# Introduction to Text Mining

## Part VIII: Text Mining using Supervised Learning

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# Text Mining using Supervised Learning: Learning Objectives

## Concepts

- How to prepare datasets for supervised learning
- How to employ classification within text mining
- How to employ regression within text mining

## Text analysis techniques

- Classification of a text with support vector machines
- Engineering of features for a given text analysis task
- Scoring of texts with linear regression

## Covered text analyses

- Named entity recognition
- Sentiment polarity classification
- Sentiment scoring

# Outline of the Course

I. Overview

II. Basics of Linguistics

III. Text Mining using Rules

IV. Basics of Empirical Methods

V. Text Mining using Grammars

VI. Basics of Machine Learning

VII. Text Mining using Unsupervised Learning

VIII. Text Mining using Supervised Learning

- What Is Text Mining using Supervised Learning?
- Dataset Preparations
- Supervised Classification
- Supervised Regression

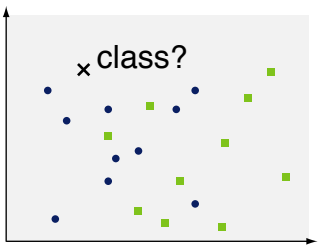
IX. Practical Issues

# What Is Text Mining using Supervised Learning?

# Classification and Regression

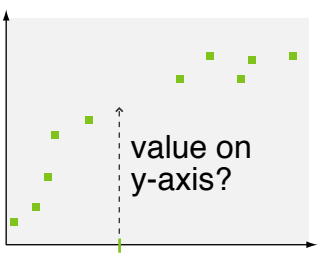
## Classification

- The task to assign an instance to the most likely of a set of $k > 1$ predefined classes.
- Class values (aka labels) are interpreted as nominal.
  Also holds if the values actually have an order or even distance.




## Regression

- The task to assign an instance to the most likely value from a real-valued scale.
- Values are continuous, but possibly have upper and lower bounds.




## How to tackle these tasks?

- Classification. Can be done with hand-crafted rules (as seen earlier), but supervised learning is mostly more successful.
- Regression. Real values can be calculated using rules or arithmetics, but the idea of *regression* is inseparable from statistics.

# Classification and Regression

## Supervised Classification and Regression

### Supervised machine learning (recap)

- Aims to find statistical patterns in training pairs of instances $\mathbf{x}^{(i)}$ and associated target output information $c(\mathbf{x}^{(i)})$.
- The resulting model $y : X \rightarrow C$ can assign arbitrary instances $\mathbf{x} \in X$ to output information $c(\mathbf{x}) \in C$.

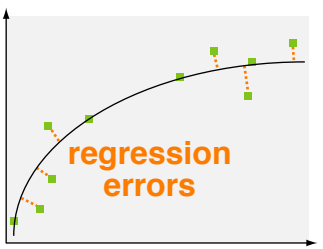
  Machine learning does not “care” about the actual meaning of output information.

### Evaluation of supervised classification

- Goal. Classify as many test instances as possible correctly (from all or particular classes).
- Metrics. Accuracy, precision, recall, $F_1$-score, ...


### Evaluation of supervised regression

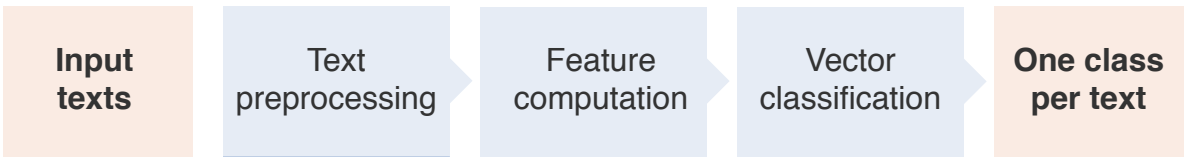
- Goal. Minimize the mean difference between predicted and correct test values.
- Metrics. Mean absolute error, mean squared error, ...



# Text Mining using Supervised Learning

## Classification in text mining (regression analog)

- Input. Usually plain texts or text spans, in training with class information.
- Output. A class for each text + a model that maps from texts to classes.




## Roles in text mining

- Classification. Decide about span boundaries, span types, text labels, relations between spans, relation types, ...
- Regression. Assign scores, rating, probabilities, ...

## Applications in text mining

- Classification. Ubiquitous text analysis technique (see next slide).
- Regression. Scoring is the most common use case.

# Text Mining using Supervised Learning

## Text Analyses Overview from Lecture Part I

### Lexical and syntactic

- Tokenization → Classification
- Sentence splitting → Classification
- Paragraph detection → Classification
- Stemming
- Lemmatization → Classification
- Part-of-speech tagging → Classification
- Similarity computation
- Spelling correction
- Phrase chunking → Classification
- Dependency parsing → Classification
- Constituency parsing

  ... and some more

### Semantic and pragmatic

- Term extraction
- Numerical entity recognition → Classificat.
- Named entity recognition → Classification
- Reference resolution → Classification
- Entity relation extraction → Classification
- Temporal relation extraction → Classificat.
- Topic detection
- Authorship attribution → Classification
- Sentiment analysis → Classification
- Discourse parsing → Classification
- Spam detection → Classification
- Argument mining → Classification

  ... and many many more

### Notice

- The label Classification denotes here that the standard approach to the respective analysis involves classification.

# Text Mining using Supervised Learning

## Dataset Preparation

### Why dataset preparation?

- Text corpora usually contain annotations for the task to be studied.
- Not always, these annotations match with the task instances required for supervised classification and regression.

### Creation of task instances

- Particularly "negative" instances often need to be created for learning.

  "$[\text{Jaguar}]_{ORG}$ is named after the animal jaguar."

- Also, annotations may be mapped to other target variables.

  Ratings 1–2 $\rightarrow$ "negative", 3 $\rightarrow$ ignore, 4–5 $\rightarrow$ "positive"

### Balancing of datasets

- For learning, a balanced distribution of the target variable in the training set is often preferable.
- Different ways to oversample or undersample a dataset exist.

# Dataset Preparations

# Dataset Preparations

## Text corpus (recap)

- A collection of real-world texts with known properties, compiled to study a language problem.
- The texts are often annotated for some target variable.

## Characteristics of corpus annotations

- Often cover only the instances of a concept, not “negative” instances.

  In entity corpora, it is only marked what is an entity.

- Define the maximum specificity level at which a problem can be studied.

  If different organization types are marked, they can be abstracted into one class.

- Include values from a potentially application-specific scale.

  $[1, 4]$ is the typical range of essay grading in the US.

- Do not to always match across corpora for the same problem.

  Hotel reviews with scores $\in [1, 5]$ vs. movie reviews with scores $\in [0, 2]$

- Are possibly distributed neither balanced nor representative.

# Dataset Preparations

## Negative Instances

### Why negative instances?

- In many classification tasks, one ("positive") class is in the focus.
- Other classes may not be annotated, or are more specific than needed.

  False token boundaries, spans that are *not* entities, different neutral sentiments, ...

### Defining negative instances

- What is seen as a negative instance is a design decision.
- The decision should be based on what a classifier should be used for.
- Trivial cases may distract classifiers from learning relevant differences.

### Example: Negative instances in person entity recognition

"[tim]$_{PER}$ works in [cupertino]$_{LOC}$. [san fran]$_{LOC}$ is his home. as a cook, he cooks all day."

- All other named entities? → Can only distinguish entity *types* then.
- All other content words? → Verbs will never be person names (somewhat trivial).
- All other noun phrases? → Seems reasonable.

# Dataset Preparations

## Target Variable Mapping

### Mapping of target variables

- The alteration of the target classes or values in a given corpus/dataset.
- May require expert knowledge about the target variable.

### Why mapping?

- Corpus annotations may be more fine-grained than needed.

  **Sentiment scores:** $[1, 2] \rightarrow$ "negative", $]2, 4[ \rightarrow$ "neutral", $[4, 5] \rightarrow$ "positive"

- Some values or differences may be irrelevant in a given application.

  **Polarities:** "negative", $\rightarrow$ "negative", ignore "neutral", "positive" $\rightarrow$ "positive"

- The ranges of the "same" target variable may not match across corpora.

  **Sentiment scores:** $\{1, 2\} \rightarrow 0$, $\{3\} \rightarrow 1$, $\{4, 5\} \rightarrow 2$

- The values may just not be those desired (rather "aesthetical").

  **Polarities:** "bad", $\rightarrow$ "negative", "medium", $\rightarrow$ "neutral" "good" $\rightarrow$ "positive"

# Dataset Preparations

## Balancing Datasets

### What is dataset balancing?

- The alteration of the distribution of a dataset regarding a target variable, such that the distribution is uniform afterwards.
- Balancing is more common in classification than in regression, since in regression there is often no fixed set of target values to balance.

  An option for regression is *binning*, i.e., to balance the distribution for certain intervals.

### When to balance?

- Balancing a training set prevents machine learning from being biased towards majority classes (or values).
- Validation and test sets are rarely balanced, since evaluation is usually done on *representative* distributions.

