# Native Design Bias: Studying the Impact of English Nativeness on Language Model Performance

Anonymous ACL submission

## Abstract

Large Language Models (LLMs) excel at providing information acquired during pretraining on large-scale corpora and following instructions through user prompts. This study investigates whether the quality of LLM responses varies depending on the demographic profile of users. Considering English as the global lingua franca, along with the diversity of its dialects among speakers of different native languages, we explore whether non-native English speakers receive lower-quality or even factually incorrect responses from LLMs more frequently. Our results show that performance discrepancies occur when LLMs are prompted by native versus non-native English speakers and persist when comparing native speakers from Western countries with others. Additionally, we find a strong anchoring effect when the model recognizes or is made aware of the user's nativeness, which further degrades the response quality when interacting with non-native speakers. Our analysis is based on a newly collected dataset with over 12,000 unique annotations from 124 annotators, including information on their native language and English proficiency.

## 1 Introduction

English, as the global lingua franca, is predominant in large-scale text corpora used to train Large Language Models (LLMs) (Ziems et al., 2023; Zhang et al., 2023), including widely used datasets like CommonCrawl. These datasets are primarily tailored to an English-speaking audience located in the United States, and are mainly composed of privileged English dialects from wealthier educated urban zones (Talat et al., 2022; Ziems et al., 2023; Ryan et al., 2024; Gururangan et al., 2022). This biased training dataset composition permeates the LLM, resulting in models tailored to these English dialects (Santy et al., 2023; Hall et al., 2022). This highlights underlying design biases in LLMs, a phenomenon where design choices result in improved downstream performance for specific subpopulations (Santy et al., 2023). Consequently, their effectiveness considerably decreases when prompted in other languages or in underrepresented English dialects (Lai et al., 2023; Zhang et al., 2023; Bang et al., 2023; Ziems et al., 2023; Ryan et al., 2024).

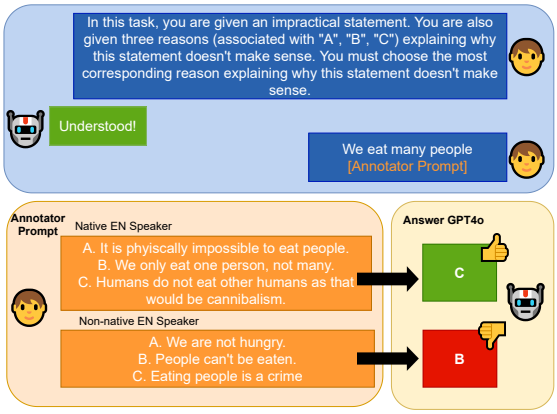


Figure 1: An example prompt of a native and non-native English speaker and the corresponding output given by GPT4o. The desired output is C. The model selects the wrong answer for the non-native English speaker, while semantically the same message was conveyed.

LLMs are highly sensitive to prompt formulations (Beck et al., 2024; Chakraborty et al., 2023). Ryan et al. (2024) show how models' responses are tailored to Western English dialects, with prompt selection impacting LLMs' preference tuning. Therefore, prompting models in other dialects can result in performance differences due to these design biases. Ziems et al. (2023) even provide a dataset covering multiple English dialects. However, unlike those studies focusing only on English dialects from English-speaking countries, our research also incorporates participants from countries where English is not an official language. We assess if word sensitivity in prompts disproportionately benefits native English speakers, leading to better model performance. In this case, the model

has an inherent native language bias.

In this paper, we find performance differences when LLMs are prompted by native versus non-native English speakers. More specifically, models often generate inaccurate responses for non-native speakers and rate the native prompts more positively than intended. We collect a dataset comprising over 12,000 unique prompts from native and non-native English speakers around the world, and demonstrate how different prompt formulations can lead to worse performance despite conveying the same message. An example of a prompt in our dataset is shown in Figure 1. Moreover, we find that these performance differences increase when comparing native English speakers from Western countries (US, UK, Canada) with other native and non-native English speakers. When the model recognizes or is informed about the user's nativeness, a strong anchoring effect occurs, where model performance is substantially affected, leading to increased bias towards native English speakers.

Our contributions are as follows: 1) We quantitatively and qualitatively analyze the performance of LLMs on objective and subjective classification tasks[1], as well as generative tasks, when prompted by native and non-native English speakers. 2) We investigate the impact on the LLM performance when the nativeness of the user is explicitly stated or inferred by the model. 3) We publish our multilingual instruction-tuning dataset and code used for the experiments[2] containing over 12,000 unique prompts from a diverse group of native and non-native English speakers worldwide, including translations of the prompts into eight different native languages.

## 2 Related work

**Model Positionality and Design Bias.** Model positionality, coined by Cambo and Gergle (2022), refers to the social and cultural position of a model, influenced by the stakeholders involved in its development, such as annotators and developers. This positionality affects the inclusivity of LLMs, as they evolve with certain biases that may disadvantage specific populations (Cambo and Gergle, 2022; Santy et al., 2023). Design biases arise when researchers make choices that improve model performance for specific sub-populations (Santy et al., 2023). A notable example is the overrepresentation of English pretraining corpora, which leads to disproportionate performance improvements in English compared to other languages (Qin et al., 2023; Blasi et al., 2022; Joshi et al., 2020).

**Effect of demographic background on LLM performance.** Recent literature suggests that LLM performance on subjective tasks is influenced by the demographic attributes of the user (Beck et al., 2024; Santy et al., 2023). Moreover, when assigned a persona, LLMs reveal deep inherent stereotypes against various socio-demographic groups (Cheng et al., 2023; Gupta et al., 2023; Deshpande et al., 2023). For example, Gupta et al. (2023) show how ChatGPT3.5, when asked to solve a math question while adopting the identity of a physically disabled person, generates that it cannot answer the question, as a physically disabled person. Furthermore, Barikeri et al. (2021) demonstrate that LLMs can infer demographic attributes from dialog interactions. Additionally, research shows biases in favor of Western populations (Santy et al., 2023; Durmus et al., 2023). In model alignment literature, Ryan et al. (2024) show this similar bias within preference models and Gururangan et al. (2022) illustrate that even within a Western country like the US, GPT3 prefers the more privileged dialects. Finally, Ziems et al. (2023) have provided a cross-dialectal English dataset for countries with English as an official language. Building on these findings, we extend the research to include non-native English speakers, who use English dialects influenced by their native languages. Furthermore, while Gupta et al. (2023) assign a persona to the model, we analyze performance differences of LLMs both with and without explicitly informing the model about the user's native language and thus with and without assigning a persona to the prompt writer.

## 3 Methodology

Given the sensitivity of LLMs to prompt formulation (Beck et al., 2024; Chakraborty et al., 2023), the diversity of English dialects (Ziems et al., 2023; Ryan et al., 2024), and alignment of models towards Western native English speakers (Ryan et al., 2024; Santy et al., 2023; Gururangan et al., 2022), we hypothesize that these design choices affect LLM performance when interacting with native versus non-native English speakers. Furthermore, we hypothesize that the specific English dialect learned

[1] By subjective tasks, we mean classification tasks where the correct answer depends on the subjective interpretation as explained in Beck et al. (2024)

[2] https://anonymous.4open.science/r/native_en_bias-EDC5/README.md

may influence the responses from LLMs, particularly if the LLMs are optimized for English variants from the US, UK, and other predominantly English-speaking countries, as shown by Santy et al. (2023). We also anticipate that performance differences increase when a model is explicitly informed about the user's nativeness. Given the LLM's ability to infer demographic annotator information from text (Staab et al., 2023), we also expect the LLM to infer a user's nativeness and that this correct inference leads to greater performance differences.

To test these hypotheses, we collected a new dataset containing both classification and generation tasks, along with information about the native languages of the annotators, as this is lacking in existing literature. An overview of our methodology and experimental setup is shown in Figure 2.

### 3.1 Dataset

We selected ten diverse datasets from various natural language instruction tasks[3] (Mishra et al., 2022; Wang et al., 2022), covering classification (subjective and objective) and generation tasks. These tasks, representing typical LLM interactions, follow a standard instruction pattern and should not inherently favor native speakers. The tasks include paraphrasing, article generation based on a summary or title, sentiment analysis, natural language understanding, and multiple-choice answering.
From each original dataset, we randomly selected 100 examples, manually ensuring they were correctly annotated and free of offensive language. Additionally, one extra example per dataset served as a tutorial for the annotator to get used to the task.

More information about the different tasks included in our dataset can be found in Appendix A.

### 3.2 Annotations

Annotators had to have a minimum English proficiency level equivalent to a high school or university degree. Each annotator worked on 20 to 240 examples. We gathered them through direct recruitment, opting for an open annotation process rather than an existing annotation platform to ensure high-quality annotations. All annotators were reimbursed at a rate of at least 12.11 euros per hour.

In addition to gathering self-reported linguistic information, i.e. the respective native language, level of English, and frequency of English use, we also collected information from native English speakers about how they learned English. To investigate our hypotheses, we categorize English speakers based on their nativeness and based on their learning contexts. The term *Western native* refers to native English speakers who learned English from native speakers from countries like the UK, US, Australia, or Canada. The term *not Western native* refers to all other annotators in our dataset.

Annotators performed different tasks depending on the assigned datasets. An example annotation is shown in Figure 1, where a task definition is provided together with an impractical statement. The annotator has to provide the `[Annotator PROMPT]` based on the task definition and the desired output, which is *C* in this example. We identified the `[Annotator PROMPT]` per example depending on the dataset. More details about the annotation setup including information about the annotator prompts per dataset can be found in Appendix B.

The authors manually validated the annotations before including them in the final dataset, deeming one invalid if it met any of the following criteria: 1) The response was unrelated to the task, i.e. *"I don't know / understand"*, or a response for a different topic or question. 2) The response contained (part of) the answer. 3) The response did not follow the required format or task definition. 4) The annotator misunderstood the task. Examples per validation criterion are included in Appendix C.

After validation, we removed instances with more than 50% rejected annotations to ensure the quality of the dataset. In total, we removed 12 examples entirely and a total of 162 individual annotations. Our final dataset contains 12,519 annotations from 124 annotators. More information on the dataset statistics can be found in Appendix D[4].

## 4 Experimental setup

### 4.1 Gathering LLM responses

Using gathered annotations, we conducted experiments with the chat-versions of well-established LLMs, as these are used in daily life. An overview of the checkpoints per model is shown in Appendix F. We included GPT3.5[5], GPT4o[6], Haiku (Anthropic, 2024), Sonnet (Anthropic, 2024), using the appropriate APIs, and Qwen1.5

[3] https://github.com/allenai/natural-instructions

[4] Due to the nature of the tasks, we did not calculate inter-annotator agreement scores, as annotators were providing prompts, and invalid prompts were filtered out.

[5] https://openai.com/index/gpt-3-5-turbo-fine-tuning-and-api-updates/

[6] https://openai.com/index/hello-gpt-4o/

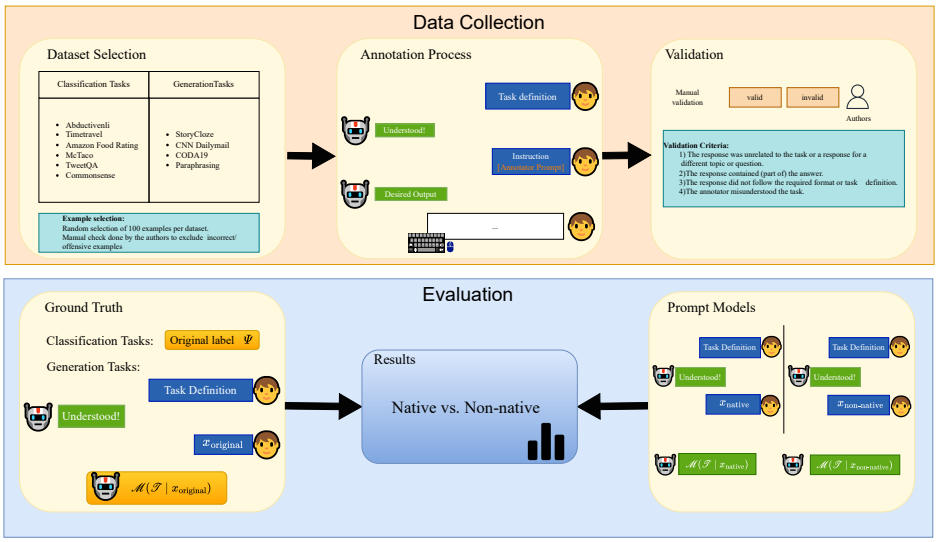


Figure 2: Methodology and experimental setup. The upper part of the figure shows the data collection steps. After gathering the different datasets, study participants annotated the examples. Then we validated them and used them as input to generate LLM responses. The lower part of the figure shows the evaluation phase. Before gathering the results, we got a new ground truth value for the dataset based on the original example for the generation tasks.

