An Introduction to Semi-Supervised Learning

Foundations of Language Science and Technology

By Michael Wiegand

November 27th, 2009

Outline of Talk

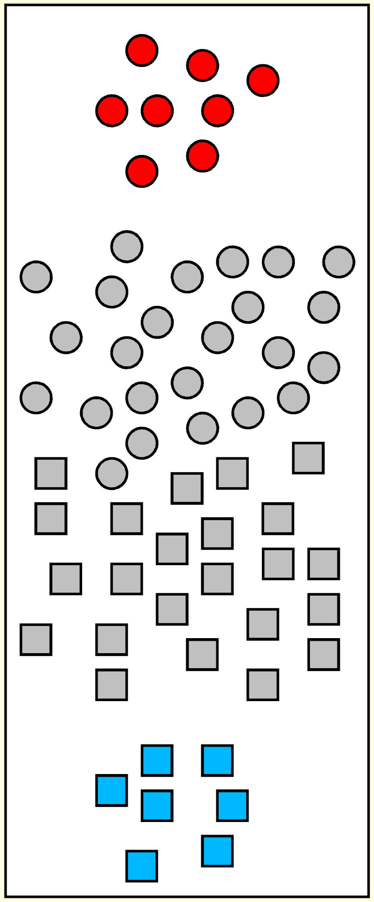
- The Concept of Semi-Supervised Learning
- Bootstrapping
- The Yarowksy Algorithm
- The Expectation Maximization Algorithm
- The Importance of Feature Selection in Semi-Supervised Learning (on Text Classification)

Aknowledgements

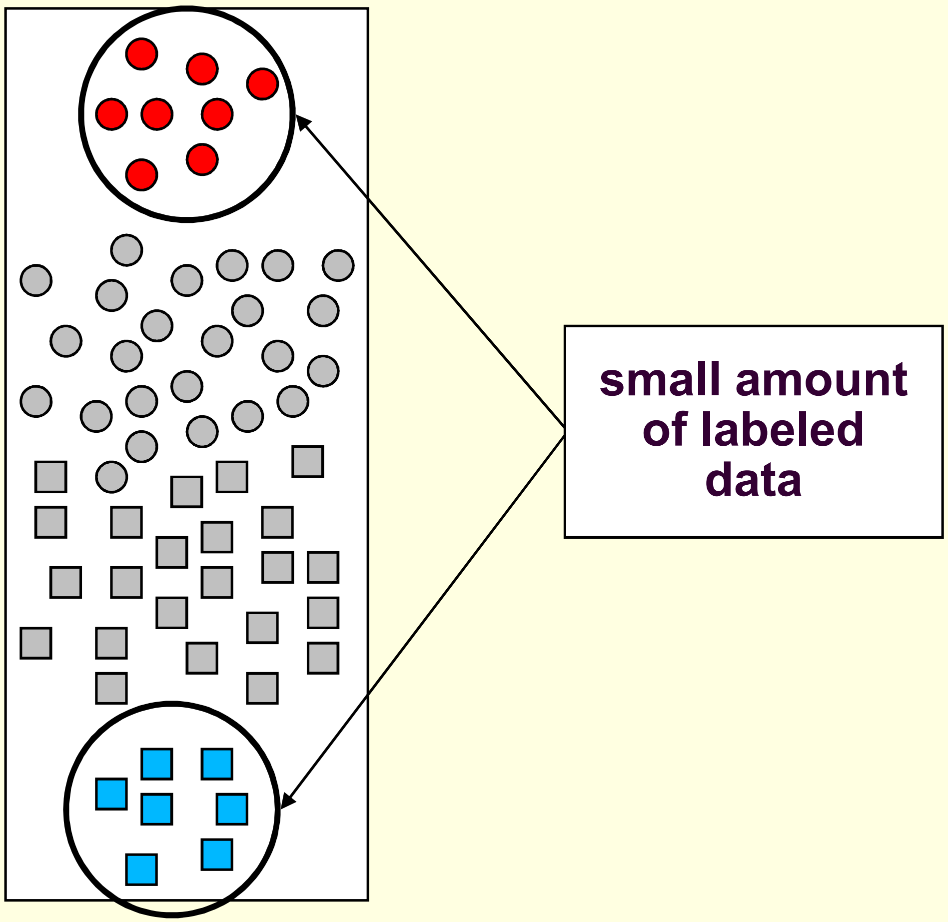
- Dietrich Klakow‘s lecture slides from *„Statistical Natural Language Processing“* (Spring 2008, Saarland University)
- Bing Liu‘s lecture slides from *„Data Mining and Text Mining“* (Spring 2008, University of Illinois at Chicago)
- William Cohen‘s and Tom Mitchell‘s lecture slides from *„Information Extraction“* (Spring 2007, Carnegie Mellon University)

The Concept of Semi-Supervised Learning

Semi-Supervised Learning - An Illustration



Semi-Supervised Learning - An Illustration



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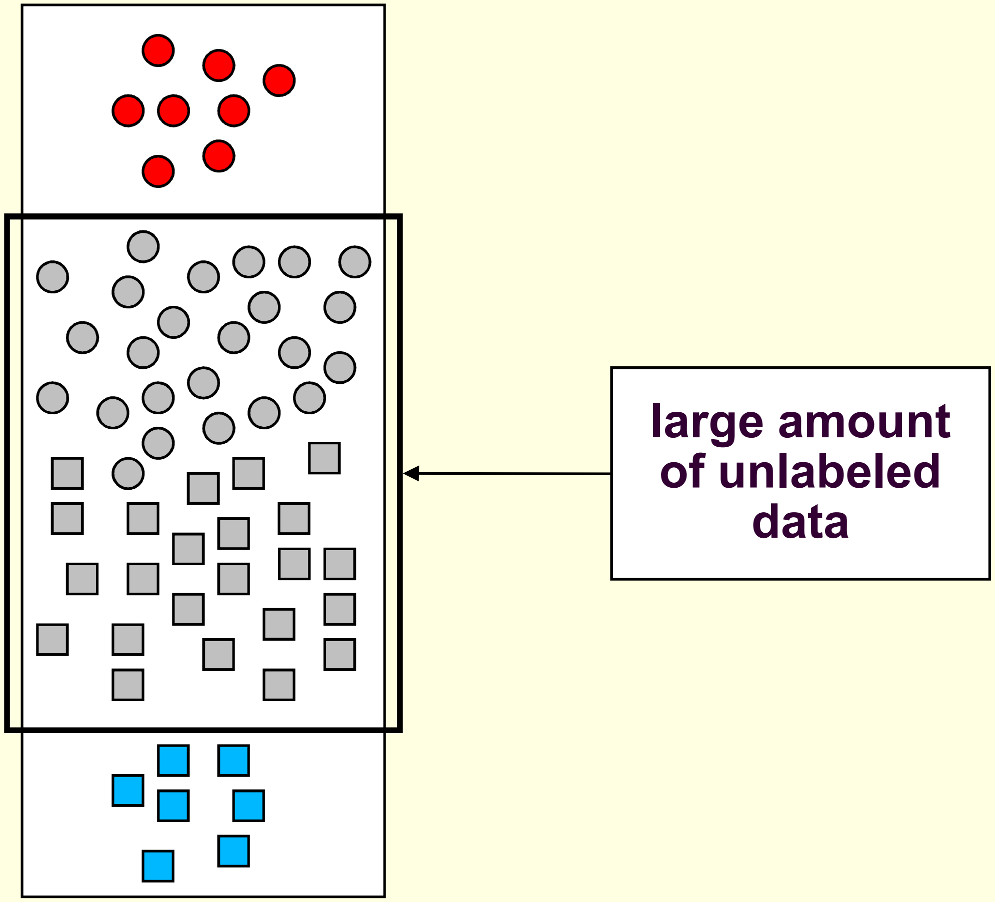

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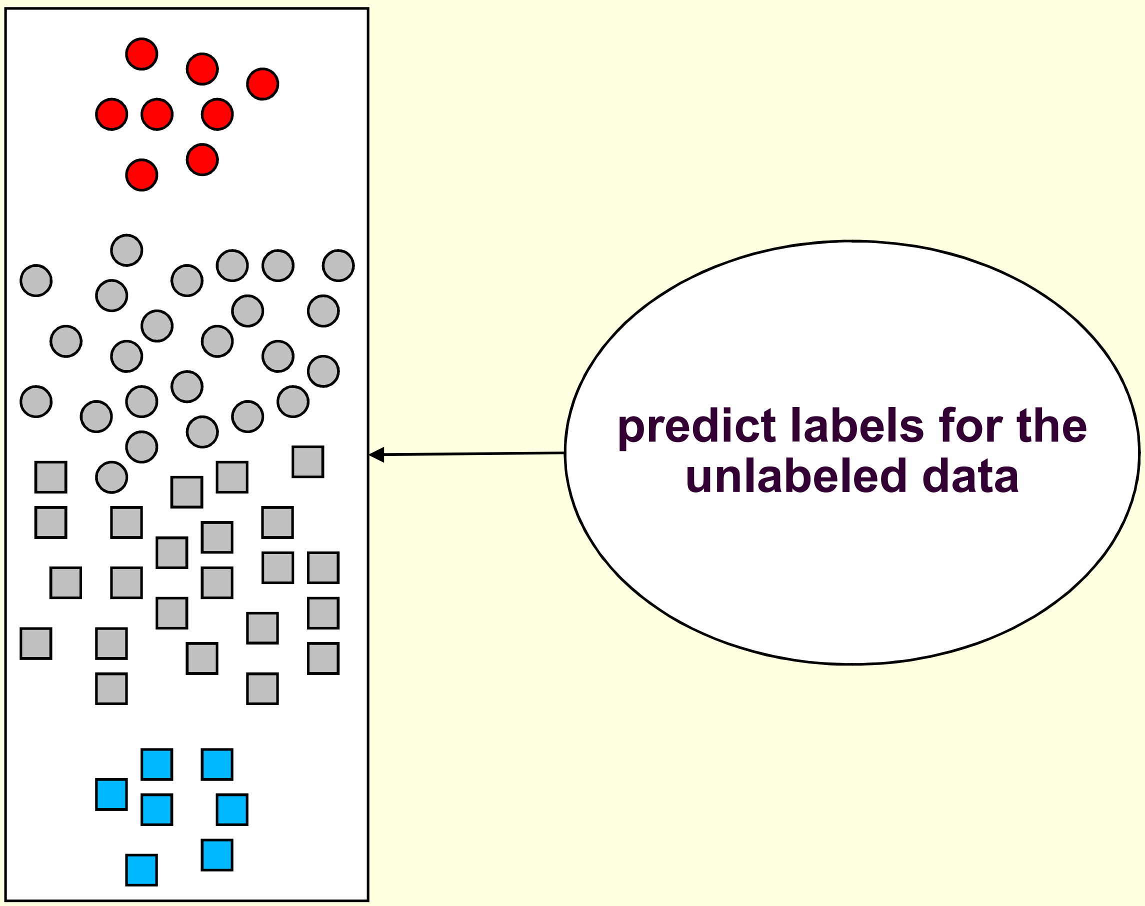

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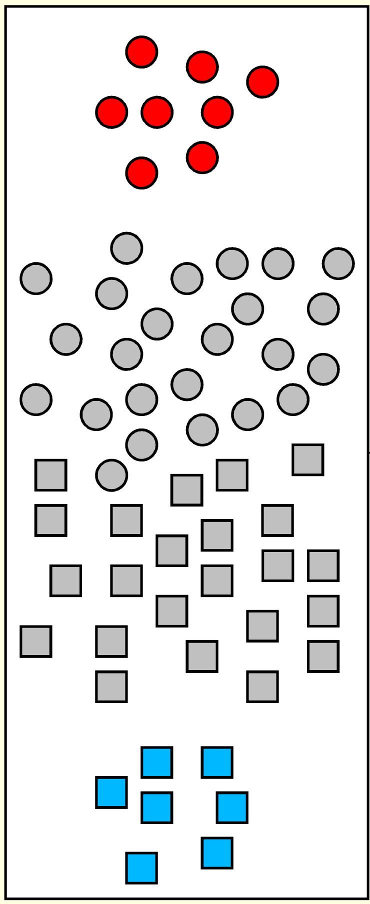
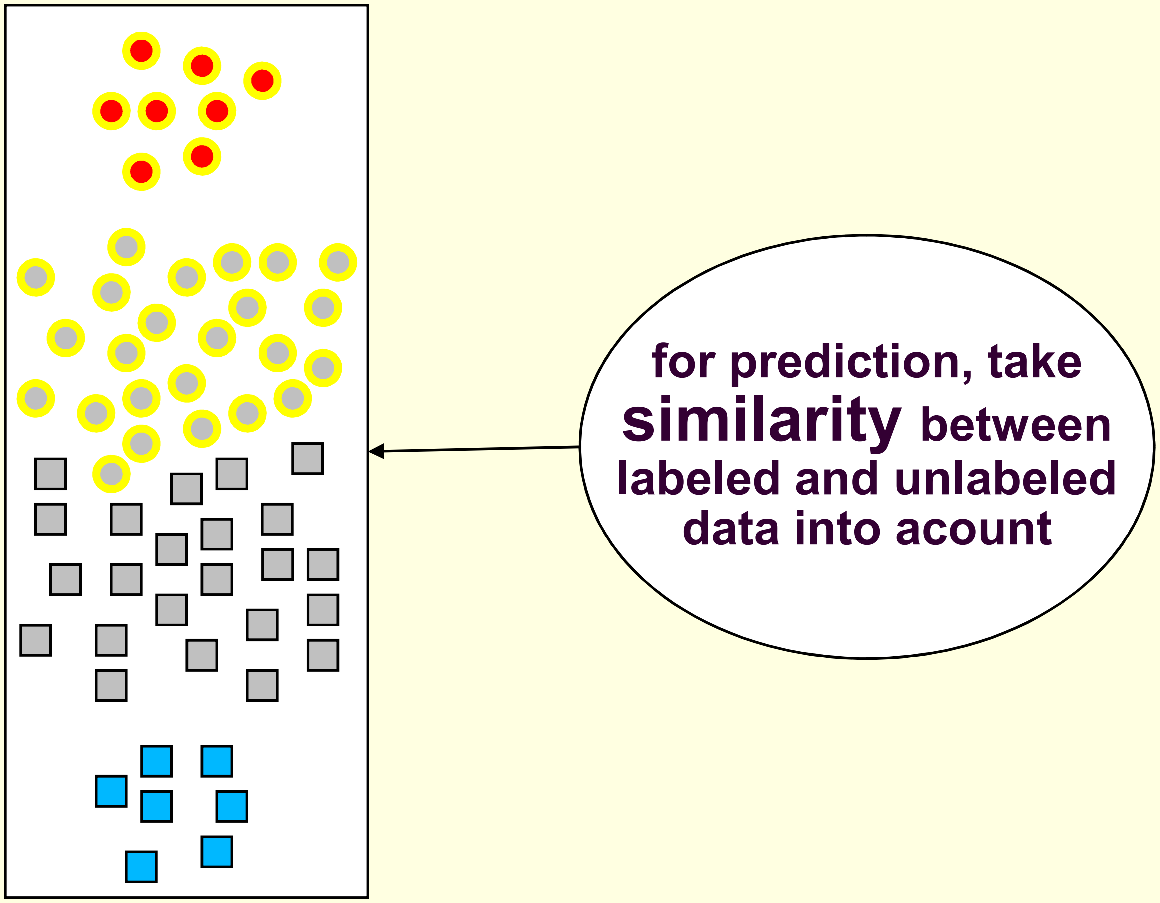


for prediction, take **similarity** between labeled and unlabeled data into acount

