The Mafiascum Dataset: A Large Text Corpus for Deception Detection

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Abstract

Detecting deception in natural language has a wide variety of applications, but because of its hidden nature there are currently no public, large-scale sources of labeled deceptive text. This work introduces the Mafiascum dataset\(^1\), a collection of over 700 games of Mafia, in which players are randomly assigned either deceptive or non-deceptive roles and then interact via forum postings. Over 9000 documents were compiled from the dataset, which each contained all messages written by a single player in a single game. This corpus was used to construct a set of hand-picked linguistic features based on prior deception research, as well as a set of average word vectors enriched with subword information. A logistic regression classifier fit on a combination of these feature sets achieved an average precision of 0.39 (chance = 0.26) and an AUROC of 0.68 on 5000+ word documents. On 50+ word documents, an average precision of 0.29 (chance = 0.23) and an AUROC of 0.59 was achieved.

1 Introduction

A reliable automatic deception detector for written communication would find wide application in intelligence agencies, law enforcement, and online marketplaces. Of course, deception is hard to find and label because of its deceitful nature: deceivers are aiming to not be caught, and as such do not advertise their successes. Moreover, it is often unclear whether falsehoods are deliberate, and, in the case of spam, whether lies are deliberately transparent (Herley, 2012). As such, a major hurdle in applying supervised learning techniques to deception detection is the lack of a suitable publicly available dataset.

Although deception takes place in a large number of datasets, such as court transcripts (Pérez-Rosas et al., 2015), the Enron email corpus (Keila and Skillicorn, 2005), and laboratory experiments (Pérez-Rosas and Mihalcea, 2015), to date all public labeled datasets comparable in size to high-profile sentiment analysis benchmarks (e.g. Rosenthal et al., 2017) focus on single-sentence non-interactive deception (e.g. Pérez-Rosas et al., 2015; Wang, 2017). In this paper, we introduce a naturalistic dataset, a collection of over 700 games of Mafia played on an Internet forum, in which players are assigned either a deceptive or a non-deceptive role. The final dataset contains over 9000 documents. The average document contains 3940 words. We test a variety of established linguistic cues to deception on this dataset, as well as testing word embeddings.

1.1 Linguistic Cues to Deception

Until the 1970s, research aimed at detecting deception was largely focused on finding nonverbal cues (e.g., body language and facial expressions) for use in face-to-face interactions. After Mehrabian (1971) found that slow, erroneous and sparse speech can indicate deception, research into linguistic cues to deception took off.

In a recent meta-analysis of 79 linguistic cues to deception from 44 studies, Hauch et al. (2015) found that deceivers express more negative emotions, distance themselves from events (using less perceptual and sensory language), and generally experience more cognitive load as compared to non-deceivers. More specifically, deceivers produced fewer words and fewer distinct words than

\(^1\)https://bitbucket.org/bopjesvla/thesis/src
truth-tellers, while using more sentences. Additionally, deception was found to correlate with the use of negation terms (e.g., ‘no’, ‘never’, and ‘not’) and words specifically related to negative emotions and anger (e.g., ‘hate’, ‘worthless’, ‘enemy’). Deceivers used fewer exclusive words (e.g., ‘but’, ‘except’, and ‘without’) than non-deceivers, as well as fewer tentative words (e.g., ‘may’, ‘seem’, and ‘perhaps’). Deceivers used fewer total first-person pronouns than truth-tellers, but used second- and third-person pronouns more often than truth-tellers do. Deceivers also used fewer sensory and perceptual details than truth-tellers, especially in the acoustic realm (e.g., ‘listen’, ‘sound’, or ‘speak’), as opposed to sight or feeling. Deceivers produced more motion verbs (e.g., walk, go, or move). Finally, compared to truth-tellers deceivers also used fewer words concerning their inner thoughts (insight) and cognitive processes.

The meta-analysis supported the observation by Hancock and Woodworth (2013) that the significance of linguistic cues to deception is heavily dependent on context. In some cases, even the direction of the effect of significant linguistic cues differed between contexts. In particular, effect sizes varied wildly across different interaction conditions, types of deception, modes of communication, deceivers’ motivations, and differences in emotional valence.

