Improving Zero-Shot Entity Retrieval through Effective Dense Representations

Eleni Partalidou
Department of Informatics
Aristotle University of Thessaloniki
54124 Thessaloniki – Greece
epartalid@csd.auth.gr

Despina Christou
Department of Informatics
Aristotle University of Thessaloniki
54124 Thessaloniki – Greece
christoud@csd.auth.gr

Grigorios Tsoumakas
Department of Informatics
Aristotle University of Thessaloniki
54124 Thessaloniki – Greece
greg@csd.auth.gr

Abstract
Entity Linking (EL) seeks to align entity mentions in text to entries in a knowledge-base and is usually comprised of two phases: candidate generation and candidate ranking. While most methods focus on the latter, it is the candidate generation phase that sets an upper bound to both time and accuracy performance of the overall EL system. This work’s contribution is a significant improvement in candidate generation which thus raises the performance threshold for EL, by generating candidates that include the gold entity in the least candidate set (top-K). We propose a simple approach that efficiently embeds mention-entity pairs in dense space through a BERT-based bi-encoder. Specifically, we extend (Wu et al., 2020) by introducing a new pooling function and incorporating entity type side-information. We achieve a new state-of-the-art 84.28% accuracy on top-50 candidates on the Zeshel dataset, compared to the previous 82.06% on the top-64 of (Wu et al., 2020). We report the results from extensive experimentation using our proposed model on both seen and unseen entity datasets. Our results suggest that our method could be a useful complement to existing EL approaches.

1 Introduction
Entity Linking (EL) aims to disambiguate entity mentions in a document against entries in a knowledge base (KB) or a dictionary of entities. Accurately linking these entities plays a key role in various natural language processing (NLP) tasks, including information extraction (Lin et al., 2012; Hasibi et al., 2016), KB population (Dredze et al., 2010), content analysis (Huang et al., 2018) and question answering (Li et al., 2020), with potential applications in many fields, including technical writing, digital humanities, and biomedical data analysis.

While EL systems typically rely on external KBs and assume entities at inference time known, real-world applications are usually accompanied by minimal to zero labeled data, highlighting the importance of approaches that can generalize to unseen entities. Logeswaran et al. (2019) introduced Zero-shot EL, where mentions must be linked to unseen entities, without in-domain labeled data, given only the entities’ text description. By comparing two texts - a mention in context and a candidate entity description - the task goes closer to reading comprehension.

Most EL systems consist of two subsystems: Candidate Generation (CG), where for each entity mention the system detects entities related to the mention and document, and Candidate Ranking (CR) where the system chooses the most probable entity link among the found candidates. Most state-of-the-art models (Logeswaran et al., 2019; Li et al., 2020; Yao et al., 2020) rely on traditional frequency-based CG and focus on building robust candidate rankers using cross-encoders to jointly encode mention and entity candidate descriptions. However, the memory-intensive CR phase depends on the set of candidates provided by CG. Therefore, the accuracy of CR (and, by extension, the overall EL system), is capped by that of the CG phase.

The goal of this work is to advance the state of the art in the CG phase (Wu et al., 2020), in order to set a higher performance ceiling for CR and for EL overall. We start from (Wu et al., 2020), which encodes mention and entity descriptions in dense space through a BERT-based bi-encoder and then retrieves the closest $K$ entities to each mention using the dot product method. Although this method
increased accuracy at top-64 retrieved candidates from 69.13% (Logeswaran et al., 2019) to 82.06%, an approach that allows higher CG accuracy with fewer candidates is yet to be developed.

We introduce a new state-of-the-art CG model that achieves 84.28% accuracy on the top-50 candidates; namely, we obtain a 2.22 higher unit threshold in CR and EL overall using 21.88% fewer candidates, compared to (Wu et al., 2020). Our proposed model uses a BERT-based bi-encoder and incorporates a special pooling function that efficiently encodes mention and entity descriptions in dense space by aggregating information from special tokens. We experimented on various pooling function alternatives, retrieval methods, and the effect of entity type side-information. At the same time, we report our results on both seen and unseen entity sets to evaluate our model’s efficiency on both typical and zero-shot EL. Our results revealed that concatenating special tokens of the proposed BERT-based input representation and using dot product to retrieve candidates yield the best outcomes on both test and heldout train seen sets. Meanwhile, state-of-the-art results were preserved without the entity type information, warranting our model’s robustness regardless of additional information.

