Cross-Lingual Transfer in Zero-Shot Cross-Language Entity Linking

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Abstract

Cross-language entity linking grounds mentions in multiple languages to a singlelanguage knowledge base. We propose a neural ranking architecture for this task that uses multilingual BERT representations of the mention and the context in a neural network. We find that the multilingual ability of BERT leads to robust performance in monolingual and multilingual settings. Furthermore, we explore zero-shot language transfer and find surprisingly robust performance. We investigate the zero-shot degradation and find that it can be partially mitigated by a proposed auxiliary training objective, but that the remaining error can best be attributed to domain shift rather than language transfer.

1 Introduction

Historically, entity linking—grounding named entities mentioned in text to a reference knowledge base (KB) or ontology – considered English documents and ontologies. In recent years, the task has been expanded to consider multiple languages (McNamee et al., 2011). In cross-language entity linking, an entity in a document in one language is linked to a KB in another. The TAC KBP shared task (Ji et al., 2015), for example, considers documents in Chinese and Spanish and links them to an English KB. Success in building cross-language linking systems can be helpful in tasks such as discovering all documents relevant to an entity, regardless of language.

Successfully linking a mention across languages requires adapting several components to the cross-language setting. Consider the example in Figure 1, which contains a Spanish mention *Oficina de la Presidencia*, a reference to the entity *President of Mexico* in an English KB. To link the mention to the relevant entity we need features that compare the mention text and its context in Spanish

to the English entity name and entity description, and compare the mention and entity type. Previous work has focused on transliteration or translation approaches to handling the name and possibly the context (McNamee et al., 2011; Pan et al., 2015), or leveraging large amounts of cross-language information (Tsai and Roth, 2016) and multilingual embeddings (Upadhyay et al., 2018).

Since this work emerged, there have been major advances in multilingual NLP (Wu and Dredze, 2019; Pires et al., 2019). The new standard approach to multilingual learning involves using multilingual encoders, trained on raw text from multiple languages (Devlin et al., 2019). These models, such as multilingual BERT or XMLR (Conneau et al., 2019), have achieved impressive results on a range of multilingual NLP tasks, including part of speech tagging (Tsai et al., 2019), parsing (Wang et al., 2019; Kondratyuk and Straka, 2019), and semantic similarity (Lo and Simard, 2019; Reimers and Gurevych, 2019).

We propose an approach to cross-language entity linking, in which we produce text representations with multilingual BERT (Devlin et al., 2019) for the mention text, entity name, mention context and entity description. We use a neural ranking objective and a deep learning model to combine these representations and a one-hot embedding for the entity and mention type to produce a cross-language linker. Even though previous work tend to use multilingual encoders for one language at a time, e.g., train a Spanish NER system with mBERT, we ask: can our model effectively link entities across languages? We find that, somewhat surprisingly, our approach does exceedingly well with scores comparable to previously reported best results. Next, we consider a multilingual setting, in which a single system is simultaneously trained to link mentions in multiple languages to an English KB. Previous work (Upadhyay et al., 2018) has

shown that multilingual models can perform robustly on cross-language entity linking. Again, we find that, surprisingly, a model trained on multiple languages at once does about as well, or in some cases better, then the same model trained separately on every language.

These encouraging results lead us to explore the challenging task of zero-short training, in which we train a model to link English documents to an English KB, but apply it to Chinese or Spanish documents. While the model certainly does worse on a language that is unobserved (in task-specific training), the reduction in performance is remarkably small. This result leads us to ask: 1) Why do zeroshot entity linking models do so well? 2) What information is needed to allow zero-shot models to perform as well as multilingually trained models? Using a series of ablation experiments we find that correctly comparing the mention text and entity name is the most important component of an entity linking model. Therefore, we propose an auxiliary pre-training objective to improve zeroshot performance. Additionally, we find that much of the remaining loss comes not from the language transfer, but from mismatches of entities mentioned across the datasets. This suggests that future work on the remaining challenges in zero-shot entity linking should think of the task as domain adaptation, rather than as language transfer.

In summary, this paper provides a new model for effective cross-language entity linking with multiple languages, demonstrates its effectiveness at zero-shot linking, introduces a pre-training objective to improve zero-shot transfer, and lays out guidelines to inform future research on zero-shot linking.

