Natural Language Processing
SoSe 2014

HPI Hasso Plattner Institut
IT Systems Engineering | Universität Potsdam

Machine Learning for NLP

Dr. Mariana Neves

April 30th, 2014

(based on the slides of Dr. Saeedeh Momtazi)

Introduction

- „Field of study that gives computers the ability to learn without being explicitly programmed"
  - Arthur Samuel, 1959

- Learning Methods
  - Supervised learning
    - Active learning
  - Unsupervised learning
  - Semi-supervised learning
  - Reinforcement learning

Outline

- Supervised Learning
- Semi-supervised learning
- Unsupervised learning

Outline

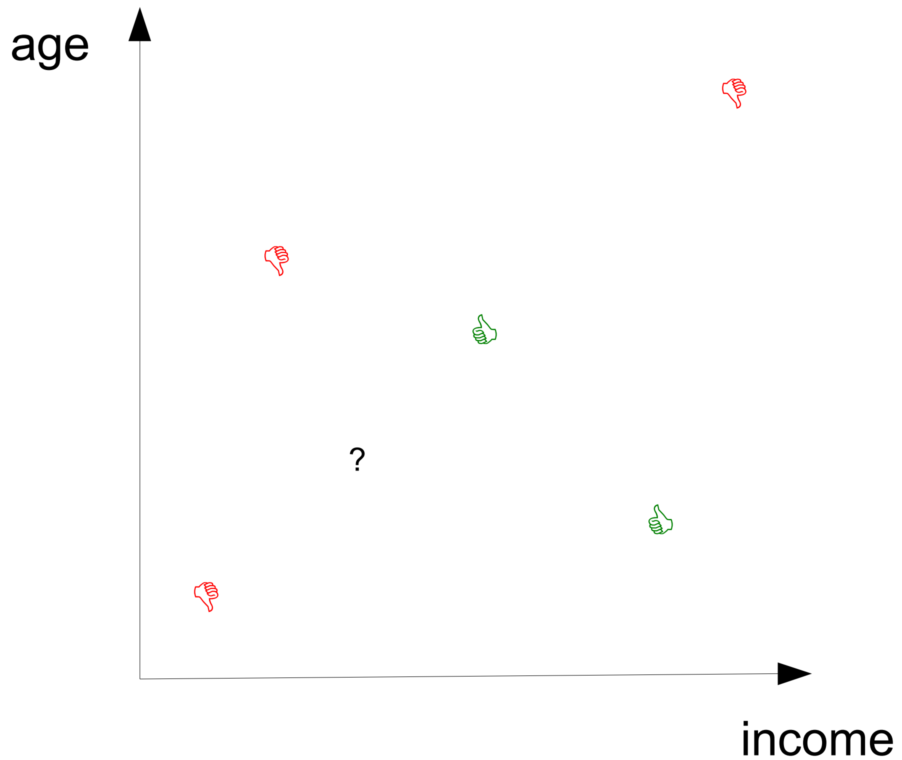
- Supervised Learning
- Semi-supervised learning
- Unsupervised learning

Supervised Learning

- Example: mortgage credit decision
  - Age
  - Income

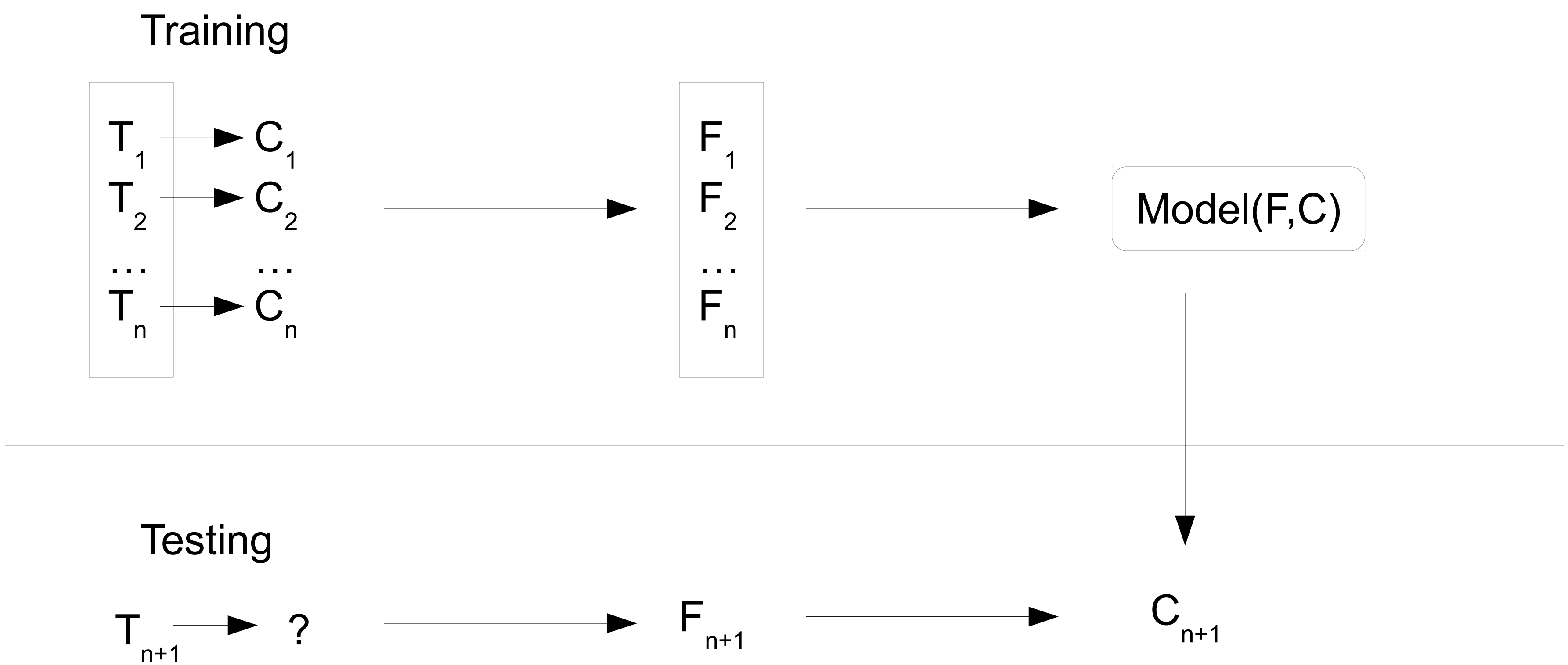
http://nationalmortgageprofessional.com/news24271/regulatory-compliance-outlook-new-risk-based-pricing-rules

Supervised Learning



http://nationalmortgageprofessional.com/news24271/regulatory-compliance-outlook-new-risk-based-pricing-rules

