Efficient Overshadowed Entity Disambiguation by Mitigating Shortcut Learning

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Abstract

Entity disambiguation (ED) is crucial in natural language processing (NLP) for tasks such as question-answering and information extraction. A major challenge in ED is handling overshadowed entities—uncommon entities sharing mention surfaces with common entities. The current approach to enhance performance on these entities involves reasoning over facts in a knowledge base (KB), increasing computational overhead during inference. We argue that the ED performance on overshadowed entities can be enhanced during training by addressing shortcut learning, which does not add computational overhead at inference. We propose a simple yet effective debiasing technique to prevent models from shortcut learning during training. Experiments on a range of ED datasets show that our method achieves state-of-the-art performance without compromising inference speed. Our findings suggest a new research direction for improving entity disambiguation via shortcut learning mitigation.

1 Introduction

Entity disambiguation (ED) is an essential task in many natural language processing (NLP) applications, for instance, open-domain question answering (Hu et al., 2022; Saffari et al., 2021; Srivastava et al., 2021; Wang et al., 2021), fact verification (Zhou et al., 2019), and information extraction (Baldini Soares et al., 2019). The task is to identify the correct entity recorded in a KB, e.g., Wikidata, for each ambiguous entity mention in a given text, which is a crucial capability when performing entity linking (EL). In real-world ED applications, there are two important properties:

- ***Context-awareness***: The method should be able to accurately resolve entities based on the surrounding context of the entity mentions. For example, the mention of *Michael Jordan* can refer to a basketball player (Michael Jeffrey Jordan) or a machine learning researcher (Michael Irwin Jordan), depending on the context.
- ***Scalability***: The method should be capable of handling large amounts of input data efficiently. This leads to faster processing times and lower costs associated with running the ED system.

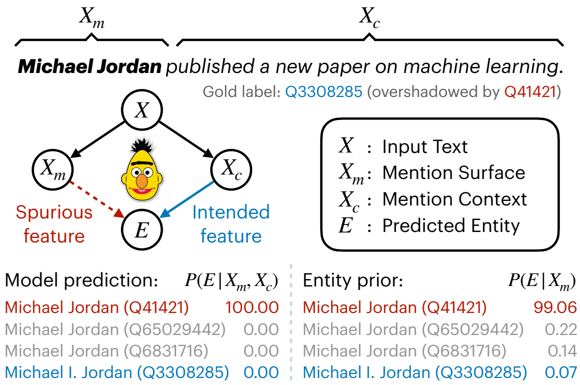

Figure 1: The causal graph of ED models. Due to the strong correlations between the spurious feature and training labels, typical ED models are prone to shortcut learning and fail to resolve overshadowed entities.

The existing ED approaches can be categorized into: (i) Classification-based approaches fine-tune a classification layer on top of a pre-trained language model (PLM) to predict a score distribution over entity vocabulary (Broscheit, 2019; Yamada et al., 2022) or entity types (Onoe and Durrett, 2020; Tedeschi et al., 2021). (ii) Generative-based approaches fine-tune a generative PLM to generate a unique entity name (Cao et al., 2021; De Cao et al., 2021; Du et al., 2022) or entity description (Procopio et al., 2023). (iii) Retrieval-based approaches fine-tune a bi-encoder (Li et al., 2020) or a cross-encoder (Wu et al., 2020) to compute similarity scores between mentions and entity descriptions. ReFinED (Ayoola et al., 2022b) enhanced the bi-encoder's performance by incorporating entity type classification and entity priors to re-rank the bi-encoder predictions.

Nonetheless, ED methods often struggle with overshadowed entities (Provatorova et al., 2021), in-

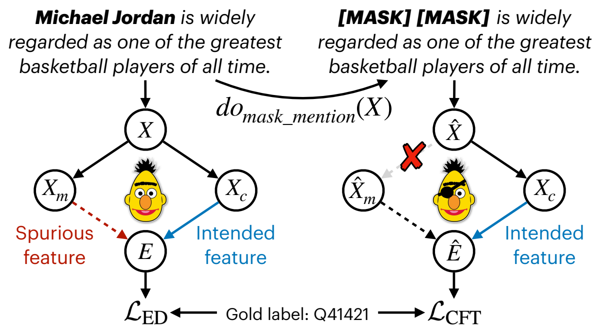

Figure 2: The system overview of the proposed method.

dicating a lack of *Context-awareness* in current ED methods. KBED (Ayoola et al., 2022a) improved ReFinED's performance on overshadowed entities by leveraging KB facts. Specifically, they extract relations between every pair of mentions in input and perform reasoning over external knowledge retrieved from KB to re-rank the ReFinED's predictions. Although this method has the potential to enhance *Context-awareness* and reduce the overshadowing problem, it requires input to contain multiple mentions, and its computational burden grows as the number of mentions increases, hence compromising the *Scalability* of the ReFinED method. According to our empirical results, KBED slows down the throughput of ReFinED from 3.3 to 0.6 queries per second (Q/s) on standard ED datasets.

