POLITECNICO DI MILANO

Information Retrieval & Text Mining

Data Mining and Text Mining (UIC 583 @ Politecnico di Milano)

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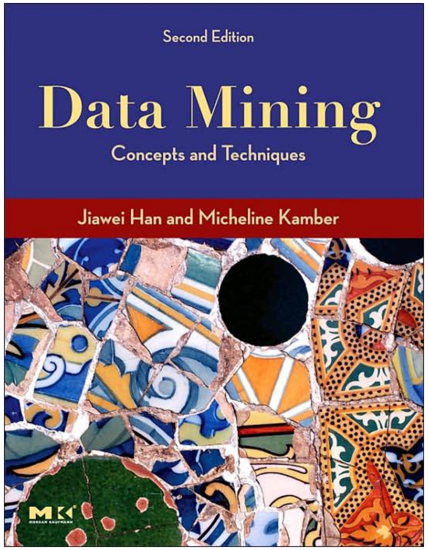
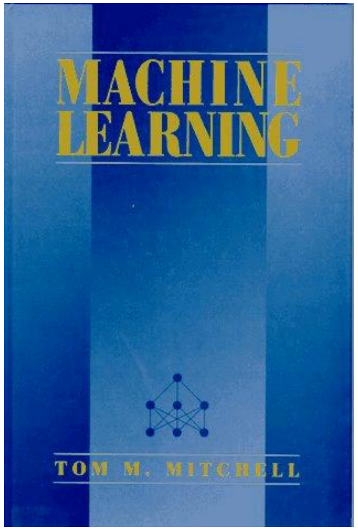
References

- Jiawei Han and Micheline Kamber, "Data Mining: Concepts and Techniques", The Morgan Kaufmann Series in Data Management Systems (Second Edition)
  - Chapter 10



- Tom M. Mitchell. “Machine Learning” McGraw Hill 1997
  - Chapter 6



Introduction

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	FALSE	No
Sunny	Hot	High	TRUE	No
Overcast	Hot	High	FALSE	Yes
Rainy	Mild	High	FALSE	Yes
Rainy	Cool	Normal	FALSE	Yes
Rainy	Cool	Normal	TRUE	No
Overcast	Cool	Normal	TRUE	Yes
Sunny	Mild	High	FALSE	No
Sunny	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	FALSE	Yes
Sunny	Mild	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes
Rainy	Mild	High	TRUE	No

Play?

Introduction

Sorry mom, n ... this year.
Flowers migh ... e Mother's Day gift of choice ... s recession fears and soa ... and gas prices are forcing A ... curb their spending.

?

Russia investor ...
Foreign investo ... a are finding it easy to turn a b ... the expulsion of U.S. diplomats ... singly bellicose rhetoric over Ge ...

?

Video games don't c ... rs, new book says.
SAN FRANCISCO (R ... laying video games does not turn children int ... d, blood-thirsty super-killers, according to ... k by a pair of Harvard researchers

?

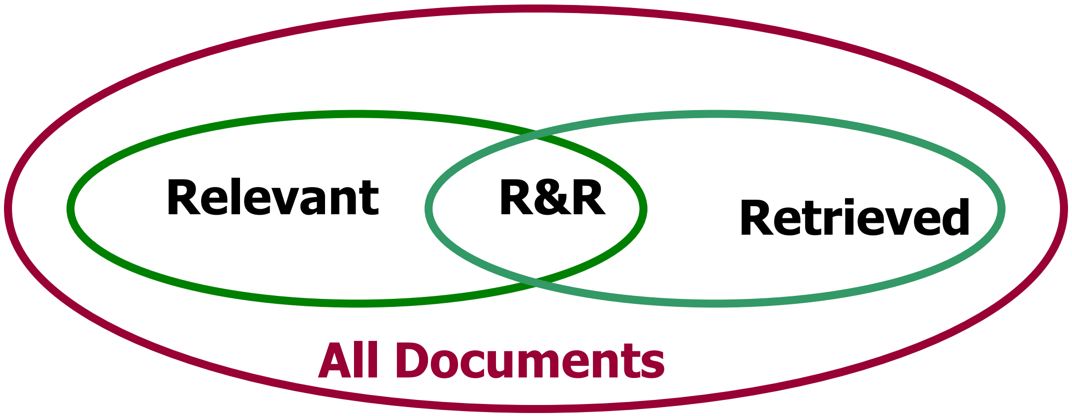
Interesting?

