An Introduction to Text Classification

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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 in the Memphis Project

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 J

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”
- Representation as decision tree

  nodes represent rules that route the document to a subtree

  documents traverse the tree top down

  leafs represent categories

Rule-based Classification Approaches

- Advantages
  - transparent
  - easy to understand
  - easy to expand
  - easy to modify
- 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 space”
- Documents are considered as “Bag-of-Words”
- 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

Naive Bayes

- Result is a ranking of categories
- Adaptive
  - probabilities are updated with each correctly classified document
- Naive Bayes is used very effectively in adaptive spam filters
- But why “naive”?
  - assumption of word independence –> Bag-of-Words model
  - 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
- Developed by Gerard Salton in the 60s
- Documents have to be presented as vectors
- 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

  WWWWWWWWWWWWWWWWWWWWBWWWWWWWWWWWWWW

  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
- Contrary to idf weight
  - Effectively applies an upper bound to idf weight

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

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

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

- 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 dependence 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

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

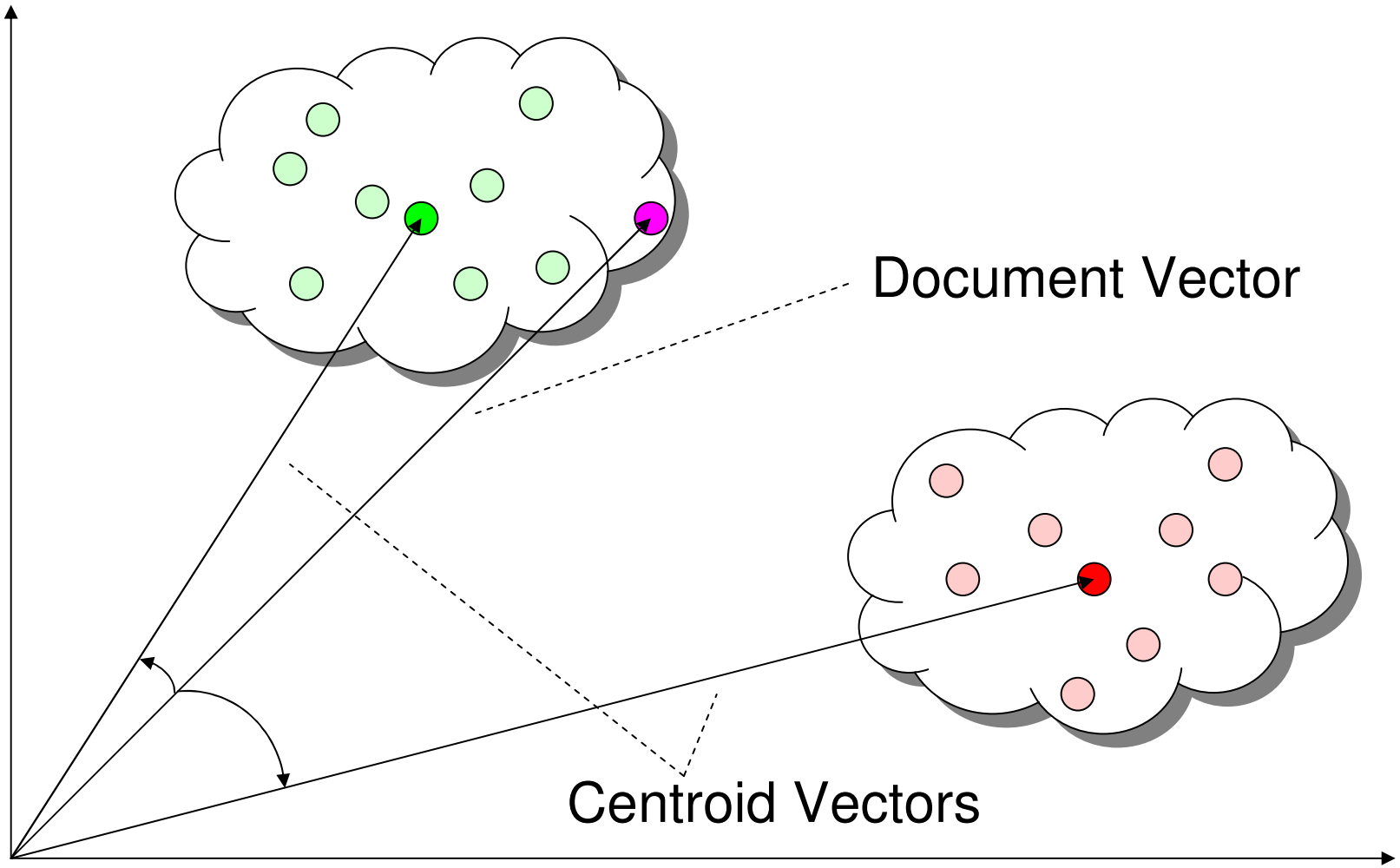
- Result is a word ranking
- Select top section as feature set

