THE SEMANTIC HUB HYPOTHESIS: LANGUAGE MODELS SHARE SEMANTIC REPRESENTATIONS ACROSS LANGUAGES AND MODALITIES

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ABSTRACT

Modern language models can process inputs across diverse languages and modalities. We hypothesize that models acquire this capability through learning a shared representation space across heterogeneous data types (e.g., different languages and modalities), which places semantically similar inputs near one another, even if they are from different modalities/languages. We term this the semantic hub hypothesis, following the hub-and-spoke model from neuroscience (Patterson et al., 2007) which posits that semantic knowledge in the human brain is organized through a transmodal semantic "hub" which integrates information from various modality-specific "spokes" regions. We first show that model representations for semantically equivalent inputs in different languages are similar in the intermediate layers, and that this space can be interpreted using the model's dominant pretraining language via the logit lens. This tendency extends to other data types, including arithmetic expressions, code, and visual/audio inputs. Interventions in the shared representation space in one data type also predictably affect model outputs in other data types, suggesting that this shared representations space is not simply a vestigial byproduct of large-scale training on broad data, but something that is actively utilized by the model during input processing.

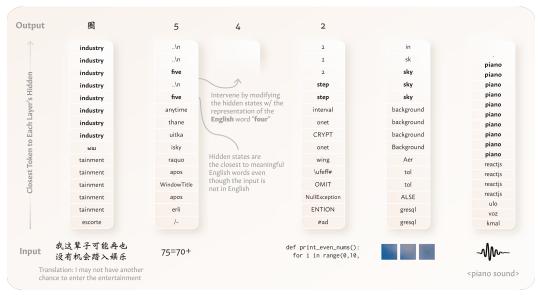


Figure 1: Examples of the semantic hub effect across input data types. For every other layer, we show the closest output token to the hidden state based on the logit lens. Llama-3's hidden states are often closest to English tokens when processing Chinese texts, arithmetic expressions, and code, in a semantically corresponding way. LLaVA, a vision-language model, and SALMONN, an audio-language model, have similar behavior when processing images/audio. As shown for the arithmetic expression example, models can be intervened cross-lingually or cross-modally, such as using English even though the input is non-English, and be steered towards corresponding effects. Boldface is only for emphasis.

1 Introduction

Modern language and multimodal models (LMs)¹ are capable of processing heterogeneous data types: text in different languages, non-linguistic inputs such as code and math expressions, and even other modalities such as images and sound. How do LMs process these distinct data types with a single set of parameters? One strategy might be to learn specialized subspaces for each data type that are only employed when processing it. In many cases, however, data types that are surface-distinct share underlying semantic concepts. This is most obvious for sentences in different languages with the same meaning; but such shared concepts are present across other data types, e.g., between an image and its caption, or a piece of code and its natural language description. The human brain, for example, is believed to have a transmodal "semantic hub" (Patterson et al., 2007; Ralph et al., 2017) located in the anterior temporal lobe that integrates and stores semantic information from various modality-specific "spokes" (e.g., visual/auditory cortices). A model, leveraging the structural commonalities across data types, could similarly project their surface forms into a *shared* representation space, perform computations in it, and then project back out into surface forms when needed.

To what extent is this idealized strategy adopted by actual models? Wendler et al. (2024) find that on simple synthetic tasks, Llama-2 (Touvron et al., 2023) maps various input languages into a shared "English space" before projecting back out into another language, hinting that it leverages this shared representation scheme to an extent, at least for different languages. We show that this is a much more general phenomenon: when a model processes inputs from multiple data types, there is a shared representation space, and this space is scaffolded by the LM's inherently dominant language (usually English). By scaffolded, we mean that the shared space can be interpreted to an extent in the dominant data type via the logit lens (nostalgebraist, 2020). Following the cognitive science nomenclature, we call this shared representation space the LM's "semantic hub."

We first show that LMs represent semantically similar inputs from distinct data types (across languages, or between natural language and arithmetic expressions, code, formal semantic structures, and multimodal inputs) to be close to one another in intermediate LM layers. We further show that we can interpret these hidden representations to an extent using the LM's dominant data type—e.g., when processing a Chinese input, an English-dominant LM "thinks" in English before projecting back out to a Chinese space. Finally, we perform intervention experiments showing that intervening in the shared representation space using the LM's dominant data type, predictably affects model output when processing other data types; that is, the shared representation space (and the processing of these representations through subsequent layers) is not a vestigial byproduct of the model's being trained on (say) English-dominant text, but causally impacts model behavior.

Our work is complementary and distinct from prior work which finds structural similarities between the representation spaces of models trained (usually independently) on different data types, such as those showing that text representations from text-only LMs can be aligned, via a transformation, to vision/audio representations of modality-specific models (Ilharco et al., 2021; Merullo et al., 2022; Li et al., 2023; Ngo & Kim, 2024; Huh et al., 2024; *i.a.*), and the literature on cross-lingual word embedding alignment (Mikolov et al., 2013; Artetxe et al., 2017; Conneau et al., 2018; Schuster et al., 2019; *i.a.*). We instead show that an LM trained on multiple data types represents and processes them in a shared space *without* requiring explicit alignment transformation. We hope our findings shed light on ways to more easily interpret the mechanisms of current models and motivate future work aimed at better controlling models using these insights.²

2 THE SEMANTIC HUB HYPOTHESIS

Let \mathcal{X}_z be the domain of some data type $z \in \mathcal{Z}$ where \mathcal{Z} is the set of model-supported data types. E.g., for languages, $\mathcal{X}_{\text{Chinese}}$ could be all Chinese tokens, while for images $\mathcal{X}_{\text{Image}} = [0, 255]^{w \times h \times 3}$ could be the RGB values for an $w \times h$ -sized image patch. Consider a function $M_z : \mathcal{X}_z^* \to \mathcal{S}_z$ mapping an input sequence into a semantic representation space \mathcal{S}_z (i.e., the "hub"), and a verbalization function $V_z : \mathcal{S}_z \to \mathcal{X}_z^*$. Given an input prefix $w_{1:t}^z \in \mathcal{X}_z^*$ of length t where $w_i^z \in \mathcal{X}_z$, a sensible (implementation-agnostic) way to continue the sequence is to first encode the input into a modality-

¹Hereafter, we use the term "language model" loosely and also consider multimodal language models that process additional data modalities, since such models are commonly trained on top of a text LM backbone.

²We release our code at https://github.com/ZhaofengWu/semantic-hub.

agnostic representation $m^{in} = M_z(w_{1:t})$, reason and formulate a representation of possible futures to obtain $m^{out} \in \mathcal{S}_z$, and finally verbalize it via $V_z(m^{out})$.

