Emergent Spatio-Semantic Structure in Large Language Model Embedding Spaces

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Abstract

Large Language Models (LLMs) are increasingly used in geospatial applications typically as generators of geographic text or as natural language interfaces to spatial data. Here, we explore whether LLM embedding spaces can instead function as geospatial representations that can be exploited directly. Using embeddings extracted from Airbnb property descriptions in London, we show that off-the-shelf LLM embeddings exhibit emergent spatial structure. We further demonstrate that a lightweight residual geo-adapter substantially sharpens this spatial signal, enabling approximate localisation even when explicit geographic references are removed, while preserving semantic relationships learned during LLM pre-training. These results suggest a path toward spatially explicit foundation models which operate over the spatio-semantic embedding space, rather than generated text.

1 Introduction

Geospatial Artificial Intelligence (GeoAI) seeks to integrate geographic knowledge with AI systems capable of learning, reasoning, and analysing spatial information. Recent work has shown that large language models (LLMs), when appropriately constrained, can support geographic information extraction and tool-assisted geospatial workflows [1, 2, 3]. However, many such approaches rely on text generation to produce geographic outputs, which can be slow, non-deterministic, and difficult to validate or reproduce [4].

This paper adopts an alternative perspective: rather than treating large language models primarily as generators of geographic text, we explore whether their internal embedding spaces can function directly as geospatial representations. Using high-dimensional text embeddings produced by a pre-trained LLM (e5-Mistral-7B; [5]) from Airbnb property descriptions in London, we show that spatially coherent structure emerges naturally in embedding space, even when descriptions contain only vague, implicit, or masked location references.

We further demonstrate that this latent spatial structure can be substantially sharpened using a lightweight residual geo-adapter trained with minimal geographic supervision. The resulting embeddings support efficient nearest neighbour retrieval for both continuous and discrete geolocation, without requiring explicit geocoding, structured spatial inputs, or text generation at inference time.

Our work builds on recent studies examining geographic information in internal LLM representations. De Sabbata et al. [6] identify geographically coherent neuron activations in Mistral-7B, while He et al. [7] show that LLM embeddings can enhance spatio-temporal learning when trained on structured spatial data. In contrast, we focus on the extent to which spatial structure is already present in embeddings derived from unstructured, non-specific descriptions, and on how this structure can be operationalised for downstream GeoAI tasks.

Specifically, we make three contributions:

(i) We show that off-the-shelf LLM embeddings already function as weak geospatial representations suitable for localisation tasks.
(ii) We demonstrate that this structure can be substantially sharpened using a lightweight residual geo-adapter trained post-hoc.
(iii) We show that these representations support approximate localisation even when explicit geographic references are removed, and that they generalise to localisable queries not seen during training.

2 Methods

2.1 Data

We collected 28,243 non-duplicated Airbnb property descriptions of at least 400 characters in length from the Inside Airbnb dataset [8]. We focus on Airbnb property descriptions since they are intrinsically linked to a ground-truth location, and often describe nearby amenities [4] and urban characteristics [5]. We select London as the study area due to its high density of Airbnb properties and its relatively heterogeneous spatial structure.

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The dataset is split into 25,243 training samples, 1,000 validation samples, and 2,000 test samples. To mitigate data leakage, 9 test samples with highly similar descriptions (string similarity ratio $r > 0.8$) to training examples were removed using fuzzy string matching [9].

2.2 Embedding Model

We use e5-Mistral-7B-Instruct as the embedding model in this work. The model is based on the Mistral-7B-Instruct architecture [10] and has been fine-tuned for general-purpose information retrieval [**wang2024**]. The final embedding layer is left exposed, and embeddings are extracted via last-token pooling followed by L2 normalisation, producing vectors of dimension 4096.

2.3 Geo-Adapter

To sharpen spatial structure in the base embeddings, we train a lightweight geo-adapter that encourages geographically proximate property descriptions to be closer in embedding space.

The adapter is a residual Multi-Layer Perceptron (MLP) [11] (Layers: $4096 \rightarrow 2048 \rightarrow 1024$) applied as a learned correction to the original embedding:

$$z' = \|g(z) + \alpha f_\theta(z)\|_2, \quad (1)$$

where f_θ denotes the MLP, $g(\cdot)$ is a learned linear skip connection [12], and α is a learned gate parameter ($\alpha = 0.360$ after 100 epochs) which modulates the influence of the residual.

Training uses logistic ranking loss [13]. For each anchor embedding z_a, a positive example z_+ is sampled from properties within 500 m and negative example, z_- from properties at least 4 km away. The per-sample loss is:

$$\ell = \ln\left(1 + \exp\left(-\frac{s(z_a, z_+) - s(z_a, z_-)}{T}\right)\right), \quad (2)$$

where $s(\cdot,\cdot)$ denotes cosine similarity and $T = 0.1$ is a temperature parameter. The adapter is trained over 100 epochs using an AdamW optimizer (learning rate $= 3 \times 10^{-4}$, batch size = 128).

