

Topic Classification in R

A Tutorial on Using Text Mining and
Machine Learning Technologies to
Classify Documents

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Thanks

- Marco Maier (PhD Student at WU Wien)
 - Answering all of my R-related questions
 - Endless Patience
- Ingo Feinerer (Lecturer at TU Wien)
 - Creator of the **tm-package** for R
 - Answering all of my tm-related questions
 - Answers were always quick and profound although we never met in person

About the Talk

- I want you to **learn something** today
- If you **feel bored** you may **leave at any time** and I will not be mad at you
- Please **ask** at any(!) time if something is unclear
- Please **tell me** if I'm too fast or speak too low or loud
- Please **contact me** per email if you have any **questions** about the talk, R, Text Mining or Support Vector Machines
- This **presentation** is under a **Creative Commons license**
- The **source code** is under an **LGPL license**
- Both are non-restrictive! (use it, alter it – just refer to me)
- Everything is **online** at www.contextualism.net/talks

Critique

- Please tell me what you think about this presentation
- Just send me an email and tell me one thing you liked and one you didn't

Outline

- Why?
- Classification
 - Introduction
 - Support Vector Machines
 - Topic Classification
- Reuters 21578 Dataset
- SVM Training in R
- Evaluation
 - Measures
 - Results

Why? (me)

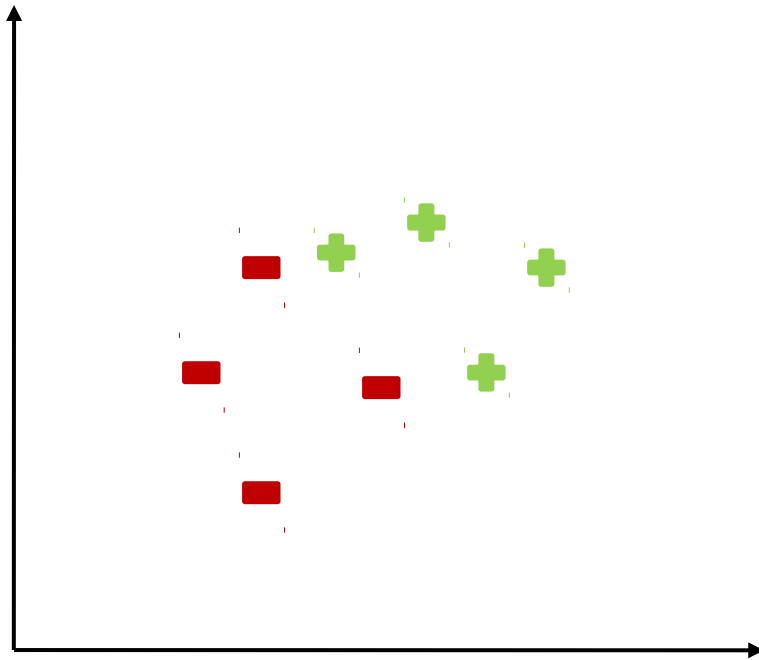
- Wanted to do Text Classification
- Wanted to train a Support Vector Machine
- Wanted to use R
- Wanted to reproduce the results of a scientific article

Why? (you)

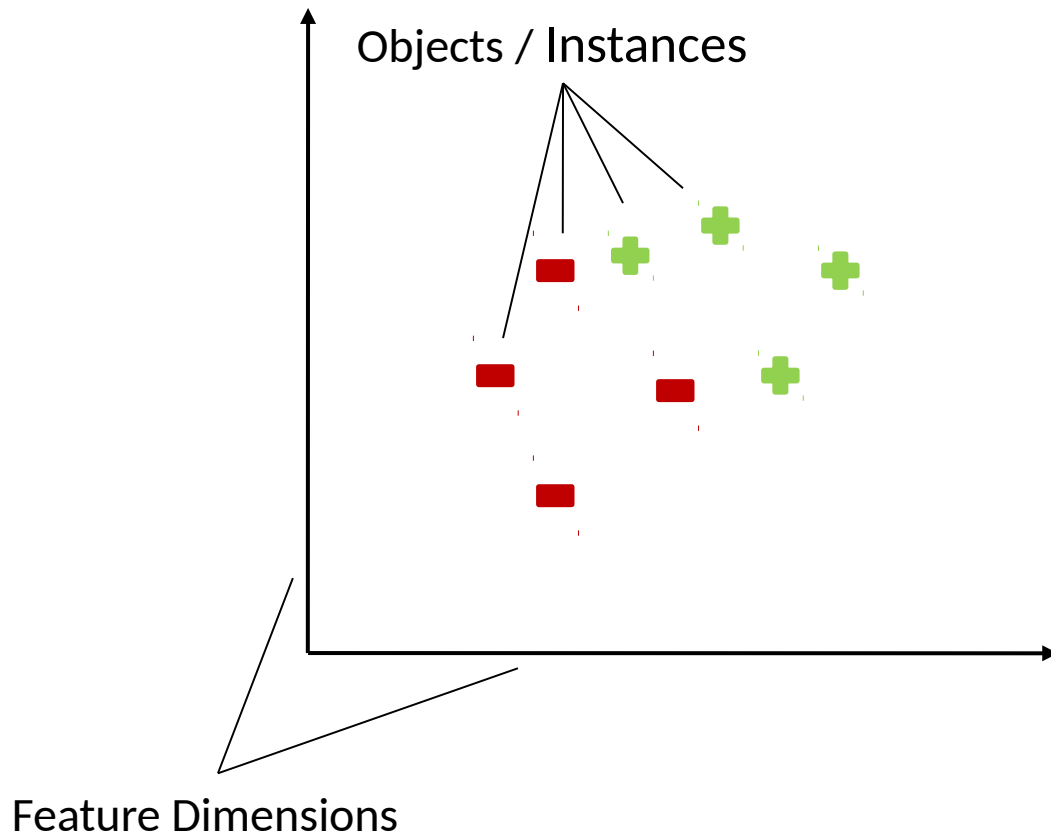
- Support Vector Machines are very good classifiers
- They are used in a lot of recent publications – they're kind of the „new black“
- SVMs are a neat tool in your analytic armory
- If you understand topic classification you know how your SPAM is filtered
- Term-Document-Matrices are a very easy but powerful data-structure
- Usage of Text Mining Techniques could be fruitful for your research

