

Data Mining and Machine Learning: Techniques and Algorithms

Eneldo Loza Mencía

eneldo@ke.tu-darmstadt.de



Knowledge Engineering Group, TU Darmstadt



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Outline



- Preprocessing
 - Vector space model
 - Text preprocessing pipeline
 - Similarity of Documents
- Text Classification Algorithms
 - Rocchio Classifer
 - Naïve Bayes classifier
 - Linear classification
 - Support Vector Machines
- Occam's Razor and Overfitting Avoidance



Text Classification: Examples

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Text Categorization: Assign (class) labels to each document

- Labels are most often topics such as Yahoo-categories
 - •e.g., "finance," "sports," "news::world::asia::business"
- Labels may be genres
 - e.g., "editorials" "movie-reviews" "news"
- Labels may be opinion
 - e.g., "like", "hate", "neutral"
- Labels may be binary concepts
 - •e.g., "interesting-to-me" : "not-interesting-to-me"
 - ■e.g., "spam" : "not-spam"
 - •e.g., "contains adult language" :"doesn't"

More than one learning task could be defined over the same documents



News categorization



<?xml version="1.0" encoding="iso-8859-1" ?> <newsitem itemid="477551" id="root" date="1997-03-31" xml:lang="en"> <title>SPAIN: Spain's Banesto issue \$150 mln in subordinated loaN.</title> <headline>Spain's Banesto issue \$150 mln in subordinated loaN.</headline> <dateline>MADRID 1997-03-31</dateline> <text> Sanco Espanol de Credito Banesto said on Monday it issued \$150 million in subordinated 10-year 7.5 percent debt. Lead manager is Lehman Brothers. The statement added that this is the first international issue Banesto has launched since 1993. Banco Santander has a 50 percent stake in Banesto. - Madrid Newsroom, + 341 585 8340 </text> **Funding/Capital** <code code = "C17"> <editdetai attributior ="Reuters BIP Coding Group" action="confirmed" date="1997-03-31"/> </code> Bonds/Debt issues <code code="C172"> <editdetai attributior ="Reuters BIP Coding Group" action="confirmed" date="1997-03-31"/> </code> Corporate/Industrial <code code="CCAT"> <editdetai attributior ="Reuters BIP Coding Group" action="confirmed" date="1997-03-31"/> </code>

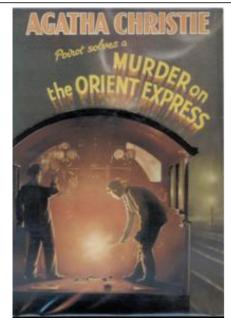
The Reuters RCV1 dataset has in total 103 assignable news categories for 804.414 news articles



Book Scenario



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Summary: Returning from an important case in Syria, Hercule Poirot boards the Orient Express in Istanbul. The train is unusually crowded for the time of year. Poirot secures a berth only with ...

Text: It was five o'clock on a winter's morning in Syria. ... "Then," said Poirot, "having placed my solution before you, I have the honour to retire from the case."

Author:
Agatha Christie
Genres:
Crime, Mystery, Thriller
Subjects (LOC):
Private Investigators, Orient Express,
Keywords:
mystery, fiction, crime, murder, british,
poirot,
Rate:
4 of 5 stars
Epoch:
1930ies
Country:
UK

. . .



The Vector Space Model



• Origin:

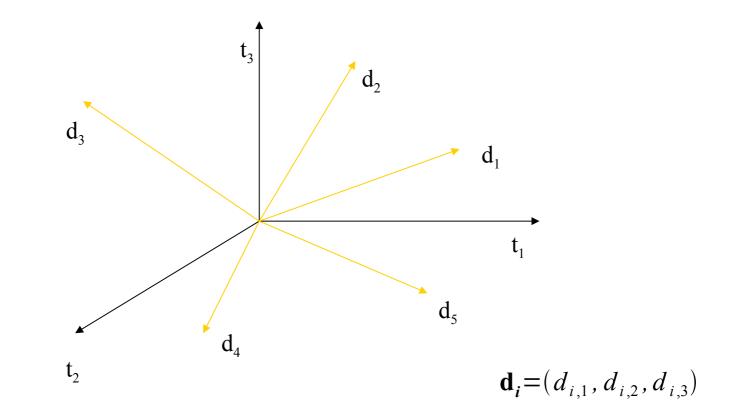
Information Retrieval, SMART system (Salton et al.)

