G^3: Geolocation via Guidebook Grounding

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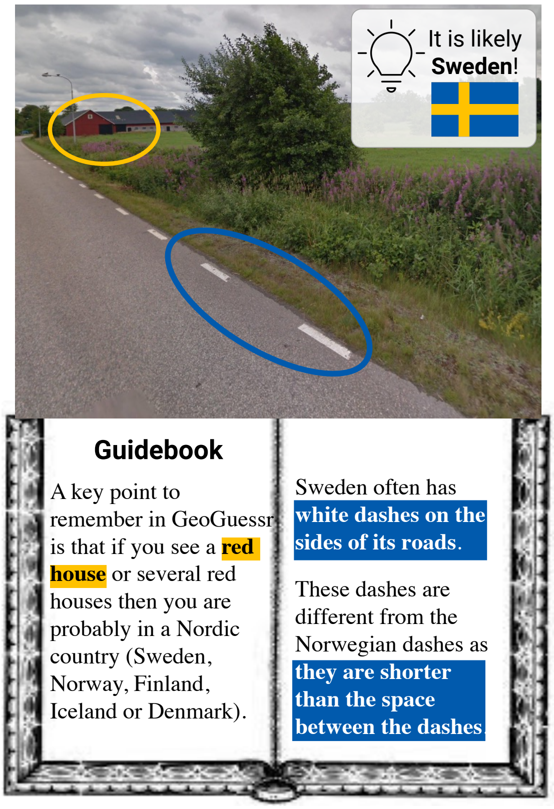
Abstract

We demonstrate how language can improve geolocation: the task of predicting the location where an image was taken. Here we study explicit knowledge from human-written guidebooks that describe the salient and class-discriminative visual features humans use for geolocation. We propose the task of *Geolocation via Guidebook Grounding* that uses a dataset of StreetView images from a diverse set of locations and an associated textual guidebook for GeoGuessr, a popular interactive geolocation game. Our approach predicts a country for each image by attending over the clues automatically extracted from the guidebook. Supervising attention with country-level pseudo labels achieves the best performance. Our approach substantially outperforms a state-of-the-art image-only geolocation method, with an improvement of over 5% in Top-1 accuracy. Our dataset and code can be found at https://github.com/g-luo/geolocation_via_guidebook_grounding.

1 Introduction

Image geolocation plays an important role in many applications, notably in fact checking and investigative journalism, as a means of verifying or debunking claims that are illustrated with images. For example, to verify the authenticity of video evidence of human rights abuses in Cameroon, an investigator manually matched the depicted roof coloring, building architecture, and sign text to StreetView imagery.[1] Given the rising volume of online mis- and disinformation, it is increasingly important to develop accurate automated geolocation methods. Beyond the recent importance of geolocation in fact-checking, it has also become a popular pastime in the form of online games like GeoGuessr[2] or Pursued.[3] Since these games are so popular, human experts often publish guidebooks curating the most salient and discriminative cues for geolocating an image to teach novice players. For example, a guide might state that *Sweden often has white dashes on the sides of its roads* (Figure 1), knowledge a human can quickly understand and apply towards all future geolocation attempts. In contrast, most prior methods rely on training vision



A key point to remember in GeoGuessr is that if you see a **red house** or several red houses then you are probably in a Nordic country (Sweden, Norway, Finland, Iceland or Denmark).

Sweden often has **white dashes on the sides of its roads**.

These dashes are different from the Norwegian dashes as **they are shorter than the space between the dashes**

Figure 1: When asked to guess a country where an image was taken (e.g., *Sweden*), a person can ground the knowledge expressed in a guidebook (e.g., *red house*, *white dashes*) to an image to inform their prediction. We propose the task of Geolocation via Guidebook Grounding, where models are tasked to do the same.

[*] Denotes equal contribution.

[1] https://www.bellingcat.com/resources/case-studies/2018/11/21/geolocation-infrastructure-destruction-cameroon-case-study-kumbo-kumfutu

[2] http://www.geoguessr.com

[3] https://www.nemesys.hu/Pursued

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models on millions of images paired with GPS locations in order to learn this task (Kalogerakis et al., 2009; Weyand et al., 2016; Muller-Budack et al., 2018; Theiner et al., 2022). Recently, the authors of CLIP (Radford et al., 2021), a large-scale multimodal model, showed that CLIP's implicit world knowledge allows it to perform geolocation once a linear classifier is added, but it does not reach the state-of-the-art performance.

In this work we explore human-written text guides as an additional source of knowledge to complement image-based geolocation methods. Our first contribution is the new task of Geolocation via Guidebook Grounding that consists of a diverse dataset of StreetView images and an associated text guidebook created for the GeoGuessr game. The goal is to classify images into one of 90 countries, while leveraging the text clues by grounding them to the target images. Our second contribution is the proposed approach, G^3, which learns to leverage the guidebook. Namely, we combine a state-of-the-art image-only representation with our novel textual clue representation. To obtain a clue representation, we attend over the guidebook sentences (clues), while weakly supervising attention with country-specific information. Adding the final attended clue representation substantially improves performance by more than 5% in Top-1 accuracy of a state-of-the-art geolocation model.

2 Related Work

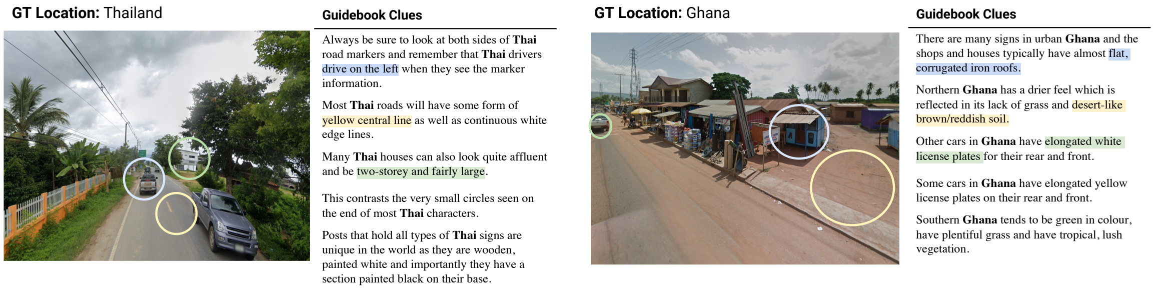
Geolocation. One of the first image-based geolocation methods was introduced by Hays and Efros (2008), who use various handcrafted visual features to predict locations. Concretely, they use a nearest neighbor method against a database of labeled images. More recent works use convolutional neural networks (CNNs) rather than handcrafted features (Weyand et al., 2016; Muller-Budack et al., 2018; Theiner et al., 2022). Many works treat geolocation as a classification problem (Kalogerakis et al., 2009; Weyand et al., 2016; Muller-Budack et al., 2018; Theiner et al., 2022), which requires partitioning the world map into discrete cells.