An LM parameterizes a similar process: it uses $M_{\rm LM}$ to map various input data types into a representation space $\mathcal{S}_{\rm LM}\subseteq\mathbb{R}^d$ (early layers), performs computations in the space (middle layers), and verbalizes the output via $V_{\rm LM}$ (end layers and the LM head). However, it is unknown as to how different data types are structured in the representation space. For example, one possibility is that the LM partitions \mathbb{R}^d into disjoint subspaces for each data type and processes them separately. We instead hypothesize that LMs, through training, learn to represent and process different data types in a *shared* representation space that functions as a modality-agnostic "semantic hub." That is, semantically similar inputs $w_{1:t}^{z_1}$ and $w_{1:t'}^{z_2}$ from distinct data types—for example texts in different languages that are mutual translations—are similarly mapped in $\mathcal{S}_{\rm LM}$; informally, $M_{\rm LM}(w_{1:t'}^{z_1}) \approx M_{\rm LM}(w_{1:t'}^{z_2})$. However, absolute similarity measures (i.e., $\sin(M_{\rm LM}(w_{1:t'}^{z_1}), M_{\rm LM}(w_{1:t'}^{z_2}))$) are generally difficult and unintuitive to interpret in high dimensional spaces. We thus focus on relative similarity measures, taking a semantically unrelated sequence $w_{1:t'}^{z_2}$, and evaluating whether $w_{1:t'}^{z_1}$ is closer to $w_{1:t'}^{z_2}$ than $w_{1:t'}^{z_2}$, as illustrated on the left of Figure 2. Formally:

$$\sin\left(M_{LM}(w_{1:t}^{z_1}), M_{LM}(w_{1:t'}^{z_2})\right) > \sin\left(M_{LM}(w_{1:t}^{z_1}), M_{LM}(u_{1:t''}^{z_2})\right). \tag{1}$$

Moreover, when the LM has a dominant data type z^* in training (e.g., English for Llama-2), we hypothesize that this shared representation space is "anchored" by tokens in z^* (denoted as τ^{z^*}), thereby allowing the semantic hub to be interpretable. We focus on anchor tokens that represent a continuation of the input, which autoregressive LMs are trained to model. Informally, $M_{LM}(w_{1:t}^z)$ is close to the embedding of token τ^{z^*} , which represents a corresponding continuation in z^* , more than some τ^{z° in a nondominant data type z° , even when z° is the input data type. In Figure 2, e.g., with an English-dominant LM, its encoding of the Chinese prefix $w_{1:t}^{z^{\circ}}$ ="这篇 论文太难"(trans. "This paper is so

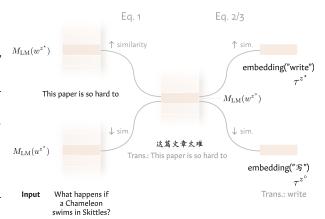


Figure 2: An illustration of our hypothesis, where semantically equivalent inputs (across data types) have similar representations, and this representation is close to the continuation token in the dominant data type. Here, z^* is English and z° is Chinese.

hard to") should be closer to the representation of the continuation word in English τ^{z^*} ="write" than its Chinese translation τ^{z° =" Ξ ". Formally:

$$\operatorname{sim}\left(M_{\operatorname{LM}}(w_{1:t}^{z^{\circ}}), \operatorname{emb}(\tau^{z^{\star}})\right) > \operatorname{sim}\left(M_{\operatorname{LM}}(w_{1:t}^{z^{\circ}}), \operatorname{emb}(\tau^{z^{\circ}})\right). \tag{2}$$

2.1 METHOD: TESTING THE SEMANTIC HUB HYPOTHESIS

We test the semantic hub hypothesis for LMs by considering pairs of distinct data types, the dominant one z^* and a non-dominant one z° , different for each experiment. When semantically related inputs are available (e.g., an image and its caption), we directly test Eq. 1 by using h_t^ℓ , the LM's hidden state at position t and layer ℓ , as $M_{\rm LM}(w_{1:t}^z)$, and using cosine similarity for the similarity function.

We operationalize Eq. 2 via the *logit lens* (nostalgebraist, 2020), a simple training-free approach for interpreting the hidden states of a model. Transformer LMs produce the next-token distribution using softmax (Oh_t^L) (omitting the bias term) where O is the output token embeddings (or "unembeddings") and h_t^L is the final layer hidden state. Logit lens applies the same operation to the intermediate layers $\ell \in [L]$ to obtain $p^{\text{logitlens}}(\cdot \mid h_t^\ell) := \operatorname{softmax} (Oh_t^\ell)$. Logit lens has been found to produce meaningful distributions that shed light on an LM's internal representations and computations.

³See for example Beyer et al. (1999). Most prior work on probe also implicitly use a relative similarity measures since the similarity scores are normalized over a finite label set.

Under the logit lens, $emb(\cdot)$ in Eq. 2 is the output embedding of a token. Using the dot product for $sim(\cdot)$, Eq. 2 is equivalent to comparing the logit lens probabilities,

$$p^{\text{logitlens}}\left(\tau^{z^{\star}} \mid h_{t}^{\ell}\right) > p^{\text{logitlens}}\left(\tau^{z^{\circ}} \mid h_{t}^{\ell}\right),\tag{3}$$

i.e., testing whether the probability of the continuation in the dominant language is more likely than the continuation in the original input data type. Since the logit lens is tailored for probing out a single token, we usually consider short-enough verbalizations such that a single BPE token can reliability identify it, such as when the two verbalizations are two single words that are semantic equivalents. But we also consider longer future verbalizations when its first token unambiguously suggests one interpretation in that context, which allows more flexibility. Since $\tau^{z^{\circ}}$ is unavailable in many multimodal models without vocabulary tokens for z° ; we only test Eq. 1 in those cases.

3 EVIDENCE OF A SEMANTIC HUB

We apply our tests across diverse data types and models: inputs in different languages, arithmetic expressions, code, formal semantic structures, visual inputs, and audio. We consistently find evidence of a shared representation space in all cases.

3.1 Multilingual

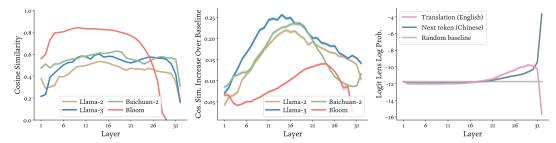
Much past work has categorized language representations in multilingual LMs (Hua et al., 2024; Alabi et al., 2024; Tang et al., 2024b; Zhao et al., 2024; Zeng et al., 2024; *i.a.*). Wendler et al. (2024) recently find that when processing specific in-context learning (ICL) templates for highly synthetic lexical-level tasks (word repetition, word translation, etc.) in non-English languages, the intermediate hidden states of Llama-2 are closer to the unembeddings of English tokens than in the output language. This is consistent with our hypothesis, albeit constrained to a simple synthetic task and one LM. We show that this shared representation space is a general property of LMs and also occurs when processing naturalistic text.

Experiment 1: Representations are similar for translations. Translation datasets enable a direct test for Eq. 1, with semantically equivalent cross-lingual sentences as $w_{1:t}^{z_1}$ and $w_{1:t'}^{z_2}$ and a randomly chosen non-matching sentence as $u_{1:t''}^{z_2}$. We use the professionally-translated English-Chinese parallel sentences from Chen et al. (2016) (N=5260). For each sentence pair, we use a template to transform each sentence and compute the representation cosine similarity for each layer, using the last token position as the sentence representation, which has been shown to preserve sentential information (Morris et al., 2023). We consider two English-dominant LMs, Llama-2 and Llama-3 (Llama-3-Team, 2024), one Chinese-dominant LM, Baichuan-2 (Yang et al., 2023), and one multilingual LM, BLOOM (BigScience, 2023), specifically the 7B/8B variants. See §A.1 for more details.

Figure 3a shows high raw cosine similarity. We also follow Eq. 1 and subtract the average similarity between non-matching sentence pairs as a baseline, separately for each layer. Figure 3b shows that the similarity between translations is higher than this baseline, most prominently in the middle layers. These trends support the hypothesis that the middle layers act as the semantic hub of the LM. Notably, this trend also exists for BLOOM which does not have a dominant pretraining language.

