Visual correspondence-based explanations improve AI robustness and human-AI team accuracy

Giang Nguyen * nguyengiangbkhn@gmail.com
Mohammad Reza Taesiri * mtaesiri@gmail.com
Anh Nguyen anh.ng@live.com
Auburn University

Abstract
Explaining artificial intelligence (AI) predictions is increasingly important and even imperative in many high-stakes applications where humans are the ultimate decision makers. In this work, we propose two novel architectures of self-interpretable image classifiers that first explain, and then predict (as opposed to post-hoc explanations) by harnessing the visual correspondences between a query image and exemplars. Our models consistently improve (+1 to +4 points) on out-of-distribution (OOD) datasets while performing marginally worse (-1 to -2 points) on in-distribution tests than ResNet-50 and a k-nearest neighbor classifier (kNN). Via a large-scale, human study on ImageNet and CUB, our correspondence-based explanations are found to be more useful to users than kNN explanations. Our explanations help users more accurately reject AI’s wrong decisions than all other tested methods. Interestingly, for the first time, we show that it is possible to achieve complementary human-AI team accuracy (i.e., that is higher than either AI-alone or human-alone), in ImageNet and CUB image classification tasks.

1 Introduction
Comparing the input image with training-set exemplars is the backbone for many applications, such as face identification [29], bird identification [17, 79], and image search [79]. This non-parametric approach may improve classification accuracy on out-of-distribution (OOD) data [29, 75, 79, 57] and enables a class of prototype-based explanations [17, 52, 53, 66, 41] that provide insights into the decision making of Artificial Intelligence (AI) systems. Interestingly, prototype-based explanations are more effective in improving human classification accuracy [55, 24, 42] than attribution maps—a common eXplainable AI (XAI) technique in computer vision. Yet, it remains an open question how to make prototype-based XAI classifiers (1) accurate on in-distribution and OOD data and (2) improve human decisions. For example, in face identification, AIs can be confused by partially occluded, never-seen faces and are unable to explain their decisions to users, causing numerous people falsely arrested [5, 7, 3, 6] or wrongly denied unemployment benefits [1] by the law enforcement.

To address the above questions, we propose two interpretable [61], (i.e., first-explain-then-decide) image classifiers that perform three common steps: (1) rank the training-set images based on their distances to the input using image-level features; (2) re-rank the top-50 shortlisted candidates by their

*Equal contribution. Listing order is random. GN led the development of EMD-Corr and human studies on Gorilla. MRT led the development of CHM-Corr, pilot studies on HuggingFace, and the analysis of human-study data from Gorilla. AN advised the project. MRT’s work was done before he joined University of Alberta.
Figure 1: The ibex image is misclassified into parachute due to its similarity (clouds in blue sky) to parachute scenes (a). In contrast, CHM-Corr correctly labels the input as it matches ibex images mostly using the animal’s features, discarding the background information (b).

Figure 2: Operating at the image-level visual similarity, kNN incorrectly labels the input toaster due to the adversarial toaster patch (a). EMD-Corr instead ignores the adversarial patch and only uses the head and neck patches of the hen to make decisions (b).

 Patch-wise correspondences w.r.t. the input [51, 29]; and then (3) take the dominant class among the top-20 candidates as the predicted label. That is, our classifiers base their decisions on a set of support image-patch pairs, which also serve as explanations to users (Figs. 1b and 2b). Our main findings include:

- On ImageNet, a simple $k$-nearest-neighbor classifier (kNN) based on ResNet-50 features slightly but consistently outperforms ResNet-50 on many OOD datasets (Sec. 3.1). This is further improved after a re-ranking step based on patch-wise similarity (Sec. 3.2).
- Via a large-scale human study, we find visual correspondence-based explanations to improve AI-assisted, human-alone accuracy and human-AI team accuracy on ImageNet and CUB over the baseline kNN explanations (Sec. 3.4).
- Having interpretable AIs label images that they are confident and humans label the rest yields better accuracy than letting AIs or humans alone label all images (Sec. 3.5 and Appendix M).

To the best of our knowledge, our work is the first to demonstrate the utility of correspondence-based explanations to users on ImageNet [63] and CUB [71] classification tasks.

2 Methods

2.1 Datasets

We test our ImageNet classifiers on the original 50K-image ILSVRC 2012 ImageNet validation set (i.e., in-distribution data) and four common OOD benchmarks below.

- **ImageNet-R** [35] contains 30K images in 200 ImageNet categories, mostly artworks – ranging from cartoons to video-game renditions.
- **ImageNet-Sketch** [72] consists of 50,889 black-and-white sketches of all 1,000 ImageNet classes.
- **DAmageNet** [18] consists of 50K ImageNet validation-set images that contain universal, adversarial perturbations for fooling classifiers.
- **Adversarial Patch** [15] are 50K ImageNet validation-set images that are modified to contain an adversarial patch that aims to cause ResNet-50 [31] into labeling every image toaster (see Fig. 2).

\footnote{Code and models are available at https://github.com/anguyen8/visual-correspondence-XAI.}
Using the implementation by [2], we generate this dataset, which causes ResNet-50 accuracy to drop from 76.13% to 55.04% (Table 1). See Appendix A.5 for how to download and generate this dataset.

**CUB-200-2011** [71] (hereafter, CUB) is a fine-grained, bird-image classification task chosen to complement ImageNet. CUB contains 11,788 images (5,994/5,794 for train/test) of 200 bird species.

### 2.2 Classifiers

We harness the same ResNet-50 layer4 backbone [8] as the main feature extractor for all four main classifiers, including our two interpretable models. Therefore, to test the effectiveness of our models, we compare them with (1) a vanilla ResNet-50 classifier; and (2) a kNN classifier that uses the same pretrained layer4 features. We report the top-1 accuracy of all classifiers in Table 1.

**ResNet-50** For experiments on ImageNet and its four OOD benchmarks, we use the ImageNet-trained ResNet-50 from TorchVision [8] (top-1 accuracy: 76.13%).

