Zero-shot Visual Commonsense Immorality Prediction

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Abstract

Artificial intelligence is currently powering diverse real-world applications. These applications have shown promising performance, but raise complicated ethical issues, i.e. how to embed ethics to make AI applications behave morally. One way toward moral AI systems is by imitating human prosocial behavior and encouraging some form of good behavior in systems. However, learning such normative ethics (especially from images) is challenging mainly due to a lack of data and labeling complexity. Here, we propose a model that predicts visual commonsense immorality in a zero-shot manner. We train our model with an ETHICS dataset (a pair of text and immorality annotation) via a CLIP-based image-text joint embedding. Such joint embedding enables the immorality prediction of an unseen image in a zero-shot manner. We evaluate our model with existing moral/immoral image datasets and show fair prediction performance consistent with human intuitions, which is confirmed by our human study. Further, we create a visual commonsense immorality benchmark with more general and extensive immoral visual content. Codes and dataset are available at https://github.com/ku-vai/ Zero-shot-Visual-Commonsense-Immorality-Prediction. Note that this paper might contain offensive images and descriptions.

1 Introduction

Despite the explosive developments of Artificial Intelligence, AI ethics research has been overlooked from many researchers. The previous research on ethical artificial intelligence has been analyzed solely from the philosophical view, but not from the computational perspective [3, [23], [23]]. Philosophers kept speculating that if computer scientists had focused only on optimization or problem solving, artificial intelligence will encounter catastrophes of immorality [3, [2, [23]]]. Fortunately, the demand for ethical machine learning has been increasing and resulted in narrow ethical applications in Artificial Intelligence.



Figure 1: Examples found by our model from ImageNet [1] dataset. Note that we make some images blurry due to their inappropriate content.

With ETHICS dataset [\square], we are now able to evaluate how much a machine learning system understands human's ethical judgment for the open-world settings. This dataset consists of some scenarios of justice, deontology, virtue ethics, utilitarianism, and commonsense moral intuitions. The modality that this dataset covers, however, is only natural language. In other words, in computer vision field, this research is still limited to some specific tasks such as detecting gun in the CCTV image [\square , \square , \square], violent scene in the movies [\square , \square , \square , and sexual contents in social networks [\square , \square].

Despite the fact that visual commonsense immorality prediction task is necessary for the content moderation, it has not been taken into consideration since supervising a model with proper visual inputs is challenging. This mainly resulted from two reasons: First, existing immorality datasets are limited to specific sub-categories of commonsense immorality (e.g. NSFW as known as "Not Safe For Work" for sexual contents), where models (trained on them) are prone to overfit and do not generalize well. Second, collecting a wide range of images that can fully cover commonsense immorality is difficult. Judging the immorality of a given image is also not an intuitive task, making it hard to create reliable visual datasets. Thus, we advocate for leveraging a text-image joint embedding space with a large-scale textual commonsense immorality dataset; we used ETHICS dataset in this paper.

To extend ETHICS dataset to ethical judgement of vision tasks for open-world settings, we bring the recent advances of large vision-language pretrained models (VLMs) such as CLIP [5] and DALL-E [56]. For VLMs, language supervision permits zero-shot transfer for various computer vision tasks. Also, researchers have recently reported that we can retrieve toxic image from CLIP with only soft prompt tuning and without additional training for the vision encoder [5]. This is a promising report in that CLIP model can detect offensive features from the given image. However, the extension of CLIP for predicting ethical judgements in open-ended settings is not trivial as these retrieved images are not easily generalized to other ethical scenarios.

To address this issue, we propose a zero-shot visual immorality prediction method. As shown in Figure 2, our model consists of two main modules: (i) CLIP-based textual and visual encoders and (ii) a commonsense immorality predictor (described as a classifier in the Figure 2). We train commonsense immorality predictor only with the ETHICS dataset by mapping a text (e.g. "I painted the entire school with a nude lady") to a binary class (immoral vs. moral). Immorality of an unseen image is then predicted through the CLIP-based visual encoder and the trained immorality predictor in a zero-shot manner.

