Towards Rich Word Embedding for Text Generation Using Recurrent Neural Networks

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***Abstract*—Language modeling and text generation have been studied for decades, but more recently deep learning and other machine learning techniques have been applied to these tasks. Although work has been done with Markov modeling and recurrent neural networks (RNNs), not much progress has been made with higher-level linguistic structure such as subject-participle construction or parts of speech. The team's work infused standard word embedding techniques with the respective part of speech, with the hopes of improving the sensibility of generated text. The tea, compared the structure between this enriched word embedding technique applied to RNNs to word-level Markov chains and non- enriched word embedding-based RNNs. However, both qualitatively and quantitatively results were disappointing, where none of the proposed methods performed well. The selected string distance metrics are not sensible as a means of comparing generated text, and more work must be done to improve data preprocessing, metric exploration, model improvements, and feature selection.**

***Index Terms*—text generation, recurrent neural network, natural language processing, language modeling, computational linguistics, part of speech tagging, word2vec, word embedding**

I. Introduction

Semantic understanding of natural language has been a difficult problem in computer science for decades. [1] While many great strides have been made in many subfields such as sentiment analysis [2], word embeddings [3], text generation [4], classification [5], and summarization [6], there still lacks an effective means of human-level text modeling [7] [8] [9]. Recently, more tools have become available to help in this endeavour [3] [10] [11], and the aggregation of techniques is now possible. One such example is the generation of a caption given an image [12], which uses a convolutional neural network in tandem with an RNN and is trained on parsed and tokenized natural language data. This method utilizes dependency trees as a way of building vectors which embeds the word with its respective part of speech context at once, as well as incorporating neighboring words and their contexts.

Currently, the more popular generative methods aim to model languages from the character-level upwards rather than from the word-level. Even those that operate on a word-by-word basis such as Markov chain modeling [13] and n-gram modeling [14] may not incorporate parts of speech nor long-term memory. Traditionally, these word-level models are stochastic; that is, they construct internal representations of language by building a probabilistic mapping between previous words in the sequence to the current word. However, natural language is a complex system [15] and thus has more depth than the surface-level words present, such as semantics, grammar, parts of speech, etc, and it would be advantageous to encode this information alongside the words themselves.

In conducting the research for this paper, the team evaluated the efficacy of tokenizing words alongside their parts of speech with unique identifiers for use in a recurrent neural network (RNN). Specifically, the team aimed to generate text using the long short-term memory (LSTM) variant of the RNN by employing training data comprised of a subset of scripts from the contemporary popular American cartoon television show, Rick and Morty. This method of encoding natural language has an advantage over the previously mentioned dependency trees by being fully transparent and providing full customization capacities for the user; it is, for example, possible to manually change the embedding of the parts of speech, the words themselves, or to add more language features as needed in order to achieve the desired goal.

II. Methods

A. Data

The data used in this study was a short subset of a transcript found online [16] from the American television series Rick and Morty. The team arbitrarily gathered 50 sequential sentences from the first episode of Rick and Morty. The number of total words, unique words, and outlier words in the dataset are outlined in Table I, where an outlier word is defined as any word with a frequency of less than 5 occurrences.

TABLE I
DATASET STATISTICS. 50 TOTAL SENTENCES WERE USED. AN UNCOMMON WORD IS DEFINED AS A WORD WHICH OCCURS LESS THAN 5 TIMES.

Series	Total Words	Unique Words	Uncommon Words
Rick and Morty	649	220	21

B. Preprocessing

As the data was found via an online source, there was much heterogeneity in the scripts. Therefore, there were several cleaning steps to ensure the data could be handled by the model properly. First, through a programmatic approach, the data was split by the presence of the English sentence delimiters ".", "!", and "?" while accounting for periods in abbreviations, prefixes, suffixes, and numbers. Next, extraneous white space was removed, and then the case of all characters was set to be lower. The starts of all sentences were then verified to start with words rather than symbols such as -, or spaces, and finally, special ST and EN tokens were appended to the beginnings and ends of each sentence, to allow the model to easily learn when sentences should begin and end.

