COSC420: Transformer based language model

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1 Introduction

This report discusses the development and evaluation of a text generation framework using the novels *Pride and Prejudice* and *War and Peace*. Many of the decisions made here were close to arbitrary in nature due to time constraints, and I did not get to explore as much as I would have liked. However, I do believe that the models created are still adequate at creating text that is at least interesting. In terms of text choice, I decided to use all of both books. This provided the most data, but at a cost of potential bias. This was a trade off I was willing to take as I hoped that generally the model would perform better, if skewed towards talking *War and Peace*.

2 Task 1: Tok2Vec Encoder

2.1 Methodology

Word2vec embeddings can be created using two primary approaches: Skip-gram (SG) and Continuous Bag of Words (CBOW). These methods are essentially opposites; CBOW predicts a word based on the context of surrounding words, while Skip-gram, conversely, predicts the surrounding context from a given word. CBOW is effective for identifying common links among frequently used words, making it ideal for smaller datasets where the focus is on simpler relationships that require less data to discern. However, the method's tendency to average context can lead to a less detailed understanding. In contrast, Skip-gram excels in capturing more complex relationships but requires more data and longer training times. Each position in the context window must be trained separately, unlike CBOW, which integrates all context simultaneously.

I chose to use Skip-gram for its potential to uncover interesting patterns despite the limitations of our dataset. The exploration process was somewhat limited due to early corruption in my token-to-vector models. To expedite the process, I saved the encoded vectors of the entire corpus to be read in each time, which significantly reduced processing time. However, at some point, the dataset I believe the saved encoded dataset was corrupted, as the predictions were always the tokens *i*, *æ*, *=*. Unfortunately the t-SNE plots of the models indicated that they were generally successful in clustering semantically similar words and so I didnt not realise the models were corrupted until after I began training the transformer models. After reencoding the dataset this pattern went away on all versions of the model.

Regarding the context window for the model, I found that a size below 3 yielded poor results in prediction tests. I experimented with sizes up to 5, but choosing between 3, 4, and 5 proved challenging. The larger the context window, the more it prioritized punctuation, as shown in Table 1. Eventually, I opted for a context window of 4, aiming to balance the difference and reduce training time. I was ultimately

Table 1: Frequency of Words with Different Context Window Sizes

Context window size 3		Context window size 4		Context window size 5	
Token	Probability	Token	Probability	Token	Probability
\s	0.0655	\s	0.0673	\s	0.0911
the	0.0322	,	0.0329	the	0.0446
,	0.0301	the	0.0315	,	0.0419
and	0.0205	and	0.0216	.	0.0272
.	0.0185	.	0.0210	and	0.0260
of	0.0176	of	0.0210	of	0.0238
to	0.0169	to	0.0150	to	0.0175
a	0.0114	in	0.0112	a	0.0135
in	0.0100	a	0.0107	in	0.0121
his	0.0086	his	0.0084	his	0.0097
was	0.0076	was	0.0075	was	0.0083
that	0.0073	with	0.0070	with	0.0076
he	0.0067	that	0.0063	that	0.0071
her	0.0064	he	0.0061	he	0.0069
with	0.0064	had	0.0053	her	0.0063
’	0.0061	at	0.0053	had	0.0059
had	0.0052	on	0.0051	at	0.0056
at	0.0050	her	0.0051	’	0.0054
it	0.0046	’	0.0049	on	0.0052
”	0.0045	for	0.0041	”	0.0051

satisfied with the punctuation versus text balance, though the model still occasionally struggles with quotations. Models with a context window of 4 generally showed a nicely distributed clustering of semantically similar words such as ”would, should, could, must, shall.”

To determine the vocabulary size, I performed a rough count of unique words using a series of Bash commands[1], resulting in approximately 25,000 words. However, this count included many duplicates or near-duplicates due to punctuation, as demonstrated by the list of variations of the word ’your’.

- ‘your
- “your
- your
- “you’re
- you’re

To maximize coverage while managing memory and model size limitations, I capped the token count at 5,000, reasoning that if ChatGPT operates effectively with around 50,000 unique tokens, 10% should be sufficient for a corpus of this size.

