# LANGUAGE MODELS REPRESENT SPACE AND TIME

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## ABSTRACT

The capabilities of large language models (LLMs) have sparked debate over whether such systems just learn an enormous collection of superficial statistics or a coherent model of the data generating process—a world model. We find evidence for the latter by analyzing the learned representations of three spatial datasets (world, US, NYC places) and three temporal datasets (historical figures, artworks, news headlines) in the Llama-2 family of models. We discover that LLMs learn linear representations of space and time across multiple scales. These representations are robust to prompting variations and unified across different entity types (e.g. cities and landmarks). In addition, we identify individual "space neurons" and "time neurons" that reliably encode spatial and temporal coordinates. Our analysis demonstrates that modern LLMs acquire structured knowledge about fundamental dimensions such as space and time, supporting the view that they learn not merely superficial statistics, but literal world models.

## 1 INTRODUCTION

Despite being trained to just predict the next token, modern large language models (LLMs) have demonstrated an impressive set of capabilities (Bubeck et al., 2023; Wei et al., 2022), raising questions and concerns about what such models have actually learned. One hypothesis is that LLMs learn a massive collection of correlations but lack any coherent model or "understanding" of the underlying data generating process given text-only training (Bender & Koller, 2020; Bisk et al., 2020). An alternative hypothesis is that LLMs, in the course of compressing the data, learn more compact, coherent, and interpretable models of the generative process underlying the training data, i.e., a *world model*. For instance, Li et al. (2022) have shown that transformers trained with next token prediction to play the board game Othello learn explicit representations of the game state, with Nanda et al. (2023) subsequently showing these representations are linear. Others have shown that LLMs track boolean states of subjects within the context (Li et al., 2021) and have representations that reflect perceptual and conceptual structure in spatial and color domains (Patel & Pavlick, 2021; Abdou et al., 2021). Better understanding of if and how LLMs model the world is critical for reasoning about the robustness, fairness, and safety of current and future AI systems (Bender et al., 2021; Weidinger et al., 2022; Bommasani et al., 2021; Hendrycks et al., 2023; Ngo et al., 2023).

In this work, we take the question of whether LLMs form world (and temporal) models as literally as possible—we attempt to extract an actual map of the world! Specifically, we construct six datasets containing the names of places or events with corresponding space or time coordinates that span multiple spatiotemporal scales: locations within the whole world, the United States, and New York City in addition the death year of historical figures from the past 3000 years, the release date of art and entertainment from 1950s onward, and the publication date of news headlines from 2010 to 2020. Using the Llama-2 family of models (Touvron et al., 2023), we train linear regression probes (Alain & Bengio, 2016; Belinkov, 2022) on the internal activations of the names of these places and events at each layer to predict their real-world location or time.

These probing experiments reveal evidence that models build spatial and temporal representations throughout the early layers before plateauing at around the model halfway point with larger models consistently outperforming smaller ones (§ 3.1). We then show these representations are (1) linear, given that nonlinear probes do not perform better (§ 3.2), (2) fairly robust to changes in prompting (§ 3.3), and (3) unified across different kinds of entities (e.g. cities and natural landmarks).
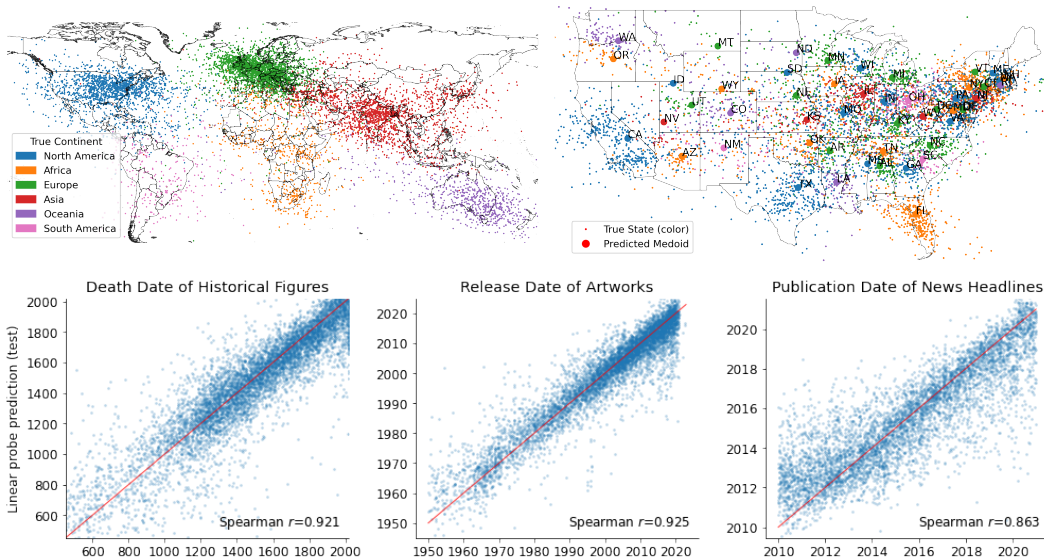
Figure 1: Spatial and temporal world models of Llama-2-70b. Each point corresponds to the layer 50 activations of the last token of a place (top) or event (bottom) projected on to a learned linear probe direction. All points depicted are from the test set.

One possible explanation for our results is that the model only learns a mapping from place to a country (for example) and it is the probe that actually learns the global geometry of how these different groups are geospatially (or temporally) related. To study this, we conduct a series of robustness checks to understand how the probes generalize across different data distributions (§ 4.1) and how probes trained on the PCA components perform (§ 4.2). Our findings suggest that the probes memorize the absolute positioning of these groups, but that the model does have representations which reflect the relative positioning. In other words, the probe learns the mapping from model coordinates to human interpretable coordinates. Finally, we use our probes to find individual neurons which activate as a function of space or time, providing strong evidence that the model is truly using these features (§ 5).

## 2 EMPIRICAL OVERVIEW

### 2.1 SPACE AND TIME RAW DATASETS

To enable our investigation, we construct six datasets of names of *entities* (people, places, events, etc.) with their respective location or occurrence in time, each at a different order of magnitude of scale. For each dataset, we included multiple types of entities, e.g., both populated places like cities and natural landmarks like lakes, to study how unified representations are across different object types. Furthermore, we maintain or enrich relevant metadata to enable analyzing the data with more detailed breakdowns, identify sources of train-test leakage, and support future work on factual recall within LLMs. We also attempt to deduplicate and filter out obscure or otherwise noisy data.

