Extracting Family Relationship Networks from Novels

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Abstract

We present an approach to the extraction of family relations from literary narrative, which incorporates a technique for utterance attribution proposed recently by Elson and McKeown (2010). In our work this technique is used in combination with the detection of vocatives — the explicit forms of address used by the characters in a novel. We take advantage of the fact that certain vocatives indicate family relations between speakers. The extracted relations are then propagated using a set of rules. We report the results of the application of our method to Jane Austen’s Pride and Prejudice.

1 Introduction

Relationships between characters can be viewed as both the basis of the narrative as they become established and dynamics of it as they evolve. In this respect family relations are naturally established and relatively stable phenomena. Automated extraction of such relations can assist literary analysis by providing basic facts for further reasoning on the story. In the present work we address the problem of extracting family relations from English narrative.

Relation extraction has been studied in depth over the past two decades, and there is a number of existing approaches to the problem. Among others Open Information Extraction approach (Banko et al., 2007) seems appealing due to the unsupervised nature of the method and the availability of readily applicable tools. We have experimented with one of such tools, namely, ReVerb (Fader et al., 2011), a state of the art Open IE system. Using the tool with the default settings, we have extracted a lot of relations from Jane Austen’s Pride and Prejudice. However, none of those were family relations between two characters of the novel. Apart from giving a rough estimate on the difficulty of the addressed problem, this fact also suggests that the domain-specific approaches may be of better use.

Traditionally, computer assisted literary analysis has focused on the word-level methods. Techniques based on distinguishing word usage have been successfully applied to the tasks of the authorship attribution (Mostellar and Wallace, 1984), and the inference of authorial writing style (Burrows, 2004). However, an analysis of character interactions may require a different level of sophistication. In this respect, techniques for attributing utterances to literary characters have been applied to conduct an automated evaluation of different literary hypotheses (Elson et al., 2010).

Our method extracts family relations from a narrative combining word level techniques with utterance attribution approach. We regard verbal interactions between characters as candidate relations, and speakers themselves as their potential arguments. In order to extract the arguments of candidate relations we attribute all utterances. Here by a vocative we mean a verbal address in a conversation. Speakers may address each other by name (named vocative), or may use phrases

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such as My dear sister (nominal vocative). Nominal vocatives may express sympathy, respect and, importantly, the family relation between a speaker and an intended listener. We will refer to nominal vocatives simply as vocatives, and to utterances containing a vocative as vocative utterances.

The intuition behind our approach is to infer family relations from nominal vocatives. For instance, if in a conversation a speaker addresses someone as mother, we can infer a mother of relation between the speaker and an intended listener. In a dialog scenario such a listener, typically is a speaker of the previous or the following utterance. We refer to the relations extracted in a described manner as seed relations or seeds. As the final step our method infers new relations from the extracted seeds by applying a set of well defined propagation rules, e.g. two female characters with a common mother and/or father are considered sisters. Our results suggest that this technique trades recall over precision with a positive increase in F-measure.

The structure of the paper is as follows. We discuss the related work in Section 2. In Section 3 we thoroughly describe our method. Section 4 outlines the properties of our data set. We present and analyze the results in Section 5. Section 6 discusses possible directions for future work.

2 Related Work

Relation extraction has been studied in depth over considerably long time in different domains and on different scales. Most of the effort traditionally was concentrated on developing Open RE systems (Banko et al., 2007; Fader et al., 2011), that could easily scale on Web size corpora, and required no labeled data or predefined set of relation categories. Therefore it is hard to point out works concerned specifically with extracting family relations from literary fiction. Recently, however, there has been some research in this direction.

Santos et al. (2010) develop a rule based approach towards extracting family relations from Portuguese narrative. The authors develop 99 rules including some propagation rules and combine them with NER and anaphora resolution systems. The work has been evaluated on two corpora: bibliographical texts and a collection of sentences. For both corpora the authors report close results with .71 precision and .24 recall under the best settings.

Kokkinakis and Malm (2011) develop an unsupervised approach to the extraction of interpersonal relations, including family. The method relies on co-occurrences of character names in same sentences. Such co-occurrences are labeled as relations using context similarity and on-line lists of common relations. The authors evaluate the method on three volumes of Swedish XIX century fiction, and report precision in the range of 91%-100% and recall in the range of 70%-75% under the best settings. Although the reported results include different types of relations, results on the extraction of family relations were not reported.

