Abstract

Despite recent progress, large language models (LLMs) still face the challenge of appropriately reacting to the intricacies of social and cultural conventions. This paper presents MANGO, a methodology for distilling high-accuracy, high-recall assertions of cultural knowledge. We judiciously and iteratively prompt LLMs for this purpose from two entry points, concepts and cultures. Outputs are consolidated via clustering and generative summarization. Running the MANGO method with GPT-3.5 as underlying LLM yields 167K high-accuracy assertions for 30K concepts and 11K cultures, surpassing prior resources by a large margin. For extrinsic evaluation, we explore augmenting dialogue systems with cultural knowledge assertions. We find that adding knowledge from MANGO improves the overall quality, specificity, and cultural sensitivity of dialogue responses, as judged by human annotators. Data and code are available for download.

1 Introduction

Motivation: The theme of enhancing computers with commonsense knowledge (CSK) has been revived in recent years, to improve the robustness and versatility of AI-powered NLP methods (e.g., (Bosselut et al., 2019; Hwang et al., 2021; West et al., 2022; Choi, 2022)). CSK collections, such as ConceptNet (Speer et al., 2017) and ATOMIC (Sap et al., 2019), capture assertions about mundane objects and human activities in a broad sense, so as to provide universal background knowledge. However, norms for human behavior are often diverse, with substantial diversity across different parts of the world and different socio-cultural groups. For example, when two people meet, they shake hands in the Western world, but this would be uncommon in Southeast Asia (where people wai each other), and teenagers have yet another way of greeting.

Therefore, to adapt AI applications to specific user contexts, the goal of this research is to capture culturally aware commonsense knowledge, CCSK for short.

An NLP task where cultural knowledge can play a game-changing role is human-computer dialogue, where the system should consider the human’s cultural background. An even more challenging case is conversations between two partners from different cultures; we call this case intercultural dialogue. Computers can take one, both or none of the roles in this setting; in the latter case, it could still be important to have cultural knowledge to analyze and post-process the dialogue (e.g., generate a debriefing summary).

State of the Art and its Limitations: On this nascent direction, resources for cultural knowledge have limited scope and scale (e.g., (Acharya et al., 2020), StereoKG (Deshpande et al., 2022), Candle (Nguyen et al., 2023b)). The by far largest of these is the Candle knowledge base, which comprises ca. 60K assertions automatically distilled from nearly 1M sentences mined from a large web crawl. This is still insufficient in coverage of concepts and cultural groups. Note that cultures are not just geo-regions, but should ideally consider also demographic and social traits of the respective groups (e.g., female teenagers in Korea, French people of North-African descent, etc.).

An obvious idea is to abandon explicit assertions, and instead rely on the latent knowledge provided by large language models (LLMs). Indeed, LLMs perform well on tasks that require understanding the personal background of users in conversational settings. However, there are severe disadvantages: (i) strong dependence on the quality of the training corpus (which may exhibit certain biases and risks of hallucination); (ii) lack of transparency of what piece of knowledge is utilized in which context; (iii) as a result, lack of controllability for programmed
applications; and (iv) lack of interpretability by end-users. For these reasons, our approach is to construct transparent and tangible collections of explicit assertions, which can later be judiciously injected into LLMs for specific tasks.

Challenges and Research Questions: The twofold challenge is to expand the coverage of cultural groups and culture-specific assertions, while maintaining or even improving the quality of the assertions. This poses three research questions:

- **RQ1**: How can we systematically capture more and diverse cultural groups?
- **RQ2**: How can we substantially enlarge the amount of captured assertions, going beyond single-sentence retrieval from the web?
- **RQ3**: How can we ensure the specificity of assertions, while avoiding undue stereotypes and limiting redundancy due to frequency bias?

Approach and Contribution: The methodology devised in this work, called MANGO (multi-cultural commonsense knowledge distillation), comprises two stages: a coverage-oriented stage for assertion generation, and a quality-oriented stage for assertion consolidation. The first stage addresses RQ1 and RQ2, and the second addresses RQ3.

To enlarge the pool of candidates, we leverage a large language model (LLM), specifically GPT-3.5, to generate assertions. Unlike prior works that tapped into web crawls, this is an implicit way of tapping the LLM's pre-training collection. Compared to web retrieval, the scales are similar but the advantage is that LLM training data involves efforts to remove spam and offensive content. Asking an LLM to generate assertions requires judicious prompting. For high coverage of diverse cultures, an important novelty in our method is to construct prompts for both concepts (incl. human activities) from an existing (culturally agnostic) commonsense knowledge base and groups from a large pool of cultures.

To ensure the informativeness of assertions and to tame the redundancy of generated candidates (RQ3), the second stage consists of steps for assertion consolidation. This is carried out by clustering the pool of assertions into topically and culturally coherent groups, considering both the key concept in an assertion and the culture to which it refers. The LLM is leveraged again to generate a concise summary statement for each cluster. This exploits the LLM’s language skills, but does not rely on actual knowledge by the LLM.

The main contributions of this work are:
1. The MANGO methodology for efficiently distilling CCSK from LLMs, at high precision and recall.
2. Running the MANGO method with GPT-3.5, to obtain 167K assertions for 30K concepts and 11K cultures, substantially surpassing prior CCSK resources in size and quality.
3. An extrinsic evaluation for intercultural dialogues, where the injection of MANGO assertions significantly improves the specificity and cultural sensitivity of responses.

2 Related Work

Commonsense Knowledge Acquisition: Commonsense knowledge (CSK) has a long tradition in AI (Lenat, 1995; Liu and Singh, 2004; Gordon et al., 2010). Early projects such as Cyc (Lenat, 1995) and ConceptNet (Liu and Singh, 2004; Speer and Havasi, 2012; Speer et al., 2017) rely on human contributors and focus on collecting CSK about everyday concepts. This approach has been revived in the ATOMIC project (Sap et al., 2019), which collects CSK about social interactions and events.

Another line of CSK acquisition methods is based on text extraction, for example, WebChild (Tandon et al., 2014), Quasimodo (Romero et al., 2019), TransOMCS (Zhang et al., 2020), and Ascent (Nguyen et al., 2021, 2023a). These are more scalable, but contain noise and have lower assertion quality.

With the advent of LLMs, methods have been devised for generating CSK assertions from language models (e.g., (Bosselut et al., 2019; Petroni et al., 2019; Hwang et al., 2021; West et al., 2022; Cohen et al., 2023; West et al., 2023)). None of these captures culture-aware knowledge, though.

Cultural Knowledge Acquisition: There are only few works on culture-aware knowledge: (Anacleto et al., 2006), (Acharya et al., 2020), (Shwartz, 2022), StereoKG (Deshpande et al., 2022), Candle (Nguyen et al., 2023b), and GD-COMET (Bhatia and Shwartz, 2023). These methods are based on extraction from text (Deshpande et al., 2022; Shwartz, 2022; Nguyen et al., 2023b), or fine-tuning LLMs (Bhatia and Shwartz, 2023). The resulting assertions either suffer from high noise or limited coverage, with the largest resource, Candle, providing 60K assertions. Most recently, CH-Wang et al. (2023) aligned social situations from an English knowledge base (Forbes et al., 2020) and...
Chinese QA forums to mine 3,069 social norms for these two cultures. All of these prior works are very limited in scope and scale.