**Space** We constructed three datasets of place names within the world, the United States, and New York City. Our world dataset is built from raw data queried from DBpedia Lehmann et al. (2015). In particular, we query for populated places, natural places, and structures (e.g. buildings or infrastructure). We then match these against Wikipedia articles, and filter out entities which do not have at least 5,000 page views over a three year period. Our United States dataset is constructed from DB-Pedia and a census data aggregator, and includes the names of cities, counties, zipcodes, colleges, natural places, and structures where sparsely populated or viewed locations were similarly filtered out. Finally, our New York City dataset is adapted from the NYC OpenData points of interest dataset (NYC OpenData, 2023) containing locations such as schools, churches, transportation facilities, and public housing within the city.

**Time** Our three temporal datasets consist of (1) the names and occupations of historical figures who died between 1000BC and 2000AD adapted from (Annamoradnejad & Annamoradnejad, 2022); (2) the titles and creators of songs, movies, and books from 1950 to 2020 constructed from DBpedia with the Wikipedia page views filtering technique; and (3) New York Times news headlines from 2010-2020 from news desks that write about current events, adapted from (Bandy, 2021).

Table 1: Entity count and representative examples for each of our datasets.

| Dataset | Count | Examples |
|---|---|---|
| World | 39585 | "Los Angeles", "St. Peter's Basilica", "Caspian Sea", "Canary Islands" |
| USA | 29997 | "Fenway Park", "Columbia University", "Riverside County" |
| NYC | 19838 | "Borden Avenue Bridge", "Trump International Hotel" |
| Figures | 37539 | "Cleopatra", "Dante Alighieri", "Carl Sagan", "Blanche of Castile" |
| Art | 31321 | "Stephen King's It", "Queen's Bohemian Rhapsody" |
| Headlines | 28389 | "Pilgrims, Fewer and Socially Distanced, Arrive in Mecca for Annual Hajj" |

## 2.2 Models and Methods

**Data Preparation** All of our experiments are run with the base Llama-2 (Touvron et al., 2023) series of auto-regressive transformer language models, spanning 7 billion to 70 billion parameters. For each dataset, we run every entity name through the model, potentially prepended with a short prompt, and save the activations of the hidden state (residual stream) on the last entity token for each layer. For a set of $n$ entities, this yields an $n \times d_{model}$ activation dataset for each layer.

**Probing** To find evidence of spatial and temporal representations in LLMs, we use the standard technique of probing Alain & Bengio (2016); Belinkov (2022), which fits a simple model on the network activations to predict some target label associated with labeled input data. In particular, given an activation dataset $A \in \mathbb{R}^{n \times d_{model}}$, and a target $Y$ containing either the time or two-dimensional latitude and longitude coordinates, we fit linear ridge regression probes

$$\hat{W} = \arg\min_{W} \|Y - AW\|_2^2 + \lambda\|W\|_2^2 = (A^T A + \lambda I)^{-1} A^T Y$$

yielding a linear predictor $\hat{Y} = A\hat{W}$. High predictive performance on out-of-sample data indicates that the base model has temporal and spatial information linearly decodable in its representations, although this does not imply that the model actually uses these representations (Ravichander et al., 2020). In all experiments, we tune $\lambda$ using efficient leave-out-out cross validation (Hastie et al., 2009) on the probe training set.

## 2.3 Evaluation

To evaluate the performance of our probes we report standard regression metrics such as $R^2$ and Spearman rank correlation on our test data (correlations averaged over latitude and longitude for spatial features). An additional metric we compute is the *proximity error* for each prediction, defined as the fraction of predictions closer to the target point than the actual prediction. The intuition is that for spatial data, absolute error metrics can be misleading (a 500km error for a city on the East Coast of the United States is far more significant than a 500km error in Siberia), so when analyzing errors per prediction, we often report this metric to account for the local differences in desired precision.

## 3 Linear Models of Space and Time

### 3.1 Existence

We first investigate the following empirical questions: do models represent time and space at all? If so, where internally in the model? Does the representation quality change substantially with model scale? In our first experiment, we train probes for every layer of Llama-2-{7B, 13B, 70B} for each of our space and time datasets. Our main results, depicted in Figure 2, show fairly consistent patterns across datasets. In particular, both spatial and temporal features can be recovered with a linear
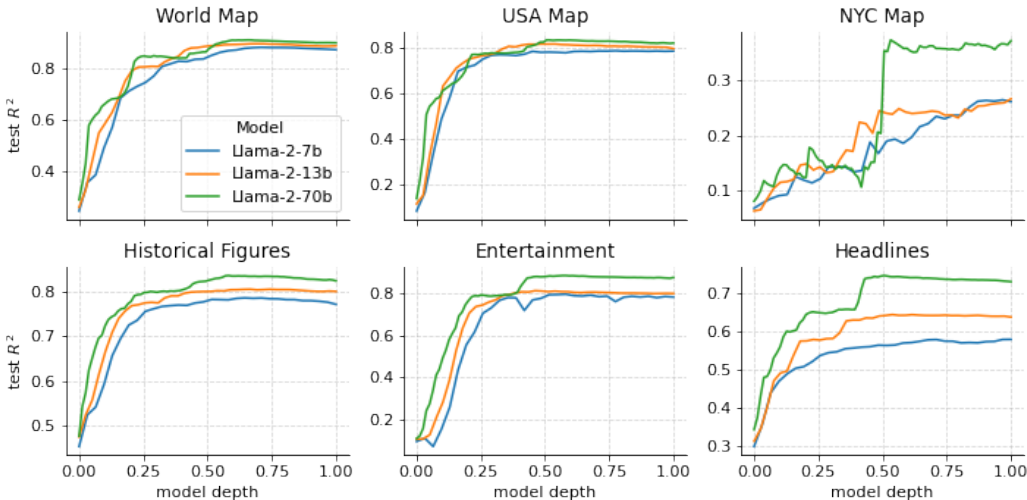
Figure 2: Out-of-sample $R^2$ for linear probes trained on every model, dataset, and layer.

probe, these representations are more accurate with increasing model scale, and the representations smoothly increase in quality throughout the first half of the layers of the model before reaching a plateau. These observations are consistent with results from the factual recall literature demonstrating that early-to-mid MLP layers are responsible for recalling information about factual subjects (Meng et al., 2022a; Geva et al., 2023).

The dataset with the worst performance is the New York City dataset. This was expected given the relative obscurity of most of the entities compared with other datasets. However, this is also the dataset where the largest model has the best relative performance, at nearly 2x the $R^2$ of smaller models, suggesting that sufficiently large LLMs could eventually form detailed spatial models of individual cities.

## 3.2 LINEAR REPRESENTATIONS

Within the interpretability literature, there is a growing body of evidence supporting the *linear representation hypothesis* that features within neural networks are represented linearly, that is, the presence or strength of a feature can be read out by projecting the relevant activation on to some feature vector (Mikolov et al., 2013; Olah et al., 2020; Elhage et al., 2022b). However, these results are almost always for binary or categorical features, unlike the naturally continuous features of space or time.