2 Cross-Language Entity Linking

A long line of work on entity linking has developed standard models to link textual mentions to entities in a KB (Dredze et al., 2010; Durrett and Klein, 2014; Gupta et al., 2017). The models in this area have served as the basis for developing multilingual and cross-language entity linking systems, and they inform our own model development. We define **multilingual** to mean a model that can operate on mentions from more than one language at the same time (link both English and Chinese mentions to an ontology) and **cross-language** to refer to linking mentions in one language (*e.g.*, Spanish) to an ontology in another (*e.g.*, English).

A common approach to cross-language entity linking is to use transliteration data to transform non-English mentions into English strings. Early transliteration work (McNamee et al., 2011) uses a transliteration corpus to train a support vector machine ranker, which uses common entity linking features such as name and context matching, co-occurring entities, and an indicator for NIL (no matching candidate.) Pan et al. (2017) uses transliteration data for a set of 282 languages to generate all possible combinations of mentions. A related approach is to use machine translation to translate a document into English, and then use an English entity linker. However, an MT system may not be available, and it further needs a specialized name module to properly translate entity names. Several systems from the TAC 2015 KBP Entity Discovery and Linking task (Ji et al., 2015) translate non-English documents into English, then use standard Entity Linking systems.

Cross-language Wikification is a closely related task, which uses links within Wikipedia, combined with equivalent pages in other languages to train an entity linker with Wikipedia as the KB. This approach typically uses English Wikipedia as the KB, though it could use a KB in other languages. Tsai and Roth (2016) use a two-step linking approach, first using an IR-based triage system (which we also use). Second, they use a candidate ranking step based on a linear ranking SVM model with several features, including contextual, document, and coreference.

The most closely related work to our own is that of Upadhyay et al. (2018), who use multilingual embeddings as the basis for their representations, and Wikipedia as training data. They use Fast-Text (Bojanowski et al., 2017; Smith et al., 2017) to align embeddings across languages, and a small dictionary to identify alignments. They pass these representations through a convolutional neural network to create a mention representation. They in turn use the other mention representations in the document to create a contextual representation, and also use a separate type vector. They train their network on hyperlinks from multiple languages in Wikipedia. Before the ranking step, they use a triage system similar to that of Tsai and Roth (2016). They evaluate on several entity linking datasets, including **TAC**. As their system only uses English Wikipedia as the KB, they set all mentions that link to a entity outside of Wikipedia to NIL;

... Además de los titulares del PEMEX, Conaculta; el jefe de la **Oficina de la Presidencia** (m.01p1k, ORG), Aurelio Nuño y ...

name	President of Mexico (m.01p1k)
description	The President of the United
type(s)	government_office_or_title,

Figure 1: Example Spanish mention Oficina de la Presidencia, which is a link to entity President of Mexico.

this results in a different evaluation setup than we need for our work. Their results show that training on all languages, instead of monolingual or bilingual training, generally performs best. For zero-shot entity linking, they train on English language Wikipedia. They find that their performance is heavily dependent on a prior probability derived from the triage system—otherwise, there is a large drop in performance.

Rijhwani et al. (2019) investigate zero-shot entity linking on low-resource languages. They propose a model consisting of a similarity model using encoders separately trained on high-resource language mentions, related to the low-resource language, and English entities. They then use the high-resource language as a pivot language for low resource language mentions, allowing them to score mentions in an unseen language. Raiman and Raiman (2018) consider multilingual entity linking, in which they use a KB in the same language as the mention, but exploit multilingual transfer for the model's type system. They formulate a type system as a mixed integer problem, which they use to learn a type system from knowledge graph relations. Other work focuses on zero-shot cross-language entity linking for low-resource languages.

3 Entity Linking Model

We propose a cross-language entity linker based on a pointwise neural ranker that scores a mention m and entity e pair, adapting from an architecture discussed in Dehghani et al. (2017). Unlike a classification architecture, a ranking architecture is able to score previously unseen entities. As is standard, we use a two stage system: triage followed by ranking; this reduces the number of entities that must be ranked, and results in better performance. Our system is shown in Figure 2.

The ranker takes as input several pieces of information about the mention and entity: 1) the mention string and entity name; 2) the context of the mention and entity description; and 3) the types of both the mention and entity. We represent the men-

tion string, entity name, mention context and entity description using a pre-trained multilingual deep transformer encoder (Devlin et al., 2019), while the mention and entity type are represented as one-hot embeddings. We describe the multilingual representation, model architecture and training procedure.

