KARL-Trans-NER: Knowledge Aware Representation Learning for Named Entity Recognition using Transformers

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Abstract

The inception of modeling contextual information using models such as BERT, ELMo, and Flair has significantly improved representation learning for words. It has also given SOTA results in almost every NLP task — Machine Translation, Text Summarization and Named Entity Recognition, to name a few. In this work, in addition to using these dominant context-aware representations, we propose a Knowledge Aware Representation Learning (KARL) Network for Named Entity Recognition (NER). We discuss the challenges of using existing methods in incorporating world knowledge for NER and show how our proposed methods could be leveraged to overcome those challenges. KARL is based on a Transformer Encoder that utilizes large knowledge bases represented as fact triplets, converts them to a graph context, and extracts essential entity information residing inside to generate contextualized triplet representation for feature augmentation. Experimental results show that the augmentation done using KARL can considerably boost the performance of our NER system and achieve significantly better results than existing approaches in the literature on three publicly available NER datasets, namely CoNLL 2003, CoNLL++, and OntoNotes v5. We also observe better generalization and application to a real-world setting from KARL on unseen entities.

Introduction

Named Entity Recognition (NER) is the task of locating and classifying named entities in a given piece of text into predefined entity categories such as Person (PER), Location (LOC), Organisation (ORG), etc. NER is considered an essential preprocessing step that can benefit many downstream applications in Natural Language Processing (NLP), such as Machine Translation (Babych and Hartley 2003), Information Retrieval (Antony and GS 2015) and Text Classification (Armour, Japkowicz, and Matwin 2005).

Over the past few years, Deep Learning has been the key to solving not only NER but many other NLP applications (Le et al. 2018; Kouris, Alexandridis, and Stafylopatis 2019). On the downside, these models also demand a lot of well-structured and annotated data for their training. This restricts the applicability of trained models to a real-world scenario as the model’s behavior and predictions become very specific to the type of data they are trained on. To conquer this, many studies have recently evolved that focus on building models that can incorporate world knowledge for enhanced modeling and inference on the task at hand, such as He et al. (2020) for NER, Denk and Peleteiro Ramallo (2020) for Representation Learning and Kim et al. (2015) for Dependency Parsing, etc.

Although recent works in literature have successfully incorporated world knowledge for Sequence Labeling (He et al. 2020), they come with certain limitations, which we discuss ahead. First, as words in a language can be polysemous (Lin et al. 2002), entities and relations in a knowledge graph can be polysemous too (Xiao, Huang, and Zhu 2016). To introduce Knowledge Graph Embeddings (KGEs), we noticed that previously proposed approaches have primarily used pre-trained static embeddings obtained from extensive sources such as Wikidata. KGEs in these models fundamentally relies on the assumption that the tail entity is a linear transformation of the head entity and the relation, making them non-contextualized in nature. Second, we noticed that prior work only considered head-entity and relation embedding to get the knowledge graph embedding and ignored the tail-entity of the triplet completely. Dropping the tail entity entirely could lead to a potential loss of information. We observed that in addition to carrying information about the triplet itself, the head-relation-tail also helps in understanding and extracting implicit relationships existing between entities across triplets. Therefore, the model must know where the head and the relation are leaning towards to achieve accurate embedding estimation. The final limitation lies in applying a Recurrent architecture to obtain KGEs, introducing time inefficiency and a high computation cost (Annervaz, Chowdhury, and Dukkipati 2018).

To further understand the importance and our motivation behind using world knowledge for NER, consider a couple of examples mentioned below.

A: Google announced the launch of Maps.
B: Pichai announced the launch of Maps.

In the training phase, the significant contextual overlap between sentences can confuse the model in labeling the named entities correctly. The model is likely to memorize sentence templates rather than learn to predict correct entity labels, leading to misclassifications. Also, suppose we trained our NER model on an out-of-domain NER
dataset. In that case, the model would have hardly received any information from the training set that "Google" is an organization and "Pichai" indicates a Person.

A: Berlin died in Season 2 of Money Heist.
B: Messi saved Barcelona with an equalizer.

In the first sentence above, "Berlin" refers to a person, whereas in the second sentence, "Barcelona" refers to an organization. There are reasonable chances of misclassification in these two sentences because of a high probability of training data missing such nuance differences in all the possible entity tags for a named entity.

