

# Towards Explaining Subjective Ground of Individuals on Social Media

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## Abstract

Large-scale language models have been reducing the gap between machines and humans in understanding the real world, yet understanding an individual’s theory of mind and behavior from text is far from being resolved.

This research proposes a neural model—Subjective Ground Attention—that learns subjective grounds of individuals and accounts for their judgments on situations of others posted on social media. Using simple attention modules as well as taking one’s previous activities into consideration, we empirically show that our model provides human-readable explanations of an individual’s subjective preference in judging social situations. We further qualitatively evaluate the explanations generated by the model and claim that our model learns an individual’s subjective orientation towards abstract moral concepts.

## 1 Introduction

For the last few years, large-scale language models have shown substantial performance gains in many different sub-fields of natural language processing (Liu et al., 2019; Raffel et al., 2020). Researchers have hypothesized that such language models contain knowledge of linguistic characteristics, logical inference, and real world events in their parameters, and this knowledge can be fine-tuned and adapted to downstream tasks (Wang et al., 2019). The recent success of commonsense reasoning, for instance, shows that language model parameters can be used as a knowledge base while they comprehensively learn commonsense patterns (Hwang et al., 2021).

Although deeper and larger language models have led machines to better comprehend how the real world works, understanding an individual’s perspective and behavior from text is yet far from being resolved. Humans perceive daily situations and events differently, and employ certain biases

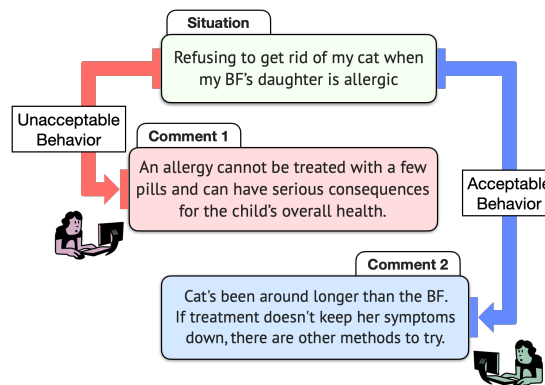


Figure 1: An example of a reddit post and its comments crawled from r/AmITheAsshole. The author describes a situation of not giving up on the pet over the health of significant other’s daughter. The author’s behavior is unacceptable to the first redditor (red arrow), while the second redditor (blue arrow) has an opposite view.

(Kahneman, 2011) and social expectations (Hilton, 1990) when they evaluate the given event and social behavior of others (Miller, 2019). An individual’s process of attributing, evaluating, and explaining an event has been widely investigated by cognitive and social psychologists for the past few decades (McClure, 2002; Hilton, 2017), yet its application to neural language models is outside the mainstream natural language processing research.

This paper proposes a neural model, Subjective Ground Attention, that learns cognitive models of individuals and explains their subjective judgments on situations that are posted on social media. We analyze a Reddit community, r/AmITheAsshole, where users submit posts asking whether their behaviors are justifiable, and other users leave comments with their judgments. Figure 1 shows an example of a reddit post where an author describes a situation, and different redditors provide their subjective judgment through comments.

The research hypothesis is that people comprehend and account for others’ situations based on their subjective ground, a maxim that plays a cen-

tral role in human moral judgments (Neuhouser et al., 1990), which can be represented from their previous activities. To investigate this hypothesis, we formulate a task to predict the redditors’ judgment given diverse situations. Each redditor is represented by their subjective ground which is estimated from their previous comments. Using clustering methods, the model selects a set of the most relevant subjective ground to a given situation. The model then learns attention weights among subjective ground comments to predict the redditor’s moral judgments. Through learned attention weights, we present human-readable subjective ground and how they contribute to the model’s prediction about the judgments.

From empirical results, we suggest that our proposed model provides explanations for the redditors’ subjective judgments on diverse social situations and contributes to downstream task performance in a statistically significant way. We additionally compute the consistency score of attention weights with respect to the model’s final prediction, and show that the model efficiently uses attended subjective ground. From qualitative analysis results, we further claim that our model not only learns an individual’s subjective preference on real world situations (e.g. reporting my best friend for cheating), but also infers an individual’s perspective on more abstract concepts of competing moral values (e.g. fairness is more important than a friendship).

**Key Contributions:** To the best of our knowledge, this is the first attempt to estimate subjective ground of individuals, using it to explain their activities on social media. With better representation of human cognitive models and real world situations, we expect machines to perform more meaningful and accurate inference. This would ultimately help artificial intelligence agents by enabling maximal personalization; not only will it remember an individual’s previous history and preference, it will empathize with one’s state and situation in a human-understandable way.

## 2 Data Preparation

We analyze daily situations and individuals’ subjective judgments on them posted on a Reddit community, r/AmITheAsshole. Users submit posts describing their situations and ask whether or not their behaviors are acceptable. One of the advantages of using this data domain is that most of the

Modified Social Chemistry 101 ( $\mathcal{D}$ )	
# of total instances	14,391
# of unique situations	9,663
Max / Min # of instances per redditor	965 / 298
# Acceptable / Unacceptable labels	9,817 / 4,574
Crawled r/AmITheAsshole ( $\mathcal{D}^+$ )	
# of total instances	66,603
# of unique situations	52,075
Max / Min # of instances per redditor	9,711 / 513
# Acceptable / Unacceptable labels	42,961 / 23,642

Table 1: Statistics of the two datasets. Both datasets take the most active 30 redditors into consideration, keeping the instances that contain coded judgments in the comments.

situations are generic (e.g. getting annoyed at my roommate) rather than related to specific world events (e.g. new climate change policies in U.S.), thus the models benefit from implicit knowledge in language model parameters to better understand the situation.

### 2.1 Social Chemistry 101 Dataset

Forbes et al. (2020) annotated moral rules-of-thumb (RoT) that can be used in judging whether or not the input situations are acceptable. The authors released Social Chemistry 101 dataset, which contains around 30k situations posted on r/AmITheAsshole. Consider the following situation and its rules-of-thumb as an example:

**Situation:** Asking someone at the gym to stop talking to me.

**RoT 1:** It is okay to not want to randomly make new friends.

**RoT 2:** It is expected that you are kind when others are extroverted and try to speak to you.

We make use of moral rule-of-thumb annotations as a tool for explaining an individual’s subjectivity. Observing the number of annotated rules-of-thumb is small for many instances and most of these instances have rules-of-thumb supporting only one side of moral judgment, we manually extend rules-of-thumb. Each rule-of-thumb annotation in Social Chemistry 101 consists of a judgment (e.g. It is okay) and an action (e.g. not wanting to randomly make new friends). We extend the rules-of-thumb for each situation by replacing judgment words (e.g. It is okay  $\rightarrow$  It is not okay) while keeping the action description. We prioritize replacing judgment words with their opposite meaning, which is crucial to ensure obtaining both sides of rules-of-thumb. To efficiently train the model, we set a fixed number, 5, as the number of rules-of-thumb for all situations.

