Transductive Inference for Text Classification using Support Vector Machines

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Introduction

Main Goals

- Introduce a new method for text classification - Transductive Support Vector Machines (TSVMs)
- Analyze why TSVMs are well-suited for text classification
- Describe a novel algorithm for training TSVMs
- Experimentally demonstrate classification improvements using TSVMs compared to standard inductive learning methods
**Talk Outline**

I. **Text classification**  
II. Transductive inference  
III. TSVMs for text classification  
IV. TSVM algorithm  
V. Experimental results  
VI. Conclusions and future work

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**Text Classification**

**Problem**  
- Classify documents into multiple, exactly one, or no semantic categories  
- Learn a classifier to assign categories automatically

**Applications**  
- Netnews Filtering - find interesting news articles  
- Reorganizing a document collection - automatically classify document databases after new categories are introduced
Document Preprocessing

Information Extraction
- Documents are strings of characters
- Words are represented as word stems
- Example: “computes”, “computing”, and “computer” are all mapped to the word stem “comput”
- Information retrieval research suggests that word stems work well without information loss

Documents as Feature Vectors

Feature Vectors (see Figure 1)
- Each document has one feature vector, indexed by word stems
- Each vector entry is $TF(w, x)$, the number of times word stem $w_i$ occurs in document $x$

Scaling by Inverse Document Frequency (IDF)
- Each feature vector entry is multiplied by

$$IDF \ (w_i) = \log \left( \frac{n}{DF \ (w_i)} \right)$$

where $n$ is the total number of documents, and $DF(w_i)$ is the number of documents the word $w_i$ occurs in
- IDF scaling assigns greater weight to word stems that are infrequent across all documents, and lesser weight to frequent word stems
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Inductive Support Vector Machines

• Input vectors are separated into two regions: $H_1$ and $H_2$
• Margin is maximized given minimal separation error
• Data points that lie on the margin are “support vectors”
Inductive versus Transductive Learning

Objectives of Inductive and Transductive Inference

- Inductive learning: generalize for any future test set
- Transductive learning: predict the classes for a specific test set
- In transduction we use information from the given test set

Transduction using Support Vector Machines

- Inductive Support Vector Machines (SVMs) learn a decision boundary between two classes to predict labels for future test sets
- Transductive Support Vector Machines (TSVMs) attempt to minimize the number of erroneous predictions on a specific test set
- A variation of supervised and unsupervised learning

Transductive Support Vector Machines

- Positive/negative training examples are marked +/-
- Test examples are dots
- The solid line gives the TSVM separating hyperplane

Redrawn from figure 2 in [Joachims, 1999]
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TSVMs and Text Classification

Text Classification Task Features
- High dimensional input space (10,000 features)
- Document feature vectors are sparse
- Every feature is important, since most words are relevant

What makes TSVMs good for this task?
- TSVMs inherit properties of SVMs, which work well
- TSVMs exploit co-occurring patterns of text

Alta Vista Search Example (number of hits in year 2001)
pepper, salt: 181,827
pepper, physics: 19,425
salt: 1.9 million
physics: 4.2 million
**TSVMs Using the Test Set: An Example**

<table>
<thead>
<tr>
<th></th>
<th>nuclear</th>
<th>physics</th>
<th>atom</th>
<th>parsley</th>
<th>basil</th>
<th>salt</th>
<th>and</th>
</tr>
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<td>D1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>D2</td>
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<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>D3</td>
<td></td>
<td>1</td>
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<td></td>
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<td>1</td>
<td></td>
</tr>
<tr>
<td>D4</td>
<td>1</td>
<td></td>
<td>1</td>
<td></td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>D5</td>
<td></td>
<td></td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>D6</td>
<td></td>
<td></td>
<td>1</td>
<td></td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 3 in [Joachims, 1999]

- Documents **D1** and **D6** are the training feature vectors
- Documents D2 through D5 are the test feature vectors
- D1, D2, and D3 are classified into class A
- D4, D5, and D6 are classified into class B

✓ This is possible since the test vectors D2 and D3 share a common word (atom), as do D4 and D5 (parsley)

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TSVM Training Algorithm Overview

Algorithm Overview
Input:  
- labeled training examples \((\bar{x}_1, y_1), \ldots, (\bar{x}_n, y_n)\)
- unlabeled test examples \(\bar{x}^+, \ldots, \bar{x}^i\)
- \(C, C^*\) from OP(2) in [Joachims, 1999]
- num+: anticipated number of positive test examples
Output:  
- predicted labels of the test examples \(y_1^+, \ldots, y_k^+\)

User Parameters
• \(C\) and \(C^*\) specify the SVM margin size
• num+ allows the tradeoff of recall versus precision
  – recall: proportion of items in the category that are actually placed in the category
  – precision: proportion of items placed in the category that are really in the category

