Towards the Human Global Context: Does the Vision-Language Model Really Judge Like a Human Being?

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Abstract
As computer vision and NLP make progress, Vision-Language (VL) is becoming an important area of research. Despite the importance, evaluation metrics of the research domain is still at a preliminary stage of development. In this paper, we propose a quantitative metric "Equivariance Score" and evaluation dataset "Human Puzzle" to assess whether a VL model is understanding an image like a human. We observed that the VL model does not interpret the overall context of an input image but instead shows biases toward a specific object or shape that forms the local context. We aim to quantitatively measure a model’s performance in understanding context. To verify the current existing VL model’s capability, we sliced the original input image into pieces and randomly placed them, distorting the global context of the image. Our paper discusses each VL model’s level of interpretation on global context and addresses how the structural characteristics influenced the results.

1 Introduction
Vision-Language task interprets the context of the given image and attempts to represent it in a human language. Image captioning (Wang et al., 2022; Zeng et al., 2021; Wang et al., 2021; Pan et al., 2020) for example, analyzes context (relations between objects, situational background, etc.) to construct a sentence that adequately explains the given image. In a similar domain, VQA (Antol et al., 2015) uses multi-modal to generate adequate answers to the text (question) associated with the image. As image-based text generation models infer results from fusing computer vision domain and NLP domain, majority of VL models are classified into “vision task” (He et al., 2016; Ren et al., 2015), which interprets the given image, and “text task” which generates the associated texts. Most common methodologies used is the 2-stage approach, where the vision model first extracts the features from the image that are easier for the language model to interpret and train from. In the case of OSCAR (Li et al., 2020), the maximum number of objects are detected from the object detection model and are passed on to a language model with the object’s class name. In the case of X-VLM (Zeng et al., 2021), inter-object relation was used in training for better information sharing between image-text models. In the case of OFA (Wang et al., 2022), conveying information that is much more comprehensible for language models was the focus to enhancing performance. As stated above, there has been a growing body of research that explores how recent VL models can better interpret images and deliver critical information to the language model.

Then what evaluation method would be appropriate to compare which structure is better at Vision-Language process? Perplexity (Jelinek et al., 1977) at language generation? BLEU (Papineni et al., 2002) score? CIDEr (Vedantam et al., 2015)? These are all valid metrics to measure VL model’s performance, but they all do not properly evaluate all aspects of VL model. Figure 1 depicts results of captioning from several VL models. Each model came up with its own answer for the image of a distorted human body. We human beings can easily recognize differences between normal and distorted images, so VL models are expected to be equivariant (explained in section 2.4) as well but that is not the case. In view of the captioning results, all VL models seem to concentrate more on local-context without considering distorted human body(a.k.a global context of human body). Despite VL models being invariant(non-equivariant) with captioning, each model has different understandings in global context of human body. This is obvious because...
they all have their own feature extraction stage on image. To perform evaluation on such VL models, we propose Equivariance Score and dataset named as “Human Puzzle”. As a result, our contributions are the following:

1. We illustrate how Vision-Language models are biased towards local context instead of global context.

2. We present an evaluation dataset and metrics to measure global context interpretation.

2 Related Works

2.1 Vision-Language Networks

As vision and language studies make progress, importance in the Vision-Language model is also steadily rising. In recent years, OSCAR+, which replaces image interpreting stage of OSCAR with VinVL (Zhang et al., 2021), has demonstrated notable performance. Through the method of placing an object’s label with its extracted feature from the image and sending it to the transformer-encoder structure, OSCAR+ has achieved state-of-the-art performances in numerous VL tasks and quickly became a dominant model in the VL field. In a similar fashion, X-VLM also extracts features from images and trains them to language model, but through many layers of contrastive learning on inter-object relations, the model sought to understand not only the single object context but also the relationship between objects in general. OFA also tried to extract information from the image and made the language model interpret the results. In addition, unique tokens were allocated to help the language model have a better perception of the extracted information, and this kind of process played a pivotal role in narrowing the gap between the language and image models. In Vision Language Processing, researchers are still studying various models to find a better way of extracting information from images.
2.2 Image Networks

