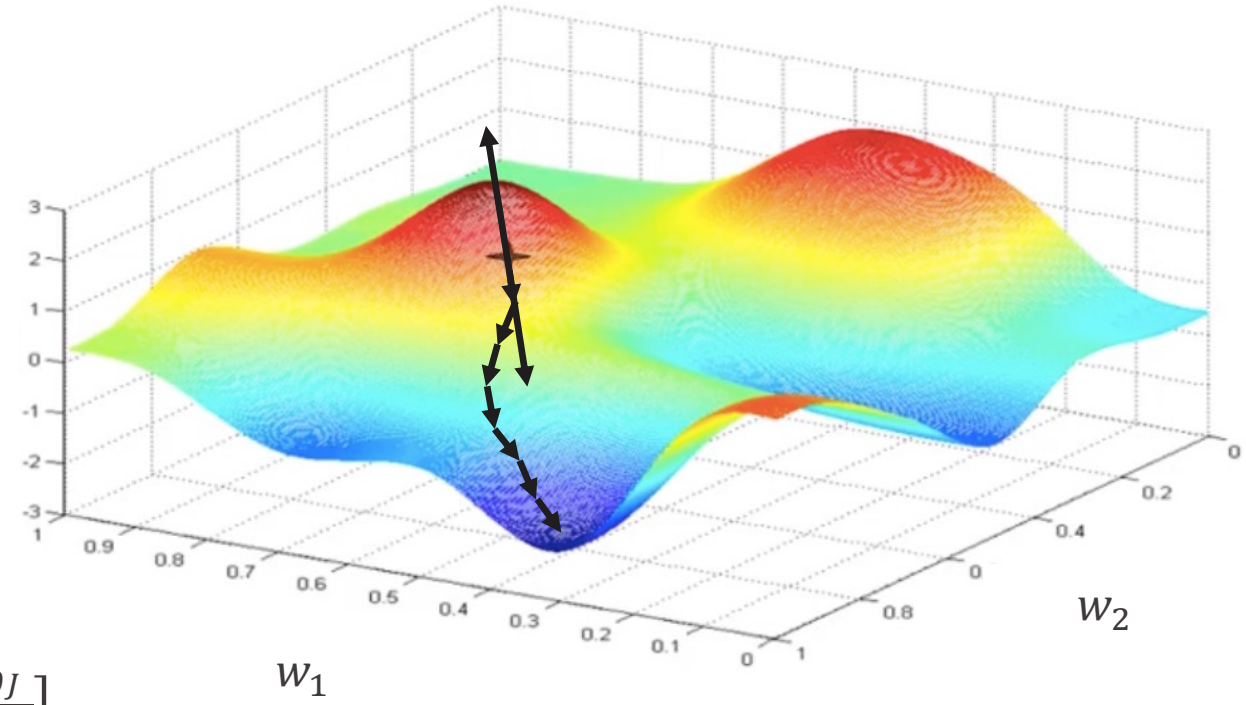
Weight in current step t

Weight adjustment based on gradient



Idea Behind Gradient Descent

$J(w_1, w_2)$

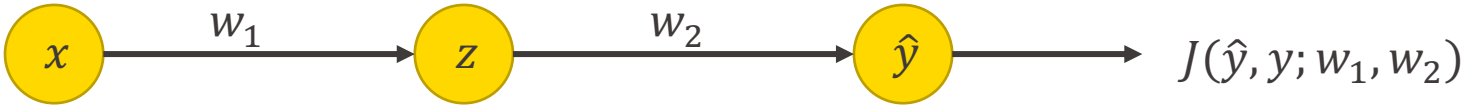


$$\nabla_W J(x, W) = \begin{bmatrix} \frac{\partial J}{\partial w_1} \\ \frac{\partial J}{\partial w_2} \end{bmatrix}$$

Backpropagation

- Efficient way to calculate the gradient during optimization

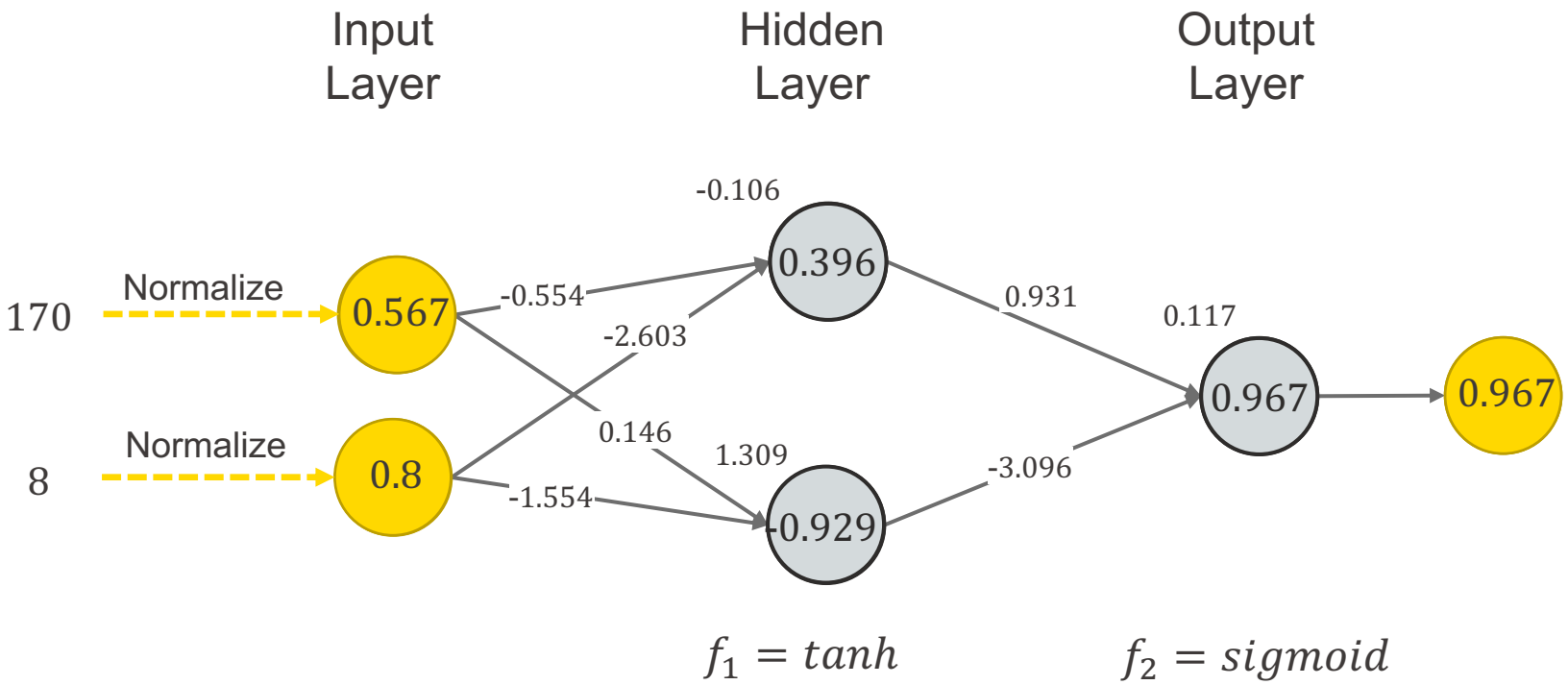
Forward pass



Backward pass

$$\frac{\partial J}{\partial w_2} = \frac{\partial J}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_2} \qquad \frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z} * \frac{\partial z}{\partial w_1}$$

Example: Passing the KNIME L1 Certification



Input features:
x_1= minutes attended
x_2= workflows build

Output:
y = Probability that a person passed
$y \geq 0.5 \Rightarrow Passed$ and $y < 0.5 \Rightarrow Failed$

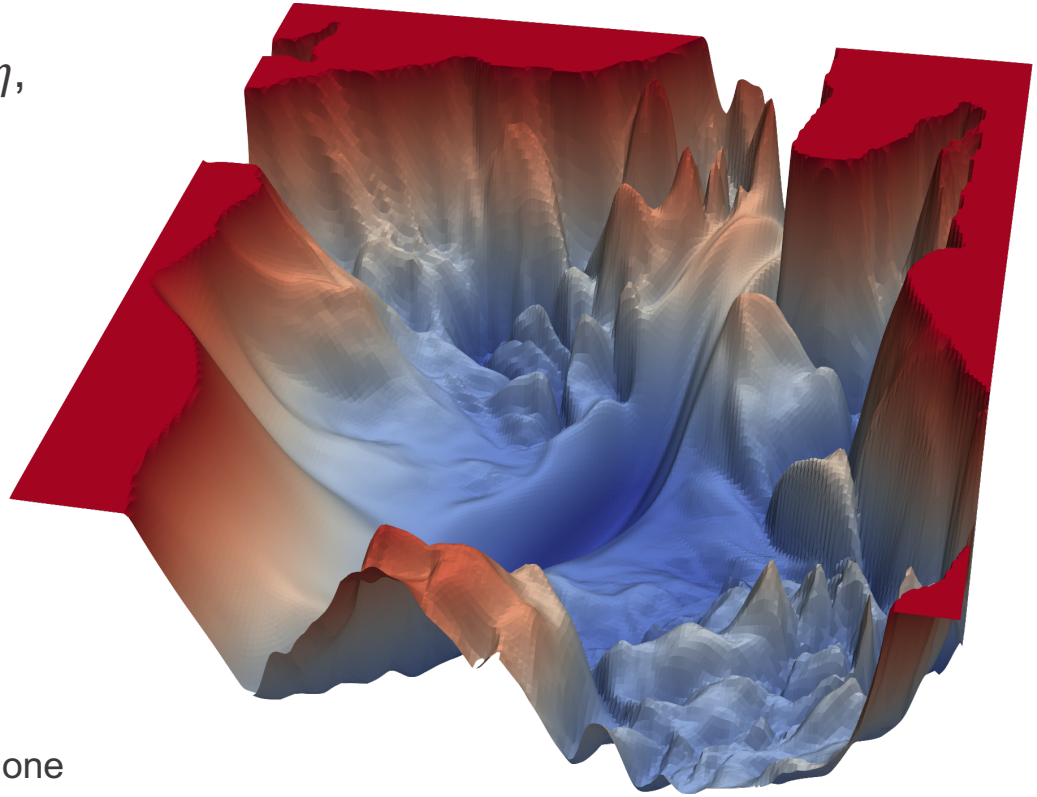
Loss Landscape of a Real Neural Network

- A good choice for the step size η, aka learning rate, is important

$$W \leftarrow W - \eta \nabla_W J(x, W)$$

- Many different optimizers with adaptive learning rates are available
  - Adam, Adadelta, Adagrad, ect

- Other important settings
  - Batch size, aka number of samples for one update
  - Number of epochs, aka how often each sample is used



Source: https://www.cs.umd.edu/~tomg/projects/landscapes/

Optimizers in Keras

Optimizer	How it works	Strengths	Weaknesses	When to use
SGD with momentum	Use the previous gradient to accelerate convergence	-Reduces oscillation near maxima	-Const learning rate	
NAG (Nesterov accelerated gradient)	Use the current gradient to predict gradient	-Increased responsiveness	-Additional hyperparameter	RNN
Adagrad	Updating by cumulating sum of sq gradients from past	-Different learning parameters for different features	-Computationally expensive -Shrinking learning rate	Sparse data (e.g. text)
Adadelta	Modified Adagrad with decaying average of sq gradients from past	-Learning rate not dramatically shrinking like Adagrad	-Computationally expensive	Sparse data (e.g. text)
RMSProp	Modified Adagrad with sq gradients added very slowly	-Learning rate not dramatically shrinking like Adagrad		
Adam (Adaptive Moment Estimation)	RMSProp plus decaying average of gradients from past	-Fast convergence	-Computationally expensive	

Which Activation Functions? Which Loss Functions?

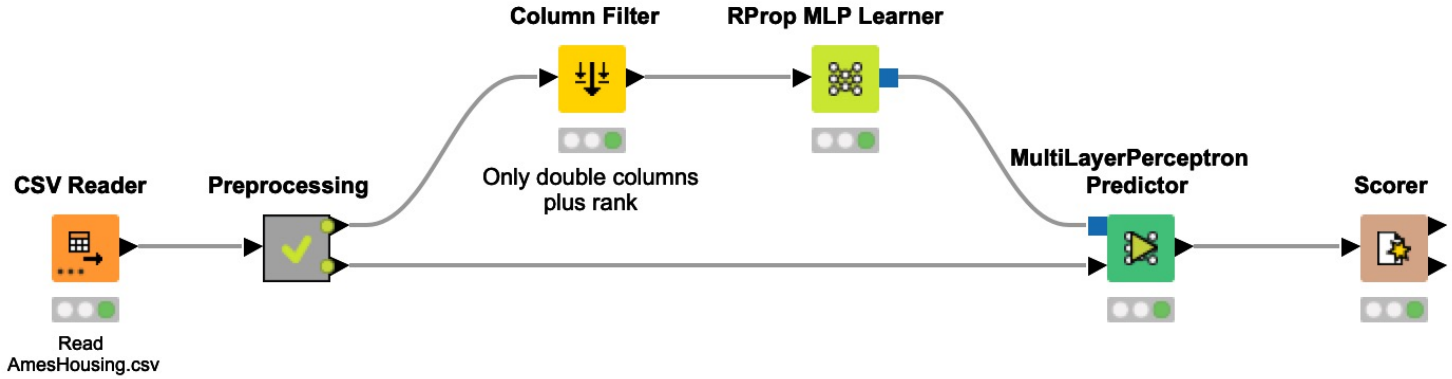
- Depends on the problem you are working on

✓ Recommended
Δ Can be used

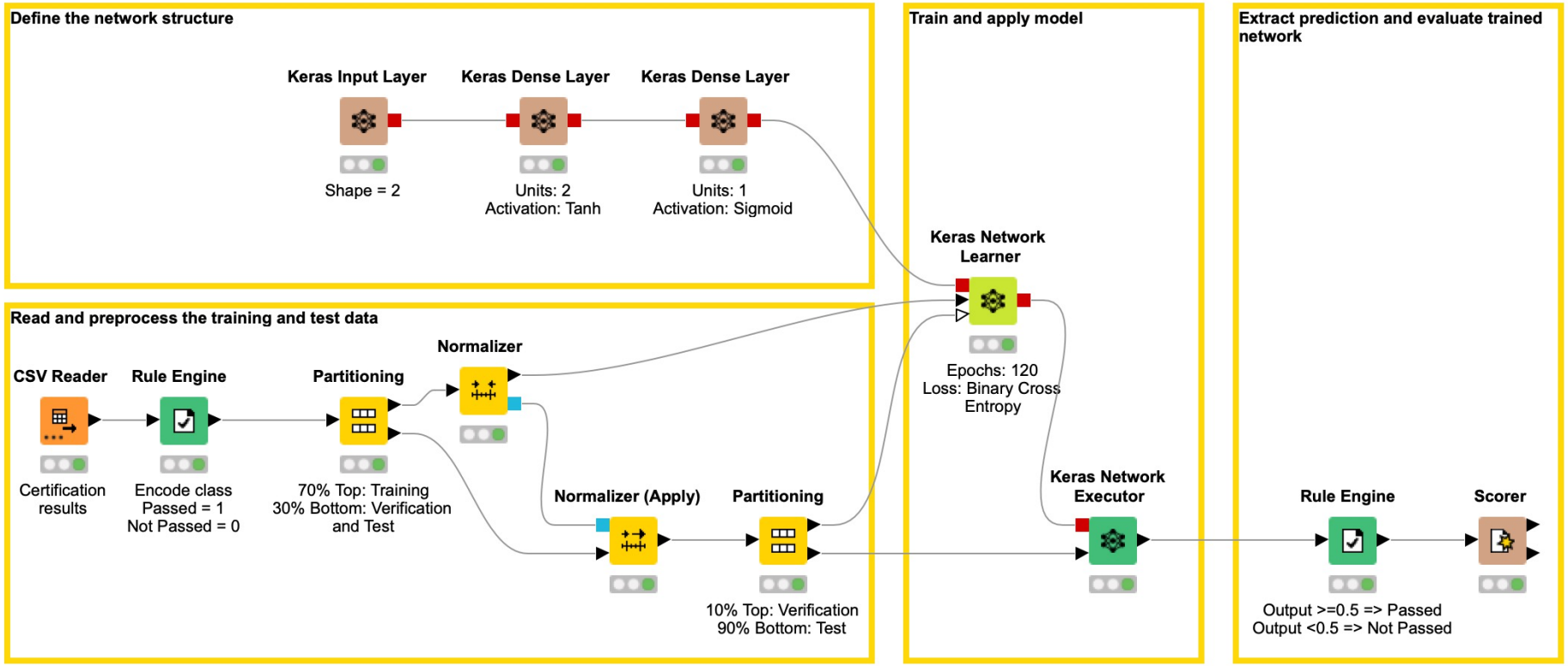
		Activation Functions								Loss Functions					
		Hidden Layers			Output Layer										
Problems		Sigmoid	Tanh	ReLU	Sigmoid	Tanh	Linear	ReLU	Softmax	Binary CE	Hinge	Categorical CE	MSE	MSLE	MAE
Classification	Binary classification (0 vs 1)	✓	✓	✓	✓					✓					
	Binary classification (-1 vs 1)	✓	✓	✓		✓					✓				
	Multi-class classification	✓	✓	✓					✓			✓			
Regression	Regression	✓	✓	✓	Δ	Δ	✓	Δ					✓		
	Regression (wide range)	✓	✓	✓			✓							✓	
	Regression (possible outliers)	✓	✓	✓			✓								✓

Codeless Deep Learning with KNIME Analytics Platform

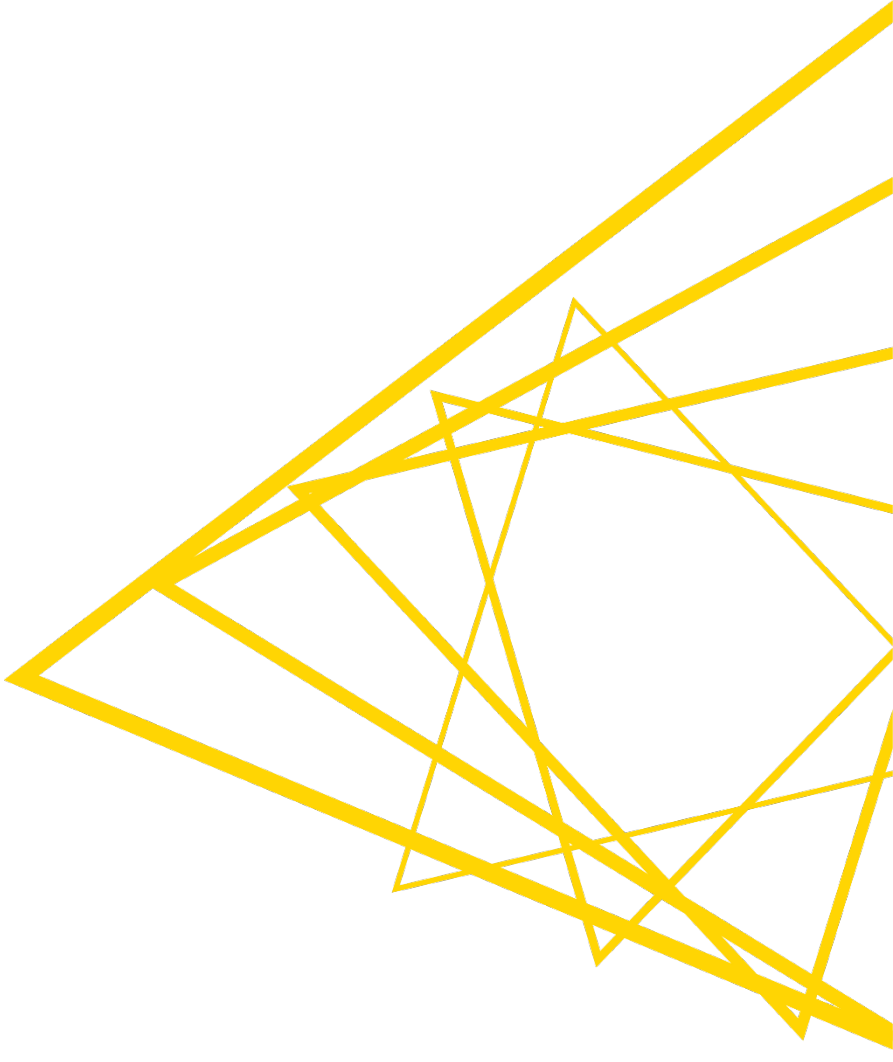
- Simple option for feed forward neural networks with activation function sigmoid



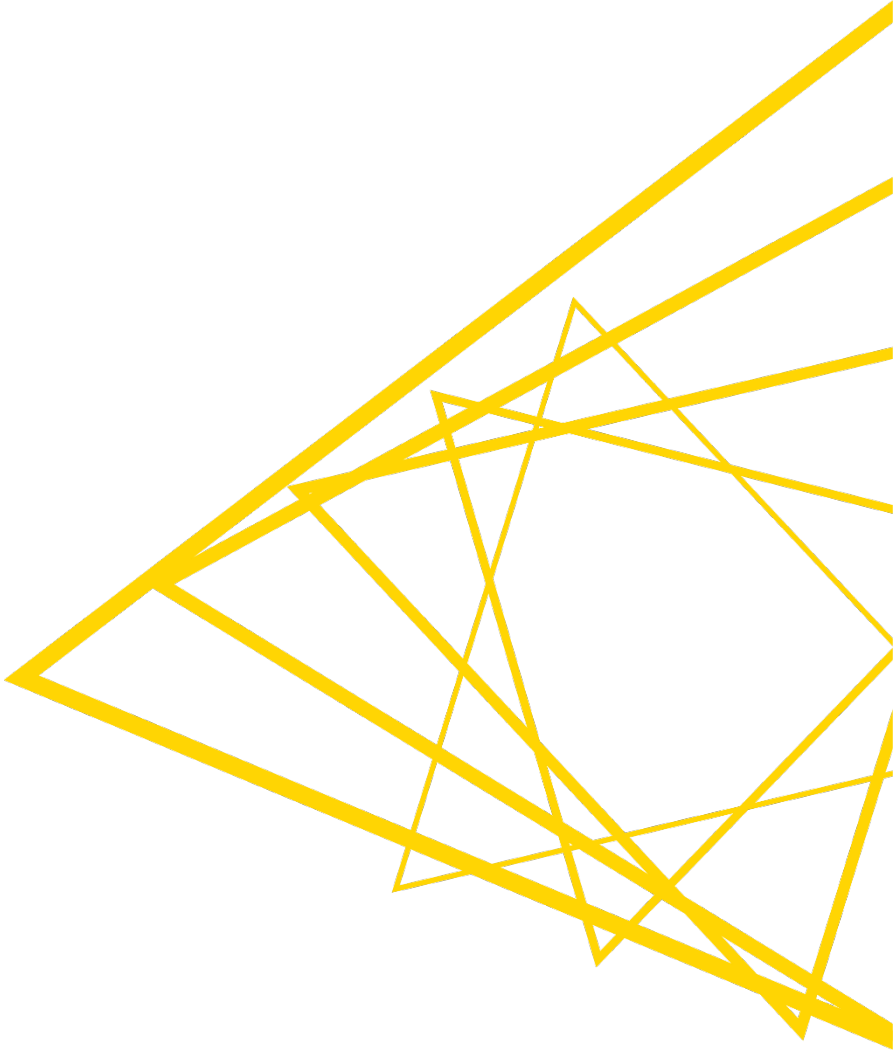
Codeless Deep Learning with KNIME Analytics Platform



Deep Learning



Recurrent Neural Networks



What are Recurrent Neural Networks?

- **R**ecurrent **N**eural **N**etwork (RNN) are a family of neural networks used for processing of sequential data
- RNNs are used for all sorts of tasks:
  - Language modeling / Text generation
  - Text classification
  - Neural machine translation
  - Image captioning
  - Speech to text
  - Numerical time series data, e.g. sensor data

Why do we need RNNs for Sequential Data?

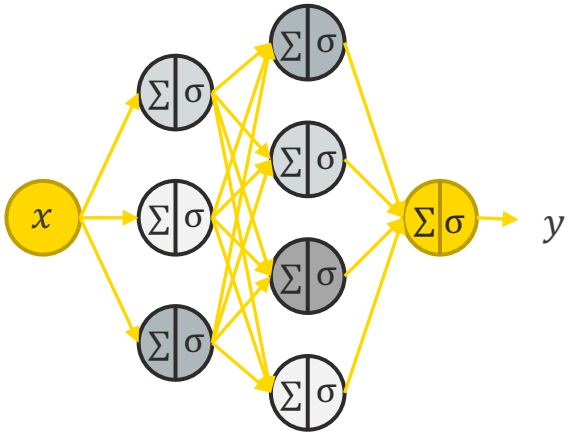
- Goal: Translation network from German to English

  “Ich mag Schokolade”
  => “I like chocolate”

- One option: Use feed forward network to translate word by word

- But what happens with this question?