Semi-Supervised Learning - An Illustration



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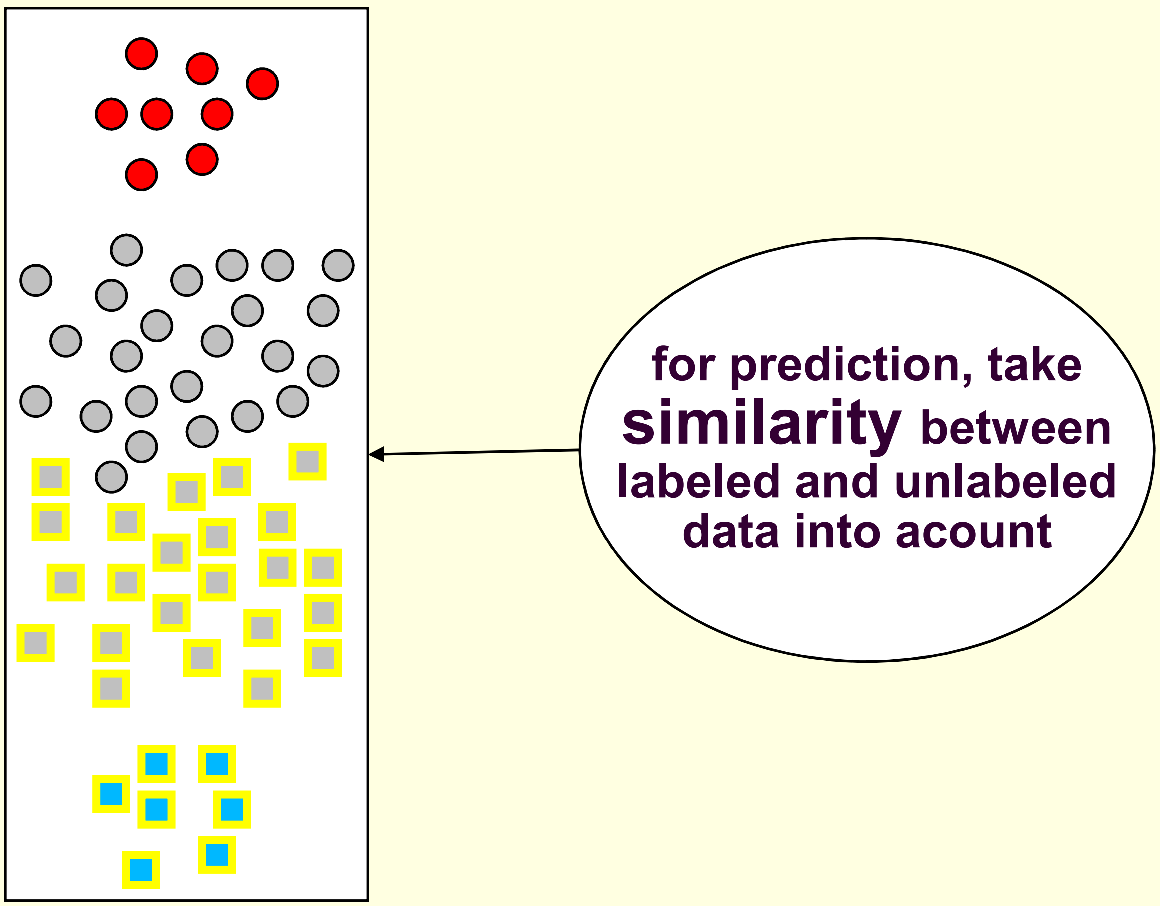

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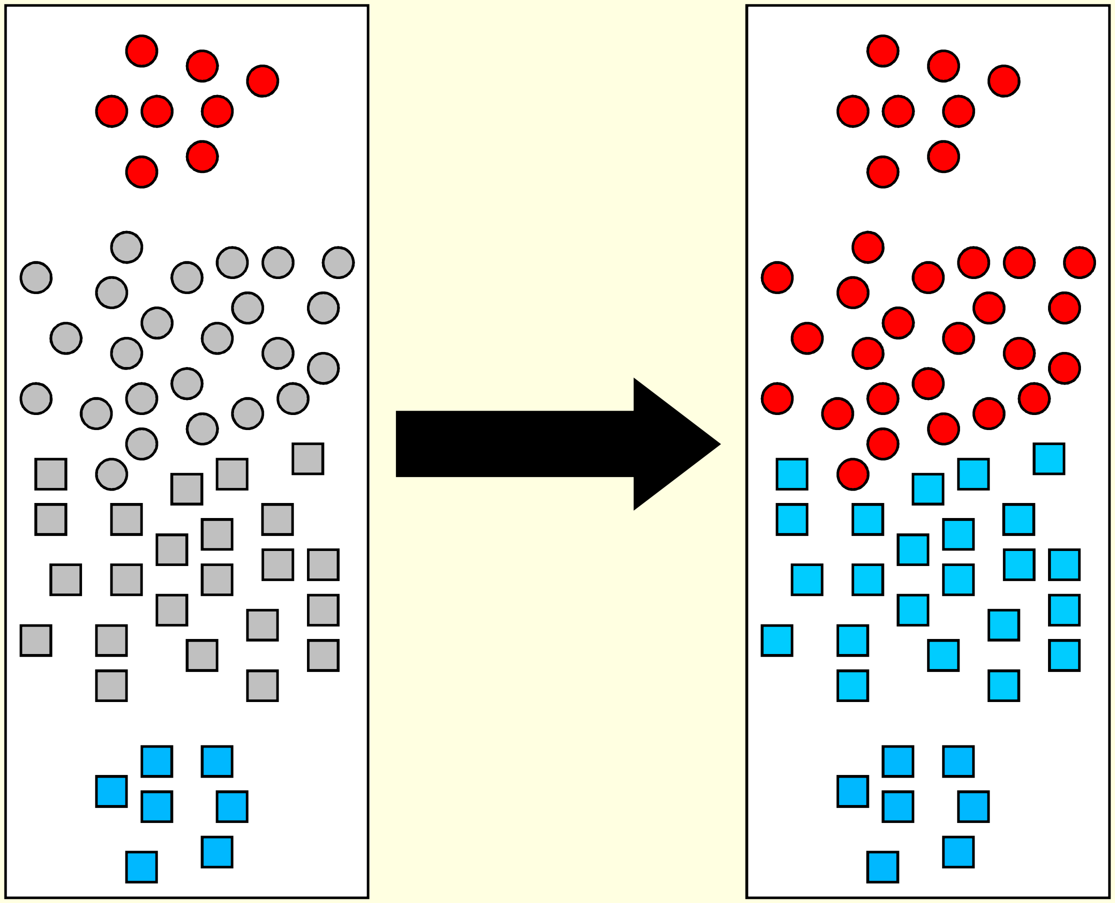
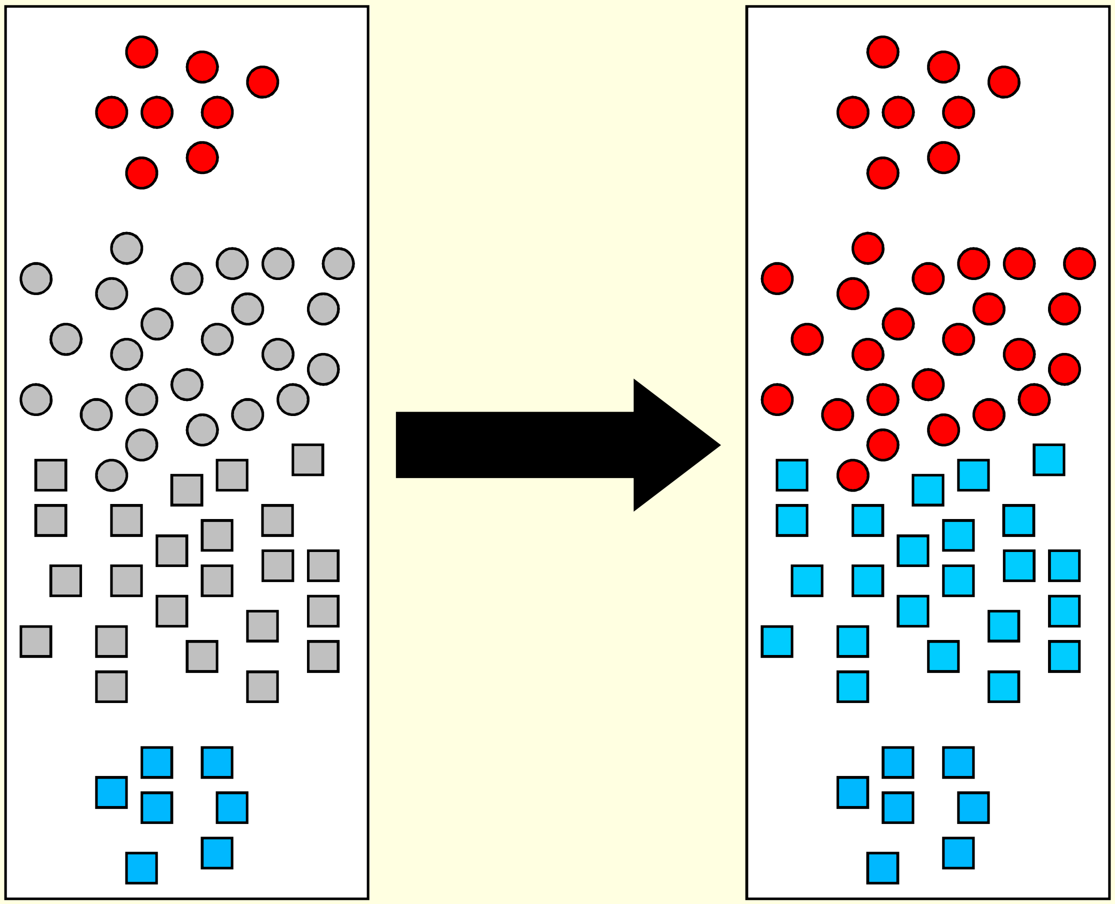
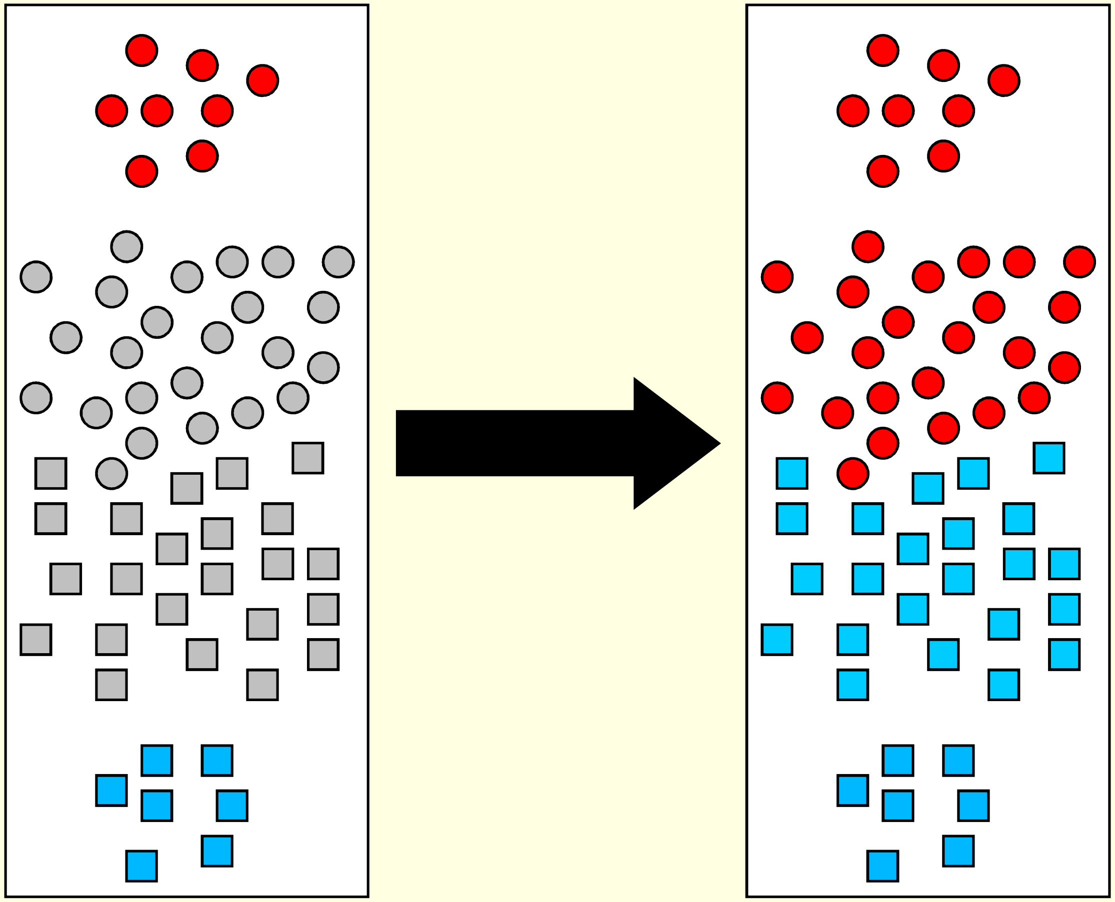


Semi-Supervised Learning - An Illustration



construct a classifier which also uses the predicted labels for the unlabeled data

Semi-Supervised Learning - An Illustration



more labeled data may improve classification accuracy

Why are unlabeled data useful?

- We will use (binary) text classification to study this problem
- Unlabeled data are usually plentiful, labeled data are expensive
- Unlabeled data provide information about the joint probability distribution over words and collocations (in texts)

Why are unlabeled data useful?

- Imagine the following setting:
  - You want to build a classifier which is able to detect text documents about „Machine Learning“
  - We have labeled and unlabeled documents
  - For simplification we denote
    - „+“: label for machine learning documents
    - „-“: label for other documents

Why are unlabeled data useful?

labeled documents

…
… classifier…
…
+

…
… classifier…
…
+

…
… classifier…
…
+

…
… classifier…
…
+

unlabeled documents

…
… Bayes classifier…
…
?

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… Bayes classifier…
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… Bayes…
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?

