Hate Speech and Counter Speech Detection: Conversational Context Does Matter

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Abstract

Hate speech is plaguing the cyberspace along with user-generated content. This paper investigates the role of conversational context in the annotation and detection of online hate and counter speech, where context is defined as the preceding comment in a conversation thread. We created a context-aware dataset for a 3-way classification task on Reddit comments: hate speech, counter speech, or neutral. Our analyses indicate that context is critical to identify hate and counter speech: human judgments change for most comments depending on whether we show annotators the context. A linguistic analysis draws insights into the language people use to express hate and counter speech. Experimental results show that neural networks obtain significantly better results if context is taken into account. We also present qualitative error analyses shedding light into (a) when and why context is beneficial and (b) the remaining errors made by our best model when context is taken into account.

1 Introduction

The advent of social media has democratized public discourse on an unparalleled scale. Meanwhile, it is considered a particularly conducive arena for hate speech (Caiani et al., 2021). Online hate speech is prevalent and can lead to serious consequences. At the individual level, the victims targeted by hate speech are frightened by online threats that may materialize in the real world (Olteanu et al., 2018). At the societal level, it has been reported that there is an upsurge in offline hate crimes targeting minorities (Olteanu et al., 2018; Farrell et al., 2019).

There are two common strategies to combat online hate: disruption and counter speech. Disruption refers to blocking hateful content or users. To scale this strategy, researchers have proposed methods to identify hate (Waseem and Hovy, 2016; Davidson et al., 2017; Nobata et al., 2016). While these interventions could de-escalate the impact of

| Parent | As an average height male, idgaf how tall you are, if that's your issue then spend the money and get a better seat, or just f**king make the seat selection online to get more space. |
| Target | Found the short guy! |

-*Target* is Neutral if considering only *Target*.
-*Target* is Hate if considering *Parent* and *Target*.

| Parent | I deal with women all day with my job and this is how they are - extremely stupid, hate-filled, bizarre and they appreciate nothing. |
| Target | Maybe you're an a**hole if they treat you like that? |

-*Target* is Hate if considering only *Target*.
-*Target* is Counter-hate if considering *Parent* and *Target*.

Table 1: Reddit comments (*Target*s) deemed to be Hate, Neutral, or Counter-hate depending on whether one takes into account the previous comment (*Parent*).

hate speech, they may violate online free speech (Mathew et al., 2019). Additionally, attacks at the micro-level may be ineffective as hate networks often have rapid rewiring and self-repairing mechanisms (Johnson et al., 2019). Counter speech refers to the "direct response that counters hate speech" (Mathew et al., 2019). It has been shown to be more effective in the long term than disruption in theoretical and empirical studies (Richards and Calvert, 2000; Mathew et al., 2020). Identifying hate and counter speech in natural conversations is critical to understand effective counter speech strategies and the generation of counter speech.

Most corpora with either hate speech (Hate) or counter speech (Counter-hate) annotations do not include conversational context. Indeed, they annotate a user-generated comment as Hate or Counter-hate based on the comment in isolation (Davidson et al., 2017; Waseem and Hovy, 2016; Mathew et al., 2019; He et al., 2021). Therefore, systems trained on these corpora fail to consider the effect of contextual information on the identification of Hate and Counter-hate. Recent studies have shown that context affects annotations in toxic-

ity and abuse detection (Pavlopoulos et al., 2020; Menini et al., 2021). We further investigate the effect of context on the task of identifying Hate and Counter-hate. Table 1 shows examples where a comment, denoted as *Target*, is Hate, Neutral or Counter-hate depending on whether the preceding comment, denoted as *Parent*, is taken into account.[1] In the top example, the *Target* goes from Neutral to Hate when taking into account the *Parent*: it becomes clear that the author is disparaging short men. In the bottom example, the *Target* goes from Hate to Counter-hate as the author uses offensive language to counter the hateful content in the *Parent*. This is a common strategy to express counter speech (Mathew et al., 2019).

In this study, we answer the following questions:

1. Does conversational context affect if a comment is perceived as Hate, Neutral, or Counter-hate by humans? (It does.)
2. Do models to identify Hate, Neutral, and Counter-hate benefit from incorporating context? (They do.)

To answer the first question, we create a collection of (*Parent*, *Target*) Reddit comments and annotate the *Targets* with three labels (Hate, Neutral, Counter-hate) in two independent phases: showing annotators (a) only the *Target* or (b) the *Parent* and the *Target*. We limit context to the parent comment. While the full conversation could provide additional information, it is also known to affect annotators' stance (Dutta et al., 2020) and introduce biases. We find that human judgments are substantially different when the *Parent* is shown. Thus the task of annotating Hate and Counter-hate requires taking into account the context.

To answer the second question, we experiment with context-unaware and context-aware classifiers to detect if a given *Target* is Hate, Neutral, or Counter-hate. Results show that adding context does benefit the classifiers significantly.

