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

Introduction

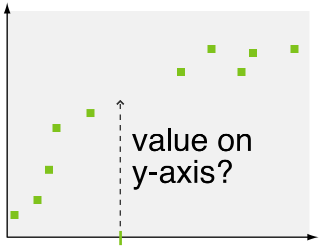
Classification and Regression

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.

  Even in case the values actually have an order or 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.

Use of supervised learning

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

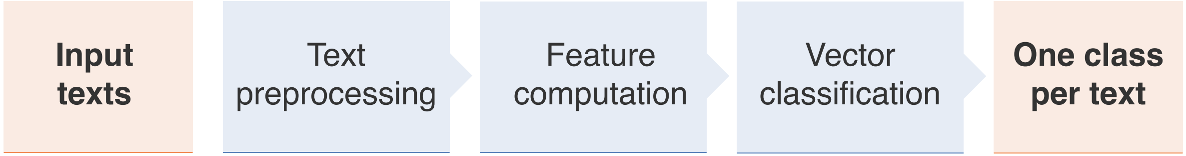
  Neural methods follows later in Lecture Part VIII.

Classification and Regression

NLP using Supervised Classification and Regression

Feature-based text classification (regression analog)

- Supervised classification based on features of texts
- 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 $y : X \to C$



Input texts

Text preprocessing

Feature computation

Vector classification

One class per text

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.

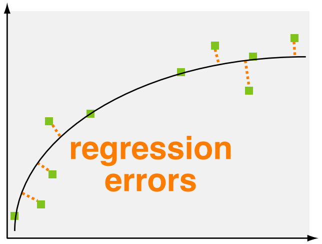
Classification and Regression

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 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 → "negative", 3 → discard, 4–5 → "positive"

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

1000 negative, 600 neutral, 800 positive → 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 the negative class

- What is seen as a negative instance is a design decision.
- This 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

“[tim]$_{PER}$ works in [cupertino]$_{LOC}$. [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
- 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?

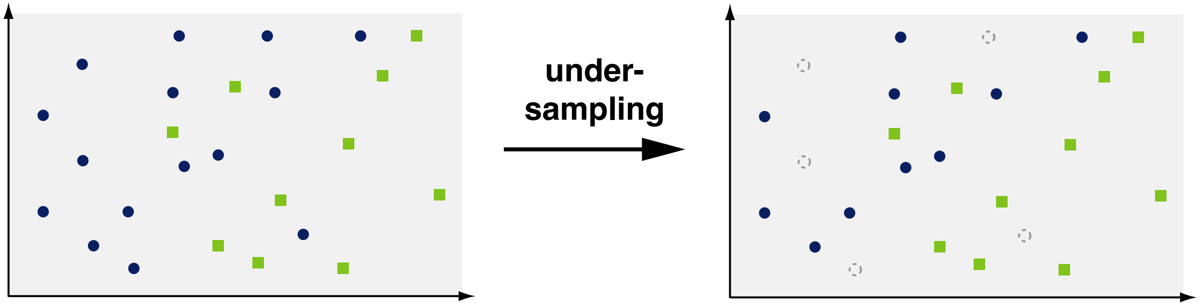
- Some optimization procedures can penalize wrong predictions more for minority instances than for majority instances.
- This is the more sound but also more complex way of preventing bias.

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.

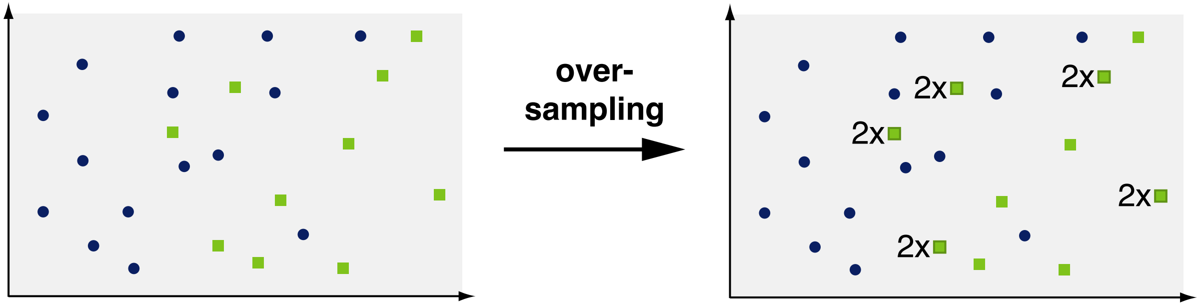
Dataset Preparation

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 via 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 some instances is artificially boosted, which may make features discriminative that are actually noise.

Supervised Classification

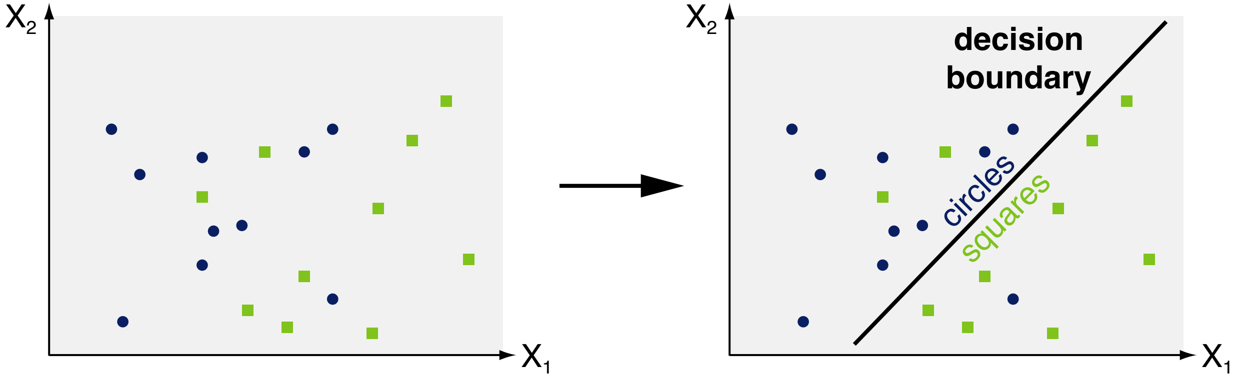
Supervised Classification

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 $X \to C$ 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

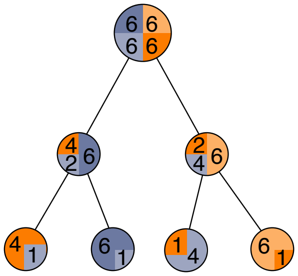
Classification Algorithms

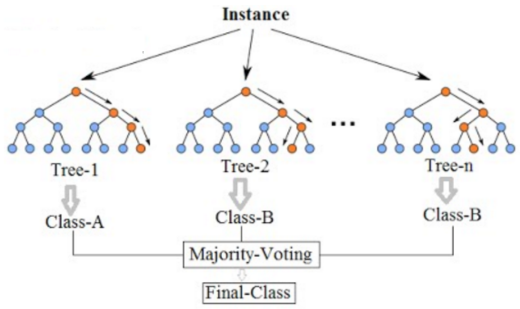
Selected classification algorithms

- 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.