This paper tackles the overshadowing issue by addressing *shortcut learning* (Geirhos et al., 2020) during training, which does not impose a computational burden at inference. We introduce *Counterfactual Training (CFT)* as a technique to prevent the models from learning shortcut solutions and to enhance *Context-awareness*. As shown in Figure 1, each input text X to ED models contains two input features: the mention surface X_m (spurious feature) and the mention context X_c (intended feature). The intended solution is to use the contextual feature X_c to determine entity E. Nevertheless, the strong correlations between the spurious feature X_m and training labels can induce the models to learn a shortcut (i.e., using the mention surface to determine entity E), obscuring the intended solution. This shortcut solution allows the models to achieve high performance on common entities but poor performance on overshadowed entities.

We assess CFT against existing methods on six standard datasets and three challenging datasets. The results show that CFT achieves the best performance on seven out of nine datasets for overshadowed entities and six out of nine datasets for overall entities without compromising the throughput at inference. We find that CFT performs surprisingly well on texts with limited contextual information (i.e., short sentences with a small number of mentions) while other methods struggle. Source code and models will be available upon acceptance.

2 Counterfactual Training (CFT)

2.1 Counterfactual Example

For every training example X, we perform an intervention $do_{mask\_mention}(\cdot)$ to mask all mention surface tokens X_m with special [MASK] tokens and leave the mention context tokens X_c as original:

$$\hat{X} = do_{mask\_mention}(X) = \langle w_1, w_2, ..., w_n \rangle$$
$$\forall w_i \in X, \begin{cases} w_i \leftarrow \text{[MASK]} & \text{if } w_i \in X_m \\ w_i \leftarrow w_i & \text{if } w_i \in X_c \end{cases} \tag{1}$$

thereby creating a counterfactual example $\hat{X}$ that excludes the mention surface X_m (spurious feature) and only contains the mention context X_c (intended feature) as shown in Figure 2. We denote the masked tokens in $\hat{X}$ as $\hat{X}_m$.

2.2 Training Objective

The typical training objective of ED is to minimize the negative log-likelihood between the gold entity label $\tilde{E}$ and the model prediction E given a mention surface X_m and mention context X_c:

$$\begin{aligned} \mathcal{L}_{\text{ED}} &= \mathcal{L}(\tilde{E}, E) \\ E &= f(X_m, X_c, \theta) \end{aligned} \tag{2}$$

where $\mathcal{L}$ is any loss function (e.g., cross-entropy) and θ is parameters of the model f. However, due to a strong correlation between mention surface X_m (spurious feature) and training labels $\tilde{E}$, training the model merely on $\mathcal{L}_{\text{ED}}$ could mislead the model to use the mention surface X_m (spurious feature) to resolve entities during inference.

To enforce the model to rely on contextual information, enhancing *Context-awareness*, we incorporate the counterfactual example $\hat{X}$ in Section 2.1 to provide regularization during the training process:

$$\begin{aligned} \mathcal{L}_{\text{CFT}} &= \mathcal{L}(\tilde{E}, \hat{E}) \\ \hat{E} &= f(\hat{X}_m, X_c, \theta) \end{aligned} \tag{3}$$

We combine the $\mathcal{L}_{\text{CFT}}$ auxiliary term with the $\mathcal{L}_{\text{ED}}$ to obtain the final training objective:

$$\mathcal{L}_{\text{Final}} = \mathcal{L}_{\text{ED}} + \mu \cdot \mathcal{L}_{\text{CFT}} \tag{4}$$

where μ is a hyperparameter that controls the strength of the regularization.

