

Interpretable Entity Representations through Large-Scale Typing

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Abstract

In standard methodology for natural language processing, entities in text are typically embedded in dense vector spaces with pre-trained models. Such approaches are strong building blocks for entity-related tasks, but the embeddings they produce require extensive additional processing in neural models, and these entity embeddings are fundamentally difficult to interpret. In this paper, we present an approach to creating interpretable entity representations that are human readable and achieve high performance on entity-related tasks out of the box. Our representations are vectors whose values correspond to posterior probabilities over fine-grained entity types, indicating the confidence of a typing model’s decision that the entity belongs to the corresponding type. We obtain these representations using a fine-grained entity typing model, trained either on supervised ultra-fine entity typing data (Choi et al., 2018) or distantly-supervised examples from Wikipedia. On entity probing tasks involving recognizing entity identity, our embeddings achieve competitive performance with ELMo and BERT without using any extra parameters. We also show that it is possible to reduce the size of our type set in a learning-based way for particular domains. Finally, we show that these embeddings can be post-hoc modified through simple rules to incorporate domain knowledge and improve performance.

1 Introduction

In typical neural NLP systems, entities are embedded in the same space as other words either in context-independent (Mikolov et al., 2013; Pennington et al., 2014) or in context-dependent ways (Peters et al., 2018; Devlin et al., 2019). Such approaches are powerful: pre-trained language models implicitly learn factual knowledge about those entities (Petroni et al., 2019; Roberts et al.,

2020; Jiang et al., 2020), and these representations can be explicitly grounded in structured and human-curated knowledge bases (Logan et al., 2019; Levine et al., 2019; Peters et al., 2019; Zhang et al., 2019; Poerner et al., 2019; Xiong et al., 2020; Wang et al., 2020). However, these representations do not *explicitly* maintain representations of this knowledge, and dense entity representations are not directly interpretable. Knowledge probing tasks can be used to measure LMs’ factual knowledge (Petroni et al., 2019), but designing the right probing task is another hard problem (Poerner et al., 2019). Probes to extract this information often have significant numbers of parameters themselves (Chen et al., 2019), raising the question of how naturally this knowledge is captured (Hewitt and Manning, 2019; Voita and Titov, 2020).

In this work, we explore using a set of interpretable entity representations that are simultaneously human and machine readable. The key idea of this approach is to use fine-grained entity typing models with large type inventories (Gillick et al., 2014; Choi et al., 2018; Onoe and Durrett, 2020). Given an entity mention and context words, our typing model outputs a high-dimensional vector whose values correspond to predefined fine-grained entity types. Each value ranges between 0 and 1, so it can be viewed as the confidence of the model’s decision that the entity has the property given by the corresponding type. These typing models are pre-trained Transformer-based entity typing models, trained either on a supervised dataset (the ultra-fine entity typing dataset of Choi et al. (2018)) or on a distantly-supervised type set from Wikipedia. The embedding vectors produced by these models, which contain tens of thousands of types, can then be used in downstream tasks. Most importantly, the models used to do so can be **lightweight** and are **interpretable**, making them easier to extend and debug, as we will show.

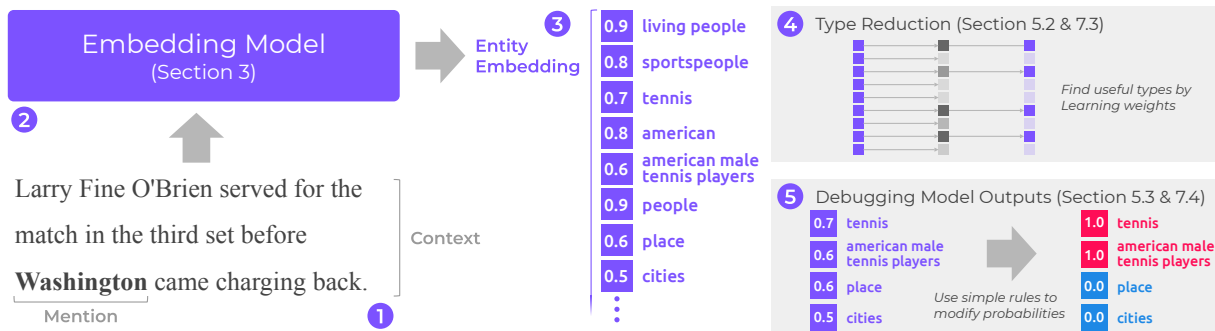


Figure 1: Interpretable entity representations. (1) A mention and its context are fed into (2) an embedding model. (3) An entity embedding vector consists of probabilities for corresponding types. (4) We can reduce the size of the type set for a particular downstream task in a learning-based (Section 7.3). (5) We can also incorporate domain knowledge via rules to modify bad probabilities and improve model performance.