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

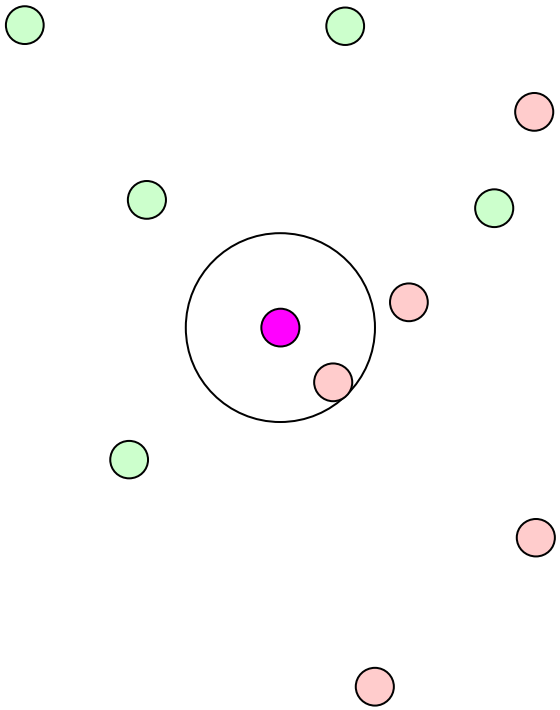
- Advantages
  - fast training phase
  - fast classification
- Disadvantages
  - precision drops with increasing number of categories

