Outline

1. Introduction

2. Graph-Based Term Weighting for Text Categorization

3. Experimental Evaluation

4. Conclusions and Future Work
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Introduction

- Online social media and networking platforms produce a vast amount of textual data
- Analyze and extract useful information from textual data is a crucial task
- **Text categorization (TC)** refers to the supervised learning task of assigning a document to a set of two or more pre-defined categories, based on learning models that have been trained using labeled data
- Plethora of applications
  - Opinion mining for risk assessment and management
  - Email filtering
  - Spam detection
  - News classification
  - ...

Experimental Evaluation

Conclusions and Future Work
Basic pipeline of the text categorization task

Textual Data

Feature Extraction
Document-Term Matrix

Dimensionality Reduction

Model Learning

Text Categorization

Evaluation
Term weighting in the Bag-of-words model

**Vector Space Model**

- $\mathcal{D} = \{ d_1, d_2, \ldots, d_m \}$ denotes a collection of $m$ documents
- $\mathcal{T} = \{ t_1, t_2, \ldots, t_n \}$ be the dictionary

**Feature extraction**

Every document is represented by a feature vector that contains boolean or weighted representation of unigrams or $n$-grams

- TF (Term Frequency), TF-IDF (Term Frequency - Inverse Document Frequency)

\[
\text{tf-idf}(t, d) = \text{tf}(t, d) \times \text{idf}(t, \mathcal{D}),
\]

where \( \text{idf}(t, \mathcal{D}) = \log \frac{m + 1}{|\{d \in \mathcal{D} : t \in d\}|} \)
Contributions of this work

- **Graph-based term weighting schemes for TC**
  - Propose a simple graph-based representation of documents for text categorization
  - Derive novel term weighting schemes, that go beyond single term frequency

- **Exploration of model’s parameter space and experimental evaluation**
  - We discuss how to construct the graph
  - We examine the performance of the different proposed weighting criteria using standard document collections
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Graph-of-words: overview

Why Graph-of-words?

- Capture relationships between terms
- Questioning the term independence assumption
- Already applied in other data analytics tasks (e.g., IR [Blanco and Lioma, ’12], [Rousseau and Vazirgiannis, ’13])

Representation of a document

Each document $d \in \mathcal{D}$ is represented by a graph $G_d = (V, E)$

- Nodes correspond to the terms $t$ of the document
- Edges capture co-occurrence relations between terms within a fixed-size sliding window of size $w$
Proposed graph-based term weighting method for TC

**Input:** Collection of documents $\mathcal{D} = \{d_1, d_2, \ldots, d_m\}$ and set (dictionary) of terms $\mathcal{T} = \{t_1, t_2, \ldots, t_n\}$

**Output:** Term weights $tw(t, d)$ for each term $t \in \mathcal{T}$ to each document $d \in \mathcal{D}$

1:  
   for $d \in \mathcal{D}$ do
2:    **(Graph Construction)** Construct a graph $G_d = (V, E)$. Each node $v \in V$ corresponds to a term $t \in \mathcal{T}$ of document $d$. Add edge $e = (u, v)$ between terms $u$ and $v$ if they co-occur within the same window of size $w$
3:    **(Term Weighting)** Consider a node centrality criterion. For each term $t \in \mathcal{T}$, compute the weight $tw(t, d)$ based on the centrality score of node $t$ in graph $G_d$ and fill in the Document-Term matrix
4:  end for
Graph construction: parameters of the model

- **Directed vs. undirected graph**
  - Directed graphs are able to preserve actual flow of a text
  - In undirected ones, an edge captures co-occurrence of two terms whatever the respective order between them is ✓

- **Weighted vs. unweighted graph**
  - Weighted: the higher the number of co-occurrences of two terms in the document, the higher the weight of the corresponding edge
  - Unweighted (our choice due to the simplicity of the model) ✓

- **Size $w$ of the sliding window**
  - We add edges between the terms of the document that co-occur within a sliding window of size $w$
  - $w = 3$ performed well in TC ✓
  - Larger window sizes produce graphs that are relatively dense
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Example: text to graph representation

Graph representation of a document ($w = 3$; undirected graph)

Data Science is the extraction of knowledge from large volumes of data that are structured or unstructured which is a continuation of the field of data mining and predictive analytics, also known as knowledge discovery and data mining.
Term weighting criteria

- Utilize **node centrality criteria** of the graph
  - The importance of a term in a document can be inferred by the importance of the corresponding node in the graph

- Consider information of the graph:
  - **Local**: degree centrality, in-degree/out-degree centrality in directed networks, weighted degree in weighted graphs, clustering coefficient
  - **Global**: PageRank centrality, eigenvector centrality, betweenness centrality, closeness centrality

\[
\text{degree}_\text{centrality}(i) = \frac{|\mathcal{N}(i)|}{|V| - 1}, \quad \text{closeness}(i) = \frac{|V| - 1}{\sum_{j \in V} \text{dist}(i, j)}
\]

- Proposed weighting schemes for TC:
  - TW
  - TW-IDF
Experimental set-up

- **Datasets**
     - # of **train** docs: 5,485; # of **test** docs: 2,189; total: 7,674
     - # of categories: 8
  2. *WebKB*: academic webpages
     - # of **train** docs: 2,803; # of **test** docs: 1,396; total: 4,199
     - # of categories: 4

- **Evaluation**
  - Linear SVM classifier
  - Train the model on the **train** documents
  - Report classification results from the **test** documents
  - Macro-averaged F1 score and classification accuracy

- **Baseline methods**
  - Traditional TF and TF-IDF weighting schemes vs. the proposed TW and TW-IDF (degree, in-degree, out-degree and closeness centrality; window-size=3)
# Experimental results

## Reuters-21578 R8 and WebKB datasets

<table>
<thead>
<tr>
<th>Weighting</th>
<th>F1-score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF</td>
<td>0.9127</td>
<td>0.9634</td>
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<tr>
<td>TW, degree</td>
<td>0.8991</td>
<td>0.9611</td>
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<tr>
<td>TW, in-degree</td>
<td>0.8037</td>
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<tr>
<td>TW, out-degree</td>
<td>0.8585</td>
<td>0.9546</td>
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<tr>
<td>TW, closeness</td>
<td>0.9125</td>
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<tr>
<td>TF-IDF</td>
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<tr>
<td>TW-IDF, degree</td>
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<td>TW-IDF, out-degree</td>
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<tr>
<td>TW-IDF, closeness</td>
<td>0.8846</td>
<td>0.9547</td>
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</table>

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<thead>
<tr>
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<th>F1-score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF</td>
<td>0.8741</td>
<td>0.8853</td>
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<td>TW, out-degree</td>
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<tr>
<td>TW, closeness</td>
<td>0.8960</td>
<td>0.9004</td>
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<tr>
<td>TF-IDF</td>
<td>0.8331</td>
<td>0.8538</td>
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<td>TW-IDF, degree</td>
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<tr>
<td>TW-IDF, closeness</td>
<td>0.8505</td>
<td>0.8674</td>
</tr>
</tbody>
</table>

*Reuters-21578 R8*

*WebKB*
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Conclusions and future work

Contributions:
- Introduce a new paradigm for TC
- Potential of graph-based weighting mechanisms in TC

Future work:
- Exploration of parameter’s space: many diverse centrality criteria can be applied in order to weight the terms
- Graph-based inverse collection weight: a more thorough theoretical analysis of its properties is also an interesting future direction
- Graph-based dimensionality reduction: extend the task of dimensionality reduction to the graph representation of the documents
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Thank You!!