Semantic Convergence: Investigating Shared Representations Across Scaled LLMs

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Abstract

We investigate feature universality in Gemma-2 language models (Gemma-2-2B & Gemma-2-9B), asking whether models with a fourfold difference in scale still converge on comparable internal concepts. Using the sparse autoencoder (SAE) dictionary learning pipeline, we used pretrained SAEs on each model's residual-stream activations, aligned the resulting monosemantic features via activation correlation, and compared the matched feature spaces with metrics such as SVCCA and RSA. Middle layers yield the strongest overlap, indicating that this is where both models most similarly represent concepts, while early and late layers show much less similarity. Preliminary experiments extending the analysis from single tokens to multi-token subspaces show that semantically similar subspaces tend to interact similarly with LLMs. These results offer further evidence that large language models carve the world into broadly similar, interpretable features despite size differences, reinforcing universality as a foundation for cross-model interpretability.

1 Introduction

Large Language Models (LLMs) (Achiam et al., 2023; Touvron et al., 2023; Guo et al., 2025) have demonstrated increasing reasoning abilities across many tasks (Bubeck et al., 2023). However, our understanding of the internal representations and computations that support this behavior remains limited (Bereska and Gavves, 2024).

Previous work (Lan et al., 2024) has shown that models with the same tokenizer rely on similar internal representations and structures, indicating that universal feature spaces might exist. We define a feature as being universal if its activation corresponds to the same semantic concept regardless of model size or architecture. Universal feature spaces may be encoded across different layers or neurons in different models, but there would exist a sparse direction in each model's activation space that consistently "lights up" on these concepts. Understanding universal feature spaces is a crucial step in learning if general rules govern how LLMs internally structure and use their nodes. This key would increase the generalizability of interpreting different LLMs and may accelerate LLM training efficiency as well as LLM safety (Chughtai et al., 2023; Gurnee et al., 2024; Bricken et al., 2023).

Comparing features between LLMs is challenging because nodes in the model usually represent multiple features, rather than one specific feature. This is called polysemanticity (Elhage et al., 2022). In this paper, we build on the methods shown in Lan et al. (2024) that leverage Sparse Autoencoders (SAEs) to transform LLM node activations into lower dimensional spaces that are easier to interpret. The main advantage of using SAEs is that they have the ability to decompose the complex, polysemantic representations in an LLM into distinct features that can be interpreted more easily (Cunningham et al., 2023; Bricken et al., 2023). Then, representational space similarity metrics are used on these SAE features to check for similarities in the internal structure of the LLM.

Although results for feature universality in Lan et al. (2024) were promising, only single token words, in a limited number of semantic subspaces, were tested for the semantic experiments. Furthermore, the experiments were only carried out against similar sized models, namely Pythia-70m with Pythia-160m (Biderman et al., 2023) and Gemma-1-2B with Gemma-2-2B (Team et al., 2024b,a). Therefore, in this paper, we will further investigate the universality of feature spaces.

In our experiments, we use models with a four

fold size difference. Our results demonstrate that the similarity in internal feature representations remains across these models despite difference in complexity. Furthermore, in our semantic subspaces studies, we show that there are certain groups of overlapping concepts that the models internally represent similarly. This is another indication of feature universality.
In summary, our contributions are the following:

1. Probe universality in multi-token semantic subspaces, including overlaps of related concepts, to see whether phrase-level and higher-order features align across models.

2. Quantify universality across a 4× model-size gap and compare similarity measures (e.g., SVCCA, RSA) to test how metric choice affects the result.

Our results reveal that, despite the fourfold size difference, models share strongly aligned internal representations. In addition, we demonstrate that conceptually coherent semantic groups align. We also illustrate that models encode multi-token phrases across the layers, where phrases are represented more strongly than individual tokens in the earlier layers.

Understanding whether different-sized language models develop similar internal representations has significant practical implications. If models trained independently converge to shared semantic features, this suggests the existence of a common representational structure, opening the door to transferable interpretability tools, cross-scale safety interventions (Engels et al., 2025), and more efficient model distillation pipelines (Turc et al., 2019). These insights could fundamentally reshape how we evaluate, interpret and design future language models.

This result supports the idea that universality is a structural property of the Gemma family, not an accident of size or training noise. It gives practitioners a clear path to build and test interpretability tools on the lighter 2 B model before deploying them unchanged on the 9 B model. Similar mid-layer convergence has also been reported for the Pythia family (70 M → 160 M) by Lan et al. (2024). Taken together with our Gemma results, this suggests that feature universality extends across at least two independent model families.

This work opens up several branches of future research that we believe are worth studying. Training SAEs on multiple model layers can reveal internal representations that are not captured in a single layer. In addition, comparing the internal representations of SAEs trained on MLP layers may provide deeper insights about the universality of MLP features. These findings can accelerate AI reasoning and safety training (Hendrycks et al., 2023). Through understanding the similarities between models, and their differences, a more complete picture of how LLMs process, reason and understand natural language would be formed (Lan et al., 2024).

