CS 391L: Machine Learning
Text Categorization

Raymond J. Mooney

University of Texas at Austin

Text Categorization Applications

- Web pages
  - Recommending
  - Yahoo-like classification
- Newsgroup/Blog Messages
  - Recommending
  - spam filtering
  - Sentiment analysis for marketing
- News articles
  - Personalized newspaper
- Email messages
  - Routing
  - Prioritizing
  - Folderizing
  - spam filtering
  - Advertising on Gmail

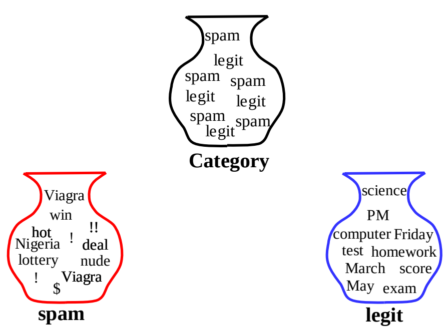
Text Categorization Methods

- Representations of text are very high dimensional (one feature for each word).
- Vectors are sparse since most words are rare.
  - Zipf's law and heavy-tailed distributions
- High-bias algorithms that prevent overfitting in high-dimensional space are best.
  - SVMs maximize margin to avoid over-fitting in hi-D
- For most text categorization tasks, there are many irrelevant and many relevant features.
- Methods that sum evidence from many or all features (e.g. naïve Bayes, KNN, neural-net, SVM) tend to work better than ones that try to isolate just a few relevant features (decision-tree or rule induction).

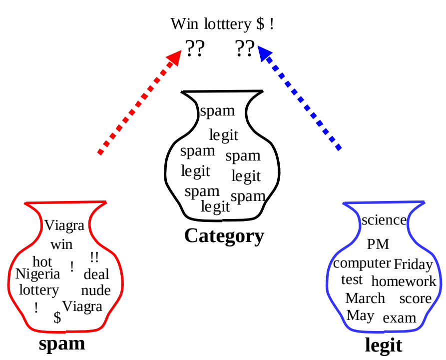
Naïve Bayes for Text

- Modeled as generating a bag of words for a document in a given category by repeatedly sampling with replacement from a vocabulary $V = \{w_1, w_2,\ldots w_m\}$ based on the probabilities $P(w_j \mid c_i)$.
- Smooth probability estimates with Laplace *m*-estimates assuming a uniform distribution over all words ($p = 1/|V|$) and $m = |V|$
  - Equivalent to a virtual sample of seeing each word in each category exactly once.

Naïve Bayes Generative Model for Text



Naïve Bayes Classification



Text Naïve Bayes Algorithm (Train)

Let V be the vocabulary of all words in the documents in D
For each category $c_i \in C$
  Let D_i be the subset of documents in D in category c_i
  $P(c_i) = |D_i| / |D|$
  Let T_i be the concatenation of all the documents in D_i
  Let n_i be the total number of word occurrences in T_i
  For each word $w_j \in V$
    Let n_{ij} be the number of occurrences of w_j in T_i
    Let $P(w_j \mid c_i) = (n_{ij} + 1) / (n_i + |V|)$

7

Text Naïve Bayes Algorithm (Test)

Given a test document X
Let n be the number of word occurrences in X
Return the category:

$$\operatorname*{argmax}_{c_i \in C} P(c_i) \prod_{i=1}^{n} P(a_i \mid c_i)$$

where a_i is the word occurring the ith position in X

8

Underflow Prevention

- Multiplying lots of probabilities, which are between 0 and 1 by definition, can result in floating-point underflow.
- Since $\log(xy) = \log(x) + \log(y)$, it is better to perform all computations by summing logs of probabilities rather than multiplying probabilities.
- Class with highest final un-normalized log probability score is still the most probable.

9

Naïve Bayes Posterior Probabilities

- Classification results of naïve Bayes (the class with maximum posterior probability) are usually fairly accurate.
- However, due to the inadequacy of the conditional independence assumption, the actual posterior-probability numerical estimates are not.
  - Output probabilities are generally very close to 0 or 1.

10

Textual Similarity Metrics

- Measuring similarity of two texts is a well-studied problem.
- Standard metrics are based on a “bag of words” model of a document that ignores word order and syntactic structure.
- May involve removing common “stop words” and stemming to reduce words to their root form.
- Vector-space model from Information Retrieval (IR) is the standard approach.
- Other metrics (e.g. edit-distance) are also used.