Classification

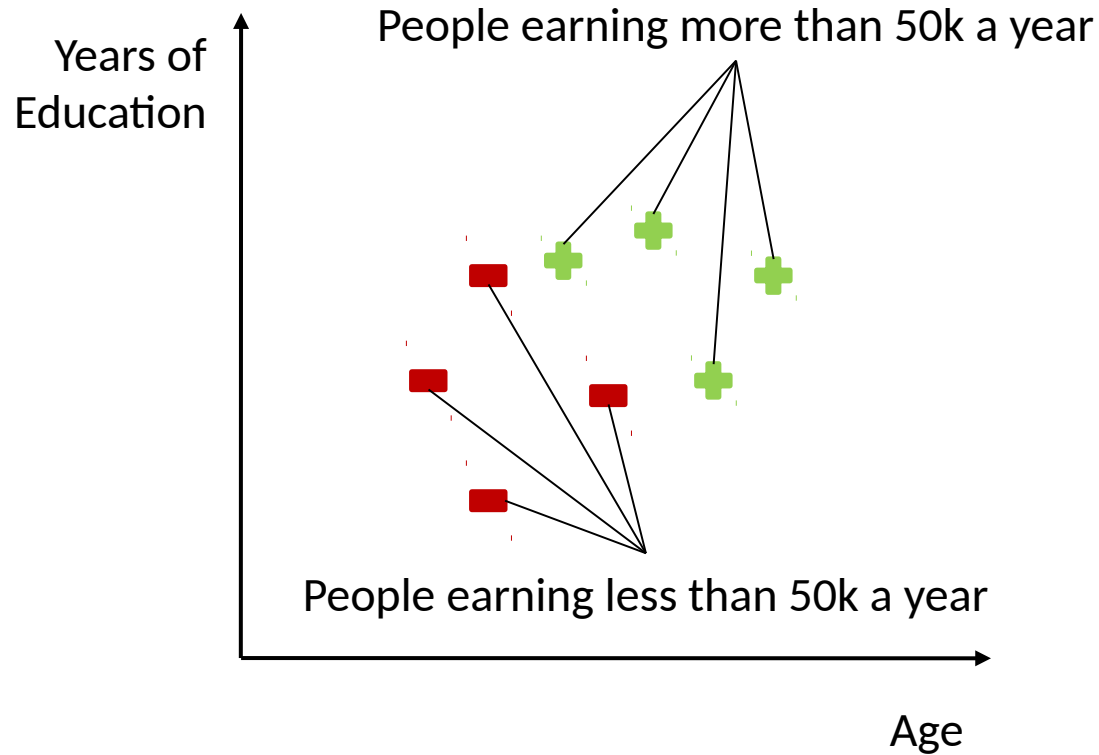
Classification



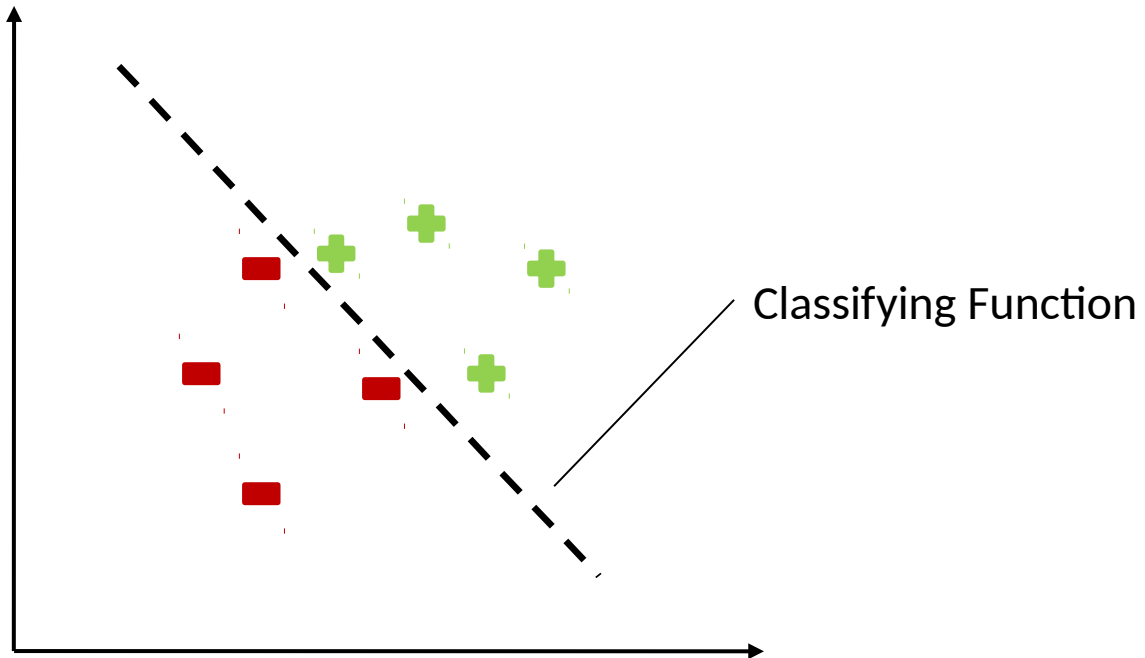
Classification



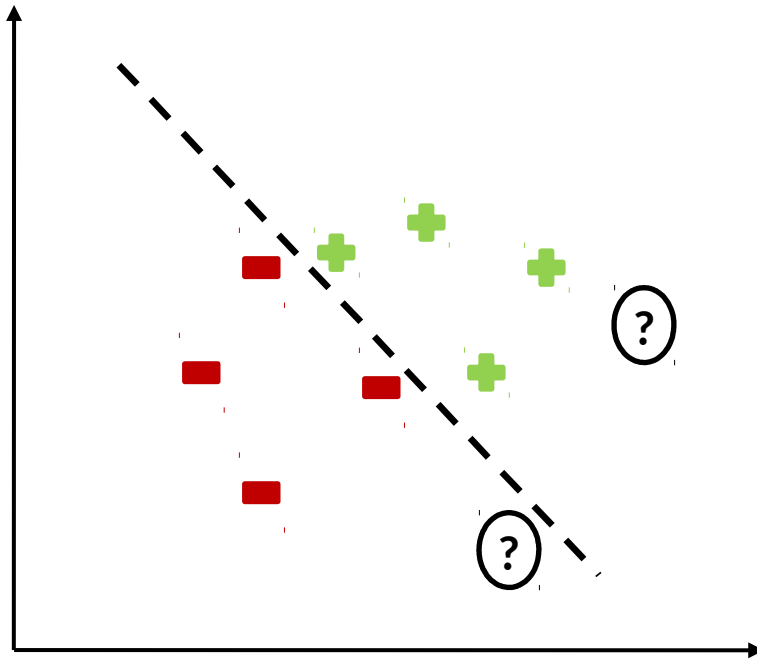
Classification



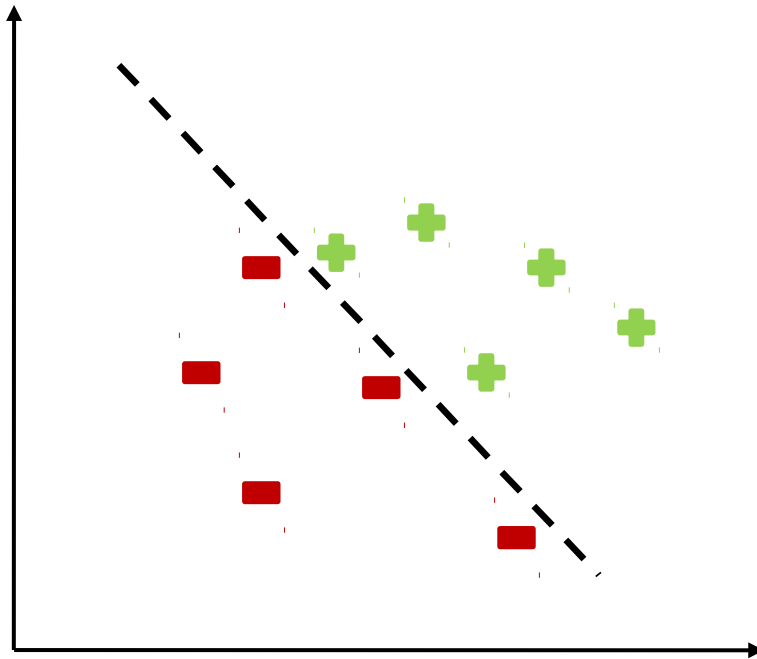
Classification



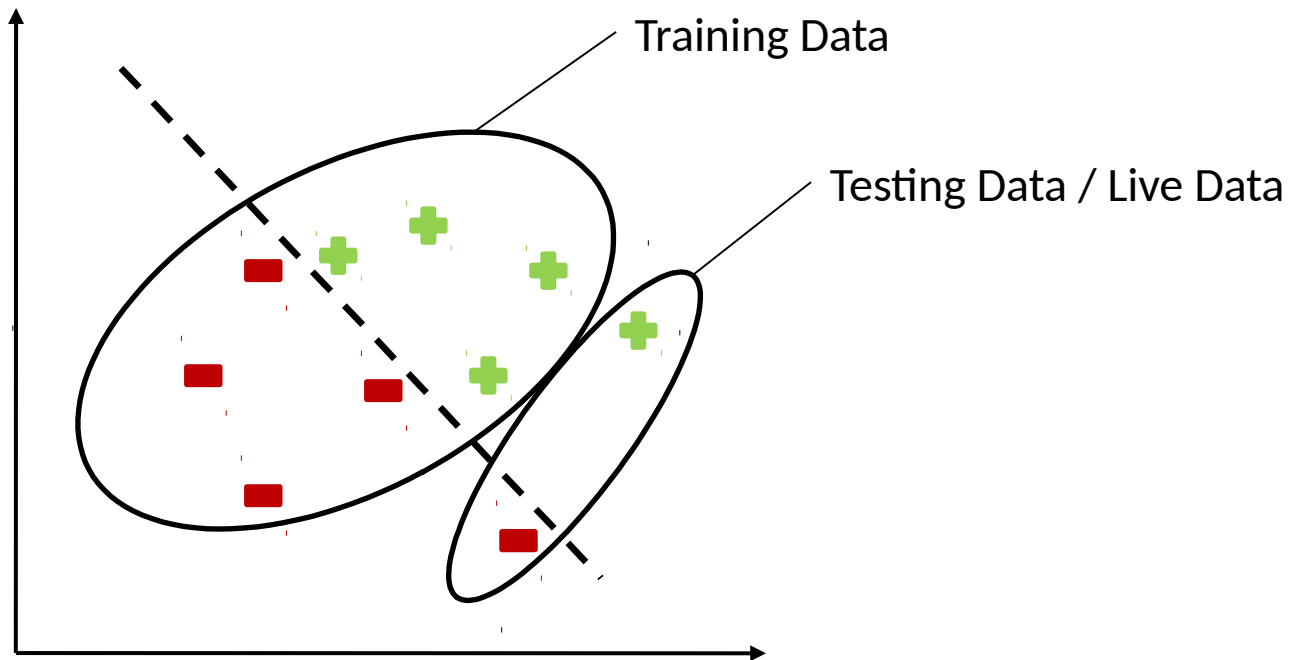
Classification



Classification



Classification



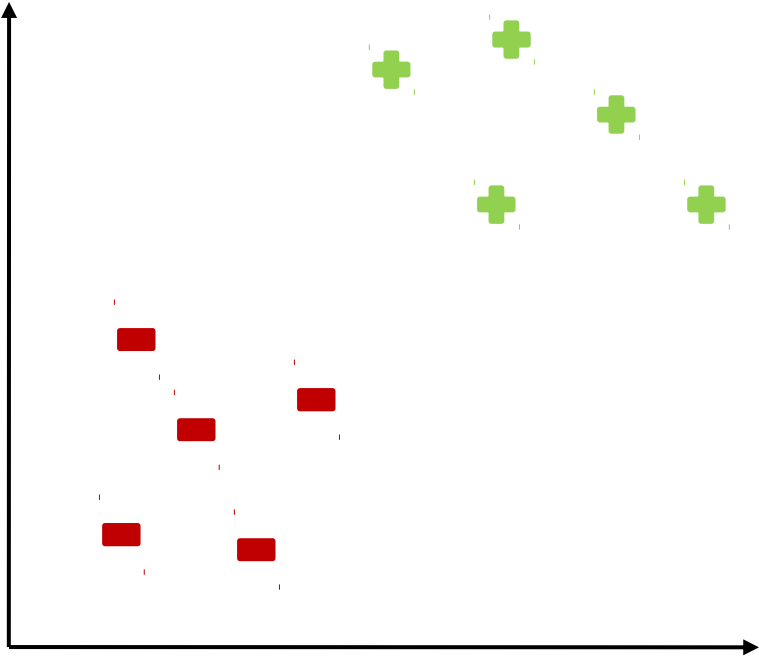
Classification

- Many different Classifiers available
- Strengths and weaknesses
- Decision Tree Classifiers
 - Good in Explaining the Classification Result
- Naive Bayes Classifiers
 - Strong Theory
- K-nn Classifiers
 - Lazy Classifiers
- **Support Vector Machines**
 - **Currently the state of the art**
 - **Perform very well across different domains in practice**

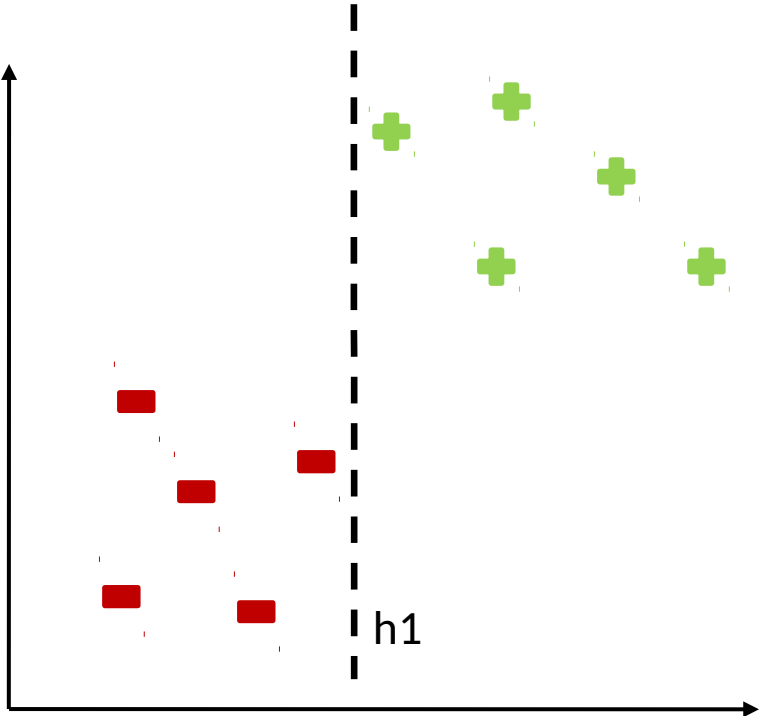
Support Vector Machines

- Solve a linear optimization problem
- Try to find the hyperplane with the largest margin (Large Margine Classifier)
- Use the „Kernel Trick“ to separate instances that are linearly unseparable

