Multiple Word Embeddings for Increased Diversity of Representation

Brian Lester, Daniel Pressel, Amy Hemmeter, Sagnik Ray Choudhury, and Srinivas Bangalore

Interactions, Ann Arbor MI 48104
{blester, dpressel, ahemmeter, schoudhury, sbangalore}@interactions.com

Abstract

Most state-of-the-art models in natural language processing (NLP) are neural models built on top of large, pre-trained, contextual language models that generate representations of words in context and are fine-tuned for the task at hand. The improvements afforded by these “contextual embeddings” come with a high computational cost. In this work, we explore a simple technique that substantially and consistently improves performance over a strong baseline with negligible increase in run time. We concatenate multiple pre-trained embeddings to strengthen our representation of words. We show that this concatenation technique works across many tasks, datasets, and model types. We analyze aspects of pre-trained embedding similarity and vocabulary coverage and find that the representational diversity between different pre-trained embeddings is the driving force of why this technique works. We provide open source implementations of our models in both TensorFlow and PyTorch.

1 Introduction

Much of the recent work in NLP has 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., 2019). These models vary in architecture and pre-training objective but they all encode the input based on the surrounding context in some way. These papers normally compare to baselines like a bidirectional LSTM-CRF (biLSTM-CRF) where words are represented by a single pre-trained word embedding. Peters et al. (2018, 2017) and Akbik et al. (2018) pre-train large language models based on LSTMs. Task-specific architectures are then built on top of these pre-trained models. Peters et al. (2018) introduce a technique for extracting word representations as a linear combination of layers in the pre-trained model. Gradient updates are only applied to this weighting factor, which simplifies the training to some extent, but forward propagation is still required for the full network which makes the model slow to train and evaluate.

Radford et al. (2018), followed by Devlin et al. (2019), pre-train deep transformers (Vaswani et al., 2017) on massive corpora. They both use a simple output layer on top of the pre-trained model and tune the parameters of the whole model. In this case, training requires the forward and backward pass of the entire pre-trained model, which has a significant impact on size and speed. Devlin et al. (2019) used specialized hardware which may be unrealistic for many inference scenarios.

The prevailing wisdom is that, because these pre-trained models are contextual, they can create representations of a word that is different in different contexts. For example, a polysemous word can be represented by different vectors when its context suggests a different sense of a word, while context-independent word vectors need to represent a mix of all the senses of a word. The majority of NLP models have a similar “contextualization” step, typically done via a biLSTM, convolutional layers, or self-attention, but it is only learned from a smaller, task-specific corpus in contrast to the massive corpora used by contextual embeddings.

Contextual embeddings and transfer learning architectures are slow to train and evaluate, which may make them infeasible for many types of deployments. Using multiple pre-trained embeddings trained on different datasets, we can exploit the bias in different datasets that results in different representations of the same word. By combining these embeddings, we can create richer representations of the word without the high computational overhead required by contextual alternatives. We find
that the concatenation of multiple pre-trained word embeddings show consistent improvements over single embeddings yielding results 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 example, GloVe embeddings were used for CONLL 2003 in (Ma and Hovy, 2016) and Senna embeddings in (Chiu and Nichols, 2016; Peters et al., 2018). Embeddings were also chosen based on how well the embedding training data fit the task, i.e., we used GloVe vectors trained on twitter for the twitter part of speech tagging task. Once we developed tests for which embeddings worked together in Section 3 we checked if there were any more embeddings combinations we should try but did not find any additional combinations. For all tagging tasks, a biLSTM-CRF model with convolutional character compositional inputs, following (Ma and Hovy, 2016), 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 (Kim, 2014) is used. The hyperparameters 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, pre-trained GloVe embeddings (Pennington et al., 2014) distributed via the authors site, w2v-30M (Pressel 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 the Senna embeddings were trained by Collobert et al. (2011).

