Cross-Lingual Fine-Grained Entity Typing

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Abstract

The growth of cross-lingual pre-trained models has enabled NLP tools to rapidly generalize to new languages. While these models have been applied to tasks involving entities, their ability to explicitly predict typological features of these entities across languages has not been established. In this paper, we present a unified cross-lingual fine-grained entity typing model capable of handling over 100 languages and analyze this model’s ability to generalize to languages and entities unseen during training. We train this model on cross-lingual training data collected from Wikipedia hyperlinks in multiple languages (training languages). During inference, our model takes an entity mention and context in a particular language (test language, possibly not in the training languages) and predicts fine-grained types for that entity. Generalizing to new languages and unseen entities are the fundamental challenges of this entity typing setup, so we focus our evaluation on these settings and compare against simple yet powerful string match baselines. Experimental results show that our approach outperforms the baselines on unseen languages such as Japanese, Tamil, Arabic, Serbian, and Persian. In addition, our approach substantially improves performance on unseen entities (even in unseen languages) over the baselines, and human evaluation shows a strong ability to predict relevant types in these settings.

1 Introduction

Entity typing is the task of assigning types to entity mentions in natural language text (Weischedel and Brunstein, 2005; Ling and Weld, 2012; Gillick et al., 2014; Choi et al., 2018). Fine-grained types provide richer information and are useful for many tasks, such as coreference resolution, entity linking (Durrett and Klein, 2014; Gupta et al., 2017; Raiman and Raiman, 2018), relation extraction (Yaghoobzadeh et al., 2017), and question answering (Lin et al., 2012; Yavuz et al., 2016). Most prior work in fine-grained entity typing has predominantly focused on monolingual models in English (Yaghoobzadeh and Schütze, 2015; Shimaoka et al., 2017; Dai et al., 2019) or other often high-resource languages (van Erp and Vossen, 2017; Lee et al., 2020). Unified cross-lingual entity typing models that can cover a wide range of languages have never been established. However, the cross-lingual
setting is vital for the accessibility, inclusivity, and success of future NLP systems, to better serve more of the world’s population (Joshi et al., 2020).

In this work, we first define a cross-lingual entity typing task that associates entity mentions in any language with predefined fine-grained types without employing translation. Then, we build a unified cross-lingual entity typing model that can take an entity mention in context in over 100 different languages, outputting fine-grained types for that entity. To train this model, we automatically create entity typing datasets based on distant supervision techniques first explored in Mintz et al. (2009), using Wikipedia articles in four languages: English, Finnish, German, and Spanish. Our typing model uses an encoder based on pre-trained multilingual BERT (Devlin et al., 2019, mBERT) to output 10k fine-grained types derived from the Wikipedia categories. Figure 1 shows an overview of our system.

Our evaluation primarily focuses on two questions: 1) can a cross-lingual entity typing model generalize to unseen languages? and 2) how does a cross-lingual entity typing model handle unseen entities? For the first question, we design a zero-shot languages experimental setup in which an entity typing model is trained on the training languages (English, Finnish, German, and Spanish) and evaluated on test languages (such as Tamil) which are unseen during training. To investigate the second question, we perform experiments on unseen entities, where the entity typing model is evaluated a set of entities held out from the model during training. In our experiments, we use entity typing test examples adapted from Mewsli-9 (Botha et al., 2020), an entity linking dataset derived from WikiNews (Section 3.2). We compare our model with a string match baseline (Section 5.1), which is simple but shows strong performance on the seen entities in the training languages, as well as a mention-string similarity approach. In addition, we perform human evaluation on the predicted types by our model and investigate performance breakdown by type frequency (Section 5.4 and Section 5.5).

In the zero-shot languages setting, our approach outperforms baselines on unseen languages by a substantial margin. Surprisingly, our models can make reasonable predictions on languages with different (non-Latin) scripts from the training languages, such as Arabic, Persian, Japanese, and Tamil, which suggests that our model generalizes to unseen languages. In the unseen entities setting, our model also shows much higher performance compared to the baselines, and can even predict plausible types for unseen entities in unseen languages.

2 Cross-Linguual Entity Typing

Our model takes an input sequence consisting of a mention in its context. Because our model encoder is pre-trained mBERT (Devlin et al., 2019), the model can accept input from any language of the 104 languages in the mBERT vocabulary\(^1\). Next, a multi-label classifier outputs predictions for the input entity mention’s types. The model can handle a large typeset with tens of thousands of types. We train the model using text in English, Finnish, German, and Spanish, and evaluate its performance on Arabic, German, English, Spanish, Persian, Japanese, Serbian, Tamil, and Turkish. We analyze the entity typing performance in the zero-shot languages and unseen entities settings (Section 5.2).