2 Background

Sparse Autoencoders. Sparse Autoencoders (SAEs) are a type of neural network used to learn efficient, sparse representations of input data (Makhzani and Frey, 2013). Unlike other autoencoders, SAEs incorporate a sparsity constraint, typically an L1 penalty on the hidden layer activations or a KL divergence term, which pushes most hidden units to be inactive (i.e. any output values close to zero) for any input given. This leads to features that are more interpretable and disentangled. The aim is to discover a basis of features, similar to dictionary learning (Olshausen and Field, 1997), where each feature activates for semantically meaningful concepts.
Mathematically, an input $x \in \mathbb{R}^n$ is given to the neural network which is reconstructed into $\hat{x}$ using $\hat{x} = W'\sigma(Wx + b)$, where $W \in \mathbb{R}^{hxn}$ is the encoder weight matrix, b is the bias term, σ is a nonlinear activation function, and W' is the decoder matrix, which often uses the transpose of the encoder weights. SAE training seeks to both encourage sparsity in the activations $h = \sigma(Wx + b)$ and to minimize the reconstruction loss $L_{\text{rec}}(x, \hat{x}) = \|x - \hat{x}\|^2$.

3 Methods

3.1 Feature Pairings

To determine whether different models of varying sizes converge on similar internal representations, generalizations of feature spaces, spaces formed by feature groups, and feature relations must be explored. To quantitatively measure these

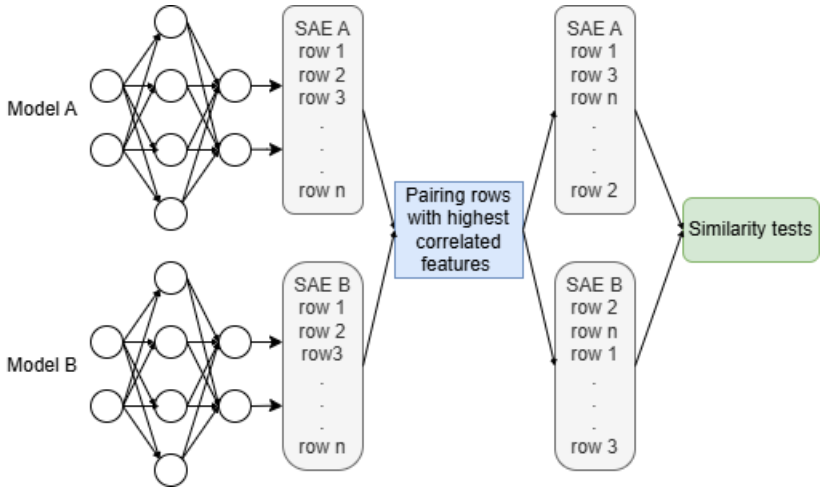

Figure 1: Workflow of pairing rows with the highest correlated features between two models (Gemma-2-2B and Gemma-2-9B) and performing similarity tests to assess feature alignment.

similarities, we follow the methods of Lan et al. (2024). Overall, we compare an SAE trained on layer A_i from LLM A with another SAE trained on layer B_j from LLM B for every layer pairing.

However, accurate comparisons between spaces hinges on solving two issues:
Permutation issue. To solve the permutation issue, we find neuron pairings that are the most similar in SAE_A and SAE_B. Since the mapping of features is unknown due to arbitrary neuron indexing and some features may not have a "similar" feature in the other SAE, we pairwise match them using a correlation metric.
Rotational Alignment issue. Even after permutation alignment, each SAE may use its own orthonormal basis for latent space. To ensure that the true relational similarity is captured, we apply rotation-invariant similarity measures, namely SVCCA and RSA.

To score the results against a baseline, randomly paired features are obtained. Then, the score of the features paired by correlation (referred to as "paired features") is compared with the average score of N runs of randomly paired features to obtain a p-value score.

3.1.1 1-to-1 vs. Many-to-1 Feature Matching

Following Lan et al. (2024), we consider two ways of pairing SAE features from layer A_i of the first model with layer B_j of the second.

1-to-1 (bijective) matching. We iteratively build a one–to–one assignment: at each step we pick the still–unmatched pair of features with the highest Pearson correlation. Each feature is used at most once, yielding a bijection of size $K = \min(|A_i|, |B_j|)$.

Many-to-1 matching. To probe whether the entire dictionary of the smaller layer can be embedded inside the larger one, we relax the uniqueness constraint on layer B_j. Every feature in A_i is matched to its most-correlated partner in B_j, even if that target has already been claimed by other sources. Thus one feature in B_j may receive multiple links, while each feature in A_i is still matched exactly once.

Unless stated otherwise, all correlations are computed with Pearson correlation; the aligned pairs returned by the chosen strategy are then fed into the subsequent SVCCA and RSA calculations.

3.2 Representational Similarity Metrics

3.2.1 Singular Value Canonical Correlation Analysis (SVCCA)

Singular Value Canonical Correlation Analysis (Raghu et al., 2017) is a variation of the Canonical Correlation Analysis CCA (Hotelling, 1936) which finds a pair of the most correlated variables, u_i and v_i from two sets of variables $X \in \mathbb{R}^{n \times d_1}$ and $Y \in \mathbb{R}^{n \times d_2}$. Before applying CCA, SVCCA reduces noise by applying Singular Value Decomposition (SVD) to X and Y using $X = U_X S_X V_X^T$ and $Y = U_Y S_Y V_Y^T$, where U_X and U_Y are the matrices containing the left singular vectors (informative directions), and S_X and S_Y are diagonal matrices containing the singular values. After CCA is applied on the new data, correlation scores

between the most informative components are obtained, which are then averaged to get a similarity score. SVCCA measures how well subspaces of two SAE weight matrices align, essentially quantifying the global feature space overlap.