Kalogerakis et al. (2009) discretize the map into roughly equal size rectangular bins, and Weyand et al. (2016) use a hierarchical partitioning via a Quad tree (Finkel and Bentley, 1974) that splits cells according to image density in order to address data imbalances. (Theiner et al., 2022) uses a semantic partitioning where the cells have irregular shapes that are influenced by man-made geographies (city/country borders) and natural features (rivers, mountains, etc) in order to achieve more interpretable results. Prior works typically use large datasets of (image; GPS coordinate) pairs sourced from websites such as Flickr (Hays and Efros, 2008; Weyand et al., 2016; Kalogerakis et al., 2009).

Our work differs from these in several key ways. We are the first to show the usefulness of language (e.g., in the form of a guidebook) for geolocation. Moreover, in our problem statement, the task is to classify images into 90 countries. We believe this is a practical yet under-explored formulation, which allows for a more natural connection between target labels and knowledge expressed in textual form (as opposed to a somewhat arbitrary cell partitioning). Finally, our benchmark for Geolocation via Guidebook Grounding consists of StreetView images, a more focused domain than Flickr images, which allows us to leverage the human-written guidebook for the GeoGuessr game.

Learning with Knowledge. Prior works have explored using external language knowledge for various downstream tasks. For example, Yang et al. (2021) adopt GPT-3 to visual question answering (VQA) by leveraging the extensive knowledge of GPT-3 for answering questions given an image caption as input. Marino et al. (2021) use external knowledge bases and a graph neural network to boost VQA performance. Similar to a line of work in language grounding that condition on information from instructive text or game manuals to improve task performance (Eisenstein et al., 2009; Branavan et al., 2009, 2012; Narasimhan et al., 2018; Andreas et al., 2018; Zhong et al., 2020), we leverage a guidebook to improve the performance of an image-only geolocation model.

Advisable Visual Learning. A related line of work explores the use of language to advise vision models. Kim et al. (2020) show how to leverage language advice in the form of observation-action rules to better train an autonomous self-driving agent. In another work, a reinforcement learning soccer agent is trained from both the environment rewards and human-generated advice (Kuhlmann et al., 2004). Rupprecht et al. (2018) use inference-time language guidance to improve a trained CNN's performance on a segmentation task. Mu et al. (2020) use captions associated with images to define an auxiliary loss to improve visual



GT Location: Thailand

Guidebook Clues

Always be sure to look at both sides of **Thai** road markers and remember that **Thai** drivers drive on the left when they see the marker information.

Most **Thai** roads will have some form of yellow central line as well as continuous white edge lines.

Many **Thai** houses can also look quite affluent and be two-storey and fairly large.

This contrasts the very small circles seen on the end of most **Thai** characters.

Posts that hold all types of **Thai** signs are unique in the world as they are wooden, painted white and importantly they have a section painted black on their base.

GT Location: Ghana

Guidebook Clues

There are many signs in urban **Ghana** and the shops and houses typically have almost flat, corrugated iron roofs.

Northern **Ghana** has a drier feel which is reflected in its lack of grass and desert-like brown/reddish soil.

Other cars in **Ghana** have elongated white license plates for their rear and front.

Some cars in **Ghana** have elongated yellow license plates on their rear and front.

Southern **Ghana** tends to be green in colour, have plentiful grass and have tropical, lush vegetation.

Figure 2: Examples from our dataset of StreetView Images and relevant Guidebook Text. Note how some clues are grounded in the image, for example the image in Thailand depicts cars that *drive on the left*, *a yellow central line*, and a house that is *two-storey and fairly large*. The image in Ghana depicts houses with *flat, corrugated iron roofs*, *brown/reddish soil*, and a car with *elongated white license plates*. These relevant clues were found using our country-based pseudo labels, discussed further in Section 4.

features for few-shot image classification. Here, we leverage a human-written guidebook during training, however we do not have any specific instructions or advice aligned to individual images; instead we have a set of textual clues which we ground to images.

3 Geolocation via Guidebook Grounding

While prior works (Hays and Efros, 2008; Weyand et al., 2016; Larson et al., 2017) propose datasets of paired images and locations, to the best of our knowledge, none have proposed datasets with images, locations, and *relevant textual knowledge*. To this end, we look to guidebooks for the interactive geolocation game GeoGuessr[4] as a source of knowledge for the specific domain of StreetView images. For our task of Geolocation via Guidebook Grounding we put together a new diverse corpus of StreetView images and an associated text from a GeoGuessr guidebook (see examples in Figure 2).

Guidebook Text: GeoGuessr is a popular geolocation game where the user is placed into a navigable StreetView scene and must predict either the GPS coordinates or the country (depending on the gameplay mode). The game is so popular that people have built a community of online forums and guidebooks where they trade strategies for gameplay. To take advantage of this wealth of human knowledge, we mine text from a popular guide for playing the GeoGuessr game.[5] Some of the key features of this guide are that it has a broad country coverage, is well structured, and has a more "formal" style. The guide is meant to teach novice players visual cues that discriminate various countries, for example the fact that *Dashed white lines on the edges of roads are quite common in the countries of Denmark, Norway, Iceland and Sweden*. The guide is organized into sections for specific countries and specific visual cues, covering **102 countries** and over 13 visual cue types (see Figure 3). For our final knowledge base, we select sentences from the guide that mention at least one location. We use NER tags predicted by spaCy (Honnibal and Montani, 2017) and filter for sentences with an entity tagged "GPE", "LOC", or "NORP", resulting in **3,832 sentences**, with an average length of 14 words. The clue sentences contain a total of 3,712 unique words and 3,182 unique lemmas.

