Improving the Efficiency and Effectiveness for BERT-based Entity Resolution

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Abstract

BERT has set a new state-of-the-art performance on entity resolution (ER) task, largely owed to fine-tuning pre-trained language models and the deep pair-wise interaction. Albeit being remarkably effective, it comes with a steep increase in computational cost, as the deep-interaction requires to exhaustively compute every tuple pair to search for co-references. For ER task, it is often prohibitively expensive due to the large cardinality to be matched. To tackle this, we introduce a siamese network structure that independently encodes tuples using BERT but delays the pair-wise interaction via an enhanced alignment network. This siamese structure enables a dedicated blocking module to quickly filter out obviously dissimilar tuple pairs, and thus drastically reduces the cardinality of fine-grained matching. Further, the blocking and entity matching are integrated into a multi-task learning framework for facilitating both tasks. Extensive experiments on multiple datasets demonstrate that our model significantly outperforms state-of-the-art models (including BERT) in both efficiency and effectiveness.

Introduction

The task of entity resolution aims at identifying co-referent tuples that refer to the same real-world entity from different data sources. Consider the two tables in Fig. 1, each table is a set of tuples about products gathered from Google and Amazon, respectively. Entity resolution identifies pairs of tuples that refer to the same product, e.g., tuples 587 from Google and 2837 from Amazon are identified as a co-reference, and the same goes for tuples 1213 and 2837.

As a fundamental essence for data cleaning and data integration (Dong and Srivastava 2013), entity resolution has been widely applied in knowledge graph construction (Chen et al. 2015), e-commerce (Gokhale et al. 2014), etc. It has been extensively studied by means of various methodologies such as declarative rules (Hernández and Stolfo 1995), crowd-sourcing (Wang et al. 2012), and machine learning (Faruqui et al. 2015). Over the past few years, deep learning (DL) based ER models (Mudgal et al. 2018; Fu et al. 2019) have become the de-facto standard. They typically present a representation-then-interaction scheme: first-

![Figure 1: An example of entity resolution: identifying co-referent tuples from two tables.](image-url)
We make three major contributions: (1) we show a formal analysis that BERT’s representation and interaction processes can approximately be decomposed. The interaction part can be judiciously delayed yet enhanced to achieve an even better results. Also, with the delayed interaction, the model actually presents a siamese network structure that makes it able to integrate blocking modules. (2) For blocking, to better leverage the expressiveness of BERT, we propose an adaptive blocking model. Different from other learning-to-hashing methods, we propose a SVD-based hyperplanes orthogonalization to make BERT dominate the similarity measurement. (3) Existing ER models regard blocking and matching as two isolated tasks. We made the first effort to integrate the two tasks into a multi-task learning (MTL) framework. As such, the error can be back propagated to generalize better on both tasks. Further, the proposed framework is independent of a specific LM, and could be applied not only on BERT, but also on other LMs such as RoBERTA and ALBERT.

The extensive experiments on various datasets demonstrate that, comparing to BERT, BERT-ER has a significantly better effectiveness (1.5 pts in F1), while at the same time, improves the empirical efficiency by two orders of magnitude (219× ×304×).
In Eq. 1, \( s_i \) can be decomposed into two parts: an inner-
encoding \( s_i^I \) that only focuses on the tuple that \( t_i \) belongs to;
and a cross-encoding \( s_i^C \) that incorporates information from
the other tuple. After applying position-wise feed-forward
network (PFFN), the final encoding \( e_i \) can be approximated
as the sum of applying PFFN on \( s_i^I \) and \( s_i^C \), separately:
\[
e_i = \text{PFFN}(s_i^I + s_i^C) \approx \text{PFFN}(s_i^I) + \text{PFFN}(s_i^C)
\]  

(2)

According to Eqs. 1 and 2, each layer of BERT can func-
tionally be decomposed into two parts: (a) one for gener-
ating representation using the contextual information within
respective tuple; and (b) the other one performs a deep-
interaction between tuples. For ER task, we believe part (a)
mainly works for capturing the contextualized features of
token itself and part (b) works for implicitly (and effective-
ly) aligning the two tuples. This can be illustrated using the
example in Fig. 3, where the final attentions focus on infor-
mative yet unmatching tokens (e.g., “word” and “upgrade”).