Experiment 2: Representations are anchored by semantically-equivalent dominant-language tokens. We next test Eq. 3, i.e., whether continuations in the dominant language have a higher probability than those in the input language at intermediate LM layers. For the English-dominant Llama-3, we use 1,000 Chinese prefixes $w_{1:t}^{z^{\circ}}$ from Wikipedia (Wikimedia-Foundation, 2023) as input. For each, we take $\tau^{z^{\circ}}$ to be the next Chinese token (i.e., $w_{t+1}^{z^{\circ}}$) and $\tau^{z^{\star}}$ to be the (first token of the) English translation of $w_{t+1}^{z^{\circ}}$. See §A.1 for more details. Figure 3c plots the logit lens probability for the two tokens as well as the uniform distribution probability. In early layers, we cannot read out either token better than random chance. After layer 17, the model representations are substantially closer to the English token than the Chinese token until layer 31, showing that the model hidden space is indeed better scaffolded by English than Chinese.

Next, we extend this analysis to consider global language-level trends $p^{\ell}(z)$ where z is a language, at some layer ℓ . We first compute $p(w \mid z)$, the token distribution under a language z, by running the



- (a) The cosine similarity of interme- (b) Same as (a), but subtracted by a diate representations of English and baseline over non-parallel texts. Chinese parallel texts.
- (c) Llama-3 logit lens log prob. of parallel English vs. Chinese tokens when processing Chinese text.

Figure 3: Results for the multilingual experiments. The 95% CI is plotted in all. Parallel texts have similar representations. Hidden states for Chinese texts are close to the unembedding of English tokens.

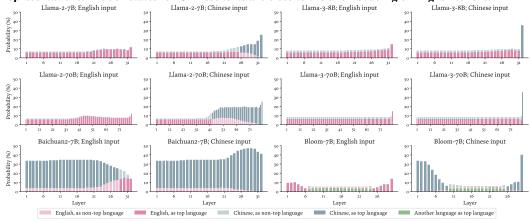


Figure 4: Language probabilities of English and Chinese (and the top language, when it is neither, which only happens for Bloom). Regardless of the input language, the dominant LM language is more salient in the early-middle layers, and the input language is more salient in the final layers. Bloom does not have a clear intermediate latent language.

LM tokenizer on the language-specific split of the mC4 dataset (Xue et al., 2021). We then use Bayes' rule to estimate $p(z \mid w) \propto p(w \mid z)p(z)$ with a uniform prior p(z). We compute the probability of h_t^ℓ 's belonging to each language as $p(z \mid h_t^\ell) \propto \sum_{w \in \mathcal{V}} p(z \mid w) p^{\text{logitlens}}(w \mid h_t^\ell)$. Finally, again with a uniform prior assumption, we average $p(z \mid h_t^\ell)$ across tokens t to obtain a language distribution $p^\ell(z)$. If our hypothesis that the shared representation space is better scaffolded by the dominant language is true, we expect the dominant language z^* to have the highest probability across input languages in the middle layers.

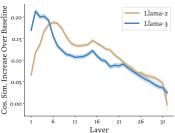
Figure 4 shows the probability of English and Chinese (and of the top language when it is neither) for each layer on 10,000 English/Chinese Wikipedia sentences. When English-dominant models process Chinese text, Wendler et al.'s finding generalizes, where English dominates in the intermediate layers and Chinese only dominates in the final layers. On the Chinese-dominant LM, this trend flips: when processing English text, its intermediate layers are closer to Chinese space and the final layers are closer to English space. For BLOOM, a multilingual model with a relatively balanced training language mixture, we do not see a clear dominating language in the intermediate layers; when we manually inspect the closest token, in most cases we observe symbols with no clear semantics (though this does not mean it does not have a unified representation space: see Exp. 1). 70B model trends are also highly similar to the 7B/8B ones.

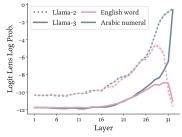
3.2 ARITHMETIC

We hypothesize that a similar trend exists when LMs process arithmetic expressions where they route to a shared space anchored by numerical words in English in intermediate layers. We consider simple

⁴This prior obviously does not reflect the training language distribution, but in fact makes our trends even more salient, since using a real (or estimated) p(z) would make $p(z \mid w)$ even larger for the dominant language.







merals vs. English words, broken the others. down into separate categories.

(a) Cosine similarity between an (b) Same as (a), but only the exact (c) Logit lens log probability when arithmetic expression in Arabic nu-translation similarities subtracted by predicting a number, between either

the number itself or its English equiv-

Figure 5: Results for the arithmetic experiments. The 95% CI is plotted in all. Expressions in Arabic numerals have similar representation as corresponding expressions in English, as well as the unembeddings of corresponding number words in English.

expressions in the form of "a=b+c" or "a=b*c"; for simplicity, we restrict "a" and "b" to be at most two digits and "c" to be a single positive digit.

Experiment 1: Representations are similar for translations. Here, we only consider the righthand side, "b+c" and "b*c", as $w_{1:t}^{z_1}$ in Eq. 1. Like in the multilingual case, we translate them into English (e.g., "five plus three") as $w_{1:t'}^{z_2}$, and evaluate the representation cosine similarity between every English expression and every numeric expression, throughout layers. We group the pairwise cosine similarities in three buckets: (1) exact translation (e.g., "5+3" and "five plus three"; N = 1123), (2) non-exact but same value (e.g., "5+3" and "two plus six"; N = 13293), and (3) different value (N = 1247836). Figure 5a shows that exact translations have high cosine similarity, although this is to be expected since embeddings of numbers and their corresponding English words are near one another (thus even a bag-of-word-embeddings should also have high similarity). More interestingly, we that the similarities are still higher when the surface forms are distinct but the "meaning" of the expression (i.e., the value of the expression) is the same. Next, like in §3.1, we subtract the cosine similarities among non-translation pairs as a baseline $(u_{1,i'}^{z_2})$. Figure 5b shows high similarity in the early-middle layers for translations over the baseline, but gradually decreasing to near 0.

Experiment 2: Representations are anchored by semantically-equivalent English words. We hypothesize that, for some prefix such as "a=b+", the intermediate representations h_t^{ℓ} are close to the English word for "c" that would make the equality hold (see Figure 1). First, we randomly sample 100 such prefixes and take the representation of the last token at all layers. For each prefix, we plot the representation evolution throughout layers using PCA, as well as the unembeddings of numbers in English τ^{z^*} vs. numerals $\tau^{z^{\circ}}$. Figure 6 shows that the representations indeed go through the space occupied by the English words in intermediate layers. Next, we repeat our logit lens experiments, inspecting the log probability of the following numeral token vs. its English version (N = 1123). Figure 5c shows that the two tokens have similar log probability until around layer 25, after which the numeral token dominates.

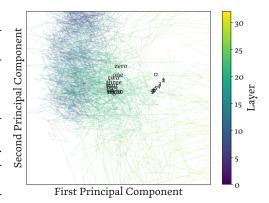
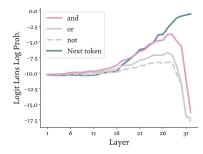
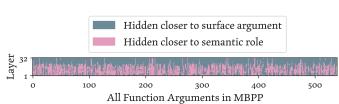


Figure 6: The Llama-3 hidden representation evolution when predicting a number, projected by PCA where the principal components are learned on the output embeddings of 20 number tokens, 10 in English and 10 numerals.

3.3 CODE

Many recent LMs are trained on code corpora (Llama-3-Team, 2024; Gemini-Team, 2024; i.a.). We find that they similarly process code input by projecting it into a unified representation space shared with regular language tokens. Figure 7 shows some examples, where the LM in the intermediate layers tends to verbalize the future in free-form English, unconstrained by program syntax. E.g.,





(a) Llama-2 logit lens log probabilities (and the 95% CI) at commas in Python list literals, of the English "and" token (and baseline tokens) vs. the actual next token in the program, from MBPP.

(b) The distance between Llama-2 hidden states when predicting a function argument, to the unembedding of the argument's name (its semantic role) vs. the actual argument expression, in MBPP.

