Learning Text Classification Rules

(Intro)

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Learning Text Classification Rules

• Examples
  – In-class exercise
• Classification methods
  – Supervised machine learning
• Evaluating text classifiers
• Other issues

Text Classification Example

E.D. And F. MAN TO BUY INTO HONG KONG FIRM
The U.K. Based commodity house E.D. And F. Man Ltd and Singapore’s Yeo Hiap Seng Ltd jointly announced that Man will buy a substantial stake in Yeo’s 71.1 pct held unit, Yeo Hiap Seng Enterprises Ltd. Man will develop the locally listed soft drinks manufacturer into a securities and commodities brokerage arm and will rename the firm Man Pacific (Holdings) Ltd.

About a corporate acquisition?

Yes
No

Text Classification

• Assign pieces of text to predefined categories based on content
• Types of text
  – Documents (typical)
  – Paragraphs
  – Sentences
  – Websites
• Different types of categories
  – By topic
  – By function
  – By author
  – By style
Text Classification Examples

• Assigning labels to documents or web-pages
• Labels are most often topics such as Yahoo-categories
  – "finance," "sports," "news>world>asia>business"
• Labels may be genres
  – "editorials" "movie-reviews" "news"
• Labels may be opinion on a person/product
  – "like", "hate", "neutral"
• Labels may be domain-specific
  – "interesting-to-me" : "not-interesting-to-me"
  – "contains adult language" : "doesn’t"
  – language identification: English, French, Chinese, ...
  – search vertical: about Linux versus not
  – "link spam" : "not link spam"

Examples of Text Categorization?

Text categorization projects from previous years

• Digital government
  – Predict U.S. Supreme Court decisions based on court transcripts and amicus briefs
• Movie reviews: + or -?
  – Built upon existing techniques by also including information (features) about the director and actors.
• Automatic categorization of iphone apps
• Build text categorization system
  – Implement and evaluate a number of approaches
  – Extensive testing of many parameters of the system
  – Employed large, standard dataset (Reuters)

In-class Exercise

• Reuters-21578 – the most famous text classification evaluation set
  – 90 topics
  – ~13,000 documents
  – Still widely used by lazy people (but now it’s too small for realistic experiments – you should use Reuters RCV1)
KENYAN ECONOMY FACES PROBLEMS, PRESIDENT SAYS

The Kenyan economy is heading for difficult times after a boom last year, and the country must tighten its belt to prevent the balance of payments swinging too far into deficit, President Daniel Arap Moi said.

In a speech at the state opening of parliament, Moi said high coffee prices and cheap oil in 1986 led to economic growth of five pct, compared with 4.1 pct in 1985. The same factors produced a two billion shilling balance of payments surplus and inflation fell to 5.6 pt from 10.7 pt in 1985, he added.

"But both these factors are no longer in our favour ... As a result, we cannot expect an increase in foreign exchange reserves during the year," he said.

...

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- **Examples**
  - In-class exercise

- **Classification methods**
  - Supervised machine learning

- **Evaluating text classifiers**

- **Other issues**
Classification Methods (1)

• Manual classification
  – Used by the original Yahoo! Directory
  – Looksmart, about.com, PubMed
  – Very accurate when job is done by experts
  – Consistent when the problem size and team is small
  – Difficult and expensive to scale
    • Means we need automatic classification methods for big problems

Classification Methods (2)

• Automatic document classification
  – Hand-coded rule-based systems
    • One technique used by CS dept’s spam filter, Reuters, CIA, etc.
    • It’s what Google Alerts is doing
      – Widely deployed in government and enterprise
    • Companies provide “IDE” for writing such rules
    • E.g., assign category if document contains a given (boolean) combination of words
    • Standing queries: Commercial systems have complex query languages (everything in IR query languages + score accumulators)
    • Accuracy is often very high if a rule has been carefully refined over time by a subject expert
    • Building and maintaining these rules is expensive

A Verity topic
A complex classification rule

Note:
  – maintenance issues (author, etc.)
  – hand-weighting of terms

Why learn text classifiers
Classifying documents by hand is costly and does not scale well
  – e.g. browse all WWW pages to filter out those about job announcements

People are not really all that good at constructing text classification rules
  – It is hard to write good queries

Sometimes there is no expert available
  – e.g. rules for routing email

Often training data is cheap and plenty
  – e.g. clickthrough from users

Classification Methods (3)

• Supervised inductive learning of a document-label assignment function
  – Many systems partly rely on machine learning (Autonomy, Microsoft, Yahoo!, …)
    • k-Nearest Neighbors (simple, powerful)
    • Naive Bayes (simple, common method)
    • Support-vector machines (new, more powerful)
    • … plus many other methods
  • No free lunch: requires hand-classified training data
  • But data can be built up (and refined) by amateurs

• Many commercial systems use a mixture of methods
Project Info: Text Categorization