We wish to represent its interaction part but delay and en-
force its alignment. As such, we can leverage the expres-
siveness of BERT, while at the same time, being able to in-
tegrate blocking to speed-up the processing.

Delayed and Enhanced Alignment. The original align-
ment PFFN\((s_i^C)\) can be enhanced in three aspects: (1) cross-
encoding may not be the most appropriate features since it is
less-effective and implicit for aligning tuples; (2) instead of
sharing parameters, token representation and alignment fea-
tures should have separated parameters, since their semantic
for ER is different; (3) multi-gram features have been proved
to be effective for ER (Li et al. 2020), while the PFFN is only
able to extract uni-gram features.

For aspect (1), we use bilateral comparison features, rather than solely relying on cross-encodings. Firstly, we de-
define the cross-encodings \( E_{u1}^C \) and \( E_{u2}^C \) as:
\[
E_{u1}^C = \text{softmax}(Q_u K_{u1}^T) E_{u2}^I,
E_{u2}^C = \text{softmax}(Q_{u2} K_{u1}^T) E_{u1}^I,
\]

(3)

where \( E_{u1}^I \in \mathbb{R}^{m \times d_B} \) and \( E_{u2}^I \in \mathbb{R}^{n \times d_B} \) are BERT-based
representations for \( u1 \) and \( u2 \) (dimensionality \( m \) and \( n \) are
token sequence lengths, \( d_B \) are the output dimension of
BERT). \( Q \) and \( K \) are queries and keys matrices, which are
defined as
\[
Q = E^I W_Q, \quad K = E^I W_K,
\]

(4)

where \( W_Q \in \mathbb{R}^{d_B \times d_B} \) and \( W_K \in \mathbb{R}^{d_B \times d_B} \) are parameters
for query and key projection, respectively.

We define two comparison functions, the first is the sub-
traction function (Wang and Jiang 2017; Li et al. 2020)
\[
f_{\text{sub}}(E^I, E^C) = (E^I - E^C) \odot (E^I - E^C),
\]

(5)

where \( \odot \) denotes the Hadamard product. The other one is
the multiplication function (Wang and Jiang 2017), which is
defined as:
\[
f_{\text{mul}}(E^I, E^C) = E^I \odot E^C.
\]

(6)

The above two functions would be collapsed to \( L_2 \) dis-
tance and dot-product if we sum up the vector. By not sum-
ming up, they can keep more information to be trained by
the following layers.

To make the comparison robust, we make a bilateral
matching (Wang, Hamza, and Florian 2017) that compares
\( u1 \) and \( u2 \) in both \( u1 \rightarrow u2 \) and \( u2 \rightarrow u1 \) directions, i.e.,
compare \( u1 \) against \( u2 \), and compare \( u2 \) against \( u1 \). Take
\( u1 \rightarrow u2 \) direction as an example, we concatenate the sub-
traction and multiplication comparison features:
\[
E_{u1 \rightarrow u2} = [f_{\text{sub}}(E_{u1}^I, E_{u1}^C); f_{\text{mul}}(E_{u1}^I, E_{u1}^C)]
\]

(7)

Compared with cross-encoding, the enhanced comparison
features \( E_{u1 \rightarrow u2} \in \mathbb{R}^{m \times 2d_B} \) are more explicit and could
provide more information to reason to what extent a token
in \( u1 \) is matched with its counterpart in \( u2 \).

To incorporate representation features, \( u1 \)'s encoding
\( E_{u1} \in \mathbb{R}^{m \times 3d_B} \) is represented as the concatenation (rather
than sum) of \( u1 \)'s representation \( E_{u1}^I \) and comparison fea-
ture \( E_{u1 \rightarrow u2} \):
\[
E_{u1} = [E_{u1}^I; E_{u1 \rightarrow u2}].
\]

(8)

The concatenation make the two terms use different weight
parameters to enhance aspect (2).

