Abstract

Contextual string embeddings are a recent type of contextualized word embedding that were shown to yield state-of-the-art results when utilized in a range of sequence labeling tasks. They are based on character-level language models which treat text as distributions over characters and are capable of generating embeddings for any string of characters within any textual context. However, such purely character-based approaches struggle to produce meaningful embeddings if a rare string is used in a underspecified context. To address this drawback, we propose a method in which we dynamically aggregate contextualized embeddings of each unique string that we encounter. We then use a pooling operation to distill a global word representation from all contextualized instances. We evaluate these pooled contextualized embeddings on common named entity recognition (NER) tasks such as CoNLL-03 and WNUT and show that our approach significantly improves the state-of-the-art for NER. We make all code and pre-trained models available to the research community for use and reproduction.

1 Introduction

Word embeddings are a crucial component in many NLP approaches (Mikolov et al., 2013; Pennington et al., 2014) since they capture latent semantics of words and thus allow models to better train and generalize. Recent work has moved away from the original “one word, one embedding” paradigm to investigate contextualized embedding models (Peters et al., 2017, 2018; Akbik et al., 2018). Such approaches produce different embeddings for the same word depending on its context and are thus capable of capturing latent contextualized semantics of ambiguous words.

Recently, Akbik et al. (2018) proposed a character-level contextualized embeddings approach they refer to as contextual string embeddings. They leverage pre-trained character-level language models from which they extract hidden states at the beginning and end character positions of each word to produce embeddings for any string of characters in a sentential context. They showed these embeddings to yield state-of-the-art results when utilized in sequence labeling tasks such as named entity recognition (NER) or part-of-speech (PoS) tagging.

Underspecified contexts. However, such contextualized character-level models suffer from an inherent weakness when encountering rare words in an underspecified context. Consider the example text segment shown in Figure 1: “Fung Permadi (Taiwan) v Indra”, from the English CoNLL-03 test data split (Tjong Kim Sang and De Meulder, 2003). If we consider the word “Indra” to be rare (meaning no prior occurrence in the corpus used to generate word embeddings), the underspecified context allows this word to be interpreted as either a person or an organization. This leads to an underspecified embedding that ultimately causes an incorrect classification of “Indra” as an organization (ORG) instead of person (PER) in a downstream NER task.

Pooled Contextual Embeddings. In this paper, we present a simple but effective approach to address this issue. We intuit that entities are normally only used in underspecified contexts if they are expected to be known to the reader. That is, they are either more clearly introduced in an earlier sentence, or part of general in-domain knowl-

![Figure 1: Example sentence that provides underspecified context. This leads to an underspecified contextual word embedding for the string “Indra” that ultimately causes a misclassification of “Indra” as an organization (ORG) instead of person (PER) in a downstream NER task.](image-url)
Figure 2: Example of how we generate our proposed embedding ($emb_{proposed}$) for the word “Indra” in the example text segment “Fung Permadi v Indra”. We extract a contextual string embedding ($emb_{context}$) for this word and retrieve from the memory all embeddings that were produced for this string on previous sentences. We pool and concatenate all local contextualized embeddings to produce the final embedding.

...edge a reader is expected to have. Indeed, the string “Indra” in the CoNLL-03 data also occurs in the earlier sentence “Indra Wijaya (Indonesia) beat Ong Ewe Hock”.

Based on this, we propose an approach in which we dynamically aggregate contextualized embeddings of each unique string that we encounter as we process a dataset. We then use a pooling operation to distill a global word representation from all contextualized instances that we use in combination with the current contextualized representation as new word embedding. Our approach thus produces evolving word representations that change over time as more instances of the same word are observed in the data.

We evaluate our proposed embedding approach on the task of named entity recognition on the CoNLL-03 (English, German and Dutch) and WNUT datasets. In all cases, we find that our approach outperforms previous approaches and yields new state-of-the-art scores. We contribute our approach and all pre-trained models to the open source FLAIR\footnote{https://github.com/zalandoresearch/flair} framework (Akbik et al., 2019), to ensure reproducibility of these results.

2 Method

Our proposed approach (see Figure 2) dynamically builds up a “memory” of contextualized embeddings and applies a pooling operation to distill a global contextualized embedding for each word. It requires an $embed()$ function that produces a contextualized embedding for a given word in a sentence context (see Akbik et al. (2018)). It also requires a memory that records for each unique word all previous contextual embeddings, and a pool() operation to pool embedding vectors.

This is illustrated in Algorithm 1: to embed a word (in a sentential context), we first call the $embed()$ function (line 2) and add the resulting embedding to the memory for this word (line 3). We then call the pooling operation over all contextualized embeddings for this word in the memory (line 4) to compute the pooled contextualized embedding. Finally, we concatenate the original contextual embedding together with the pooled representation, to ensure that both local and global interpretations are represented (line 5). This means that the resulting pooled contextualized embedding has twice the dimensionality of the original embedding.

