From Polarity to Intensity: Mining Morality from Semantic Space

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Abstract

Most works on computational morality focus on moral polarity recognition, i.e., distinguishing right from wrong. However, a discrete polarity label is not informative enough to reflect morality as it does not contain any degree or intensity information. Existing approaches to compute moral intensity are limited to word-level measurement and heavily rely on human labelling. In this paper, we propose MORALSCORE, a weakly-supervised framework that can automatically measure moral intensity from text. It only needs moral polarity labels, which are more robust and easier to acquire. Besides, the framework can capture latent moral information not only from words but also from sentence-level semantics which can provide a more comprehensive measurement. To evaluate the performance of our method, we introduce a set of evaluation metrics and conduct extensive experiments. Results show that our method achieves good performance on both automatic and human evaluations.

1 Introduction

Moral intensity is a degree of feeling that a person has about a behaviour (Barnett, 2001). As shown in Figure 1, although speeding on streets and killing a child are both immoral, the latter is more severe in most people’s perception. Understanding the above difference is an ability that humans have gradually developed in everyday life. It affects individuals’ ethical judgments and reflects the ideology of our society (Jones, 1991). As AI gets ever more involved in people’s lives, it has become increasingly important for machine to acquire this ability and behave ethically. Researchers have studied the problem from early rule-based methods to today’s deep learning-based paradigms (Yu et al., 2018; Hendrycks et al., 2021). It remains a fundamental but unsolved problem in computational morality (Moor, 2006).

Previous work in the NLP community often treats this problem as a supervised text classification task, i.e., judging the moral polarity for a text (Xie et al., 2020; Nahian et al., 2021). This way of modelling morality is inadequate because it oversimplifies morality into a Bernoulli distribution, i.e., being only moral or immoral. We model morality into a continuous distribution by introducing moral intensity to include degree information. Computing moral intensity is challenging in two aspects: 1) In supervised settings, unlike labelling moral polarity, building a large corpus with precise intensity values is time consuming and prone to subjectivity. 2) In unsupervised settings, there is no direct link between text and moral intensity. Even when moral polarity labels are available, building such link is nontrivial because the binary labels do not reflect any information about moral intensity.

To address these challenges, we propose MORALSCORE, a weakly-supervised framework that outputs a numerical value as the measurement of moral intensity for action-consequence pairs. The framework contains two parts. The first part is a semantic-aware moral detector, which measures moral intensity by detecting latent moral information from word to sentence level in semantic space. This incremental computing process can provide a comprehensive measurement of moral intensity for a text where both coarse-grained and fine-grained moral information can be captured. The second
2 Related Work

Computational morality has received increased attention recently, especially in the NLP community (Yu et al., 2018). There are several relevant datasets concerning different aspects of this topic (Hendrycks et al., 2021; Lourie et al., 2021a; Sap et al., 2020; Forbes et al., 2020a). The detection of moral polarity is a primary line of work, which is often modelled as a supervised classification task (Hendrycks et al., 2021; Nahian et al., 2021; Forbes et al., 2020b; Xie et al., 2020). Unlike the above, we focus on measuring moral intensity. It requires a numeric measurement rather than a discrete one, which is more expressive and informative. Araque et al. (2020) introduces MoralStrength to study word-level strength related to moral traits by crowdsourcing. Our work, in contrast, can measure moral intensity for sentences without massive manual effort and direct supervision.

Another line of work uses NLP tools to analyze morality in text, largely based on the Moral Foundations Dictionary (Graham et al., 2009). For example, it has been used in analyzing moral rhetoric in social media (Tshimula et al., 2021), moral sentiment in argumentation (Kobbe et al., 2020), and moral framing in political tweets (Reiter-Haas et al., 2021). These works demonstrate that moral properties are an important aspect of the semantics of words but have two limitations. First, their analysis dimension highly relies on the prior lexicon, which is untested for their domains. In our work, we do
not require a pre-defined domain dictionary. Second, the purely lexical analysis does not include sentence-level information. By contrast, we incrementally compute moral intensity using semantics from word to sentence level.

3 Methodology

3.1 Task Definition

In this study, we focus on measuring moral intensity based on actions and their consequences. Previous studies about components for judging moral intensity (Tsalikis et al., 2008; Dukerich et al., 2000) proved that the social consensus of acts and magnitude of consequences are significant and robust in moral decision-making processes, with limited support for the other components.