In contrast to the aforementioned works, our method utilizes utterance attribution and vocative detection techniques, and employs propagation to infer implicit family relations.

3 Extracting Family Relations

Our method consists of the following four steps:

1. Utterance attribution: attribute each utterance to one of the characters.
2. Vocatives detection: identify vocative utterances.
3. Relation extraction: extract relations between the speakers and the characters they address.
4. Relation propagation: derive new relations between indirectly related characters.

In the following subsections we discuss each of the steps in details.

3.1 Utterance Attribution

The cornerstone of our approach is the utterance attribution (UA) method. In the present work, we employ the UA method of Elson and McKeown (2010). Before describing the method we give some basic definitions.

- Utterance - A span of narrative enclosed in quotation marks. Quoted words, phrases, aphorisms, and other instances of indirect speech enclosed in quotations are left without attribution as they are considered non speaker utterances.
• **Character mention** - a named entity of the *person* class or a *nominal*. Nominals consist of a determiner and a head noun. Determiners include articles, ordinal and cardinal numbers as well as possessives (*her mother, Elizabeth’s sister*)\(^1\).

• **Speaker** - a character mention to whom certain utterance is attributed.

The method is a mixture of the heuristic and supervised approaches: based on a category an utterance is either immediately attributed, using context and dialog chain information (heuristic), or a feature vector is created per each candidate speaker found in the close proximity to an utterance and fed to trained classifiers (supervised). The method attributes each utterance to one of the following six categories:

1. **Character trigram.** Utterances followed or preceded by a character mention and an expression verb\(^2\) (in any order) fall under this category. Such an utterance is attributed to a respective character mention.

2. **Added quote.** An utterance that immediately follows another one in a paragraph belongs to this category, and is attributed to the speaker of the preceding utterance.

3. **Quote alone.** An utterance appears by itself in a paragraph. The attribution requires a supervised approach.

4. **Apparent conversation.** This category is designed to account for dialog chains, where two characters speak taking turns. To fall under this category an utterance must fall under “Quote alone” category and two previous paragraphs must begin with utterances and contain only one utterance each. The speaker of the first of the two preceding utterances is assigned to the current one.

5. **Anaphora.** This category is the same as the “Character trigram”, but instead of character mentions pronouns are treated as possible candidates. An utterance is attributed based on a supervised approach. Basically, classifiers try to perform anaphora resolution given a set of candidate speakers.

6. **Backoff.** An utterance is assigned this category if it does not fall under any other. The attribution requires a supervised approach.

If an utterance cannot be attributed heuristically a supervised approach is considered. To this end, for each candidate-utterance pair a feature vector is extracted. Features include various quantitative (e.g. a number of appearances of a speaker, a length of an utterance, etc.) and qualitative (e.g. presence and type of punctuation and verbs surrounding an utterance, etc.) characteristics\(^3\). As in the original work, for classification we used J48, JRip, and Logistic Regression classifiers as provided by Weka (Hall et al., 2009) and performed a standard 10 fold cross validation. The predictions generated per each candidate are ranked in the following ways:

1. Label based ranking simply predicts a candidate positively labeled by a classifier. If more than one candidate is labeled positively all candidates are rejected.

2. Single probability based ranking uses probabilities supplied by a classifier and predicts the candidate with the highest probability. If all probabilities fall below a certain threshold, all candidates are rejected. The threshold is varied as a parameter.

3. Hybrid method first tries the label based ranking and if all candidates are rejected the method employs the probability based ranking.

4. The final ranking method works exactly as the single probability method except it combines probabilities provided by different classifiers in different ways (max, mean, median, product).

\[^1\]In the original work the list of head nouns is compiled using the development corpus. It includes nouns that have words *person, man or woman* among the hypernyms of the first two WordNet senses (Fellbaum, 1998).

\[^2\]A verb whose WordNet lexical file is categorized as communication or cognition.

\[^3\]A complete and thoroughly described list of features can be found in the original work. (Elson and McKeown, 2010).
It is important to note that when attributing speakers to utterances in “Added quote” and “Apparent conversation” categories Elson and McKeown (2010) utilize the ground truth information about the speakers of the preceding utterances. The authors explain such a behavior as an attempt to escape possible propagation errors that would occur if preceding utterances were incorrectly attributed. We adopt this approach and also rely on the ground truth.

