

GETTING ALIGNED ON REPRESENTATIONAL ALIGNMENT

Ilia Sucholutsky*

Princeton University

is2961@princeton.edu

Lukas Muttenthaler*

Google DeepMind; TU Berlin

lukas.muttenthaler@tu-berlin.de

Adrian Weller

University of Cambridge

Andi Peng

MIT

Andreea Bobu

UC Berkeley

Been Kim

Google DeepMind

Bradley C. Love

UCL

Erin Grant

UCL

Iris Groen

University of Amsterdam

Jascha Achterberg

University of Cambridge[†]

Joshua B. Tenenbaum

MIT

Katherine M. Collins

University of Cambridge[‡]

Katherine L. Hermann

Google DeepMind

Kerem Oktar

Princeton University

Klaus Greff

Google DeepMind

Martin N. Hebart

MPI for Human Cognitive and Brain Sciences

Nori Jacoby

MPI for Empirical Aesthetics

Qiuyi (Richard) Zhang

Google DeepMind

Raja Marjieh

Princeton University

Robert Geirhos

Google DeepMind

Sherol Chen

Google Research

Simon Kornblith

Google DeepMind[§]

Sunayana Rane

Princeton University

Talia Konkle

Harvard University

Thomas P. O'Connell

MIT

Thomas Unterthiner

Google DeepMind

Andrew K. Lampinen[¶]

Google DeepMind

Klaus-Robert Müller[¶]

Google DeepMind; TU Berlin

Mariya Toneva[¶]

MPI for Software Systems

Thomas L. Griffiths[¶]

Princeton University

ABSTRACT

Biological and artificial information processing systems form representations of the world that they can use to categorize, reason, plan, navigate, and make decisions. How can we measure the extent to which the representations formed by these diverse systems agree? Do similarities in representations then translate into similar behavior? And if so, then how can a system's representations be modified to better match those of another system? These questions pertaining to the study of *representational alignment* are at the heart of some of the most active research areas in contemporary cognitive science, neuroscience, and machine learning. For example, cognitive scientists seek to measure the representational alignment of multiple individuals to identify shared cognitive priors, neuroscientists seek to align fMRI responses from multiple individuals into a shared representational space to boost the signal for group-level analyses, and machine learning researchers seek to distill knowledge from large teacher models into small student models by increasing their representational alignment. Unfortunately, there is limited knowledge transfer between research communities interested in representational alignment, so progress in one field often ends up being rediscovered independently in another. Thus, greater cross-field communication would be advantageous. To improve communication between fields, we propose a unifying framework that can serve as a common language between researchers studying representational alignment. We survey the literature from the fields of cognitive science, neuroscience, and machine learning, and demonstrate how prior work fits into this framework. Finally, we lay out open problems in representational alignment where progress can benefit all three of these fields. We hope that our work can catalyze cross-disciplinary collaboration and accelerate progress for all communities studying and developing information processing systems. We note that this is a working paper and encourage readers to reach out with their suggestions for future revisions.

*Equal contributions as first author. Each block of authors is sorted alphabetically.

[†]Work partly done while an intern at Intel Labs.

[‡]Work partly done while a Student Researcher at Google DeepMind.

[§]Presently at Anthropic.

[¶]Equal advising/senior authors.

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1 Introduction

Cognitive science, neuroscience, and machine learning have a long history of studying the kinds of representations that humans, machines, and other biological and artificial information processing systems construct. Numerous factors can affect what representations each system will form, including exposure to and experience with stimuli, diverging training tasks and goals, and differences in architecture – for biological and artificial systems alike. *Representational alignment* refers to the extent to which the internal representations of two or more information processing systems agree. This concept has gone by many names in different contexts, including latent space alignment, concept(ual) alignment, systems alignment, representational similarity, model alignment, and representational alignment [Goldstone and Rogosky, 2002; Kriegeskorte et al., 2008a; Stolk et al., 2016; Peterson et al., 2018; Roads and Love, 2020; Haxby et al., 2020; Aho et al., 2022; Fel et al., 2022; Marjeh et al., 2022c; Nanda et al., 2022; Tucker et al., 2022; Muttenthaler et al., 2023a; Bobu et al., 2023; Sucholutsky and Griffiths, 2023; Muttenthaler et al., 2023b; Rane et al., 2023a,b]. In addition, representational alignment has implicitly or explicitly been an objective in many subareas of machine learning including knowledge distillation [Hinton et al., 2015; Tian et al., 2019], disentanglement [Montero et al., 2022], and concept-based models [Koh et al., 2020].

While cognitive scientists, neuroscientists, machine learning researchers, and others actively study representational alignment (see Figure 1 for some curated examples), there is often limited knowledge transfer between these communities, which leads to duplicated efforts and slows down progress. We believe that this, in part, stems from the lack of a shared, standardized language for describing the full spectrum of research on representational alignment. While frameworks like Representational Similarity Analysis (RSA; Kriegeskorte et al., 2008a) have been broadly adopted, they do not cover the full range of work within representational alignment, nor are they applied equally across all disciplines. Ironically, what is needed is greater representational alignment between researchers in the different disciplines that study representational alignment.

With this paper, our goal is to provide a theoretical foundation for research on representational alignment across these different disciplines. We find that studies of representational alignment generally consist of the same five key components, and we use this insight to propose a unifying framework (visualized in Figure 2) for describing research on representational alignment in a common language. We conduct a literature review (summarized in Table 2) that illustrates how a broad spectrum of existing studies are easily interpretable when viewed through the lens of our framework. Crucially, our framework provides a way to synthesize insights across disciplines, paving a path towards solving the *three central challenges of representational alignment*: measuring alignment, bringing representations into a shared space (which we alternatively refer to as “bridging representational spaces”), and increasing the alignment between systems. Each of these challenges arises in cognitive science, neuroscience, and machine learning (see Figure 1 for an illustrated example of a study from each field for each central challenge).

Challenge 1 – Measuring: The challenge of *measuring representational alignment* is typically expressed in terms of determining the degree of similarity between the representational structures of two information processing systems [Shepard and Chipman, 1970; Kriegeskorte et al., 2008a]. Thus, measuring representational alignment offers a principled way of comparing the internal processing of two systems, even if those systems are very different. This approach can be used to validate one system as a model of another, or to help locate the cases where there are differences between two systems. For example, cognitive scientists measure representational alignment between semantic neighborhoods in different languages [Thompson et al., 2020] and different individuals [Marti et al., 2023], as well as between representational maps of musical priors in different cultures [Jacoby and McDermott, 2017; Jacoby et al., 2023; Anglada-Tort et al., 2023]. Neuroscientists measure alignment between humans and monkeys to establish homology (i.e., the presence of a “common code” in a particular brain region in humans and a particular brain region in monkeys) [Kriegeskorte et al., 2008b]; measure alignment between a deep neural network model and neural activity recordings to infer which models best capture aspects of perceptual or cognitive processing [Yamins et al., 2014; Khaligh-Razavi and Kriegeskorte, 2014; Yamins and DiCarlo, 2016; Kell et al., 2018; Conwell et al., 2022]; and measure alignment between two or more individuals to determine shared structure [Hasson et al., 2004; Stephens et al., 2010; Hasson et al., 2012a] or how synchronization in neural responses facilitates cooperative behavior [Hasson et al., 2012a; Chen et al., 2015a; Haxby et al., 2020]. Machine learning researchers measure the representational alignment of deep neural networks, such as computer vision models, with humans to test whether the models are learning generalizable human-like representations [Langlois et al., 2021a; Sucholutsky and Griffiths, 2023; Muttenthaler et al., 2023a]. Typically, the two systems are static, and the data used to measure their alignment is paired (i.e. the same set of stimuli presented to both systems).

Challenge 2 – Bridging: The challenge of *bringing the representations of two systems into a shared space* (i.e., “bridging” representational spaces) typically involves establishing a correspondence between the representations of the two systems to enable direct comparison. This correspondence unlocks ways of pooling representations across different systems, and of making more directed comparisons than simple measurements of alignment allow. Cognitive

scientists try to compare the representations of different individuals along the same set of dimensions [Wish and Carroll, 1974; Hebart et al., 2020]. Neuroscientists align fMRI responses from different individuals into a common space to determine what information is shared across individuals and boost the signal for group-level analyses [Haxby et al., 2011; O’Connell and Chun, 2018]. Machine learning researchers learn projections from pre-trained image embedding models and pre-trained text embedding models to a joint space in order to enable multimodal prompting [Gupta et al., 2017; Ramesh et al., 2022; Huang et al., 2022]. Typically, the two systems are still static, the data may or may not be paired, and the representations from at least one of the systems are projected into a new space.

Challenge 3 – Increasing: The challenge of *increasing representational alignment of two systems* involves trying to make two systems more similar to each other by updating the representations of at least one of the systems. Increasing representational alignment thus can help to make the processing in one system more like another; this can be useful in and of itself (e.g., to improve a computational model of biological system), or as a means to an end (e.g., improved downstream performance). Cognitive scientists try to increase the representational alignment of deep neural networks with humans to better predict human judgments [e.g. Geirhos et al., 2019a; Seeliger et al., 2021; Fel et al., 2022; Muttenhaler et al., 2023b]. Neuroscientists optimize deep neural networks to predict brain activity to create computational models of brain function [Schrimpf et al., 2018; Toneva and Wehbe, 2019; Schrimpf et al., 2021; Allen et al., 2022; Khosla and Wehbe, 2022; Conwell et al., 2022; Doerig et al., 2023]. Machine learning researchers train small, efficient student networks to be as similar as possible to a much larger, more expensive, but highly-performant teacher network [Hinton et al., 2015; Phuong and Lampert, 2019; Tian et al., 2019] Typically, at least one of the systems is dynamic (i.e., it can learn or otherwise update its representations), and the data may or may not be paired data.

Researchers across and beyond these three fields would benefit from progress in each of these areas. We hope that our paper will serve as a call to action for researchers working on representational alignment and catalyze inter-disciplinary collaboration to accelerate progress on these and related problems in the study of information processing systems. To encourage such cross-disciplinary engagement, in addition to proposing a unifying framework for representational alignment in §2 and highlighting key works through the lens of this framework in §3, we also identify key open problems and challenges across disciplines in §5. We believe that resolving these problems would greatly benefit each of the communities that study representational alignment.

While we believe that all sections of this paper are relevant and of interest to anyone studying representational alignment, for a more abridged read-through, we suggest focusing on the high-level overview of the framework (§2.1 and Figure 2) rather than the mathematical details, the highlighted examples (§3 and Figure 1), and the summary of open problems (§5).

2 Framework for representational alignment

2.1 High-level overview

Conceptually, there are five major components to every study of representational alignment (see Figure 2 for a schematic description):

- (a) The *data* used for alignment, which is a subset of a stimulus space such as images.
- (b) The *systems* whose representational alignment is being measured (e.g., humans, animals, deep neural networks, etc.). The internal representations of many system states are latent. For human participants, this might be the latent state of their brain as they view an image. In the case of a machine learning system, however, the system can be accessed in principle. An example would be the entire network activation pattern in response to a given stimulus.
- (c) The *measurements* that are being collected about each of the systems (e.g. behavioral similarity judgments, activation of a region for fMRI, hidden layer activations for a neural network, etc.).
- (d) The *embeddings or inferred representations* that are being extracted or (re)constructed from each system.
- (e) The *alignment function* that is being used to measure the degree of alignment between the embeddings.

Studies focused on measuring alignment typically just involve computing an alignment score from the alignment function. Meanwhile, studies focused on bridging representational spaces or increasing alignment usually involve using this score as a feedback signal on how to update the embedding function (in the bridging case) and the internal representations or their measurements (in the increasing case). We visualize this framework in Figure 2.

As a concrete example, consider the work by Kriegeskorte et al. [2008b] highlighted in Panel b of Figure 1. Say we want to measure the representational alignment of two *systems*: a rhesus macaque monkey and a human. In this case,

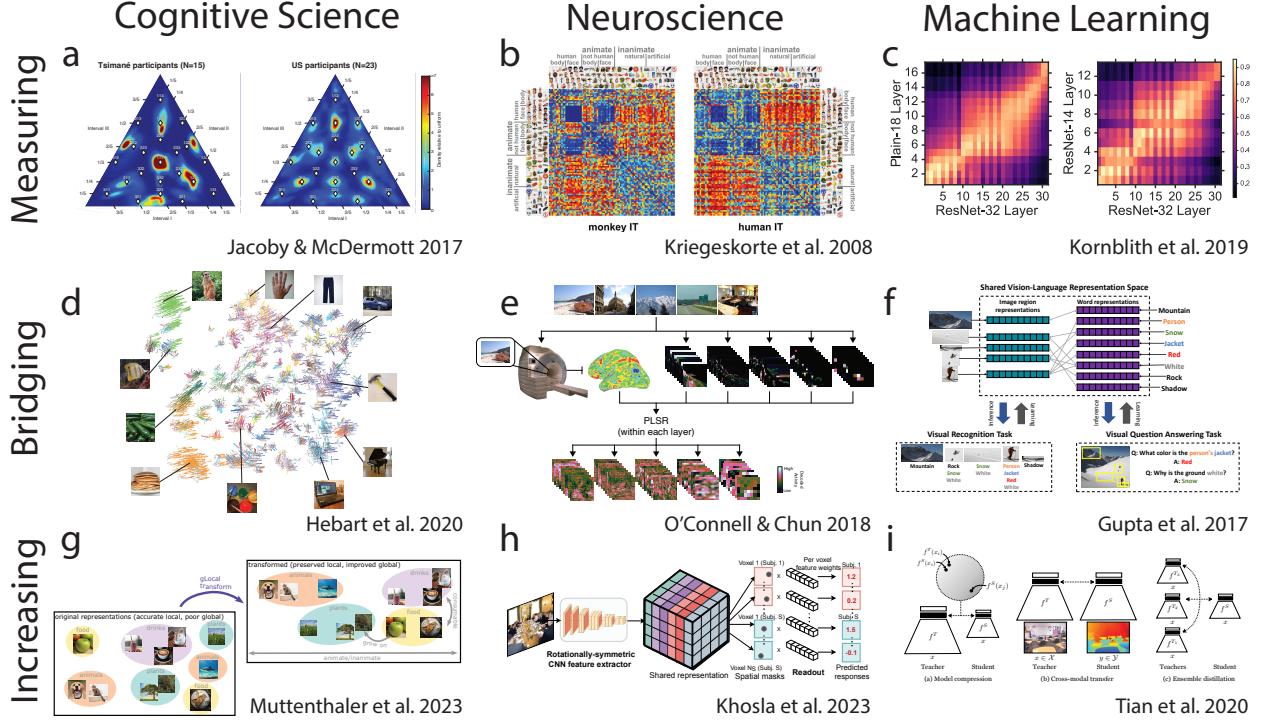


Figure 1: Examples of contemporary representational alignment research in cognitive science, neuroscience, and machine learning. We discuss three types of representational alignment research. *Measuring* representational alignment aims to measure the degree of alignment between two systems as a dependent measure in an experiment (a. Jacoby and McDermott [2017], b. Kriegeskorte et al. [2008b], c. Kornblith et al. [2019]). *Bridging* representational spaces aims to bring representations into a shared space to facilitate some downstream application (d. Hebart et al. [2020], e. O'Connell and Chun [2018], f. Gupta et al. [2017]). *Increasing* representational alignment aims to update the internal representations or measurements of one system to increase its alignment with another system (g. Muttenthaler et al. [2023b], h. Khosla and Wehbe [2022], i. Tian et al. [2019]). (Reproduced with permission from the cited papers.)

the *data* over which we want to measure alignment might be a collection of scene images. In both monkeys and humans, the state of the two systems would be the activation pattern in all the neurons while they observe the image. This state cannot be directly accessed, but only through *measurement*. For the monkey, this could be the neural responses in the inferotemporal cortex measured with electrophysiology, and for the human, we could define it as neural responses in the inferotemporal cortex measured with fMRI. In this case, a suitable set of *embeddings* might be to first construct distance matrices for each system which encode the pairwise distances between the activation pattern of each image, and then the *alignment function* can be the correlation between these two matrices (in neuroscience, this is known as representational similarity analysis; e.g., Kriegeskorte, 2015).

