What Makes it Ok to Set a Fire? Iterative Self-distillation of Contexts and Rationales for Disambiguating Defeasible Social and Moral Situations

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Abstract

Moral or ethical judgments rely heavily on the specific contexts in which they occur. Understanding varying shades of *defeasible contextualizations* (*i.e.*, additional information that strengthens or attenuates the moral acceptability of an action) is critical to accurately represent the subtlety and intricacy of grounded human moral judgment in real-life scenarios.

We introduce *defeasible moral reasoning*: a task to provide grounded contexts that make an action more or less morally acceptable, along with commonsense rationales that justify the reasoning. To elicit high-quality task data, we take an iterative self-distillation approach that starts from a small amount of unstructured seed knowledge from GPT-3 and then alternates between (1) self-distillation from student models; (2) targeted filtering with a critic model trained by human judgment (to boost validity) and NLI (to boost diversity); (3) self-imitation learning (to amplify the desired data quality). This process yields a student model that produces defeasible contexts with improved *validity*, *diversity*, and *defeasibility*. From this model we distill a high-quality dataset, δ-RULES-OF-THUMB (δ-ROT), of 1.2M entries of contextualizations and rationales for 115K defeasible moral actions rated highly by human annotators 85.9% to 99.8% of the time.[1] Using δ-ROT we obtain a final student model that wins over all intermediate student models by a notable margin.

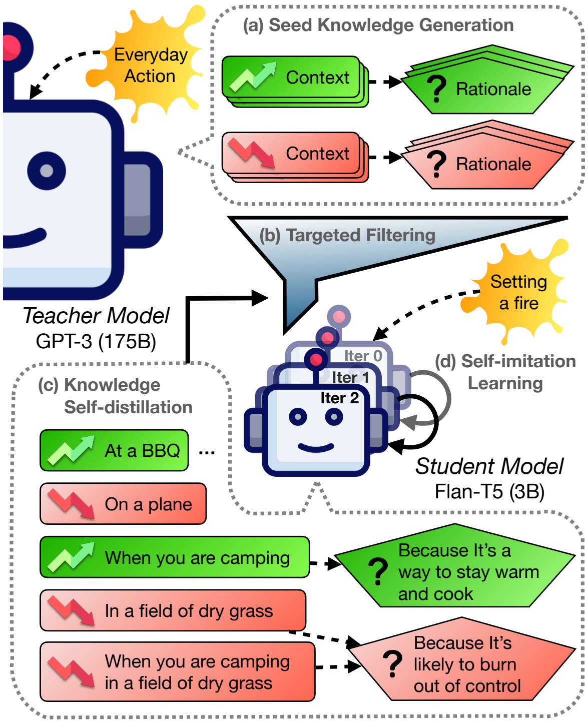


Figure 1: An illustration of the iterative self-distillation pipeline on eliciting *defeasible moral reasoning contexualizations* and *rationales*. For the event "setting a fire," different contextualizations of the action can bend its moral acceptability *up* (*e.g.*, "at a BBQ") or *down* (*e.g.*, "to get revenge"). Capturing the nuances of how additional contexts interplay with base actions is critical for grasping the flexible defeasibility of moral judgments.

1 Introduction

Moral or social judgments play a vital role in decision-making, influencing how we perceive actions and behaviors daily. However, these judgments are far from fixed; instead, they are highly *context-dependent*. Contexts surrounding a core action can significantly *strengthen* or *weaken* its moral acceptability. For instance, the act of "knowing where someone lives" may carry no inherent moral weight. But when supplemented by the context that "the purpose is to provide assistance to a person in need," the action becomes more morally justified. Conversely, if the context shifts to "for the purpose of surveillance or spying," the same action loses its moral grounding. This phenomenon of flexibly bending moral rules in instantiations of scenarios is widely recognized in assorted cognitive science studies (Kwon et al., 2022; Levine et al., 2020; Awad et al., 2022; Levine et al., 2018).

The inherent context dependence of moral judg-

[*] Equal contribution.
[1]Dataset is publically available at https://huggingface.co/datasets/kavelrao/d-Rules-of-Thumb

Findings of the Association for Computational Linguistics: EMNLP 2023, pages 12140–12159
December 6-10, 2023 ©2023 Association for Computational Linguistics

ments underscores the importance of understanding the complex interplay between actions and their grounded contexts in real-life scenarios. Delving into how different contexts bend the moral acceptability of an action, along with the reasons behind these shifts, enables us to make informed moral judgments geared toward situational nuances.

Previous works about contextualized moral judgment pose several challenges. First, they focus primarily on atomic contexts with limited situational complexity. For instance, Ziems et al. (2023) rigidly prescribe grounded contexts to fall under concepts such as settings, roles, and behaviors, narrowing and fragmenting the scope of contextualization. Pyatkin et al. (2023) propose a stepwise clarification question generation system to elicit elementary contexts of moral actions. Another limitation lies in the emphasis on the defeasibility of assumed moral and social judgments (*e.g.*, "it's wrong to yell to your friend"), rather than the natural defeasibility of moral scenarios themselves (Rudinger et al., 2020). Finally, existing works lack the rationales to explain why a particular context renders a situation more or less morally acceptable. We address all the above limitations in this work.

We introduce *defeasible moral reasoning*, a task to provide grounded *contextualizations* (or contexts) that alter the moral acceptability of action, accompanied by commonsense *rationales* that justify the reasoning. We aim to explicitly state underspecified contexts of actions, providing nuance and interpretability to moral judgments. To substantiate this task, we introduce δ-RULES-OF-THUMB (δ-ROT), a high-quality dataset of 1.2M entries of combined contextualizations and rationales for 115K defeasible moral actions. δ-ROT is created through an iterative self-distillation approach. Starting with a small amount of unstructured seed knowledge from GPT-3, we alternate between (1) **self-distillation from student models** to move away from the reliance on expensive API calls for GPT-3; (2) **targeted filtering** using a critic model trained with human judgment to enhance generation validity and natural language inference (NLI) to enhance diversity; and (3) **self-imitation learning** to magnify the desired model properties.

The iterative self-distillation process yields a student model that generates defeasible contexts with enhanced *validity*, *diversity*, and *defeasibility*. From the best-performing student model, we distill the final dataset, δ-ROT. These contextualizations

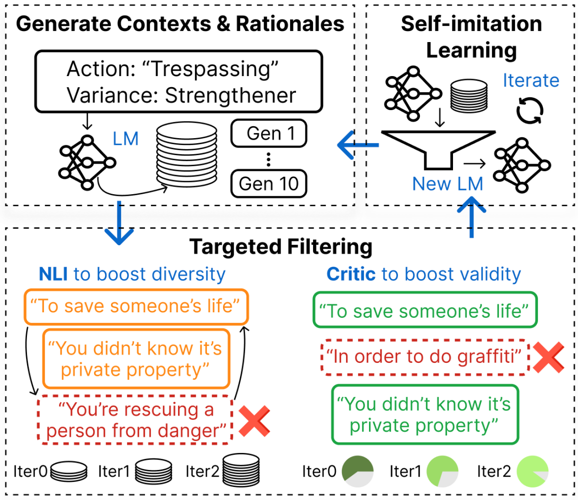


Figure 2: Iterative self-distillation that repeats generation, filtering, and self-imitation learning.

and rationales have been rated highly by human annotators on both validity (85.9%) and language quality (99.8%), ensuring their reliability in capturing the complexities of moral judgment within various contexts. Using δ-ROT, we further train a final downstream student model that prevailed over all intermediate student models.

In sum, in this work, we introduce the defeasible moral reasoning task that involves contexts and rationales for making defeasible moral judgments. We present the iterative self-distillation methodology to gather high-quality and diverse training data for student models (§3) along with careful ablations of each component involved in the pipeline (§5). We distill a sizeable, human-verified dataset under the defeasible moral reasoning task formulation (§2) and a high-performing downstream task model. We will release all student models and δ-RULES-OF-THUMB, along with a subset of human-annotated gold data for training a supervised critic model that mimics human ratings of the validity of contextualizations.

2 δ-RULES-OF-THUMB: Dataset Design

We introduce δ-RULES-OF-THUMB (δ-ROT), a dataset for the *defeasible moral reasoning* task. Given an everyday action with a default commonsense moral judgment, δ-ROT captures nuances of the defeasible moral action through contextualizations that either strengthen or attenuate the acceptability of an action. It also contains rationales that explain why the contextualizations affect the judgment. See example data in Figure 1.

As shown in Table 1, δ-ROT contains 115K actions and 578K entries each of contextualizations and rationales. Extensive human evaluation confirms that δ-RULES-OF-THUMB is of high quality, demonstrating high *validity* (85.9% for contexts; 98.5% for rationales) and *language quality* reflected by fluency and grammar correctness (99.8% for contexts; 99.7% for rationales), on par with human written datasets (West et al., 2022).

Action and Commonsense Moral Judgment. We source our scenarios from SOCIAL-CHEM-101 (Forbes et al., 2020), a bank of rules-of-thumb (RoTs) that describe various social, cultural, and moral norms. Each RoT consists of an action and a sociomoral judgment annotated by workers based on natural language snippets of real-life situations.