3.2 Vocative Detection
Once we have attributed all utterances, we need to detect vocatives. We first define target nominals, i.e. nouns that describe family relations. A list of basic family relations is shown in Table 1. We further extend it by including WordNet synonyms and hypernyms for each nominal to have a total of 635 target nominals. Having the list ready, we proceed to select candidate utterances for the vocative detection task. An utterance is considered a candidate if it contains at least one target nominal.

For the detection task we tried both unsupervised and supervised methods. The unsupervised method predicts a vocative utterance if a candidate matches the following pattern: \(<P\ my\ dear(est)\ T\ P>\). Here T stands for the target nominal and P denotes punctuation marks. We consider all punctuation marks commonly used, including quotations. The occurrence of words “my” and “dear(est)” is optional.

Our supervised method is the extended version of the approach proposed by He (2011). The method extracts a feature vector per each occurrence of a target nominal in a given candidate utterance. We use the following set of binary features:

- **Lexical features.** Whether words “my” and “dear(est)” precede a nominal either by themselves or in combination. Whether a nominal is preceded or followed (ignoring punctuation) by the word “you”, Whether the word “oh” appears anywhere before a nominal in an utterance. Whether the words “you” or “my dear” appear in an utterance regardless of the distance and direction towards a nominal.

- **Punctuation.** Whether a comma, period, question or exclamation marks appear immediately to the right (ignoring spaces) of a nominal. Whether a nominal is surrounded by commas or by any other punctuation marks, including quotations.

- **Positional and other features.** Whether a nominal is found in the beginning or the end of an utterance. Whether a nominal occurs more than once in an utterance.

To generate the predictions we manually label extracted feature vectors and perform a standard 10 fold cross validation.

3.3 Relation Extraction
Once we have identified vocative utterances we proceed with the relation extraction. We extract relations in the form of a standard (A1, R, A2) triple, where A1 and A2 denote the arguments of a relation, and R denotes the relation itself. From a given vocative utterance we can immediately recover the relation, which is the vocative itself, e.g. mother, son, etc. Moreover, the speaker assigned to the utterance becomes the second argument of the relation. So, the main challenge is to extract the first argument of the relation, or, in other words, is to identify a recipient to whom a vocative was addressed.

Given an utterance we have up to two potential recipients of the vocative: the speakers of the preceding and the following utterances. Sometimes one or even both may not be present. To eliminate unsuitable candidates we introduce the following three constrains:

1. The gender of a candidate must match the gender of a vocative, i.e. if a vocative is “my dear sister” we reject male candidates.
2. The utterance spoken by a candidate must be in the paragraph immediately preceding or following the given vocative utterance.
3. If both candidates satisfy the first two constrains the speaker of the following utterance is chosen.
Compliment rules

1. (A, cousin of, B) \(\Rightarrow\) (B, cousin of, A)
2. (A, wife / husband of, B) \(\Rightarrow\) (B, husband / wife of, A)
3. (A, Mr. and Mrs., B) \& FEMALE(B) \(\Rightarrow\) (B, wife of, A)

Transitivity rules

1. (A, cousin of, B) \& (B, cousin of, C) \(\Rightarrow\) (A, cousin of, C)
2. (A, sister / brother of, B) \& (B, sister / brother of, C) \(\Rightarrow\) (A, sister / brother of, C)

Compound rules

1. (A, father / mother of, B) \& (B, sister / brother of, C) \(\Rightarrow\) (A, father / mother of, C)
2. (A, father / mother of, B) \& (C, sister / brother of, A) \(\Rightarrow\) (C, aunt / uncle of, B)

Table 2: Sample propagation rules by categories

The last two constrains were set empirically based on the experiments with a development corpus. If both candidates got rejected, we abandon a relation.

