Improving the Utility of Knowledge Graph Embeddings with Calibration

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Abstract

This paper addresses machine learning models that embed knowledge graph entities and relationships toward the goal of predicting unseen triples, which is an important task because most knowledge graphs are by nature incomplete. We posit that while offline link prediction accuracy using embeddings has been steadily improving on benchmark datasets, such embedding models have limited practical utility in real-world knowledge graph completion tasks because it is not clear when their predictions should be accepted or trusted. To this end, we propose to calibrate knowledge graph embedding models to output reliable confidence estimates for predicted triples. In crowdsourcing experiments, we demonstrate that calibrated confidence scores can make knowledge graph embeddings more useful to practitioners and data annotators in knowledge graph completion tasks. We also release two resources from our evaluation tasks: An enriched version of the FB15K benchmark and a new knowledge graph dataset extracted from Wikidata.

1 Introduction

Knowledge graphs are essential resources in many machine learning tasks, including question answering (Shen et al., 2019), reading comprehension (Yang et al., 2019), language modeling (Logan et al., 2019), product recommendation (Wang et al., 2019a), semantic search (Xiong et al., 2017), and more. Because most knowledge graphs are by nature incomplete, extensive research efforts have been invested into manually and automatically completing them (Nickel et al., 2015).

In this paper we focus on machine learning models that embed knowledge graph entities and relationships toward the goal of predicting unseen triples. Such embeddings are typically evaluated in downstream link prediction tasks, the most common of which involves ranking entities or relations in order of predicted likelihood that they “fill in the blanks” of incomplete triples (Bordes et al., 2013). While model accuracy using this approach has been steadily improving on benchmark datasets over the past decade (Wang et al., 2017), ranking-based evaluations can be misleading: They only consider the ordering of plausibility for each predicted triple, so models can perform well according to ranking-based metrics even if they assign high scores to incorrect, impossible, or even nonsensical triples (Wang et al., 2019b). As such, the practical utility of embeddings for automatic knowledge graph completion remains unclear, especially given that other completion techniques like relation extraction (Suchanek et al., 2007; Dong et al., 2014; Ammar et al., 2018) and manual curation (Miller, 1995) can directly and reliably complete triples with answers obtained from external data sources.

Goal The outstanding issue that we address relates to trustworthiness: That is, when should one trust (or further verify) the facts predicted by knowledge graph embedding models? We believe that trustworthiness is an important step toward making embedding-based predictions useful for knowledge graph completion, and posit that model calibration, or scaling output triple scores to represent true correctness probabilities, is one technique in this direction. For example, machine learning systems that construct or rely on knowledge graphs can use calibrated confidence scores to determine which automatically predicted triples to trust (Dong et al., 2014; West et al., 2014). From a human-AI perspective, which is our main focus, practitioners and data annotators can use calibrated confidence estimates as decision support for accepting or verifying model predictions.

∗This work was done during an internship at Bloomberg.
1.1 Research questions and contributions

The key contributions of this paper are to answer the following research questions:

**R1** Are off-the-shelf knowledge graph embedding models calibrated for link prediction?

**R2** How can practitioners use predictions generated by calibrated embedding models for knowledge graph completion tasks, and how much does calibration improve performance in these tasks?

**R3** Do data annotators perform better in knowledge graph completion tasks with or without help from calibrated confidence estimates generated by embedding models?

We also release two resources associated with questions R2 and R3: (1) An updated version of the FB15k benchmark (Bordes et al., 2013; Xie et al., 2016) with additional triples and mappings to Wikidata, and (2) a new knowledge graph dataset extracted from Wikidata about authors and writers.¹

1.2 Outline

The remainder of this paper is structured as follows. First, we give preliminaries in § 2. Next, we answer research question R1 in § 3 by showing that while all embedding models we study suffer a degree of miscalibration, standard calibration techniques can significantly decrease calibration error.

We address R2 in § 4 by demonstrating how practitioners can use calibrated embedding-based predictions for knowledge graph augmentation and error detection. Unlike works that complete triples with known ground-truth answers (Bordes et al., 2013; Wang et al., 2014; Dettmers et al., 2018) or find synthetic injected errors (Pezeshkpour et al., 2019), we use embedding models to predict actual missing and erroneous triples in a benchmark knowledge graph, and turn to crowdsourcing to verify the truth values of these predictions.

Finally, to answer R3 in § 5, we conduct an A/B test in which crowd workers complete triples with or without the help of calibrated confidence estimates from embedding models. Our results indicate that crowd workers are more accurate, efficient, and satisfied with the task when provided these confidence estimates. Finally, we outline related work in § 6 and conclude with a discussion in § 7.

2 Preliminaries

2.1 Terminology

**Knowledge graphs** A knowledge graph G comprises a set of entities E, relations R, and (head, relation, tail) triples or facts (h, r, t) ∈ E × R × E. Let ŷ_{hrt} be a binary random variable with value 1 if triple (h, r, t) is true or factual, and 0 otherwise. We address the task of **link prediction for knowledge graph completion**, which is typically cast as a “fill-in-the-blank” problem. For example, given triple (h, r, ?) with missing tail entity t, rank all candidate tail entities t in decreasing order of prediction likelihood that ŷ_{hrt} = 1 for (h, r, t).

A knowledge graph embedding model takes triples (h, r, t) as input and learns corresponding embeddings (h, r, t) to maximize a scoring function \( f : E \times R \times E \to \mathbb{R} \), such that more plausible triples receive higher scores and are ranked higher in the link prediction task. Table 4 in Appendix A gives examples of scoring functions.

**Calibration** Calibration is the extent to which models output prediction scores that are representative of true correctness probabilities (Guo et al., 2017). As an example, for a set of 100 triples predicted to be true (ŷ_{hrt} = 1) by a perfectly calibrated link prediction model, each at confidence level \( \hat{p} = 0.9 \), we expect 90 of these predictions to be correct (ŷ_{hrt} = 1) according to some binary correctness metric.

