

The World According to LLMs: How Geographic Origin Influences LLMs’ Entity Deduction Capabilities

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Abstract

Large Language Models (LLMs) have been extensively tuned to mitigate explicit biases, yet they often exhibit subtle implicit biases rooted in their pre-training data. Rather than directly probing LLMs with human-crafted questions that may trigger guardrails, we propose studying how models behave when they proactively ask questions themselves. The 20 Questions game, a multi-turn deduction task, serves as an ideal testbed for this purpose. We systematically evaluate geographic performance disparities in entity deduction using a new dataset, **Geo20Q⁺**, consisting of both notable people and culturally significant objects (e.g., foods, landmarks, animals) from diverse regions. We test popular LLMs across two game-play configurations (canonical 20-question and unlimited turns) and in seven languages (English, Hindi, Mandarin, Japanese, French, Spanish, and Turkish). Our results reveal geographic disparities: LLMs are substantially more successful at deducing entities from the *Global North* than the *Global South*, and the *Global West* than the *Global East*. While Wikipedia pageviews and pre-training corpus frequency correlate mildly with performance, they fail to fully explain these disparities. Notably, the language in which the game is played has minimal impact on performance gaps. These findings demonstrate the value of creative, *free-form* evaluation frameworks for uncovering subtle biases in LLMs that remain hidden in standard prompting setups. By analyzing how models initiate and pursue reasoning goals over multiple turns, we find geographic and cultural disparities embedded in their reasoning processes. We release the dataset (**Geo20Q⁺**) and code at <https://sites.google.com/view/llmbias20q/home>.

1 Introduction

In response to growing concerns around bias and fairness, Large Language Models (LLMs) like Google’s Gemini (Team, 2023), Meta’s LLaMA 3 (Touvron et al., 2023), and OpenAI’s GPT-4 (OpenAI, 2023) have undergone extensive alignment to minimize explicit biases (Bai et al., 2024). Paradoxically, these alignment efforts have made subtle biases harder to detect: models now avoid overtly problematic responses but may still encode prejudices in their reasoning processes and knowledge hierarchies (Borah & Mihalcea, 2024; Kumar et al., 2024; Lim & Pérez-Ortiz, 2024). As a result, standard prompting-based evaluations that only examine model outputs can give a false impression of fairness.

To study such behaviors, we must move beyond surface-level probing with human-formulated questions, which often trigger guardrails and only reveal what models say, not how they reason. Instead, we propose a complementary approach: *allow LLMs to*

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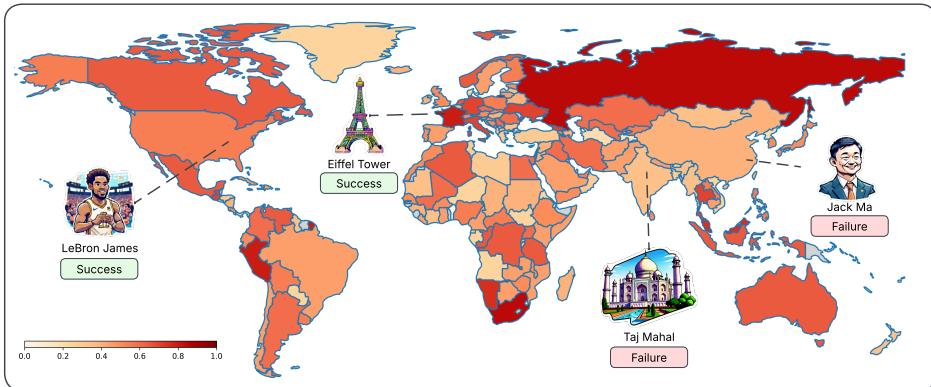


Figure 1: Country-level success rates of Gemini 2.0 on entity deduction across 20 regionally specific entities (10 each for Things and Notable people). Darker shades indicate higher deduction success rates. We also show illustrative examples highlighting performance gaps: the model successfully deduces entities like the Eiffel Tower and LeBron James while struggling with counterparts like the Taj Mahal and Jack Ma¹.

proactively ask a sequence of questions to deduce the answer and analyze their inquiry chains. By examining which questions models prioritize, how they navigate ambiguity, and what hypotheses they generate when left to their own devices, we can observe biases in their reasoning that remain hidden in standard evaluations.

The 20 Questions game provides a compelling testbed for this form of evaluation (Zhang et al., 2023). In this interactive task, different instances of an LLM play both roles, the guesser: attempting to identify an unknown entity by asking a sequence of yes/no/maybe questions, and the judge: responding to these queries based on knowledge of the target entity (Figure 2 shows an example of a game). To succeed as a guesser, a model must maintain multi-turn coherence, systematically narrow the hypothesis space, and ask strategically informative questions (Mazzaccara et al., 2024). This process reveals which features and associations the model prioritizes when reasoning about entities from different regions, with unique insights into its implicit geographic knowledge hierarchies and cultural assumptions.

In particular, we focus on one principal axis for bias, geographic origin, and ask: *Do models demonstrate systematic differences in their ability to deduce entities based on geographic origin?* As illustrated in Figure 1, our findings show substantial regional variation in deduction success rates, with models performing notably better on Western entities like the Eiffel Tower compared to their Eastern counterparts like the Taj Mahal.

To support this investigation, we introduce **Geo20Q⁺**, a new dataset of geographically diverse entities curated from Wikipedia. Unlike traditional 20 Questions datasets, which focus on generic entities (e.g., popcorn, cars, etc.), **Geo20Q⁺** consists of popular, geographically specific entities from around the world, including both culturally salient things (Things; e.g., foods, landmarks, animals) and notable individuals (Notable people; e.g., politicians, academics, sport players, etc.). To our knowledge, this is the first geographically balanced entity deduction dataset specifically designed to evaluate implicit bias in LLM reasoning.

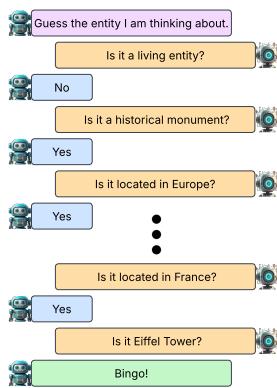


Figure 2: An example 20 Questions game played by Gemini 2.0 for the entity “Eiffel Tower.”

¹Note: (1) We use AI-generated cartoon representations of entities and are not intended to be accurate or factual depictions. (2) The map is shown using a standard projection; results hold regardless of projection choice, though equal-area projections may represent country sizes differently.

In addition to the standard 20-question limit (the canonical setting), we introduce an unlimited-turn configuration that removes constraints on reasoning depth. While the 20-question setting is naturalistic and faithful to the original game, it may prematurely truncate valid reasoning paths. The unlimited-turn setting allows models to follow deeper, exploratory inquiry chains, providing richer insights into deduction behavior and failure modes.

We organize our investigation around the following research questions:

- RQ1: What is the top-line deduction performance of popular LLMs on our **Geo20Q⁺** dataset? How do they vary across entity types (Things vs. Notable people) and gameplay settings (canonical vs. unlimited turns)?
- RQ2: Can entity popularity (Wikipedia pageviews) and pre-training corpus-based frequency of entity explain the observed disparities?
- RQ3: To what extent does the language in which the game is played influence the model’s ability to deduce entities from different geographic origins?
- RQ4: Do LLMs exhibit geographic performance disparities in their ability to deduce entities, particularly between the Global North and Global South, and the Global West and Global East?

To answer these questions, we evaluate three widely used LLMs across multiple gameplay configurations and seven languages. Our findings reveal significant geographic disparities in model performance. LLMs consistently demonstrate a superior ability to deduce entities from the Global North and West compared to those from the Global South and East. These disparities persist even when controlling for entity popularity and appear largely unaffected by the language of gameplay. Our analysis reveals geographic biases in model-initiated reasoning that standard evaluations miss, showing the value of creative benchmarking approaches for assessing fairness in LLMs.

2 Related Work

Bias and Fairness: Recent years have seen growing attention to fairness and bias in LLMs (Gallegos et al., 2024b), with research addressing various dimensions of social bias, including gender (de Vassimon Manela et al., 2021; Dong et al., 2024), race (Nadeem et al., 2021; Yang et al., 2024), ethnicity (Ahn & Oh, 2021; Hanna et al., 2025), age (Nangia et al., 2020), and sexual orientation (Cao & Daumé III, 2020). While techniques like data augmentation (Gallegos et al., 2024a) and model alignment (Ouyang et al., 2022) have reduced overt biases, they’ve created a new challenge: models whose surface-level outputs appear unbiased but whose reasoning processes still contain implicit biases (Bai et al., 2025; Zhao et al., 2025).

These subtle biases are particularly difficult to detect with traditional evaluation methods that rely on direct questioning or classification-based probes. Our work advances this literature by introducing a novel evaluation paradigm that studies bias through model-initiated inquiry chains rather than responses to human-crafted prompts, allowing us to uncover biases that remain hidden in standard evaluations.

Entity Deduction and Interactive Evaluation: Deductive tasks involving ambiguous entities have been used to evaluate reasoning capabilities in various contexts, from dialogue systems (Aliannejadi et al., 2019) to vision-language models (Cho et al., 2021). Early interactive frameworks like ESP (von Ahn & Dabbish, 2004) and Peekaboom (von Ahn et al., 2006) demonstrated the effectiveness of deduction-based gameplay for collaborative tasks, while visual reasoning datasets like GuessWhat?! (De Vries et al., 2017) extended this paradigm to object identification through interactive dialogues.

