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Literacy situation models knowledge base creation

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Abstract

The paper strives to build a knowledge base based on situation models from selected English short stories. A simple pipeline is proposed - it consists of named entity extraction, character sentiment analysis and character co-occurrence and relation. Fictional characters are extracted from short literature excerpts. A simple sentiment analysis on all characters follows, and finally the co-occurrence of recognized characters is studied. In short the goal is to, as accurately as possible, provide meaningful short story character analysis.

Keywords

named entity recognition, sentiment analysis, literature, text processing, character analysis

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Introduction

Our motivation for this project was to build a knowledge base based on situation models from selected English short stories. The output of natural language processing methods on such stories can be used to quickly grasp the content of the story and either build a better model of the story in our minds before reading, or solidify the content we've read. There is a lot going on in these stories and therefore a lot of data and different representations to extract, for example we can extract different characters, general sentiment about them, how they are connected with each other and so on. We can also extract the events in the stories, analyse the space and time around these events and build a model that can represent the story according to this data in a concise way. Because there is so much to extract from these stories, we decided to focus only on a subset - the extraction of characters and sentiment analysis based on the context they appear in, building a model and implementing its representation which will reveal the connections between them.

Related work

There is plenty of literature covering the complex task of extracting data from various sources, but the implementation of knowledge base creation on English short stories has not been yet established, as longer texts were used for data extraction and focus was directed on only a subset of the problems we intend to solve. One of similar works was done by Jacobs, 2019[1], where the entire collection of Harry Potter books was made into a corpus and analyzed by a novel tool called `SentiArt` and then compared to some other deep neural network approaches. It used vector space models(VSM) to compute the valence of each word in a text by locating its position in a 2D emotion potential space spanned by the words of the vector space model. The tool produces plausible predictions regarding the emotional and personality profile of the characters and calculates so called "big5" personality traits, which can then be further classified into the "good" or "bad" category. SentiArt achieved 100% accuracy in predicting the sentiment category of 120 excerpts from the Harry Potter books, outperforming the standard sentiment analysis tool, VADER (Hutto and Gilbert, 2014 [2])

We can split the sentiment analysis into three classes: dictionary (word list) based, Value Steam Mapping (VSM) based, neural and a hybrid between the three. The first one determines the valence of a word from text by looking it up in a reference list (Also used to compute the "emotion" of characters as discussed in Elsner 2012 [3]), while the second uses unsupervised learning approach by implementing either the Latent Semantic Analysis (LSA) discussed by the Laundauer et al.[4] or Pointwise Mutual Information (PMI) and Information Retrieval (IR) to measure the similarity of pairs of words.

Of course our goal is to also create a character network and not only the sentiment analysis of individual characters, which was vaguely adressed in Labatut 2019[5]. One of the relevant works that touched multiple aspects of our task is the LitBank [6] corpus which provides an annotated dataset (Entity annotations, Event annotations, Coreference annotations, Quotation annotations) of 100 works of English-language fic-

tion. This corpus is as close as we can get to our target data and even contains a tagger, which can be used to tag entities and events in new text.

We have also reviewed some other papers that gave us the initial understanding on how people construct mental models of narrative stories such as Zwaan 1995[7] and 1998[8] but they did not help us form the initial idea.

Methods

The general pipeline for our task was imagined as follows:

1. Named entity recognition (NER)
2. Character sentiment analysis
3. Character co-occurrence
4. Visualizing the data and final remarks

Corpus analysis

Our corpus is made up of 3 subcorpora:

- short stories - a set of 81 very short classic Aesop fables. Very simple plots and few characters. The characters are often recurring cliches (selfish Man, cunning Fox, evil Wolf, brave Lion etc.). A full story example can be seen below.

```
The Man and the Wood
A Man came into a Wood one day with an axe in
his hand, and begged all the Trees to give
him a small branch which he wanted for a
particular purpose. The Trees were goodnatu-
-red and gave him one of their branches.
What did the Man do but fix it into the axe
head, and soon set to work cutting down tree
after tree. Then the Trees saw how foolish
they had been in giving their enemy the means
of destroying themselves.
```

- medium stories - a set of 7 early 20th century American literature short stories. Plots are more developed, and the characters are more detailed compared to our short subcorpus. A short excerpt from the story The Ransom of Red Chief can be seen below.

```
We selected for our victim the only child of
a prominent citizen named Ebenezer Dorset.
(...) The kid was a boy of ten, with bas-re
-lief freckles, and hair the colour of the
cover of the magazine you buy at the news-
-stand when you want to catch a train. Bill
and me figured that Ebenezer would melt down
for a ransom of two thousand dollars to a
cent. (...) "Hey, little boy!" says Bill,
"would you like to have a bag of candy and a
nice ride?"
```