We believe that our framework provides a simple, general language for clearly communicating the methodology and results of representational alignment studies in a way that is accessible to many researchers. In Table 2, we present diverse examples of literature from various fields summarized by the components of the framework. The remainder of this section goes into more detail on how to mathematically formalize descriptions of each of the components and decisions that go into a study of representational alignment. In Section 3, we lay out in detail how the nine highlighted examples from Figure 1 can be described in the language of our formalism.

2.2 Formalizing representation spaces

Figure 2 shows a schematic description of our framework which contains the following components:

Data. Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be a dataset of n trials, where each $s_i \in \mathcal{S}$ is a stimulus that can be processed by any information processing function. Note that a stimulus is not restricted to a single element; s_i can be an image, a set of images (e.g., triplets), a string, a sequence (of strings or other realizations of time steps), a video (or frame thereof), etc.

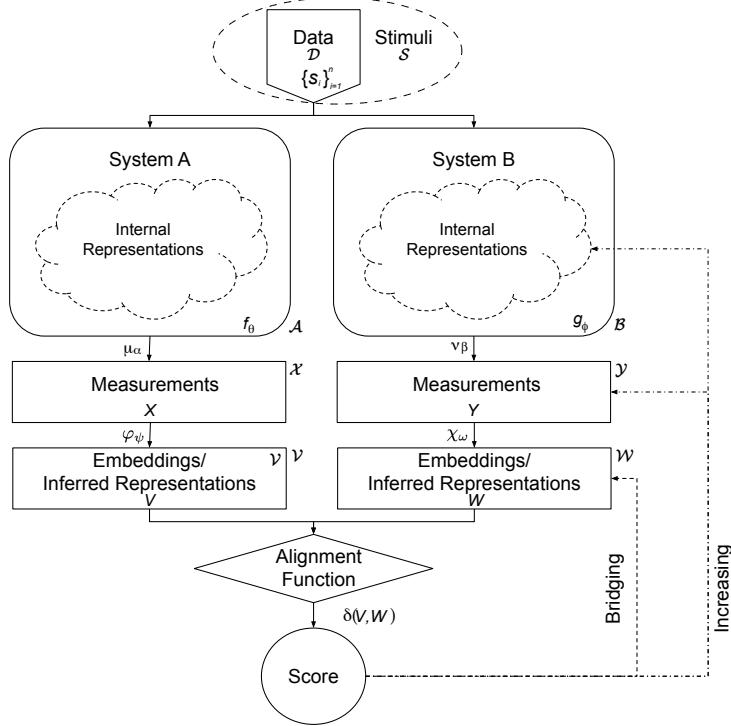


Figure 2: A general framework for describing representational alignment research.

Systems. We assume that we test two systems A and B , which can be described in terms of their internal states $f_\theta := S \mapsto \mathcal{A}$ and $g_\phi := S \mapsto \mathcal{B}$, where \mathcal{A} and \mathcal{B} denote the space of all possible states of systems A and B , respectively.

Measurements. For each of the systems A and B we obtain a summary of the measurement $X := \mu_\alpha(f_\theta(s_i), \dots, f_\theta(s_n)) \in \mathcal{X}$ and $Y := \nu_\beta(g_\phi(s_i), \dots, g_\phi(s_n)) \in \mathcal{Y}$, respectively. This is obtained by sequentially applying the functions f_θ and g_ϕ (returning the state of the systems for each of the stimuli) to all of the n trials and then passing the output through some (possibly) parameterized functions μ_α and ν_β . The parameters α and β will often reflect hyperparameters of the measurement process (e.g., in machine learning this parameter could specify which layer activations are being measured from; in human fMRI this can represent parameters of the scanning procedure as well as parameters of processing the raw fMRI data). However, in some cases (typically in machine learning), we simply directly use the entire internal state, and thus $\mu_\alpha = \nu_\beta = \mathbb{1}$ are the identity maps. In this case, $X := (f_\theta(s_i), \dots, f_\theta(s_n)) \in \mathcal{X}^{n \times p}$ and $Y := (g_\phi(s_i), \dots, g_\phi(s_n)) \in \mathcal{Y}^{n \times d}$ are the two-dimensional tensors of stacked measurements of lengths p and d respectively.

Embeddings. To map categorical behaviors to a continuous number space, denoise a set of high-dimensional measurements that potentially have a low “signal-to-noise” ratio, or essentially any other reason for why we would need a mapping from the output space (e.g., neural activity) of the information processing functions to another — possibly lower-dimensional — embedding space (e.g., real-numbered values), we can optionally define a function that transforms the measurements into an embedding space where similarity can be quantified. We assume the existence of two embedding functions, $\varphi_\psi := \mathcal{X} \mapsto \mathcal{V}$ and $\chi_\omega := \mathcal{Y} \mapsto \mathcal{W}$, which can be either linear or non-linear. We also assume that these functions have two optionally learnable arrays of parameters ψ and ω .⁶ We emphasize that the embedding function(s) are not necessary but may be advantageous in specific situations. One such scenario includes *increasing representational alignment* [cf., Muttenthaler et al., 2023a,b, see §3 for further examples where this may be desirable]. Note that if we do not have an embedding step we can simply assume $\varphi_\psi = \chi_\omega = \mathbb{1}$ are the identity map and do not change the summary measurements.

⁶Dimensionality reduction techniques such as SVD or PCA can serve as valid (optional) embedding functions even though they do not consist of any learnable variables. However, one may be interested in learning a particular (non-)linear transformation for which learnable variables are necessary (e.g., to increase alignment).

For simplicity, we consider flattening the representations in all stages into vectors. However, we emphasize that in general, the measurements can have any shape and type — e.g., they may be matrices, graphs, programs, or strings — as long as the two sets of measurements admit an appropriate measure of alignment.

2.3 Measuring alignment

There exists a function $\delta : \mathcal{V} \times \mathcal{W} \mapsto \mathbb{R}$ that we can apply to the embedded vectors V and W such that $\delta(V, W) \in \mathbb{R}$ yields a scalar value that quantifies the degree of alignment. For simplicity, we define $\delta(V, W) = \Delta_{V,W}$ to be a dissimilarity measure where $\Delta_{V,W} = 0$ implies that $V = W$, and, therefore is V is fully aligned with W .

General conditions. The following conditions have to be satisfied for any function δ that measures representational alignment.

- **Measurable.** δ must be a measurable (dis-)similarity function. However, we do not restrict δ to be a metric because symmetry is not a necessary condition for assessing the alignment between two embedding spaces.
- **Scalar-valued.** To meaningfully quantify representational alignment, we restrict δ to map to a scalar. Hence, $\delta : \mathcal{V} \times \mathcal{W} \mapsto \mathbb{R}$. For simplicity, in the remainder of this section, for V and W , we focus on (flattened) vector representations.
- **(Dis-)similarity-quantifying.** The scalar-valued output of δ is required to quantify a (dis-)similarity. For convenience, we generally use the notation of a dissimilarity measure, where δ has a lower bound at zero at which the two embedding spaces are equivalent. Hence, $\delta : \mathcal{V} \times \mathcal{W} \mapsto [0, \infty) \subset \mathbb{R}$. The advantage of a dissimilarity measure is that it can be viewed as an error function or a loss that can be minimized. However, alignment functions could also measure similarity (see §2.3.1).

In the following, we will elaborate on properties of alignment functions we think are useful to distinguish from one another. We distinguish *similarity-quantifying* from *dissimilarity-quantifying*, *descriptive* from *differentiable*, and *symmetric* from *directional* alignment. A valid alignment function must satisfy at least one of two properties that we contrast in each case. It must be (dis-)similarity quantifying; descriptive, differentiable, or both; and symmetric or directional. We list examples of alignment functions in Table 1 but a more in-depth survey can be found in [Klabunde et al., 2023].

2.3.1 Similarity or dissimilarity quantifying

Any alignment function δ has to quantify (dis-)similarity. Although any similarity can in principle be transformed into a dissimilarity, here we distinguish between the two measures. Differentiating between *similarity-quantifying* and *dissimilarity-quantifying* alignment functions offers several advantages. First, similarity-quantifying alignment functions are often bounded in both directions. As such, they are interpretable measures and therefore useful for describing the relationship between representational spaces. Second, dissimilarity-quantifying functions are a superset of error functions and thus are often useful alignment functions for gradient-based optimization. Note that similarity-quantifying alignment functions can still be optimized. However, for convenience, they are often not used directly as a loss function despite being the quantity that the optimization process aims to maximize (e.g., in contrastive representation learning [Chen et al., 2020a; Radford et al., 2021], cross-entropy is used as the loss function for maximizing the cosine similarity between representations).

Similarity-quantifying. Similarity-quantifying alignment functions are often used for describing the relationship between two sets of measurements \mathcal{X} and \mathcal{Y} . Among the set of similarity-quantifying alignment functions exist functions that are bounded in both directions. Examples include the Pearson correlation, the Spearman rank correlation, the cosine similarity, and any centered or normalized inner product. For these function, we have $\delta : \mathcal{V} \times \mathcal{W} \mapsto [-1, 1] \subset \mathbb{R}$ and often $m = z$. The bounded nature of these functions renders them particularly insightful for describing a relationship between representations, as its output is easily interpretable.

Dissimilarity-quantifying. For all dissimilarity-quantifying alignment functions, $\delta : \mathcal{V} \times \mathcal{W} \mapsto [0, \infty) \subset \mathbb{R}$, holds. That is, dissimilarity-quantifying alignment functions have a lower bound at 0 where we know that two representation spaces are equivalent. However, it is difficult to put an upper bound on these functions. Thus, dissimilarity-quantifying functions are often difficult to interpret. Information-theoretic measures such as the cross-entropy or relative entropy and ℓ_p -norms of the difference between two embeddings V and W , e.g., $\|V - W\|_F^2$, are common examples of dissimilarity-quantifying alignment functions. Although their outputs can be difficult to interpret and are not recommended to merely describe the relationship between two sets of measurements, they are useful error functions for computing $\nabla \mathcal{L}$. In addition, it is possible to use a dissimilarity-quantifying function (e.g., cross-entropy) to maximize a similarity-quantifying function (e.g., cosine similarity) as is often done in contrastive representation learning [Chen et al., 2020a; Radford et al., 2021].

2.3.2 Descriptive or differentiable

An alignment function must be *descriptive* or *differentiable* or both. These properties are not mutually exclusive, but in general, we either want to use δ for describing or increasing representational alignment.

Descriptive. A *descriptive* alignment function does not need to be differentiable. Such a function mainly serves to quantify the (dis-)similarity between the two sets of measurements X and Y . Hence, they are used when researchers aim to establish the conditions and system setups that cause representational alignment to emerge rather than directly forcing representations to be aligned (see §5 for a more detailed discussion). Descriptive alignment functions are often *symmetric*, as it is desirable to obtain the same description of representational alignment if we change the order of the embeddings when we compute $\delta(V, W)$. For example, descriptive alignment functions are used in Representational Similarity Analysis [e.g., Kriegeskorte et al., 2008a] where the similarity between different Representational Dissimilarity Matrices (RDMs) is quantified by a correlation coefficient (which is symmetric).

Differentiable. In contrast to descriptive alignment functions, we can compute a gradient for *differentiable* alignment functions. Generally, any differentiable alignment function can be regarded as an error function or loss that can be minimized, such that $\mathcal{L}_{\text{alignment}} := \delta(V, W)$. If we want to minimize $\mathcal{L}_{\text{alignment}}$ using a gradient, then δ must be restricted to the set of differentiable functions over the embedding spaces V and W . These are the functions for which we can compute a gradient matrix $\nabla \mathcal{L}_{\text{alignment}}(\psi, \alpha, \theta)$ of first-order derivatives to update the variables $\psi \cup \alpha \cup \theta$ or $\omega \cup \beta \cup \phi$. For all differentiable alignment functions, we consider the settings of *alignment transformation* and *alignment fine-tuning* respectively for minimizing $\mathcal{L}_{\text{alignment}}$.

- *Alignment transformation:* Alignment transformation poses a trade-off between leaving each representation space unaltered and allowing more distortions of those spaces for better alignment. Although taking the representation spaces as is may be descriptive, manipulating them allows us to compare spaces that are less obviously similar (e.g., by ranking which ones are *relatively* more similar to each other). Thus, there exists a spectrum of transformations, ranging from the identity function (i.e., no transformation), over linear transformations, up until non-linear functions under a constraint such as Lipschitz continuity, weight bounds, or anything else that constrains the output space of the transform to not move too far from the original space. In alignment transformation, we consider two sets of embeddings V and W to be fixed and immutable tensor representations. We do not need access to any of the two sets of source parameters θ or ϕ . We learn a transformation $h_{\Omega}(\varphi_{\psi}(x_i))$ for one of the two embedding spaces. Here, for simplicity, we choose V . Hence, we are interested in the gradient matrix of all first-order derivatives, $\nabla \mathcal{L}(\Omega)$, where we optimize the bounded parameters Ω of the transformation by solving the following minimization problem,

$$\arg \min_{\Omega} \mathcal{L}_{\text{alignment}}(h_{\Omega}(V), W) \quad (1)$$

In this case, the alignment function is defined to be a dissimilarity measure that can be minimized and used as an error function rather than a similarity measure that has to be maximized.

- *Alignment fine-tuning:* In alignment fine-tuning, we are interested in differentiating through all functions that are evaluated at a trial s . To perform alignment fine-tuning, two conditions have to be satisfied:

1. *Source parameter fixing:* First, we have to fix one of the two sets of parameters θ or ϕ which can be seen as a special case of directional alignment (see below). Here, only one of the sets of measurements X or Y is subject to change.
2. *Source parameter availability:* Second, the parameters or *sources* θ or ϕ , depending on which of the two sets we want to fix, have to be readily available. That is, we need access to the set of parameters that we want to update. Although theoretically possible $\forall f \in \mathcal{F}$, in practice it is unlikely to have access to the synapses of a human or monkey brain after obtaining measurements from them.

Let us assume that both of the above conditions are met. We fix the parameter set ϕ , assume access to θ , and evaluate the dissimilarity of V from W . That is, we want to differentiate through δ , φ_{ψ} , and f_{θ} to minimize $\Delta_{V,W}$ and consequently updating the source parameters θ . As such, we are interested in the following quantity,

$$d(\delta \circ \varphi_{\psi} \circ \mu_{\alpha} \circ f_{\theta})_{s_i} = d\delta_{\varphi_{\psi} \mu_{\alpha}(f_{\theta}(s_i))} \cdot d\varphi_{\psi} \mu_{\alpha}(f_{\theta}(s_i)) \cdot d\mu_{\alpha} f_{\theta}(s_i) \cdot df_{\theta}(s_i). \quad (2)$$

Remark. Note that alignment fine-tuning is not particularly useful if we are interested in whether two sets of measurements X and Y are (dis-)similar because, in high-dimensional spaces, it is likely that there exists a non-linear transformation (e.g., a multi-layered neural network) that can map one space to the other. For alignment fine-tuning to be useful, we must test the *generalizability* of the learned mapping to held-out measurements of the target system (here, Y), thereby satisfying at least one of the following two conditions

- (a) *Few-shot fine-tuning.* We must limit the number of training examples used for fine-tuning the set of parameters. So, if n denotes the number of training examples used for fine-tuning, n should be small; how small exactly depends on the particular task and research question.
- (b) *Regularization.* We must put an upper bound on the quantity $\|\theta - \theta^*\|_2$ such that $\sup \|\theta - \theta^*\|_2 < \epsilon$, where θ is the set of original source parameters and θ^* is the set of fine-tuned source parameters and ϵ is a small real-numbered value. That is, we do not want the fine-tuned parameters to move too far away from the original source parameters.