Previous research has shown that rich representations of real world entities play a crucial role in natural language understanding tasks such as entity linking (Yamada et al., 2016), relation extraction (Baldini Soares et al., 2019), entity typing (Ling et al., 2020), and question answering (Févy et al., 2020). Those approaches use millions of predefined entities, while our approach uses a much smaller number of types (10k or 60k). This makes it simultaneously more compact and also more flexible when generalizing to unknown entities.

We evaluate our embedding approach on benchmark tasks for entity representations. We use coreference arc prediction (CAP) and named entity disambiguation on CoNLL-YAGO, two tasks in the EntEval suite (Chen et al., 2019), as well as the WikilinksNED dataset (Eshel et al., 2017), which covers broader entities and writing styles. We compare our approach against entity representations produced by pre-trained word embeddings (e.g. GloVe, ELMo, BERT). Our “out-of-the-box” entity representations used in a very lightweight way (using dot product or cosine similarity) can achieve competitive results on CAP without using additional trainable parameters that the baselines employ. On NED tasks, our approach outperforms all baselines with a substantial margin. We observe that even a smaller type set obtained by a simple type reduction technique can achieve similar performance. Finally, we show that our approach potentially eases the debugging process of black-box models by leveraging its interpretability.

2 Interpretable Entity Representations

Our approach for producing entity representations is shown in Figure 1. For an entity mention in con-

text,¹ we compute a vector of probabilities, each of which reflects (independently) the probability of an entity exhibiting a particular type. Types are predefined concepts that could be derived from existing knowledge bases. We hypothesize that real world entities can be represented as a combination of those concepts if we have a large and varied enough concept inventory. This representation can be used as a dense vector since the values are still continuous numbers (though restricted between 0 and 1). It is interpretable like a discrete feature vector since each dimension has been named (with the corresponding entity types).

We define $s = (w_1, \dots, w_N)$ to denote a sequence of context words, and $m = (w_i, \dots, w_j)$ to denote an entity mention span in s . The input word sequence s could be naturally co-occurring *context* words for the mention, or *descriptive* words such as might be found in a definition. The output variable is a vector $\mathbf{t} \in [0, 1]^{|T|}$ whose values are probabilities corresponding to fine-grained entity types \mathcal{T} . Those entity types are predefined and static, so their meanings are identical for all entities. Our goal here is to learn parameters θ of a function f_θ that maps the mention m and its context s to a vector \mathbf{t} , which capture salient features of the entity mention with the context.

We learn the parameters θ in a supervised manner. We use a labeled dataset $\mathcal{D} = \{(m, s, \mathbf{t}^*)^{(1)}, \dots, (m, s, \mathbf{t}^*)^{(k)}\}$ to train an entity typing model. The gold labels \mathbf{t}^* , where $t_i^* \in \{0, 1\}$, are obtained by manual annotation or distant-supervision techniques (Craven and Kumlien, 1999; Mintz et al., 2009). Manual annotation

¹Our approach can also embed entities knowledge bases, if these knowledge bases contain appropriate descriptive text. We discuss this in Section 4.

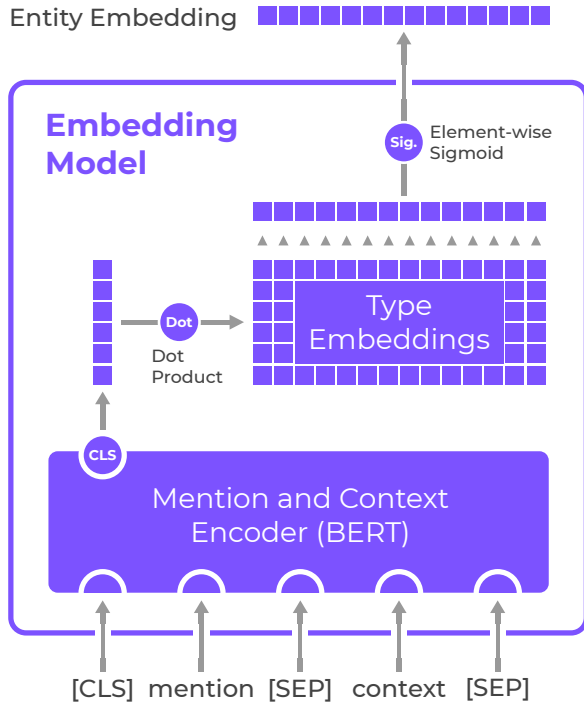


Figure 2: Embedding model architecture. We use BERT to embed the mention and context, then multiply by an output matrix and apply an elementwise sigmoid to compute posterior probabilities for each type.

usually guarantees high-quality labels while distant supervision often results noisy labels, but is more flexible. We select a predefined types \mathcal{T} from modified Wikipedia categories, or we use an existing type set such as UFET (Choi et al., 2018) (discussed in Section 4).

We use the output vectors \mathbf{t} as general purpose entity representations in downstream tasks. Notably, using off-the-shelf similarity measures like dot product and cosine similarity can lead to good performance on the tasks we consider. These representations can also be customized depending on task specific requirements. We show that the number of entity types can be reduced drastically (by 90%) with maintaining similar performance (top right of Figure 1). This can be done by training a simple bilinear model using the target task’s training examples (Section 7.3).