- litbank - a curated set of 100 varied shorter stories from Anglo-Saxon literature. They range in complexity, from children's stories to delicate and mature passages. Some classic stories are featured here, and these passages are perhaps the most complex in our corpus. A short excerpt from the book Ulysses can be seen below.

```
- Our mighty mother! Buck Mulligan said.
He turned abruptly his grey searching eyes
from the sea to Stephen 's face.
- The aunt thinks you killed your mother,
he said.
That's why she won't let me have anything to
do with you.
- Someone killed her, Stephen said gloomily.
- You could have knelt down, damn it, Kinch,
when your dying mother asked you, Buck
Mulligan said.
I'm hyperborean as much as you.
But to think of your mother begging you with
her last breath to kneel down and pray for
her. And you refused. There is something
sinister in you.
```

By using 3 subcorpora we can examine the model performance in different scenarios. Table 1 represents a primitive corpus analysis - the character count, word count, sentence count, for each subcorpora along with some mean values (letters per word, words per sentence, sentences per story). Therefore, a short description, some examples and statistical evaluation to conclude our corpus analysis.

	short_stories_corpus	medium_stories_corpus	litbank_corpus
characters	61483	161421	1034539
words	13823	35176	216213
sentences	499.00	2035.00	8687.00
letters per word	4.32	4.37	4.7
words per sentence	28.79	18.37	28.21
sentences per story	6.09	290.71	86.87

Table 1. Corpus analysis (characters, words, sentences, letters/word, words/sentence, sentences/story).

Named entity recognition (NER)

The precondition to extract any sort of value from our work was to extract the characters in the story - to perform named entity recogniton.

We evaluated 2 different NER solutions for Python - *Stanza* and *Spacy*.

Stanza provides a complete NN network pipeline (tokenization, POS tagging, dependency parsing, and of course, named entity recognition) and contains some already pretrained neural models. Moreover, it is a native Python implementation with minimal set-up hassle.

Spacy is a similar toolkit, again allowing swift and varied natural language processing (tokenization, visualizing, pretrained transformers) by identifying non-overlapping labelled spans of tokens. SpaCy is by default faster than Stanza as it is optimized under Cython (Python and C mixture).

The NER pipeline for Spacy can be seen on figure 1. The process was done in a similar manner for Stanza.

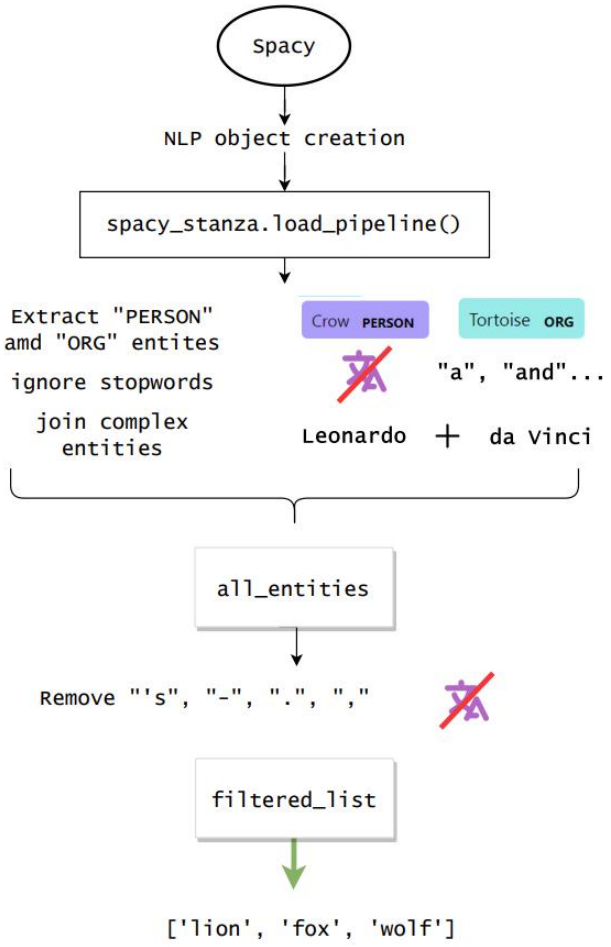

Figure 1. NER pipeline for Spacy

We compared the performance of the two above stated NER solutions on three different corpora. First, we compared the running times of both implementations, which can be seen in table 2. We can observe, that Spacy is noticably faster.

