Part II-3: Sentiment Analysis

Outline

i. Word Embeddings
ii. Feature Collection
iii. Sentiment Analysis
    i. Machine Learning Background
    ii. Training & Prediction
    iii. Performance Evaluation
    iv. Visualization
iv. Excursus: AutoML Pipeline

Part II-3: Sentiment Analysis

Word Embeddings

Word Embeddings **Setting**

- **Recall our goal:** numeric representation of texts by variables that co-occur across documents

- **Approaches**
  - Vocabulary-based → *done*
  - Neural network representations → *later: BERT*
  - Word embeddings → *let‘s see*

Word Embeddings **Vocabulary-Based**

- **Revisited: BOW**
  - Vocabulary with all occurring words in documents
  - Assumption: each word independent from others present in document
  - No accounting for word order
  - Each document represented by **term frequency vector** (occurrence of all distinct words present in document)
- **Idea**: weighting
- **Term Frequency - Inverse Document Frequency (TF-IDF)**
  - Not implying that all terms are considered equally important
  - **Idea**: penalize words that are too frequent

Word Embeddings **Example BOW**

Documents

"Die Ausgrenzung von MigrantInnen ist inakzeptabel und rassistisch."

"Die Maskenpflicht ist sinnvoll."

"Die Diskriminierung von Frauen ist inakzeptabel."

Vector-space representations

	die	ausgrenzung	von	migrantinnen	ist	inakzeptabel	und	rassistisch	maskenpflicht	sinnvoll	diskriminierung	frauen
Doc1	1	1	1	1	1	1	1	1	0	0	0	0
Doc2	1	0	0	0	1	0	0	0	1	1	0	0
Doc3	1	0	1	0	1	1	0	0	0	0	1	1

Word Embeddings **Example TF-IDF**

Documents

"Die Ausgrenzung von MigrantInnen ist inakzeptabel und rassistisch."

"Die Maskenpflicht ist sinnvoll."

"Die Diskriminierung von Frauen ist inakzeptabel."

Vector-space representations

	die	ausgrenzung	von	migrantinnen	ist	inakzeptabel	und	rassistisch	maskenpflicht	sinnvoll	diskriminierung	frauen
Doc1	0	.48	.18	.48	0	.18	.48	.48	0	0	0	0
Doc2	0	0	0	0	0	0	0	0	.48	.48	0	0
Doc3	0	0	.18	0	0	.18	0	0	0	0	.48	.48

Word Embeddings **Idea**

- Word embeddings *aka* word vectors *aka* word representations
- **Idea:** model semantic importance of words in numeric form

we wish to embed words into the continuous space of real numbers

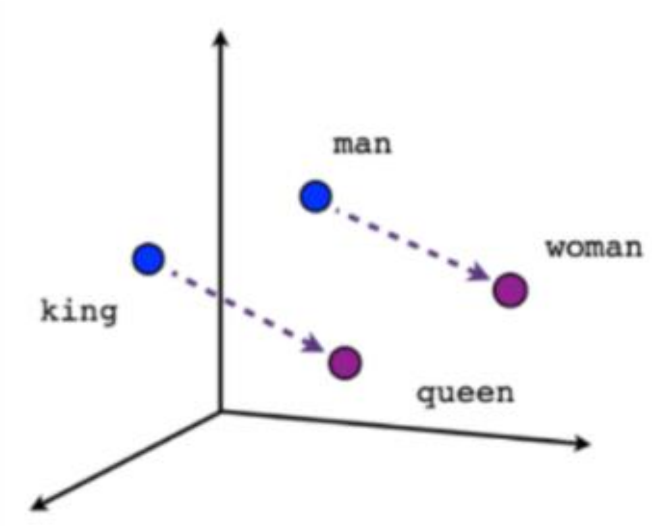
- Unsupervised learning task
- Also achieved by BOW/TF-IDF, but: **high dimensionality**
- **Goal:** dense representation