For CUB, we take the ResNet-50 pretrained on iNaturalist [70] from [53] (hereafter, iNaturalist ResNet) and retrain only the last 200-output classification layer (right after avgpool) to create a competitive, baseline ResNet-50 classifier for CUB (top-1 accuracy: 85.83%). See Appendix A.1 for finetuning details.

**kNN** We implement a vanilla kNN classifier that operates at the avgpool of the last convolutional layer of ResNet-50. That is, given a query image $Q$, we sort all training-set images $\{G_i\}$ based on their distance $D(Q, G_i)$, which is the cosine distance between the two corresponding image features $f(Q)$ and $f(G_i) \in \mathbb{R}^{2048}$ where $f(\cdot)$ outputs the avgpool feature of layer4 (see code) of ResNet-50.

The predicted label of $Q$ is the dominant class among the top-$k$ nearest neighbors. We choose $k = 20$ as it performs the best among the tested values of $k \in \{10, 20, 50, 100\}$.

Figure 3: EMD-Corr and CHM-Corr both re-rank kNN’s top-50 candidates using the patch-wise similarity between the query and each candidate over the top-5 pairs of patches that are the most important and the most similar (i.e. highest EMD flows in EMD-Corr and highest cosine similarity in CHM-Corr).

**EMD-Corr** As kNN compares images using only image-level features, it lacks the capability of paying attention to fine details in images. Therefore, we propose EMD-Corr, a visual correspondence-based classifier that (1) re-ranks the top-$N$ (here, $N = 50$) candidates of kNN using their Earth Mover’s Distance (EMD) with the query in a patch embedding space (see Fig. 3a); and (2), similarly to kNN, takes the dominant class among the re-ranked top-20 as the predicted label.

That is, our PyTorch implementation is the same as that in [79, 29] except for three key differences. First, using layer4 features ($7 \times 7 \times 2048$), we divide an image into 49 patches, whose embeddings are $\in \mathbb{R}^{2048}$. Second, for interpretability, in re-ranking, we only use patch-wise EMD instead of a
We ask users to decide Y/N whether the top-1 label is correct (example screen in Fig. A7). We find N where we offload most inputs to AIs while users only handle the harder cases.

A query image may have weighting patches, on CUB, we compare our EMD-Corr and CHM-Corr to CHM-Corr+, a CHM-Corr variant where we use a set of five human-defined important patches instead of those inferred by CC. After testing NC-Net [60], ANC-Net [48], and CHM [51] in our classifier, we choose CHM as it has most confident, leaving the rest for users to label. That is, model 2 (Fig. 4b–c) is a practical scenario deciding, and explanations (Fig. 4a).

Model 1:

Model 2:

2.3 User-study design

The interpretable classifiers (Sec. 2.2) are not only capable of classifying images but also generating explanations, which may inform and improve users’ decision-making [55]. Here, we design a large-scale study to understand the effectiveness of explanations in two human-AI interaction models in classification (see Fig. 4): Model 1: Users make all the decisions after observing the input, AI decisions, and explanations (Fig. 4a). Model 2: AIs make decisions on only inputs that they are the most confident, leaving the rest for users to label. That is, model 2 (Fig. 4b–c) is a practical scenario where we offload most inputs to AIs while users only handle the harder cases.

Like [55], we show each user: (1) a query image; (2) AI top-1 label and confidence score; and (3) an explanation (here, available in kNN, EMD-Corr, CHM-Corr, and CHM-Corr+, but not in ResNet-50). We ask users to decide Y/N whether the top-1 label is correct (example screen in Fig. A7).
2.3.1 Explanation methods

We test the explanations of four main classifiers: ResNet-50, kNN, EMD-Corr, and CHM-Corr. Additionally, we test two ablated versions (i.e., EMD-NN and CHM-NN) of the explanations of EMD-Corr and CHM-Corr. In total, we test 6 explanation methods (see examples in Appendix D).

ResNet-50 is a representative black-box classifier, which only outputs a top-1 label and a confidence score (i.e., no explanations).

kNN explanations From the top-20 nearest neighbors (as $k = 20$ in our kNN), we show the first five images that are from the predicted class (example in Fig. 1a). In some cases where the predicted class has only $M < 5$ exemplars in the top-20, we still show only those $M$ images (see Fig. A46). That is, we only show at most five neighbors following prior works [55, 67, 49, 65] that reported utility of such few-image explanations. We find explanations consisting of $\geq 10$ images such as those of ProtoPNet [17] are hard to interpret for users [42]. Note that our kNN explanations consist of five support images for each decision of kNN (described in Sec. 2.2) as opposed to the post-hoc nearest examples in [55], which do not reflect a classifier’s decisions.

EMD-Corr and CHM-Corr explanations As EMD-Corr and CHM-Corr re-rank the top-50 candidates (shortlisted by kNN) and take the dominant class among the resultant top-20 as the predicted label, we show the five nearest neighbors from the predicted class as in kNN explanations. Instead of showing only five post-reranking neighbors, we also annotate, in each image, all five patches (example in Fig. 1b and Fig. 2b) that contribute to the patch-wise re-ranking (Sec. 2.2).

EMD-NN and CHM-NN To understand the effects of showing correspondences in the explanations to EMD-Corr and CHM-Corr users, we also test an ablated version where we show exactly the same explanations but without the patch annotations (bottom panels in Fig. 1a and Fig. 2a).

Confidence scores While ResNet-50’s confidence score is the top-1 output softmax probability, the confidence of kNN, EMD-Corr, and CHM-Corr is the count of the predicted-class examples among the top $k = 20$. In human studies, we display this confidence in percentage (e.g. 10% instead of 2/20; Fig. A46) to be consistent with the confidence score of ResNet-50.