	Short Stories	Medium Stories	Litbank
Spacy	0.03 s	1.23 s	0.41 s
Stanza	2.95 s	52.33 s	30.76 s

Table 2. Comparison of average running times of entity extraction algorithms.

Next we compared the number and quality of recognized entities of the two above stated NER solutions.

Two NER visualization examples are shown in figure 2 below. A near perfect entity extraction is present in the first story, while the second shows some errors, missing ”Stag” as an entity or marking ”Humph” as an entity.

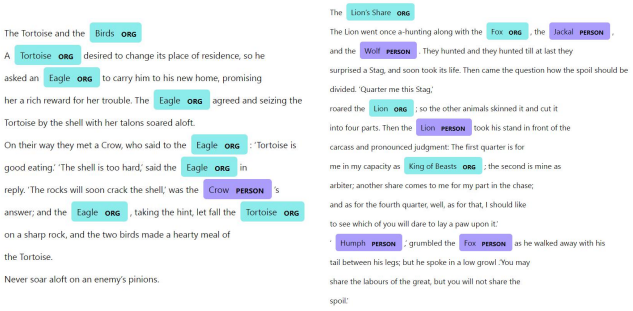

Figure 2. Varying success of NER (good vs ok results)

We then tested the quality of NER more formally, results of which can be seen in table 3. To explain it a little further, ”Equal” shows how many times, was the output of both, Stanza and Spacy, identical. That could indicate, that on those examples, that all the entities have been found, and that these are in fact correct. In case of ”Equal with different output”, the number of recognized entities was the same, but at least one of the entities was different.

On manual inspection of the outputs on a couple of randomly chosen stories from all corpora, given by both implementations, we could conclude, that Stanza gave higher quality results, i.e. is more reliable than Spacy. That also shows, that in table 3 in case of ”Stanza = 0” has a lower number, which means, that there were fewer cases, given an input where Stanza did not find any entities. Another sign of better quality and reliability is that in majority of short stories, Stanza was able to extract more entities than Spacy. It can also be seen, that in longer texts, there were no cases, where either of the implementations would not be able to extract any entity.

Because we reason, that the reliability of Spacy is worse than Stanza, it is expectable, that Spacy would find more entities given longer text, where their quality would be worse, despite the fact that the data was preprocessed and postprocessed in the same manner in both implementations. After manual review of the output of both implementations on a couple of randomly chosen stories, this proved to be true.

	Short Stories	Medium Stories	Litbank
Equal	27	0	7
Equal with different output	2	0	0
Stanza	35	0	16
Spacy	18	7	77
Stanza = 0	6	0	0
Spacy = 0	14	0	0

Table 3. Comparison of number of extracted entities using Spacy and Stanza.

Character sentiment analysis

To obtain the general consensus of a fictional character, we had to perform sentiment analysis on given stories. A lot of tools that calculate overall sentiment of the story already exist and can be found in different Python libraries out of the box, but existing implementations of sentiment analysis only for parts (aspects) of text - called aspect based sentiment analysis

are very rare and and limited in nature. We have attempted to solve this problem with few different approaches with varying success.

POS tagging and Dependency Parsing

Our first idea was to extract the words describing our characters, and then classify our characters by calculating the sentiment of these words. To extract characters (aspects) and the corresponding opinions we used POS tagging and Dependency Parsing as described in the paper [9]. We used the Stanza pipeline to extract Parts of Speech Tagging (POS) to parse sentences into constituent elements and then Dependency parsing to determine the relationships between words. After that, rule based analysis can be applied to the extracted opinion words to determine the general sentiment about the aspect. We have managed to implement the method from the paper, but further testing revealed that it only works reliably on texts where the sentiment is expressed directly (Example 1 below), unlike the fiction stories where sentiment is usually hidden in more complex ways (Example 2).

Example 1:
'The pool is great but the water is very cold.'
returns [['pool', ['great']], ['water', ['cold']]

Example 2:
'There was Soon the Lion was let loose from his den, and rushed bounding and roaring towards his victim.'
returns [['lion', []]

Afinn

For our second idea, we first tried a more basic approach, using Afinn [10] - a list of words rated for valence with an integer between minus five (for negative sentiment) and plus five (for positive sentiment). We first extracted the general sentiment of the story by calculating sentiment score on the whole text. Then we also calculated the sentiment for each character by calculating the average sentiment score of the each sentence in which this character appears. We then normalized the results in order for them to be comparable with results we get from sentiment analysis using Stanza. Of course, even though such a naive approach is easy to implement it has some obvious faults. Sentiment analysis in such a way is in the end, just a mathematical evaluation. For example, such an approach can be overwhelmed by repetition even though the overall sentiment is negative. A sentence such as "John is a happy happy murderer." could be characterized as positive, as the positive value of two "happy"'s together outweigh the negative value of "murderer".