3.1 Multilingual Representations

The mention m and entity e both have a name and context/description. While the entity is in English, the mention may be in a different language. We seek a multilingual representation to allow comparisons across languages.

We use multilingual BERT (mBERT) (Devlin et al., 2019), which has been widely shown to create effective multilingual representations for downstream NLP tasks (Wu and Dredze, 2019). Consider the Spanish example in Figure 1. First, we create a representation of the mention text m_s , Oficina de la Presidencia, by creating an mBERT representation of the entire sentence, selecting the lowest layer representations of each of the sub-words, and form a single representation using max pooling. Similarly, we create a representation of the entity name e_s , President of Mexico, by using BERT in the same way although unlike the mention, the entity does not have a surrounding sentence, so only the name is used.

For the mention context m_c we pass sentences surrounding the mention through BERT and use the top layer of the [CLS] token.² We create a similar representation for the entity context e_c from the definition or other text in the KB, using the first 512 subword tokens from the text.

For the mention type m_t and entity type e_t we create one-hot embeddings, omitting ones that do not occur more than 100 times in the training set.

¹We experimented with several BERT layers and found this to be the best performing on the **TAC** development set.

²We select the surrounding sentences up to BERT's 512 sub-word limit, positioning the mention's sentence in the middle.

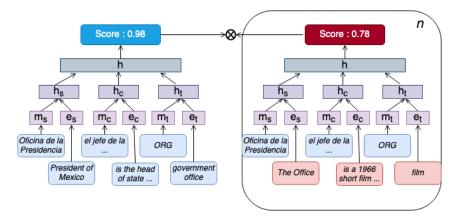


Figure 2: Architecture for our neural ranker, using the example from Figure 1 and a negatively-sampled entity *The Office*. The left ranker scores the example correct mention *Oficina de la Presidencia* and the entity *President of Mexico* pair.

3.2 Architecture

We feed the representations of the name (m_s and (e_s) , context (m_c, e_c) and type (m_t, e_t) into a neural ranker. Each of these three pairs are passed into a distinct multilayer perceptron, which produces an embedding that captures the similarity between each type of information. For example, we input m_s and e_s into a text-specific hidden layer, which produces a combined representation r_s . The same is done for the context and type representations, producing representations r_c and r_t , respectively. These three representations are then fed into a final MLP, which produces a final score in the range of [-1,1]. The entire network is jointly trained with a ranking objective. We apply dropout at every layer, and use the ADAM optimizer. The intermediate activation function is ReLu, but in the final layer we use Tanh.

3.3 Model Training

We learn the parameters θ of our scoring function S using a pairwise approach; this allows us to train our model without annotated scores. Our ranker scores a mention m and positive entity e_+ pair, and separately scores the same mention paired with n sampled negative entities e_- . We apply the hinge loss between our correct entity and the highest scoring negative entity,

$$L(\theta) = \max\{0, \epsilon - (S(\{m, e_+\}; \theta) - \max\{S(\{m, e_{0-}\}; \theta) \dots S(\{m, e_{n-}\}; \theta)\}\}$$

We jointly train all components of the network, including the positive and negative portions of the network. The major benefit of this pairwise approach

is that it does not rely on annotated scores, but instead uses negative sampling to train the ranker.

We tested random combinations of hidden layer sizes and dropout rates to find the best configuration (using the values included in Appendix A). We use hidden layers of size 512 for text and context, and 64 for the type representations. The upper hidden layers are 512 and 256, and we set the dropout rate to be 0.2. We used random parameter selection as described in Appendix A.

4 Datasets

We conduct our evaluation on two cross-language entity linking datasets.