- Basic idea:
 - A document is regarded as a vector in an *n*-dimensional space
 - I dimension for each possible word (*feature, token*)
 - the value in each dimension is (in the simplest case) the number of times the word occurs in the document (term frequency – TF)
 - a document is a linear combination of the base vectors
 - Inear algebra can be used for various computations





Intuition



Postulate: Documents that are "close together" in the vector space talk about the same things.



Document Representation



- The vector space models allows to transform a text into a document-term table
- In the simplest case
 - Rows:
 - training documents
 - Columns:
 - words in the training documents
 - More complex representation possible
- Most machine learning and data mining algorithms need this type of representation
 - they can now be applied to, e.g., text classification



Document Representation



CS414: Systems Programming and Operating Systems

CS415: Practicum in Operating Systems

Selections that display this symbol 🖻 correspond to postcript documents.

How to hand in phase 3 of HOCA

Course Information

Course Schedule (Last Changed: 9/14/95)

<u>Groups</u>

Handouts

- Handout 1
 - <u>GIF Format</u>
 - Postcript Format
- Penne ai Broccoli -- 9/4/95

Questions and Answers (Last Changed: 10/23/95)

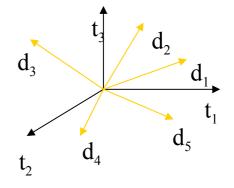
The CHIP Computer System

- <u>Console Window Example</u>
- Using CHIP
- <u>Chip Console Tutorial</u>
- Principles of Operation
- <u>Configuration File</u>

The HOCA Operating System

The HOCA Operating System Specifications

	baseball	specs	graphics	 quicktime	computer
D1	0	3	0	 2	0
D2	1	2	0	 0	0
D3	0	0	2	 1	5





Text Preprocessing Pipeline Tokenization



- Identification of basic document entities ("words")
 typically performed in indexing phase
- Issues in tokenization:
 - •Finland's capital \rightarrow

Finland? Finlands? Finland's?

- ■Hewlett-Packard → Hewlett and Packard as two tokens?
 - *State-of-the-art*: break up hyphenated sequence.
 - co-education ?
 - the hold-him-back-and-drag-him-away-maneuver ?
 - It's effective to get the user to put in possible hyphens
- San Francisco: one token or two? How do you decide it is one token?

Text Preprocessing Pipeline



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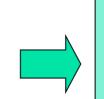


Text Preprocessing Pipeline Stemming



- Reduce terms to their "roots" before indexing
- "Stemming" suggest crude affix chopping
 - Ianguage dependent
 - e.g., automate(s), automatic, automation all reduced to automat.
- Stemming may reduce number of terms by ~35%

for example compressed and compression are both accepted as equivalent to compress.



for exampl compress and compress ar both accept as equival to compress



Text Preprocessing Pipeline Stop Words



- Remove most frequent words in the (English) language
 - a, about, above, across, after, afterwards, again, against, all, almost, alone, along, already, also, although, always, am, yet, you, your, yours, yourself, yourselves
- Assumption:
 - These words occur in all documents and are irrelevant for retrieval
- Rule of 30: ~30 words account for ~30% of all term occurrences in written text
- Stop lists used to be popular, but are sometimes avoided, because important information may be lost
 - polysemous words: "can" as a verb vs. "can" as a noun
 - phrases: "Let it be", "To be or not to be", pop group "The The"
 - relations: "flights to London" vs. "flights from London"



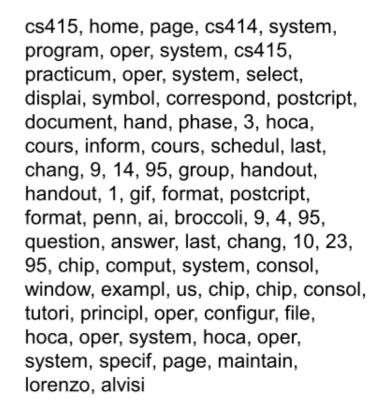
Text Preprocessing Pipeline



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Text Preprocessing Pipeline Term Weighting

Different ways for computing the d_{ii} :

- Boolean
 - possible values are only
 - 0 (term does not occur in document)
 - 1 (term does occur)
- Term Frequency (TF)
 - term is weighted with the frequency of its occurrence in the text
- Term Frequency Inverse Document Frequency (TF-IDF)
 - Idea: A term is characteristic for a document if
 - it occurs frequently in this document (TF)
 - occurs infrequently in other documents (IDF)
 - divides TF by DF (or multiplies TF with IDF)

$$d_{i,j} = \begin{cases} 0 \text{ if } t_j \notin \mathbf{d}_i \\ 1 \text{ if } t_j \in \mathbf{d}_i \end{cases}$$

$$d_{i,j} = TF(\mathbf{d}_i, t_j)$$

 $d_{i,j} = \frac{TF(\mathbf{d}_i, t_j)}{DF(t_j)} = TF(\mathbf{d}_i, t_j) \cdot IDF(t_j)$

