Representation Potentials of Foundation Models for Multimodal Alignment: A Survey

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Resouce: https://github.com/Jianglin954/Representation-Alignment-Survey

Abstract

Foundation models learn highly transferable representations through large-scale pretraining on diverse data. An increasing body of research indicates that these representations exhibit a remarkable degree of similarity across architectures and modalities. In this survey, we investigate the *representation potentials* of foundation models, defined as the latent capacity of their learned representations to capture task-specific information within a single modality while also providing a transferable basis for alignment and unification across modalities. We begin by reviewing representative foundation models and the key metrics that make alignment measurable. We then synthesize empirical evidence of representation potentials from studies in vision, language, speech, multimodality, and neuroscience. The evidence suggests that foundation models often exhibit structural regularities and semantic consistencies in their representation spaces, positioning them as strong candidates for cross-modal transfer and alignment. We further analyze the key factors that foster representation potentials, discuss open questions, and highlight potential challenges.

1 Introduction

Foundation models, trained through large-scale pretraining on vast and heterogeneous data, have driven remarkable progress and significantly accelerated the pursuit of artificial general intelligence (Bommasani et al., 2021; Cui et al., 2022; Firoozi et al., 2023; Azad et al., 2023; Zhou et al., 2024). By acquiring highly transferable and general-purpose representations, they have become the backbone of a wide spectrum of applications, spanning natural language processing (Liu et al., 2019; He et al., 2020; Rajendran et al., 2024), computer vision (Dosovitskiy et al., 2021; Liu et al., 2022; Woo et al., 2023; Siméoni et al., 2025), speech processing (Belinkov and Glass, 2017; Baevski et al., 2020; Radford et al., 2023), robotics (Brohan et al., 2022; Team et al., 2025), and medical domains (Moor et al., 2023; Huang et al., 2024; Khan et al., 2025).

A growing body of research has shown that the representations learned by foundation models are not only powerful in isolation but also exhibit strong similarity across architectures, training objectives, and even modalities (Wentworth, 2021; Ng et al., 2023; Liu et al., 2023; Sharma et al., 2024; Huh et al., 2024; Maniparambil et al., 2024; Wang et al., 2025). We refer to this capacity as the *representation potential* of foundation models. This perspective carries significant implications: if foundation models naturally converge toward shared representational structures, they may approximate modality-agnostic abstractions and encode common statistical regularities of the world, even without explicit alignment. Understanding these potentials is essential, not only for advancing scientific theories of representation learning but also for enabling practical benefits such as model interoperability, transferability, interpretability, and alignment with biological cognition.

In this survey, we focus on the representation potentials of unimodal foundation models, with the goal of assessing their capacity for alignment. We structure our discussion around four central themes. First, we introduce representative foundation models in vision, language, speech, and multimodality. Second, we review the metrics that make representation alignment measurable, including centered kernel alignment (Kornblith et al., 2019), canonical correlation analysis (Morcos et al., 2018), and mutual nearest neighbors (Haghverdi et al., 2018). Third, we synthesize empirical evidence for representation potentials, drawing from studies in vision, language, speech, cross-modal alignment, and neuroscience. Fourth, we analyze the key factors that drive representation potentials, such as scale, architectural inductive biases, training objectives, and

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task and instruction diversity. Alongside these advances, we highlight pressing open questions: the limits of convergence across modalities, the need for robust evaluation standards, the influence of bias and sociotechnical context, and cases where domain-specific divergence may arise.

The remainder of this survey is organized as follows. In Section 2, we introduce foundation models across modalities. Section 3 reviews major metrics for quantifying representation similarity and alignment. Section 4 presents evidence for representation potentials in vision, language, speech, cross-modal, and neuroscience contexts. Section 5 analyzes the underlying drivers of alignment, including scale, architectures, training paradigms, and tasks. Section 6 discusses open questions and challenges. In Section 7, we conclude with key insights and directions for future research.

2 Foundation Models

This section provides a general definition of foundation models and then presents representative examples across computer vision, natural language processing, speech and multimodal domains.

2.1 Definition

Bommasani et al. (2021) first introduced the term *foundation model* to describe machine learning models trained on vast and diverse datasets, typically with large-scale self-supervision, that can be applied to a broad range of downstream tasks. Three features distinguish foundation models from their earlier predecessors: ① *Broad data*: They are trained on extensive and diverse datasets, often collected at web scale, which provide robust and transferable representations. ② *Self-supervision*: They learn directly from raw, unlabeled data by predicting missing information or inherent structures, thus avoiding the reliance on large volumes of manually annotated data. ③ *Adaptability*: Once trained, they can be fine-tuned, prompted, or otherwise adapted to a wide range of downstream tasks, underscores their general-purpose nature and their ability to serve as a foundation for numerous specialized applications. Based on these characteristics, the following subsections briefly introduce representative foundation models in computer vision, language, speech, and multimodal learning.