2.4 Downstream Analyses

- **Clustering.** We apply k-means clustering ($k = 16$, cosine distance) to the embedding vectors and assess the spatial coherence of the resulting clusters using visual inspection.
- **Continuous geolocation retrieval.** We estimate property locations by retrieving the $k = 10$ nearest neighbours in embedding space from the training set and taking the median of their geographic coordinates, evaluating accuracy using distance-based error statistics.
- **Discrete geolocation retrieval.** We compute a mean embedding for each Middle Layer Super Output Area (MSOA) in London [14] represented by at least five training examples. Test embeddings are ranked against these MSOA representations by cosine similarity, and performance is reported using hit@k [15] and dist@k [16] metrics. We also report the median similarity quantile of the true MSOA among all candidate MSOAs.

To asses robustness to missing geographic references, we take a random subset of $N = 200$ descriptions from our test data, and manually construct two masked test-sets: $m_{explicit}$, which removes all explicit and specific place names, and M_{all} further removes vague location references such as *East London* or *Northern Line*.

3 Results

3.1 Clustering

Figure 1 maps the K-Means clustering ($k = 16$, cosine distance) on property description embeddings for (a) the unadapted e5-Mistral-7B model and (b, c) the geo-adapted model on the training and test sets, respectively. Even without geospatial adaptation, the raw embeddings demonstrate clear spatial organisation, though several clusters exhibit weaker spatial concentration, resulting in larger within-cluster dispersion (standard distance = 4.62 km). The geo-adapter provides stronger spatial structure, with all clusters having a clear geographic centre of mass and significantly lower dispersion (standard distance = 3.19 km). This suggests that much of the spatial information is already present in the original embedding space, with the adapter surfacing deeper latent structure.

3.2 Continuous Geolocalisation

Table 1 reports continuous geolocalisation using a k-nearest neighbour estimator in embedding space ($k = 10$). Raw e5-Mistral-7B embeddings already support relatively accurate localisation, and applying the geo-adapter consistently improves performance across all metrics, indicating that geographic supervision sharpens spatial structure present in the base embedding space.

Table 2 shows performance on masked subsets. As expected, localisation accuracy degrades when

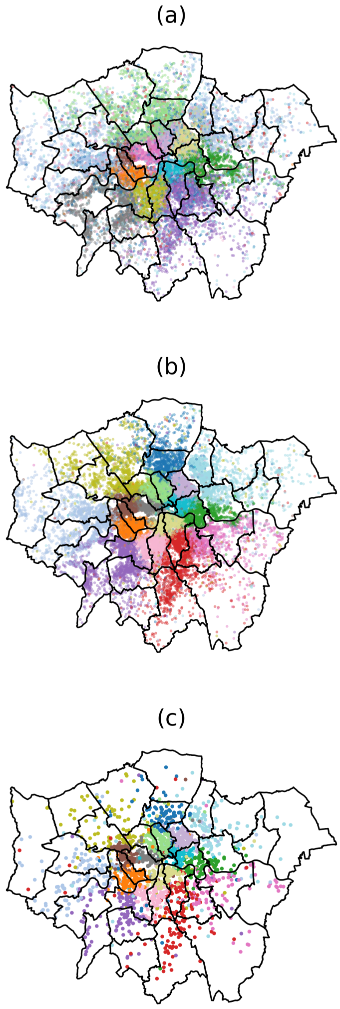

Figure 1: *Spatial distribution of K-means clusters ($k = 16$) derived from Airbnb property description embeddings: (a) using the raw embeddings from e5-mistral-7B, (b) geo-adapted embeddings on the adapter training set; and (c) geo-adapted embeddings on the held-out test set.*

explicit geographic references are removed, but remains substantially above chance. This suggests that the embeddings retain coarse semantic cues that support approximate localisation even in the absence of explicit place names, or vague geographic references.

The random baseline, constructed by repeatedly taking the median coordinates of randomly sampled training properties, performs substantially worse across all metrics. It is important to note that once explicit geographic references are removed, many property descriptions become fundamentally unlocalisable, making this a deliberately challenging setting in which any performance above chance is informative.

3.3 Discrete Geolocalisation

Table 3 reports MSOA-level geolocalisation performance using embedding similarity. On the full test set, the geo-adapted embeddings achieve strong discrete localisation, with the correct MSOA frequently ranked among the top candidates and small geographic error when exact recovery fails.

Performance degrades on the masked subsets, but remains well above chance (random sampling over 747 viable MSOAs). Even when all geographic references are removed, the true MSOA is typically ranked within the top 15% of the similarity distribution, indicating that the embedding space retains spatially informative structure beyond explicit place names.