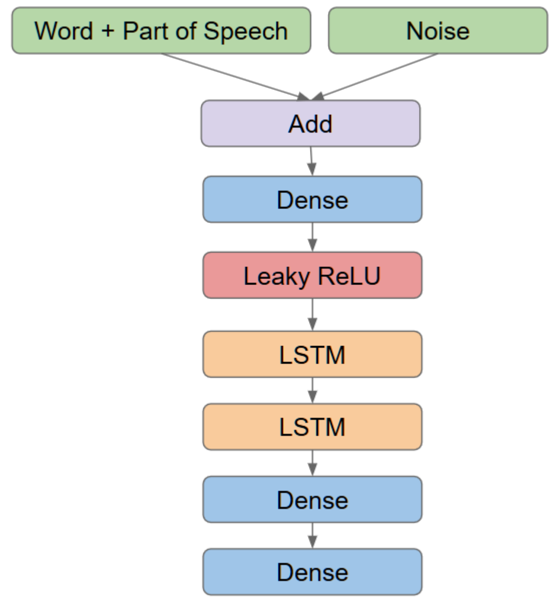
Each unique word was encoded into a one-hot vector such that each word was represented by a single 244-dimensional sparse vector in which only a single element is set to 1, and the rest are set to 0. Next, NLTK [10] was used to generate the appropriate part of speech tag for every word in our corpus. The tag, generated by NLTK, was converted into a one-hot vector of length 47, and, subsequently, each word was mapped into its respective one-hot space. To finalize preprocessing, the one-hot vector representing the word was concatenated with the one-hot vector representing the part of speech. This resulted in a 291-element vector.

C. Recurrent Neural Network Architecture

The model selected for this problem was a RNN model comprised of a fully-connected layer leading into two LSTM layers, and, finally, into one fully-connected layer of size 244, corresponding to the length of the one-hot word vector, which was subsequently activated with the softmax function. As this is a classification problem, the team used categorical crossentropy for loss. To aid with learning, a LeakyReLU activation was utilized before the LSTM layers to allow gradient values below 0 to flow through to the prior layer. The model is depicted in Figure 1.

Since neural networks are deterministic models, text generation is prone to falling into a so-called loop, where the model may map A to B, B to C, and C to A. To avoid this, the network was supplied with an auxiliary input vector of equal length to the word and part of speech vector. This auxiliary input has random entries pulled from the Gaussian standard normal distribution. The random entries were linearly scaled down by a factor of 10 such that entries were $\in [-0.1, 0.1]$. To

Fig. 1. RNN architecture. The word and part of speech vectors are concatenated prior to being fed into the network. Noise is supplied to the network in parallel, then is added element-wise to the data vector. The signal subsequently flows through a fully-connected (dense) layer, LeakyReLU activation, two LSTMs, and two final fully-connected layers where the final activation is softmax.



allow for this auxiliary input, the model takes an independent input, then performs an element-wise sum with the word and part of speech vector before feeding the tensor into the first fully-connected layer.

D. Training and Text Generation

For training, the team supplied the network with 10 sequential words, and provided as ground truth each of those words subsequent words. The model was trained for an arbitrary 10000 epochs with a batch size of 50; in other words, the entire training set was used as the batch size.

To generate text, the team defined a sentence to be the existence of the EN tag. First, the network was supplied with the one-hot encoding for the start token ST alongside the random auxiliary vector, and the team utilized the above-described method to feed the models predictions back as inputs. By this approach, the team generated words until the EN tag appeared 50 times, thus matching the number of sentences in the dataset.

E. Postprocessing

The output of the RNN is a 244-element vector corresponding to the previously-mentioned one-hot encoding. To map this output back into word space, the team calculated the vector distances between the models output and each word vector in the teams dataset to find the closest match. The team then wrote the corresponding word to a file, and used the exact one-hot encoding for the closest word as input for the RNN to generate its next output. The part of speech of the closest word was also found, and concatenated to the one-hot encoding as done during preprocessing. In this manner, the RNN always takes the two concatenated one-hot encodings in as its input, despite it generating dense vectors as output.

III. Results

To validate the model, it was compared to two other methods: a word-level Markov chain and the same word-level RNN without part of speech embeddings. Qualitative results are shown in 2, where the two most realistic sentences from each model were chosen.

