E Less Enigma

Final Report

1. Abstract

The problem of constrained text generation has been around for a long time. This project centers on generating coherent and readable text without the ubiquitous letter 'e' akin to the notable 1939 novel "Gadsby" (*Gadsby*, 2023) by Ernest Vincent Wright. We aspire to extend this feat into modern natural language processing, employing state-of-the-art language models to produce e-less versions of texts. Through this project, we aim to decipher the intricacies of generative models, specifically addressing how to constrain text generation effectively. Notably, the focus extends beyond mere letter omission; we endeavor to ensure coherence, consistency, and contextual integrity, even without the letter' e'. Additionally, we aspire to establish a robust evaluation framework, incorporating static metrics and Language model-based judgment to assess the quality of the generated text.

2. Introduction

Imagine attempting to compose an entire narrative while abstaining from using one of the most prevalent letters in the English lexicon - the ubiquitous 'e'. Translating the problem to modern computational models is a mystery we are eager to unravel. Now, why does this endeavor hold significance? It extends far beyond being a mere intellectual exercise. If we can fine-tune these models into generating text that omits the letter 'e', it could be helpful in cases like creative writing. Moreover, this is a linguistic puzzle on how words interlock and form coherent thoughts. To omit just one letter may appear deceptively simple, but ensuring that the resulting text remains coherent with seamless narrative flow is complex.

In our approach, we first muster data from multiple text sources like "Gadsby", "A Void" (*A Void*, 2023), and "Eunoia" (*Eunoia*, 2022), etc., along with filtered text from massive corpora like Wiki and Reddit to identify and put together sentences that do not use the alphabet 'e'. We hope these datasets provide standards and knowledge in writing e-less text. Furthermore, we must establish a robust evaluation framework to evaluate the quality of the produced output e-less text. This framework should work like a litmus test for our output, which evaluates the actual words and sentences and quantifies the coherence and its adherence to the context at hand.

3. Dataset

Before we explore the selected dataset, we must answer some critical questions about the qualities and the reasoning behind what makes up a good dataset. A good dataset for this project should possess most, if not all, of the following qualities. First, it should encompass a wide range of writing styles and should have good diversity and range of vocabulary. Second, the text should have a correct logical structure and be human-readable. Also, the data should have a balanced representation of different styles, genres, and topics while having contextual relevance.

One of the first steps in creating a model that generates e-less paraphrases is creating a model that generates normal paraphrases. We can then constrain the text generation and extend its functionality in the later stages. Some of the datasets that help us achieve this paraphrase generation are the PAWS (*PAWS*, n.d.) and MRPC (*MRPC*, 2016) datasets which encompass a wide range of writing styles while providing us with English-to-English paraphrases of input sentences.

In the final evaluation stage, we need the e-less texts from the novels mentioned above, which the evaluation uses to score various aspects of the generated e-less text. The preparation and cleaning of the dataset include sentence tokenization, handling punctuation, filtering e-text (not applicable to native e-less text sources), and part-of-speech tagging. We will soon see how these datasets are useful in various stages of model development.

4. Exploration

Our primary aim for the exploration phase was to profoundly understand the characteristics of the e-less text present in our data sources, followed by comparing the current best commercial language models in e-less text generation. We have generated three exploratory figures to examine the dataset and understand the performance of the current best Language models on the market.

Figure (1) is a Stacked Bar Chart that assesses the performance of famous Language models in the market by paraphrasing one paragraph from the intended novel *"The Great Gatsby"* (*The Great Gatsby*, 2023), which contains traditional e-text. We considered Chat-GPT, Google's BARD, and Microsoft Windows Co-Pilot and gave the same prompt for each test case, which starts with *"I am providing you a section of text from the American novel titled 'The Great Gatsby'. I want you to paraphrase it such that the paraphrased text does not contain the letter 'e' anywhere."* – followed by a randomly taken paragraph directly from the novel.

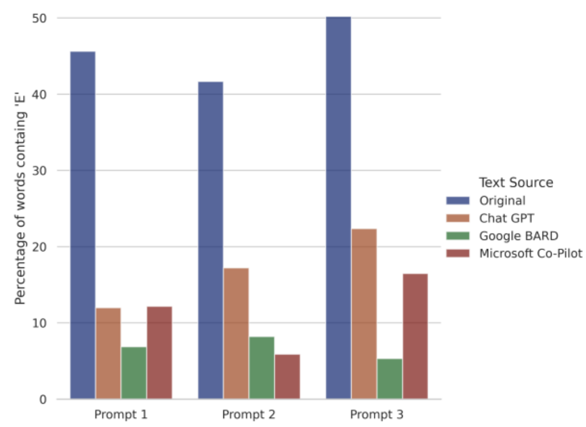


Figure (1)

We calculated the relative frequency of the letter' e' compared to each prompt. We can see that none of the models could capture the essence of the prompt and still leaked the alphabet 'e' all over the place. A critical observation here is that, although Google's BARD looks like it is performing the best at this task, on further observation, it has directly hard-cut the letter' e' from its output and replaced it with single quotes.

5. Methodology

We must first identify some pivotal choices in devising a plan for this project. The language model's decoding phase is the place we need to modify to handle the current constraints of paraphrasing and text generation. Using transformer architecture-based models works perfectly for our use case because their attention computation of input sentences can help us capture the context effectively while paraphrasing sentences. We experimented with model selection, training, and fine-tuning steps before deciding on the final methodology.

5.1 Using GPT-2

After deciding on transformer-based models, we used the Hugging Face Transformers library to import the necessary model before training it to generate e-less paraphrases. One of the first models we used was Open AI's GPT-2 (*GPT-2*, 2019), a decoder-only architecture generally used for auto-regressive or causal text generation. In this paradigm, the model predicts the next most probable output word-by-word by considering the combined representation of all the input tokens and previously generated output tokens.