Differentiable alignment functions are specifically of interest for the goal of *increasing* alignment but under certain conditions may also be useful for *bridging* the representation spaces of systems.

2.3.3 Symmetric or directional

An alignment function δ can either be *symmetric* or *directional*; a function cannot be both at the same time. We recommend symmetric alignment functions over directional alignment functions for describing the relationship between two information processing systems if the goal is “just” to *measure* representational alignment rather than bridging their representation spaces or increasing their alignment.

Symmetric. For any *symmetric alignment* function, $\delta(V, W) = \delta(W, V)$ must hold. Changing the order of W and V as inputs to δ is not allowed to change the (dis-)similarity between the embedding spaces W and V . symmetric similarity functions may be desirable for describing the relationship between \mathcal{X} and \mathcal{Y} rather than optimizing for aligning the two spaces. Examples of symmetric alignment functions that are widely used are the inner product, the cosine similarity, or the Pearson correlation, of which the latter two are modified versions of the former.

Directional. *Directional alignment* functions define *alignment in terms of one space*. For these functions, $\delta(V, W)$ has to be defined in terms of one of the two embedding spaces V or W . Hence, any directional alignment function either measures the dissimilarity of V from W or, the other way around, it measures the dissimilarity of W from V . Most information-theoretic measures are directional alignment functions of which common examples are the discrete versions of the cross-entropy and the relative entropy (or KL divergence), where discrete KL divergence is defined as

$$\delta(\sigma(\varphi_\psi(\mathbf{x}_i)), \sigma(\chi_\omega(\mathbf{y}_i))) := \text{KL}(\sigma(\varphi_\psi(\mathbf{x}_i)), \sigma(\chi_\omega(\mathbf{y}_i))) := -\sum_{j=1}^m \sigma(\varphi_\psi(\mathbf{x}_i))_j \log \left(\frac{\sigma(\chi_\omega(\mathbf{y}_i))_j}{\sigma(\varphi_\psi(\mathbf{x}_i))_j} \right), \quad (3)$$

where $\sigma : \mathcal{V} \cup \mathcal{W} \mapsto [0, 1]$ is a function that transforms the embedding representations into probability distributions (e.g., softmax) and the condition $m = z$ must be satisfied. That is, $\sigma(\varphi_\psi(\mathbf{x}_i))$ and $\sigma(\chi_\omega(\mathbf{y}_i))$ must have the same shape. Information-theoretic directional alignment functions are generally not recommended for describing the relationship between V and W because they are difficult to interpret. However, they are useful error functions for minimizing the dissimilarity between two sets of representations and therefore often used for solving general machine-learning problems.

2.3.4 Different measures afford different inferences

In the points above, we have outlined different attributes that a measure of alignment may have. But which measure should we use? Rather than advocating for a particular measure, our goal is to communicate that different measures are sensitive to different features, and therefore afford different inferences. Indeed, we have been less strict in our analysis than some prior works [e.g. Williams et al., 2021]; for example, we do not require that a measure satisfy the mathematical criteria of a metric. For example, we highlight that measures may not be symmetric, or may not satisfy the triangle inequality. However, these distinct features can each be advantageous in certain situations.

As a simple conceptual example, imagine that the set of embeddings X encodes signal A in 99% of its components and signal B in 1%, whereas Y encodes signal A in 1% and signal B in 99%. Similarity-by-regression might say these systems are very similar because they encode the same information, but they represent information very differently. That is, linear regression is relatively insensitive to redundant encoding. On the other hand, RSA-based measures with an ℓ^2 metric would generally find these systems to be very poorly aligned; most of the variance in their representations is explained by different variables. However, they represent exactly the same information (and indeed, RSA could capture this similarity with other metrics).

More generally, symmetric measures of alignment can be more intuitive, but also elide important distinctions, such as which of two systems contains more information, or which is noisier (though see Duong et al. 2023). Asymmetric measures can provide more insight into features like these, but can lead to other kinds of failures (as above). Likewise, measures that do not fit parameters may underestimate how similar two systems are, if they use slightly different coding schemes that capture on the same information. However, sometimes methods that fit parameters — even using methods

Alignment function (δ)	(Dis-)Similarity	Descriptive/Differentiable	Symmetric/Directional
Centered Kernel Alignment (CKA)	Similarity	Differentiable	$\delta(x, y) = \delta(y, x)$
Representational Similarity Analysis (RSA)	Similarity	Descriptive	$\delta(x, y) = \delta(y, x)$
cos-similarity	Similarity	Differentiable	$\delta(x, y) = \delta(y, x)$
Mutual Information (MI)	Similarity	Descriptive	$\delta(x, y) = \delta(y, x)$
ℓ_2 -distance	Dissimilarity	Differentiable	$\delta(x, y) = \delta(y, x)$
KL-divergence (KL)	Dissimilarity	Differentiable	$\delta(x, y) \neq \delta(y, x)$
Cross-entropy (CE)	Dissimilarity	Differentiable	$\delta(x, y) \neq \delta(y, x)$

Table 1: Examples of alignment functions and their properties.

Research paper(s) \ Setting	Trials	SYSTEMS		ALIGNMENT	
		A	B	Objective	$\delta(x, y)$
351; 245	Images	Monkey (brain)	DNN	measuring	ℓ_2 -distance
300	Images	Human/Monkey (brain)	DNN	bridging	Task accuracy
79; 61	Images	Monkey (brain), Human (behavior)	DNN	increasing	Task accuracy
274	Images	Human/Monkey (behavior)	DNN	measuring	RSA
220	Images	Salamander (retina)	DNN	bridging	Pearson correlation
175; 59; 5; 54; 160; 72; 349	Images	Human (brain)	DNN	measuring	RSA
158; 59; 315	Images	Human (brain)	DNN	bridging	RSA
163; 109; 320	Images	Human (brain, behavior)	DNN	measuring	RSA
110; 169	Images	Human (brain)	DNN	measuring	ℓ_2 -distance
195; 60; 141	Images	Human (brain)	Semantic model	measuring	ℓ_2 -distance
125	Images	Human (brain)	Texture model	measuring	ℓ_2 -distance
316; 239; 240; 263; 215; 216; 178	Images	Human (behavior)	DNN	measuring	RSA
239; 240	Images	Human (behavior)	DNN	increasing	cross-entropy error
316	Images	Human (behavior)	DNN	measuring	Pearson correlation
58; 57; 318	Images	Human (behavior)	DNN	increasing	ℓ_2 -distance
314; 320	Images	Human (behavior)	DNN	bridging	RSA
217; 216	Audio/Video	Human (behavior)	DNN	measuring	RSA
111	Video	Human (brain)	DNN	measuring	ℓ_2 -distance
215; 217; 216	Text sequences	Human (behavior)	LLM	measuring	RSA
10	Text sequences	Human (brain)	LLM	measuring	ℓ_2 -distance
131; 265; 317	Images	DNN	DNN	increasing	KL-divergence
171	Images	DNN	DNN	measuring	CKA
202; 236	Images	DNN	DNN	measuring	RSA

Table 2: Examples of research articles from cognitive science, neuroscience, machine learning, and other fields, that relate to representational alignment.

as simple as linear regression — can be too flexible [Conwell et al., 2022]. Depending on the measures we use, we may arrive at very different conclusions. Thus, where possible, it is useful to consider multiple measures of similarity and evaluate how conclusions generalize (see §5.3 for further discussion).

3 Representational alignment in diverse communities

The goal of our framework is to introduce a common language that can highlight similarities in the approaches and goals across a diversity of fields concerned with the alignment of intelligent systems. To demonstrate how our framework fulfills this role, in this section we describe how representational alignment plays a role in specific research projects (those visualized in Figure 1). For each of the highlighted examples, we present a short conceptual summary followed by a formal mathematical description structured according to the framework. We hope that learning about *how* alignment is studied by different communities will enable readers to see connections between topics, and hopefully empower them to transfer best practices from other research communities to their own research topics. Table 2 provides a concise summary of how additional related literature fits into the unifying framework.

3.1 Cognitive Science & Perception Research

3.1.1 Measuring representational alignment (Figure 1a)

Jacoby and McDermott [2017] use a serial reproduction paradigm [Griffiths and Kalish, 2005] to elicit rhythm priors from participants. In this paradigm participants are initially introduced with a simple rhythm that is randomized from

the possible “universe” of simple rhythmic patterns. Participants reproduced the pattern, and the average reproduction became the stimulus for a new iteration. After repeating the process a fixed number of times, the experimenter identifies the density of responses within the stimulus space. In this way, categories emerge as high-density response areas. One can show that this paradigm, under certain experimentally verifiable conditions, converges to a sample from the perceptual prior over the relevant domain [Griffiths and Kalish, 2005; Langlois et al., 2021b]. Jacoby and McDermott [2017] showed that categories identified with this method overlap with integer ratios, and that they differ between speech and musical stimuli. A big advantage of this paradigm is that it can be used to study non-experts and participants with no musical experience as it relies on minimal verbal instructions. A large-scale cross-cultural replication of this work [Jacoby et al., 2021] tested the paradigm with 39 groups from 15 countries. The results showed categorical prototypes in all cultures that are near simple integer ratios. However, the weight (importance) of categories varied substantially from place to place. This is in contrast to another follow-up work where American and Canadian children were tested [Nave et al., 2024]. Here, there were small differences between adults and children underscoring the idea that rhythm presentations are learned at an early age.

- **Data \mathcal{D} :** Let $\mathcal{D} := \{(i_1, i_2, i_3) \mid i_1 + i_2 + i_3 = T, \min(i_1, i_2, i_3) > f\}$ be all possible 3-interval rhythms, where T is the total duration, i_1 , i_2 , and i_3 are the three intervals and f is the minimal possible interval (so that we avoid presenting rhythms that are too short).
- **System A:** Let f_θ be a representative group of human subjects who perform the task. The analysis is done at the group level and the output is a probability function (kernel density) of the three-interval space.
 - **Its measurements X :** Human tapping response for n randomly sampled initial seeds from \mathcal{D} . Data was collected from a group of m participants. Participants perform the serial reproduction process and repeat the initial seed. The seed becomes the input of new iterations. After a finite number of iterations (typically $K = 5$) the process stops and a new block begins with another random seed.
 - **Its embedding V :** V is the kernel density estimate for the data from the last two iterations.
- **System B:** This function stems from the same system as the function f_θ but for another group of people — hence, g_ϕ — with corresponding measurements \bar{Y} and embeddings \bar{W} . For example, the first system can be participants from the US and the second system can be participants from the Bolivian Amazon.
- **Differentiable and symmetric alignment function $\delta(V, W)$:** $\text{JSD}(V \| W) = \frac{1}{2} \sum V(\log V - \log M) + \frac{1}{2} \sum W(\log W - \log M)$ is the Jensen–Shannon divergence computed over the two kernel density functions where $M = \frac{1}{2}(V + W)$ is a mixture distribution of the two kernels.

3.1.2 Bridging representational spaces (Figure 1d)

Hebart et al. [2020] collected 1.46 million human triplet odd-one-out judgments to generate a sparse positive similarity embedding [SPOSE; Zheng et al., 2019] underlying these similarity judgments. In contrast to much previous work that has manually identified candidate dimensions, focused on small, non-representative representational spaces, or yielded low interpretability, Hebart et al. [2020] revealed 49 interpretable embedding dimensions in a data-driven fashion for a broad set of 1854 object categories that were highly predictive of single trial choice behavior. Instead of comparing representations using representational similarity analysis [Kriegeskorte et al., 2008a] or similar measures, this approach of identifying core representational dimensions allows for direct comparison of candidate dimensions that determine representational alignment. Therefore, it provides a pathway for interpretable representational alignment between different individuals or modalities.

- **Data \mathcal{D} :** Let $\mathcal{D} := (\{i_s, j_s, k_s\})_{s=1}^n$ be a dataset of n sets of three objects where each object in the triad is an image. Let m denote the number of distinct objects in this dataset where $m = 1854$.
- **System A:** Let f_θ be a representative human participant who outputs a discrete (odd-one-out) choice for each triplet in the data. The analysis is done at the participant level with choices pooled across participants, and the output is an odd-one-out choice for each triplet in the data.
 - **Its measurements X :** Asking each human participant to select the odd-one-out object for each triplet in the data yields $X := (\{a_s, b_s\} \mid \{i_s, j_s, k_s\})_{s=1}^n$, a human-response dataset of n ordered tuples of discrete choices. Note that f_θ is a non-deterministic function and thus its measurements are sampled from different human participants (the responses might as well be aggregated).
 - **Its embedding V :** Let $\varphi_\psi(x)$ be a differentiable embedding function with learnable variables $\mathbf{W}_X \in \mathbb{R}^{m \times p}$ where $p \ll m$ and \mathbf{W} is initialized with Gaussian random variables. Let $S_{ij} := \mathbf{w}_i^\top \mathbf{w}_j$ indicate the similarity between object representations $\mathbf{w}_i, \mathbf{w}_j$ in the p -dimensional embedding space where $S_X \in \mathbb{R}^{m \times m}$ is the affinity matrix of all pairwise object similarities. Thus, the embedding $V := W$ is the learnable variables.

- **System B:** There is no function g_ϕ in Hebart et al. [2020] but in principle one can imagine this function to stem from the same system as the function f_ϕ but for another group of people (e.g., different cultural groups). However, it might as well stem from other systems, such as neural network representations or brain data. In the latter cases, no triplets are directly accessible, but we can easily generate them from the measurements of the function g_ϕ , where the measurements $\mathbf{Y} := (g_\phi(s_1), \dots, g_\phi(s_m)) \in \mathbb{R}^{m \times d}$ are a stacked matrix of m object representations⁷ from which we can infer a similarity matrix (e.g., $\mathbf{S}_Y := \mathbf{Y}\mathbf{Y}^\top$). Subsequently, we can sample triplets from S_Y and learn the low-dimensional SPoSE embedding using these generated triplets.

- **Differentiable and directional alignment function $\delta(X, W)$:**

$$\delta(X, W) := \arg \min_W \frac{1}{n} - \sum_{s=1}^n \log p(\{a_s, b_s\} | \{i_s, j_s, k_s\}, W) + \lambda \|W\|_1,$$

where $p(\{a_s, b_s\} | \{i_s, j_s, k_s\}, W) = \exp(\mathbf{w}_a^\top \mathbf{w}_b) / (\exp(\mathbf{w}_i^\top \mathbf{w}_j) + \exp(\mathbf{w}_i^\top \mathbf{w}_k) + \exp(\mathbf{w}_j^\top \mathbf{w}_k))$ and λ is a hyper-parameter that determines the strength of the sparsity-inducing ℓ_1 -regularization.

Similarly, Muttenthaler et al. [2022] used the same set of measurements in combination with a similar alignment function (same data log-likelihood function but different regularization) for learning a more robust version of the embedding W using approximate Bayesian inference. They used a *spike-and-slab* Gaussian mixture prior instead of vanilla ℓ_1 -regularization and learned a matrix for the variance over the human odd-one-out choices in addition to the (mean) embedding matrix, demonstrating that this more appropriate than the above deterministic version when n is small.