2.2 Vision Foundation Models

Vision foundation models (VFMs) (Liu et al., 2022; Siméoni et al., 2025) are large-scale neural architectures designed to learn robust visual representations that transfer across tasks. Canonical examples include ResNet (He et al., 2016), Vision Transformer (ViT) (Dosovitskiy et al., 2021), ConvNeXt (Woo et al., 2023), Dinov2 (Oquab et al., 2023), and the Segment Anything Model (SAM) (Kirillov et al., 2023). VFMs are typically trained on billion-scale image datasets using self-supervised learning, weakly supervised signals, or multimodal objectives. Earlier vision models depended on task-specific annotated datasets, but VFMs provide universal feature embeddings that can be reused or lightly adapted. These features support a wide range of applications, including image classification, object detection, and segmentation, as well as higher-level reasoning tasks such as visual question answering and captioning. Recently, VFMs have also become essential in vision systems such as segmentation-anything frameworks (Kirillov et al., 2023; Ravi et al., 2025), image generative pipelines (Yang et al., 2023; Zhang et al., 2023), and world models (Ha and Schmidhuber, 2018; Zhou et al., 2025). This transition marks a shift in computer vision from narrowly specialized solutions to foundational infrastructures.

2.3 Large Language Models

Large language models (LLMs) (Radford et al., 2019; Touvron et al., 2023; Achiam et al., 2023) are trained on massive text corpora to acquire broad linguistic and semantic knowledge. Representative examples include BERT (Devlin et al., 2019), T5 (Raffel et al., 2020), Qwen (Bai et al., 2023), and the LLaMA-series (Grattafiori et al., 2024), and conversational agents such as ChatGPT (Brown et al., 2020). By predicting masked spans or next tokens, LLMs capture both syntactic structures and semantic relations that generalize across diverse tasks. They can be adapted through fine-tuning, prompting, or in-context learning to applications such as summarization, translation, question answering, reasoning, and dialogue. A defining feature is their scale: empirical studies show that performance improves predictably as the number of parameters, the volume of training data, and the compute budget increase (Kaplan et al., 2020). Beyond higher accuracy, larger models also exhibit emergent abilities that are absent in smaller counterparts (Wei et al., 2022). These findings have shaped both research practices and industrial applications, positioning LLMs as the foundation for multimodal (Yin et al., 2024) and agentic extensions (Li, 2025).

2.4 Speech Foundation Models

Speech foundation models (SFMs) are trained on extensive audio corpora, focusing on speech signals while learning both acoustic-level and linguistic-level abstractions. Representative examples include wav2vec (Schneider et al., 2019; Baevski et al., 2020), HuBERT (Hsu et al., 2021), WavLM (Chen et al., 2022a), Whisper (Radford et al., 2023), and SeamlessM4T (Barrault et al., 2023). These models learn by predicting masked or latent units from raw waveforms, enabling them to serve as universal encoders of speech. SFMs support a wide variety of tasks, ranging from automatic speech recognition and speaker verification to emotion recognition, speech translation, and speech-to-speech generation (Cui et al., 2024; Radford et al., 2023). Beyond supervised fine-tuning, SFMs also demonstrate robust performance in zero-shot and few-shot settings. As a result, SFMs mark a decisive transition from specialized pipelines to broadly adaptable foundation-level architectures.

2.5 Multimodal Foundation Models

Multimodal foundation models (MFMs) integrate signals from multiple modalities, such as vision, language, audio, and video, into a unified architecture. Early MFMs include CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021), which use image–text contrastive learning. Later developments such as BLIP (Li et al., 2022) and CoCa (Yu et al., 2022) focus on vision–language generation, while Flamingo (Alayrac et al., 2022) and PaLI (Chen et al., 2022b) advance few-shot multimodal reasoning. More recent large-scale systems such as GPT-4 (Achiam et al., 2023) and Gemini (Team et al., 2023) demonstrate general-purpose multimodal intelligence. Training MFMs typically combines contrastive alignment (for paired modalities such as image and text), cross-modal reconstruction (predicting one modality from another), masked modeling (learning contextual cross-modal embeddings), and instruction tuning (adapting multimodal reasoning to natural language instructions) (Yin et al., 2024). These strategies allow MFMs to generalize across perception tasks such as image captioning and speech-to-text translation, as well as reasoning tasks including visual question answering and multimodal dialogue. Their growing influence signals an important trend: foundation models are evolving from unimodal encoders into integrated multimodal systems that support increasingly rich forms of human–AI interaction.

