Leveraging deep neural networks to capture psychological representations

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ABSTRACT: Artificial neural networks have seen a recent surge in popularity for their ability to solve complex problems as well as or better than humans. In computer vision, deep convolutional neural networks have become the standard for object classification and image understanding due to their ability to learn efficient representations of high-dimensional data. However, the relationship between these representations and human psychological representations has remained unclear. Here we evaluate the quantitative and qualitative nature of this correspondence. We find that state-of-the-art object classification networks provide a reasonable first approximation to human similarity judgments, but fail to capture some of the structure of psychological representations. We show that a simple transformation that corrects these discrepancies can be obtained through convex optimization. Such representations provide a tool that can be used to study human performance on complex tasks with naturalistic stimuli, such as predicting the difficulty of learning novel categories. Our results extend the scope of psychological experiments and computational modeling of cognition by enabling tractable use of large natural stimulus sets.
The behaviour of modern deep neural networks approaches or exceeds human performance in a number of key perceptual tasks such as object categorization and scene understanding \(^{14}\), and has led to breakthroughs in other AI-related fields such as natural language processing \(^2\) and reinforcement learning \(^{17}\). Despite this rapid progress, the status of these networks as models of human intelligence is still unclear. For example, while deep convolutional neural networks (CNNs) were popularized in computer vision through their human-level classification performance for thousands of object classes \(^{10}\), the extent to which the representations and strategies learned and used by these networks mirror those of humans is still largely unknown (although there has been some recent progress on this question \(^{13}\), and work comparing CNNs with neural representations \(^{1,18,27}\)). If a strong correspondence exists, then there may be another important application for deep neural networks: providing representations of complex stimuli such as images or text that can be used to make models of human behaviour in naturalistic tasks. The vast majority of research on human cognition is conducted with simple artificial stimuli, because it is straightforward to identify how people represent those stimuli. Being able to evaluate models of how people perform tasks such as learning categories with realistic stimuli is important for expanding the scope of psychological research \(^{16}\).

Comparing the representations formed by deep neural networks with those used by people is challenging, as human psychological representations cannot be observed directly. To solve this problem, we measure the correspondence between human representations of a set of images and those produced by several neural networks by subjecting both to an ensemble of classic psychological methods for identifying the rich structure implied by similarity relations among stimuli. In
this way, we provide an empirical basis for the evaluation of deep neural network models as an approximation to human psychological representations (similar methods have been used to compare psychological representations to brain imaging data\cite{15}). Having conducted this basic analysis, we then consider whether a better model of human representations of images can be constructed by taking a linear transformation of the feature space recovered by the deep neural networks. The resulting methodological tool opens the door to ecological validation of decades of psychological theory using large datasets of highly complex, natural stimuli, which we demonstrate by predicting the difficulty with which people learn categories of natural images.

We obtained pairwise stimulus similarities for five sets of 120 natural images from visual object categories (animals, automobiles, fruits, furniture, vegetables) and an additional set of 120 images that contained various categories from human raters (over 400,000 ratings in total). We then calculated similarity by taking the inner product between the vector representations of these images in the final hidden layer of several state-of-the-art deep image classifiers (AlexNet\cite{10}, VGG\cite{24}, GoogLeNet\cite{25}, and ResNet\cite{8}), treating each hidden unit as encoding some distinct feature of the image. Human similarity matrices capture stimulus generalization behaviour\cite{22} and have been shown to encode the complex spatial, hierarchical\cite{21}, and overlapping\cite{23} structure of human psychological representations, around which numerous psychological models of categorization and inference are built\cite{6,11,20}. The variance explained in human similarities by those from the best performing deep CNN classifier (this was VGG in all cases) is plotted in panel A of Figure 1 (lighter colors).

These results indicate that the raw representations formed by the CNNs can capture a reason-
able amount of variance in human similarity judgments. To better understand how they succeed and fail to reproduce the structure of psychological representations, we applied two classic psychological tools: non-metric multidimensional scaling, which converts similarities into a spatial representation, and hierarchical clustering, which produces a tree structure (dendrogram). The results for the best-performing CNN on the animals stimuli are shown in Figure 2, and point out the most crucial differences in these two representations. Human representations exhibit highly distinguished clusters in the spatial projections and intuitive taxonomic structure in the dendrograms, neither of which are present in the CNN representations.

