Author Profiling

Using Deep Learning to Identify Age Groups and Genders

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Motivation

- Huge volume of user-generated content $\implies$ appealing to profile users based on it.
- Profiling has multi-faceted advantages:

  Commercial Analyze the demographics of people that like or dislike certain products.

  Forensic Find out the linguistic profile of the author of a harassing text message and identify certain characteristics (*language as evidence*).

Task

Definition (Author Profiling)

Author profiling is the task of identifying certain features of authors of text.

- We will focus on the *genders* and *age groups* of authors of Twitter posts.
- Genders are either `male` or `female`.
- Age groups are 18–24, 25–34, 35–49, 50–64, and 65–`xx`.

Dataset

- Data are provided as part of the PAN 2016 event[1].
- There are 277 792 tweets written in English by 436 users, or an average of 637.14 tweets per user.
- 218 users are male and 218 are female.
- The distribution of age groups is given in table 1.
- We additionally used the data provided by the 2013, 2014, and 2017 PAN events for the unsupervised part of our classification pipeline (stay tuned).

[1] http://pan.webis.de/clef16/pan16-web/author-profiling.html

Age Groups

Table: Distribution of age groups.

Age group	Number of users
18–24	28
25–34	140
35–49	182
50–64	80
64–xx	6

One can see that there is class imbalance here. However, we are not going to attempt to rectify this by weighing or resampling.

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Parsing

- Data are given in XML files: there is one XML file per author named by the author's hexadecimal ID.
- We used the Beautiful Soup library to parse the files.
- Additionally, there is a file called `truth.txt` which consists of lines of the form

  ```
  <filename>:::<gender>:::<age-group>
  ```

  and gives the ground truth.

Normalization

1. Hash tags, replies, and external links are replaced by new and unique tokens.
2. Tweets are tokenized into words using the Punkt tokenizer [2] from NLTK, the natural language toolkit.
3. Abbreviations and nonstandard words such as “ur” and “lol” are converted to their standard forms using a dictionary constructed from the ACL 2015 workshop on noisy user-generated content [1].

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Distributed Representations

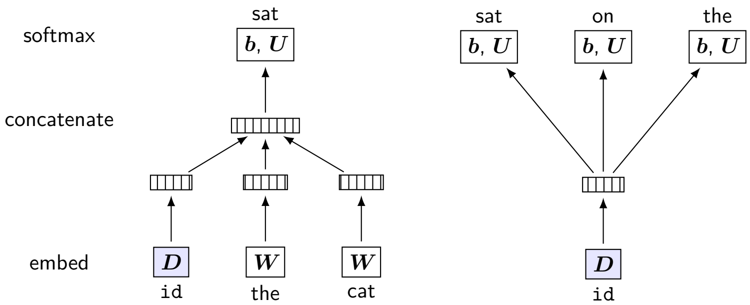
Motivation

The Doc2Vec model learns distributed representations of both words and entire documents. In our case, $\mathrm{document} := \mathrm{author}$.

- Semantically related entities, e.g., Prague, Rome, Berlin, etc., should be close to each other.
- Two entities are considered close if they appear in the same context (Word2Vec [4]).
- The context is a simple window of k words to the left and to the right of a target word.
- The "leftovers" of the context are explained by the *document's ID* itself (Doc2Vec [3]).

Distributed Representations

Architecture



(a) DM model.

(b) DBOW model.

Figure: Doc2Vec with embeddings $\boldsymbol{W}$ and $\boldsymbol{D}$.

Distributed Representations

Learning

- We trained the DM model (figure 1a) using Gensim [5] on 1 047 358 posts from social media (PAN 2013, 2014, and 2017) to learn embeddings of size 256.
- Training was carried for 20 epochs using a context window of size 8.
- Some examples for closest representations can be seen on figure 2.

Distributed Representations

Examples

```
>>> mdl.most_similar('substantial')

[('higher', 0.72),
 ('large', 0.70),
 ('high', 0.69),
 ('significant', 0.6),
 ('huge', 0.6),
 ('reduced', 0.6),
 ('massive', 0.59),
 ('increased', 0.58),
 ('considerable', 0.57),
 ('enormous', 0.56)]
```

```
>>> mdl.most_similar('trump')

[('ivanka', 0.5),
 ('donald', 0.41),
 ('gould', 0.4),
 ('melania', 0.38),
 ('selby', 0.38),
 ('osullivan', 0.35),
 ('finalist', 0.34),
 ('hudson', 0.31),
 ('qingyang', 0.31),
 ('ferguson', 0.31)]
```

Figure: Similarities between the learned word vectors.

The Pipeline

1. Words are padded to a length of 512, transformed to their distributed representations, and fed to two CNNs:
   1.1 128 filters using a kernel size of 4, rectified linear units (ReLUs) for activation, and max-pooled with a factor of 4; and
   1.2 128 filters using a kernel size of 4, ReLUs for activation, and max-pooled with a factor of 16.
2. Author IDs are transformed to their distributed representations and fed to a densely-connected network of 128 ReLUs.
3. The two outputs are concatenated and fed to:
   3.1 Densely-connected layer of 128 ReLUs;
   3.2 Densely-connected layer of 32 ReLUs; and a
   3.3 Softmax panel for classification.

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Results

- Training the architecture for 3 epochs yielded an accuracy of 81.30 % for gender, and 61.18 % for age groups.
- The accuracy was estimated using 1/3 of the data for validation.
- Better results than the ones observed at PAN 2016.

Future Work

- We would like to determine why over-fitting began to occur after the 3rd epoch. It might be worthwhile to apply L_1 or L_2 regularization, or more aggressive dropout.
- Lexical normalization is not perfect: since a dictionary is used, "ur" will always be translated to "your" even though it might sometimes stand for "you are".
- An obvious improvement is to train the distributed representations on more data, and perhaps lemmatize the texts before processing them.

References I

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