In the context of LLMs, the 20 Questions framework has recently emerged as a valuable probe for studying deductive reasoning (Zhang et al., 2023), decision-making (Bertolazzi et al., 2023), and question generation (Mazzaccara et al., 2024). However, prior work has primarily focused on using this framework to evaluate general reasoning capabilities rather than to detect biases. Our research represents the first application of the 20 Questions

paradigm specifically for uncovering geographic bias in LLMs, with a new methodological approach to fairness evaluation through multi-turn, model-initiated reasoning.

Geographic and Cultural Representation in NLP: While research on fairness has increasingly addressed demographic biases, geographic performance disparities remain underexplored, with most studies focusing on Western contexts, particularly the U.S. (Yogarajan et al., 2023; Besse et al., 2022; Yin et al., 2022). The limited work in this area has typically measured surface-level representations, such as entity coverage or language support, rather than evaluating how models reason about entities from different regions (Gupta et al., 2023; Bhagat et al., 2024; Li et al., 2023).

Recent studies have emphasized the importance of geographic diversity in NLP evaluations (Manvi et al., 2024; Mirza et al., 2024; Shafayat et al., 2024; Schwöbel et al., 2023), but few have operationalized this concern through multi-turn reasoning tasks. Our work fills this gap by systematically evaluating how geographic origin shapes both success rates and reasoning efficiency in entity deduction.

3 Task Setup

This section describes the implementation of the 20 Questions deduction game, the evaluation metrics for LLM performance, and the construction of our geographically diverse entity dataset designed to probe performance disparities.

3.1 Game Design

Our 20 Questions framework, adapted from Zhang et al. (2023), simulates the classic deduction game where two instances of the same base LLM play different roles: one as the “judge,” (aware of the target entity) and one as the “guesser,” (attempting to identify the entity through strategic questioning). The game proceeds through two key configurations:

- **Canonical setting:** The guesser has exactly 20 turns to correctly identify the entity, mirroring the traditional game format.
- **Unlimited-turn setting:** The guesser can continue questioning until it either makes a correct guess, gives up, or reaches 150 turns – an empirical upper bound based on performance gains plateau (see Appendix Figure 4).

Role Definitions:

- **Judge:** Receives the target entity and the guesser’s questions, responding only with “Yes,” “No,” or “Maybe”. The judge confirms correct guesses with “Bingo!” and acknowledges when the guesser gives up. In the canonical setting, the judge prompts for a final guess on the 20th turn.
- **Guesser:** Has no knowledge of the entity and must rely solely on the dialogue history to formulate informative questions and ultimately identify the target. The guesser must maintain coherence across turns while systematically narrowing the hypothesis space.

Implementation Details: Since different LLMs may have varying training corpora and temporal knowledge cutoffs, we use two instances of the same model for the judge and guesser roles to ensure consistent knowledge access and eliminate cross-model mismatches. For example, an LLM might associate Lionel Messi with FC Barcelona, while another, trained on newer data, might link him to Inter Miami, leading to inconsistent game dynamics if used together. All entities are based on Wikipedia articles, a source that is extensively used in the pre-training corpora of all LLMs under consideration. This design choice mitigates the risk that the judge (or guesser) completely lacks knowledge about a given entity, as these entities are highly likely to be present in the models’ knowledge base. Next, all prompts follow each model’s recommended formatting and include appropriate instructions to guide the guesser’s inquiry strategy (full prompts in Appendix A.4.1). Our evaluation focuses on model performance in the guesser role, as this captures the abilities we aim to assess.

3.2 Evaluation Metrics

We evaluate model performance using two primary metrics:

- **Success Rate (Accuracy):** The percentage of games in which the guesser correctly identifies the target entity. This serves as our primary metric for evaluating more efficient reasoning.
- **Number of Turns to Answer:** The average number of turns required for the guesser to deduce the correct entity in *successful* games. Lower values indicate faster and more efficient reasoning.

We focus on these performance indicators rather than other potential metrics, for example, the number of “Yes” responses (Zhang et al., 2023), which we find to be unreliable. For instance, entities with broadly applicable attributes (e.g., celebrities or landmarks) may elicit more “Yes” answers, simply because a broader range of questions apply to them. In the Appendix A.6, we also examine early termination behavior, where models abandon the game after multiple turns with outputs like “I give up.”

3.3 Geo20Q⁺: A Curated Dataset of Geographically Specific Entities

To evaluate geographic variation in deduction performance, we introduce Geo20Q⁺, a curated dataset of regionally specific entities spanning diverse locations. Entities fall into two broad categories: *culturally significant objects* (reference: Things; e.g., foods, landmarks, animals, and other culturally significant objects) and *notable individuals* (reference: Notable people; e.g., public figures, artists, politicians). Figure 3 shows the distribution of categories for Things and professions amongst Notable people.

Entity Sourcing. For Things, we collect pages from the English Wikipedia across thematic categories such as tourist attractions, mountains, rivers, universities, animals, foods, plants, and cultural artifacts. Using a custom scraper, we extract region-tagged pages within each category, rank them by pageviews, and collect up to 50 entities per country, yielding $N = 8375$ Things. For Notable people, we source data from the global notability dataset by Laouenan et al. (2022), which contains 2.1 million notable individuals from 172 countries. We rank individuals based on their English Wikipedia pageviews and choose the most popular individuals until every country has at least 50 representatives, resulting in a total of $N = 24049$ Notable people.

Disambiguation and Filtering. Many entities have associations with multiple countries; for instance, Elon Musk has ties to South Africa, Canada, and the U.S., while saffron is cultivated in several regions. To assign a single country of origin, we query each LLM to identify the country with which the entity is most strongly associated, constrained to options explicitly mentioned on the entity’s Wikipedia page. We retain only those entities for which all models agree on a primary country (approximately 88% of candidates), ensuring consistent geographic attribution. This filtering step reduces ambiguity and ensures that any differences in model performance reflect reasoning about clearly attributed entities, not inconsistencies in geographic labeling or background knowledge in model training data.

Avoiding Contamination. Rather than using generic, high-frequency entities (e.g., “car,” “fruit”) that are likely to be memorized during pretraining, we focus on geographically specific and fine-grained instances (e.g., “Audi,” “Alphonso mango”). This reduces the risk

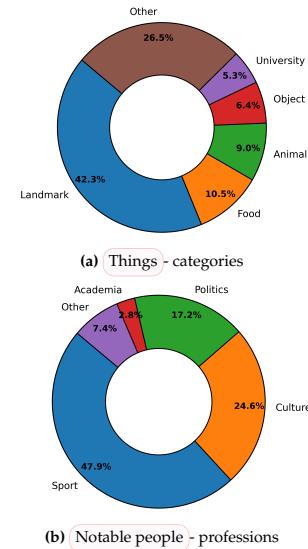


Figure 3: Distribution of entity types across (a) Things and (b) Notable people. Detailed breakdown in Appendix Figure 6.

of models succeeding through rote recall and encourages evaluation of genuine deductive reasoning over entity-specific knowledge.

4 Experimental Setup

4.1 Models evaluated

In our experiments, we evaluate the performance of widely used LLMs with strong scores on public benchmarks (Chiang et al., 2024). These include proprietary models such as GPT-4o-mini (OpenAI, 2023), and Gemini-2.0-Flash (Team, 2023), as well as one leading open-source model, Llama-3.3-70B-Instruct (Touvron et al., 2023). All models claim strong multilingual capabilities and represent different architectural approaches and training methodologies. By including both proprietary and open-source models from different developers, we ensure our findings reflect broader patterns in state-of-the-art LLMs rather than idiosyncrasies of a particular model family.

4.2 Multilingual Evaluation

To assess whether language influences geographic performance disparities (RQ3), we conduct experiments in seven high-resource languages spanning multiple language families and writing systems: English, French, Hindi, Spanish, Japanese, Mandarin, and Turkish (Robinson et al., 2023). While some LLMs support multilingual capabilities more robustly than others, all models evaluated in this work explicitly claim support for these high-resource languages. In particular, we focus on high-resource languages because they are substantially better represented in pretraining corpora, helping to ensure a minimum level of output quality across languages.

To play a game in a language, we first automatically localize the game setup, including using an LLM (GPT-4o) to translate the judge and guesser prompts as well as the entity names to match the expected usage of the target language. Next, for each language, we ask at least one in-house native/fluent speaker to review and, if needed, modify the prompt templates, observe a few games, and verify the consistency of LLM behavior in gameplay (see appendix A.9). Finally, all native/fluent speakers confirmed the quality of translation and the functional integrity of the deduction game across all seven languages.

4.3 Geographic Granularity

To efficiently test our research questions while maintaining comprehensive coverage, we organize entities at two levels of geographic granularity:

Continent-Level Analysis (RQ1-3): For each of the six inhabited continents (Africa, Asia, Europe, North America, South America, and Australia), we select the 100 most-viewed entities from Wikipedia in each category (Things and Notable people). This yields 1,200 entities evaluated per model, with a total of 50,400 games across all models, languages, and configurations (3 models \times 1,200 entities \times 7 languages \times 2 configurations).

Country-Level Analysis (RQ4): To examine geopolitical and cultural divides more precisely, we collect the 10 most popular entities of each type from 172 countries. We then organize countries into four key groupings:

- **Global North** (23 countries): Economically developed regions, including North America, Europe, and parts of East Asia (Odeh, 2010)
- **Global South** (149 countries): Less economically dominant regions across Africa, Latin America, South and Southeast Asia (Odeh, 2010)
- **Global West** (32 countries): Regions with predominantly Western cultural traditions, primarily North America and Western Europe (Turner & Khondker, 2010)
- **Global East** (142 countries): Regions with distinct non-Western cultural traditions, including much of Asia and the Middle East (Turner & Khondker, 2010)

These groupings allow us to examine how both development-related disparities (North/-South) and cultural representation biases (West/East) might influence model performance. For more details regarding country grouping, refer to Appendix A.10.