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

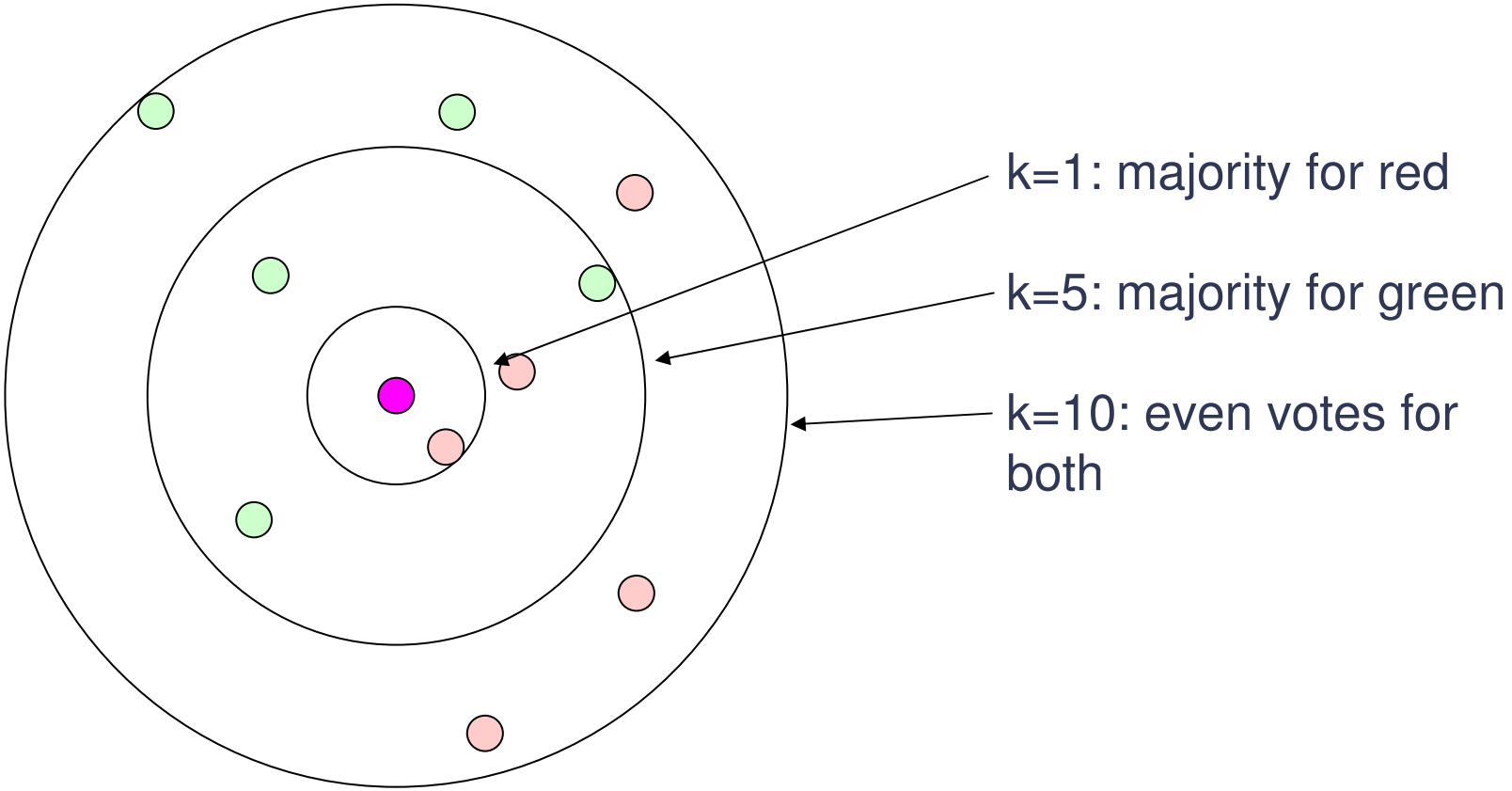
1-nearest Neighbor

- Assign new document the category of its nearest neighbor



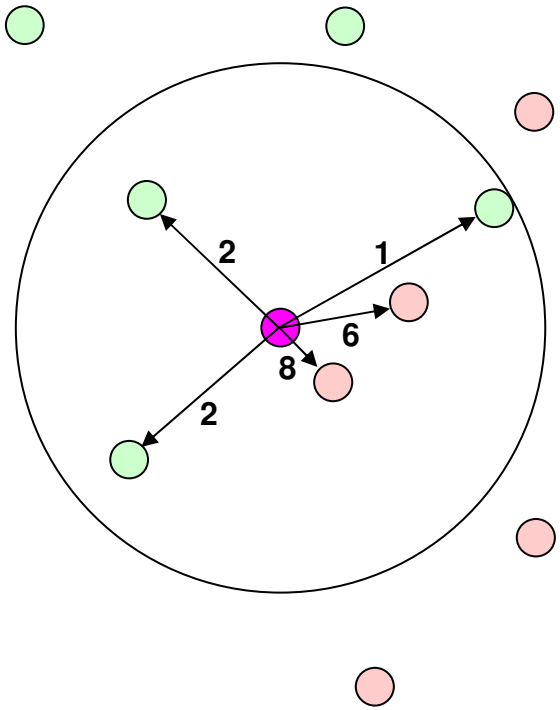
K-nearest Neighbors

- Majority voting scheme



