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CS47300: Web Information Search and Management

Text Categorization

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Material adapted from course created by Dr. Luo Si, now leading Alibaba research group

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Text Categorization

- Introduction to the task of text categorization
  - Manual vs. automatic text categorization
- Text categorization applications
- Evaluation of text categorization
- K nearest neighbor text categorization method

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Text Categorization

- Tasks
  - Assign predefined categories to text documents / objects
- Motivation
  - Provide an organizational view of the data
- Large cost of manual text categorization
  - Millions of dollars spent for manual categorization in companies, governments, public libraries, hospitals
  - Manual categorization is almost impossible for some large scale application (Classification or Web pages)

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Text Categorization

- Automatic text categorization
  - Learn algorithm to automatically assign predefined categories to text documents / objects
  - automatic or semi-automatic
- Procedures
  - Training: Given a set of categories and labeled document examples; learn a method to map a document to correct category (categories)
  - Testing: Predict the category (categories) of a new document
- Automatic or semi-automatic categorization can significantly reduce manual effort

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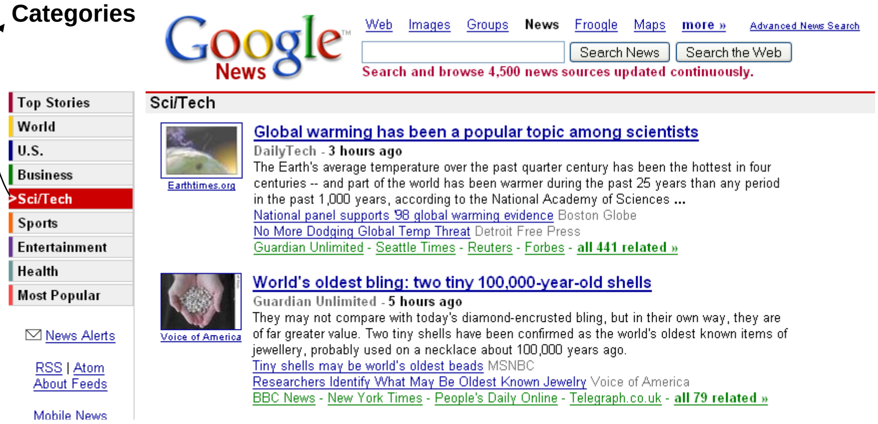
Text Categorization: Examples

News Categories



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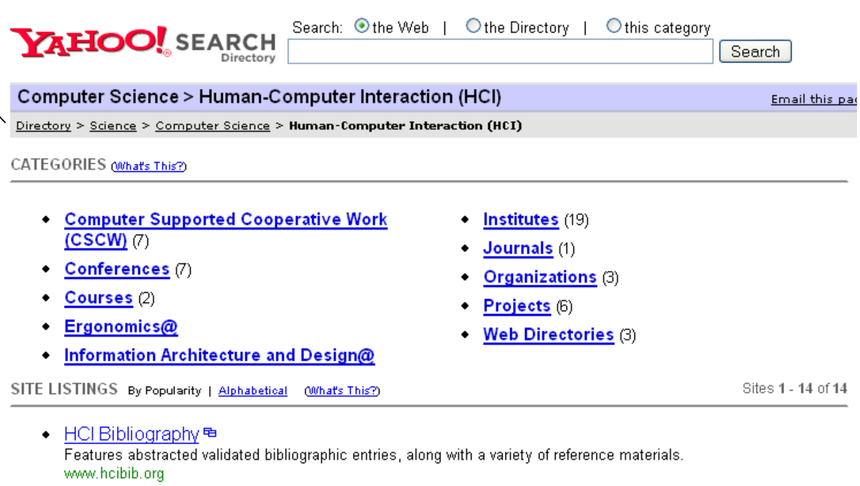
Text Categorization: Examples

Categories



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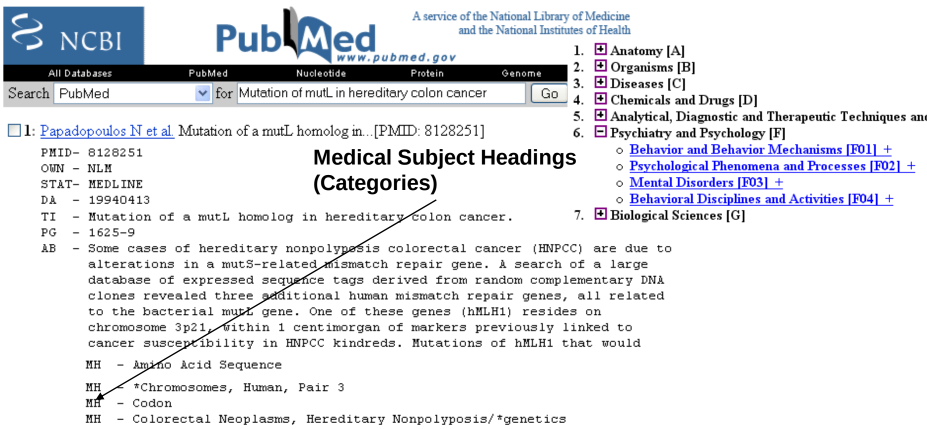
Text Categorization: Examples