General sentence occurrence sentiment

The third idea was to calculate the general theme of the sentences the character occurs in and then draw the conclusions about the character from that. The idea is, that on average, positive characters will more often appear in positive context and negative characters will appear in a negative context. We used the Stanza pipeline with the pre-trained model to get the sentiment of each sentence (-1 for negative, 0 for neutral and +1 for positive sentiment) and then identify if the character appears in the given sentence. We kept a list of sentiments for each character occurrence and calculated the average sentiment. We quickly noticed that some stories are overwhelmingly negative and others positive. To counter this effect, we normalized the average sentiment score of the character with the average sentiment score of all sentences. The equation 1 below shows the formula to calculate the sentiment of each character, where $V_{sentiment}$ represents the list of sentiments in which the character appears and $SEN_{sentiment}$ represents the list of sentiments for all sentences.

$$X_{sentiment} = \frac{\sum V^i_{sentiment}}{|V_{sentiment}|} - \frac{\sum SEN^i_{sentiment}}{|SEN_{sentiment}|} \quad (1)$$

In the Listing 1 below, we can see the output of our program before and after normalization. We can see that the general sentiment of the story is negative, which skews how we rate our characters. Androcles is is overall a positive character, but the negativity of the entire text skews the perception, which is fixed in the normalized version. We also implemented the representation of the sentiment for each character in the co-occurrence graph with different colors and levels of saturation (green for good characters, red for bad and white for neutral. More saturated greens and reds for the characters closer to the edges of the interval) as seen in the Figure 3.

Listing 1. Comparison of sentiment analysis with and without normalization

```
## Without normalization
"Androcles.txt": {
        "general": -0.2857142857142857,
        "entities": {
            "androcles": -0.1111111111111111,
            "lion": -0.6666666666666663
        }
    },
## Normalized
"Androcles.txt": {
        "general": -0.2857142857142857,
        "entities": {
            "androcles": 0.1746031746031746,
            "lion": -0.38095238095238093
        }
    },
```

Character co-occurrence

After mapping sentiment values to all characters, we decided to determine which characters actually interact. This can be determined by studying co-occurrence.

The process was as follows:

- extract entities (characters)
- extract all sentences from story and filter them
- create bigrams from filtered sentences
- create network from bigrams

The prerequisite for character co-occurrence is naturally knowledge which characters actually exist (the process was explained in detail in the subsection about NER). It was then necessary to study their coexistence and interaction, which is why the next step consisted of extracting all sentences but only such where our characters are directly mentioned. A thorough bigram generation followed for each filtered sentence. The final step was constructing a co-occurrence network of all characters. A simple iteration over all bigrams sufficed. If the bigram contained two already recognized characters - it was added as an edge in the network. More frequent bigrams consequently have a larger weight that is resembled with the thicker edge on the graph. Green nodes represent characters with 'good' sentiment score and red nodes represent characters with 'bad' sentiment score. The more faded the color is, the closer to neutral the character is and white nodes represent the neutral characters. The sentiment score can also be seen in the parentheses next to the entity names. Co-occurrence network for the excerpt from 'The Adventures of Huckleberry Finn' can be seen on figure 3. Characters that appear together in bigrams can be seen as the connected nodes on the graph ('Huckleberry' and 'Watson'), while 'Jim' wasn't found in the bigrams with other entities. Colors of the nodes visually represent the character sentiment scores. We would also like to note, that sometimes running the same code on different systems gave us slightly different results

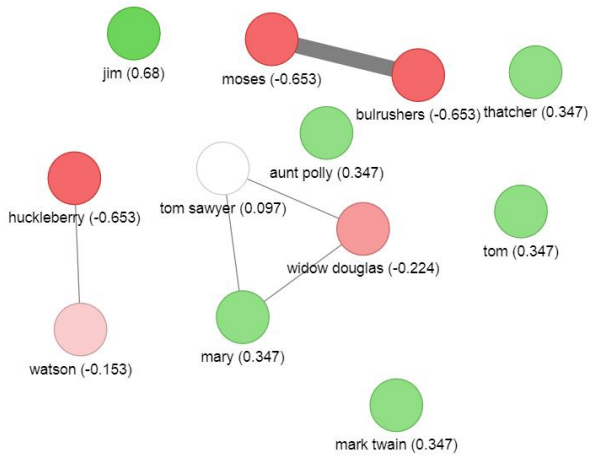

Figure 3. Co-occurrence network in Huckleberry Finn excerpt

Of course, such an approach leaves plenty of room for improvement. For example, detecting character co-occurrence on an excerpt from The Picture of Dorian Gray was not as successful. Dorian, the main character, is just an isolated node in the network! This is because throughout the excerpt he is mentioned frequently but almost exclusively indirectly (through different pronouns, nouns and descriptions). A possible solution might be not to filter the sentences so strictly, to look at the wider context, neighboring bigrams etc.