2.3.2 ImageNet and CUB datasets

For XAI evaluation, we run two human studies, one on ImageNet and one on CUB. For ImageNet, we use ImageNet-RealL [14] labels in attempt to minimize the confounders of the human evaluation as ImageNet labels are sometimes misleading and inaccurate to users [55].

Nearest-neighbor images To generate the nearest-neighbor explanations for kNN, EMD-Corr, and CHM-Corr, we search for neighbors in the entire training set of ImageNet or CUB (no filtering).

Query images In attempt to ensure the quality of the query images that we ask users to label, from 50K-image ImageNet validation set, we discard images that: (a) do not have an ImageNet-RealL [14]
(b) are grayscale or low-resolution (i.e., either width or height < 224 px) as in [55]; (c) have duplicates in the ImageNet training set (see Appendix L), resulting in 44,424 images available for sampling for the study. In CUB, we sample from the entire 5,794-image test set and apply no filters.

### 2.3.3 Training, Validation, and Test phases

From the set of query images (Sec. 2.3.2), we sample images for three phases in a user study: Training, validation, and test. Following [55], we first introduce participants to the task and provide them 5 training examples. Then, each user is given a validation job (10 trials for ImageNet and 5 for CUB), where they must score 100% in order to be invited to our 30-trial test phase. Otherwise, they will be rejected and unpaid. Among the 10 validation trials for ImageNet, 5 are correctly-labeled and 5 are misclassified by AIs. This ratio is 3/2 for CUB validation (examples in Appendix E.2).

Right before each trial, we describe the AI’s top-1 label to users by showing them 3 training-set images and a 1-sentence WordNet description for each ImageNet class. For CUB classes, we show 6 representative images (instead of 3) for users to better recognize the characteristics of each bird (see Fig. A6).

#### Sampling

For every classifier, we randomly sample 300 correctly- and 300 incorrectly-predicted images together with their corresponding explanations for the test trials. Over all 6 explanation methods, we have 2 datasets × 600 images × 6 methods = 7,200 test images in total.

### 2.3.4 Participants

We host human studies on Gorilla [11] and recruit lay participants who are native English speakers worldwide via Prolific [56] at a pay rate of USD 13.5/hr. We have 360 and 355 users who successfully passed our validation test for ImageNet and CUB datasets, respectively. We remove low-quality, bottom-outlier submissions, i.e., who score ≤ 0.55 (near-random accuracy), resulting in 354 and 355 submissions for ImageNet and CUB, respectively. In each dataset, every explanation method is tested on ~60 users and each pair of (query, explanation) is seen by almost 3 users (details in Table 2).

### 3 Experimental Results

#### 3.1 ImageNet kNN classifiers improve upon ResNet-50 on out-of-distribution datasets

Despite impressive test-set performance, ImageNet-trained convolutional neural networks (CNNs) may fail to generalize to natural OOD data [72] or inputs specifically crafted to fool them [54, 18, 15]. It is unknown whether prototype-based classifiers can leverage the known exemplars (i.e. support images) to generalize better to unseen, rare inputs. To test this question, here, we compare kNN with the baseline ResNet-50 classifier (both described in Sec. 2) on ImageNet and related OOD datasets.

On ImageNet and ImageNet-ReaL, kNN performs slightly worse than ResNet-50 by -1.36 and -0.99 points, respectively (Table 1). Yet, interestingly, on all four OOD datasets, kNN consistently outperforms ResNet-50. Notably, kNN improves upon ResNet-50 by +1.66 and +4.26 points on DAImageNet and Adversarial Patch. That is, while ResNet-50 and kNN share the exact same backbone, the kNN’s process of comparing the input image against the training-set examples prove to be beneficial for generalizing to OOD inputs. Intuitively, our results suggest that it is useful to “look back” at the training-set exemplars to decide a label for hard, long-tail or OOD images.

Consistently, using the same CUB-finetuned backbone, kNN is only marginally worse than ResNet-50 on CUB (85.46% vs. 85.83%; Table 1).

#### 3.2 Visual correspondence-based explanations improve kNN robustness further

Recent work found that re-ranking kNN’s shortlisted candidates using the patch-wise similarity between the query and training set examples can further improve classification accuracy on OOD data for some image matching tasks [29, 79, 75] such as face identification [29]. Furthermore, patch-level comparison is also useful in prototype-based bird classifiers [17, 22]. Inspired by these prior successes and the fact that EMD-Corr and CHM-Corr base the patch-wise similarity of two images on only 5 patch pairs instead of all $49 \times 49 = 2,401$ pairs as in [29, 79, 75], here we test whether our two proposed re-rankers are able to improve the test-set accuracy and robustness over kNN.
Table 1: Top-1 accuracy (%). ResNet-50 models’ classification layer is fine-tuned on a specified training set in (b). All other classifiers are non-parametric, nearest-neighbor models based on pretrained ResNet-50 features (a) and retrieve neighbors from the training set (b) during testing. EMD-Corr & CHM-Corr outperform ResNet-50 models on all OOD datasets (e.g. +4.39 on Adversarial Patch) and slightly underperform on in-distribution sets (e.g. -0.72 on ImageNet-Real).

| Test set          | Features (a) | Training set (b) | ResNet-50 | kNN | EMD-Corr | CHM-Corr | CHM-Corr+ |
|-------------------|--------------|------------------|-----------|-----|----------|----------|----------|
| ImageNet          | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| ImageNet-Real     | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| ImageNet-R        | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| ImageNet Sketch   | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| DAmageNet         | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| Adversarial Patch | ImageNet     | ImageNet         | 76.13     | 83.04 | 81.97    | n/a      |
| CUB               | ImageNet     | CUB              | 85.83     | 85.46 | 85.32    | 81.54    |
| iNaturalist       | ImageNet     | CUB              | 85.83     | 85.46 | 85.32    | 81.54    |

**Experiment** We run EMD-Corr and CHM-Corr on all datasets and compare their results with that of kNN (Table 1). Both methods (described in Sec. 2) re-rank the top N = 50 shortlisted candidates returned by kNN and then take the dominant class in the top-k (where k = 20) as the predicted label.

