Personal Entity, Concept, and Named Entity Linking in Conversations

Hideaki Joko
Radboud University
hideaki.joko@ru.nl

Faegheh Hasibi
Radboud University
f.hasibi@cs.ru.nl

ABSTRACT
Building conversational agents that can have natural and knowledge-grounded interactions with humans requires understanding user utterances. Entity Linking (EL) is an effective technique for understanding natural language text and connecting it to external knowledge. It is, however, shown that the existing EL methods developed for annotating documents are suboptimal for conversations, where concepts and personal entities (e.g., “my cars”) are essential for understanding user utterances. In this paper, we introduce a collection and a tool for entity linking in conversations. We provide EL annotations for 1,327 conversational utterances, consisting of links to named entities, concepts, and personal entities. The dataset is used for training our toolkit for conversational entity linking, CREL. Unlike existing EL methods, CREL is developed to identify both named entities and concepts. It also utilizes coreference resolution techniques to identify personal entities and their references to the explicit entity mentions in the conversations. We compare CREL with state-of-the-art techniques and show that it outperforms all existing baselines.

CCS CONCEPTS
• Information systems → Users and interactive retrieval; Question answering; Information extraction.

KEYWORDS
Entity Linking; Conversational System; Datasets

ACM Reference Format:
Hideaki Joko and Faegheh Hasibi. 2022. Personal Entity, Concept, and Named Entity Linking in Conversations. In Proceedings of the 31st ACM Int’l Conference on Information and Knowledge Management (CIKM ’22), Oct. 17–21, 2022, Atlanta, GA, USA. ACM, New York, NY, USA, 5 pages.
https://doi.org/10.1145/3511808.3557667

1 INTRODUCTION
Understanding user utterances in conversational systems is fundamental to creating natural and informative interactions with users. Entity Linking (EL) is a powerful text understanding technique that has been extensively explored in previous studies [12, 25] and has been shown to be effective in question-answering and retrieval tasks [4, 5, 9, 10, 31, 34]. However, the EL approaches developed for documents prove to be suboptimal for conversations, to the extent that the state-of-the-art EL models are outperformed by the outdated models when evaluated on conversational EL datasets [12]. The reasons are three-fold: (i) Personal Entity Annotation: Conversations often contain personal statements, referring to entities by their pronouns; e.g., “my cars.” Identifying personal entities is essential for building personal knowledge graphs [1, 19, 27, 28] and also generating personalized responses to users [13, 22]. Existing approaches for annotating documents, or even conversations [16, 25, 32], do not identify and link personal entity mentions. (ii) Concept Annotation: EL models developed for documents or short texts focus mainly on annotating named entities [3, 29]. In conversations, however, both named entities and concepts contribute to machine understanding of text [12] and should be annotated. (iii) Training Data: Existing EL approaches are trained on well-written texts, while conversations have multiple (informal) turns with information spread over the turns.

In this paper, we overcome the above challenges and provide a toolkit and a training dataset as two resources for EL in conversations. The challenges are addressed in the following ways.

Personal Entity Annotation. We detect personal entity mentions (e.g., “my cars”), find their corresponding explicit entity mentions (e.g., “Life” and “Pilot”), and link them to the corresponding entities in the knowledge graph (see Figure 1). This task and coreference resolution both connect and stand in contrast to each other: they both aim to find mentions referring to the same entity [14, 15, 18, 26], but personal entity mentions are sparse and different from common pronominal expressions that are resolved in coreference resolution. This implies that state-of-the-art coreference resolution methods cannot be used out-of-box for resolving personal entities. We, therefore, identify personal entity mentions in a separate module and modify coreference resolution techniques to map personal entities to their explicit entity mentions.

Concept Annotation. While open-domain knowledge graphs (e.g., Wikipedia) contain both named entities and concepts, conventional EL approaches are optimized for annotating only named...
entities, which hampers their performance for annotating conver-
sations [3, 29, 30, 36]. Specifically, the performance of named entity
and concept linking in the widely used REL entity linker [29] varies
dramatically (F-score of 43.1 and 2.5, respectively). We mitigate this
problem by training a mention detection model that can identify
both concepts and named entity mentions in conversations and
optimize the entity disambiguation model of REL [29] for all entity
types. Our methods for personal entity, concept and named entity
linking are integrated into our conversational EL tool, which is pro-
vided as a resource to the community. We show that this method
outperforms state-of-the-art EL models.

