Computationally Efficient NER Taggers with Combined Embeddings and Constrained Decoding

Brian Lester, Daniel Pressel, Amy Hemmeter, and Sagnik Ray Choudhury
Interactions Digital Roots, Ann Arbor MI 48104
{blester, dpressel, ahemmeter, schoudhury}@interactions.com

Abstract

Current State-of-the-Art models in Named Entity Recognition (NER) are neural models with a Conditional Random Field (CRF) as the final network layer, and pre-trained “contextual embeddings”. The CRF layer is used to facilitate global coherence between labels, and the contextual embeddings provide a better representation of words in context. However, both of these improvements come at a high computational cost. In this work, we explore two simple techniques that substantially improve NER performance over a strong baseline with negligible cost. First, we use multiple pre-trained embeddings as word representations via concatenation. Second, we constrain the tagger, trained using a cross-entropy loss, during decoding to eliminate illegal transitions. While training a tagger on CoNLL 2003 we find a 786% speed-up over a contextual embeddings-based tagger without sacrificing strong performance. We also show that the concatenation technique works across multiple tasks and datasets. We analyze aspects of similarity and coverage between pre-trained embeddings and the dynamics of tag co-occurrence to explain why these techniques work. We provide an open source implementation of our tagger using these techniques in three popular deep learning frameworks — TensorFlow, Pytorch, and DyNet.

1 Introduction and Motivations

Named Entity Recognition (NER) is usually cast as a sequence labeling task where the goal is to identify objects in the world, such as people (“PER”) or locations (“LOC”). Multi-token spans are traditionally handled by having “Beginning” and “Inside” indicators identifying which tokens start, continue, or signal a change to a different entity. Ratinov and Roth (2009) show that the IOBES tagging scheme, where entity spans must begin with a “B” token, end with an “E” and single token entities are labeled with an “S”, performs better than BIO tagging schemes. IOBES tagging schemes dictate that some token sequences are illegal. It is possible to impose decoding constraints on the model rather than relying only on what is seen in the training data.

It is conventional wisdom in NER that models with a Linear Chain Conditional Random Field (CRF) (Lafferty et al., 2001) layer perform better than those without (Collobert et al., 2011; Ma and Hovy, 2016; Lample et al., 2016), yielding relative performance increases between 2 and 3 percent (Ma and Hovy, 2016; Lample et al., 2016). A CRF with Viterbi decoding promotes global coherence where simple greedy decoding does not. Therefore, in a bidirectional LSTM (biLSTM) model with a CRF layer illegal transitions are rare compared to models that select just the best scoring tag for each token. However, as the CRF forward algorithm is $O(N^2)$ where $N$ is the length of the sentence and $T$ is the number of possible tags, it slows down the training significantly. Moreover, substantial effort is required to build an optimized, correct implementation of this layer. Alternately, training with a cross-entropy loss runs in $O(N)$ for sparse labels. It can also be computed in parallel. Instead of traditional CRF training, we propose Viterbi decoding at test time with heuristically determined transition probabilities that prohibit illegal transitions. We find that this simple modification allows taggers trained with cross-entropy loss to compete with those trained using a CRF loss while yielding much faster training times.

Our approach is similar to previous work in NLP where constraints are introduced during inference (Roth and Yih, 2005; Punyakanok et al., 2005). There have been other attempts to eliminate the CRF layer in taggers, notably Shen et al. (2018), which found that an additional LSTM
A greedy decoder layer is competitive with the CRF layer, though their baseline is much weaker than the models found in other work, and the source code was never released. Additionally, their decoder has an auto-regressive relationship that is difficult to parallelize and, in practice, there is still significant overhead at training time. Chiu and Nichols (2016) mention good results with a similar decoding scheme but don’t provide in-depth analysis, metrics, or test its generality.

Many recent NLP publications have focused on better feature representations via contextual word embeddings (Peters et al., 2018, 2017; Radford et al., 2018; Akbik et al., 2018; Devlin et al., 2018). These models vary in architecture and pre-training objective but they all encode the input based on the surrounding context in some way. For NER, these papers normally use biLSTM-CRF baselines where words are represented by single pre-trained word embeddings.

Contextual embeddings and transfer learning architectures are slow to train and evaluate, which may make them unfeasible for many types of deployments. We find that the concatenation of multiple pre-trained word embeddings instead is much faster and shows consistent improvements over single embeddings, much closer to contextual alternatives.