We leverage multiple pre-trained embeddings in a model by creating one embeddings table per pre-trained embedding. Each input token in embedded into each vector space and the resulting vectors are concatenated into a single vector. This means that it is possible for there to be a type that is unattested in one pre-trained embedding vocabulary but present in the other. This results in a pre-trained vector from one embedding being concatenated with a randomly initialized vector form the other embedding space.

As hypothesized, we see improvements across tasks, datasets, and model architectures when using multiple embeddings.

Models using the concatenation of pre-trained and randomly initialized embeddings do 0.6% worse on average compared to models that only use a single pre-trained embedding. This demonstrates that the performance gains are from the combination of different pre-trained 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.

Table 2 summarizes the results of using the multiple embedding approach on internal datasets. These datasets are drawn from the tasks defined earlier and span a variety of specialized domains. Due to the nature of the datasets the results are presented as the relative change in performance. Table 3 is provided to help frame the relative performance numbers from the internal datasets.

The models were trained with MEAD/Baseline (Pressel et al., 2018), an open-source framework for developing, training, and deploying NLP models.

3 Analysis

There are three logical places where the observed improvements could come from. 1) The use of multiple pre-trained embeddings creates a slightly larger model, increasing the network capacity—the embeddings are larger and therefore the projection from the embeddings to the first layer of the model will also be slightly bigger. 2) The use of a second pre-trained embedding increases the vocabulary size and more words are attested. A word that has a pre-trained representation will start the model in a better spot than a randomly initialized representation. 3) The second set of pre-trained embeddings gives a different perspective of the words. Most pre-trained embeddings are trained on different data and encode different biases and senses into the embedding that reflect the quirks and unique contexts found in the pre-training data. This representational diversity will allow a model to capitalize on different senses, or the combination

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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 token-level and example-level accuracy respectively. Using multiple pre-trained embeddings helps across a wide range of tasks and datasets as well as across different model architectures within a given task. 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  | 91.61  | 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            |            | 87.02  | 9.15   | 86.75  | 87.24  |
|              |         |                | 6B, Senna  | 87.54  | 0.16   | 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  | 96.35  |
| 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  |
| 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  |
| Classification | 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: Performance using multiple embeddings on internal datasets. Although smaller than well-known datasets, we see consistent improvements across internal tasks and domains.

| Task         | Domain   | ∆   |
|--------------|----------|-----|
| NER          | General NER | 0.51 |
| Slot Filling | Automotive | 0.14 |
|              | Cyber Security | 0.06 |
|              | Customer Service | 0.34 |
| Intent       | Automotive | 0.52 |
|              | Cyber Security | 0.03 |
|              | Customer Service | 0.16 |
| POS          | TW-POS   | 1.25 |
| Classification | SST2 | 0.20 |
|              | AG-NEWS | 0.08 |
|              | Snips    | 0.16 |

### Table 3: Relative difference for well-known datasets to help frame the results in Table 2

| Task         | Dataset   | ∆   |
|--------------|-----------|-----|
| NER          | CoNLL     | 0.54 |
| Slot Filling | WNUT-17   | 2.88 |
|              | OntoNotes | 0.45 |
| POS          | TW-POS    | 1.25 |
| Classification | SST2 | 0.20 |
|              | AG-NEWS  | 0.08 |
|              | Snips     | 0.16 |

of senses, that would not be present when using a single embedding.

In order to tease apart which of these factors are at play we designed a series of models that aim to isolate each effect and report results in Table 4. First, we train a model that uses a single pre-trained embedding and a second set of vectors that are initialized randomly. If the main improvement is due to increased model capacity this configuration should perform well. The second model uses a special version of the second pre-trained embedding where we remove all the words that already appear in the original pre-trained vocabulary. In
Table 4: An ablation to explain why multiple embeddings work. The majority of the improvement comes the case where we take only the words from the second pre-trained embedding that appear in the first vocab (the matched row). This suggests that having different representations for a word is much more important than increased model capacity (tested in the Random init row) or the increased coverage in the pre-trained vocabulary (represented by the complement row).