- Select the task
- Map the task onto the text categorization definition
  - How many classes/categories?
- ML approach
  - Find (or create --- ugh!) the appropriate data set / test collection
  - Text representation
  - Choose appropriate learning algorithm
  - Determine the evaluation/performance measures
  - Determine reasonable baselines to compare to

Categorization/Classification

- **Given:**
  - A description of an instance, \( d \in X \)
    - \( X \) is the instance language or instance space.
    - Issue: how to represent text documents.
    - Usually some type of high-dimensional space
    - A fixed set of classes:
      \( C = \{ c_1, c_2, \ldots, c_J \} \)
- **Determine:**
  - The category of \( d \): \( h(d) \in C \), where \( h(d) \) is a classification function whose domain is \( X \) and whose range is \( C \).
    - We want to know how to build classification functions ("classifiers").
Representing Text for ML Approaches

- Attribute-value representation

  - Each distinct word $w_i$ corresponds to a feature (attribute)
  - Value is $TF(w_i, x)$
    - # of times word $w_i$ occurs in document $x$
  - Scale the values of the feature vector with their inverse document frequency $IDF(w_i)$
    - $DF(w_i)$ is the # of documents $w_i$ appears in
    - $IDF(w_i) = \log (n / DF(w_i))$
    - $n$ is the total # of documents
  - Each document vector is normalized to unit length

Learning Setting

- **Process:**
  - Generator: Generate documents/snippets according to distribution $P(X)$.
  - Teacher: Assigns a value to each document based on $P(Y|X)$.

- **Training Examples**
  - $(x_1, y_1), ..., (x_n, y_n) \sim P(X, Y)$

- **Goal:**
  - Find a classification rule $h$ with low prediction error on new examples from distribution $P(X,Y)$

  \[ Err_P(h) = P(h(x) \neq y) = \int \Delta(h(x), y) P(x, y) dx dy \]

Test Collections

- **Reuters-21578**
  - Reuters newswire articles classified by topic
  - 90 categories (multi-label)
  - 9603 training documents / 3299 test documents (ModApte)
  - ~27,000 features

- **WebKB Collection**
  - WWW pages classified by function (e.g. personal HP, project HP)
  - 4 categories (multi-class)
  - 4183 training documents / 226 test documents
  - ~38,000 features

- **Ohsumed MeSH**
  - Medical abstracts classified by subject heading
  - 20 categories from “disease” subtree (multi-label)
  - 10,000 training documents / 10,000 test documents
  - ~38,000 features
Assumptions of Naïve Bayes

- Words occur independently given the class according to one multinomial distribution per class
- Each document is in exactly one class
- Word probabilities do not depend on the document length

Pros and Cons for Naïve Bayes

**Pros:**
- Explicit theoretical foundation
- Relatively effective
- Very simple
- Fast in learning and classification

**Cons:**
- Multinomial model / independence assumption clearly wrong for text
- On some datasets it really fails badly

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- **Classification methods**
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- **Other issues**

ML no-no’s

- Train on dataset A, test on dataset A
- Estimating any parameters based on the test set
- Evaluating w.r.t. (or looking at) the test set repeatedly while developing your approach
- Evaluation methodology is key
Evaluating Categorization

- Evaluation must be done on test data that are independent of the training data (usually a disjoint set of instances).
  - Sometimes use cross-validation (averaging results over multiple training and test splits of the overall data)
- It’s easy to get good performance on a test set that was available to the learner during training (e.g., just memorize the test set).

Performance Measures

- Precision/Recall /F/Break-Even Point
  - Intersection of PR-curve with the identity line
- Accuracy
  - Adequate if one class per document
  - Otherwise F measure for each class
- Macro-averaging
  - First compute the measure, then compute average
  - Means average over tasks
- Micro-averaging
  - Compute the measure for each decision, then compute average
  - Means average over each individual classification decision

Go to Sebastiani results

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Multi-Class / Multi-Label

• Cannot learn multi-label rules directly
  – Most classifiers assume that each document is in exactly one class
  – Many classifiers can only learn binary classification rules

• Most common solution: Multi-Class
  – Learn one binary classifier for each label
  – Put example into the class with the highest probability (or some approximation thereof)

• Most common solution: Multi-Label
  – Learn one binary classifier for each label
  – Attach all labels, for which some classifier says positive

Feature Selection: Why?

• Text collections have a large number of features
  – 10,000 – 1,000,000 unique words … and more

• May make using a particular classifier feasible
  – Some classifiers can’t deal with 100,000 of features

• Reduces training time
  – Training time for some methods is quadratic or worse in the number of features

• Can improve generalization (performance)
  – Eliminates noise features
  – Avoids overfitting

Feature selection: How?

• Forward/backward selection

• Hypothesis testing statistics:
  – Are we confident that the value of one categorical variable is associated with the value of another
    • Chi-square test ($\chi^2$)
    • Statistical foundation
    • May select very slightly informative frequent terms that are not very useful for classification

• Use another learning algorithm
  – E.g. decision tree induction (Cardie, ICML 1994)

• Just use the commonest terms?
  – No particular foundation
  – In practice, this is often 90% as good