To the best of our knowledge, there are only a limited number of image datasets to evaluate the performance of visual immorality prediction. Thus, we create a visual immorality prediction benchmark, which provides more generalized domains suitable for our task. Overall 2,172 immoral images are collected through Google Image queries followed by a manual filtering of irrelevant images. Our contributions are summarized as follows:

- We propose a novel zero-shot visual immorality prediction method. Based on CLIPbased visual and textual joint embedders, we train an immorality prediction head with a large-scale ETHICS commonsense dataset. Such a prediction head is then reused for predicting immorality of an unseen image.
- We evaluate our method with the following five existing moral and immoral image datasets: MS-COCO [26], Socio-Moral Image Dataset [12], Sexual Intent Detection Images [16], NSFW [10], and Real-life Violence Situation Dataset [12]. Further, we create a more generalized version of immoral image benchmark.
- Our human study with 172 participants from Amazon Mechanical Turk confirms that our model's behavior aligns well with human intuition and validates our created dataset's effectiveness for the visual commonsense immorality classification task.

2 Related Work

AI Ethics. There has been a great deal of effort in the field of philosophy towards the concept of ethical machine learning. A Turing test was developed by Alan Turing to determine if a machine could act like a human being $[\square 3]$. Asimov suggested the three laws of robotics as the underlying principle of machine behavior, but simple rules are unable to make machines moral due to the complexity of ethics and conflict between rules $[\square]$. Moreover, Bostrom *et al.* $[\square]$ argued that morality cannot be assured if machines are focused solely on problem solving and may result in serious catastrophes such as paperclip maximizers $[\square]$. In addition, some existing studies in the philosophical literature have examined AI ethics dilemmas $[\square]$.

It has become apparent that machine ethics is of paramount importance; yet, this has been previously assessed only to a very limited extent due to the fact that machine learning engineers have focused solely on problem solving. Natural Language field have examined four ethical categories in general so far: Fairness [22], Safety [53], Prosocial [51, 53] and Utility [11, 23]. In addition to four categories, Commonsense Morality is newly discussed by Hendrycks *et al.* [13] Computer Vision has, however, focused primarily on Safety, since surveillance video (CCTV) and visual content review have been the main tasks in the area. [51]. In recent computer vision studies, the domain has been broaden to Fairness for preventing discrimination caused by the dataset bias [2, 52, 53]. As part of this domain expansion in Computer Vision, we focused on the Commonsense Morality by proposing a novel visual immorality prediction model which utilizes the power of the generality of natural language.

Visual Immorality Benchmarks. As the importance of AI ethics has been highlighted, datasets that provide value judgments as labels become required, which is a new perspective since conventional datasets provided factual judgments. In the Natural Language field, large datasets have been released to detect aggressive languages [52], [11], and some studies have also been conducted to collect tweets to judge moral values in SNS conversations [21], [50]. Especially, the recently released ETHICS dataset [11] is a comprehensive dataset, which combines five strands of morality values that have been studied individually.

In comparison, visual datasets have dealt with solely specific domains. In terms of violence, images and videos from CCTV are collected for weapon detection $[5, \Box]$ and brutal scene detection $[5, \Box]$. Similarly, movies $[5, \Box]$, \Box , sports $[5, \Box]$, and Youtube $[\Box]$

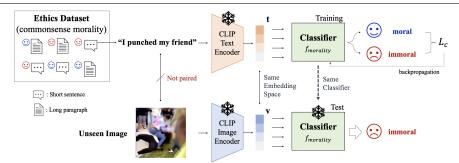


Figure 2: An overview of our visual commonsense immorality prediction model. In the training phase, we train our classifier f_{morality} to predict the degree of commonsense immorality from a given text prompt, e.g. "I punched my friend". To train such a module, we use the ETHICS dataset [13], which contains over 13,000 pairs of sentences or paragraphs and the corresponding binary annotations of morality for training. We utilize a frozen CLIP [13]-based image-text joint embedding space, which learns to map pairs of an image and a text to have the same latent vector. This allows us to predict the degree of morality from an unseen image in a zero-shot manner.

video datasets are constructed for a violence detection. NSFW [II] and Sexual Intent Detection [II] datasets consist of images concerning sexuality. To the best of our knowledge, Socio-Moral Image Database (SMID) [II] is the only dataset that does not deal with a specific domain. However, this dataset, which provides only the morality score of the image through the human study, does not explain why the image is immoral. Therefore, we create a more general and explainable visual commonsense immorality benchmark, providing images from 25 immoral keywords in 3 categories.