4.4 Measuring Entity Prevalence

To determine whether performance disparities can be explained by entity prominence in training data (RQ2), we employ two complementary measures:

Wikipedia Popularity: We use Wikipedia pageview statistics as a proxy for an entity’s overall cultural prominence and information availability.

Corpus Frequency: We estimate how frequently models may have encountered entities during pretraining using the Dolma dataset (Soldaini et al., 2024) through the WiMBD project (Elazar et al., 2023). This 3-trillion token corpus drawn from diverse internet sources allows us to calculate frequencies that approximate representation in typical LLM training data. Since the actual training corpora for our evaluated models are not publicly available, these frequencies serve as a reasonable proxy for training exposure.

Together, these measurements help us assess whether geographic performance disparities simply reflect data availability or suggest more fundamental biases in how models represent and reason about entities from different regions.

5 Findings

RQ1: Top-line model performance across entity types and gameplay settings

To establish baseline performance characteristics, we first examine deduction success rates and efficiency across models, entity types, and gameplay configurations.

Entity Type	Canonical gameplay			Unlimited turns		
	⑥	∞	↑ 2.0	⑥	∞	↑ 2.0
Things	9.2 (16.6)	12.5 (15.2)	10.7 (15.1)	42.7 (44.8)	43.3 (43.1)	44.7 (50.3)
Notable people	24.8 (15.1)	35.7 (15.2)	36.0 (16.1)	66.7 (34.5)	78.0 (30.1)	85.1 (31.2)
Average	17.0 (15.9)	24.1 (15.2)	23.4 (15.6)	54.7 (39.7)	60.7 (36.6)	64.9 (40.8)

Table 1: Average Success Rates (in %) and Number of Turns to Answer (in parentheses) across different models. For example, in the Canonical setting and for Notable people, Gemini 2.0 has a Success rate of 85.1 % and takes an average of 31.1 Turns to answer. Results are based on a continent-level evaluation (1,200 entities per model). Success rates are shown as percentages, and lower numbers of turns indicate more efficient deduction.

Key performance patterns (Table 1): Across both settings, models demonstrate consistently higher success with Notable people than Things (canonical: 25-36% vs. 9-13%; unlimited: 67-85% vs. 43-45%), suggesting stronger knowledge representation for notable individuals than regionally specific objects. Allowing unlimited turns improves performance across all conditions by 2.5-3x (e.g., GPT-4o-mini’s Things success increases from 9% to 43%), though at the cost of requiring 2-3x more turns for successful deductions. Among the models, Gemini 2.0 achieves the highest overall performance in the unlimited setting (65% average, 85% for Notable people), while LLaMA 3.3 shows competitive results with greater efficiency in some conditions, indicating differences in reasoning paths across model architectures.

Continent-wise variation in performance (Table 2): We observe significant geographic performance disparities that vary by setting. In the canonical 20-turn game play with Notable people, models show a clear western advantage, with nearly double the success rates for European and North American celebrities (43.8% and 45.0%) compared to those from Asia (26.5%), South America (24.8%), Africa (21.3%), and Australia (20.8%). When allowed unlimited turns, performance gaps narrow considerably as success rates increase

Setting	Entity Type	Asia	Africa	Australia	Europe	N. America	S. America
Can.	Notable people	26.5 (16.3)	21.3 (16.8)	20.8 (15.4)	43.8 (14.3)	45.0 (13.6)	24.8 (16.5)
	Things	8.0 (14.3)	15.5 (15.5)	7.5 (15.4)	12.5 (16.0)	9.0 (14.2)	9.5 (16.2)
Unl.	Notable people	72.8 (32.2)	77.8 (33.5)	62.0 (35.4)	76.8 (25.6)	78.8 (27.5)	73.3 (35.3)
	Things	43.0 (45.1)	46.5 (38.3)	37.8 (46.5)	45.0 (43.6)	34.3 (41.8)	39.5 (45.5)

Table 2: Average Success Rates (in %) and Number of Turns to Answer (in parentheses, averaged over all models) for the 100 most popular entities per continent. Results are shown separately for Notable people and Things in both the canonical (20 turns) and unlimited (150 turns) settings. The highest values in each row are highlighted in bold. More detailed results are available in Appendix Table 6.

across all regions (Notable people : 62-79%, Things : 34-47%), with Africa showing particularly strong gains. However, efficiency disparities persist even with convergent success rates, Western entities are deduced in significantly fewer turns (Notable people : Europe: 25.6, North America: 27.5) compared to other regions (32-35 turns). This pattern suggests that while models possess information about entities from diverse regions, they require more reasoning steps to access it for non-Western entities, indicating differences in how this knowledge is structured and retrieved. In contrast, gameplay with Things reveals a different pattern, with models achieving the highest success rates for African entities rather than Western ones.

RQ2: Can entity popularity and pre-training corpus frequency explain geographic performance disparities?

To investigate whether the performance disparities observed in RQ1 simply reflect differences in entity prominence, we analyze two explanatory variables: (1) **popularity** and (2) **corpus frequency**. If performance differences primarily stem from data availability, we would expect these metrics to strongly predict accuracy and the number of turns required for deduction.

Entity Type	Variable	Turns	@		∞		◆ 2.0	
			O.R.	R ²	O.R.	R ²	O.R.	R ²
Things	Popularity	Can.	1.000 [△]	0.000	1.000**	-0.119**	1.000***	-0.011
		Unl.	1.000 [△]	-0.006	1.000***	0.000	1.000***	-0.068***
	Frequency	Can.	1.001	0.000	1.003	-0.109***	1.001 [△]	-0.040 [△]
		Unl.	1.002***	-0.009	1.000	0.000	1.001	-0.018*
Notable people	Popularity	Can.	1.002***	-0.288***	1.003***	-0.153***	1.003***	-0.190***
		Unl.	1.001 [△]	-0.023**	1.002***	-0.039***	1.000	-0.048***
	Frequency	Can.	1.002***	-0.133***	1.003***	-0.073***	1.002***	-0.065***
		Unl.	1.001***	-0.012*	1.002***	-0.024***	1.001**	0.074***

Table 3: Regression analyses of the relationship between entity characteristics and model performance. For logistic regressions predicting **Success**, we report Odds Ratios (O.R.) where values greater than 1.0 indicate positive effects (higher frequency/popularity → higher success probability). For linear regressions predicting **Number of Turns**, we report R² values indicating variance explained. Significance: ***p < 0.001, **p < 0.01, *p < 0.05, △p < 0.1.

We conducted two types of regression analyses: (1) logistic regression with *Success* as the dependent variable, reporting odds ratios as $e^{0.01 \times \beta}$ to represent the effect of a 1% increase in the predictor; and (2) linear regression with *Number of Turns* as the dependent variable, reporting R² to measure explanatory power. Given the heavy-tailed distribution of entity frequency (Appendix Figure 5), we used log-transformed values to capture the relationship.

Table 3 presents the results of our regression analyses examining these relationships. Despite statistically significant associations in many cases, the predictors show surprisingly limited explanatory power. For success prediction, odds ratios hover near 1.0, indicating that even large popularity or frequency increases correspond to minimal success probability

changes. For predicting the number of turns, R^2 values, while significant, are consistently low (typically below 0.1), showing that these factors explain less than 10% of the variance in deduction efficiency. These patterns hold across all models, entity types, and gameplay settings, suggesting that while data availability contributes to model performance, it cannot fully explain the substantial geographic performance disparities observed in RQ1.

RQ3: To what extent does the language in which the game is played influence the model’s ability to deduce entities from different geographic origins?

Entity Type	Continent	English	Hindi	Mandarin	Spanish	Japanese	Turkish	French	Average
Things	Asia	53 (49.8)	15 (40.0)	11 (51.9)	35 (52.0)	22 (41.5)	6 (73.8)	42 (42.9)	26 (50.2)
	Africa	46 (42.3)	10 (31.8)	25 (34.4)	42 (44.3)	25 (33.0)	11 (36.2)	55 (35.9)	31 (36.8)
	Australia	44 (60.7)	17 (48.3)	14 (62.1)	36 (42.5)	18 (34.2)	11 (35.5)	49 (46.0)	27 (47.1)
	Europe	49 (37.8)	25 (33.5)	23 (49.1)	45 (39.3)	26 (32.7)	20 (52.4)	48 (41.9)	34 (40.1)
	North Am	34 (54.8)	18 (46.9)	10 (58.6)	22 (47.4)	16 (34.1)	5 (30.6)	36 (50.8)	20 (46.1)
	South Am	42 (56.6)	13 (40.3)	16 (51.3)	39 (35.2)	13 (47.8)	8 (56.4)	48 (39.1)	26 (46.6)
Notable people	Asia	95 (28.5)	89 (28.8)	72 (24.3)	84 (27.3)	68 (23.1)	60 (29.9)	80 (28.1)	78 (27.1)
	Africa	89 (35.4)	79 (33.9)	71 (32.0)	86 (40.6)	63 (27.4)	41 (34.5)	82 (33.1)	73 (33.8)
	Australia	81 (32.4)	66 (35.8)	63 (32.5)	69 (31.9)	51 (35.5)	53 (26.4)	70 (37.3)	65 (33.1)
	Europe	87 (26.8)	83 (25.6)	81 (22.7)	83 (32.5)	76 (23.0)	48 (25.2)	81 (29.8)	77 (26.5)
	N. America	80 (25.2)	77 (31.4)	73 (27.4)	75 (34.1)	68 (23.5)	51 (23.0)	73 (35.6)	71 (28.5)
	S. America	79 (39.5)	88 (28.8)	68 (26.2)	80 (33.5)	64 (29.4)	41 (31.0)	84 (31.1)	72 (31.3)

Table 4: Success Rates (in %) and Number of Turns to Answer (in parentheses) for Gemini-2.0-Flash in the unlimited-turn setting. Detailed results are available in Appendix Table 8.