### How to balance?

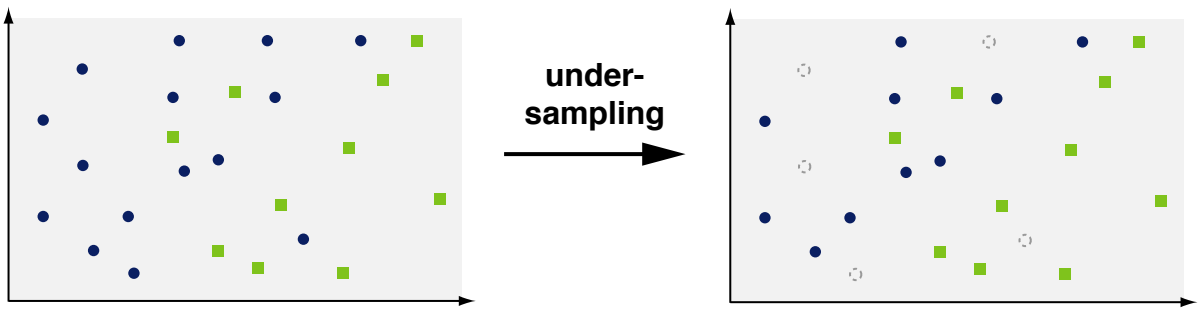
- Undersampling. Removal of instances from majority classes.
- Oversampling. Addition of instances from minority classes.

# Dataset Preparations

## Undersampling

### How to balance with undersampling?

- By removing instances of all non-minority classes until all classes have the size of the minority class.
- Instances to be removed are usually chosen (pseudo-) randomly.




### Pros and cons

- Pro. All remaining data is real.
- Pro. Downsizing of a dataset makes training less time-intensive.
- Con. Instances that may be helpful in learning are discarded, i.e., potentially relevant information is lost.

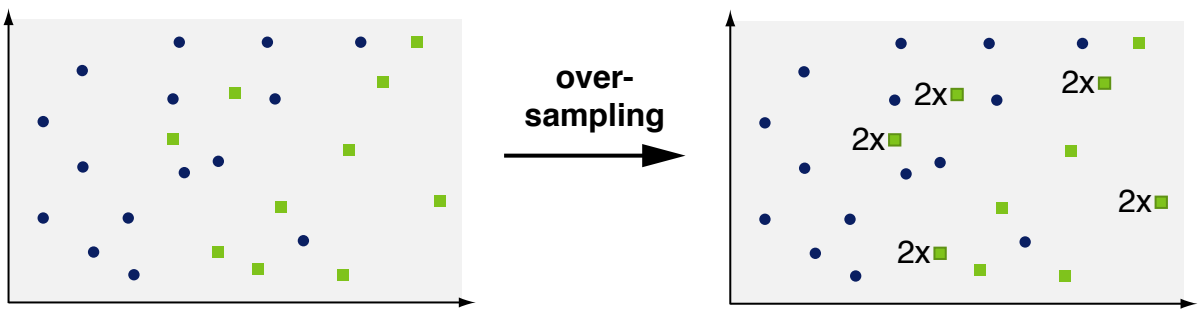
# Dataset Preparations

## Oversampling

### How to balance with oversampling?

- By adding instances of all minority classes until all classes have the size of the majority class.
- Usually, the instances to be added are random (pseudo-) duplicates.

  Where reasonable, an alternative is to create artificial instances using interpolation.




### Pros and cons

- Pro. No instance is discarded, i.e., all information is preserved.
- Con. Upsizing of a dataset makes training more time-intensive.
- Con. The importance of certain instances is artificially boosted, which may make features discriminative that are actually noise.

# Dataset Preparations

## Undersampling vs. Oversampling

### Example: A sentiment training set

- 1000 positive, 500 negative, 100 neutral instances.
- After undersampling? → 100+100+100 instances
- After oversampling? → 1000+1000+1000 instances

### What to use?

- When more than enough data is available, undersampling is preferable.
- When the class imbalance is low, oversampling is rather unproblematic.
- When the class imbalance is high, no really good choice exists.

### Alternatives to balancing?

- Many machine learning optimization procedures can penalize wrong predictions more for minority instances than for majority instances.
- Conceptually, this is the more sound way of preventing the bias.
- Practically, it makes the learning process more complex, which is why balancing is often used.

# Supervised Classification

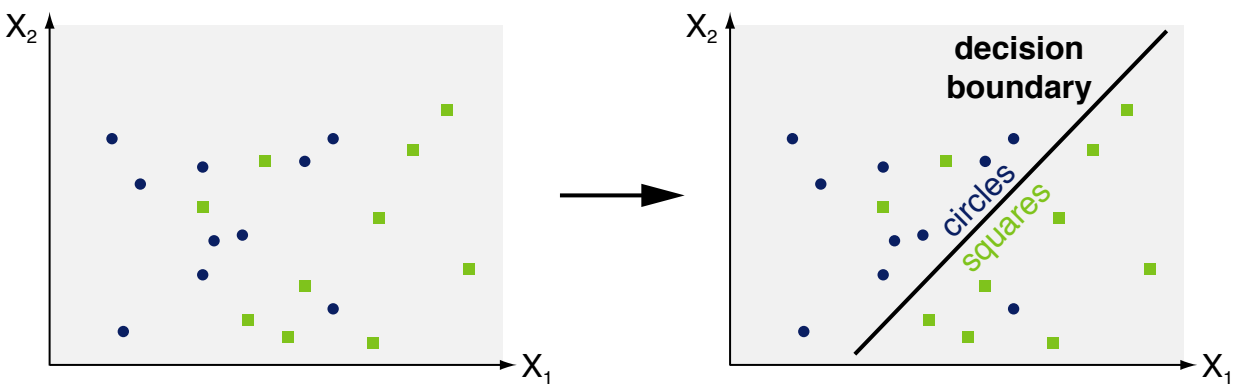
# Supervised Classification

## What is supervised classification?

- The learned prediction of the most likely of a set of $k > 1$ predefined nominal classes for an instance.

## Learning phase (training)

- Input. A set of known instances $\mathbf{x}^{(i)}$ with correct output class $c(\mathbf{x}^{(i)})$.
- Output. A model $X \rightarrow C$ that maps any instance to its output class.




## Application phase (prediction)

- Input. A set of unknown instances $\mathbf{x}^{(i)}$ without output classes.
- Output. The output class $c(\mathbf{x}^{(i)})$ for each instance.

# Supervised Classification

## Feature-based Classification

### Feature-based representation (recap)

- A feature vector is an ordered set of values of the form $\mathbf{x} = (x_1, \ldots, x_m)$.
- Each feature $x_j$ denotes a measurable property of an input, $1 \leq j \leq m$.

  We consider only real-valued features here.
- Each instance $o_j$ is mapped to a vector $\mathbf{x}^{(i)} = (x_1^{(u)}, \ldots, x_m^{(i)})$ where $x_j^{(i)}$ denotes the value of feature $x_j$.

  We consider only values normalized to the range $[0, 1]$ here.

### Text mining using feature-based classification

- The main challenge is to engineer features that help solve a given task.
- In addition, a suitable classification algorithm needs to be chosen.

### Feature-based vs. neural classification (recap)

- We restrict our view to feature-based classification here.

  Same for regression below.
- In neural classification, features are not explicitly represented anymore.

# Supervised Classification

## Classification Algorithms

### Binary vs. multiple-class classification (recap)

- Binary. Many classification algorithms work for $k = 2$ classes only.
- Multiple. Handled via multiple binary classifiers, e.g., one-versus-all.

### Selected supervised classification algorithms

- Naïve Bayes. Predicts classes based on conditional probabilities.
- Support vector machine. Maximizes the margin between classes.
- Decision tree. Sequentially compares instances on single features.
- Random forest. Majority voting based on several decision trees.
- Neural network. Learns complex functions on feature combinations.

  ... and many more

### Focus on support vector machines here

- One of the most widely used classification algorithms.
- Often, a good default choice. Much theoretical and empirical appeal.

# Support Vector Machines

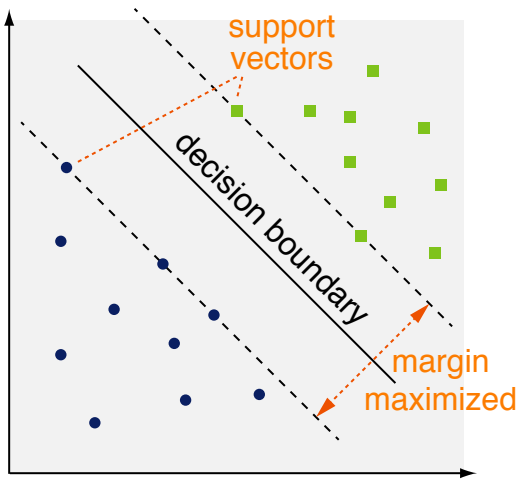
## What is a support vector machine (SVM)?

- A supervised learning algorithm that aims to find a linear decision boundary which maximizes the margin between two classes.
- Non-linear classification is possible through the *kernel trick* (see below).

