Reverse Dictionary

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Abstract

In this project, we produce a reverse dictionary, which allows one to find a word that they can't remember by describing its meaning. A reverse dictionary takes in a word definition as an input query and returns the top-k candidate words that are most likely to match this definition. The input can be similar to a dictionary definition, or even a colloquial description of the desired word. For example, the input "a small vessel propelled on water" should yield an output of "boat".

We compare multiple possible approaches to find the best way to implement a reverse dictionary, both in terms of accuracy and in terms of computational workload and speed. We find that an encoder-decoder model using a BERT encoder with either linear decoder layers or an LSTM decoder yield the best results, but similar accuracy can be obtained even with lightweight BERT models.

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Problem

A common phenomenon is the tip-of-the-tongue problem, where you can't quite remember a specific word or phrase you are thinking of. We propose a "reverse dictionary" as a solution to this problem, which takes a word description or definition as an input query and returns a list of the top candidate words.

Sample Input	Sample Output
Small amount	smidgen, scrap, speck, little, bit
Winter sport	skiing, snowboarding, sledding, ice skating, curling

Some use cases for a reverse dictionary:

- *Recalling a word on the tip of your tongue*
- *Finding synonyms for a word*
- *Learning new words for non-native speakers*

Background

The research space for reverse dictionaries is relatively sparse. There are very few papers that utilize recent state-of-the-art methods like BERT or neural networks[1]. Reverse dictionary implementations online simply compare word counts in inputs to known word definitions. As a result, there is still lots of research that can be done to improve the performance of reverse dictionaries.

Dataset

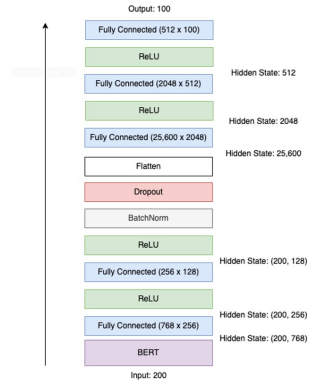
For our dataset, we use word-definition pairs from WordNET and the Online Plain Text English Dictionary, combining for approximately 300 thousand pairs. We construct an 80/20 training/validation split.

We use pre-trained GloVe embeddings[2] for our model. The pre-trained set contains 100-dimensional embeddings for 400 thousand words

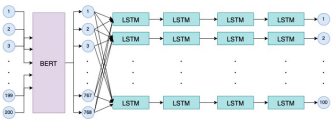
Methods

We tokenize all input queries, then pad and truncate to the same length. Tokens are passed into a BERT layer to generate the query encoding.

We test two different model variants. First, we use a decoder stack composed of fully connected linear layers, ReLU, BatchNorm, and DropOut layers to train for 20 epochs. The final output is a 100-dimensional predicted word embedding.

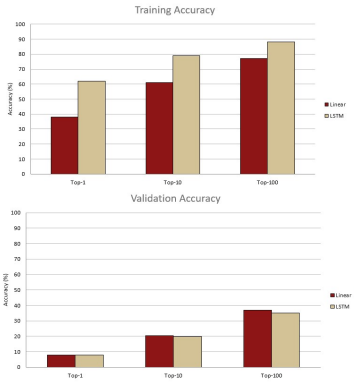


Our second model variant is composed of a four-layer long short-term memory (LSTM) RNN with dropout in all layers besides the final layer. The input and output for this model is the same as those described above.



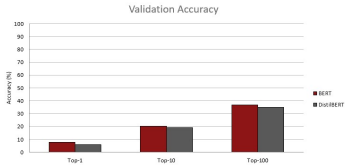
Experiments

After training both our model variants, we see that the linear decoder and LSTM decoder both reach similar accuracy levels on the validation set. However, LSTM reaches significantly higher accuracy on the training set.



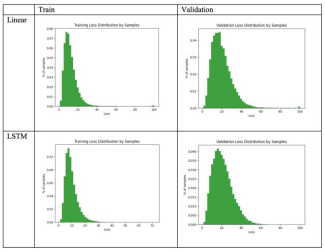
However, the LSTM needed 100 epochs to reach the same validation accuracy as the linear decoder which only needed 20. This also resulted in significantly higher training time for the LSTM decoder.

We also trained our model with DistilBERT instead of BERT large for our encoder layer.



Analysis

We find distribution of loss among samples is similar, but the LSTM model is more robust with fewer outliers.



We also find that the top-1 and top-10 accuracy scores increase by nearly 1.5x if evaluated on just the 2000 most frequent words.

Conclusion

We find that our approach can accurately extract semantic meaning from a description of a word and provide a good prediction of target words. Overall, we believe the LSTM decoder has more robust behavior even if it is slower to train.

Although our model finds the top-k words out of a vocabulary of 400,000, a typical English speaker's vocabulary is much more limited (order of a few thousand per day). Our reverse dictionary could be even more accurate and useful if we removed rare and unused words.

Key References

[1] Qi, Zhang, et al. "WantWords: An Open-source Online Reverse Dictionary System". Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations. 2020

[2] Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, 2014.