We define \( s = (w_1, ..., w_N) \) as a sequence of context words, and \( m = (w_i, ..., w_j) \) as an entity mention span contained within \( s \). We also define a list of types \( T \) in English. Each mention and context sequence is associated with some subset of types in \( T \), which we denote as \( t^* \). The inputs to our cross-lingual fine-grained entity typing system consist of mention and context sequences. Given the input tuple \((m, s)\), the model \( f \) outputs a vector \( t \in [0, 1]^{|T|} \), where each element of \( t \) corresponds to one of the fine-grained types in \( T \). Our list of predefined types \( T \) is in English, but in general, the types can be in any language; they should represent language-agnostic semantic meaning.\(^2\) By controlling the number of types or the types themselves, this entity-typing approach can generalize to different settings and knowledge bases.

3 Data Collection

Entity typing requires lots of annotated data to train large models, but manually annotating entities

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\(^1\)mBERT uses 110k subword tokens while the English BERT model has a vocabulary size of 30k; this higher number particularly includes a range of unicode characters and sequences beyond Latin script.

\(^2\)This assumption might be flawed in two ways. First, an English typeset may be English-centric in type coverage, such as having more types around regions and states in the United States compared to other countries. Second, certain concepts in other languages may not be easily expressible in English.
To train our entity typing model, we need labeled examples of \((m, s, t^*)\) triples of an entity mention, context, and gold types. We start with a dump of Wikipedia articles in four languages: English, Finnish, German, and Spanish, languages picked for their dissimilarity (among languages supported by the SLING API) and to increase entity coverage. We sample all languages in a balanced way, which in practice takes a larger fraction of data from rarer languages. Table 1 shows a detailed breakdown of our training examples. We use Wikipedia hyperlinks as the mention sequences \(m\), situating each mention with up to 50 context words from the article on either side of the hyperlinked text. This forms the entire context sequence \(s\).

Using the SLING natural language frame semantics parser (Ringgaard et al., 2017),\(^3\) we connect each hyperlink to the WikiData QID of its target entity (the destination of the hyperlink). QIDs are language-agnostic identifiers that label each entity in the WikiData knowledge base. For each QID, we use the MediaWiki Action API to find the corresponding English Wikipedia page, and we derive the entity’s gold types \(t^*\) from the Wikipedia categories of this page. Lastly, we filter out examples that did not fit at least one of our 10,000 predefined types \(T\) (defined in Section 3.3), leaving us with 8.9 million distantly-supervised entity typing training examples.

### 3.2 Test Data

We derive test data from Mewsl-9 (Botha et al., 2020), a dataset of entity mentions extracted from WikiNews articles. These entities come linked to WikiData QIDs, so we again used our pipeline with the MediaWiki Action API to annotate the mentions \(m\) with gold types \(t^*\) based on the categories of the corresponding English Wikipedia pages. This process gave us typing datasets in nine languages: Arabic, German, English, Persian, Japanese, Serbian, Spanish, Turkish, and Tamil.

### 3.3 Types

Our types are derived based on post-processing English Wikipedia categories. Using a set of

\(^3\)https://github.com/google/sling
rules from prior work (Onoe and Durrett, 2020a,b), we map each Wikipedia category to one or more
carer types based on removing information. Specifically, we apply lowercasing, split categories
on prepositions, and remove stopwords. We also split up categories with years or centuries, remov-
ing the temporal information: for example, “20th-century atheists” would become just “atheists.”
These steps help reduce the frequency of highly specific types that are unlikely to be predictable
from context. These post-processed Wikipedia categories become the gold types \( t^* \) associated with
each entity mention in our training data. Our final typeset \( T \) consists of the 10,000 most frequently
occurring types in the training set. See the supplementary material for some examples of common,
less common, and rare types.

4 Typing Model

Our model \( f \) accepts as input the entity mention \( m \) and its context \( s \) and predicts probabilities for pre-
defined entity types \( T \). Our model is similar to the one in Onoe and Durrett (2020b), which we extend
to use pre-trained multilingual BERT (mBERT) (Devlin et al., 2019). Thus, our model accepts input
in any language in the mBERT vocabulary.

First, we use mBERT as the mention and context encoder. This Transformer-based en-
coder takes an input sequence of the form \( x = [\text{CLS}]m[\text{SEP}]s[\text{SEP}] \), with the mention \( m \) and the
context \( s \) split into WordPiece tokens. We use the hidden vector \( h_{[\text{CLS}]} \in \mathbb{R}^d \) at the [CLS] to-
ken as an intermediate vector representation of the mention and context, where \( d \) is the dimension
of hidden states. Then, we compute a dot product between \( h_{[\text{CLS}]} \) and the type embedding matrix
\( T \in \mathbb{R}^{d \times |T|} \) to produce a vector whose components are scores for the entity types \( T \).