The contributions of this paper are summarized as follows:

• We introduce a new CG approach, based on BERT-based bi-encoder and a new pooling function that manages to encode mention and entities in the same dense space very effectively, achieving state-of-the-art results.

• A 84.28% accuracy on top-50 candidates, compared to 82.06% at top-64 of (Wu et al., 2020), measured on the Zeshel test dataset. We thus increase the CR accuracy by 2.22 units while requiring 21.88% fewer candidates, allowing more accurate and faster inference.

• State-of-the-art results on both seen and unseen entity sets, with and without entity type information, reveal the robustness of our model in both the typical and the zero-shot EL settings.

2 Related Work

Former work has pointed out the importance of building entity linking systems that can generalize to unknown named entities, either via a reduced candidate set or through a more robust candidate ranker. Our work falls into the first category, namely the candidate generation phase and is related to BERT-based sequence modeling, pooling techniques, entity type side-information, and candidate retrieval methods.

Candidate Generation (CG) Traditional CG has been based on string comparison (Phan et al., 2017) and alias tables. These methods lack rich representation and restrict to a small entity set, respectively, thus proving inefficient for the challenging task of entity candidates retrieval, especially in the zero-shot set, where generalization to new entities is on the spot. Over the last years, many works (Sil et al., 2012; Murty et al., 2018; Logeswaran et al., 2019) focused on frequency-based methods, with most of them following TF-IDF and BM25 approaches. Gillick et al. (2019) introduces a simple neural bi-encoder and shows that encoding mention and entities in dense space works well. Inspired by this idea, (Wu et al., 2020) proposed the, to our knowledge, current state-of-the-art CG model, using a more robust transformer-based bi-encoder (Humeau et al., 2019). Precisely, they achieve an 82.06% acc. on top-64 retrieved candidates in the Zeshel dataset. Their model uses a BERT-based bi-encoder to encode mention and entities’ descriptions in dense space, where the top-K entities are then retrieved based on the two vectors’ maximum dot product. Our work extends the work of (Wu et al., 2020) by investigating other than the default BERT (Devlin et al., 2019) pooling functions, additional entity type side-information, and alternate retrieval methods.

Entity Type side-information Apart from model architecture, several methods (Raiman and Raiman, 2018; Khalife and Vazirgiannis, 2018) show that fine-grained entity type side-information helps to further disambiguate entities in EL. First attempts to integrate type information in the task consisted of end-to-end systems (Durrett and Klein, 2014; Luo et al., 2015; Nguyen et al., 2016) that jointly modeled entity linking and named entity recognition to capture the mutual dependency between them, typically using structured CRF and hand-crafted features. Automatically extracted entity features were captured by (Yamada et al., 2016; Ganea and Hofmann, 2017) using typical embedding methods proposed by (Mikolov
et al., 2013), while (Martins et al., 2019) learned entity features using Stack-LSTMs (Dyer et al., 2015) in multi-task learning. Latest works in EL (Hou et al., 2020; Chen et al., 2020) suggest to build entity type embeddings by modeling the mentions’ near context and its semantics using Word2Vec (Mikolov et al., 2013) and BERT (Devlin et al., 2019) embeddings, respectively. In our work, we choose to model entities as special tokens in BERT representation and let the model automatically capture relevant information across all sequence, following similar BERT-based entity representations (Shi and Lin, 2019; Poerner et al., 2020; Christou and Tsoumakas, 2021) applied in other NLP applications.

Candidate Retrieval methods As mentioned above, most approaches (Logeswaran et al., 2019; Sil et al., 2012) retrieve entity candidates using frequency-based methods, such as BM25 (Robertson et al., 2009). Meanwhile, recent bi-encoder approaches in EL (Gillick et al., 2019; Wu et al., 2020) score mention-candidate pairs using dot product during training while retrieving top-K candidates using the same vector similarity measure. In our work, we experiment on alternate candidate retrieval methods, i.e., euclidean, cosine, and dot methods, to find out cosine (Manning, 2008) and dot product to outperform the euclidean metric significantly.