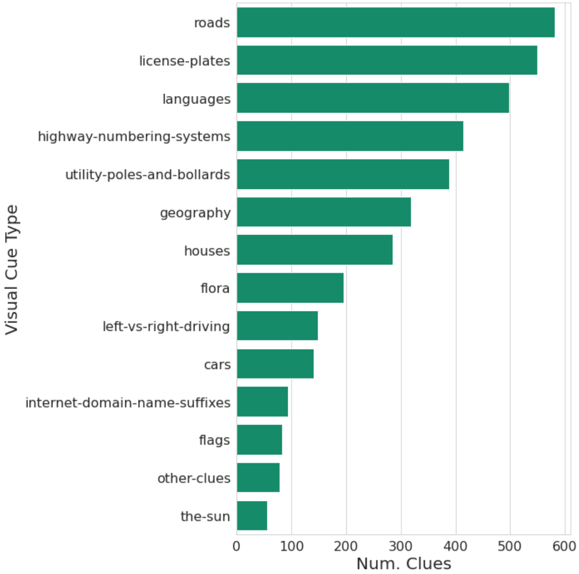


Figure 3: Number of guidebook clues associated with each visual cue type.

StreetView Images: We collect a geo-diverse dataset of StreetView panoramas that covers **90**

[4] https://www.geoguessr.com

[5] https://somerandomstuff1.wordpress.com/2019/02/08/geoguessr-the-top-tips-tricks-and-techniques/

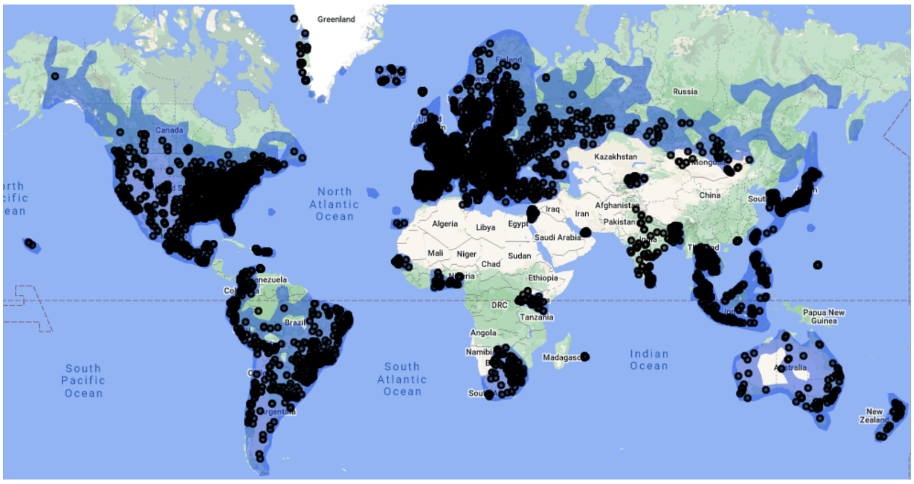


Figure 4: Locations of 10k random panoramas in our geo-diverse StreetView dataset. Black dots denote locations present in our dataset, and blue shadings denote locations available in StreetView.

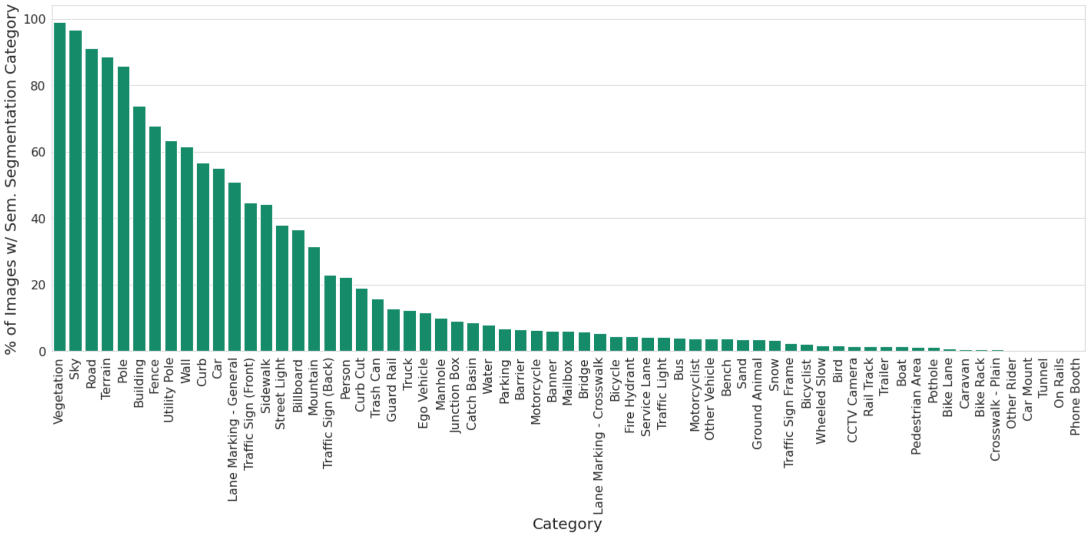


Figure 5: Breakdown of semantic segmentation categories according to what percentage of images they appear in.

	Train	Validation	Test
Count	322,536	3,888	3,600

Table 1: Our StreetView Images dataset statistics. Our validation set is roughly balanced and our test set is perfectly balanced with respect to 90 country classes.

countries. The Google StreetView API's coverage is fairly skewed, with countries in North America having some of the most extensive coverage and countries in Africa having the sparsest coverage (see Figure 4). We gather at least **426 panoramas** per available country, as seen in Figure 4. We then randomly split panoramas into training / validation / test sets. Finally, we "cut" each panorama into four disjoint images, as our baseline models were pretrained on images rather than 360-degree panoramas. See Table 1 for the number of images in each split of the dataset. Our training set contains all four panorama cuts for a given image, but our validation and test sets only contain one cut to enforce independence of the evaluation samples. While our training set is imbalanced, our validation and test sets are balanced to ensure that each country is equally represented in the final classification performance.

