D3CODE: Disentangling Disagreements in Data across Cultures on Offensiveness Detection and Evaluation

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Abstract

While human annotations play a crucial role in language technologies, annotator subjectivity has long been overlooked in data collection. Recent studies that have critically examined this issue are often situated in the Western context, and solely document differences across age, gender, or racial groups. As a result, NLP research on subjectivity have overlooked the fact that individuals within demographic groups may hold diverse values, which can influence their perceptions beyond their group norms. To effectively incorporate these considerations into NLP pipelines, we need datasets with extensive parallel annotations from various social and cultural groups. In this paper we introduce the D3CODE dataset: a large-scale cross-cultural dataset of parallel annotations for offensive language in over 4.5K sentences annotated by a pool of over 4k annotators, balanced across gender and age, from across 21 countries, representing eight geo-cultural regions. The dataset contains annotators' moral values captured along six moral foundations: care, equality, proportionality, authority, loyalty, and purity. Our analyses reveal substantial regional variations in annotators' perceptions that are shaped by individual moral values, offering crucial insights for building pluralistic, culturally sensitive NLP models.

1 Introduction

Designing Natural Language Processing (NLP) tools for detecting offensive or toxic text has long been an active area of research (Wulczyn et al., 2017; Founta et al., 2018). However, applying traditional NLP solutions have led to overlooking the cultural and individual factors that shape humans' varying perspectives and disagreements on what is deemed offensive (Aroyo and Welty, 2015; Waseem, 2016; Salminen et al., 2019; Uma et al., 2021; Prabhakaran et al., 2021). Perceiving language as offensive can depend inherently on one's moral judgments as well as the social norms dictated by the socio-cultural context within which one's assessments are made (Eickhoff, 2018; Aroyo et al., 2019; Waseem et al., 2021; Rottger et al., 2022; Davani et al., 2023). Therefore, data curating and modeling efforts should appropriately handle such subjective factors in order to better capture and learn human perspectives about offensiveness.

Figure 1: The distribution of labels provided from different countries. Annotators from China, Brazil, and Egypt provided significantly different labels.

As a result, recent efforts call for diversifying the rater pools as well as designing models that look beyond predicting a singular ground truth (Davani et al., 2022; Aroyo et al., 2023a). However, the efforts for diversifying annotator pools often risk reducing annotators' differences to demographic variations. Moreover, subjectivity is often studied in relation to annotators' gender and race, in particular, within the Western context. In reality, perceptions of what is offensive extend far beyond mere differences in demographics, shaped by an individual's lived experiences, cultural background and other psychological factors.

For instance, the intricate interplay of social media content moderation and principles of freedom of speech brings the task of offensive language detection into the realm of moral and political deliberation (instances of such discussions can be found in Balkin (2017), Brannon (2019), and Kiritchenko et al. (2021)). More generally, individuals might systematically disagree on notions of offensiveness, reflecting the complexity of beliefs and values that shape their perspectives and judgments within any given cultural context. Therefore, we argue that the high divergence in annotators' perceptions of offensiveness (Prabhakaran et al., 2021) can be traced back to individuals' diverse moral values along with the cultural and social norms that dictate the boundaries of acceptable language within a society.

In this work we introduce the **D3CODE** dataset, built through a cross-cultural annotation effort aimed at collecting perspectives of offensiveness from 4309 participants of different age and genders across 21 countries within eight larger geo-cultural regions. Through an in-depth analysis of our dataset, we shed light on cultural and moral values that sets people apart during the annotation. We believe that this dataset can be used for assessing modeling approaches that are designed to incorporate annotators' subjective views on language, as well as for evaluating different models' cultural and moral alignment.

2 Related Work

Recent studies have shown that treating annotators as interchangeable is not an effective approach for dealing with subjective language understanding tasks (Pavlick and Kwiatkowski, 2019; Díaz et al., 2022b; Prabhakaran et al., 2021; Davani et al., 2023). Alternatively, modeling the nuances encoded in annotations and inter-annotator disagreements has recently been explored as an alternative solution for subjective tasks.

2.1 Disagreement-aware Modeling

When datasets include a set of annotations per instance, the distribution of these labels, and the disagreement extracted from the set, become two possible pieces of information that potentially help the modeling process. Basile et al. (2021) argue that disagreement — even on objective tasks (Parrish et al., 2023) — should be considered as a source of information rather than being resolved. Rottger et al. (2022) propose a descriptive annotation paradigm for operationalizing subjectivity when surveying and modeling different beliefs.

Therefore, incorporating inter-annotator agreements into the modeling process has gained more attention in the NLP community: Plank et al. (2014) considered the item-level agreement as the loss function weights and achieved improvements on the downstream tasks. Fornaciari et al. (2021) leveraged annotator disagreement as an auxiliary task to be predicted along with ground-truth labels, which improves the performance even in less subjective tasks such as part-of-speech tagging.

Kennedy et al. (2020) apply an item response theory model to the variations in annotations of hate speech to decompose the binary labels and use them in a multi-task model for predicting the latent variables. While these methods intend to consider the variations in annotators' perspectives, they still fall short on regarding the integrity of the labels provided by each annotator and aggregate their varying subjectivities into a single construct.

2.2 Annotator-aware Modeling

The social nature of language means that social groups and relations play meaningful roles in how individuals use language, such as offensive speech (Díaz et al., 2022a). Acknowledging the differences in annotators' perceptions of subjective tasks has led model designers to consider information at the annotator level as the social factors needed for contextualizing language (Hovy and Yang, 2021). Hovy (2015) show that providing the age or gender of the authors to text classifiers consistently and significantly improves the performance over demographic-agnostic models. Garten et al. (2019) model users' responses to questionnaire items based on their demographic information by training a demographics embedding layer, which can further be used in isolation to generate embeddings for any unseen sets of demographics.

Ferracane et al. (2021) add annotators' sentiment about the writer of the text into modeling their labels. They show that incorporating contextual information about annotators increases the performance. Davani et al. (2022) introduce a multi-annotator architecture that models each annotators' perspectives separately using a multi-task approach. And Orlikowski et al. (2023) extend the multi-task model to capture perspectives of different groups, although they argued against modeling annotator groups. While these methods model annotations based on annotators' differences they do not incorporate psychological profile of annotators into modeling their perceptions of language, which are impacted by individual psychological traits, experiences, cultural background, and cognitive abilities.

2.3 Annotators in NLP Datasets

Although attending to annotators' background is gaining more importance, documenting how annotators' identity, which shapes their comprehension of the world – and in turn language –, is still missing in many data curation efforts (Díaz et al., 2022b; Scheuerman et al., 2021). A number of scholars have begun to not only document annotator identity, but also develop principled approaches for obtaining a diversity of identities and perspectives in datasets.

Aroyo et al. (2023b) developed a dataset that specifically focuses on evaluating disagreement and diverse perspectives on conversational safety, and (Homan et al., 2023) leverages this same dataset to demonstrate multilevel modeling as an approach for measuring annotation differences across a range of sociodemographic groups. Others have also successfully integrated annotator differences into model predictions, such as through personalized model tuning (Kumar et al., 2021), and jury learning (Gordon et al., 2022).

Disagreement among annotators in subjective tasks such as offensive language detection has roots beyond mere differences in socio-cultural backgrounds. One such nuanced factor, often not studied in AI research, is morality. Moral considerations play significant roles in how humans navigate prejudicial thoughts and behaviors (Molina et al., 2016), often manifesting in language through offensive content. The interplay between morality and group identity (Reed II and Aquino, 2003) influences many aspects of our social dynamics, including perceptions, interactions, stereotypes, and prejudices. Moreover, research in computational social science addressing harmful language reveals a concurrent occurrence of moral sentiment alongside expressions of hatred directed at other social groups (Kennedy et al., 2023).

