ABSTRACT

Semantic annotation of long texts, such as novels, remains an open challenge in Natural Language Processing (NLP). This research investigates the problem of detecting person entities and assigning them unique identities, i.e., recognizing people (especially main characters) in novels. We prepared a method for person entity linkage (named entity recognition and disambiguation) and new testing datasets. The datasets comprise 1,300 sentences from 13 classic novels of different genres that a novel reader had manually annotated. Our process of identifying literary characters in a text, implemented in protagonistTagger, comprises two stages: (1) named entity recognition (NER) of persons, (2) named entity disambiguation (NED) – matching each recognized person with the literary character’s full name, based on approximate text matching. The protagonistTagger achieves both precision and recall of above 83% on the prepared testing sets. Finally, we gathered a corpus of 13 full-text novels tagged with protagonistTagger that comprises more than 35,000 mentions of literary characters.

1 Introduction

Novels are a fascinating field of study, not only for philologists or literary scholars but also for scientists involved in NLP. They are an excellent repository of knowledge about the language, people and their relations, historical events, places, expected behaviours, etc. Analysis of novels can be applied to detecting the relations between protagonists, creating summaries, location detection, creating timelines of events, and many more.

The first type of annotations that is crucial when discussing novels is related to protagonists. Marking all appearances of the novel’s main characters is vital in the corpus to make a more advanced analysis. Due to many ambiguities appearing in novels, their complex structure, and often a broad spectrum of protagonists, this task is challenging. Furthermore, there are no annotated sets that can be used for testing or training models for this specific task in the literary domain. People’s recognition or disambiguation in novels is similar to non-literary texts, such as newspaper articles or blogs. However, in some aspects, this task is more complex in the literary domain. To mention a few of them: (1) dialogues in which the form of the name depends on the person addressing given protagonist (for example, using diminutive), (2) a vast amount of literary characters, very often sharing the same surname and (3) surprising names of protagonists (for example, the Creature in Frankenstein or Black Dog in Treasure Island).

In most use cases, it may not be enough to annotate each literary character with a general tag person. To be able to analyze the novel on deeper levels, we need contradistinction between protagonists. The most desired way is to have a unique identity for each protagonist and assign it to this literary character’s appearance in a text. Ideally, each instance should be associated/link with a tag containing the full name of a protagonist along with her/his personal title to identify and differentiate literary characters precisely (Gupta et al., 2017). Extracting parts of the novels associated with specific characters makes an in-depth analysis of long texts, such as sentiment-based analysis of individual protagonists, possible (see Section 2.3).
An example of such annotated text is given in Table 1. Our prepared tool – called \textit{protagonistTagger} – works automatically with a list of protagonists’ names and a text of the novel given as input.

\begin{quote}
"Her disappointment in Charlotte Lucas made her turn with fonder regard to her sister, of whose rectitude and delicacy she was sure her opinion could never be shaken, and for whose happiness she grew daily more anxious, as Charles Bingley, had now been gone a week and nothing more was heard of his return. Jane Bennet, had sent Caroline Bingley, an early answer to her letter and was counting the days till she might reasonably hope to hear again. The promised letter of thanks from Mr. Collins, arrived on Tuesday, addressed to their father, and written with all the solemnity of gratitude which a twelve month’s abode in the family might have prompted."
\end{quote}

\begin{table}[ht]
\centering
\begin{tabular}{p{0.95\textwidth}}
\hline
Table 1: An exemplary text extracted from novel \textit{Pride and Prejudice} by Jane Austen. Correct tags are written in a subscript of each recognized named entity of category person. \\
\hline
\end{tabular}
\end{table}

Our main contributions in this research include:

\begin{itemize}
  \item verification of the standard NER model performance in the literary domain and describing a method for preparing training sets for model fine-tuning (Section 5),
  \item the \textit{protagonistTagger} tool for recognition and disambiguation of person entities (entity linkage) in literary texts (Section 3),
  \item entity linkage benchmark testing datasets for entities of category person manually annotated also with full names of literary characters (1,300 sentences each) (Section 4),
  \item a vast corpus of novels annotated with \textit{protagonistTagger} (13 novels, more than 50,000 sentences and more than 35,000 mentions of literary characters) (Section 8).
\end{itemize}

The tool’s good performance verified on two different testing sets proves that \textit{protagonistTagger} can be used successfully to recognize and identify people in complex texts. The tool and the corpus can help detect and analyze the relationships between literary characters and create a social semantic network of them. Furthermore, the fine-tuned NER model and the whole tool can be applied to texts from a non-literary domain, containing named entities of category person, as long as a list of full names to be linked with them is available.

In this paper, we provide an overview of the related works (Section 2), followed by the general description of the approach and the created tool – \textit{protagonistTagger} (Section 3). All prepared testing sets are presented in Section 4. Section 5 describes NER models used, whereas Section 6 presents the name matching algorithm of literary characters. The performance of the approach presented in this paper is described in Section 7. Section 8 introduces a corpus of full-text novels with mentions of literary characters. The paper completes with conclusions and future works (Section 9).

The detailed analysis of datasets, parameters for models reproducibility and other detailed analysis and statistics regarding this paper are given in the appendixes.\footnote{The source code of \textit{protagonistTagger}, the corpus of 13 annotated full-text novels and manually annotated datasets are available, along with documentation and manual, on \url{https://doi.org/10.5281/zenodo.4699418}.}

2 Related Works

Literary text analysis has been performed for centuries by humanists and linguists in a manual, arduous way. Now, this field is offered a brand new perspective thanks to digital literary studies. Computational linguistics makes tasks such as in-depth statistical analysis of literary texts much quicker (less labour-intensive) and more precise.

2.1 Named Entity Recognition and Disambiguation

The general conclusion can be drawn that standard NER and NED models can be used successfully on dissected datasets. However, they may have lower performance on novels containing verifiable sentences (Stanislawek et al., 2019). Further, we show these challenges in Sections 5 and 6.