11

The Vector-Space Model

- Assume t distinct terms remain after preprocessing; call them index terms or the vocabulary.
- These “orthogonal” terms form a vector space.
  Dimension = t = |vocabulary|
- Each term, i, in a document or query, j, is given a real-valued weight, w_{ij}.
- Both documents and queries are expressed as t-dimensional vectors:
  $d_j = (w_{1j}, w_{2j}, \ldots, w_{tj})$

12

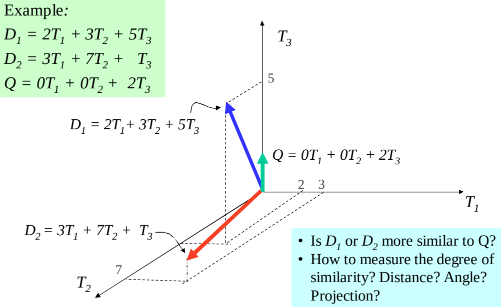
Graphic Representation

Example:

$D_1 = 2T_1 + 3T_2 + 5T_3$

$D_2 = 3T_1 + 7T_2 + T_3$

$Q = 0T_1 + 0T_2 + 2T_3$



- Is D_1 or D_2 more similar to Q?
- How to measure the degree of similarity? Distance? Angle? Projection?

Document Collection

- A collection of *n* documents can be represented in the vector space model by a term-document matrix.
- An entry in the matrix corresponds to the "weight" of a term in the document; zero means the term has no significance in the document or it simply doesn't exist in the document.

$$\begin{array}{c|cccc} & T_1 & T_2 & \dots & T_t \\ \hline D_1 & w_{11} & w_{21} & \dots & w_{t1} \\ D_2 & w_{12} & w_{22} & \dots & w_{t2} \\ : & : & : & & : \\ : & : & : & & : \\ D_n & w_{1n} & w_{2n} & \dots & w_{tn} \end{array}$$

Term Weights: Term Frequency

- More frequent terms in a document are more important, i.e. more indicative of the topic.

  f_{ij} = frequency of term *i* in document *j*

- May want to normalize *term frequency* (*tf*) by dividing by the frequency of the most common term in the document:

  $tf_{ij} = f_{ij} / max_i\{f_{ij}\}$

Term Weights: Inverse Document Frequency

- Terms that appear in many *different* documents are *less* indicative of overall topic.

  df_i = document frequency of term *i*

  = number of documents containing term *i*

  idf_i = inverse document frequency of term *i*,

  $= \log_2 (N/ df_i)$

  (N: total number of documents)

- An indication of a term's *discrimination* power.
- Log used to dampen the effect relative to *tf*.

TF-IDF Weighting

- A typical combined term importance indicator is *tf-idf weighting*:

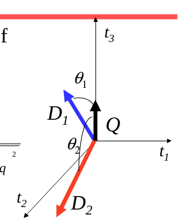
  $w_{ij} = tf_{ij}\, idf_i = tf_{ij} \log_2 (N/ df_i)$

- A term occurring frequently in the document but rarely in the rest of the collection is given high weight.
- Many other ways of determining term weights have been proposed.
- Experimentally, *tf-idf* has been found to work well.

Cosine Similarity Measure

- Cosine similarity measures the cosine of the angle between two vectors.
- Inner product normalized by the vector lengths.

$$\text{CosSim}(\boldsymbol{d_j}, \boldsymbol{q}) = \frac{\vec{d}_j \cdot \vec{q}}{|\vec{d}_j| \cdot |\vec{q}|} = \frac{\sum_{i=1}^{t} (w_{ij} \cdot w_{iq})}{\sqrt{\sum_{i=1}^{t} w_{ij}^2 \cdot \sum_{i=1}^{t} w_{iq}^2}}$$



$D_1 = 2T_1 + 3T_2 + 5T_3$ CosSim(D_1 , Q) = 10 / $\sqrt{(4+9+25)(0+0+4)}$ = 0.81

$D_2 = 3T_1 + 7T_2 + 1T_3$ CosSim(D_2 , Q) = 2 / $\sqrt{(9+49+1)(0+0+4)}$ = 0.13

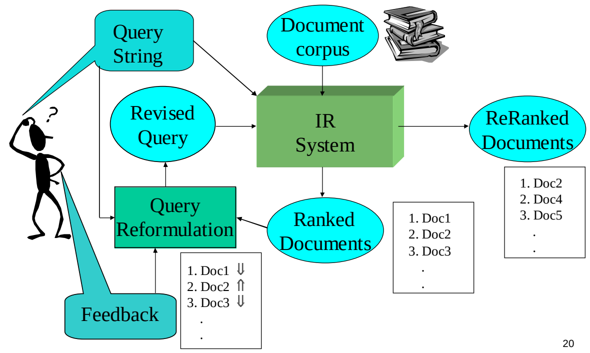
$Q = 0T_1 + 0T_2 + 2T_3$

D_1 is 6 times better than D_2 using cosine similarity but only 5 times better using inner product.

Relevance Feedback in IR

- After initial retrieval results are presented, allow the user to provide feedback on the relevance of one or more of the retrieved documents.
- Use this feedback information to reformulate the query.
- Produce new results based on reformulated query.
- Allows more interactive, multi-pass process.