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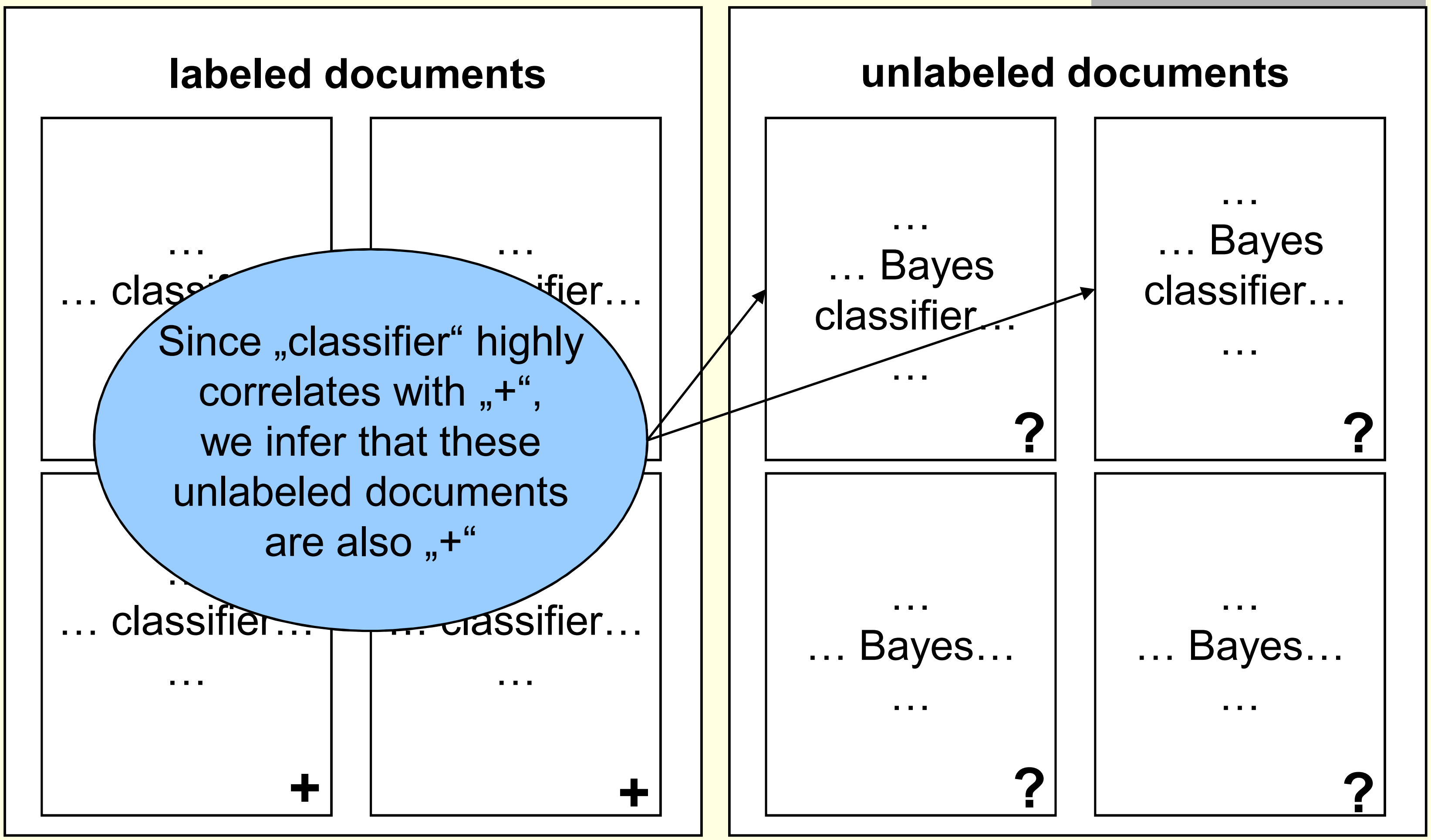
… Bayes…
…
?

Why are unlabeled data useful?



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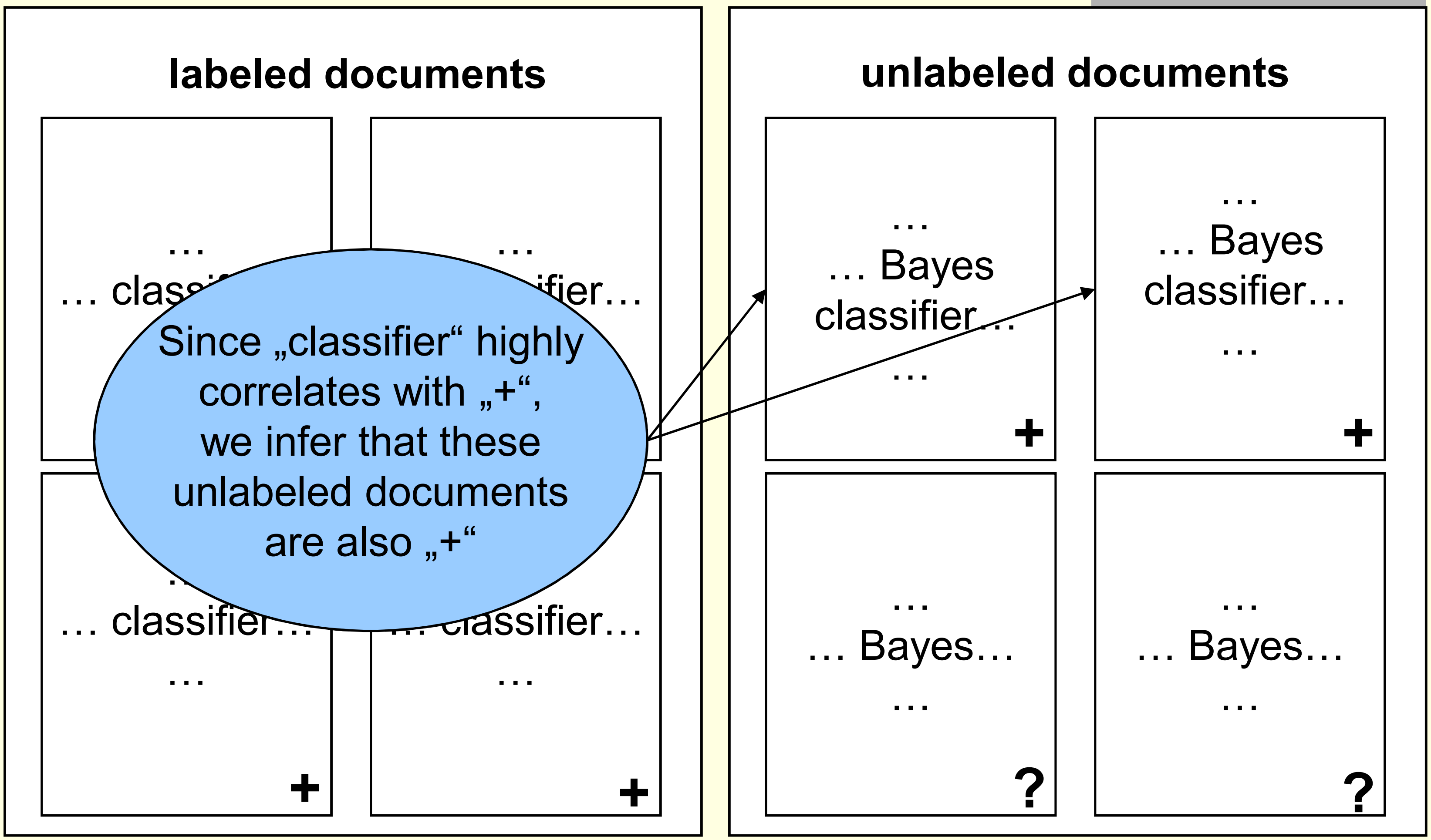

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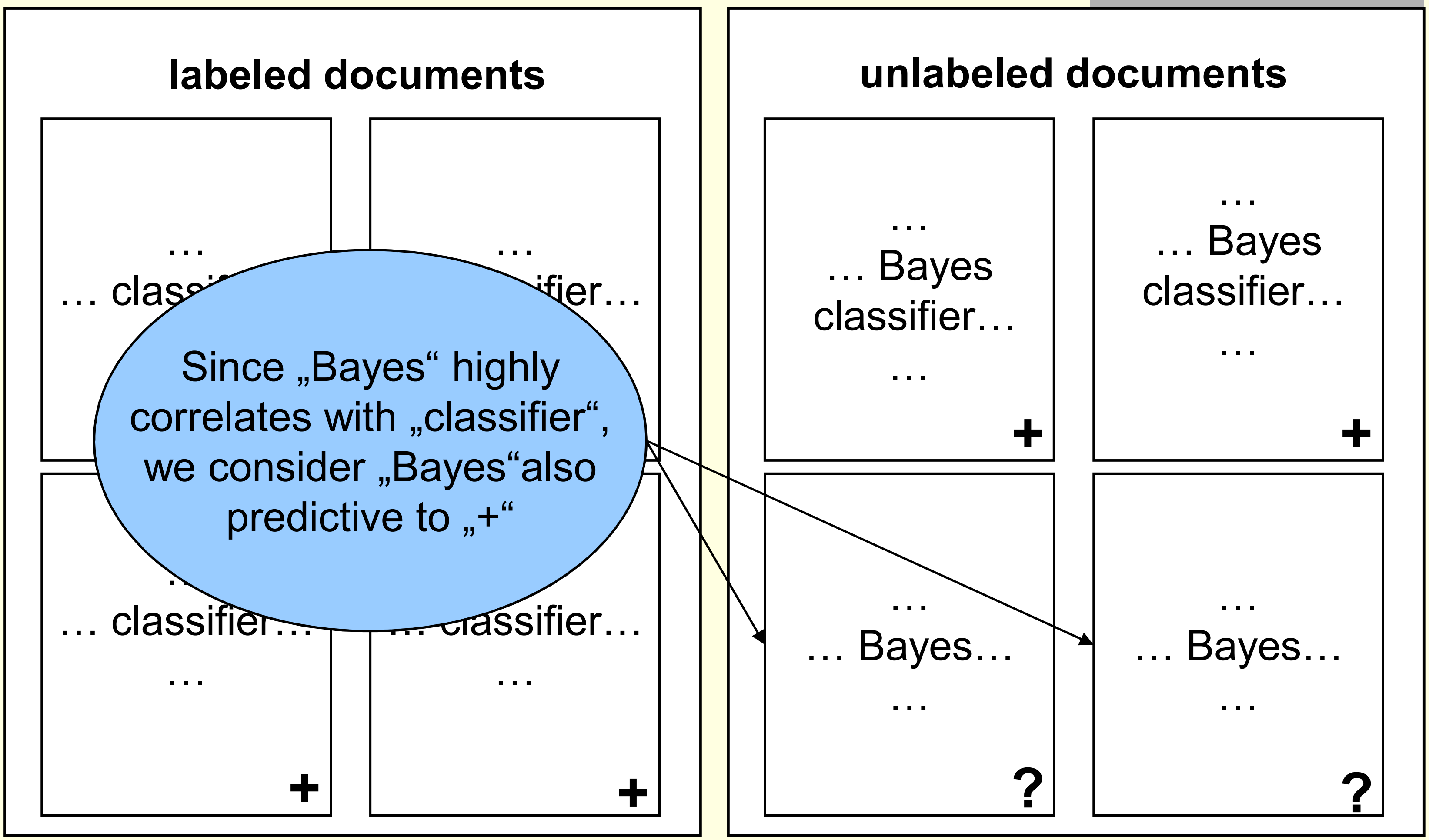