Our empirical comparison suggests that deep network representations are reasonable but incomplete approximations of psychological representations. However, given a lack of alternatives for modeling cognitive processing of complex stimuli, it may be more promising to consider methods for bringing deep network representations into closer alignment with human behaviour. To do this, we developed a method for rescaling the CNN features to better align with human data by modeling human similarity judgments as a weighted inner product of the network features, with the similarity $s_{ij}$ between images $i$ and $j$ being modeled as $s_{ij} = \sum_k w_k f_{ik} f_{jk}$, where $f_{ik}$ is the $k$th feature of image $i$ and $w_k$ is its weight. This is formally equivalent to a classic model of similarity in cognitive science that takes into account the salience of individual features, and is related to metric learning methods in machine learning. The squared error in reconstructing the human similarity judgments can be minimized by convex optimization. The new feature representation that emerges explained nearly twice the variance for all datasets after cross-validating predictions (Figure 1, Panel A, darker colors), and compares favorably to several rigorous baselines.
constructed to avoid overfitting (see supplementary information). The MDS and dendrogram plots for the transformed representations in Figure 2 show a strong resemblance to the original human judgments. Notably, taxonomic structure and spatial clustering is almost perfectly reconstructed.

Given the success in finding such transformations, we wanted to understand how competing networks compare in their ability to adapt to humans, as well as a number of other interesting baseline models. Figure 1, panel B demonstrates these findings. We compared the weighted representations from all four classification networks, as well as a recent high-performing unsupervised deep architecture (BiGAN) and an older, non-deep standard from computer vision (HOG+SIFT). We find that most classification networks perform essentially the same, yet VGG is slightly better on average, even though its depth is relatively modest compared to GoogLeNet and ResNet. Surprisingly, representations from the BiGAN, while useful for machine object classification, don’t seem to correspond as well to human representations, and are even less effective than shallow methods like HOG+SIFT. Additionally, using AlexNet, which has a manageable yet still large number of layers, we examined weighted transformations at each layer of the network, including final class probabilities and discrete labels. As Figure 1, panel C shows, performance climbs as the depth of the network increases, but falls off near the end when the final classification outputs near. For all datasets, the best layer was “fc7” from VGG, which is 4096 features, as opposed to the classification layers, which shrink to 1000 numbers. This indicates that relatively high-level, but still non-semantic information is most relevant to the human judgments we obtained.

The value of these representations for broadening the scope of psychological research can
only be assessed by establishing that they generalize to new stimuli, and are predictive of other aspects of human behaviour. To further explore the generalizability and applicability of this rescaling, we applied the learned transformation to the CNN representations (from VGG) of six new datasets of unseen images drawn from the same categories and assessed the ease with which people could learn categories constructed from the original and transformed similarities. These categories were constructed using $k$-means clustering, ensuring that each category consisted of a coherent group of images as assessed by the appropriate similarity measure. Consequently, we should expect the ease of learning those categories to reflect the extent to which people’s sense of similarity has been captured. Figure 4 shows the difference in the ease with which people learned 2-, 3-, and 4-category partitions derived from the original and transformed similarities. In most cases, categorization performance is higher for categories derived from the transformed spaces, and an ANOVA confirmed that this effect was statistically significant ($F_{1,1404} = 66.28, p < .0001$).

The proliferation of machine learning methods for representing complex stimuli is likely to continue. We see our approach as a way to leverage these advances and combine them with decades of research on psychological methods to shed light on deep questions about human cognition. This allows us to learn something about the potential weaknesses in artificial systems, and inspires new ideas for engineering those systems to more closely match human abilities. Most importantly, it provides a way for psychologists to begin to answer questions about the exercise of intelligence in a complex world, abstracting over the representational challenges that can make it difficult to identify higher-level principles of cognition in natural settings.
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Figure 1: **Quantitative Evaluations of Deep Representations.** a, Model performance (proportion of variance accounted for, $R^2$) in predicting human similarity judgments for each image set using the best raw (light colors) and best transformed (dark colors) deep CNN representations. b, Similarity prediction performance using the best weighted representations from four popular deep classifiers, an unsupervised network (BiGAN), and a non-deep baseline (HOG+SIFT). Results are averaged across all six image sets. c, Similarity prediction performance using transformed representations at each layer of AlexNet for each dataset (“softmax” is predicted class probabilities, and “one-hot” is predicted class labels). d, Classification difference scores (performance in learning categories derived from transformed representations minus performance in learning categories derived from raw deep representations) across six new image sets not used to supervise the original transformation. Scores are averaged across participants. Three bars from left to right for three between-subjects conditions in which the number of categories to learn varied from 2 to 4 are shown for each dataset. Error bars are 95% confidence intervals from a bootstrap analysis of the difference scores.
Figure 2: **Representations of Animals.** a, Non-metric multidimensional scaling solutions for human similarity judgments (left), deep CNN representations (middle), and the transformed CNN representations (right). b, Dendrograms of hierarchical clusterings (centroid method) for human similarity judgments (top), deep CNN representations (middle), and the transformed CNN representations (bottom).
Appendix