**ImageNet results** Interestingly, despite using only 5 pairs of patches to compute image similarity for re-ranking, both classifiers consistently improve upon kNN further, especially on all OOD datasets. Overall, EMD-Corr and CHM-Corr outperform kNN and ResNet-50 baselines from +1.27 to +4.82 points (Table 1). Intuitively, in some hard cases where the main object is small, the two Corr classifiers ignore irrelevant patches (e.g. the sky in ibex images; Fig. 1) and only use the five most relevant patches to make decisions. Similarly, on Adversarial Patch, relying on a few key patches while ignoring adversarial patches enables our classifiers to outperform baselines (Fig. 2). See Appendix I for many qualitative examples comparing Corr and kNN predictions.

**CUB results** Interestingly, using the same ImageNet-pretrained backbones, EMD-Corr outperforms kNN by an absolute +5.57 points when tested on CUB (60.29% vs. 54.72%; Table 1). However, this difference vanishes when using CUB-pretrained backbones (Table 1: 84.98% vs. 85.46%).

Our CUB and ImageNet results are consistent and together reveal a trend: On i.i.d test sets, Corr models perform on par with kNN; however, on OOD images, they consistently outperform kNN, highlighting the benefits of patch-wise comparison.

### 3.3 Corr classifiers leverage five patches that are more important than five bird keypoints

EMD-Corr and CHM-Corr harness five patches per image for computing a patch-wise similarity score for a pair of images (Sec. 2.2). As these five patches are automatically inferred by cross-correlation (Fig. 3), it is interesting to understand further whether replacing these five patches by five user-defined patches in [71] would improve classification accuracy.

**Experiment** Since there are no keypoints provided for ImageNet, we test the importance of the five key patches chosen by Corr methods on CUB because CUB provides ornithologist-defined annotations for each bird image. That is, we create a baseline CHM-Corr+, which is the same as CHM-Corr, except that we use five important patches that correspond to five keypoints in a bird image—beak, belly, tail, right wing, and right foot—as described in Sec. 2.2. We also test CHM-Corr+ sweeping across the number of keypoints $\in \{5, 10, 15\}$.

**Results** On CUB, CHM-Corr outperforms CHM-Corr+ despite the fact that the baseline method leverages five human-defined bird keypoints (Table 1: 83.27% vs. 81.51%) while CHM-Corr may also use background patches. Interestingly, when increasing the number of keypoints to 10 and 15, the accuracy of CHM-Corr+ is still lower than that of CHM-Corr (i.e., from 81.51% to 82.34% and 82.27%, respectively). That is, 15 keypoints may correspond to $\leq 15$ different patches per image (15 if each keypoint lies in a unique, non-overlapping patch among all the 49 patches per image).

Our results show strong evidence that the five key patches inferred by CC used in EMD- and CHM-Corr do not necessarily cover the birds but are more important than expert-defined bird keypoints. Qualitative comparisons between CHM-Corr and CHM-Corr+ predictions are in Appendix J.
3.4 On ImageNet-ReaL, correspondence-based explanations are more useful to users than kNN explanations

Given that EMD-Corr and CHM-Corr classifiers outperform kNN classifiers on OOD datasets (Sec. 3.2), it is interesting to test how their respective explanations help humans perform classification on ImageNet. Furthermore, in image classification, kNN explanations were found to be more useful to humans than saliency maps [55].

Experiment We perform a human study to assess the ImageNet-ReaL classification accuracy of users of each classifier (described in Sec. 2.2) when they are provided with a classifier’s predictions and explanations. That is, we measure the AI-assisted classification accuracy of users following human-AI interaction model 1 (Fig. 4a). We compare the accuracy between user groups of four classifiers ResNet-50, kNN, EMD-Corr, and CHM-Corr (described in Sec. 2.3.1).

Additionally, to thoroughly assess the impact of showing the correspondence boxes compared to showing only nearest neighbor images (e.g., CHM-Corr vs. CHM-NN in Fig. 1), we test two more user groups of EMD-NN and CHM-NN, i.e. the same explanations as those of the Corr classifiers but with the correspondence boxes hidden.

Results First, the mean accuracy of kNN users is consistently lower than that of the other models’ users (e.g., 75.76% vs. 78.87% of EMD-Corr; Table 2). The EMD-Corr improvement over kNN is statistically significant ($p < 0.01$ via Mann-Whitney U test; Fig. 5a).

Second, interestingly, we find the differences between EMD-, CHM-Corr and their respective baselines are small and not statistically significant (Fig. 5a). That is, on ImageNet-ReaL, quantitatively, showing the correspondence boxes on top of nearest neighbors is not more useful to users. Third, surprisingly, the users of ResNet-50 (mean accuracy of 81.56%; Table 2) outperform all other methods’ users, suggesting that on ImageNet, a task of many familiar classes to users, ante-hoc explanations hurt user accuracy rather than help. Note that in Nguyen et al. [55], post-hoc kNN explanations were found useful to humans compared to not showing any explanations. Yet, here, each classifier’s users are provided with a different set of images and AI decisions, which can also influence the user accuracy. When ResNet-50 is wrong, their users are substantially better in detecting such misclassifications compared to other models’ users (Fig. A11a).

3.5 On CUB fine-grained bird classification, correspondence-based explanations are the most useful to users, helping them to more accurately reject AI misclassifications

To assess whether the findings on ImageNet-ReaL in Sec. 3.4 generalize to a fine-grained classification task, we repeat the user study on CUB—which is considered much harder to lay users than ImageNet.