The task input includes two parts, an action and its consequence. The task requires a scalar score \( s \) to measure the overall moral intensity of the input. The higher the score is, the more moral the input is. For example, given \( \text{Joe is speeding on city streets} \) and \( \text{Joe has a car accident} \), we wish to get a low score (e.g., 0.4) that indicates a relatively strong intensity towards immorality.

3.2 Semantic-Aware Moral Detector

Figure 2 presents an overview of the moral detector. The detector can give a specific score as the measurement of moral intensity for an arbitrary text\(^2\). It contains two complementary scoring modules, which incrementally computes moral intensity from word to sentence level by detecting latent moral dimensions in semantic space.

3.2.1 Word-Level Self Scoring

Intuitively, words can convey the first impression of intensity level. For example, actions related to \textit{kill} or \textit{donate} usually have stronger moral intensity than those related to \textit{buy} or \textit{eat}. In this module, we aim to initialize intensity scores by characterizing word-level semantics from potential moral axes (i.e., a vector that represents a specific moral trait such as kindness) in the space of word vectors.

We believe that word embeddings contain not only semantic information but also moral properties of words. Inspired by SemAxis (An et al., 2018), we can measure a word’s bias between moral and immoral directions of a moral trait if a moral axis can be found in the vector space.

\(^2\)Arbitrary means we don’t need to know whether the text is an action or a consequence which are treated equally in this part.

Computing Moral Bias

Formally, given two sets of words \( S^+ \) and \( S^- \), which are synonymous and antonymous respectively to a specific word \( a \), the semantic axis \( v \) of \( a \) is defined as

\[
\mathbf{v}_a = \mathbf{v}^+ - \mathbf{v}^-
\]

where \( \mathbf{v}^+ \) and \( \mathbf{v}^- \) are the averaged word vectors\(^3\) for \( S^+ \) and \( S^- \). For each word in the input text, we can compute its contribution to the axis. Here, we use the cosine similarity to measure the contribution

\[
\mathbf{c}^a_w = \frac{\mathbf{vec}(w) \cdot \mathbf{v}_a}{\|\mathbf{vec}(w)\| \|\mathbf{v}_a\|}
\]

where \( \mathbf{c}^a_w \) is the contribution of the word \( w \) to the axis of \( a \) and \( \mathbf{vec}(w) \) is the word vector of \( w \). For example, the red line in the left part of Fig. 2 represents the positive contribution of \textit{speeding} to the axis of \textit{rude}.

To aggregate the overall contributions of words in text \( t \), we first represent \( t \) by the bag-of-words model. Then, we define the moral bias \( b \) of \( t \) on the axis of \( a \) as

\[
b^a_t = \frac{\sum_{w \in t} (n_w \mathbf{c}^a_w)}{\sum_{w \in t} n_w}
\]

where \( n_w \) is the number of occurrences of word \( w \) in the text. We expect that a text with distinct word-level semantics towards morality should have large positive biases on the axes of good moral traits (e.g., honesty) while large negative biases on the axes of bad moral traits (e.g., selfish).

Identifying Moral Axes

Moral axes are the subset of semantic axes. We identify moral axes from a dictionary of synonyms and antonyms (Fallows, 2020) using statistical significance and effect size. More specifically, we first split the full corpus into moral corpus \( D^+ \) and immoral corpus \( D^- \) according to the moral polarity of each instance. If the semantic axis of a word in the dictionary is a potential moral axis, the moral bias of the texts in \( D^+ \) should be significantly different compared with that in \( D^- \). We use a two-tail hypothesis test based around \( D^+ \) and \( D^- \) to find the axes with a statistical difference \((p <= 0.05)\) of moral bias. Having statistical significance only indicates that potential moral axes exist among semantic axes but cannot reflect the magnitude of differences, i.e., to what extent an axis would be a moral axis. We hope that final selected moral axes are the most representative.

\(^3\)We use G4080B.300d. in this module.
ones. Therefore, after finding a set of statistically significant moral axes $V = \{v_0, v_2, \ldots, v_d\}$, we filter $V$ to obtain a smaller set $V^K$ that contains the top $K$ axes with the highest Cohen’s d effect size (Cohen, 2013).