3 Experimental Settings

3.1 Baselines and Competitive Methods

We report the performance of three baseline ED methods. **ReFinED** (Ayoola et al., 2022b) and **BLINK** (Wu et al., 2020) are retrieval-based ED methods that use the bi-encoder and cross-encoder architectures, respectively. **GENRE** (Cao et al., 2021) is a generative encoder-decoder ED method. We use the same candidate generation method for all baselines as previous works (Ayoola et al., 2022b; Cao et al., 2021; Le and Titov, 2018).

We compare CFT with the current state-of-the-art method for improving overshadowed entity disambiguation. **KBED** (Ayoola et al., 2022a) is a ReFinED extension with overshadowed entity disambiguation improvement. The method applies reasoning over KB facts to promote candidate entities that are coherent with entities in the context.

Since we formulate the overshadowing problem as shortcut learning, we also compare our work with existing shortcut mitigation methods. **Focal loss (Focal)** (Lin et al., 2017) and **Counterfactual inference (CFI)** (Wang et al., 2022; Qian et al., 2021) are well-known debiasing techniques for mitigating shortcut learning in computer vision and NLP. We applied these two methods to the ED problem by treating the mention surface as a spurious feature. **Entity Masking (EM)** is a technique used in Relation Extraction (RE) literature (Zhang et al., 2017; Liu et al., 2022) to prevent the model from using the mention surface feature as a shortcut for predicting relations. To the best of our knowledge, this work is the first to evaluate these three methods in entity disambiguation. See the implementation details in Appendix A.1.

3.2 Training Details

While CFT can be applied to any existing ED method, we employ a publicly available ED method called ReFinED (Ayoola et al., 2022b) due to its practicality in resolving entities at scales. ReFinED also forms the basis of the current state-of-the-art method, KBED, allowing for direct comparison between KBED and CFT. We trained CFT, KBED, Focal, and EM base on ReFinED by pretraining on the Wikipedia dataset and finetuning on the training set of AIDA-CoNLL (Hoffart et al., 2011). The training datasets comprise approximately 140M mention spans, covering approximately 5.3M entities. We use the validation set of the AIDA-CoNLL dataset to tune hyperparameters (Appendix A.2). We trained each method using three different seeds. We report here that we cannot reproduce the original ReFinED results using their source code. [1]

3.3 Datasets and Evaluations

We evaluate the effectiveness of CFT on overshadowed and common entities under two scenarios.

Standard Set. We employ commonly used six datasets for evaluating ED performance: AIDA-CoNLL (Hoffart et al., 2011), MSNBC (Cucerzan, 2007), AQUAINT (Milne and Witten, 2008), ACE2004 (Ratinov et al., 2011), WNED-CWED (CWED) (Gabrilovich et al., 2013), and WNED-WIKI (WIKI) (Alani et al., 2018). These datasets contain lengthy texts collected from news and web articles across several domains, such as sports, politics, and technology. The average sequence length of these datasets is 565.9, with each sequence having an average of 24.5 mention spans.

Challenge Set. Let us now assess the ED method with limited contextual information. We employ three test datasets: TWEEKI (Harandizadeh and Singh, 2020), MINTAKA (Sen et al., 2022), and ShadowLink (SLINK) (Provatorova et al., 2021). The datasets contain short sentences from a variety of domains, including social media, question answering, and text snippets from Wikipedia pages. The average sequence length is 17.9, with each sequence having an average of 1.3 mention spans.

For each dataset, we split mention spans into "Sha" and "Top" for overshadowed and common entities using entity prior obtained from training data. Specifically, any mention span unresolvable using the prior is considered an overshadowed entity; otherwise, it is a common entity. The statistics of each dataset are reported in Appendix A.3.

Evaluation. We report average *InKB* micro-F1 over three different seeds for each method. We measure the inference rate (Q/s) on a V100 GPU. We exclude "Sha" and "Top" results from BLINK and GENRE because each baseline is trained on a different dataset and possesses a different entity prior, making results incomparable to those of ReFinED-based.

4 Experimental Results

Standard Set. The results in Table 1 demonstrate the effectiveness and efficiency of our method

[1] https://github.com/amazon-science/ReFinED. We noticed that the original ReFinED model is trained using a different implementation from the source code provided, as the number of parameters is inconsistent with the model in the code.