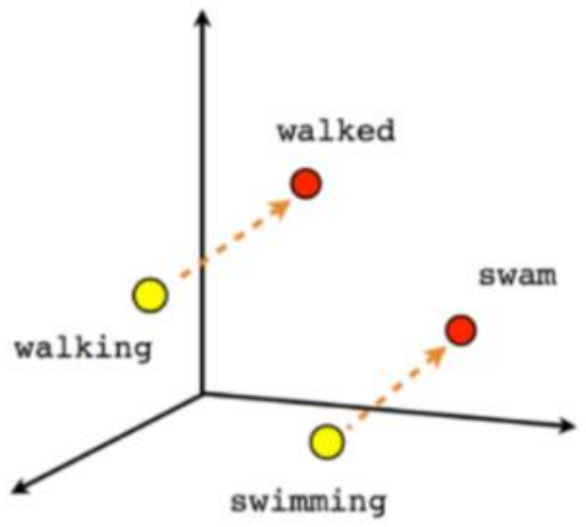
Word Embeddings **Idea**

- **Dimensionality reduction**
- **Embeddings** / factor loadings
  - Characterize words by their surrounding context
  - Latent dimensions by which words can be represented
  - Similar meaning = similar representation in the vector space

		masculinity?	*royalty?*
word	embedding 1	embedding 2
king	0.87	0.73
queen	-0.12	0.75
woman	0.03	-0.08

Word Embeddings **Example**





https://towardsdatascience.com/the-magic-behind-embedding-models-c3af62f71fb

Enabling mathematical operations on the vocabulary:

- ϕ: $W \rightarrow R^n$
- $\phi(\text{"king"}) - \phi(\text{"man"}) + \phi(\text{"woman"}) = \phi(\text{"queen"})$

Word Embeddings **Approaches**

- **Approaches**: various possibilities, often adopted from general dimensionality reduction
  - Unifying idea: data observed in (extremely) high-dimensional space but truly much lower-dimensional $\rightarrow$ retrieve principal dimensions
  - **GloVe**
  - Word2vec
  - fastText
  - t-distributed stochastic neighbor embedding (t-SNE)
  - ...

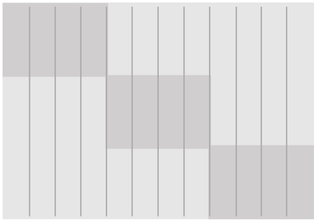
Word Embeddings **GloVe**

- **GloVe**: **Glo**bal **Ve**ctors
- Developed by Stanford University (2014)
- Based on word co-occurrence matrix
  - Studying neighborhood relations between words
  - Defined via window size (symmetric/asymmetric)
  - Underlying assumption: close-lying words are more strongly linked
  - Entry in *i*-th row & *j*-th column: how likely is word *i* to appear in the context of word *j*?

*The quick brown **fox** jumps over the lazy dog.*

Word Embeddings **GloVe**

- **Computation**
  - R: package `text2vec`
  - Most important hyperparameters: number of embedding dimensions & skip-gram window size
- Alternatively: pre-trained embeddings
- Here: **topic-specific** embeddings
  - Subset corpus by topic labels
  - Compute embeddings for subsets



words have different meanings in different contexts

Word Embeddings **Embeddings vs BOW**

- Both result in vector representations for each word in a corpus.
  - **BOW**
    - ⊕ Easy to understand and implement
    - ⊕ Feasible for any corpus
    - ⊖ No accounting for order, semantics
    - ⊖ High-dimensional representations
  - **Embeddings**
    - ⊕ Capturing semantics and heeding word order
    - ⊕ Low-dimensional representations
    - ⊖ Large and „high-quality“ corpus required for meaningful embeddings
    - ⊖ Pre-trained models often computationally demanding and not applicable to tasks with different domain (zero vector for unknown words)