**Aggregating along Axes** The initial intensity score of text $t$ can be calculated by

$$s_{\text{ini}} = \exp \left( \sum_{v_a \in V^K} \text{Sign}(v_a) b^a_t \right) \quad (4)$$

where we sum up all the bias for each axis in $V^K$ according to the moral trait of the axis. The sign function outputs 1 if $v_a$ represents a good moral trait otherwise it outputs -1. The exponential function is to ensure the positive value of initial scores. A higher $s_{\text{ini}}$ means a higher word-level intensity towards morality.

### 3.2.2 Sentence-Level Interactive Scoring

The previous module only captures coarse-grained information at the word level without including the overall semantic meaning of a text. The lack of sentence-level semantics may lead to the inability to distinguish subtle moral differences. For example, both *kill a person* and *kill time* contain *kill* that has strong intensity. The latter is obviously more acceptable. In this module, we adjust the initial scores based on context information from sentence representations.

In addition, we argue that moral intensity can be measured more comprehensively through comparison. The intuition is that degree information emphasises fine-grained differences between samples which cannot be well measured solely based on a single sample in the self scoring stage. We propose an interactive comparison mechanism that measures moral differences between texts and blends word-level and sentence-level moral information.

**Grouping** Specifically, we first split the corpus into $N$ groups $G_1 G_2 \cdots G_N$ according to the equal-width intervals of initial scores. For each group, we assign a weight $r$ that represents the ratio of moral text in the group, which is calculated as

$$r = \frac{p^t}{1 - p^t} \quad (5)$$

where $p^t$ is the percentage of moral texts in the group and can be obtained by counting moral polarity labels. A group with a large $r$ indicates that the texts in it have distinct lexical semantics towards morality. In this way, the word-level moral information is integrated into the group weight$^5$, which is then interacted with sentence-level moral information as shown in Eq. (8).

**Sampling** Then, we create a candidate set $C = \{t_1^M \cdots t_M, t_2^M \cdots t_M, \ldots, t_N^M \cdots t_M\}$ for the input text by sampling from the groups $G_1 G_2 \cdots G_N$ where $M$ is the number of texts sampled from each group. Intuitively, when comparing the morality between two texts, it would be more reasonable to compare between semantically closer texts than unrelated ones because subtle differences are more likely to be captured in a similar context. Therefore, we add sampling weights for each instance in the corpus. Concretely, given a text $t^*$ that is to be compared and a sampling pool $t_1 \cdots t_K$ with the size of $K$, the sampling weight $w_i$ for $t_i$ in the pool can be derived as

$$w_i = \text{Softmax}(\mathbf{w})_i$$

where $\mathbf{w}$ is a list of similarity scores, $\mathbf{H}_{t^*}$ and $\mathbf{H}_{t_i}$ are the sentence representations of $t^*$ and $t_i$. Here, we use cosine similarity and obtain representations by mean pooling of token embeddings$^6$.

**Comparing** Finally, we update the initial score by aggregating the rewards from comparisons between the input text and each instance in the candidate set. Formally, the updated score of text $t^*$ is calculated as

$$s_{\text{cmp}} = \frac{\sum_{i=1}^M \sum_{j=1}^N g^i_j}{|C|} \quad (7)$$

where $g^i_j$ is the reward from the comparison between $t^*$ and $t_i^j$ in candidate set $C$, $|C|$ is the total number of sampled instances, $N$ and $M$ are the number of groups and sampled texts for each group in $C$ respectively. The reward is defined as

$$g^i_j = r_i \times o_{ij} \quad (8)$$

where $r_i$ is the weight of group $G_i$ and $o_{ij}$ is the moral difference between $t^*$ and $t_i^j$. To measure moral difference, we leverage moral knowledge encoded in pre-trained language models. Specifically, $^5$Another way of integrating word-level moral information here is using $s_{\text{ini}}$ directly. But we find that it may lead to unbalanced performance (See Section 4.5).

$^6$https://huggingface.co/nreimers/MiniLM-L6-H384-uncased
we use two variants of methods. A straightforward way is to explicitly calculate the probability that one text is more ethical than another, i.e., probability-based measurement. Here we adopt Norms (Lourie et al., 2021b) to get this probability. Norms is a Roberta-based model (Liu et al., 2019) fine-tuned with the task of predicting which is more ethical for given two texts. Formally, the difference $o_{ij}$ can be calculated as

$$o_{ij} = \frac{p_{ij}^+}{1 - p_{ij}^-}$$

(9)