3.2.2 Representational Similarity Analysis (RSA)

Representational Similarity Analysis (Kriegeskorte et al., 2008) calculates, for each space, a Representation Dissimilarity Matrix (RDM) $D \in \mathbb{R}^{nxn}$. Each element in this matrix represents the dissimilarity between every pair of data points in the space. Following RDM, a correlation metric such as Spearman's rank correlation coefficient is used to compute a similarity score.

3.3 Semantic Subspaces

In addition to the layer-wise SAE comparisons, we also test semantic subspaces, collections of words defined by a high-level concept that contain concept-specific keywords. For example, "emotions" is a subspace with concept-specific keywords like "happy"and "sad". By testing these subspaces, we can evaluate whether LLMs encode the same semantic categories.

For each high-level concept, we first use GPT-4o (Achiam et al., 2023) to generate three independent lists of representative keywords. We then intersect these lists and retain only terms that are unambiguous (each having a single and clear meaning). Next, we add to the keyword set their hyponyms from WordNet (wor, 2010). This combined collection of keywords plus and their hyponyms defines the final semantic subspace for that concept.

To evaluate semantic subspaces more rigorously, we combine two different subspaces in the following ways:

Multi-token subspaces: In the multi-token subspaces, we concatenate keywords from different concepts together. For instance, "happy" (from "emotions") and "child" (from "person") becomes "happy child". In these types of subspaces, we aim to understand if different LLMs internally process longer sentences similarly. Furthermore, we concatenated unlikely pairs of concepts, such as "calendar" and "emotions", which the LLMs were unlikely to see during their training to check whether the LLMs process previously unseen data in a similar manner.

Overlapping subspaces: Overlapping subspaces are formed by taking the union of whole subspaces together. For instance, the "emotions" and "person" subspaces would yield ("happy", "teacher", "sad", "child", ...). This aims to test if the different LLMs interact with multiple concepts similarly.

4 Experiments and Results

4.1 Feature Analysis

Layer-wise similarity of full SAE spaces

1-to-1 (5 run mean): In Fig. 2a the diagonal band of Paired SVCCA now peaks at 0.73 (Gemma-2-2B L14 and Gemma-2-9B L19) and stays consistently high across contiguous mid-layer pairs (0.64 – 0.71). Early layers sit at 0.35 ± 0.05, and the last decoder layer of Gemma-2-9B (L39) experiences a drop to an average of 0.374. Through these visualizations (Fig. 2a & Fig. 2b), it is observable that the middle layers between both models share the most similarity compared to other layers.

Paired RSA (Fig. 2b) follows the same shape but at roughly one-third of the magnitude: maxima of 0.22 and a midlayer plateau of 0.15 – 0.20, with edges staying less than 0.08. Yet again, the last decoder layer of Gemma-2-9B (L39) experiences a drop. This figure further displays the pattern of middle layers sharing the most similarity, especially compared to early and late layers.

Many-to-1 (Single run): When we allow duplicates (Fig. 4a) the peak SVCCA softens to 0.69 (Gemma-2-2B L14 and Gemma-2-9B L19) and the mid-layer plateau narrows (0.54 – 0.66). RSA follows suit, topping out at around 0.18 - 0.2. This confirms that when features are matched more than once, the alignment scores drop slightly, but the overall pattern is maintained.

Many-to-1 (5 run mean): Averaging five random initializations barely changes the picture (Fig. 6a): peak SVCCA = 0.69, peak RSA = 0.20. The variance across runs is <0.02 for every cell, indicating that the many-to-one procedure is stable, but still consistently lower than the ceiling of the 1-to-1 strategy.

Random-pair baselines and significance. Across the three experiments, the mean random SVCCA spans 0.005 – 0.034, with a majority of cells below 0.02 (Fig. 8a, Fig. 9a, Fig. 10a). Consequently, every empirical SVCCA score

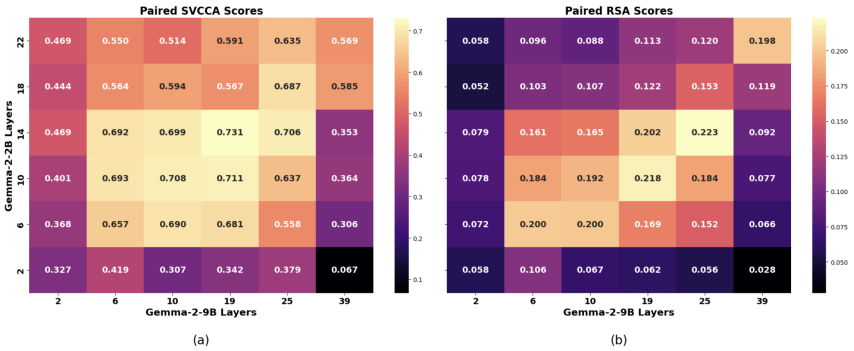

Figure 2: (a) SVCCA and (b) RSA 1-to-1 paired scores of SAEs for layers in Gemma-2-2B vs Gemma-2-9B. Note the pattern of higher scores between the middle layer pairings indicating similarity in middle layers between both models.