2.2 Obtaining confidence scores

To convert the scores of knowledge graph embedding models into confidence estimates, we use two standard transformation functions. The first, the **logistic sigmoid**, is applied to each triple score to obtain a confidence

\[
\hat{p} = \sigma_{\text{sig}}(f(h, r, t)) = \frac{1}{1 + \exp[-f(h, r, t)]}. \tag{1}
\]

By contrast, the **softmax** is applied over a group of candidates in which it is assumed that a single answer completes a given triple (i.e., multi-class classification). For example, assume that a single relation “fills in the blank” in triple (h, ?, t). To predict this relation, we fix the head-tail entity pair (h, t) and compute the scores \( f(h, r_i, t) \) for all relations \( r_i \in R \). Then, given triple scores \( z = [f(h, r_1, t), \ldots, f(h, r_{|R|}, t)]^\top \), confidence

¹https://zenodo.org/record/3738264
values for each triple are obtained via the softmax
\[ \sigma_{sm}(z) = \frac{\exp[z]}{\sum_{k=1}^{M} \exp[z_k]}. \] (2)

The predicted relation is \( \hat{r} = \arg \max \sigma_{sm}(z) \) with confidence \( \hat{p} = \max \sigma_{sm}(z) \). The softmax works well in practice for relation prediction, as we demonstrate in our empirical analysis (§ 3).

2.3 Calibrating confidence scores

To calibrate a model, calibration parameters are learned on a validation set using the output scores of the uncalibrated model. Calibration does not alter the embedding parameters directly, but rather transforms how the model scores predicted triples.

**Platt scaling**  Platt scaling encompasses several linear parametric calibration techniques (Platt et al., 1999; Guo et al., 2017). In binary classification, Platt scaling uses uncalibrated output scores \( z = [f(h, r, t)_1, \ldots, f(h, r, t)_n]^\top \) as input features for a logistic regression \( \sigma_{sig}(az + b) \), and learns the scalars \( a \) and \( b \) to output calibrated probabilities for each triple. Note that negative examples are required. Since determining true negatives can be difficult, the standard approach is to corrupt randomly sampled triples, although more sophisticated methods have been proposed (Cai and Wang, 2018; Tabacof and Costabello, 2020).

In the multiclass case, Guo et al. (2017) proposed a two-dimensional extension of Platt scaling that learns \( 2k \) parameters for \( k \) classes. Letting \( A \in \mathbb{R}^{k \times k} \) be a diagonal matrix and \( b \in \mathbb{R}^k \) be a bias vector, \( A \) and \( b \) are learned such that the calibrated confidence for a single instance over \( k \) classes is \( \hat{p} = \max \sigma_{sm}(Az + b). \) We optimize Platt scaling with negative log-likelihood loss.

Note that one-dimensional Platt scaling transforms all scores by a constant factor, so it does not alter model accuracy because triple scores are ranked in the same order before and after calibration. By contrast, in two-dimensional Platt scaling, the learned scaling factors are allowed to vary across classes, which means that the ordering of triple scores may differ before and after calibration.

**Isotonic regression**  Isotonic regression is a non-parametric method that fits a nondecreasing, piecewise constant function \( g \) by minimizing the sum of squares \( \sum_{i=1}^{n} (\hat{y}_{hrt} - g(\hat{p}))^2 \) for predictions \( \hat{y}_{hrt} \) with uncalibrated confidences \( \hat{p} \) (Zadrozny and Elkan, 2002). It can be extended to multiclass prediction by setting up \( k \) binary calibration problems for \( k \) classes. Like one-dimensional Platt scaling, isotonic regression does not alter model accuracy.

3 Empirical calibration analysis

To answer research question R1 on the calibration of off-the-shelf knowledge graph embeddings (§ 1.1), we conduct a brief empirical analysis.

3.1 Data

We use two knowledge graph completion benchmarks: (1) WN18RR (Dettmers et al., 2018), a semantic relation network from the WordNet lexical database (Miller, 1995) with 40,943 entities, 11 relationships, and 93,003 triples; and (2) a version of the open-domain FB15K knowledge graph (Bordes et al., 2013; Xie et al., 2016) with 14,290 entities, 773 relationships, and 272,192 triples. Appendix B.1 provides more details on how we preprocessed FB15K for our experiments.

For each knowledge graph described in this paper, we construct five random splits consisting of 80% train, 10% validation, and 10% test triples, and report averages over those five splits.

3.2 Models

We compare four embedding models that are commonly used as baselines for knowledge graph completion: (1) TransE (Bordes et al., 2013), (2) TransH (Wang et al., 2014), (3) DistMult (Yang et al., 2015), and (4) ComplEx (Trouillon et al., 2016). Appendix A.1 describes each model further and provides implementation details.

3.3 Metrics

We evaluate link prediction accuracy with hits@k, which measures the proportion of test triples in which the ground-truth entity (relation) is ranked in the top \( k \) predicted entities (relations).

We evaluate calibration with a variant of expected calibration error (ECE) (Guo et al., 2017), which is a weighted average of the difference between confidence and link prediction accuracy in \( M \) equally-sized bins partitioning [0, 1]:
\[ \frac{1}{n} \sum_{m=1}^{M} \frac{|B_m|}{n} \text{hits}@k(B_m) - \text{conf}(B_m), \] (3)

where \( n \) is the total number of test triples, \( B_m \) is the bin containing all predictions with confidence in a
Table 1: ECE ($M = 10$ bins) on WN18RR and FB15K, averaged over five dataset splits (all stdevs $< 0.01$.) Lower is better.

|            | WN18RR ($h, r, ?$) | FB15K ($h, ?, t$) |
|------------|---------------------|---------------------|
|            | Uncalib. | Iso. | Platt 1D | Uncalib. | Iso. | Platt 1D | Platt 2D |
| TransE     | 0.026 | 0.006 | 0.013 | 0.795 | 0.016 | 0.071 | 0.026 |
| TransH     | 0.495 | 0.007 | 0.014 | 0.177 | 0.024 | 0.081 | 0.031 |
| DistMult   | 0.314 | 0.016 | 0.021 | 0.104 | 0.031 | 0.095 | 0.018 |
| ComplEx    | 0.320 | 0.017 | 0.030 | 0.055 | 0.037 | 0.102 | 0.024 |

given region of $[0, 1]$, hits@$k(\cdot)$ measures the average hits@$k$ score in bin $B_m$, and conf$(\cdot)$ measures the average confidence score in bin $B_m$.

Both hits@$k$ and ECE are in $[0, 1]$. Higher is better for hits@$k$, and lower is better for ECE. For all reported ECE values, we use $M = 10$ bins.

3.4 Results and discussion

For brevity, here we provide results for ($h, r, ?$) tail entity prediction on WN18RR and ($h, ?, t$) relation prediction on FB15K; Appendix A.2 provides additional results. We treat entity prediction as binary and compute accuracy with hits@10. By contrast, since most head-tail entity pairs in knowledge graphs are linked by a single relation type, we treat relation prediction as a multiclass classification problem, and compute accuracy with hits@1.

