Marmara Turkish Coreference Corpus and Coreference Resolution Baseline

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Abstract

We describe the Marmara Turkish Coreference Corpus, which is an annotation of the whole METU-Sabanci Turkish Treebank with mentions and coreference chains. Collecting nine or more independent annotations for each document allowed for fully automatic adjudication. We provide a baseline system for Turkish mention detection and coreference resolution and evaluate it on the corpus.

1 Introduction

Coreference Resolution is the task of identifying groups of phrases in a text that refer to the same discourse entity. Such referring phrases are called mentions, a set of mentions that all refer to the same discourse entity is called a chain. Annotated corpora are important resources for developing and evaluating automatic coreference resolution methods.

Turkish is an agglutinative language and Turkish coreference resolution poses several challenges different from many other languages, in particular the absence of grammatical gender, the possibility of null pronouns in subject and object position, possessive pronouns that can be expressed as suffixes, and ambiguities among possessive and number morphemes, e.g., ‘çocuklari’ can be analyzed as ‘their children’ or as ‘his/her children’, depending on context (Oflazer and Bozşahin [1994]).

No coreference resolution corpus exists for Turkish so far. We here describe the result of an effort to create such a corpus based on the METU-Sabanci Turkish Treebank (Atalay et al. 2003; Oflazer...
et al., 2003; Say et al., 2004), which is, to the best of our knowledge, the only publicly available Turkish Treebank.

Our contributions are as follows.

- We describe two stages of annotation: in Phase I, annotators created mentions and chains, which did not yield sufficient inter-annotator agreement. In Phase II, mentions were given to annotators who created only chains. We collected on average more than ten independent annotations per document for each document in the METU-Sabanci Turkish Treebank.

- We describe annotator profiles and adjudication, which was done semi-automatically in Phase I and fully automatically in Phase II. We describe the principles of our automatic adjudication tool which uses a voting-like approach. Such an automatic approach is possible because we collected enough (on average 10) annotations per document.

- We describe the XML format used to address documents, sentences, and tokens in the METU-Sabanci Turkish Treebank. We provide a public version of the corpus as XML, including tools to convert the corpus to CoNLL format. (For licensing reasons we cannot re-publish the Turkish Treebank data.)

- We describe and provide a baseline method for mention detection and coreference resolution, compatible with the format of the corpus. We evaluate this baseline method on the corpus with leave-one-out cross-validation.

Section 2 gives preliminaries of Coreference Resolution and the Turkish language and describes related work. Section 3 explains the annotation and adjudication process and discusses properties of the corpus, annotator profiles, and supporting tools. Section 4 describes the baseline system and its evaluation on the corpus. Section 5 concludes and gives an outlook on future work.

We provide the Marmara Turkish Coreference Corpus, tools, and the baseline system, at https://bitbucket.org/knowlp/marmara-turkish-coreference-corpus.

2 Preliminaries and Related Work

Next we give background and related work on coreference resolution, the Turkish language, and specific challenges of coreference resolution in Turkish.

2.1 Coreference Resolution

Coreference resolution is the task of marking noun phrases that refer to the same discourse entity as coreferent. Mention detection, which identifies such noun phrases, is usually included in that task. Coreference resolution is not limited to resolving pronouns: in computer linguistics it was first introduced as a benchmark for deep semantic understanding of text in the message understanding conference series (Grishman and Sundheim, 1995) and later continued in the Automatic Content Extraction (ACE) program (Doddington et al., 2004) which required English coreference resolution as foundation for all tasks of years 2000–2004. The SemEval competition series followed ACE and featured the first multilingual coreference resolution challenge in 2010 (Recasens et al., 2010). Connected to that is the freely available, large, and multilingual OntoNotes (Hovy et al., 2006) corpus, which was used in the multilingual coreference task in SemEval 2012 (Pradhan et al., 2012) and contains coreference annotations for English, Arabic, and Mandarin (Pradhan et al., 2007).