where $p_{ij}^+$ is the probability of text $t^*$ being judged as moral when comparing with sampled text $t_j^*$. Another way is to implicitly measure the distance between two texts in the moral space, i.e., distance-based measurement. A short distance means they share a similar moral property. To compute the distance, we first need to define the position of a text in the space. Following Schramowski et al. (2021), we select the most positive and negative associated verbs identified in Jentzsch et al. (2019a) and add some neutral verbs. We create a list of phrases by adding context information for each verb, which are then formulated as sentences based on templates\(^7\). For each sentence, we obtain its sentence representation $s \in \mathbb{R}^d$ from mean pooling over tokens’ contextualized embeddings\(^8\). Then, we perform PCA on all sentence representations $S \in \mathbb{R}^{N \times d}$ where $N$ is the number of sentences. In this way, we can get principal axes $A \in \mathbb{R}^{K \times d}$ in sentence embedding space, representing the top $K$ directions of maximum variance in $S$. We regard the direction with maximum variance as the moral dimension $m \in \mathbb{R}^d$ that can recognize the moral difference in space. The position of text $t$ in the moral space is defined as the projection to $m$

$$\text{Pos}(t) = H_t \cdot m$$

(10)

where $H_t$ is the mean of contextualized token embeddings in $t$. Then, the $o_{ij}$ can be computed as

$$o_{ij} = \text{Exp}(d_{ij})$$

$$d_{ij} = \text{Pos}(t^*) - \text{Pos}(t_j^*)$$

(11)

where $d_{ij}$ is the distance between $t^*$ and $t_j^*$ in the moral space.

When $o_{ij}$ is closer to 0, it means that $t^*$ is less moral compared with $t_j^*$. A large reward can be obtained only when being considered far more moral and comparing with a moral text sampled from the group that has distinct lexical moral properties, i.e., both $o_{ij}$ and $r_i$ are large. In this way, sentence and word-level semantics can work together on computing the reward size in each comparison.

### 3.3 Score Combiner

The combiner is a simple function to combine intensity scores of an act and its consequence. Proper weights for moral intensity measurement should be at least capable of judging moral polarity. In other words, given a classifier used for judging moral polarity of texts, we can adopt its weights to the moral intensity measurement task. Specifically, we take the moral intensity scores of the act and consequence (i.e., $s_{act}^{cmp}$ and $s_{comp}^{consq}$ obtained from the moral detector) as features. We then use them to fit a logistic regression model on the moral classification task and get the weights from the model’s coefficients. The overall intensity score can be calculated as

$$s = \alpha \times s_{act}^{cmp} + \beta \times s_{comp}^{consq}$$

(12)

where $\alpha$ and $\beta$ are the model’s coefficients.

### 4 Experiments

#### 4.1 Dataset

We adopt Moral Stories (Emelin et al., 2021), a structured dataset of 12k short stories for social reasoning. Each story has moral and immoral versions where the actions and consequences are different. We focus on the action and consequence part of the dataset in this paper. Therefore, the total number of action-consequence pairs is 24k\(^9\).

#### 4.2 Evaluation Metrics

We hope that predicted moral intensity scores correlate to human perception while retaining the ability to distinguish moral polarity. We use automatic evaluations (i.e., KS and IV values) to detect if moral polarity can be reflected from intensity scores (Massey Jr, 1951; Koláček and Rezác, 2010). The details of these metrics are shown in Appendix A.
Table 1: Experiment results of moral intensity measurement in terms of Kolmogorov-Smirnov value (KS), Information Value (IV) and averaged Spearman’s Footrule ($F$) distance. The subscript of IV is the number of bins. Prob. and Dist. means using probability-based and distance-based measurement respectively. $F_m$ and $F_{im}$ represent the $F$ for moral and immoral texts respectively. w/o Sel., w/o Int. and w/o Wei. means ablating the self scoring, interactive scoring and weighting stage respectively. w/o Sim. means sampling without considering semantic similarity. $N$ is the sampling size of the probability-based variant. Entries with - mean the metric is not comparable for the model. Note that higher is better for KS, IV$_5$ and IV$_{10}$ while lower is better for $F$, $F_m$ and $F_{im}$.

### D. Automatic evaluation can only reflect the models’ predictiveness of moral polarity. It may not correlate with human’s perception of moral intensity. We conduct human evaluations to measure the correlation between human judgement and models’ prediction.