Training Data. A key to solving the aforementioned problems
is training data. Existing studies on conversational entity linking
either use private proprietary datasets [25] or public datasets with
insufficient number of conversations for both training and evalua-
tion purposes [12]. In this work, we build on the existing ConEL
dataset [12] and address its shortcomings in our new dataset: (i)
In ConEL, each personal entity mention is only to a single
explicit entity, while in real conversations, personal entity mentions
can have multiple corresponding entities (see Figure 1); (ii) ConEL
contains a limited number of conversations with personal entities,
as it synthesizes conversations mainly from question-answering
and task-oriented benchmarks with a limited number of personal
statements. Additionally, the ConEL-PE dataset [12], generated by
annotating real social chats, contains only 25 annotated conver-
sations, which cannot be used for training purposes. Our newly
developed dataset, referred to as ConEL-2, consists of 1,327 utter-
ces, annotated with personal entities, concepts, and named enti-
ties. This dataset has been used for training and evaluation of our
conversational EL tool.

In summary, this work makes the following resources available
to the community:

• An open-source tool for entity linking in conversations, which
can uniquely identify personal entities, concepts, and named
entities. Our developed conversational EL methods outperform
state-of-the-art baselines.
• A dataset containing EL annotations for conversations, which
can be used for training and evaluation purposes.

2 METHOD
Our conversational entity linking approach consists of two compo-
nents; (1) personal entity linking, and (2) concept and named entity
linking.

2.1 Personal Entity Linking
Inpired by coreference resolution approaches [14, 15, 17, 18], our
model identifies personal entity mentions and their entity antecedents
from conversation history. We disentangle mention detection from
entity antecedent assignment and employ a BERT-based model (cf. Sect. 2.2) for detecting entity mentions and a rule-based ap-
proach [19] for identifying personal entity mentions. Specifically,
we follow Joko et al. [12] to identify personal mentions, starting
with “my” or “our” tokens followed by adjectives, common nouns,
proper nouns, pronouns, numbers, particles, and articles. Also, “of”
and “in” are allowed to be part of the mention. While admittedly
this approach cannot capture all forms of personal entity mentions,
we believe that it covers a reasonably large number of cases to be
used for early experimentation in this direction. We leave the com-
prehensive research on different forms of personal entity mention
for future work.

Similar to [15], we denote the start (s) and end token (e) represen-
tations of mentions as:

\[ m^s = \text{ReLU}(W^s o) \quad m^e = \text{ReLU}(W^e o), \]

where \( W^s \) and \( W^e \) are trainable weights and \( o \) is contextualized
representation of a token. We use LongFormer [2] to obtain contextu-
alized embeddings as it can accommodate the long conversation
history. The input to the LongFormer model is the current turn and
conversational history. The hidden state in the output of the last
layer of the model is used as \( o \).

Assuming mention \( m_{bf} \) appears before mention \( m_{af} \), the
compatibility score between the two mentions is computed by:

\[ \text{score}(m_{bf}, m_{af}) = m_{bf} \cdot B^s \cdot m_{af} + m_{bf} \cdot B^e \cdot m_{af} \]
\[ + m_e \cdot B^s \cdot m_{af} + m_e \cdot B^e \cdot m_{af}, \]

where \( B \) represents trainable weights and the superscripts \( s \) and \( e \)
denote the start and end tokens of a mention. Equation 2 is com-
puted for all pairs of personal entity mentions and explicit entity
mentions. During inference, personal and explicit entity mention
pairs with the score higher than threshold \( \tau \) are selected.