Pre-calibration Table 1 demonstrates that all off-the-shelf models suffer a degree of miscalibration, except for TransE on WN18RR, which predicts all instances with $\hat{p} \approx 0.52$ at a hits@10 of $\approx 0.5$. One explanation for the relatively high error follows our discussion in § 1: Most knowledge graph embeddings are trained by minimizing a pairwise margin-based ranking loss between positive examples and sampled negatives, which does not account for the actual values of model scores, but only their ordering. Appendix A.2 provides more analysis and insights into how each model scores triples.

Post-calibration The techniques in § 2.3 are able to calibrate all models to around 1-2% error. On WN18RR, isotonic regression consistently performs the best. On FB15K, isotonic regression performs best for TransE and TransH, whereas two-dimensional Platt scaling performs best for DistMult and ComplEx. In fact, two-dimensional Platt scaling, the only calibration technique we use that can alter model accuracy, improves hits@1 by up to 3.27% (Figure 1). We speculate that this improvement may be due to increased model complexity from the extra set of parameters learned, but leave further investigation to future work.

In summary, to answer research question R1, although the knowledge graph embedding models we study are not well-calibrated, standard techniques can significantly reduce their calibration error and in some cases improve their link prediction accuracy. Next, we turn to crowdsourcing to answer our remaining research questions.

4 True or False Facts

Our first crowdsourcing experiment, called True or False Facts, answers research question R2 (§ 1.1): We explore the ways that practitioners can use calibrated embedding-based predictions in knowledge graph completion tasks, and demonstrate how calibrated predictions can improve performance in such tasks compared to uncalibrated predictions.

We emphasize that in these experiments we use knowledge graph embeddings to predict actual unseen and erroneous triples in a benchmark dataset. We verify these predictions via crowdsourcing, and release the correct predictions as part of an updated, enriched version of that benchmark.

4.1 Setup

This experiment focuses on relation prediction. For each ($h, r, t$) triple in a knowledge graph, a pre-trained embedding model predicts a relation $\hat{r}$. We are interested in predicted triples ($h, \hat{r}, t$) for which $\hat{r} \neq r$ and ($h, r, t$) $\not{\in} G$: These are potential missing facts in the knowledge graph.

To simulate how a practitioner might explore these triples, we follow a binary model in which only high-confidence predictions are considered: We take only the triples with confidence level $\hat{p}$ greater than a manually-defined threshold $\theta \in [0, 1]$, and discard the rest. The crowdsourcing task then becomes a matter of labeling the high-confidence predictions ($h, \hat{r}, t$) $\not{\in} G$ and corresponding observed triples ($h, r, t$) $\in G$ with their truth values $y_{hrt} \in \{0, 1\}$. In the next section we outline our hypotheses regarding the truth
values of these triples.

4.2 Hypotheses

Our first hypothesis (H1) addresses the **task of augmenting knowledge graphs**, and is motivated by the idea that high-confidence calibrated predictions should, by definition, be highly accurate. Specifically, we hypothesized that the high-confidence calibrated predictions generated by the process in § 4.1 would more frequently correspond to unobserved but factual triples, i.e., false negatives

\[
\{(h, \hat{r}, t) \notin G \mid y_{hrt} = 1\},
\]

(4) than the high-confidence uncalibrated predictions.

Our second hypothesis (H2) concerns the **task of error detection**, or the detection of false positives. We hypothesized that the high-confidence calibrated predictions \((h, \hat{r}, t) \notin G\) would more frequently correspond to **erroneous observed** triples

\[
\{(h, r, t) \in G \mid y_{hrt} = 0\}
\]

(5) than the high-confidence uncalibrated predictions.

4.3 Data

**Knowledge graph** We use FB15K (§ 3.1) in this task because it is relatively large and diverse, and is not highly specialized toward a specific domain of expertise. To help crowd workers efficiently verify the predicted triples, we linked FB15K to Wikidata (Vrandečić and Krötzsch, 2014) and the IMDb movie database using Freebase machine IDs as keys, and discarded triples containing entities without corresponding Wikidata pages. We provided links to entities’ Wikidata pages (or IMDb pages for /film relations) in the task (§ 4.4).

**Task input** We constructed two samples of triple pairs to be annotated by crowd workers: A **(1) calibrated sample** and a **(2) baseline uncalibrated sample**, both consisting of predictions made by the models in § 3.2 (we used 2D Platt scaling as the calibrator for the first sample). We limited these samples to all predictions with confidence level \(\hat{p} > 0.8\) (§ 4.1) to obtain a manageable sample size for exploration and annotation; we discuss the effects of varying \(\theta\) on sample size in § 4.6. For the purpose of presenting triples to crowd workers, we automatically converted each triple to natural language using pre-defined sentence templates for each relation. We discarded triples with relations that were not interpretable by fluent English speakers, and manually edited sentences for grammar (e.g., articles, plurals). After preprocessing, the calibrated and uncalibrated sample sizes were \(n = 974\) and 178 respectively; the baseline sample was smaller because the uncalibrated models made fewer predictions at confidence level \(\hat{p} \geq 0.8\). Appendix B.1 provides more details on data preprocessing.

4.4 Task design

In the crowdsourcing task interface, each triple was presented in sentence form, with the head and tail entities linked to Wikidata or IMDb (we give examples in Appendix B.2). For each sentence, crowd workers answered three questions:

**Q1** Is this sentence factually correct?

**Q2** Which Wikidata or Wikipedia (IMDb) link did you use to arrive at your answer?

**Q3** Which sentence(s) or information from Wikidata or Wikipedia (IMDb) did you use to arrive at your answer?

The answer choices for question **Q1** were **Yes**, **No**, and **Unsure**. Exactly one answer was required. Questions **Q2** and **Q3** were freeform text answers. For question **Q2**, we rejected answers that did not match regexes for Wikidata, Wikipedia, and IMDb URL string patterns.