We also collect semantic segmentations to better understand the content of our StreetView images (and for potential use in future work). We use MaskFormer pretrained on Mapillary Vistas (Cheng et al., 2021; Neuhold et al., 2017), which provides segmentations for 66 categories specific to street scenes. We report the distribution of these categories present in our StreetView dataset in Figure

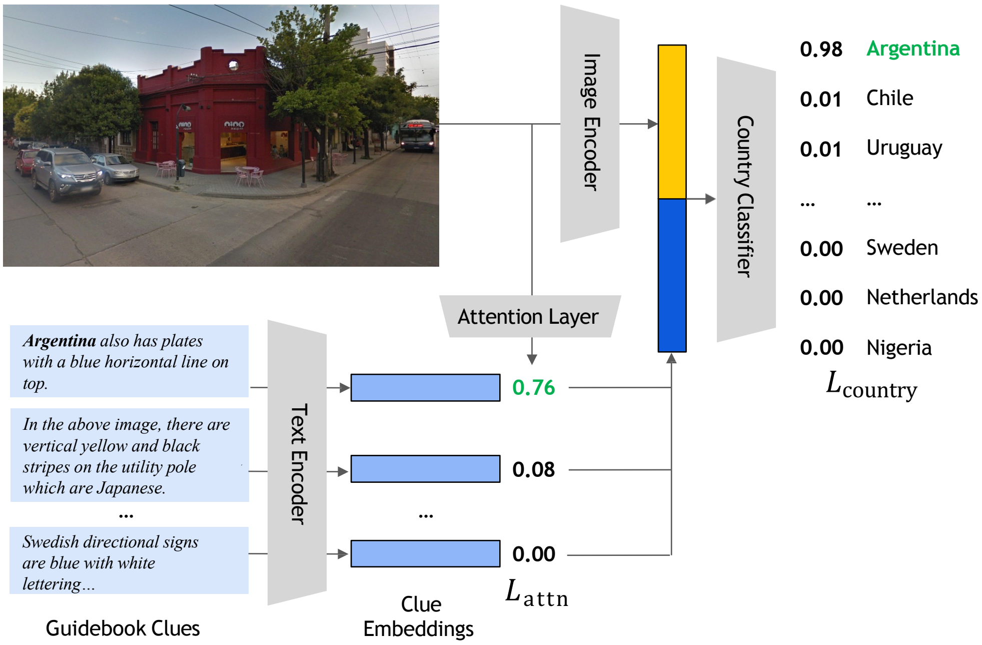


Figure 6: Overview of our G^3 approach: We compute image embeddings for the query image, and a weakly supervised attention layer computes a weighted average over the clue embeddings to generate an image-relevant textual clue representation. During training the attention layer is weakly supervised with positive examples of clues that match the image's ground truth country. The image embedding is then concatenated with the clue representation before being passed to a classifier.

5. As expected, most images contain "vegetation", "sky", "road", many contain "cars" and "lane markings", and fewer contain "people", "billboards", "mailboxes", "fire hydrants" etc.

4 Approach

Our multimodal approach, G^3, improves upon traditional image-only methods for geolocation with the help of guidebook text. We concatenate the visual representation of an image-only geolocation model with a relevant textual clue representation derived from our guidebook, and use it in a linear country classification layer, see Figure 6.

Textual Clue Representation: Given an input image to geolocate, we use a soft attention layer to compute attention scores over each sentence (clue) extracted from our guidebook to indicate its relevance. We opt to use the location-based attention mechanism of Luong et al. (2015) as other attention mechanisms would take significantly more memory and time to train for a guidebook the size of ours. Our soft attention layer takes an image query d, encodes it with a frozen CLIP RN50x16 image encoder f_{CLIP}, and passes it through a fully connected layer with a ReLU activation to obtain attention logits for each clue in our guidebook:

$$f_{attn}(d) = \mathsf{ReLU}(W \cdot f_{CLIP}(d) + b). \quad (1)$$

We precompute clue representations by applying a frozen RoBERTa Base model (Liu et al., 2019) to each clue in our guidebook.[6] We then take the weighted average of these clue representations to obtain $\hat{G}$, an image-specific summary textual clue representation:

$$\hat{G} = \frac{1}{|G|} \sum_{i=1}^{|G|} \sigma(f_{attn_i}(d)) \times G_i, \quad (2)$$

where we apply a sigmoid activation to the attention logits $f_{attn}(d)$ and take the i-th score to scale G_i, the i-th clue representation.

Guiding Attention with Pseudo Labels: Given the large number of clues in our dataset, we use weak supervision to guide the attention mechanism during training. We create pseudo labels associating clues to images using country information. Specifically, we geoparse the clues via country demonyms and lexical matching,[7] mapping the

[6] For each sentence, we use the RoBERTa representation of the CLS token.

[7] We also tried the neural geoparser Mordecai (`https://github.com/openeventdata/mordecai`) but found that lexical matching had higher precision and recall.

named entities (as predicted by spaCy, see Section 3) in the clues to country labels, and therefore associated images. For example, a clue that mentions "Japanese" would be associated with images where Japan is the ground truth label. On average each image is matched to 76 country-relevant clues (2% of all guidebook clues).

We then supervise the attention mechanism over clues with these pseudo labels. We add a binary cross entropy loss on our attention logits, where the label is a one-hot vector for each clue in our guidebook, defined by whether the clue mentions the country of the input image. Our final loss function is as follows:

$$(1-\alpha) \times L_{country} + \alpha \times L_{attn} \tag{3}$$

where $L_{country}$ is the cross entropy loss for our country classification objective and $\alpha = 0.75$ is the weighting factor for our attention loss, determined using grid search on our validation set. Since each image is only associated with a handful of clues (i.e. there are significantly more negatives than positives, or clues we do *not* want to attend over), we also upweight the loss of positive pseudo labels.[8]

In summary, our pseudo labels map clues (e.g. *Argentina's license plates are ...*) to countries (e.g. Argentina). At *training time*, we encourage the model to attend to the clues relevant to the image's ground-truth country via the auxiliary loss L_{attn}. At *test time*, given an input image, G3 predicts attention weights over all guidebook clues without any access to the ground-truth information.

5 Experiments

Baseline Models: For our baseline models we use ISN, a unimodal model consisting of a visual encoder and linear classification layer trained to predict a hierarchical cell on Earth given an image (Muller-Budack et al., 2018), and CLIP, a multimodal model consisting of a visual and text encoder trained to maximize the cosine similarity of matched image-text pairs via contrastive learning (Radford et al., 2021). We adapt the ISN ResNet50 model pretrained on millions of Flickr images (Muller-Budack et al., 2018; Choi et al., 2014) by modifying the output size of the final classification layer from the number of cells on Earth to the number of countries in our dataset and further fine-tune the model on our StreetView images. While CLIP was not trained specifically for the geolocation task, Radford et al. (2021) demonstrate reasonable performance on a number of geolocation benchmarks such as Countries211 (Radford et al., 2021) and Im2GPS (Hays and Efros, 2008) via nearest neighbors regression, zero-shot prediction, and/or linear probing. We adapt the CLIP RN50x16 model pretrained on a large-scale web image-text dataset (Radford et al., 2021) by taking a frozen representation from its visual encoder and feeding it to a linear classification layer (denoted by 'CLIP Linear Probe'). We also include the nearest neighbor version (CLIP Nearest Neighbor).