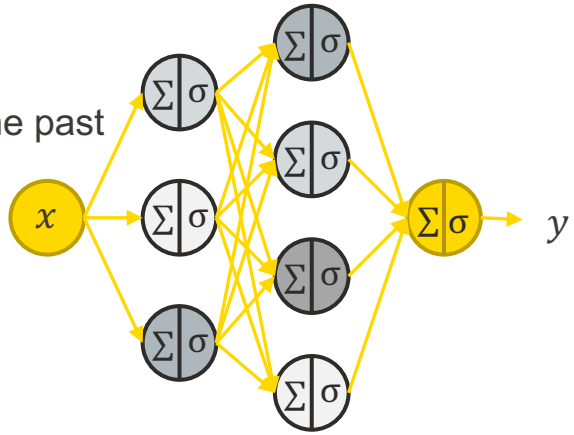
  “Mag ich Schokolade?”
  => “Do I like chocolate?”



Input x	Output y
Ich	I
mag	like
Schokolade	chocolate

Why do we need RNNs for Sequential Data?

- Problems:
  - Each time step is completely independent
  - For translations we need context
  - More general: we need a network that remembers inputs from the past
- Solution: Recurrent neural networks



Input x	Output y
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mag	like
Schokolade	chocolate

What are RNNs?

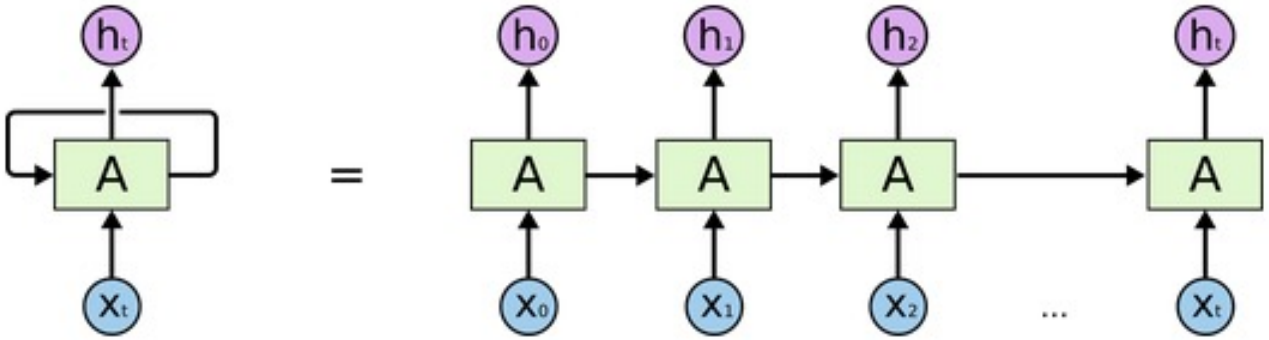
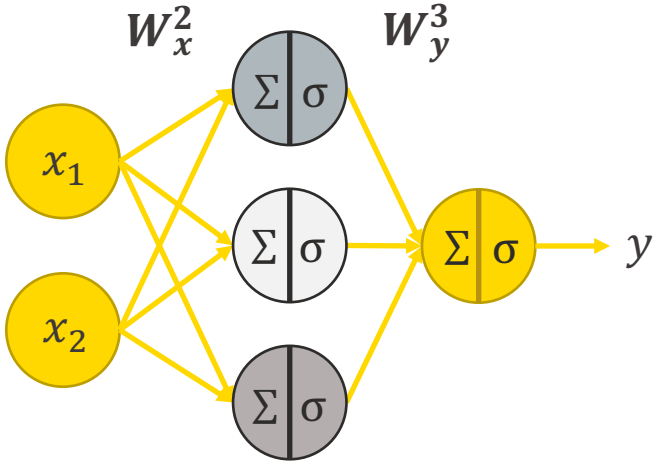
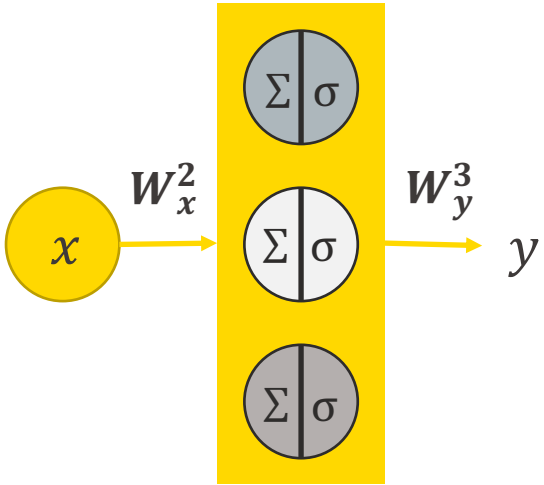


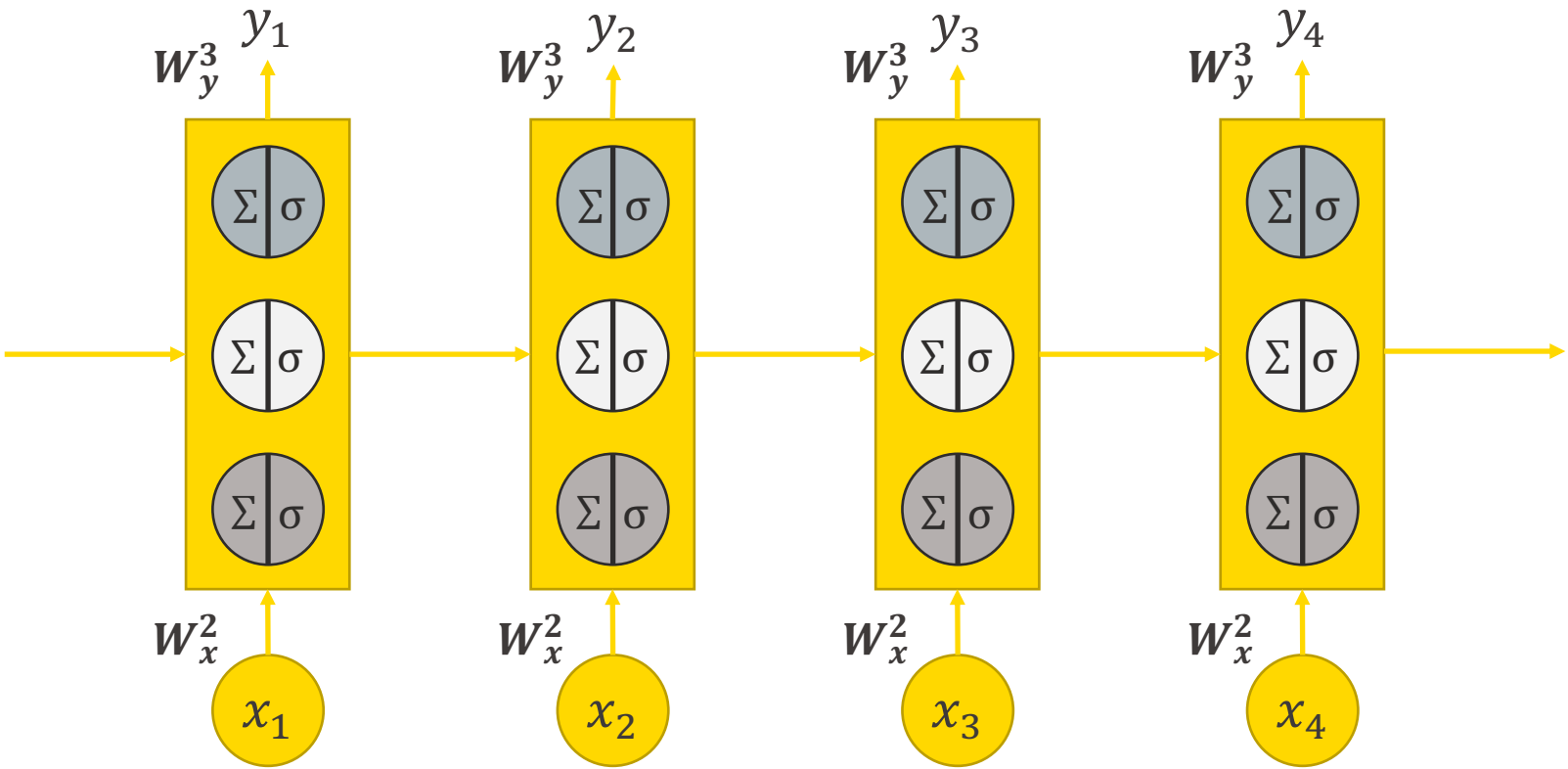
Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

From Feed Forward to Recurrent Neural Networks





From Feed Forward to Recurrent Neural Networks



Simple RNN unit

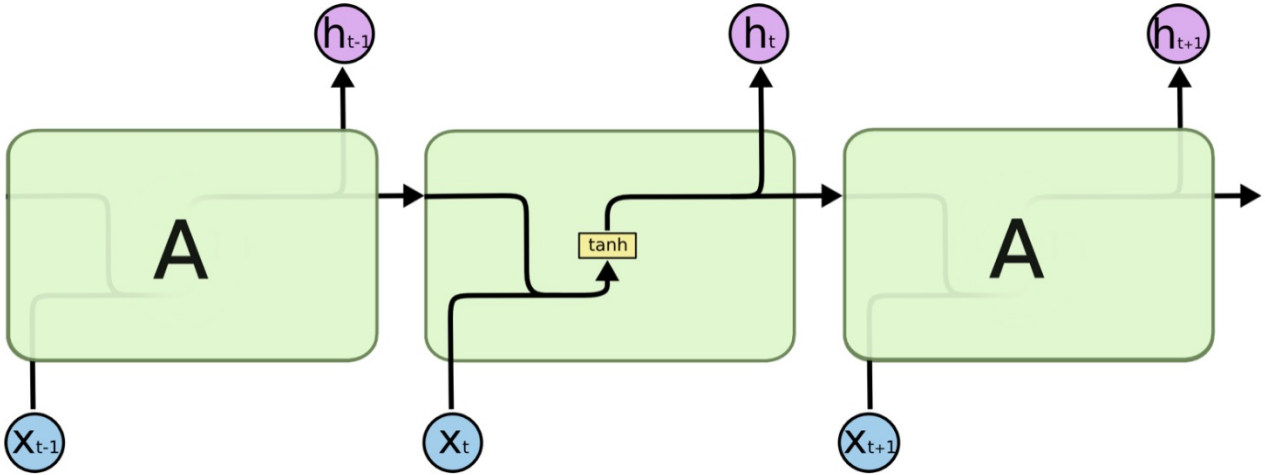


Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Limitations of Simple Layer Structures

The “memory” of simple RNNs is sometimes too limited to be useful

- “Cars drive on the ____” (road)
- “I love the beach – my favorite sound is the crashing of the _____“ (cars? glass? waves?)

LSTM = Long Short Term Memory Unit

- Special type of unit with three gates
  - Forget gate
  - Input gate
  - Output gate

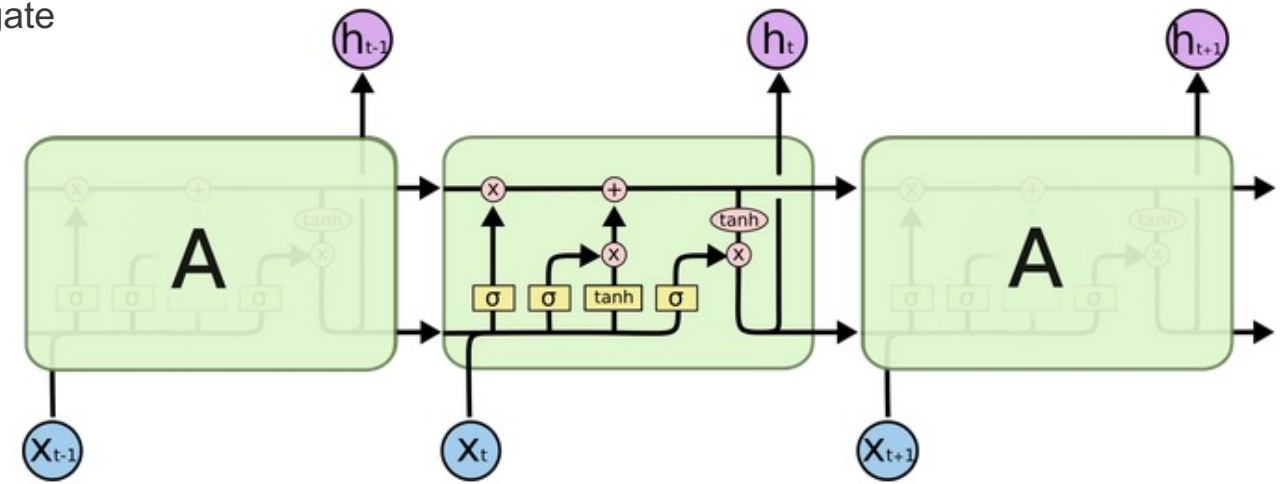
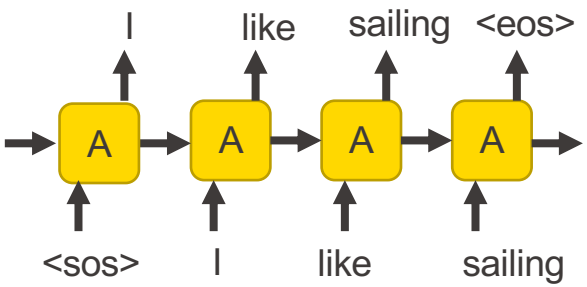
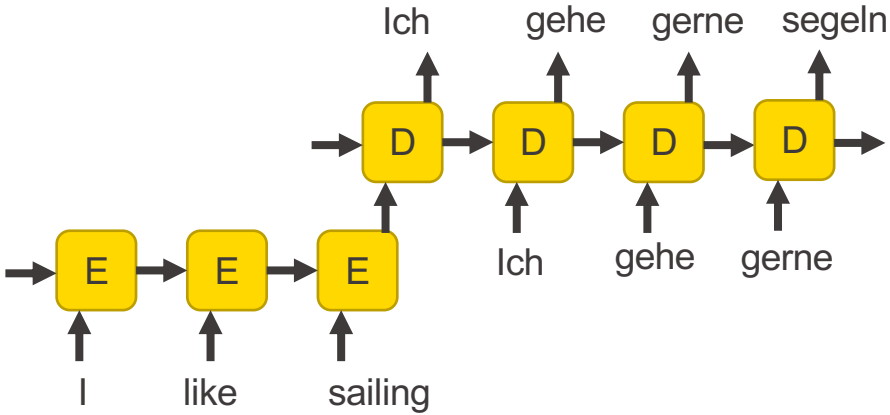


Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Different Network-Structures and Applications

Many to Many



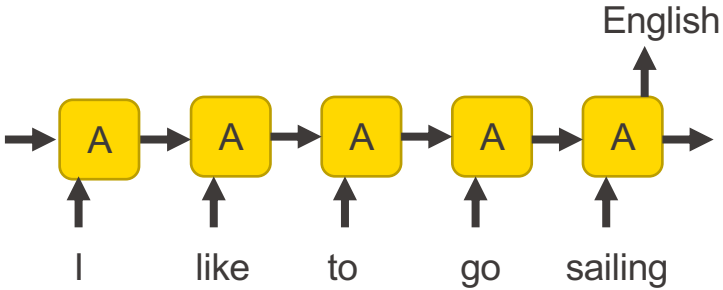


Language model

Neural machine translation

Different Network-Structures and Applications

Many to one



Language classification

Text classification

One to many

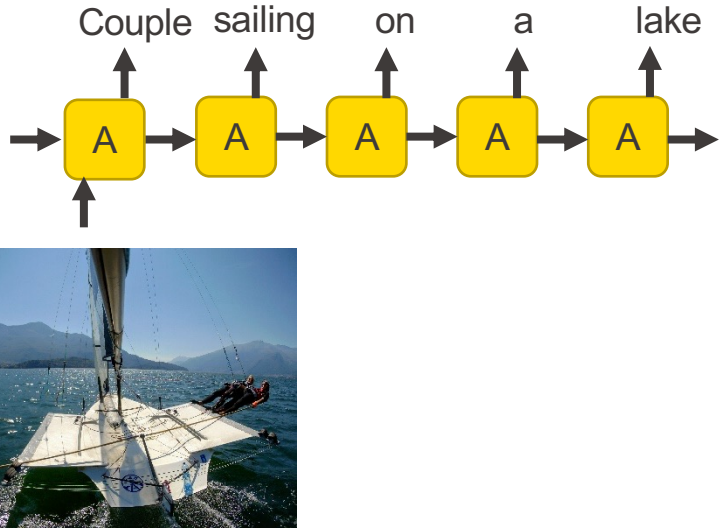
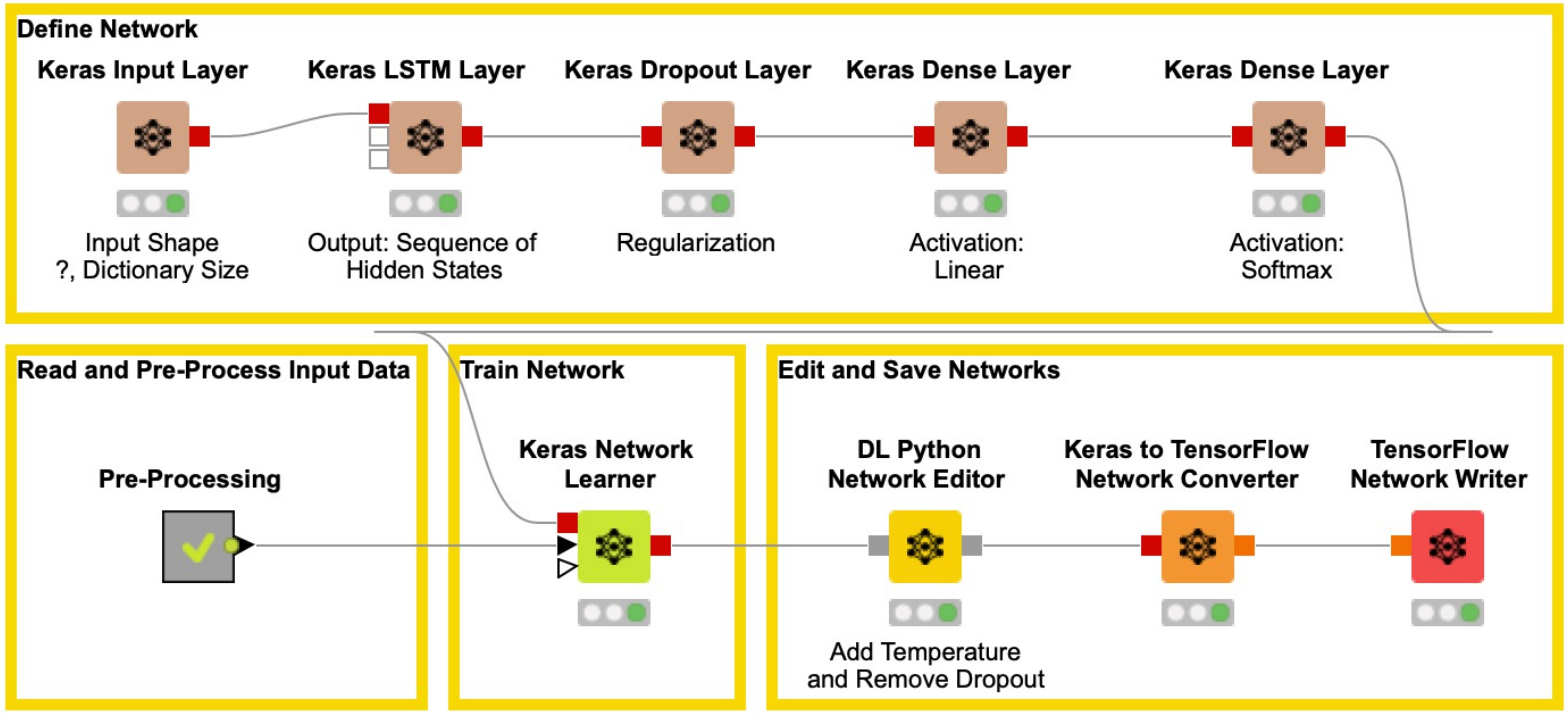
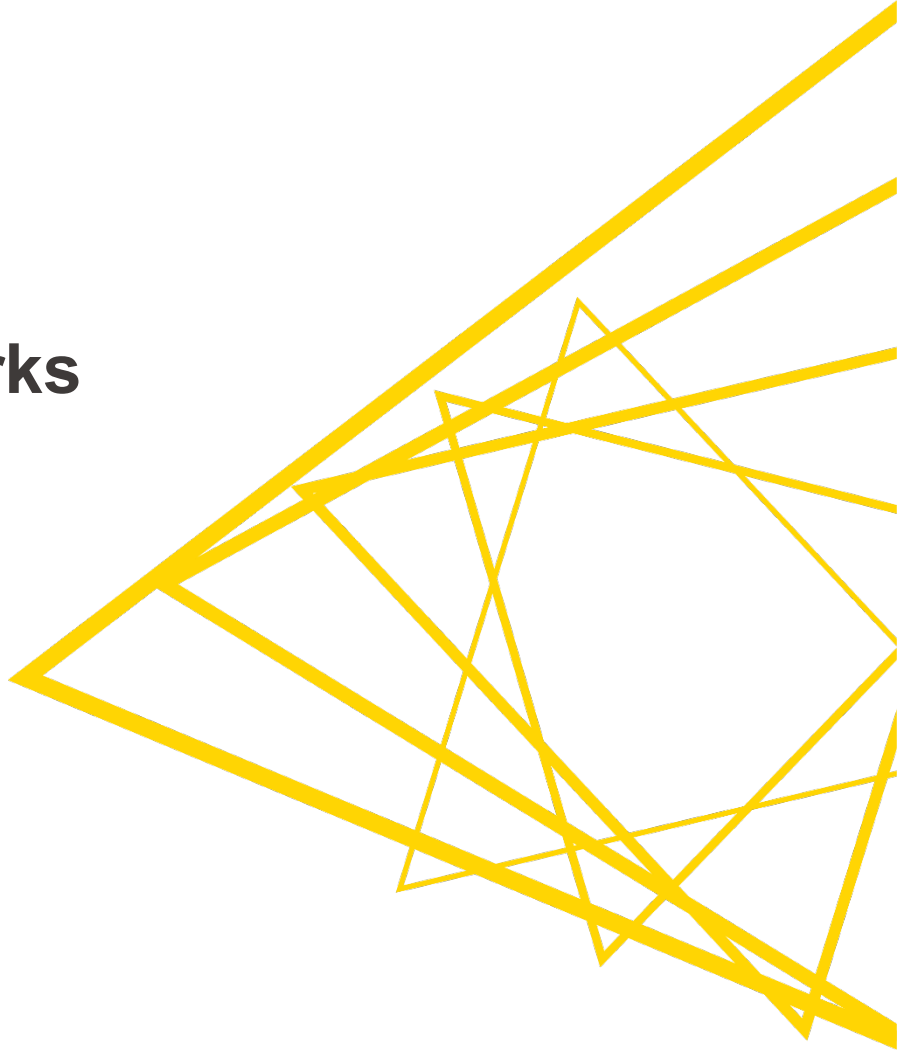


Image captioning

Neural Network: Code-free

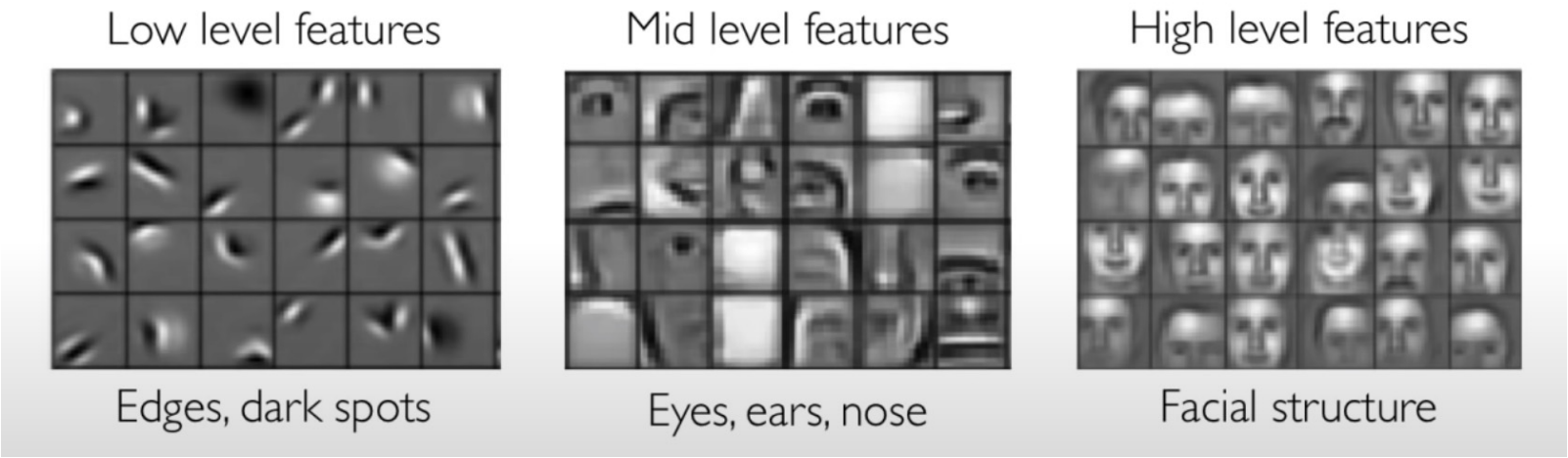


Convolutional Neural Networks (CNN)



Convolutional Neural Network (CNN)

- A CNN is a neural network with at least one convolutional layer.
- CNNs are commonly used when data has spatial relationships, e.g. images
- CNN learns a hierarchy of features using multiple convolution layers that detect different features.