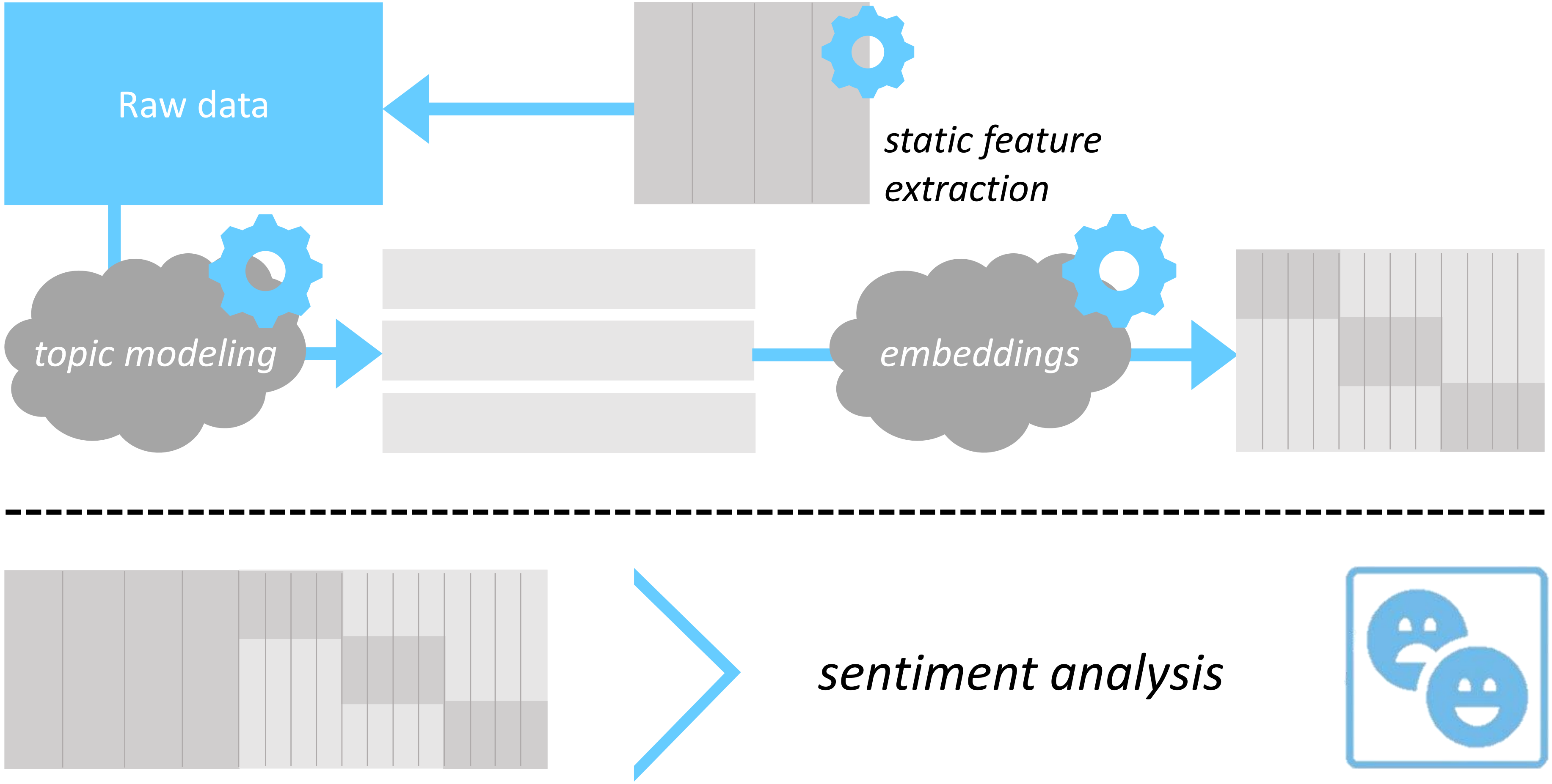
Word Embeddings **Example**

Demo 8: Word Embeddings

Part II-3: Sentiment Analysis

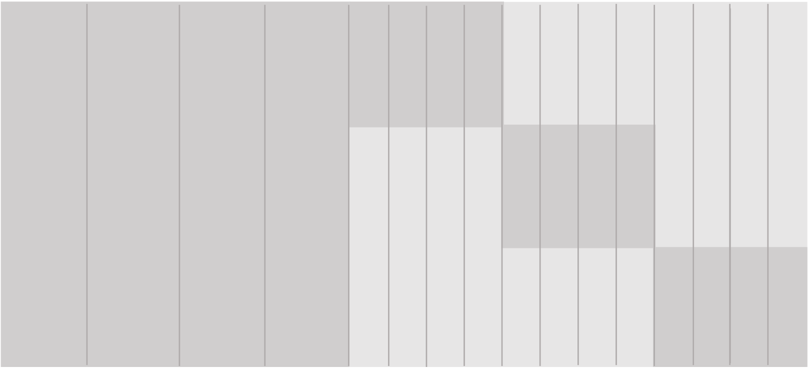
Feature Collection

Feature Collection **Recall: Task Structure**



Feature Collection Recall: Task Structure

- **Static features**
  - Polarity clues
  - Negations, intensifications, punctuations, repetitions
  - Word/character *n*-grams
  - Part-of-speech (POS) tags
  - Twitter-specific features
- **Dynamic features**
  - Word embeddings per topic

