

GAEA: A Geolocation Aware Conversational Model

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Abstract

Image geolocalization, in which, traditionally, an AI model predicts the precise GPS coordinates of an image is a challenging task with many downstream applications. However, the user cannot utilize the model to further their knowledge other than the GPS coordinate; the model lacks an understanding of the location and the conversational ability to communicate with the user. In recent days, with tremendous progress of large multimodal models (LMMs)—proprietary and open-source—researchers have attempted to geolocalize images via LMMs. However, the issues remain unaddressed; beyond general tasks, for more specialized downstream tasks, one of which is geolocalization, LMMs struggle. In this work, we propose to solve this problem by introducing a conversational model GAEA that can provide information regarding the location of an image, as required by a user. No large-scale dataset enabling the training of such a model exists. Thus we propose GAEA-1.6M, a comprehensive dataset with 800K images and around 1.6M question-answer pairs constructed by leveraging OpenStreetMap (OSM) attributes and geographical context clues. For quantitative evaluation, we propose a diverse benchmark, GAEA-Bench, comprising 4K image-text pairs to evaluate conversational capabilities equipped with diverse question types. We consider 11 state-of-the-art open-source and proprietary LMMs and demonstrate that GAEA significantly outperforms the best open-source model, LLaVA-OneVision by 25.69% and the best proprietary model, GPT-4o by 8.28%. Our dataset, model and codes are available <https://ucf-crcv.github.io/GAEA>.

1. Introduction

Image geolocalization [23, 32, 50, 55, 59] is a notoriously challenging task, in which, conventional AI models predict the precise GPS coordinate of an image taken anywhere on Earth. Moreover, seasonal changes, geographical and climatic diversity, changes in solar zenith angle, and lack of diverse image distributions make the geolocalization task more challenging. Although difficult, geolocaliza-

	Location:
	Bangkok, Thailand (13.7465, 100.4924)
	Input Question:
	Can you name a coffee shop near this image with takeaway services?
	Ground Truth: Cafe Amazon is a coffee shop with takeaway services, near the location of this image.
	The image you've shared is of a statue at Wat Pho... While Wat Pho is a significant landmark, it's not a coffee shop...
	Unfortunately, I'm unable to provide a specific coffee shop near the image with takeaway services as I don't have access to real-time information...
	For coffee lovers, many local cafes offer takeaway services, such as Gallery Drip Coffee and Cafe Baan.
	While I can identify the image as a statue at Wat Pho... I do not have real-time access to information about coffee shops...
	In Bangkok, Thailand, near the location of this image, you can find Cafe Amazon, which offers both coffee and takeaway options.

Figure 1. **Performance of GAEA and other LMMs** on global scale image geo-localization. GAEA makes correct predictions when asked different questions about summarizing a scene, location, and geographical context. While GPT-4o-mini can give correct suggestions relevant to the region, GAEA provides a correct amenity with proximity to the location of the image.

tion has direct applications in multiple domains, including tourism, navigation [16], urban planning [46], and security [50], among many.

Recently, CLIP-inspired image-to-GPS retrieval approach, GeoCLIP [50], has shown significant performance in global-scale image geolocalization. To further mitigate the performance gap, and to increase the generalization capacity of the models, interestingly, a new wave of works infuse *human-level cognition and inference capacity* in their model training [23, 32, 55]. E.g., PIGEON is trained on data from the popular geolocalization game GeoGuesser

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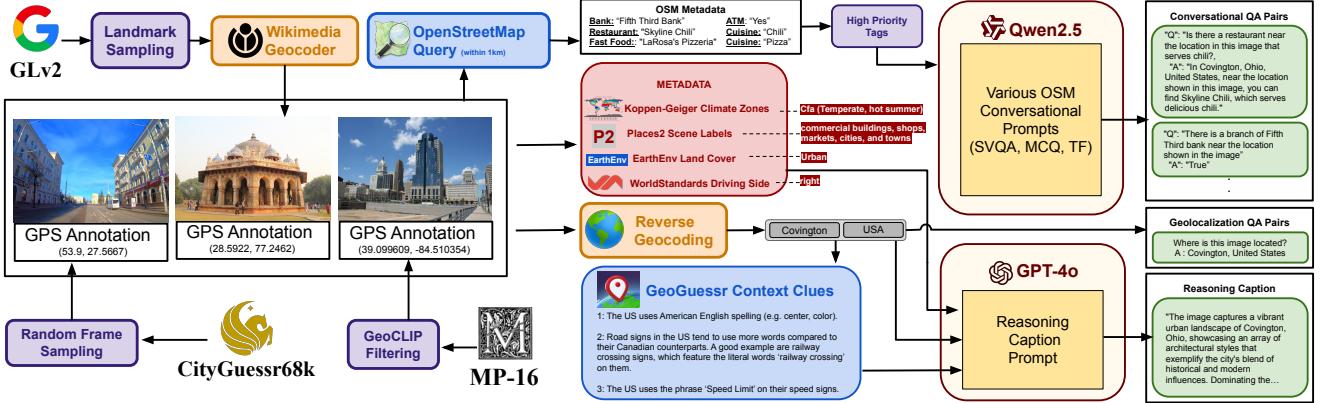


Figure 2. **Data Collection and Annotation Pipeline.** GAEA-1.6M includes geographically diverse visual samples from various data sources, such as MP-16, GLD-v2, and CityGuessr68k (*left*). We also incorporate OpenStreetMap (OSM) metadata and auxiliary context for each image, ranging from climate zones to geographical clues about the country (*middle*). Using open-source LLMs and GPT-4o, we generate four diverse question-answer pairs across geolocation, reasoning, and conversational subsets (*right*).

[2]; a recent vision-language model, GeoReasoner [32] use user- and administrator-maintained approximately 3K textual clues from GeoGuessr and Tuxun gaming platforms.

These focused geolocalization models, however, lack geographical understanding of the predicted locations beyond their GPS coordinates. They cannot provide additional information that might be invaluable for applications such as tourism, navigation, urban planning, etc. Even if the models possess that understanding, they do not have the conversational ability to convey that information and fail to meet the user’s needs. In contrast, despite having the conversational capability, visually and textually prompted large language models (LLMs) [20, 48, 56] and their multimodal variants, popularly referred to as large multimodal models (LMMs) [10, 11, 14, 35, 47], fail to capture fine-grained nuances from an image in specialized downstream tasks such as geolocalization, making their predictions vastly imprecise and worse than random guesses in many cases; see Figure 1.

Motivated by all these aspects, in this paper, we propose GAEA, an open-source conversational model with a global-scale geolocalization capability. To the best of our knowledge, this is the first work in the ground-view geolocalization domain that introduces an open-source conversational chatbot, where the user can obtain image geolocalization, relevant description of the image, and engage in a meaningful conversation about the surrounding landmarks, natural attractions, restaurants or coffee shops, medical or emergency facilities, and recreational areas.

However, training an open-source LMM with conversational capacity is not straightforward. These models are data-hungry and their training is compute intensive. Unfortunately, no dataset can facilitate the training of such a model. To this end, we meticulously curate a GAEA-1.6M —a high-quality conversational VQA pair equipped with

diversity in scene understanding and image captions used for training and instruction tuning the LMMs on the street-level geolocalization task. GAEA-1.6M is a comprehensive dataset consisting over 800K images from *MP-16* [29], covering locations around the Earth. We augment these images with rich meta-data from the OpenStreetMap (OSM) [38] at a 1km radius, a first effort of its kind. OSM attributes contain details about the surrounding area, nearby landmarks, accessible services, and historical buildup of the region. The QA subset of GAEA-1.6M contains 380K QA pairs; the geolocalizable explanatory captions set contains 385K images and is equipped with their corresponding knowledge and reasoning captions. These knowledge and reasoning captions are constructed using a set of geographical context clues from GeoGuessr [2] that enable the model to gain a holistic understanding of the location. Taken together, GAEA-1.6M is the largest and most comprehensive collection of geolocalizable and conversational QA pairs. We use this data source to design our conversational chatbot, GAEA.

To quantitatively evaluate the conversational capability of LMMs and address the scarcity of benchmark datasets in a geolocalization setting, we propose GAEA-Bench, a diverse set of 4K conversational question samples.

GAEA-bench comprises multiple-choice (MCQs) and true/false (T/Fs) for checking a model’s understanding and choosing capability, short questions (SVQAs) for testing a model’s knowledge, and long questions (LVQAs) for evaluating a model’s descriptive and in-depth explanation ability about the location in question.