Text Preprocessing Pipeline



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Text Preprocessing Pipeline Feature Subset Selection



- Using each word as a feature results in tens, hundreds, or thousands of thousands of features
- Many of them are
 - irrelevant
 - redundant
- Removing them can
 - increase efficiency
 - prevent overfitting
- Feature Subsect Selection techniques try to determine appropriate features automatically





Text Preprocessing Pipeline Feature Subset Selection



Unsupervised Feature Subset Selection

- Using domain knowledge
 - some features may be known to be irrelevant, uninteresting or redundant
- Frequency-based selection
 - select features based on statistical properties
 - e.g. IDF: hypothesis that terms with high document frequency are more important (except stop words)

Supervised Feature Subset Selection

- Filter approaches
 - compute some measure (e.g. statistical) for estimating the ability to discriminate between classes
- Wrapper approaches
 - each search subset is tried with the learning algorithm



Text Preprocessing Pipeline



S415: Practicum in Operating System



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Text Preprocessing Pipeline



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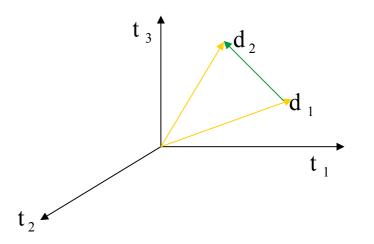
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Similarity of Document Vectors

- First Idea:
 - Distance between d₁ and d₂ is the length of the vector |d₁ - d₂| (measured with Euclidean distance)
- Why is this not a great idea?



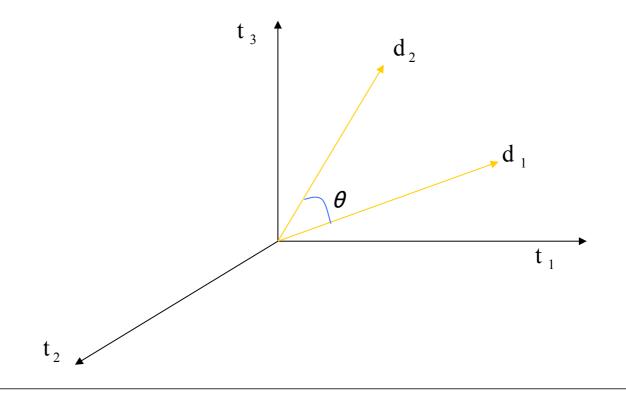
- Short documents would be more similar to each other by virtue of length, not topic
- \rightarrow We have to deal with the issue of length normalization
- explicit normalization (as, e.g., through normalized TF)
- Alternative approaches?
 - We can also implicitly normalize by looking at angles between document vectors instead



Cosine similarity



• Distance between vectors \mathbf{d}_1 and \mathbf{d}_2 *captured* by the cosine of the angle θ between them.

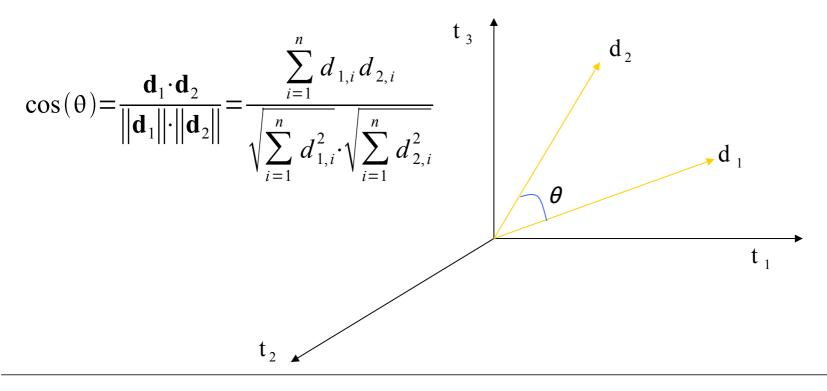




Cosine similarity



• Distance between vectors \mathbf{d}_1 and \mathbf{d}_2 *captured* by the cosine of the angle θ between them.