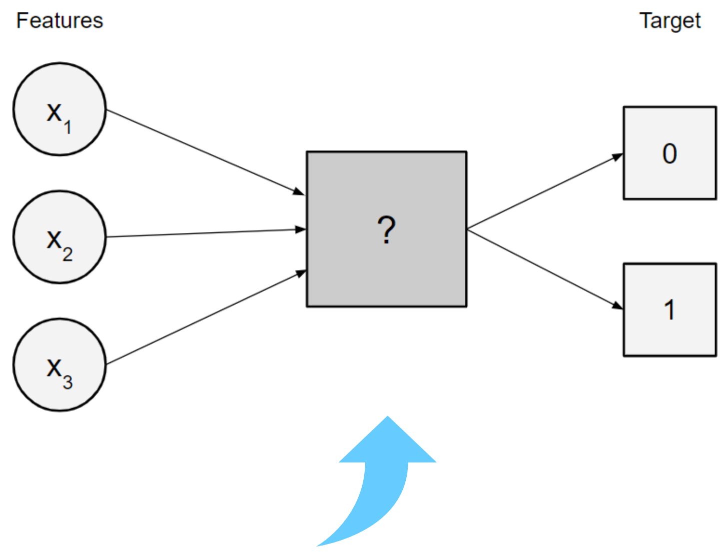


Part II-3: Sentiment Analysis

Sentiment Analysis

ML Background **Overview**

- **Machine Learning (ML)**
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
  - Deep learning methods for all three



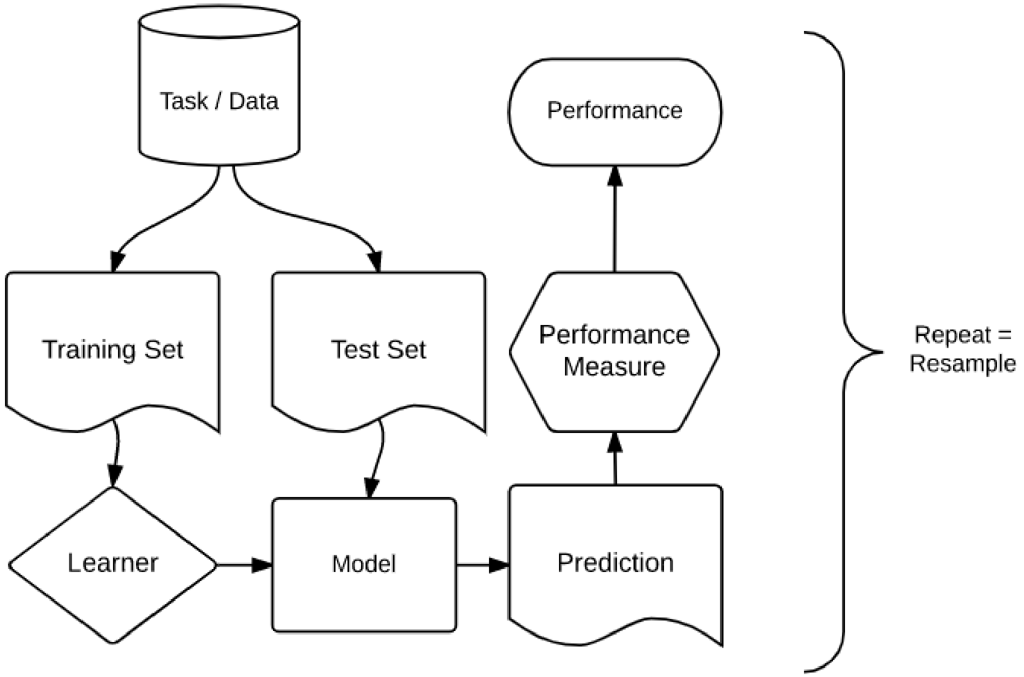
- Supervised learning
  - Learn feature-target relationship from labeled data
  - Classification: predict class label from data features
  - **Regression**: predict continuous response from data features