7B[7] (Bai et al., 2023) in line with the provided licenses and all consistent with the intended use. This set includes models of varying sizes, different performances, and from different developers, ensuring a diverse representation. Moreover, Qwen, developed by Chinese researchers, provides an interesting comparison in terms of design bias.

We experimented with various prompt schemata, structuring our methodological setup as follows. Firstly, we analyzed the results on our dataset without any modifications, comparing responses for native and non-native English speakers. Additionally, we distinguished between Western native English speaking and not Western native English speaking. Secondly, we hypothesize that the bias becomes more pronounced when adding explicit information on whether the annotator is a native or non-native English speaker, thereby analyzing whether an anchoring effect occurs. Anchoring is a term used for human cognitive bias indicating that a person might insufficiently change its estimates away from an initially provided value (Jones and Steinhardt, 2022; Tversky and Kahneman, 1974). This effect is demonstrated in LLMs by Jones and Steinhardt (2022), who found that code generation models modify their outputs to align with related solutions included in the prompt. Finally, we analyze the performance difference when letting the model first guess the nativeness of the annotator.

[7]We ran the experiments for Qwen using A100 GPUs.

### 4.2 Evaluation

To measure the bias within the models, we look into the performance difference between two groups, i.e. native versus non-native and Western native versus not Western native. We measure these performance differences across classification tasks and generative tasks. Concretely, native bias measured for the classification tasks is defined as follows:

$$\Delta_{\text{native}} = \phi\left(\mathcal{M}\left(\mathcal{T} \mid x_{\text{native}}\right), \psi\right)$$
$$\Delta_{\text{non-native}} = \phi\left(\mathcal{M}\left(\mathcal{T} \mid x_{\text{non-native}}\right), \psi\right)$$

with native bias discriminative = $\Delta_{\text{native}} - \Delta_{\text{non-native}}$, template $\mathcal{T}$, user prompt $x$, model $\mathcal{M}$, accuracy $\phi$, and original ground truth $\psi$. The native generative bias is defined as follows:

$$\Delta_{native} = \phi\left(\mathcal{M}\left(\mathcal{T} \mid x_{\text{native}}\right), \mathcal{M}\left(\mathcal{T} \mid x_{\text{original}}\right)\right)$$
$$\Delta_{\text{non-native}} = \phi(\mathcal{M}\left(\mathcal{T} \mid x_{\text{non-native}}\right), \mathcal{M}\left(\mathcal{T} \mid x_{\text{original}}\right))$$

with native bias generative = $\Delta_{\text{native}} - \Delta_{\text{non-native}}$, template $\mathcal{T}$, user prompt $x$, model $\mathcal{M}$, performance metric $\phi$, and generated ground truth from the original prompt $\mathcal{M}\left(\mathcal{T} \mid x_{\text{original}}\right)$. The Western native bias can be similarly inferred.

**Classification tasks.** When assessing classification tasks, we focus on the accuracy of the predictions. We only consider classifications as correct if they follow the instructions correctly or if the correct classification can be determined automatically.

**Generative tasks.** In assessing the generative tasks, we include the following metrics: BLEU, ROUGE,

BERT-score, and BART-score. These metrics are explained in detail in Appendix G.

The performance metrics for generative tasks are calculated using the LLM-generated gold answer as reference. This gold answer was generated using the original prompt in the dataset as displayed in Figure 2. We used this instead of the original gold answer in the dataset, given that optimal answers are model and context-dependent. By employing the LLM-generated gold answers, we align responses for each model.

## 5 Results

In line with our hypotheses, the results indicate performance differences between native and non-native English speakers and Western and not Western native speakers for GPT4o, Sonnet, and Qwen for the objective classification tasks, as shown in Table 1. However, the generative tasks indicate an opposite preference as displayed in Table 4. Informing the models about the user's nativeness further reduces answer quality for non-native English speakers, also resulting in a strong anchoring effect.

### 5.1 Classification tasks

**Do LLMs perform better for certain groups on both objective and subjective classification tasks?** Table 1 shows the average performance and standard deviation over three runs on the objective and subjective classification tasks for the different models and groups. The subjective classification task entails all tasks without an objectively correct answer, as this depends on subjective interpretation. The only subjective task included in our paper is the Amazon Food review task.

We find that for the objective classification tasks, **only GPT4o, Sonnet, and Qwen 7B perform significantly better for the native group of annotators**. For the other models, no significant differences are found between the groups. For the western native group, we find that only **GPT4o and Qwen 7B a significantly higher performance for the Western native English speakers**. Interestingly, we thus conclude that Sonnet is less tailored towards Western native English, which suggests efforts to take into account different English dialects. GPT4o on the other hand, is tailored towards native English speakers, and more specifically to Western native speakers. Interestingly, Qwen, which is predominantly trained on Chinese text, also prefers native and Western native English speakers.

For both the Claude and GPT models, we find that the larger model of the model family is more sensitive to the subtle differences in the prompts of native and non-native speakers. In literature, we find similar positive correlation between model size and bias that slips into models in terms of gender bias (Tal et al., 2022). Moreover, Sclar et al. (2023) even show that prompt sensitivity does not decrease for larger model size.
Surprisingly, Table 1 shows the opposite effect for the subjective classification tasks, preferring both the non-native and not Western native English speakers. This finding is remarkable, given the results in the subjective classification literature (Santy et al., 2023; Durmus et al., 2023).

To understand this contrasting phenomenon, we first analyze the results for both the native and non-native English speakers, and the Western native and not Western native English speakers, in depth. **We find that for the native English-speaking group, the models often predict the rating more positively than actually intended, and this effect is even more pronounced for the Western native English speakers.** While for the non-native English group and not Western native English speaking group, GPT4o predicted 50% of all wrongly predicted annotations to be more positive than intended, this was around 60% for the native English speaking group and even 70% for the Western native English speaking group for GPT4o indicating cultural differences. Appendix H includes the different distributions per model.

**What is the effect on the performance when informing the model about the nativeness of the annotator?** For these experiments, we added the user's nativeness to the system prompt. More specifically, we asked the model to respond as if interacting with a (non-)native English speaker.

Table 2 shows the effect of adding (in)correct information about the nativeness of the annotator to the system prompt on the performance of the models. Compared to Table 1, we now find that **all models significantly perform better for the objective classification tasks for the native group compared to the non-native group when correct information is added**. When inaccurately labeling native speakers as non-native and vice versa, we see that only GP4o and Qwen still significantly perform better for the native group, suggesting that they are less affected by this additional information. Interestingly, Sonnet is most affected by the information about the (in)correct nativeness of the

| | objective tasks | | | | subjective tasks | | | |
|---|---|---|---|---|---|---|---|---|
| | native | non-native | western native | not western native | native | non-native | western native | not western native |
| GPT3.5 | $0.82 \pm 0.01$ | $0.81 \pm 0.01$ | $0.81 \pm 0.00$ | $0.81 \pm 0.01$ | $0.76 \pm 0.01$ | $\mathbf{0.80 \pm 0.01}$ | $0.76 \pm 0.00$ | $\mathbf{0.80 \pm 0.00}$ |
| GPT4o | $\mathbf{0.94 \pm 0.00}$ | $0.93 \pm 0.00$ | $\mathbf{0.95 \pm 0.01}$ | $0.93 \pm 0.01$ | $0.77 \pm 0.00$ | $\mathbf{0.84 \pm 0.01}$ | $0.77 \pm 0.01$ | $\mathbf{0.83 \pm 0.01}$ |
| Haiku | $0.87 \pm 0.01$ | $0.86 \pm 0.00$ | $0.86 \pm 0.00$ | $0.87 \pm 0.00$ | $0.75 \pm 0.00$ | $\mathbf{0.80 \pm 0.00}$ | $0.71 \pm 0.00$ | $\mathbf{0.81 \pm 0.00}$ |
| Sonnet | $\mathbf{0.87 \pm 0.00}$ | $0.87 \pm 0.00$ | $0.87 \pm 0.01$ | $0.87 \pm 0.00$ | $0.77 \pm 0.00$ | $0.79 \pm 0.01$ | $0.76 \pm 0.01$ | $\mathbf{0.80 \pm 0.00}$ |
| Qwen 7B | $\mathbf{0.83 \pm 0.00}$ | $0.82 \pm 0.01$ | $\mathbf{0.83 \pm 0.00}$ | $0.82 \pm 0.00$ | $0.75 \pm 0.00$ | $\mathbf{0.79 \pm 0.00}$ | $0.72 \pm 0.00$ | $\mathbf{0.79 \pm 0.00}$ |

Table 1: Overall average accuracy of the objective and subjective classification tasks per model and group averaged over three runs and including the standard deviation over these different runs. Significant differences with $p < 0.05$ for a Wilcoxon signed-rank test are indicated in bold.

| | **objective tasks** | | | | **subjective tasks** | | | |
|---|---|---|---|---|---|---|---|---|
| | correct information | | wrong information | | correct information | | wrong information | |
| | native | non-native | native | non-native | native | non-native | native | non-native |
| GPT3.5 | $\mathbf{0.84 \pm 0.00}$ | $0.81 \pm 0.01$ | $0.83 \pm 0.01$ | $0.83 \pm 0.01$ | $0.76 \pm 0.00$ | $\mathbf{0.83 \pm 0.01}$ | $0.78 \pm 0.00$ | $\mathbf{0.83 \pm 0.00}$ |
| GPT4o | $\mathbf{0.94 \pm 0.00}$ | $0.93 \pm 0.00$ | $\mathbf{0.94 \pm 0.00}$ | $0.93 \pm 0.00$ | $0.77 \pm 0.01$ | $\mathbf{0.82 \pm 0.01}$ | $0.77 \pm 0.01$ | $\mathbf{0.84 \pm 0.00}$ |
| Haiku | $\mathbf{0.87 \pm 0.01}$ | $0.84 \pm 0.00$ | $0.85 \pm 0.00$ | $0.86 \pm 0.00$ | $0.75 \pm 0.00$ | $\mathbf{0.80 \pm 0.00}$ | $0.74 \pm 0.00$ | $\mathbf{0.81 \pm 0.01}$ |
| Sonnet | $\mathbf{0.88 \pm 0.00}$ | $0.63 \pm 0.00$ | $0.63 \pm 0.00$ | $\mathbf{0.87 \pm 0.00}$ | $0.77 \pm 0.00$ | $0.78 \pm 0.00$ | $0.78 \pm 0.00$ | $0.80 \pm 0.00$ |
| Qwen 7B | $\mathbf{0.83 \pm 0.00}$ | $0.82 \pm 0.00$ | $\mathbf{0.83 \pm 0.00}$ | $0.83 \pm 0.00$ | $0.75 \pm 0.00$ | $\mathbf{0.79 \pm 0.00}$ | $0.75 \pm 0.00$ | $\mathbf{0.79 \pm 0.00}$ |

Table 2: Overall average accuracy and standard deviation of the objective and subjective classification tasks per model and group averaged over three runs when adding information about the annotator's nativeness to the prompt. Significant differences with $p < 0.05$ for a Wilcoxon signed-rank test are indicated in bold.

prompt writer. We find that Sonnet answered several questions in languages other than English, such as Spanish, French or Indonesian, when responding as if interacting with non-native speakers. This is remarkable and shows a clear anchoring effect, considering we only instructed the model to respond as if interacting with a non-native English speaker. Interestingly, this did not occur for the other models

Moreover, also for the other two models that are mostly affected by this anchoring effect, we manually analyzed the errors. GPT3.5 makes more mistakes when informed about the prompt writer being non-native, due to repetition of the instructions, rather than answering the question. Haiku explains the answers, arguing why one option is better than another, thereby failing to follow the instructions, making it hard to assess performance automatically. If both answers are mentioned, we classify the response as inaccurate. Note that this anchoring effect is only seen for the objective classification tasks. It only slightly impacts the subjective classification tasks and does not result in new significant differences than those shown in Table 1. This overall anchoring effect, shows that these three models (GPT3.5, Haiku, and Sonnet) are still sensitive to (useless) information that is given within the prompt as also shown by (Shi et al., 2023; Jones and Steinhardt, 2022)

**What is the result of first asking the model to guess about the nativeness of the prompt writer?** In these experiments, the model first guesses the user's nativeness from their annotation, and then generates a task response within the same chat.