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

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





- Support vector machine. Maximize the margin between classes.
- Neural network. Learn complex functions from features.

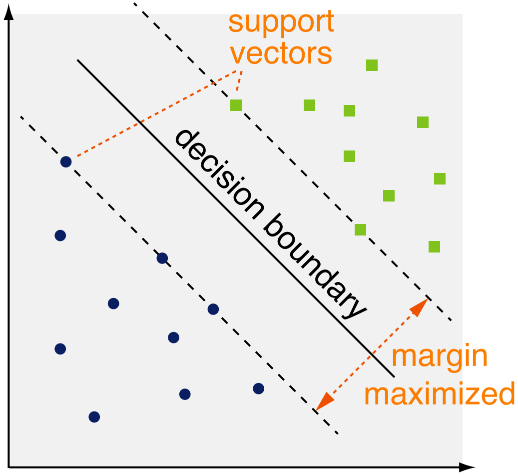
Focus on support vector machines here

- 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

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 outliers, but penalize them. This always works.

Support Vector Machines

Linearly Separable Training Sets

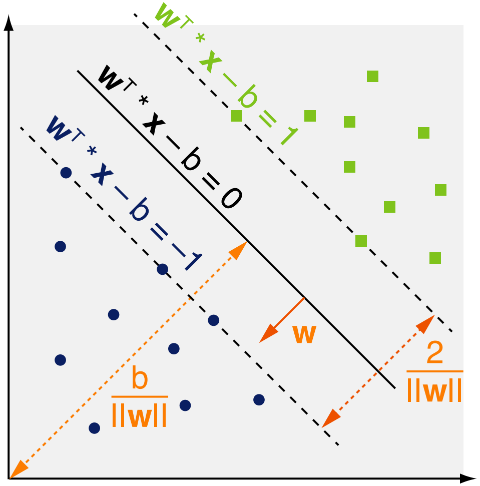
Maximum-margin decision boundary

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

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

- 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.

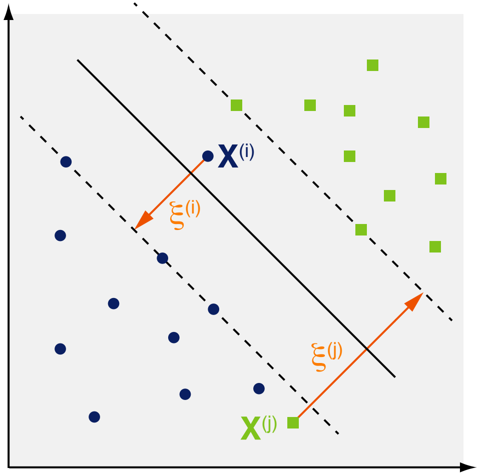
Minimization problem of hard-margin SVMs

- 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 to a higher-dimensional space where it is (better) 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

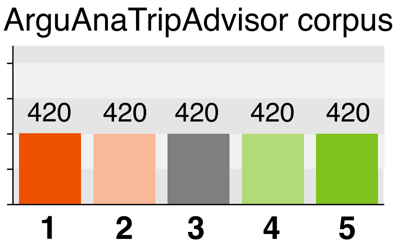
- Polynomial kernels. $K(\mathbf{x}, \mathbf{x}^{(j)}) := (1 + \mathbf{x}^T\mathbf{x}^{(j)})^d$

  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 more flexible Gaussian distribution, with additional hyperparameter γ.
- Kernel functions can also be designed for the specific data at hand.

Review Sentiment Analysis

Data (Wachsmuth et al., 2014a)


ArguAnaTripAdvisor corpus

- 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 "global" sentiment label 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

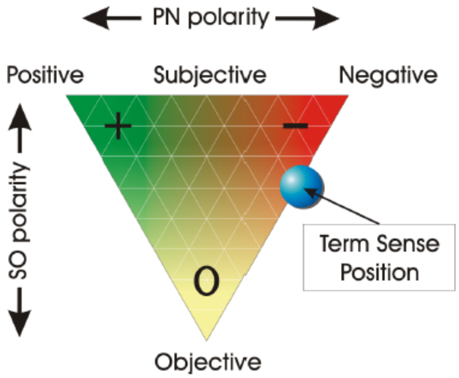
Style features

- 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

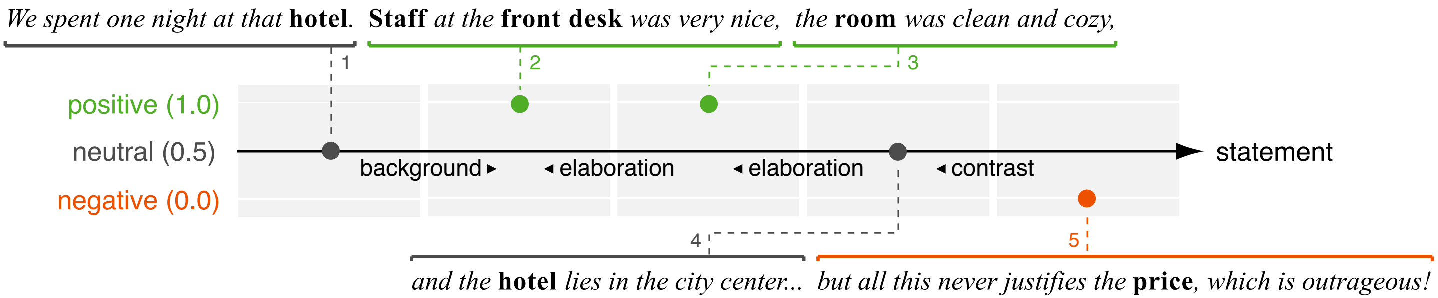
- SentiWordNet scores. Mean positivity, negativity, and objectivity of all first and average word senses in *SentiWordNet*

  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)



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!*

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)

