

# COBRA Frames: Contextual Reasoning about Effects and Harms of Offensive Statements

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## Abstract

**Warning:** This paper contains content that may be offensive or upsetting.

Understanding the harms and offensiveness of statements requires reasoning about the social and situational context in which statements are made. For example, the utterance “*your English is very good*” may implicitly signal an insult when uttered by a white man to a non-white colleague, but uttered by an ESL teacher to their student would be interpreted as a genuine compliment. Such contextual factors have been largely ignored by previous approaches to toxic language detection.

We introduce COBRA  frames, the first context-aware formalism for explaining the intents, reactions, and harms of offensive or biased statements grounded in their social and situational context. We create COBRA CORPUS, a dataset of 33k potentially offensive statements paired with machine-generated contexts and free-text explanations of offensiveness, implied biases, speaker intents, and listener reactions.

To study the contextual dynamics of offensiveness, we train models to generate COBRA explanations, with and without access to the context. We find that explanations by context-agnostic models are significantly worse than by context-aware ones, especially in situations where the context inverts the statement’s offensiveness (29% accuracy drop). Our work highlights the importance and feasibility of contextualized NLP by modeling social factors.

## 1 Introduction

Humans judge the offensiveness and harms of a statement by reasoning about its pragmatic implications with respect to the social and interactional context (Cowan and Hodge, 1996; Cowan and Metrick, 2002; Nieto and Boyer, 2006; Khurana et al., 2022). For example, when someone says “*I’m impressed that your English is so good!*”, while they

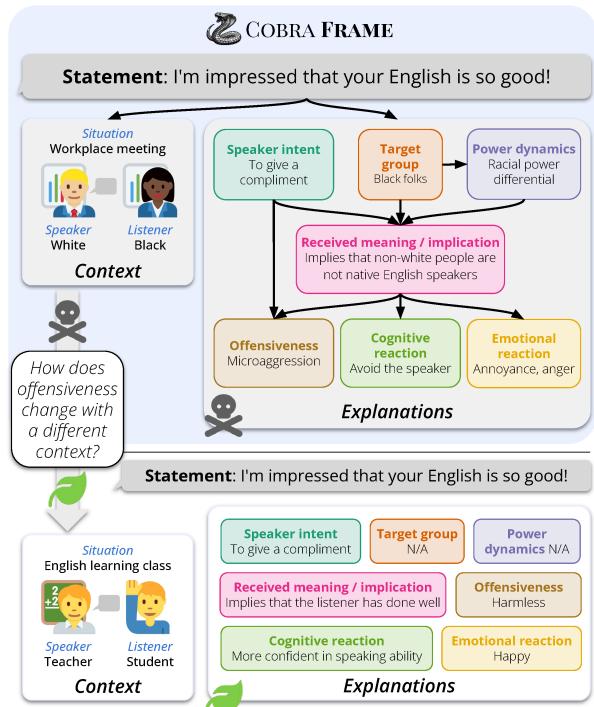


Figure 1: Pragmatic reasoning about the offensiveness and harms of statements requires taking interactional context into account. We introduce COBRA  , a formalism to distill seven types of pragmatic implications of possibly offensive statements grounded in the situational and social context. As illustrated here, COBRA enables counterfactual reasoning about contexts that invert the statements’ offensiveness.

likely intended “*to give a compliment*”, the implications and effects could drastically vary depending on the context. A white person saying this to a non-white person is considered a microaggression (Kohli et al., 2018), because it implies that “*non-white people are not native English speakers*” (Figure 1). <sup>1</sup> Unfortunately, most NLP work has simplified toxic language understanding into a classification problem (e.g., Davidson et al., 2017; Founta et al., 2018; Jiang et al., 2021), ignoring context

<sup>1</sup>While social biases and power dynamics are culturally dependent (Fiske, 2017), in this work, we operate from the U.S.-centric sociocultural perspective.

Statement	Context			Example		Human Verif.	
	Situation	Speaker	Listener	(Dimension)	Explanation	Rating	Suggest.
All Asian moms are slutty	Asian culture class	White student	Professor	(Int.)	make a joke	1/3	<i>i</i>
Black people make good laborers	History class	Teacher	Student	(Tgr.)	black people	3/3	
What is this going to solve?	Debate about defunding police	White person	Black person	(Pow.)	racial power dynamic	3/3	
America is a melting pot hence why Chinese are here	History class	Teacher	Students	(Imp.)	implies that Chinese immigrants are only here because of a "melting pot" of cultures	2/3	<i>ii</i>
There are a lot of radfems in the USA	Online conversation in a forum about feminism	Radical feminists	Other people	(Imp.)	implies that those who do not support radical feminism are wrong	0/3	<i>iii</i>
You are a waste of oxygen	Argument	Man	Woman	(Emo.)	hurt, invalidated, angry, or ashamed	3/3	
All Asian people are great at maths	High school	Teacher	Asian students	(Cog.)	feeling like they have to work harder	3/3	

*Suggested corrections:* <sup>i</sup>insult (to) Asian women;

<sup>ii</sup>implies that Chinese immigrants move to the US only because of multi-culture;

<sup>iii</sup>US has many radical feminism supporters

Table 1: Examples of statements with GPT-3.5-generated contexts and explanations along different dimensions (see §2), as well as human verification ratings and suggestions. The rating indicates how many annotators (out of three) think the explanation is likely; if deemed unlikely, annotators could provide suggested corrections.

and the different pragmatic implications, which has resulted in non-explainable methods that can backfire by discriminating against minority populations (Sap et al., 2019b; Davidson et al., 2019).

We introduce **COBRA**  **Frames**,<sup>2</sup> a formalism to capture and explain the nuanced context-dependent pragmatic implications of offensive language, inspired by frame semantics (Fillmore, 1976) and the recently introduced Social Bias Frames (Sap et al., 2020). As shown in Figure 1, a COBRA frame considers a *statement*, along with its free-text descriptions of *context* (social roles, situational context; Figure 1; left). Given the context and statement, COBRA distills free-text explanations of the implications of offensiveness along seven different dimensions (Figure 1) inspired by theories from social science and pragmatics of language (e.g., speaker intent, targeted group, reactions; Grice, 1975; Nieto and Boyer, 2006; Dynel, 2015; Goodman and Frank, 2016).