Table 3 shows that for GPT3.5, GPT4o, and Sonnet, first explicitly letting the model guess about the nativeness of the prompt writer, results in a significantly better score for the prompts from native than from non-native English speakers, regardless of having correctly guessed the nativeness. Compared to our initial experiments, we thus see that GPT3.5 is more led by this added question and its information and starts performing better for the native class. We find that both GPT models provide accurate explanations of the models' guesses, recognizing words within the prompt as i.e. British English. Generally, non-native prompts are identified through grammatical errors or *awkward phrasing*.

The performance difference for Haiku between the two correctly guessed groups is remarkable. The model has predicted many well-performing non-native annotations to be actually native for the objective classification tasks. Qwen now shows a non-significant difference between both. We find that these models struggle with following the guideline to respond with only *(non-)native* explaining why one is more likely than the other, as does Sonnet. Additionally, Qwen often refrains from guessing, stating it is difficult to determine the nativeness. This results in a lower performance and a non-significant difference between both groups. For the subjective tasks, we find that GPT4o, Sonnet, and Qwen are robust to this prompt, still providing significant differences for the non-native group, while Haiku and GPT3.5 are more impacted.

| | objective tasks | | | | subjective tasks | | | |
|---|---|---|---|---|---|---|---|---|
| | guess native | guess non-native | guess native correctly | guess non-native correctly | guess native | guess non-native | guess native correctly | guess non-native correctly |
| GPT3.5 | $\mathbf{0.80 \pm 0.01}$ | $0.77 \pm 0.00$ | $0.75 \pm 0.02$ | $0.72 \pm 0.01$ | $0.75 \pm 0.01$ | $0.75 \pm 0.01$ | $0.77 \pm 0.03$ | $0.77 \pm 0.02$ |
| GPT4o | $\mathbf{0.85 \pm 0.00}$ | $0.84 \pm 0.01$ | $0.82 \pm 0.05$ | $0.82 \pm 0.02$ | $0.77 \pm 0.01$ | $\mathbf{0.83 \pm 0.01}$ | $0.74 \pm 0.1$ | $0.71 \pm 0.02$ |
| Haiku | $0.65 \pm 0.00$ | $0.64 \pm 0.01$ | $0.47 \pm 0.03$ | $0.66 \pm 0.01$ | $0.67 \pm 0.00$ | $0.66 \pm 0.01$ | $0.74 \pm 0.05$ | $0.51 \pm 0.04$ |
| Sonnet | $\mathbf{0.63 \pm 0.01}$ | $0.62 \pm 0.01$ | $\mathbf{0.52 \pm 0.01}$ | $0.51 \pm 0.01$ | $0.72 \pm 0.01$ | $\mathbf{0.77 \pm 0.00}$ | $0.64 \pm 0.12$ | $0.75 \pm 0.04$ |
| Qwen 7B | $0.69 \pm 0.00$ | $0.69 \pm 0.00$ | $0.74 \pm 0.00$ | $\mathbf{0.74 \pm 0.00}$ | $0.67 \pm 0.00$ | $\mathbf{0.71 \pm 0.00}$ | $0.44 \pm 0.00$ | $0.77 \pm 0.00$ |

Table 3: Overall average accuracy and standard deviation over the three runs of all classification tasks per model and group when guessed by the model whether the person is a native or non-native speaker, and when it is guessed correctly. Significant differences with $p < 0.05$ for a Wilcoxon signed-rank test are indicated in bold. No statistical testing is done for the correctly guessed category for the subjective tasks due to the low amount of observations.

| | native | non-native | western native | not western native |
|---|---|---|---|---|
| GPT3.5 | $0.44 \pm 0.00$ | $\mathbf{0.44 \pm 0.00}$ | $0.44 \pm 0.00$ | $\mathbf{0.44 \pm 0.00}$ |
| GPT4o | $0.47 \pm 0.00$ | $\mathbf{0.47 \pm 0.00}$ | $0.47 \pm 0.00$ | $0.47 \pm 0.00$ |
| Haiku | $0.45 \pm 0.00$ | $\mathbf{0.46 \pm 0.01}$ | $0.45 \pm 0.01$ | $\mathbf{0.46 \pm 0.01}$ |
| Sonnet | $0.45 \pm 0.00$ | $\mathbf{0.43 \pm 0.02}$ | $0.45 \pm 0.00$ | $0.45 \pm 0.00$ |
| Qwen 7B | $0.41 \pm 0.00$ | $\mathbf{0.44 \pm 0.02}$ | $0.41 \pm 0.01$ | $\mathbf{0.42 \pm 0.01}$ |

Table 4: Overall average BLEU score of the generative task per model and group averaged over three runs and including the standard deviation over these different runs. Significant differences with $p < 0.05$ for a Wilcoxon signed-rank test are indicated in bold.

## 5.2 Generative tasks

**Do we find similar performance differences for the generative tasks?**

Table 4 shows the average BLEU scores and standard deviation over the three different runs per model and group. The statistical analysis includes all performance metrics. These metrics are included in Appendix L. For the generative tasks, all models perform overall significantly better for the non-native group, and all models except for GPT4o and Sonnet prefer the not western native group.

Despite this clear preference for the non-native group, we do find that the performance highly depends on the specific task at hand. In general, the generative tasks can be divided into two groups: group one with CODA19, which includes a medical research article generation task, and the paraphrasing dataset, group two with StoryCloze and CNN Dailymail. We find that all models prefer the non-native English speakers or not Western native English speakers for group one. Most models prefer (Western) native English speakers for group two. Detailed results are shown in Table 19 in Appendix.

In interpreting these results, it is important to consider the specific nature of the generation tasks involved. CODA19 comprises medical articles that utilize specialized medical terminology. Given that most annotators were unfamiliar with this vocabulary, native English speakers did not have a specific advantage over non-native speakers. Additionally, research articles are commonly written in English by authors from various backgrounds. Therefore, it might be that this specific task is robust against the native versus non-native preference. Finally, for the paraphrasing task, through manual error analysis, we found that native and non-native English annotators handled this task differently. While native English speakers often paraphrased the sentences more freely, non-native English speakers closely followed the original structure, mainly providing synonyms and maintaining the original sentence's format. An example is added in Appendix J.

**How does informing the model about the user's nativeness impact performance?**

Interestingly, Table 5 shows that adding the correct information about the user's nativeness affects the GPT-models largely. Now, no significant difference is found between both groups, whereas previously both models significantly preferred the non-native group. However, the result again depends on the specific task. For both GPT3.5 and GPT4o, a better performance is found for native English speakers for StoryCloze and CNN Dailymail, while the other datasets are preferred for non-native speakers. However, this difference between the native and non-native scores has increased for GPT3.5, again showing the anchoring effect. Similar to the classification tasks, this is less visible for GPT4o. While Haiku and Sonnet follow this preference for the native group on these datasets, Qwen always prefers the native group.

Additionally, when incorrect information about the user's nativeness is introduced, all models show improved or on-par performance for the non-native group, which is presented to the model as native speakers, compared to when they are represented as non-native speakers. This is a remarkable finding, as it emphasizes the importance of the prompt over the user's nativeness, unlike the results for the

| | (non-)native system prompt | | | | guess native system prompt | | | |
|---|---|---|---|---|---|---|---|---|
| | correct information | | wrong information | | overall guess | | guess correctly | |
| model | native | non-native | native | non-native | native | non-native | native | non-native |
| GPT3.5 | $0.42 \pm 0.01$ | $0.40 \pm 0.01$ | $0.40 \pm 0.00$ | $0.42 \pm 0.01$ | $0.42 \pm 0.00$ | $0.42 \pm 0.00$ | $0.45 \pm 0.01$ | $0.42 \pm 0.00$ |
| GPT4o | $0.47 \pm 0.01$ | $0.45 \pm 0.01$ | $0.45 \pm 0.00$ | $0.47 \pm 0.00$ | $0.46 \pm 0.00$ | $\mathbf{0.46 \pm 0.00}$ | $\mathbf{0.48 \pm 0.01}$ | $0.45 \pm 0.01$ |
| Haiku | $0.45 \pm 0.01$ | $\mathbf{0.45 \pm 0.01}$ | $0.45 \pm 0.01$ | $\mathbf{0.45 \pm 0.01}$ | $0.44 \pm 0.00$ | $\mathbf{0.45 \pm 0.00}$ | $\mathbf{0.34 \pm 0.03}$ | $0.43 \pm 0.00$ |
| Sonnet | $0.45 \pm 0.00$ | $\mathbf{0.45 \pm 0.00}$ | $0.45 \pm 0.00$ | $\mathbf{0.45 \pm 0.00}$ | $0.44 \pm 0.01$ | $0.45 \pm 0.00$ | $0.38 \pm 0.02$ | $\mathbf{0.46 \pm 0.01}$ |
| Qwen 7B | $0.41 \pm 0.00$ | $\mathbf{0.42 \pm 0.00}$ | $0.41 \pm 0.01$ | $0.42 \pm 0.01$ | $0.39 \pm 0.01$ | $0.39 \pm 0.00$ | $\mathbf{0.43 \pm 0.02}$ | $0.32 \pm 0.01$ |

Table 5: Overall average BLEU score of generative tasks per model when adding correct/wrong information about whether or not the prompt was written by a native English speaker and when (correctly)guessed by the model whether the person is a native or non-native speaker. We indicated significant differences ($p < 0.05$) in bold.

subjective classification tasks. The GPT-models are most affected by this as shown in the table.

**What is the result of first asking the model to guess about the nativeness of the prompt writer?** Table 5 includes the average BLEU scores when the model (correctly) guessed the nativeness of the prompt writer. Overall, no significant differences are found for GPT3.5 and Qwen, contrary to the original experiments in Table 4. Similar to the classification tasks, we find that this is probably due to Qwen's indecisiveness, which adds extra noise and shows the model sensitivity to useless information as in Shi et al. (2023). When looking at the guesses that were made correctly, GPT4o, Haiku, and Qwen perform significantly better for the native group than for the non-native groups. Sonnet, however still prefers the non-native group, and for GPT3.5 no significant differences are found.

## 6 Discussion

In our experiments, we define native bias, or western native bias, as the model's performance disparity when prompted by native versus non-native English speakers, or Western versus not Western natives respectively. **We find that there are performance differences when the model is prompted by people from different backgrounds.**

We find that GPT4o, Sonnet, and Qwen perform significantly better for the native groups for the objective classification tasks. For the subjective classification task, however, we find an opposite effect, where they interpret prompts of (Western) native English speakers more positively. Similarly, the models significantly prefer the non-native group for generative tasks, but the bias varies per dataset.