NER task can be approached in several different ways (Yadav and Bethard, 2018). The most recent approaches are designed using mainly neural networks. They do not require domain-specific resources or feature engineering, thanks to word embeddings used as feature vectors (Akbik et al., 2019). Neural network-based NER systems can be classified into several groups depending upon their representation of the words in a sentence. Such representations can be based on words (Collobert and Weston, 2011), characters (Yu et al., 2018; Chiu and Nichols, 2016; Lample et al., 2016), sub-word units different than characters (Yadav et al., 2018) or any combination of these. This last approach, originating
from feature engineering, where affixes play a significant role, offers an exhaustive way of creating word representations utilizing the semantics of morphemes.

An up-to-date list of entity linkage techniques and datasets are given in (Ruder, 2021; Barrena et al., 2015). However, these resources are concentrated on texts such as news and most models are not prepared to face particular challenges appearing in literary texts.

2.2 Recognition and Disambiguation of the Literary Characters

The most popular library of texts of various kinds is Project Gutenberg (Hart, 1992). It is accompanied by GutenTag (Brooke et al., 2015; Hammond and Brooke, 2017) – a software tool offering NLP techniques for the analysis of literary texts. It contains an automatic corpus reader, subcorpus filters and a tagging functionality based on different tags specified by a user, performing statistical analysis of the selected subcorpus. Even though the NER is used to identify the main literary characters, the information gained is used only for statistical measures. There is no advanced mechanism of recognition and disambiguation of literary characters.

One of the possible approaches to detecting and matching characters in literary texts, based on characters clustering (Bamman et al., 2014; Elson et al., 2010), assumes that the noun phrases recognized in the text by the NER model can be clustered into groups referring to the same person. In the case of both papers, the presented results are more qualitative than numeric and they are based on verifying preregistered hypotheses. Another method (Vala et al., 2015) is based on representing characters using a graph, where each node corresponds to a name found using NER and edges connect nodes referring to the same character. Furthermore, this method attempts to identify entities that the NER has not recognized by uncovering prototypical characters’ behaviours. Accuracy of character detection using this method varies between 45% and even 75%, depending on the novel and the challenges appearing in it.

Even though numerous papers devoted to recognizing literary characters are quoted here, in most cases there are no available datasets to compare the results or models’ parameters to recreate the experiments (Elson et al., 2010). Moreover, some of the proposed methods are applicable only to some narrow set of texts and require a manual contribution. A good quality, general-purpose method for long, complex texts such as novels and benchmark datasets would be of great applicability.

2.3 Further Applications Based on Recognized Literary Characters

Constructing the representation and interpretation of narratives, extracting social networks from novels, modelling social conversations that occur between characters in the form of a network (Elson et al., 2010) are promising directions when a corpus with recognized protagonists is available. Besides, literary characters and their relationships evolve with the progress of the novel. Modelling dynamic relationships between pairs of characters by detecting relationship sequences in data is much more adequate in the case of long texts (Chaturvedi and Srivastava, 2016; Chaturvedi and Iyyer, 2017).

Another aspect of the interpretation of narratives is sentiment analysis (Kim and Klinger, 2018). It includes, among others, a classification of literary texts by literary genre based on emotions they convey (Reagan and Mitchell, 2016; Zehe et al., 2016) and emotion-based character analysis (Groza and Corde, 2015; Flekova and Gurevych, 2015).

3 ProtagonistTagger Workflow

The process of creating the corpus of annotated novels employed in the protagonistTagger tool comprises several stages (see Figure 1):

1. Gathering an initial corpus with plain novels’ texts without annotations.
2. Creating a list of full names of all protagonists for each novel in the initial corpus. These names are the predefined tags that will be used in further steps for annotations. This step uses Wikipedia parser, which goes through an article about a given novel looking for a section devoted to its literary characters.
3. Recognizing named entities of category person in the novels’ texts in the initial corpus. Training the NER model from scratch for this specific problem is not reasonable due to the amount of time and computing power required. Instead, we used a pretrained NER model and fine-tuned it using a sample of manually annotated texts. The NER evaluation is done on a testing set extracted from the novels.
4. Each named entity of category person, recognized by the NER model in the previous step, is a potential candidate to be annotated with one of our tags predefined in step 2. At this point, the matching algorithm is used to choose from the predefined tags the one that matches most accurately the recognized named entity.
5. The annotations done by the matching algorithm are evaluated according to their accuracy and correctness.

The protagonistTagger (fine-tuned NER model + matching algorithm) is used to annotate more novels in order to create the corpus of annotated texts. The two most important parts of the above procedure are fine-tuning NER from step 3 and the matching algorithm from step 4. They are described in detail in the two following chapters.

4 Our Testing Sets

Two testing sets are prepared for verifying the performance of the NER model. The novels included in Test_large_person are also used in the training data for the NER model; however, the training sets and the testing sets are disjoint. Additionally, the same novels were used to verify which named entities are not recognized and classified correctly by the standard NER model. Taking this into consideration, the results on this dataset may not be entirely trustworthy. Therefore, additional independent testing set containing sentences from totally new novels was created – Test_small_person. The results of the NER model on this testing set are undoubtedly authoritative. The sentences from both testing sets contain various named entities of the category person. The gold standard for both datasets was annotated manually, by a passionate novel reader, with a tag person.

The overall performance of protagonistTagger is evaluated on two testing sets: Test_large_names and Test_small_names. Both testing sets include the same sentences as the corresponding sets used for testing the NER model. The only difference is that this time the sentences are manually annotated with full names of literary characters while creating the gold standard. Table 2 sums up all the testing sets.

All testing sets contain sentences chosen randomly from 13 novels differing in style and genre. The testing sets used for protagonistTagger contain all together 1,300 sentences (100 sentences from each novel). Each sentence in the testing set contains at least one named entity of category person recognized by the NER model. We need to bear in mind that not all literary characters appearing in a novel are given on Wikipedia. Therefore, not all literary characters appearing in the novel are included in the predefined tags (the lists of protagonists extracted from Wikipedia). Nevertheless, sentences
Protagonists’ Tagger in Literary Domain

containing some names of minor literary characters not included in the tag lists are also included in the testing set. They should be given only a general tag person. It helps to verify if some additional, undesired annotations are not put in by our protagonistTagger.