Finally, we pass the score vector through an element-wise sigmoid function to produce the final
probabilities for each type. Each element of the vector corresponds to the model’s confidence that
the given input entity belongs to the corresponding type. To get the final set of predicted types for
a given mention \( m \) and context \( s \), we add a type \( k \in T \) to the set if the corresponding vector value
\( t_k \) is greater than a threshold value of 0.5.

Following Onoe and Durrett (2020b), the loss is the sum of binary cross-entropy losses over all
types \( T \) over the whole training dataset \( D \), ignoring type hierarchy in order to reduce model complexity.

We predict each type independently and optimize a multi-label binary cross entropy objective:

\[
\mathcal{L} = - \sum_x \sum_k t_k^* \cdot \log(t_k) + (1 - t_k^*) \cdot \log(1 - t_k)
\]

where \( t_k \) is the \( k \)th component of \( t^* \), taking the value 1 if the \( k \)th type is active on the input entity
mention, and \( x \) represents each training example. With each iteration through the training data, we
update parameters in the mBERT encoder as well as the type embedding matrix.

5 Experiments

Our focus here is to shed light on the performance of our entity typing model as well as its ability
to generalize along two axes: zero-shot languages and unseen entities. To this end, we first com-
pare the performance of our typing model to two baselines (see Section 5.1). We also compare the
performance of models trained on single language (e.g., English) with training on multiple languages.
Finally, we breakdown our model’s performance on unseen entities. We report macro-averaged pre-
cision, recall, and F1 metrics for our experiments.

5.1 Baselines

Given the new problem setting we tackle, few suitable baselines exist. Any pre-existing monolin-
gual model will fail to generalize to new languages, and existing multilingual typing methods use much
smaller ontologies than our model. With these limitations, we have formulated two comparison
methods to contextualize our model’s results.

String-Match Baseline This baseline tests how
well the model can type entities by simply regurgi-
tating types for entities it has already seen, with no
disambiguation. We create a dictionary \( M \) which
maps all entity mention strings \( m \) in the training
dataset to their most frequent QID, which we then
map to the corresponding gold entity types \( t^* \). At
test time, we predict the categories as follows:

\[
T = \begin{cases} M(m) & \text{if } m \text{ present in training data} \\ \emptyset & \text{otherwise} \end{cases}
\]

As expected, this STRING MATCH approach forms a strong baseline for the test languages that
are also in the training data: English, German, and Spanish. However, because this baseline only
matches the exact string of an entity mention, it fails to generalize effectively to any new languages,
Table 2: Macro-averaged P/R/F1 on the test sets, comparing entity typing for the mention-similarity and string-match baselines, single-language models (English/Spanish), and multi-language models.

| Language | Unseen Languages | Seen Languages |
|----------|------------------|----------------|
|          | Mention Similarity | String Match | English only | Spanish only | Multi-lang |
|          | P     | R     | F1    | P     | R     | F1    | P     | R     | F1    | P     | R     | F1    | P     | R     | F1    | P     | R     | F1    |
| Arabic   | 17.4  | 11.2  | 13.7  | 25.1  | 0.1   | 0.3   | 61.2  | 32.6  | 42.5  | 63.3  | 33.8  | 44.0  | 68.4  | 33.8  | 44.0  | 44.9  |
| Persian  | 16.9  | 11.5  | 13.7  | 100   | 0.2   | 0.4   | 54.4  | 34.4  | 42.1  | 60.1  | 32.9  | 42.5  | 58.4  | 34.1  | 43.0  |        |
| Japanese | 17.5  | 16.8  | 17.1  | 78.7  | 1.3   | 1.8   | 43.1  | 36.6  | 39.6  | 42.4  | 31.5  | 36.2  | 46.7  | 31.5  | 36.2  | 40.7  |        |
| Serbian  | 20.1  | 14.2  | 16.6  | 50.5  | 0.9   | 1.8   | 69.0  | 50.7  | 58.5  | 72.9  | 45.7  | 56.2  | 74.1  | 58.3  | 65.3  |        |
| Tamil    | 12.4  | 8.2   | 9.9   | 0.0   | 0.0   | 0.0   | 38.8  | 59.0  | 22.5  | 37.0  | 35.0  | 19.8  | 44.1  | 18.5  | 26.0  |        |
| Turkish  | 40.8  | 37.47 | 39.1  | 75.8  | 34.9  | 47.8  | 64.9  | 55.9  | 60.1  | 62.1  | 55.6  | 58.7  | 68.1  | 61.1  | 64.4  |        |

Table 2: Macro-averaged P/R/F1 on the test sets, comparing entity typing for the mention-similarity and string-match baselines, single-language models (English/Spanish), and multi-language models.

especially those that do not use Latin characters. Comparing against string matching specifically highlights our system’s ability to both understand the mention string itself deeply using a multilingual encoder as well as use context around the mention string to make predictions.

