Removing <unk>

Brian Lester

ML Research Engineer

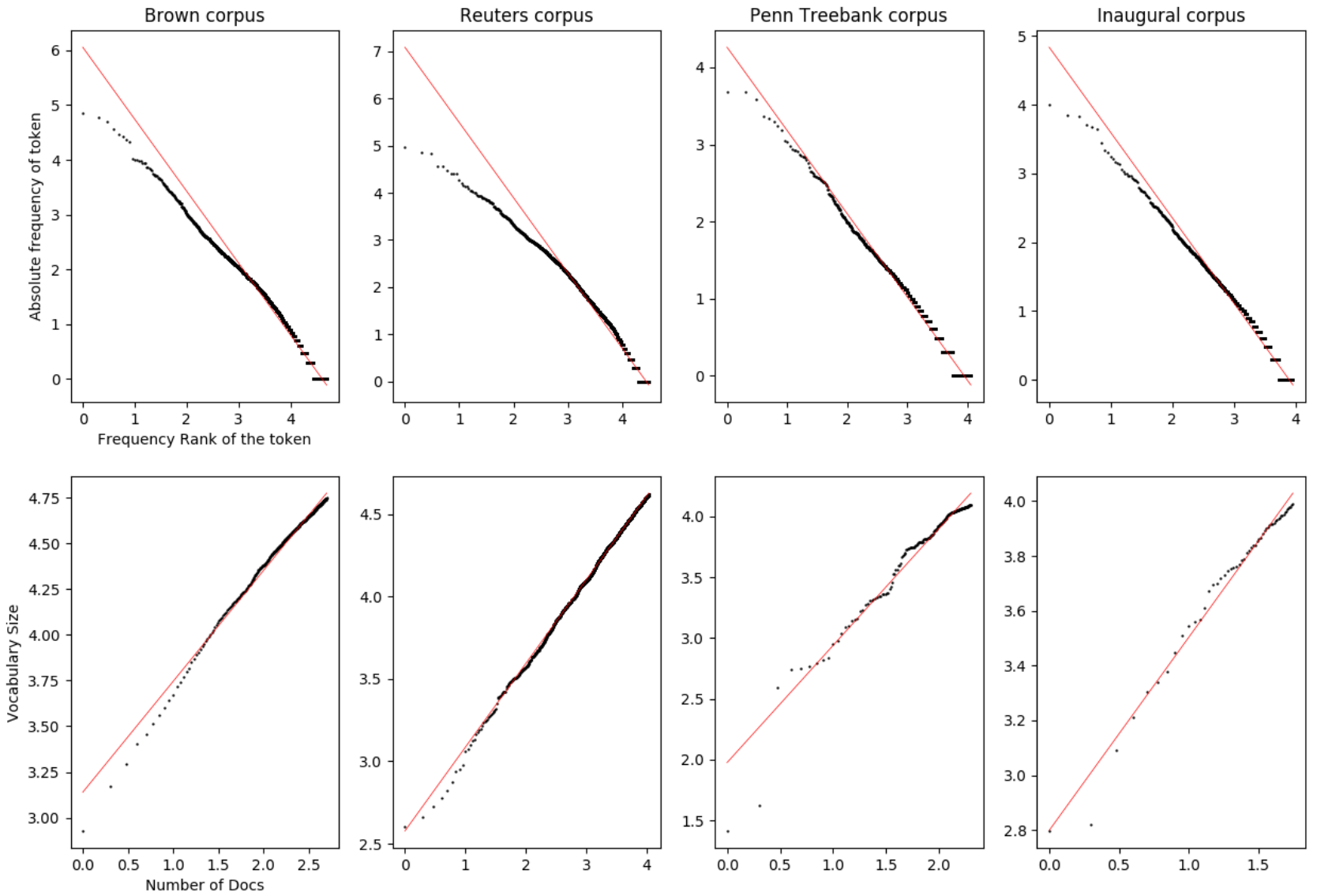
Trove

<unk>

- A token to handle uncommon words
- You need several examples to learn a good embedding
- Keeps the vocabulary smaller

Removes a lot

- the u.s. is one of the few industrialized nations that does n't have a higher standard of regulation for the smooth <unk> fibers such as <unk> that are classified as <unk> according to <unk> t. <unk> a professor of <unk> at the university of vermont college of medicine
- The game takes place during the Second Europan War . Gallian Army Squad 422 , also known as " The Nameless " , are a penal military unit composed of criminals , foreign <unk> , and military offenders whose real names are erased from the records and <unk> officially referred to by numbers . <unk> by the Gallian military to perform the most dangerous missions that the Regular Army and Militia will not do , they are nevertheless up to the task , exemplified by their motto , <unk> <unk> , meaning " Always Ready .