## Large-margin classification

- The margin is the distance from the decision boundary to all closest instances.
- SVMs maximize the mininum margin of the boundary to the training instances.

  Some instances may be discounted as outliers/noise.




## Support vectors

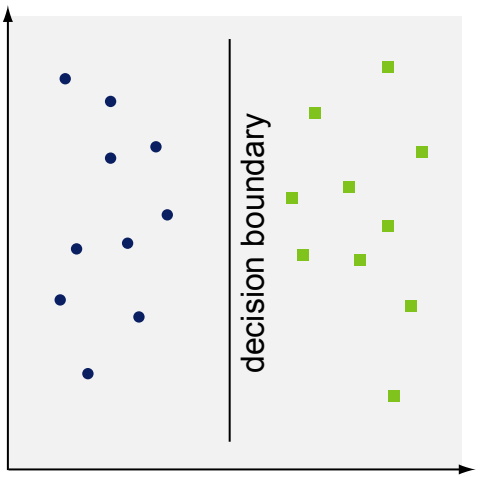
- A (usually small) subset of training instances that are used by an SVM to define the decision boundary.
- Other instances are disregarded.

# Support Vector Machines

## Intuition

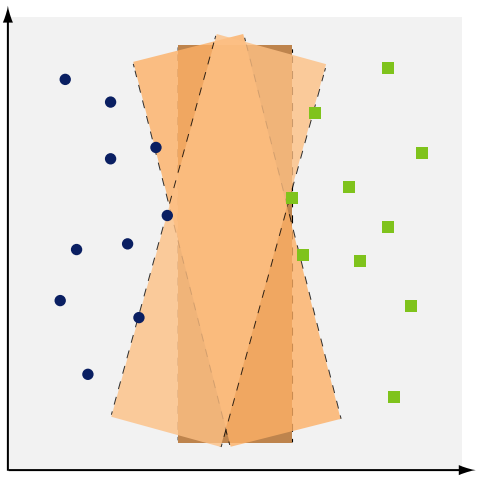
### Maximization of certainty

- SVMs aim to put the decision boundary in the middle between the classes.
- This avoids low-certainty training decisions, i.e., those for instances near the boundary.
- A slight instance variation will thus not cause a misclassification.




### Better generalization

- SVMs aim to make the “separator” between classes as large as possible.
- Fewer positions for such separators exist. This reduces variance.
- The ability to correctly generalize to test data is thus increased.



# Support Vector Machines

## Linear SVMs

### Decision boundary

- A decision boundary is a hyperplane $\mathbf{w}^T\mathbf{x} = b$, where $\mathbf{w}$ is the *normal* perpendicular to the hyperplane and $b$ is the *intercept term*.

  $\mathbf{w}$ is a weight vector, $b$ is a constant. All points $\mathbf{x}$ on the hyperplane satisfy $\mathbf{w}^T\mathbf{x} = b$.
- $b$ represents the distance to the origin, scaled by the length $||\mathbf{w}||$ of $\mathbf{w}$.

### Training of a Linear SVM

- Input. A set of $n$ training instances $\mathbf{x}^{(i)}$ with class $y^{(i)} = c(\mathbf{x}^{(i)}) \in \{-1, 1\}$.

  Nominal classes are mapped to –1 and 1. Feature values are normalized to $[0, 1]$.
- Output. A linear SVM classifier $y(\mathbf{x}) = sign(\mathbf{w}^T\mathbf{x} - b)$, such that $\mathbf{w}^T\mathbf{x} = b$ maximizes the minimum distance to instances $\mathbf{x}^{(i)}$.

### Optimization Variants for a Linear SVM

- Hard margin. Find the best separating hyperplane. This works only for linearly separable training sets.
- Soft margin. Allow but penalize outliers. This always works.

# Support Vector Machines

## Linearly Separable Training Sets

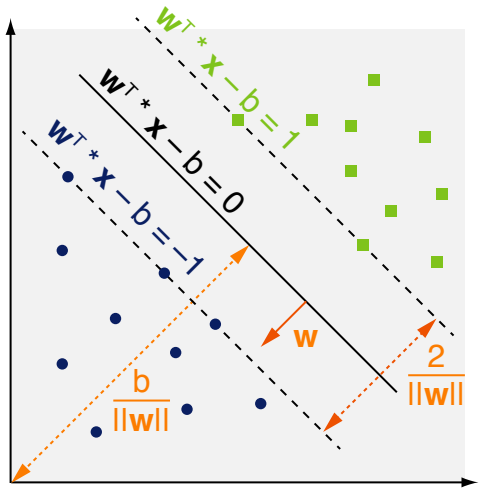
### Maximum-margin decision boundary

- If the training set is linearly separable, any $\mathbf{x}^{(i)}$ must fulfill either of:

$$\mathbf{w}^T\mathbf{x}^{(i)} - b \geq \quad 1 \quad \text{if } y^{(i)} = \quad 1$$
$$\mathbf{w}^T\mathbf{x}^{(i)} - b \leq -1 \quad \text{if } y^{(i)} = -1$$

- From this, we can infer:

$$\forall i \in \{1, \ldots, n\} : \; y^{(i)} \cdot (\mathbf{w}^T\mathbf{x}^{(i)} - b) \; \geq \; 1$$




- Also, it follows that the size of the margin is $\frac{2}{||\mathbf{w}||} = \frac{b+1}{||\mathbf{w}||} - \frac{b-1}{||\mathbf{w}||}$.
- To maximize the margin, $||\mathbf{w}||$ must be minimized.

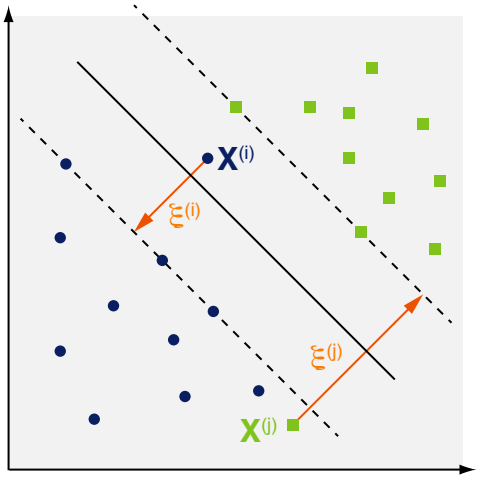
### Hard-margin SVM as a minimization problem

- Find $\mathbf{w}$ and $b$ such that $||\mathbf{w}||$ is minimized, and $\forall i : y^{(i)} \cdot (\mathbf{w}^T\mathbf{x}^{(i)} - b) \geq 1$.
- The support vectors that represent the hyperplane for these $\mathbf{w}$ and $b$ can be found on a training set.

# Support Vector Machines

## Linearly Inseparable Training Sets

### Slack variables




- For linearly inseparable training sets, an SVM can allow instances $\mathbf{x}^{(i)}$ to be misclassified via slack variables $\xi^{(i)} \geq 0$.
- If $\xi^{(i)} > 0$, the margin of $\mathbf{x}^{(i)}$ can be less than 1 at a cost $C \cdot \xi^{(i)}$ proportional to $\xi^{(i)}$.
- The SVM then trades the size of the margin against the number of correctly classified training instances.

### Soft-margin SVM as a minimization problem

- Find $\mathbf{w}$, $b$, and $\xi^{(i)} \geq 0$, such that $||\mathbf{w}|| + C \cdot \sum_i \xi^{(i)}$ is minimized, and $\forall i : y^{(i)} \cdot (\mathbf{w}^T \mathbf{x}^{(i)} - b) \geq 1 - \xi^{(i)}$.
- $C > 0$ is a regularization term, used to control overfitting. It must be optimized against a validation set.

# Support Vector Machines

## Cost Hyperparameter Optimization

### The cost hyperparameter $C$

- If $C$ is small, training instances may be misclassified at low cost.
- As $C$ becomes larger, training misclassifications get more expensive.
- So, the higher $C$, the more an SVM will fit the training data.

### Typical cost optimization process

- First find best magnitude of $C$ on the validation set.
  For instance, by testing each $C \in \{10^{-5}, 10^{-4}, \ldots, 10^{4}, 10^{5}\}$.
- Then validate more fine-grained $C$ values in this magnitude.
- The best found $C$ is used on the test set (or in the application).

### Notice

- Non-linear SVMs often have a second hyperparameter $\gamma$ (see below).
- The combination $C$ and $\gamma$ needs to be optimized in a grid search.

# Support Vector Machines

## Non-Linear Classification

### Non-linear SVMs

- Some data is only linearly “separable” with many misclassifications.
- As a solution, non-linear SVMs use the *kernel trick*.

### Kernel trick

- Map the original feature space of such data to a higher-dimensional space where it is linearly separable.
- A linear classifier is then learned for the higher-dimensional space.
- Conceptually. The mapping is a non-linear transformation $\Phi : \mathbf{x} \mapsto \phi(\mathbf{x})$.
- Practically. A *kernel function* $K$ is used that computes the dot product of two transformed instances in the original feature space.