**Mention String Similarity Baseline**

Exact string match does not handle cases like transliteration; we implement a simple mBERT-based method to do this. For every unique entity in our training set, we encode the corresponding mention string using (non-fine-tuned) mBERT and store the hidden vector at the [CLS] token. At test time, we encode each example mention string in the same way, and we then perform a similarity search over the training mention representations using the FAISS library (Johnson et al., 2017). Finally, we predict the categories of the entity with the highest similarity to the training mention representation.

Because we use mBERT to encode our representations, this model can make better predictions in new languages when compared to STRING MATCH, and it can also generalize to unseen entities if there is a semantically similar mention in the training data. However, this baseline does not have access to context.

**5.2 Zero-shot Languages**

We measure the model’s performance at entity typing on six new languages: Arabic, Persian, Japanese, Serbian, Spanish, Turkish, and Tamil, evaluating how well it can generalize to new languages without any additional training data in those languages.

**Typing Performance**

Table 2 reports macro-averaged precision, recall, and F1 on the test sets, compared to the STRING MATCH and the MENTION SIMILARITY baselines. Our multi-language entity typing model trained on English, Finnish, German, and Spanish data together (Multi-lang), outperforms the MENTION SIMILARITY baseline on all of the six test languages by a substantial margin, and even more so compared to the STRING MATCH baseline. We compare the Multi-lang model with models trained only on English or Spanish. Notably, our results in Table 2 show that multi-language training boosts performance on entity typing over single-language training, even in completely separate languages, with the exception of Spanish, for which the Spanish model performs slightly better. This fits with Wu and Dredze (2020), which found that high-resources languages often benefit from single-language training, but interestingly, we found that did not apply to English.

We also report performance on the training languages for completeness. The STRING MATCH baseline outperforms the model on these test sets in the three languages which overlap with the training set languages: English, Spanish, and German. One possible reason for this is that the entity mentions in Mewsli-9 are often unambiguous, which can be inferred from the high entity linking accuracy by the alias table baseline (Botha et al., 2020). However, unlike the STRING MATCH baseline, the model is also able to generalize to new languages, even those that do not use Latin characters, so it achieves much higher results than the baseline when considering these six new languages. The model outperforms the MENTION SIMILARITY baseline on all these training languages.
Table 3: Unseen entities. Macro-averaged P/R/F1 on the test sets, filtered to those entities which were held out from the model during training ($D'_n$), compared to the same model’s performance on all the test data ($D_n$).

| Language | Mention Similarity | String Match | Multi-lang |
|----------|--------------------|--------------|------------|
|          | P      | R      | F1    | P      | R      | F1    | P      | R      | F1    |
| Arabic'  | 16.9   | 7.4    | 10.3  | 0.0    | 0.0    | 0.0   | 64.5   | 25.4   | 36.5  |
| German'  | 26.1   | 12.3   | 16.7  | 19.3   | 6.2    | 9.4   | 55.0   | 31.9   | 40.4  |
| English' | 22.7   | 15.2   | 18.2  | 21.3   | 6.8    | 10.3  | 55.7   | 36.2   | 43.9  |
| Spanish' | 19.1   | 9.9    | 13.0  | 24.0   | 6.6    | 10.4  | 53.3   | 28.9   | 37.5  |
| Persian' | 15.5   | 5.3    | 7.9   | 85.7   | 0.4    | 0.8   | 55.9   | 19.3   | 28.7  |
| Japanese' | 14.7 | 12.6   | 13.6  | 19.3   | 0.1    | 0.2   | 44.3   | 25.8   | 32.6  |
| Serbian' | 19.6   | 6.3    | 9.6   | 8.1    | 0.0    | 0.0   | 42.8   | 14.9   | 22.2  |
| Tamil'   | 7.9    | 3.5    | 4.8   | 0.0    | 0.0    | 0.0   | 42.8   | 14.9   | 22.2  |
| Turkish' | 19.0   | 9.3    | 12.5  | 29.3   | 4.5    | 7.8   | 56.3   | 26.5   | 36.0  |

Sequence: ...Su PlayStation 3 ha tenido que competir contra la Xbox 360 de Microsoft y la Nintendo Wii...
Translation: ...Their PlayStation 3 has had to compete against Microsoft’s Xbox 360 and the Nintendo Wii...
Predictions: academy of interactive arts & sciences members, based, companies, companies listed on the tokyo stock exchange, entertainment, entertainment software association members, established, game, japanese, japanese brands, toy, video, video game companies of japan, video game development companies, video game publishers...
Gold Types: same as predictions above

Figure 3: Model’s predictions for a familiar entity in a language on which it was trained.