We use the best-performing model (Gemini_{2.0}) to evaluate whether the language of gameplay affects deduction performance across geographic regions. Table 4 presents success rates and efficiency metrics for seven languages (English, Hindi, Mandarin, Spanish, Japanese, Turkish, and French) across entities from all six inhabited continents.

The results show that English consistently has the highest success rates for most regions, while the language of gameplay has unreliable impact on performance. For Notable people, performance remains stable across languages, with success often exceeding 70% in all regions for most languages (except Turkish), while, for Things, success rates vary noticeably by language. Importantly, we find no evidence that regionally associated languages provide a systematic advantage for entities from those regions (Yin et al., 2022). For example, Hindi (mainly spoken in Asia) achieves only 15% accuracy on Asian Things compared to 53% in English, and Mandarin shows no advantage for Asian entities either.

RQ4: Geopolitical Disparities in deduction – Global North vs South and West vs East.

Turns	Model	Notable people						Things					
		Global North vs South			Global West vs East			Global North vs South			Global West vs East		
Acc.North	Acc.South	Sig.	Acc.West	Acc.East	Sig.	Acc.North	Acc.South	Sig.	Acc.West	Acc.East	Sig.		
Can.	⊗	20.9	7.5	✓***	17.0	7.0	✓**	6.4	2.7	✓*	4.0	3.0	✗
	∞	21.7	4.7	✓***	14.4	5.3	✓***	8.5	2.9	✓***	35.0	17.7	✓***
	△ _{2.0}	30.9	10.2	✓***	23.4	10.6	✓***	12.0	3.6	✓***	8.4	3.8	✓*
Unl.	⊗	63.9	53.8	✓*	62.0	53.0	✓*	38.3	31.0	✗	36.0	31.0	✗
	∞	63.9	39.6	✓***	52.6	40.6	✓**	35.0	17.7	✓***	32.1	17.3	✓***
	△ _{2.0}	71.6	83.9	✓***	77.8	70.2	✓*	47.1	35.7	✓**	45.8	35.3	✓**

Table 5: Comparison of Success Rates (in %) for entities from the Global North vs. South and Global West vs. East across different models, entity types, and gameplay settings. We report the Average Success Rate for each group, along with the statistical significance of their differences, using the Mann-Whitney U test. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $\triangle p < 0.1$. Results based on country-level aggregation.

Based on Table 5, we observe consistent deduction performance disparities across the Global North vs. South and Global West vs. East divide.

Global North vs. South (Development-Oriented Divide): Our results show that models are significantly more successful at deducing entities from the Global North than from the Global South across all models, most settings, and entity types, particularly for Notable people. For example, Gemini_{2.0} achieves 30.9% success on Northern Notable People vs. 10.2%

on Southern ones in the canonical setting ($p < 0.001$). These gaps persist even in the unlimited-turn setting, though they narrow slightly.

Global West vs. East (Cultural Representation Divide): We find similar patterns here. LLMs are consistently more successful at deducing entities from the Global West, especially for people-based entities. In the canonical setting, Gemini 2.0 succeeds on 23.4% of Western Notable People vs. only 10.6% of Eastern ones ($p < 0.001$).

Together, these findings suggest that development-related and cultural biases are implicitly embedded in how LLMs conduct inquiry, with models favoring more economically and epistemically dominant regions, even when not explicitly asked to do so.

6 Conclusion

We present a novel, inquiry-based framework using the 20 Questions game to surface implicit geographic biases in LLMs. Evaluating three models on our constructed geographically diverse dataset, Geo20Q⁺, we find that: (1) LLMs perform better on Notable people than Things, with Gemini 2.0 achieving the highest accuracy. (2) Entity popularity and corpus frequency weakly correlate with performance but do not explain observed disparities. (3) The language of gameplay has minimal impact on performance. (4) **Most importantly, models show geopolitical bias (Global North/West > South/East), by favoring more economically and culturally dominant regions.** Our results argue for creative, free-form evaluation frameworks that shift the focus from outputs to reasoning processes, enabling the discovery of subtle and often hidden biases in LLM behavior.

7 Discussions and Limitations

Our primary goal was to propose a novel evaluation strategy that effectively surfaces implicit geographic biases in LLMs. Our analyses tested a specific hypothesis, whether pretraining data coverage could explain geographic performance disparities, and demonstrated that such biases are only partially explained by entity popularity and frequency, indicating these behaviors arise from a complex interplay of factors. While our framework provides a unique lens into LLM reasoning, it is ultimately a tool for *surfacing* potential biases, *not proving their absence*. A lack of bias observed within our game setup does not imply that a model is unbiased overall; it may simply reflect the limitations of the task structure.

In this work, we do not explicitly analyze *misidentification behavior*, where models guess entities from more dominant regions (e.g., the Global North) in place of less-represented ones. Next, we do not investigate specific *failure modes* in deduction, such as repetitive questioning, planning inefficiencies, or inconsistent reasoning. Our findings are embedded in a single interactive framework; other evaluation paradigms may reveal different forms of bias. Moreover, due to academic resource constraints, our set of models used is limited, and our language coverage focuses on high-resource languages. Finally, we do not perform a profession-wise and category-wise breakdown of Things and Notable people, which can help describe which types of entities are more susceptible to bias.

To understand the sources of these observed biases, we propose several future experiments:

1. Analyze model attention and reasoning patterns during deduction to determine if certain activation paths and model regions are systematically favored at decision points, leveraging interpretability methods such as Patchscopes Ghandeharioun et al. (2024).
2. Systematically evaluate the impact of different tuning and alignment techniques (e.g., instruction tuning, reinforcement learning) on geographic bias by retraining models with regionally balanced data and assessing shifts in deduction performance.

We believe these directions will help disentangle the contributions of data coverage, model architecture, and training dynamics to observed biases. We encourage further suggestions from the community for additional experiments toward this goal.

Ethics Statement

This research investigates implicit geographic biases in LLMs using a model-initiated 20 Questions framework. Rather than designing probes, which may themselves encode assumptions, we adopt a free-form deduction setup and curate a geographically diverse dataset spanning cultural and economic axes (e.g., Global North vs. Global South, Global West vs. East). Our goal is not to rank or hierarchize regions, but to surface systemic disparities in how LLMs reason about entities from different parts of the world. We acknowledge that these geographic groupings are broad and imperfect proxies for cultural and political complexity. While they help quantify disparities, they do not fully capture the nuance of global representation.

Data access and model use: No personal or sensitive data was used in this study. All models were accessed via official APIs or publicly released weights. Results are reported in aggregate to avoid singling out individuals or groups. We validated multilingual prompts in-house and did not employ external annotators.

Intended Impact: We hope this work contributes to more inclusive, robust evaluation practices and motivates broader inquiry into multilingual and region-specific model assessment, particularly in underrepresented linguistic and cultural contexts.

References

- Jaimeen Ahn and Alice Oh. Mitigating language-dependent ethnic bias in BERT. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 533–549, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.42. URL <https://aclanthology.org/2021.emnlp-main.42/>.
- Mohammad Aliannejadi, Hamed Zamani, Fabio Crestani, and W Bruce Croft. Asking clarifying questions in open-domain information-seeking conversations. In *Proceedings of the 42nd international acm sigir conference on research and development in information retrieval*, pp. 475–484, 2019.
- Xuechunzi Bai, Angelina Wang, Ilia Sucholutsky, and Thomas L Griffiths. Measuring implicit bias in explicitly unbiased large language models. *arXiv preprint arXiv:2402.04105*, 2024.
- Xuechunzi Bai, Angelina Wang, Ilia Sucholutsky, and Thomas L. Griffiths. Explicitly unbiased large language models still form biased associations. *Proceedings of the National Academy of Sciences*, 122(8):e2416228122, 2025. doi: 10.1073/pnas.2416228122. URL <https://www.pnas.org/doi/abs/10.1073/pnas.2416228122>.
- Leonardo Bertolazzi, Davide Mazzaccara, Filippo Merlo, and Raffaella Bernardi. Chat-GPT’s information seeking strategy: Insights from the 20-questions game. In C. Maria Keet, Hung-Yi Lee, and Sina Zarrieß (eds.), *Proceedings of the 16th International Natural Language Generation Conference*, pp. 153–162, Prague, Czechia, September 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.inlg-main.11. URL <https://aclanthology.org/2023.inlg-main.11/>.
- Philippe Besse, Eustasio del Barrio, Paula Gordaliza, Jean-Michel Loubes, and Laurent Risser. A survey of bias in machine learning through the prism of statistical parity. *The American Statistician*, 76(2):188–198, 2022.
- Kirti Bhagat, Kinshuk Vasisht, and Danish Pruthi. Richer output for richer countries: Uncovering geographical disparities in generated stories and travel recommendations. *arXiv preprint arXiv:2411.07320*, 2024.
- Angana Borah and Rada Mihalcea. Towards implicit bias detection and mitigation in multi-agent llm interactions. *arXiv preprint arXiv:2410.02584*, 2024.

Yang Trista Cao and Hal Daumé III. Toward gender-inclusive coreference resolution. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (eds.), *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 4568–4595, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.418. URL <https://aclanthology.org/2020.acl-main.418/>.

Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolaos Angelopoulos, Tianle Li, Dacheng Li, Banghua Zhu, Hao Zhang, Michael Jordan, Joseph E Gonzalez, et al. Chatbot arena: An open platform for evaluating llms by human preference. In *Forty-first International Conference on Machine Learning*, 2024.

Woon Sang Cho, Yizhe Zhang, Sudha Rao, Asli Celikyilmaz, Chenyan Xiong, Jianfeng Gao, Mengdi Wang, and Bill Dolan. Contrastive multi-document question generation. In Paola Merlo, Jorg Tiedemann, and Reut Tsarfaty (eds.), *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pp. 12–30, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.2. URL <https://aclanthology.org/2021.eacl-main.2/>.

Daniel de Vassimon Manela, David Errington, Thomas Fisher, Boris van Breugel, and Pasquale Minervini. Stereotype and skew: Quantifying gender bias in pre-trained and fine-tuned language models. In Paola Merlo, Jorg Tiedemann, and Reut Tsarfaty (eds.), *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pp. 2232–2242, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.190. URL <https://aclanthology.org/2021.eacl-main.190/>.

Harm De Vries, Florian Strub, Sarath Chandar, Olivier Pietquin, Hugo Larochelle, and Aaron Courville. Guesswhat?! visual object discovery through multi-modal dialogue. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 5503–5512, 2017.

Xiangjue Dong, Yibo Wang, Philip S Yu, and James Caverlee. Disclosure and mitigation of gender bias in llms. *arXiv preprint arXiv:2402.11190*, 2024.

Yanai Elazar, Akshita Bhagia, Ian Magnusson, Abhilasha Ravichander, Dustin Schwenk, Alane Suhr, Pete Walsh, Dirk Groeneveld, Luca Soldaini, Sameer Singh, et al. What’s in my big data? *arXiv preprint arXiv:2310.20707*, 2023.

Isabel O. Gallegos, Ryan A. Rossi, Joe Barrow, Md Mehrab Tanjim, Sungchul Kim, Franck Dernoncourt, Tong Yu, Ruiyi Zhang, and Nesreen K. Ahmed. Bias and fairness in large language models: A survey. *Computational Linguistics*, 50(3):1097–1179, 09 2024a. ISSN 0891-2017. doi: 10.1162/coli_a_00524. URL https://doi.org/10.1162/coli_a_00524.

Isabel O Gallegos, Ryan A Rossi, Joe Barrow, Md Mehrab Tanjim, Sungchul Kim, Franck Dernoncourt, Tong Yu, Ruiyi Zhang, and Nesreen K Ahmed. Bias and fairness in large language models: A survey. *Computational Linguistics*, 50(3):1097–1179, 2024b.

Asma Ghandeharioun, Avi Caciularu, Adam Pearce, Lucas Dixon, and Mor Geva. Patch-scopes: A unifying framework for inspecting hidden representations of language models. In *Forty-first International Conference on Machine Learning*, 2024. URL <https://arxiv.org/abs/2401.06102>.

Vipul Gupta, Pranav Narayanan Venkit, Shomir Wilson, and Rebecca J Passonneau. Sociodemographic bias in language models: A survey and forward path. *arXiv preprint arXiv:2306.08158*, 2023.

John J Hanna, Abdi D Wakene, Andrew O Johnson, Christoph U Lehmann, and Richard J Medford. Assessing racial and ethnic bias in text generation by large language models for health care-related tasks: Cross-sectional study. *Journal of Medical Internet Research*, 27: e57257, 2025.

Divyanshu Kumar, Umang Jain, Sahil Agarwal, and Prashanth Harshangi. Investigating implicit bias in large language models: A large-scale study of over 50 llms. *arXiv preprint arXiv:2410.12864*, 2024.

Morgane Laouenan, Palaash Bhargava, Jean-Benoît Eyméoud, Olivier Gergaud, Guillaume Plique, and Etienne Wasmer. A cross-verified database of notable people, 3500bc-2018ad. *Scientific Data*, 9(1):290, 2022.

Bryan Li, Samar Haider, and Chris Callison-Burch. This land is {Your, My} land: Evaluating geopolitical biases in language models. *arXiv preprint arXiv:2305.14610*, 2023.

Serene Lim and María Pérez-Ortiz. The african woman is rhythmic and soulful: An investigation of implicit biases in llm open-ended text generation. *arXiv preprint arXiv:2407.01270*, 2024.

Rohin Manvi, Samar Khanna, Marshall Burke, David Lobell, and Stefano Ermon. Large language models are geographically biased. *arXiv preprint arXiv:2402.02680*, 2024.

Davide Mazzaccara, Alberto Testoni, and Raffaella Bernardi. Learning to ask informative questions: Enhancing llms with preference optimization and expected information gain. *arXiv preprint arXiv:2406.17453*, 2024.

Shujaat Mirza, Bruno Coelho, Yuyuan Cui, Christina Pöpper, and Damon McCoy. Global-liar: Factuality of llms over time and geographic regions. *arXiv preprint arXiv:2401.17839*, 2024.

Moin Nadeem, Anna Bethke, and Siva Reddy. StereoSet: Measuring stereotypical bias in pretrained language models. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 5356–5371, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.416. URL <https://aclanthology.org/2021.acl-long.416/>.

Nikita Nangia, Clara Vania, Rasika Bhalerao, and Samuel R. Bowman. CrowS-pairs: A challenge dataset for measuring social biases in masked language models. In Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu (eds.), *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1953–1967, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.154. URL <https://aclanthology.org/2020.emnlp-main.154/>.

Lemuel Ekedegwa Odeh. A comparative analysis of global north and global south economies. 2010.

OpenAI. GPT-4 technical report. Technical report, 2023.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35:27730–27744, 2022.

Nathaniel R Robinson, Perez Ogayo, David R Mortensen, and Graham Neubig. Chatgpt mt: Competitive for high-(but not low-) resource languages. *arXiv preprint arXiv:2309.07423*, 2023.

Pola Schwöbel, Jacek Golebiowski, Michele Donini, Cédric Archambeau, and Danish Pruthi. Geographical erasure in language generation. *arXiv preprint arXiv:2310.14777*, 2023.

Sheikh Shafayat, Eunsu Kim, Juhyun Oh, and Alice Oh. Multi-fact: Assessing factuality of multilingual llms using factscore. *arXiv preprint arXiv:2402.18045*, 2024.

Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Arthur, Ben Beglin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, et al. Dolma: An open corpus of three trillion tokens for language model pretraining research. *arXiv preprint arXiv:2402.00159*, 2024.

Gemini Team. Gemini: A family of highly capable multimodal models, 2023.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023.

Bryan S Turner and Habibul Haque Khondker. Globalization east and west. 2010.

Luis von Ahn and Laura Dabbish. Labeling images with a computer game. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '04, pp. 319–326, New York, NY, USA, 2004. Association for Computing Machinery. ISBN 1581137028. doi: 10.1145/985692.985733. URL <https://doi.org/10.1145/985692.985733>.

Luis von Ahn, Ruoran Liu, and Manuel Blum. Peekaboom: a game for locating objects in images. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '06, pp. 55–64, New York, NY, USA, 2006. Association for Computing Machinery. ISBN 1595933727. doi: 10.1145/1124772.1124782. URL <https://doi.org/10.1145/1124772.1124782>.

Yifan Yang, Xiaoyu Liu, Qiao Jin, Furong Huang, and Zhiyong Lu. Unmasking and quantifying racial bias of large language models in medical report generation. *Communications Medicine*, 4(1):176, 2024.

Da Yin, Hritik Bansal, Masoud MonajatiPoor, Liunian Harold Li, and Kai-Wei Chang. Geomlama: Geo-diverse commonsense probing on multilingual pre-trained language models. *arXiv preprint arXiv:2205.12247*, 2022.

Vithya Yogarajan, Gillian Dobbie, Te Taka Keegan, and Rostam J Neuwirth. Tackling bias in pre-trained language models: Current trends and under-represented societies. *arXiv preprint arXiv:2312.01509*, 2023.

Yizhe Zhang, Jiarui Lu, and Navdeep Jaitly. Probing the multi-turn planning capabilities of llms via 20 question games. *arXiv preprint arXiv:2310.01468*, 2023.

Yachao Zhao, Bo Wang, and Yan Wang. Explicit vs. implicit: Investigating social bias in large language models through self-reflection. *arXiv preprint arXiv:2501.02295*, 2025.

A Appendix

A.1 Empirical upper bound for unlimited-turn setting

To examine the impact of increasing the number of allowable turns in the deduction game, we identify the optimal cutoff point to be around 150 turns, beyond which the Success Rate no longer improves significantly (Figure 4). Hence, we can use 150 turns as a proxy for the unlimited-turn setting.