K-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

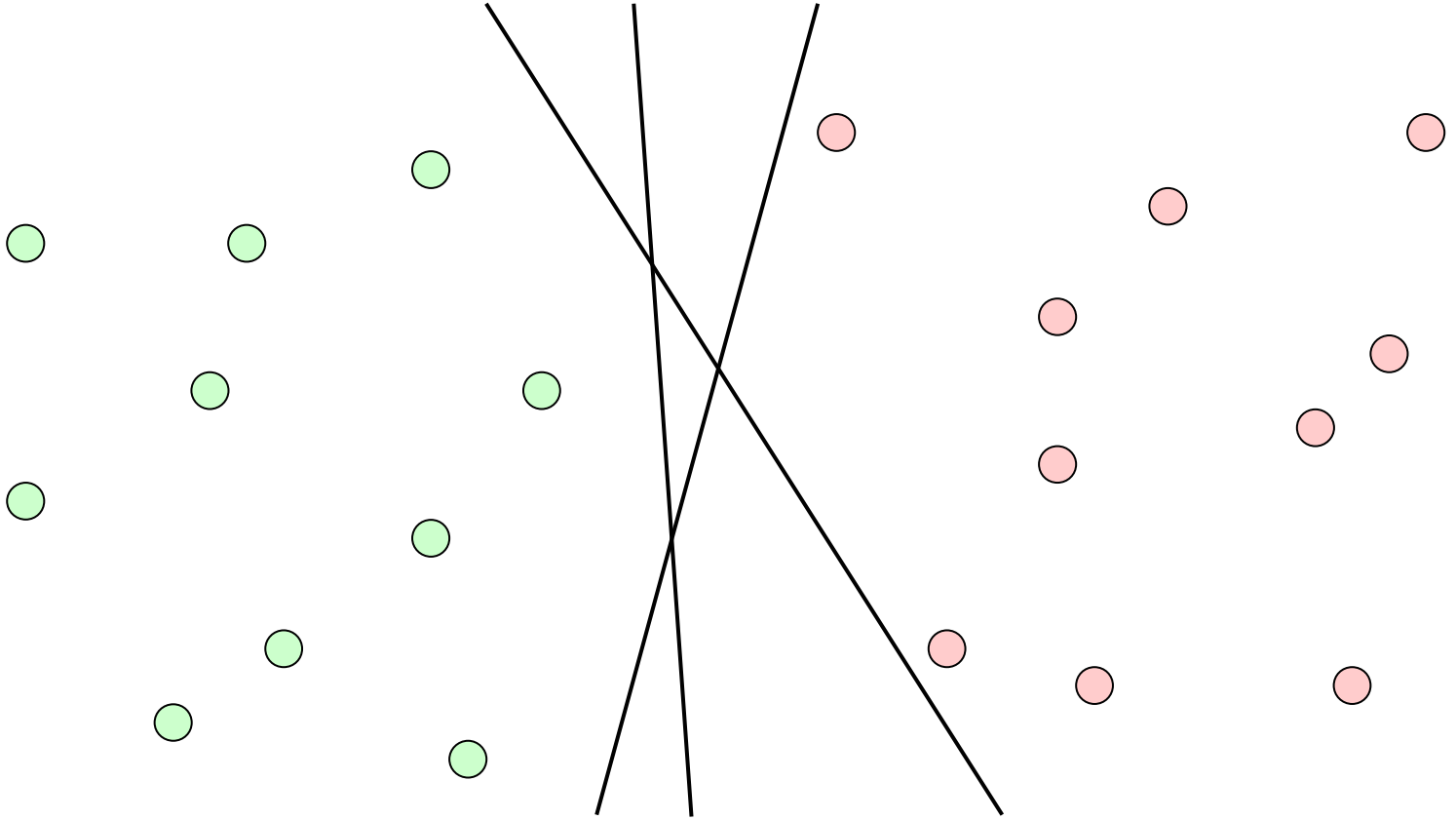
- Advantages
  - no training phase required
  - good scalability if number of categories increases
- Disadvantages
  - large models for large training sets
  - requires a lot of memory
  - slow performance