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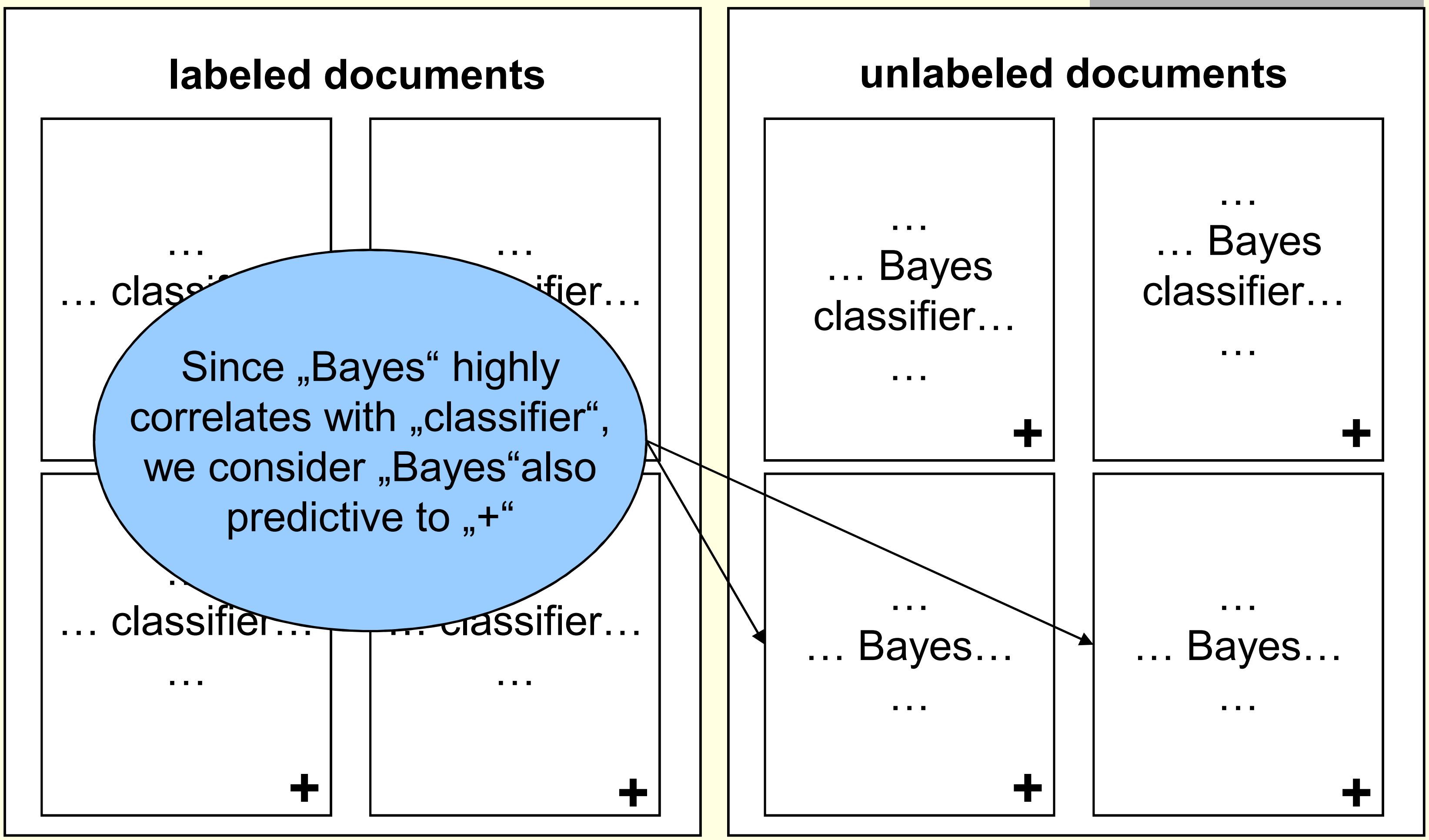
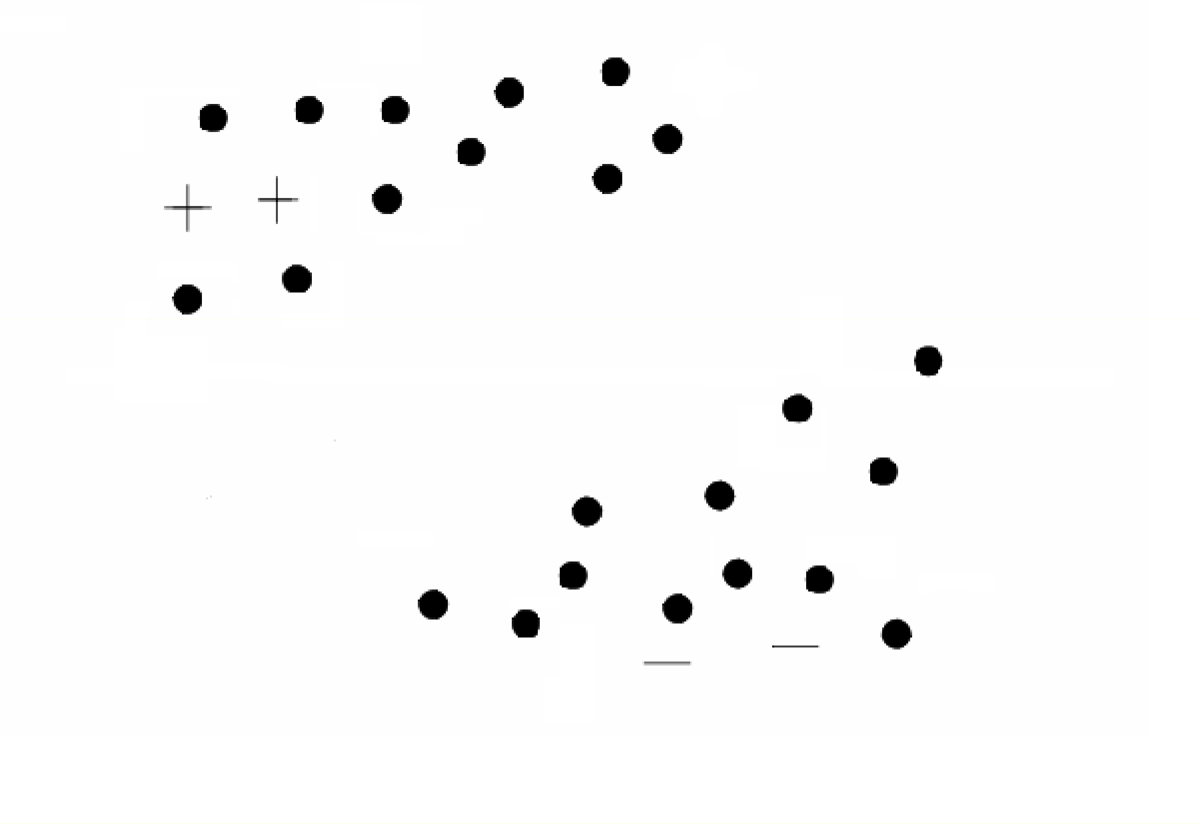
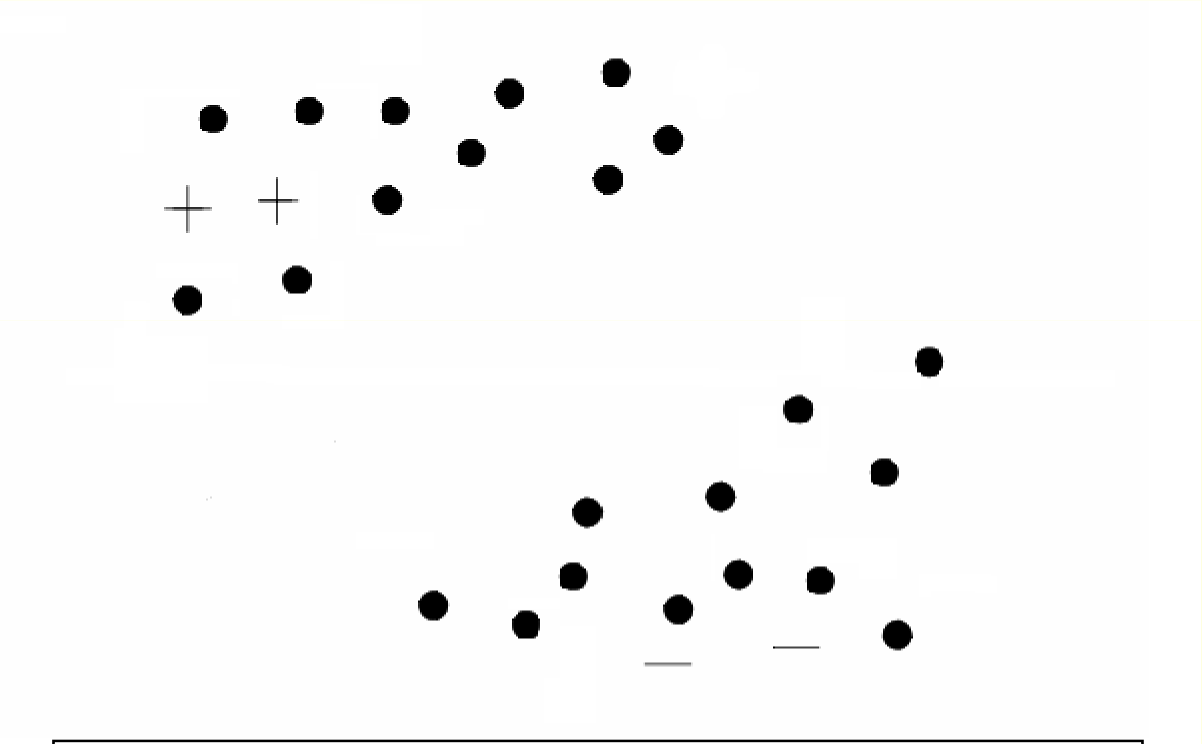


A Dataset favourable for Semi-Supervised Learning

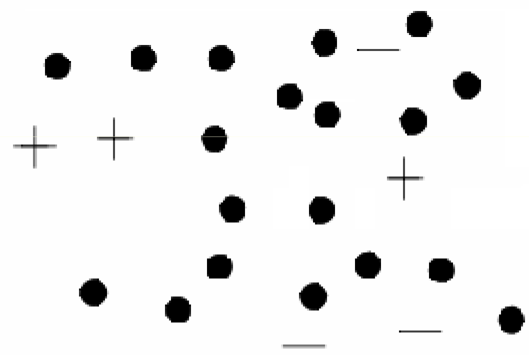


A Dataset favourable for Semi-Supervised Learning

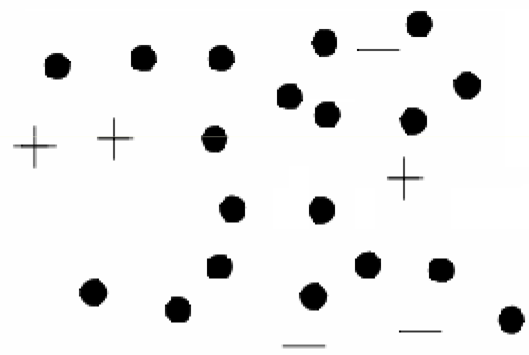


Unlabeled data instances cluster with labeled data instances of their pertaining class

A Dataset unfavourable for Semi-Supervised Learning



A Dataset unfavourable for Semi-Supervised Learning



Unlabeled data instances do **not** cluster with labeled data instances of their pertaining class

Bootstrapping

In computing, **bootstrapping** refers to a process where a simple system activates another more complicated system that serves the same purpose. It is a solution to the *chicken-and-egg problem* of starting a certain system without the system already functioning.

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How does this translate to Semi-Supervised Learning?

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How does this translate to Semi-Supervised Learning?

Bootstrapping

In computing, **bootstrapping** refers to a process where a *simple system* *(=supervised classifier using small amounts of labeled data)* activates *another more complicated system* *(=semi-supervised classifier that uses labeled and unlabeled data)* that serves the same purpose. It is a solution to the *chicken-and-egg problem* of starting a certain system without the system already functioning.

How does this translate to Semi-Supervised Learning?

Bootstrapping – The Origin of the Term

Bootstrapping alludes to a German legend about a **Baron Muench-hausen**, who was able to lift himself out of a swamp by pulling himself up by his own hair *(see picture on the right)*.

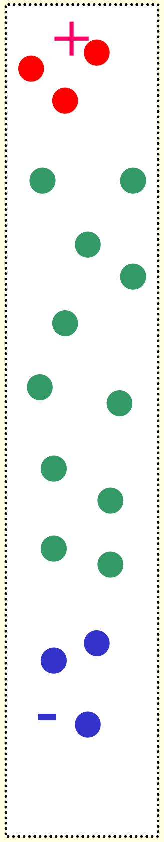
Bootstrapping – The Origin of the Term

In later versions he was using his own **bootstraps** to pull himself out of the sea.

The Yarowsky Algorithm

The Yarowsky Algorithm

Iteration: 0



The Yarowsky Algorithm

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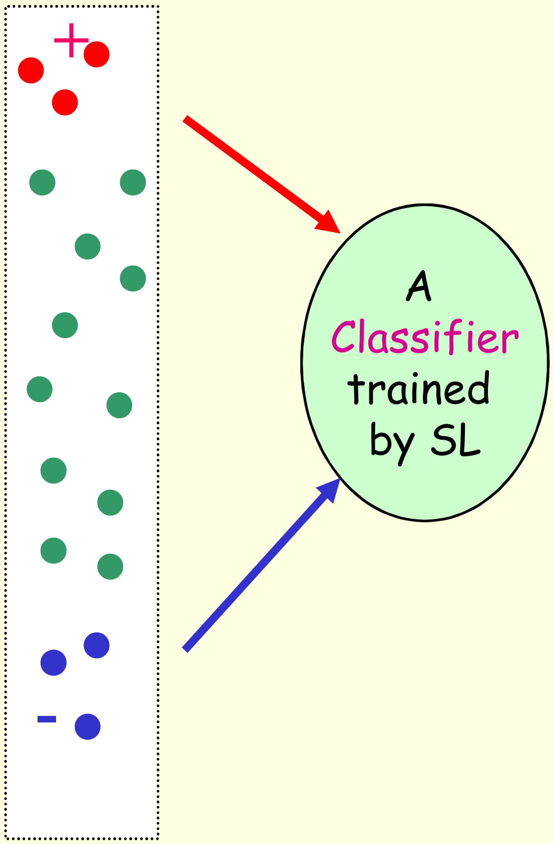

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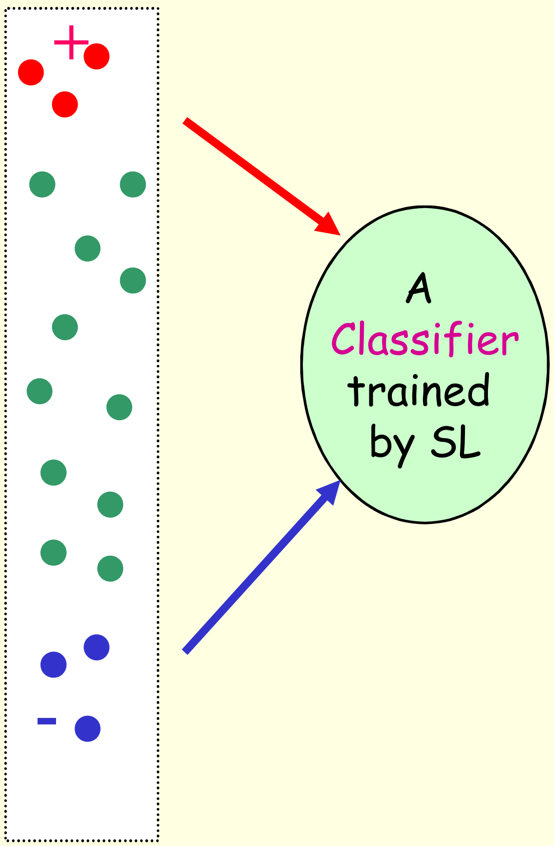
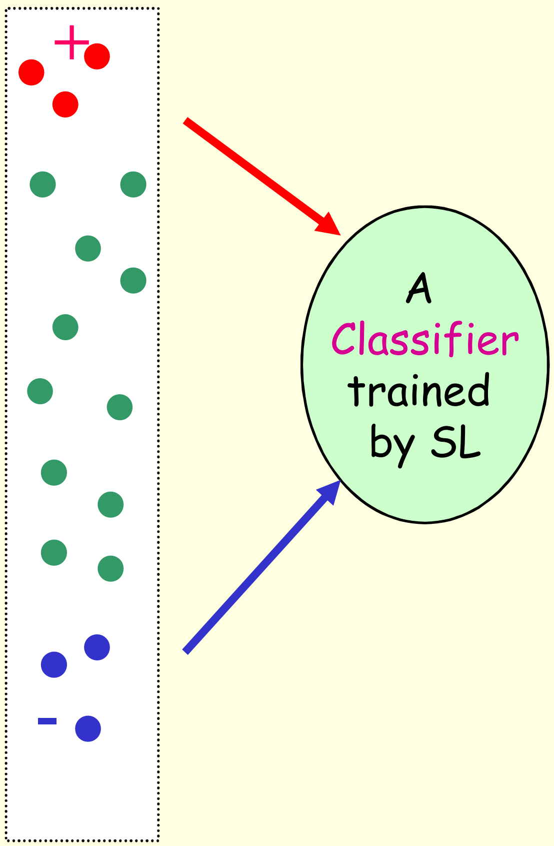