From the examples mentioned above, we can infer that for the model to be aware of such subtle differences, we should provide it with the ability to look up relevant details from a reliable source. Therefore, world knowledge can open the gates for the model to access such information and learn details about entities that it might never come across in the training data. In addition to this, with access to structured world knowledge, far better applicability to a real-world setting can be expected.

Setting these points as our objective, in this work, we propose Knowledge Aware Representational Learning Network for Named Entity Recognition using Transformer (KARL-Trans-NER), which

1. Encodes the entities and relations existing in a knowledge base using a self-attention network to obtain Knowledge Graph Embeddings (KGEs). The embeddings thus obtained are dynamic and fully contextualized in nature.
2. Takes the encoded contextualized representations for entities and relations and generates a knowledge-aware representation for words. The representation obtained, which we also call "Global Representation" for words, can be augmented with the other underlying features to boost the NER model's performance.
3. Generates sentence embeddings using BERT by fusing task-specific information through NER tag embeddings.
4. And lastly, relies on a Transformer as its context encoder incorporating direction-aware, distance-aware, and unscaled attention for enhanced encoder representation learning.

To verify the effectiveness of our proposed model, we conduct our experiments on three publicly available datasets for NER. These are CoNLL 2003 (Sang and Meulder 2003), CoNLL++ (Wang et al. 2019) and OntoNotes v5 (Pradhan et al. 2013). Experimental results show that the global embeddings generated for every word using KARL, when used for feature augmentation, can result in significant performance gains of over 0.35-0.5 $F_1$ on all the three NER datasets. Also, to validate the model's generalizability and applicability in a real-world setting, we generate the model's prediction on random texts taken from the web. Results suggest that incorporating world knowledge enables the model to make accurate predictions for every entity in the sentence.

Related work
The research community in NER moved from approaches using character and word representations (Yao et al. 2015; Zhou et al. 2017) to sentence-level contextual representations (Yang, Zhang, and Dong 2017; Zhang, Liu, and Song 2018), and recently to document-level representations as proposed by Qian et al. (2018) and Akbik, Blythe, and Vollgraf (2018). Expanding the scope of embeddings from character and word level to document level has shown significant improvements in the results for many NLP tasks, including NER (Luo, Xiao, and Zhao 2019). To expand the scope further, researchers have explored external knowledge bases to learn facts existing in the universe that may not be present in the training data (Annervaz, Chowdhury, and Dukkipati 2018; He et al. 2020).

Incorporating information present in Knowledge Graph is an emerging research topic in NLP. While some methods focus on graph structure encoding (Lin et al. 2015; Das et al. 2017), others focus on learning entity-relationship embeddings (Wang et al. 2020a; Jiang, Wang, and Wang 2019). Zhong et al. (2015) proposed an alignment model for jointly embedding a knowledge base and a text corpus that achieved better or comparable performance on four NLP tasks: link prediction, triplet classification, relational fact extraction, and analogy reasoning. Xiao, Huang, and Zhu (2016) proposed a generative embedding model, TransG, which can discover the latent semantics of a relation and leverage a mixture of related components for generating embedding. They also reported substantial improvements over the state-of-the-art baselines on the task of link prediction.

Lukovnikov et al. (2017) presented a neural network to answer simple questions over large-scale knowledge graphs using a hierarchical word and character-level question encoder. Annervaz, Chowdhury, and Dukkipati (2018) leveraged world knowledge in training task-specific models and proposes a novel convolution-based architecture to reduce the attention space over entities and relations. It outperformed other models on text classification and natural language inference tasks.

Despite producing state-of-the-art results in many NLP tasks, Knowledge Graphs are relatively unexplored for NER. He et al. (2020) introduced a Knowledge-Graph Augmented Word Representation (KAWR). The proposed model encoded the prior knowledge of entities from an external knowledge base into the representation. Though KAWR performed better than its benchmark BERT (Devlin et al. 2018), the model underperformed compared to the SOTA models for NER.

Knowledge Augmented Representation Learning Network
In this section, we describe the end-to-end proposed model for the task of NER (KARL-Trans-NER).