Method	AIDA Sha	AIDA Top	AIDA All	MSNBC* Sha	MSNBC* Top	MSNBC* All	AQUAINT* Sha	AQUAINT* Top	AQUAINT* All	ACE2004* Sha	ACE2004* Top	ACE2004* All	CWEB* Sha	CWEB* Top	CWEB* All	WIKI* Sha	WIKI* Top	WIKI* All	Avg. Sha	Avg. Top	Avg. All	Rate (Q/s)
BLINK†	-	-	86.7	-	-	90.3	-	-	88.9	-	-	88.7	-	-	**82.6**	-	-	86.1	-	-	87.2	0.1
GENRE†	-	-	93.3	-	-	**94.3**	-	-	**89.9**	-	-	90.1	-	-	77.3	-	-	87.4	-	-	88.7	0.4
ReFinED	79.4	98.3	92.9	73.4	96.4	93.6	45.8	94.2	88.6	54.1	98.1	91.4	50.5	**90.3**	78.4	63.9	97.7	86.8	61.2	95.8	88.6	**3.3**
w/ Focal	81.6	98.3	93.5	73.2	96.1	93.3	43.8	94.6	88.8	54.1	97.9	91.2	49.7	90.2	78.1	60.7	97.2	85.4	60.5	95.7	88.4	**3.3**
w/ EM	70.2	97.7	89.9	72.6	95.1	92.3	42.7	90.8	85.3	47.3	95.9	88.5	43.5	88.3	74.7	57.5	96.5	83.9	55.6	94.0	85.8	**3.3**
w/ CFI	80.5	98.1	93.1	72.7	96.6	93.6	46.3	93.7	88.3	56.1	98.1	91.7	50.3	90.1	78.1	65.3	97.5	87.1	61.9	95.7	88.6	3.1
w/ KBED	82.2	**98.4**	93.8	**76.0**	**96.9**	**94.3**	45.8	**95.3**	89.6	**57.4**	**98.3**	**92.1**	50.2	90.2	78.1	65.0	97.6	87.0	62.8	**96.1**	89.1	0.6
w/ **CFT**	**83.8**	98.2	**94.1**	74.2	96.3	93.5	**49.0**	94.7	89.4	56.8	97.9	91.7	**51.5**	**90.3**	78.7	**66.2**	**97.8**	**87.6**	**63.6**	95.9	**89.2**	**3.3**

Table 1: Experimental (InKB micro F1-Score) results on standard datasets with abundant contextual information. We report results for overshadowed entities (Sha), common entities (Top), and all entities (All). **bold** and underline represent the best and second-performing, respectively. (*) denotes out-of-domain datasets. (†) denotes methods that we used their original parameters.

(CFT) on texts with abundant context. CFT outperforms the state-of-the-art method (KBED) on overshadowed entity disambiguation by a significant margin. CFT also performs the best compared to other debiasing methods. Focal performs well only on the in-domain dataset (AIDA) but struggles to perform on out-of-domain datasets. Although EM and CFI are widely used in RE to mitigate shortcut learning, it is ineffective in ED. For the Q/s rate, Focal, EM, and CFT achieve the same throughput as ReFinED, while CFI and KBED show a drop in throughput. The case study and analysis of CFT and KBED are discussed in Appendix A.4.

Challenge Set. Table 2 shows that CFT is the most effective method for disambiguating entities on out-of-domain datasets with limited contextual information (TWEEKI and MINTAKA). BLINK performs well only on the Wikipedia domain dataset (SLINK). Although KBED performs well on input texts with abundant context, it struggles when context is limited. The results of the Q/s rates conform with those of the standard set.

Method	TWEEKI* Sha	TWEEKI* Top	TWEEKI* All	MINTAKA* Sha	MINTAKA* Top	MINTAKA* All	SLINK Sha	SLINK Top	SLINK All	Rate (Q/s)
BLINK†	-	-	80.5	-	-	85.1	-	-	**74.6**	0.4
GENRE†	-	-	79.8	-	-	84.2	-	-	56.5	15.7
ReFinED	42.1	**93.5**	82.1	37.3	95.9	87.1	43.0	93.0	69.2	**39.0**
w/ Focal	42.0	93.1	81.8	35.7	95.7	86.7	41.8	93.0	68.8	**39.0**
w/ EM	32.3	90.1	77.3	27.9	91.9	82.3	43.1	91.7	68.0	**39.0**
w/ CFI	42.6	93.3	81.9	38.3	95.8	87.1	43.5	**93.1**	69.2	24.3
w/ KBED	40.9	92.8	81.2	37.1	95.5	86.6	41.5	93.0	68.1	27.5
w/ **CFT**	**44.6**	**93.5**	**82.6**	**38.7**	**96.0**	**87.3**	**44.1**	92.8	69.5	**39.0**

Table 2: Results on challenge datasets with limited contextual information. (*) denotes out-of-domain datasets.