In summary, the main contributions of this paper are:[2] (a) a corpus with 6,846 pairs of (*Parent*, *Target*) Reddit comments and annotations indicating whether the *Targets* are Hate, Neutral, or Counter-hate; (b) annotation analysis showing that the problem requires taking into account context, as the ground truth changes; (c) corpus analysis detailing the kind of language people use to express Hate

and Counter-hate; (d) experiments showing that context-aware neural models obtain significantly better results; and (e) qualitative analysis revealing when context is beneficial and the remaining errors made by the best context-aware model.

2 Related Work

Hate speech in user-generated content has been an active research area recently (Fortuna and Nunes, 2018). Researchers have built several datasets for hate speech detection from diverse sources such as Twitter (Waseem and Hovy, 2016; Davidson et al., 2017), Yahoo! (Nobata et al., 2016), Fox News (Gao and Huang, 2017), Gab (Mathew et al., 2021) and Reddit (Qian et al., 2019).

Compared to hate speech detection, few studies focus on detecting counter speech (Mathew et al., 2019; Garland et al., 2020; He et al., 2021). Mathew et al. (2019) collect and hand-code 6,898 counter hate comments from YouTube videos targeting Jews, Blacks and LGBT communities. Garland et al. (2020) work with German tweets and define hate and counter speech based on the communities to which the authors belong. He et al. (2021) use a collection of hate and counter hate keywords relevant to COVID-19 and create a dataset containing 359 counter hate tweets targeting Asians. Another line of research focuses on curating datasets for counter speech generation using crowdsourcing (Qian et al., 2019) or with the help of trained operators (Chung et al., 2019; Fanton et al., 2021). However, synthetic language is rarely as rich as language in the wild. Even if it were, conclusions and models from synthetic data may not transfer to the real world. In this paper, we work with user-generated content expressing hate and counter-hate rather than synthetic content.

Table 2 summarizes existing datasets for Hate and Counter-hate detection. Most of them do not include context information. In other words, the preceding comments are not provided when annotating *Targets*. Context does affect human judgments and has been taken into account for Hate detection (Gao and Huang, 2017; Pavlopoulos et al., 2020; Menini et al., 2021; Vidgen et al., 2021). Gao and Huang (2017) annotate hateful comments in the nested structures of Fox News discussion threads. Vidgen et al. (2021) introduce a dataset of Reddit comments with annotations in 6 categories taking into account context. However, the inter annotator agreement is low (Fleiss' Kappa 0.267) and the

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[1]The examples in this paper contain hateful content. We cannot avoid it due to the nature of our work.

[2]Code and data available at https://github.com/xinchenyu/counter_context

Authors	Source	Size	Labels	Context?	Counter?
Waseem and Hovy (2016)	Twitter	1,607	Sexism/Racism/Normal	✗	✗
Davidson et al. (2017)	Twitter	24,783	Hate/Offense/Neither	✗	✗
Nobata et al. (2016)	Yahoo!	2,000	Hate/Derogatory/Profanity/Clean	✗	✗
Mathew et al. (2021)	Gab	1,1093	Hateful/Offensive/Normal	✗	✗
Gao and Huang (2017)	Fox News	1,528	Hateful/Non-hateful	preceding comment	✗
Qian et al. (2019)	Reddit	22,324	Hate/Non-hate	full conversation	✗
Pavlopoulos et al. (2020)	Wikipedia	20,000	Toxic/Non-toxic	preceding comment	✗
Menini et al. (2021)	Twitter	8,018	Abuse/Non-abuse	preceding comment	✗
Mathew et al. (2019)	YouTube	13,924	Non-counter/Counter (6,898)	✗	✓
He et al. (2021)	Twitter	2,400	Hate/Neutral/Counter (517)	✗	✓
Vidgen et al. (2021)	Reddit	27,494	Taxonomy including Counter (220)	full conversation	✓
Ours	Reddit	6,846	Hate/Neutral/Counter (1,622)	preceding comment	✓

Table 2: Comparison of corpora with hate (above dashed line) and counter-hate annotations (below dashed line, some also include hate). Vidgen et al. (2021) is the only one considering counter-hate and context, but they only have 220 instances of counter hate. Numbers between parenthesis indicate the number of counter-hate instances.

number of Counter-hate instances is small (220). Moreover, both studies use contextual information without identifying the role context plays in the annotation and detection. Pavlopoulos et al. (2020) allow annotators to see one previous comment to annotate Wikipedia conversations. They find context matters in the annotation but provide no empirical evidence showing whether models to detect toxicity benefit from incorporating context. Menini et al. (2021) re-annotate an existing corpus to investigate the role of context in abusive language. They found context does matter. Utilizing conversational context has also been explored in text classification tasks such as sentiment analysis (Ren et al., 2016), stance (Zubiaga et al., 2018) and sarcasm (Ghosh et al., 2020). In this paper, we investigate the role of context in Hate and Counter-hate detection.

3 Dataset Collection and Annotation

We first describe our procedure to collect (*Parent*, *Target*) pairs, where both *Parents* and *Targets* are Reddit comments in English. Then, we describe the annotation guidelines and the two annotation phases: showing annotators (a) only the *Target* and (b) the *Parent* and *Target*. The two independent phases allow us to quantify how often context affects the annotation of Hate and Counter-hate.