2 Experiments & Results

We use three sequential prediction tasks to test the performance of our concatenated embeddings: NER (CoNLL 2003 (Tjong Kim Sang and De Meulder, 2003), WNUT-17 (Derczynski et al., 2017), and Ontonotes (Hovy et al., 2006)) , Slot filling (Snips (Coucke et al., 2018)) and POS tagging (TW-POS (Gimpel et al., 2011)). We also show results on three classification datasets: SST2 (Socher et al., 2013), Snips intent classification (Coucke et al., 2018), and AG-News1. For each (task, dataset) pair we use the most common embedding used in literature. For all tagging tasks, a biLSTM-CRF model is used. For all classification tasks, a single layer LSTM model is used except for the Snips classification dataset, where a convolutional word-based model is used. The hyper-parameters are omitted here for brevity but can be found in our implementation.

The results are presented in Table 1. 6B, 27B and 840B are well-known GloVe embeddings (Pennington et al., 2014), w2v-30M (Pres- sel et al., 2018) and GN (Mikolov et al., 2013) are Word2Vec embeddings trained on a corpus of 30 million tweets and Google News respectively, and Senna embedding was trained by (Collobert et al., 2011). As hypothesized, we see improvements across tasks, datasets, and model architectures when multiple embeddings are concatenated (except for Ontonotes). When compared to a model that only uses a single pre-trained embedding, a model that uses the concatenation of pre-trained and randomly initialized embeddings does 0.6% worse on average, demonstrating that the performance gains are from the combination of different pretrained embeddings rather than the increase in the number of parameters in the model. In some cases we were able to improve results further by adding several sets of additional embeddings.

To test whether constrained decoding provides results comparable to a CRF layer, we implement a mask that effectively eliminates invalid IOBES transitions by setting those transition score to large negative values. This mask is generated via the rule of IOBES encoding. For example, an “I-” of one class cannot follow a “B-” of a different class or how entities must end in “E-“, i.e. “B-” cannot transition directly to an “O”. This mask can be applied to the CRF transition scores or used directly to facilitate Viterbi decoding when no CRF is used.

We investigate the effect of constrained decoding on three NER datasets and one Slot Filling dataset. The results are presented in table 2. In three out of four datasets constrained decoding performs comparably or better than CRF, again Ontonotes is the only exception. We observe a 50% improvement in training time on average.

The models were trained using Baseline (Pres- sel et al., 2018), an open-source framework for creating, training, evaluating and deploying models for NLP.

3 Analysis

We observe that concatenated embeddings trained on sufficiently different datasets perform well in our experiments. We hypothesized that each embedding set augments the meaning representations, making them more useful for the downstream tagging task. To test this theory, we looked

1http://www.di.unipi.it/~gulli/AG_corpus_of_news_articles.html
Table 1: Results using multiple embeddings applied to several tasks and datasets. NER and Slot Filling tasks report entity level F1. POS tagging and Classification report accuracy. All results are reported across 10 runs.

| Task          | Dataset | Model     | Embeddings      | mean   | std    | min   | max   |
|---------------|---------|-----------|-----------------|--------|--------|-------|-------|
| NER           | CoNLL   | biLSTM-CRF| 6B              | 91.12  | 0.21   | 90.62 | 91.37 |
|               |         |           | Senna           | 90.48  | 0.27   | 90.02 | 90.81 |
|               |         |           | 6B, Senna       | **91.47** | 0.25 | 91.15 | **92.00** |
| WNUT-17       |         | biLSTM-CRF| 27B             | 39.20  | 0.71   | 37.98 | 40.33 |
|               |         |           | 27B, w2v-30M    | 39.52  | 0.83   | 38.09 | 40.39 |
|               |         |           | 27B, w2v-30M, 840B | **40.33** | 1.13 | 38.38 | **41.99** |
| Ontonotes     |         | biLSTM-CRF| 6B              | 87.43  | 0.13   | 87.15 | 87.57 |
|               |         |           | 6B, Senna       | 87.41  | 0.17   | 87.14 | **87.74** |
| Slot Filling  | Snips   | biLSTM-CRF| 6B              | 95.84  | 0.29   | 95.39 | 96.21 |
|               |         |           | GN              | 95.28  | 0.41   | 94.51 | 95.81 |
|               |         |           | 6B, GN          | **96.04** | 0.28 | 95.39 | **96.21** |
| POS           | TW-POS  | biLSTM-CRF| w2v-30M         | 89.21  | 0.28   | 88.72 | 89.74 |
|               |         |           | 27B             | 89.63  | 0.19   | 89.35 | 89.92 |
|               |         |           | 27B, w2v-30M    | 90.35  | 0.20   | 89.99 | 90.60 |
|               |         |           | 27B, w2v-30M, 840B | **90.75** | 0.14 | 90.53 | **91.02** |
| Classification| SST2    | LSTM      | 840B            | 88.39  | 0.45   | 87.42 | 89.07 |
|               |         |           | GN              | 87.58  | 0.54   | 86.16 | 88.19 |
|               |         |           | 840B, GN        | **88.57** | 0.44 | 87.59 | **89.24** |
|               | AG-NEWS | LSTM      | 840B            | 92.53  | 0.45   | 87.42 | 89.07 |
|               |         |           | GN              | 92.20  | 0.18   | 91.80 | 92.40 |
|               |         |           | 840B, GN        | **92.60** | 0.20 | 92.30 | **92.86** |
|               | Snips   | Conv      | 840B            | 97.47  | 0.33   | 97.01 | 97.86 |
|               |         |           | GN              | 97.40  | 0.27   | 97.00 | 97.86 |
|               |         |           | 840B, GN        | **97.63** | 0.52 | 97.00 | **98.29** |

