A Decomposition-Based Approach for Evaluating Inter-Annotator Disagreement in Narrative Analysis

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Abstract

In this work, we explore sources of inter-annotator disagreement in narrative analysis, in light of the question of whether or not a narrative plot exists in the text. For this purpose, we present a method for a conceptual decomposition of an existing annotation into two separate levels: (1) whether or not a narrative plot exists in the text, and (2) which plot elements exist in the text. We apply this method to an existing dataset of sentences annotated with three different narrative plot elements: Complication, Resolution, and Success. We then employ statistical analysis in order to quantify how much of the inter-annotator disagreement can be explained by each of the two levels. We further perform a qualitative analysis of disagreement cases in each level, observing several sources of disagreement, such as text ambiguity, scheme definition and personal differences between the annotators. The insights gathered on the dataset may serve to reduce inter-annotator disagreement in future annotation endeavors. We conclude with a broader discussion on the potential implications of our approach in studying and evaluating inter-annotator disagreement in other settings.

1. Introduction

Annotated language resources play a fundamental role in both theoretical and computational linguistic research, aiding in analyzing and studying linguistic phenomena, as well as providing a “ground truth” or “gold label” for training supervised models for various NLP tasks. The annotation process commonly involves acquiring multiple annotator judgements on each of the data samples, a practice which is considered to increase annotation quality (Snow et al., 2008). Inter-annotator disagreement may originate from various sources (Artstein, 2017; Beck et al., 2020; Basile et al., 2021), and is generally resolved using methods such as majority voting, averaging or resorting to expert judgement. While this may be perceived as relatively simple for “objective” tasks (e.g. part-of-speech tagging, syntactic grammar), more “subjective” tasks, where it is not always clear whether a “correct” judgement actually exists, pose a considerable challenge (Alm, 2011).

Narrative analysis is an example of such a subjective task. Scholars of various disciplines have used the concept of narrative to mean different things, making the study of narratives rather confusing. Even though there is a general agreement among narratologists that succession of events is the core of narrativity (Abbott, 2021; Genette, 1980; Rimmon-Kenan, 2003), there is still an ongoing debate regarding the actual conditions for a text to even be qualified as a narrative (Shenhav, 2015). In the field of NLP, several works have constructed and annotated datasets for capturing various narrative aspects in texts (Baiamonte et al., 2016; Delmonte and Marchesini, 2017; Papalampidi et al., 2019; Volpetti et al., 2020). A more specific line of work is inspired by the works of Labov and Waletzky (1967) and Labov (2013) on characterizing narratives by identifying different narrative element types (Swanson et al., 2014; Ouyang and McKeown, 2014; Li et al., 2017; Saldis and Roy, 2020; Levi et al., 2022). However, we are not aware of any work which focuses on addressing the sources of inter-annotator disagreement in narrative analysis, and more specifically, through the question of whether or not the text contains narrative elements at all.

In this work, we evaluate and discuss sources of inter-annotator disagreement in narrative analysis in light of this very question. For this purpose, we examine an existing dataset of sentences annotated with three different narrative plot elements: Complication, Resolution and Success (Levi et al., 2022). Together, these three elements capture a typical tension-release plot type, varied by the different possible elements combinations. We perform a conceptual decomposition of the annotation task into two separate questions/levels, each addressing a different level of disagreement: (1) whether or not a narrative plot exists in the text, and (2) which plot elements exist in the text. We then employ statistical analysis in order to quantify how much of the inter-annotator disagreement can be explained by each of the two levels.

We make two main observations: first – there is notable disagreement on the first level, i.e., on whether or not there is a narrative plot in the sentence at all; and second – given an agreement on the first level, the agreement on the second level, i.e., on which of the narrative elements appear in the sentence, is considerably higher. We move on to perform a qualitative analysis of disagreement cases, and discuss different sources
of disagreement in each of the two decomposed levels of annotation. We conclude by suggesting how to use these insights to improve inter-annotator agreement (or rather preserve it where appropriate), as well as how to utilize our decomposition-based analysis to detect and evaluate sources of inter-annotator disagreement in other annotation schemes.

