KG-TRICK: Unifying Textual and Relational Information Completion of Knowledge for Multilingual Knowledge Graphs

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Abstract

Multilingual knowledge graphs (KGs) provide high-quality relational and textual information for various NLP applications but they are often incomplete, especially in non-English languages. Previous research has shown that combining information from several knowledge graphs in different languages aids both Knowledge Graph Completion (KGC), the task of predicting of missing relations between entities, and Knowledge Graph Enhancement (KGE), the task of predicting missing textual information for entities. While previous efforts have considered KGC and KGE as independent tasks, we hypothesize that they are interdependent and mutually beneficial. To this end, we introduce KG-TRICK, a novel sequence-to-sequence framework that unifies the tasks of textual and relational information completion for multilingual knowledge graphs. KG-TRICK demonstrates that i) it is possible to unify the tasks of KGC and KGE into one single framework, and ii) combining textual information from multiple languages is beneficial to improve the completeness of a KG. As part of our contributions, we also introduce WikiKGE-10++, the largest manually-curated benchmark for textual information completion of KGs, which features over 30,000 instances across 10 diverse languages.

1 Introduction

Knowledge graphs (KGs) aim to encode structured information about the world in a machine-readable format (Hogan et al., 2021), providing high-quality relational and textual information for various NLP applications, such as question answering (Mckenna and Sen, 2023), information retrieval (Reinanda et al., 2020), entity linking (Hu et al., 2023), and machine translation (Modrzejewski et al., 2020), among others. While large language models (LLMs) are increasingly retrieving information from KGs to improve their factuality and performance on many NLP tasks (Wang et al., 2023), their effectiveness in multilingual applications is limited due to the important gap between the completeness of English and non-English information in multilingual KGs (Peng et al., 2023). Indeed, KGs are not complete: a non-negligible quantity of information about entities (e.g., entity names, aliases, and descriptions) and relations (e.g., the connections between entities) is missing in non-English languages (Conia et al., 2023a). Therefore, improving the completeness of KGs has attracted significant attention over the years.

To address this issue, the research community has worked on two main tasks: Knowledge Graph Completion (KGC) and Knowledge Graph Enhancement (KGE). KGC is the task of predicting missing relations between entities already defined in a KG (Bordes et al., 2013), while KGE is the task of predicting missing textual information for entities in a KG (Conia et al., 2023b). More formally, KGC is defined as follows: given a KG $\mathcal{G}$, the task of KGC is to predict the missing tail entity t given the head entity h and the relation r in a triplet $(h, r, ?)$. For example, given the triplet `(Joe Biden, occupation, ?)`, a possible answer could be *politician* or, more specifically, the ID of the politician entity in the KG. On the other hand, KGE is defined as follows: given an entity e in a KG $\mathcal{G}$, the task of KGE is to predict missing textual information (e.g., an entity name, alias, or description) for e in a target language. For example, given the entity *Joe Biden* in English, a possible alias would be *Joseph R. Biden Jr.* or *Joseph Robinette Biden Jr.* in English, or the primary name in Chinese would be 乔·拜登. In this simple example, we can already demonstrate the interdependence between KGC and KGE: the same head and tail entities can have different names in different languages, but the relation between them should hold across languages. However, their interdependence becomes challenging when dealing with ambiguous entities (e.g., *Paris* the city and *Paris* the prince of Troy) and entities whose names are not directly translatable (e.g., *The Matrix* in English and 黑客帝国 (*Hacker's Empire*) in Chinese).

While KGC and KGE have previously been considered as independent tasks, in this work, we investigate their interdependence and hypothesize that they are mutually beneficial. Our hypothesis is based on two symmetric observations. First, solving KGC provides rich language-independent relational information about entities, which may aid KGE to generate higher quality textual information across languages. Second, solving KGE provides rich language-dependent textual information about entities, which may aid KGC to align entities with names and descriptions across languages more effectively. To this end, we introduce KG-TRICK (Textual and Relational Information Completion of Knowledge), a novel unified framework that combines the tasks of KGC and KGE into one single task. Different from previous approaches, the KG-TRICK framework is multilingual by design and is able to leverage the complementary textual information from multiple languages to improve the completeness of a multilingual KG. Not only does KG-TRICK remove the need for separate KGC and KGE models, but it also outperforms similarly-sized state-of-the-art approaches tailored for each individual task, while achieving competitive performance compared to much larger language models. To evaluate the robustness of KG-TRICK and encourage future systems on textual information completion of KGs, we also introduce WikiKGE-10++, the largest manually-curated benchmark for textual information completion for multilingual KG in 10 languages.

We can summarize our contributions as follows:

- We unify the tasks of KGC and KGE to encompass not only the task of predicting missing links in a KG but also the task of completing its multilingual textual information;
- We introduce WikiKGE-10++, the largest manually-curated benchmark for textual information completion of KGs, including over 30,000 entities over 10 languages, to accompany KGC benchmarks and create a comprehensive evaluation suite;
- We present KG-TRICK, a novel sequence-to-sequence model that is able to combine information from multiple languages in an effective way to tackle textual and relation completion of knowledge graphs in a joint fashion;
- We show that KG-TRICK outperforms similarly-sized state-of-the-art models tailored for each task, while achieving competitive performance compared to larger LMs.

We believe that our work – our task reformulation, manual benchmark, and unified method – is a significant step forward to improve the quality of multilingual KGs and broaden their applicability to multilingual downstream tasks. To encourage future work in this direction, we release our software and benchmark at `https://anonymized`.

2 Related Work

In this section, we briefly review the literature on Knowledge Graph Completion (KGC) and Knowledge Graph Enhancement (KGE) and discuss the challenges of completing textual and relational information in multilingual knowledge graphs.

Multilingual Knowledge Graphs. As mentioned above, KGs aim to encode information about our world knowledge in a structured, machine-readable format (Hogan et al., 2021). Such information also includes lexicalizations like entity names, aliases, and descriptions; when these are available in multiple languages, the KG is called a multilingual KG. There are different ways to construct and organize multilingual KGs. For example, in DBPedia (Lehmann et al., 2015), an entity is language-dependent and is represented in different languages using different entity IDs, whereas in Wikidata (Vrandečić and Krötzsch, 2014), an entity is language-specific and is represented by the same entity ID to which different language-specific labels are attached. The construction of multilingual KGs is an active area of research, and there are several challenges to be addressed, such as the alignment of entities across languages (Chakrabarti et al., 2022), the completion of missing relational information (Chen et al., 2020b), and the addition of textual information, especially in non-English languages (Conia et al., 2023b).

Knowledge Graph Completion. The task of KGC is to predict missing relations between entities already defined in a KG (Bordes et al., 2013). This task has been studied extensively in the literature, and there are categories of methods to solve it, including embedding-based methods (Lin et al., 2015b), path-based methods (Lin et al., 2015a), and rule-based methods (Chen et al., 2020a). More recently, sequence-to-sequence models have been proposed to solve KGC, by treating it as a text-to-text generation task where the input is a partial triplet and the output is the missing entity (Saxena et al., 2022). However, these approaches have been designed for monolingual KGs, as multilinguality adds a layer of complexity to the task. Chakrabarti et al. (2022) have taken a step in this direction by including an auxiliary task to translate entity names, but they neither consider completing triples across languages nor the completion of more complex textual information, such as entity descriptions.

Knowledge Graph Enhancement. The task of KGE is to predict missing textual information for entities in a KG. This task is more recent in the literature, but there are several approaches to tackle it, such as machine translation, web search, and language model-based methods (Conia et al., 2023a). However, Conia et al. (2023a) have mainly focused on i) combining answers from multiple KGE systems to improve coverage and precision, and ii) evaluating the quality of the textual information generated by KGE systems for popular entities only, while iii) ignoring the connection between KGE and KGC, especially in the multilingual setting.