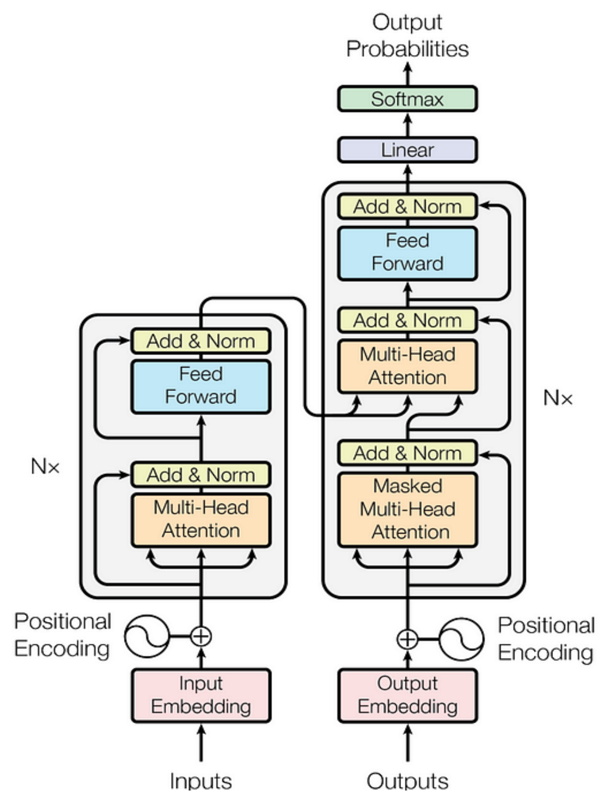
In this method, we took the PAWS and MRPC paraphrase datasets. We prepared the training examples that generally look like *"sentence1 <paraphrase> sentence2,"* in which *sentence1* represents an original English sentence and *sentence2* represents the paraphrased version of *sentence1*. The *<paraphrase>* is a special token we registered with the model, which is used as a boundary marker while training and helps guide the model to start generating the paraphrased text during the text generation.

This method of constrained text generation, although producing e-less text, was not proving to be capable of generating coherent text with good grammatical structure. This behavior could have been because after processing the logits, the model was trying a *greedy* decoding strategy where it only considers the e-less token with the highest probability at each step.

To alleviate this problem, we have decided to use an approach that keeps multiple options open at each time step before producing an output token, the *Beam Search* algorithm. The idea was to force the model to break its greedy decoding strategy and instead choose a context-aware strategy that optimizes for the global maximum likelihood. Although the grammatical structure of the paraphrased sentence improved, the output text still seemed to need to be more coherent and sometimes even produced garbage text or repeated n-grams.

5.2 Transitioning to T-5

Upon further investigation, we figured out that the missing piece of the puzzle is the lack of an encoded representation of the input sentence, and the need for a model with an encoder layer was evident. Preferably, a sequence-to-sequence model like Google's T5 (Raffel, 2020) (Figure 2), also a transformer-based LLM, felt like the perfect choice. T5 has much pre-existing knowledge and capabilities for various language modeling tasks like inference, question-answering, and summarization.



Using the same paraphrase datasets mentioned before, we trained and fine-tuned the *t5-base* model to generate general English-to-English paraphrases. We adjusted the model generation parameters to use Beam Search, along with providing the list of banned and suppressed token_ids (collected from all the tokens with the alphabet 'e'), essentially creating a model capable of *Constrained Beam Search* for text generation.

Once we trained our paraphrasing model on the PAWS dataset, it underwent a second round of training on a generated backphrase dataset, a reverse paraphrase dataset containing the multiple paraphrased versions of e-less text to standard English text. The full training process flow can be seen in Figure (3).

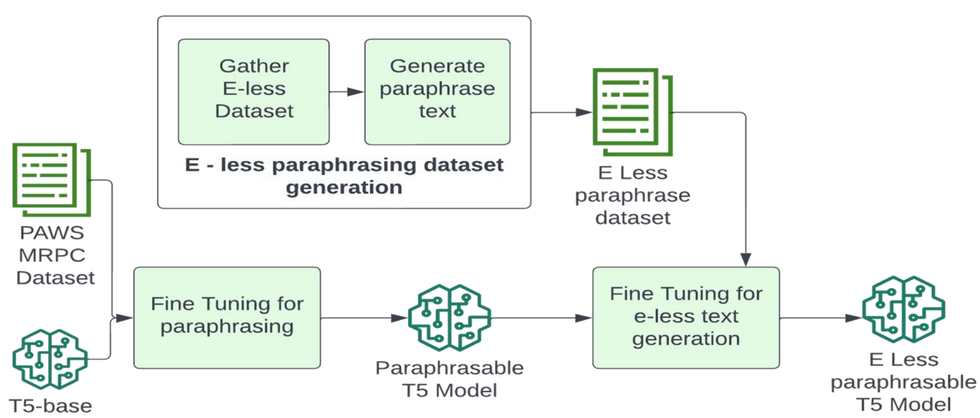


Figure (3)

Since we could not find a paraphrase data set with text → e-less text directly, we created an augmented version ourselves. It is to be noted that we are still going to use our Constrained Beam Search at the last step before generating e-less paraphrases. The following table compares the models' performance for different length prompts:

Prompt (e-underlined)	Paraphrase Tuned T5	Paraphrase Tuned GPT-2
"I got a nice place here," he said, his eyes flashing about restlessly.	*"I got a good spot in this," said him, his hands flashing around uncontrollably.*	*I got a kind of a good-for-thing spot, said Mr. Smith. I got a lot of spots.*
When I came back from the East last autumn I felt that I wanted the world to be in uniform and at a sort of moral attention forever; I wanted no more riotous excursions with privileged glimpses into the human heart.	*Last autumn, as I was coming back from China, I thought that I would always want that world in uniform and at a sort of moral focus ; I did not want to go on riotous trips with privy insights into humanity.*	*I was back in autumn last, and in a sort of moral mood I was about to find out that I was going to want a world in uniform, and at a kind of moral look at a sort of moral way of doing things.*

Table (1)

The results are significantly impressive compared to the previous model and prove to be strong contenders for the final paraphrasing of the input novel. For the first prompt, the T5 paraphrase is closer to the original meaning and maintains the context well. It successfully captures the idea of having a good place and restlessness in the eyes.