Our data collection effort not only provides social factors and demographic information regarding annotators but also considers the moral values that may vary across regions and among individuals. Such information facilitates drawing connections between annotations from culturally diverse annotators, the sociocultural norms shaping their environment, and the moral values they hold.

3 D3CODE Dataset

In order to study a broad range of cultural perceptions of offensiveness, we recruited 4309 participants from 21 countries, representing eight geo-cultural regions, with each region represented by 2-4 countries (Table 1).[1] We discuss the reasoning behind our selection of countries and regions in more depth in Appendix A.1; however, the final selection of countries and regions was chosen to maximize cultural diversity while balancing participant access through our recruitment panel. Participants were recruited through an online survey pool, compensated in accordance to their local law, and were informed of the intended use of their responses. In order to capture the participants' perceptions of offensiveness, we asked each participant to annotate offensiveness of social media comments selected from Jigsaw datasets (Jigsaw, 2018, 2019). Furthermore, we also asked them to respond to a measurement of self-reported moral concerns, using the Moral Foundations Questionnaire (MFQ-2; Graham et al., 2013; Atari et al., 2023).[2]

		Gender			Age		
Region	#	M	W	Other	18–30	30–50	50+
AC.	516	306	205	5	269	168	79
ICS.	554	308	245	1	237	198	119
LA.	549	271	275	3	302	176	71
NA.	551	220	325	6	263	175	113
Oc.	517	203	307	7	161	221	135
Si.	540	280	249	11	208	228	104
SSA.	530	309	219	2	320	157	53
WE.	552	252	294	6	259	172	121

Table 1: Demographic distribution of annotators from each region, region names are shortened and represent: Arab Culture (AC.), Indian Cultural Sphere (ICS.), Latin America (LA.), North America (NA.), Oceania (Oc.), Sinosphere (Si.), Sun-Saharan Africa (SSA), and Western Europe (WE.).

3.1 Recruitment

Recruitment criteria account for various demographic attributes: (1) *Region of residence*: we recruited at least 500 participants from each of the eight regions with at least 100 participants per country, except for South Korea and Qatar where we managed to recruit only a smaller number of raters (See Table 5), (2) *Gender*: within regions, we set a maximum limit of 60% representations for Men and Women separately (for a loosely bal-

[1] We based the categorization of regions loosely on the UN Sustainable Development Goals groupings https://unstats.un.org/sdgs/indicators/regional-groups with minor modifications: combining Australia, NZ and Oceania to "Oceania", and separating North America and Europe, to facilitate easier data collection.

[2] The data card and dataset will be available upon the paper

anced representation of the two genders), while including options for selecting "non-binary / third gender," "prefer not to say," and "prefer to self identify" (with a textual input field). We recognize that collecting non-binary gender information is not safe for annotators in many countries, so we limited the specification of recruitment quota to binary genders to ensure consistency across countries. (3) *Age*: in each region at most 60% of participants are 18 to 30 years old and at least 15% are 50 years old or older. We specifically aimed to ensure adequate representation of annotators of age 50 or older, because this age group have lower engagement with crowdsourcing platforms but are equally impacted by technology advancements. Table 1 provides the final distribution of participants across different demographic groups in each region.

We further set an exclusion criterion based on *English fluency* since our study is done on English language text; we only selected participants who self-reported a high level of proficiency in reading and writing English. We performed this study in the English language, as the most wide-spoken language across the globe, to simulate the most common data annotation settings, in which annotators (who are no necessarily English speakers) are asked to interact with and label textual data in English. Additionally, we collected participants' self-reported subjective socio-economic status (Adler et al., 2000) that may serve as a potential confound in follow-up analyses.

3.2 Annotation items

We performed this study in the English language. In order to collect textual items for participants to annotate, we selected items from Jigsaw's Toxic Comments Classification dataset (Jigsaw, 2018), and the Unintended Bias in Toxicity Classification dataset (Jigsaw, 2019), both of which consist of social media comments labeled for toxicity. We built a dataset of N_{items} = 4554 consisting of three categories of items sampled from the above datasets:

Random: As the basic strategy, we randomly select 50% of the data from items that are likely to evoke disagreement. To measure disagreements on each item, we averaged the toxicity scores assigned to the item in the original dataset, ranging from 0 (lowest toxicity) to 1 (highest toxicity). Items on the two ends of the range evoke no disagreement because all annotators labeled them either as toxic or non-toxic. Therefore, we chose items with a normal distribution centered around a toxicity score of 0.5 (indicating highest disagreement) with a standard deviation of 0.2.

Moral Sentiment: Second, 10% of the dataset consists of a balanced set of items include different moral sentiments, identified through a supervised moral language tagger trained on the MFTC dataset (Hoover et al., 2020). This strategy is aimed at enabling follow up studies to investigate potential content-level correlates of disagreements, particularly as previous computational social science studies on harmful language have shown specific correlation of moral sentiment with expressions of hatred (Kennedy et al., 2023). Our tagger identified very few items with moral sentiment throughout the dataset, selecting a balances set led to a set of 500 such items.

Social Group Mentions: Finally, the rest (40%) of the dataset consists of a balanced set of items that mention specific social group identities related to gender, sexual orientation, or religion (this information is provided in the Jigsaw's raw data). We specifically selected such items as online harmful language is largely directed at specific social groups and resonates real-world group conflicts.

3.3 Annotation task

Each participant was tasked with labeling 40 items on a 5-point Likert scale (from *not offensive at all* to *extremely offensive*). Half of the participants were provided with a note that defined *extremely offensive language* as *"profanity, strongly impolite, rude or vulgar language expressed with fighting or hurtful words in order to insult a targeted individual or group."* Other participants were expected to label items based on their own definition of offensiveness. The latter group served as a control setting of participants who are expected to lean on their individual notion of offensiveness.[3].

In case of unfamiliarity with the annotation item, participants were asked to select the option *"I do not understand this message."* Participants' reliability was tested by 5 undeniably non-offensive, control questions randomly distributed among the 40-items annotation process. Those who failed at least one quality control check were removed, and not counted against our final set of 4309 participants (refer to Appendix A.2 for test items). Each

[3]We did not explicitly ask participants to provide their definition of offensiveness

item in the final dataset was labeled by at least three participants from each region who passed the control check (a total of 24 labels). Participants were compensated at rates above the prevalent market rates for the task (which took at most 20 minutes, with a median of 13 minutes), and respecting the local regulations regarding minimum wage in their respective countries.

3.4 Moral Foundation Questionnaire

After annotation, participants were also asked to fill out the Moral Foundations Questionnaire (MFQ-2; Graham et al., 2013; Atari et al., 2023), which assesses their moral values along six different dimensions: *Care*: "avoiding emotional and physical damage to another individual," *Equality*: "equal treatment and equal outcome for individuals," *Proportionality*: "individuals getting rewarded in proportion to their merit or contribution," *Authority*: "deference toward legitimate authorities and the defense of traditions," *Loyalty*: "cooperating with ingroups and competing with outgroups," and *Purity*: "avoiding bodily and spiritual contamination and degradation" (Atari et al., 2023). We specifically rely on the MFQ-2 because it is developed and validated through extensive cross-cultural assessments of moral judgments. This characteristic makes the questionnaire a reliable tool for integrating a pluralistic definition of values into AI research. The questionnaire includes 36 statements to assess participants' priorities along each of the six foundations (see Figure 6 which shows one of the MFQ-2 questions in our survey). For instance, one MFQ-2 statement that targets the *Care* foundation is: "*Everyone should try to comfort people who are going through something hard*". We aggregate each participant's responses to compute a value between 1 to 5 to capture their moral foundations along each of these dimensions.

