# HOW ALIGNED ARE DIFFERENT ALIGNMENT METRICS?

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## ABSTRACT

In recent years, various methods and benchmarks have been proposed to empirically evaluate the alignment of artificial neural networks to human neural and behavioral data. But how aligned are different alignment metrics? To answer this question, we analyze visual data from Brain-Score (Schrimpf et al., 2018), including metrics from the model-vs-human toolbox (Geirhos et al., 2021), together with human feature alignment (Linsley et al., 2018; Fel et al., 2022) and human similarity judgements (Muttenthaler et al., 2022). We find that pairwise correlations between neural scores and behavioral scores are quite low and sometimes even negative. For instance, the average correlation between those $88$ models on Brain-Score that were fully evaluated on all $50$ alignment metrics we considered is only $0.161$. Assuming that all of the employed metrics are sound, this implies that alignment with human perception may best be thought of as a multidimensional concept, with different methods measuring fundamentally different aspects. Our results underline the importance of integrative benchmarking, but also raise questions about how to correctly combine and aggregate individual metrics. Aggregating by taking the arithmetic average, as done in Brain-Score, leads to the overall performance currently being dominated by behavior (95.25% explained variance) while the neural predictivity plays a less important role (only 33.33% explained variance). As a first step towards making sure that different alignment metrics all contribute fairly towards an integrative benchmark score, we therefore conclude by comparing three different aggregation options.

## 1 INTRODUCTION

A central question in the field of representational alignment is whether two given perceptual systems apply the same transformation to their inputs, thereby extracting equivalent representations from data. These systems could be artificial deep neural networks (DNNs) and biological systems like primate brains, or arbitrary other image-computable models. For a number of reasons, the perceptual alignment of artificial to biological systems has seen growing interest in recent years. Well-aligned DNNs could serve as models of biological visual processing and ultimately be an important step towards building neural prosthetics. Furthermore, measuring discrepancies between machine and biological perception can help to identify shortcomings in DNNs and improve machine perception (Wichmann & Geirhos, 2023). For example, aligning DNNs with the human visual system promises to increase their robustness and generalization abilities (Dapello et al., 2022; Sucholutsky & Griffiths, 2023).

Since the question of representational alignment between brains and machines cannot be answered theoretically, various empirical methods have been proposed to measure the representational alignment of different systems. These efforts include the comprehensive Brain-Score benchmark (Schrimpf et al., 2018; 2020), which integrates $51$ different metrics to capture the alignment of different models to biological systems. In addition to neural data extracted from primates, other metrics also capture behavioral similarity, such as error pattern analysis (Rajalingham et al., 2018; Geirhos et al., 2020; 2021) and shape bias (Geirhos et al., 2018; Baker et al., 2018; Hermann et al., 2020). Other commonly used datasets in the literature include behavioral similarity judgements (e.g., Hebart et al., 2023; Muttenthaler et al., 2022).

In light of this wealth of different metrics and datasets, all of which intend to quantify how "human-like" (or brain-like, or primate-like) machine learning models are, a fundamental question arises:

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**How aligned are different alignment metrics?** For instance, if two metrics are highly correlated, it may be sufficient to evaluate models on one of them instead of both. On the other hand, if two metrics lead to highly dissimilar results, they measure different aspects and would lead to very different conclusions and model rankings—assuming the metrics are sound. In contrast, if inconsistencies between different metrics were for instance caused by methodological errors that do not reflect different aspects of brain-likeness, those cases could equally be surfaced by analyzing the agreement of metrics as we do in this study. In order to determine how aligned different alignment metrics are, we therefore analyze a broad set of up to $241$ models evaluated on $50$ different metrics, depending on data availability.

## 2 METHODS

**Nomenclature.** In the following, we will refer to any function that maps a model to a scalar *score* measuring some form of alignment as a *metric* or *measure*. Any set of metrics that together estimate alignment is referred to as a *benchmark*. The point of this distinction is that for a benchmark, some method of integrating its constituent metrics is necessary, like taking their average.

**Data sources.** A central hub for collecting and integrating similarity measurements between DNNs and biological neural data is the Brain-Score benchmark (Schrimpf et al., 2018; 2020). We use data from Brain-Score as the foundation of our analyses, but also integrate data from three other sources: Muttenthaler et al. (2022), Fel et al. (2022) and Geirhos et al. (2021).