4.5 Participants

We recruited 299 participants from the Figure 8 crowdsourcing platform. The task was limited to the highest-trusted group of contributors on the platform, those who had completed 10 or more jobs with an accuracy of at least 85%. To ensure contributor accuracy and quality, we pre-labeled 20% of all triples. Participants were required to pass a 5-question “quiz” before starting the task and maintain 90% accuracy or higher on the remaining gold questions, which were inserted randomly throughout. Those who fell below the minimum accuracy threshold were removed from the task, and their annotations were discarded. We collected five judgments per triple and took the majority label as ground-truth. The inter-annotator agreement using Fleiss’ kappa (Fleiss, 1971) was \(\kappa = 0.7489\).
Table 2: Examples of ground-truth \((h, r, t) \in G\) triples and their corresponding \((h, \hat{r}, t) \notin G\) predictions in the FB15K calibrated sample from True or False Facts. Each group of triples is explained in § 4.6. Blue (+): A factual relation. Red (−): An erroneous relation. Best viewed in color.

| Head \(h\) | Ground-truth relation \(r\) | Predicted relation \(\hat{r}\) | Tail \(t\) |
|----------------|----------------|----------------|----------------|
| House of Windsor | /people/family/members* | /royalty/monarch/royal_line* | Charles, Prince of Wales |
| James Wong Jin | /people/deceased_person/place_of_death* | /people/person/nationality* | Hong Kong |
| John Ottman | /film/editor/film† | /film/music_contributor/film | Management |
| Elijah Wood | /food/diet_follower/follows_diet† | /eating/practicer_of_diet/diet | veganism |
| Gujarati Girls | /language/human_language/main_country† | /language/human_language/countries_spoken_in† | Uganda |
| †Girls | /tv/tv_program/country_of_origin† | /tv/tv_program/country | United States of America |

![Image](72x566 to 179x632)

Figure 2: Calibrated predictions have better precision and recall for identifying missing triples (false negatives) and erroneous triples (false positives) in FB15K.

4.6 Results and discussion

In this section we address how our collected annotations support or refute each hypothesis in § 4.2. We provide additional results in Appendix B.3.

**Augmentation** Addressing hypothesis H1. Figure 2a gives the precision and recall of the uncalibrated and calibrated models in predicting factual triples \((h, \hat{r}, t) \notin G\). We define precision as the number of \((h, \hat{r}, t)\) predictions in each sample that were judged by crowd workers as true, divided by the number of predictions in that sample:

\[
\text{Prec} = \frac{|\{(h, \hat{r}, t) \mid y_{hrt} = 1\}_\text{sample}|}{|\{(h, \hat{r}, t)\}_\text{sample}|}. \quad (6)
\]

The precision of the calibrated sample was 0.549 versus 0.295 for the uncalibrated sample, corresponding to an increase of 25.4 percentage points.

To compute recall, we pool all \((h, \hat{r}, t) \notin G\) triples across both samples that were judged by crowd workers as factual:

\[
\text{Rec} = \frac{|\{(h, \hat{r}, t) \notin G \mid y_{hrt} = 1\}_\text{sample}|}{|\{(h, \hat{r}, t) \notin G \mid y_{hrt} = 1\}_\text{all}|}. \quad (7)
\]

The recall of the calibrated sample was 0.938, compared to 0.108 for the uncalibrated sample. As discussed in § 4.3, this disparity is (partially) because the uncalibrated embedding models were underconfident for relation prediction, making few predictions with confidence \(\hat{p} \geq 0.8\). The maximum recall of the uncalibrated sample (i.e., if all uncalibrated predictions were correct) was 0.2904.

We also study the effect of increasing the confidence threshold \(\theta\) on sample size and model precision in predicting missing triples (false negatives).

Figure 3 demonstrates that, as expected, precision increases with \(\theta\) in the calibrated sample and peaks around 0.6 at the highest confidence threshold. By contrast, the trend in the uncalibrated sample is more erratic as \(\theta\) increases, which is consistent with our observation that off-the-shelf knowledge graph embedding models are not calibrated (§ 3.4).

The first and third group of rows in Table 2 gives illustrative examples of missing, factual triples \(\{(h, \hat{r}, t) \notin G \mid y_{hrt} = 1\}\) predicted by the calibrated models. Some ground-truth/predicted relation pairs can be considered synonyms in the context of their head and tail entities (e.g., /people/family/members and /royalty/monarch/royal_line for members of royalty.

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and royal families), whereas others likely exploit common correlations, for example that people may die in their country of citizenship. Others are minor factual corrections to errors in the knowledge graph, for example concerning entity types.

**Error detection** Addressing hypothesis H2, Figure 2b compares the precision and recall of the calibrated and uncalibrated models in finding erroneous triples. We compute precision as the number of \((h, r, t) \in G\) triples judged by crowd workers as false in each sample divided by the number of triples in that sample; we compute recall by pooling all such false positives across both samples. The precision was 0.118 for the calibrated sample and 0.056 for the uncalibrated sample (+6.2 percentage points improvement). The calibrated sample’s recall was 0.963; the uncalibrated sample’s recall was 0.093 out of a maximum recall of 0.6475 (i.e., assuming all uncalibrated predictions corresponded to erroneous ground-truth triples).

Table 2 gives examples of instances of erroneous ground-truth triples \(\{(h, r, t) \in G \mid y_{hrt} = 0\}\) detected by the calibrated models in the second and third group of rows. For example, one false positive triple says that the actor Elijah Wood is vegan, but no information on Wikidata or Wikipedia supports this claim. Another false positive says the main country in which Gujarati is spoken is Uganda, whereas its true main country is India. However, Gujarati is spoken by a small minority of people in Uganda, so the predicted relation /language/human_language/countries_spoken_in corrects this error. Overall, to address our hypotheses in § 4.2, we conclude that calibrated knowledge graph embeddings are better at predicting both false negative (H1) and false positive (H2) triples than their uncalibrated counterparts.

5 **Fill In the Blanks**

Our final experiment, an A/B test called Fill In the Blanks, answers research question R3 (§ 1.1) by investigating whether data annotators perform better in knowledge graph completion tasks when given calibrated confidence scores.

5.1 Hypotheses

In this experiment, given “fill-in-the-blank” sentences corresponding to incomplete knowledge graph triples, crowd workers chose from multiple-choice answer lists generated by embedding model predictions to complete the sentences. Motivated by the idea that calibrated confidences can be used as decision support, we hypothesized that, compared to crowd workers not provided with confidence scores for this task, workers provided with calibrated confidence scores for answer choices would (H1) complete triples with higher accuracy; (H2) more efficiently complete triples; and (H3) report higher task satisfaction.

5.2 Data

**Knowledge graph** We constructed a knowledge graph consisting of 23,887 entities, 13 relations, and 86,376 triples from Wikidata; we release it to the community for further research. We limited the graph to triples in which the head entity was a person categorized as an “author” or “writer” on Wikidata, and 13 people-centric relations (e.g., born in, married to). We chose Wikidata to ensure that all answers could be resolved using a single public-domain source of information, so that crowd workers’ efficiency would not be affected by the need to use search engines. We chose writing as a domain because it is less “common knowledge” than, e.g., pop culture or current affairs. We describe the dataset in more detail in Appendix C.1.