On the other hand, the GPT-2 paraphrase seems to lose coherence and introduces unrelated elements like "Mr. Smith" and "a lot of spots." For the second prompt, T5 once again provides a more coherent and contextually accurate paraphrase. It maintains the essence of the original text, expressing a desire for a uniform and morally focused world. At the same time, the GPT-2 paraphrase needs to be more precise and more faithful to the original meaning.

5.3 Challenges

5.3.1 Sentence Similarity

Once we had the model capable of producing e-less text, there were still a lot of variables to consider and a lot of pieces needed to be included. One of the first pieces added was for evaluating the similarity of the sentences or paragraphs the model generates while choosing the final output. Initially, our model only generated one output sequence, which was the sequence we decided to be the perfect output. Still, other sequences of similar probabilities could be much more analogous to the input text and might need us to give more likelihood. To achieve this, we adjusted our model generation code to return more than one paraphrase candidate so that we could heuristically choose our best option. Then, we tried to analyze the sentence similarity between the input and the generated list of output candidates at each step before selecting the best one. To calculate this sentence similarity, we used a pre-trained sentence transformer model, 'all-MiniLM-L6-v2' (*Sentence Transformers (All-MiniLM-L6-V2)*, n.d.), the highest-rated open-source transformer-based model, and provided an API to compute the similarity score. This optimization ultimately helped us achieve better overall results and increased the total average similarity of the e-less Gatsby Novel by about 4-5%, which is an excellent gain.

5.3.2 Grammar and Syntactic Corrections

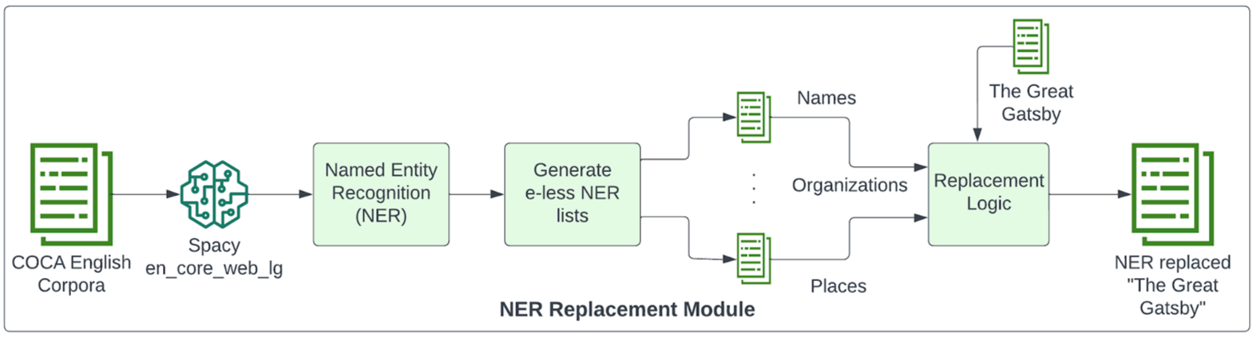
The next challenge we faced during model generation was that although T5 does an outstanding job producing coherent text, it sometimes needs a little nudge toward good grammatical structure and syntactic correctness. So, we added a grammar correction layer using Python's LanguageTool library (Morris, n.d.) at the end, as a separate block, as part of the text post-processing to get highly coherent outputs while ensuring grammatical correctness. We have experimented with this correction module by plugging it at different stages in the output generation process, like at the candidate selection level and once at the end for the entire output, and concluded that there is not a significant difference in the overall grammar score, and therefore is used once, at the end as a post-processing module.

5.3.3 Handling Proper Nouns

One of the most crucial aspects of storytelling is the characters. Proper Nouns such as names, places, and locations describe various situations in a story, and consistently handling them is of utmost importance. One of the challenges we faced with our paraphrasing model was the consistent replacement of proper nouns in the generated text. Because the scope of a model generation iteration is only a part of the input text, the model replaces the proper nouns that contain the alphabet 'e' with a different arbitrary noun each time. A key insight we got from looking at the generated output samples of different examples was that our model would not modify a proper noun that doesn't have the alphabet 'e' in it. This behavior can be attributed to how logits are generated at each step, and the proper nouns without the alphabet 'e' will most likely be the top contending token. Therefore, we decided to handle these replacements during the pre-processing phase to avoid an issue down the generation pipeline.

To solve this problem, we have introduced the NER Replacement Module, which consistently replaces proper nouns throughout the entire input novel text. This module does this replacement using an NLP technique called Named Entity Recognition. In this technique, we tokenize the whole input text to identify the parts of speech and filter out the proper nouns that need replacement by checking if they contain the alphabet 'e'.

Before replacing the proper nouns, we needed a database of e-less proper nouns that we could choose from. As this dataset is not readily available, we built one ourselves. We used a massive open-source text corpus from Corpus of Contemporary American English - COCA (950 million) (*English-Corpora: COCA*, n.d.) and the mentioned NER technique to muster this e-less proper noun dataset. The replacement logic was straightforward: iterating through the input text and replacing all the occurrences after choosing a random replacement for the first occurrence and keeping it in a map for all future ones.