3 Metrics for Representation Alignment

In this survey, we review the capacity of unimodal foundation models to achieve representation alignment, with a focus on how their learned representations behave across architectures and modalities. The central goal is to uncover potential commonalities and similarities among representations learned by different models and to evaluate the extent to which unimodal foundation models converge in their representation spaces.

Formally, let $\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_n\} \in \mathbb{R}^{n\times d_1}$ and $\mathbf{Y} = \{\mathbf{y}_1, \ldots, \mathbf{y}_n\} \in \mathbb{R}^{n\times d_2}$ denote two sets of representations, extracted from distinct neural network layers or from different foundation models. Here, n is the number of samples, and d_1 and d_2 are the feature dimensionalities. The central question is whether $\mathbf{X}$ and $\mathbf{Y}$ encode similar information, possibly up to admissible transformations such as rotation, scaling, or affine mapping. To address this question, we first review representative similarity metrics that have been widely adopted in representation alignment analysis. These metrics provide principled tools for quantifying alignment quality.

3.1 Centered Kernel Alignment

Centered kernel alignment (CKA) (Kornblith et al., 2019; Davari et al., 2023) compares two representation sets by measuring the similarity of their kernel (Gram) matrices, which capture pairwise relationships between samples. We denote $\mathbf{K} = \mathbf{X}\mathbf{X}^\top$ and $\mathbf{L} = \mathbf{Y}\mathbf{Y}^\top$ as the linear Gram (kernel) matrices of $\mathbf{X}$ and $\mathbf{Y}$, which represent inner products between samples in the respective feature spaces. Typically, CKA first centers both kernel matrices to remove the influence of mean offsets:

$$\tilde{\mathbf{K}} = \mathbf{HKH}, \;\; \tilde{\mathbf{L}} = \mathbf{HLH}. \tag{1}$$

where $\mathbf{H} = \mathbf{I}_n - \frac{1}{n}\mathbf{1}_n\mathbf{1}_n^\top$ denotes the centering matrix, $\mathbf{I}_n \in \mathbb{R}^{n\times n}$ is the identity matrix, and $\mathbf{1}_n \in \mathbb{R}^n$ denotes the all-ones column vector. Then, the linear CKA between $\mathbf{X}$ and $\mathbf{Y}$ can be defined as:

$$\mathrm{CKA}(\mathbf{X},\mathbf{Y}) = \frac{\mathtt{HSIC}(\mathbf{K},\mathbf{L})}{\sqrt{\mathtt{HSIC}(\mathbf{K},\mathbf{K})\mathtt{HSIC}(\mathbf{L},\mathbf{L})}}, \tag{2}$$

where $\mathtt{HSIC}(\cdot,\cdot)$ denotes the Hilbert-Schmidt Independence Criterion (HSIC) that measures the dependence between the two kernel spaces:

$$\mathtt{HSIC}(\mathbf{K},\mathbf{L}) = \mathrm{tr}(\tilde{\mathbf{K}}\tilde{\mathbf{L}}). \tag{3}$$

CKA normalizes HSIC to produce a scale-invariant similarity measure. It can be interpreted as the cosine of the angle between the centered kernel matrices $\tilde{K}$ and $\tilde{L}$, when viewed as elements in the Hilbert-Schmidt space. It is invariant to isotropic scaling, i.e., $\mathrm{CKA}(c\mathbf{X}, \mathbf{Y}) = \mathrm{CKA}(\mathbf{X}, \mathbf{Y})$ for any scalar $c \neq 0$, and to orthogonal transformations, i.e., $\mathrm{CKA}(\mathbf{XQ}, \mathbf{Y}) = \mathrm{CKA}(\mathbf{X}, \mathbf{Y})$ for any orthogonal matrix $\mathbf{Q}$. The resulting CKA score ranges from 0 to 1, with 1 indicating perfect alignment between $\mathbf{X}$ and $\mathbf{Y}$. Based on CKA, several variants have been proposed to enhance its robustness or adapt it to specific settings, such as unbiased CKA (Song et al., 2007), kernel CKA (Kornblith et al., 2019), and class-conditional CKA (Nguyen et al., 2021). These refinements have made CKA one of the most widely used metrics for comparing neural representations across architectures and training settings.