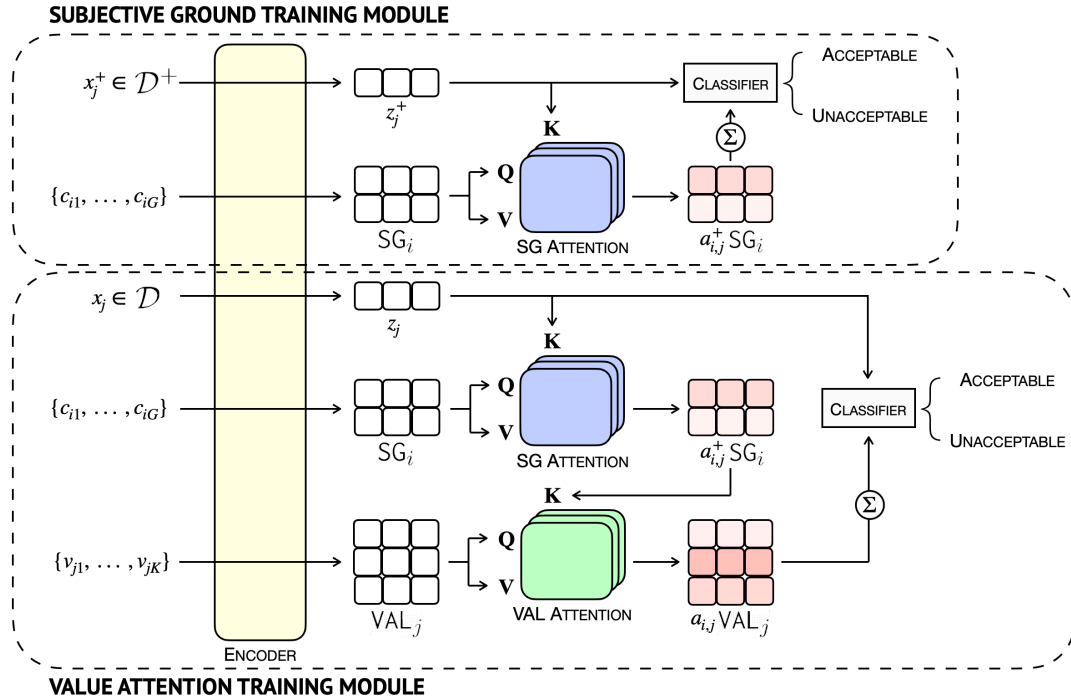


Figure 2: Training process of our proposed model.  $x$  is input situations,  $c$  is subjective ground comments, and  $v$  is rule-of-thumb candidates. After the subjective ground module has been trained on  $\mathcal{D}^+$ , the parameters of the encoder and the subjective ground attention layers are shared in value attention training.

A small number of training instances prevent the model from generalization. We thus identify redditors who are actively involved in r/AmITheAsshole; we focus on the 30 redditors who have commented the most on the posts in the Social Chemistry 101 dataset.

## 2.2 Crawling from r/AmITheAsshole

In this work, we estimate an individual’s subjective ground using their previous activities. The redditor’s previous activities are defined as the comments they have left on r/AmITheAsshole; comments on other subreddits are mostly irrelevant to moral judgments. We crawl active redditors’ comments<sup>1</sup> and denote the intersection of crawled data and Social Chemistry 101 as  $\mathcal{D}$ . All other instances of the crawled data are denoted as  $\mathcal{D}^+$ . Note that the instances in  $\mathcal{D}$  have annotated rules-of-thumb while  $\mathcal{D}^+$  doesn’t.

## 2.3 Preprocess Comments and Obtain Moral Judgments

Rather than predicting the authorship of the comments, this work solely focuses on analyzing the

<sup>1</sup>We mainly used Pushshift Reddit API (<https://github.com/pushshift/api>) and Python Reddit API Wrapper (<https://praw.readthedocs.io/>).

moral judgment. This is to prevent the model from picking up shallow features, such as a redditor’s linguistic styles, without focusing on learning their subjectivity.

We preprocess the redditors’ comments and obtain their moral judgments on input situations. In the r/AmITheAsshole community, redditors provide their judgments on the situation with predefined codes; YTA (You’re The Asshole), NTA (Not The A-hole), ESH (Everyone Sucks Here), NAH (No A-holes Here), and INFO (Not Enough Info).<sup>2</sup> We identify these code words from the comments and mark them as the redditor’s judgments on the situation. We group NTA and NAH as ‘acceptable’, and YTA and ESH as ‘unacceptable’. Instances with the code INFO are discarded, as there is no moral subjectivity included in them. Detailed statistics of the two datasets are described in Table 1.

## 3 Model

In this work, we develop neural models with two main components: subjective ground training module and value attention training module. This is followed by a classifier to predict the redditor’s moral judgments. Figure 2 illustrates the model

<sup>2</sup>Abbreviation for the moral judgments is described in <https://www.reddit.com/r/AmITheAsshole/>