To test whether spatial and temporal features are represented linearly, we compare the performance of our linear ridge regression probes with that of substantially more expressive nonlinear MLP

Table 2: Out-of-sample $R^2$ of linear and nonlinear (one layer MLP) probes for all models and features at 60% layer depth.

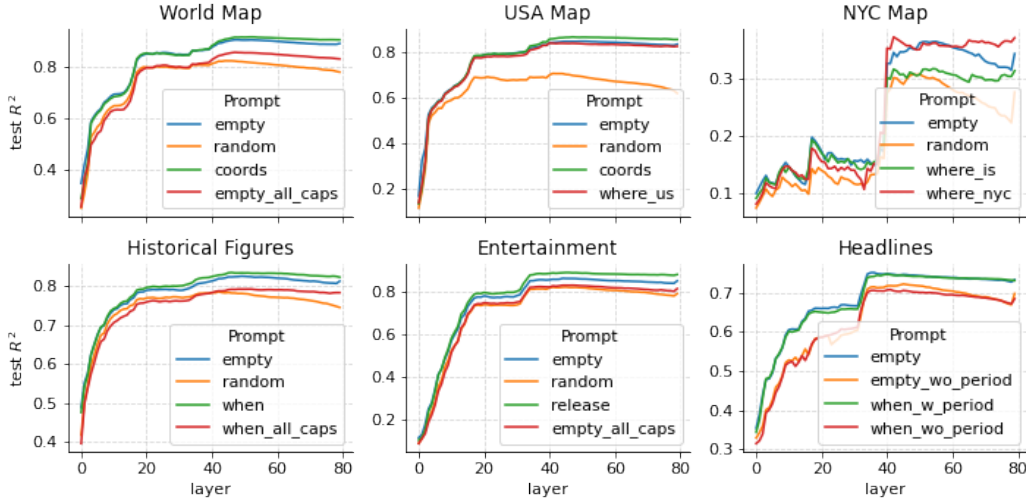| | | Dataset | | | | | |
|---|---|---|---|---|---|---|---|
| Model | Probe | World | USA | NYC | Historical | Entertainment | Headlines |
| Llama-2-7b | Linear | 0.881 | 0.799 | 0.219 | 0.785 | 0.788 | 0.564 |
| | MLP | 0.897 | 0.819 | 0.204 | 0.775 | 0.746 | 0.467 |
| Llama-2-13b | Linear | 0.896 | 0.825 | 0.237 | 0.804 | 0.806 | 0.645 |
| | MLP | 0.916 | 0.824 | 0.230 | 0.818 | 0.808 | 0.656 |
| Llama-2-70b | Linear | 0.911 | 0.864 | 0.359 | 0.835 | 0.885 | 0.746 |
| | MLP | 0.926 | 0.869 | 0.312 | 0.839 | 0.884 | 0.739 |

Figure 3: Out-of-sample $R^2$ when entity names are included in different prompts for Llama-2-70b.

probes of the form $\boldsymbol{W}_2\mathrm{ReLU}(\boldsymbol{W}_1\boldsymbol{x} + \boldsymbol{b}_1) + \boldsymbol{b}_2$ with 256 neurons. Table 2 reports our results and shows that using nonlinear probes results in minimal improvement to $R^2$ for any dataset or model. We take this as strong evidence that space and time are also represented linearly (or at the very least are linearly decodable), despite being continuous.

## 3.3 SENSITIVITY TO PROMPTING

Another natural question is if these spatial or temporal features are sensitive to prompting, that is, can the context induce or suppress the recall of these facts? Intuitively, for any entity token, an autoregressive model is incentivized to produce a representation suitable for addressing any future possible context or question.

To study this, we create new activation datasets where we prepend different prompts to each of the entity tokens, following a few basic themes. In all cases, we include an "empty" prompt containing nothing other than the entity tokens (and a beginning of sequence token). We then include a prompt which asks the model to recall the relevant fact, e.g., "What is the latitude and longitude of <place>" or "What was the release date of <author>'s <book>." For the United States and NYC datasets we also include versions of these prompts asking where in the US or NYC this location is, in an attempt to disambiguate common names of places (e.g. City Hall). As a baseline we include a prompt of 10 random tokens (sampled for each entity). To determine if we can obfuscate the subject, for some datasets we fully capitalize the names of all entities. Lastly, for the headlines dataset, we try probing on both the last token and on a period token appended to the headline.

We report results for the 70B model in Figure 3 and all models in Figure 7. We find that explicitly prompting the model for the information, or giving disambiguation hints like that a place is in the US or NYC, makes little to no difference in performance. However, we were surprised by the degree to which random distracting tokens degrades performance. Capitalizing the entities also degrades performance, though less severely and less surprisingly, as this likely interferes with "detokenizing" the entity (Elhage et al., 2022a; Gurnee et al., 2023; Geva et al., 2023). The one modification that did notably improve performance is probing on the period token following a headline, suggesting that periods are used to contain some summary information of the sentences they end.

## 4 ROBUSTNESS CHECKS

The previous section has shown that the true point in time or space of diverse types of events or locations can be linearly recovered from the internal activations of the mid-to-late layers of LLMs. However, this does not imply if (or how) a model actually uses the feature direction learned by the

probe, as the probe itself could be learning some linear combination of simpler features which are actually used by the model.

## 4.1 Verification via Generalization

### 4.1.1 Block holdout generalization

To illustrate a potential issue with our results, consider the task of representing the full world map. If the model has, as we expect it does, an almost orthogonal binary feature for `is_in_country_X`, then one could construct a high quality latitude (longitude) probe by summing these orthogonal feature vectors for each country with coefficient equal to the latitude (longitude) of that country. Assuming a place is in only one country, such a probe would place each entity at its country centroid. However, in this case, the model does not actually represent space, only country membership, and it is only the probe which learns the geometry of the different countries from the explicit supervision.

To better distinguish these cases, we analyze how the probes generalize when holding out specific blocks of data. In particular, we train a series of probes, where for each one, we hold out one country, state, borough, century, decade, or year for the world, USA, NYC, historical figure, entertainment, and headlines dataset respectively. We then evaluate the probes on the held out block of data. In Table 3, we report the average proximity error for the block of data when completely held out, compared to the error of the test points from that block in the default train-test split, averaged over all held out blocks.

