**Motivation**

Email conversations often discuss multiple topics
e.g., a conversation about arranging a conference may cover:
- Location and time
- Registration
- Food menu
- Workshops

Two subtasks:
- **Segmentation**: Grouping sentences into coherent clusters
- **Identification**: Assigning topic labels to the clusters

Prerequisite for:
- Higher-level conversation analysis (e.g., speech act tagging).
- Text summarization and Automatic question answering.
- Intelligent user interfaces for emails.

**Challenge**

Topics in emails do not change in a sequential way
Models in monolog and synchronous dialog not so effective

**Our Supervised Graph-theoretic Approach**

1. **Sentence Pair Classification**
2. **Graph Construction**
3. **Graph Partitioning**

- Integrates lexical and topic features with conversational ones.

**Results**

- Our sup approach achieves better accuracy than unsupervised method of [Joty et al. 2010] with very limited amount of training data.

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**Step1 Sentence Pair Classification**

- A binary classifier marks each pair of sentences of a conversation as ‘same’ or ‘different’ topics.
- A conversation of n sentences produces O(n²) training examples.

**Comparison of classifiers:**

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Regularizer</th>
<th>Train error</th>
<th>Test error</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>-</td>
<td>47.7%</td>
<td>46.7%</td>
</tr>
<tr>
<td>SVM (lin)</td>
<td>-</td>
<td>33.2%</td>
<td>32.6%</td>
</tr>
<tr>
<td>SVM (rbf)</td>
<td>-</td>
<td>26.4%</td>
<td>34.3%</td>
</tr>
<tr>
<td>LR</td>
<td>l₁</td>
<td>30.6%</td>
<td>30.9%</td>
</tr>
<tr>
<td>LR</td>
<td>l₂</td>
<td>32.1%</td>
<td>33.3%</td>
</tr>
<tr>
<td>RMLR (rbf)</td>
<td>l₂</td>
<td>10.8%</td>
<td>38.9%</td>
</tr>
</tbody>
</table>

**Features with average performance:**

- **Lexical**
  - Acc: 59.6  Pre: 59.7  Rec: 99.8

- **Topic**
  - Acc: 65.2  Pre: 64.4  Rec: 79.6

- **Conv**
  - Acc: 65.3  Pre: 66.7  Rec: 85.1

**Step2&3 Graph Construction and Partitioning**

- Construct the graph:
  - Nodes => Sentences
  - Edge-weights => Probability (‘same’ class)

- Partition the graph by optimizing the ‘normalized cut’ criterion.

**Evaluation of our Sup. Topic Segmenter**


<table>
<thead>
<tr>
<th>Model</th>
<th>Baseline</th>
<th>Unsupervised</th>
<th>Models</th>
<th>Human</th>
<th>Sup.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Speaker</td>
<td>Block 5</td>
<td>LDA</td>
<td>LDA+FQG</td>
<td>LCSeg</td>
</tr>
<tr>
<td>Scores</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean 1-1</td>
<td>0.52</td>
<td>0.38</td>
<td>0.57</td>
<td>0.62</td>
<td>0.68</td>
</tr>
<tr>
<td>Mean loc.</td>
<td>0.64</td>
<td>0.57</td>
<td>0.54</td>
<td>0.61</td>
<td>0.72</td>
</tr>
</tbody>
</table>

**Reference**

Joty, S.; Carenini, G.; Murray, G.; Ng, R. Exploiting conversation structure in unsupervised topic segmentation for emails. In EMNLP-2010.