3.1 Collecting (*Parent*, *Target*) pairs

In this work, we focus on Reddit, a popular social media site. It is an ideal platform for data collection due to the large size of user populations and many diverse topics (Baumgartner et al., 2020). We use a list of hate words to retrieve Reddit conversations to keep the annotation costs reasonable while creating a (relatively) large corpus

of counter speech. We start with a set of 1,726 hate words from two lexicons: Hatebase[3] and a harassment corpus (Rezvan et al., 2018). We remove ambiguous words following ElSherief et al. (2018). To collect (*Parent*, *Target*) pairs, we use the following steps. First, we retrieve comments containing at least one hate word (comment$_{w/ hateword}$). Second, we create a (*Parent*, *Target*) pair using comment$_{w/ hateword}$ as *Target* and its preceding comment as *Parent*. Third, we create a *(Parent, Target)* pair using comment$_{w/ hateword}$ as *Parent* and each of its replies as *Target*. Lastly, we remove pairs if the same author posted the *Parent* and *Target*. We retrieve 6,846 (*Parent*, *Target*) pairs with PushShift (Baumgartner et al., 2020) from 416 submissions. We also collect the title of the discussion from which each pair is retrieved.

3.2 Annotation Guidelines

To identify whether a *Target* is Hate, Neutral, or Counter-hate, we crowdsource human judgments from non-experts. Our guidelines reuse the definitions of Hate by Ward (1997) and Counter-hate by Mathew et al. (2019) and Vidgen et al. (2021):

- **Hate**: the author attacks an individual or a group with the intention to vilify, humiliate, or incite hatred;
- **Counter-hate**: the author challenges, condemns the hate expressed in another comment, or calls out a comment for being hateful;
- **Neutral**: the author neither conveys hate nor opposes hate expressed in another comment.

Annotation Process We chose Amazon Mechanical Turk (MTurk) as the crowdsourcing platform. We replace user names with placeholders (User_A

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[3] http://hatebase.org/

and User_B) owing to privacy concerns. The annotations took place in two independent phases. In the first phase, annotators are first shown the *Parent* comment. After a short delay, they click a button to show the *Target* and then after another short delay they submit their annotation. Delays are at most a few seconds and proportional to the length of the comments. Our rationale behind the delays is to "force" annotators to read the *Parent* and *Target* in order. In the second phase, annotators label each *Target* without seeing the preceding *Parent* comment. A total of 375 annotators were involved in the first phase and 299 in the second phase. There is no overlap between annotators thus we eliminated the possibility of biased annotators remembering the *Parent* in the second phase.

Annotation Quality Crowdsourcing may attract spammers (Sabou et al., 2014). For quality control, we first set a few requirements for annotators: they must be located in the US and have a 95% approval rate over at least 100 Human Intelligence Tasks (HITs). We also block annotators who submit more than 10 HITs with an average completion time below 5 seconds (half the time required in our pilot study). As the corpus contains vulgar words, we require annotators to pass the Adult Content Qualification Test. The reward per HIT is $0.05.

The second effort is to identify bad annotators and filter out their annotations until we obtain *substantial* inter-annotator agreement. We collect five annotations per HIT and compute MACE (Hovy et al., 2013, Multi-Annotator Competence Estimation) for each annotator. MACE is devised to rank annotators by their competence and adjudicate disagreements based on annotator competence (not the majority label). Then, we use Krippendorff's α (Krippendorff, 2011) to estimate inter-annotator agreement: α coefficients at or above 0.6 are considered *substantial* (above 0.8 are considered *nearly perfect*) (Artstein and Poesio, 2008). We repeat the following steps until $\alpha \geq 0.6$:

1. Use MACE to calculate the competence score of all annotators.
2. Discard all the annotations by the annotator with the lowest MACE score.
3. Check Krippendorff's α on the remaining annotations. Go to (1) if $\alpha < 0.6$.

The final corpus consists of 6,846 (*Parent*, *Target*) pairs and a label assigned to each *Target* (Hate, Counter-hate, or Neutral). The ground truth we experiment with (Section 5) is the label obtained

| | | Without *Parent* | | |
		Hate	Counter-hate	Neutral
With	Hate	57.4	8.4	34.2
	Counter-hate	18.7	26.2	55.1
	Neutral	9.7	8.1	82.2

Table 3: Confusion matrix (percentages) showing annotation changes depending on whether annotators are shown the *Parent* of the *Target* comment.

Example	With	Without
Parent: That chick needs a high-five in the face with a chair. Damn her for making us look bad! *Target*: A brick is more effective.	Hate	Neutral
Parent: If I knew her I would sh*t in her mailbox. *Target*: The poor mail carrier in that neighborhood doesn't deserve that.	Counter	Neutral
Parent: Go watch your incest porn on your own time. *Target*: You're a sick person.	Counter	Hate

Table 4: Examples of *Target* comments whose labels change depending on whether annotators are shown the *Parent* of the *Target* comment (with and without).

taking into account the *Parent* (first phase). The second phase, which disregards the *Parent*, was conducted for analysis purposes (Section 4). We split the corpus into two subsets: (a) Gold (4,751 pairs with $\alpha \geq 0.6$) and (b) Silver (2,095 remaining pairs). As we shall see, the Silver pairs are useful to learn models.