3.2 Canonical Correlation Analysis

Canonical correlation analysis (CCA) (Hotelling, 1936; Morcos et al., 2018) is a classical statistical technique that identifies linear relationships between two multivariate datasets. It seeks linear projections of two random vectors such that their resulting projected representations are maximally correlated. Assume that both input matrices $\mathbf{X}$ and $\mathbf{Y}$ are centered (i.e., each column has zero mean). CCA aims to find directions $\mathbf{a} \in \mathbb{R}^{d_1}$ and $\mathbf{b} \in \mathbb{R}^{d_2}$ such that the projections $\mathbf{Xa}$ and $\mathbf{Yb}$ are maximally correlated. This is formalized as:

$$\max_{\mathbf{a},\mathbf{b}} \rho = \frac{\mathbf{a}^\top \mathbf{C}_{XY} \mathbf{b}}{\sqrt{\mathbf{a}^\top \mathbf{C}_{XX} \mathbf{a}} \cdot \sqrt{\mathbf{b}^\top \mathbf{C}_{YY} \mathbf{b}}} \tag{4}$$

where $\mathbf{C}_{XX} = \frac{1}{n}\mathbf{X}^\top\mathbf{X}$ and $\mathbf{C}_{YY} = \frac{1}{n}\mathbf{Y}^\top\mathbf{Y}$ are the covariance matrices of $\mathbf{X}$ and $\mathbf{Y}$, respectively, and $\mathbf{C}_{XY} = \frac{1}{n}\mathbf{X}^\top\mathbf{Y}$ is the corresponding cross-covariance matrix. The solution yields the first pair of canonical variates:

$$\mathbf{u}_1 = \mathbf{X}\mathbf{a}_1, \quad \mathbf{v}_1 = \mathbf{Y}\mathbf{b}_1, \tag{5}$$

where $\rho_1 = \mathrm{corr}(\mathbf{u}_1, \mathbf{v}_1)$ is the largest (first) canonical correlation. Subsequent pairs $(\mathbf{a}_i, \mathbf{b}_i)$ can be derived in a similar manner, subject to the orthogonality constraints:

$$\mathbf{u}_i^\top \mathbf{u}_j = 0, \quad \mathbf{v}_i^\top \mathbf{v}_j = 0 \quad \text{for} \quad \forall i \neq j. \tag{6}$$

The number of nonzero canonical correlations is at most $r = \min(d_1, d_2)$, and the sequence $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_r \geq 0$ quantifies the strength of the linear relationship between $\mathbf{X}$ and $\mathbf{Y}$.

An important extension is singular vector CCA (SVCCA) (Raghu et al., 2017a; Artetxe et al., 2020), which first reduces both $\mathbf{X}$ and $\mathbf{Y}$ to their dominant subspaces using singular value decomposition and then applies CCA. This improves robustness to noise and has become a standard technique for comparing deep learning representations. Both CCA and SVCCA are invariant to affine transformations, while SVCCA further filters out low-variance directions, improving stability in practice.

3.3 Mutual Nearest Neighbors

Mutual nearest neighbors (MNN) (Haghverdi et al., 2018) define a symmetric relationship between samples from two sets and are commonly used to establish robust correspondences between learned representations. Let $\mathtt{NN}_k(\mathbf{x}_i; \mathbf{Y})$ denote the set of k nearest neighbors of $\mathbf{x}_i \in \mathbf{X}$ in $\mathbf{Y}$, measured under a specific distance metric. A pair $(\mathbf{x}_i, \mathbf{y}_j)$ is said to form a mutual nearest neighbor pair if:

$$\mathbf{y}_j \in \mathtt{NN}_k(\mathbf{x}_i; \mathbf{Y}) \quad \text{and} \quad \mathbf{x}_i \in \mathtt{NN}_k(\mathbf{y}_j; \mathbf{X}). \tag{7}$$

MNN is widely used to reduce false-positive matches, particularly in high-dimensional or noisy representation spaces. Several variants have been developed based on the MNN principle. For example, mutual k-nearest neighbor matching (Huh et al., 2024) has been applied to evaluate cross-modal representation alignment.

The selection of metric depends on the specific aspect of similarity one seeks to capture. In practice, CKA is often preferred for its robustness and interpretability across architectures and tasks, whereas CCA provides useful insights when comparing closely related spaces, and MNN proves valuable when local semantic structures are of interest. Beyond CKA, CCA, and MNN, a number of additional metrics have been developed to capture complementary aspects of representation similarity. Examples include Riemannian distance (Shahbazi et al., 2021), which accounts for the geometry of covariance matrices; similarity-of-similarity matrices (SSM) (Diedrichsen and Kriegeskorte, 2017), which measure agreement in pairwise similarity structures; and rank-based or Jaccard similarity metrics (Wang et al., 2020), which focus on relational consistency. For a systematic overview of these approaches, refer to the paper by Klabunde et al. (2025), which provides a detailed survey of similarity metrics for representation analysis.

4 Representation Potentials of Foundation Models for Alignment

In the following subsections, we review existing works in vision, language, speech, modalities, and neuroscience that explore the representation potentials of foundation models for alignment.