Results Interestingly, we find EMD-Corr and CHM-Corr users consistently outperform ResNet-50, kNN, EMD-NN, and CHM-NN users (Table 2). The differences between EMD-Corr (or CHM-Corr) and every other baseline are statistically significant ($p < 0.05$ via Mann-Whitney U test; Fig. 5b). That is, on CUB, the visual correspondence boxes help users make more accurate decisions compared to (a) having no explanations at all (ResNet-50); (b) showing nearest neighbors sorted by image similarity only, not patch correspondences (Fig. 1a; kNN); and (c) having patch-wise correspondence neighbors but not displaying the boxes (Fig. A39; CHM-NN and EMD-NN).

Corr explanations help users reject AI misclassifications while kNN is poorly trust-calibrated

In an attempt to understand why the two Corr classifiers help users the most, we find that EMD-Corr and CHM-Corr users reject AI predictions at the highest rates (32.70% and 33.73%; Table A6) while kNN users reject the least (18.47%).

This might have led to the substantially higher accuracy of CHM-Corr users, compared to all other models’ user groups, when AI predictions are wrong (Fig. A11b; e.g., 53.45% of CHM-Corr vs.
41.22% of ResNet-50). That is, CHM-Corr users correctly reject 53.45% of the images that the CHM-Corr classifier mislabels. In contrast, kNN users reject the least, only 33.22% of incorrect predictions (Fig. A11b). KNN explanations tend to fool users into trusting the kNN’s wrong decisions (Fig. 6)—the accuracy of kNN users is 33.22%, much lower than the 41.22% of ResNet-50 users who observe no explanations. On ImageNet (Fig. A11), kNN is also poorly “trust-calibrated” [69, 74].

We hypothesize that kNN explanations tend to fool users more as their nearest neighbors, by design, show images that are image-wise similar to the query (regardless of whether the kNN prediction is correct or not) while EMD-Corr and CHM-Corr re-rank the images based on patch-wise similarity. Furthermore, we find the images in kNN explanations are also less diverse than those in Corr explanations in both LPIPS [77] and MS-SSIM [73] (Appendix H.2). Corr explanations tend to include more diverse images (Fig. 6a; top vs. bottom) and provide users with more contrastive evidence in order to reject AI’s incorrect predictions.

Additionally, we also hypothesize that users are less confident about AI’s decisions (and thus reject more) when Corr explanations show some background and uninformative patches used in the matching process (e.g., the 1st and 4th image in Fig. 6b). Yet, such boxes are not available in kNN explanations.

When Corr explanations allow for more disagreement between AI and users, humans also tend to incorrectly reject AI’s correct predictions more often (Fig. A11b; Corr users are the least accurate among 6 methods when the AI is correct). EMD-Corr and CHM-Corr users score ~4 points below ResNet-50 users (84.94% and 85.99% vs. 89.87% of ResNet-50). When most users reject AI’s correct predictions, we observe that some discriminative features (e.g., the belly stripes of the Field Sparrow; Fig. A35c) are often occluded in the query, leading to human-AI disagreement.

4 Related Work

Patch-wise similarity Calculating patch-wise similarity, either intra-image [23] or inter-image [29, 79, 75], has been useful in many tasks as the comparison enables machines to attend to fine-grained details and compute more accurate decisions. Our EMD-Corr harnesses a similar approach to that in [29, 79]: which, however, was not tested on ImageNet classification as in our work. Furthermore, we only compute the total patch-wise similarity over the top-5 patch pairs between the query and each exemplar instead of all pairs as in [29, 79]. Compared to recent patch-wise similarity works that use either cross-attention in ViTs [23] or EMD [79, 75, 29, 43], our work is the first to perform human evaluation of the correspondence-based explanations.
Prototype-based XAI methods Our work is motivated by the recent finding that exemplar-based explanations are more effective than heatmap-based explanations in improving human classification accuracy [55, 38, 42, 24]. However, showing an entire image as an exemplar without any further localization may be confusing as it is unknown which parts of the image the AI is paying attention to [55, 38]. Our EMD-Corr and CHM-Corr present a novel combination of heatmap-based and prototype-based XAI approaches. None of the prior prototype-based XAI methods that operate at the patch level [17, 53, 79, 22] (see Table 3 in [22]) were tested on humans yet. Also, in preliminary tests, we find their explanation formats too dense (i.e., showing over 10 prototypes [17], 9 correspondence pairs per image [22], or an entire prototype tree to humans [52, 53]) to be useful for lay users.

Another major difference is that our Corr classifiers are nonparametric, allowing the training set to be adjusted or swapped with any external knowledgebase for debugging purposes. In contrast, recent prototype-based classifiers [17, 53, 79, 22] are parametric, using a set of learned prototypes and thus may not perform well on OOD datasets as EMD-Corr and CHM-Corr.

Post-hoc prototype-based explanations Some prototype-based methods are post-hoc [41, 55, 20], i.e., generating explanations to explain a decision after-the-fact, which could be highly unfaithful [61, 62]. Instead, our approach is inherently interpretable [62], i.e., retrieving the patches first, and then using them to make classification decisions. While our binary classification task is adopted from [55], our study compares 4 different classifiers while Nguyen et al. [55] instead tested a single classifier with multiple post-hoc explanations.

Human studies Our study has 709 users in total, i.e. ~60 users per method per dataset, which is substantially larger than that in most prior works. That is, ~30 and 40 users per method participated in [55] and in [49], respectively while Adebayo et al. [9] had 54 persons in total for the entire study of multiple methods.

Human-AI teaming Human-AI collaboration is becoming more essential in the modern AI era [32]. A large body of prior works has investigated such collaboration in other domains (e.g., NLP [12, 76], healthcare [16] and others [33, 16, 78, 19]); however, only few works investigated human-AI collaboration in the image classification setting [55, 42, 24].

Some prior works predict when to defer the decision-making to humans [58, 37, 40]. However, by simply offloading some inputs to humans based on confidence scores, we achieve complementary human-AI team performance in both ImageNet and CUB. Previous works [12, 64] found that algorithmic explanations benefit human decision-making in general, but did not find XAI methods to yield team complementary performance [32], which we report in this work.

