Automated classification

insights into benefits, costs and lessons learned

Anders Ardö
Anders.Ardo@eit.lth.se
http://www.eit.lth.se/staff/anders.ardo

EIT – Electrical and Information Technology,
Lund University, Sweden

International UDC Seminar 2009:
Classification at a Crossroads
The Hague 29-30 October 2009

Outline

1. Background
2. SVM (Support Vector Machines)
3. String matching
4. Evaluation
5. Lessons learned
6. References

Why automated classification?

- Information explosion

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- Challenging research issue
- Fun!

History ...

(Personal - NetLab)

1992 Automated classification of WAIS databases using 2 top levels of UDC

1993 Demonstrated at SIGWAIS/SIGNIDR III conference

1997 Automated classification of Engineering Web resources using Ei

2000 EU project DESIRE: toolkit (Matcher)

2003 EU project ALVIS: Matcher + Crawler => Focused Web crawler (Combine)

2007 PhD thesis: "*Automated Subject Classification of Textual Documents in the Context of Web-based Hierarchical Browsing*", Koraljka Golub

2009 Vertical Search Engines Demo

Automated Classification technologies

- Machine learning methods
  - Statistical models (Bayes, **SVM**, ...)
  - ANN
- Information Retrieval methods
  - Clustering (no predefined categories)
- Library Science methods
  - **String matching** + Thesaurus

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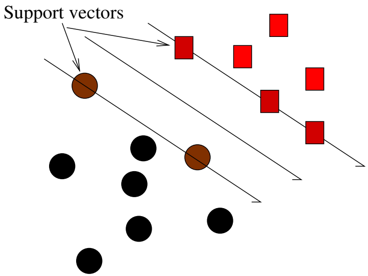
- Finds the optimal hyper-plane for linearly separable patterns
- Can be extended to multiclass/hierarchical classification

SVM



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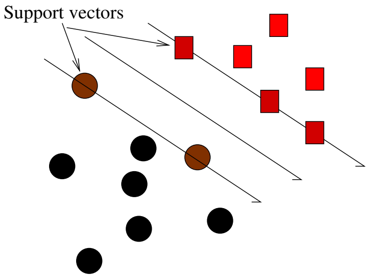

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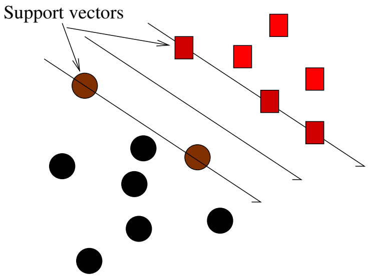

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- Decision function specified by support vectors (from training examples)
- SVM maximize the margin around the separating hyper-plane

Why SVM for text categorization?

Advantages

- "Most popular and effective method"
- High dimensionality input
- Uses all features - no feature selection
- Sound mathematical theory for optimal decision function
- Performs well when collection characteristics does not change
- Bag-Of-Words model - document vectors
- Fast once trained

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Problems

- Requires training examples
- Language
- Depends on a relatively homogeneous collection
- Sensitive for selection of negative examples
- Error propagation for deep classification hierarchies
- One classifier per class