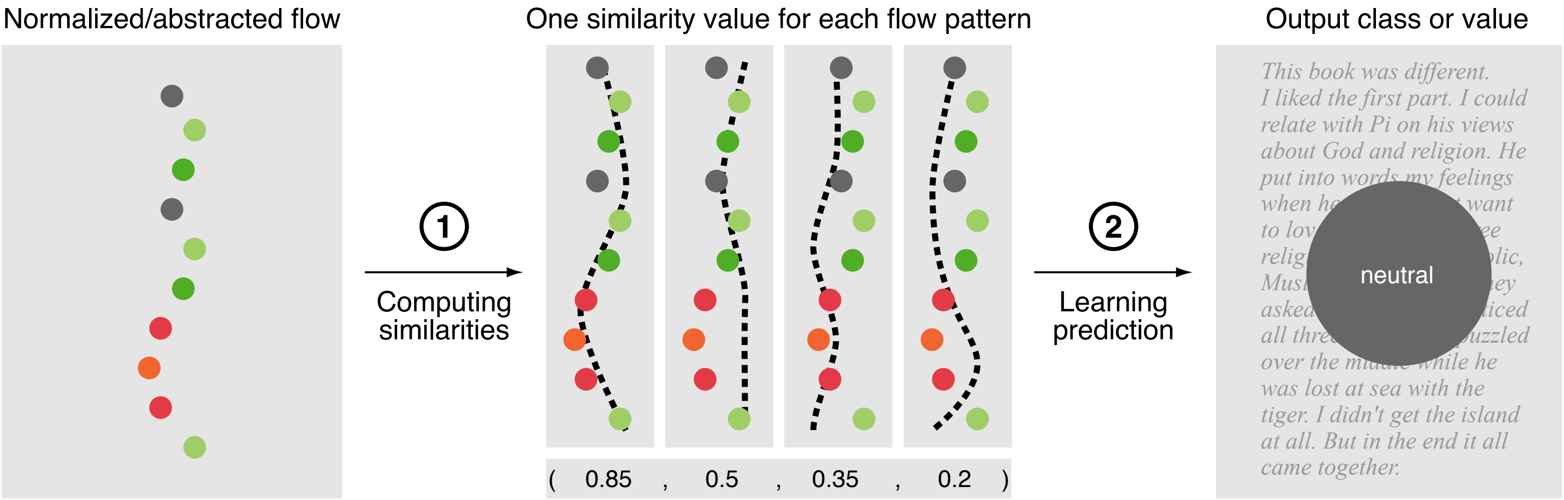
background(neutral, positive) 0.25 elaboration(positive, positive) 0.25 ...

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

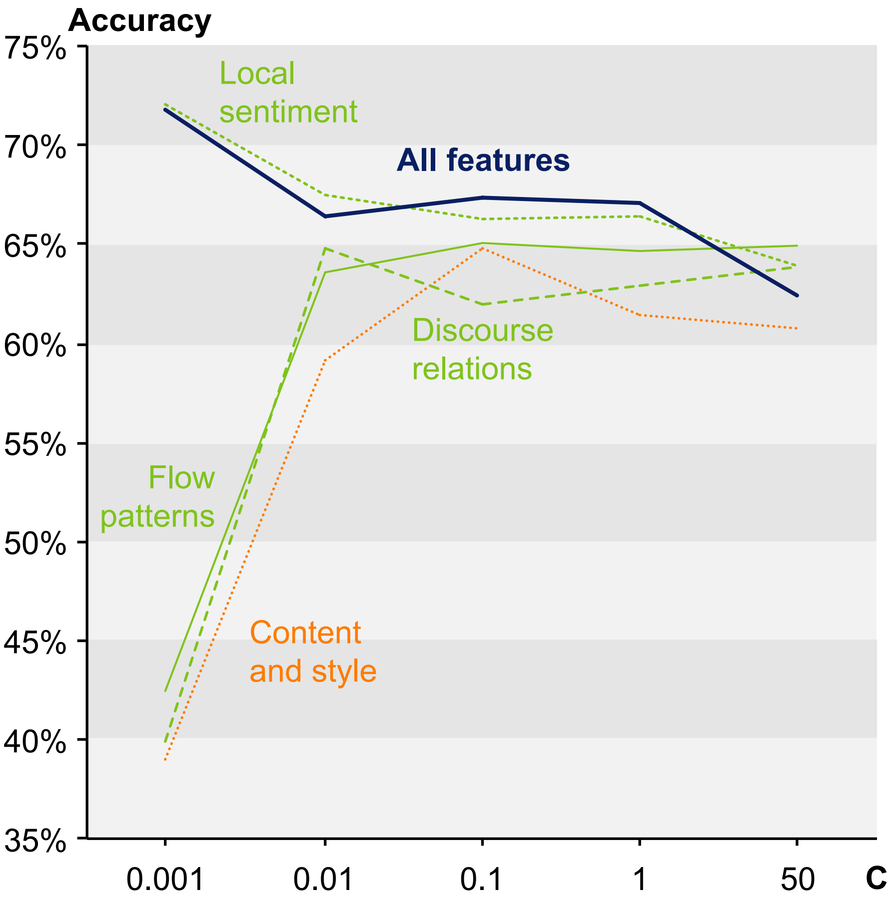
Experimental setup

- 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
- Combination of features. Works best, indicating they are complimentary
- Sentiment flow patterns. Impact more visible across domains

  This will be demonstrated in Lecture Part IX.

- Particularly the 5-class accuracy seems insufficient.
- Classification misses to model the ordinal relation between classes.

Supervised Regression

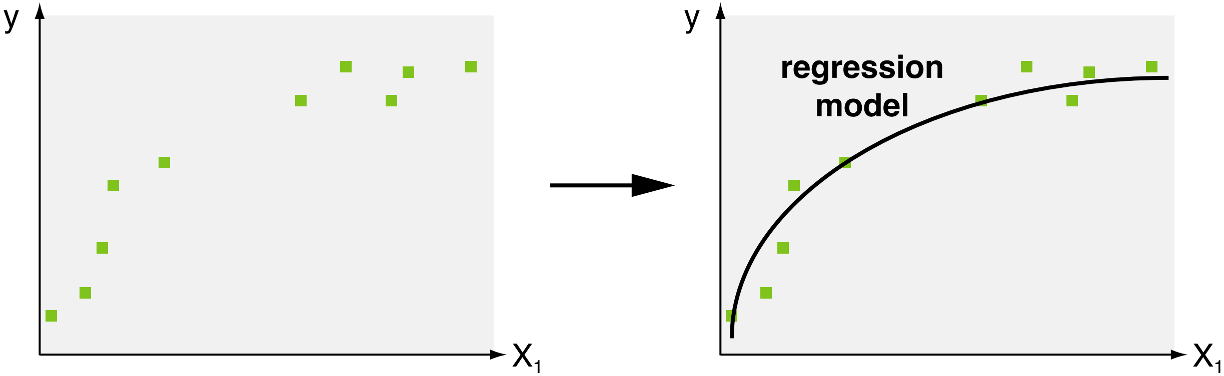
Supervised Regression

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



Application phase (prediction)