TAC. The 2015 TAC KBP Entity Discovery and Linking dataset (Ji et al., 2015) consists of newswire and discussion form posts in English, Spanish, and Mandarin Chinese. The training set consists of 30,834 mentions (6,857 NIL) across 447 documents. We reserved a randomly selected 20% of these documents as our development set, and will release development splits. The evaluation set consists of 32,459 mentions (8,756 NIL) across 502 documents. A mention is linked to NIL if there is no relevant entity in the KB. The KB derived from a version of BaseKB. Although BaseKB includes some non-English information within the KB, our model only uses English text. We provide a comparison to the numbers noted in Ji et al. (2015), as we use their evaluation set and script. Later papers, such as Upadhyay et al. (2018), also use this dataset but only for evaluation, instead training on Wikipedia and treating mentions that are linked to TAC entities without Wikipedia links as NIL. Therefore, we cannot compare our evaluation to

M	lodel	avg.	prec.	recall	F ₁
	prev	_	0.736	0.738	0.737
en	mono	0.466	0.871	0.447	0.590
	multi	0.629	0.583	0.733	0.649
	prev	_	0.854	0.809	0.831
zh	mono	0.717	0.82	0.729	0.794
	multi	0.750	0.873	0.751	0.807
	prev	_	0.804	0.804	0.804
es	mono	0.506	0.920	0.488	0.638
	multi	0.585	0.910	0.547	0.683
all	multi	0.666	0.684	0.690	0.687
	mono	0.632	0.625	0.888	0.734
ar	multi	0.690	0.718	0.815	0.763
	mono	0.737	0.809	0.905	0.854
fa	multi	0.824	0.872	0.951	0.910
ko	mono	0.758	0.795	0.928	0.856
KO	multi	0.843	0.868	0.935	0.900
411	mono	0.686	0.815	0.857	0.836
ru	multi	0.819	0.913	0.922	0.917
all	_	0.786	0.815	0.882	0.847

Table 1: Micro-avg, precision, recall, and F₁ for **TAC** and **Wiki** datasets.

this work.

Wiki. We created a cross-language entity linking dataset from Wikipedia links (Pan et al., 2017) that includes Korean, Farsi, Arabic, and Russian.³. The preprocessed data had links in non-English Wikipedia pages to other non-English pages annotated with that link and an English page link if a corresponding page was available. From these annotations we created a dataset consisting of a non-English mention linked to a English-language entity (Wikipedia page). We consider this to be silverstandard data because-unlike the TAC dataset-the annotations have not be reviewed by human annotators. The KB for this dataset consists of English Wikipedia. Some BaseKB entities used in the TAC dataset have Wikipedia links provided, so we used those links as seed entities for retrieving mentions, retrieving mentions in proportion to their presence in the TAC dataset, and to sample a roughly equivalent number of non-TAC entities. We mark 20% of the remaining mentions as NIL. Since we do not have a separate development set for this dataset, we apply the selected hyperparameters selected on **TAC** development data to this dataset. In total, we train and evaluate on 5,923 and 1,859 Arabic, 3,927 and 1,033 Farsi, 5,978 and 1,694 Korean, and 5,337 and 1,337 Russian mentions, respectively.

We produce NIL predictions by using a threshold; mentions where all entities are below a given threshold are marked as NIL. The threshold is selected based on the development set of the **TAC** dataset. We find that for all non-English documents the best performing threshold is -1. We only report a higher threshold (0.0) only for the multilingual **TAC** setting, based on development performance. We evaluate all models using the evaluation script provided by Ji et al. (2015), which reports Precision, Recall, F_1 , and Micro-average.

4.1 Triage

We assume gold NER mentions in our analysis. We use the triage system of Upadhyay et al. (2018), which is largely based on work in Tsai and Roth (2016). This allows us to score a smaller set of entities for each mention as opposed to the entire KB. For a give mention m, a triage system will provide a set of k candidate entities $e_1 \dots e_k$. The system uses Wikipedia cross-links (as discussed previously) to generate a prior probability $P_{\text{prior}}(e_i|m)$ by estimating counts from those mentions. This prior is used to provide the top k English Wikipedia page titles for each mention (k = 10 for **TAC** and k = 100 for **Wiki**. Further implementation details specific to the **TAC** dataset are provided in Appendix B.

5 Model Evaluation

We consider several different training and evaluation settings to explore the abilities of our model. Recent studies suggest that multilingual models can achieve similar or even better performance on cross-language entity linking (Upadhyay et al., 2018). Other work (Mueller et al., 2020) has shown that this is not always the case. Therefore, we begin by asking: does our linker do better when trained on all languages (multilingual crosslanguage) or trained separately on each individual language (monolingual cross-language)?