Example RoT (judgment, action):
"It's dangerous to set a fire"

Because RoTs combine everyday atomic actions (*e.g.*, "set a fire") with commonsense sociomoral judgments (*e.g.*, "it's dangerous"), they serve as ideal seeds to be expanded with contextual nuances.

Morally Variant Contextualization. *Moral variance* is a binary label such that *strengthening* contextualizations further ground the original action to be more morally acceptable, while *weakening* contextualizations have the opposite effect. Note that meaningful morally variant contextualizations range from simple properties such as locations (*e.g.*, "in a field of dry grass") or auxiliary actions (*e.g.*, "when you're camping") to complex compositional contexts with an intricate interplay between multiple atomic variations such as "when you're camping in a field of dry grass." Thus, we focus on eliciting flexible contexts that exercise concrete and natural effects *tailored* to given actions, instead of pre-defining the categories of the contextualizations regardless of situational nuances (Ziems et al., 2023).

Commonsense Rationales. A critical missing piece from previous works on grounded moral judgments is rationale that ties together the actions and contextualizations by explaining the reasoning behind the defeasible effect (*e.g.*, the context "in a field of dry grass" might make the action "setting a fire" less morally acceptable "because it's likely to burn out of control"). δ-RULES-OF-THUMB provides a complete picture of *how* each context achieves a moral variance, paving the way toward dissecting and understanding the varying shades of moral judgments.

		Statistics		Human Val.	
Type	**Pol.**	**#Entry**	**#3-Grams**	**%Vld.**	**%Lan.**
Action	-	115K	110K	-	-
Context	All	578K	182K	85.9	99.8
	Stren.	266K	108K	84.2	100
	Weak.	312K	130K	87.6	99.7
Rationale	All	578K	275K	98.5	99.7
	Stren.	266K	170K	98.6	99.6
	Weak.	312K	182K	98.4	99.8

Table 1: Statistics and human validation results of δ-RULES-OF-THUMB. **#Entry** is the total number of data entries, and **#3-Grams** is the number of unique 3-Grams of each data type. **%Vld.** is the percentage of valid data rated by humans, and **%Lan.** is the percentage with proper language form (*i.e.*, fluency and grammar).

Human Critic Gold Data. In addition to δ-ROT, we also release a dataset of human-annotated quality assessments of machine-generated contextualizations and rationales used to train the critic model for distillation filtering (§3.1). Actions are sampled from SOCIAL-CHEM-101, and we use GPT-3 to generate contextualizations and rationales for both moral variances, each annotated by three crowdworkers. Labels are obtained by majority votes across annotators, but we keep only the subset with full agreement for validation and test sets to ensure high confidence in their labels. The critic gold data contains 11K actions and 20K contextualizations with quality labels across all splits.

3 Dataset Creation via Iterative Self-distillation

Competent large language models has opened up new opportunities for automatic dataset creation through symbolic knowledge distillation (West et al., 2022). In this framework, knowledge is generated from a large teacher model, filtered to improve data quality, and then instilled into a smaller student model. Previous works have found that machine-generated datasets can surpass human-authored datasets in their quality and diversity while also achieving greater scale (West et al., 2022; Bhagavatula et al., 2023; Sclar et al., 2022; Jung et al., 2023; Wang et al., 2023).

In this work, we create δ-RULES-OF-THUMB with an iterative self-distillation approach which minimizes the resource bottleneck from expensive GPT-3 API calls. Our approach follows three stages after producing an initial student model using relatively small-scale seed knowledge from GPT-3: (1) **self-distillation from student mod-**

		Top 1 Greedy							Top 10 Sampling			
		Auto (Critic)		Human					Auto (Critic)		Human	
Model	#Trn.	Vld.	Avg.	Vld.	Defease.	Lan.	Rationale.		#Vld.	#Unq. Vld.	#Vld.	#Unq. Vld.
GPT-3	-	0.53	0.69	0.56	0.37	0.98	0.93		-	-	-	-
Distill$_{\text{base}}$	85K	0.68	0.75	0.54	0.42	0.98	0.91		6.40	5.63	5.36	4.78
- No Critic	143K	0.60	0.68	0.51	0.39	0.98	0.94		5.63	5.00	4.66	4.23
SelfDistill$_1$	434K	0.75	0.80	0.60	0.48	0.97	0.93		7.08	5.83	6.04	5.05
- Top 1 Only	53K	0.71	0.77	0.59	0.48	0.98	0.93		7.06	3.16	5.74	2.54
- No NLI	492K	0.75	0.80	<u>0.64</u>	0.50	0.98	0.92		7.12	5.89	5.93	4.97
SelfDistill$_2$	466K	0.79	<u>0.83</u>	0.62	0.50	0.98	0.93		7.60	<u>6.15</u>	<u>6.26</u>	<u>5.21</u>
- Top 1 Only	57K	0.73	0.78	0.62	0.49	0.97	0.93		7.28	2.60	6.13	2.16
- No NLI	567K	<u>0.80</u>	<u>0.83</u>	0.63	<u>0.51</u>	0.98	0.91		<u>7.65</u>	5.92	5.93	4.73
- No Self-distill	869K	0.75	0.80	0.62	0.50	0.98	0.94		7.19	5.95	6.01	5.08
Distill$_{\text{final}}$	578K	**0.86**	**0.88**	**0.71**	**0.56**	0.99	0.92		**8.40**	**6.45**	**7.26**	**5.69**

Table 2: Automatic and human evaluation of distilled models across three iterations. We evaluate both the top 1 model generation by greedy decoding and the top 10 candidates by nucleus sampling. Best results are **bolded** and second best results are <u>underlined</u> (to declutter the table, we remove the styles for Lan. and Rationale. as their results are approximately the same across all models).

els to move away from reliance on the expensive GPT-3 model; (2) **targeted filtering** to critically select high-quality and diverse data; and (3) **self-imitation learning** to amplify learning signals.

3.1 Gathering Medium-quality Seed Data to Train an Initial Student Model

Eliciting Raw Seed Data from GPT-3. To set the stage for the later knowledge amplification process via iterative self-distillation, we gather seed knowledge from GPT-3 (175B)[2], the teacher model, to instill into Flan-T5 (3B), a smaller base student model. To do so, we jointly generate defeasible contextualizations for moral actions and associated rationales with carefully engineered task-directed prompts.[3] To encourage diverse alternatives of this initial seed, we generate two contexts/rationales each for both strengthening and weakening moral variances; in total, we obtain 212K contextualizations and rationales for 60K base actions.

Filtering Raw Seed Data with Critic Model. Despite careful prompting following the task formulation, raw generations from GPT-3 remain noisy. Thus, we train a binary classifier to simulate human quality assessments on GPT-3 generated contextualizations as inspired by West et al. (2022).[4] To train the critic model, we use the human quality-assessment gold labels introduced in §2. We fine-tune DeBERTa-V3 (He et al., 2021) on these annotations, resulting in a critic model that achieves high accuracy on a held-out validation set.[5] Using the trained critic model, we filter the teacher model generations to remove errors from the distillation data and obtain an initial medium-quality training corpus, D_0, of 85K examples.

Training Initial Student Model Our goal is to train an initial student model capable of generating contextualizations and rationales for a given action and moral variance. We fine-tune Flan-T5 (3B) (Chung et al., 2022) on D_0 for 3 epochs to produce **Distill$_{\text{base}}$**, our base student model.

3.2 Refining Intermediate Student Models via Iterative Self-distillation

We refine the quality of the base student model by further amplifying desired generation properties through an iterative self-distillation process, utilizing no additional generations from the teacher model. Our iterative process has some key differences from Bhagavatula et al. (2023), in that we focus on improving *diversity* in addition to quality.

Self-distillation from Student Models. First, we generate a corpus of contextualizations and rationales using **Distill$_{\text{base}}$** on a set of newly sampled actions from the training split of SOCIAL-CHEM-101. Given an action, we use nucleus sampling (Holtzman et al., 2020) ($p = 0.9$) to produce 10 contextualizations and rationales for each moral variance.

[2] *text-davinci-003* is used wherever GPT-3 is mentioned

[3] See Appendix A for GPT-3 prompt details.

[4] Preliminary human evaluation results show that whenever contextualization is deemed high quality, the rationale is most likely to be high quality too (over 90% of the time). Therefore, although some improvements could be gained on the rationales, in this work, we focus on improving the quality of contexts which starts at ∼50% valid, as there's much more room to improve their quality.

[5] See critic model training details in Appendix D.1

Targeted Filtering. Next, we again perform targeted filtering on the newly self-distilled data to (1) ensure the validity of the data via the supervised critic model, similarly to the treatment of D_0 described in §3.1; (2) encourage diverse model outputs by reducing repetition among valid contextualizations using a Natural Language Inference filter (NLI) (Liu et al., 2022).