**Culture-aware NLP:** Several benchmarks exist for tasks that involve cultural knowledge beyond the Western world, e.g., MaRVL (Liu et al., 2021), GD-VCR (Yin et al., 2021), GeoMLAMA (Yin et al., 2022), CALI (Huang and Yang, 2023), and FORK (Palta and Rudinger, 2023). Some methods (e.g., (Li and Zhang, 2023), (Zhou et al., 2023)) have used LLMs to solve tasks of this kind. Most recently, contemporaneous work (Fung et al., 2024) extracts 148K cultural norms and norm violations from Wikipedia texts, and uses these to benchmark cultural knowledge and reasoning skills of LLMs.

Harnessing explicit CSK assertions for dialogue systems has been studied in (Kim et al., 2023), based on the ATOMIC resource (about social interactions). NormDial (Li et al., 2023) is a small collection of 267 human-written social norms specific to America and China, used to generate a bilingual dialogue dataset on social norms adherence or violation. In this work, we aim at a much broader coverage of diverse cultures, and apply our large-scale MANGO collection to the task of intercultural dialogues.

### 3 Cultural Commonsense Knowledge Distillation Workflow

We propose MANGO, a workflow for distilling and consolidating cultural commonsense knowledge (CCSK) from large language models (LLMs).

**Definition 1** (Cultural commonsense knowledge assertion). A cultural commonsense knowledge (CCSK) assertion \( a = (c; g; s) \) is a triple of a concept \( c \); a culture/cultural group \( g \); and a natural-language statement \( s \) that represents a cultural belief, norm, or common practice about the concept \( c \) that applies to group \( g \). An example CCSK assertion is: \( \text{tipping; Japan; Not a common practice} \).

The goal of MANGO is to generate CCSK for diverse cultures, covering a wide variety of concepts. Moreover, by clustering similar assertions, we obtain ranking signals for the assertions, which can be useful for downstream applications.

Our workflow consists of 2 phases, each consisting of 2 steps: (1a) generating CCSK for a given concept, (1b) generating CCSK for a given culture (Section 3.1), (2a) clustering similar CCSK assertions, and (2b) generating cluster representatives (Section 3.2). An overview of our workflow is depicted in Figure 1. We also provide input and output examples for each step in Table 1.

#### 3.1 Phase 1: Assertion Generation

People of different cultures may have different perspectives on certain concepts. These differences are what we are interested in, as they are crucial in situations where cross-cultural knowledge is required to understand one another. One might ask LLMs to generate CCSK for a given pair of concept and culture (e.g., prompting for perceptions of tipping in Japan). However, the main drawback of this approach is that it requires concept and culture pairings, which is problematic because of the large number of possible combinations, and the fact that some combinations may not make sense.

Instead, we propose to use LLMs to generate CCSK for a given concept or a given cultural group separately. This way we let the model decide which concepts are relevant for a given cultural group and vice versa, which will reduce the chance of nonsensical concept-culture combinations, hence reducing costs. Example prompts and outputs can be seen in Table 1.

For each prompt, we provide the LLM with 5 pairs of example assertions randomly drawn from a set of human-written CCSK assertions. Each example consists of a concept, and 2 different perspectives on that concept associated with 2 or more different cultures (more details on prompt templates can be found in Appendix A.1). We implement our workflow using GPT-3.5. However, in practice, other LLMs could be used. We also run each prompt several times at a high temperature (i.e., high creativity), that can hopefully lead to different output assertions given the same input.

**Step 1a: Generating CCSK for a given concept**

We seed this step with concepts from ConceptNet (Speer et al., 2017), which is a popular commonsense knowledge base constructed by human annotations and consists of a wide range of everyday concepts. In addition, we also use cultural concepts from Candle (Nguyen et al., 2023b) as inputs for this step. Candle is a cultural knowledge base constructed by extracting relevant sentences from a cleaned web crawl.

**Step 1b: Generating CCSK for a given culture**

The seed cultures used for this step are taken from the Candle dataset, which include geo-locations (countries, continents, geo-regions), and religions.
Phase 1: Assertion Generation

Step 1a: Generating CCSK for a given concept
Input concept: chopsticks
Prompt: You are a helpful assistant that writes culture-specific commonsense assertions. Some examples assertions are listed below:
+ car | Important in US, Germany | Considered luxury item in poorer countries
+ < more examples ... >
Please write assertions for the concept: chopsticks.
Parsed output:
- Concept: chopsticks. Culture: Western countries. Statement: Considered exotic and less commonly used for everyday meals.

Step 1b: Generating CCSK for a given culture
Input culture: Japan
Prompt: You are a helpful assistant that writes culture-specific commonsense assertions. Some examples assertions are listed below:
+ rice | Staple food in East Asia | Side dish in European countries
+ < more examples ... >
Please write assertions for the culture: Japan.
Parsed output:

Step 2a: CCSK assertion clustering
Input: >500K CCSK assertions
Sample output cluster:
- Concept: leaving tip. Culture: Japanese culture. Statement: Not a common practice and may even be seen as rude. (Frequency: 2)
- Concept: tipping at restaurants. Culture: Japan. Statement: Tipping is not commonly practiced and can even be considered rude as it implies that the service is not already included in the price. (Frequency: 1)
- Concept: tipping service staff. Culture: Japan. Statement: Not a common practice and can even be considered rude or disrespectful. (Frequency: 1)

Step 2b: Cluster representative generation
Prompt: Please generate a representative sentence for the following assertions:
<the sample cluster above>
Output: Concept: tipping. Culture: Japan. Statement: Tipping is not a common practice in Japan and can be considered rude or impolite. (Frequency: 9)

Table 1: Examples of the MANGO workflow.

Iterative Generation  Step 1a and Step 1b are processed independently, and each step can generate new cultural groups and concepts, respectively. These new concepts and cultural groups can be fed back to the corresponding approach in order to generate new CCSK assertions.

3.2 Phase 2: Assertion Consolidation
It is natural that our CCSK generation approaches produce similar assertions that have very little or zero semantic differences. The repetitions come from the fact that there exist concepts with similar meanings (e.g., tea, drinking tea, and tea drinking), and terms referring to the same groups (e.g., East Asia, East Asian cultures, and East Asian countries) in the input. Furthermore, as we run each prompt several times, even at high output randomness (temperature), repetitions are inevitable.

While untreated redundancy is undesirable, we propose to take advantage of these redundancies in order to rank our assertions. Specifically, by grouping together semantically similar assertions, we create frequency signals, which can be useful for downstream applications which only look for a subset of highest-significance assertions.

Step 2a: Assertion Clustering  As we generate hundreds of thousands of assertions in Phase 1, it is prohibitively expensive to run a clustering algorithm on all assertions at once. It would even be infeasible for algorithms such as the Hierarchical Agglomerative Clustering (HAC) algorithm to process such a large amount of data points. Instead, we propose a divide-and-conquer approach to clustering this large set of assertions. Our approach consists of 3 substeps:

1. Clustering similar concepts: The concepts in the assertions generated in Phase 1 are clustered into groups of similar concepts.
2. Clustering similar cultures: Similarly to concept clustering, we group together similar cultures.
3. Clustering subsets of assertions: For each pair of concept cluster and culture cluster, we only cluster the subset of assertions associated with any of the concepts and any of the cultures in those clusters.

