

Giorgi, Salvatore, Ke Zhao, Alexander H. Feng, and Lara J. Martin. 2023. "Author As Character and Narrator: Deconstructing Personal Narratives from the r/AmITheAsshole Reddit Community". Proceedings of the International AAAI Conference on Web and Social Media 17 (1):233-44. <https://doi.org/10.1609/icwsm.v17i1.22141>.

Access to this work was provided by the University of Maryland, Baltimore County (UMBC) ScholarWorks@UMBC digital repository on the Maryland Shared Open Access (MD-SOAR) platform.

**Please provide feedback**

Please support the ScholarWorks@UMBC repository by emailing [scholarworks-group@umbc.edu](mailto:scholarworks-group@umbc.edu) and telling us what having access to this work means to you and why it's important to you. Thank you.

---

# AUTHOR AS CHARACTER AND NARRATOR: DECONSTRUCTING PERSONAL NARRATIVES FROM THE *r/AmITheAsshole* REDDIT COMMUNITY

---

Salvatore Giorgi, Ke Zhao, Alexander H. Feng, Lara J. Martin

Department of Computer and Information Science

University of Pennsylvania

Philadelphia, PA

sgiorgi@sas.upenn.edu, cocozhao321@gmail.com, {ahfeng, lamar}@seas.upenn.edu

## ABSTRACT

In the *r/AmITheAsshole* subreddit, people anonymously share first person narratives that contain some moral dilemma or conflict and ask the community to judge who is at fault (i.e., who is “the asshole”). In general, first person narratives are a unique storytelling domain where the author is the narrator (the person telling the story) but can also be a character (the person living the story) and, thus, the author has two distinct voices presented in the story. In this study, we identify linguistic and narrative features associated with the author as the character or as a narrator. We use these features to answer the following questions: (1) what makes an asshole character and (2) what makes an asshole narrator? We extract both Author-as-Character features (e.g., demographics, narrative event chain, and emotional arc) and Author-as-Narrator features (i.e., the style and emotion of the story as a whole) in order to identify which aspects of the narrative are correlated with the final moral judgment. Our work shows that “assholes” as Characters frame themselves as lacking agency with a more positive personal arc, while “assholes” as Narrators will tell emotional and opinionated stories.

## 1 Introduction

When you read a story, you might identify with the characters and their dilemmas and not realize the biases behind the person telling the story. Readers might fail to consider the author as the narrator until external events bring the author’s opinions to light, giving them extra information as they reread and reinterpret the story. On one end, there is a clear difference between character and narrator. Consider the world of fan fiction, where fans of a particular work will tell their own stories using the same characters as the original work. This divide is exacerbated when the original creator’s and the fan fiction writers’ values diverge (e.g., J.K. Rowling’s *Harry Potter* vs *Harry Potter* fan fiction by LGBTQ+ authors; Duggan, 2022 [1]).

On the other end of the spectrum, the characters and the narrator are intertwined. This is especially relevant when the author is both a character in the story and the narrator, making it difficult to differentiate between what moral values the author has vs what moral values the character has. These types of stories are found in autobiographies and memoirs, but they can also be found on the internet in the form of subreddits such as *r/AmITheAsshole*.

In this study, we look at anonymous, autobiographic tales (i.e., first person narratives, or personal narratives) from the *r/AmITheAsshole* community. In *r/AmITheAsshole*, people post their stories to help them determine (or convince themselves) that they have the moral high ground. Other people—who we will refer to as the Commenters—will vote on whether they believe the Original Poster (OP)<sup>1</sup> is in the right (labeled “Not the Asshole”, or *NTA* for short) or in the wrong (“You’re the Asshole”, *YTA*) and occasionally give their reasoning why. Then the final label is selected through majority voting.

---

<sup>1</sup>“OP” and “author” will be used interchangeably throughout the paper. This is not to be confused with “narrator,” which we are considering to be the style of the written work.

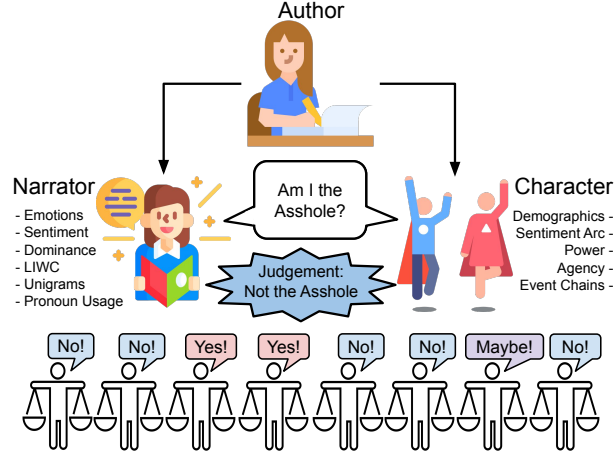


Figure 1: Crowd judgments of both the author as the narrator and a story character.

When looking at stories with a deeply-intertwined character/narrator dichotomy, such as in the *r/AmITheAsshole* stories, it is worth noting how the moral judgment of the OP can change when the story is read from a different perspective. Sagae et al., 2013 [2] consider the separation of the “diegetic” (the aspects of the story itself) and “extradiegetic” (the influence of the narrator) levels vital to understanding the amount of subjectivity in a story. While narratives are known to be more persuasive than non-narratives, the mechanisms behind this are less well-understood [3]. Previous research has suggested that *identification*—the adoption of the perspective of the character—aids in narrative persuasion [4] among other mechanisms.

In this study, we take a computational linguistics approach to disentangle both the character and narrator in personal narratives in order to understand their downstream effects on moral judgments. Here we define the *author-as-character* features as those that relate to the content of the story that refers to the author (e.g, sentences where the author is the subject or direct object), whereas the *author-as-narrator* features relate to the overall style of the story. As such, we look at various linguistic and narrative features in order to ask **RQ-C: What makes an asshole character?** compared to **RQ-N: What makes an asshole narrator?**

Our contributions are as follows:

1. the introduction of a set of features for separating the author as character and the author as narrator;
2. a framework for analyzing autobiographical (or personal) narratives; and
3. the analysis of these features on both parts of the RQ.

This work also acts as one answer to Piper et al.’s (2021 [5]) call for more story understanding work from a narrative perspective using information processing techniques.

In the rest of the paper, we will go into more detail on the specifics of the *r/AmITheAsshole* dataset and discuss related work that uses this (or similar) data and other work investigating identities within stories. We then describe our two sets of features for the Author-as-Character & Author-as-Narrator dichotomy. Next, we perform a logistic regression and show and discuss the results for answering RQ-C & RQ-N, respectively. We end with a discussion about possible next directions.

## 2 The *r/AmITheAsshole* Data Set

*r/AmITheAsshole*—an English-language subreddit on Reddit—is a forum where users can anonymously share their personal experiences (i.e., first person narratives) of a particular event or series of events they have been blamed for or believe they should be blamed for. In these accounts, authors are encouraged to explain any details of the events that they deem necessary in order for other Reddit users to pass judgment: is the original writer an asshole (**YTA**—You’re the Asshole) or not the asshole (**NTA**) in the story? The other Reddit readers (the Commenters) vote on it and leave comments explaining their reasoning. Occasionally, readers also ask the original poster questions to clarify certain points, where the original poster can respond. According to the forum rules, Commenters are asked to start their

comment with one of the following (1) You’re The Asshole (YTA), (2) Not The Asshole (NTA), (3) Everybody Sucks Here (ESH), (4) No Assholes Here (NAH), and (5) Not Enough Info (INFO). In the end, after 18 hours, each post is officially labeled by the tag corresponding to its top comments.