The Brain-Score benchmark (Schrimpf et al., 2018) provides comparative data for two domains, vision and language. Throughout this paper, we focus exclusively on vision and thus on the visual Brain-Score. Brain-Score evaluation results can be thought of as a table, where the columns are different metrics and the rows are models evaluated on these metrics. The columns are semantically grouped into three sets: Neural, behavioral and engineering benchmarks. The neural benchmark can be further subdivided into groups that measure a model's similarity to different brain areas: V1, V2, V4 and IT. The behavioral benchmark consists of image classification metrics like error consistency, either for humans or monkey subjects. The engineering benchmark, which does not enter the final scoring, captures technical properties of models like ImageNet top-1 accuracy.

We are particularly interested in the agreement between neural and behavioral measures of similarity between humans and machines, so we use data from Geirhos et al. (2021), who record human classification performance on (corrupted) ImageNet images and calculate multiple types of behavioral similarity: *error consistency* (Do humans and machines make mistakes on the same images?) and *shape bias* (When presented with shape-texture cue conflicts, do models prefer shape, like humans?). Muttenthaler et al. (2022) systematically analyze which design choices affect the human-machine alignment for various DNNs, finding that neither architecture nor model scale are relevant, but that the training data and objective function are driving factors of alignment. They quantify human-machine alignment as a network's ability to predict human behavior on triplet tasks (Hebart et al., 2020), for which human subjects are presented with three natural images and classify one of them as the odd-one-out. Hence, we call this metric *odd-one-out similarity*. Fel et al. (2022) define human-machine alignment as the similarity between model attention maps and attention maps obtained from human crowd-workers. Linsley et al. (2018) collected about 500k of these human attention maps, which quantify which regions of an image humans attend. We refer to this metric as *attention map similarity*. See Appendix A.2 for a detailed breakdown of models used in our analyses.

**Pairwise comparisons.** To perform pairwise comparisons between two benchmarks, we calculate correlations between their respective scores for the same set of models. We calculate Spearman's rank correlation, which we believe to be appropriate since we are interested in the ranking of models (rather than measuring linear relationships as Pearson's correlation does). We apply very conservative Bonferroni-corrections to the thresholds of significance to account for multiple comparisons. Specifically, we divide the threshold of $\alpha = 0.05$ by the number of metric-pairs, resulting in $\alpha = 0.0009$ for Figure 1 and $\alpha = 0.001$ for Figure 5.

**Integrating metrics: arithmetic mean, z-transformed mean, mean rank.** Given a set of metrics, what is the best way of aggregating them to a single, unified score? While a one-size-fits-all solution is unlikely to exist, we observe that aggregation choices can influence conclusions and thus

warrant attention. Brain-Score uses a simple arithmetic average; in Section 4 we explore alternatives. A typical technique for dealing with different scales involves z-transforming values before aggregating them, which enforces that all individual metrics have zero mean and unit standard deviation. Alternatively, a ranking of models at some level of the Brain-Score hierarchy could be achieved by first ranking all metrics individually, and then calculating the average rank for every model.

## 3 How aligned are different metrics?

**Correlations between Brain-Score benchmarks.** To investigate the internal consistency of metrics on Brain-Score, we calculate Spearman's rank correlation coefficient for every pair of metrics, taking only those 95 models into account for which all scores are available. Removing duplicates and one model with an ImageNet accuracy below 13% leaves 88 models. We find that behavioral measures correlate strongly, especially those that all use the same dataset (Geirhos et al., 2021). For many neural metric groups such as V4 and IT, as well as sub-groups within the V1 region relating to texture and receptive field size, internal consistency is higher than consistency with other metrics. We relegate detailed results to the Appendix, see Figure 4.

**Moving beyond Brain-Score.** Next, we investigate how the two new metrics that are not yet included in the Brain-Score project, odd-one-out similarity and attention map similarity, correlate with metrics on Brain-Score in Figure 1. We again calculate pairwise Spearman's rank correlations between metrics for the set of models for which scores are available on all metrics. The odd-one-out similarity metric by Muttenthaler et al. (2022), which is of behavioral nature, is more correlated with metrics of V1 than with other behavioral metrics or later neural areas such as IT. The attention map similarity by Fel et al. (2022) is not significantly correlated with any other metric.