**Task input** After training and calibrating each embedding model from § 3.2 over the Wikidata graph, we predicted held-out relations of triples similar to § 4.1. Per triple, we took the top-five predicted relations \(\hat{r}\) and their calibrated confidence scores \(\hat{p}\). We then filtered these predictions to a sample of \(n = 678\) triples by choosing only instances whose ground-truth relation \(r\) was in the top-five predictions \(\hat{r}\), balancing the proportion of correct answers by relation type, discarding questions with multiple correct answers, and discarding questions with answers that were easy to guess based on type matching or keywords. We give more details on preprocessing in Appendix C.1.

5.3 Task design

Each incomplete triple was presented as a sentence consisting of a head entity linked to Wikidata, a blank underlined space, and a tail entity linked to Wikidata (we give examples in Appendix C.2). Each sentence was associated with three questions:

**Q1** Which answer correctly fills in the blank?

5https://bit.ly/3cchW4M

6https://bit.ly/2I1Bjjm

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https://bit.ly/2I1Bjjm

https://bit.ly/3cchW4M
Table 3: Compared to the control group in Fill In the Blanks, crowd workers in the treatment group: (1) Provided judgments that were 1-3% more accurate; (2) Were 2-5 seconds faster per judgment on average; and (3) Reported higher task satisfaction on all survey questions. § 5.5 provides detailed analysis. ↑: Higher is better. ↓: Lower is better. **Bold:** Significant at $p < 0.05$. **Underline:** Significant at $p < 0.01$. *: $p$-value not applicable.

|                  | Accuracy ↑ | Sec/judgment ↓ | Satisfaction (points out of 5) ↑ |
|------------------|------------|----------------|----------------------------------|
|                  | Overall    | Per triple     | Per worker                       | No filt. | All Qs | Ease | Fairness | Pay | Clarity | Overall |
| Control          | 0.8977     | 0.8969         | 0.9120                           | 33.63    | 36.88  | 3.200 | 3.333    | 3.333 | 3.733   | 3.200   |
| Treatment        | **0.9175** | **0.9230**     | **0.9478**                       | 31.18    | **31.91** | 3.500 | 3.742    | 3.875 | 4.031   | **4.000** |
| **Abs. diff.**   | +0.0198    | +0.0251        | +0.0358                          | −2.45    | −4.97  | +0.300 | +0.409   | +0.542 | +0.298  | +0.800  |
| **Rel. diff.**   | +2.21%     | +2.79%         | +3.93%                           | −7.29%   | −13.48% | +9.37% | +12.26%  | +12.50% | +6.29%  | +25.00% |

Q2 Which Wikidata link did you use to arrive at your answer?

Q3 Which sentence(s) or information from Wikidata did you use to arrive at your answer?

The answer choices for Q1 were the triple’s top-five predicted relations $\{\bar{r}_i\}_{i=1}^5$ in natural language, and exactly one answer was required.

To investigate the utility of calibrated confidences in a controlled manner, we conducted a between-subjects randomized controlled experiment whereby we varied how the confidence scores for answer choices $\{\bar{p}_i\}_{i=1}^5$ were presented to participants. Crowd workers were assigned to one of two conditions that varied the presentation of Q1:

- **No confidence (control):** All multiple-choice answers for question Q1 were provided in their natural language form without any accompanying confidence estimates.

- **Calibrated confidence (treatment):** A calibrated confidence score was provided along with each answer candidate to question Q1 in parentheses. The following text was included in the task instructions: *Please note that we have used a computer system to generate “confidence values” for each answer choice in order to help you with the task. These values signify our system’s belief about which answer is most likely to be correct.*

To mitigate position bias (Craswell et al., 2008), we randomized the presentation order of answer choices for question Q1 so that the answers were not necessarily ranked in decreasing order of confidence. The answer candidates were presented in the same randomized order for both groups. The only difference in presentation was the addition of parenthetical confidences and the extra paragraph of task instructions for the treatment group.

Post-task, an optional satisfaction survey was presented, consisting of five questions: (1) The ease of the task; (2) The fairness of the pre-labeled gold questions; (3) The level of pay relative to other tasks; (4) The clarity of task instructions and interface; and (5) Overall satisfaction. All answers were given on a scale of one to five points.

5.4 Participants

We recruited 226 participants for the control group and 202 participants for the treatment group from Figure 8. We limited the task to the highest-trusted contributors on the platform. For quality control, we pre-labeled 10% of all triples. Participants in both groups were required to pass a 10-question “quiz” prior to starting the task and maintain a 50% minimum accuracy during the task on the remaining gold questions, which were inserted randomly throughout. To prevent one person’s performance from dominating the results, each participant provided a maximum of 20 judgments. We collected three judgments per triple.

5.5 Results and discussion

We address each hypothesis in § 5.1. For the efficiency (H2) hypothesis, statistical significance is determined with an independent two-sample $t$-test. For the accuracy (H1) and satisfaction (H3) hypotheses, statistical significance is determined with the Wilcoxon rank-sum test due to non-normality. For reference, Table 3 summarizes our results.

**Accuracy** Overall, the proportion of correct judgments in the control group was 89.77%, compared to 91.75% in the treatment group (+1.98 percentage points improvement). In terms of average judgment accuracy per triple, or the number of correct judgments per triple divided by the number of judgments for that triple, the control group average was 0.8909, compared to 0.9220 for the treatment
group. This difference was significant ($p < 10^{-3}$). In terms of average judgment accuracy per participant, or the number of correct judgments per participant divided by the number of judgments by that participant, the average in the control group was 0.9120, compared to 0.9478 in the treatment group. This difference was also significant ($p < 10^{-6}$).

Finally, model accuracy was 0.6268, meaning that for 62.68% (425/678) of triples seen by crowd workers in the treatment group, the answer choice with the highest confidence score was the correct answer. Given that the treatment group’s accuracy was much higher (0.9175 versus 0.6268), we can conclude that the participants in this group did not blindly trust the confidence scores.

**Efficiency** For this analysis we removed participants with average judgment times more than two standard deviations away from the mean of their respective experimental group, leaving 216 participants in the control group and 192 participants in the treatment group. On average, the remaining participants in the control group took 33.63 seconds per judgment, whereas those assigned to the treatment group took 31.18 seconds per judgment. While this difference corresponded to an average efficiency gain of 7.29%, it was not statistically significant ($p = 0.1835$).

However, some crowd workers tended to **skip** question Q3 (“Which sentence(s) or information from Wikidata did you use to arrive at your answer?”), which made their average judgment times faster. When excluding such participants from both groups, which reduced the control and treatment group sizes to 194 and 179 respectively, the mean time per judgment was 36.88 seconds in the control group compared to 31.91 seconds in the treatment group. This difference was significant ($p = 0.010$). Interestingly, this result suggests that quality control affected the control group more than the treatment group: Average efficiency in the treatment group was nearly constant even after removing those who skipped Q3 (31.18 seconds versus 31.91 seconds), whereas average time per judgment in the control group increased by 3.25 seconds when removing those who skipped Q3.