4 Corpus Analysis

Does conversational context affect if a comment is perceived as Hate or Counter-hate? Yes, it does. Table 3 presents the percentage of labels that change and remain the same depending on whether annotators are shown the *Parent*, i.e., the context. Many *Target* comments that are perceived as Hate or Counter-hate become Neutral (34.2% and 55.1% respectively) when the *Parent* is provided. More surprisingly, many *Target* comments are perceived with the opposite label (from Hate to Counter-hate (8.4%) or from Counter-hate to Hate (18.7%)) when the *Parent* comments are shown.

We show examples of label changes in Table 4. In the first example, annotators identify the *Target* ("A brick is more effective.") as Neutral without seeing the *Parent*. In fact, a female is the target of hate in the *Parent*, and the author of *Target* replies

	Title		Parent		Target	
	p-value	Bonferroni	p-value	Bonferroni	p-value	Bonferroni
Textual factors						
Total tokens	↓↓	✗	↑↑↑	✓		
Question marks					↑↑↑	✓
1st person pronouns			↓↓↓	✓		
2nd person pronouns			↑↑↑	✓	↑↑	✗
Sentiment and cognitive factors						
Profanity words			↑↑↑	✓	↓↓↓	✓
Problem-solving words					↑↑↑	✓
Awareness words					↑↑↑	✓
Negative words	↓	✗	↑↑↑	✓	↓↓↓	✓
Disgust words					↓↓↓	✓
Enlightenment words					↑↑↑	✓
Conflicting words	↓↓↓	✓				

Table 5: Linguistic analysis comparing the *Titles*, *Parents* and *Targets* in Counter-hate and Hate *Target* comments. Number of arrows indicate the p-value (t-test; one: p<0.05, two: p<0.01, and three: p<0.001). Arrow direction indicates whether higher values correlate with Counter-hate (up) or Hate (down). A check mark (✓) indicates that the test passes the Bonferroni correction.
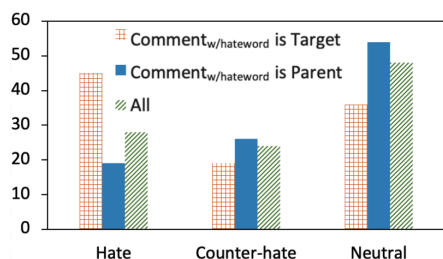

Figure 1: Label distribution in *Target*s depending on whether comment$_{w/\ hateword}$ is the *Parent* or the *Target*.

with even more hatred (and the ground truth label is Hate). In the second example, the *Target* alone is insufficient to tell if it is Counter-hate. When annotators see the *Parent*, however, they understand the author of *Target* counters the hateful content in the *Parent* by showing empathy towards the mail carrier. In the last example, the *Target* alone is considered Hate because it attacks someone by using the phrase "sick person". When the *Parent* is shown, however, the annotators understand the *Target* as calling out the *Parent* to be inappropriate.

Label distribution and linguistic insights Figure 1 shows the label distribution for all pairs (rightmost column in each block) and for pairs in which comment$_{w/\ hateword}$ (i.e., the comment containing at least one hate word) is the *Parent* or *Target*. The most frequent label assigned to *Target* comments is Neutral (49%) followed by Hate (28%) and Counter-hate (23%). While *Target* comments containing a hate word are likely to be Hate (45%), some are Counter-hate (19%) with context.

We analyze the linguistic characteristics of *Titles*, *Parents* and *Targets* when the *Targets* are Hate or Counter-hate with context to shed light on the differences between the language people use in hate and counter speech. We combine the set of hate words with profanity words to check for profanity words.[4] We analyze sentiment and cognitive factors using the Sentiment Analysis and Cognition Engine (SEANCE) lexicon, a popular tool for psychological linguistic analysis (Crossley et al., 2017). Statistical tests are conducted using unpaired t-tests between the groups, of which the *Target*s are Counter-hate or Hate (Table 5). We also report whether each feature passes the Bonferroni correction as multiple hypothesis tests are performed. We draw several interesting insights:

- Questions marks in *Target* signal Counter-hate. They are often rhetorical questions.
- Fewer 1st person pronouns (e.g., I, me) and more 2nd person pronouns (e.g., you, your) in the *Parent* signal that the *Target* is more likely to be Counter-hate. This is due to the fact that people tend to target others in hateful content.
- High profanity count in the *Parent* signals that the *Target* is Counter-hate, while high profanity count in the *Target* signals Hate.
- More words related to awareness, enlightenment and problem-solving in the *Target* signal Counter-hate.
- When there are more negative words in the *Parent*, the *Target* tends to be Counter-hate. *Target*s labeled as Counter-hate contain fewer negative and disgusting words.