NLI is an NLP task that determines whether a premise statement entails or implies the truth of a hypothesis statement (Bowman et al., 2015; Liu et al., 2022). For a given pair of contextualizations A and B, we say the pair is mutually entailed if both $A \rightarrow B$ and $B \rightarrow A$ are entailments, indicating a high confidence of not only lexically but also semantically repetitive content. We filter out these mutual entailments such that at most one example from each pair remains in the dataset, thereby removing redundant signals in the training data. We use RoBERTa-Large pretrained on the WANLI dataset (Liu et al., 2022) to compute entailment scores between each of the generated contextualizations for a given input. Formally, the filtering process is defined as:

$$\text{accept}_{NLI}(c_i) = \forall j \in [1, i) : \neg\text{accept}_{NLI}(c_j) \vee (P_{NLI}(c_i, c_j) < 0.5 \vee P_{NLI}(c_j, c_i) < 0.5)$$

where $\text{accept}_{NLI}(c)$ determines if a context c is accepted into the filtered set of unique candidates, c_k is the k'th candidate, and $P_{NLI}(c_1, c_2)$ is the predicted score that context c_1 entails c_2.

This process results in a filtered self-generated corpus, D_1, of 434K examples. We then train **SelfDistill**$_1$ using D_1 starting from **Distill**$_{\text{base}}$.

To improve the student model further, we repeat the self-distillation process using **SelfDistill**$_1$ as the base. Using **SelfDistill**$_1$, we generate a high-quality corpus, D_2, automatically filtered by the supervised critic model and NLI to train a second-iteration self-distilled student model, **SelfDistill**$_2$.

3.3 Training a Final Student Model with Large-scale, High-quality Data from Refined Self-distilled Model

Using **SelfDistill**$_2$, we produce δ-RULES-OF-THUMB by generating contextualizations and rationales for 94K actions and combining them with previous training sets. We apply the NLI filter as above and filter by a restrictive critic model threshold of 0.96 to ensure high confidence of quality in the dataset. Human evaluation of a subset of 1000 samples shows that 85.9% of contextualizations and 98.5% of rationales are deemed high quality (see details of dataset stats and human validation in Table 1). Using this large-scale, high-quality dataset, we train a final student model, **Distill**$_{\text{final}}$, outperforming all previous intermediate student models and the teacher model (*i.e.*, GPT-3).

Model	Vld.	Avg.
GPT-3 (Teacher)	0.53	0.69
Falcon-7B-Instruct	0.39	0.54
GPT-3.5 (ChatGPT)	0.71	0.77
GPT-4	0.77	0.82
Distill$_{\text{final}}$	**0.86**	**0.88**

Table 3: Our **Distill**$_{\text{final}}$ model outperforms all other baseline models on the top 1 generation via the automatic evaluation.

4 Experimentation Setups

4.1 Evaluation Data

We hold out a test set of 6K actions from the same distribution in SOCIAL-CHEM-101. For each model we generate contextualizations and rationales over the test set using both greedy decoding (top 1 candidate) and nucleus sampling (top 10 candidates) with $p = 0.9$.

4.2 Evaluation Metrics

We aim to evaluate the overall quality of model-generated contextualizations and rationales (*validity*), a model's capability to produce diverse contextualizations for a given action and moral variance (*diversity*), and also the degree of moral variance that the model's contextualizations provide (*defeasibility*). Finally, we also evaluate the general *language quality* of model generations reflected by fluency and grammatical correctness.

Validity. For contextualizations, we use the critic model for automatic evaluation. For greedy generations, we compute the ratio of generations in the test set that pass the critic filter threshold as defined in §3 (**Auto/Vld.**) and the average predicted critic score across the test set (**Auto/Avg.**). For sampled generations, we compute the average number of contextualizations out of the top 10 candidates that pass the critic filter threshold (**Auto/#Vld.**). We also conduct human evaluation to vet validity of contextualizations to complement conclusions drawn from automatic evaluation (**Human/Vld., #Vld.**). We evaluate the validity of rationales with human evaluation (**Rationale.**).

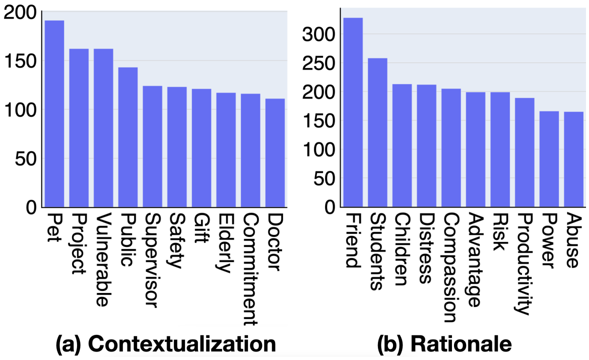


Figure 3: Top 10 topics and their counts among 10K sampled contextualizations and rationales from δ-RoT.

Diversity. We use automatic evaluation to assess the diversity of generated contextualizations as it is a generally well-defined dimension. Similarly to the mutual entailment NLI filter in §3, we compute the bidirectional entailment probabilities between each pair of contextualizations across valid candidates and report the average number of semantically unique generations (**Auto/#Unq. Vld.**). This metric describes the model's capability to produce multiple varied contextualizations for a given input, directly indicating the diversity of model outputs.

Defeasibility. We break down human evaluation of contextualization validity into more granular answer choices—"significantly" or "slightly" shifting the moral implication of the base action. Defeasibility of the contextualization (**Defease.**) is computed as $(\#\text{contexts}_{\text{significant}} * 1 + \#\text{contexts}_{\text{slight}} * 0.5)/\#\text{all}$, indicating the degree to which the contextualizations affect the morality of the original actions. See Appendix B for annotation details.

Language Quality. We evaluate the language quality (*i.e.*, fluency and grammar correctness) of generated contexulizations and rationales with human evaluations (**Lan.**).

5 Results and Discussions

In this section, we present results and insights of the iterative self-distillation process and an analysis of the resulting dataset, δ-RoT.

5.1 Insights of Iterative Self-distillation

As shown in Table 2, student models improve across iterations during the iterative self-distillation process on all of *validity* (0.54→0.71), *diversity* (4.78→5.69), and *defeasibility* (0.42→0.56). In particular, the final student model, **Distill**$_{\text{final}}$, wins over GPT-3 (the teacher model orders of magnitude larger) by a substantial relative gain on validity (26.8%) and defeasibility (51.4%), demonstrating the effectiveness of distilling small specialized knowledge models from large general-purpose close-sourced models like GPT-3.

Filtering by the critic model improves the quality of contextualizations. Our results show that filtering training examples by the critic model improves the quality of generated contextualizations, in line with previous findings (West et al., 2022; Bhagavatula et al., 2023). In particular, we conduct an ablation study without using critic filtering (**Distill**$_{\text{base}}$-*No critic*), resulting in lower performance on almost all contextualization metrics and similar performance on others, despite its training set being ∼70% larger than **Distill**$_{\text{base}}$.

Training student models on diverse self-generated data improves validity and diversity over greedy decoding. We find that omitting diverse candidates during the self-distillation process results in a drastic decrease in the diversity of the subsequent models. In particular, ablations using only the top 1 candidate in distillation (**SelfDistill**$_1$-*Top 1 Only* and **SelfDistill**$_2$-*Top 1 Only*) produce significantly less valid and unique generations compared to **SelfDistill**$_1$ (5.05→2.54) and **SelfDistill**$_2$ (5.21→2.16). This insight is critical as previous symbolic knowledge distillation works (West et al., 2022; Bhagavatula et al., 2023) focused primarily on improving the validity of downstream student models without screening the diversity.

Filtering repetitions with NLI improves the diversity of candidates from student models. Is training on more candidates itself, without filtering out repetitions, sufficient for improving the diversity of downstream models? To answer this question, we conduct ablation studies without using the NLI mutual entailment filter, *i.e.*, **SelfDistill**$_1$-*No NLI* and **SelfDistill**$_2$-*No NLI*. Our results show that despite being trained with more data, these two models generate less valid and unique contextualizations compared to **SelfDistill**$_1$ (5.05→4.97) and **SelfDistill**$_2$ (5.21→4.73), shedding light on the importance of having *truly* diverse training data by removing redundancy.

Successive iterative training leads to a higher quality student model than a single iteration. We train an ablation model (**SelfDistill**$_2$-No Self-distill) combining the actions in the training sets of both the first and second rounds of distillation,

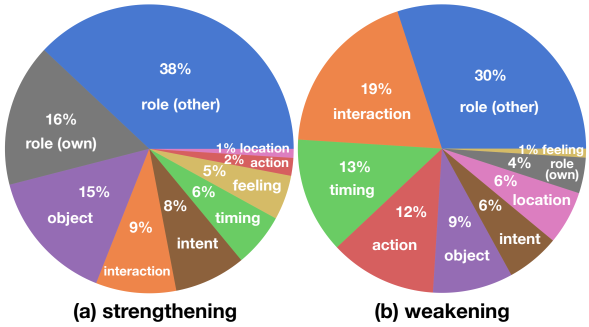


Figure 4: Qualitative analysis of contextualization categories per moral variance. (a) and (b) are for strengthening and weakening contexulizations, respectively.

