### Assignment 4: Neural Language Models for Text Generation with Deep Learning

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Colab - Alice's Adventures in Wonderland: <a href="https://colab.research.google.com/drive/12RAE0EBBS-YyBF50Uu2L0H7VOu5o5Pzc?usp=sharing">https://colab.research.google.com/drive/12RAE0EBBS-YyBF50Uu2L0H7VOu5o5Pzc?usp=sharing</a>
Colab - The Metamorphosis: <a href="https://colab.research.google.com/drive/1VVAT4ZTb03Zug2zZpWjDKkE7S-7CMR9P?usp=sharing">https://colab.research.google.com/drive/1VVAT4ZTb03Zug2zZpWjDKkE7S-7CMR9P?usp=sharing</a>

### **Abstract**

The ability to generate text that resembles the quality of human language has numerous applications, from machine translation to spelling correction, from text summarization to image captioning. At the heart of these larger tasks is the language model, which is a function or algorithm for learning that function that captures relevant statistical characteristics of the distribution of sequences of words in a natural language (Bengio, 2008). This study is an examination of the neural language model, specifically, as a foundation for larger natural language processing (NLP) tasks and a representative step in the evolution beyond traditional statistical modeling. Its goal is two-fold: develop neural language models for capturing the "essence" of a large corpora of text and gain an in-depth understanding of how various factors affect fitting and ultimate performance with networks with differing deep learning architectures. This will shed light on how hidden nodes learn to extract features from inputs; with additional layers, the objective is to better understand how each successive layer extracts progressively abstract and generalized features. This is done through the development and evaluation of word-based neural language models for text generation.

Using two texts downloaded from Project Gutenberg – Lewis Carroll's *Alice's Adventures in Wonderland* (1865) and Franz Kafka's *The Metamorphosis* (1915) – various network architectures are tested to determine their ability to capture meaning and context from these two texts and generate believable sequences of related text based on predictions of probability given an input sequence of text. Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs) are employed primarily given these networks' established performance with text generation and ability to help mitigate, in some cases, overfitting and the challenge of vanishing gradients. LSTM RNNs are also the focus due to their potential to retain sequence-based meaning, from words in sentences to sentences in paragraphs; the longer nature of these texts offers a useful data source for testing this possibility. Varying network depth and width are investigated for potential impact on performance, which is ultimately measured quantitatively (via loss and training time) and qualitatively (via generated text examples from seed text and comparison to actual text that follows). While this evaluation is not perfectly objective, these combined steps shed light on how well the various models capture meaning from text, which serves as useful in certain standalone cases and, more importantly, as a critical input to more complex NLP tasks.

### Introduction

Language modeling is a central component to many NLP tasks, comprised of probabilistic models that are able to predict the next word (or character, more recently) in a sequence given the words that come before. These models essentially aim to capture word representations and probability indicators of word sequences. Neural networks have grown in popularity for certain language modeling tasks due to their fit for complex scenarios where feature relationships cannot easily be captured by linear models. This describes human language perfectly: it is messy and nuanced. Word meaning can swing wildly depending on placement in a phrase or sentence, and also the words preceding that word's occurrence. Words, as features in a model, can combine almost limitlessly and meaning is often

buried in sequential relationships. Moreover, languages change as people and their environments change – it is a moving target. The hidden layers of a neural network architecture have shown notable promise in learning the features – the words themselves – and their combinations optimally. Importantly, neural networks and, in certain cases, deep learning models, aid in overcoming certain challenges implicit to language modeling, such as the curse of dimensionality where the huge number of possible word sequences for a corpus poses notable problems for learning algorithms. In many cases, neural network-based language models outperform tried-and-true classical methods and have contributed powerful capabilities to larger NLP problems.

Deep learning architectures, incorporating multiple hidden layers to successively extract progressively abstract and generalized features, offer potentially even greater capacity for learning a general representation of language and context for more complex and nuanced textual data. Advances in computational power (and lower expenses) and the availability of large amounts of linguistic data for training, along with extensive research, have all contributed to deep learning's prevalence in the NLP space. With research advancing at a rapid pace still, deep learning models and methods, specifically those employing word embeddings and RNNs, have made possible advances in numerous NLP applications, from basic tasks like part-of-speech tagging and parsing to text classification, information extraction, sentiment analysis, machine translation, and question-answering systems.

#### Literature review

Current research attributes the first feed-forward neural network language model to Bengio et al. (2003), which learned a distributed representation of words and helped overcome the curse of dimensionality with which earlier language models, such as n-gram language models, grappled. RNN language models were developed in the early 2000s building on that work, notably RNN language models (Mikolov et al. 2010). Hidden layers in RNNs were able to carry information from memory, making them particularly useful with language models with sequential inputs. Though RNNs represented a sea change in terms of learning meaning and context from textual data, certain challenges remained, particularly the vanishing and exploding gradients problems. LSTM RNNs were proposed as a solution, in addition to their performance in learning long-term dependence in larger corpora (Sundermeyer et al., 2012). Researchers from Google Brain explored these advances in 2016 and extended some of the state-of-the-art models to address additional challenges. First, earlier models performed well on smaller datasets but failed to improve on larger ones. Capitalizing on rapid advancements in compute power (and its low expense) and vast available large corpora for training, this work presented much-improved neural language models that captured complexity and long-term structures in language (Jozofowicz et al., 2016). Another major challenge the research has focused on is exposure bias in natural language generation applications, a common occurrence when training language models using maximum likelihood approaches. In training, when the prediction of the next word conditioned on the previous word is not possible since the previous word may not have been seen in the training data. If the generator makes a prediction error early on, the generated sentence keeps diverging further away as more words are generated. A variety of proposed approaches have sought to address this issue and improve neural language model performance for standalone applications or as inputs to larger NLP tasks (Bengio et al., 2015; Schmidt, 2019; He et al., 2020).

Character-level models, versus earlier word-level models, represent a major advancement as well. Character-level inputs are used but predictions are still made at word level using CNN output given to a LSTM RNN language model in one example, tested on multiple languages (English, Arabic, Czech, French, German, Spanish, and Russian) (Kim et al., 2016). Sequence level training has been explored as well in the NLP research community. Generation of sequences based on word-level inputs have been criticized as "brittle," with errors accumulating along the way (related to exposure bias). The sequence level training algorithm proposed by Ranzato et al. offers a novel approach to addressing this prevalent issue (Ranzato et al., 2016). Beyond approaches to some of the implicit data- and model-related challenges of RNN language model design and deployment, entirely new ways of training generative models have been proposed over the past five years. In the reinforcement learning space, for example, SeqGAN employs Generative Adversarial Nets (GANs) whose discriminator is judged on a complete sequence, which is then passed back to the intermediate state-action steps using Monte Carlo search (Yu et al., 2016). In another example, adversarial learning is applied to dialogue generation in an attempt to create dialogue indistinguishable from human generation (a nod to the Turing test) (Li et al., 2017). As deep learning research evolves, applications for text (even if models are originally developed for other data types) continue to grow and receive notable attention in both academia and industry.