5 NER Models

The novel is a particular type of text in terms of writing style, the links between sentences, the plot’s complexity, the number of characters, etc. Therefore, we needed to verify the standard NER model’s performance on exemplary sentences extracted from novels. It is mainly because all the standard NER models are pretrained on web data such as blogs, news, and comments (Schmitt et al., 2019; Jiang et al., 2016). We tested several NER models on literary domain and based on preliminary results, we decided to use a pretrained language model offered by SpaCy.²

5.1 Standard NER Model Performance

The overall recall metric on the whole testing set Test_large_person for the pretrained NER model was 80% (see Table 5). In some of the tested novels, the most alarming thing is that the NER model does not recognize the main protagonist’s name as an entity of category person. It is the case in The Picture of Dorian Gray, where the entity Dorian is recognized as norp – nationalities or religious or political groups, and in the novel Emma, where the entity Emma is given a label org that should be assigned to companies, agencies, or institutions.

However, we need to bear in mind that NER is the first part of the protagonists’ annotation process and there is still a potential error of the further steps, i.e., matching algorithm. The overall performance of the protagonistTagger on a novel drops drastically, even with an excellent process of NED, when the main protagonist’s name is not detected correctly. Therefore, it is crucial to fine-tune the NER model so that it can handle the recognition of these entities.

5.2 NER Model Fine-Tuning

NER model aims at finding all named entities of category person which may be matched in the further step with the proper label (i.e., a full name of a novel’s protagonist). Therefore, we want the NER model to find as many person entities as possible to have the highest possible number of candidate entities for the matching phase. It means that the recall metric is high enough. The NER model’s precision at this step is not crucial because the named entities of other categories, for example, location, identified as person, are not matched with any protagonist’s label in the matching phase. The matching algorithm ignores (filters out) named entities that do not resemble any of the predefined tags.

5.2.1 NER Model Fine-Tuning Procedure

Fine-tuning the NER model is used to improve its performance on novels (Rodriguez et al., 2018). As a base for fine-tuning, we use an existing, pretrained language model.

This procedure comprises the following steps:

1. NER model is applied to a testing set extracted from the novels. The resulted annotations are compared with the testing set annotated manually with the general tag person.

2. If the results of NER are not satisfying (many entities that are of category person are not recognized, or they are assigned a different category), then the NER model needs to be fine-tuned. Fine-tuning NER requires creating a training set with texts specific to our problem (i.e., novels).

5.2.2 Training Sets for NER Fine-Tuning

We considered two approaches to creating a training set for a NER model (Kim et al., 2020). The final training set for NER model fine-tuning is the concatenation of Training_set_1 and Training_set_2. The performance of the fine-tuned NER model is discussed in Section 7.1.

Training_set_1 contains 485 sentences with not recognized named entities of category person. This approach assumes using the named entities of type person that were not recognized or assigned a proper category during the analysis of the problem (these named entities were found manually). The novels used for creating the training set are scanned in search of sentences containing these entities. Then the chosen sentences are annotated in a semi-automatic way with a general tag person creating a training set for fine-tuning the standard NER model.

²https://spacy.io
"Jane’s delicate sense of honour would not allow her to speak to Elizabeth privately of what Lydia had let fall; Elizabeth was glad of it; till it appeared whether her inquiries would receive any satisfaction, she had rather be without a confidante."

"Deborah’s delicate sense of honour would not allow her to speak to Harvey privately of what Lydia had let fall; Harvey was glad of it; till it appeared whether her inquiries would receive any satisfaction, she had rather be without a confidante."

Table 3: An example of injecting common English names in the sentence extracted from Pride and Prejudice by Jane Austen. In this case Jane is replaced by Deborah and Elizabeth is replaced by Harvey.

Training set 2 contains 1,600 sentences from novels with injected common English names. Many common English names, such as Emma, Charlotte, Arthur or Grace, are not recognized at all by a standard NER model, or they are classified as entities of a type different than person. For the NER model to recognize common names and thus improve its performance, the training set needs to contain sentences typical for novels regarding style, vocabulary, and syntax. These sentences should additionally contain as many common English names as possible. The easiest way to create such a set of correct sentences is to extract from novels sentences containing the main protagonists’ names. Then each such name can be replaced by some other common English name to enrich our training set, employing the approach described in (Stanislawek et al., 2019). An example of such replacement is given in Table 3. The considered list of most common English names contains 300 female and 300 male names in their basic forms.

6 Name Matching Algorithm

The matching algorithm matches all protagonists in a given text with a proper tag (i.e., a proper name), having been given the list of protagonists’ proper names predefined for each novel. The algorithm evaluates the match between the recognized named entity and each full name from this predefined list. The tag with the highest resemblance is chosen as an answer. The method is mainly based on approximate string matching. The algorithm attempts to solve several particular problems encountered during the problem analysis, such as diminutives or surnames preceded with personal titles. Encountered problems along with the proposed solutions are presented in Sections 6.1, 6.2 and 6.3. The matching algorithm, of course, cannot handle all of the possible cases. It would be highly ineffective due to complexity issues. However, the problems appearing most frequently in the analyzed novels are considered.

We assumed in our approach that we possess a list of protagonists’ full names for the processed novel (either thanks to Wikipedia parser or by creating it manually and proving as an input for the tool in case of novels that do not have Wikipedia entries). The task is to recognize the named entities in the text and match them appropriately with labels from this list (named entities disambiguation). It is crucial to point out that the named entities in the novel’s text rarely take the same form as in the list. Sometimes only the first name is used; in other cases, the surname preceded with a personal title appears. In extreme cases, a diminutive or a nickname may be used (for example, Lizzy instead of Elizabeth or Nelly instead of Ellen).

Considering the above, it needs to be verified how similar a named entity is to each label from the list. Only then will it be possible to assign a proper, most similar label to the entity. A technique called approximate text matching can be used to calculate this similarity. The problem of approximate text matching can be formally stated as follows: given a long text \( T_1, \ldots, T_n \) of length \( n \) and a comparatively short pattern \( P_1, \ldots, P_m \) of length \( m \), both sequences over an alphabet \( \sum \) of size \( \rho \), find the text positions that match the pattern with at most \( k \) “errors” (Navarro and Baeza-Yates, 2001).