5 Discussion and Conclusion

Limitations Due to the limited amount of time and expensive cost of computation related to EMD-Corr or CHM-Corr, we did not experiment on a wider range of OOD datasets (e.g., adversarial poses [10]). We tested our methods on ImageNet-A [36], ObjectNet [13], and ImageNet-C [34] as well, but on a small scale of 5K-image sets (see Table A2). As using online crowdworkers for the XAI human evaluation, we share the same limitations with [55, 9, 42]. That is, despite our best efforts to minimize biases, the human data quality can be improved in highly-controlled laboratory conditions like in [27]. Algorithm-wise, EMD-Corr and CHM-Corr are re-ranking methods and therefore run substantially slower than ResNet-50 (see Fig. A10 for a speed comparison of all models).

Our work is the first attempt to: (1) study the effectiveness of patch-wise comparison in improving the robustness of deep image classifiers on ImageNet OOD benchmarks; (2) show the utility of visual correspondence-based explanations in helping users make more accurate image-classification decisions; (3) achieve human-AI complementary team performance in the image domain.

Acknowledgement

The authors would like to thank Ken Stanley for the great idea of using correspondences as an explanation for image classification, leading to this work. We also thank Thang Pham, Peijie Chen, and Hai Phan for feedback and discussions of the earlier results. AN was supported by the NSF Grant No. 1850117 & 2145767, and donations from NaphCare Foundation & Adobe Research.
References

[1] The pandemic is testing the limits of face recognition | MIT Technology Review. https://www.technologyreview.com/2021/09/28/1036279/pandemic-unemployment-government-face-recognition/. (Accessed on 11/09/2021).

[2] jhayes14/adversarial-patch: Pytorch implementation of adversarial patch. https://github.com/jhayes14/adversarial-patch. (Accessed on 05/18/2022).

[3] Wrongfully arrested man sues detroit police following false facial-recognition match - the washington post. https://www.washingtonpost.com/technology/2021/04/13/facial-recognition-false-arrest-lawsuit/. (Accessed on 11/09/2021).

[4] M-nauta/prototree: Prototrees: Neural prototype trees for interpretable fine-grained image recognition, published at cvpr2021. https://github.com/M-Nauta/ProtoTree. (Accessed on 06/14/2022).

[5] The new lawsuit that shows facial recognition is officially a civil rights issue | MIT Technology Review. https://www.technologyreview.com/2021/04/14/1022676/robert-williams-facial-recognition-lawsuit-aclu-detroit-police/. (Accessed on 04/15/2021).

[6] Michigan man wrongfully accused with facial recognition urges congress to act. https://www.detroitnews.com/story/news/politics/2021/07/13/house-panel-hear-michigan-man-wrongfully-accused-facial-recognition/7948908002/. (Accessed on 11/09/2021).

[7] Flawed facial recognition leads to arrest and jail for new jersey man - the new york times. https://www.nytimes.com/2020/12/29/technology/facial-recognition-misidentify-jail.html. (Accessed on 11/09/2021).

[8] vision at master · pytorch/vision. https://github.com/pytorch/vision/blob/master/torchvision/models. (Accessed on 05/08/2022).

[9] Adebayo, J., Muellly, M., Liccardi, I., and Kim, B. Debugging tests for model explanations. Advances in Neural Information Processing Systems, 33:700–712, 2020.

[10] Alcorn, M. A., Li, Q., Gong, Z., Wang, C., Mai, L., Ku, W.-S., and Nguyen, A. Strike (with) a pose: Neural networks are easily fooled by strange poses of familiar objects. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4845–4854, 2019.

[11] Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., and Evershed, J. K. Gorilla in our midst: An online behavioral experiment builder. Behavior research methods, 52(1):388–407, 2020.

[12] Bansal, G., Wu, T., Zhou, J., Fok, R., Nushi, B., Kamar, E., Ribeiro, M. T., and Weld, D. Does the whole exceed its parts? the effect of ai explanations on complementary team performance. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, pp. 1–16, 2021.

[13] Barbu, A., Mayo, D., Alverio, J., Luo, W., Wang, C., Gutfreund, D., Tenenbaum, J., and Katz, B. Objectnet: A large-scale bias-controlled dataset for pushing the limits of object recognition models. Advances in neural information processing systems, 32, 2019.

[14] Beyer, L., Hénaff, O. J., Kolesnikov, A., Zhai, X., and Oord, A. v. d. Are we done with imagenet? arXiv preprint arXiv:2006.07159, 2020.

[15] Brown, T. B., Mané, D., Roy, A., Abadi, M., and Gilmer, J. Adversarial patch. arXiv preprint arXiv:1712.09665, 2017.

[16] Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M., and Elhadad, N. Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. In Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining, pp. 1721–1730, 2015.

[17] Chen, C., Li, O., Tao, D., Barnett, A., Rudin, C., and Su, J. K. This looks like that: deep learning for interpretable image recognition. Advances in neural information processing systems, 32, 2019.

[18] Chen, S., He, Z., Sun, C., Yang, J., and Huang, X. Universal adversarial attack on attention and the resulting dataset damagenet. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.