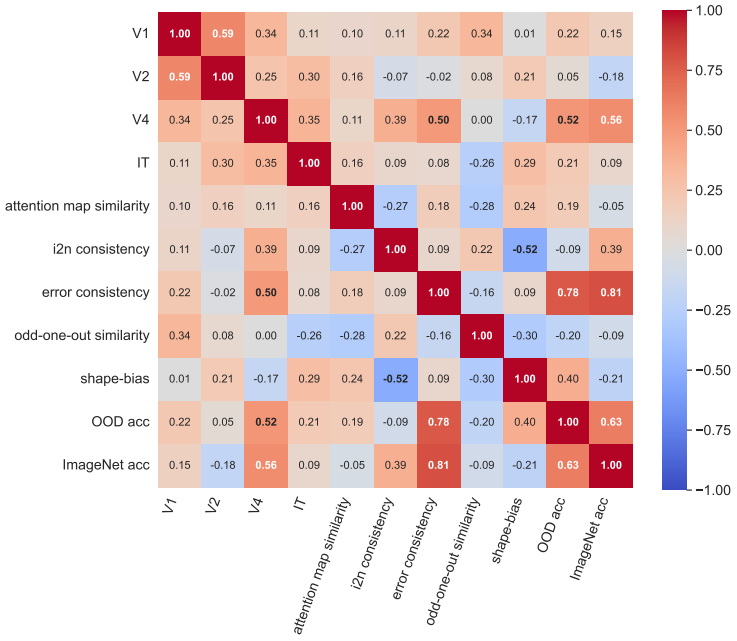


Figure 1: **How aligned are different alignment metrics?** Pairwise Spearman's rank correlations of different Brain-Score metrics, as well as odd-one-out similarity judgements and attention map similarity. Correlations that are significant after Bonferroni-correction are bold. We include only those 42 models that were evaluated on all metrics. Note that (a) variance of correlation coefficients is quite high and (b) similar metrics tend to agree, with the exception of the odd-one-out similarities. See also Figure 5 for the 80 Brain-Score models that have all scores within Brain-Score.

## 4 ALTERNATIVES TO THE ARITHMETIC AVERAGE: HOW DO AGGREGATION CHOICES INFLUENCE ALIGNMENT RESULTS?

The overall score that a model achieves on Brain-Score is calculated as the arithmetic mean of its neural and behavioral scores. In order for this to work well, the two values should at least have roughly the same magnitude, and ideally live in a common metric space. In Figure 2, we scatter behavioral against neural scores, demonstrating the differences in their variance. Note also Linsley et al. (2023), who find that models which perform better on ImageNet (which is a behavioral metric) tend to have worse IT-alignment (a neural metric). It is evident that the best behavioral scores of about $0.6$ are quite a bit higher than the best neural scores of $0.5$, meaning that models with mediocre neural scores can still rank highly in the benchmark by virtue of their good behavioral scores. In the overall model rank, we find examples of this: The two best models on Brain-Score, a Convolutional Vision Transformer [1] and a ResNeXt variant [2] by Mahajan et al. (2018) are only the 71st and 75th best model according to neural scores, respectively.

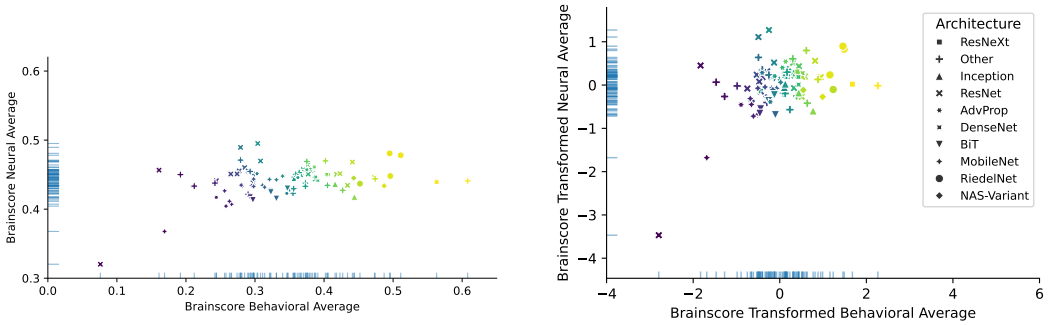


Figure 2: **Left: Relationship between neural and behavioral scores.** Coloring represents the model rank in Brain-Score, which is the average of the neural and behavioral scores (brighter color indicates higher overall score). **Right: Same data after z-transforming both scores.** The dominance of behavioral scores prevails, because there are extreme outliers in the neural scores.

