An Introduction to Text Classification

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28.10.2013

Overview

- Application Areas
- Rule-Based Approaches
- Statistical Approaches
  - Naive Bayes
  - Vector-Based Approaches
    - Rocchio
    - K-nearest Neighbors
    - Support Vector Machine
- Evaluation Measures
- Evaluation Corpora
- N-Gram Based Classification

Example Application Scenario

- Bertelsmann “Der Club” uses text classification to assign incoming emails to a category, e.g.
  - change of bank connection
  - change of address
  - delivery inquiry
  - cancellation of membership
- Emails are forwarded to the responsible editor
- Advantages
  - decrease of response time
  - more flexible resource management
  - happy customers ☺

Other Application Areas !

- Spam filtering
- Language identification
- News topic classification
- Authorship attribution
- Genre classification
- Email surveillance

Rule-based Classification Approaches !

- Use Boolean operators AND, OR and NOT
- Example rule
  - if an email contains “address change” or “new address”, assign it to the category “address changes”
- Organized as decision tree
  - nodes represent rules that route the document to a subtree
  - documents traverse the tree top down
  - leafs represent categories
  - rules are not independent of each other

Rule-based Classification Approaches !

- Advantages
  - transparent
  - easy to understand
  - easy to modify
  - easy to expand
- Disadvantages
  - complex and time consuming
  - intelligence is not in the system but with the system designer
  - not adaptive
  - only absolute assignment, no confidence values
- Statistical classification approaches solve some of these disadvantages

Hybrid Approaches

- Use statistics to automatically create decision trees
  - e.g. ID3 or CART
- Idea: identify the feature of the training data with the highest information content
  - most valuable to differentiate between categories
  - establish the top level node of the decision tree
  - recursively applied to the subtrees
- Advanced approaches “tune” the decision tree
  - merging of nodes
  - pruning of branches

Statistical Classification Approaches !

- Advantages
  - work with probabilities
  - allows thresholds
  - adaptive
- Disadvantage
  - require a set of training documents annotated with a category
- Most popular
  - Naive Bayes
  - Rocchio
  - K-nearest neighbor
  - Support Vector Machines (SVM)

Linguistic Preprocessing !

- Remove HTML/XML tags and stop words
- Perform word stemming
- Replace all synonyms of a word with a single representative
  - e.g. { car, machine, automobile } → car
- Composites analysis (for German texts)
  - split “Hausboot” into “Haus” and “Boot”
- Set of remaining words is called “feature set”
- Importance of linguistic preprocessing increases with
  - number of categories
  - lack of training data

Naive Bayes !

- Based on Thomas Bayes theorem from the 18th century
- Idea: Use the training data to estimate the probability of a new, unclassified document $d = \{w_1, \ldots, w_M\}$ belonging to each category $c_1, \ldots, c_K$

$$P(c_j \mid d) = \frac{P(c_j)P(d \mid c_j)}{P(d)}$$

- This simplifies to

$$P(c_j \mid d) = P(c_j)\prod_{i=1}^{M} P(w_i \mid c_j)$$

Naive Bayes !

- The following estimates can be done using the training documents

$$P(c_j) = \frac{N_j}{N}$$

$$P(w_i \mid c_j) = \frac{1 + N_{ij}}{M + \sum_{k=1}^{M} N_{kj}}$$

where

- N is the total number of training documents
- N_j is the number of training documents for category c_j
- N_{ij} is the number of times word w_i occurred within documents of category c_j
- M is the total number of words in the document

Naive Bayes !

- Result is a ranking of categories
- Adaptive
  - probabilities can be updated with each correctly classified document
- Naive Bayes is used very effectively in adaptive spam filters
- But why “naive”?
  - assumption of word independence
  - generally not true for word appearances in documents
- Conclusion
  - Text classification can be done by just counting words

Documents as Vectors !

- Some classification approaches are based on vector models
- Documents have to be presented as vectors
- Developed by Gerard Salton in the 60s
- Example
  - the vector space for two documents consisting of "I walk" and "I drive" consists of three dimension, one for each unique word
  - "I walk" → (1, 1, 0)
  - "I drive" → (1, 0, 1)
- Collection of documents is represented by a word-by-document matrix $A = (a_{ik})$ where each entry represents the occurrences of a word *i* in a document *k*

Weight of Words in Document Vectors !

- Boolean weighting

$$a_{ik} = \begin{cases} 1 & \text{if } f_{ik} > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Word frequency weighting

$$a_{ik} = f_{ik}$$

- tf.idf weighting

$$a_{ik} = f_{ik} \times \log\left(\frac{N}{n_i}\right)$$

  - considers distribution of words over the training corpus
  - n_i is the number of training documents that contain at least one occurrence of word *i*

Run Length Encoding

- Vectors representing documents contain almost only zeros
  - ➢ only a fraction of the total words of a corpus appear in a single document
- *Run Length Encoding* is used to compress vectors
  - ➢ Store sequences of length *n* of the same value *v* as *nv*
  - ➢ **`WWWWWWWWWWWWBWWWWWWWWWWWWBBBWWWWWW`**

    `WWWWWWWWWWWWWWWWWWBWWWWWWWWWWWWWW`

    would be stored as

    `12W1B12W3B24W1B14W`

Dimensionality Reduction !

- Large training corpora contain hundreds of thousands of unique words, even after linguistic preprocessing
- Result is a high dimensional feature space
- Processing is extremely costly in computational terms
- Use feature selection to remove non-informative words from documents
  - document frequency thresholding
  - information gain
  - χ^2-statistic

Document Frequency Thresholding

- Compute document frequency for each word in the training corpus
- Remove words whose document frequency is less than predetermined threshold
- These words are non-informative or not influential for classification performance

Information Gain

- Measure for each word how much its presence or absence in a document contributes to category prediction
- Remove words whose information gain is less than predetermined threshold

$$IG(w) = -\sum_{j=1}^{K} P(c_j)\log P(c_j) + P(w)\sum_{j=1}^{K} P(c_j \mid w)\log P(c_j \mid w) +$$

$$P(\overline{w})\sum_{j=1}^{K} P(c_j \mid \overline{w})\log P(c_j \mid \overline{w})$$