Figure 8: Results for the code experiments. Code expressions are close to semantically meaningful free-form English words in early-middle layers, such as "and" in list literals and the argument's semantic role in function calls; in the final layers, the representation converges to the context-constrained Python token.

in the first program, given the Python prefix "... for idx, e in enumerate(numbers): for idx2, e2 in enumerate(numbers", instead of the ground-truth continuation in Python "): if idx != idx2:", the most salient intermediate token is "except", likely attempting to predict in English "(for each element in numbers) except if it is equal to idx". Similarly, in a list literal expression "[1.0, 2.0," instead of continuing in Python "3.0", it predicts "and", which is a natural way to continue in English. In these cases, it is difficult to obtain semantically equivalent English-Python prefix pairs like in §3.1 for testing Eq. 1,5 so we only test Eq. 3 across a few targeted cases in Python below.

Experiment 1: Representations are anchored by semanticallyequivalent English words: **literals.** We systematically the list case, where h_t^l is the hidden state after processing "," during list processing. We use τ^{z^*} ="and" and further take $\tau^{z^{\circ}}$ to be the actual next token. Figure 8a shows that this trend holds on all such commas in the MBPP dataset (Austin et al., 2021) (N = 6923, including unit tests):as expected, in the final layers, the representation is closer to the ground truth next token's unembedding, and closer to "and" in the middle layers. We also show the probability with two other tokens, "or" and "not", as baselines, both of which are lower than "and".

Experiment 2: Representations are anchored by semantically-equivalent English words: function

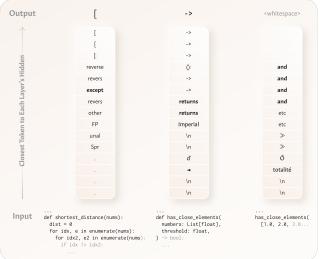
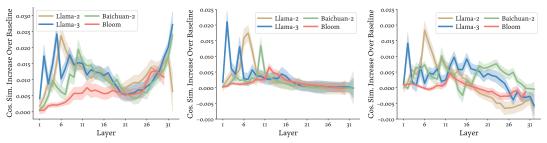


Figure 7: Logit lens analysis on Llama-2 processing Python programs. For every other layer, we show the closest token (sometimes whitespace) to the hidden states *before* the grayed-out texts. **The model tends to verbalize the future prediction in English that corresponds to the code continuations (in gray**).

call arguments. Function arguments have names in the definition, such as "range(start, end, step)"; but when invoked, they are filled with actual context-appropriate expressions. We call the argument names "semantic roles", and the context-specific expressions the "surface forms", inspired by thematic relations in linguistics (Fillmore, 1968; Jackendoff, 1974; *i.a.*). Like in the second example in Figure 1, we show that LMs predict the arguments by first "thinking" about their semantic role (τ^{z^*}) and then instantiating with surface-constrained expressions (τ^{z^*}). We extract all function calls and arguments from MBPP with simple filtering, resulting in 540 arguments (see §A.2 for

⁵We may argue that functions and their specifications constitute such pairs, but we found that their correspondence is often too abstract and non-exact to manifest as similar representations.



(a) Similarity between a sentence and its semantic structure, subtracted by a baseline over non-parallel texts.

(b) Similar as (a), but the baseline is (c) Same as (b), but we shuffle the computed by swapping the positions predicates in the semantic structure of names in the semantic structure.

Figure 9: Representation similarity experiments for formal semantics. A sentence and its semantic structure have high representation similarity, even with strict controls.

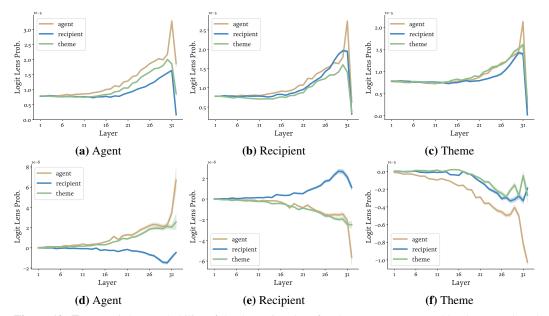


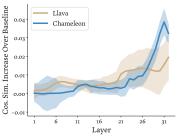
Figure 10: Top: Logit lens probability of the thematic roles of verb arguments, grouped by the ground-truth argument thematic role in each subplot, for Llama-3. **Bottom**: The same quantity, subtracted by the average probability as the baseline, separately for each role. The 95% CI is plotted in all. **The prefix representation before an argument with a particular thematic role has high similarity with the unembedding of that role in English**, when the baseline is adjusted for.

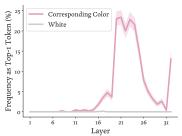
details). For each argument, we use the logit lens to inspect the hidden states h_t^ℓ at the preceding token ("(" or ","). For each argument, Figure 8b visualizes if the semantic role or the surface form is closer to each layer's hidden state. The semantic role (τ^{z^*}) dominates for the early to middle layers, and only in the final layers do the representations converge towards the surface form argument (τ^{z°).

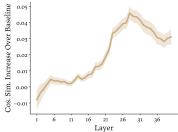
3.4 FORMAL SEMANTICS

Much probing work has shown that semantic information can be probed out from LM's hidden states (Tenney et al., 2019; Wu et al., 2021; Li et al., 2021; *i.a.*). We show that this manifests without a learned probe. We use the COGS data (Kim & Linzen, 2020), which contains synthetically generated English sentences and their semantic structures (in a fairly standard format rooted in the Neo-Davidsonian tradition (Parsons, 1990)). E.g., the sentence "Eleanor sold Evelyn the cake." has the representation "*cake(x4); sell.agent(x1, Eleanor) AND sell.recipient(x1, Evelyn) AND sell.theme(x1, x4)".

⁶It also has a similar number of active vs. passive sentences, thus providing a clean testbed since one cannot simply use word order to predict the thematic role.







- (a) The cosine similarity difference (b) The frequency of the closest to- (c) The cosine similarity difference over non-matching ones.
- between intermediate representations ken to LLaVA's hidden states describ- between intermediate SALMONN of matching images and captions, ing the image color, against a base- representations of matching audios line using "white".
- and labels, over non-matching ones.

Figure 11: Results for the multimodal experiments. The 95% CI is plotted in all. Model representation of (a) visual and (c) audio inputs and their textual labels are similar. Furthermore, in (b), model representations of individual color patch tokens are close to English words for those colors. More results are in §C.

Experiment 1: Representations are similar between a sentence and its semantic structure. Like in §3.1 and §3.2, Figure 9a shows that the representation of a sentence is closer to its semantic structure than a non-matching baseline. As in the arithmetic expression case however, there is a confounder: this could be due to surface lexical overlap between the two (e.g., "Eleanor", "Evelyn", "cake", and "sell"/"sold" in our example) rather than a deep understanding of their equivalence. To control for this, we find COGS sentences with two proper names like the above example (N = 2233), swap their positions in the semantic structure such that it no longer corresponds to the sentence, and yet the lexical overlap is unchanged. With this stronger baseline (where bag-of-words models would do no better than chance), we still see in Figure 9b that semantically matching pairs have more similar representations. On top of this, we further control potential positional confounders of predicates in the semantic structure by randomly swapping their positions, and results in Figure 9c have the same trend. We also note that Bloom, arguably the "weakest" model (smaller pretraining set and older architecture) does not do much better than chance, potentially suggesting that this representation strategy correlates with model capacity.

