Processing of large document collections

Part 2 (Text categorization, term selection)

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Text categorization, continues

- problem setting
- machine learning approach
- example of a learner: Rocchio method
- term selection (for text categorization)

Text categorization: problem setting

- let
  - D: a collection of documents
  - $C = \{c_1, \ldots, c_{|C|}\}$: a set of predefined categories
  - T = true, F = false
- the task is to approximate the unknown target function Φ': D x C -> {T,F} by means of a function Φ : D x C -> {T,F}, such that the functions "coincide as much as possible"
- function Φ' : how documents should be classified
- function Φ : classifier (hypothesis, model…)

Some assumptions

- categories are just symbolic labels
  - no additional knowledge of their meaning is available
- no knowledge outside of the documents is available
  - all decisions have to be made on the basis of the knowledge extracted from the documents
  - metadata, e.g., publication date, document type, source etc. is not used

Some assumptions

- methods do not depend on any application-dependent knowledge
  - but: in operational ("real life") applications all kind of knowledge can be used (e.g. in spam filtering)
- note: content-based decisions are necessarily subjective
  - it is often difficult to measure the effectiveness of the classifiers
  - even human classifiers do not always agree

Single-label, multi-label TC

- single-label text categorization
  - exactly 1 category must be assigned to each $d_j \in D$
- multi-label text categorization
  - any number of categories may be assigned to the same $d_j \in D$

Single-label, multi-label TC

- special case of single-label: binary
  - each d_j must be assigned either to category c_i or to its complement $\neg c_i$
- the binary case (and, hence, the single-label case) is more general than the multi-label
  - an algorithm for binary classification can also be used for multi-label classification
  - the converse is not true

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Single-label, multi-label TC

- in the following, we will use the binary case only:
  - classification under a set of categories C = set of |C| independent problems of classifying the documents in D under a given category c_i, for i = 1, ..., |C|

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Machine learning approach

- a general inductive process (learner) automatically builds a classifier for a category c_i by observing the characteristics of a set of documents manually classified under c_i or $\neg c_i$ by a domain expert
- from these characteristics the learner extracts the characteristics that a new unseen document should have in order to be classified under c_i
- use of classifier: the classifier observes the characteristics of a new document and decides whether it should be classified under c_i or $\neg c_i$

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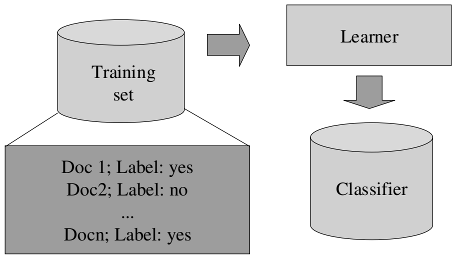
Classification process: classifier construction



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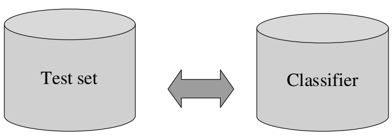
Classification process: testing the classifier



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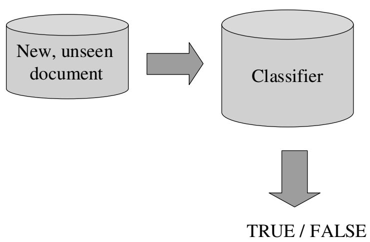
Classification process: use of the classifier



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Training set, test set, validation set

- initial corpus of manually classified documents
  - let d_j belong to the initial corpus
  - for each pair $<d_j, c_i>$ it is known if d_j should be filed under c_i
- positive examples, negative examples of a category

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Training set, test set, validation set

- the initial corpus is divided into two sets
  - a training set
  - a test set
- the training set is used to build the classifier
- the test set is used for testing the effectiveness of the classifier
  - each document is fed to the classifier and the decision is compared to the manual category

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Training set, test set, validation set

- the documents in the test set are not used in the construction of the classifier
- alternative: k-fold cross-validation
  - k different classifiers are built by partitioning the initial corpus into k disjoint sets and then iteratively applying the train-and-test approach on pairs, where k-1 sets construct a training set and 1 set is used as a test set
  - individual results are then averaged

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Training set, test set, validation set

- training set can be split to two parts
- one part is used for optimising parameters
  - test which values of parameters yield the best effectiveness
- test set and validation set must be kept separate

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Strengths of machine learning approach

- the learner is domain independent
  - usually available 'off-the-shelf'
- the inductive process is easily repeated, if the set of categories changes
  - only the training set has to be replaced
- manually classified documents often already available
  - manual process may exist
  - if not, it is still easier to manually classify a set of documents than to build and tune a set of rules