Specifically, we first randomly sample 100 texts and ask five annotators to rank them based on their moral intensity. The obtained ranking is denoted by $r_{true}$. Then we get the predicted ranking from their intensity scores given by models, denoted by $r_{pred}$. To measure the similarity between the rankings, we use Spearman’s Footrule Distance ($F$), which is the sum of the absolute values of the difference between two rankings (Diaconis and Graham, 1977). We further normalize it by dividing the number of elements in the ranking. Formally, it is defined as

$$F(r_1, r_2) = \frac{\sum_i |r_1(i) - r_2(i)|}{N}$$

(13)

where $i$ is the element of a ranking, $r_1(i)$ and $r_2(i)$ is the position of the element $i$ in $r_1$ and $r_2$ respectively, $N$ is the total number of elements.

To reduce the subjectivity of the annotators’ perception of moral intensity, we select the top 3 similar human rankings with respect to their averaged Footrule distance ($F$). Formally, given a set of rankings $R = \{r_1, r_2, \ldots, r_N\}$, the $F$ of the ranking $r_1$ in $R$ is calculated as

$$F(r_1) = \frac{1}{N - 1} \sum_{j \neq i} F(r_1, r_j)$$

(14)

We use the mean of $F$ of the selected rankings as human’s performance, which can be viewed as the upper bound for this metric. The predicted ranking $r_{pred}$ is compared with each selected ranking. We used the $F$ as the measurement of the correlation between the model’s prediction and human’s judgement.

Note that we do not pursue a higher performance on the automatic evaluations but only require the performance on them can reach a certain level (> 0.5). The reasons are: 1) Exceeding a particular value can indicate a relatively clear line between moral and immoral instances. 2) It is normal that the intensity scores of relatively neutral or ambiguous situations distribute closely.

### 4.3 Baseline Models

To our knowledge, there is no related work that can be directly used to compare with our framework. We implement several baseline models based on the previous works. Note that the action and consequence are treated equally in the baselines without considering their weights.
Lexi. To compare with the method using domain lexical features, we adopt the logistic regression model proposed in MoralStrenght (Araque et al., 2020) to estimate probabilities that the text is relevant to virtues or vices of the prior moral traits (Haidt and Joseph, 2004; Haidt and Graham, 2007). The model is trained with lexical features based on a moral lexicon, including unigrams, count and word frequency. We sum up all the probabilities towards virtues for each moral trait as the moral intensity score.

MCM To compare with the method using latent moral information, we use Moral Choice Machine, a QA system to calculate moral scores (Jentzsch et al., 2019b). Concretely, it first formulates the input text as a question. In our implementation, the question template is Is it ok if [placeholder]? where the placeholder can be replaced by input texts. Then, the question and the answers (i.e., Yes, it is. / No, it isn’t.) are encoded by a Universal Sentence Encoder. Finally, the score is given by the difference of the similarities between the question and the opposite answers.

Sup. To compare with supervised models, we first fine-tune a Bert-base-uncased model on the 5-point scale of social judgment labels (i.e., {1: very bad, 2: bad, 3: neutral, 4: good, 5: very good}) in Social Chemistry 101 (Forbes et al., 2020b). Then, we use the model to predict the texts in the test set of moral intensity measurement task. Each text can get a probability distribution over 5-point. We take a weighted add of the points with the top 2 highest probabilities as the intensity score. More details are shown in Appendix E.

4.4 Result Analysis

We present the experiment results in Table 1. We do not provide the KS and IV scores for the baselines and w/o Wei. They do not explicitly use the moral polarity label, making them not comparable to those who use it.

In general, both variants of our framework outperform the baselines and have a gap with human performance in terms of the overall rank distance ($\overline{F}$). They also significantly exceed the minimal requirement of KS and IV, indicating the effectiveness of our method for both correlating with human’s perception of moral intensity and retaining moral polarity. We provide the examples of model judgement in Appendix G. For baseline models, their performance is comparable with others on $\overline{F}_{m}$ and $\overline{F}_{im}$ but obviously bad on $\overline{F}$. This indicates that they can distinguish different levels of intensity but may confuse the relative positions of moral and immoral texts.