Zipf and Heaps Laws
Brown corpus
Reuters corpus
Penn Treebank corpus
Inaugural corpus
Absolute frequency of token
Frequency Rank of the token
Vocabulary Size
Number of Docs

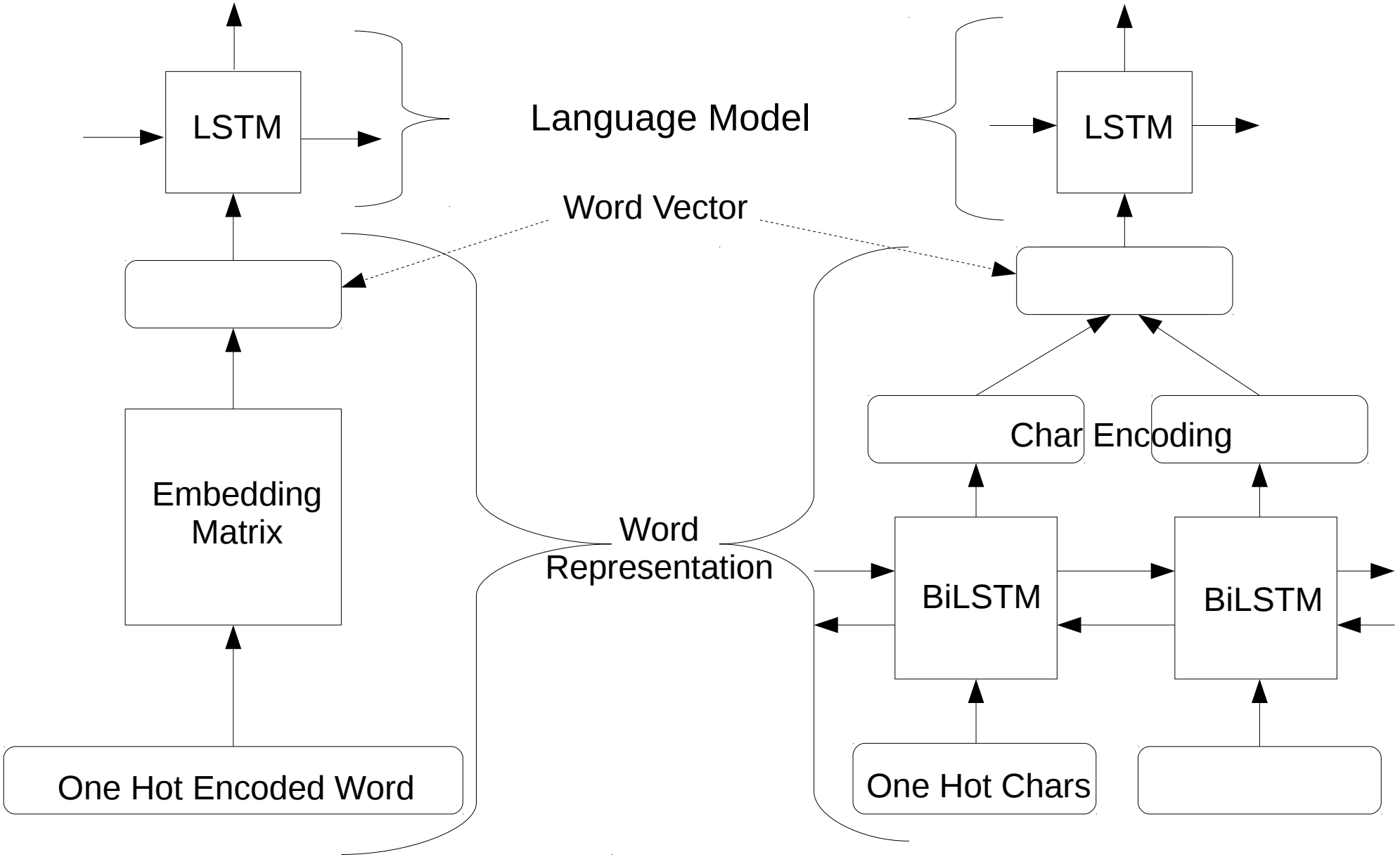
Keep some information

- <unk> before you train word vectors
- Average uncommon word vectors together

Use an open vocabulary

- Memorize
  - Dad – D + B = Bad
- Generalize
  - Car + s = Cars
  - “I love it!” vs. “I looooooove it”
- LSTM on the Characters

Not a CharLSTM



But my word embeddings!

- Semantic Analogies

  Kitty – Cat + Dog = Puppy

- Syntactic Analogies

  Shorter – Short + Tall = Taller

We have those too!

increased	John	Noahshire	phding
reduced	Richard	Nottinghamshire	mixing
improved	George	Bucharest	modeling
expected	James	Saxony	styling
decreased	Robert	Johannesburg	blaming
targeted	Edward	Gloucestershire	christening

http://www.cs.cmu.edu/~lingwang/papers/emnlp2015.pdf

Character Backoff

- This is a compromise
- Take advantage of large datasets

```
def word_rep(word, fw_init, bw_init):
    if word_vocab.counts[word] > 5:
        index = word_vocab.get(word)
        return WORD_EMBEDDING_MATRIX[index]
    else:
        pad = char_vocab.get("<*>")
        indices = [pad] + [char_vocab.get(c) for c in w] + [pad]
        embedded = [CHAR_EMBEDDING_MATRIX[i] for i in indices]
        forward = fw_init.transduce(embedded)
        backward = bw_init.transduce(reversed(embedded))
        return dy.concatenate([forward[-1], backward[-1]])
```

Results

Model	Unk Percent	Perplexity	Parameter Count
Word Level	4.84	145	5.6M
Composition Model	0	146	3.2M
Back-off Model	5.04	142	5.8M

http://www.github.com/blester125/language_model

Future Research

- Build Robust Models
- Composeable output
- Pretrained input representation
- Byte Pair Encoding as subwords.
- Linguistic informed subwords, prefixes, suffixes, etc.
- Smarter combination of character encoding.