Assuming that we have obtained a matrix of model scores on different, possibly uncorrelated metrics with different distributions, we should ask ourselves how to best integrate these scores into a final model-score, or at least into an overall ranking of models. We now consider three different possible ranking schemes. The first strategy, which is the default in Brain-Score, is to integrate metrics via their arithmetic mean, which is sensitive to scaling issues and high-variance metrics. As an alternative, we consider *z-transforming* the score for every metric before averaging. We demonstrate how this scheme would change scores in Figure 2b. A drawback of this approach is that such scores are no longer stable over time, but depend on the scores of other models evaluated on that metric. Alternatively, if one does not care much about absolute model scores but only about their relative order, a possible integration scheme is obtaining the *rank order* for every metric, to then average over these ranks for the final score. Such a scheme would drop quantitative information about differences, but avoids inconsistency issues like the examples with high overall rank despite extremely low-rank performance on some metrics. In practice, applying these ranking schemes to Brain-Score does indeed lead to changes in model ordering (see Figure 3). Each row corresponds to a ranking scheme, and each model is represented as one point. A model's position on the x-axis corresponds to its score: Good models are further on the right, worse models further on the left, with scores normalized to span the range $[0-1]$. To visualize the impact of the ranking scheme, we color-code models by their position in the default ranking, with higher scores colored brighter. Arguably, the differences in the resulting rank orderings are not "dramatic". However, if further studies were to e.g. correlate brain-likeness against other quantities, the effects of such changes could be quite large. We believe the issue of how to aggregate metrics deserves more scrutiny in the future.

[1] `https://www.brain-score.org/model/vision/1885`
[2] `https://www.brain-score.org/model/vision/646`

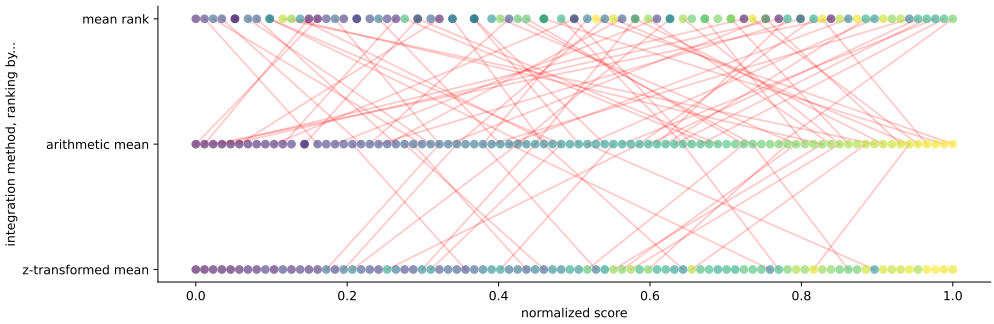


Figure 3: **Comparison of rankings resulting from different integration schemes.** We compare three different ranking algorithms: (1) Arithmetic mean corresponds to the current standard in Brain-Score, where scores are simply averaged. (2) The z-transformed ranking is obtained by z-transforming scores first, then averaging them. (3) Mean Rank is the result of averaging the ranks implied by the metrics (ranks are inverted for consistency, so higher is still better). All scores are normalized to the interval $[0-1]$ using Min-Max Normalization and colored according to a model's position under the original integration scheme. Rank-order changes greater than 10 positions (relative to the rank implied by the arithmetic mean) are highlighted in red. Spearman's rank correlations between the resulting orderings are very high, $r > 0.96$ for all three pairs.