Our data consists of scraped content from the *r/AmITheAsshole* subreddit pulled from the Pushshift Reddit Data set [6]. The raw data is a collection of the initial posts of over 959,996 Reddit threads from June 2013 to June 2021. Since Reddit posts may stay online after deletion or the user has deleted their account, The Pushshift Reddit Data set contains deleted entries. Our data has been cleaned and filtered to remove deleted submissions and submissions with no text in the body of the post. Submissions with no text in the body of the post are typically posts with a title only or a title plus some non-textual body (such as an image).

The posts contain metadata such as creation time and subreddit names, as well as comments, but do not include the original poster’s user handle or the post’s actual content. We remove posts from bots and moderators. Bots were identified through multiple methods: (1) bots identified in the subreddits *r/botwatch*, *r/spambotwatch*, and *r/markov\_chain\_bots*, (2) a manual inspection of frequent posters, and (3) a manual inspection of user handles which contain the substring “bot”. Moderators were also identified by manually inspecting high frequency posters or accounts with “mod” or “moderator” in their posts or user handle.

The final judgment label was not available in the Pushshift Reddit Data set, and thus needed to be scraped. We were able to scrape labels for 216,318 submissions via Selenium<sup>2</sup>. In this study, we focus on two primary labels (YTA and NTA) and dropped all remaining submissions.

Additionally, we only consider submissions with at least 500 words and 20 comments. These minimums, respectively, have been used for accurately measuring person-level constructs (see the feature set below which includes emotions and sentiment; Eichstaedt et al., 2021 [7]) and as a threshold for *r/AmITheAsshole* submissions with high engagement [8]. Our final dataset consists of 38,060 submissions: 29,111 NTA (76.5%) and 8,949 YTA (23.5%).

All data (including the features described below) will be anonymized and publicly released.<sup>3</sup> In particular, unigram frequencies will be manually inspected and any possibly sensitive data (e.g., names) will be removed. To respect the privacy of Reddit users (who have the ability to delete their posts), the full text associated with each Reddit post will not be released. A unique identifier associated with each post will be released which will allow researchers to merge our data set with data from the Reddit API and other publicly available data sets.

### 3 Related Work

Personal narratives differ structurally from fictional stories as they are more likely to be nonlinear but tend to contain more salient events [9]. Researchers have used various methods to understand these types of narratives, including text processing tools, such as word embeddings [10], topic modeling [11, 12], sentiment analysis [11], or low-level features like part-of-speech tagging and tokenization [13]. Others rely on annotations for classifying complex aspects of personal narratives, such as identifying the intention of the narrator [11, 14] or where there is subjectivity [2, 15]. We have found others who use pre-existing narrative models from the psychology community [16].

Although earlier work in computational analysis of personal narratives focused on blog posts [17, 2, 13], recent work has largely focused on social media sites such as Twitter and Reddit.

Reddit is a large public, potentially anonymous social media site, which is organized into hundreds of thousands of forums (or “subreddits”) related to specific topics. Reddit is a rich data source for a number of NLP and Computational Social Science tasks: asking a favor [18], gender differences in discussions of parenting [19], political discussions [20, 21], maternal health [22], narrative power in birth stories written by mothers [23], and self-improvement [24]. Reddit has also extensively been used to study mental health [25], including depression [26], non-suicidal self-injury [27], and suicide [28, 29].

Due to its unique nature, a number of recent studies have used the *r/AmITheAsshole* subreddit. Botzer et al. (2021 [30]) investigated how users provide moral judgments of others, finding that users prefer posts that have a positive moral valence. Similar work using *r/AmITheAsshole* attempts to automatically classify “reasonability” of people’s actions based on a retelling of events from a story using a number of social and linguistic features (e.g., up/down votes and sentiment; Haworth et al., 2021 [31]). Efstathiadis et al., 2021 [32] built BERT-based classifiers for submissions and comments and attempts to predict both the final label and the comment labels. *r/AmITheAsshole* has also been included in studies on advice communities (which includes the *r/relationships* subreddit; Cannon et al., 2022 [33]) and ethical judgments [34]. Finally, a number of studies attempt to understand judgments of moral dilemmas, rather than focus

<sup>2</sup><https://github.com/baijum/selenium-python>

<sup>3</sup><https://github.com/<redacted>/<redacted>>

on a classification task. For example, Nguyen et al., 2022 [12] used topic modeling with expert and crowd-sourced annotations to understand moral dilemmas, showing that pairs of topics (e.g., family and money) are informative. Similarly, Zhou et al., 2021 [8] showed that the *NTA* label is associated with more use of 1st person passive voice.

It is worth noting that other work [35, 36] has framed moral/ethical judgments in stories as normative or non-normative behavior, acknowledging that morality is often person or culture-dependent, which we can see in the variance of judgments in the *r/AmITheAsshole* data set as well.

## 4 Feature Extraction

We will explore features that represent the author as a character in the story and the narrator of the story. To reiterate from before: *Author-as-character* features relate to the author as a character within the content of the story. *Author-as-narrator* features relate to how the author narrates the story. We will use both *theoretically-driven* and *open-vocabulary* features. The theoretically-driven features are interpretable features which we hypothesize will be related to the final submission label. On the other hand, open-vocabulary features do not correspond to any prior hypotheses and make use of large feature spaces (e.g., unigrams and LIWC categories).

### 4.1 Text Preprocessing

Since all lexical and dictionary features (i.e., NRC, LIWC, Concreteness and Familiarity, and unigrams) are calculated via bag-of-words approaches, we apply the same text preprocessing steps. Submissions are first normalized: white space is collapsed, all characters are set to lowercase, and non-UTF8 characters are removed. We then extract unigrams from each submission using a tokenizer designed to capture the idiosyncrasies of social media text (e.g., emoticons, misspellings; Schwartz et al., 2017 [37]). Dictionary scores are then computed as the weighted sum of the unigram frequencies per submission (where LIWC weights are set to 1). All other features (power/agency, chain of events, emotional story arc) are processed within spaCy.

### 4.2 Author as Character

The following feature categories describe who the author is as a person, their relationship to other characters in the story, and the story progression.

**Demographics.** Many of the stories in the *r/AmITheAsshole* submission corpus contain demographics (i.e., age and gender) of the author. For example, a typical submission will contain a line like “my sister (66f), my two cousins (24F) and (18M), and me (51F)” which denotes the age and gender of the author and various characters in the story. We extract author demographics through a series of regular expressions. Gender is numerically encoded such that male is -1, gender neutral is 0, and female is 1<sup>4</sup>. We set age and gender equal to zero when narrators do not disclose their own demographics. To control for setting non-disclosed demographics to zero we include two binary covariates (one for age and another for gender) which are set to 1 for all authors who do not disclose either age or gender. The demographic information gives us 4 features: **OP Age**, **OP Gender**, **Other Character Age**, **Other Character Gender**. Both **Other Character Age** and **Other Character Gender** are averaged over all non-author characters in the narrative.

**Power and Agency.** This is the amount of power and agency the OP has as a character. Here we use the Power and Agency frames developed by Sap et al., 2017 [38], where power is defined as control over the world while agency is control over oneself. The frames consist of a list of labeled verbs (1,737 for power and 2,146 for agency) where the label denotes the direction of the power between the subject and the direct object. For example, if “X dreads Y” then Y (the *theme* or direct object) has power, and if “X excludes Y” then X (the *agent* or subject) has power. To measure the power of author in each story, we use the spaCy dependency parser<sup>5</sup> to extract subject-verb-object tuples. We use a standard list of 1st person pronouns (including common misspellings) to identify the author: i, i’m, mine, myself, me. The author’s power score is positively incremented if (1) they are the subject and verb’s power label is *agent* or (2) if they are the object and the verb’s power label is *theme*. We then normalize the power score by the number of times the author was included in a subject-verb-object tuple. When operationalized in this way, negative power means that the non-author entities exert power over the author, while positive power means that the author exerts power over other entities. Examples of different power and agency combinations are given in the Appendix Table 1. This gives us two features: **OP Power** over other characters and **OP Agency**.