# Support Vector Machines

## Kernel Functions *

### Linear SVMs with kernel functions

- A linear SVM can be specified using dot products $K(\mathbf{x}, \mathbf{x}^{(j)}) = \mathbf{x}^T\mathbf{x}^{(j)}$ for an instance $\mathbf{x}$ and each support vector $\mathbf{x}^{(j)}$:

$$f(\mathbf{x}) = sign(\textstyle\sum_j y^{(j)} \cdot K(\mathbf{x}, \mathbf{x}^{(j)}) - b)$$

### Non-linear SVMs with kernel functions

- Replace $K$ above by a kernel function that computes the dot product of two transformed instances, $\phi(\mathbf{x})$ and $\phi(\mathbf{x}^{(j)})$.

  For SVM optimization, $K$ must fulfill certain properties omitted here for simplicity.

### Common kernel functions

- Polynomial kernels. $K(\mathbf{x}, \mathbf{x}^{(j)}) = (1 + \mathbf{x}^T\mathbf{x}^{(j)})^d$.

  A quadratic kernel ($d = 2$) is often used. $d = 1$ results in a linear kernel.
- Radial basis function. $K(\mathbf{x}, \mathbf{x}^{(j)}) = e^{-\gamma \cdot (\mathbf{x} - \mathbf{x}^{(j)})^2}$.

  A Gaussian distribution that maps to a potentially infinite feature space.
- Also, kernel functions can be designed for the specific data at hand.

# Support Vector Machines

## Empirical Results *

### Experiments with text classification (Joachims, 2002)

- Corpus. Reuters-21578, 90 topics, 9603 training and 3299 test texts.
- Features. More than 10,000 word-based features.
- Classification. Four baseline algorithms and different SVM variations.
- Optimization. Hyperparameters (incl. #features) tuned for all algorithms.

### Effectiveness results ($F_1$-score)

| **Learning** | **10 Most Frequent Topics** | | | | | | | | | | **Micro** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Algorithm** | earn | acq | mny-fx | grain | crude | trade | intrst. | ship | wheat | corn | **$F_1$** |
| Naïve Bayes | 96.0 | 90.7 | 59.6 | 69.8 | 81.2 | 52.2 | 57.6 | 80.9 | 63.4 | 45.2 | 72.3 |
| Rocchio | 96.1 | 92.1 | 67.6 | 79.5 | 81.5 | 77.4 | 72.5 | 83.1 | 79.4 | 62.2 | 79.9 |
| Decision trees | 96.1 | 85.3 | 69.4 | 89.1 | 75.5 | 59.2 | 49.1 | 80.9 | 85.5 | 87.7 | 79.4 |
| $k$ nearest neighbors | 97.8 | 91.8 | 75.4 | 82.6 | 85.8 | 77.9 | **76.7** | 79.8 | 72.9 | 71.4 | 82.6 |
| Linear SVM ($C$ 0.5) | 98.0 | 95.5 | **78.8** | 91.9 | **89.4** | **79.2** | 75.6 | **87.4** | 86.6 | 87.5 | 86.7 |
| Linear SVM ($C$ 1.0) | **98.2** | **95.6** | 78.5 | 93.1 | **89.4** | **79.2** | 74.8 | 86.5 | **86.8** | **87.8** | **87.5** |
| RBF-SVM | 98.1 | 94.7 | 74.3 | **93.4** | 88.7 | 76.6 | 69.1 | 85.8 | 82.4 | 84.6 | 86.4 |

# Support Vector Machines

## Discussion

### Benefits of SVMs

- Effective in high-dimensional feature spaces.
- Comparably effective for small numbers $n$ of training instances.
- May still be effective if number $m$ of features is greater than $n$.
- Memory-efficient, as SVMs use only a subset of the training instances.
- Different kernel functions can be specified.

### Challenges with SVMs

- If $m$ is much greater than $n$, SVMs may overfit.
  Simple kernel functions and enough regularization are crucial then.
- SVMs do not directly provide probability estimates.
  Estimates can be calculated internally using an expensive cross-validation.
- Higher-dimensional spaces increase the generalization error of SVMs.
  Enough training data should be given, when using non-linear SVMs.
- Hyperparameter optimization is a must.

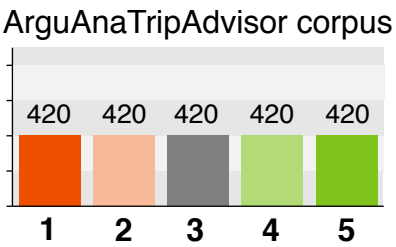
# Review Sentiment Analysis

## Sentiment classification of reviews

- Classification of the nominal sentiment polarity or score of a customer review on a product, service, or work of art.

## Data

- 2100 English hotel reviews from TripAdvisor.
  900 training, 600 validation, and 600 test reviews.
- Each review has a sentiment score from {1, ..., 5}.




## Tasks

- 3-class sentiment. 1–2 mapped to negative, 3 to neutral, 4–5 to positive.
  Training set balanced with random undersampling.
- 5-class sentiment. Each score interpreted as one (nominal) class.

## Approach

- Algorithm. Linear SVM with one-versus-all multi-class handling.
  Cost hyperparameter tuned on validation sets.
- Features. Combination of several standard and specific feature types.

# Review Sentiment Analysis

## Feature Engineering

### What is feature engineering? (recap)

- The design and development of the feature representation of instances used to address a given task.

  Key step in feature-based machine learning.
- The representation governs what patterns can be found during learning.

### Standard vs. specific features

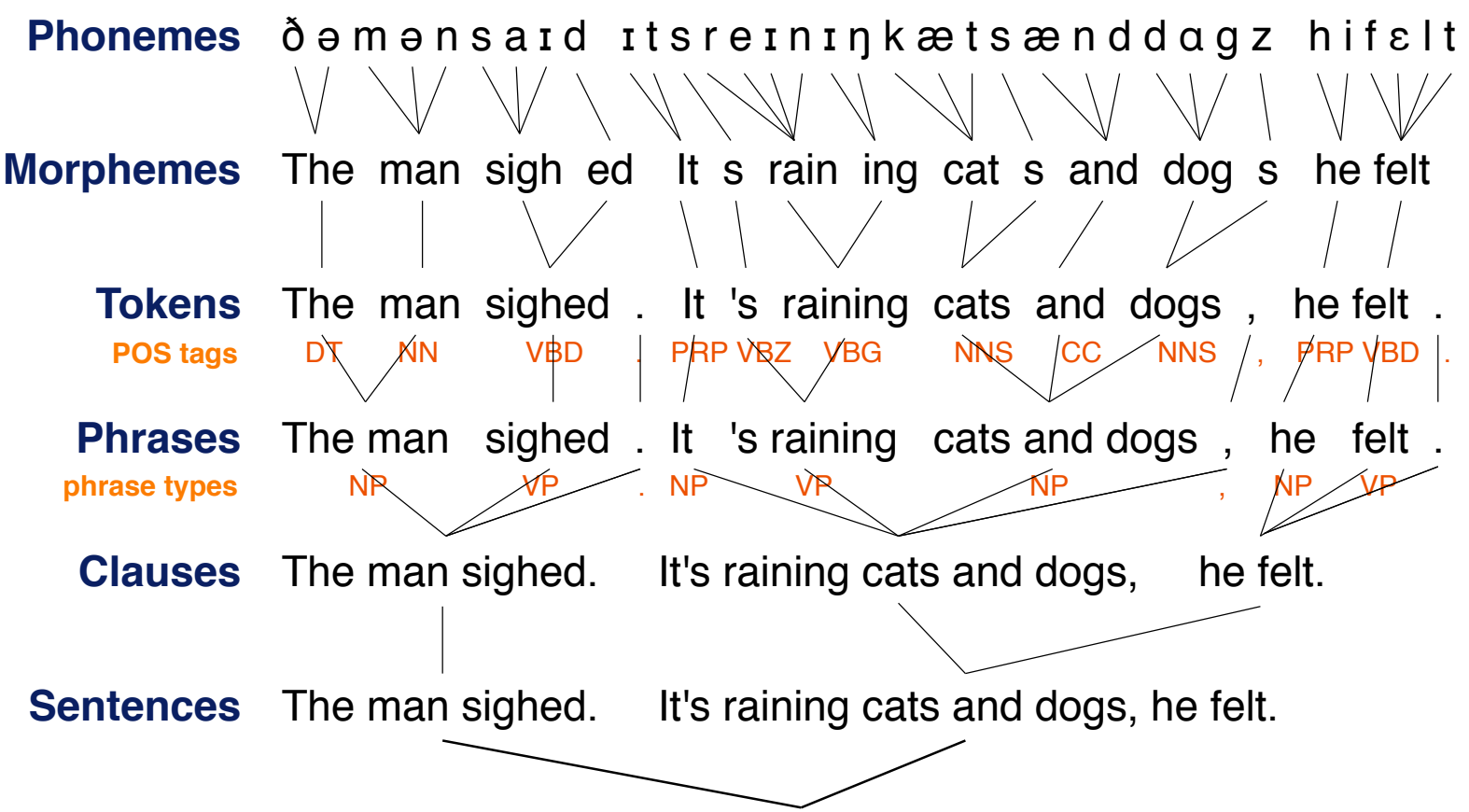
- Standard. Features that can be derived from (more or less) general linguistic phenomena and that may help in several tasks.
- Specific. Features that are engineered for a specific tasks, usually based on expert knowledge about the task.