Knowledge Graph Embedding Model
World Knowledge is represented in the form of fact triplets in a Knowledge Graph, such as ("Albert Einstein", "BornYear", "1879"). Like any other representation technique, to incorporate the information residing inside these fact triplets, they need to be encoded into a numeral representation. To take into account polysemy and learn graph embeddings as a function of the graph context, we take inspiration from
CoKE (Wang et al. 2020a) and train our knowledge graph embedding model on an entity prediction task using the idea of Masked Language Modeling (Devlin et al. 2018).

**Model Architecture**

Our KGE model is based on a Transformer architecture (Vaswani et al. 2017). The corresponding architecture is shown in Figure 1. Training objective of our KG embedding module is inspired from that of CoKE. Since its application to a task like NER was not straightforward, we designed a character-level rich knowledge graph embeddings to understand the underlying representation of characters in a KG. For. e.g., in the fact-triplet "(BarackObama, HasChild, SashaObama)" , the tokens do not appear the way words do in English sentences. Introducing a character-level representation layer in CoKE can help the model understand the intrinsic character sequence representations of entities and relations alongside word-sequence representation to achieve an enhanced representation learning of the knowledge graph. Also, as a collection of fact triplets in the form of a knowledge graph is an ever-expanding resource, only entity/relation level embeddings will not adapt to newer entities, thereby introducing trouble in obtaining embeddings that were not observed during training the KGEs. We used two different character sequence encoders, one for the entities and another for the relations. Also, instead of feeding sinusoidal positional embeddings with the input embeddings (Vaswani et al. 2017), we adopt relative positional embeddings (Shaw, Uszkoreit, and Vaswani 2018; Dai et al. 2019). Positional embeddings are distance-aware, but they are unaware of the directionality. Our intuition of using relative positional embeddings here relies on the findings of Yan et al. (2019).

**Training Data Preparation**

We are given a Knowledge Graph composed of fact triplets as follows:

\[
KG = \{ <s, r, o> | (s, o) \in E, r \in R \}
\]

where, \(s, o\) is the subject and object entity respectively, \(r\) is the relation between them, \(E\) is the entity set and \(R\) is the relation set. A sequence of tokens or a context is created using each triplet as \(s \rightarrow r \rightarrow o\). All the triplets in the knowledge graph are formulated in this manner to obtain a set of graph contexts as follows:

\[
S = \{(s \rightarrow r \rightarrow o) | (s, o) \in E, r \in R\}
\]

Next, we create the training set \(T\) from \(S\). This is done by replacing each object entity \(o\) in \(S\) with the "[MASK]" token and defining the object entity \(o\) as the prediction label for the triplet as follows:

\[
T = \{ <s, r, [MASK] > | o \}
\]

**Model Training**

Consider an input sequence \(T = (t_1, t_2, t_3)\). First, each token \(t_i\) is passed through its corresponding character level encoder to obtain the character sequence representation. Further, for each token \(t_i\) in the input sequence \(T\), we obtain its word-level representation which is tuned during model’s training.

The character sequence representation \(x_i^{\text{char}}\) and the word-level representation \(x_i^{\text{word}}\) are then concatenated together to obtain the element or the token embedding \(x_i^{\text{ele}}\) for \(t_i\).

\[
x_i^{\text{ele}} = [x_i^{\text{word}}; x_i^{\text{char}}]
\]

The final embedding input \((h_i^0)\) which is given as an input to the transformer encoder for token \(t_i\) is obtained by the element wise sum of its element embedding \(x_i^{\text{ele}}\) and its relative positional embedding \(x_i^{\text{pos}}\).

\[
h_i^0 = x_i^{\text{ele}} + x_i^{\text{pos}}
\]

Once the input representation is generated, it is fed to a transformer encoder with \(L\) successive layers. The hidden state for token \(t_i\) at layer \(j\) is denoted as \(h_i^j\) and is given by:

\[
h_i^j = \text{TransEnc}(h_i^{j-1})^L, j = 1, 2, \ldots, L
\]

We treat the hidden representations obtained at the very last layer as the output of the transformer encoder. This is denoted by \(h_i^L, h^L_2, h^L_3\).