*Human Puzzle* dataset was first constructed by producing large amounts of data with distorted context of human body. We then filtered by choosing ones where the vision model could not identify correctly from the undistorted. Vision models utilized in this process are ResNet (He et al., 2016), Vision Transformer (Dosovitskiy et al., 2020), and Swin Transformer (Liu et al., 2021), which were selected based on prevalence. In ResNet, skip-connection was applied to increase the model’s depth without vanishing gradient problem. As a result, stable training while maintaining deep networks became possible, propelling ResNet to be a dominant backbone in fields of vision. Vision Transformer is a model that integrated the structure of a transformer, a model that made compelling breakthroughs in the field of NLP. By partitioning images into patches and treating them like text tokens, Vision Transformer shows state-of-the-art performance comparable to conventional CNN-based models regarding classification. Swin Transformer is a model derived from CNN’s approach to overcome shortcomings of Transformer and likewise exhibits state-of-the-art performance in classification.

2.3 Interpretation of Global Context

There have been many preceding attempts (Huang et al., 2019) to analyze global context in the field of vision. In prior studies, DeepLabV3 (Chen et al., 2017) and CCNet (Huang et al., 2019) applied ASPP (Atrous Spatial Pyramid Pooling) and CC-attention (Criss-Cross attention) to widen feature’s receptive field to utilize global context, reporting high performances.

In Vision Language Processing, there also has been implicit attempts to interpret global context in images. VL models are generally directed towards extracting additional information from the image such as specifying object relation with natural languages, giving positional information of detected object to Language Model, translating image features into natural language, and so on. These can all be seen as an attempt to make models have a better grasp of understanding global context. In the case of OSCAR+, the most dominant model in the field of VL that tried to convey positional information with features and labels of detected object however, has been observed that intentionally corrupting an object’s positional information has no impact on its performance. Based on these findings, we guess that OSCAR+ has less consideration in interpretation of global context.

2.4 Equivariance and Invariance

From previous works, equivariance is defined as change in output according to corresponding change in input’s context. Invariance is the opposite of equivariance where output does not change to change in input. Figure 3 simply shows concept...
of equivariance. In vision task, many researchers try to boost invariance to get better efficiency by using sub-sampling such as max-pooling. This way of boosting invariance makes model focus more on shape or texture, but gives limitation in understanding context such as objects’ relations. To overcome this limitation, Romero et al. (2020) proposes “attentive group equivariant convolutions” (Romero et al., 2020) and shows that it has effect on equivariant training. In addition, Sabour et al. (2017) leads model to be more equivariant by applying “dynamic routing” (Sabour et al., 2017). From insights above, we believe that goal of VL tasks should lean towards equivariant model because goal of VL is to mimic human expressions, and we humans are equivariant. In this paper, We construct “Human Puzzle” dataset which contains distorted context of human body and propose “Equivariance Score” that can quantify the VL models’ equivariance.

3 Framework for Global Context and Equivariance

In Vision-Language Processing, understanding the global context of an image is an evident matter of emphasis for human-like understanding. We suggest a simple approach to quantify how much a model is comprehending global context. Figure 2 is an overview of our approach. Each image is forwarded to the VL model, where normal image is set to \textit{True}, while image with distorted global context in human body is set to \textit{False}.

The output of the model is then sent to a classifier instead of word embedding to distinguish its boolean value. Over this course, weights of the VL model are frozen, and only the classifier proceeds to train from the process. If a model is well capable of understanding global context, it would excel in classifying normal images from images with distorted human body, and this suggests the model is equivariant. If it can’t classify well, then the model would be seen as invariant. In section 6, we suggest the quantifying metric of equivariance as \textit{Equivariance Score}, and this metric with \textit{Human Puzzle} dataset could reflect how model understands global context of human body. The above process is applicable to both VL models and vision models that take image as an input.

4 Dataset Construction

Our suggestion to measure if a model is equivariant at global context is comparing the output of the normal image with that of image with distorted context. For this process, a complementary dataset is essential. To prepare normal images and images with distorted global contexts, we had to construct synthesized data. Basic concept originates from the fact that VL models do not fully understand human shape as shown in Figure 1. To acquire enough synthetic data, raw data with humans separated from the background was necessary.
VideoMatte240K (Lin et al., 2021) dataset was selected as the source of raw data for human figures as it met such criteria. Total of 958 human figure images were collected by sampling the frame from VideoMatte240K dataset, which filmed humans in diverse actions without any background. In addition, 193 background images from PhotoMatte85 dataset were used as source of raw data.