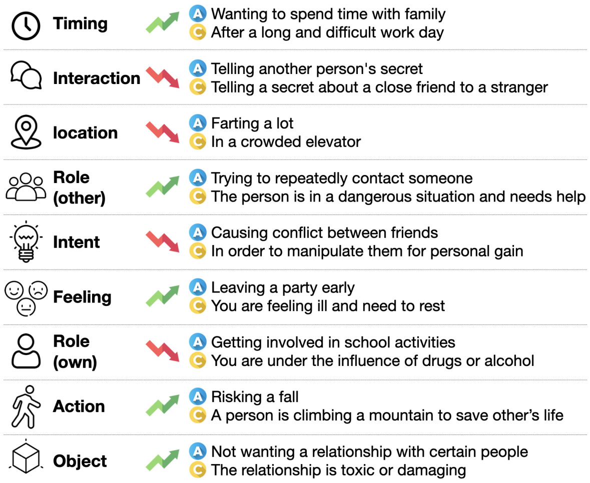


Figure 5: Example rich contextualizations per category.

but with only one iteration of self-learning from **Distill**$_{\text{base}}$. **SelfDistill**$_2$, which has been trained using the same actions over two rounds of successive training for the same number of total training steps, outperforms this ablation on almost all metrics, showing the effectiveness of amplifying learning signals via successive iterations of self-learning.

The final student model outperforms orders of magnitude larger off-the-shelf models. We evaluate the zero-shot performance of some of the most powerful general-purpose LLMs of varied sizes with 1000 sampled examples from our test set. We use the same instructions as we used to distill the seed knowledge from GPT-3 to prompt these baselines in a zero-shot manner (see Appendix §A). Results in Table 3 show that despite some of the zero-shot models being orders of magnitude larger than our final student model (*e.g.*, 175B vs. 3B), our model outperforms them all, proving the effectiveness of our proposed approach.

5.2 Delving into δ-Rules-of-Thumb

We analyze δ-Rules-of-Thumb to gauge the dataset composition and gain a comprehensive picture of captured contextualizations and rationales.

Contextualization. To understand what topics contextualizations in δ-RoT represent, we conduct a topic analysis with BERTopic (Grootendorst, 2022), an easily interpretable off-the-shelf topic modeling technique. Frequent topics of contextualizations are shown in Figure 3(a), which involve *daily objects or entities* (*e.g.*, pet, project, supervisor, gift, doctor) and *characters or properties that carry moral weights* (*e.g.*, vulnerable, public, safety, elderly, commitment). In particular, *vulnerability* serves as a critical weakening context if characters in the action are among vulnerable populations (*e.g.*, "taking advantage of people" becomes less acceptable if "they are in a vulnerable state"). See topics analysis details in Appendix §E.1.

We also manually analyze the categories of 200 contextualizations sampled from δ-RoT. As shown in Figure 4, frequent types of contextualizations include role specifications of the action taker (own), other characters involved in the scene (other), and setting specifications such as object, timing, and location. In addition to individual role specifications, interactions, relationships, and dynamics between multiple roles add rich groundings that carry moral significance. Figure 5 shows example contextualizations under each category. Contextualizations in δ-RoT have an average of 11.7 words, providing concrete, specific contexts tailored to each action.

We further conduct a qualitative *error analysis* over generations from the **Distill**$_{\text{final}}$ to gauge what makes a context implausible or incorrect.

Trivial Context: Context that adds details that may often be relevant to morality for other actions, but is rendered trivial in this particular case, *e.g.*, "Staying up all night" vs. "Staying up all night while in a relationship."

Infeasible/Unlikely/Unnatural Context: Context that is infeasible, highly unlikely in a real world setting, or unnatural by itself and/or in relation with the action, *e.g.*, "Participating in a chess team" vs. "The team is made up of people who have been convicted of a serious crime."

Opposite Context: Context that adds details opposite to the desired moral variance, *e.g.*, "Offering people money" vs. "Offering money to someone who is in a vulnerable financial situation" when prompted for a weakening context.

Rationales. We conduct the same topic analysis on rationales. Results in Figure 3(b) highlight that common topics in justifying a moral decision involve *important roles* (*e.g.*, friend, students, children) and *common human values* (*e.g.*, distress, compassion, risk, productivity, power, abuse). See topics analysis details in Appendix §E.1.

Diving into specific examples of why contexts shift the moral implications of actions, we find common values that uplift the acceptability of an action include *empathy*, *kindness*, *support*, and *respect* (*e.g.*, "...someone who is in need of emotional support, which shows empathy and kindness"). Additionally, *(in)equality* or *(un)fairness* is another dimension of value that carries significant weight on moral implications (*e.g.*, "...taking advantage of someone else's generosity when you have the resources to provide for yourself"). Finally, contexts that are explained to promote or impede *physical/mental wellbeing*, *financial health*, or *learning/working productivity* (*e.g.*, "...helping them learn, which is beneficial for their future") are also common. These qualitative results show consistency with the automatic topic analysis.

Toxicity Analysis. Since the seed actions of δ-ROT sourced from SOCIAL-CHEM-101 (Forbes et al., 2020) mainly concern everyday situations, they are at a low risk of containing toxic content. In addition, due to the careful filtering with the critic model and the iteratively refined self-distillation process, we expect most of the low-quality (including potentially biased data points) to be already filtered out from the final dataset. However, because any toxicity in moral reasoning data is especially detrimental and could easily propagate through downstream tasks, we run a toxicity analysis on a subset of 40K data points from δ-ROT using the Perspective API (Lees et al., 2022). Our results show that the average toxicity score is *0.09*, indicating very low toxicity overall. In a qualitative analysis of the data rows with higher toxicity scores (with a max of 0.83), we observe a strong pattern where the base action itself is problematic, and the distilled contexts produce the target moral variance without contributing significantly to the toxicity of the complete statement (see examples in Table 9 of Appendix §E.2). While no existing toxicity detection method can accurately measure all potential biases, this analysis provides reasonable confidence in the lack of toxicity in our generated contextualizations and rationales.

Cultural Biases It's also important to note the sensitivity of moral reasoning to cultural differences. In fact, previous studies have pointed out that cultural bias is a pervasive phenomenon across many NLP models (e.g., GPT-3/3.5/4) and tasks (e.g., hate speech detection with Perspective API, RewireAPI, HateRoberta) (Santy et al., 2023). To better represent diverse perspectives to our contextualizations, we (1) abstain from producing an absolute moral judgment given an action and (2) promote diverse distillation as discussed previously.

However, these measures cannot eliminate all traces of bias in the final model, so we also qualitatively probe δ-ROT to examine cultural biases. Admittedly, as our dataset and student models are distilled from GPT-3, which is shown to present *Western-centric* perspectives, it is likely that our dataset and models inherit this cultural bias as well (Santurkar et al., 2023; Abdulhai et al., 2023). For example, when prompted for a weakening contextualization for the action "Not having freedom of speech in {country}." For some countries such as Japan, the United Kingdom, and the United States, the top generated context is "in a workplace setting." Yet for other countries such as China, India, Thailand, Korea, and Russia, **Distill**$_{\text{final}}$ produces different results which might imply these countries have varying levels of human rights concerns (see details in Appendix §E.3). This example aligns with our intuition that the student model might display Western-centric biases, and it fits with a previous finding by Fraser et al. (2022) that such models are likely to encode the cultural biases aligned with those involved in training data annotation.

Thus, despite our careful filtering process, it is clear that culturally biased generations can still be produced by our model and may be present in δ-ROT. As such, users of this dataset must exercise discretion and care when applying it to novel use cases, and it should never be used as prescriptive ethical advice. This points to a key direction for future work to further enrich multicultural representations in computational moral reasoning and other commonsense understanding tasks.

6 Related Work

Computational Morality. Jiang et al. (2022) present Delphi, a commonsense moral model trained to present a descriptive view of ethical judgments. Ammanabrolu et al. (2022); Hendrycks et al. (2021); Pan et al. (2023) incorporate moral values in an interactive game environment to align agent actions with social norms. Kim et al. (2022) uses social norms to guide conversational agents' prosocial responses. Jin et al. (2022) introduce MoralExceptQA, a task of identifying the acceptability of breaking a well-known moral rule in different situations. Fung et al. (2023) introduce NormSAGE, a framework to discover multi-Lingual and multicultural norms on-the-fly. There is also a prominent line of work in quantifying social, political, and moral values and views presented in language models by using well-established public opinion surveys or social science instruments (Santurkar et al., 2023; Hartmann et al., 2023; Fraser et al., 2022). Recently, Sorensen et al. (2023) builds the Kaleido model to capture the importance of pluralistic human values in moral decision-making.