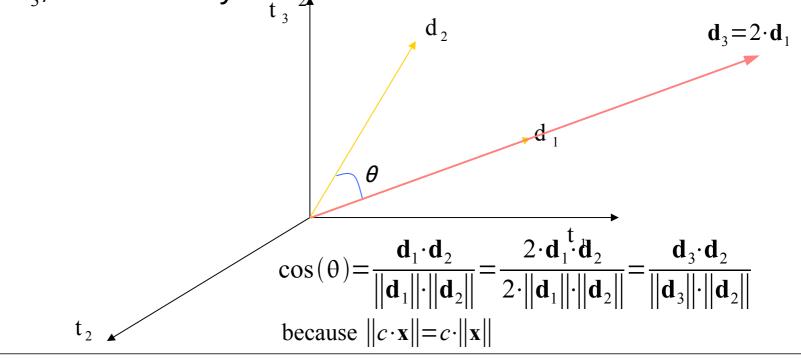




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Cosine similarity

- Distance between vectors \mathbf{d}_1 and \mathbf{d}_2 *captured* by the cosine of the angle θ between them.
- the distance is invariant to re-scaling the vector
 - e.g., if two copies of document \mathbf{d}_1 are concatenated to a new document \mathbf{d}_3 , the similarity to \mathbf{d}_2 remains the same

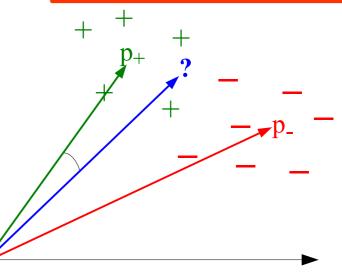


Rocchio Classifier (Nearest Centroid Classifier)



- based on ideas for Rocchio Relevance Feedback
- compute a prototype vector \mathbf{p}_c for each class c
 - average the document vectors for each class
- classify a new document according to distance to prototype vectors instead of documents
 O: Imagine simple set
- assumption:
 - documents that belong to the same class are close to each other (form one cluster)

Q: Imagine simple scenarios where Rocchio would not work!





Bag of Words Model



- assumes that the document has been generated by repeatedly drawing one word out of a bag of words
 - like drawing letters out of a Scrabble-bag, but with replacement
- words in the bag may occur multiple times, some more frequently than others
 - Iike letters in a Scrabble-bag
 - each word w is drawn with a different probability

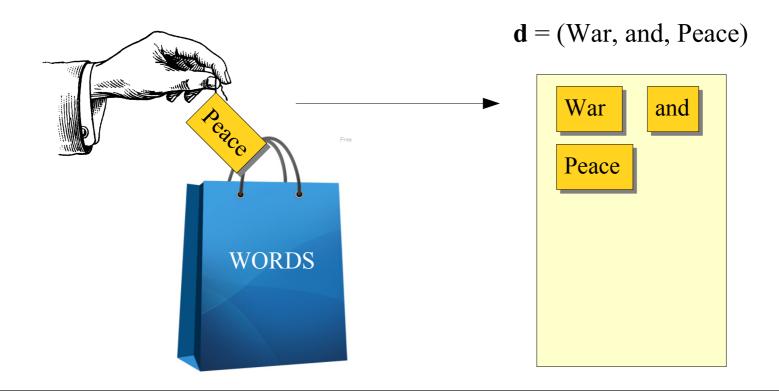




Probabilistic Document Model



■ Repeatedly drawing from the bag of words results in a sequence of randomly drawn words → a document ■ $\mathbf{d} = (t_1, t_2, ..., t_{|\mathbf{d}|})$ where $t_j = w_{k_j} \in W$

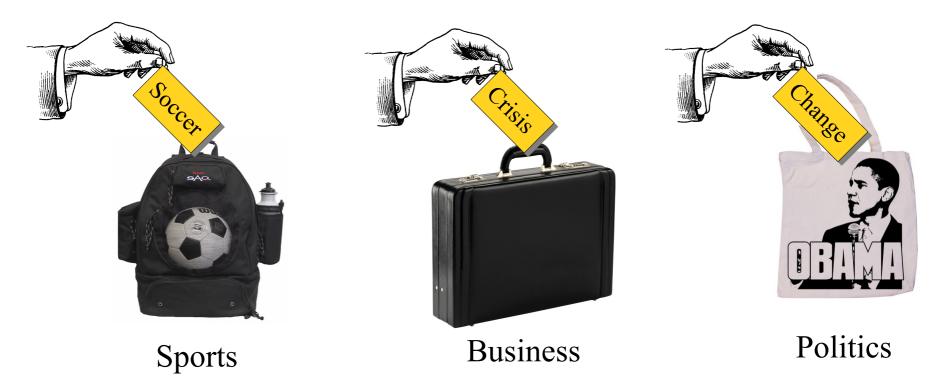




Class-conditional Probabilities



Different classes have different bags of words



- probabilities of words in different classes are different
 - the sports bag contains more sports words, etc.
 - Formally: $p(w|c_i) \neq p(w|c_j) \neq p(w)$