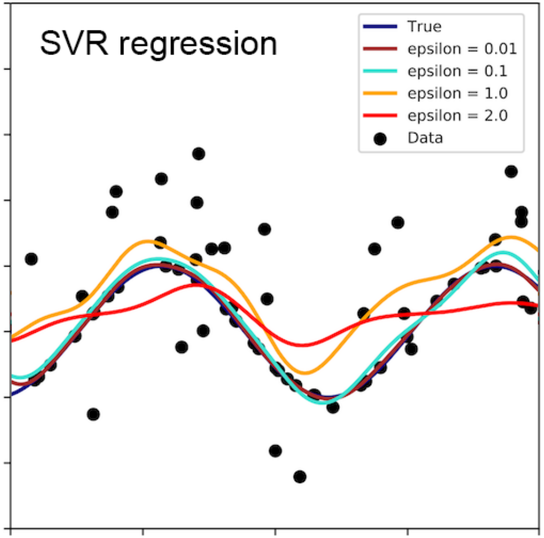
- Input. A set of unknown instances $\mathbf{x}^{(i)}$ without output value
- Output. The predicted output value $y(\mathbf{x}^{(i)})$ for each instance

Supervised Regression

Regression Algorithms

Selected supervised regression algorithms

- Linear regression. Predict output values using a learned linear function.
- Neural network. Learn complex functions on features
- Support vector regression. Maximize the flatness of a regression model.



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:

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

- 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 deviation of the predictions $y(\mathbf{x}^{(i)})$ from the correct values $y^{(i)}$

Loss function in linear regression

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

Linear Regression

Optimization

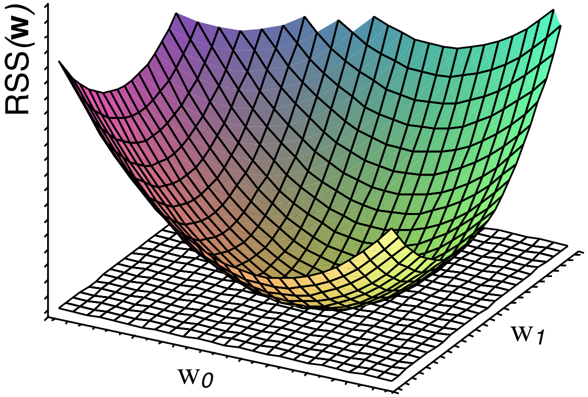
Residual sum of squares (RSS)

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

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

- 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:

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

- 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.