4 Analyses

Our analyses focus on annotators' varying perspectives and how shared social, cultural or moral attributes can help shed light on annotation behaviors. We begin by analyzing how different groups vary on expressing their lack of understanding the message by selecting the *"I don't understand this message"* option. We then study annotators' geo-cultural regions and moral values in relation to their annotations. Specifically, we consider annotator clustering either based on their similar moral values or their region of residence, and assess in-group homogeneity and out-group disagreements for clusters. The remainder of this section delves deeper into how groups of annotators from the same region or with similar moral values tend to label content differently.

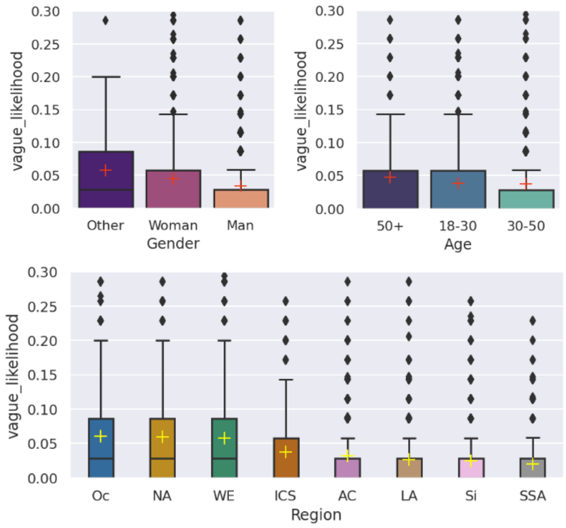


Figure 2: The likelihood of an annotator not understanding the message, grouped based on their sociodemographic information. Annotators identifying as Men, or of 50 years of old or younger are generally less likely to state they did not understand a message.

4.1 Analysis of Lack Understanding

We start our analyses by investigating the patterns of annotators not understanding the provided text.While recent modeling efforts have shown the practical ways in which annotators' ambiguity or confidence can help inform the model. However, in many data annotation efforts, annotators' lack of understanding is either not captured or discarded. We ask whether specific groups of annotators are more likely to not understand the annotation item, and as a result, their responses are more likely to be discarded.

We compared annotators with different demographics (along Gender, Age, and Region) on how likely they are to select the "I don't understand" answer (Figure 2). All further studies of the paper relies on the dataset after removing these answers.

Gender: When grouping annotators based on their gender or age, Men are overall less probable to state lack of understanding (M = .03, SD = .07), compared to Women (M = .05, SD = .08, $p <$ .001), and other genders (M = 0.06, SD = .07, $p =$ .03). However, Women and other genders did not differently select this label (p = .34).

Age: Participants who were aged 50 or more were distinctly more likely to state lack of understanding (M = .05, SD = .09), compared to 30 to 50 year-old (M = .04, SD = .08, $p < .01$), and 18 to 30 year-old participants (M = .04, SD = .07, $p < .01$). The difference of the latter two groups was insignificant (p = .85)

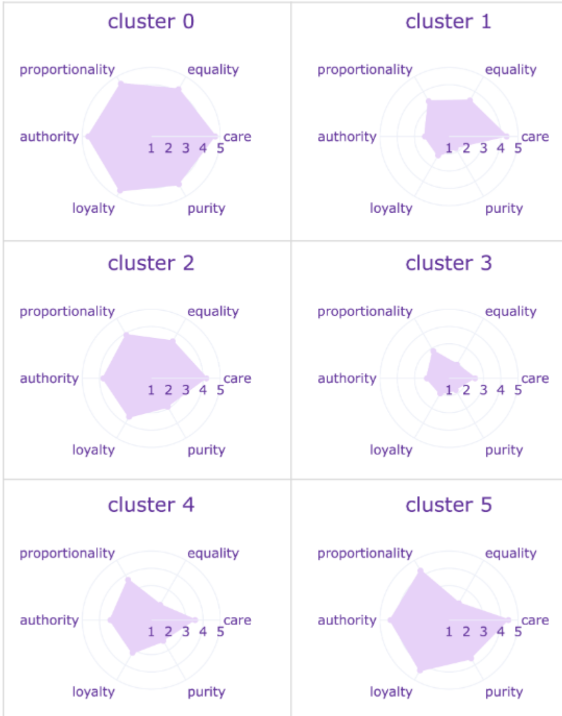
Region: We further looked into the regional differences in not understanding the answers; a pairwise Tukey test shows that annotators from Oceania (M = 0.06, SD = 0.1), North America (M = 0.06, SD = 0.09), and Western Europe (M = 0.06, SD = 0.09) were all significantly more probably to state lack of understanding compared to Indian Cultural Sphere (M = 0.04, SD = 0.08), Arab Culture (M = 0.03, SD = 0.06), Latin America (M = 0.03, SD = 0.06), Sinosphere (M = 0.02, SD = 0.07), and Sub Saharan Africa (M = 0.02, SD = 0.05) with all p values lower than .05.

4.2 Morally Aligned Annotators

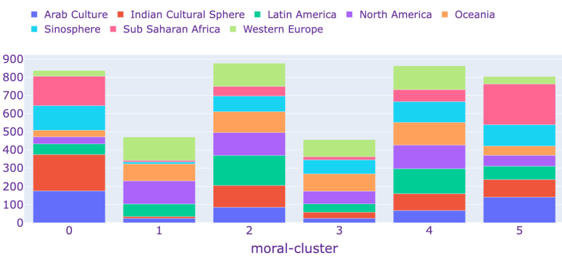
To systematically study annotators' perspectives with regard to varying moral values we first cluster annotators into groups with high internal moral similarity through a K-means algorithm, applying elbow method for finding the optimal number of clusters (see Appendix A.4). Figure 3a represents the resulting six clusters by the average moral values of their members. Figure 3b represents the distribution of annotators from different regions across the six moral clusters. As shown by the plots, regions have varying presence in the moral clusters; cluster 0 consists of annotators who agreed most with all dimensions of the moral foundations questionnaire, most participants in this cluster are from Indian Cultural Sphere, Sub Saharan Africa and Arab Culture. On the other hand, cluster 3 includes annotators who agreed the least with MFQ-2 values along most dimensions; while this cluster has the fewest annotators, most of them were from Western Europe, Oceania, and Sinosphere, in our data. Other 4 clusters each have their specific distribution of moral values across the axes, that show the most prevalent moral values in the annotator pool.

4.3 Disagreement among Groups

Additionally, we explore the homogeneity of annotations within various clusters of annotators. We specifically compare moral clusters' homogeneity



(a) The six moral clusters represented by the moral profile of their centroids. Clusters 0, 2 and 5 generally consist of participants who agreed more with the moral statements, with cluster 0 reporting the highest agreement. On the other hand, clusters 2, 3, and 4 report lower agreement with the moral statements, with cluster 3 consisting of participants who agreed the least.