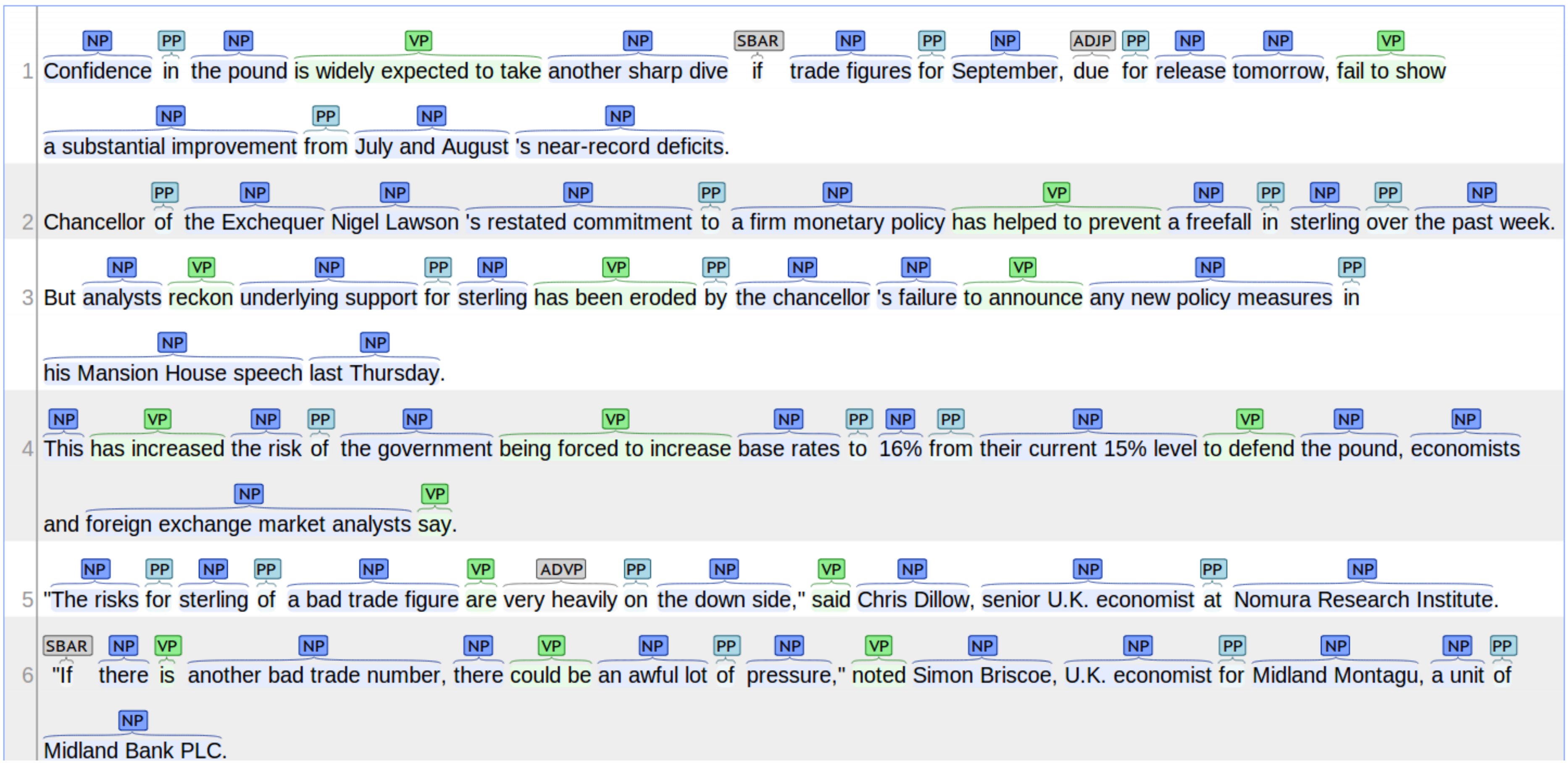
Classification



Applications

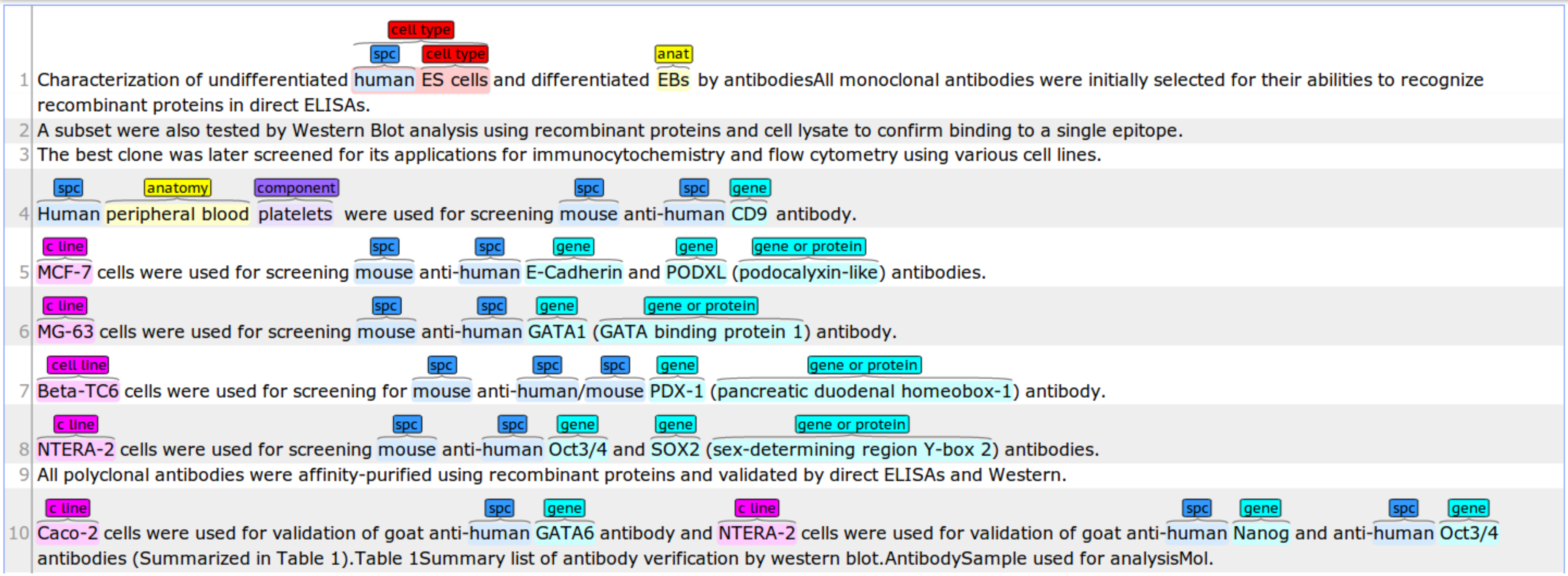
Problems	Items	Categories
POS tagging	Word	POS
Named entity recognition	Word	Named entity
Word sense disambiguation	Word	Word's sense
Spam mail detection	Document	Spam/Not Spam
Language identification	Document	Language
Text categorization	Document	Topic
Information retrieval	Document	Relevant/Not relevant

Part-of-speech tagging



http://weaver.nlplab.org/~brat/demo/latest/#/not-editable/CoNLL-00-Chunking/train.txt-doc-1

Named entity recognition



http://corpora.informatik.hu-berlin.de/index.xhtml#/cellfinder/version1_sections/16316465_03_results

Word sense disambiguation

Michael Jordan (born 1963) is an American basketball player.

Michael Jordan may also refer to:

- Michael Jordan (mycologist), English mycologist
- Michael Jordan (footballer) (born 1986), English goalkeeper (Arsenal, Chesterfield, Lewes)
- Michael Jordan (insolvency baron) (born 1931), English businessman
- Mike Jordan (born 1958), English racing driver
- Mike Jordan (baseball) (1863–1940), baseball player
- Michael Jordan (Irish politician), Irish Farmers' Party TD from Wexford, 1927–1932
- Michael B. Jordan (born 1987), American actor
- Michael I. Jordan (born 1957), American researcher in machine learning and artificial intelligence
- Michael H. Jordan (1936–2010), American executive for CBS, PepsiCo, Westinghouse
- Michael-Hakim Jordan (born 1977), American professional basketball player
- Michal Jordan (born 1990), Czech ice hockey player
- "Michael Jordan", a song by Kendrick Lamar featuring ScHoolboy Q on the album Overly Dedicated'

Spam mail detection

Neue Nachricht
Peter Schmidt [noreply@comment.am]

Sent: Tuesday, April 29, 2014 10:32 AM
To: Forschungskolleg

Guten Tag,

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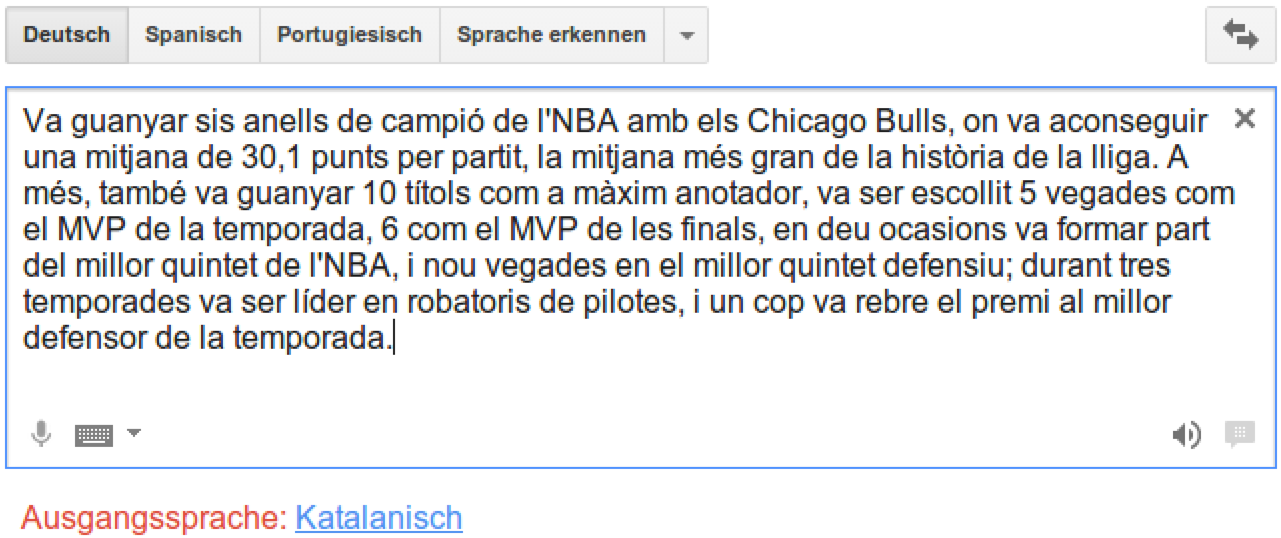
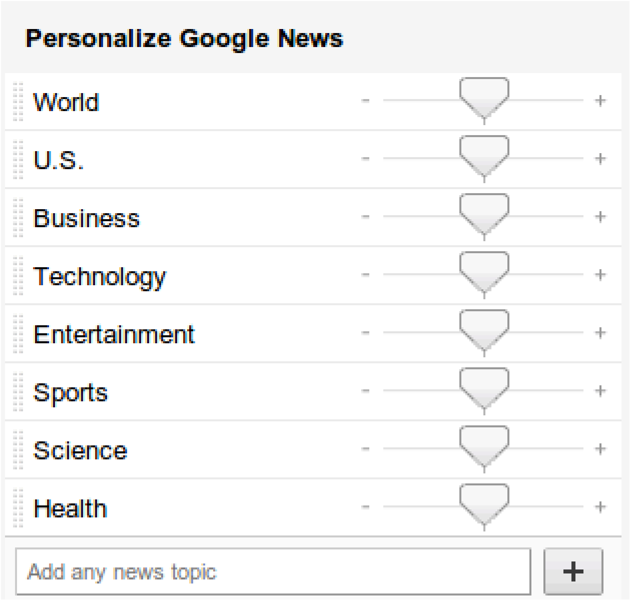
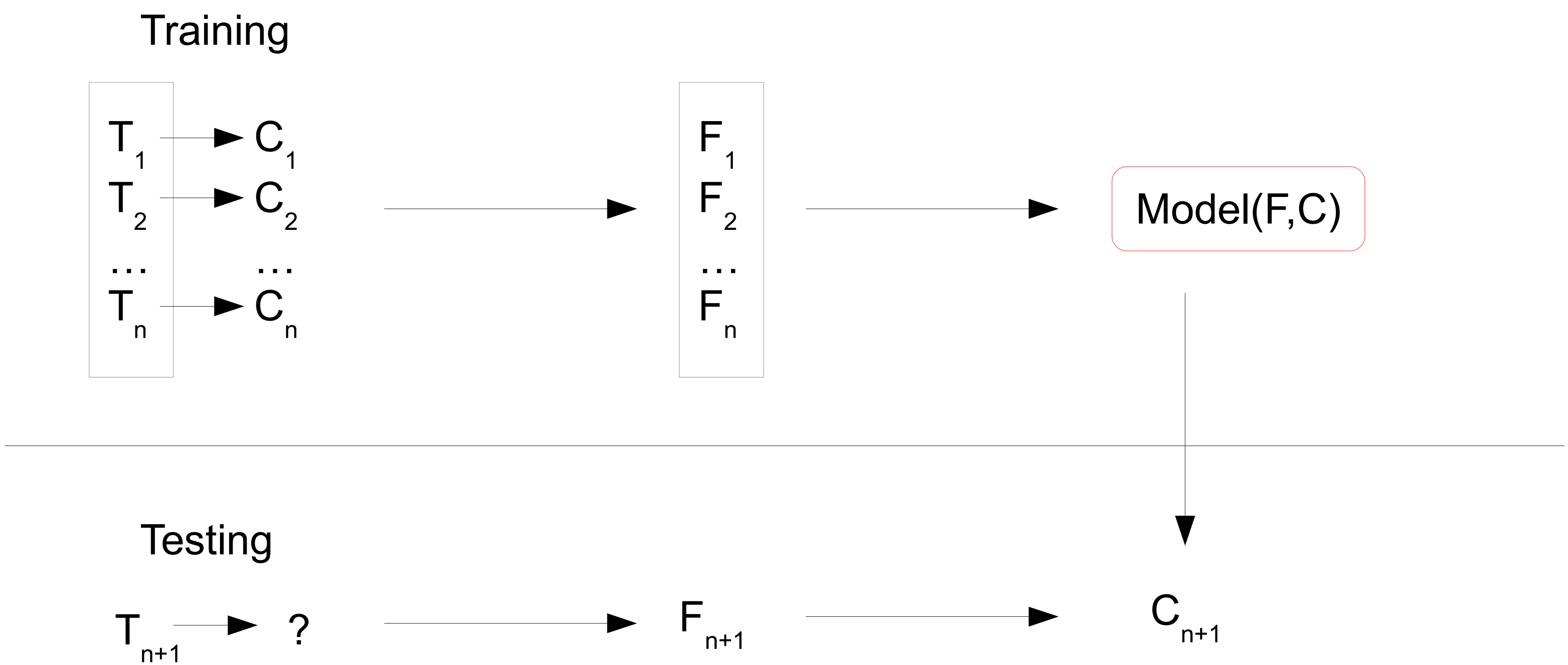
Language identification



Text categorization



Classification



Classification algorithms

- K Nearest Neighbor
- Support Vector Machines
- Naïve Bayes
- Maximum Entropy
- Linear Regression
- Logistic Regression
- Neural Networks
- Decision Trees
- Boosting
- ...