1.2 The Game of Mafia

The original face-to-face version of the game of Mafia, also known as Werewolf, was designed by Dmitry Davidoff in the 1980s to model a conspiracy of an informed minority, the Mafia, within an uninformed majority, the townsfolk. Before the game starts, every player is randomly assigned to one of these teams. The goal of the Mafia, who, unlike the townsfolk, are aware each others’ identities, is to vote out all townsfolk, while the town’s objective is to vote out all Mafiosi. Being eliminated precludes townsfolk nor Mafia from winning with their team, to prevent conflict of interest.

The game starts with an in-game Day, during which the players discuss their suspicions, or, in the case of the Mafia, pretend to, and try to agree on a vote. When a majority vote is reached on a player, that player is eliminated from the game, their role and alignment are announced publicly by the moderator, and the game goes on to the Night. In games without special roles, also known as vanilla or mountainous, the only action performed during the Night is the elimination of another player by the Mafia. In face-to-face games, this is usually done by the Mafia pointing at the target while the townsfolk have their eyes closed. When the Mafia have reached a non-verbal agreement and their eyes are closed again, the game moderator announces the name, role, and alignment of the eliminated player, everyone “wakes up” and the game goes on to the next Day.

Mafia has been adopted by a large number of online communities. On the Internet, Days are usually played out in a public forum thread or chat room and the Mafia decide on the eliminated player by private messages.

An experiment run by Zhou et al. (2004) shares multiple similarities with later studies that use the online game of Mafia as a model for deception, which includes our study. Rather than Mafia, another consensus-building task was used, in which the goal is to persuade another person of a plan in a hypothetical survival scenario. The test group was told to convince their partner of a predetermined solution they were told was incorrect, while the control group was instructed to argue for their true views. Task communication occurred outside the lab over email, across a timespan of several days. The authors noted that this reduced the amount of experimental control, but also in their eyes lessened the pressure and unnaturalness felt by participants, perhaps making the experiment more representative of real-life deception. Participation was compulsory for students, and no additional reward was given for successful deception.

In contrast with prior research, the study found that deceivers wrote more than truth-tellers. The authors pointed to the persuasive nature of the task, which requires deceivers to come up with arguments to support their claims. Another possible explanation, not discussed by the authors, is that the task was more interesting for deceivers than for the control group, causing a difference in the amount of effort put in.

Zhou and Wei Sung (2008) collected 1192 Mafia games from a popular Chinese website dedicated to this game. The dataset differs from the Mafiascum dataset used in our study, which is explored in detail below, in many respects. All players were Chinese and all messages were written in Chinese. The deadline to decide on a single elimination was
3 minutes, during which all players were expected to stay in the chat room. The dataset only included games with a size ranging from 6 to 8 players, of which only one player was a deceiver.

In this setting, the deceivers’ average word count was found to be low compared to truth-tellers, which is inconsistent with Zhou et al. (2004), but consistent with most other previous research. Additionally, the vocabulary of the deceivers tended to be more diverse, which is inconsistent with both Zhou et al. (2004) and other previous research. The authors attributed these inconsistencies to cultural differences between the Chinese Mafia players and American students and differences between email and chat rooms, but they could also be the result of higher engagement from the truth-tellers: since the Chinese players chose to play voluntarily, it is reasonable to assume that they were more invested in hunting for deceptive players than the students who were required to participate in an experiment and who did not even know they might be deceived.

1.3 Machine Learning Classification

The performance of many recent text classification techniques on deception datasets is unknown. This is unfortunate for those interested in systematically detecting deception, but also for those in the business of creating general text classification techniques.

Intuitively, deception detection is quite different from most text classification problems, as it does not allow classifiers to base their predictions solely on explicit information the author intended to convey, such as their opinion on a movie. Instead, it requires classifiers to find implicit information the author intended to hide.

As a bonus, the truth-telling and deceiving conditions are randomly assigned to players in the game of Mafia, whereas many popular text classification benchmarks, such as most large sentiment analysis datasets, are passively observed. Because of this, the negative signal a performant sentiment classifier picks up on may not be negative sentiment, but the writing style of the type of person who publishes negative movie reviews on the Internet, for example.

Much of the less recent machine learning research on deception used Support Vector Machines. Mihalcea and Strapparava (2009) collected data from three written deception tasks. Applying only basic stemming and using nothing but raw stem counts, a Support Vector Machine trained on one of the tasks correctly classified 70% of the documents from that task on average. Using the same setup, a Naive Bayes classifier reached 71%. Additionally, an SVM trained on two tasks was able to correctly classify 58% of the documents from the third task, while the Naive Bayes classifier reached a classification rate of 60%.

