E-BERT: Efficient-Yet-Effective Entity Embeddings for BERT

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Abstract

We present a novel way of injecting factual knowledge about entities into the pretrained BERT model (Devlin et al., 2019): We align Wikipedia2Vec entity vectors (Yamada et al., 2016) with BERT’s native wordpiece vector space and use the aligned entity vectors as if they were wordpiece vectors. The resulting entity-enhanced version of BERT (called E-BERT) is similar in spirit to ERNIE (Zhang et al., 2019) and KnowBert (Peters et al., 2019), but it requires no expensive further pretraining of the BERT encoder. We evaluate E-BERT on unsupervised question answering (QA), supervised relation classification (RC) and entity linking (EL). On all three tasks, E-BERT outperforms BERT and other baselines. We also show quantitatively that the original BERT model is overly reliant on the surface form of entity names (e.g., guessing that someone with an Italian-sounding name speaks Italian), and that E-BERT mitigates this problem.

1 Introduction

BERT (Devlin et al., 2019) and its successors (e.g., Yang et al. (2019); Liu et al. (2019); Wang et al. (2019b)) continue to achieve state of the art performance on various NLP tasks. Recently, there has been interest in enhancing BERT with factual knowledge about entities (Zhang et al., 2019; Peters et al., 2019). To this end, we introduce E-BERT: We align Wikipedia2Vec entity vectors (Yamada et al., 2016) with BERT’s wordpiece vector space (Section 3.1) and feed the aligned vectors into BERT as if they were wordpiece vectors (Section 3.2). Importantly, we do not make any changes to the BERT encoder itself, and we do no additional pretraining. This stands in contrast to previous entity-enhanced versions of BERT, such as ERNIE or KnowBert, which require additional encoder pretraining.

In Section 4, we evaluate our approach on LAMA (Petroni et al., 2019), a recent unsupervised QA benchmark for pretrained Language Models (LMs). We set a new state of the art on LAMA, with improvements over original BERT, ERNIE and KnowBert. We also find that the original BERT model is overly reliant on the surface form of entity names, e.g., it predicts that a person with an Italian-sounding name speaks Italian, regardless of whether this is factually correct. To quantify this effect, we create LAMA-UHN (UnHelpfulNames), a subset of LAMA where questions with overly helpful entity names were deleted (Section 4.4).

In Section 5, we show how to apply E-BERT to two entity-centric downstream tasks: relation classification (Section 5.1) and entity linking (Section 5.2). On the former task, we feed aligned entity vectors as inputs, on the latter, they serve as inputs and outputs. In both cases, E-BERT outperforms original BERT and other baselines.

Summary of contributions.

• Introduction of E-BERT: Feeding entity vectors into BERT without additional encoder pretraining. (Section 3)
• Evaluation on the LAMA unsupervised QA benchmark: E-BERT outperforms BERT, ERNIE and KnowBert. (Section 4)
• LAMA-UHN: A harder version of the LAMA benchmark with less informative entity names. (Section 4.4)
• Evaluation on supervised relation classification (Section 5.1) and entity linking (Section 5.2).
• Upon publication, we will release LAMA-UHN as well as E-BERTBASE and E-BERTLARGE.1

https://github.com/npoe/ebert
2 Related work

2.1 BERT

BERT (Bidirectional Encoder Representations from Transformers) is a Transformer (Vaswani et al., 2017) that was pretrained as a masked LM (MLM) on unlabeled text. At its base, BERT segments text into wordpieces from a vocabulary \( \mathbb{L}_{WP} \). Wordpieces are embedded into real-valued vectors by a lookup function (denoted \( \mathcal{E}^{\text{BERT}} : \mathbb{L}_{WP} \rightarrow \mathbb{R}^{d_{\text{BERT}}} \)). The wordpiece vectors are combined with position and segment embeddings and then fed into a stack of Transformer layers (the encoder, denoted \( \mathcal{F}^{\text{BERT}} \)). During pretraining, some wordpieces are replaced by a special \([\text{MASK}]\) token. The output of BERT is fed into a final feed-forward net (the MLM head, denoted \( \mathcal{F}^{\text{MLM}} \)), to predict the identity of the masked wordpieces. After pretraining, the MLM head is usually replaced by a task-specific layer, and the entire model is finetuned on supervised data.

2.2 Entity-enhanced BERT

This paper adds to recent work on entity-enhanced BERT models, most notably ERNIE (Zhang et al., 2019) and KnowBert (Peters et al., 2019). ERNIE and KnowBert are based on the design principle that BERT be adapted to entity vectors: They introduce new encoder layers to feed pretrained entity vectors into the Transformer, and they require additional pretraining to integrate the new parameters. In contrast, E-BERT’s design principle is that entity vectors be adapted to BERT, which makes our approach more efficient (see Section 3.3).

Two other knowledge-enhanced MLMs are KEP-LER (Wang et al., 2019c) and K-Adapter (Wang et al., 2020), which are based on Roberta (Liu et al., 2019) rather than BERT. Their factual knowledge does not stem from entity vectors — instead, they are trained in a multi-task setting on relation classification and knowledge base completion.

2.3 Wikipedia2Vec

Wikipedia2Vec (Yamada et al., 2016) embeds words and entities (Wikipedia URLs) into a common space. Given a vocabulary of words \( \mathbb{L}_{\text{Word}} \) and a vocabulary of entities \( \mathbb{L}_{\text{Ent}} \), it learns a lookup embedding function \( \mathcal{E}^{\text{Wikipedia}} : \mathbb{L}_{\text{Word}} \cup \mathbb{L}_{\text{Ent}} \rightarrow \mathbb{R}^{d_{\text{Wikipedia}}} \). The Wikipedia2Vec loss has three components: (1) skipgram Word2Vec (Mikolov et al., 2013a) operating on \( \mathbb{L}_{\text{Word}} \), (2) a graph loss operating on the Wikipedia hyperlink graph, whose vertices are \( \mathbb{L}_{\text{Ent}} \) and (3) a version of Word2Vec where words are predicted from entities. Loss (3) ensures that entities and words are embedded into the same space.

2.4 Vector space alignment

Our vector space alignment strategy is inspired by cross-lingual word vector alignment (e.g., Mikolov et al. (2013b); Smith et al. (2017)). A related method was recently applied by Wang et al. (2019a) to map cross-lingual word vectors into the multilingual BERT wordpiece vector space.

2.5 Unsupervised QA

QA has typically been tackled as a supervised problem (e.g., Das et al. (2017); Sun et al. (2018)). Recently, there has been interest in using unsupervised LMs such as GPT-2 or BERT for this task (Radford et al., 2019; Petroni et al., 2019). Davison et al. (2019) mine unsupervised commonsense knowledge from BERT, and Jiang et al. (2019) show the importance of using good prompts for unsupervised QA. None of this prior work differentiates quantitatively between factual knowledge of LMs and their ability to reason about the surface form of entity names.