2.2 Concept and Named Entity Linking
Entity linking typically involves two subtasks: (i) identifying men-
tion boundaries and (ii) disambiguating mentions using a knowl-
dge graph. In order to utilize existing advancements on these two
subtasks, we need to adapt them to the conversational setup. For
mention detection (MD), this translates to adapting MD models to
the conversational domain and identifying mentions of both named
entities and concepts. We employ the vanilla BERT [6] architecture
and fine-tune it to predict BIO labels, corresponding to begin, inside,
and outside of mentions. The BERT model utilized in this work is
pre-trained on conversational datasets such as DailyDialogues [20],
OpenSubtitles [21], Debates [35], and Blogs [24].

For entity disambiguation, we train REL [29] disambiguation
approach on our ConEL-2 dataset. REL is one of the state-of-the-
art EL tools that is optimized for document annotation, but its
disambiguation approach, considering both the local and global
context of mentions, can be seamlessly adapted to conversations.
Our entity linking method, consisting of the aforementioned MD
and ED models is named CREL, which is an extension of REL tool
for conversations.

3 THE CONEL-2 COLLECTION
To Facilitate the development of EL approaches for conversations,
we construct the ConEL-2 collection. We draw the conversations
from an existing conversational dataset. To select the dataset, we
focus on social chat datasets, as personal entities are mainly found
in social chat conversations [12]. We choose the Wizard of Wikipedia
(WoW) [7] dataset, which contains multi-domain multi-turn con-
versations collected from actual interactions between two people.

1https://github.com/informagi/conversational-entity-linking-2022
Step 1: Read this dialogue.

SYSTEM: I think science fiction is an amazing genre for anything.
USER: I'm a huge fan of science fiction myself!
SYSTEM: Awesome! I really love how sci-fi storytellers focus on ...
USER: I agree. My favorite theme of science fiction is time travel.

Step 2: Select the appropriate text span that represents the user's personal object or thing that can be referred to.

- My favorite
- My favorite theme
- ...
- My favorite theme of science fiction
- None of the above

Figure 2: Annotation interface for identifying personal entity mentions (stage 1 of annotation process).

Table 1: Statistics of the ConEL-2 collection. Personal entity annotations represent the number of annotations for personal entity mentions, with or without corresponding explicit entity mention in the dialogue.

|                        | Train | Val | Test |
|------------------------|-------|-----|------|
| Conversations          | 174   | 58  | 58   |
| User utterances        | 800   | 267 | 260  |
| NE and concept annotations | 1428 | 523 | 452  |
| Personal entity annotations | 268  | 89  | 73   |

The selected dialogues are annotated in three stages: (i) identifying personal entity mentions, (ii) pairing personal and explicit entity mentions, and (iii) entity linking. Unless stated otherwise, each HIT is annotated by three turkers, and additional turkers are added when needed based on our quality check strategies.

Stage 1: Identifying personal entity mentions. In this stage, we ask turkers to identify text spans referring to personal entities (i.e., personal entity mentions). First, we extract conversations that contain “my” or “our” in at least one user utterance, which amounts to 7,888 out of 22,311 conversations in the WoW dataset. To make the annotation process technically and financially feasible, we randomly select 1,000 conversations from the extracted dialogues. We then show the dialogue history and a set of candidate mentions to the turkers and ask them to find the best personal entity mention; the interface is shown in Fig. 2. Candidate mentions are text spans starting with “my” or “our,” followed by a maximum of 10 subsequent words. Our statistics on the collected annotations show that 98.9% of the HITs were agreed upon by two or more turkers, with a Fleiss’ kappa of 0.839, which highlights the high quality of the annotation process.

Stage 2: Pairing personal and explicit entity mentions. In this stage, we ask turkers to find the corresponding explicit entity mention for a given personal entity mention. For example, in Figure 1, the personal entity mention “my cars” is shown to turkers, and they are asked to find the corresponding explicit entity mention “Life” and “Pilot.” We create a pool of candidate explicit entity mentions by using existing EL tools: TagMe [8], WAT [23], REL [29], and GENRE [3]. The detected mentions are manually processed and meaningless duplicates such as “a restaurant” and “restaurant” are resolved. Turkers are then given the option to select one corresponding explicit entity mention or the “not in dialogue” option if the corresponding entity mention is not found in the dialogue. Fleiss’ kappa for the inter-annotator agreement is 0.434, which is considered moderate. To improve the annotation quality, two extra annotations are collected for HITs where two turkers agreed on one option. We then select all conversations with equal or more than three turkers agreed on one option (either an explicit entity mention or the "not in dialogue" option). This selection amounts to 290 conversations, which are passed to the next step.