3 Unifying Textual and Relational Information Completion

In this section, we introduce KG-TRICK, or how we unify the tasks of KGC and KGE into one single framework, and how we leverage the complementary textual information from multiple languages to improve the completeness of a multilingual KG.

3.1 Task Reformulation

Given the similarities between the two tasks of KGC and KGE and the interdependence between them (see Section 1, in which we provide a high-level intuition), we reformulate both tasks as a single multilingual text-to-text generation task as shown in Figure 1. KG-TRICK consists of three main components, namely the verbalization, the fine-tuned multilingual sequence-to-sequence model and the ensemble module to obtain the predicted entities for KGC task. This unified framework allows us to i) treat KGC and KGE as a single task, and ii) to leverage the complementary textual information from multiple languages to better complete factual information and reversely to improve the latent, dense representation of the fine-tuned sequence-to-sequence model leading to improved KGE performance. Figure 1 illustrates the pipeline of KG-TRICK for both KGC and KGE. Thanks to our reformulation, KG-TRICK sees both tasks as the task of predicting the tail entity t given the head entity h and the relation r in a triplet $(h, r, ?)$, as we will detail in the following sections.

3.1.1 KGC as Text-to-Text Generation

In KGC, the task is to predict the missing tail entity t given the head entity h and the relation r in a triplet $(h, r, ?)$. We first reformulate this task as a text-to-text generation task, where the input is a partial triplet composed of the primary name and short description of the head entity h and the relation r. The model is then asked to generate the missing tail, or, more precisely, the primary name and short description of the tail entity t.

One important drawback of this reformulation is that it does not take into account the input and output languages, which is crucial for multilingual KGs. We overcome this limitation by extending the triplet to a tuple of five elements, which include the source and target languages, as shown in Figure 1. More specifically, the input to the model is now a tuple $(l_s, l_t, h, r, ?)$, where l_s is the source language of the input, l_t is the target language of the output, h = primary name + short description, and r is the relation. The model then predicts t, i.e., the primary name and short description of the tail entity in l_t. For example, given the input $(\text{en}, \text{es}, h, r, ?)$, the model generates the primary name and short description of the entity *político | persona involucrada en la política*; while given the input $(\text{en}, \text{zh}, h, r)$, the model generates the primary name and short description of the entity 政治家 | 从事政治活动的人 . This reformulation significantly increases the training data pairs by extending cross lingual name based entity alignment to cross lingual relation based entity alignment resulting in higher quality of entity alignment.

3.1.2 KGE as Text-to-Text Generation

In KGE, the task is to predict missing textual information for entities in a KG. This task can also be reformulated as a text-to-text generation task, similar to KGC. We can immediately see that the formulation outlined above for KGC can be directly applied to KGE, with the only difference being that the head entity h may be represented only by its primary name in case we want to generate a short

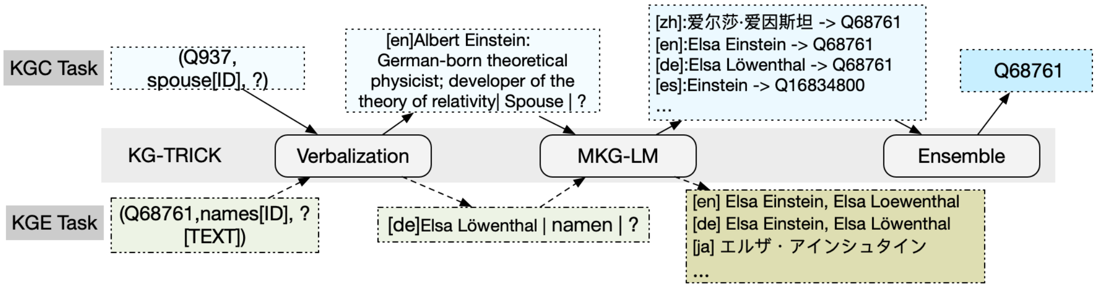

Figure 1: KG-TRICK: a unified seq-to-seq framework for KGC and KGE. KGC dataflow is in blue; KGE dataflow is in green. For KGE, an input triplet $(\texttt{Q68761}, \text{names}, ?)$ is verbalized as "[de] Elsa Löwenthal|namen|?" and then passed to the model, which can generate the names in multiple languages. For KGC, an input triplet $(\texttt{Q937}, \text{spouse}, ?)$ is verbalized as "[en] Albert Einstein | spouse | ?" and then passed to the model, which can generate the name Elsa Einstein in multiple languages. The ensemble module consolidates all the outputs into the best one.

description for h itself. Moreover, we also allow the head entity h and the tail entity t to be the same entity, which allows us to generate aliases for an entity in a specific language. For example, given the partial triplet *Joe Biden: President of the US* | *has name* |, the model predicts the primary name of the entity *Joe Biden* in the target language but it can also generate one or more aliases, such as *Joseph R. Biden Jr.* or *Joseph Robinette Biden Jr.* in English, or 乔·拜登 or 乔·罗宾内特·拜登 in Chinese. Interestingly, when this reformulation is used in its most simple form, i.e., by using only the primary name of the head entity, it becomes equivalent to translation into the target language. This is a powerful feature, as it allows us to generate missing textual information in any language in KG.

3.2 The KG-TRICK Model

Unifying KGE and KGC, we implement KG-TRICK as a general sequence-to-sequence model, which learns to generate both missing relational and textual missing information in a KG. More formally, given a tuple $(l_s, l_t, h, r, ?)$, the model is asked to generate t from the source language l_s to the target language l_t conditioned on h and r as following:

$$o = \text{KG-TRICK}(l_s, l_t, h, r, ?) \tag{1}$$

where o is the output generated by the model. In other words, o is the primary name and short description of the tail entity in the target language, and KG-TRICK learns to estimate the probability of generating o given the input $(l_s, l_t, h, r, ?)$.

KG-TRICK can be implemented using any sequence-to-sequence architecture, such as a transformer (Vaswani et al., 2017) or a recurrent neural network (Rumelhart et al., 1985). In practice, we conducted our experiments with one main architecture, i.e., multilingual BART, which is a transformer-based encoder-decoder model, and we found that it performs well on the task, as shown in Section 5. The model can be trained using a standard maximum likelihood estimation (MLE) objective, and it can be evaluated using standard metrics for text generation, such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), and COMET (Rei et al., 2020). In this work, we study three main variants of KG-TRICK, which differ in the training data they use: i) $\text{TRICK}_{\text{KGC}}$, which uses only the relational information of the KG, ii) $\text{TRICK}_{\text{KGE}}$, which uses only the textual information of the KG, and iii) $\text{TRICK}_{\text{KGC+KGE}}$, which uses both the relational and textual information of the KG.

3.3 Inference for KGC and KGE

Once the output is generated, it can be used to complete the KG in two ways. The application to KGE is straightforward, as the output is the missing textual information for an entity in the target language. The application to KGC is slightly more complex, as the output is the textual representation (i.e., the primary name and short description) of the missing tail entity in the target language. Relying only on an exact match between primary names may not be sufficient to determine the correct entity, especially in the case of ambiguous entities, such as *Paris* the city and *Paris* the prince of Troy. While previous work (Saxena et al., 2022) enumerates the entities with the same name (e.g., $\textit{Paris}_1$, $\textit{Paris}_2$, etc.), we incorporate entity descriptions as additional information from KG-TRICK to help disambiguate entities with the same primary name resulting in higher entity linking accuracy.

Ensemble across languages. Since KG-TRICK can generate text in any target language for which it has been (pre-)trained, we leverage this capability to complete the missing information from multiple languages. When corresponding entity ID are linked from generated text by different languages, we then ensemble and choose the most common predictions as is showed in Figure 1.

