Statistical Natural Language Processing

Part VI: NLP using Classification and Regression

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Learning Objectives

Concepts

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

Methods

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

Tasks

- Sentiment polarity classification
- Sentiment scoring

Outline of the Course

I. Overview

II. Basics of Data Science

III. Basics of Natural Language Processing

IV. Representation Learning

V. NLP using Clustering

VI. NLP using Classification and Regression

- Introduction
- Data Preparation
- Supervised Classification
- Supervised Regression
- Conclusion

VII. NLP using Sequence Labeling

VIII. NLP using Neural Networks

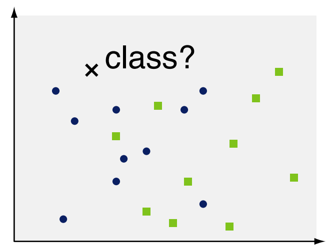
IX. NLP using Transformers

X. Practical Issues

Introduction

Classification and Regression

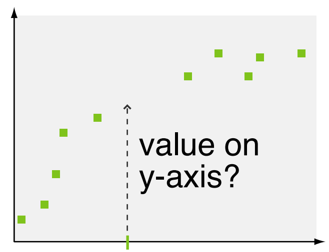
Classification



- 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 having upper and lower bounds.

Use of supervised learning

- Hand-crafted rules/arithmetics might be used to predict classes/values.
- With sufficient data, supervised learning is mostly more successful.
- We restrict our view to feature-based methods here.

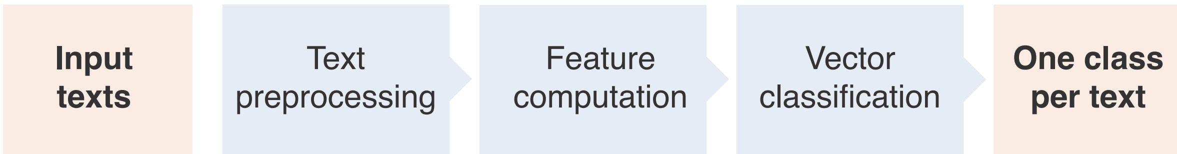
  Neural methods follows later in Lecture Part VIII.

Classification and Regression

NLP using Supervised Classification and Regression

Feature-based text classification (regression analog)

- Supervised classification based on a feature representation
- Input. A set of texts or text spans O, represented in a feature space X (in training with class information C)
- Output. A class c for each $o \in O$, and a model $y : X \to C$



Challenges of feature-based methods

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

Notice

- Neural methods may incorporate features as part of the prediction, too.

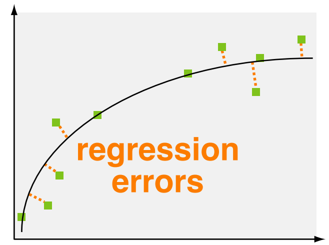
Classification and Regression

Evaluation and Application

Evaluation of supervised classification

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

Evaluation of supervised regression



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

Applications in NLP

- Classification. Deciding about span boundaries, span types, text labels, relations between spans, relation types, ...
- Regression. Assigning scores and ratings, estimating probabilities, ...

Data Preparation

Dataset Preparation

Why data preparation?

- Not always, the annotations in a corpus match with the task instances required for supervised learning.

Typical preparations

- Instance creation. Add missing “negative” instances, e.g., entity corpora only show what *is* an entity:

  “$[$Jaguar$]_{ORG}$ is named after the animal jaguar.”

- Variable mapping. Map annotations to other target variables, especially for abstraction or unification:

  Ratings 1–2 $\rightarrow$ “negative”, 3 $\rightarrow$ discard, 4–5 $\rightarrow$ “positive”

- Dataset balancing. Make the distribution of the target variable uniform:

  1000 negative, 600 neutral, 800 positive $\rightarrow$ 600 negative, 600 neutral, 600 positive

Dataset Preparation

Instance Creation

Why creating 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 name recognition

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

- All other named entities? → Can distinguish only entity *types* then
- All other content words? → Verbs will never be person names (somewhat trivial)
- All other noun phrases? → Reasonable choice (alternative: map to token-level task)

Dataset Preparation

Dataset Balancing

Dataset balancing

- The alteration of the distribution of a dataset regarding a target variable, such that the distribution is uniform afterwards
- Balancing works by either *undersampling* or *oversampling* instances

  For regression, an alternative is *binning*, i.e., to make certain intervals uniform.

When to balance?

- Balancing a training set prevents machine learning from being biased towards majority classes (or values).
- Validation and test sets should usually have *representative* distributions.

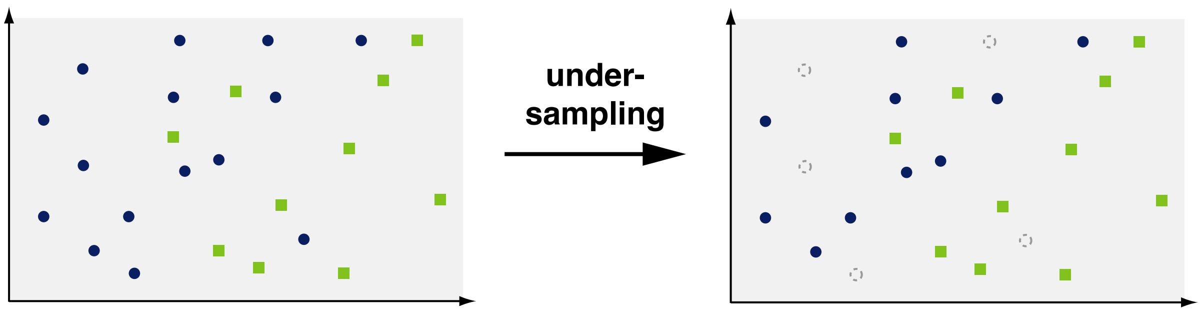
Alternatives to balancing?

- Many optimization procedures can penalize wrong predictions more for minority instances than for majority instances.
- This is the more sound but also more complex way of preventing bias.

Dataset Preparation
Undersampling

Balancing with undersampling

- Remove 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.

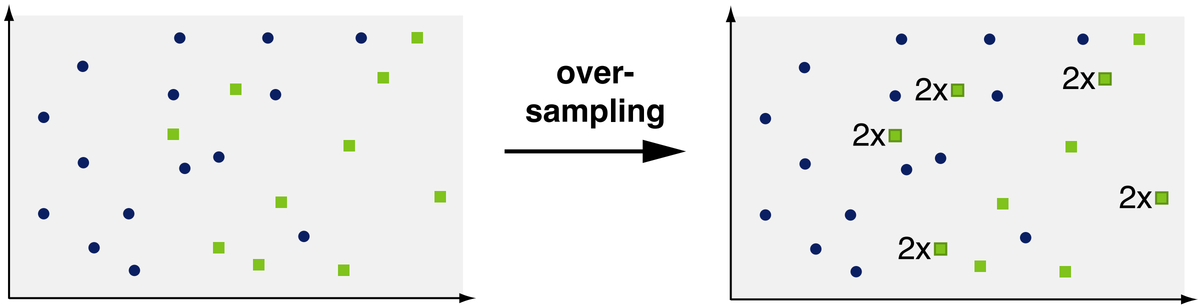
Dataset Preparation

Oversampling

Balancing with oversampling

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

  In some cases, 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.