An advantage of our interpretable embeddings is that they give us a hook to “debug” our downstream models. Debugging black-box models built on embeddings is typically challenging, but since our entity representations are directly interpretable, we can modify the output vectors \mathbf{t} using our prior knowledge about entities (bottom right of Figure 1). For example, we might know *wall street* usually

means *the financial industry* in our target domain. We show that simple rules based on prior knowledge can improve performance further (discussed in Section 5); critically, this is done without having to annotate data in the target domain, giving system designers another technique for adapting these models.

3 Embedding Model

Our model f_θ to produce these embeddings is shown in Figure 2: it takes as input the mention m and its context s and predicts probabilities for predefined entity types \mathcal{T} . This is a Transformer-based typing model similar to the BERT model of Onoe and Durrett (2019). First, a Transformer-based encoder (Vaswani et al., 2017) maps the input variables, m and s , to an intermediate vector representation. A type embedding layer then projects the intermediate representation to a vector whose dimensions correspond to the entity types \mathcal{T} . Finally, we apply a sigmoid function on each real-valued score in the vector to obtain the posterior probabilities that form our entity representation \mathbf{t} (top of the figure).

Mention and Context Encoder We use pre-trained BERT² (Devlin et al., 2019) for the mention and context encoder. This BERT-based encoder accepts as input a token sequence formatted as $\mathbf{x} = [\text{CLS}] m [\text{SEP}] s [\text{SEP}]$, where the mention m and context s are chunked into WordPiece tokens (Wu et al., 2016). We encode the whole sequence using BERT and use the hidden vector at the [CLS] token as the mention and context representation: $\mathbf{h}_{[\text{CLS}]} = \text{BERTENCODER}(\mathbf{x})$.

Type Embeddings This output layer is a single linear layer whose parameter matrix can be viewed as type embeddings $\mathbf{E} \in \mathbb{R}^{|\mathcal{T}| \times d}$, where d is the dimension of the mention and context representation $\mathbf{h}_{[\text{CLS}]}$. The type embeddings \mathbf{E} learn semantic information about entity types. The dot product of the mention and context representation $\mathbf{h}_{[\text{CLS}]}$ and i th row vector \mathbf{e}_i is a score that indicates if an entity type \mathcal{T}_i is relevant with the entity mention m . Similar to previous work (Choi et al., 2018; Onoe and Durrett, 2019), we assume independence between all entity type in \mathcal{T} (i.e., we ignore hierarchical relationships between types). This design choice

²We use BERT-large uncased (whole word masking) in our experiments. We experimented with RoBERTa (Liu et al., 2019) but found it to work less well.

reduces the model complexity and eases optimization challenges. We obtain the output probabilities \mathbf{t} by taking a dot product between the type embedding \mathbf{E} and $\mathbf{h}_{[\text{CLS}]}$ followed by element-wise sigmoid function: $\mathbf{t} = \sigma(\mathbf{E} \cdot \mathbf{h}_{[\text{CLS}]})$.³

One assumption in our model is that the model’s output probabilities are a meaningful measure of class membership. Past work (Desai and Durrett, 2020) has observed that this is true for other models involving BERT variants.

Training Following Onoe and Durrett (2020), the loss is a sum of binary cross-entropy losses over all entity types \mathcal{T} over all training examples \mathcal{D} . We predict each type independently and optimize a multi-label binary cross entropy objective:

$$\mathcal{L} = - \sum_i t_i^* \cdot \log(t_i) + (1 - t_i^*) \cdot \log(1 - t_i),$$

where i are indices over types, t_i is the i th component of \mathbf{t} , and t_i^* is the i th component of \mathbf{t}^* that takes the value 1 if the i th type applies to the current entity mention. We update all parameters in the BERT encoder and the type embedding matrix.

Hyperparameters We use pre-trained BERT-large uncased (24-layer, 1024-hidden, 16-heads, 340M parameters, whole word masking) (Devlin et al., 2019) for our mention and context encoder. All BERT hyperparameters are unchanged. We train our models with batch size 32 (8×4 gradient accumulation steps) using NVIDIA V100 GPUs. We use the AdamW optimizer (Kingma and Ba, 2014; Loshchilov and Hutter, 2018) with learning rate $2e-5$ for BERT parameters and learning rate $1e-3$ for the type embedding matrix. We use HuggingFace’s Transformers library (Wolf et al., 2019) to implement our models.

4 Training Data

To train our entity typing model, we need labeled examples consisting of (m, s, \mathbf{t}^*) triples. Although there are labeled typing datasets such as UFET (Choi et al., 2018), getting large amounts of manually labeled data is expensive. Moreover, the UFET dataset contains instances of entities in context, so it is suitable for training models for *contextual*

³Note that this makes our entities occupy a d -dimensional subspace in the type representation logit space (pre-sigmoid). A different model could be used to combat this low-rankness. Regardless, the explicit type space has advantages in terms of out-of-the-box functionality as well as interpretability.

embeddings, but it doesn’t have examples of definitions for *descriptive embeddings* (following the terminology of (Chen et al., 2019)).