Choose instances labeled with high confidence

The Yarowsky Algorithm

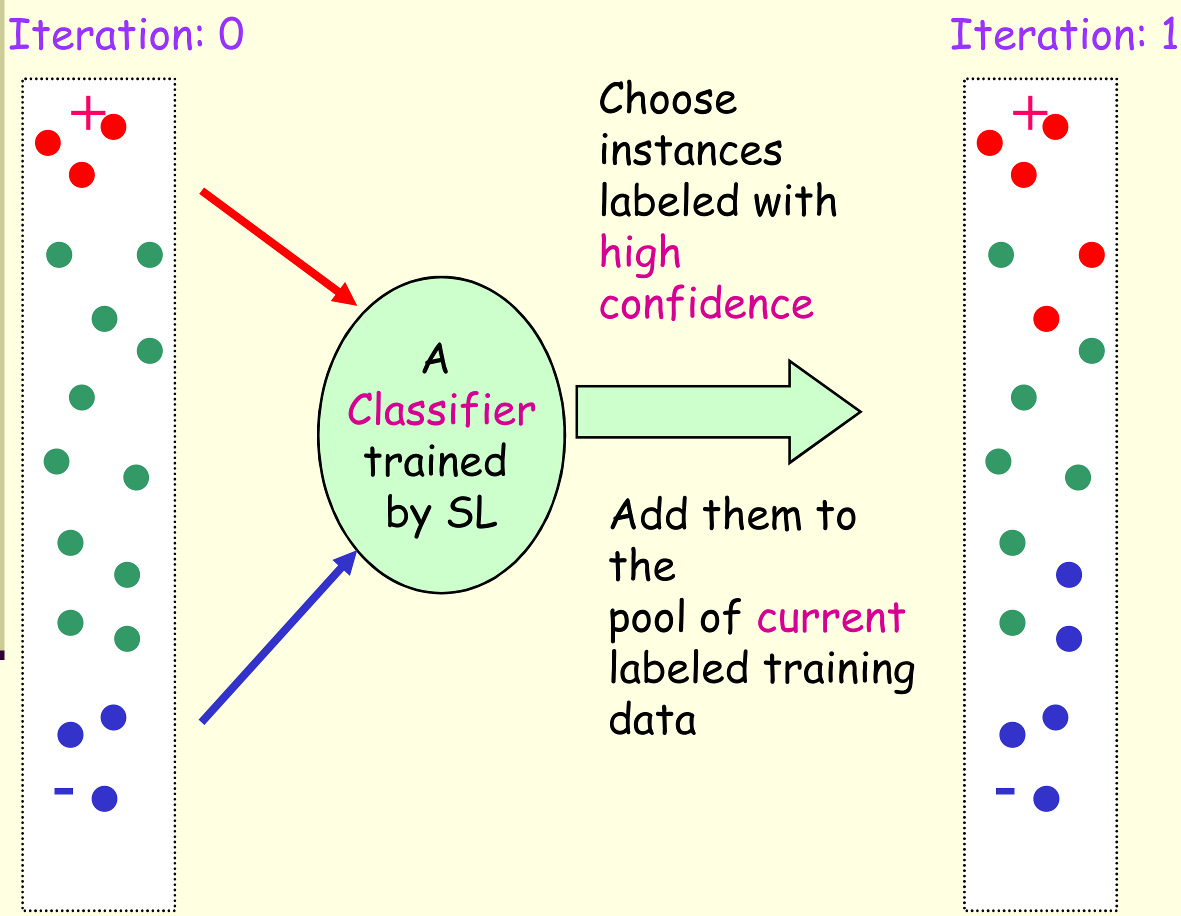
Iteration: 0



Choose instances labeled with high confidence

Add them to the pool of current labeled training data

The Yarowsky Algorithm



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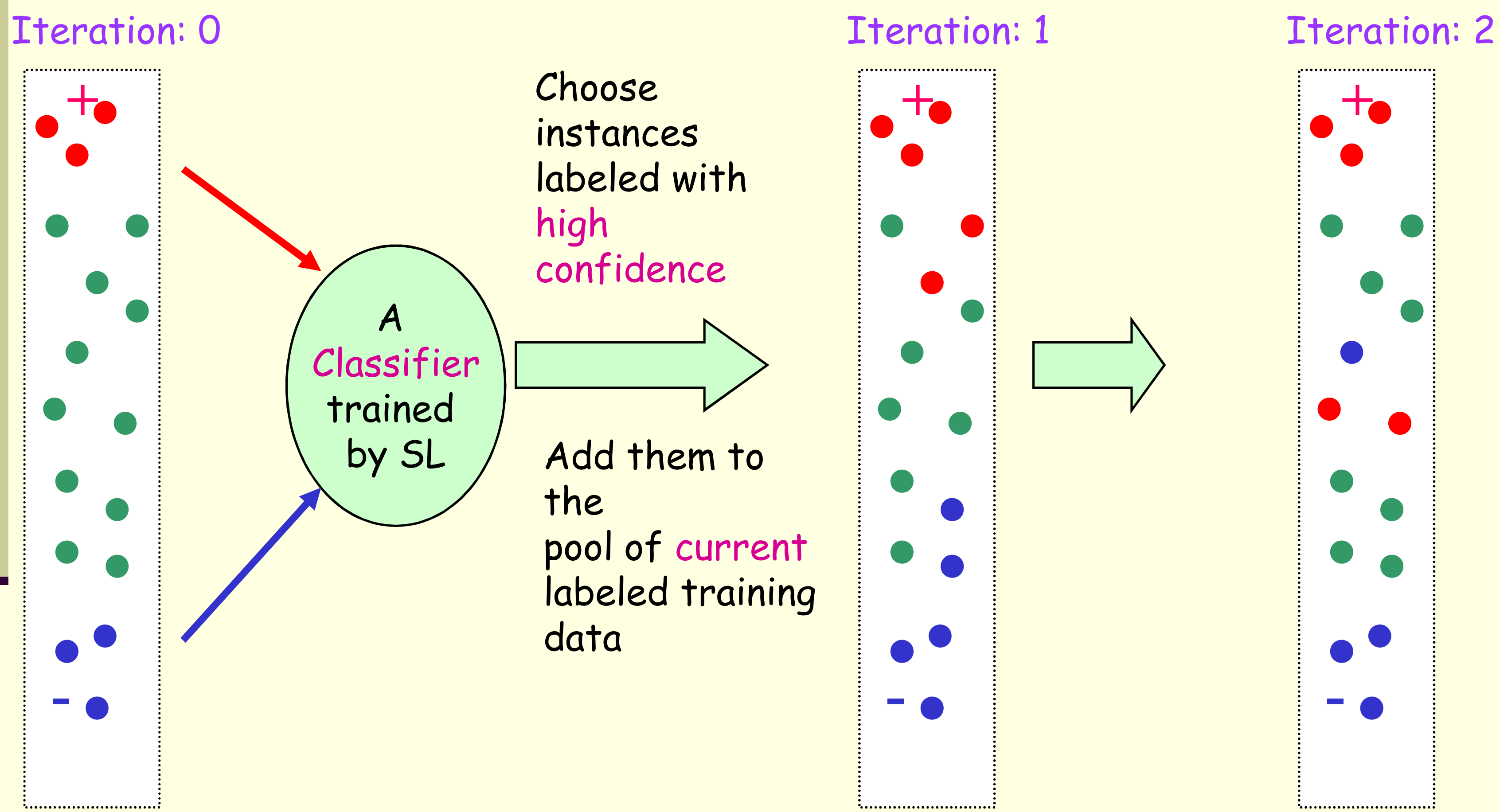

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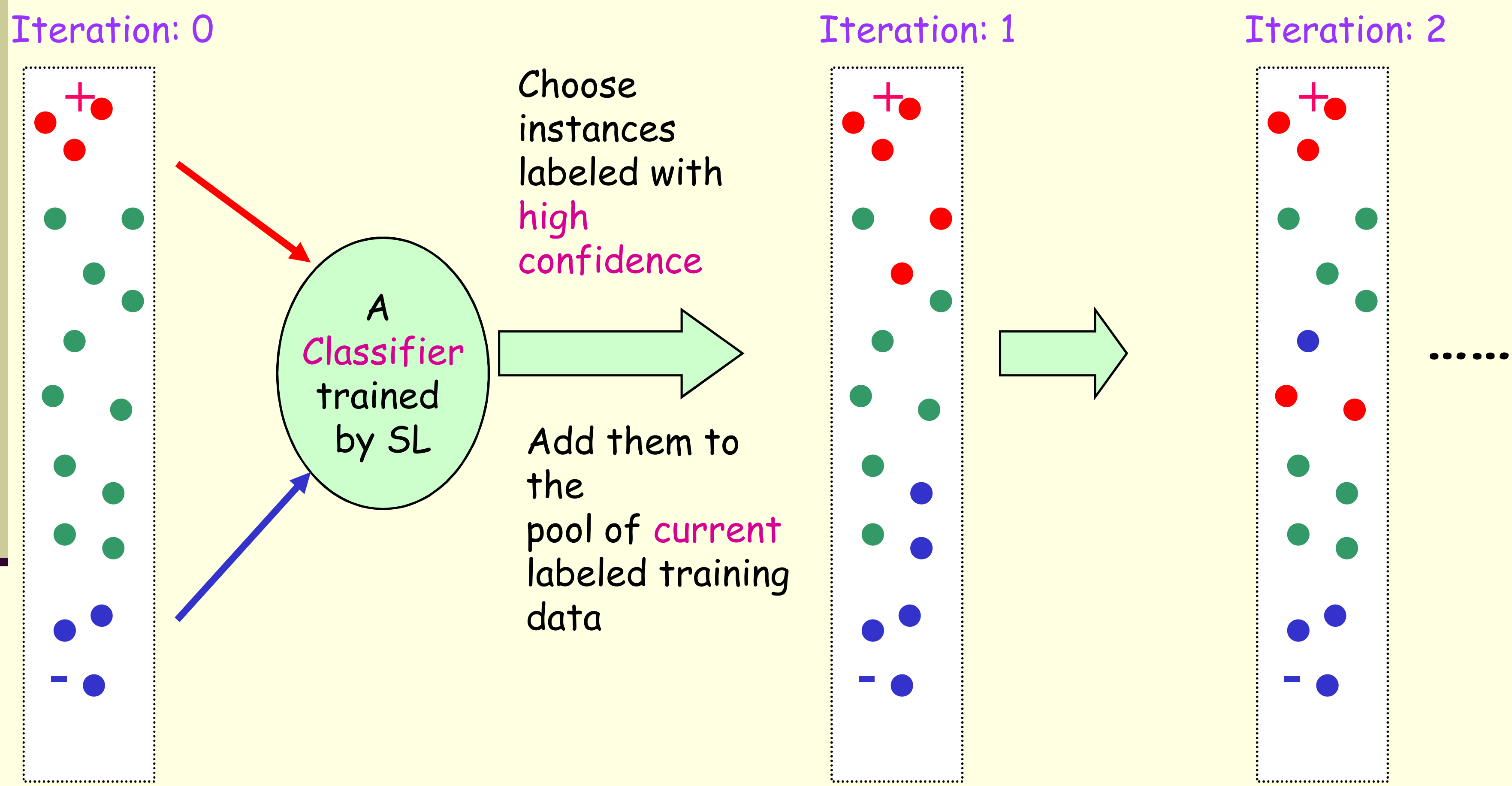
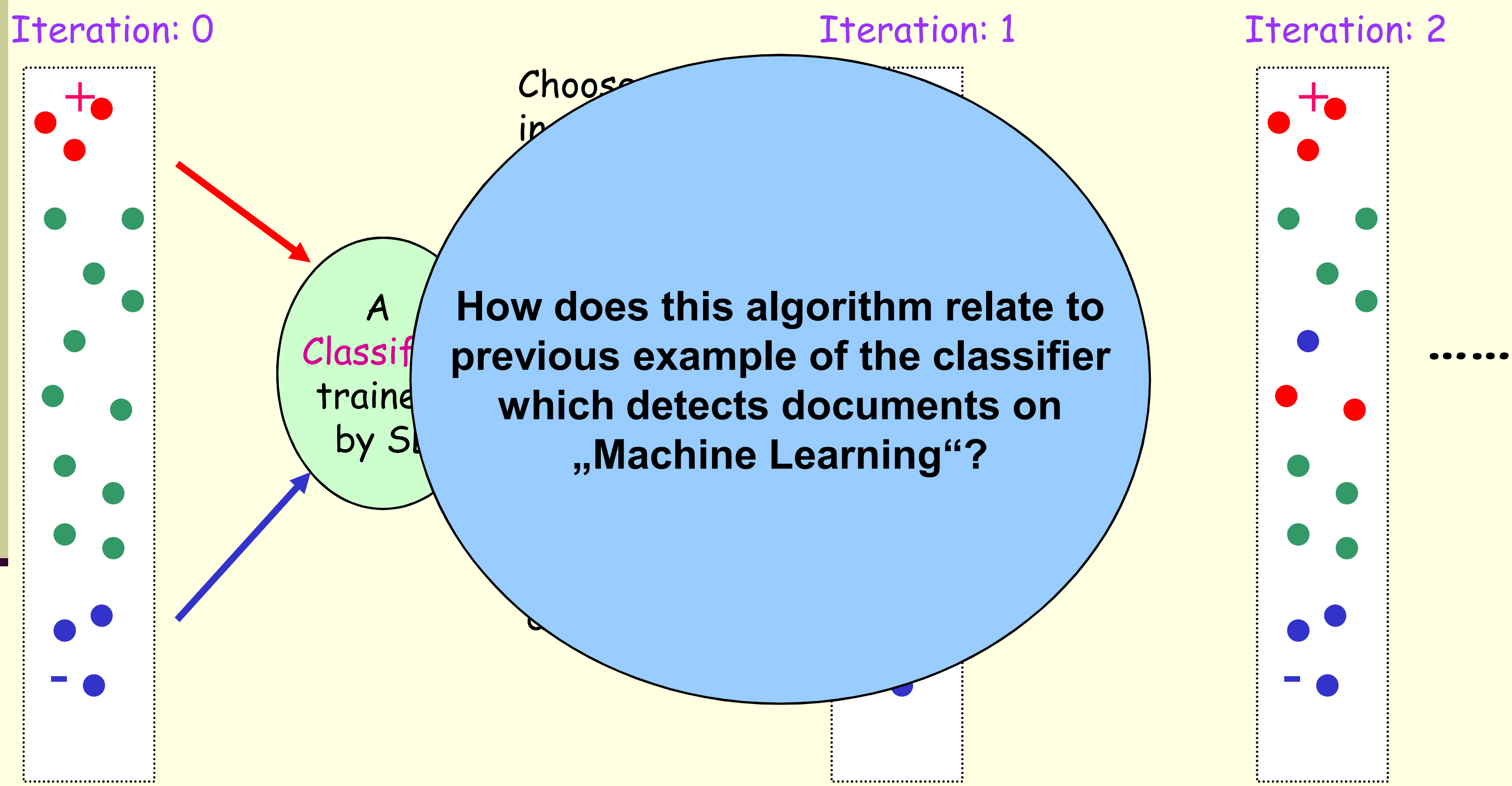


The Yarowsky Algorithm



How does this algorithm relate to previous example of the classifier which detects documents on „Machine Learning“?

The Expectation Maximization (EM) Algorithm

Expectation Maximization Algorithm

- The EM algorithm is a **meta algorithm** that can be applied to any probabilistic model which depends on *unobserved/hidden* variables
- We consider the derivation for a ***Multinomial Naive Bayes*** classifier in this lecture
- The standard supervised version was presented last lecture!