To find out the vocab size I calculated a rough count of unique words over the whole corpus which gave me approximately 25,000 words. From the eye test, though, there were many duplicates/close duplicates in there, mainly due to punctuation, for example.

To capture as much as I could I went up to 5000 tokens which was the limit due to memory and model size concerns at higher token counts. Additionally, if chatgpt can manage with only 50000 unique tokens, 10% for a corpus of this size seems reasonable to me.

I also explored various sizes for the hidden layer dimensions, ranging from 32 to 512. Limited testing made it difficult to determine the best size quantitatively, though it was evident that dimensions of 32 and 64 were insufficient, as they resulted in a noticeable skew in the graphical outputs. While t-SNE reduces dimensionality and may not make a linear skew inherently problematic, my interpretation was that such skewness indicated a simpler embedding representation.

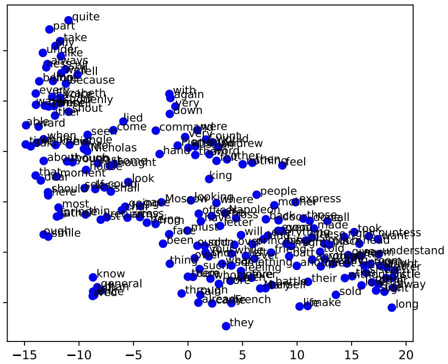
- **Context Window**: 4
- **Hidden Layer Dimension**: 256
- **Vocab Size**: 5000

3 Task 2: Transformer-based Text Prediction

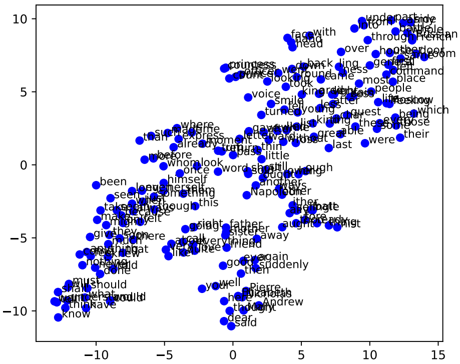
3.1 Methodology

Using the transformer provided, I adjusted the model to take my 256 dimension embeddings, as well to be able to use one-hot vectors as input. I chose to only train for 1 epoch, partly due to time constraints, and due to the validation accuracy not improv-

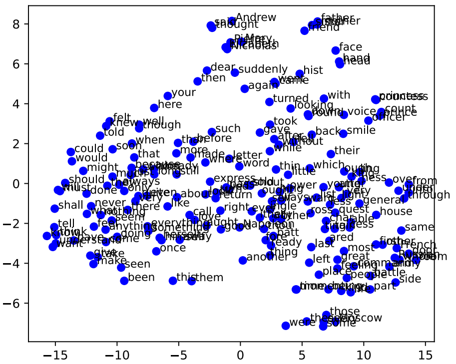
[1] bash command: `tr '[:upper:]' '[:lower:]' < combined_books_text | tr -d '[:punct:]' | tr ' ' '\n' | sort | uniq | wc -l`