Therefore, we additionally use two distantly labeled entity typing datasets derived from Wikipedia. We select the appropriate dataset for each setting depending on task-specific requirements (see Section 6).

Wiki-Context We collect a set of occurrences of typed entity mentions using hyperlinks in Wikipedia. Given a sentence with a hyperlink, we use the hyperlink as an entity mention m , the sentence as a context sentence s , and the Wiki categories of the destination page as the gold entity types \mathbf{t}^* . We follow the preprocessing of Onoe and Durrett (2020) in modifying the type set. In particular, the original Wikipedia categories are mostly fine-grained and lack general categories. We expand the raw Wikipedia categories using simple rules to include more coarse-grained types, and filter to keep the 60,000 most frequent types. This yields 6M training examples that cover a wide range of entities and fine-grained entity types. We compute entity typing macro F1 using development examples (1k) to check model convergence.

Wiki-Description Following a similar paradigm as for Wiki-Context, we create description-focused training examples from Wikipedia. We use the same entity type set as the Wiki-Context dataset. We collect lead paragraphs from all Wikipedia pages and filter to keep examples that contain at least 1 entity type in the 60k entity types. We use the Wikipedia page title (usually boldfaced) in the lead paragraph as the entity mention m , and retain at most 100 words on either side to form the context s . The Wiki categories of the same page would be the gold entity types \mathbf{t}^* . We obtain 2M training examples after filtering. We compute macro F1 using development examples (1k) to check model convergence. The size of entity type set is 60k.⁴

UFET This ultra-fine entity typing dataset is created by Choi et al. (2018). This dataset consists of 6k manually annotated examples. The entity mention spans could be named entities, nominal expressions, and pronouns while Wiki-based datasets mostly provide named entity mention spans. We

⁴For tasks like entity linking, we could in principle just use gold type vectors for each entity, as in Onoe and Durrett (2020). However, the paradigm here matches that of Chen et al. (2019), and the descriptive entity embedding model we train can generalize to unseen descriptions at test time.

use 5.5k examples for training and 500 examples for validation. Note that because our goal in this work is downstream task performance, we deviate from the standard train/dev/test splits of 2k/2k/2k in favor of higher performance.

The entity type set combines 9 coarse types (e.g. person, location etc.) and existing fine-grained types (Ling and Weld, 2012; Gillick et al., 2014). In addition, approximately 10k popular noun phrases are included as ultra-fine types.

5 Tailoring to a Task

Our interpretable entity embeddings are designed for general-purpose uses and intended to work “out-of-the-box”. However, their interpretability enables us to customize the representations depending on task-specific requirements. We first discuss two scenarios (tasks) and then show two modifications we can make: reducing the size of types and debugging model output using prior knowledge.

5.1 Case Study

Coreference Arc Prediction (CAP) This task focuses on resolving local coreference arcs. For each instance, two entity mention spans and their context are provided. The task is to predict if those two mention spans are coreferent or not, so this is a binary classification problem.⁵

Named Entity Disambiguation (NED) NED is the task of connecting entity mentions in text with real world entities in a knowledge base such as Wikipedia. This requires nuanced understanding of context to select the correct entity from a large number of sometimes highly related candidates (e.g., the same movie produced in different years). We use the local resolution setting where each instance has one entity mention span in the input text (e.g. a sentence). We consider the setting where descriptions for candidates entities are available (e.g. the first sentence of the Wiki page). The number of candidates can be more than two, so we generally have to score several candidates and choose the highest one.

5.2 Type Reduction

The size of predefined entity types can be large; the type sets we consider in this work consist of

⁵The mentions in this case are always drawn from the same or adjacent sentences, so constraints from saliency that would need to be incorporated in a full coreference system are less relevant in this setting.

10k or 60k types. Although larger type set provides more precise entity representations, these may have redundant types or types which are unimportant for a particular domain. For both statistical and computational efficiency, we would like to compute the types useful for a downstream task in a data-driven way.

For all tasks we consider in this work, our model will depend chiefly on a function $\text{sim}(\mathbf{t}_1, \mathbf{t}_2)$ for two different type vectors. These type vectors are computed from mention and context pairs using the trained entity typing model $\mathbf{t} = f_\theta(m, s)$. In experiments, we will use both dot product and cosine similarity as our similarity function.