We summarize the main contributions as follows:

- We propose GAEA-1.6M (§Section 3), a new dataset for training conversational image geolocalization models.
- For evaluating conversational capabilities in geolocal-

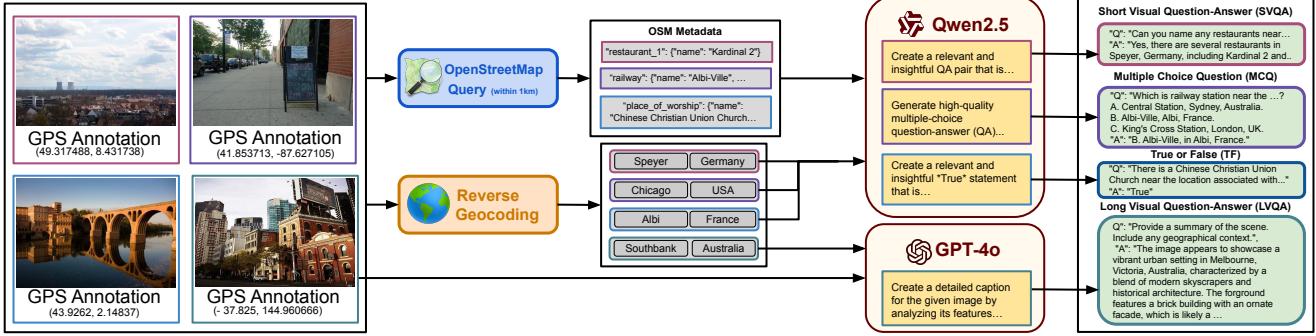


Figure 3. Overview of GAEA-Bench. GAEA-Bench is designed to evaluate the conversational abilities of various LMMs across different question types, including MCQs, T/F, and both short and long VQAs. We have carefully selected a subset of 4k samples from MP-16 and generated corresponding OSM metadata to generate QA pairs using GPT-4o. GAEA-Bench aims to fill the gap in conversational benchmarks by incorporating geolocalization capabilities.

ization setting (§Section 5), we propose GAEA-Bench, a novel benchmark with different types of question-answers.

- We propose GAEA, a conversational chatbot (§4) that goes beyond global-scale geolocalization and provides information about the location described by an image.
- We quantitatively compare the performance of our model to 8 state-of-the-art open-source, and 3 proprietary LMMs, including GPT-4o [9] and Gemini-2.0-Flash [47].

2. Related Work

Vision language models (VLMs) have been at the forefront of computer vision research; geo-localizable VLMs are in their nascent stages.

Vision Language Models. Multimodal learning unifies different modalities by a common representation. By *contrastively* fitting text and images into the same feature space, CLIP [39] has revolutionized multimodal learning. LLMs like GPT2 [40] made strides in representing text and next token prediction. Visual question answering (VQA) was of interest before, but, after LLaVA [34] and BLIP2 [31] combined the conversational aspects of LLMs and the representational capabilities of CLIP-like models, many problems of VQA are addressed. After that, numerous modern works emerged, such as GeoChat [27], Qwen2.5-VL [12], LLaMA-3.2 Vision [10], and LLaVA-OneVision [30] as well as proprietary models like GPT4 [9] and Gemini [47]. Even though most of these models are excellent for general VQA, they perform poorly on specialized tasks in fields like medicine, statistics, and geolocalization. This inspires the need for specialized VLMs that can address specific tasks.

Geo-localization is a crucial field in vision research with essential applications in forensics, social media, and exploration; see [16, 46, 50]. On a global scale, Weyand et al. [53] first introduced a classification-based approach on the

Im2GPS [24] dataset. Vo et al. [51] introduced classification in multiple hierarchies, while CPlaNet [45] introduced a combinatorial partitioning technique for combining coarse hierarchies to predict finer ones. Over the years many other works like ISNs [25], TransGeo [59], TransLocator [52], and GeoDecoder [15] have made significant advancements in this classification-based worldwide geolocalization by introducing scene-based specialized encoders and hierarchical evaluation, auxiliary scene recognition, and twin encoder approach, and query-based encoder-decoder architecture respectively. PIGEON [23], the most recent work, leverages the image representation capabilities of the CLIP vision encoder, and a unique clustering approach to improve its geo-localization performance. Image-to-image retrieval models tend to be more accurate than their classification-based counterparts but infeasible on a global scale due to their requirement for large reference image galleries. GeoCLIP [50] was the first work to incorporate the contrastive multimodal learning between images and raw GPS information that revolutionized this domain by introducing a more accurate retrieval-based model for a global scale.

These specialized models work well for worldwide image geo-localization but lack the conversational aspect that can aid an individual in gaining a holistic understanding of a location portrayed in an image. GeoReasoner [32] attempts to incorporate an inherent geospatial understanding into a VLM by looking at specific information displayed in the image. It also introduces the idea of *locatability*, which can determine the extent of that information present in the image which may improve the reasoning capability of the model. The model however lacks the *conversational aspect*, and the locatability-based filtering of data might hurt its generalization capability. We address these issues in GAEA by primarily focusing on its conversational ability.

The generalizability of GAEA comes from its training data. All specialized geo-localization models that function

Data Source: MP-16	Data Source: GLDv2	Data Source: MP-16	Data Source: GLDv2
<p>Location: Cuenca, Spain (40.074511, -2.134486)</p> <p>OSM:</p> <ol style="list-style-type: none"> 1. Pharmacy: Farmacia García Hondúvilla 2. Bank: Santander Bank 3. Fast Food: La que ha liado el pollito 4. Cuisine: Chicken  <p>Question: Is there a fast-food option near the location in this image that serves chicken? If so, can you name it?</p> <p>Answer: In Cuenca, Spain, near the location depicted in this image, you can find La Que Ha Liado El Pollito, which specializes in chicken dishes.</p>	<p>Location: Zürich, Switzerland (47.3964, 8.54778)</p> <p>OSM:</p> <ol style="list-style-type: none"> 1. River: Spitalerbach 2. University: Universität Zürich Irchel 3. Bus Route: VBZ route: Bus 69; Zürich, Milchbuck --> ETH Hönggerberg  <p>Question: Is there a specific bus route near the location in this image that could help tourists get around?</p> <p>Answer: In Zürich, Kreis 6, Switzerland, the Bus 69 runs from Zürich, Milchbuck to ETH Hönggerberg, providing convenient transportation options for visitors.</p>	<p>Location: New Orleans, United States (29.946846, -90.062592)</p> <p>OSM:</p> <ol style="list-style-type: none"> 1. Restaurant: Felipe's Taqueria 2. Cuisine: Mexican 3. Cafe: Café Fleur De Lis  <p>Question: Is there a cafe near the location of this image in New Orleans? Choose one option: A) Café Du Monde B) Starbucks Reserve C) Café Fleur De Lis D) Blue Bottle Coffee</p> <p>Answer: C. Café Fleur De Lis</p>	<p>Location: Rio de Janeiro, Brazil (-22.93836, -43.25942)</p> <p>OSM:</p> <ol style="list-style-type: none"> 1. River: Rio Andarai 2. Bus Route: STPC Borel  <p>Question: Answer the following question with either True or False: This image is located in São Paulo, Brazil.</p> <p>Answer: False</p>

Figure 4. **Qualitative examples** showcasing various question-types, including multiple-choice, true/false, short and long VQAs generated using an open-source model on our GAEA-1.6M dataset. We carefully select geographical tags from OSM metadata to generate QA pairs.

on a global scale train their model on MP-16 [29] which is a large-scale worldwide dataset. However, it lacks the verbal context required in VLM training. Hence, we introduce a new conversational dataset GAEA-1.6M; see details in §Section 3. Additionally, we introduce the first conversational benchmark in §Section 4 to evaluate Geolocalization VLMs and an evaluation pipeline to judge the efficacy of such models.

3. GAEA-1.6M

The GAEA-1.6M dataset provides comprehensive global coverage, featuring both rich conversational and diverse geolocalization sets. It includes various QA formats, such as MCQs, True/False, and open-ended VQA (long and short), from more than 234 countries/territories, grouped under conversational and geolocalization groups. Spanning 40k cities across 7 continents, GAEA-1.6M is structured into two key groups: conversational and geolocalization. With over 1.6 million QA pairs, it captures the geographical diversity of both underrepresented and widely recognized regions worldwide.