Experiment 2: Word representations are correlated with their thematic roles in semantics theory. Formal semantic structures are naturally not a dominant data type, and we hence do not expect Eq. 3 to hold. Instead, we perform a logit-lens-style analysis that still tests Eq. 1, but with finer granularity, focusing on token-level representation similarity, specifically the arguments of verbs and their thematic roles. For example, "Eleanor" in the earlier example has the role "agent" and "Evelyn" is the "recipient". We expect that, when predicting an argument, the hidden states are more similar to the corresponding thematic role than non-matching ones. We again only consider proper names in COGS, excluding those that start a sentence, as in this case there is no context in which to predict the semantic role. This results in 3257 agents, 2583 recipients, and 714 themes. To avoid any memorization effects arising from the LMs' being potentially trained on COGS, we further randomly replace the proper names with another one in COGS and make sure the new sentence does not appear in the dataset.

For each proper name with a given thematic role, we look at the logit lens probability of all roles. Figures 10a to 10c show that, for Llama-3, the role probabilities tend to peak in the middle-late layers and drop down in the final layers, a familiar trend. Nevertheless, the corresponding role token does not always receive the highest probability. We believe this is because Llama-3 has a "prior" that is closer to the word "agent", which almost always has the highest probability. So we adjust for this prior by subtracting from each curve a baseline probability, separately for each role and for each layer, that is the average role probability across all instances. Figures 10d to 10f show this "posterior": when predicting the argument with a given thematic role, the corresponding thematic role token is always the closest to the intermediate representations. We do not observe these trends in Llama-2.

3.5 VISUAL INPUT

Past work has investigated the representation of separately trained vision and text models, often finding that their representation spaces are similarly structured and alignable (Merullo et al., 2022; Li et al., 2023; Huh et al., 2024; i.a.). We show that when trained together, vision-language models

learn to project both modalities into a joint representation space. Current vision-language models typically represent images by segmenting them into patches, embedding them into "image tokens", and then feeding them into the transformer model along with other text tokens (Lu et al., 2023; 2024; Liu et al., 2023; *i.a.*). We hypothesize that the intermediate representations of the image patches are close to the corresponding language tokens that describe the scene. Experimental details are in §A.3.

Experiment 1: Representations are similar between an image and its caption. Though not constituting exact semantic equivalence, an image paired with its caption provides one possible test for Eq. 1. We take 1000 images and corresponding captions in the MSCOCO dataset (Lin et al., 2014) and measure their hidden states cosine similarity in LLaVA-7B (Liu et al., 2023) and Chameleon-7B (Chameleon-Team, 2024). Again, we subtract the average similarity between non-matching image-caption pairs as a baseline, separately for each layer. Figure 11a shows that semantically matching inputs across modalities are closer to one another than would be expected from chance, as in the translation experiments. Importantly, these models do not explicitly optimize cross-modal representation similarity (unlike in CLIP (Radford et al., 2021)), and such similarity only emerges through autoregressive training.

As mentioned in §2.1, we do not perform a test of dominant data type anchoring (Eq. 3) due to a lack of non-text tokens in the vocabulary. But, like in §3.4, we perform a fine-grained image-patch-level analysis using the logit lens. As a toy setting for illustration, we inspect LLaVA's representations of pure color images, specifically those in red, green, blue, and black. Figure 11b shows that, in up to more than 20% of the time in the intermediate layers (averaged across the patches and the four colors, N=2304), the closest token is the corresponding color word (out of all vocabulary tokens). §C.1 details more comprehensive experiments where we similarly find an alignment between the patches and the caption, as well as between a patch and its semantic segmentation label.

3.6 Audio

Audio is another modality that is often modeled jointly with text (Lu et al., 2024; Gong et al., 2023; 2024; *i.a.*), and we perform similar experiments using SALMONN (Tang et al., 2024a), an audio-text model. We use the VGGSound dataset (Chen et al., 2020) which contains 10-second audio clips with labels, e.g., "duck quacking" or "playing cello".

Experiment 1: Representations are similar between audio and its label. We study the representation cosine similarity between an audio and its label description, and subtract from it a baseline which is the average similarity between non-matching pairs, separately for each layer. On 1000 samples from VGGSound, we see in Figure 11c that semantically matching audios and labels have more similar representations in the intermediate layers.

Like for visual inputs, we do not investigate the dominant data type anchoring effect, but instead use the logit lens to confirm that the representation alignment also occurs on a token level, in §C.2.

4 Intervening in the Semantic Hub

Prior work has argued that interpretability results should be tested under a causal framework, to ensure that the observation is not a vestigial byproduct of model training that has no actual effect on model behavior (Vig et al., 2020; Ravichander et al., 2021; Elazar et al., 2021; Chan et al., 2022; *i.a.*). In this section, we show that the semantic hub does causally affect model output. Specifically, semantically transforming hidden representations according to (dominant) English representations leads to predictable behavior changes in non-dominant data types. For different experiments, we use different kinds of intervention, and we explain our design decisions at the end of this section. We report hyperparameters and further experimental details in §B.

Multilingual. Past work has shown that (monolingual) interventions in the middle layers can steer the output of LMs in predictable ways (Subramani et al., 2022; Turner et al., 2024; Rimsky et al., 2024; *i.a.*). If the English-dominant LMs have a shared representation space, we should be able to intervene on this space in English even when processing other languages (Dumas et al., 2024). We use a popular hidden space intervention technique, Activation Addition (ActAdd; Turner et al., 2024), which works by: (1) taking a pair of contrasting steering words that semantically represent the steering effect (e.g., "Good" and "Bad" for sentiment steering), (2) taking their hidden state difference at an intermediate layer, and (3) scaling and adding the steering vector to the hidden states for the original forward pass of the regular generation process, at the same layer, at the beginning of the

Table 1: Steering Llama-3's output sentiments using trigger words in English vs. the input language (either Spanish or Chinese). We report the mean sentiment, disfluency (perplexity), and relevance of the continuation, as well as the standard deviation across 10 seeds. **Cross-lingual steering is consistently successful, sometimes even more than monolingual steering, without substantial damage in text fluency and relevance.**

Text Lang.	Steering Dir.	Steering Lang.	Sentiment	Disfluency (↓)	Relevance (†)
Spanish	None	None	0.143 _{±0.022}	$7.35_{\pm 1.19}$	$0.861_{\pm 0.002}$
	+	Spanish English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$10.54_{\pm 2.39} \\ 8.75_{\pm 2.20}$	$\begin{array}{c} 0.842_{\pm 0.004} \\ 0.857_{\pm 0.002} \end{array}$
	<u></u>	Spanish English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$7.98_{\pm 2.04} \\ 7.35_{\pm 1.01}$	$\begin{array}{c} 0.856_{\pm 0.002} \\ 0.859_{\pm 0.003} \end{array}$
Chinese	None	None	0.178 _{±0.030}	$11.06_{\pm 3.12}$	$0.869_{\pm0.004}$
	+	Chinese English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$10.78 \scriptstyle{\pm 2.66} \\ 11.36 \scriptstyle{\pm 1.13}$	$\begin{array}{c} 0.866_{\pm 0.005} \\ 0.864_{\pm 0.004} \end{array}$
	<u></u>	Chinese English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$11.12_{\pm 3.12} \\ 10.90_{\pm 3.25}$	$\begin{array}{c} 0.870_{\pm 0.004} \\ 0.869_{\pm 0.003} \end{array}$

sequence. We generalize their sentiment-steering experiment cross-lingually. See Turner et al. (2024) for details.