6.1 Regular and Partial String Matching

String similarity, based on approximate text matching (Navarro, 2001), can be computed in multiple different ways. The general method uses Levenshtein distance to calculate differences between two sequences of characters. Formally speaking, the distance/error \( d(x, y) \) between two strings \( x \) and \( y \) is the minimum number of single-character operations (such as insertion, deletion, and substitution) needed to convert one into the other.

In the context of our problem, the basic measurement of Levenshtein distance between a named entity found in a text and a character name from a list may not solve the problem. Using this method for entity Elizabeth and full name Elizabeth Bennet gives the similarity of only 72%. A modification of the basic method, which calculates the so-called partial string similarity, gives the similarity of 100%, which is precisely what we expected (see Table 4). This modification uses a heuristic called best partial which, given one sequence of length \( n \) and a noticeably shorter string of length \( m \), calculates the score of the best matching substring of length \( m \) of the sequence.
Protagonists’ Tagger in Literary Domain

| Named entity | Literary character’s full name | Regular str. sim. | Partial str. sim. |
|--------------|--------------------------------|-------------------|-------------------|
| Elizabeth    | Elizabeth Bennet               | 72%               | 100%              |
| Lizzy        | Elizabeth Bennet               | 19%               | 40%               |
| Lizzy        | Mr Fitzwilliam Darcy           | 24%               | 40%               |

Table 4: Examples of calculated string similarities (str. sim.) for some of the named entities recognized in the novel *Pride and Prejudice*.

6.2 Diminutives of Literary Characters

The most difficult cases in the matching process are diminutives and nicknames. The problem accompanies the character *Elizabeth Bennet*, who is sometimes called *Lizzy* by her family. We do not have any information about the possible forms of the name in our list of labels, which contains only the base forms. *Lizzy* is recognized as a named entity of category *person*, but it is not similar enough to any of the protagonists from the list. The partial string similarity between *Lizzy* and *Elizabeth Bennet* equals 40% and is the same as between *Lizzy* and *Mr Fitzwilliam Darcy* (see Table 4). Therefore, the straightforward approximate string matching technique is not enough in this case. Instead, the complete list of diminutives containing more than 3300 different forms of names is used. We investigate it only when the recognized named entity is not similar enough to any of the protagonists listed in a list of labels for a given novel.

6.3 Surnames Preceded with Personal Title

Another case that needs special consideration is a named entity consisting only of a surname. For example, the named entity *Bennet* is not the name of any specific character, but instead the whole family’s name. To distinguish between *Bennet* meaning the whole family and *Bennet* being the surname of a single character, we can analyze the word preceding it. *Bennet* preceded with a personal title such as Mr., Mrs., Ms., or Miss, should be identified as a single person, whose surname is *Bennet*. Additionally, each prefix stores valuable information about the gender of the literary character that should be assigned to the analysed entity. In all other cases, *Bennet* is treated as the whole family and not a single person identified in a text. For example, the entity *Bennet* appears 323 times in the novel (which has 121,533 words), out of which 314 cases can be analyzed more precisely thanks to the preceding personal title.

6.4 Matching Algorithm Outline

The general idea behind the matching algorithm is finding the best match for a recognized named entity of category *person* in the predefined list of considered protagonists appearing in the novel. First, it collects potential candidates that may correspond to the given named entity from the protagonists’ list. Then the algorithm, based on the approximate string matching method, chooses the best match from this list of potential candidates.

7 Experiments and Evaluation

7.1 Fine-tuned NER Model Performance

We have tested the standard NER model and the standard NER model fine-tuned with the prepared training set (see Section 5.2.2). Performance of these NER models on the *Test_large_person* is presented in Table 5. At this point, we were interested mostly in the recall (see Section 5.2). We fine-tuned NER in order to be able to detect most of the named entities of category *person*. The obvious conclusion from the results on this testing set is that the recall for the standard NER model, in almost all cases, is significantly lower than for the fine-tuned model. It confirms our hypothesis that the standard NER models are not prepared for novels.

The performance of all NER models on the *Test_small_person* makes us draw similar conclusions. The fine-tuned model has a higher recall on the whole testing set in general and in the case of almost every novel analyzed individually. What is important, its performance on a new testing set is also very high. Furthermore, the results on this smaller set are more reliable and independent, due to the fact that the larger set is extracted from novels used in problem analysis and NER model fine-tuning (even though training set and testing sets are disjoint).
Table 5: Metrics computed for the standard, pretrained NER model and the fine-tuned NER model for annotations with general label person. The support is the number of occurrences (mentions) of class person.

| Testing set        | Precision | Recall | F-measure | Support |
|--------------------|-----------|--------|-----------|---------|
| Test_large_person  | 0.84      | 0.8    | 0.82      | 1,021   |
| fine-tuned         | 0.77      | 0.99   | 0.87      | 1,021   |
| Test_small_person  | 0.78      | 0.79   | 0.78      | 273     |
| fine-tuned         | 0.69      | 0.95   | 0.8       | 273     |

Table 6: Performance of the protagonistTagger.

| Testing set        | Precision | Recall | F-measure |
|--------------------|-----------|--------|-----------|
| Test_large_names   | 0.88      | 0.87   | 0.87      |
| Test_small_names   | 0.83      | 0.83   | 0.83      |

7.2 **ProtagonistTagger Performance**

All the named entities of category person are included in the performance, not only the main characters’ names. Therefore, the performance addresses recognizing and annotating the most important protagonists in the novel appearing in the predefined tags and the minor, tangential ones. Generally, the tool achieves high results on both testing sets – precision and recall above 83% (see Table 6). The tool’s performance on Test_small_names shows that it can be successfully used for new novels to create a larger corpus of annotated texts.

It should be emphasized that the novel is a term defining a wide range of various texts. The best proof of novels’ diversity is the tool’s performance, whose precision varies from 79% to even 96% for different novels. Even though the performance is tested on various texts, the precision of the annotations remains high, proving the applicability of the proposed method in the literary domain.

7.3 **Experiment Limitations**

Considering only the novels included in the testing sets, it can be concluded that there are numerous factors negatively influencing the performance of the protagonistTagger. It depends on the number of literary characters appearing in the novel, its complexity, literary genre, uniqueness of predefined tags, and probably many more. The main challenge is to assign tags to named entities appearing in a form common for the novel (for example, only surnames preceded with the personal title or many diminutives). What is crucial, this last dependency is novel-specific and author-specific.