We find that while generalization performance suffers, especially for the spatial datasets, it is clearly better than random. By plotting the predictions of the held out states or countries in Figures 10 and 11, a qualitatively clearer picture emerges. That is, the probe correctly generalizes by placing the points in the correct relative position (as measured by the angle between the true and predicted centroid) but not in their absolute position. We take this as weak evidence that the probes are extracting explicitly learned features by the model, but are memorizing the transformation from model coordinates to human coordinates. However, this does not fully rule out the underlying binary features hypothesis, as there could be a hierarchy of such features that do not follow country or decade boundaries.

Table 3: Average proximity error across blocks of data (e.g., countries, states, decades) when included in the training data compared to completely held out. Random performance is 0.5.

| Model | Block | Dataset | | | | | |
| | | World | USA | NYC | Historical | Entertainment | Headlines |
|---|---|---|---|---|---|---|---|
| Llama-2-7b | nominal | 0.071 | 0.144 | 0.331 | 0.129 | 0.147 | 0.258 |
| | held out | 0.170 | 0.192 | 0.473 | 0.133 | 0.158 | 0.264 |
| Llama-2-13b | nominal | 0.068 | 0.144 | 0.319 | 0.121 | 0.141 | 0.223 |
| | held out | 0.156 | 0.189 | 0.470 | 0.126 | 0.152 | 0.235 |
| Llama-2-70b | nominal | 0.071 | 0.121 | 0.262 | 0.115 | 0.105 | 0.182 |
| | held out | 0.164 | 0.188 | 0.433 | 0.119 | 0.122 | 0.200 |

### 4.1.2 Cross entity generalization

Implicit in our discussion so far is the claim that the model represents the space or time coordinates of different types of entities (like cities or natural landmarks) in a unified manner. However, similar to the concern that a latitude probe could be a weighted sum of membership features, a latitude probe could also be the sum of different (orthogonal) directions for the latitudes of cities and for the latitudes of natural landmarks.

Similar to the above, we distinguish these hypotheses by training a series of probes where the train-test split is performed to hold out all points of a particular entity class [1] Table 4 reports the proximity

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[1] We only do this entities which do not make up the majority of the training data (e.g., as is the case with populated places for the world dataset and songs for the entertainment dataset) which is partially responsible for the discrepancies in the nominal cases for Tables 3 and 4.

error for the entities in the default test split compared to when heldout, averaged over all such splits as before. The results suggest that the probes largely generalize across entity types, with the main exception of the entertainment dataset[2].

Table 4: Average proximity error across entity subtypes (e.g. books and movies) when included in the training data compared to being fully held out. Random performance is 0.5.

| Model | Entity | Dataset | | | | | |
|---|---|---|---|---|---|---|---|
| | | World | USA | NYC | Historical | Entertainment | Headlines |
| Llama-2-7b | nominal | 0.120 | 0.206 | 0.313 | 0.164 | 0.224 | 0.199 |
| | held out | 0.151 | 0.262 | 0.367 | 0.168 | 0.305 | 0.289 |
| Llama-2-13b | nominal | 0.117 | 0.197 | 0.310 | 0.153 | 0.207 | 0.171 |
| | held out | 0.147 | 0.259 | 0.377 | 0.159 | 0.283 | 0.266 |
| Llama-2-70b | nominal | 0.113 | 0.173 | 0.266 | 0.149 | 0.159 | 0.144 |
| | held out | 0.147 | 0.203 | 0.322 | 0.149 | 0.271 | 0.219 |

## 4.2 DIMENSIONALITY REDUCTION

Despite being linear, our probes still have $d_{model}$ learnable parameters (ranging from 4096 to 8192 for the 7B to 70B models), enabling it to engage in substantial memorization. As a complementary form of evidence to the generalization experiments, we train probes with 2 to 3 orders of magnitude fewer parameters by projecting the activation datasets onto their $k$ largest principal components.

Figure 4 illustrates the test $R^2$ for probes trained on each model and dataset over a range of $k$ values, as compared to the performance of the full $d_{model}$-dimensional probe. We also report the test Spearman correlation in Figure 12 which increases much more rapidly with increasing $k$ than the $R^2$. Notably, the Spearman correlation only depends on the rank order of the predictions while $R^2$ also depends on their actual value. We view this gap as further evidence that the model explicitly represents space and time as these features must account for enough variance to be in the top dozen principal components, but that the probe requires more parameters to convert from the model's coordinate system to literal spatial coordinates or timestamps. We also observed that the first several principal components clustered the different entity types within the dataset, explaining why more than a few are needed.
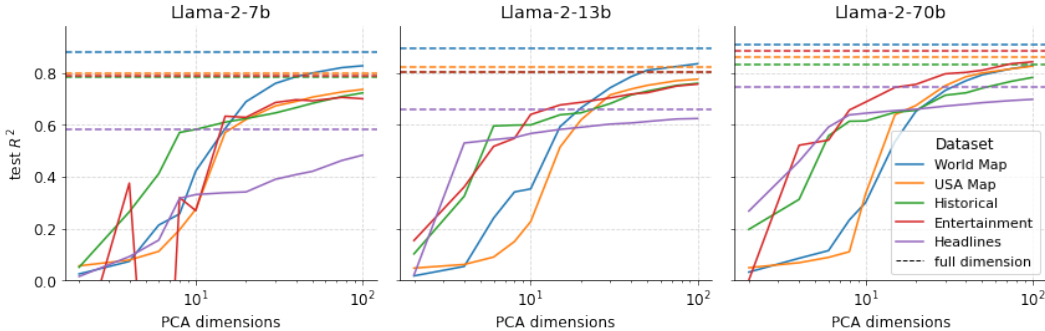


Figure 4: Test $R^2$ for probes trained on activations projected onto $k$ largest principal components for each dataset and model compared to training on the full activations.

## 5 SPACE AND TIME NEURONS

While the previous results are suggestive, none of our evidence directly shows that the model *uses* the features learned by the probe. To address this, we search for individual neurons with input or