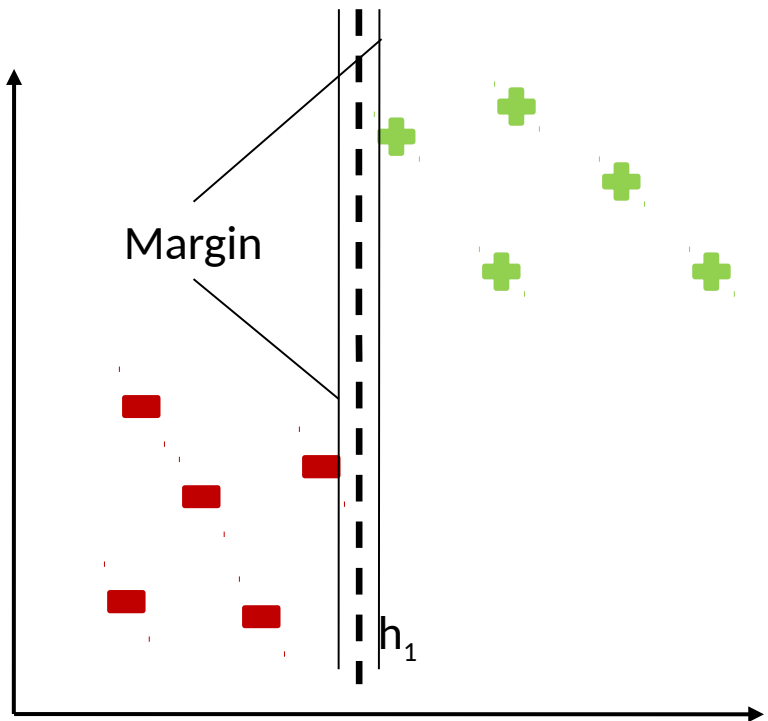
Largest Margin Hyperplane



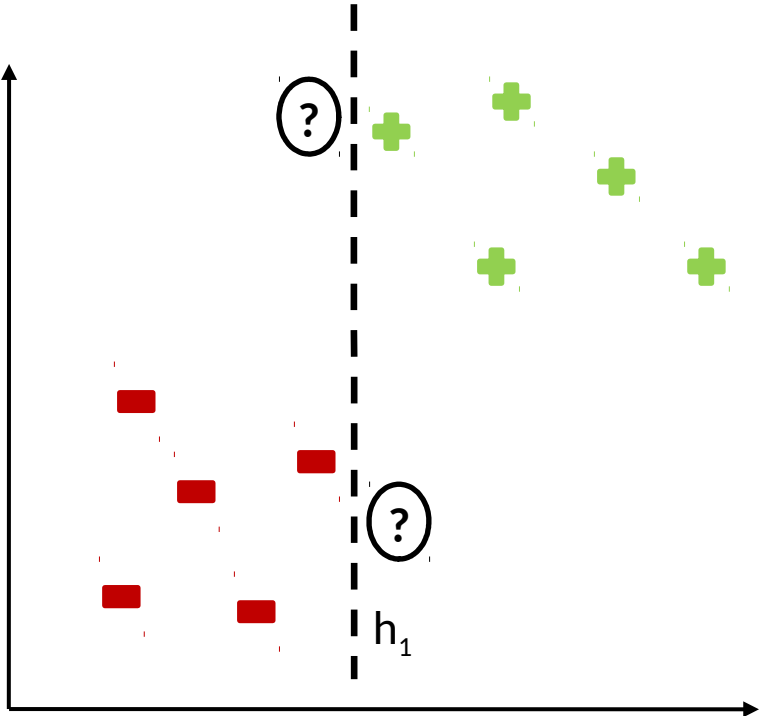
Largest Margin Hyperplane



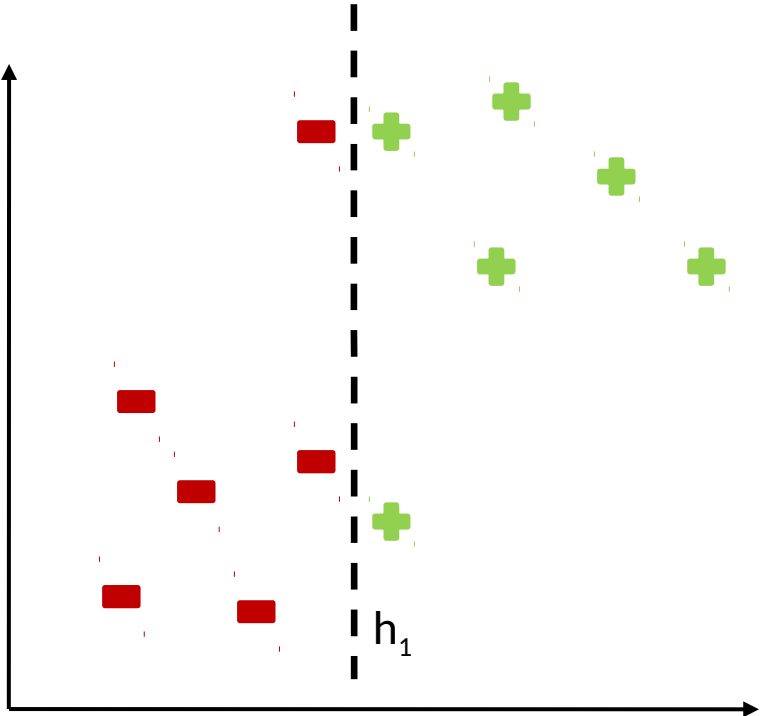
Largest Margin Hyperplane



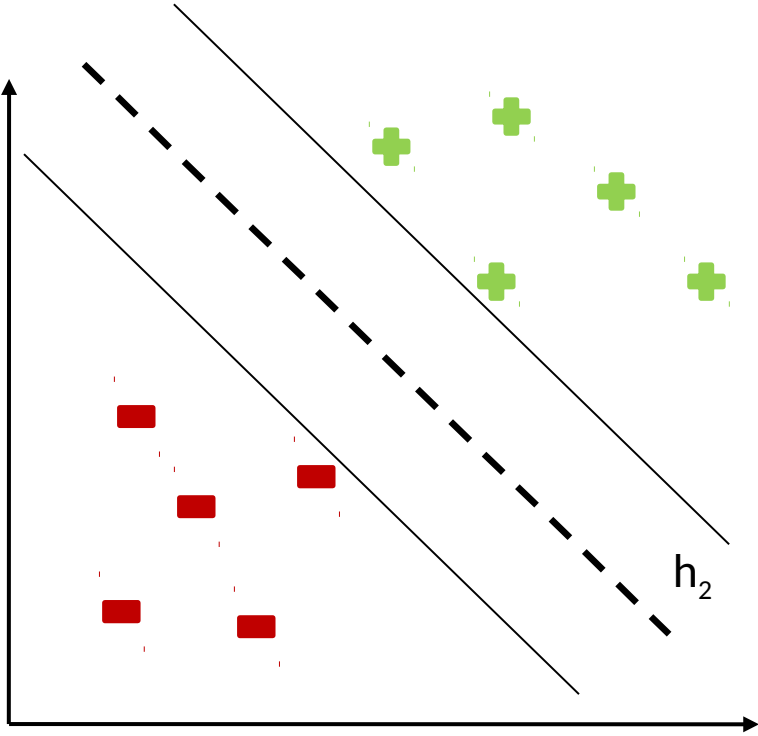
Largest Margin Hyperplane



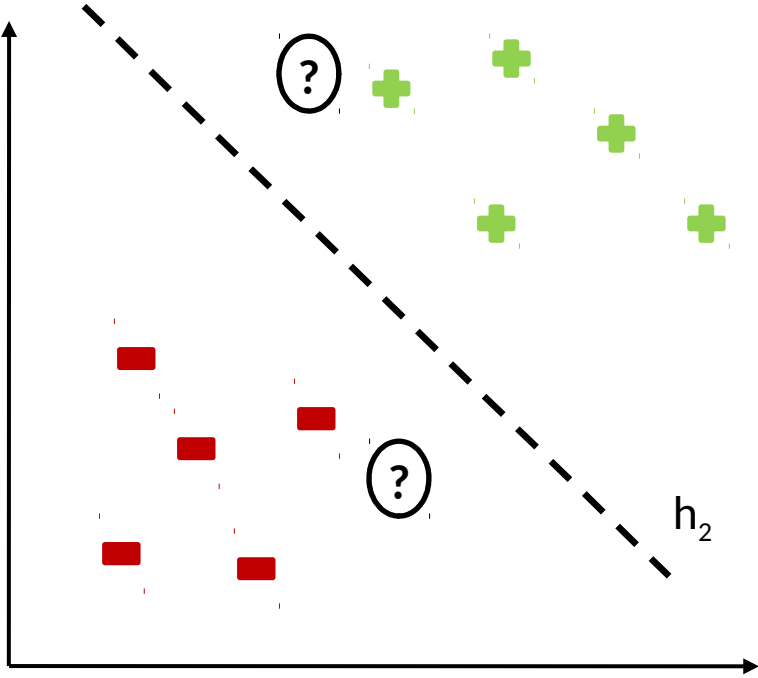
Largest Margin Hyperplane



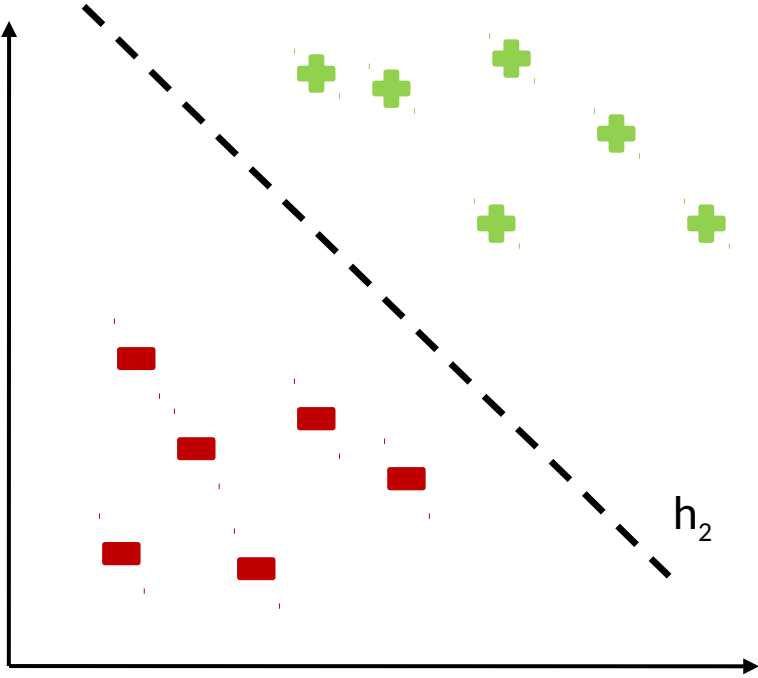
Largest Margin Hyperplane



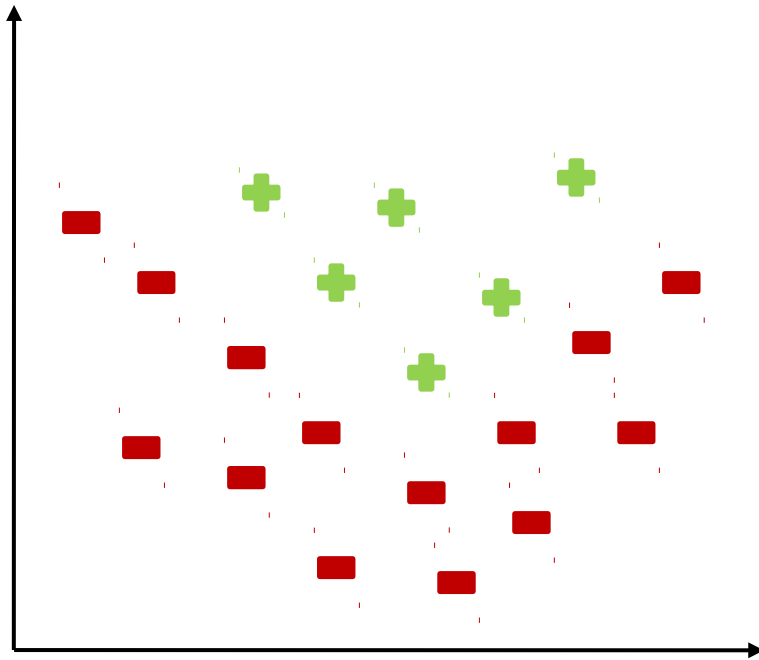
Largest Margin Hyperplane