Qualitative Analysis  Figure 3 shows an example of the model’s predictions in Spanish, one of the languages in the training data. The model manages to predict the gold types exactly. In contrast, the example in Figure 4 shows an input sequence in an unseen language, Japanese. Although the model does not predict every single type in the gold list for the given entity, it still picks out several of the most salient ones, and notably predicts with 100% precision.

Our multi-language approach can be seen as an effective way to augment training data for entity typing using different languages of data available. Increasing the number of languages increases entity coverage in the training set, which boosts performance. Critically, this works even on unrelated languages. The poor performance of the STRING MATCH baseline on these new languages makes it evident that the entity strings do not directly match languages the model has already seen, but because types can model entities in a language-agnostic way, the model still benefits from seeing more entities during training, and it can generalize that typing knowledge to new languages. This approach may be especially useful for entity typing with low-resource languages.

5.3 Unseen Entities
One of the greatest difficulties in entity typing is predicting types for new entities (i.e., entities that do not appear during training), so we want to isolate these unseen types to test generalizability. In order to have a reasonable dataset to evaluate entity typing performance, we hold out certain entities from the model during training so we could later test on them. We took a random sample of 5288 entities, ensuring that we collected at least 2% of the entities from each test set (i.e., each language). Then, we filtered out every training example referring to any of these 5288 entities to train a new model. During evaluation, we filtered the test sets to only contain examples that referred to these 5288 entities. We denote these filtered sets as $D'_n$, where $n$ represents the language.
Figure 5: Model’s predictions for an unseen entity in a new language.

Typing Performance Table 3 shows the full results with macro-averaged precision, recall, and F1 metrics on the held-out entities as well as the original test sets. When filtering to unseen entities, the STRING MATCH and MENTION SIMILARITY baselines perform poorly, especially for languages like Arabic and Tamil. By contrast, our model is able to achieve much higher results. When predicting types for unseen entities, the model still works best on languages that overlap with the training set: English, German, and Spanish. However, it is able to predict entity types reasonably well for all languages.

Qualitative Analysis When the model’s predicted types do not match the gold types, they generally still provide sensible information about the entity in question. For example, in the example in Figure 5 with an unseen entity, the model predicts “in india” instead of “indian films.” Some of our model’s performance in Table 2 clearly comes as a result of simply memorizing common entities in the training data; however, this memorization is not necessarily a bad thing if the model can still generalize to new languages and new entities like this one that did not appear during training.

In some cases with unseen entities, our typeset is not exhaustive enough to cover an entity, so the gold types are empty, as seen in Figure 6. However, our model is still able to predict types that are semantically relevant. For example, in this example, “causes of death” is a valid type when considering the mention in conjunction with its surrounding context. This example shows that despite the noisy, distantly-supervised nature of the data, the model does learn to predict types contextually.

5.4 Human Evaluation on Predicted Types

Due to the distantly-supervised nature of our testing data, we may be underestimating the precision; as seen in the previous examples, some types that our model predicts may be relevant even if they do not exist in the actual Wikipedia categories. We take one seen language (Spanish) and one unseen language (Japanese) as case studies to perform human evaluation. We examine the model’s predicted types which did not exist in the gold types for 50 examples with seen entities and 50 examples with unseen entities in each language. For each type such that $t \not\in t^*$, we assign a label of either correct, incorrect, or maybe. We use the third category to describe types where either the meaning or scope of the type is unclear, such as “autonomous,” or those that are closely related but may narrowly fail to apply to this particular entity, such as predicting “pandemics” for the entity “HIV.”

We report our results in Table 4. After including the correct types by human evaluation, macro-averaged precision increased significantly in both Spanish and Japanese, increasing even further when also including types with the maybe labels. The model performs poorly with certain kinds of entities with lots of highly specific type information, especially those that cannot typically be inferred by context. For example, with many sports figures, the model predicts a wide variety of semi-related categories about their origins, teams, or positions, many of which are factually incorrect and sometimes mutually exclusive, such as predicting both “association football forwards” and “association football midfielders.” However, even when the model predicts a type outside the set of gold types, the majority of these predictions are still correct. Many of these examples highlight the model’s strengths in predicting types using contextual information, which the Wikipedia categories...
Correct Correct + Maybe

|                | Correct | Correct + Maybe |
|----------------|---------|-----------------|
| Seen Entities  |         |                 |
| Spanish        | 91.4    | 97.6            |
| Japanese       | 83.8    | 92.8            |
| Unseen Entities|         |                 |
| Spanish'       | 71.4    | 89.4            |
| Japanese'      | 67.0    | 88.6            |

Table 4: Macro-averaged precision for 50 examples, using human evaluation. We look at one training language (Spanish) and one zero-shot language (Japanese).

could not make use of and which is not inherently “taught” by our training data.