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[2]We note in this case the Spearman correlation is still high, suggesting this is an issue with bias generalization, as the different entity types are not uniformly distributed in time.
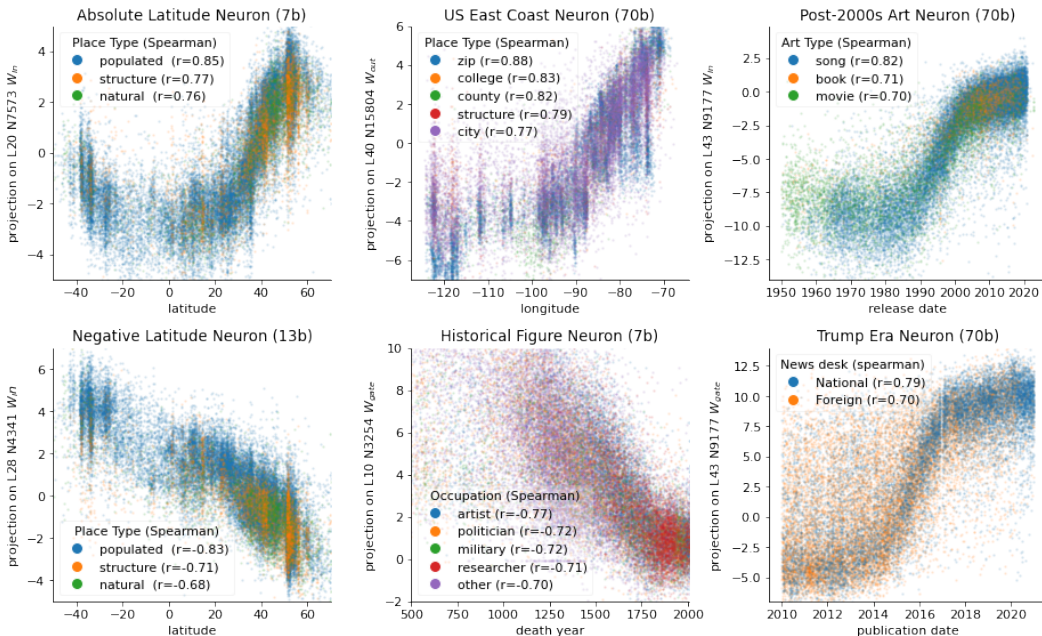
Figure 5: Space and time neurons in Llama-2 models. Depicts the result of projecting activation datasets onto neuron weights compared to true space or time coordinates with Spearman correlation by entity type.

output weights that have high cosine similarity with the learned probe direction. That is, we search for neurons which read from or write to a direction similar to the one learned by the probe.

We find that when we project the activation datasets on to the weights of the most similar neurons, these neurons are indeed highly sensitive to the true location of entities in space or time (see Figure 5). In other words, there exist individual neurons within the model that are themselves fairly predictive feature probes. Moreover, these neurons are sensitive to all of the entity types within our datasets, providing stronger evidence for the claim these representations are unified.

If probes trained with explicit supervision are an approximate upper bound on the extent to which a model represents these spatial and temporal features, then the performance of individual neurons is a lower bound. In particular, we generally expect features to be distributed in superposition (Elhage et al., 2022b), making individual neurons the wrong level of analysis. Nevertheless, the existence of these individual neurons, which received no supervision other than from next-token prediction, is very strong evidence that the model has learned and makes use of spatial and temporal features.

# 6 RELATED WORK

**Neural World Models** Our work is most directly inspired by prior research into the extent to which deep learning systems form interpretable models of their data generating process. The cleanest demonstrations have from come from GPT style models trained on chess (Toshniwal et al., 2022) and Othello games (Li et al., 2022) which were shown to have explicit representations of the board and game state. Subsequent work on Othello has shown these representations are also linear (Nanda et al., 2023). In true language models, Li et al. (2021) show that an entity's dynamic properties or relations can be linearly read out from representations at different points in the context. Abdou et al. (2021) and Patel & Pavlick (2021) show LLMs have representations that reflect perceptual and conceptual structure in color and spatial (but not geographic) domains, analogous to our attempts to show representations reflect geographic structure. Most related to our work is Konkol et al. (2017) and Liétard et al. (2021) who study the degree to which geography is reflected in word embeddings or small language models. Liétard et al. (2021) conclude the amount of information is "limited" but

that larger models show more signs of geographic knowledge. By studying models with 100x the parameters on 10x the labeled data, we confirm this hypothesis.

**Factual Recall**    The point in time or space of an event or place is a particular kind of fact. Our investigation is informed by prior work on the mechanisms of factual recall in LLMs (Meng et al., 2022a;b; Geva et al., 2023) indicating that early-to-mid MLP layers are responsible for outputting information about factual subjects, typically on the last token of the subject. Many of these works also show linear structure, for example in the factuality of a statement (Burns et al., 2022) or in the structure of subject-object relations (Hernandez et al., 2023). To our knowledge, our work is unique in considering continuous facts.

**Intepretability**    More broadly, our work draws upon many results and ideas from the interpretability literature (Räuker et al., 2023), especially in topics related to probing (Belinkov, 2022), BERTology (Rogers et al., 2021), the linearity hypothesis and superposition (Elhage et al., 2022b), and mechanistic interpretability (Olah et al., 2020). More specific results related to our work include Hanna et al. (2023) who find a circuit implementing greater-than in the context of years, and Goh et al. (2021) who find neurons in multimodal models corresponding to places, similar to our time and space neurons.

## 7   DISCUSSION

We have provided evidence that LLMs learn linear representations of space and time that are unified across entity types and fairly robust to prompting, and that there exists individual neurons that are highly sensitive to these features. The corollary is that next token prediction alone is sufficient for learning a literal map of the world give sufficient model and data size.

Our analysis raises many interesting questions for future work. While we showed that it is possible to linearly reconstruct a sample's absolute position in space or time, and that some neurons use these probe directions, the true extent and structure of spatial and temporal representations remain unclear. In particular, we conjecture that the most canonical form of this structure is a discretized hierarchical mesh, where any sample is represented as a linear combination of its nearest basis points at each level of granularity. Moreover, the model can and does use this coordinate system to represent absolute position using the correct linear combination of basis directions in the same way a linear probe would. We expect that as models scale, this mesh is enhanced with more basis points, more scales of granularity (e.g. neighborhoods in cities), and more accurate mapping of entities to model coordinates (Michaud et al., 2023).

This suggests future work on extracting representations in the model's coordinate system rather than trying to reconstruct human interpretable coordinates, perhaps with sparse autoencoders (Cunningham et al., 2023). Another confounder in our analysis, and factual recall research more broadly, is the existence of many entities in our dataset which the model is unaware of, contaminating our activation datasets. We would be interested in methods that can identify when a model recognizes a particular entity beyond simply prompting for specific facts and risking hallucinations.

We also barely scratched the surface of understanding how these spatial and temporal world models are learned, recalled, or used internally. By looking across training checkpoints, it may be possible to localize a point in training when a model organizes constituent `is_in_place_X` features into a coherent geometry or else conclude this process is gradual (Liu et al., 2021). We expect that the model components which construct these representations are similar or identical to those for factual recall (Meng et al., 2022a; Geva et al., 2023). In preliminary experiments, we found our models had trouble answering basic spatial and temporal relations questions without relying on multi-step reasoning, complicating any causal intervention analysis Wang et al. (2022), but think that this is the natural next step for understanding when and how these features are used.