Coreference resolution has been surveyed by Ng (2010). Approaches are manifold and include machine-learning-based approaches, rule-based systems, and combinations of both. In most machine-learning approaches, equivalence relations of chains (sometimes called clusters) are assembled from predictions of the relatedness of pairs of mentions (mention-mention links). The earliest machine-learning approach is due to Soon et al. (2001), methods for building chains from link predictions include local greedy heuristics as done by Bengtson and Roth (2008) or Stoyanov and Eisner (2012), global optimization formulations such as relaxation labeling (Sapena et al., 2012) or ranking with ILP or Markov Logic (Culotta et al., 2007; Denis and Baldrige, 2009), and representations of trees of mention-mention links (Chang et al., 2013; Fernandes et al., 2012). The first rule-based algorithm for anaphora resolution.
was done by Hobbs (1978). More recent rule-based systems merge chains based on several sets of rules in a multi-stage filtering approach (Lee et al., 2013), moreover there are hybrid systems combining rules and machine learning such as the one by Chen and Ng (2012). Other approaches use curated or distributed knowledge sources such as WordNet, Google distance, and Wikipedia (Poesio et al., 2004; Zheng et al., 2013).

Note that anaphora resolution (Hirst, 1981; Mitkov, 2002) is a problem orthogonal to coreference resolution (van Deemter and Kibble, 2000), because anaphora resolution focuses on referring expressions that point to previous expressions in the text. Cataphora (pointing to later occurrences in the text) are excluded. On the other hand, different from most works on coreference, anaphora resolution includes bound pronouns that do not refer to concrete entities because they are quantified using, e.g., ‘some’ or ‘none’.

2.2 Turkish

Turkish is a member of the family of Altaic languages, it is an agglutinative language where suffixes are attached to a root word. Derivational and inflectional suffixes are very productive (Oflazer, 1993; Oflazer et al., 1994) and are subject to vowel harmony from the root word. Morphological analysis is challenging due to ambiguities between different types of suffixes, for example ‘izin’ can mean ‘your trace’ (iz+P2Sg+Nom), ‘trace’ (iz+Pnon+Gen), or ‘permission’ (izin+Pnon+Nom) (Hakkani-Tür et al., 2002).

The METU-Sabancı Turkish Treebank (in the following just called Turkish Treebank) (Atalay et al., 2003; Oflazer et al., 2003; Say et al., 2004) contains a subset of the METU Turkish Corpus (Say et al., 2004) in tokenized form. Each token is analyzed morphologically and split into inflectional groups (IGs). Sentences are annotated with dependency parse information, where dependencies point to specific IGs within tokens. The Turkish Treebank splits tokens into IGs on derivational boundaries, for example, ‘evimdekiler’ (those in my house) is analyzed (Oflazer et al., 2003) as
ev+Noun+A3sg+P1sg+Loc^DB+Adj^DB+Noun+Zero+A3pl+Pnon+Nom
where ‘DB’ indicates derivation boundaries and the token consists of three IGs ‘evimde’, ‘ki’ (adjectivization), and ‘ler’ (nominalization+plural). A CoNLL format that provides a CoNLL token corresponding to each IG of a token has been created for Turkish dependency parsing (Buchholz and Marsi, 2006).

Named entities in the Turkish Treebank are not marked specially, but multi-word named entities are represented as single tokens.

**Turkish Coreference Resolution.** The following properties of Turkish are in particular relevant for coreference resolution. In the above example, ‘those in my house’ as well as ‘my house’ as well as ‘my’ could be coreferent with mentions in the document. However, neither ‘my house’ nor ‘my’ is available as a separate unit of analysis: both are parts of the first IG (‘evimde’). Gender is not marked in Turkish with the exception of honorifics ‘Bey’ and ‘Hanım’ which corresponds to English ‘Mr’ and ‘Mrs’. Moreover several common first names apply to both genders. Hence gender-based syntactic compatibility checks for mentions are only possible in some cases. Personal pronoun subjects in Turkish are usually realized as suffixes of the verb, e.g., ‘gidiyoruz’ (we are going) and ‘gidiyorlar’ (they are going) but they can also be realized explicitly as in ‘biz gidiyoruz’, depending on discourse conditions (Turan, 1996). Suffixes of proper nouns in written Turkish are systematically separated from the proper nouns using a single quote, e.g., ‘Türkiye’den’ (from Turkey) and ‘Türkiye’deki’ (the thing in Turkey). This systematic rule simplifies finding equal proper noun mentions in coreference resolution for Turkish.