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

- 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 ← getMRandomValues(-1, 1)
for int l ← 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 ← $\frac{\partial}{\partial w_j}((y^{(i)} - y(\mathbf{x}^{(i)})^2 + \frac{\lambda}{n} \cdot \sum_{j=0}^{m} w_j^2)$
        $\mathbf{w} \leftarrow \mathbf{w} - \eta$ · gradient
return w
```

Impact of hyperparameters

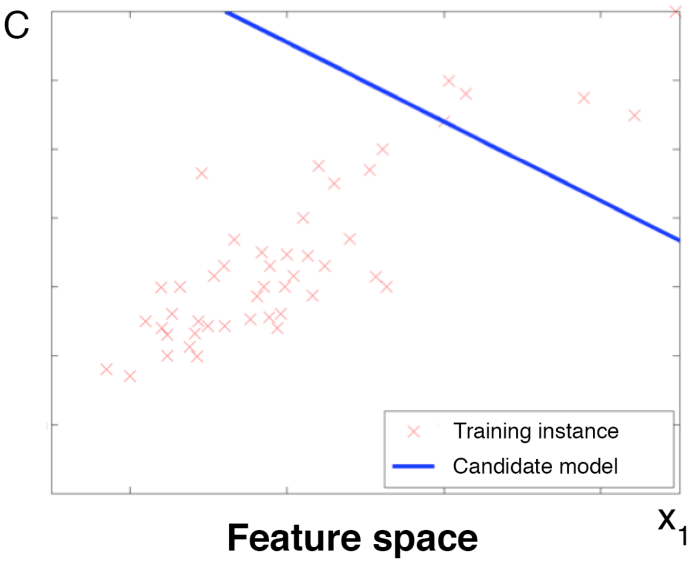
- Number of epochs. The higher k, the more y will fit the data.
- Learning rate. Higher η may speed up learning, but may fail to optimize.

Linear Regression

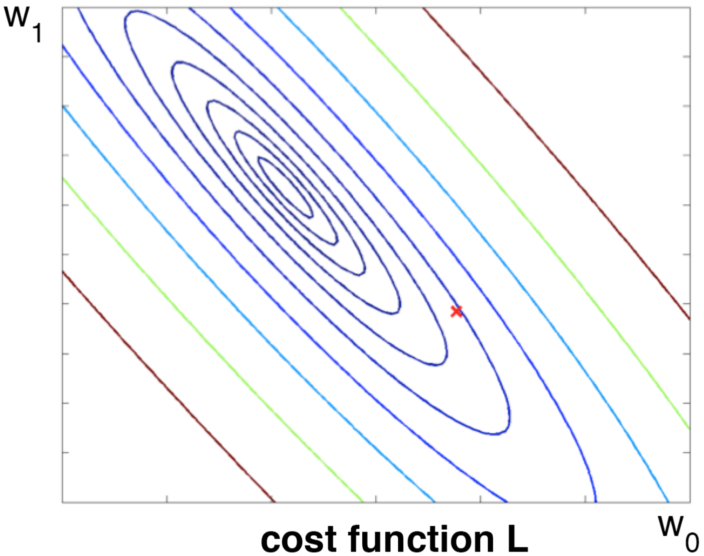
Gradient Descent: Example (1 out of 9)

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

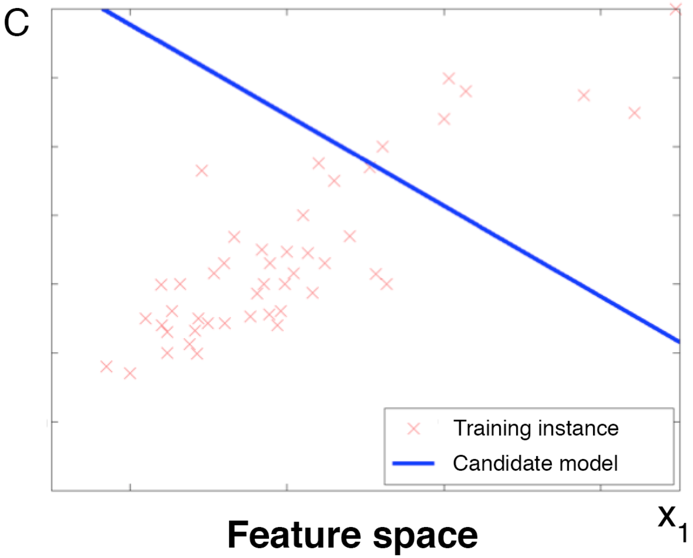
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

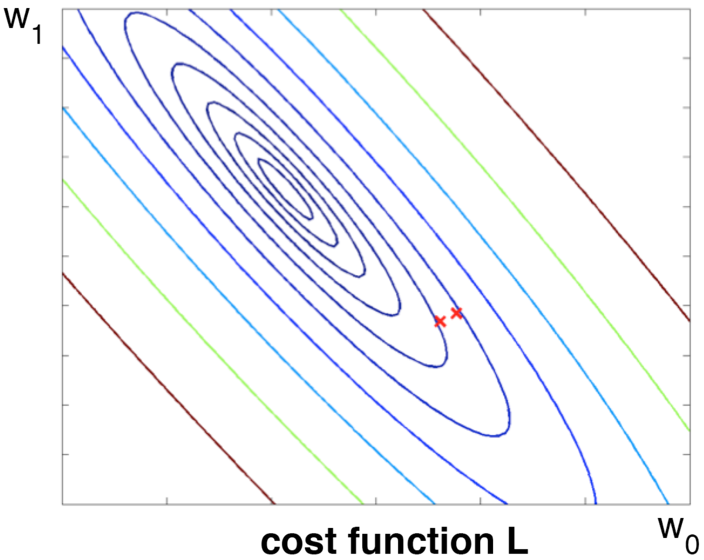
Gradient Descent: Example (2 out of 9)