Support Vector Machine

- Find a decision surface (hyperplane) in the vector space that separates the document vectors of 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 maximal
- Training result for each pair of classes: vectors closest to the hyperplane –> support vectors
- Classification: calculate distance to support vectors

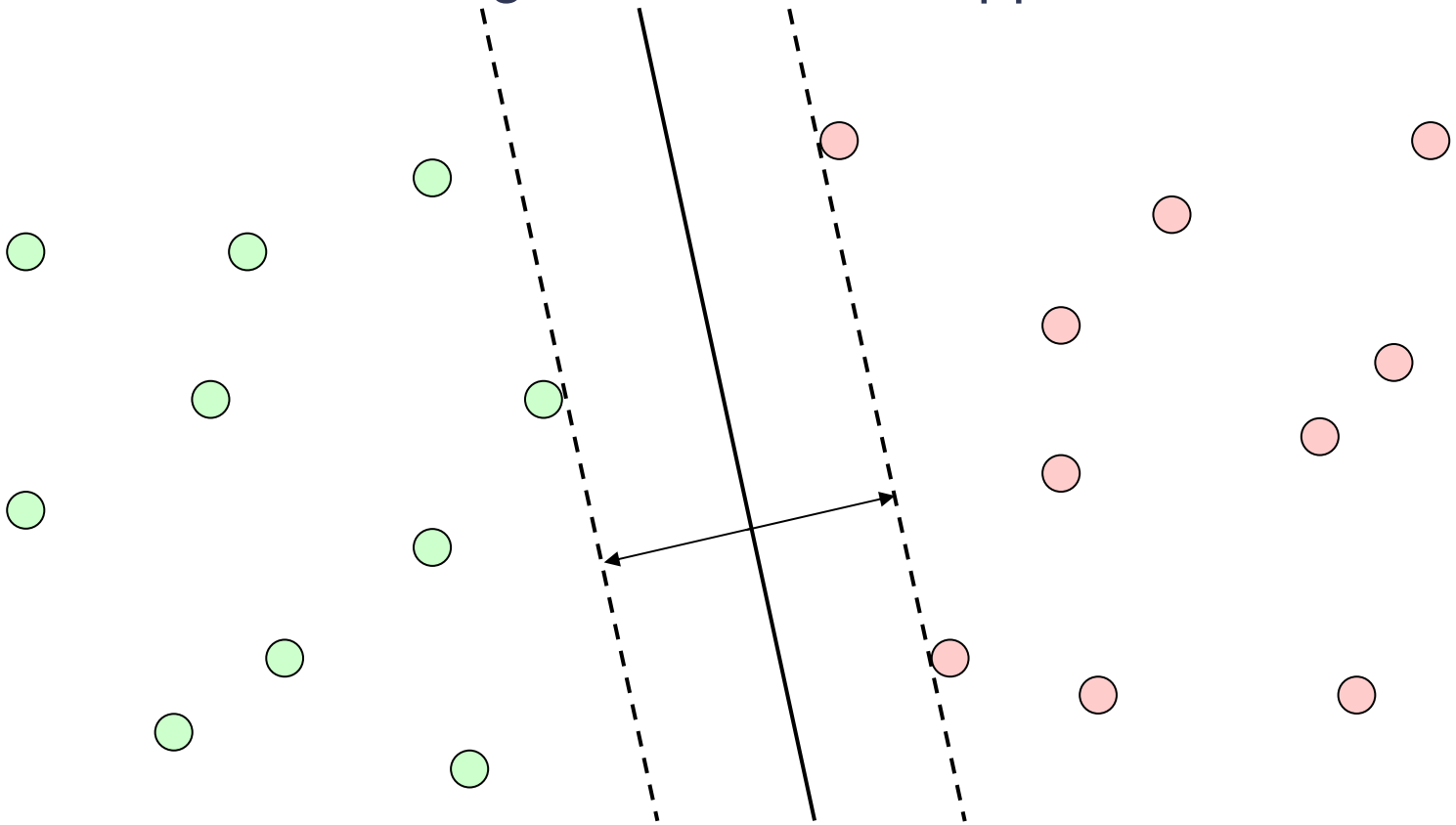
Support Vector Machine

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



Support Vector Machine

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