Results and discussion

In this section we will provide some metrics on 15 randomized short stories. As our corpus is not already analyzed/tagged we opted to, as a start, manually analyze these 15 in terms of entity recognition and sentiment analysis and compare the algorithm results with our baseline values.

Detailed results of the named entity recognition (in terms of true positives, false negatives, false positives) are seen in table 4.

The meaning of these metrics are described as follows:

1. true positive - both we and the algorithm found an entity

2. false negative - we found an entity, while the algorithm did not

3. false positive - the algorithm found an entity, while we did not

The results are solid, the algorithm occasionally misses an entity, and almost never misinterprets a false entity.

We can find similar results for sentiment analysis in table 5, where two different approaches were evaluated and compared with manually obtained results. Both algorithms performed similarly - with around average classification success.

To evaluate the performance of our models on non annotated data, we decided to evaluate it "by hand". We looked at the calculated response (Which is ideally in the [-1, 1] interval before normalization) and rated the character with score less than -0.2 as bad, with more than 0.2 as good and everything in-between as neutral. We then compared this rough estimation to how we felt about the character after reading the story ourselves. To keep sane, this was done on really short stories so we would argue that our method would do better on longer stories, as the algorithm would have way more context to draw from - instead of only 2 to 3 sentences.

While evaluating those results, we also have to take into consideration, that the sentiment of a character is a subjective opinion based on ones interpretation of the story and some other person can potentially classify the character sentiment in a different way and obtain different results.

Story	TP	FN	FP
Androcles	2	0	0
Avaricious and Envious	1	2	0
Belling the Cat	1	1	0
Hercules and the Waggoner	2	0	0
The Ant and the Grasshopper	2	0	0
The Four Oxen and the Lion	1	2	0
The Fox and the Cat	3	2	0
The Fox and the Crow	4	0	0
The Fox and the Goat	1	1	0
The Fox and the Grapes	0	1	0
The Wind and the Sun	1	2	0
The Wolf and the Crane	2	0	0
The Wolf and the Kid	1	1	0
The Wolf and the Lamb	1	1	1
The Tortoise and the Birds	3	0	0
Overall	*25*	*13*	*1*

Table 4. Comparison of detected entities vs. actual entities

Corresponding precision and recall metrics for NER are calculated in equation 2 below.

$$Precision = 0.96, Recall = 0.66 \quad (2)$$

Story	Afinn(correct/all)	Stanza(correct/all)
Androcles	0/2	1/2
Avaricious and Envious	1/1	1/1
Belling the Cat	1/1	1/1
Hercules and the Waggoner	2/2	2/2
The Ant and the Grasshopper	2/2	0/2
The Four Oxen and the Lion	0/1	1/1
The Fox and the Cat	0/3	1/3
The Fox and the Crow	3/4	2/4
The Fox and the Goat	1/1	0/1
The Fox and the Grapes	1/1	0/1
The Wind and the Sun	1/1	0/1
The Wolf and the Crane	0/2	0/2
The Wolf and the Kid	0/1	0/1
The Wolf and the Lamb	1/2	2/2
The Tortoise and the Birds	1/3	1/3
Overall	*14/27*	*13/27*

Table 5. Comparison of detected sentiments vs. actual sentiments

Conclusion

One of the shortcomings on these approaches is setting the correct threshold in sentiment recognition and evaluation of the results. Since we, the authors of this paper, read some stories from the corpus and assigned the sentiment to the entities based on our subjective opinion. One of the future improvements of this problem would be to have a professional annotate these stories, then we could assign the threshold more appropriately and the algorithm would work better even on more general stories.

Possible ideas for future work include: analyzing sentiment between characters, maybe even adding visual cues to edges on the co-occurrence graph. An edge that connects the antagonist with the protagonist could be darker in color, while one connecting friends would be lighter.

Some way of mitigating indirect mentions could prove productive in all stages of the pipeline. That way all pronouns that refer to entities are actually taken into consideration in subsequent sentiment and co-occurrence analysis.

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