Information Gain

$$P(c_j) = \frac{N_j}{N} \qquad P(w) = \frac{N_w}{N} \qquad P(c_j \mid w) = \frac{N_{jw}}{N_w}$$

$$P(\overline{w}) = \frac{N_{\overline{w}}}{N} \qquad P(c_j \mid \overline{w}) = \frac{N_{j\overline{w}}}{N_{\overline{w}}}$$

- N total no. of documents
- N_j no. of docs in category c_j
- N_w no. of docs containing w
- $N_{\overline{w}}$ no. of docs not containing w
- N_{jw} no. of docs in category c_j containing w
- $N_{j\overline{w}}$ no. of docs in category c_j not containing w

χ^2-Statistic

- Measure dependance between words and categories

$$\chi^2(w, c_j) = \frac{N \times (N_{jw} N_{\bar{j}\bar{w}} - N_{j\bar{w}} N_{\bar{j}w})^2}{(N_{jw} + N_{j\bar{w}}) \times (N_{\bar{j}w} + N_{\bar{j}\bar{w}}) \times (N_{jw} + N_{\bar{j}w}) \times (N_{j\bar{w}} + N_{\bar{j}\bar{w}})}$$

- Define measure as

$$\chi^2(w) = \sum_{j=1}^{K} P(c_j)\, \chi^2(w, c_j)$$

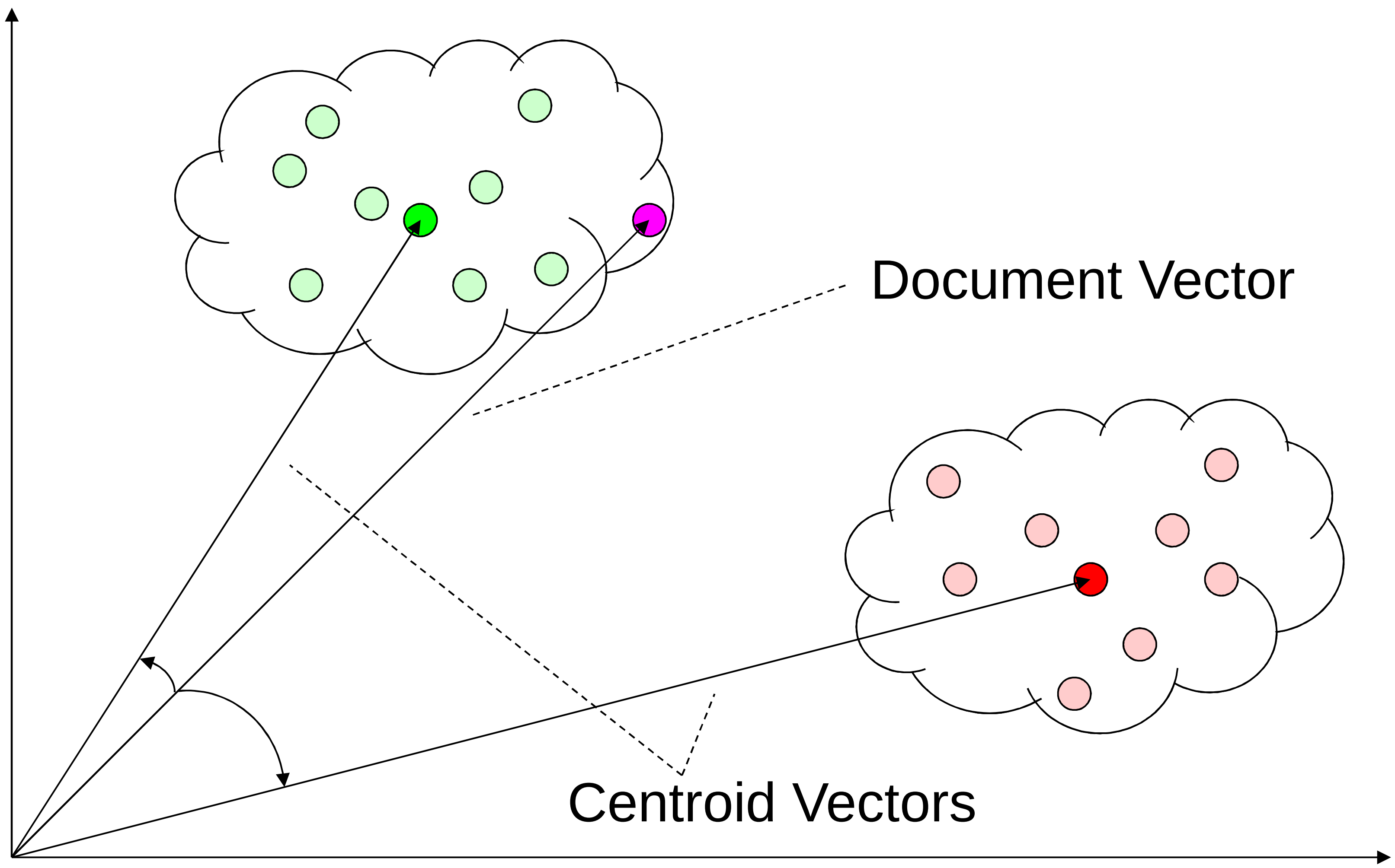
- Result is a word ranking
- Select top section as feature set

Rocchio !

- Uses centroid vectors to represent a category
- Centroid vector is the average vector of all document vectors of a category
- Centroid vectors are calculated in the training phase
- To classify a new document, just calculate its distance to the centroid vector of each category
- Use cosine similarity as distance measure

$$\cos(\vec{x}, \vec{y}) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2} \times \sqrt{\sum_i y_i^2}}$$

Rocchio !



Rocchio !