Independence Assumption



- the probability that a word occurs does not depend on the context (the occurrence or not-occurrence of other words)
 - it only depends on the class of the document
- In other words:
 - Knowing the previous word in the document (or any other word) does not change the probability that a word occurs in position t_i $p(t_i = w_{k_i} | t_j = w_{k_i}, c) = p(t_i = w_{k_i} | c)$

we will write this shorter as

$$p(t_i|t_j, c) = p(t_i|c)$$

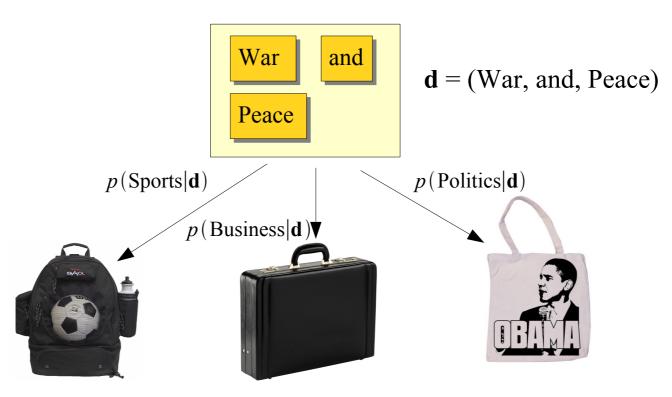
- Important:
 - the independence assumption does not hold in real texts!
 - but it turns out that it can still be used in practice



Probabilistic Text Classification



- Answer the question:
 - From which bag was a given document d generated?



-Answer is found by estimating the probabilities $p(c|\mathbf{d})$



Simple Naïve Bayes Classifier for Text (Mitchell 1997)

- a document is a sequence of n terms
- Apply Independence Assumption: • $p(t_i|c)$ is the probability with which the word $t_i = w_{i_i}$ occurs in documents of class c
- Naïve Bayes Classifier
 - putting things together:

$$c = \arg\max_{c} \prod_{i=1}^{|\mathbf{d}|} p(t_i | c) p(c)$$





Estimating Probabilities



 $p(t_i = w | c) = \frac{n_{w,c}}{\sum n_{w,c}}$

 $n_{w,c} = \sum_{\mathbf{d} \in c} n(\mathbf{d}, w)$

- Estimate for prior class probability p(c)
 - $\hfill \hfill \hfill$
- Word probabilities can be estimated from data
 - estimated from fraction of document positions in each class on which the term occurs
 - put all documents of class c into a single (virtual) document
 - compute the frequencies of the words in this document
- Straight-forward approach:
 - estimate probabilities from the frequencies in the training set
 - word w occurs n(d,w) times in document d
 - •What happens if there is a new word in a test document? Solutions?



Estimating Probabilities Laplace Correction

- Straight-forward approach:
 - estimate probabilities from the frequencies in the training set
 - word w occurs n(d,w) times in document d

Problem:

- test documents may contain new words
- those will be have estimated probabilities 0
- assigned probability 0 for all classes
- Smoothing of probabilities:
 - basic idea: assume a prior distribution on word probabilities

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 e.g., Laplace correction assumes each word occurs at least once in a document

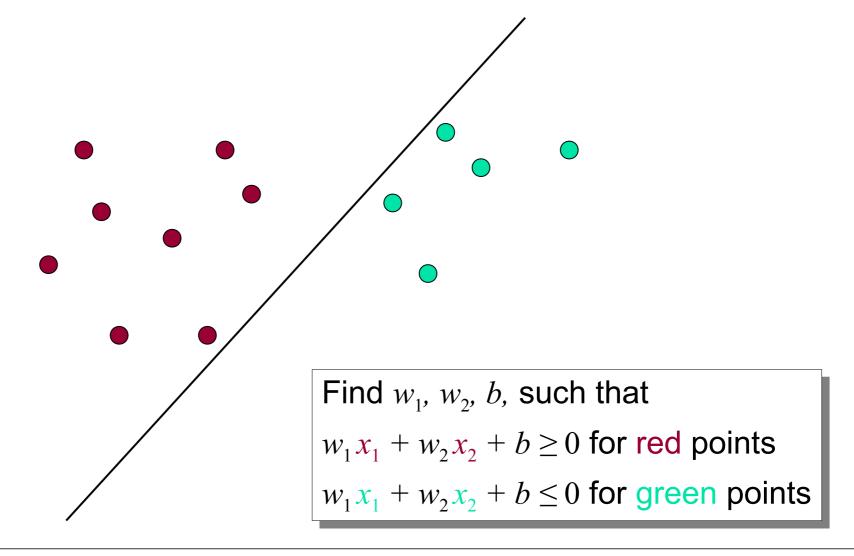
$$p(t_i = w | c) = \frac{n_{w,c} + 1}{\sum_{w \in W} (n_{w,c} + 1)} = \frac{n_{w,c} + 1}{\sum_{w \in W} n_{w,c} + |W|}$$