4.1 Representation Alignment in Vision

Within computer vision, a growing body of evidence suggests that models with different architectures, training objectives, and datasets can develop compatible understandings of visual information. Early studies established that shallow features and early convolutional layers behave in similar ways. For example, Lenc and Vedaldi (2015) demonstrated that representations such as histograms of oriented gradients (HOG) and early convolutional filters respond linearly to geometric transformations like warps and flips, revealing that these early features are broadly interchangeable across architectures. Li et al. (2015) showed that independently trained networks often develop neuron clusters with overlapping functions, indicating partial convergence in learned representations. Raghu et al. (2017b) introduced SVCCA and reported that neural representations exhibit strong cross-initialization similarity, with lower layers converging early into compact shared subspaces while higher layers continue to evolve more gradually. Morcos et al. (2018) found that networks with better generalization exhibit higher representation similarity across random initializations, while overfitted networks diverge more. Kornblith et al. (2019) provided systematic evidence that wider models learn more similar representations, early layers converge quickly, and deeper layers often contain redundancies across consecutive layers.

Subsequent works examined alignment under varied training objectives and architectures. Csiszárik et al. (2021) showed that inner representations in deep convolutional networks with identical architectures but different initializations can be closely matched using only a single affine stitching layer. Roeder et al. (2021) proved that a broad class of discriminative and autoregressive models are identifiable in function space up to a linear transformation. Grigg et al. (2021) compared supervised and self-supervised training, finding that intermediate layers are strikingly similar across paradigms, but final layers diverge: supervised models emphasize class-specific structure, whereas self-supervised models emphasize invariance to augmentations. Bansal et al. (2021) introduced the concept of stitching connectivity, showing that identically structured networks trained in different ways can be stitched together at intermediate layers with minimal performance degradation. Caron et al. (2021) highlighted how self-supervised Vision Transformers (ViTs) consistently converge to similar spatial attention patterns and semantic structures, regardless of the specific training setup. Raghu et al. (2021) compared CNNs and ViTs using CKA, finding divergence in early layers but convergence in later ones. Moschella et al. (2023) noted that although absolute coordinates of latent embeddings vary across training runs, relative angular relationships are preserved, reflecting alignment at a relational level.

More recent studies have reinforced and expanded these findings. Shekhar et al. (2023) reported that models trained with the same self-supervised objective tend to learn more similar representations, even when the architectures differ. Oquab et al. (2023) showed that self-supervised ViTs trained on different datasets or initializations learn similar high-level visual structures and that their features are compatible with those of supervised models. Dravid et al. (2023) identified Rosetta neurons, which reliably emerge across model architectures, training paradigms, and tasks. Stoica et al. (2024) demonstrated that independently trained networks can be merged without retraining by aligning and zipping their feature spaces. Sharon and Dar (2025) showed that during training, representation similarity exhibits distinct phases whose clarity depends on both architecture and optimizer: SGD and ViTs exhibit more synchronized, sharply delineated evolution of layer representations, whereas ResNets and Adam yield more gradual or less aligned dynamics. Li et al. (2025) highlighted that bidirectional Transformers serve as strong representation learners, enabling unified modeling of multimodal data distributions through likelihood estimation.

Beyond classification, alignment has also been observed in generative contexts. Yu et al. (2025) argued that the success of diffusion-based generation hinges on learning meaningful representations, and proposed a regularization strategy that aligns noisy denoising states with clean embeddings from pretrained encoders. Moreover, several studies (Balestriero and richard baraniuk, 2018; Kornblith et al., 2019; Roeder et al., 2021; Huh et al.,

2024) converge on a broader trend: representation similarity increases with model scale and performance. In other words, as vision models become larger, more expressive, and more generalizable, their internal representations tend to align more closely, pointing to a fundamental convergence.

4.2 Representation Alignment in Language

LLMs are increasingly demonstrating human-level proficiency across a broad spectrum of natural language processing tasks, including knowledge extraction, reasoning, and dialogue. This widespread improvement suggests a potential convergence in how these models process and represent linguistic information. A growing body of research provides evidence that diverse LLMs, often trained with different architectures and datasets, nonetheless develop aligned internal representations. One line of work highlights consistent structural patterns. Phang et al. (2021) found a block-structured similarity pattern in the hidden representations of fine-tuned RoBERTa (Liu et al., 2019) and ALBERT (Lan et al., 2020), suggesting that training induces stable, repeatable alignment across models. Jiang et al. (2025) similarly observed that representation similarity in transformer models is strongest between adjacent layers, pointing to a layerwise convergence mechanism.

Another direction emphasizes concept-level alignment. Park et al. (2024) formalized what it means for high-level concepts to be linearly represented in LLMs, introduced a causal inner product to capture semantic separability, and showed that high-level concepts in LLaMA2 (Touvron et al., 2023) can be probed or steered as approximate linear directions. Lan et al. (2024) decomposed LLM activations with sparse autoencoders, revealing disentangled features that align closely across different models. Bürger et al. (2024) reported the emergence of a universal two-dimensional truth representation across LLMs of varying sizes and architectures, while Tan et al. (2024) identified strong correlations in both in-distribution and out-of-distribution steerability between LLaMA (Touvron et al., 2023) and Qwen (Bai et al., 2023).