3 E-BERT

3.1 Aligning entity and wordpiece vectors

Conceptually, we want to transform the vectors of the entity vector space \( \mathcal{E}^{\text{Wikipedia}}(\mathbb{L}_{\text{Ent}}) \) in such a way that they look to BERT like vectors from its native wordpiece vector space \( \mathcal{E}^{\text{BERT}}(\mathbb{L}_{\text{WP}}) \). We model the transformation as an unconstrained linear mapping \( \mathbf{W} \in \mathbb{R}^{d_{\text{BERT}} \times d_{\text{Wikipedia}}} \). Since \( \mathbb{L}_{\text{WP}} \) does not contain any entities (i.e., \( \mathbb{L}_{\text{WP}} \cap \mathbb{L}_{\text{Ent}} = \{\} \)), we fit the mapping on \( \mathbb{L}_{\text{WP}} \cap \mathbb{L}_{\text{Word}} \):

\[
\sum_{x \in \mathbb{L}_{\text{WP}} \cap \mathbb{L}_{\text{Word}}} || \mathbf{W} \mathcal{E}^{\text{Wikipedia}}(x) - \mathcal{E}^{\text{BERT}}(x) ||_2^2
\]

Since Wikipedia2Vec embeds \( \mathbb{L}_{\text{Word}} \) and \( \mathbb{L}_{\text{Ent}} \) into the same space (see Section 2.3), \( \mathbf{W} \) can be applied to \( \mathbb{L}_{\text{Ent}} \) as well. We define the E-BERT embedding function as:

\[
\mathcal{E}^{\text{E-BERT}} : \mathbb{L}_{\text{Ent}} \rightarrow \mathbb{R}^{d_{\text{BERT}}}
\]

\[
\mathcal{E}^{\text{E-BERT}}(a) = \mathbf{W} \mathcal{E}^{\text{Wikipedia}}(a)
\]

Table 1 shows that despite its simplicity, the linear mapping achieves high alignment accuracies on seen and unseen vector pairs.
Table 1: $\text{L}_\text{Word} \rightarrow \text{L}_\text{WP}$ alignment accuracy (%), i.e., how often the correct wordpiece vector is among the top-K Nearest Neighbors (by cosine) of an aligned Wikipedia2Vec word vector. In this table, we hold out 10% of $\text{L}_\text{WP} \cap \text{L}_\text{Word}$ as a development set. In all other experiments, we fit $W$ on the entire intersection.

### 3.2 Using aligned entity vectors

We explore two strategies for feeding the aligned entity vectors into the BERT encoder:

**E-BERT-concat.** E-BERT-concat combines entity IDs and wordpieces by string concatenation, with the slash symbol as separator (Schick and Schütze, 2019). For example, the wordpiece-tokenized input

\[
\text{The native language of Jean Mara} / \text{Jean Marais} \#\#\# \text{is [MASK]}.
\]

becomes

\[
\text{The native language of Je} \underline{n} \underline{a} \underline{r} \underline{a} \underline{i}s / \text{Jean Marais} \#\#\# \text{is [MASK]}.
\]

The entity ID (bold) is embedded by $E_{\text{E-BERT}}$ and all wordpieces (italics) are embedded by $E_{\text{BERT}}$ (see Figure 1). After the embedding operation, the sequence of vectors is combined with position and segment embeddings and fed into $F_{\text{BERT}}$, just like any normal sequence of wordpiece vectors.

E-BERT-concat is comparable to ERNIE or KnowBert, which also represent entities as a combination of surface form (wordpieces) and entity vectors. But in contrast to ERNIE and KnowBERT, we do not change or further pretrain the BERT encoder itself.

**E-BERT-replace.** For ablation purposes, we define another variant of E-BERT that substitutes the entity surface form with the entity vector. With E-BERT-replace, our example becomes:

\[
\text{The native language of \underline{Jean Marais} is [MASK]}.
\]

### 3.3 Implementation

We train cased Wikipedia2Vec on a recent Wikipedia dump (2019-09-02), setting $d_{\text{Wikipedia}} = d_{\text{BERT}}$. We ignore Wikipedia pages with fewer than 5 links (Wikipedia2Vec’s default), with the exception of entities needed for the downstream entity linking experiments (see Section 5.2). This results in an entity vocabulary of size $|L_{\text{Ent}}| = 2.7$M.

**Computational cost.** Training Wikipedia2Vec took us $\sim 6$ hours on 32 CPUs, and the cost of fitting the linear transformation $W$ is negligible. We did not require a GPU. For comparison, KnowBert $W+W$ was pretrained for 1.25M steps on up to four Titan RTX GPUs, and ERNIE took one epoch on the English Wikipedia. (ERNIE’s pretraining hardware was not disclosed, but it seems likely that a GPU was involved.)

### 4 Unsupervised QA

#### 4.1 Data

The LAMA (LAnguage Model Analysis) benchmark (Petroni et al., 2019) probes for “factual and commonsense knowledge” of pretrained LMs. In

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\[\text{For readability, we omit the special tokens [CLS] and [SEP] from all examples.}\]
this paper, we use LAMA-Google-RE and LAMA-T-Rex (Elsahar et al., 2018), which are aimed at factual knowledge. Contrary to most previous work on QA, LAMA tests LMs without supervised fine-tuning. Petroni et al. (2019) claim that BERT’s performance on LAMA is comparable with a knowledge base (KB) automatically extracted from text, and speculate that BERT and similar models “might become a viable alternative” to such KBs.

The LAMA task follows this schema: Given a KB triple (sub, rel, obj), the object is elicited with a relation-specific cloze-style question, e.g., *(Jean Marais, native-language, French)* becomes: “The native language of Jean Marais is [MASK].” The model predicts a probability distribution over a limited vocabulary \( \mathbb{L}_{\text{LAMA}} \subset \mathbb{L}_{\text{WP}} \) to replace [MASK], which is evaluated against the surface form of the object (here: French).

### 4.2 Baselines

Our primary baselines are cased BERT\(_{\text{BASE}}\) and BERT\(_{\text{LARGE}}\)\(^5\) as evaluated in Petroni et al. (2019). We also test ERNIE (Zhang et al., 2019)\(^6\) and KnowBert W+W (Peters et al., 2019),\(^7\) two entity-enhanced BERT\(_{\text{BASE}}\)-type models.\(^8\) E-BERT, ERNIE and KnowBert have entity vocabularies of size 2.7M, 5M and 470K, respectively. As this might put KnowBert at a disadvantage, Table 4 also reports performance on the subset of questions whose gold subject is known to KnowBert.