### Features covered here

- Standard content features. Token $n$-grams, target class features.
- Standard style features. POS and phrase $n$-grams, stylometric features.
- Specific features. Local sentiment, discourse relations, flow patterns.

# Review Sentiment Analysis

## Some General Linguistic Phenomena (Recap)



# Review Sentiment Analysis

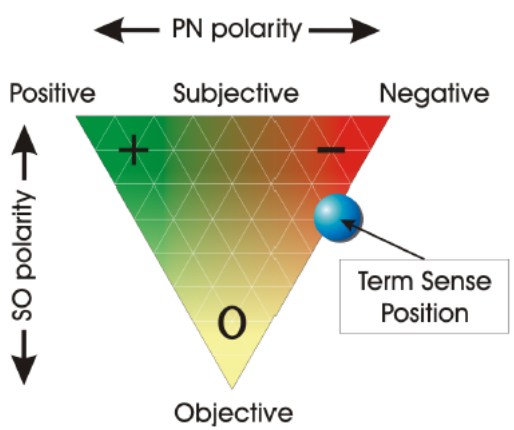
## Standard Content Feature Types

### Token $n$-grams

- Token unigrams (bag-of-words). The distribution of all token 1-grams that occur in at least 5% of all training texts.
- Token bigrams/trigrams. Analog for 2-grams and 3-grams.

### Target class features

- Core vocabulary. The distribution of all words that occur at least three times as often in one class as in every other.
- Sentiment scores. The mean positivity, negativity, and objectivity of all first and average word senses in *SentiWordNet*.
  SentiWordNet is a lexicon with subjectivity and polarity values for words (Baccianella et al., 2010).
- Sentiment words. The distribution of all subjective words in SentiWordNet.



# Review Sentiment Analysis

## Standard Style Feature Types

### Part-of-speech (POS) tag n-grams

- POS unigrams. The distribution of all part-of-speech 1-grams that occur in at least 5% of all training texts.
- POS bigrams/trigrams. Analog for 2-grams and 3-grams.

### Phrase type n-grams

- Phrase unigrams. The distribution of all phrase type 1-grams that occur in at least 5% of all training texts.
- Phrase bigrams/trigrams. Analog for 2-grams and 3-grams.

### Stylometric features

- Character trigrams. The distribution of all character 3-grams that occur in at least 5% of all training texts.
- Function words. The distribution of the top 100 words in the training set.
- Lexical statistics. Average numbers of tokens, clauses, and sentences.

# Review Sentiment Analysis

## Evaluation of the Standard Feature Types *

### Evaluation

- One linear SVM for each feature type alone and for their combination.
- Training on training set, tuning on validation set, test on test set.

### Discussion

- Token unigrams best, but some other types close.
- Combination does not outperform single types.
- 60.8% accuracy does not seem satisfying.

### Effectiveness results (accuracy)

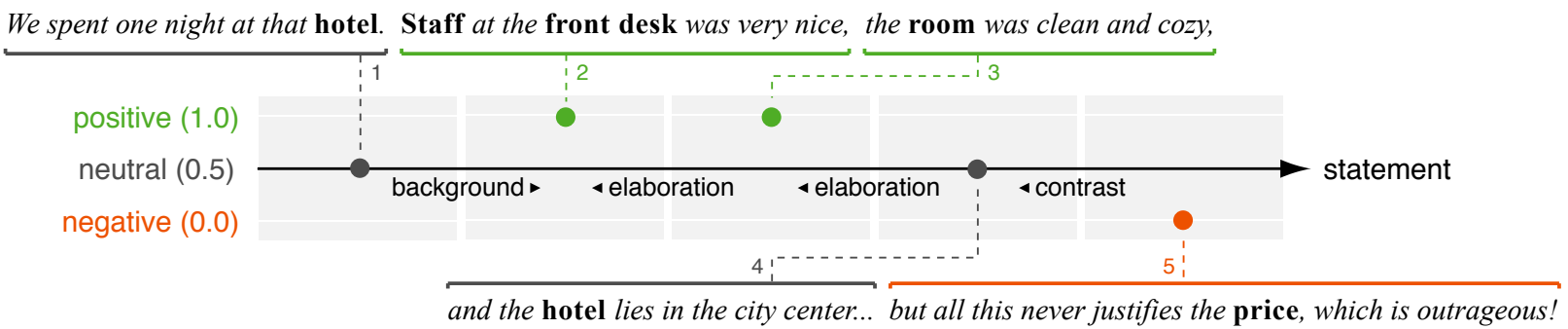
| Category | Feature type | # Features | 3 classes |
|---|---|---|---|
| Content | Token unigrams | 426 | **60.8%** |
| | Token bigrams | 112 | 49.5% |
| | Token trigrams | 64 | 24.5% |
| | Core vocabulary | 83 | 41.7% |
| | Sentiment scores | 6 | 59.3% |
| | Sentiment words | 123 | 60.5% |
| Style | POS unigrams | 48 | 51.3% |
| | POS bigrams | 70 | 49.0% |
| | POS trigrams | 118 | 45.5% |
| | Phrase unigrams | 13 | 48.8% |
| | Phrase bigrams | 43 | 52.5% |
| | Phrase trigrams | 122 | 50.8% |
| | Function words | 100 | 57.3% |
| | Character trigrams | 200 | 48.7% |
| | Lexical statistics | 6 | 42.8% |
| **Combination of features** | | **1534** | **60.8%** |

# Review Sentiment Analysis

## Review Argumentation *

### Example hotel review

> *"We spent one night at that hotel. Staff at the front desk was very nice, the room was clean and cozy, and the hotel lies in the city center... but all this never justifies the price, which is outrageous!"*




### A shallow model of review argumentation

- A review can be seen as a flow of local sentiments on domain concepts that are connected by discourse relations.

  The domain concepts (aka aspects) are omitted in the following for brevity.

# Review Sentiment Analysis

## Specific Feature Types for Review Sentiment Analysis (1 of 2) *

### Local sentiment distribution

- The frequencies of positive, neutral, and negative local sentiment as well as of changes of local sentiments.

  positive 0.4 neutral 0.4 negative 0.2 (neutral, positive) 0.25 ...

- The average local sentiment value from 0.0 (negative) to 1.0 (positive).

  average sentiment 0.6

- The interpolated local sentiment at each normalized position in the text.

  e.g., normalization length 9: (0.5, 0.75, 1.0, 1.0, 1.0, 0.75, 0.5, 0.25, 0.0)

### Discourse relation distribution

- The distribution of discourse relation types in the text.

  background 0.25 elaboration 0.5 contrast 0.25 (all others 0.0)

- The distribution of combinations of relation types and local sentiments.

  background(neutral, positive) 0.25 elaboration(positive, positive) 0.25 ...

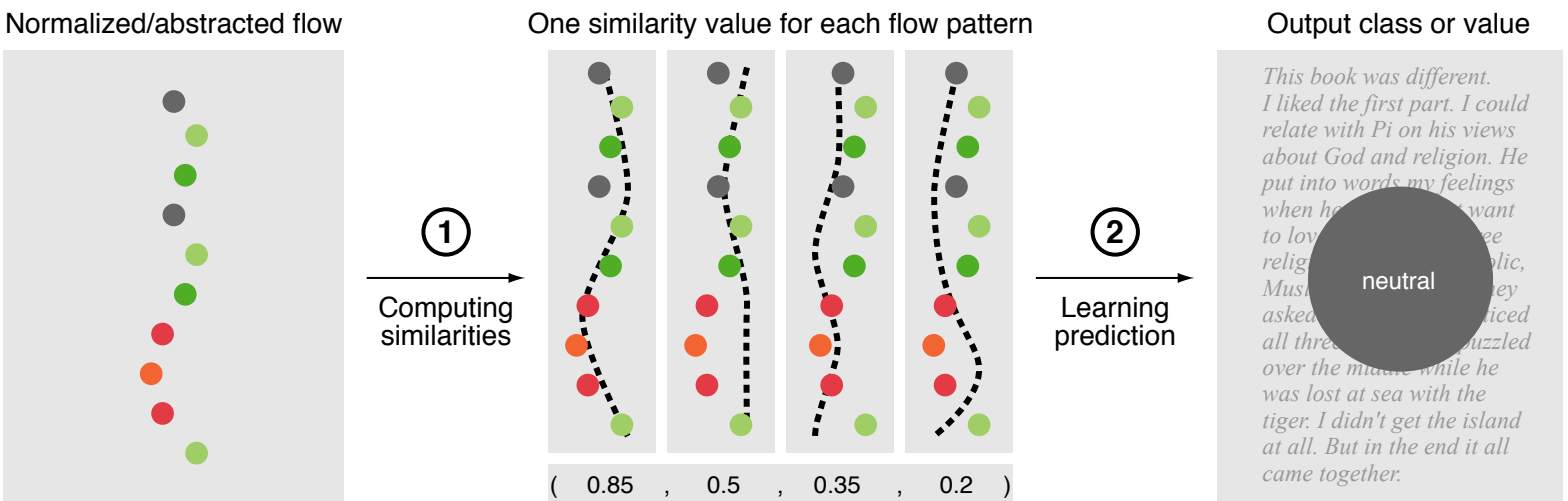
# Review Sentiment Analysis

## Specific Feature Types for Review Sentiment Analysis (2 of 2) *

### Sentiment flow patterns

- The similarity of the normalized flow of the text to each flow pattern.