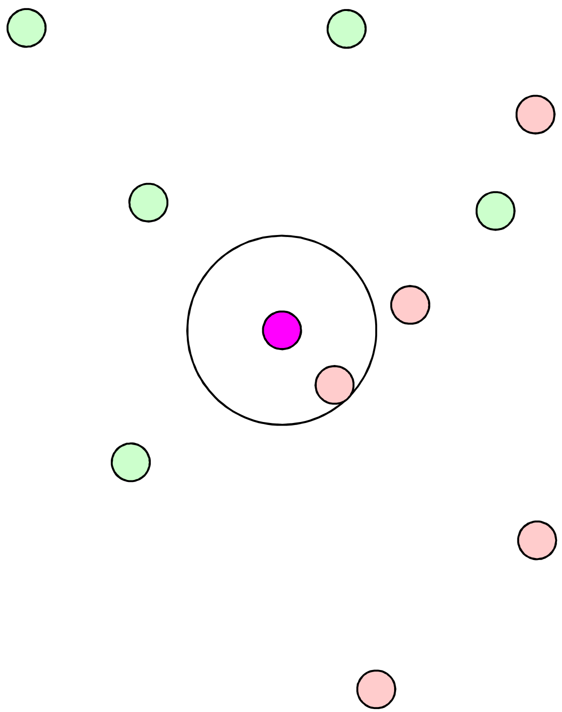
- Advantages
  - fast training phase
  - small models
  - fast classification
- Disadvantages
  - precision drops with increasing number of categories

K-nearest Neighbors !

- Similar to Rocchio
- Check the *k* nearest neighbor vectors of a new document vector
- Value of *k* determined empirically
- Define “nearest” using a similarity measure, e.g. Euclidean distance or cosine similarity

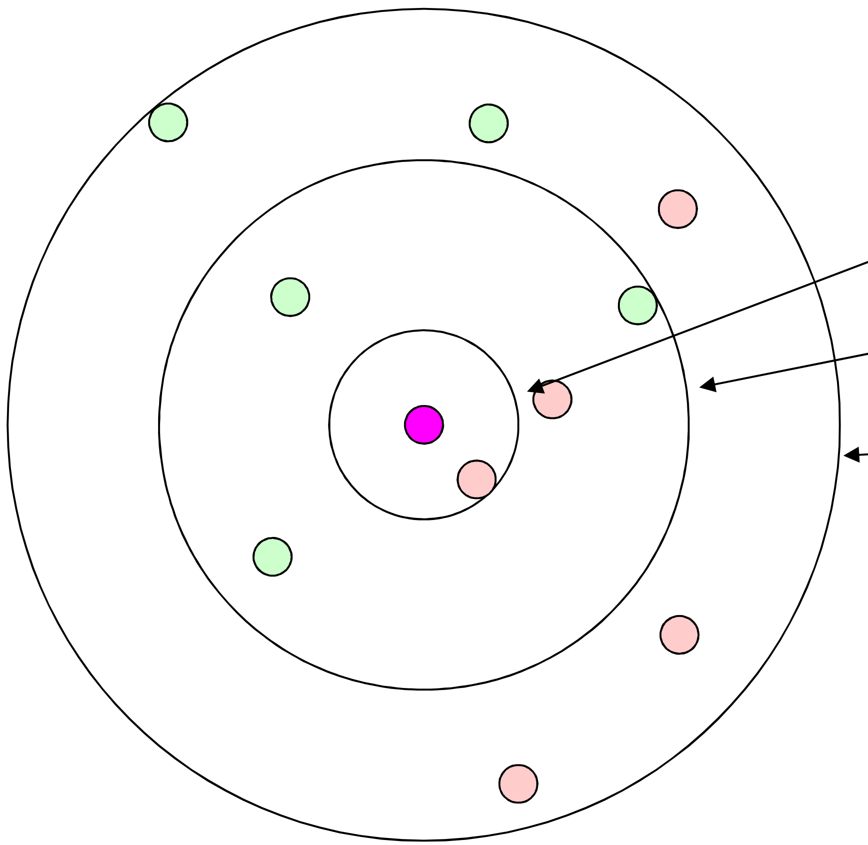
1-nearest Neighbor !

- Assign new document the category of its nearest neighbor



K-nearest Neighbors !

- Majority voting scheme



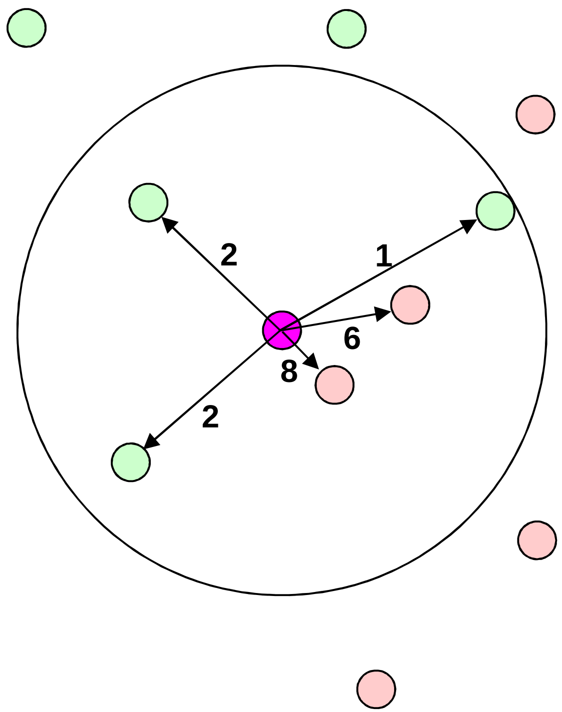
k=1: majority for red

k=5: majority for green

k=10: even votes for both

K-nearest Neighbors !

- Weighted sum voting scheme for k = 5
- Neighbors are given weights according to their nearness



weighted sum for red: 14

weighted sum for green: 5

K-nearest Neighbors !