3.1. Dataset Curation and Annotation

Acquiring Diverse Geo-localizable Images. We sample geographically diverse visual data from MediaEval 2016 (MP-16) [29], Google Landmarks v2 (GLDv2) [54], and CityGuessr [28] to curate GAEA-1.6M.

MP-16 contains over 4.6 million geotagged Flickr images, including indoor and outdoor scenes. For our street-view geolocalization subset, we filter out indoor images, retaining 3 million outdoor images. However, some of these images are non-geolocalizable, such as close-up shots of doors, grass, or wires, which are excluded from the final dataset. To filter out non-geolocalizable images, we process all 3 million samples using GeoCLIP [50], which is trained on the full MP-16 dataset and effectively identifies non-geolocalizable outlier images. GeoCLIP assigns a confidence score based on its ability to predict GPS coordi-

nates, with higher scores indicating geo-localizability. We set a confidence threshold of 0.75 and computed the distance between the ground truth MP-16 GPS coordinates and the GeoCLIP’s predicted location. We retain the images if this distance is less than 500 km; see additional ablations on different thresholds and distance metrics in the Appendix.

To achieve a balanced geographical distribution in GAEA-1.6M, we use the 10th hierarchy of S2-Cells [5] to partition our filtered MP-16 dataset into 16,753 spatial grid cells. S2-Cells enable hierarchical spatial indexing, ensuring diverse global coverage while preventing overrepresenting densely imaged regions. We randomly sample up to 200 images from each cell, resulting in a final set of over 750K distinct samples.

GLDv2 [54] is a fine-grained landmark recognition dataset featuring natural and human-made landmarks across diverse time zones, climates, and lighting conditions. Given the significance of landmark geolocation for real-world applications, we randomly sample 50K distinct landmarks from GLDv2. These highly recognizable landmarks offer rich geographic and cultural context. Each image is linked to Wikipedia metadata, from which we extract GPS coordinates using the `reverse_geocoder` Python library to determine each landmark’s corresponding city and country.

CityGuessr68k [28] focuses on global video-based geolocalization emphasizing urban regions and hierarchical prediction across 166 major cities. To incorporate this diversity, we randomly sample one frame from each of the 54K training videos and include them in our dataset. These three sources provide over 852K geographically diverse geolocalizable images, forming GAEA-1.6M dataset.

3.2. Meta-data curation for dataset annotation

After acquiring all visual samples for our GAEA-Conversational Assistant, we churn the metadata for each image for a comprehensive QA-pair generation.

Churning OSM metadata. OpenStreetMap (OSM) [38] is

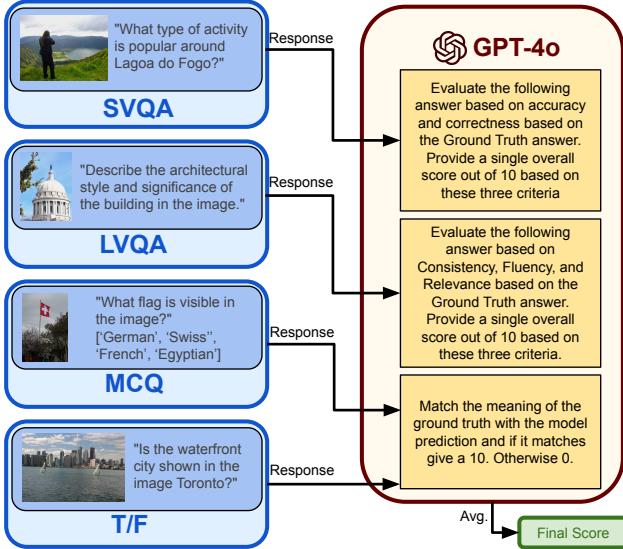


Figure 5. **Evaluation pipeline** highlights various question types we introduce in our GAEA-1.6M. We use GPT-4o as a judge to score such responses.

a collaborative open-source mapping platform that provides extensive geographical data. In our work, OSM plays a central role by enriching geolocation and conversational capabilities. We retrieve metadata from a 1 km radius around the GPS coordinates of 850K images, leveraging OSM’s detailed, publicly annotated tags. These tags cover many real-world elements, including amenities, transportation, hotels, and restaurants, making them invaluable for our ground-view geolocation and QA generation.

OSM data is multilingual, which is a key challenge. To ensure accessibility, we use GPT-4o [9] to translate these annotations into English. Additionally, many retrieved tags consisted of plain numbers or non-meaningful entries, which we systematically filtered out to retain only informative and contextually relevant metadata. To our knowledge, this is the first work to utilize OSM’s rich metadata to develop a conversational chatbot for ground-view geolocation. We curated the OSM metadata for MP-16 and GLDv2 visual samples.

Curating Country-Specific Geographical Clues. We web-crawled diverse clues from Plonkit[4], an open-source community resource for the GeoGuessr [2] game, which has over 65 million players. Similar datasets have been used in recent works [23, 32]. We obtained 129 country clues but found gaps for some countries, such as New Zealand and France. To address this, we curated clues for 58 additional countries using GPT-4o, aligning them with Plonkit’s style, resulting in altogether 187 countries. These clues are incorporated into our dataset for generating reasoning-based QAs. For examples of the type of clues utilized, see Figure 19 in the Appendix.

Additional Metadata. For auxiliary context, we group our country-specific, geographically diverse dataset in 31 Köppen-Geiger climate zones [13]. We obtain the traffic direction data through WorldStandards [7] and *Land Cover Use* statistics from EarthEnv [1]. Additionally, we compute scene labels for each image using the Places2 [58] database.

3.3. Question-Answer (QA) Pairs Generation

As seen in Figure 2, GAEA-1.6M is carefully curated to enhance ground-view geolocation through diverse, context-rich QA pairs. Comprising over 800K distinct images and around 1.6 million QA pairs, it stands as the largest and most comprehensive dataset for this task; see Figure 4. Unlike existing works, such as [19, 32], which are limited to JSON structures and fewer question types, our work emphasizes the conversational capabilities of the model, providing a broader range of QA formats. The dataset is divided into three subsets—Conversational, Reasoning, and GeoLocalization, each designed to capture different aspects of geographic understanding. These subsets feature various question formats, including multiple-choice [37], true/false, and open-ended questions (SVQA and LVQA) [49]. Below, we detail the curation process for each subset.

Conversational QA Generation. We generate conversational QA pairs using OSM metadata from the sampled MP-16 and GLDv2 subsets. We prompt Qwen-2.5-14B [56] with enriched OSM attributes to create diverse question formats, including short-form, multiple-choice, and true/false questions. These OSM tags cover various categories such as amenities, food places, financial institutions, government offices, accommodation, transportation, healthcare, religious sites, education, and waterways. This subset comprises over 380K questions.

Geolocation Questions. To enhance the geolocation capabilities of our GAEA model, we introduce large-scale meta-geographic information through geolocation-specific QA pairs. This subset consists of 820K image-question pairs designed to help the model predict the correct location of an image. We curate 50K geolocation questions from GLDv2, each corresponding to a distinct landmark, leveraging their global recognition to improve location-based reasoning. Additionally, we incorporate 54K geolocation QA pairs from CityGuessr, which focuses on urban environments, and 720K from MP-16, ensuring broad geographic coverage. This results in a diverse and well-distributed geolocation QA dataset spanning 234 countries and territories, 40K cities, and 7 continents.

Reasoning Questions. We generate detailed image-caption QA pairs (Long-VQA) to enhance fine-grained reasoning in our GAEA model. We prompt GPT-4o [9] with each image, its scene labels, and country-specific geographical attributes, including GeoGuessr clues, traffic-side driving information, Köppen-Geiger climate zone, and land cover

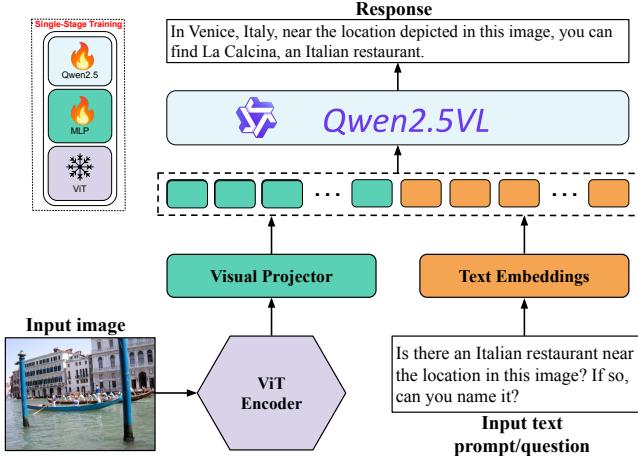


Figure 6. **GAEA architecture** with a single-stage training strategy including trainable MLP layers and LLM weights.

data. While scene labels are unique to each image, the other attributes provide country-level context. GPT-4o integrates this information to generate contextually rich and highly correlated captions with the provided geographic labels. These reasoning-based captions strengthen the model’s geolocation and conversational capabilities and induce a rich semantic understanding in our model by infusing *human-level cognition and inference capability*, deducing the model to emphasize why particular image features might be associated with specific geographical contexts, reducing disinformation [42, 43]. In total, we curate 385K knowledge-driven LVQA pairs.