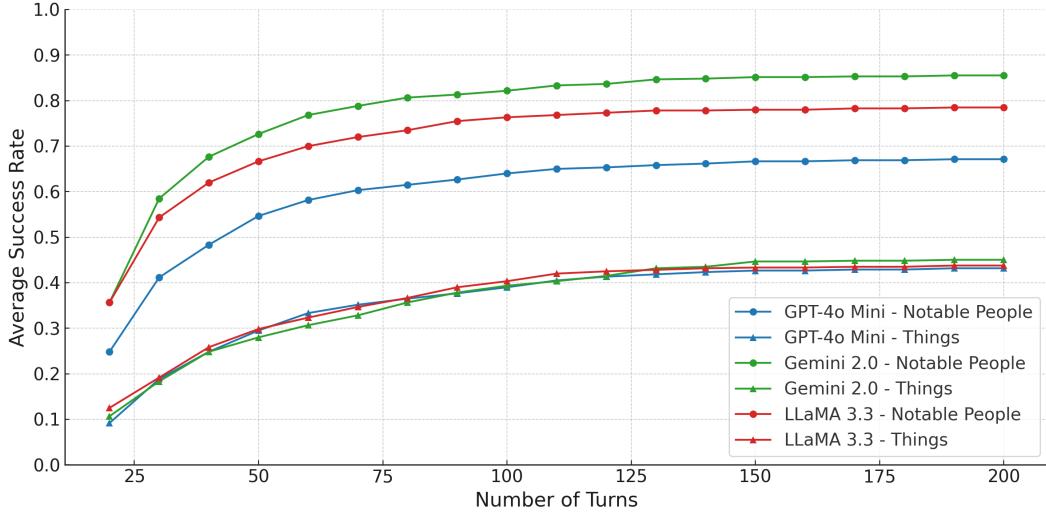


Figure 4: Average Success Rates for the varying maximum Number of Turns across different models using 100 most popular entities from each continent. The Success Rates are almost horizontal for the model after 150 turns.

A.2 Continent-wise variation in performance for each model

We present a detailed continent-level analysis for each model, revealing geographic disparities in entity deduction across different regions. LLMs have superior performance on **Things** from Africa and Europe, whereas **Notable people** from Europe and North America (Table 6).

Turns	Entity	Model	Asia	Africa	Australia	Europe	North Am	South Am
20	Things	∅	2 (16.5)	16 (15.4)	8 (16.1)	10 (18.5)	8 (16.1)	11 (17.1)
		∞	15 (13.4)	17 (15.7)	7 (16.5)	13 (15.2)	15 (15.0)	8 (15.5)
		◆ 1.5	7 (13.3)	14 (14.9)	9 (14.8)	7 (16.4)	8 (13.0)	9 (16.2)
		◆ 2.0	8 (14.0)	15 (16.0)	6 (16.1)	20 (15.9)	5 (12.8)	10 (16.3)
	Notable people	Avg.	8 (14.3)	15 (15.5)	7 (15.4)	12 (16.0)	9 (14.2)	9 (16.2)
		∅	14 (15.1)	23 (16.5)	11 (16.3)	38 (14.6)	37 (12.5)	26 (16.0)
		∞	29 (16.2)	26 (17.3)	23 (14.5)	53 (13.8)	54 (13.5)	29 (15.9)
		◆ 1.5	23 (16.7)	16 (16.4)	19 (14.7)	35 (13.6)	44 (12.4)	14 (17.1)
	Things	◆ 2.0	40 (17.1)	20 (17.2)	30 (16.0)	49 (15.3)	45 (14.1)	30 (16.9)
		Avg.	26 (16.3)	21 (16.8)	20 (15.4)	43 (14.3)	45 (13.6)	24 (16.5)
		∅	48 (48.5)	56 (40.1)	37 (47.0)	38 (51.0)	38 (40.7)	39 (41.8)
		∞	40 (41.2)	42 (36.4)	38 (42.4)	54 (49.0)	43 (40.4)	43 (48.7)
150	Notable people	◆ 1.5	31 (41.9)	42 (34.5)	28 (36.1)	39 (36.4)	22 (27.3)	34 (35.1)
		◆ 2.0	53 (49.8)	46 (42.2)	44 (60.7)	49 (37.8)	34 (54.7)	42 (56.6)
		Avg.	43 (45.1)	46 (38.3)	37 (46.5)	45 (43.6)	34 (41.8)	39 (45.5)
		∅	58 (38.0)	78 (36.0)	51 (41.0)	64 (27.6)	78 (31.5)	71 (33.1)
	Things	∞	88 (37.2)	79 (31.6)	56 (34.1)	83 (19.7)	86 (28.8)	76 (29.3)
		◆ 1.5	50 (28.2)	63 (31.0)	60 (34.0)	73 (28.4)	71 (24.7)	67 (40.4)
		◆ 2.0	95 (25.5)	89 (35.3)	81 (32.4)	87 (26.8)	80 (25.1)	79 (39.5)
		Avg.	72 (32.2)	77 (33.5)	62 (35.4)	76 (25.6)	78 (27.5)	73 (35.3)

Table 6: Average Success Rates (in %) and Number of Turns to Answer (in parenthesis) across different models and continents taking 100 most popular entities from each continent

A.3 Verifying model’s entity knowledge via prompt-based evaluation

Our experiments are conducted with a single run per entity for each model-language-configuration combination, which results in a total of 50,400+ games (3 models × 1,200 entities × 7 languages × 2 configurations for RQ1-3). Therefore having multiple runs conducted per entity would incur non-trivial computation costs.

To better account for the stochasticity in model behavior, we conduct a small-scale robustness analysis using 50 entities with 5 independent runs per entity (**Notable people**, ◆ 1.5) as shown in Table 7. Overall, we see that the aggregate-level patterns and behaviors remain consistent.

A.4 Prompts used in the paper

We document the exact prompts used for both the judge and guesser roles in the English language (prompts for other languages provided on GitHub). This ensures reproducibility and transparency in our experimental setup. Note that for ambiguous questions, the judge is permitted to reply with “Maybe”, which serves as a soft signal of uncertainty rather than misleading the guesser. On average, “Maybe” occurs infrequently, only in about 1.8% of the turns.

Setting	Metric	Asia	Africa	Australia	Europe	N. America	S. America
Can.	Success	14% ± 9%	22% ± 4%	42% ± 16%	40% ± 19%	32% ± 11%	36% ± 13%
	Num. Turns	11.90 ± 7.02	13.17 ± 2.87	11.68 ± 1.48	11.61 ± 0.85	9.89 ± 2.02	16.65 ± 0.91
Unl.	Success	40% ± 19%	50% ± 10%	64% ± 13%	62% ± 13%	54% ± 5%	62% ± 13%
	Num. Turns	26.95 ± 11.52	23.20 ± 3.24	24.45 ± 10.32	18.82 ± 3.65	19.46 ± 3.96	24.59 ± 7.76

Table 7: Average Success rates and Number of Turns to Answer across continents. Results are based on 5 independent runs per entity (50 entities) for Notable people using $\diamond_{1.5}$. We report mean ± standard deviation to account for randomness in model behavior.

A.4.1 English prompts

Prompt for the judge model - Notable people

Based on your knowledge about the celebrity: {entity}, respond to the following question or guess. Limit your respond to only 'Yes.', 'No.' or 'Dunno.', with no explanation or other words. Never say the name {entity} in your response. Do not say 'Dunno.' if it can be answered by 'Yes.' or 'No.' If the question is to solicit the answer, respond 'No.'

For the celebrity {entity}, {question}(Yes/No/Dunno)

Prompt for the judge model - Things

Based on your knowledge about {entity}, respond to the following question or guess. Limit your respond to only 'Yes.', 'No.' or 'Maybe.', with no explanation or other words. Never say the answer {entity} in your response. If the question is to solicit the answer, respond 'No.'

For the thing {entity}, {question}(Yes/No/Dunno)

Prompt for the guesser model - Notable people

Your task is to ask a series of questions to deduce the celebrity that I'm thinking of with as few queries as possible. Only ask factual questions that can be answered by 'Yes.', 'No.' or 'Dunno.'. Do not ask for a hint. Make your question brief with no linebreaker. Now start asking a question.

{dialogue history}

Prompt for the guesser model - Things

Your task is to ask a series of questions to deduce the entity that I'm thinking of with as few queries as possible. Only ask questions that can be answered by 'yes', 'no' or 'maybe'. Do not ask for a hint. Make your question brief with no line breakers. Now, start asking a question.

{dialogue history}

A.5 Language-wise performance of different models

We report detailed language-specific results across different continents and models (Table 8).