Here we describe empirical data collection methods and our analyses in more detail.

Stimuli  Stimuli were hand collected for each of the six categories: animals, automobiles, fruits, furniture, vegetables, and “various”, and were meant to exhibit wide variety in pose, lighting, formality, and subordinate class. Each category contained 240 total images, each cropped and resized to $300 \times 300$ pixel dimensions. An example subset of these images for each dataset is given in Figure 1. Half of these images (120 for each category) were used for training and testing our transformations discussed in the analysis section. The second half was used for categorization experiments to validate these transformations.

Human Similarity Judgments  For all six stimulus categories, we collected pairwise image similarity ratings (within each category) from human participants on Amazon Mechanical Turk. Participants were paid $0.02 to rate the similarity of four pairs of images within one of the six categories on a scale from 0 (“not similar at all”) to 10 (“very similar”). They could repeat the task as many times as they wanted, but we did not allow repeat ratings of the same unique image pair. We obtained exactly 10 unique ratings for each pair of images (7,140 total) in each category, yielding 71,400 ratings per category (428,400 total ratings), from over 1,200 unique participants. The result is six $120 \times 120$ similarity matrices after averaging over individual judgments, for which each entry represents human psychological similarity between a pair of objects.
Deep Neural Network Representations  For each image in all six categories, we extracted deep feature representations using four highly popular convolutional neural network image classifiers that were pretrained in Caffe\cite{caffe} on ILSVRC12, a large dataset of 1.2 million images taken from 1000 objects categories in the ImageNet database\cite{imagenet}. This dataset serves as a central benchmark in the computer vision community. The networks, in order of depth, are AlexNet\cite{alexnet}, VGG\cite{vgg}, GoogLeNet\cite{googlenet}, and ResNet\cite{resnet}, three of which are ILSVRC competition winners. VGG, GoogLeNet, and ResNet all achieve at least half the error rate of AlexNet. Images are fed forward through each network as a flattened vector, and activations are recorded at each layer of the network. For most of our analyses besides the AlexNet layer analysis, we extract only the activations at the final hidden layer of each network. For AlexNet and VGG, this is a 4096-dimensional fully-connected layer, while the last layer in GoogleNet and ResNet is a 1000-dimensional pooling layer. As an example, feature extraction for the animals training image set provides a $120 \times 4096$ matrix. Beyond these classification networks, we also included a very recent state-of-the-art unsupervised deep image network\cite{bigan}, a generative model trained to model the probability of the entire ILSVRC12 dataset. This network (BiGAN) is a bidirectional variant of a Generative Adversarial Network\cite{gan} that can both generate images from a uniform latent variable and perform inference to project real images into this latent space. We use the 200-dimensional projections into this latent space as our representation for this network. As an additional baseline, we also extract two forms of shallow (non-deep) features using previously popular methods from computer vision called the Scale-invariant feature transform (SIFT)\cite{sift}, using the bag-of-words technique trained on a large image database, and Histogram of Oriented Gradients (HOG)\cite{hog}, with a bin size of $2 \times 2$. 
**Aligning Representations** A similarity matrix $S$ can be approximated by the matrix product of a feature-by-object matrix $F$, its transpose $F^T$, and a diagonal weight matrix $W$.

$$S = FWF^T.$$  \hfill (1)

This formulation is similar to that employed by additive clustering models\textsuperscript{23}, wherein $F$ represents a binary feature identity matrix (and is similar to Tversky’s model of similarity\textsuperscript{19,26}). When used with continuous features, this approach is akin to factor analysis. Given an existing feature-by-object matrix $F$, the diagonal of $W$, the vector of weights $w$, can be formulated as the solution to a linear regression problem where the predictors for each similarity $s_{ij}$ are the (elementwise) product of the values of each feature for the objects $i$ and $j$. When $W$ is the identity matrix, this reduces to the standard method for computing similarities as inner products.