## 5 Discussion

Recent years have seen a wealth of datasets, benchmarks and metrics to measure the alignment between brains and machines. This is a promising research avenue, but in light of an ever-expanding set of measures, this raises the question of how aligned different alignment metrics truly are. We have contributed an analysis of the relationships between different alignment measures. The resulting correlations clearly indicate that different metrics capture different aspects of perceptual alignment, sometimes leading to contradictory results. For instance, models that score as highly human-like on one metric may be among the worst models according to a different metric. Consequently, alignment with human perception may best be thought of as a multidimensional concept, and as a community we may need to spend more time thinking about how to properly integrate different metrics. As a first step in this direction, we have investigated how different aggregation choices influence alignment results. Going beyond simple aggregation methods, in which metrics are treated equally and independently, one could also consider aspects like the semantic structure of metrics: Should we discount a model's high IT-score if it performs poorly on V1 and V2, indicating that it arrives at the right solution via the wrong path? Ultimately, it could be valuable for the community to derive a set of axiomatic requirements that an ideal integration scheme should fulfill, and categorize existing aggregation choices according to how well they conform to those. Overall, it seems clear that while there is a need for unified and comprehensive benchmarks, it may be important to consider alignment as an inherently multidimensional concept.

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## REFERENCES

Nicholas Baker, Hongjing Lu, Gennady Erlikhman, and Philip J Kellman. Deep convolutional networks do not classify based on global object shape. *PLoS Computational Biology*, 14(12): e1006613, 2018.

Joel Dapello, Kohitij Kar, Martin Schrimpf, Robert Geary, Michael Ferguson, David D Cox, and James J DiCarlo. Aligning model and macaque inferior temporal cortex representations improves model-to-human behavioral alignment and adversarial robustness. *bioRxiv*, pp. 2022–07, 2022.

Thomas Fel, Ivan Felipe Rodriguez, Drew Linsley, and Thomas Serre. Harmonizing the object recognition strategies of deep neural networks with humans. *Advances in Neural Information Processing Systems*, 35:9432–9446, 2022.

Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness. In *International Conference on Learning Representations*, 2018.

Robert Geirhos, Kristof Meding, and Felix A Wichmann. Beyond accuracy: quantifying trial-by-trial behaviour of cnns and humans by measuring error consistency. *Advances in Neural Information Processing Systems*, 33:13890–13902, 2020.

Robert Geirhos, Kantharaju Narayanappa, Benjamin Mitzkus, Tizian Thieringer, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Partial success in closing the gap between human and machine vision. In *Advances in Neural Information Processing Systems 34*, 2021.

Martin N Hebart, Charles Y Zheng, Francisco Pereira, and Chris I Baker. Revealing the multidimensional mental representations of natural objects underlying human similarity judgements. *Nature human behaviour*, 4(11):1173–1185, 2020.

Martin N Hebart, Oliver Contier, Lina Teichmann, Adam H Rockter, Charles Y Zheng, Alexis Kidder, Anna Corriveau, Maryam Vaziri-Pashkam, and Chris I Baker. Things-data, a multimodal collection of large-scale datasets for investigating object representations in human brain and behavior. *Elife*, 12:e82580, 2023.

Katherine Hermann, Ting Chen, and Simon Kornblith. The origins and prevalence of texture bias in convolutional neural networks. *Advances in Neural Information Processing Systems*, 33:19000–19015, 2020.

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Joan Puigcerver, Jessica Yung, Sylvain Gelly, and Neil Houlsby. Big transfer (bit): General visual representation learning. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part V 16*, pp. 491–507. Springer, 2020.

Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2661–2671, 2019.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25, 2012.

Drew Linsley, Dan Shiebler, Sven Eberhardt, and Thomas Serre. Learning what and where to attend. *arXiv preprint arXiv:1805.08819*, 2018.

Drew Linsley, Ivan F Rodriguez, Thomas Fel, Michael Arcaro, Saloni Sharma, Margaret Livingstone, and Thomas Serre. Performance-optimized deep neural networks are evolving into worse models of inferotemporal visual cortex. *arXiv preprint arXiv:2306.03779*, 2023.

Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 116–131, 2018.

Dhruv Mahajan, Ross Girshick, Vignesh Ramanathan, Kaiming He, Manohar Paluri, Yixuan Li, Ashwin Bharambe, and Laurens van der Maaten. Exploring the limits of weakly supervised pretraining. In *Proceedings of the European Conference on Computer Vision (ECCV)*, September 2018.