Information Retrieval

- Text databases (document databases)
  - Large collections of documents from various sources: news articles, research papers, books, digital libraries, E-mail messages, and Web pages, library database, etc.
  - Data stored is usually **semi-structured**
  - Traditional search techniques become inadequate for the increasingly vast amounts of text data
- Information retrieval (IR)
  - A field developed in parallel with database systems
  - Information is organized into (a large number of) documents

- IR deals with the problem of locating **relevant** documents with respect to the user **input** or **preference**
- IR Systems and DBMS deal with different problems
  - Typical DBMS issues are update, transaction management, complex objects
  - Typical IR issues are management of unstructured documents, approximate search using keywords and relevance
- Typical IR systems
  - Online library catalogs
  - Online document management systems
- Main IR approaches
  - **"pull"** for short-term information need
  - **"push"** for long-term information need (e.g., recommender systems)

Basic Measures for Text Retrieval



$$precision = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Retrieved\}|}$$

$$recall = \frac{|\{Relevant\} \cap \{Retrieved\}|}{|\{Relevant\}|}$$

$$F_{score} = \frac{recall \times precision}{(recall + precision)/2}$$

Text Retrieval Methods

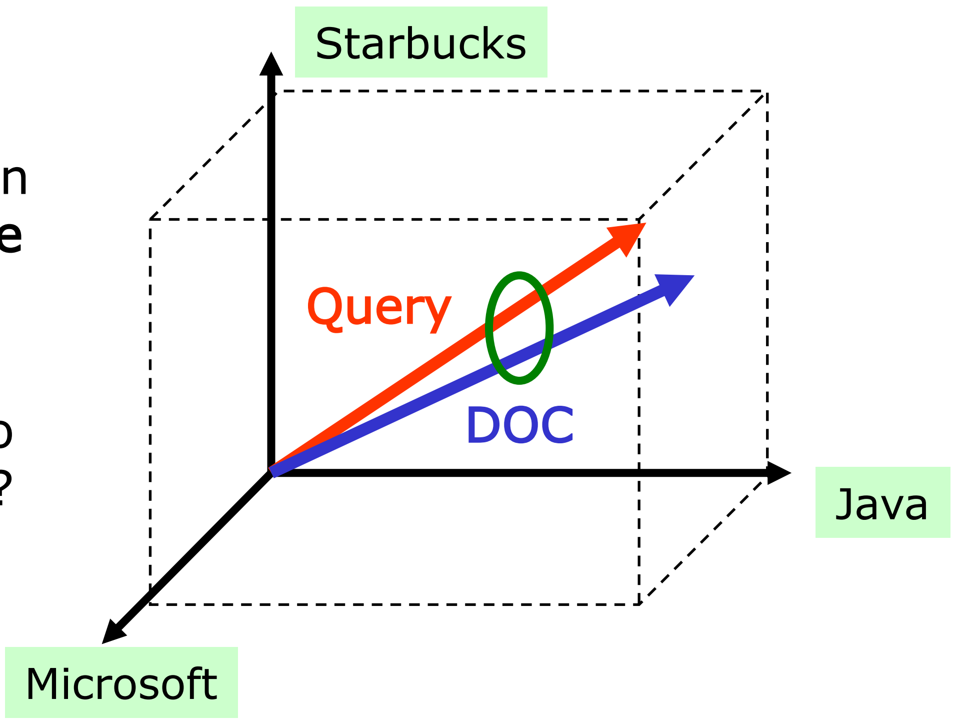
- Document Selection (keyword-based retrieval)
  - Query defines a set of requisites
  - Only the documents that satisfy the query are returned
  - A typical approach is the **Boolean Retrieval Model**
- Document Ranking (similarity-based retrieval)
  - Documents are ranked on the basis of their relevance with respect to the user query
  - For each document a "degree of relevance" to the query is measured
  - A typical approach is the **Vector Space Model**