Subjective Ground Comments	
Redditor 1	<ul style="list-style-type: none"> <li>• Maybe a visit from an SPCA or animal <b>control</b> officer will press the importance of adequate <b>care</b> into their minds.</li> <li>• Your <b>mother</b> needs to remember that older cats don't take <b>care</b> of themselves like younger cats do.</li> <li>• As much as I <b>love</b> animals, and 99.9% of ours have been <b>rescues</b>, you have legitimate reasons for wanting a particular breed.</li> <li>• You do live <b>together</b>, and he would have to <b>share</b> space with the new dog.</li> <li>• But completely and totally uprooting her and moving her to a new <b>family</b> is too much.</li> <li>• You are absolutely within your <b>rights</b> to prevent your cousin from seeing the dog.</li> </ul>
Redditor 2	<ul style="list-style-type: none"> <li>• In my town, a young girl was <b>killed</b> in our town when she was mauled by a <b>family</b> members pet, no one could get the dog off of her, the grandmother was <b>stabbing</b> the dog and screaming, and the <b>police</b> had to shoot and <b>kill</b> the dog to stop the <b>attack</b>.</li> <li>• Tell them <b>family</b> it is to <b>control</b> their new begging behavior, and stop giving people the chance to <b>feed</b> them because your vet specifically told you not to allow people <b>food</b>.</li> <li>• My SIL was <b>attacked</b> and has bad facial scars from a <b>trusted family</b> pet, my <b>childhood</b> best friend's 2 year old was attacked by a friend's dog, and is absolutely terrified by them now.</li> <li>• You have to <b>protect</b> your <b>child</b></li> <li>• I bet his dream dog listens to <b>commands</b> and is <b>loyal</b> and <b>obedient</b>.</li> <li>• She thinks the pets at home would be <b>betrayed</b> by you two getting one <b>together</b>?</li> </ul>

Care / Harm
Fairness / Cheating
Loyalty / Betrayal
Authority / Subversion
Purity / Degradation

Table 2: Subjective ground comments of the two redditors in the same cluster. The topic of this cluster is pet / companion animals, and the two redditors express different subjective ground—one mentions methods providing better environments for the pets (Redditor 1), while the other feels that pets can be harmful (Redditor 2). Color-coded parts in each comment indicate the words that match with the Moral Foundation Dictionary vocabularies.

diagram. Mathematical details of the model components are described in Appendix A.1

### 3.1 Subjective Ground Training Module

Subjective ground base consists of a set of previous comments left on r/AmITheAsshole. We hypothesize that an individual’s subjectivity towards situations related to a specific topic can be applied to other situations within the same topic. For instance, if an individual has a positive subjectivity in raising pets, their moral judgments on animal abuse would be ‘unacceptable’. Following this intuition, we vectorize input situations in  $\mathcal{D}^+$  using Sentence-BERT (Reimers and Gurevych, 2019), apply K-Means clustering to identify a fixed number of topic groups among situations, and cluster the redditor’s comments on situations within the same topic group. We set the number of clusters to 20, based on the computed inertia values.

Recognizing the majority of comments in the subjective ground base are not informative with respect to estimating the redditor’s subjectivity, we prune unnecessary comments and obtain the subjective ground that is potentially more relevant. In order to determine the relevance of subjective ground comments, we apply Moral Foundations Theory (Haidt and Joseph, 2004; Graham et al., 2013), a framework to explain the origins of human moral reasoning with foundations such as care/harm, fairness/cheating, loyalty/betrayal, authority/subversion, and purity/degradation. We focus on comments that are more related to moral

foundations.

We compute each comment’s moral foundations score by counting the number of word matches with the Moral Foundation Dictionary (Frimer et al., 2019), which has approximately 2,000 words with their corresponding moral foundations. For each cluster, we keep the top 6 comments with the largest moral foundations score, resulting in 120 comments in total for each redditor. The major reason to keep the small number of the comments is because there are users who commented very little to specific clusters, and setting the same fixed number of comments is more efficient in model training. Examples are illustrated in Table 2.

Rather than equally considering all subjective ground comments in the cluster, a separate attention module is trained using  $\mathcal{D}^+$ . The module computes the attention score between the redditor’s subjective ground and situation representations, and is followed by feed-forward networks to predict moral judgments. We assume that this module learns weights over subjective ground comments when they are conditioned to the input situation. In other words, we expect the attention layer to highlight the redditor’s subjective ground comments that are most relevant to predict correct moral judgments on the given situation.

### 3.2 Value Attention Training Module

Schwartz (1992) introduced a theory of basic human values to characterize cultural groups, societies, and individuals. In this study, values are used

to explain an individual’s motivational bases of certain behavior. Value attention training module aims to map individual’s subjective ground comments to more abstract values—in our case, moral rules-of-thumb in  $\mathcal{D}$  can be used as value candidates. This process is essential because situation clusters capture broad topics rather than fine-grained talking points, thus the redditor’s subjective ground comments might not be directly applied to an input situation. For instance, clusters regarding romantic relationships, family members, or kids tend to vary a great extent, and it is challenging to acquire a fixed number of comments that could cover all situations in the cluster.

In value attention training, we compute attention scores between value candidates and the subjective ground of the redditors which has already been trained in the previous module. Assuming that the subjective ground has high correlation with moral judgments of the situation, the rule-of-thumb that has the highest attention weight would be highly correlated to the judgment as well. This module projects one’s subjective ground on the value candidates to assess the given situation.

After computing attention weights among the value candidates, we obtain a weighted sum and consider it as the representation of the value that would speak for the redditor. The final feed-forward classifier layer takes the weighted sum of values and the input situation representation, concatenates them, and predicts the redditor’s moral judgments on the situation.

## 4 Experiments

We implement models varying in attention structures and subjective ground representations. Macro F1 is used as an evaluation metric for accuracy since the label distribution is unbalanced and the two classes are equally important. Implementation details are described in Appendix A.2. Codes are released for future reference.<sup>3</sup>

### 4.1 Baseline

Baseline models are implemented to measure the difficulty of identifying a redditor’s judgment pattern on given situations without providing context information. We define Transformer-based sequence classifiers for each redditor and train the models to predict the redditor’s judgments given the input situations.

Observing the limited amount of training instances in  $\mathcal{D}$  per redditor, we make use of a larger dataset,  $\mathcal{D}^+$  to fine-tune the encoder layer. We first train sequence classifiers with the same objectives using  $\mathcal{D}^+$  and share the encoder for fitting the model to  $\mathcal{D}$ . This model is denoted as Baseline, fine-tuned encoder.

### 4.2 Rules-of-Thumb Self Attention

As a part of ablation studies, we implement a model that predicts redditors’ judgments with the help of rule-of-thumb candidates of input situations. The major difference between this model and our proposed model is the use of the redditor subjective ground; this model does not take subjective ground into consideration. We compute the self attention of rule-of-thumb representations and concatenate with input representations to predict the judgments.

### 4.3 Subjective Ground Models

Our model learns the correlation between the input situations and the redditor’s subjective ground, and later identifies the most relevant value to the subjective ground for predicting moral judgments. We denote our model as Subjective Ground Attention.