Expectation Maximization Algorithm

- Conceptional Idea:
  1. Estimate a model from the labeled data
  2. Label the unlabeled data using current model
  3. Re-estimate the model incl. the newly labeled data from Step 2
  4. Repeat Steps 2-3 until convergence has been reached
- See also (Dempster1977)

Expectation Maximization Algorithm

- Conceptional Idea:
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Expectation Maximization Algorithm

- Conceptional Idea:
  1. Estimate a model from the labeled data
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  3. Re-estimate the model incl. the newly labeled data from Step 2 ***(M-Step)***
  4. Repeat Steps 2-3 until convergence has been reached
- See also (Dempster1977)

Notation

- The set of classes is C and a specific class is denoted by c_i
- The set of documents is D and a specific document is denoted by d_j
- The set of documents D can be divided into the set of labeled documents D^l and unlabeled documents D^u (specific documents are d^l and d^u, respectively)
- The class of a labeled document d^l is denoted by c_{d^l}
- The vocabulary is V and a specific word is denoted by x_k

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)}$$

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)}$$

Bayes Theorem

Expectation Maximization Algorithm

E-Step:
$$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i) \cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot P(d_j \mid c_l)}$$

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i) \cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot P(d_j \mid c_l)}$$

Multiplication Rule

Expectation Maximization Algorithm

E-Step:

$$P(c_i \mid d_j) = \frac{P(c_i)\cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i)\cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot P(d_j \mid c_l)} = \frac{P(c_i)\cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i)\cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i)\cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot P(d_j \mid c_l)} = \frac{P(c_i)\cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

Independence Assumption of Words in a Document

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i) \cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot P(d_j \mid c_l)} = \frac{P(c_i) \cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

At iteration 0:

- All $P(c_i)$ and $P(x_k|c_i)$ are directly estimated from the labeled data
- **No** information is drawn from the unlabeled data yet
- Initial estimates of $P(x_k|c_i)$ heavily rely on smoothing

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i) \cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot P(d_j \mid c_l)} = \frac{P(c_i) \cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

M-Step: $$P(x_k \mid c_i) = \frac{\sum_{j=1}^{|D|} N(x_k, d_j) \cdot P(c_i \mid d_j)}{Z(c_i)}$$

Expectation Maximization Algorithm

E-Step:

$$P(c_i \mid d_j) = \frac{P(c_i) \cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i) \cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot P(d_j \mid c_l)} = \frac{P(c_i) \cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l) \cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

M-Step:

$$P(x_k \mid c_i) = \frac{\sum_{j=1}^{|D|} N(x_k, d_j) \cdot P(c_i \mid d_j)}{Z(c_i)} = \frac{\sum_{j=1}^{|D|} N(x_k, d_j) \cdot P(c_i \mid d_j)}{\sum_{n=1}^{|V|} \sum_{m=1}^{|D|} N(x_n, d_m) \cdot P(c_i \mid d_m)}$$

Expectation Maximization Algorithm

E-Step: $$P(c_i \mid d_j) = \frac{P(c_i)\cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i)\cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot P(d_j \mid c_l)} = \frac{P(c_i)\cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

M-Step: $$P(x_k \mid c_i) = \frac{\sum_{j=1}^{|D|} N(x_k, d_j)\cdot P(c_i \mid d_j)}{Z(c_i)} = \frac{\sum_{j=1}^{|D|} N(x_k, d_j)\cdot P(c_i \mid d_j)}{\sum_{n=1}^{|V|}\sum_{m=1}^{|D|} N(x_n, d_m)\cdot P(c_i \mid d_m)}$$

$$P(c_i) = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{Z}$$

Expectation Maximization Algorithm

E-Step:
$$P(c_i \mid d_j) = \frac{P(c_i)\cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i)\cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot P(d_j \mid c_l)} = \frac{P(c_i)\cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

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$$P(c_i) = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{Z} = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{\sum_{l=1}^{|C|}\sum_{m=1}^{|D|} P(c_l \mid d_m)}$$

Expectation Maximization Algorithm

E-Step:
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$$P(c_i) = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{Z} = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{\sum_{l=1}^{|C|}\sum_{m=1}^{|D|} P(c_l \mid d_m)} = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{|D|}$$

Expectation Maximization Algorithm

E-Step:

$$P(c_i \mid d_j) = \frac{P(c_i)\cdot P(d_j \mid c_i)}{P(d_j)} = \frac{P(c_i)\cdot P(d_j \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot P(d_j \mid c_l)} = \frac{P(c_i)\cdot \prod_{x_k \in d_j} P(x_k \mid c_i)}{\sum_{l=1}^{|C|} P(c_l)\cdot \prod_{x_k \in d_j} P(x_k \mid c_l)}$$

M-Step:

$$P(x_k \mid c_i) = \frac{\sum_{j=1}^{|D|} N(x_k, d_j)\cdot P(c_i \mid d_j)}{\sum_{n=1}^{|V|}\sum_{m=1}^{|D|} N(x_n, d_m)\cdot P(c_i \mid d_m)}$$

Use $P(x_k|c_i)$ and $P(c_i)$ from iteration *n* for the estimation of $P(c_i|d_j)$ at iteration *n+1*

$$P(c_i) = \frac{\sum_{j=1}^{|D|} P(c_i \mid d_j)}{|D|}$$

Expectation Maximization Algorithm

- After each interation compute Likelihood of the entire dataset *L(D)* with current model:

$$L(D) = \prod_{j=1}^{|D^l|} P(c_{d_j^l}) P(d_j^l \mid c_{d_j^l}) \prod_{n=1}^{|D^u|} \sum_{i=1}^{|C|} P(c_i) P(d_n^u \mid c_i)$$

Expectation Maximization Algorithm

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For labeled documents only use the actual class the document has been labeled with

Expectation Maximization Algorithm

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For unlabeled documents use the weighted sum over all classes

Expectation Maximization Algorithm

- After each interation compute Likelihood of the entire dataset *L(D)* with current model:

$$L(D) = \prod_{j=1}^{|D^l|} P(c_{d_j^l}) P(d_j^l \mid c_{d_j^l}) \prod_{n=1}^{|D^u|} \sum_{i=1}^{|C|} P(c_i) P(d_n^u \mid c_i)$$

- Iterate until Likelihood converges
- Alternatively: fix number of iterations

EM – What actually happens

- Initialization:
  - **Problem 1:** Many words in the vocabulary are not observed in the labeled training set → they are assigned a *low* back-off probability (probability is too low for predictive words!)
  - **Problem 2:** Other words occurring in the labeled training set might have received a too high probability
- Iteration:
  - Solution to Problem 1:
    - Use correlation among features to determine which words only observed in the unlabeled dataset also correlate with the different classes
    - $P(x_j|c_i)$ *(initially estimated with back-off!)* will increase during model re-estimation for these features
  - Solution to Problem 2:
    - Hopefully words which have occurred disproportionately frequently in the labeled data will be less often observed in the unlabeled training set
    - $P(x_j|c_i)$ should gradually decrease

EM - What actually happens

- Experiments on the **WebKB** dataset from (Nigam2000)
- Webpages gathered from computer science departments
- Subset used in these experiments:
  - Classes: *student*, *faculty*, *course*, and *project*
  - Approximately 4200 webpages
- 2500 documents are used as unlabeled data
- Iteration 0 uses only 1 labeled data instance per class

Highest ranked words in class *course* throughout different iterations

Iteration 0	Iteration 1	Iteration 2
intelligence	*DD*	*D*
DD	*D*	*DD*
artificial	lecture	lecture
understanding	cc	cc
*DD*w	*D**	*DD:DD*
dist	*DD:DD*	due
identical	handout	*D**
rus	due	homework
arrange	problem	assignment
games	set	handout
dartmouth	tay	set
natural	*DD*am	hw
cognitive	yurttas	exam
logic	homework	problem
proving	kfoury	*DD*am
prolog	sec	postscript
knowledge	postscript	solution
human	exam	quiz
representation	solution	chapter
field	assaf	ascii

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Terms with **no** general significance for the class to be modeled

Highest ranked words in class *course* throughout different iterations

Iteration 0	Iteration 1	Iteration 2
intelligence	DD	D
DD	D	DD
artificial	lecture	lecture
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DDw	D*	$DD{:}DD$
dist	$DD{:}DD$	due
identical	handout	D*
rus	due	homework
arrange	problem	assignment
games	set	handout
dartmouth	tay	set
natural	DDam	hw
cognitive	yurttas	exam
logic	homework	problem
proving	kfoury	DDam
prolog	sec	postscript
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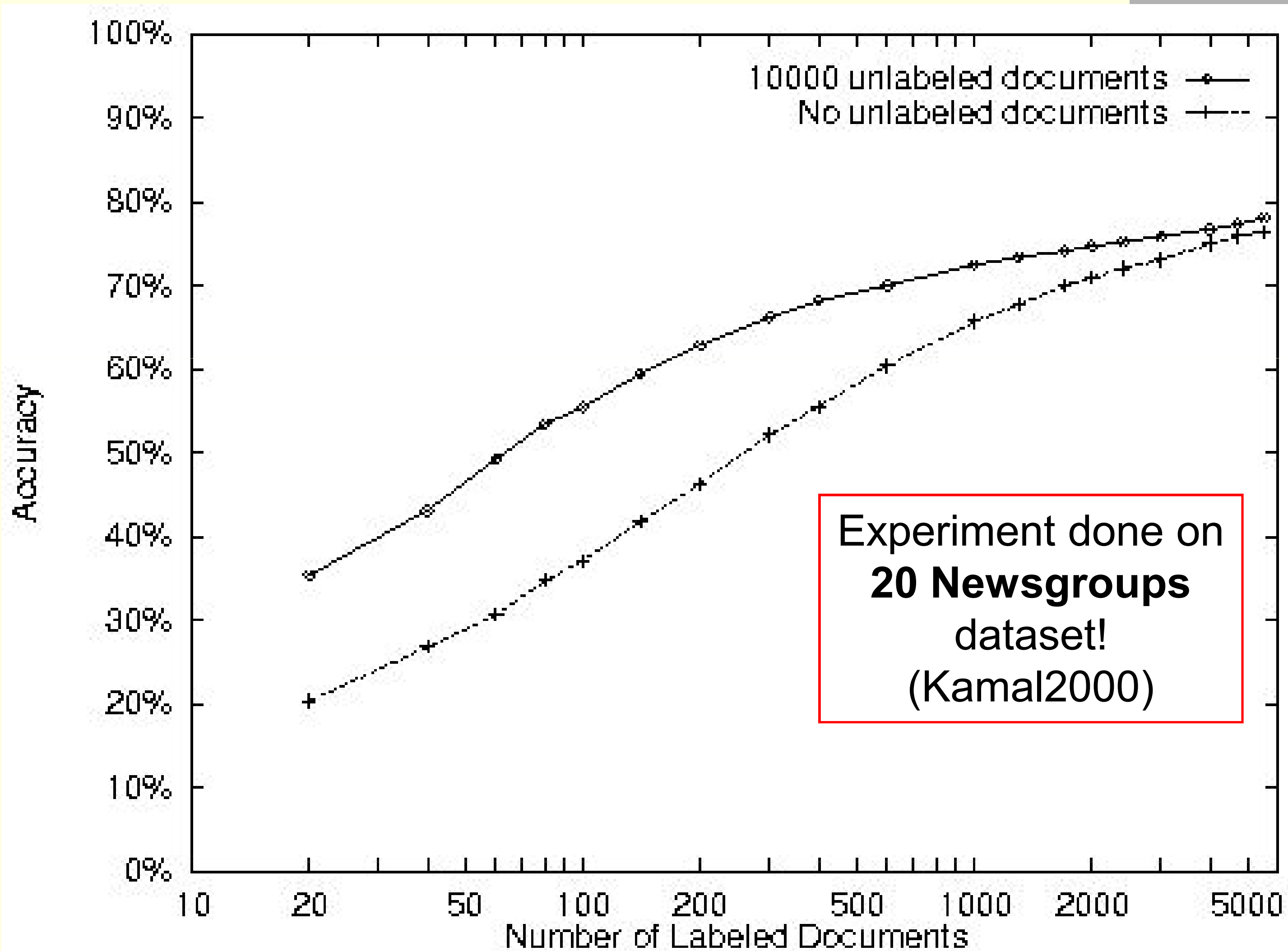
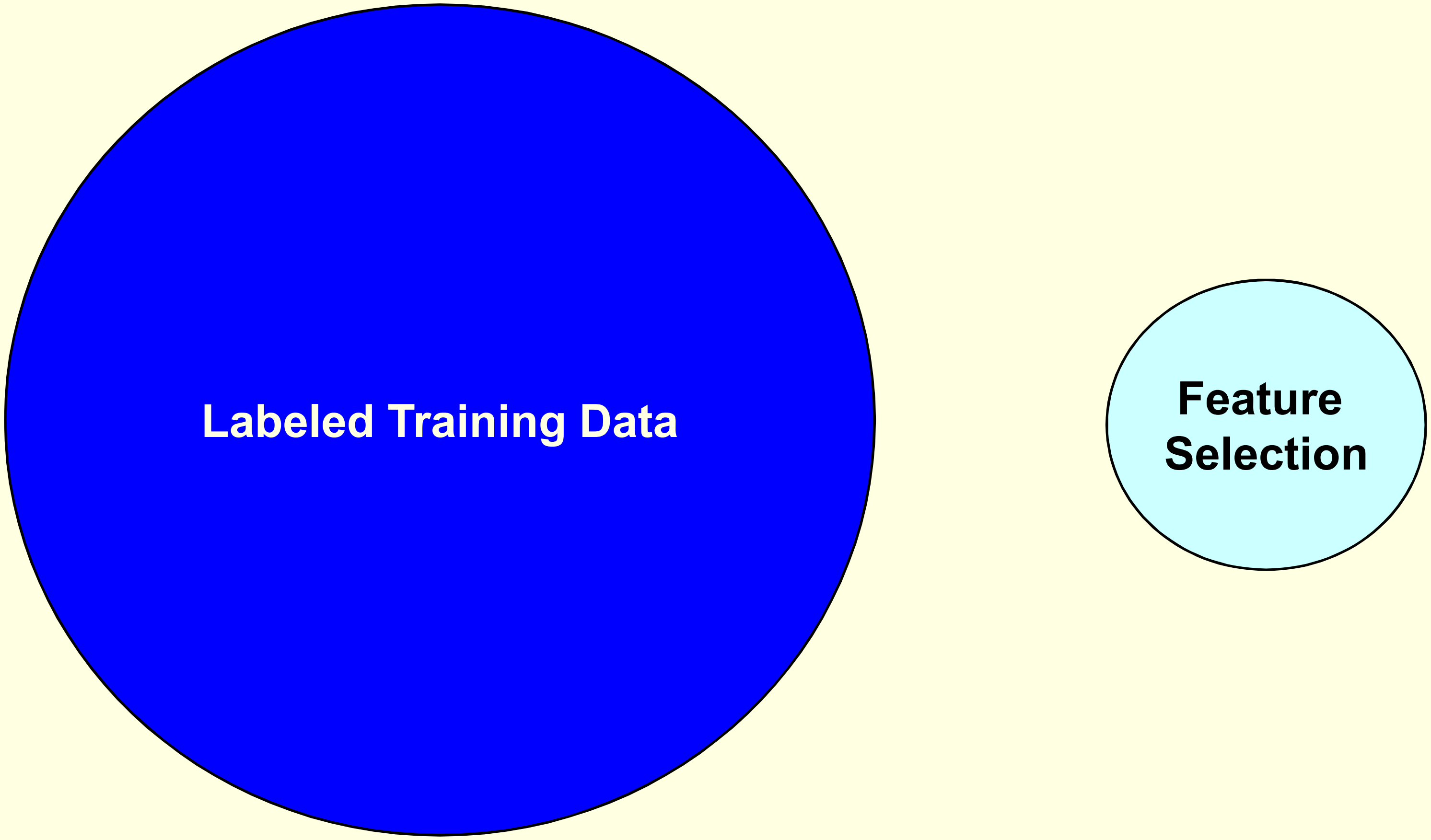
Terms with general significance for the class to be modeled