4 WikiKGE-10++

In this section, we introduce WikiKGE-10++, the largest manually-curated benchmark for textual information completion of KGs, which features over 30,000 instances across 10 diverse languages. Having realized the importance of evaluating systems on textual information completion of multilingual KGs, in 2023, Conia et al. created WikiKGE-10, a benchmark for evaluating KGE systems on the completion of entity names and aliases in 10 languages. However, WikiKGE-10 is limited in two dimensions: i) it only allows for the evaluation of entity names and aliases, and ii) the entities included in the benchmark are popular entities only, i.e., they belong to the top-10% most popular entities in Wikidata according to number of page views of their corresponding Wikipedia pages.

A core contribution of our work is the creation of WikiKGE-10++, which extends WikiKGE-10 in two above-mentioned dimensions, hence the two "+" signs in the name of our benchmark. First, WikiKGE-10++ includes not only entity names and aliases, but also entity descriptions, which are crucial for many downstream tasks to create better entity representations (Ri et al., 2022). Second, WikiKGE-10++ includes a much larger set of entities, which belong to the torso of the popularity distribution of Wikidata (i.e., between the top-10% and top-50% most popular entities) and also the tail of the popularity distribution (i.e., below the top-50% most popular entities). This is important because the majority of entities in a KG are not popular, and different conclusions can be drawn when evaluating systems on different popularity tiers. Overall, WikiKGE-10++ is around 3 times larger than WikiKGE-10 in terms of the number of entities while also including entity descriptions.

Including torso and tail entities. The inclusion of torso and tail entities in WikiKGE-10++ is important to assess the robustness of KGE systems on the completion of textual information for entities for which the amount of information available inside (and also outside) the KG is limited. While most of the search queries and user interactions may be focused on popular entities, the majority of entities in a KG are not popular, and they are often the most challenging. Therefore, we asked a team of annotators to manually curate 1000 torso entities and 1000 tail entities per language.

Including entity descriptions. The inclusion of entity descriptions in WikiKGE-10++ is important for evaluating KGE systems on the completion of textual information that is usually longer and more complex than entity names and aliases. However, evaluating KGE systems on the entity descriptions already available in Wikidata is not ideal, as those are not always manually curated and often underspecific, e.g., the description of many cities is simply *city in country*. Therefore, we asked a team of annotators to produce high-quality descriptions for 1000 entities per popularity tier per language.

5 Experiments and Results

5.1 Datasets and Benchmarks

KGC. We carry out our KGC experiments on Wikidata5M (Wang et al., 2021a) transductive split. We stress that, although entities in Wikidata are language-agnostic, the original Wikidata5M dataset is English-only, i.e., the textual information (names and descriptions) for the 5 million entities is only in English. Therefore, this English-only setting may not be ideal to evaluate our multilingual KGC system; however, as is illustrated in Table 3, our reformulation could further enhance $\mathsf{TRICK}_{\mathsf{KGE}}$'s performance with multilinguality.

KGE. We carry out our KGE experiments on our newly annotated WikiKGE-10++ dataset, which features 10 languages and 30,000 entities as introduced in Section 4. We use this dataset to evaluate KGE models on the completion of entity names, aliases, and descriptions in 10 languages.

5.2 Comparison Systems

KGC. Baseline approaches for KGC can be divided into two categories: *embedding-based* and *text-based*. Embedding-based methods derive an embedding for each entity and relation from the graph structure of the KG, and rank the most probable tail entity via a vector similarity function, e.g., L2 distance (Bordes et al., 2013), complex space distance (Trouillon et al., 2016b) or other distance measures. Text-based methods use encoder-only language models (Wang et al., 2022, SimKGC) to encode both the head entity and the relation using their textual information, or encoder-decoder language models (Saxena et al., 2022, KG-T5) to generate the missing tail entity. Concurrent work (Kochsiek et al., 2023, KGT5-context) combines subgraph-structure information and sequence-to-sequence models. Since we build upon text-based methods, we compare our KG-TRICK models with SimKGC and KG-T5, which are the most relevant baselines for a fair comparison.

KGE. While KGE is a relatively recent task, previous work has already indicated several strong baselines, including i) using NLLB-200[1] (Costa-jussà et al., 2022) to translate entity names and descriptions from a language , and ii) prompting LLMs (e.g. GPT-3.5 or Llama), to generate textual information for an entity.

5.3 Experimental Setup

We use the entities within Wikidata5M which contains a set of around 5 million entities and a collection of around 20 million triplets and collect their available textual information (entity names, aliases, and descriptions) for English and 9 other languages from a Wikidata dump[2] to create a silver training set $\mathcal{E}$ for KGE in multiple EN→XX directions containing around 16 million records. For KGC, the original Wikidata5M triplets are expanded with our downloaded Wikidata dump to form over 150 million triplets $\mathcal{T}$ multilingually (EN→XX) in 9 languages pairs. We train three variants of KG-TRICK: one on $\mathcal{E}$ (denoted as $\text{TRICK}_{\text{KGE}}$), one on $\mathcal{T}$ (denoted as $\text{TRICK}_{\text{KGC}}$), and one on the mixture of both (denoted as $\text{TRICK}_{\text{KGC+KGE}}$). [3] To verify the multilinguality of $\text{TRICK}_{\text{KGE}}$, we also include a bilingual version train with single language pair (e.g. EN→IT) on KGE task, denoted as $\text{TRICK}_{\text{KGE}}$(bilingual) in Table 3. While the number of training samples are disproportional for KGC and KGE, to trade off the performance between the two tasks, as is shown in Table 5, we find a sweet spot of combining 50% of KGC data into the joint training. We denote this derivative as $\text{TRICK}_{\text{50\%KGC+KGE}}$ in Table 2 and Table 3. We provide more details balancing the training data of the two tasks in Appendix C.

Evaluation. For KGC, we evaluate the systems using standard ranking-based metrics, namely, *hit@1*, *hit@3*, *hit@10*, and *Mean Reciprocal Rank* (MRR). Hit@k measures the proportion of correct answers in the top-k predictions, while MRR measures the average rank of the correct answer. For KGE, we follow the evaluation protocol proposed by Conia et al. (2023a), which includes two main metrics: coverage and precision. *Coverage* evaluates the number of entities for which a system is able to produce at least one correct entity name, while *Precision* evaluates the ability of a system to identify incorrect entity names and aliases. Finally, we report the COMET scores for the completion of entity descriptions, a standard metric for text generation and machine translation.

Model	MRR	hit@1	hit@3	hit@10
TransE (Bordes et al., 2013)	25.3	17.0	31.1	39.2
DisMult (Yang et al., 2014)	25.3	20.8	27.8	33.4
SimpIE (Kazemi and Poole, 2018)	29.6	25.2	31.7	37.7
RotatE (Sun et al., 2019)	29.0	23.4	32.2	39.0
QuatE (Zhang et al., 2019)	27.6	22.7	30.1	35.9
ComplEx (Trouillon et al., 2016a)	30.8	25.5.	-	39.8
DKRL (Xie et al., 2016)	16.0	12.0	18.1	22.9
KEPLER (Wang et al., 2021b)	21.0	17.3	22.4	27.7
MLMLM (Clouatre et al., 2021)	22.3	20.1	23.2	26.4
SimKGC + Desc.	35.8	31.3	37.6	**44.1**
KG-T5	30.0	26.7	31.8	36.5
KG-T5 + Desc.	38.1	35.7	39.7	42.2
KG-T5 + Desc.*	37.0	34.7	38.4	41.1
$\text{TRICK}_{\text{KGC}}$	38.2	36.0	39.7	41.8
$\text{TRICK}_{\text{KGC+KGE}}$	**38.8**	**36.6**	**40.4**	42.6

Table 1: KGC results on the test set of Wikidata5M. TRICK achieves strong performance over competitive baselines. *: retrained in the same setting as $\text{TRICK}_{\text{KGC}}$.