3 Methodology

Our proposed method for candidate generation uses BERT (Devlin et al., 2019) in a bi-encoder set. The bi-encoder uses two independent BERT transformers to encode the mention’s context and all entity descriptions into two dense vectors. Then, the best candidates are retrieved by scoring the mention-entity pair vectors with a vector similarity measure. This section presents specific sequence representation methods, and other than the typical dot-product metric used to retrieve the best candidates.

3.1 Bi-encoder

We use a BERT-based bi-encoder, following (Wu et al., 2020) to model the mention-entity pairs, because it allows for fast, real-time inference, as the candidate representations can be cached. Below, we present our structured input to the bi-encoder, our proposed pooling functions for sequence representation and brief notes on entity type incorporation in the structured input.

**Input Representation** The mention context and the entity description are encoded into the following vectors:

\[ y_m = \text{red}(T_1(t_m)) \]
\[ y_e = \text{red}(T_2(t_e)) \]

where \( t_m \) is the representation of mention, \( t_e \) is the representation of entity, \( T_1 \) and \( T_2 \) are two transformers. The function \( \text{red}() \) reduces the sequence of vectors into one. By default, the last layer of the output of the [CLS] token is returned.

The representation \( t_m \) is composed of the mention text surrounded by two special tokens that denote the existence of the mention, the context from the left and the right side of the mention text plus the special tokens that BERT inserts. Specifically, the construction of the mention is:

\[ [\text{CLS}] \text{ ctxtl } [\text{Ms}] \text{ mention } [\text{Me}] \text{ ctxtr } [\text{SEP}] \]

and with the addition of the entity type it is:

\[ [\text{CLS}] [\text{ent\_type}] \text{ mention } [\text{H\_SEP}] \text{ ctxtl}... \]

where [Ms] and [Me] are the special tokens that tag the mention, ctxtl and ctxtr are the word-pieces tokens of the context before and after the mention and [CLS] and [SEP] are BERT’s special tokens.

The representation \( t_e \) is composed of the entity title, the special token [ENT] separating the entity’s title and description plus the special tokens that BERT inserts.

\[ [\text{CLS}] \text{ title } [\text{ENT}] \text{ description } [\text{SEP}] \]

and with the addition of the entity type it is:

\[ [\text{CLS}] [\text{ent\_type}] \text{ title}... \]

For simplicity in both input representations a maximum length of the document is retrieved.

The score of the entity candidate \( e_i \) given a mention is computed by the dot-product:

\[ s(m, e_i) = y_m \cdot y_e \]

The network is trained to maximize the score of the correct entity with respect to the entities of the same batch. For each training pair \((m_i, e_i)\) in a batch of B pairs, the loss is computed as:

\[ L(m_i, e_i) = -s(m_i, e_i) + \log \left( \sum_{j=1}^{B} \exp(s(m_i, e_j)) \right) \]
Input Encoding The dataset needed to be processed by the models to understand information and to extract representative vectors from it. For that reason, a Tokenizer was used to split each document into a list of tokens and to give each token a respective id. The Bert Tokenizer used a special technique called Byte Pair Encoding (Sennrich et al., 2016). BPE makes use of a simple data compression technique that iteratively replaces the most frequent pair of bytes in a sequence with a single, unused byte. Instead of merging frequent pairs of bytes, characters or character sequences are merged. The reason this technique is used by the algorithm is to compute subwords from unknown tokens, so words that the algorithm may known can be associated with unknown words that tend to be similar to them and consequently are given proper token ids.