Turns	Entity	Model	Continent	English	Hindi	Mandarin	Spanish	Japanese	Turkish	French	Average
Things	◎	1.5	Asia	2 (16.5)	2 (18.5)	3 (17.3)	5 (17.8)	4 (17.0)	4 (15.2)	10 (15.3)	4 (16.8)
			Africa	16 (15.4)	3 (15.7)	8 (17.6)	7 (16.4)	5 (15.4)	6 (17.7)	13 (16.2)	8 (16.3)
			Australia	8 (16.1)	3 (18.3)	1 (20.0)	4 (18.5)	0 (-)	6 (17.2)	4 (15.2)	4 (15.1)
			Europe	10 (18.5)	4 (15.0)	4 (17.5)	6 (15.5)	2 (17.0)	5 (14.4)	17 (17.0)	7 (16.4)
			North Am	8 (16.1)	1 (17.0)	6 (17.0)	4 (15.5)	6 (17.3)	4 (14.8)	6 (16.0)	5 (16.2)
	◆	1.5	South Am	11 (17.1)	1 (16.0)	8 (17.1)	7 (17.1)	2 (18.0)	4 (17.5)	9 (17.8)	6 (17.2)
			Asia	7 (13.3)	6 (14.7)	3 (11.7)	10 (14.7)	6 (13.2)	2 (10.0)	7 (15.1)	5 (13.2)
			Africa	14 (14.9)	2 (16.5)	4 (16.2)	6 (15.3)	3 (16.3)	1 (10.0)	9 (15.9)	5 (15.1)
			Australia	9 (14.8)	2 (18.0)	2 (14.0)	8 (14.9)	4 (16.8)	0 (-)	7 (17.0)	5 (13.6)
			Europe	7 (16.4)	2 (16.0)	2 (16.0)	4 (17.0)	2 (18.0)	1 (18.0)	9 (14.7)	4 (16.5)
20	◆	2.0	North Am	8 (13.0)	1 (12.0)	1 (12.0)	5 (15.6)	2 (10.5)	1 (12.0)	7 (13.4)	4 (12.6)
			South Am	9 (16.2)	2 (15.0)	3 (13.3)	6 (16.2)	0 (-)	1 (19.0)	6 (17.5)	4 (13.8)
			Asia	8 (14.0)	4 (16.8)	3 (15.0)	7 (14.7)	7 (15.1)	0 (0.0)	14 (15.5)	6 (13.0)
			Africa	15 (16.1)	4 (16.0)	6 (17.2)	11 (15.4)	8 (15.9)	4 (13.5)	17 (17.5)	9 (15.9)
			Australia	6 (16.0)	1 (20.0)	3 (19.0)	9 (16.8)	9 (15.9)	3 (13.3)	7 (17.6)	5 (16.9)
	◎	2.0	Europe	20 (15.9)	5 (16.2)	3 (16.3)	12 (15.7)	8 (15.0)	3 (17.0)	18 (16.0)	10 (16.0)
			North Am	5 (12.8)	3 (17.3)	1 (19.0)	5 (16.2)	4 (18.2)	2 (14.0)	9 (14.7)	4 (16.0)
			South Am	10 (16.3)	3 (14.0)	0 (0.0)	12 (16.9)	4 (13.8)	1 (20.0)	12 (16.5)	6 (13.9)
			Asia	14 (15.1)	17 (15.5)	27 (15.6)	23 (15.3)	22 (15.9)	28 (16.9)	23 (15.9)	22 (15.7)
			Africa	23 (16.5)	7 (17.7)	22 (17.4)	21 (16.4)	21 (17.0)	27 (17.8)	28 (17.3)	21 (17.1)
Notable people	◆	1.5	Australia	11 (16.4)	6 (13.8)	16 (15.9)	7 (16.9)	14 (16.1)	14 (16.1)	19 (16.5)	12 (15.9)
			Europe	38 (14.6)	28 (13.5)	43 (13.5)	28 (15.1)	46 (14.7)	37 (14.3)	32 (13.9)	36 (14.2)
			North Am	37 (12.5)	24 (14.6)	39 (13.5)	31 (14.1)	28 (13.3)	48 (13.0)	42 (14.0)	36 (13.5)
			South Am	26 (16.0)	24 (16.3)	36 (15.6)	23 (16.4)	24 (16.1)	18 (16.2)	27 (16.0)	25 (16.1)
			Asia	23 (16.7)	19 (15.7)	20 (15.9)	20 (15.4)	19 (15.5)	16 (14.6)	12 (15.6)	18 (15.6)
	◆	2.0	Africa	16 (16.4)	11 (16.4)	11 (17.8)	13 (16.8)	9 (15.6)	7 (13.9)	11 (15.5)	11 (16.0)
			Australia	19 (14.7)	13 (15.9)	14 (15.0)	16 (15.2)	13 (14.7)	7 (13.3)	8 (15.9)	13 (15.0)
			Europe	35 (13.7)	34 (13.7)	34 (13.4)	41 (14.2)	41 (12.7)	26 (11.3)	28 (14.1)	34 (13.2)
			North Am	44 (12.5)	17 (13.6)	28 (12.9)	36 (13.5)	33 (12.0)	19 (10.2)	38 (14.4)	31 (12.7)
			South Am	14 (17.1)	12 (14.9)	21 (17.0)	18 (16.1)	16 (15.8)	9 (15.1)	13 (15.3)	15 (15.9)
150	◎	1.5	Asia	40 (17.2)	40 (16.1)	39 (15.8)	32 (15.3)	36 (15.3)	30 (14.2)	32 (16.9)	35 (15.8)
			Africa	20 (17.2)	24 (16.8)	26 (15.4)	21 (16.7)	28 (15.3)	14 (16.3)	21 (15.9)	22 (16.2)
			Australia	30 (16.0)	19 (15.7)	20 (16.1)	28 (15.2)	22 (14.9)	19 (13.2)	21 (16.2)	22 (15.3)
			Europe	49 (15.3)	47 (14.7)	55 (15.1)	46 (14.0)	49 (13.7)	27 (12.4)	46 (14.1)	46 (14.1)
			North Am	45 (14.2)	37 (14.5)	35 (12.7)	35 (13.5)	44 (12.8)	30 (11.6)	27 (14.7)	36 (13.4)
	◆	2.0	South Am	30 (16.9)	30 (16.9)	34 (15.2)	30 (15.9)	28 (16.6)	19 (14.9)	32 (15.4)	29 (16.0)
			Asia	48 (48.5)	18 (51.7)	14 (35.9)	30 (42.3)	15 (37.9)	20 (53.5)	35 (36.5)	25 (43.7)
			Africa	56 (40.2)	15 (38.9)	28 (30.0)	37 (34.9)	16 (41.7)	28 (47.2)	36 (33.2)	31 (38.0)
			Australia	37 (47.0)	15 (48.9)	20 (42.0)	19 (39.5)	13 (48.0)	20 (38.9)	27 (42.1)	22 (43.7)
			Europe	38 (51.0)	12 (36.2)	26 (33.5)	26 (36.0)	13 (36.7)	22 (45.0)	38 (30.4)	25 (38.3)
Notable people	◆	1.5	North Am	38 (40.7)	14 (41.7)	25 (30.0)	21 (43.6)	24 (36.8)	18 (33.4)	33 (35.2)	25 (37.3)
			South Am	39 (41.8)	7 (50.7)	24 (31.9)	31 (40.4)	12 (53.4)	18 (60.1)	38 (43.1)	24 (45.9)
			Asia	31 (41.9)	21 (38.9)	10 (25.1)	21 (38.6)	13 (40.9)	4 (58.0)	17 (25.5)	16 (13.4)
			Africa	42 (34.5)	13 (45.7)	8 (27.6)	21 (33.3)	9 (37.3)	3 (39.7)	26 (26.5)	17 (34.9)
			Australia	28 (36.1)	10 (51.3)	10 (35.5)	15 (30.1)	11 (43.1)	2 (97.0)	20 (27.7)	14 (45.8)
	◆	2.0	Europe	39 (36.4)	18 (42.4)	6 (36.7)	13 (51.8)	11 (34.0)	4 (58.5)	28 (33.0)	17 (41.8)
			North Am	12 (27.4)	13 (45.5)	8 (58.5)	13 (35.4)	5 (43.4)	1 (12.0)	14 (27.2)	11 (35.6)
			South Am	34 (35.1)	15 (45.4)	8 (48.1)	19 (38.9)	4 (49.5)	3 (38.3)	15 (27.1)	14 (40.3)
			Asia	53 (49.8)	15 (40.0)	11 (51.9)	35 (52.0)	22 (41.5)	6 (73.8)	42 (42.9)	26 (50.2)
			Africa	46 (42.3)	10 (31.8)	25 (34.4)	42 (44.3)	25 (33.0)	11 (36.2)	55 (35.9)	31 (36.8)
150	◎	1.5	Australia	44 (60.7)	17 (48.3)	14 (62.1)	36 (42.5)	18 (34.2)	11 (35.5)	49 (46.0)	27 (47.1)
			Europe	49 (37.8)	25 (33.5)	23 (49.1)	45 (39.3)	26 (32.7)	20 (52.4)	48 (41.9)	34 (40.1)
			North Am	34 (54.8)	18 (46.9)	10 (58.6)	22 (47.4)	16 (34.1)	5 (30.6)	36 (50.8)	20 (46.1)
			South Am	42 (56.6)	13 (40.3)	16 (51.3)	39 (35.2)	13 (47.8)	8 (56.4)	48 (39.1)	26 (46.6)
			Asia	57 (38.0)	46 (36.5)	69 (35.2)	65 (30.5)	67 (31.1)	62 (31.1)	64 (26.2)	61 (32.6)
	◆	2.0	Africa	78 (36.0)	44 (40.3)	64 (32.2)	69 (38.4)	67 (35.1)	69 (30.9)	69 (27.6)	65 (34.3)
			Australia	51 (41.0)	23 (34.3)	41 (32.3)	40 (45.6)	41 (40.0)	37 (36.1)	47 (35.2)	40 (37.8)
			Europe	64 (27.6)	56 (29.4)	75 (25.6)	54 (31.2)	84 (26.7)	71 (32.4)	65 (25.5)	67 (28.3)
			North Am	78 (31.5)	56 (31.1)	75 (27.4)	60 (29.6)	63 (34.7)	71 (25.7)	74 (26.2)	68 (29.4)
			South Am	71 (33.2)	60 (28.6)	78 (30.2)	70 (29.8)	76 (30.3)	65 (33.0)	67 (27.2)	70 (30.3)
Notable people	◆	1.5	Asia	50 (28.2)	46 (27.5)	49 (24.6)	56 (27.5)	33 (23.1)	23 (20.5)	51 (31.4)	44 (26.1)
			Africa	63 (31.0)	47 (31.8)	38 (27.3)	53 (34.1)	37 (33.4)	15 (23.9)	51 (30.8)	43 (30.3)
			Australia	60 (34.0)	28 (27.1)	32 (26.7)	52 (33.3)	31 (27.3)	18 (27.2)	40 (32.2)	37 (29.6)
			Europe	73 (28.4)	65 (25.9)	65 (22.3)	72 (22.8)	64 (19.7)	33 (14.2)	65 (28.5)	62 (23.1)
			North Am	71 (24.7)	46 (28.0)	40 (18.1)	72 (24.0)	47 (18.8)	28 (17.4)	68 (24.5)	53 (22.2)
	◆	2.0	South Am	67 (40.4)	54 (34.3)	52 (26.2)	69 (34.7)	41 (27.9)	23 (22.4)	62 (36.9)	53 (31.8)
			Asia	95 (28.5)	89 (28.8)	72 (24.3)	84 (27.3)	68 (23.1)	60 (29.9)	80 (28.1)	78 (27.1)
			Africa	89 (35.4)	79 (33.9)	71 (32.0)	86 (40.6)	63 (27.4)	41 (34.5)	82 (33.1)	73 (33.8)
			Australia	81 (32.4)	66 (35.8)	63 (32.5)	69 (31.9)	51 (35.5)	53 (26.4)	70 (37.3)	65 (33.1)
			Europe	87 (26.8)	83 (25.6)	81 (22.7)	83 (32.5)	76 (23.0)	48 (25.2)	81 (29.8)	77 (26.5)
	◆	2.0	North Am	80 (25.2)	77 (31.4)	73 (27.4)	75 (34.1)	68 (23.5)	51 (23.0)	73 (35.6)	71 (28.5)
			South Am	79 (39.5)	88 (28.8)	68 (26.2)	80 (33.5)	64 (29.4)	41 (31.0)	84 (31.1)	72 (31.3)

