Targeted Aspect-Based Sentiment Analysis for Lithuanian social media reviews

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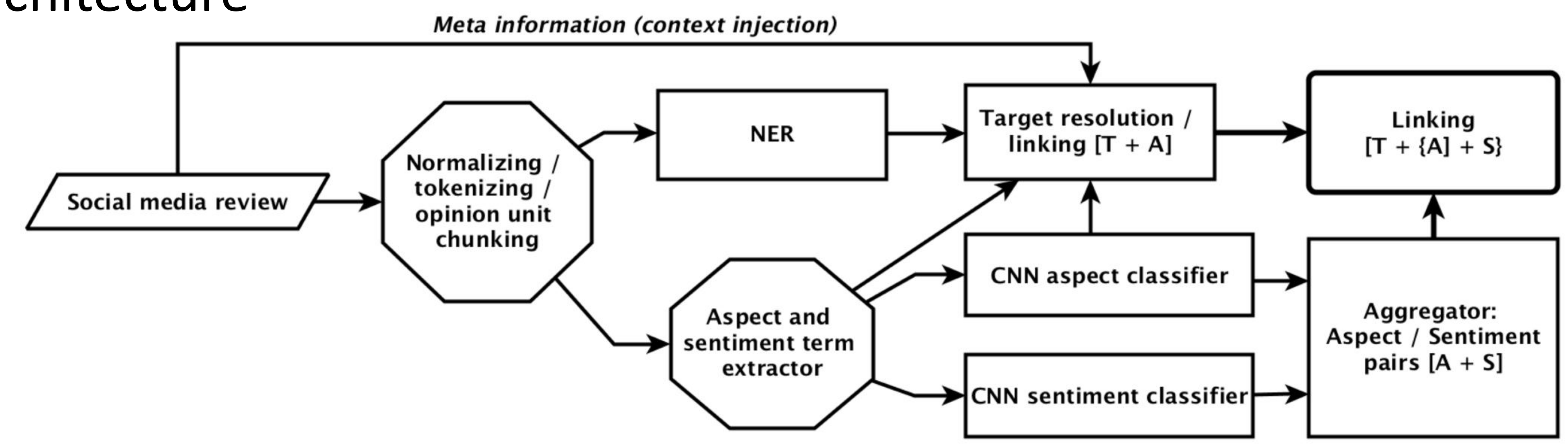
About TABSA

- Targeted Aspect-Based Sentiment Analysis (TABSA) is aimed at classifying aspect-based sentiments towards target entity mentions in a given sentence.
- Several sequential tasks must be solved – identifying entity mentions, resolving aspect categories and classifying sentiment polarities with respect to aspect categories. Different combinations of information extraction, deep learning and natural language processing (NLP) techniques are used for these tasks.
- We propose a TABSA architecture for the Lithuanian language, combining CNN-based classification models and commonsense language knowledge embedded in NLP components.

Architecture



Experiment setup

- Experiments were carried out for university study program sentiment analysis in social media reviews.
- To solve aspect-based sentiment multi-class classification problem, two classifiers with identical CNN architecture were used: one for aspect classification task, and the second - for sentiment classification task. Classifiers were used in two scenarios: S1) Baseline model – simple CNN architecture for multi-class classification with mini-batch size of 256; and S2) Advanced model - CNN consisting of the embedding layer, two 1D convolutional layers, max polling layer, global max pooling layer and two dense layers. Rectified linear unit activation function is used, and the final dense layer uses the Sigmoid activation function.
- We used our own FastText embedding model using our custom Lithuanian review corpus. CNNs were trained on a targeted studies' review corpus, where reviews were labeled by human experts.
- For Target recognition (NER) spaCy's rule-based matcher was utilized where a set of patterns comprise a ruleset. These rules were deducted from the knowledge base.

Methodology

- Our approach handles target recognition and aspect-sentiment learning as separate tasks, sharing aspect classification results and corresponding datasets. Rule-based linking phase is included for aggregating the results of those two tasks at the end of the overall process.
- Entity recognizer consists of two main components: the main logic, consisting of a ruleset and a knowledge base. Entities are recognized and linked throughout multiple phases – candidate entity generation, candidate entity ranking and unlinkable mention prediction.
- For the prediction of aspect and sentiment categories we implement two Convolutional Neural Network (CNN) classifiers using the Keras library with TensorFlow as the backend.
- The results from both Target Recognizer and Aspect-Sentiment Classifier are
- passed over to the Linking component for aggregation, using rule-based techniques and aspect category as the key.

Results

Selected examples

Review	NER	Aspect	Sentiment
Complex sentence (two opinion units, two named entities):			
Opinion unit 1: Šiaip **[university1]** gali pasigirti geresne technika straipsnyje aiškiai parašyta tai *(In general [university1] can be proud of better equipment as stated in the article)*	[university1]	Infrastructure	Positive
Opinion unit 2: [university2] gal kai kurie dėstytojai aukštesnio lygio *(in [university2] maybe some teachers can be considered superior)*	[university1]	Teaching	Negative
Complex sentence (two opinion units, one named entity):			
Opinion unit 1: Šiaip **[university1]** dėstytojai puikūs *(In [university1] teachers are excelent)*	[university1]	Teaching	Positive
Opinion unit 2: bet technika pasenusi *(but the equipment is outdated)*	[injected university1]	Infrastructure	Negative
Non-complex sentence (one opinion unit, one named entity):			
Nieko nesupratau ką dėstė visą semestrą *(didn't understand a single thing they were teaching)*	[injected university1]	Teaching	Negative

Evaluation

	NER	Aspect classifier (S1)	Sentiment classifier (S1)	Aspect classifier (S2)	Sentiment classifier (S2)
Precision	0.66	0.88	0.89	0.89	0.92
Recall	0.76	0.85	0.83	0.86	0.86
Accuracy	83%	93%	91%	94%	93%
F1-score	0.71	0.86	0.85	0.87	0.88

Conclusions

- Scenario S2 with a more complex CNN architecture has shown slightly better results, however, It requires much more computational resources, but, at the same time, much less human expert efforts for resorce preparation.
- For under-resourced language or/and under-resourced domain cases, efficient and high-quality data augmentation technique is needed in both scenarios.
- A TensorFlow friendly combo: tagger and dependency-based parser is of crucial importance for TABSA. Nowadays the best solution is spaCy, but all the implementations for spaCy's Lithuanian support must be retrained for Lithuanian language.