Learning of a linear regression model

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



Feature space



cost function L

Note on example

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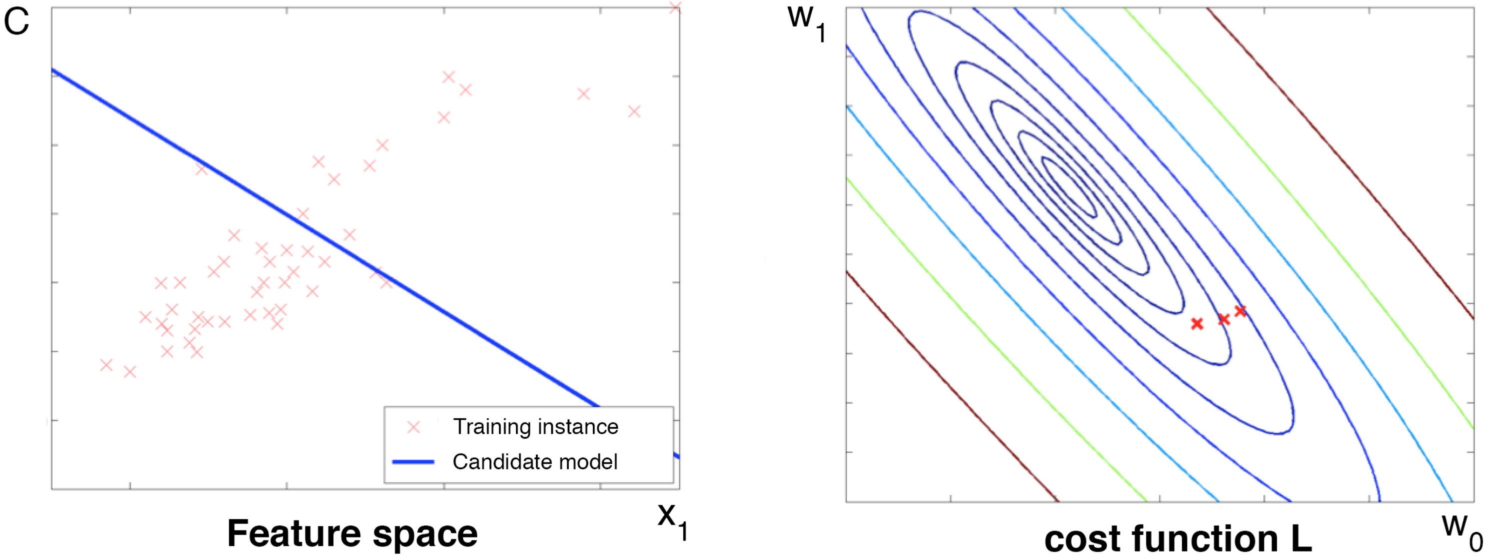
- Each pair w_0, w_1 defines one candidate model.

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

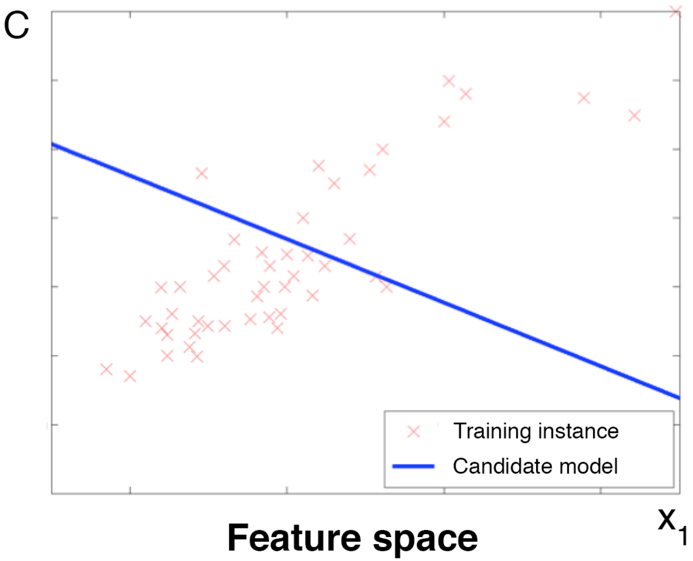
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

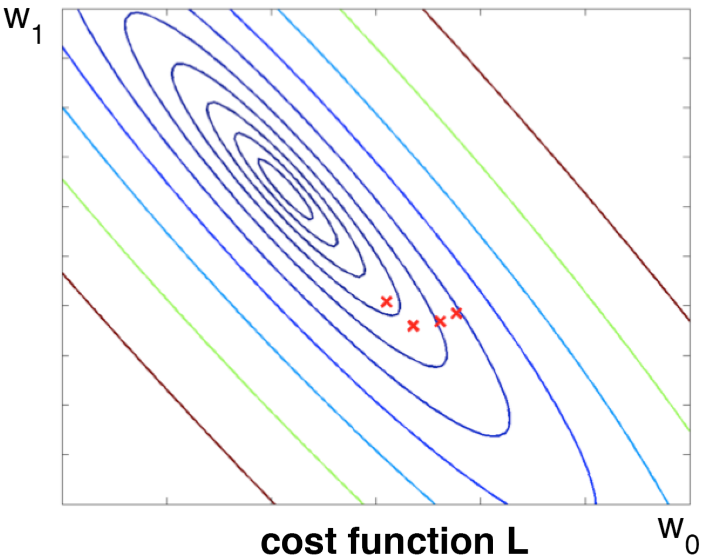
Gradient Descent: Example (4 out of 9)

Learning of a linear regression model

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



Feature space



cost function L

Note on example

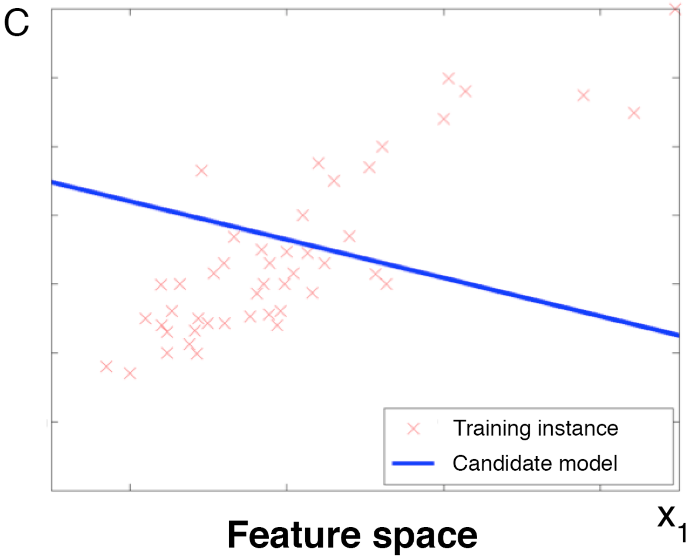
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

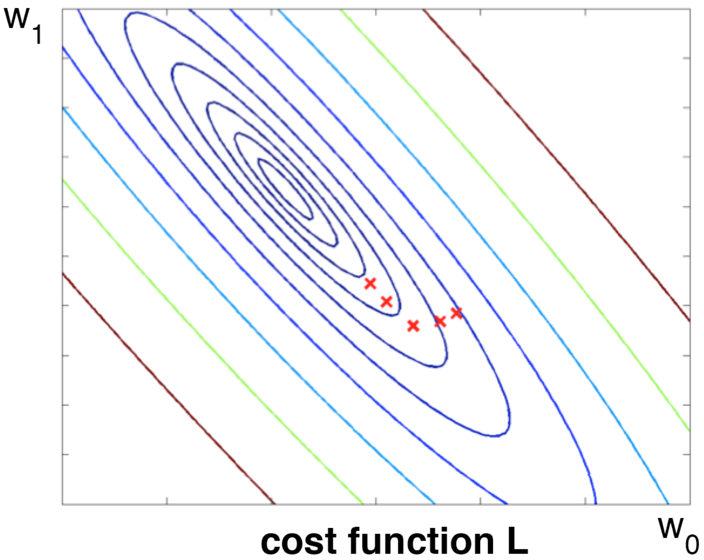
Gradient Descent: Example (5 out of 9)

Learning of a linear regression model

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



Feature space