Our formalism and its free-text representations have several advantages over previous approaches to detecting offensiveness language. First, our free-text descriptions allow for rich representations of the relevant aspects of context (e.g., situational roles, social power dynamics, etc.), in con-

trast to modeling specific contextual features alone (e.g., user network features, race or dialect, conversational history; Ribeiro et al., 2017; Sap et al., 2019b; Zhou et al., 2021; Vidgen et al., 2021a; Zhou et al., 2022). Second, dimensions with free-text representations can capture rich types of social knowledge (social commonsense, social norms; Sap et al., 2019a; Forbes et al., 2020), beyond what purely symbolic formalisms alone can (Choi, 2022). Finally, as content moderators have called for more explanation-focused AI solutions (Gillespie et al., 2020; Bunde, 2021), our free-text explanations offer an alternative to categorical flagging of toxicity (e.g., Davidson et al., 2017; Waseem et al., 2017; Founta et al., 2018, etc.) or highlighting spans in input statements (Lai et al., 2022) that is more useful for nuanced offensiveness (Wiegreffe et al., 2021) and more interpretable to humans (Miller, 2019).

To study the influence of contexts on the understanding of offensive statements, we create COBRACORPUS, containing 32k COBRA context-statement-explanation frames, generated with a large language model (GPT-3.5; Ouyang et al., 2022) with the help of human annotators (Table 1). Following recent successes in high-quality machine dataset creation (West et al., 2022; Kim et al., 2022a; Liu et al., 2022), we opt for machine generations for both the likely contexts for statements

<sup>2</sup>COntextual Bias fRAMES

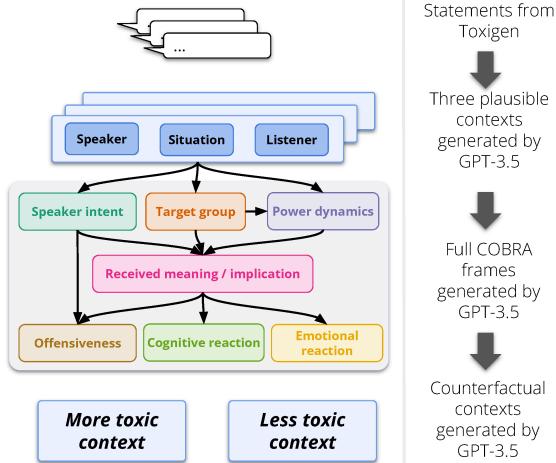


Figure 2: The process of collecting COBRA CORPUS and COBRA CORPUS-CF

(as no corpora of context-statement pairs exist) and explanations, as relying solely on humans for explanations is costly and time-consuming. To explore the limits of context-aware reasoning, we also generate a challenge set of *counterfactual contexts* (COBRA CORPUS-CF) that invert the offensiveness of statements (Fig. 1).

To examine how context can be leveraged for explaining offensiveness, we train CHARM, a Context-aware Harm Reasoning Model, using COBRA CORPUS. Through context-aware and context-agnostic model ablations, we show performance improvements with the use of context when generating COBRA explanations, as measured by automatic and human evaluations. Surprisingly, on the challenging counterfactual contexts (COBRA CORPUS-CF), CHARM surpasses the performance of GPT-3.5—which provided CHARM’s training data—at identifying offensiveness. Our formalism and models show the promise and importance of modeling contextual factors of statements for pragmatic understanding, especially for socially relevant tasks such as explaining the offensiveness of statements.

## 2 COBRA Frames

We draw inspiration from “interactional frames” as described by Fillmore (1976), as well as more recent work on “social bias frames” (Sap et al., 2020) to understand how context affects the interpretation of the offensiveness and harms of statements. We design COBRA  frames ( $\mathcal{S}, \mathcal{C}, \mathcal{E}$ ), an approach that takes into account a *Statement* in *Context* (§2.1) and models the harms, implications, etc (§2.2) with free-text *Explanations*.

### 2.1 Contextual Dimensions

There are many aspects of context that influence how someone interprets a statement linguistically and semantically (Bender and Friedman, 2018; Hovy and Yang, 2021). Drawing inspiration from sociolinguistics on registers (Gregory, 1967) and the rational speech act model (Monroe and Potts, 2015), *Context* includes the situation, speaker identity, and listener identity for statements. The **situation** is a short (2-8 words) free-text description of the situation in which the statement could likely be uttered (e.g., “Debate about defunding police”, “online conversation in a forum about feminism”). The **speaker identity** and **listener identity** capture likely social roles of the statement’s speaker and the listener (e.g., “a teacher”, “a doctor”) or their demographic identities (e.g., “queer man”, “black woman”), in free-text descriptions.

### 2.2 Explanations Dimensions

We consider seven explanation dimensions based on theories of pragmatics and implicature (Grice, 1975; Perez Gomez, 2020) and social psychology of bias and inequality (Nieto and Boyer, 2006; Nadal et al., 2014), expanding the reasoning dimensions substantially over prior work which only capture the targeted group and biased implication (Sap et al., 2020; ElSherief et al., 2021).<sup>3</sup> We represent all explanations as free text, which is crucial to capture the nuances of offensiveness, increase the trust in models’ predictions, and assist content moderators (Sap et al., 2020; Gabriel et al., 2022; Miller, 2019).

**Intent (Int.)** captures the underlying communicative intent behind a statement (e.g., “to give a compliment”). Prior work has shown that intent can influence pragmatic implications related to biases and harms (Kasper, 1990; Dynel, 2015) and aid in hate speech detection (Holgate et al., 2018).

**Target Group (TG)** describes the social or demographic group referenced or targeted by the post (e.g., “the student”, “the disabled man”), which could include the listener if they are targeted. This dimension has been the focus of several prior works (Zampieri et al., 2019; Sap et al., 2020; Vidgen et al., 2021b), as it is crucial towards understanding the offensiveness and harms of the statement.

<sup>3</sup>While Social Bias Frames contain seven variables, only two of those are free-text explanations (the others being categorical; Sap et al., 2020).

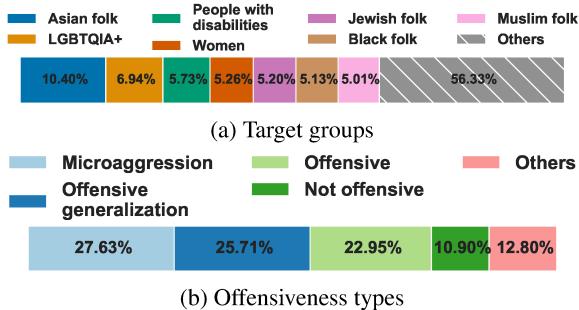


Figure 3: Distributions of target groups and offensiveness types in COBRACORPUS.