<sup>4</sup>We realize that this is a very limited sense of gender and that reducing gender to a binary representation is problematic. That said, our data is limited in its gender representation.

<sup>5</sup><https://spacy.io/api/dependencyparser>

**Emotional Story Arc.** This is the emotional arc of the author as the main character, defined as the sentiment flow or progression across the story (or, more specifically, sentiment across sequences of sentences). Here we follow the methods of Antoniak et al. (2019 [23]) and consider sentiment across the narrative. We used the VADER sentiment analysis tool [39] to compute sentence-level sentiment across all submissions as implemented in the NLTK Python package [40]. We ignore sentences with 5 words or less (due to their noisy sentiment estimates) and we only look at sentences that include the author (i.e., exclude sentences that do not reference the author in the subject-verb-object tuple). We use a normalized sentiment score that ranges from -1 to 1, with negative numbers representing negative sentiment and positive numbers representing positive sentiment. Next, for each submission, we average the sentence-level sentiment across 10 sequential and equal-sized chunks. We calculate the slope of the arc to see how the slope relates to the **NTA/YTA** labels. Finally, we visualize the arcs by averaging the sentiment for each of the 10 chunks for both labels **NTA** and **YTA** and plotting the resulting averages.

**Chain of Events.** This is the narrative event chain of the story for all characters, focused on the verbs of the story’s sentences. We generate **NTA/YTA** narrative event chains similar to the methods outlined in Tambwekar et al. (2019 [41]). We first extract the sequence of events (stemmed verbs from each sentence). Then, for stories in each label type (**NTA** or **YTA**), we calculate two components: 1) the depth of the verb in the story (how many sentences in), and 2) the frequency of the verb across all stories. We then normalize the verb depth by dividing it by its frequency to get the average depth of each verb across all stories. Using this value, we cluster the verbs using the Jenks Natural Breaks optimization technique [42] to group together verbs found in similar positions across the stories, and this is our event chain. The process is repeated for both **NTA** and **YTA** stories. For each submission, we extract all the verbs in the order they appear and compare this to both **NTA/YTA** chains via Damerau-Levenshtein distance, which gives us an approximation of how similar this post is to either of our event chains. Finally, we pick the label with the higher matching score. We considered chains of length 3, 5, and 10, picking chains of 3 clusters for achieving the highest accuracy in label prediction. Having this feature highly correlate with **NTA** or **YTA** would mean that posts within the label show a similar sequence of events.

### 4.3 Author as Narrator

The following features are centered around analyzing the author’s tone and word choice.

**Pronoun Usage.** This is the amount of 1st-person and 3rd-person pronouns in the story. Pronoun Usage will be measured using the Linguistic Inquiry and Word Count (LIWC) dictionary [43]. Here we will measure both 1st and 3rd person pronouns and encode each submission as a ratio of the two. This will give us an estimate of the narrator’s focus on the self vs. others in the story. This gives us 5 features: **1st Person Singular**, **1st Person Plural**, **3rd Person Singular**, **3rd Person Plural**, and the **1st/3rd Person Ratio**, regardless of plurality.

**Sentiment-NRC.** This is the quantity of positive and negative sentiment words found in the story, providing the narrator’s tone. We measure it via the *Positive Sentiment* and *Negative Sentiment* categories in the NRC Word-Emotion Association Lexicon, a crowd-sourced, word-level lexicon (Emolex; Mohammad and Turney, 2013 [44]). This gives us the features **Positive Sent** and **Negative Sent**.

**Emotions-NRC.** Using the NRC Hashtag Emotion Lexicon [45] we estimate Plutchik’s eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust [46]. The NRC Hashtag emotion lexicon, which is a set of weighted words for each emotion category, was automatically derived over tweets with emotion hashtags (e.g., *#anger* and *#joy*). This gives us the features **Anger**, **Anticipation**, **Disgust**, **Fear**, **Joy**, **Sadness**, **Surprise**, and **Trust**.

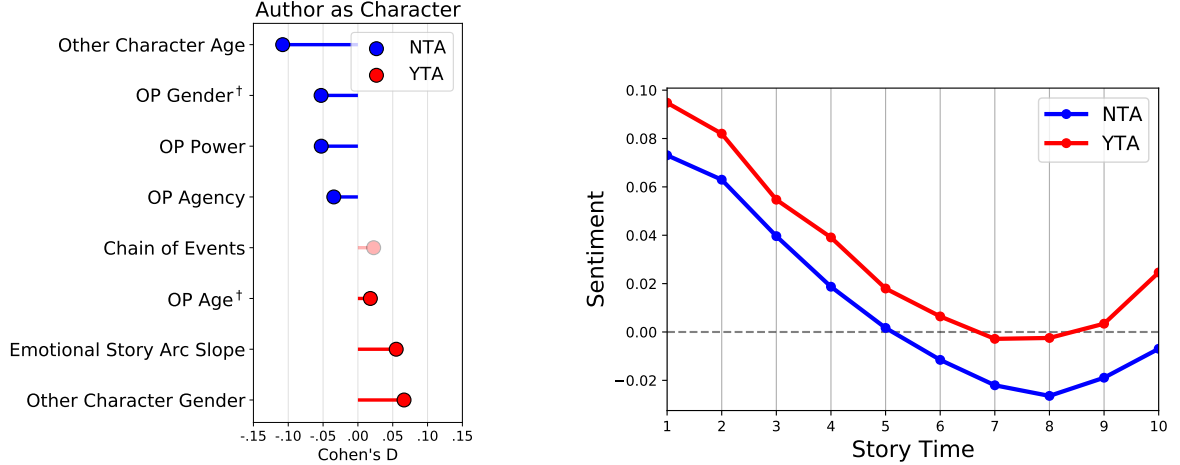
**Dominant Tone.** From the NRC Valance, Arousal, Dominance (VAD) lexicon [47], we will use the dominance dimension which consists of 20,000 weighted (between 0 and 1) English words. High-dominance words include “powerful” & “success” while low-dominance words include “frail” and “empty”. This lexicon has previously been used to study the dehumanization (i.e., negative evaluation of a target group) of LGBTQ people in news articles [48].

**Concreteness and Familiarity.** We use the MRC Psycholinguistic Database which includes a lexicon of 85,941 weighted words for estimating **Concreteness** and **Familiarity** [49]. Concreteness is a measure of how much a word refers to a tangible entity, while Familiarity refers to how often a word is seen or heard.

**LIWC.** Linguistic Inquiry and Word Count (LIWC) dictionary, which consists of 73 manually curated categories (e.g., both function and content categories such as positive emotions, sadness, and pronouns; Pennebaker et al., 2015 [50]). LIWC is the most widely used dictionary in social and psychological sciences with over 8,800 citations as of April 2020 [7]. This is an example of an *open-vocabulary feature* since we are considering the entire feature space.



**Unigrams.** Using the tokenizer described above, we extract unigrams for each submission. This results in a total of 84,781 unigrams. We removed any unigram which was not used in at least 380 (1%) of the submissions. This produced a final set of 2,726 unigrams. This number is smaller than the total number of observations (38,060 submissions), which will help prevent model over-fitting. As with LIWC, this is an example of an *open-vocabulary feature* since it uses the entire feature space.