### 4.3 Evaluation measure

We use the same evaluation measure as Petroni et al. (2019): For a given \(k\), we count a question as 1 if the correct answer is among the top-\(k\) predictions and as 0 otherwise. Petroni et al. (2019) call this measure Precision@\(k\) (P@k). Since this is not in line with the typical use of the term “precision” in information retrieval (Manning et al., 2008, p. 161), we call the evaluation measure Hits@\(k\).

Like Petroni et al. (2019), we first average within relations and then across relations.

### 4.4 LAMA-UHN

Imagine a person who claims to know a lot of facts. During a quiz, you ask them about the native language of actor Jean Marais. They correctly answer “French.” For a moment you are impressed, until you realize that Jean is a typical French name. So you ask the same question about Daniel Ceccaldi (a French actor with an Italian-sounding name). This time, the person says “Italian.”

If this quiz were a QA benchmark, the person would have achieved a respectable Hits@1 score of 50%. Yet, you doubt that they really knew the first answer.

Qualitative inspection of BERT’s answers to LAMA suggests that the model often behaves less like a KB and more like the person just described. In Table 2 for instance, BERT predicts native languages that are plausible for people’s names, even when there is no factual basis for these predictions. This kind of name-based reasoning is a useful strategy for getting a high score on LAMA, as the correct answer and the best name-based guess tend to coincide (e.g., people with Italian-sounding names frequently speak Italian). Hence, LAMA in its current form cannot differentiate whether a model is good at reasoning about (the surface form of) entity names, good at memorizing facts, or both. To quantify the effect, we create LAMA-UHN (UnHelpful Names), a subset of LAMA where overly helpful entity names are heuristically deleted:

**Heuristic 1 (string match filter).** We first delete all KB triples (questions) where the correct answer (e.g., *Apple*) is a case-insensitive substring of the subject entity name (e.g., *Apple Watch*). This affects 12% of all triples, and up to 81% for individual relations (see Table 3, top).

| Name                  | original | E-BERT-replace | E-BERT-concat | ERNIE | KnowBert |
|-----------------------|----------|----------------|---------------|-------|----------|
| Jean Marais           | French   | French         | French        | French| French   |
| Daniel Ceccaldi       | Italian  | French         | French        | French| French   |
| Orane Demazis         | Albanian | French         | French        | French| French   |
| Sylvia Lopez          | Spanish  | French         | Spanish       | Spanish| Spanish  |
| Annick Alane          | English  | French         | French        | English| English  |

Table 2: Native language (LAMA-T-REx:P103) of French-speaking actors according to different models. Model size is BASE.
Heuristic 2 (person name filter). Entity names can be revealing in ways that are more subtle than string matches. As illustrated by our Jean Marais example, a person’s name can be a useful prior for guessing their native language and by extension, their nationality, place of birth, etc. We therefore use cloze-style questions to elicit name associations inherent in BERT, and delete triples that correlate with them.

The heuristic is best explained via an example. Consider again (Jean Marais, native-language, French). We whitespace-tokenize the subject’s surface form Jean Marais into Jean and Marais. If BERT considers either name to be a common French name, then a correct answer is insufficient evidence for factual knowledge about the entity Jean Marais. On the other hand, if neither Jean nor Marais are considered French, but a correct answer is given regardless, we consider it sufficient evidence of factual knowledge.

We query BERT with “[X] is a common name in the following language: [MASK].” for [X] = Jean and [X] = Marais. (Depending on the relation, we replace “language” with “city” or “country”.) If French is among the top-3 answers for either question, we delete the original triple. We apply this heuristic to T-REx:P19 (place of birth), T-REx:P20 (place of death), T-REx:P27 (nationality), T-REx:P103 (native language), T-REx:P1412 (language used), Google-RE:place-of-death and Google-RE:place-of-birth. See Table 3 (bottom) for examples and statistics.

### 4.5 Results and discussion

Table 4 shows mean Hits@1 on the original LAMA dataset (0), after applying the string match filter (1), and after applying both filters (2, LAMA-UHN). We also show mean Hits@1 on the LAMA-UHN complement, i.e., on the set of all questions with helpful entity names.

E-BERT-concatBASE sets a new state of the art on LAMA, with major gains over original BERT. To understand why, compare the performances of original BERTBASE and E-BERT-replaceBASE on LAMA-UHN and the LAMA-UHN complement: On LAMA-UHN, BERTBASE drops by 9% (relative to original LAMA), while E-BERT-replaceBASE drops by less than 1%. On the comple-

### Table 3: Statistics and examples of LAMA questions with helpful entity names, which were deleted from LAMA-UHN. We show the top-5 most strongly affected relations per heuristic. Numbers in brackets indicate which part(s) of the person name triggered the person name filter, e.g., (-,1) means that the correct answer was ranked first for the person’s last name, but was not in the top-3 for their first name.

| Heuristic | Relation | % deleted | Example of a deleted question |
|-----------|----------|-----------|------------------------------|
| string match filter | T-REx:P176 (manufacturer) | 81% | Fiat Multipla is produced by [MASK:Fiat] |
| | T-REx:P138 (named after) | 75% | Christmas Island is named after [MASK:Christmas] |
| | T-REx:P1001 (applies to jurisdiction) | 73% | Australian Senate is a legal term in [MASK:Australia] |
| | T-REx:P279 (subclass of) | 51% | Lentil galaxy is a subclass of [MASK:galaxy] |
| | T-REx:P31 (instance of) | 39% | [Tantalon Castle] is a [MASK:castle] |
| person name filter | T-REx:P1412 (language used) | 63% | Fulvio Tomizza used to communicate in [MASK:Italian] (1,1) |
| | T-REx:P103 (native language) | 58% | The native language of Tommy Nilsson is [MASK:Swedish] (-,1) |
| | T-REx:P27 (nationality) | 56% | Harumi Inoue is a [MASK:Japan] citizen (-,1) |
| | T-REx:P20 (place of death) | 31% | Avraham Harman died in [MASK:Jerusalem] (1,-) |
| | T-REx:P19 (place of birth) | 23% | [Christel Bodenstein] was born in [MASK:Munich] (3,3) |

| Model size | BASE | LARGE |
|-----------|------|-------|
| Dataset | E-BERT-replace | E-BERT-concat | ERNIE | Know-Bert | E-BERT-replace | E-BERT-concat | K-Adapter |
| All subjects | | | | | | | |
| 0 (original LAMA) | 29.2 | 29.1 | 36.2 | 30.4 | 31.7 | 30.6 | 28.5 | 34.2 | 27.6 |
| 1 | 22.3 | 29.2 | 32.6 | 25.5 | 25.6 | 24.6 | 28.6 | 30.8 | - |
| 2 (LAMA-UHN) | 20.2 | 28.2 | 31.1 | 24.7 | 24.6 | 23.0 | 27.8 | 29.5 | 21.7 |
| LAMA-UHN complement | 52.7 | 25.9 | 56.8 | 36.2 | 47.0 | 52.7 | 32.1 | 34.5 | - |
| KnowBert subjects | | | | | | | |
| 0 (original LAMA) | 32.0 | 28.5 | 35.8 | 30.4 | 32.0 | 33.1 | 28.2 | 34.9 | - |
| 1 | 24.8 | 28.6 | 32.0 | 25.7 | 25.9 | 27.0 | 28.3 | 31.5 | - |
| only 2 (LAMA-UHN) | 22.8 | 27.7 | 30.6 | 24.9 | 25.1 | 25.5 | 27.4 | 30.6 | - |