Table 5: Embedding similarity as defined by average Jaccard similarity of the 10 nearest neighbors on the top 200 words in CoNLL 2003. Performance is the entity-level F1 score of each embedding when paired with Glove 6B 100 dimension embeddings. Here we can see that using pairs of dissimilar embeddings correlate with better performance as long as the embeddings have enough coverage to be effectively leveraged.
teristics when combining embeddings: the word representations should have low “similarity” and the unique types in the dataset should be highly attested in both pre-trained vocabularies.

4 Conclusion

Recent large-scale, contextual, pre-trained models are exciting but produce relatively slow models. We propose a simple, lightweight technique: concatenation of pre-trained embeddings. We show that this technique has a significant impact on error reduction and a negligible effect of speed.

However, the concatenation on any two random pre-trained embeddings is not guaranteed to work well. From our analysis, we are able to suggest a recipe for finding an effective combination: there should be a high degree of coverage of the unique types in each of the pre-trained embedding vocabularies and the word vectors should exhibit representational diversity. In future work, we intend to try other methods of embeddings combination while remaining computationally cheap. We also plan to find more principled ways to quantify the diversity in pre-trained embeddings, which can suggest ways to induce representational diversity into the embedding pre-training procedure itself.

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A Reproducibility

A.1 Hyperparameters

Mead/Baseline is a configuration file driven model training framework. All hyperparameters are fully specified in the configuration files included with the source code for our experiments.

A.2 Computational Resources

All models were trained on a single NVIDIA 1080Ti. While multiple GPUs were used for training many models in parallel to facilitate a testing many datasets and to estimate the variability of the method the actual model can easily be trained on a single GPU.

A.3 Evaluation

To calculate metrics, entity-level F1 is used for NER and slot-filling. In entity level F1 first entities are created from the token level labels and compared to the gold ones. Entities that match on both type and boundaries are considered correct while a mismatch in either causes an error. The F1 score is then calculated from these entities. Accuracy is used for classification and part of speech tagging. Accuracy is defined as the proportion of correct elements to all elements. In classification a single example is an element. In part of speech tagging each token is an element so our accuracy is the the number of correct tokens divided by the number of tokens in the dataset. We use the evaluation code that ships with the framework we use, MEAD/Baseline, which we have bundled with the source code of our experiments.

A.4 Dataset Information

Relevant information about datasets can be found in Table 7. The majority of data is used as distributed except we convert NER and slot-filling datasets to the IOBES format. All public dataset used are included in the supplementary material. A quick overview of each dataset follows:

CoNLL: A NER dataset based on news text. We converted the IOB labels into the IOBES format. There are 4 entity types, MISC, LOC, PER, and LOC.

WNUT-17: A NER dataset of new and emerging entities based on noisy user text. We converted the BIO labels into the IOBES format. There are 6 entity types, corporation, creative-work, group, location, person, and product.

OntoNotes: A much larger NER dataset. We converted the labels into the IOBES format. There are 18 entity types, CARDINAL, DATE, EVENT, FAC, GPE, LANGUAGE, LAW, LOC, MONEY, NORP, ORG, ORDINAL, ORG, PERCENT, PERSON, PRODUCT, QUANTITY, TIME, and WORK_OF_ART.