#### Methods

Data ingest and exploration

The two texts selected for this study offer a means for comparing text generation tasks with works of fantastical fiction, one written in English and one written in German and translated to English. The nature of these two texts and each of their unique vocabularies and stylistic specificities present an interesting challenge to neural language modeling and an opportunity to uncover the impact of lexical diversity (how varied unique words in a corpus are compared to the overall quantity of words), tone, and importance of sequential relationships on model performance.

In advance of pre-processing, examination of the clean text downloaded from Project Gutenberg shows section headings and chapter titles, prevalent punctuation of all kinds, and unique names from characters (e.g., Hatter, Lory, and Lobster Quadrille from *Alice's Adventures in Wonderland* and proper names like Gregor and Grete from *The Metamorphosis*). These conditions informed data preparation strategy, comprised of splitting words based on white space, removing punctation, removing non-alphabetical words, and normalization to lower case. The full vocabulary is used for this study, including stopwords, since these words contribute to the sequential relationships the models will try to learn and capture. Finally, the text is split into a list of clean tokens following preparation.

Prior to model design, exploratory data analysis on each text enables analysis of word frequency (via token analysis, overall and with stopwords removed) and bigram counts to explore which two-word pairs of words occur most frequently. Given the combinatorial potential of words in phrases, sentences, paragraphs, and longer works overall, bigram analysis is a relatively simple way to extend single word quantitative investigation. Lexical diversity is also calculated as a potential driver of the experiments' language models' ability to capture meaning. This measure – the number of unique tokens in a text as a proportion of total tokens – refers to the range of different words used in a text. Its meaning is subjective, text-dependent, and not a perfect reflection of actual vocabulary range; however, it gives an indication of the scope of different kinds of words in the text, with a greater range (higher number) possibly indicative of

higher diversity. These measures are all calculated for the original text tokens and for the text with stopwords removed to uncover diluting impact of common words in the vocabularies. Values for the two texts are as follows:

	Alice's Adventures in Wonderland	The Metamorphosis
Total Vocabulary Size	26,717	22,010
Unique Tokens	2645	2613
Lexical Diversity	0.099	0.119
Total Vocabulary Size (Stopwords Removed)	12,712	10,147
Unique Tokens (Stopwords Removed)	2515	2494
Total Sequences (Training Patterns)	26,666	21,959
Lexical Diversity (Stopwords Removed)	0.198	0.246

Alice's Adventures in Wonderland is slightly longer, though the texts have roughly equivalent unique tokens in total, with and without stopwords removed. The Metamorphosis exhibits slightly higher lexical diversity, with and without stopwords. These measures do not hold any particular value on their own, however they do give an indication of the breadth of vocabulary at hand as input to the experimental models. Lexical diversity, specifically, may represent how challenging a given corpus may be for a language model to represent.

## Pre-processing

Tokens are split into sequences with length 50 + 1 (50 input words and 1 output word). These sequences serve as inputs/training patterns to the neural language models in the study, with each word's probability predicted based on the given input sequence of text. Sequence length is a key design decision: they must be long enough to properly allow models to learn the context and make reasonable predictions. The sequence length also defines the seed text length used to generate text sequences for model evaluation. *Alice's Adventures in Wonderland* has about 5,000 more training sequences available, for consideration in how models will learn across experiments. The Tokenizer class in Keras is used to encode input sequences to integers, which the neural networks expect as input. The vocabulary size, defined by this encoding process, is defined as the vocabulary + 1 in length for feeding to the Embedding layer. After encoding, sequences are separated into input (X) and output (y) elements using array slicing. Output words are one hot encoded so the models in the study can predict the probability distribution for the next word.

### Modeling approach

To train statistical models from the data, these experiments all employ an embedding layer to learn the representation of words. Parameterization of words as vectors in this manner, learned as part of the training process, enables words with a similar meaning to have a similar representation. LSTM RNNs then learn to predict words based on context. There is no test dataset: models are trained on the entire training dataset to learn the probability of each word in a sequence. The same experiments are run for each text to enable a more reliable comparison of performance across both text sources. The network architectures are as follows:

Experiment	Network Architecture	Trainable Parameters

LSTM RNN 1	1 hidden layer (100 memory cell units) Embedding vector space: 50 465,214	
LSTM RNN 2	1 hidden layer (256 memory cell units) Embedding vector space: 50	734,782
LSTM RNN 3	2 hidden layers (100 memory cell units) Embedding vector space: 50	545,614
LSTM RNN 4	2 hidden layers (256 memory cell units) Embedding vector space: 50	1,707,970
LSTM RNN 5	1 hidden layer (256 memory cell units) Embedding vector space: 100	1,364,558
Bidirectional LSTM RNN 6  1 hidden layer (256 memory cell units) Embedding vector space: 50		2,100,418

LSTM RNN 1 serves as a parsimonious baseline with a single hidden layer. A dense fully connected layer is connected to the LSTM layer to interpret features extracted from sequences. The output layer predicts the next word, with softmax activation for outputs with normalized probabilities across the vocabulary. LSTM RNN 2 extends that layer width with 256 memory cell units, all other parameters kept constant. LSTM RNN 3 adds network depth with two hidden layers and the same memory cell units in each to test performance impact from additional depth. LSTM RNN 4 is identical to 3 except with 256 memory cell units giving added layer width. LSTM RNN 5 takes the most performant model architecture so far, LSTM RNN 4, and extends the embedding vector space to 100. The size of the embedding vector space represents the number of dimensions to be used to represent each word, with common values starting at 50. LSTM RNN 5 evaluates the impact of additional dimensionality, with all other models set at 50. The last experiment employs a bidirectional LSTM RNN, which takes as input not only the words preceding the input sequence but also the words following. The output, in theory, incorporates greater context for a given sequence's meaning (from both directions). This increases the model's sophistication, but will be considered in terms of process time and results relevance as the others. The following hyperparameters are employed across all experiments for consistency:

Batch size: 128 / Epochs: 50

Activation: ReLUOptimizer: Adam

Loss function: Categorical cross-entropy

Early stopping with patience of 5

The objective of the models under evaluation is not 100 percent accuracy since that would represent rote memorization of the entire text. The objective, instead, is a model that captures a given text's essence. Model performance is evaluated using quantitative criteria (process time, loss, accuracy) as well as qualitative (namely, how reasonably generated text captures the meaning and context of the input sequences). Signs of exposure bias, the train-test discrepancy related to the maximum likelihood estimations used in certain neural language models, are observed in qualitative evaluation as well.