Pooling Functions The different sequence representations that were tested fall into the following categories:

- Usage of [CLS]: The default representation of the sequence.
  
  \[CLS = h_L[0] \]

- Average of tokens: Averages all token representations from BERT’s last hidden layer.
  
  \[avg = \frac{\sum_{i=0}^{n}(h_L[i])}{n}\]

- Sum of tokens: Sums all token representations from BERT’s last hidden layer.
  
  \[sum = \sum_{i=0}^{n}(h_L[i])\]

- Average special: Averages only the special token representations from BERT’s last hidden layer.
  
  \[avg special = \frac{\sum_{i=0}^{n}(h_L[i])}{n}\]

- Sum of special tokens: Sums only the special token representations from BERT’s last hidden layer.
  
  \[sum special = \sum_{i=0}^{n}(h_L[i])\]

- Concatenation of special tokens: Concatenates only the special token representations from BERT’s last hidden layer.

  \[conespecial = [h_L[j_1], ..., h_L[j_M]]\]

  where \(j\) refers to the index of special tokens with \(M\) being the total number of special tokens.

Entity Type Representation In the extent that entity types put some constraint on the possible entity to link, we also experimented on incorporating the entity type in the model’s structured input. Precisely, we incorporate 18 generic entity types, captured from recognizing mention’s and entity titles’ entity types with the spaCy model\(^1\). SpaCy is an open-source software library for advanced natural language processing, written in the programming languages Python and Cython (Honnibal et al., 2020). We note that entity types, include the \(<unk>\) type for unclassified mentions/entity titles. Also, all entity types are encoded as special tokens; consequently, sequence representations that make use of special tokens also consider the entity type embeddings.

3.2 Retrieval Methods
In the candidate generation step different methods were performed, in order to find a proper candidate set. The first method was to initialize a k-nearest neighbors classifier and fit the model with the representations of the entity descriptions from the bi-encoder and their respective id. After that, for each context mention the k closest neighbors were returned, where k the number of candidates the candidate set should have.

Another approach was to compute the similarity between each context mention with each entity and construct the candidate set with the h more common ones. To find the similarity between two vectors \(A = [a_1, a_2, ..., a_n]\) and \(B = [b_1, b_2, ..., b_n]\), some main similarity measures were used to choose from.

\(^1\)https://github.com/explosion/spacy-models/releases/tag/en_core_web_lg-2.3.0
The cosine similarity method measures the cosine of angle $\theta$ between two vectors. The cosine increases as the two vectors tend to look alike.

$$\cos(A, B) = \frac{A^T B}{|A||B|}$$

The dot product method measures the cosine multiplied by lengths of both vectors. For very similar vectors the value is increased and also for vectors with big length.

$$A \cdot B = a_1b_1 + a_2b_2 + \ldots + a_nb_n = |A||B|\cos(\theta)$$

The euclidean distance method measures the distance between ends of vectors. For vectors that are similar and consequently very close to the vector space the value is small.

$$d(A, B) = \sqrt{(a_1 - b_1)^2 + \ldots + (a_N - b_N)^2}$$

4 Experimental Setup

4.1 Dataset

For our experiments, we use the Zeshel\(^2\) dataset, which to our knowledge, is the prevailing benchmark for zero-shot EL. The dataset was constructed using documents from Wikias, namely community-written encyclopedias, each specialized in a particular subject. Documents in Wikias exhibit rich document context, thus are an excellent source for natural language comprehension models. Meanwhile, each encyclopedia contains domain-specific entity dictionaries, making it an ideal dataset for evaluating the EL system’s generalization on new domains.

Table 1 presents the number of unique entities per domain (world) and train/val/test sets. Regarding mentions, the training set includes 49,275 labeled mentions, while the validation and test sets consist of 10,000 and 10,000 unseen mentions, respectively. Moreover, an extra 5,000 seen and 5,000 unseen mentions from the training set are provided. The goal of this discrimination is to explore the models’ performance to known domains. We present our model’s performance on both known and unknown worlds in section 5.3.

| Set   | World              | Entities |
|-------|--------------------|----------|
| Train | American Football  | 31929    |
|       | Doctor Who         | 40281    |
|       | Fallout            | 16992    |
|       | Final Fantasy      | 14044    |
|       | Military           | 104520   |
|       | Pro Wrestling      | 10133    |
|       | StarWars           | 87056    |
|       | World of Warcraft  | 27677    |
| Val   | Coronation Street  | 17809    |
|       | Muppets            | 21344    |
|       | Ice Hockey         | 28684    |
|       | Elder Scrolls      | 21712    |
| Test  | Forgotten Realms   | 15603    |
|       | Lego               | 10076    |
|       | Star Trek          | 34430    |
|       | YuGiOh             | 10031    |

Table 1: Number of Entities per world and train, val, test sets in the Zeshel dataset.