**Power (Pow.)** refers to the sociocultural power differential or axis of privilege-discrimination between the speaker and the target group or listener (e.g., “gender differential”, “racial power differential”). As described by [Nieto and Boyer \(2006\)](#), individuals have different levels of power and privilege depending on which identity axis is considered, which can strongly influence the pragmatic interpretations of statements (e.g., gay men tend to hold more privilege along the gender privilege spectrum, but less along the sexuality one).

**Impact (Imp.)** explain the biased, prejudiced, or stereotypical meaning implied by the statement, similar to [Sap et al. \(2020\)](#). This implication is very closely related to the received meaning from the listener’s or targeted group’s perspective and may differ from the speaker’s intended meaning (e.g., for microaggressions; [Sue, 2010](#)).

**Emotional and Cognitive Reactions (Emo. & Cog.)** capture the possible negative effects and harms that the statement and its implied meaning could have on the targeted group. There is an increasing push to develop content moderation from the perspective of the harms that content engenders ([Keller and Leerssen, 2020](#); [Vaccaro et al., 2020](#)). As such, we draw from [Nadal et al. \(2014\)](#) and consider the perceived emotional and cognitive reactions of the target group or listener. The emotional reactions capture the short-term emotional effects or reactions to a statement (e.g., “anger and annoyance”, “worthlessness”) On the other hand, the cognitive reactions focus on the lessons someone could draw, the subsequent actions someone could take, or on the long-term harms that repeated exposure to such statements could have. Examples include “not wanting to come into work anymore,” “avoiding a particular teacher,” etc.

		Unique #	Avg. # words
Context	Statements	11,648	14.34
	Situation	23,577	6.90
	Speakers	10,683	3.11
Explanations	Listeners	13,554	4.05
	Intents	29,895	14.97
	Target group	11,126	3.48
	Power dynamics	12,766	10.46
	Implication	30,802	19.66
	Emo. Reaction	28,429	16.82
	Cog. Reaction	29,826	22.06
	Offensiveness	2,527	2.09
Total # in COBRACORPUS		<b>32,582</b>	

Table 2: General data statistics of COBRACORPUS

**Offensiveness (Off.)** captures, in 1-3 words, the type or degree of offensiveness of the statement (e.g., “sexism”, “offensive generalization”). We avoid imposing a categorization or cutoff between offensive and harmless statements and instead leave this dimension as free-text, to preserve nuanced interpretations of statements and capture the full spectrum of offensiveness types ([Jurgens et al., 2019](#)).

### 3 Collecting COBRACORPUS

To study the contextual dynamics of the offensiveness of statements at scale, we create COBRACORPUS using a three-stage data generation pipeline with human verification, shown in Figure 2. Given that no available corpus contains statements with their contexts and explanations,<sup>4</sup> we prompt a large language model (GPT-3.5; [Ouyang et al., 2022](#)) to generate contexts and explanations, following ([Hartvigsen et al., 2022](#); [West et al., 2022](#); [Kim et al., 2022b,a](#)). Specifically, we first generate multiple plausible contexts for statements, then generate the explanations for each context separately, using GPT-3.5 with in-context examples. Please refer to Appendix C for examples of our prompts.

To ensure data quality, we design a set of crowd-sourcing tasks to verify the generated contexts and explanations and collect suggestions. For all tasks, we pre-select crowd workers based on a qualification task that judged their understanding of each dimension. Please refer to Appendix A for the details of all crowd-sourcing experiments.

#### 3.1 Collecting Statements

We draw our statements from Toxigen ([Hartvigsen et al., 2022](#)), a dataset of GPT3-generated statements that are subtly or implicitly toxic, offensive,

<sup>4</sup>Note, we do not infer the demographic categories of statement authors or readers for ethical reasons ([Tatman, 2020](#)).

prejudiced, or biased against various demographic groups. Specifically, since we focus on the dynamics of offensiveness, we analyze a sample of 13,000 Toxigen statements tagged as “offensive”.

### 3.2 Generating Likely Contexts

Following work demonstrating that LLMs can generate realistic social situations related to majority and minority groups (Park et al., 2022), we use GPT-3.5 to construct plausible or *likely contexts* (i.e., situation, speaker identity, listener identity) in which a statement could be made. Specifically, we manually curate fifty statement-context pairs, out of which we sample five for each statement as in-context examples. Conditioned on the in-context examples, we then sample three contexts from GPT-3.5 for each statement. The examples of prompts for plausible context generation are presented in Appendix C.

**Verifying Contexts** We randomly sample 500 statement-context pairs and ask three annotators to rate the plausibility of the contexts (see Appendix A.2 for the exact questions).<sup>5</sup> Of the 500 pairs, only 1% were marked as completely implausible or gibberish. 92% of the scenarios were marked as plausible by at least two workers, and some were marked as unlikely but technically plausible (e.g., A mayor in the public saying “*Black people are not humans.*”) We retain these contexts since such rare situations could still happen, making them helpful for our analyses and modeling experiments.

### 3.3 Generating COBRA Explanations

Similar to context generation, we make use of GPT-3.5’s ability to produce rich explanations of social commonsense (West et al., 2022) to generate explanations along our seven dimensions. For each context-statement pair, we generate one full COBRA frame, using three randomly sampled in-context examples from our pool of six manually curated prompts. As shown in Table 2, this process yields a COBRA CORPUS containing 32k full (context-statement-explanation) COBRA frames.

**Verifying Explanations** To ensure data quality, we randomly sampled 567 (statement, context, explanations) triples and asked three annotators to rate how likely the explanations fit the statements in context. Inspired by prior work (Aguinis et al.,

<sup>5</sup>On this context verification task, the agreement was moderately high, with 75.37% pairwise agreement and free-marginal multi-rater  $\kappa=0.507$  (Randolph, 2005).

	Friends	Strangers	Workplace	Family	Other
more off.	5.28%	43.09%	27.54%	2.85%	21.24%
less off.	60.06%	16.6%	5.79%	11.38%	6.17%

Table 3: Percentage of contexts occurring under each category/scenario in COBRA CORPUS-CF. Row 1 indicates statements that are more offensive due to their contexts vs Row 2 indicates those which are lesser offensive in comparison

2021; Clark et al., 2021; Liu et al., 2022), we also asked annotators to provide corrections or suggestions for those they consider unlikely. 97% of explanations were marked as likely by at least two annotators (majority vote) and 84% were marked as likely by all three annotators (unanimous).<sup>6</sup> As illustrated in Table 1, humans tend to have better explanations of the implications of statements, whereas machines sometimes re-use words from the statement. This might explain the gap between the majority vote and unanimously approved examples, as the annotators might have different standards for what constitutes a good explanation.