Images from: http://introtodeeplearning.com/slides/6S191_MIT_DeepLearning_L3.pdf

Convolutional Neural Networks (CNN)

- Instead of connecting every neuron to the new layer a sliding window is used, which applies a filter on different parts of the image
- Some convolutions may detect edges or corners, while others may detect cats, dogs, or street signs inside an image

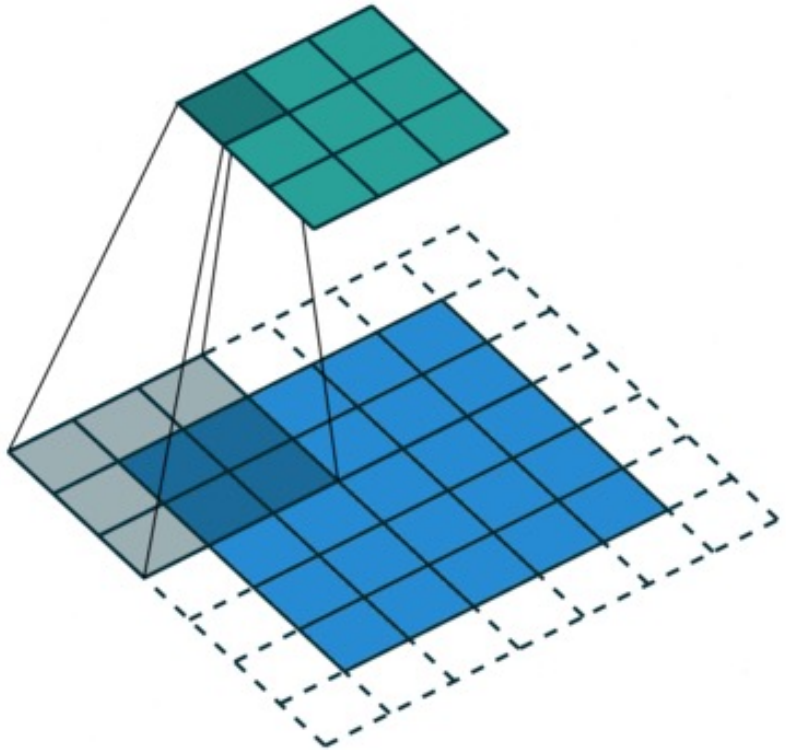
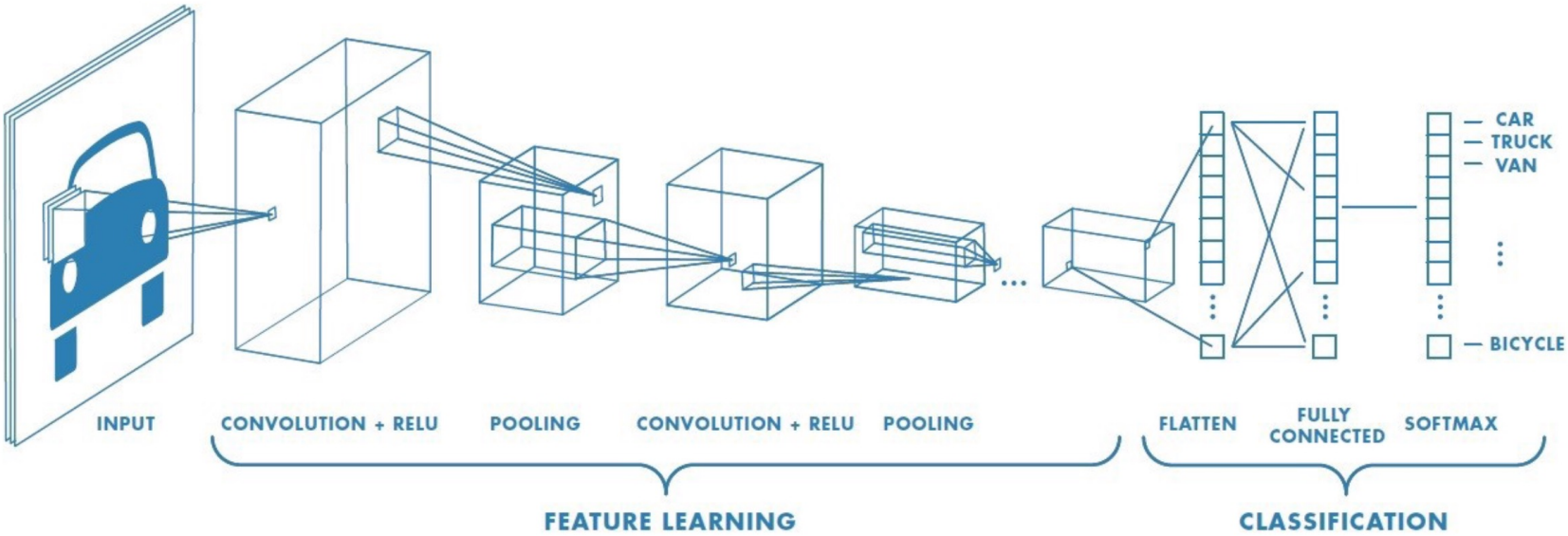
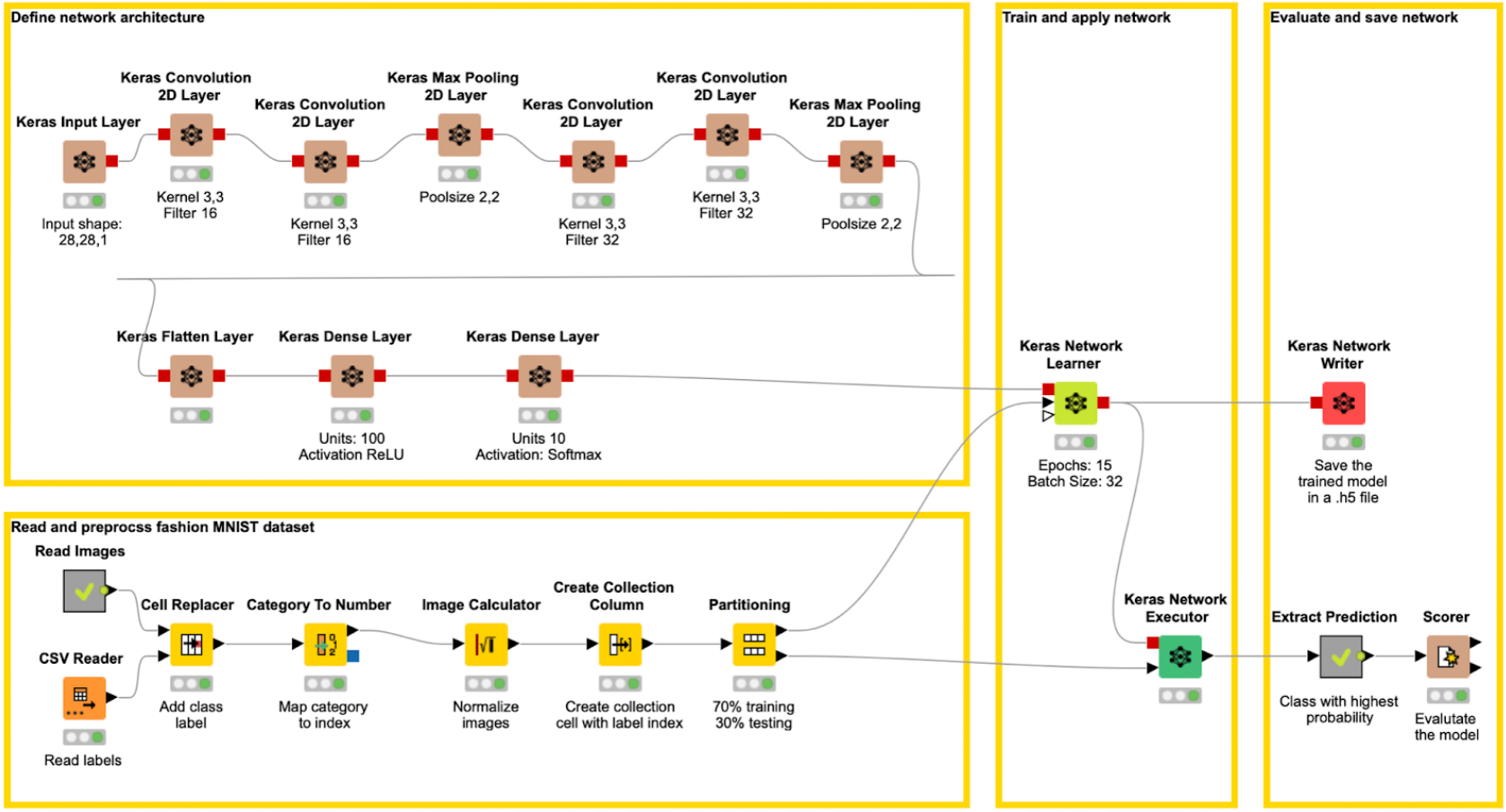


Image from: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

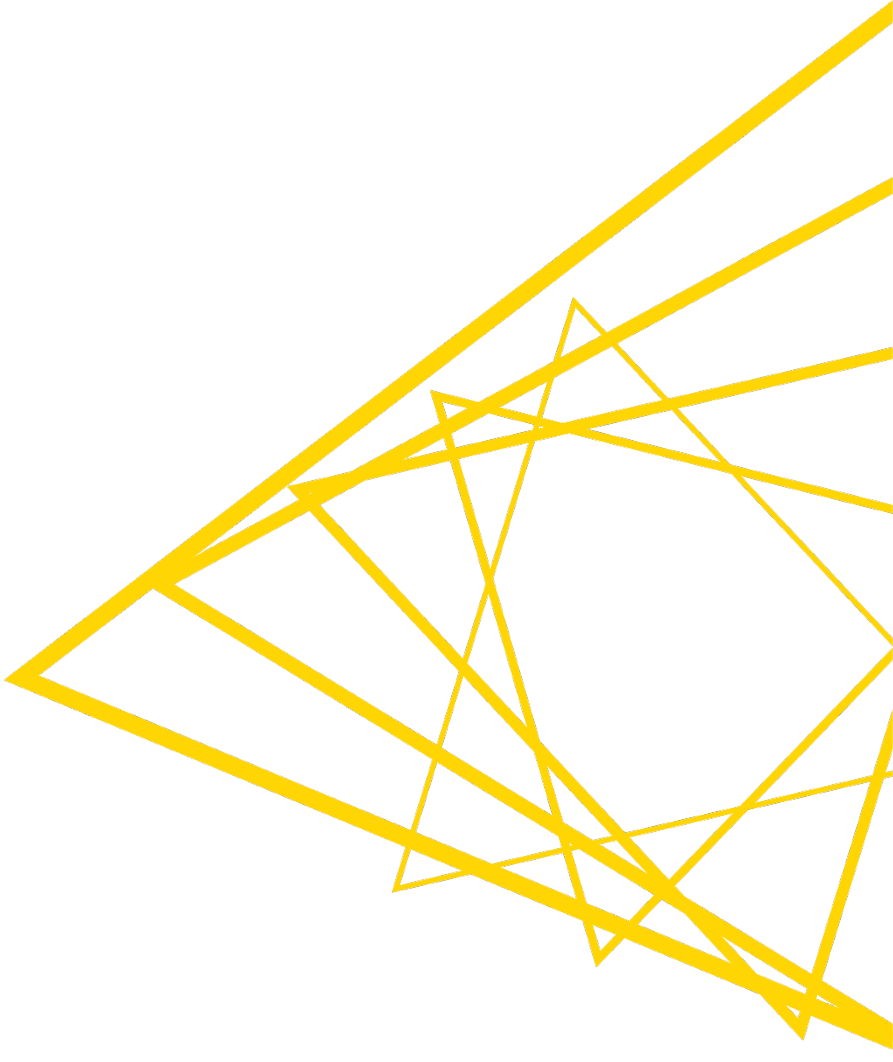
Convolutional Neural Networks



Building CNNs with KNIME



Recommendation Engines



Recommendation Engines and Market Basket Analysis

From the analysis of many shopping baskets ...

A-priori algorithm

Recommendation

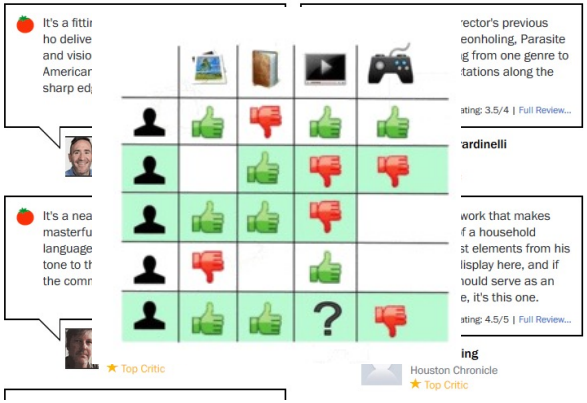
IF

+

THEN

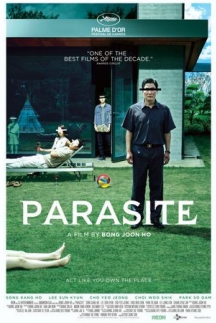
Recommendation Engines or Market Basket Analysis

From the analysis of the reactions of many people to the same item ...

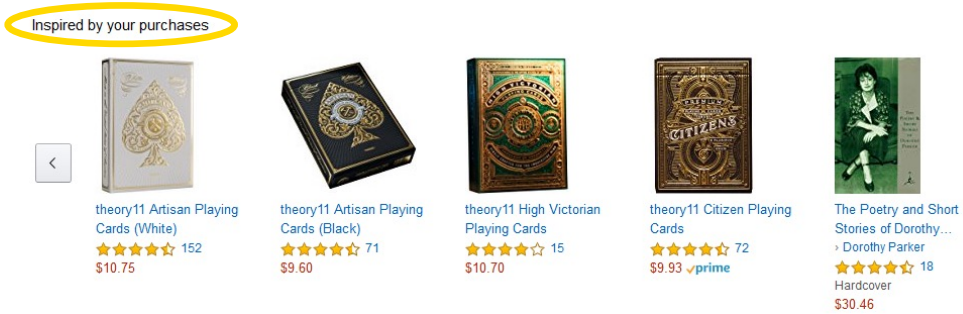


Collaborative Filtering

Recommendation



IF *A* has the same opinion as *B* on an item,
THEN A is more likely to have B's opinion on another item than that of a randomly chosen person



A-priori Algorithm: the Association Rule

IF  + 

Antecedent

THEN 

Consequent

Building the Association Rule

N shopping baskets

Search for
frequent itemsets

{A, B, F, H}
{A, B, C}
{B, C, H}
{D, E , F}
{D, E}
{A, B}
{A, C}
{H, F}
…

From “Frequent Itemsets“ to “Rules“

{A, B, F, H}

{A, B, F} ➔ H

{A, B, H} ➔ F

{A, F, H} ➔ B

{B, F, H} ➔ A

Which rules shall I choose?

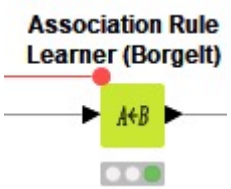
Support, Confidence, and Lift

{A, B, F} → H

- Item set support $s = \frac{freq(A,B,F,H)}{N}$ ← How often these items are found together
- Rule confidence $c = \frac{freq(A,B,F,H)}{freq(A,B,F)}$ ← How often the antecedent is together with the consequent
- Rule lift $= \frac{support\ (\{A,B,F\} \Rightarrow H)}{support\ (A,B,F) \times support(H)}$ ← How often antecedent and consequent happen together compared with random chance

The rules with support, confidence and lift above a threshold → most reliable ones

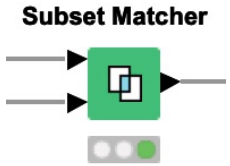
Association Rule Mining (ARM): Two Phases



Discover all frequent and strong association rules

$X \Rightarrow Y$ → "if X then Y"

with sufficient support and confidence



Two phases:

1. find all frequent itemsets (FI) ← Most of the complexity
   - Select itemsets with a minimum support

$$FI = \{\{X, Y\}, X, Y \subset I | s(X, Y) \geq S_{min}\}$$

2. build strong association rules
   - Select rules with a minimum confidence:

$$Rules: \{X \Rightarrow Y, X, Y \subset FI, | c(X \Rightarrow Y) \geq C_{min}\}$$

User parameters

A-Priori Algorithm: Example

- Let‘s consider milk, diaper, and beer: $\{milk, diaper\} \Rightarrow beer$

- How often are they found together across all shopping baskets?
- How often are they found together across all shopping baskets containing the antecedents?

TID	Transactions
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

support

$$s(milk, diaper, beer) = \frac{P(milk, diaper, beer)}{|T|} = \frac{2}{5} = 0.4$$

$$c = \frac{P(milk, diaper, beer)}{P(milk, diaper)} = \frac{2}{3} = 0.67$$

confidence

A-priori algorithm: an example

- Let‘s consider milk, diaper, and beer: $\{milk, diaper\} \Rightarrow beer$
- How often are they found together across all shooping baskets?
- How often are they found together across all shopping baskets containing the antecedents?

TID	Transactions
1	Bread, Milk
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3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

$$s(milk, diaper) = \frac{P(milk, diaper)}{|T|} = \frac{3}{5} = 0.6$$

$$s(beer) = \frac{P(beer)}{|T|} = \frac{3}{5} = 0.6$$

$$Rule\ lift = \frac{s(milk, diaper, beer)}{s(milk, diaper) \times s(beer)}$$

$$= \frac{0.4}{0.6 \times 0.6} = 1.11$$

Association Rule Mining: Is it Useful?

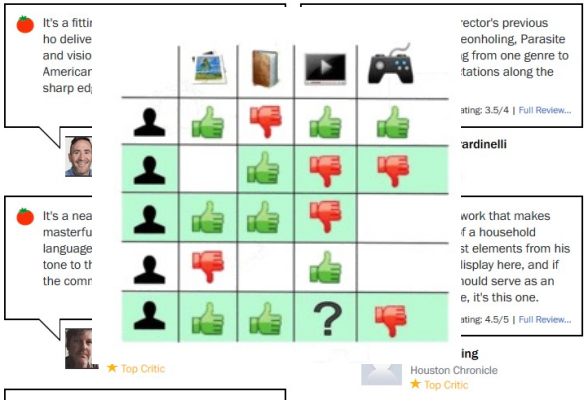
- David J. Hand (2004):
  „*Association Rule Mining is likely the field with the highest ratio of number of published papers per reported application.*“

- KNIME Blog post:

https://www.knime.com/knime-applications/market-basket-analysis-and-recommendation-engines

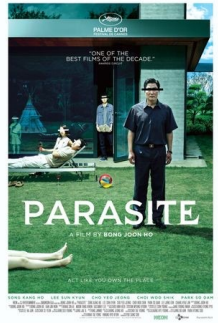
Recommendation Engines or Market Basket Analysis

From the analysis of the reactions of many people to the same item ...



Collaborative Filtering

Recommendation



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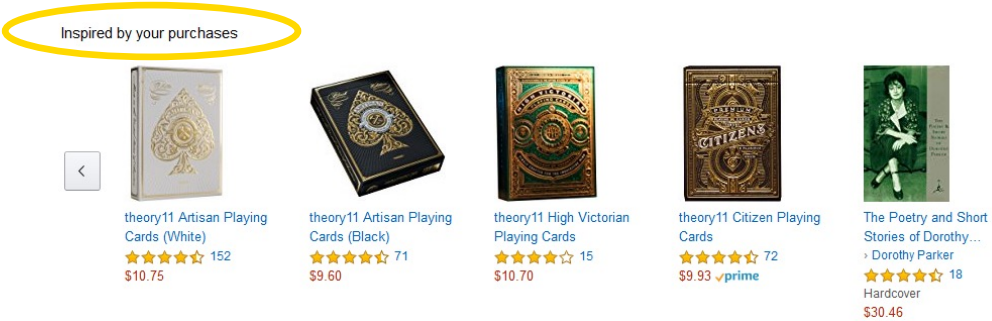


Collaborative Filtering (CF)

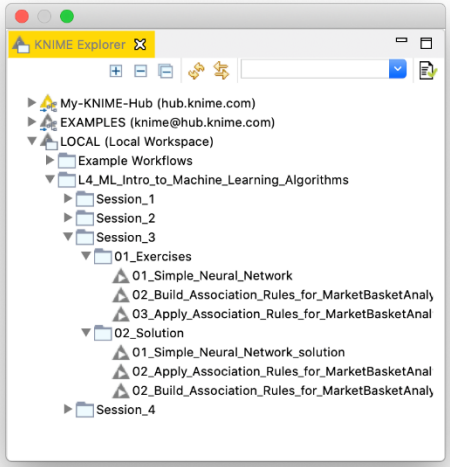
Collaborative filtering systems have many forms, but many common systems can be reduced to two steps:

1. Look for users who share the same rating patterns with the active user (the user whom the recommendation is for)
2. Use the ratings from those like-minded users found in step 1 to calculate a prediction for the active user
3. Implemented in Spark

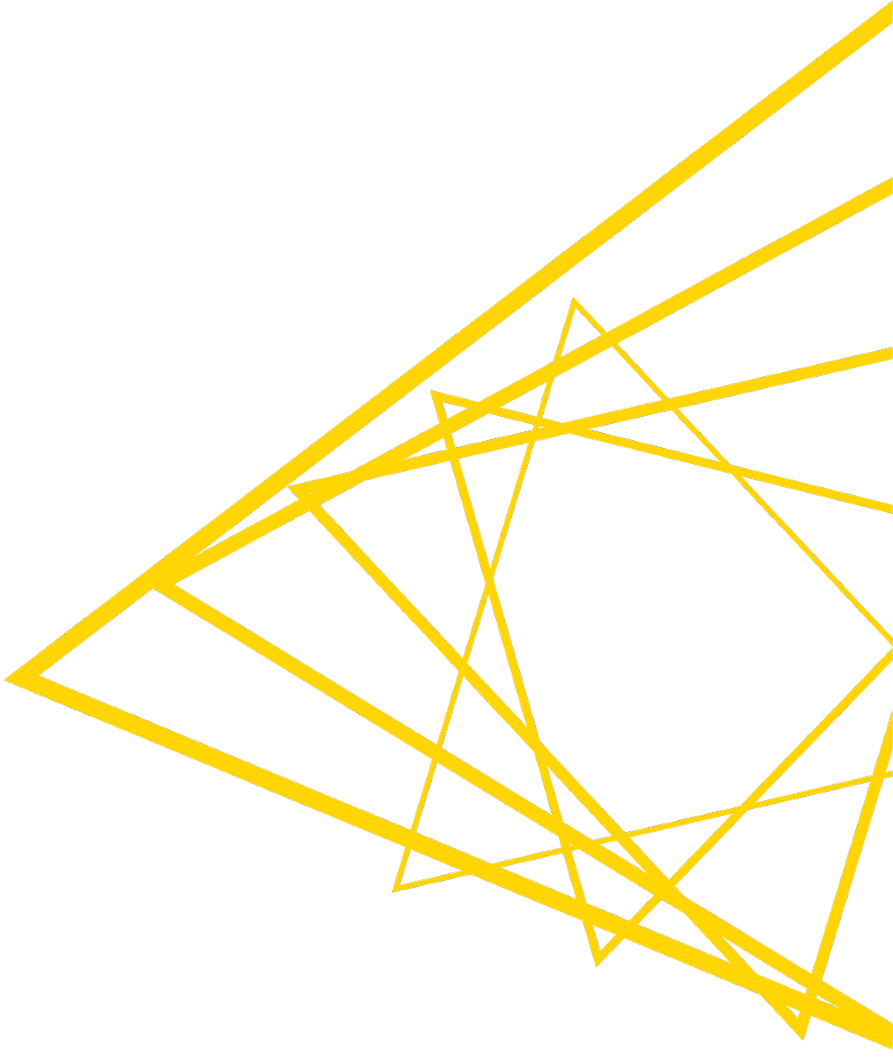
https://www.knime.com/blog/movie-recommendations-with-spark-collaborative-filtering

Exercises:

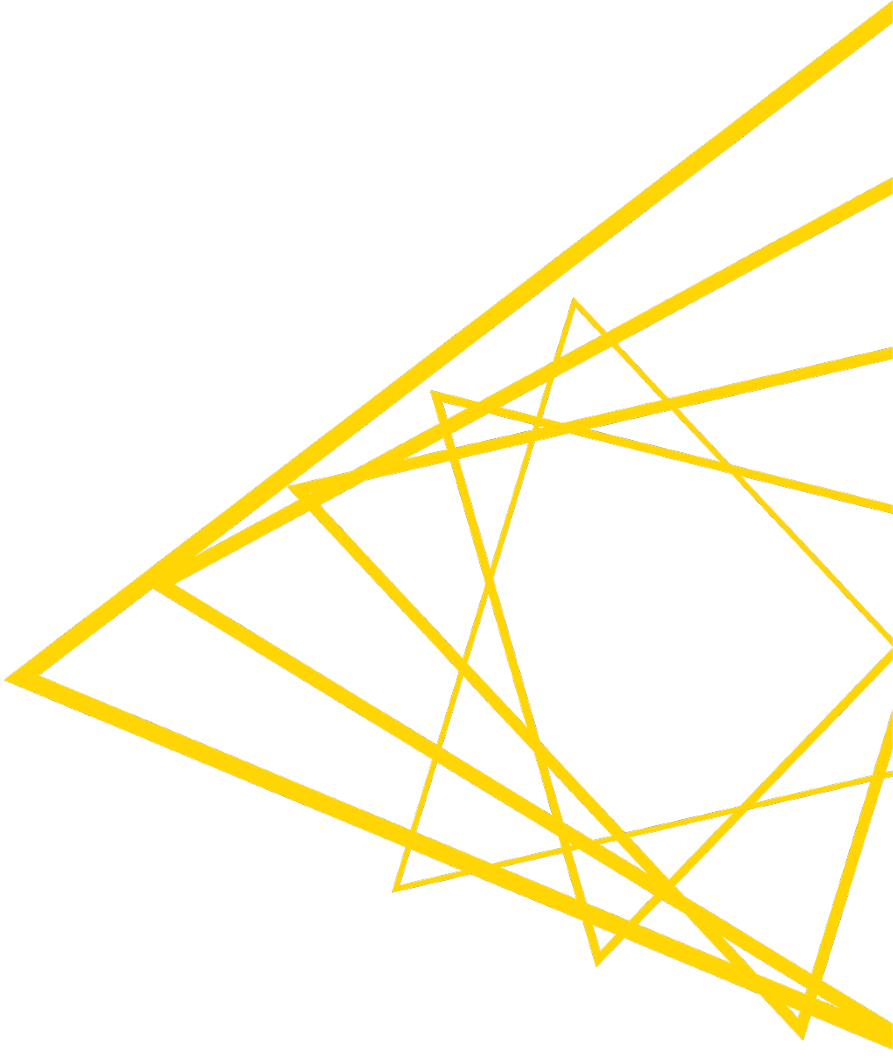
- Neural Network
  - Goal: Train an MLP to solve our classification problem (rank: high/low)
  - 01_Simple_Neural_Network
- Market Basket Analysis
  - 02_Build_Association_Rules_for_MarketBasketAnalysis
  - 03_Apply_Association_Rules_for_MarketBasketAnalysis



Session 4: Clustering & Data Preparation



Unsupervised Learning: Clustering

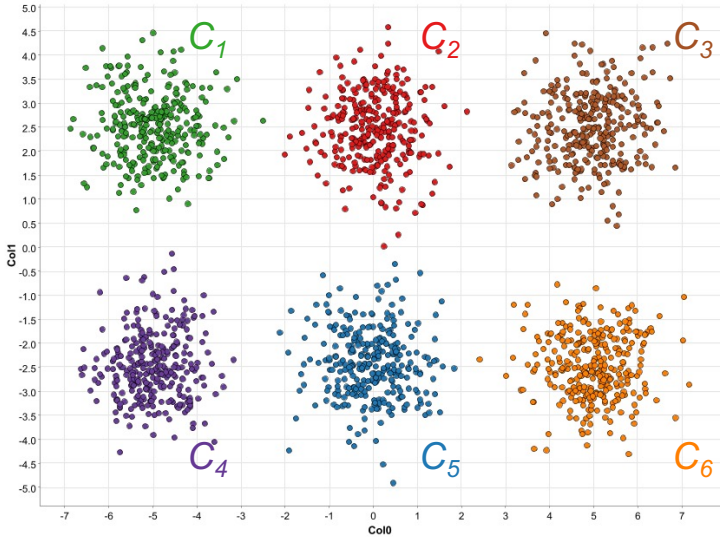


Goal of Clustering Analysis

Discover hidden structures in unlabeled data (unsupervised)

Clustering identifies a finite set of groups (*clusters*) $C_1, C_2 \cdots, C_k$ in the dataset such that:

- Objects within the *same* cluster C_i shall be as similar as possible
- Objects of *different* clusters C_i, C_j $(i \neq j)$ shall be as dissimilar as possible



Clustering Applications

- Find “natural” clusters and desc
  - Data understanding
- Find useful and suitable groups
  - Data Class Identification
- Find representatives for homogenous groups
  - Data Reduction
- Find unusual data objects
  - Outlier Detection
- Find random perturbations of the data
  - Noise Detection

Methods

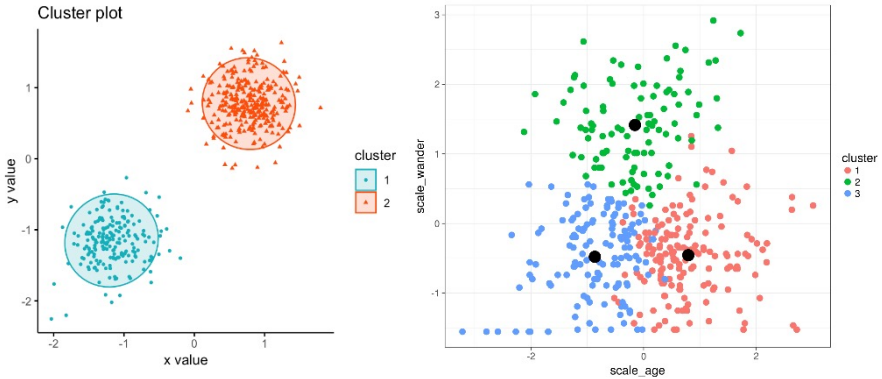
- K-means
- Hierarchical
- DBScan

Examples

- Customer segmentation
- Molecule search
- Anomaly detection

Cluster Properties

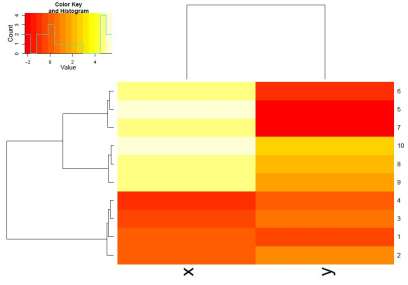
- Clusters may have different sizes, shapes, densities
- Clusters may form a hierarchy
- Clusters may be overlapping or disjoint



Types of Clustering Approaches

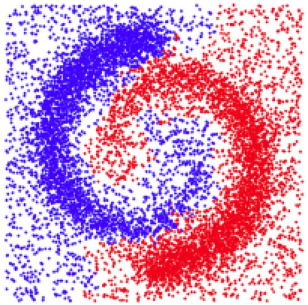
Linkage Based

e.g. Hierarchical Clustering



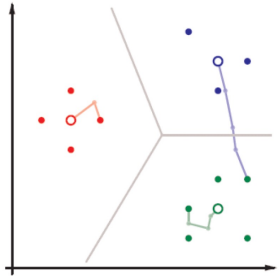
Density based Clustering

e.g. DBSCAN



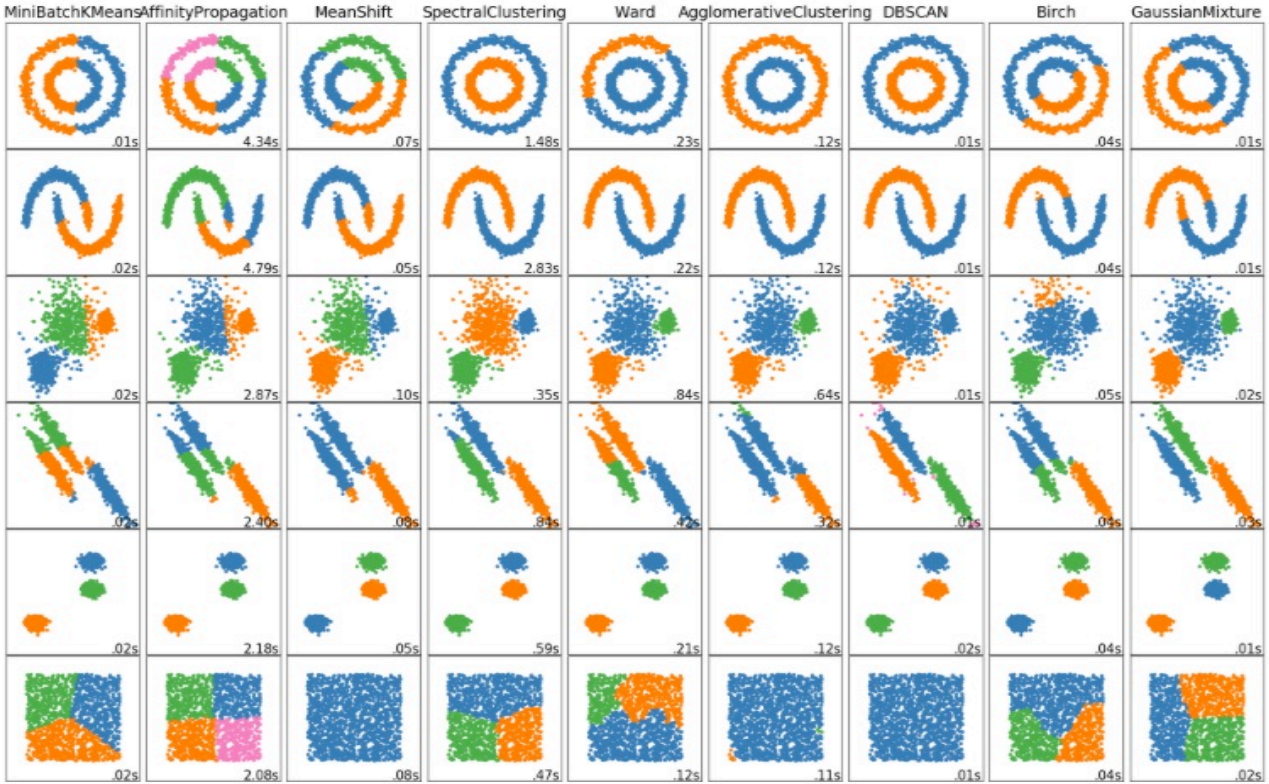
Clustering by Partitioning

e.g. k-Means

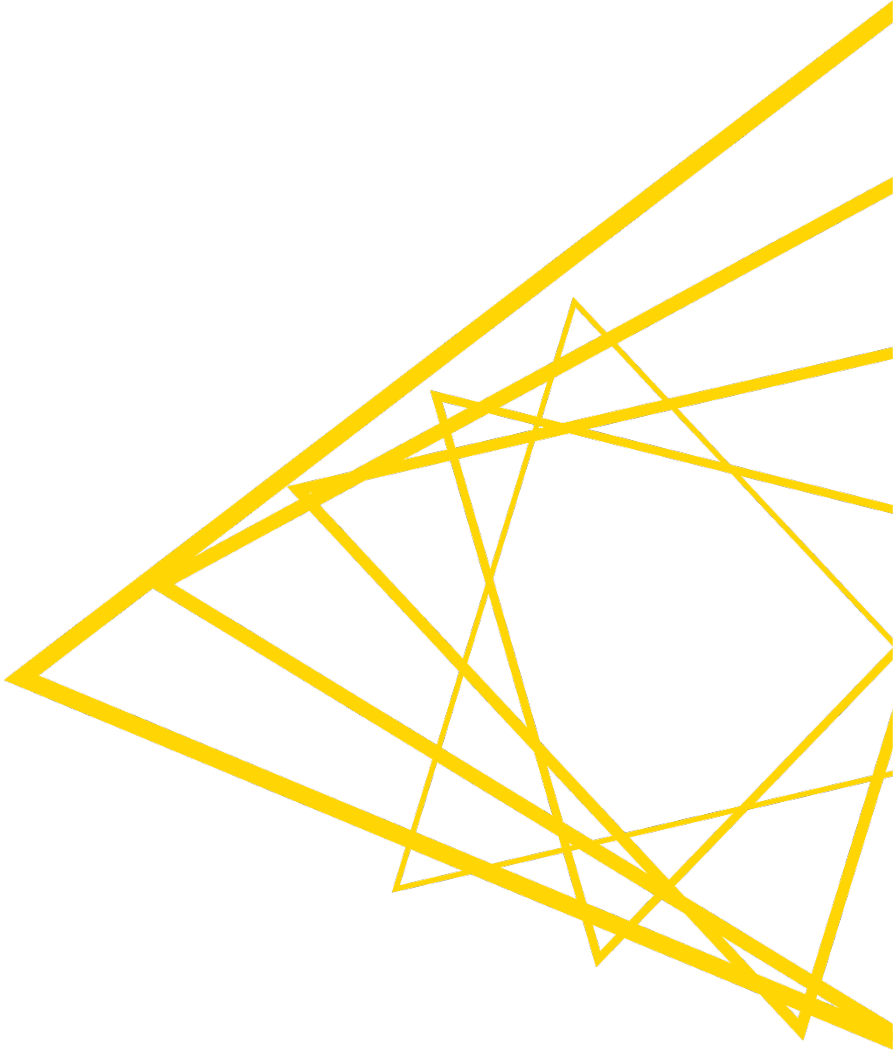


Types of Clustering Approaches

- No clustering method works universally well



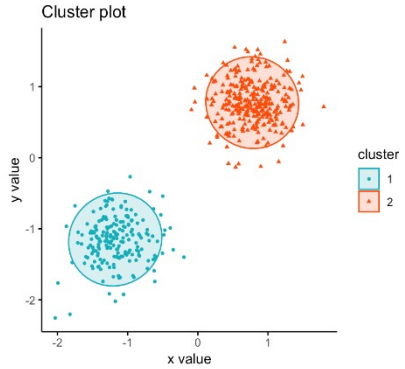
Clustering: Partitioning
k-Means



Partitioning

Goal:

A (disjoint) partitioning into k clusters with minimal costs

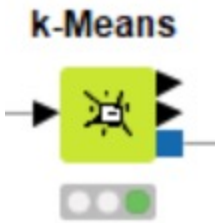


- Local optimization method:
  - choose k initial cluster representatives
  - optimize these representatives iteratively
  - assign each object to its most similar cluster representative
- Types of cluster representatives:
  - Mean of a cluster (*construction of central points*)
  - Median of a cluster (*selection of representative points*)
  - Probability density function of a cluster (*expectation maximization*)

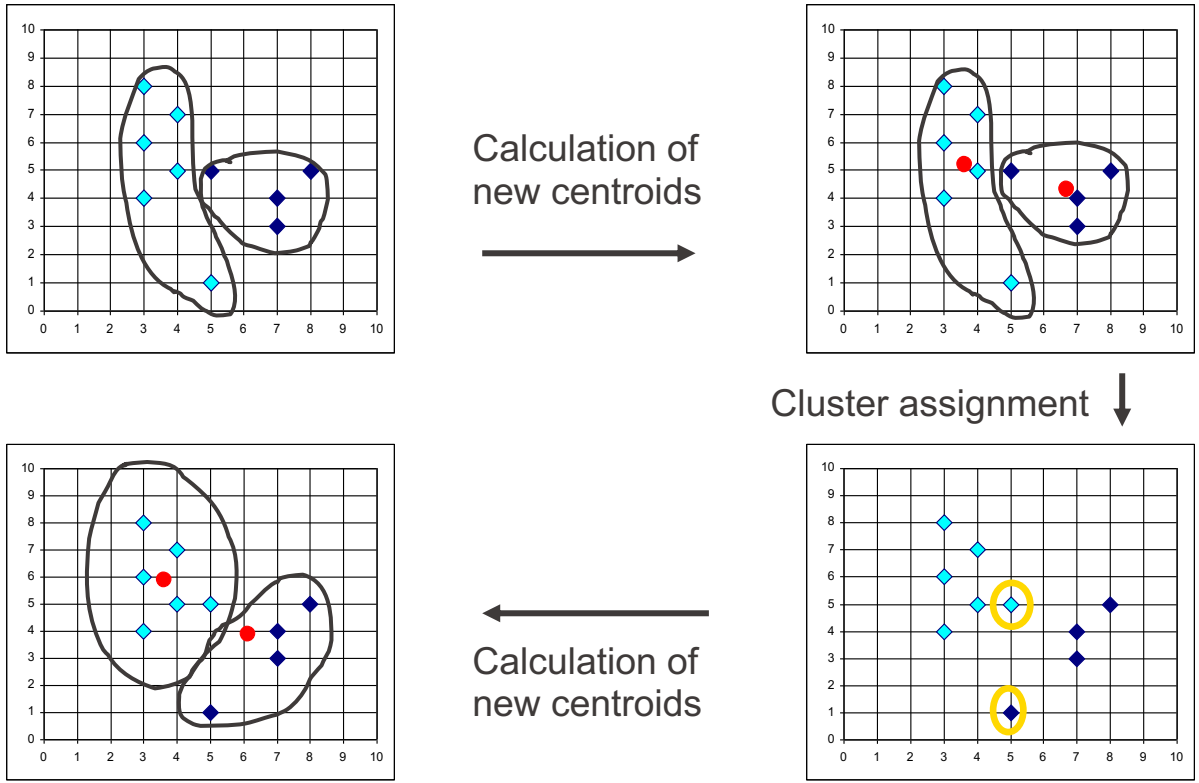
k-Means-Algorithm

Given k, the k-Means algorithm is implemented in four steps:

1. Use k objects / rows as the initial centroids
2. Assign each object to the cluster with the **nearest** centroid — Euclidean distance
3. Compute the centroids from the current partition
4. Go back to Step 2, repeat until the updated centroids stop moving significantly



k-Means Algorithm



Comments of the k-Means Method

- Advantages:
  - Relatively efficient
  - Simple implementation
- Weaknesses:
  - Often terminates at a local optimum
  - Applicable only when mean is defined (what about categorical data?)
  - Need to specify k, the number of clusters, in advance
  - Unable to handle noisy data and outliers
  - Not suitable to discover clusters with non-convex shapes

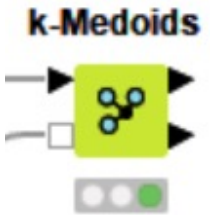
Outliers: k-Means vs k-Medoids

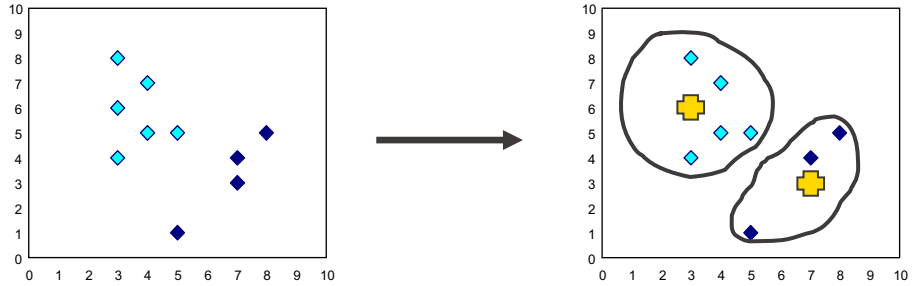
Problem with K-Means

An object with an extremely large value can substantially distort the distribution of the data.

One solution: K-Medoids

Instead of taking the **mean** value of the objects in a cluster as a reference point, **medoids** can be used, which are the most centrally located objects in a cluster.





Clustering: Distance Functions

Distance Functions for Numeric Attributes

For two objects $x = (x_1, x_2, \cdots, x_d)$ and $y = (y_1, y_2, \cdots, y_d)$:

- *L_p-Metric* (*Minkowski-Distance*)

$$dist(x,y) = \sqrt[p]{\sum_{i=1}^{d} |x_i - y_i|^p}$$

- *Euclidean Distance* ($p = 2$)

$$dist(x,y) = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2}$$

- *Manhattan-Distance* ($p = 1$)

$$dist(x,y) = \sum_{i=1}^{d} |x_i - y_i|$$

- *Maximum-Distance* ($p = \infty$)

$$dist(x,y) = \max_{1 \le i \le d} \{|x_i - y_i|\}$$

Influence of Distance Function / Similarity

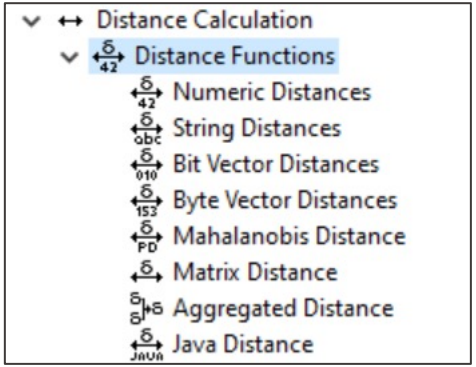
- Clustering vehicles:
  - red Ferrari
  - green Porsche
  - red Bobby car

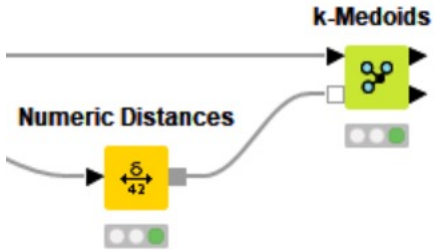


- Distance Function based on maximum speed (numeric distance function):
  - Cluster 1: Ferrari & Porsche
  - Cluster 2: Bobby car

- Distance Function based on color (nominal attributes):
  - Cluster 1: Ferrari and Bobby car
  - Cluster 2: Porsche

The distance function affects the shape of the clusters

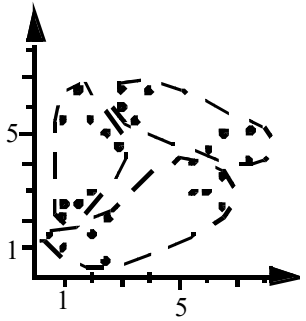


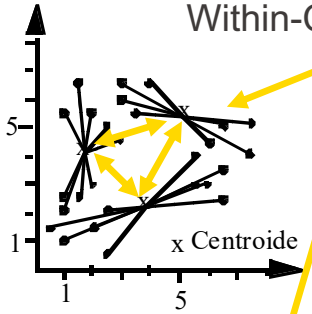


Clustering: Quality Measures
Silhouette

Optimal Clustering: Example

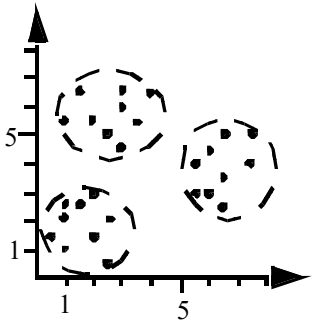
Bad Clustering

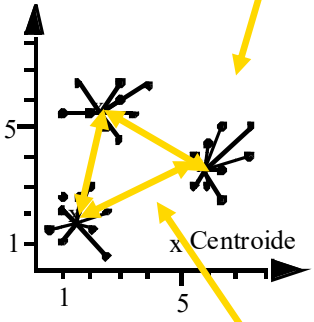




Within-Cluster Variation

Good Clustering





Between-Cluster Variation

Cluster Quality Measures

Centroid μ_C: mean vector of all objects in clustering C

- Within-Cluster Variation:

$$TD^2 = \sum_{i=1}^{k} \sum_{p \in C_i} dist(p, \mu_{C_i})^2$$

- Between-Cluster Variation:

$$BC^2 = \sum_{j=1}^{k} \sum_{i=1}^{k} dist(\mu_{C_j}, \mu_{C_i})^2$$

- Clustering Quality (one possible measure):

$$CQ = \frac{BC^2}{TD^2}$$

Silhouette-Coefficient for object x

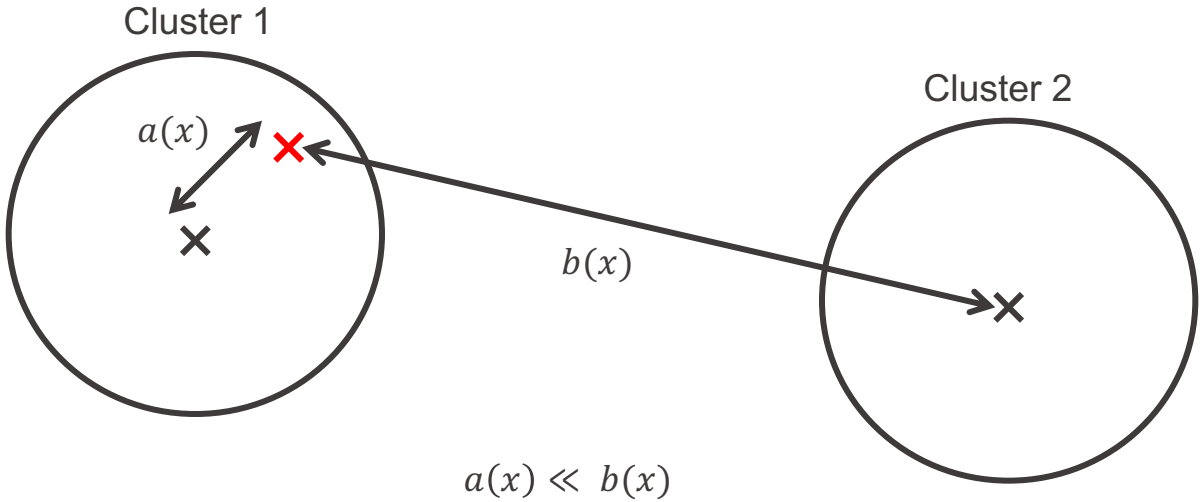
Silhouette-Coefficient [Kaufman & Rousseeuw 1990] measures the quality of clustering