3.4. GAEA-Bench

Existing benchmarks for evaluating geolocation tasks mainly focus on retrieval and classification-based methods, such as IM2GPS [24], IM2GPS3k [51], and GSW15k [18], which assess the distance between ground-truth and predicted GPS coordinates. However, there is a lack of conversational benchmarking datasets to evaluate the geolocation and conversational capabilities of LMMs. We introduce GAEA-Bench, a geographically diverse and conversationally rich multimodal benchmark to address these shortcomings. GAEA-Bench is designed to assess LMMs across various question types, including MCQs, true/false, and long and short VQAs while integrating geolocation tasks. It includes 4K image-text QA pairs that provide a rich geographical context for each image.

GAEA-Bench Curation. We curate a non-overlapping subset of highly geolocalizable MP-16 images, manually filtering out the non-geolocalizable ones. Using OpenStreetMaps (OSM), we generate metadata within a 1km radius and curate 1,000 short-form (SVQA), 1,000 multiple-choice (MCQ), and 1,000 true/false (T/F) questions. For

long-form questions (LVQAs), we follow a similar process for generating reasoning questions in GAEA-Bench, resulting in an additional 1,000 questions. In total, we curate 4K diverse image-text QA pairs. To ensure that the GAEA-Bench remains independent of the training set, we select geographically distinct locations for its 4K samples. We show our GAEA-Bench annotation and curation process in Figure 3. The OSM metadata are fetched for each image and are passed to Qwen2.5-14B for generating several QA pairs, including SVQA, MCQ, and T/F.

4. GAEA Architecture

GAEA follows the architecture of the open-source model, Qwen2.5-VL [12], which seamlessly integrates (1) a vision encoder, (2) a vision-to-language projector, and (3) a language model. The re-engineered vision-transformer (ViT) architecture incorporates 2D-RoPE and window attention. The projector is a two-layer multi-layer perception (MLP) to align raw patch features from the ViT and provides the final representation $\mathbf{E}^{\text{Joint}}$ by concatenating the image embeddings, \mathbf{E}^{Img} with the text embeddings, \mathbf{E}^{Text} such that $\mathbf{E}^{\text{Joint}} = [\mathbf{E}^{\text{Img}}, \mathbf{E}^{\text{Text}}]$; see Figure 6.

Training Details. We perform single-stage fine-tuning of Qwen2.5VL on our GAEA Conversational Assistant dataset. The model is trained across all three subsets—*geolocation, reasoning, and conversational*—covering both open-ended QA formats (short and long answers) and decision-based questions (multiple-choice and true/false). This fine-tuning process enables the model to integrate rich geographical cues, contextual metadata, and image-specific attributes, enhancing its spatial reasoning, location inference, and multimodal conversational capabilities. We employ LoRA fine-tuning [26] with a rank of $r = 16$ and $\alpha = 32$ along with the unfrozen vision-to-language MLP projector. To handle varying image resolutions, we apply dynamic resolution processing: Images below 448×448 are upsampled, while those exceeding 1000×1000 are downsampled, similar to [12]. The model is trained for one epoch over 12,600 steps.

5. Benchmarking and Evaluations

GAEA-1.6M training set comprises four distinct question types: Multiple Choice Questions (MCQs), True/False (T/F), and Short and Long Visual Question Answering (VQA). The GAEA model is meticulously trained to ensure conversational fluency while possessing the capability to geolocalize visual samples. Current evaluation frameworks primarily focus on standard geo-localization datasets, measuring accuracy using distance-based metrics at various scales, including Street (1 km), City (25 km), Region (200 km), Country (750 km), and Continent (2,500 km). However, these methods fail to assess the conversational capa-

Model Name	Performance on Different QA Formats				
	LVQA	SVQA	MCQ	TF	Average
GeoChat-7B [27]	24.06 (\downarrow 59.71%)	16.38 (\downarrow 67.96%)	54.00 (\downarrow 27.90%)	32.20 (\downarrow 58.98%)	31.66 (\downarrow 52.07%)
LLaMA-3.2-Vision-11B [10]	47.45 (\downarrow 20.55%)	26.84 (\downarrow 47.50%)	52.40 (\downarrow 30.04%)	47.20 (\downarrow 39.87%)	43.47 (\downarrow 34.20%)
LLaVA-Next-Mistral-7B [33]	47.57 (\downarrow 20.34%)	23.20 (\downarrow 54.63%)	28.90 (\downarrow 61.42%)	56.70 (\downarrow 27.77%)	39.09 (\downarrow 40.83%)
GLM-4V-9B [22]	40.63 (\downarrow 31.97%)	21.29 (\downarrow 58.36%)	56.30 (\downarrow 24.83%)	50.60 (\downarrow 35.54%)	42.21 (\downarrow 36.10%)
Phi-3.5-Vision-Instruct [8]	48.04 (\downarrow 19.56%)	14.31 (\downarrow 91.57%)	54.40 (\downarrow 27.36%)	57.20 (\downarrow 27.13%)	43.49 (\downarrow 34.17%)
InternVL2-8B [57]	52.42 (\downarrow 12.22%)	30.93 (\downarrow 39.51%)	55.30 (\downarrow 26.17%)	56.90 (\downarrow 27.52%)	48.89 (\downarrow 25.99%)
LLaVA-OV-7B [30]	53.34 (\downarrow 10.68%)	29.32 (\downarrow 42.66%)	57.60 (\downarrow 23.10%)	56.10 (\downarrow 28.54%)	49.09 (\downarrow 25.69%)
Qwen2.5-VL [12]	54.84 (\downarrow 8.17%)	35.14 (\downarrow 31.27%)	47.20 (\downarrow 36.98%)	59.10 (\downarrow 24.71%)	49.07 (\downarrow 25.72%)
GPT-2.0-Flash [47]	55.47 (\downarrow 7.12%)	34.72 (\downarrow 32.09%)	56.20 (\downarrow 24.97%)	56.10 (\downarrow 28.54%)	50.62 (\downarrow 23.37%)
GPT-4o-mini [9]	58.82 (\downarrow 1.51%)	34.13 (\downarrow 33.25%)	54.00 (\downarrow 27.90%)	34.17 (\downarrow 56.47%)	45.28 (\downarrow 31.46%)
GPT-4o [9]	63.62 (\uparrow 6.53%)	49.56 (\downarrow 3.07%)	59.37 (\downarrow 20.73%)	69.83 (\downarrow 11.04%)	60.59 (\downarrow 8.28%)
GAEA (Ours)	59.72	51.13	74.90	78.50	66.06

Table 1. We benchmark 11 open-source and proprietary LMMs on GAEA-Bench. Notably, GAEA outperforms all open-source models and fares higher than the proprietary models on decision-making questions (*MCQs* and *TFs*). We provide the relative performance change for each model compared to GAEA.

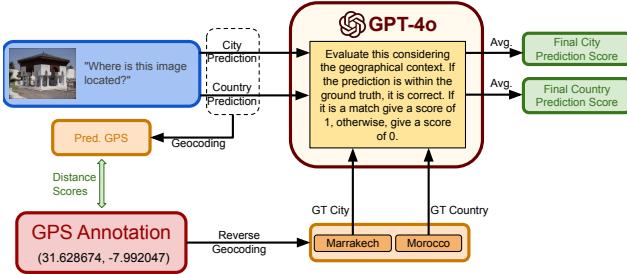


Figure 7. Our classification accuracy pipeline evaluates city and country predictions by comparing them against ground truth annotations derived from GPS coordinates, with GPT-4o serving as the evaluator.

bilities of LMMs. To address this gap, we define our evaluation process in three key dimensions: (a) Conversational accuracy, (b) Quantitative geo-localization accuracy, and (c) Classification accuracy.