Snips: A slot-filling dataset focusing on
| Task                | Dataset | Model         | Embeddings | Number of parameters |
|---------------------|---------|---------------|------------|----------------------|
| NER                 | CoNLL   | biLSTM-CRF    | 6B         | 3,234,440            |
|                     |         |               | Senna      | 1,810,690            |
|                     |         |               | 6B, Senna  | 4,658,190            |
| WNUT-17             | biLSTM-CRF | 27B         |            | 3,849,632            |
|                     |         | 27B, w2v-30M  |            | 6,499,532            |
|                     |         | 27B, w2v-30M, 840B | | 12,090,032    |
| OntoNotes           | biLSTM-CRF | 6B         |            | 5,569,382            |
|                     |         | 6B, Senna    |            | 7,673,632            |
| Slot Filling        | Snips   | biLSTM-CRF   | 6B         | 1,819,466            |
|                     |         | GN           |            | 4,567,066            |
|                     |         | 6B, GN       |            | 5,940,866            |
| POS                 | TW-POS  | biLSTM-CRF   | w2v-30M    | 1,241,332            |
|                     |         | 27B          |            | 1,788,982            |
|                     |         | 27B, w2v-30M |            | 2,908,132            |
|                     |         | 27B, w2v-30M, 840B | | 5,408,332    |
| Classification      | SST2    | LSTM         | 840B       | 6,456,702            |
|                     |         | GN           |            | 6,456,702            |
|                     |         | 840B, GN     |            | 12,109,002           |
| AG-NEWS             | LSTM    |              | 840B       | 20,842,604           |
|                     |         | GN           |            | 20,842,604           |
|                     |         | 840B, GN     |            | 41,522,804           |
| Snips               | Conv    | 840B         |            | 4,003,807            |
|                     |         | GN           |            | 4,003,807            |
|                     |         | 840B, GN     |            | 8,005,207            |

Table 6: The number of parameters for different models.

commands one would give a virtual assistant. We converted the dataset from its normal format of two associated files, one containing surface terms and one containing labels to the more standard CoNLL file format and converted the labels to the IOBES format. There are 39 entity types, album, artist, best_rating, city, condition_description, condition_temperature, country, cuisine, current_location, entity_name, facility, genre, geographic.poi, location_name, movie_name, movie_type, music_item, object_location_type, object_name, object_part_of_series_type, object_select, object.type, party_size_description, party_size_number, playlist, playlist_owner, poi, rating_unit, rating_value, restaurant_name, restaurant_type, served_dish, service, sort, spatial_relation, state, timeRange, track, and year.

**TW-POS**: A twitter part of speech dataset. There are 25 parts of speech, !, #, $, &, ′, @, A, D, E, G, L, M, N, O, P, R, S, T, U, V, X, Y, Z, `′, and "".

**SST2**: A binary sentiment analysis dataset based on movie reviews. We use the version where the training data is made up of phrases.

**AG-NEWS**: A four class text classification dataset for categorizing news data based on the 4 most common categories. There is not a standardized train and development split (there is a defined test set) so we created our own split which is included in the supplementary material.

**Snips-Intent**: The intent classification portion of the snips dataset. Again the intents pertain to requests one would make to a virtual assistant. There are 7 intents, SearchScreeningEvent, PlayMusic, AddToPlaylist, BookRestaurant, RateBook, SearchCreativeWork, and GetWeather.
Table 7: Example and token count statistics for public datasets used.

| Dataset   | Train | Dev  | Test  | Total  |
|-----------|-------|------|-------|--------|
| CoNLL     | 14,987| 3,466| 3674  | 22137  |
| Tokens    | 204,567| 51,578| 46,666| 302,811|
| WNUT-17   | 3,394 | 1,009| 1,287 | 5,690  |
| Tokens    | 62,730| 15,733| 23,394| 101,857|
| OntoNotes | 59,924| 8,528| 8,262 | 76,714 |
| Tokens    | 1,088,503| 147,724| 152,728| 1,388,955|
| Snips     | 13,084| 700  | 700   | 14,484 |
| Tokens    | 117,700| 6,384 | 6,354 | 130,438|
| TW-POS    | 1,000 | 327  | 500   | 1,827  |
| Tokens    | 14,619| 4,823| 7,152 | 26,594 |
| SST2      | 76,961| 872  | 1,821 | 79,654 |
| Tokens    | 717,127| 17,046| 35,023| 769,196|
| AG-NEWS   | 110,000| 10,000| 7,600 | 127,600|
| Tokens    | 4,806,909| 433,659| 329,617| 5,570,185|