Stage 3: Entity linking. In this stage, we ask turkers to select the corresponding Wikipedia article to the given entity mention, e.g., mapping the mention “car dealers” to the entity Car dealership in Figure 1. We first use the EL tools described in the stage 2 to create the pool of candidate mention-entity pairs. Noisy mentions such as “please” and “I am” are manually removed from the pool. We also include top-10 Wikipedia search results using mentions as queries. Turkers are then asked to select one of the candidate entities for each entity mention if any.

The statistics show 98.7% of the HITs were agreed by two or more turkers (Fleiss’ kappa of 0.839), which highlights the high quality of our annotation process. We therefore include all annotation results which are agreed by at least two turkers. For the remaining 1.3% of the non-agreed HITs, we recollected two extra annotations for each and select the entity that is selected by the majority of turkers. The annotation results are shown in Table 1. We split the dataset to train, validation, and test set with the 60%-20%-20% ratio.

Table 2: Personal entity linking results. Micro-averaged precision, recall, and F1 scores are computed.

|                  | ConEL-2 (Val) | ConEL-2 (Test) | ConEL-PE |
|------------------|---------------|----------------|----------|
|                  | P  | R  | F  | P  | R  | F  | P  | R  | F  |
| S2E [15]         | .375 | .415 | .394 | .292 | .302 | .297 | .317 | .481 | .382 |
| W2V [12]         | .324 | .508 | .395 | .458 | .429 | .443 | .436 | .630 | .515 |
| S2E_{conv}       | .494 | .615 | .548 | .450 | .571 | .503 | .400 | .741 | .519 |
| S2E_{conv}       | .714 | .538 | .614 | .673 | .524 | .589 | .613 | .704 | .655 |

4 RESULTS

4.1 Personal Entity Linking

Experimental Setup. We take the LongFormer-large model3 [2] pre-trained on OntoNote Release 5.0 [11], and fine-tune it on the training set of the ConEL-2 dataset. This model is referred to as S2E_{conv}. We perform training with the batch size of 8 and learning rate of 1e-5 using AdamW optimizer, and the validation set of

3https://www.mediawiki.org/wiki/API:Main_page
4https://huggingface.co/allenai/longformer-large-4096
Table 3: Concept and named entity linking results. $F_{\text{MD}}$ and $F_{\text{EL}}$ represent the micro-averaged F1 scores for mention detection and entity linking, respectively.

|          | ConEL-2 (Val) | ConEL-2 (Test) | ConEL |
|----------|---------------|----------------|--------|
|          | $F_{\text{MD}}$ | $F_{\text{EL}}$ | $F_{\text{MD}}$ | $F_{\text{EL}}$ | $F_{\text{MD}}$ | $F_{\text{EL}}$ |
| GENRE [3] | 0.56 | 0.49 | 0.56 | 0.50 | 0.56 | 0.50 |
| REL [29] | 0.54 | 0.47 | 0.54 | 0.47 | 0.54 | 0.47 |
| TagMe [8] | 0.52 | 0.45 | 0.52 | 0.45 | 0.52 | 0.45 |
| WAT [23] | 0.50 | 0.43 | 0.50 | 0.43 | 0.50 | 0.43 |
| REL* (BERT$_\text{conv}$) | 0.74 | 0.65 | 0.74 | 0.65 | 0.74 | 0.65 |
| REL* (BERT$_\text{WP-conv}$) | 0.72 | 0.64 | 0.72 | 0.64 | 0.72 | 0.64 |
| REL* (BERT$_\text{NER-conv}$) | 0.72 | 0.65 | 0.72 | 0.65 | 0.72 | 0.65 |
| CREL | 0.72 | 0.65 | 0.72 | 0.65 | 0.72 | 0.65 |