5.3.4 Miscellaneous

This section outlines minor challenges and improvement strategies we used for output generation. First, we faced a problem of repeated n-gram generation, typical for sequence generation models where a similar sub-sequence of words is repeatedly generated until the max generation length is reached. To alleviate this, we introduced parameters that promote early stopping of the generation and prevent n-gram repetition by setting the maximum allowed repeated n-gram size to a small number like 2.

After repeated experimentation, we fine-tuned the temperature parameter in model generation, which acts as a control mechanism, influencing the balance between creativity and determinism in the generated output. A higher temperature introduces more randomness, fostering creativity and diversity by allowing the model to explore a broader range of vocabulary. Conversely, a lower temperature produces more focused and deterministic output, emphasizing high-confidence predictions and adherence to familiar patterns.

We also opted to use nucleus sampling in conjunction with beam search. Nucleus sampling, also known as top-p sampling, is a probabilistic approach where the model samples from the top-k most likely candidates instead of sampling from the entire probability distribution. This strategy helped us in controlling the randomness of the generated output. When combined with beam search, nucleus sampling enhanced the diversity and quality of the generated sequences.

5.4 Final Generation Pipeline

It is time to put all the puzzle pieces together, and the final generation pipeline can be seen in Figure (5). The generation pipeline starts with generating sentences and paragraphs using the NER-replaced version of The Great Gatsby. This process employs a trained model utilizing constrained beam search. Multiple e-less versions of the input text are produced, and a subsequent module using the all-MiniLM-L6-v2 model evaluates their similarity, assigning a score to each. The most suitable candidate is then selected to create the e-less version of the novel. Grammatical errors identified in this version are rectified using a grammar correction module, resulting in the ultimate e-less rendition of The Great Gatsby.

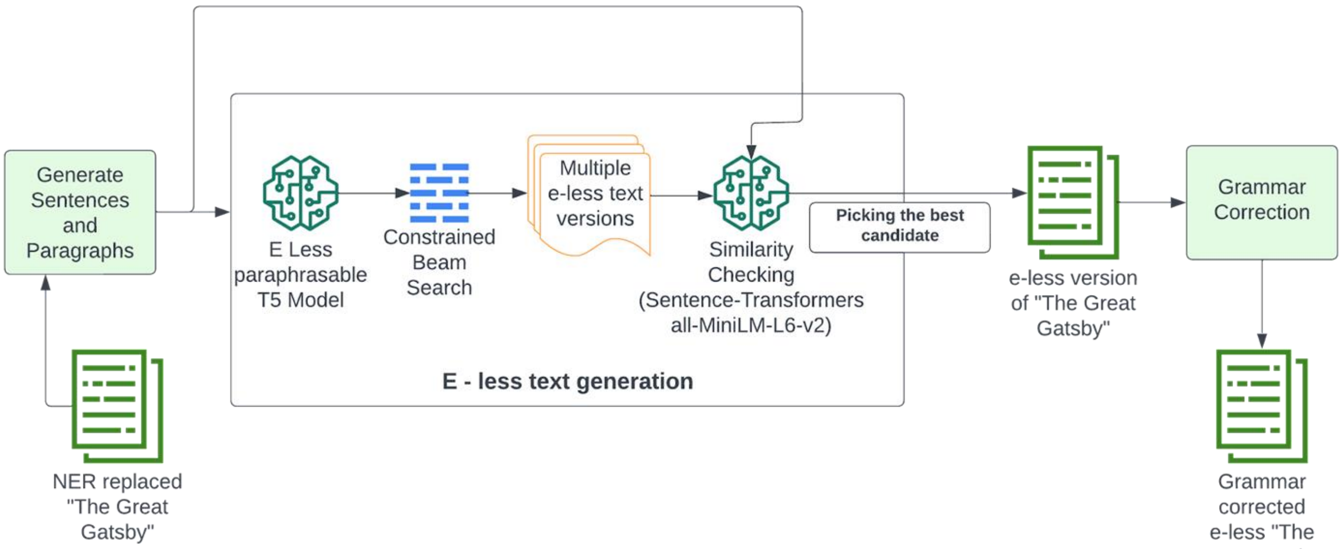


Figure (5)

6. Evaluation

We have computed static and comparative scores for different outputs of the model generation pipeline. In the columns of Tables (2) and Tables (3), we can see four variations of the e-less novel text. The first variation attributes to whether we split the input text into sentences or paragraphs; the second variation is whether we added the Grammar Correction module at the end of the output text. We aimed to show that the grammar correction module doesn't affect their respective uncorrected counterparts' overall similarity or other evaluation scores.

Score Type (Avg across entire text)	**Original Gatsby Text**	**Sentence wise Generated**	**Sentence wise Generated (Grammar Corrected)**	**Paragraph wise Generated**	**Paragraph wise Generated (Grammar Corrected)**
Average Word Length	3.729	3.285	3.268	3.282	3.271
Average Sentence Length	71.501	66.515	66.187	77.114	76.374
Number of Syllables	63356	50083	49771	39784	39281
Number of Complex Words	3059	2059	1973	1715	1692
Number of Long Words	19	31	30	39	27
Number of Unique Words	6380	4966	4898	4063	4025
Number of Monosyllabic Words	37187	34045	33858	27079	26592
Number of Polysyllabic Words	3066	1772	1740	1384	1327
Flesch-Kincaid Grade	5.6	3.8	3.7	4.7	4.6
Gunning Fog Index	7.09	6.12	6.05	7.07	6.98
Dale-Chall Readability Score	5.78	5.64	5.62	5.81	5.79

Table (2) Static Scores

The generated outputs' word and sentence static scores are reasonably close to the original human-written novel text. The paragraph-wise generated output is generally more straightforward and shorter, which might be because the model is trying to summarize the input text a little bit, producing shorter paragraphs with a lesser number of total sentences. We can also see that the number of complex and unique words also takes a significant hit due to the reduced vocabulary available to the model.