To enhance aspect (3), we employ a convolutional lay-
er (Conv) with multiple kernel sizes to effectively extract
multi-gram features and aggregate \( E_{u1} \) into a fixed-size
matching vector \( M_{u1} \in \mathbb{R}^{1 \times gc} \):
\[
M_{u1} = \text{Conv}(E_{u1}),
\]

(9)

where \( \text{Conv}(*) \) is a composite function consisting of
cascaded operations: a set of convolutions \( c_{o1}, c_{o2}, \ldots, c_{og} \),
a batch normalization (BN) (Ioffe and Szegedy 2015), a
rectified linear unit (ReLU), and a 1-max-over-time pool-
ing (Kim 2014). The \( i \)-th convolution has learnable parame-
ters \( W_i \in \mathbb{R}^{h \times 3d_B} \) indicating that there are \( c \) kernels.
Each kernel has size \( h \times 3d_B \) convolving \( h \) adjacent vectors
to capture \( h \)-gram matching features. The 1-max-pooling
operation selects the largest value over the feature map of
a particular kernel. The outputs are with fixed size \( 1 \times gc \).

The output matching vector \( M \in \mathbb{R}^{1 \times 2gc} \) is the concate-
nation of the matching vectors of both \( u1 \) and \( u2 \) \((M = \left[ M_{u1}; M_{u2} \right])\), which is then fed into a simple linear layer for
ER decision.
Loss Function for Entity Matching. For entity matching task, we adopt the standard cross-entropy loss:

\[ \mathcal{L}_M = C(y, h(W, M)), \]  

(10)

where \( h(W, M) \) is the predicted distribution based on the final matching vector \( M \), \( C(t, p) \) denotes cross-entropy function between \( t \) and \( p \), and \( y \) is the annotated label.

Adaptive Blocking with Orthogonalized Hyperplanes

Majority of prior ER models regard blocking as an isolated process with the entity matching, and the blocking methods (e.g., key-based (Papadakis et al. 2020) or LSH-based blocking (Ebraheem et al. 2018)) are designed to be data-independent and matching-unaware. As such, they cannot learn to flexibly fit the data, and utilise the results of matching to rectify blocking-incurred error.

To tackle this, we use a learnable hash-based blocking method, which could be aware of the matching features from the shared BERT encoder.

Learnable Hash Model. The goal is to learn a mapping \( \mathcal{H} \) from BERT encoding space \( \mathbb{R}^d \) to \( k \)-bit binary hash space, namely, \( \mathcal{H} : \mathbb{R}^d \to \{+1, -1\}^k \). Typically, the hash codes of co-referent tuples should be close in Hamming space, and the hash codes of dissimilar tuples should be far away.

The mapping \( \mathcal{H} \) consists of \( k \) hash functions \( h_1, h_2, ..., h_k \), each of which is a learnable hyperplane through the origin and used for generating a binary value. Formally, \( \mathcal{H} \) can be defined as:

\[ \mathcal{H}(t) = \text{sign}(t \mathcal{X}), \]  

(11)

where \( \mathcal{X} \in \mathbb{R}^{d \times k} \) is \( k \) learnable hyperplanes, and \text{sign} is the sign function to binarize real values.

\( L_2 \) Relaxation for Training. Directly optimizing Eq. 11 is infeasible since the sign function is not differentiable. Thus, we adopt the \( L_2 \) relaxation (Liu et al. 2016; Chen et al. 2018) as it is more training-efficient and has stellar results.

The main idea of \( L_2 \) relaxation is to move the binary constraint from hash functions to a regularizer in the loss function, and use \( L_2 \) distance in Euclidean space to approximate the Hamming distance. With \( L_2 \) relaxation, the mapping \( \mathcal{H} \) is relaxed to \( \mathcal{H}^{'} \):

\[ \mathcal{H}^{'}(t) = t \mathcal{X}. \]  

(12)