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Examples of learners

- Rocchio method
- probabilistic classifiers (Naïve Bayes)
- decision tree classifiers
- decision rule classifiers
- regression methods
- on-line methods
- neural networks
- example-based classifiers (k-NN)
- boosting methods
- support vector machines

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Rocchio method

- learner
- for each category, an explicit profile (or prototypical document) is constructed from the documents in the training set
  - the same representation as for the documents
  - benefit: profile is understandable even for humans

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Rocchio method

- a profile of a category is a vector of the same dimension as the documents
  - in our example: 118 terms
    - categories medicine, energy, and environment are represented by vectors of 118 elements
  - the weight of each element represents the importance of the respective term for the category

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Rocchio method

- weight of the k^{th} term of the category i:

$$w_{ki} = \beta \cdot \sum_{\{d_j \in POS_i\}} \frac{w_{kj}}{|POS_i|} - \gamma \cdot \sum_{\{d_j \in NEG_i\}} \frac{w_{kj}}{|NEG_i|}$$

- POS_i: set of positive examples
  - documents that are of category i
- NEG_i: set of negative examples

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Rocchio method

- in the formula, β and γ are control parameters that are used to set the relative importance of positive and negative examples
- for instance, if β=2 and γ=1, we don't want the negative examples to have as strong influence as the positive examples

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Rocchio method

- in our sample dataset: what is the weight of term 'nuclear' in the category 'medicine'?
  - $POS_{medicine}$ contains the documents Doc1-Doc4, and $NEG_{medicine}$ contains the documents Doc5-Doc10
    - $|POS_{medicine}| = 4$ and $|NEG_{medicine}| = 6$

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Rocchio method

- the weights of term ´nuclear´ in documents in $POS_{medicine}$
  - w_nuclear_doc1 = 0.5
  - w_nuclear_doc2 = 0
  - w_nuclear_doc3 = 0
  - w_nuclear_doc4 = 0.5
- and in documents in $NEG_{medicine}$
  - w_nuclear_doc6 = 0.5

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Rocchio method

- weight of 'nuclear' in the category 'medicine':
  - w_nuclear_medicine = 2* (0.5 + 0.5)/4 – 1 * 0.5/6 = 0.5 - 0.08 = 0.42

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Rocchio method

- using the classifier: cosine similarity of the category vector and the document vector is computed
  - |T| is the number of terms

$$S(c_i, d_j) = \frac{\sum_{k=1}^{|T|} w_{ki} \cdot w_{kj}}{\sqrt{\sum_{k=1}^{|T|} w_{ki}^2} \cdot \sqrt{\sum_{k=1}^{|T|} w_{kj}^2}}$$

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Rocchio method

- the cosine similarity function returns a value between 0 and 1
- a threshold is given
  - if the value is higher than the threshold -> true (the document belongs to the category)
  - otherwise -> false (the document does not belong to the category)

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Strengths of Rocchio method

- simple to implement
- fast to train
- search engines can be used to run a classifier

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Weaknesses of Rocchio method

- if the documents in a category occur in disjoint clusters, a classifier may miss most of them
  - e.g. two types of Sports news: boxing and rock-climbing
  - the centroid of these clusters may fall outside all of these clusters

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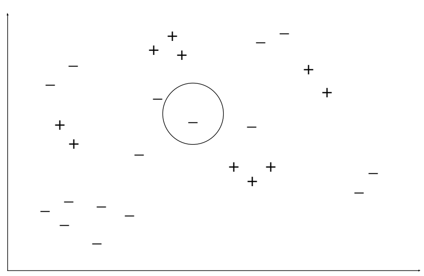

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Enhancement to the Rocchio Method

- instead of considering the set of negative examples in its entirety, a smaller sample can be used
  - for instance, the set of near-positive examples
- near-positives ($NPOS_c$): the most positive amongst the negative training examples

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Enhancement to the Rocchio Method

- the new formula:

$$w_{ki} = \beta \cdot \sum_{\{d_j \in POS_i\}} \frac{w_{kj}}{|POS_i|} - \gamma \cdot \sum_{\{d_j \in NPOS_i\}} \frac{w_{kj}}{|NPOS_i|}$$

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Enhancement to the Rocchio Method

- the use of near-positives is motivated, as they are the most difficult documents to distinguish from the positive documents
- near-positives can be found, e.g., by querying the set of negative examples with the centroid of the positive examples
  - the top documents retrieved are most similar to this centroid, and therefore near-positives
- with this and other enhancements, the performance of Rocchio is comparable to the best methods

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Term selection

- a large document collection may contain millions of words -> document vectors would contain millions of dimensions
  - many algorithms cannot handle high dimensionality of the term space (= large number of terms)
  - very specific terms may lead to overfitting: the classifier can classify the documents in the training data well but fails often with unseen documents