State-of-the-art document classification techniques that have not been used in deception detection tasks include deep neural networks and word embeddings enriched with subword information (Bojanowski et al., 2016). The latter is promising because of its performance on syntactic tasks, since many cues to deception are plain syntactic groups. The FastText project provides word embeddings enriched with subword information for 294 languages, opening up the possibility to transfer some of the methods in this paper to deception in other languages. Regular word embeddings (Bengio et al., 2003) have been used to detect deception, producing results comparable to simpler techniques (Mihaylov and Nakov, 2016), although this may be explained by the fact that the dataset used in the relevant study was not randomized with large differences between groups. Ren and Zhang (2016) compares a simple neural document model using paragraph vectors and Gated Neural Networks, and finds that GNNs outperform paragraph vectors, which is consistent with the result found in sentiment classification (Tang et al., 2015).

In this paper, hand-picked text features that have previously been proven to be successful in classifying deception are compared to average word vectors enriched with subword information. Additionally, we define a benchmark for text classification pipelines on the Mafiascum dataset.

2 The Dataset

In 2002, Mafiascum\(^2\), a forum dedicated to games of Mafia and discussion of Mafia theory, was started. It has six million posts and remains active to date. In-game Day phases on Mafiascum usually last two weeks, during which players are expected to post at least every 48 hours. If a player cannot play anymore because of unforeseen circumstances, their slot is filled by a new player who

\(^2\)https://forum.mafiascum.net
is expected to read the entire game before continuing in their place.

Although Mafiascum currently runs four types of Mafia games, only the Normal archives include easily parsable alignment distributions for almost all games. Normal games are characterized by the use of a limited set of well-known roles and mechanics. This is fortunate, since extreme deviations to Mafia present in some non-Normal games may introduce linguistic noise that is unrelated to deception.

Possibly problematic mechanics that are allowed in Normal games were the practice of allowing multiple players to play as a single player under a single account, which was abolished in August 2014, and the inclusion of multiple competing minority factions, which remains an option for game moderators to date.

Real-time games of Mafia have surpassed forum games in popularity. Unfortunately, most real-time games of Mafia have a high number of additional roles, making the game less suitable as a linguistic model for deception. For example, on Epicmafia\(^3\), which has been used in non-linguistic deception research (Pak and Zhou, 2012), the optimal strategy for players with special roles is often to immediately publicly claim to have such a role, confirming their alignment. In other games, the optimal strategy for the Mafia is to have one Mafia member falsely claim to have a leading role themselves, effectively confirming to the townsfolk that one of two players is Mafia. In most Normal games, the list of roles and alignments present in the game is not known to players.

Critically, in these games, deceptive language is not the only signal a classifier can detect to differentiate between the Mafia and the townsfolk. A classifier that can detect uncontested role claims could correctly identify some townsfolk, not based on their linguistic signature, but based on the fact that the Mafia cannot make uncontested role claims in most Epicmafia games. In the Mafiascum dataset, the extent of this problem is smaller, since absolute public confirmation of non-eliminated players is relatively rare. Exact numbers are hard to come by, but in a random sample of 5 13-player games, no such confirmations occurred.

### 2.1 Investigation of Possible Confounders

In some online gaming communities, a small number of unusually active players account for a disproportionately large part of finished games, which may bias a classifier to perform well only on this small set of players. After preprocessing, our dataset includes 9676 documents from 685 games. The most active user account has played in 57 games, accounting for an equal number of documents in the dataset. It should be noted that many active players have less-used alternative accounts, making this a lower bound. Nonetheless, looking at the activity distribution, we expect that no player has played in more than 20% of all games, accounting for no more than 1.6% of all documents.

Another concern pertains to the fact that Mafia are slightly more likely to be replaced than townsfolk. In our dataset, an average town-aligned slot has 0.33 replacements, while an average Mafia-aligned slot has 0.35 replacements, meaning that a replacement is 6% more likely to be Mafia. Since replacements often use very distinctive language, providing comments on the entirety of the game when they first catch up, we expect that replacement detection can reliably be used as a proxy for deception. Throwing out all documents from slots with replacements would solve this, but it is a harsh measure, since they make up a sizable portion of the dataset, even among the larger documents (Figure 1). In the results section, we show that the removal of replacement documents does not decrease the overall performance, at least not for our simple linear model. Because of this, we included the replacement documents in the published dataset.