[19] Chu, E., Roy, D., and Andreas, J. Are visual explanations useful? a case study in model-in-the-loop prediction. arXiv preprint arXiv:2007.12249, 2020.
[20] Crabbé, J., Qian, Z., Imrie, F., and van der Schaar, M. Explaining latent representations with a corpus of examples. *Advances in Neural Information Processing Systems*, 34, 2021. 10

[21] Cuturi, M. Sinkhorn distances: Lightspeed computation of optimal transport. *Advances in neural information processing systems*, 26, 2013. 4, 17

[22] Donnelly, J., Barnett, A. J., and Chen, C. Deformable protopnet: An interpretable image classifier using deformable prototypes. *arXiv preprint arXiv:2111.15000*, 2021. 6, 10

[23] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., and Houlsby, N. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=YicbFdNTTy. 9

[24] Fel, T., Colin, J., Cadène, R., and Serre, T. What i cannot predict, i do not understand: A human-centered evaluation framework for explainability methods. *arXiv preprint arXiv:2112.04417*, 2021. 1, 10

[25] Feng, H., Wang, S., and Ge, S. S. Fine-grained visual recognition with salient feature detection. *arXiv preprint arXiv:1808.03935*, 2018. 4

[26] Feng, S. and Boyd-Graber, J. What can ai do for me? evaluating machine learning interpretations in cooperative play. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*, pp. 229–239, 2019. 65

[27] Geirhos, R., Narayananappa, K., Mitzkus, B., Thireringer, T., Bethge, M., Wichmann, F. A., and Brendel, W. Partial success in closing the gap between human and machine vision. *Advances in Neural Information Processing Systems*, 34, 2021. 10

[28] Ghaeini, R., Fern, X. Z., and Tadepalli, P. Interpreting recurrent and attention-based neural models: a case study on natural language inference. *arXiv preprint arXiv:1808.03894*, 2018. 65

[29] Hai Phan, A. N. Deepface-emd: Re-ranking using patch-wise earth mover’s distance improves out-of-distribution face identification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022. 1, 2, 3, 4, 6, 9, 16, 17

[30] Ham, B., Cho, M., Schmid, C., and Ponce, J. Proposal flow: Semantic correspondences from object proposals. *IEEE transactions on pattern analysis and machine intelligence*, 40(7):1711–1725, 2017. 17

[31] He, K., Zhang, X., Ren, S., and Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016. 2, 4, 18

[32] Hemmer, P., Schemmer, M., Vössing, M., and Kühl, N. Human-ai complementarity in hybrid intelligence systems: A structured literature review. *PACIS 2021 Proceedings*, 2021. 10

[33] Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., and Satzger, G. On the effect of information asymmetry in human-ai teams. *arXiv preprint arXiv:2205.01467*, 2022. 10

[34] Hendrycks, D. and Dietterich, T. Benchmarking neural network robustness to common corruptions and perturbations. *arXiv preprint arXiv:1903.12261*, 2019. 10, 19

[35] Hendrycks, D., Basart, S., Mu, N., Kadavath, S., Wang, F., Dorundo, E., Desai, R., Zhu, T., Parajuli, S., Guo, M., et al. The many faces of robustness: A critical analysis of out-of-distribution generalization. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 8340–8349, 2021. 2, 7, 19

[36] Hendrycks, D., Zhao, K., Basart, S., Steinhardt, J., and Song, D. Natural adversarial examples. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 15262–15271, 2021. 10, 19

[37] Horvitz, E. and Paek, T. Complementary computing: policies for transferring callers from dialog systems to human receptionists. *User Modeling and User-Adapted Interaction*, 17(1):159–182, 2007. 10

[38] Jeyakumar, J. V., Noor, J., Cheng, Y.-H., Garcia, L., and Srivastava, M. How can i explain this to you? an empirical study of deep neural network explanation methods. *Advances in Neural Information Processing Systems*, 33:4211–4222, 2020. 10

[39] Johnson, J., Douze, M., and Jégou, H. Billion-scale similarity search with GPUs. *IEEE Transactions on Big Data*, 7(3):535–547, 2019. 20
[40] Kamar, E., Hacker, S., and Horvitz, E. Combining human and machine intelligence in large-scale crowdsourcing. In AAMAS, volume 12, pp. 467–474, 2012. 10

[41] Kenny, E. M. and Keane, M. T. Twin-systems to explain artificial neural networks using case-based reasoning: Comparative tests of feature-weighting methods in ann-cbr twins for xai. In Twenty-Eighth International Joint Conferences on Artificial Intelligence (IJCAI), Macau, 10–16 August 2019, pp. 2708–2715, 2019. 1, 10

[42] Kim, S. S., Meister, N., Ramaswamy, V. V., Fong, R., and Russakovsky, O. Hive: Evaluating the human interpretability of visual explanations. arXiv preprint arXiv:2112.03184, 2021. 1, 5, 10

[43] Kim, W., Son, B., and Kim, I. Vilt: Vision-and-language transformer without convolution or region supervision. In International Conference on Machine Learning, pp. 5583–5594. PMLR, 2021. 9

[44] Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014. 16

[45] Krizhevsky, A., Sutskever, I., and Hinton, G. E. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25, 2012. 4

[46] Lee, J., Kim, D., Ponce, J., and Ham, B. Sfnet: Learning object-aware semantic correspondence. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2278–2287, 2019. 17

[47] Li, H., Wang, Y., Wu, A., Wei, H., and Qu, H. Structure-aware visualization retrieval. In CHI Conference on Human Factors in Computing Systems, pp. 1–14, 2022. 4

[48] Li, S., Han, K., Costain, T. W., Howard-Jenkins, H., and Prisacariu, V. Correspondence networks with adaptive neighbourhood consensus. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 10196–10205, 2020. 4

[49] Mac Aodha, O., Su, S., Chen, Y., Perona, P., and Yue, Y. Teaching categories to human learners with visual explanations. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3820–3828, 2018. 5, 10

[50] Miller, G. A. Wordnet: a lexical database for english. Communications of the ACM, 38(11):39–41, 1995. 32

[51] Min, J. and Cho, M. Convolutional hough matching networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2940–2950, 2021. 2, 3, 4, 17

[52] Nauta, M., Jutte, A., Provoost, J., and Seifert, C. This looks like that, because... explaining prototypes for interpretable image recognition. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pp. 441–456. Springer, 2021. 1, 10

[53] Nauta, M., van Bree, R., and Seifert, C. Neural prototype trees for interpretable fine-grained image recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 14933–14943, 2021. 1, 3, 10

[54] Nguyen, A., Yosinski, J., and Clune, J. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 427–436, 2015. 6