Most works about referring expressions in Turkish focus on anaphora resolution and not on full coreference resolution. One exception is the work of Küçük and Yazıcı (2008) on political news texts extracted from videos: they focus on Gazetteers for extracting mentions (without considering general NPs or syntactic information), provide a rule-based heuristic based on recency for creating coreference chains, and evaluate their approach on three documents (which are not part of the Turkish Treebank).

In the following we describe work on Turkish anaphora resolution, which is related to coreference resolution.
Turkish Anaphora Resolution. Erkan and Akman (1998) describe an implementation of pronoun anaphora resolution in a framework for situation theory which is based on knowledge representation and logical reasoning. Hobbs’s naïve pronoun resolution algorithm (Hobbs 1978) was realized for Turkish and tested on 10 toy sentences (Tüfekçi and Kılıçaslan 2007).

Centering theory (Grosz et al. 1995) is the foundation of several works on Turkish pronouns. Turan (1996) performed a study about discourse conditions for referring vs. nonreferring expressions and null vs. overt pronouns, and evaluated the theory on 2500 annotated tokens. Yüksel and Bozsahin (2002) created a system for generating referring expressions that was tested on a machine translation task. Furthermore, there is a theoretical model of anaphora resolution based on centering theory by Yıldırım et al. (2004).

Küçük and Yöndem (2007) described a system for finding and resolving Turkish pronominal anaphora and annotated 12266 anaphor candidate instances in the METU Turkish Corpus to evaluate their candidate extractor and decision tree learner for anaphora resolution. Kılıçaslan et al. (2009) performed a comprehensive study on pronoun resolution and evaluated various machine learning methods for resolving overt and null pronouns in a corpus of 20 children stories.

3 Marmara Turkish Coreference Corpus

We next describe the annotation and adjudication process including formal adjudication criteria, key properties of the resulting corpus, and supporting tools.

3.1 Annotation Process

Figure 1 visualizes the process that led to the final corpus. Annotations were collected in two phases: Phase I took place in October–December 2015 and Phase II during October–December 2016.

Annotations were collected from computer engineering students participating in a lecture on natural language processing, after educating them in basic linguistic analysis and coreference resolution. To achieve reasonable annotation quality, we aimed to keep annotation simple and therefore based it on few principles and examples. We designed an annotation manual (Sürmeli et al. 2016) for marking coreference according to the following principles:

- all concrete entities that are mentioned more than once shall be annotated,
- mentions shall be marked as the biggest possible span of tokens that describes the entity,
- lists shall not be annotated (elements of lists can be annotated), and
Table 1: Key metrics about corpus and inter-annotator agreement per genre and overall. Doc is the number of documents, Ann the number of annotations received, IAA1 and IAA2 are inter-annotator agreements, Tok and CM indicate the number of tokens and given mentions, AM and AC show the number of received mentions and chains, and Ph1 indicates how many documents were annotated in both annotation phases. Columns Doc through CM and Ph1 are accumulated over documents, while AM and AC are accumulated over annotations.

| Genre         | Doc # | Ann # | IAA1 % | IAA2 % | Tok # | CM # | AM # | AC # | Ph1 # |
|---------------|-------|-------|--------|--------|-------|------|------|------|-------|
| News          | 9     | 10.2  | 87     | 94     | 1324  | 139  | 126  | 35   | 2     |
| Short Story   | 8     | 10.1  | 64     | 84     | 1540  | 170  | 164  | 23   | 5     |
| Novel         | 7     | 10.4  | 67     | 87     | 1798  | 183  | 176  | 22   | 5     |
| Essay         | 2     | 9.5   | 85     | 93     | 2058  | 92   | 87   | 28   | 2     |
| Research Monogr. | 2 | 10.5  | 72     | 89     | 2020  | 182  | 179  | 27   | 2     |
| Article       | 3     | 10.7  | 90     | 96     | 1506  | 121  | 120  | 32   | 3     |
| Travel        | 1     | 11.0  | 79     | 92     | 2142  | 178  | 173  | 44   | 1     |
| Other         | 1     | 10.0  | 62     | 83     | 2284  | 201  | 275  | 44   | 1     |
| Overall       | 33    | 10.3  | 76     | 90     | 1634  | 160  | 152  | 29   | 21    |

- predication shall not be annotated.