Given the encodings of two tuples \( t_i \) and \( t_j \), and the label \( y (y = 1 \) if they are co-referent; otherwise, \( y = 0 \)), the loss function is naturally designed to pull co-referent tuples closer, while pushing unmatched tuples away from each other:

\[ \mathcal{L}^B \big|_{\mathcal{H}^{'}} = \frac{1}{2} y \| \mathcal{H}^{'}(t_i), \mathcal{H}^{'}(t_j) \|_2^2 \]

\[ + \frac{1}{2} (1 - y) \max(m - \| \mathcal{H}^{'}(t_i), \mathcal{H}^{'}(t_j) \|_2, 0) \]

\[ + \gamma (\| \mathcal{H}(t_i) - 1 \|_1 + \| \mathcal{H}(t_j) - 1 \|_1), \]

where \( \| \cdot \|_1 \) and \( \| \cdot \|_2 \) are the \( L_1 \) and \( L_2 \)-norm, respectively. \( \text{sign} \) is the absolute operation, \( \gamma \) is the weight of the regularizer. Notably, the last term is the regularizer (Liu et al. 2016) of \( L_2 \) relaxation, which aims to push the values to either \(+1\) or \(-1\) to facilitate the binary constraint.

Hyperplanes Orthogonalization. The mapping \( \mathcal{H} \) is supposed to faithfully preserve two tuples’ similarity in the BERT encoding space (i.e., isometry). To this end, the mapping should satisfy the following constraint:

\[ ||t_i, t_j||_2 = ||\mathcal{H}^{'}(t_i), \mathcal{H}^{'}(t_j)||_2 \]

\[ = \sqrt{(t_i - t_j)^T \mathcal{X} \mathcal{X}^T (t_i - t_j)^T} \]  

(14)

A sufficient condition makes Eq. 14 hold is \( \mathcal{X} \mathcal{X}^T = I \) (\( I \) is the identity matrix), indicating \( \mathcal{X} \) is a unitary matrix. The orthogonality of unitary matrix also ensures independency of hash functions.

To orthogonalize hyperplanes, a straightforward solution is adding a regularizer term \( R_o \) (Muja and Lowe 2014):

\[ R_o = ||\mathcal{X} \mathcal{X}^T - I||_F, \]  

(15)

where \( || \cdot ||_F \) denotes the Frobenius-norm.

As the regularization is not strict, it may lead to suboptimal results. To keep \( \mathcal{X} \) strictly unitary, we propose another SVD-based approach. This approach decomposes \( \mathcal{X} \) using singular vector decomposition (SVD) (i.e., \( \mathcal{X} = USV^T \)) to get three decomposed matrices, \( U \), \( S \), and \( V \), where \( U \) and \( V \) is \( d \times d \) and \( k \times k \) unitary matrix, respectively, and \( S \) is a \( d \times k \) diagonal singular value matrix. Then, we replace \( \mathcal{X} \) with orthogonal matrix \( US \). As we have

\[ ||\mathcal{H}^{'}(t_i), \mathcal{H}^{'}(t_j)||_2 = \sqrt{(t_i - t_j)^T USV^T USV^T (t_i - t_j)^T} \]

\[ = \sqrt{(t_i - t_j)^T US US^T (t_i - t_j)^T} \]

\[ = \sqrt{(t_i - t_j)^T US(UUS)^T (t_i - t_j)^T}, \]

the discriminative ability of learned hyperplanes will be kept, while at the same time, the \( L_2 \) distance remains unchanged. It is worth noting that, since \( \mathcal{X} \) is not full rank, back propagation through SVD is intractable. To make it trainable, we assume \( \mathcal{X} \) is a latent matrix, from which \( US \) are decomposed. Initially, \( S \) is assigned with an identity matrix, and \( U \) and \( V \) are randomly initialized. During training, gradients can be back-propagated on \( US \). Then, we restore the latent matrix \( \mathcal{X} \) by multiplying the \( V \) with \( US \). At this step, the gradients are indirectly applied on \( \mathcal{X} \). Finally, the new \( US \) and \( V \) can be fetched by decomposing \( \mathcal{X} \).

Hash Code for Prediction. In the prediction phase, we use the original definition of \( \mathcal{H} \) in Eq. 11 to generate a \( k \)-bit hash code for a tuple. To balance the trade-off between recall and the number of matchings, we merge \( q \)-nearest buckets \((0 \leq q \leq 2 \) in common practice) into a block for searching co-references.

