The RNN in the Hat: Generating a Dr. Seuss Picture Book

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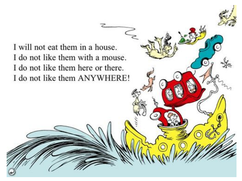
Abstract

- Dr. Seuss is one of the most popular children's book authors of all time.
- Recent trends in artificial intelligence have attempted to generate works of art, scripts, and books given a particular art or writing style.
- Given the unique structure of a Dr. Seuss book, it is an interesting challenge to generate lines out of a Dr. Seuss book.
- **Goal: Implement a character-based Recurrent Neural Network that generates Seussian text.**

Introduction

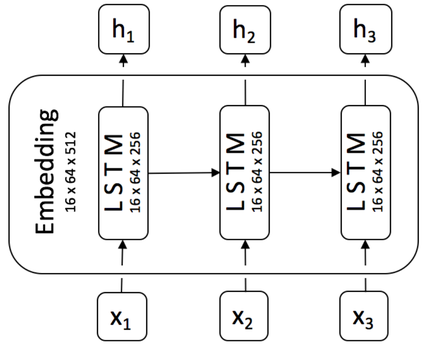
- Seussian rhyme schemes- rhyming pattern of last word in line
  - "Alternate rhyme": ABAB
  - "Couplet": AABBCCDD
  - "Seussian": XaXaXbXb



- Meter- the basic rhythm structure of a verse
  - Iambic trimeter
  - Iambic tetrameter
  - Anapestic tetrameter
  - Trochaic pentameter
- Stanza- grouped set of lines within a poem
  - Quatrains- 4 lines
  - Sonnet- 14 lines
- Sight words- high-frequency words
- Made-up words

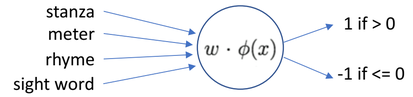
Method

1. Dataset
   - Used a corpus of 7 most popular Dr. Seuss books
   - Created a corpus of works of other popular poets
2. Requirements
   - Each generated sample tested on classifier
   - Same dimension vocabulary size vector
3. Training Process
   - Implemented in Keras with TensorFlow backend
   - Trained for 100 epochs with batch size of 16 and sequence length of 64
   - Cross-entropy loss using Adam optimization
   - Built custom classifier for generated text using predefined "Seussian" criteria



Classification

- Use Poetry Tools Python library to estimate the stanza, rhyme scheme, and meter features of a given .txt file (classifies 1 if is of Seussian style).
  - Uses Levenshtein Distance to find closest estimates
- Calculate proportion of .txt file that are sight words (1 if is Seussian proportion)
- Initialize weights to [0] vector, then optimize using stochastic gradient descent
- Linear classifier: 1 (Seussian), -1 (Non-Seussian)

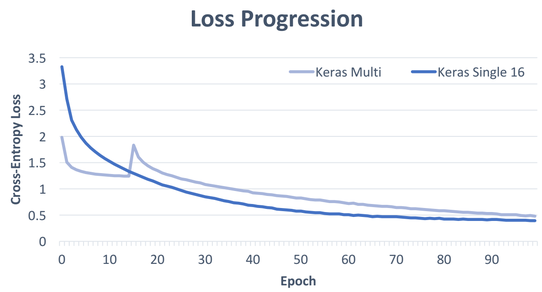


Results

N-Grams	Vanilla RNN	Keras RNN (Seq. Length = 64)	Keras RNN (Seq. Length = 16)	**Keras RNN Multi-Corpus Training**
… you did not know what to say. our mother like this? we don't know. and you may. try them and you may …	… in took." I hook same, at is you fas. Saws fithet wise at thing OB.? At, to up they wild thin they way? Note fen, And Thow" …	… "Why do you like to go away. On the Grinch pump light on your shown to be went. And the magical things you can do with that ball …	… Mr. Knox. Now come to chew, sir. You're off to the fir. On their is heart or the small, Was singing! Without any putn. So shake …	**… "Then I say, "I must stop this whole tible, Around the father bags in a bottle, While these Things had everywhere. …**
The N-grams model represented our attempt at a baseline, using N = 3 to generate words solely off of the pattern in the text provided.	Our Vanilla RNN was a bare-bones RNN in which we manipulated the weights and gradients manually, leading to suboptimal performance.	We decided to convert our model to Keras to give us more freedom in analysis, also switching the optimization from Adagrad to Adam.	The results too closely mirrored the input text, so we decremented the Sequence Length to get less accurate, but more creative results.	**To provide the RNN with a larger language context, we trained on first a poetry corpus and later on the Seuss corpus to emphasize Seuss's writing style.**

Table 1. Accuracy, Loss, and Classification for Various Models

	Accuracy	Loss	Classification
N-Grams	N/A	N/A	**1** (1e-16)
Vanilla RNN	N/A	33.14	**-1** (-0.3)
Keras RNN (64)	0.96	0.13	**1** (1e-16)
Keras RNN (16)	0.88	0.39	**1** (0.5)
Keras RNN (Multi)	0.84	0.48	**1** (1e-16)



Conclusions

- Keras RNN with a sequence length of 16 yielded the strongest results according to the classifier
- Samples from Keras RNN classified as Seussian, whereas Vanilla RNN classified as non-Seussian
- Keras RNN samples lack a clear, consistent rhyme pattern, but some rhymes are present
- Achieve a more confident classification when sequence length is 16 rather than 64, only training on Seuss
- Decrementing the sequence length gave the samples less syntactically correct, but more "creative" results
  - This is due to a higher character volatility leading to less consistent word outputs
  - Mimics higher temperature results

Future Directions

- We would have liked to find the optimal training ratio between the standard poetry and Seuss texts in order to yield the most Seuss-like results
- Furthermore, we would like to add more robust poetry feature classification and generation mechanisms

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