For all of our models, we use L2 regularization on $w$. If we minimize the squared error in the reconstruction of $s_{ij}$, the result is a convex optimization problem that can be solved for $w$. Given the size of the problem, we find $w$ by gradient descent on an objective function combining the squared error and the L2 norm of $w$, with the latter weighted by a regularization parameter $\lambda$. We use 6-fold crossvalidation to find the best value for this regularization parameter, optimizing generalization performance on held-out data.

If $w$ is also constrained to be nonnegative, then the square root of these weights can be interpreted as a multiplicative rescaling of the features. This makes it possible to directly construct transformed spatial representations of stimuli.
**Representational Structure Analyses** The structure implied by similarity judgments is almost certainly obscured when in pure matrix form. To get a better idea of the structure of both the deep feature and human representations, we use two common methods from psychology: non-metric multidimensional scaling (NMDS) and hierarchical cluster analysis (HCA)\(^2\). For our NMDS analysis, we used the scikit-learn library of Python to obtain only two-dimensional solutions, with a maximum iteration limit of 10,000 in fitting the models through gradient descent, and a convergence tolerance of 1e-100. Embeddings were first initialized with standard metric MDS, and we took the best fitting solution of four independent initializations. For HCA, we used the scipy Python library, with a centroid linkage function in all models.

**Additional Baseline Models** As additional check for overfitting, we constructed baseline models for each set of deep representations for each image dataset in which either (1) the rows, (2) the columns (separately for each row), or (3) both row and columns of the regression design matrix \(F \circ F\) were randomly permuted. The order of the targets \(S\) remained unchanged. When all three models were subject to the same crossvalidation procedure as the unshuffled models, variance explained \(R^2\) never reached or exceeded 0.01. This confirms that our regularization procedure was successful in controlling overfitting.

**Categorization Experiments** Using the best performing network and layer for each image dataset, we applied the learned transformation to a second set of 120 new images in each category. This produced six predicted similarity matrices for each set. Using the rows of these matrices as image representations, we calculated \(k\)-means clusterings where the number of clusters \(k\) was either 2,
3, or 4. We repeated this process using the untransformed representations, for which similarities were simply inner products. This resulted in the following between-subjects conditions for our experiment: 2 spaces (transformed, raw) × \(k\) (2, 3, 4) × dataset (e.g., animals). Participants in each condition were shown a single random sequence of the images from the dataset corresponding to their assigned condition and were instructed to press a key to indicate the correct category (where the correct category was the pre-defined cluster). If a participant guessed incorrectly, an “incorrect” message was shown for 1.5 seconds. If they guessed correctly, this message read “correct”.

Initially, participants performed poorly as they had little information to associate keys with clusters, but showed consistent progress after a few examples from each cluster. Participants were recruited on Amazon Mechanical Turk, paid $1.00, and were not allowed to participate in multiple conditions. For our analysis of the contribution of the between-subjects factor space (original versus transformed), along with the other between-subjects factor (dataset), and the within-subjects factor (\(k\), number of clusters/categories), we used anova_lm from the Python statsmodels library.

Aside from the effect of space reported in the main article, we also found substantial main effects for \(k\) (\(F_{2,1404} = 614.95, p < .0001\)), and dataset (\(F_{5,1404} = 137.52, p < .0001\)). All two-way interactions were also statistically significant, including \(k\times\text{dataset} (F_{10,1404} = 7.14, p < .0001)\), \(k\times\text{space} (F_{2,1404} = 3.42, p < .05)\), and \(\text{dataset}\times\text{space} (F_{5,1404} = 29.20, p < .0001)\), as well as the three-way interaction between all three factors (\(F_{10,1404} = 3.17, p < .001\)).
Figure 3: **Stimulus Examples.** Random samples of images from each of the six datasets used in our experiments.
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