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Term selection

- usually only a part of terms is used
- how to select terms that are used?
  - term selection (often called feature selection or dimensionality reduction) methods

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Term selection

- goal: select terms that yield the highest effectiveness in the given application
- wrapper approach
  - the reduced set of terms is found iteratively and tested with the application
- filtering approach
  - keep the terms that receive the highest score according to a function that measures the "importance" of the term for the task

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Term selection

- many functions available
  - document frequency: keep the high frequency terms
    - stopwords have been already removed
    - 50% of the words occur only once in the document collection
    - e.g. remove all terms occurring in at most 3 documents

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Term selection functions: document frequency

- document frequency is the number of documents in which a term occurs
- in our sample, the ranking of terms:
  - 9 current
  - 7 project
  - 4 environment
  - 3 nuclear
  - 2 application
  - 2 area … 2 water
  - 1 use …

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Term selection functions: document frequency

- we might now set the threshold to 2 and remove all the words that occur only once
- result: 29 words of 118 words (~25%) selected

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Term selection: other functions

- Information-theoretic term selection functions, e.g.
  - chi-square
  - information gain
  - mutual information
  - odds ratio
  - relevancy score

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Term selection: information gain

- Information gain: measures the (number of bits of) information obtained for category prediction by knowing the presence or absence of a term in a document
- information gain is calculated for each term and the best n terms are selected

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Term selection: IG

- information gain for term t:
  - m: the number of categories

$$
\begin{aligned}
&G(t) = -\sum_{i=1}^{m} p(c_i)\log p(c_i) \\
&+ p(t)\sum_{i=1}^{m} p(c_i \mid t)\log p(c_i \mid t) \\
&+ p(\sim t)\sum_{i=1}^{m} p(c_i \mid \sim t)\log p(c_i \mid \sim t)
\end{aligned}
$$

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Estimating probabilities

- Doc 1: cat cat cat (c)
- Doc 2: cat cat cat dog (c)
- Doc 3: cat dog mouse (~c)
- Doc 4: cat cat cat dog dog dog (~c)
- Doc 5: mouse (~c)

- 2 classes: c and ~c

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Term selection: estimating probabilities

- P(t): probability of a term t
  - P(cat) = 4/5, or
    - 'cat' occurs in 4 docs of 5
  - P(cat) = 10/17
    - the proportion of the occurrences of ´cat' of the all term occurrences

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Term selection: estimating probabilities

- P(~t): probability of the absence of t
  - P(~cat) = 1/5, or
  - P(~cat) = 7/17

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Term selection: estimating probabilities

- P(c_i): probability of category i
  - P(c) = 2/5 (the proportion of documents belonging to c in the collection), or
  - P(c) = 7/17 (7 of the 17 terms occur in the documents belonging to c)

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Term selection: estimating probabilities

- P(c_i | t): probability of category i if t is in the document; i.e., which proportion of the documents where t occurs belong to the category i
  - P(c | cat) = 2/4 (or 6/10)
  - P(~c | cat) = 2/4 (or 4/10)
  - P(c | mouse) = 0
  - P(~c | mouse) = 1

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Term selection: estimating probabilities

- P(c_i | ~t): probability of category i if t is not in the document; i.e., which proportion of the documents where t does not occur belongs to the category i
  - P(c | ~cat) = 0 (or 1/7)
  - P(c | ~dog) = ½ (or 6/12)
  - P(c | ~mouse) = 2/3 (or 7/15)

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Term selection: estimating probabilities

- In other words...
- Let
  - term t occurs in B documents, A of them are in category c
  - category c has D documents, of the whole of N documents in the collection

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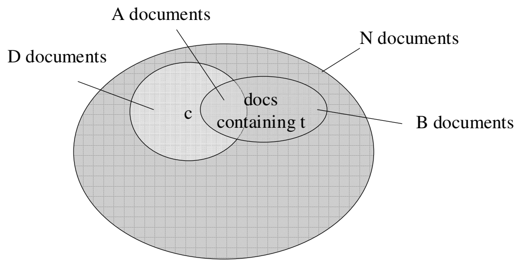
Term selection: estimating probabilities



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Term selection: estimating probabilities

- For instance,
  - P(t): B/N
  - P(~t): (N-B)/N
  - P(c): D/N
  - P(c|t): A/B
  - P(c|~t): (D-A)/(N-B)

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Term selection: IG

- information gain for a term t:

$$G(t) = -\sum_{i=1}^{m} p(c_i) \log p(c_i)$$
$$+ p(t) \sum_{i=1}^{m} p(c_i | t) \log p(c_i | t) + p(\sim t) \sum_{i=1}^{m} p(c_i | \sim t) \log p(c_i | \sim t)$$

- G(cat) = -0.40
- G(dog) = -0.38
- G(mouse) = -0.01

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