5.1. Evaluation and Metrics

Conversational Evaluation. Most geolocation-specific models operate as “black box” systems, providing GPS coordinates without offering any reasoning or justification behind their outputs. In contrast, GAEA is the first model of its kind, explicitly trained on 1.6 million instructions, which include a significant number of knowledge-reasoning question-answer pairs. This enables GAEA to integrate world knowledge, such as geographical clues, conversational meta-tags, and advanced reasoning capabilities, making its geolocation predictions more transparent and insightful. To address the challenges of complex conversational evaluation, we benchmark 10 state-of-the-art open-source and closed-source LMMs on GAEA-Bench, which is meticulously curated to evaluate LMMs on diverse ques-

tion types, including multiple-choice, true/false, and open-ended questions (short and long VQAs). See §Section 8.1 for the baselines used in this work.

We employ different prompts for each type of question. We use GPT-4o as a judge and prompt it to score responses to various types of questions with different criteria. We use *accuracy* for MCQs and T/F, *correctness* for SVQA, and *consistency, relevance, and geographical correctness* for long VQAs (LVQAs); see the evaluation pipeline in Figure 5. Here, *correctness* refers to how closely the model’s output matches the location and the correct answer in the ground-truth response [49]. For LVQA, the *consistency* metric evaluates the fluency and readability of the model’s prediction [44, 48, 49], while *geographical correctness* assesses whether the model’s prediction accurately identifies the correct city and country, directly matching the ground-truth answer. This is further discussed in §Section 8.2, and Figures 16, 20 and 21.

Quantitative Geo-localization Evaluation. We compared the performance of GAEA against six state-of-the-art (SoTA) geo-localization models, namely PlaNet [53], CPlaNet [45], ISNs [25], TransLocator [52], GeoDecoder [18], and PIGEON [23] on three standard geo-localization benchmarks including IM2GPS [24], IM2GPS3k [51], GWS15k [18]. We prompt various LMMs to output the corresponding city and country to which the image belongs. We retrieve GPS coordinates using GeoPy [3] and compute distance with ground truth. We compare the output with distance thresholds of 1 km, 25 km, 200 km, 750 km, and 2,500 km; see Table 2.

Classification Accuracy. Figure 7 illustrates the classification accuracy pipeline at the city and country levels. For this evaluation, we introduce three new datasets: GeoDE [41],

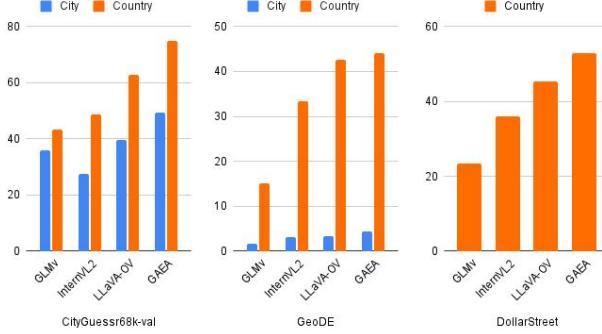


Figure 8. Classification accuracy for both city and country labels, where GAEA establishes itself as a strong baseline, surpassing several recent LMMs in performance.

DollarStreet [21], and CityGuessr68k [28]. From GeoDE, we sampled 22K images based on 16 meta-tags having geolocalizable features. From DollarStreet, we manually sampled 1.3K images, removing indoor and non-geolocalizable samples. Since its metadata contains only country-level information, we evaluate this dataset solely for country classification. Additionally, we use the validation set of 14K images from CityGuessr and all 22K GeoDE samples for city and country classification tasks.

5.2. Results and Discussion

GAEA-Bench Evaluation. Table 1 presents the per-model performance of 12 recent LMMs on GAEA-Bench. The results offer several insights: (i) Our proposed model, GAEA, achieves the highest average performance across decision-making questions (T/F and MCQs) and Short VQAs. Among proprietary models, GPT-4o [9] overall performs the best, with an accuracy of 60.59%, excelling particularly in Long VQAs—outperforming GAEA by 6.53% in this category. However, both open-source and proprietary models struggle with short-form questions. E.g., GPT-4o’s accuracy drops from 63.62% on long questions to 49.5% on short questions. (ii) GAEA outperforms all LMMs with an average accuracy of 66.06%, surpassing GPT-4o by 8.28% and outperforming the second-best open-source model, LLaVA-OneVision [30], by 25.69%. (iii) Several open-source models, including LLaMA-3.2-11B [20], GLM-4V-9B [22], and Phi-3.5-Vision [8], achieve comparable overall performance. (iv) LMMs perform better on decision-making questions (MCQs and T/F) than open-ended questions; see Figure 17. E.g., LLaVA-OneVision experiences a 57.8% drop in accuracy on SVQA compared to T/F questions. The low performance on free-form questions underscores the challenge of using short questions to effectively assess conversational capabilities in the GAEA-Bench. We provide qualitative comparisons with several LMMs in Figures 10, 14 and 15

Benchmark	Model	City 25 km	Region 200 km	Country 750 km	Continent 2500 km
IM2GPS [24]	PlaNet [53]	24.5	37.6	53.6	71.3
	CPlaNet [45]	37.1	46.4	62.0	78.5
	ISNs [25]	43.0	51.9	66.7	80.2
	TransLocator [52]	48.1	64.6	75.6	86.7
	GeoCLIP [50]	41.8	60.8	77.2	89.9
	GeoDecoder [18]	50.2	69.0	80.0	89.1
	PIGEON [23]	40.9	63.3	82.3	91.1
	GaGA [19]	38.8	54.8	75.1	87.7
<hr/>					
GAEA (Ours)					
IM2GPS3k [51]	PlaNet [53]	24.8	34.3	48.4	64.6
	CPlaNet [45]	26.5	34.6	48.6	64.6
	ISNs [25]	28.0	36.6	49.7	66.0
	TransLocator [52]	31.1	46.7	58.9	80.1
	GeoDecoder [18]	33.5	45.9	61.0	76.1
	GeoCLIP [50]	34.5	50.7	69.7	83.8
	PIGEON [23]	36.7	53.8	72.4	85.3
	GaGA [19]	33.0	48.0	67.1	82.1
<hr/>					
GAEA (Ours)					
GWS15k [18]	ISNs [25]	0.6	4.2	15.5	38.5
	TransLocator [52]	1.1	8.0	25.5	48.3
	GeoDecoder [18]	1.5	8.7	26.9	50.5
	GeoCLIP [50]	3.1	16.9	45.7	74.1
	PIGEON [23]	9.2	31.2	65.7	85.1
	GAEA (Ours)	3.1	15.9	41.9	71.4

Table 2. We benchmark the performance of various specialized models on standard geolocation datasets. GAEA demonstrates competitive results, outperforming GaGA on multiple distance thresholds in both IM2GPS and IM2GPS3k.

Standard Geo-localization Evaluation Table 2 compares GAEA’s performance with various specialized encoder-only methods across three geolocation benchmarks. While GAEA is trained on a large-scale conversational dataset with geolocation capabilities, it achieves competitive results against specialized models. We also evaluate against GaGA [19], which is trained on a dataset five times larger than ours, on IM2GPS and IM2GPS3k. However, we exclude comparisons on GSW-15K due to differences in dataset curation. Following the guidelines of [18], we reconstruct the GSW-15K benchmark.

In IM2GPS3k, GAEA achieves the second-highest scores after PIGEON, outperforming GaGA across all four distance thresholds. It surpasses GaGA by 2.5% at the 25km radius and 3.66% at the country level. Additionally, GAEA outperforms the specialized model GeoCLIP [50] across all thresholds, with a 1.5% higher score in the region category and 1% improvements at the city and country levels. In IM2GPS, GAEA outperforms GaGA at 25 km and 2,500 km, remains competitive at 200 km and 750 km, and slightly surpasses PIGEON at the city level while maintaining competitive performance across other thresholds. We also evaluate GAEA on GSW-15K, one of the most challenging datasets, which includes non-geolocalizable landmarks. GAEA outperforms GeoCLIP [50] and GeoDecoder [18] on city-level distance and achieves comparable performance at the region and country levels. Figure 8 presents GAEA’s **Classification Accuracy** on three new datasets: CityGuessr68k-val [28], GeoDE [41], and DollarStreet [21]. GAEA outperforms recent LMMs, including

LLaVA-OneVision [30], InternVL [17], and GLM-4V-9B [22], on both city- and country-level classification. These results highlight GAEA’s extensive geographical coverage and strong geolocation capabilities.