Table 8: Average Success Rates (in %) and Number of Turns to Answer (in parenthesis) across different models, continents, and languages taking 100 most popular entities from each continent

A.6 Qualitative analysis: Model give up behavior

In qualitative analyses, we observed that LLMs often abandon the game after many turns with outputs like “I give up.” We include this metric to measure the average number of turns before such early termination. To detect when the guesser has given up, we use GPT-4o-mini to verify at each turn. Lower values indicate quick abandonment, while higher values suggest greater persistence. GPT-4o-mini showed the highest persistence while deducing entities, while Gemini-1.5-flash showed the least (Table 9).

Model	Turns to Give Up
∞	108.9
∞	87.9
◆ 1.5	67.2
◆ 2.0	84.8

Table 9: Average Turns at which different models Give Up on deducing an entity

Here is an example of a game with target entity University of Otago (a public research collegiate university based in Dunedin, Otago, New Zealand) in which the model eventually abandons the game after being unable to guess the target entity.

```
Turn 81, [Guesser]: Is it a university located in the United Kingdom?
Turn 81, [Judge]: No.
Turn 82, [Guesser]: Is it a university located in Canada?
Turn 82, [Judge]: No.
Turn 83, [Guesser]: Is it a university located in Europe?
Turn 83, [Judge]: No.
Turn 84, [Guesser]: Is it a university located in Australia?
Turn 84, [Judge]: No.
Turn 85, [Guesser]: Is it a university located in Asia?
Turn 85, [Judge]: No.
Turn 86, [Guesser]: Is it a university located in the United States?
Turn 86, [Judge]: No.
Turn 87, [Guesser]: I am unable to guess the entity you are thinking of. I give up.
```

A.7 Example of geographic bias deduction path:

The following example shows the deduction path for the target entity A. P. J. Abdul Kalam (an Indian president, poet, and scientist). Despite the answer being an Indian figure, the model’s reasoning chain systematically eliminates Western options before considering Asian and Indian possibilities:

```
Turn 9, [Judge]: Yes.
Turn 10, [Guesser]: Is the poet American?
Turn 10, [Judge]: No.
Turn 11, [Guesser]: Is the poet British?
Turn 11, [Judge]: No.
Turn 12, [Guesser]: Is the poet from France?
Turn 12, [Judge]: No.
Turn 13, [Guesser]: Is the poet from Latin America?
Turn 13, [Judge]: No.
Turn 14, [Guesser]: Is the poet from Asia?
Turn 14, [Judge]: Yes.
Turn 15, [Guesser]: Is the poet Japanese?
Turn 15, [Judge]: No.
Turn 16, [Guesser]: Is the poet from India?
Turn 16, [Judge]: Yes.
Turn 17, [Guesser]: Is the poet Rabindranath Tagore?
Turn 17, [Judge]: No.
Turn 18, [Guesser]: Is the poet Rumi?
Turn 18, [Judge]: No.
```

A.8 Heavy-tail distribution of entity frequency in Dolma dataset

The frequency vs. rank distribution of the combined entities follows a heavy-tailed, power-law-like behavior, consistent with Herd-Immunity Power Scale Invariant (HiPSI) laws observed in natural language (Figure 5). This motivated us to use log transformations of frequency while doing the regression analysis.

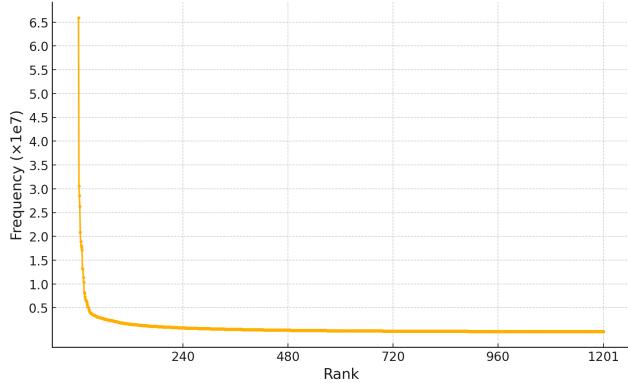


Figure 5: Heavy-tail distribution of entity frequency values in Dolma dataset

A.9 Multilingual prompt validation process

For each language, at least one native or fluent speaker, recruited from our academic networks, reviewed all translations, edited prompts as needed, and observed multiple games to check for accuracy and consistency. Their review protocol included:

1. Verifying and, if needed, editing the prompt templates and translations to ensure naturalness and accuracy in each language.
2. Observing several sample games played in the target language to check the consistency of the game play. We suggested every speaker to review around 3 games, however, they were free to review as many games as they would like.
3. Confirming the final quality of translations and reporting any issues or corrections (e.g., overly literal translations, culturally inappropriate terminology, or ambiguous instructions).

Any issues (such as awkward phrasing or ambiguous instructions) were corrected based on their feedback.

A.10 Division of countries

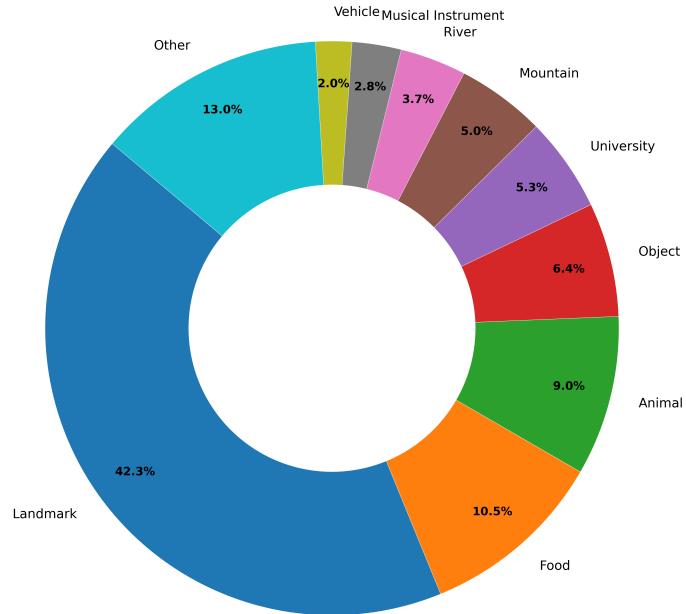
Global West United States, Canada, United Kingdom, France, Germany, Italy, Spain, Portugal, Netherlands, Belgium, Sweden, Norway, Finland, Denmark, Iceland, Austria, Switzerland, Luxembourg, Ireland, Australia, New Zealand, Estonia, Latvia, Lithuania, Poland, Czech Republic, Slovakia, Hungary, Slovenia, Malta, Greece, Croatia

Global North *United States, Canada, United Kingdom, France, Germany, Italy, Spain, Portugal, Netherlands, Belgium, Sweden, Norway, Finland, Denmark, Iceland, Austria, Switzerland, Luxembourg, Ireland, Australia, New Zealand, Japan, South Korea*

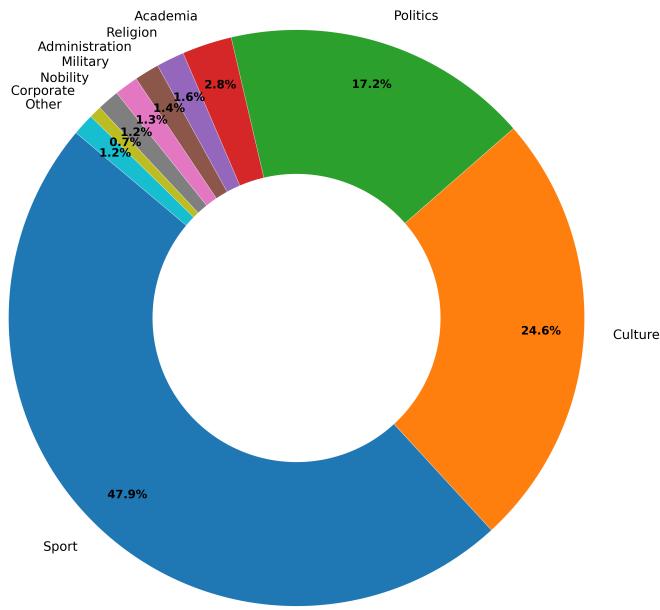
The countries in the Global North marked in italics are also part of the Global West.

A.11 Detailed breakdown of Things and Notable people

We categorize Things into groups such as landmarks, food, animals, etc., and Notable people into professions such as sports, politics, academia, etc. (Figure 6).



(a) Top categories of culturally significant things.



(b) Top professions among notable individuals.

Figure 6: Distribution of entity types across Things and Notable people.