(b) Distribution of participants from different regions across different moral clusters. Variances of regional presence are noticeable in several cases, e.g., cluster 0 mostly consists of participants from Indian Cultural Sphere, Arab Culture, and Sub-Saharan Africa.

with the alternative clustering approach that considers annotators of the same region to have similar perceptions. We considered region as an alternative means for clustering annotators because collected annotations tend to vary significantly across regions and countries (the distribution of ratings collected from different countries is provided in Figure 7). Inspired by Prabhakaran et al. (2023), we use the GAI metric which provides a measurement of perspective diversities within annotator groups. In other words, for each specific group of annotators, GAI provides the ratio of an in-group measurement of agreement to a cross-group measurement of cohesion. In our specific case, we measure in-group agreement through Inter-Rater Reliability (IRR;), and cross-group cohesion through Cross-Replication Reliability (XRR;). The GAI metric is then defined as the ratio to IRR to XRR, and value higher than 1 reports a group with blah blah.

As Table 2 shows, while the highest GAI score is achieved by one of the moral cluster (cluster 2, with low moral values on all axes), moral cluster in general have high variation in their homogeneity. On the other hand, regional clusters are generally more distinct in their perspectives.

Dimension	Group	IRR	XRR	GAI
Region	AC.	↑**0.13****	↑0.11	↑**1.17***
	ICS.	↓0.10	↓**0.10***	↑1.04
	LA.	↑**0.13****	↑0.11	↑**1.15***
	NA.	↑**0.14****	↑0.11	↑**1.31****
	Oc.	↑0.12	↓0.10	↑**1.15***
	Si.	↓**0.09***	↓**0.09****	↓1.00
	SSA.	↑**0.14****	↓0.10	↑**1.36****
	WE.	↑**0.14****	↑0.11	↑**1.22****
Moral Cluster	0	↑**0.12***	↑**0.12****	↑1.05
	1	↑0.12	↑0.11	↑1.04
	2	↑**0.18****	↑**0.12****	↑**1.46****
	3	↓**0.07****	↓**0.10****	↓**0.75****
	4	↑0.11	↑0.11	↑1.00
	5	↓**0.09***	↓**0.09****	↓0.97

Table 2: Results for in-group and cross-group cohesion, and GAI. Significant results are in **bold**: * for significance at $p < 0.05$, ** for significance after Benjamini-Hochberg correction. A ↓ (or ↑) means that the result is less (or greater) than expected under the null hypothesis. GAI results based on C_X = XRR and C_I = IRR.

4.4 Disagreement on Categories of Content

We further analyze the various types of content that annotators may label as offensive. As outlined in Section 3, annotated items are chosen using three strategies: random selection, morality-based selection, and social identity-based selection. Figure 4 shows that annotators tend to have varying degrees of disagreement (calculated as the standard deviation of labels assigned to the item) when labeling items selected based on different strategies. As the plot shows, items that mention specific social identity groups evoke highest levels of disagreement (Mean = .47, SD = .06), significantly higher than items with moral sentiment (Mean = .31, SD = .16) and the randomly selected items (Mean = .41, SD = .10), both with p < .001. It is important to note that our randomly selected items were deliberately chosen from those with high disagreement in the original Jigsaw dataset. Our analysis indicates that items mentioning social identity groups tend to evoke even more disagreement.

	Offensive		
Item	Yes	No	Category
Transgender athletes..... Transgender students..... This is what feminism gets you in society. This was unheard of only a short 20 years ago.	AC, LA, NA, Oc	ICS, Si, SSA, WE	transgender
Does pointing out that a growing majority of Americans support adultery (abortion, same sex marriage, even theft), change God's law an iota?	AC, ICS, LA, NA	Oc, Si, SSA, WE	LGB
The women came out because he is a hypocrite, a child predator. Come on trumpers, defend the child predator Christian, lol	ICS, LA, Oc, SSA	AC, NA, Si, WE	christian

Table 3: Instances with highest disagreement across regions.

In addition to disagreement between annotators, items can be labeled differently by various groups of annotators. In our case looking into the aggregated labels from each region demonstrates how recruiting annotators from specific regions could lead to having thoroughly different final dataset. Table 3 represents items with high cross-region disagreement.

5 Discussion

Research on safety considerations of large language models has mostly focused on evaluations of model harms through crowdsourced benchmarks (Srivastava et al., 2023; Wang et al., 2022). However, while annotators from different regions are shown to have different perspectives regarding this task (Salminen et al., 2018), current benchmarks fail to represent the cultural and individual variations in human moral judgements about generated language and model outputs. They also lack comprehensive understanding of human values and cultural norms that drive diversity of perspectives in annotations. This work presents a cross-cultural experiment with participants across various cultural and demographic backgrounds. Our dataset captures valuable insights into human perceptions on offensive language, revealing demographic differences in annotation certainty, and regional, as well as moral psychological variations in perceiving of-

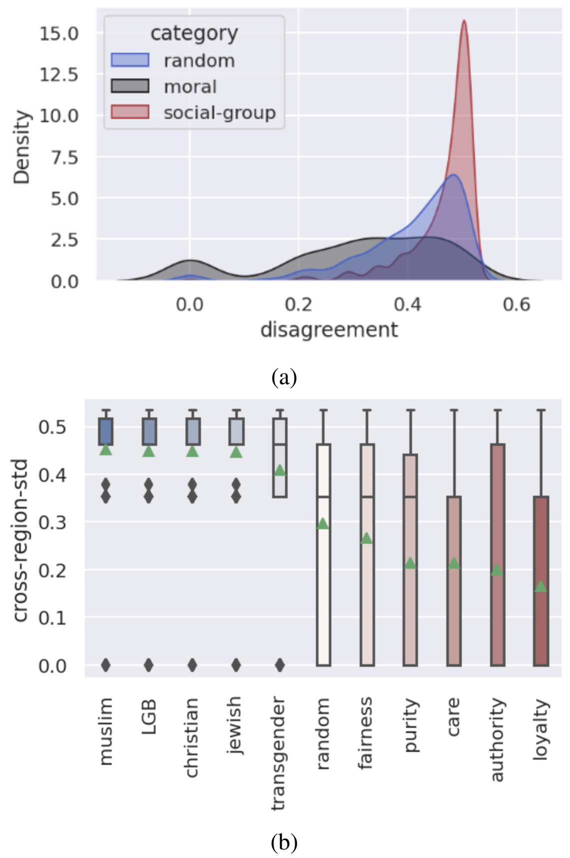


Figure 4: Disagreement between regions on items from each category (a) and each sub-category (b). We considered the standard deviation of majority votes from different regions as the cross-regional disagreement. The plot shows that items related to social groups (christian, transgender, jewish, muslim and LGB) generally evoke more disagreement compared to random items.

fensiveness.

Our first analyses captures how participants with different demographic background might express their unfamiliarity with the annotation. In general, annotators not identifying as Men and annotators aged 50 and above are more likely to select the "I don't understand" option. Moreover, annotators from Oceania, North America, and Western Europe were significantly more probably to state that they did not understand the message compared to Indian Cultural Sphere, Arab Culture, Latin America, Sinosphere, and Sub Saharan Africa. Although we remove these responses for the remaining analyses and experiments in this paper, it is important to note this kind of uncertainty in annotating occurred disproportionately in these groups.

Our dataset also represent different categories of content within a well-known machine learning corpus, with annotators having varying levels of disagreement for labeling content from different categories. While items with moral sentiment are the least likely to evoke disagreement, items mentioning specific social groups are more likely to have a varying range of annotation. This finding replicates several previous findings on how group perception and stereotypes can affect harm perception targeting different social groups, in a cross-cultural context. Consequently, these findings underscore the need for further empirical research into social dynamics within diverse cultural contexts to better understand harmful language and mitigate harmful risks of language technologies for different social groups.