Boolean Retrieval Model

- A query is composed of keywords linked by the three logical connectives: **not**, **and**, **or**
  - E.g.: “car and repair”, “plane or airplane”
- In the Boolean model each document is either relevant or non-relevant, depending it matches or not the query
- Limitations
  - Generally not suitable to satisfy information need
  - Useful only in very specific domain where users have a big expertise

Vector Space Model

- A document and a query are represented as **vectors** in high-dimensional space corresponding to all the **keywords**
- Relevance is measured with an appropriate **similarity measure** defined over the vector space
- Issues:
  - How to select keywords to capture “basic concepts” ?
  - How to assign weights to each term?
  - How to measure the similarity?



Keywords Selection

- Text is preprocessed through **tokenization**
- **Stop list** and **word stemming** are used to identify significant keywords
  - Stop List
    - e.g. “a”, “the”, “always”, “along”
  - Word stemming
    - e.g. “computer”, “computing”, “computerize” => “compute”

Keywords Weighting

- **Term Frequency** (TF)
  - Computed as the **frequency** of a term t in a document d (or as the **relative frequency**)
  - More frequent a term is → more relevant it is
- **Inverse Document Frequency** (IDF)

$$\mathrm{IDF}(t) = \log \frac{|D|}{1 + |D_t|}$$

  - D is the documents collection, D_t is the subset of D that contains t
  - Less frequent among documents → more discriminant
    - e.g., database in a collection of papers on DBMS
- Mixing TF and IDF

$$\text{TF-IDF}(d,t) = \mathrm{TF}(d,t) \times \mathrm{IDF}(t)$$

How to Measure Similarity?

- Given two documents (or a document and a query)

$$D_i = (w_{i1}, w_{i2}, \cdots, w_{iN}) \qquad D_j = (w_{j1}, w_{j2}, \cdots, w_{jN})$$

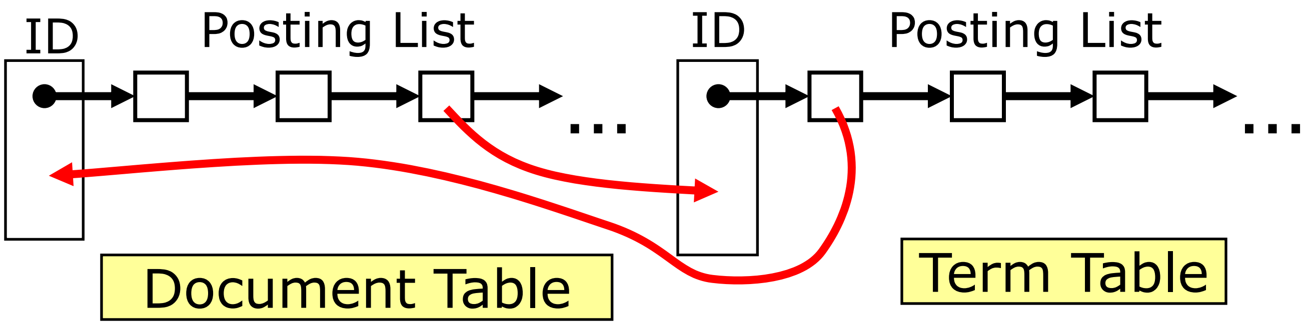
- Similarity definition
  - dot product

$$Sim(D_i, D_j) = \sum_{t=i}^{N} w_{it} * w_{jt}$$

  - normalized dot product (or cosine)

$$Sim(D_i, D_j) = \frac{\sum_{t=i}^{N} w_{it} * w_{jt}}{\sqrt{\sum_{t=1}^{N} (w_{it})^2 * \sum_{t=1}^{N} (w_{jt})^2}}$$

- Inverted index
  - Mantains 2 tables:



  - Implemented with hash tables or B+ trees
    - Find all docs associated to one or to a set of terms
    - Find all terms associated to a doc
- Signature file
  - Signature bitstring for each document
  - Each bit represents one or terms (1 if present 0 otherwise)
  - Signatures are used to retrieve an initial match of the query