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[4] https://github.com/RobertJGabriel/google-profanity-words-node-module/blob/master/lib/profanity.js

	Hate			Counter-hate			Neutral			Weighted Average		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Majority Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.51	1.00	0.67	0.26	0.51	0.34
Trained with Target	0.56	0.55	0.56	0.41	0.36	0.38	0.67	0.71	0.69	0.58	0.59	0.58
+ Silver	0.58	0.55	0.57	0.44	0.42	0.43	0.69	0.72	0.70	0.60	0.61	0.61
+ Related task	0.56	0.55	0.56	0.51	0.41	0.45	0.68	0.74	0.71	0.61	0.61	0.61
+ Silver + Related task	0.55	0.56	0.56	0.49	0.53	0.51	0.67	0.69	0.70	0.61	0.61	0.61
Trained with Parent_Target	0.56	0.62	0.59	0.52	0.38	0.44	0.68	0.72	0.70	0.61	0.62	0.61
+ Silver†	0.58	0.57	0.57	0.49	0.51	0.50	**0.72**	**0.71**	**0.72**	0.63	0.63	0.63
+ Related task†	**0.55**	**0.66**	**0.60**	0.54	0.43	0.48	0.71	0.70	0.71	0.63	0.63	0.63
+ Silver + Related task‡	0.55	0.65	0.60	**0.54**	**0.52**	**0.53**	0.74	0.68	0.71	**0.64**	**0.64**	**0.64**

Table 6: Results obtained with several systems. We indicate statistical significance (McNemar's test (McNemar, 1947) over weighted average) with respect to the model trained with the *Target* only using neither Silver nor pretraining on related tasks as follows: † indicates $p < 0.05$ and ‡ indicates $p < 0.01$. Training with the *Parent* and *Target* coupled with blending Silver annotations and pretraining with stance corpora yields the best results. The supplementary materials detail the results pretraining with all related tasks we consider.

5 Experiments and Results

We build neural network models to identify if a *Target* comment is Hate, Counter-hate, or Neutral. We randomly split Gold instances (4,751) as follows: 70% for training, 15% for validation and 15% for testing. Silver instances are only used for training.

Neural Network Architecture We experiment with neural classifiers built on top of the RoBERTa transformer (Liu et al., 2019). The neural architecture consists of a pretrained RoBERTa transformer, a fully connected layer (768 neurons and Tanh activation), and another fully connected layer (3 neurons and softmax activation) to make predictions (Hate, Counter-hate, or Neutral). To investigate the role of context, we consider two textual inputs:

- the *Target* alone (Target), and
- the *Parent* and the *Target* (Parent_Target).

We concatenate the *Target* and the *Parent* with the [SEP] special token. We conduct multiple runs of experiments, which show consistent results. The hyperparameters and other implementation details are presented in the Appendix. We also experiment models that take the title of the discussion as part of the context, but it is not beneficial.

We implement two strategies to enhance the performance of neural models:

Blending Gold and Silver We adopt the method by Shnarch et al. (2018) to determine whether Silver annotations are beneficial. There are two phases in the training process: m blending epochs using all Gold and a fraction of Silver, and then n epochs using all Gold. In each blending epoch, Silver instances are fed in a random order to the network.

The fraction of Silver is determined by a blending factor $\alpha \in [0..1]$. The first blending epoch is trained with all Gold and all Silver, and the amount of Silver to blend is reduced by α in each epoch.

Pretraining with Related Tasks We also experiment with several corpora to investigate whether pretraining with related tasks is beneficial. Specifically, we pretrain our models with existing corpora annotating: (1) hateful comments: hateful or not hateful (Qian et al., 2019), and hate speech, offensive, or neither (Davidson et al., 2017); (2) sentiment: negative, neutral, or positive (Rosenthal et al., 2017); (3) sarcasm: sarcasm or not sarcasm (Ghosh et al., 2020); and (4) stance: agree, neutral, or attack (Pougué-Biyong et al., 2021).

5.1 Quantitative Results

We present results with the test split in Table 6. The majority baseline always predicts Neutral. The remaining rows present the results with the different training settings: training with the *Target* or both the *Parent* and *Target*; training with only Gold or blending Silver annotations; and pretraining with related tasks. We provide here results pretraining with the most beneficial task, stance detection, and present additional results in the Appendices. Blending Gold and Silver annotations requires tuning α. We did so empirically using the training and validations splits, like other hyperparameters. We found the optimal value to be 0.3 when blending Silver (+ Silver rows) and 1.0 when blending Silver and pretraining with a related task (+Silver + Related task rows).