cost function L

Note on example

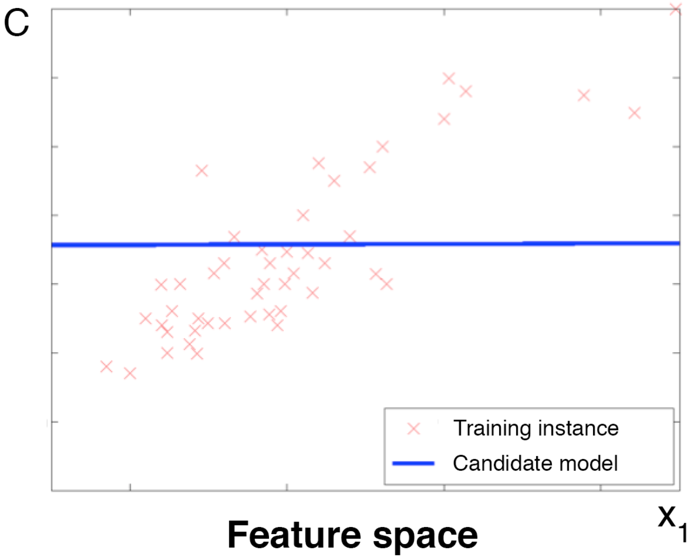
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

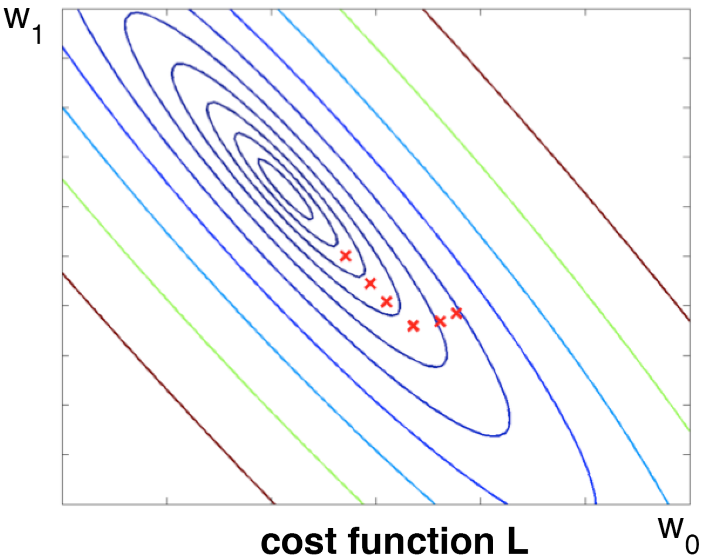
Gradient Descent: Example (6 out of 9)

Learning of a linear regression model

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



Feature space



cost function L

Note on example

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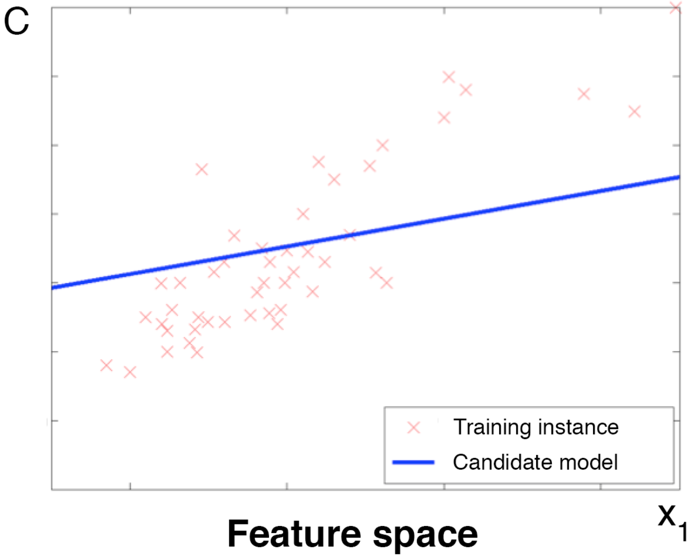
- Each pair w_0, w_1 defines one candidate model.

Linear Regression

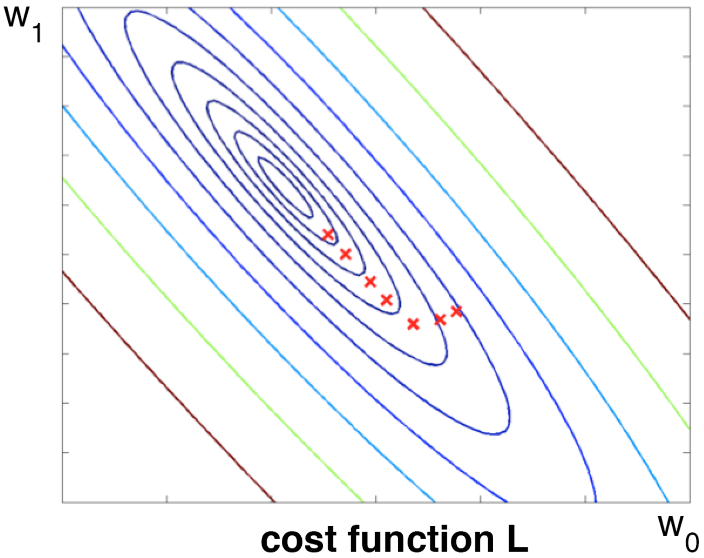
Gradient Descent: Example (7 out of 9)

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

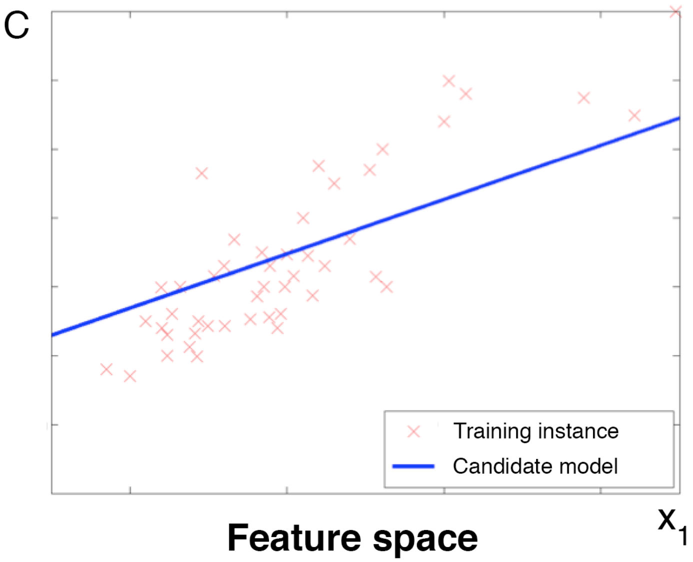
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

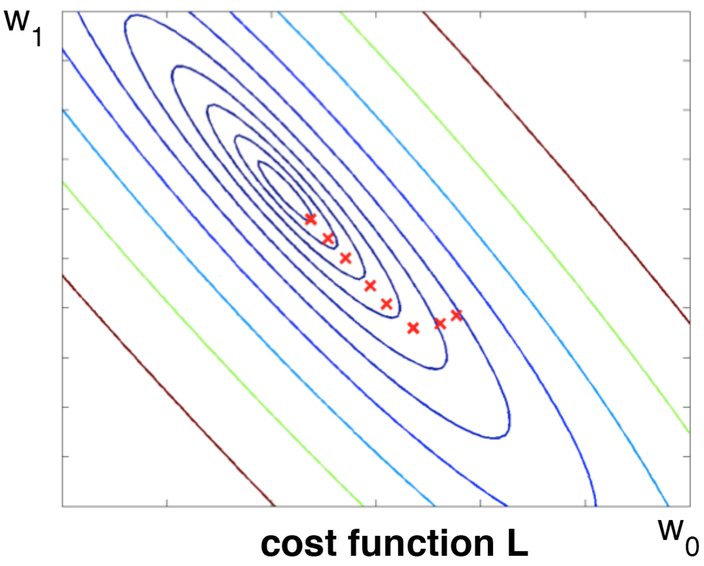
Linear Regression

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

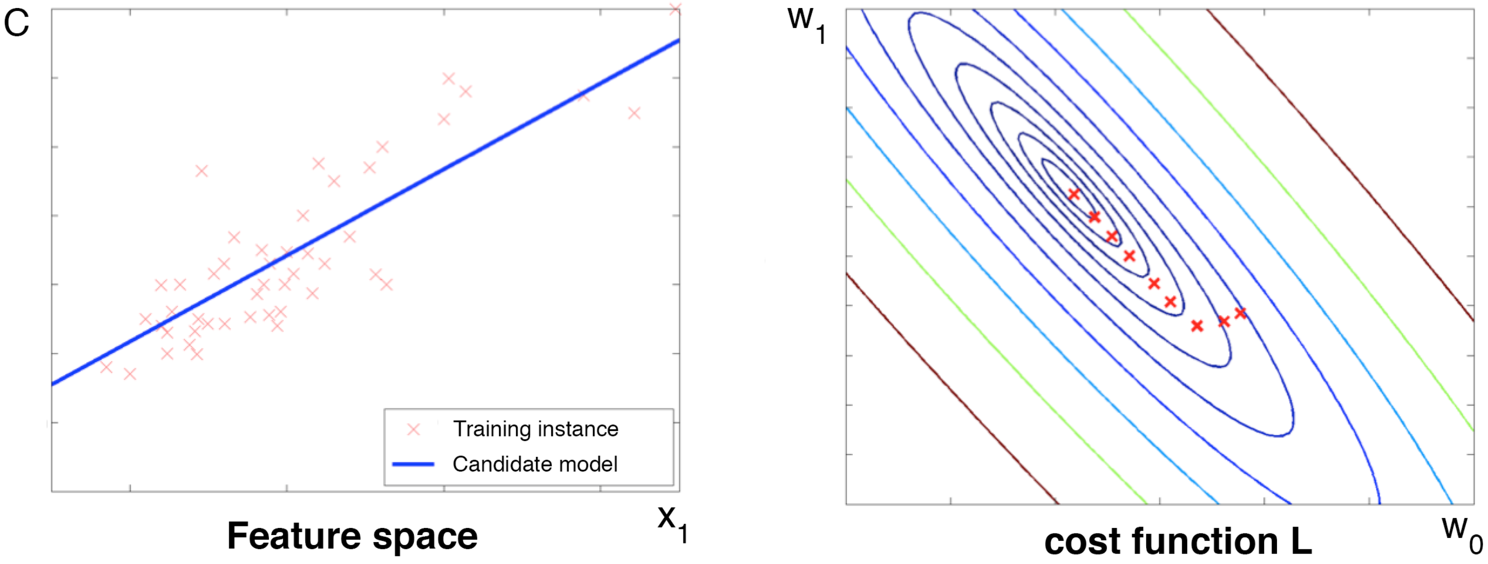
- A regression model $y = w_0 + w_1 \cdot x_1$ is learned for one single feature x_1.