- $a(x)$: distance of object x to its cluster representative
- $b(x)$: distance of object x to the representative of the „second-best“ cluster
- **Silhouette** $s(x)$ of x

$$s(x) = \frac{b(x) - a(x)}{\max\{a(x), b(x)\}}$$

Silhouette-Coefficient

Good clustering…

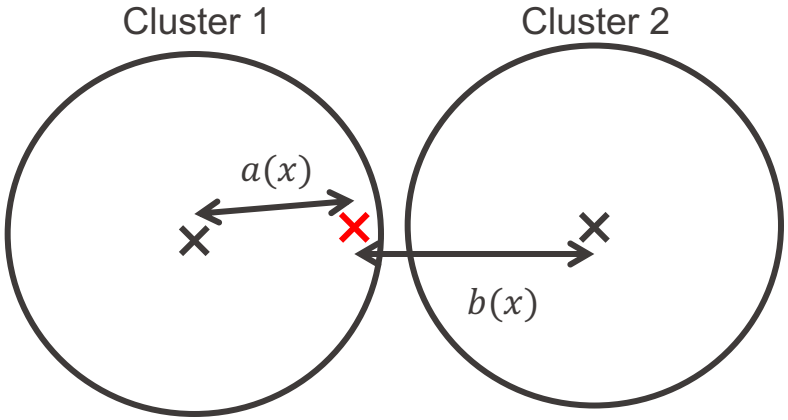


$$a(x) \ll b(x)$$

$$s(x) = \frac{b(x) - a(x)}{\max\{a(x), b(x)\}} \approx \frac{b(x)}{b(x)} = 1$$

Silhouette-Coefficient

…not so good…

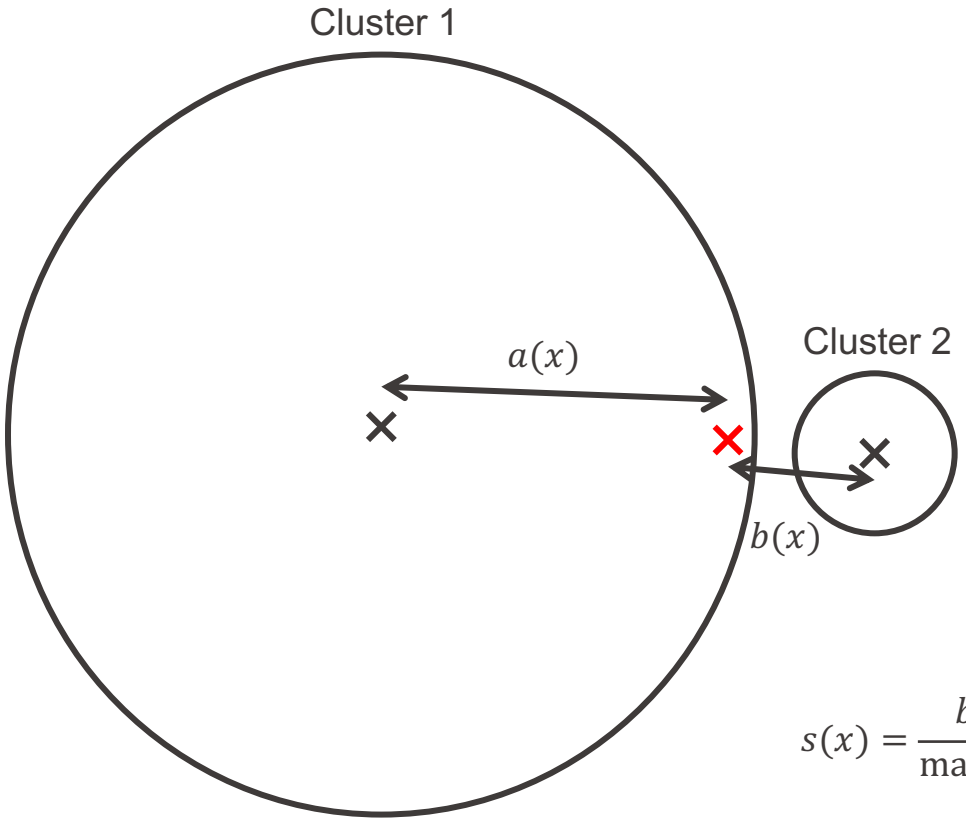


$$a(x) \approx b(x)$$

$$s(x) = \frac{b(x) - a(x)}{\max\{a(x), b(x)\}} \approx \frac{0}{b(x)} = 0$$

Silhouette-Coefficient

…bad clustering.



$$a(x) \gg b(x)$$

$$s(x) = \frac{b(x) - a(x)}{\max\{a(x), b(x)\}} \approx \frac{-a(x)}{a(x)} = -1$$

Silhouette-Coefficient for Clustering C

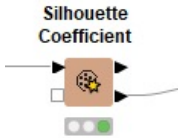
- Silhouette coefficient s_c for clustering C is the average silhouette over all objects $x \in C$

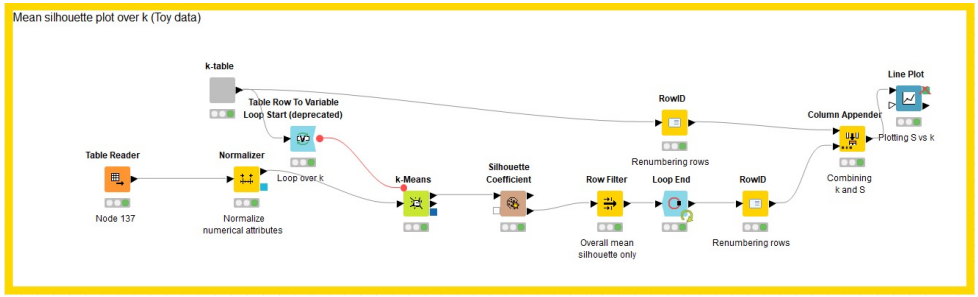
$$s_c = \frac{1}{n} \sum_{x \in C} s(x)$$

- Interpretation of silhouette coefficient:
  - $s_c > 0.7$: strong cluster structure,
  - $s_c > 0.5$: reasonable cluster structure,
  - . . .

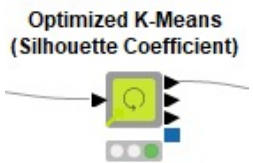
Silhouette Coefficient over a Range of k

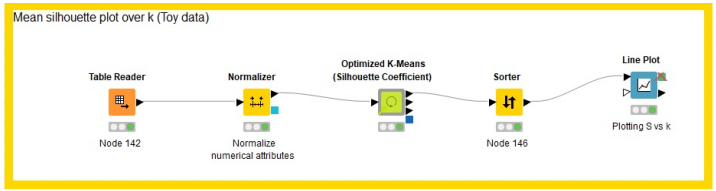
- Silhouette Coefficient Node in KNIME Analytics Platform
- Loop over various values of k



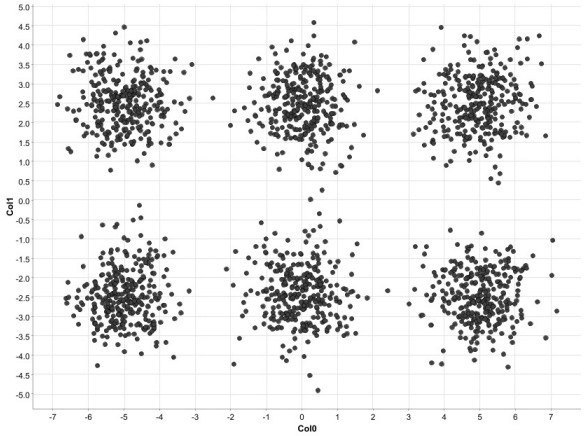


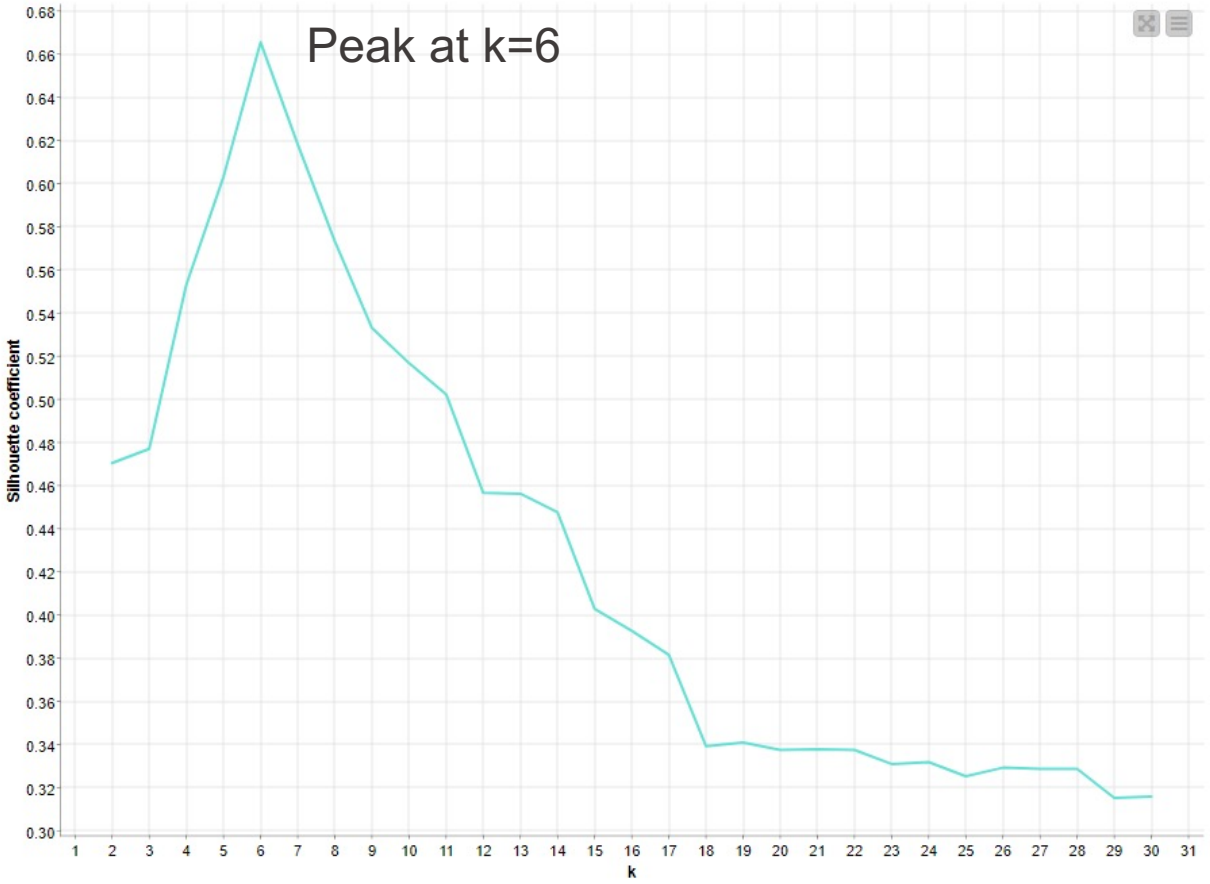
- Optimized k-means component
- Loop over various values of k





Silhouette Coefficient over k

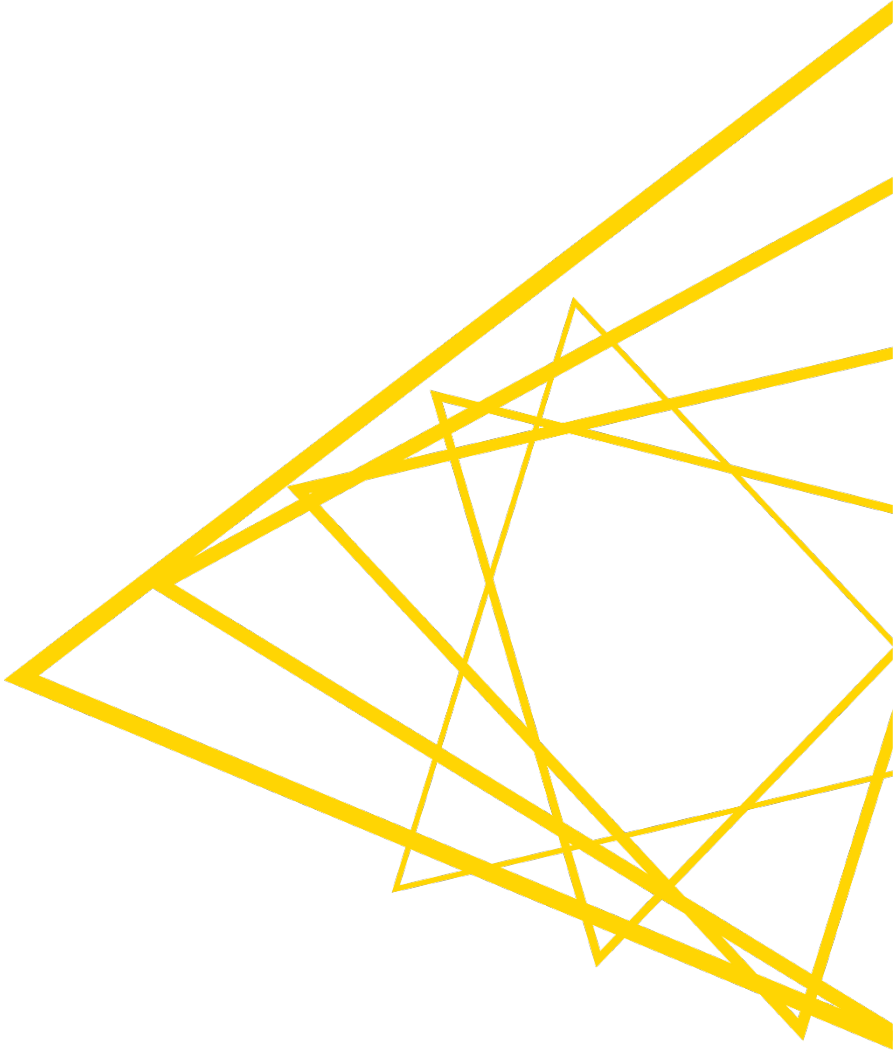




Summary: Clustering by Partitioning

- Scheme always similar:
  - Find (random) starting clusters
  - Iteratively improve cluster positions
    (compute new mean, swap medoids, compute new distribution parameters,…)
- Important:
  - Number of clusters k
  - Initial cluster position influences (heavily):
    - quality of results
    - speed of convergence
- Problems for iterative clustering methods:
  - Clusters of varied size, density and shape

Clustering: Linkage
Hierarchical Clustering



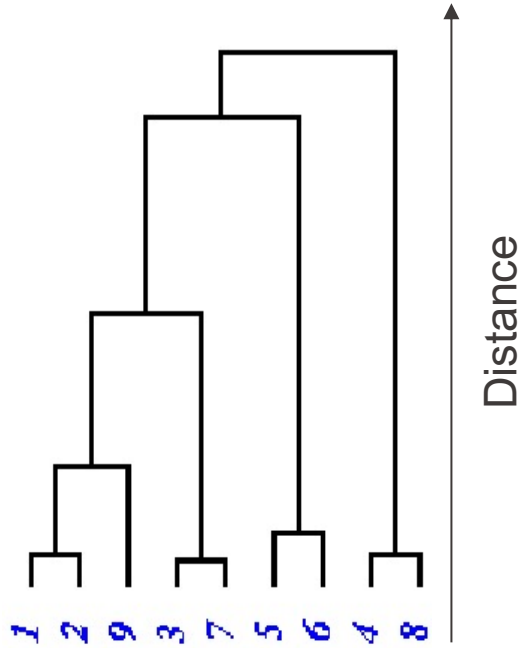
Linkage Hierarchies: Basics

Goal

- Construction of a hierarchy of clusters (*dendrogram*) by merging/separating clusters with minimum/maximum distance

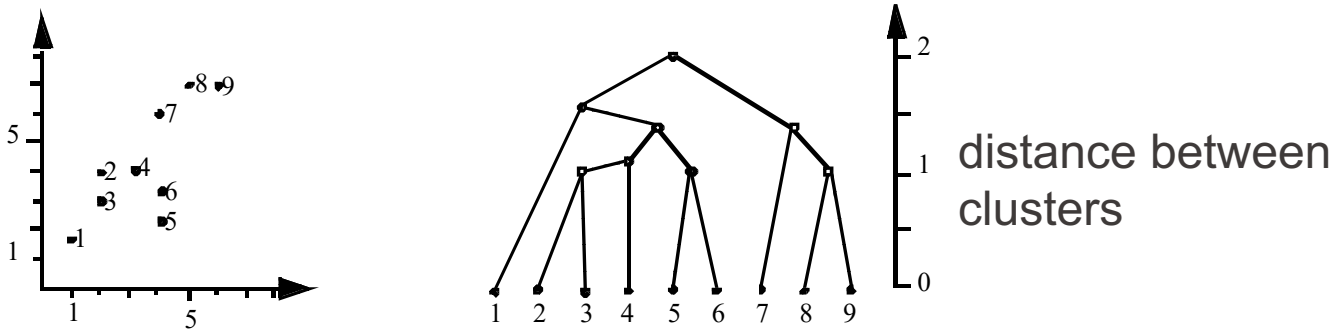
Dendrogram:

- A tree representing hierarchy of clusters, with the following properties:
  - Root: single cluster with the whole data set.
  - Leaves: clusters containing a single object.
  - Branches: merges / separations between larger clusters and smaller clusters / objects



Linkage Hierarchies: Basics

- Example dendrogram



- Types of hierarchical methods
  - Bottom-up construction of dendrogram (*agglomerative*)
  - Top-down construction of dendrogram (*divisive*)

Base Algorithm

1. Form initial clusters consisting of a single object, and compute the distance between each pair of clusters.
2. Merge the two clusters having minimum distance.
3. Calculate the distance between the new cluster and all other clusters.
4. If there is only one cluster containing all objects:
   Stop, otherwise go to step 2.

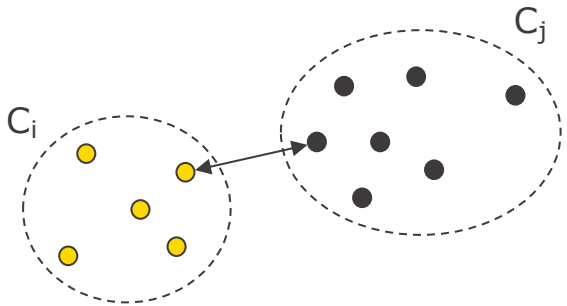
Single Linkage

- Distance between clusters (nodes):

$$Dist(C_1, C_2) = \min_{p \in C_1, q \in C_2} \{dist(p, q)\}$$

Distance of the closest two points, one from each cluster

- Merge Step: Union of two subsets of data points



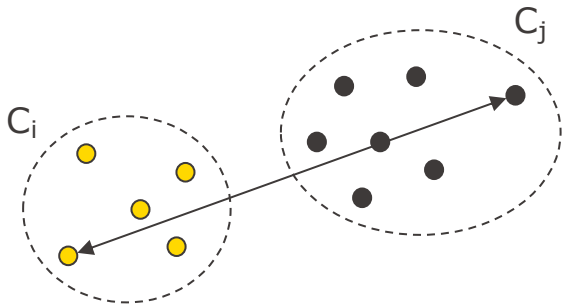
Complete Linkage

- Distance between clusters (nodes):

$$Dist(C_1, C_2) = \max_{p \in C_1, q \in C_2} \{dist(p, q)\}$$

Distance of the farthest two points, one from each cluster

- Merge Step: Union of two subsets of data points



Average Linkage / Centroid Method

- Distance between clusters (nodes):

$$Dist_{avg}(C_1, C_2) = \frac{1}{|C_1| \cdot |C_2|} \sum_{p \in C_1} \sum_{p \in C_2} dist(p, q)$$

Average distance of all possible pairs of points between C_1 and C_2

$$Dist_{mean}(C_1, C_2) = dist\big(mean(C_1), mean(C_2)\big)$$

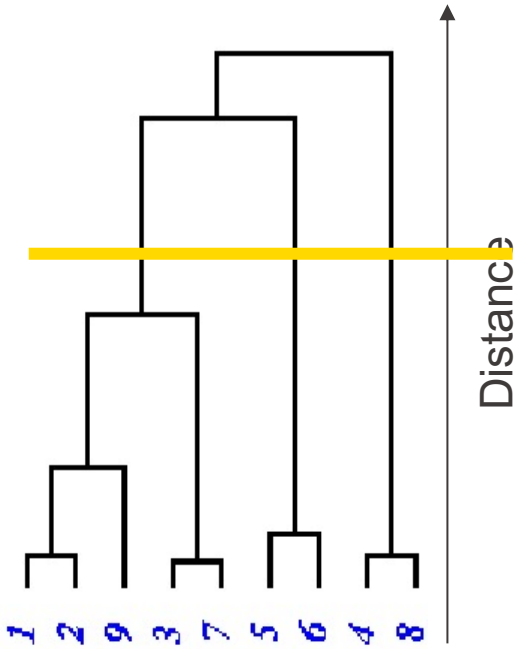
Distance between two centroids

- Merge Step:
  - union of two subsets of data points
  - construct the mean point of the two clusters

Comments on Single Linkage and Variants

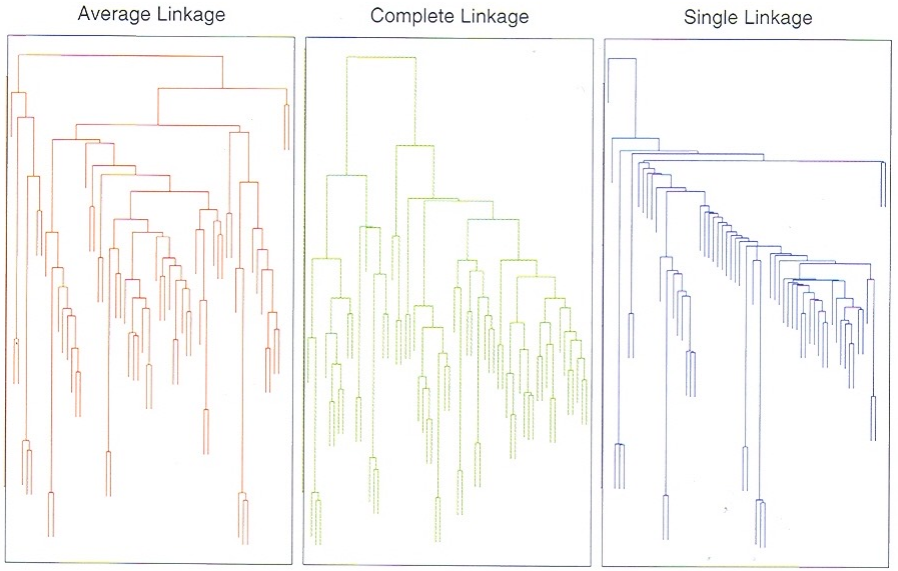
+ Finds not only a „flat“ clustering, but a hierarchy of clusters (dendrogram)
+ A single clustering can be obtained from the dendrogram (e.g., by performing a horizontal cut)

- Decisions (merges/splits) cannot be undone
- Sensitive to noise (Single-Link)
  (a „line“ of objects can connect two clusters)
- Inefficient
  → Runtime complexity at least $O(n^2)$ for n objects

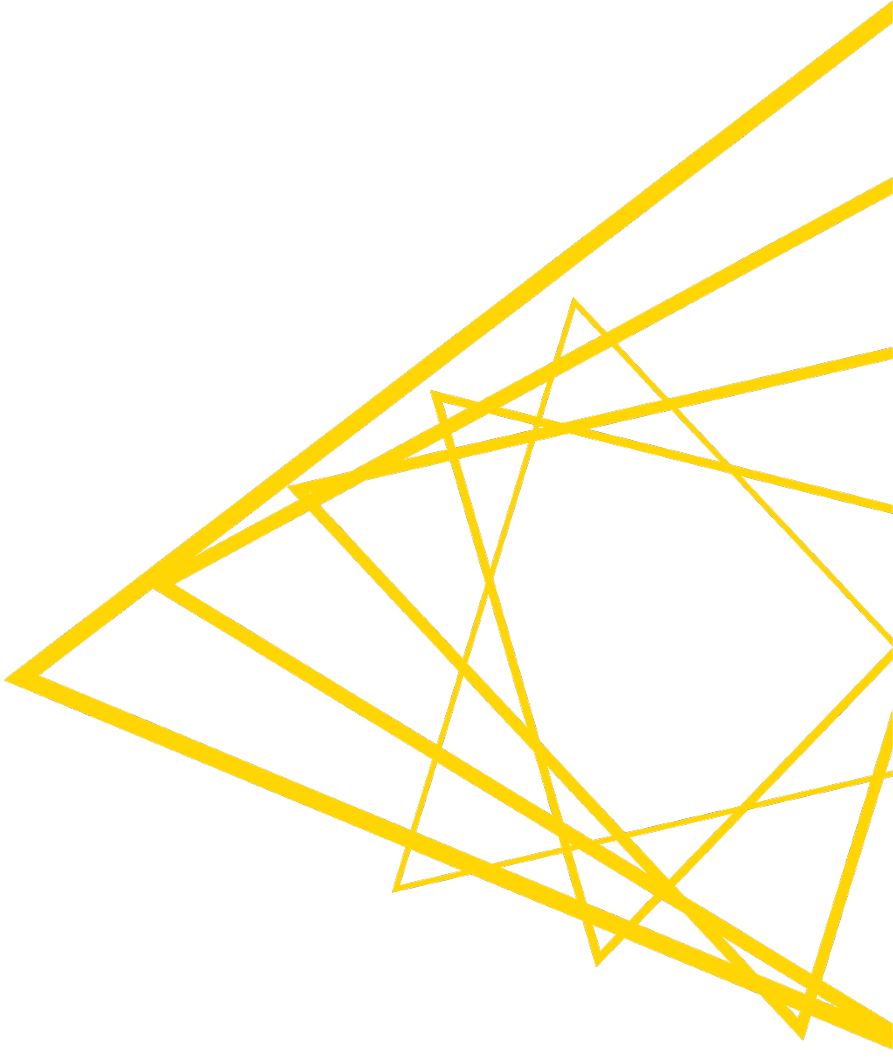


Linkage Based Clustering

- Single Linkage:
  - Prefers well-separated clusters
- Complete Linkage:
  - Prefers small, compact clusters
- Average Linkage:
  - Prefers small, well-separated clusters…



Clustering: Density
DBSCAN



Clustering: DBSCAN

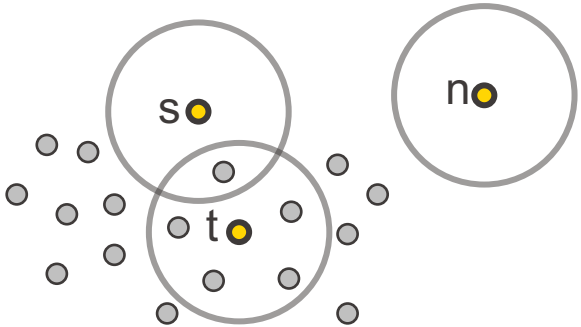
DBSCAN - a density-based clustering algorithm - defines five types of points in a dataset.