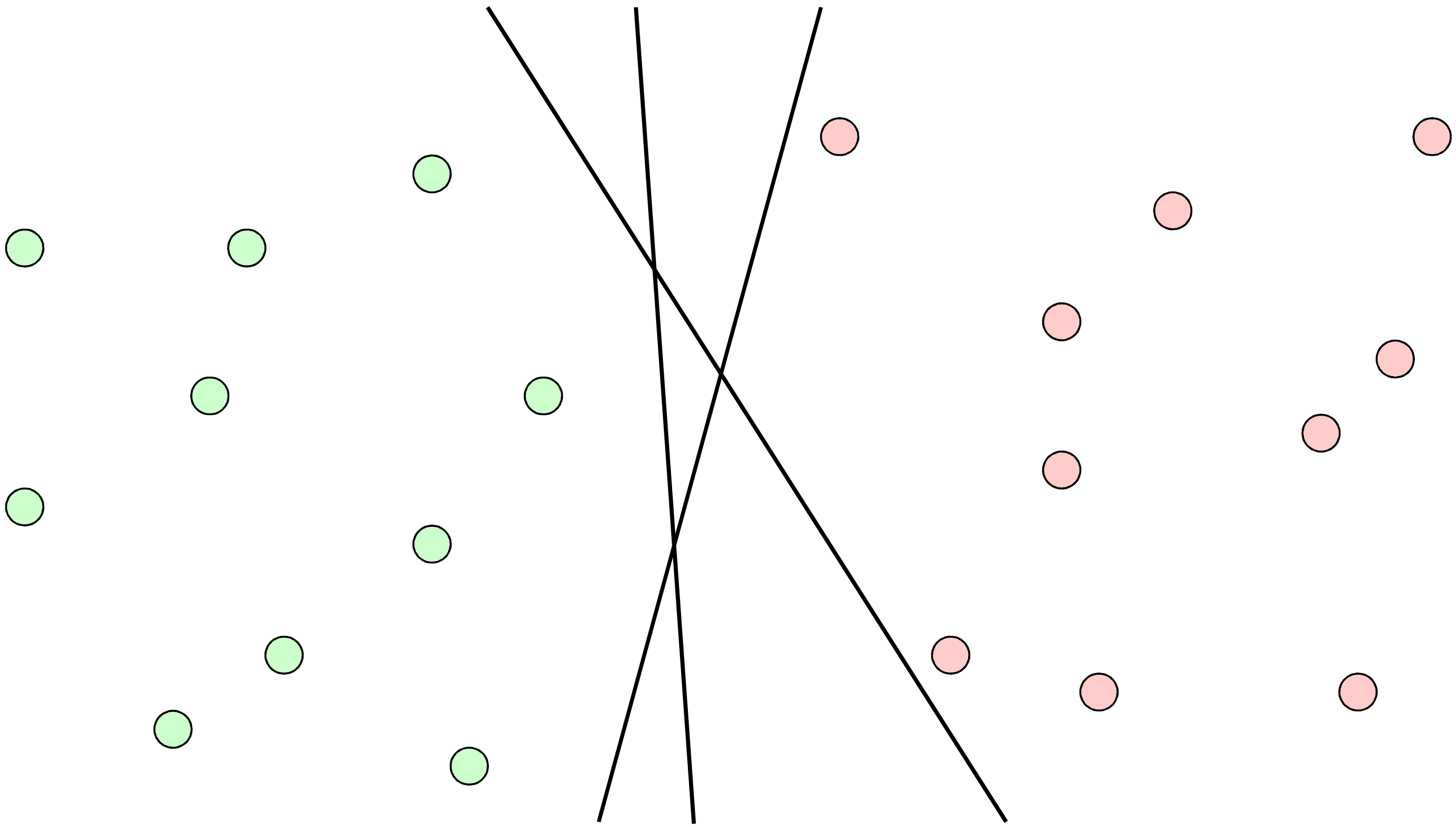
- Advantages
  - ➢ no training phase required
  - ➢ good scalability if number of categories increases
- Disadvantages
  - ➢ large models for large training sets
  - ➢ requires a lot of memory
  - ➢ slow performance

Support Vector Machine !

- For each pair of categories find a decision surface (hyperplane) in the vector space that separates the document vectors of the two categories
- Usually, there are many possible separating hyperplanes
- Find the “best” one: maximum-margin hyperplane
  - ➢ equal distance to both document sets
  - ➢ margin between hyperplane and document sets is at maximum
- Training result for each pair of categories: vectors closest to the hyperplane → support vectors
- Classification: calculate distance of document vector to support vectors

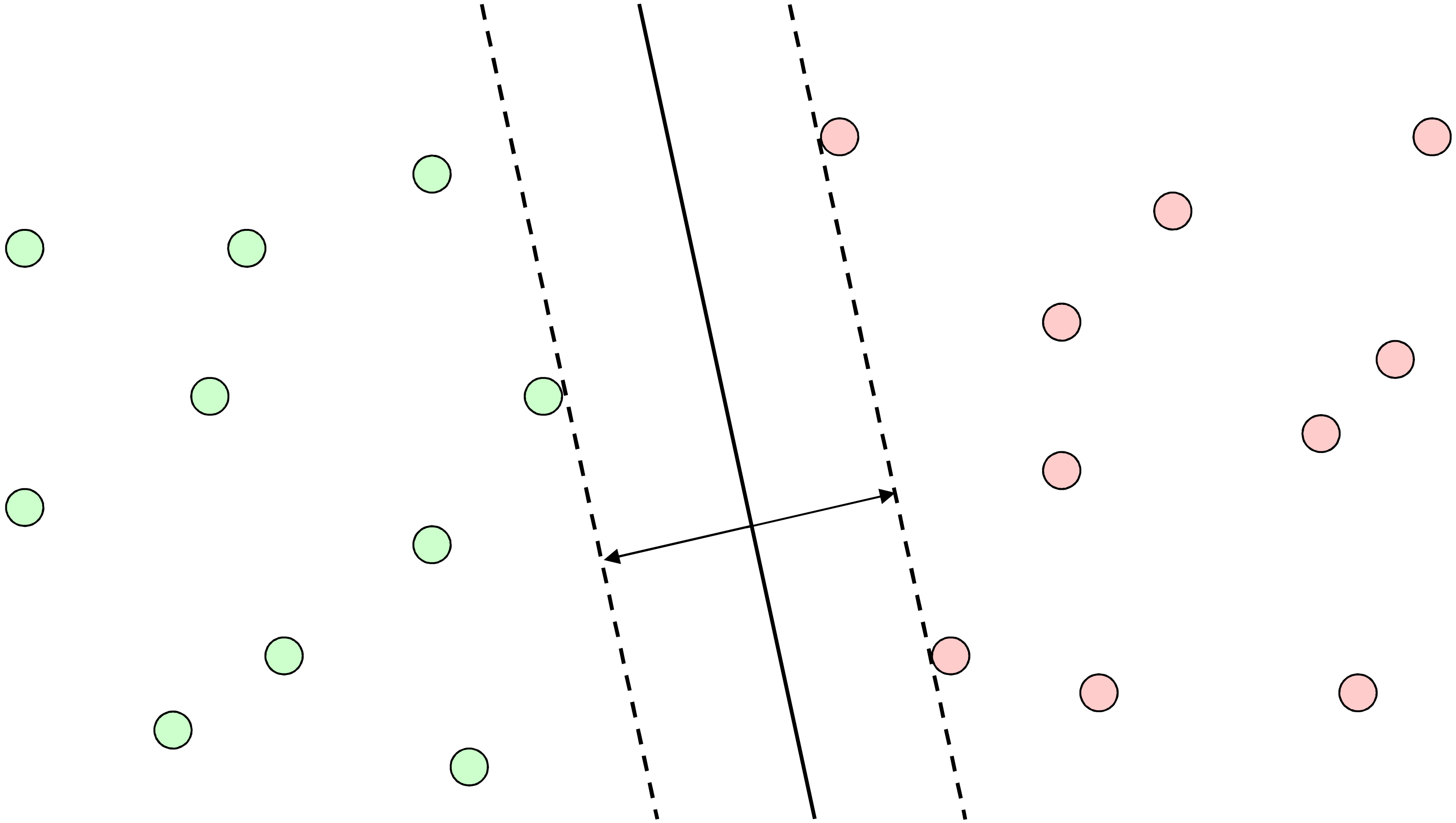
Support Vector Machine !