Although player alignments are randomized within games, the townsfolk-Mafia ratio is decided by moderators on a per-game basis. As the game progresses, it may become clear to players that a large number of Mafia are in the game, either because of setup speculation or because players of multiple Mafia factions have been eliminated already. Player may discuss this: “This game probably has lots of Mafia.” If such a phrase were to be used consistently by all players in games with a high Mafia-townsfolk ratio, including the Mafia, a classifier would assume this phrase to be indicative of deception. This is not necessarily problematic: in real life, deception occurs more in some groups than others, and people’s speculation on this mat-
Figure 1: Histogram of word counts per user per game

According to veteran players, the way Mafia is played on Mafiascum has shifted over time. This includes high-level subjective criteria such as the preferred way to start discussion at the start of the game, popular modes of analysis, and the extent to which players express emotion, but it also includes the average post count and post length in a game. While communication was very structured and reminiscent of debating in the early days, bursts of stream-of-consciousness posting have become more and more common over time. Initially, we expected the townsfolk–Mafia ratio to have varied over time as well, since setup design has changed in many ways since 2002. Fortunately, the townsfolk–Mafia ratio has remained consistent over time, making time period an unlikely confounding variable.

Another possible confounder that ended up being moot was game size. Large games typically have more experienced players, more replacements, and a higher game length than small games, all of which could be reflected in language use. We also expected game size to influence the dependent variable, since the percentage of players aligned to the Mafia needed to balance a vanilla game of Mafia decreases as game size increases (Migdal, 2010). Surprisingly, this effect seems to be entirely counteracted by the special roles and mechanics on Mafiascum; no relation between the percentage of Mafia members and game size exists.

Finally, one should keep in mind that although there is no known public record of demographics, the Mafiascum userbase is unlikely to be representative of the global population or the population of regular participants of scientific studies.

2.2 Unpublished Work by Mafiascum Members

Multiple Mafiascum members have performed a systemic analysis of cues to deception, one of which uses linguistic cues. In a private forum, Mafiascum user Psyche posted that logistic regression, multinomial naive Bayes classification, binomial naive Bayes, and an ensemble performed no better than random on a recursive feature selection of an unspecified feature set. Equal numbers of town and scum were taken from each game.

Mafiascum user goodmorning found that Mafia are just as likely as townsfolk to be part of an elimination vote on another Mafia member in games for new players. Also in games for new players, Mafiascum user Toomai found that the Mafia elimination rate is higher than chance in the majority of game states, although there are states, such as the start of the game, where random and directed lynching have equal performance. Even in game states where the elimination rate is better than chance, this is not necessarily caused by good player judgment, as it could also be the result of the special roles included in games for new players.

3 Machine Learning Benchmark

The Mafiascum dataset seems promising not only for deception research but also as a general benchmark for supervised text classification pipelines. We propose the following benchmark task: Take a twenty-fold stratified shuffle split of all documents with a word count of 50 or higher. For every fold, fit a fresh instance of the pipeline on the training set. Use that instance to generate predictions for the test set. These predictions should at least be scored using the area under the precision-recall curve. The baseline score set by this paper is 0.286. A Python implementation of this benchmark is included with the dataset.

4 Methods

Games of Mafia and alignment distributions were scraped from Mafiascum’s Normal Game

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*https://forum.mafiascum.net/viewtopic.php?f=5&t=59076
*https://forum.mafiascum.net/viewtopic.php?f=5&t=39739
archives. The scraping code, which uses the JavaScript bookmarklet artoo.js, and the resulting JSON output are included in the dataset along with the output of the preprocessing and feature construction described below.

4.1 Preprocessing

Games that did not have a complete alignment distribution available were discarded.

Since games are moderated by humans, there is a period between a conclusive elimination vote and the role reveal, which is known as twilight. Eliminated townsfolk usually speak freely during this period, but eliminated Mafia members often clam up, wary of giving the town additional information on their partners. The exception to this is the moments after the final elimination, when many players have often revealed their alignment before the moderator has officially declared a win. In any case, seeing that eliminated players have no incentive to keep up their personal facade, post-elimination and post-game posts should not be included in the dataset. As such, all posts after the final vote count, which signifies the end of the game, were discarded. Additionally, to catch posts from eliminated players in twilight, all posts a player made in the 24 hours before their last in-game post, including their last in-game post, was also discarded. A 24-hour cut-off was chosen because moderators typically check in on a game at least once a day.