(a) Cohen's D values showing the correlation of features for YTA & NTA classes. Lighter shaded points are not significant at a with Benjamini-Hochberg corrected significance  $\alpha < 0.05$ ). The higher the absolute effect size, the more that feature is associated with the YTA/NTA class. † includes a binary covariate equal to 1 for undisclosed age/gender.

(b) Emotional Story Arc. Average VADER sentiment across 10 equally-sized sentence-level chunks. Positive values are positive sentiment, negative values are negative sentiment.

Figure 2: Author as Character results.

## 5 The Makings of an Asshole

### 5.1 Methods

In order to see which features in both sets (author as narrator and character) are indicative of a post being labeled YTA, we run a correlational analysis. These features will be used to quantify the content of the stories and how they related to the final vote of YTA or NTA. For each feature we correlate, via logistic regression, the standardized feature value (mean-centered and normalized by their respective standard deviation) with the binary crowd-sourced label YTA/NTA, which is operationalized as 1 and 0, respectively. Due to a large number of comparisons (e.g., up to 2,726 unigrams), we apply a Benjamini-Hochberg False Discovery Rate correction [51]. Since logistic regression coefficients are not comparable across models in the same way OLS regression coefficients are, we report Cohen's D, which measures the difference between two group means (the YTA/NTA classes). This is measured as the absolute difference in group means divided by the pooled standard deviation, with value close to 1 having a larger effect size. We note that Cohen's D is traditionally a positive number (due to the absolute difference). In order to aid interpretation, we set Cohen's D values for features correlated with the NTA class to be negative.

Due to shared methodologies across the feature space (e.g., the NRC lexica or the subject-verb-object tuples used to calculate power/agency and the emotional story arcs), we examine how the various features overlap in their relationship to the binary YTA/NTA label. For each pair of features  $f_1$  and  $f_2$ , we perform a logistic regression where the dependent variable is the binary NTA/YTA label. Each regression contains three independent variables: two additive terms and a multiplicative term (the product of the two additive terms, i.e., the interaction term):

$$y = \frac{\exp(\beta_0 + \beta_1 f_1 + \beta_2 f_2 + \beta_3 (f_1 \times f_2))}{1 + \exp(\beta_0 + \beta_1 f_1 + \beta_2 f_2 + \beta_3 (f_1 \times f_2))} \quad (1)$$

When applicable, we also include the binary covariates for undisclosed author age and gender (discussed in the Feature Extraction section). All independent variables are standardized (mean-centered and divided by the standard deviation).

Again, we apply a Benjamini-Hochberg False Discovery Rate correction since there are a large number of comparisons (18 total features).

A significant interaction term  $\beta_3$  indicates that the dependent variable and one of the additive independent variables depend on (or moderate) the other. Due to the symmetry of the equation, the moderator is typically chosen for theoretical reasons. Since we have no a priori hypotheses, we simply examine whether or not  $\beta_3$  is significant and make no further claims on the relationships between  $f_1$  and  $f_2$ . Due to the large feature space, in this analysis we only consider features that are significantly correlated with the NTA/YTA label.

## 5.2 RQ-C - Results & Discussion

**Demographics.** For the Character features in Figure 2a, we see the strongest correlation of younger and female authors associated with the NTA class (or similarly, older and male authors associated with the YTA class). Stories with other characters who are younger (on average) and female (on average) are associated with YTA; or similarly, stories with other characters who are older, male are associated with NTA. Note that for author age and gender, Cohen’s D cannot take into account the binary variables (in the logistic regression) used to indicate undisclosed demographics. When the author’s age or gender is undisclosed, we set the value to zero, which will drive Cohen’s D toward 0, thus artificially deflating the effect size.

**Power and Agency.** Both high author power (control over the world) and high author agency (control over themselves) are associated with the NTA class. Conversely, this could mean that YTA posters are having events happen to them.

**Emotional Story Arc.** The arc shapes in Figure 2b are often called a “riches to rags” or “tragedy” story arc [52]. While both arcs are similar, the YTA arc is consistently higher than the NTA arc (i.e., more positive on average), slightly crossing the 0 threshold (i.e., neutral or slightly negative sentiment), and has a larger upswing at the tail-end of the story. Meanwhile, the NTA arc, while following the same general shape, has a more neutral and negative sentiment overall. At each point, we compute a two-sided t-test (difference in means across the two classes) and see that the NTA and YTA are significantly different, with an average  $t = 6.07$  across the 10 story points. Thus, while the shapes are similar, there is a significant difference between the overall sentiment level at each point. The arc significantly interacts with other character’s age and gender as well as the emotion **Disgust** (Table 3).

In Figure 2a we also see more a positive Emotional Story Arc *slope* associated with the YTA class. Given the overall “riches to rags” story shapes in Figure 2b slopes downwards (i.e., a decline in sentiment), a more positive slope for the YTA class would imply a less dramatic decline or even a constant or upward sentiment arc. Research on cinematic tragedies has shown that those who experience greater lows during tragedies also experience increased highs at the end of the tragedy [53]. One possible explanation is that these increased highs or transitions from low to high may increase engagement with the NTA posts, though further research is needed to examine this relationship with moral judgments.

The Chain of Events features are not significantly correlated with the final label after applying the FDR correction. The stories are most likely too unique to have the events signify NTA or YTA.

## 5.3 RQ-N - Results & Discussion

Figures 3 & 4 show the results of our analyses of features corresponding to the Author as Narrator, and whether or not they correlate with YTA or NTA labels.

**Pronoun Usage.** More “I” usage was highly correlated with NTA. We had assumed we would see the opposite results—as a sign of OP’s self-centeredness when labeled YTA. Instead, we believe these results might show Commenters the accountability of OP in NTA stories. NTA posts are also more likely to use 3rd person plural pronouns, but YTA posts use 1st person plural pronouns more.

Tausczik and Pennebaker, 2010 [54] have found that 1st person plural pronouns are a sign of having high status (i.e., “the royal we”) or being detached, while 1st person singular pronouns are a sign of honesty and depression and 3rd person singular pronouns show social interest. We believe that, by using 1st person plural pronouns, YTA posters could be seen as detaching themselves from what they know to be a bad situation or thinking highly of themselves, while NTA posters are seen as more honest about their account and caring about the others in the story because of their pronoun usage. We see similar patterns with the LIWC data in Figure 3b: mentions of distinct entities (i.e., *Family* terms, personal pronouns (*I*, *Personal pronouns*, and *Male*) are more correlated with NTA posts.

In terms of interactions (Table 3), first person singular pronouns and first person plural pronouns significantly interact. Additionally, first person singular pronouns interact with **Trust** (negative coefficient) and first person plural pronouns

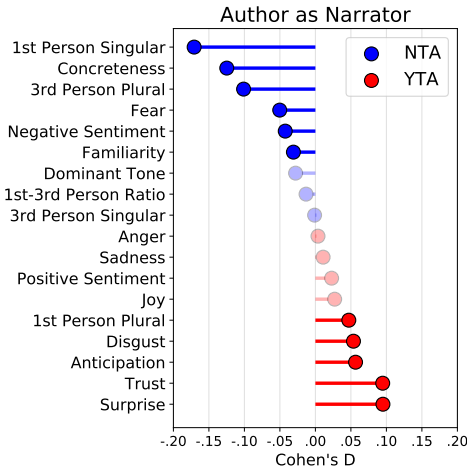


interact with **Familiarity** (positive coefficient). Thus, referring to singular others who the narrator trusts increases the probability of the **NTA** class, while familiarity and first person plural pronouns increase the probability of the **YTA** class.