- More than one hyperplane separate the document vectors of each category



Support Vector Machine !

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



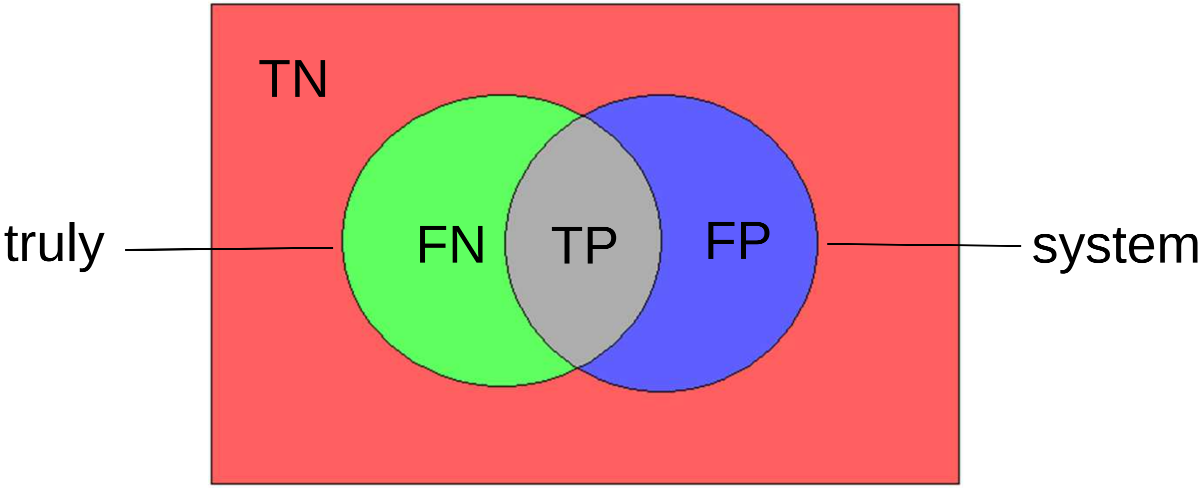
Support Vector Machine !

- Advantages
  - only the support vectors are required to classify new documents
  - small models
  - feature selection can be omitted
  - no overfitting
    - when given too much training data, other classification approaches only return a correct classification for training documents
    - main advantage of SVM over other vector-based approaches
- Disadvantage
  - very complex training (optimization problem)

Classification Evaluation !

- Possible results of a binary classification

	truly YES	truly NO
system YES	true positives	false positives
system NO	false negatives	true negatives



Evaluation Measures !

- Precision
  - percentage of documents correctly identified as belonging to the category

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

- Recall
  - percentage of documents found belonging to the category

$$recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

Evaluation Measures !

- Precision and recall are misleading when examined alone
- There is always a tradeoff between precision and recall
  - Increase in recall often comes with a decrease in precision
  - If precision and recall are tuned to have the same value, it is called the break-even point
- F-Measure combines both precision and recall in one value

$$F_{\beta} = \frac{(\beta^2 + 1) \times precision \times recall}{\beta^2 \times precision + recall}$$

  - β allows different weighting of precision and recall
  - for equal weighting, $\beta = 1$

Evaluation Corpora

- To compare different classification approaches, a common set of data is required
- Popular evaluation corpora
  - Reuters-21578 collection
  - 20-newsgroup-corpus
- Evaluation corpora are usually split up into a training corpus and a test corpus
- Beware: You can score top precision and recall values if you test your classification approach on the training data!

Reuters-21578 Collection

- Collected from the Reuters newswire in 1987
- Contains 12902 news articles from 135 different categories
- Documents have up to 14 categories assigned
- Average is 1.24 categories per document
- Default split
  - ➢ 9603 training documents
  - ➢ 3299 test documents