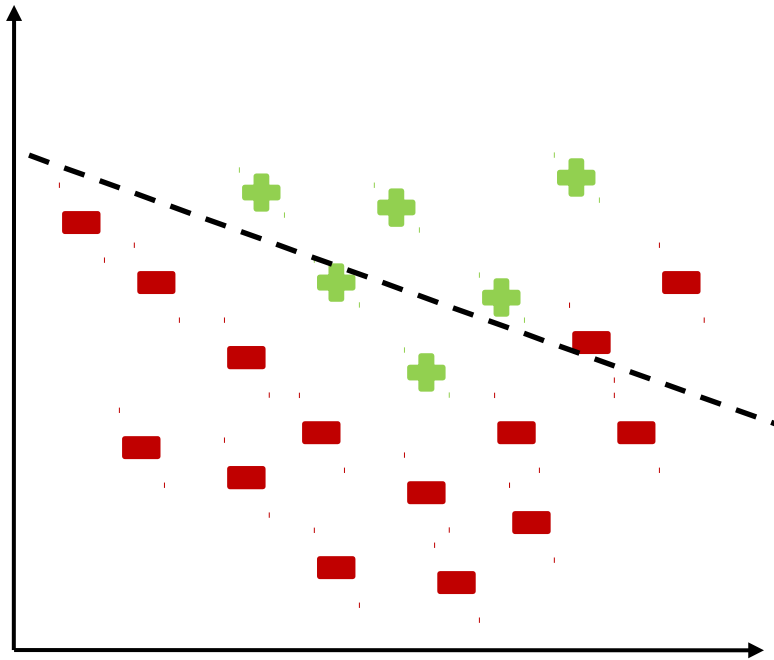
Largest Margin Hyperplane



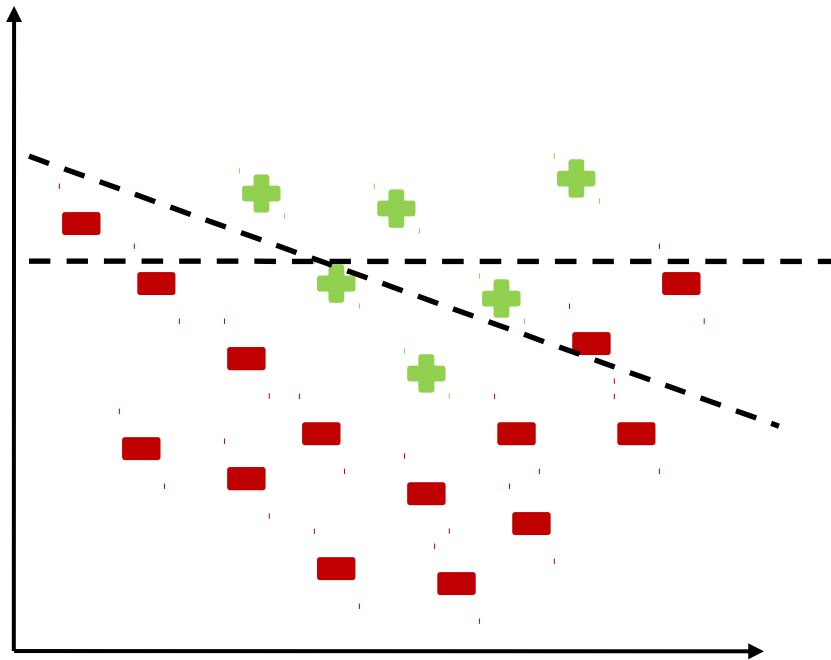
Kernel Trick



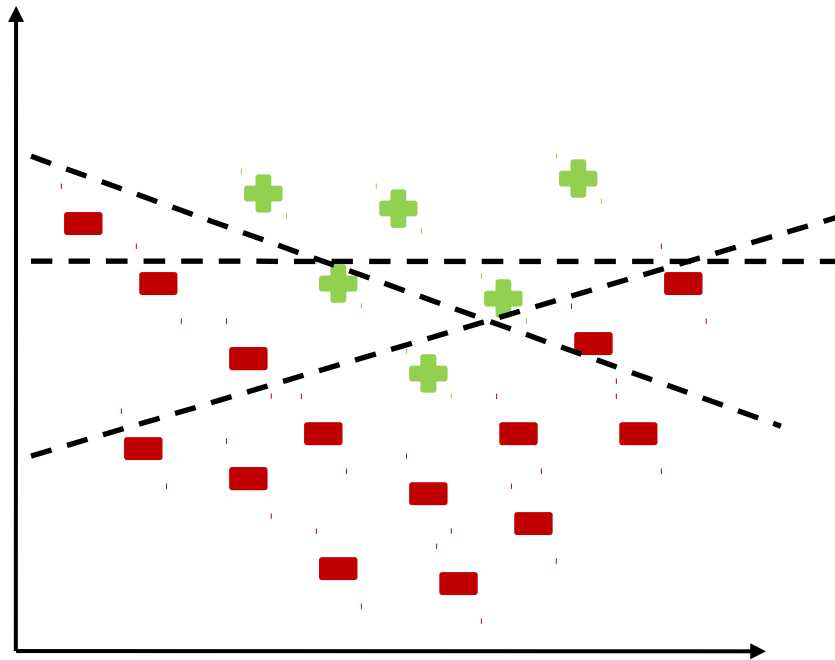
Kernel Trick



Kernel Trick

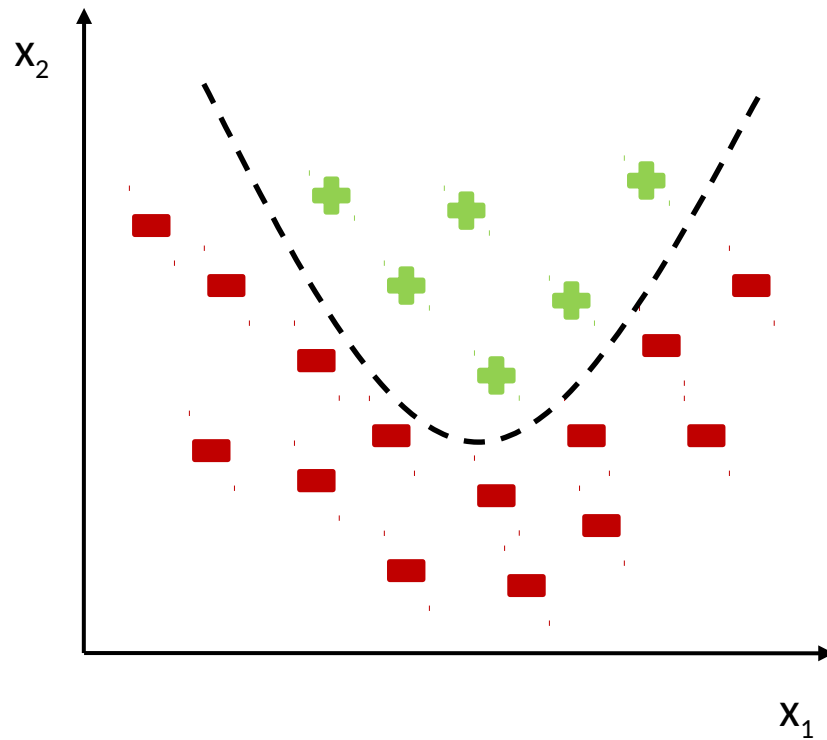


Kernel Trick



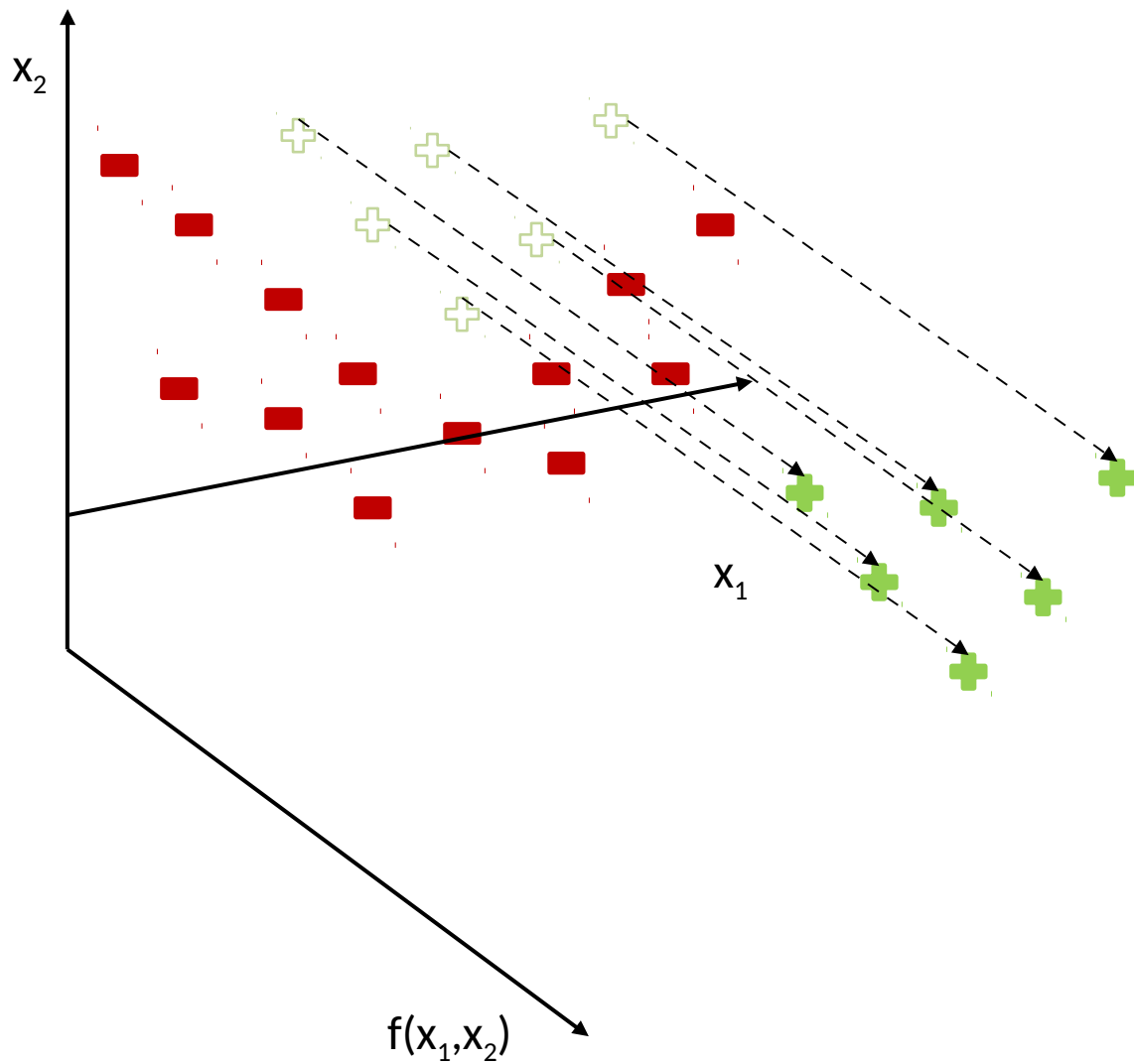
no linear function
that separates the
data

Kernel Trick

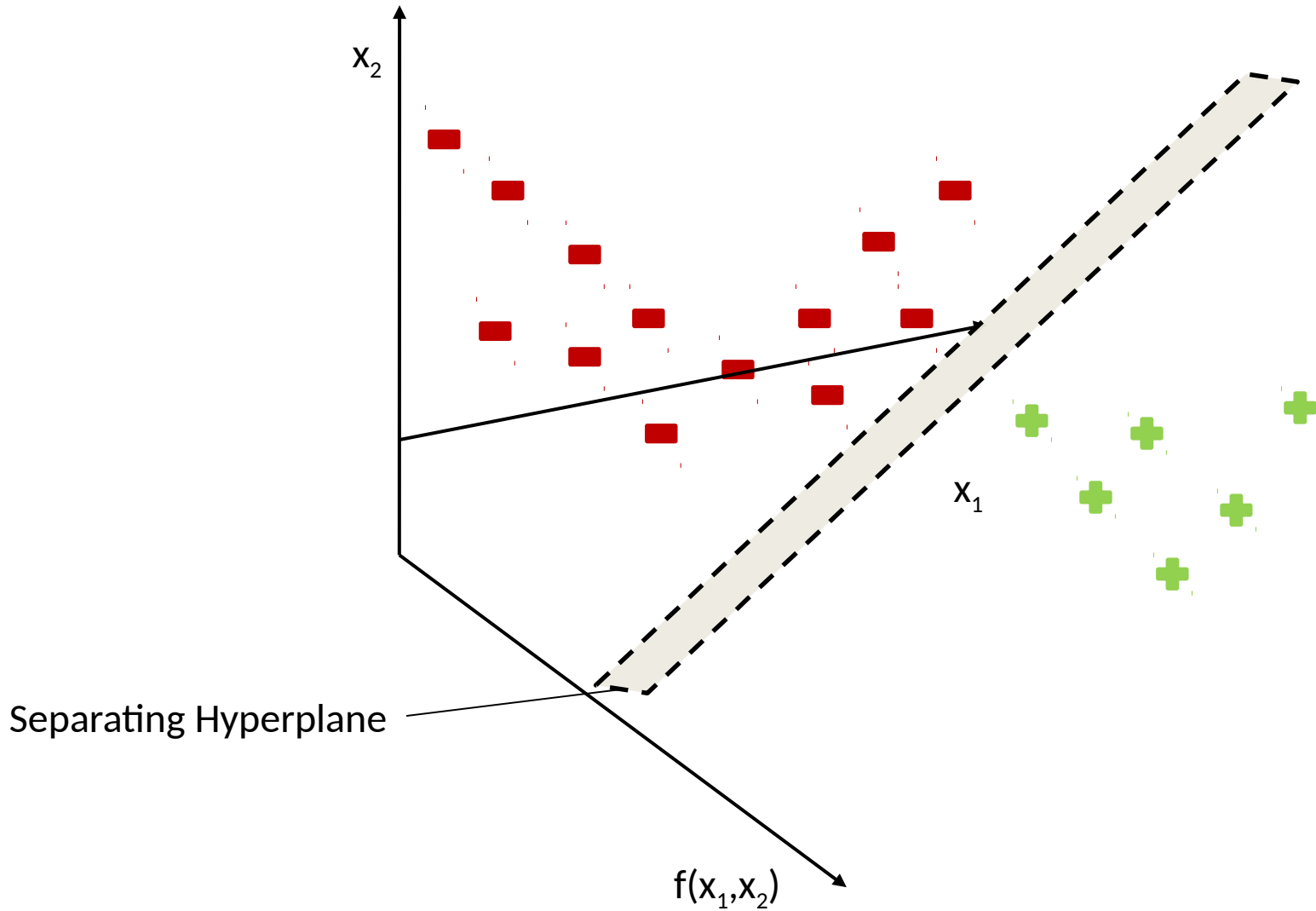


polynomial
function separating
the data

Kernel Trick



Kernel Trick



Kernel Trick

[Video](#)