After obtaining the transformer encoder representations of the last layer, \(\{h_i^L\}_{i=1}^3\), we select the encoder representation corresponding to the "[MASK]" token, i.e., \(h_3^L\). This is fed through a feedforward layer, which is followed by softmax classification layer to predict the third token, or the object entity \(t_3\) in \((t_1, t_2, t_3)\). Mathematically, the above feedforward layer and softmax classification layer is defined as follows:

\[
f = W * h_i^L + b,
\]

\[
o = \exp(f_i) / \sum_k \exp(f_k)
\]

Here, \(W \in \mathbb{R}^{V \times D}\) and \(b \in \mathbb{R}^{V \times 1}\) are learnable parameters of the feedforward layer, \(V\) is entity vocabulary size, \(D\) is the hidden size, \(f\) is the output of the feedforward layer and \(o\) is the predicted probabilities through softmax layer over all the entities in the entity vocabulary.

The model is trained using Adam Optimizer (Kingma and Ba 2017) and we define training loss as the cross-entropy loss.
loss (Nasr, Badr, and Joum 2002) between the predicted entity probabilities \( o \) and one-hot ground truth entity \( p \) as follows:

\[
loss = - \sum_k p_k \log o_k
\]

Here, \( p_k \) and \( o_k \) are the \( k^{th} \) components of \( p \) and \( o \) respectively.

**NER Model**

The architecture of the proposed model is shown in Figure 2. We describe each component of our NER model in detail below.

**Input Representation Layer**  Given an input sequence of tokens \( S = (x_1, x_2, \ldots, x_n) \), we first obtain the embeddings by generating features in six different ways of varying scope. These features are defined below:

**Word-level Representations:** For word-level features, we use the pre-trained 100-dimensional Glove Embeddings (Pennington, Socher, and Manning 2014) and tune them during model’s training.

**Character-level Representations:** Using word-level representations alone typically is not considered the best approach to NER (dos Santos and Guimarães 2015) due to the out-of-vocabulary (OOV) problem. To address this, many neural NER systems have shown the effectiveness of incorporating character-level representations for words (Ma and Hovy 2016; Chiu and Nichols 2016). In addition to solving the OOV problem, they also help the model understand the underlying structure of words. This includes learning the arrangement of chars, the distinctive features a named entity follows such as the capitalization of the first letter of named entities, etc. Most works in the literature prefer a CNN-based character-level encoder over an LSTM based encoder (Li et al. 2017). This is because of CNN’s parallelization capabilities and almost similar or even better performance than the latter. To enrich our NER model with character-level features, we adopt IntNet (Xin et al. 2018), a funnel-shaped convolutional neural network. IntNet combines kernels of various sizes to extract different n-grams from words and learn an enhanced representation of words.

The entire network of IntNet comprises a series of convolution blocks, and each block consists of two layers. The first layer is a basic \( N \times 1 \) convolution on the input. The second layer applies convolutions of different kernel sizes on the first layer’s output, concatenates them, and feeds it to the next convolution block.

**Context-level Representations:** To enlighten the model with contextual knowledge, here, we use the dominant pre-trained contextualized embedding model BERT (Devlin et al. 2018). As BERT generates embeddings at the word-piece-level, we take the average of all the word pieces to obtain the contextualized word embedding of a word.

**Sentence-level Representations:** Most sentence embedding learning techniques rely on word-level embeddings to generate sentence-level features (Farouk 2018). For computational ease, some methods compute the average of all the token embeddings in a sentence (Annervaz, Chowdhury, and Dukkipati 2018; Coates and Bollegala 2018) to obtain the sentence representation.

\[
s = \sum_{i=1}^{n} w_i
\]

where,\( n \) in the sequence length and \( w_i \) is the word embedding of token \( i \). Averaging words embeddings neglects the word order information. It also assumes an equal contribution from each word towards the sentence representation. Therefore, it is not the best approach to obtain sentence embeddings.

Sentence transformers proposed by Reimers and Gurevych (2019) generate sentence embeddings using contextualized word embeddings, making them adaptive to new contexts. Though sentence transformers have provided SOTA results in many NLP tasks (Ke et al. 2020; Li et al. 2020b), we believe that these representations could be enhanced by incorporating task-specific information. To achieve this, we adopt the techniques proposed by Wang et al. (2018) and incorporate task-specific information by learning the NER label embeddings. We discuss our approach of generating sentence embeddings using the contextualized word embeddings obtained from BERT in detail below.