Lukas Muttenthaler, Jonas Dippel, Lorenz Linhardt, Robert A Vandermeulen, and Simon Kornblith. Human alignment of neural network representations. *arXiv preprint arXiv:2211.01201*, 2022.

Rishi Rajalingham, Elias B. Issa, Pouya Bashivan, Kohitij Kar, Kailyn Schmidt, and James J. DiCarlo. Large-scale, high-resolution comparison of the core visual object recognition behavior of humans, monkeys, and state-of-the-art deep artificial neural networks. *Journal of Neuroscience*, 38(33):7255–7269, August 2018. ISSN 15292401. doi: 10.1523/JNEUROSCI.0388-18.2018. Publisher: Society for Neuroscience.

Hadi Salman, Andrew Ilyas, Logan Engstrom, Ashish Kapoor, and Aleksander Madry. Do adversarially robust imagenet models transfer better? *Advances in Neural Information Processing Systems*, 33:3533–3545, 2020.

Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4510–4520, 2018.

Martin Schrimpf, Jonas Kubilius, Ha Hong, Najib J. Majaj, Rishi Rajalingham, Elias B. Issa, Kohitij Kar, Pouya Bashivan, Jonathan Prescott-Roy, Franziska Geiger, Kailyn Schmidt, Daniel L. K. Yamins, and James J. DiCarlo. Brain-score: Which artificial neural network for object recognition is most brain-like? *bioRxiv preprint*, 2018.

Martin Schrimpf, Jonas Kubilius, Michael J Lee, N Apurva Ratan Murty, Robert Ajemian, and James J DiCarlo. Integrative benchmarking to advance neurally mechanistic models of human intelligence. *Neuron*, 2020.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Ilia Sucholutsky and Thomas L Griffiths. Alignment with human representations supports robust few-shot learning. *arXiv preprint arXiv:2301.11990*, 2023.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1–9, 2015.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818–2826, 2016.

Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017.

Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pp. 6105–6114. PMLR, 2019.

Felix A Wichmann and Robert Geirhos. Are deep neural networks adequate behavioural models of human visual perception? *Annual Review of Vision Science*, 9:501–524, 2023.

Cihang Xie, Mingxing Tan, Boqing Gong, Jiang Wang, Alan L Yuille, and Quoc V Le. Adversarial examples improve image recognition. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 819–828, 2020.

# A APPENDIX

## A.1 LIMITATIONS

Our analyses are limited by several technical issues. First, most of the pairwise correlations calculated in Figure 1 are not statistically significant, because so few models were present in all datasets. There also is some uncertainty about whether model weights were matched perfectly.

## A.2 METHODOLOGICAL DETAILS (MODEL SELECTION)

At the time of writing, Brain-Score consists of 241 models. However, not all of those models were evaluated on all metrics: Only 88 models were evaluated on all metrics that contribute to the final score (i.e. all neural and behavioral metrics) and only 77 of those were also evaluated on the complete engineering benchmark. Completing this evaluation would be valuable to allow broader analyses, as would adding exact pointers to model checkpoints where this is feasible.

For the analysis in Figure 1, we determine a subset of the models on Brain-Score that were either already evaluated by Muttenthaler et al. (2022) and Fel et al. (2022) or are publicly available, so we can evaluate them ourselves. A slight caveat is that many of the models included in the analysis do not match exactly, since Muttenthaler et al. (2022) used checkpoints from Kornblith et al. (2019), who re-trained many classical architectures. We exclude EfficientNet-B7 from our analyses, because its ImageNet accuracy reported on Brain-Score does not match the value reported by Muttenthaler et al. (2022) and the torchvision reference implementation. The complete list of models is thus:

1. AlexNet (Krizhevsky et al., 2012) via torchvision
2. DenseNet 121, 169 and 201 (Huang et al., 2017) via torchvision
3. EfficientNet B0 and B7 (Tan & Le, 2019) via torchvision
4. Inception V1 (Szegedy et al., 2015) and V3 (Szegedy et al., 2016) via torchvision
5. Inception V4 (Szegedy et al., 2017) via timm
6. VGG 16 and 19 (Simonyan & Zisserman, 2014) via torchvision
7. ShuffleNetV2-x1.0 (Ma et al., 2018) via torchvision
8. Robust ResNet50-$\ell_2$ with $\epsilon = 1$ and $\epsilon = 3$ from (Salman et al., 2020)
9. 13 MobileNetV2 variants (Sandler et al., 2018)
10. 6 BiT-S Variants by (Kolesnikov et al., 2020)
11. 6 AdvProp-EfficientNet variants by Xie et al. (2020)
12. ResNet50 trained on SIN, SIN & IN, SIN & IN & finetuned on IN from (Geirhos et al., 2018)