Kernel Trick

- A lot of different Kernels available
 - Linear Kernel
 - Polynomial Kernel
 - RBF Kernel
 - Sigmoid Kernel
- You don't have to find your own one!
- Actually it's more or less a trial and error approach
- Best Case: Literature tells you the best Kernel for your domain

Topic Classification

- Decide if a given text-document belongs to a given topic or not (e.g. merger, oil, sports)
- Features for learning are term-counts (words)
- Every term becomes a feature dimension
- Feature-Space is high-dimensional
- Good for learning because probability of linear separability rises with the number of dimensions

Reuters 21578 Dataset

- 21.578 text documents (newswire articles)
- 135 topics
- Every document has one or more topics
- ModApte Split creates 3 sets
 - **Training set** (9.603 docs, at least 1 topic per doc, earlier April 7th 1987)
 - **Test set** (3.299 docs, at least 1 topic per doc, April 7th 1987 or later)
 - Unused set (8676 docs)
 - Topic distribution uneven in sets

Reuters 21578 Dataset

Topics with most Documents assigned

Class	Document Count
Earn	3987
Acq	2448
Money-Fx	801
Grain	628
Crude	634
Trade	551
Interest	513
Ship	305
Wheat	306
Corn	254

A Reuters Document

```
<?xml version="1.0"?>
<REUTERS TOPICS="YES" LEWISSPLIT="TRAIN" CGISPLIT="TRAINING-SET" OLDID="5552"
NEWID="9">
  <DATE>26-FEB-1987 15:17:11.20</DATE>
  <TOPICS>
    <D>earn</D>
  </TOPICS>
  <PLACES>
    <D>usa</D>
  </PLACES>
  <PEOPLE/>
  <ORGS/>
  <EXCHANGES/>
  <COMPANIES/>
  <UNKNOWN>Ff0762 reuter f BC-CHAMPION-PRODUCTS-&lt;CH02-26 0067</UNKNOWN>
  <TEXT>
    <TITLE>CHAMPION PRODUCTS &lt;CH&gt; APPROVES STOCK SPLIT</TITLE>
    <DATELINE>ROCHESTER, N.Y., Feb 26 -</DATELINE>
    <BODY>Champion Products Inc said its board of directors approved a two-for-one
stock split of its common shares for shareholders of record as of April 1, 1987.
The company also said its board voted to recommend to shareholders at the annual
meeting April 23 an increase in the authorized capital stock from five mln to 25
mln shares. Reuter
  </BODY>
  </TEXT>
</REUTERS>
```

A Reuters Document

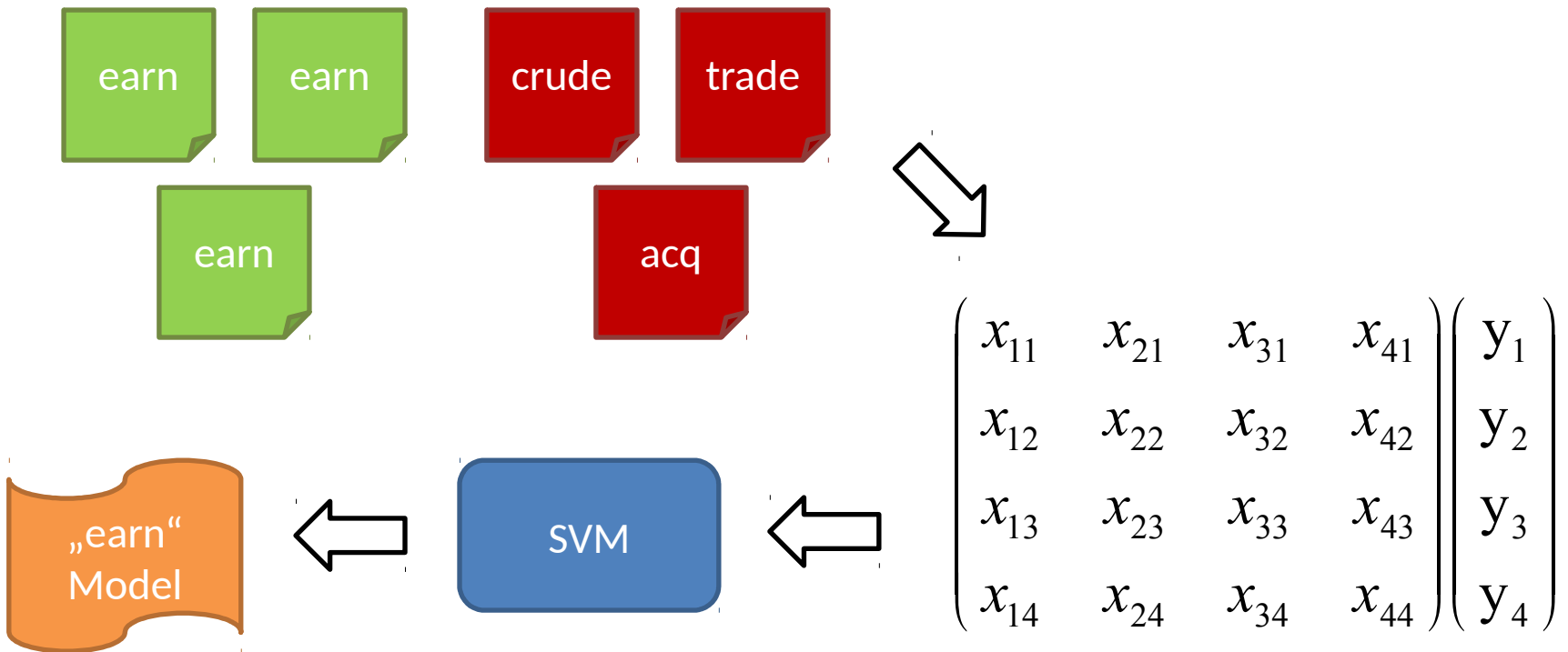
```
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<REUTERS TOPICS="YES" LEWISSPLIT="TRAIN" CGISPLIT="TRAINING-SET" OLDID="5552"
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  <DATE>26-FEB-1987 15:17:11.20</DATE>
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  </TOPICS>
  <PLACES>
    <D>usa</D>
  </PLACES>
  <PEOPLE/>
  <ORGS/>
  <EXCHANGES/>
  <COMPANIES/>
  <UNKNOWN>Ff0762 reuter f BC-CHAMPION-PRODUCTS-&lt;CH02-26 0067</UNKNOWN>
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mln shares. Reuter
  </BODY>
  </TEXT>
</REUTERS>
```

SVM Training in R

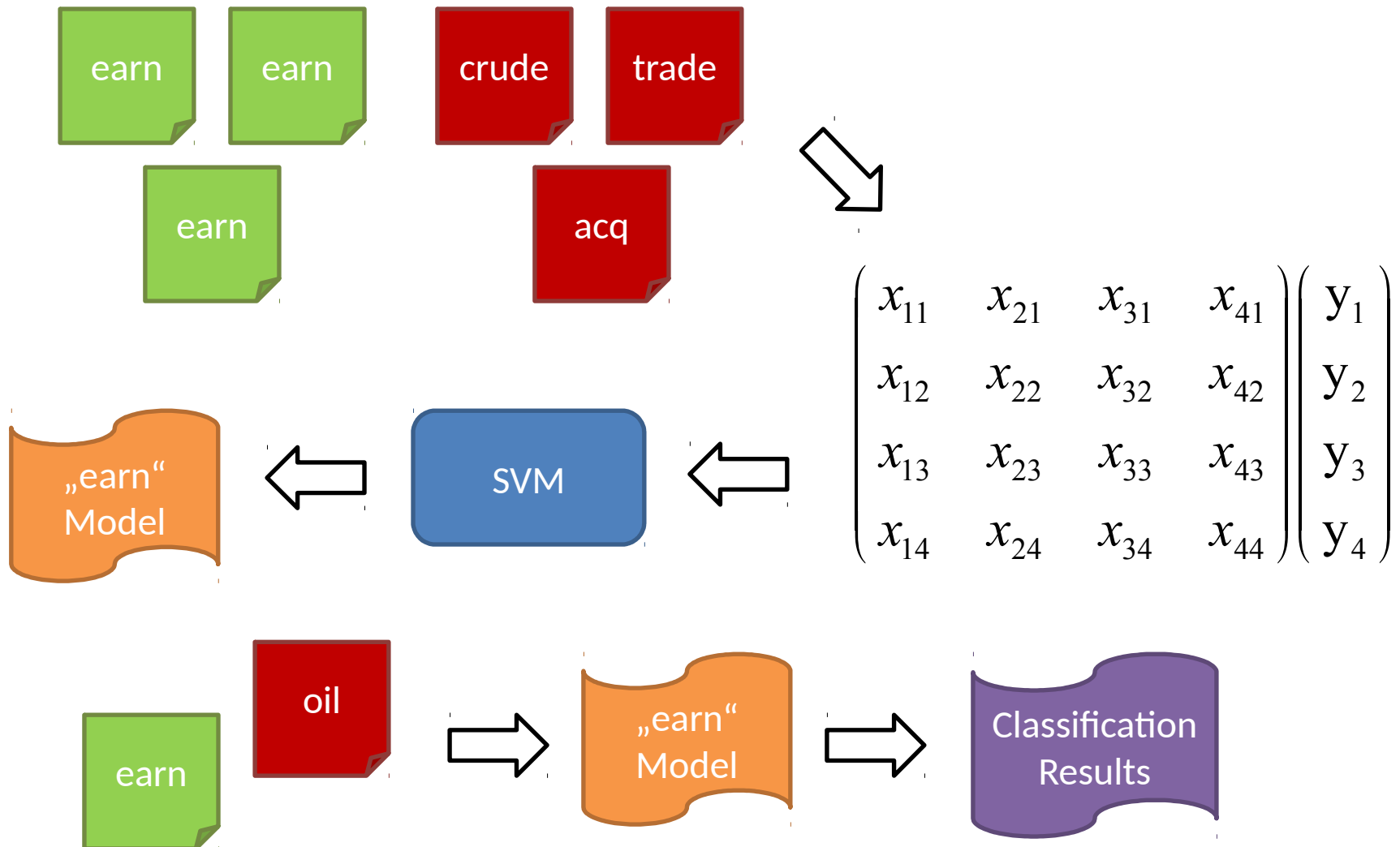
Our Goal

- Take a topic like „**earn**“
- Take *enough* „earn“ and „not earn“ documents from the training set and **create a training corpus**
- Bring training corpus in **adequate format** (data-structure) for SVM training
- Train a **SVM** (model)
- **Predict** test data
- **Compare Results** with those of Joachims