  Details on the patterns in the lecture part on clustering.




### Content and style features

- Content. Token $n$-grams, sentiment scores.
- Style. Part-of-speech $n$-grams, character trigrams, lexical statistics.

  Subset of the standard features above, here as baseline features.

# Review Sentiment Analysis

## Evaluation of the Specific Feature Types *

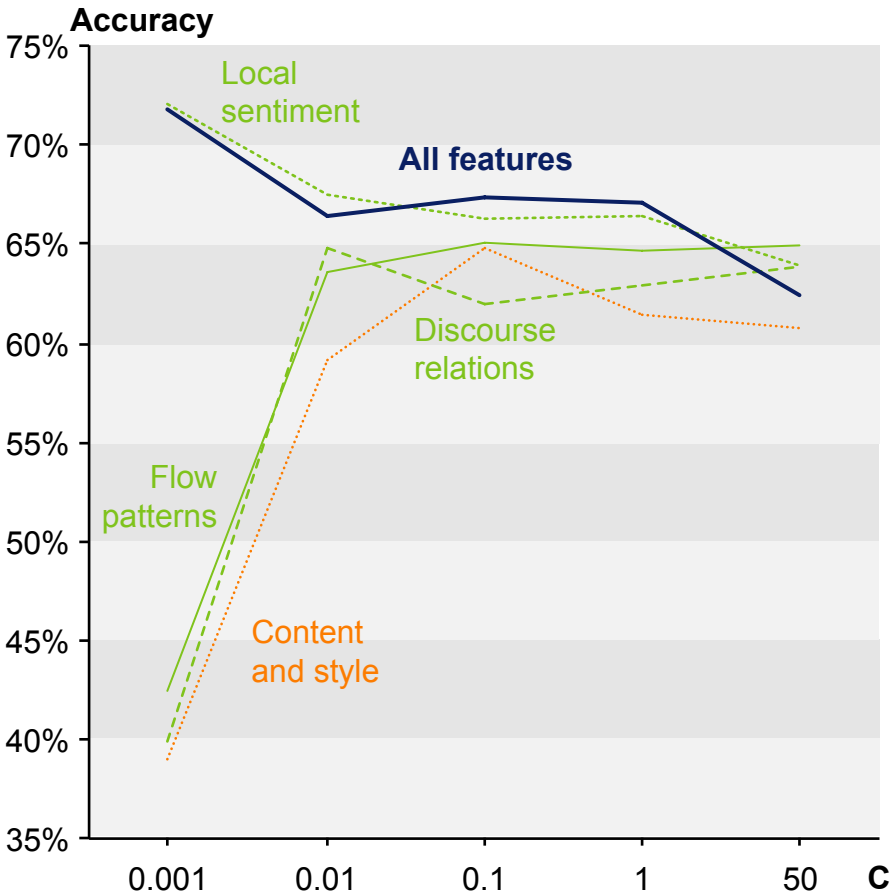
### Evaluation

- One linear SVM for each feature type alone and for their combination.
- Training on training set, tuning on validation set, test on test set.
- Both 3-class and 5-class.

### Cost hyperparameter tuning

- Tested $C$ values. 0.001, 0.01, 0.1, 1.0, 50.0
- Best $C$ used on test set.
- Results shown here for the 3-class task only.

### Validation accuracy depending on C



# Review Sentiment Analysis

## Results and Discussion for the Specific Features *

### Effectiveness results on test set (accuracy)

| Feature type | # Features | 3 Classes | 5 Classes |
|---|---|---|---|
| Local sentiment distribution | 50 | 69.8% | 42.2% |
| Discourse relation distribution | 75 | 65.3% | 40.6% |
| Sentiment flow patterns | 42 | 63.1% | 39.7% |
| Content and style features | 1026 | 58.9% | 43.2% |
| **Combination of features** | 1193 | **71.5%** | **48.1%** |
| Random baseline | | 33.3% | 20.0% |

### Discussion

- Content and style features. A bit weaker than in the experiment above, due to slight differences in the experiment setting.
- Sentiment flow patterns. Impact is more visible across domains (later).
- Combination of features. Works out this time, so more complementary.

- The 5-class accuracy seems insufficient.
- Classification misses to model the ordinal relation between classes; regression might be better.

# Supervised Regression

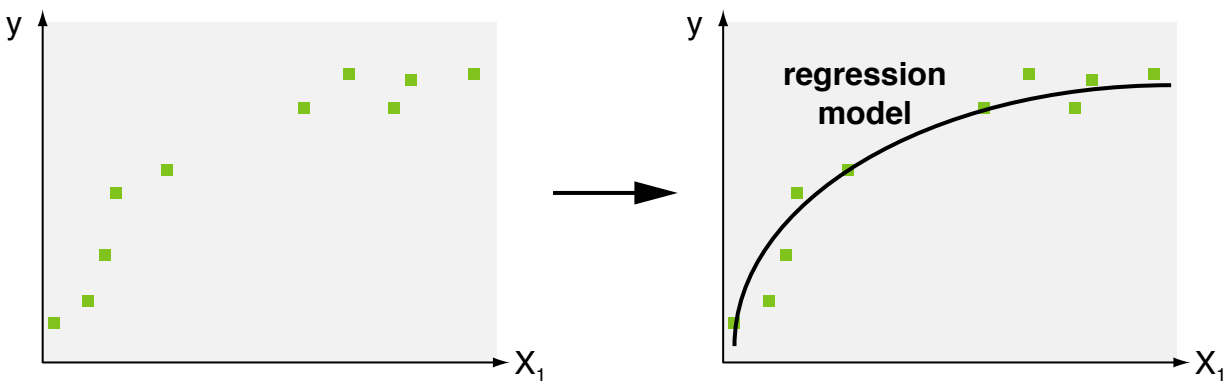
# Supervised Regression

## What is supervised regression?

- The learned prediction of the most likely value from a real-valued scale for an instance.

## Learning phase (training)

- Input. A set of known instances $\mathbf{x}^{(i)}$ with correct output value $y = c(\mathbf{x}^{(i)})$.
- Output. A model $X \rightarrow C$ that maps any instance to its output value.




## Application phase (prediction)

- Input. A set of unknown instances $\mathbf{x}^{(i)}$ without output value.
- Output. The output value $y = c(\mathbf{x}^{(i)})$ for each instance.

# Supervised Regression

## Regression Algorithms

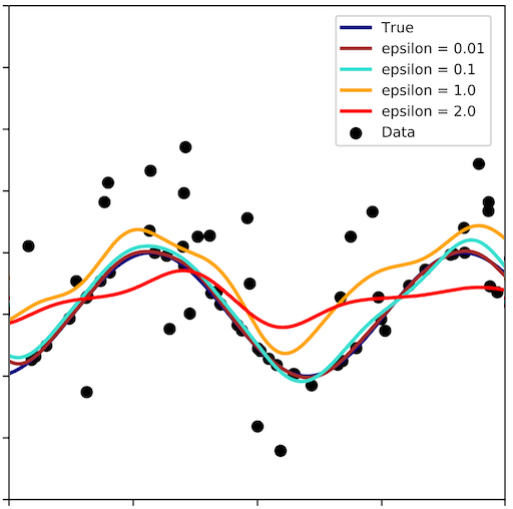
### Selected supervised regression algorithms

- Linear regression. Predict output values using a learned linear function.
- Support vector regression. Maximize the flatness of a regression model.

### Support vector regression

- In a “tube” of some size $\varepsilon$ around a model, regression errors are ignored.
- The ideas of support vectors and kernels apply to regression, too.
- The flatness of a model is maximized to reduce overfitting.

  Correspondent to the margin in classification.




### Focus on linear regression here

- Shows the general idea of regression more clearly.
- Despite its simplicity, often effective and well-interpretable.

# Linear Regression

## What is linear regression?

- A supervised learning algorithm that learns to predict a real-valued output under a linear model function:

$$y(\mathbf{x}) \;=\; \mathbf{w}^T\mathbf{x} \;=\; w_0 + \sum_{j=1}^{m} w_j \cdot x_j \;=\; w_0 + w_1 \cdot x_1 + \ldots + w_m \cdot x_m$$

- The weight vector $\mathbf{w} = (w_0, w_1, \ldots, w_m)$ is learned on training instances.

## Training of a linear regression model

- Input. A set of $n$ training pairs $(\mathbf{x}^{(i)}, y^{(i)})$, where $\mathbf{x}^{(i)}$ is an instance and $y^{(i)} = c(\mathbf{x}^{(i)})$ its correct output value.
- Output. A model $y(\mathbf{x})$ that minimizes the *regression error*, i.e., the difference between observed values $y^{(i)}$ and predictions $y(\mathbf{x}^{(i)})$.