Table 4: Mean Hits@1 on LAMA-Google-RE and LAMA-T-REx combined. 0: original LAMA dataset (Petroni et al., 2019), 1: after string match filter, 2: after string match filter and person name filter (LAMA-UHN). “LAMA-UHN complement”: Evaluating on all questions that were deleted from LAMA-UHN. “KnowBert subjects only”: Evaluating on questions whose gold subject is in the KnowBert entity vocabulary. Results for K-Adapter are calculated from Wang et al. (2020, Table 5). See Appendix for individual relations.
ment, BERT\textsubscript{BASE} gains over 20\%, while E-BERT-replace\textsubscript{BASE} drops slightly. This suggests that BERT’s performance on original LAMA is partly due to the exploitation of helpful entity names, while that of E-BERT-replace is due to factual knowledge. Since E-BERT-concat\textsubscript{BASE} has access to entity names and entity vectors, it can leverage and combine these complementary sources of information.

For a more in-depth analysis, Figure 2 shows Delta(Hits@1) w.r.t. BERT (bars, left axis) on individual relations, along with the frequency of questions whose correct answer is a substring of the subject name (crosses, right axis). The losses of E-BERT-replace are almost exclusively on relations with a high frequency of “easy” substring answers, while its gains are on relations where such answers are rare. E-BERT-concat mitigates most of the losses of E-BERT-replace while keeping most of its gains. Figure 3 shows that gains of E-BERT-concat over BERT, KnowBert and ERNIE in terms of mean Hits@k are especially big for $k > 1$. This means that while E-BERT-concat is moderately better than the baselines at giving the correct answer, it is a lot better at “almost giving the correct answer”. Petroni et al. (2019) speculate that even when factual knowledge is not salient enough for a top-1 answer, it may still be useful when finetuning on a downstream task.

5 Downstream tasks

We now demonstrate how to use E-BERT on two downstream tasks: relation classification (RC) and entity linking (EL). In both experiments, we keep the embedding layer ($\hat{E}_\text{BERT}$ and/or $\hat{E}_E$-BERT) fixed but finetune all other encoder parameters. We use the BERT\textsubscript{BASE} architecture throughout.

5.1 Relation classification

In relation classification (RC), a model learns to predict the directed relation of entities $a_\text{sub}$ and $a_\text{obj}$ from text. For instance, given the sentence

```
Taylor was later part of the ensemble cast in MGM’s classic World War II drama “Battleground” (1949).
```

with surface forms Battleground and World War II referring to $a_\text{sub} = \text{Battleground (film)}$ and $a_\text{obj} = \text{World War II}$, the model should predict the relation primary-topic-of-work. We have three ways of embedding this example:

- original BERT (wordpieces): [...] classic World War II drama “Battleground” (1949).
- E-BERT-concat: [...] classic World War II / World War II drama “Battleground (film)” (1949).
- E-BERT-replace: [...] classic World War II drama “Battleground (film)” (1949).

As before, entity IDs (bold) are embedded by $\hat{E}_E$-BERT and wordpieces (italics) by $\hat{E}_\text{BERT}$.

Baselines. To assess the impact of vector space alignment, we train two additional models (Wikipedia2Vec-BERT-concat and Wikipedia2Vec-BERT-replace) that feed non-aligned Wikipedia2Vec vectors directly into BERT (i.e., they use $\hat{E}_\text{Wikipedia}$ instead of $\hat{E}_E$-BERT to embed entity IDs).

Data. We evaluate on a preprocessed dataset from Zhang et al. (2019), which is a subset of the FewRel corpus (Sun et al., 2018) (see Appendix for details). We use the FewRel oracle entity IDs, which are also used by ERNIE. Our entity coverage is lower than ERNIE’s (90\% vs. 96\%), which should put us at a disadvantage. See Appendix for details on data and preprocessing.
### 5.2 Entity linking

Entity linking (EL) is the task of detecting entity spans in a text and linking them to the underlying entity ID. While there are recent advances in fully end-to-end EL (Broscheit, 2019), the task is typically broken down into three steps: (1) detecting spans that are potential entity spans, (2) generating sets of candidate entities for these spans, (3) selecting the correct candidate for each span.

For steps (1) and (2), we use KnowBert's candidate generator (Peters et al., 2019), which is based on a precomputed span-entity co-occurrence table (Hoffart et al., 2011). Given an input sentence, the generator finds all spans that occur in the table, and annotates each with a set of candidates \( A = \{a_1, \ldots, a_N\} \) and prior probabilities \( \{p(a_1) \ldots p(a_N)\} \). Note that the candidates and priors are span- but not context-specific, and that the generator may over-generate. For step (3), our model must therefore learn to (a) reject over-generated spans and (b) disambiguate candidates based on context.

**Modeling.** Recall that BERT was pretrained as a masked LM (MLM). Given a wordpiece-tokenized input \( X \) with \( x_i = [\text{MASK}] \), it predicts a probability distribution over \( L_{WP} \) to replace \( x_i \):

\[
p(w|X) \propto \exp(e_w \cdot F_{\text{MLM}}(h_i) + b_w)
\]

(1)

where \( h_i \) is the contextualized embedding of \( [\text{MASK}] \), \( b_w \) is a learned bias and \( e_w = E_{\text{BERT}}(w) \). (See also Section 2.1 for notation.) Since \( \hat{E}_{\text{BERT}^i}[L_{\text{Ent}}] \) is aligned with \( \hat{E}_{\text{BERT}^i}[L_{WP}] \), the pretrained MLM should have a good initialization for predicting entities from context as well.
Based on this intuition, our E-BERT-MLM model repurposes the MLM for the entity selection step. Given a wordpiece-tokenized span $s_1 \ldots s_{T_s}$ with left context $l_1 \ldots l_{T_l}$, right context $r_1 \ldots r_{T_r}$, candidates $A$ and priors $p(a)$, we define:

$$X = l_1 \ldots l_{T_l}, [E\text{-}MASK] / s_1 \ldots s_{T_s} \oplus r_1 \ldots r_{T_r}$$

All tokens in $X$ except $[E\text{-}MASK]$ are embedded by $E_{\text{BERT}}$. $[E\text{-}MASK]$ is embedded as $\sum_{a \in A} E_{\text{E-BERT}}(a)$, to inform the encoder about its options for the current span. (See Table 6 for an ablation with the standard [MASK] token.)