8 **Corpus of Annotated Novels**

The protagonistTagger was employed to create a corpus of annotated novels. Named entities of category person are annotated in the texts with the full names of the corresponding literary characters. The corpus contains 13 novels (altogether more than 50,000 sentences) and more than 35,000 annotations of literary characters. The annotations done on this corpus are guaranteed to be of good quality (precision and recall on average above 83%) because the annotation tool was tested on the independent testing sets extracted from the novels included in this corpus.

9 **Conclusions and Further Work**

In this paper, we presented the tool protagonistTagger and the corpus of annotated novels where each literary character is tagged with her/his full name. The protagonistTagger achieved both the precision and the recall of above 83% on the testing sets containing texts from thirteen novels. This research shows the relatively low performance of the standard NER models on novels for recognizing entities of category person. It is caused by the fact that novels differ significantly from texts on which standard NER models are trained. Our contribution was to describe the method for preparing training sets and fine-tuning the NER model. It resulted in a very high recall (above 95%) in recognizing named entities of category person in novels.

Further contributions concern a method for matching appearances of protagonists in texts of the novels to their full names, i.e., linking the recognized person named entity with the literary character’s identity. The analysis of the problem unveiled this process’s complexity. Thus, even though the tool protagonistTagger partially builds upon existing approaches and resources, it points out the challenges of the task in the literary domain and adapts the existing materials.
for it. Furthermore, we introduce new benchmark sets for NER and NED in the literary domain, i.e., datasets for tuning testing NER models and testing NED, and the corpus annotated automatically with protagonistTagger.

The variety of possibilities presented in Section 2 makes further analysis of novels based on the created corpus very tempting. The created corpus and the tool for annotating new novels seem to be a good starting point in many NLP tasks. We also performed initial tests to apply our results, i.e., analyzing sentiment and relationships in novels using our corpus. The experiments’ main goal was to determine each character’s sentiment in terms of positive, neutral, and negative and the degree of affiliation to a specific class. In addition, we examined how the character’s sentiment changes over the time of the novel. Furthermore, we attempted to discover how relationships between the two characters develop over time. The performed analysis was more manageable and precise, thanks to the available annotations of literary characters than the standard tool used so far.

The protagonistTagger was created initially for a literary domain, especially novels. Nevertheless, it has the potential to be easily applied to other kinds of texts in which we want to annotate person named entities. The only condition is the access to the predefined tags defining the full names to be matched with named entities detected in a text. Texts extracted from social media very often feature many names in different forms. Therefore, recognizing and annotating them can be very beneficial from the point of view of investigating human opinions and analyzing the sentiments.

References

Alan Akbik, Tanja Bergmann, and Roland Vollgraf. 2019. Pooled contextualized embeddings for named entity recognition. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 724–728. Association for Computational Linguistics.

David Bamman, Ted Underwood, and Noah A. Smith. 2014. A Bayesian mixed effects model of literary character. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 370–379. Association for Computational Linguistics.

Ander Barrena, Aitor Soroa, and Eneko Agirre. 2015. Combining mention context and hyperlinks from wikipedia for named entity disambiguation. In Proceedings of the Fourth Joint Conference on Lexical and Computational Semantics, pages 101–105.

Julian Brooke, Adam Hammond, and Graeme Hirst. 2015. GutenTag: an NLP-driven tool for digital humanities research in the Project Gutenberg corpus. In Proceedings of the Fourth Workshop on Computational Linguistics for Literature, pages 42–47. Association for Computational Linguistics.

Snigdha Chaturvedi and Mohit Iyyer. 2017. Unsupervised learning of evolving relationships between literary characters. In AAAI, pages 3159–3165.

Snigdha Chaturvedi and Shashank Srivastava. 2016. Modeling evolving relationships between characters in literary novels. In 13th AAAI Conference on Artificial Intelligence.

Jason P.C. Chiu and Eric Nichols. 2016. Named entity recognition with bidirectional LSTM-CNNs. Transactions of the Association for Computational Linguistics, 4:357–370.

Ronan Collobert and Jason Weston. 2011. Natural language processing (almost) from scratch. In Journal of machine learning research, pages 2493–2537.

David Elson, Nicholas Dames, and Kathleen McKeown. 2010. Extracting social networks from literary fiction. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, pages 138–147. Association for Computational Linguistics.

Lucie Flekova and Iryna Gurevych. 2015. Personality profiling of fictional characters using sense-level links between lexical resources. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 1805–1816. Association for Computational Linguistics.

Ian Goodfellow, David Warde-Farley, Mehdi Mirza, Aaron Courville, and Yoshua Bengio. 2013. Maxout networks. In International conference on machine learning, pages 1319–1327. PMLR.

Adrian Groza and Lidia Corde. 2015. Information retrieval in falktales using natural language processing. In 2015 IEEE International Conference on Intelligent Computer Communication and Processing (ICCP), pages 59–66. IEEE.
Nitish Gupta, Sameer Singh, and Dan Roth. 2017. *Entity linking via joint encoding of types, descriptions, and context*. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2681–2690. Association for Computational Linguistics.

Adam Hammond and Julian Brooke. 2017. *Gutentag: A user-friendly, open-access, open-source system for reproducible large-scale computational literary*.

Michael Hart. 1992. *The history and philosophy of project gutenberg*. In *Project Gutenberg*.

Ridong Jiang, Rafael E. Banchs, and Haizhou Li. 2016. *Evaluating and combining name entity recognition systems*. In *Proceedings of the Sixth Named Entity Workshop*, pages 21–27. Association for Computational Linguistics.

Evgeny Kim and Roman Klinger. 2018. *A survey on sentiment and emotion analysis for computational literary studies*. In *arXiv preprint arXiv:1808.03137*.

Juae Kim, Youngjoong Ko, and Jungyun Seo. 2020. *Construction of machine-labeled data for improving named entity recognition by transfer learning*. *IEEE Access*, 8:59684–59693.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. *Neural architectures for named entity recognition*. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 260–270. Association for Computational Linguistics.