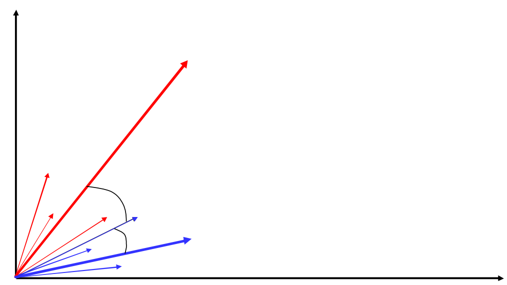
Relevance Feedback Architecture



Using Relevance Feedback (Rocchio)

- Relevance feedback methods can be adapted for text categorization.
- Use standard TF/IDF weighted vectors to represent text documents (normalized by maximum term frequency).
- For each category, compute a *prototype* vector by summing the vectors of the training documents in the category.
- Assign test documents to the category with the closest prototype vector based on cosine similarity.

Illustration of Rocchio Text Categorization



Rocchio Text Categorization Algorithm (Training)

Assume the set of categories is $\{c_1, c_2, \ldots c_n\}$
For i from 1 to n let $\mathbf{p}_i = \langle 0, 0, \ldots, 0 \rangle$ (*init. prototype vectors*)
For each training example $\langle x, c(x) \rangle \in D$
  Let $\mathbf{d}$ be the frequency normalized TF/IDF term vector for doc x
  Let $i = j$: ($c_j = c(x)$)
  (*sum all the document vectors in c_i to get $\mathbf{p}_i$*)
  Let $\mathbf{p}_i = \mathbf{p}_i + \mathbf{d}$

Rocchio Text Categorization Algorithm (Test)

Given test document x
Let $\mathbf{d}$ be the TF/IDF weighted term vector for x
Let $m = -2$ (*init. maximum cosSim*)
For i from 1 to n:
  (*compute similarity to prototype vector*)
  Let $s = \text{cosSim}(\mathbf{d}, \mathbf{p}_i)$
  if $s > m$
    let $m = s$
    let $r = c_i$ (*update most similar class prototype*)
Return class r

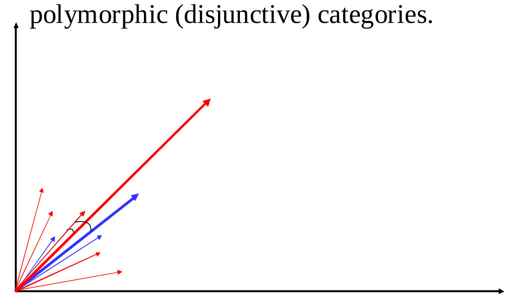
Rocchio Properties

- Does not guarantee a consistent hypothesis.
- Forms a simple generalization of the examples in each class (a *prototype*).
- Prototype vector does not need to be averaged or otherwise normalized for length since cosine similarity is insensitive to vector length.
- Classification is based on similarity to class prototypes.

25

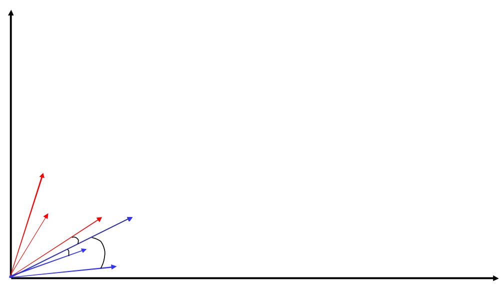
Rocchio Anomoly

- Prototype models have problems with polymorphic (disjunctive) categories.



26

Illustration of 3 Nearest Neighbor for Text



27

K Nearest Neighbor for Text

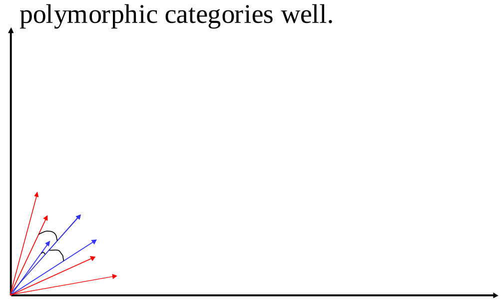
Training:
For each each training example <x, c(x)> $\in$ *D*
    Compute the corresponding TF-IDF vector, $\mathbf{d}_x$, for document *x*

Test instance *y*:
Compute TF-IDF vector **d** for document *y*
For each <x, c(x)> $\in$ *D*
    Let $s_x = \text{cosSim}(\mathbf{d}, \mathbf{d}_x)$
Sort examples, *x*, in *D* by decreasing value of s_x
Let *N* be the first *k* examples in D.   (*get most similar neighbors*)
Return the majority class of examples in *N*

28

3 Nearest Neighbor Comparison

- Nearest Neighbor tends to handle polymorphic categories well.



29

Inverted Index

- Linear search through training texts is not scalable.
- An index that points from words to documents that contain them allows more rapid retrieval of similar documents.
- Once stop-words are eliminated, the remaining words are rare, so an inverted index narrows attention to a relatively small number of documents that share meaningful vocabulary with the test document.

30

Conclusions

- Many important applications of classification to text.
- Requires an approach that works well with large, sparse features vectors, since typically each word is a feature and most words are rare.
  - Naïve Bayes
  - kNN with cosine similarity
  - SVMs

31