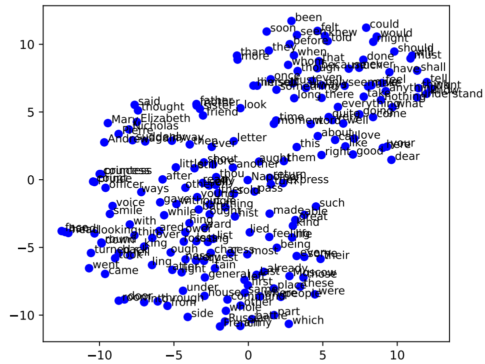
(a) neurons: 32, context window of 1



(b) neurons: 32, context window of 4

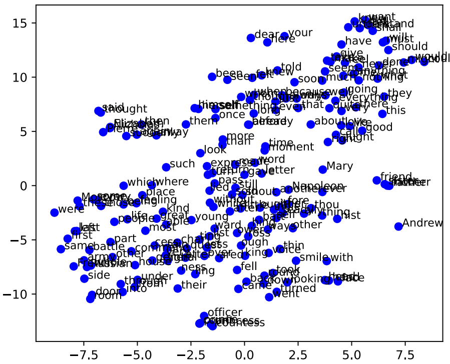


(c) neurons: 64, context window of 3

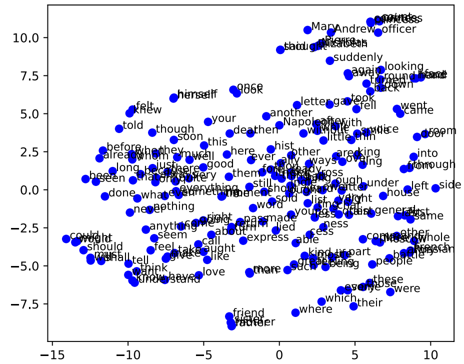


(d) neurons: 64, context window of 5

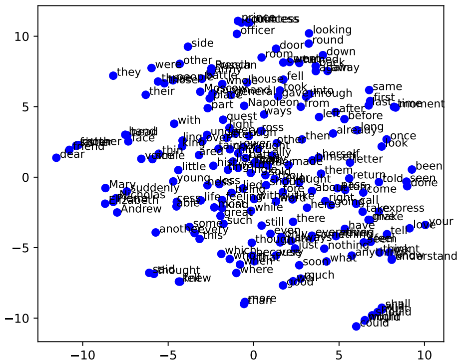
Figure 1: t-SNE plots of embedding space with varying sizes of neurons and context windows



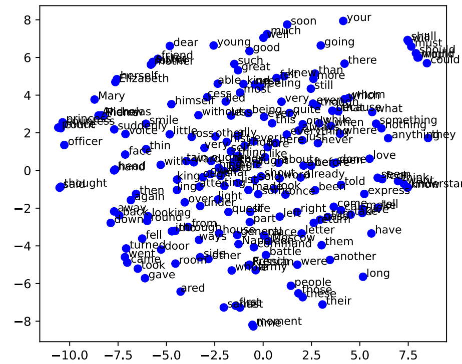
(a) neurons: 64, context window: 4



(b) neurons: 128, context window: 4



(c) neurons: 256, context window: 4



(d) neurons: 512, context window: 4

Figure 2: t-SNE plots of embedding space with varying sizes of neurons and context windows

ing over multiple epochs. After finding this, I did not both including the validation split and went by qualitative measures to ascertain the performance.

3.2 Implementation

The models were all trained on all of the training data, this has influenced it to prefer to talk more about things seen in War and Peace, though sections of Pride and Prejudice still show through.

Table 2: Performance Metrics for Different Configurations

Transformer with Embeddings				
Attention Heads	**Transformer Layers**	**DFF**	**Loss**	**Masked Accuracy**
4	4	256	2.8427	0.4136
4	4	512	2.6718	0.4373
4	6	256	2.6647	0.4402
4	6	512	2.4718	0.4695
16	4	256	2.3300	0.4995
16	4	512	2.2095	0.5197
16	6	256	2.0522	0.5551
16	6	512	1.9590	0.5725
Transformer using One-hot Representation				
4	4	256	2.2441	0.5154
4	4	512	2.1719	0.5289
4	6	256	2.0241	0.5586
4	6	512	1.9068	0.5823
16	4	256	1.6985	0.6311
16	4	512	1.6726	0.6358
16	6	256	1.4977	0.6802
16	6	512	1.4662	0.6856

3.3 Results

Analysis of training and, if applicable, validation accuracies. Qualitative assessment of the text generation capabilities for both the one-hot encoded and Tok2Vec encoded models. Comparison of outputs when prompted with extracts from the training texts versus new, unseen prompts.

4 Task 3: Report and Evaluation

4.1 Overview of Tasks

Summary of the methodologies and key decisions taken during the project.

4.2 Evaluation and Comparison

Critical evaluation of the models based on the tasks' results, discussing the effectiveness and limitations of each approach.

5 Conclusion

Reflections on the project outcomes, lessons learned, and potential areas for future research.

6 References