5 Human Puzzle Dataset

Generating tens of millions of images by mix-and-matching 958 human images with 193 background images is not difficult. Yet, we cannot argue that the entirety of arbitrarily modified and synthesized image dataset is suitable for qualifying degree of interpretation on global context as we suggested. Hence, highly recognized vision models were used to select relevant and meaningful images from the pool of millions. The methods used to impair the global contexts of human images are simple. Methods of slicing, reflecting, relocating, etc. depending on arbitrary offsets were applied while maintaining the axis of the original image. Raw synthetic data reached 2.6M by combining background images with all possible numbers of cases of modification on original human images. To filter out the 2.6M images, ResNet, ViT (Dosovitskiy et al., 2020), and SwinT (Liu et al., 2021) were used. After training each model’s classifier while the individual weights were frozen, images that models could not accurately classify from a separate test set were chosen. Finalists for the dataset were selected from images where 2 out of 3 models gave incorrect classification. In the end, we manually filtered out the remaining images to create the Human Puzzle dataset.

6 Equivariance Score

The aim of our research is not to classify distorted data, but to carry out regression analysis on the extent of global context interpretation. Hence, simply measuring accuracy would be inappropriate, while applying entropy would serve as an adequate metric to quantify a model’s rate of confusion. We suggest an entropy-based metric like Equation 2 to assess the model’s global context comprehension level.

\[ H(p) = -p \log_2 p - (1 - p) \log_2 (1 - p), \]  
\[ p \in P \]

Equation 1 calculates the entropy of the probability value after applying softmax on Human Puzzle-trained model’s logits. Applying Equation 1, we calculate the entropy of this probability \( p \) to finally calculate Equivariance Score written in Equation 2.

\[ \text{Equivariance Score} = \frac{\sum_t (1 - H(p_t)) + \sum_f H(p_f)}{N_t + N_f} \]  

Equation 2

In Equation 2, \( p_t \) and \( p_f \) (\( p_t, p_f \in P \)) represent the probabilities of correct and incorrect prediction. Here, \( N_t \) and \( N_f \) refer to the number of \( p_t \) and \( p_f \) respectively. Through Equation 2, the value of rightfully predicted results becomes substantial, while the value of wrongfully predicted results goes minimal. Theoretically, if all the predicted answers are correct, and entropy of the result is also zero, then a perfect score would be given.

7 Experiment

7.1 Experiment Details

For training of the Human Puzzle dataset in this study, we used encoders of the pre-trained VL and vision model. In the case of VL, since most of the models use transformers, the last hidden layer output was applied. In the case of CNN-based vision model, since ResNet backbone forms the majority, features of ResNet’s fourth stage were applied. In the case of DeepLabV3, and CCNet, we extracted from each model’s ASPP, and CC-attention module. We designed the extracted features from each of the models to be forwarded to independent individual fully-connected layers to carry out binary prediction. This was done to differentiate the features with distorted global context.

7.2 Quantitative Result

Table 1 shows the result of the measured Equivariance Score trained and evaluated with Human Puzzle dataset. We proceeded with training and testing on the latest VL models and vision models. In the case of OSCAR+, it was trained with tremendous amounts of data compared to other VL models and performed very well in most of VL tasks. Nonetheless, OSCAR+ only extracts as many features as...
Table 1: Comparison of quantitative performance and *Equivariance Score* for each model on *Human Puzzle* dataset.

| model                  | pre-trained dataset | entropy | acc.   | equivariance score |
|------------------------|---------------------|---------|--------|-------------------|
| Virtex (Desai and Johnson, 2021) | COCO (Chen et al., 2015) | 0.039   | 91.57% | 0.736             |
| OSCAR+ (Li et al., 2020)  | COCO (Chen et al., 2015) + extra* | 0.299   | 93.0%  | 0.740             |
| X-VLM (Zeng et al., 2021) | COCO (Chen et al., 2015) | 0.216   | 96.42% | 0.830             |
| OFA (Wang et al., 2022)  | COCO (Chen et al., 2015) | 0.0928  |        | 0.914             |
| ViT (Dosovitskiy et al., 2020) | ImageNet-1K (Deng et al., 2009) | 0.806   | 63.7%  | 0.473             |
| DViT (Zhou et al., 2021)  | ImageNet-1K (Deng et al., 2009) | 0.678   | 73.72% | 0.500             |
| SwinT (Liu et al., 2021)  | ImageNet-1K (Deng et al., 2009) | 0.205   | 95.3%  | 0.821             |
| ResNet (He et al., 2016)  | ImageNet-1K (Deng et al., 2009) | 0.096   | 95.5%  | 0.910             |
| SE-ResNet (Hu et al., 2018) | ImageNet-1K (Deng et al., 2009) | 0.079   | 96.1%  | 0.920             |