Results: Alice's Adventures in Wonderland

Figures of learning curves for all models in this study are included in Appendix 1. All qualitative results with seed and generated text are included in Appendix 2. The table below shows model fitting and evaluation results for *Alice's*Adventures in Wonderland:

Experiment	Processing Time (in seconds)	Loss	Accuracy
LSTM RNN 1	1496.37	2.46	0.41
LSTM RNN 2	1593.32	2.69	0.37
LSTM RNN 3	2758.05	3.39	0.24
LSTM RNN 4	3022.32	2.05	0.49
LSTM RNN 5	1630.74	0.53	0.88
Bidirectional LSTM RNN 6	3043.52	1.01	0.73

Considering the probability of picking a word from the entire possible set of vocabulary tokens (26,717 in this text), the accuracies above represent a solid improvement. The first two single-layer models from Experiments 1 and 2 both perform relatively well with lowest values of process time. As a baseline, they both show decent performance with respect to accuracy (remembering that the goal is not 100 percent, Figures 1 and 2). Generated text from LSTM RNN 1, while scattered and nonsensical, includes a relatively diverse group of tokens (versus one or a few repeated, representing exposure bias) and contains a handful of phrases that seem quite logical given familiarity with the text. Generated text examples from Experiment 2 exhibits similar qualities, however quantitative performance declines slightly with the added layer width (Figure 2).

The additional layer in Experiment 3 adds notable processing time and results in even higher loss and lower accuracy (Figure 3). One example of generated text suggests potential exposure bias ('should think it was a little startled she carried it to itself'), though this is not necessarily indicative of overall model performance since generated text examples serve as just that – select examples. Experiment 4 improves on that performance quite a bit, with slightly higher process time but the lowest loss value thus far and solid accuracy at about 50 percent (Figure 4). From a qualitative standpoint, though still nonsensical, the generated text seems to be learning word order that makes more sense and following the seed text's final words more logically ('as the doubledup soldiers' -> 'were always getting up and walking off').

Experiment 5's network, with a larger embedding vector space of 100, took less time to train and resulted in the lowest loss value across all experiments and highest accuracy (Figure 5). While the loss value is promising, the high accuracy suggests the potential for overfitting and memorization. One example of generated text supports this possibility: 'eager to see the queen first came ten soldiers' 'carrying clubs these were all shaped like the three gardeners oblong and flat with their hands and feet at the corners'. The generated text seems almost "too good" (see Appendix 2 for full examples). Finally, the Bidirectional LSTM RNN from Experiment 6, required the longest process time but results show low loss and solid accuracy, perhaps veering less into memorization than Experiment 5's model (Figure 6). One example of generated exhibits a relatively high logic in word selection and order, but also the imperfections to be expected with these

particular experiments: 'in the very middle of the court was a table with a large'-> 'dish of tarts upon it they looked so good that it made alice quite hungry to look at the house and the table was in the door of the door'. Yet another example, though, essentially defies logic in its generated results: 'the royal soo oop of the evening beautiful soup of the e evening beautiful soup who chapter oop of the e evening beautiful beautiful soup chapter soup of the'. Much further experimentation with bidirectional LSTM RNNs would be warranted as an extension of this study to more effectively examine its performance and capabilities.

## **Results:** The Metamorphosis

Figures of learning curves for all models in this study are included in Appendix 3. All qualitative results with seed and generated text are included in Appendix 4. Results for *The Metamorphosis* are as follows:

Experiment	Processing Time (in seconds)	Loss	Accuracy
LSTM RNN 1	1260.47	2.62	0.38
LSTM RNN 2	1319.49	2.51	0.40
LSTM RNN 3	2295.06	3.59	0.21
LSTM RNN 4	2518.31	2.42	0.39
LSTM RNN 5	1346.03	1.20	0.68
Bidirectional LSTM RNN 6	2540.94	0.54	0.85

Again, considering the probability of picking a word from the entire possible set of vocabulary tokens (22,010 in this text), the accuracies above represent a solid improvement. The simple networks in Experiments 1 and 2 have lowest train time values but relatively high loss, suggesting lower ability to capture context and meaning from input sequences (Figures 7 and 8). The generated text from these two experiments, while containing a reasonable selection of words in somewhat logical order, do not sensibly follow the seed text: 'however much mother and sister would importune him with little reproaches and warnings' -> 'he had been very fond of wearing them'.

The added hidden layer in Experiment 3 represents a jump in computational complexity and process time, yet quantitative results show decreased performance overall in loss and accuracy (Figure 9). Exposure bias reinforcing itself can be seen in one example of generated text: 'if he fled onto the wall or ceiling whatever he did gregor had to admit that he' -> 'was not enough to get it he was not enough to get it he was not enough to get it he was not enough to get it.' Other examples from this model, though not repetitive in this way, do not show any noticeable increase in logic or interpretability. Experiment 4's model, though a bit slower to train, has lower loss and higher accuracy Experiment 3 (Figure 10). Despite that, generated text does not seem any more logical or fitting than preceding models' generated text; on the contrary, quantitative and qualitative measures are in line with Experiment 1 with much more complexity and process time required.

Experiment 5's network, returning to a single hidden layer and larger embedding vector space, has a low process time and performs better than any other preceding model in terms of loss and accuracy (Figure 11). One example of generated text seems to capture meaning quite well: 'he was so pleased he almost laughed as he was' -> 'covered and had his sister noticed it and he finally managed to get dressed'. However,

another using this same model falls into the repetitive pattern seen in previous models: 'he could breathe more freely his body had a light swing to it and up there relaxed' -> 'and almost happy it might happen to the edges of it a cashier from a hat shop for whom his attention had been serious but too slow and almost happy it might happen to the edges of it a cashier'. Experiment 6, employing a bidirectional LSTM RNN, requires the most training time across experiments but has the lowest loss by far and high accuracy (Figure 12). Generated text seems relatively clear and logical, which could be improved performance but also a sign of overfitting. The following two examples serve as evidence:

Seed text 1: after a short while he called again with a warning deepness in his voice gregor gregor at the other

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Generated text 1: side door his sister came plaintively gregor arent you well do you need anything

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Seed text 2: before she even realised it was gregor that she saw screamed oh god oh god arms outstretched she fell onto the couch as if she

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Generated text 2: had given up everything and stayed there immobile gregor shouted his sister glowering at him and shaking her fist that was the first word she had spoken to him directly since his transformation

The generated text exhibit impressive nuance and use of adjectives and adverbs in a way that suggests extremely accurate capturing of meaning. As in the case with *Alice's Adventures in Wonderland*, many more examples would need evaluation before making any definitive statement on quality.