Implementation Details: In our experiments, we either use the ISN visual representation alone or concatenated with the CLIP visual embedding ("ISN + CLIP"). We do this to study the complementarity of CLIP's world knowledge to ISN.

Experimental Setup: We train our visual encoder and linear classifier at a learning rate of 1e-2 and attention layer at a learning rate of 1e-3 using an SGD optimizer (following Muller-Budack et al. 2018), and batch size of 128 for 15 epochs. We upweight the loss for countries that appear more infrequently in our training data to account for its distributional imbalance. We also apply batch normalization on the inputs to the attention and linear classifier layers.

Main Results: We report country classification accuracy on the test set of our StreetView dataset in Table 2 (we report the mean and standard deviation over five seeds). Prior approaches such as ISN and CLIP demonstrate competitive performance, with 61% and 65% top-1 performance respectively. CLIP Linear Probe provides a significant boost of 17% over the nearest neighbor prediction. Finally, we observe the best performance from our full method, G^3, while using both the ISN and CLIP visual representations along with the domain-specific clue representations from our guidebooks, achieving a 70% Top-1 classification accuracy.

Ablations: We further ablate the effect of the different components of our approach in Table 3.[9] For both ISN and ISN + CLIP as visual representations we report the effects of using no text,

[8] We also tried supervising our attention with MIL-NCE (Miech et al., 2020) but observed that our approach empirically outperformed MIL-NCE in early experiments.

[9] We report the respective ablations on the validation set in the Appendix.

Model	Top-1	Top-5	Top-10
CLIP Nearest Neighbor	0.4336	0.6858	0.7806
CLIP Linear Probe	0.6081 ± 0.001	0.8789 ± 0.003	0.9417 ± 0.001
ISN	0.6527 ± 0.015	0.8817 ± 0.004	0.9379 ± 0.004
G^3 (Ours)	**0.7031** ± 0.002	**0.9178** ± 0.004	**0.9618** ± 0.002

Table 2: StreetView Image Country Classification Accuracy (Test)

Model	Attn Supervision	Top-1	Top-5	Top-10
ISN	N/A	0.6527 ± 0.015	0.8817 ± 0.004	0.9379 ± 0.004
ISN + Random Text	N/A	0.6559 ± 0.027	0.8840 ± 0.012	0.9403 ± 0.010
ISN + Guidebook	No	0.6733 ± 0.011	0.8927 ± 0.008	0.9449 ± 0.005
ISN + Guidebook	Yes	0.6972 ± 0.006	0.9115 ± 0.001	0.9561 ± 0.002
ISN + CLIP	N/A	0.6448 ± 0.030	0.8908 ± 0.011	0.9470 ± 0.006
ISN + CLIP + Random Text	N/A	0.6037 ± 0.035	0.8571 ± 0.017	0.9232 ± 0.010
ISN + CLIP + Guidebook	No	0.6364 ± 0.037	0.8716 ± 0.018	0.9328 ± 0.013
G^3= ISN + CLIP + Guidebook	Yes	**0.7031** ± 0.002	**0.9178** ± 0.004	**0.9618** ± 0.002

Table 3: Ablated StreetView Image Country Classification Accuracy (Test)

attending over random text, attending over guidebook text, and including weak country supervision for the latter. Our location-based attention mechanism introduces additional parameters into the prediction network. To disentangle the degree to which the improvements of our full method are due to its use of the guidebook text versus this additional parameterization, we perform an experiment that replaces guidebook sentences with the same amount of sentences from the news domain (Biten et al., 2019) ("Random Text"). For the ISN model, we see that attending over random text maintains the same performance as the image-only method while guidebook text boosts the performance by 2%. For the ISN + CLIP model, random text significantly hurts performance while guidebook text maintains similar performance within 1%, which implies that random text can have an adverse effect and guidebook text can be redundant when combined with CLIP embeddings. However, when we use guidebook text and weakly-supervise the attention mechanism to encourage it to correctly select country-relevant clues, we obtain the best performance for both feature classes: 69.7% Top-1 for ISN, and 70.3% Top-1 for ISN+CLIP.

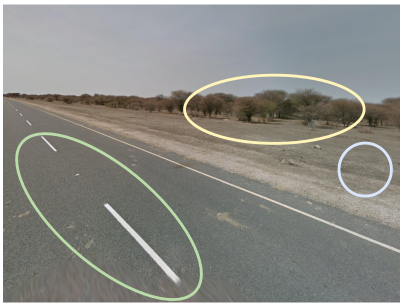
6 Analysis

Here we discuss qualitative success and failure cases of G^3 and the top clues attended over as well as comparisons with baseline image-only methods.

Success Cases: In Figure 7, we show a qualitative example where baseline methods such as ISN and ISN + CLIP incorrectly predict Kenya and the UAE when the ground truth location is Botswana. Both incorrect predictions are plausible — Kenya is geographically close to Botswana, and the UAE is also covered in desert. On the other hand G^3 correctly predicts Botswana, and we visualize the Top-10 clues retrieved by our attention mechanism. G^3 retrieves clues that mention its final prediction, Botswana, that describe how the roads are a *blend of desert and savanna* and *in excellent condition*. It also retrieves clues relevant to the countries it did not predict, such as the fact that the UAE often has *skyscrapers in the background* and *sandy desert* or Kenya often has soil that is *red*. As such, our guidebook demonstrates how language can efficiently communicate what locations are commonly confused (i.e. through the co-occurence of two countries in text) and key visual cues that remedy this confusion (i.e. a country may be distinct because *the soil is typically not as red* as its neighbors).