We begin by first taking the contextualized representations of words obtained from BERT and linearly projecting them to a different space. Let us denote the obtained representations by \( c = (c_1, c_2, \ldots, c_n) \), where \( c \in \mathbb{R}^{n \times d} \), \( c_i \) denotes the contextualized embedding of word \( i \), \( n \) is the number of words in the sentence and \( d \) is the dimension BERT embeddings were projected to. The next step involves embedding the labels (PER, LOC etc.) to the same space. The unique set of labels in the data are embedded into dense representations. Let these representations be defined as \( l = (l_1, l_2, \ldots, l_m) \).

Here, \( l \in \mathbb{R}^{m \times d} \), \( m \) denotes the number of tag labels and \( d \) is the hidden size.

Next, we apply the label embedding attention over the word representations. Cosine-similarity between each token embeddings \( c_i \) and label embedding \( l_j \) is treated as the com-
patibility function.
\[
simi(c_i, t_j) = \frac{\mathbf{c}_i^T \mathbf{t}_j}{||\mathbf{c}_i|| ||\mathbf{t}_j||}
\]

A convolution operation is applied to the similarities obtained above. This enables the model to capture the behavior of the same label in its neighboring words. In other words, the application of a convolution layer captures the relative spatial information for a particular label over a phrase.

Considering a phrase of length \(2k + 1\) where \(k\) is the kernel size, the convolution for token \(i\) is applied over \(\text{simi}_{(i-k:i+k,:)}\) which is followed by max-pooling. The attention weights for the entire sentence are generated after that by applying softmax operation over the scores. Finally, sentence-level representation \(s\) is computed as the weighted sum of the token embeddings over the attention weights. This is mathematically defined as follows:
\[
scores = \max(W^T \text{simi}_{(i-k:i+k,:)} + b) \\
\alpha = \text{softmax}(scores) \\
s = \sum_{i=1}^{n} \alpha_i c_i
\]

Here, \(W \in \mathbb{R}^{2k+1}\) and \(b \in \mathbb{R}^m\) are learnable parameters, \(\alpha \in \mathbb{R}^n\) and \(s \in \mathbb{R}^d\).

**Document-level Representations:** To obtain document-level features, we adopt a key-value Memory Network ([Weston, Chopra, and Bordes 2015](#)) that generates document-aware representations of every unique word in the training data. Specifically, we refer to the model adopted by Luo, Xiao, and Zhao (2019) to create features at a document level.

**Global-level Representations:** [Annervaz, Chowdhury, and Dukkipati (2018)](#) was among the first attempts to augment learning models with structured graph knowledge. They tested their model in a sentence classification setting. To retrieve entities and relations from the knowledge base, they first clustered entities and relations. A convolution network was used to obtain the cluster representation. Though the technique did work well for sentence classification, we identified a couple of limitations in their approach.

The first lies in the clustering step. To retrieve relevant entities and relations, clustering should be accurate. Also, clustering generally results in a loss of information. The cluster representations are always assumed to be a generalized representation of its constituents. Being generalized, it can neglect essential information existing inside the cluster’s objects. Second, they augmented their model with graph knowledge at a sentence level. For sequence labeling, augmentation at the sentence level will not be effective as we require precise entity-level information from the knowledge graph. We address the limitations mentioned above and propose more efficient and reliable technique for incorporating relevant information from the knowledge graph.

Instead of performing clustering, we first shortlist entities and relations that are relevant to our task. The shortlisted entities and relations are passed through the already trained knowledge graph embedding module. Here, we remove the classification layer of the knowledge graph embedding module and keep the representations generated by the transformer network to create the fact triplet embeddings. Next, we discuss the entity and relation shortlisting step.

**Entity Shortlisting:** One caveat of similarity-based methods is that their performance heavily depends on the modeling of adopted features for similarity estimation. This can introduce errors. Therefore, we adopt an n-gram based matching with the input document to shortlist entities from the Knowledge Graph. The idea here is to generate a candidate set for each entity in the document. More specifically, we refer to the rules proposed by [Lukovnikov et al. (2017)](#) for candidate set generation. As a particular entity in the document can match with multiple entities in the knowledge graph, we first rank all the entities based on the number of triplets they appear as subjects in the knowledge graph. The top \(k_1\) entities with the highest rank are selected and added to the candidate entity set \(C_w\) of the current word \(w\).