Classification algorithms

- K Nearest Neighbor
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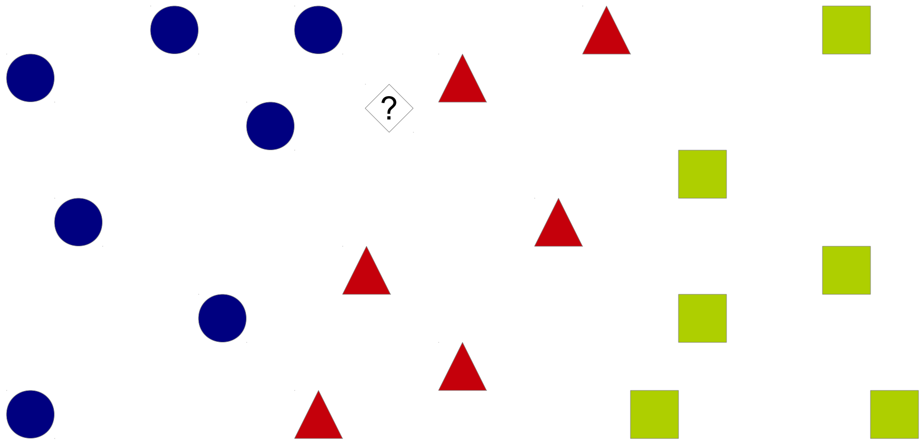
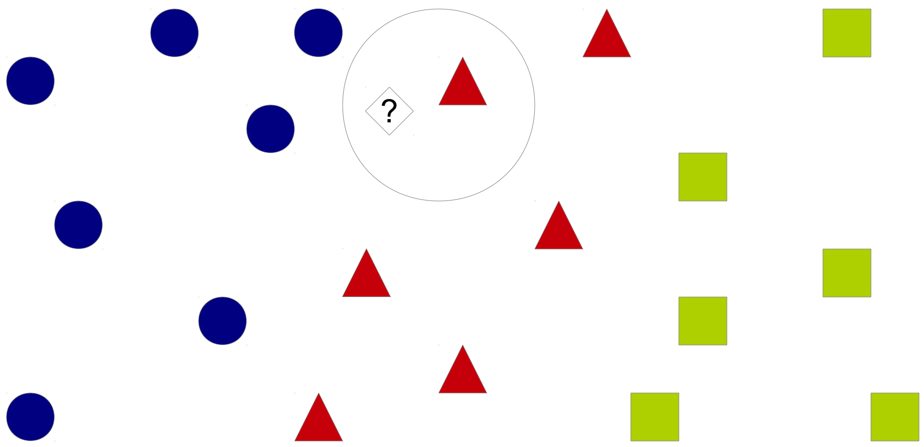
K Nearest Neighbor

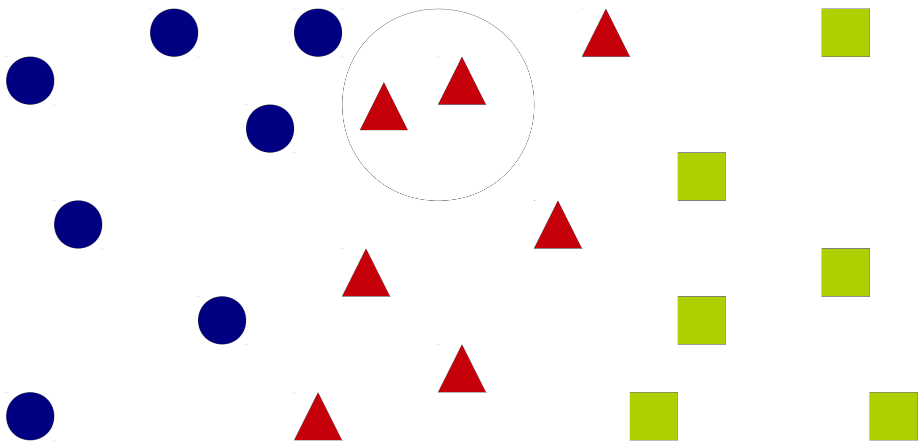


K Nearest Neighbor



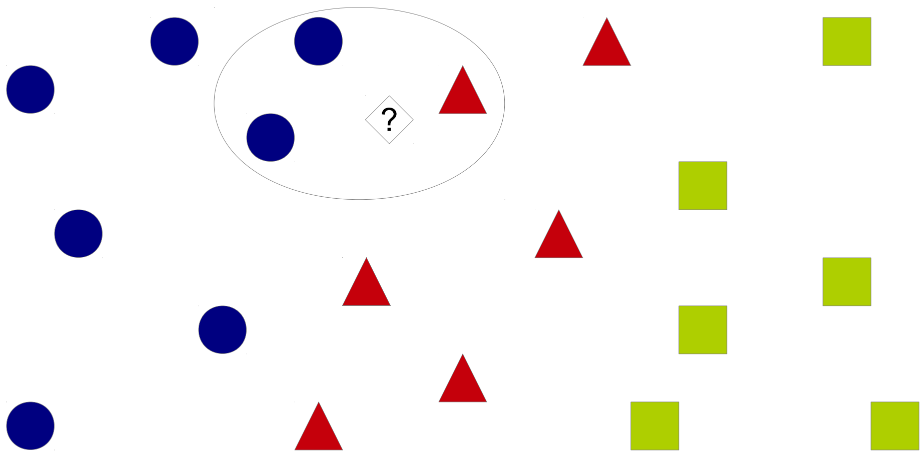
K Nearest Neighbor

- 1-nearest neighbor



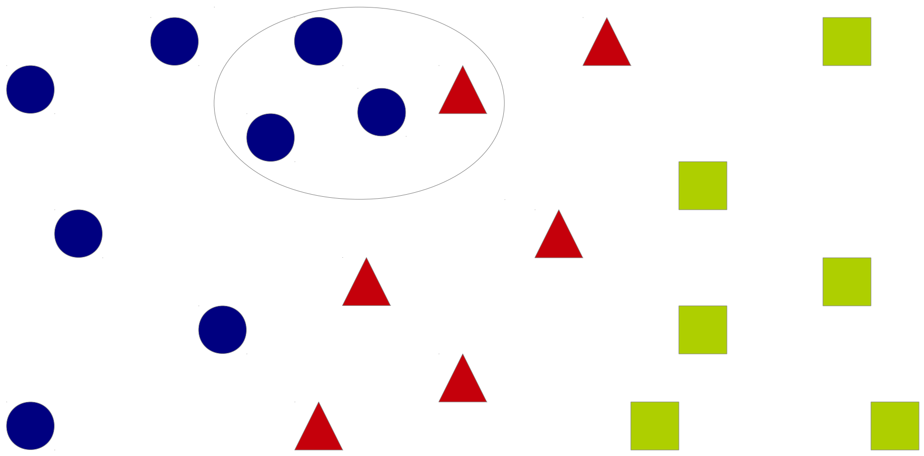
K Nearest Neighbor

- 3-nearest neighbors



K Nearest Neighbor

- 3-nearest neighbors



Classification algorithms

- K Nearest Neighbor
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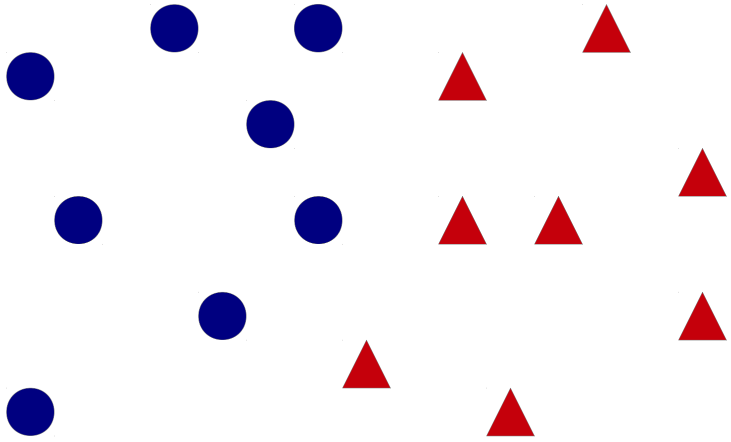
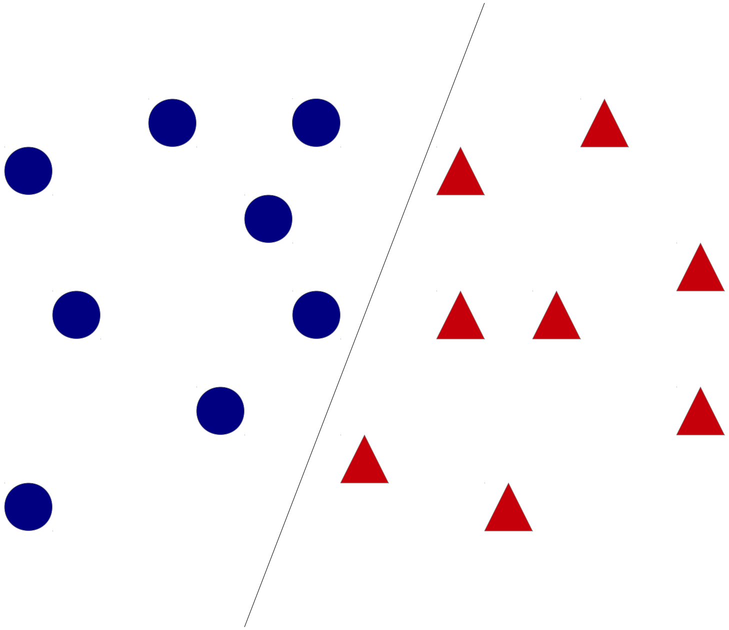
- ...