The output probability distribution for $[E\text{-}MASK]$ is not defined over $\mathbb{L}_\text{WP}$ but over $A \cup \{\epsilon\}$, where $\epsilon$ stands for rejected spans (see below):

$$p(a|X) \propto \exp(e_a \cdot F_{\text{MLM}}(h_{l+1}) + b_a)$$

(2)

where $e_a = E_{\text{E-BERT}}(a)$ and $b_a = \log(p(a))$. The null-entity $\epsilon$ has parameters $e_\epsilon, b_\epsilon$ that are trained from scratch.

**Finetuning.** We finetune E-BERT-MLM on the training set to minimize $\sum (X, a) \log(p(\hat{a}|X))$, where $(X, \hat{a})$ are pairs of potential spans and their gold entities. If $X$ has no gold entity (if it was over-generated), then $\hat{a} = \epsilon$.\(^9\)

\(^9\)To understand why we set $b_\epsilon = \log(p(a))$, assume that the priors are implicitly generated as $p(a) = \exp(b_a) / Z$, with $Z = \sum_a \exp(b_a)$. It follows that $b_\epsilon = \log(p(\epsilon)) + \log(Z)$. Since $\log(Z)$ is the same for all $a$, and the softmax function is invariant to constant offsets, we can drop $\log(Z)$ from Eq. 2.

\(^{10}\)If $\hat{a} = \epsilon \land \hat{a} \notin A$, we remove the span from the training set. We do not do this at test time, i.e., we evaluate on all gold standard entities.

**Iterative refinement.** We found it useful to iteratively refine predictions during inference, similar to techniques from non-autoregressive Machine Translation (Ghazvininejad et al., 2019). We start with a wordpiece-tokenized input, e.g.:

**Adams and P #\text{Platt} are both injured and will miss England’s opening World Cup qualifier…**

We make predictions for all potential spans that the candidate generator finds in the input. We gather all spans with $\arg \max_a [p(a|X)] \neq \epsilon$, sort them by $1 - p(\epsilon|X)$ and replace the top-$k$\(^{11}\) non-overlapping spans with the predicted entity. Our previous example might be partially decoded as:

**Tony\_Adams,(footballer) and P #\text{Platt} are both injured and will miss England’s opening 1998\_FIFA\_World\_Cup qualifier…**

In the next iteration, decoded entities (bold) are represented by $E_{\text{E-BERT}}$ in the input, while non-decoded spans continue to be represented by $E_{\text{BERT}}$ (see Figure 4). We set the maximum number of iterations to $J = 3$, as there were no improvements beyond that point on the dev set.

**Baselines.** We train two baselines that combine BERT and Wikipedia2Vec without vector space alignment:

**Wikipedia2Vec-BERT-MLM:** BERT and its pretrained MLM head, finetuned to predict non-aligned Wikipedia2Vec vectors. In practice, this means replacing $E_{\text{E-BERT}}$ with $\hat{E}_{\text{Wikipedia}}$ in Eq. 2. Embedding the [MASK] token with non-aligned $\hat{E}_{\text{Wikipedia}}$ led to a drop in dev set micro F1, therefore we report this baseline with the standard [MASK] token.

| & AIDA-A (dev) & & AIDA-B (test) |
|----------------|-----------------|-----------------|
| **Micro** & **Macro** & **Micro** & **Macro** |
| E-BERT-MLM & 90.8 & 89.1 & 85.0 & 84.2 |
| w/o iterative refinement & 90.6 & 89.0 & - & - |
| w/ standard [MASK] token & 90.3 & 88.8 & - & - |
| Wikipedia2Vec-BERT-MLM & 88.7 & 86.4 & 80.6 & 81.0 |
| Wikipedia2Vec-BERT-random & 88.2 & 86.1 & 80.5 & 81.2 |
| Kiolos et al. (2018) & 89.4 & 86.6 & 82.4 & 82.6 |
| Broscheit (2019) & 86.0 & - & 79.3 & - |
| KnowBert (Peters et al., 2019) & 82.1 & - & 73.7 & - |
| Chen et al. (2019) & 92.6 & 93.6 & 87.5 & 87.7 |

\(^{11}\)Might not be comparable: Chen et al. (2019) evaluate on in-vocabulary entities only, without ensuring (or reporting) the vocabulary’s coverage of the AIDA data.

![Figure 4: Schematic depiction of E-BERT-MLM in inference mode, predicting an entity vector for the name “Platt” in context. Blue: $E_{\text{BERT}}$ wordpiece vectors. Red: $E_{\text{E-BERT}}$ entity vectors. The candidates $A$ and their priors $p(a)$ are given by the current span generator. Assume that the entity Tony\_Adams,(footballer) was decoded in a previous iteration (see “Iterative refinement”).](image_url)
Wikipedia2Vec-BERT-random: Like Wikipedia2Vec-BERT-MLM, but the MLM head is replaced by a randomly initialized layer.

**Data.** We train and evaluate on AIDA, a news dataset annotated with Wikipedia URLs (Hoffart et al., 2011). To ensure coverage of the necessary entities, we include all gold entities and all generator candidates in the entity vocabulary \( L_{\text{Ent}} \), even if they fall under the Wikipedia2Vec link threshold (see Section 3.3). While this is based on the unrealistic assumption that we know the contents of the test set in advance, it is necessary for comparability with Peters et al. (2019), Kolitsas et al. (2018) and Broscheit (2019), who also design their entity vocabulary around the data. See Appendix for more details on data and preprocessing. We evaluate strong match F1, i.e., a prediction must have the same start, end and entity (URL) as the gold standard. URLs that redirect to the same Wikipedia page are considered equivalent.

**Hyperparameters.** We train with Adam and a linear learning rate scheduler (10% warmup) for 10 epochs, and we select the best epoch on the dev set. Peak learning rate and batch size are tuned on the dev set (see Appendix).

| E-BERT-MLM w/ standard [MASK] token | P   | R   | F1  |
|-----------------------------------|-----|-----|-----|
| Wikipedia2Vec-BERT-MLM            | 21.1| 61.8| 31.5|
| Wikipedia2Vec-BERT-random         | 1.3 | 8.3 | 2.3 |

Table 7: AIDA dev set micro precision / recall / F1 (%) before finetuning. Results without iterative refinement.

**Results and discussion.** Table 6 shows that E-BERT-MLM is competitive with previous work on AIDA. The aligned entity vectors play a key role in this performance, as they give the model a good initialization for predicting entities from context. When we remove this initialization by using non-aligned entity vectors (Wikipedia2Vec-BERT baselines), we get worse unsupervised performance (Table 7), slower convergence during finetuning (Figure 5), and a lower final F1 (Table 6).