Moreover, **a strong anchoring effect occurs when the model knows whether or not the prompt writer is a native English speaker, either by correctly guessing, or by inserted information in the system prompt**. The bias is so deeply engraved that informing the models of the wrong native and non-native groups, results in a preference towards the group that was indicated as native. The model is largely led by this added information, more than by the prompt itself. However, we find differences between the models. GPT4o appears most resistant to this anchoring effect, while Sonnet on the other hand even changes the language of the response based on this anchor. Furthermore, this anchoring effect seems to be less present for the generative tasks than for the classification tasks. For Qwen, this anchoring effect is a result of the model's sensitivity to useless information, as this noise results in worse predictions for both groups.

Interestingly, the results also suggest that **the more advanced versions of models, such as GPT4o compared to GPT3.5 and Sonnet compared to Haiku, tend to be more sensitive to the subtleties of native English**. On the other hand, we also notice that GPT4o is less sensitive to added explicit information of the nativeness or non-nativeness of the annotator, and thus seems to be better hedged against explicitly added bias.

## 7 Conclusion

In this work, we analyze bias in LLMs towards native English speakers. We analyze whether models perform better for native compared to non-native English speakers and whether the models are even further tuned towards Western native English speakers. We find that there are significant performance differences between native and non-native prompts. More specifically, models become more inaccurate for the latter and this effect is even more pronounced for the Western native English versus not Western native English comparison for objective classification tasks. Furthermore, we find a strong anchoring effect when information about the user's nativeness is added or inferred by the model. For our experiments, we used a newly collected dataset consisting of over 12,000 unique prompts from a diverse set of annotators.

## 8 Limitations

Our dataset contained a very diverse set of annotators. Nevertheless, it would be interesting to have more study participants for every sub-population, such that general findings at sub-population level could be made as well. Furthermore, our experiments contained mostly annotators having a self-reported level of English of C1 and C2. It would be very interesting to analyze the effects on the performance of LLMs when prompted by people having different levels of English as this will probably also be impactful. Additionally, our results were only gathered for five different models. It would be insightful to extend this analysis to more models, as every model is trained differently and therefore these design choices might lead to different biases within the model. An important limitation of using LLMs and especially the closed-source variant thereof, is the lack of reproducibility of the results. We make available a multilingual dataset, however, have only analyzed the English answers. We leave the analysis of bias in the multilingual dataset for future research. Finally, we acknowledge that our way of evaluating, using the LLM-generated answers as reference sentences for the generative sentences, might be affected by the prompt of the original prompt writer. We have also analyzed the performance when letting the model first annotate the example and then use this to gather the response from the chatbot. However, we find that this resulted in large performance drops for the smaller models. Moreover, for the models that did offer adequate results, we find similar results as when we used the original prompt. The results are included in Appendix N.

## 9 Ethical considerations

We included human annotators in this study. All annotators were paid for the provided annotations and the annotations were done on a voluntary base. Moreover, our paper shows some of the consequences of unfair design choices when developing models. We think this work is important to highlight the necessity of taking into account multiple English dialects, as these models should work equally well for everyone. In this paper, we focus on the English language. We wanted to point out that even in English, this problem of not having enough diversified training data might also result in performance differences among certain populations. However, this does not mean that other languages do not require the same attention.

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## A Dataset overview

We used the datasets as they were assembled by Mishra et al. (2022) and Wang et al. (2022). Table 6 shows an overview of the selected datasets, together with their task ID in the original instructions dataset. The task definition given in the table is the one we used when prompting the models. For CNN Dailymail and CODA19, this differs from the original task definition in the dataset because we flipped the task. Instead of letting our annotators write the article, we asked them to write the summary or title respectively. Datasets Abductivenli, Timetravel, Amazonfood, McTaco, TweetQA, and Commonsense are thus classification tasks, while datasets StoryCloze, CNN Dailymail, CODA19, and Paraphrase are generation tasks.

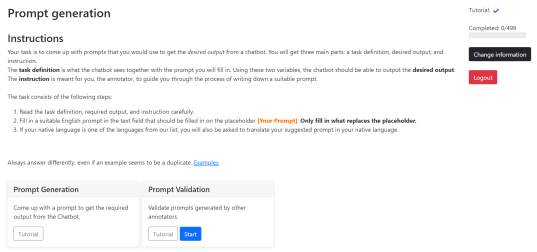



Figure 3: Screenshot of the landing page of the annotation platform.

Figure 4: An annotation example of the Abductivenli dataset.

## B Annotation set-up

We have set up an annotation platform to gather the annotations. The annotators first get information about the task. They will get a task definition, a prompt where part of the answer is marked out with the placeholder [YOUR PROMPT], and the desired output of the LLM. The annotators should complete the prompt such that the desired output would be generated by the LLMs. Figure 3 shows a screenshot of the landing page of the annotation platform together with annotation instructions. An example of an annotation that had to be annotated is shown in Figure 4. An example of the different `[Annotator PROMPT]` per dataset is shown in Table 7. We have anonymized all annotations by only providing the self-reported linguistic information in the dataset along with the user ID number.

| Task ID | Name | Task Definition |
|---|---|---|
| task069 | Abductivenli | In this task, you will be shown a short story with a beginning, two potential middles, and an ending. Your job is to choose the middle statement that makes the story coherent / plausible by writing Ïör 2ïn the output. If both sentences are plausible, pick the one that makes most sense. |
| task105 | Story Cloze | In this task, you're given four sentences of a story written in natural language. Your job is to complete the end part of the story by predicting the appropriate last sentence which is coherent with the given sentences. |
| task065 | Timetravel | In this task, you are given a short story consisting of exactly 5 sentences where the second sentence is missing. You are given two options and you need to select the one that best connects the first sentence with the rest of the story. Indicate your answer by 'Option 1' if the first option is correct, otherwise 'Option 2'. The incorrect option will change the subsequent storyline, so that at least one of the three subsequent sentences is no longer consistent with the story. |
| task588 | Amazonfood rating | In this task, you're given a review from Amazon's food products. Your task is to generate a rating for the product on a scale of 1-5 based on the review. The rating means 1: extremely poor, 2: poor, 3: neutral or mixed, 4: good, 5: extremely good. |
| task020 | Mctaco | The answer will be 'yes' if the provided sentence contains an explicit mention that answers the given question. Otherwise, the answer should be 'no'. Instances where the answer is implied from the sentence using ïnstinctör cömmon sense(ïas opposed to being written explicitly in the sentence) should be labeled as 'no'. |
| task241 | TweetQA | In this task, you are given a context tweet, a question and the corresponding answer of the given question. Your task is to classify this question-answer pair into two categories: (1) ÿesïf the given answer is right for question, and (2) ñoïf the given answer is wrong for question. |
| task1553 | CNN Dailymail | In this task, you are given highlights ,i.e., a short summary, in a couple of sentences, of news articles and you need to generate the news article with a maximum length of 2 paragraphs. |
| task1161 | CODA19 | In this task, you're given a title from a research paper and your task is to generate a paragraph for the research paper based on the given title. Under 10 lines is a good paragraph length. |
| task177 | Paraphrase | This is a paraphrasing task. In this task, you're given a sentence and your task is to generate another sentence which express same meaning as the input using different words. |
| task295 | Commonsense | In this task, you are given an impractical statement. You are also given three reasons (associated with Ä, B̈, C̈) explaining why this statement doesn't make sense. You must choose the most corresponding reason explaining why this statement doesn't make sense. |

Table 6: Overview of the different datasets used for the experiments in this paper.

| Dataset | Example Prompt |
|---|---|
| Abductivenli | Beginning: Mike was in the car on the highway. Middle 1 : `[Annotator Prompt]`. Middle 2: A deer never ran in front of his car. Ending: When he got to the hospital, they saw that it had been broken |
| Story Cloze | Sentence1: `[Annotator Prompt]` Sentence2: Suddenly, there was an announcement. Sentence3: The school was on a lockdown. Sentence4: The kids sat quietly, and waited. |
| Timetravel | Sentence 1: Little Charlie and his dad were painting the garage. Sentence 3: His dad turned around and started to laugh Sentence 4: Charlie had paint on him from head to toe Sentence 5: His dad rinsed him off with water from the hose Option 1: `[Annotator Prompt]` Option 2: Charlie had some trouble controlling the brush. |
| AmazonFood rating | This is `[Annotator Prompt]` |
| McTaco | Sentence: The legitimization of gambling led to its increased legalization across the US. Question: `[Annotator Prompt]` |
| TweetQA | Context: Praying for everyone here in Vegas. I witnessed the most unimaginable event tonight. We are okay. Others arent. Please pray. –Jake Owen (@jakeowen) October 2, 2017 Question: `[Annotator Prompt]` Answer: people were not okay |
| CNN DailyMail | `[Annotator Prompt]` |
| CODA19 | `[Annotator Prompt]` |
| Paraphrase | `[Annotator Prompt]` |
| Commonsense | I walk under the park. `[Annotator Prompt]` |

Table 7: Example of a prompt to annotate per dataset. `[Annotator Prompt]` indicates where the prompt of that the annotator should come up with, should fit in the text.

## C Annotation validation

Examples for each of the criteria of an invalid annotation are shown in Table 8.

For the annotations that did not follow the required format, we tried to change it into the correct format without changing the content of the prompt, if possible (i.e. removing *Question:* ). If this was not possible, the annotation was rejected.

## D Dataset Statistics -Annotations

The native-bias dataset consists of 12,519 annotations from 124 annotators. Our dataset initially contained 1,000 different examples. After deleting the examples that were not validly annotated by at least 50 % of annotators, we retained 988 examples for 10 different tasks.

The annotators have varying native languages as shown in Table 9. The languages are shown in isocode format. Moreover, per native language, we have also included the average validation rate, that is the amount of annotations per person that were valid over the total number of annotated examples.

Table 10 shows an overview of the number of annotators per group and set-id. All annotators were given sets of examples that had to be annotated. Every example has a unique set-id.

### D.1 Prompt length

Table 11 shows the average prompt length per dataset and per group. It is interesting to note the large difference for the CNN dailymail dataset, where the non-native English speakers have provided on average longer summaries. For the Western native English group versus the not Western native English group, the summaries for the latter are on average 10 words longer than for the former.

### D.2 Time analysis annotators

Table 12 shows an overview of the average duration of annotating one example per group in minutes. Table 13, on the other hand, shows the average time for annotating the given set in hours.

## E Prompt templates

**General**
system prompt:*You are a helpful assistant.*
chat history:
User: *task definition*,
Assistant:*'Understood'*,
User: *Full English Prompt*

**Add Native**
system prompt:*You are a helpful assistant. Respond as if you are interacting with a native English speaker*
chat history:
User: *[task definition]*,
Assistant:*Understood*,
User: *[Full English Prompt]*

**Add Non-Native**
system prompt:*You are a helpful assistant. Respond as if you are interacting with a non-native English speaker*
chat history:
User: *[task definition]*,
Assistant:*Understood*,
User: *[Full English Prompt]*

**Guess Native**
system prompt: *You are a helpful assistant.*
chat history1:
User: *Guess whether the writer of the following prompt is a native or non-native English speaker: [ANNOTATOR PROMPT]*,

chat history2:
User: *Guess whether the writer of the following prompt is a native or non-native English speaker: [ANNOTATOR PROMPT]*,
Assistant:*[RESPONSE]*,
User: *Next, execute the following task taking this information into account. [task definition]*,
Assistant:*Understood*,
User: *[Full English Prompt]*

Since we found that some of the models were not following the task definitions correctly for some of the tasks, we added extra instructions as to how the model should reply. Table 14 shows the instructions that were added to the task definition for the different datasets.

## F Checkpoints models

We used the following checkpoints of the different models:
**GPT 3.5** was made by OpenAI[8]. We used *gpt-3.5-turbo-0125*.