Algorithm 1 Compute pooled embedding

**Input:** sentence, memory

1: for word in sentence do
2: $emb_{context} \leftarrow embed(word)$ within sentence
3: add $emb_{context}$ to memory[$word$]
4: $emb_{pooled} \leftarrow pool(memory[word])$
5: word.embedding $\leftarrow$ concat($emb_{pooled}, emb_{context}$)
6: end for

Pooling operations. We experiment with different pooling operations: mean pooling to average a word’s contextualized embedding vectors, and min and max pooling to compute a vector of all
are built up (e.g. evolve) model learns to leverage pooled embeddings that can be used in combination with standard word embeddings. We use GLOVe embeddings (Pennington et al., 2014) for the English tasks and FASTText embeddings (Bojanowski et al., 2017) for all newswire tasks.

**Baselines.** Our baseline is contextual string embeddings without pooling, i.e. the original setup proposed in Akbik et al. (2018)\(^2\). By comparing against this baseline, we isolate the impact of our proposed pooled contextualized embeddings.

\(^2\)Our reproduced numbers are slightly lower than we reported in Akbik et al. (2018) where we used the official CoNLL-03 evaluation script over BILOES tagged entities. This introduced errors since this script was not designed for S-tagged entities.
In addition, we list the best reported numbers for the four tasks. This includes the recent BERT approach using bidirectional transformers by Devlin et al. (2018), the semi-supervised multitask learning approach by Clark et al. (2018), the ELMo word-level language modeling approach by Peters et al. (2018), and the best published numbers for WNUT-17 (Aguilar et al., 2018) and German and Dutch CoNLL-03 (Lample et al., 2016).

### 3.2 Results

Our experimental results are summarized in Table 1 for each of the four tasks.

**New state-of-the-art scores.** We find that our approach outperforms all previously published results, raising the state-of-the-art for CoNLL-03 on English to 93.18 F1-score (↑0.32 pp vs. previous best), German to 88.27 (↑0.86 pp) and Dutch to 90.44 (↑0.28 pp). The consistent improvements against the contextual string embeddings baseline indicate that our approach is generally a viable option for embedding entities in sequence labeling.

**Less pronounced impact on WNUT-17.** However, we also find no significant improvements on the WNUT-17 task on emerging entities. Depending on the pooling operation, we find comparable results to the baseline. This result is expected since most entities appear only few times in this dataset, giving our approach little evidence to aggregate and pool. Nevertheless, since recent work has not yet experimented with contextual embeddings on WNUT, as side result we report a new state-of-the-art of 49.59 F1 vs. the previous best reported number of 45.55 (Aguilar et al., 2018).

**Pooling operations.** Comparing the pooling operations discussed in Section 2, we generally find similar results. As Table 1 shows, min pooling performs best for English and German CoNLL, while mean pooling is best for Dutch and WNUT.

### 3.3 Ablation: Character Embeddings Only

To better isolate the impact of our proposed approach, we run experiments in which we do not use any classic word embeddings, but rather rely solely on contextual string embeddings. As Table 2 shows, we observe more pronounced improvements of pooling vis-a-vis the baseline approach in this setup. This indicates that pooled contextualized embeddings capture global semantics words similar in nature to classical word embeddings.

### 4 Discussion and Conclusion

We presented a simple but effective approach that addresses the problem of embedding rare strings in underspecified contexts. Our experimental evaluation shows that this approach improves the state-of-the-art across named entity recognition tasks, enabling us to report new state-of-the-art scores for CoNLL-03 NER and WNUT emerging entity detection. These results indicate that our embedding approach is well suited for NER.

**Evolving embeddings.** Our dynamic aggregation approach means that embeddings for the same words will change over time, even when used in exactly the same contexts. Assuming that entity names are more often used in well-specified contexts, their pooled embeddings will improve as more data is processed. The embedding model thus continues to “learn” from data even after the training of the downstream NER model is complete and it is used in prediction mode. We consider this idea of constantly evolving representations a very promising research direction.

**Future work.** Our pooling operation makes the conceptual simplification that all previous instances of a word are equally important. However, we may find more recent mentions of a word - such as words within the same document or news cycle - to be more important for creating embeddings than mentions that belong to other documents or news cycles. Future work will therefore examine methods to learn weighted poolings of previous mentions. We will also investigate applicability of our proposed embeddings to tasks beside NER.

**Public release.** We contribute our code to the FLAIR framework\(^3\). This allows full reproduction of all experiments presented in this paper, and al-

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\(^3\)The proposed embedding is added to FLAIR in release 0.4.1, as the PooledFlairEmbeddings class (see Akbik et al. (2019) for more details).

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**Table 2: Ablation experiment using contextual string embeddings without word embeddings.** We find a more significant impact on evaluation numbers across all datasets, illustrating the need for capturing global next to contextualized semantics.

| Approach                               | CoNLL-03 EN | CoNLL-03 DE | CoNLL-03 NL | WNUT-17 |
|----------------------------------------|-------------|-------------|-------------|---------|
| Pooled Contextualized Embeddings (only)| 92.42 ± 0.07| 86.21 ± 0.07| 88.25 ± 0.11| 44.29 ± 0.59|
| Contextual String Embeddings (only)    | 91.81 ± 0.12| 85.25 ± 0.21| 86.71 ± 0.12| 43.43 ± 0.93|
lows the research community to use our embeddings for training downstream task models.

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