A third body of evidence focuses on transferable features and universal neurons. Del and Fishel (2022) proposed a neuron-wise correlation metric that reveals the "first align, then predict" pattern across languages in multilingual models more faithfully. Gurnee et al. (2024) showed that about one to five percent of neurons in independently seeded GPT2 models are universal, interpretable, and causally relevant for predictions. Oozeer et al. (2025) found that safety-intervention vectors discovered in the activation space of one LLM can be mapped into the activation spaces of other LLMs via learned autoencoder mappings. Chen et al. (2025) find that affine mappings between residual streams allow for effective transfer of learned feature modules, probes, and steering vectors from small to large models. Rinaldi et al. (2025) further demonstrated that task vectors can be transferred from older to newer models without data or retraining by aligning weight structures of the two pretrained models. Lee et al. (2025) showed that token embeddings within a model family share both global and local geometry, enabling cross-model steering despite dimensional differences.

Finally, several studies point to broader universality across model classes. Wang et al. (2025) compared Transformer and Mamba models (Gu and Dao, 2024) trained on the same data and found that they share many internal features and circuits, suggesting substantial but imperfect universality of mechanisms across architectures. Cheng et al. (2025) analyzed intrinsic dimensionality of internal representations in transformer-based language models and identify a high-dimensional abstraction phase within the middle layers. This phase, consistently observed across architectures and datasets, reflects the point where models begin to form abstract, task-relevant representations that generalize well across tasks and models.

4.3 Representation Alignment in Speech

The study of speech models, particularly those trained using self-supervised learning (SSL) (Mohamed et al., 2022; Riera et al., 2023), also reveals emerging evidence of representation alignment. For instance, Ollerenshaw et al. (2021) examined end-to-end automatic speech recognition systems and found that CNN-based models exhibited progressively hierarchical and stable representation similarity as depth increased, whereas LSTM and Transformer architectures displayed less clean or more irregular similarity structures across layers. Chung et al. (2021) reported that the choice of learning objective has a larger impact on how similar representations are across models than architectural choices. Pasad et al. (2023, 2024) provided a detailed analysis of how acoustic, phonetic, and word-level information emerge at different layers, showing that both pretraining objectives and model size determine where key linguistic properties such as identity, pronunciation, syntax, and semantics are encoded. Waheed et al. (2024) showed that certain SFMs achieve strong zero-shot performance on tasks for which they were never explicitly trained, and that this performance correlates with higher-quality underlying representations. Dorszewski et al. (2025) found that Transformer-based speech representation models exhibit a block-structured similarity pattern across layers, with substantial redundancy within blocks. Huo and Dunbar (2025) demonstrated that the contrast between HuBERT (Hsu et al., 2021) and wav2vec2.0 (Baevski et al., 2020) lies not in whether a contrastive or classification objective is used, but in the iterative pseudo-label refinement strategy: multiple clustering iterations yield more aligned representations.

4.4 Representation Alignment Across Modalities

Beyond alignment within individual modalities, an increasing number of studies highlight the potential for foundation model representations to align across different modalities, even when trained independently. One line of studies shows that representations from language and vision models can be brought into correspondence with lightweight mappings. For example, Merullo et al. (2023) investigated the extent to which conceptual representations from frozen text-only and vision-only models align, and found that visual information encoded by image models can be transferred to language models using only a single learned linear projection. Similarly, Koh et al. (2023) proposed a lightweight framework for adapting pre-trained text-only LLMs to handle multimodal inputs. Their approach enables LLMs to process interleaved image–text data and generate text interleaved with retrieved images, all without retraining the base model. Maniparambil et al. (2024) examined whether inherent alignment exists between independently trained unimodal vision and language encoders, and found that such models encode semantically similar structures, enabling zero-shot latent space communication without explicit alignment. Zhang et al. (2025) evaluated the degree to which independently trained vision and language models can be aligned and propose an efficient alignment framework for downstream tasks.

Other studies explore alignment between language and auditory representations. Ngo and Kim (2024) showed that auditory and language representations can be approximately aligned through a simple linear transformation, pointing to a shared structural basis across modalities. They further demonstrated that text-only LLMs encode features that align with auditory object representations, such that a contrastive probe can successfully retrieve the correct object label from an audio snippet. Lee et al. (2024) revealed that cross-modal representations, particularly between text and speech, tend to converge in the deeper layers of the models, while the early layers remain modality-specific and specialized for raw input processing. This layer-wise convergence reflects a progressive transformation toward modality-agnostic abstraction as signals propagate through the network.