Table 4: Overall entity linking results, annotating both personal entities (PE) and concepts and named entities (EL).

|          | ConEL-2 (Val) | ConEL-2 (Test) | ConEL-PE |
|----------|---------------|----------------|----------|
|          | $F_{\text{MD}}$ | $F_{\text{EL}}$ | $F_{\text{MD}}$ | $F_{\text{EL}}$ | $F_{\text{MD}}$ | $F_{\text{EL}}$ |
| REL W2V | 0.52 | 0.45 | 0.52 | 0.45 | 0.52 | 0.45 |
| REL S2E$_\text{conv}$ | 0.52 | 0.45 | 0.52 | 0.45 | 0.52 | 0.45 |
| GENRE W2V | 0.48 | 0.41 | 0.48 | 0.41 | 0.48 | 0.41 |
| GENRE S2E$_\text{conv}$ | 0.48 | 0.41 | 0.48 | 0.41 | 0.48 | 0.41 |
| TagMe W2V | 0.50 | 0.43 | 0.50 | 0.43 | 0.50 | 0.43 |
| TagMe S2E$_\text{conv}$ | 0.50 | 0.43 | 0.50 | 0.43 | 0.50 | 0.43 |
| WAT W2V | 0.50 | 0.43 | 0.50 | 0.43 | 0.50 | 0.43 |
| WAT S2E$_\text{conv}$ | 0.50 | 0.43 | 0.50 | 0.43 | 0.50 | 0.43 |
| CREL W2V | 0.72 | 0.65 | 0.72 | 0.65 | 0.72 | 0.65 |
| CREL S2E$_\text{conv}$ | 0.72 | 0.65 | 0.72 | 0.65 | 0.72 | 0.65 |

ConEL-2 is used for early stopping. For evaluation, we use validation and test sets of the ConEL-2 datasets as well as the ConEL-PE dataset [12]. ConEL-PE contains 25 dialogues from the WoW dataset. We only use personal entity annotations for this evaluation.

Baselines. We compare our model with the Wikipedia2Vec-based method (W2V) [12], where antecedent assignment is based on similarity between Wikipedia2vec [33] embeddings of entities and personal entity mentions. We also report on the official S2E model [15] and its variation S2E$_\text{conv}$, where fine-tuning is performed only on our conversational dataset (without using OntoNote dataset).

Results. We measured the performance of our rule-based personal entity mention detection approach and obtained micro-averaged precision, recall, and F1 of 0.908, 0.898, and 0.903, respectively. This indicates that identifying personal entity mentions can be handled effectively by a simple approach. Assigning entity antecedents, on the hand, is a challenging task.

Table 2 shows the results for personal entity linking. We observe that S2E$_\text{conv}$ fine-tuned on both OntoNote and conversational datasets outperforms all baselines. It also indicates that, fine-tuning on conversational data substantially improves personal entity linking performance (S2E vs. S2E$_\text{conv}$ results).

42 Concept and Named Entity Linking

Experimental Setup. For mention detection, we fine-tune bert-base-conversational on our training data with the batch size of 16, learning rate of 5e-5, and AdamW optimizer, with the validation set of ConEL-2 for early stopping. For ED, we train the REL ED model, following the same training procedure as van Hulst et al. [29]. As input for these models, we use only current turns for efficiency; although using the entire conversation history has shown slightly better performance [12], it doesn’t change our conclusion, as it mainly benefits REL, with marginal benefits for WAT and TagMe. For evaluation, we use the ConEL-2 and ConEL [12] datasets. ConEL consists of 100 conversations that are collected from three different conversational tasks (question answering, task-oriented, and social chat) and annotated with concepts and named entities. Only concept and named entity annotations are used for this evaluation.