Fig. 2. Two example sentences as qualitative results from each of the Markov Chain, word-RNN (w-RNN), and enriched word-RNN (e-RNN) models. These are the subjectively best sentences picked by human raters.

```
MARKOV CHAIN
ST please , crying at an obituary for grandpa , geez , morty EN
ST everyone wants to go through interdimensional customs unless

they 'll fall right out of seven hours over the last two months . EN

W-RNN
we're ST ST you're your principal ST ST ST ST ST you're a a
ST ST ST you're ST a a ST ST ST ST your ST ST ST ST ST EN

ST ST ST ST ST ST ST ST ST you're (burps) ST ST ST EN

E-RNN
i'm this attended put aren't ST EN

morty's you ST ST to inside ST ST ST ST ST EN
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For quantitative comparison, 4 different known string comparison metrics [17] were used over the resulting parts of speech of each of the 3 methods' output. Specifically, for each sentence in the outputs of each of the Markov chain (MC), the word-RNN (w-RNN) and the enriched word-RNN (e-RNN), parts of speech were tagged, and these tags were compared to the original dataset's part of speech tags using Hamming distance [18], cosine similarity [17], Gotoh's algorithm [19], and Levenshtein distance [20]. These 50 measured distances were then averaged to produce the results seen in Table II

The Hamming distance measures the number of differences between a pair of strings. In this circumstance, this is the number of mismatches between the parts of speech in the original data, and each of the generated samples. With regards to tokenized natural language, cosine similarity measures distances as vectors according to the formula:

$$similarity = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Gotohs algorithm originally was proposed as a more efficient means of comparing biological sequences, but can also be applied to natural language. Finally, similar to Hamming distance, Levenshtein distance measures mismatches of arbitrary length.

IV. Discussion

Although the team did see an improvement both qualitatively and quantitatively with the inclusion of parts of speech in RNNs, the overall results were disappointing. Subjectively inspecting the output data as a human rater, the sentences generated by both variants of the RNN failed. Additionally, while the quantitative results from distances between parts of speech look promising, the apparent dichotomy between the chosen string comparison metrics and the actual generated text demonstrates that metrics alone are not sufficient to capture the complexities of natural language. Even the training curves with and without the part of speech features are very similar. The loss dips a couple hundred epochs earlier without the parts of speech. This is sensible though, as with fewer elements in the input vector the model can converge quicker.

Fig. 3. Training curve for data without parts of speech appended. Accuracy is $\in [0, 1]$ and represents the accuracy with which the model correctly selects the next words in the sequence.

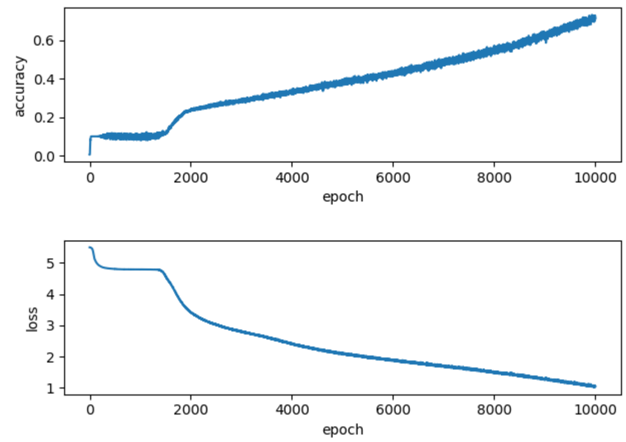

Fig. 4. Training curve for data with parts of speech appended. Accuracy is $\in [0, 1]$ and represents the accuracy with which the model correctly selects the next words in the sequence.

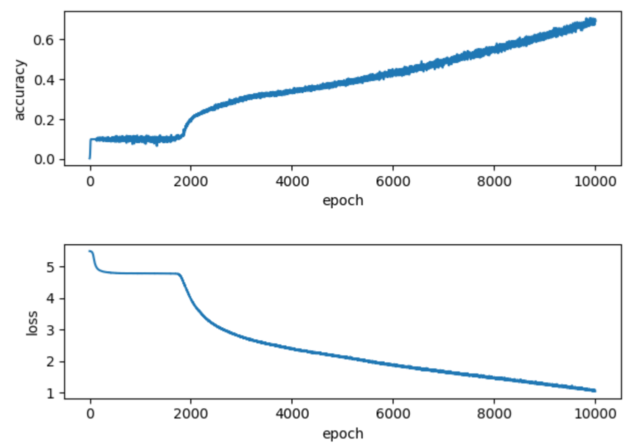

TABLE II
Distance metrics between generated corpus and the original corpus. For comparison, the distance of the ground truth compared against itself is shown. Best results are highlighted in bold, excluding the ground truth.

Metric	Ground Truth	MC	w-RNN	e-RNN
Hamming	0	3.901	4.439	**3.427**
Cosine	0.05	0.035	0.030	**0.0296**
Gotoh	3.732	**1.225**	0.347	0.119
Levenshtein	0	**2.532**	3.301	2.684

Future work in the application of deep learning to natural language generation includes exploring better quantitative metrics, more attention towards RNN architecture design and hyper-parameter choice, more directed efforts with respect to data preprocessing, and investigation of choices of alternative text encodings such as using word2vec or other grammatical or semantic features as auxiliary inputs.

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