To investigate the effect of subjective ground attention layers, we implement the Static Subjective Ground model; this model uses the exact same structure as Subjective Ground Attention, without assigning or learning any attention weights. This model therefore takes all subjective ground comments equally.

Another variation, Subjective Ground Attention w/o RoT, is a model that uses attention-weighted subjective ground comments without integrating moral rules-of-thumb. This model evaluates the efficacy of mapping subjective ground comments to rule-of-thumb candidates that are directly related to input situations.

One may argue that simply adding more layers and parameters could help improve the performance regardless of the learning aspects of the model. Thus to analyze the efficacy of using a redditor’s previous comments as subjective ground, we put a randomly initialized matrix as the subjective ground. This model is denoted as Latent Subjective Ground.

## 5 Discussion

In this section, we analyze the prediction results of different models and discuss the effectiveness of

<sup>3</sup><https://github.com/younggns/subjective-ground>

Model	F1 (stdev)
Random Prediction	48.77 (0.60)
Baseline	58.61 (0.97)
Baseline, fine-tuned encoder	59.12 (0.34)
Rules-of-Thumb Self Attention	59.66 (0.72)
Latent Subjective Ground	59.16 (0.67)
Static Subjective Ground	60.15 (0.73)
Subjective Ground Attention w/o RoT	60.83 (0.61)
Subjective Ground Attention	<b>61.05 (0.21)</b>

Table 3: F1 measures of the models in predicting moral judgments.

each model component. Additionally, we perform a qualitative analysis of subjectivity explanations of the model.

### 5.1 Prediction Accuracy

Table 3 reports the average macro F1 scores and standard deviation of five experiments of each model. The overall macro F1 scores of the implemented models are not high. We suppose the task is naturally challenging because the number of training instances is insufficient to learn the moral judgment patterns of input situations—there are less than 500 instances for each redditor on average. Using more data to fine-tune the encoder slightly influences the performance on  $\mathcal{D}$ —the baseline model with its Transformer encoder fine-tuned with  $\mathcal{D}^+$  shows higher accuracy compared to the baseline model.

Using more context information such as rule-of-thumb candidates and subjective ground comments improve the model accuracy to a certain extent. Both Rules-of-Thumb Self Attention and Static Subjective Ground models perform better while Latent Subjective Ground model does not. This shows that the redditor’s previous comments help understand their subjectivity. Subjective Ground Attention, our proposed model, is the most efficient way of integrating both rules-of-thumb and subjective ground comments. The prediction accuracy of Subjective Ground Attention is more improved than that of the models without subjective ground comments in a statistically significant way, showing p-value less than 0.01.

We further break down the outputs and analyze prediction accuracy for each cluster, assuming that the difficulty of prediction varies based on the topic and the quality of clustering. The gap between the highest and the lowest accuracy cluster is 24% which supports our assumption. To identify the attributes that are correlated to the cluster accuracy, we investigate a few attributes such as cluster size,

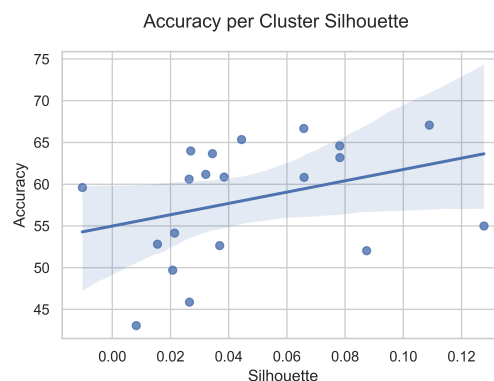


Figure 3: Prediction accuracy of different clusters with respect to silhouette scores. Each dot in the graph represents a distinct cluster.

intra-cluster distances, and label distributions.

Figure 3 shows cluster accuracy based on their silhouette score, which is high when items in a cluster are close together and distant from other clusters. There are a few outliers showing high accuracy with low silhouette and vice versa, yet the graph shows positive correlations with Pearson’s correlation coefficient of 0.34. This implies that more well-clustered and semantically distinctive situations tend to provide better accuracy. Detailed descriptions of each cluster and their predictions are described in Appendix A.3.

### 5.2 Consistency in Attention Weights

We define a new metric for evaluating the consistency of the attention modules on test data. One of the desired behaviors of the model is its consistency; the rule-of-thumb with the largest attention weight needs to be consistent with the model’s prediction. For instance, if the most attended rule-of-thumb supports the acceptability of the input situation, we want the model prediction to be ‘acceptable’ regardless of the ground truth. We manually annotate the acceptability label of 500 rules-of-thumb. Value consistency is then defined as a portion of instances where the highest weighted rule-of-thumb’s acceptability label matches the model’s final prediction.

It is more challenging to annotate the acceptability label of subjective ground comments. Thus we design another test, input perturbation, to measure the consistency of subjective ground attentions. The redditor’s subjective ground needs to account for situations at inference, and we expect the model to behave consistently for similar situations. From this intuition, we manually create situations that

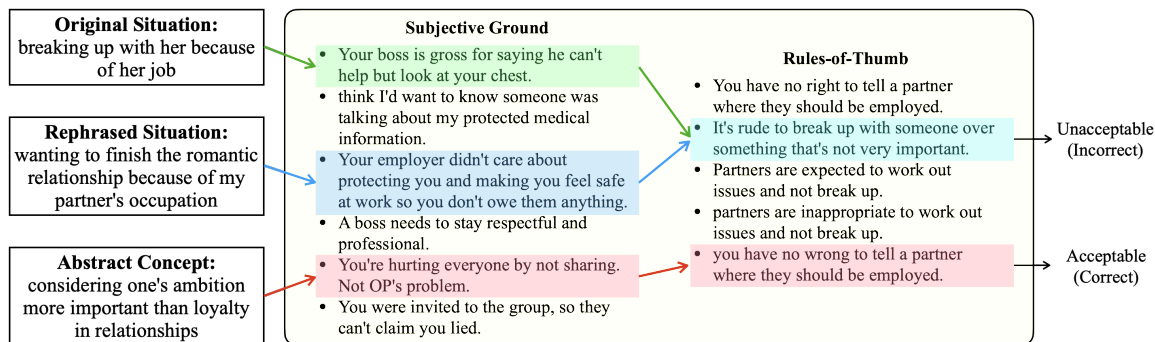


Figure 4: Attention weight flows of the original situations and perturbed inputs. When an abstract concept is given, the model attends to the redditor’s subjective ground differently and predicts the judgment correctly.