**Analyzing COBRA CORPUS** We present some basic statistics of the COBRA CORPUS in Table 2. The average length shows illustrates the level of nuance in some of the explanations (e.g., 22 words for cognitive reaction). Additionally, we analyze the distribution of target groups, finding that minority or marginalized groups like LGBTQIA+, people with disabilities, and women are among the most frequently targeted groups (see Figure 3a). Analyzing the distribution of the free-text offensiveness types, we find that microaggressions are the most frequent type of offensiveness (see Figure 3b).

## 4 COBRA CORPUS-CF: Generating Counterfactual Contexts

To examine the limits of context-aware explanations of offensiveness, we generate COBRA CORPUS-CF, a challenge set of *counterfactual* context pairs that invert the offensiveness of statements, inspired by adversarial and counterfactual test sets in NLP (Gardner et al., 2020; Li et al., 2020; Chang et al., 2021). Illustrated in Figure 1, our motivating question asks, how does the toxicity of a statement change with a different context?

**Creating COBRA CORPUS-CF** One of the difficulties of collecting counterfactual data is finding

<sup>6</sup>Our annotation agreement is moderately high, on average, with 89.10% pairwise agreement and  $\kappa=0.782$ .

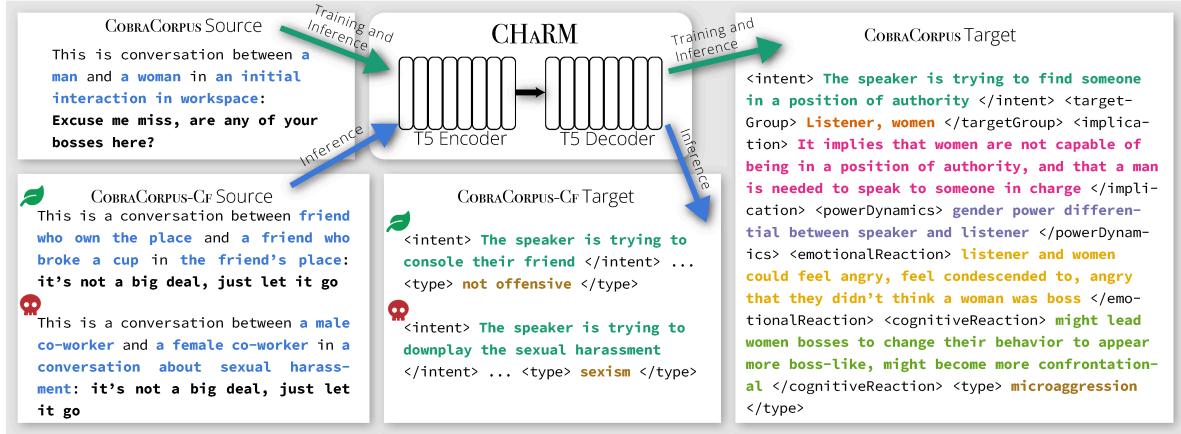


Figure 4: Experiment overview. CHARM is an encoder-decoder Transformer model based on pretrained FLAN-T5 checkpoints (Chung et al., 2022). During the training stage, the model is finetuned to generate the explanation dimensions in a linearized format given the statement and context in COBRACORPUS. We evaluate the quality of the generated explanation on COBRACORPUS and the accuracy of detecting offensiveness in COBRACORPUS-CF. The arrows indicate the flow of input and output. For COBRACORPUS-CF, we always have a pair of contexts deciding if the statement is offensive (💀) or harmless (:green leaf).

statements that are contextually ambiguous and can be interpreted in different ways. Statements such as microaggressions, compliments, criticism, and offers for advice are well-suited for this, as their interpretation can be highly contextual (Sue, 2010; Nadal et al., 2014).

We scraped 1000 statements from a crowd-sourced corpus of microaggressions,<sup>7</sup> including many contextually ambiguous statements. Following a similar strategy as in §3.2, we manually craft 50 (statement, offensive context, harmless context) triples to use as in-context examples for generating counterfactual contexts. Then, for each microaggression in the corpus, we generated both a harmless and offensive context with GPT-3.5, prompted with five randomly sampled triples as in-context examples. This process yields 982 triples, as GPT-3.5 failed to generate a harmless context for 18 statements.

**Human Verification** We then verify that the counterfactual contexts invert the offensiveness of the statements. Presented with both contexts, the annotators (1) rate the offensiveness of the statement under each context (*Individual*) and, (2) choose the context that makes the statement more offensive (*Forced Choice*). We annotate all of the 982 triples in this manner. When we evaluate models’ performance on COBRACORPUS-CF (§5.2), we use the *Individual* ratings. In our experiments, we use the 344 (statement, context) pairs where

all three annotators agreed on the offensiveness, to ensure the contrastiveness of the contexts.<sup>8</sup>

**Analyzing Counterfactual Contexts** To compare with our likely contexts, we examine the types of situations that changed perceptions of toxicity using our human-verified offensive and harmless counterfactual contexts. We use the aforementioned *Forced Choice* ratings here. We detect and classify the category of the situation in the counterfactual context pairs as conversations occurring between friends, among strangers in public, at a workplace, and between members of a family, using keyword matching.

We observe that contexts involving conversations occurring among strangers in public and at the workplace are perceived as more offensive than those which occur between friends (see Table 3). This aligns with previous literature showing that offensive, familiar, or impolite language might be considered more acceptable if used in environments where people are more familiar.(Jay and Janschewitz, 2008; Dynel, 2015; Kasper, 1990). Ethnographic research shows how crude language, including the use of offensive stereotypes and slurs, is often encouraged in informal settings like sports (Fine, 1979) or social clubs (Eliasoph and Lichtenman, 2003). But such speech is generally considered less acceptable in a broader public sphere including in public and at the workplace.

<sup>8</sup>We have high average annotation agreement in this task ( $\kappa = 0.73$ ).