Scalability. Figure 3 displays a bar chart with the average inference time per query on the y-axis. The x-axis organizes the queries into eight octiles ranked according to the number of mentions per query, where queries in the eighth octile have the highest number of mentions. We can see that the performance gap between CFT and KBED widens as we move from the first to the eighth octile. This finding shows that not only is CFT faster, but it can also scale better than KBED as the number of mentions per query grows. The statistics of each octile are reported in Appendix A.5

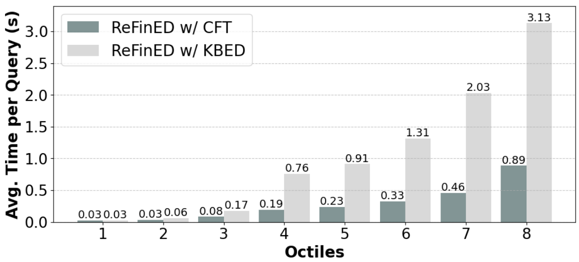

Figure 3: Time taken to process queries with different numbers of mentions. The queries are organized into eight octiles ranked by the number of mentions.

5 Conclusion

This paper addresses the challenge of handling overshadowed entities in *Entity Disambiguation (ED)*. By formulating the ED problem as shortcut learning mitigation, the spurious correlation between mention surfaces and training labels can be mitigated via CFT, which reduces the model's reliance on surface forms for common entities. As opposed to the current SOTA (KBED), our solution does not impose additional inference time, making it 5 times faster than KBED. The empirical results show that CFT achieves the best performance on overshadowed entities. These results support the new research direction of modeling the entity disambiguation problem with counterfactual learning.

Limitations

The limitations of our work are as follows.

- The scope of experiments in this paper does not cover the performance of downstream tasks. Further studies are needed to assess the effect of our method on tasks that rely on ED, e.g., knowledge-graph question answering (KGQA).
- Although our approach does not incur any computational overhead during inference, it incurs a computational overhead during training which is equivalent to performing two forward passes per input. Consequently, this approach might not be appropriate for larger models such as LLMs.

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A Appendix

A.1 Implementation Details

A.1.1 Counterfactual Training

In this subsection, we explain how we implement our method over the state-of-the-art instance-based ED method, ReFinED. The ReFinED model predicts entities's scores based on the descriptions, types, and priors of the entities. The model comprises three sub-modules:

- **Entity description module** calculates the description score for each entity by computing the dot product between the two embeddings of mention and description of the entity obtained from the knowledge base. The module is trained using a cross-entropy loss $\mathcal{L}_d$.
- **Entity typing module** predicts types probability distribution for each mention and then calculates the typing score by computing the Euclidean distance between the predicted types and entity types obtained from the knowledge base. The module is trained using a binary cross-entropy loss $\mathcal{L}_t$.
- **Combined score module** uses a linear layer to aggregate the description score, typing score, and entity prior to a final prediction score. The module is trained using a cross-entropy loss $\mathcal{L}_c$. Note that the inputs to this module, description score and typing score, are detached. Thus, the update gradients from $\mathcal{L}_c$ will not affect other parts of the model.

During training, we employ CFT on the Entity description module. Specifically, we replace the training objective of the Entity description module with obj_{CFT} (Eq. 4) where $\mathcal{L} = \mathcal{L}_d$.

A.1.2 Counterfactual Inference

This section explains how we implement counterfactual inference (Wang et al., 2022; Qian et al., 2021) for ED. For every test example X, we perform an intervention $do_{\textit{mask\_context}}(\cdot)$ to mask all context tokens X_c with special [MASK] tokens and leave the mention surface tokens X_m as original:

$$X' = do_{\textit{mask\_context}}(X) = \langle w_1, w_2, ..., w_n \rangle$$
$$\forall w_i \in X, \begin{cases} w_i \leftarrow \text{[MASK]} & \text{if } w_i \in X_c \\ w_i \leftarrow w_i & \text{if } w_i \in X_m \end{cases} \quad (5)$$

thereby creating a counterfactual example X' that excludes the mention context X_c (intended feature) and only contains the mention surface X_m (spurious feature). We denote the masked tokens in X' as X'_c. This counterfactual example X' is then used to estimate the effect of mention surfaces X_m on output predictions:

$$E' = f(X_m, X'_c, \theta) \quad (6)$$

To mitigate the effect of mention surfaces X_m on output predictions, we subtract the original model prediction E with the estimated effect E':

$$E_{\text{final}} = E - \lambda \cdot E' \quad (7)$$

where λ is a hyperparameter that controls the effect of the mention surfaces that we want to reduce.