### A.3 Further Results

In Section 3, we briefly summarized that the data on Brain-Score is generally internally consistent, and that especially those behavioral metrics that employ the same data (from Geirhos et al. (2021)) agree strongly. Here, we present the full matrix of pairwise comparisons.

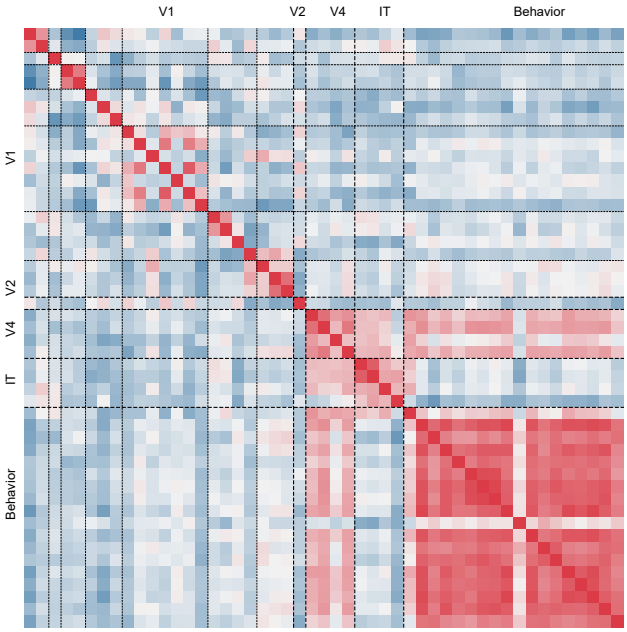


Figure 4: **How consistent are Brain-Score metrics?** Pairwise Spearman's rank correlations of different metrics, from V1 to IT and finally to behavioral measures. Note how the agreement between the behavioral metrics is much higher than the agreement of the neural measures.

To calculate the correlations presented in Figure 1, we included all models that were evaluated both on Brain-Score and the metrics proposed by Muttenthaler et al. (2022) and Fel et al. (2022). However, this set of models is relatively small (42 models total), so the correlations reported between the different Brain-Score metrics are not necessarily representative. We demonstrate how Figure 1 would have looked like if all Brain-Score models had been included in Figure 5.

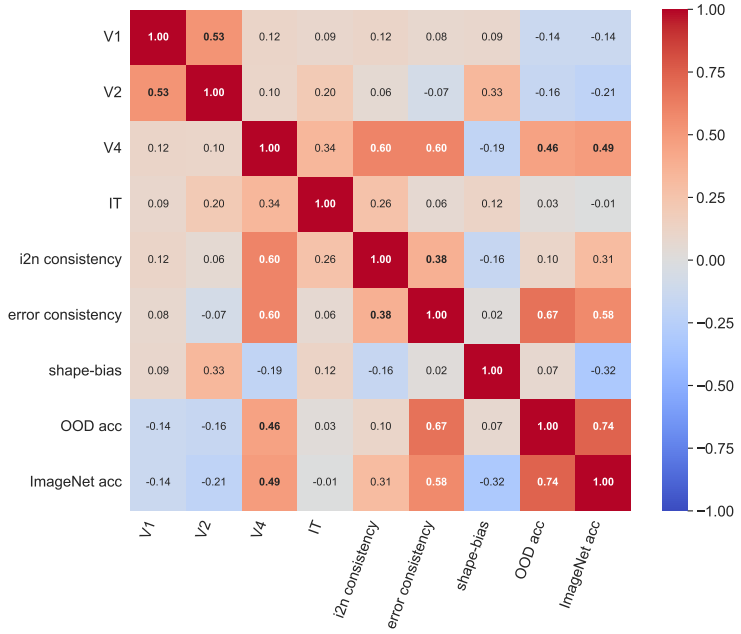


Figure 5: **Pairwise Spearman's rank correlations of Brain-Score metrics, from V1 to IT and behavioral measures.** In contrast to Figure 1, we include all Brain-Score models that had a value available for each metric, not only the subset that was also evaluated on the metrics by Muttenthaler et al. (2022) and Fel et al. (2022). This amounts to a total of 80 models. This visualization exemplifies the importance of thorough evaluations, as the correlations obtained for this subset are much bigger.