Finally, we note that the representation of space and time has received much more attention in biological neural networks than artificial ones (Buzsáki & Llinás, 2017). Place and grid cells (O'Keefe & Dostrovsky, 1971; Hafting et al., 2005) in particular are among the most well-studied in the brain, as we expect it to be productive source of inspiration for future work on LLMs.

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# A  DATASETS

We describe the construction and post-processing of our data in more detail in addition to known limitations. All datasets and code are available at `https://github.com/wesg52/world-models`.

**World Places**   We ran three separate queries to obtain the names, location, country, and associated Wikipedia article of all physical places, natural places, and structures within the DBPedia database Lehmann et al. (2015). Using the Wikipedia article link, we joined this information with data from the Wikipedia pageview statistics database [3] to query how many times this page was accessed over 2018-2020. We use this as a proxy for whether we should expect an LLM to know of this place or not, and filter those with less than 5000 views over this time period.

Several limitation are worth highlighting. First, our data only comes from English Wikipedia, and hence is skewed towards the Anglosphere. Additionally, the distribution of entity types is not uniform, e.g. we noticed the United Kingdom has many more railway stations than any other country, which could introduce unwanted correlations in the data that may affect the probes. Finally, about 25% of the samples had some sort of state or province modifier at the end like "Dallas County, Iowa". Because many of these locations were more obscure or would be ambiguous without the modifier, so we chose to rearrange the string to be of the from "Iowa's Dallas County" such the entity is disambiguated but that we are not probing on a token that is a common country or state name.

**USA Places**   The United States places dataset uses structures and natural places within the US from the world places dataset as a starting point, in addition to another DBPedia for US colleges. We then collect the name, population total, and state for every county[4], zipcode [5], and city [6] from a census data aggregator. We then remove all duplicate county or city names (there are 31 Washington counties in the US!), though we keep any duplicates that have 2x the population has the next largest place of the same name. We also filter out cities with fewer than 500 people, zipcodes with fewer than 10000 (or with population density greater than 50 and population greater than 2000), and any place not in the lower 48 contiguous states (or Washington D.C.).

**NYC Places**   Our New York City dataset is adapted from the NYC Open Date points of interest dataset (NYC OpenData, 2023) containing the names of locations tracked by the city government. This includes the names of schools, places of worship, transit locations, important roads or bridges, government buildings, public housing, and more. Each of these places comes with a complex ID for locations comprised of multiple such buildings (e.g. New York University or LaGuardia airport). We construct our test train splits to make sure that all locations within the same complex are put in the same split to avoid test-train leakage. We filtered out a large number of locations describing the position of bouys in the multiple waterways surrounding NYC.

**Historical Figures**   Our historical figures dataset contains the names and occupation of historical figures who died between 1000BC-2000AD adapted from (Annamoradnejad & Annamoradnejad, 2022). We filtered the dataset to only contain the 350 most famous people who died from each decade, imperfectly measured by the index of their Wikidata entity identifier.

**Art and Entertainment**   Our art and entertainment dataset consists of the names of songs, movies, and books with their corresponding artist, director, and author release date. We constructed this dataset from DBpedia and similarly filtered out entities which had received less than 5000 page views over 2018-2020. Because many songs or books have fairly generic titles, we include the creator's name in the prompt to disambiguate (e.g. "Stephen Kings' It" for the `empty` prompt). However, because some artists or authors release many songs or books, we sample our test-train split by creator to avoid leakage.

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[3] `https://en.wikipedia.org/wiki/Wikipedia:Pageview_statistics`
[4] `https://simplemaps.com/data/us-counties`
[5] `https://simplemaps.com/data/us-zips`
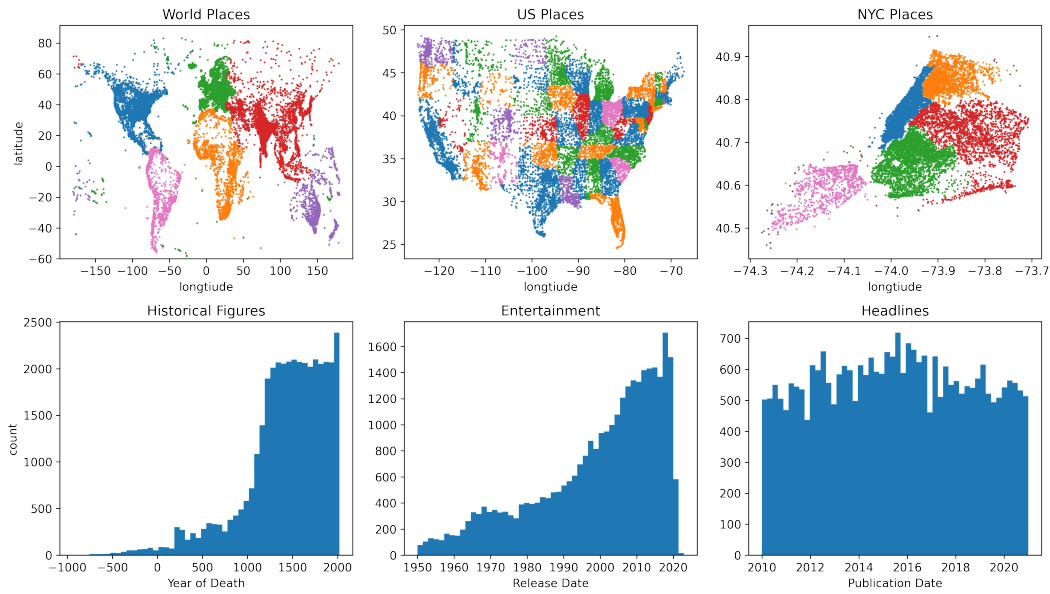[6] `https://simplemaps.com/data/us-cities`

Figure 6: Distribution of samples in space or time for all datasets.