**Sentiment-NRC & Emotions-NRC.** **Fear** and **Negative Sentiment** are more correlated with **NTA** posts. Zhou et al., 2021 [55] found that stories with emotional themes of “distress” or “sadness” garnered more empathy from readers. This could explain the association of **Fear** and **Negative Sentiment**, with Commenters empathizing with the Narrator and labeling the post as **NTA**. That said, **Sadness** was not significantly correlated with either label. Other emotions, such as **Disgust**, **Anticipation**, **Trust**, and **Surprise** are all more correlated with **YTA** posts. This could imply **YTA** stories relying more on emotional persuasion to get Commenters on their side and less on factual descriptions of the events of the story.

**Concreteness and Familiarity.** Both **Concreteness** and **Familiarity** are correlated with the **NTA** label. Past research has shown that using abstract language to describe others is perceived to have biased motivations when compared to more concrete language [56]. This may suggest that **YTA** posts are perceived as having biased or hidden motives.

It has also been shown that online engagement depends on the complexity of the language: people spend more time and pay more attention to simple language; however, they are also more likely to give money if complex language is used, such as in grant proposals or crowdfunding [57]. This may explain the association between **Familiarity** and **NTA**, as Commenters may spend more time reading and pay closer attention to **NTA** posts. Further, **Familiarity** interacts with **Anticipation** (negative logistic regression coefficient) and, thus, increases the probability of the **NTA** class (Table 3). **Concreteness** and **Familiarity** significantly interact increasing the probability of the **YTA** class.



(a) Lighter shaded points are not significant at a with Benjamini-Hochberg corrected significance  $\alpha < 0.05$ .

Category	Most Frequent Words	D
NTA	<i>Family</i>	-0.24***
	<i>I</i>	-0.17***
	<i>Home</i>	-0.17***
	<i>Pers. pronouns</i>	-0.16***
	<i>Male</i>	-0.14***
YTA	<i>Insight</i>	0.22***
	<i>Cognitive Proc.</i>	0.22***
	<i>Differentiation</i>	0.19***
	<i>Tentative</i>	0.18***
	<i>Impers. pronouns</i>	0.17***

(b) LIWC Correlation results. Benjamini-Hochberg corrected significance levels: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ . We also report the top 5 most frequent words in each category.

Figure 3: Author as Narrator results. Cohen's D values showing the correlation of features for **YTA** & **NTA** classes for LIWC categories (3b) and other theoretically-driven Narrator features (3a).

**LIWC.** The results we found with the LIWC categories (Figure 3b) were more predictable. In addition to personal pronouns, **NTA** posts also mention specific *Home* locations, while **YTA** posts use more *Insight* words (i.e. opinion words; see Figure 3b for examples), *Tentative* words, and *Impersonal Pronouns*. This backs up our theory that **NTA**-rated stories have a tendency for having more concrete reports, while **YTA** OPs will be vaguer. Toma, 2014 [58] saw that people perceive more information to be more trustworthy when looking at the Facebook profiles of strangers. They believed this to be because of Uncertainty Reduction Theory (URT)—the theory that people need more information about each other in order to decrease the amount of uncertainty [59].

**YTA** posts will also give more opinions of events in the story with *Cognitive Processes* and *Differentiation* words. This could be because they either feel as if the events of the story could not be understood without some extra context or that they did not hold up on their own. Regardless of their intentions, using more opinion words can create narrative distance. Andringa1996, (1996 [60]) has seen that more opinionated narrators can make readers feel less “emotional involvement” in a story. Perhaps Commenters with less interest in stories are more likely to vote **YTA**.

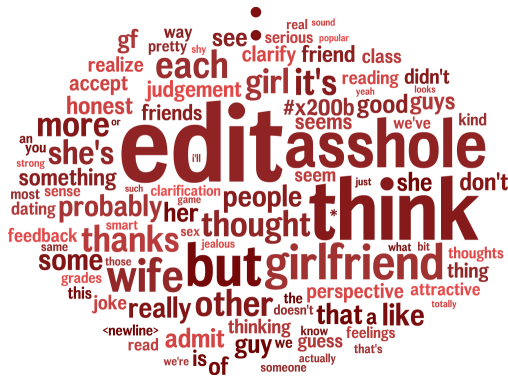
**Unigrams.** The most-associated unigrams for each label are shown in the word clouds in Figure 4 (see Appendix 2 for exact effect sizes). In Figure 4a (YTA), we see the word “edit” largest effect size (Cohen’s D). This means that the OP had gone back to change/add to their original story. This result goes along with YTA posters feeling the need to provide extra context. Anecdotally, across Reddit, OPs usually tend to edit their post when they are being criticized by Commenters and feel the need to elaborate or defend themselves. YTA stories are more likely to mention “asshole” directly.

There is also more mention of romantic and sexual relationships: “dating”, “attractive”, and “sex”, especially with a focus on words referring to women: “girlfriend”, “gf”, “wife”, “she’s”, “girl”. Although we do not know the exact context that these words are used, we suspect them to denote sexist undertones in the post, especially if the OP is more likely to be older and male if tagged YTA (see: OP Gender & OP Age results in the Author-as-Character analysis). Very few mentions of men are in the YTA word cloud, with the exception of “guy”/“guys”.

We also see “thinking” words (“think”, “thought”, “perspective”, “feedback”, “judgement”, “realize”, “admit”), which can be seen as attempts to understand what they (might have) done wrong or could be more evidence that opinionated posts create too much narrative distance (see: LIWC discussion).

In Figure 4b (NTA), we see mentions of family (“mom”, “family”, “dad”, “siblings”), self-focus (“my” and “me”), conflict (“refused”, “horrible”, “yelling”, “demanded”), as well as financial and health problems (“bills”, “money”, “covid”) and stressful life-changing events (“moved”, “divorced”, “custody”). We also see open and close parenthesis, which could indicate parentheticals containing extra information and details given by the narrator, backing up the URT theory. NTA posts also contain more quotation marks, which either indicate direct quotes or disagreement with the word or phrase someone else has said.

Dominant Tone was not statistically significant.



(a) YTA-Correlated Unigrams



(b) NTA-Correlated Unigrams

Figure 4: Author as Narrator, open-vocabulary features: Unigrams most correlated with the (a) YTA label (left) and (b) NTA (right). The size of the word indicates the strength of the correlation (large sizes correspond to larger Cohen’s D); color indicates the relative frequency of usage (rare words are lighter shades, very frequent words darker). All correlations are significant at a Benjamini-Hochberg significance level of  $p < 0.05$ . Cohen’s D ranged from (a) 0.06 to 0.24 and (b) -0.06 to -0.27 (see Appendix Table 2 for full Cohen’s D value by unigrams).

## 5.4 Discussion Summary

Now we will summarize the results in order to answer our research questions.

**RQ-C: What makes an asshole character?** Typically, if the OP is older and male with younger and female other characters in the story, the author is considered an asshole, probably due to an uneven power dynamic. These OP characters, which lack both agency and power, are written as having events *happen to them*. One possible explanation is that the author is framing their character as the victim. Meanwhile, the events that include them are generally positive, implying that good things are happening to their characters in the story.

**RQ-N: What makes an asshole narrator?** An “asshole narrator” is more detached from the story but tells more emotional and opinionated stories with fewer concrete facts all-the-while framing stories as a matter of perspective. The distance that the OP creates through this style makes Commenters less invested in the narrative. These posts might also be seen as less truthful. Furthermore, “asshole narrators” focus on topics such as relationships with women instead of family or stressful situations.

## 6 Limitations and Future Work

We admit that a lot of our conclusions about what the results may mean are conjecture until further analysis is done. However, we believe that our methods of separating out the narrator’s style from the character’s actions are helpful for understanding autobiographical narratives, as the narrator is not just an impartial observer. This linguistic breakdown (or similar) might be used in situations such as identifying con artists online, quickly determining who reliable narrators are in humanitarian crisis live-tweeting, or in narrative criminology.