6. Conclusion

We introduced GAEA, the first interactive conversational model with specialized geolocation capabilities, explicitly trained on a large-scale conversational dataset, GAEA-1.6M. We meticulously designed the dataset to enhance GAEA’s reasoning, conversational abilities, and geolocation accuracy. We curated geolocalizable images from MP-16, GLDv2, and CityGuessr68k, enriching them with auxiliary context and metadata, such as geographic clues, and climate zones. In addition to a high-quality instruction set, we present GAEA-Bench, a comprehensive benchmark that evaluates LMMs across multiple question types, including MCQs, True/False, short- and long-VQAs. Our results show that GAEA outperforms recent LMMs on GAEA-Bench, demonstrating strong geolocation and conversational capabilities by leveraging OpenStreetMap (OSM) data. These findings establish GAEA as a strong baseline for future research in geolocalization.

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GAEA: A Geolocation Aware Conversational Model

Supplementary Material

Total images	822,951
Total cities / countries	41,481 / 234
Total Questions	1,580,531
Total geo-localization questions	822,951
Total explanatory captions	384,947
Total open-ended questions	267,668
Total multiple-choice questions	48,673
Total true/false questions	56,292

Table 3. Dataset Statistics

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We organize the rest of the Supplementary Material as follows: In Section 7, we provide the additional details of our dataset, GAEA-1.6M . In Section 8, we provide additional baseline results on GAEA. Section Section 9 discusses the reproducibility of the GAEA-1.6M and provides details on privacy, safety, and broader impact.

7. Addendum to the Dataset

In this section, we present the dataset statistics and challenges encountered in its creation. Additionally, we discuss our plans to address these limitations in future works.

7.1. Challenges with Open Street Maps (OSM)

OpenStreetMaps (OSM) [38] is a rich data source for geospatial applications. It contains a wide variety of geographic and infrastructure-related information. Using such a vast open-source dataset, we can collect data about stationary objects in the world, including infrastructure, topological information, various types of amenities (e.g., schools, hospitals, restaurants), transportation networks, international country boundaries, historical and cultural sites, and natural features (e.g., forests, rivers, and seas). Each feature from the OSM dataset has several associated features, such as names and physical characteristics. In GAEA-1.6M, we geocode the visual sample with its GPS coordinates and use the location information (longitude and latitude) as a query to the OSM database to fetch geospatial information in 1 KM radius and further utilize that information to generate question-answer pairs for the training of GAEA.

Despite being such a rich source of data, OSM faces several challenges. One major issue is the variability in data quality and completeness, as contributions to OSM are

made by the open-source community, which may result in inconsistent information across different regions. Urban areas often have much more detailed information than rural areas, leading to less comprehensive annotations for rural regions. Another inconsistency related to human annotations stems from the different representations of the same label in different areas, introducing inherent heterogeneity in the structure of OSM data. For instance, some users might label a path as a “trail,” while others might call it a “footway,” and distinctions between what counts as a “park” versus a “garden” are not always clear. Moreover, querying and retrieving data from OSM is a compute-intensive task. It often becomes slower as the number of queries increases and struggles to handle dense or redundant information, necessitating efficient filtering and optimization techniques. Lastly, the information is not always up-to-date, as volunteers update different areas at different times. While some locations may have very recent data, others may be outdated, and sometimes different parts of the same area may contain information from varying periods.

7.2. Statistics

GAEA-1.6M covers 234 different countries and territories, and 41,481 cities. Table 3 denotes the exact sample numbers.

7.3. Motivation for constructing GAEA-1.6M

The dataset contains a wide spectrum of questions, with varying difficulty levels. Figure 11 outlines a category consisting of easily geo-localizable landmarks such as the Statue of Liberty, and Figure 12 represents one of the many difficult questions found in our dataset, which attempts to fine-tune an LMM to respond with location information that an average human could struggle to identify [36]. In Figure 13, we show a full example of one of our LVQA prompts.

Training an LMM with some of the metadata found in OSM [38] can be a challenging task. For instance, questions like, What are the hours of operation of the nearest coffee shop located in this area? could be difficult for a model to learn effectively and respond to accurately. We encourage the research community to explore and develop methods that could help LMMs meaningfully represent such fine-grained geo-localization information.

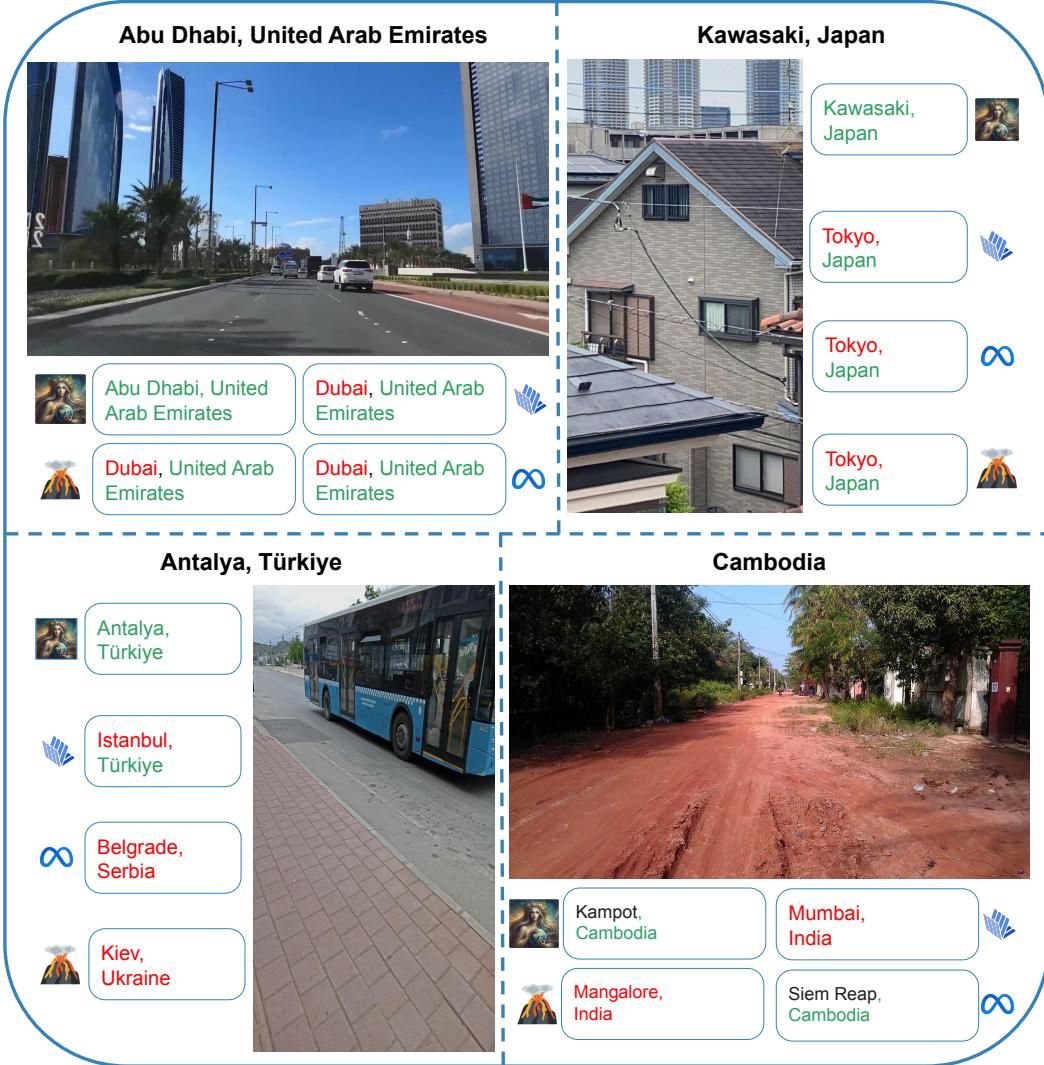


Figure 9. **Geo-localization qualitative example.** GAEA’s performance on geo-localization tasks is compared to open-source LMMs using CityGuessr, DollarStreet, and GeoDE datasets.

8. Addendum to Baseline and Evaluation

This section covers the models used for comparison with GAEA, the prompts used during training and inference, the prompts used for evaluating GAEA-Bench, and the training hyperparameters.