Note that, by marking mentions as the biggest spans, mentions and potentially available appositives are annotated as single mentions, which is different from OntoNotes where appositives are a special type of coreference annotation. We do not mark predications because they are a different type of coreference as argued by van Deemter and Kibble (2000).

In Phase I, annotations were created by 19 annotators with the GATE (Cunningham et al., 2013; Gaizauskas et al., 1996) coreference annotation tool. This yielded on average 6.5 annotations per document for 21 documents in the Treebank. Adjudication of these documents was done semi-automatically (see Sections 3.2 and 3.4). However, due to low inter-annotator agreement about mention boundaries, decisions often depended on the adjudicator. Therefore, in order to make the setting simpler, we decided to collect more annotations with given mentions. We used the list of mentions resulting from the adjudicated documents of Phase I. Mentions for those 12 documents that were not annotated in Phase I were manually created in a collaboration of two annotators for each document.

In Phase II, 46 annotators were given CoNLL files with token and coreference columns where each mention was given in its own chain. Annotators created files with equalities between chain IDs and uploaded these files to a web service where they were checked for syntactical correctness. The submission file format is described in (Sürmeli et al., 2016). Phase II yielded 339 individual annotations of sufficient inter-annotator agreement to perform fully automatic adjudication (see next section).

This method of collecting annotation as text files might seem archaic, however, in practice, annotators were more comfortable with such a system than with the graphical user interface of GATE in Phase I. We were not able to use the BRAT (Stenetorp et al., 2012) annotation tool, because of difficulties representing sentence and word addresses in a way that they can be extracted from annotations.

3.2 Adjudication

Table 1 shows key properties of the annotated corpus including inter-annotator agreement. Statistics are accumulated per genre as well as over the whole corpus. Coreference IAA scores IAA1 and IAA2 are calculated as described in (Passonneau, 2004) and (Passonneau et al., 2006), respectively. IAA1 is an adaption of Krippendorff’s α (Krippendorff, 1980) where a pair of chains gets a score of 1 for a perfect match, 2/3 if one chain is a subset of the other one, 1/3 if they are intersecting, and 0 otherwise. (Krippendorff’s α assigns 1 for a perfect match and 0 in all other cases.) IAA2 uses Jaccard distance instead of fixed scores for the above cases, which provides more realistic results if chains have heterogeneous sizes. (This is often the case in coreference corpora.) Over all documents, IAA1 is 76% and IAA2 is 90%. We observe
worse IAA for genres that are based on writing as an art form, i.e., for short stories, novels, and the Other genre (a first-person narrative).

The amount of annotations per document, combined with the observed IAA, allows us to automatically adjudicate the corpus. This is different from other coreference annotations, in particular in OntoNotes, where two annotators created annotations followed by adjudication done by a single human expert (Weischedel et al., 2012). Automatic adjudication is based on combinatorial optimization, where we search for a solution of chains that has overall minimal divergence from all annotator inputs. Divergence is measured in terms of mention-mention links given and omitted by annotators.

Formally, given a set \( M \) of mentions in a document, a chain is a subset of these mentions, and \( k \) annotators produce annotations (sets of chains that are nonintersecting) \( A_1, \ldots, A_k \) over \( M \). A solution \( G \) is also a set of chains over \( M \) and we search for \( G \) such that the following objective becomes minimal:

\[
\sum_{m, m' \in M, i \in \{1, \ldots, k\}} 2 \cdot a(m, m', A_i) \cdot na(m, m', G) + na(m, m', A_i) \cdot a(m, m', G)
\]  

where \( a(\cdot \cdot \cdot) \) is an indicator function for mentions in the same chain within an annotation \( A \), formally

\[
a(m, m', A) = \begin{cases} 1 & \text{if there is a chain } C \in A \text{ with } \{m, m'\} \subseteq C \\ 0 & \text{otherwise} \end{cases}
\]

and \( na(\cdot \cdot \cdot) \) is an indicator for mention pairs that are not in the same chain in an annotation \( A \):

\[
a(m_1, m_2, A) = 1 - a(m_1, m_2, A).
\]

Objective (1) incurs a cost of \( 2j \) for each mention pair that is not in the same chain in the solution \( G \) contrary to the opinion of \( j \) annotators. Moreover, (1) incurs a cost of \( l \) for each mention-pair that is in the same chain in \( G \) contrary to the opinion of \( l \) annotators. This makes optimal solutions ignore as little as possible information from annotators. The coefficient 2 has the effect, that not annotating a mention to be in some chain has less weight than annotating a mention as part of some chain. We introduced this preference into the objective, because not annotating some mention can be due to an oversight, while putting a mention into a chain is more likely done intentionally.

