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### Pipeline

**STEP 1**

- Feature 1
  - If a bill number is included in a given sentence, return true.
  - If one or more patterns of "all (全て)" or "agree (賛成)" is included, and if one or more patterns of "disagree (反対)" is included, return true.

**STEP 2**

- Feature 1
  - Its value is "1" when there is a "agree (賛成)" immediately after the bill number, "2" when there is a "disagree (反対)" and "0" when there is no such string occurs.
- Feature 2
  - Final layer of BERT output, dimensionally compressed by PCA
- Feature 3
  - Polarity scores using a Japanese Sentiment Polarity Dictionary
  
\[
\text{Polarity score} = \frac{\text{sum of the polarity values}}{\text{number of words}}
\]

### Experiment

**Training Strategy**

- Model: LightGBM
- Features: Party, BillClass, Proponent, Feature 1~3
- Cross-validation: Stratified 5-fold

<table>
<thead>
<tr>
<th>Feature</th>
<th>Cross Validation</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Feature 1</td>
<td>0.892</td>
<td>0.942</td>
</tr>
<tr>
<td>Without Feature 2</td>
<td>0.901</td>
<td>0.947</td>
</tr>
<tr>
<td>Without Feature 3</td>
<td>0.911</td>
<td>0.952</td>
</tr>
<tr>
<td>All Features</td>
<td>0.906</td>
<td>0.951</td>
</tr>
</tbody>
</table>

Each feature contributed to the performance.

### Conclusion

We proposed a machine learning based method using LightGBM. We designed our features includes linguistic information, and a polarity score. The experimental result showed our machine learning method and our features were effective.