There is a limitation to how much we can tease apart the author as narrator from the author as character given that they are both presented in the same medium: text. We attempted to treat the problem as style vs. content, but we admit some of the lines are unclear. For example, we treat OP’s gender as a character feature, but does the OP’s gender also affect how they write their stories?

Furthermore, we only ran our analysis on a single data set—the *r/AmITheAsshole* subreddit. It is possible that there are other data sets, such as the similarly-themed *r/relationship\_advice* subreddit, that could also work for both analyzing first-person narratives and comparing it to moral judgments from external parties. Other data sets can also be created using first-person narratives with crowd-sourced moral judgements [34].

All models used throughout this paper (LIWC, NRC lexica, Vader) were originally built on monolingual English datasets, and we have applied them in the same setting. Therefore, we do not expect any findings to generalize to non-English or minority populations.

Although we used several different features for analyzing posts from the perspective of the author as the narrator or character, we admit that there could be features that we did not think of. Our features are not an exhaustive list of all possible ways of characterizing these posts.

One major source of data that we have not analyzed, for instance, is the comments left on the posts. Future work could compare the text from the comments to the events or wording of the story in order to determine what readers are actually paying attention to when making their moral judgments. Style matching has been shown to predict author credibility [61], and thus one might expect Commenters to match the narrator in emotions or function words. This, however, we deemed out of the scope of this paper and we leave for future work.

Future work could also expand on the analytic framework for measuring positioning in narratives as developed by Kayi-Aydar (2021 [62]) which attempts to formalize how narrative identities are constructed, projected, or negotiated. Finally, one could examine narrative framing and related causal structures. For example, one could take these posts, modify the power direction of the verbs, and reevaluate the story in a crowd-sourced setting (like Amazon Mechanical Turk) to see if the final *NTA/YTA* label changes.

## 7 Broader Perspective and Ethical Concerns

While the methods in this paper are evaluated on a single data set, *r/AmITheAsshole*, we believe the general concept of separating the author-as-narrator from the author-as-character is potentially useful across several domains. From a computational perspective, those working in narrative understanding or character extraction could build on the methods here [63, 64]. From a social science perspective, political scientists and those working in media communications could be interested in disambiguating the author in the context of narrative persuasion [65] or how narratives shape public opinion (a situation comparable to asking “who is the asshole?”) [66].

When working with public social media data there are always a number of ethical concerns. While *r/AmITheAsshole* subreddit is a public forum where users are requesting moral judgments from their online peers, it is important to note that the Redditors have not consented to any research studies. Indeed, this problem is not particular to *r/AmITheAsshole* and is part of a larger issue of using publicly available social media data in research. While focused on mental health applications, Chancellor et al., 2019 [67] consider who is the “human” in machine learning research that uses social media data and discuss a number of implications around informed consent. As such, to preserve anonymity, all results are reported in aggregate, and we do not report direct quotes.

Also of note is the fact that we use age and gender to classify moral judgments, including a very narrow (binary) definition of gender. We do not intend to imply that any given age or gender is or should be considered an “asshole.”

## 8 Conclusion

In this paper, we have distinguished two facets of the author in first person narratives: the Author as Character and the Author as Narrator, and quantify what makes each an asshole. To do this, we automatically extracted a large number of

interpretable linguistic features designed to measure story characters and events as well as narrative tone and style. We performed a correlational analysis to give insight into which character and narrator features are related to overall moral judgments. Among other things, we found that asshole characters are older and male who have events passively happen to them, while asshole narrators frame the story as a matter of perspective. We believe by considering the narrator as separate from their character in the story, we are able to get a deeper insight into not just how these narratives are stylized but also how the author writes themselves into the story. Future work should be done to understand how readers understand these two aspects of autobiographical stories.

## References

- [1] Jennifer Duggan. Transformative Readings: Harry Potter Fan Fiction, Trans/Queer Reader Response, and J. K. Rowling. *Children’s Literature in Education*, 53:147–168, 2022.
- [2] Kenji Sagae, Andrew S. Gordon, Morteza Dehghani, Mike Metke, Jackie S. Kim, Sarah I. Gimbel, Christine Tipper, Jonas Kaplan, and Mary Helen Immordino-Yang. A Data-Driven Approach for Classification of Subjectivity in Personal Narratives. In *2013 Workshop on Computational Models of Narrative*, volume 32, page 198–213. Schloss Dagstuhl - Leibniz-Zentrum fuer Informatik GmbH, Wadern/Saarbruecken, Germany, Jan 2013.
- [3] Olivia M Bullock, Hillary C Shulman, and Richard Huskey. Narratives are persuasive because they are easier to understand: examining processing fluency as a mechanism of narrative persuasion. *Frontiers in Communication*, page 188, 2021.
- [4] Jonathan Cohen. Defining identification: A theoretical look at the identification of audiences with media characters. *Mass communication & society*, 4(3):245–264, 2001.
- [5] Andrew Piper, Richard Jean So, and David Bamman. Narrative theory for computational narrative understanding. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 298–311, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics.
- [6] Jason Baumgartner, Savvas Zannettou, Brian Keegan, Megan Squire, and Jeremy Blackburn. The Pushshift Reddit Dataset. In *International AAAI Conference on Web and Social Media (ICWSM)*, volume 14, pages 830–839, 2020.
- [7] Johannes C Eichstaedt, Margaret L Kern, David B Yaden, HA Schwartz, Salvatore Giorgi, Gregory Park, Courtney A Hagan, Victoria A Tobolsky, Laura K Smith, Anneke Buffone, et al. Closed- and open-vocabulary approaches to text analysis: A review, quantitative comparison, and recommendations. *Psychological Methods*, 26(4):398, 2021.
- [8] Karen Zhou, Ana Smith, and Lillian Lee. Assessing Cognitive Linguistic Influences in the Assignment of Blame. In *Ninth International Workshop on Natural Language Processing for Social Media (SocialNLP) at NAACL*, pages 61–69, 2021.
- [9] Maarten Sap, Anna Jafarpour, Yejin Choi, Noah A. Smith, James W. Pennebaker, and Eric Horvitz. Quantifying the narrative flow of imagined versus autobiographical stories. *Proceedings of the National Academy of Sciences (PNAS)*, 119(45):e2211715119, Nov 2022.
- [10] Alon Bartal, Kathleen M. Jagodnik, Ms Sabrina J. Chan, Ms Mrithula S. Babu, and Sharon Dekel. Identifying Women with Post-Delivery Posttraumatic Stress Disorder using Natural Language Processing of Personal Childbirth Narratives. *American Journal of Obstetrics & Gynecology MFM*, page 100834, Dec 2022.
- [11] Stephanie M. Lukin, Kevin Bowden, Casey Barackman, and Marilyn A. Walker. PersonaBank: A Corpus of Personal Narratives and Their Story Intention Graphs. In *International Conference on Language Resources and Evaluation (LREC)*, page 1026–1033, Portorož, Slovenia, 2016.
- [12] Tuan Dung Nguyen, Georgiana Lyall, Alasdair Tran, Minjeong Shin, Nicholas George Carroll, Colin Klein, and Lexing Xie. Mapping topics in 100,000 real-life moral dilemmas. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 16, pages 699–710, 2022.
- [13] Reid Swanson, Elahe Rahimtoroghi, Thomas Corcoran, and Marilyn Walker. Identifying Narrative Clause Types in Personal Stories. In *Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL)*, page 171–180, Philadelphia, PA, U.S.A., Jun 2014. Association for Computational Linguistics.
- [14] Liye Fu, Jonathan P. Chang, and Cristian Danescu-Niculescu-Mizil. Asking the Right Question: Inferring Advice-Seeking Intentions from Personal Narratives. 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)*, page 528–541, Minneapolis, Minnesota, 2019. Association for Computational Linguistics.