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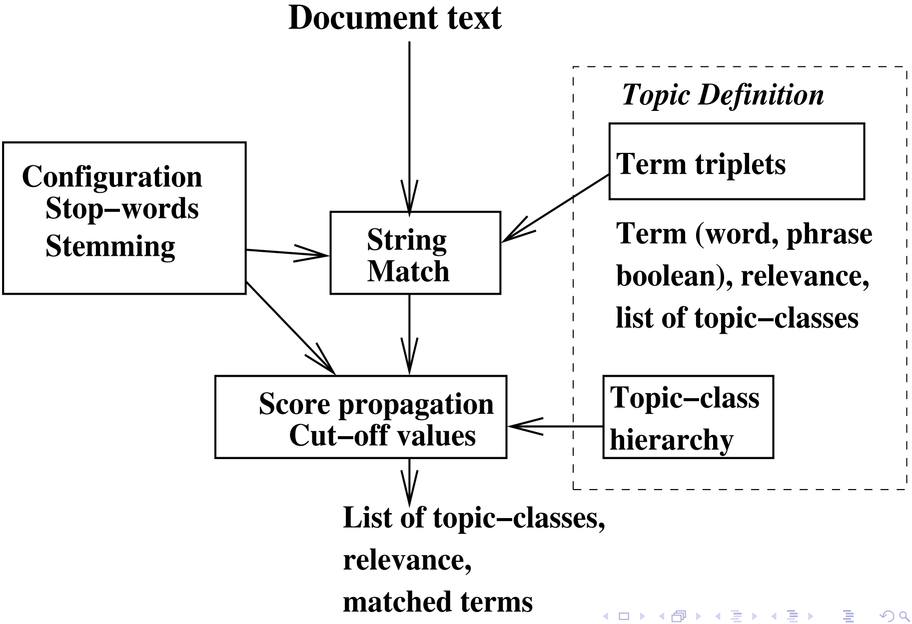
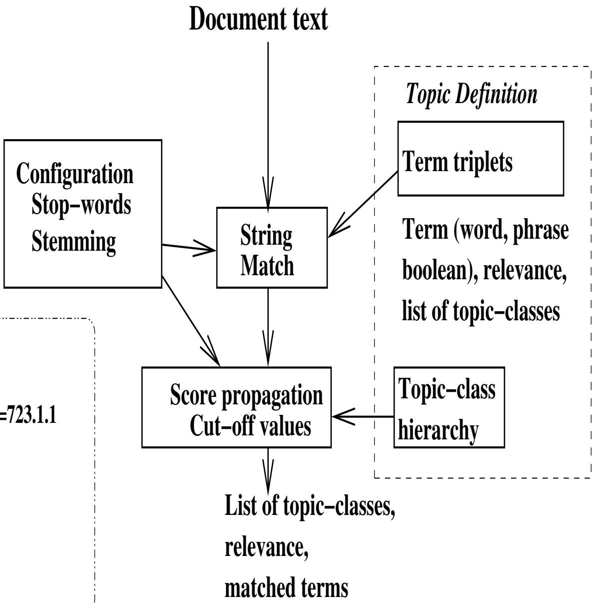
Classification process





Example term triplets

40: ALGOL @and programming language=723.1.1

15: CCTV=716.4

40: CAT scans=723.5

20: CAT scans=531, 801, 461.1

−10000: hotel=7

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Normalize with respect to document size

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Advantages

- Reuse intellectual effort
- Can take advantage of document structure
- Feature selection by thesaurus
- Language
- No training
- Deep hierarchies
- Multiclass classification

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- No context for topic terms
- Stopwords can cause trouble
- Relies on a good thesaurus
- No generalization

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Evaluation challenge

Comparing human assigned classes to automated classification

- Collection policies
- Users vs indexers
- Inter- and intra-indexers consistency
- Availability of representative pre-classified collections

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Hard to do good evaluations

Evaluation

- SVM
  - Most evaluations done in “lab-like environments”
  - Very good - 70 - 90 % correctness
  - Popular

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Examples:

1: Precision for classification of Compendex bibliographic records:

SVM	0.74 - 0.91
String match	0.26 - 0.97

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2: Depends on the hierarchical depth of the classification

Correct to	**String match**	**SVM**
3 levels	0.71p	0.61p
2 levels	0.87p	0.81p
top level	p	p

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- Good training examples (both positive and negative)
- Shallow hierarchy

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- gamma, coef0, cost, degree, nu, epsilon, shrinking, degree, ...

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- text preprocessing
- add synonyms
- word sense disambiguation
- word weights
- cut-off value

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    - ... but useful

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References/More info

- This presentation:
  http://combine.it.lth.se/UDCseminar2009/

- Koraljka Golub PhD thesis: "*Automated Subject Classification of Textual Documents in the Context of Web-based Hierarchical Browsing*"
- Combine focused crawler
  tools download: *http://combine.it.lth.se/#downloads*
  documentation on automated classification:
  http://combine.it.lth.se/documentation/DocMain/node6.html
- Demonstrators (incl UDC classifiers):
  http://dbkit05.eit.lth.se/exp/Demos/