These results resonate with the Platonic Representation Hypothesis (Huh et al., 2024), which argues that foundation models are converging toward a common statistical model of reality embedded within their representation spaces. All these findings suggest that cross-modal convergence may reflect a deeper tendency of foundation models to discover modality-agnostic abstractions. This emerging evidence points to the possibility that foundation models, even when trained separately, may inhabit overlapping representational manifolds that facilitate alignment, transfer, and integration across modalities.

4.5 Representation Alignment with Neuroscience

While the previous sections focus on alignment within and across artificial modalities, a natural question is whether the representations learned by foundation models also correspond to those observed in biological systems. In this context, representation alignment does not refer to internal consistency within neuroscience, but rather to the similarity and correspondence between model-derived features and neural representations measured in cognitive neuroscience (Pham et al., 2023). This perspective bridges artificial and biological intelligence, providing insights into the extent to which foundation models capture structures present in natural cognition. For example, Chen et al. (2024) showed that both Wav2Vec2.0 and GPT2 predict human auditory cortex responses, with model activations exhibiting strong correlations to brain activity during speech and language perception. Khosla et al. (2024) developed axis-sensitive metrics for alignment and demonstrated that both biological and artificial neural networks exhibit privileged, non-arbitrary axes of representation that converge across systems. Hosseini et al. (2024) examined the representation universality hypothesis, and proposed that artificial neural networks trained on naturalistic data converge toward shared representational structures that also align with the brain. Their findings show that inter-model representational agreement reliably predicts brain alignment, implying that shared tasks and environments naturally drive both artificial and biological systems toward similar representational structures. Doerig et al. (2025) reported that embeddings from LLMs of whole scene captions align closely with high-level visual cortex responses to corresponding images, outperform many image-based models, and that image models trained to predict these caption embeddings can match or exceed vision model alignment to brain activity. Raugel et al. (2025) added that model size, training scale, and the nature of image data all critically drive how well vision transformer models develop representations aligned with human brain activity, with larger, more human-centric models aligning later brain regions and temporal dynamics when given enough training. Feather et al. (2025) proposed the NeuroAI Turing Test, a benchmark that requires models to match both behavior and internal neural representations of brains, arguing that this stronger criterion is necessary for model-brain evaluations in NeuroAI. Taken together, these findings suggest that artificial and biological systems, despite differences in architecture and learning mechanisms, converge toward similar representational frameworks when exposed to comparable sensory inputs and functional objectives. This bridges the gap between artificial intelligence and neuroscience, offering insights into both machine learning and human cognition.

5 Factors Driving Representation Potential for Alignment

A variety of factors contribute to the alignment potential of foundation model representations. Among the most prominent is scale, which encompasses model capacity, dataset size, and computational resources. Kaplan et al. (2020) established scaling laws showing that performance improves predictably with these factors, and subsequent work has demonstrated their impact on representation similarity. For instance, Gammelgaard et al. (2023) showed that as LLMs increase in size and quality, they organize concepts in embedding spaces in ways increasingly similar to the structures of knowledge graphs, suggesting convergence toward human-like conceptual organization derived from text alone. Nguyen et al. (2024) demonstrated that linguistic and cultural diversity in data enhances generalization and robustness. Huh et al. (2024) proposed that across multiple modalities, larger models trained on more diverse datasets naturally develop more aligned representations.

While the Platonic Representation Hypothesis (Huh et al., 2024) suggests that convergence may occur independently of architectural or training objectives, evidence shows that these factors can nonetheless shape the dynamics of alignment. The Transformer architecture (Vaswani et al., 2017), now dominant in foundation models, is argued to inherently facilitate generalizable representations due to its flexible inductive biases (Edelman et al., 2022; Bhattamishra et al., 2023; Geerts et al., 2025). Training paradigms are equally influential. Self-supervision, in particular, has been shown to encourage representations that generalize broadly across tasks and domains. Ciernik et al. (2025) found that self-supervised vision models yield stronger pairwise similarity generalization across datasets compared to models trained with image classification or image–text matching objectives. These results indicate that although convergence may not depend strictly on architecture or objective, both exert important shaping effects on representational outcomes.

The generality of tasks and instructions also affect representation potentials. As foundation models are trained on increasingly diverse task mixtures and fine-tuned with a wide range of instructions, their representation spaces become progressively constrained, encouraging the development of task-agnostic abstractions that potentially support alignment. Sanh et al. (2022) found that prompt-based multitask fine-tuning yields strong zero-shot generalization, frequently exceeding the performance of larger models. Chung et al. (2024) further showed that scaling instruction-finetuning by expanding both the number and variety of finetuning tasks substantially boosts performance across zero-shot, few-shot, reasoning, multilingual, and open-ended benchmarks. Zhang et al. (2024) highlighted that instruction diversity, rather than the sheer number of examples per instruction, is the critical factor for driving generalization.