## Cost function in linear regression

- Usually, a regression error is quantified as the *residual sum of squares*.

# Linear Regression

## Optimization

### Residual sum of squares (RSS)

- The sum of squared differences between predicted output values $y(\mathbf{x}^{(i)})$ and correct output values $y^{(i)}$ over all instances $\mathbf{x}^{(i)}$.

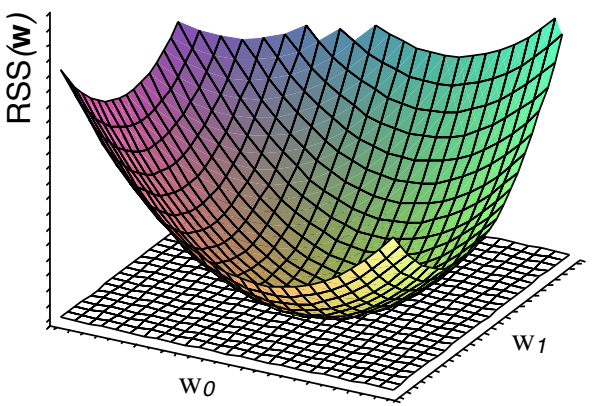
$$RSS(\mathbf{w}) \quad = \quad \sum_{i=1}^{n}(y^{(i)} - y(\mathbf{x}^{(i)}))^2 \quad = \quad \sum_{i=1}^{n}(y^{(i)} - \mathbf{w}^T\mathbf{x}^{(i)})^2$$

- RSS works with any type of model function $y$ (linear or other) as well as with any dimensionality of $\mathbf{x}^{(i)}$.

### Minimization of RSS

- The best weight vector $\hat{\mathbf{w}}$ is found by minimizing $RSS(\mathbf{w})$ on the training set.

$$\hat{\mathbf{w}} \quad = \quad \underset{\mathbf{w}\in\mathbf{R}^{m+1}}{\operatorname{argmin}} \; RSS(\mathbf{w}),$$




- If $y$ is linear, $RSS(\mathbf{w})$ is a convex function with a single, global optimum.

# Linear Regression

## Regularization and RSS Optimization

### Regularization

- To avoid overfitting, a regularization term is added to the cost function, which prevents the model $y$ from becoming too complex.

$$RSS(\mathbf{w}) = \sum_{i=1}^{n}(y^{(i)} - \mathbf{w}^T\mathbf{x}^{(i)})^2 + \lambda \cdot \sum_{j=0}^{m} w_j^2$$

- The regularization term restricts the absolute values of the weights $\mathbf{w}$.
- The hyperparameter $\lambda$ trades the training error against model simplicity.

### RSS Optimization

- Regression methods based on the minimization of squared residuals are called *methods of least squares.*
- Various methods have been devised, particularly for linear models.
- General types. Batch methods, iterative methods.

# Linear Regression

## Gradient Descent in Linear Regression

### Linear regression with batch gradient descent

- In each step, $y$ is adapted to all training instances.
- The adaptation is based on the gradient of $RSS(\mathbf{w})$ at the current point.
- Stepwise heads towards the minimum of $RSS(\mathbf{w})$ until convergence.
- Pro. Guarantees to find the global minimum of $RSS(\mathbf{w})$.
- Con. Computationally expensive on bigger data.

### Linear regression with stochastic gradient descent (SGD)

- In each step, $y$ is adapted to one training instance.
- The adaptation is repeated for some number of *epochs* $k$.
- The higher $k$, the more $y$ will fit the data.
- Pro. Linear in $n$ and $k$ and, thus, scales well with data size.
- Pro. Can continually learn *online*, whenever given new training data.
- Pro. Can make use of stochastic sampling methods.
- Con. Does not guarantee to find the minimum.

# Linear Regression

## Learning Rate

### Learning rate of gradient descent

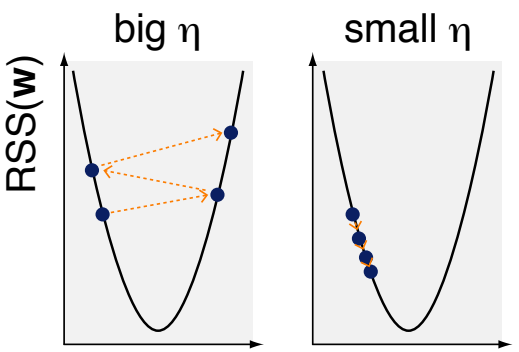
- To fit the weights in $\mathbf{w}$, gradient descent adapts them based on the gradient of the residuals.

  The gradient is the correspondent of derivates for multiple dimensions.

- The learning rate $\eta$ is a hyperparameter that governs the step size of the adaptation.

### Large or small learning rate?

- If $\eta$ is big, the minimization may fail to converge.
- If $\eta$ is small, the optimization may take long.




### Adaptative learning rate

- A solution is to stepwise decrease the learning rate during optimization.
- Below, this is left out for simplicity.

# Linear Regression

## Pseudocode of Linear Regression with SGD

### Signature

- Input. $n$ training instances $X$ of the form $(\mathbf{x}, y)$, a learning rate $\eta$, and a number of epochs $k$.
- Output. A vector $\mathbf{w}$ with one weight $w_j$ for each feature $x_j \in \mathbf{x}$, $1 \leq j \leq m$.

**linearRegressionWithSGD(List<Instance>** $X$**, double** $\eta$**, int** $k$**)**

```
1.    List<double> w ← getNRandomValues(-1, 1)
2.    for int j ← 1 to k do
3.        for each Instance (x^(i), y^(i)) in X do
4.            double y(x^(i)) ← w^T x^(i) = w_0 + w_1 · x_1^(i) + ... + w_m · x_m^(i)
5.            List<double> gradient ← ∂/∂w_j ((y^(i) − y(x^(i))^2 + λ/n · Σ_{j=0}^{m} w_j^2)
6.            w ← w − η · gradient
7.    return w
```

### Notice

- Differs from the pseudocode in lecture part VI, due to focus on RSS, inclusion of regularization, and similar.

# Review Sentiment Analysis

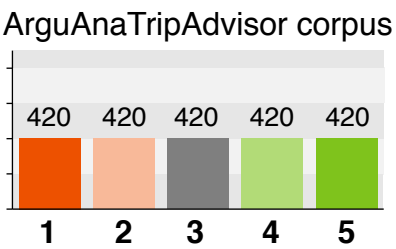
## Sentiment Scoring

### Sentiment scoring of reviews

- Regression of the numeric sentiment score of a customer review on a product, service, or work of art.

### Data (as above)

- 2100 English hotel reviews from TripAdvisor.
  900 training, 600 validation, and 600 test reviews.
- Each review has a sentiment score from {1, ..., 5}.




### Tasks

- 5-class sentiment. Each score used as numeric value.

### Approach

- Algorithm. Linear regression with stochastic gradient descent (SGD).
  Epoch hyperparameter tuned on validation sets, other parameters fixed.
- Features. Combination of standard and specific features (as above).

# Review Sentiment Analysis

## Evaluation of Sentiment Regression

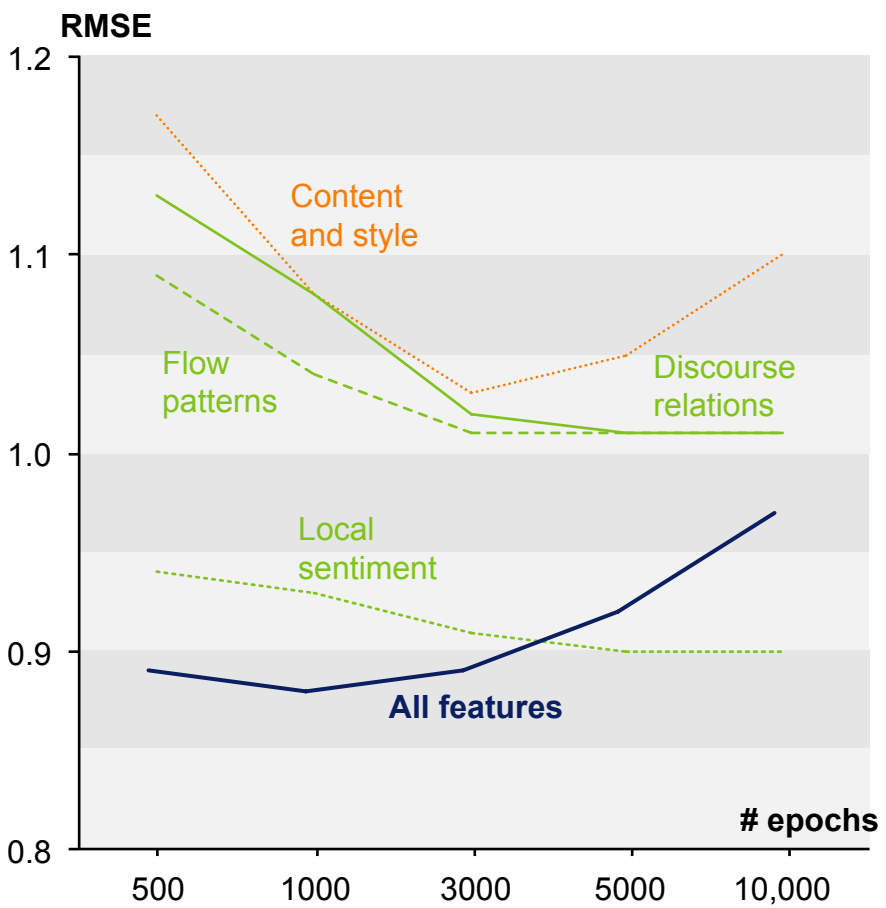
### Evaluation

- Linear regressor for each feature type alone and for their combination.
- Training on training set, tuning on validation set, test on test set.
- Main measure. RMSE: root mean squared error.