Besides, the distance-based variant achieves better performance than the probability-based one on $\overline{F}$. We further separately study the performance on moral and immoral texts. There are two interesting findings:

1. The distance-based variant has a smaller variance on moral and immoral texts, showing a balanced performance. Compared with the probability-based variant, it consistently performs better on moral text but worse on immoral texts. This may be due to a different moral knowledge probing method for the backbone models used in the two variants. In the probability-based variant, the model we use would be biased by imbalanced corpus during fine-tuning (i.e., train with more immoral examples), thereby performing better on immoral texts than moral ones. In the distance-based variant, we retrieve moral values from embedding space rather than directly using model outputs. This may reduce the impact of bias induced from corpora or the training process.

2. The performance of models on moral texts ($\overline{F}_{m}$) is always below that on immoral texts, indicating that measuring the intensity for moral texts is more difficult than for immoral texts. A similar trend is shown in human performance, which shows a relative inconsistency in our perception of what is more moral. Surprisingly, the baseline (Lexi.) that uses lexical knowledge based on the moral foundation theory (Haidt and Joseph, 2004) performs best on this metric. In our ablation experiments, a drop in performance on $\overline{F}_{m}$ can be seen for both variants without initializing with lexical information (w/o Sel.), which further demonstrates the importance of lexical knowledge for measuring the intensity on moral texts.

4.5 Ablation Study

To further evaluate the effects of different components in our framework, we conduct ablation studies on both of our variants. Specifically, we test the following ablations: (1) without self scoring stage (w/o Sel.); (2) without interactive scoring

https://github.com/oaraque/moral-foundations
https://github.com/ml-research/moral-choice-machine
Table 2: Bad Case Examples. For each instance in our test set, we compute the averaged difference of its position in the predicted ranking and human rankings. We study the instances with large difference and presented the typical cases above. Prob. and Dist. represent the two variants of our framework.

| Moral | Immoral |
|-------|---------|
| Jake has unprotected sex but takes PrEP and gets tested regularly. Jake stays safe and keeps partners informed and has fun. Casey takes the dog to an animal shelter. The crowded shelter puts the dog to sleep after no one adopts it. | Oliver finds his parking spot and sprints all the way to his door. Oliver gets home quickly and cracks open a beer. Jill explains her reasons for wanting to break up to Yolanda over the phone. Yolanda is sad but understands. Kim orders pizza. The kids don’t want the healthy food Kim makes next time. Mack surprises his brother with a visit and stays for a month. His brother ends up becoming tired of Mack being there so long and tells Mack he has to leave immediately. Mary leaves her kids with her parents in order to be free to pursue her relationship. Mary’s kids grow distant as time passes. Mr. Green gives Harry a scholarship even though his grades aren’t up to par. Harry fails all his classes and is not eligible to play football anyway. Mary leaves her kids with her parents in order to be free to pursue her relationship. Mary’s kids grow distant as time passes. |
Clauses or phrases without obvious moral polarity have moral polarity after combination. For example, both surprise his brother with a visit and stays for a month are relatively neutral but tend to be immoral when being combined. ii. Clauses or phrases with clear moral polarity experience polarity shift after combination. For example, gives Harry a scholarship would be judged immoral if the premise is his grade aren’t up to par. Therefore, it is still challenging for models to handle complex moral situations.

Our framework largely depends on latent moral information from language representation. It may inherit some potential biases (e.g., gender) that exist in the representation. Moreover, moral judgments can differ across time, space, and culture (Talat et al., 2021), which is beyond the scope of this paper but is a valuable direction in future work.

6 Conclusion

The computational study of moral intensity remains a challenging yet less explored topic in the field of NLP. We present MoralScore, which can measure moral intensity for text. So far, most works have tried to directly teach models morality through fully supervised learning. Our work demonstrates that mining linguistically moral information from text is also a feasible approach. Besides, injecting the knowledge from moral frameworks or theories would be beneficial, especially when people’s perception of morality is under divergence. We hope our findings can inspire future work on this topic.

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A  Experiment Settings

To evaluate our proposed framework, we split 30% data as the test set and the rest as train set. In the moral detector, we set the number of identified moral axis $K = 9$, the group number $N = 7$ and the number of sampled text for each group $M = 10$.

B  Identified Moral Axes

We present the moral axes that we use in the following table.

| Action       | Identified Moral Axes |
|--------------|-----------------------|
|             | regardless*, needless*, thoughtful, judicious, atrocious*, inadvertent*, discreet, humanize, bloodthirsty* |
| Consequence  | felicitous, reconcilable, agreeable, fortunate, righteous, considerate, fair, abusive* beneficent |

Table 4: Identified moral axes. The axes with * are immoral axes while the axes without * are moral axes.