- Each pair w_0, w_1 defines one candidate model.

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)

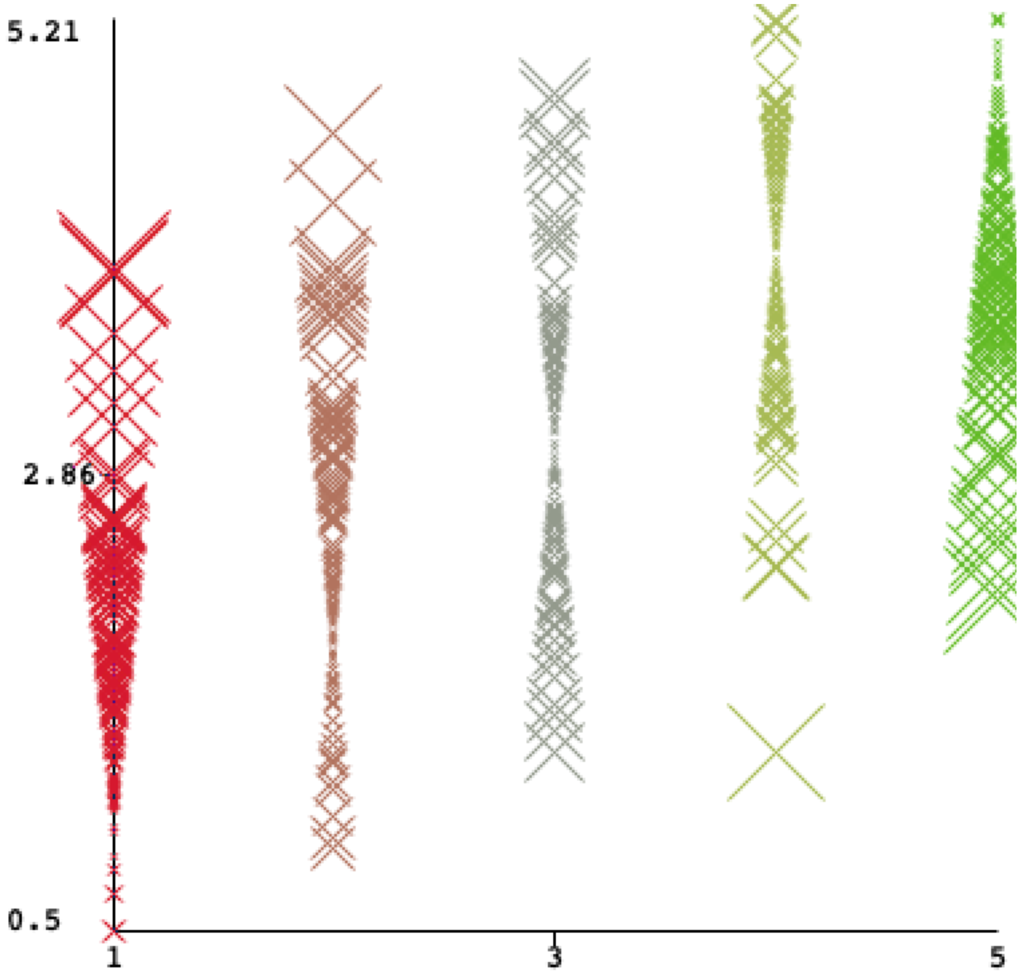
Visualization

- 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



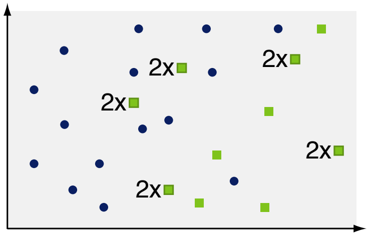
(cross size reflects regression error)

Conclusion

Conclusion

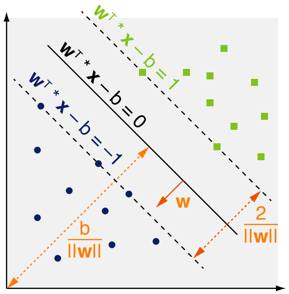
NLP using classification and regression

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



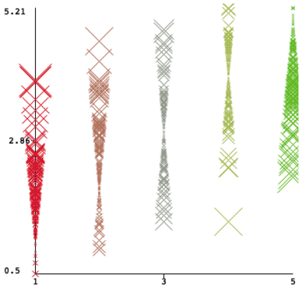
Supervised classification

- 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.



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Some content and examples taken from

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- **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.

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- **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.