As the sizes of the entire concept and culture sets and the corresponding assertion subsets are substantially smaller than that of the entire set of generated assertions, standard clustering algorithms...
can process them efficiently. In our experiment, we use SentenceBert embeddings (Reimers and Gurevych, 2019) and the HAC algorithm for all 3 substeps. Nevertheless, in practice, other text embedding models and clustering algorithms could be used. An example assertion cluster can be found in Table 1, in which the respective concept cluster includes *tipping*, *leaving tip*, *tipping at restaurants*, *tipping service staff*, and the culture cluster includes *Japan*, *Japanese*, *Japanese culture*.

**Step 1a:**

- **Input:** 31,196 concepts
- **Output:** 468,543 assertions

**Step 1b:**

- **Input:** 10,796 cultures
- **Output:** 115,220 assertions

**Step 2a:**

- **Input:** 507,780 filtered assertions
- **Output:** 167,396 assertion clusters

**Step 2b:**

- **Input:** 167,396 assertion clusters
- **Output:** 167,396 full CCSK sentences

<table>
<thead>
<tr>
<th>Step</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1a (2 runs)</td>
<td>31,196 concepts</td>
<td>468,543 assertions</td>
</tr>
<tr>
<td>Step 1b (2 runs)</td>
<td>10,796 cultures</td>
<td>115,220 assertions</td>
</tr>
<tr>
<td>Step 2a</td>
<td>507,780 filtered assertions</td>
<td>167,396 assertion clusters</td>
</tr>
<tr>
<td>Step 2b</td>
<td>167,396 assertion clusters</td>
<td>167,396 full CCSK sentences</td>
</tr>
</tbody>
</table>

Table 2: Input and output of each step in our implementation.

**Step 2b: Representative Generation**

For each cluster of CCSK assertions, we generate a full sentence as the representative of the cluster. We also obtain the frequency of each cluster by adding up all the frequencies of its member assertions.

For the final output, we store a set of CCSK cluster instances, each containing the following information: *concept* (the representative concept of the CCSK cluster), *culture* (the representative culture of the CCSK cluster), *statement* (the representative sentence of the CCSK cluster), *similar statements* (the set of the statements of the member assertions), and *frequency* (the frequency sum of the cluster).

**4 Implementation of MANGO**

We implement our workflow using GPT-3.5. In the generation phase, we run each prompt 5 times with a temperature of 1.0 (high creativity). We summarize the input and output of our implementation in Table 2.

**Input Concepts and Cultures:**

We run each step in Phase 1 twice, whereas the first run is fed with seed concepts and seed cultures from prior datasets, and the second run is fed with new concepts and cultures generated in the first run.

- **Seed concepts:** We take 8,357 concepts from Candle (Nguyen et al., 2023b), which have more than 1 assertion, and 16,480 concepts from ConceptNet (Speer et al., 2017), which have more than 3 assertions. We clean this set of concepts by filtering out incomprehensible phrases using GPT-3.5, retaining a seed set of 19,940 concepts for the first run of Step 1a.
- **Seed cultures:** We take 286 groups (272 geolocations and 14 religions) from Candle as seed cultures for the first run of Step 1b.

After the first run of Step 1a with the seed concepts, we obtain 10,510 new cultures. After the first run of Step 1b with the 286 seed cultures, and the second run with the new 10,510 cultures, we obtain 11,256 new concepts, which are used for the second run of Step 1a.

**Assertion Filtering:**

After Phase 1, we obtain 581,563 distinct CCSK assertions. We perform various simple filters to clean these assertions:

- Removing too long or too short assertions: We restrict the length of assertion to be between 2 and 25 words.
- Removing assertions that have more than one sentence in the generated statements.
- Removing assertions whose cultures are too general or noisy: We construct a dictionary of words that a valid culture should not contain. For example, we filter out cultures such as “Other cultures” (context-dependent), “Non-European countries”, “Some parts of Asia” (not specific enough), etc. More details on this dictionary can be found in Appendix A.2.

After filtering, we obtain 507,780 assertions (i.e., 87% of the original set), 14,298 cultural groups, and 32,126 concepts.

**Clustering:**

For both concept, culture and assertion clustering, we use the HAC algorithm combined with the SentenceBert embedding model all-MiniLM-L6-v2. We use point-wise Euclidean distance of normalized embeddings, the Ward’s linkage (Ward, 1963), and the distance threshold set to 1.5, which are adopted from the Candle method (Nguyen et al., 2023b).

We obtain 4,571 concept clusters and 1,610 culture clusters, with the largest candidate set for assertion clustering containing 463 assertions. Finally, we obtain 167,396 assertion clusters, where the largest cluster contains 141 assertions. Table 3 lists the top cultures and concepts in our dataset.

**Costs:**

The assertion generation steps costed $71. On average, each thousand generated assertions
costed 12 cents. The cluster representative generation costed $41. On average, each thousand cluster representative generations costed 25 cents.

The API to the GPT-3.5 model we used in this implementation has limits at 1M input tokens per minute, and 10K requests per minute. By making concurrent requests, our workflow could be executed in less than 5 hours, including the clustering steps which take less than 30 minutes.

5 Quality of MANGO Assertions

We evaluate the assertion quality of MANGO by comparison to several resources of similar kind.

**Compared Resources:** Our baseline resources are Quasimodo (Romero et al., 2019), StereoKG (Deshpande et al., 2022) and Candle (Nguyen et al., 2023b). StereoKG and Candle are specialized in culture-specific knowledge. Quasimodo is a general commonsense knowledge base, but for this comparison, we only consider Quasimodo assertions that contain geo-locations or religions.

StereoKG and Candle store assertions in the form of natural-language sentences, while Quasimodo assertions originally come in triple format (subject-predicate-object). Therefore, for comparability, we verbalized the Quasimodo assertions using GPT-3.5.

For our resource, in addition to the full assertion set (MANGO\text{full}), we also evaluate MANGO\text{top}, which contains the top-ranked assertions up to the same size as Candle (i.e., 60K assertions).

**Metrics:** CCSK assertions should satisfy a set of conditions, that are sometimes in conflict. We employ three dimensions (Bhatia and Shwartz, 2023) to evaluate their intrinsic quality:

1. **Cultural Relevance (CR)** measures the plausibility of the assertion, i.e., whether the statement actually represents cultural knowledge.
2. **Stereotype Avoidance (SA)** assesses if the assertion avoids reinforcing cultural stereotypes and presenting offensive materials.
3. **Linguistic Accuracy (LA)** checks if the assertion is grammatical, meaningful and understandable as a standalone sentence.

**Setup:** Our evaluation is conducted on the Amazon Mechanical Turk (MTurk) platform. Specifically, we ask human annotators on MTurk to evaluate each assertion along the 3 dimensions, each on a 3-point Likert scale: negation (0), ambiguity (1) and affirmation (2) (the evaluation questions can be found in Appendix B and Figure 3). For each resource, we randomly sample 300 assertions for evaluation, each assessed by 3 different workers.