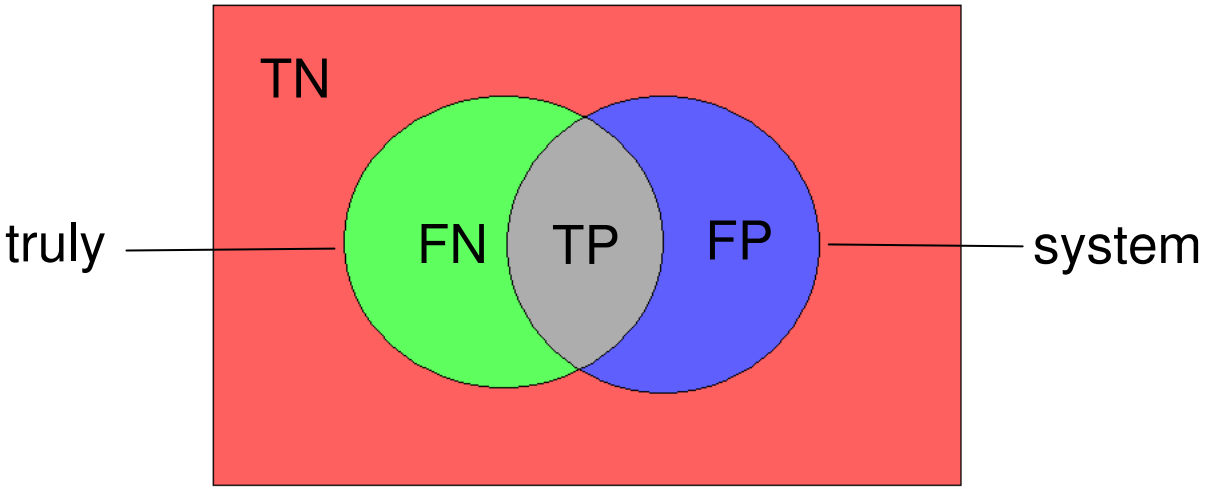
Support Vector Machine

- 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, β = 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

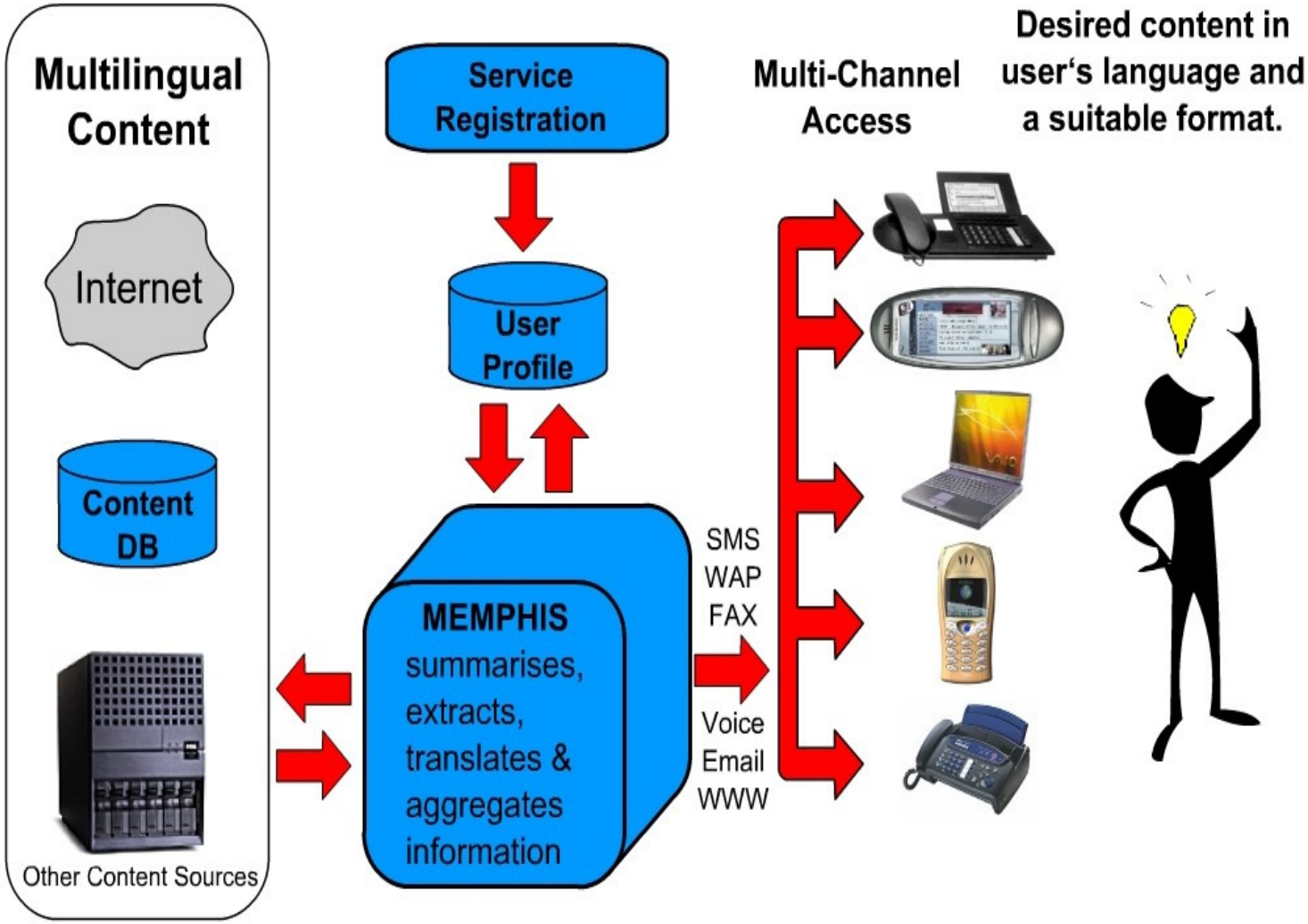
- Consists of newsgroup articles from 20 different newsgroups
- Some newsgroups closely related, e.g. alt.atheism and talk.religion.misc
- Contains 20.000 articles, 1000 articles for each newsgroup
- Corpus size: 36 MB
- Average size of article: 2 KB
- Newsgroup header of articles has been removed