Failure Cases: In Figure 8, we show a failure case where all three methods — ISN, ISN + CLIP, and G^3, are unable to predict the ground truth location Hungary. Interestingly, while ISN and ISN + CLIP predict the same country — Italy — G^3 instead predicts Bulgaria. In fact, most of our attention mechanism's top clue retrievals mention countries within the Balkan Peninsula, including Croatia, Albania, Turkey, Greece, North Macedonia, and finally Bulgaria. Many of the clues retrieved also mention objects that can be grounded

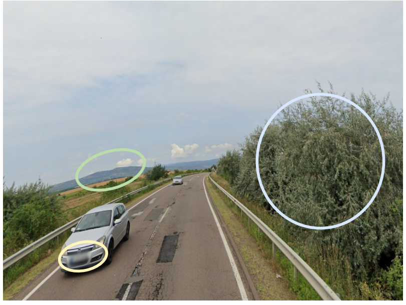
GT Location: Botswana
ISN Prediction: Kenya
ISN + CLIP Prediction: UAE
G^3 **Prediction:** Botswana



Guidebook Clues			
0.9410	As large amounts of the UAE Street View coverage centres around Dubai, you may be able to see the city's skyscrapers in the background.	0.9230	Occasionally there will be no car visible if you pan down in the UAE although this is fairly uncommon.
0.9332	There is a sandy desert almost everywhere you look in the UAE.	0.9216	The first letter of local roads can indicate where in the UAE you are.
0.9302	The yellow continuous roads lines are also abundant in **Botswana**, like these aforementioned places.	0.9211	**Botswana** typically has high quality main roads and the environment is a blend of desert and savanna.
0.9278	The UAE landscape consists of a sandy desert and fair-coloured buildings.	0.9204	**Botswana's** main roads are in excellent condition, looking almost brand new.
0.9244	Directional information in the UAE is sometimes provided on green signs with white lettering.	0.9173	The soil is typically not as red as the Ugandan and Kenyan soils.

Figure 7: An example success case from our StreetView test set. Note how ISN and ISN + CLIP make incorrect predictions, while G^3 correctly predicts Botswana. We also depict the Top-10 clues attended over by G^3, many of which mention relevant countries and can be grounded in the image.

GT Location: Hungary
ISN Prediction: Italy
ISN + CLIP Prediction: Italy
G^3 **Prediction:** Bulgaria



Guidebook Clues			
0.8926	Croatian is spoken in Croatia as well as Bosnia and Herzegovina.	0.8722	The front of Greek bollards have a thick red rectangle.
0.8830	This is thinner than the blue stripe on Albanian and **Italian** plates.	0.8634	Some parts of **Bulgaria** have rolling hills and trees with green leaves.
0.8823	The easiest way to identify Israel is arguably via its distinctive yellow license plates which feature on the front and rear of their cars.	0.8613	Israel has yellow license plates, both front and back.
0.8803	Albania also has rifts in seemingly random positions throughout the country.	0.8611	Turkey uses either blue or green coloured directional signs.
0.8768	Chevron's are most common in Turkey (red arrows on white background), the Austrian alps (yellow and red or white and red) as well as the mountainous parts of the Balkans, which vary in colour depending on the country.	0.8585	Many small, North Macedonian signs have a black rear.

Figure 8: An example failure case from our StreetView test set. Note how G^3 incorrectly predicts Bulgaria, and how its Top-10 attended clues mention many countries in the Balkan Peninsula.

in the image, including *license plates*, *mountainous parts*, and *green leaves*. The plausibility of many of the retrieved clues also indicates how in some cases, the geolocation task is incredibly difficult with a single image and how many different countries can all be plausible given the same visual cues. Many failure cases can be attributed to this fact, and it seems to suggest reducing the remaining errors of existing models on the geolocation task requires a setting closer to that of GeoGuessr, where a scene may be navigable and grant access to multiple views of the same location. Although this setting is less realistic in the context of real-world geolocation tasks that often involve a single social media image, this potential future evaluation setting is particularly interesting because it gives rise to methods that can model uncertainty or enumerate the additional visual cues needed for it to be more confident in its prediction.

7 Conclusion

We presented Geolocation via Guidebook Grounding, a new multimodal task that includes a geo-diverse dataset of images from StreetView and text from a guidebook for the GeoGuessr game. We demonstrated that adding clues from guidebooks via our approach, G^3, substantially outperforms past state-of-the-art image-only geolocation models on our task, with an absolute improvement of 5% to reach 70% in Top-1 country classification.

At the same time, there is still significant room left for improvement, and we hope that other practitioners will find this task interesting and relevant. The unique feature of our dataset is that the guidebook contains references to many nuanced and detailed characteristics of the visual scenes, posing challenging grounding problems. From recognizing specific road markings and reasoning about the scene geography, to recognizing flags, languages and other symbols, there are many skills necessary to solve the task. The focused domain of street scenes enables us to study this problem, while still being conceptually rich and capturing a multitude of diverse geographic locations.

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8 Limitations, Ethics, and Broader Impacts

Dataset: The copyright and usage rights of the StreetView dataset are subject to that of Google. Unlike prior works that train and evaluate on datasets of user uploaded data, which are often skewed towards Western and industrialized countries, we take measures to collect a minimum number of samples from a diverse set of countries and reward performance on each country equally during evaluation. That being said, our findings are limited to the 90 countries in our dataset since there exist countries that do not have Google StreetView coverage due to legal or resource reasons. However, we hope that our work contributes to a broader discussion of collecting geo-diverse data, which is important for building systems that work equally well for diverse sets of populations.

While our collection of clues used to encode human-written knowledge discusses an extensive set of countries, we note that the clues are from a guidebook with a single author and are therefore limited to the experiences of one person. We encourage future work to also consider community forums such as `https://www.reddit.com/r/geoguessr/` which includes discussion from a broader range of players but contains noisier data.

Approach: Since we build upon pretrained models such as ISN (Muller-Budack et al., 2018) and CLIP (Radford et al., 2021) for our visual representations, our approach is subject to the pre-existing biases learned by these models. For example, CLIP has demonstrated biases w.r.t. race and gender when classifying images of individuals (Radford et al., 2021). Our final model G^3 is 27.9M total trainable parameters and its training takes on average 5 hours on one NVIDIA GeForce Titan X GPU, which is estimated to be 0.54 kgCO2eq in total emissions (Lacoste et al., 2019).