Table 2: Results of tagging with constraints vs a CRF. For each, we use the best embedding combination as found in table 1. Scores are reported across 10 runs.

| Dataset   | Model | mean   | std    | max   |
|-----------|-------|--------|--------|-------|
| CoNLL     | CRF   | **91.47** | 0.25   | **92.00** |
|           | Constrain | 91.44  | 0.23   | 91.90 |
| WNUT-17   | CRF   | 40.33  | 1.13   | **41.99** |
|           | Constrain | 40.59  | 1.06   | 41.71 |
| Snips     | CRF   | 96.04  | 0.28   | **96.35** |
|           | Constrain | 96.07  | 0.17   | 96.29 |
| Ontonotes | CRF   | **87.43** | 0.26   | **87.57** |
|           | Constrain | 86.13  | 0.17   | 86.72 |

at the similarity of various pre-trained embeddings. We define similarity as the Jaccard overlap percentage between the 10 nearest neighbors for each of the top 200 words in the dataset by frequency. Embeddings that complement the base embedding set should have a low similarity, otherwise they would not add much extra information. More similar embeddings experienced less of a performance boost than dissimilar embeddings. However, similarity was not a perfect predictor of whether the model will improve with concatenated embeddings. We also investigated coverage — the proportion of words in the dataset found in the pre-trained vocabulary. While Google News vectors have low overlap with the GloVe 6B embeddings, which should augment the information in the word representations, they are used so rarely that they do not add a significant performance gain. Table 3 shows how model performance changes with different embedding combinations on CoNLL 2003 dataset. When finding complementary embeddings, it seems necessary both that embedding sets are highly attested and have low similarity to one another to improve performance.

For constrained decoding, we leverage the IOBES tagging scheme rather than BIO tagging, allowing us to inject more structure into the decoding mask. Our tests with BIO tagging failed to show the large gains we realized when we applied IOBES tagging. When run on the develop-
Embeddings & Overlap & Attested & Performance 
|         | train | dev | train | dev | mean | std  |
|---------|-------|-----|-------|-----|------|------|
| Senna   | 18.9  | 20.8| 74.3  | 80.3| 91.466| 0.247|
| GloVe twitter 27B | 24.9 | 27.2| 68.1  | 76.1| 91.098| 0.135|
| GloVe 840B | 41.7 | 40.6| 83.2  | 88.5| 91.011| 0.228|
| GloVe 42B | 45.5 | 45.3| 90.4  | 93.8| 91.163| 0.146|
| GoogleNews| 25.2 | 26.8| 55.9  | 65.1| 90.948| 0.180|

Table 3: Embedding similarity as defined by average Jaccard similarity of the 10 nearest neighbors on the top 200 words in CoNLL 2003. Performance is the F1 score of each embedding when paired with Glove-6B-100d vectors.

4 Conclusion

Recent large-scale contextual pre-training and transfer learning efforts are exciting but produce relatively slow models. For tagging tasks a CRF layer introduces substantial computational cost as well. We propose two lightweight techniques: concatenation of pre-trained embeddings and constrained decoding. We show that individually each of these techniques has a significant impact on error reduction and, when used together, improves speed significantly with very little cost in performance.

Our analysis suggests that each concatenated embedding should individually have good coverage over the training set and exhibit representational diversity from the rest of the embeddings. For constrained decoding, our performance either exceeds or is on par with that of a CRF while exhibiting a 50% wall clock improvement at training time. We show that the constrained decoder can be used on common datasets where many tokens are conditionally unambiguous based on the rules of IOBES encoding.

In future work, we intend to try other methods of embeddings combination. The constrained decoder can be extended to use transition probabilities estimated from the training set in addition to masking illegal moves. In theory this should boost performance without adversely impacting speed. Also, automated tools can be developed towards a more principled approach for finding out which embeddings should be combined or whether CRFs should be replaced by a constrained decoder for a particular (task, dataset) pair.

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