Supervised Classification

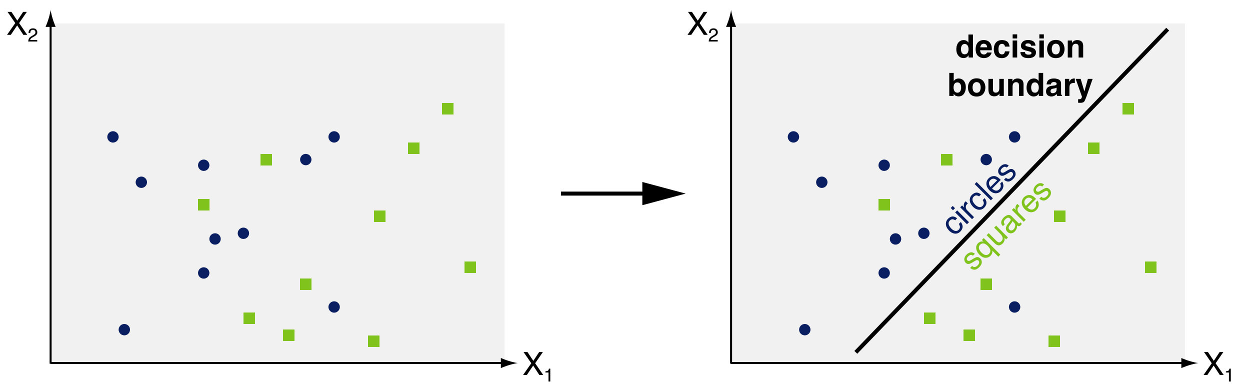
Supervised Classification

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

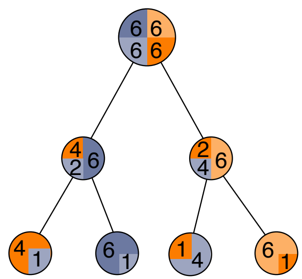
Classification Algorithms

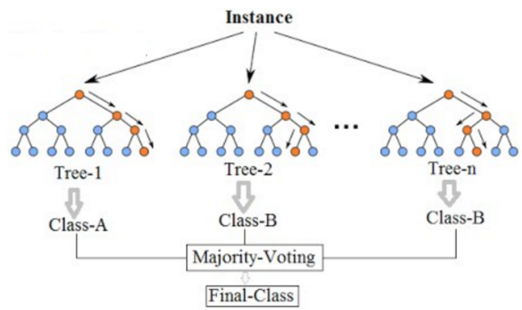
Selected classification algorithms

- Naïve Bayes. Predict classes based on conditional probabilities.
- Decision tree. Stepwise compare instances on single features.
- Random forest. Take the majority vote of several decision trees.

$$P(c|x) = \frac{P(x|c) \cdot P(c)}{P(x)}$$

$$P(c|\mathbf{x}) \propto P(x_1|x) \cdot \ldots \cdot P(x_m|c) \cdot P(c)$$





- Support vector machine. Maximize the margin between classes.
- Neural network. Learn complex functions on feature combinations.

Focus on support vector machines here

- One of the most widely used feature-based classification algorithms
- Often, a good default choice; much theoretical and empirical appeal

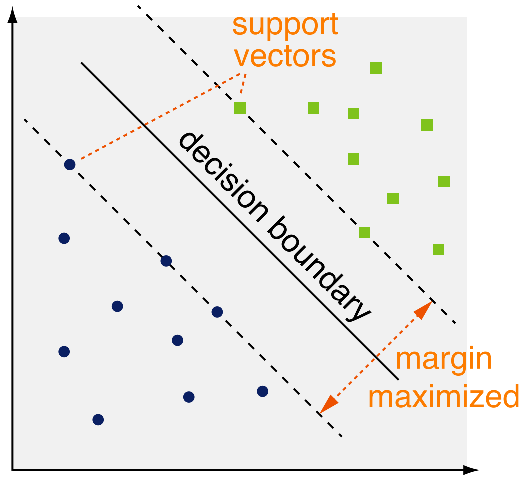
Support Vector Machines

Support vector machine (SVM)

- A 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.



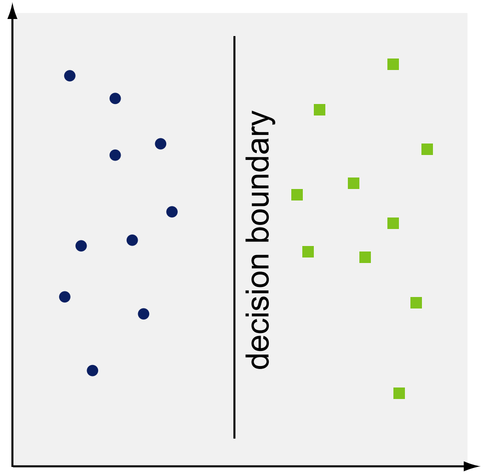
Support vectors

- A (usually small) subset of training instances that are used by an SVM to define the decision boundary
- Other instances are not memorized after training.

Support Vector Machines
Intuition of SVMs

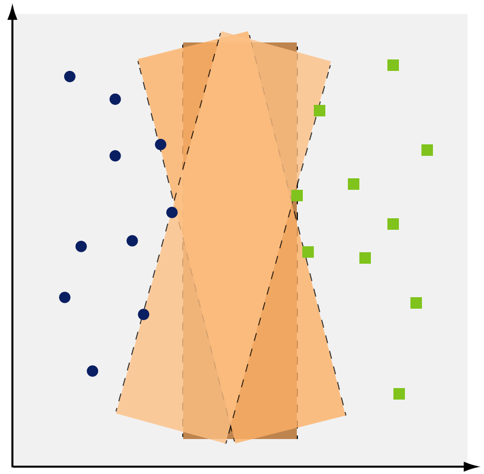
Maximization of certainty

- By putting the boundary in the middle of two classes, low-certainty decisions are avoided.
- A slight instance variation in test data will, thus, not cause a misclassification.



Better generalization

- By maximizing the “separator” between two classes, fewer possible separators exist.
- This reduces variance and, thus, increases the ability to generalize to test data.



Support Vector Machines

Linear SVMs

Decision boundary

- A hyperplane $\mathbf{w}^T\mathbf{x} = b$, i.e., all points $\mathbf{x}$ on it satisfy the equation
- The weight vector $\mathbf{w}$ is the *normal* perpendicular to the hyperplane.
- The intercept term b denotes the distance to the origin, scaled by $||\mathbf{w}||$.

Training

- 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.
- Output. A linear 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 $\mathbf{x}^{(i)}$

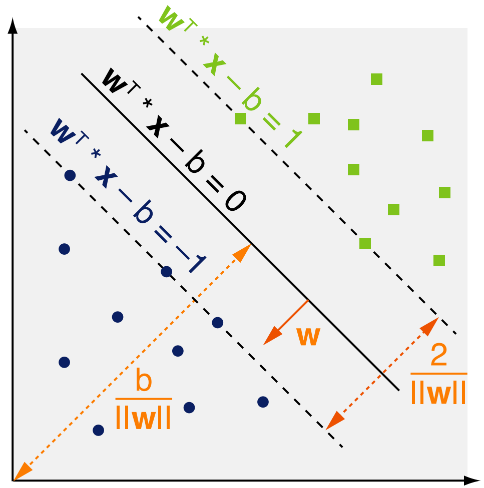
Optimization variants

- 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:

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

- From this, we can infer:

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

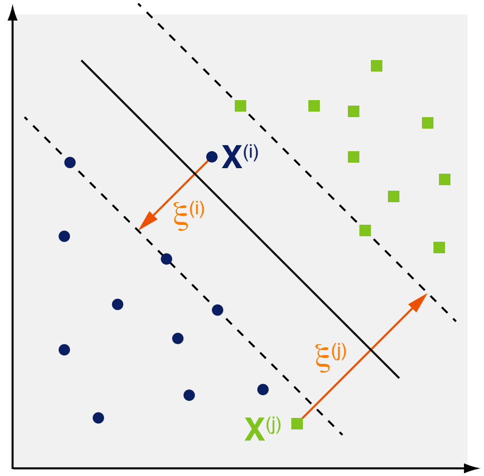
- Also, it follows that the size of the margin is $\frac{2}{||\mathbf{w}||} = \frac{b+1}{||\mathbf{w}||} - \frac{b-1}{||\mathbf{w}||}$.
- To maximize the margin, $||\mathbf{w}||$ must be minimized.

Minimization problem of hard-margin SVMs

- 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.