2. Study

2.1. Data

We analyzed the dataset created by Levi et al. (2022) for narrative analysis, consisting of 2,209 sentences (taken from news articles). The authors employed a total of three annotators (henceforth denoted as $A_1$, $A_2$ and $A_3$). The annotators assigned each sentence with a subset of the three narrative elements Complication, Resolution and Success. Note that these elements are not mutually exclusive, so a sentence may be annotated with any combination of the three, or none at all. All the sentences were annotated by $A_1$, while each sentence was additionally annotated by either $A_2$ or $A_3$ (statistics are given in Table 1). Further details on the annotation scheme, guidelines and dataset can be found in [Levi et al. (2022)].

| # Sentences | Comp. | Res. | Suc. |
|-------------|-------|------|------|
| $A_1$       | 2,209 | 1,083| 448  |
| $A_2$       | 1,135 | 504  | 262  |
| $A_3$       | 1,074 | 569  | 296  |

Table 1: Annotation statistics: the number of annotated sentences (out of a total of 2,209) and the number of sentences annotated with each of the three narrative elements, for each of the three annotators

2.2. Methods

2.2.1. Agreement Metrics

In order to measure inter-annotator agreement, we utilize two commonly-used metrics. The first is the pairwise percent agreement (PPA), which is the percentage of instances on which the annotators agree (i.e. assigned identical annotation) out of all the instances which are annotated by both. While this is the simplest and most intuitive way to measure agreement, it has the drawback of not accounting for chance agreement. This may pose a problem in some cases, e.g. in cases of significant class imbalance, as is our case (evident in Table 1). The second metric we employ, Cohen’s Kappa coefficient ($\kappa$), was designed to address this very issue (Cohen, 1960; Landis and Koch, 1977) by correcting the PPA for chance agreement between the annotators. It is defined as:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$  \hspace{1cm} (1)

where $p_o$ is the observed agreement (namely, the PPA), and $p_e$ is the expected probability for chance agreement, which is calculated from the individual empirical distributions of the annotators over the annotated instances.

2.2.2. Annotation Decomposition

Our goal is to decompose the annotations described in 2.1 into two separate levels: whether a narrative plot was identified in the sentence, and which narrative elements were detected in the sentence. To do that, we define a new label denoted “Plot”, which represents the existence of a narrative plot as defined by our three narrative elements. From a theoretical perspective, this label indicates whether or not the sentence facilitates the plot type captured by this annotation scheme. We compute this label from the existing annotations as follows. Given a sentence $s$ annotated by annotator $A_i$ ($i \in \{1, 2, 3\}$), and a narrative element $e \in E = \{\text{Complication}, \text{Resolution}, \text{Success}\}$, let us define:

$$A_i^e(s) = \begin{cases} 1 & A_i \text{ detected element } e \text{ in } s \\ 0 & \text{Otherwise} \end{cases}$$  \hspace{1cm} (2)

Then

$$A_i^{Plot}(s) = \bigvee_{e \in E} A_i^e(s)$$  \hspace{1cm} (3)

Hence, Plot is considered to be identified in a sentence by an annotator if and only if the annotator detected at least one of the three narrative elements in that sentence. Next, we quantify how much of the inter-annotator disagreement is explained by each of the two separate levels of the annotation. For this purpose, we perform the following 2-stage procedure for each pair of annotators $A_1A_2$ and $A_1A_3$:

1. We measure the inter-annotator agreement for the Plot label, to obtain the agreement for the first level of the annotation.
2. We neutralize the disagreement stemming from the first level by discarding all the sentences on which the annotators disagree on the Plot label, leaving only the sentences on which they agree. By measuring the agreement on the remaining sentences, we obtain the inter-annotator agreement for the second level of the annotation.