5.4 Results on KGC

Table 1 shows the results obtained by our KG-TRICK models compared to other KGC-only models on the test set of Wikidata5M. In general, we can observe that KG-TRICK generally outperforms all the other strong baselines on MRR, hit@1, and hit@3, and it is the second best model for hit@10. More specifically, $\text{TRICK}_{\text{KGC}}$ (trained only on KGC data but in multiple languages) already outperforms both SimKGC and KG-T5, on almost all the metrics. Notably, this first result demonstrates that our model is able to outperform strong baselines that are tailored for KGC on a dataset Wikidata5M that is designed for KGC (and that is biased in its creation towards entities that have English lexicalizations). Moreover, we can observe that $\text{TRICK}_{\text{KGC+KGE}}$ achieves scores that are even higher than $\text{TRICK}_{\text{KGC}}$, which demonstrates that unifying KGC and KGE leads to additional

[1]In this work we use NLLB-200-Distilled (600M).
[2]Downloaded in November 2023.
[3]All TRICK models are fine-tuned from mBART-large-50.

	Coverage				Precision				COMET		
	Head	Torso	Tail	Avg.	Head	Torso	Tail	Avg.	Head	Torso	Tail
NLLB-200 $_{\text{EN}\rightarrow\text{XX}}$	29.1	26.1	24.3	26.5	47.6	39.6	34.9	40.7	0.64	0.63	0.63
Llama3-8B	27.2	22.9	20.4	23.5	46.0	36.6	31.2	37.9	0.62	0.62	0.62
GPT-3.5	**35.0**	29.6	26.7	30.4	51.9	42.7	36.8	43.8	**0.66**	<u>0.64</u>	<u>0.64</u>
TRICK$_{\text{KGE}}$	31.5	**31.4**	29.9	30.9	56.4	51.4	46.5	51.4	0.63	<u>0.64</u>	<u>0.64</u>
TRICK$_{\text{50\%KGC+KGE}}$	33.1	31.2	**30.1**	**31.5**	57.7	51.7	**47.1**	52.1	0.61	0.62	0.62
TRICK$_{\text{KGC+KGE}}$	31.6	29.5	28.2	29.7	**57.8**	**52.2**	46.5	**52.2**	0.60	0.60	0.61

Table 2: KGE results on WikiKGE-10++ split by head, torso and tail entities. Best results in bold.

improvements on the KGC task. This second result empirically shows that the two tasks are indeed interdependent and mutually beneficial, and that the combination of the two tasks can lead to better results than the two tasks individually.

On the other hand, we can observe that the performance of TRICK$_{\text{KGC}}$ and TRICK$_{\text{KGC+KGE}}$ is not as good as the performance of SimKGC on hit@10. We hypothesize that this is likely due to the fact that the sampling capacity of sequence-to-sequence models is limited and constrains their performance with higher values of k. Indeed, for SimKGC, TransE and ComplEx, due to their closed-world assumption, the candidates for the tail entities are known during inference for similarity search. However, for text generation models, such as KG-T5 and KG-TRICK, which operate under a more challenging open-world assumption, the diversity of generated candidates may be limited by the sampling strategy used for decoding. Future work could focus on improving the sampling capacity of generative models.

5.5 Results on KGE

Table 2 shows the KGE results on our new WikiKGE-10++ benchmark split by entity popularity, while Table 3 shows the results by language.

Coverage. Overall, we could observe that TRICK$_{\text{50\%KGC+KGE}}$ outperforms strong baselines on average and across most languages. Interestingly in Table 2, TRICK$_{\text{KGE}}$ and TRICK$_{\text{KGC+KGE}}$ perform worse than GPT-3.5 on Coverage of head entities. This is likely due to the fact that GPT-3.5 has seen substantially more popular entity names during its pre-training and is equipped with considerably more parameters to store such information. However, TRICK series quickly catch up with GPT-3.5 on Coverage of torso entities, and significantly outperform GPT-3.5 on Coverage of tail entities. It shows that GPT-3.5 quickly loses its advantage when the entities are less popular, and that KG-TRICK models feature a more balanced and consistent performance across different popularity tiers.

Precision. Overall, we can observe that TRICK significantly outperforms strong baselines on precision on head, torso, and tail entities, i.e., it is a more reliable system in identifying incorrect entity names and aliases in a given target language in a multilingual knowledge graph. In fact, TRICK is particularly effective on torso and tail entities, where it improves over NLLB-200 and GPT-3.5 by around 10% points in F1 score. This is important as completing missing knowledge is not only about providing the correct information but also about avoiding incorrect information.

Entity descriptions. Finally, we also report the COMET score for the completion of entity descriptions, borrowing a metric for open-ended text generation from MT. In this task, we can observe that TRICK$_{\text{KGE}}$ is comparable with NLLB-200 and GPT-3.5, while TRICK$_{\text{KGC+KGE}}$ is slightly worse on average than TRICK$_{\text{KGE}}$. These results open the door to future work: indeed, very different methods achieve comparable results on entity description completion, meaning that there is still a wide room for improvement in this task or COMET is not a good metric for comparing descriptions. We note that BLEU is not appropriate either, as its score is not defined for short texts, e.g., one word.

Multilingual and Multi-task As is illustrated in Table 3, TRICK$_{\text{KGE}}$ outperforms TRICK$_{\text{KGE}}$(bilingual) on almost all languages for both Precision and Coverage, indicating that jointly train a unified model for all languages could inherently benefit its multilinguality. On the multi-task side, combining KGC and KGE tasks requires caution, as is demonstrated by TRICK$_{\text{KGC+KGE}}$ and TRICK$_{\text{50\%KGC+KGE}}$. KGC and KGE are mutually

	Coverage F1	#Params	AR	DE	ES	FR	IT	JA	KO	ZH	Avg
names & aliases	NLLB-200 $_{\text{EN}\rightarrow\text{XX}}$	0.6B	16.9	39.8	37.9	40.8	40.5	9.4	18.6	8.1	26.5
	Llama3-8B	8B	11.3	35.9	32.8	35.0	32.6	12.4	15.5	12.5	23.5
	GPT-3.5	175B	20.1	40.8	39.1	41.3	40.9	19.6	21.5	**20.0**	30.4
	TRICK$_{\text{KGE}}$(bilingual)	0.6B	24.4	39.5	33.7	37.2	34.0	18.4	23.3	15.3	27.5
	TRICK$_{\text{KGE}}$		24.4	39.5	38.8	40.8	40	20.4	26.3	17.0	30.9
	TRICK$_{\text{50\%KGC+KGE}}$		23.0	**40.9**	**40.0**	**41.9**	**41.1**	**20.5**	**26.0**	18.2	**31.5**
	TRICK$_{\text{KGC+KGE}}$		22.6	39.2	37.2	39.4	39.4	19.8	24.3	16.0	29.7
	Precision F1	**#Params**	**AR**	**DE**	**ES**	**FR**	**IT**	**JA**	**KO**	**ZH**	**Avg**
	NLLB-200 $_{\text{EN}\rightarrow\text{XX}}$	0.6B	30.3	49.1	48.9	51.2	52.0	28.3	30.6	34.9	40.7
	Llama3-8B	8B	24.1	46.0	45.0	47.7	45.4	30.4	26.6	38.3	37.9
	GPT-3.5	175B	33.2	49.5	49.7	51.9	52.3	36.9	33.1	43.8	43.8
	TRICK$_{\text{KGE}}$(bilingual)	0.6B	46.3	52.3	53.1	54.5	55.3	43.8	46.3	45.5	49.6
	TRICK$_{\text{KGE}}$		48.4	54.3	55.2	**57.0**	56.2	45.6	47.5	47.5	51.4
	TRICK$_{\text{50\%KGC+KGE}}$		48.1	**55.9**	**55.6**	56.4	**56.9**	45.7	**50.0**	**48.5**	52.1
	TRICK$_{\text{KGC+KGE}}$		**49.4**	54.8	55.5	56.7	56.6	**47**	49.0	48.3	**52.2**
	COMET Score	**#Params**	**AR**	**DE**	**ES**	**FR**	**IT**	**JA**	**KO**	**ZH**	**Avg**
descriptions	NLLB-200 $_{\text{EN}\rightarrow\text{XX}}$	0.6B	0.59	0.62	0.66	0.63	0.65	0.63	0.65	0.64	0.63
	Llama3-8B	8B	0.56	0.62	0.65	0.63	0.65	0.60	0.60	0.61	0.62
	GPT-3.5	175B	**0.60**	0.63	0.66	0.63	**0.66**	0.66	**0.67**	**0.67**	**0.65**
	TRICK$_{\text{KGE}}$	0.6B	0.58	0.63	0.66	0.63	0.65	**0.67**	0.64	0.64	0.64
	TRICK$_{\text{50\%KGC+KGE}}$		0.56	0.61	0.63	0.60	0.64	0.64	0.62	0.60	0.61
	TRICK$_{\text{KGC+KGE}}$		0.55	0.59	0.63	0.58	0.62	0.63	0.62	0.60	0.60