Defeasible Reasoning. Defeasibility describes the idea that new information might strengthen or weaken a given interpretation (Rudinger et al., 2020). This concept has been used in multiple works for different applications: Rudinger et al. (2020) introduced two task formulations, one which concerns generating strengthening or weakening updates to a premise and hypothesis, and the other one which concerns classifying whether a premise and an update strengthen or weaken the hypothesis. Madaan et al. (2021) improved upon the latter task by modeling inference graphs. Our work relates to recent efforts towards contextualizing moral reasoning. Pyatkin et al. (2023) developed ClarifyDelphi, a system capable of asking clarification questions to elicit the context surrounding a judgment. With NormBank, Ziems et al. (2023) introduce a framework for grounded reasoning about norms, adding environmental conditions and agent characteristics. Rather than a QA setup or providing an atomic groundings, in δ-RoT, we instead provide free-text contextualizations along with supporting rationales which justify how each piece of context alters the morality of the an action.

Explanations and Rationales. Free-form rationales have emerged as a promising direction to promote models' reasoning capabilities and aid interpretability by filling in the knowledge gap. Prior works on rationale generations take either a supervised approach by training on human-written explanations (Camburu et al., 2018; Rajani et al., 2019; Narang et al., 2020; Kumar and Talukdar, 2020) or a weakly supervised approach (Glockner et al., 2020; Brahman et al., 2021). The advent of in-context learning (Brown et al., 2020; *inter alia*) led to growing interest in using LLMs to generate rationales in few-shot prompting mode (Wiegreffe et al., 2022; Marasovic et al., 2022; Wei et al., 2022). While so-called explanation-based prompting shows encouraging results, it is hindered by costly API calls. We instead endow accessible models with joint generation of contextualizations and rationales, reducing the computation required.

Automatic Data Generation. Previous works on automatic data generation have worked on creating datasets for commonsense reasoning (West et al., 2022; Bhagavatula et al., 2023; Liu et al., 2022; Wang et al., 2023; Kim et al., 2023), dialogues (Kim et al., 2023; Xu et al., 2023; Geng et al., 2023; Chiang et al., 2023), and summarization (Sclar et al., 2022; Jung et al., 2023). West et al. (2022) propose the symbolic knowledge distillation framework, with several follow-up works to extend it with iterative distillation (Sclar et al., 2022; Jung et al., 2023; Bhagavatula et al., 2023). We further build on this paradigm to encourage diversity in distillation and apply our method to moral contextualization and rationales.

7 Conclusion

In this work, we highlight the importance of dynamic contexts in shaping moral reasoning. We introduce *defeasible moral reasoning*, a task of providing grounded contexts to elucidate varying degrees of moral acceptability, accompanied by commonsense rationales to justify the reasoning.

We employ an iterative self-distillation methodology to create a high-quality and diverse dataset, δ-RULES-OF-THUMB, comprising over 1.2M combined entries of contextualizations and rationales for 116K defeasible moral actions. Through this iterative approach, we also obtain a small student model capable of generating defeasible contexts with improved validity, diversity, and defeasibility.

Our work aims to promote a deeper understanding of the intricate interplay between defeasible moral actions and grounded contexts that shape moral acceptability in a nuanced and complicated way, building a strong foundation for future works on enriching cultural representations in computational moral reasoning research. We hope δ-RoT serves as a rich resource for the community to study how moral judgments are made to unveil this unique perspective of human intelligence.

Limitations & Ethical Considerations

Large-language models can generate text that might be biased and insensitive to a user's socio-cultural context (Bordia and Bowman, 2019; Sharma et al., 2021; Hovy and Prabhumoye, 2021). By introducing the *defeasible moral reasoning* task, we consider different contexts and rationales, making a step towards being more diverse and inclusive in accounting for different perspectives.

However, even with our filtering by the critic model, it is possible for biased or incorrect outputs to be produced by distilled models. The critic model is trained to be a strong approximation of human judgment, but it is not perfect, and due to the scale we cannot collect human annotations to verify all examples in model training data or δ-RULES-OF-THUMB.

In addition, determining moral variance is a form of moral judgment and so may not have a clear answer in some cases, *e.g.*, trolley problems. There are certainly contextualizations which different groups of people disagree over whether they make the base action more or less acceptable, as could be seen in our critic gold data, where we employed inter-annotator voting to reconcile differing opinions.

With these points in mind, our dataset and models should *never* be used as direct moral advice to humans; they are solely intended to be resources for more nuanced reasoning and interpretation in computational morality research.

We will publicly release our dataset and final student model to promote open-source research but for gated research purposes only. To mitigate risks of misuse, we will inform all users about potential ethical implications and risks of the resource and require them to complete a data/model user agreement form to acknowledge their consent to proper usage of the resource. This will also help us track how our resource is repurposed for downstream applications.

Finally, for extremely morally negative situations, there might not be any reasonable contextualizations to make the action justifiable (*e.g.*, "genocide"). However, the situations we source from SOCIAL-CHEM-101 focus on everyday actions that do not carry extreme moral implications. Therefore, we consider identifying impossible cases to further contextualize out of the scope of our current study. Future work could investigate more inherently morally charged cases that could not be justified even with further contextualizations.

Acknowledgement

The authors thank the anonymous reviewers. This research was supported in part by DARPA under the ITM program (FA8650-23-C-7316) and the Allen Institute for AI.

References

Marwa Abdulhai, Cl'ement Crepy, Daria Valter, John Canny, and Natasha Jaques. 2023. Moral foundations of large language models.

Prithviraj Ammanabrolu, Liwei Jiang, Maarten Sap, Hannaneh Hajishirzi, and Yejin Choi. 2022. Aligning to social norms and values in interactive narratives.

Edmond Awad, Sydney Levine, Andrea Loreggia, Nicholas Mattei, Iyad Rahwan, Francesca Rossi, Kartik Talamadupula, Joshua Tenenbaum, and Max Kleiman-Weiner. 2022. When is it acceptable to break the rules? knowledge representation of moral judgement based on empirical data. *arXiv preprint arXiv:2201.07763*.

Chandra Bhagavatula, Jena D. Hwang, Doug Downey, Ronan Le Bras, Ximing Lu, Lianhui Qin, Keisuke Sakaguchi, Swabha Swayamdipta, Peter West, and Yejin Choi. 2023. I2d2: Inductive knowledge distillation with neurologic and self-imitation.

Shikha Bordia and Samuel R. Bowman. 2019. Identifying and reducing gender bias in word-level language models. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 7–15, Minneapolis, Minnesota. Association for Computational Linguistics.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 632–642, Lisbon, Portugal. Association for Computational Linguistics.

Faeze Brahman, Vered Shwartz, Rachel Rudinger, and Yejin Choi. 2021. Learning to rationalize for nonmonotonic reasoning with distant supervision. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(14):12592–12601.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Oana-Maria Camburu, Tim Rocktäschel, Thomas Lukasiewicz, and Phil Blunsom. 2018. e-snli: Natural language inference with natural language explanations. In *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. Scaling instruction-finetuned language models.

Maxwell Forbes, Jena D. Hwang, Vered Shwartz, Maarten Sap, and Yejin Choi. 2020. Social chemistry 101: Learning to reason about social and moral norms. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 653–670, Online. Association for Computational Linguistics.

Kathleen C. Fraser, Svetlana Kiritchenko, and Esma Balkir. 2022. Does moral code have a moral code? probing delphi's moral philosophy. In *Proceedings of the 2nd Workshop on Trustworthy Natural Language Processing (TrustNLP 2022)*, pages 26–42, Seattle, U.S.A. Association for Computational Linguistics.

Yi R. Fung, Tuhin Chakraborty, Hao Guo, Owen Rambow, Smaranda Muresan, and Heng Ji. 2023. Normsage: Multi-lingual multi-cultural norm discovery from conversations on-the-fly.

Xinyang Geng, Arnav Gudibande, Hao Liu, Eric Wallace, Pieter Abbeel, Sergey Levine, and Dawn Song. 2023. Koala: A dialogue model for academic research. Blog post.

Max Glockner, Ivan Habernal, and Iryna Gurevych. 2020. Why do you think that? exploring faithful sentence-level rationales without supervision. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1080–1095, Online. Association for Computational Linguistics.

Maarten Grootendorst. 2022. Bertopic: Neural topic modeling with a class-based tf-idf procedure. *arXiv preprint arXiv:2203.05794*.

Jochen Hartmann, Jasper Schwenzow, and Maximilian Witte. 2023. The political ideology of conversational ai: Converging evidence on chatgpt's pro-environmental, left-libertarian orientation.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. Deberta: Decoding-enhanced bert with disentangled attention. In *International Conference on Learning Representations*.

Dan Hendrycks and Kevin Gimpel. 2016. Bridging nonlinearities and stochastic regularizers with gaussian error linear units. *CoRR*, abs/1606.08415.

Dan Hendrycks, Mantas Mazeika, Andy Zou, Sahil Patel, Christine Zhu, Jesus Navarro, Dawn Song, Bo Li, and Jacob Steinhardt. 2021. What would jiminy cricket do? towards agents that behave morally. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. The curious case of neural text degeneration.

Dirk Hovy and Shrimai Prabhumoye. 2021. Five sources of bias in natural language processing. *Language and Linguistics Compass*, 15(8):e12432.

