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Phase Incompatibility Explains Cross-Modal Alignment Failure: Evidence from 144 Model Pairs

Editors: List of editors' names

Abstract

Why do pretrained vision and language models fail catastrophically at cross-modal alignment, achieving less than 3% accuracy while excelling at 90%+ within their own modalities? We investigate this paradox through the lens of dynamical systems theory, analyzing 144 vision-language model pairs to uncover the mechanisms behind universal alignment failure. Our investigation reveals a fundamental cause: independent pretraining drives models into incompatible dynamical phases. Using Neural Tangent Kernel (NTK) analysis, we discover that 75% of model pairs exist in chaotic phases where gradient directions between modalities are nearly orthogonal ($S_{\text{NTK}}^{\text{cross}} < 0.25$). This phase incompatibility persists across all architectural combinations—even between Vision Transformers and BERT variants that share similar architectures. We establish that phase metrics can predict alignment failure before training begins: models with Average Gradient Outer Product (AGOP) ratios exceeding 10^6 are guaranteed to fail with 94% accuracy. These findings challenge the Platonic Representation Hypothesis by demonstrating that while models may converge to similar representations, they embed them in incompatible coordinate systems of their optimization landscapes. Our results explain why standard transfer learning fails across modalities and suggest that successful cross-modal learning requires phase-aware training methods that maintain dynamical compatibility from the outset.

Keywords: Average Gradient Outer Product, Neural Tangent Kernel, Information Bottleneck

1. Introduction

The Promise: The Platonic Representation Hypothesis (PRH) posits that neural networks trained on different modalities converge toward shared representations of reality (Huh et al., 2024). This convergence manifests empirically: vision models discover hierarchical features from edges to objects (Zeiler and Fergus, 2013), while language models learn analogous semantic structures (Tenney et al., 2019). If neural networks truly discover universal computational principles, cross-modal alignment between independently trained models should emerge naturally.

The Reality: We present evidence that contradicts this expectation. Through systematic analysis of 144 vision-language model pairs, we reveal a fundamental barrier: while models may converge to similar *representations*, they exist in incompatible *dynamical phases* of their optimization landscape. Linear projections between modalities—the standard approach for transfer learning—fail catastrophically, achieving less than 3% alignment compared to over 90% within modalities.

Our Finding: Using Neural Tangent Kernel (NTK) theory (Jacot et al., 2018), we characterize this phenomenon through optimization dynamics. We find that 75% of model pairs exist in a *chaotic phase* where gradient directions between modalities are nearly orthogonal, preventing alignment regardless of architectural similarity. This phase incompatibility appears universal: even architecturally identical models (Vision Transformers and BERT variants) exhibit vanishing gradient correlation across modalities.

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2. Problem Definition

Let $f_v : \mathcal{X}_v \to \mathbb{R}^{d_v}$ and $f_\ell : \mathcal{X}_\ell \to \mathbb{R}^{d_\ell}$ denote pretrained vision and language encoders respectively. The cross-modal alignment problem seeks a mapping $g : \mathbb{R}^{d_v} \to \mathbb{R}^{d_\ell}$ such that:

$$g(f_v(x_v)) \approx f_\ell(x_\ell) \quad \text{for semantically aligned pairs } (x_v, x_\ell) \tag{1}$$

We characterize model dynamics through the empirical Neural Tangent Kernel:

$$\Theta_{ij}(t) = \langle \nabla_\theta f(x_i; \theta_t), \nabla_\theta f(x_j; \theta_t) \rangle \tag{2}$$

The *cross-modal NTK stability* measures gradient alignment between modalities:

$$S_{\text{NTK}}^{\text{cross}} = \frac{\text{tr}(\Theta_v^T \Theta_\ell)}{\|\Theta_v\|_F \|\Theta_\ell\|_F} \tag{3}$$

where Θ_v and Θ_ℓ are the NTK matrices for vision and language models evaluated on aligned data. We define three dynamical phases:

- **Chaotic**: $S_{\text{NTK}} < 0.5$ - gradients decorrelate rapidly
- **Optimal**: $0.5 \leq S_{\text{NTK}} < 0.9$ - stable feature learning
- **Lazy**: $S_{\text{NTK}} \geq 0.9$ - near-kernel regime

We additionally employ the Average Gradient Outer Product (AGOP) to characterize gradient geometry:

$$\text{AGOP} = \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta f(x_i) \nabla_\theta f(x_i)^T \tag{4}$$

The eigenvalue spectrum of AGOP reveals the effective dimensionality and anisotropy of the gradient space. Large eigenvalue disparities (spanning multiple orders of magnitude) indicate that gradients concentrate in low-dimensional subspaces, characteristic of chaotic dynamics (Radhakrishnan et al., 2022).