Readability Scores like the Flesch-Kincaid Grade, Gunning Fog Index, and Dale-Chall Readability Score also show similar trends. Our outputs are slightly less readable, but this is a reasonable difference. The paragraph-wise generated models perform better in the readability section.

Score Type (Avg across entire text)	Sentence wise Generated	Sentence wise Generated (Grammar Corrected)	Paragraph wise Generated	Paragraph wise Generated (Grammar Corrected)
BLEU Score	0.059	0.058	0.056	0.061
TF-IDF Similarity	0.525	0.525	0.519	0.531
Word Error Rate	2246.273	2259.409	2287.778	2277.412
Character Error Rate	7904.591	7931.455	8055.556	7950.765
Cosine Similarity	0.643	0.644	0.638	0.651
Jaccard Similarity	0.149	0.148	0.141	0.146
SpaCy Cosine Similarity	0.971	0.970	0.972	0.975

Table (3) Comparative Scores (Each output is compared with the same original text)

BLEU is an n-gram-based similarity measurement, and we see very low scores around the 5-7% similarity range. This score is expected as few common n-grams between a text and its e-less paraphrased version exist. TF-IDF is a numerical statistic that reflects the importance of words in a document relative to a collection of documents. The edit distance metrics are as follows: Word Error Rate (WER) and Character Error Rate (CER). For WER, the texts are tokenized into words, and the edit distance is calculated on a word level. These scores help assess the accuracy of systems like automatic speech recognition or machine translation, as lower WER indicates higher similarity at the word level. On the other hand, CER directly calculates the edit distance on the character level for the entire text, making it valuable for evaluating the accuracy of text recognition or generation systems. Lower CER values indicate higher similarity at the character level.

We also compute cosine similarity, where we transform the raw texts into numerical vectors by counting the occurrences of each word, creating a count matrix. This metric measures the cosine of the angle between the vectors, reflecting how similar the two texts are in terms of the frequency distribution of words. A higher cosine similarity suggests a more significant overlap in the word usage patterns between the original and paraphrased texts, providing a quantitative measure of their lexical resemblance and overall textual similarity.

Our output doesn’t fare significantly close to the original text in these mathematical scores since the difference in vocabulary space ultimately produces less word or sentence level similarity. We also used an NLP Model based cosine similarity for which we used the SpaCy Library’s ‘en_core_web_lg’ (*English · SpaCy Models*, n.d.) model to tokenize the input text and output text before calculating the cosine similarity in the n-dimensional space. This metric is the most powerful as it considers the meaning before giving us a similarity score. Our models excel in this scenario, producing close to 97% similarity in retaining the context and meaning of the original Gatsby novel text.

We now want to show some merits and limitations of our current generation pipeline along with some interesting and innovative ideas used by the model while text paraphrasing.

6.1 The Good Parts

Firstly, there is not a single instance of ‘e’ character in the generated text.

Next, the basic constructs like Chapter and The End are handled correctly and are replaced with shortened or synonyms like *“Chap. 1”* and *“Final Part”*.

Futhermore, we can see some freedom of expression in generating poetic sentences.
Input text: *“So we beat on, boats against the current, borne back ceaselessly into the past.”*.
Generated text: *“So on, boats fought against a cyclic flow ; stumbling back and forth.”*

We also see our NER module in action, replacing proper nouns with e-less variants.
Input text: *“How do you get to West Egg village?” he asked helplessly.*

Generated text: *“How do you go to Tuba City? “, sat him numbly.*

6.2 The Bad parts

It's not all sunshine and rainbows on our generation's land. Our model still needs to improve in some very rare scenarios. For example, random and repeating characters that do not make much sense pop in. E.g., "M & p : �__...? �! ��n o k r u t h y d l x v g / c�b w f 0". This type of behavior is extremely rare (about 0.05% of the total length of the novel), and it might be because of how the model operates. Because of the heavy constraints on top of sampling and probability requirements, there could be cases where the probability distribution for the next token is so low that the model has no way other than picking a random token with low probability. We intend to address this problem by customizing how the model handles the logits.

Another potential problem we need to address is to modify the NER module to not pick replacements from proper nouns that already exist in the original text. Also, we intend to add additional logic to pick replacements to be gender consistent. For example, the model might not produce coherent text in cases like:

Input text: *“I talked with Miss Baker,” I said after a moment.*
Generated text: *“I sat down with Miss Dylan”, I said.*

7. Conclusion

This report presents our efforts to tackle the complex challenge of constrained text generation, focusing on generating coherent and readable content without using the letter 'e'. We draw inspiration from historical works like "Gadsby" and employ a meticulous approach to explore diverse datasets and refine our model from GPT-2 to T5. Our comparative analysis highlights T5's superior ability to retain context, which we view as critical in generating high-quality, coherent text.

The methodology involves dataset selection, model exploration, and iterative refinement to overcome challenges in sentence similarity, grammar correction, and proper noun handling. The final generation pipeline integrates diverse modules, leading to a thorough evaluation using static and comparative scores. While the project showcases successful instances of e-less paraphrasing, it also acknowledges areas for improvement, contributing valuable insights to the field of constrained text generation.

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Appendix

The text below is the entire 1st Chapter from The Great Gatsby but in an e-less version

Chap. 1

In my young and tumultuous days, my dad has a lot of wisdom that I'm constantly turning to in my mind.