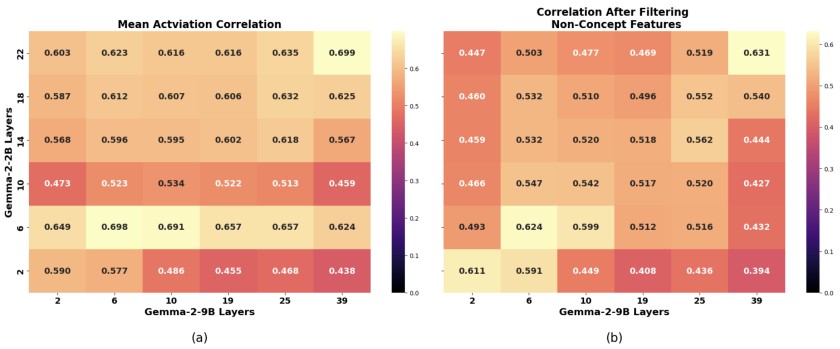

Figure 3: (a) 1-to-1 Mean Activation Correlation before and (b) after filtering non-concept features for Gemma-2-2B vs Gemma-2-9B. Note these patterns generally contrast from those of the SVCCA and RSA scores in Figure 2, indicating that these metrics each reveal different patterns not shown previously such as the pattern of middle layers between both models exhibiting higher correlation.

beyond the first residual layer lands in the 0.0 p-value bucket ($\leq 0.1\%$ chance of getting such a good alignment by random) (Fig. 8b, Fig. 9b, Fig. 10b). In other words, even the weakest observed alignment (SVCCA $\approxeq 0.30$) is simply too strong to be by chance.

Effect of filtering non-concept features. Mean activation correlation before filtering peaks at 0.70 (L22 & L39) and averages 0.60 ± 0.07 on the mid-layer block (Fig. 3a). After removing unimportant features (Fig. 3b) the pattern of middle layers having an increased correlation between the two models becomes more evident, while more surrounding random matches fall by 0.10 – 0.15, raising the peak correlation from 0.70 to 0.74. Another result to note is that early layers and late layers of both models share strikingly higher similarity compared to other layers; for example L2 of both models, L6 of both models, and Gemma-2-2B L22 & Gemma-2-9B L39 all have the highest correlation (Fig. 3b, Fig. 5b, Fig. 7b). In other words, removing low-level features (such as punctuation) made strong alignments clearer and more meaningful, without just artificially boosting scores.

4.2 Semantic Subspace Analysis

Semantic subspace alignment. When we fix a single Gemma-2-2B layer and correlate every semantic-concept row against layers 2, 6, 10, 19, 25, and 39 for Gemma-2-9B, the same mid-on-mid pattern re-emerges: mid-stack layers in both models align best. Among the 2-2B sources we tried, the layer centered around L14 most consistently exhibited the highest SVCCA and RSA scores, reinforcing the idea that internal concept geometry more commonly converges in the middle of the networks. Full heat-maps for every source layer and metric are collected in Appendix B.

Overlapping Semantic Subspaces. When two semantic subspaces are combined, there are two different trends in the results based on the compatibility of the subspaces. For instance, combining

Overlapping Concept	Paired SVCCA Mean	Random Shuffling Mean	p-value
Emotion and Time	0.62	0.13	0.0
Nature and People	0.63	0.17	0.0

Table 1: Comparison of paired SVCCA, random shuffling mean, and p-values for reasonable pairs of concepts at layers 10 of both Gemma-2-2B and Gemma-2-9B.

Overlapping Concept	Paired SVCCA Mean	Random Shuffling Mean	p-value
Country and People	0.03	0.13	0.02

Table 2: Comparison of paired SVCCA, random shuffling mean, and p-values for bad pairs of concepts at layers 10 of Gemma-2-2B and layer 19 of Gemma-2-9B. These results indicate that these pairs are not encoded similarly

the subspaces "country" and "people" in Table 2 which is a non-ideal pair results in low average SVCCA and RSA scores across the layers, indicating that there is insignificant correlation in how the models internally represent this subspace. This phenomenon could be caused by the fact that the models are unlikely to group these subspaces together during training. However, when the pair of subspaces being combined makes sense, such as "nature" and "people" in Table 1, both the SVCCA and RSA scores are high, leading to the conclusion that both models represent these subspaces very similarly. All of the results are in Appendix C.

Multi-token Semantic Subspaces. Despite resource constraints limiting our evaluations to the "emotions time" subspace, our preliminary results on multi-token subspace (see Table 3) provide key insights. Notably, high SVCCA scores remained in the early and middle layers, providing strong empirical evidence that models sometimes encode multi-token concepts. Furthermore, the SVCCA scores are drastically higher than "emotions" or "time" alone in the early layers (see Appendix B), indicating that earlier layers represent multi-token subspaces rather than single-token ones. This result challenges the popular, underlying assumption that models internally encode single-token concepts (Dehouck, 2023; Valois et al., 2024). Hence, we believe that meaning is sometimes distributed across multiple tokens, and that semantic subspaces are the better level of analysis.

Distance metrics. During layer-to-layer SAE feature analysis, we have used the Pearson correlation as done in Lan et al. (2024). We tested other metrics such as the cosine similarity and euclidean distance; however, changing the similarity metric did not yield any statistically significant changes in the results, implying that the distance metric used does not affect the accuracy of our results.