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 in the MEMPHIS Project

Memphis 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	Travel
Film	Health
Music	Food
Sports	

- 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:

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

- Approximation in n-gram models:

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

- 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

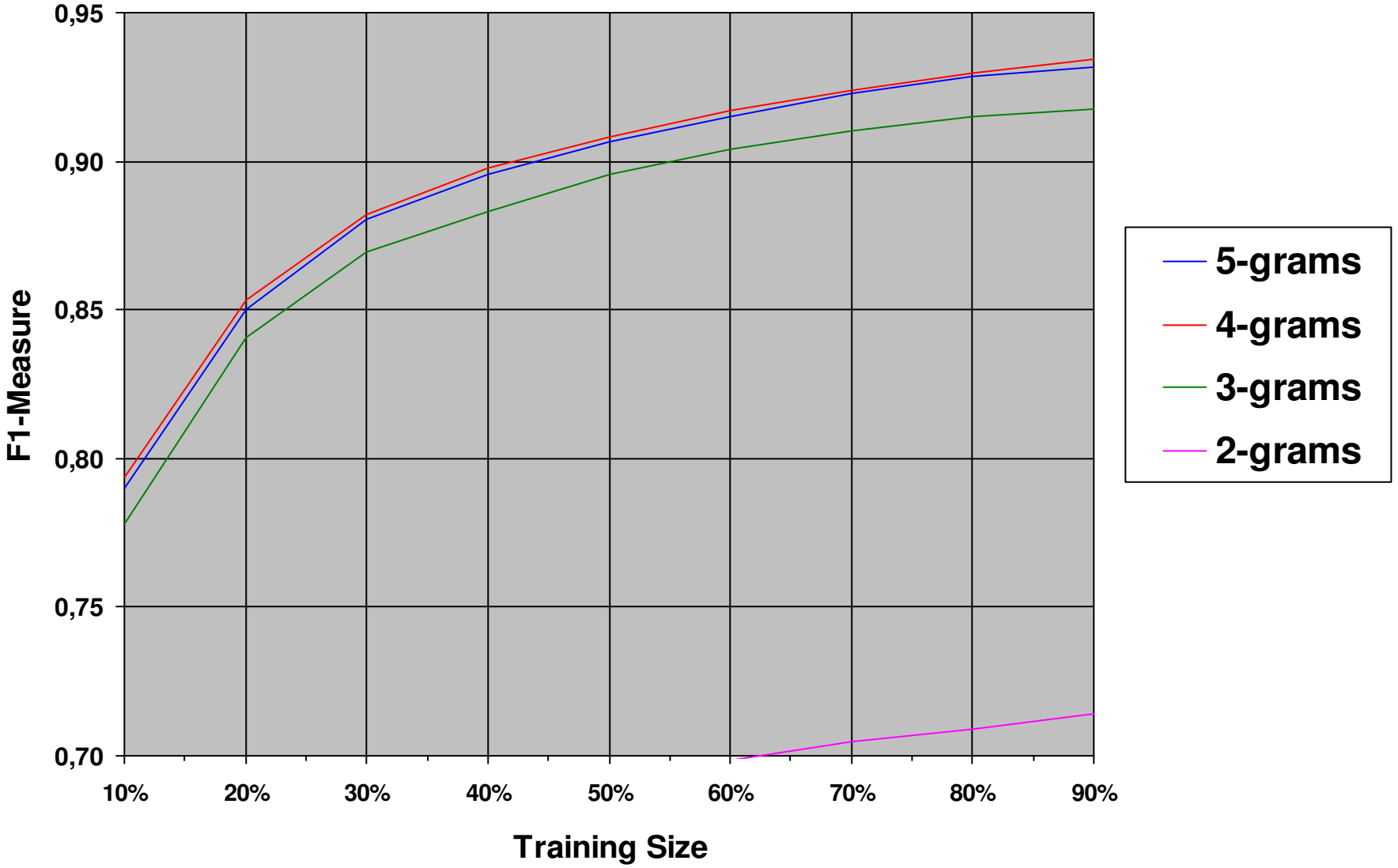
Whitespace Stripping

- 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

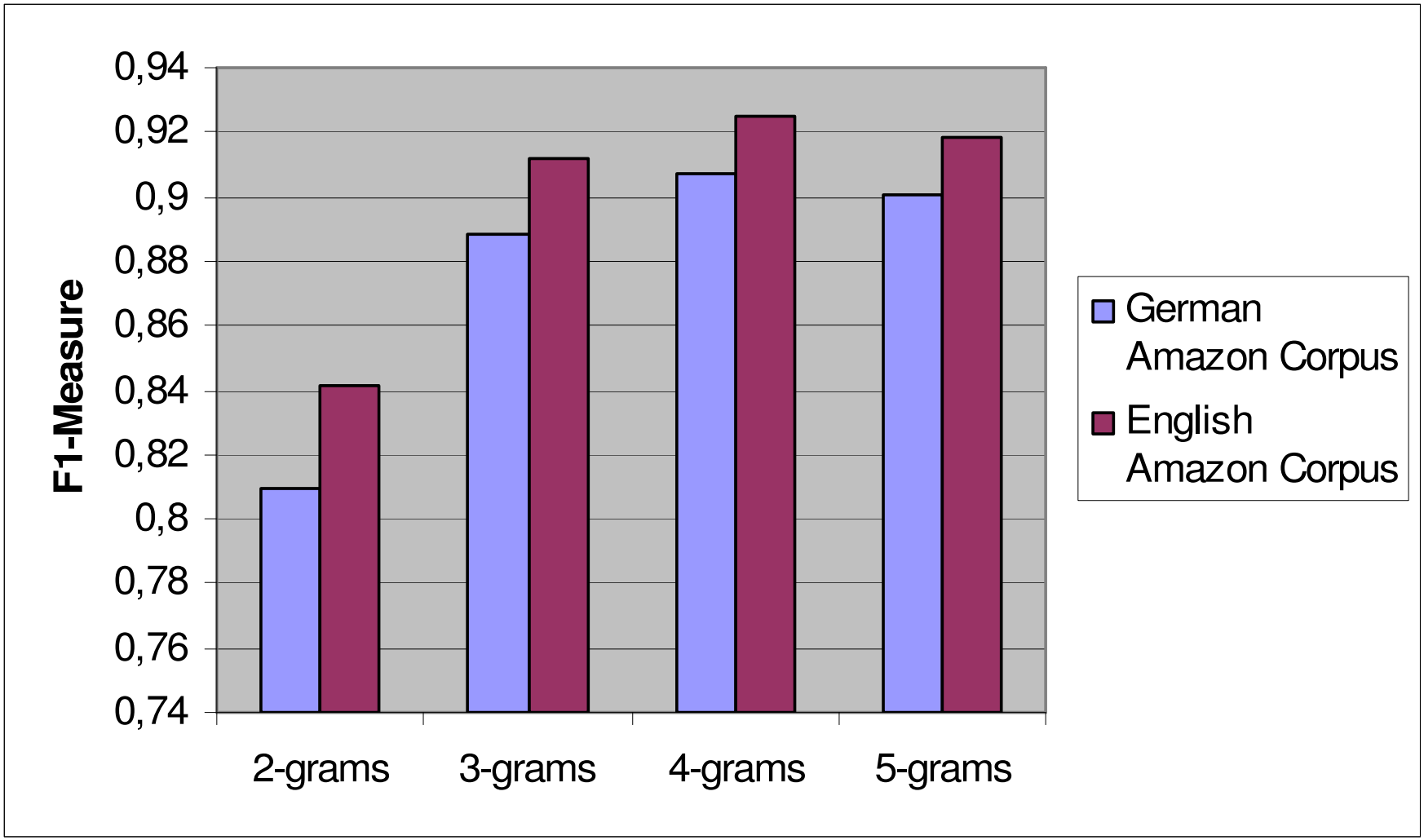
- Amazon corpora
  - 1000 docs per category
  - English (13MB) and German (10MB)
  - Acquired using the Amazon web service
- Other English corpora:
  - Randomhouse.com (3000 docs, 4 MB)
  - Powells.com (8000 docs, 7MB)
- Other German corpora:
  - Bol.de (1200 docs, 1 MB)
  - Buecher.de (2300 docs, 2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