Baselines. REL [29], GENRE [3], TagMe [8], and WAT [23] are strong publicly available EL tools that are used as our baselines. Additionally, we train three BERT-based MD models: (i) BERT$_\text{conv}$: The bert-base-uncased model, fine-tuned on our training data, (ii) BERT$_\text{WP-conv}$: Similar to BERT$_\text{conv}$, but fine-tuned on the Wikipedia anchor links from [3] before fine-tuning on ConEL-2 training data, and (iii) BERT$_\text{NER-conv}$: The bert-base-NER model, fine-tuned on our training data. The fine-tuning procedures are the same as CREL. We combine these models with the REL ED model trained on conversations (denoted as REL*) and report on their results.

Results. The results are reported in Table 3. $F_{\text{MD}}$ and $F_{\text{EL}}$ are the F1 scores for MD and EL, respectively. The results show that the REL and GENRE, while being state-of-the-art EL toolskits, perform worse than TagMe and WAT. This is because REL and GENRE are intended to detect only NEs, while TagMe and WAT are able to identify concepts as well. Comparing CREL with REL* methods, we observe that adaptation of BERT for conversational domain plays an important role in conversational entity linking, reflected by the highest score for ConEL-2 (test) and ConEL datasets.

4.3 Overall Performance

Putting all the pieces together, we report on the overall performance of our model for linking personal entities, concepts and NEs. For this experiment, we report only on the ConEL-2 and ConEL-PE datasets, as ConEL does not have annotations for personal entities. The results are shown in Table 4. We notice at first glance that our proposed personal entity linking extension (S2E$_\text{conv}$) leads to improved F-scores compared to W2V in most cases. The results also show that our EL tool (CREL with S2E$_\text{conv}$) achieves the highest F-score for all sets, reinforcing the importance of adapting EL approaches for conversations.

5 CONCLUSION

In this paper, we tackled the problem of entity linking in conversational settings, where not only named entities, but also concepts and
personal entities are important. To this end, we collected conversa-
tional entity annotations, which allows us to train and evaluate
entity linking in conversations. Additionally, based on the collected
annotations, we develop a conversational EL tool. Our empirical
results show that our EL tool achieves the highest performance over
conventional EL tools for documents and short texts. The collected
annotations and our EL tool with detailed instructions are publicly
available as a research resource for further study in conversation.
Future work includes incorporating coreference resolution methods
to identify more diverse personal entity mentions.