We train our model on each of the 7 individual languages in the two datasets (noted as **Mono**). Next, we train a single model for each dataset

³We thank the authors of Pan et al. (2017) for providing us with a preprocessed version of Wikipedia to use in creating this dataset. We are working with the authors to release the dataset

	TAC Training data			
Eval	Multi	en	zh	es
en	0.65	0.59	0.55	0.54
zh	0.81		0.79	
es	0.68		0.65	
all	0.68	0.62	0.62	0.58

	Wiki Training data				
Eval	Multi	ar	fa	ko	ru
ar	0.76	0.73	0.63	0.51	0.52
fa	0.91	0.82	0.85	0.80	0.81
ko	0.90	0.84	0.84	0.86	0.83
ru	0.92	0.83	0.83	0.83	0.84
all	0.85	0.78	0.75	0.71	0.72

Table 2: F₁ performance for Zero Shot models for the **TAC** and **Wiki** datasets. Each column represents a model, trained on all (Multi) and language-specific training sets. Each row represents an evaluation set language specific and all.

(3 languages in TAC, 4 in Wiki, noted as Multi). Note that Mono and Multi share the exact same architecture - there are no multilingual adjustments made, and the model contains no language-specific features. We note the best performing architecture from (Ji et al., 2015) as Prev. Comparing to the previously reported results, our models often have a lower recall rate. This is due to the challenges involved with the Triage for the TAC dataset, which is discussed in Appendix B. Our triage system is tuned to have high recall on the development set and thus we selected a large candidate set; this led to many NIL mentions in the evaluation set being incorrectly assigned an entity.

Table 1 shows that for **TAC** there is a small difference between the **Mono** and **Multi** models. For **Wiki** the difference is often larger. **Multi** often does better than **Mono**, suggesting that additional training data is helpful. Overall, these results are encouraging as they suggest that a single trained model for our system can be used for crosslanguage linking for multiple languages. This can reduce the complexity associated with developing, deploying and maintaining multiple models in a multilingual environment.

6 Zero-shot Language Transfer

Encouraged by the results on multilingual training, we next explore performance in a zero-shot setting. How does a model trained on a single language

	en		zh		es	
						F_1
name	0.51	0.64	0.44	0.71	0.36	0.69 0.71 0.63 0.71
+cont	0.62	0.68	0.52	0.67	0.45	0.71
+type	0.54	0.64	0.44	0.62	0.35	0.63
All	0.62	0.68	0.54	0.68	0.46	0.71

Table 3: Zero Shot ablation micro-average and F_1 on TAC development data

perform when applied to a new, unseen language? We consider all pairs of languages, *i.e.*, train on each language and evaluate on all others within the same dataset. ⁴

Table 2 shows results for all zero-shot settings. While zero-shot performance does worse than a model with access to within-language training data, the degradation is surprisingly small: often less than $0.1 \, F_1$. For example, a model trained on all 3 **TAC** languages achieves an F_1 of 0.81 on Chinese, but if only trained on English, achieves an F_1 of 0.76. This pattern is consistent across both models trained on related languages (Arabic \rightarrow Farsi, loss of $0.09 \, F_1$), and on unrelated languages (Russian \rightarrow Korean, loss of $0.07 \, F_1$).

6.1 Zero-Shot Analysis

Why does zero-shot language transfer do so well for cross-language entity linking? What challenges remain to eliminate the reduction in performance from zero-shot transfer?

We answer these questions by exploring the importance of each component of our cross-language ranking system: mention string, context, and type. We conduct ablation experiments investigating the performance loss from removing these information sources. We then evaluate each model in a zero-shot setting. First, we train a zero shot model using only the mention text and entity name. We then add the context, the type, and both context and type (all features).

Table 3 shows that comparing the name and mention text alone accounts for most of the performance of the model, a sensible result given that most of the task involves matching names of entities. We find that context accounts for most of the remaining performance, with type information

⁴Work in Cross-language entity linking (Upadhyay et al., 2018; Tsai and Roth, 2016) has done similar evaluations, but focus on using larger data sources (Wikipedia) to train their models, and use the triage prior as an important signal.

having a marginal effect. This highlights the importance of the multilingual encoder, since both name and context rely on effective multilingual representations. The exception is that the Chinese nameonly model has a higher F₁ than the All model - the name-only performs better on NIL entities, while the All performs better on non-NIL, as evidenced by the difference in micro-average.