Joint Learning of Blocking and Entity Matching

The final training objective of the MTL framework is to minimize the following loss function:

\[ \mathcal{L} = \alpha \mathcal{L}_B + (1 - \alpha) \mathcal{L}_M, \]  

(16)

where \( \mathcal{L}_B \) (Eq. 13) and \( \mathcal{L}_M \) (Eq. 10) is the loss for blocking and entity matching, respectively. \( \alpha \) is the weight to balance the two tasks.

\footnote{We can keep \( S \) fixed to the identity matrix during training, but leave it as free parameters could slightly improve performance.}
Experimental Evaluation

We evaluated the effectiveness and efficiency of our model on both entity resolution and blocking tasks.

Evaluation Datasets

Entity Matching. We used four widely used benchmark datasets covering diverse domains such as products, music, and scholar. Table 1 lists some statistics (the first four datasets). Each dataset contains a list of after-blocking tuple pair followed with gold labels. All datasets have been split into train/dev/test subsets by Mudgal et al. (2018).

Blocking. We adopted two widely used datasets Walmart-Amazon (B) and Amazon-Google (B). Their detailed statistics are listed in Table 1 (the last two datasets). Following Ebraheem (2018), the negative examples are randomly sampled with a positive to negative ratio 1:100. All positive and negative examples are shuffled and split into train/test with the ratio 4:1.

Training Settings

Our model was implemented using Pytorch 1.4 with Python 3.7, and ran on an Nvidia Titan V GPU. We used the popular transformers library for the pre-trained BERT model.

BERT Encoder. The BERT was initialized using a standard BERT_BASE model. Each tuple was tokenized with pre-trained BERT tokenizer and packed with the form [CLS]tuple tensors[SEP], and padded the tokenized sequences to a max length of 120.

Blocking Decoder. The blocking decoder was on the last-layer [CLS] token. The hash bits k and tolerance threshold q were set to 8 and 1. Following Liu et al. (2016), m was set to 2k = 16, and the regularizer weight γ was 0.01. We undersampled negative instances to yield a 1:10 pos/neg rate.

Entity Matching Decoder. The entity matching decoder was performed on the output of the 2nd layer of BERT. The weights of query and key projections, and the final linear layer were initialized using Xavier with gain 1. Kernel sizes of the convolutional layer was set to [1, 2, 3], each has c = 128 kernels. The balance weight α = 0.2.

For optimization, we used AdamW (Loshchilov and Hutter 2019) with an initial learning rate 10−5, eps 10−8, and the gradient clipping 5; the batch size is set to 32; all other hyper-parameters were their default values.

In each round, the model was run 10 times with a maximum of 50 epochs and reported the best performing models as the result.

Evaluating Entity Matching

Baselines and Metrics. We compared our model with seven state-of-the-art entity matching models, including a feature-based model Magellan, and four DL-based models RNN, Hybrid, MPM, and GraphER. Besides, we also compared with two BERT-based models: the standard interactive BERT, and a siamese BERT model SBERT (Reimers and Gurevych 2019).

Following common practices, we use the F1 score on test datasets as the metric.

Main Results. Table 2 presents the performance comparison of our BERT-ER model compared with baselines on the four benchmark datasets. We can see that:

1) Our model significantly outperforms all baselines, achieving new state-of-the-art results. On average, our model achieved a 1.45 pts improvement over the best baselines, and 1.5 pts improvement over BERT. This demonstrates our delayed and enhanced alignment paradigm is highly effective on alignment-focused tasks such as entity resolution: one can get a even better results by judiciously delaying and enhancing BERT’s deep-interaction part.

2) Compared with the four non-BERT DL model (i.e., RNN, MPM, Hybrid, and GraphER), the two BERT-based models (i.e., BERT and BERT-ER) have an average 2.34 pts improvement. This demonstrates the deep pretrained LMs are more expressive than traditional DL-based models. Comparing deep-interactive model BERT-ER with shallow-interactive model SBERT, although they are both BERT-based, the performance gap is huge (over 25 pts). This indicates the deep-interaction is vitally important for performance improvements of ER tasks. Our enhanced alignment is more effective than the shallow-alignment of SBERT.