3.4 Relation Propagation

As the final step we try to infer new relations from the extracted seed relations using a rule based propagation technique. We have applied a total of 21 rules to further propagate the seeds. These rules can be divided into three major categories:

- Simple compliment rules
- Transitivity rules
- Compound rules

Table 2 lists sample propagation rules by categories. Each rule has an analogue that works in the opposite direction. Similarly each gendered rule has an analogue that works for the opposite gender. Depending on the accuracy of an initial extraction propagation rules may arrive to contradictions. For example, suppose we have extracted the following relations: (i) (A, father of, B), (ii) (C, sister of, A) and (iii) (C, sister of, B). According to the second compound rule in Table 2, we can propagate the relation (C, aunt of, B) from the first two relations. However, it contradicts to the already existing third relation. We solve possible contradictions with the help of relation counts. Let us assume that the first relation from the previous example were found \(n\) times during the extraction, and the second and the third relations were found \(m\) and \(q\) times respectively. We propagate these counts together with the relations. If the maximum of counts corresponding to the relations on the left hand side of a rule is larger than the count of the existing contradictory relation, we replace such a relation with the propagated one, otherwise we cancel the propagation. In the case of our example we propagate the (C, aunt of, B) relation if \(\max(n, m) > q\).

4 Data Set Description

We have developed and tested our method on Jane Austen’s Pride and Prejudice. A fairly high number of characters and a rich set of family relations make this novel a plausible choice. Moreover, in Victorian novels family relations are well defined, making propagation rules perfectly applicable. We used first volume of 23 chapters as the development corpus and keep the rest for the evaluation. Basic characteristics of the data are given in Table 3. We will refer to the test set as the PnP corpus.

We have annotated the novel in the Columbia QSA corpus fashion [Elson and McKeown, 2010], labeling named entities and nominals exactly as they were labeled in the original work. The ground truth information obtained from human annotators includes utterance attribution, a list of family relations and a gender-labeled list of characters.

The list of family relations has a total of 202 relations between 28 characters. All relations are bidirectional. The gendered list of characters also includes cross-linked references for character names, i.e. mentions like Elizabeth, Miss Eliza, Eliza, etc.

|                  | Dev. corpus | Test corpus |
|------------------|-------------|-------------|
| chapters         | 23          | 38          |
| utterances       | 734         | 1019        |
| utterances with  |             |             |
| target nominals  | 67          | 251         |
| vocative utterances |        | 10          | 38          |

Table 3: Data set description
Table 4: Performance of our implementation of QSA method on different corpora compared to the original work

| Method | Corpus | # utterances | Accuracy |
|--------|--------|--------------|----------|
| Original | CQSA | 3064 | .83 |
| Ours | CQSA | 3064 | .78 |
| Ours | PnP | 1014 | .79 |

are linked as the same entity. Although we did perform gender attribution and co-reference resolution for NEs, in the present work we use the ground truth information.

5 Results

In this section we report the performance of our method at each step that contributes to the final result. We start with the utterance attribution and compare our implementation of the method to the original work. We then report results for the vocative detection task. Here we compare supervised and unsupervised approaches. Finally, we report results of the relation extraction, assess the impact of the propagation step, and carry out the error analysis.

5.1 Utterance Attribution

Table 4 shows the performance of utterance attribution method on different corpora. In order to assess the quality of our implementation of the method by Elson and McKeown (2010), we report the overall accuracy of our method on the data used in the original work, i.e. Columbia Quoted Speech Attribution (CQSA) corpus. In this experiment our implementation achieves the accuracy of 78% which is 5% lower than the results reported in the original work. We found that heuristics perform closely to the original method, but the classifiers do not perform as good. On the PnP corpus the overall accuracy of the method was 79%. A closer analysis of the results revealed a trend similar to the one observed for the CQSA corpus: heuristics performed better than classifiers.

5.2 Vocative Detection

Table 5 shows the results of the vocative detection task. When experimenting with our supervised method we tried a number of classifiers. The Naive Bayes as provided by Weka achieved the highest F-measure, and recognized 33 vocative utterances, making four false positive predictions. The unsupervised method, however, despite achieving higher recall, produced twice as much false positives as true positives. This suggests that pattern matching, although unsupervised, can potentially lead to a high false positives rate at the relation extraction step. Therefore, at the extraction step we use vocative utterances detected by the supervised method.

5.3 Relation Extraction and Propagation

Both relation extraction and propagation depend on the accuracy of the utterance attribution. In order to account for this dependency and for comparison purposes we introduce the oracle, which utilizes ground truth speaker information at the relation extraction step; hence, it is free from the utterance attribution errors. Also, we would like to assess the impact of propagation from both positive and negative angles. Propagation increases recall, but due to possible propagation errors it may hurt precision. In order to account for such errors we employ manual cleaning of the seed relations after the extraction step. Cleaning entails removing the incorrect seeds, not correcting them.