Dimensionality Reduction

- Approaches presented so far involves high dimensional space (huge number of keywords)
  - Computationally expensive
  - Difficult to deal with **synonymy** and **polysemy** problems
    - "vehicle" is similar to "car"
    - "mining" has different meanings in different contexts
- Dimensionality reduction techniques
  - Latent Semantic Indexing (LSI)
  - Locality Preserving Indexing (LPI)
  - Probabilistic Semantic Indexing (PLSI)

Latent Semantic Indexing (LSI)

- Let x_i be vectors representing documents and X (term frequency matrix) the all set of documents:

$$\vec{x}_1, \cdots, \vec{x}_n \in R^m \qquad X = [\vec{x_1}, \vec{x_2}, \cdots, \vec{x_n}]$$

- Let use the **singular value decomposition** (SVD) to reduce the size of frequency table:

$$X = U \Sigma V^T$$

- Approximate X with X_k that is obtained from the first K vectors of U
- It can be shown that such transformation minimizes the error for the reconstruction of X

Locality preserving Indexing (LPI)

- Goal is preserving the **locality** information
  - Two documents close in the original space should be close also in the transformed space
- More formally

$$\vec{x}_1, \cdots, \vec{x}_n \in R^m \qquad S \in R^{n \times m}$$

Set of Documents   Similarity Matrix

$$\vec{a}^* = \operatorname{argmin}_{\vec{a}} \sum_{i,,j} (\vec{a}^T \vec{x}_i - \vec{a}^T \vec{x}_j)^2 \, S_{ij} \quad \Rightarrow \quad X' = \vec{a^*} \vec{a^*}^T X$$

Optimal transformation

- Similarity matrix:

$$S_{ij} = \begin{cases} \frac{\vec{x}_i^T \vec{x}_j}{||\vec{x}_i^T \vec{x}_j||}, & \text{if } \vec{x}_i \text{ is in the } p \text{ nearest neighbors of } \vec{x}_j \text{ or viceversa} \\ 0, & \text{otherwise} \end{cases}$$

Probabilistic Latent Semantic Indexing (PLSI)

- Similar to LSI but does not apply SVD to identify the k most relevant features
- Assumption: all the documents have k common **"themes"**
- Word distribution in documents can be modeled as

$$p_{d_i}(w) = \sum_{j=1}^{k} [\pi_{d_i,j} \, p(w|\theta_j)]$$

Theme distributions

Mixing weights

- Mixing weights are identified with Expectation-Maximization (EM) algorithms and define new representation of the documents

Text Mining

Overview

- Text Mining aims to **extract useful knowledge** from **text documents**
- Approaches
  - **Keyword-based**
    - Relies on IR techniques
  - **Tagging**
    - Manual tagging
    - Automatic categorization
  - **Information-extraction**
    - Natural Language Processing (NLP)
- Tasks
  - Keyword-Based Association Analysis
  - Document Classification

Why NLP?