Note that, if annotators produce different sets of mentions, we can build \( M \) from the union of all mentions produced by annotators with unused mentions becoming singleton partitions. We describe practical issues of our adjudication tool in Section 3.4.

3.3 Corpus Properties and Annotator Profiles

Table 1 shows key properties of the annotated corpus, accumulated over genres and overall figures. Average number of tokens and mentions per genre varies a lot. In particular, the Essay genre contains texts discussing abstract concepts like ‘home’ and ‘science’ which are not annotated. The narrative in genre Other contains many person names which are repeatedly mentioned.

Column Ph1 indicates how many of the documents were annotated in both phases of the annotation process. For example the News genre contains 9 documents. Mentions of 2 News documents were obtained from Phase I, the others from Phase II (see Figure 1). We observe better IAA values for Phase II than for Phase I (not shown in table). This might be due to the high ratio of documents from genre News (7 out of 12) in Phase II, because we observed that IAA for News is higher than in other genres, independent from the annotation phase.

By comparing column CM (given mentions) and AM (annotated mentions) we see that annotators rarely use all mentions in the annotated chains. To reduce the chance that these mentions were omitted due to an oversight, the annotation submission system indicated which mentions were left unused.

Annotator Profiles. Anonymized learner profiles were collected from all students in Phase II (written permission for using and publishing the data was also obtained). Learner profiles include age, gender, native language, languages spoken at home, in primary and secondary school, foreign language knowledge, and the number of years the annotator spent in Turkish-speaking communities.

Annotators are on average 23 years old university students at Marmara University in Istanbul. Annotations were done after basic introduction to linguistics and coreference resolution and after discussing the annotation manual (Sürmeli et al., 2016).
Out of 46 annotators, 29 are male and 17 are female. One annotator indicated Azerbaijani as a native language, all others indicated Turkish as one of their native languages. (Azerbaijani is close to Turkish.) Two annotators indicated Kurdish as further native language, and one each Arabic, English, and Macedonian. Primary and secondary school education was Turkish for 43 annotators, English for two and Azerbaijani for one. Moreover 43 annotators lived at least 20 years in predominantly Turkish-speaking communities, the remaining annotators answered 4, 5, and 14 years, respectively, for this question.

According to this data we consider our annotators to be capable of understanding and annotating the texts in the corpus.

3.4 Tools

For creating this corpus, we built several tools.

**Document Extractor.** The METU-Sabancı Turkish Treebank contains 1960 text fragments, distributed over 33 documents. Most documents are split over several XML files, however there is also one XML file containing two distinct documents. We provide a tool for extracting documents from the Turkish Treebank and store each document in a single XML file. The Turkish Treebank is licensed in a way that it cannot be redistributed with the Marmara Turkish Coreference Corpus, therefore the tool generates document files from a directory containing the unpacked Turkish Treebank. Our tool not only creates one XML file for each document, it also recodes all data to UTF-8 and fixes problematic (non-encoded) attributes that are present in the original corpus.

**Coreference XML Format.** For representing coreference information we created an XML format that contains pointers to sentence and word IDs into documents extracted from the Turkish Treebank. A sample of such an XML file with two mentions and one chain is as follows.

```
<coref>
  <mentions>
    <mention fromWordIX="1" id="0" sentenceNo="00016112313.1" toWordIX="1">Prof._Dr._Semih_Koray’ın</mention>
    <mention fromWordIX="1" id="2" sentenceNo="00016112313.2" toWordIX="1">Koray</mention>
  </mentions>
  <chains>
    <chain>
      <mention mentionId="0">Prof._Dr._Semih_Koray’ın</mention>
      <mention mentionId="2">Koray</mention>
    </chain>
  </chains>
</coref>
```

In this example, ‘Prof._Dr._Semih_Koray’ın’ is a mention with ID 0 containing token 1 (called ‘word’ in the Treebank) in sentence ‘00016112313.1’ of the document assembled from the Treebank. Moreover there is a chain containing that mention and another mention in the first token of sentence ‘00016112313.2’.