Furthermore, this study underscores the importance of incorporating cultural and individual perspectives into the development and evaluation of language models. By acknowledging and accounting for the diversity of moral judgments and values across different cultures and demographics, we can enhance the fairness and inclusivity of language technologies. This necessitates not only expanding the scope of data collection to include more diverse cultural perspectives but also implementing more nuanced evaluation metrics that consider the contextual nuances of language usage and interpretation. That paves a way towards language models that are not only proficient in generating text but also sensitive to the diverse range of societal norms and values, ultimately fostering more respectful and inclusive interactions in digital spaces.

6 Conclusion

We introduce the D3CODE dataset, which captures the results of a cross-cultural annotation experiment for understanding disagreements on perceiving offensiveness in language. Our findings reveal significant demographic and regional variations in perceptions of offensive language, underlining the necessity of incorporating diverse perspectives into reinforcement learning with human feedback. Additionally, the dataset showcases differences in annotation certainty and disagreement levels across various content categories, particularly concerning mentions of specific social groups. These findings underscore the imperative for further research into social dynamics within diverse cultural contexts to mitigate the risks associated with harmful language in language technologies and promote fairness and inclusivity in digital interactions.

Limitations

In our work, we focus on moral foundations as a way to measure differences in values across groups; however, values can be measured in other ways, such as... Importantly, while our annotator sample represents diverse cultural perspectives, the items in our dataset are in English, which may explain the different rates of "I don't know" responses observed across regions. Moreover, English data likely features lower representation of certain content, such as offensive content about social groups, celebrations, or politics specific to certain regions and languages. In addition, to preserve our ability to compare data cross-culturally, we focused on demographic categories that are broadly recognized. As a result, we did not conduct analyses of demographic differences that are specific to particular cultural regions, such as caste, and we did not collect highly sensitive demographic information, such as sexual orientation. We acknowledge that salient social categories can differ greatly across geocultural reasons, therefore our selection of categories should not be considered exhaustive. Finally, our selection of countries within each cultural region was informed by access feasibility via our data collection platform, which may have introduced unexpected sampling biases.

Ethics Statement

In this work, we collected and modeled annotator responses primarily to demonstrate geocultural differences. Our results and approaches are not meant to be used to define user preferences or platform policies. For example, a subgroup's higher or lower tendency to identify content as offensive does not necessarily mean that content moderation policies should differ for that group. In addition, our work does not advocate for treating any particular cultural group's labels as more "correct" than those of another cultural group.

Acknowledgements

References

Nancy E Adler, Elissa S Epel, Grace Castellazzo, and Jeannette R Ickovics. 2000. Relationship of subjective and objective social status with psychological and physiological functioning: Preliminary data in healthy, white women. *Health psychology*, 19(6):586.

Lora Aroyo, Mark Diaz, Christopher Homan, Vinodkumar Prabhakaran, Alex Taylor, and Ding Wang. 2023a. The reasonable effectiveness of diverse evaluation data.

Lora Aroyo, Lucas Dixon, Nithum Thain, Olivia Redfield, and Rachel Rosen. 2019. Crowdsourcing subjective tasks: the case study of understanding toxicity in online discussions. In *Companion proceedings of the 2019 world wide web conference*, pages 1100–1105.

Lora Aroyo, Alex S Taylor, Mark Díaz, Christopher M Homan, Alicia Parrish, Greg Serapio-García, Vinodkumar Prabhakaran, and Ding Wang. 2023b. DICES dataset: Diversity in conversational ai evaluation for safety. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks*.

Lora Aroyo and Chris Welty. 2015. Truth is a lie: Crowd truth and the seven myths of human annotation. *AI Magazine*, 36(1):15–24.

Mohammad Atari, Jonathan Haidt, Jesse Graham, Sena Koleva, Sean T Stevens, and Morteza Dehghani. 2023. Morality beyond the weird: How the nomological network of morality varies across cultures. *Journal of Personality and Social Psychology*, 125.

Jack M Balkin. 2017. Digital speech and democratic culture: A theory of freedom of expression for the information society. In *Law and society approaches to cyberspace*, pages 325–382. Routledge.

Valerio Basile, Michael Fell, Tommaso Fornaciari, Dirk Hovy, Silviu Paun, Barbara Plank, Massimo Poesio, and Alexandra Uma. 2021. We need to consider disagreement in evaluation. In *Proceedings of the 1st Workshop on Benchmarking: Past, Present and Future*, Online. Association for Computational Linguistics.

Valerie C Brannon. 2019. Free speech and the regulation of social media content. *Congressional Research Service*, 27.

Aida Mostafazadeh Davani, Mohammad Atari, Brendan Kennedy, and Morteza Dehghani. 2023. Hate speech classifiers learn normative social stereotypes. *Transactions of the Association for Computational Linguistics*, 11:300–319.

Aida Mostafazadeh Davani, Mark Díaz, and Vinodkumar Prabhakaran. 2022. Dealing with disagreements: Looking beyond the majority vote in subjective annotations. *Transactions of the Association for Computational Linguistics*, 10:92–110.

Mark Díaz, Razvan Amironesei, Laura Weidinger, and Iason Gabriel. 2022a. Accounting for offensive speech as a practice of resistance. In *Proceedings of the sixth workshop on online abuse and harms (woah)*, pages 192–202.

Mark Díaz, Ian Kivlichan, Rachel Rosen, Dylan Baker, Razvan Amironesei, Vinodkumar Prabhakaran, and

Emily Denton. 2022b. Crowdworksheets: Accounting for individual and collective identities underlying crowdsourced dataset annotation. In *2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 2342–2351.

Carsten Eickhoff. 2018. Cognitive biases in crowdsourcing. In *Proceedings of the eleventh ACM international conference on web search and data mining*, pages 162–170.

Elisa Ferracane, Greg Durrett, Junyi Jessy Li, and Katrin Erk. 2021. Did they answer? Subjective acts and intents in conversational discourse. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1626–1644, Online. Association for Computational Linguistics.

Tommaso Fornaciari, Alexandra Uma, Silviu Paun, Barbara Plank, Dirk Hovy, and Massimo Poesio. 2021. Beyond black & white: Leveraging annotator disagreement via soft-label multi-task learning. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2591–2597.

Antigoni Founta, Constantinos Djouvas, Despoina Chatzakou, Ilias Leontiadis, Jeremy Blackburn, Gianluca Stringhini, Athena Vakali, Michael Sirivianos, and Nicolas Kourtellis. 2018. Large scale crowdsourcing and characterization of twitter abusive behavior. In *Proceedings of the international AAAI conference on web and social media*, volume 12.

Justin Garten, Brendan Kennedy, Joe Hoover, Kenji Sagae, and Morteza Dehghani. 2019. Incorporating demographic embeddings into language understanding. *Cognitive science*, 43(1):e12701.

Mitchell L Gordon, Michelle S Lam, Joon Sung Park, Kayur Patel, Jeff Hancock, Tatsunori Hashimoto, and Michael S Bernstein. 2022. Jury learning: Integrating dissenting voices into machine learning models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, pages 1–19.

Jesse Graham, Jonathan Haidt, Sena Koleva, Matt Motyl, Ravi Iyer, Sean P Wojcik, and Peter H Ditto. 2013. Moral foundations theory: The pragmatic validity of moral pluralism. In *Advances in experimental social psychology*, volume 47, pages 55–130. Elsevier.