For every player in every game, the remaining in-game posts were merged into a single text document. If the remaining number of words in a document was lower than 1000, the document was discarded. Each document was assigned a binary label, signifying whether or not the document’s author was Mafia. Documents from players with a role named the Serial Killer, a third-party lone wolf faction, were removed.

If multiple players occupied a slot at different times because of player replacement, their posts were put in separate documents, but if two players played together under a single account, this could not automatically be detected. As a result, a minority of the documents contain posts written by different players. This introduces no systemic bias, but it may weaken the deceptive signal.

4.2 Feature Construction

All remaining documents were split into words, where a word is defined as a series of Unicode word characters. The term frequency of first-person pronouns, the term frequency of third-person pronouns, the term frequency of the word “or”, the term frequency of the word “but”, the average word length, the average post length, the average sentence length, the average word count per 24 hours, the average post count per 24 hours, and the ratio of unique words over all words, also known as the type-token ratio, were computed for every document. Every feature was then scaled based on its variance.

Although all selected features are established cues to deception, the counts of the word “but” and the word “or” are usually combined into a single count, along with all other exclusive words. Because exclusive words are less related to each other than the other word categories that we use to identify deception, such as first-person pronouns, we believe distinct exclusive words may relate to deception in different ways. The counts of other exclusive words were not used as features, since “but” and “or” are much more common than all other exclusive words combined. Therefore, the signal found in previous research likely originated from one of these subfeatures.

Pretrained 300-dimensional word vectors with subword information, trained on the English Wikipedia, were obtained from the FastText project. The words in each document were mapped to their corresponding word vectors, using the subword information to compute word vectors for out-of-vocabulary words. After this, we computed the average of all word vectors for each document, resulting in a single vector with a dimensionality of 300 per document.

A third feature set was created by repeating the previous procedure, this time using word vectors without subword information trained on Wikipedia and Gigaword, obtained from the GloVe project page. In this case, out-of-vocabulary words had to be discarded.

Two more feature sets were created by concatenating the hand-picked features to each of the word vector feature sets.

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6 https://medialab.github.io/artoo/
7 https://bitbucket.org/bopjesvla/thesis/src
8 https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md
9 https://nlp.stanford.edu/projects/glove/
Feature Correlation

| Feature       | Correlation |
|---------------|-------------|
| wc24h         | 0.019       |
| or ratio      | 0.005       |
| tpp ratio     | -0.043      |
| spp ratio     | 0.032       |
| fpp ratio     | 0.006       |
| but ratio     | -0.056      |
| token length  | -0.001      |
| unique tokens | 0.022       |
| message length| -0.060      |
| sentence length| 0.068     |
| msg24h        | 0.044       |
| anger ratio   | 0.006       |
| sensory ratio | -0.026      |
| cog. ratio    | -0.006      |
| insight ratio | -0.003      |
| motion ratio  | 0.016       |
| not ratio     | 0.006       |
| quant ratio   | -0.039      |
| neg. em. ratio| 0.010       |
| tent. ratio   | -0.014      |

Table 1: Person’s correlations between linguistic variables and truthful roles. Negative values indicate higher prevalence among deceivers, following conventions in deception research. Significant correlations are shown in bold. (wc24h = word count per 24 hours, t/s/fpp ratio = ratio of third/second/first-person pronouns, unique tokens = type-token ratio, cog. ratio = ratio of words referring to cognitive processes, quant ratio = ratio of quantifiers, neg. em. ratio = ratio of negative emotion words, tent. ratio = ratio of tentative words.)

4.3 Machine Learning Benchmark

Implementing the benchmark described above, a regularized (C = 1.0) logistic regression model was trained and tested on a stratified 20-fold split of each feature set. For training, the two classes were reweighted using the heuristic devised by King and Zeng (2001).

In addition to class weighting, we also reweighted individual training samples based on their word count. The intuition behind this is simple: a 10000-word deceptive document typically contains more information about deception than a 100-word document, but not as much as 100 independent 100-word documents. Because no literature could be found on this type of reweighting, we took a conservative approach: the sample weight of a document was set to the log of the word count, meaning that the weight of a 10000-word document was set twice as high as the weight of a 100-word document of the same class.

Experiments with paragraph vectors, single-post classification (as opposed to the practice of concatenating multiple posts into documents), and a combination of the two approaches were all abandoned in early stages as they did not seem to hold any promise.