Table 6 shows precision/recall of the relation extraction step. Precision of the extraction is fairly high, in fact it is higher than that of the oracle. This happens due to semantic errors which we will discuss later. Both extracted and oracle seeds have a low recall, which is depicted by the sparsity of networks shown on Figures 1a and 2a. Cleaning obviously results in a 100% precision, but it has no effect on recall at this stage.

Table 7 shows results of propagating all four sets of seed relations listed in Table 6. The first line of Table 7 shows the final, overall performance of our method. Precision of the method was 77%, which is very close to the oracle results. However, 27% recall is still lower than the oracle performance. As
Table 6: Results of the relation extraction task

|                    | P   | R   | F   |
|--------------------|-----|-----|-----|
| Extracted seeds    | 0.88| 0.03| 0.06|
| Cleaned seeds      | 1.00| 0.03| 0.06|
| Oracle seeds       | 0.82| 0.04| 0.08|
| Cleaned oracle seeds| 1.00| 0.04| 0.08|

Table 7: Results of the propagation task

|                    | P   | R   | F   |
|--------------------|-----|-----|-----|
| Extracted seeds    | 0.77| 0.27| 0.40|
| Cleaned seeds      | 1.00| 0.27| 0.42|
| Oracle seeds       | 0.78| 0.43| 0.55|
| Cleaned oracle seeds| 1.00| 0.44| 0.61|

we have expected propagation have increased recall and slightly decreased precision. Propagation resulted in 9 and 11 times increase in recall for extracted and oracle seeds respectively. The respective decrease in precision was 1.14 and 1.05 times. In both cases positive increase in F-measure is obvious, which speaks in favor of propagation. Cleaning does not seem to have notable effect on recall, as propagating extracted and oracle seeds with and without cleaning yields almost the same recall. However, the main advantage of cleaning is that it yields a 100% precision and no propagation errors.

Figures 1b and 2b show extracted and oracle seeds after the cleaning and propagation. For the clarity of presentation we do not show duplicate edges. Also, for the same reasons, we drop relation labels on the latter figure. The increase in recall is apparent from the increase in densities of the respective networks.

Lastly we would like to point out the importance of one particular propagation rule. Clearly, the network on Figure 1a is disconnected, but after propagation it becomes connected as shown on Figure 1b. This happens due to the 3rd compliment rule listed...
in Table 2. According to the rule we infer wife of relation between Mrs. Bennet and Mr. Bennet and Mrs. Gardiner and Mr. Gardiner on the basis of the titles and the same last names. This connects the network of extracted seeds and makes further propagation possible.

5.4 Error Analysis

In this section we discuss possible problems with our approach. First, we would like to point out the impact of inaccurate utterance attribution. Comparing Figures 1a and 2a one can immediately notice that the former one misses the nodes Mary and Lydia and the relations (Lydia, sister of, Mary) and (Mrs. Bennet, mother of, Lydia). This is the main reason why recall of the propagation of extracted seeds was lower than that of the oracle seeds. In the case with the relation between Lydia and Mary, a vocative utterance was mis-attributed to Lydia, resulting in an invalid (Lydia, sister of, Lydia) relation, which was rejected. Similarly, an utterance was mis-attributed to Lydia again, in the case of a relation between Lydia and Mrs. Bennet. This also resulted in a rejected relation. In short, for our method it really matters to whom a given utterance was mis-attributed to.

Unfortunately, there is another problem with some vocative utterances. Notice dashed, incorrect arrows in Figures 1a and 2a (Elizabeth, sister of, Mr. Whickham) relation was extracted because Whickham addressed Elizabeth as sister-in-law. Similarly Mr. Gardiner addressed Mr. Bennet as brother in-law which lead to inaccurate extraction. In fact, these were the only extraction errors our method produced. This problem is of semantic nature and we will seek ways to solve it in our future work.

6 Conclusion and Future Work

We have developed a method that extracts family relations from a narrative based on the utterance attribution and the vocative detection techniques. Our method successfully applies propagation rules to infer new relations from initially extracted ones. We carried out an error analysis and concluded that the method is sensitive to the accuracy of utterance attribution and vulnerable to the semantics of vocatives. We plan to work on these issues in the future. As the additional line of work we plan to explore context clues. For example, given a passage like "Mr. Bennet," replied his wife, we can infer (current speaker, wife of, Mr. Bennet) relation from the utterance and the surrounding context.

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