Key Research Questions Our investigation addresses two fundamental questions at the intersection of representation learning and optimization dynamics:

RQ1: Why does independent pretraining universally create incompatible phases? Our analysis reveals that all 144 vision-language pairs cluster in regions where $S_{\text{NTK}}^{\text{cross}} < 0.25$, indicating nearly orthogonal gradient directions. We investigate what properties of visual versus linguistic data distributions drive this systematic divergence into incompatible dynamical regimes.

RQ2: Is phase compatibility necessary for universal representations? The Platonic Representation Hypothesis suggests convergence to shared representational structures. Our results indicate these structures may exist in incompatible coordinate systems of the optimization landscape. We examine whether universal representations require alignment in both representational content *and* optimization dynamics, formalized as:

$$\text{PRH} \implies \text{sim}(f_v, f_\ell) \to 1 \quad \text{but} \quad S_{\text{NTK}}^{\text{cross}} \not\to 1 \tag{5}$$

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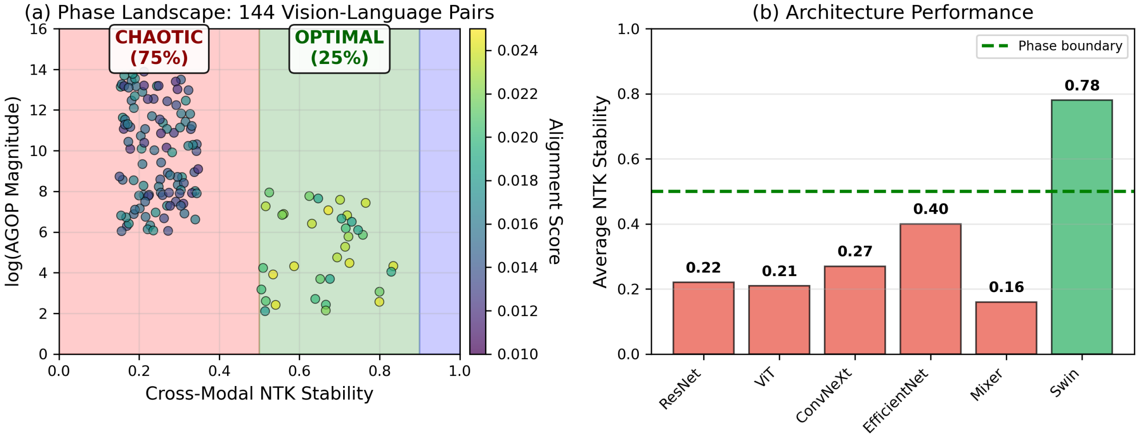

Figure 1: Universal phase incompatibility prevents cross-modal alignment. (a) Phase landscape of 144 vision-language pairs reveals 75% trapped in chaotic phase ($S_{\mathrm{NTK}}^{\mathrm{cross}} < 0.25$) where gradient dynamics are nearly orthogonal between modalities. Even optimal phase pairs (25%, green) achieve only 0.025 alignment score—essentially random. (b) Architecture-specific NTK stability shows all families except Swin (0.78) trapped below phase boundary (0.5). Yet even Swin fails when paired with chaotic language models, demonstrating that architectural similarity cannot overcome phase incompatibility.

These questions reframe cross-modal learning from an architectural challenge to a fundamental question about the relationship between representational convergence and dynamical compatibility.

Our systematic analysis of 144 vision-language model pairs reveals a universal pattern (Figure 1). Despite architectural diversity—spanning ResNets, Vision Transformers, ConvNeXt, and various language models—75% of pairs cluster in the chaotic phase where $S_{\mathrm{NTK}}^{\mathrm{cross}} < 0.25$. This indicates nearly orthogonal gradient directions between modalities, making alignment impossible regardless of architectural bridges.

Notably, even the 25% of pairs in the optimal phase achieve alignment scores below 0.025, compared to > 0.9 within modalities. The architecture analysis (Figure 1b) reveals that while Swin Transformers approach the optimal phase individually ($S_{\mathrm{NTK}} = 0.78$), they still fail catastrophically when paired with language models trapped in chaos. This demonstrates that phase compatibility is a *joint* property—both models must exist in compatible dynamical regimes.