Attention Consistency Test		
Model	Consistency	
	Value	SG
Rules-of-Thumb Self Attention	35.94	N/A
Static Subjective Ground	<b>65.63</b>	71.15
Latent Subjective Ground	42.19	67.96
Subjective Ground Attention	56.25	<b>72.32</b>

Input Perturbation Test	
Data	Accuracy
Original Situation	51.07
Altered Gender	45.15
Rephrased Situation	46.73
Abstract Concept	<b>58.18</b>

Table 4: Quality evaluation of attention weights. The upper table reports the consistency measure of the value attentions (**Value**) and the subjective ground attentions (**SG**). Note that subjective ground consistency can’t be measured in Rules-of-Thumb Self Attention because this model doesn’t refer to subjective ground comments. The lower table shows the accuracy of Subjective Ground Attention model on modified inputs.

are similar to the original reddit posts.<sup>4</sup> We apply three levels of similarity; (1) situations where pronouns and gender-specific nouns are altered (e.g. not respecting my mom → not respecting my dad), (2) rephrased situations (e.g. not respecting → being mean to), (3) abstract concept of the situations where it can be applied to other situations (e.g. revealing someone’s secret → honesty is more important than relationships). Subjective ground consistency is defined as the portion of modified inputs that have the same attention weight order as the original input. Evaluation results are described in Table 4.

The value consistency of Rules-of-Thumb Self Attention and Latent Subjective Ground models are surprisingly low, implying these models learn

<sup>4</sup>Examples are described in Appendix B.1

rules-of-thumb attention weights without their actual relatedness to the moral judgments—right for the wrong reasons. We further investigate the reason and observe that the model tends to give high weights on some specific rules-of-thumb, possibly texts that are more familiar to the pre-trained Transformers regardless of the redditor’s judgments. Static Subjective Ground model gives the highest consistency score, confirming the efficacy of using redditor’s subjective ground comments. This model exceeds the value consistency measure of our proposed model, Subjective Ground Attention, suggesting rules-of-thumb attentions become more consistent with the model’s final prediction when using all subjective ground comments equally. Our proposed model achieves the highest score in subjective ground consistency tests. This implies that Subjective Ground Attention learns consistent attention weights with respect to similar inputs.

Another interesting finding is that our model gives more accurate predictions on the abstract concept inputs; when the model is conditioned to the abstract concepts, the order of the subjective ground attention weights changes and it leads to better prediction results. Referring to an example illustrated in Figure 4, the model attends more on the first and the third comments when the original situation and the rephrased situation is given. This is because the model picks up keywords like job and occupation, and considers the situation as a job/work related issue. For an abstract concept input, however, the fifth subjective ground is attended the most as the model now sees the situation as one regarding relationships. The different weights over subjective ground affects the attention weights on rules-of-thumb, hence they impact the final model prediction. These results suggest that our proposed model learns one’s general perspectives on morally

**Situation: Having a gender preference in our selective abortion**

Redditor Judgment: Acceptable / Model Prediction: Acceptable / Consistency: No	
Subjective Ground	Rules-of-Thumb
<ul style="list-style-type: none"> <li>Considering that this woman agreed to sacrifice her body without compensation as a solely altruistic thing for OP's family...not sure how OP gets to force her to sacrifice her bodily autonomy through forcing her into an unwanted abortion.</li> <li>Injuring is only self defense if you have no other means of protecting yourself-in OP's case, it was probably anger/vengeance, not self defense.</li> <li>You're not forbidding him from caring for his child, you're forbidding his family member from caring for child.</li> <li>I'm a devout Catholic, so I actually do believe in religious stuff.</li> <li>A lot of prolife people are Catholic, and the Catholic Church is against birth control.</li> <li>You weren't stopping her from going out, or being controlling about her actions, you were just watching out for her safety.</li> </ul>	<ul style="list-style-type: none"> <li>Abortion is bad because it takes a person's life.</li> <li>It's fine to have an abortion for any reason that</li> <li>It's fine to want to choose the sex of your child.</li> <li>It's wrong to have an abortion just because you don't like the features of the child.</li> <li>It's not allowed to have an abortion just because you don't like the features of the child.</li> </ul>
Redditor Judgment: Acceptable / Model Prediction: Acceptable / Consistency: Yes	
Subjective Ground	Rules-of-Thumb
<ul style="list-style-type: none"> <li>I suspect that the issues that plague her family aren't completely removed from her because she lacks the common sense to realize that she can't help them and the 13 year old needs an intervention and foster care</li> <li>Your wife "won't work" and here you were working 7 am to midnight, and she's not only refusing to do laundry, etc., but she expects you to do it at midnight??</li> <li>Only foolish and misguided humans stay together for the kids, causing more misery than they would have if they had just divorced and been amazing parents separately</li> <li>I still would get arrested for public nudity, assault, robbery, theft.</li> <li>You went way above and beyond for people ..., but also couldn't be bothered to ... spend extra money on for baby sitters you didn't have to hire.</li> <li>A childhood friend only wished his parents had divorced because they treated each other like strangers.</li> </ul>	<ul style="list-style-type: none"> <li>Abortion is bad because it takes a person's life.</li> <li>It's fine to have an abortion for any reason that</li> <li>It's fine to want to choose the sex of your child.</li> <li>It's wrong to have an abortion just because you don't like the features of the child.</li> <li>It's not allowed to have an abortion just because you don't like the features of the child.</li> </ul>

Table 5: Attention weights among subjective ground comments and rule-of-thumb candidates given an input situation. The two redditors have the same judgments yet they differ in the rules-of-thumb attention and their consistency.

competing values although applying this knowledge to specific situations is yet challenging.

### 5.3 Qualitative Analysis of Subjective Ground

In this section, we qualitatively analyze the redditors' subjective ground attention and its relatedness to rules-of-thumb attention.

We illustrate a case where two redditors comment on the same post in Table 5. The upper case is where the model prediction is not consistent with the most attended rule-of-thumb. We observe that the model gives higher weights to abortion-related subjective ground comments, implying that the redditor would consider the given situation unacceptable. The value attention module chooses the last rule-of-thumb which opposes the idea of abortion, showing the consistency between subjective ground and value attention. However, the final prediction of the model is 'acceptable', suggesting that the classifier does not use the weighted rule-of-thumb representations correctly. This analysis matches suboptimal value consistency results of Subjective Ground Attention in Table 4 and raises the

necessity of developing classifiers that can better understand value attentions with respect to moral judgments.