C  Selected Verbs and Templates

| Selected Verb | Context |
|---------------|---------|
| harm          | people, animals, friends |
| kill          | people, a killer, time |
| greet         | my enemy, my guests, my friend |
| love          | myself, my colleagues, my pet, my work, my parents |
| eat           | healthy, vegetables, dirt, meat |
| steal         | money, other's work, time |
| travel        | to North Korea, to Germany, to United States, to Africa |
| waste         | money, energy, time |
| help          | a thief, old people, coworkers |
| become        | evil, a better person, a good parent |
| be            | an evil person, a bad person, an asshole, a good person |
| have          | a life partner, fan, savings, a gun |
| lie           | to a friend, to my boyfriend, to my girlfriend, to my husband, to my wife |
| go            | to church, to work, to cinema |
| marry         | my boyfriend, my girlfriend |
| divorce       | my husband, my wife |
| trust         | a machine, my friends, humans, strangers |
| borrow        | a book, money |
| drink         | beer, water |

Table 5: Selected verbs and their contexts.

| Templates                                      |
|------------------------------------------------|
| Should I ____?                                |
| Is it okay to ____?                           |
| Is it allowed to ____?                        |
| Is it recommended to ____?                    |
| Is it a good behaviour to ____?               |

Table 6: Templates that are used to transform phrases into sentences.

D  Automatic Evaluation Metrics

Kolmogorov-Smirnov Test We adopt Kolmogorov-Smirnov (KS) Test (Massey Jr, 1951), a statistical test that reports the maximum difference between the two cumulative distributions, which can be computed as

$$KS = \max |F_m(x) - F_{im}(x)|$$

where $F_m$ and $F_{im}$ are the cumulative distributions of moral and immoral texts along the intensity score $x$.

Information Value KS value only measures the largest difference of score distributions from different moral polarities without considering the predictive power for each intervals in one score distribution. To evaluate the fine-grained predictive power, we adopt Information Value (Koláček and Rezác, 2010), which is calculated as

$$IV = \sum_i \left( \frac{N_{mor. \ in \ i}}{N_{total \ mor.}} - \frac{N_{imm. \ in \ i}}{N_{total \ imm.}} \right) \cdot woe_i$$

$$woe_i = \ln \left( \frac{N_{mor. \ in \ i}}{N_{total \ mor.}} \right) / \ln \left( \frac{N_{imm. \ in \ i}}{N_{total \ imm.}} \right)$$

where $i$ represents a bin, $N_{mor. \ in \ i}$ and $N_{imm. \ in \ i}$ are the number of moral and immoral instances in the bin $i$, $N_{total \ mor.}$ and $N_{total \ imm.}$ are the number of moral and immoral instances in all bins.

E  Further Explanation of Sup. Baseline

Specifically, we first split the Social Chemistry 101 dataset into train set (70%) and validation set (30%) and fine-tune on the five-class moral classification task (i.e., very bad, bad, neutral, good, very good). We train with the batch size of 128 and the learning rate of 5e-5 for 10 epochs. We select the checkpoint with the best F1 score on validation set. We use the selected model to predict the texts in the test set of moral intensity measurement task. In this way, each text will get a probability distribution of 5-point scale of morality, denoted by $p_i$ where $i \in [1, 5]$ is the index of a moral label (i.e., {1: very bad, 2: bad, 3: neutral, 4: good, 5: very good}). Then, we get the moral intensity of the text by

$$score = \sum_{i \in I} i \cdot p_i$$

where $I$ is the indices of labels with top K highest probabilities. As shown in Figure 3, the model

\footnote{https://github.com/mbforbes/social-chemistry-101}

\footnote{We use the Bert model here (https://huggingface.co/bert-base-uncased).}
have clearer judgement on the groups with bigger differences (e.g. very bad v.s. very good) but is often uncertain between similar groups (e.g., very good v.s. good or good v.s. neutral). Therefore, we set $K = 2$ here to fuse the model’s judgment of the similar groups.

### F Inter-annotator Agreement

We use Kendall’s $\tau$ coefficient (Kruskal, 1958) to compute inter-annotator agreement. The result is shown below.

| annotator | $\tau$ | $p$ value |
|-----------|--------|-----------|
| (1, 2)    | 0.58   | 8.78e-18  |
| (1, 3)    | 0.62   | 3.13e-20  |
| (2, 3)    | 0.72   | 1.19e-26  |

Table 7: Inter-annotator Agreement.