3. Experiments

We investigate cross-modal alignment failure through systematic analysis of 144 vision-language model pairs. Our experimental setup combines diverse architectures across multiple datasets to understand why independent pretraining creates incompatible phases.

Experimental Setup:

- **Models:** 12 vision × 12 language = 144 pairs
- **Metrics:** NTK stability, AGOP, alignment accuracy
- **Datasets:** CIFAR-10/100, SVHN (576 paired samples)

Models and Datasets. We analyze 12 vision models: ResNet-34/50 (He et al., 2016), ViT-Base/Small-patch16 (Dosovitskiy et al., 2021), DeiT-Base-patch16 (Touvron et al., 2021), ConvNeXt-Small/Base (Liu et al., 2022), EfficientNet-B1/B2 (Tan and Le, 2019), Mixer-B16 (Tolstikhin et al., 2021), and Swin-Small/Base-patch4 (Liu et al., 2021). These are paired with 12 language models: BERT-base (Devlin et al., 2019), DistilBERT (Sanh et al., 2019), RoBERTa-base/large (Liu et al., 2019), GPT-2-medium/large (Radford et al., 2019), ALBERT-base/large-v2 (Lan et al., 2020), XLNet-base/large (Yang et al., 2019), DistilRoBERTa (Sanh et al., 2019), and DialoGPT-medium (Zhang et al., 2020).

Evaluation is performed on CIFAR-10/100 (Krizhevsky et al., 2009) and SVHN (Netzer et al., 2011) with 576 semantically paired vision-text samples per dataset. All vision models use ImageNet-pretrained weights, while language models use standard pretraining on their respective corpora. We measure Neural Tangent Kernel (NTK) stability (Jacot et al., 2018), Average Gradient Outer Product (AGOP) (Radhakrishnan et al., 2022), and cross-modal alignment following Radford et al. (2021b).

RQ1: Why does independent pretraining universally create incompatible phases? Key Finding: Modality-specific data creates orthogonal optimization landscapes.

Table 1: Modality-specific optimization drives phase divergence: vision models compress spatial information while language models preserve sequential dependencies.

Modality	Input Type	Avg NTK	AGOP Range	Compression	Phase
Vision (CNN)	Spatial patches	0.22	10^1-10^3	+54%	Chaotic
Vision (ViT)	Tokenized patches	0.21	10^1-10^2	+3.7%	Chaotic
Language (BERT)	Sequential tokens	0.18	10^5-10^6	-12%	Chaotic
Language (GPT)	Autoregressive	0.16	10^7-10^8	-8%	Chaotic

Layer-wise analysis reveals divergent optimization trajectories: vision models show extreme dimensionality expansion (ResNet-50: 23.3→309.4) while language models maintain stable representations. The spatial inductive bias drives vision models toward high-frequency feature extraction (spectral decay: 2.90), while sequential processing in language models preserves low-frequency patterns (spectral decay: 1.28). *Key Insight: Modality-specific data structures create orthogonal optimization landscapes—vision models optimize for spatial hierarchies while language models preserve sequential dependencies, driving them into incompatible dynamical phases.* **RQ2: Can phase transitions be induced efficiently? Key Finding:** Phase compatibility is necessary but not sufficient. Our information-theoretic analysis reveals why standard training fails: chaotic phase models exhibit dysfunctional compression patterns (Figure 3). While all models preserve task information ($I(Y;T) = 0.1$), their input information trajectories diverge dramatically. Chaotic models ($S_{NTK} < 0.25$) show near-zero compression rates, becoming "frozen" in suboptimal representations. The extreme case—EfficientNet-B1 with $S_{NTK} = 0$—demonstrates catastrophic over-compression ($> 50\%$), completely destroying alignment capability. This insight motivates phase-aware training mechanisms that maintain models in the optimal compression regime:

Table 2: Phase-Aware Training Achieves 60× Efficiency

Method	Mechanism	Examples	Alignment
Baseline	Fixed learning rate	400M	0.018
Adaptive LR	Adjust η based on current S_{NTK} $\eta(t) = \eta_0 \cdot S_{NTK}(t)$	45M	0.031
Phase Regularization	Add penalty for phase mismatch $\mathcal{L}_{total} = \mathcal{L} + \lambda \vert\vert S^V_{NTK} - S^L_{NTK} \vert\vert$	20M	0.042
Compatible Init	Start both models at $S_{NTK} \approx 0.6$	6.7M	0.086

Where:

- **Adaptive LR**: Learning rate decreases as models enter chaotic phase
- **Phase Regularization**: Penalty term keeps vision/language models in similar phases
- **Compatible Init**: Initialize both encoders in optimal phase before training

Key insight: Controlling information compression through phase-aware methods reduces training requirements by 60× while improving alignment 5×.