Support vector machines



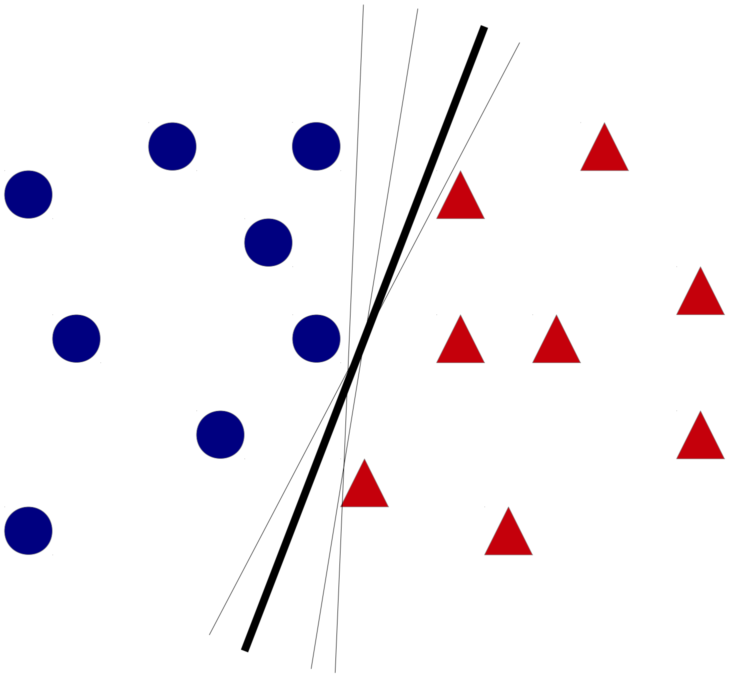
Support vector machines

- Find a hyperplane in the vector space that separates the items of the two categories



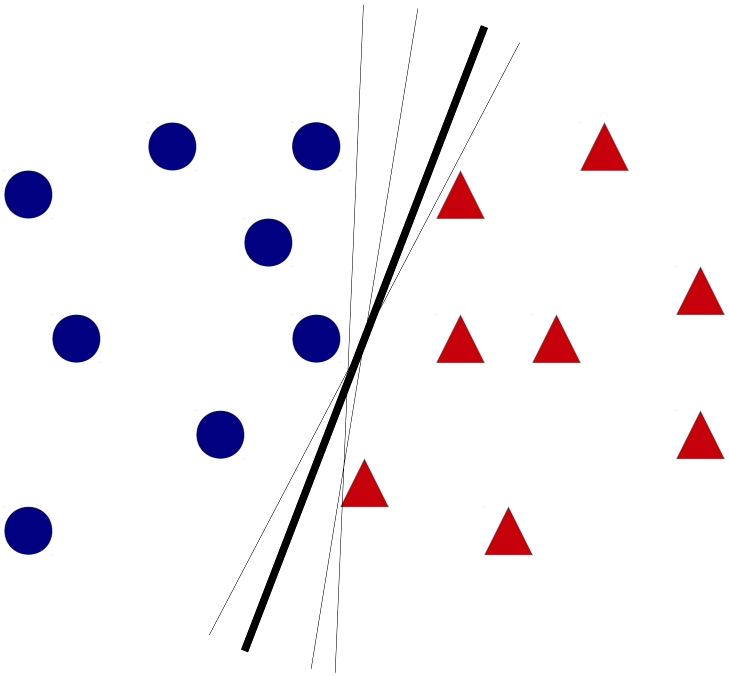
Support vector machines

- There might be more than one possible separating hyperplane



Support vector machines

- Find the hyperplane with maximum margin
- Vectors at the margins are called support vectors



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- ...

Naïve Bayes

- Selecting the class with highest probability
  - Minimizing the number of items with wrong labels

$$\hat{c} = argmax_{c_i} P(c_i)$$

  - Probability should depend on the to be classified data (d)

$$P(c_i | d)$$

Naïve Bayes

$$\hat{c} = argmax_{c_i} P(c_i)$$

$$\hat{c} = argmax_{c_i} P(c_i | d)$$

$$\hat{c} = argmax_{c_i} \frac{P(d | c_i) \cdot P(c_i)}{P(d)}$$

$$\hat{c} = argmax_{c_i} P(d | c_i) \cdot P(c_i)$$

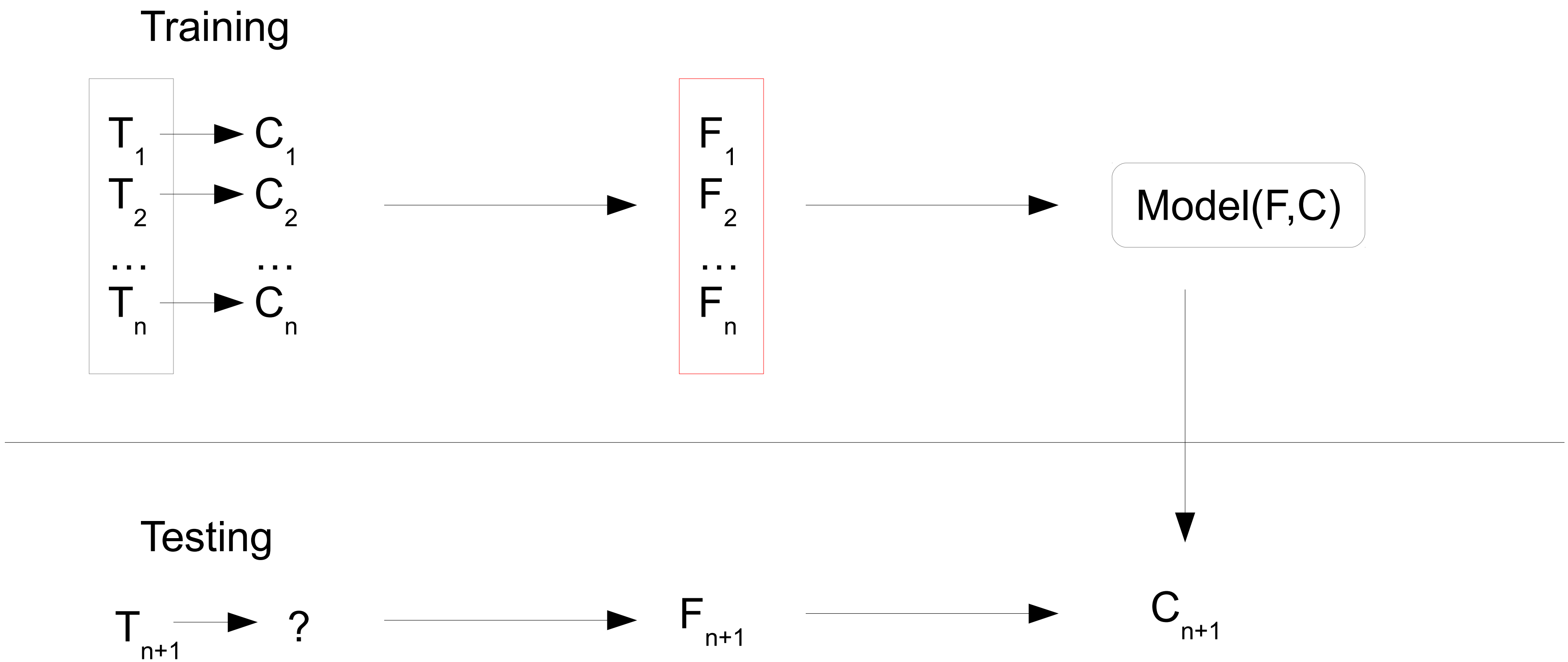
Naïve Bayes

$$\hat{c} = argmax_{c_i} P(d|c_i) \cdot P(c_i)$$

Prior probability

Likelihood probability

Classification



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Features:
- words
- sender's email
- contains links
- contains attachments
- contains money amounts

...

Feature selection

- Bag-of-words:
  - Each document can be represented by the set of words that appear in the document
  - Result is a high dimensional feature space
  - The process is computationally expensive

- Solution
  - Using a feature selection method to select informative words

Feature selection methods

- Information gain
- Mutual information
- χ-Square

Information gain

- Measuring the number of bits required for category prediction w.r.t. the presence or absence of a term in the document
- Removing words whose information gain is less than a predefined threshold

$$IG(w) = \sum_{i=1}^{K} P(c_i) \cdot \log P(c_i)$$

$$+ P(w) \cdot \sum_{i=1}^{K} P(c_i|w) \cdot \log P(c_i|w)$$

$$+ P(\bar{w}) \cdot \sum_{i=1}^{K} P(c_i|\bar{w}) \cdot \log P(c_i|\bar{w})$$

Information gain

- N = # docs
- N_i = # docs in category c_i
- N_w = # docs containing *w*
- $N_{\bar{w}}$ = # docs not containing *w*
- N_{iw} = # docs in category c_i containing *w*
- $N_{i\bar{w}}$ = *# docs in category c_i not containing w*

$$P(c_i) = \frac{N_i}{N}$$

$$P(w) = \frac{N_w}{N}$$

$$P(c_i|w) = \frac{N_{iw}}{N_i}$$

$$P(\bar{w}) = \frac{N_{\bar{w}}}{N}$$

$$P(c_i|\bar{w}) = \frac{N_{i\bar{w}}}{N_i}$$

Mutual information

- Measuring the effect of each word in predicting the category
  - How much does its presence or absence in a document contribute to category prediction?

$$MI(w, c_i) = \log \frac{P(w, c_i)}{P(w) \cdot P(c_i)}$$

- Removing words whose mutual information is less than a predefined threshold

$$MI(w) = max_i\, MI(w, c_i)$$

$$MI(w) = {}_i\sum P(c_i) \cdot MI(w, c_i)$$

χ-Square

- Measuring the dependencies between words and categories

$$\chi^2(w, c_i) = \frac{N \cdot \left(N_{iw} N_{\bar{i}\bar{w}} - N_{i\bar{w}} N_{\bar{i}w}\right)^2}{\left(N_{iw} + N_{i\bar{w}}\right) \cdot \left(N_{\bar{i}w} + N_{\bar{i}\bar{w}}\right) \cdot \left(N_{iw} + N_{\bar{i}w}\right) \cdot \left(N_{i\bar{w}} + N_{\bar{i}\bar{w}}\right)}$$

- Ranking words based on their χ-square measure

$$\chi^2(w) = \sum_{i=1}^{K} P(c_i) \cdot \chi^2(w, c_i)$$

- Selecting the top words as features

Feature selection

- These models perform well for document-level classification
  - Spam Mail Detection
  - Language Identification
  - Text Categorization

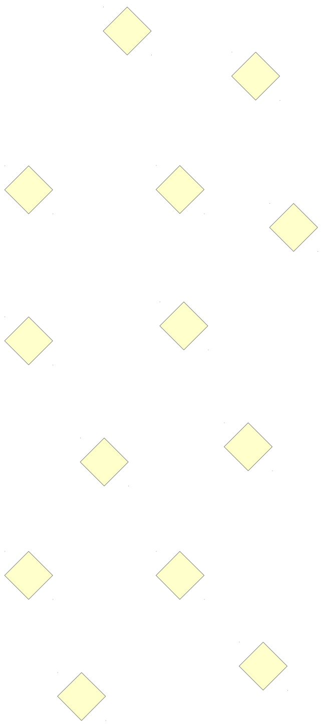
- Word-level Classification might need another types of features
  - Part-of-speech tagging
  - Named Entity Recognition