Note that the actual text within mentions is only for readability purposes, the information about mention content is fully represented in attributes.

**CoNLL ⇔ XML Converters.** As the CoNLL reference coreference scorer [Pradhan et al., 2014] is based on CoNLL format, we provide tools for converting a document and a coreference XML file into a CoNLL file (and vice versa). CoNLL format is also more readable than XML Format for humans. We use XML to be consistent with the Turkish Treebank and because the Treebank license prevents redistribution.
(Semi-)automatic coreference adjudication tool. Merging several distinct coreference annotations into a single gold standard is a complex task, in particular if annotators do not agree on mentions. To simplify this task we created a tool that merges multiple annotations into a single solution according to objective 1 from Section 3.2. Manual intervention for editing mentions and chains is also possible, details about a preliminary (Phase I) version of the tool is described by Schüller (2016). Note that, in Phase II we performed only automatic adjudication and did not need manual intervention.

For the purpose of this project, it was sufficient to use our tool directly on CoNLL files without a GUI. In the future, to make the tool accessible to a wider part of the community, we consider integrating it into an existing software, for example BART (Broscheit et al. 2010).

4 Baseline

We have created a baseline for mention detection, based on the work of Sapena et al. (2012), and for coreference resolution, inspired by Bengtson and Roth (2008). The baseline is based on Python and scikit-learn (Pedregosa et al. 2011). We considered to integrate also the Named Entity Recognition (NER) module of the ITU-pipeline (Eryiğit 2014) because NER is not annotated in the Turkish Treebank, however we found that the output the web service changed significantly several times during the development of the baseline. To facilitate reproducibility of results we decided to create a stand-alone baseline that allows reproducing our results using only the METU-Sabanci Turkish Treebank (Say et al. 2004) and scikit-learn.

Mention Detection. Our Mention Detection baseline marks all

(i) noun phrases,

(ii) pronouns, and

(iii) capitalized common nouns or proper names that occur two or more times in the document as mentions, similar to the approach of Sapena et al. (2012) for English.

Coreference Resolution. Our Coreference Resolution baseline is inspired by the work of Bengtson and Roth (2008) who describe a simple method with reasonable accuracy and without the need for custom machine learning models and algorithms that are specific to coreference resolution.

As input the baseline uses a set of candidate mentions (either gold or predicted), furthermore lemma and dependency parsing information for obtaining mention heads, as available in the Turkish Treebank. The type of a mention is marked as pronoun if the lemma of the head is one of ben, sen, biz, siz, bu, şu, o, bura, şura, ora, kendi, birbiri. To separate proper noun from noun phrase mention types, we realized our own heuristic which (i) collects all uppercase tokens not at sentence-initial position, (ii) strips case markers, and (iii) uses the resulting set of strings to mark all (including sentence-initial) tokens as proper nouns. All remaining mentions obtain the type noun phrase.

Based on mention types and head information we create the following features for each mention-mention pair \((m_1, m_2)\):

(i) type of \(m_1\) and type of \(m_2\) (2 features),

(ii) both mentions are pronouns, proper nouns, or noun phrases (3 features),

(iii) heads of \(m_1\) and \(m_2\) match, and the same for head lemmas (2 features),

(iv) last part of name is equal in \(m_1\) and \(m_2\), and

(v) \(m_1\) is an acronym of \(m_2\),

(vi) head of \(m_1\) is a substring of head of \(m_2\), and the same for head lemmas (2 features),

(vii) \(m_1\) is an acronym of \(m_2\).
| Genre        | $R_{MD}$ | $P_{MD}$ | MUC  | $B^3$ | CEAF$_e$ | CEAF$_m$ | BLANC |
|--------------|----------|----------|------|-------|----------|----------|-------|
| News         | 82.6     | 14.7     | 81.1 | 74.9  | 71.8     | 73.2     | 72.3  |
| Short Story  | 89.6     | 22.0     | 77.4 | 55.5  | 57.2     | 56.6     | 60.7  |
| Novel        | 84.0     | 19.9     | 79.0 | 56.0  | 51.2     | 55.4     | 61.7  |
| Essay        | 85.7     | 7.1      | 76.1 | 70.4  | 66.8     | 67.1     | 63.4  |
| Research.M   | 76.5     | 13.4     | 76.5 | 56.0  | 51.8     | 55.6     | 62.8  |
| Article      | 71.4     | 11.6     | 78.1 | 70.7  | 68.7     | 70.6     | 68.6  |
| Travel       | 71.4     | 10.5     | 66.1 | 57.6  | 55.2     | 55.3     | 52.6  |
| Other        | 89.6     | 23.9     | 72.1 | 47.7  | 46.6     | 45.6     | 50.9  |
| Total        | 83.2     | 16.9     | 77.8 | 62.1  | 59.7     | 61.4     | 63.8  |