The neural score that a model obtains on Brain-Score is defined as the average over four metrics measuring alignment to different brain regions (V1, V2, V4, IT). This averaging strategy will work well if those scores are highly correlated and similarly distributed. We therefore investigate the distributions of neural scores in Figure 6, revealing highly dissimilar distributions.

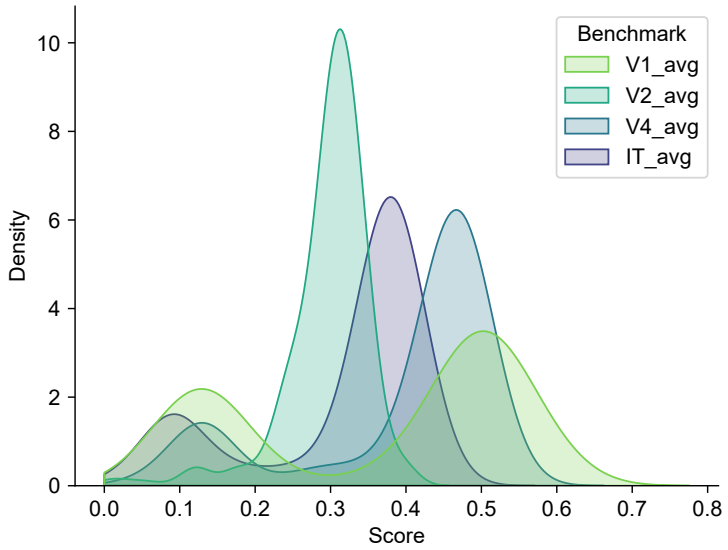


Figure 6: **Kernel Density Estimates of different neural metrics in Brain-Score.** Evidently, the distributions are quite different, indicating that merely averaging these values does not optimally capture which entries represent the most promising research directions. Scores for V1 are highest on average, with all modes notably separate. The distributions are notably bi-modal, with a main mode for well-performing models and a second mode slightly above baseline performance.

While we find that behavior already accounts for a disproportionate amount of the overall score variance on the current Brain-Score leaderboard, we next investigate which role missing values play in determining the aggregate scoresFigure 7. Coloring each model by the number of non-zero scores available across metrics reveals a striking pattern: Most models fall into one of a few homogeneous groups, having 50, 33, 30 or 5 non-zero metrics respectively. Presumably, not all authors re-triggered scoring when new chunks of metrics were added to Brain-Score. The plot reveals that behavioral scores account for even larger portions of variance when only comparing models that have the same number of non-zero metrics with each other.

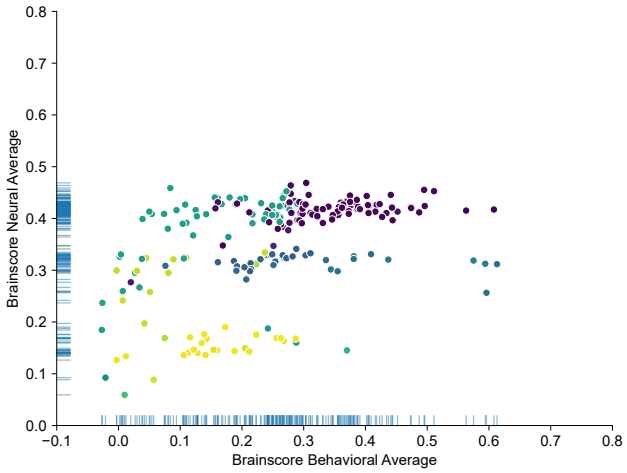


Figure 7: **How do missing scores shape Brain-Score?** Scatterplot of neural and behavioral averages for all models on Brain-Score. Models are colored according to the number of benchmarks they have been evaluated on, as determined by counting scores that are not exactly zero. Darker colors indicate more non-zero scores, yellow models have only been evaluated on 5 of 51 possible metrics.