3.4 Semantic Generalisation

The geolocalisation results demonstrate that property descriptions can often be localised even when geographic information is removed. To better understand this behaviour, we probe the embedding space using short descriptive phrases and analyse the spatial structure of their induced similarity surfaces.

Figures 2 (a) and (b) show cosine similarity between each mean MSOA embedding and embeddings for the phrases *Georgian townhouse* and *affluent area*. In both cases, similarity values exhibit geographically coherent structure, with high-scoring areas corresponding to regions where these descriptors could reasonably reflect real urban characteristics. Although these exact phrases appear only 45 and 10 times in the training corpus, respectively, the adapter aligns them with meaningful spatial patterns.

The model further generalises beyond the adapter's training data. Figures 2(c) and (d) present similarity surfaces for the names *Harry Kane* and *Didier Drogba*, footballers strongly associated with Tottenham Hotspurs and Chelsea, respectively. These names do not occur in the adapter training data, yet induce geographically coherent similarity patterns centred on the areas associated with each club. This indicates that geo-adaptation preserves semantic relationships learned during LLM pre-training.

4 Conclusion

By examining the spatial structure of LLM embedding spaces, this work points toward spatially explicit foundation models that extract geographic information directly from internal representations, without relying on expensive or non-deterministic text generation. We further show that lightweight geo-adaptation strengthens the spatial signal while preserving semantic relationships learned during LLM

Table 1: *Continuous geolocalisation performance on the London test set ($N = 1991$), using the median coordinate of $k = 30$ nearest neighbours. Acc@d measures the proportion of properties localised to within a distance d of their true location.*

Method	**Acc@1km**	**Acc@5km**	**Median Err. (km)**
Raw embedding (e5-Mistral-7B)	0.624	0.873	0.702
Geo-adapted embedding	0.680	0.907	0.633
Random baseline	0.011	0.245	7.753

Table 2: *Continuous geolocalisation on masked subsets ($N = 200$) using geo-adapted embeddings. Subset $M_{explicit}$ has geographically specific place names removed, while M_{all} has both specific and vague locations removed. Random baseline performance is shown in Table 1 for reference.*

Dataset	**Acc@1km**	**Acc@5km**	**Median Err. (km)**
$M_{explicit}$	0.100	0.495	5.143
M_{all}	0.050	0.380	7.501

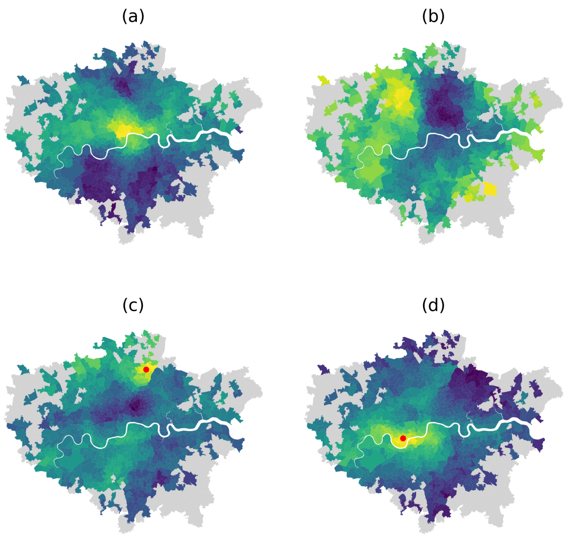

Figure 2: *Similarity surfaces induced by textual queries. Panels show cosine similarity between query embeddings and mean MSOA embeddings for (a) "Georgian townhouse", (b) "affluent area", (c) "Harry Kane", and (d) "Didier Drogba". Yellow areas indicate higher cosine similarity with the mean MSOA embedding. Red points indicate the stadium locations of the football clubs associated with (c) "Harry Kane" (Tottenham Hotspur FC) and (d) "Didier Drogba" (Chelsea FC).*

pre-training, enabling spatio-semantic generalisation beyond the training data.

While this study focuses on a single data source and geographic context, the approach is general. Extending it to other geolocalisable text corpora, such as Wikipedia articles, news articles, or place-based reviews, offers a clear path toward richer spatio-semantic representations that are not tied to the biases of any single domain.

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Table 3: *Discrete MSOA-level geolocalisation performance using geo-adapted embeddings. Results are reported for the full test set ($N = 1991$) and masked subsets ($N = 200$). Higher quantiles indicate better ranking of the true MSOA among all candidates.*

Subset	Hit@1	Hit@50	Dist@50 (km)	Median Quantile
All test samples	0.289	0.873	0.627	0.997
$M_{explicit}$	0.025	0.425	3.18	0.910
M_{all}	0.015	0.285	4.262	0.859
Random baseline	0.001	0.067	-	0.500

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