Supervised learning

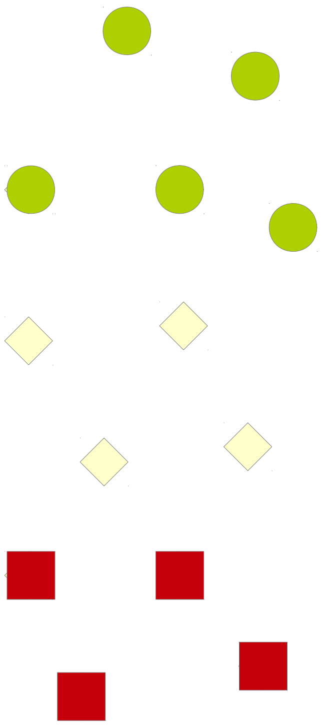
- Shortcoming
  - Relies heavily on annotated data
  - Time consuming and expensive task

- Solution
  - Active learning
    - Using a minimum amount of annotated data
    - Annotating further data by human, if they are very informative

Active learning

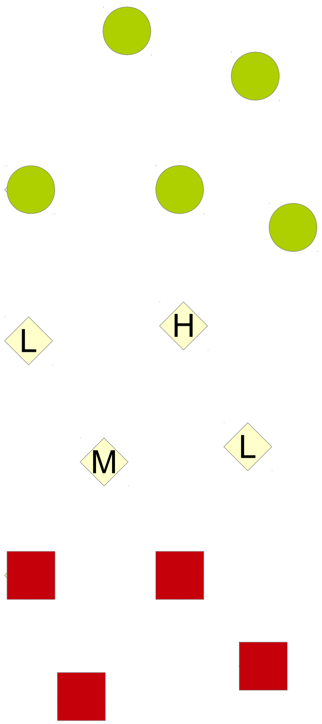


Active learning



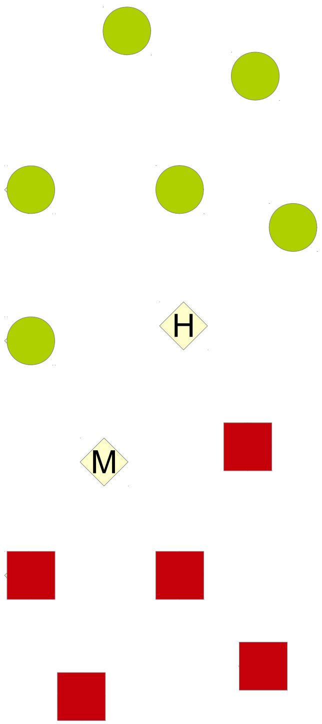
- Annotating a small amount of data

Active learning



- Calculating the confidence score of the classifier on unlabeled data

Active learning



- Finding the informative unlabeled data (data with lowest confidence)

- manually annotating the informative data

Outline

- Supervised Learning
- Semi-supervised learning
- Unsupervised learning

Semi-supervised learning

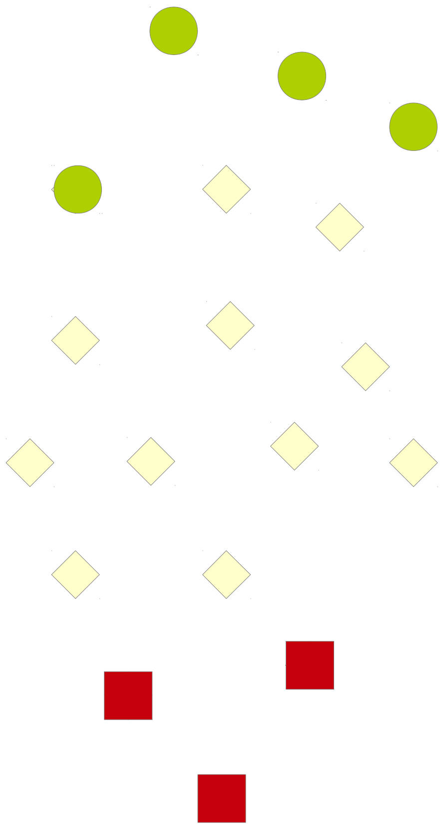
- Annotating data is a time consuming and expensive task

- Solution
  - Using a minimum amount of annotated data
  - Annotating further data automatically

Semi-supervised learning

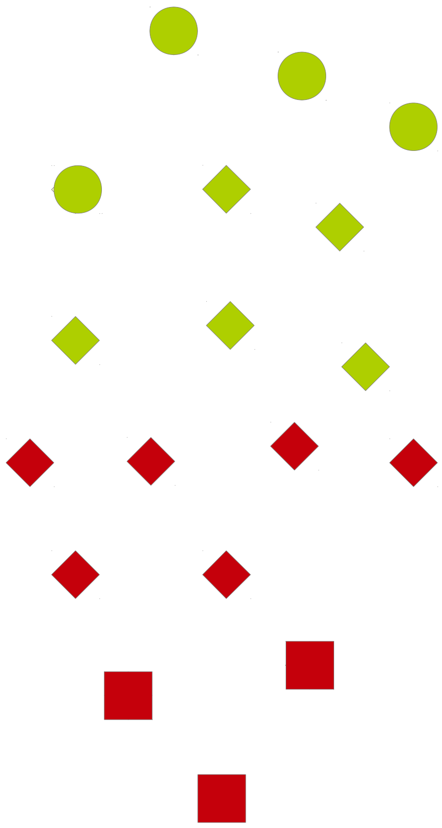
- A small amount of labeled data

Semi-supervised learning



- A large amount of unlabeled data

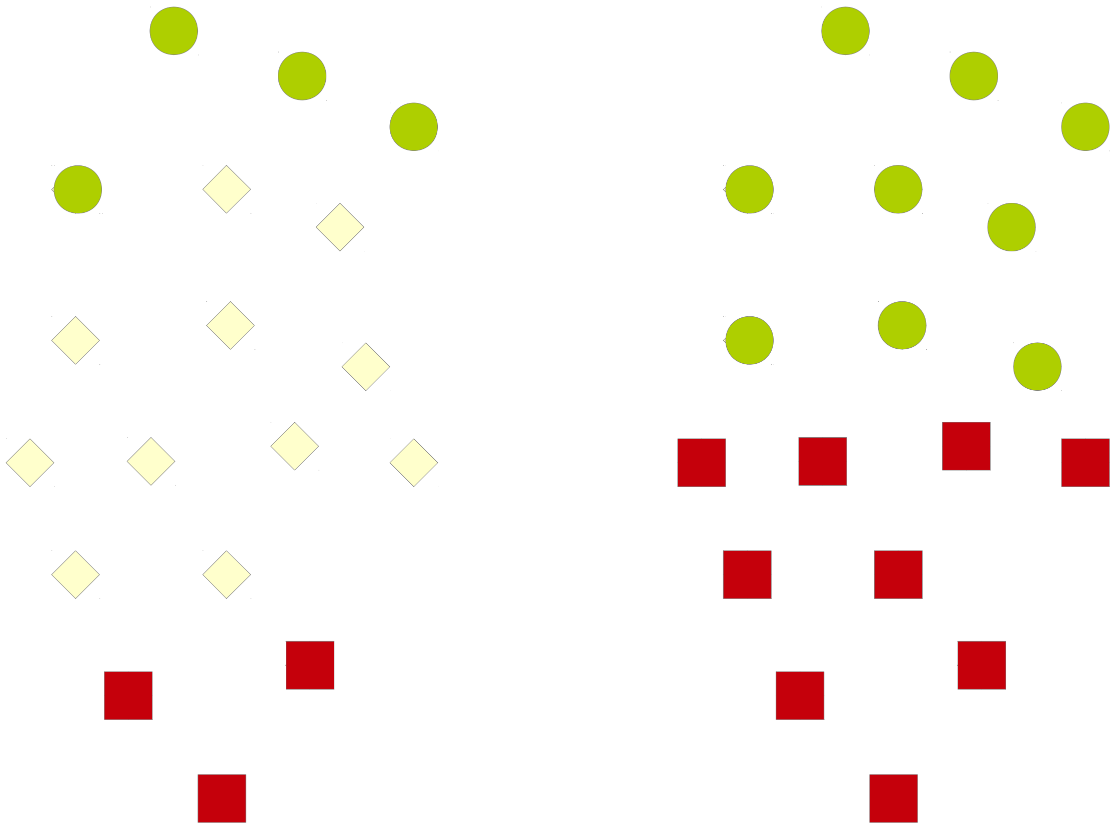
Semi-supervised learning



- Finding the similarity between the labeled and unlabeled data

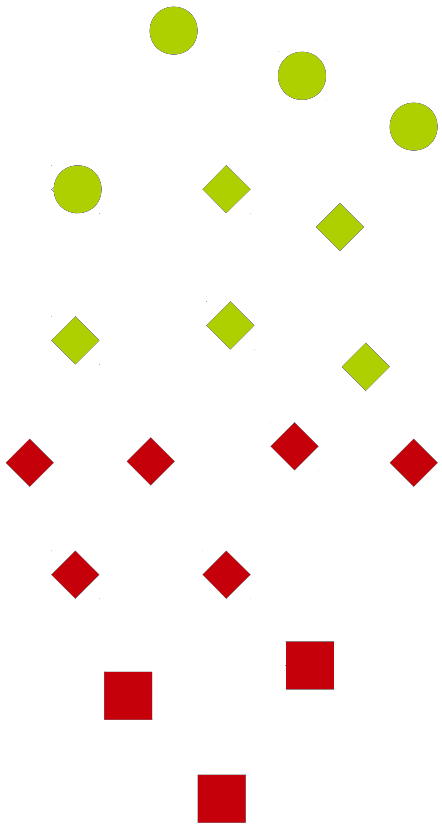
- Predicting the labels of the unlabeled data

Semi-supervised learning



- Training the classifier using labeled data and predicted labels of unlabeled data

Semi-supervised learning



- Introducing a lot of noisy data to the system

- Adding unlabeled data to the training set, if the predicted label has a high confidence