20-Newsgroups-Corpus

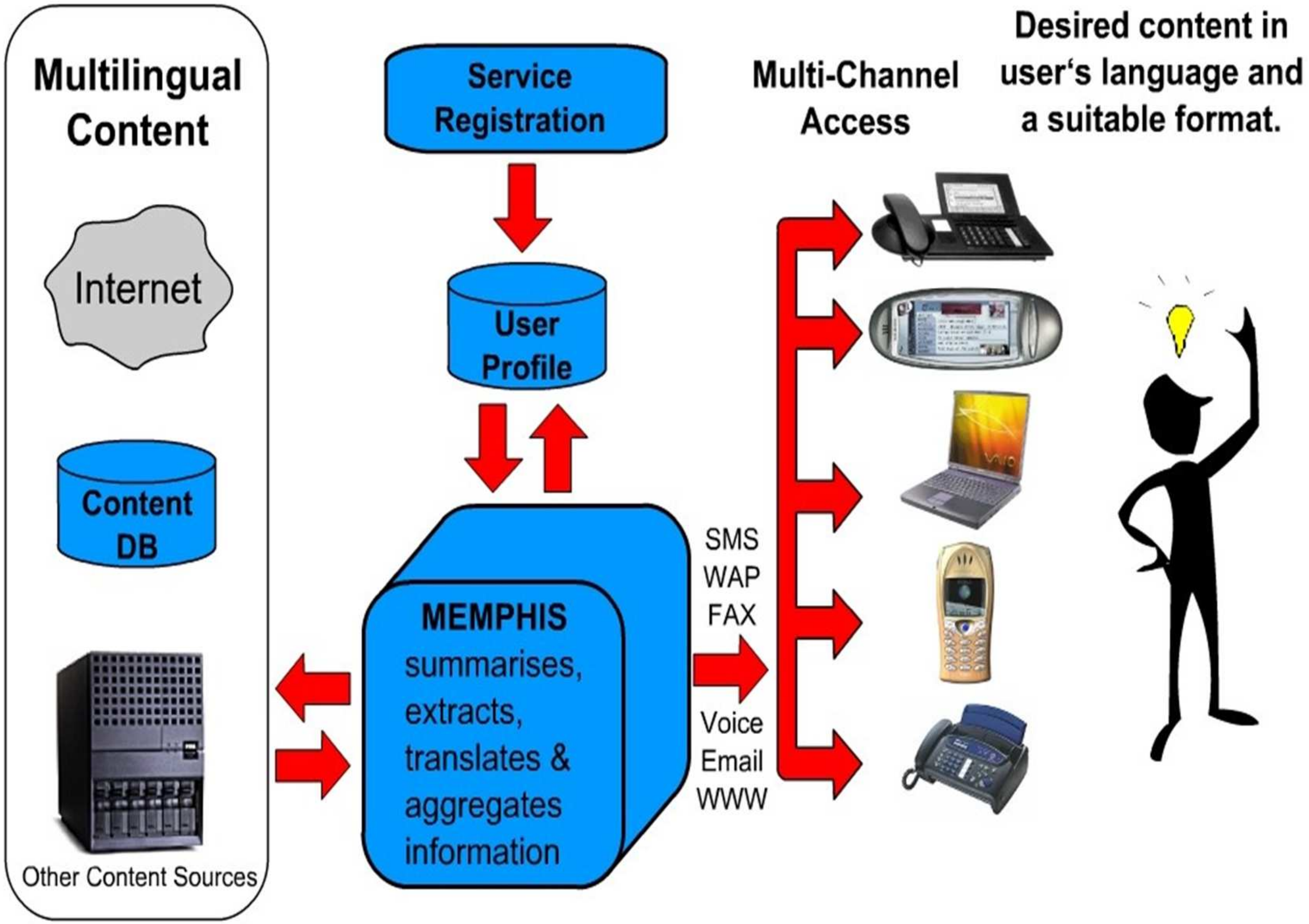
- Consists of newsgroup articles from 20 different newsgroups
- Some newsgroups closely related, e.g. alt.atheism and talk.religion.misc
- Contains 20.000 articles, 1000 articles for each newsgroup
- Corpus size: 36 MB
- Average size of article: 2 KB
- Newsgroup header of articles has been removed

What is the best classification approach? !

- This depends on the application scenario and the data
- “Hard” facts are easy to model with rules
- “Soft” facts are better modeled with statistic
- If there is few or no training data, statistic doesn’t work
- Among statistical approaches the ranking is
  - SVM
  - K-nearest neighbors
  - Rocchio
  - Naive Bayes
- In real life, rule-based and statistical approaches are often combined to get the best results

N-Gram Based Multilingual and Robust Document Classification

Memphis Project Overview



The MediAlert Service

- Domain: book announcements
- Sources: internet sites of book shops and publishers in English, German and Italian
- Classification task: assign topic to book announcement
  - Biographies
  - Film
  - Music
  - Sports
  - Travel
  - Health
  - Food
- Classification Challenges:
  - Informal texts with open-ended vocabulary
  - Content in several languages
  - Spelling mistakes and missing case distinction

Character-Level N-Grams

- MEMPHIS classifier based on character-level n-grams instead of terms
- Example
  - “Well, this is an example!”
  - 3-grams: “Wel” “ell” “ll,” “l, ” “, t” “ th” “thi” “his” … “le!”
- Advantages of character-level n-grams
  - No linguistic preprocessing necessary
  - Language independent
  - Very robust
  - Less sparse data

Model Training

- Training requires a corpus of documents
- Each training document must be tagged with one or more categories
- For each category, a statistical model is created
- Each model contains conditional probabilities based on character-level n-gram frequencies counted in training documents
- Models are independent of each other

Model Training

- Document is a character sequence

$$s = c_1, \ldots, c_N$$

- Maximum Likelihood Estimate:

$$P(c_i \mid c_{i-n+1}, \ldots, c_{i-1}) = \frac{\#(c_{i-n+1}, \ldots, c_i)}{\#(c_{i-n+1}, \ldots, c_{i-1})}$$

- Example:

$$P(\mathrm{d} \mid \mathrm{win}) = \frac{\#(\mathrm{wind})}{\#(\mathrm{win})}$$

Document Classification

- Based on Bayesian decision theory
- For each model, predict probability of test document using the chain rule of probability:

$$P(c_1, \ldots, c_N) = \prod_{i=1}^{N} P(c_i \mid c_1, \ldots, c_{i-1})$$

- Approximation in n-gram models:

$$P(c_i \mid c_1, \ldots, c_{i-1}) = P(c_i \mid c_{i-n+1}, \ldots, c_{i-1})$$

- Result is a ranking of categories derived from the probability of the test document in each model

Sparse Data Problem

- N-grams in test documents that are unseen in training get zero probability
- As a consequence, probability for test document becomes zero
- No matter how much training data, there can always be unseen n-grams in some test documents
- Solution: Probability Smoothing
  - Assign non-zero probability to unseen n-grams
  - To keep a valid model, reduce the probability of known n-grams and reserve some room in the probability space for unseen n-grams