ML Background **mlr3 Package**

- **`mlr3`**
  - Very extensive, all-purpose ML package developed and maintained by LMU‘s Statistical Learning & Data Science chair
  - **Unifying framework** for many ML functionalities
  - End-to-end programming from feature generation to prediction
- Useful sources
  - Introduction to Machine Learning lecture *https://introduction-to-machine-learning.netlify.app/*
  - `mlr3` book *https://mlr3book.mlr-org.com/*

ML Background **Components**

- **ML components**
  - Task
    - Train set
    - Test set
  - Learner
    - Hypothesis space
    - Risk
    - Optimization
  - Performance measure



https://mlr3book.mlr-org.com/

Training & Prediction **Classification Tasks**

- Components of a (classification) task
  - **Features X**: all (numeric) variables describing our observations
  - **Target *y***: class label, here $\in$ {positive, negative}

- Train-test split
  - Fundamental ML principle: **dichotomy** between training and test sphere
    $\rightarrow$ Avoid bias in performance estimation
  - Train on training data, evaluate on test data
  - Possibly create repeated splits (**resampling**)

Training & Prediction **Learners**

- Components of a learner
  - **Hypothesis space**: defines what kind of model can be learned, e.g.,
    - Logistic regression model
    - Decision tree
    - Random forest
  - **Risk**: quantifies by how much our predictions deviate from the true target $\rightarrow$ To be minimized
  - **Optimization**: defines how to search for the best model
- **Empirical risk minimization (ERM)**
- **Result**: model with trained parameters