Broader Impacts: We acknowledge that approaches for the domain of geolocation can be misused in applications such as surveillance. However, we would also like to highlight that our work specifically focuses on the more coarse-level task of country classification to better align our modeling with our problem statement of language and grounding. As such, our work is less useful for fine-grained surveillance, which usually searches for locations on a city or street level. We caution against these unintended use cases, and we also emphasize that geolocation has many other positive applications in disaster response (e.g. interpreting social media imagery and appropriately directing disaster resources), arts and culture (e.g. understanding key identifying features of different locations around the world to produce more inclusive animations and films), and fact checking (e.g. determining the provenance of an image in journalism and content moderation).

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A Appendix

In Section A.1 we discuss results on our StreetView validation set. In Section A.2 we show example predictions along with the attended clues. In Section A.3 we provide details about the guidebook clues.

A.1 Validation Set Results

In Tables 4 and 5 we present experimental results on our Validation set corresponding to the Test set results from Tables 2 and 3 of Section 5. The trends observed here are similar to those discussed previously on our Test set.

A.2 Example Predictions with Attended Guidebook Clues

Figure 9 shows an example where ISN and ISN + CLIP both make the correct prediction but our method G^3 makes an incorrect prediction, which occurs 2% of the time in our test set (whereas the inverse, where only G^3 predicts correctly, occurs 4% of the time). G^3 attends to clues mentioning both the ground truth country (Albania) and its incorrect prediction (Turkey). In fact, some clues that mention Turkey can be grounded in the image, for example the *[wide] roads* and *blue or green coloured directional signs*. In many such failure cases, the ground truth country is mentioned in the retrieved clues but lacks visual cues that can be related to the given image.

Figure 10 shows examples of *random* images drawn from our StreetView test set, the predictions of our model G^3, and the Top-5 most relevant guidebook clues according to the model's attention scores. In the top left example the model correctly predicts Palestinian Territory and four of the five top clues are related to Palestine. In the top right example the prediction is again correct (Taiwan), and while none of the clues mention Taiwan, they are all related to nearby geographic regions in Asia. In contrast, the bottom left example shows an incorrect prediction, though the clues relate to an overall correct geographic region. In the bottom right the photo shows few visual cues (i.e., only vegetation is depicted) and thus the clues mention a wide spread of countries.

A.3 Guidebook Clues

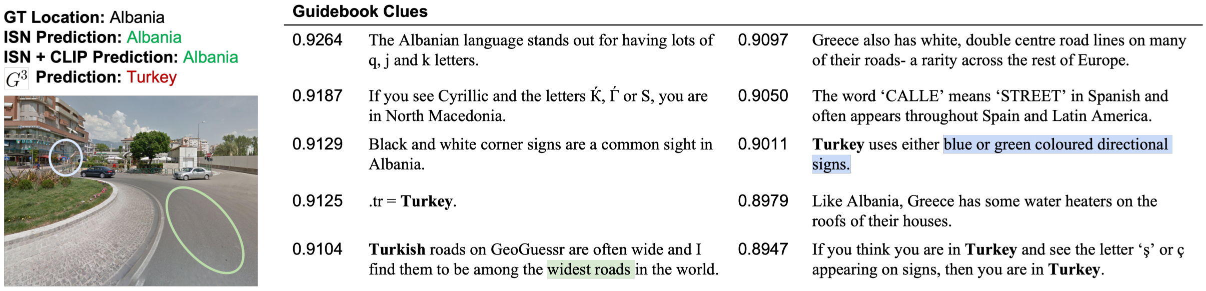
Figure 11 shows a breakdown of clue counts by country. Some clues are not matched to a country, as in the example *Birch trees are only found north of the 40th parallel,* because the clue applies to a broader geographical area rather than a country.

Model	Top-1	Top-5	Top-10
CLIP Nearest Neighbor	0.4313	0.6826	0.7832
CLIP Linear Probe	0.6238 ± 0.001	0.8860 ± 0.003	0.9473 ± 0.002
ISN	0.6548 ± 0.013	0.8852 ± 0.006	0.9442 ± 0.005
G^3 (Ours)	**0.7020** ± 0.005	**0.9224** ± 0.003	**0.9661** ± 0.002

Table 4: StreetView Image Country Classification Accuracy (Val)

Model	Attn Supervision	Top-1	Top-5	Top-10
ISN	N/A	0.6548 ± 0.013	0.8852 ± 0.006	0.9442 ± 0.005
ISN + Random Text	N/A	0.6615 ± 0.024	0.8932 ± 0.012	0.9471 ± 0.008
ISN + Guidebook	No	0.6776 ± 0.013	0.9007 ± 0.007	0.9521 ± 0.005
ISN + Guidebook	Yes	0.6966 ± 0.003	0.9193 ± 0.003	0.9634 ± 0.003
ISN + CLIP	N/A	0.6576 ± 0.027	0.9000 ± 0.010	0.9549 ± 0.004
ISN + CLIP + Random Text	N/A	0.6131 ± 0.029	0.8633 ± 0.012	0.9315 ± 0.010
ISN + CLIP + Guidebook	No	0.6434 ± 0.036	0.8800 ± 0.019	0.9392 ± 0.013
G^3= ISN + CLIP + Guidebook	Yes	**0.7020** ± 0.005	**0.9224** ± 0.003	**0.9661** ± 0.002

Table 5: Ablated StreetView Image Country Classification Accuracy (Val)


GT Location: Albania
ISN Prediction: Albania
ISN + CLIP Prediction: Albania
G^3 **Prediction:** Turkey

Guidebook Clues

0.9264	The Albanian language stands out for having lots of q, j and k letters.	0.9097	Greece also has white, double centre road lines on many of their roads- a rarity across the rest of Europe.
0.9187	If you see Cyrillic and the letters Ќ, Ѓ or S, you are in North Macedonia.	0.9050	The word ‘CALLE’ means ‘STREET’ in Spanish and often appears throughout Spain and Latin America.
0.9129	Black and white corner signs are a common sight in Albania.	0.9011	**Turkey** uses either blue or green coloured directional signs.
0.9125	.tr = **Turkey**.	0.8979	Like Albania, Greece has some water heaters on the roofs of their houses.
0.9104	**Turkish** roads on GeoGuessr are often wide and I find them to be among the widest roads in the world.	0.8947	If you think you are in **Turkey** and see the letter ‘ş’ or ç appearing on signs, then you are in **Turkey**.

Figure 9: Sample from our StreetView test dataset where ISN, ISN + CLIP predict correctly but G^3 predicts incorrectly. Note how G^3 incorrectly predicts Turkey, and how its Top-10 attended clues mention either Turkey or the ground truth country Albania.