5.5 Rare Types

We finally break down entity typing performance by the type frequency ranking in three buckets: [0, 99], [100, 999], and [1000, 9999]. We report macro-averaged precision, recall, and F1 metrics in Table 5, both on the full dataset and on unseen entities. For the languages in the training data (English, German, Spanish), entity-typing performance is relatively high across all three buckets. The model also achieves good results on unseen languages for frequent types. Most of the categories in this first bucket are more coarse-grained, corresponding to certain locations or professions, and the model performs relatively well at distinguishing these types.

Next, we look at the type-frequency breakdown of entity typing limited to unseen entities. For predicting the rarest types on unseen entities, performance drops off in the second and third buckets for certain languages, such as Tamil, Serbian, Arabic, and Persian. However, the model is able to predict rare types on unseen entities in other unseen languages, such as Japanese and Turkish. Although the numbers here are hard to draw strong conclusions from, given the results of the previous human evaluation, they show some success even on the most challenging cases.

6 Related Work

Entity Typing Entity typing has been a long-studied subtask in NLP, characterized by a growth in the size and complexity of type sets, from 4 (Tjong Kim Sang and De Meulder, 2003) to 17 (Hovy et al., 2006) to hundreds and even thousands (Choi et al., 2018; Ling and Weld, 2012; Gillick et al., 2014). Recent work has shifted towards predicting fine-grained entity types because these types offer much richer information and are more useful for various downstream NLP tasks, such as entity linking, coreference resolution, and question answering (Durrett and Klein, 2014; Lin et al., 2012; Yavuz et al., 2016).

Cross-Lingual Models The task of cross-lingual entity typing has not yet been explored much. Most prior works focus on one languages at a time, such as English (Yaghoobzadeh and Schütze, 2015), Japanese (Suzuki et al., 2016), Dutch and Spanish (van Erp and Vossen, 2017), or Chinese (Lee et al., 2020). Additionally, these models predominantly focus on fewer than one hundred types. For example, Nothman et al. (2013) performs named entity recognition on nine different languages, but they only use coarse-grained types.

|                | P   | R   | F1  | P   | R   | F1  | P   | R   | F1  |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Seen Entities  |     |     |     |     |     |     |     |     |     |
| Arabic         | 67.5| 55.6| 61.0| 39.0| 31.7| 34.9| 36.4| 17.2| 23.4|
| German         | 75.6| 88.6| 81.6| 71.9| 82.2| 76.7| 73.7| 74.7| 74.2|
| English        | 62.9| 81.7| 71.1| 57.9| 69.1| 63.0| 59.4| 59.2| 59.3|
| Spanish        | 70.9| 87.3| 78.2| 68.9| 80.4| 74.2| 66.9| 72.5| 69.6|
| Persian        | 63.5| 61.9| 62.7| 38.8| 29.9| 33.8| 27.8| 16.9| 21.0|
| Japanese       | 39.8| 59.6| 47.7| 40.3| 40.9| 40.6| 27.0| 26.0| 26.5|
| Serbian        | 76.0| 73.3| 74.6| 61.8| 55.4| 58.4| 62.2| 52.1| 56.7|
| Tamil          | 46.6| 35.5| 40.3| 23.0| 14.2| 17.6| 12.0| 6.8  | 8.7 |
| Turkish        | 68.1| 76.1| 71.9| 61.7| 63.2| 62.4| 51.6| 51.9| 51.8|
| Unseen Entities|     |     |     |     |     |     |     |     |     |
| Arabic'        | 67.9| 50.7| 58.1| 26.7| 15.4| 19.5| 13.1| 6.1  | 8.3 |
| German'        | 60.9| 48.2| 53.8| 42.6| 27.7| 33.6| 34.4| 19.0 | 24.5|
| English'       | 57.2| 57.2| 57.2| 45.2| 37.3| 40.8| 37.6| 22.7 | 28.3|
| Spanish'       | 55.1| 46.2| 50.3| 38.9| 30.5| 43.4| 31.1| 21.3 | 25.3|
| Persian'       | 61.1| 41.4| 49.4| 27.6| 13.1| 17.7| 14.0| 4.7  | 7.1 |
| Japanese'      | 34.9| 38.4| 36.6| 31.4| 25.8| 28.3| 23.5| 22.0 | 22.7|
| Serbian'       | 74.9| 50.9| 60.6| 44.7| 10.6| 17.1| 7.1  | 2.4  | 3.6 |
| Tamil'         | 34.2| 44.3| 35.9| 16.3| 6.9  | 9.7 | 4.3  | 2.3  | 0.3 |
| Turkish'       | 60.4| 42.0| 49.5| 42.2| 22.9| 29.7| 23.8| 11.9 | 15.9|

