PatternRank: Leveraging Pretrained Language Models and Part of Speech for Unsupervised Keyphrase Extraction

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**Motivation**
- Provide a quick overview of the content of a text.
- Keyphrases consist of several compound words and can concisely reflect the semantic context of a text.
- Unsupervised keyphrase extraction approaches do not require labeled training data and are mostly domain independent.

**Keyphrase Extraction**

1. Keyphrases
2. Document Content
3. Main Topics
4. Document
5. Applications

**PatternRank**

**Noun Phrase:**
(Zero or more adjectives followed by one or more nouns.)
\[
\{AD\} \ast \{NOUN\} +
\]

**Part of Speech Pattern:**
(Arbitrary parts-of-speech separated by a hyphen, followed by zero or more nouns OR zero or one verb, followed by zero or more adjectives, followed by one or more nouns.)
\[
\{((\ast)\{HYPH\}\{\ast\})\{NOUN\} \ast\} \\
\{(VBG)\{VBN\}\? \{AD\} \ast \{NOUN\} +\}
\]

**Evaluation**

<table>
<thead>
<tr>
<th>Method</th>
<th>$F_1@5$</th>
<th>$F_1@10$</th>
<th>$F_1@20$</th>
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</thead>
<tbody>
<tr>
<td>YAKE</td>
<td>15.37</td>
<td>18.50</td>
<td>19.65</td>
</tr>
<tr>
<td>SingleRank</td>
<td>21.97</td>
<td>28.55</td>
<td>30.80</td>
</tr>
<tr>
<td>KeyBERT</td>
<td>7.82</td>
<td>10.30</td>
<td>11.76</td>
</tr>
<tr>
<td>PatternRank$_{NP}$</td>
<td>23.92</td>
<td>29.66</td>
<td>29.19</td>
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<tr>
<td>PatternRank$_{PoS}$</td>
<td>24.35</td>
<td>30.99</td>
<td>31.37</td>
</tr>
</tbody>
</table>

- Inspect dataset consisting of 2,000 English computer science abstracts. Each abstract has assigned a set of gold keyphrases.
- Evaluation based on exact match of extracted keyphrases and gold keyphrases.

**Approach**
1. The input consists of a single text document which is being word tokenized.
2. The word tokens are then tagged with part-of-speech tags.
3. Tokens whose tags match a previously defined part-of-speech pattern are selected as candidate keyphrases.
4. Then, a pretrained language model embeds the entire text document as well as all candidate keyphrases as semantic vector representations.
5. Subsequently, the cosine similarities between the document representation and the candidate keyphrase representations are computed and the candidate keyphrases are ranked in descending order based on the computed similarity scores.
6. Finally, the top-N ranked keyphrases, which are most representative of the input document, are extracted.

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