Table 3: KGE experiments on WikiKGE-10++. TRICK achieves best performance on Precision and Coverage F1 scores. Best results in bold.

beneficial when training data is properly balanced, otherwise one task would dominate the distribution and cause regression on the other. More analysis on data balancing is discussed in Appendix C. We could also observe that the multilingual capability of Llama3-8B is far from ideal in KGE task.

5.6 Downstream Application: Results on Multilingual Question Answering

In addition to the KGC and KGE tasks, we also evaluate our KG-TRICK on a downstream application: our intuition is that (post-)pretraining on KGC and KGE tasks can allow a model to store more factoid knowledge, which can be useful for multilingual question answering. Therefore, we evaluate the performance of our TRICK$_{\text{KGC+KGE}}$ when fine-tuned on answering the questions in the Mintaka dataset (Sen et al., 2022), which is a multilingual question answering dataset that contains knowledge-seeking questions, and compare its results in the same setting with directly fine-tune on Mintaka using mBART-large-50 that has not been (post-)pretrined on KGC and KGE tasks. Our experiments show that our model outperforms mBART-large-50 by 3.1% (29.2% vs. 26.1%) on average in terms of EM (Exact Match), which demonstrates that the knowledge embedded in KGC and KGE training data could be easily transferred to the QA task in cross-lingual settings.

6 Conclusion

The contributions of this paper are threefold. First, we propose a novel multilingual KGC and KGE system, TRICK, which is able to complete relational and textual information in and across 10 languages. Second, we introduce a new human-curated dataset, WikiKGE-10++, which contains 10 languages and 30,000 entities for KGE evaluation. Third, we demonstrate that our TRICK system outperforms strong baselines on both KGC and KGE tasks, and that the combination of the two tasks can lead to better results than the two tasks individually. We also show that the knowledge embedded in KGC and KGE training data could be easily transferred cross-lingual QA. We hope our work and our WikiKGE-10++ can inspire future research on multilingual KGC and KGE.

Limitations

Closed world assumption of KGC. In this paper, we assume that the entities within KGC tasks exist in the KG. If the model predicts some entities that do not exist, we simply ignore the inference. This assumption limits the model's capability to explore the encoded knowledge within pre-trained multilingual LMs. Although our model can be extended to predict and extract entities outside of KG, our experiments in section Section 5 demonstrate that there is still a big headroom to further complete the relation information when KG are extended into multilingual setting since we can combine the knowledge across languages that are not considered in a monolingual setting. We leave the deeper exploration into future work.

Limited exploration of pre-trained multilingual LMs. Our KGE task pays great attention to enrich the entity names and descriptions of entities with limited attention to other textual information such as mottos , quotes. Given the pre-trained LMs have been trained on huge amount of data, there are great potential to extract out the information that has been seen by the pre-trained LMs which does not exist in KG. Even though KG-Trick can be extended to infer other entity facts, our analysis shows that entity names and descriptions are most essential to enrich and disambiguate entities and have led to great improvement of KGC task. Especially that description is a summarized free form text that is highly representative of a particular entity.

Support unified multilingual KGs. We focus on the multilingual KGs that has entities represented by entity IDs and language dependent textual information are structured as the attributes associated with corresponding entities. Thus, different from other research work that needs to align entities and relationships together, our systems eliminate such requirement. The benefit of this setting is that we enriched the KG that are unified at the very beginning and derive the knowledge from the KG itself by extracting and inferring information that can be derived by the multilingual KG itself. Our system do not suffer from the error propagation introduced by entity and relation alignment between different KGs. Nonetheless, our system is limited to the setting of unified multilingual KGs such as Wikidata. KG-Trick is complementary to the other related work on multilingual KG completion which calls for integration of different KGs. Our system can be applied to further improve the completeness after the KGs are unified since such techniques focus on fusing different KGs but not inferring knowledge from the unified KG itself.

WikiKGE-10++ While WikiKGE-10++ significantly extends WikiKGE-10 by adding 2X entities sampled from torso and tail entities and descriptions for such comprehensively sampled set of entities, it contains only two types of facts including entities names and descriptions. By extending the WikiKGE-10++ to cover more facts associated with the entities, the research community can be able to get a more accurate and thorough picture on how the proposed approach can improve KG.

Potential risks for generative textual information completion As we employ a text-to-text framework for multilingual KG textual information completion task, it may generate biased or inaccurate text that could be misleading for downstream tasks. If this work is considered for production use, human annotators might be in the loop to reduce the risks of harmful text generation.

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A Creating WikiKGE-10++

In this section, we describe the in-depth details on the creation of WikiKGE-10++, our novel human-curated dataset for evaluation automatic approaches on KGE of Wikidata entity names and descriptiptions.

A.1 Choice of Languages

Aligned with the previous work completed in Conia et al., the benchmark sustains the selection of 9 languages from a set of topologically diverse linguistic families, while interchanging the Russian (Slavic) language for the Turkish (Altaic) language:

- West Germanic: English, German;
- Romance: Spanish, French, Italian;
- Semitic: Arabic;
- Sino-Tibetan: Chinese (simplified);
- Altaic: Turkish;
- Koreanic: Korean;
- Japonic: Japanese.

The Russian language was interchanged for the Turkish language due to export and import restrictions placed on Russia, thereby, restricting access to Russia-based human annotators.

A.2 Human annotation process

The objective of the annotation process was to (i) rate and suggest entity names in the target language, (ii), verify the suggest entity names in the target languages, (iii) curate description for the entity in the target language, (iv) validate the provided descriptions quality.

A.2.1 Rate and suggest entity names.

The objective of the annotation process was the rate entity names in a target language. Detailed information on the annotation process and UI design can be found in Conia et al..

A.2.2 Verify suggested entity names.

The objective of the annotation process was the verify the suggested entity names in the target language provided by the human annotators. Detailed information on the annotation process and UI design can be found in Conia et al..

A.2.3 Curate entity descriptions.

The objective of the annotation process was curate descriptions for the given entity in the target language.

Given an entity name in a target language, annotations were required to familiarize themselves with the its information: the user interface provided the entity names, as well as a built-in panel that directly displayed Wikipedia articles for the corresponding entity in English and the target language, if available. In addition, annotators were recommended to further familiarize themselves with the entity outside of the provided information.