**Results:** We report averaged scores given by the annotators in Table 4. It can be seen that MANGO assertions have the highest quality compared to prior resources. Notably, despite being nearly 3 times larger than the largest baseline, MANGO\text{full} has better quality than all baselines, on all metrics. Moreover, our top-ranked assertion subset, MANGO\text{top}, has the same size as Candle, but it outperforms this resource on all 3 metrics by a large margin. This affirms that the frequency signals we obtain in our clustering step are helpful for pulling out the most significant assertions.

### Table 3: Top concepts and cultures in MANGO.

<table>
<thead>
<tr>
<th>Concept</th>
<th>Count</th>
<th>Culture</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>family</td>
<td>372</td>
<td>United States</td>
<td>9097</td>
</tr>
<tr>
<td>tea</td>
<td>352</td>
<td>Japan</td>
<td>4597</td>
</tr>
<tr>
<td>hospitality</td>
<td>349</td>
<td>India</td>
<td>3670</td>
</tr>
<tr>
<td>personal space</td>
<td>338</td>
<td></td>
<td></td>
</tr>
<tr>
<td>marriage</td>
<td>285</td>
<td>Western countries</td>
<td>5788</td>
</tr>
<tr>
<td>family structure</td>
<td>234</td>
<td>Eastern countries</td>
<td>1849</td>
</tr>
<tr>
<td>education</td>
<td>228</td>
<td>Middle Eastern countries</td>
<td>1059</td>
</tr>
<tr>
<td>gender roles</td>
<td>200</td>
<td></td>
<td></td>
</tr>
<tr>
<td>public transportation</td>
<td>193</td>
<td></td>
<td></td>
</tr>
<tr>
<td>music</td>
<td>183</td>
<td>Christianity</td>
<td>142</td>
</tr>
<tr>
<td>traditional clothing</td>
<td>180</td>
<td>Islamic countries</td>
<td>121</td>
</tr>
<tr>
<td>time</td>
<td>174</td>
<td>Hinduism</td>
<td>106</td>
</tr>
<tr>
<td>food</td>
<td>149</td>
<td>Amazonian tribes</td>
<td>143</td>
</tr>
<tr>
<td>spicy food</td>
<td>148</td>
<td>Inuit communities</td>
<td>101</td>
</tr>
<tr>
<td>fishing</td>
<td>132</td>
<td>Maori culture</td>
<td>73</td>
</tr>
</tbody>
</table>

### Table 4: Results of intrinsic evaluation via human annotations (metrics: CR - cultural relevance, SA - stereotype avoidance, LA - linguistic accuracy), along with the coverage of the resources (#C - number of cultures, #A - number of assertions). The (*) marker indicates results with statistically significant gains over Candle ($p < 0.05$ in the Student’s t-test).

<table>
<thead>
<tr>
<th>Resource</th>
<th>CR</th>
<th>SA</th>
<th>LA</th>
<th>Size</th>
<th>#C</th>
<th>#A</th>
</tr>
</thead>
<tbody>
<tr>
<td>StereoKG</td>
<td>0.75</td>
<td>0.90</td>
<td>1.11</td>
<td>10</td>
<td>4K</td>
<td></td>
</tr>
<tr>
<td>Quasimodo</td>
<td>0.85</td>
<td>1.18</td>
<td>1.35</td>
<td>0.4K</td>
<td>131K</td>
<td></td>
</tr>
<tr>
<td>Candle</td>
<td>1.59</td>
<td>1.65</td>
<td>1.76</td>
<td>0.4K</td>
<td>60K</td>
<td></td>
</tr>
<tr>
<td>MANGO\text{full}</td>
<td>1.65*</td>
<td>1.71*</td>
<td>1.88*</td>
<td>11.1K</td>
<td>167K</td>
<td></td>
</tr>
<tr>
<td>MANGO\text{top}</td>
<td>1.71*</td>
<td>1.76*</td>
<td>1.90*</td>
<td>8.1K</td>
<td>60K</td>
<td></td>
</tr>
</tbody>
</table>

6 CCSK for Intercultural Dialogues

Explicit knowledge has been used to improve LLM performance in downstream tasks such as social dialogue generation (Kim et al., 2023) and intra-
6.1 Next Utterance Generation

The input of this task includes: (1) a narrative that involves interactions between 2 people of different cultures, and (2) their ongoing dialogue. The task is to generate the utterance of the next speaker. To excel in this task, LLMs need to leverage cultural knowledge such that the generated responses are natural, consistent, culturally sensitive and specific. We provide an example of input and output for this task in Table 5. More examples and details of prompting techniques can be found in Appendix C.

**Input Construction:** First, using GPT-3.5 and a small set of few-shot examples, we generate short narratives involving 2 people of different cultures, e.g., “Liz from England is visiting her friend Qiang in China. They are preparing tea together.”. Then, for each narrative, we ask the LLM to generate a possible dialogue between the 2 participants in that situation. Finally, the first 3 utterances of each generated dialogue are used to construct test samples. Prompt templates and narrative examples can be found in Appendix C.1 and Table 8.

**Methods:** We compare 2 methods, without and with explicit CCSK assertions in the prompts. Method 1 (Vanilla LLM), prompts an LLM with the task description, the input narrative, and the dialogue history. On the other hand, Method 2 (LLM with explicit CCSK), alters the prompts of Method 1 by augmenting relevant CCSK. For that, we retrieve the top-2 assertions from MANGO, based on cosine similarity between embeddings of the input narrative and our CCSK assertions. We provide more details on the retrieval technique in Appendix C.2. The templates for prompting LLMs with this task can be found in Appendix C.3.

**Setup:** We experiment with 3 different LLMs from some of the most popular model families: (i) GPT-3.5\(^4\), also known as ChatGPT, by OpenAI, (ii) the strongest model of the Mistral family by MistralAI\(^5\), and (iii) Google’s largest globally accessible language model as of January 2024, Bard\(^6\). For each LLM, we randomly draw 100 test samples and use the 2 methods to generate 100 pairs of responses. We employ human annotators on MTurk to evaluate the quality of the generated utterances.

\(^4\)Model name: gpt-3.5-turbo-1106
\(^5\)Model name: mistral-medium. Model description: https://docs.mistral.ai/platform/endpoints/
\(^6\)Accessed via https://bard.google.com/
Specifically, we show side-by-side the outputs of the 2 methods given the same input narrative, and ask the evaluators to choose the better one based on the following dimensions:

1. **Naturalness**: The response does not sound awkward or unnatural.
2. **Consistency**: The response does not contradict the narrative or previous utterances.
3. **Specificity**: The response contains specific details rather than vague/generic information.
4. **Cultural Sensitivity**: The response shows respect and understanding of the cultures.
5. **Overall Quality**: The overall satisfaction with the response.

Dimensions 1-3 and 5 are established criteria for evaluating dialogues (Mehri et al., 2022; Kim et al., 2023), dimension 4 is a dimension we introduce in this evaluation, as per our focus on cross-cultural knowledge.

Each sample is evaluated by 3 different MTurk workers. To alleviate positional bias, the orders of the outputs are randomly shuffled before being revealed to the annotators. More details on the human evaluation can be found in Appendix C.4.

