Method	Fine-grained	Binary
DAN		
- Word2vec	46.2	84.5
- GloVe	46.9	85.7
- Re(Word2vec)	48.1	87.0
- Re(GloVe)	**48.3**	**87.3**
- HyRank	47.2	86.6
CNN		
- Word2vec	48.0	87.2
- GloVe	46.4	85.7
- Re(Word2vec)	**48.8**	**87.9**
- Re(GloVe)	47.7	87.5
- HyRank	47.3	87.6
Bi-LSTM		
- Word2vec	48.8	86.3
- GloVe	49.1	87.5
- Re(Word2vec)	49.6	88.2
- Re(GloVe)	**49.7**	**88.6**
- HyRank	49.0	87.3
Tree-LSTM		
- Word2vec	48.8	86.7
- GloVe	51.8	89.1
- Re(Word2vec)	50.1	88.3
- Re(GloVe)	**54.0**	**90.3**
- HyRank	49.2	88.2

Table 1: Accuracy of different classifiers with different word embeddings for binary and fine-grained classification.

word embeddings. For the two semantic-oriented word vectors, GloVe and Word2vec, on average around 24% of the top 10 nearest neighbors for each word are noisy words. After refinement, both Re(GloVe) and Re(Word2vec) can reduce noise@10 to around 14%. The HyRank also yielded better performance than both GloVe and Word2vec.

4 Conclusion

This study presents a word vector refinement model that requires no labeled corpus and can be applied to any pre-trained word vectors. The proposed method selects a set of semantically similar nearest neighbors and then ranks the sentimentally similar neighbors higher and dissimilar neighbors lower based on a sentiment lexicon. This ranked list can guide the refinement procedure to iteratively improve the word vector representations.

Word Embeddings	Noise@10 (%)
Word2vec	24.3
GloVe	24.0
HyRank	18.5
Re(Word2vec)	14.4
Re(GloVe)	13.8

Table 2: Average percentages of noisy words in the top 10 nearest neighbors for different word embeddings.

Experiments on SST show that the proposed method yielded better performance than both conventional word embeddings and sentiment embeddings for both binary and fine-grained sentiment classification. In addition, the performances of various deep neural network models have also been improved. Future work will evaluate the proposed method on another datasets. More experiments will also be conducted to provide more in-depth analysis.

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References

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2016. Enriching word vectors with subword information. *arXiv preprint arXiv: 1607.04606*.

Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th International Conference on Machine Learning (ICML-08)*, pages 160–167.

Ronan Collobert, Jason Weston, L´eon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12:2493–2537.

Andrea Esuli, and Fabrizio Sebastiani. 2006. SentiWordNet: A publicly available lexical resource for opinion mining. In *Proceedings of the 5th International Conference on Language Resources and Evaluation (LREC-06)*, pages 417-422.

Manaal Faruqui, Jesse Dodge, Sujay K. Jauhar, Chris Dyer, Eduard H. Hovy and Noah A. Smith. 2015. Retrofitting word vectors to semantic lexicons. In