**Relation Shortlisting:** After generating the candidate entity set \(C_w\) for a word \(w\), we extract the \(k_2\) most frequent relations that emerge from entities in the candidate entity set \(C_w\). This results in the Entity Relation set \(E_{R_w}\) for a word \(w\) as follows:
\[
E_{R_w} = \{ (e_1, r_1), (e_1, r_2), \ldots, (e_1, r_{k_2}), (e_2, r_1), (e_2, r_2), \ldots, (e_2, r_{k_2}), \ldots, (e_{k_1}, r_1), (e_{k_1}, r_2), \ldots, (e_{k_1}, r_{k_2}) \}
\]

After shortlisting relevant entities and relations, we augment the current word with world knowledge. We do this by first encoding all the triples in the set \(E_{R_w}\) using the pre-trained knowledge graph embedding model. Each entity-relation pair in \(E_{R_w}\) is appended with the [MASK] token and fed to the transformer network. The hidden state obtained from the last layer of the transformer network acts as the contextualized representation for these triplets. Finally, we apply soft-attention over the hidden states obtained from the transformer encoder and treat the input contextualized embeddings obtained from BERT as the query vector for augmentation at word-level. For a word \(w\), this is mathematically defined as follows:
\[
I = [h_{w,1}^L; h_{w,2}^L; h_{w,3}^L] \\
Q, K, V = W^q B_w, W^k I, W^v I \\
A_j = QK_j^T/\sqrt{d} \\
g_w = \sum_{i} \text{Softmax}(A_j)V_i
\]

Here, \(W^q \in \mathbb{R}^{3d \times h}, W^k \in \mathbb{R}^{n \times 3d}\) and \(W^v \in \mathbb{R}^{n \times 3d}\) are learnable parameters, \(B_w \in \mathbb{R}^{h}\) is the contextualized word embedding of word \(w\) obtained from BERT, \(I \in \mathbb{R}^{n \times 3d}\) is the concatenation of the individual hidden states \((h_{w,1}^L)_{i=1}^n\) corresponding to the last layer of the transformer encoder, \(n\) is the number of triplets in the set \(E_{R_w}\), \(d\) is the output dim of individual hidden state from the transformer encoder and lastly, \(g_w \in \mathbb{R}^{3d}\) is the global representation of word \(w\).

This concludes our input representation layer. The output of the input representation layer is treated as the concatenation of the above-described features at token-level to obtain the word-level representation, which is 1) character-
We evaluated our models on three NER tasks. To reduce the impact of randomness, we conducted each experiment three times and reported the average span-level F1 score and standard deviation. Starting with word-level, we incrementally conducted our experiments and augmented features in increasing order of the extent of information modeled by them. To verify the performance of these trained models in a real-world scenario and compare their adaptability to unseen entities, we also generated predictions on two random pieces of texts taken from the web. In the subsequent section, we discuss the data statistics, model details, results, and performance on unseen entities.

**Experiments and Results**

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**NER datasets and Knowledge Graph**

The statistics of the three NER datasets we experimented on are listed in Table 1. Wikidata is one of the largest sources of real-world knowledge data covering concepts belonging to various domains. We filter the Wikidata and use only those fact triplets that were relevant to our task. This left us with approximately 10 million fact triplets out of roughly 400 million fact triplets present in Wikidata.

| Dataset     | Type        | Train     | Test      | Dev       | Tags |
|-------------|-------------|-----------|-----------|-----------|------|
| CoNLL 2003  | Sentence    | 14041     | 3453      | 3250      | 4    |
|             | Token       | 203621    | 46435     | 51362     |      |
| OntoNotes v5| Sentence    | 59924     | 8262      | 8528      | 18   |
|             | Token       | 1088503   | 152728    | 147724    |      |

Table 1: The table represents the details for CoNLL2003 and OntoNotes v5 datasets. The statistics for CoNLL++ dataset are same as that of CoNLL 2003.