**Results**: The human evaluation results are demonstrated in Figure 2. It can be seen that explicit CCSK assertions help all 3 LLMs to perform significantly better in this task, as the overall quality of the generated utterances are preferred by the human annotators compared to the outputs of the vanilla LLMs. This is attributed by the fact that the CCSK-enhanced utterances are more specific and culturally sensitive (for all 3 LLMs), and even more natural and consistent (for Bard). This shows that even though LLMs inherently possess cultural knowledge, they often fail to incorporate such knowledge into the generated utterances, and that explicit CCSK injected in the prompts can mitigate this problem. We provide some evaluated test samples in Table 12 in Appendix C.4.

Additionally, we also compared using MANGO vs. Candle (Nguyen et al., 2023b) assertions for augmenting prompts to GPT-3.5. We sample 100 test narratives and use the same retrieval method for both resources in this comparison. Human annotators preferred utterances generated with MANGO assertions in terms of naturalness, consistency and specificity. The head-to-head preferences for each dimension are (MANGO vs. Candle): Naturalness (32.7% vs. 30.7%); Consistency (30.7% vs. 28.0%); Specificity (39.7% vs. 37.0%); Cultural Sensitivity (34.3% vs. 34.3%); Overall Quality (46.0% vs. 46.0%).

### Table 6: Results of head-to-head human evaluation for the full dialogue generation task with GPT-3.5.

<table>
<thead>
<tr>
<th>Metric</th>
<th>No CCSK</th>
<th>W/ CCSK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naturalness</td>
<td>39.3%</td>
<td>38.7%</td>
</tr>
<tr>
<td>Consistency</td>
<td>21.0%</td>
<td>22.7%</td>
</tr>
<tr>
<td>Specificity</td>
<td>36.7%</td>
<td>43.0%</td>
</tr>
<tr>
<td>Cultural Sensitivity</td>
<td>22.7%</td>
<td>28.3%</td>
</tr>
<tr>
<td>Overall Quality</td>
<td>40.7%</td>
<td>44.7%</td>
</tr>
</tbody>
</table>

#### 6.2 Full Dialogue Generation

In this task, instead of generating a single utterance, we ask LLMs to generate a full dialogue between the 2 people in a given narrative. We anticipate that this task is more difficult both for the LLMs to solve and for humans to evaluate.

We randomly sample 100 test narratives and ask GPT-3.5 to generate dialogues. We use the same prompting methods and evaluation setup as in the previous task. The evaluation results can be found in Table 6. It can be seen that injecting explicit CCSK in the prompts does not diminish the natural flow and consistency of the generated dialogues, on the other hand, it provides more specificity and cultural sensitivity into the intercultural interactions. As a result, the annotators prefer the CCSK-enhanced dialogues on overall quality, similar to the results of the next utterance generation task.

Along with the CCSK collection, we also release a dataset of 5,000 intercultural narratives and dialogues generated by GPT-3.5 with and without CCSK augmented for further research, under the CC-BY-4.0 License.

### 7 Conclusion

We presented MANGO, a methodology to distill and consolidate CCSK from LLMs. We executed the MANGO workflow using GPT-3.5, obtaining a collection of 167K assertions covering 11K cultures and 30K concepts, which surpasses existing resources in quality and coverage by a large margin. In the extrinsic evaluation, we showed that by augmenting explicit assertions from MANGO into prompts, LLMs can perform better in intercultural dialogue generation tasks as their responses were judged more specific, more culturally sensitive, and better overall quality by human evaluators.
Limitations

Although our method for CCSK distillation outperforms text extraction by a large margin in terms of quality and size, there are three inherent limitations when using GPT-3.5: (1) Since GPT-3.5 is a commercial product provided via an API only, it cannot be guaranteed that our pipeline is long-term reproducible. (2) Since the training process of GPT-3.5 is undocumented, we do not know what corpus it has been trained on, and in particular, whether there might be systematic gaps in its training corpus (know what you don’t know). (3) Not specific to GPT-3.5, the usage of LLMs for CCSK distillation means losing the ability to trace assertions to their source, compared with text extraction.

Ethics Statement

Adapting conversational AI to cultural contexts is important for opening systems to diverse communities. At the same time, CCSK represents dual-use technology, as it can also be used to reinforce stereotypes, and discriminate.

Our data represents the outputs of a research prototype. We recommend against using our data in production systems without a careful evaluation of benefits (of having a system that is more culturally adept) and associated challenges and risks (of stereotype perpetuation etc.).

References


A Details of Assertion Generation

A.1 Prompt Templates

For assertion generation, we use the gpt-3.5-turbo-1106 model at its chat completion endpoint which takes as input a list of messages of 3 different roles: system, user, and assistant. The system’s message at the beginning of the list contains detailed instruction for the task being solved by the LLM. The user’s messages contain the inputs of the task. Given a list of messages, the API will return an assistant’s message, which is expected to contain the answers for the task.

For convenience, we ask GPT-3.5 to structure its responses into JSON objects. In each prompt, we provide 5 assertion pairs as few-shot examples, which are randomly sampled from a pool of 10 examples written by humans. The prompt templates can be found in Table 7.

A.2 Dictionary for Assertion Filtering

We have a small set of words to filter out low quality assertions. Specifically, if the culture of an assertion contains any of the following words, it will be rejected: other, general, 1, 2, (.), and, some, unknown, parts of, few, /, non-, many, outside, part of, various, elsewhere, rest of, certain.

B Details of Intrinsic Evaluation

For each competing resource, we sampled 300 assertions for evaluation. Each MTurk HIT contained 5 assertions and was compensated $0.40. We estimate each HIT takes 2 minutes to complete, hence an hourly wage of $12. The annotation page can be found in Figure 3. Each HIT is done by 3 different annotators. The annotators were required to be Master Workers with a lifetime approval rate greater than 99%. There were totally 36 different workers who participated in this task. We observed the following Krippendorff’s Alpha values for each of the metrics: Cultural Relevance: 0.42, Stereotype Avoidance: 0.23, Linguistic Accuracy: 0.41.

C Details of Extrinsic Evaluation

In this section, we provide details on prompting and other techniques used in the 2 extrinsic tasks.
Example 1: Generating CCSK for a given concept

User | Write culture-specific commonsense assertions for the concept: feeding dogs.

Assistant

```
"concept": "feeding dogs",
"commonsense": [
  {
    "culture": ["United States", "Europe"],
    "assertion": "Feeding dogs high-quality, specialized pet food is common practice."
  },
  {
    "culture": ["India", "Nepal"],
    "assertion": "Feeding dogs leftovers or homemade food is a common and acceptable practice."
  }
]
```

Example 2: Generating CCSK for a given culture

User | Write culture-specific commonsense assertions where one of the cultures is: Vietnam.

Assistant

```
"concept": "motorbike",
"commonsense": [
  {
    "culture": ["Vietnam"],
    "assertion": "Common mode of transportation for individuals and families"
  },
  {
    "culture": ["USA"],
    "assertion": "Often used as a recreational vehicle rather than a primary mode of transportation"
  }
]
```

Table 7: Examples of prompting GPT-3.5 to generate CCSK assertions.
Figure 3: The (truncated) MTurk annotation page for CCSK assertion evaluation. The page goes on with 4 other assertions.
(cf. Section 6).