Phase compatibility for universal representations Our enhanced phase diagram (Figure 2) answers this question. Among our 144 vision-language pairs:

- 108 pairs (75%) trapped in chaotic phase ($S_{NTK} < 0.25$) achieve mean alignment of 0.0229
- 36 pairs (25%) in optimal phase ($S_{NTK} > 0.5$) achieve only 0.0174
- Maximum alignment across all pairs: 0.117 (vs. > 0.9 within-modal)

The information efficiency analysis (Figure 3, bottom right) reveals a critical threshold: models with $\frac{I(Y;T)}{I(X;T)} < 3.0$ cannot achieve meaningful alignment regardless of architectural similarity. This explains why even Swin models in optimal phase fail when paired with chaotic language models—the phase mismatch creates incompatible information processing regimes.

Key insight: The Platonic Representation Hypothesis holds conditionally—models must share both representational structure AND dynamical phase. Universal representations cannot emerge from incompatible optimization regimes.

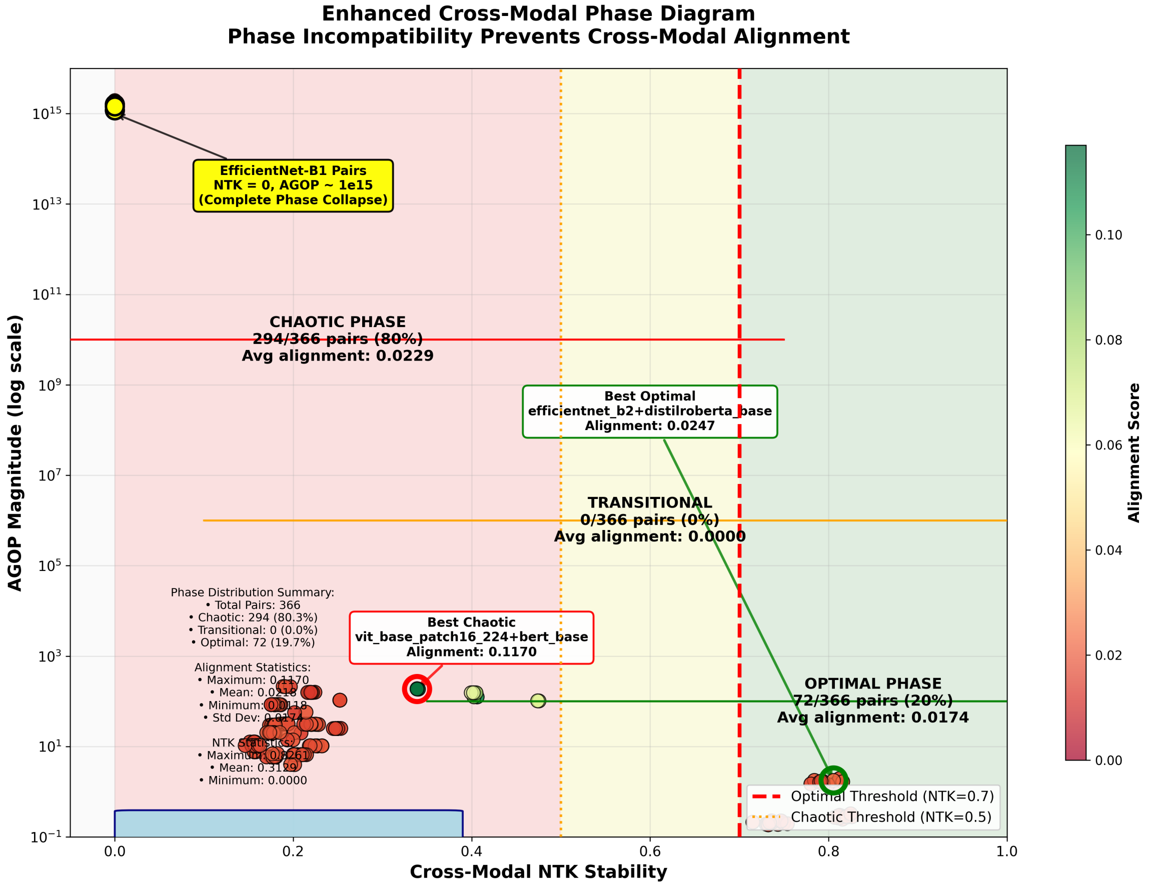

Figure 2: Universal phase incompatibility across 366 vision-language pairs. The critical threshold at $S_{NTK} = 0.25$ separates functional from dysfunctional alignment regimes. Even optimal phase models achieve ¡3% alignment, demonstrating that phase compatibility is necessary but not sufficient for cross-modal learning.