7 Improving Zero-shot Transfer

7.1 Name Matching Objective

Given the importance of matching the mention string with the entity name, perhaps improving this component can reduce zero-shot transfer loss. While obtaining within-language entity linking data isn't possibly in a zero-shot setting, we could use cross-language name matching data, which is often easier to produce. For example, Irvine et al. (2010) and Peng et al. (2015) construct name corpora automatically from Wikipedia. Since Chinese performance suffers the most zero-shot loss when compared to the multilingual setting, we use Chinese English name pair data to support an auxiliary training objective. We use a corpus of 1,451,032 Chinese/English name pairs (Huang, 2005). An example: the Chinese name "巴尔的摩-俄亥俄 铁路公司" with the English translation Baltimore & Ohio Railroad.

We augment model training as follows. In each training epoch, we first train the subset of the model that considers the mention string and entity name on a random subset k=50,000 of the Chinese/English name pair corpus. We score a Chinese name z and a correctly matched English name e_+ pair, and separately score the same Chinese name paired with n negatively sampled English names e_- . We create representations for both z and s using the method described for names in §3.1 which are passed to the name-only hidden layer. We add a matching-specific hidden layer, which produces a single score. We apply the hinge loss between positive and negative examples

$$L(\theta) = \max\{0, \epsilon - (S(\{z, e_+\}; \theta) - \max\{S(\{z, e_{0-}\}; \theta) \dots S(\{z, e_{n-}\}; \theta)\}\}$$

We use this loss function to back-propagate and update parameters of that part of the model. We then run an epoch of the standard training procedure (§3.3). After training, we discard the layer used to produce a score for name matches. Therefore,

this procedure still only uses source language entity linking training data, but makes use of auxiliary resources to improve the name matching component, the most important aspect of the model.

We further analyze the resulting performance by considering modifications to our training setting, which are designed to replicate scenarios where there is little training data available. First, we select a random 50% of mentions, partitioned by document (**Random**). This reduces the size of the training corpus. Second, we select 50% of mentions that are linked to the least frequent entities in the English dataset (noted as **Tail**). This setting shows the effect of removing mentions of the most common entities from the training data.

Table 5 shows the results on each of the three TAC languages. For the Random training set, while Chinese shows the largest improvement, we see improvements for all three languages, even though the auxiliary data was Chinese/English. This suggests that improvements to the name matcher for one language can benefit other languages. However, despite these improvements there is still loss from zero-shot transfer. Therefore, we next look at the Tail training setting, where the results are less clear. Chinese does improve slightly, yet performance degrades in other languages. This suggests that improvements may be concentrated in the more common entities, an effect we explore in our next experiment.

7.2 Entities

Another possible source of zero-shot degradation is the lack of information on specific entities mentioned in the target language. For entity linking, knowledge of the distribution over the ontology can be very helpful in making linking decisions. This is especially the case with entities that have common names, as there are many entities in the ontology with these names, *e.g.*, multiple entities with the name United States. Which of these entities to select often depends on annotation choices specific to a dataset. Since each language may prefer different entities, a zero-shot model would struggle to disambiguate correctly.

We measure this effect through several diagnostic experiments where we train on a reduced amount of English training data in the following ways, then evaluate on the development set for all languages. First, we sample all entities that have at most n=19 example mentions (**N-19**). Next, we

	e	n	\mathbf{z}	h	e	S
	avg	F_1	avg	F_1	avg	F_1
Multi	.71	.73	.77	.81	.64	.82
Rand	.55	.65	.55	.68	.46	.71
N-19	.67	.69	.61	.70	.51	.73
N-1	.69	.71	.69	.76	.54	.75
N-1U	.47	.60	.42	.62	.37	.59
Tail	.47	.60	.38	.62	.39	.66

Table 4: Micro-average and F₁ on English, Chinese, and Spanish **TAC** development data, on training data sets described in §7.2

sample all entities that have at most n=1 example mentions (N-1). Both procedures result in a much smaller training as compared to the **Tail** and **Random** datasets above. Finally, we take **DS-1** and remove all evaluation set entities (N-1U), leaving all evaluation entities unseen at train time.