Minimization problem of soft-margin SVMs

- Find $\mathbf{w}$, b, and $\forall i : \xi^{(i)} \geq 0$, 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

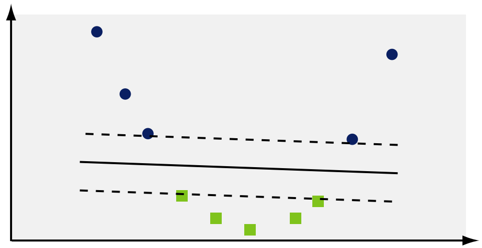
- Non-linear SVMs often have a second hyperparameter γ (see below).
- The combination C and γ needs to be optimized in a grid search.

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 $\mathbf{x}^{(j)}$:

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

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

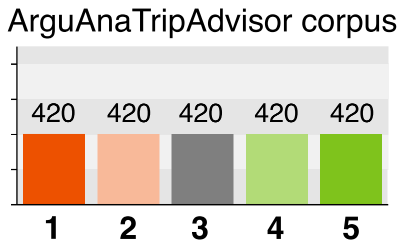
  A quadratic kernel ($d = 2$) is often used. $d = 1$ results in a linear kernel.
- Radial basis function. $K(\mathbf{x}, \mathbf{x}^{(j)}) := e^{-\gamma \cdot (\mathbf{x}-\mathbf{x}^{(j)})^2}$

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

Review Sentiment Analysis

Data (Wachsmuth et al., 2014a)

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



Case Study: Sentiment Polarity classification (Wachsmuth, 2015)

- Classification of the nominal “global” sentiment score of hotel reviews
- 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
  Details on next slides

Review Sentiment Analysis

Case Study: Selected Standard Feature Types

Content features

- 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

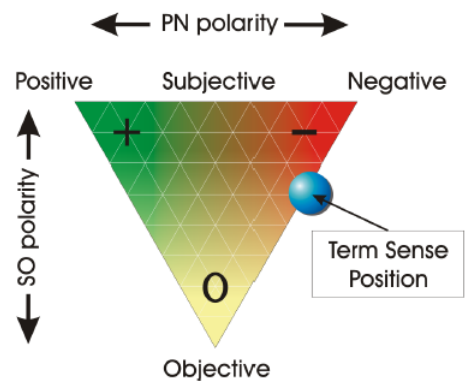
Style features

- POS n-grams. Analog for part-of-speech $\{1, 2, 3\}$-grams
- Character trigrams. Analog for character 3-grams
- Lengths. Average numbers of tokens, sentences, tokens/sentence, ...

Target class features

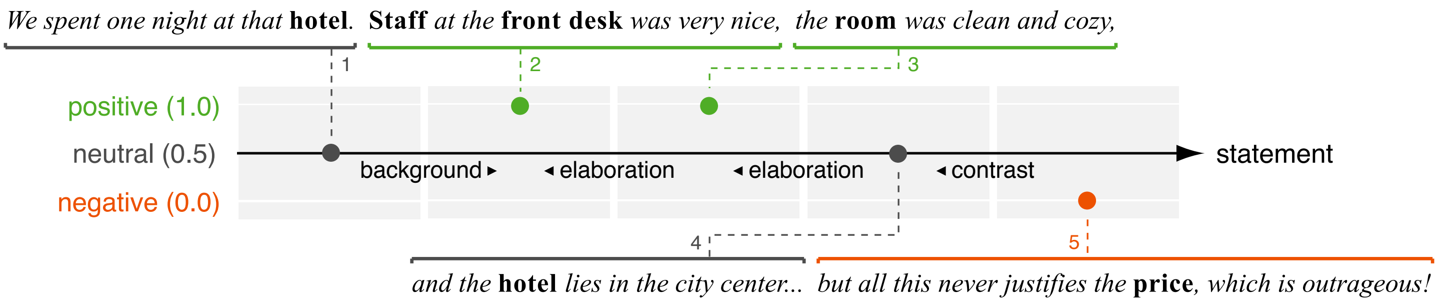
- SentiWordNet scores. Mean positivity, negativity, and objectivity of all first and average word senses in *SentiWordNet*

  A lexicon with subjectivity and polarity values for words (Baccianella et al., 2010).



Review Sentiment Analysis

Case Study: Selected Specific Feature Types (1 of 2)



Local sentiment distribution

- Local sentiment mean, frequencies, changes, and normalized positions

mean 0.6 | positive 0.4 neutral 0.4 negative 0.2 | (neutral, positive) 0.25 ...

9 normalized positions: (0.5, 0.75, 1.0, 1.0, 1.0, 0.75, 0.5, 0.25, 0.0)

Discourse relation distribution

- Frequency of discourse relations and their combination with sentiment

background 0.25 elaboration 0.5 contrast 0.25 (all others 0.0)

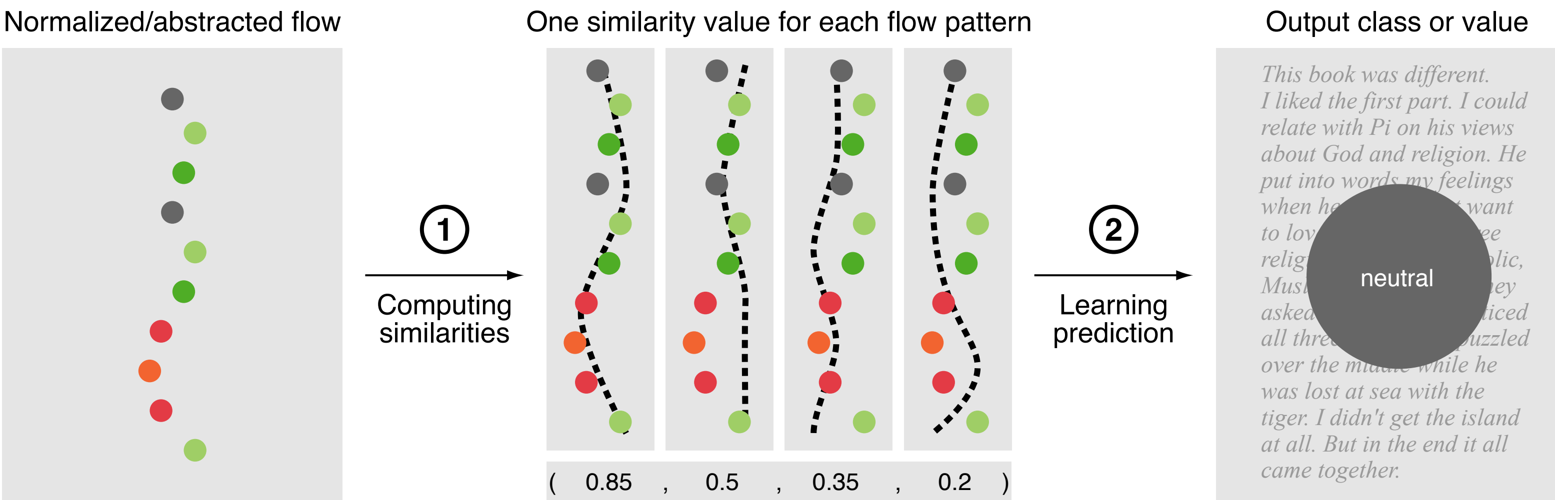
background(neutral, positive) 0.25 elaboration(positive, positive) 0.25 ...

Review Sentiment Analysis

Case Study: Selected Specific Feature Types (2 of 2)

Sentiment flow patterns (see previous lecture part)

- Compute similarity of sentiment flow to each learned flow pattern.
- Each similarity becomes one global-structure feature for prediction.