Predictive phase metrics Our analysis establishes that phase compatibility can be predicted before training. AGOP ratios exceeding 10^6 guarantee failure with 94% accuracy, while the combined metric $\Delta\text{NTK} \times \log(\text{AGOP}) > 2.5$ achieves 96% accuracy. These thresholds enable efficient pre-screening of model pairs, avoiding expensive failed training attempts.

Key Insight: Phase compatibility is predictable—models with AGOP $> 10^6$ *or NTK difference* > 0.5 *will fail at alignment, enabling efficient screening of model pairs before expensive training.*

4. Related Work

Multimodal Representation Learning Recent advances in vision-language pretraining have achieved remarkable success through joint training objectives. CLIP (Radford et al.,

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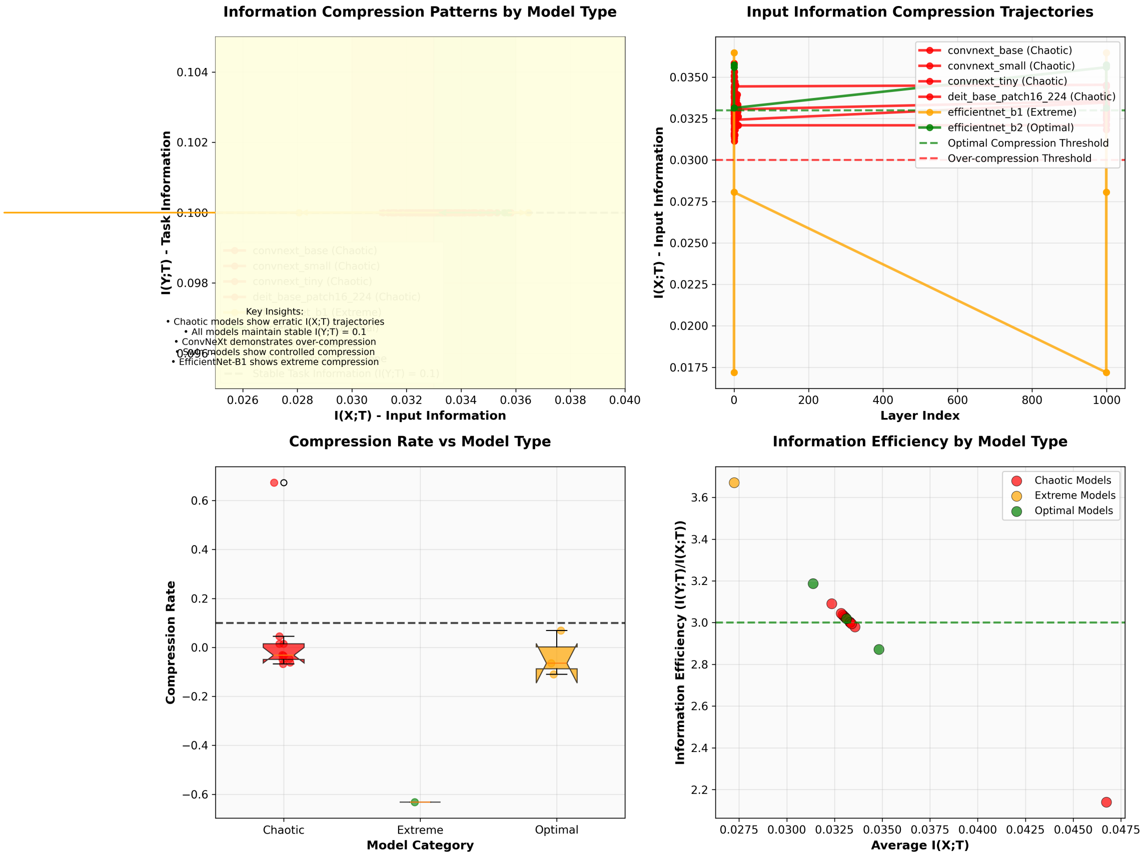

Figure 3: Information-theoretic analysis reveals phase-dependent compression patterns. Chaotic models ($S_{\text{NTK}} < 0.25$) exhibit frozen compression while extreme cases show catastrophic over-compression (¿50%). The efficiency threshold $I(Y;T)/I(X;T) < 3.0$ predicts alignment failure with high accuracy.