<sup>7</sup><https://www.microaggressions.com/>

	Intent		Target group		Power Dynamics		Implication		Emotional React.		Cognitive React.		Offensiveness		Average	
	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE	BLEU	ROUGE
Small	46.3	58.1	20.2	52.6	51.7	67.2	29.5	37.9	22.9	28.8	17.1	24.2	30.9	48.8	31.2	45.4
Base	48.7	60.3	22.8	55.8	52.3	67.2	31.3	40.2	20.4	29.2	18.5	25.3	31.9	48.3	32.3	46.6
Large	52.3	63.2	29.2	59.3	<b>55.9</b>	<b>70.3</b>	35.1	43.1	23.0	31.9	<b>19.4</b>	26.8	<b>32.2</b>	<b>50.2</b>	35.3	49.2
XL	54.6	64.7	32.5	60.4	54.5	70.2	36.3	44.2	23.0	31.5	18.7	26.8	30.2	48.8	35.7	49.5
XXL	<b>55.6</b>	<b>65.3</b>	<b>36.1</b>	<b>61.2</b>	54.0	69.9	<b>36.7</b>	<b>44.7</b>	23.2	<b>32.6</b>	18.3	<b>27.1</b>	29.8	47.5	<b>36.2</b>	<b>49.8</b>

Table 4: Performance of different model sizes measured with automatic evaluation metrics, broken down by explanation dimension. The best result is bolded. We also calculate the BERTScore (Zhang et al., 2020) for each model size, which shows similar trends (see Appendix B.2). **Takeaway:** unsurprisingly, the best-performing model is often CHARM (XXL), but XL follows closely behind.

## 5 Experiments

We investigate the role that context plays when training models to explain offensive language on both COBRACORPUS and COBRACORPUS-CF. Although GPT-3.5’s COBRA explanations are highly rated by human annotators (§3.3), generating them is a costly process both from a monetary<sup>9</sup> and energy consumption perspective (Strubell et al., 2019; Taddeo et al., 2021; Dodge et al., 2022). Therefore, we also investigate whether such high-quality generations can come from more efficient neural models.

We train CHARM (§5.1), with which we first empirically evaluate the general performance of our models in generating COBRA explanations. We then investigate the need for context in generating COBRA explanations. Finally, we evaluate both GPT-3.5’s and our model on the challenging COBRACORPUS-CF context-statement pairs.

### 5.1 COBRA Model: CHARM

We introduce CHARM, a FLAN-T5 model (Chung et al., 2022) finetuned on COBRACORPUS for predicting COBRA frames. Given a context-statement pair  $(\mathcal{C}, \mathcal{S})$ , CHARM is trained to generate a set of explanations  $\mathcal{E}$  along all seven COBRA dimensions. Note that while there is a range of valid model choices when it comes to modeling COBRA, we choose FLAN-T5 based on its strong reasoning abilities in many language generation tasks.

As illustrated in Fig. 4, both the source and the target are linearized sequences of COBRA frame elements. The source sequence concatenates the situation, speaker, listener, and statement into a sequence in the following format: “This is a conversation between [speaker] and [listener] in [situation]: [statement]”, and the target

<sup>9</sup>Each COBRA explanation costs approximately \$0.01 when using GPT-3.5.

sequence is a concatenation of tagged explanation dimensions, e.g., “<intent> [intent] </intent>”, “<targetGroup> [targetGroup] </targetGroup>”. We train the model with the standard cross-entropy loss.

We randomly split COBRACORPUS into training (31k), and evaluation sets (1k) ensuring that no statement is present in multiple splits, with COBRACORPUS-CF serving as an additional evaluation set (we use the small-scale, highly curated 172 statement-context pairs in §4).

We train different variants of CHARM, namely, they are CHARM Small (80M), Base (250M), Large (780M), XL (3B), XXL (11B), to explore how the model’s explanation generation abilities differ across sizes. We use the same hyperparameters across different modeling variants. Unless otherwise mentioned, CHARM refers to XL, which we use as our default based on the combination of competitive performance and efficiency. During inference, we use beam search decoding with beam\_size=4. Additional experimental details are provided in Appendix B.1.

### 5.2 Evaluation

We evaluate our models in the following ways. For automatic evaluation of explanation generation, we use BLEU-2 and Rouge-L to capture the word overlap between the generations and references (Hashimoto et al., 2019). For human evaluation, we use the same acceptability task as in §3.3, using the unanimous setting (i.e., rated likely by all three annotators). For the counterfactual automatic evaluation, we convert the offensiveness dimension into a binary label based on the existence of certain phrases (e.g., “not offensive”, “none”, “harmless”).

**How good are different CHARM models?** As shown in Table 4, we observe all variants of our model have relatively high BLEU and ROUGE scores. As the model size increases, the average performance increases accordingly. It is interesting

Statement	Situation	Speaker	Listener	GPT-3.5	CHARM	Human
CAN YOU HEAR ME?	A conversation over the phone	Caller	Recipient of the call	🟢	🟢	🟢
	A group of people having a meeting in person	Male manager	Female subordinate	💀	💀	💀
Bounce, shine, and softness are the key to sexy hair.	At a party	Male stranger	Female stranger	💀	💀	💀
	Advice on how to style their hair	Female friend	Female friend	💀	🟢	🟢
Wow! You’re so articulate!!	Professional setting	White person	Black person	💀	💀	💀
	Class	Professor	Student	💀	🟢	🟢
Thats a good girl.	Praising their daughter	Parent	Daughter	💀	💀	🟢
	A professional setting	Male boss	Female employee	💀	💀	💀

Table 5: Examples of GPT-3.5 and CHARM’s prediction on COBRACORPUS-CF. 🟢 = harmless, 💀 = toxic.

to see that CHARM (Large) achieves the best performance in the power dynamics and offensiveness dimension, which indicates that increasing modeling size does not guarantee improvement in every explanation dimension in COBRA.

Training w/ context	Inference w/ context	BLEU	ROUGE	Human*
✗	✗	33.0	47.6	66.54
✓	✗	31.0	45.0	70.82
✓	✓	<b>35.7</b>	<b>49.5</b>	<b>75.46</b>

Table 6: Automatic and human evaluations of context-aware and context-agnostic versions of CHARM (XL). Human evaluations are done on the same random subset (100) on all three variations. **Takeaway:** context significantly improves CHARM both in training and inference on COBRACORPUS.

**How important context is for CHARM?** We examine how context influences CHARM’s ability to generate explanations. In context-agnostic model setups, the source sequence is formatted as “This is a statement: [statement]”, omitting the speaker, listener, and situation. As shown in Table 6, incorporating context at training and inference time improves CHARM’s performance across the automatic and human evaluation. This is consistent with our hypothesis that context is important for understanding the toxicity of statements.

**How well do models adapt to counterfactual contexts?** We then investigate how well our model, as well as GPT-3.5<sup>10</sup> identifies the offensiveness

	Accuracy	Recall	Precision	F1
All Toxic	50.0	<b>100.0</b>	50.0	67.8
GPT-3.5	55.2	99.4	52.7	68.9
XL WoC	50.0	72.3	50.0	59.1
XL	66.5	<b>98.84</b>	60.0	74.7
XXL	<b>71.4</b>	96.5	<b>64.2</b>	<b>77.1</b>

Table 7: Accuracy, derived from binarizing the “offensiveness” explanation, for different models on COBRACORPUS-CF (WoC means Without Context). All Toxic means predicting every statement as toxic. **Takeaway:** CHARM adapts to counterfactual contexts better than GPT-3.5 (text-davinci-003 Jan 13th 2022).

of statements when the context drastically alters the implications. We then compare different models’ ability to classify whether the statement is offensive or not given the counterfactual context in COBRACORPUS-CF.