Our approach to compression involves learning a sparse trainable mask that restricts the set of types considered. We modify these operations as below:

$$\text{sim}_{\text{dot}}(\mathbf{t}_1, \mathbf{t}_2) = \mathbf{t}_1^\top \mathbf{W} \mathbf{t}_2, \tag{Dot}$$

$$\text{sim}_{\text{cos}}(\mathbf{t}_1, \mathbf{t}_2) = \frac{\mathbf{t}_1^\top \mathbf{W} \mathbf{t}_2}{\sqrt{\mathbf{t}_1^\top \mathbf{W} \mathbf{t}_1} \sqrt{\mathbf{t}_2^\top \mathbf{W} \mathbf{t}_2}}, \tag{Cosine}$$

where the weight matrix \mathbf{W} is a diagonal matrix $\text{diag}(w_1, w_2, \dots, w_{|\mathcal{T}|})$ whose components are corresponding to the entity types in \mathcal{T} . These similarity functions can be plugged into learning for downstream tasks (e.g., CAP and NED) and trained end-to-end to learn the mask parameters \mathbf{W} . Note that in the cosine scoring function, we clip these parameter values to be between 0 and 1.

We train with the standard downstream task objective, but with an additional L_1 regularization term applied to \mathbf{W} (Tibshirani, 1994). This encourages the \mathbf{W} values to be sparse.

This approach naturally leads to around 20–35% sparsity in the vector $\text{diag}(w_1, w_2, \dots, w_{|\mathcal{T}|})$ with settings of the regularization parameter we found effective. In practice, to achieve a higher level of sparsity, we further reduce the entity type set based on the magnitude of \mathbf{W} (e.g., keep the 10% of types with the highest values). Finally, we use the reduced entity types for further experiments on the target task.

5.3 Debuggability

Our interpretable entity representations allow us to more easily understand when our models for downstream tasks make incorrect predictions, typically by misunderstanding the use of a word in

context. Such wrong predictions can be traced back to incorrectly assigned high/low probabilities on irrelevant/relevant entity types.

As an example from the CONLL-YAGO dataset, we observe that our model gets confused if the mention span *Spain* should refer to *Women’s national tennis team* or *Men’s national tennis team*. If we are trying to adapt to this scenario without annotating more data, a domain expert may nevertheless be able to articulate a rule to fix this error. Such a rule might be: whenever *Fed Cup* (the international team competition in women’s tennis) appears in the context, we assign 1 to a collection of relevant entity types such as *women’s* and 0 to irrelevant types such as *davis cup teams* (the international team competition in men’s tennis). Critically, because our representations have interpretable axes, we can more easily transform our entity representations and incorporate this kind of domain knowledge.

6 Experimental Setup

We evaluate the “out-of-the-box” quality of our entity representations and baselines on two entity probing tasks as discussed in the previous section.

6.1 Datasets

Coreference Arc Prediction (CAP) We use the CAP dataset derived from PreCo (Chen et al., 2018) by Chen et al. (2019). In this dataset, two entity mention spans could be in the same sentence or split into two consecutive sentences. The creators of the dataset partition the data by cosine similarity of GloVe (Pennington et al., 2014) embeddings of mention spans and balance the number of positive and negative examples in each bucket, so that models do not solve problems by capturing surface features of entity mention spans. The original data split provides 8k examples for each of the training, development, and test sets.

Named Entity Disambiguation (NED) We use the standard CoNLL-YAGO benchmark (Hoffart et al., 2011) preprocessed by Chen et al. (2019). For each entity mention, at most 30 candidate entities are selected using the CrossWikis dictionary (Spitkovsky and Chang, 2012). This dataset contains 18.5k training, 4.8k development, and 4.5k test examples from newswire text, so the variety of entities and the writing styles are limited. For this reason, we create another NED dataset from WikilinksNED (Eshel et al., 2017), which includes

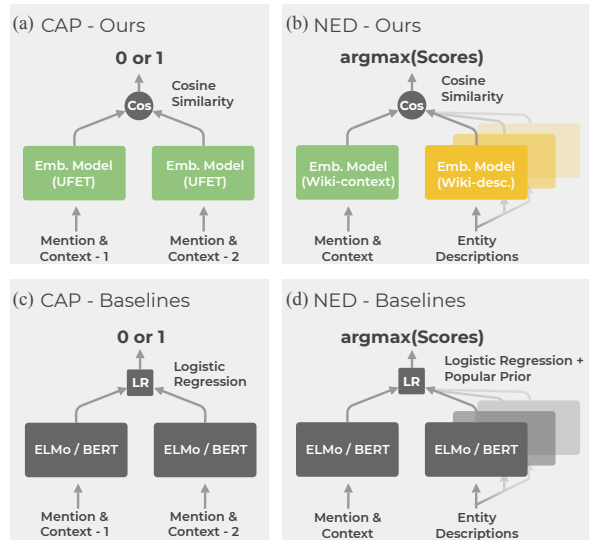


Figure 3: Overview of own downstream architectures. Our method simply computes cosine similarity and uses it as a score. Our baselines use logistic regression over pre-trained embeddings to compute a score. (a) Our entity embeddings on CAP (Section 7.1). (b) Our entity embeddings on NED (Section 7.2). (c) Baseline models on CAP (Section 7.1). (d) Baseline models on NED (Section 7.2).

a wide range of entities and diverse writing styles.⁶ We limit the number of candidate entities to 3 for each instance, which still leaves us with a challenging benchmark. We create 5k training, 1k development, and 1k test examples and call this dataset WLNE D. In both CoNLL-YAGO and WLNE D, we form descriptions of candidate entities using the Wiki-Context data, but otherwise do not use any structured information from Wikipedia (hyperlinks, etc.).