Table 2: Evaluation of baseline by genres: $R_{MD}$ and $P_{MD}$ show recall and precision for mention detection, other columns show F1 scores of the respective metrics for coreference resolution on gold mentions using linear SVC all-links method. Accumulations are averages weighted by document size (\# tokens).

Features (v)–(vii) are asymmetric, that means exchanging $m_1$ and $m_2$ can change the feature value. For these features we also add the respective reverse direction feature, as well as the disjunction of features of both directions. Moreover we add all possible pairs of features (i)–(ii) and (iii)–(vii) to allow the machine learning to give separate weight to features (iii)–(vii) per mention type.

We implemented two machine learning methods for predicting coreference based on classification (SVC) and regression (SVR).

SVC is based on classification with a linear-kernel SVM [Corinna Cortes and Vapnik 1995]. Positive examples are mentions and their closest predecessors within all chains, while negative examples are all mention pairs that are not in the same chain with less than 100 mentions distance. For predicting chains, we first generate candidate mention pairs for all mentions except for noun phrases with pronoun predecessor, then we predict whether they are in the same chain using the SVM. Finally, each mention starts in its own chain and we go through mentions from the beginning of the document to the end, and merge mentions to (potentially several) previous chains for all predicted mention-mention links. We prevent merges that lead to chains with overlapping mentions.

SVR is based on support vector regression with a linear-kernel SVM [Drucker et al. 1997] trained on the same examples as SVC. For prediction we generate the same candidate mentions as in SVC. For building chains we also start with one chain per mention, but this time we use the Best-Link [Bengtson and Roth 2008] strategy: we iterate over mentions in order of occurrence in the document, and merge each mention with at most one predecessor chain if its highest-scored candidate link to a predecessor mention is above 0.1 and if the resulting chain does not contain overlapping mentions.

In addition to the above, when predicting coreference on predicted mentions, we include incorrect mentions predicted on the training documents to generate negative examples. We randomly sample at most as many incorrect mentions as already contained in the gold annotation. When predicting coreference on gold mentions, we train only on gold mentions. We balance example weight by class size (we have significantly more negative examples), and we use L2 regularization for both SVC and SVR.

### 4.1 Evaluation

We evaluate our baseline using the CoNLL reference coreference scorer [Pradhan et al. 2014] and report MUC, $B^3$, CEAF$_m$, CEAF$_e$, and BLANC scores. Intuitively, MUC [Vilain et al. 1995] computes precision and recall of mention-mention links over all gold chains compared with all predicted chains. $B^3$ [Bagga and Baldwin 1998] computes precision and recall over each individual mention which makes the score also applicable to singleton mentions. CEAF$_m$ [Luo 2005] creates an optimal matching between predicted and gold mentions and evaluates the percentage of mentions correctly assigned to chains, while CEAF$_e$ does the same from the perspective of chains. BLANC [Recasens and Hovy 2010] gives equal importance to mention-mention links and non-existing mention-mention links, without the need to consider per-mention or per-chain score accumulations.