5 Related Works

Superposition and Sparse Autoencoders. Previous studies have shown that, when there are more features to be represented than available parameters, feature representations are distributed across multiple parameters, leading to polysemantic neurons (Elhage et al., 2022). Polysemanticity causes challenges in interpreting models, which is crucial for AI safety in identifying goal misgeneralization (Shah et al., 2022; Langosco et al., 2022) as well as deceptive misalignment (Hubinger et al., 2024; Greenblatt et al., 2024). For these reasons, Sparse Autoencoders (SAEs) have been used to transform polysemantic neuron activations into monosemantic feature neurons that usually correspond to one feature (Makhzani and Frey, 2013; Cunningham et al., 2023; Gao et al., 2024; Rajamanoharan et al., 2024a,b). It is much easier to conduct quantitative interpretability studies on these monosemantic features.

Feature Universality. The existance of "universal" neurons across LLMs were first uncovered in a study of GPT-2 (Gurnee et al., 2024). Furthermore, previous studies that have performed quantitative analysis using SAEs to test for feature universality (Lan et al., 2024; Bricken et al., 2023) have shown universality in analogous features and representational features (Olah et al., 2020; Yosinski et al., 2014; Gurnee et al., 2024; Kornblith et al., 2019). These are not measures of "true features", which are stricter ground-truth features (Bricken et al., 2023) that represent atomic linear directions (Till, 2023).

Previous research on SAEs to test for feature universality (Lan et al., 2024) has demonstrated that, after aligning neurons via mean activation correlation, there exists statistically significant alignment ($p < 0.05$) for almost all non-input

Multi-token Concept	Paired SVCCA Mean	Random Shuffling Mean	p-value
Emotion and Time (L6 vs L2)	0.27	0.02	0.0
Emotion and Time (L6 vs L10)	0.53	0.02	0.0

Table 3: Comparison of paired SVCCA, random shuffling mean, and p-values for bad pairs of concepts at layers 6 of Gemma-2-2B and layer 2 and 10 of Gemma-2-9B. These results indicate that multi-token inputs are encoded similarly.

layers. The middle layers exhibited the strongest correspondence, indicating that distinct LLMs learn a shared set of features. Beyond layer-wise comparisons, semantically defined subspaces were tested by filtering features whose top activating tokens match curated keyword lists linked to a conceptual category such as "Emotions"or "Time". These subspaces yielded high SVCCA scores with $p \ll 0.05$, illustrating that semantic concept feature groups are more consistent across models.

Mechanistic Interpretability. Interpreting neurons and MLP analysis have become increasingly popular (Foote et al., 2023; Garde et al., 2023) techniques to understand the inner workings of LLMs. Other mechanistic interpretability methods have used SAEs (Lan et al., 2024; Nanda and Conmy, 2024) because of their more interpretable feature spaces.

6 Conclusion

In this paper, we provided a comprehensive study on feature universality in models of different sizes. Our experiments reveal that, in many cases, internal representations are similar across models regardless of size. In addition, our semantic subspace experiments revealed that different models encode pairs of subspaces and multi-token subspaces similarly, further enforcing the concept of LLM universality. These findings are a key step in forming a comprehensive understanding of how LLMs internally function.

7 Limitations

This study focused only on the Gemma-2-2B and Gemma-2-9B models due to resource constraints, particularly GPU availability and compute time. While this size comparison captures meaningful differences in model scale, further work could extend our approach to a wider range of architectures, parameter counts, tokenizers and layer comparisons. It is important to note that using models with the same tokenizer leads to higher quality pairings and thus higher accuracy results (Lan et al., 2024). Additionally, the number of SAE-derived subspaces we analyzed was limited to keep manual inspection and downstream evaluations manageable. Expanding this analysis to a larger, more diverse set of subspaces could help further characterize the extent and nature of feature space universality. Furthermore, our experiments with multi-token subspaces only tested a single subspace due to further resource limitations.

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A Additional Results

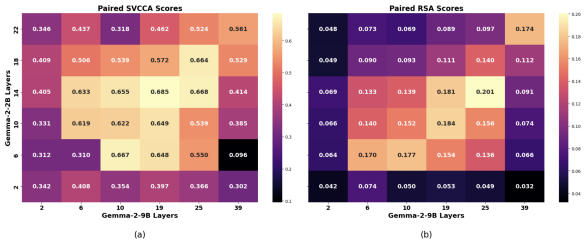

Figure 4: (a) SVCCA and (b) RSA Many-to-1 paired scores of SAEs for layers in Gemma-2-2B vs Gemma-2-9B. Note the pattern of higher scores in the middle layers indicating similarity in middle layers between both models.

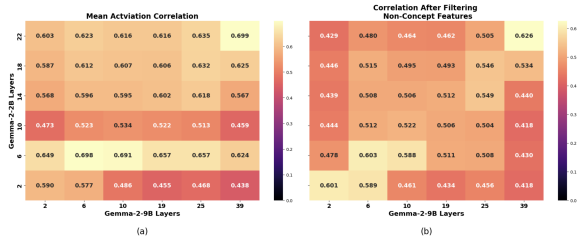

Figure 5: (a) Many-to-1 Mean Activation Correlation before and (b) after filtering non-concept features for Gemma-2-2B vs Gemma-2-9B. Note these patterns generally contrast from those of the SVCCA and RSA scores in Figure 2, indicating that these metrics each reveal different patterns not shown previously.