3) Our model has more advantages on Amazon-Googe and iTunes-Amazon. While on DBLP-ACM, the performances for all models are similar. The main reason is that Amazon-Googe and iTunes-Amazon are semantically deep, as they have more textual attributes, whereas DBLP-ACM is much cleaner and well-formatted. Finding coreferences on semantically deep datasets hinges on aligning informative “key” tokens (e.g., “upgrade” in Fig. 3) by bridging vocabulary mismatch. Thus, the models with deep-interaction (e.g., BERT and BERT-ER) are desired.

Ablation Study. We conducted an ablation study to evaluate the contribution of each component. Table 3 shows the results. The biggest performance gaps happened in removing comparison functions. This indicates comparison fea-

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Domain</th>
<th>Size</th>
<th># Pos.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon-Googe</td>
<td>software</td>
<td>11460</td>
<td>962</td>
</tr>
<tr>
<td>BeerAdv-RateBeer</td>
<td>beer</td>
<td>450</td>
<td>68</td>
</tr>
<tr>
<td>iTunes-Amazon</td>
<td>music</td>
<td>539</td>
<td>132</td>
</tr>
<tr>
<td>DBLP-ACM</td>
<td>scholar</td>
<td>12363</td>
<td>2220</td>
</tr>
<tr>
<td>Walmart-Amazon(B)</td>
<td>electronic</td>
<td>56.4 million</td>
<td>1154</td>
</tr>
<tr>
<td>Amazon-Google(B)</td>
<td>software</td>
<td>4.4 million</td>
<td>1300</td>
</tr>
</tbody>
</table>

Table 1: Evaluation datasets for our experiments.
eral trends for both datasets are similar: with the increasing $k$, respectively. We can see that the gen-

Table 2: F1 (%) of our model and baselines on entity matching task. Since the benchmark datasets only contains after-blocking instances, to be consistent, our model is trained only with entity matching decoder.

<table>
<thead>
<tr>
<th>Model</th>
<th>Amazon-Google</th>
<th>BeerAdv-RateBeer</th>
<th>iTunes-Amazon</th>
<th>DBLP-ACM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magellan (Konda et al. 2016)</td>
<td>49.1</td>
<td>78.8</td>
<td>91.2</td>
<td>98.4</td>
</tr>
<tr>
<td>RNN (Mudgal et al. 2018)</td>
<td>59.9</td>
<td>72.2</td>
<td>88.5</td>
<td>98.3</td>
</tr>
<tr>
<td>Hybrid (Mudgal et al. 2018)</td>
<td>69.3</td>
<td>72.7</td>
<td>88</td>
<td>98.4</td>
</tr>
<tr>
<td>MPM (Fu et al. 2019)</td>
<td>70.7</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GraphER (Li et al. 2020)</td>
<td>68.1</td>
<td>79.7</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SBERT (Reimers and Gurevych 2019)</td>
<td>44.8</td>
<td>42.1</td>
<td>74.1</td>
<td>94.3</td>
</tr>
<tr>
<td>BERT</td>
<td>73.1</td>
<td>87.5</td>
<td>93.1</td>
<td>98.2</td>
</tr>
<tr>
<td>BERT-ER</td>
<td>75.3</td>
<td>87.5</td>
<td>96.4</td>
<td>98.7</td>
</tr>
</tbody>
</table>

Table 3: Ablation test for entity matching task. In each test, we remove a component from the full BERT-ER model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Amazon-Google</th>
<th>BeerAdv-RateBeer</th>
<th>iTunes-Amazon</th>
<th>DBLP-ACM</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT-ER</td>
<td>75.3</td>
<td>87.5</td>
<td>96.4</td>
<td>98.7</td>
</tr>
<tr>
<td>- Comparison functions</td>
<td>62.4</td>
<td>-12.9</td>
<td>92.6</td>
<td>-3.8</td>
</tr>
<tr>
<td>- Multi-gram kernel</td>
<td>73.9</td>
<td>-1.4</td>
<td>94.3</td>
<td>-2.1</td>
</tr>
<tr>
<td>- Attribute embeddings</td>
<td>74.4</td>
<td>-0.9</td>
<td>95.5</td>
<td>-0.9</td>
</tr>
<tr>
<td>- Pre-training</td>
<td>65.8</td>
<td>-9.5</td>
<td>87.1</td>
<td>-9.3</td>
</tr>
</tbody>
</table>

Evaluating Blocking

Baselines and Metrics. We tested two settings of our model: ABOH-regularizer (with the regularizer of Eq. 15) and ABOH-SVD (with SVD-based orthogonalization). We adopted LSH as the baseline, as it represents the de-facto blocking technique for DL-based ER systems (Ebraheem et al. 2018; Papadakis et al. 2020).