* OSCAR+ follow the datasets settings of VinVL (Zhang et al., 2021)

Table 2: *Equivariance Score* performance comparison for CNN-based networks.

| model                  | pre-trained dataset | entropy | acc.   | equivariance score |
|------------------------|---------------------|---------|--------|-------------------|
| FCN (Long et al., 2015) | Cityscapes (Cordts et al., 2016) | 0.538   | 89.1%  | 0.544             |
| DeepLabV3 (Chen et al., 2017) | Cityscapes (Cordts et al., 2016) | 0.447   | 84.2%  | 0.633             |
| CCNet (Huang et al., 2019) | Cityscapes (Cordts et al., 2016) | 0.382   | 84.3%  | 0.677             |

it can from images without processing relational information, leading us to predict relatively low *Equivariance Score*, and this was found to be true based on our experiment results. In the case of X-VLM, it was aimed to apply global context to its training. By constructing inter-object relations as a separate dataset, X-VLM carried out step-by-step contrastive learning. Despite X-VLM being trained on a much smaller dataset compared to OSCAR+, it demonstrated a much better *Equivariance Score*. Unified vocab suggested in OFA consists of not only the vocab’s text but also locational information or even image itself. This was implemented to convert transferred information to the model for better interpretation. We expected that unified vocab will enhance global context interpretation, and OFA in our experiment result indeed conveyed the highest *Equivariance Score*.

We also proceeded on experimenting on vision models. In general, CNN-based models showed higher *Equivariance Score* over transformer-based models. This can be seen as a result of structural characteristics of CNN, where features of the input layer are forwarded to the end layer.

Drastic difference between ViT and SwinT’s *Equivariance Score* is implying this as well. ViT showed that it can apply images to transformer by slicing images into patches, and to overcome ViT’s shortcoming of inductive bias, SwinT applied shifted window structure ideated from CNN. Drawing from this, we expected SwinT’s *Equivariance Score* to be higher than ViT’s, and this was indeed true, as SwinT’s *Equivariance Score* was closer to CNN-based model, far exceeding that of ViT.

Furthermore, we explored studies exploiting the global context in the field of vision to extensively validate the usefulness of our *Human Puzzle dataset*. Table 2 shows results of evaluating context score on semantic segmentation models. Amongst them, FCN did not put global context in consideration, and each model all used the ResNet backbone. FCN displayed the highest performance in classification on our *Human Puzzle dataset*, but in contrast, scored the lowest on *Equivariance Score*. Meanwhile, other models that utilized global context measured higher in *Equivariance Score* compared to FCN. This result establishes that our *Human Puzzle dataset* and our suggested *Equivariance Score* are, indeed, valid.

8 Conclusion

In this paper, we propose the *Equivariance Score* to measure Vision-Language model’s degree of equivariance and provide the *Human Puzzle* dataset. These two can help future works with measuring how VL models are equivariant in global context. Overall, models that attempted to extract information on global context measured relatively higher *Equivariance Score* than models that did not, and our *Equivariance Score* is a valid metric to indicate how much such attempts are meaningful. The proposed method in our paper is applicable not only to the fields of VL, but also
in the fields of vision and can serve as a basis for research in many different domains.

9 Limitation and Discussion

Human Puzzle dataset and Equivariance Score metric suggested in this paper are not just restricted to VL, but in all fields that work with images. However, the dataset has its own limitations in that it only considers the global context of human body. In consequence, there exists a need to construct appropriate dataset with distorted global context in both humans and diverse objects with backgrounds as well. Through this additional construction, metrics to quantify VL and vision models’ equivariance in global context can become more robust. Furthermore, Equivariance Score suggested in this paper is a new measuring metric that is previously nonexistent, implying focus on global context for future research in VL and vision.

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