Improvement of Semi-Supervised Learning Using Different Amounts of Labeled Documents

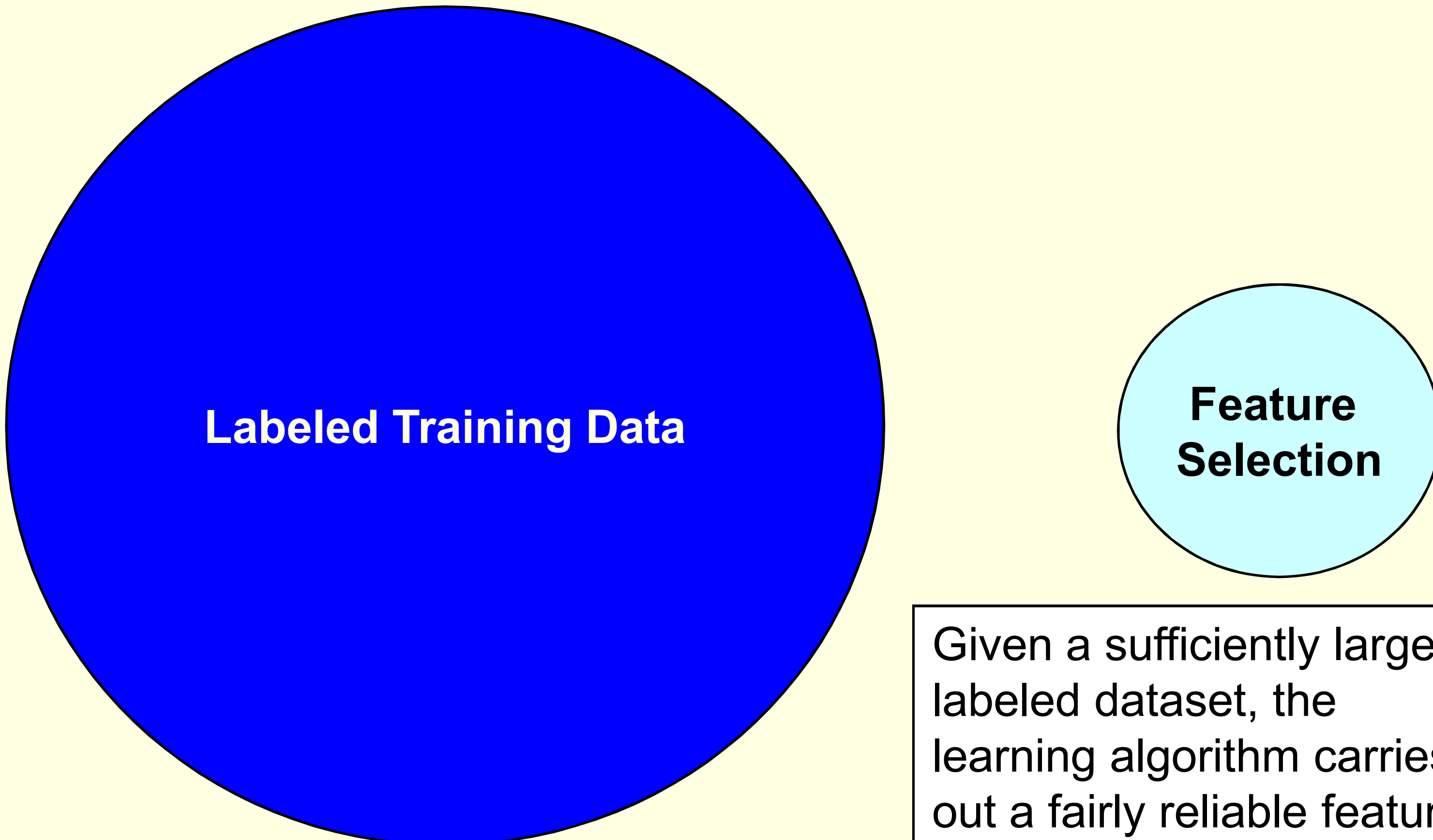


The Importance of Feature Selection in Semi-Supervised Learning (on Text Classification)

The Relation between Labeled Training Data and Feature Selection in **Supervised Learning** on Text Classification

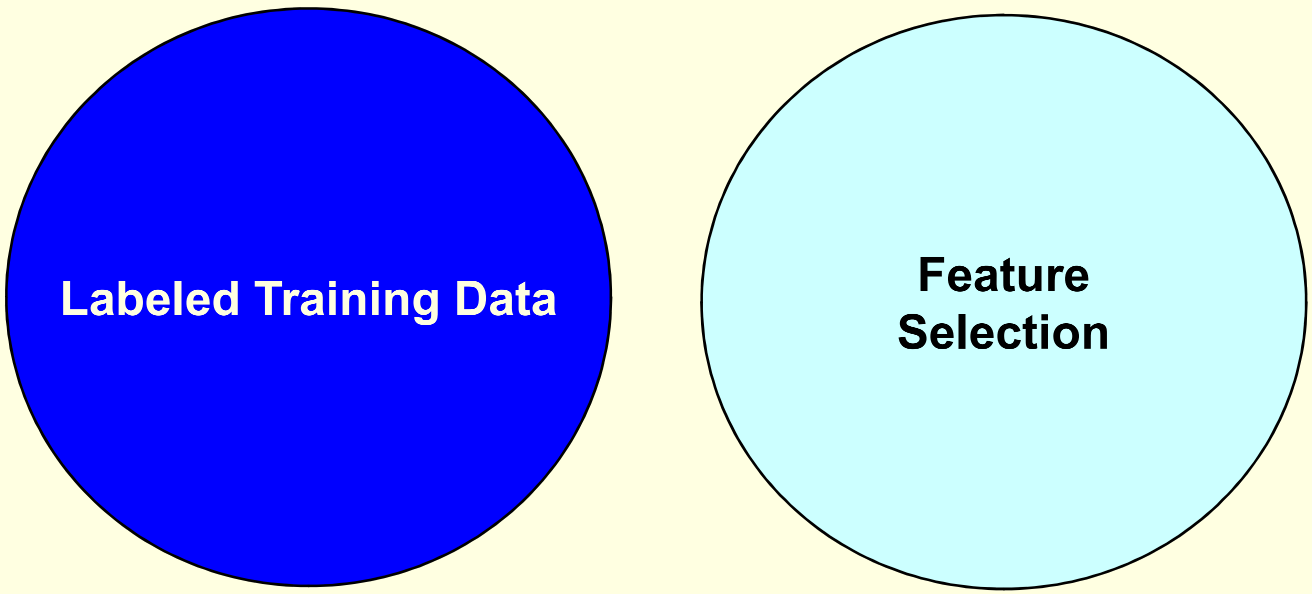


The Relation between Labeled Training Data and Feature Selection in **Supervised Learning** on Text Classification

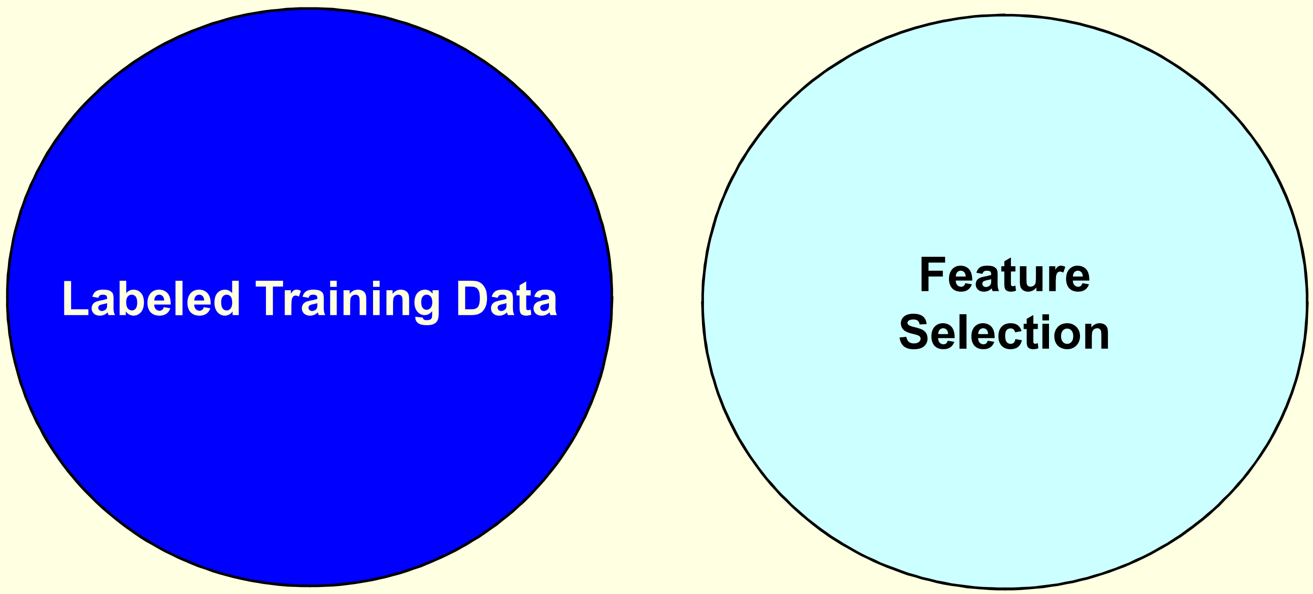


Given a sufficiently large labeled dataset, the learning algorithm carries out a fairly reliable feature selection internally.

The Relation between Labeled Training Data and Feature Selection in **Semi-Supervised Learning** on Text Classification



The Relation between Labeled Training Data and Feature Selection in **Semi-Supervised Learning** on Text Classification



In SSL, the learning algorithm is less robust and a separate feature selection is more important.

A Unified Representation of Machine Learning Classifiers

- Most Machine Learning classifiers learn a function *g* which is a linear combination of weighted features:

$$g(\vec{x}) = x_1 \cdot w_1 + x_2 \cdot w_2 + ... + x_n w_n \; (+b)$$

- *g* is transformed into a binary classifier:

$$if \; g(\vec{x}) > \delta \; then \; c_1 \; else \; c_2$$

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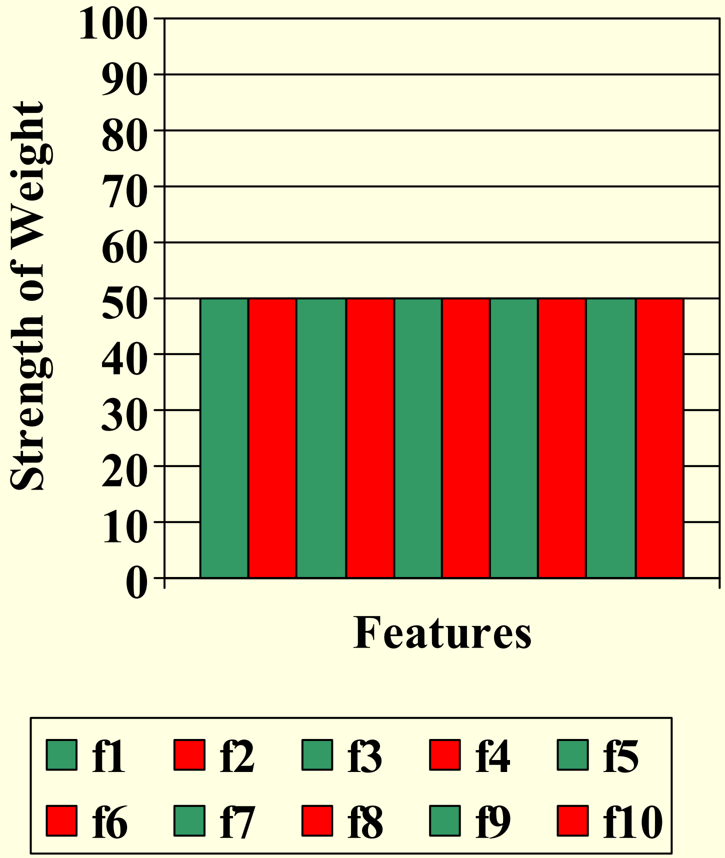
$$if \ g(\vec{x}) > \delta \ then \ c_1 \ else \ c_2$$

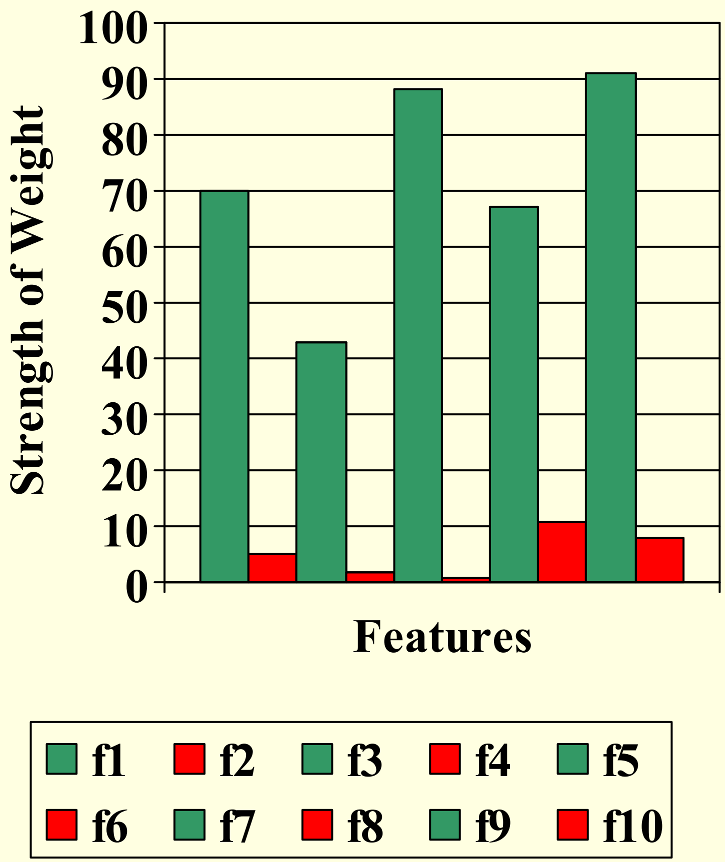
δ is a threshold value

Feature Weights and Feature Selection



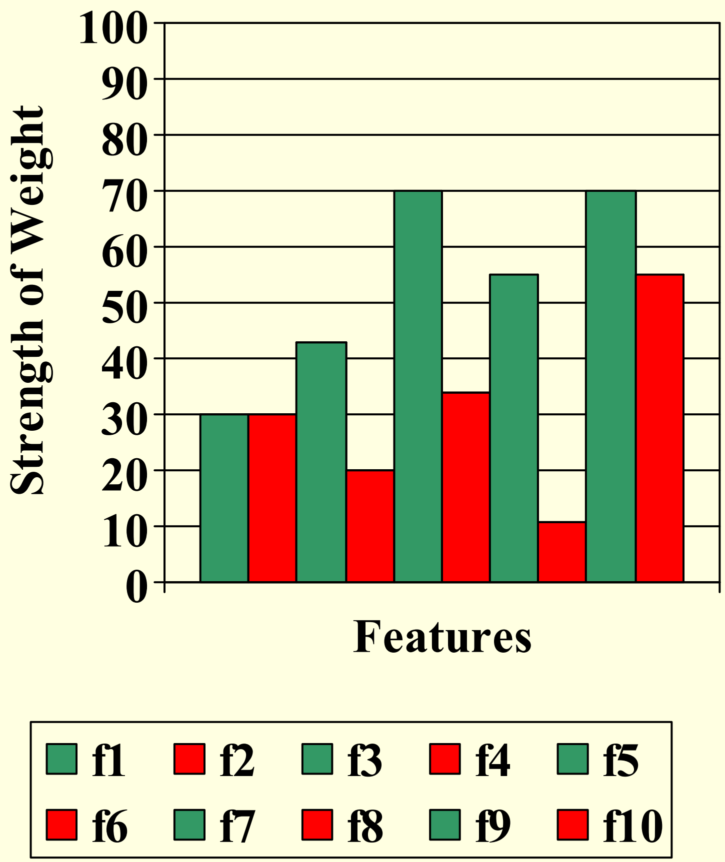
- Figure left displays features
- **Green** features are discriminative (helpful) features
- **Red** features are noisy (obstructive) features

