Emotion Recognition in Text
Using Graph Similarity Criteria

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Nadezhda Komarova
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AIM

1. Developing the approach to emotion recognition employing $n$-grams to obtain graph representation of text
2. Text represented as a sequence of characters divided into $n$-grams
3. Constructing the graphs of $n$-grams

Capturing the relations between words in the text that occur close together using graph representation
RELATED WORK

- Employing word embedding vectors
- **GNN** enhanced by utilizing BERT to obtain semantic features
- Probabilistic classifiers, e.g., Bayes Classification, Support Vector Machine
- Similarity criteria: subgraph matching, edit distance, belief propagation
METHODOLOGY

GRAPH REPRESENTATION OF THE TEXT

Using $n$-grams; testing different values of $n$

Text example: “i have a good feeling about this so i am excited”

**Vertices:** $n$-grams of characters

**Edges:** the connections between the adjacent $n$-grams; directed and undirected graphs
CLASSIFICATION USING GRAPH COMPARISON

- Given the data set of texts labeled with emotions
- Construct the graphs corresponding to emotions using all the labeled texts

Given an unlabeled text:

1) construct the graph of the text
2) compare with the category graphs
3) the highest score of similarity → an emotion predicted
EXAMPLES
OF CLASSIFICATION

**happy**
“joy was in every face and every heart”

**fearful**
“peter sat down to rest he was out of breath and trembling with fright and he had not the least idea which way to go”

**surprised**
“the duck stared at it and exclaimed it is very large and not at all like the others”
VARIABLES

Testing different similarity criteria between the two graphs

- Number of common **vertices** in the graphs
- Number of common **edges** in the graphs
- Number of edges in the **maximum common subgraph** (MCS)
- Number of vertices in the MCS (**m**) 
- The difference between the number of edges in the complete graph with **m** vertices and the number of edges in the MCS (**z**)
## EXPERIMENTAL RESULTS

**TABLE 1: Results of text classification using directed graphs**

<table>
<thead>
<tr>
<th>Similarity criterion</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common vertices</td>
<td>0.488</td>
<td>0.506</td>
<td>0.332</td>
<td>0.323</td>
</tr>
<tr>
<td>Common edges</td>
<td>0.537</td>
<td><strong>0.683</strong></td>
<td>0.408</td>
<td>0.432</td>
</tr>
<tr>
<td>z</td>
<td>0.372</td>
<td>0.074</td>
<td>0.200</td>
<td>0.108</td>
</tr>
<tr>
<td>Vertices in the MCS</td>
<td>0.570</td>
<td>0.622</td>
<td>0.426</td>
<td>0.446</td>
</tr>
<tr>
<td>Edges in the MCS</td>
<td><strong>0.579</strong></td>
<td>0.625</td>
<td><strong>0.454</strong></td>
<td><strong>0.478</strong></td>
</tr>
</tbody>
</table>
EXPERIMENTAL RESULTS

- **TABLE 2: Results of text classification using undirected graphs**

<table>
<thead>
<tr>
<th>Similarity criterion</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Common vertices</td>
<td>0.488</td>
<td>0.506</td>
<td>0.332</td>
<td>0.323</td>
</tr>
<tr>
<td>Common edges</td>
<td>0.554</td>
<td><strong>0.669</strong></td>
<td>0.429</td>
<td><strong>0.460</strong></td>
</tr>
<tr>
<td>z</td>
<td>0.372</td>
<td>0.074</td>
<td>0.200</td>
<td>0.108</td>
</tr>
<tr>
<td>Vertices in the MCS</td>
<td>0.545</td>
<td>0.527</td>
<td>0.399</td>
<td>0.406</td>
</tr>
<tr>
<td>Edges in the MCS</td>
<td><strong>0.570</strong></td>
<td>0.581</td>
<td><strong>0.439</strong></td>
<td>0.453</td>
</tr>
</tbody>
</table>
EXPERIMENTAL RESULTS

Confusion matrix for the setup utilizing the similarity criteria based on the construction of the MCS

<table>
<thead>
<tr>
<th>The prediction</th>
<th>Happy</th>
<th>Fearful</th>
<th>Surprised</th>
<th>Sad</th>
<th>Angry-Disgusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>The actual label</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Happy</td>
<td>0.98</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.02</td>
</tr>
<tr>
<td>Fearful</td>
<td>0.65</td>
<td>0.24</td>
<td>0.06</td>
<td>0.06</td>
<td>0</td>
</tr>
<tr>
<td>Surprised</td>
<td>0.55</td>
<td>0.18</td>
<td>0.09</td>
<td>0</td>
<td>0.18</td>
</tr>
<tr>
<td>Sad</td>
<td>0.54</td>
<td>0</td>
<td>0</td>
<td>0.46</td>
<td>0</td>
</tr>
<tr>
<td>Angry-Disgusted</td>
<td>0.50</td>
<td>0.05</td>
<td>0</td>
<td>0.09</td>
<td>0.36</td>
</tr>
</tbody>
</table>
DISCUSSION

**Strengths**
- Ability to capture the context of the given words on different levels
- Breadth of the contextual frame varied by altering the number of $n$-grams with which a certain $n$-gram is connected

**Limitations**
- Imbalanced data set
- Large graphs when training on bigger data sets: complex to compute
CONCLUSION

Constructing a graph of $n$-grams for a given text; comparing this graph to each of the emotion category graphs

Future work

- Employing alternative graph similarity measures
- Using clustering algorithms to obtain patterns characteristic to emotion categories
- Utilizing graph neural network architecture