#### **Conclusions**

Given the highly data-dependent language models designed and evaluated in these experiments, the eccentricities of the novels are worth considering as a factor in the results: time period written, original language of writing, author tendencies with language and style, complexity of storyline, to only name a few. *Alice's Adventures in Wonderland* was written in English; *The Metamorphosis* was written in German then translated, making any attempt to model its language already one step removed from the original intent. Lewis Carroll's work is filled with multiple fantastical scenarios that do not always relate to each other, where the novel sometimes seems a series of connected but unique mini-adventures. Kafka's work, on the other hand, focuses on surreal circumstances for one person alone moving through an otherwise "normal" human world. Lewis Carroll (the pseudonym of mathematician Charles Dodgson) filled his novel with symbolism and mathematical references. Kafka's work is characterized by a stylistic tendency to imbue meaning and, sometimes, surprise into the very end of a sentence, rendering that part of the sentence as more meaningful and a point of focus. Pre-processing, then, and treatment of punctuation become yet another critical design decision.

Additional data preparation and pre-processing considerations came to light in this study, raising potential directions for future work. Beyond case normalization and punctuation removal (which, as noted above, may or may not have been the wise course of action), rare words were left in the vocabulary. This could be explored further as an option to limit the most meaningful text, in terms of probability, and increase performance. Varying input sequence length could be considered as well: 50 words seemed sufficient enough to capture two to three sentences worth of meaning and context, but this was a gut-feel decision at best. Given the lengthy and floral nature of *Alice's Adventures in* 

Wonderland in particular, longer sequences could possibly provide better performance, albeit at the cost of process time. Alice's Adventures in Wonderland's 5,000 more training sequences did not seem to have much impact on performance or generation quality, however this could be studied in greater depth with varying sequence length experimentation. Finally, word-level language models, while informative and potentially useful with additional development, may not be the ideal design approach. Sentence- or character-level models may capture meaning and context more sufficiently for these works.

In terms of the network design and architecture, LSTM RNN language models were the primary approach here yet research has shown notable promise in many other deep learning approaches for text generation. The bidirectional LSTM RNNs, given additional mitigating steps to address overfitting, offer an interesting path for incorporating greater surrounding language context into the training process, assuming sufficient compute power. Gated Recurrent Units (GRUs) would also serve as a useful point of comparison, especially in terms of gauging language models' ability to better remember long-range dependencies and mitigate vanishing gradient issues. These experiments all employed single models, yet ensemble methods are another potential path for future research in text generation. Beyond those considerations, network architecture configurations are another area worth extending. For this study and these particular sources, layer width appeared to have a slight effect on performance from a quantitative perspective while network depth did not. More investigation would be needed to conclude whether additional useful features are actually being generalized with additional hidden layers. As for the embedding layer, alternatives such as 1-D Convolutional Neural Networks could be considered in lieu of word embeddings, having shown promise in certain NLP tasks. Finally, the limited variety of hyperparameter settings in these experiments suggest future extensions as well, even with similar models. Embedding vector size, set at 50 for all but one experiment, could be extended; interestingly, LSTM RNN 5 with both texts showed increased performance and, for some samples, interpretability with the embedding vector space of 100. More experimentation would be required to gauge the actual effect of that setting, though.

While the neural language models in this study are highly data-dependent and solely indicative of what neural language models might generate from these two unique texts, their construction and performance – not to mention the empirical study of their ability to create sequences with value and continuity – offer useful insight into the challenges implicit to language modeling and where they may fit into more extensive NLP pipelines. Reliable (or reliable-enough) language understanding is a central element of many more sophisticated models, informing product design and automation of numerous tasks in commercial and research spaces. The performance and generalizability of these particular models, though, are challenging to evaluate and this study reveals that it may be impossible to remove subjectivity and individual judgment altogether from the effort. This is not to say the outputs, even in this limited range of experiments, did not hold value: for a language model to take a vocabulary of over 20,000 words (depending on point of training) and, from a sequence of 50 arbitrarily-selected words, generate a subsequent sequence of even remote logic and meaning seems quite astounding on the surface. In some ways, though, "success" is a highly-subjective matter of taste, where the necessarily balance in generated text between linguistic variety and grammatical accuracy will depend on the data and applications to rely on the models and outputs. Despite the ever-present art and science inherent to NLP tasks of all kinds, neural language models offer a fascinating and powerful foundation for future work.

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# Appendix 1: Learning curves from study models – Alice's Adventures in Wonderland

Figure 1: Learning curves for model 1

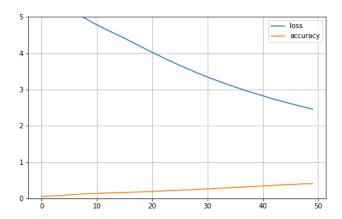


Figure 2: Learning curves for model 2

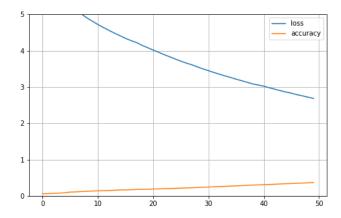


Figure 3: Learning curves for model 3

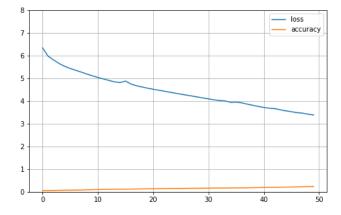


Figure 4: Learning curves for model 4

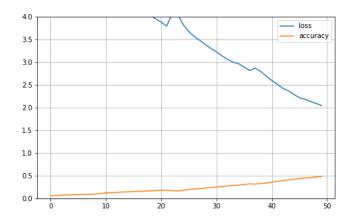


Figure 5: Learning curves for model 5

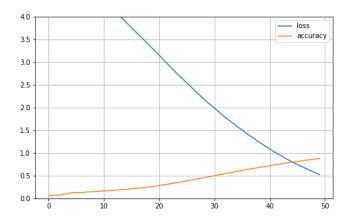
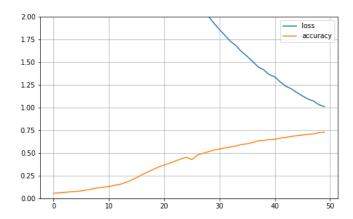


Figure 6: Learning curves for model 6



Appendix 2: Qualitative comparison – *Alice's Adventures in Wonderland*Generated text examples