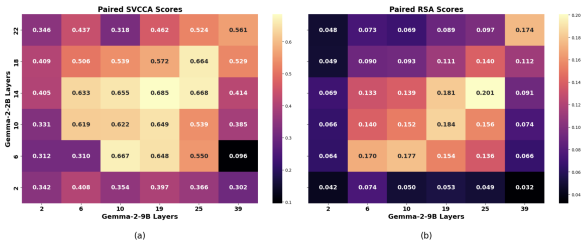

Figure 6: (a) SVCCA and (b) RSA Many-to-1 (5 run average) paired scores of SAEs for layers in Gemma-2-2B vs Gemma-2-9B. Note the pattern of higher scores in the middle layers indicating similarity in middle layers between both models. This pattern is a trend in layer similarity between the three experiments as seen in Fig. 2a, Fig. 2b, Fig. 10a, and Fig. 4b.

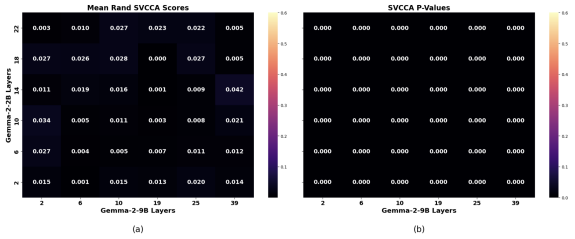

Figure 9: (a) Mean Randomly Paired SVCCA Many-to-1 scores and (b) SVCCA Many-to-1 P-values of SAEs for layers in Gemma-2-2B vs Gemma-2-9B.

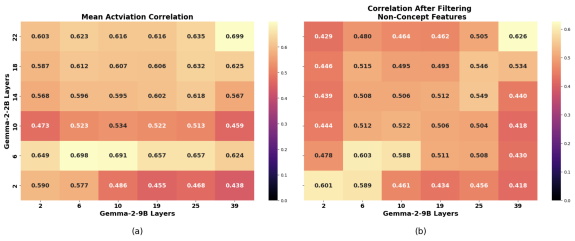

Figure 7: (a) Many-to-1 (5 run average) Mean Activation Correlation before and (b) after filtering non-concept features for Gemma-2-2B vs Gemma-2-9B. Note these patterns generally contrast from those of the SVCCA and RSA scores in Figures 2, 4, and 6, indicating that these metrics each reveal different patterns not shown previously.

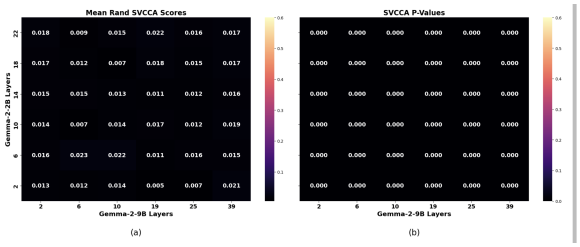

Figure 8: (a) Mean Randomly Paired SVCCA 1-to-1 scores and (b) SVCCA 1-to-1 P-values of SAEs for layers in Gemma-2-2B vs Gemma-2-9B.

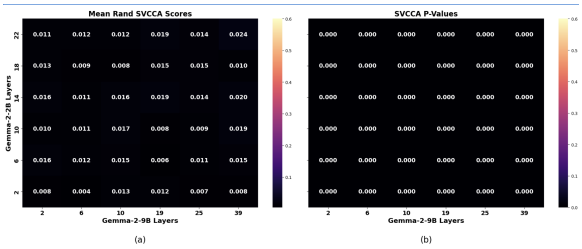

Figure 10: (a) Mean Randomly Paired SVCCA Many-to-1 scores and (b) SVCCA Many-to-1 (5 run average) P-values of SAEs for layers in Gemma-2-2B vs Gemma-2-9B.

B Semantic Subspace Similarity (Gemma-2-2B → Gemma-2-9B).

The following figures visualize concept-wise alignment from fixed layers of Gemma-2-2B to all layers of Gemma-2-9B. Each heatmap row corresponds to a semantic category (e.g., *Emotions*, *Biology*) and each column is a layer in Gemma-2-9B.

We show both SVCCA and RSA 1-to-1 results for 2-2B source layers L6, L10, L14, and L17. These help assess which layers in Gemma-2-9B best match the concept geometry of the smaller model. For most layers, similarity scores peak in the mid-stack (L10–L19), further supporting the cross-model alignment trend observed in Section 4.

* *Some concepts may not appear across all rows if they lacked sufficient matched features or token coverage.*

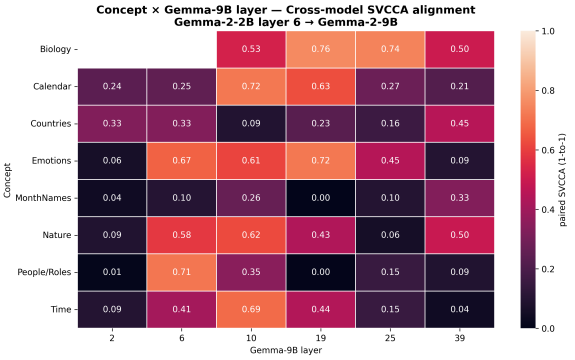

Figure 11: Scores rise into the mid-layers, peaking near 0.40 at L10–L19.