### Hyperparameter tuning

- Epochs tested for SGD. 0.5k, 1k, 3k, 5k, 10k.
- Best epochs for test set.
- Learning rate set to $10^{-5}$, same for regularization.

### Validation of RMSE for different epochs



# Review Sentiment Analysis

## Model Interpretation: Main Features of the Model

### Interpretability of linear regression

- Linear regression simply assigns one weight to each given feature.

### Features with highest/lowest weights of the given model

- 0.6457 First local sentiment in text
- 0.2768 Proportion of neutral clauses
- 0.2186 elaboration(positive, positive)
- 0.2001 Last local sentiment in text
- 0.1682 # Clauses per sentence
- 0.1681 SentiWordnet objectivity score
- 0.1477 (1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)
- –0.0691 Token bigram ". i"
- –0.0714 sequence(negative, neutral)
- –0.0714 Character trigram "t o"
- –0.0800 sequence(neutral, neutral)
- –0.0858 Character trigram "d s"
- –0.1246 Local sentiment change (negative, neutral)
- –0.2438 elaboration(negative, negative)

# Review Sentiment Analysis

## Results and Discussion of Sentiment Regression *

### Effectiveness results on test set

| Feature type | # Features | MAE | RMSE |
|---|---|---|---|
| Local sentiment distribution | 50 | 0.77 | 0.99 |
| Discourse relation distribution | 75 | 0.82 | 1.01 |
| Sentiment flow patterns | 42 | 0.86 | 1.07 |
| Content and style features | 1026 | 0.90 | 1.11 |
| **Combination of features** | 1193 | **0.73** | **0.93** |
| Random baseline | | 1.20 | 1.41 |

### Discussion

- Content and style features. Worst in regression, unlike in classification. Indicates that they sometimes fail strongly.
- Local sentiment distribution. Consistently most effective in hotel review sentiment analysis.
- Combination of features. Improves over single feature types here, too.
- The best MAE and RMSE values do not seem fully convincing.

# Review Sentiment Analysis

## Error Analysis: Ground-truth Scores vs. Predictions of the Model *

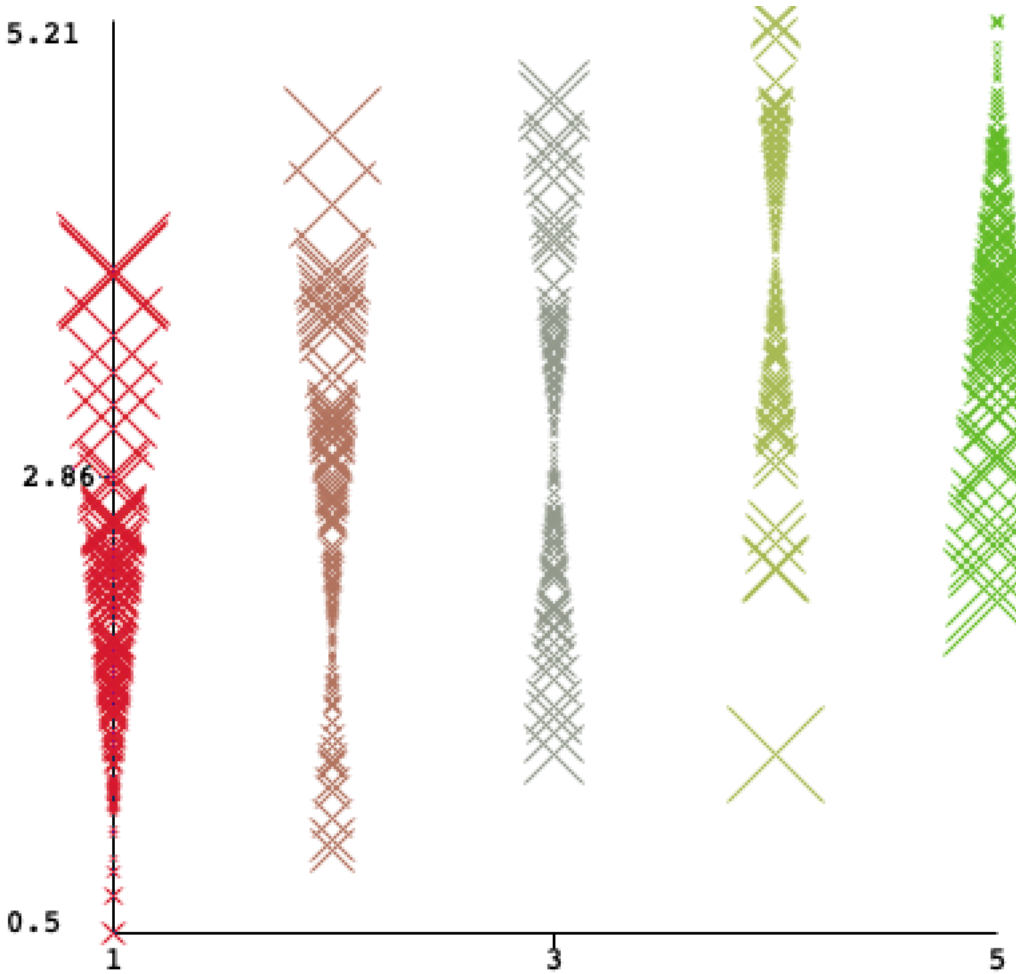
### Visualization

- Scatter plot of the ground-truth scores in the test set vs. predicted scores of the best regressor.

### Observations

- General tendency of regressor okay.
- Clear outliers exist for all scores.
- Few high and low predicted scores.

  Effect of the regression towards the mean.




(cross size reflects regression error)

# Review Sentiment Analysis

## Error Analysis: Impact of Preprocessing *

### Evaluation on ground-truth local sentiment

- The specific features rely on the output of local sentiment classifiers.
  Subjectivity accuracy 78.1%, polarity accuracy 80.4%
- Using the ground-truth local sentiment available in the given data, the impact of errors in this output can be assessed.

### Effectiveness results with ground-truth local sentiment

| Feature type | # Features | MAE | RMSE |
|---|---|---|---|
| Local sentiment distribution | 50 | **0.61** | 0.77 |
| Discourse relation distribution | 75 | 0.68 | 0.84 |
| Sentiment flow patterns | 42 | 0.67 | 0.86 |
| Content and style features | 1026 | 0.90 | 1.11 |
| **Combination of features** | 1193 | **0.61** | **0.75** |
| Random baseline | | 1.20 | 1.41 |

### Discussion

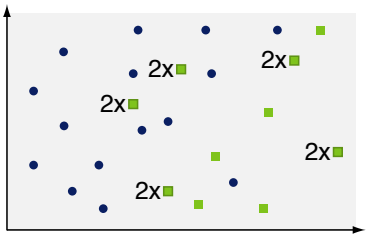
- Notable error reduction, but room for further improvement remains.

# Conclusion

# Summary

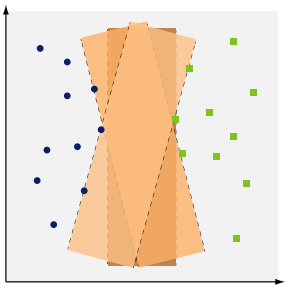
## Text mining using supervised learning

- Decisions about and assessment of text properties.
- Usually done with supervised learning.
- Datasets may have to be prepared for learning.



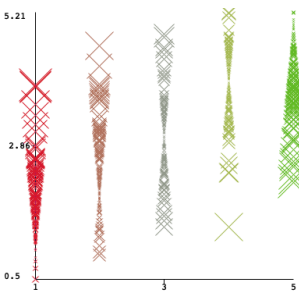

## Supervised classification

- Learning to predict nominal labels of texts / text spans.
- One of the most used learning algorithms is the SVM.
- Feature engineering is key to high effectiveness.



## Supervised regression

- Learning to predict numeric values of texts / text spans.
- Simple linear regression is effective and interpretable.
- Also here: Feature engineering is key.



# References

## Some content and examples taken from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- Henning Wachsmuth (2015): Text Analysis Pipelines — Towards Ad-hoc Large-scale Text Mining. LNCS 9383, Springer.
- Ian H. Witten and Eibe Frank (2005): Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann Publishers, San Francisco, CA, 2nd edition.