**Headlines** Our headlines dataset is adapted from a scrape of all New York Times headlines of the past 30 years (Bandy, 2021). In an attempt to filter out headlines which do not describe an event that could be localized in time, we employ a number of strategies. First we filter anything which is not within the first 10 pages of the print edition. Second we filter out articles that don't come from the Foreign, National, Politics, Washington, or Obits news desks. Third we removed any titles that contained a question mark.
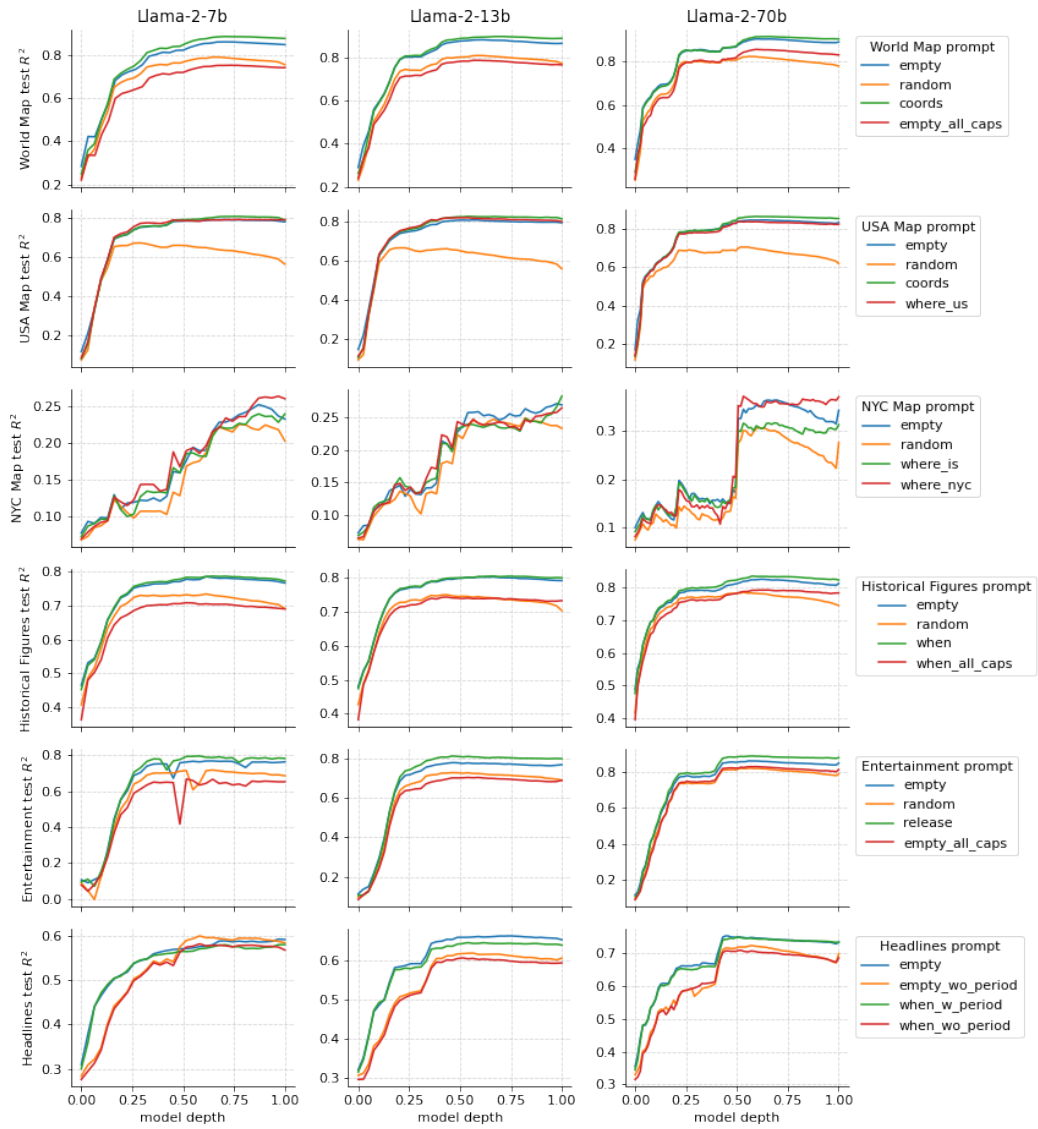
## B  ADDITIONAL RESULTS

Figure 7: Out-of-sample $R^2$ when entity names are included in different prompts for all models.

Figure 8: Llama-2-70b layer 50 model of the United states. Points are projections of activations of heldout US places onto learned latitude and longitude directions colored by true state, with median state prediction enlarged. All points depicted are from the test set.