4.2 Hyper-parameter Settings

In our experiments we utilize bert-base-uncased model with hidden layer dimension $D_h = 768$, while we fine-tune the model with max_seq_length $D_t = 128$. Regarding model’s hyper-parameters, we manually tune them on the training set. For fine-tuning, we assigned batch_size = 8, epochs = 5, all the BERT’s layers are updated during back-propagation, learning rate $lr = 3e^{-5}$ and weight_decay = 0.01. Moreover, we fine-tune our model using the Adam optimization scheme (Loshchilov and Hutter, 2017) with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a linear learning rate decay schedule. We minimize loss using cross entropy criterion.

Experiments were conducted on a PC with 15 GB RAM, an AMD FX-8350 Eight-Core Processor with a base frequency of 4.00 GHz and a NVIDIA GeForce GTX TITAN X graphics card with 12 GB memory.

Training time took about 150min for the whole process. For the CG task and to process all test set (10K mentions, 70,140 entities), the model takes 90min using cosine method, 60min with the euclidean distance method and 50min with the dot product method. For the heldout_train_seen set, the model takes 30min with the cosine method, 25min with the euclidean distance method and 20min with the dot product method.

\(^2\)https://github.com/lajanugen/zeshel
4.3 Evaluation

To evaluate the performance of our model against the rest state-of-the-art models, we report the accuracy at top-k. Namely, we assess the performance on the subset of test instances for which the gold entity is among the top-k retrieved candidates. We highlight that since EL systems’ overall performance is upper-bounded by the CG accuracy and their speed is associated with the number of retrieved candidates, a model that will increase CG performance in fewer candidate entities is crucial.

4.4 State-of-the-art CG Models

For evaluating our method, we compare against the following state-of-the-art models in Zero-Shot EL:

**BM25 (Logeswaran et al., 2019):** Use a traditional, frequency-based method (BM25) for the candidate generation. To re-rank the top K candidates propose the use of a cross-encoder to jointly encode mention context and entity description.

**Bi-encoder (Wu et al., 2020):** First to perform the candidate retrieval on a dense space. Mention context and candidate entities are encoded into vectors using a bi-encoder and the retrieval phase is then reduced to finding the maximum dot product between mention and entity candidate representations. Final entity selection is performed using the top K candidates from the retrieval phase and re-ranked through a cross-encoder, similar to (Logeswaran et al., 2019). As an encoder BERT model is selected.

While state-of-the-art models in Zero-shot EL (Logeswaran et al., 2019; Yao et al., 2020) focus on the CR phase, Wu et al. (2020) are the only to propose a different to traditional IR approach for CG. Our focus is to further push the boundaries of the CG phase and set a higher performance threshold to CR and EL overall.

5 Results

5.1 Comparison with Baselines

Here, we compare our CG model against the previous state-of-the-art works and our model’s various alternatives that use different pooling functions for sequence representation and incorporate or not entity type side-information. Table 2 shows our model to significantly outperform the previous state-of-the-art works with fewer candidates regardless of chosen pooling function and additional side-information. Precisely, the best version of our model achieves 2.22 and 15.15 higher normalized accuracy than (Wu et al., 2020) and (Logeswaran et al., 2019) respectively, using 21.88% fewer candidates and without incorporating any additional side-information.

![Figure 1: Top-K entity retrieval accuracy of Ours (conc special) model.](image)

Meanwhile, in Figure 1, which shows our best model’s accuracy across various top-K retrieved candidates, we can see that choosing more candidates could further increase accuracy. Still, we decided on fifty (50) candidates due to its small enough size and performance improvement over the rest baselines.

5.2 Ablation Studies

In this section, we review the effect of pooling functions, entity type side-information and retrieval methods.