8.1. Baselines

We benchmark 8 top-performing open-source LMMs, including LLaMA 3.2-Vision [10], InternVL2 [17], Qwen2.5-VL [12], Phi3.5-vision-instruct [8], GeoChat [27], LLaVA-OneVision [30], GLM-4V-9B [22], LLaVA-NeXT-Mistral-7B [33], and 3 proprietary models, Open-AI’s GPT-4o, GPT-4o-mini [9], and Google’s Gemini-2.0-Flash [47] on GAEA-Bench.

Additionally, we compared the performance of GAEA against six state-of-the-art (SoTA) geo-localization models, namely PlaNet [53], CPlaNet [45], ISNs [25], TransLocator [52], GeoDecoder [18], and PIGEON [23] on three standard geo-localization benchmarks including IM2GPS [24], IM2GPS3k [51], and GWS15k [18]. For a comprehensive overview of the hyperparameter configuration for GAEA, see Table 4 in the Supplementary Material.

8.2. Prompts Used During Training and Inference

When training GAEA, we employed the task-specific prompts shown in Figure 18 to align the model’s understanding with target objectives. During inference, these identical prompts were used for all models evaluated on GAEA-Bench to ensure comparability.

	<p>Location: San Pedro de Atacama, Chile (-22.910728, -68.201408)</p> <p>Input Question: Can you name any hostels or guest houses near this image?</p> <p>Ground Truth: Yes, there are several hostels and guest house in San Pedro de Atacama, including Hostelling International, Casa Corvatsch, Casa de Piedra, and Eden Atacameno.</p>
	The image you've provided appears to be of ancient rock carvings, which are likely part of an archaeological site...
	Unfortunately, I'm unable to provide a specific information about hostels or guest houses near the image, as I don't have access to real-time information.
	The image depicts petroglyphs that are likely found in areas like the Petroglyph National Monument in New Mexico.
	It's difficult to pinpoint specific hostels or guest houses based solely on an image of petroglyphs...
	If the site is in a place like Petra in Jordan , you could look for accommodations in nearby areas like Wadi Musa or Aqaba.
	Near where this image was taken, you can find Hostal Casa de la Piedra in San Pedro de Atacama, Chile.

Figure 10. **SVQA qualitative example.** GAEA’s performance on SVQA tasks is compared to open-source and proprietary LMMs.

8.3. Prompts Used in Evaluation

To obtain our results from Figure Figure 17, we use three prompts in evaluating the questions in GAEA-Bench. Since the question types of our benchmark vary, a multi-prompt approach is needed. We have reformatted certain elements of the actual prompts for conciseness, though figures Figures 16, 20 and 21 closely reflect these three prompts.

8.4. Training Hyperparameters

We perform single-stage training on our baseline [12] using GAEA-1.6M. The training is conducted for 1 epoch with a global batch size of 128, utilizing gradient accumulation steps of 4 to optimize resource usage for small batch sizes. The initial learning rate is set to 10^{-5} , using a cosine learning rate scheduler to provide a smooth decay in the learning rate for effective convergence. A weight decay of 0 is applied to avoid penalizing weights during updates, which can be advantageous for certain model architectures. The warmup ratio is configured at 0.03 to ensure a grad-

Number of epochs	1
Global batch size	128
Gradient accumulation steps	4
Initial learning rate	10^{-5}
Learning rate scheduler	cosine
Weight decay	0
Warmup ratio	0.03
LoRA rank (r)	16
LoRA α	32
LoRA dropout	0.01
Model data type	bfloat16
Maximum context length of LLM	128,000
Attention type	flash attention

Table 4. Hyperparameters used for training GAEA.

ual increase in the learning rate during the initial training phase, stabilizing early optimization. We employed low-Rank adaptation (LoRA) [26] for efficient fine-tuning, with a rank, $r = 16$, $\alpha = 32$, and a dropout rate of 0.01, enabling

Q: What is the name of the statue that is depicted in this image?	Q: What is the name of the control gate at the entrance to the site shown in this image?	Q: Provide a summary of the scene and include any relevant geographical context.
GT: The name of the statue on Liberty Island is the Statue of Liberty.	GT: The name of the control gate at the entrance to Machu Picchu is Ruta Montaña Wayna Picchu	<p>GT: The image depicts a construction site in an urban setting, characterized by cranes and ongoing building activity. This scene closely correlates with features specific to Poland, particularly in its larger cities like Warsaw or Wroclaw, which are undergoing significant development and modernization. One notable clue that supports identifying this image as being from Poland is the presence of tram lines and buses, which are integral to the public transportation system found in many Polish cities. Poland is known for its extensive and efficient public transit networks, including trams, which are commonly seen in urban areas. The visible layout of the area, including organized lanes and pedestrian spaces, also reflects a typical Polish urban design, where planning emphasizes pedestrian accessibility alongside vehicle traffic. Additionally, the architecture often features a mix of modern construction and remnants of historical influences, a characteristic evident in many Polish cities that have rebuilt and renovated post-communism. This blend is highlighted in the cranes, symbolizing ongoing urban transformation, likely in a city that values such development alongside its historical context. The grey and overcast sky seen in the image is also typical of the weather conditions in Poland, especially in the fall or winter. Overall, this construction site embodies Poland's commitment to modernization while retaining its unique urban characteristics, corroborating the clues provided about the country's distinct urban landscape and ongoing developments.</p>

Figure 11. These two images display examples of what we consider as easy questions. Easy questions include the questions that pertain to easily identifiable landmarks that are associated with celebrated locations.

Q: Is there a post office near the location depicted in this image?	Q: What is the name of the plaza that is located in the area depicted in this image?
GT: Yes, there is a post office near Tiberias Post Office, it is First International Bank of Israel.	GT: Plaza del General Torrijos is located in Malaga, Spain at the intersection of Paseo del Parque and Plaza del General Torrijos.

Figure 12. The two images above denote examples of what we consider as hard questions. Hard questions include the questions that prompt the model to answer specific details pertaining to locations.

targeted model adjustments with minimal overhead. The model operates in `bfloat16` precision to balance computational efficiency and numerical stability. A maximum context length of 128,000 allows for processing extremely long sequences, while flash attention enhances the computational efficiency of attention mechanisms, especially for extended contexts. These settings collectively optimize the model’s performance and adaptability for vision-language tasks. We list the training hyperparameters in the Table 4.

8.5. Additional Qualitative Results

In this Section, we discuss additional qualitative results of GAEA and compare them with selected open-source and

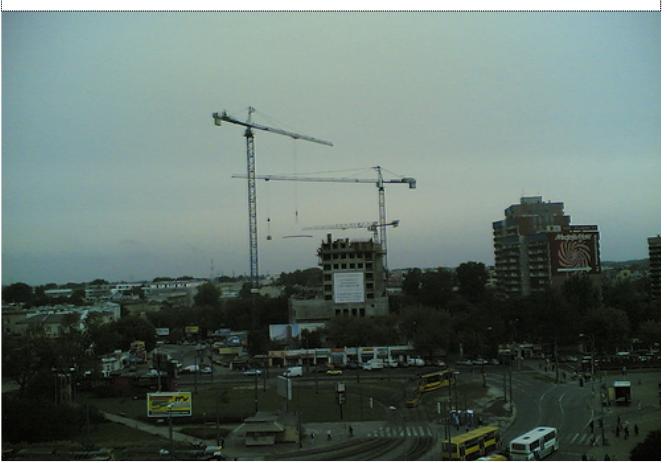


Figure 13. Through our explanatory captions (LVQA), we introduce the reasoning capabilities in our GAEAt to identify the geographical information about that visual sample. Outlined in bold, we provide explanations of the correlation between specific visual cues and their associated geographical contexts, encouraging GAEAt to refine its reasoning capabilities.

proprietary models (as mentioned in Table 1 in the main paper). Figure 9 presents a comparison of city-country predictions against other competing models. We also show the qualitative results of GAEA on short version questions (SVQA), multiple-choice questions (MCQs), and true or false questions (TF) in Figures 10, 14 and 15 respectively. For these Figures, we highlight correct predictions with **green**, while incorrect predictions are marked as **red**. Together with our quantitative metrics, we conclude that GAEA appears to outperform many of these models across various tasks.