Next, the annotators were tasked with learning about the required format of the requested description with detailed instructions. This was facilitated by providing: (i) examples of correctly curated description given an example entity, and (ii) strict rules that the descriptions had to comply by.

After learning about the entity and the required description format, the human annotator was requested to manually curate the description for the corresponding entity in the target language. During this task, the human annotator was provided with descriptions from other sources (such as Wikidata) in English and the target language. Human annotators were instructed that they could leverage the extraneous descriptions, but not to copy and paste unless satisfactory.

A.2.4 Validate entity descriptions.

The objective of the annotation process was the validate the quality of the descriptions in the target language provided by the human annotators.

First, given an entity, the human annotator was provided corresponding information (i.e., entity names/aliases, Wikipedia pages, etc) as done in the previous task. In addition, the description requirements were detailed (in-depth guidelines provided in a different document).

Then, they were prompted to analyze the corresponding description for the entity in the target language with a series of questions. The questions were reformulated to from description requirements, to verify the presented description in the target language followed the requested format. If the annotator negatively responded to any of the presented questions, they were prompted to edit the description to satisfy the requirements. If the initial description the requirements, the originally provided description was sustained.

A.3 Quality assurance and inter-annotator agreement.

B Short Description Evaluation

As is shown in Table Table 4, we calculate the BLEU score for every baseline and our method. However, the BLEU score for all languages and all baselines are under 10, which suggests that the translated text from English can hardly relate to ground truth in target languages. This phenomenon could suggest that BLEU is not a proper metric for entity short description evaluation, as (i) Short description for the same entity in different languages are not directly translatable. (ii) A large amount of short descriptions are less than 4 tokens (e.g. *Politician*), which could biases the judgement of BLEU when calculating the weighted average.

C Balancing the training data for KGC and KGE

In this section, we provide more details on how balancing the training data between KGC and KGE tasks can impact the performance of the two tasks. Indeed, the training datasets available for the two tasks are not balanced: the KGC dataset contains 150 million records generated multilingually from 20 million triplets, while the KGE dataset contains around 16 million records generated multilingually from 5 million entities. Therefore, we investigate the impact of mixing different proportions of the

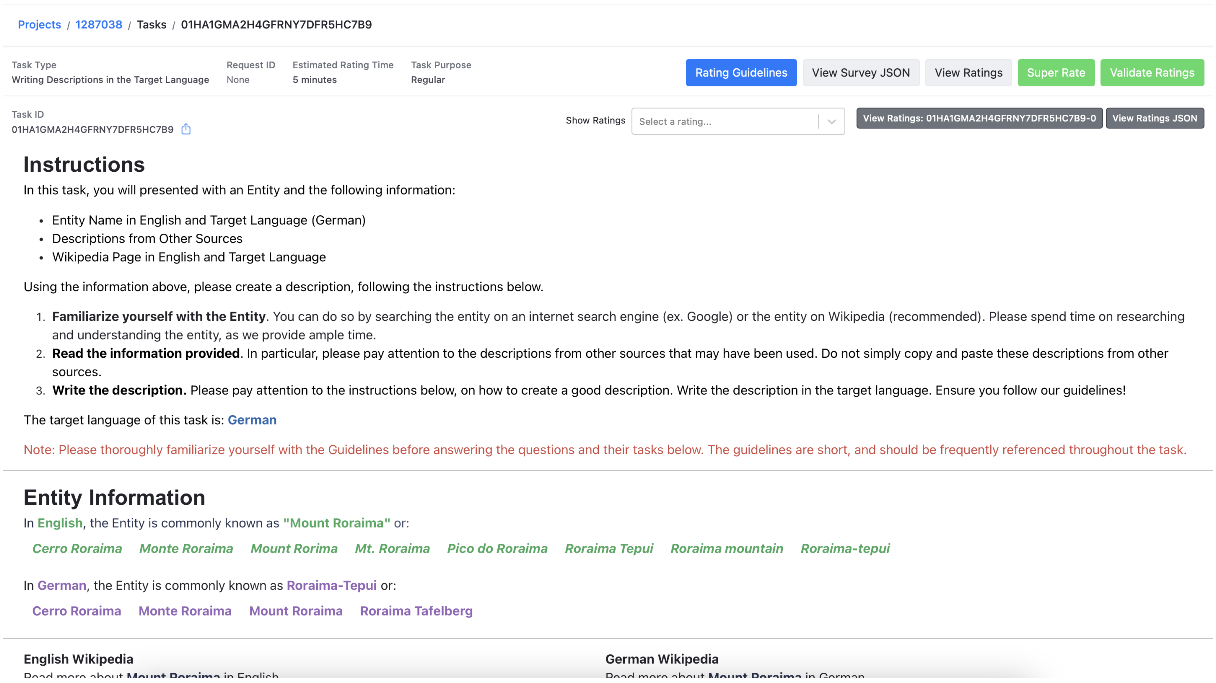


Figure 2: UI used for the annotation task: the annotators could familiarize themselves with the task with an outline of the task instructions (detailed guidelines could be read in a separate page) and the information about the entity, including its names in English and its Wikipedia pages in English and the target language (Italian in this case).

	BLEU Score	#Params	AR	DE	ES	FR	IT	JA	KO	ZH	Avg
descriptions	NLLB-200 $_{\text{EN}\rightarrow\text{XX}} \rightarrow$	0.6B	2	3.4	7	4.8	4.6	1.5	4.1	5.9	4.2
	GPT-3.5	175B	**2.8**	**4.2**	7.2	4.9	5.5	**3.9**	**4.3**	**9.8**	**5.3**
	$\text{TRICK}_{\text{KGE}}$		2.2	3.4	**8.0**	**5.1**	**5.9**	3.8	2.5	4.9	4.5
	$\text{TRICK}_{50\%\text{KGC+KGE}}$	0.6B	1.4	2.1	5.8	2.8	4.1	2.3	1.6	2.8	2.9
	$\text{TRICK}_{\text{KGC+KGE}}$		1	0.8	2.6	1.3	2.1	2	1.5	2.2	1.7

Table 4: BLEU score for entity short description evaluation

two datasets on the performance of the two tasks. More specifically, we investigate different proportions of the KGC and KGE datasets, ranging from 0% to 100% of the KGC dataset, and evaluate the performance of the two tasks on WikiKGE-10++. The results are reported in Table 5. We can observe that the best performance on KGC is achieved when the full KGC dataset is used, which suggests that the KGC task is more difficult than the KGE task. On the other hand, the best performance on KGE is achieved when up to 50% of the KGC dataset is used. Therefore, the best compromise between the data mixing proportion for the two tasks is to use 50% of the KGC dataset.