Liwei Jiang, Jena D. Hwang, Chandra Bhagavatula, Ronan Le Bras, Jenny Liang, Jesse Dodge, Keisuke Sakaguchi, Maxwell Forbes, Jon Borchardt, Saadia Gabriel, Yulia Tsvetkov, Oren Etzioni, Maarten Sap, Regina Rini, and Yejin Choi. 2022. Can machines learn morality? the delphi experiment.

Zhijing Jin, Sydney Levine, Fernando Gonzalez, Ojasv Kamal, Maarten Sap, Mrinmaya Sachan, Rada Mihalcea, Josh Tenenbaum, and Bernhard Schölkopf. 2022. When to make exceptions: Exploring language models as accounts of human moral judgment.

Jaehun Jung, Peter West, Liwei Jiang, Faeze Brahman, Ximing Lu, Jillian Fisher, Taylor Sorensen, and Yejin Choi. 2023. Impossible distillation: from low-quality model to high-quality dataset & model for summarization and paraphrasing.

Hyunwoo Kim, Jack Hessel, Liwei Jiang, Peter West, Ximing Lu, Youngjae Yu, Pei Zhou, Ronan Le Bras, Malihe Alikhani, Gunhee Kim, Maarten Sap, and Yejin Choi. 2023. Soda: Million-scale dialogue distillation with social commonsense contextualization.

Hyunwoo Kim, Youngjae Yu, Liwei Jiang, Ximing Lu, Daniel Khashabi, Gunhee Kim, Yejin Choi, and Maarten Sap. 2022. ProsocialDialog: A prosocial backbone for conversational agents. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 4005–4029, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Sawan Kumar and Partha Talukdar. 2020. NILE : Natural language inference with faithful natural language explanations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8730–8742, Online. Association for Computational Linguistics.

Joseph Kwon, Josh Tenenbaum, and Sydney Levine. 2022. Flexibility in moral cognition: When is it okay to break the rules? In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 44.

Alyssa Lees, Vinh Q. Tran, Yi Tay, Jeffrey Sorensen, Jai Gupta, Donald Metzler, and Lucy Vasserman. 2022. A new generation of perspective api: Efficient multilingual character-level transformers.

Sydney Levine, Max Kleiman-Weiner, Nick Chater, Fiery Andrews Cushman, and Joshua B. Tenenbaum. 2018. The cognitive mechanisms of contractualist moral decision-making. *Cognitive Science*.

Sydney Levine, Max Kleiman-Weiner, Laura Schulz, Joshua Tenenbaum, and Fiery Cushman. 2020. The logic of universalization guides moral judgment. *Proceedings of the National Academy of Sciences*, 117(42):26158–26169.

Alisa Liu, Swabha Swayamdipta, Noah A. Smith, and Yejin Choi. 2022. WANLI: Worker and AI collaboration for natural language inference dataset creation. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 6826–6847, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Aman Madaan, Niket Tandon, Dheeraj Rajagopal, Peter Clark, Yiming Yang, and Eduard Hovy. 2021. Think about it! improving defeasible reasoning by first modeling the question scenario. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6291–6310.

Ana Marasovic, Iz Beltagy, Doug Downey, and Matthew Peters. 2022. Few-shot self-rationalization with natural language prompts. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 410–424, Seattle, United States. Association for Computational Linguistics.

Sharan Narang, Colin Raffel, Katherine Lee, Adam Roberts, Noah Fiedel, and Karishma Malkan. 2020. Wt5?! training text-to-text models to explain their predictions. *ArXiv*, abs/2004.14546.

Alexander Pan, Jun Shern Chan, Andy Zou, Nathaniel Li, Steven Basart, Thomas Woodside, Hanlin Zhang, Scott Emmons, and Dan Hendrycks. 2023. Do the rewards justify the means? Measuring trade-offs between rewards and ethical behavior in the machiavelli benchmark. In *Proceedings of the 40th International Conference on Machine Learning*, volume 202 of *Proceedings of Machine Learning Research*, pages 26837–26867. PMLR.

Valentina Pyatkin, Jena D. Hwang, Vivek Srikumar, Ximing Lu, Liwei Jiang, Yejin Choi, and Chandra Bhagavatula. 2023. Clarifydelphi: Reinforced clarification questions with defeasibility rewards for social and moral situations.

Nazneen Fatema Rajani, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. Explain yourself! leveraging language models for commonsense reasoning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4932–4942, Florence, Italy. Association for Computational Linguistics.

Rachel Rudinger, Vered Shwartz, Jena D. Hwang, Chandra Bhagavatula, Maxwell Forbes, Ronan Le Bras, Noah A. Smith, and Yejin Choi. 2020. Thinking like a skeptic: Defeasible inference in natural language. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4661–4675, Online. Association for Computational Linguistics.

Shibani Santurkar, Esin Durmus, Faisal Ladhak, Cinoo Lee, Percy Liang, and Tatsunori Hashimoto. 2023. Whose opinions do language models reflect?

Sebastin Santy, Jenny Liang, Ronan Le Bras, Katharina Reinecke, and Maarten Sap. 2023. NLPositionality: Characterizing design biases of datasets and models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 9080–9102, Toronto, Canada. Association for Computational Linguistics.

Melanie Sclar, Peter West, Sachin Kumar, Yulia Tsvetkov, and Yejin Choi. 2022. Referee: Reference-free sentence summarization with sharper controllability through symbolic knowledge distillation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9649–9668, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Shanya Sharma, Manan Dey, and Koustuv Sinha. 2021. Evaluating gender bias in natural language inference. *arXiv preprint arXiv:2105.05541*.

Taylor Sorensen, Liwei Jiang, Jena Hwang, Sydney Levine, Valentina Pyatkin, Peter West, Nouha Dziri, Ximing Lu, Kavel Rao, Chandra Bhagavatula, Maarten Sap, John Tasioulas, and Yejin Choi. 2023. Value kaleidoscope: Engaging ai with pluralistic human values, rights, and duties.

Peifeng Wang, Zhengyang Wang, Zheng Li, Yifan Gao, Bing Yin, and Xiang Ren. 2023. Scott: Self-consistent chain-of-thought distillation.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Huai hsin Chi, F. Xia, Quoc Le, and Denny Zhou. 2022. Chain of thought prompting elicits reasoning in large language models. *ArXiv*, abs/2201.11903.

Peter West, Chandra Bhagavatula, Jack Hessel, Jena Hwang, Liwei Jiang, Ronan Le Bras, Ximing Lu, Sean Welleck, and Yejin Choi. 2022. Symbolic knowledge distillation: from general language models to commonsense models. In *Proceedings of the 2022 Conference of the North American Chapter of* *the Association for Computational Linguistics: Human Language Technologies*, pages 4602–4625, Seattle, United States. Association for Computational Linguistics.

Sarah Wiegreffe, Jack Hessel, Swabha Swayamdipta, Mark O. Riedl, and Yejin Choi. 2022. Reframing human-ai collaboration for generating free-text explanations. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL 2022, Seattle, WA, United States, July 10-15, 2022*, pages 632–658. Association for Computational Linguistics.

Canwen Xu, Daya Guo, Nan Duan, and Julian McAuley. 2023. Baize: An open-source chat model with parameter-efficient tuning on self-chat data.

Caleb Ziems, Jane Dwivedi-Yu, Yi-Chia Wang, Alon Halevy, and Diyi Yang. 2023. Normbank: A knowledge bank of situational social norms.

A GPT-3 Prompt for Seed Data Generation

We prompt GPT-3 with the action and moral variance to jointly generate the contextualization and rationale in a zero-shot setting. We use nucleus sampling with $p = 0.9$ and presence and frequency penalties of 0.5.

We explore multiple prompts, including few-shot versus zero-shot prompting and multiple variations of wording. From qualitative analysis, we find that this zero-shot prompt performs well, while also reducing the number of tokens required for each request.

```
Given an action, write down a
situation in which the action is
more {ethical/unethical}
and give a reason for
why it makes the action
more {ethical/unethical}.
Use the following format.

Action:
Situation:
Explanation:

Action: {action}
Situation:
```

		Human Val.		
Type	**Pol.**	**%Vld.**	**%Significant.**	**%Slight**
Context	All	85.9	79.5	20.5
	Stren.	84.2	79.0	21.0
	Weak.	87.6	80.0	20.0
Rationale	All	98.5	93.4	6.6
	Stren.	98.6	92.9	7.1
	Weak.	98.4	93.9	6.1

Table 4: Expanded human validation results of δ-RULES-OF-THUMB, breaking down the degree of moral variance and logical completeness. **%Vld.** is the same as Table 1. **%Significant** and **%Slight** are (for Context) the percent of **Vld.** which significantly or slightly impact the moral variance relative to the base action; and (for Rationale) the percent of **Vld.** which are annotated as fully or somewhat valid respectively.

B Human Annotation Details

We use Amazon Mechanical Turk as the interface for all human annotations and evaluations. For each task, we estimate the completion time by doing a selection of jobs ourselves in order to target a compensation rate of \$15 per hour.