3.1.3 Increasing representational alignment (Figure 1g)

Muttenthaler et al. [2023b] use human triplet odd-one-out choices to increase the alignment between neural network representation and human object similarity spaces. The human odd-one-out choices were collected using large-scale online crowd-sourcing in a previous study [Hebart et al., 2020]. The objective in Muttenthaler et al. [2023b] was to align a neural network function f_θ with the behavior of human participants g_ϕ where g_ϕ is not a deterministic function and thus the human behavior is aggregated across multiple participants. That is, their goal was to perform *alignment transformation* (see §2.3.2) from the neural network representation space into the human object similarity space. Therefore, they used a *directional* and *differentiable* alignment function which — as we have seen in §2.3 — are both desirable but not necessary properties of an alignment function.

- **Data \mathcal{D} :** Let $\mathcal{D} := (\{i_s, j_s, k_s\})_{s=1}^n$ be a dataset of n sets of three objects where each object in the triad is an image. Let m denote the number of distinct objects in this dataset where $m = 1854$.
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^p$ be a deterministic neural network function that maps an image to a p -dimensional vector representation (in its penultimate layer/image encoder space).
 - **Its measurements X :** Applying f_θ to each image in the data yields $\mathbf{X} := \mu_\alpha(f_\theta(s_1), \dots, f_\theta(s_m)) \in \mathbb{R}^{m \times p}$, a stacked matrix of m (penultimate layer) object representations.
 - **Its embedding V :** Let $S_{ij} := \mathbf{x}_i^\top \mathbf{x}_j$ be the similarity between object representations $\mathbf{x}_i, \mathbf{x}_j$ in the original representation space and $V_{ij} = \varphi_\psi(X_{ij}) := (\mathbf{W}\mathbf{x}_i + \mathbf{b})^\top (\mathbf{W}\mathbf{x}_j + \mathbf{b})$ indicate the similarity between object representations $\mathbf{x}_i, \mathbf{x}_j$ in the transformed representation space. So, $\mathbf{V} \in \mathbb{R}^{m \times m}$ is the affinity matrix of all pairwise object similarities in the transformed space. Here, the transformation matrix $\mathbf{W} \in \mathbb{R}^{p \times p}$ and the bias vector $\mathbf{b} \in \mathbb{R}^p$ are both learnable variables (optimized via SGD).
- **System B:** Let g_ϕ be a representative human participant who outputs a discrete (odd-one-out) choice for each triplet in the data.
 - **Its measurements Y :** Asking each human participant to select the odd-one-out object for each triplet in the data yields $\mathbf{Y} := (\{a_s, b_s\} | \{i_s, j_s, k_s\})_{s=1}^n$, a human-response dataset of n ordered tuples of discrete choices. Note that g_ϕ is a non-deterministic function and thus its measurements are sampled from different human participants.
 - **Its embedding W :** There is no embedding function. Here, $W = Y$, a human response dataset of discrete odd-one-out choices.
- **Differentiable and directional alignment function $\delta(V, W)$:**

$$\delta(V, W) := \arg \min_{W, b} \frac{1}{n} - \sum_{s=1}^n \log p(\{a_s, b_s\} | \{i_s, j_s, k_s\}, V) + \lambda \left\| \mathbf{W} - \left(\sum_{j=1}^p \mathbf{W}_{jj}/p \right) \mathbf{I} \right\|_F^2,$$

⁷The dimensionality d of the object representations may or may not be collapsed. It may be collapsed if the representations are inferred from brain data or from a convolutional layer of a CNN which are both generally of tensor format.

where $p(\{a_s, b_s\} \mid \{i_s, j_s, k_s\}, \mathbf{V}) = \exp(\mathbf{v}_a^\top \mathbf{v}_b) / (\exp(\mathbf{v}_i^\top \mathbf{v}_j) + \exp(\mathbf{v}_i^\top \mathbf{v}_k) + \exp(\mathbf{v}_j^\top \mathbf{v}_k))$ and λ is a hyper-parameter that determines the strength of the ℓ_2 -regularization.

Using the above (constrained) alignment function plus an additional contrastive learning objective that preserves the local similarity structure from the original neural network representation space allowed the authors to obtain a human-aligned representation space that showed increased representational alignment with human perception and better downstream task performance on various computer vision tasks [Muttenthaler et al., 2023b].

3.2 Neuroscience

3.2.1 Measuring representational alignment (Figure 1b)

Kriegeskorte et al. [2008b] used RSA to measure alignment between neural responses in monkey and human inferotemporal cortex. The monkey neural responses were measured with multi-array electrophysiology and the human neural responses were measured with fMRI. The objective was to compare the representational geometry across monkeys and humans to determine if IT cortex is homologous across primate species using a descriptive and symmetric alignment function.

- **Dataset \mathcal{D} :** Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be a set of images depicting objects on plain white backgrounds.
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^p$ be a Rhesus macaque monkey whose neural activity we want to record for each image in the data using electrophysiology measures.
 - **Its measurements X :** Let $X := \mu_\alpha(f_\theta(s_1), \dots, f_\theta(s_n)) \in \mathbb{R}^{n \times p}$ be the monkey's electrophysiology signals from inferior temporal cortex for each image in the data \mathcal{D} . For each image, the electrophysiology measurements are represented by a vector of p electrodes that reflect neural activity.
 - **Its embedding V :** Upper-triangular off-diagonal elements of the representational dissimilarity matrix $S_X \in \mathbb{R}^{n \times n}$ where each entry $s_{ij}^X := 1 - ((\mathbf{x}_i - \bar{\mathbf{x}}_i)^\top (\mathbf{x}_j - \bar{\mathbf{x}}_j) / (\|\mathbf{x}_i - \bar{\mathbf{x}}_i\|_2 \|\mathbf{x}_j - \bar{\mathbf{x}}_j\|_2))$ is determined by 1 minus the Pearson correlation coefficient between image representations $\mathbf{x}_i, \mathbf{x}_j$. Thus, we have that the embedding $\mathbf{v} \in \mathbb{R}^{nn/2-n}$ is a (flattened) vector representation rather than a matrix.
- **System B:** Let $g_\phi : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{v \times d}$ be a human participant who transforms images into neural activity.
 - **Its measurements Y :** Let $Y := \nu_\beta(g_\phi(s_1), \dots, g_\phi(s_n)) \in \mathbb{R}^{n \times v \times d}$ be the human participant's fMRI responses from inferior temporal cortex for each image in the data \mathcal{D} . For each image, the fMRI responses are represented by a matrix of voxel \times individual neuron activities with v voxels and d neurons.
 - **Its embedding W :** Upper-triangular off-diagonal elements of the representational dissimilarity matrix $S_Y \in \mathbb{R}^{n \times n}$ where each entry $s_{ij}^Y := 1 - ((\mathbf{y}_i - \bar{\mathbf{y}}_i)^\top (\mathbf{y}_j - \bar{\mathbf{y}}_j) / (\|\mathbf{y}_i - \bar{\mathbf{y}}_i\|_2 \|\mathbf{y}_j - \bar{\mathbf{y}}_j\|_2))$ is determined by 1 minus the Pearson correlation coefficient between image representations $\mathbf{y}_i, \mathbf{y}_j$. Thus, we have that the embedding $\mathbf{w} \in \mathbb{R}^{nn/2-n}$ is a (flattened) vector representation of the same shape as \mathbf{v} .
- **Descriptive and symmetric alignment function $\delta(\mathbf{v}, \mathbf{w})$:** Spearman's rank correlation coefficient between the embedding vectors \mathbf{v} and \mathbf{w} .

3.2.2 Bridging representational spaces (Figure 1e)

O'Connell and Chun [2018] introduced techniques to (a) align fMRI responses across different individuals and (b) align fMRI responses to eye movement behavior within individuals. Humans viewed images depicting natural scenes while undergoing fMRI scanning, then in a separate session viewed the images while their eye movements were recorded. To align brain activity across individuals, a linear decoding analysis was used to map each individual's fMRI responses into a common space defined as the unit activity of a CNN, which allowed for group-level analysis over the mean of the aligned responses. To align human brain activity to eye movements, a computational salience model is applied to the CNN-aligned fMRI responses to derive a brain-based spatial priority map which was then compared to human eye movement patterns. The objective was to identify brain regions in humans that capture spatial information predictive of human eye movement patterns.

(a) *aligning fMRI responses across individuals into a common (CNN-determined) representation space:*

- **Data \mathcal{D} :** Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be a set of n images, each depicting a natural scene.
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{v \times p}$ be a human participant who transforms images into neural activity.

- **Its measurements X :** Let $\mathbf{X} := \mu_\alpha(f_\theta(s_1), \dots, f_\theta(s_n)) \in \mathbb{R}^{n \times v \times p}$ be the individual’s fMRI responses for each image in the data \mathcal{D} . For each image, the fMRI responses are represented by a matrix of voxel \times individual neuron activities with v voxels and p neurons.
- **Its embedding V :** Let $\varphi_\psi(\mathbf{x}_i) : \mathbb{R}^{v \times p} \mapsto \mathbb{R}^d$ denote partial least-squares (PLS) regression that learns a linear transformation from the participant’s measurements space \mathbf{X} to the representation space of a CNN. The transformation was applied to held-out data to map the individual fMRI responses to the embedding space such that $\mathbf{V} := (\varphi_\psi(\mathbf{x}_1), \dots, \varphi_\psi(\mathbf{x}_n)) \in \mathbb{R}^{n \times d}$. Note that a flattening operation was applied to the rows of \mathbf{X} before employing PLS regression.
- **System B:** Let $g_\phi : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{v \times p}$ be a different human participant who transforms images into neural activity.
 - **Its measurements Y :** Let $\mathbf{Y} := \nu_\beta(g_\phi(s_1), \dots, g_\phi(s_n)) \in \mathbb{R}^{n \times v \times p}$ be the individual’s fMRI responses for each natural scenes image in the data \mathcal{D} .
 - **Its embedding W :** The same PLS regression mapping as above was used to map from the participant’s measurements space \mathbf{Y} to the representation space of a CNN. Similarly, the transformation was applied to held-out data to map the individual fMRI responses to the embedding space such that $\mathbf{W} := (\chi_\omega(y_1), \dots, \chi_\omega(y_n)) \in \mathbb{R}^{n \times d}$.
- **Symmetric alignment function $\delta(V, W)$:** $\delta(\mathbf{v}_i, \mathbf{w}_i) := \frac{(\mathbf{v}_i - \bar{\mathbf{v}}_i)^\top (\mathbf{w}_i - \bar{\mathbf{w}}_i)}{\|\mathbf{v}_i - \bar{\mathbf{v}}_i\|_2 \|\mathbf{w}_i - \bar{\mathbf{w}}_i\|_2}$, where $\delta(\mathbf{v}_i, \mathbf{w}_i)$ denotes the Pearson correlation (coefficient) between the representations of function f_θ and function g_ϕ respectively for the same image in the shared (CNN-determined) embedding space.

(b) *aligning fMRI responses to eye movement behavior:*

- **Data \mathcal{D} :** Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be the same set of images as in (a).
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{v \times p}$ be a human participant whose neural activity is recorded for each image in the data.
 - **Its measurements X :** Let $\mathbf{X} := \mu_\alpha(\varphi_\psi(f_\theta(s_1)), \dots, \varphi_\psi(f_\theta(s_n))) \in \mathbb{R}^{n \times d}$ be the group-level human fMRI responses transformed into a shared (CNN-determined) representation space (see embedding space above).
 - **Its embedding V :** The group-level CNN-transformed fMRI responses were averaged across the CNN activity feature dimension and layers to derive a brain-based spatial priority map predicting where people would look in an image. So, $\mathbf{V} \in \mathbb{R}^{n \times m}$
- **System B:** Let $g_\phi : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{t \times z}$ be the same human participant whose continuous eye movement patterns (instead of neural activity) is recorded for each image in the data.
 - **Its measurements Y :** Let $\mathbf{Y} := \nu_\beta(g_\phi(s_1), \dots, g_\phi(s_n)) \in \mathbb{R}^{n \times t \times p}$ be the individual participant’s (continuous) eye movement recordings (derived from an eye-tracking camera) for each image in the data \mathcal{D} .
 - **Its embedding W :** Let $W = \{(x_i, y_i)\}_{i=1}^n$ be the set of $(x, y) \in \mathbb{R}_+^2$ coordinates defining the location of all fixations for a given image in \mathcal{D} where n is the number of fixations.
- **Descriptive and directional alignment function $\delta(V, W)$:** The Normalized Scanpath Salience (NSS) is the mean of the spatial priority map activations corresponding to fixation locations such that $\text{NSS}(\mathbf{v}, \mathbf{w}) = \frac{1}{n} \sum_{(a,b) \in W} V_{ab}$.

3.2.3 Increasing representational alignment (Figure 1h)

Khosla and Wehbe [2022] trained CNNs to predict human fMRI responses in visual brain regions. While previous work had compared alignment in fMRI and image-optimized CNN representations using descriptive measures, this work aimed to increase human fMRI and CNN alignment by directly optimizing CNNs to be aligned with fMRI responses. They find that CNNs optimized to predict responses in high-level visual brain regions recapitulate visual behaviors including classification and making aligned similarity judgments to humans.

- **Data \mathcal{D} :** Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be a set of n images, each depicting a natural scene.
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^{v \times p}$ be a human participant whose neural activity we want to measure for a set of images.
 - **Its measurements X :** Let $\mathbf{X} := (f_\theta(s_1), \dots, f_\theta(s_n)) \in \mathbb{R}^{n \times v \times p}$ be the individual’s fMRI responses for each image in the data \mathcal{D} . For each image, the fMRI responses are represented by a matrix of voxel \times individual neuron activities with v voxels and p neurons.
 - **Its embedding V :** Let $\varphi_\psi(\mathbf{X}_i) : \mathbb{R}^{v \times p} \mapsto \mathbb{R}^v$ be an aggregation function that maps a matrix of voxel by neuron activities to a single activity per voxel. Thus, $\mathbf{V} \in \mathbb{R}^{n \times v}$.

- **System B:** Let $g_\phi : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^p$ be a deterministic neural network function that maps an image to a p -dimensional vector representation (in its penultimate layer space).
 - **Its measurements Y :** Applying g_ϕ to each image in the data \mathcal{D} yields $\mathbf{Y} := (g_\phi(s_1), \dots, g_\phi(s_n)) \in \mathbb{R}^{n \times p}$, a stacked matrix of n (penultimate layer) image representations.
 - **Its embedding W :** Let $\chi_\omega(\mathbf{y}_i) : \mathbb{R}^p \mapsto \mathbb{R}^v$ be a factorized linear readout (with learnable variables) that transforms penultimate layer image representations into human brain activity. Therefore, $\mathbf{W} := (\chi_\omega(\mathbf{y}_1), \dots, \chi_\omega(\mathbf{y}_n)) \in \mathbb{R}^{n \times v}$.
- **Differentiable and symmetric alignment function $\delta(V, W)$:** $\text{MSE}(\mathbf{v}_i, \mathbf{w}_i) = \frac{1}{v} \sum_{j=1}^v (\mathbf{v}_{ij} - \mathbf{w}_{ij})^2$.