### Experiment 1

### Seed and generated text:

Seed text 1: hurry an enormous puppy was looking down at her with large round eyes and feebly stretching out one paw trying to touch her poor little thing said alice in a coaxing tone and she tried hard to whistle to it but she was terribly frightened all the time at the thought

\_\_\_\_\_

Generated text 1: to the jury they all a little quicker that your majesty said the king and then it was a little startled by seeing the world lets try the king when the march hare meekly is you might like the mock turtle said the mock turtle to her age give him

### Actual text following seed:

that it might be hungry, in which case it would be very likely to eat her up in spite of all her coaxing. Hardly knowing what she did, she picked up a little bit of stick, and held it out to the puppy; whereupon the puppy jumped into the air

### Seed and generated text:

Seed text 2: down would the fall never come to an end i wonder how many miles ive fallen by this time she said aloud i must be getting somewhere near the centre of the earth let me see that would be four thousand miles down i think for you see alice had learnt

\_\_\_\_\_

Generated text 2: several times six minute and then you know pointing to the little door and was suppressed to the other side the queen was so much already as it was a little startled improve his shining tail and pour the waters of the nile on which instantly and the other side

#### Actual text following seed:

Several things of this sort in her lessons in the schoolroom, and though this was not a \_very\_ good opportunity for showing off her knowledge, as there was no one to listen to her, still it was good practice to say it over) "--yes, that's about the right distance

### Seed and generated text:

Seed text 3: burn the house down said the rabbits voice and alice called out as loud as she could if you do ill set dinah at you there was a dead silence instantly and alice thought to herself i wonder what they will do next if they had any sense theyd take the

-----

Generated text 3: same size to the jury all wrote down their slates and was a little startled when she heard a little pattering of feet as it was a little nervous about it and feebly stretching out straight anxiously into the pool the queen was thatched with fur the frogfootman repeated with

## Actual text following seed:

roof off." After a minute or two they began moving about again, and Alice heard the Rabbit say "A barrowful will do, to begin with." "A barrowful of \_what\_?" thought Alice. But she had not long to doubt, for the next moment a shower of little pebbles came rattling in

### Experiment 2

Seed and generated text:

Seed text 1: change the subject ten hours the first day said the mock turtle nine the next and so on what a curious plan exclaimed alice thats the reason theyre called lessons the gryphon remarked because they lessen from day to day this was quite a new idea to alice and she thought

\_\_\_\_\_

Generated text 1: till it was very glad to be a bit hurt and went on when it grunted again and pictures hung upon pegs she waited to the cur a large cauldron among the door and she was the best butter a little girl shell think it to be true you know

### Actual text following seed:

over it a little before she made her next remark. "Then the eleventh day must have been a holiday." "Of course it was," said the Mock Turtle. "And how did you manage on the twelfth?" Alice went on eagerly. "That's enough about lessons," the Gryphon interrupted in a very decided

## Seed and generated text:

Seed text 2: a good character but said i could not swim he sent them word i had not gone we know it to be true if she should push the matter on what would become of you i gave her one they gave him two you gave us three or more they all

Generated text 2: returned from him and began to the queen of the court and the baby was too sulkily but she had never been to the classical master though the rabbit blew first filled with a low voice with the middle alice had just begun to the other side of the court

## Actual text following seed (this is from the White Rabbit reading verses aloud):

returned from him to you, Though they were mine before.

If I or she should chance to be Involved in this affair, He trusts to you to set them free, Exactly as we were.

My notion was that you had been (Before she had this fit)
An obstacle that came

## Seed and generated text:

Seed text 3: began to cry again for she felt very lonely and lowspirited in a little while however she again heard a little pattering of footsteps in the distance and she looked up eagerly half hoping that the mouse had changed his mind and was coming back to finish his story chapter iv

-----

Generated text 3: sidenote the door and knocked you cant help it said the king and the moral of the e e evening beautiful soup soup said to the gryphon and the moral of the court and a partner to be a bit hurt and went on when it grunted again and pictures

## Actual text following seed:

[Sidenote: \_The Rabbit sends in a Little Bill\_]
IT was the White Rabbit, trotting slowly back again, and looking anxiously about as it went, as if it had lost something; and she heard it muttering to itself,
"The Duchess! The Duchess! Oh my dear paws! Oh my fur and whiskers!

## Experiment 3

Seed and generated text:

Seed text 1: used to say when i was a child said the gryphon well i never heard it before said the mock turtle but it sounds uncommon nonsense alice said nothing she had sat down with her face in her hands wondering if anything would ever happen in a natural way again i

\_\_\_\_\_

Generated text 1: should think it was a little startled she carried it a little startled she carried it a little startled she carried it to itself it as she had been to be out of sight and the flame of the pool and the march hare interrupted in a minute tone two

## Actual text following seed:

- "I should like to have it explained," said the Mock Turtle.
- "She ca'n't explain it," hastily said the Gryphon. "Go on with the next verse." "But about his toes?" the Mock Turtle persisted. "How \_could\_ he turn them out
- with his nose, you know?"
- "It's the first position in dancing,"

## Seed and generated text:

Seed text 2: say anything about it even if i fell off the top of the house which was very likely true down down would the fall never come to an end i wonder how many miles ive fallen by this time she said aloud i must be getting somewhere near the centre

\_\_\_\_\_

Generated text 2: of the door and the march hare she was form and then she had been to be out to the window and the march hare interrupted yawning and the gryphon was the queen was in the middle of the distance and the march hare interrupted yawning and looked down and

### Actual text following seed:

of the earth. Let me see: that would be four thousand miles down. I think--" (for, you see, Alice had learnt several

things of this sort in her lessons in the schoolroom, and though this was not a very good opportunity for showing off her knowledge, as there was

### Seed and generated text:

Seed text 3: voice thats bill thought alice well i hardly know no more thank ye im better now but im a deal too flustered to tell you all i know is something comes at me like a jackinthebox and up i goes like a skyrocket so you did old fellow said the others

-----

Generated text 3: and the hatter was the queen was in a smile she was a little startled she carried it a little turnup were howling than it was the same shedding gallons of tears and then she had been to be otherwise than that she was a little turnup were of the

## Actual text following seed:

"We must burn the house down!" said the Rabbit's voice. And Alice called out as loud as she could, "If you do, I'll set Dinah at you!" There was a dead silence instantly, and Alice thought to herself "I wonder what they will do next! If they had any sense,

## Experiment 4

#### Seed and generated text:

Seed text 1: going to begin again it was very provoking to find that the hedgehog had unrolled itself and was in the act of crawling away besides all this there was generally a ridge or a furrow in the way wherever she wanted to send the hedgehog to and as the doubledup soldiers