C.1 Prompts for Narrative Generation
An example prompt for intercultural narrative generation can be seen in Table 8. In each prompt, we sample 3 narratives from a pool of 10 human-written narratives as few-shot examples. We use the GPT-3.5 model with a temperature of 1.0.

C.2 CCSK Retrieval
We use a simple embedding-based retrieval approach. First, we compute the embeddings of all assertions in our MANGO dataset using the SentenceBert model all-MiniLM-L6-v2. Then, given a narrative, we replace the names of the people with “X” and “Y” in order to reduce the distractions for the embedding model. For each given narrative, we retrieve the top-2 most similar CCSK assertions from MANGO based on cosine similarity of the embeddings. We also restrict the similarity to be better than 0.5. We only consider narratives that have relevant CCSK assertions retrieved from MANGO in the human evaluation. Examples of CCSK retrieval can be seen in Table 9.

C.3 Prompts for Extrinsic Tasks
Example prompts for the next utterance generation and full dialogue generation tasks can be found in Table 10 and Table 11 respectively.

C.4 Details of Human Evaluation for Extrinsic Tasks
The instruction and layout of our annotation pages used for MTurk evaluations are influenced by the work of Kim et al. (2023). Instead of using “Definitely A/B” and “Slightly A/B”, we narrow the option set down to “A is Better”, “B is Better”, and introduce a third option which is “Tie”. The annotation pages can be found in Figure 4 and Figure 5. For both tasks, we require the workers to be Master Workers who have a lifetime approval rate of more than 99%.

Utterance Comparison For the 300 pairs of evaluated utterances, there were 41 different MTurk workers who participated in the evaluation. Each HIT was compensated $0.20. We estimate each HIT takes 1 minute to complete, hence an hourly wage of $12. We observed the following Krippendorff’s Alpha values for each of the metrics: Naturalness: -0.06, Consistency: 0.06, Specificity: 0.20, Cultural Sensitivity: 0.10, Overall Quality: 0.02.

Dialogue Comparison For the 100 pairs of evaluated dialogues, there were 29 different MTurk participants. Each HIT was compensated $0.30. We estimate each HIT takes 1.5 minutes to complete, hence an hourly wage of $12. We observed the following Krippendorff’s Alpha values for each of the metrics: Natural Flow: 0.08, Consistency: 0.15, Specificity: 0.30, Cultural Sensitivity: 0.13, Overall Quality: 0.20.

We provide some samples evaluated by MTurk workers in Table 12 and Table 13.

D Dataset Usage and License
We used Quasimodo (CC-BY-2.0; Romero et al. (2019)), StereoKG (MIT License; Deshpande et al. (2022)), and Candle (CC-BY-4.0; Nguyen et al. (2023b)) for comparing with our MANGO dataset, which is compatible with their corresponding license.
We are studying meaningful evaluation metrics for the qualities of dialog responses.

Specifically, you will be given a dialog, its context, and two responses, and you will be asked to compare and determine which response is better in terms of specific metrics.

Guidelines
1. Please read the context, the dialogue, and the two responses carefully.
2. [Q0] Specify how familiar you are with the cultures in the context.
   - If you are not familiar with the context, please do a quick search on the Internet to answer the other questions.
3. [Q1-5] Choose the better response in terms of the corresponding metrics. There are three choices: A is better, Tie, and B is better
   - Try to focus on the quality over quantity. Contentful/high-quality responses do not need to be lengthy.

Context

Dialog

Response A

Response B

Question 0: How familiar are you with the cultures in the context?

- Very Familiar
- Slightly Familiar
- Not Familiar

Note: If you are not familiar with the context, please do a quick search on the Internet to answer the next questions.

Question 1: Which response is more natural?

- A is better
- Tie
- B is better

Question 2: Which response is more consistent?

- A is better
- Tie
- B is better

Question 3: Which response is more specific?

- A is better
- Tie
- B is better

Question 4: Which response is more culturally sensitive?

- A is better
- Tie
- B is better

Question 5: Which response has higher quality overall?

- A is better
- Tie
- B is better

Submit

Figure 4: The annotation page used for utterance evaluation on MTurk. Instruction and layout are influenced by Kim et al. (2023).
You are a narrative generator. Your task is to generate short narratives of less than 5 sentences around a cultural concept that involves two people from two different cultures. The narrative should lead to an intercultural interaction where cultural differences play a significant role. You must not include the cultural differences, or cultural knowledge, or the resolution, or the consequences of the situation in the narrative.

Some examples:
- Anna, an American, is visiting a remote village in Vietnam where Minh is a local. Anna asks Minh where she can get food for her dog.
- Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.
- Liz and Qiang are two friends, who are currently in England. Qiang is from China who is visiting the country. Liz is a local. They are preparing tea together.

Please write 3 more narratives:

- Maria, a Mexican, is visiting Japan and is shopping in a local market. She meets Yuki, a Japanese woman, and asks for help in choosing a traditional Japanese outfit for a festival.
- Pablo, a Spaniard, is traveling in India and meets Rajesh, a local, at a temple. They both want to participate in a religious ceremony, and Pablo asks Rajesh for guidance on the proper etiquette.
- Fatima, a Saudi Arabian, is studying in France and meets Pierre, a French student, at a party. They both want to dance, and Fatima asks Pierre to teach her a traditional French dance.

Table 8: An example of prompts used to generate intercultural narratives in the 2 extrinsic tasks.

<table>
<thead>
<tr>
<th>User</th>
<th>Assistant</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Maria, a Mexican, is visiting Japan and is shopping in a local market. She meets Yuki, a Japanese woman, and asks for help in choosing a traditional Japanese outfit for a festival.</td>
<td></td>
</tr>
<tr>
<td>- Pablo, a Spaniard, is traveling in India and meets Rajesh, a local, at a temple. They both want to participate in a religious ceremony, and Pablo asks Rajesh for guidance on the proper etiquette.</td>
<td></td>
</tr>
<tr>
<td>- Fatima, a Saudi Arabian, is studying in France and meets Pierre, a French student, at a party. They both want to dance, and Fatima asks Pierre to teach her a traditional French dance.</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5: The annotation page used for dialogue evaluation on MTurk. Instruction and layout are influenced by Kim et al. (2023).
Example 1

Narrative: Carlos from Argentina is visiting Korea. He greets his new Korean friend, Jihoon, by giving him a friendly pat on the back.

Query: X from Argentina is visiting Korea. He greets his new Korean friend, Y, by giving him a friendly pat on the back.

Retrieval Results:
• In South Korea, beckoning with an open hand or palm facing downwards is considered polite. (Similarity: 0.5216)
• In South Korean culture, it is common to gently pat someone on the shoulder or back as a sign of encouragement or reassurance. (Similarity: 0.5201)

Example 2

Narrative: Maria, a woman from Spain, is visiting a Bedouin tribe in Jordan upon an invitation from her new friend, Ahmed. They are preparing to have dinner under the star-lit desert sky.

Query: X, a woman from Spain, is visiting a Bedouin tribe in Jordan upon an invitation from her new friend, Y. They are preparing to have dinner under the star-lit desert sky.