3.3 Artificial Intelligence and Machine Learning

3.3.1 Measuring representational alignment (Figure 1c)

Just as it is possible to measure the similarity between representations of biological neurons, it is also possible to measure the similarity between representations of artificial neural networks. A variety of neural network representational similarity measures have been proposed [Raghu et al., 2017; Morcos et al., 2018; Williams et al., 2021; Ding et al., 2021]. Centered Kernel Alignment (CKA) is a particularly simple and widely-used approach for this purpose [Kornblith et al., 2019]:

- **Data \mathcal{D} :** Let $\mathcal{D} := \{s_i\}_{i=1}^n$ be a dataset of n images or text sequences.
- **System A:** Any neural network function. Let $f_\theta : \mathbb{R}^{H \times W \times C} \cup \mathbb{R}^{T \times K} \mapsto \mathbb{R}^p$ be a deterministic neural network function that maps a set of inputs (images or text sequences) to a set of outputs.
 - **Its measurements X :** Let $\mathbf{X} \in \mathbb{R}^{n \times p}$ be the matrix of activations extracted from a layer/module of the neural network function f_θ where $\mathbf{X} := \mu_\alpha(f_\theta(s_1), \dots, f_\theta(s_n))$.
 - **Its embedding V :** Here, φ_ψ is the identity function (in the case of linear CKA) or an arbitrary feature mapping applied to the set of measurements \mathbf{X} where $\mathbf{V} := (\varphi_\psi(\mathbf{x}_1), \dots, \varphi_\psi(\mathbf{x}_n)) \in \mathbb{R}^{n \times m}$.
- **System B:** Any neural network function. Let $g_\phi : \mathbb{R}^{H \times W \times C} \cup \mathbb{R}^{T \times K} \mapsto \mathbb{R}^d$ be another deterministic neural network function that maps a set of inputs (images or text sequences) to a set of outputs.
 - **Its measurements Y :** Let $\mathbf{Y} \in \mathbb{R}^{n \times d}$ be the matrix of activations extracted from a layer/module of the neural network function g_ϕ where $\mathbf{Y} := \nu_\beta(g_\phi(s_1), \dots, g_\phi(s_n))$.
 - **Its embedding W :** Here, φ is the identity function (in the case of linear CKA) or an arbitrary feature mapping applied to the set of measurements \mathbf{Y} where $\mathbf{W} := (\chi_\omega(\mathbf{y}_1), \dots, \chi_\omega(\mathbf{y}_n)) \in \mathbb{R}^{n \times z}$.
- **Differentiable and symmetric alignment function $\delta(V, W)$:**

$$\text{CKA} = \frac{\|\mathbf{V}^\top \mathbf{H} \mathbf{W}\|_{\text{F}}^2}{\|\mathbf{V}^\top \mathbf{H} \mathbf{V}\|_{\text{F}} \|\mathbf{W}^\top \mathbf{H} \mathbf{W}\|_{\text{F}}} = \frac{\text{tr}(\mathbf{V} \mathbf{V}^\top \mathbf{H} \mathbf{W} \mathbf{W}^\top \mathbf{H})}{\|\mathbf{H} \mathbf{V} \mathbf{V}^\top \mathbf{H}\|_{\text{F}} \|\mathbf{H} \mathbf{W} \mathbf{W}^\top \mathbf{H}\|_{\text{F}}},$$

where $\mathbf{H}_n = \mathbf{I}_n - \frac{1}{n} \mathbf{1} \mathbf{1}^\top$ is the centering matrix.

Depending on the choice of the feature mapping, \mathbf{V} and \mathbf{W} can be expensive or impossible to compute directly. For example, the feature mapping associated with the radial basis function kernel is infinite-dimensional. In these cases one has to compute similarity matrices $\mathbf{K} = \mathbf{V} \mathbf{V}^\top$ and $\mathbf{L} = \mathbf{W} \mathbf{W}^\top$ by evaluating kernel functions $K_{ij} = k(\mathbf{x}_i, \mathbf{x}_j)$ and $L_{ij} = l(\mathbf{x}_i, \mathbf{x}_j)$.

3.3.2 Bridging representational spaces (Figure 1f)

By enforcing text and image representational alignment, multimodal models achieve better cross-task transfer compared to standard multitask learning. Specifically, Gupta et al. [2017] demonstrate better inductive transfer from visual recognition to visual question answering (VQA) than standard methods, stating that visual recognition additionally improves, in particular for categories that have relatively few recognition training labels but frequently appear in the query setting. Their setup is the following:

- **Data \mathcal{D} :** Let $\mathcal{D} := \{r_i, w_i\}_{i=1}^n$ be a dataset of n images with corresponding text descriptions.
- **System A:** Any neural network function. Let $f_\theta : \mathbb{R}^{H \times W \times C} \mapsto \mathbb{R}^p$ be a deterministic neural network function that maps a set of images to a set of vectorized outputs.

- **Its measurements X :** Let $\mathbf{X} := \mu_\alpha(f_\theta(r_1), \dots, f_\theta(r_n)) \in \mathbb{R}^{n \times p}$ be the average pooled features from an ImageNet-trained ResNet-50 — which represents the neural network function f_θ — for all n images in the dataset \mathcal{D} .
- **Its embedding V :** Let $\mathbf{V} := (\varphi_\psi(\mathbf{x}_1), \dots, \varphi_\psi(\mathbf{x}_n)) \in \mathbb{R}^{n \times m}$ the embedding matrix where $\varphi = \mathbb{1}$ and $m = p$.
- **System B:** Any neural network function. Let $g_\phi : \mathbb{R}^{T \times K} \mapsto \mathbb{R}^{t \times d}$ be another deterministic neural network function that maps a set of text sequences to a set of vectorized outputs.
 - **Its measurements Y :** By applying two fully connected layers (that have 300 output units each) from the neural network function g_ϕ to pretrained word2vec representations [Mikolov et al., 2013b] of the text descriptions w we obtain $\mathbf{Y} := \nu_\beta(g_\phi(\mathbf{w}'_1), \dots, g_\phi(\mathbf{w}'_n)) \in \mathbb{R}^{n \times t \times d}$, a stacked tensor of d -dimensional representations for each word in the text description.
 - **Its embedding W :** Let $\mathbf{W} := (\chi_\omega(y_1), \dots, \chi_\omega(y_n)) \in \mathbb{R}^{n \times t \times z}$ be the embedding tensor where $\varphi = \mathbb{1}$ and $z = d$.
- **Differentiable and directional alignment function $\delta(V, W)$:** Depending on whether a word in the text description is an object or an attribute, Gupta et al. [2017] use a different loss function for aligning image and text representations. Therefore, the authors partition the text descriptions into object and attribute sets. If a word in the text description w_i corresponding to an image r_i is an object, then the alignment between the image and text representations is increased by minimizing the following objective,

$$\delta(V, W) := \mathcal{L}_{\text{obj}}(f_\theta, g_\phi) := \frac{1}{|w_i^{\text{obj}}|} \sum_{l \in w_i^{\text{obj}}} \frac{1}{|\mathcal{O}|} \sum_{k \in \{\mathcal{O} \setminus w_i^{\text{obj}}\}} \max \{0, \eta_{\text{obj}} + \mathbf{x}_i^\top g_\phi(\mathcal{O})_k - \mathbf{x}_i^\top Y_{il}^{\text{obj}}\},$$

where \mathcal{O}^8 is the set of the 1000 most frequent object categories in the Visual Genome dataset [Krishna et al., 2017] and $\eta_{\text{obj}} \in \mathbb{R}$ is a margin. If the word, however, is an attribute, then the following loss function is minimized instead,

$$\mathcal{L}_{\text{attr}}(f_\theta, g_\phi) := \sum_{t \in \mathcal{T}} \mathbb{1}[t \in \mathcal{T}] (1 - \Gamma(t)) \log[\sigma(\mathbf{x}_i^\top g_\phi(\mathcal{T})_t)] + \mathbb{1}[t \notin \mathcal{T}] \Gamma(t) \log[1 - \sigma(\mathbf{x}_i^\top g_\phi(\mathcal{T})_t)],$$

where $\sigma : \mathbb{R} \mapsto [0, 1]$ is a sigmoid activation function, $\Gamma(t)$ is the fraction of positive samples for attribute t in a mini-batch, and \mathcal{T}^9 denotes the set of the 1000 most frequent attribute categories in the Visual Genome dataset [Krishna et al., 2017].

3.3.3 Increasing representational alignment (Figure 1i)

The distillation of knowledge from a teacher network into a student network is a powerful tool in machine learning. It is used to a) compress a large teacher network into a smaller (and faster) student model, b) transfer knowledge from one modality to another (e.g. RGB to depth images), and c) combine the knowledge from an ensemble of teachers into a single student network. While initial work in this area Hinton et al. [2015] focused on behavioral alignment, Tian et al. [2019] proposed a general framework for transferring knowledge by aligning (intermediate) representations. Their setup for transfer between modalities (b) is as follows:

- **Data \mathcal{D} :** Let $\mathcal{D} := \{(s_i, r_i)\}_{i=1}^n$ be a dataset of n pairs of different modalities (e.g., RGB and depth images).
- **System A:** Let $f_\theta : \mathbb{R}^{H \times W \times C_1} \mapsto \mathbb{R}^p$ be any (pretrained) neural network function that maps a set of inputs (e.g., RGB images) to a set of outputs and takes the role of the teacher network.
 - **Its measurements X :** Let $\mathbf{X} \in \mathbb{R}^{n \times p}$ be the matrix of activations extracted from a layer/module of the neural network function f_θ for all n RGB images where $\mathbf{X} := \mu_\alpha(f_\theta(s_1), \dots, f_\theta(s_n))$.
 - **Its embedding V :** Here φ_ψ is the identity function, so $\mathbf{V} = \mathbf{X}$.
- **System B:** Any trainable neural network function that takes the role of the student network. Let $g_\phi : \mathbb{R}^{H \times W \times C_2} \mapsto \mathbb{R}^d$ be another deterministic neural network function that maps a different set of inputs (e.g., depth images) to a set of outputs.

⁸Since we deal with non-contextual word representations, here, we can simply treat \mathcal{O} as a sequence of words rather than a set and apply the neural network function g_ϕ (sequentially) to it.

⁹Again, here we can treat \mathcal{T} as a sequence of words rather than a set and apply g_ϕ to the sequence to obtain a representation for each attribute word.

- **Its measurements Y :** Let $\mathbf{Y} \in \mathbb{R}^{n \times q}$ be the matrix of activations extracted from a layer/module of the neural network function g_ϕ for all n depth images where $\mathbf{Y} := \nu_\beta(g_\phi(r_1), \dots, f_\phi(r_n))$.
- **Its embedding W :** Here χ_ω is the identity function, so $\mathbf{W} = \mathbf{Y}$.
- **Differentiable and directional alignment function $\delta(V, W)$:**

$$\begin{aligned}\delta(V, W) &= \max_h \mathcal{L}_{\text{critic}}(g_\phi, h) \\ &= \mathbb{E}_{P(X, Y)} [\log h(\mathbf{x}, \mathbf{y})] + N \mathbb{E}_{P(X)P(Y)} [\log(1 - h(\mathbf{x}, \mathbf{y}))].\end{aligned}$$

Here $h : \mathbb{R}^p \times \mathbb{R}^q \mapsto [0, 1]$ is a differentiable function that is trained alongside the student. Thus in this case, the alignment function $\delta(V, W)$ is not fixed but instead fitted to the teacher and student networks f_θ and g_ϕ . Note that the two expectations are taken over sampling matching pairs of inputs (i.e. (s_i, r_i)) and over non-matching pairs of inputs (i.e. (s_i, r_j) with $i \neq j$) respectively. The factor N is a hyperparameter that determines the relative frequency of non-matching pairs with respect to matching pairs. Tian et al. [2019] show that in this setup $\mathcal{L}_{\text{critic}}$ is a lower bound on the mutual information $I(V; W)$.

4 Background and review

As exemplified above, researchers in cognitive science, neuroscience, and machine learning, study various aspects of representational alignment. In the following section, we complement these detailed examples by painting a broad landscape of the related literature, which we link to our framework in Table 2.

4.1 Cognitive Science

Whether different people have the same representation of the world is a central question in the cognitive sciences. Questions about potential differences in people’s experience of the same stimuli go back to Locke [Locke, 1847], who considered whether it might be possible to identify whether two people had different perceptual experiences of color. In contemporary cognitive science, questions about whether people share the same representations are prominent in cross-cultural and developmental psychology [Berry, 2002; Miller, 2002; Henrich et al., 2010b]. Following the work of Sapir [Sapir, 1968] and Whorf [Whorf, 2012], cross-cultural psychologists ask whether people from different cultures or language groups represent the world in different ways [Berlin and Kay, 1991; Majid et al., 2004; Frank et al., 2008; McDermott et al., 2010; Henrich et al., 2010a; Dolscheid et al., 2013; Majid and Burenhult, 2014; Jacoby et al., 2019; Barrett, 2020; O’Shaughnessy et al., 2023]. Likewise, following Piaget [Piaget, 1973], developmental psychologists consider the possibility that children undergo significant conceptual changes as they develop, creating the possibility of incommensurability between the mental representations of children (system *A*) and adults (system *B*) [Carey, 1988]. Most of these approaches attempt to *measure* alignment between different people, or characterize changes in representations over time [e.g., moral concepts; Kohlberg, 1984; Turiel, 2008].

4.1.1 Similarity judgments and multidimensional scaling

One tool that has proven useful in exploring these questions is that of multidimensional scaling [Shepard, 1962, 1980]. By collecting similarity judgments from human participants, it becomes possible to explore their representations of a set of stimuli [Ekman, 1954; Tversky, 1977; Kriegeskorte and Mur, 2012; Peterson et al., 2018; Cichy et al., 2019; King et al., 2019; Hebart et al., 2020]. Multidimensional scaling uses these similarity judgments to construct a Euclidean space in which each stimulus is represented by a point and similarity is assumed to decrease with the distance between those points. For example, multidimensional scaling has been used to map the changes in children’s representation of numbers as they develop [Miller and Gelman, 1983]. Such analyses are facilitated by variants on multidimensional scaling such as INDSCAL, which makes it possible to capture the differences between people’s similarity judgments by assuming those people represent stimuli with the same values along different dimensions of a subjective space, but differ in how much weight they assign to those dimensions [Wish and Carroll, 1974; Roads and Love, 2024]. Alternatively, methods like second-order isomorphism rely on analyzing the similarity between two sets of relations among different representations of the same objects – e.g., measuring correlation between pairwise similarity judgments for a set of objects and the degree of featural agreement between that same set of objects [Shepard and Chipman, 1970]. Similarly, contrast models analyze similarity of relations for systems with discrete properties [Shepard and Arabie, 1979; Tversky, 1977; Tenenbaum, 1995].

Representational similarity methods are powerful because they are compatible with systems that are either continuous or discrete, symmetric or asymmetric, hierarchical or nonhierarchical, etc. [Edelman, 1998] but leave open the question of how to assess whether two representations really capture the same information about the world. Goldstone and Rogosky [2002] presented a method for answering this question, based on discovering alignments between two different

concept systems that were represented by spatial locations. Crucially, their approach did not require that the matching concepts be identified in advance – it was able to extract plausible alignable concepts at the same time as learning the global mapping between the systems. More recent work demonstrates that natural environments support the alignment of everyday concepts [Roads and Love, 2020] and that children’s early concepts appear to exploit these regularities [Aho et al., 2023].

4.1.2 Human-machine alignment

More recent work has begun to use some of these tools to explore the alignment between humans and machine learning systems. For example, Peterson et al. [2018] used similarity judgments as the basis for a comparison of representations of images in humans and machines. Reasonably high correlations were observed between human similarity judgments and the inner product of the activations at the final layer of convolutional neural networks applied to the same images. However, methods such as multidimensional scaling and hierarchical clustering [Shepard, 1980] revealed systematic qualitative differences between these representations. These differences could be reduced by rescaling the activation dimensions, resulting in a close correspondence between the representations recovered from humans and machines.