- **Core Points** are points that have at least a minimum number of neighbors (**MinPts**) within a specified distance (ε).
- **Noise Points** are neither core points nor border points.
- **Border Points** are points that are within ε of a core point, but have less than **MinPts** neighbors.
- **Directly Density Reachable Points** are within ε of a core point.
- **Density Reachable Points** are reachable with a chain of Directly Density Reachable points.

Clusters are built by joining core and density-reachable points to one another.

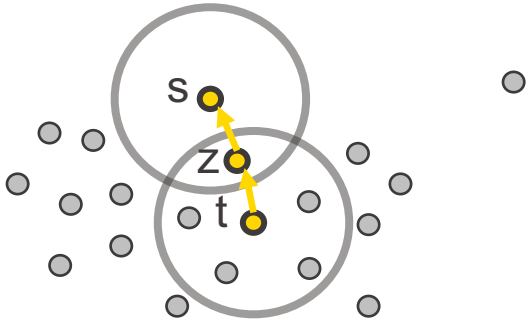
Example with MinPts = 3

Core Point
vs. Border Point
vs. Noise



- t = Core point
- s = Boarder point
- n = Noise point

Directly Density Reachable
vs. Density Reachable

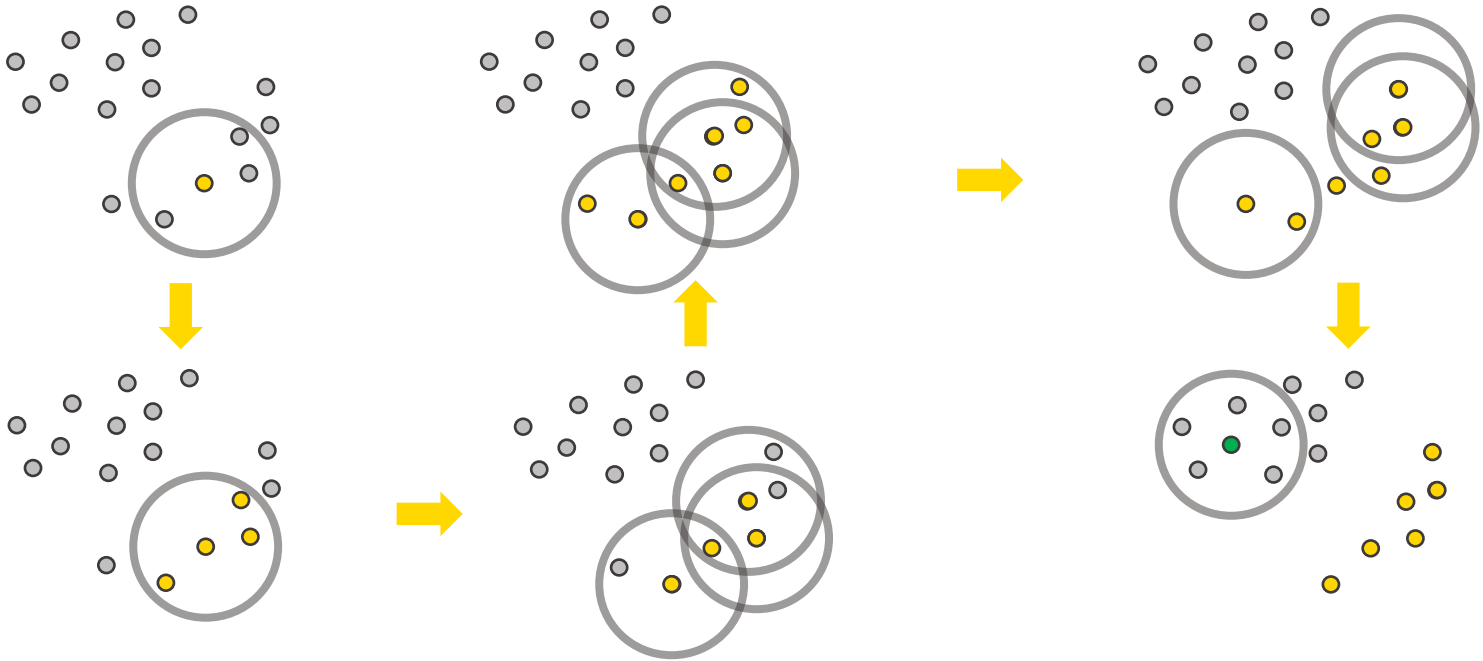


- z is directly density reachable from t
- s is not directly density reachable from t, but density reachable via z

Note: But t is not density reachable from s, because s is not a Core point

DBSCAN [Density Based Spatial Clustering of Applications with Noise]

- For each point, DBSCAN determines the ε-environment and checks whether it contains more than *MinPts* data points ➔ **core** point
- Iteratively increases the cluster by adding density-reachable points



Summary: DBSCAN

Clustering:

- A density-based clustering C of a dataset D w.r.t. ε and MinPts is the set of all density-based clusters C_i w.r.t. ε and MinPts in D.
- The set $NoiseCL$ („noise“) is defined as the set of all objects in D which do not belong to any of the clusters.

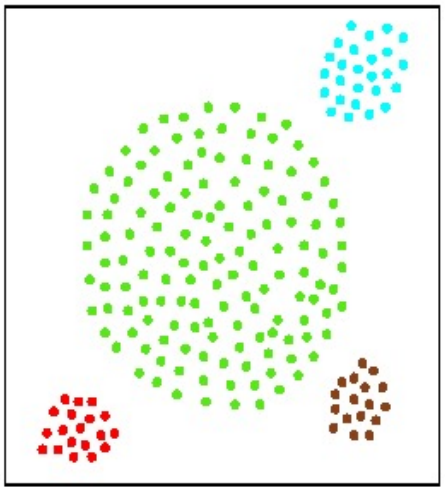
Property:

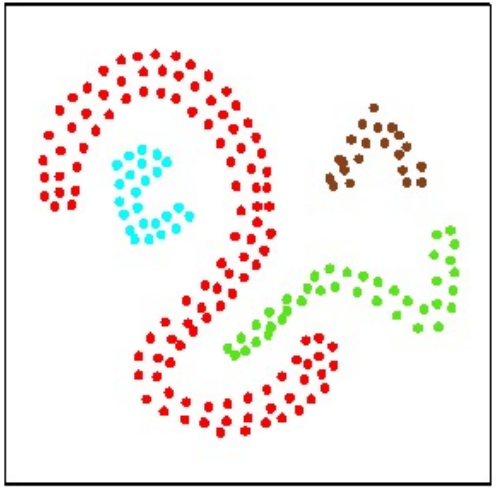
- Let C_i be a density-based cluster and $p \in C_i$ be a core object.

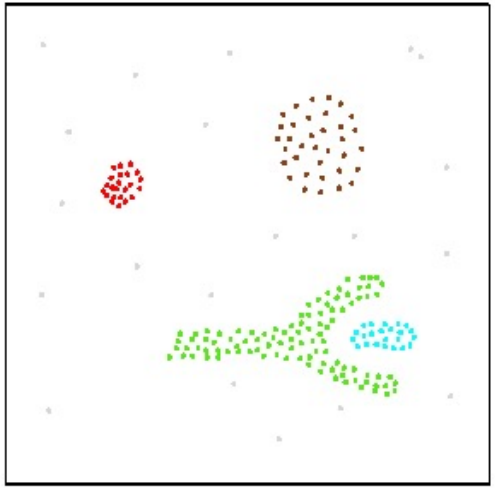
$$C_i = \{o \in D \mid o \text{ density-reachable from } p \text{ w.r.t. } \varepsilon \text{ and } MinPts\}.$$

DBSCAN [Density Based Spatial Clustering of Applications with Noise]

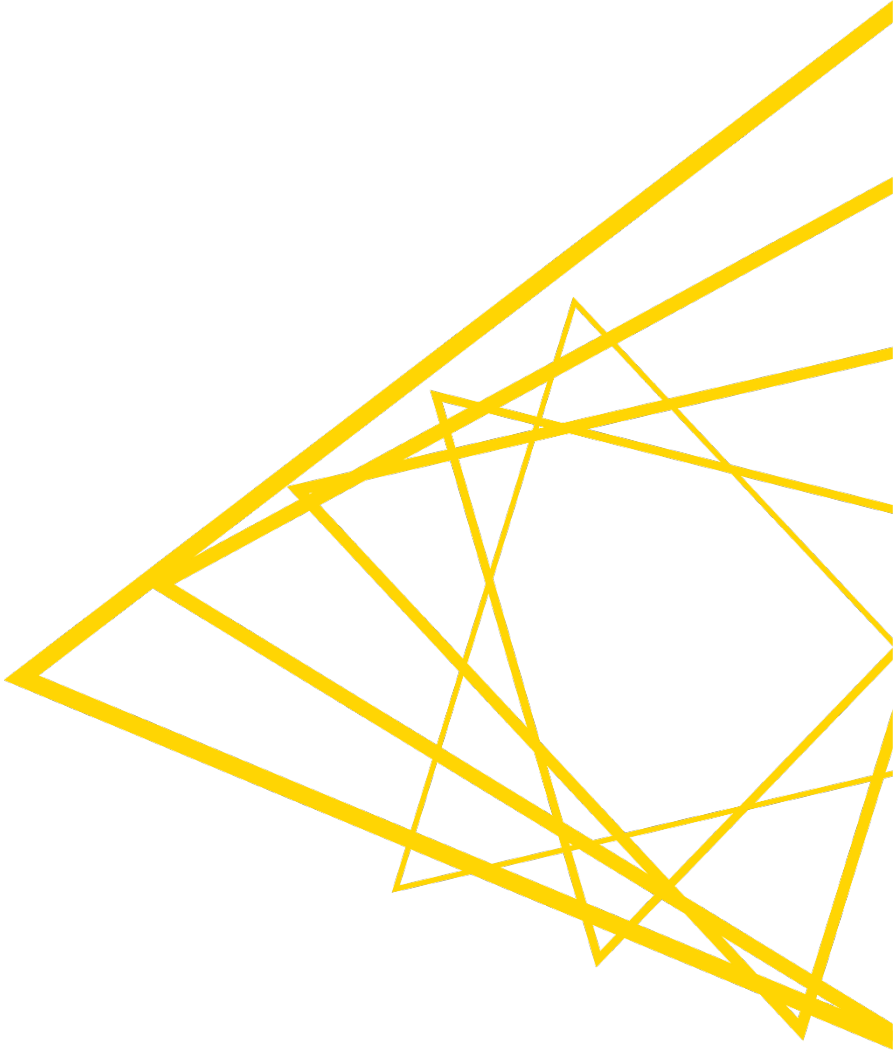
- DBSCAN uses (spatial) index structures for determining the ε-environment:
  → computational complexity $O(n \log n)$ instead of $O(n^2)$
- Arbitrary shape clusters found by DBSCAN
- Parameters: ε and $MinPts$







Data Preparation



Motivation

- **Real world data is „dirty“**
  - → Contains missing values, noises, outliers, inconsistencies
- **Comes from different information sources**
  - → Different attribute names, values expressed differently, related tuples
- **Different value ranges and hierarchies**
  - → One attribute range may overpower another
- **Huge amount of data**
  - → Makes analyis difficult and time consuming

Data Preparation

- Data Cleaning & Standardization (domain dependent)
- Aggregations (often domain dependent)
- Normalization
- Dimensionality Reduction
- Outlier Detection
- Missing Value Imputation
- Feature Selection
- Feature Engineering
- Sampling
- Integration of multiple Data Sources

Data Preparation: Normalization

Normalization: Motivation

Example:

- Lengths in cm (100 – 200) and weights in kilogram (30 – 150) fall both in approximately the same scale
- What about lengths in m (1-2) and weights also in gram (30000 – 150000)?
  → The weight values in mg dominate over the length values for the similarity of records!

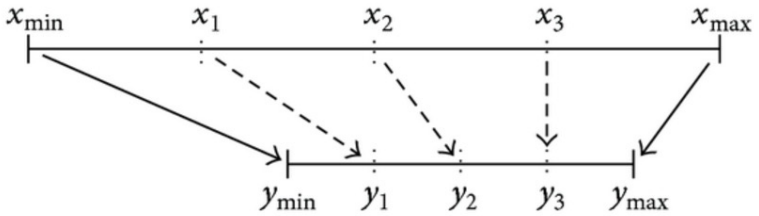
Goal of normalization:

- Transformation of attributes to make record ranges comparable

Normalization: Techniques

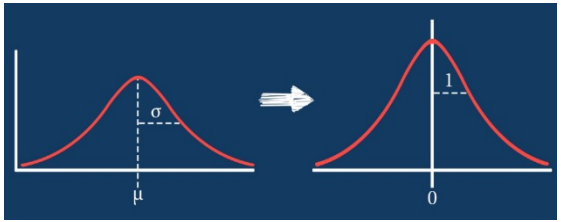
- **min-max normalization**

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} (y_{max} - y_{min}) + y_{min}$$



- **z-score normalization**

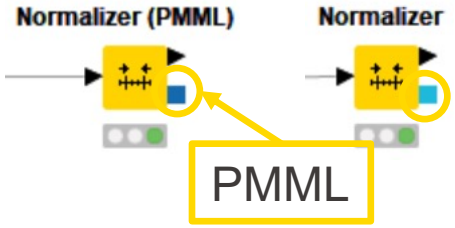
$$y = \frac{x - mean(x)}{stddev(x)}$$



- **normalization by decimal scaling**

$$y = \frac{x}{10^j}$$ where j is the smallest integer for $\max(y) < 1$

Here $[ymin, ymax]$ is $[0,1]$



PMML

- **Predictive Model Mark-up Language** (**PMML**) standard XML-based interchange format for predictive models.
- **Interchange.** PMML provides a way to describe and exchange predictive models produced by machine learning algorithms
- **Standard**. In theory, a PMML model exported from KNIME can be read by PMML compatible functions in other tools
- It does not work that well for the modern / ensemble algorithms, such as random forest or deep learning. In this case, other formats have been experimented.

Data Preparation: Missing Value Imputation

Missing Value Imputation: Motivation

Data is not always available

- E.g., many tuples have no recorded value for several attributes, such as weight in a people database

Missing data may be due to

- Equipment malfunctioning
- Inconsistency with other recorded data and thus deleted
- Data not entered (manually)
- Data not considered important at the time of collection
- Data format / contents of database changes

Missing Values: Types

Types of missing values:

Example: Suppose you are modeling weight Y as a function of sex X

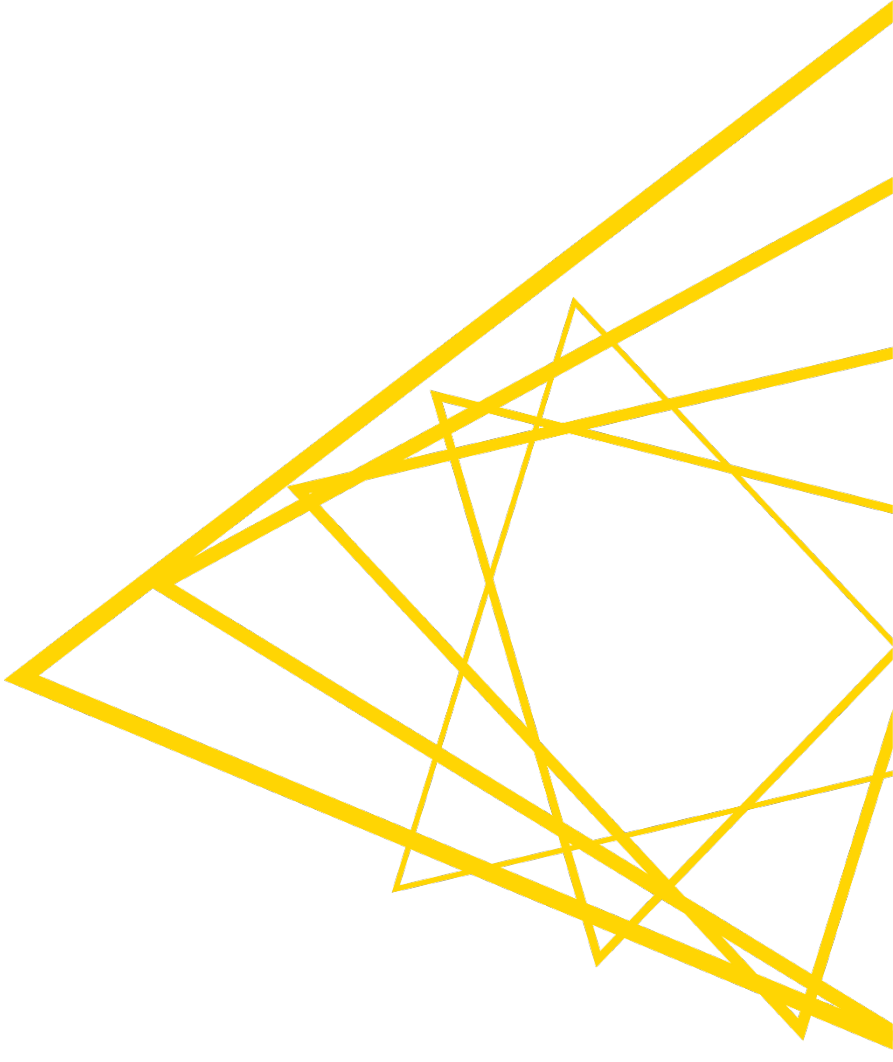
- **Missing Completely At Random** (MCAR): reason does not depend on its value or lack of value.
  There may be no particular reason why some people told you their weights and others didn't.
- **Missing At Random** (MAR): the probability that Y is missing depends only on the value of X.
  One sex X may be less likely to disclose its weight Y.
- **Not Missing At Random** (NMAR): the probability that Y is missing depends on the unobserved value of Y itself.
  Heavy (or light) people may be less likely to disclose their weight.

Missing Values Imputation

How to handle missing values?

- Ignore the record
- Remove the record
- Fill in missing value as:
  - Fixed value: e.g., “unknown”, -9999, etc.
  - Attribute mean / median / max. / min.
  - Attribute most frequent value
  - Next / previous /avg interpolation / moving avg value (in time series)
  - A predicted value based on the other attributes (inference-based such as Bayesian, Decision Tree, ...)

Data Preparation: Outlier Detection



Outlier Detection

- An outlier could be, for example, rare behavior, system defect, measurement error, or reaction to an unexpected event

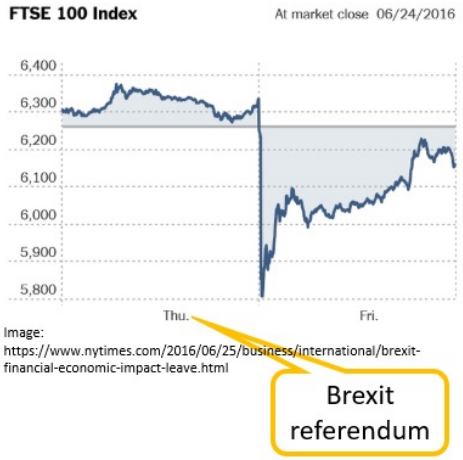
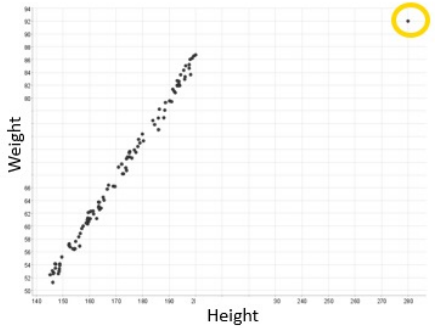


Image: https://www.nytimes.com/2016/06/25/business/international/brexit-financial-economic-impact-leave.html

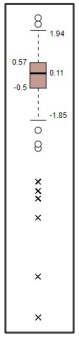


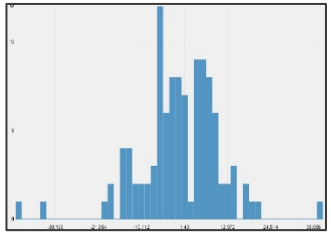
Outlier Detection: Motivation

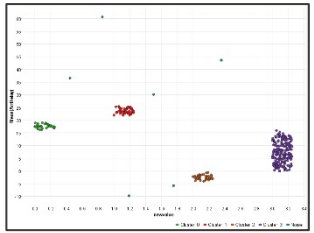
- Why finding outliers is important?
  - Summarize data by statistics that represent the majority of the data
  - Train a model that generalizes to new data
  - Finding the outliers can also be the focus of the analysis and not only data cleaning

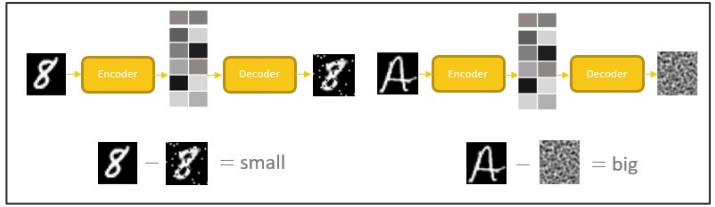
Outlier Detection Techniques

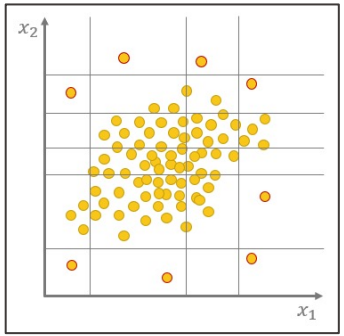
- Knowledge-based
- Statistics-based
  - Distance from the median
  - Position in the distribution tails
  - Distance to the closest cluster center
  - Error produced by an autoencoder
  - Number of random splits to isolate a data point from other data