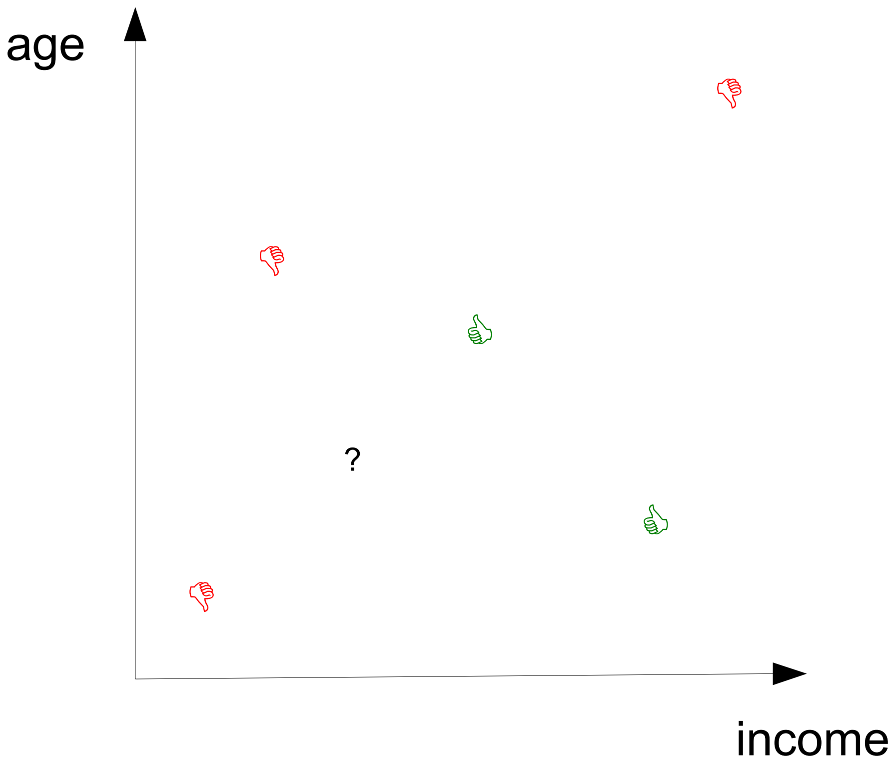
Outline

- Supervised Learning

- Semi-supervised learning

- Unsupervised learning

Supervised Learning



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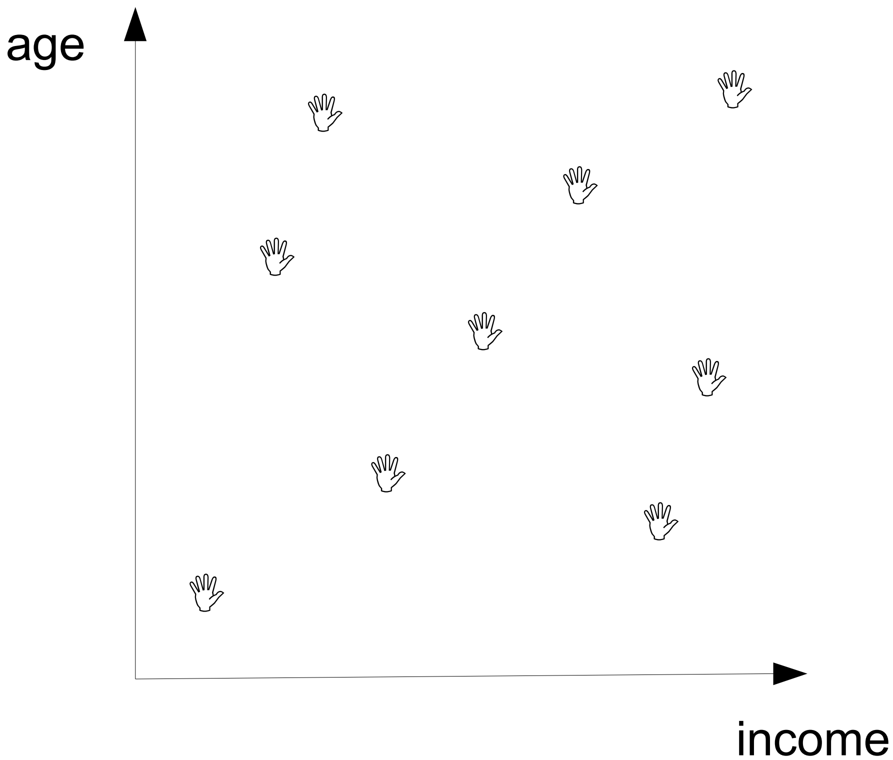
Unsupervised Learning



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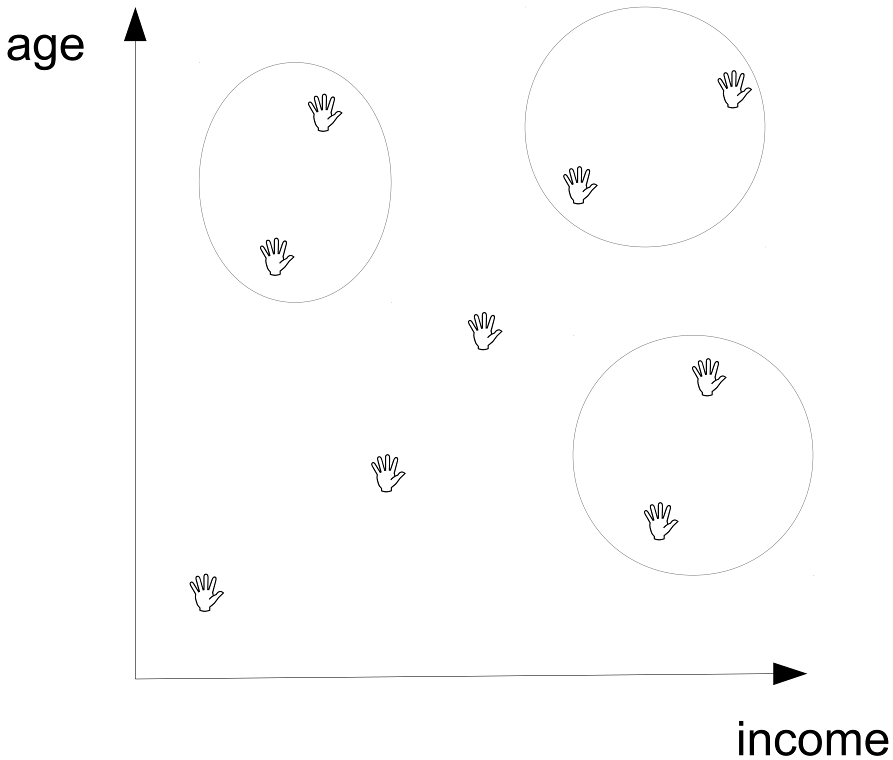
Unsupervised Learning



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Clustering

- Calculating similarities between the data items

- Assigning similar data items to the same cluster

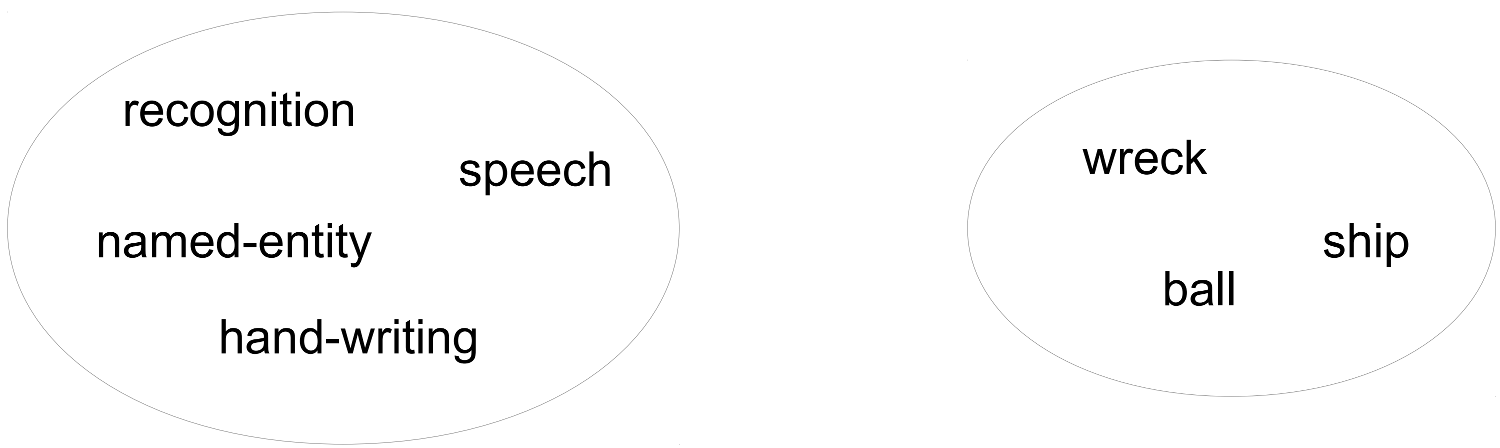
Applications

- Word clustering
  - Speech recognition
  - Machine translation
  - Named entity recognition
  - Information retrieval
  - ...

- Document clustering
  - Text classification
  - Information retrieval
  - ...

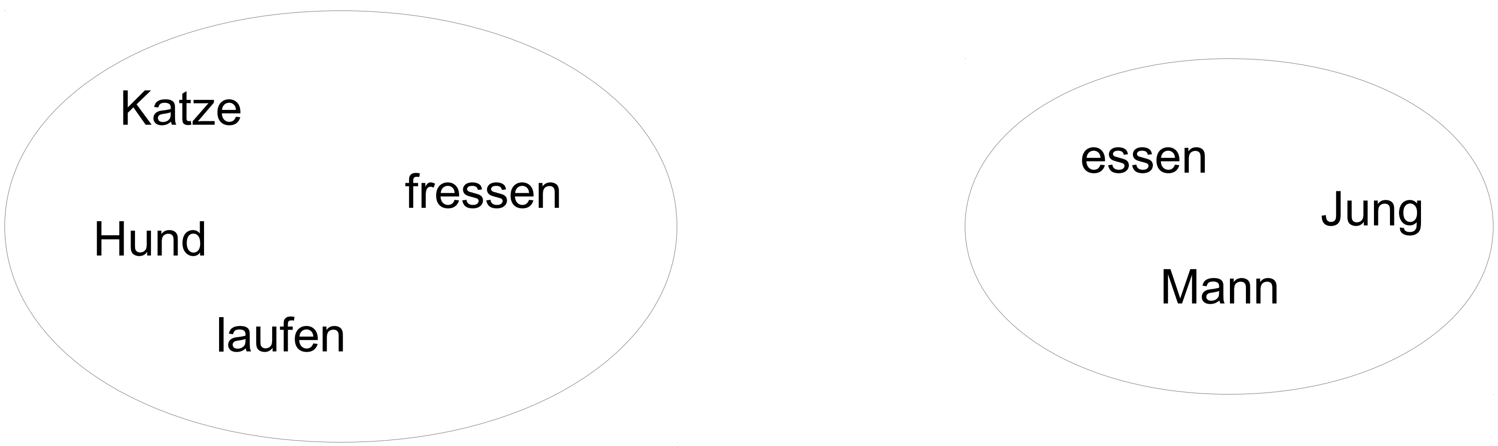
Speech recognition

- „Computers can recognize a speeech.“
- „Computers can wreck a nice peach.“



Machine translation

- „The cat eats...“
  - „Die Katze frisst...“
  - „Die Katze isst...“



Language modelling

- „I have a meeting on Moday evening.“
- „You should work on Wednesday afternoon.“
- „The next session is on Thursday morning.“