Unfortunately, improving model performance (i.e., behavior) does not guarantee an improvement in alignment [Langlois et al., 2021a]. In fact, object recognition models that perform better often show worse alignment with human judgments [Roads and Love, 2021]. In a similar vein, Muttenthaler et al. [2023a] used triplet odd-one-out choices for a set of naturalistic images to identify the degree of alignment in object similarity between different neural network models and human participants. While most models showed poor correspondence to the human choices when used out-of-the-box, a learned linear transformation to the human similarity space could minimize that gap — that is, they were able to *increase* representational alignment. However, they observed a substantial difference in alignment between the different models, depending on the models’ pretraining data and the objective function with which they were trained. Similarly, higher representational alignment does not always translate to improved performance or more aligned behavior. For example, Sucholutsky and Griffiths [2023] discovered a U-shaped relationship between the degree of representational alignment of a teacher and student and their downstream performance on few-shot transfer learning. Both highly aligned and highly misaligned models can generalize effectively from much less data than models with medium degrees of representational alignment with humans.

4.1.3 Semantic representations

Representational alignment also arises in the study of semantic representations [Rogers and McClelland, 2004; Bhatia et al., 2019]. Measuring alignment of the changing representations over learning (and their decay under neurodegenerative disease) between humans and computational and mathematical models [Rogers and McClelland, 2004; Ralph et al., 2017; Saxe et al., 2019] has played an important role in understanding the computational origins of human semantic cognition. Representational alignment has also been used to study the neuroanatomical basis of these processes [e.g. Ralph et al., 2017], as we discuss below.

More specifically, research in the alignment of language with other perceptual modalities has been propelled recently by the remarkable advances in large language models which facilitate the quantitative analysis of semantic similarity and provide a rich comparison class against which human behavior can be studied [Bhatia and Richie, 2022; Bhatia, 2023]. For example, Marjeh et al. [2023a] showed that embeddings of textual descriptors can be used to construct good proxies for human similarity judgments across different modalities (visual, audio, and audiovisual) and can perform on par with a large set of domain-specific neural networks that directly process the stimuli. This line of work suggests exciting possibilities of bridging between the representational spaces of computational models and humans.

4.1.4 Alignment across cultures

More generally, the study of alignment across cultures the study of representational alignment across different cultures [Berlin and Kay, 1991; Henrich et al., 2010a; Majid et al., 2004; Majid and Burenhult, 2014; Dolscheid et al., 2013; Barrett, 2020; McDermott et al., 2010; Jacoby et al., 2019; O’Shaughnessy et al., 2023; Frank et al., 2008] plays an important role in cognitive science. Cross-cultural research offers an approach to addressing core problems in cognitive science such as 1) what cognitive and perceptual principles underlie the structure of a given representation (e.g. statistical learning vs. physiological constraints)?, and 2) how is meaning shaped and (mis-)communicated across languages and cultures? As a concrete example of the first problem, Jacoby et al. [2021] analyzed the representation of musical rhythm in a massive cross-cultural dataset comprising 39 participant groups in 15 countries and showed that participants exhibited a universal inductive bias towards discrete rhythm categories at small integer ratios, though the degree in which specific discrete categories emerged was heavily contingent on culture and the corresponding local musical systems. As for the second problem, Thompson et al. [2020] analyzed the alignment of semantic neighborhoods of 1,010 meanings in 41 languages and showed that semantic domains with high internal structure such as number and

kinship tend to be the most aligned, whereas domains such as natural kinds and common actions aligned much less so, suggesting that the meanings of common words are strongly contingent on the culture, geography and history of their users.

4.1.5 Alignment across individual participants' behavior

Research in social psychology and psycholinguistics has also begun investigating alignment across humans. Prior work in these domains, such as the Stereotype Content Model [Fiske, 2018], focused on characterizing group-level phenomena to uncover generalizable insights about how people perceive, understand, and interact with others. For example, distributional semantics investigates bodies of text to understand shared conceptual relations [Boleda, 2020] and average impression ratings are used to study the systemic dehumanization of repressed groups [Haslam and Loughnan, 2014]. Recent work has also highlighted individual differences in the structure of representations across people. Such variance is present in people's representations of basic semantic categories [Hoffman, 2018], such as animals [Marti et al., 2023], as well as representations of social groups, in the form of stereotypes[Xie et al., 2021], and even complex concepts, such as war and taxes [Brandt, 2022].

Differences in representation can have functional consequences for collaboration and communication. For instance, misalignment of word meanings predicts failures of communication across people [Duan and Lupyan, 2023]. Strategies for resolving conflict and disagreement hence need to account for both divergence of opinions and alignment of representations [Oktar et al., 2023].

4.2 Neuroscience

Neuroscientists often measure representational alignment to evaluate theoretical accounts, such as whether a computational model captures patterns of task-related brain activity [Turner et al., 2017]. In particular, the framework of Representational Similarity Analysis or RSA Kriegeskorte et al. [2008a] has been particularly influential in representational alignment. RSA was motivated by a fundamental challenge in cognitive neuroscience: how can we compare neural measurements from different species, behavior, and computational or theoretical models, all of which are measured in different spaces? RSA addresses this challenge by comparing representational similarity structures (see below). The development of RSA thus reflects the longstanding interest in representational alignment within neuroscience; reciprocally, RSA itself has driven substantial new interest in representational alignment within neuroscience. Here we overview (not comprehensively) some areas of neuroscience from the perspective of representational alignment.

4.2.1 Alignment across individuals' brain activities

The degree of alignment between neural representations from multiple people (or animals) is central to many questions in cognitive neuroscience, including communication, planning, and learning [Hasson et al., 2012b]. Representational alignment between two individuals' brains (systems *A* & *B*) can be measured as the similarity of neural recordings across individuals completing common or complementary tasks. For example, spoken language has been construed as a form of representational transmission, in which a speaker uses language to instantiate a representation in a listener. Several experiments have shown widespread alignment between speakers and listeners by recording a speaker's brain activity while they tell a verbal story, and measuring the similarity of brain responses between the speaker and listener who hears the same story [Stephens et al., 2010; Silbert et al., 2014; Liu et al., 2017]. Using fMRI, speaker-listener neural alignment is found across a diverse range of brain regions spanning temporal, parietal, auditory, and prefrontal cortices and only emerges during successful communication (e.g. the listener understands the language spoken by the speaker) [Stephens et al., 2010]. Further work also with fMRI mapped speech-production and speech-comprehension networks in speakers and listeners, and found widespread alignment across production and comprehension in bilateral temporal, linguistic, and extralinguistic brain areas [Silbert et al., 2014]. Characterizing the dynamics of speaker-listener alignment with functional near infrared spectroscopy (fNIRS) found a lag of about 5 seconds between the neural responses driving speaker-listener alignment [Liu et al., 2017]. In a more naturalistic design, adults' and infants' neural responses were measured simultaneously in an unstructured play environment using fNIRS, and neural alignment, especially in the prefrontal cortex, emerges during joint but not independent play [Piazza et al., 2020]. Even in the absence of a structured social task, non-verbal social cues such as eye contact and smiling induce neural alignment between two interacting individuals [Koul et al., 2023].

Representational alignment between individuals also plays an important role in communication and learning. Building on techniques used to measure neural alignment between speakers and listeners, subsequent work has explored how learning outcomes depend on neural alignment between students and teachers. Student outcomes in a real-world computer science course were predicted by neural alignment amongst students and between students and graduate student experts while watching course lectures during fMRI. When comparing one student's neural response to the n-1

class-average neural response, alignment in hippocampus, angular gyrus, anterior cingulate cortex, and visual cortex predicted final exam outcomes, as does measuring alignment in responses between individual students and a population of graduate students who were experts on the course materials [Meshulam et al., 2021]. Building on this, [Nguyen et al., 2022] measured neural alignment between a teacher giving a lecture in an fMRI and students who watched this lecture in separate fMRI sessions. Widespread neural alignment was observed between students and the teacher across the brain, and teacher-student alignment in posterior medial cortex predicted student test score improvement.

Representational alignment has also been used in fMRI research, in the form of bridging responses from individuals into a common space for subsequent group-level analysis. Standard fMRI preprocessing involves warping to a common anatomical space, but this approach leads to a loss of information due to individual differences in brain morphology. An alternative set of techniques aim to learn a new representational space derived from all participants' functional data to which each individual's data is then aligned to alleviate the loss of information in anatomical alignment. The most common of these functional alignment techniques is hyperalignment [Haxby et al., 2011, 2020], which uses Generalized Procrustes Analysis to learn transformation matrices applied to individuals' data matrices that minimize the distances between individual data transformed to the common space. Variants of hyperalignment have been introduced that further refine the transformations using functional connectivity in addition to spatial response patterns [Busch et al., 2021]. Another approach, shared response modeling, uses a probabilistic generative framework to isolate individual-specific and shared components on neural responses [Chen et al., 2015b], which can be applied to improve searchlight analysis of fMRI data [Kumar et al., 2020]. Another approach to align individual fMRI responses into a common basis-space defined by a computational model (usually a CNN) using a linear transformation [Horikawa and Kamitani, 2017; O'Connell and Chun, 2018; Shen et al., 2019; Horikawa and Kamitani, 2022; Sexton and Love, 2022]. Once all individuals are aligned to the model, responses can be averaged to perform a group-level analysis or analyzed individually. This approach also has the advantage that by aligning all individuals to a model-defined space, secondary models trained on the same basis-space can be applied to brain data in a zero-shot fashion to accomplish decoding feats such as object classification [Horikawa and Kamitani, 2017; Sexton and Love, 2022], eye movement prediction [O'Connell and Chun, 2018], image reconstruction [Shen et al., 2019].

4.2.2 Alignment across different species and brain recording techniques

Another problem in neuroscience is defining homologies across brain regions in different species. In animals, electrophysiology and microscopy-based methods are commonplace, whereas in humans fMRI, EEG, fNIRS, and MEG are common. As noted above, RSA [Kriegeskorte et al., 2008a] was developed in part to address this problem. In RSA, data (neural responses, model activations, behavior, etc.) are converted to a representational dissimilarity matrix (RDM) capturing the pairwise differences between all stimuli in the dataset. The upper-triangular off-diagonal matrices of the two RDMs are then correlated to determine whether the two spaces capture the same similarity structure meaning that alignment between representational geometries of virtually any pair of systems can be measured even if the systems use very different representational spaces or measurement techniques. While this technique has been applied broadly in several domains of cognitive neuroscience (more below), one of its earliest empirical applications was to establish homology between rhesus macaque (system *A*) and human (system *B*) inferotemporal cortex [IT; Kriegeskorte et al., 2008b]. The same set of stimuli, consisting of common objects, were shown to monkeys undergoing electrophysiological recording and humans undergoing fMRI scanning. Using RSA, they found aligned representations between monkey and human IT. RSA-based techniques have also been used for cross-modal alignment of neural responses collected with different modalities. Cichy et al. [2014] derived RDMs over time from human MEG and monkey electrophysiology recordings and RDMs over space from human fMRI responses, then used RSA to align MEG/electrophysiology signals over time and MEG/fMRI signals over space and time, capturing spatio-temporal activation patterns not measurable with either modality alone [e.g. Mack et al., 2016].

4.2.3 Alignment between brain activity and models

Another challenge in neuroscience is measuring alignment (or bridging) between brain activity (system *A*) to computational models (system *B*) ; this challenge provided key motivation for RSA [Kriegeskorte et al., 2008a]. In addition to elucidating the information processed by an individual brain region, representational alignment has been used to contribute to mechanistic explanations of task-dependent processing in vision [Cukur et al., 2013; Wang et al., 2019] and language [Toneva et al., 2020; Oota et al., 2022] by investigating which of a number of possible candidate hypotheses aligns best with brain responses to a new stimulus. With a similar goal in mind, neuroscientists have started to investigate the utility of AI models as possible model organisms [Toneva, 2021] for different cognitive tasks, using representational alignment. In vision, early work by Yamins et al. [2014] revealed a hierarchy of alignment between mid and late vision regions in rhesus macaques and mid and late layers in neural networks optimized for image classification. Contemporaneously, in language research, work by Wehbe et al. [2014] revealed significant word-by-word alignment between human brain activity evoked by reading a story and representations from early language models (e.g. LSTMs).

Progress in AI in the last 10 years has spurred huge amounts of research in this area and has revealed impressive brain alignment for more recent models in the domains of vision [Cichy et al., 2016; Zhuang et al., 2021; Konkle and Alvarez, 2022] and language [Khaligh-Razavi and Kriegeskorte, 2014; Schrimpf et al., 2018; Jain and Huth, 2018; Hollenstein et al., 2019; Kubilius et al., 2019; Toneva and Wehbe, 2019; Schrimpf et al., 2021; Caucheteux and King, 2022; Goldstein et al., 2022; Kumar et al., 2023b]. Specifically in the domain of language, where a lot of current AI progress is due to the rapid development of powerful language models, scientists have used representational alignment to claim that a key mechanism that aligns the representations in language models and brains is the next-word prediction objective function [Schrimpf et al., 2021; Caucheteux and King, 2022; Goldstein et al., 2022]. However, it is still unclear whether next-word prediction is necessary or simply sufficient to obtain the degree of observed representational alignment [Merlin and Toneva, 2022; Antonello and Huth, 2022], and other scientists have shown that the alignment is due in part to joint syntactic processing [Oota et al., 2023] and lexical-level semantics [Kauf et al., 2023].

Measuring representational alignment across different brain regions and computational models has also been used to study details of the relationship between computational models and the anatomy of neural computation. For example, computational models of human semantic representation [Rogers and McClelland, 2004] have been linked to the neuroanatomy of human multimodal integration — in particular, the idea that anterior temporal regions produce semantic representations that are aligned across modalities [Pobric et al., 2010], which play a key role in binding representations across modalities [Ralph et al., 2017]. Other work computed finer-grained maps of semantic representation across the cortex, by playing stories for participants and then measuring alignment between semantic features and representations in different cortical areas [Huth et al., 2016]. Similarly, anatomical alignment of representations at the boundaries between visual and linguistic brain regions has been suggested to play a role in binding of semantic representations across these modalities [Popham et al., 2021]. Thus, alignment of representations within and across brain regions can help to concretely link computational models to their neural substrates.

4.2.4 Alignment for hypothesis testing

Representational alignment is also often used by neuroscientists to test hypotheses about information processing in the human brain. For instance, some neuroscientists investigate the information content of brain representations in different brain regions (system *A*) by measuring the degree of alignment with the numerical representation of a specific stimulus property (system *B*; e.g., the depth of a syntax tree for a sentence stimulus, the number of objects present in a scene for an image stimulus). In this approach, a high degree of representational alignment suggests that a brain region processes information related to this stimulus property. To estimate this alignment, neuroscientists often use either RSA or decoding and encoding approaches. Decoding learns a function, very often parameterized as linear, which predicts the stimulus representation directly from the brain representation, while encoding learns the inverse function to predict brain representations as a function of the stimulus representations. Using these approaches, neuroscientists have investigated the processing of information related to a wide range of stimulus properties, such as manipulability and size of individual objects [Sudre et al., 2012], and changes in the content of continuous visual input [Isik et al., 2018].

4.2.5 Alignment for stimulus selection or design

Several recent neuroscience and cognitive science papers use representational alignment to select data for use as stimuli. For example, trying to select “controversial” stimuli that *decrease* alignment between models, and then testing these stimuli on humans or animals, can be an optimal way to compare two models as candidates for explaining the biological neural representations [Groen et al., 2018; Golan et al., 2022] or behavior [Golan et al., 2020]. Other works have used representational alignment between human neural representations and transformer language models to design unusual stimuli that will drive or suppress activity in the human language network [Tuckute et al., 2023]. Thus, representational alignment can also be used for optimization in *stimulus* space. While these methods are only starting to be explored in neuroscience and cognitive science, we believe they open exciting new directions for representational alignment research more broadly (see §5.1).