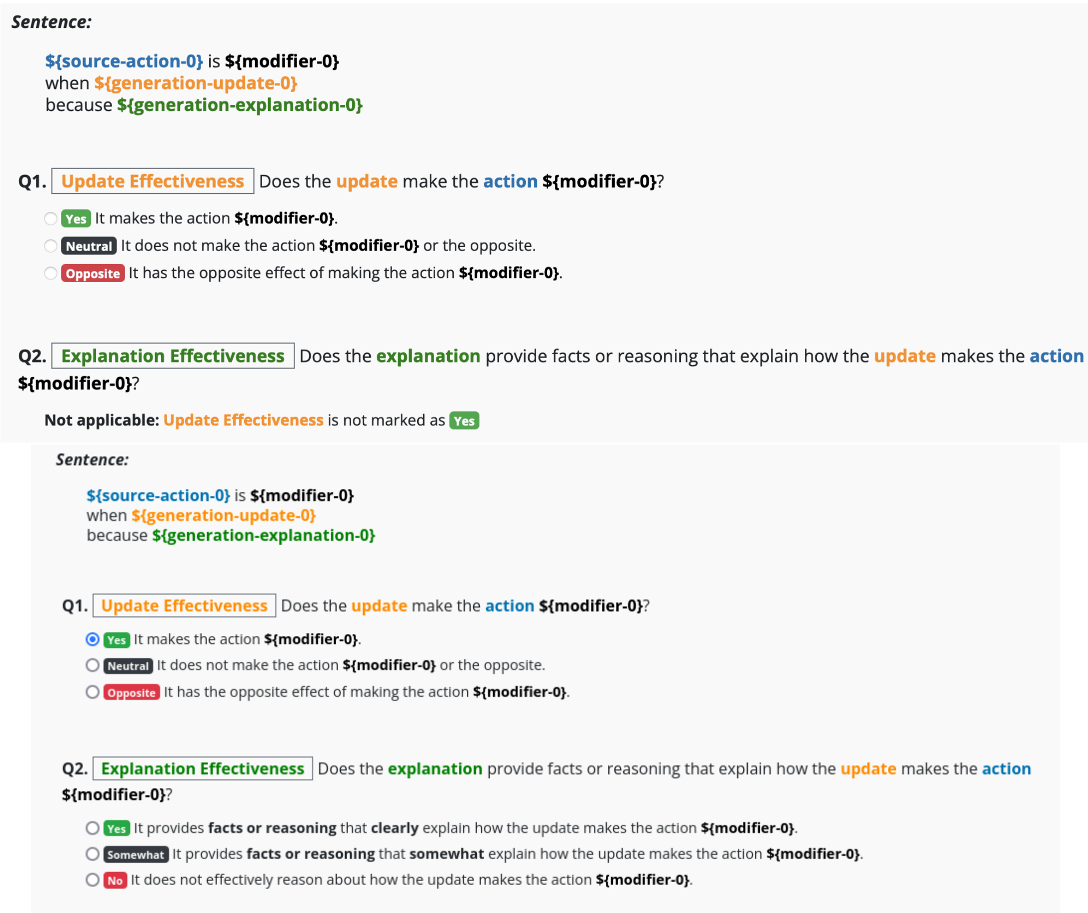
B.1 Critic Model Data Collection

For the critic training data, we collect human annotations on the quality of GPT-3 generated contextualizations, which we then portion into an 80%/10%/10% train/validation/test split. We combine the "Neutral" and "Opposite" answer choices into a single "Invalid" label. As described in §2, to reduce noise in the dataset, we collect 3 annotations per generation and vote to produce the gold label; for validation and test sets we include only cases where all three annotators agree.

B.2 Human Evaluation of Model Generations and the Final Distilled Dataset

We design the dataset human evaluation to gather fine-grained assessments on contextualizations and rationales. As such, we include options for "slightly" valid contextualizations and "somewhat" valid rationales along with "invalid", which allows us to gain a more in-depth understanding of the quality of the data. In Table 1 we collapse these labels into simply "valid" and "invalid", considering the first two options "valid" and only the last option "invalid".

We find high inter-annotator agreement on these evaluations, with the questions on language quality and rationale validity at over 90% full three-



Sentence:

${source-action-0} is **${modifier-0}**
when ${generation-update-0}
because ${generation-explanation-0}

Q1. Update Effectiveness Does the update make the action **${modifier-0}**?

- Yes It makes the action **${modifier-0}**.
- Neutral It does not make the action **${modifier-0}** or the opposite.
- Opposite It has the opposite effect of making the action **${modifier-0}**.

Q2. Explanation Effectiveness Does the explanation provide facts or reasoning that explain how the update makes the action **${modifier-0}**?

Not applicable: Update Effectiveness is not marked as Yes

Sentence:

${source-action-0} is **${modifier-0}**
when ${generation-update-0}
because ${generation-explanation-0}

Q1. Update Effectiveness Does the update make the action **${modifier-0}**?

- Yes It makes the action **${modifier-0}**.
- Neutral It does not make the action **${modifier-0}** or the opposite.
- Opposite It has the opposite effect of making the action **${modifier-0}**.

Q2. Explanation Effectiveness Does the explanation provide facts or reasoning that explain how the update makes the action **${modifier-0}**?

- Yes It provides **facts or reasoning** that **clearly** explain how the update makes the action **${modifier-0}**.
- Somewhat It provides **facts or reasoning** that **somewhat** explain how the update makes the action **${modifier-0}**.
- No It does not effectively reason about how the update makes the action **${modifier-0}**.

Figure 6: The human data collection template for the critic model gold training data collection.

annotator agreement. On the context validity question, we find 57% full agreement, and in 82% of cases, two out of three annotators agree on a label. We expect a lower agreement on this question compared to others, since the moral judgment of the action and context is an inherently subjective task, and the answer may not be clearly defined in all cases. With the high two-way agreement, we have confidence in the accuracy of labels after applying voting across annotators.

C Full Iterative Self-distillation Algorithm

Algorithm 1 Iterative Self-distillation of δ-RoT

Require: teacher model τ, critic model ρ, $A_{\text{SocialChem}}$

$A_0 \leftarrow$ sample $A_{\text{SocialChem}}$

$A_{\text{SocialChem}} \leftarrow A_{\text{SocialChem}} \setminus A_0$

$D_0 \leftarrow \textsc{GenerateDiverse}(\tau, A_0)$

$D_0 \leftarrow \textsc{Filter}(\rho, D_0, \text{Threshold}_{\text{distill}})$

Distill$_{base}$ $\leftarrow$ Fine-tune base model on D_0

for $i = 1, 2$ **do**

  $A_i \leftarrow$ sample $A_{\text{SocialChem}}$

  $A_{\text{SocialChem}} \leftarrow A_{\text{SocialChem}} \setminus A_i$

  SelfDistill$_i$, $D_i \leftarrow \textsc{SelfDistill}(\sigma, A_i, \rho)$

$D_{\text{rem}} \leftarrow \textsc{GenerateDiverse}(\sigma, A_{\text{SocialChem}})$

return $\textsc{Filter}(\rho, D_0 \cup D_1 \cup D_2 \cup D_{\text{rem}}, \text{Threshold}_{\text{dataset}})$

procedure $\textsc{SelfDistill}(\sigma_{\text{old}}, A, \rho)$

  $D \leftarrow \textsc{GenerateDiverse}(\sigma, A)$

  $D_f \leftarrow \textsc{Filter}(\rho, D, \text{Threshold}_{\text{distill}})$

  $\sigma_{\text{new}} \leftarrow$ Fine-tune σ_{old} on D_f

  return σ_{new}, D_f

procedure $\textsc{GenerateDiverse}(\mu, A)$

  $D \leftarrow \emptyset$

  for a in A **do**

    for $p = +, -$ **do**

      $b \leftarrow$ {Top 10 beams from μ_{old} for a, p }

      $D_b \leftarrow \emptyset$

      for (a, p, c, r) in b **do**

        if $\forall c' \in D_b : \neg\textsc{MutualNLI}(c, c')$ **then**

          $D_b \leftarrow D_b \cup \{(a, p, c, r)\}$

      $D \leftarrow D \cup D_b$

  return D

procedure $\textsc{Filter}(\rho, D, \kappa)$ $D_f \leftarrow \emptyset$

  for (a, p, c, r) in D **do**

    if $\rho(a, p, c) > \kappa$ **then**

      $D_f \leftarrow D_f \cup \{(a, p, c, r)\}$

  return D_f

procedure $\textsc{MutualNLI}(c1, c2)$

  return $\text{Entail}(c1, c2) \wedge \text{Entail}(c2, c1)$

D Model Training Details

D.1 Critic Model

We fine-tune the critic model from DeBERTa-V3-Large (He et al., 2021) on the human critic gold data §2, attaching a 2-layer classificaton head with a hidden size of 512 and GELU (Hendrycks and Gimpel, 2016) as the activation function.

Since the moral variance of a given contextualization may be ambiguous or contested between different annotators, we filter the validation and test data to only the subset on which all annotators agree on a label.