Gov. Schwarzenegger helps inaugurate pricey new bridge approach

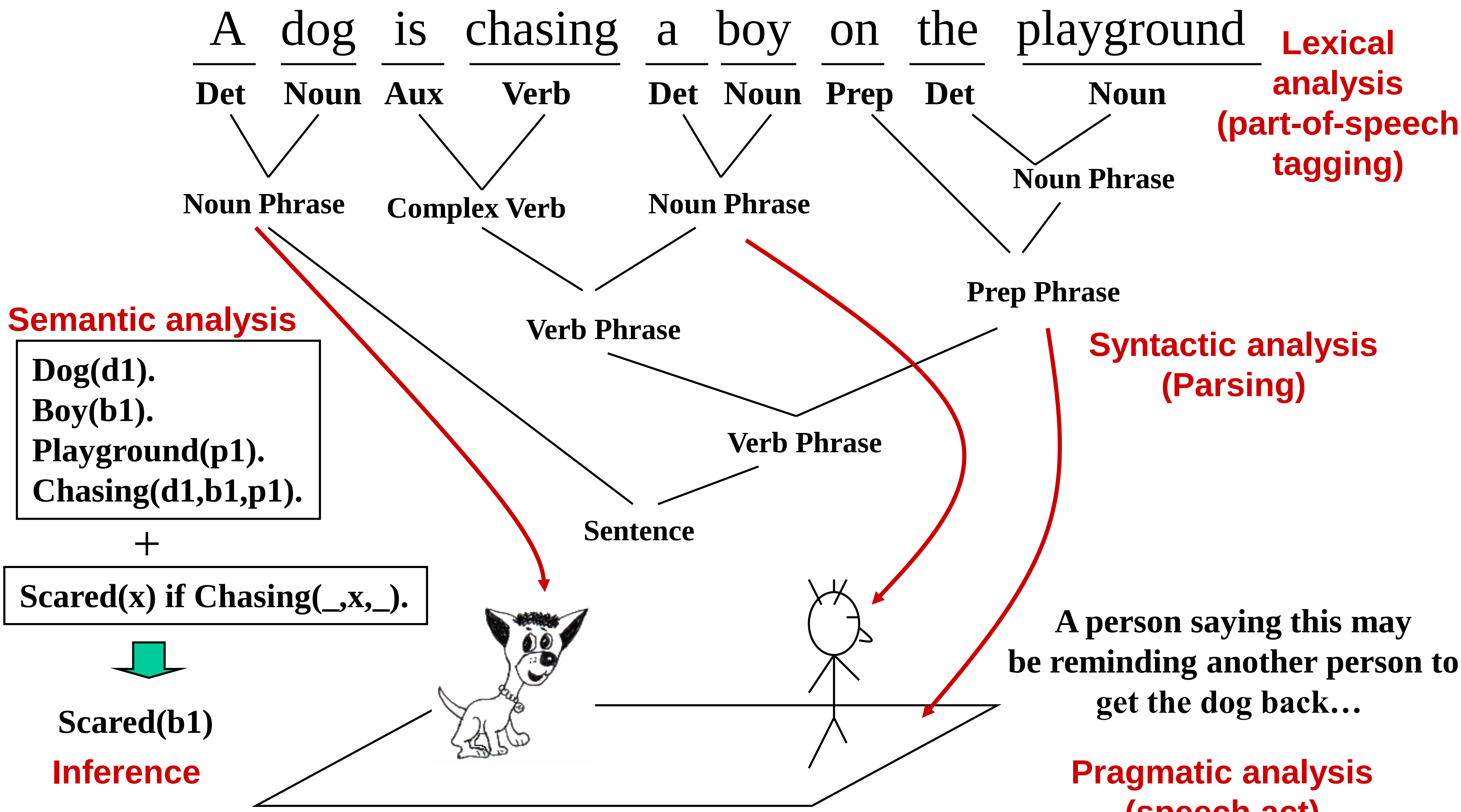
The Associated Press

Article Launched: 04/11/2008 01:40:31 PM PDT

SAN FRANCISCO—It briefly looked like a scene out of a "Terminator" movie, with Governor Arnold Schwarzenegger standing in the middle of San Francisco wielding a blow-torch in his hands. Actually, the governor was just helping to inaugurate a new approach to the San Francisco-Oakland Bay Bridge.
Caltrans thinks the new approach will make it faster for commuters to get on the bridge from the San Francisco side.
The new section of the highway is scheduled to open tomorrow morning and cost 429 million dollars to construct.

- Entertainment or Politics?
- Bag-of-tokens approaches have severe limitations

- Schwarzenegger
- Bridge
- Caltrans
- Governor
- Scene
- Terminator



(Taken from ChengXiang Zhai, CS 397cxz – Fall 2003)

Obstacles to NLP

- Ambiguity

A man saw a boy <u>with a telescope</u>.

- Computational Intensity

Imposes a <u>context horizon</u>.