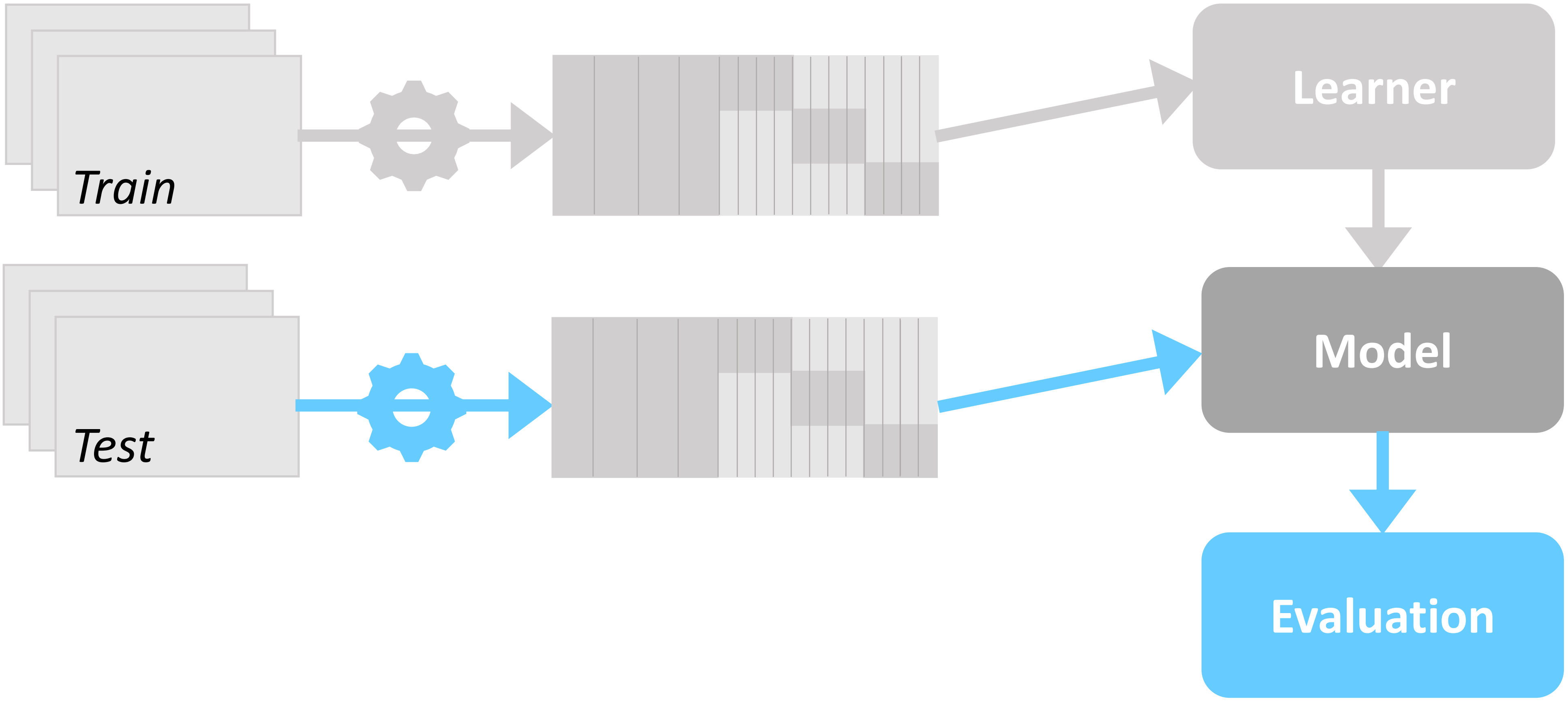
Performance Evaluation **Idea**

- How well does our model **perform** on unseen data?
  $\rightarrow$ **Generalization** ability

typically, test error > training error

- Measured on test set(s)
- *Aka* **outer loss** $\leftrightarrow$ inner loss used for training the model via ERM
  - We might or might not use the same metric for both.
  - Various evaluation metrics exist.

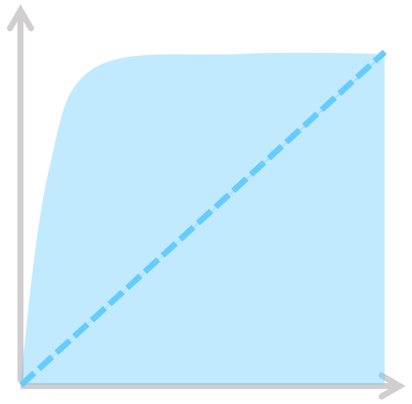
Performance Evaluation **Idea**



Performance Evaluation **Metrics**

- Many different ones, reflecting what kind of error we wish to keep small
- Special metrics for binary classification: **ROC**-based

	Actual: YES	**Actual: NO**
Predicted: YES	True Positive (TP)	False Positive (FP)
Predicted: NO	False Negative (FN)	True Negative (TN)



Performance Evaluation **Metrics**

<table>
<tr><td></td><td></td><td colspan="2">True condition</td><td></td><td colspan="2"></td></tr>
<tr><td></td><td>Total population</td><td>Condition positive</td><td>Condition negative</td><td>Prevalence $= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$</td><td colspan="2">Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$</td></tr>
<tr><td rowspan="2">Predicted condition</td><td>Predicted condition positive</td><td>True positive, Power</td><td>False positive, Type I error</td><td>Positive predictive value (PPV), Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$</td><td colspan="2">False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$</td></tr>
<tr><td>Predicted condition negative</td><td>False negative, Type II error</td><td>True negative</td><td>False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$</td><td colspan="2">Negative predictive value (NPV) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$</td></tr>
<tr><td></td><td></td><td>True positive rate (TPR), Recall, Sensitivity, probability of detection $= \frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$</td><td>False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$</td><td>Positive likelihood ratio (LR+) $= \frac{\text{TPR}}{\text{FPR}}$</td><td rowspan="2">Diagnostic odds ratio (DOR) $= \frac{\text{LR+}}{\text{LR−}}$</td><td rowspan="2">$F_1$ score = $\frac{1}{\frac{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}{2}}$</td></tr>
<tr><td></td><td></td><td>False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$</td><td>Specificity (SPC), Selectivity, True negative rate (TNR) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$</td><td>Negative likelihood ratio (LR−) $= \frac{\text{FNR}}{\text{TNR}}$</td></tr>
</table>