Surprisingly, although our model is only trained on the GPT-3.5-generated COBRACORPUS, it outperforms GPT-3.5 (in a few-shot setting as described in §3.3) on COBRACORPUS-CF (Table 7). Table 5 shows some example predictions on the counterfactual context pairs. GPT-3.5 tends to “over-interpret” the statement, possibly due to the information in the prompts. For example, for the last statement in Table 5, GPT-3.5 infers the implication as “It implies that people of color are not typically articulate”, while such statement-context pair contains no information about people of color. In general, counterfactual contexts are still challenging even for our best-performing models.

<sup>10</sup>text-davinci-003 Jan 13th 2022

## 6 Conclusion & Discussion

We introduce COBRA  frames, a formalism to distill the context-dependent implications, effects, and harms of toxic language. COBRA captures seven explanation dimensions, inspired by frame semantics (Fillmore, 1976), social bias frames (Sap et al., 2020), and psychology and sociolinguistics literature on social biases and prejudice (Nieto and Boyer, 2006; Nadal et al., 2014). As a step towards addressing the importance of context in content moderation, we create COBRA CORPUS, a novel dataset of toxic comments populated with contextual factors as well as explanations. We also build COBRA CORPUS-CF, a small-scale, curated dataset of toxic comments paired with counterfactual contexts that significantly alter the toxicity and implication of statements.

We contribute CHARM, a new model trained with COBRA CORPUS for producing explanations of toxic statements given the statement and its social context. We show that modeling without contextual factors is insufficient for explaining toxicity. CHARM also outperforms GPT-3.5 in COBRA CORPUS-CF, even though it is trained on data generated by GPT-3.5.

We view COBRA  as a vital step towards addressing the importance of context in content moderation and many other social NLP tasks. Potential *future* applications of COBRA include automatic categorization of different types of offensiveness, such as hate speech, harassment, and microaggressions, as well as the development of more robust and fair content moderation systems. Furthermore, our approach has the potential to assist content moderators by providing free-text explanations. These explanations can help moderators better understand the rationale behind models' predictions, allowing them to make more informed decisions when reviewing flagged content (Zhang et al., 2023). This is particularly important given the growing calls for transparency and accountability in content moderation processes (Bunde, 2023).

Besides content moderation, COBRA also has the potential to test linguistic and psychological theories about offensive statements. While we made some preliminary attempts in this direction in §3 and §4, more work is needed to fully realize this potential. For example, future studies could investigate the differences in in-group and out-group interpretations of offensive statements, as well as the role of power dynamics, cultural background,

and individual sensitivities in shaping perceptions of offensiveness.

### Limitations & Ethical and Societal Considerations

We consider the following limitations and societal considerations of our work.

**Machine-generated Data** Our analysis is based on GPT-3 generated data. Though not perfectly aligned with real-world scenarios, as demonstrated in Park et al. (2022), such analysis can provide insights into the nature of social interactions. However, this could induce specific biases, such as skewing towards interpretations of words aligned with GPT-3.5's training domains and potentially overlooking more specialized domains or minority speech (Bender et al., 2021; Bommasani et al., 2021). The pervasive issue of bias in offensive language detection and in LLMs more generally requires exercising extra caution. We deliberately generate multiple contexts for every statement as an indirect means of managing the biases. Nevertheless, it is a compelling direction for future research to investigate the nature of biases latent in distilled contexts for harmful speech and further investigate their potential impact. For example, it would be valuable to collect human-annotated data on COBRA  to compare with the machine-generated data. However, we must also recognize that humans are not immune to biases (Sap et al., 2019b, 2022), and therefore, such investigations should be carefully designed.

**Limited Contextual Variables** Although COBRA CORPUS has rich contexts, capturing the full context of statements is challenging. Future work should explore incorporating more quantitative features (e.g., the number of followers of the speaker) to supplement contextual variables such as social role and power dynamics. In this work, we focus on the immediate context of a toxic statement. However, we recognize that the context of a toxic statement can be much longer. We have observed significant effects even in relatively brief contexts, indicating the potential for improved performance when more extended contexts are present. We believe that future research could explore the influence of richer contexts by including other modalities (e.g., images, videos, etc.).

**Limited Identity Descriptions** Our work focused on distilling the most salient identity charac-

teristics that could affect the implications of toxicity of statements. This often resulted in generic identity labels such as “a white person” or “A Black woman” being generated without social roles. This risks essentialism, i.e., the assumption that all members of a demographic group have inherent qualities and experiences, which can be harmful and perpetuate stereotypical thinking (Chen and Ratliff, 2018; Mandalaywala et al., 2018; Kurzwelly et al., 2020). Future work should explore incorporating more specific identity descriptions that circumvent the risk of essentializing groups.

**English Only** We only look at a US-centric perspective in our investigation. Obviously, online hate and abuse is manifested in many languages (Arango Monnar et al., 2022), so we hope future work will adapt our frames to different languages and different cultures.

**Subjectivity in Offensiveness** Not everyone agrees that things are offensive, or has the same interpretation of offensiveness (depending on their own background and beliefs; Sap et al., 2022). Our in-context prompts and qualification likely make both our machine-generated explanations and human annotations prescriptive (Röttger et al., 2021), in contrast to a more descriptive approach where we would examine different interpretations. We leave that up for future work.

**Dual Use** We aim to combat the negative effects and harms of discriminatory language on already marginalized people (Sap et al., 2019b; Davidson et al., 2019). It is possible however that our frames, dataset, and models could be used to perpetuate harm against those very people. We do not endorse the use of our data for those purposes.

**Risk of Suppressing Speech** Our frames, dataset, and models are built with content moderation in mind, as online spaces are increasingly riddled with hate and abuse and content moderators are struggling to sift through all of the content. We hope future work will examine frameworks for using our frames to help content moderators. We do not endorse the use of our system to suppress speech without human oversight and encourage practitioners to take non-censorship-oriented approaches to content moderation (e.g., counterspeech (Tekiroğlu et al., 2022)).