[55] Nguyen, G., Kim, D., and Nguyen, A. The effectiveness of feature attribution methods and its correlation with automatic evaluation scores. Advances in Neural Information Processing Systems, 34, 2021. 1, 4, 5, 6, 8, 10

[56] Palan, S. and Schitter, C. Prolific. ac—a subject pool for online experiments. Journal of Behavioral and Experimental Finance, 17:22–27, 2018. 6

[57] Papernot, N. and McDaniel, P. Deep k-nearest neighbors: Towards confident, interpretable and robust deep learning. arXiv preprint arXiv:1803.04765, 2018. 1

[58] Raghu, M., Blumer, K., Corrado, G., Kleinberg, J., Obermeyer, Z., and Mullainathan, S. The algorithmic automation problem: Prediction, triage, and human effort. arXiv preprint arXiv:1903.12220, 2019. 10

[59] Ribeiro, M. T., Singh, S., and Guestrin, C. Why should i trust you?: Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1135–1144. ACM, 2016. 65
[60] Rocco, I., Cimpoi, M., Arandjelović, R., Torii, A., Pajdla, T., and Sivic, J. Neighbourhood consensus networks. *Advances in neural information processing systems*, 31, 2018. 4

[61] Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1(5):206–215, 2019. 1, 10

[62] Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., and Zhong, C. Interpretable machine learning: Fundamental principles and 10 grand challenges. *arXiv preprint arXiv:2103.11251*, 2021. 10

[63] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., et al. Imagenet large scale visual recognition challenge. *International Journal of Computer Vision*, 115(3):211–252, 2015. 2, 7, 19

[64] Schemmer, M., Hemmer, P., Kühn, N., Benz, C., and Satzger, G. Should i follow ai-based advice? measuring appropriate reliance in human-ai decision-making. *arXiv preprint arXiv:2204.06916*, 2022. 10

[65] Shen, H. and Huang, T.-H. How useful are the machine-generated interpretations to general users? a human evaluation on guessing the incorrectly predicted labels. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, volume 8, pp. 168–172, 2020. 5

[66] Singh, G. and Yow, K.-C. These do not look like those: An interpretable deep learning model for image recognition. *IEEE Access*, 9:41482–41493, 2021. 1

[67] Singla, A., Bogunovic, I., Bartók, G., Karbasi, A., and Krause, A. Near-optimally teaching the crowd to classify. In *International Conference on Machine Learning*, pp. 154–162. PMLR, 2014. 5

[68] Stylianou, A., Souvenir, R., and Pless, R. Visualizing deep similarity networks. In *2019 IEEE winter conference on applications of computer vision (WACV)*, pp. 2029–2037. IEEE, 2019. 17

[69] Turner, A., Kaushik, M., Huang, M.-T., and Varanasi, S. Calibrating trust in ai-assisted decision making. 9

[70] Van Horn, G., Mac Aodha, O., Song, Y., Cui, Y., Sun, C., Shepard, A., Adam, H., Perona, P., and Belongie, S. The inaturalist species classification and detection dataset. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 8769–8778, 2018. 3, 7

[71] Wah, C., Branson, S., Welinder, P., Perona, P., and Belongie, S. The caltech-ucsd birds-200-2011 dataset. 2011. 2, 3, 7

[72] Wang, H., Ge, S., Lipton, Z., and Xing, E. P. Learning robust global representations by penalizing local predictive power. *Advances in Neural Information Processing Systems*, 32, 2019. 2, 6, 7, 19

[73] Wang, Z., Simoncelli, E. P., and Bovik, A. C. Multiscale structural similarity for image quality assessment. In *The Thirty-Seventh Asilomar Conference on Signals, Systems & Computers*, 2003, volume 2, pp. 1398–1402. Ieee, 2003. 9

[74] Yang, X. J., Unhelkar, V. V., Li, K., and Shah, J. A. Evaluating effects of user experience and system transparency on trust in automation. In *2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 408–416. IEEE, 2017. 9

[75] Zhang, C., Cai, Y., Lin, G., and Shen, C. Deepermd: Few-shot image classification with differentiable earth mover’s distance and structured classifiers. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 12203–12213, 2020. 1, 6, 9, 16

[76] Zhang, Q., Lee, M. L., and Carter, S. You complete me: Human-ai teams and complementary expertise. In *CHI Conference on Human Factors in Computing Systems*, pp. 1–28, 2022. 10

[77] Zhang, R., Isola, P., Efros, A. A., Shechtman, E., and Wang, O. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 586–595, 2018. 9

[78] Zhang, Y., Liao, Q. V., and Bellamy, R. K. Effect of confidence and explanation on accuracy and trust calibration in ai-assisted decision making. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pp. 295–305, 2020. 10, 65

[79] Zhao, W., Rao, Y., Wang, Z., Lu, J., and Zhou, J. Towards interpretable deep metric learning with structural matching. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 9887–9896, 2021. 1, 3, 4, 6, 9, 10, 16, 17
Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default [TODO] to [Yes], [No], or [N/A]. You are strongly encouraged to include a justification to your answer, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section ??.
- Did you include the license to the code and datasets? [No] The code and the data are proprietary.
- Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]. Please see Sec. 3.
   (b) Did you describe the limitations of your work? [Yes]. Please see Sec. 5.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A].
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes].

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes].
   (b) Did you include complete proofs of all theoretical results? [N/A].

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No].
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]. Please see Sec. 2.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]. We reported whenever possible. See $\mu$ and $\sigma$ in Table 2.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No].

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]. We cited the authors and include the URLs.
   (b) Did you mention the license of the assets? [N/A]. We used publicly-available datasets and code.
   (c) Did you include any new assets either in the supplemental material or as a URL? [No].
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes]. We explained to participants how their data will be used.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes]. We checked and ensured that our data does not contain personally identifiable information or offensive content.

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes]. See screenshots in Appendix E.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A].
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [Yes]. See Sec. 2.3.4. Our rate was $13.5/\text{hr}$, higher than the Prolific recommended rate wage of $9.60/\text{hr}.