Large Vision-Language Pretrained Models. A large-scale pretraining of vision and language modality has significantly improved performance in several downstream tasks. CLIP [53] and ALIGN [20] demonstrate that the pretrained models are able to learn strong multi-modal representations for crossmodal alignment tasks and zero-shot image classification using dualencoder model. FLAVA [53] and BLIP [23] have explored image-text unification with the pretraining of multiple unimodal and multimodal modules. CoCa [52] is a latest model that is trained from scratch in a single pretraining stage. CLIP is jointly trained to associate joint embeddings of texts and images that share the similar semantics with a 400M imagecaption pair dataset. Vision Transformers (ViT) or ResNets are used for a vision encoder and Transformer is used for a text encoder. As a result, CLIP generates the robust image and text features. This model can perform various downstream tasks such as image search and zero-shot image classification. With the help of such pretrained model's remarkable transferability, we deliver vast quantities of information about morality embedded in ETHICS dataset to image modality.

3 Visual Commonsense Immorality Prediction

Learning Visual Commonsense Immorality from ETHICS dataset. In this work, we rely on the ETHICS dataset [1], which contains over 130,000 text ethical examples of 5 ethical perspectives: justice, virtue, deontology, utilitarianism, and commonsense. Among them, we utilize the commonsense morality dataset, which consists of more than 21,000 examples

and corresponding binary labels of the commonsense immorality. This dataset is ideal for the commonsense immorality prediction task: (i) they provide diverse open-world scenarios (see the supplemental material for details), (ii) they collect over 21,000 text examples from four different countries, and (iii) it is designed to evaluate machine understanding about everyday situations, not ambiguous moral dilemmas. There are two reasons for utilizing text data rather than visual data: (i) there is no such large-scale dataset for the visual commonsense immorality prediction task, (ii) collecting such a high-quality and large-scale dataset is challenging regarding volume, quality, and consistency.

Thus, we advocate for utilizing a pre-trained image-text joint embedding space, which maps a pair of a text prompt and an image into the same embedding. Given this joint embedding space, we first train a text-based commonsense immorality predictor, which learns to predict the degree of the immorality of a given text prompt (e.g. "I punched my friend"). Such an immorality predictor can be reused for an image-based commonsense immorality predictor. Our image encoder maps an input image to a joint text-image embedding space, and the learned immorality predictor predicts the degree of visual commonsense immorality. In Figure 2, we visualize an overview of our proposed visual commonsense immorality prediction model. In the following sections, we explain it in detail.

CLIP-based Image-Text Joint Embedding. Our model depends on a text-image joint embedder, which maps a pair of an image $x_v \in \mathcal{I}$ (e.g. a photo of people punching each other) and a text $x_t \in \mathcal{T}$ (e.g. "I punched my friend") into the same embedding space by minimizing the (cosine) distance between a mini-batch of *n* image and text representation pairs $\{\mathbf{v}_i, \mathbf{t}_i\}$ for $i \in \{1, 2, ..., n\}$. We use two different encoders f_v and f_t to obtain a set of *d*-dimensional latent representations, i.e. $\mathbf{v} = f_v(x_v) \in \mathcal{R}^d$ and $\mathbf{t} = f_t(x_t) \in \mathcal{R}^d$. CLIP learns these latent representations via a typical contrastive learning approach by mapping a positive pair close together in the embedding space, while that of negative pair samples further away. However, learning such a joint embedding from scratch is generally challenging due to the lack of multi-modal datasets and computing resources. Thus, we leverage the pretrained CLIP model, which optimized a visual-textual joint representation by contrastive learning.