"If you think that criticizing a group is too much," told him, "you just don't know that all of us in this world has not had what you had."

I didn't say anything to him, but in a snobbish way, I'm always unusually communicating - I know that this habit has brought up many curious kinds of things and has also faint my wits about this quality if it shows up in my normal body--and, so it was that I was unjustly bluffing about as an opportunistic politician. I am still afraid that at birth, as my dad has

And, by boasting about this way of my totality, I find that it has a limit. Conduct may fall on hard rock or dry sands, but I don't know what it is built on - only Gatsby, who has brought this book to my mind, had nothing to do with that flabby impossibility that I had not found in any of us and which I will not find again.

My family has a long history of high-ranking, good-to-do folks in this mid-wold city -'s Carraways, which is sort of clan and has tradition of coming from Hinton's of Anathoth ; but in fifty-ninths my grandma was my Grandpa who coming to this town in 61st c. and sprang up to start up my dad �.

I'm not a good-looking man, but I should look as if I was his son - with an unusually hard painting that hangs in Dad's room. In 1915, I'm graduating from Pontoon and sat so thoroughly in that tawdry migration known as World War II that I thought I had to go back and study bonding--so that all my aunts and cousins talk about it and finally say, "Why??" in two springs

It was a practical thing to find rooms in town, but it was warm, and I had just sat in commuting town of broad lawns and flora and fauna, so if at last I could find him in Washington and an old ALCOA and Finnish woman who built my cot and cooks & mutts Finnish wisdom

It was for a day or so until, on an upcoming morning, an old man, who was coming to my aid, sat on my road.

"How do you go to Tuba City? ", shook him ill.

I told him, and as I was walking on, I wasn't 't a solitary man ; I was an original colonial man, who had casually roast - u. O n g :

And so with sun and big bursts of moss growing on twigs--just as things grow in fast films - I had that familiar conviction that's all about to start again.

I bought a tad of books on banking and gold, as if in old gold from mint, promising to unfold all such things that only Midas and Morgan and Jr. could know, and now I was going to bring all this back into my world and that most limiting of all pragmatists, " I would say. This isn't just an idiom, but it's much judiciously thought of from...

It was a random act of luck that I had to taint, on that small riotous island which is south of D.C. and on which two unusual formations of land jut out into California's most inland body of salt - both sunk flat at contact--but its physical similarity to that of gulls that flit around.

I was living in Tuba City, which is a bit of an oddity to say that it was only fifty yards from sound, and snuck into two colossal spots that - as I didn't know Mr. Gatsby--was an imitation of 1985 in Normandy, with an octavo of ivy-spanking 'n' ; if I had known it, my own mansion was an out-of-body sight, but

Across a kindly bay glints swaths of Costa Rica's stylish villas, and on my way to Sharia Giza, Daisy was my first cousin, and I'd known Tom in high school. And just two days in Chicago - I was...

His husband had, among various physical aims, a solitary goal that fought football at Ponton--a national icon in that way, as if to attain such an irrational limit that all of it is anti-climax, his family was colossally rich and now had thrown away Chicago and brought out polo - pony from Saudi Arabia. It was hard to think that in my owns ;

I don't know why, for no particular ado about it.'; & : /!? - I had no sight into Daisy's soul, but I thought that Tom would always drift on wistfully looking for that dramatic tumultuous stomping ball...

And so it was that on a warm, windy night, I sat down to look at two old pals whom I did not know at all " ... ; & /. - oh my!? �i �I ran to my front door and ran around sun-dials and brick walks and flora--finally as if from its run it's drooping upwards in bright plants as though from

Until his Pontoon days, a sturdy, straw man of thirty-two with an unusually hard mouth and an arrogant way of approaching had two shining, Arrogant forming dominion and giving him that look of always stomping forward. Not only that, but his dazzling boots - if you did not strain his top lacing--would show you that it was an imposing body that couldn't hold it back ; it had an awful body.

His symphony, a gruff husky twang, adds to his portrayal of fractiously. It was also racial indignation, so much so that it was thrown away against things that's liking him--and at Pontoon had guys who hath his guts.

"Now don't think my opinion on this is final,". " told him, "just as I'm strong and a man... I was always in that group and I always had to think that I'm approving of him and wanting him to look at him with his own harsh, wistful wits."

On a sunny porch, I sat down for.

"I'm got a Hilo", told him, his brows flashing snoozing.

Turning my arm around by a broad flat hand along front vista, including in its snub-nooding " - oasis an Italian pond, half an inch of tan-styrofoam and a hunky motorboat that bluffs off.

It was to Kazan, oil man, who again shook my hand kindly and abruptly : "

A high hallway swung into a bright rosy room, tightly bound to it by frangipani windows at both octagons. A wind blowing through it blown curtains in and out of it as light flags, twisting it up toward that flint-wound ring of roof--and robbing it of its shadow, as winds do on land. '

During a short flight around town, Tom Buchanan snuck in his back windows and caught wind was blown out about room and curtains and rugs and two young woman slowly flung up on it.

I was a narrator : if I saw it out of my chin, I had no hint of it--in fact, I was almost surprising to murmur an apology for having stumbling in.

Daisy " ; s - a girl who was trying to stand up--napping slightly forward, with an opportunism.... tanks, an absurd, charming small laugh, and I humbly laugh too!

"I'm p-paralyzing with joy."

In a murmur, sassy said that Daisy's rumor was only to annoy us - as if it was witty. "

At any cost, Miss Dylan's lips fluttling, snoozing almost unassailably and quickly turning back again--it had obviously a bit of twitching and had thrown my lips again. Almost any display of totality - "

I look back at my cousin, who in a low, high-falutination sprang up and down with that kind of vocality as if it is an array of words that won't play again--so sad and charming with bright things in it, bright brows and bright passion - but it was an anticipation in his vocal compulsion that was difficult for all of us who had caring for him: o'; ...