6.2 Baselines

Figure 3 schematically shows the use of our model compared to baselines, which we now describe.

Entity Embeddings We create entity representations of a mention span m and a context s using ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019). We largely follow the embedding procedure of Chen et al. (2019)

ELMO We first run ELMo on the entire sentence s . We combine the three layer outputs using uniform weights.⁷ Then, we average contextualized

⁶WikilinksNED is created from scraped noisy web text that links to Wikipedia, and it does not include any text from Wikipedia itself.

⁷Results from Chen et al. (2019) (Table 1 and Table 2) use trainable layer weights. Our results in Table 3 use fixed weights.

Model	Test Acc.
GLOVE (Chen et al., 2019)	71.9
ELMO (Chen et al., 2019)	80.2
BERT BASE (Chen et al., 2019)	80.6
BERT LARGE (Chen et al., 2019)	79.1
EntEmbeddings \rightarrow Cosine	80.2

Table 1: Accuracy on the CAP test set. All baselines use logistic regression (LR) trained on the CAP training set. Ours predicts based on cosine similarity (no additional training required).

vectors of the mention span m to obtain the entity representation.

BERT BASE We concatenate an entity mention m and its context s and feed it into BERT-base. We average the $[CLS]$ vectors⁸ from the last 4 layers and use it as an entity representation.⁷

BERT LARGE Similar to the BERT-base baseline, we feed an entity mention m and its context s into BERT-large. We average the $[CLS]$ vectors⁸ from the last 8 layers and use it as an entity representation.⁷

Classification Layer for Baselines Following Chen et al. (2019), we train a simple classifier (binary for CAP or multiclass for NED) to make final predictions. A feature vector of two entity representations x_1 and x_2 is a concatenation of x_1 , x_2 , element-wise product, and absolute difference: $[x_1, x_2, x_1 \odot x_2, |x_1 - x_2|]$. These are depicted in Figure 3 as “LR” blocks.

This classifier is used for baselines only. Our approach only uses dot product or cosine similarity only and does not require additional training. Because our embeddings are longer by default, an additional classifier would have more parameters than those of the other models and therefore make direct comparison difficult.

7 Results and Discussion

7.1 Coreference Arc Prediction (CAP)

How to use embeddings We choose the entity typing model trained on the UFET dataset (Choi et al., 2018) (Section 4) for CAP. We choose this dataset because many of mention spans in the CAP examples are nominal expressions or pronouns, and the Wiki-Context dataset includes almost entirely mentions of proper nouns. The size of the UFET

⁸We tried pooling span representations like for ELMO and saw similar results.

Model	Test Acc.
MOST FREQUENT (Chen et al., 2019)	58.2
ELMO Description (Chen et al., 2019)	63.4
ELMO Name (Chen et al., 2019)	71.2
BERT BASE Description (Chen et al., 2019)	64.7
BERT BASE Name (Chen et al., 2019)	74.3
BERT LARGE Description (Chen et al., 2019)	64.6
BERT LARGE Name (Chen et al., 2019)	74.8
EntEmbeddings \rightarrow Cosine	84.8

Table 2: Accuracy on the CoNLL-YAGO test set. All baselines use logistic regression (LR) trained on the CoNLL-YAGO training set and the prior probability. Ours predicts based on cosine similarity (no additional training required).

type set is 10k, so the output of the typing model, our entity representation, is a 10k dimensional vector. We do not use the training examples of the CAP dataset here; we only use the development/test examples to assess our approach. To make a prediction if two mentions are coreferent, we compute $\text{sim}_{\text{cos}}(\mathbf{t}_1, \mathbf{t}_2)$ over the type vectors for each mention and check if this is greater than a threshold, which we set to 0.5.

Baseline Details We compare our approach with ELMO and BERT baselines reported in Chen et al. (2019). They use three pre-trained LM embeddings: ELMO, BERT-base, and BERT-large. They also use two different types of entity representations. One uses entity descriptions, and another uses entity names only.

Results Table 1 compares test accuracy on the CAP task. Our entity representations (EntEmbeddings) achieve comparable accuracy, 80.2, with ELMO and BERT baselines reported in Chen et al. (2019) without training an additional classifier. This validates our hypothesis that these embeddings are useful out-of-the-box.