Learning Textual Commonsense Immorality Predictor. Given a feature $\mathbf{t} = f_t(x_t)$ in the joint embedding space, we further train an immorality classifier f_{morality} that outputs as a binary whether the input x_t is moral or immoral. Following Hendrycks *et al.* [13], we use a MLP for this classifier. To train our classifier, we rely on the ETHICS commonsense morality dataset [13], which contains a combination of (i) over 6K short scenarios (1-2 sentences) and (ii) over 7K detailed scenarios (1-8 paragraphs). Note that these short scenarios are from Amazon Mechanical Turk, while long scenarios are from Reddit followed by multiple filters. Given a frozen CLIP-based visual-textual joint encoder and a trained immorality classifier f_{morality} , our model is capable of predicting visual commonsense immorality given an unseen image x_v , i.e., $\hat{y} = f_{\text{morality}}(\mathbf{v}) = f_{\text{morality}}(f_v(x_v))$.

Loss Function. We use the following Binary Cross-Entropy loss (BCELoss) \mathcal{L}_c between the target $y_i \in \{0,1\}$ and the classification output $\hat{y}_i = f_{\text{morality}}(\mathbf{t}_i) = f_{\text{morality}}(f_t(x_t^i))$ for $i \in \{1,2,\ldots,n\}$:

$$\mathcal{L}_{c} = -\frac{1}{n} \sum_{i=1}^{n} [y_{i} \log \sigma(\hat{y}_{i}) + (1 - y_{i}) \log(1 - \sigma(\hat{y}_{i}))]$$
(1)

where σ represents a sigmoid function.



Figure 3: Examples from different visual immorality datasets: (a) Socio-Moral (SMID) [1], (b) Sexual Intent Detection [1], (c) Real Life Violence Situation [1], and (d) Visual Commonsense Immorality (ours).

4 Visual Immorality Benchmark

To effectively evaluate the ability of our proposed model to predict immorality, a benchmark consisting of immoral images is generally required. However, as we summarized in Table 1 and Figure 3, existing benchmarks often focus on particular domains (e.g. sexual intent and violence) and would not be generalized well toward commonsense immorality. Thus, in this paper, we create a Visual Commonsense Immorality benchmark. We collect 2, 172 immoral images to proceed with more general and extensive immoral image detection. Inspired by ImageNet-Sketch data [50], all images are collected through Google Image queries and manually filtered by removing the irrelevant images (see examples in the supplemental material).

Design Criteria. In line with the previous research that deals with commonsense [13], we define the terminology "commonsense immorality" as the following: action that clearly should not have been done. We apply the following two criteria to collect and filter images

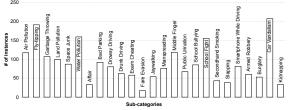


Figure 4: Class distribution of our benchmark.

based on the definition. First, all immoral keywords are selected based on *commonsense*. Since morality is an area of value judgment, it can vary given the specificity of culture or situation. However, it is generally clear that crime or violence is a value to be rejected. Second, images are *intuitive* in terms of morality. This is because, unlike text, which can take into account the context, the greatest difficulty of the image is that it is necessary to judge morality with limited information (i.e., static situation) only. Entire processes are constructed on human consensus because ethics is the domain of humanity.

Categories. Our benchmark consists of three categories: felony, antisocial behavior, and environmental pollution.

- Felony is based on title 18 of the United States Code (U.S.C. Title 18), which is the main criminal code of the federal government of the United States. For example, as 18 U.S.C. §2113. defines terminology and sentence about a bank robbery and incidental crimes, the keyword "armed robbery" is selected based on this statute. The most apparent immoral keywords are included in this category, such as "kidnapping", "burglary", and "vandalism".
- Antisocial behavior contains misdemeanors, social problems, and other unethical actions. As an example of driving, Driving Under the Influence (DUI) is a misdemeanor unless it leads to other accidents. In comparison, whether drowsy driving can be considered a misdemeanor might be vague and disputable. However, drowsy driving can

also be a latent cause of a tragic accident. Therefore, we classify these antisocial behaviors based on its dictionary definition: harmful to society. Social problems exist in this category in the same vein. "smartphone while driving", "exam cheating", and "secondhand smoking" are some examples of antisocial behavior.