The next redditor, on the other hand, does not include any abortion-related comments as subjective ground. The model attends to the last subjective ground comment that contains keywords related to family and their separation—divorced, strangers. This example highlights the case where the topic distribution of a redditor's subjective ground is not comprehensive enough with respect to the given situation. In such case, the attention module focuses on the ground that is potentially associated with the situation and give high attention weights on the related rules-of-thumb. We anticipate that the model will be more accurate and consistent using subjective ground that is clustered based on more fine-grained talking points.

Overall, we observe the consistency in subjective ground and value attentions. We expect the model's prediction accuracy and the quality of explanations can be further improved using more fine-grained activities of individuals and a neural component



that can better learn the correlation between rules-of-thumb and moral judgments.

## 6 Related Work

**Explainable AI** As deep neural language models improve the accuracy of many different downstream NLP tasks, measuring the accountability and interpretability of these models has been recently gaining interest in the research community.

Local explanation methods aim to provide rationales of the model in predicting a specific input. Recent neural models majorly explain the model behaviors by visualizing the saliency map of the first derivatives of the encoder (Ross et al., 2017; Wallace et al., 2018), attention layers (Xie et al., 2017; Mullenbach et al., 2018), perturbing inputs (Sydorova et al., 2019), and applying rules and templates (Abujabal et al., 2017; Pezeshkpour et al., 2019). Rajani et al. (2019) collect human explanations for commonsense reasoning in the form of text, and train language models to generate the explanations given pairs of commonsense questions and answers. Aubakirova and Bansal (2016) investigate how neural network models predict the politeness of input text by visualizing activation clusters, saliency heatmaps of the first derivatives, and word representation transformations in the embedding space. Ribeiro et al. (2016) proposes a framework where an interpretable model, trained to minimize the distance to the classifier predictions, explains the model prediction with absence/presence of specific words.

**Perspective Identification** Identifying perspectives from the text has been steadily studied in many sub-fields of NLP. Greene and Resnik (2009) defines perspectives as an individual's syntactic packaging of the information and analyzes different usage of linguistic cues in articles. Choi and Wiebe (2014) adopts a simple symbolic relation, positive and negative connotations towards events and concepts, to the existing WordNet (Miller et al., 1990) hierarchy for inferring the point of view of an opinion. There are more complex concepts and structures—analyzing political framing and agenda-setting (Field et al., 2018; Roy and Goldwasser, 2021), encoding political perspective flows in social settings via Graph Convolutional Network (Li and Goldwasser, 2019)—have been studied.

This research paper is positioned in the intersection of explainable AI and perspective identification. We examine several models that can approxi-

mate an individual's subjective ground in a human-readable way, as well as interact with diverse daily situations to infer individual's perspectives on the author and their situations.

## 7 Conclusion

This paper proposes a neural model, Subjective Ground Attention, that represents an individual's subjective preference with their previous activities and explains the reasoning behind their moral judgments on diverse social situations by spotlighting the most relevant subjective ground. We explore situations posted on a Reddit community, r/AmITheAsshole, and analyze active redditors' judgments on these situations indicating whether or not the author's behavior is acceptable. Upon attending subjective comments and moral rules-of-thumb, experimental results show that the model provides reasonable explanations without sacrificing prediction accuracy. Although attention weights on moral rules-of-thumb show suboptimal consistency with the model's prediction, we illustrate the model's consistency in attention weights on subjective ground comments. We further claim that our model better captures one's perspectives on abstract moral concepts.

## Limitations

One of the major limitations of this work is the absence of Reddit post contents. Although reading the content of the post is crucial in fully comprehending and judging the situation, we decide not to include the content mainly because of the size of training instances. A large volume of the text in the post content would have hindered the model from good generalization.

Another shortcoming is the subjectivity explanation tool—moral foundation annotations. Ideally moral rules-of-thumb represent an individual's biases in judging situations, yet in reality the annotated rules-of-thumb do not cover all types of biases related to the situation. Additionally, many of the manually crafted rules-of-thumb will not help the model learn different types of biases since they are largely similar to the original rules-of-thumb.

Lastly, individual subject ground modeling in this work is over-simplified. We construct the redditors' subjective ground solely based on their previous comments in the same subreddit, and there is more context information that could potentially help analyze an individual, such as the posts submit-

ted by the redditor and information about subreddits they are actively involved. Rather than choosing the subjective ground comments based on the word matches with Moral Foundation Dictionary, applying more sophisticated methods in identifying moral foundations, such as moral foundations framing (Roy and Goldwasser, 2021), would also lead to a better subjective ground. In analyzing a different domain in future work, we could also take an individual’s identity—demographic, social, political—into consideration when modeling subjective ground.

## Ethics Statement

To the best of our knowledge, this work has not violated any code of ethics. We anonymize redditor information in the paper as well as in the datasets we share to the public. This paper shows different redditors’ subjective ground, yet there is no discrimination in choosing redditors of the interest; the redditors are selected solely based on the number of comments they have left on this subreddit. We provide the code and datasets for future reproducibility of the work.

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## A Experiment Details

### A.1 Model Formalization

While training the subjective ground module of the redditors, we make use of the input situations

$X^+ = \{x_1^+, x_2^+, \dots, x_N^+\} \in \mathcal{D}^+$ , where  $M$  redditors in  $\{u_1, u_2, \dots, u_M\}$  have commented on. An  $i$ -th redditor  $u_i$  is represented as a set of  $G$  subjective ground comments,  $u_i = \{c_{i1}, \dots, c_{iG}\}$ . Binary output labels,  $Y^+$ , indicating acceptable / unacceptable judgments on each input situation can be denoted as  $Y^+ = \{0, 1\}^L$  where  $L$  is the total number of instances. Note that  $L \neq NM$  since not all redditors commented on all input situations in the dataset.

We use another dataset with moral rules-of-thumb annotation,  $\mathcal{D}$ , for training and testing the model. Similar to  $\mathcal{D}^+$ , input situations and output labels are denoted as  $X = \{x_1, x_2, \dots, x_n\}$ , and  $Y = \{0, 1\}^l$ , where  $n$  and  $l$  are the number of situations and instances in  $\mathcal{D}$ , respectively. Additionally, there are  $K$  rules-of-thumb annotated for each situation. An input situation  $x_j$  is mapped to the rule-of-thumb candidates,  $V_j = \{v_{j1}, \dots, v_{jK}\}$ .