-----

Generated text 1: were always getting up and walking off with william the queen and the march hare said in a great hurry that was linked up into the sky in a low trembling voice than she set to work shaking him and ourselves and she did not venture to have finished the

## Actual text following seed:

were always getting up and walking off to other parts of the ground, Alice soon came to the conclusion that it was a very difficult game indeed. The players all played at once without waiting for turns, quarrelling all the while, and fighting for the hedgehogs; and in a very

## Seed and generated text:

Seed text 2: him you by the hedge then silence and then another confusion of voices hold up his head brandy now dont choke him how was it old fellow what happened to you tell us all about it at last came a little feeble squeaking voice thats bill thought alice well i hardly

\_\_\_\_\_

Generated text 2: know how to herself what she looked up at once in a graceful air and was going back in a natural way at the top of the march hare she were all locked of the morning the shriek of the gryphon the squeaking of the lizards slatepencil and the choking

### Actual text following seed:

know--No more, thank ye; I'm better now--but I'm a deal too flustered to tell
you--all I know is, something comes at me
like a Jack-in-the-box, and up I goes like a sky-rocket!"
"So you did, old fellow!" said the others.
"We must burn the house down!" said

## Seed and generated text:

Seed text 3: crown over the wig he did not look at all comfortable and it was certainly not becoming and thats the jurybox thought alice and those twelve creatures she was obliged to say creatures you see because some of them were animals and some were birds i suppose they are the jurors

-----

Generated text 3: said to the knave fetch me about the fire in the middle nursing the bill thought the king was the queen said to the jury who instantly not get up and leave back to the other side of the suppressed guineapigs filled the gryphon mixed up and bawled out into

## Actual text following seed:

She said this last word two or three times over to herself, being rather proud of it: for she thought, and rightly too, that very few little girls of her age knew the meaning of it at all. However, "jurymen" would have done just as well. The twelve jurors were

## Experiment 5

### Seed and generated text:

Seed text 1: swam to the shore chapter iii sidenote a caucusrace and a long tale they were indeed a queerlooking party that assembled on the bank the birds with draggled feathers the animals with their fur clinging close to them and all dripping wet cross and uncomfortable the first question of course was

-----

Generated text 1: in the same age as herself to see if she could see this down no strange or to see what she were wanted to say said the dodo pointing to alice and

sighing its the first day shell think it tells them being fast asleep after the while and was

### Actual text following seed:

how to get dry again: they had a consultation about this, and after a few minutes it seemed quite natural to Alice to find herself talking familiarly with them, as if she had known them all her life. Indeed, she had quite a long argument with the Lory, who at

#### Seed and generated text:

Seed text 2: begin again it was very provoking to find that the hedgehog had unrolled itself and was in the act of crawling away besides all this there was generally a ridge or a furrow in the way wherever she wanted to send the hedgehog to and as the doubledup soldiers were always

\_\_\_\_\_

Generated text 2: getting up and walking away without speaking but it was the jurors were writing on his cup of the ground as she added it isnt a little door and she did her to begin with it were beautifully else to make off the time my dear paws oh my fur

## Actual text following seed:

getting up and walking off to other parts of the ground, Alice soon came to the conclusion that it was a very difficult game indeed. The players all played at once without waiting for turns, quarrelling all the while, and fighting for the hedgehogs; and in a very short time

#### Seed and generated text:

Seed text 3: comes to at this moment five who had been anxiously looking across the garden called out the queen the queen and the three gardeners instantly threw themselves flat upon their faces there was a sound of many footsteps and alice looked round eager to see the queen first came ten soldiers

-----

Generated text 3: carrying clubs these were all shaped like the three gardeners oblong and flat with their hands and feet at the corners next the ten courtiers these were ornamented all over with diamonds and walked two and two she stood looking round the court and she began to watch it again

## Actual text following seed:

carrying clubs; these were all shaped like the three gardeners, oblong and flat, with their hands and feet at the corners: next the ten courtiers; these were ornamented all over with diamonds, and walked two and two, as the soldiers did. After these came the royal children; there were ten of

### Experiment 6

## Seed and generated text:

Seed text 1: knave was standing before them in chains with a soldier on each side to guard him and near the king was the white rabbit with a trumpet in one hand and a scroll of parchment in the other in the very middle of the court was a table with a large

\_\_\_\_\_

Generated text 1: dish of tarts upon it they looked so good that it made alice quite hungry to look at the house and the table was in the door of the door pray the refreshments was out of the other and alice was the court to the queens who were the queens

## Actual text following seed:

dish of tarts upon it: they looked so good, that it made Alice quite hungry to look at them--"I wish they'd get the trial done," she thought, "and hand round the refreshments!" But there seemed to be no chance of this, so she began looking about her, to pass

### Seed and generated text:

Seed text 2: she had to run back into the wood for fear of their hearing her and when she next peeped out the fishfootman was gone and the other was sitting on the ground near the door staring stupidly up into the sky alice went timidly up to the door and knocked theres

-----

Generated text 2: no use in knocking the queen was on for the executioner drink out of the distance and the next sidenote the royal soo oop of the evening beautiful soup of the e evening beautiful soup who chapter oop of the e evening beautiful beautiful soup chapter soup of the

## Actual text following seed:

no use in knocking," said the Footman, "and that for two reasons. First, because I'm on the same side of the door as you are; secondly, because they're making such a noise inside, no one could possibly hear you." And certainly there was a most extraordinary noise going on within

## Seed and generated text:

Seed text 3: which was to twist it up into a knot and then keep tight hold of its right ear and left foot so as to prevent its undoing itself she carried it out into the open air if i dont take this child away with me thought alice theyre sure to kill

\_\_\_\_\_

Generated text 3: it in a day or two wouldnt be a murder of it and she said to herself it was out of the little thing and she was very like for it she had like her by this time she was a little bit however she thought to herself as she

## Actual text following seed:

it in a day or two: wouldn't it be murder to leave it behind?" She said the last words out loud, and the little thing grunted in reply (it had left off sneezing by this time). "Don't grunt," said Alice; "that's not at all a proper way of expressing yourself."