I told it how I had sat for a day in Chicago on my way to Atlanta and how, through my mind, "a dinghy -.

"Do I miss you? ", crying statically.

"It's a dandy town, all cars tawny black as if it is mourning, and all night long 'til...

"How stunning, Tom, go back tomorrow!", ad libtiously adding: "You should look at baby."

"I'd want to."

"It's snoozing, is two and hasn't you all had to?"

"Nay.".

"You ought to look at it ----"

Tom Buchanan, who had sat numbing in my room, halts and puts his hand on my arm.

Nick, what do you do?"

"I'm a bond man."

"Who with?"

I told him.

"Nor had a word of " him. -

This annoys you.

I just said, "You will if you stay in Costa Rica."

"Oh, I'll stay in Costa Rica, don't worry," shook him, glancing at Daisy and back at him, as if a god-damning fool was about to flinch away. "

At this point, Miss Dylan said "Absolutly!" with such a snub that I was - it was as much as I did it, for yawning and standing up with's rapid, frank motions.

"I'm stiff," sighs, "and for as long as I can think I lull on that couch."

"Don't look at us," Daisy said. "I'm trying to bring you to D.C. all day."

"No, thanks," said Miss Dylan to four cocktails just from pantry, "I'm totally in training."

Its host sat irrationally in front of him.

"You'll do it!", told him as if it was a drop in's bottom glass. "How you do anything? I don't know."

I sat at Miss Dylan thinking what it was that "got to do", a slim, small-brown girl, with an oblong body - which as if by throwing it backwards at my chin �was highlighting. My gray constraint brows look back with wistful, charming dissatisfaction now's to my mind that I had had it, or...

"You living in Tuba City", sarcastically said, "I know a guy in that town."

"I don't know a ----"

"You must know Gatsby."

Daisy appoints "Gatsby?", "What Gat??"

Tom Buchanan, who had a tight arm imploring him to go from room to room as if sabotaging.

Smith, languidly, his hands lightly sat on his hips, took us out onto a rosy porch that hung out toward twilight. Four clumsy lights lit up in dwindling wind.

"Why CANALS?" said Daisy, frowning, and snuck it out with hands. "It's in two days it'll'; I always watch for a long day in...

"It's a plan," yawns Miss Dylan, sitting down at tv as if it was going to go in.

"All right," said Daisy. "What will you plan?", snorting idly to.

I could not say a word, but I sat down with an aghast grin on my tiny hand.

"Look!", smirking, "I hurt it."

All of us sat -- knuckling was black and bluish.

"You did it, Tom," said accusingly. "I know you didn't want to do it, but you did. That's what I got for marrying a brutish man, an imposing big hulking physical form of ---"

"I hulk that word," Tom crossly said, "so in kidding."

Daisy insists on "Hulking"

It was a sharp contrast to Indian Country, in which a night was always rushing toward its closing in an unassailably dismal anticipation or simply in stifling incongruity of an instant - as cool as Tom and I';.

Daisy, "You don't want to talk about crops or anything?"

I did not say anything in particular by this ad, but it was thrown in an unusual way.

"Civilization is going to rip", Tom bluffs. "I'm a horridist about things - has this man Goddard's book??"

"Why, no," I said, a bit baffling by his sound.

"It's a good book, and anybody ought to watch it, but if you don't look it out, it will " ; it is all logical stuff. It is proof."

"Tom is so profound," Daisy said with an unthoughtful sigh :, ". -

"This book is all physics," insists Tom, glancing at it in unison. " It's up to us to watch out if this is a dominating racial group, or this will control things."

"It's going to go down," said Daisy, roaring furiously towards a hot sun.

"You should go to California--", said Miss Dylan, but Tom sat in his chair.

"This is a notion that I'm Nordics, and I am and you and ----", with an infinitival nod. Daisy shook up again and said : "-and all things that go to build civilization--oh, physics and art and all that."

As if his complaisantism was too much for him, it was almost instantly ringing a call in front of him and as Daisy sat back on his porch.

"I'll show you a family story," jokingly said, "it's about's. Do you want to know about his?

"That's why I sat up tonight."

"No, not always - ". :) ;]?... �In D.C. for a small group of folks who had sand for two thousand, hr had to polish it from morning till night until finally it was starting to afflict his insofar"

"Things go from bad to bad," said Miss Dylan.

"No, things sank from bad to bad until finally a man had to quit his position."

For an instant, my last sunburst slid with romantic adoration upon my glowing skin ; my vocal compulsion drooping as I stood forward - but that glow fading away, as if any light was torn off by its longing to abandon it at dusk.

But, coming back and murmuring a bit to Tom's throat, Tom frowns, slams back his chair and Goths in without saying. As if his absconding was quick, Daisy stood up again and bluffing and singing.

Nick, "I am a liar if I saw you at my dining room, but you don't think I know of 'a-of-a' - oh no, is that? ".

This was untruthful. I am not faintly as if I was a rhyming, but swaying warmth flung from it as though it was trying to go out to you - hid in's brisk, thrilling words. But thrashing on tack thrown out and going in and out...

Miss Dylan and I sat consciously without a thought and said 'Sh!' as I was about to talk. A calm, impassion - murmur was audibly obstructing in that room, and miss Dylan stood forward, unhurt, trying to find out ; mrs. Dylan twiddling, rumbling and halting it all.

"This Mr. Gatsby you said is my ----", I said.

"Don't talk - I want to know what occurs."

"Is anything going on?", I oblivion.

"You want to say you don't know?" said Miss Dylan, who was a bit surprising : "I thought all of you know."