Evaluation

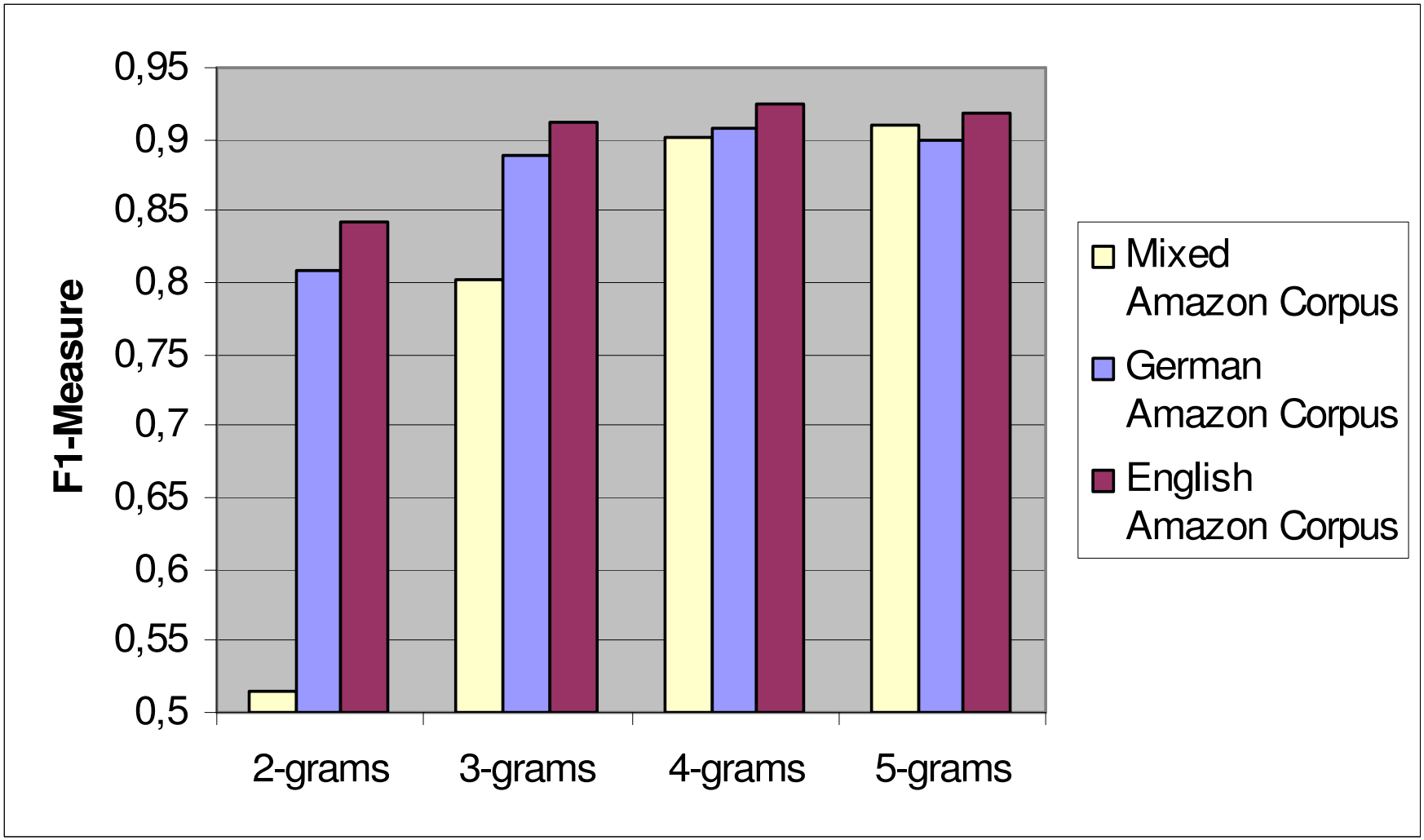
- Classification parameters
  - Smoothing technique
  - N-gram length
  - Mono-lingual vs multi-lingual models
- Setting:
  - Split corpus randomly into training docs (80%) and test docs (20%)
  - Performance as average F_1-Measure of 10 runs

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