Feature Weights and Feature Selection



- In Supervised Learning there are plenty of labeled data instances
- Feature weights are estimated very reliably
- Discriminative features obtain a high weight
- Noisy features obtain a low weight

Feature Weights and Feature Selection

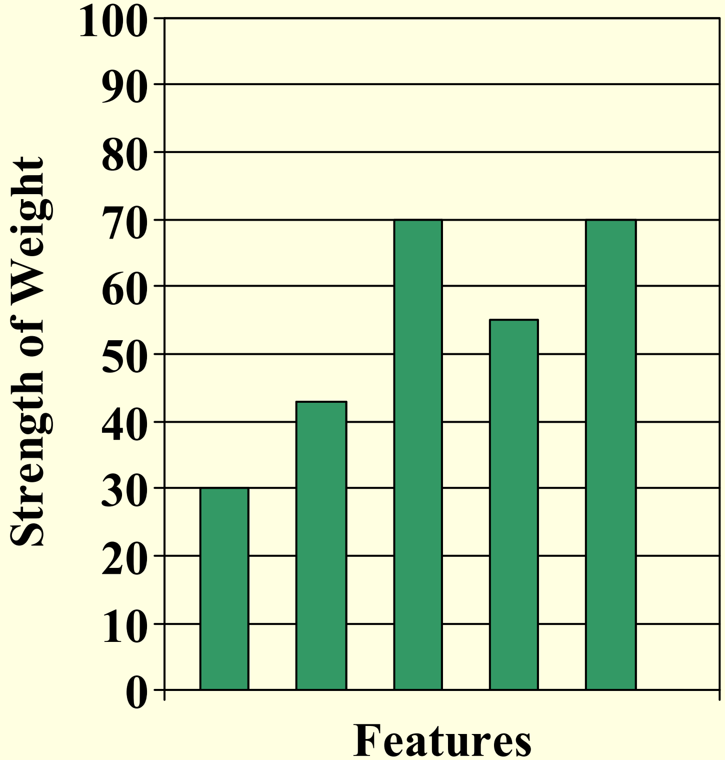


- In Semi-Supervised Learning there are only few labeled data instances available
- Noisy data features may not be properly downweighted
- Noisy features may lead classifier astray during bootstrapping

What does „Leading Astray“ Mean?

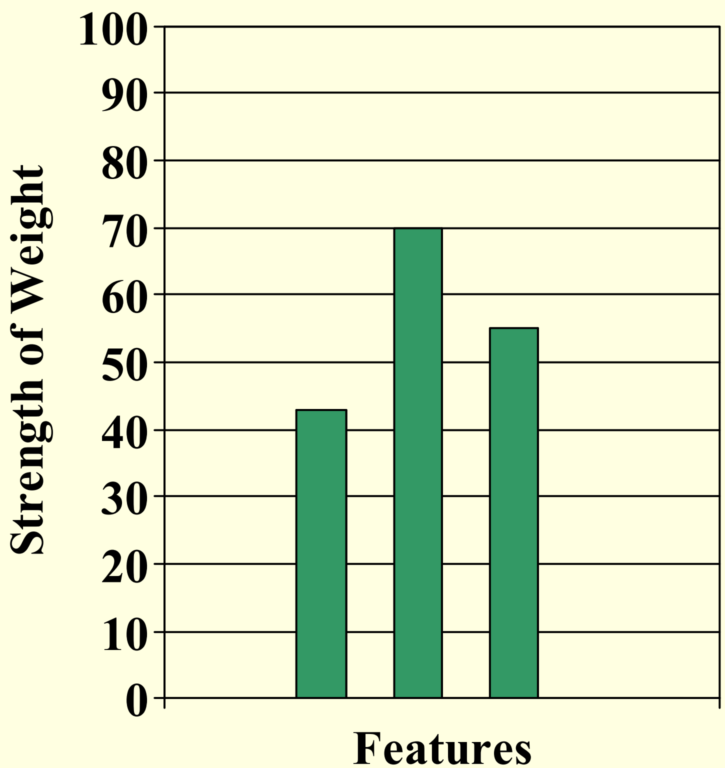
- Imagine a bad feature set applied to EM
- The classifier considers feature x_i a good predictor of class c_j because it is only co-occurring in labeled instances of this class
- However this co-occurrence is *coincidental* (remember the labeled dataset is usually very small in SSL) → feature x_i is a bad feature
- In subsequent iterations other features co-occurring with bad feature x_i will also be inferred to be predictive for c_j, but this is actually wrong and will degrade the performance of the classifier

Feature Weights and Feature Selection



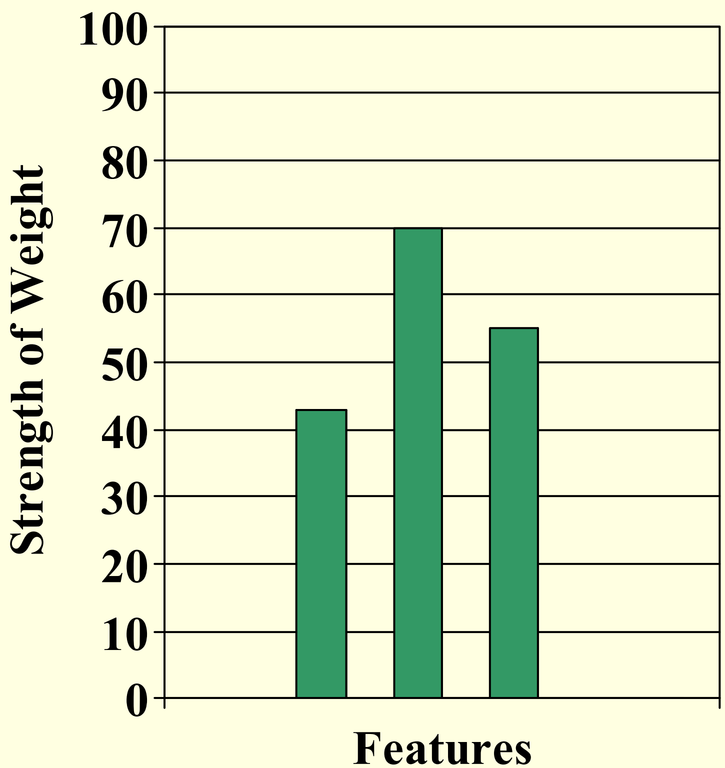
- Solution: use a good feature set, i.e. a feature set with only discriminative features

Feature Weights and Feature Selection



- Solution: use a good feature set, i.e. a feature set with only discriminative features
- Feature selection can be fairly restrictive, so that some discriminative features get lost as well

Feature Weights and Feature Selection



- Solution: use a good feature set, i.e. a feature set with only discriminative features
- Feature selection can be fairly restrictive, so that some discriminative features get lost as well
- But that is still better for SSL than using all features!!!

How can feature selection be done in SSL on text classification

- Correlation-based feature selection methods (e.g. *Point-wise Mutual Information*) do not work well in SSL, since too few labeled instances are available
- Stopword removal may help (i.e. download a list of function words from the web)
- Only consider frequent words in your entire data-set (e.g. Top 2000 words)
- Use your prior knowledge and construct your feature set manually (in case this is cheaper than providing more labeled data instances, otherwise try supervised learning!)

Applications of Semi-Supervised Learning in NLP

- Text Classification
- Part-of-Speech Tagging
- Syntactic Parsing
- Word Sense Disambiguation
- Information Extraction (e.g. Relation Extraction)
- Machine Translation

Other state-of-the-art algorithms

- Extensions to EM (Kamal2000)
  - Lambda-EM (weighting unlabeled and labeled data)
  - M-EM (i.e. with multiple mixture components)
- Co-Training (Blum1998)
- Transductive Support Vector Machines (Joachims1999)
- Label Propagation (Niu2005)
- Spectral Graph Clustering (Joachims2003)

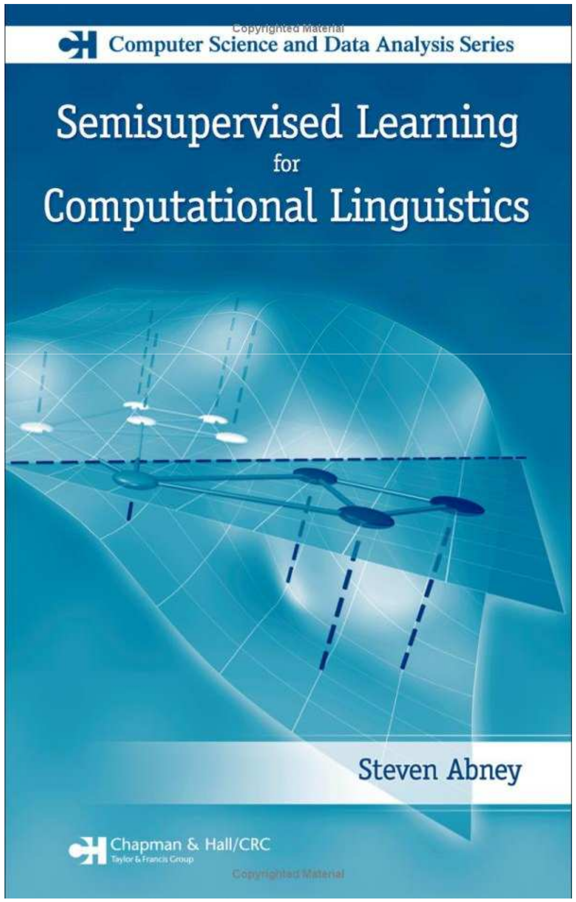
A Word of Warning

- Semi-Supervised Learning does not always work!
  - Classification performance of initial model might be too low (bootstrapping only adds further noise)
  - Classifier from initial (supervised) model might already produce maximal performance
- There are more degrees of freedom that have to be taken into account:
  - Size of the feature set
  - Size of the unlabeled data set
  - Many classifier-specific parameters!

Summary

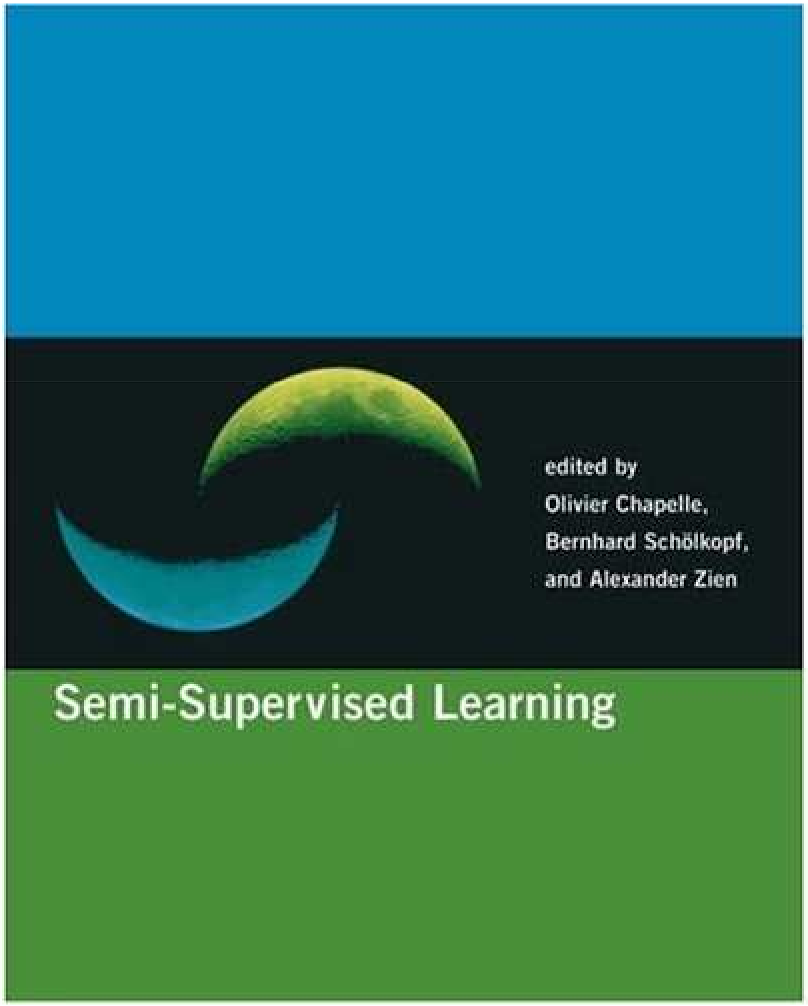
- Semi-Supervised Learning works well when only few labeled data are available
- Most Semi-Supervised Learning algorithms are *bootstrapping algorithms*
- Feature selection is more important in Semi-Supervised Learning than in Supervised Learning (on text classification)
- Bad feature sets may lead classifier astray

Relevant Books



Semisupervised Learning for Computational Linguistics
by *Steven Abney*
Chapman & Hall
2007

Relevant Books



Semi-Supervised Learning
by *Olivier Chapelle, Bernhard Schölkopf, Alexander Zien* (Editors)
MIT Press
2006

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- ***Combining Labeled and Unlabeled Data with Co-Training.*** A. Blum and T. Mitchell, *1998*.
- ***Transductive Inference for Text Classification using Support Vector Machines*****.** T. Joachims. *Proceedings of ICML 1999.*
- ***Text Classification from Labeled and Unlabeled Documents using EM.*** K. Nigam, A. McCallum, S. Thrun, and T. Mitchell. *Machine Learning, 39(2/3),2000.*
- ***Transductive Learning via Spectral Graph Partitioning.*** T. Joachims. *Proceedings of ICML 2003.*
- ***Understanding the Yarowsky Algorithm.*** S. Abney. *Computational Linguistics, vol. 30, 2004.*
- ***Word Sense Disambiguation Using Label Propagation Based Semi-Supervised Learning.*** Z.-Y. Niu, D. Ji, and C. Tan, *Proceedings of ACL 2005.*