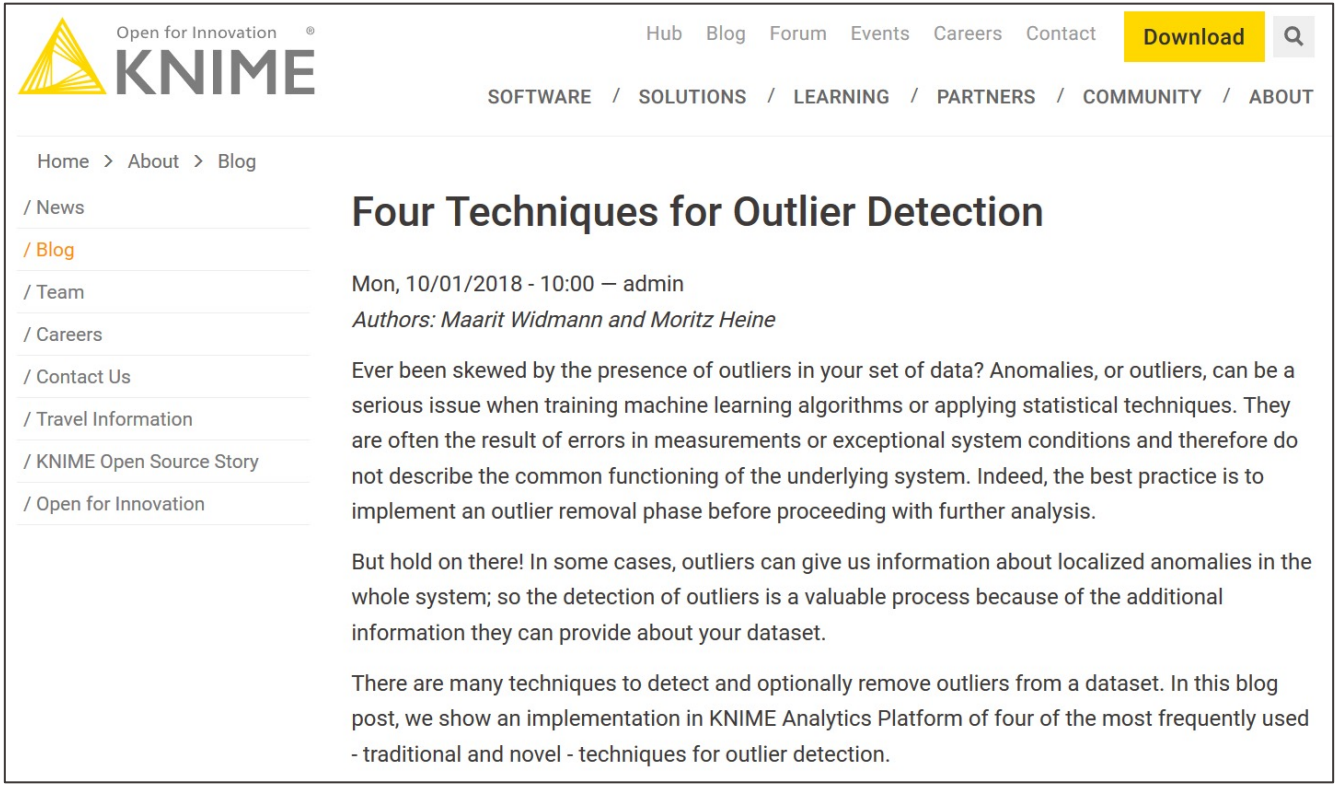






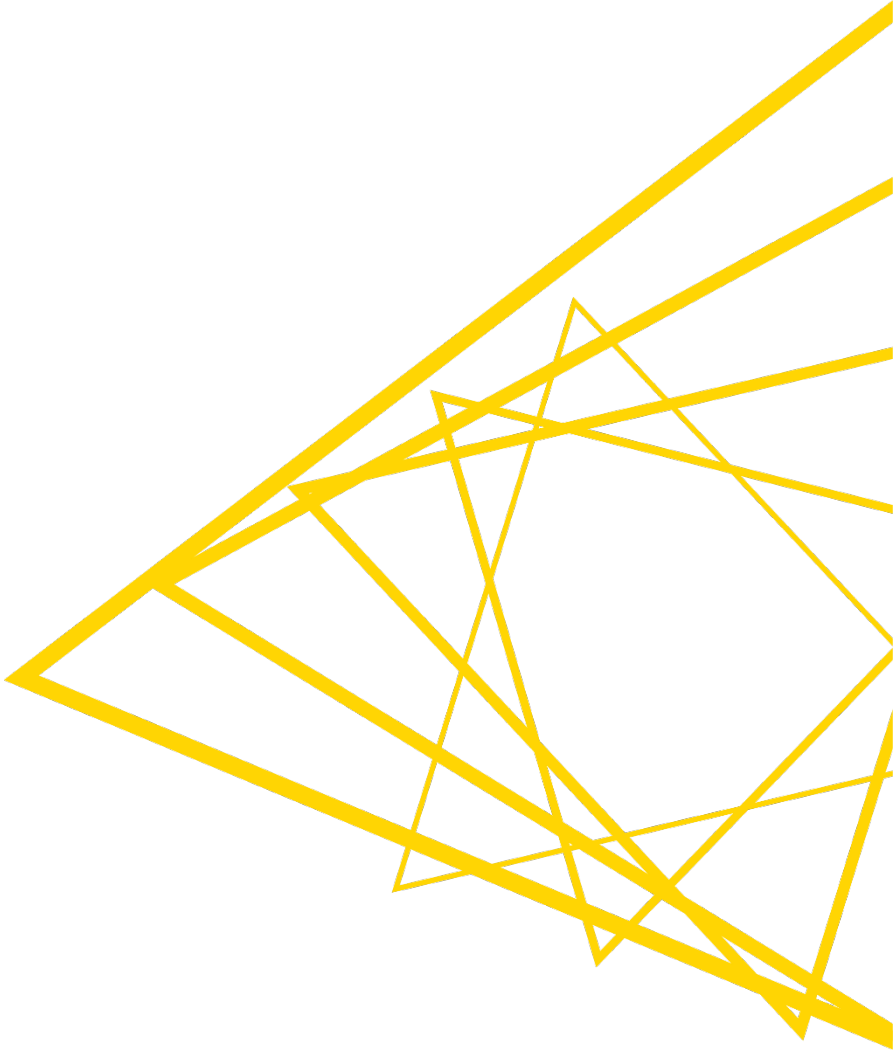


Material



https://www.knime.com/blog/four-techniques-for-outlier-detection

Data Preparation: Dimensionality Reduction



Is there such a thing as “too much data”?

“Too much data”:

- Consumes storage space
- Eats up processing time
- Is difficult to visualize
- Inhibits ML algorithm performance
- Beware of the model: Garbage in → Garbage out

Dimensionality Reduction Techniques

- Measure based
  - Ratio of missing values
  - Low variance
  - High Correlation
- Transformation based
  - Principal Component Analysis (PCA)
  - Linear Discriminant Analysis (LDA)
  - t-SNE
- Machine Learning based
  - Random Forest of shallow trees
  - Neural auto-encoder

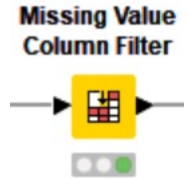
Missing Values Ratio

First partition (as defined in dialog) - 0:337:0:276 - Partitioning (80% vs. 20%)

File Hilite Navigation View

Table "default" - Rows: 40000 | Spec - Columns: 231 | Properties | Flow Variables

Row ID	Var16	Var17	Var18	Var19	Var20	Var21	Var22	Var23	Var24	Var25	Var26	Var27	Var28
Row0	?	?	?	?	?	464	580	?	14	128	?	?	166.56
Row1	?	?	?	?	?	168	210	?	2	24	?	?	353.52
Row2	?	?	?	?	?	1212	1515	?	26	816	?	?	220.08
Row4	?	?	?	?	?	64	80	?	4	64	?	?	200
Row7	?	?	?	?	?	32	40	?	2	16	?	?	230.56
Row8	?	?	?	?	?	200	250	?	2	64	?	?	300.32
Row10	?	?	?	?	?	92	115	?	6	112	?	?	133.12
Row11	?	?	?	?	?	236	295	?	8	40	?	?	133.12
Row12	?	?	?	?	?	0	0	?	?	0	?	?	240.56
Row13	?	?	?	?	?	480	600	?	10	216	?	?	176.56
Row14	?	?	?	?	?	148	185	?	0	8	?	?	236.08
Row16	?	?	?	?	?	584	730	?	6	320	?	?	220.08
Row17	?	?	?	?	?	168	210	?	2	32	?	?	166.56
Row18	?	?	?	?	?	12	15	?	2	0	?	?	253.52
Row20	?	?	?	?	?	168	210	?	2	56	?	?	272.08
Row21	?	?	?	?	?	20	25	?	2	0	?	?	86.96
Row22	?	?	?	?	?	192	240	?	2	80	?	?	166.56
Row23	?	?	?	?	?	52	65	?	0	56	?	?	198.88
Row24	?	?	?	?	?	216	270	?	8	128	?	?	200
Row25	?	?	?	?	?	152	190	?	4	16	?	?	20.08
Row26	?	0	0	0	?	?	?	?	?	?	?	?	?
Row28	?	?	?	?	?	0	0	?	?	0	?	?	257.28
Row29	?	?	?	?	?	312	390	?	0	120	?	?	200
Row30	?	?	?	?	?	112	140	?	4	56	?	?	166.56
Row31	?	?	?	?	?	28	35	?	0	16	?	?	285.2
Row33	?	?	?	?	?	160	200	?	4	40	?	?	[illegible]
Row36	?	?	?	?	?	612	765	?	14	360	?	?	200
Row37	?	?	?	?	?	380	475	?	4	208	?	?	336.56
Row38	?	?	?	?	?	76	95	?	0	16	?	?	213.36
Row40	?	?	?	?	?	228	285	?	22	56	?	?	200
Row41	?	?	?	?	?	120	150	?	10	80	?	?	133.12
Row42	?	5	0	0	?	?	?	?	?	?	?	?	?
Row43	?	?	?	?	?	72	90	?	0	40	?	?	191.36
Row44	?	?	?	?	?	0	0	?	?	0	?	?	120.4
Row47	?	?	?	?	?	0	0	?	?	0	?	?	186.64
Row48	?	?	?	?	?	172	215	?	4	200	?	?	137.68
Row49	?	?	?	?	?	0	0	?	?	0	?	?	274.16



IF (% missing value > threshold) THEN remove column

Low Variance

Output table - 0:347:0:337 - Missing Value (Numeric: 0)

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Table "default" - Rows: 40000 | Spec - Columns: 231 | Properties | Flow Variables

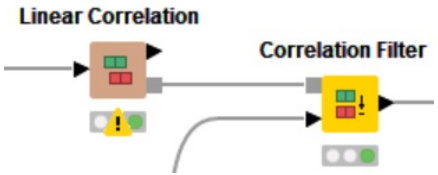
Row ID	20	Var21	Var22	Var23	Var24	Var25	Var26	Var27	Var28
Row51	?	336	420	0	8	72	0	0	133.12
Row52	?	120	150	0	0	16	0	0	286.96
Row54	?	124	155	0	0	0	0	0	234.72
Row55	?	184	230	0	4	64	0	0	642.64
Row56	?	268	335	0	4	88	0	0	133.12
Row57	?	128	160	0	0	96	0	0	198.88
Row59	?	132	165	0	0	112	0	0	253.52
Row60	?	44	55	0	0	24	0	0	186.64
Row61	?	104	130	0	4	72	0	0	166.56
Row62	?	212	265	0	6	136	0	0	379.6
Row63	?	20	25	0	0	0	0	0	166.56
Row65	?	492	615	0	18	256	0	0	133.12
Row66	?	148	185	0	2	8	0	0	186.64
Row68	?	140	175	0	2	40	0	0	176.56
Row69	?	0	0	0	0	0	0	0	166.56
Row71	?	0	0	0	0	0	0	0	392.08
Row72	?	124	155	0	6	88	0	0	153.2
Row73	?	152	190	0	0	32	0	0	253.52
Row74	?	324	405	0	8	104	0	0	186.64
Row75	?	0	0	0	0	0	0	0	0
Row76	?	60	75	0	6	0	0	0	200
Row77	?	180	225	0	4	88	0	0	166.56
Row78	?	232	290	0	4	144	0	0	200
Row79	?	16	20	0	0	16	0	0	313.68
Row81	?	152	190	0	0	48	0	0	220.08
Row82	?	108	135	0	4	88	0	0	166.56

Note: requires min-max-normalization, and only works for numeric columns

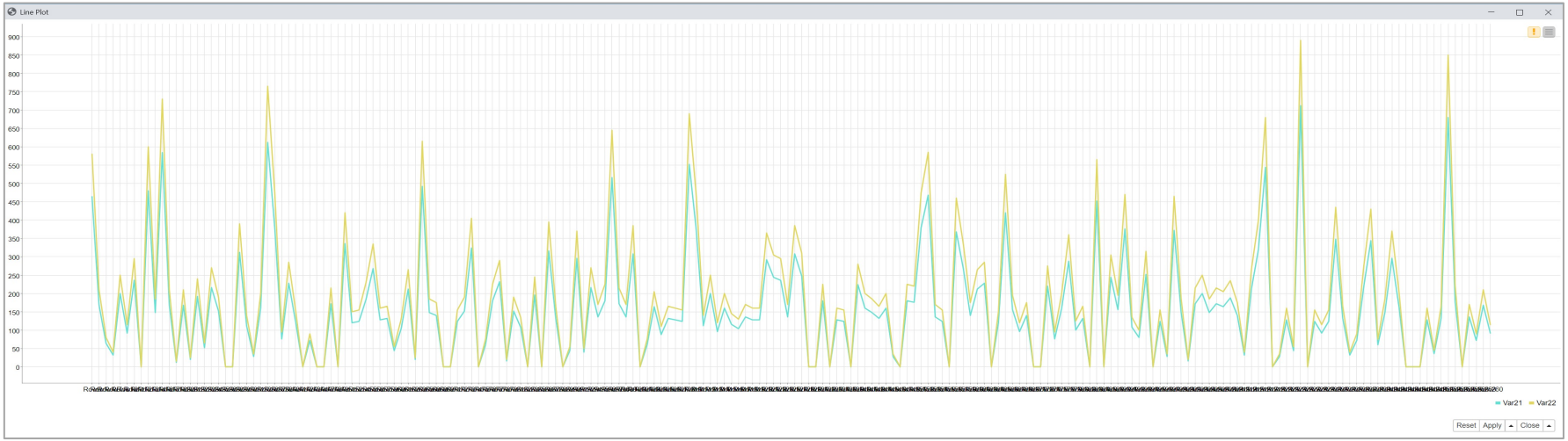
- If column has **constant** value (variance = **0**), it contains no useful information
- In general: IF (variance < threshold) THEN remove column

High Correlation

- Two **highly correlated** input variables probably carry similar information
- IF (**corr(var1, var2)** > threshold) => remove var1



Note: requires min-max-normalization of numeric columns



Principal Component Analysis (PCA)

- PCA is a statistical procedure that **orthogonally** transforms the original n coordinates of a data set into a new set of n coordinates, called principal components.

$$(PC_1, PC_2, \cdots PC_n) = PCA(X_1, X_2, \cdots X_n)$$

- The first principal component PC_1 follows the direction (eigenvector) of the **largest possible variance** (largest eigenvalue of the covariance matrix) in the data.

- Each succeeding component PC_k follows the direction of the **next largest possible variance** under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components $(PC_1, PC_2, \cdots PC_{k-1})$.

If you're still curious, there's LOTS of different ways to think about PCA: https://stats.stackexchange.com/questions/2691/making-sense-of-principal-component-analysis-eigenvectors-eigenvalues

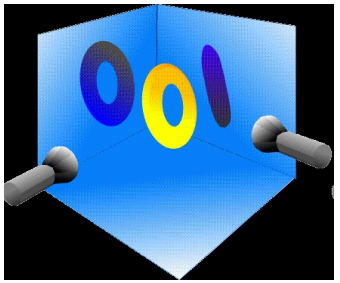
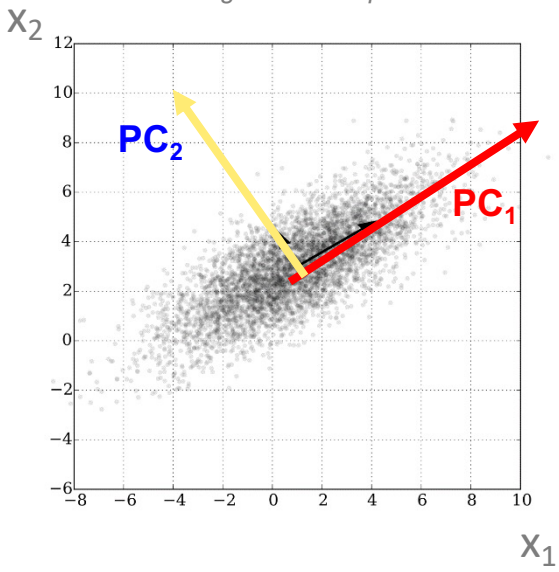


Image from Wikipedia



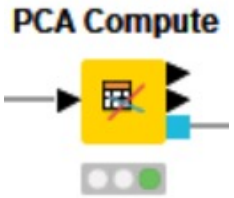
Principal Component Analysis (PCA)

- PC_1 describes most of the variability in the data, PC_2 adds the next big contribution, and so on. In the end, the last PCs do not bring much more information to describe the data.

- Thus, to describe the data we could use only the top $m < n$ (i.e., $PC_1, PC_2, \cdots PC_m$) components with little - if any - loss of information

Dimensionality Reduction

- Caveats:
  - Results of PCA are quite difficult to interpret
  - Normalization required
  - Only effective on numeric columns

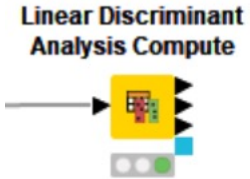


Linear Discriminant Analysis (LDA)

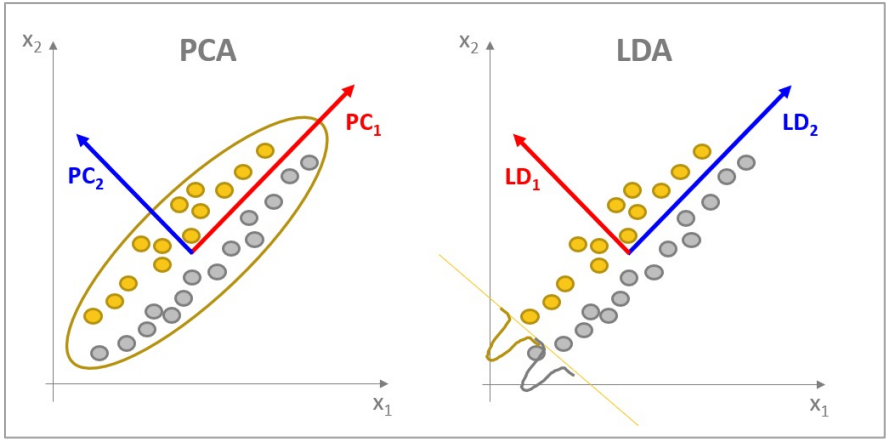
- LDA is a statistical procedure that **orthogonally** transforms the original n coordinates of a data set into a new set of n coordinates, called linear discriminants.

$$(LD_1, LD_2, \cdots LD_n) = LDA(X_1, X_2, \cdots X_n)$$

- Here, however, discriminants (components) **maximize the separation between classes**



- PCA : unsupervised
- LDA : supervised



Linear Discriminant Analysis (LDA)

- LD_1 describes best the class separation in the data, LD_2 adds the next big contribution, and so on. In the end, the last LDs do not bring much more information to separate the classes.

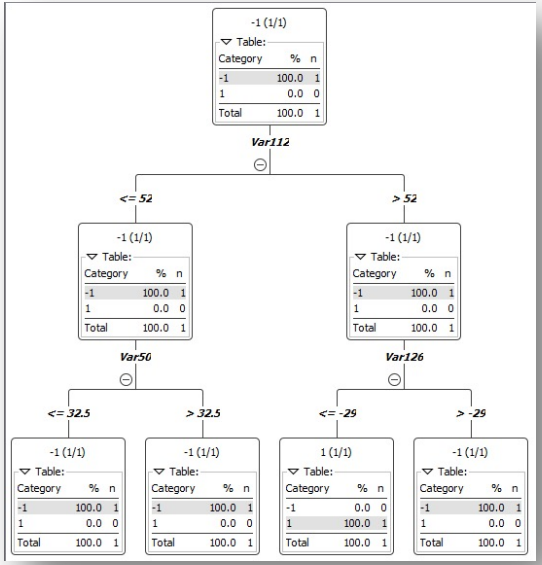
- Thus, for our classification problem we could use only the top $m < n$ (i.e., $LD_1, LD_2, \cdots LD_m$) discriminants with little - if any - loss of information

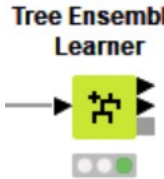
- Caveats:
  - Results of LDA are quite difficult to interpret
  - Normalization required
  - Only effective on numeric columns

Dimensionality Reduction

Ensembles of Shallow Decision Trees

- Often used for classification, but can be used for feature selection too
- Generate a large number (we used 2000) of trees that are very shallow (2 levels, 3 sampled features)
- Calculate the statistics of candidates and selected features. The more often a feature is selected in such trees, the more likely it contains predictive information
- Compare the same statistics with a forest of trees trained on a random dataset.

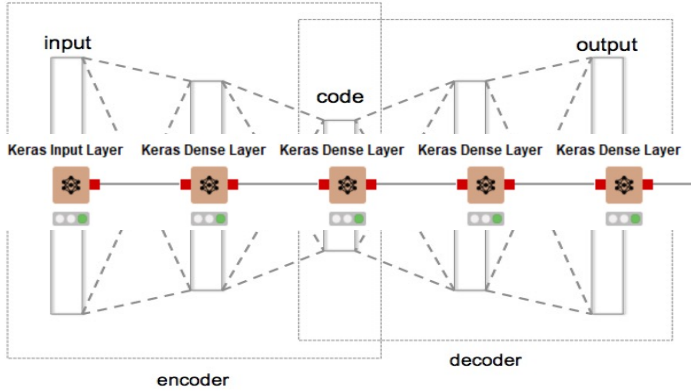




Autoencoder

- Feed-Forward Neural Network architecture with encoder / decoder structure.
  The network is trained to reproduce the input vector onto the output layer.

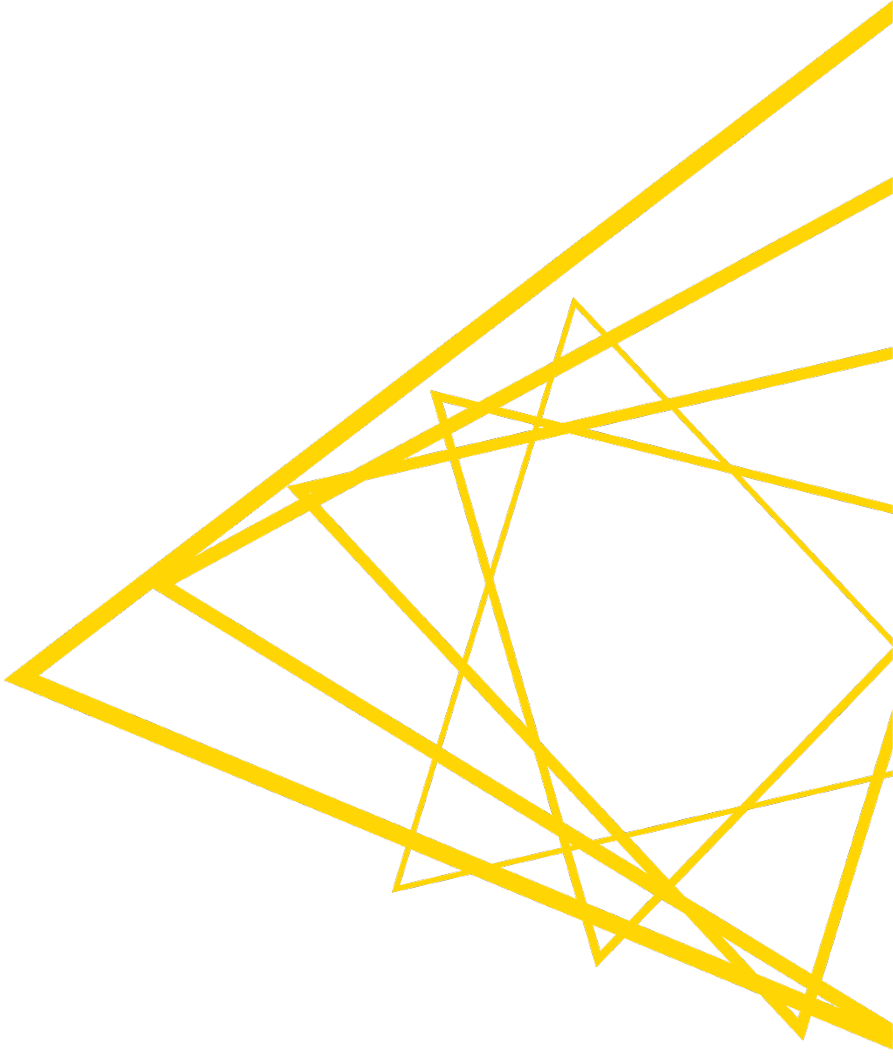
Image: Wikipedia



- That is, it compresses the input vector (dimension n) into a smaller vector space on layer “code” (dimension m<n) and then it reconstructs the original vector onto the output layer.

- If the network was trained well, the reconstruction operation happens with minimal loss of information.