The evaluation is based on two metrics that are widely used by prior research (Michelson and Knoblock 2006; Papadakis et al. 2020): Pair Completeness (PC) and Reduction Ratio (RR). PC corresponds to recall, evaluating the ratio of co-references assigned with the same blocks against the total number of co-references. RR measures the reduction in the number of pairwise comparisons against the brute-force approach. Higher values for PC indicate higher effectiveness of the blocking method, while higher values for RR indicates higher efficiency.

Main Results. Figs. 4(a) and 4(b) show RRs and PC of the blocking method, while higher values for RR indicates a better PC (on average 3.75 pts) but slightly lower RR (2.1 pts). Since our entity matching decoder is efficient enough, of $k$, RRs quickly raise to a flat peak region and PCs gradually decreases. This is due to the fact that the increasing bit size exponentially increases the number of hash buckets, which makes more options of assignment. While at meantime, it reduces the likelihood of two true co-referent tuples being placed in the same block.

All the three models have similar RRs in both Figs. 4(a) and 4(b). With more than 8 bits, all models have a high RR (more than 0.85), indicating they avoid most of comparisons and only need to compare the remaining few. For PCs, the two variants of ABOH are better than LSH nearly in all cases. Take $k = 8$ as an example, ABOH-SVD is roughly 9 pts and 3 pts better on the two datasets, respectively. ABOH-regularizer is roughly 2 pts better than LSH. Further, the advantage of ABOH is more obvious on Walmart-Amazon (B). We believe the main reason is that, the adaptive and orthogonalized hyperplane could better use the expressiveness of BERT.
a model with better PCs (ABOH-SVD) is preferred. The experimental results demonstrate our blocking method could drastically reduce the number to be matched, in the meanwhile, keeps a high recall.

<table>
<thead>
<tr>
<th>Version</th>
<th>Walmart-Amazon (B)</th>
<th>Amazon-Google (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RR</td>
<td>PC</td>
</tr>
<tr>
<td>MTL</td>
<td>86.2</td>
<td>96.1</td>
</tr>
<tr>
<td>Matching</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Blocking</td>
<td><strong>86.5</strong></td>
<td>94.1</td>
</tr>
</tbody>
</table>

Table 4: Performance (%) comparison of the multi-task and single-task BERT-ER.

Effectiveness of the MTL Scheme

To evaluate the effectiveness of the MTL scheme, we compared BERT-ER’s MTL version with its single-task learning versions. Table 4 presents the results. From Table 4, we can see that by joint-learning blocking and entity matching, both tasks have considerable improvements comparing with solely learning one. On average, the F1 scores of entity matching improve 0.55 pt. For blocking, owing to being aware of fine-grained matching features, the improvements are more obvious: RR and PC improves 1.5 pts and 1.6 pts, respectively. This demonstrates that our MTL framework can effectively improve model’s generalization ability to facilitate the performance improvements of both tasks.

<table>
<thead>
<tr>
<th>Model</th>
<th>Phase</th>
<th>WA (B)</th>
<th>AG (B)</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT-ER</td>
<td>Encoding</td>
<td>43.69 s</td>
<td>22.38 s</td>
<td>247.80 t/s</td>
</tr>
<tr>
<td></td>
<td>Blocking</td>
<td>19.42 s</td>
<td>6.56 s</td>
<td>601.06 t/s</td>
</tr>
<tr>
<td></td>
<td>Matching</td>
<td>18.48 m</td>
<td>98.16 s</td>
<td>9003.06 p/s</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td><strong>19.54 m</strong></td>
<td><strong>127.1 s</strong></td>
<td>-</td>
</tr>
<tr>
<td>BERT</td>
<td>Total</td>
<td>99.18 h</td>
<td>7.73 h</td>
<td>157.90 p/s</td>
</tr>
</tbody>
</table>

Table 5: The empirical decoding time and speed of BERT-ER and BERT on full-size WA(B) and AG(B) datasets. t/s: # of tuples per second; p/s: # of pairs per second.