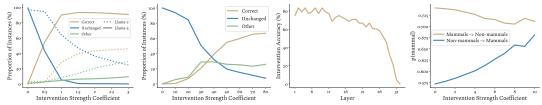
We consider two non-dominant languages, Spanish and Chinese, and take 1000 prefixes each from the InterTASS dataset (Spanish; Díaz-Galiano et al., 2018) and the multilingual Amazon reviews corpus (Chinese; Keung et al., 2020), and generate continuations either without modifications or intervened using ActAdd. As the steering vector, we use the difference between positive vs. negative sentiment trigger words, in the appropriate direction. Specifically, we use "Good" and "Bad" for English, "Bueno" and "Malo" for Spanish, and "奸" and "坏" for Chinese. In addition to sentiment evaluation, we also measure the generation fluency and compute the relevance of the generation with the prefix using trained models, following Turner et al. (2024). Ideally, the intervention should achieve the desired sentiment without hurting text fluency and relevance, and the English intervention should be just as effective as the text language intervention (see §B.1 for more details).

Because we take intermediate layer representations of the steering words (step (1)), if the semantic hub is language-agnostic, we expect similar cross-lingual representations and in turn similar steering effects across steering languages. Table 1 shows that this is indeed true for Llama-3: ActAdd in the text language is often effective, achieving the intended effect on sentiment, with usually only a statistically insignificant decrease in fluency and relevance. This aligns with the English-only findings in Turner et al. (2024). And intervening in English is similarly effective as using the text language. Table 2 (appendix) shows the results for Llama-2, with very similar trends.

Arithmetic. We perform intervention using our arithmetic expressions in §3.2, for example "4=1+3". We intervene by attempting to modify the token after "+" to be one smaller, e.g. "2" here, and expect this to not only lead the model to output "2" instead of "3", but also fundamentally affects the model's reasoning process and causes the model to patch this error with an additional suffix "+1", i.e., "4=1+2+1". We use ActAdd except for adding the intervention vector (e.g., "three" – "two") only at the position of "+". For all addition expressions in §3.2 (N=846), we perform such intervention at an intermediate layer (25 for Llama-3 and 30 for Llama-2) and measure how often this leads to the model correctly outputting the decremented number followed by "+1", versus unchanged, or changed to some other output. Figure 12a shows that, as the intervention coefficient (i.e., the scaling constant of the vector) increases, this procedure leads to the expected output for up to > 90% of the instances.

Code. Based on our "semantic role" observation in §3.3, we intervene using the "range" function. We focus on two overloaded versions of "range": "range(start, end)" and "range(end)". If the semantic hub causally affects model output, then we can intervene in it to select the function version to use after "range(" in some context, using the English words "start" and "end". Specifically, we take all single-argument "range(end)" calls in the MBPP dataset (N=159) and attempt to

⁷Another difference is that we do not use the hidden representation after seeing e.g. "three", because that usually represents the *next* token. Instead, we use a prefix that uniquely determines the number, e.g. "Eight equals to five plus", and take the last token hidden representation, which *is* supposed to represent "three".



(a) Steering arithmetic ex-(b) Steering a single-(c) Replacing image repre-(d) Steering mammal pressions' results to a dif-argument "range(end)" sentations of a color with sounds to be predicted ferent value.

call to be predicted as English tokens of another as non-mammal sounds double argument.

color, and expecting the using English words of model to predict the latter. non-mammals; vice versa.

Figure 12: For (a) arithmetic (Llama-2 and -3), (b) code (Llama-2), (c) images (Chameleon), and (d) audio (SALMONN), steering model output using English words, for various intervention strengths ((a), (b), (d)) and layers ((c)). (a)-(c) measure successfulness with the proportion of instances steered to the correct output, and (d) measures the probability of predicting mammals. Overall, intervening in the unified representation space in English reliably leads to desired model output changes.

expand it into "range(0, end)". We use a similar intervention method, except simply using the unembeddings of trigger tokens instead of intermediate LM hidden states. We use as trigger tokens ("start" – "end") and add the intervention vector to the hidden states corresponding to the open parenthesis "(" at an intermediate layer (layer 17). For all these "range" calls in the dataset, we let Llama- 2^8 generate without and with intervention. Figure 12b shows that, with increasing intervention strength, more instances are successfully steered to "range(0, end)", up to 67%.

Formal semantics. Unlike in the cases above where we modify the surface continuation by manipulating some underlying concept structure, a natural language prefix usually licenses one single possible thematic role to follow. So we do not perform an intervention experiment here.

Visual input. We show that we can steer the output of Chameleon by intervening on the image patches using language tokens and analyzing how this affects the textual output. Focusing on the color setup, if the representation for a color is similar between visual and language inputs, we hypothesize that we can *replace* the image hidden states corresponding to one pure color image patch with the unembedding of the language token for another color, and mislead the model to "perceive" the new color when asked about the image color. Note that replacing the hidden state is a more invasive intervention than addition. However, there is a confounder: the intervened word may lexically bias the model to generate the same word, without performing reasoning that incorporates the new color, because the desired answer after intervening is equivalent to the intervention word itself (unlike in the previous cases). To control for this, we show two colors in one image and only intervene at the positions corresponding to one color: if the intervention unconditionally and lexically biases the generation to the new color, this effect would (incorrectly) affect both colors. 9

We consider all color pairs using the same colors as in §3.5: red, green, blue, and black, 10 and picking one color in the pair and intervene to a new third color (N=48). As the intervention, we start from a layer ℓ and replace all hidden states at and after ℓ to be the unembedding of the new color minus the old color. We ask the model what the two colors in the image are, and only consider the intervention successful if the model answers both the new color and the other unintervened color correctly. Figure 12c shows the success rate across all ℓ : it gets as high as above 80%. 11 We highlight

⁸We do not consider Llama-3 in this case because its default behavior usually generates "range(0, end)" in the first place, and it is unclear how to steer from "range(0, end)" to "range(end)".

⁹We tested settings that require more sophisticated reasoning such as asking for a country flag with the two colors, or asking about spatial relationships of the colors. They seem to be beyond the capability of Chameleon-7B—even without interventions, the model cannot answer the questions correctly.

¹⁰We tried other colors but Chameleon-7B, without interventions, cannot recognize those colors reliably

 $^{^{11}}$ One may argue this is conceptually similar to a half-language half-image input. There are many distinctions: most importantly, a half-image is not processable by Chameleon and severely goes out of its training distribution, since it only ever processes images of size exactly 512×512 . Other distinctions include: the presence of a special token marking the beginning of the image; our intervention repeats the new color token, once for each patch, rather than just one; and the token representation is held constant across layers rather than evolving; etc.

that, for both this experiment and the earlier ones in this section, the interventions are not even necessarily guaranteed to lead sensible outputs, let alone correct ones.

Audio. We perform a similar intervention with SALMONN, with the same desideratum that the question-answering process should require some reasoning rather than outputting the intervened token as-is. We consider 1000 animal sounds in the VGGSound dataset, specifically only single-word animals, and ask "Is this animal a mammal?" We intervene both on mammal sounds with a random non-mammal word (and expecting the model to be more likely to reply with "No") and vice versa. We perform the invention similarly to the code case, adding the unembedding difference between the new trigger word and the original animal name, scaled by a constant, at layer 13. We measure the probability of the "Yes" token and the "No" token and compute the normalized "Yes" probability. Figure 12d visualizes the two cases across multiple intervention strengths. As the strength increases, the model is more likely to predict in the steered direction, again demonstrating cross-data-type intervention effectiveness.