The $\tau$ values show substantial agreement between annotators ($\tau > 0.5$ with $p < 0.01$).

### G MORALCORE’s Perception of Moral Intensity

We provide some examples to show the judgement given by our framework. Specifically, we first normalize intensity scores into $[-5, 5]$ and group them with the interval of 1. The buckets are $[-5, -4), [-4, 3), ..., (4, 5]$. Then, we sample three instances for each bucket, which are shown in the Table 8. The difference of moral intensity is more distinct on the immoral side but relatively blurred on the moral side, which is similar to human performance.
| Level | Examples |
|-------|----------|
| $[-5, -4]$ | ① Nadia believes Rhonda cannot do the job properly because of her autism and tries to get Rhonda fired. Nadia is reprimanded by HR and the efficiency of her team is greatly disrupted.  
② John stabs his dog with a knife. John’s dog bleeds to death.  
③ Tim gives his mother a high dose of poison to drink. Tim’s mother dies from the poison, and he is arrested.  
④ Jim makes a racist joke at a housewarming party. Jim’s neighbors are appalled and avoid Jim from then on.  
⑤ Wesley hits the dog every time it scratches itself. Wesley’s dog becomes terrified of Wesley and won’t come near him anymore. |
| $[-4, -3]$ | ① James knocks out a window in his neighbor’s house and takes their TV. James’ neighbor calls the police, but they don’t take much action on the case.  
② Jim makes a racist joke at a housewarming party. Jim’s neighbors are appalled and avoid Jim from then on.  
③ Wesley hits the dog every time it scratches itself. Wesley’s dog becomes terrified of Wesley and won’t come near him anymore.  
④ Jason offers to pay for the vase because he’s the one broke it. Jason’s girlfriend respects Jason’s honesty.  
⑤ Ray reports his friend’s website to the FBI so that people stop stealing content. Ray feels like he’s helping content creators and is happy that people have to pay for movies now. |
| $[-3, -2]$ | ① Brandon throws a party at his apartment without asking his roommate first. Brandon’s roommate feels disrespected and can’t study for an important test.  
② Jerry leaves the garbage behind as he rushes to his car, assuming that his wife will take care of it. Jerry’s wife doesn’t take the garbage out in time and it starts attracting flies as they wait for the next garbage day.  
③ Gary drinks his beer and eats his pizza, but leaves the cans all over the room along with the empty pizza box laying out. Greg thinks Gary makes their apartment unsanitary and begins looking for somewhere else to live.  
④ Nick considers each applicant, both men and woman, and finally settles on a highly qualified woman. The company does well because the woman Nick chose is an excellent programmer.  
⑤ Sandra gives her employees a typical amount of work. Sandra’s employees are able to do a good job on the work given to them. |
| $[-2, -1]$ | ① Dean tells his friend what happened while in the middle of class. The class ends up getting interrupted by Dean talking to his friend.  
② Jordan goes to the soccer game and forgets the dishes afterward. Jordan gets in trouble for not doing the dishes and feels like a failure.  
③ Justine tells Cindy that she is not comfortable lending out her credit card to anyone, even a sister. Cindy understands Justine’s reason, and she looks elsewhere for the money.  
④ Evan gets to the interview ten minutes before it was scheduled. The person doing the interview is impressed with Evan, and he gets the job.  
⑤ Sam limits himself to three drinks. Sam has a good time at his brother’s wedding. |
| $[-1, 0]$ | ① Cindy walks all the way to Jimmy’s house and knocks at the door. It turns out Jimmy’s not home and Cindy walked all that way for nothing.  
② Violet complains about the prices to her friends quietly. Violet’s friends advise her to shop at a cheaper store.  
③ Connie vents her feelings in a private blog post that she sends to Dennis. After reading the post, Denis learns to stop being so pushy about his political beliefs.  
④ Phil tips the waiter for his service. Jenny is impressed with her dates generosity.  
⑤ Jason offers to pay for the vase because he’s the one broke it. Jason’s girlfriend respects Jason’s honesty.  
⑥ Rob gives his employee paid time off for the entire week. Rob’s employee feels grateful and wants to work even harder when they come back.  
⑦ Steve drives all the way to Scott’s house to give him the invitation. Scott thanks Steve for the invitation and later enjoys the party. |

Table 8: Examples with different levels of moral intensity given by MORALSCORE