REFERENCES
[1] Kristian Balog and Tom Kentor. 2019. Personal Knowledge Graphs: A Research
Agenda. In Proceedings of the 2019 ACM SIGIR International Conference on Theory
of Information Retrieval (ICTIR ’19). 217–220.
[2] In Bletagy, Matthew E. Peters, and Arman Cohanim. 2020. Longformer: The Long-
Document Transformer. arXiv:2004.05190 (2020).
[3] Nicola De Cao, Gautier Iazcard, Sebastian Riedel, and Fabio Petroni. 2021. Autore-
gressive Entity Retrieval. In Proceedings of International Conference on Learning
Representations (ICLR ’21).
[4] Jeffrey Dalton, Laura Diete, and James Allan. 2014. Entity Query Feature Expans-
ion Using Knowledge Base Links. In Proceedings of the 37th International ACM
SIGIR Conference on Research and Development in Information Retrieval (SIGIR
’14). 365–374.
[5] Arash Dargahi Nobari, Arien Askari, Faegheh Hashibi, and Mohamad Neshati.
2018. Query Understanding via Entity Attribute Identification. In Proceedings of the
27th ACM International Conference on Information and Knowledge Management
(SIGKDD ’18). 1759–1762.
[6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT:
Pre-training of Deep Bidirectional Transformers for Language Understanding. In
Proceedings of the 2019 Conference of the North American Chapter of the Association
for Computational Linguistics: Human Language Technologies (NAACL-HLT ’19):
4171–4186.
[7] Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason
Wen. 2020. Wizard of Wikipedia: Knowledge-Powered Conversational Agents.
In International Conference on Learning Representations (ICLR ’19).
[8] Paolo Ferragina and Ugo Scalzo. 2010. TAGE: On-the-fly Annotation of Short Text
Fragments (by Wikipedia Entities). In Proceedings of the 19th ACM International
Conference on Information and Knowledge Management (CIKM ’10). 1625–1628.
[9] Emma J Gerritse, Faegheh Hashibi, and Arjen P. de Vries. 2020. Entity-aware
Transformers for Entity Search. In Proceedings of the 43rd International ACM
SIGIR Conference on Research and Development in Information Retrieval (SIGIR
’20). 1455–1466.
[10] Faegheh Hashibi, Kristian Balog, and Svein Erik Bratsberg. 2016. Exploiting
Entity Linking in Queries for Entity Retrieval. In Proceedings of the 2016 ACM
International Conference on the Theory of Information Retrieval (ICTIR ’16).
209–218.
[11] Eduard Hovy, Mitchell Marcus, Martha Palmer, Lance Ramshaw, and Ralph
Weisschedel. 2006. OntoNotes: The 90% Solution. In Proceedings of the Human-
Language Technology Conference of the NAACL. 57–60.
[12] Hideaki Joko, Faegheh Hashibi, Kristian Balog, and Arjen P. de Vries. 2021.
Conversational Entity Linking: Problem Definition and Datasets. In Proceedings of the
44rd International ACM SIGIR Conference on Research and Development in
Information Retrieval (SIGIR ’21). 2390–2397.
[13] Chaitanya K Joshi, Fei Mi, and Boi Faltings. 2017. Personalization in Goal-oriented
Dialogue. In Proceedings of the NeurIPS’17 Workshop on Conversational AI.
[14] Mandar Joshi, Omer Levy, Luke Zettlemoyer, and Daniel Weld. 2019. BERT for
Coreference Resolution: Baselines and Analysis. In Proceedings of the 2019
Conference on Empirical Methods in Natural Language Processing and the 9th
International Joint Conference on Natural Language Processing (EMNLP-IJCNLP
’19). 5802–5807.
[15] Alkssandr Martinovich, Jonathan Johnston, Xue-Yong Fu, Shashi Bhusan, and
Simon Corson-Cloutier. 2002. BLINK with Elasticsearch for Efficient Entity Linking in
Business Conversations. In Proceedings of the 2002 Conference of the North American
Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT ’22).
[16] Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. 2017. End-to-end
Neural Coreference Resolution. In Proceedings of the 2017 Conference on Empirical
Methods in Natural Language Processing. 188–197.
[17] Kenton Lee, Luheng He, and Luke Zettlemoyer. 2018. Higher-Order Coreference
Resolution with Coarse-to-Fine Inference. In Proceedings of the 2018 Conference of the North American
Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT ’18). 687–692.
[18] X. Li, G. Tur, D. Hakkani-Tür, and Q. Li. 2014. Personal knowledge graph popula-
tion from user utterances in conversational understanding. In 2014 IEEE Spoken
Language Technology Workshop. 224–229.
[19] Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziquang Cao, and Shuzi Ni. 2017.