Data Preparation: Feature Selection



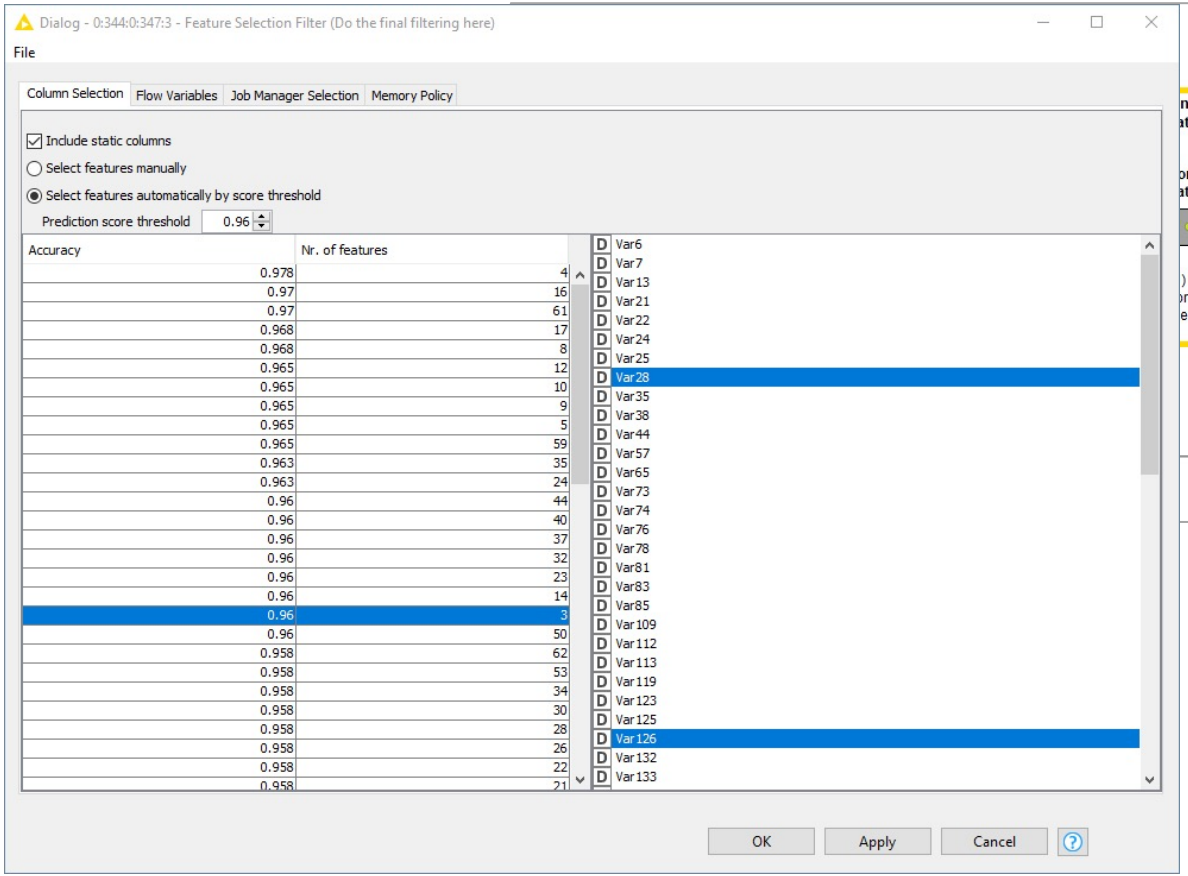
Feature Selection vs. Dimensionality Reduction

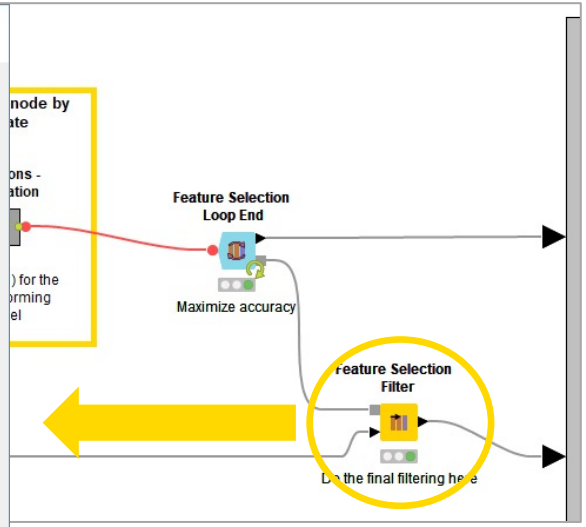
- Both methods are used for reducing the number of features in a dataset. However:
- Feature selection is simply selecting and excluding given features **without changing** them.
- Dimensionality reduction **might transform** the features into a lower dimension.
- Feature selection is often a somewhat more aggressive and more computationally expensive process.
  - Backward Feature Elimination
  - Forward Feature Construction

Backward Feature Elimination (greedy top-down)

1. First train one model on n input features
2. Then train n separate models each on $n - 1$ input features and remove the feature whose removal produced the least disturbance
3. Then train $n - 1$ separate models each on $n - 2$ input features and remove the feature whose removal produced the least disturbance
4. And so on. Continue until desired maximum error rate on *training* data is reached.

Backward Feature Elimination

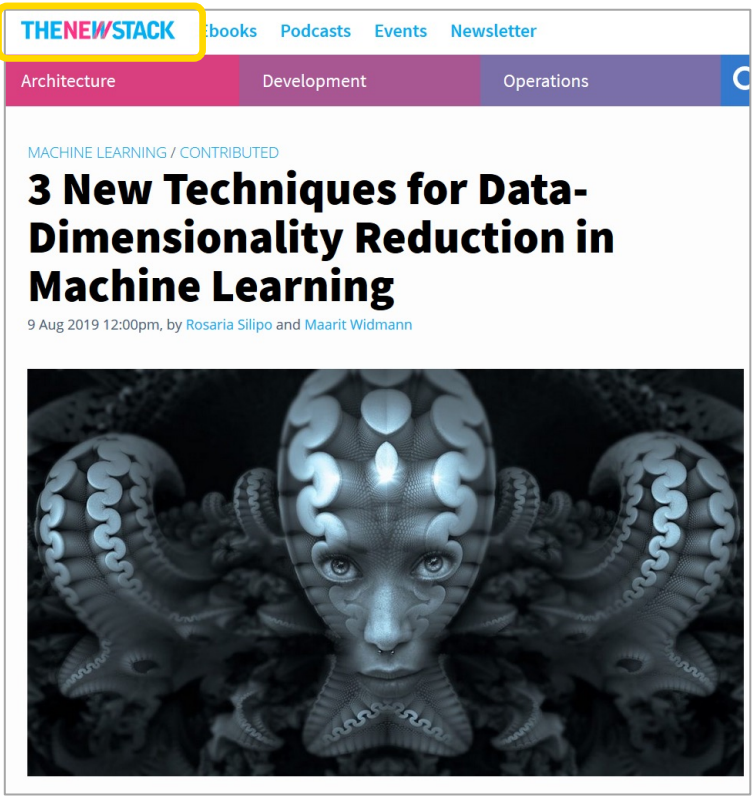




Forward Feature Construction (greedy bottom-up)

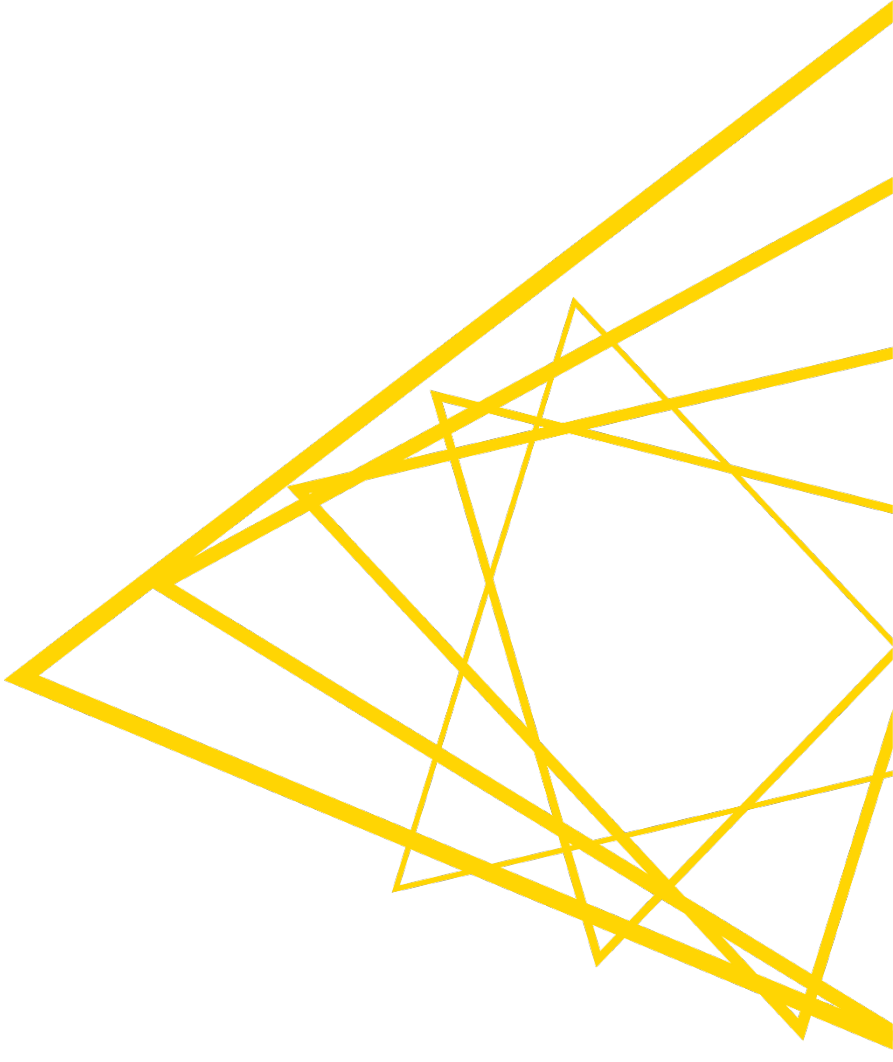
1. First, train n separate models on one single input feature and keep the feature that produces the best accuracy.
2. Then, train $n - 1$ separate models on 2 input features, the selected one and one more. At the end keep the additional feature that produces the best accuracy.
3. And so on … Continue until an acceptable error rate is reached.

Material



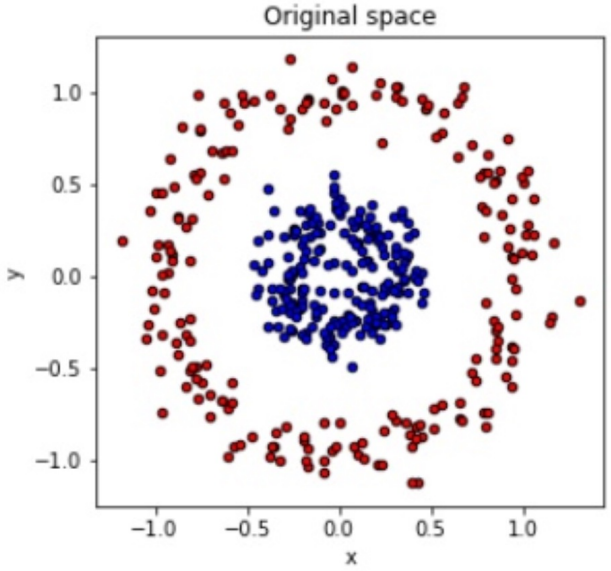
https://thenewstack.io/3-new-techniques-for-data-dimensionality-reduction-in-machine-learning/

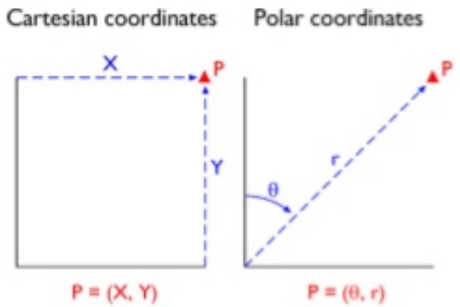
Data Preparation: Feature Engineering

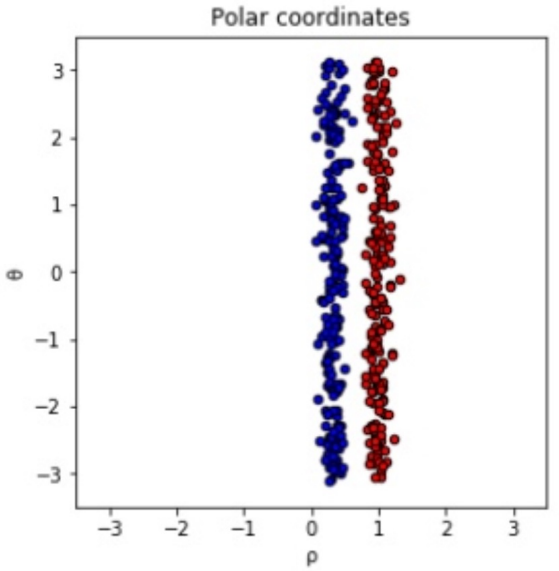


Feature Engineering: Motivation

Sometimes transforming the original data allows for better discrimination by ML algorithms.

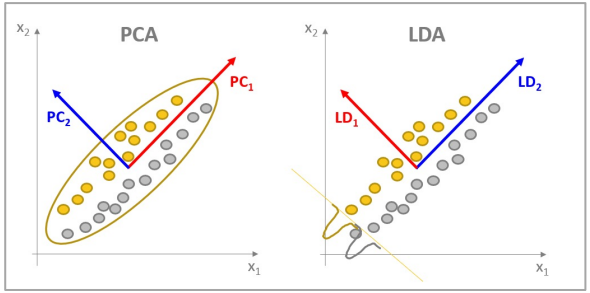






Feature Engineering: Techniques

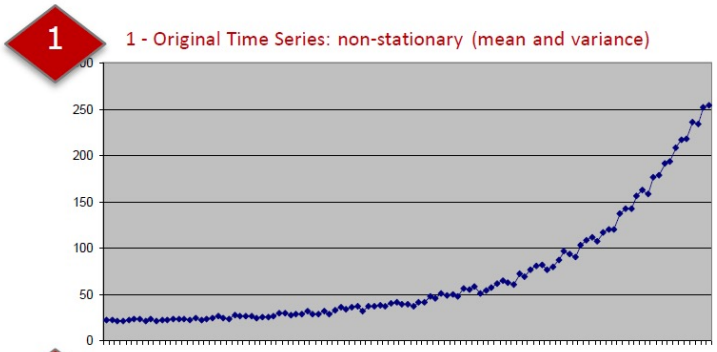
- Coordinate Transformations
  Remember PCA and LDA?
  Polar coordinates , …

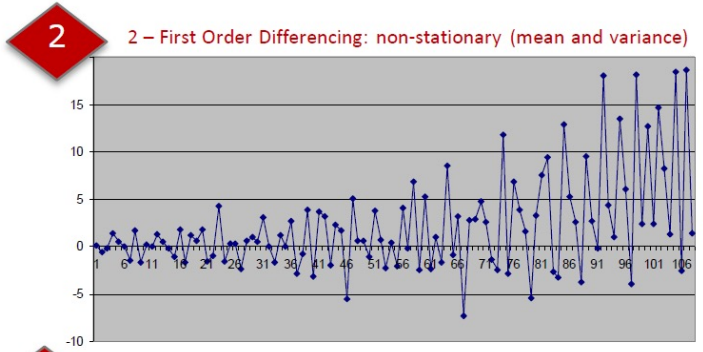


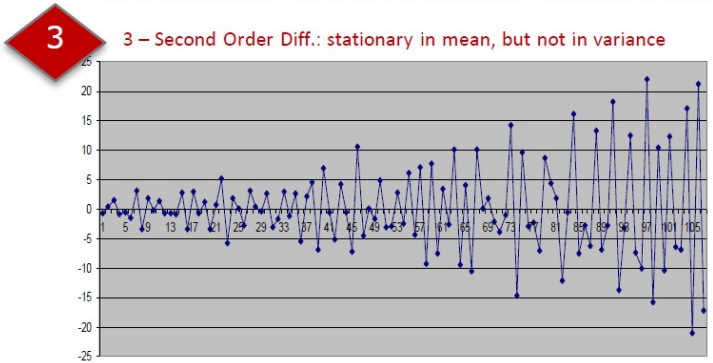
- Distances to cluster centres, after data clustering
- Simple math transformations on single columns
  $(e^x, x^2, x^3, \tanh(x), \log(x)\ , \ldots)$
- Combining together multiple columns in math functions
  $(f(x_1, x_2, \ldots\ xn), x_2 - x_1, \ldots)$
- The whole process is domain dependent

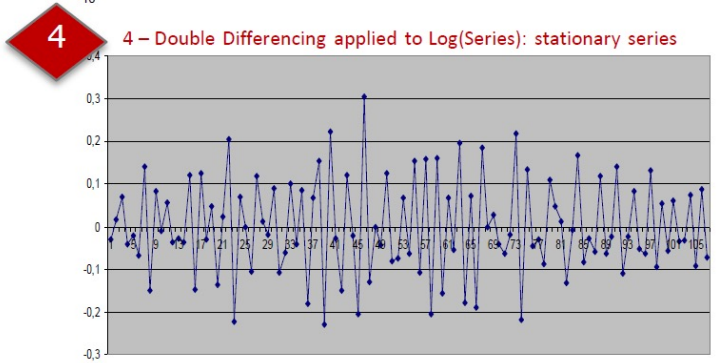
Feature Engineering in Time Series Analysis

- Second order differences: $y = x(t) - x(t-1)$ & $y'(t) = y(t) - y(t-1)$
- Logarithm: $\log(y'(t))$



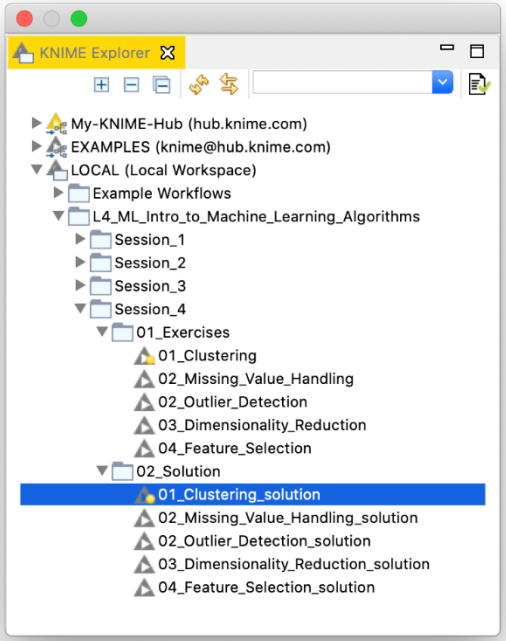




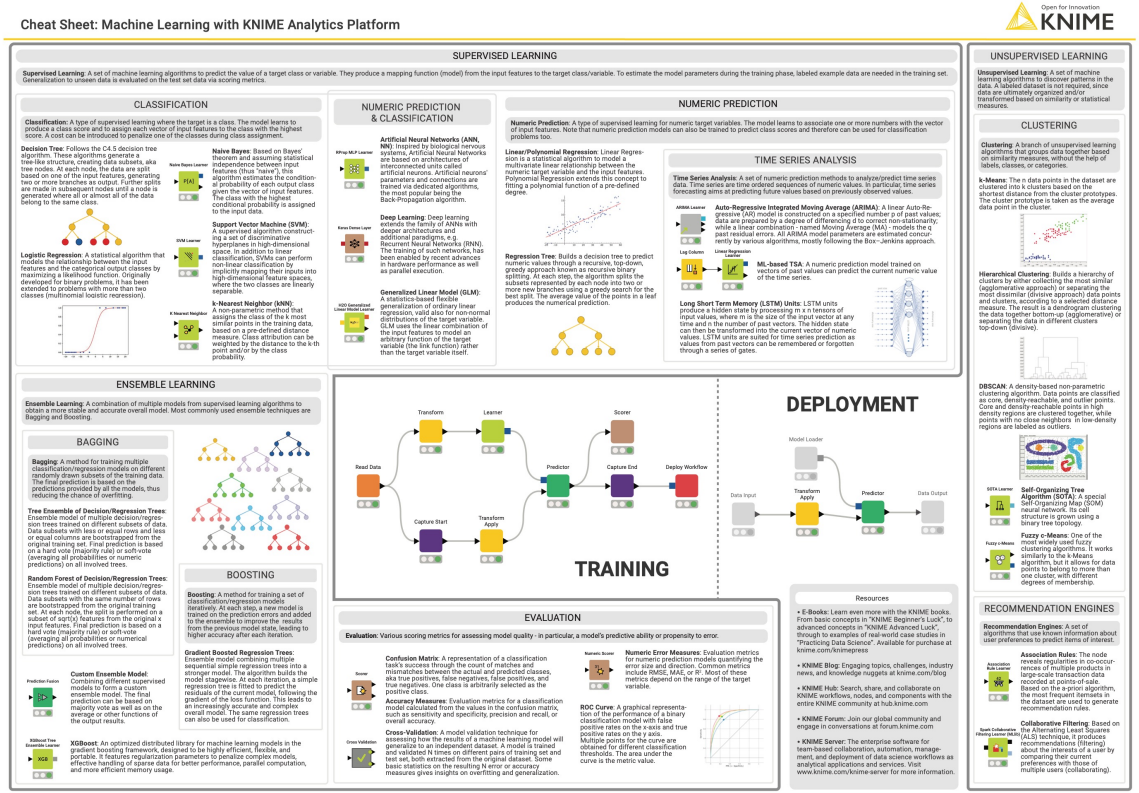


Exercises

- Clustering
  - Goal: Cluster location data from California
  - 01_Clustering
- Data Preparation
  - 02_Missing_Value_Handling
  - 03_Outlier_Detection
  - 04_Dimensionality_Reduction
  - 05_Feature_Selection



Machine Learning Cheat Sheet



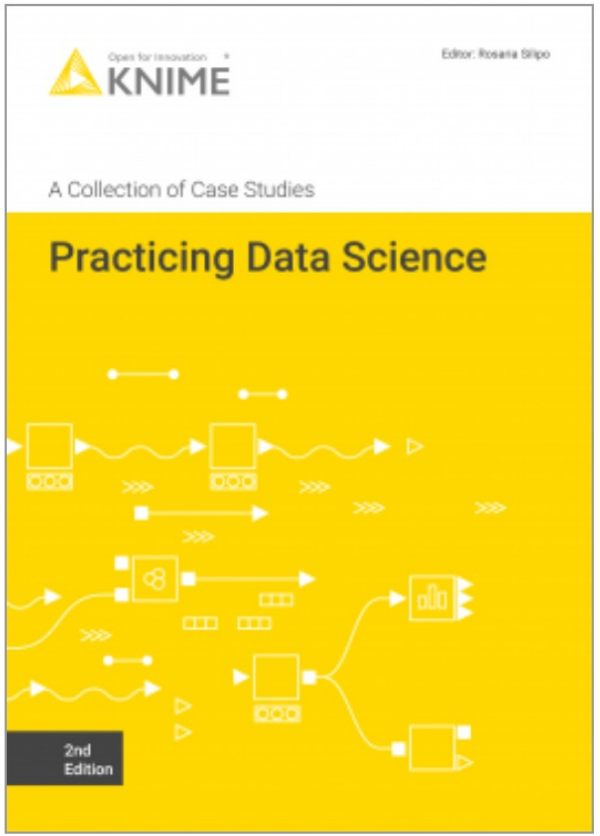
https://www.knime.com/sites/default/files/2021-07/CheatSheet_ML_A3.pdf

KNIME Books

Course books downloadable from KNIME Press

https://www.knime.com/knimepress

with code: L4-ML-0721



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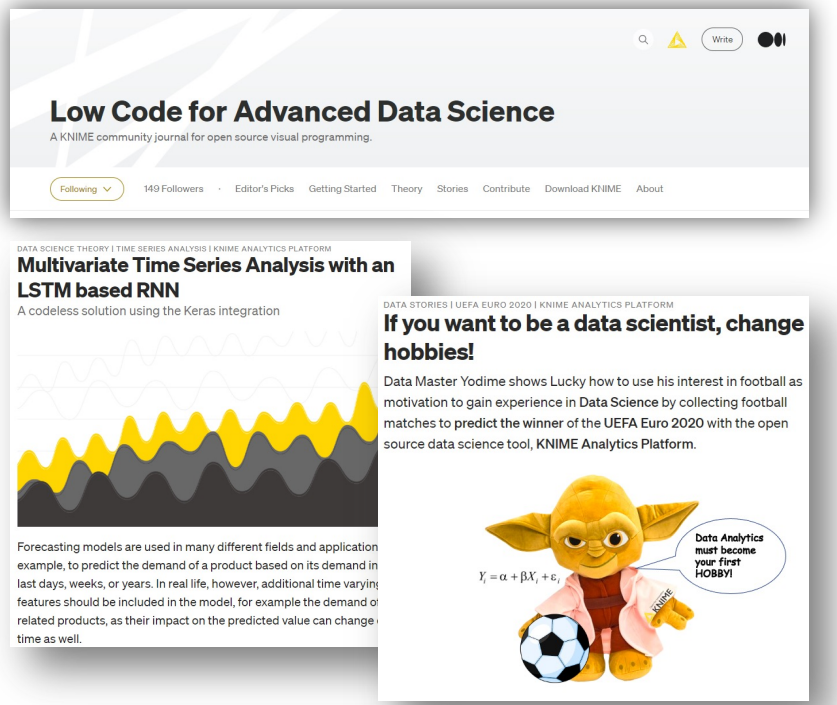
  [Low Code for Advanced Data Science]

- Daily content on data stories, data science theory, getting started with KNIME and more for the community by the community

- Would you like to share your data story with the KNIME community?



[Contributions] are always welcome!

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KNIME

Thank You!