	KGE		*KGC*	
KGC%	Precision	Coverage	MRR	hit@1
0%	51.5	30.9	-	30.4
1%	**52.4**	30.4	32.7	32.1
10%	**52.4**	30.6	34.4	31.7
20%	51.7	28.8	34	32.8
50%	52.1	**31.5**	35.2	33
full	52.2	29.7	**38.8**	**36.6**

Table 5: Investigation on the different data mixing proportion between KGC and KGE, and their impact on KGC and KGE tasks performance

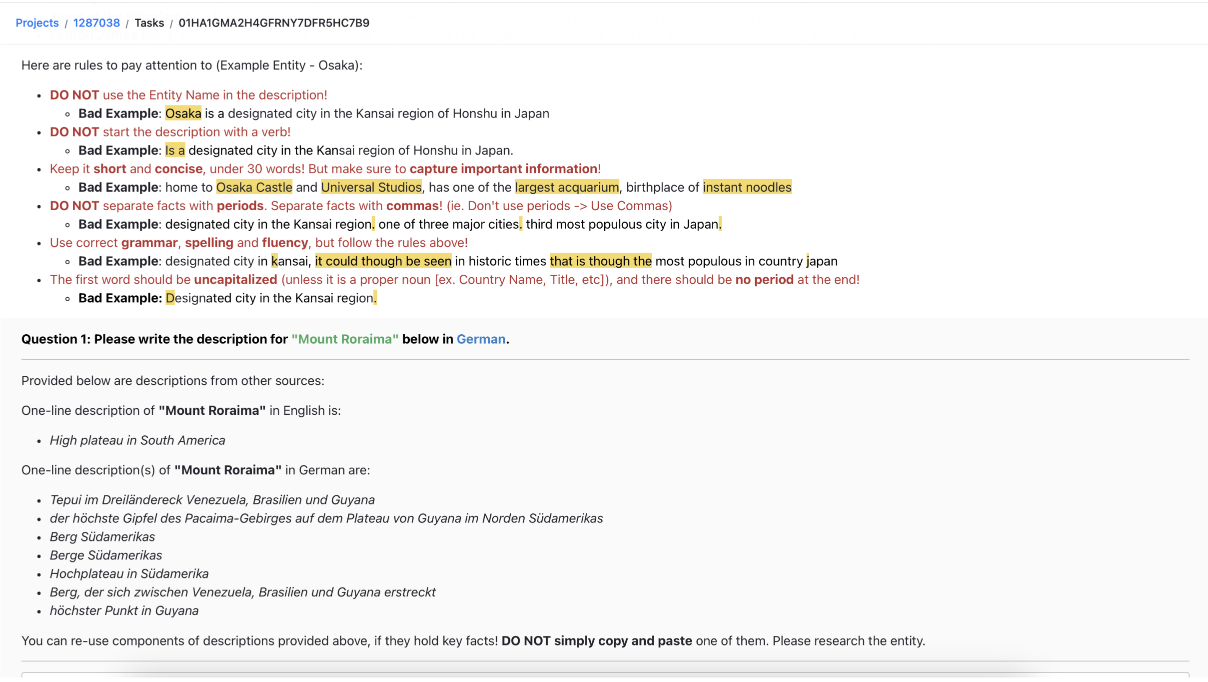


Figure 3: UI used for the annotation task: the annotators familiarized themselves with the description format with an outline of the requirements (detailed guidelines could be read in a separate page).

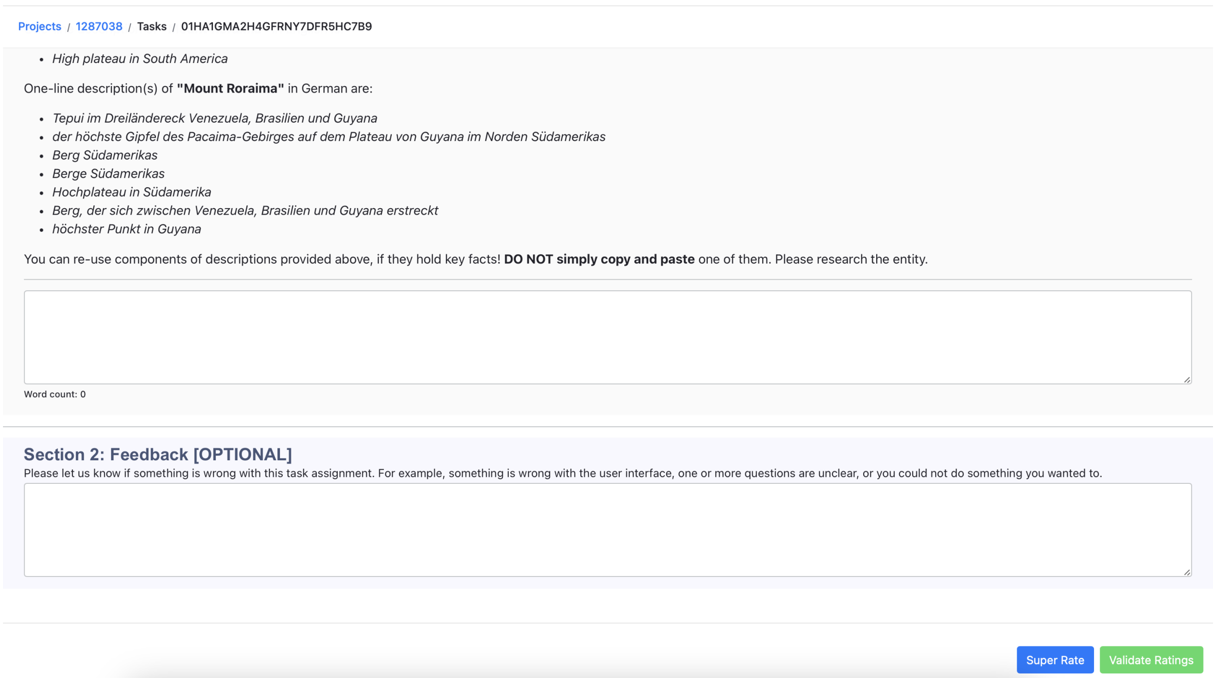
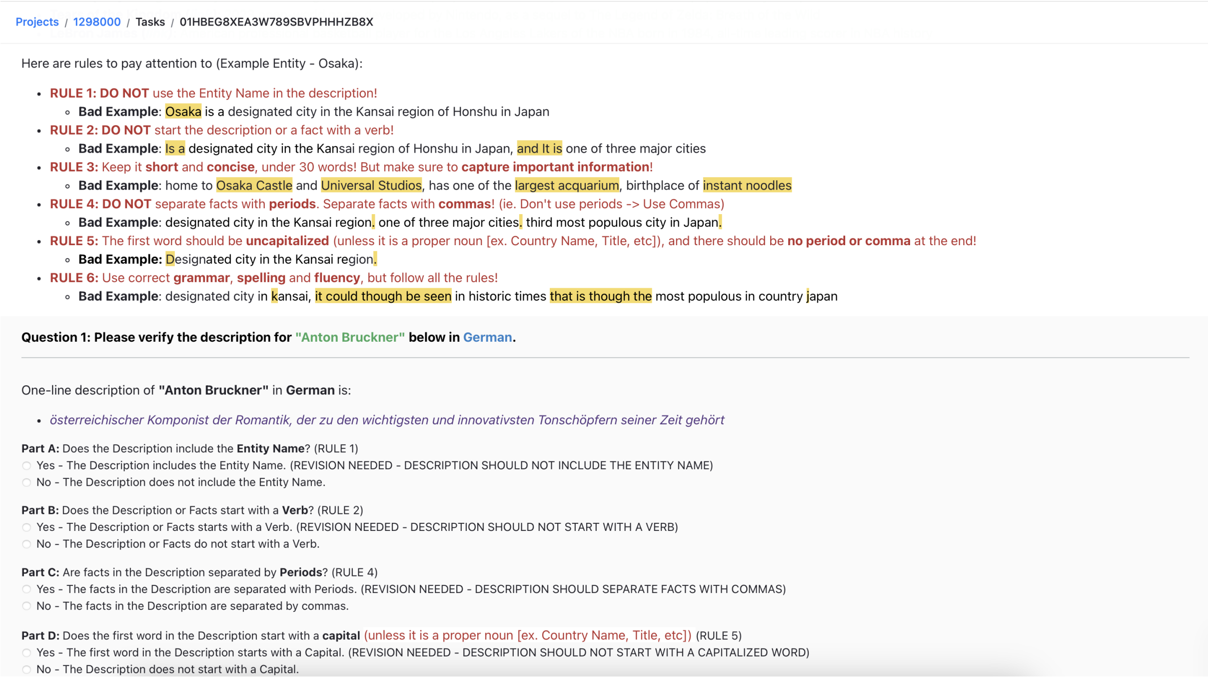


Figure 4: UI used for the annotation task: the annotator provied the description in a text box. A warning message was prompted if the token length of the description was too short or too long.