As shown in Table 6, blending Gold and Sil-

Error Type	%	Example		Parent_Target	Target
Lack of information	48	*Parent*: Women can hover..?		Hate	Neutral
		Target: No, they can't, but for some reason they keep trying and it gets sh*t everywhere.			
Negation	27	*Parent*: It's a joke you pu**y.		Counter-hate	Neutral
		Target: I don't see sexism as a joke, especially on a site dedicated to calling out sexism.			
Sarcasm or irony	19	*Parent*: You must have been a real baller banging out those eighth graders as a High School senior.		Counter-hate	Hate
		Target: Glad to see you have no rational argument left except childish jokes. We're done here pal.			
Hate without swear words	8	*Parent*: Name a dildo 'misogyny' so you can *literally* internalize it.		Hate	Neutral
		Target: lol. Misogyny can already turn me on so that's a good idea.			

Table 7: Most common error types made by the *Target* only network (Target) that are fixed by the context-aware neural network (Parent_Target).

ver annotations obtains better results (F1 weighted average) than using only Gold (Target: 0.61 vs. 0.58; Parent_Target: 0.63 vs. 0.61). We also find that models pretrained for stance detection obtain better results than pretrained with other tasks (see detailed results in the Appendices). Pretraining with stance detection data benefits models trained without context (Target: 0.61 vs. 0.58) and models with context (Parent_Target: 0.63 vs. 0.61). These results indicate that stance information between *Parent* and *Target* is useful to determine whether the *Target* is Hate, Counter-Hate or Neutral.

We make two observations about the results obtained using neither strategy. First, using the *Target* alone obtains much better results than the majority baseline (0.58 vs. 0.34). In other words, modeling the *Target* allows the network to identify *some* instances of Hate and Counter-hate despite the ground truth requires the *Parent*. Second, incorporating the *Parent* comment is beneficial: the F1 score for all classes are higher (Hate: 0.59 vs. 0.56, Counter-hate 0.44 vs. 0.38, Neutral 0.70 vs. 0.69), and so is the weighted average (0.61 vs. 0.58). The findings are consistent (weighted F1) using either strategy (+Silver: 0.63 vs 0.61, +Related task: 0.63 vs 0.61) or both (0.64 vs. 0.61). The F1 scores of the three classes with Parent_Target models are equal to or better than those by Target only models.

Finally, the network (a) blending Gold and Silver annotations and (b) pretraining with stance detection achieves the best performance (Parent_Target+Silver+Related task: 0.64). This result is statistically significant ($p < 0.01$) compared to Target only model without blending Silver or pretraining with related tasks.

6   Qualitative Analysis

When is adding the context beneficial? When does our best model make mistakes? To investigate these questions, we manually analyze the following:

- The errors made by the *Target* only network that are fixed by the context-aware network (Trained with Parent_Target, Table 7).
- The errors made by the context-aware network pretrained on related task (stance) and blending Silver annotations (Parent_Target+Silver+Related task, Table 8).

When does the context complement *Target*? We analyze the errors made by the network using only the *Target* that are fixed by the context-aware network (Trained with Parent_Target). Table 7 exemplifies the most common error types.

The most frequent type of error fixed by the context-aware model is when there is *Lack of information* in the *Target* (48%). In this case, the *Parent* comment is crucial to determine the label of the *Target*. In the example, knowing what the author of *Target* refers to (i.e., a rhetorical question, *Women can hover?*) is crucial to determine that the *Target* is humiliating women as a group.

The second most frequent error type is *Negation* (27%). In the example in Table 7, taking into account the *Parent* allows the context-aware network to identify that the author of the *Target* is scolding the author of *Parent* and thus countering hate.

Nobata et al. (2016) and Qian et al. (2019) have pointed out that sarcasm and irony make detecting abusive and hateful content difficult. We find evidence supporting this claim. We also discover that by incorporating the *Parent* comment, a substantial amount of these errors are fixed. Indeed, 19% of

Error Type	%	Example		Ground Truth	Predicted
Negation	28	*Parent*: Those damn f**king white males, ruining it for everyone else. I'm going to a corner to process my guilt.			
		Target: Don't forget male isn't a gender, it's a disease.		Hate	Counter-hate
Rhetorical question	27	*Parent*: Men are the ones that made inequality.			
		Target: Do you get paid to be a dumba** in the internet?		Hate	Counter-hate
Hate without swear words	8	Parent: Circumcision is good for men.			
		Target: Cut off the clitoris of women and cut of their breasts because of breast cancer then.		Hate	Neutral
Non-hate with swear words	8	*Parent*: <I wonder if feminists ever consider that? No. They are b**ches incapable of empathy.			
		Target: This is the sh*t that gets screen capped and spread around to give this sub a bad name.		Counter-hate	Hate
Intricate text	7	*Parent*: Ah it's this again, f**king her and her cronies.			
		Target: I have lost all respect for her.		Neutral	Hate

Table 8: Most common errors made by the best context-aware network (predictions by Parent_Target+Silver+Related task) compared to the ground truth.

errors fixed by the context-aware network include sarcasm or irony in the *Target* comment.

Finally, the context-aware network taking into account the *Parent* fixes many errors (8%) in which the *Target* comment is Hate despite it does not contain swear words. In the example, the *Target* is introducing additional hateful content, which can be identified by the context-aware model when the *Parent* information is used.