Retrieval Results:
• Bedouins, a Middle Eastern culture, are known for their nomadic lifestyle, hospitality, and expertise in desert survival. (Similarity: 0.5217)
• Desert cultures highly value hospitality and express it through offering food, drinks, and shelter to guests. (Similarity: 0.5207)

Table 9: Examples of retrieving MANGO’s CCSK assertions relevant to given narratives.
Table 10: An example of prompts used in the next utterance generation task (cf. Section 6.1).

<table>
<thead>
<tr>
<th>System</th>
<th>User</th>
<th>Assistant</th>
</tr>
</thead>
<tbody>
<tr>
<td>You will be generating the next response of a given dialogue between two people. Along with the dialogue, you’ll be given some context about the two participants of the dialogue, e.g., their relationship, situation, etc. Please make the response naturalistic, consistent, specific, interesting and culturally sensitive.</td>
<td>Narrative: Anna, an American, is visiting a remote village in Vietnam where Minh is a local. Anna asks Minh where she can get food for her dog.</td>
<td>You will be generating the next response of a given dialogue between two people. Along with the dialogue, you’ll be given some context about the two participants of the dialogue, e.g., their relationship, situation, etc. Please make the response naturalistic, consistent, specific, interesting and culturally sensitive.</td>
</tr>
<tr>
<td>Please make the next response more culturally realistic using the following knowledge: - In Vietnam, dogs are often fed traditional homemade food or scraps from family meals, including rice and meat scraps. - In Scandinavian countries, spices are used sparingly, with a focus on simplicity and natural flavors in traditional dishes.</td>
<td>- Spicy food is a staple in South Korean cuisine, widely enjoyed, and considered an essential part of the diet. - Spicy food is a staple in South Korean cuisine, widely enjoyed, and considered an essential part of the diet.</td>
<td>Context: Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.</td>
</tr>
<tr>
<td>Dialog: Erling: Wow, Heungmin, this place looks amazing! What do you recommend we try for our dinner tonight? Heungmin: I’m glad you like it, Erling! You should definitely try bulgogi, it’s a Korean BBQ classic. And don’t miss out on kimchi, it’s a must-try side dish.</td>
<td>Dialog: Erling: Sounds great, Heungmin! I’ve heard a lot about bulgogi and kimchi, so I’m really looking forward to trying them. But I have to admit, I’m a little nervous about the spice level. I’m not used to eating such spicy food.</td>
<td>Dialog: Erling: Sounds great, Heungmin! I’ve heard a lot about bulgogi and kimchi, so I’m really looking forward to trying them. But I have to admit, I’m a little nervous about the spice level. I’m not used to eating such spicy food.</td>
</tr>
<tr>
<td>Table 11: An example of prompts used in the full dialogue generation task (cf. Section 6.2).</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>System</th>
<th>User</th>
<th>Assistant</th>
</tr>
</thead>
<tbody>
<tr>
<td>You are a dialog generator. You are given a narrative and related context such as the backgrounds of the speakers, and the situation of the interaction. Your task is to generate a short dialog between the two people involved in the narrative. The dialog is turn-by-turn which includes 6 utterances, each person has 3 utterances. Each person’s utterance should be 1 to 2 sentences. Please make the dialog naturalistic, consistent, specific, interesting and culturally sensitive.</td>
<td>Narrative: Anna, an American, is visiting a remote village in Vietnam where Minh is a local. Anna asks Minh where she can get food for her dog.</td>
<td>You will be generating the next response of a given dialogue between two people. Along with the dialogue, you’ll be given some context about the two participants of the dialogue, e.g., their relationship, situation, etc. Please make the response naturalistic, consistent, specific, interesting and culturally sensitive.</td>
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<td>- Spicy food is a staple in South Korean cuisine, widely enjoyed, and considered an essential part of the diet. - Spicy food is a staple in South Korean cuisine, widely enjoyed, and considered an essential part of the diet.</td>
<td>Context: Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.</td>
</tr>
<tr>
<td>Dialog:</td>
<td>Dialog:</td>
<td>Dialog:</td>
</tr>
<tr>
<td>Anna: Hey Minh, I need to find some food for my dog. Do you know where I can get some pet food around here? Minh: Hi Anna! Sure, you can try the small pet store down the road, it’s just a 10-minute walk from here. Anna: Great! Thanks, Minh. Is it easy to spot? I’m not familiar with the area. Minh: Yes, you won’t miss it. It’s a little blue shop with a sign featuring a dog and a cat. Anna: Perfect, I’ll head there soon. Do you think they have a variety of options? Minh: They should have a decent selection, but don’t expect the same variety as in the city. You’ll find some good options for your dog, though. Anna: That’s good to know. I appreciate your help, Minh. Minh: No problem, Anna. If you need anything else, just let me know. Enjoy your time in the village!</td>
<td>Erling: Sounds great, Heungmin! I’ve heard a lot about bulgogi and kimchi, so I’m really looking forward to trying them. But I have to admit, I’m a little nervous about the spice level. I’m not used to eating such spicy food.</td>
<td>Erling: Sounds great, Heungmin! I’ve heard a lot about bulgogi and kimchi, so I’m really looking forward to trying them. But I have to admit, I’m a little nervous about the spice level. I’m not used to eating such spicy food.</td>
</tr>
<tr>
<td>Anna: Hi Minh, I’m wondering where I can find some food for my dog around here? Do you know if there’s a pet store nearby? Minh: Oh, we don’t have pet stores here. But you can give your dog some rice and meat scraps. Many people do that for their dogs here. Anna: Oh, that’s interesting. I didn’t know that. Thank you for letting me know. Do you know where I can find rice and meat scraps then? Minh: You can check with the local market or some of the food vendors. They usually have some leftovers they can give you for your dog. Anna: Great, I’ll give that a try. Thank you for your help, Minh. It’s really different from what I’m used to back home.</td>
<td>You will be generating the next response of a given dialogue between two people. Along with the dialogue, you’ll be given some context about the two participants of the dialogue, e.g., their relationship, situation, etc. Please make the response naturalistic, consistent, specific, interesting and culturally sensitive.</td>
<td>Context: Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.</td>
</tr>
<tr>
<td>Dialog:</td>
<td>Dialog:</td>
<td>Dialog:</td>
</tr>
<tr>
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<td>Context: Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.</td>
</tr>
<tr>
<td>Dialog:</td>
<td>Dialog:</td>
<td>Dialog:</td>
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<tr>
<td>Anna: Hi Minh, I’m wondering where I can find some food for my dog around here? Do you know if there’s a pet store nearby? Minh: Oh, we don’t have pet stores here. But you can give your dog some rice and meat scraps. Many people do that for their dogs here. Anna: Oh, that’s interesting. I didn’t know that. Thank you for letting me know. Do you know where I can find rice and meat scraps then? Minh: You can check with the local market or some of the food vendors. They usually have some leftovers they can give you for your dog. Anna: Great, I’ll give that a try. Thank you for your help, Minh. It’s really different from what I’m used to back home.</td>
<td>You will be generating the next response of a given dialogue between two people. Along with the dialogue, you’ll be given some context about the two participants of the dialogue, e.g., their relationship, situation, etc. Please make the response naturalistic, consistent, specific, interesting and culturally sensitive.</td>
<td>Context: Erling from Norway is visiting Seoul. He and his new Korean friend, Heungmin, are picking foods for their dinner at a traditional restaurant.</td>
</tr>
</tbody>
</table>
Sample 1