**6 Conclusion**

We introduced **E-BERT**, an efficient yet effective way of injecting factual knowledge about entities into the BERT pretrained Language Model. We showed how to align Wikipedia2Vec entity vectors with BERT’s wordpiece vector space, and how to feed the aligned vectors into BERT as if they were wordpiece vectors. In doing so, we made no changes to the BERT encoder itself. This stands in contrast to other entity-enhanced versions of BERT, such as ERNIE or KnowBert, which add encoder layers and require expensive further pretraining.

We set a new state of the art on LAMA, a recent unsupervised QA benchmark. Furthermore, we presented evidence that the original BERT model sometimes relies on the surface forms of entity names (rather than “true” factual knowledge) for this task. To quantify this effect, we introduced LAMA-UHN, a subset of LAMA where questions with helpful entity names are deleted.

We also showed how to apply E-BERT to two supervised tasks: relation classification and entity linking. On both tasks, we achieve results competitive with or better than existing baselines, but without the need for expensive pretraining.

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E-BERT: Efficient-Yet-Effective Entity Embeddings for BERT (Appendix)

Unsupervised QA (LAMA)

Data

We downloaded the LAMA dataset from https://dl.fbaipublicfiles.com/LAMA/data.zip. We use the LAMA-T-REx and LAMA-Google-RE relations, which are aimed at factual knowledge. Table 10 shows results on individual relations, as well as the number of questions per relation before and after applying the LAMA-UHN heuristics.

Preprocessing

As mentioned in Section 4.1, we do not use LAMA’s oracle entity IDs. Instead, we map surface forms to entity IDs via the Wikidata query API (https://query.wikidata.org). For example, to look up Jean Marais:

```
SELECT ?id ?str WHERE {
  ?id rdfs:label ?str .
  VALUES ?str { 'Jean Marais'@en } .
  FILTER((LANG(?str)) = 'en') .
}
```

If more than one Wikidata ID is returned, we select the lowest one. We then map Wikidata IDs to the corresponding Wikipedia URLs:

```
SELECT ?id ?wikiurl WHERE {
  VALUES ?id { wd:Q168359 } .
  ?wikiurl schema:about ?id .
  ?wikiurl schema:inLanguage 'en' .
  FILTER REGEX(str(?wikiurl), '.*en.wikipedia.org.*') .
}
```

Relation classification

Data

The RC dataset, which is a subset of the FewRel corpus, was compiled by Zhang et al. (2019). We downloaded it from https://cloud.tsinghua.edu.cn/f/32668247e4fd4f9789f2/. Table 8 shows dataset statistics.

Preprocessing

The dataset contains sentences with annotated subject and object entity mentions, their oracle entity IDs and their relation (which must be predicted). We use the BERT wordpiece tokenizer to tokenize the sentence and insert special wordpieces to mark the entity mentions: # for subjects and $ for objects. Then, we insert the entity IDs. For example, an input to E-BERT-concat would look like this:

```
[CLS] Taylor was later part of the ensemble cast in MGM’s classic World War II / World War II $ drama " Battle #ground #(film) / Battle #ground # ( 1949 ). [SEP]
```

We use the oracle entity IDs of the dataset, which are also used by ERNIE (Zhang et al., 2019).

Hyperparameters

We tune peak learning rate and number of epochs on the dev set (selection criterion: macro F1). We do a full search over the same hyperparameter space as Zhang et al. (2019):

- **Learning rate**: $[2 \cdot 10^{-5}, 3 \cdot 10^{-5}, 5 \cdot 10^{-5}]$
- **Number of epochs**: $[3, 4, 5, 6, 7, 8, 9, 10]$

The best configuration for E-BERT-concat is marked in bold. Figure 6 shows expected maximum performance as a function of the number of evaluated configurations (Dodge et al., 2019).

Entity linking (AIDA)

Data

We downloaded the AIDA dataset from:

- https://allennlp.s3-us-west-2.amazonaws.com/knowbert/wiki_entity_linking/aida_train.txt
- https://allennlp.s3-us-west-2.amazonaws.com/knowbert/wiki_entity_linking/aida_dev.txt
- https://allennlp.s3-us-west-2.amazonaws.com/knowbert/wiki_entity_linking/aida_test.txt

Preprocessing

Each AIDA file contains documents with annotated entity spans (which must be predicted). The documents are already whitespace tokenized, and we further tokenize words into wordpieces with the standard BERT tokenizer. If a document is too long (length > 512), we split it into smaller chunks by (a) finding the sentence boundary that is closest to the document midpoint, (b) splitting the document, and (c) repeating this process recursively until all chunks are short enough. Table 9 shows dataset statistics.

Hyperparameters

We tune batch size and peak learning rate on the AIDA dev set (selection criterion: strong match micro F1). We do a full search over the following hyperparameter space:
**Batch size:** [16, 32, 64, 128]

**Learning rate:** $[2 \cdot 10^{-5}, 3 \cdot 10^{-5}, 5 \cdot 10^{-5}]$

The best configuration for E-BERT-MLM is marked in bold. Figure 7 shows expected maximum performance as a function of the number of evaluated configurations (Dodge et al., 2019).

| # relations | 80 |
|-------------|----|
| # unique entities | 54648 |

| # samples | train | dev | test |
|-----------|-------|-----|------|
| # samples per relation | 8000 | 16000 | 16000 |
| # samples per relation | 100 | 200 | 200 |

Table 8: Relation classification dataset statistics.

| # unique gold entities | 5574 |
| # unique candidate entities | 46363 |

| # documents | train | dev | test |
|-------------|-------|-----|------|
| # documents (after chunking) | 946 | 216 | 231 |
| # potential spans (candidate generator) | 1111 | 276 | 271 |
| # gold entities | 153103 | 38012 | 34936 |

| # gold entities | train | dev | test |
|----------------|-------|-----|------|
| # gold entities | 18454 | 4778 | 4478 |

Table 9: Entity linking (AIDA) dataset statistics.

Figure 6: Relation classification: Expected maximum macro F1 (dev set) as a function of the number of hyperparameter configurations.