When does the best model make errors? In order to find out the most common error types made by the best model (context-aware, Parent_Target+Silver+Related task), we manually analyze 200 random samples in which the output of the network differs from the ground truth. Table 8 shows the results of the analysis.

Despite 27% of errors fixed by the context-aware network (i.e., taking into account the *Parent*) include negation in the *Target*, *negation* is the most common type of errors made by our best network (28%). The example in Table 8 is especially challenging as it includes a double negation.

We observe that *Rhetorical questions* are almost as common (27%). This finding is consistent with the findings by Schmidt and Wiegand (2017). In the example, the best model fails to realize that the *Target* is hateful, as it disdains the author of *Parent*.

Swear words are present in a substantial number of errors. Wrongly predicting a *Target* without swear words as Counter-hate or Neutral accounts for 8% of errors, and wrongly predicting a *Target* with swear words as Hate accounts for another 8% of errors. As pointed out by Davidson et al. (2017),

hate speech may not contain hate or swear words. And vice versa, comments containing swear words may not be hateful (Zhang and Luo, 2019).

Finally, we observe *Intricate text* in 7% errors. Our best model identifies the *Target* ("I have lost all respect for her.") as Hate probably because by identifying the agreeing stance on the *Parent*. Indeed, the author of *Target* expresses his/her attitude without vilifying others. Hence, the ground truth label is Neutral.

7 Conclusions and Future Work

Conversational context does matter in Hate and Counter-hate detection. We have demonstrated so by (a) analyzing whether humans perceive user-generated content as Hate or Counter-hate depending on whether we show them the *Parent* comment and (b) investigating whether neural networks benefit from incorporating the *Parent*. We find that 38.3% of human judgments change when we show the *Parent* to annotators. Experimental results demonstrate that networks incorporating the *Parent* yield better results. Additionally, we show that noisy instances (Silver data) and pretraining with relevant datasets improves model performance. We have created and released a corpus of 6,846 (*Parent*, *Target*) pairs of Reddit comments with the *Target* annotated as Hate, Neutral or Counter-hate.

Our work have several limitations. First, we only consider context as the parent comment. While considering additional context might be sometimes beneficial, doing so would require careful design to not bias annotations (Dutta et al., 2020). Our research agenda includes exploring reliably strate-

gies to consider more context and identify which parts are most important. Second, people may have different opinions about what constitutes hate and counter speech due to different tolerances in online aggression. We obtained the ground truth according to annotators' reliability (MACE scores), which may lead to controversial samples falling in the Silver set and thus being considered only for training (not for testing). Finally, the keywords sampling used to create our corpus may introduce biases. Despite we partially mitigate the issue by considering hateful comments in both the *Parent* and *Target*, community-based sampling (Vidgen et al., 2021) could be applied in our future work.

8 Ethical Considerations

We use the PushShift API to collect data from Reddit.[5] Our collection process is consistent with Reddit's Terms of Service. The data are accessed through the data dumps on Google's BigQuery using Python.[6]

Reddit can be considered a public space for discussion which differs from a private messaging service (Vidgen et al., 2021). Users consent to have their data made available to third parties including academics when they sign up to Reddit. Existing ethical guidelines state that in this situation explicit consent is not required from each user (Procter et al., 2019). We obfuscate user names as User_A or User_B to reduce the possibility of identifying users. In compliance with Reddit's policy, we would like to make sure that our dataset will be reused for non-commercial research only.[7]

The Reddit comments in this dataset were annotated by annotators using Amazon Mechanical Turk. We have followed all requirements introduced by the platform for tasks containing adult content. A warning was added in the task title. Annotators need to pass the Adult Content Qualification Test before working on our tasks. Annotators were compensated on average with $8 per hour. We paid them regardless of whether we accepted their work. Annotators' IDs are not included in the dataset.

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[5]https://pushshift.io/api-parameters/
[6]https://pushshift.io/using-bigquery-with-reddit-data/
[7]https://www.reddit.com/wiki/api-terms/

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A   Annotation Interface

We show a screenshot of the annotation interface in Figure 2.

B   Detailed Results

Table 9 presents detailed results complementing Table 6 in the paper. We provide Precision, Recall and weighted F1-score using each related task for pre-training when the input is Target and Parent_Target respectively in Table 9.

Identify hate speech and counter-hate speech

Instructions:

In this task, you will see a short Reddit conversation between User_A and User_B. The conversation will include the title of the discussion and one comment by each user. **Your job is to label the comment by User_B as Hate, Counter-hate or Neutral.** You will follow these steps:
1. First, see the title of the discussion.
2. Second, click a button to see the comment by User_A, and then click another button to see the comment by User_B.
3. Third, label the comment by User_B as Hate, Counter-hate or Neutral.