Table 5: Macro-averaged P/R/F1 on the test sets, broken down into buckets by the types’ frequency rankings. Results are shown both for the full dataset (Dn) and on unseen entities (D’n).
Other Multilingual Tasks  
Pretrained contextual representation models trained on masked language modeling (Devlin et al., 2019; Conneau et al., 2020) have set a new standard for many NLP systems. They have achieved surprising success in multilingual settings even without explicit cross-lingual signals by pre-training on text from multiple languages with one unified vocabulary. This growth has motivated work in cross-lingual modeling for tasks such as natural language inference, document classification, named entity recognition, part-of-speech tagging, and dependency parsing (Wu and Dredze, 2019; Pires et al., 2019). However, further analysis has indicated a high level of variety in their performance across different languages and tasks (Hu et al., 2020). Wu and Dredze (2020) observed that BERT does not learn high-quality representations particularly for low-resource languages, suggesting that these languages require more data or more efficient pre-training techniques.

Knowledge Probing and Knowledge in BERT  
Our model’s capability to memorize tracts of Wikipedia connects to past work on extracting knowledge from language models (Petroni et al., 2019); our task is easier because it is also possible to make type predictions based on context, giving our model a “backoff” capability. Recently, knowledge probing settings have been proposed for the multilingual setting as well (Kassner et al., 2021). Another related line of work attempts to add entity information into BERT (Zhang et al., 2019; Peters et al., 2019; Poerner et al., 2020; Févry et al., 2020, inter alia); our model could potentially benefit from this, but given our focus on generalizing to new entities, a model that more easily memorizes common entities may actually work less well.

7 Conclusion  
In this work, we have presented an approach to fine-grained cross-lingual entity typing. Our typing model accepts input in over 100 different languages and outputs categories in English. We generated a dataset of distantly supervised Wikipedia typing examples in four different languages, and we show that the multi-language model outperformed single-language models, even on completely new languages. We also show that this model was able to generalize to completely new languages, predicting rare types on unseen entities, and using contextual information to do so.

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Appendix A: Typeset

The following lists show the top 10 types in our three frequency groups. We use frequency as an approximation for sorting our types from course-grained to fine-grained. The coarse-grained types are useful to infer distinctions like living vs. dead people (living people vs deaths). They also highlight locations with differing granularities (continents, countries, cities) and some relational information (like in Europe). The rarer categories become highly specific and fine-grained types.

**Coarse-Grained**
1. established
2. establishments
3. births
4. people
5. deaths
6. states
7. territories
8. living people
9. places
10. in europe

**Fine-Grained**
101. province
102. of finland
103. government
104. players
105. personnel
106. competitions
107. geography
108. politicians
109. film
110. unit

**Very Fine-Grained**
1001. republican
1002. former capitals of the united states
1003. of the community of portuguese language countries
1004. in the roman empire
1005. former portuguese colonies
1006. in new spain
1007. british islands
1008. emigrants
1009. association football
1010. of scotland

Appendix B: Selected Examples

We present some example predictions in Figure 8 below. The model can make accurate predictions on unseen entities, such as “DMDK,” “TerraSAR-X,” and “Spirited Away,” especially on coarse-grained types. Even when our set of gold types is empty according to Wikipedia categories, the model can use contextual information to output relevant types, as in the case of “openSUSE” or “magnitude.” For common entities such as countries, the model typically memorizes the gold types and can apply this knowledge even to entity mentions in new languages, like Tamil. However, sometimes this memorization leads the model to fail to account for contextual information, such as with the “Paris” example below.

Appendix C: Distribution of Entities

Figure 7 shows how entities are distributed across the training set.

Appendix D: Hyperparameters

**Hyperparameters** We use pre-trained mBERT-base-uncased (Devlin et al., 2019) for our mention and context encoder. We train our model with batch size 16 using NVIDIA V100 GPUs. We use the AdamW optimizer (Kingma and Ba, 2015; Loshchilov and Hutter, 2018) with learning rate 2e-5 for BERT parameters and learning rate 1e-3 for the type embedding matrix. We use Pytorch (Paszke et al., 2019) and the HuggingFace Transformers library (Wolf et al., 2019) to implement our models.