Hyperparameter	Value
learning rate	3e-5
batch size	56
max sequence length	300
dropout	0.05
description embeddings dim.	300
# training steps	1M
# candidates	30
# entity types	1400
mention transformer init.	roberta-base
# mention encoder layers	12
description transformer init.	roberta-base
# description encoder layers	2
# description tokens	32
mention mask prob.	0.0
$(\lambda_2, \lambda_3, \lambda_4)$	(1, 0.01, 1)
μ	0.1

Table 3: ReFinED with CFT hyperparameters.

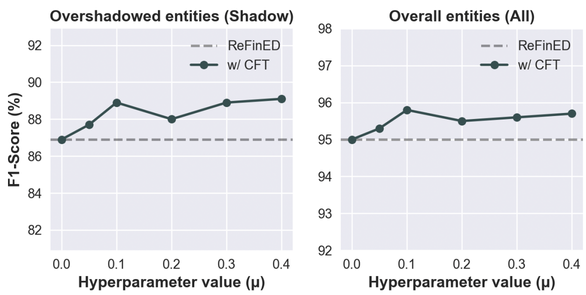

Figure 4: Results of ReFinED with CFT with different μ values on the validation set of AIDA dataset.

A.2 Hyperparameter details

To train our model (ReFinED with CFT), we trained the model using the hyperparameters setting in Table 3 following the original ReFinED setting.

We performed a hyperparameter search for μ in a range of [0.05, 0.1, 0.2, 0.3, 0.4] on the validation set of AIDA-CoNLL, we got the best value of 0.1 as shown in Figure 4. We reduced the *batch size* from 64 to 56 due to the additional memory requirement of CFT during the training. Since this paper focuses on entity disambiguation, we omit the mention detection module. The model has approximately 154M parameters. The training took approximately 87 hours on an A100 GPU.

A.3 Datasets statistics

Table 4 shows the InKB statistics of each test dataset. The overshadowed entities are determined using entity prior collected from the training dataset of ReFinED. The standard set contains long article ED datasets that have approximately 24.5 mentions and 564.9 words per query. The challenge set contains short sentence ED datasets that have approximately 1.3 mentions and 17.9 words per query. The standard and challenge sets have similar proportion of overshadowed entities, 30.1% and 27.4%, respectively.

	Mentions		**Seq. Length**	**Shadow**
Dataset	Count	Mean	Mean	%
Standard Set				
AIDA	4,464	19.4	177.2	28.8%
MSNBC	651	32.6	565.9	12.6%
AQUAINT	719	14.4	220.5	13.1%
ACE2004	253	7.2	375.5	18.2%
CWEB	11,035	34.5	1,212.3	31.1%
WIKI	6,734	21.1	269.8	33.5%
Avg.	23,856	24.5	564.9	30.1%
Challenge Set				
TWEEKI	860	1.8	16.4	24.1%
MINTAKA	5,703	1.5	10.1	17.1%
SLINK	2,674	1.0	29.7	50.5%
Avg.	9,237	1.3	17.9	27.4%

Table 4: Statistics of test datasets.

A.4 Case Study and Analysis

To comprehend how our debiasing method (CFT) can outperform the best current method (KBED) on overshadowed entities, we analyze the predictions of our method on various scenarios of overshadowed entities compared with other methods. In Table 6, example 1 illustrates the situation when an overshadowed entity *Guardian newspaper (Nigerian independent daily newspaper)* appears in a text with related entities in context, i.e., *Lagos (Largest city in Nigeria)*. In this case, both CFT and KBED can resolve the overshadowed entity *Guardian newspaper (Nigerian independent daily newspaper)* correctly as they are sufficient contextual information, allowing KBED to perform reasoning over KB facts.In contrast, example 2 demonstrates the situation when an overshadowed entity appears in a text without related entities, disabling KBED from performing reasoning. This results in KBED predicting an incorrect entity while CFT can still resolve the entity correctly. These findings show that, compared to KBED, CFT can resolve overshadowed entities in a broader range of scenarios, making it outperforms KBED, especially in short texts with few mentions.