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Example: US Census Business Survey (1990)

- Included 22 million responses
- Needed to be classified into industry categories (200+) and occupation categories (500+)
- Estimated $15 million if done by hand
- Two alternative automatic text categorization methods evaluated
  - Knowledge-Engineering (Expert System)
  - Machine Learning (k-nearest neighbor method)

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Example: US Census Business Survey

- Knowledge-Engineering Approach
  - Expert System (Designed by domain expert)
  - Hand-Coded rule
    (e.g., “Professor” and “Lecturer” ➔ “Education”)
  - Development cost: 2 experts, 8 years (192 Person-months)
  - Accuracy = 47%
- Machine Learning Approach
  - k-Nearest Neighbor (KNN) classification
    - “You are like people like you”, details later
  - Fully automatic
  - Development cost: 4 Person-months
  - Accuracy = 60%

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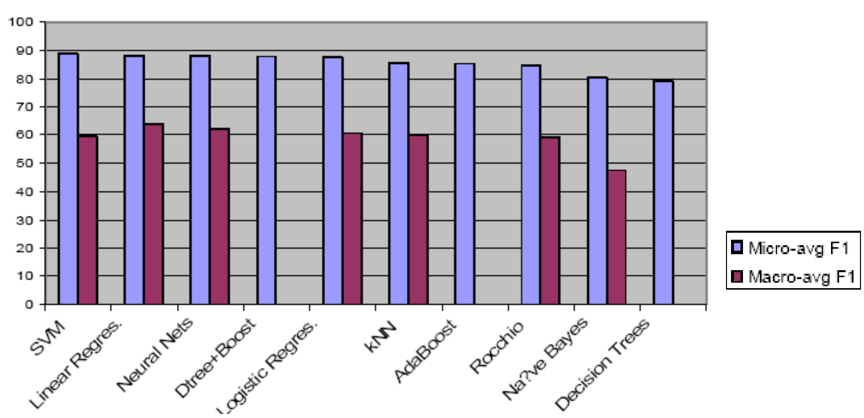
Many Applications!

- Web page classification (Yahoo-like category taxonomies)
- News article classification (more formal than most Web pages)
- Automatic email sorting (spam detection; into different folders)
- Word sense disambiguation (Java programming vs. Java in Indonesia)
- Gene function classification (find the functions of a gene from the articles talking about the gene)
- What is your favorite application?...

Techniques Explored in Text Categorization

- Rule-based Expert system (Hayes, 1990)
- Nearest Neighbor methods (Creecy'92; Yang'94)
- Decision symbolic rule induction (Apte'94)
- Naïve Bayes (Language Model) (Lewis'94; McCallum'98)
- Regression method (Furh'92; Yang'92)
- Support Vector Machines (Joachims'98)
- Boosting or Bagging (Schapier'98)
- Neural networks (Wiener'95)
- ……

Text Categorization: Evaluation



Performance of different algorithms on Reuters-21578 corpus: 90 categories, 7769 Training docs, 3019 test docs, (Yang, JIR 1999)

Text Categorization: Evaluation

Contingency Table Per Category (for all docs)

	Truth: True	Truth: False	
Predicted Positive	a	b	a+b
Predicted Negative	c	d	c+d
	a+c	b+d	n=a+b+c+d

a: number of truly positive docs b: number of false-positive docs

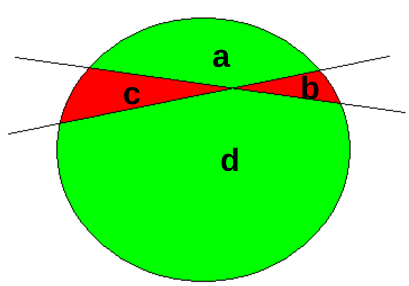
c: number of false negative docs d: number of truly-negative docs

n: total number of test documents

Text Categorization: Evaluation

Contingency Table Per Category (for all docs)

n: total number of docs



Sensitivity: a/(a+c) truly-positive rate, the larger the better

Specificity: d/(b+d) truly-negative rate, the larger the better

Depends on decision threshold, trade off between the values

Text Categorization: Evaluation

- Micro F1-Measure
  - Calculate a single contingency table for all categories and calculate F1 measure
  - Treat each prediction with equal weight; better for algorithms that work well on large categories
- Macro F1-Measure
  - Calculate a single contingency table for every category; calculate F1 measure separately and average the values
  - Treat each category with equal weight; better for algorithms that work well on many small categories

K-Nearest Neighbor Classifier

- Also called “Instance-based learning” or “lazy learning”
  - low/no cost in “training”, high cost in online prediction
- Commonly used in pattern recognition (5 decades)
- Theoretical error bound analyzed by Duda & Hart (1957)
- Applied to text categorization in 1990’s
- Among top-performing text categorization methods

K-Nearest Neighbor Classifier

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From all training examples:

- Find *k* examples that are most similar to the new document
  - "neighbor" documents
- Assign the category that is most common in these neighbor documents
  - neighbors "vote" for the category
- Can also consider the distance of a neighbor
  - a closer neighbor has more weight/influence