Appendix E: Limitations of the Data Collection Pipeline

Our data collection approach has a few limitations. We picked English Wikipedia categories because
| Partial Input Sequence                                                                 | Entity seen? | Predictions                                                                 | Gold Types                                                                 |
|---------------------------------------------------------------------------------------|--------------|------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| …the court hearing. Various Linux distributions like Debian, Ubuntu, and openSUSE allow users to download freely licensed material through torrents. | Yes          | free, programmed, software, system                                           | animated, anime, annie award winners, children’s, coming-of-age, directed, fantasy, films, films about witchcraft, in anime and manga, in japan, in popular culture, japanese, japanese-language films, mythology, scored, set |
| …a su divulgación como Nausicaä del Valle del Viento, El castillo en el cielo, Susurros del corazón, La princesa Mononoke y El viaje de Chihiro entre otras… | No           | anime, directed, fantasy, films, in japan, japanese films, japanese-language films, set | launched, of germany, satellites, spacecraft                                |
| …to their popularization such as Nausicaä: Valley of the Wind, The Castle in the Sky, Whisper of the Heart, Princess Mononoke and Spirited Away… | No           | earth, launched, of germany, satellites, spacecraft                         | launched, of germany, satellites, spacecraft                                |
| Mit Hilfe des deutschen Satelliten TerraSAR-X gelangen hochauflösende Aufnahmen vom Moment des Zusammenstoßes. *With the help of the German TerraSAR-X satellite, high-resolution images of the moment of the collision were obtained. | No           | of measurement, units                                                       | established, establishments, in india, parties, political                 |
| 震源の深さは約37kmとされており、地震の規模を示すマグニチュード(M)は6.7とされている。A magnitude 6.7 earthquake occurred at a depth of 37km beneath the epicenter… | No           | established, establishments, in india, parties, political                  | established, establishments, in india, parties, political                 |
| Former Panamanian President Manuel Noriega was deported to France after serving more than 20 years in prison in the United States. | Yes          | countries, countries in europe, countries in north america, english-speaking countries and territories, established, establishments, federal monarchies, french-speaking countries and territories, g20 nations, g7 nations, group, group of eight nations, in north america, island countries, member, of eight nations, of nato, of the commonwealth of nations, of the european union, of the organisation internationale de la francophonie, of the united nations, states, territories, union | countries, countries in europe, established establishments, for the mediterranean, france, french-speaking countries and territories, g20 nations, g7 nations, group, group of eight nations, in europe, in france, member, of eight nations, of nato, of the council of europe, of the europeanunion, of the organisation internationale de la francophonie, of the united nations, republics, southwestern european countries, states, territories, transcontinental countries, union, western european countries |
| Gösteri sebebiyle, Fransa’nın başkenti Paris’teki ana istasyonlardan birinde tren seferleri 90 dakika (1.5 saat) kadar aksadi, binlerce yolcu birikti. *Due to the demonstration, train services were interrupted for 90 minutes (1.5 hours) at one of the main stations in Paris, the capital of France, and thousands of passengers piled up. | No           | characters, children, in greek mythology, princes                            | capitals, capitals in europe, catholic pilgrimage sites, cities, cities in france, cities in ile-de-france, companions, companions of the liberation, departments, departments of ile-de-france, established, european culture, french culture, in europe, in france, in the 3rd century bc, in ile-de-france, of the liberation, of ile-de-france, paris, places, populated, populated places established in the 3rd century bc, prefectures, prefectures in france |

Figure 8: Selected examples of typing predictions across different languages. Starred translations were obtained using Google Translate and may be inaccurate.
English Wikipedia has the most comprehensive category annotations. However, we had to omit some language-specific entities that did not have a corresponding English Wikipedia page, which account for about 20% of the non-English hyperlinks. Additionally, Wikipedia articles only hyperlink the first instance of an entity mention in an article, which often skew towards less ambiguous entity mention strings. For example, the first mention of a person typically includes their full name, while subsequent mentions often only contain their last name.

Furthermore, it would be interesting to test our approach on a domain entirely outside Wikipedia or Wikidata. However, we focus specifically on fine-grained entity typing, and no suitable datasets exist already, as annotating datasets with large and fine-grained ontologies is very challenging.

**Appendix F: Testing Datasets**

Table 6 provides the number of examples in the testing datasets derived from Mewsli-9 (Botha et al., 2020).

| Language  | # Examples ($D_n$) | # Examples ($D'_n$) |
|-----------|--------------------|---------------------|
| Arabic    | 7038               | 1995                |
| German    | 60631              | 13661               |
| English   | 79675              | 10589               |
| Spanish   | 47064              | 10878               |
| Persian   | 521                | 127                 |
| Japanese  | 27731              | 4662                |
| Serbian   | 34944              | 20414               |
| Tamil     | 2660               | 938                 |
| Turkish   | 5530               | 1430                |

Table 6: A description of the test datasets derived from Mewsli-9. $D_n$ refers to the total test size of each dataset per language. $D'_n$ refers to test datasets filtered to examples with entities we held out during training in order to test the model’s ability to generalize to new languages.