Finally, we examine failed cases of our method for overshadowed and non-overshadowed entities compared with other methods. In Table 6, example 3 demonstrates the case when all methods fail to resolve an overshadowed entity. Interestingly, they predict entities that suit the context well and are semantically similar to the gold entity label. Example 4 demonstrates a fail case when our method and KBED fail to resolve a non-overshadowed entity in a context containing entities that related to incorrect entities, e.g., *Foreign minister (Ministry of Foreign Affairs of Iran)* is located in *Iran (Country in Western Asia)*. Both CFT and KBED predict a specific entity that suits the context but is mismatched with the gold label. These findings show the problem of annotations in ED datasets where multiple entities in KB are correct answers.

A.5 Scalability Study

Table 5 shows the statistics of each octile in Figure 3. The octiles are created by ranking queries from seven datasets: AIDA, MSNBC, AQUAINT, ACE2004, CWEB, WIKI, and TWEEKI, in ascending order according to the number of mentions in queries, then divided into eight equal-sized octiles.

	Queries	**Number of Mentions**		
Octile	Count	Min	Max	Mean ± Std.
1	549	1	1	1.0 ± 0.0
2	549	1	2	1.7 ± 0.5
3	549	2	5	3.2 ± 1.0
4	549	5	16	11.4 ± 3.2
5	549	16	21	18.7 ± 1.6
6	549	21	27	23.7 ± 1.8
7	549	27	36	31.2 ± 2.6
8	537	36	114	45.1 ± 10.4

Table 5: Statistics of octiles.

No.	Example	Prediction
1	*... An Air Afrique Boeing-727 jet was the third passenger liner looted in the past month by armed robbers while awaiting takeoff at Nigeria's largest international airport, the <u>Lagos</u>* ***Guardian newspaper*** *reported on Thursday. The thieves broke into the aircraft's luggage compartment and escaped with a large quantity of baggage as the plane was awaiting permission to take off ...*	Entity Prior → Q11148 × ReFinED → Q11148 × w/ KBED → Q7738431 ✓ w/ **CFT** → Q7738431 ✓
Remark: *Q7738431 (Nigerian independent daily newspaper), Q11148 (British national daily newspaper)		
2	*... Word of the agreement leaked out when former captain Courtney Walsh, head of the* ***West Indies*** *players association, told the Caribbean News Agency that Lara and Hooper had been reinstated and the tour was going ahead. The crisis came to a head last Wednesday when the West Indies Cricket Board fired superstar batsman Lara as captain and Hooper as vice-captain. The two ...*	Entity Prior → Q669037 × ReFinED → Q920396 × w/ KBED → Q920396 × w/ **CFT** → Q912881 ✓
Remark: *Q912881 (West Indies cricket team), Q669037 (West Indies) Q920396 (British West Indies)		
3	*... Saban was introduced as Alabama's coach on Thursday, touting his championship aspirations and citing his love of college football as a reason for taking a pay cut to leave the Miami Dolphins.* ***Alabama*** *has had four losing seasons since '97. "His teams always play with confidence and pride and I know that in order to win a national championship, a team has to be mentally as well as ...*	Entity Prior → Q173 × ReFinED → Q4705216 × w/ KBED → Q4705216 × w/ **CFT** → Q4705216 ×
Remark: *Q492318 (University of Alabama), Q4705216 (Alabama Crimson Tide football), Q173 (State of the United States of America)		
4	*... <u>Iran</u> will protest to the International Court of Justice at the Hague and other global bodies about the U.S.-funded Radio Free Europe, the Iran Daily reported Monday. It quoted* ***Foreign Minister*** *Kamal Kharrazi as saying the radio "was set up to interfere in Iran's internal affairs" It did not say when the complaints will be filed. The English-language daily also did not say ...*	Entity Prior → Q7330070 ✓ ReFinED → Q7330070 ✓ w/ KBED → Q2565708 × w/ **CFT** → Q2565708 ×
Remark: *Q7330070 (Foreign minister), Q2565708 (Ministry of Foreign Affairs of Iran)		

Table 6: Case studies for our debiasing method on ED datasets. We highlight the target entity and related context entities with **bold** and <u>underline</u> respectively. * indicates the gold entity label.