Projects / 1298000 / Tasks / 01HBEG8XEA3W789SBVPHHHZB8X

Here are rules to pay attention to (Example Entity - Osaka):

- **RULE 1: DO NOT** use the Entity Name in the description!
  - **Bad Example**: Osaka is a designated city in the Kansai region of Honshu in Japan
- **RULE 2: DO NOT** start the description or a fact with a verb!
  - **Bad Example**: Is a designated city in the Kansai region of Honshu in Japan, and It is one of three major cities
- **RULE 3:** Keep it **short** and **concise**, under 30 words! But make sure to **capture important information**!
  - **Bad Example**: home to Osaka Castle and Universal Studios, has one of the largest acquarium, birthplace of instant noodles
- **RULE 4: DO NOT** separate facts with **periods**. Separate facts with **commas**! (ie. Don't use periods -> Use Commas)
  - **Bad Example**: designated city in the Kansai region. one of three major cities. third most populous city in Japan.
- **RULE 5:** The first word should be **uncapitalized** (unless it is a proper noun [ex. Country Name, Title, etc]), and there should be **no period or comma** at the end!
  - **Bad Example:** Designated city in the Kansai region.
- **RULE 6:** Use correct **grammar**, **spelling** and **fluency**, but follow all the rules!
  - **Bad Example**: designated city in kansai, it could though be seen in historic times that is though the most populous in country japan

Question 1: Please verify the description for "Anton Bruckner" below in German.

One-line description of **"Anton Bruckner"** in **German** is:

- *österreichischer Komponist der Romantik, der zu den wichtigsten und innovativsten Tonschöpfern seiner Zeit gehört*

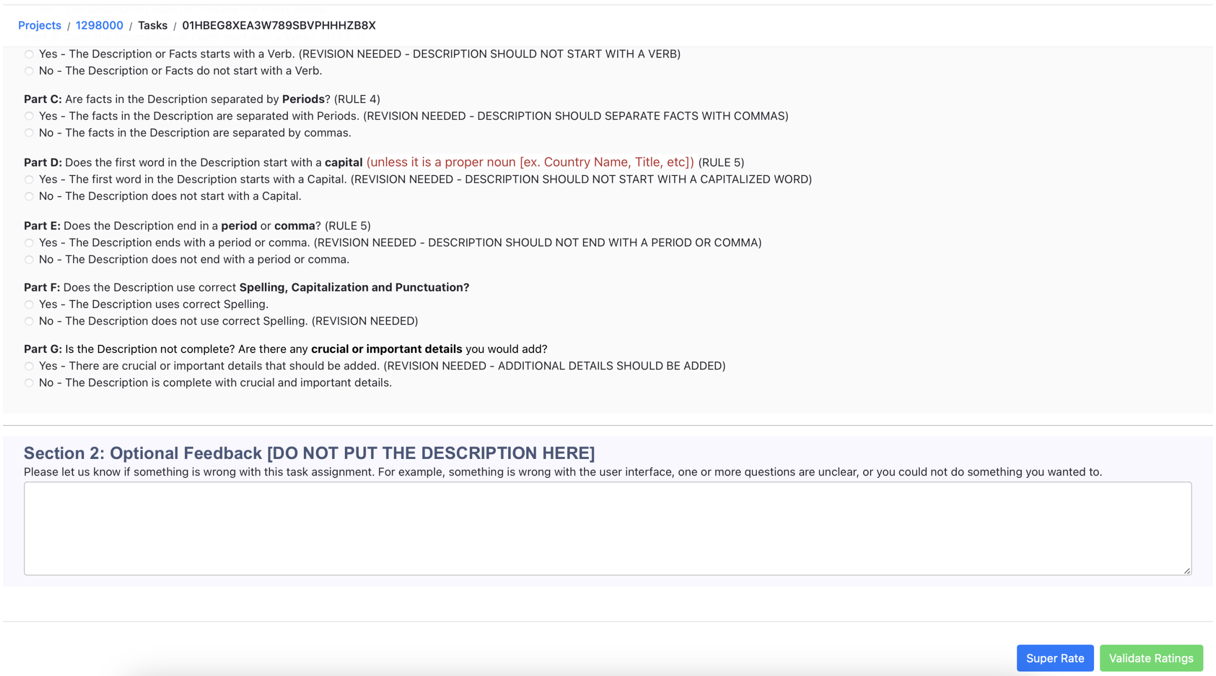
Part A: Does the Description include the **Entity Name**? (RULE 1)
Yes - The Description includes the Entity Name. (REVISION NEEDED - DESCRIPTION SHOULD NOT INCLUDE THE ENTITY NAME)
No - The Description does not include the Entity Name.

Part B: Does the Description or Facts start with a **Verb**? (RULE 2)
Yes - The Description or Facts starts with a Verb. (REVISION NEEDED - DESCRIPTION SHOULD NOT START WITH A VERB)
No - The Description or Facts do not start with a Verb.

Part C: Are facts in the Description separated by **Periods**? (RULE 4)
Yes - The facts in the Description are separated with Periods. (REVISION NEEDED - DESCRIPTION SHOULD SEPARATE FACTS WITH COMMAS)
No - The facts in the Description are separated by commas.

Part D: Does the first word in the Description start with a **capital** (unless it is a proper noun [ex. Country Name, Title, etc]) (RULE 5)
Yes - The first word in the Description starts with a Capital. (REVISION NEEDED - DESCRIPTION SHOULD NOT START WITH A CAPITALIZED WORD)
No - The Description does not start with a Capital.

Figure 5: UI used for the annotation task: annotators were required to examine the description in the target language, and answer a series of questions that reflected the description requirements.


Projects / 1298000 / Tasks / 01HBEG8XEA3W789SBVPHHHZB8X

Yes - The Description or Facts starts with a Verb. (REVISION NEEDED - DESCRIPTION SHOULD NOT START WITH A VERB)
No - The Description or Facts do not start with a Verb.

Part C: Are facts in the Description separated by **Periods**? (RULE 4)
Yes - The facts in the Description are separated with Periods. (REVISION NEEDED - DESCRIPTION SHOULD SEPARATE FACTS WITH COMMAS)
No - The facts in the Description are separated by commas.

Part D: Does the first word in the Description start with a **capital** (unless it is a proper noun [ex. Country Name, Title, etc]) (RULE 5)
Yes - The first word in the Description starts with a Capital. (REVISION NEEDED - DESCRIPTION SHOULD NOT START WITH A CAPITALIZED WORD)
No - The Description does not start with a Capital.

Part E: Does the Description end in a **period** or **comma**? (RULE 5)
Yes - The Description ends with a period or comma. (REVISION NEEDED - DESCRIPTION SHOULD NOT END WITH A PERIOD OR COMMA)
No - The Description does not end with a period or comma.

Part F: Does the Description use correct **Spelling, Capitalization and Punctuation?**
Yes - The Description uses correct Spelling.
No - The Description does not use correct Spelling. (REVISION NEEDED)

Part G: Is the Description not complete? Are there any **crucial or important details** you would add?
Yes - There are crucial or important details that should be added. (REVISION NEEDED - ADDITIONAL DETAILS SHOULD BE ADDED)
No - The Description is complete with crucial and important details.

Section 2: Optional Feedback [DO NOT PUT THE DESCRIPTION HERE]
Please let us know if something is wrong with this task assignment. For example, something is wrong with the user interface, one or more questions are unclear, or you could not do something you wanted to.

Super Rate
Validate Ratings

Figure 6: UI used for the annotation task: annotators were prompted to correct the description by rewriting it, if they negatively answer the series of questions provided.