Note on the intervention methods used. In the majority of our experiments, we add an intervention vector to a particular layer at a particular input position, and the intervention vector is computed using the difference between the unembeddings of two trigger tokens in another data type, scaled by a constant. This is simple and naturally follows the results of our logit lens experiments. However, this may not be convincing for data types highly parallel to English. For example, for the multilingual intervention where we use the difference between the unembeddings of, e.g., "Good" and "Bad", the intervention may succeed only because this difference is similar to the unembedding difference between "Bueno" (trans. "Good") and "Malo" (trans. "Bad") due to cross-lingual embedding alignment (Mikolov et al., 2013; i.a.). 12 So instead, as the intervention vector, we use not the unembedding difference but the difference between intermediate model hidden states, and they are expected to be the same across modalities as our hypothesis predicts. We do this for multilingual intervention and arithmetic intervention. The former, using ActAdd, further differs by adding the vector not at a targeted position but in the beginning of the sentence. In addition to it being an established intervention method, we used it because in sentiment steering, there is no targeted position of interest (unlike for arithmetic), but we want to steer the sentence representation globally. Finally, we use a more invasive intervention for visual inputs where we do not just add, but replace, hidden representations because we found it to work well, providing a stronger result.

5 DISCUSSION

Our experiments across diverse languages and modalities give empirical support to the semantic hub hypothesis; language models seem to make efficient use of model capacity and learn to represent semantically similar inputs from different modalities near one another. Such a semantic hub has been hypothesized to exist in the human brain (Patterson et al., 2007; Patterson & Ralph, 2016; Ralph et al., 2017). Inasmuch as both the human brain and language models are resource-constrained information processing systems, it is perhaps unsurprising that both systems make use of a semantic hub. This also supports prior findings that multilingual models usually reason best in English (Shi et al., 2023).

We note however that this dominant-language-reliance may not always be a desirable property of language models. Wendler et al. (2024) conjectured that language models might inherit biases present in the training data of the dominant language; if true, an extreme implementation of this strategy could force an alignment of ideology across languages and potentially harm inclusivity. Similarly, internalizing arithmetic expressions in natural language may not be ideal as a part of the "algorithm" with which a language model implements arithmetic, considering their structural differences and the vast linguistic variation in number expressions in their composition (c.f. Danish "tooghalvfems"; trans. ninety-two, but compositionally representing 2+(5-0.5)×20) or even bases (c.f. the base-23 numeral system in the Kalam language (Laycock, 1975)). In general, an over-reliance on the dominant data type could be detrimental.

¹²Note that this is less problematic for other data types such as code, where it is unlikely that the unembedding difference between "end" and "start" is similar to that between the actual surface form end argument and "0".

6 RELATED WORK

Representation alignment between separately trained models. A long line of work has investigated the representations of separately trained mono-data-type models, and showed that they can be aligned through a transformation. In the multilingual case, it has been found that separately trained word embeddings for different languages can be aligned (Mikolov et al., 2013; Smith et al., 2017; Cao et al., 2020; *i.a.*). Similarly, prior work has shown that visual representations and text representations from different models can be mapped together (Merullo et al., 2022; Koh et al., 2023; Maniparambil et al., 2024; *i.a.*). Huh et al. (2024) argued that these are possible because the different data modalities are projections of the same underlying reality. Lu et al. (2021) showed that language-only models can be minimally finetuned to achieve high performance in other modalities. Our work, in contrast, looks at a *single* static model that processes multiple input data types, and finds that the resulting representations align, without needing a transformation. Concurrent work (Luo et al., 2024) found similar alignments of "task vectors" (Ilharco et al., 2022; Hendel et al., 2023) in vision-language models.

Representation evolution throughout layers. Much past work has analyzed the representation evolution throughout transformer layers, inspecting how it affects reasoning (Yang et al., 2024), factuality (Chuang et al., 2024), knowledge (Jin et al., 2024), etc. From another angle, work on layer pruning and early exiting also speaks to the representation dynamics across layers (Gromov et al., 2024; Sanyal et al., 2024; *i.a.*). More mechanistically, Merullo et al. (2024), Todd et al. (2024), Hendel et al. (2023), *i.a.*, more precisely characterized the representation changes algorithmically.

Inspecting model hidden states. We adopted the logit lens for its simplicity which brings few confounders. However, alternatives exist, usually requiring some training (Belrose et al., 2023; Ghandeharioun et al., 2024; Templeton et al., 2024; *i.a.*). They allow for more expressive explanations, though at the risk of overfitting. Similar methods have been developed for other modalities, such as Toker et al. (2024). Testing our hypothesis using these methods would be valuable future work.

7 Conclusion

This work proposed and investigated the semantic hub hypothesis, which posits that language models represent semantically similar inputs from distinct modalities near one another in their intermediate layers. We find evidence of this phenomena across multiple language models and data types, and further observe that intervening in this space through the model's dominant language (usually English) leads to predictable model behavior changes.

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A EXPERIMENTAL DETAILS FOR §3

We first note a tokenization detail regarding "prefix spaces." For example, "_llama" (where _ denotes whitespace) is a token in the Llama-3 vocabulary, but not "llama". When comparing token-level logit lens probabilities, we use the configuration that maximizes the probability, which may be different for each setting. For example, the token with the prefix space usually is more likely, but for arithmetic expressions "a=b+c", after "+", the surface token "c" is more likely than "_c".

A.1 MULTILINGUAL

For Experiment 1, for each sentence pair, we use a template to transform each sentence. This is due to the automatic code-switching behavior of LMs. For an English model processing Chinese text, we expect the Chinese tokens to have high probabilities in the final layer because they need to be output; however, we observe these models tend to code-switch back to their dominant language after a full sentence, which confounds our analysis. We therefore put the parallel sentences into a template, "{English Sentence} This represents" (and the corresponding Chinese version), as the model is less likely to code-switch mid-sentence after "represents". We experimented with other templates that led to similar results. Furthermore, for sentence in GALE (Chen et al., 2016), we make sure the transcript; unicode is not empty for both the source and the translation.

For Experiment 2, due to tokenization, it is challenging to obtain exactly parallel English-Chinese tokens, and hence we perform aggressive filtering. We consider only text positions where the next BPE token (1) is a valid Chinese word (as segmented by Jieba (Sun, 2024)), and (2) has an English translation (using the English-Chinese dictionary CC-CEDICT (MDBG, 2024)). E.g., "今天是开心的一天" (Today is a happy day), Llama-3 tokenizes it as ['今天', '是', '开', '心', '的一', '天'], while Jieba segments it as ['今天', '是', '开心', '的', '一天']. We keep {'今天', '是'}. Furthermore, only '今天''s translation is a single token, the only token that survives the cutoff is '今天'.

A.2 CODE

For all experiments using the MBPP dataset, we concatenate all dataset splits with a total of 974 programs. For the function call argument experiment, we consider all non-zero-argument function calls in MBPP, excluding unit tests. We automatically identify the argument names (the "semantic roles") by function inspection for built-in functions and by looking at the function definition for those defined in-context, and skip when this is not possible. We also ignore arguments whose semantic roles are generically called "obj" or "object", and instances where the instantiated surface-form argument is the same as the semantic role. We look the hidden state corresponding to the previous token, either "(" or ",", except when tokenization renders this impossible (e.g., when the previous token is merged with a part of the surface argument; we find this happens often with the Llama-3 tokenizer and thus do not include it in this experiment). This leaves 540 arguments.

A.3 VISION-LANGUAGE

To pass the images through the model, we embed them in templates, only for the logit lens experiments. For the color experiment, we use the template "USER: What is the color in the image?<image>\n ASSISTANT:". For the caption and segmentation experiments, we use "USER: What is in the image? $\n<$ image> ASSISTANT:" for LLaVA and "What is in the image? $\n<$ image>" for Chameleon.