[8] https://openai.com/index/gpt-3-5-turbo-fine-tuning-and-api-updates/

| Criteria | Dataset | Example | Desired Answer |
|---|---|---|---|
| The response is unrelated to the task or it includes a response for a different topic or question | TweetQA | Context: I lost the role in 50 Shades of Grey so you won't be hearing from me for awhile— Lena Dunham (@lenadunham) September 2, 2013 Question: which countries are next to France? Answer: liverpool and everybody. | no |
| The response contains (part of) the answer. | Amazonfood | These are Amazon fish fingers, 5 stars from me - extremely good! | 5 |
| The response does not follow the required format or task definition. | TweetQA | Context: Kasich's daughter on his dance moves: "You're not going to go on 'Dancing with the Stars'" #KasichFamily CNN Politics (@CNNPolitics) April 12, 2016 Question: no, as he is terrible at dancing Answer: dozen | no |
| The person misunderstood the task. | Commonsense | He is wearing a green car choose an alphabet rating for this sentence, "A" for unreasonable meaning, otherwise "B" | A |

Table 8: Examples for the criteria of an invalid annotation.

| Native language | Number of annotators | Languages | Validation rate |
|---|---|---|---|
| Other | 36 | BG, SL, RU, SW, ML, HU, FA, VI, BE, EL, TN, ID,PL, MR, TR, PT, T, RO, FIL, UR, SQ | 0.83 |
| NL | 23 | | 0.80 |
| EN | 28 | | 0.83 |
| ZH | 11 | | 0.82 |
| EN, other | 9 | PA, JA, SW, UR, VI, MR, EL | 0.86 |
| EN, ZH | 1 | | 0.88 |
| ES | 5 | | 0.77 |
| FR | 4 | | 0.94 |
| IT | 3 | | 0.94 |
| HI | 2 | | 0.93 |
| AR | 1 | | 0.94 |
| ES, Other | 1 | CA | 0.84 |

Table 9: Overview of the native languages of the annotators and the validation rate per native language.

| Set ids | Native or not | | Western native or not | | Total |
|---|---|---|---|---|---|
| | Native | Non-native | Western | Not Western | |
| 10 | 7 | 16 | 5 | 18 | 23 |
| 20 | 7 | 12 | 4 | 15 | 19 |
| 30 | 7 | 10 | 4 | 13 | 17 |
| 40 | 4 | 8 | 3 | 9 | 12 |
| 50 | 4 | 9 | 2 | 11 | 13 |
| 60 | 5 | 14 | 3 | 16 | 19 |
| 70 | 5 | 11 | 4 | 12 | 16 |
| 80 | 3 | 10 | 3 | 10 | 13 |
| 90 | 4 | 10 | 4 | 10 | 14 |
| 100 | 6 | 5 | 4 | 7 | 11 |

Table 10: Overview of the number of annotators per group and set.

| Dataset ids | Native or not | | Western native or not | |
|---|---|---|---|---|
| | native | non-native | not Western native | Western native |
| **0** | 11.08 | 10.17 | 11.52 | 10.14 |
| **1** | 9.15 | 8.94 | 8.31 | 9.26 |
| **2** | 9.40 | 9.71 | 9.73 | 9.58 |
| **3** | 14.95 | 13.00 | 14.8 | 13.39 |
| **4** | 7.56 | 7.57 | 7.41 | 7.61 |
| **5** | 7.53 | 7.74 | 6.91 | 7.93 |
| **6** | 59.32 | 66.14 | 56.48 | 66.41 |
| **7** | 12.09 | 11.74 | 12.04 | 11.77 |
| **8** | 11.28 | 11.38 | 11.38 | 11.34 |
| **9** | 25.91 | 28.30 | 24.65 | 28.66 |

Table 11: Average prompt length per group and dataset.

| group | duration (in min) |
|---|---|
| native | 2.07 |
| non native | 3.27 |
| Western native | 1.87 |
| not Western native | 3.25 |

Table 12: Average duration of annotating 1 example per group, in minutes

| Set-ids | Native or not | | Western native or not | |
|---|---|---|---|---|
| | native | non-native | Western native | not Western native |
| 10 | 2.70 | 3.06 | 2.33 | 3.12 |
| 20 | 3.22 | 4.01 | 3.72 | 3.71 |
| 30 | 3.05 | 5.95 | 3.68 | 5.09 |
| 40 | 3.31 | 5.12 | 2.95 | 5.04 |
| 50 | 4.82 | 4.68 | 2.98 | 5.04 |
| 60 | 1.30 | 3.37 | 1.33 | 3.10 |
| 70 | 1.39 | 3.66 | 1.45 | 3.46 |
| 80 | 2.39 | 4.54 | 2.39 | 4.54 |
| 90 | 4.63 | 7.14 | 4.63 | 7.14 |
| 100 | 2.79 | 3.39 | 2.03 | 3.65 |

Table 13: Average overall duration of annotating all annotations in set per group, in hours

| Task | Task definition |
|---|---|
| StoryCloze | Only respond with the predicted last sentence. |
| AmazonFood | Only respond with the rating. |
| McTaco | Only respond with "yes" or "no". |
| TweetQA | Only respond with "yes" or "no". |
| CNN Dailymail | Only respond with the news article. |
| CODA19 | Only respond with the paragraph. |
| Paraphrase | Only respond with the paraphrased sentence. |
| Commonsense | Only respond with the letter indicating the most corresponding reason. |

Table 14: Overview of the added instructions per dataset to ensure consistent answers from the LLMs.

**GPT 4o** was made by OpenAI[9]. We used *gpt-4o-2024-05-13*.
**Haiku** was made by Anthropic (Anthropic, 2024). We used *claude-3-Haiku-20240307*.
**Sonnet** was made by Anthropic (Anthropic, 2024). We used *claude-3-Sonnet-20240229*.
**Qwen 7B** is an open source model made by the Alibaba group (Bai et al., 2023). We used *Qwen/Qwen1.5-7B-Chat*

## G Evaluation metrics

**BLEU.**[10] This established performance measure relies on counting the n-gram overlap between candi-

[9] https://openai.com/index/hello-gpt-4o/
[10] https://www.nltk.org/api/nltk.translate.bleu_score.html

date and reference sentence(Papineni et al., 2002).

**ROUGE.**[11] This metric is commonly used for summarization tasks and calculates the n-gram recall between a reference and candidate summary. We employ ROUGE-1, ROUGE-2, and ROUGE-L (Lin, 2004).

**BERT-score.**[12] This evaluation metric calculates and aggregates a similarity score between the BERT input embeddings for both the candidate and reference sentences. We employed *microsoft/deberta-xlarge-mnli* which was mentioned to be the best-performing model at the moment of writing the paper (Zhang et al., 2019).

**BART-score.**[13] This evaluation measure approaches the evaluation as a text-generation task, including all parameters learned during the pre-training phase (Yuan et al., 2021).

All metrics were implemented using the default parameters of the cited packages.

## H Distribution Amazon food reviews

Figures 5 and 6 show an overview of the wrong predictions of the AmazonFood review dataset for the different groups and models for one of the three runs. This shows the distribution between what was predicted and what should be predicted. We only consider here the cases where the model predicted one of the given ratings, and excluded cases where no prediction was given. As shown, for both the native and Western native group, we find a large amount of misclassification for the highest rating. Additionally, neutral is not often predicted for these classes compared to the other groups.

## I Results Sonnet different languages

When adding that the model is interacting with a non-native English speaker, we find that Sonnet starts to answer in different languages. We find that for 668 prompts the model answers in Spanish, for 25 sentences in French, and for 5 sentences in Indonesian. There were a couple of other languages that also occurred sporadically. An overview is shown in Table 15. However, these answers were not related to the native language of the prompt writer. This phenomenon was encountered mainly for the Timetravel dataset. Interestingly, this effect was not seen for the other models, not even for Haiku.

| Language | Times Occurring |
|---|---|
| es | 668 |
| fr | 25 |
| id | 5 |
| it | 2 |
| lt | 1 |
| sw | 1 |
| ru | 1 |

Table 15: Occurrences of different languages in Sonnet

| | amount guess native correctly | amount guess non-native correctly |
|---|---|---|
| GPT3.5 | 350 | 3080 |
| GPT4o | 114 | 436 |
| Haiku | 164 | 914 |
| Sonnet | 87 | 304 |
| qwen 7B | 95 | 152 |

Table 16: Amount of times the user's nativeness was correctly guessed by the different models.

## J Example Paraphrase

As said, there are differences between native and non-native speakers as to how they perceived the paraphrasing task. For example given this desired output: *At this time of rapid change, those who lag behind fall into irrelevance*. Native speakers came up with very freely paraphrased sentences, such as: *If you are not adapting to the quick changes of the world, you will not succeed.* while non-native speakers stuck to *In this fast changing ages, whoever is lagging becomes irrelevant*. When giving these different sentences to the model to paraphrase, the result for the more freely paraphrased sentences might cause the model to shift away further from the initial sentence or gold answer.

## K Prompt guess native

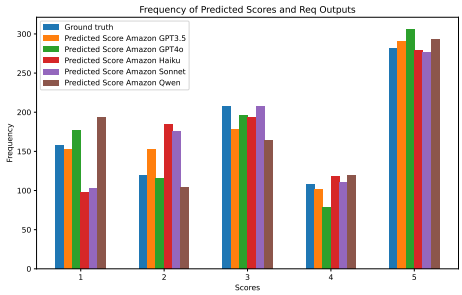
For this prompt, the number of identified correct predictions by the models was gathered automatically. Table 16 shows an overview of the correctly identified native and non native prompts for the entire dataset. In total there are 4264 native prompts and 8255 non-native prompts in our dataset. Many of the incorrectly predicted prompts, where in fact indecisive guesses or when the model was in doubt.

[11] https://huggingface.co/spaces/evaluate-metric/rouge

[12] https://huggingface.co/spaces/evaluate-metric/bertscore

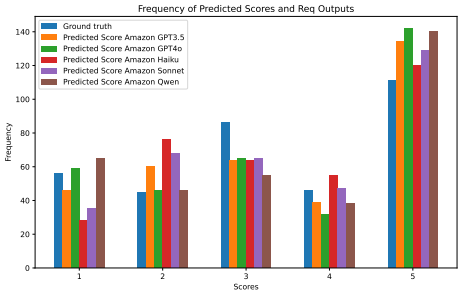
[13] github.com/neulab/BARTScore

(a) Overview of the wrong predictions for the native English speakers.

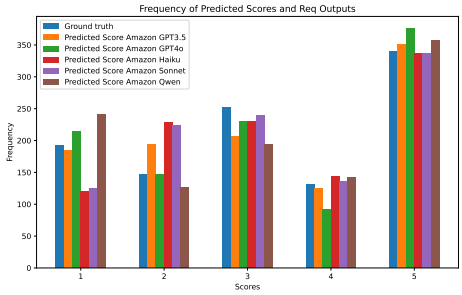



(b) Overview of the wrong predictions for the non-native English speakers.

Figure 5: Overall misclassification for native and non-native English speakers




(a) Overview of the wrong predictions for the Western native English speakers.




(b) Overview of the wrong predictions for the not Western native English speakers.

Figure 6: Overall misclassification for Western native English speakers and not Western native English speakers

## L Generative results

Tables 17 and 18 show the full performance metrics for the different experiments throughout the paper averaged over three runs including the standard deviation. In bold, we indicated the significant differences where ($p<0.05$). We tested this using a Wilcoxon signed-rank test over all runs and metrics.

Table 19 shows the overall average BLEU scores and standard deviation over the three runs per dataset and model. All models perform significantly better the non-native group for CODA19, which includes a medical research article generation task, and all models except Haiku for the Paraphrase dataset. For these two tasks, also all models prefer the non western group, except Sonnet on CODA19. Interestingly, for the StoryCloze, we see that GPT3.5 and GPT4o perform significantly better for both the native and western native groups. For the CNN dailymail dataset, almost no significant differences are found.

## M Overall results per prompt

Tables 20, 21, 22, 23, and 24 show an overview of the overall average results per group, model, and prompt.