	Location: Elantxobe, Spain (43.403913, -2.638521)
Input Question: Is there a bank with an ATM near the location of this image?	
A. BBVA has an ATM B. No banks with ATMs nearby C. Kutxabank has an ATM D. Santander has an ATM	
Ground Truth: C. Kutxabank has an ATM	
	B. No banks with ATMs nearby
	B. No banks with ATMs nearby
	B. No banks with ATMs nearby
	D. Santander has an ATM
	B. No banks with ATMs nearby
	C. Kutxabank has an ATM
	B. No banks with ATMs nearby
	C. Kutxabank has an ATM

Figure 14. **MCQ qualitative example.** GAEA’s performance on MCQ answering tasks is compared to open-source and proprietary LMMs.

	Location: Minneapolis, United States (44.984413, -93.255192)
Input Question: There is a restaurant named ‘Mr. Santana’ near the location associated with this image.	
Ground Truth: True	
	False
	False
	False
	False
	True
	False
	False
	True

Figure 15. **T/F qualitative example.** GAEA’s performance on T/F answering tasks is compared to open-source and proprietary LMMs.

9. Reproducibility, Privacy, Safety, and Broader Impact

GAEA-1.6M takes the first step in infusing conversational elements into the geo-localization task. The dataset is open-

Evaluation Prompt for LVQA

Evaluate the following predicted answer by comparing it to the provided ground truth. Focus on the accuracy of 1) location prediction, 2) cultural aspect matching, 3) consistency and quality of reasoning, 4) specificity and relevance, 5) and fluency and clarity.

- **Question:** {question}
- **Ground Truth:** {ground_truth}
- **Model Prediction:** {predicted_answer}

Instructions:

- How accurately does the predicted answer identify the specific country, city, or state mentioned in the ground truth?
- Does the predicted answer capture and reflect the cultural aspects present in the ground truth?
- Is the predicted answer logically consistent and demonstrates sound reasoning based on the information provided?
- Does the predicted answer provide specific information that is directly relevant to the question and closely aligns with the ground truth?
- Is the language in the predicted answer fluent, clear, and well-articulated?
- Provide a single overall score out of 10, based on these five criteria, weighing the criteria in the order listed, with location relevance and cultural aspect matching receiving the most weight.
- Return only the numeric score, without additional commentary.

Figure 16. Evaluation prompt for longer form open-ended questions (LVQA). We assess model predictions based on location prediction, cultural aspect matching, and quality of reasoning, with an emphasis on location relevance.

source, and we plan to release it via an academic website for research, academic, and commercial use. The dataset is protected under the CC-BY license of Creative Commons, which allows the users to distribute, remix, adapt, and build upon the material in any medium or format, as long as the creator is attributed. The license allows GAEA-1.6M for commercial use. As the authors of this manuscript and collectors of this dataset, we reserve the right to distribute the data. Additionally, we provide the code, data, and instructions needed to reproduce the main experimental baseline results, and the statistics pertinent to the dataset. We specify all the training details (e.g., data splits, hyperparameters, model-specific implementation details, compute resources used, etc.).

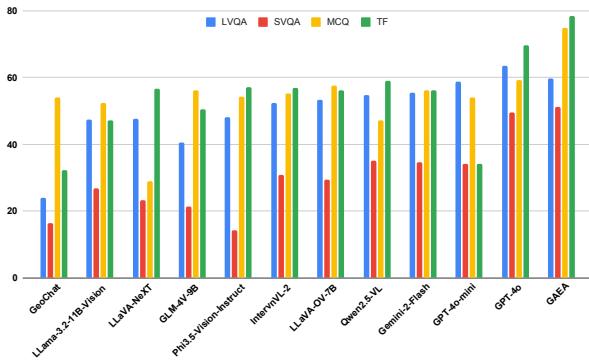


Figure 17. We showcase the performance of various LMMs on four diverse question types. GAEA outperforms on average across all question forms. GPT-4o achieves the highest accuracy on long questions.

Geolocation Prompt	
As a geography and tourism expert, analyze the image to determine its exact location. Utilize your extensive knowledge of geography, terrain, landscapes, flora, fauna, infrastructure, and recognizable landmarks to identify the city and country where the image was taken. Question:	
LVQA Prompt	
Drawing upon your expertise in geography and tourism, examine the image and provide a comprehensive description of the community or lifestyle depicted. Include insights about cultural practices, geographic features, terrain, local flora and fauna, infrastructure, and any natural or man-made elements that characterize the location. Consider how these factors influence the lifestyle and community in the area. Question:	
SVQA Prompt	
Provide a short answer on notable landmarks, museums, parks, restaurants, or activities that visitors might enjoy in the area. Highlight amenities and services that enhance the tourism experience at this location. Question:	
MCQ Prompt	
Use your comprehensive knowledge of geography, landmarks, and tourism to analyze the image and determine the correct answer from the options provided. Note, your final answer should be a choice of either A, B, C, or D, including both the letter and the complete text of the option exactly as presented. Question:	
TF Prompt	
Use your comprehensive knowledge of notable landmarks, museums, parks, restaurants, and related attractions to evaluate the following statement. Provide your final answer as either 'True' or 'False'. Question:	

Figure 18. Task-specific prompts used to train and evaluate GAEA

The dataset can be used by multiple domain experts. Its application includes but is not only limited to tourist assistance, government analysts, and GeoGuessr [2] enthusiasts. Although we do not find any foreseeable harm that the dataset can pose to human society, it is always possible that some individual or an organization can use this idea to devise a *technique* that can appear harmful to society and can have evil consequences. However, as authors, we are

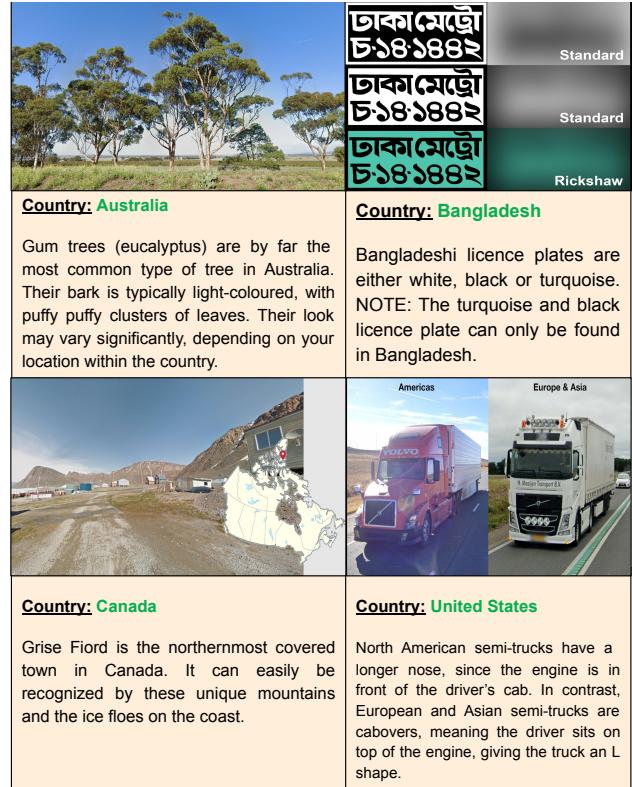


Figure 19. Example of the country-specific clues we used to generate reasoning questions.

absolutely against any detrimental usage of this dataset, regardless of whether it is by an individual or an organization, under profit or non-profitable motivation, and we pledge not to support any detrimental endeavors concerning our data or the idea therein.

Evaluation Prompt for SVQA

Evaluate the following predicted answer by comparing it to the provided ground truth. Focus on the accuracy of 1) location prediction, and 2) specificity and relevance.

- **Question:** {question}
- **Ground Truth:** {ground_truth}
- **Model Prediction:** {predicted_answer}

Scoring Guidelines:

- High score: Predicted response closely matches the specific location and provides specific information that closely aligns with the ground truth.
- Low score: Predicted response lacks knowledge or is unrelated to the ground truth
- Provide a score out of 10 for each criterion.
- Return only the numeric score, without additional commentary

Figure 20. Evaluation prompt for free-form open-ended questions (SVQA). We assess model predictions based on location accuracy, specificity, and correctness.

Evaluation Prompt for MCQ/TF

Evaluate the following answer based on Accuracy:

- **Question:** {question}
- **Ground Truth:** {ground_truth}
- **Model Prediction:** {predicted_answer}

Instructions:

- Match the meaning of the ground truth with the model prediction.
- If it matches, give a score of 10. Otherwise, give a score of 0.
- Strictly return only the numeric score, without any additional commentary.

Figure 21. Evaluation prompt for multiple-choice (MCQ) and true/false (TF) questions.