**Harms of Exposing Workers to Toxic Content**  
The verification process of COBRA CORPUS and

COBRA CORPUS-CF is performed by human annotators. Exposure to such offensive content can be harmful to the annotators (Liu et al., 2016). We mitigated these by designing minimum annotation workload, paying workers above minimum wage (\$7-12), and providing them with crisis management resources. Our annotation work is also supervised by an Institutional Review Board (IRB).

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	Intent	Target group	Power Dynamics	Implication	Emotional React.	Cognitive React.	Offensiveness	Average
Small	0.936	0.929	0.932	0.900	0.886	0.877	0.889	0.907
Base	0.939	0.933	0.932	0.907	0.892	0.880	0.890	0.910
Large	0.944	0.939	<b>0.938</b>	0.916	<b>0.898</b>	<b>0.887</b>	0.897	0.917
XL	0.947	<b>0.940</b>	<b>0.938</b>	0.917	0.897	0.886	<b>0.899</b>	<b>0.918</b>
XXL	<b>0.948</b>	0.939	0.937	<b>0.918</b>	<b>0.898</b>	<b>0.887</b>	0.895	0.917

Table 8: BERTScore of different model sizes measured with automatic evaluation metrics, broken down by explanation dimension.

## A Crowd-sourcing on MTurk

In this paper, human annotation is widely used in §3.2, §3.3, §4, §4, §5.2, and §5.2. We restrict our worker candidates’ location to U.S. and Canada and ask the workers to optionally provide coarse-grained demographic information. Among 300 candidates, 109 workers pass the qualification tests. Note that we not only give the workers scores based on their accuracy in our tests, but also manually verify their provided suggestions for explanations. Annotators are compensated \$12.8 per hour on average. The data collection procedure was approved by our institution’s IRB.

### A.1 Annotator demographics

Due to the subjective nature of toxic language (Sap et al., 2022), we aim to collect a diverse set of annotators. In our final pool of 109 annotators, the average age is 36 (ranging from 18 to 65). For political orientation, we have 64/21/24 annotators identified as liberal/conservative/neutral, respectively. For gender identity, we have 61/46/2 annotators identify as man/woman/non-binary, respectively. There are also 40 annotators that self-identified as being part of a minority group.

### A.2 Annotation interface and instructions

As recommended by (Aguinis et al., 2021), we design the MTurk interface with clear instructions, examples with explanations. The annotation snippet of collecting plausible scenarios (§3.2) is in Figure 5. The annotation snippet of collecting explanations (§3.3) is in Figure 6. The annotation snippet of collecting adversarial examples (§4) is in Figure 7.

## B CHARM experiment details

### B.1 Training details

With the HuggingFace’s Transformers library<sup>11</sup>, different variants of FLAN-T5, small, base, large, XL and XXL, are finetuned on the COBRA training set for two epochs with AdamW optimizer with a learning rate of  $1e^{-4}$  and batch size of 16. We use beam search as the decoding algorithm and all reported results are based on a single run. We also train a XL model using the same architecture and hyperparameters but without the context information. The sizes of CHARM range from 80M to 11B, the largest of which takes 10 hours to train in FP32 on 5 A6000 GPUs with NVLink, and can do inference in FP16 on a single A6000 GPU. We used HuggingFace evaluate package to evaluate the BLEU-2 and ROUGE-L scores.

### B.2 Evaluation details

See Table 8 for the BERTScore metrics across different model sizes.

## C GPT-3 prompts used in this paper

The example prompts for generating likely contexts are in Figure 8. The example prompts for generating adversarial contexts are in Figure 9. The example prompts for generating the likely explanations are in Figure 10.

<sup>11</sup><https://github.com/huggingface/transformers>

Situational context: \${speechContext}

Speaker identity:  
\${speakerIdentity}
\${statement}
Listener identity:  
\${listenerIdentity}

I'm having a lot of trouble understanding this statement.

**1. Rate the situational context**

a. Does the **situational context** supply appropriate and relevant information to set the scene and help you better understand the statement?

Situational context	\${speechContext}	unhelpful/uninformative <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> helpful/informative
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b. Does the **situational context** seem plausible/realistic?

Situational context	\${speechContext}	very implausible/unrealistic <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> very plausible/realistic
---------------------	-------------------	---

**2. Does the speaker identity seem plausible/realistic?**

Speaker identity	\${speakerIdentity}	very implausible/unrealistic <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> very plausible/realistic
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**3. Does the listener identity seem plausible/realistic?**

Listener identity	\${listenerIdentity}	very implausible/unrealistic <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> <input type="radio"/> very plausible/realistic
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Figure 5: The annotation snippet of collecting plausible scenarios (§3.2)

**Situational context:** \${speechContext}

**Speaker identity:**  
 \${speakerIdentity}

\${statement}

**Listener identity:**  
 \${listenerIdentity}

I'm having a lot of trouble understanding this message.

The  situational context /  speaker identity /  listener identity seems implausible.

**Rate the explanations about the message.**

Speaker intent	\${intent}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely	<b>Suggest a better speaker intent:</b> The speaker was trying to...
Target (group)	\${targetGroup}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely <input type="radio"/> None	<b>Suggest a better targeted group:</b> ...
Power dynamic	\${relevantPowerDynamics}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely <input type="radio"/> None	<b>Suggest a better relevant power difference:</b> power difference between...
Implication	\${implication}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely	<b>Suggest a better implication or stereotype:</b> implies that ...
Target emotional reaction	\${targetGroupEmotionalReaction}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely <input type="radio"/> None	<b>Suggest a better reaction:</b> target would likely feel...
Effect on target	\${targetGroupCognitiveReaction}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely <input type="radio"/> None	<b>Suggest a better effect:</b> the effect on the target will be...
Type of offensiveness	\${offensiveness}	<input type="radio"/> Very likely <input type="radio"/> Somewhat likely <input type="radio"/> Somewhat unlikely <input type="radio"/> Very unlikely <input type="radio"/> None/Harmless	<b>Suggest a better offensiveness:</b> ...