5.2.1 Effect of Entity Type across all Pooling Functions

We experimented with various pooling functions to find the most efficient sequence representation, whereas for each representation, we explore the addition of the mention’s entity type at the sequence encoding (see section 3.1).
Table 3 presents the normalized accuracy on top-50 candidates for all pooling functions presented in section 3.1 incorporating or not the entity type side-information. As can be seen, state-of-the-art accuracy is achieved by representing the sequence as the concatenation of its special tokens without incorporating entity-type information. Meanwhile, the addition of entity type in the rest representation techniques seems to improve performance, but only slightly (up to 0.63%). We suspect that the reason that entity type does not add significant value is that about 60% of mentions are detected with UNKNOWN entity type; thus, the model was not able to capture robust patterns. From manual inspection, we notice that most UNKNOWN entity types are associated with pronouns or co-references.

5.2.2 Effect of the Retrieval Methods

Regarding the retrieval phase, we wanted to explore the effect of other common distance metrics, apart from the typical one used, i.e., the dot product.

Table 4: Comparison of all methods using Euclidean, Cosine, and Dot product distance metrics to retrieve the best candidates. The Euclidean distance presents the worst performance for all methods, with dot product consistently slightly outperform the cosine. Figure 2, which shows our best model’s performance for all three distance metrics across top-\{1, 10, 25, 50\} retrieved candidates, exhibits similar observations. Namely, the dot product achieves higher accuracy across all top candidates, closely followed by cosine and then by the euclidean distance. Consequently, our findings are in sync with (Manning, 2008). Comparing the three distance metrics, cosine and dot product metrics are advantageous to euclidean as they measure the angle between documents; namely, they measure documents’ similarity regardless of their size. Moreover, the dot product considers both the angle and the magnitude of two vectors, which makes it competitive to the cosine similarity metric.

Figure 2: Performance of (conc special) model for all Euclidean, Cosine, and Dot product distance metrics across the top retrieved candidates.

5.3 Case Study: Performance on the typical EL set

So far, we have tested our methods’ efficiency in the most challenging set of EL, the zero-shot set, where we must prove the model’s generalization in out-of-domain, unseen entities. In this section, our scope is to examine the in-domain generalization performance and prove our method as a valuable complement to all existing EL approaches.

Table 5: Comparison of normalized accuracy on top-50 candidates for all pooling functions incorporating or not the entity type side-information, where in Table 6 we show the performance of our best model using different distance metrics in the retrieval phase.
Table 5: Comparison of results with and without entity type for each pooling function on the Heldout Train Seen set. We report results on the top-50 candidates, using the dot product as retrieval method.

| Pooling functions | Heldout Train Seen |
|-------------------|--------------------|
|                   | w/o Ent.Type | Ent.Type |
| [CLS]             | 98.42%       | 98.56%   |
| Avg tokens        | 98.56%       | 98.05%   |
| Sum tokens        | 97.60%       | 97.62%   |
| Avg special tokens| 98.76%       | 98.54%   |
| Sum special tokens| 98.26%       | 98.30%   |
| Conc special tokens| **98.86%** | 98.36%   |

Both tables reveal same observations to our methods’ performance in the Zero-shot set. Namely, using the concatenation of special tokens to represent sequences and the dot product to retrieve the best candidates leads to greater accuracy. Moreover, entity type only slightly boosts few sequence representation methods, and euclidean distance performs the poorest. At last, we provide a great upper threshold (98.86%) for EL under its typical, supervised set.

Distance metrics Results

| Distance metrics | Results |
|------------------|---------|
| Euclidean        | 97.3%   |
| Cosine           | 98.64%  |
| Dot product      | **98.86%** |

Table 6: Comparison of the similarity methods for concatenation of special tokens and 50 candidates. Results for the heldout train seen set.