7.2 Named Entity Disambiguation (NED)

How to use embeddings In CoNLL-YAGO and WLNED, a single instance consists of one entity mention with context and multiple candidate entities. We use the entity typing model trained on the Wiki-Context data (see Section 4) to get the mention and context representation \mathbf{t} . Similar to Onoe and Durrett (2019), we prepend the document title and the first sentence to the input to enrich the context information.⁹ To obtain the candi-

⁹We retrieve the document-level information by using the original CoNLL data.

Model	Test Acc.
MOST FREQUENT	64.6
ELMO embeddings \rightarrow LR + prior	71.6
BERT BASE embeddings \rightarrow LR + prior	65.6
BERT LARGE embeddings \rightarrow LR + prior	69.8
EntEmbeddings \rightarrow Cosine	75.6

Table 3: Accuracy on the WLNED test set. All baselines use logistic regression (LR) trained on the WLNED training set and the prior probability. Ours predicts based on cosine similarity (no additional training required).

date representations $\{c_1, c_2, \dots, c_j, \dots\}$, we use the model trained on the Wiki-Description data, which is specialized for entity descriptions (see Section 4). We choose Wikipedia datasets here because UFET does not support entity descriptions. We rank the candidate entities based on cosine similarity between t and c_j , and the entity with the highest score would be the model prediction.

Baselines Details The MOST FREQUENT baseline is simply picking the most frequent mention and entity pair as a prediction. This relies on prior probability p_{prior} based on the count statistics from Wikipedia. All baselines except MOST FREQUENT combine the classifier output and the prior probability to make a prediction: $\arg \max_c [p_{\text{prior}}(c) + p_{\text{classifier}}(c)]$.

Results Table 2 lists test accuracy on the CoNLL-YAGO data. Our approach outperforms all baselines, indicating that our entity representations include useful information about entities out-of-the-box. Such a performance gap is expected since our entity representations can directly encode some factual knowledge from Wikipedia. However, these results also imply that pre-trained LMs do not have enough factual information out-of-the-box; they may rely on in-domain fine-tuning to achieve high performance in the target domain, and often fail to generalize to new settings (Onoe and Durrett, 2020).

Table 3 shows test accuracy on the WLNED data. The general trend is similar to the CoNLL-YAGO results, and our approach outperforms all baselines. ELMO embeddings achieves the highest accuracy, and BERT BASE embeddings marks the lowest accuracy of 65.6, which only add 1 point to MOST FREQUENT.

Task	#Types	reduced
	Dev Acc.	change
CAP	10k \rightarrow 1k	90%
	80.1 \rightarrow 78.9	-1.2
CoNLL-YAGO	60k \rightarrow 5k	92%
	85.3 \rightarrow 85.0	-0.3

Table 4: Accuracy on the development sets before and after applying type reduction.

7.3 Reducing the Number of Types

In Section 7.3, we described a technique to reduce the size of entity types using a simple model. In this section, we show that our approach effectively prune unnecessary types, and it leads to a compact task-specific entity typing model.

CAP We train a simple bilinear model on the CAP training examples. We use the dot scoring function and the binary loss for this task. We sort the entity types \mathcal{T} by the weight values, $(w_1, w_2, \dots, w_{10k})$, and keep the top 1k types as the new type set. As can be seen in Table 4, the reduced type set only results in a reduction of 1.2% in development accuracy after removing 90% of types.

CoNLL-YAGO To learn the type reduction, we convert the CoNLL-YAGO training data to a binary classification problem for simplicity by choosing positive and random negative entities. We train a bilinear model with the cosine scoring function and keep the top 5k types by weight as described in Section . The reduced type set achieves the comparable development accuracy just using around 10% of the original entity types.

Combined, these results show that the computational tractability of our approach can be improved given a specific downstream task. While our large type vectors are domain-general, they can be specialized and made sparse for particular applications.

7.4 Debugging Model Outputs

We investigate if simple rules made by our domain knowledge can further fix errors as discussed in Section 5.3. For CoNLL-YAGO, we create 11 rules and directly modify probabilities for certain types in entity representations t . Those rules are based on our observations in errors, in the same way that a user might want to inject domain knowledge to fix errors. The CoNLL data is heavily focused

	Dev Acc.
EntEmbeddings → Cosine	85.3
EntEmbeddings + Debug → Cosine	87.0

Table 5: Accuracy on the CoNLL-YAGO development set before and after applying debugging rules.

on sports, so in some sentences about baseball, we find that *New York* usually means *New York Yankees*, which belongs to the American League. If a mention is *Chicago*, our model gives a high probability to *Chicago Cubs*, which belongs to the National League. So, we create a rule that modifies the probabilities for *Chicago White Sox* to 1 and *Chicago Cubs* to 0. This simple rule fixes this particular case.

Table 5 shows that by applying our 11 rules (see Appendix A), which *only* modify our type embeddings post-hoc, the development accuracy goes up by 1.7 points. We believe that more generally, this could be a recipe for injecting knowledge when porting the system to new domains, as opposed to annotating training data.