"I don't."

"Why----", said smugly, "Tom's got a woman in D.C."
"Got a woman?" I said blankly.

Miss Dylan nods.

"It could do a good job not to call him at lunch, don't you think?"

Almost as soon as I had a grasp of its implication, it was soaring and crunch of boots and Tom and Daisy was back at it.

"It couldn't';" Daisy said with a stifling gay.

It sat down, glancing at Miss Dylan frantically and said: "I look outdoors for a bit and it's so romantic outdoors. I think it must " ; ----", and singing "---It is romantic, isn't it?"

"Variant romantic," told him, and now strikingly I said to him: "If it's light, I want you to go down to Stalls."

It rang, startlingly, and as Daisy shook Tom firmly, all of Tom's occupants, in fact, vanish into air again. I could not think of what Daisy and Tom thought, but I doubt if Miss Dylan, who had a particular hardy suspicion, could put out of mind that shrill claustrophobia of this fifth visitor...

In its dark gloom sat Tom and Miss Dylan, with lots of twilight to walk back in, as if to a vigil, in front of an amazingly lucid body. As I was trying to look curious and slightly blind, I took Daisy around to an array of adjoining roods and laid down on an armchair in its midst.

Daisy took it in its hands, as if savoring its soft form, and gradually moving out into tan dusk, I saw that a whirlpool of agitation had. So I thought that I would ask what I did not want to say about this small girl :

Nick said, "I don't know a lot about you, Nick."

"I wasn't back from war."

"That's right." Nick, I'm a bit cynical about it all. "

It was obvious that it had a right to say, but it didn't say much, and I sat down to talk about it again.

"I think, and talks and all."

"Oh, no." I sat blankly looking at Nick: "Hold on, I told you what I said as I was born. Would you want to know?"

"A lot."

"It'll show you how I'm gaining a lot about things. I was about an hour old and Tom was God knows what.

" I sat out of my coma with an almost abandoning hunch, and right away I said : I am glad it's girl - and I pray that it will turn into an obnoxious young fool--that' ;!

"You know I think anything is awful anyhow", sat in a convincing way. "All of us think so--and I KNOW. I'm all around, and I saw it and did it all," and with thrilling scorn. "

In that instant, a smirk of oblivion, my compulsion to taint it off my mind and my faith, I was struck by this basic insinuation of what it had said, as if all of this had to do with tricking, and I stood up and found out that in I had " ; i....

. ", a crimson room brimming with light. Tom and Miss Dylan sat at both paws of long couch and said aloud to him from "Saturday Morning Post"--words murmurous and unflinching, running in an uplifting song. Lamp-light, bright on his boots and dull on autumn-brown of his hair glint dripping along with it as if it had flitting

Upon coming in, with a slouchy hand, nip us.

"To go on," said it, tossing a copy of ", "in our th Arthur. "

With a numbing motion of thigh, and stood up.

"Two o'clock", savoring a bit of clockwork, said : 'Till this good girl to go to...

"Jordan is going to play in tomorrow's championship," Daisy said, "at Indian Country.

"Oh,--you JORdan Dylan."

I now know why it was familiar -- from many rotogravur photographs of sporting living in Old ham and Hot Springs and Pacific, it had also told a critical, unsavory story, but what was it I had forgot long ago.

"Good night," said softly, "won't you snort at ".

"If you'll climb up."

"I will. Good night, Mr. Carraway. I'll look for anon."

"Of you will," said Daisy. "In fact I think I'll sort of--oh - fling you with Nick. You know -- lock you up in a laundry room and push you out on board and all that kind of thing --"

"Good night," said Miss Dylan from upstairs, "I had no word."

Tom said's a good girl, and shouldn't allow it to run around this way.'

Daisy sat coldly asking "Who should not?"

"His family."

"His family is about a thousand old. Nick's going to look for it, isn't you, Nick, who is going out for lots of Sundays in July - I think that is good for you."

Daisy and Tom sat for a whirlwind.

"Is it from D.C.?" I quickly said.

"From North Africa, our black girlhood was a part of that - ---. "

"Did you Nick a bit of " hors d' talk on?

"Did I?" I said, "I can't think of it, but I think I did. It kind of clung to us and first thing you know --"
"Don't think all you know, Nick", I told him.

I said lightly that I had nothing at all, and a whirlwind I got up to go back to my car and stood with him in solitary light. As I was starting my motor, Daisy callously "Wait!!"

"I forgot to ask you a thing, and it's important, ".

"That's right," Tom kindly sat down and said : "

"It's a lying, I'm too poor."

"But it was us," insists Daisy, snorting again in a floral way : " "Wait... it has -. "

Of all that I know, but I was not a tad livid about that fact that gossip had spouting banns. You can't stop going on account of rumors with an old pal, and I had no plan to marry if it was to.

It was a bit of an intrusion on my part, and I was not particularly rich--no doubt, I thought that what Daisy should do was to hurl out of town, child in arms - but appartiously no such insinuation was in his mind. As for Tom, nothing was making him nip away at d.c.'s indignation as if his sturdy physical ambition did not nourish his sanctimonious soul!

It was now a tumultuous spring on roads and in front of ways caravans, in pools of light, and as I got to my land in Tuba City I ran my car and sat on an old grass rolling in my yard for 'til I saw that I was not only frankly blown away by an animal that had sprung out of its shadow and was standing with his hands in his paws on lawn indicating that it was Mr. Gatsby who had

I sat down to call him, as Miss Dylan had told him at lunch, and that would do for an introduction, but I didn't call to him for a jolting intimation. As far as I was away from him, I could taint I had no thought that it was his own fault - and if I did look again for Gatsby's light, it had vanish ; and I again was in untidy dark.