Definitions and Examples (click HERE to see more details and examples):

[Hate] User_B attacks an individual or a group with the intention to vilify, humiliate, or incite hatred in two ways:
1. User_B may explicitly express hate in the comment
2. User_B may agree with the hate expressed by User_A

[Counter-hate] User_B challenges, condemns the hate expressed by User_A where:
1. User_A is considered as hate
2. User_B counters User_A

[Neutral] User_B neither conveys hate nor counters hate expressed by User_A

Read the Reddit conversation and answer the question about the comment by User_B:

Title: The ignorance and loathing is real

User_A:
Here here. I'm short and the exit row is still better. Being tall doesn't make you entitled to it because you think I'm just as comfortable in those shit cramped seats.

User_B:
You're an angry little guy aren't you?

The comment posted by User_B is:
○ Hate   ○ Counter-hate   ○ Neutral

Submit

Figure 2: Screenshot of the annotation interface. The left panel displays the instructions and examples. The right panel displays the *Parent* and the *Target* to be annotated.

	Hate			Counter-hate			Neutral			Weighted Average		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Majority Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.51	1.00	0.67	0.26	0.51	0.34
Trained with ...												
Target	0.56	0.55	0.56	0.41	0.36	0.38	0.67	0.71	0.69	0.58	0.59	0.58
+ Hate_Twitter	0.58	0.53	0.55	0.46	0.07	0.12	0.61	0.88	0.72	0.57	0.6	0.54
+ Hate_Reddit	0.57	0.52	0.55	0.44	0.32	0.37	0.64	0.75	0.69	0.58	0.59	0.58
+ Sentiment	0.59	0.47	0.53	0.00	0.00	0.00	0.59	0.92	0.72	0.45	0.59	0.50
+ Sarcasm	0.59	0.51	0.55	0.50	0.04	0.08	0.59	0.51	0.55	0.57	0.58	0.51
+ Stance	0.56	0.55	0.56	0.51	0.41	0.45	0.68	0.74	0.71	0.61	0.61	0.61
Trained with ...												
Parent_Target	0.55	0.62	0.59	0.52	0.38	0.44	0.68	0.72	0.70	0.61	0.62	0.61
+ Hate_Twitter	0.49	0.64	0.56	0.29	0.13	0.18	0.66	0.73	0.7	0.53	0.57	0.54
+ Hate_Reddit	0.55	0.64	0.59	0.48	0.33	0.39	0.69	0.73	0.71	0.61	0.62	0.61
+ Sentiment	0.53	0.59	0.56	0.40	0.23	0.29	0.68	0.77	0.72	0.57	0.60	0.58
+ Sarcasm	0.56	0.54	0.55	0.45	0.09	0.15	0.62	0.86	0.72	0.56	0.60	0.54
+ Stance	0.55	0.66	0.60	0.54	0.43	0.48	0.71	0.70	0.71	0.63	0.63	0.63

Table 9: Detailed results (P, R, and F) predicting whether the *Target* is Hate, Neutral or Counter-hate when the input is only the Target or the Parent_Target. These results are using RoBERTa and pretrained with each related task. This table complements Table 6 in the paper.

	Hate			Counter-hate			Neutral			Weighted Average		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Majority Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.51	1.00	0.67	0.26	0.51	0.34
Trained with Target												
+ Silver + Related Task												
Mean	0.56	0.54	0.55	0.48	0.46	0.47	0.67	0.71	0.70	0.60	0.60	0.60
(SD)	0.04	0.05	0.01	0.01	0.05	0.03	0.01	0.04	0.01	0.00	0.01	0.01
Trained with Parent_Target												
+ Silver + Related Task												
Mean	0.55	0.6	0.59	0.51	0.49	0.50	0.72	0.72	0.72	0.64	0.64	0.63
(SD)	0.03	0.04	0.01	0.04	0.05	0.02	0.02	0.06	0.02	0.00	0.01	0.01

Table 10: Detailed results (P, R, and F) predicting whether the *Target* is Hate, Neutral or Counter-hate when the input is only the Target or the Parent_Target. The results are using both Silver and pretraining on related tasks. We experiment with multiple runs using different random seeds and report the mean scores and their standard deviation.

Table 10 presents the mean scores of Precision, Recall and weighted F1-score and their standard deviation when we use both Silver data and pretraining on related tasks with different random seeds.

	Epochs	Batch size	Learning rate	Dropout
Target	5	16	1e-5	0.5
+ Silver	2	16	1e-5	0.5
+ Related task	2	8	1e-5	0.5
+ Silver + Related task	4	16	1e-5	0.5

Table 11: Hyperparameters used to fine-tune RoBERTa individually for each training setting. We accept default settings for the other hyperparameters as defined in the implementation by Pruksachatkun et al. (2020).

The results are consistent with the findings in our study: adding the *Parent* does improve the performance compared to the system that does not (0.63 vs. 0.60).

C   Hyperparamters to Fine-tune the Systems

The neural model takes about half an hour on average to train on a single GPU of NVIDIA TITAN Xp. We use an implementation by Pruksachatkun et al. (2020) and fine-tune the RoBERTa (base architecture; 12 layers) (Liu et al., 2019) model for each of the four training settings. For each setting, we set the hyperparameters to be the same when the textual input is Target and Parent_Target respectively. Hence we only report tuned hyperparameters for each setting when the input is Target in Table 11.