For all caption and segmentation experiments, we use the MSCOCO 2017 dataset. In particular, for the segmentation evaluation, we use the MSCOCO 2017 panoptic segmentation labels. We evaluate the alignment score between all corresponding patches and labels. We consider a patch and a label as "corresponding" if there is an image segment with that label that occupies more than half of the pixels in the patch.

B EXPERIMENTAL DETAILS FOR §4

For both the code and vision-language intervention experiments, we use argmax decoding. We perform most of our intervention experiments using the pyvene library (Wu et al., 2024).

B.1 MULTILINGUAL

For each language, we sample N=1000 instances from the training set of InterTASS for Spanish and the multilingual Amazon reviews corpus for Chinese. Following Turner et al. (2024), we use trained models for various metrics. We found that Llama models tend to code-switch back to English when processing texts in other languages, and discovered that we can mitigate this with an instruction: "接下来的文字全部是中文的。" for Chinese and "Todo el texto siguiente está en español." for Spanish (trans. "All of the following text is in Chinese/Spanish.").

We automatically evaluate the sentiment of the generation using a DistillBERT-based (Sanh et al., 2020) model finetuned for multilingual sentiment analysis,, ¹³ judge the generation fluency by taking the conditional perplexity of the generation given the prefix from Llama-3.1-70B (Llama-3-Team, 2024), ¹⁴ and compute the relevance of the generation with the prefix by computing the cosine similarity between the generation and the prefix using a XLM-R-Large-based (Conneau et al., 2020) model finetuned for sentence representation ¹⁵ (Wang et al., 2024). All these models support both Spanish and Chinese.

We perform ActAdd by passing both the positive and negative steering words through the LM, taking their hidden states at layer 17, computing their difference, scaling it by a constant, and adding it to the normal generation forward pass also at layer 17, exactly following Turner et al. (2024), except we use a scaling coefficient of 5, rather than 2 in their experiments, for which we observed a larger effect. For generation, we use a temperature of 1, top-p=0.3, and a frequency penalty of 1, all following Turner et al. (2024), without tuning.

¹³https://huggingface.co/lxyuan/distilbert-base-multilingual-cased-sentiments-student

¹⁴We also tried using Mistral-Nemo-Base (https://huggingface.co/mistralai/Mistral-Nemo-Base-2407), and found similar trends.

¹⁵https://huggingface.co/intfloat/multilingual-e5-large

Table 2: Steering Llama-2's output sentiments using trigger words in English vs. the input language (either Spanish or Chinese). We report the mean sentiment, disfluency (perplexity), and relevance of the continuation, as well as the standard deviation across 10 seeds. **Cross-lingual steering is consistently successful, sometimes even more than monolingual steering, without substantial damage in text fluency and relevance.**

Text Lang.	Steering Dir.	Steering Lang.	Sentiment	Disfluency (↓)	Relevance (†)
Spanish	None	None	$0.144_{\pm 0.014}$	$8.58_{\pm 0.57}$	$0.850_{\pm 0.006}$
	+	Spanish English	$\begin{array}{ c c c c c }\hline 0.143_{\pm 0.012}\\ 0.097_{\pm 0.024}\\ \end{array}$	$\begin{array}{c} 8.84_{\pm 0.79} \\ 8.99_{\pm 0.72} \end{array}$	$\begin{array}{c} 0.847_{\pm 0.006} \\ 0.847_{\pm 0.005} \end{array}$
	↑	Spanish English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$\begin{array}{c} 9.11_{\pm 0.50} \\ 8.35_{\pm 0.30} \end{array}$	$\begin{array}{c} 0.844_{\pm 0.005} \\ 0.849_{\pm 0.006} \end{array}$
Chinese	None	None	$0.223_{\pm 0.036}$	$14.63_{\pm 2.65}$	$0.844_{\pm 0.009}$
	+	Chinese English	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	$15.29_{\pm 2.47} \\ 14.80_{\pm 2.24}$	$\begin{array}{c} 0.840_{\pm 0.011} \\ 0.842_{\pm 0.008} \end{array}$
		Chinese English	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$545.94_{\pm 1544.36}$ $14.14_{\pm 2.42}$	$0.839_{\pm 0.010} \\ 0.845_{\pm 0.009}$

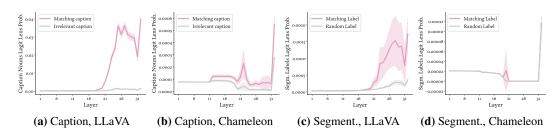


Figure 13: When processing an image patch, model logit lens probabilities of either the nouns in the corresponding caption or the patch segmentation label, as well as a baseline for each with no correspondence between the patch and the label. **The image representations better match the semantically corresponding English words.**

We showed the Llama-3 intervention results in Table 1, and here in Table 2 we show the results on Llama2, with similar trends.

C TOKEN-LEVEL MULTIMODAL EXPERIMENTS USING THE LOGIT LENS

As mentioned in §2.1, we do not perform a logit lens analysis for the multimodal experiments. But we can perform a logit-lens-style test for Eq. 1 that test representation equivalence not on a sequence level but on a token level. At each individual token (e.g., image patches), we measure the alignment of it representation and a natural language description token of it, using the logit lens.

C.1 VISUAL INPUT.

We consider the alignment of image tokens (corresponding to patches in the original image) to their description words. First, we use the nouns ¹⁶ in the image caption as a coarse description—although they do not precisely describe all patches, they should better align with the patches on average than nouns irrelevant to the image. We consider the same 1000 image captions as in §3.5. For each patch, we compute a scalar patch-caption alignment score (for each layer separately) by summing over the logit lens probabilities for all the nouns in the caption at that image patch position. We average this alignment score over all patches in all images, separately for each transformer layer. For the irrelevant nouns baseline, for each image, we compute the alignment score with an unrelated caption that has the smallest noun overlap with the groundtruth matching caption (we also normalize the number of nouns so that the score is comparable). Figures 13a and 13b show that the matching caption better aligns with the image patch representations than an unmatched caption for both LLaVA and Chameleon.

¹⁶Words with NOUN or PROPN tags given by SpaCy's en_core_web_trf model (Honnibal & Montani, 2017).

Image segmentation labels, which annotate objects in specific image locations, provide a finer-grained patch description. The setup is near-identical to captions, but the scalar alignment score for a given patch is not computed using its logit lens probability of caption nouns, but of its corresponding object label. We say a label correspond to the patch if more than half of the patch's pixels have that label. For the irrelevant token baseline, we compute the alignment by aligning each patch with a different randomly chosen object category from all categories. Figures 13c and 13d show that, for LLaVA, the patches are much better aligned to the corresponding labels than randomly assigned labels (which have near-0 logit lens probability). For Chameleon, this is the case for only one middle layer, and not in a statistically significant way, though, as we showed in §4, Chameleon's latent space can be reliably steered using English tokens.

C.2 AUDIO

Unlike for vision-language models where we can map individual image patches to model input token positions, such correspondence does not exist in SALMONN. This limits us to position-agnostic evaluations like the captioning study, preventing a fine-grained analysis such as using segmentation labels. Similar to the captioning experimental design, we measure the average logit lens probabilities of the words in the label, and consider a random label in the dataset with no word overlap as the baseline. On the same 1000 samples, Figure 14 shows a familiar trend, where the audio hidden states are closer to semantically corresponding label words. We note that this is a lower bound—many words in some labels, such as the prepositions in the label "writing on blackboard with chalk", are unlikely to be represented in the audio hidden states.

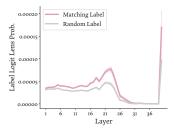


Figure 14: When SALMONN processes an audio clip, the logit lens probabilities of the English words in the audio label vs. another random label. The audio representations better match the semantically corresponding label in English.