Figure 7: Entity linking: Expected maximum micro F1 (dev set) as a function of the number of hyperparameter configurations.
Table 10: Mean Hits@1 and number of questions per LAMA relation. 0: original LAMA dataset, 1: after applying heuristic 1 (string match filter), 2: after applying both heuristics (LAMA-UHN).
| Relation (dataset) | Model | BASE | LARGE |
|-------------------|-------|------|-------|
|                   | Model | original E-BERT replace | E-BERT concat | E-RNIE | Know-Bert | original E-BERT replace | E-BERT concat | number of questions |
| T-REx:P131 (0, original LAMA) | 23.3 33.4 36.4 37.3 27.7 | 26.3 31.4 37.2 | 881 |
| T-REx:P131 (1) | 16.7 32.0 33.9 32.7 21.5 | 20.1 31.0 33.4 | 706 |
| T-REx:P131 (2, LAMA-UHN) | 16.7 32.0 33.9 32.7 21.5 | 20.1 31.0 33.4 | 706 |
| T-REx:P136 (0, original LAMA) | 0.8 5.2 9.1 0.6 0.6 | 1.3 6.9 13.1 | 931 |
| T-REx:P136 (1) | 0.2 5.1 8.7 0.2 0.1 | 0.2 6.9 12.2 | 913 |
| T-REx:P136 (2, LAMA-UHN) | 0.2 5.1 8.7 0.2 0.1 | 0.2 6.9 12.2 | 913 |
| T-REx:P138 (0, original LAMA) | 61.6 8.8 26.5 0.2 63.7 | 45.1 2.6 24.0 | 645 |
| T-REx:P138 (1) | 5.0 10.0 8.8 0.0 6.9 | 4.4 4.4 6.2 | 160 |
| T-REx:P138 (2, LAMA-UHN) | 5.0 10.0 8.8 0.0 6.9 | 4.4 4.4 6.2 | 160 |
| T-REx:P140 (0, original LAMA) | 0.6 0.6 1.1 0.0 0.8 | 0.6 1.1 0.6 | 473 |
| T-REx:P140 (1) | 0.4 0.6 0.9 0.0 0.6 | 0.4 0.9 0.4 | 467 |
| T-REx:P140 (2, LAMA-UHN) | 0.4 0.6 0.9 0.0 0.6 | 0.4 0.9 0.4 | 467 |
| T-REx:P159 (0, original LAMA) | 32.4 30.3 48.3 41.8 36.8 | 34.7 22.3 45.2 | 967 |
| T-REx:P159 (1) | 23.1 31.6 41.9 34.4 28.7 | 25.6 20.9 37.8 | 843 |
| T-REx:P159 (2, LAMA-UHN) | 23.1 31.6 41.9 34.4 28.7 | 25.6 20.9 37.8 | 843 |
| T-REx:P176 (0, original LAMA) | 85.6 41.6 74.6 81.8 90.0 | 87.5 36.6 81.3 | 982 |
| T-REx:P176 (1) | 31.4 42.9 51.8 26.2 51.3 | 40.8 44.5 57.1 | 191 |
| T-REx:P176 (2, LAMA-UHN) | 31.4 42.9 51.8 26.2 51.3 | 40.8 44.5 57.1 | 191 |
| T-REx:P178 (0, original LAMA) | 41.5 23.8 47.7 41.8 36.8 | 34.7 22.3 45.2 | 967 |
| T-REx:P178 (1) | 19.8 26.1 31.7 27.0 20.6 | 23.4 25.0 36.0 | 625 |
| T-REx:P178 (2, LAMA-UHN) | 19.8 26.1 31.7 27.0 20.6 | 23.4 25.0 36.0 | 625 |
| T-REx:P190 (0, original LAMA) | 2.4 2.9 2.5 2.6 2.8 | 2.3 2.3 2.8 | 995 |
| T-REx:P190 (1) | 1.5 2.4 1.6 1.6 2.0 | 1.7 1.9 2.3 | 981 |
| T-REx:P190 (2, LAMA-UHN) | 1.5 2.4 1.6 1.6 2.0 | 1.7 1.9 2.3 | 981 |
| T-REx:P264 (0, original LAMA) | 44.5 61.7 64.0 48.0 40.9 | 51.1 60.6 61.3 | 856 |
| T-REx:P264 (1) | 3.8 8.6 8.0 4.6 5.3 | 6.8 8.6 10.1 | 474 |
| T-REx:P264 (2, LAMA-UHN) | 3.8 8.6 8.0 4.6 5.3 | 6.8 8.6 10.1 | 474 |
| T-REx:P276 (0, original LAMA) | 41.5 23.8 47.7 41.8 43.3 | 43.8 23.1 51.8 | 959 |
| T-REx:P276 (1) | 19.8 26.1 31.7 27.0 20.6 | 23.4 25.0 36.0 | 625 |
| T-REx:P276 (2, LAMA-UHN) | 19.8 26.1 31.7 27.0 20.6 | 23.4 25.0 36.0 | 625 |
| T-REx:P279 (0, original LAMA) | 30.7 14.7 30.7 29.4 31.6 | 33.5 15.5 29.8 | 963 |
| T-REx:P279 (1) | 3.8 8.6 8.0 4.6 5.3 | 6.8 8.6 10.1 | 474 |
| T-REx:P279 (2, LAMA-UHN) | 3.8 8.6 8.0 4.6 5.3 | 6.8 8.6 10.1 | 474 |
| T-REx:P361 (0, original LAMA) | 23.6 19.6 23.0 25.8 26.6 | 27.4 22.3 25.4 | 932 |
| T-REx:P361 (1) | 12.6 17.9 17.7 13.7 15.3 | 18.5 20.2 22.0 | 633 |
| T-REx:P361 (2, LAMA-UHN) | 12.6 17.9 17.7 13.7 15.3 | 18.5 20.2 22.0 | 633 |
| T-REx:P364 (0, original LAMA) | 44.5 61.7 64.0 48.0 40.9 | 51.1 60.6 61.3 | 856 |
| T-REx:P364 (1) | 43.5 61.7 63.5 47.4 40.0 | 50.7 60.5 61.2 | 841 |
| T-REx:P364 (2, LAMA-UHN) | 43.5 61.7 63.5 47.4 40.0 | 50.7 60.5 61.2 | 841 |