We conduct a small search of hyperparameters using the dev set around the values suggested by West et al. (2022), and we find training with batch size of 4, learning rate of $5e{-}06$, and dropout of 0.1 to be effective to produce a discerning critic model. Because the dataset is heavily class-imbalanced with about 3:1 high-quality to low-quality contextualizations, we weight the loss of low-quality examples in training with the reciprocal of the imbalance. We employ early stopping to save the checkpoint with the lowest validation loss after 15000 training steps. We use the special tokens **[ACTION]** to denote the start of the action, and **[POS]** and **[NEG]** respectively to denote a contextualization with positive and negative moral variance. The critic model training takes approximately 3 hours to train on a single NVIDIA Titan XP GPU.

	Accuracy	**F1 Score**	**AUC PR Curve**
Val	0.88	0.93	0.98
Test	0.86	0.92	0.98

Table 5: Critic model metrics on evaluation sets from gold human-annotated data (§2)

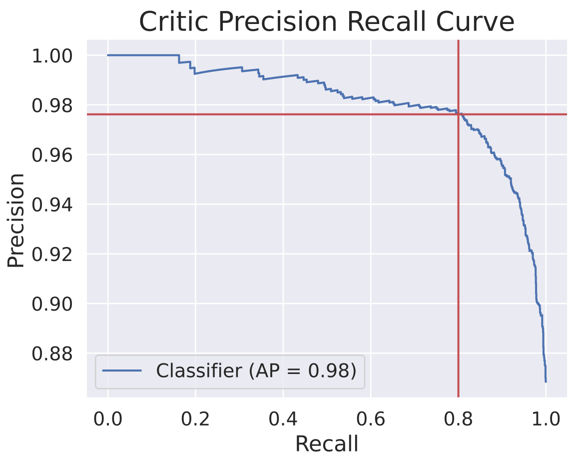


Figure 8: PR Curve on Validation Set. Red lines display recall of 0.8 with high precision used to select threshold

Using the precision-recall curve, we determine a critic threshold of 0.8 for distillation, which achieves high precision and recall on the validation set.

Original Situation:
${situation}

Update Scenario:
${update}

Explanation:
${explanation}

Update Scenario Questions

Q1. Does the update scenario convey meaning fluently and with good grammar, independent from the original situation?

- Yes It is fluent and well-formed.
- Somewhat It is somewhat fluent and well-formed, with some errors.
- No It is not fluent and well-formed, with many errors.

Q2. Does the update scenario make the original situation **more** morally acceptable?

- Yes, significantly It makes the original situation **significantly** more morally acceptable.
- Yes, slightly It makes the original situation **slightly** more morally acceptable.
- No It does not make the original situation more morally acceptable.

Explanation Questions

Q3. Does the explanation convey meaning fluently and with good grammar, independent from the original situation and update scenario?

- Yes It is fluent and well-formed.
- Somewhat It is somewhat fluent and well-formed, with some errors.
- No It is not fluent and well-formed, with many errors.

Q4. Does the explanation provide a valid rationale for how the update scenario makes the original situation **more** morally acceptable?

- Yes It provides a valid rationale with commonsense reasoning.
- Somewhat It provides a somewhat valid rationale, with potentially incomplete reasoning.
- No It does not provide a valid rationale.

Figure 7: The human evaluation template for evaluating or validating distilled generations from teacher and student models.

D.2 Student Model

The base model for distillation is Flan-T5-XL (Chung et al., 2022), with 3 billion parameters.

Student model prompts follow the format:

```
Action: {action}.
Modifier: more {ethical/unethical}.
```

And target generations follow this format:

```
Update: {context}. Explanation: {rationale}.
```

We fine-tune each student model for a fixed 3 epochs using a maximum target length of 512, per-device batch size of 8, and learning rate of $5e^{-5}$. We use the AdamW optimizer, keeping other hyperparameters at default. Each student model takes about 28 hours to fine-tune using 8 NVIDIA RTX A6000 GPUs.

E Data Analysis

E.1 Dataset Examples and Topics Analysis

We show examples from the δ-RULES-OF-THUMB in Table 6, and common topics of contexualizations in Table 7 and of rationales in Table 8.

E.2 Toxicity Analysis

Table 9 shows examples of δ-RULES-OF-THUMB with high toxicity rated by the Perspective API. Essentially, all data with higher toxicity scores are cases where the base action itself is inappropriate, and the distilled contexts with the desired moral variance do not contribute significantly to the toxicity of the total statement.

E.3 Cultural Bias Analysis

As it's extremely challenging to systematically quantify cultural biases with state-of-the-art tools such as hate speech detectors, we thus have probed the model qualitatively to gauge evidence of cultural biases inherent in the dataset/model. Table 10 Shows examples generated by the final distilled student model that potentially implies cultural biases. We can see that the model indeed comes back with different updates for the prompt "Not having freedom of speech in {country}" for different countries. For some countries such as Japan, the United Kingdom, and the United States, the generated weakener context is "in a workplace setting." Yet, for other countries such as China, India, Thailand, and Korea, or Russia, the model comes back with different results, which might imply these countries have varying levels of human rights concerns. This example confirms our intuition that the student model might encode Western-centric biases.

Attribute	Content
Action	Not wanting to be friends with my ex
Judgment	It's ok
Strengthen Context	My ex and I had a really bad breakup and they are now dating someone new
Strengthen Rationale	It would be really awkward and uncomfortable to be friends with my ex, especially since they are dating someone new
Weaken Context	My ex and I have kids together
Weaken Rationale	If we're not friends, it'll be harder to co-parent our kids and it'll be confusing for them
Action	Letting your mom borrow your car
Judgment	It's nice
Strengthen Context	Your mom is unable to afford a car and needs transportation for her job interview
Strengthen Rationale	It demonstrates kindness and generosity towards your mother
Weaken Context	Your mom is driving under the influence of drugs or alcohol
Weaken Rationale	It increases the risk of her driving while impaired, which could put other people in danger
Action	Flaking out on someone
Judgment	It's rude
Strengthen Context	The person has been acting in a way that is damaging to themselves or someone else
Strengthen Rationale	It is an act of self-preservation and ensuring that the person's safety is prioritized
Weaken Context	Flaking out a close friend who is going through a difficult time and you know that they need your support
Weaken Rationale	It can be seen as taking advantage of their vulnerability and disregarding their feelings
Action	Buying lottery tickets at the store
Judgment	It's common
Strengthen Context	The lottery tickets are bought in order to support a charitable cause
Strengthen Rationale	It supports a good cause and helps to raise money for a cause that can benefit those in need
Weaken Context	Buying lottery tickets at the store to cover up a theft
Weaken Rationale	It is enabling illegal activity

Table 6: Example data from δ-ROT.

Count	Topic
191	Pet
162	project
121	gift
124	supervisor
143	public
111	doctor
90	siblings
93	race
94	food
162	vulnerable
123	safety
109	decision
84	teacher
95	minor
90	ex
116	committed
86	friends
98	years
86	stealing
117	elderly
93	abusive
99	relationship
80	pandemic
85	overwhelmed
59	roommate
98	mental health
88	power
98	child
53	interview
78	neglecting
93	harm
59	expensive
50	gatherings
55	married
72	stranger
65	workplace
79	protect
71	advice
64	parents
51	formal
60	consistently

Table 7: Topics and their Appearance Counts for 10K Sampled Contextualizations from δ-ROT, supplementing Figure 3

Count	Topic
328	friends
258	students
213	children
199	taking advantage
121	family
144	commitment
124	partner
118	vulnerability
88	marriage
121	care
88	interview
134	protect
72	pet
87	virus
88	parent
69	animals
76	discrimination
71	elderly
91	respect
89	helping
157	mental health
88	informed
96	decision
77	minors
64	endangering
101	financial hardship
62	customer
75	violates trust
60	motivated
68	hard work
60	safety
68	self-preservation
80	autonomy
59	relax
55	growth
110	resources
49	pedestrians
57	overspending
105	support
60	colleagues
61	exploitation

Table 8: Common Topics and their Appearance Counts for 10K Sampled Rationales from δ-ROT, supplementing Figure 3

Action	Moral Variance	Content
Telling someone to f*ck off	Weakener	in a professional setting
Telling someone to f*ck off	Strengthener	Your friend has been being verbally abusive and manipulative to you for a long time
Engaging in bullshit	Strengthener	in order to protect a vulnerable person from harm
Touching your friend's butt	Weakener	while they are in the middle of a private conversation

Table 9: Example data with high toxicity rated by the Perspective API.

Country	Context
China	In a situation where the government is using its power to oppress citizens
India	In a country where people are expressing their opinions on controversial topics
Thailand	A country with a history of human rights abuses
Korea	A country with a history of human rights abuses
Russia	In a country with a history of human rights abuses
Japan	In a workplace setting
United Kingdom	In a workplace setting
United States	In a workplace setting

Table 10: Examples that potentially imply cultural biases generated by the final distilled student model, for the action - "Not having freedom of speech in {country}" and the moral variance - "weakener."