Introduction to FastText

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FastText

- Developed by Facebook team
- Allows computing word vectors
- Shallow neural model relying on a hidden layer
- In the hidden layer, a sentence is represented by averaging the vector representations of each word.
- This text representation is then input to a linear classifier
  $\rightarrow$ hierarchical softmax (reduces computational complexity)

FastText

- Extension of word2vec
- Both Word2Vec architectures available:

    - Continuous bag of words (CBOW): the context is used to predict target word; does not capture the order of words

    - Skip-gram: each word is used to predict a target context

      Mikolov, T., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. Advances in neural information processing systems.

FastText

- Subword information (character n-grams) can be considered:

  - Words are represented as the sum of the n-gram vectors
    $\rightarrow$ Word morphology

  - Processing of out-of-vocabulary (OOV) words
    $\rightarrow$ OOV words are represented by summing
    the representation of character n-grams

    ```
    ./fasttext print-vectors model.bin < OOV_words
    ```

FastText

- Can be used for supervised classification tasks:

  ```
  ./fasttext supervised -input train -output model
  ```

  ```
  ./fasttext test model.bin test.txt k
  ```

  k: optional argument to compute precission/recall at the given value (default is 1)

  ```
  ./fasttext predict model.bin test.txt k
  ```

  - By default, target values need to be declared with __label__:
    This is a positive sentence __label__1
    This is a negative sentence __label__0

Parameters (list not exhaustive; default value in brackets)

- cbow / skipgram
- vector dimension [100]
- context window (before and after the target word) [5]
- negative: negative sample size [5]; "negative sampling only calculates the probability with reference to a set number of other randomly chosen negative words" (Chiu et al 2016)
  $\rightarrow$ The larger it is, the slower it takes to train.
- learning rate [0.05]
- sampling thresold [0.0001]

Parameters (list not exhaustive; default value in brackets)

- minimum number of word occurrences [5]
- **word n-grams** [1]
- **minimun [3] and maximum [6] length of character-n-grams**
- **pretrained vectors** (.vec format)
- number of threads [12]
- number of buckets: nº of n-gram keys in the vocabulary hash [2 mill.]

  /!**Only UTF8 encoding** /!\\

- Python version of FastText:
  https://pypi.python.org/pypi/fasttext

Sample use cases

- Context of modeling out-of-vocabulary terms and relate them to semantic types of in-vocabulary terms
- Hypothesis: a new term (δ) will share semantic properties of known terms (τ) occurring in similar contexts $\rightarrow$ **word-similarity task**
- Pretrained vectors on a subset (>7M tks) of the European Medicine Agency corpus
  `http://opus.lingfil.uu.se/EMEA.php/`

Tests

Follow the activities prepared...

```
insomniantes
('insomnies', 0.8454272150993347) → disease
('insomnie3', 0.7903878688812256) → OOV (typo)
('insomniea', 0.7886084914207458) → OOV (typo)
('insomnia', 0.7879734635353088)
('insomnie', 0.7849773168563843) → disease
('somnifères', 0.7168412208557129) → OOV
('anxiétés', 0.6793801188468933) → disease
('anxiété', 0.674299418926239) → disease
('délirantes', 0.6704117059707642)→ disease
('anxiété†', 0.6630647778511047) → OOV (typo)
```
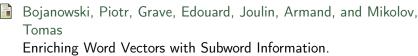
Points to discuss?

Influence of:

- Corpus size and source
- Lemmatization and normalization (lowercase, removing hyphen and accents...)
- General / domain applications
- Tasks...

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