https://en.wikipedia.org/wiki/F-score#Diagnostic_testing

Training & Prediction **Example**

Demo 9: Sentiment Analysis

ML Pipeline **Exercise**

Exercise 5: Sentiment Analysis

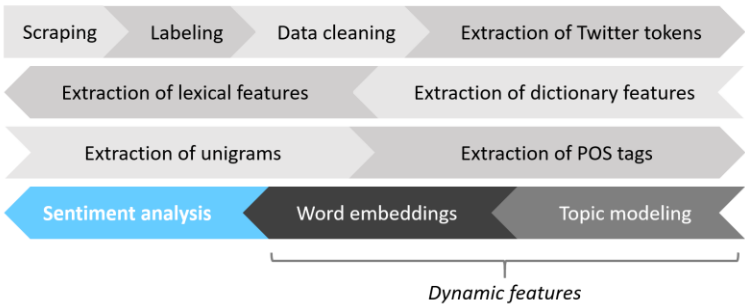
Visualization **Plotting Results**

Demo 10: Visualizing Results

Part II-3: Sentiment Analysis

Excursus: AutoML Pipeline

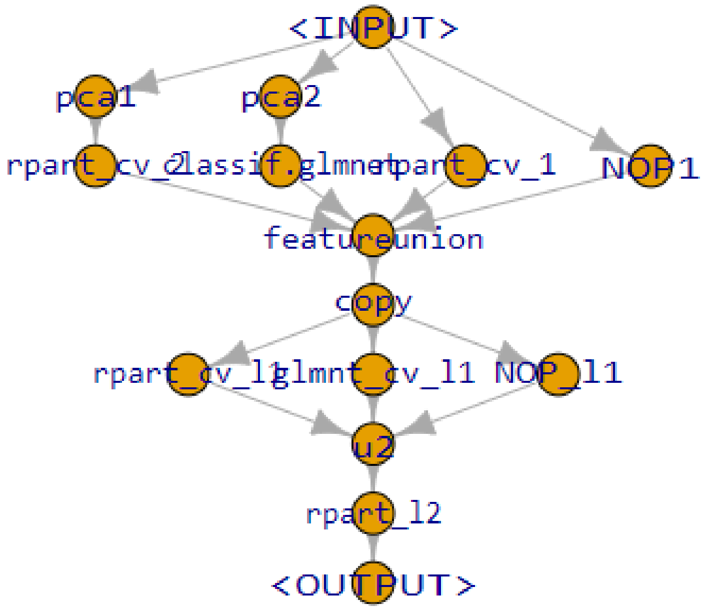
AutoML Pipeline **Motivation**



- **Recall**: static vs dynamic features
- Frequently, we are in situations where
  - we tune/evaluate multiple learners, and/or
  - feature generation affects surrounding observations.
- These steps typically call for repeated train-test splits (**resampling**, nested resampling).
- For predictions to remain unbiased this requires training & evaluation of the entire (AutoML) **pipeline**.

AutoML Pipeline **Graph Learners**

- Building pipelines via **graph learners**
  - Encompassing all steps from pre-processing to evaluation
  - Modular building approach
  - All methods (training, prediction, tuning, ...) applicable as usual
- Automatization of entire procedure possible to large extent



tutorial on creating AutoML systems on https://mlr3gallery.mlr-org.com/

Part II-3: Sentiment Analysis

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