• Environmental pollution is an another social domain of increasing importance recently. It has been underestimated so far because it is tacit and long-term change compared to other social problems. However, as sustainable development has become a principal challenge for the present era, global movements such as carbon emission regulations continue. It is no exaggeration to say that environmental pollution is one of the most important issues in the world at this point in time. In this context, we compose this category with some environmental keywords such as "fly-tipping", "air pollution", and "water pollution".

5 Experiments

Datasets. We use ETHICS [1] dataset to train our commonsense immorality assessment classifier. This dataset is based on natural language scenarios, which involves interpersonal events in an open-world setting (see details in the supplemental material). Note that we focus on contextualized scenarios with commonsense moral intuitions. To further evaluate the model's ability to judge commonsense morality, we use the following eight datasets: (1) MS-COCO [27], (2) ImageNet [12], (3) Socio-Moral Image [12], (4) Sexual Intent Detection [1], (5) Real Life Violence Situations [1], (6) NSFW [1], (7) XD-Violence [1], and (8) our Visual Commonsense Immorality. In detail, MS-COCO [26] and ImageNet [12] are widely-used image datasets throughout computer vision field. Especially, MS-COCO contains highly-curated images (though contain some images with immoral intents), which is thus ideal to be used as moral images. Socio-Moral Image Database [12] (SMID) contains photographic images, representing a wide range of morally positive, negative, and neutral. Sexual Intent Detection dataset [11] contains celebrity images with sexual and non-sexual content. In addition, Real Life Violence Situations dataset [25] contains 1,000 violence (e.g. street fights) and 1,000 non-violence videos collected from youtube videos. Lastly, similar to Sexual Intent Detection dataset, NSFW [I] as known as the word for not safe for work contains neutral, drawing, sexy and porn graphics. Further, validation datasets from ImageNet [12] are also used to examine whether our model may detect images with immoral intents from large scale dataset for profound discussions. Lastly, we use test video dataset of XD-Violence [1] to see if our model can classify immoral scenes with high immorality probability in long sequence video.

Textual Commonsense Immorality Classification Performance. Given the joint embedding space, we train an immorality predictor that outputs as a binary whether the input is moral or immoral. To train such a classifier, we use the ETHICS commonsense morality dataset [13] as supervision. It is proven that CLIP based on Vision transformer has a superior performance in downstream tasks than ResNet models. [53], which means text-image embedding space from the encoders are aligned more closely. Therefore, we conduct an experiment by using pre-trained CLIP text encoders which are Transformers that have been jointly trained with CLIP image encoders based on Vision Transformer. (see implementation details in the supplemental material) In supplemental material, we compare the classification performance on test data with variants of the CLIP-based model and uni-modal NLP-based baselines [15], [24], [25]. We observe that our model achieves an accuracy of 74.4%–79.2%, Table 1: We report zero-shot visual commonsense immorality classification performance of variants of our model in terms of F-measure. Six image benchmarks are used: MS-COCO [27], Socio-Moral Image [17], Sexual Intent Detection Images [17], Real Life Violence Situation [17], NSFW [1], and our Visual Commonsense Immorality. Note that we set alpha to 0.2 to emphasize on recall.

Dataset	Contents	# of Immoral	F-measure ($\alpha = 0.2$)		
Duniou	contents	Examples	ViT-B/32	ViT-B/16	ViT-L/14
MS-COCO [(mostly) non-immoral images	-	0.668	0.681	0.632
Socio-Moral Image [photographic images of morally positive, negative, and neutral	962	0.591	0.552	0.511
Sexual Intent Detection Images [11]	sexual and non-sexual	466	0.434	0.724	0.431
Real Life Violence Situation [violence and non-violence	1,000	0.807	0.645	0.743
NSFW [sexy and porn graphics	16,103	0.243	0.837	0.243
Visual Commonsense Immorality (ours)	felony, antisocial behavior, environmental pollution	2.172	0.962	0.776	0.720