7.5 Analysis: Entity Typing Performance

One important factor for our model is the performance of the underlying entity typing model. Table 6 shows the entity typing results on the development set of Wiki-Context, Wiki-Description, and UFET. On Wiki-Context, our entity typing model achieves 82.0 F1, which can be considered as a high number given that this is 60k multi-label classification. All Wiki-Description development examples are unseen during the training time; thus, F1 is lower compared to Wiki-Context. The results on UFET are not directly comparable with past work¹⁰ since we use different data split.

Overall, a BERT-based entity typing model handle large number of entity types (10k or 60k) well. Some of the high performance here can be attributed to memorizing common entities in the training data. However, we argue that this memorization is not a bad thing when the embeddings still generalize to work well on less frequent entities and in scenarios like CAP.

8 Related Work

Typing information Entity typing information has been used across a range of NLP tasks, in-

¹⁰The SOTA performance on the original split is around 40 F1.

Model	#Types	P	R	F1
WIKI-CONTEXT	60k	86.7	77.7	82.0
WIKI-DESCRIPTION	60k	77.6	71.2	74.2
UFET	10k	54.6	40.5	46.5

Table 6: Macro-averaged P/R/F1 on the development sets.

cluding models for entity linking and coreference (Durrett and Klein, 2014). In entity linking specifically, typing has been explored for cross-domain entity linking (Gupta et al., 2017; Onoe and Durrett, 2020). Past work by Raiman and Raiman (2018) has also explored learning a type system for this task. Our approach to learning types starts from a large set and filters it down, which is a simpler problem. A range of approaches have also considered augmenting pre-trained models with type information (Peters et al., 2019); however, in these models, the types inform dense embeddings which are still uninterpretable.

Representing words as properties Past work has looked at understanding entities using interpretable embeddings based around feature norms (McRae et al., 2005); this has advantages for learning in few-shot setups (Wang et al., 2017). However, most of this past work has used embeddings that are much lower-dimensional than ours, and don’t necessarily to scale to broad-domain text or all of Wikipedia.

Interpretability To understand what information is captured by pre-trained LMs, past work tests LMs using probing techniques. Peters et al. (2018) report that ELMo performs well on word sense disambiguation and POS tagging. Some other work also investigates models’ ability to induce syntactic information by measuring accuracy of a probe (Zhang and Bowman, 2018; Hewitt and Manning, 2019; Hewitt and Liang, 2019). However, there is significant uncertainty about how to calibrate such probing results (Voita and Titov, 2020); our model’s representations are more directly interpretable and don’t require post-hoc probing.

Entity embeddings Some past work learns static vectors for millions of predefined entities. Yamada et al. (2016) and Eshel et al. (2017) embed words and entities in the same continuous space particularly for NED. Ling et al. (2020) learn general purpose entity embeddings from context and entity relationships in a knowledge base while Févry et al.

(2020) does not rely on those structured information about entities. Our approach only stores type embeddings which can be substantially smaller than the entity embedding matrix.

9 Conclusion

In this work, we presented an approach to creating interpretable entity representations that are human readable and achieve high performance on entity-related tasks out of the box. We show that it is possible to reduce the size of our type set in a learning-based way for particular domains. In addition, these embeddings can be post-hoc modified through simple rules to incorporate domain knowledge and improve performance.

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A Debugging Rules

(see table)

Rule	Types to be set to 1	Types to be set to 0
<i>fed cup</i> is in the context.	women's, tennis, teams, sports	davis cup teams, davis cup
<i>soccer</i> is in the context.	football	uefa member associations
<i>cricket</i> is in the context.	england in international cricket, men's, national cricket teams, in english cricket	women's, women, women's national cricket teams, football
<i>tennis</i> is in the context, and the mention is <i>washington</i> .	tennis, living people	cities, in washington (state), in washington, d.c, established, establishments, capital districts and territories, populated, 'places
The mention is <i>wall street</i> .	exchanges, stock	streets, tourist
<i>soccer</i> and <i>1996</i> are in the context, and the mention is <i>world-cup</i> .	1998	1996
<i>baseball</i> and <i>new york</i> are in the context, and the mention is <i>chicago</i> .	chicago white sox	chicago cubs
<i>yeltsin</i> is in the context, and the mention is <i>lebed</i> .	living people, of russia	
<i>venice festival</i> is in the context, and the mention is <i>jordan</i> .	living people, people, irish, irish male novelists, 1950 births, male screenwriters, bafta winners (people), writers, for best director winners, people from dublin (city), 20th-century irish novelists	member states of the organisation of islamic cooperation, of the organisation of islamic cooperation, in jordan, territories, countries, states, of the arab league, member, western asian countries, member states of the arab league, member states of the united nations, jordan, tourism
<i>baseball</i> is in the context.	major, baseball	soccer, football, major league soccer, professional sports leagues in canada, professional, in the united states, in canada
<i>squash</i> is in the context, and the mention is <i>jansher</i> .	1969 births	1963 births

Table 7: Debugging rules applied for the CoNLL-YAGO development set.