Gonzalo Navarro. 2001. *A guided tour to approximate string matching*. In *ACM computing surveys*, volume 33, pages 31–88.

Gonzalo Navarro and Ricardo A. Baeza-Yates. 2001. *Indexing methods for approximate string matching*. In *IEEE Data Eng. Bull.*, volume 24, pages 19–27.

Andrew J Reagan and Lewis Mitchell. 2016. *The emotional arcs of stories are dominated by six basic shapes*. In *EPJ Data Science*, volume 5, pages 1–12. SpringerOpen.

Juan Diego Rodriguez, Adam Caldwell, and Alexander Liu. 2018. *Transfer learning for entity recognition of novel classes*. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1974–1985. Association for Computational Linguistics.

Sebartien Ruder. 2021. *Entity linking – progress in natural language processing (nlp)*.

Xavier Schmitt, Sylvain Kubler, Jérémy Robert, Mike Papadakis, and Yves LeTraon. 2019. *A replicable comparison study of ner software: Stanfordnlp, nlkt, opennlp, spacy, gate*. In *2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS)*, pages 338–343. IEEE.

Tomasz Stanislawek, Anna Wróblewska, Alicja Wójcicka, Daniel Ziembicki, and Przemyslaw Biecek. 2019. *Named entity recognition - is there a glass ceiling?*. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 624–633. Association for Computational Linguistics.

Hardik Vala, David Jurgens, Andrew Piper, and Derek Ruths. 2015. *Mr. bennet, his coachman, and the archbishop walk into a bar but only one of them gets recognized: On the difficulty of detecting characters in literary texts*. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 769–774, Lisbon, Portugal. Association for Computational Linguistics.

Vikas Yadav and Steven Bethard. 2018. *A survey on recent advances in named entity recognition from deep learning models*. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 2145–2158. Association for Computational Linguistics.

Vikas Yadav, Rebecca Sharp, and Steven Bethard. 2018. *Deep affix features improve neural named entity recognizers*. In *Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics*, pages 167–172. Association for Computational Linguistics.

Xiaodong Yu, Stephen Mayhew, Mark Sammons, and Dan Roth. 2018. *On the strength of character language models for multilingual named entity recognition*. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3073–3077. Association for Computational Linguistics.

Albin Zehe, Martin Becker, Lena Hettinger, Andreas Hotho, Isabella Reger, and Fotis Jannidis. 2016. *Prediction of happy endings in german novels based on sentiment information*. In *3rd Workshop on Interactions between Data Mining and Natural Language Processing*, Riva del Garda, Italy, pages 9–16.
Appendices

A  Matching Algorithm Pseudocode

The algorithm takes as inputs:

- **named_entity** – a named entity of category *person* found by NER model,
- **protagonists** – a predefined list of all considered literary characters/protagonists,
- **prefix** – a prefix that is a token appearing before the recognized named entity; it can be a personal title, the article *the*, or an empty string,
- **partial_similarity_precision** – value indicating how similar two strings need to be in order to be considered as potential matches; it is used as lower bound for *partial string similarity* described in the main paper.

Algorithm 1: Finding best match for the recognized named entity in the list of literary characters predefined for the analysed novel

```plaintext
potential_matches = [];
for protagonist in protagonists do
    ratio = regular_string_similarity(protagonist, named_entity);
    if ratio == 100 then
        return match = protagonist;
    partial_ratio = partial_string_similarity(protagonist, named_entity);
    if partial_ratio >= partial_similarity_precision then
        potential_matches.add(protagonist);
    end
    potential_matches = sorted(potential_matches) # with respect to partial_ratio ;
match = None ;
if len(potential_matches) > 1 then
    match = potential_matches[0];
if prefix is not None then
    if prefix == the then
        return match = the + named_entity;
    title_gender = get_title_gender(prefix) # either female or male ;
    for potential_match in potential_matches do
        if get_name_gender(potential_match) == title_gender then
            return match = potential_match
    end
end
return match
else if len(potential_matches) == 0 then
    original_name = get_name_from_diminutive(named_entity);
    if original_name is not None then
        return match = protagonist from protagonists that contains original_name
    else
        return "person"
return potential_match[0]
```

The first step of the matching algorithm is to check (using *regular_string_similarity*) if the **named_entity** is identical to any of the literary characters from the **protagonists’** list (lines 3-5 in Algorithm 1). If so, the algorithm ends and returns it as the best match. However, if it is not the case, the **partial_ratio** is computed for the **named_entity** and each literary character from the protagonists’ list using *partial_string_similarity*. If it is above the given threshold (**partial_similarity_precision**), a given name from the protagonists’ list is considered as a potential match (see lines 6-8 in Algorithm 1). The list of potential matches is sorted decreasingly concerning the computed **partial_ratio** (line 10).

At this stage, the only thing left to do is check whether the considered named entity is one of the exceptions that we are handling. First of all, we check whether the prefix (token preceding the recognized named entity) can give us any clue (see lines 14-21 in Algorithm 1). If the prefix is:

- the article *the* – the whole family with the surname given in the named entity is considered;
- one of the personal titles – prefix’s gender is recognized, then the first literary character from **potential_matches** list that has the same gender as the personal title in the prefix is returned (see lines 17-21 in Algorithm 1).
Here, we need to assume that the name higher in the list is more probable due to the higher similarity score. It may not always be the case, but some simplifications are necessary.

The last considered variant appears when not even a single literary character was qualified as a potential match. The reason for such a situation may be that the named entity includes not the basic form of the name of the literary character but the diminutive. In such a case, the additional search is performed in an external dictionary of diminutives containing more than 3300 different forms of names (see lines 23-26 in Algorithm 1). If the named entity is not found in the diminutive dictionary, a general tag person is returned. It means that any of the predefined tags match the named entity.