4.3 Artificial Intelligence and Machine Learning

Machine learning researchers use representational alignment in many diverse ways including measuring the relationship between models to interpret their performance, bridging between models to fuse different sources of data, learning useful representations by increasing representational alignment, mimicking human-like biases and behaviors, and more. In this section, we provide a non-exhaustive overview of some of these use cases.

4.3.1 Model-to-model alignment

Machine learning researchers are increasingly interested in increasing the alignment between the representation spaces of different models — in particular since the rise of pre-trained foundation models which are difficult and expensive to train but serve as useful priors for other models.

Often, increasing alignment begins with works that simply *measure* model-to-model alignment — often with RSA — in an attempt to characterize how different learning objectives [Lindsay et al., 2021], tasks [Hermann and Lampinen, 2020], or simply differences in random initialization [Mehrer et al., 2020] may lead to differences among models. These differences can either be deleterious to reliability; for example, in applied settings, an ML model may be employed in a pipeline for fault detection at the end of a conveyor belt. — if the model is to be replaced by an updated version, it is often important to know whether the new model will still show similar failure modes (e.g. works well on most produced items except for grey toys, which need to be checked manually) or different ones (e.g. the updated model suddenly works on grey toys but not on small toys anymore).

However, differences between models can also be desirable; indeed, there are many cases where one would like to measure and even *decrease* alignment between models. For instance, to use multiple models in an ensemble, and is thus interested in diverse models that have very different representations [Lakshminarayanan et al., 2017; Fort et al., 2019; Pang et al., 2019; Wu et al., 2021]. If diversity is not specifically encouraged, different deep learning models end up being highly aligned with each other because they tend to converge to similar local minima [Mania et al., 2019; Geirhos et al., 2020b; Meding et al., 2021; Moschella et al., 2023]. Other works attempt to improve representation quality by learning to make representational similarity structures invariant under data augmentation [Mitrovic et al., 2020].

Multimodality. Combining several input modalities into a single learning system has a long history [Mori et al., 2000]. Deep learning allows us to combine neural architectures designed for different input modalities, and to optimize them jointly. For example, an early such model by Karpathy and Fei-Fei [2015] combined a text representation from an LSTM [Hochreiter and Schmidhuber, 1997] and an image representation from a Convolutional Neural Network [LeCun and Bengio, 1998], and jointly optimized them to produce descriptive captions of images. Other models such as CLIP [Radford et al., 2021] explicitly aim to align visual and textual embeddings using a contrastive learning objective [Sohn, 2016; van den Oord et al., 2018a]. This pushes its image- and text-submodules to produce representations that have a high inner product when the alignment between a given text and image is high, and low otherwise. Fusing architectures designed for a single modality can both be used to transform from one modality into another one, e.g., to align visual inputs and their textual descriptions to caption an image [Karpathy and Fei-Fei, 2015; Xu et al., 2015], to learn a combined embedding space for vision and language [Radford et al., 2021; Zhai et al., 2023], to generate images from a textual description [Mansimov et al., 2016; Ramesh et al., 2021; Saharia et al., 2022; Yu et al., 2022] or to combine text, images, and speech into a single prediction model [Kaiser et al., 2017]. All of these models go beyond just bridging the representations learned by their constituent sub-modules, but rather fine-tune them to optimize the alignment between them. This field is quickly evolving, with modern large language models slowly but surely acquiring the ability to understand [Alayrac et al., 2022; OpenAI, 2023] and produce [Koh et al., 2022] images in addition to text.

The techniques involved in this research are often similar to those we see in related fields. For example, a recent article employed cross-model alignment [Moayeri et al., 2023] to align image representations with text representations. The technique—which essentially boils down to linear regression—is the same as the one often employed in neuroscience when bridging representational spaces, where a linear mapping from one representation space to another is learned from data.

Knowledge distillation. Knowledge distillation [Hinton et al., 2015; Phuong and Lampert, 2019] is another way of aligning the representation spaces of two models. The goal of knowledge distillation is to distill the (prior) knowledge of a teacher – usually a large model – about a dataset into a student network – usually a smaller model than the teacher. So, instead of training the student network on the labels associated with the data, the student is optimized to match the probabilistic outputs [Hinton et al., 2015], the representational geometry [Cho and Hariharan, 2019], or the pairwise similarities [Tung and Mori, 2019] of a (larger) teacher network. Knowledge distillation can be seen as a form of neural compression or a regularization technique. It has seen successes in various fields of ML, such as machine translation [e.g., Kim and Rush, 2016] and Computer Vision [e.g., Park et al., 2019; Cho and Hariharan, 2019]. Part of its success is likely attributable to the use of soft labels which have been shown to yield tighter class clusters [Müller et al., 2019] and improved data efficiency [Sucholutsky and Schonlau, 2021; Collins et al., 2022; Sucholutsky et al., 2023] compared to hard labels. In contrast to soft labels, hard labels assign zero probability mass to all but the correct class, which is a highly unlikely scenario to occur in reality. Moreover, the probabilistic outputs of a teacher network convey implicit information about the relationships between the classes in the data rather than serving the purpose of replacing the zero entries of hard labels with non-zero probabilities that contain no class-relationship information at all [cf., Müller et al., 2019; Muttenthaler et al., 2023c].

4.3.2 Learning human-like representational geometries

There has recently been growing interest in the machine learning community in increasing alignment between human (system A) and neural network (system B) representational spaces [e.g., Peterson et al., 2018, 2019; Attarian et al., 2020; Roads and Love, 2021; Marjeh et al., 2022c] either to obtain a better understanding of the (dis-)similarities between these spaces or improve the representational structure of neural networks for increasing their generalizability [e.g., Muttenthaler et al., 2023b]. Muttenthaler et al. [2023b] attempt to increase representational alignment to align the outputs of computer vision models with human odd-one-out choices for the same set of images, thereby altering the original behavior of the models to improve their downstream task performance on various few-shot learning and anomaly detection tasks. Fu et al. [2023] manipulate the representation spaces of neural nets to align their local similarity structure with that of human observers and, as a consequence, improve nearest neighbor retrieval and local structure. Fel et al. [2022] transform the representations of neural networks to better match the visual strategies used by humans, in doing so improving object categorization performance of neural network models. Sucholutsky et al. [2023] analyze the representational information contained in commonly-used supervision signals (like hard labels and soft labels) to optimize the cost associated with annotating datasets for learning human-like representations.

Although this line of research is still developing, increasing representational alignment offers vast potential in improving the outputs of systems at a relatively low computational cost — learning a linear transformation [Attarian et al., 2020; Muttenthaler et al., 2023a,b] or fine-tuning the parameters of an information processing function [Toneva and Wehbe, 2019; Schwartz et al., 2019; Fu et al., 2023] is much cheaper than optimizing these parameters from scratch — while at the same time contributing to understanding the factors that drive the alignment between systems [Konkle et al., 2022; Fel et al., 2022; Muttenthaler et al., 2023a].

4.3.3 Interpretability/explainability

A notable effort to understand neural networks' representational spaces in a human-interpretable way. Much of this work can be understood as attempting to *bridge* between neural network representational spaces and lower-dimensional or conceptually simpler spaces that researchers can understand. These ideas date back to early representation learning work at the intersection of AI and cognitive science [Hinton et al., 1986], and were reinvigorated by recent findings in representation learning in language and other areas [Bengio et al., 2012; Mikolov et al., 2013a]. In particular, the fact that word representation spaces of words learned by predicting co-occurrence [Mikolov et al., 2013a; Pennington et al., 2014] allowed analogical reasoning by simple linear algebra operations (e.g., king – man + woman = queen), attracted a great deal of interest and investigations [Ethayarajh et al., 2018].

Early efforts in interpretability focused on studying activation vectors. Some have been interested in interpreting the behavior of artificial neural networks at the level of individual neurons [Bau et al., 2017; Olah et al., 2018; Geirhos et al., 2023], while others investigated how to represent and use human-specified concepts in a neural network [Kim et al., 2018] for post-hoc interpretability. Embedding or learning human-aligned concepts during training has also been an active area of research [Koh et al., 2020; Zarlenga et al., 2022] as well as discovering new meanings of learned representations using linear vectors [Yeh et al., 2020; Ghandeharioun et al., 2021]. Another notable attempt at alignment is mechanistic interpretability — the effort to find a *procedure* in a network (i.e., how a network *does* X rather than just a *concept* Y). For example, finding circuits [Olah et al., 2020; Nanda et al., 2023] that qualitatively align with semantic meaning (e.g., curves) could provide insights.

While these are all interesting directions, many challenges remain, particularly for evaluation: how do we know the alignment is good and useful? Although a synthetic setup can provide quantitative evaluation, large-scale impact on a concrete application remains a desirable but prohibitively expensive target. In concept vectors, the linearity assumption is limited [Chen et al., 2020b; Soni et al., 2020], and the faithfulness of the alignment between the vector and humans' mental models of the concept has been challenged [Mahinpei et al., 2021]. For example, interpretations may only be faithful within a restricted data distribution (see §5.1) For mechanistic interpretability, scalability is a predominant concern; with the rise of large foundation models [e.g. OpenAI, 2022] there are simply too many circuits for humans to comprehend, even if we can find faithful interpretations of particular circuits.

4.3.4 Behavioral alignment

Behavioral alignment is a form of alignment that aims specifically at aligning the output, or behavior, of one system with another (often humans). Behavioral alignment can also be seen as an instance of representational alignment, insofar as output behaviors are produced by a representation (e.g., an image embedding) followed by a mapping from representation to output (a softmax layer, a k-nearest-neighbor classifier, etc.) [LeCun et al., 2015]. However, the relationship between penultimate representations and behavioral outputs is not one-to-one. Two systems that have very different representations and mappings could still produce the exact same output/behavior [cf. Hermann and

Lampinen, 2020], just like very different sorting algorithms (say, “quicksort” and “bubblesort”) produce the same output. The reverse is not the case: if there are differences in behavior, this implies differences in either the mapping, the representation, or both. If the mapping is fixed, perfect behavioral alignment is a necessary condition of perfect representational alignment.¹⁰

Given that we can learn a lot about the differences between systems by observing the behavior or output of a system alone, it is only natural that behavioral comparisons between deep neural networks and human perception have seen substantial interest over recent years. For instance, contrasting error patterns of different systems (a behavioral measure), ideally at the fine-grained individual stimulus level [Green, 1964], can be a powerful way to learn about differences in underlying representations [Rajalingham et al., 2018; Geirhos et al., 2020a]; and numerous severe differences between neural networks and human perception have been discovered using behavioral experiments [Baker et al., 2018; Peterson et al., 2018; Geirhos et al., 2018, 2019b; Feather et al., 2019; Jacobs and Bates, 2019; Serre, 2019; Geirhos et al., 2020a; Hermann et al., 2020; Lonnqvist et al., 2020; Funke et al., 2021; Geirhos et al., 2021; Kumar et al., 2021; Abbas and Deny, 2022; Bowers et al., 2022; Dong et al., 2022; Malhotra et al., 2022; Huber et al., 2022; Jaini et al., 2023; Muttenthaler et al., 2023a; Wichmann and Geirhos, 2023; Kumar et al., 2023a]. Similarities in behavior can also serve as clues to phenomena happening under the surface both in neural networks and in humans. Rane et al. [2023c] finds a correlation between neural networks’ performance in learning visual words and the age at which children acquire those same words, ultimately showing that both are capturing human judgments of how *concrete* or *abstract* a word is. Such behavioral insights often serve as a tool to isolate relevant phenomena that are then further characterized in interpretability and representational alignment work. Ultimately, different communities weigh output and representational alignment differently. In neuroscience, for instance, representations are a central research focus, while robotics and reinforcement learning focus more on output (often assessed by downstream reward or task performance on the user desired task [Bobu et al., 2023]). In this context, one currently widely used form of output alignment is Reinforcement Learning from Human Feedback (RLHF) [Ziegler et al., 2019; Christiano et al., 2017; Ouyang et al., 2022; Casper et al., 2023], which uses human ratings of an AI system’s behavior to learn a separate model which scores new outputs of the system, in an attempt to better align the model’s outputs towards those which a human would prefer.

4.3.5 Value alignment

One avenue of exploration in human-model alignment has focused on value alignment [Taylor et al., 2016; Gabriel, 2020; Kirchner et al., 2022]: the goal of building a model (system A) that aligns with the values of humans (system B), often with the hope that such a model could broadly benefit humanity. Value alignment is notoriously difficult to define and measure—in particular, it is unclear how to define a function g_ϕ that corresponds to model values. Moreover, aligning to various notions of commonly accepted societal values is an impossible task [Eckersley, 2018; Floridi et al., 2021]. For example, the field of constitutional AI uses a set of language-based contracts (e.g., constitutions or rule sets) to guide the in-context performance of a language model for better safety [Bai et al., 2022; Glaese et al., 2022]; however, value alignment also requires figuring out which person or group of people System B ought to represent—there is no agreed-upon constitution and even if some general rules are universally accepted [Anthropic, 2023], each rule must be subjectively calibrated with varying desired outcomes [Goyal et al., 2022; Lee et al., 2023]. Casper et al. [2023] also outlines the problems with using methods like RLHF for value alignment.

As such, researchers instead often evaluate the alignment of model and human behavioral outputs or task performance [Hadfield-Menell et al., 2017; Hubinger et al., 2019]. However, monitoring output alignment is insufficient for predicting whether a model will continue to be aligned with humans, or merely appears that way in a constrained evaluation setting, which is important for detecting the emergence of potentially charged behavior, e.g., agency [Chan et al., 2023]. For instance, it has been found that deep neural networks can generate similar behavior to humans on ImageNet by relying on fundamentally different visual strategies and features [Linsley et al., 2018; Fel et al., 2022]. Because representations are tightly coupled to computations and downstream behavior, we believe that a deeper understanding of representational alignment will help us understand whether guarantees on representational similarity can subserve general value alignment, and conversely, under what circumstances behavioral alignment is sufficient for value alignment.

For example, while most prior work on value alignment relies on output behavior, concurrent work proposes to pursue value alignment via “representation engineering” [Zou et al., 2023]. Specifically, the approach involves finding representational dimensions that are related to valued behaviors like honesty [cf. Burns et al., 2022], and then manipulating those representations to affect the models’ tendency to exhibit these behaviors. This strategy hints that

¹⁰If alignment is not perfect, the relationship between representation and behavior or output depends on the mapping’s properties, for instance, whether it preserves monotone relationships. Typically, alignment is best thought of as a spectrum rather than a binary concept.

4.3.6 Robotics

In robotics, we often seek to build robots (system *B*) that perform tasks specified by human users (system *A*). To do so, robots need to rely on a representation of salient *aspects* that capture the end user’s desired task [Bobu et al., 2023]. For example, to carry a cup of coffee, the robot must learn features that the human user cares about, e.g. cup orientation and distance from obstacles, as part of its representation of the task. There are currently two dominant approaches for learning human task representations: one that *explicitly* builds in structures for learning salient task aspects, e.g. feature sets or graphs [Levine et al., 2010; Daruna et al., 2021; Bobu et al., 2021; Peng et al., 2023], and one that *implicitly* extracts them by mapping input directly to desired robot behavior, e.g. end-to-end approaches like the identity representation [Finn et al., 2016, 2017; Torabi et al., 2018; Xu et al., 2019]. Each of these approaches comes with its own set of tradeoffs.