**Satisfaction** We obtained 15 responses to the satisfaction survey (§5.3) from participants assigned to the control group and 32 responses from participants assigned to the treatment group. Those assigned to the treatment group responded to all questions with higher average satisfaction scores (Table 3). In particular, the average “overall satisfaction” in the control group was 3.2 out of 5, as opposed to 4 out of 5 for the treatment group, a difference that was significant ($p = 2.9 \times 10^{-3}$). There were also significant differences in ratings for the “fairness of pre-labeled gold questions” and “payrate relativity” questions at $p < 0.05$ ($p = 0.042$ and $p = 0.025$, respectively).

Overall, to address our hypotheses in §5.1, we conclude that our results provide numerous indications that data annotators are more accurate (H1), efficient (H2), and satisfied (H3) when provided calibrated confidence scores generated by embedding models in a knowledge graph completion task. These results suggest that calibrated confidence scores are indeed trustworthy and/or useful.

### 6 Related work

While calibrating machine learning models has a long history (Platt et al., 1999; Zadrozny and Elkan, 2002; Niculescu-Mizil and Caruana, 2005), relatively little work on calibration for knowledge graphs exists. A few works calibrate predicted knowledge graph triples as components of large-scale relation extraction systems: Dong et al. (2014) used Platt scaling to calibrate the probabilities of factual triples in the proprietary Knowledge Vault dataset, and West et al. (2014) used Platt scaling as a final step in a search-based fact extraction system. These works suggest that practitioners do indeed prefer calibrated confidences in the “real world”, although neither explores the downstream benefits of calibration in detail.

Recently, Tabacof and Costabello (2020) proposed a new method for negative sampling to calibrate knowledge graph embeddings. This is the only work of which we are aware that explicitly proposes to calibrate knowledge graph embeddings for link prediction. However, unlike Tabacof and Costabello (2020), we conduct both automatic and human evaluation, emphasizing the human-AI perspective to calibration by demonstrating its benefits to practitioners and data annotators in completion tasks. While AI trustworthiness as it relates to prediction confidences has been studied in the

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8 We acknowledge that the relatively few responses to the survey is a limitation. Note, however, that contributor satisfaction surveys are strictly optional on the Figure 8 platform.
human-computer interaction community (Dudley and Kristensson, 2018), we are not aware of work specifically tailored to knowledge graphs.

7 Discussion and conclusion

We conduct a unique study on improving the utility of knowledge graph embeddings in completion tasks with calibrated confidences. Our findings indicate that, given a knowledge graph for which embedding-based link prediction models can be calibrated successfully (i.e., within a few percentage points of error), the calibrated confidences from these models’ predictions can be useful to practitioners and data annotators as decision support. We also release two knowledge graph datasets to the community for further research.

Future work could introduce additional conditions in randomized controlled experiments to compare, e.g., how crowd worker performance changes given miscalibrated versus calibrated confidences. Another direction could investigate calibrated knowledge graph embeddings for critical domains like finance or healthcare. As knowledge graphs are increasingly used as gold standard data sources for downstream machine learning and human-AI systems, our work is a step toward making embedding-based predictions over knowledge graphs more practical.

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Table 4: Scoring functions of models used in our evaluation. Bold letters indicate vectors, i.e., embeddings.

| Scoring function $f$ | Scoring function notes | Loss function |
|----------------------|------------------------|---------------|
| TransE (Bordes et al., 2013) | $-∥h + r - t∥_2$ | Margin ranking loss |
| TransH (Wang et al., 2014) | $-∥h + r - t∥_2$ | Margin ranking loss |
| DistMult (Yang et al., 2015) | $h$, diag$(r)t$, diag$(t)$ turns a vector into a diagonal matrix | Margin ranking loss |
| ComplEx (Trouillon et al., 2016) | Re $(h$, diag$(r)t)$ | Negative log-likelihood |

Table 5: ECE ($M = 10$ bins) on WN18RR and FB15K, averaged over five dataset splits (all stdevs $< 0.01$.) Lower is better.

|     | Uncalib. | Iso. | Platt 1D | Platt 2D | Uncalib. | Iso. | Platt 1D | Platt 2D |
|-----|----------|------|---------|---------|----------|------|---------|---------|
| TransE | 0.022 | 0.014 | 0.017 | 0.018 | 0.022 | 0.002 | 0.002 | 0.002 |
| TransH | 0.046 | 0.029 | 0.040 | 0.044 | 0.894 | 0.002 | 0.002 | 0.004 |
| DistMult | 0.028 | 0.034 | 0.041 | 0.035 | 0.910 | 0.004 | 0.004 | 0.005 |

Figure 4: 2D Platt scaling improves hits@$1$ for relation prediction on WN18RR.

A Empirical calibration analysis

A.1 Implementation details

Models We use four embedding models that are both widely used and amenable being interpreted in terms of their calibration behaviors. The first two, TransE (Bordes et al., 2013) and TransH (Wang et al., 2014), are additive; the latter, DistMult (Yang et al., 2015) and ComplEx (Trouillon et al., 2016), are multiplicative. Both TransE and DistMult treat all relations as symmetrical. TransH and ComplEx improve upon TransE and DistMult, respectively, by handling asymmetric relations. Table 4 summarizes each model.

Given a triple $(h, r, t)$, TransE learns respective embeddings $h, r, t$ such that $h + r \approx t$, and scores each triple with $f(h, r, t) = -∥h + r - t∥_2$. TransH improves upon TransE by first projecting entity representations $h$ and $t$ onto a relation-specific hyperplane specified by normal vector $w_r$ to obtain embeddings $h_{||r||}$ and $t_{||r||}$, then scores triples with translational distance: $f(h, r, t) = -∥h_{||r||} + r - t_{||r||}∥_2$. By contrast, DistMult uses a simple bilinear function to score triples: $f(h, r, t) = h^T \text{diag}(r)t$, where diag$(\cdot)$ turns a vector into a diagonal matrix. Finally, ComplEx extends DistMult with complex-valued embeddings, captured by score function $f(h, r, t) = \text{Re } (h^T \text{diag}(r)t)$, where $\text{Re}$ is the complex conjugate of $t$ and Re denotes the real part of a complex number. TransE, TransH, and DistMult are trained by minimizing a margin-based ranking loss between the scores of positive (observed) and negative (unseen, corrupted) triples. ComplEx is trained by minimizing the binary negative log-likelihood between positive and negative triples.