GT Location: Palestinian Territory
G^3 **Prediction:** Palestinian Territory

Score	Guidebook Sentence
0.9185	The Palestinian rural landscape features small bushes, lots of rocks, rolling hills and short, dry grass.
0.9142	Sometimes you will see the yellow license plates of Israel within Palestine however these plates are far outnumbered by the Palestinian plates.
0.9097	Very little outside this narrow area is covered in Tunisia.
0.9079	Palestine also has elongated, white coloured plates which are a contrast to Israel’s yellow plates.
0.9047	Sometimes you will see the yellow license plates of Israel within Palestine however these plates are far outnumbered by the Palestinian plates.

GT Location: Taiwan
G^3 **Prediction:** Taiwan

Score	Guidebook Sentence
0.9090	The first script can be easily confused with Chinese and appears on the top section of the sign.
0.9089	Yellow guardrails are a common sight in the southern Japanese prefecture of Yamaguchi.
0.8968	South Korea has a unique writing system that can be easily identified.
0.8928	Mobile numbers begin with 08 or 09 in Japan and toll free numbers start with 0120.
0.8835	In Taiwan and South Korea, they also have the yellow and black markings on some poles however these countries have diagonal stripes, not vertical like the standard Japanese stripes.

GT Location: Philippines
G^3 **Prediction:** Cambodia

Score	Guidebook Sentence
0.9162	This contrasts the Thai written language that contains a straight component to almost every character.
0.9143	Sri Lanka is also my go to guess if I see narrow, paved paths with few other clues.
0.9082	Sri Lanka has yellow rear plates and white front plates.
0.9056	Another method to pinpoint your province in Indonesia involves signs.
0.8929	Angkor beer signs are scattered frequently throughout Cambodia.

GT Location: Greece
G^3 **Prediction:** Bulgaria

Score	Guidebook Sentence
0.8875	Additionally, the USA uses miles and Canada uses kilometres.
0.8650	Ireland is a unique country in GeoGuessr for several reasons.
0.8574	This means the license plate is from Spain (Espanol).
0.8518	The Thai script below the bird means ‘kilometre’.
0.8476	It has license plates with the blue vertical stripe on both sides of the plate, like Italy.

Figure 10: Random samples from our StreetView test dataset and the Top-5 guidebook sentences attended to by G^3.

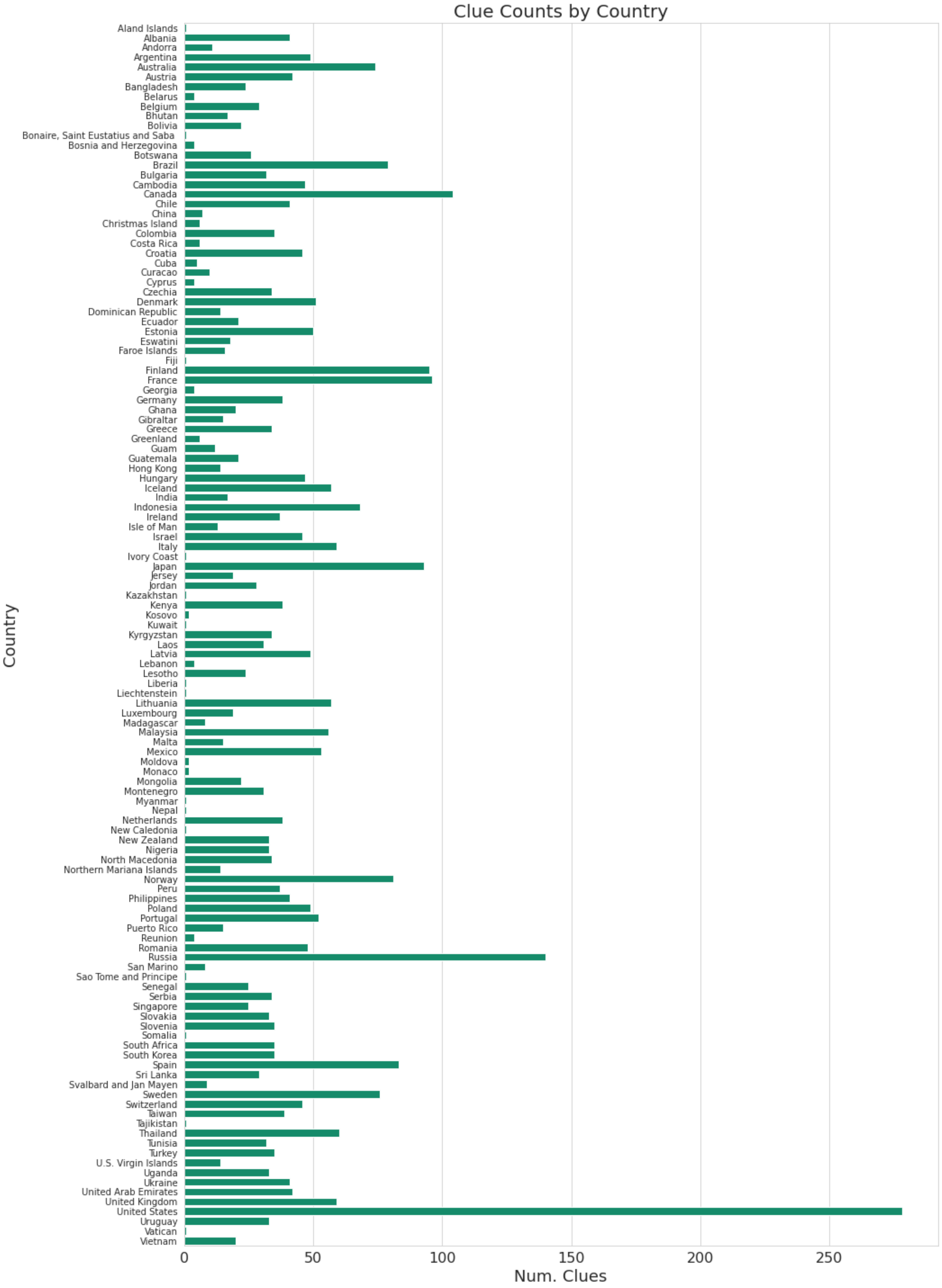


Figure 11: A histogram of the number of clues for each country.