Table 4 reports results on these reduced training sets. Compared to the multilingual baseline (Multi) trained on all languages, there is a decrease in performance in all settings. Several patterns emerge. First, the models trained on a subset of the English training data containing more example entities -N-19 and N-1 - have much higher performance than the models that do not. Unobserved entities do poorly at test time, suggesting that observing entities in the training data is important. However, an mention training example can improve the performance of a mention in another language if linked to the same entity, which suggests that this provides the model with data-specific entity information. Therefore, the remaining zero-shot performance degradation can be largely attributed not to a change in language, but to a change in dataset, i.e., what entities are commonly linked to in the data. This may also explain why the name matching component is so important in zero-shot transfer, but our auxiliary training objective was unable to fully mitigate the problem. The model may be overfitting to observed entities, forcing the name component to memorize specific names of popular entities seen in the training data. This means we are faced with a domain adaptation rather than a language adaptation problem.

We validate this hypothesis by experimenting with information about entity popularity. Will including information about which entities are popular improve zero-shot transfer? We answer this question by re-ranking the entity linker's top ten

			Popularity	
	Baseline	Name Match	All	Train
en	0.658	0.665	0.693	0.676
zh	0.678	0.705	0.772	0.740
es	0.713	0.733	0.769	0.735
all	0.641	0.658	0.716	0.685
en	0.559	0.547	0.639	0.620
zh	0.620	0.624	0.714	0.670
es	0.664	0.657	0.772	0.730
all	0.560	0.557	0.658	0.619

Table 5: Name matching and popularity re-ranking F₁ results for **Random** (top) and **Tail** (bottom).

predicted entities using popularity information, selecting the most most popular entity from the list. Adding this feature into the model and re-training did not lead to a significant performance gain. We define the popularity of an entity to be the number of times it occurred in the training data. We report results for two popularity measures—one using the popularity of the English subset of the data used for training, and one using all of the training data (including for excluded languages).

Table 5 shows that both strategies improve F_1 , meaning that a missing component of zero-shot transfer is information about which entities are favored in a specific dataset. The gain from using popularity estimated from the training data only is smaller than using the popularity data drawn from all of **TAC**. With more accurate popularity information, we can better mitigate loss.

8 Conclusion

We demonstrate that a neural ranking architecture for cross-language entity linking produces a multilingual model that comes close to or improves upon a monolingual cross-language model. This is encouraging, as it means we can use a single trained model across multiple languages. Additionally, we find that this model does surprisingly well at zeroshot language transfer. We find that the zero-shot transfer loss can be partly mitigated by an auxiliary training objective to improve the name matching components. However, we find that the remaining error is not due to language transfer, but to dataset transfer. Future work that improves zero-shot transfer should focus on better ways to estimate entity popularity in target datasets. We plan to release our code, trained models and data split.

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A Architecture information

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Parameter Values

Context Layer(s) [768], [512], [256], [512,256]

Mention Layer(s) [768], [512], [256], [512,256]

Type Layer [128], [64], [32], [16]

Final Layer(s) [512,256], [256,128], [128,64], [1024,512], [512], [256]

Dropout probability 0.1, 0.2, 0.5

Learning rate 1e-5, 5e-4, 1e-4, 5e-3, 1e-3
```

Table 6: To select parameters for the ranker, we tried 10 random combinations of the above parameters, and selected the configuration that performed best on the TAC development set. The selected parameter is in bold. We report results after training for 250 epochs. The full multilingual model takes approximately 1 day to train on a single NVIDIA GeForce Titan RTX GPU, including candidate generation, representation caching, and prediction on the full evaluation dataset.

B TAC Triage Implementation

We use the system discussed in for both the TAC and Wiki datasets. However, while the triage system provides candidates in the same KB as the Wiki data, not all entities in the TAC KB have Wikipedia page titles. Therefore, the TAC triage step requires an intermediate step - using the Wikipedia titles generated by triage (k = 10), we query a Lucene database of BaseKB for relevant entities. For each title, we query BaseKB proportional to the prior provided by the triage system, meaning that we retrieve more BaseKB entities for titles that have a higher triage score, resulting in l=200 entities. First, entities with Wikipedia titles are queried, followed by the entity name itself. If none are found, we query the mention string this provides a small increase in triage recall. This necessary intermediate step results in a lower recall rate for the **TAC** dataset (included in Table 7) than the Wiki dataset, which was 96.3% for the evaluation set.

	Training	Evaluation
es	85.86%	88.7%
en	76.73%	82.1%
zh	79.88%	87.9%

Table 7: Percentage of gold entities included for the **TAC** triage step.