Hypotheses

- Similar flows indicate similar global sentiment. (evaluated below)
- Similar flow patterns occur across review domains. (evaluated later)

Review Sentiment Analysis

Case Study: Experimental Setup and Hyperparameter Optimization

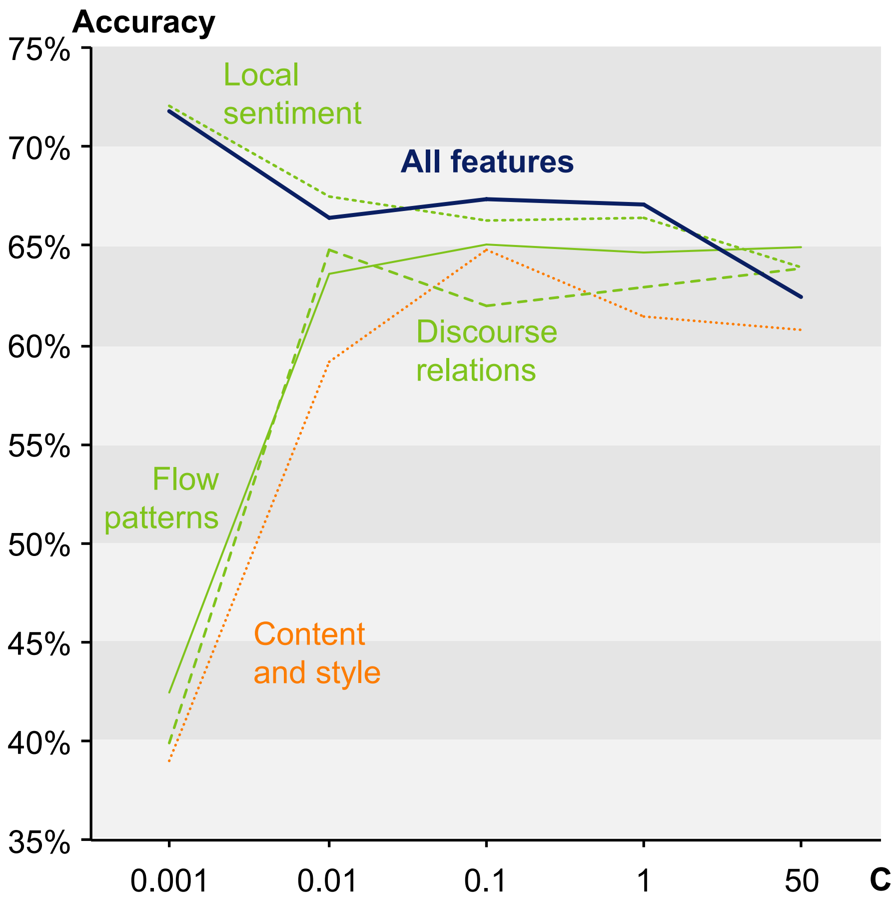
Experimental setup

- 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

Case Study: Results and Discussion

Effectiveness results on test set (accuracy)

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

Discussion

- Standard features. Worse than specific features in the 3-class task only
- Sentiment flow patterns. Impact more visible across domains

  This will be demonstrated in Lecture Part IX.
- Combination of features. Works best, indicating they are complimentary
- Particularly the 5-class accuracy seems insufficient.
- Classification misses to model the ordinal relation between classes.

Supervised Regression

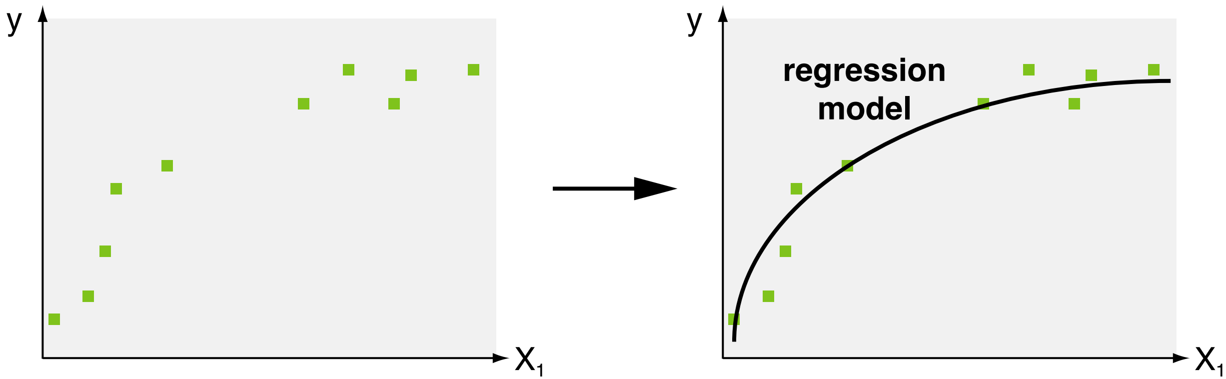
Supervised Regression

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 $X \to C$ that maps any instance to its output value



Application phase (prediction)

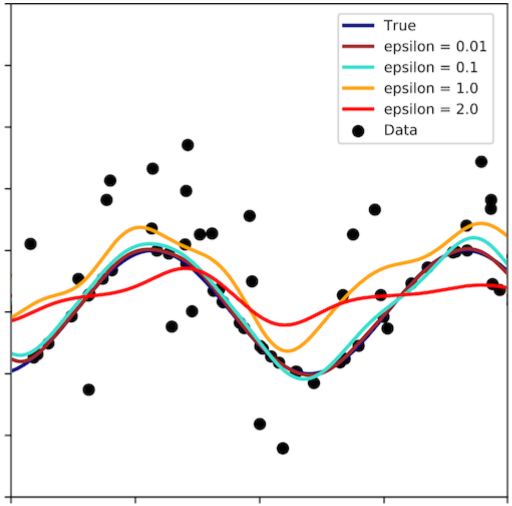
- Input. A set of unknown instances $\mathbf{x}^{(i)}$ without output value
- Output. The predicted output value $y(\mathbf{x}^{(i)})$ for each instance

Supervised Regression

Regression Algorithms

Selected supervised regression algorithms

- Support vector regression. Maximize the flatness of a regression model.



- Linear regression. Predict output values using a learned linear function.

Focus on linear regression here

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

Linear Regression

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. The model $y(\mathbf{x})$ found to minimize the *regression error*, i.e., the difference between correct values $y^{(i)}$ and predictions $y(\mathbf{x}^{(i)})$

Loss 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 $\mathbf{x}^{(i)}$:

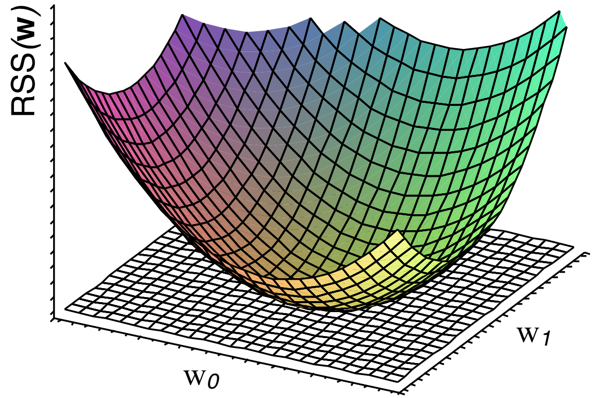
$$RSS(\mathbf{w}) \quad := \quad \sum_{i=1}^{n}(y^{(i)} - y(\mathbf{x}^{(i)}))^2 \quad = \quad \sum_{i=1}^{n}(y^{(i)} - \mathbf{w}^T\mathbf{x}^{(i)})^2$$

- RSS works as a loss function for any regression function y (linear or not) and for 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 Optimization

RSS regularization

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

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

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

RSS optimization

- The most common optimization method is *gradient descent*.
- It stepwise adapts a model y based on the gradient of the loss function.
- We here look at the variant *stochastic gradient descent* (SGD), which adapts y to a single training instance in each step.
- Pro. Scales well, allows for online learning and stochastic sampling
- Con. Does not guarantee to find the minimum

Linear Regression

Pseudocode of Linear Regression with SGD

Signature

- Input. n training instances X of the form $(\mathbf{x}, y)$, a learning rate η, 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** η**, int** k**)**