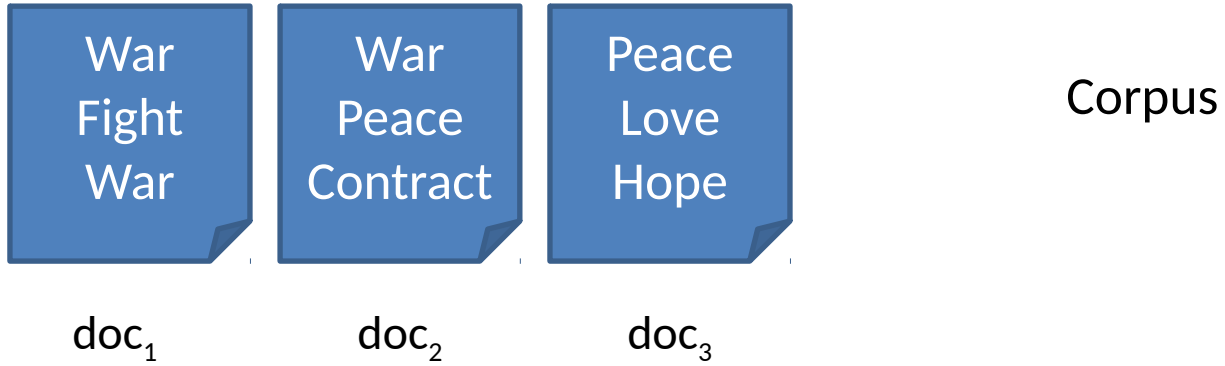
Our Goal



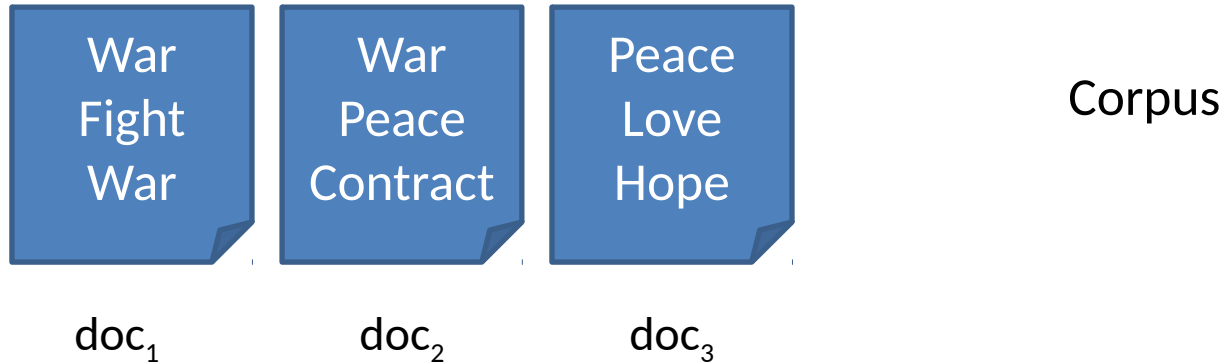
Our Goal



Document Term Matrices



Document Term Matrices

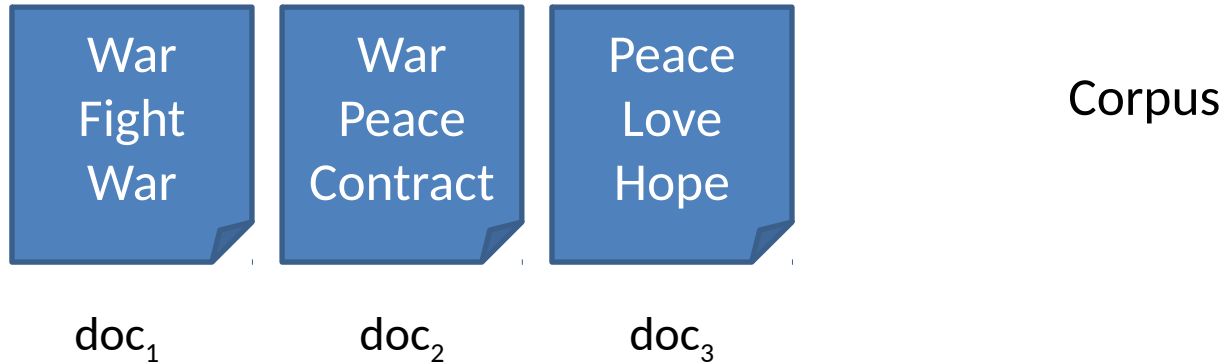


Document Term Matrix

	war	fight	peace	contract	love	hope
doc ₁	2	1	0	0	0	0
doc ₂	1	0	1	1	0	0
doc ₃	0	0	1	0	1	1

Term Weight

Document Term Matrices

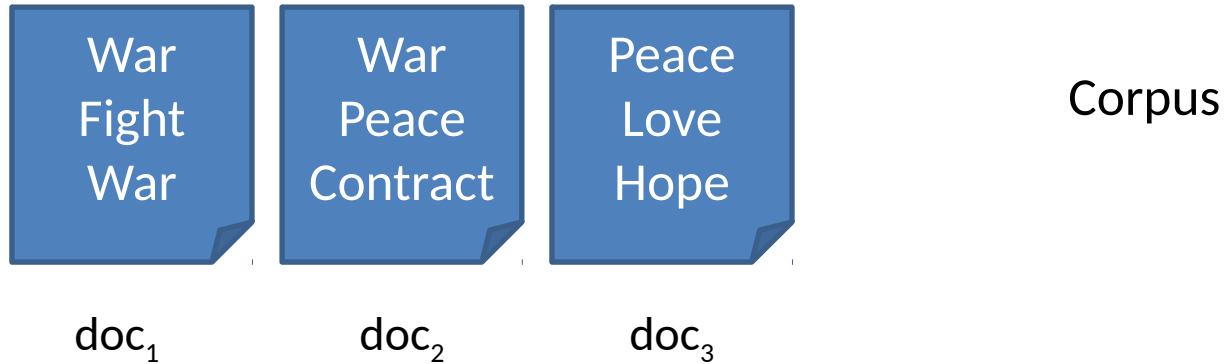


Document Term Matrix

	war	fight	peace	contract	love	hope
doc ₁	2	1	0	0	0	0
doc ₂	1	0	1	1	0	0
doc ₃	0	0	1	0	1	1

Document Vector

Document Term Matrices



Document Term Matrix

	war	fight	peace	contract	love	hope
doc ₁	2	1	0	0	0	0
doc ₂	1	0	1	1	0	0
doc ₃	0	0	1	0	1	1

Term Vector

Term Weighting

- Term Frequency (TF)
 - Number of times a term occurs in a document
- Term Frequency – Inverse Document Frequency (TF-IDF)
 - $(1 + \log(tf_{t,d})) \times \log(N / df_t)$
- Term Frequency – Inverse Document Frequency – Cosine Normalization (TFC)

$$- \frac{tf_t \log \frac{N}{df_t}}{\sqrt{\sum \left(tf_i \log \frac{N}{df_i} \right)^2}}$$

Term Weighting

- Weighting strategy is crucial for the classification results
- IDF factor puts heavier weight on terms that occur seldomly (strong discriminative power)
- Normalization dampens the impact of outliers on the model to be built

Questions?

Assumption

- Training and test documents of Reuters ModApte split reside in two separate directories
 - `/reuters-21578-xml-train`
 - `/reuters-21578-xml-test`
- Documents are in XML format
- There's a preprocessing script (in R) that accomplishes this task
- The script will be online too and you can ask me anytime if you have problems with it

DirSource

- Abstracts the input location
- Other sources are available for different file formats like CSVSource and GmaneSource
- The source concept eases internal processes in the TM package (standardized interfaces)
- **Our DirSources** will just contain a **list of XML documents** from a given directory

Corpus

- Collection or DB for text documents
- In our case it holds the documents from the training set and test set
- Does some transformation on the XML files
- Strips off XML
- Extracts and stores **meta Information** (topics)
- **XML -> Plain Text**
- Access to documents via Indices
- Some statistics about contained documents

Document Term Matrix & Dictionary

Dictionary: List of all the terms in a Corpus/DTM

	aaa	abbett	...	zones	zuckerman
doc ₁	2	1	...	0	1
doc ₂	1	0	...	0	0
...					
doc ₉₆₀₂	0	0	...	1	1

tm_filter

- Returns a **filtered corpus**
- Predefined filters available
 - searchFullText
 - sFilter (Meta Data)
- **Custom filters** can be added (e.g. TopicFilter and maxDocNumPerTopicFilter)
- **doclevel** decides if filter is applied on corpus as a whole or each single document
- Theoretically easy – Practically kind of cumbersome (R-internals)

Topic Filter Function

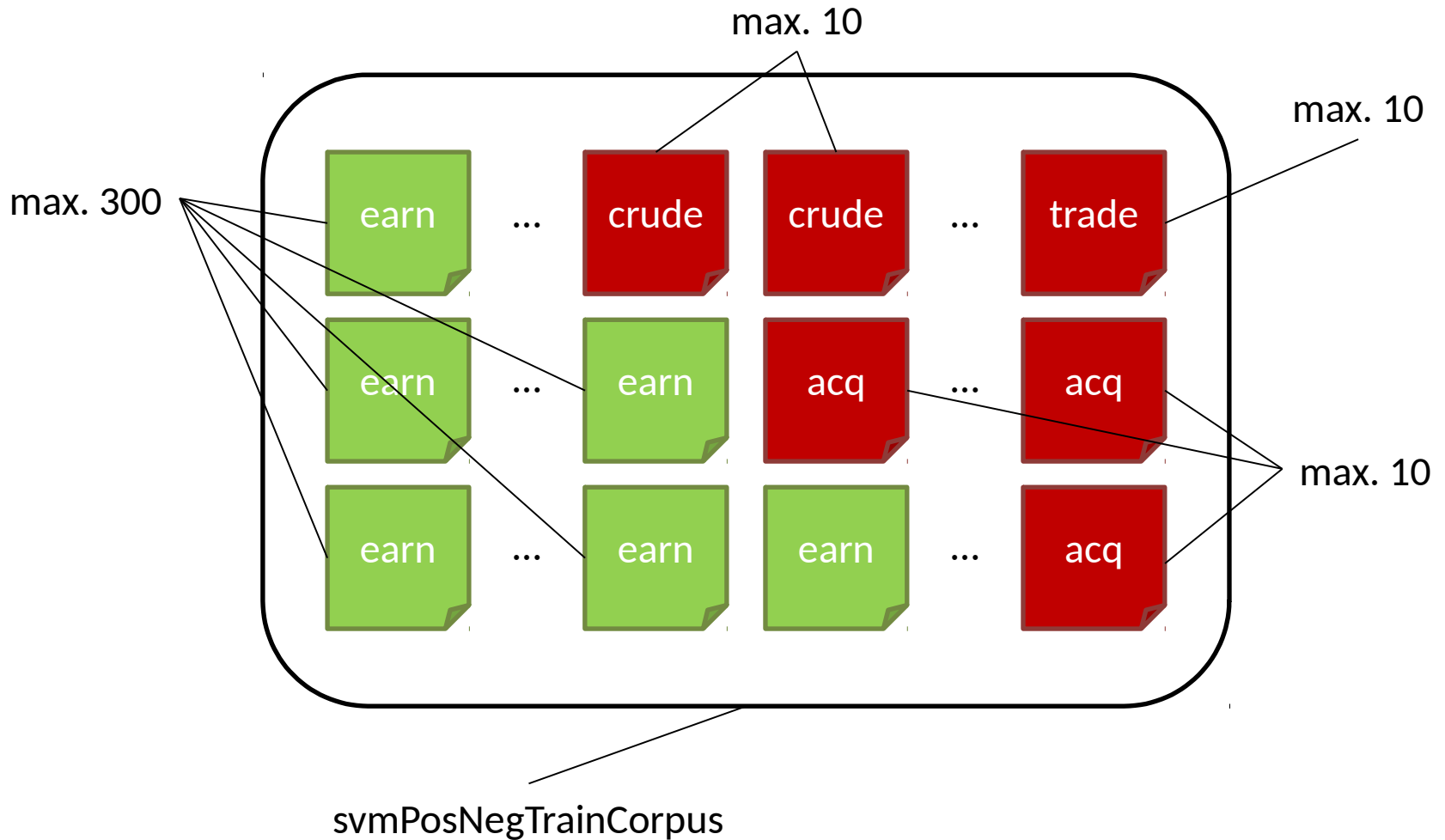
```
topicFilter <- function (object, s, topicOfDoc) {
  query.df <- prescindMeta(object, c("Topics"))
  attach(query.df)
  boolFilter <- c()
  i <- 1

  while (i <= length(Topics)) {
    res <- c(s) %in% Topics[[i]]
    boolFilter <- c(boolFilter, res)
    i <- i + 1
  }
  if (!topicOfDoc)
    boolFilter <- unlist(lapply(boolFilter, `!`))

  try (result <- rownames(query.df) %in% row.names(query.df[boolFilter,]))

  detach(query.df)
  result
}
```


The Training Corpus



Document Term Matrix

- Actually we could construct the DTM now and feed it together with the label vector to the SVM
- But, we have to ensure, that all terms in the dictionary (from ModApte Training Split) are used!
- DocumentTermMatrix removes terms that don't occur in the corpus – which would fall back on us during evaluation
- We have to ensure that the matrices always have the same structure using the same terms on the same place (column)

Auxiliary 1-Document Corpus

- Create corpus with just one document
- This document contains all terms from the dictionary
- Merge Auxiliary Corpus with Training Corpus