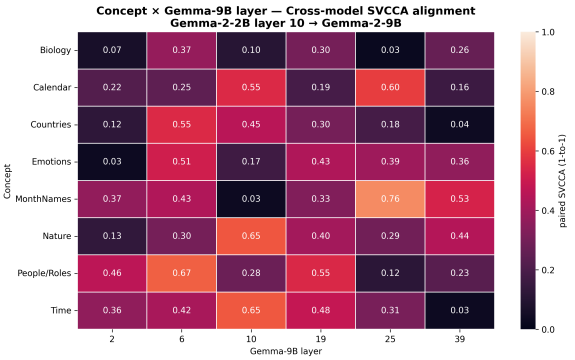

Figure 12: Mid-layer alignment strengthens; several concepts surpass 0.60.

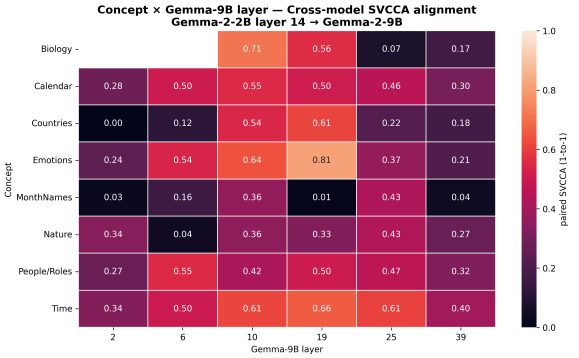

Figure 13: Highest similarity sits in the center stack; edge layers lag.

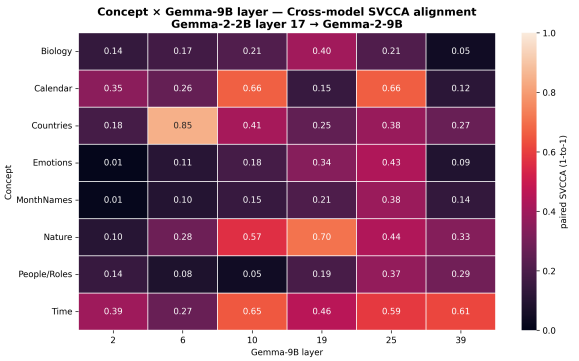

Figure 14: Alignment remains centered; deep and early layers score lower.

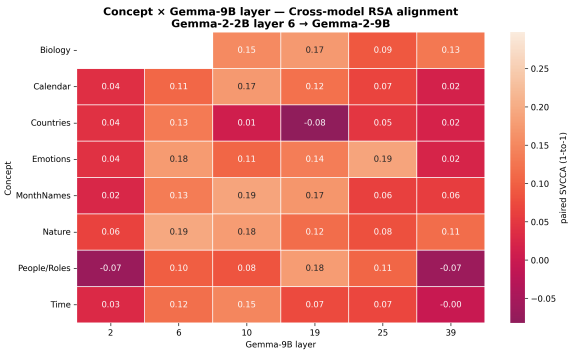

Figure 15: Mid-layer RSA peaks near 0.17; edge layers stay low. *People/Roles* dips below 0 at L2.

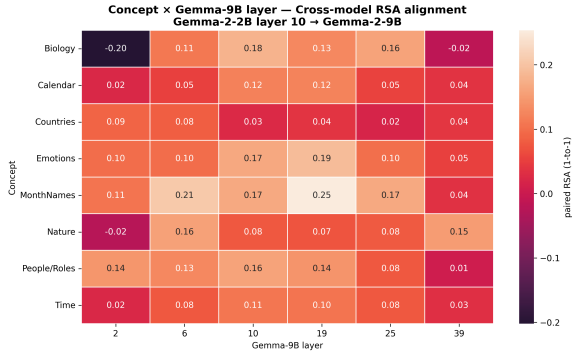

Figure 16: Mid-to-deep pairs score higher: *Biology*, *Month-Names* reach ∼0.25 at L19.

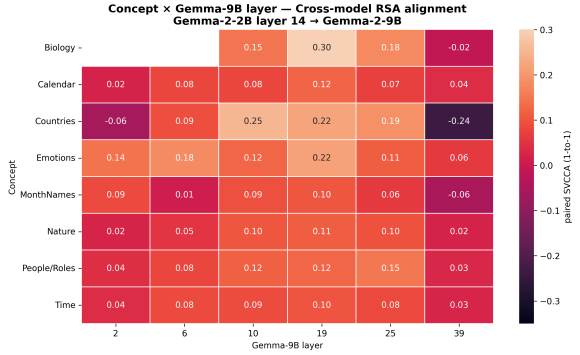

Figure 17: Highest scores at 9B L19: *Biology* ∼0.30, *Countries* ∼0.25. L2 and L39 remain near zero.

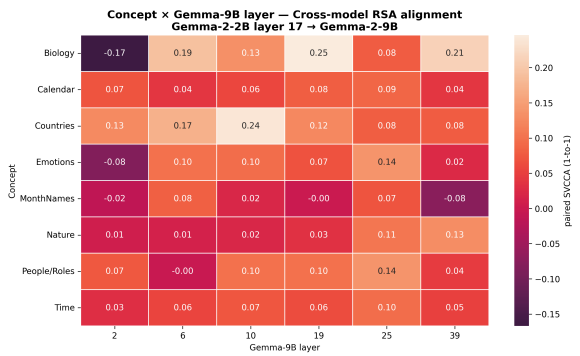

Figure 18: Strongest alignment at L19; outer layers weak or negative.

