Embedding	Dimension	NCBI		BC5CDR	
		Recognition	Normalization	Recognition	Normalization
Random	100	0.7532	0.7746	0.7665	0.7725
Senna	50	0.7944	0.8016	0.7911	0.7966
GloVe	100	0.7963	0.8042	0.8009	0.8062
Word2Vec	50	**0.8743**	**0.8823**	**0.8763**	**0.8917**

Table 4: Results with different choices of word embeddings on the two tasks (F1 score).

ratios of boundary inconsistency of MER and MEN on each test set of both corpora. It is clear that our proposed MTL framework with two feedback strategies on MER and MEN can significantly alleviate the boundary inconsistency of MER and MEN thus improve the performance.

	NCBI	BC5CDR
Bi-LSTM-CNNs-CRF	0.0635	0.0563
MTL +Bi-LSTM-CNNs-CRF	0.0412	0.0383
MTL-MEN&MER_feedback +Bi-LSTM-CNNs-CRF	**0.0134**	**0.0114**

Table 5: Ratios of the boundary inconsistency of MER and MEN on two test sets.

OOV Entities Error Analysis

To better understand the behavior of our model, we perform error analysis on Out-of-Vocabulary words (OOV). Specifically, we partition each data set into four subsets — in-vocabulary words (IV), out-of-training-vocabulary words (OOTV), out-of-embedding-vocabulary words (OOEV) and out-of-both-vocabulary words (OOBV). A word is considered IV if it appears in both the training and embedding vocabulary, while OOBV if neither. OOTV words are the ones do not appear in training set but in embedding vocabulary, while OOEV are the ones do not appear in embedding vocabulary but in training set. An entity is considered as OOBV if there exists at lease one word not in training set and at least one word not in embedding vocabulary, and the other three subsets can be done in similar manner. Table 6 presents the statistics of the partition on each corpus. The embedding we used is pre-trained 50-dimensional embeddings in (**?**), the same as Section .

	NCBI	BC5CDR
IV	987	5,421
OOTV	33	127
OOEV	16	33
OOBV	10	142

Table 6: Statistics of the partition on each test set. It lists the number of unique entities.

Table 7 illustrates the performance of our best model on different subsets of entities. The largest improvements appear on the IV and OOTV subsets of both the two corpora on both tasks. This demonstrates that by feeding into multi-task learning framework with explicit feedback, our model is more powerful on entities that appear in pre-trained embedding sets, which shows the superiority of our model to make better use of pre-trained word embeddings and deal with entities which do not appear in training set.

	NCBI		BC5CDR	
	MER	MEN	MER	MEN
Bi-LSTM-CNNs-CRF				
IV	0.8451	0.8254	0.8738	0.8677
OOTV	0.8046	0.8094	0.8279	0.8354
OOEV	0.7776	0.8064	0.7835	0.7821
OOBV	0.7221	0.7354	0.6937	0.7223
MTL-MEN&MER_feedback+Bi-LSTM-CNNs-CRF				
IV	0.8931	0.9017	0.9042	0.9136
OOTV	0.8667	0.8753	0.8661	0.8832
OOEV	0.8053	0.8132	0.8163	0.82217
OOBV	0.7668	0.7713	0.7345	0.7804

Table 7: Comparison of performance of our model on different subsets of entities (F1 score).

Conclusion

We study the practical valuable task of MER and MEN. They are fundamental tasks in medical literature mining because many developments in this area are related to these two tasks. Previous state-of-the-art studies have demonstrated that the mutual benefits between medical named entity recognition and normalization are very useful. To make use of the mutual benefits in a more advanced and intelligent way, we proposed a novel deep neural multi-task learning framework with two explicit feedback strategies to jointly model MER and MEN. Our method can convert hierarchical tasks, i.e., MER and MEN, into parallel multi-task mode while maintaining mutual supports between tasks. Experimental results indicate that our model outperforms previous state-of-the-art studies.

Acknowledgments

We thank anonymous reviewers for their insightful comments and suggestions. This work is supported by NSF IIS-1716432 and IIS-1750326.

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