Sparse Matrices

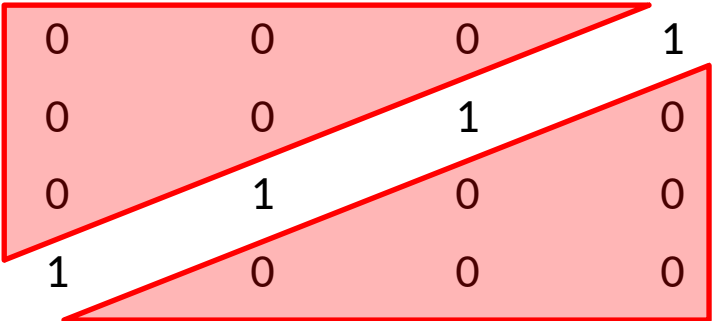
- Most of the values in a DTM are zero (→ sparse)
- Storing the 0s would be waste of space
- Sparse matrices only store non-zero values and some structure
- DTM in tm-package is backed by `simple_triplet_matrix`
- SVM is backed by `CompressedSparseRowMatrix`
- Conversion needed

Sparse Matrices

	book	car	peace	war	
doc ₁	0	0	0	1	Plain Storage 16 numbers
doc ₂	0	0	1	0	
doc ₃	0	1	0	0	
doc ₄	1	0	0	0	

Sparse Matrices

	book	car	peace	war
doc ₁	0	0	0	1
doc ₂	0	0	1	0
doc ₃	0	1	0	0
doc ₄	1	0	0	0



Plain Storage
16 numbers

Sparse Matrices

	book	car	peace	war
doc ₁	0	0	0	1
doc ₂	0	0	1	0
doc ₃	0	1	0	0
doc ₄	1	0	0	0

Plain Storage
16 numbers

payload

Simple Triplet Matrix
12 numbers (TM)

Compressed Sparse Row Matrix
13 numbers (SVM)

(1 1 1 1)

(1 1 1 1)

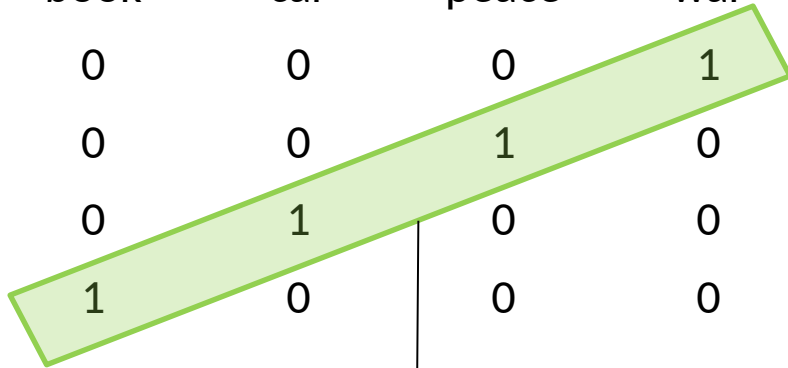
(1 2 3 4)

(4 3 2 1)

(4 3 2 1)

Structure

(1 2 3 4 5)



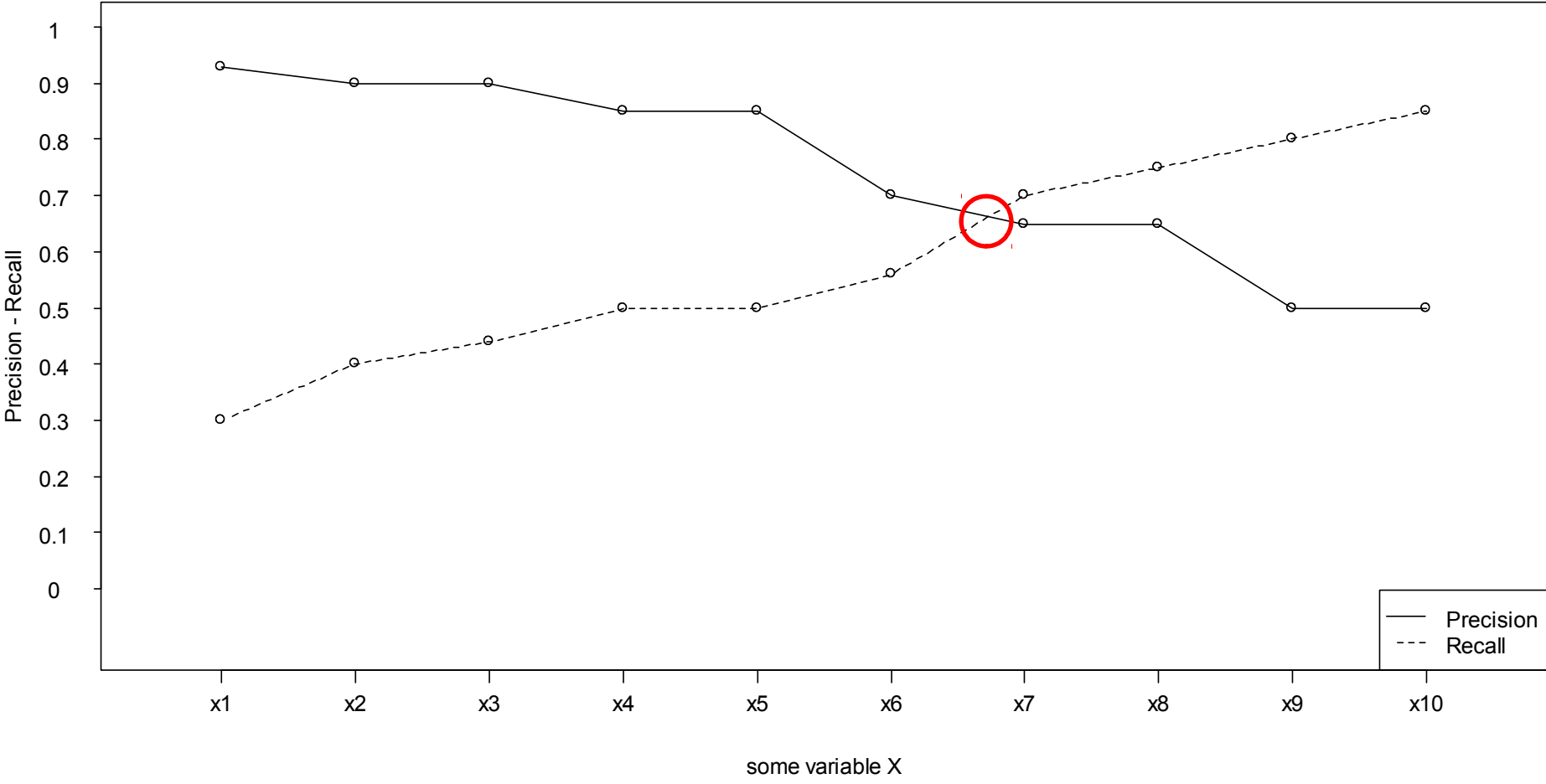
Label Vector

$$y_{Pos} = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{pmatrix} \left. \vphantom{\begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{pmatrix}} \right\} 300 \quad y_{Neg} = \begin{pmatrix} -1 \\ -1 \\ \vdots \\ -1 \\ -1 \end{pmatrix} \left. \vphantom{\begin{pmatrix} -1 \\ -1 \\ \vdots \\ -1 \\ -1 \end{pmatrix}} \right\} 422 \quad y = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ -1 \\ -1 \end{pmatrix} \left. \vphantom{\begin{pmatrix} 1 \\ 1 \\ \vdots \\ -1 \\ -1 \end{pmatrix}} \right\} \begin{matrix} 300 \\ 422 \end{matrix}$$





Evaluation Measures

- Joachims uses Precision-Recall Breakeven points
- To do so you'd have to alter a variable in the setting over a range of values
- But he never states which variable he alters
- So I decided to use the Precision and Recall results without their Breakeven point





Precision Recall Breakeven Point







Confusion Matrix

	predicted 	predicted 
true 	a	b
true 	c	d





Confusion Matrix

	predicted 	predicted 
true 	true positive	false negative
true 	false positive	true negative