$$p(t_i = w | c) = \frac{n_{w,c}}{\sum_{w \in W} n_{w,c}}$$
$$n_{w,c} = \sum_{\mathbf{d} \in c} n(\mathbf{d}, w)$$





Finding a Linear Decision Boundary





Fitting a linear decision boundary

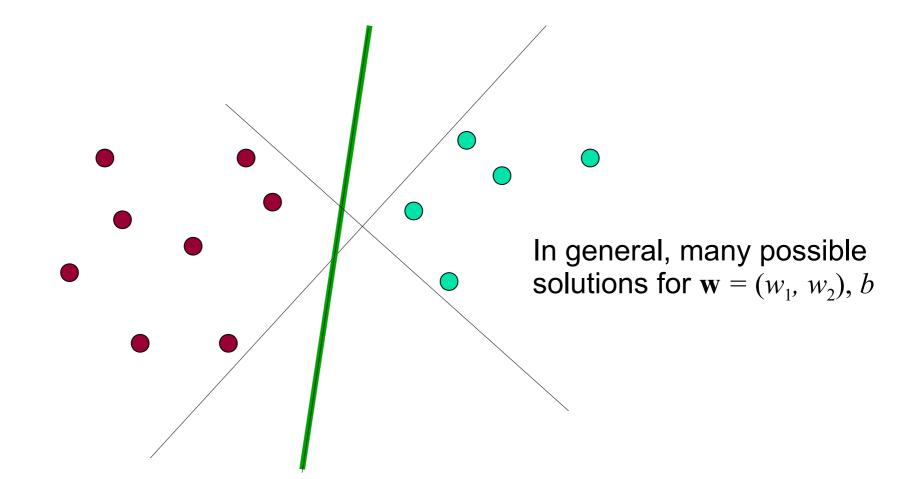


- Discriminative approach
 - $\hfill \hfill \hfill$
 - statistical approaches:
 - perceptrons (neural networks with a single layer)
 - logistic regression
 - most common approach in text categorization
 - \rightarrow support vector machines





Which Hyperplane?



Intuition 1: If there are no points near the decision surface, then there are no very uncertain classifications → better

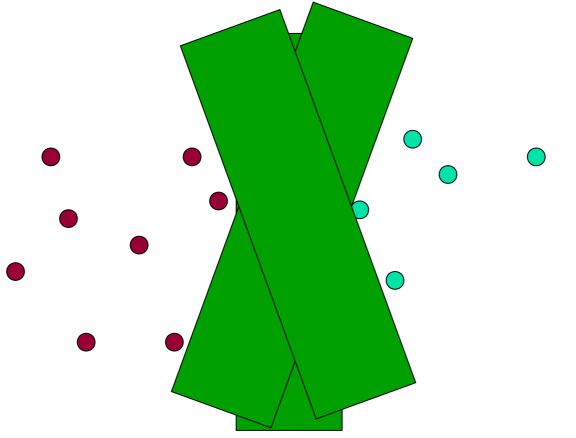
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Support Vector Machines: Intuition



 Intuition 2: If you have to place a fat separator between classes, you have less choices, and so overfitting is not so easy





Support Vector Machine (SVM)

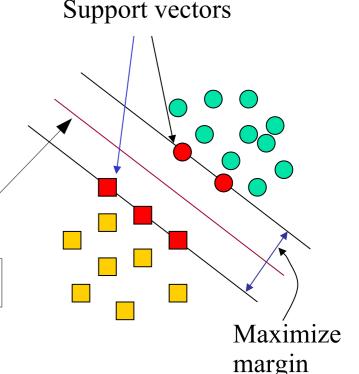


- SVMs maximize the margin around the separating hyperplane.
 - a.k.a. large margin classifiers
- The decision function is fully specified by a subset of training samples, the support vectors.