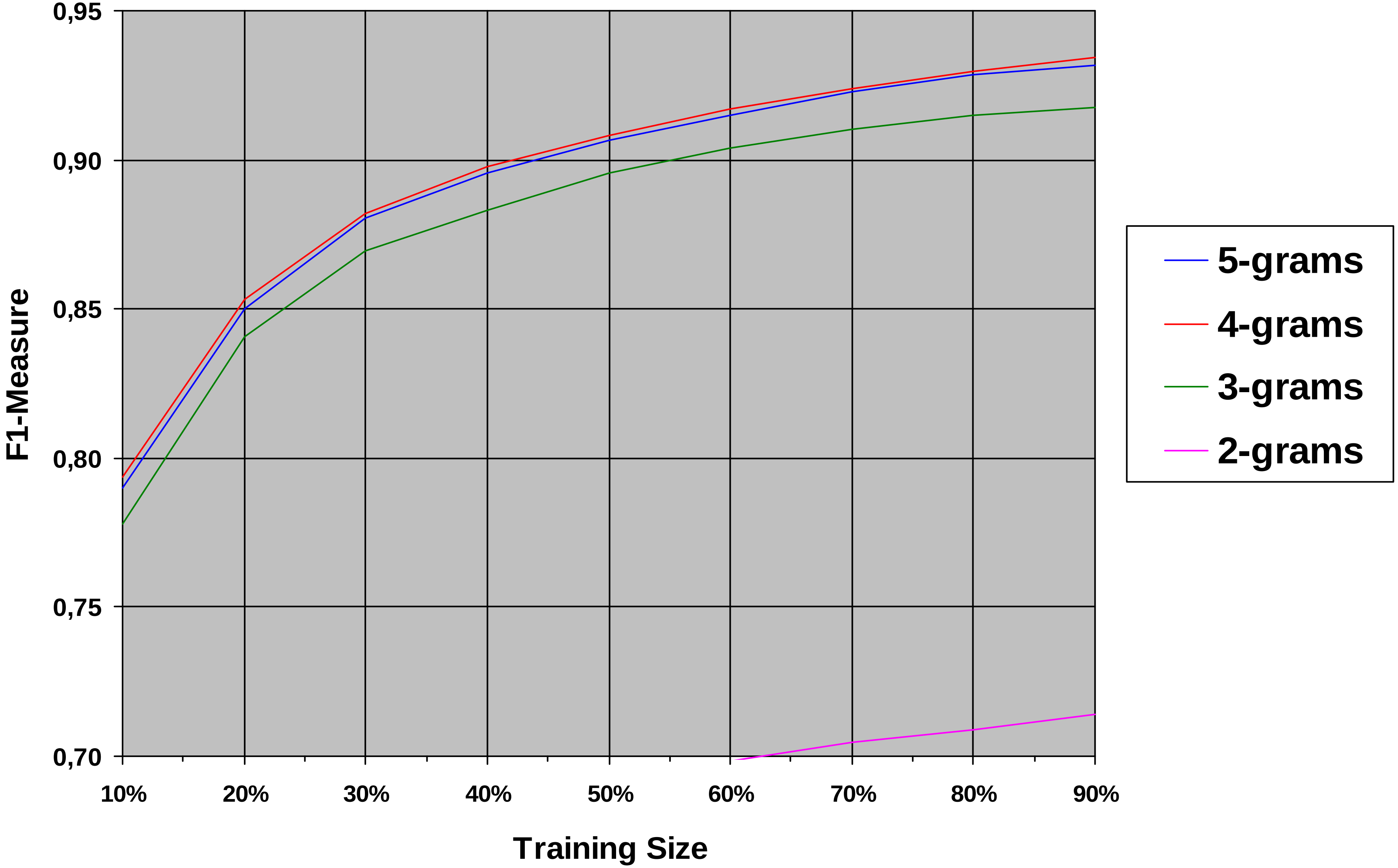
Smoothing Techniques

- Several smoothing techniques have been adapted for character-level n-grams that yield backoff models and interpolated models:
    - Katz Smoothing
    - Simple Good-Turing Smoothing
    - Absolute Smoothing
    - Kneser-Ney Smoothing
    - Modified Kneser-Ney Smoothing

Whitespace Stripping

- Non-linguistic preprocessing step
- Strip all whitespaces
- Convert all characters to lower case
- To preserve word border information, first character is always upper case
- Example:
  - LIFE STORIES: Profiles from the New Yorker
  - LifeStories:ProfilesFromTheNewYorker
- Improves average F_1-Measure by up to 5%
- Larger models

20-Newsgroups Evaluation Results



Linguistic Resources

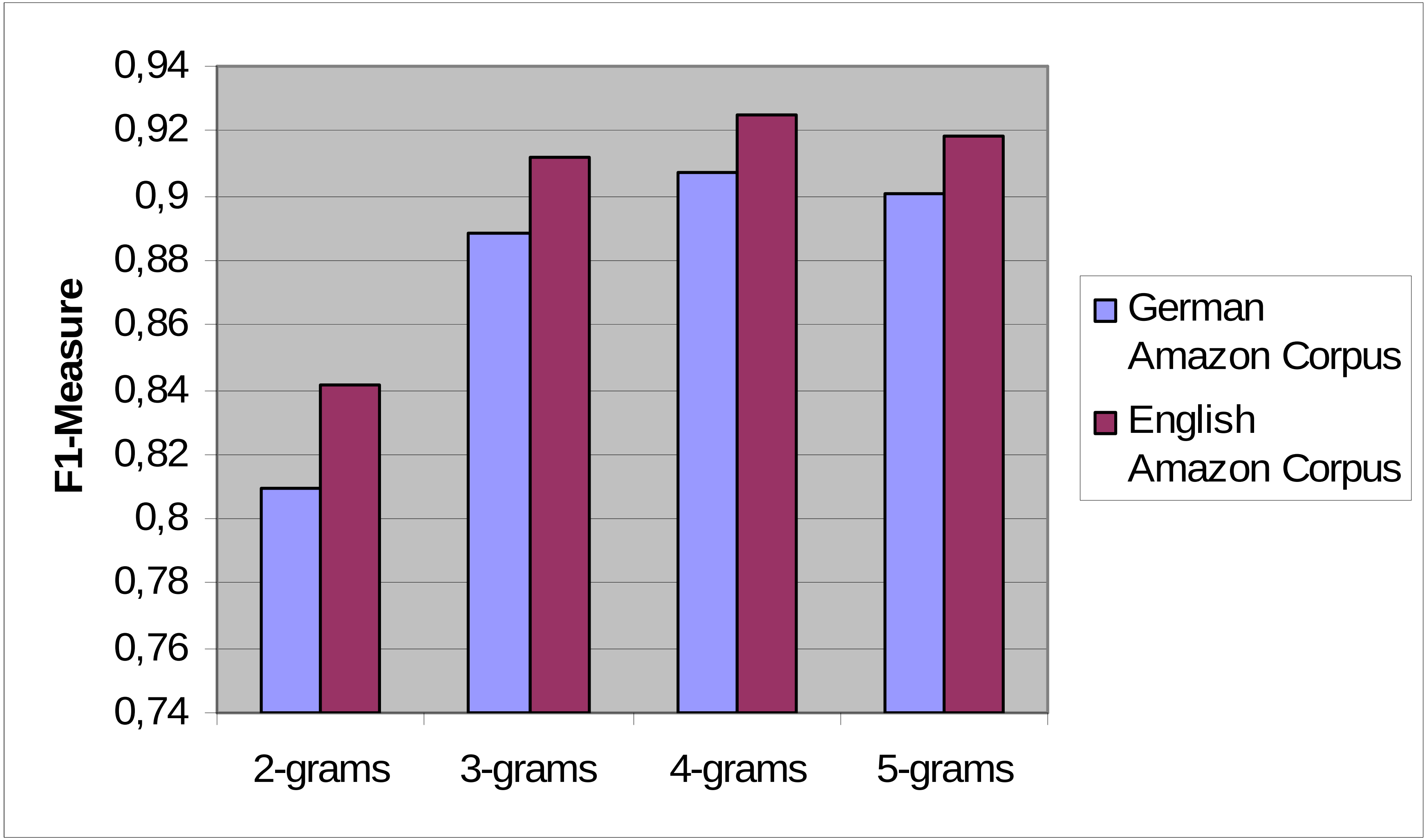
- Amazon corpora
  - 1000 docs per category
  - English (13MB) and German (10MB)
  - Acquired using the Amazon web service
- Other English corpora:
  - Randomhouse.com (3000 docs, 4 MB)
  - Powells.com (8000 docs, 7MB)
- Other German corpora:
  - Bol.de (1200 docs, 1 MB)
  - Buecher.de (2300 docs, 2 MB)