- „The talk is on Monday morning.“
- „The talk is on Monday molding.“

Monday
Sunday
Thursday
Saturday
Friday
Tuesday
Tuesday

morning
afternoon
evening
night

Clustering algorithms

- Flat
  - K-means

- Hierarchical
  - Top-Down (Divisive)
  - Bottom-Up (Agglomerative)
    - Single-link
    - Complete-link
    - Average-link

K-means

- The best known clustering algorithm
- Works well for many cases
- Used as default/baseline for clustering documents
- Defining each cluster center as the mean or centroid of the items in the cluster

$$\vec{\mu} = \frac{1}{|c|} \sum_{\vec{x} \in c} \vec{x}$$

- Minimizing the average squared Euclidean distance of the items from their cluster centers

K-means

Initialization: Randomly choose k items as initial centroids

while stopping criterion has not been met **do**

    for each item **do**

        Find the nearest centroid

        Assign the item to the cluster associated with the nearest centroid

    end for

    for each cluster **do**

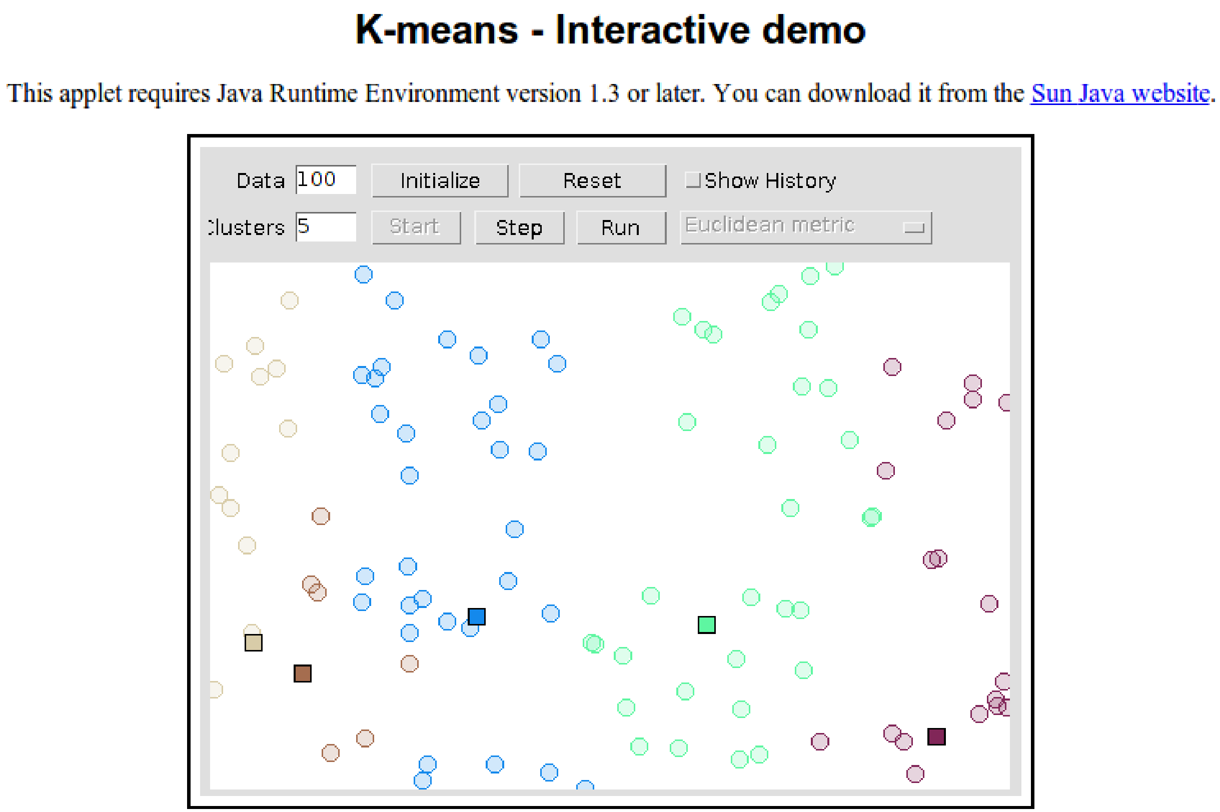
        Update the centroid of the cluster based on the average of all items in the cluster

    end for

end while

- Iterating two steps:
  - Re-assignment
    - Assigning each vector to its closest centroid
  - Re-computation
    - Computing each centroid as the average of the vectors that were assigned to it in re-assignment

K-means

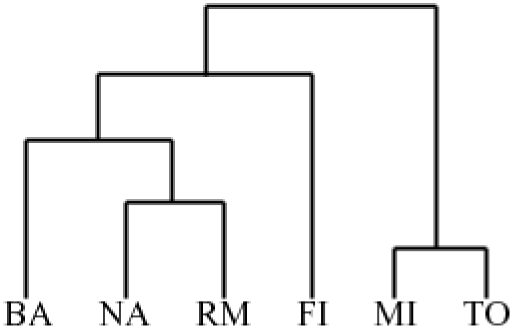


http://home.deib.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

Hierarchical Agglomerative Clustering (HAC)

- Creating a hierarchy in the form of a binary tree

	BA	FI	MI	NA	RM	TO
BA	0	662	877	255	412	996
FI	662	0	295	468	268	400
MI	877	295	0	754	564	138
NA	255	468	754	0	219	869
RM	412	268	564	219	0	669
TO	996	400	138	869	669	0



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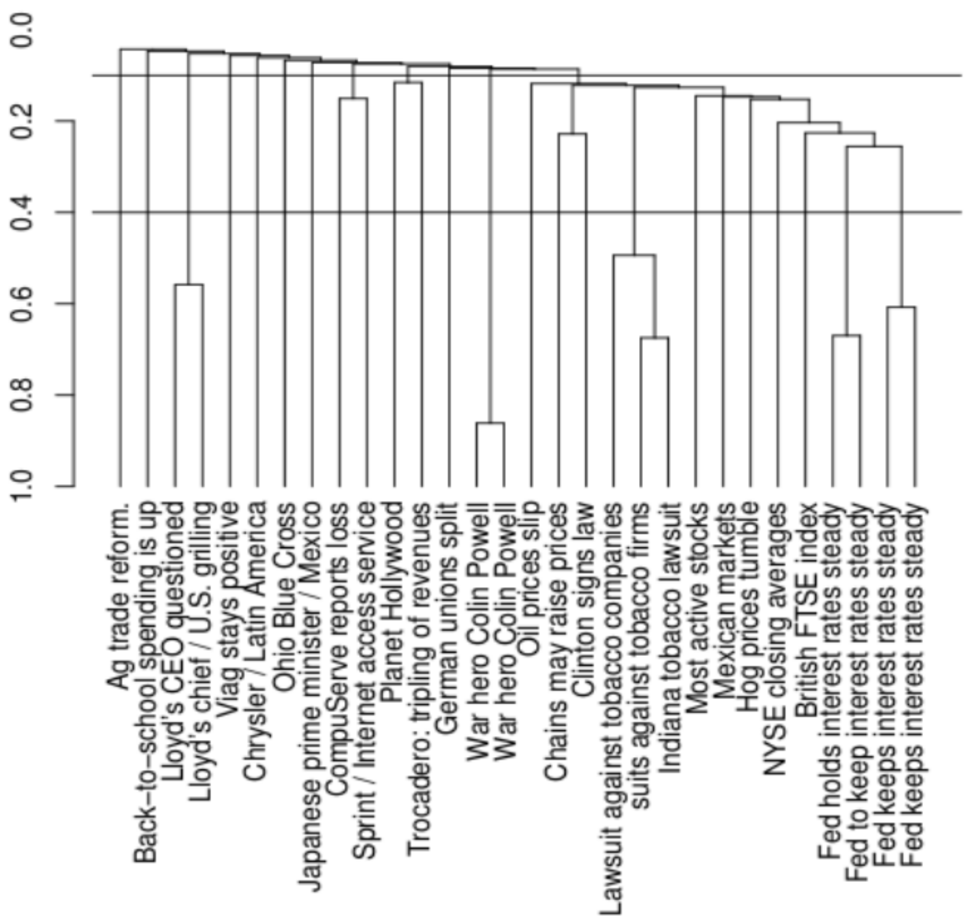


Hierarchical Agglomerative Clustering (HAC)

Initial Mapping: Put a single item in each cluster

while reaching the predefined number of clusters **do**

  for each pair of clusters **do**

    Measure the similarity of two clusters

  end for

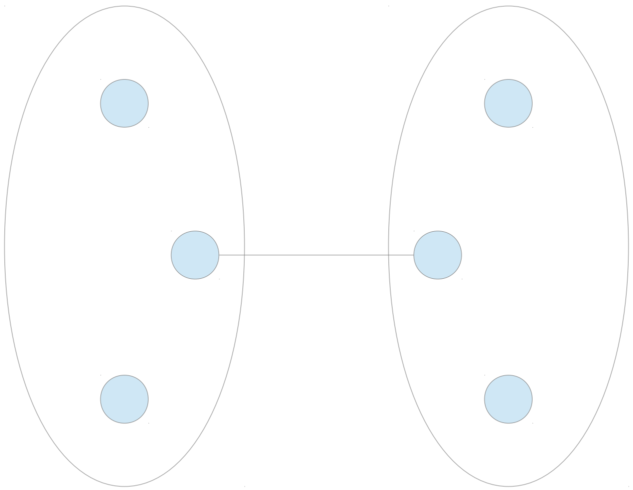
  Merge the two clusters that are most similar

end while

- Measuring the similarity in three ways:
  - Single-link
  - Complete-link
  - Average-link

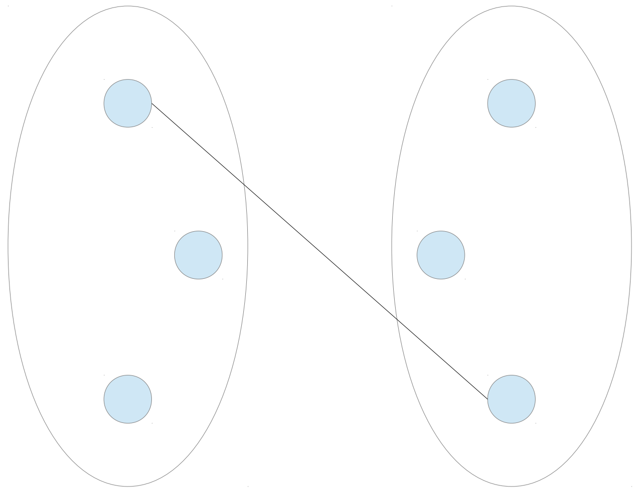
Hierarchical Agglomerative Clustering (HAC)