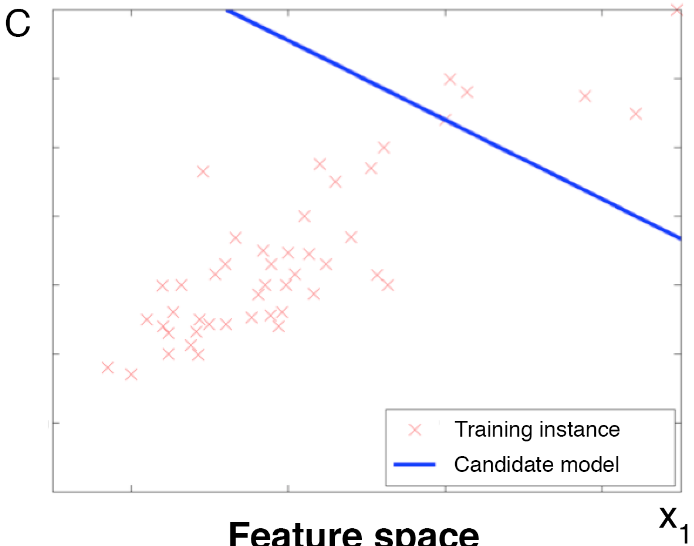
List<**double**> **w** $\leftarrow$ getMRandomValues(-1, 1)
for int l $\leftarrow$ 1 **to** k **do**
  for each Instance $(\mathbf{x}^{(i)}, y^{(i)})$ **in** X **do**
    double $y(\mathbf{x}^{(i)}) \leftarrow \mathbf{w}^T\mathbf{x}^{(i)} = w_0 + w_1 \cdot x_1^{(i)} + \ldots + w_m \cdot x_m^{(i)}$
    List<**double**> gradient $\leftarrow \frac{\partial}{\partial w_j}((y^{(i)} - y(\mathbf{x}^{(i)})^2 + \frac{\lambda}{n} \cdot \sum_{j=0}^{m} w_j^2)$
    $\mathbf{w} \leftarrow \mathbf{w} - \eta \cdot$ gradient
return w

Impact of hyperparameters

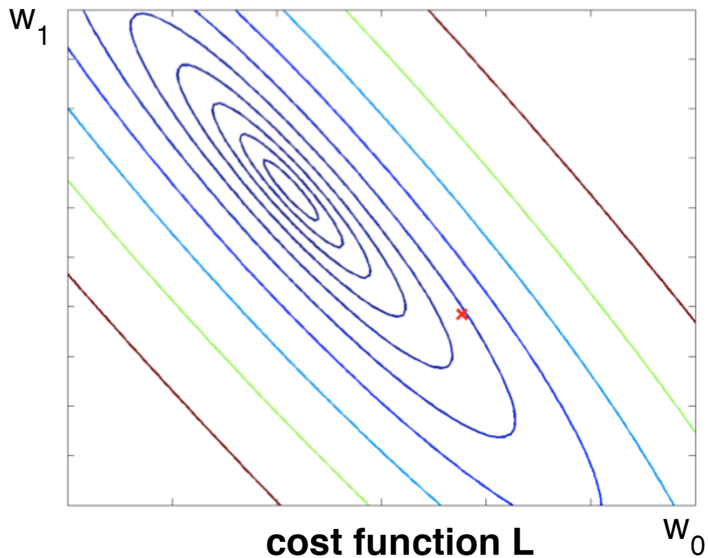
- Number of epochs. The higher k, the more y will fit the data.
- Learning rate. Higher η may speed up learning, but may fail to optimize.

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training



Feature space



cost function L

Note on example

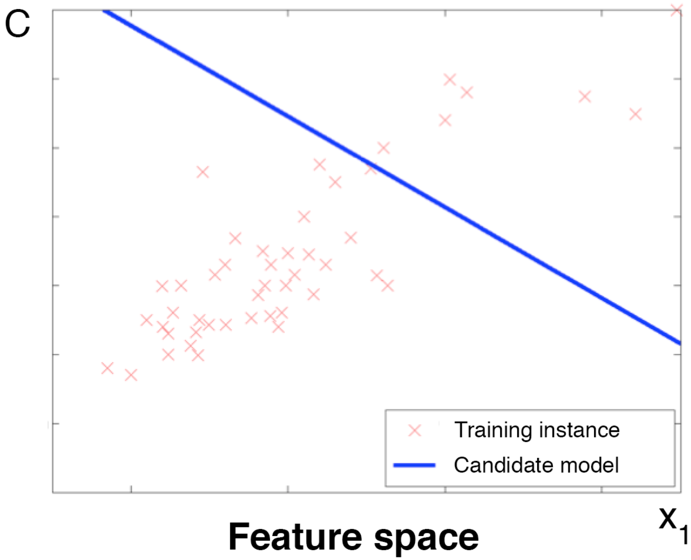
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

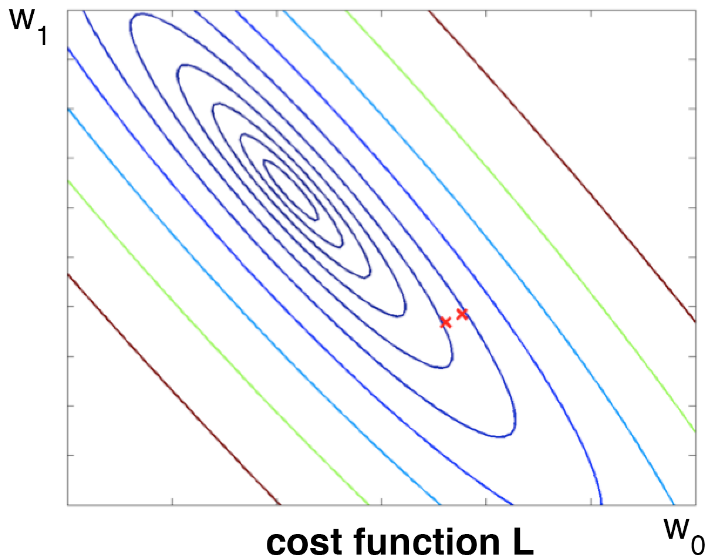
Linear Regression

Gradient Descent: Example (2 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

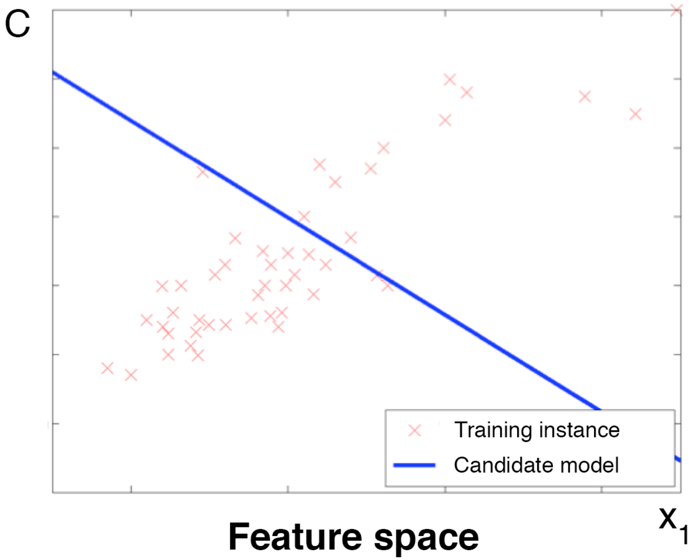
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

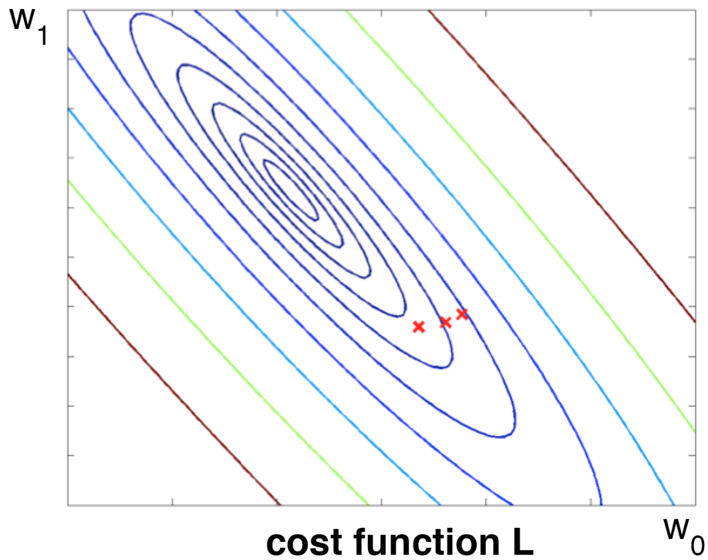
Linear Regression

Gradient Descent: Example (3 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