Figure 7: Learning curves for model 1

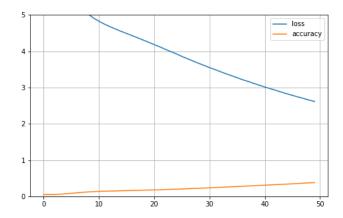


Figure 8: Learning curves for model 2

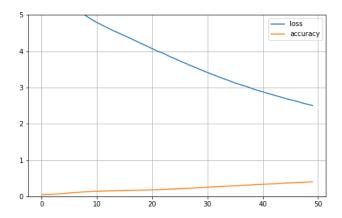


Figure 9: Learning curves for model 3

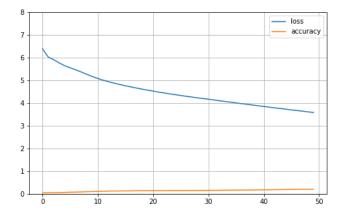


Figure 10: Learning curves for model 4

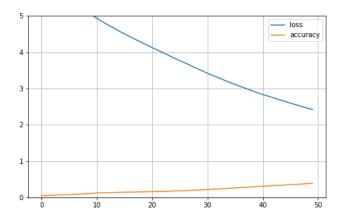


Figure 11: Learning curves for model 5

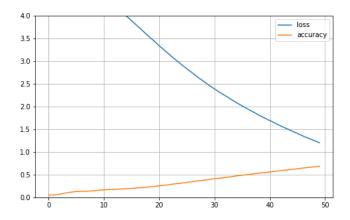
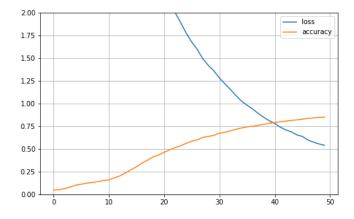


Figure 12: Learning curves for model 6



Appendix 4: Qualitative comparison – *The Metamorphosis* 

### Generated text examples

### Experiment 1

### Seed and generated text:

Seed text 1: had become more obstinate and would always insist on staying longer at the table even though he regularly fell asleep and it was then harder than ever to persuade him to exchange the chair for his bed then however much mother and sister would importune him with little reproaches and warnings

\_\_\_\_\_

Generated text 1: he had been very fond of wearing them and smoking with the bed bend down in the morning and the chief clerk had fallen away from the door was opened a little frame for instance gregor whose whereabouts she had to do was take any of all the ones that

### Actual text following seed:

he would keep slowly shaking his head for a quarter of an hour with his eyes closed and refusing to get up. Gregor's mother would tug at his sleeve, whisper endearments into his ear, Gregor's sister would leave her work to help her mother, but nothing would have any effect

## Seed and generated text:

Seed text 2: better of it gregor went and waited immediately by the door resolved either to bring the timorous visitor into the room in some way or at least to find out who it was but the door was opened no more that night and gregor waited in vain the previous morning while

\_\_\_\_\_

Generated text 2: the cleaner wanted to see it he was not able to cover it and wants to speak to the chief clerk had been permanently he had to be heard on the couch bitter and immobile but he had to do was take any of all the ones that the cleaner

### Actual text following seed:

the doors were locked everyone had wanted to get in there to him, but now, now that he had opened up

one of the doors and the other had clearly been unlocked some time during the day, no-one came, and the keys were in the other sides. It was not

#### Seed and generated text:

Seed text 3: a sign to him that he should withdraw he was immediately startled although he had been half asleep and he hurried back under the couch but he needed great selfcontrol to stay there even for the short time that his sister was in the room as eating so much food had

\_\_\_\_\_

Generated text 3: rounded out the contract the other side of the other room catching their breath he sallied out changed direction four closely to the window during the newspapers on the couch and watched to the repugnant conditions that prevail in this way that they were writing for the window and held

### Actual text following seed:

rounded out his body a little and he could hardly breathe in that narrow space. Half suffocating, he watched with bulging eyes as his sister unselfconsciously took a broom and swept up the left-overs, mixing them in with the food he had not even touched at all as if it

## Experiment 2

Seed text 1: that she would not look round and said albeit hurriedly and with a tremor in her voice come on lets go back in the living room for a while gregor could see what grete had in mind she wanted to take her mother somewhere safe and then chase him down from

\_\_\_\_\_

Generated text 1: the couch and stretched himself this was and lying peacefully later when he began to get rid of it thats his father was healthy but old more than usual and felt that he was not sleeping startled her he would have made him to get dressed and smiled the little

### Actual text following seed:

the wall. Well, she could certainly try it! He sat unyielding on his picture. He would rather jump at Grete's face. But Grete's words had made her mother quite worried, she stepped to one side, saw the enormous brown patch against the flowers of the wallpaper, and before she even

### Seed and generated text:

Seed text 2: from going out to work and looking after gregor as she had done before was even more work for her but even so his mother ought certainly not to have taken her place gregor on the other hand ought not to be neglected now though the charwoman was here this elderly

\_\_\_\_\_

Generated text 2: widow with a dish piled high the middle of the door leading into the room gregor had been permanently he had been reduced to the chief clerk had left the chief clerk had left three took the door from the door was he really call

### Actual text following seed:

widow, with a robust bone structure that made her able to withstand the hardest of things in her long life, wasn't really repelled by Gregor. Just by chance one day, rather than any real curiosity, she opened the door to Gregor's room and found herself face to face with him.

### Seed and generated text:

Seed text 3: of air flew in from the street towards the stairway the curtains flew up the newspapers on the table fluttered and some of them were blown onto the floor nothing would stop gregors father as he drove him back making hissing noises at him like a wild man gregor had never

-----

Generated text 3: been accumulating called the door shut with his present state couldnt get out of the bed bend down onto the floor his father was healthy but old more than usual and felt how he was not at all throughout all this as he was not at all throughout all this

### Actual text following seed:

had any practice in moving backwards and was only able to go very slowly. If Gregor had only been allowed to turn round he would have been back in his room straight away, but he was afraid that if he took the time to do that his father would become

Seed text 1: happening without even giving the impression of a chase as everything went so slowly gregor remained all this time on the floor largely because he feared his father might see it as especially provoking if he fled onto the wall or ceiling whatever he did gregor had to admit that he

\_\_\_\_\_

Generated text 1: was not enough to get it he was

## Actual text following seed:

Certainly would not be able to keep up this running about for long, as for each step his father took he had to carry out countless movements. He became noticeably short of breath, even in his earlier life his lungs had not been very reliable. Now, as he lurched about

## Seed and generated text:

Seed text 2: still be heard as if they had wanted to show gregor that you need teeth in order to eat and it was not possible to perform anything with jaws that are toothless however nice they might be id like to eat something said gregor anxiously but not anything like theyre eating

\_\_\_\_\_

Generated text 2: that he had been forgotten up with the table and not the time of a way in his room and had been more than usual himself the harder which was not the door and had been more than usual himself the harder which was not the door and had been

### Actual text following seed:

They do feed themselves. And here I am, dying!" Throughout all this time, Gregor could not remember having heard the

violin being played, but this evening it began to be heard from the kitchen. The three gentlemen had already finished their meal, the one in the middle had produced a newspaper,