In the following we compute scores per document and accumulate them into overall and genre-based scores using the number of tokens in each document as weight. Mention detection is done on the Turkish
Table 3: Evaluation of our baseline using support vector machine classification (SVC) and regression (SVR) on gold (GM) and predicted mentions (PM). Scores are F1 scores, averages are again weighted by document size, best/worst rows are over single documents. SVC on PM is not applicable (see text).

| Method  | Accumulation | MUC | B$^3$ | CEAF$_e$ | CEAF$_m$ | BLANC |
|---------|--------------|-----|-------|----------|----------|-------|
| SVC/GM  | average      | 77.8| 62.1  | 59.8     | 61.4     | 63.8  |
|         | best         | 92.3| 89.8  | 88.5     | 90.4     | 88.1  |
|         | worst        | 61.8| 39.6  | 37.2     | 45.2     | 45.0  |
| SVR/GM  | average      | 75.0| 60.6  | 60.5     | 61.3     | 61.7  |
|         | best         | 92.4| 90.0  | 89.2     | 90.8     | 87.8  |
|         | worst        | 60.6| 36.3  | 39.5     | 42.6     | 38.9  |
| SVR/PM  | average      | 32.2| 23.3  | 17.2     | 24.7     | 18.1  |
|         | best         | 55.0| 35.7  | 31.2     | 37.9     | 33.5  |
|         | worst        | 7.6 | 8.5   | 9.9      | 9.3      | 1.4   |

Table 3 shows baseline results for mention detection and coreference with SVC on gold mentions. We obtain 83.2% recall for mention detection over the whole Treebank. As expected and as intended, precision is much worse because we expect the coreference resolution step to eliminate spurious mentions. Coreference resolution yields a MUC score of 77.8%, while the stricter B$^3$, CEAF, and BLANC scores are lower. The worst scores for BLANC, MUC, and CEAF$_m$ are obtained from genres Travel and Other, which is logical because these genres contain only one document each. Hence, in cross-validation, the training set contains only documents from other genres.

Table 3 shows results for the best and worst document in the corpus, and overall average of scores for SVC, SVR on gold mentions and SVR on predicted mentions. Average is again weighted by document size. SVC on gold mentions is the same setup as in Table 2. For comparison we show again the average score, and additionally the best and worst score obtained from a single document. Using SVR on gold mentions yields scores similar to SVC except for BLANC where the worst document is 6.1% worse than with SVM. On predicted mentions, SVC puts nearly all mentions into a single chain, which yields reasonable MUC score but low other scores. Therefore, we omit SVC results on predicted mentions from the table, and show only results for SVR which has the systematic advantage of selecting only the best link. Naturally, coreference prediction on predicted mentions yields significantly worse results than on gold mentions, with an average MUC score of 32.2% and an average BLANC score of 18.1%. The document producing the worst BLANC score of 1.4% is a scientific article about the meaning of the word ‘home’, which is a text that contains mainly abstract examples about the animal world, hence the score is not surprising. The best BLANC score on predicted mentions is obtained from a story about street children which is about concrete events and individuals.

As this is only a baseline, we did not include more sophisticated features described in Bengtson and Roth [2008]. For example, semantic features based on WordNet [Bilgin et al. 2004; Miller 1995] could rule out certain predicted mentions as relevant and thus could improve precision of the baseline.

5 Conclusion

The Turkish coreference corpus and the Turkish coreference resolution baseline are a starting point for further research.

Annotations on the token level have the consequence that coreference between morphemes and other tokens (or morphemes) cannot be annotated. While such coreference annotations are desirable, we decided to reduce the complexity of the annotation task by omitting such coreference links and by presenting tokens without morphological analysis to annotators. For future annotation projects it could be interesting to extend annotations to include morpheme coreference links. Scoring with the reference
scorer tool would require development of a novel CoNLL representation for tokens that are split within IGs. If this representation is not used for annotation, development of a tool for such annotations is also necessary. We think this would also require annotators with a higher level of expertise than available for our study.

As the only pronoun anaphora annotations [Küçük and Yöndem 2007] that were done on the METU-Sabancı Turkish Treebank can no longer be found by the authors (personal communication), we have no possibility of validating the annotations performed in our annotation project.

To improve the mention detection baseline, information about appositives as well as finding a way to filter out generic mentions could be useful. To improve the coreference resolution baseline, adding more complex features by integrating Turkish WordNet (Bilgin et al. 2004), Turkish NER (Şeker and Eryiğit 2012), and Turkish WSD (İlgen et al. 2012) could be helpful. For a full processing pipeline from plain text to coreference annotations, we need at least morphological analysis (Sak et al. 2007), disambiguation (Sak et al. 2007), and dependency parsing (Eryiğit et al. 2008). Available tools are the ITU-pipeline (Eryiğit 2014) and the older Zemberek system (Akın and Akın 2007).

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