TSVM Training Algorithm Description

Algorithm Idea
• Refer to Figure 4 in the paper, [Joachims, 1999]
• First label the test data based on inductive SVM classification
• Set the cost factors \(C_-^*\) and \(C_+^*\) to a small number

Outer loop (loop 1)
  – Increment the cost factors up to the user defined value of \(C^*\)

Inner loop (loop 2)
  – Locate two test examples for which changing the class labels leads to a decrease in the current objective function OP(2)
  – If these two examples exist, switch them

Algorithm Notes
• SVMlight (Joachims) is web software for the inductive SVM
**TSVM Inner Loop**

**Motivation**
- Goal is to minimize objective function $OP(2)$
- Algorithm will switch two examples that further minimize $OP(2)$, if two such examples exist
- Same example can have its label switched repeatedly
- $OP(2)$ decreases with every iteration
- Converges in a finite number of steps (proof given in paper)

**Issues**
- Why is it reasonable to switch to examples - randomness?

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Test Set Collections

**Reuters-21578**
- Consists of Reuters news data collected in 1987.
- ModApte split: 9,603 (75%) training and 3,299 (25%) test documents
- Can be in one or more of 10 classes (e.g., earn, grain, crude, etc.)

**WebKB collection**
- A collection of World Wide Web pages
- 4,183 examples: Cornell University for training, others for testing
- Can be in only one of 4 classes: course, faculty, project, student

**Ohsumed corpus**
- Medical documents compiled in 1991
- 10,000 training examples; 10,000 testing examples
- Can be in one or more of 5 classes (e.g., pathology, neoplasms, etc.)

Performance Metrics

Recall and Precision (defined intuitively before)
- recall: $\frac{tp}{tp + fn}$, where $tp$ is true positives, and $fn$ is false negatives
- precision: $\frac{tp}{tp + fp}$, where $fp$ is false positives

**Precision/Recall (P/R) Breakeven Point**
- Standard measure of performance in text classification
- Defined as the value for which precision and recall are equal
- Number of false positives equals number of false negatives
Breakeven point: Recall = Precision

\[ \text{Recall} = \frac{\text{tp}}{\text{tp} + \text{fn}} \]
\[ \text{Precision} = \frac{\text{tp}}{\text{tp} + \text{fp}} \]

\[ \text{Breakeven point} = \text{tp} = \text{fp} \]
\[ \text{Recall} = \text{Precision} \]

Reuters Experiment

<table>
<thead>
<tr>
<th></th>
<th>Bayes</th>
<th>SVM</th>
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<tr>
<td>earn</td>
<td>78.8</td>
<td>91.3</td>
<td>95.4</td>
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<tr>
<td>acq</td>
<td>57.4</td>
<td>67.8</td>
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<tr>
<td>money-fx</td>
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<td>41.3</td>
<td>60.0</td>
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<tr>
<td>grain</td>
<td>40.1</td>
<td>56.2</td>
<td>68.5</td>
</tr>
<tr>
<td>crude</td>
<td>24.8</td>
<td>40.9</td>
<td>83.6</td>
</tr>
<tr>
<td>trade</td>
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<td>interest</td>
<td>24.5</td>
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<tr>
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<td>32.5</td>
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<tr>
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<tr>
<td>average</td>
<td>35.9</td>
<td>48.4</td>
<td>60.8</td>
</tr>
</tbody>
</table>

Results

- 17 training and 3,299 test examples
- The TSVM gives better performance on all classes
- TSVMs are better for small training sets (Figure 6)
- TSVMs are less superior for larger training sets (Figure 7)
### WebKB Experiment

<table>
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<th></th>
<th>Bayes</th>
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<th>TSVM</th>
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<tbody>
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<tr>
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<tr>
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<tr>
<td>student</td>
<td>63.5</td>
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<tr>
<td>average</td>
<td>46.1</td>
<td>57.2</td>
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</tbody>
</table>

Results

- 9 training and 3,957 test examples
- **course** is especially good, **project** is especially bad. Why?
  - **course** pages at Cornell do not give topic information
  - With more training examples SVM catches up to TSVM (figure 10)
  - **project** is smallest class (1/9), and pages give topic information
  - With more training examples TSVM overcomes SVM (figure 11)

### Ohsumed Experiment

<table>
<thead>
<tr>
<th></th>
<th>Bayes</th>
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<th>TSVM</th>
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<tr>
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<td>48.6</td>
<td>53.5</td>
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</table>

Redrawn from figure 9 in [Joachims, 1999]

Results

- 120 training and 10,000 test examples
- The TSVM gives better performance on all classes
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Conclusions and Future Work

TSVMs combine powerful tools
• use prior knowledge about the test set
• exploit co-occurrence properties of text
• use separating hyperplane margin (SVM)
✓ TSVMs are well-motivated for text classification
✓ Improved performance verified experimentally using three challenging datasets

Open questions
? type of concepts that benefit best from transductive learning
? better way to represent text and documents
? further exploration of better training algorithms
? extend transductive classifiers to be inductive classifiers
Questions?