### Table 7: Metrics computed for the standard NER model and the fine-tuned NER model for annotations with general label person. The support is the number of occurrences (mentions) of class person.

| Novel title / NER model                  | Precision | Recall | F-measure | Support |
|-----------------------------------------|-----------|--------|-----------|---------|
| **Test_large_person**                   |           |        |           |         |
| The Picture of Dorian Gray standard     | 0.69      | 0.41   | 0.51      | 90      |
| The Picture of Dorian Gray fine-tuned   | 0.74      | 1      | 0.85      | 90      |
| Frankenstein standard                   | 0.91      | 0.62   | 0.74      | 93      |
| Frankenstein fine-tuned                 | 0.78      | 0.98   | 0.87      | 93      |
| Treasure Island standard                | 0.75      | 0.66   | 0.7       | 97      |
| Treasure Island fine-tuned              | 0.78      | 1      | 0.87      | 97      |
| Emma standard                           | 0.84      | 0.77   | 0.86      | 115     |
| Emma fine-tuned                         | 0.85      | 1      | 0.92      | 115     |
| Jane Eyre standard                      | 0.86      | 0.78   | 0.82      | 97      |
| Jane Eyre fine-tuned                    | 0.74      | 0.95   | 0.83      | 97      |
| Wuthering Heights standard              | 0.95      | 0.87   | 0.91      | 108     |
| Wuthering Heights fine-tuned            | 0.88      | 0.99   | 0.93      | 108     |
| Pride and Prejudice standard            | 0.85      | 0.87   | 0.86      | 124     |
| Pride and Prejudice fine-tuned          | 0.8       | 0.98   | 0.88      | 124     |
| Dracula standard                        | 0.86      | 0.94   | 0.9       | 97      |
| Dracula fine-tuned                      | 0.72      | 0.99   | 0.83      | 97      |
| Anne of Green Gables standard           | 0.91      | 0.96   | 0.94      | 114     |
| Anne of Green Gables fine-tuned         | 0.85      | 0.99   | 0.92      | 114     |
| Adventures of Huckleberry Finn standard | 0.71      | 0.99   | 0.83      | 86      |
| Adventures of Huckleberry Finn fine-tuned| 0.61    | 1      | 0.75      | 86      |
| **Overall results –**                   | 0.84      | 0.8    | 0.82      | 1021    |
| **Test_small_person**                   | 0.77      | 0.99   | 0.87      | 1021    |

| **Test_small_person**                   |           |        |           |         |
| The Catcher in the Rye standard         | 0.68      | 0.68   | 0.68      | 74      |
| The Catcher in the Rye fine-tuned       | 0.58      | 0.91   | 0.71      | 74      |
| The Great Gatsby standard               | 0.75      | 0.84   | 0.79      | 102     |
| The Great Gatsby fine-tuned             | 0.66      | 0.98   | 0.79      | 102     |
| The Secret Garden standard              | 0.9       | 0.82   | 0.86      | 97      |
| The Secret Garden fine-tuned            | 0.83      | 0.95   | 0.88      | 97      |
| **Overall results –**                   | 0.78      | 0.79   | 0.78      | 275     |

**B Detailed Statistics of NER models’ and ProtagonistTagger’s Performance**

Our prepared testing sets for NER models (pretrained and fine-tuned) comprises: Test_large_person and Test_small_person. These testing sets are manually annotated with general tag person creating a gold standard for the NER model. The performance of protagonistTagger is evaluated on Test_large_names and Test_small_names. Testing sets for protagonistTagger include the same sentences as the corresponding sets used for testing the NER model. The only difference is that this time the sentences are manually annotated with full names of literary characters while creating the gold standard.

The performance of NER models (pretrained and fine-tuned) is evaluated on two testing sets: Test_large_person and Test_small_person. The overall performance of protagonistTagger is evaluated on Test_large_names and Test_small_names.
### Table 8: Performance of the protagonistTagger.

| Novel title                        | Precision | Recall | F-measure |
|------------------------------------|-----------|--------|-----------|
| **Test_large_names**               |           |        |           |
| Pride and Prejudice                | 0.84      | 0.85   | 0.83      |
| The Picture of Dorian Gray        | 0.96      | 0.97   | 0.96      |
| Anne of Green Gables               | 0.94      | 0.96   | 0.95      |
| Wuthering Heights                 | 0.79      | 0.77   | 0.77      |
| Jane Eyre                          | 0.8       | 0.75   | 0.76      |
| Frankenstein                       | 0.91      | 0.88   | 0.89      |
| Treasure Island                    | 0.92      | 0.91   | 0.91      |
| Adventures of Huckleberry Finn     | 0.89      | 0.93   | 0.9       |
| Emma                               | 0.93      | 0.86   | 0.88      |
| Dracula                            | 0.9       | 0.89   | 0.89      |
| **Overall results**                | **0.88**  | **0.87** | **0.87** |
| **Test_small_names**               |           |        |           |
| The Catcher in the Rye             | 0.8       | 0.77   | 0.78      |
| The Great Gatsby                   | 0.88      | 0.9    | 0.89      |
| The Secret Garden                  | 0.8       | 0.79   | 0.79      |
| **Overall results**                | **0.83**  | **0.83** | **0.83** |

The metrics for the performance of the NER model are presented in Table 7 and the performance of the whole protagonistTagger tool is presented in Table 8. All the metrics are given for each novel individually and for each testing set in general.

### C Detailed Statistics for Problems Handled by the Matching Algorithm

The most problematic cases in the matching process are diminutives and nicknames. The problem accompanies the character Elizabeth Bennet, who is sometimes called Lizzy by her family. Statistics presented in Table 9 shows that in the case of *Pride and Prejudice* by Jane Austen this problem is quite common. In order to discover a base form of a diminutive detected in a text, we use the external list containing the most common variants of names.

Another case that needs special consideration is a named entity consisting only of a surname. We consider this situation on the example of Bennet named entity. As it is discussed in the paper, we want to distinguish between Bennet meaning the whole family and Bennet being the surname of a single character. We can do it by analyzing the word preceding the detected named entity. Bennet preceded with a personal title such as Mr., Mrs., Ms. or Miss, should be identified as a single person, whose surname is Bennet. In all other cases, Bennet is treated as the whole family and not a single person identified in a text. The statistics presented in Table 10 illustrates the scale of the problem in this specific novel, which has 121,533 words. The entity Bennet appears 323 times, out of which 314 cases can be analyzed more precisely thanks to the preceding personal title.

| Named entity | # of appearances |
|--------------|------------------|
| Bennet       | 323              |
| Mrs. Bennet  | 153              |
| Mr. Bennet   | 89               |
| Miss Bennet  | 72               |

Table 10: Appearances of the named entity Bennet in *Pride and Prejudice* with different personal titles.
D  ProtagonistTagger’s Performance vs Number of Literary Characters

One of the factors that intuitively should influence the performance of the ProtagonistTagger is the number of literary characters in a novel that is analysed. The number of protagonists in a novel determines the number of tags that are used by the ProtagonistTagger. The more tags the tool has to choose from, the more difficult is the task of matching them correctly to each recognized named entity. The relation between the precision of the ProtagonistTagger and the number of tags per each novel is presented in Figure 2. It can not be said unambiguously that these two values are in inverse proportion in the analysed testing sets. The novels for which the tool achieved both the lowest and the highest precision – The Picture of Dorian Gray and The Secret Garden – have a relatively small number of literary characters.