- Single-link / single-linkage clustering
  - Based on the similarity of the most similar members



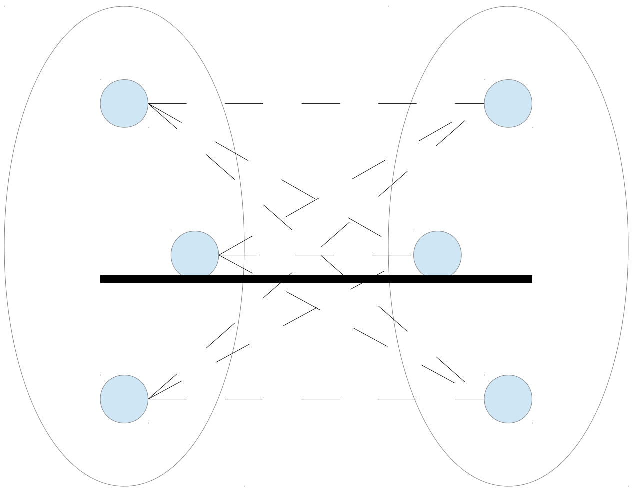
Hierarchical Agglomerative Clustering (HAC)

- Complete-link / complete-linkage clustering
  - Based on the similarity of the most dissimilar members

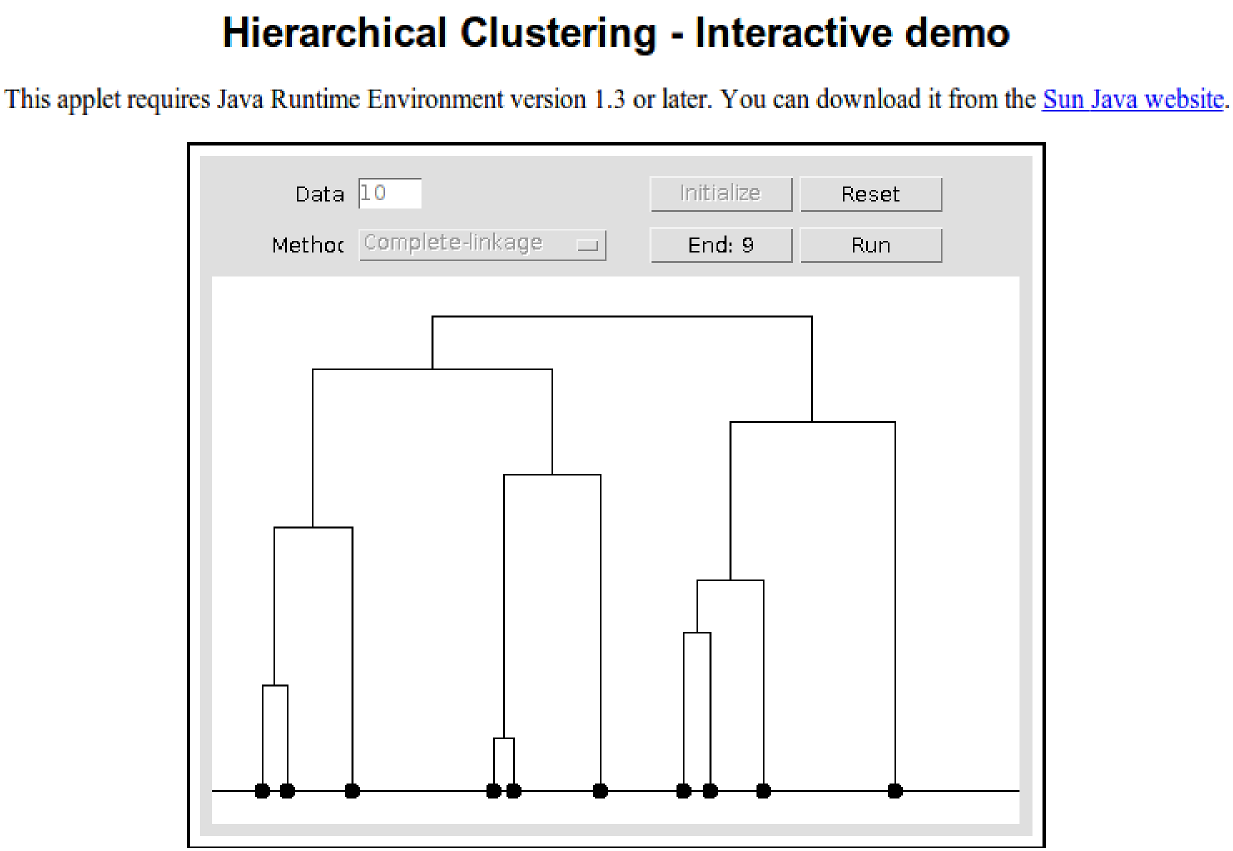


Hierarchical Agglomerative Clustering (HAC)

- Average-link / average-linkage clustering
  - Based on the average of all similarities between the members



Hierarchical Agglomerative Clustering (HAC)

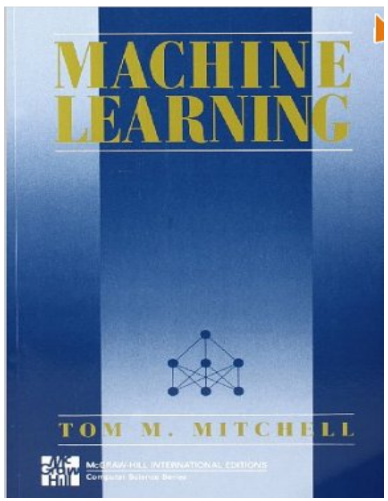


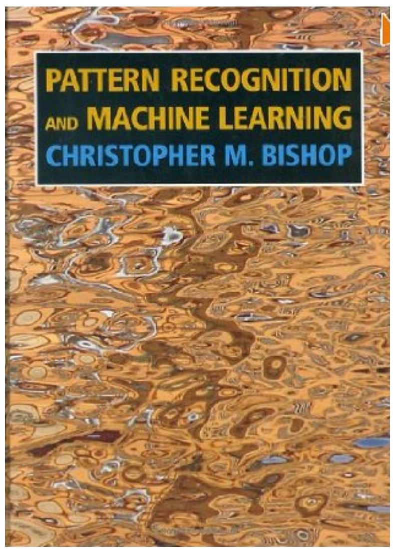
http://home.deib.polimi.it/matteucc/Clustering/tutorial_html/AppletH.html

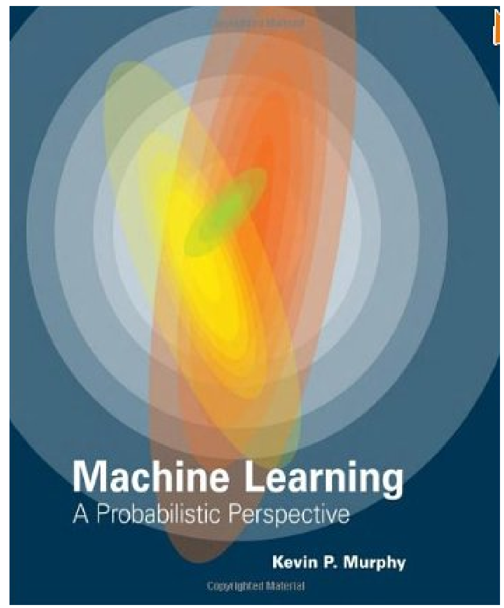
This is no clustering…just word frequencies

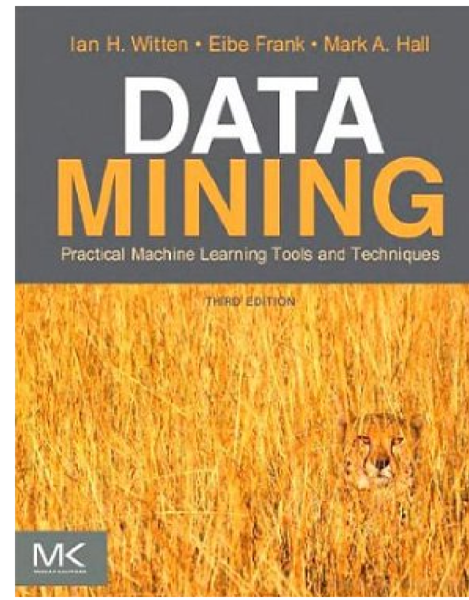
http://www.wordle.net/display/wrdl/1059224/English_notebook_cover

Further reading

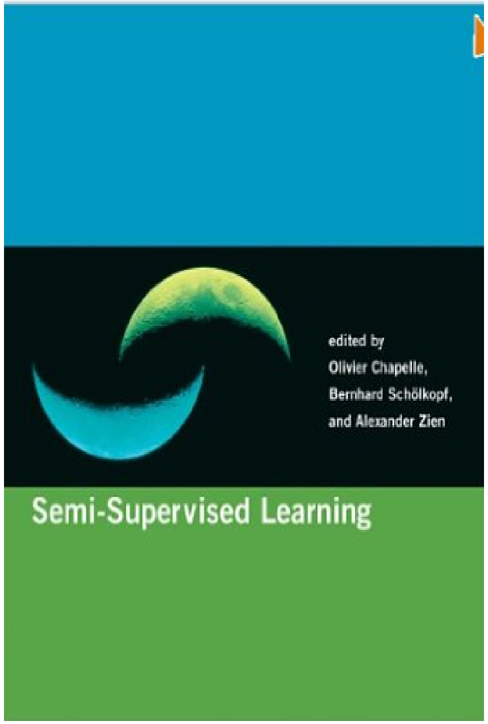


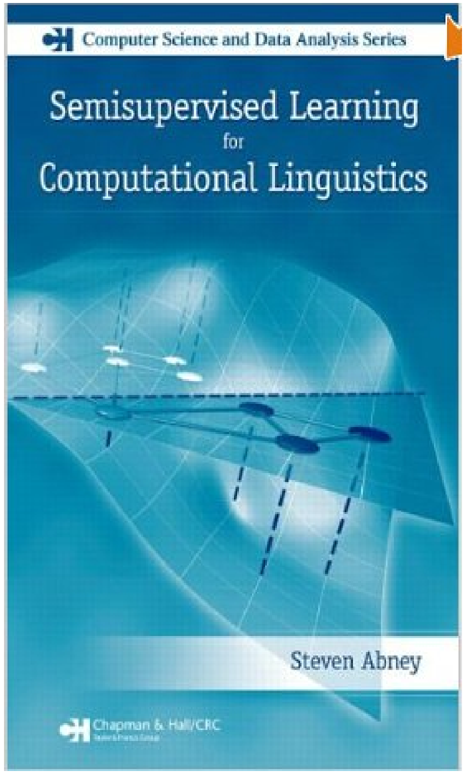






Further reading





Further reading