Evaluation

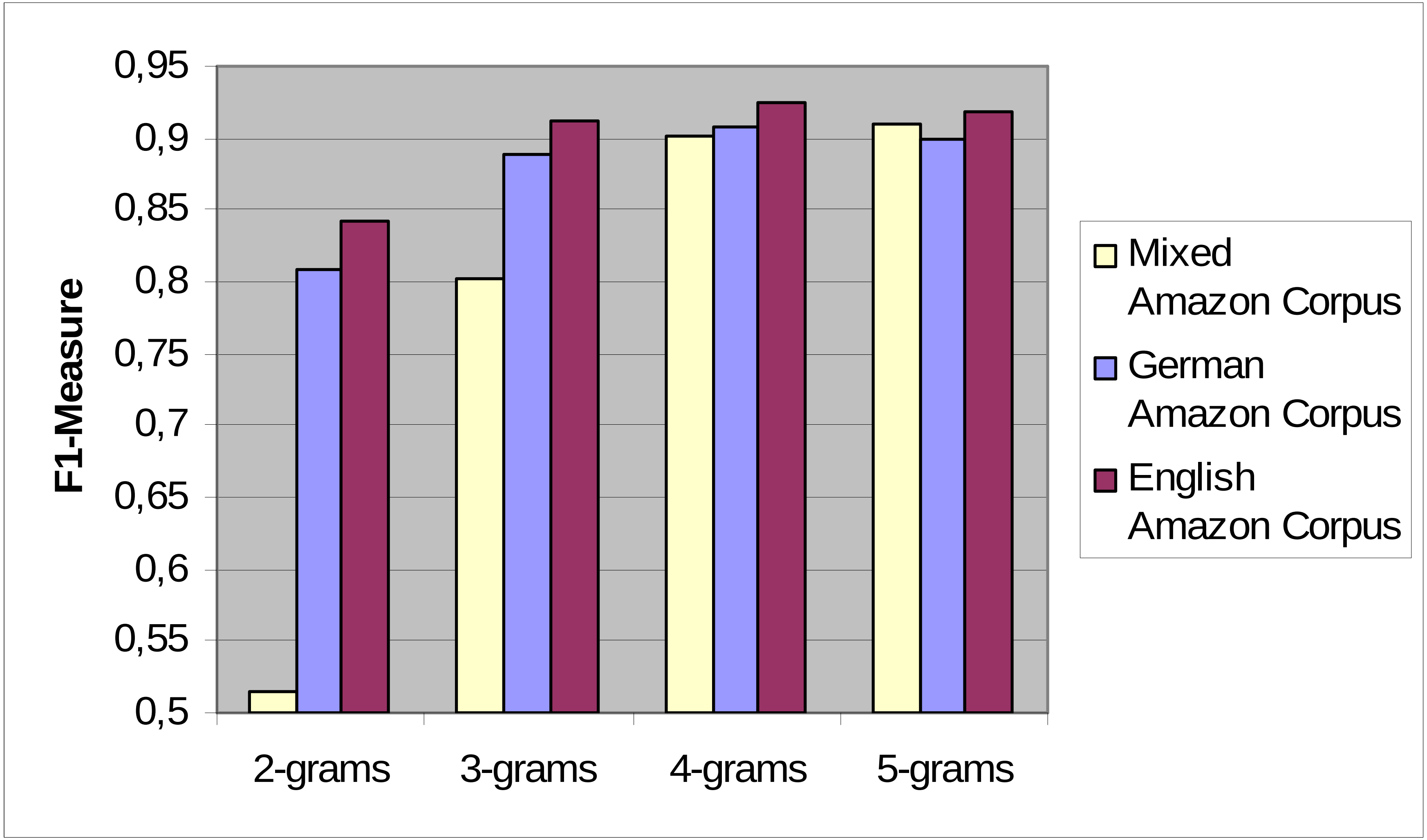
- Classification parameters
  - Smoothing technique
  - N-gram length
  - Mono-lingual vs multi-lingual models
- Setting:
  - Split corpus randomly into training docs (80%) and test docs (20%)
  - Performance as average F_1-Measure of 10 runs

Smoothing Techniques

Mono-Lingual Models



Multi-Lingual Models



Conclusions

- Classification using character-level n-grams performs very good in assigning topics to multi-lingual, informal documents
- Approach is robust enough to allow multi-lingual models