Figure 9: Llama-2-70b layer 50 model of the world. Points are projections of activations of heldout world places onto learned latitude and longitude directions colored by true continent. All points depicted are from the test set.
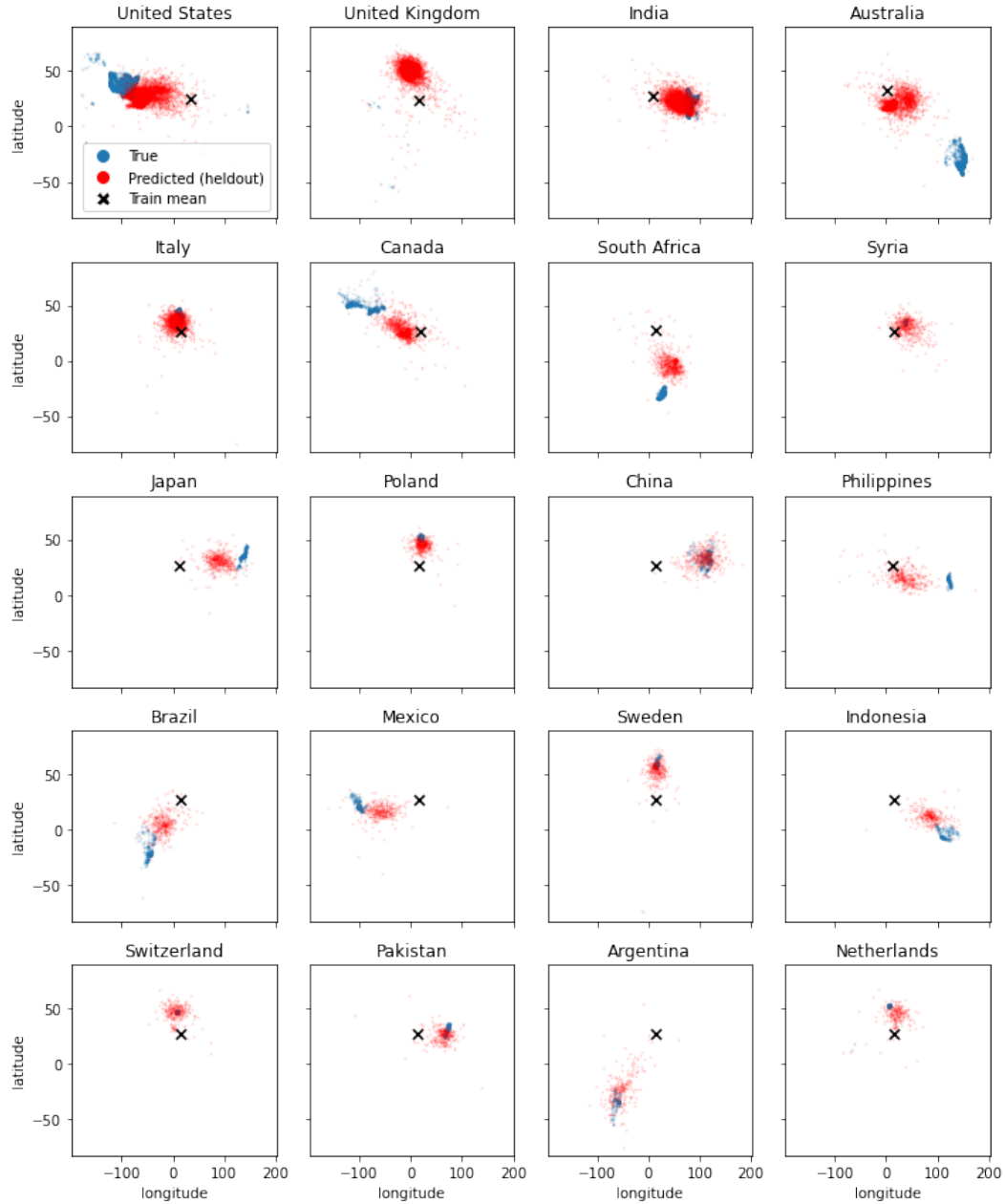
Figure 10: Out-of-sample predictions for each country when the probe training data contains no samples from the country as compared to true locations and the mean of the training data. The results imply that the learned feature direction correctly generalizes to the relative position of a country but that the probes memorizes the absolute positions.
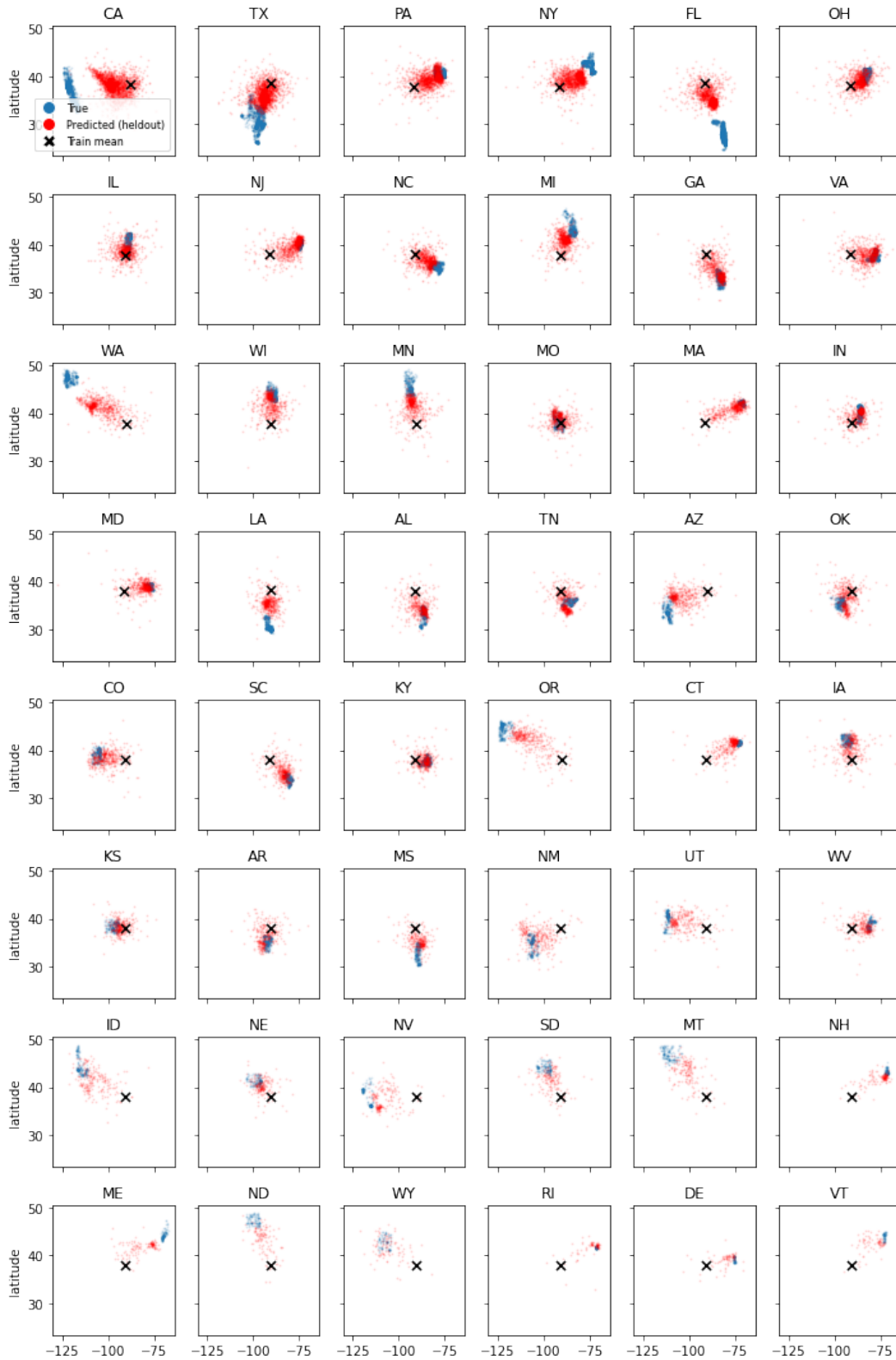
Figure 11: Out-of-sample predictions for each state when the probe training data contains no samples from the state as compared to true locations and the mean of the training data. The results imply that the learned feature direction correctly generalizes to the relative position of a country but that the probes memorizes the absolute positions.
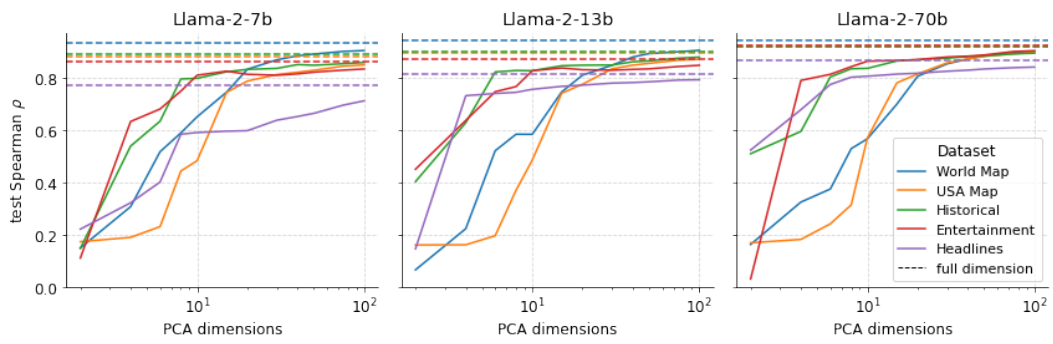
Figure 12: Test Spearman rank correlation for probes trained on activations projected onto $k$ largest principal components.