## N Generative results generated label after annotation

Table 25 show the results for the overall average results for the generative tasks per model when letting the model first annotate the example and then gathering the output from this generated annotation as our ground truth label. As shown, this results in performance drops for both Qwen and GPT3.5. The larger models show similar performance to the experiments discussed in the paper.

| | GPT3.5 | | GPT4o | |
|---|---|---|---|---|
| | native | non-native | native | non-native |
| BLEU | $0.44 \pm 0.00$ | $\mathbf{0.44 \pm 0.00}$ | $0.47 \pm 0.00$ | $\mathbf{0.47 \pm 0.00}$ |
| ROUGE-1 | $0.39 \pm 0.01$ | $\mathbf{0.39 \pm 0.00}$ | $0.40 \pm 0.00$ | $\mathbf{0.41 \pm 0.00}$ |
| ROUGE-2 | $0.15 \pm 0.01$ | $\mathbf{0.15 \pm 0.01}$ | $0.16 \pm 0.01$ | $\mathbf{0.16 \pm 0.00}$ |
| ROUGE-L | $0.28 \pm 0.01$ | $\mathbf{0.29 \pm 0.00}$ | $0.29 \pm 0.00$ | $\mathbf{0.29 \pm 0.00}$ |
| BERTscore precision | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ |
| BERTscore recall | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ |
| BERTscore F1 | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ |
| BARTscore faithful | $-2.79 \pm 0.01$ | $\mathbf{-2.79 \pm 0.01}$ | $-2.96 \pm 0.01$ | $\mathbf{-2.97 \pm 0.00}$ |
| BARTscore precision | $-2.73 \pm 0.00$ | $\mathbf{-2.72 \pm 0.01}$ | $-2.75 \pm 0.01$ | $\mathbf{-2.75 \pm 0.01}$ |
| BARTscore recall | $-2.73 \pm 0.00$ | $\mathbf{-2.71 \pm 0.01}$ | $-2.77 \pm 0.01$ | $\mathbf{-2.76 \pm 0.00}$ |
| BARTscore F1 | $-2.70 \pm 0.01$ | $\mathbf{-2.69 \pm 0.00}$ | $-2.74 \pm 0.01$ | $\mathbf{-2.73 \pm 0.00}$ |

| | Haiku | | Sonnet | | Qwen 7B | |
|---|---|---|---|---|---|---|
| | native | non-native | native | non-native | native | non-native |
| BLEU | $0.45 \pm 0.00$ | $\mathbf{0.46 \pm 0.01}$ | $0.45 \pm 0.00$ | $\mathbf{0.45 \pm 0.00}$ | $0.41 \pm 0.00$ | $\mathbf{0.42 \pm 0.01}$ |
| ROUGE-1 | $0.41 \pm 0.01$ | $\mathbf{0.42 \pm 0.01}$ | $0.38 \pm 0.00$ | $\mathbf{0.38 \pm 0.01}$ | $0.37 \pm 0.01$ | $\mathbf{0.38 \pm 0.00}$ |
| ROUGE-2 | $0.16 \pm 0.00$ | $\mathbf{0.17 \pm 0.01}$ | $0.13 \pm 0.01$ | $\mathbf{0.14 \pm 0.00}$ | $0.14 \pm 0.01$ | $\mathbf{0.14 \pm 0.00}$ |
| ROUGE-L | $0.30 \pm 0.01$ | $\mathbf{0.30 \pm 0.00}$ | $0.27 \pm 0.00$ | $\mathbf{0.27 \pm 0.00}$ | $0.26 \pm 0.01$ | $\mathbf{0.27 \pm 0.00}$ |
| BERTscore precision | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $\mathbf{0.71 \pm 0.01}$ | $0.70 \pm 0.00$ | $\mathbf{0.70 \pm 0.00}$ |
| BERTscore recall | $0.71 \pm 0.01$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $\mathbf{0.71 \pm 0.00}$ | $0.69 \pm 0.01$ | $\mathbf{0.70 \pm 0.00}$ |
| BERTscore F1 | $0.72 \pm 0.01$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $\mathbf{0.71 \pm 0.00}$ | $0.70 \pm 0.01$ | $\mathbf{0.70 \pm 0.00}$ |
| BARTscore faithful | $-2.89 \pm 0.01$ | $\mathbf{-2.90 \pm 0.01}$ | $-3.13 \pm 0.01$ | $\mathbf{-3.12 \pm 0.01}$ | $-3.11 \pm 0.02$ | $\mathbf{-3.10 \pm 0.00}$ |
| BARTscore precision | $-2.69 \pm 0.01$ | $\mathbf{-2.70 \pm 0.01}$ | $-2.87 \pm 0.01$ | $\mathbf{-2.86 \pm 0.01}$ | $-2.9 \pm 0.01$ | $\mathbf{-2.91 \pm 0.01}$ |
| BARTscore recall | $-2.69 \pm 0.01$ | $\mathbf{-2.67 \pm 0.01}$ | $-2.88 \pm 0.00$ | $\mathbf{-2.87 \pm 0.00}$ | $-2.95 \pm 0.02$ | $\mathbf{-2.93 \pm 0.01}$ |
| BARTscore F1 | $-2.67 \pm 0.01$ | $\mathbf{-2.66 \pm 0.00}$ | $-2.85 \pm 0.01$ | $\mathbf{-2.84 \pm 0.01}$ | $-2.9 \pm 0.01$ | $\mathbf{-2.89 \pm 0.01}$ |

Table 17: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per model and group .

| | GPT3.5 | | GPT4o | |
|---|---|---|---|---|
| | western native | not western native | western native | not western native |
| BLEU | $0.44 \pm 0.00$ | $\mathbf{0.44 \pm 0.00}$ | $0.47 \pm 0.00$ | $0.47 \pm 0.00$ |
| ROUGE-1 | $0.39 \pm 0.01$ | $\mathbf{0.39 \pm 0.00}$ | $0.40 \pm 0.00$ | $0.41 \pm 0.00$ |
| ROUGE-2 | $0.14 \pm 0.01$ | $\mathbf{0.15 \pm 0.00}$ | $0.16 \pm 0.00$ | $0.16 \pm 0.01$ |
| ROUGE-L | $0.28 \pm 0.01$ | $\mathbf{0.29 \pm 0.00}$ | $0.29 \pm 0.00$ | $0.29 \pm 0.00$ |
| BERTscore precision | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| BERTscore recall | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| BERTscore F1 | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| BARTscore faithful | $-2.79 \pm 0.01$ | $\mathbf{-2.79 \pm 0.02}$ | $-2.97 \pm 0.01$ | $-2.96 \pm 0.01$ |
| BARTscore precision | $-2.73 \pm 0.01$ | $\mathbf{-2.72 \pm 0.01}$ | $-2.74 \pm 0.01$ | $-2.75 \pm 0.00$ |
| BARTscore recall | $-2.73 \pm 0.00$ | $\mathbf{-2.71 \pm 0.00}$ | $-2.76 \pm 0.01$ | $-2.76 \pm 0.00$ |
| BARTscore F1 | $-2.71 \pm 0.01$ | $\mathbf{-2.69 \pm 0.00}$ | $-2.73 \pm 0.00$ | $-2.73 \pm 0.00$ |

| | Haiku | | Sonnet | | Qwen 7B | |
|---|---|---|---|---|---|---|
| | western native | not western native | western native | not western native | western native | not western native |
| BLEU | $0.45 \pm 0.00$ | $\mathbf{0.46 \pm 0.01}$ | $0.45 \pm 0.00$ | $0.45 \pm 0.00$ | $0.41 \pm 0.00$ | $\mathbf{0.42 \pm 0.01}$ |
| ROUGE-1 | $0.40 \pm 0.01$ | $\mathbf{0.42 \pm 0.01}$ | $0.38 \pm 0.00$ | $0.38 \pm 0.01$ | $0.37 \pm 0.01$ | $\mathbf{0.38 \pm 0.00}$ |
| ROUGE-2 | $0.16 \pm 0.00$ | $\mathbf{0.17 \pm 0.01}$ | $0.14 \pm 0.01$ | $0.14 \pm 0.00$ | $0.14 \pm 0.01$ | $\mathbf{0.14 \pm 0.00}$ |
| ROUGE-L | $0.29 \pm 0.01$ | $\mathbf{0.30 \pm 0.00}$ | $0.27 \pm 0.00$ | $0.27 \pm 0.00$ | $0.26 \pm 0.01$ | $\mathbf{0.27 \pm 0.00}$ |
| BERTscore precision | $0.72 \pm 0.00$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $0.71 \pm 0.01$ | $0.70 \pm 0.00$ | $\mathbf{0.70 \pm 0.00}$ |
| BERTscore recall | $0.71 \pm 0.01$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.70 \pm 0.01$ | $\mathbf{0.70 \pm 0.00}$ |
| BERTscore F1 | $0.72 \pm 0.01$ | $\mathbf{0.72 \pm 0.00}$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.70 \pm 0.01$ | $\mathbf{0.70 \pm 0.00}$ |
| BARTscore faithful | $-2.90 \pm 0.01$ | $\mathbf{-2.89 \pm 0.01}$ | $-3.13 \pm 0.01$ | $-3.12 \pm 0.01$ | $-3.11 \pm 0.02$ | $\mathbf{-3.10 \pm 0.00}$ |
| BARTscore precision | $-2.70 \pm 0.01$ | $\mathbf{-2.69 \pm 0.01}$ | $-2.86 \pm 0.01$ | $-2.86 \pm 0.01$ | $-2.91 \pm 0.01$ | $\mathbf{-2.90 \pm 0.01}$ |
| BARTscore recall | $-2.70 \pm 0.01$ | $\mathbf{-2.67 \pm 0.01}$ | $-2.88 \pm 0.00$ | $-2.87 \pm 0.00$ | $-2.96 \pm 0.02$ | $\mathbf{-2.93 \pm 0.01}$ |
| BARTscore F1 | $-2.67 \pm 0.01$ | $\mathbf{-2.66 \pm 0.00}$ | $-2.84 \pm 0.01$ | $-2.84 \pm 0.01$ | $-2.90 \pm 0.01$ | $\mathbf{-2.88 \pm 0.01}$ |

Table 18: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per model and group.

| | Story Cloze | | CNN dailymail | | CODA19 | | Paraphrasing | |
|---|---|---|---|---|---|---|---|---|
| | native | non-native | native | non-native | native | non-native | native | non-native |
| GPT3.5 | **$0.39 \pm 0.01$** | $0.38 \pm 0.01$ | $0.47 \pm 0.01$ | $0.45 \pm 0.01$ | $0.55 \pm 0.00$ | **$0.56 \pm 0.00$** | $0.35 \pm 0.01$ | **$0.36 \pm 0.00$** |
| GPT4o | **$0.42 \pm 0.01$** | $0.41 \pm 0$ | $0.53 \pm 0.00$ | $0.53 \pm 0.00$ | $0.57 \pm 0.00$ | **$0.58 \pm 0.00$** | $0.35 \pm 0.00$ | **$0.37 \pm 0.00$** |
| Haiku | $0.40 \pm 0.02$ | $0.39 \pm 0.03$ | $0.50 \pm 0.01$ | $0.51 \pm 0.02$ | $0.57 \pm 0.00$ | **$0.58 \pm 0.00$** | $0.34 \pm 0.02$ | $0.35 \pm 0.03$ |
| Sonnet | $0.39 \pm 0.00$ | **$0.39 \pm 0.01$** | **$0.51 \pm 0.01$** | $0.50 \pm 0.00$ | $0.57 \pm 0.00$ | **$0.58 \pm 0.00$** | $0.32 \pm 0.00$ | **$0.33 \pm 0.00$** |
| Qwen 7B | $0.38 \pm 0.01$ | $0.38 \pm 0.01$ | $0.42 \pm 0.01$ | $0.43 \pm 0.01$ | $0.52 \pm 0.01$ | **$0.53 \pm 0.00$** | $0.31 \pm 0.01$ | **$0.32 \pm 0.01$** |

| | Story Cloze | | CNN dailymail | | CODA19 | | Paraphrasing | |
|---|---|---|---|---|---|---|---|---|
| | Western | non Western | Western | non Western | Western | non Western | Western | non Western |
| GPT3.5 | **$0.39 \pm 0.01$** | $0.38 \pm 0.00$ | $0.47 \pm 0.01$ | $0.46 \pm 0.00$ | $0.55 \pm 0.00$ | **$0.56 \pm 0.00$** | $0.35 \pm 0.01$ | **$0.36 \pm 0.00$** |
| GPT4o | **$0.43 \pm 0.00$** | $0.41 \pm 0$ | $0.53 \pm 0.01$ | $0.53 \pm 0.00$ | $0.58 \pm 0.00$ | **$0.58 \pm 0.00$** | $0.35 \pm 0.00$ | **$0.37 \pm 0.00$** |
| Haiku | $0.39 \pm 0.03$ | **$0.40 \pm 0.02$** | $0.50 \pm 0.01$ | **$0.51 \pm 0.02$** | $0.57 \pm 0.01$ | **$0.58 \pm 0.00$** | $0.33 \pm 0.02$ | **$0.35 \pm 0.03$** |
| Sonnet | **$0.40 \pm 0.01$** | $0.39 \pm 0.00$ | $0.51 \pm 0.01$ | $0.50 \pm 0.00$ | $0.57 \pm 0.01$ | $0.58 \pm 0.00$ | $0.32 \pm 0.00$ | **$0.33 \pm 0.00$** |
| Qwen 7B | $0.38 \pm 0.01$ | $0.38 \pm 0.01$ | $0.42 \pm 0.01$ | $0.43 \pm 0.01$ | $0.52 \pm 0.00$ | **$0.53 \pm 0.01$** | $0.30 \pm 0.01$ | **$0.33 \pm 0.00$** |