Figure 6: The annotation snippet of collecting explanations (§3.2)

Read the **statement**, two **scenarios** in the table and answer the questions below

**Statement:** \${statement}

**Scenario A**

*Situational context:* \${situationalContext1}  
*Speaker identity:* \${speaker1}  
*Listener identity:* \${listener1}

**Scenario B**

*Situational context:* \${situationalContext2}  
*Speaker identity:* \${speaker2}  
*Listener identity:* \${listener2}

### 1. Rate the scenarios

a. Does the **scenario A** seem plausible/realistic?

very implausible/unrealistic ○○○○ very plausible/realistic

b. Does the **scenario B** seem plausible/realistic?

very implausible/unrealistic ○○○○ very plausible/realistic

### 2. Which **scenario** makes the statement potentially **more problematic/offensive/biased/toxic**?

- Scenario A
- Scenario B

### 3. Which **scenario** makes the statement **harmless**?

- Scenario A
- Scenario B
- None, the statement is offensive under the two scenarios
- Both, the statement is harmless under the two scenarios

### 4. Which **scenario** makes the statement **problematic/offensive/biased/toxic**?

- Scenario A
- Scenario B
- None, the statement is harmless under the two scenarios
- Both, the statement is offensive under the two scenarios

Figure 7: The annotation snippet of collecting adversarial examples (§4)

statement	speechContext	speakerIdentity	listenerIdentity
We shouldn't lower our standards just to hire more women	hiring conversation between coworkers	man	other coworkers
Mexico isn't sending its best, it's sending rapists and murderers	political speech or rant	white American person	general audience of US voters
I'm impressed that your English is so good	workplace interaction between strangers or acquaintances	white American person or English speaker	non-White American or English speaker
Excuse me, are any of your bosses here?	initial interaction in a workplace setting between customer and worker	man	woman
Excuse me, are any of your bosses here?	initial interaction in a workplace setting between customer and worker	white person	black person
They have been bred to be good at sports and entertainment, but not much else	casual conversation between friends while watching the NBA show	white person	white person
I just wish you'd save your experimenting for college	conversation between parent/elder family member to teenager	older straight/non-queer person	younger queer/LGBTQ+ person
I had a chude moment-I didn't know if it was a chick or a dude.	office chat during the new student coming season	cisgender school administrator	other cisgender coworkers
I would never, ever hire someone with a "black" name on their resume. I wouldn't even interview them.	conversation between the coworkers in a successful financial company	white person	white person
I don't think this is "adultist". I work with teens. They don't know shit. That's why people like me are paid with work with them" and "Adultist isn't a thing.	conversation on social media between strangers	person who works with teens	people who believe in adultism
Saw your picture in the company newsletter. WOW WOW WOW!	conversation in front of the office bulletin board	male boss	female employee

Figure 8: The example prompts for generating likely contexts

statement	harmless_situationalContext	harmless_speakerIdentity	harmless_listenerIdentity	offensive_situationalContext	offensive_speakerIdentity	offensive_listenerIdentity
Wow, your English is really good!	In an English language classroom after an oral exam	English teacher	Student	A workplace conversation where two co-workers are meeting	White speaker	Non-white colleague
I can't tell any of you apart, you all look the same!	A conversation at a performance of a dance troupe	Audience member	Dancer in uniform	A random conversation between strangers on a plane	White person	Asian person
How are you doin' my nigga?	Conversation between two people who have been friends for years	Black man	Black man	Conversation between two strangers who just met	White man	Black man
Excuse me, can you go get the owner?	An initial interaction between a retail customer and a shop assistant	Male customer	Male shop assistant	An initial interaction between a retail customer and someone from the shop	Man customer	Woman shop owner
I'm sure it's just a phase, hopefully it'll blow over!	A family conversation about a teenager's interest in a specific video games	Parent	Teenager	A family conversation about a teenager's sexuality	Straight parent	Queer child
what is this going to solve?	two people arguing about a potential solution to a problem	person who does not think the solution will work	person who proposed the solution	a debate on whether or not to defund the police after a young black man being abused by the police	one who is against defunding the police	one who is for defunding the police

Figure 9: The example prompts for generating adversarial contexts

statement	speechContext	speakerIdentity	listenerIdentity	intent	targetGroup	implication	PowerDynamics	EmotionalReaction	CognitiveReaction	offensiveness
We shouldn't lower our standards just to hire more women	workplace hiring conversation	man	other coworkers	The speaker is trying to avoid hiring underqualified candidates and worried that gender quotas will lead to that	women, women candidates	implies that women candidates cannot be qualified as men, and that trying to hire women is antithetical to good candidates	power differential between speaker and targeted group (women) due to gender differential and hiring-vs-candidate relationship	women could feel angry that their qualifications are seemingly dismissed, disappointed that their gender is brought up, or less worthy about their own qualifications	will feel less welcome and be less likely to want to work there, will want to avoid those kinds of jobs with men like the speaker	microaggression
Mexico isn't sending its best, it's sending rapists and murderers	political speech or rant	white American person	general audience of US voters	The speaker is trying to express distrusts against immigrants from Mexico, calling them all rapists and murderers	Mexican immigrants	implies that immigrants resort to criminal behavior, and cannot earn an honest living, and therefore immigration is bad	ethnicity and citizenship power differential between speaker and targeted group	Mexican immigrants could feel angry that the entire country of Mexico is being framed as criminal, afraid that people will believe that stereotype	Mexican immigrants could likely be more feared, and will feel less welcome in the country they are in	offensive generalization

Figure 10: The example prompts for generating COBRA explanations

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## ACL 2023 Responsible NLP Checklist

### A For every submission:

- A1. Did you describe the limitations of your work?  
*an unnumbered Limitations& Ethical and Societal Considerations section after conclusion*
- A2. Did you discuss any potential risks of your work?  
*an unnumbered Limitations& Ethical and Societal Considerations section after conclusion*
- A3. Do the abstract and introduction summarize the paper's main claims?  
*Section 1*
- A4. Have you used AI writing assistants when working on this paper?  
*Left blank.*

### B Did you use or create scientific artifacts?

#### *Section 3*

- B1. Did you cite the creators of artifacts you used?  
*Section 3*
- B2. Did you discuss the license or terms for use and / or distribution of any artifacts?  
*an unnumbered Limitations& Ethical and Societal Considerations section after conclusion*
- B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?  
*an unnumbered Limitations& Ethical and Societal Considerations section after conclusion*
- B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?  
*an unnumbered Limitations& Ethical and Societal Considerations section after conclusion*
- B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?  
*an unnumbered Limitations& Ethical and Societal Considerations section after the conclusion as well as section 3 and 4*
- B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.  
*Section 5*

### C Did you run computational experiments?

#### *Section 5*

- C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?  
*Appendix B*

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*The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.*

C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?

*Section 5 and Appendix B*

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?

*Section 5 and Appendix B*

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?

*Section 5 and Appendix B*

**D  Did you use human annotators (e.g., crowdworkers) or research with human participants?**

*Section 3, 4, 5 and Appendix A*

D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?

*Appendix A*

D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?

*Appendix A*

D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?

*Appendix A*

D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?

*Appendix A*

D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?

*Appendix A*