K-Nearest Neighbor Classifier

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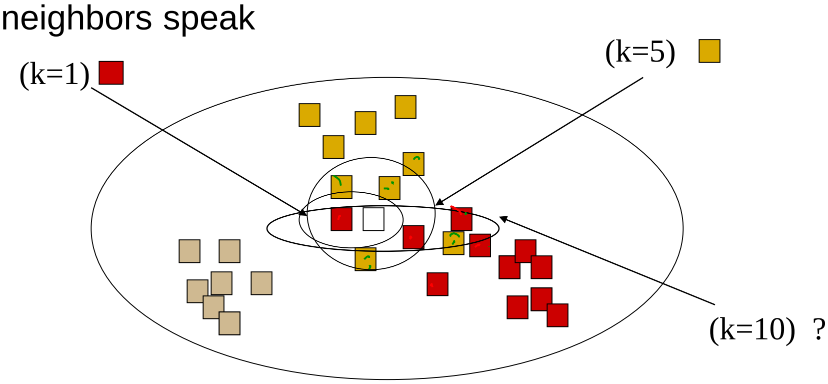
- Idea: find your language by what language your neighbors speak



- Use K nearest neighbors to vote

1-NN:Red; 5-NN:Brown; 10-NN:?; Weighted 10-NN:Brown

K Nearest Neighbor: Technical Elements

- Document representation
- Document distance measure: closer documents should have similar labels; neighbors speak the same language
- Number of nearest neighbors (value of K)
- Decision threshold

K Nearest Neighbor: Framework

Training data $D = \{(x_i, y_i)\}, \quad x_i \in R^M, \text{docs}, \quad y_i \in \{0,1\}$

Test data $x \in R^M$ The neighborhood is $D_k \in D$

Scoring Function $\hat{y}(x) = \frac{1}{k} \sum_{x_i \in D_k(x)} \text{sim}(x, x_i) y_i$

Classification: $\begin{cases} 1 & \text{if } \hat{y}(x) - t > 0 \\ 0 & \text{otherwise} \end{cases}$

Document Representation: X_i uses tf.idf weighting for each dimension

Choices of Similarity Functions

Euclidean distance $d(\vec{x}_1, \vec{x}_2) = \sqrt{\sum_v (x_{1v} - x_{2v})^2}$

Kullback Leibler distance $d(\vec{x}_1, \vec{x}_2) = \sum_v x_{1v} \log \frac{x_{1v}}{x_{2v}}$

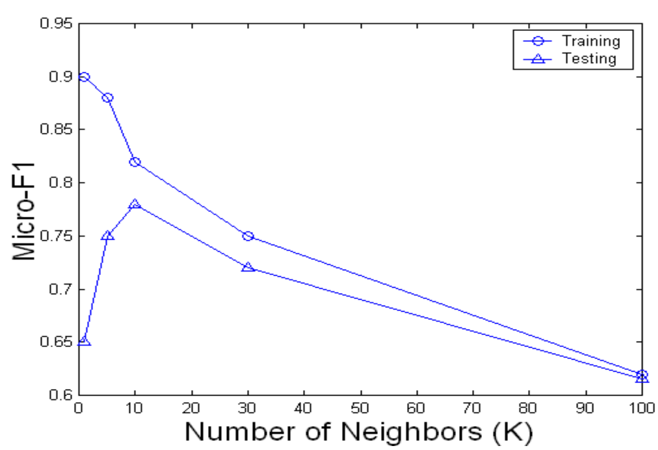
Dot product $\vec{x}_1 * \vec{x}_2 = \sum_v x_{1v} * x_{2v}$

Cosine Similarity $\cos(\vec{x}_1, \vec{x}_2) = \frac{\sum_v x_{1v} * x_{2v}}{\sqrt{\sum_v x_{1v}^2}\sqrt{\sum_v x_{2v}^2}}$

Kernel functions $k(\vec{x}_1, \vec{x}_2) = e^{-d(\vec{x}_1, \vec{x}_2)/2\sigma^2}$ (Gaussian Kernel)

Automatic learning of the metrics

Choices of Number of Neighbors (K)



Trade off between small number of neighbors and large number of neighbors

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Choices of Number of Neighbors (K)

- Find desired number of neighbors by cross validation
  - Choose a subset of available data as training data, the rest as validation data
  - Find the desired number of neighbors on the validation data
  - The procedure can be repeated for different splits; find the consistent good number for the splits

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Characteristics of KNN

Pros

- Simple and intuitive, based on local-continuity assumption
- Widely used and provide strong baseline in TC Evaluation
- No training needed, low training cost
- Easy to implement; can use standard IR techniques (e.g., tf.idf)

Cons

- Heuristic approach, no explicit objective function
- Difficult to determine the number of neighbors
- High online cost in testing; find nearest neighbors has high time complexity

Problem: Weighting of Terms

- K-NN treats all terms equally
  - Frequent but unimportant terms may dominate
- Which terms are more important?
  - TF.IDF?
  - …
- Solution – machine learning
  - We have training data