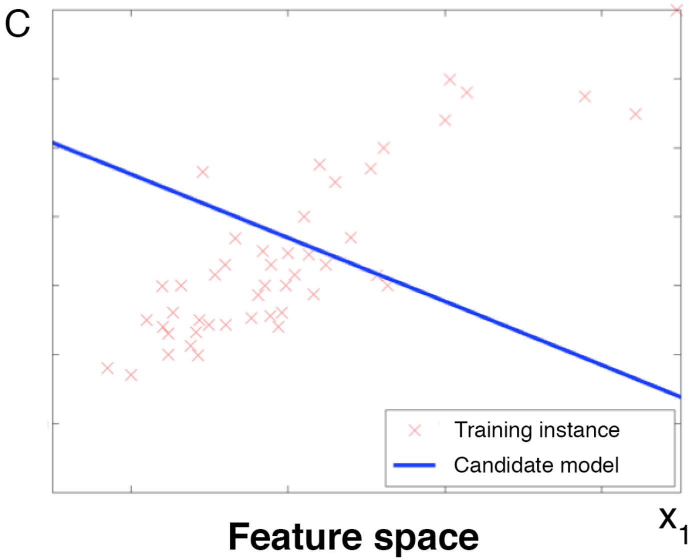
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

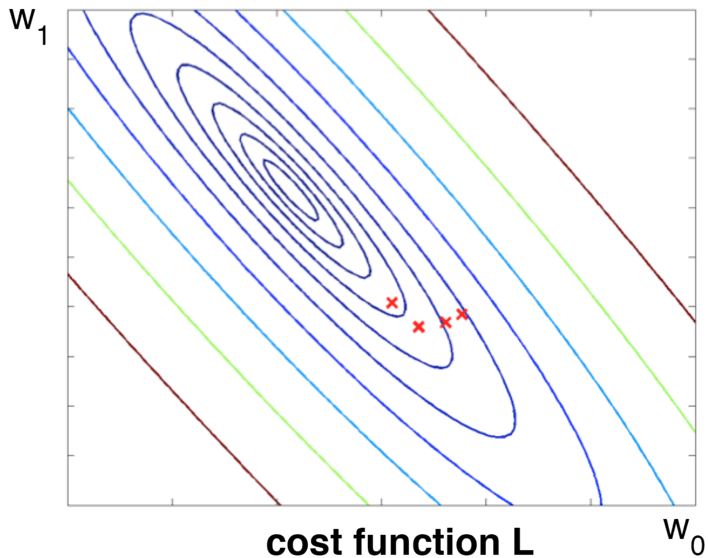
Linear Regression

Gradient Descent: Example (4 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

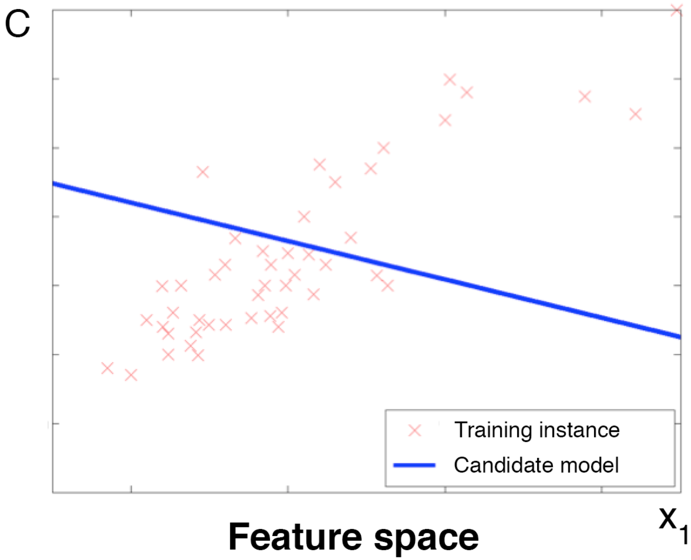
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

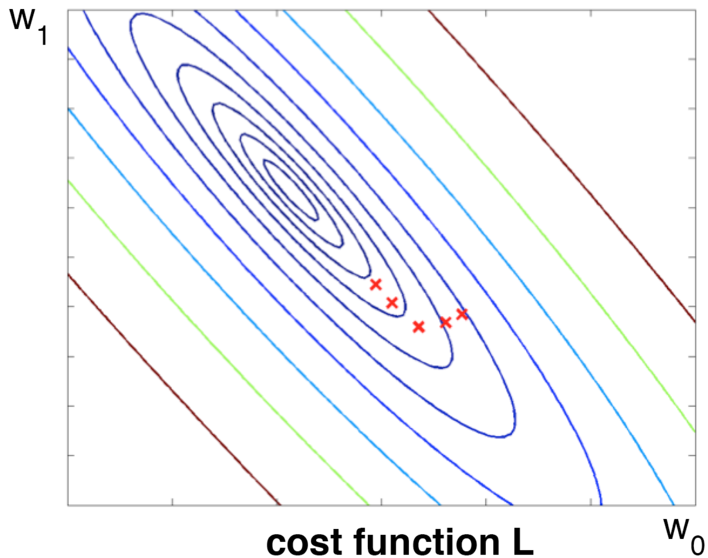
Linear Regression

Gradient Descent: Example (5 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

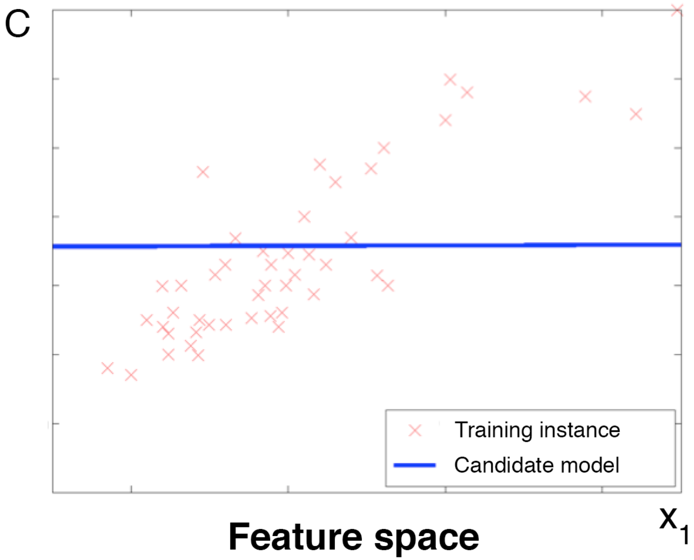
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

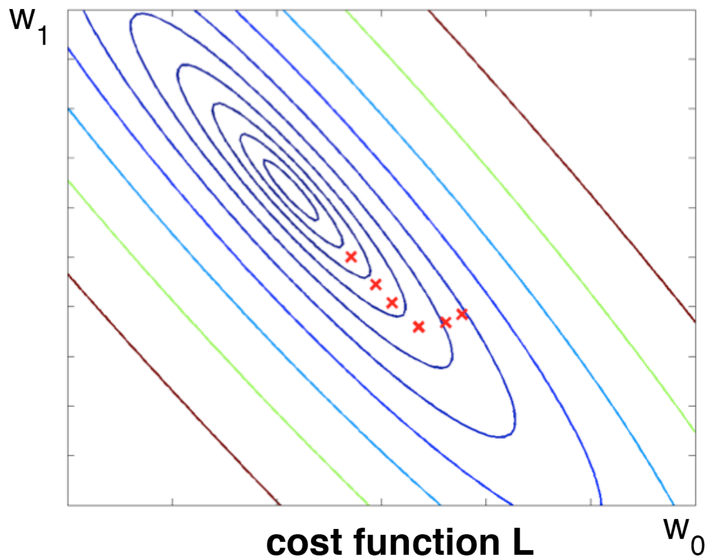
Linear Regression

Gradient Descent: Example (6 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