We tuned all the model hyper-parameters manually, and list down the respective search ranges for all the hyper-parameters involved in Table 2.

**Results and Analysis**

We report the results achieved by our models in Table 3. Starting with word-level features, we observe that as augmentation is done with different features, the performance on every dataset consistently increases. For CoNLL datasets, the accuracy lift generated by each feature augmentation step follows the following trend: Char > Context > Global > Doc > Sent. The same trend for OntoNotes v5 is Context > Char > Global > Doc > Sent.

Table 3: F1 scores on CoNLL 2003, CoNLL++ and OntoNotes v5. Results marked with △ used both Train and Dev sets for model training. The SOTA results are underlined and the best results of our model are marked in bold. Standard deviation is written in parenthesis. △ denotes change in F1 by feature addition.
in the entire literature that utilized knowledge graph embeddings and applied them to the datasets we used in our work. We compare their reported results with ours. An approximate lift of $2-F_1$ is observed here.

As the results reported by KAWR only utilized Context-level and Knowledge-level embeddings, we conducted our experiments with KARL using the exact configuration of the embeddings. Experimental results show that KARL achieved far better performance as compared to KAWR, outperforming it by approximately 0.65 units on $F_1$ on the CoNLL 2003 dataset, which indicates the effectiveness of our proposed model in incorporating world knowledge.

### Evaluation on Unseen Entities

Next, we test each model’s performance on unseen entities. We take the models trained on the CoNLL 2003 dataset and predict named entities for random pieces of text taken from the web, which we annotated manually. We show the entities identified and their corresponding entity tags as predicted by these models for two such sentences in the “Predictions” column of Table 4. We observe that the word-level model failed to identify any named entity from the first sentence. With the introduction of character-level features, the model made one classification error and classified “SpaceX” as a person rather than an Organisation. After augmenting features at the context level, all the subsequent models generated accurate predictions and identified all the named entities and the corresponding tags precisely.

In the second sentence, the word-level model again failed to identify any named entities from the input text. Although the model did start to identify parts of named entities with further feature augmentations, we observe that majority of the tag labels predicted were wrong. For instance, the “+Bert”, “+Sent” and “+Doc” models misclassified “Sheffield” as a person. It is not until the augmentation of world knowledge do we start observing accurate predictions. The Global model, just as before, achieved an accuracy of 100% in named entity identification and tag labeling.

To introduce some complexity, we repeated the above experiments on the same two sentences, but the entire sentence had been lowercased this time. We did this to verify the model’s sensitivity towards casing. As shown in the table above, the predictions made by each of the models on lowercased inputs varied significantly, and the models committed more entity misclassifications than before. However, the predictions made by the model augmented with knowledge remained unaltered and unaffected, which verified the applicability and adaptability of our proposed method to a real-world scenario where the raw text is not guaranteed to carry any specific formatting.

### Conclusion and Future Work

This work proposed a novel world knowledge augmentation technique that leveraged large knowledge bases represented as fact triplets and successfully extracted relevant information for word-level augmentation. The model was trained and tested in an NER setting. Experimental results showed that knowledge level representation learning outperformed most NER systems in literature and made the model highly applicable to a real-world scenario by accurately predicting entities in random pieces of text.

Since we augmented features at the word level, we believe our method could facilitate many other NLP tasks, such as Chunking, Word Sense Disambiguation, Question Answering, etc. Therefore, as future work, we plan to test the applicability of the proposed methods on other NLP tasks as well. Our intuition says that any system can leverage the proposed system as a general knowledge representation learning tool. Moreover, being among the very few works in this direction, we see an ample scope of improvement. For instance, the Knowledge Graph Embedding model was trained separately on a Masked Language Modelling task, and then the trained model was used on the task at hand. This restricted the model from interacting and learning from the task at hand, NER in our case. We believe that a technique to incorporate and train the NER model with the knowledge representation module can be more beneficial. Another improvement that could be made lies in the entity shortlisting step. Although the technique is quite reliable, it does not consider any semantic information about the entities. Different entities in a knowledge base can be highly correlated to each other and yet have different names. Therefore, we plan to improve the entity shortlisting technique further for more accurate and robust shortlisting.

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