Table 19: Average BLEU scores and standard deviation per dataset and model for the native-non-native group and the Western non Western group over the three runs. The statistical analysis is done based on all different performance scores using a Wilcoxon signed-rank test with p-value 0.05. Significant differences are indicated in bold

| | (non-)native system prompt | | | |
|---|---|---|---|---|
| | correct information | | wrong information | |
| | native | non-native | native | non-native |
| **BLEU** | $0.42 \pm 0.01$ | $0.40 \pm 0.01$ | $0.40 \pm 0.00$ | $0.42 \pm 0.01$ |
| **ROUGE-1** | $0.38 \pm 0.00$ | $0.37 \pm 0.00$ | $0.37 \pm 0.00$ | $0.38 \pm 0.01$ |
| **ROUGE-2** | $0.14 \pm 0.00$ | $0.13 \pm 0.00$ | $0.13 \pm 0.00$ | $0.14 \pm 0.00$ |
| **ROUGE-L** | $0.28 \pm 0.00$ | $0.28 \pm 0.00$ | $0.27 \pm 0.00$ | $0.28 \pm 0.00$ |
| **BERTscore precision** | $0.72 \pm 0.00$ | $0.73 \pm 0.00$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.70 \pm 0.00$ | $0.70 \pm 0.00$ | $0.71 \pm 0.00$ |
| **BERTscore F1** | $0.72 \pm 0.01$ | $0.71 \pm 0.00$ | $0.71 \pm 0.01$ | $0.72 \pm 0.00$ |
| **BARTscore faithful** | $-2.75 \pm 0.00$ | $-2.7 \pm 0.01$ | $-2.71 \pm 0.00$ | $-2.78 \pm 0.01$ |
| **BARTscore precision** | $-2.71 \pm 0.01$ | $-2.7 \pm 0.00$ | $-2.69 \pm 0.00$ | $-2.75 \pm 0.00$ |
| **BARTscore recall** | $-2.77 \pm 0.01$ | $-2.79 \pm 0.00$ | $-2.8 \pm 0.00$ | $-2.76 \pm 0.00$ |
| **BARTscore F1** | $-2.71 \pm 0.00$ | $-2.72 \pm 0.01$ | $-2.72 \pm 0.00$ | $-2.73 \pm 0.00$ |

| | guess native system prompt | | | |
|---|---|---|---|---|
| | overall guess | | guess correctly | |
| | native | non-native | native | non-native |
| **BLEU** | $0.42 \pm 0.00$ | $0.42 \pm 0.00$ | $0.45 \pm 0.01$ | $0.42 \pm 0.00$ |
| **ROUGE-1** | $0.37 \pm 0.00$ | $0.38 \pm 0.01$ | $0.39 \pm 0.01$ | $0.37 \pm 0.01$ |
| **ROUGE-2** | $0.13 \pm 0.00$ | $0.13 \pm 0.00$ | $0.13 \pm 0.01$ | $0.13 \pm 0.01$ |
| **ROUGE-L** | $0.27 \pm 0.00$ | $0.27 \pm 0.01$ | $0.27 \pm 0.01$ | $0.27 \pm 0.00$ |
| **BERTscore precision** | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ | $0.71 \pm 0.01$ | $0.72 \pm 0.01$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.01$ | $0.71 \pm 0.00$ |
| **BERTscore F1** | $0.71 \pm 0.00$ | $0.72 \pm 0.01$ | $0.71 \pm 0.01$ | $0.71 \pm 0.00$ |
| **BARTscore faithful** | $-2.78 \pm 0.01$ | $-2.78 \pm 0.01$ | $-2.75 \pm 0.02$ | $-2.74 \pm 0.02$ |
| **BARTscore precision** | $-2.77 \pm 0.00$ | $-2.78 \pm 0.00$ | $-2.79 \pm 0.06$ | $-2.82 \pm 0.02$ |
| **BARTscore recall** | $-2.76 \pm 0.01$ | $-2.74 \pm 0.01$ | $-2.76 \pm 0.01$ | $-2.76 \pm 0.01$ |
| **BARTscore F1** | $-2.74 \pm 0.01$ | $-2.74 \pm 0.01$ | $-2.76 \pm 0.04$ | $-2.76 \pm 0.02$ |

Table 20: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per group and prompt of GPT3.5.

| | (non-)native system prompt | | | |
|---|---|---|---|---|
| | correct information | | wrong information | |
| | native | non-native | native | non-native |
| **BLEU** | $0.47 \pm 0.01$ | $0.45 \pm 0.01$ | $0.45 \pm 0.00$ | $0.47 \pm 0.00$ |
| **ROUGE-1** | $0.40 \pm 0.00$ | $0.40 \pm 0.00$ | $0.39 \pm 0.01$ | $0.40 \pm 0.00$ |
| **ROUGE-2** | $0.15 \pm 0.00$ | $0.14 \pm 0.01$ | $0.14 \pm 0.01$ | $0.15 \pm 0.00$ |
| **ROUGE-L** | $0.28 \pm 0.01$ | $0.28 \pm 0.01$ | $0.28 \pm 0.00$ | $0.29 \pm 0.00$ |
| **BERTscore precision** | $0.72 \pm 0.00$ | $0.72 \pm 0.01$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| **BERTscore recall** | $0.72 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.72 \pm 0.00$ |
| **BERTscore F1** | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ |
| **BARTscore faithful** | $-2.95 \pm 0.01$ | $-2.88 \pm 0.01$ | $-2.87 \pm 0.00$ | $-2.96 \pm 0.02$ |
| **BARTscore precision** | $-2.76 \pm 0.01$ | $-2.73 \pm 0.01$ | $-2.72 \pm 0.01$ | $-2.75 \pm 0.01$ |
| **BARTscore recall** | $-2.79 \pm 0.01$ | $-2.8 \pm 0.00$ | $-2.81 \pm 0.01$ | $-2.77 \pm 0.01$ |
| **BARTscore F1** | $-2.75 \pm 0.01$ | $-2.74 \pm 0.01$ | $-2.74 \pm 0.01$ | $-2.74 \pm 0.01$ |
| | guess native system prompt | | | |
| | overall guess | | guess correctly | |
| | native | non-native | native | non-native |
| **BLEU** | $0.46 \pm 0.00$ | $0.46 \pm 0.00$ | $0.48 \pm 0.01$ | $0.45 \pm 0.01$ |
| **ROUGE-1** | $0.40 \pm 0.01$ | $0.40 \pm 0.00$ | $0.39 \pm 0.01$ | $0.39 \pm 0.02$ |
| **ROUGE-2** | $0.15 \pm 0.00$ | $0.15 \pm 0.00$ | $0.13 \pm 0.01$ | $0.13 \pm 0.02$ |
| **ROUGE-L** | $0.28 \pm 0.01$ | $0.29 \pm 0.00$ | $0.25 \pm 0.01$ | $0.27 \pm 0.02$ |
| **BERTscore precision** | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ | $0.69 \pm 0.01$ | $0.71 \pm 0.01$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.72 \pm 0.01$ | $0.70 \pm 0.01$ | $0.71 \pm 0.01$ |
| **BERTscore F1** | $0.72 \pm 0.00$ | $0.72 \pm 0.00$ | $0.70 \pm 0.01$ | $0.71 \pm 0.01$ |
| **BARTscore faithful** | $-2.92 \pm 0.01$ | $-2.91 \pm 0.01$ | $-2.58 \pm 0.12$ | $-2.76 \pm 0.06$ |
| **BARTscore precision** | $-2.74 \pm 0.01$ | $-2.75 \pm 0.01$ | $-2.83 \pm 0.04$ | $-2.79 \pm 0.07$ |
| **BARTscore recall** | $-2.80 \pm 0.01$ | $-2.79 \pm 0.00$ | $-2.74 \pm 0.03$ | $-2.84 \pm 0.05$ |
| **BARTscore F1** | $-2.75 \pm 0.01$ | $-2.74 \pm 0.01$ | $-2.77 \pm 0.03$ | $-2.79 \pm 0.05$ |

Table 21: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per group and prompt of GPT4o.

| | (non-)native system prompt | | | |
|---|---|---|---|---|
| | correct information | | wrong information | |
| model | native | non-native | native | non-native |
| **BLEU** | $0.45 \pm 0.01$ | $0.45 \pm 0.01$ | $0.45 \pm 0.01$ | $0.45 \pm 0.01$ |
| **ROUGE-1** | $0.41 \pm 0.01$ | $0.41 \pm 0.00$ | $0.41 \pm 0.01$ | $0.41 \pm 0.00$ |
| **ROUGE-2** | $0.16 \pm 0.01$ | $0.17 \pm 0.00$ | $0.16 \pm 0.01$ | $0.16 \pm 0.01$ |
| **ROUGE-L** | $0.30 \pm 0.01$ | $0.30 \pm 0.00$ | $0.29 \pm 0.01$ | $0.30 \pm 0.00$ |
| **BERTscore precision** | $0.72 \pm 0.01$ | $0.72 \pm 0.00$ | $0.72 \pm 0.01$ | $0.72 \pm 0.00$ |
| **BERTscore recall** | $0.72 \pm 0.01$ | $0.72 \pm 0.00$ | $0.71 \pm 0.00$ | $0.72 \pm 0.00$ |
| **BERTscore F1** | $0.72 \pm 0.01$ | $0.72 \pm 0.00$ | $0.71 \pm 0.01$ | $0.72 \pm 0.00$ |
| **BARTscore faithful** | $-2.89 \pm 0.01$ | $-2.88 \pm 0.01$ | $-2.87 \pm 0.01$ | $-2.91 \pm 0.01$ |
| **BARTscore precision** | $-2.68 \pm 0.01$ | $-2.69 \pm 0.01$ | $-2.68 \pm 0.01$ | $-2.69 \pm 0.01$ |
| **BARTscore recall** | $-2.70 \pm 0.01$ | $-2.68 \pm 0.02$ | $-2.71 \pm 0.01$ | $-2.68 \pm 0.02$ |
| **BARTscore F1** | $-2.67 \pm 0.01$ | $-2.66 \pm 0.01$ | $-2.67 \pm 0.00$ | $-2.66 \pm 0.01$ |
| | guess native system prompt | | | |
| | overall guess | | guess correctly | |
| metric | native | non-native | native | non-native |
| **BLEU** | $0.44 \pm 0.00$ | $0.45 \pm 0.00$ | $0.34 \pm 0.03$ | $0.43 \pm 0.00$ |
| **ROUGE-1** | $0.39 \pm 0.01$ | $0.40 \pm 0.01$ | $0.38 \pm 0.02$ | $0.38 \pm 0.00$ |
| **ROUGE-2** | $0.14 \pm 0.00$ | $0.15 \pm 0.00$ | $0.17 \pm 0.02$ | $0.13 \pm 0.00$ |
| **ROUGE-L** | $0.27 \pm 0.01$ | $0.28 \pm 0.00$ | $0.33 \pm 0.02$ | $0.27 \pm 0.01$ |
| **BERTscore precision** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.74 \pm 0.01$ | $0.71 \pm 0.00$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.74 \pm 0.01$ | $0.71 \pm 0.00$ |
| **BERTscore F1** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.74 \pm 0.01$ | $0.71 \pm 0.00$ |
| **BARTscore faithful** | $-2.97 \pm 0.01$ | $-2.97 \pm 0.01$ | $-3.33 \pm 0.02$ | $-2.92 \pm 0.03$ |
| **BARTscore precision** | $-2.85 \pm 0.01$ | $-2.86 \pm 0.01$ | $-2.73 \pm 0.02$ | $-2.89 \pm 0.03$ |
| **BARTscore recall** | $-2.76 \pm 0.01$ | $-2.73 \pm 0.01$ | $-2.63 \pm 0.04$ | $-2.77 \pm 0.03$ |
| **BARTscore F1** | $-2.77 \pm 0.01$ | $-2.77 \pm 0.01$ | $-2.64 \pm 0.02$ | $-2.80 \pm 0.03$ |