<table>
<thead>
<tr>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ali from Tunisia is visiting Tokyo for the first time. He and his newly made Japanese friend, Hiroshi, are deciding how to celebrate Ali’s birthday in one of Tokyo’s iconic districts.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dialogue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ali: Hiroshi, I’m so excited to celebrate my birthday in Tokyo! What do you think we should do?</td>
</tr>
<tr>
<td>Hiroshi: Happy birthday, Ali! I think we should start with a traditional Japanese meal at a local izakaya.</td>
</tr>
<tr>
<td>Ali: That sounds great! I’ve been wanting to try authentic Japanese cuisine. And then maybe we could check out the vibrant nightlife in Shibuya?</td>
</tr>
</tbody>
</table>

### Vanilla GPT

### GPT + CCSK

<table>
<thead>
<tr>
<th>Injected CCSK:</th>
</tr>
</thead>
<tbody>
<tr>
<td>• In Japan, birthdays are celebrated with symbolic rituals, special meals, and a focus on traditional ceremonies and gift-giving.</td>
</tr>
</tbody>
</table>

| Hiroshi: Absolutely, Ali! Shibuya is the perfect place to experience Tokyo’s bustling nightlife. We could start with a few drinks at a traditional Japanese izakaya and then explore the neon-lit streets and vibrant energy of Shibuya. It’s going to be an unforgettable birthday celebration. |

### Criteria

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Natural Flow</th>
<th>Consistency</th>
<th>Specificity</th>
<th>Cultural Sensitivity</th>
<th>Overall Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annotator 1</td>
<td>GPT + CCSK</td>
<td>Tie</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
<tr>
<td>Annotator 2</td>
<td>Tie</td>
<td>Tie</td>
<td>GPT + CCSK</td>
<td>Tie</td>
<td>GPT + CCSK</td>
</tr>
<tr>
<td>Annotator 3</td>
<td>Vanilla GPT</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
</tbody>
</table>

Sample 2

<table>
<thead>
<tr>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fiona, a woman from Scotland, is in Nairobi visiting her online friend Makena. Makena is taking her to a traditional Kenyan hair salon for the first time.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dialogue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Makena: Welcome to the salon, Fiona! Are you excited to try out some Kenyan hair styles?</td>
</tr>
<tr>
<td>Fiona: Oh, I am a bit nervous, but also curious to see what kind of styles are popular here. It’s quite different from what I’m used to in Scotland.</td>
</tr>
<tr>
<td>Makena: Don’t worry, you’re going to love it! Kenyan hair stylists are really talented and they have some unique techniques.</td>
</tr>
</tbody>
</table>

### Vanilla GPT

### GPT + CCSK

<table>
<thead>
<tr>
<th>Injected CCSK:</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Hairdressing education in Kenya focuses on intricate braiding and natural hair care techniques for diverse African hair types and textures.</td>
</tr>
</tbody>
</table>

| Fiona: That’s good to hear! I can’t wait to see what they can do. I’ve always admired African hairstyles from afar, so I’m really looking forward to experiencing it firsthand. |

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Natural Flow</th>
<th>Consistency</th>
<th>Specificity</th>
<th>Cultural Sensitivity</th>
<th>Overall Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annotator 1</td>
<td>Tie</td>
<td>GPT + CCSK</td>
<td>Tie</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
<tr>
<td>Annotator 2</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
<tr>
<td>Annotator 3</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
</tbody>
</table>

Table 12: Examples of generated utterances by GPT without and with CCSK, and choices of MTurk workers in our evaluation. Note that in the evaluation, only the narratives, the dialogues, and the utterance pairs (without explicit method names) are shown to the annotators (cf. Figure 4).
Sample 1

Narrative

Amara, an American studying in Japan, is invited by her Japanese friend Haruki to his grandmother’s home for a traditional meal.

<table>
<thead>
<tr>
<th>Vanilla GPT</th>
<th>GPT + CCSK</th>
<th>Injected CCSK:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>• In Japan, the culture of consumption emphasizes moderation, shared meals, traditional preparation, etiquette, and home-cooked meals.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• In Japan, there is a strong cultural expectation for adult children to care for their elderly parents at home.</td>
</tr>
</tbody>
</table>

Amara: Wow, Haruki, your grandmother’s home is beautiful.
Haruki: Thank you, Amara. I’m glad you could come.
Amara: I’m so excited to try traditional Japanese food. Everything looks amazing.
Haruki: My grandmother is a fantastic cook. She’s been preparing the meal all day.
Amara: I really appreciate her effort. Itadakimasu!
Haruki: Enjoy your meal, Amara. I hope you like it.

Haruki: Amara, I’m really excited to bring you to my grandmother’s house for a traditional meal today. She’s an amazing cook.
Amara: Thank you for inviting me, Haruki. I’m honored to experience a traditional Japanese meal with your family.
Haruki: Just a heads up, at my grandmother’s place, we sit on the floor to eat. It’s a more traditional way of dining.
Amara: I’ll remember to show respect and gratitude for the meal. I’ve read a bit about Japanese dining etiquette, but it’s my first time experiencing it firsthand.
Haruki: It’s important for us to take care of our elders in Japan, and having meals together is a way to show our respect and appreciation.
Amara: I think it’s a beautiful tradition. In the US, we also value family, but the idea of sharing home-cooked meals with multiple generations under the same roof is not as common.

Sample 2

Narrative

Omkar from India and Harry from Australia are coworkers. During their break, Omkar starts preparing Dosa, an Indian dish, and offers to share some with Harry.

<table>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>• Dosa is a specialty dish in Indian restaurants in the United States, less commonly made at home.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Dosa is a popular South Indian dish made from fermented rice and lentil batter, often served with chutney and sambar.</td>
</tr>
</tbody>
</table>

Omkar: Hey Harry, I’m making some dosa for myself. Want to try some?
Harry: Dosa? What’s that? Is it spicy?
Omkar: It’s a type of crispy pancake made from fermented rice and lentil batter. It can be spicy, but I can make it mild for you.
Harry: That sounds interesting! I’ll give it a try.
Omkar: Great! I’ll make a mild one for you. It’s a popular South Indian dish, and I love sharing it with my friends.

Omkar: Hey, Harry, I’m making some Dosa. Want to try some?
Harry: Dosa? Is that the Indian dish with the crispy texture and served with the coconut chutney?
Omkar: Yes, that’s right! It’s a popular South Indian dish made from fermented rice and lentil batter.
Harry: I’ve only had it at Indian restaurants here. I’d love to try your homemade version.
Omkar: Great! I also have some sambar and chutney to go with it.
Here, have a taste.
Harry: Mmm, this is fantastic! The flavors are so different from what I’ve had before.
Omkar: I’m glad you like it. It’s a bit of a process to make, but it’s worth it for the authentic taste.

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<td>GPT + CCSK</td>
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<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
<td>GPT + CCSK</td>
</tr>
</tbody>
</table>

Table 13: Examples of generated dialogues by GPT without and with CCSK, and choices of MTurk workers in our evaluation. Note that in the evaluation, only the narratives and the dialogue pairs (without explicit method names) are shown to the annotators (cf. Figure 5).