The first step of training is on the redditors' subjective ground using  $\mathcal{D}^+$ . Using a pre-trained Transformer encoder (Wolf et al., 2019), we represent an  $i$ -th redditor's subjective ground as  $SG_i \in \mathbb{R}^{G \times h}$  where each row of the matrix is the encoded subjective ground comment and  $h$  is the encoder dimension. Assuming this redditor has commented on the  $j$ -th input situation in  $\mathcal{D}^+$ , encoded as  $z_j^+$ , the subjective ground training module is designed as follows:

$$\begin{aligned} z_j^+ &\leftarrow \text{Transformer}(x_{j+}) \\ SG_i &\leftarrow \text{Transformer}(\{c_{i1}, \dots, c_{iG}\}) \\ a_{i,j}^+ &= \text{Multihead}(SG_i, z_j^+, SG_i) \\ \hat{y} &= W_{CLF}[\sum a_{i,j}^+ SG_i; z_j^+] \\ \mathcal{L} &= \text{CrossEntropy}(y, \hat{y}) \end{aligned}$$

We follow the basic structure of the Multi-head attention proposed by Vaswani et al. (2017), where different representations of attention inputs are combined:

$$\begin{aligned} \text{Multihead}(Q, K, V) &= [\text{head}_1; \dots; \text{head}_h] W^O \\ \text{s.t. head}_i &= f\left(\frac{QW_i^Q(KW_i^K)^T}{\sqrt{d_k}} V W_i^V\right) \end{aligned}$$

where  $f(\cdot)$ : softmax function  
and  $d_k$ : model dimension

$W_i^Q, W_i^K, W_i^V$ : input projections

After subjective ground is trained, we learn the attention between the redditor's subjective ground and moral rules-of-thumb of the situations in  $\mathcal{D}$ .

We use the encoder that is fine-tuned in the previous step and obtain an encoded value candidate representation of a  $j$ -th situation  $x_j$  as  $VAL_j \in \mathbb{R}^{K \times h}$  where each row of the matrix is the encoded rule-of-thumb. Suppose the  $i$ -th redditor commented on  $x_j$ , the model learns the data as follows:

$$\begin{aligned} z_j &\leftarrow \text{Transformer}(x_j) \\ SG_i &\leftarrow \text{Transformer}(\{c_{i1}, \dots, c_{iG}\}) \\ VAL_j &\leftarrow \text{Transformer}(\{v_{j1}, \dots, v_{jK}\}) \\ a_{i,j}^{SG} &= \text{Multihead}(SG_i, z_j, SG_i) \\ a_{i,j}^{VAL} &= \text{Multihead}(VAL_j, a_{i,j}^{SG}, VAL_j) \\ \hat{y} &= W_{CLF}[\sum a_{i,j}^{VAL} VAL_j; z_j] \\ \mathcal{L} &= \text{CrossEntropy}(y, \hat{y}) \end{aligned}$$

## A.2 Implementation Details

We use a pre-trained DistilBERT-base-uncased for the text encoder, distributed by Wolf et al. (2019). For attention layers, we implement multi-head scaled dot-product attention layers with 12 heads. Classifiers are two-layer linear networks followed by Cross Entropy loss and Adam optimizer (Kingma and Ba, 2014) with static learning rates. The final model considers  $d_k$  as 1 in the multi-head attention layers, because normalizing attention weights by the square root of the model dimension generates more equally distributed attention weights over subjective ground comments and rules-of-thumb. All experimental results are the average of five separate runs.

Our models are trained and tested using NVIDIA Tesla V100 GPU and the average time for training the full model is approximately 6 hours, while the training time for the baseline models are 20 minutes.

We manually select the hyperparameters to tune—the number of attention heads and learning rates. The selection criterion for the hyperparameters was the average F1 score of five experiments on test data. We set the possible number of heads either 1 or 12, where 1 means single attention head. Hyperparameters are searched using grid search, in the boundary from 1e-6 to 1e-3. We also implemented learning rate warm-ups, where the learning rate increases for the first few steps, then it decreases logarithmically.

## A.3 Cluster Results

We break down the model performance based on each cluster. The F1 score of each cluster and the most representative situations in the cluster are described in Table 6.

<b>Cluster 0: kids, Accuracy: 52.81</b> telling my son's stepmom I don't care about her kid refusing to babysit our daughter not letting in laws see our child	<b>Cluster 1: romantic-relationships-GF, Accuracy: 63.99</b> telling my girlfriend to stop talking to a girl telling my gf she's over reacting accusing my girlfriend of wanting to cheat
<b>Cluster 2: not wanting, Accuracy: 45.89</b> not wanting to go to my boyfriends moms house not wanting to spend time with my mother not wanting my stepmom to meet my boyfriend again	<b>Cluster 3: romantic-relationships-BF, Accuracy: 54.14</b> not telling my boyfriend about an ex telling my boyfriend not to contact me again refusing to see a comprise with my boyfriend
<b>Cluster 4: telling, Accuracy: 61.19</b> telling my dad that his wife isn't family telling my daughter to leave my husband alone telling my girlfriend to back off from my daughter	<b>Cluster 5: siblings, Accuracy: 66.69</b> telling my sister she's not family Telling My Brother Not To Come To My Sister's Wedding asking my parents to disinherit my half sister
<b>Cluster 6: romantic-relationships, Accuracy: 63.69</b> not letting my girlfriend into my parents house giving my girlfriend an ultimatum regarding their best friend  not telling my boyfriend that his friend made a pass at me	<b>Cluster 7: wedding, Accuracy: 67.08</b> not inviting my sister-in-law to my wedding not going to my sister's wedding after being initially uninvited not letting my future in-laws invite people to our wedding
<b>Cluster 8: cars, Accuracy: 52.65</b> not giving my neighbor a parking spot telling someone not to come up to my car calling the police on someone who parked in my driveway	<b>Cluster 9: kids, Accuracy: 43.08</b> leaving my son behind on our family vacation dropping my stepdaughter off at her mothers house letting my daughter 'take over' my son's birthday present
<b>Cluster 10: roommates, Accuracy: 52.04</b> not wanting my roommate to move out asking my roommate's significant other to move out refusing to switch bedrooms with my future roommate	<b>Cluster 11: emotional-burst, Accuracy: 63.20</b> being upset at my mom being mad at my significant other being pissed off at my girlfriend
<b>Cluster 12: refusing-family-behaviors, Accuracy: 65.35</b> not letting my daughter go to my in-laws house  not allowing my mom to live with me refusing to bring my little brother to birthdays	<b>Cluster 13: money, Accuracy: 60.62</b> not wanting to pay for something my Girlfriend offered to pay for wanting my co-worker to pay me back Asking my Fiancee to Pay 1/3 of the Bills
<b>Cluster 14: coworkers, Accuracy: 60.87</b> not telling my co-worker that he's going to be fired getting a co-worker fired for something I also did Refusing To Work With My Coworker	<b>Cluster 15: pets, Accuracy: 55.01</b> not giving my dog back to his original owner telling my wife she can't get rid of the dog not letting a homeless guy pet my dog
<b>Cluster 16: offensive-behavior, Accuracy: 59.62</b> saying something embarrassing about one of my students making racist and sexist jokes refusing to forgive former classmates for being homophobic	<b>Cluster 17: parents, Accuracy: 49.71</b> telling my mom she didn't raise me telling my parents they're out of touch telling my dad's wife her family's not my family
<b>Cluster 18: food, Accuracy: 64.59</b> telling my coworker to stop eating my food not letting my spouse eat my meal prepped food not eating the food my coworkers wife made	<b>Cluster 19: friendship, Accuracy: 60.83</b> telling my friend off ruining my friend's relationship telling my friend she's out of line