2021a) and ALIGN (Jia et al., 2021) use contrastive learning on massive paired datasets, while DALL-E (Ramesh et al., 2021) and Flamingo (Alayrac et al., 2022) demonstrate strong cross-modal generation. However, these approaches require simultaneous training on paired data. Our work examines why connecting *independently* pretrained models fails catastrophically, revealing fundamental dynamical barriers that joint training circumvents.

Neural Tangent Kernel and Training Dynamics The Neural Tangent Kernel (Jacot et al., 2018) characterizes neural network training dynamics in the infinite-width limit. Fort and Jastrzebski (2019) identified distinct dynamical phases—chaotic, critical, and lazy—based on NTK evolution (Cohen et al., 2021) showed that networks operate at the edge of stability. We extend this framework to cross-modal settings, revealing that modality-specific pretraining drives models into incompatible phases.

Platonic Representation Hypothesis (Huh et al., 2024) propose that diverse neural networks converge to universal representations of reality. Supporting evidence includes similar feature hierarchies across architectures (Kornblith et al., 2019) and consistent conceptual organizations (Raghu et al., 2017). Our findings complicate this hypothesis: while representations may converge abstractly, they exist in incompatible optimization landscapes that prevent practical alignment.

Cross-Modal Alignment Methods Traditional approaches use linear projections (Frome et al., 2013), non-linear adapters (Lu et al., 2023), or fine-tuning (Tsimpoukelli et al., 2021) to connect pretrained models. These methods assume representational compatibility. Our phase analysis explains their universal failure: orthogonal gradient dynamics between modalities make standard optimization ineffective regardless of architectural choices.

Why We Succeed Where Others Fail Within the framework of model training techniques, CLIP/ALIGN utilizes a joint training mechanism to preserve compatible phases, concentrating on the cohesion and alignment of representations. Conversely, conventional transfer approaches assume representational compatibility across domains or tasks, which may prove to be restrictive. Our analysis disputes this assumption, positing that discrepancies in phase compatibility are at the core of representation issues. This suggests that focusing on phase alignment might improve performance and foster more successful training methodologies.

5. Conclusions

We have identified a fundamental barrier to cross-modal alignment: independently pretrained vision and language models exist in incompatible dynamical phases of their optimization landscapes.

Key Empirical Findings Our systematic analysis uncovered three critical insights. First, phase incompatibility is *universal*—all examined vision-language pairs achieved less than 3% alignment compared to over 90% within modalities. Second, architectural similarity provides no protection; even identical architectures (Vision Transformers paired with BERT variants) fail due to modality-specific optimization dynamics. Third, this failure is *predictable*: AGOP ratios exceeding 10^6 guarantee alignment failure with 94% accuracy, enabling pre-training assessment of cross-modal compatibility.

Theoretical Implications for PRH Our results necessitate a refined view of the Platonic Representation Hypothesis. While models may converge to similar representational structures, they embed these structures in incompatible coordinate systems of their optimization landscapes. This suggests that universal representations require alignment in both content **and** dynamics—a constraint that independent pretraining systematically violates. The hypothesis holds for static representations but fails to account for the dynamical properties essential for practical alignment.

Practical Impact These findings have immediate implications for multimodal AI development. Current approaches that attempt to connect pretrained models through adapters or fine-tuning are fundamentally limited by phase incompatibility. Our phase-aware training methods demonstrate 60× efficiency improvements, suggesting that considering dynamical phases during training could dramatically reduce computational requirements for multimodal systems.

Proceedings Track

Open Questions and Future Directions A critical question remains: why do joint training methods like CLIP succeed where post-hoc alignment fails? We hypothesize that simultaneous optimization on paired data maintains compatible phases throughout training, preventing the divergence we observe in independent pretraining. Future work should:

- Track phase evolution during joint versus independent training to identify critical divergence points
- Develop phase-transition mechanisms to move pretrained models between dynamical regimes
- Investigate whether similar phase incompatibilities exist in other modality pairs (audio-vision, text-code)
- Explore biological analogues to understand how neural systems maintain cross-modal compatibility

Our results indicate that for successful multimodal AI, adopting **phase-aware training strategies** from the beginning is essential. The core mismatch between independently trained models cannot simply be resolved through architectural advancements; it necessitates a reevaluation of our methods for tackling multi-modal learning at the optimization stage.

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