Table 11: Mean Hits@1 and number of questions per LAMA relation (cont’d). 0: original LAMA dataset, 1: after applying heuristic 1 (string match filter), 2: after applying both heuristics (LAMA-UHN).
| Relation (dataset) | Model | original E-BERT replace | E-BERT concat | ERNIE | Know-Bert | original E-BERT replace | E-BERT concat | number of questions |
|-------------------|-------|--------------------------|---------------|--------|-----------|--------------------------|---------------|-------------------|
| T-REx:P449 0, original LAMA) | 20.9 | 30.9 | 34.7 | 33.8 | 57.0 | 24.0 | 32.5 | 28.6 | 881 |
| T-REx:P449 1 | 18.8 | 31.1 | 33.4 | 32.0 | 56.0 | 21.8 | 32.9 | 27.5 | 848 |
| T-REx:P449 (2, LAMA-UHN) | 18.8 | 31.1 | 33.4 | 32.0 | 56.0 | 21.8 | 32.9 | 27.5 | 848 |
| T-REx:P463 0, original LAMA) | 67.1 | 61.8 | 68.9 | 43.1 | 35.6 | 61.3 | 52.0 | 66.7 | 225 |
| T-REx:P463 1 | 67.1 | 61.8 | 68.9 | 43.1 | 35.6 | 61.3 | 52.0 | 66.7 | 225 |
| T-REx:P463 (2, LAMA-UHN) | 67.1 | 61.8 | 68.9 | 43.1 | 35.6 | 61.3 | 52.0 | 66.7 | 225 |
| T-REx:P495 0, original LAMA) | 16.5 | 46.3 | 48.3 | 1.0 | 30.8 | 29.7 | 56.7 | 46.9 | 909 |
| T-REx:P495 1 | 16.5 | 46.3 | 48.3 | 1.0 | 30.8 | 29.7 | 56.7 | 46.9 | 909 |
| T-REx:P495 (2, LAMA-UHN) | 16.5 | 46.3 | 48.3 | 1.0 | 30.8 | 29.7 | 56.7 | 46.9 | 909 |
| T-REx:P527 0, original LAMA) | 11.1 | 7.4 | 11.9 | 5.4 | 12.9 | 10.5 | 8.9 | 12.9 | 976 |
| T-REx:P527 1 | 11.1 | 7.4 | 11.9 | 5.4 | 12.9 | 10.5 | 8.9 | 12.9 | 976 |
| T-REx:P527 (2, LAMA-UHN) | 11.1 | 7.4 | 11.9 | 5.4 | 12.9 | 10.5 | 8.9 | 12.9 | 976 |
| T-REx:P530 0, original LAMA) | 2.8 | 1.8 | 2.0 | 2.3 | 2.8 | 2.7 | 2.3 | 2.8 | 996 |
| T-REx:P530 1 | 2.8 | 1.8 | 2.0 | 2.3 | 2.8 | 2.7 | 2.3 | 2.8 | 996 |
| T-REx:P530 (2, LAMA-UHN) | 2.8 | 1.8 | 2.0 | 2.3 | 2.8 | 2.7 | 2.3 | 2.8 | 996 |
| T-REx:P740 0, original LAMA) | 7.6 | 10.5 | 14.7 | 0.0 | 10.4 | 6.0 | 13.1 | 10.4 | 936 |
| T-REx:P740 1 | 7.6 | 10.5 | 14.7 | 0.0 | 10.4 | 6.0 | 13.1 | 10.4 | 936 |
| T-REx:P740 (2, LAMA-UHN) | 7.6 | 10.5 | 14.7 | 0.0 | 10.4 | 6.0 | 13.1 | 10.4 | 936 |
| T-REx:P937 0, original LAMA) | 29.8 | 33.0 | 38.8 | 40.0 | 32.3 | 24.9 | 28.3 | 34.5 | 954 |
| T-REx:P937 1 | 29.8 | 33.0 | 38.8 | 40.0 | 32.3 | 24.9 | 28.3 | 34.5 | 954 |
| T-REx:P937 (2, LAMA-UHN) | 29.8 | 33.0 | 38.8 | 40.0 | 32.3 | 24.9 | 28.3 | 34.5 | 954 |
| T-REx:P1001 0, original LAMA) | 70.5 | 56.9 | 76.0 | 75.7 | 73.0 | 73.3 | 49.5 | 78.0 | 701 |
| T-REx:P1001 1 | 70.5 | 56.9 | 76.0 | 75.7 | 73.0 | 73.3 | 49.5 | 78.0 | 701 |
| T-REx:P1001 (2, LAMA-UHN) | 70.5 | 56.9 | 76.0 | 75.7 | 73.0 | 73.3 | 49.5 | 78.0 | 701 |
| T-REx:P1303 0, original LAMA) | 7.6 | 20.3 | 26.6 | 5.3 | 9.1 | 12.5 | 29.7 | 33.2 | 49 |
| T-REx:P1303 1 | 7.6 | 20.3 | 26.6 | 5.3 | 9.1 | 12.5 | 29.7 | 33.2 | 49 |
| T-REx:P1303 (2, LAMA-UHN) | 7.6 | 20.3 | 26.6 | 5.3 | 9.1 | 12.5 | 29.7 | 33.2 | 49 |
| T-REx:P1376 0, original LAMA) | 73.9 | 41.5 | 62.0 | 71.8 | 75.2 | 82.1 | 47.4 | 70.1 | 234 |
| T-REx:P1376 1 | 73.9 | 41.5 | 62.0 | 71.8 | 75.2 | 82.1 | 47.4 | 70.1 | 234 |
| T-REx:P1376 (2, LAMA-UHN) | 73.9 | 41.5 | 62.0 | 71.8 | 75.2 | 82.1 | 47.4 | 70.1 | 234 |
| T-REx:P1412 0, original LAMA) | 65.0 | 54.0 | 67.8 | 73.1 | 69.2 | 63.6 | 49.3 | 61.2 | 969 |
| T-REx:P1412 1 | 65.0 | 54.0 | 67.8 | 73.1 | 69.2 | 63.6 | 49.3 | 61.2 | 969 |
| T-REx:P1412 (2, LAMA-UHN) | 65.0 | 54.0 | 67.8 | 73.1 | 69.2 | 63.6 | 49.3 | 61.2 | 969 |

| Google-RE:date_of_birth (0) | 1.6 | 1.5 | 1.9 | 1.9 | 2.4 | 1.5 | 1.5 | 1.3 | 1825 |
| Google-RE:date_of_birth (1) | 1.6 | 1.5 | 1.9 | 1.9 | 2.4 | 1.5 | 1.5 | 1.3 | 1825 |
| Google-RE:date_of_birth (2) | 1.6 | 1.5 | 1.9 | 1.9 | 2.4 | 1.5 | 1.5 | 1.3 | 1825 |

| Google-RE:place_of_birth (0) | 14.9 | 16.2 | 16.9 | 17.7 | 17.4 | 16.1 | 14.8 | 16.6 | 2937 |
| Google-RE:place_of_birth (1) | 14.9 | 16.2 | 16.9 | 17.7 | 17.4 | 16.1 | 14.8 | 16.6 | 2937 |
| Google-RE:place_of_birth (2) | 5.9 | 9.4 | 8.2 | 10.3 | 9.4 | 7.2 | 8.5 | 7.9 | 2451 |

| Google-RE:place_of_death (0) | 13.1 | 12.8 | 14.9 | 6.4 | 13.4 | 14.0 | 17.0 | 14.9 | 766 |
| Google-RE:place_of_death (1) | 13.1 | 12.8 | 14.9 | 6.4 | 13.4 | 14.0 | 17.0 | 14.9 | 766 |
| Google-RE:place_of_death (2) | 6.6 | 7.5 | 7.8 | 2.0 | 7.5 | 7.6 | 11.8 | 8.9 | 655 |

Table 12: Mean Hits@1 and number of questions per LAMA relation (cont’d). 0: original LAMA dataset, 1: after applying heuristic 1 (string match filter), 2: after applying both heuristics (LAMA-UHN).