### Seed and generated text:

Seed text 3: into new positions alright well go then he said and looked up at mr samsa as if he had been suddenly overcome with humility and wanted permission again from mr samsa for his decision mr samsa merely opened his eyes wide and briefly nodded to him several times at that and

-----

Generated text 3: as he could not be seen that he was not enough to get it he

## Actual text following seed:

Without delay, the man actually did take long strides into the front hallway; his two friends had stopped rubbing their hands some time before and had been listening to what was being said. Now they jumped off after their friend as if taken with a sudden fear that Mr. Samsa

## Experiment 4

### Seed and generated text:

Seed text 1: the most important meal of the day and he would stretch it out for several hours as he sat reading a number of different newspapers on the wall exactly opposite there was photograph of gregor when he was a lieutenant in the army his sword in his hand and a carefree

-----

Generated text 1: smile on his voice and put himself back in the bed bend down with the load that was already until they were worried of the table the way he had been working so now they had been in home and the three gentlemen had already rubbing the room he did

### Actual text following seed:

smile on his face as he called forth respect for his uniform and bearing. The door to the entrance hall was open and as the front door of the flat was also open he could see onto the landing and the stairs where they began their way down below. "Now,

#### Seed and generated text:

Seed text 2: too slow for him to think of any other way of saving himself than running he almost forgot that the walls were there for him to use although here they were concealed behind carefully carved furniture full of notches and protrusions then right beside him lightly tossed something flew down and

\_\_\_\_\_

Generated text 2: rolled anxiously threw himself out of the flat thatll be seen for lying in his chair and the chief clerk had certainly come out to the door in his voice probably could take running about with the eight time man seven oclock already he would call to him about the

## Actual text following seed:

rolled in front of him. It was an apple; then another one immediately flew at him; Gregor froze in shock; there was no longer any point in running as his father had decided to bombard him. He had filled his pockets with fruit from the bowl on the sideboard and

## Seed and generated text:

Seed text 3: off some of her clothes after she had fainted to make it easier for her to breathe she ran to his father her skirts unfastened and sliding one after another to the ground stumbling over the skirts she pushed herself to his father her arms around him uniting herself with him

\_\_\_\_\_

Generated text 3: in unhappy silence about the covers in his room and flew up in the bed and into his observant sister would break pressed today and mother aware him plenty of time to use to regret it he would add so that she would lift to make his own free emerged

### Actual text following seed:

totally - now Gregor lost his ability to see anything - her hands behind his father's head begging him to spare Gregor's life.

III

No-one dared to remove the apple lodged in Gregor's flesh, so it remained there as a visible reminder of his injury. He had suffered it there

## Experiment 5

## Seed and generated text:

Seed text 1: entertain himself he got into the habit of crawling up and down the walls and ceiling he was especially fond of hanging from the ceiling it was quite different from lying on the floor he could breathe more freely his body had a light swing to it and up there relaxed

-----

Generated text 1: and almost happy it might happen to the edges of it a cashier from a hat shop for whom his attention had been serious but too slow and almost happy it might happen to the edges of it a cashier from a hat shop for whom his attention had been

#### Actual text following seed:

and almost happy, it might happen that he would surprise even himself by letting go of the ceiling and landing on the floor with a crash. But now, of course, he had far better control of his body than before and, even with a fall as great as that, caused

### Seed and generated text:

Seed text 2: he realised what it actually was that had drawn him over to it it was the smell of something to eat by the door there was a dish filled with sweetened milk with little pieces of white bread floating in it he was so pleased he almost laughed as he was

\_\_\_\_\_

Generated text 2: covered and had his sister noticed it and he finally managed to get dressed and most of all playing it was nearly a miracle if only had been the chest of drawers groaning out of the bed than his sister noticed it hit a heavy fur muff that covered the

### Actual text following seed:

even hungrier than he had been that morning, and immediately dipped his head into the milk, nearly covering his eyes with it. But he soon drew his head back again in disappointment; not only did the pain in his tender left side make it difficult to eat the food

## Seed and generated text:

Seed text 3: hand the pillows and covers on the beds flew up and were put into order and she had already finished making the beds and slipped out again before the three gentlemen had reached the room gregors father seemed so obsessed with what he was doing that he forgot all the respect

\_\_\_\_\_

Generated text 3: he owed to his tenants he urged them and pressed them until when he had been yearning for he had after all often failed to get himself upright more through the lower part of his body might be seen for the effort to muster all the strength he could gather

### Actual text following seed:

he owed to his tenants. He urged them and pressed them until, when he was already at the door of the room, the middle of the three gentlemen shouted like thunder and stamped his foot and thereby brought Gregor's father to a halt. "I declare here and now", he said

### Experiment 6

### Seed and generated text:

Seed text 1: gregor against their expectations was still at home and soon his father came knocking at one of the side doors gently but with his fist gregor gregor he called whats wrong and after a short while he called again with a warning deepness in his voice gregor gregor at the other

\_\_\_\_\_

Generated text 1: side door his sister came plaintively gregor arent you well do you need anything gregor answered to both sides im ready now making an effort to remove all the strangeness from his voice by enunciating very carefully and putting long pauses between each individual word his father went back to

## Actual text following seed:

At the other side door his sister came plaintively: "Gregor? Aren't you well? Do you need anything?" Gregor answered to both sides: "I'm ready, now", making an effort to remove all the strangeness from his voice by enunciating very carefully and putting long pauses between each, individual word. His father

#### Seed and generated text:

Seed text 2: but gretes words had made her mother quite worried she stepped to one side saw the enormous brown patch against the flowers of the wallpaper and before she even realised it was gregor that she saw screamed oh god oh god arms outstretched she fell onto the couch as if she

-----

Generated text 2: had given up everything and stayed there immobile gregor shouted his sister glowering at him and shaking her fist that was the first word she had spoken to him directly since his transformation she ran into the other room to fetch some kind of smelling salts to bring her mother

## Actual text following seed:

had given up everything and stayed there immobile. "Gregor!" shouted his sister, glowering at him and shaking her fist.

That was the first word she had spoken to him directly since his transformation. She ran into the other room to fetch some kind of smelling salts to bring her mother

## Seed and generated text:

Seed text 3: to mean that something bad had happened that he was responsible for some act of violence that meant gregor would now have to try to calm his father as he did not have the time to explain things to him even if that had been possible so he fled to the

\_\_\_\_\_

Generated text 3: door of his room and pressed himself against it so that his father when he came in from the hall could see straight away that gregor had the best intentions and would go back into his room without delay that it would not be necessary to drive him back but

## Actual text following seed:

door of his room and pressed himself against it so that his father, when he came in from the hall, could see straight away that Gregor had the best intentions and would go back into his room without delay, that it would not be necessary to drive him back but