Christopher M Homan, Greg Serapio-García, Lora Aroyo, Mark Díaz, Alicia Parrish, Vinodkumar Prabhakaran, Alex S Taylor, and Ding Wang. 2023. Intersectionality in conversational AI safety: How Bayesian multilevel models help understand diverse perceptions of safety. *arXiv preprint arXiv:2306.11530*.

Joe Hoover, Gwenyth Portillo-Wightman, Leigh Yeh, Shreya Havaldar, Aida Mostafazadeh Davani, Ying Lin, Brendan Kennedy, Mohammad Atari, Zahra Kamel, Madelyn Mendlen, et al. 2020. Moral foundations twitter corpus: A collection of 35k tweets annotated for moral sentiment. *Social Psychological and Personality Science*, 11(8):1057–1071.

Dirk Hovy. 2015. Demographic factors improve classification performance. In *Proceedings of the 53rd annual meeting of the Association for Computational Linguistics and the 7th international joint conference on natural language processing (volume 1: Long papers)*, pages 752–762.

Dirk Hovy and Diyi Yang. 2021. The importance of modeling social factors of language: Theory and practice. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 588–602.

Jigsaw. 2018. Toxic comment classification challenge. Accessed: 2021-05-01.

Jigsaw. 2019. Unintended bias in toxicity classification. Accessed: 2021-05-01.

Brendan Kennedy, Preni Golazizian, Jackson Trager, Mohammad Atari, Joe Hoover, Aida Mostafazadeh Davani, and Morteza Dehghani. 2023. The (moral) language of hate. *PNAS nexus*, 2(7):pgad210.

Chris J Kennedy, Geoff Bacon, Alexander Sahn, and Claudia von Vacano. 2020. Constructing interval variables via faceted rasch measurement and multitask deep learning: a hate speech application. *arXiv preprint arXiv:2009.10277*.

Svetlana Kiritchenko, Isar Nejadgholi, and Kathleen C Fraser. 2021. Confronting abusive language online: A survey from the ethical and human rights perspective. *Journal of Artificial Intelligence Research*, 71:431–478.

Deepak Kumar, Patrick Gage Kelley, Sunny Consolvo, Joshua Mason, Elie Bursztein, Zakir Durumeric, Kurt Thomas, and Michael Bailey. 2021. Designing toxic content classification for a diversity of perspectives. In *Seventeenth Symposium on Usable Privacy and Security (SOUPS 2021)*, pages 299–318.

Ludwin E Molina, Linda R Tropp, and Chris Goode. 2016. Reflections on prejudice and intergroup relations. *Current Opinion in Psychology*, 11:120–124.

Matthias Orlikowski, Paul Röttger, Philipp Cimiano, and Dirk Hovy. 2023. The ecological fallacy in annotation: Modeling human label variation goes beyond sociodemographics. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 1017–1029, Toronto, Canada. Association for Computational Linguistics.

Alicia Parrish, Sarah Laszlo, and Lora Aroyo. 2023. " is a picture of a bird a bird": Policy recommendations for dealing with ambiguity in machine vision models. *arXiv preprint arXiv:2306.15777*.

Ellie Pavlick and Tom Kwiatkowski. 2019. Inherent disagreements in human textual inferences. *Transactions of the Association for Computational Linguistics*, 7:677–694.

Barbara Plank, Dirk Hovy, and Anders Søgaard. 2014. Learning part-of-speech taggers with inter-annotator agreement loss. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics*, pages 742–751.

Vinodkumar Prabhakaran, Christopher Homan, Lora Aroyo, Alicia Parrish, Alex Taylor, Mark Díaz, and Ding Wang. 2023. A framework to assess (dis) agreement among diverse rater groups. *arXiv preprint arXiv:2311.05074*.

Vinodkumar Prabhakaran, Aida Mostafazadeh Davani, and Mark Diaz. 2021. On releasing annotator-level labels and information in datasets. In *Proceedings of The Joint 15th Linguistic Annotation Workshop (LAW) and 3rd Designing Meaning Representations (DMR) Workshop*, pages 133–138, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Americus Reed II and Karl F Aquino. 2003. Moral identity and the expanding circle of moral regard toward out-groups. *Journal of personality and social psychology*, 84(6):1270.

Paul Rottger, Bertie Vidgen, Dirk Hovy, and Janet Pierrehumbert. 2022. Two contrasting data annotation paradigms for subjective NLP tasks. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 175–190, Seattle, United States. Association for Computational Linguistics.

Joni Salminen, Hind Almerekhi, Ahmed Mohamed Kamel, Soon-gyo Jung, and Bernard J Jansen. 2019. Online hate ratings vary by extremes: A statistical analysis. In *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, pages 213–217.

Joni Salminen, Fabio Veronesi, Hind Almerekhi, Soon-Gvo Jung, and Bernard J Jansen. 2018. Online hate interpretation varies by country, but more by individual: A statistical analysis using crowdsourced ratings. In *2018 fifth international conference on social networks analysis, management and security (snams)*, pages 88–94. IEEE.

Morgan Klaus Scheuerman, Alex Hanna, and Emily Denton. 2021. Do datasets have politics? Disciplinary values in computer vision dataset development. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2):1–37.

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R. Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, Agnieszka Kluska, Aitor Lewkowycz, Akshat Agarwal, Alethea Power, Alex Ray, Alex Warstadt, Alexander W. Kocurek, Ali Safaya, Ali Tazarv, Alice Xiang, Alicia Parrish, Allen Nie, Aman Hussain, Amanda Askell, Amanda Dsouza, Ambrose Slone, Ameet Rahane, Anantharaman S. Iyer, Anders Andreassen, Andrea Madotto, Andrea Santilli, Andreas Stuhlmüller, Andrew Dai, Andrew La, Andrew Lampinen, Andy Zou, Angela Jiang, Angelica Chen, Anh Vuong, Animesh Gupta, Anna Gottardi, Antonio Norelli, Anu Venkatesh, Arash Gholamidavoodi, Arfa Tabassum, Arul Menezes, Arun Kirubarajan, Asher Mullokandov, Ashish Sabharwal, Austin Herrick, Avia Efrat, Aykut Erdem, Ayla Karakaş, B. Ryan Roberts, Bao Sheng Loe, Barret Zoph, Bartłomiej Bojanowski, Batuhan Özyurt, Behnam Hedayatnia, Behnam Neyshabur, Benjamin Inden, Benno Stein, Berk Ekmekci, Bill Yuchen Lin, Blake Howald, Bryan Orinion, Cameron Diao, Cameron Dour, Catherine Stinson, Cedrick Argueta, César Ferri Ramírez, Chandan Singh, Charles Rathkopf, Chenlin Meng, Chitta Baral, Chiyu Wu, Chris Callison-Burch, Chris Waites, Christian Voigt, Christopher D. Manning, Christopher Potts, Cindy Ramirez, Clara E. Rivera, Clemencia Siro, Colin Raffel, Courtney Ashcraft, Cristina Garbacea, Damien Sileo, Dan Garrette, Dan Hendrycks, Dan Kilman, Dan Roth, Daniel Freeman, Daniel Khashabi, Daniel Levy, Daniel Moseguí González, Danielle Perszyk, Danny Hernandez, Danqi Chen, Daphne Ippolito, Dar Gilboa, David Dohan, David Drakard, David Jurgens, Debajyoti Datta, Deep Ganguli, Denis Emelin, Denis Kleyko, Deniz Yuret, Derek Chen, Derek Tam, Dieuwke Hupkes, Diganta Misra, Dilyar Buzan, Dimitri Coelho Mollo, Diyi Yang, Dong-Ho Lee, Dylan Schrader, Ekaterina Shutova, Ekin Dogus Cubuk, Elad Segal, Eleanor Hagerman, Elizabeth Barnes, Elizabeth Donoway, Ellie Pavlick, Emanuele Rodola, Emma Lam, Eric Chu, Eric Tang, Erkut Erdem, Ernie Chang, Ethan A. Chi, Ethan Dyer, Ethan Jerzak, Ethan Kim, Eunice Engefu Manyasi, Evgenii Zheltonozhskii, Fanyue Xia, Fatemeh Siar, Fernando Martínez-Plumed, Francesca Happé, Francois Chollet, Frieda Rong, Gaurav Mishra, Genta Indra Winata, Gerard de Melo, Germán Kruszewski, Giambattista Parascandolo, Giorgio Mariani, Gloria Wang, Gonzalo Jaimovitch-López, Gregor Betz, Guy Gur-Ari, Hana Galijasevic, Hannah Kim, Hannah Rashkin, Hannaneh Hajishirzi, Harsh Mehta, Hayden Bogar, Henry Shevlin, Hinrich Schütze, Hiromu Yakura, Hongming Zhang, Hugh Mee Wong, Ian Ng, Isaac Noble, Jaap Jumelet, Jack Geissinger, Jackson Kernion, Jacob Hilton, Jaehoon Lee, Jaime Fernández Fisac, James B. Simon, James Koppel, James Zheng, James Zou, Jan Kocoń, Jana Thompson, Janelle Wingfield, Jared Kaplan, Jarema Radom, Jascha Sohl-Dickstein, Jason Phang, Jason Wei, Jason Yosinski, Jekaterina Novikova, Jelle Bosscher, Jennifer Marsh, Jeremy Kim, Jeroen

