Coreference resolution for Slovene language: draft

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Abstract

Abstract content (to be added later).

1 Introduction

Coreference resolution is a task where the goal is to identify and group together all entity mentions that refer to a common entity in the text. Generally, the task can be thought of as a combination of mention detection and mention clustering and many approaches explicitly perform these two steps when doing coreference resolution. The mention detection step deals with the detection of all entities that refer to some entity in the text. Mention clustering then divides the entities into groups based on the entity they refer to.

In our work, we focus on coreference resolution for Slovene language, which has not been the subject of much research. For our experiments, we use the coref149 dataset (Žitnik and Bajec, 2018), which is a corpus of 149 documents annotated with coreference information. We first introduce the baseline for mention clustering using basic methods of machine learning (linear regression). We then upgrade the process of mention clustering to use neural networks. We evaluate both approaches.

The rest of the paper is structured as follows. In Section 2 we provide an overview of existing approaches to coreference resolution. In Section 3 we describe and evaluate two approaches to coreference resolution, as well as our modifications of them. In Section 4 we provide the results of our work, which we then discuss in Section 5. In Section 6 we summarize our work and provide some possible directions for further research.

2 Related Work

Most coreference resolution systems deal with two tasks: mention detection and mention clustering.

Traditionally, the task of mention detection was performed via analysis of parse trees and the use of heuristics (Attardi et al., 2010). The problem with hand-crafting rules is that they are language-specific and can be hard to define for less-researched languages.

The mention clustering task is where the approaches differ substantially. One approach is to treat it as a binary classification problem, where the goal is to determine whether two mentions are coreferent or not (Soon et al., 2001) (Ng and Cardie, 2002). The problem of this approach is that it treats all coreference candidates independently, so it cannot choose the most probable candidate when multiple valid ones exist. A different way to do mention clustering, which solves this problem, is with mention ranking (Wiseman et al., 2015). In this approach, candidates for coreference are scored in some way and the best scoring candidate is proclaimed as the coreferent mention. The benefit of this approach is that it does not consider candidates in isolation, but rather in comparison to other mentions. An approach which takes this even further is the entity-mention approach (Wiseman et al., 2015). Here, the models are trained to determine whether the currently considered mention belongs to some preceding coreference cluster (Yang et al., 2004). In our work, we make use of the span ranking approach, which is a modification of the mention ranking approach.

Recently, an end-to-end approach to coreference resolution was introduced (Lee et al., 2017), where the two steps are combined and learned together using deep neural networks. This approach considers all spans of tokens up to specific length as candidates for coreference. The spans are then scored in isolation and as mention pairs to produce a final coreference score, which is used in the span ranking coreference resolution framework. Because the approach only considers pairs of mentions when scoring candidates, it can produce globally inconsistent clusters. An approach by Lee et al. (Lee et al., 2018) solves this by iteratively refining the obtained coreference clusters.

The end-to-end approach was further researched and improved upon, for example by using more sophisticated contextualized embeddings (Joshi et al., 2019), but as is the case in most of the other areas in nature language processing, the research is mostly focused on the English language. Some examples of research done for other languages include a Lithuanian rule-based approach (Žitkus et al., 2019) and approaches for Polish (Nitoń et al., 2018) and Basque (Urbizu et al., 2019) that use neural networks.

3 Methods

Todo: in the end

3.1 Baseline model

Our baseline model implements a simple machine learning algorithm (linear regression) for mention clustering that uses Stochastic gradient descent and calculates cross entropy loss function for updating parameters. Data from coref149 is enriched with rules from ssj500k-sl.TEI (Krek et al., 2019) data set and split into training, validation and testing sets. The process of training is repeated for changeable number of epochs.

3.2 Features

Features are used to determine which mentions are referencing the same entity. Choosing the correct features plays a key role in how the end model performs. Features used in our model are mostly derived from the ones used in SkipCor algorithm (Žitnik et al., 2014) and are described in table 1. All features use one hot encoding so the output vector consists of only 1s and 0s.

Feature	Description
string_match	exact match for pronouns or match in lemmas
same_sentence	are both mentions in same sentence
same_gender	one-hot encoded vector for values: same gender, different gender, can't determine
same_number	one-hot encoded vector for values: match in number, don't match in number, can't determine
is_appositive	both mentions have noun-related tag and previous mention is followed by comma
is_alias	one mention is a subset of another
is_prefix	one mention is prefix of another
is_suffix	one mention is suffix of another
is_reflexive	one mention is followed by another that is reflexive pronoun
jaro_winkler_dist	similarity value between two mentions according to Jaro-Winkler metric

Table 1: Features used in our model.

3.3 Evaluation metrics

For model evaluation MUC (Vilain et al., 1995), BCube (Bagga and Baldwin, 1998) and CEAFe (Luo et al., 2004) scores are used. Besides numerical metrics we also use visual representation of predictions, shown in image 1. This helps us understand how our model clusters mentions and what could be improved.

4 Results

Todo: results of baseline model, compared with results from two basic approaches (all in one cluster, every mention in separate cluster) and in the end improved with NN model.

5 Discussion

6 Conclusion

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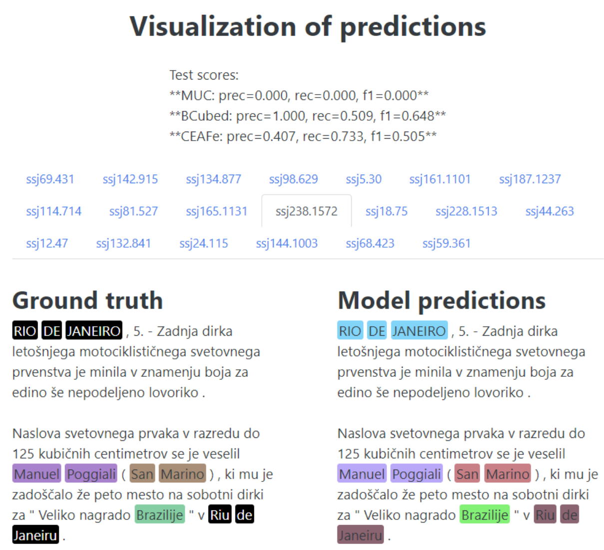

Figure 1: Visual representation of predictions next to ground truth.

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