Detecting Stance in CryptoCurrency Forums

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Introduction

Stance Detection
- Relatively young research field belonging to Opinion Mining
- Classify stance of a text author, towards a target as {*Favor*, *Against* or *Neither*}
- Unique application domains: Fake News Detection, Rumour Evaluation

"I hope ETH will go parabolic!"
Just-Hearing1110

Challenges
- Lack of annotated Datasets
- Little research on application of Transfer Learning techniques

Contributions
- Creation and annotation of two novel Datasets SEthB and SethC
- Implementation and evaluation of transfer learning with different SotA language models

Data Collection & Filtering

- 180 days worth of comments scraped from popular subreddits
- Preliminary filtering using target relevant keywords
- POS parsing tree used to remove sentences without conjugate verbs

242,648 Sentences
40,632 Authors

→

86,980 Sentences
22,208 Authors

Annotation

SEthB
- Random sampling from the 240k comments
- If the anotater was unsure, the comment would be excluded
- Total of 800 annotated data-points

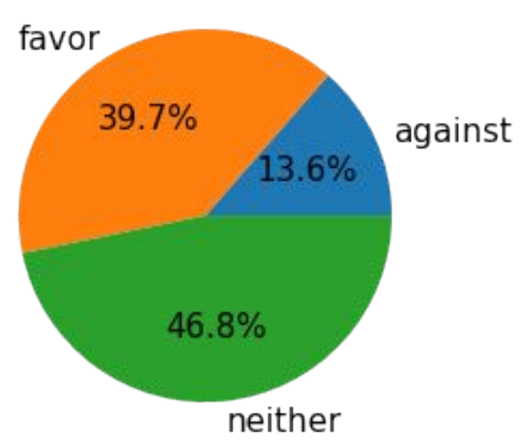

Figure 1: SEthB Stance Distribution

SEthC
- Selected 100 most active authors from the dataset
- Allocated stance to the author based on randomly sampled comments
- Applied stance to all comments of the author
- Total of 7500+ annotations

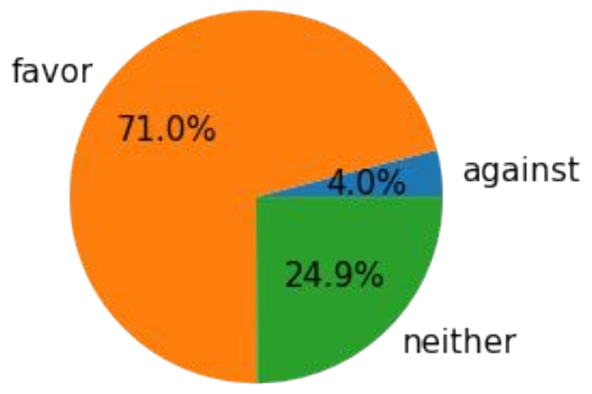

Figure 2: SEthC Stance Distribution

Benchmark Datasets

SemEval2016Task6
- 4163 tweets discussing Atheism, Climate Change, Feminism, Hillary Clinton and Abortion.
- Tweet's labeled as *Favor*, *Against* or *Neither* towards a single target topic

ARC
- Consists of conversational topics taken from the news (politics, education, etc...)
- Target's are in the form of a headline, text's consist of multi-sentence discussion posts
- 186 targets with 4 different stance classes *Agree*, *Unrelated*, *Disagree* and *Discuss*

Models

SVM
- Simple SVM with a linear kernel
- Trained on word n-grams (1-, 2-, and 3-gram) and character n-grams (2-, 3-, 4-, and 5-gram
- Single classifier per-target

Transfer Learning
- Implemented popular PLMs (BERT, RoBERTa, ALBERT, DistilBERT, XLNet)
- Target-specific models are fed with tokenized text inputs
- Fine-tuned as a multi-class classification problem without "freezing the body"
- Tried alternative architectures to create a one-model-fits-all targets

Datasets	SemEval2016		ARC		SEthB		SEthC	
Models	acc	f1	acc	f1	acc	f1	acc	f1
Random Baseline	0.3363	0.2910	0.2413	0.1663	0.3355	0.3179	0.3127	0.2526
Majority Baseline	0.5833	0.2377	0.7607	0.3684	0.4581	0.2094	0.7523	0.2862
SVM	0.6765	0.5451	0.8059	**0.4794**	0.5677	**0.4532**	0.7584	0.5385
ALBERT	0.6335	0.3419	0.7737	0.4035	0.4710	0.2135	0.7828	0.4576
BERT	0.7343	0.6366	0.7903	0.4331	**0.6065**	0.4281	0.7907	**0.6139**
DistilBERT	0.7004	0.5958	0.7935	0.4235	0.5806	0.4436	0.7946	0.5932
RoBERTa	**0.7470**	**0.6413**	0.7920	0.4359	0.6000	0.4292	**0.8071**	0.5809
XLNet	0.6887	0.5037	**0.8099**	0.4780	0.5742	0.4371	0.8038	0.5942
SotA	-	**0.6979**	**-**	**0.6583**	**0.6065**	**0.4532**	**0.8071**	**0.6139**

Table 1: Model Evaluation

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