$$\mathbf{w}^T \cdot \mathbf{x}_i + b = 0$$

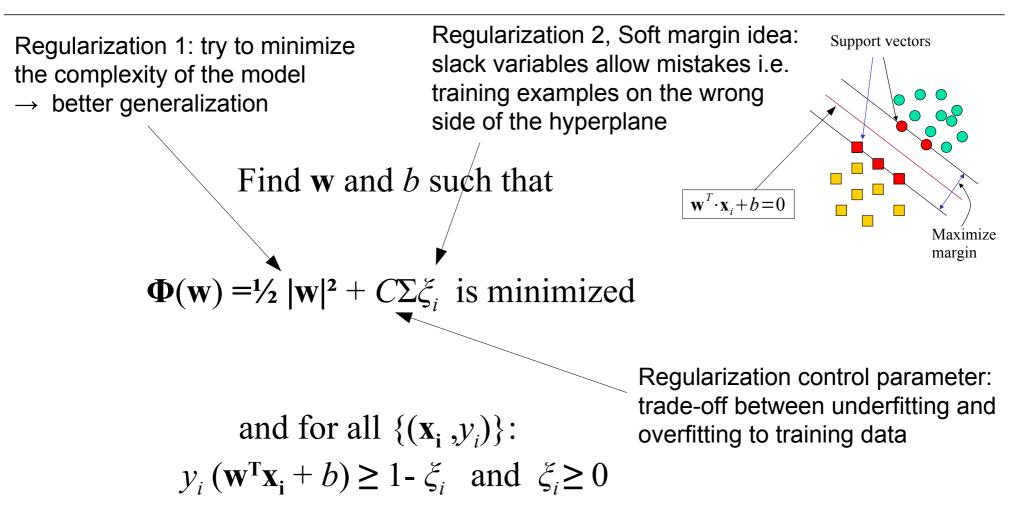
- Formalization
 - $\hfill \mathbf{w}$: normal vector to decision hyperplane
 - \mathbf{x}_i : *i*-th data point
 - y_i : class of data point *i* (+1 or -1) NB: Not 1/0
 - Classifier is:

$$f(\mathbf{x}_i) = \operatorname{sign}(\mathbf{w}^{\mathrm{T}}\mathbf{x}_i + b)$$



Support Vector Machine (SVM) Mathematics







Capacity Control Occam's Razor



Entities should not be multiplied beyond necessity. *William of Ockham (1285 - 1349)*

- Machine Learning Interpretation:
 - Among theories of (approximately) equal quality on the training data, simpler theories have a better chance to be more accurate on the test data
 - It is desirable to find a trade-off between accuracy and complexity of a model
- •(Debatable) Probabilistic Justification:
 - There are more complex theories than simple theories. Thus a simple theory is less likely to explain the observed phenomena by chance.



Capacity Control Overfitting



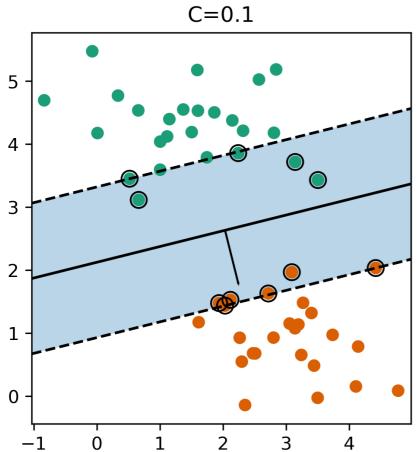
Given

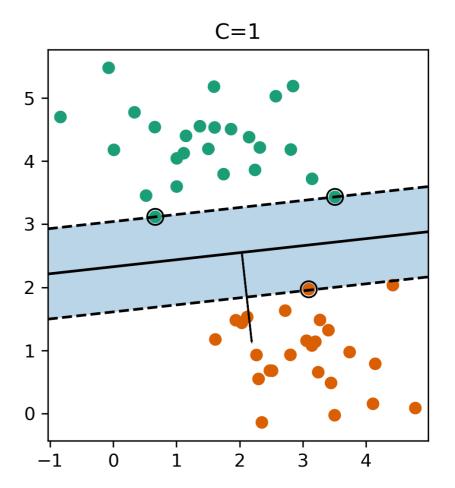
- a fairly general model class (e.g., rules)
- enough degrees of freedom (e.g., no length restriction)
- you can always find a model that explains the data
 - \rightarrow Overfitting
- Such concepts do not generalize well!
- Particularly bad for noisy data
 - Data often contain errors due to
 - inconsistent classification
 - measurement or annotation errors
 - missing values
 - some other kinds of noise
- \rightarrow Capacity control