- [15] Aniruddha Tammewar, Alessandra Cervone, Eva-Maria Messner, and Giuseppe Riccardi. Annotation of Emotion Carriers in Personal Narratives. In *Conference on Language Resources and Evaluation (LREC)*, page 1511–1516, Marseille, May 2020. European Language Resources Association (ELRA).
- [16] Belen Saldias and Deb Roy. Exploring aspects of similarity between spoken personal narratives by disentangling them into narrative clause types. In *2020 ACL Workshop on Narrative Understanding, Storylines, and Events (NUSE)*. Association for Computational Linguistics, May 2020.
- [17] Reid Swanson and Andrew S. Gordon. Say anything: A massively collaborative open domain story writing companion. In *ICIDS 2008: Interactive Storytelling*, volume 5334 of *Lecture Notes in Computer Science (LNCS)*, page 32–40. Springer, Berlin, Heidelberg, 2008.
- [18] Tim Althoff, Cristian Danescu-Niculescu-Mizil, and Dan Jurafsky. How to Ask for a Favor: A Case Study on the Success of Altruistic Requests. In *International AAAI Conference on Web and Social Media (ICWSM)*, volume 8, pages 12–21, 2014.
- [19] Melody Sepahpour-Fard and Michael Quayle. How Do Mothers and Fathers Talk About Parenting to Different Audiences?: Stereotypes and Audience Effects: An Analysis of r/Daddit, r/Mommit, and r/Parenting Using Topic Modelling. *arXiv preprint arXiv:2202.12962*, 2022.
- [20] Anna Guimaraes, Oana Balalau, Erisa Terolli, and Gerhard Weikum. Analyzing the Traits and Anomalies of Political Discussions on Reddit. In *International AAAI Conference on Web and Social Media (ICWSM)*, volume 13, pages 205–213, 2019.
- [21] Gianmarco De Francisci Morales, Corrado Monti, and Michele Starnini. No echo in the chambers of political interactions on Reddit. *Scientific Reports*, 11(1):1–12, 2021.
- [22] Shuang Gao, Shivani Pandya, Smisha Agarwal, and João Sedoc. Topic Modeling for Maternal Health Using Reddit. In *12th International Workshop on Health Text Mining and Information Analysis at EACL*, pages 69–76, 2021.
- [23] Maria Antoniak, David Mimno, and Karen Levy. Narrative Paths and Negotiation of Power in Birth Stories. *ACM on Human-Computer Interaction*, 3(CSCW):1–27, 2019.
- [24] MeiXing Dong, Xueming Xu, Yiwei Zhang, Ian Stewart, and Rada Mihalcea. Room to Grow: Understanding Personal Characteristics Behind Self Improvement Using Social Media. In *Ninth International Workshop on Natural Language Processing for Social Media (SocialNLP) at NAACL*, pages 153–162, 2021.
- [25] Munmun De Choudhury and Sushovan De. Mental Health Discourse on reddit: Self-Disclosure, Social Support, and Anonymity. In *Eighth International AAAI Conference on Weblogs and Social Media*, volume 8, 2014.
- [26] Michael M. Tadesse, Hongfei Lin, Bo Xu, and Liang Yang. Detection of Depression-Related Posts in Reddit Social Media Forum. *IEEE Access*, 7:44883–44893, 2019.
- [27] Salvatore Giorgi, McKenzie Himelein-Wachowiak, Daniel Habib, Lyle Ungar, and Brenda Curtis. Nonsuicidal Self-Injury and Substance Use Disorders: A Shared Language of Addiction. In *Eighth Workshop on Computational Linguistics and Clinical Psychology (CLPsych)*. Association for Computational Linguistics, 2022.
- [28] Matthew Matero, Akash Idnani, Youngseo Son, Salvatore Giorgi, Huy Vu, Mohammad Zamani, Parth Limbachiya, Sharath Chandra Guntuku, and H. Andrew Schwartz. Suicide risk assessment with multi-level dual-context language and BERT. In *Proceedings of the Sixth Workshop on Computational Linguistics and Clinical Psychology*, pages 39–44, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.
- [29] Ayah Zirikly, Philip Resnik, Ozlem Uzuner, and Kristy Hollingshead. CLPsych 2019 Shared Task: Predicting the Degree of Suicide Risk in Reddit Posts. In *Sixth Workshop on Computational Linguistics and Clinical Psychology at NAACL*, pages 24–33, 2019.
- [30] Nicholas Botzer, Shawn Gu, and Tim Weninger. Analysis of Moral Judgment on Reddit. *IEEE Transactions on Computational Social Systems*, 2022.
- [31] Ethan Haworth, Ted Grover, Justin Langston, Ankush Patel, Joseph West, and Alex C Williams. Classifying reasonability in retellings of personal events shared on social media: A preliminary case study with r/amatheasshole. In *International AAAI Conference on Web and Social Media*, volume 15, pages 1075–1079, 2021.
- [32] Ion Stagkos Efstathiadis, Guilherme Paulino-Passos, and Francesca Toni. Explainable Patterns for Distinction and Prediction of Moral Judgement on Reddit. In *1st Workshop on Human and Machine Decisions (WHMD 2021) at NeurIPS 2021*, 2021.
- [33] Emily Cannon, Bianca Crouse, Souvick Ghosh, Nicholas Rihn, and Kristen Chua. “Don’t Downvote A\$\$\$\$\$s!!!”: An Exploration of Reddit’s Advice Communities. In *Hawaii International Conference on System Sciences (HICSS)*, page 2940–2949, Jan 2022.