Code All code was implemented in a Python3 extension of the Tensorflow-based OpenKE library (Han et al., 2018). We used the scikit-learn implementations of 1D Platt scaling and isotonic regression⁹, and implemented 2D Platt scaling with L-BFGS in Tensorflow. To obtain negative examples for binary classification, we randomly sampled triples from the graph and corrupted their tail entities $t$ for entity prediction or their relations $r$ for relation prediction, following Bordes et al. (2013).

Hyperparameter tuning To tune model hyperparameters, we grid searched over the number of training epochs in $\{200, 300, 500\}$, the batch size in $\{100, 200, 500\}$, the embedding dimension in $\{50, 100\}$, and the number of negative entities or relations sampled in $\{1, 5\}$. For the additive models (TransE, TransH) we used SGD with learning rate 0.01 and grid searched over the margin hyperparameter in $\{1, 5, 10\}$. For the multiplicative models (DistMult, ComplEx) we used Adagrad with learning rate 0.01 and a regularization weight of 0.0001. We optimized for hits@$1$ for relation prediction and hits@$10$ for entity prediction.

A.2 Additional results

In this section we provide additional calibration analysis of the models in Table 4.

Calibration results Table 5 gives calibration results for $(h, ?, t)$ relation prediction on WN18RR and $(h, r, ?)$ tail entity prediction on FB15K. Similar to § 3, TransE is the least calibrated for relation prediction and the best calibrated for entity prediction, whereas ComplEx is the best calibrated

⁹https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.ElasticNetCV
Figure 5: Reliability diagrams for entity prediction on WN18RR.

Figure 6: Uncalibrated confidence distributions for predicting the relation in triple (Pink Floyd, ?, psychedelic rock) in the subset of FB15K containing only relations in the /music domain. The x-ticks represent all relations in the dataset (labels not shown for brevity). The red bar is the ground-truth relation /music/artist/genre.

Table 6: Example sentence templates for relations in FB15K. h: Head entity label. t: Tail entity label.

| Relation | Template |
|----------|----------|
| /architecture/structure/architect | h was designed by the architect t. |
| /aviation/airline/hubs | h is an airline with a hub at t. |
| /cvg/computer_video_game/sequel | h is a video game with sequel t. |
| /education/fraternity_sorority/careers_and_institutions | h is a fraternity or sorority at t. |
| /fight/crime_type/victims_of_this_crime_type | h is a crime that happened to t. |
| /film/writer/film | h was a writer on the film t. |
| /finance/currency/countries_formerly_used | h is the former currency of t. |
| /food/diet/follower/follows_diet | h follows a diet of t. |
| /geography/river/mouth | h is a river with a mouth into the t. |
| /government/government_agency/jurisdiction | h is a governmental agency with jurisdiction over t. |
| /internet/website/category | h has a website in the category of t. |
| /language/human_language/main_country | The main country in which h is spoken is t. |
| /medicine/risk_factor/diseases | h has the risk of causing t. |
| /music/artist/orchestra | h is or was a musician from t. |
| /people/person/nationality | h has or had t nationality. |
| /religion/religion/branched_from | h is a religion that branched from t. |
| /sports/sports_league/sport | h is a t sports league. |
| /time/holiday/featured_in_holidays | h is a holiday featured in the religion of t. |
| /tv/tv_program/country_of_origin | h is a TV program originating in t. |
for relation prediction but the least calibrated for entity prediction. Again, 2D Platt scaling and isotonic regression perform the best for relation prediction, whereas isotonic regression mostly performs the best for entity prediction. As with FB15K, 2D Platt scaling also improves relation prediction accuracy on WN18RR but with even larger performance gains, up to nearly 15% increase (Figure 4).

**Pre-calibration analysis** As demonstrated by our results, off-the-shelf calibration error is dependent on model type. As an illustrative example of the differences in pre-calibration scoring between model types, Figure 6 shows each model’s uncalibrated confidence distribution, obtained using the softmax, in predicting the relation connecting entities *Pink Floyd* and *psychedelic rock* on a subset of FB15K containing only relations in the /music domain. All models predict the correct relation /music/artist/genre, but the prediction confidences vary widely: \( \hat{p} \approx 0.05 \) for TransE; \( \hat{p} \approx 0.7 \) for TransH, and \( \hat{p} = 1 \) for DistMult and ComplEx.

Between the two additive models, TransE’s uncalibrated confidence distributions are nearly uniform (Figure 6), whereas TransH outputs larger probability masses for its predictions. This is because TransH learns a separate hyperplane for each relation, allowing entity pairs to have different embeddings and pairwise distances by relation. By contrast, because TransE embeds all entities and relations in the same space, all predictions are made by relatively uniform distances. Regarding the multiplicative models, both DistMult and ComplEx assign high probability masses to the correct relation. We speculate that this is because matrix multiplications lead to more discriminative scores between true and false triples than element-wise addition.

**Reliability diagrams** Figure 5 gives “reliability diagrams” before and after calibration for entity prediction on the WN18RR dataset using TransE and TransH. Reliability diagrams (Guo et al., 2017) bin predictions into confidence regions between [0, 1] and show the average hits@k per bin, similar to ECE (§ 3.3). However, they do not show the number of instances per bin (i.e., the “weight” for each summand in ECE), so they cannot show the extent to which each region of [0, 1] is (mis)calibrated.

It is interesting to note that in Figure 5 TransE has low off-the-shelf ECE (\( M = 10 \) bins). As discussed previously, it outputs around the same level of confidence for every prediction: Here, it predicts all instances at around the same confidence level of \( \hat{p} = 0.52 \) for the positive class and \( \hat{p} = 0.48 \) for the negative class, and gets around 50% of predictions correct with hits@10. By contrast, TransH has an S-shaped calibration curve, and is underconfident for regions [0.5, 0.9] but overconfident in [0.9, 1]. In both cases, Platt scaling and isotonic regression successfully calibrate the scores within 1 percentage point of error or less.

**B True or False Facts**

**B.1 Data**

**Knowledge graph** We use the version of FB15K provided by Xie et al. (2016), who included rare entities and relations that were discarded in the original version of the FB15K dataset (Bordes et al., 2013). To preprocess FB15K, we remove reverse relations following Toutanova and Chen (2015).