Another factor that was suspected to negatively influence the performance of the ProtagonistTagger is the number of tags sharing a common part. In the case of Bennet family in Pride and Prejudice by Jane Austen protagonists with the same surname are problematic even for human annotators. Sometimes a personal title preceding the named entity can be helpful. However, matching correctly tags that share the same surname or even name may be nontrivial. For that reason, we created statistics of tags that share some common part. These statistics, presented in Table 11, are given for each novel included in both testing sets. Additionally, they are presented in Figure 3 along with the performance of the ProtagonistTagger.

However, again no obvious relation between these two values is visible. It may be caused by the fact that common parts in tags may not be related to the main protagonists (the ones that appear most often in the novel and the testing sets). Therefore, the testing sets are not representative enough in this case. For example, in the case of Anne of Green Gables that has relatively many literary characters, half of which share the same name or surname, the tool’s performance is very high. Nonetheless, in the case of Wuthering Heights, with a similar number of protagonists, half of which again share a common name or surname, performance is much lower. It is caused by the fact that in Wuthering Heights the tags that share common parts correspond to the main protagonists. Whereas, in the case of Anne of Green Gables such common elements appear rather in tags corresponding to tangential characters.

In general, it can be concluded that the performance of the ProtagonistTagger depends on many factors, not only the number of tags and the percentage of tags with the common part in a novel. These two factors, in some cases, can negatively influence the performance of the tool. However, this impact is not certain in the case of all novels.
Protagonists’ Tagger in Literary Domain

Figure 3: The right vertical axis describes the percentage of tags sharing a common part (grey bars), as well as the precision of the protagonistTagger (given in percents) for each novel in the testing sets. Novels used in Test_small_names are marked with grey underlining.

| Title of the novel       | # literary characters/tags | # tags that share a common part | % tags that share a common part |
|--------------------------|----------------------------|---------------------------------|---------------------------------|
| Pride and Prejudice      | 18                         | 13                              | 72%                             |
| The Picture of Dorian Gray | 9                          | 4                               | 44%                             |
| Anne of Green Gables     | 21                         | 11                              | 52%                             |
| Wuthering Heights        | 19                         | 12                              | 63%                             |
| Jane Eyre                | 27                         | 13                              | 48%                             |
| Frankenstein             | 19                         | 4                               | 21%                             |
| Treasure Island          | 17                         | 4                               | 23%                             |
| Adventures of Huckleberry Finn | 16                     | 7                               | 43%                             |
| Emma                     | 14                         | 9                               | 64%                             |
| Dracula                  | 9                          | 2                               | 22%                             |
| The Catcher in the Rye   | 13                         | 4                               | 31%                             |
| The Great Gatsby         | 10                         | 4                               | 40%                             |
| The Secret Garden        | 10                         | 7                               | 70%                             |

Table 11: The number of literary characters (tags used by protagonistTagger) appearing in each novel and the number of tags that share a common part. A common part can be the same name or surname. The same personal title in two tags is not considered a common part.

| Parameter or component       | Value and/or description                                                                 |
|-----------------------------|------------------------------------------------------------------------------------------|
| pretrained Spacy model      | en_core_web_sm (https://spacy.io/models/en#en_core_web_sm)                                |
| word features               | Bloom word embeddings with sub word features                                             |
| pretrained model architecture| deep convolution neural network with residual connections                                 |
| fine-tuning iterations      | 100                                                                                      |
| dropout rate                | 0.5                                                                                      |
| batch normalization         | minibatch (size - a series of compounding values starting at 4.0, stopping at 32.0, with compound equal to 1.001) |
| optimizer                   | Adam (learning rate=0.001; beta1=0.9; beta2=0.999; eps=1e-08; L2=1e-6; grad_clip=1.0; use_averages=True; L2_is_weight_decays=True) |

Table 12: Details about the pretrained NER model and parameters used for the fine-tuning procedure.
E  Details for Reproducing the Experiments

The documented code along with the attached manual that is provided with this paper is the best starting point for reproducing experiments. The created scripts allow to repeat all the actions and run all the tests described in the paper. Annotated corpus of thirteen novels is provided as a part of the code. Nevertheless, it is possible to expand it with new annotated texts using the provided scrips (being a part of protagonistTagger). Table 12 contains the summary of the parameters and techniques applied to fine-tune the pretrained NER model.

The pretrained NER model uses embeddings with subwords features, convolutional layers with residual connections, layer normalization, and maxout non-linearity (its output is the max of a set of inputs) (Goodfellow et al., 2013). The training data is shuffled and batched. For each batch, the model is updated with the training sentences from a batch. The dropout is applied as a regularisation technique to make it a little bit harder for the model to memorize data and reduce overfitting.

In order to successfully use scripts provided as a part of protagonistTagger tool the following requirements need to be fulfilled:

- Python 3.6
- PyYAML 5.3
- gensim 3.8
- numpy 1.18.2
- pytorch.transformers 1.2
- scikit-learn 0.22
- scipy 1.4.1
- spacy 2.2.4

Additionally the following external packages are used:

- fuzzywuzzy 0.18
- gender-guesser 0.4
- nickname-and-diminutive-names-lookup

3 https://spacy.io/models/en#en_core_web_sm
4 https://pypi.org/project/fuzzywuzzy/
5 https://pypi.org/project/gender-guesser/
6 https://github.com/carltonnorthern/nickname-and-diminutive-names-lookup