Empirical Efficiency

Table 5 presents the empirical time cost and decoding speed. We can see that:

1) Due to being able to integrate the blocking techniques, BERT-ER is far more efficient than BERT: decoding WA (B) and AG (B) requires 304× less time (20 minutes v.s. 99 hours) and 219× less time (3 minutes v.s. 7.7 hours), respectively. Moreover, the encoding phase of BERT-ER could be pre-computed offline to further accelerate the processing.

2) The decoding speed of BERT-ER’s matching phase is 57× faster than BERT’s. This indicates our model will still have a better efficiency, even if BERT could be equipped with the same blocking module.

3) The matching phase is the most time-consuming one among the three phases of BERT-ER. This is due to the fact that, although the blocking could effectively reduce nearly 90% of comparisons, considering its enormous cardinality (WA (B) and AG (B) has 4.4 million and 56.4 million pairs, respectively), the remaining 10% could still be large. Fortunately, the matching phase is efficient enough, it will not incur too much overhead.

This evaluation demonstrates that our model is of high efficiency, and able to work in real ER scenarios.

Related Works

Entity Matching. Prior works can be classified as declarative rules based, crowd-sourcing-based, and machine learning (ML) based. The rule-based methods adopted declarative matching rules that are either pre-defined (Hernández and Stolfo 1995) or synthesized (Singh et al. 2017) for matching tuple pairs. The crowd-sourcing-based methods (Wang et al. 2012; Gokhale et al. 2014; Firmani, Saha, and Srivastava 2016) employ crowd-sourcing workers to manually annotate tuples. However, both methods highly rely on human efforts. ML-based methods train different classifiers, such as SVM (Bilenko and Mooney 2003), active learning (Sarawagi and Bhamidipaty 2002), MLP (Ebraheem et al. 2018), on manually collected (Konda et al. 2016) or deep neural features (Mudgal et al. 2018; Ebraheem et al. 2018; Fu et al. 2019; Li et al. 2020). Recently, BERT (Devlin et al. 2019) and DITTO (Li et al. 2021) deliver remarkable effectiveness on many ER datasets. However, they are computationally expensive as they need pair-wise deep interactions.

Blocking. Prior blocking methods could be classified as rule-based, sorting-based, and hash-based. Rule-based methods group tuples by static keys or decision rules that are derived by experts or from mere heuristics. Sorting-based methods (Papadakis et al. 2015; Kenig and Gal 2013) group tuples by efficiently sorting their textual similarities measured by various similarity functions. Hash-based approaches adopt hashing techniques (e.g., Min-Hashing (Steorts et al. 2014; Wang, Cui, and Liang 2015) and LSH (Ebraheem et al. 2018)) to map tuples into hash buckets. Ebraheem et al. (Ebraheem et al. 2018) introduced LSH into deep-learning based ER system. Zhang et al. (Zhang et al. 2020) proposed tuple signatures and use LSH to perform fast NN search. Hashing-based methods can be applied on deep-neural representations. However, the current blocking techniques are matching-unaware, which cannot utilize matching features to further improve performances.

In contrast, our model integrates a learnable blocking module to improve the efficiency of BERT. And use a MTL framework to make the blocking matching-aware.

Conclusion

In this paper, we propose a novel BERT-based ER model. By delaying and enhancing BERT’s interaction part, our model is able to integrate an adaptive blocking module. Further, the blocking and matching are integrated into a MTL framework to facilitate both tasks. Compared to a standard BERT, our model improves the effectiveness by 1.5 pts, while being 219× ~ 304× faster.
Acknowledgments

This work is supported by ARC DPs 170103710 and 180103411, and D2DCRC DC25002 and DC25003. The Titan V used for this research was donated by the NVIDIA Corporation.

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