Taal, Jesse Engel, Jesujoba Alabi, Jiacheng Xu, Jiaming Song, Jillian Tang, Joan Waweru, John Burden, John Miller, John U. Balis, Jonathan Batchelder, Jonathan Berant, Jörg Frohberg, Jos Rozen, Jose Hernandez-Orallo, Joseph Boudeman, Joseph Guerr, Joseph Jones, Joshua B. Tenenbaum, Joshua S. Rule, Joyce Chua, Kamil Kanclerz, Karen Livescu, Karl Krauth, Karthik Gopalakrishnan, Katerina Ignatyeva, Katja Markert, Kaustubh D. Dhole, Kevin Gimpel, Kevin Omondi, Kory Mathewson, Kristen Chiafullo, Ksenia Shkaruta, Kumar Shridhar, Kyle McDonell, Kyle Richardson, Laria Reynolds, Leo Gao, Li Zhang, Liam Dugan, Lianhui Qin, Lidia Contreras-Ochando, Louis-Philippe Morency, Luca Moschella, Lucas Lam, Lucy Noble, Ludwig Schmidt, Luheng He, Luis Oliveros Colón, Luke Metz, Lütfi Kerem Şenel, Maarten Bosma, Maarten Sap, Maartje ter Hoeve, Maheen Farooqi, Manaal Faruqui, Mantas Mazeika, Marco Baturan, Marco Marelli, Marco Maru, Maria Jose Ramírez Quintana, Marie Tolkiehn, Mario Giulianelli, Martha Lewis, Martin Potthast, Matthew L. Leavitt, Matthias Hagen, Mátyás Schubert, Medina Orduna Baitemirova, Melody Arnaud, Melvin McElrath, Michael A. Yee, Michael Cohen, Michael Gu, Michael Ivanitskiy, Michael Starritt, Michael Strube, Michał Swędrowski, Michele Bevilacqua, Michihiro Yasunaga, Mihir Kale, Mike Cain, Mimee Xu, Mirac Suzgun, Mitch Walker, Mo Tiwari, Mohit Bansal, Moin Aminnaseri, Mor Geva, Mozhdeh Gheini, Mukund Varma T, Nanyun Peng, Nathan A. Chi, Nayeon Lee, Neta Gur-Ari Krakover, Nicholas Cameron, Nicholas Roberts, Nick Doiron, Nicole Martinez, Nikita Nangia, Niklas Deckers, Niklas Muennighoff, Nitish Shirish Keskar, Niveditha S. Iyer, Noah Constant, Noah Fiedel, Nuan Wen, Oliver Zhang, Omar Agha, Omar Elbaghdadi, Omer Levy, Owain Evans, Pablo Antonio Moreno Casares, Parth Doshi, Pascale Fung, Paul Pu Liang, Paul Vicol, Pegah Alipoormolabashi, Peiyuan Liao, Percy Liang, Peter Chang, Peter Eckersley, Phu Mon Htut, Pinyu Hwang, Piotr Miłkowski, Piyush Patil, Pouya Pezeshkpour, Priti Oli, Qiaozhu Mei, Qing Lyu, Qinlang Chen, Rabin Banjade, Rachel Etta Rudolph, Raefer Gabriel, Rahel Habacker, Ramon Risco, Raphaël Millière, Rhythm Garg, Richard Barnes, Rif A. Saurous, Riku Arakawa, Robbe Raymaekers, Robert Frank, Rohan Sikand, Roman Novak, Roman Sitelew, Ronan LeBras, Rosanne Liu, Rowan Jacobs, Rui Zhang, Ruslan Salakhutdinov, Ryan Chi, Ryan Lee, Ryan Stovall, Ryan Teehan, Rylan Yang, Sahib Singh, Saif M. Mohammad, Sajant Anand, Sam Dillavou, Sam Shleifer, Sam Wiseman, Samuel Gruetter, Samuel R. Bowman, Samuel S. Schoenholz, Sanghyun Han, Sanjeev Kwatra, Sarah A. Rous, Sarik Ghazarian, Sayan Ghosh, Sean Casey, Sebastian Bischoff, Sebastian Gehrmann, Sebastian Schuster, Sepideh Sadeghi, Shadi Hamdan, Sharon Zhou, Shashank Srivastava, Sherry Shi, Shikhar Singh, Shima Asaadi, Shixiang Shane Gu, Shubh Pachchigar, Shubham Toshniwal, Shyam Upadhyay, Shyamolima, Debnath, Siamak Shakeri, Simon Thormeyer, Simone Melzi, Siva Reddy, Sneha Priscilla Makini, Soo-Hwan Lee, Spencer Torene, Sriharsha Hatwar, Stanislas Dehaene, Stefan Divic, Stefano Ermon, Stella Biderman, Stephanie Lin, Stephen Prasad, Steven T. Piantadosi, Stuart M. Shieber, Summer Misherghi, Svetlana Kiritchenko, Swaroop Mishra, Tal Linzen, Tal Schuster, Tao Li, Tao Yu, Tariq Ali, Tatsu Hashimoto, Te-Lin Wu, Théo Desbordes, Theodore Rothschild, Thomas Phan, Tianle Wang, Tiberius Nkinyili, Timo Schick, Timofei Kornev, Titus Tunduny, Tobias Gerstenberg, Trenton Chang, Trishala Neeraj, Tushar Khot, Tyler Shultz, Uri Shaham, Vedant Misra, Vera Demberg, Victoria Nyamai, Vikas Raunak, Vinay Ramasesh, Vinay Uday Prabhu, Vishakh Padmakumar, Vivek Srikumar, William Fedus, William Saunders, William Zhang, Wout Vossen, Xiang Ren, Xiaoyu Tong, Xinran Zhao, Xinyi Wu, Xudong Shen, Yadollah Yaghoobzadeh, Yair Lakretz, Yangqiu Song, Yasaman Bahri, Yejin Choi, Yichi Yang, Yiding Hao, Yifu Chen, Yonatan Belinkov, Yu Hou, Yufang Hou, Yuntao Bai, Zachary Seid, Zhuoye Zhao, Zijian Wang, Zijie J. Wang, Zirui Wang, and Ziyi Wu. 2023. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models.