**Task input** To construct the set of triples for judgment, we discarded relations in FB15K that could not be easily translated into natural language by fluent English speakers given the head, tail pairs observed in the dataset (e.g., /dataworld/gardening/split_to, relations with dots like /travel/transport_destination/travel_destinations_served./travel/transportation/transport_destination). We also removed relations pertaining to Netflix (e.g., /media_common/netflix_genre/titles) to avoid disagreement due to workers’ countries of origin, since Netflix title availability varies widely by country. Finally, we converted all relations to natural language with a set of pre-defined sentence templates. Table 6 gives examples of sentence templates for relations in FB15K.

**B.2 Task**

This section gives the True or False Facts task instructions as they were presented to crowd workers. Note that we conducted two separate tasks: One with links to Wikidata, and one with links to IMDb, for /film relations only. The instructions were exactly the same between the two versions of the task, except that each instance of “Wikidata and/or Wikipedia” was replaced with “IMDb” in the IMDb version of the task.

**Overview** The goal of this task is to determine whether a given sentence is true or false.

**Instructions** Given a sentence that states a potentially true fact about the world, for example
Elizabeth Alexandra Mary Windsor is the queen of the Commonwealth.

Read the sentence carefully and answer whether the sentence is factually correct by choosing one of Yes, No, or Unsure. To arrive at your answer, you must use English-language Wikidata and/or Wikipedia, even if you know the answer ahead of time. Each sentence already contains links to potentially relevant Wikidata pages; however, if you do not find an answer in the Wikidata page, you must check related Wikipedia pages. You may not use any external data sources beyond English-language Wikidata or Wikipedia.

Rules and Tips

- Read each sentence carefully and check both Wikidata and Wikipedia before choosing your answer.

- **Question 1:** If a sentence is not grammatically correct, treat it as false. If a sentence is grammatically correct but you cannot find any information on Wikidata or Wikipedia supporting or disproving its claim, or you cannot reason about whether its claim is true or false, choose Unsure.

- **Question 2:** You must copy-paste the primary Wikidata or Wikipedia link that you used to arrive at your answer. Only copy-paste the single link that contains the most complete answer to the question. You may use the provided Wikidata links, but you may also need to check related Wikipedia pages if you do not find what you are looking for. You may not use any external data sources beyond English-language Wikidata or Wikipedia.

- **Question 3:** You may copy-paste relevant textual snippets from Wikidata or Wikipedia. If there is no relevant text to copy-paste, you may write a brief explanation of how you arrived at your answer.

Examples

1. **Nawaz Sharif is or was a leader of Pakistan.**

   - Is this sentence factually correct?
     - Yes
   
   - Which Wikidata or Wikipedia link did you use to arrive at your answer?
     - https://en.wikipedia.org/wiki/Nawaz_Sharif

   - Which sentence(s) or information from Wikidata or Wikipedia did you use to arrive at your answer?
     - “Mian Muhammad Nawaz Sharif is a Pakistani businessman and politician who served as the prime minister of Pakistan for three non-consecutive terms” - from the Wikipedia page of Nawaz Sharif

2. **The capital of France is or was Avignon.**

   - Is this sentence factually correct?
     - No

   - Which Wikidata or Wikipedia link did you use to arrive at your answer?
     - https://en.wikipedia.org/wiki/List_of_capitals_of_France

Figure 7: Task interfaces for True or False Facts (§ 4) and Fill In The Blanks (§ 5).
The predicted relation with the highest frequency largely matched the ground-truth relations. Domain diversity As suggested previously, the biases toward certain types of mistakes. That the calibration process corrected for model predictions. To this end, we discarded triples with relations that could be guessed via type matching: Gender (the tail entity was always male or female in our dataset), award received (the tail entity usually contained the word “award”, “prize”, etc.), and place of burial (the tail entity usually contained the word “cemetery”). We also discarded triples with relations that could be interpreted as synonyms of one another (occupation and genre, e.g., “fiction writer”), and triples with the relation field of work for which the tail entity was synonymous with “writer” or “author”, since all people in the dataset are categorized as authors or writers on Wikidata. Finally, we removed triples for which there was more than one correct answer in the top-five predicted relations.

C.2 Task

This section gives the Fill In the Blanks task instructions as they were presented to crowd workers. Underline indicates that the enclosed text was presented to the treatment group only. Figure 7b gives a mockup of the task interface.

Overview The goal of this task is to complete a sentence so that it states a true fact about the world.
Instructions  Given a partially complete sentence, fill in the blank with exactly one of the provided answer choices so that the sentence states a true fact about the world. To arrive at your answer, you must use the provided Wikidata links in each sentence. You may not use any external data sources beyond the provided Wikidata links in each sentence. Please note that we have used a computer system to generate “confidence values” for each answer choice in order to help you with the task. These values signify our system’s belief about which answer is most likely to be correct. After you select your answer (Question 1), give the single Wikidata URL (Question 2) and the text snippet or reasoning you used to arrive at your answer (Question 3). You must provide all answers in English.

Rules and Tips

- **Question 1**: Choose the answer that makes the sentence grammatically correct and factual according to Wikidata. Every sentence has at least one correct answer. If you believe a sentence has multiple equally correct answers, choose any of them.

- **Question 2**: You must copy-paste the single, entire Wikidata link that you used to arrive at your answer. The link that you copy-paste must contain the correct answer that fills in the blank in the sentence. You must use the Wikidata links provided in each sentence. You may not use any external data sources beyond the provided Wikidata links.

- **Question 3**: You may copy-paste relevant textual snippets from Wikidata. If there is no relevant text to copy-paste, you must write a brief explanation of how you arrived at your answer. You must provide all answers in English.

Examples  We give two examples presented to crowd workers in the task instructions.

1. Anna Akhmatova ____________ Leo Tolstoy.
   (a) was or is married to (40% confident)
   (b) was influenced by (45% confident)
   (c) was the academic advisor of (5% confident)
   (d) was the child of (5% confident)
   (e) was the parent of (5% confident)
   - Which Wikidata link did you use to arrive at your answer?
     – https://www.wikidata.org/wiki/Q80440
   - Which sentence(s) or information from Wikidata did you use to arrive at your answer?
     – Wikidata says that Anna Akhmatova was influenced by Leo Tolstoy.

2. Ursula K. Le Guin ____________ Hugo Award for Best Short Story.
   (a) was awarded the (40% confident)
   (b) was influenced by (0% confident)
   (c) created the (50% confident)
   (d) was or is married to (10% confident)
   (e) lives in (0% confident)
   - Which Wikidata link did you use to arrive at your answer?
     – https://www.wikidata.org/wiki/Q181659
   - Which sentence(s) or information from Wikidata did you use to arrive at your answer?
     – Wikidata says that Ursula K Le Guin won the Hugo Award for Best Short Story.