Regularization Example for linear SVMs





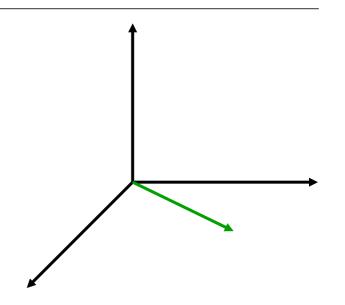


High Dimensional Data



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- Pictures like the one at right are misleading!
 - Documents are zero along almost all axes
 - Most document pairs are very far apart
 - (i.e., not strictly orthogonal, but only share very common words and a few scattered others)



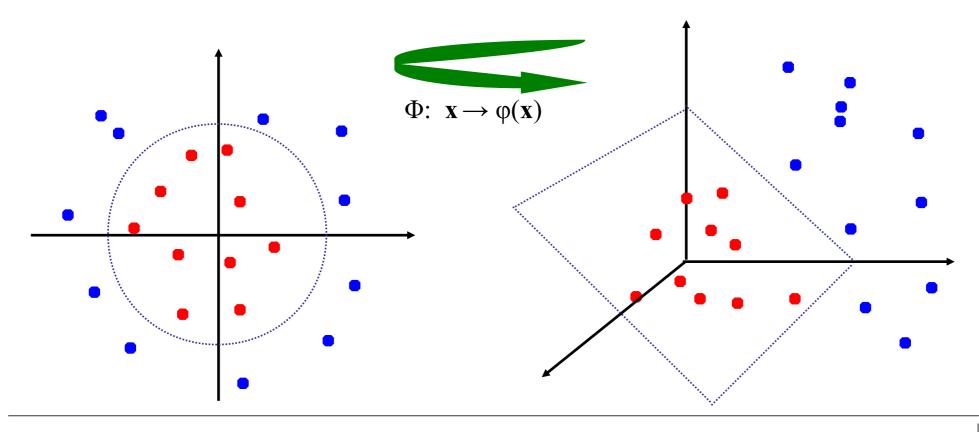
- In classification terms:
 - virtually all document sets are separable, for almost any classification
- This is part of why linear classifiers are quite successful in text classification
 - \rightarrow SVMs with linear Kernels are usually sufficient!



Non-linear SVMs Feature spaces



 General idea: the original feature space can always be mapped to some higher-dimensional feature space where the training set is separable:



Non-linear SVMs Kernel-Trick



- Replace inner product operation by Kernel function
 - $K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i)^{\mathrm{T}} \varphi(\mathbf{x}_j)$
 - \rightarrow make data separable
 - \rightarrow map data into better representational space
- Common kernels
 - Linear: $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \cdot \mathbf{x}_j$
 - Polynomial: $K(\mathbf{x}_i, \mathbf{x}_j) = (1 + \mathbf{x}_i^T \cdot \mathbf{x}_j)^d$
 - Radial basis function (infinite dimensional space) $\frac{-\|\mathbf{x}_i \mathbf{x}_j\|^2}{2}$

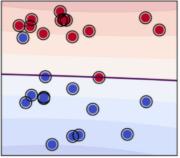
$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{\frac{||\mathbf{x}_i|}{2\sigma}}$$



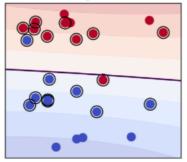
Regularization **Example for non-linear SVMs**



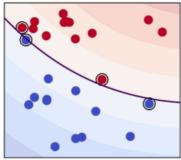
C = 0.1000 gamma = 0.01

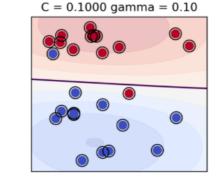


C = 1.0000 gamma = 0.01

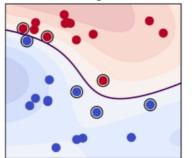


C = 1000.0000 gamma = 0.01

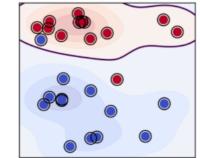




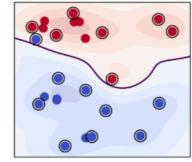
- C = 1.0000 gamma = 0.10
- C = 1000.0000 gamma = 0.10



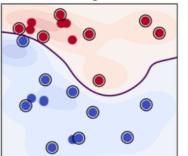
C = 0.1000 gamma = 1.00

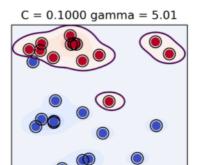


C = 1.0000 gamma = 1.00

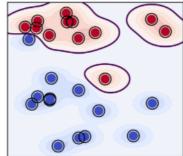


C = 1000.0000 gamma = 1.00





C = 1.0000 gamma = 5.01



C = 1000.0000 gamma = 5.01

