Moral Embeddings

Performance, Generalisability and Transferability

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Introduction

Personal values are the abstract motivations that drive our opinions and actions. Using state-of-the-art NLP methods, we design a classifier to study their expression in text.

Moral Foundations Theory [1] (MFT) proposes five "irreducible basic elements" of morality, that we can frame our study in: *care/harm, authority/subversion, fairness/cheating, loyalty/betrayal, purity/degradation.*

Embeddings convert word and sentences to meaningful vectors and they are an important step in a text classifier's pipeline. They can be domain-adapted to improve the model's performance.

Research Goal: Train embeddings to learn moral foundations and assess our method by answering three research questions:

1) Does our fine-tuning method increase the moral classifier's **performance**.
2) Do fine-tuned embeddings **generalise** across domains of discourse.
3) Are fine-tuned embeddings **transferable**.

Motivation: no prior moral classifiers focus on fine-tuning state-of-the-art embeddings (Sentence-BERT[2]) to improve the model's performance. Moreover, after training, embeddings' utility is not limited to the classification task: Semantic Textual Similarity, clustering.

Methods

1. Moral Foundations Twitter Corpus

7 datasets

ALM | BLM | Elections | Davidson | Sandy | MeToo | Baltimore

35 000 annotated tweets

3-8 annotators, moral values or non-moral

Preprocessing

- Lemmatise
- Spell correction
- Remove urls, mentions
- Remove symbols
- Remove punctuation
- Emojis -> Words

Labelling

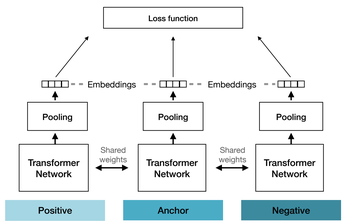
Majority vote
No consensus -> non-moral

Data Balancing

From train data, reduce size of non-moral class.

2.Sentence-BERT

Sentence embeddings with state-of-the-art results on Semantic Textual Similarity.



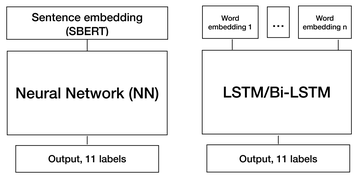
Triplet loss is used to fine-tune pre-trained SBERT embeddings

3. Classifiers

We define our problem as a **multi-label** classification problem.

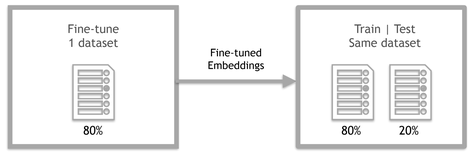
Two baseline models: LSTM[3] and BiLSTM with GloVe[4] word embeddings.

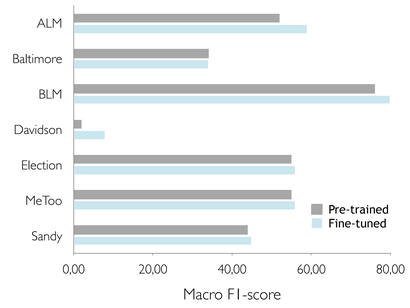
Third model: **Sentence-BERT** embeddings (pre-trained/fine-tuned) with a simple Neural Network on top.

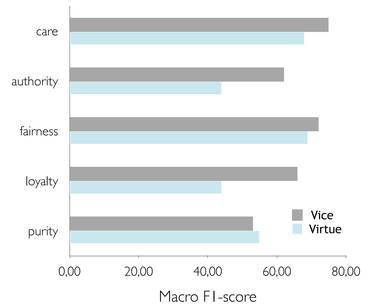


Performance

1) Does fine-tuning Sentence-BERT embeddings with triplet loss increase the moral classifier's **performance**.



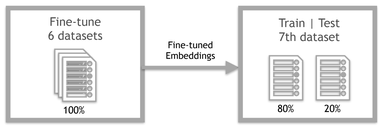




The chart on the left shows how fine-tuning SBERT improves the Macro F1-Scores for the moral classifiers. On the right, we illustrate how embeddings trained on the entire MFTC recognise each moral value.

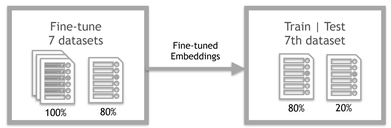
Generalisability

2) Do fine-tuned embeddings **generalise** across domains of discourse.

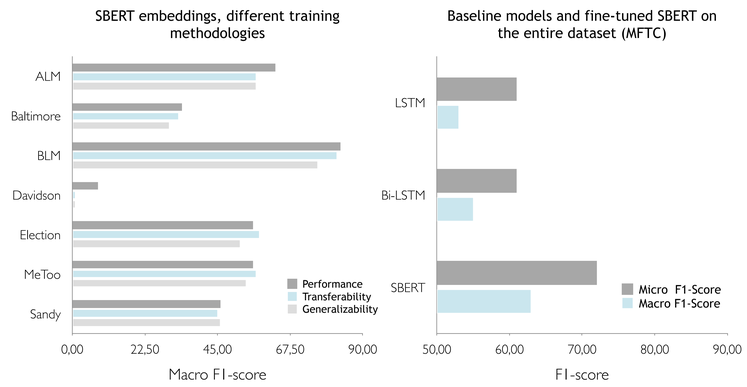


Transferability

3) Are fine-tuned embeddings **transferable**.



Results



Discussion

For the moral classification task, we proposed a method to fine-tune state-of-the-art embeddings. The resulting classifier achieves 72% Micro F1-score on the MFTC dataset.

Future work

For a complete understanding of moral embedding's transferability, MFTC should be extended. As MFT annotating is labour intensive, we recommend experimenting with semi-supervised annotating methods[5].

To better explain our method's success, it should be investigated if *semantically similar text expresses similar moral values.*

References

1. Graham, J. (2013). Moral Foundations Theory. *Advances in Experimental Social Psychology, 47, 55-130.*
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3. Hochreiter, S. (1997). Long short-term memory. *Neural Computation, 9, 1735-1780*
4. Pennington, J (2014). Glove: Global vectors for word representation
5. Settles, B. (2011). Closing The Loop: Fast, Interactive Semi-Supervised Annotation with Queries on Features and Instances.

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