6 Conclusion

We proposed a simple yet very effective candidate generation model that sets a higher performance bar for candidate ranking (CR) and EL overall. Precisely, our model achieves at least 2.22 higher threshold for CR and EL using 22% fewer candidates, compared to previous state-of-the-art works in the zero-shot set. Meanwhile, we tested our model’s efficiency with in-domain corpus, seen entities to also accomplish great results with the same parameters as in zero-shot EL, proving that the suggested method can be a valuable complement to all existing EL approaches. We also experimented with adding entity types to boost performance, without success, though. After inspecting the data, we found out that 60% of the mentions were not classified with an entity type, with most of them constituting pronouns, not named entities. On the one hand, that proves our model’s robustness regardless of side-information, but from the other suggest specific enhancements for the future. Future enhancements could incorporate entity graph information instead of entity types to capture co-references better and integrate a generic document entity type to locate the main concept of the document. At last, we plan to extend this work with respective experimentation in the candidate ranking phase.

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A Examining model errors and predictions

In tables 7, 8, 9 we show some example mentions and model predictions.


| Mention | Haga ’ s helper ( manga ) | Queue cutter | Daichi |
|---------|--------------------------|--------------|--------|
| ... When he took it off , a boy working for Insector Haga swiped it and inserted the card Parasite Paracide into his Deck as he ran away with it . Jonouchi managed to catch the boy and met up with Anzu , Bakura and Sugoroku as he did so . .... | Haga ’ s helper was a boy employed by Insector Haga to help him cheat in a Duel against Katsuya Jonouchi . Biography . Haga promised the boy a rare card if he could sneak the card ” Parasite Paracide ” into Jonouchi ’ s Deck . ... | Queue cutter The ” queue cutter ” is an elementary or junior high school kid , who appeared once in the manga . Biography . The boy cut past Yugi in a queue to a Capsule Monster Chess coin machine , outside Old Man Dentures store . ... | Daichi Daichi is one of the children in Crow ’ s care in ” Yu - Gi - Oh ! 5D ’ s ” . He has black hair in a bowl cut and dark blue eyes . ... |

Table 7: First example with the mention and the entity candidates. The correct entity candidate is the first from the candidate set.

| Mention | Jack Crusher | Kurland | Gabriel Lorca |
|---------|--------------|---------|---------------|
| ... He stole the Type / shuttlecraft ” ” , intending to join a freighter on Beltane IX and asked Captain Picard to tell his father he ’ s sorry but had to do this . .... | Lieutenant Commander Jack R . Crusher was a Starfleet officer . Considered by Jean - Luc Picard to have been his best friend , he served under Picard ’ s command on the . He was husband to Beverly Crusher and father to Wesley Crusher . ... | Kurland Kurland was a Human male aboard the in 2364 . He had one son , Jake Kurland . When Jake tried to leave the ” Enterprise ” - D with a shuttlecraft that year , he asked Captain Picard to tell his father he was sorry but he could not stay aboard the ship . Picard told him he should bring back the shuttle and tell this his father himself . ( ) ... | Gabriel Lorca Captain Gabriel Lorca was a male Human Starfleet officer who lived during the mid - 23rd century . He served as the commanding officer on board at least one Federation starship , ... |

Table 8: Second example with the mention and the entity candidates. The correct entity candidate is the second from the candidate set.
... Riker argues with him and is generally uncooperative. Remmick asks La Forge in engineering about the incident with Kosinski and the Traveler, and La Forge is forced to acknowledge that the captain lost control of the ship.

| Mention | USS Enterprise bridge holoprogram | USS Enterprise bridge holoprogram The USS "Enterprise" bridge holoprogram was a holodeck recreation of the bridge of the original. The program was accessed by Captain Montgomery Scott when he was on board the in 2369 after having been rescued from transporter stasis on the.

| USS Enterprise bridge holoprogram | Captain’s log, USS Enterprise (NCC - 1701) | Captain’s log, USS Enterprise (NCC - 1701) The captain’s log on the was the method used by the commanding officer to record the ship’s events. These logs included Captain James T. Kirk’s famous five-year mission.

| Traffic accident | Traffic accident A traffic accident was an incident involving vehicle s and their occupants in which the vehicle in question malfunctioned or crashed. Some accidents resulted in death. In 1930, Edith Keeler died in a traffic accident after she crossed the street to find out why James T. Kirk had left her abruptly.

Table 9: Third example with the mention and the entity candidates. The correct entity candidate is not part of the candidate set.