6 Open Questions

Despite compelling evidence for representation potentials of foundation models for alignment, several limitations and open questions remain. One fundamental limitation arises from differences across modalities. Distinct sensors and perspectives capture complementary aspects of reality, and certain information may be unique to a given sensory channel, which constrains the extent to which their representations can perfectly align. For example, visual data emphasizes spatial and perceptual detail, while language conveys abstract concepts and relationships. Consequently, full convergence to a single, identical representation across modalities is neither achievable nor necessarily desirable. In this sense, alignment should perhaps be understood not as perfect overlap but as the development of partially shared abstractions that remain complementary across modalities. Notably, Lu et al. (2025) recently proposed that foundation models converge toward relational, externally grounded representations, implicitly reflecting a shared relational structure underlying reality. Such representations inherently involve contextualization and mutual reference across samples, and thus offer a principled way of addressing the limitations outlined above.

Another challenge lies in how to evaluate alignment rigorously. While various metrics have been proposed to quantify the similarity between representations, an ongoing debate persists within the research community regarding the effectiveness and interpretability of these measures. It is often unclear whether a given alignment score indicates a strong degree of similarity with only minor discrepancies, or a relatively weak alignment with significant underlying differences that are yet to be fully understood. For example, Wang et al. (2018) introduced a neuron activation subspace match model to define the similarity between networks trained with the same architecture but different random initializations. They showed that convolutional layers often exhibit low similarity across independently trained networks, even with identical architectures. Brown et al. (2023) demonstrated that measures such as model stitching and CKA can reveal internal differences in language models that are invisible to performance-based evaluations. Harvey et al. (2024) provided a decoder-based perspective, arguing that high similarity in metrics like CKA or CCA implies that many features can be decoded similarly, but the reverse does not necessarily hold: models may allow similar decoding for some tasks while still differing geometrically in how information is distributed across dimensions. The absence of a universally accepted standard complicates cross-study comparisons and raises questions about what alignment scores truly capture.

The role of data bias and sociotechnical context also presents a crucial consideration. Training data are often scraped from the internet and thus inherit the biases, cultural norms, and imbalances embedded in human human-generated content. Such biases shape representation spaces and constrain the universality of alignment claims. Beyond data, the broader sociotechnical context, including who builds the models and for what purposes, also influences alignment, raising questions about whether observed consistencies reflects general cognitive structures or artifacts of specific training regimes.

Finally, there are counterexamples and scenarios where representation alignment might not emerge. Highly specialized models, optimized for narrow tasks, may develop unique representations that diverge from general-purpose abstractions. In domains such as robotics, where standardized representations for complex sensorimotor experiences are still under development, the potential for alignment may be constrained by the absence of common frameworks and data formats. In summary, while the evidence for alignment across architectures and modalities is strong, the boundaries of this phenomenon remain poorly understood. Future progress requires both more robust evaluation frameworks and a careful recognition of the contexts and biases that shape representational spaces.

7 Conclusion

In this survey, we synthesize substantial evidence for the representation potential of foundation models, demonstrating their capacity for alignment within individual modalities such as vision, language, and speech, across multimodal combinations, and in relation to representations observed in neuroscience. We further analyze the key factors that foster representation potentials and discuss open questions. Our future work will pursue a deeper theoretical grounding of representation potentials. We believe that continued exploration in this direction will not only drive the development of more interpretable foundation models but also enrich our broader understanding of the principles that underlie both artificial and natural intelligence.

Limitations

This survey has focused on the representation potentials of foundation models across vision, language, speech, multimodality, and neuroscience, emphasizing areas where substantial empirical evidence is available. However, our analysis necessarily excludes domains such as robotics, sensorimotor control, and graphs, where research on representation alignment is still fragmented and publicly available findings are limited. As a result, this survey may not fully reflect the breadth of representational behaviors across all applications of foundation models.

Another limitation arises from the evaluation of alignment itself. While we reviewed a range of commonly used metrics, including CKA, CCA, and MNN, the field still lacks a unified standard for assessing representation similarity. This makes it difficult to integrate results across studies rigorously. Comparisons across modalities, architectures, or training objectives therefore remain partly qualitative, and definitive meta-analyses are constrained by methodological inconsistencies.

Finally, foundation models are rapidly evolving. New models, training paradigms, and evaluation techniques continue to emerge, particularly in cross-modal and neuroscience-inspired settings. Consequently, the conclusions and scope presented here should be regarded as a reflection of the current state of the field rather than a definitive account. We anticipate that many of the questions identified in this survey will be revisited and refined as the field advances.

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