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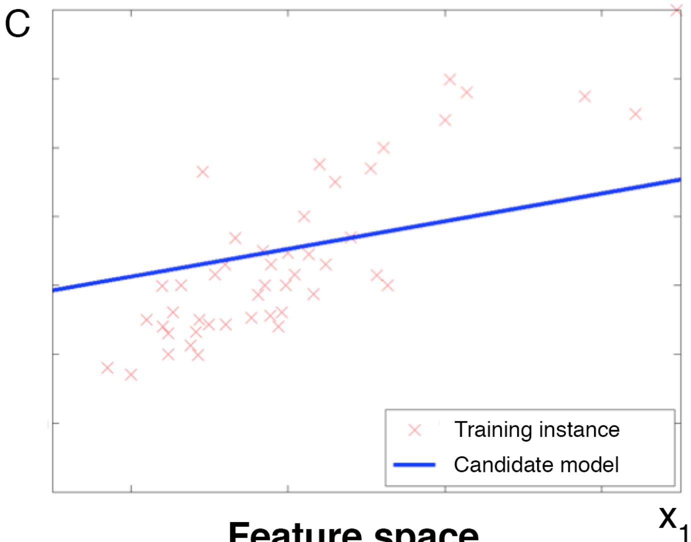
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

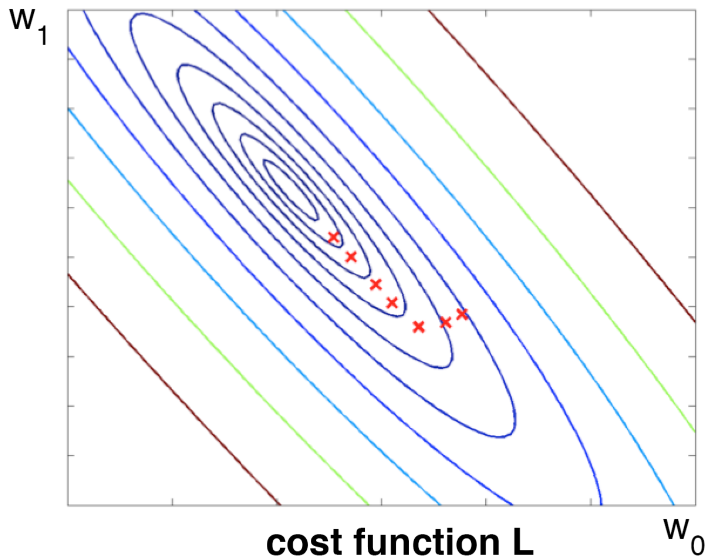
Gradient Descent: Example (7 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training



Feature space



cost function L

Note on example

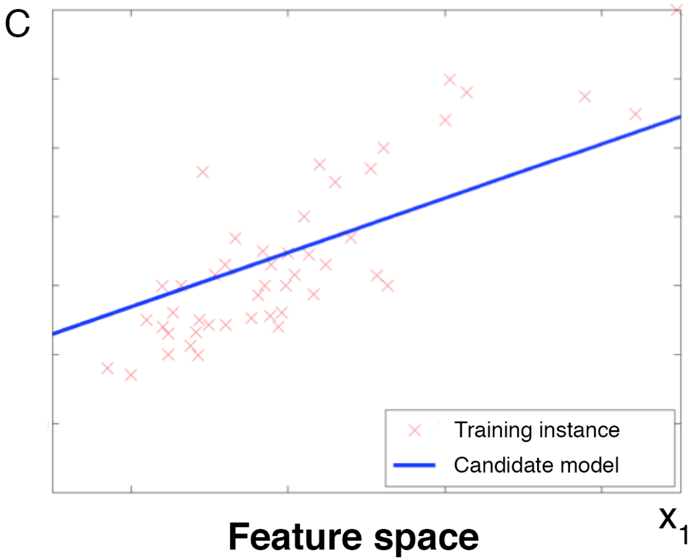
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

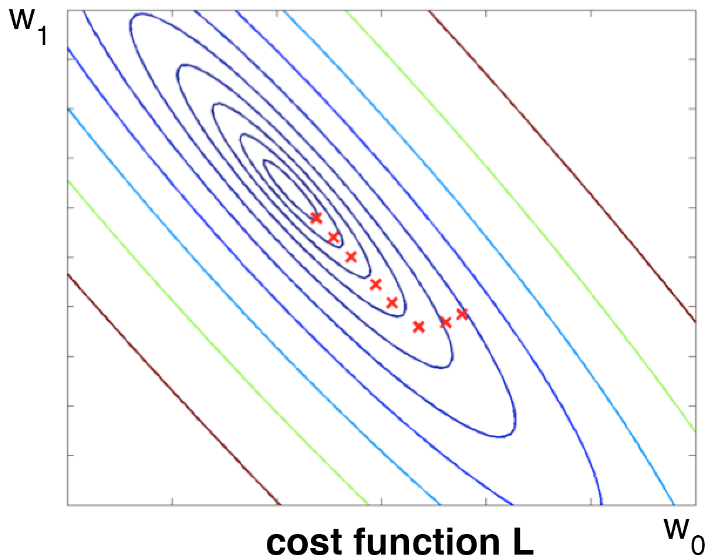
Linear Regression

Gradient Descent: Example (8 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training





Note on example

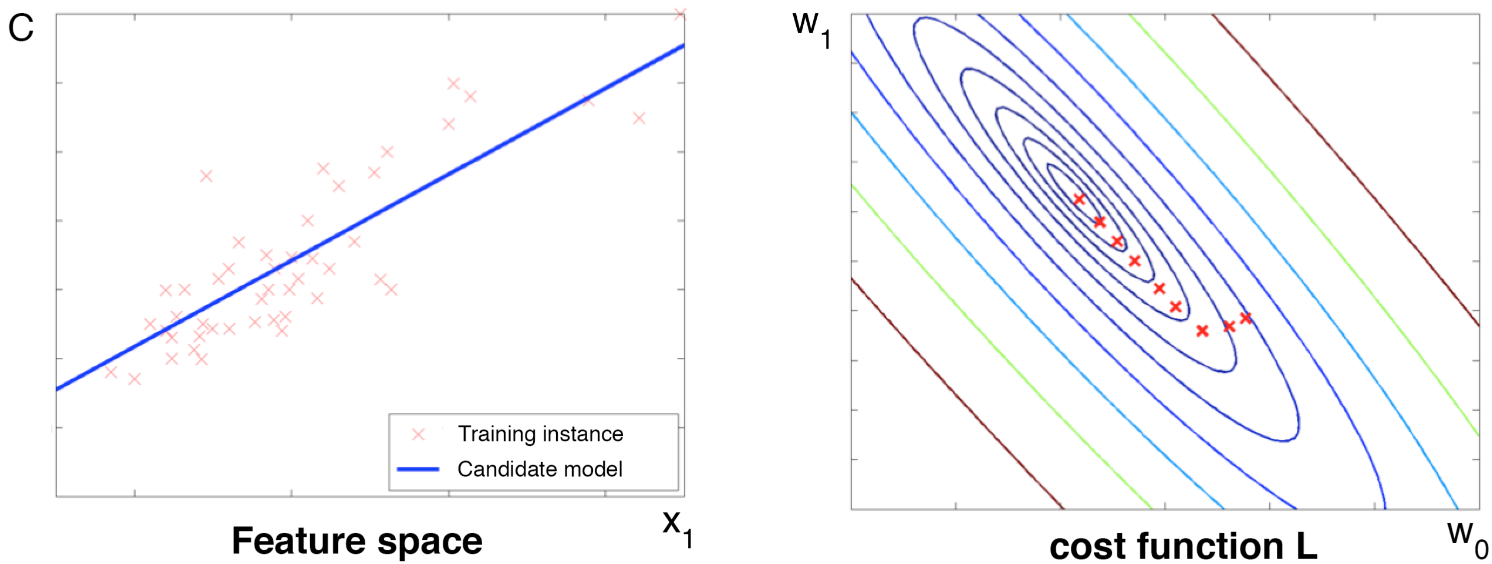
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