3. Analysis & Discussion

Overall agreement. Table 2 summarizes the overall inter-annotator agreement. For each pair of annotators we report PPA & $\kappa$ on each of the three narrative elements in the annotation scheme. We observe no significant differences between the two pairs in terms of per-element agreement (a max. difference of 1.8% in PPA and 0.04 in $\kappa$). It is, however, interesting to note the different pictures painted by PPA vs. $\kappa$. Among the three narrative elements, the highest average PPA (92.8%) is achieved by Success, while the highest average $\kappa$ (0.79) is achieved by Complication, which is
Table 2: Overall inter-annotator agreement

| PPA    | Comp. | Res. | Suc. |
|--------|-------|------|------|
| $A_1, A_2$ | 88.7% | 88.2% | 92.9% |
| $A_1, A_3$ | 90.5% | 86.8% | 92.7% |
| Average | 89.6% | 87.5% | 92.8% |

Table 3: Inter-annotator agreement, factored into the two decomposed annotation levels: whether the sentence contains a narrative plot ("Plot"), and which narrative elements the sentence contains, given an agreement on Plot ("Comp.", "Res." and "Suc.")

| PPA      | Plot    | Comp. | Res. | Suc. |
|----------|---------|-------|------|------|
| $A_1$ vs. $A_2$ | 86.3% | 95.3% | 92.0% | 95.4% |
| $A_1$ vs. $A_3$ | 86.9% | 95.7% | 89.9% | 95.9% |
| Mean     | 86.6%   | 95.5% | 91.0% | 95.7% |

| PPA      | Plot    | Comp. | Res. | Suc. |
|----------|---------|-------|------|------|
| $A_1$ vs. $A_2$ | 0.71  | 0.91 | 0.77 | 0.80 |
| $A_1$ vs. $A_3$ | 0.69  | 0.91 | 0.73 | 0.84 |
| Mean     | 0.70   | 0.91 | 0.75 | 0.82 |

The sentence contains a reference to a complicative plot element – “the DNC hack” – which is not directly described or discussed in the sentence itself, creating a narrative gap which the reader should complete in order infer this complicative plot development. This “referential narrative” is a rhetorical device which is commonly used in informational text; therefore, this type of disagreement may be resolved by formally defining how to handle such cases in the scheme level (essentially not leaving the decision to the annotators). A similar type of disagreement can be seen in the next sentence:

(2) Conventional wisdom holds that Republicans are more likely to nominate governors than are Democrats, but there’s not a lot of evidence to support the claim. ($A_1$: Complication, $A_2$: None)

Here, the complication occurs in the level of the narration itself, i.e., the narrator informs us that “there’s not a lot of evidence to support the claim”, thus facilitating a narrative plot. This being a frequent aspect of narrated texts, the resulting disagreement may also be resolved on the level of formal scheme definition. However, disagreement is sometimes rooted in the interpretation of a specific phrasing rather than in generalizable narrative aspects. For example,

(3) A 1984 rebranding included the brand’s targeting the high-end luxury market. ($A_1$: None, $A_2$: Resolution)

In this case, the disagreement between the annotators stems from the term “rebranding”. $A_2$ perceives this action as resolving a situation (or an existing tension), while $A_1$ does not. The annotators agree on the semantic meaning of the sentence’s content; however, they disagree on the narrative interpretation of that content. Unlike examples (1) and (2), this disagreement is hard to resolve via a formal definition in the scheme level, since it involves the interpretation of a specific word ("branding"). Another similar case can be found here:

(4) This led to roles abroad, including Jesus in "The Greatest Story Ever Told" (1965) and Father Lankester Merrin in "The Exorcist" (1973). ($A_1$: None, $A_2$: Success)

As in the previous example, the disagreement originates in a specific phrase – “roles abroad” – which $A_2$ interprets as a plot development (in this case, success or a desired outcome). Again, this difference is hard to resolve in the scheme level, being centered on a specific phrase.

Disagreement may also stem from the annotators’ personal perspectives and opinions:

(5) And by the 1950s, some 6,000 hospitals had sprouted throughout the country. ($A_1$: Success, $A_2$: None)
Here, $A_1$ perceives the emergence of a large number of hospitals as a success, or a desired outcome, while $A_3$ views it – in the context of this sentence – as merely a reported fact.

3.2. Second Level

Agreement on the second level (i.e., the agreement scores on the three narrative elements, after neutralizing the first level) is significantly higher than the overall agreement reported in Table 2. This suggests that once the first level is resolved (i.e., it is agreed that the text contains a narrative plot), it is significantly easier for the annotators to agree on the second level (i.e., the specific elements of which the plot consists).