DailyDialog: A Manually Labelled Multi-turn Dialogue Dataset. In Proceedings of the
Eighth International Joint Conference on Natural Language Processing (IJCNLP
’17). 966–976.
[20] Pierre Lison and Jörg Tiedemann. 2016. OpenSubtitles2016: Extracting Large
Parallel Corpora from Movie and TV Subtitles. In Proceedings of the Tenth Interna-
tional Conference on Language Resources and Evaluation (LREC ’16). 925–939.
[21] Liangchen Luo, Wenhao Huang, Qi Zeng, Zaiqing Nie, and Xu Sun. 2019. Learn-
ing Personalized End-to-end Goal-oriented Dialog. In Proceedings of the AAAI
Conference on Artificial Intelligence (AAAI’19). 6794–6801.
[22] Francesco Puccinno and Paolo Ferragina. 2014. From TagME to WAT: A New
Entity Annotator. In Proceedings of the First International Workshop on Entity
Recognition and Disambiguation. 55–62.
[23] J Schler, M Koppel, S Argamon, and JW Pennebaker. 2006. Effects of Age and Gen-
der on Blogging. In Proceedings of 2006 AAAI Spring Symposium on Computational
Approaches for Analyzing Weblogs.
[24] Mingyue Shang, Xiang Wang, Mihail Eric, Jiaying Chen, Jingyang Wang, Matthew
Welch, Tiantong Deng, Akshay Grewal, Han Wang, Yue Liu, Yang Liu, and
Dilek Hakkani-Tür. 2021. Entity Resolution in Open-domain Conversations. In
Proceedings of the 2021 Conference of the North American Chapter of the Association
for Computational Linguistics: Human Language Technologies (NAACL-HLT ’21).
26–33.
[25]Sameer Singh, Amarnag Subramanhy, Fernando Pereira, and Andrew McCallum.
2011. Large-Scale Cross-Document Coreference Using Distributed Inference and
Hierarchical Models. In Proceedings of the 49th Annual Meeting of the Association
for Computational Linguistics: Human Language Technologies (ACL-HLT ’11). 793–803.
[26] Anna Tigrunova, Andrew Yates, Paramita Mirza, and Gerhard Weikum. 2019.
Listening between the Lines: Learning Personal Attributes from Conversations.
In Proceedings of the World Wide Web Conference (WWW ’19). 1818–1828.
[27] Sameer Singh, Andrew Yates, Paramita Mirza, and Gerhard Weikum. 2020.
CHARM: Inferred Personal Attributes from Conversations. In Proceedings of the
2020 Conference on Empirical Methods in Natural Language Processing (EMNLP).
5391–5404.
[28] Johannes M. van Hulst, Faegheh Hashibi, Koen Derecken, Kristian Balog, and
Arjen P. de Vries. 2020. REL: An Entity Linker Standing on the Shoulders of
Giants. In Proceedings of the 43rd International ACM SIGIR Conference on Research
and Development in Information Retrieval (SIGIR ’20). 2197–2200.
[29] Miled Wu, Fabio Petroni, Martin Jonsdottir, Sebastian Riedel, and Luke Zett-
lemoyer. 2020. Scalable Zero-shot Entity Linking with Dense Entity Retrieval.
In Proceedings of the 2020 Conference on Empirical Methods in Natural Language
Processing (EMNLP). 6397–6407.
[30] Wenwen Xiong, Tie-Yan Liu, and Tie-Yan Liu. 2017. Word-Entity Duet Repre-
sentations for Document Ranking. In Proceedings of the 40th International ACM
SIGIR Conference on Research and Development in Information Retrieval (SIGIR
’17). 763–772.
[31] Liyan Xu and Jinho D Choi. 2020. Online Coreference Resolution for Dialogue
Processing: Improving Mention-Linking on Real-Time Conversations. arXiv
preprint arXiv:2005.10670 (2022).
[32] Ikuya Yamada, Akira Asai, Jin Sakuma, Hiroyuki Shindo, Hideaki Takeda,
Yoshiyuki Takeruji, and Yuji Matsumoto. 2020. Wikipedia2Vec: An Efficient
Toolkit for Learning and Visualizing the Embeddings of Words and Entities from
Wikipedia. In Conference on Empirical Methods in Natural Language Processing (EMNLP ’20). 23–30.
[33] Ruyu Yamada, Ryutaro Tamaki, Hiroyuki Shindo, and Yoshiyuuu Takeruji.
2018. Studio Osias’s Quiz Bowl Question Answering System. In Proceedings of the
NIPS’17 Competition: Building Intelligent Systems. 181–194.
[34] Justin Zhang, Ravi Kumar, Sojith Ravi, and Cristian Danescu-Niculescu-Mizil.
2016. Conversational Flow in Oxford-style Debates. In Proceedings of the 2016
Conference of the North American Chapter of the Association for Computational
Linguistics: Human Language Technologies (NAACL-HLT ’16). 136–141.
[35] Wenzheng Zhang, Wenjie Liu, and Carl Stratos. 2021. EMQA: Entity Linking as
Question Answering. In Proceedings of the International Conference on Learning
Representations (ICLR ’22).

Personal Entity, Concept, and Named Entity Linking in Conversations

CIKM ’22, October 17–21, 2022, Atlanta, GA, USA