Confusion Matrix

	predicted 	predicted 
true 	TP	FN
true 	FP	TN

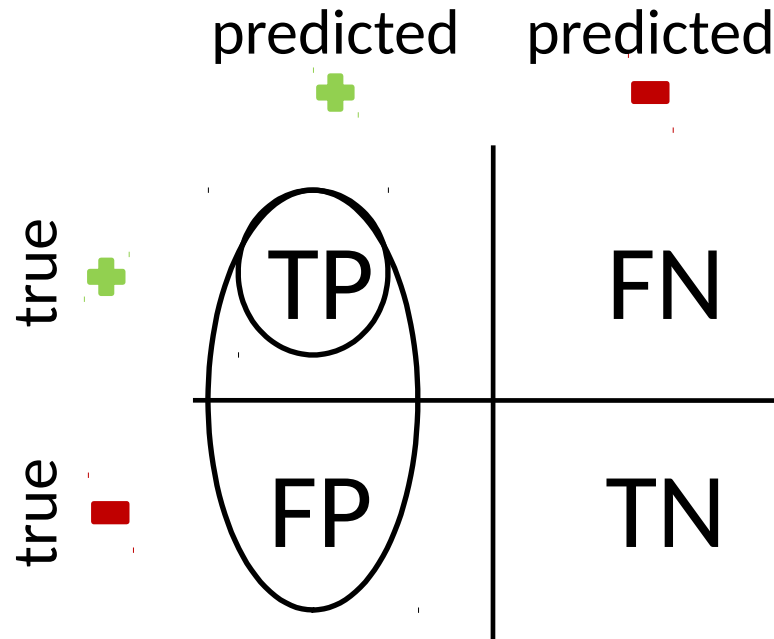
Precision

	predicted 	predicted 
true 	TP	FN
true 	FP	TN

Precision

	predicted 	predicted 
true 	 TP	FN
true 	FP	TN





Precision








measure of exactness

$$\frac{TP}{TP + FP}$$

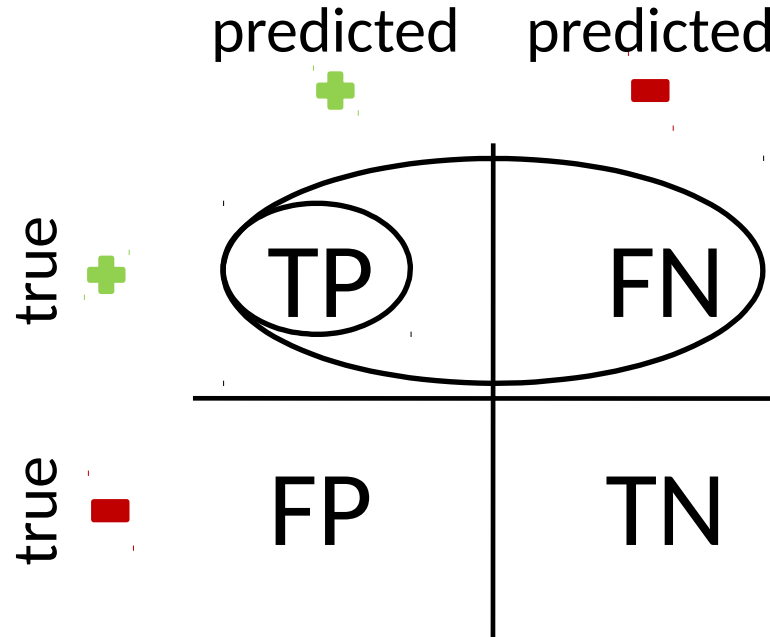
Recall

	predicted 	predicted 
true 	TP	FN
true 	FP	TN

Recall

	predicted 	predicted 
true 	 TP	FN
true 	FP	TN

Recall

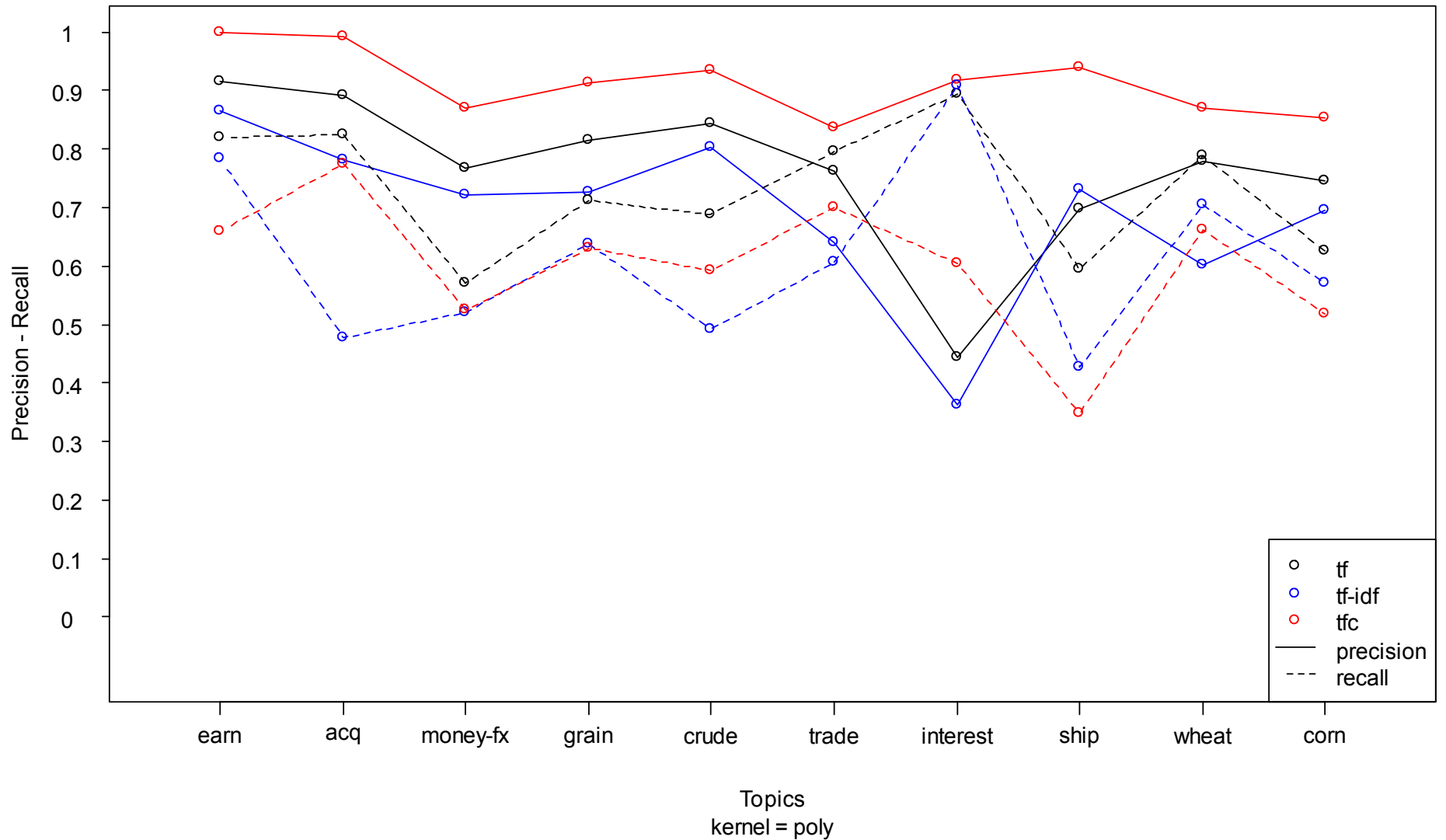


measure of completeness

$$\frac{TP}{TP + FN}$$

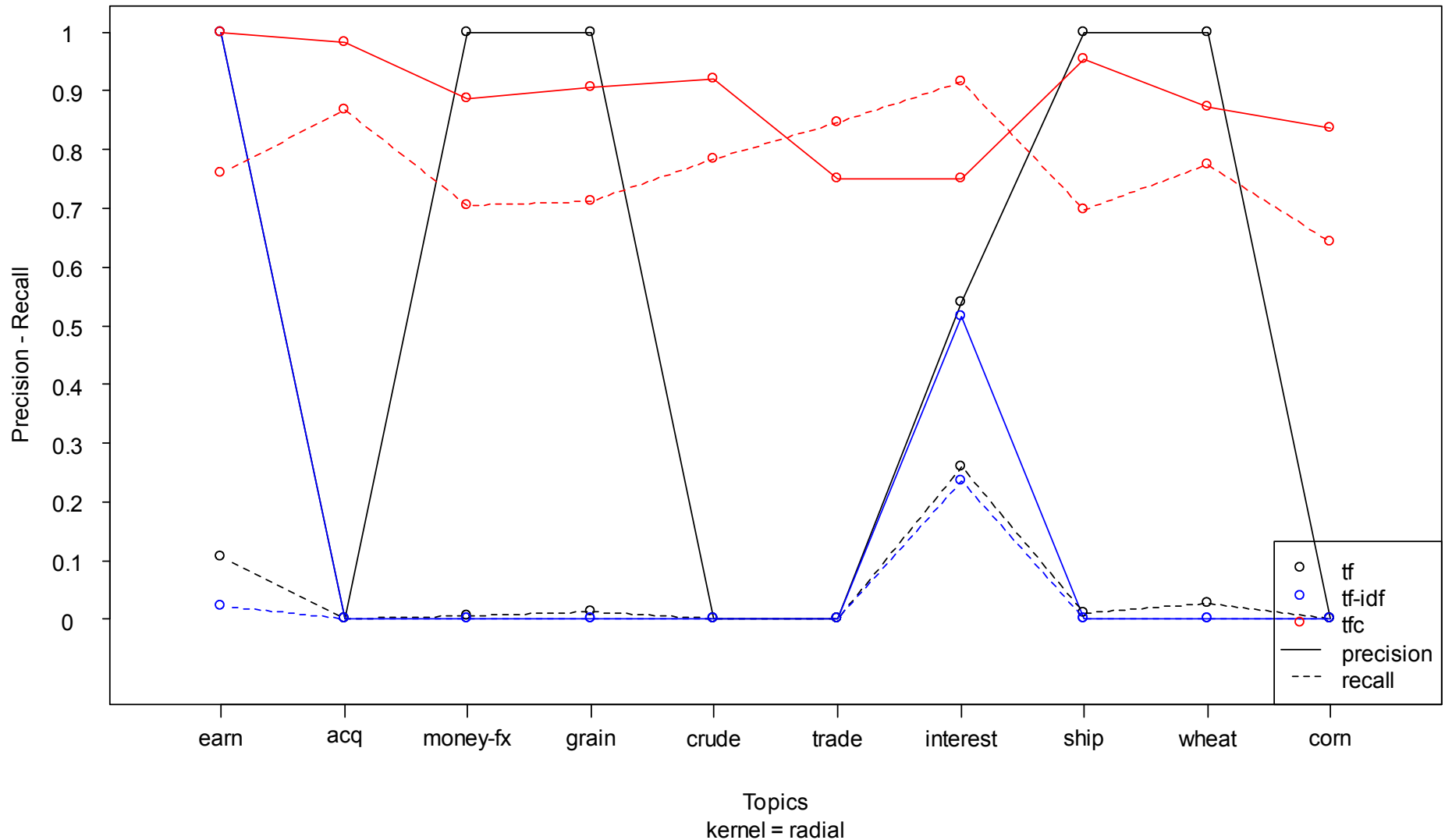
Evaluation Results

Topic Classification Results for Different Feature-Weighting Strategies



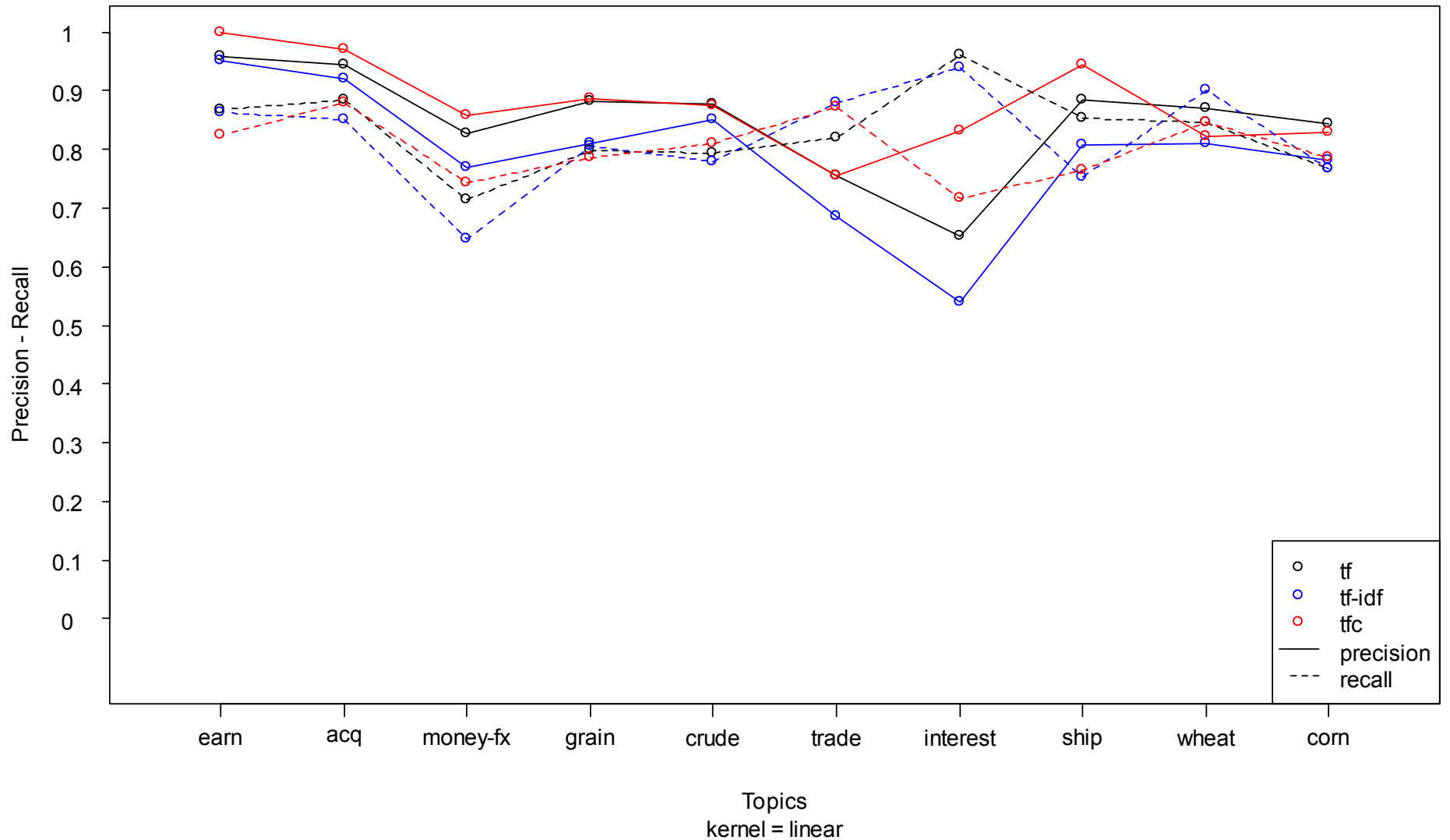
Evaluation Results

Topic Classification Results for Different Feature-Weighting Strategies



Evaluation Results

Topic Classification Results for Different Feature-Weighting Strategies



Comparison to Joachims

Kernel=poly, degree=2

Topic	Joachims		Me	
	Prec.-Rec.	Breakeven	Precision	Recall
earn	98.4		0.99	0.65
acq	94.6		0.99	0.77
money-fx	72.5		0.87	0.52
grain	93.1		0.91	0.63
crude	87.3		0.93	0.59
trade	75.5		0.83	0.7
interest	63.3		0.91	0.6
ship	85.4		0.93	0.34
wheat	84.5		0.87	0.66
corn	86.5		0.85	0.51

Findings

- Even though the paper was very detailed and well written – some information was missing to fully reproduce the results
- tm-package is very comfortable to use but adding custom functionality is cumbersome because of R-internals
- svm-package is surprisingly easy to use but memory limits are reached very soon
- Classification results are quiet good

Literature

- Feinerer I., Hornik K., Meyer D., Text Mining Infrastructure in R, Journal of Statistical Software, 2008
- Joachims T., Text categorization with Support Vector Machines: Learning with many relevant features, ECML, 1998
- Salton G., Buckley C., Term-weighting approaches in automatic text retrieval, Journal of Inf. Proc. Man., 1988
- Classification Performance Measures, 2006
- [XML Encoded Reuters 21578 Dataset](#)

Thank you!
For Attention & Patience

Apendix

Versions of R and R-Packages used

- R 2.9.2
- tm package 0.5 (text mining)
- e1071 1.5-19 (svm)
- slam package 0.1-6 (sparse matrices)
- SparseM package 0.83 (sparse matrices)