Table 6: Each cluster's topic, most representative situation examples, and their F1 accuracy on our proposed model.

<p><b>Original:</b> telling my wife that when/if she quits her job to be a SAHM I am not planing to do much in the way of household chores anymore</p> <p><b>Gender:</b> telling my husband that when/if he quits his job to be a SAHD I am not planing to do much in the way of household chores anymore</p> <p><b>Rephrase:</b> suggesting my wife to balance household chores since I will be working while she quits her job</p> <p><b>Abstract:</b> preferring more fairness over helping out my partner</p>	<p><b>Original:</b> “being triggered” by my boyfriend setting rules for my pregnancy weight gain</p> <p><b>Gender:</b> “being triggered” by my girlfriend setting rules for my weight gain</p> <p><b>Rephrase:</b> being upset at my boyfriend when he plans to prevent me from eating too much during pregnancy</p> <p><b>Abstract:</b> not wanting to be controlled by my partner’s concerns about my health</p>
<p><b>Original:</b> not going to my girlfriends dads funeral</p> <p><b>Gender:</b> not going to my boyfriends moms funeral</p> <p><b>Rephrase:</b> not wanting to attend to my girlfriends dads funeral</p> <p><b>Abstract:</b> putting my belief first even my partner has lost their loved ones</p>	<p><b>Original:</b> having a gender preference in our selective abortion</p> <p><b>Gender:</b> having a racial preference in our selective abortion</p> <p><b>Rephrase:</b> deciding to have abortion based on the baby’s sex</p> <p><b>Abstract:</b> believing choice is more important than life</p>
<p><b>Original:</b> telling DH that I will not let his mom pick her grandmother name</p> <p><b>Gender:</b> telling DH that I will not let his dad pick his grandfather name</p> <p><b>Rephrase:</b> not wanting to name my children that my MIL picked</p> <p><b>Abstract:</b> wanting more freedom in raising kids over respecting the opinion of my parents</p>	<p><b>Original:</b> shaming my sister-in-law because she was mean to me</p> <p><b>Gender:</b> shaming my borther-in-law because he was mean to me</p> <p><b>Rephrase:</b> disrespecting my sister-in-law by making fun of her because she was mean to me</p> <p><b>Abstract:</b> revenging someone in the family for their behavior on me</p>
<p><b>Original:</b> breaking up with him because of his job</p> <p><b>Gender:</b> breaking up with her because of her job</p> <p><b>Rephrase:</b> wanting to finish the romantic relationship because of my partner’s occupation</p> <p><b>Abstract:</b> considering one’s ambition more important than loyalty in relationships</p>	<p><b>Original:</b> denying my wife a new kitchen</p> <p><b>Gender:</b> denying my husband a new kitchen</p> <p><b>Rephrase:</b> not allowing my wife to get a new kitchen</p> <p><b>Abstract:</b> not wanting to waste money on my partner’s desire</p>
<p><b>Original:</b> taking my daughter to get her hair dyed against my wifes wish</p> <p><b>Gender:</b> taking my son to get his hair dyed against my husbands wish</p> <p><b>Rephrase:</b> letting my daughter to get her hair dyed although my wife did not want it</p> <p><b>Abstract:</b> putting my kid’s desire first over my partner’s thought</p>	<p><b>Original:</b> telling my sister’s boyfriend the truth about her</p> <p><b>Gender:</b> telling my brother’s girlfriend the truth about him</p> <p><b>Rephrase:</b> revealing a big secret about my sister to her boyfriend</p> <p><b>Abstract:</b> considering honesty is always more important even though it would break up the relationships</p>

Table 7: Input situations and their modification for perturbation test.

## B Datasets

Train/valid/test splits of  $\mathcal{D}$  were provided by the original dataset, Social Chemistry 101, and we used the same splits. For the additionally crawled data,  $\mathcal{D}^+$ , we randomly divided the splits into 80%, 10%, 10%, while excluding all valid and test samples of  $\mathcal{D}$  from the training data of  $\mathcal{D}^+$ .

Additionally annotated data for consistency evaluation, rules-of-thumb consistency and input perturbation consistency, are annotated by the authors.

### B.1 Input Modification for Subjective Ground Consistency

The input situations to modify are selected from the test set of  $\mathcal{D}$ . To compute the subjective ground consistency of more diverse redditors, we sort the test set situations based on the number of redditors participated. We select 10 situations where the redditors have commented the most, resulting in 162 instances in total. The examples of 10 situations with their original situation descriptions, gender altered descriptions, rephrased descriptions, and abstract concept descriptions are in Table 7.

### B.2 Value Attention Consistency

Similar to input modification tests, we sort the test set situations based on the number of redditors participated, and select the top 100 situations. The authors annotated the acceptability label of rules-of-thumb of with respect to the situations, resulting in 500 instances in total.