On the one hand, specifying explicit task structure is helpful for capturing relevant task aspects like those described above, but on the other hand, the designer or user often takes on more manual cost for comprehensively shaping the problem. The structure built in by explicit approaches is *useful only if correct*: without the right inductive bias, robots may misinterpret the humans’ guidance for the task or execute undesired behaviors [Bobu et al., 2020]. Under-specified structures can be handled by detecting misalignment and learning new/missing components over time [Nygård et al., 2018], but the field still needs more interfaces and algorithms for making that structure easier to teach. Over-complete structure, i.e. containing irrelevant information, can lead to spurious correlations, which could potentially be prevented via feature subset selection methods [Cakmak and Thomaz, 2012; Bullard et al., 2018; Luu-Duc and Miura, 2019].

On the other hand, neural networks implicitly learn task structure in a manner that is faster and less burdensome on the designer, while often being data-hungry and prone to capturing spurious correlations [Zhang et al., 2018; Rahmatizadeh et al., 2018; Rajeswaran et al., 2018]. Current trends for handling this look at clever ways to cheaply collect human data (e.g., YouTube or VR) or reuse past data sets from the robot’s lifespan [Baker et al., 2022]. However, there still is no guarantee that this data will be representative of the end user. Instead of treating humans as static data sources, these methods may benefit from including them in the alignment process.

Recent methods try to find a middle ground, explicitly focusing on learning good representations in an unsupervised, self-supervised, or semi-supervised fashion with proxy objectives to guide the learning process [van den Oord et al., 2018b; Laskin et al., 2020; Brown et al., 2020; Hafner et al., 2020; Schwarzer et al., 2021; Tucker et al., 2022]. However, even so there is a trade-off between the amount of human supervision at the representation level and how human-aligned the learned representations are. “Supervising” by coming up with proxy tasks certainly reduces the end user’s labeling effort, but may result in misaligned representations. For this reason, the burden falls on the designer to find representative proxy tasks: we now trade hand-crafting structure for hand-crafting proxy tasks. On the other hand, direct supervision more explicitly aligns the robot’s representation with the human’s, but is also more effortful for the user. Future work should explore easier ways to incorporate human input, from active learning to better user interfaces.

5 Open problems & challenges in representational alignment

In the previous sections, we have presented a unifying framework for analyzing representational alignment that encompasses a wide range of research disciplines. We highlighted commonalities in the work being pursued by researchers across these fields: despite their seemingly disparate natures, each field is conducting profound inquiries into representational alignment and researchers from each field bring complementary perspectives to the table.

In this section, we outline a series of challenging unsolved questions that transcend these disciplines. We hope that by identifying these shared challenges, we promote a holistic approach to problem-solving that can catalyze interdisciplinary collaboration and lead to further progress: not just in each individual field, but across them (and perhaps even sparking new subdisciplines). We encourage an exchange of ideas and perspectives among our diverse scientific communities, whose combined efforts are well-positioned to help unravel the complexities of representational alignment and advance the design of more representation-aligned information processing systems.

5.1 Selecting data and stimuli

Any attempt to either measure or increase representational alignment begins with selecting the dataset \mathcal{D} over which to compute alignment. The degree of alignment measured, or the results of increasing alignment, can depend dramatically on the dataset used.

In particular, if the dataset over which representation alignment is computed is too restricted, the results may not generalize. For example, various features may be confounded in naturalistic data, which can lead to overestimating alignment between models that rely on different features [e.g. Malcolm et al., 2016; Groen et al., 2018; Dujmović et al., 2022]. For example, the strong correlation between shape and texture in natural photos may mask the extent to which humans and CNNs rely on distinct features for object recognition (Landau et al., 1988; Baker et al., 2018; Geirhos et al., 2019b; Hermann et al., 2020; though cf. Jagadeesh and Gardner, 2022). Likewise, selecting natural stimuli to test an effect of a single feature can introduce biases in other correlated features [e.g. Lescroart et al., 2015]. On the other hand, it may be invalid to draw certain inferences based on representations of overly simplistic, even if carefully-controlled, stimuli. For example, processing naturalistic stimuli, such as reading a long, continuous text, may engage fundamentally different processes than more controlled tasks over shorter stimuli [Hasson et al., 2015]. As a more concrete example, retinal neurons were originally studied with simple bar and grating stimuli; however, some retinal neurons are sensitive to more complex interactions of features, such as foreground motion against a moving background [Ölveczky et al., 2003]. Thus, there are dramatic representational differences on datasets of naturalistic stimuli [Karamanlis et al., 2022]. Research in machine learning has similarly shown that studying model representations in the context of one dataset may suggest that neurons encode a particular type of feature that is quite different than what appears to be encoded when studying representations in the context of a different dataset. For example, neurons in the language model BERT [Devlin et al., 2018] appear to encode song titles given one dataset, but dates of historical events given another [Bolukbasi et al., 2021]. This issue is not restricted to sparse coding: similar issues can arise under distribution shifts when using RSA or other distributed representation analyses [Dujmović et al., 2022; Friedman et al., 2023]. Thus, it is important to assess representational similarity on as diverse a dataset as possible — ideally one that includes both naturalistic stimuli, and more controlled ones that explicitly reduce confounding among important features [Bowers et al., 2022; Hermann et al., 2023] — and to test on held-out categories of stimuli, in order to determine the generality of the analysis.

However, as noted above (§4.2.5), representational alignment and dataset selection can be mutually reinforcing. Representational alignment can be used to identify key cases where models disagree, by synthesizing optimally “controversial stimuli” that maximally distinguish between the representation spaces [Golan et al., 2022; Groen et al., 2018], which can then be tested on humans or animals. Likewise, representational alignment can be used to optimize stimuli that drive a particular response [Tuckute et al., 2023]. Thus, there can be a virtuous cycle in which measuring representational alignment allows for better selection of datasets that support measuring representational alignment, and so on. These investigations demand a multidisciplinary perspective drawing on data collection and experimentation practices across research communities.

5.2 Defining, probing, and characterizing representations

Once we have chosen systems to compare, and stimuli over which to compare them, we must decide how to extract their representations. For example, in a deep transformer language model, which layers or components (e.g. attention heads or MLPs) should we analyze? If we are interested in human brain activity, how should we record it? Indirect measures like fMRI or EEG can distort or enhance features compared to the information that is computationally available to the underlying system [Ritchie et al., 2019]. Or, if we record single-cell neural activity from cortical cells, which regions should we target? These decisions can radically change the results of the analysis. For example, certain kinds of knowledge may be localized in particular regions or components in natural [Kanwisher et al., 1997] and artificial [Manning et al., 2020; Meng et al., 2022] neural networks. Which regions should we study?

Ideally, we would compute representations over all regions and components of each system, and compare these pairwise. Pairwise comparison can reveal similarities in processing, such as parallels in progression through regions of the visual cortex and artificial CNNs [Yamins and DiCarlo, 2016]. However, it is often experimentally or computationally infeasible to do these analyses in full. Often, it is necessary to rely on the prior literature—and the available tools—to constrain the hypothesis space of representations to consider. Conversations amongst researchers spanning varied disciplines can ensure such choices are well-informed. However, even once we have selected a method of extracting representations, understanding the role that these representations play in computation remains conceptually challenging, as we discuss in the next section.

5.2.1 The relationship between representation and computation

In general, we are interested in understanding (or modifying) the representational structure of a system in order to understand (or modify) more abstract computations. However, this raises a thorn for representational alignment research: our methods and interpretation of results depend upon the complex relationship between representation and computation [cf. Churchland and Sejnowski, 1988]. Here, we highlight some challenges and questions about this relationship.

Extraneous influences on representations: Representations may be shaped by other implementation-level factors that are not essential to the computational process. For example, biological representations may be constrained by energetic demands [e.g., Laughlin, 2001], while deep learning representations may be biased by which features are already represented before training, or which are learned more readily [Hermann and Lampinen, 2020; Farrell et al., 2023]. These extraneous factors may cause us to either under- or overestimate representational similarity between systems with different learning processes and implementations [Dujimović et al., 2022; Griffiths et al., 2023].

Context-dependent & dynamic representation: Biological neural representations are dynamic and contextual; they change with repetition [Grill-Spector et al., 2006], attention [Cukur et al., 2013; Birman and Gardner, 2019], context [Brette, 2019; Deniz et al., 2023], and time [Rule et al., 2019]. When performing representational similarity analysis, we are forced to treat a single representation (or a within-participant average) as though it were a canonical representation of that stimulus. However, this inevitably elides important details of the dynamic role each representation plays in the system’s computation.

Philosophical issues in representation and computation: The practical issues above hint at deeper philosophical issues. Representational alignment is grounded in a computational perspective on natural intelligence, particularly, the notion that a system must necessarily form representations of its inputs in order to produce intelligent behavior. This perspective underlies, for example, the idea that there exists an embedding “function” that can be mapped across a set of stimuli to produce a tensor of embeddings.

However, other perspectives de-emphasize representation and computation in favor of the dynamic interaction between an intelligent system and its environment [e.g., Brooks, 1991; Cisek, 1999]. From such perspectives, measuring alignment between tensors of “representations” may seem misguided. Indeed, as noted above, the brain is a dynamical system whose responses to stimuli change and adapt. Thus, how can we philosophically justify aligning “representations” between artificial and natural intelligence?

While we acknowledge the challenges posed by these issues, we take a more *pragmatic* perspective on representation [cf., Poldrack, 2021; Cao, 2022] and interpret a system’s internal responses as representations insofar as they play a “representation-like” role in its behavior. The empirical evidence that aligning representations of neural networks to human ones can improve generalization and transferability [e.g., Muttenthaler et al., 2023b] helps to justify this approach. However, we believe that more deeply analyzing the dynamic role of the system’s internal responses in its behavioral interactions could yield greater insights, or greater ability to align systems.

5.2.2 Eliciting representations from black-box systems

How do we measure the representational alignment of black-box systems whose inner workings we cannot access? One technique that we described above is collecting similarity judgments, but there are often cases where running similarity experiments is not feasible, e.g., when we work with a high dimensional and large dataset (however see Marjeh et al. [2023a] for some recent progress in this direction). An alternative is based on Markov Chain Monte Carlo (MCMC) sampling processes that are widely used in machine learning and physics [Metropolis et al., 1953; Hastings, 1970]. A distinguishing feature of these techniques is the interaction between at least one conditional sampling step of the MCMC process and the black-box system, leading to the unveiling of its intrinsic structure. The method was first introduced by Sanborn and Griffiths [2007] where participants gradually refined high-dimensional objects. Each iteration in the process entails the modification of an object based on a dimension drawn from a proposal distribution. Participants then make a selection between the unaltered and modified versions, with their choice becoming the new reference value. Under specific conditions that can be empirically validated, this method converges to a sample from the hidden distribution [Sanborn et al., 2010].

Another technique that bears resemblance in its adaptive nature is serial reproduction [Xu and Griffiths, 2010; Langlois et al., 2017]. This method employs a Gibbs sampling algorithm where participants are tasked with directly recalling and replicating intricate objects, effectively sampling from the underlying prior. Examples include the reproduction of rhythmic sequences [Jacoby and McDermott, 2017; Jacoby et al., 2021], melodies [Anglada-Tort et al., 2023], or specific spatial positions shown to the participants [Langlois et al., 2021b]. This methodology is especially potent in areas where the black-box system, in this instance, a human, can reproduce intricate objects without intermediaries. A recent advancement by Harrison et al. [2020] suggests a technique for modifying object dimensions by interacting with it using a computer slider. Using the Gibbs sampler, this approach has been instrumental in deriving foundational

semantic "prototypes" for facial structures [Harrison et al., 2020], emotional prosody [Rijn et al., 2021; van Rijn et al., 2022], visual patterns [Kumar et al., 2022], and musical chords [Marjeh et al., 2022a].

It is noteworthy that while these methods predominantly involve human subjects, there is a significant overlap with machine learning generative paradigms. Indeed, Marjeh et al. [2022b] have recently demonstrated the mathematical parallels between serial reproduction and diffusion processes. This connection hints at the promising potential of elicitation in enhancing the interpretability of machine learning, as well as fostering generative models that better resonate with human preferences in forthcoming research.

5.3 Measuring alignment

Further, there are challenges in measuring alignment between systems. As noted above (§2.3.4), different measures of similarity have distinct advantages and disadvantages. For example, we may be interested in asymmetries which are obscured by symmetrical metrics, or we may want to evaluate how fitting parameters in the alignment changes conclusions. Thus, as noted above, it is useful to compare systems using multiple metrics.

Yet, there are also shared challenges across similarity measures that are more difficult to address, again due to the complex relationship between representation and computation. Any similarity metric inherently imposes the assumption that smaller differences between two representations are less important than larger ones. For example, (unregularized) linear regression, or RDMs computed with Euclidean distance, assume that the squared distance between two representations measures how important the distinctions between them are. However, this may not always be a good assumption. Sometimes even if a system represents two signals equally well, and uses them equally often, one will carry much less variance — i.e., changes in the signal will result in smaller changes in the representations as measured by Euclidean distance metrics — perhaps due to inductive biases or learning dynamics [e.g., Hermann and Lampinen, 2020]. Unless we have some way of knowing how “important” different aspects of a representation are to each system’s computations, and accordingly adapting our similarity measures, our measures of representational alignment will fail to perfectly capture the underlying computational similarity.

5.4 Will representational alignment help improve alignment of behavior?

Representational alignment focuses on *the representation space of a system*; i.e., the activations yielded by the information processing function of a system (see §2). However, as noted above, the relationship between representation and computation is complex. The outputs of systems can be aligned even if these systems have different representations, and vice versa [Hermann and Lampinen, 2020]; likewise, systems that have similar representations early in processing may diverge in later regions [Singer et al., 2022]. Thus, representational alignment between systems is not a prerequisite for aligned outputs, nor will it guarantee them.

However, initial representations constrain what a system will learn to output, and conversely, what a system learns to output will shape its representations. Thus, although it may be possible to achieve output alignment without representational alignment, the tight coupling between representations and outputs motivates studying representational alignment as one potential tool for achieving output alignment. Representational alignment could help researchers to pinpoint potential causes for output (mis-)alignment of systems, and could be used as a complement to more direct strategies for improving output alignment [Peterson et al., 2018; Barrett et al., 2018; Toneva and Wehbe, 2019; Fel et al., 2022; Muttenthaler et al., 2023a,b; Fu et al., 2023].

5.5 Possible risks of representational alignment

It is important to acknowledge that there may be risks to representational alignment. For instance, increased representational alignment could potentially make it more difficult for a person to detect that outputs are generated by a model rather than a person. In the case of aligning with a biological system, it is paramount to consider which systems (e.g., which humans) we do or do not wish to align towards, and what downstream biases could occur as a result of these potentially implicit design choices [cf. Gabriel, 2020]. These risks need not be examined in isolation, but rather, we encourage those working in representational alignment to engage with how risks from representational alignment interface with broader discussions around risks already under consideration in the range of fields that touch on representational alignment, e.g., machine learning, robotics, neuroscience, and cognitive science. We encourage further work to characterize possible risks and develop frameworks to guard against such possible negative ramifications.

6 Conclusion

Representational alignment is increasingly central to the various fields that study information processing, including cognitive science, neuroscience, and machine learning. In each field, researchers attempt to *measure* the alignment between representations from different systems, to *bridge* between distinct systems by bringing their representations into a shared space, and to *increase* the representational alignment of two systems. However, there is no clear common language for discussion between these different sets of researchers; thus, they are often unaware of related ideas, methods, and empirical results. In this paper, we have attempted to build bridges to help align terminology and methods across these fields. We hope that our work will simultaneously increase the sharing of related ideas and methods across fields, and raise awareness of common challenges and open questions. More broadly, we hope that seeing the varied perspectives outlined here will inspire other researchers to apply the ideas and tools of representational alignment to understanding or building intelligent systems.

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