which is comparable to or lower than uni-modal NLP-based baselines (62.9%–90.4%). This would be reasonable as CLIP text encoder is trained with simple and short image description as training input, while others are trained with text data that are more structured and complex. Further, as ETHICS dataset provides two types of textual scenarios: (i) short (1-2 sentences, focusing on actions, e.g. "I trashed his essay") and (ii) long (4-5 paragraphs, focusing on describing situations). Models with the longer descriptive texts as an input perform better than those with shorter action-centric texts (see detailed analysis in the supplemental material)

Zero-shot Visual Commonsense Immorality Analysis. Based on the CLIP-based joint embedding space and the above-mentioned immorality predictor, we further evaluate our model's ability to determine visual commonsense immorality from unseen input images. First, we evaluate our model with five existing datasets whose contents are similar with subcategories of ETHICS dataset, and we provide randomly-chosen examples in supplemental material. In Table 1, clearly, we can see all CLIP backbones outperforms in predicting immoral images in our Visual Commonsense Immorality dataset. This implies that there are some domain gaps between datasets: Compared to other dataset, our dataset is composed of images that shows the first-person character should not have done that action which is aligned with ETHICS dataset. In the same vein, our model performs well on predicting violent images in Real Life Violence Situation [13] dataset, because violent images are action-centric images compared to other existing dataset images (e.g. nude images in NSFW []). Even though the classifier with ViT-L/14 got much higher accuracy in ETHICS commonsense morality dataset, the classifier did not completely surpassed the other backbones in zero-shot classification of image datasets. According to the table 1, we set our final model which used pre-trained CLIP (ViT-B/32) image encoder since it is effective for the zero-shot prediction. Our analysis by using pre-trained CLIP (ViT-B/32) on our newly created dataset, which contains more diverse immoral scenarios, further confirms this. As shown in Table 2, similar to human intuition, images of felony produce higher immorality score (85.8%) than those of antisocial behavior (80.9%) and environment (76.2%).

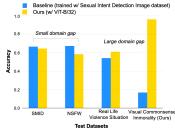
Analysis with ImageNet. Further, we apply our model to ImageNet $[\Box]$ – a large-scale widely used image classification dataset, which is thus required to ensure a generally high level of morality. As shown in Figure 1, we observe that (i) our model is indeed able to predict immoral images, which is consistent with human intuitions. (ii) We found that ImageNet dataset contains substantial number of immoral images that can potentially provide negative social impact without a proper image filtering. Furthermore, as shown in Figure 6, the immoral images are detected properly regardless of their original classes.

Table 2: We report an average visual commonsense immorality for each category (e.g. Armed Robbery) of our newly created dataset.

Felony (0.858)			Antisocial Behavior (0.809)				Environment (0.762)		
Armed Robber	0.895	Drowsy Driving	0.865	Manspreading	0.837	Smartphone while Driving	0.763	Fly-tipping	0.835
Burglary	0.865	Slapping	0.862	Fare Evasion	0.826	Jaywalking	0.760	Garbage Throwing	0.834
Kidnapping	0.862	School Fight	0.856	Bad Parking	0.786	Public Urination	0.743	Land Pollution	0.805
Car Vandalism	0.811	Secondhand Smoking	condhand Smoking 0.844 Exam Cheating 0.784			Air Pollution	0.762		
		Drunk Driving	0.842	Affair	0.766			Water Pollution	0.792
		School Bullying	0.839	Middle Finger	0.766			Space Junk	0.545
Classified as Classified di Immoral Moral									CHARLES

Figure 6: Examples of the same class but differently classified by our model. E.g., our model classifies an image of a hammer as moral, but a person striking with it as immoral.