Alexandra N Uma, Tommaso Fornaciari, Dirk Hovy, Silviu Paun, Barbara Plank, and Massimo Poesio. 2021. Learning from disagreement: A survey. *Journal of Artificial Intelligence Research*, 72:1385–1470.

Boxin Wang, Chejian Xu, Shuohang Wang, Zhe Gan, Yu Cheng, Jianfeng Gao, Ahmed Hassan Awadallah, and Bo Li. 2022. Adversarial GLUE: A multi-task benchmark for robustness evaluation of language models.

Zeerak Waseem. 2016. Are you a racist or am I seeing things? Annotator influence on hate speech detection on twitter. In *Proceedings of the first workshop on NLP and computational social science*, pages 138–142.

Zeerak Waseem, Smarika Lulz, Joachim Bingel, and Isabelle Augenstein. 2021. Disembodied machine learning: On the illusion of objectivity in nlp.

Ellery Wulczyn, Nithum Thain, and Lucas Dixon. 2017. Ex machina: Personal attacks seen at scale. In *Proceedings of the 26th international conference on world wide web*, pages 1391–1399.

A Appendix

A.1 Regions and Countries

Our selected list of geo-cultural regions and countries within regions is not meant to be exhaustive, rather just to make sure that our study is done on a set of countries with diverse cultural histories. Each region listed has countries and sub-regions that have distinct cultural practices, and it is wrong to assume that the country we choose would comprehensively represent that region. Similarly, the

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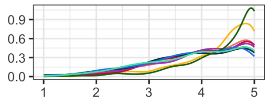
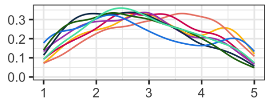
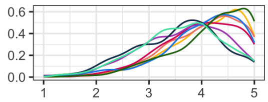
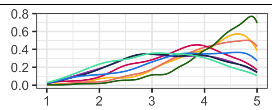
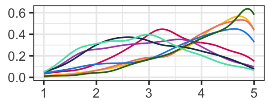
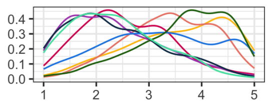
Care		34.48*
Equality		13.37*
Propor.		51.24*
Authority		102.25*
Loyalty		158.30*
Purity		203.55*

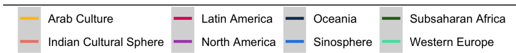


Table 4: Distribution of the moral foundations scores and the results of one-way ANOVA analysis conducted for each moral foundation across regions. *means the p-value of the analysis is lower than .001

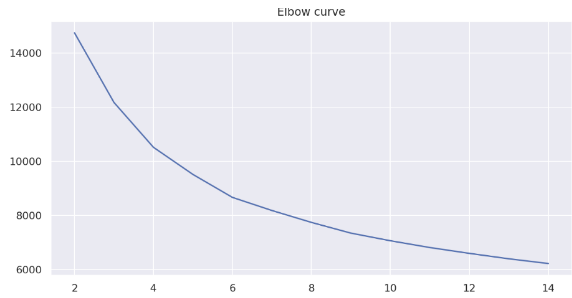


Figure 5: The distortion value captured for different options for number of moral clusters.

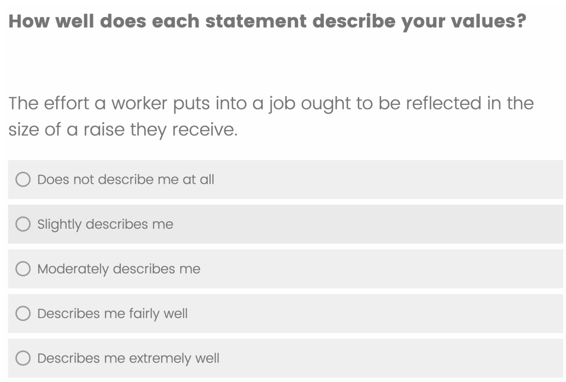


Figure 6: Sample of MFQ-2 questions in our survey

countries listed are meant as likely places to collect data from, based on familiarity with previous data collection efforts, which potentially reflect the power structures existing within those regions. Also, each country is rarely a monolith in terms of culture (e.g., India has diverse subcultures, Australia being characterized as a "Western" culture erases the vibrant Australian Aboriginal culture). Data collected would also reflect the local disparities in who tends to be in the social strata that maximally overlaps with the data-collection workforce in those respective regions, and what subcultures they represent.

A.2 Test Items

We used participants' response to 5 test items to evaluate their understanding of offensiveness. These items (listed below) were unanimously labeled as *not offensive at all* by authors and were used as an attention check to remove participants who annotated them otherwise.

- Could you explain your point in a little more detail please.
- The NY Times yesterday had a rebuttal by the Iranian UN ambassador.
- Ditto to everything said here.
- Just looked at the link. Impressive and missed opportunity.
- Don't be so hard on yourself. Your life will go on.

A.3 Data Cleaning

We selected thresholds for the amount of time needed to finish the survey and removed annotators who performed the task either quicker or slower than the expectation. Annotators with similar answers to all items were also removed from the data.

A.4 Moral clusters

Figure 5 shows the plot of distortions that led to us selecting 6 as the optimal number of moral clusters.

Region	Country
Arab Culture	Egypt, Qatar, UAE
Indian Cultural Sphere	India, Singapore
Latin America	Argentina, Brazil, Mexico
North America	Canada, USA
Oceania	Australia, New Zealand
Sinosphere	China, Japan, South Korea, Vietnam
Sub-Saharan Africa	Ghana, Nigeria
Western Europe	Germany, Netherlands, UK

Table 5: List of regions and countries within them in our dataset.

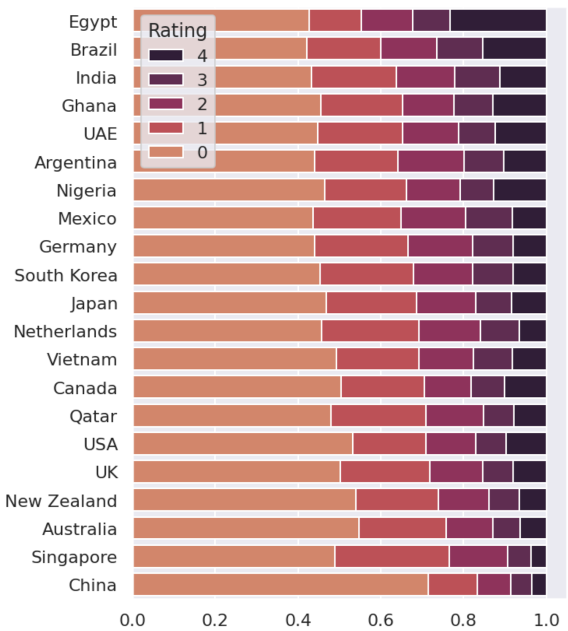


Figure 7: Distribution of the different labels provided by annotators of different countries. The y-axis is sorted based on the average offensive label captured in each country.