C SVCCA by concept in Gemma-2-2B and Gemma-2-9B.

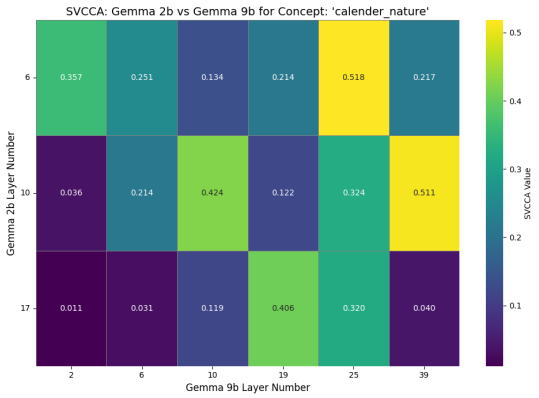

Figure 19: paired SVCCA 1-to-1 for calendar-nature concept

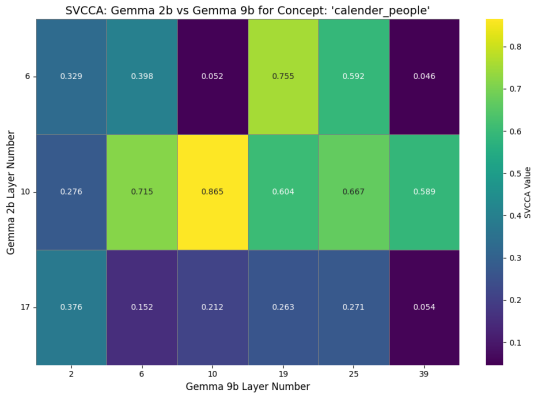

Figure 20: paired SVCCA 1-to-1 for calendar-people concept

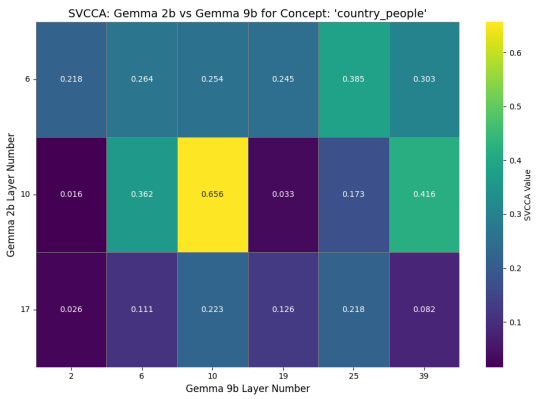

Figure 21: paired SVCCA 1-to-1 for country-people concept

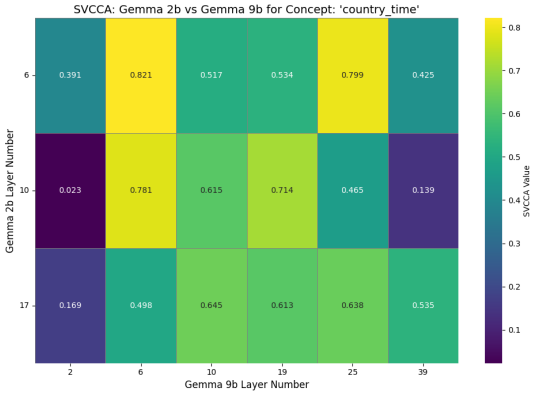

Figure 22: paired SVCCA 1-to-1 for country-time concept

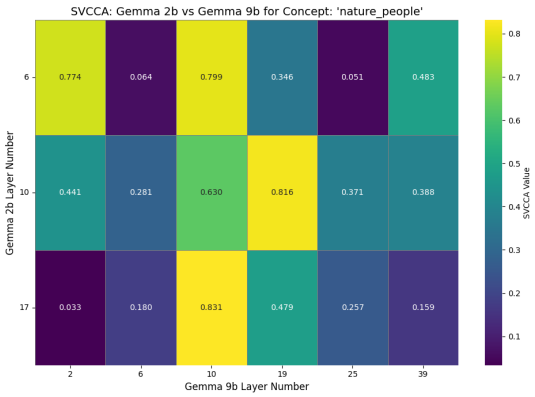

Figure 23: paired SVCCA 1-to-1 for nature-people concept

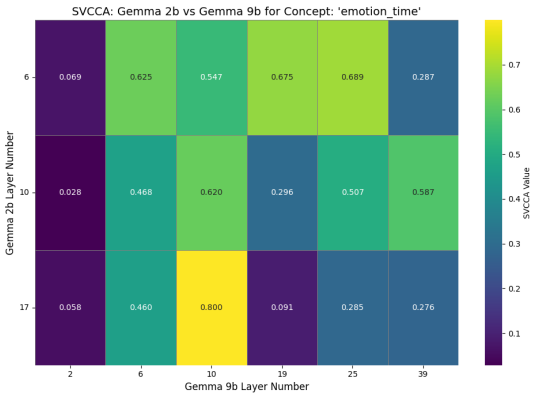

Figure 24: paired SVCCA 1-to-1 for emotion-time concept