- **Text Mining NLP Approach**
  - Locate promising fragments using **fast IR methods** (bag-of-tokens)
  - Only apply **slow NLP techniques** to promising fragments

Keyword-Based Association Analysis

- Aims to discover **sets of keywords** that **occur frequently** together in the documents
- Relies on the usual techniques for mining **associative and correlation rules**
- Each document is considered as a transaction of type

  {document id, {set of keywords}}
- Association mining may discover **set of consecutive or closely-located keywords**, called **terms** or **phrase**
  - **Compound** (e.g., {Stanford,University})
  - **Noncompound** (e.g., {dollars,shares,exchange})
- Once discovered the most frequent terms, **term-level mining** can be applied most effectively (w.r.t. single word level)

Document classification

- Solve the problem of **labeling automatically text documents** on the basis of
  - Topic
  - Style
  - Purpose
- Usual classification techniques can be used to learn from a training set of **manually labeled documents**
- Which features? **Keywords** can be thousands…
- Major approaches
  - Similarity-based
  - Dimensionality reduction
  - Naïve Bayes text classifiers

Similarity-based Text Classifiers

- Exploits **IR** and **k-nearest-neighbor** classifier
  - For a new document to classify, the **k** most similar documents in the training set are retrieved
  - Document is classified on the basis of the class distribution among the k documents retrieved
    - Majority vote
    - Weighted vote
  - Tuning **k** is very important to achieve a good performance
- Limitations
  - **Space overhead** to store all the documents in training set
  - **Time overhead** to retrieve the similar documents

Dimensionality Reduction for Text Classification

- As in the **Vector Space Model** used for IR, the goal is to reduce the number of features to represents text
- Usual dimensionality reduction approaches in IR are based on the **distribution of keywords** among the **whole** documents database
- In text classification it is important to consider also the **correlation between keywords and classes**
  - Rare keywords have an high TF-IDF but might be uniformly distributed among classes
  - LSI and LPI do not take into account classes distributions
- Usual classification techniques can be then applied on reduced features space:
  - SVM
  - Bayesian classifiers

- Definitions
  - Category Hypothesis Space: $H = \{C_1, \ldots, C_n\}$
  - Document to Classify: D
  - Probabilistic model:

$$P(C_i \mid D) = \frac{P(D \mid C_i) P(C_i)}{P(D)}$$

- We chose the class C* such that

$$C^* = \arg\max_C P(C|D) = \arg\max_C P(D|C)P(C)$$

- Issues
  - Which features?
  - How to compute the probabilities?

Naïve Bayes for Text (2)

- Features can be simply defined as the **words in the document**
- Let a_i be a keyword in the doc, and w_j a word in the vocabulary, we get:

$$P(D|C) = P(a_1 = w_{j_1}, a_2 = w_{j_2}, \cdots, a_n = w_{j_n}|C)$$

Example

H={like,dislike}

D= “Our approach to representing arbitrary text documents is disturbingly simple”

$$P(D|Like) = P(a_1 = \text{our}, a_2 = \text{approach}, \cdots, a_1 0 = \text{simple}|Like)$$

Naïve Bayes for Text (2)

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- Let a_i be a keyword in the doc, and w_j a word in the vocabulary, we get:

$$P(D|C) = P(a_1 = w_{j_1}, a_2 = w_{j_2}, \cdots, a_n = w_{j_n}|C)$$

- Assumptions
  - Keywords distributions are inter-independent
  - Keywords distributions are order-independent

$$P(D|C) = \prod_{i=1}^{n} P(w_{j_i}|C)$$

$$P(D|Like) = P(\text{our}|Like)P(\text{approach}|Like) \cdots P(\text{simple}|Like)$$

Naïve Bayes for Text (3)

- How to compute probabilities?
  - Simply counting the occurrences may lead to wrong results when probabilities are small
- M-estimate approach adapted for text:

$$P(w_k|C) = \frac{N_{c,k} + 1}{N_c + |\text{Vocabulary}|}$$

  - N_c is the whole number of word positions in documents of class C
  - $N_{c,k}$ is the number of occurrences of w_k in documents of class C
  - |Vocabulary| is the number of distinct words in training set
  - Uniform priors are assumed

Naïve Bayes for Text (4)

- Final classification is performed as

$$C^* = \arg\max_C P(C) \prod_{i=1}^{n} P(w_{j_i}|C)$$

- Despite its simplicity Naïve Bayes classifiers works very well in practice
- Applications
  - Newsgroup post classification
  - NewsWeeder (news recommender)