5 Results

5.1 Statistical Analysis

Except for message length and the number of messages sent in 24 hours (which were respectively negatively and positively correlated with truthful roles), all features in Table 1 were either taken or adapted from well-performing cues in the primary meta-analysis in Hauch et al. (2015). Of those 18 features, 6 were also significant in the Mafiascum dataset, although all effect sizes were small. Of those 6, only 2 features, sentence length and the ratio of third-person pronouns, had the same direction as in the primary meta-analysis.

This is not entirely surprising, given that the meta-analysis establishes that the strength and, in some cases, the direction of the effect of linguistic cues highly depend on context. Most studies considered in the meta-analysis differ a lot from this study.

Of all features that were originally introduced in deception research under the assumption that complexity is a proxy for truthfulness, sentence length was the only one to have the expected negative correlation to deception. Deception was not correlated with word length, nor with the rate of unique words. Neither of the exclusive words indicated truthfulness. Usage of the word “but” correlated positively with deception, while usage of the word “or” did not predict anything. This casts doubt on the common practice of grouping exclusive words together in linguistic deception research.

Deceptive roles were significantly positively correlated with post length, but negatively correlated with post frequency. No significant correlation between word count and deception was found.

5.2 Machine Learning

The logistic regression model performed significantly better than chance on all feature sets (Ta-
### Table 2: Cross-validated performance of the models trained on different feature sets (AUROC = area under the Receiver Operating Characteristic curve including 95% confidence intervals, AP = average precision [chance = 0.23], “- repl” = replacements removed from train and test set)

| Feature set       | AUROC       | AP  |
|-------------------|-------------|-----|
| Hand-picked       | 0.566 [0.552, 0.579] | 0.270  |
| FastText          | 0.578 [0.565, 0.592] | 0.279  |
| HP + FastText     | 0.593 [0.579, 0.606] | 0.286  |
| GloVe             | 0.572 [0.558, 0.585] | 0.275  |
| HP + GloVe        | 0.583 [0.570, 0.597] | 0.285  |
| HP + FT - repl    | 0.596 [0.579, 0.612] | 0.280  |

Table 3: Cross-validated performance of the model trained on HP + FastText by word count segment

| Word count     | N   | AUROC | AP  |
|----------------|-----|-------|-----|
| 50+            | 9676| 0.593 | 0.286|
| 5000+          | 2401| 0.651 | 0.344|
| 50-999         | 2592| 0.547 | 0.250|
| 1000-2999      | 3120| 0.589 | 0.292|
| 3000-4999      | 1563| 0.603 | 0.308|
| 5000-6999      | 824 | 0.678 | 0.385|
| 7000-8999      | 538 | 0.678 | 0.360|
| 9000-10999     | 310 | 0.587 | 0.301|
| 11000+         | 729 | 0.623 | 0.322|

Of the six significant hand-picked features taken or adapted from the meta-analysis by Hauch et al. (2015), only two matched the direction of the effect found in the meta-analysis. All effect sizes were small, which may be due to the slow pace of the game or the experience many players already have playing as a deceiver. The latter property matches real-world applications, since many deceivers of interest are repeat offenders. Despite the small effect sizes, a logistic regression model trained on the hand-picked features performed significantly better than chance.

Two features specific to the communication medium were included: message length and message frequency. Deceptive roles were significantly positively correlated with message length, but negatively correlated with message frequency. Considering that no significant relation between word count per 24 hours and deception was found, this likely means that deceivers refrain from posting in certain situations, perhaps because they would prefer to hear a genuine opinion first, perhaps because they think any contribution they make is going to attract unwanted attention, or perhaps because they dislike playing as a deceiver.

In a similar vein, the shorter posts from townsfolk may be the result of relatively unfiltered expression. Townsfolk may believe that they can broadcast any idea they come up with the moment they come up with it, since they know their thoughts are genuine. Mafia may feel the need to add more detail to their personal narrative.

The results in this paper are yet another strike against the idea that a linear model fit on traditional linguistic markers of deception can generalize across deception context. There is a slim chance that a linear model trained on average word vectors does generalize across context, but it is more likely that a model capable of capturing the interactions between deception context and word usage is required, such as a neural network or a gradient boosting classifier.

To train such a model, a large amount of deceptive and non-deceptive documents gathered from a multitude of contexts is needed. As such, we urge deception researchers to publish their datasets whenever possible.
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