Zero-shot Visual Supervision Baseline. Figure 5 shows a performance comparison with ResNet50 model that is trained with Sexual Intent Detection Images dataset and tested (in a zero-shot manner) with SMID (random photographic images), NSFW (sexy and porn graphics), Real Life Violence Situation, and our Viusal Commonsense Immorality. We observe that such classifier trained on a specific category of commonsense immorality often results



in overfitting and does not generalize well. In Real Life Figure 5: Performance compar-Violence Situation and Visual Commonsense Immorality ison with baseline.

dataset, there are large domain gaps between Sexual Intent Detection compared to SMID and NSFW. This leads to the poor performance of ResNet50 and results in the dramatic accuracy gap with our model in our Visual Commonsense Immorality dataset.

Human Evaluations. Since ethics is humanity's domain, aligning the model's behavior with human intuition is essential. Therefore, we conduct a human evaluation to quantify the effectiveness of our model. We use Amazon Mechanical Turk (AMT) to secure diverse cultural backgrounds

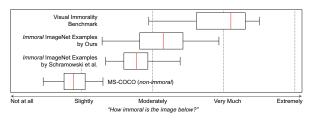


Figure 7: Box plots from our human evaluations.

in our human study. Overall, 172 respondents (from more than six different ethnic groups) were recruited and asked to evaluate the immorality of the given 100 images on the 5-point Likert Scale. Those images were randomly sampled from four different sources: (a) Visual Commonsense Immorality Benchmark, Immoral ImageNet examples found by (b) our model, and (c) existing work by Schramowski *et al.*, and (d) MS-COCO validation dataset [22]. Note that we set a threshold to 0.9 for all experiments.

In Figure 7, we visualize box plots for each image sources. We observe that participants answered that images from our created benchmark are immoral (median score was 4.10), while images from MS-COCO (mostly moral) received 1.91. This may confirm the validity

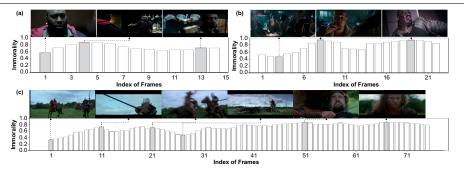


Figure 8: We visualize examples (e.g. (a) using a gun, (b) drinking or a person passed out, and (c) fighting) of the predicted level of visual commonsense immorality on XD-violence [1] video frames. Corresponding video frames are provided on top of each plot. Note that we apply a Savitzky-Golay smoothing filter (with the window size set to 5).

of our created dataset for the visual commonsense immorality classification task. Further, our study shows that our model can detect visual immorality better than existing work by Schramowski *et al.* [1] (3.14 vs. 2.82 in the median, compare 2nd and 3rd box-plots). This confirms that leveraging textual information as supervision with a text-image embedding space has better generalization compared to optimizing the model with small image dataset.

Analysis with Video. We conduct an experiment to test if our model truly capture the immoral scenes in the video. Therefore, we use violent dataset of XD-Violence [1] which have various violent scenes in long sequences. In randomly chosen videos, we extract a frame uniformly every second. Figure 8 represents that our model correctly predict the immoral scenes with higher probabilities compared to other non-immoral scenes. It leads us to the next experiment of classifying the short video clips. We classify to violent video if the average probability of all frames is higher than 0.7. We achieve 72.7% accuracy and 75.7% F-measure (α =0.2) in Real Life Violence Situation dataset [13], which means our model is reasonably able to determine visual immorality in short videos.

6 Conclusion

Predicting immorality from images is of paramount importance regarding social safety. In this work, we first utilized CLIP-based text-image joint embedding space and trained a (text-based) commonsense immorality classifier. Given these, we then predicted visual commonsense immorality from an unseen image in a zero-shot manner. Using seven benchmarks in image classification, we demonstrated that our model successfully estimates visual commonsense immorality. Our analysis with the XD-Violence dataset also showed consistency in its prediction. In fact, we observed that widely-used image classification benchmarks, such as ImageNet, contain immoral visual scenes, potentially negatively impacting the trained model's behavior. Further, we created a new Visual Commonsense Immorality benchmark, a more general image benchmark toward commonsense immorality. We hope our paper could be an initial point in discussing the importance of visual commonsense immorality towards ethical AI.

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