As in the first level, second-level annotation disagreements originate from various sources. For example:

(6) "History has suggested that the pessimists have been wrong time and time again," he said. ($A_1$: Complication, $A_3$: Resolution)

This sentence stresses the difference between the complication-resolution plot structure and the negative-positive polarity. $A_1$ detects a complicating function in "have been wrong time and time again"; however, $A_3$, having detected the same function, views the fact that it were the “pessimists” who have been wrong as a double negation of a sort and thus as a resolved situation, correlating the complication-resolution structure with the negative-positive polarity. This is a rather fundamental matter which may be resolved at the level of the formal scheme definition (similarly to examples (1) and (2)). Disagreement may also stem from text ambiguity on the semantic level:

(7) This bleeding is not expected, at least in such a significant population so quickly. ($A_1$: Complication, $A_2$: Resolution)

The origin of disagreement here is the ambiguous first part of the sentence – “This bleeding is not expected”. This can be understood in two ways: either the bleeding was not expected but has happened, in which case a complication has transpired ($A_1$), or the bleeding is not expected to happen, in which case a resolution has been reached ($A_2$). This is a noteworthy example as to how text ambiguity may produce two possible narrative interpretations.

(8) Jackson had done her own calculation for the court record, agreeing on all but one argument for a harsher sentence. ($A_1$: Complication, $A_3$: Resolution)

In this interesting example, the sentence contains several plot-driving phrases, some with resolving attributes (“agreeing on all”) and others with complicating ones (“all but one argument”, “harsher sentence”), making it fairly hard to cognitively process. Evidently, the annotators couldn’t agree whether the described situation is a complicative or a resolutive one.

As in the first level, the annotators’ points of view and personal opinions may also bias their annotation:

(9) House Republicans have invited industry lobbyists to help rewrite rules on how agencies use science. ($A_1$: Resolution, $A_3$: Complication)

Here, $A_1$ detects a resolved situation in the phrase “help rewrite rules”. However, $A_3$ sees the fact that it were “House Republicans” who had “invited industry lobbyists” to do so as a complicating action. There is no ambiguity or uncertainty as to the situation described in the sentence; rather, this disagreement may be attributed to a bias exhibited by the annotator towards the sentence’s topic or theme (similarly to example (5)).

4. Conclusion

We explored inter-annotator disagreement in narrative analysis through the fundamental question of whether or not a narrative plot exists in the text. For this purpose, we presented a method for decomposing an existing annotation into two separate levels, based on that very question: (1) whether or not a narrative plot exists in the text and (2) which narrative plot elements it contains. We applied this method to an existing dataset labeled with a specific tension-release plot type, composed of three narrative elements (Complication, Resolution and Success) and discovered that not only there is notable disagreement on the first level, but that given an agreement on the first level, the agreement on the second level is considerably higher. In addition, we performed a separate qualitative analysis of disagreement cases in each of the levels, observing various sources of disagreement, such as text ambiguity, scheme definition and personal differences between the annotators.

The insights gathered on the dataset may serve to reduce inter-annotator disagreement in future annotation endeavors. It is evident that the first level of annotation accounts for a considerable part of the disagreement; therefore, it may be beneficial to address the question of whether or not there is a plot in the text in the annotators’ guidelines. In addition, various sources of disagreement may be addressed – scheme definition (e.g. examples (1), (2) and (6)), text ambiguity (e.g. examples (7) and (8)) or personal differences between the annotators (e.g. examples (5) and (9)).

The decomposition approach presented here may have general implications on the analysis of inter-annotator agreement. Given an annotated dataset, it allows conceptually decomposing the annotation by theoretically or empirically driven aspects of the scheme, and statistically quantifying the distribution of the disagreement over these chosen aspects. In a larger sense, it offers a more flexible approach than current conventions of inter-annotation diagnosis, allowing researchers to...
study and evaluate various aspects and sources of disagreement in highly subjective tasks such as narrative annotations.

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