- [34] Nicholas Lourie, Ronan Le Bras, and Yejin Choi. SCRUPLES: A Corpus of Community Ethical Judgments on 32,000 Real-life Anecdotes. In *AAAI Conference on Artificial Intelligence*, volume 35, pages 13470–13479, 2020.
- [35] Md Sultan Al Nahian, Spencer Frazier, Mark Riedl, and Brent Harrison. Learning norms from stories: A prior for value aligned agents. In *AAAI/ACM Conference on AI, Ethics, and Society*, pages 124–130, 2020.
- [36] Maxwell Forbes, Jena D. Hwang, Vered Shwartz, Maarten Sap, and Yejin Choi. Social Chemistry 101: Learning to Reason about Social and Moral Norms. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 653–670, Online, 2020. Association for Computational Linguistics.
- [37] H Andrew Schwartz, Salvatore Giorgi, Maarten Sap, Patrick Crutchley, Lyle Ungar, and Johannes Eichstaedt. DLATK: Differential Language Analysis ToolKit. In *2017 conference on empirical methods in natural language processing: System demonstrations*, pages 55–60, 2017.
- [38] Maarten Sap, Marcella Cindy Prasettio, Ari Holtzman, Hannah Rashkin, and Yejin Choi. Connotation frames of power and agency in modern films. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2329–2334, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.
- [39] C.J. Hutto and Eric Gilbert. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. In *International AAAI Conference on Web and Social Media (ICWSM)*, volume 8, pages 216–225, 2014.
- [40] Steven Bird, Ewan Klein, and Edward Loper. *Natural language processing with Python: analyzing text with the natural language toolkit*. "O'Reilly Media, Inc.", 2009.
- [41] Pradyumna Tambwekar, Murtaza Dhuliawala, Lara J. Martin, Animesh Mehta, Brent Harrison, and Mark O. Riedl. Controllable Neural Story Plot Generation via Reinforcement Learning. In *International Joint Conference on Artificial Intelligence (IJCAI)*, pages 5982–5988, Macau, China, 2019.
- [42] George F. Jenks and Fred C. Caspall. Error on choroplethic maps: definition, measurement, reduction. *Annals of the Association of American Geographers*, 61(2):217–244, 1971.
- [43] James W. Pennebaker, Martha E. Francis, and Roger J. Booth. Linguistic inquiry and word count: LIWC 2001. Technical report, University of Texas at Austin, and The University of Auckland, New Zealand, 2001.
- [44] Saif M. Mohammad and Peter D. Turney. Crowdsourcing a Word–Emotion Association Lexicon. *Computational Intelligence*, 29(3):436–465, 2013.
- [45] Saif M. Mohammad and Svetlana Kiritchenko. Using Hashtags to Capture Fine Emotion Categories from Tweets. *Computational Intelligence*, 31(2):301–326, 2015.
- [46] Robert Plutchik. A General Psychoevolutionary Theory of Emotion. In *Theories of Emotion*, pages 3–33. Elsevier, 1980.
- [47] Saif Mohammad. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. In *56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 174–184, 2018.
- [48] Julia Mendelsohn, Yulia Tsvetkov, and Dan Jurafsky. A Framework for the Computational Linguistic Analysis of Dehumanization. *Frontiers in artificial intelligence*, 3:55, 2020.
- [49] Gustavo Paetzold and Lucia Specia. Inferring psycholinguistic properties of words. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 435–440, San Diego, California, June 2016. Association for Computational Linguistics.
- [50] James W Pennebaker, Ryan L Boyd, Kayla Jordan, and Kate Blackburn. The Development and Psychometric Properties of LIWC2015. Technical report, University of Texas at Austin, 2015.
- [51] Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300, 1995.
- [52] Andrew J Reagan, Lewis Mitchell, Dilan Kiley, Christopher M Danforth, and Peter Sheridan Dodds. The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Science*, 5(1):1–12, 2016.
- [53] Minet De Wied, Dolf Zillmann, and Virginia Ordman. The role of empathic distress in the enjoyment of cinematic tragedy. *Poetics*, 23(1-2):91–106, 1995.
- [54] Yla R. Tausczik and James W. Pennebaker. The psychological meaning of words: Liwc and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1):24–54, 2010.
- [55] Ke Zhou, Luca Maria Aiello, Sanja Scepanovic, Daniele Quercia, and Sara Konrath. The Language of Situational Empathy. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):13:1–13:19, Apr 2021.



- [56] Karen M Douglas and Robbie M Sutton. When what you say about others says something about you: Language abstraction and inferences about describers’ attitudes and goals. *Journal of Experimental Social Psychology*, 42(4):500–508, 2006.
- [57] David M Markowitz and Hillary C Shulman. The predictive utility of word familiarity for online engagements and funding. *Proceedings of the National Academy of Sciences*, 118(18):e2026045118, 2021.
- [58] Catalina Toma. Counting on friends: Cues to perceived trustworthiness in facebook profiles, 2014.
- [59] Leanne K. Knobloch. *Uncertainty Reduction Theory*, page 1–9. John Wiley & Sons, Ltd, 2015.
- [60] Els Andringa. Effects of ‘narrative distance’ on readers’ emotional involvement and response. *Poetics*, 23(6):431–452, May 1996.
- [61] R. Kelly Aune and Toshiyuki Kikuchi. Effects of language intensity similarity on perceptions of credibility relational attributions, and persuasion. *Journal of Language and Social Psychology*, 12(3):224–238, 1993.
- [62] Hayriye Kayi-Aydar. A framework for positioning analysis: From identifying to analyzing (pre)positions in narrated story lines. *System*, 102:102600, 2021.
- [63] David Bamman, Brendan O’Connor, and Noah A. Smith. Learning latent personas of film characters. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 352–361, Sofia, Bulgaria, August 2013. Association for Computational Linguistics.
- [64] Labiba Jahan and Mark Finlayson. Character identification refined: A proposal. In *Proceedings of the First Workshop on Narrative Understanding*, pages 12–18, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.
- [65] Kurt Braddock and James Price Dillard. Meta-analytic evidence for the persuasive effect of narratives on beliefs, attitudes, intentions, and behaviors. *Communication Monographs*, 83(4):446–467, 2016.
- [66] Dallas Card, Justin Gross, Amber Boydston, and Noah A. Smith. Analyzing framing through the casts of characters in the news. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1410–1420, Austin, Texas, November 2016. Association for Computational Linguistics.
- [67] Stevie Chancellor, Eric P.S. Baumer, and Munmun De Choudhury. Who is the “human” in human-centered machine learning: The case of predicting mental health from social media. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW):1–32, 2019.

## 9 Appendix

### 9.1 Power and Agency examples

Table 1 includes example sentences which for all combinations of high / low power and high / low agency. Note that all posts have been paraphrased and anonymized for privacy.

### 9.2 Unigram Correlations

In Table 2 we list the exact Cohen’s D values for the top 10 most correlated unigrams for each label.

### 9.3 Interactions

In Table 3 we report the standardized logistic regression coefficients associated with the multiplicative interaction logistic regression term.

<b>Positive Agency &amp; Theme Power</b>
I asked her many times over the last few weeks to make up her mind, but she can't.
<b>Positive Agency &amp; Agent Power</b>
Because of this and the fact that people were staying to help her i decided to leave.
<b>Negative Agency &amp; Theme Power</b>
My friend needed the money in order to stay out of debt.
<b>Negative Agency &amp; Agent Power</b>
Let me talk the way i want!

Table 1: Examples of sentences with all combinations of agent (subject) / theme (object) power and positive / negative agency. All posts have been paraphrased and anonymized.

YTA		NTA	
Unigram	Cohen's D	Unigram	Cohen's D
edit	0.24	my	-0.27
think	0.20	mom	-0.19
:	0.16	dad	-0.16
asshole	0.16	family	-0.13
but	0.15	parents	-0.13
girlfriend	0.13	mother	-0.12
wife	0.12	me	-0.12
each	0.11	sister	-0.11
it's	0.11	moved	-0.11
thanks	0.11	house	-0.11

Table 2: Cohen's D values for the top unigrams associated with each label.

	Character			Narrator						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Emo. Story Arc	-	.06	.06	ns	ns	ns	ns	.04	ns	ns
(2) Other Char. Age	.06	-	ns	ns	ns	ns	ns	ns	ns	ns
(3) Other Char. Gen.	.06	ns	-	ns	ns	ns	ns	ns	ns	ns
(4) 1st Pers. Plur.	ns	ns	ns	-	.09	ns	ns	ns	.05	ns
(5) 1st Pers. Sing.	ns	ns	ns	.09	-	ns	ns	ns	ns	-.04
(6) Anticipation	ns	ns	ns	ns	ns	-	ns	ns	-.03	ns
(7) Concreteness	ns	ns	ns	ns	ns	ns	-	ns	.02	ns
(8) Disgust	.04	ns	ns	ns	ns	ns	ns	-	ns	ns
(9) Familiarity	ns	ns	ns	.05	ns	-.03	.02	ns	-	ns
(10) Trust	ns	ns	ns	ns	-.04	ns	ns	ns	ns	-

Table 3: Pairwise interactions: Reported standardized logistic regression coefficient of the multiplicative interaction regression term. *ns*: interaction term is not significant at  $p < 0.05$  after a Benjamini-Hochberg False Discovery Rate correction. Due to a large number of comparisons, features are not included in the table if they had no significant interactions with any other feature.