Table 22: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per group and prompt of Haiku.

| | (non-)native system prompt | | | |
|---|---|---|---|---|
| | correct information | | wrong information | |
| model | native | non-native | native | non-native |
| **BLEU** | $0.45 \pm 0.00$ | $0.45 \pm 0.00$ | $0.45 \pm 0.00$ | $0.45 \pm 0.00$ |
| **ROUGE-1** | $0.38 \pm 0.00$ | $0.38 \pm 0.01$ | $0.38 \pm 0.00$ | $0.39 \pm 0.00$ |
| **ROUGE-2** | $0.14 \pm 0.00$ | $0.14 \pm 0.00$ | $0.13 \pm 0.00$ | $0.14 \pm 0.00$ |
| **ROUGE-L** | $0.27 \pm 0.00$ | $0.27 \pm 0.00$ | $0.27 \pm 0.00$ | $0.27 \pm 0.01$ |
| **BERTscore precision** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ |
| **BERTscore F1** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ |
| **BARTscore faithful** | $-3.13 \pm 0.00$ | $-3.08 \pm 0.01$ | $-3.07 \pm 0.01$ | $-3.14 \pm 0.01$ |
| **BARTscore precision** | $-2.87 \pm 0.01$ | $-2.86 \pm 0.01$ | $-2.86 \pm 0.01$ | $-2.87 \pm 0.01$ |
| **BARTscore recall** | $-2.87 \pm 0.00$ | $-2.87 \pm 0.01$ | $-2.89 \pm 0.00$ | $-2.85 \pm 0.01$ |
| **BARTscore F1** | $-2.85 \pm 0.00$ | $-2.83 \pm 0.01$ | $-2.85 \pm 0.00$ | $-2.83 \pm 0.01$ |
| | guess native system prompt | | | |
| | overall guess | | guess correctly | |
| metric | native | non-native | native | non-native |
| **BLEU** | $0.44 \pm 0.01$ | $0.45 \pm 0.00$ | $0.38 \pm 0.02$ | $0.46 \pm 0.01$ |
| **ROUGE-1** | $0.37 \pm 0.01$ | $0.38 \pm 0.00$ | $0.32 \pm 0.02$ | $0.39 \pm 0.01$ |
| **ROUGE-2** | $0.13 \pm 0.00$ | $0.13 \pm 0.00$ | $0.09 \pm 0.02$ | $0.13 \pm 0.01$ |
| **ROUGE-L** | $0.26 \pm 0.00$ | $0.26 \pm 0.00$ | $0.23 \pm 0.01$ | $0.25 \pm 0.01$ |
| **BERTscore precision** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.70 \pm 0.02$ | $0.70 \pm 0.00$ |
| **BERTscore recall** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.70 \pm 0.02$ | $0.70 \pm 0.00$ |
| **BERTscore F1** | $0.71 \pm 0.00$ | $0.71 \pm 0.00$ | $0.70 \pm 0.02$ | $0.70 \pm 0.00$ |
| **BARTscore faithful** | $-3.11 \pm 0.01$ | $-3.10 \pm 0.00$ | $-3.10 \pm 0.08$ | $-3.06 \pm 0.01$ |
| **BARTscore precision** | $-2.88 \pm 0.00$ | $-2.89 \pm 0.01$ | $-2.96 \pm 0.09$ | $-2.93 \pm 0.02$ |
| **BARTscore recall** | $-2.89 \pm 0.00$ | $-2.88 \pm 0.01$ | $-3.11 \pm 0.1$ | $-2.87 \pm 0.01$ |
| **BARTscore F1** | $-2.86 \pm 0.00$ | $-2.86 \pm 0.01$ | $-2.99 \pm 0.1$ | $-2.87 \pm 0.01$ |

Table 23: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per group and prompt of Sonnet.

| | (non-)native system prompt | | | |
|---|---|---|---|---|
| | correct information | | wrong information | |
| model | native | non-native | native | non-native |
| **BLEU** | $0.41 \pm 0.00$ | $0.42 \pm 0.00$ | $0.41 \pm 0.01$ | $0.42 \pm 0.01$ |
| **ROUGE-1** | $0.37 \pm 0.01$ | $0.38 \pm 0.00$ | $0.38 \pm 0.01$ | $0.38 \pm 0.00$ |
| **ROUGE-2** | $0.13 \pm 0.01$ | $0.14 \pm 0.00$ | $0.14 \pm 0.01$ | $0.14 \pm 0.00$ |
| **ROUGE-L** | $0.26 \pm 0.01$ | $0.27 \pm 0.00$ | $0.27 \pm 0.01$ | $0.27 \pm 0.00$ |
| **BERTscore precision** | $0.70 \pm 0.00$ | $0.70 \pm 0.00$ | $0.70 \pm 0.00$ | $0.70 \pm 0.00$ |
| **BERTscore recall** | $0.69 \pm 0.01$ | $0.70 \pm 0.00$ | $0.69 \pm 0.01$ | $0.70 \pm 0.00$ |
| **BERTscore F1** | $0.69 \pm 0.01$ | $0.70 \pm 0.00$ | $0.70 \pm 0.01$ | $0.70 \pm 0.00$ |
| **BARTscore faithful** | $-3.12 \pm 0.01$ | $-3.11 \pm 0.01$ | $-3.11 \pm 0.01$ | $-3.11 \pm 0.01$ |
| **BARTscore precision** | $-2.93 \pm 0.02$ | $-2.92 \pm 0.01$ | $-2.91 \pm 0.01$ | $-2.93 \pm 0.02$ |
| **BARTscore recall** | $-2.96 \pm 0.02$ | $-2.93 \pm 0.02$ | $-2.95 \pm 0.02$ | $-2.93 \pm 0.02$ |
| **BARTscore F1** | $-2.91 \pm 0.02$ | $-2.90 \pm 0.02$ | $-2.90 \pm 0.02$ | $-2.90 \pm 0.02$ |
| | guess native system prompt | | | |
| | overall guess | | guess correctly | |
| metric | native | non-native | native | non-native |
| **BLEU** | $0.39 \pm 0.01$ | $0.39 \pm 0.00$ | $0.43 \pm 0.02$ | $0.32 \pm 0.01$ |
| **ROUGE-1** | $0.34 \pm 0.00$ | $0.34 \pm 0.01$ | $0.39 \pm 0.01$ | $0.30 \pm 0.00$ |
| **ROUGE-2** | $0.10 \pm 0.00$ | $0.10 \pm 0.00$ | $0.12 \pm 0.02$ | $0.07 \pm 0.00$ |
| **ROUGE-L** | $0.23 \pm 0.00$ | $0.23 \pm 0.00$ | $0.24 \pm 0.02$ | $0.21 \pm 0.00$ |
| **BERTscore precision** | $0.68 \pm 0.00$ | $0.68 \pm 0.00$ | $0.65 \pm 0.01$ | $0.65 \pm 0.01$ |
| **BERTscore recall** | $0.68 \pm 0.00$ | $0.68 \pm 0.00$ | $0.67 \pm 0.01$ | $0.66 \pm 0.00$ |
| **BERTscore F1** | $0.68 \pm 0.00$ | $0.68 \pm 0.00$ | $0.66 \pm 0.01$ | $0.65 \pm 0.01$ |
| **BARTscore faithful** | $-3.26 \pm 0.01$ | $-3.25 \pm 0.01$ | $-3.01 \pm 0.03$ | $-3.14 \pm 0.07$ |
| **BARTscore precision** | $-3.16 \pm 0.01$ | $-3.17 \pm 0.01$ | $-3.14 \pm 0.05$ | $-3.36 \pm 0.07$ |
| **BARTscore recall** | $-3.04 \pm 0.01$ | $-3.03 \pm 0.00$ | $-2.98 \pm 0.04$ | $-3.14 \pm 0.03$ |
| **BARTscore F1** | $-3.06 \pm 0.01$ | $-3.07 \pm 0.01$ | $-3.03 \pm 0.04$ | $-3.21 \pm 0.04$ |

Table 24: Overall average generative performance metrics and standard deviation over three runs for all generative tasks per group and prompt of Qwen.

| | GPT3.5 | | GPT4o | | Haiku | | Sonnet | | Qwen 7B | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **native** | **non-native** | **native** | **non-native** | **native** | **non-native** | **native** | **non-native** | **native** | **non-native** |
| **BLEU** | 0.35 | 0.36 | 0.46 | 0.46 | 0.45 | 0.45 | 0.43 | 0.43 | 0.32 | 0.32 |
| **ROUGE-1** | 0.34 | 0.35 | 0.41 | 0.41 | 0.40 | 0.41 | 0.37 | 0.37 | 0.31 | 0.31 |
| **ROUGE-2** | 0.12 | 0.12 | 0.17 | 0.17 | 0.16 | 0.16 | 0.13 | 0.13 | 0.09 | 0.09 |
| **ROUGE-L** | 0.25 | 0.26 | 0.30 | 0.30 | 0.29 | 0.30 | 0.26 | 0.26 | 0.20 | 0.21 |
| **BERTscore precision** | 0.69 | 0.70 | 0.72 | 0.73 | 0.72 | 0.72 | 0.71 | 0.71 | 0.67 | 0.67 |
| **BERTscore recall** | 0.67 | 0.68 | 0.71 | 0.71 | 0.71 | 0.72 | 0.69 | 0.69 | 0.63 | 0.63 |
| **BERTscore F1** | 0.68 | 0.69 | 0.72 | 0.72 | 0.71 | 0.72 | 0.70 | 0.70 | 0.65 | 0.65 |
| **BARTscore faithful** | -2.80 | -2.81 | -2.95 | -2.97 | -2.88 | -2.90 | -3.12 | -3.13 | -3.13 | -3.10 |
| **BARTscore precision** | -2.82 | -2.81 | -2.67 | -2.68 | -2.70 | -2.71 | -2.89 | -2.90 | -3.09 | -3.07 |
| **BARTscore recall** | -2.98 | -2.95 | -2.74 | -2.72 | -2.68 | -2.66 | -2.98 | -2.97 | -3.37 | -3.34 |
| **BARTscore F1** | -2.86 | -2.84 | -2.68 | -2.68 | -2.66 | -2.66 | -2.90 | -2.89 | -3.18 | -3.17 |

Table 25: Overall average generative performance metrics for all generative tasks per model and group where the annotation process was simulated through the LLM to get the reference sentence.