Gradient Descent: Example (9 out of 9)

Learning of a linear regression model

- Feature space X (left) and loss $\mathcal{L} = RSS_{reg}(\mathbf{w})$ (right) in training



Note on example

- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Review Sentiment Analysis

Case Study: Sentiment Scoring of Hotel Reviews (Wachsmuth et al., 2014b)

Task

- Regression of the numeric “global” sentiment score of a review
- 5-class sentiment. Each score used as numeric value

  Data as for classification above

Approach

- Algorithm. Linear regression with stochastic gradient descent (SGD)

  Epoch hyperparameter tuned on validation sets, other parameters fixed
- Features. Exactly as for classfication above

Experimental Setup

- 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. Root mean squared error (RMSE)

  Mean absolute error (MAE) also given below

Review Sentiment Analysis

Case Study: Main Features used in Regression

Interpretability of linear regression

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

Top features of the best model

- +0.6457 First local sentiment in text
- +0.2768 Proportion of neutral clauses
- +0.2186 Discourse relation: elaboration(positive, positive)
- +0.2001 Last local sentiment in text
- +0.1682 # Clauses per sentence
- +0.1681 SentiWordnet objectivity score
- +0.1477 Flow pattern: 10x positive, 10x negative, 10x positive

- –0.0691 Token bigram “. i” (origin: next sentence starts with “I ...”)
- –0.0714 Local sentiment bigram (negative, neutral)
- –0.0714 Character trigram “t o” (“bit of”, “just okay”, “not one”, “without our”, ...)
- –0.0800 Local sentiment bigram (neutral, neutral)
- –0.0858 Character trigram “d s” (“had some”, “had stayed”, “‘and saw”, ...)
- –0.1246 Local sentiment change (negative, neutral)
- –0.2438 Discourse relation: elaboration(negative, negative)

Review Sentiment Analysis

Case Study: Results and Discussion

Effectiveness results on test set

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

Discussion

- Standard features. Worst here (unlike in classification); this suggests that they sometimes fail strongly.
- Local sentiment distribution. Consistently best feature in this case study
- Combination of features. Improves over single feature types here, too

- The best MAE and RMSE values do not seem fully convincing.
- More advanced techniques may be needed (neural methods?).

Review Sentiment Analysis

Case Study: Error Analysis (Ground-truth Scores vs. Predictions)

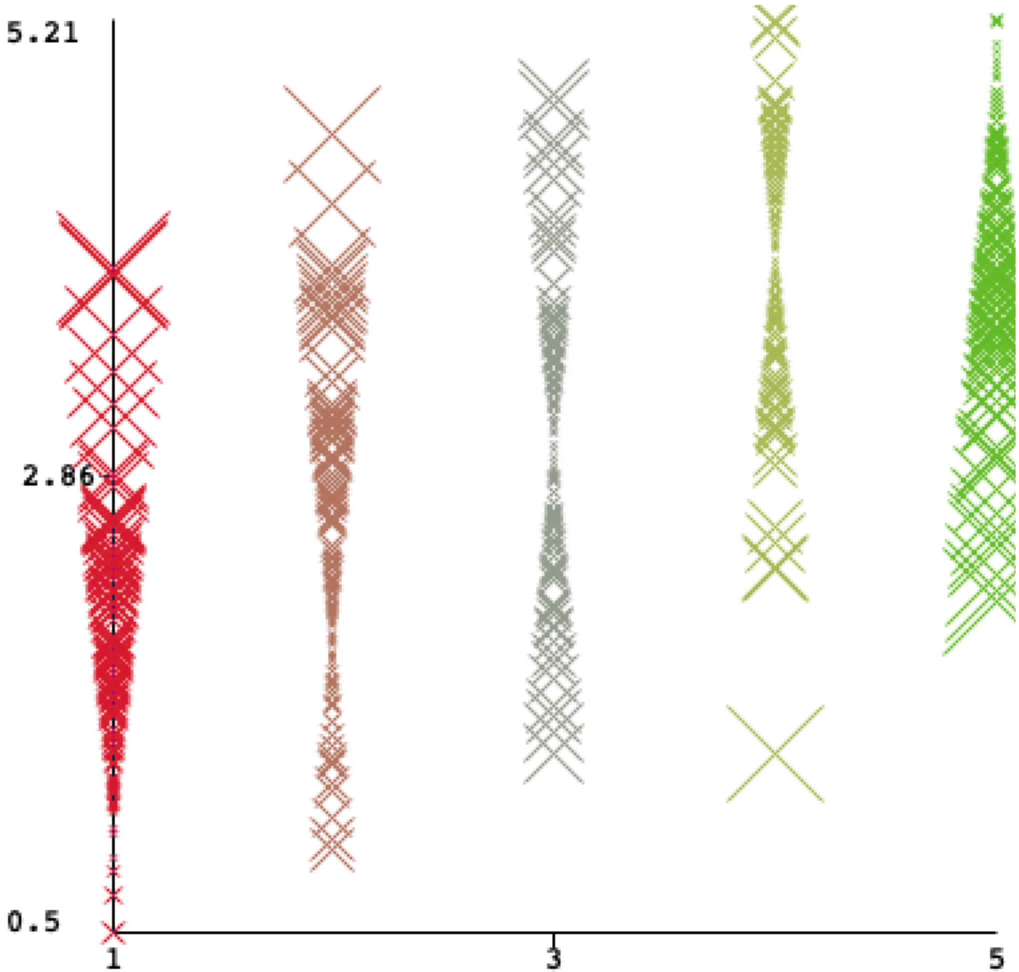
Visualization

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

Observations

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

Typical for regression

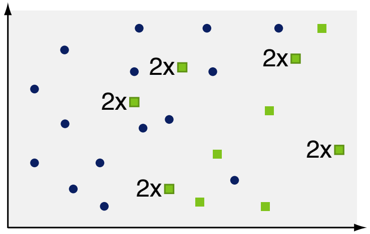


(cross size reflects regression error)

Conclusion

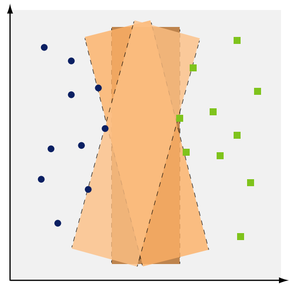
Conclusion

NLP using classification and regression



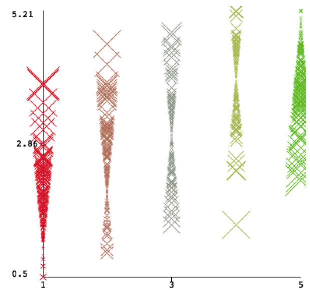
- Decisions about and assessment of text properties
- Usually done with supervised learning
- Datasets may have to be prepared for learning.

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

- **Manning et al. (2008).** Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze (2008). Introduction to Information Retrieval. Cambridge University Press.
- **Wachsmuth (2015).** Henning Wachsmuth (2015): Text Analysis Pipelines — Towards Ad-hoc Large-scale Text Mining. LNCS 9383, Springer.
- **Witten and Frank (2005).** Ian H. Witten and Eibe Frank (2005): Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann Publishers, San Francisco, CA, 2nd edition.

Other references

- **Wachsmuth et al. (2014a).** Henning Wachsmuth, Martin Trenkmann, Benno Stein, Gregor Engels, and Tsvetomira Palarkarska. A Review Corpus for Argumentation Analysis. In Proceedings of the of the 15th International Conference on Intelligent Text Processing and Computational Linguistics, pages 115–127, 2014.
- **Wachsmuth et al. (2014b).** Henning Wachsmuth, Martin Trenkmann, Benno Stein, and Gregor Engels. Modeling Review Argumentation for Robust Sentiment Analysis. In Proceedings of the 25th International Conference on Computational Linguistics: Technical Papers, pages 553–564, 2014.