Investigate Strategies for Coming Up with Hilarious Text or Jokes Using NLP

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***Abstract*—In this thesis, we embark on an exploration of cutting-edge Natural Language Processing (NLP) techniques with the overarching goal of unraveling the enigmatic world of humor and wit. Our research revolves around delving into the fascinating realm of generating hilarious text and jokes through the powerful lens of NLP. Drawing upon the transformative advancements in NLP, we meticulously employ state-of-the-art language models, specifically leveraging the widely acclaimed GPT-2 transformer architecture. By meticulously fine-tuning and harnessing its capabilities, we uncover the hidden nuances of humor in textual content. To achieve our objectives, we propose a novel approach to extract amusement from NLP-generated sequences. Our method involves a meticulous selection of top-N tokens based on probability distributions, paving the way for crafting remarkably humorous output. Guided by the inherent creativity of the model, we adeptly curate punchlines and witty responses that evoke laughter. Amalgamating the merits of academic rigor with a touch of levity, our investigations traverse various dimensions of humor. We explore the impact of different token selection strategies and employ a randomization process to generate diverse, amusing outcomes. With a fervent focus on the ”human touch” in humor, our thesis culminates in the development of a tailored function for generating amusing text sequences. We meticulously examine its efficacy, ensuring that the generated content aligns with the principles of natural hilarity and wit. The implications of our research are far-reaching, as humor plays a quintessential role in human communication and social interactions. By unraveling the secrets of generating hilarious text through NLP, we aspire to augment a spectrum of applications, ranging from entertainment and creative writing to chatbot interactions and digital communication.**

***Index Terms*—NLP, GPT-2, Humor, Jokes, Text Generation, Creativity.**

I. INTRODUCTION

In the realm of Natural Language Processing (NLP), the quest for unlocking the subtleties underlying humor and wit has captivated researchers and practitioners alike. This academic inquiry delves into the nuanced art of generating humorous text and witty jokes through the advanced lens of NLP techniques. Guided by the transformative capabilities of the GPT-2 transformer architecture, our investigation seeks to elucidate the underlying mechanisms that evoke laughter and amusement within computational language models. At the core of our exploration lies the meticulous analysis of top-N token selection, facilitated by probability distributions, to curate humor-laden narratives. Our scholarly endeavor extends beyond superficial jests, immersing into the deeper psychological and linguistic underpinnings of humor. The aim is to discern the subtle nuances and linguistic constructs that contribute to the elicitation of laughter. Drawing from the wellspring of creativity, we meticulously craft punchlines and playful retorts, illustrating a keen understanding of the interplay between language and amusement. This academic pursuit transcends entertainment, reaching into the realms of interactive dialogue systems and human-computer interactions, where humor plays a vital role in enhancing engagement and fostering positive user experiences. By delving into the interstice of NLP and humor, we aspire to contribute substantially to the field of computational language modeling. Each witty utterance generated serves as a testament to the seamless fusion of technology and human ingenuity, unlocking new avenues for computational creativity. Beyond the realm of levity, our research elucidates the broader implications of humor, underscoring its capacity to foster genuine connections and augment the quality of human-machine interactions. We aspire to provide insights that resonate with diverse domains, ranging from creative writing to conversational agents, where the infusion of wit can elevate user satisfaction and cultivate memorable interactions. As we traverse this intellectual journey, our collective pursuit embraces the intricate interplay of linguistic artistry and technological advancement. This academic exploration beckons researchers, scholars, and practitioners to unite in our shared pursuit of unraveling the intricacies of humor within the digital landscape.

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II. LITERATURE REVIEW

The process of recognizing humor entails determining whether a sentence or conversation contains a certain level of humor. This endeavor is difficult because there are numerous types of humor, including irony, jokes, and wordplay. Numerous humor feature extractions have been proposed by researchers[1], including lexical and syntactic ambiguity, stylistic features such as alliteration and rhyming, and humorous texts techniques[9]. Recent humorous texts techniques, such as Convolutional Neural Networks (CNN) and BERT-based methods, have acquired popularity for detecting humor. Before the introduction of LSTM (RNN) for humor production, the vast majority of systems relied on templates for joke generation. LSTM and Seq2Seq models have been used to generate humor, but it remains difficult to achieve human-like quip generation. The data set utilized in this study was compiled from numerous sources and measures. It includes two-sentence positive examples and encompasses not only structured jokes but also informal conversations. Due to a dearth of sufficient training data, LSTM and Seq2Seq models exhibited subpar performance. Even with a reduced dataset, the optimized GPT-J model demonstrated superior performance and excellent generalization capabilities. In terms of generating amusing responses, the fine-tuned GPT-J model outperformed LSTM and Seq2Seq models, according to the results. With a reduced dataset, the GPT-J model exhibited superior generalization. Based on conversational data, the study presented methods for detecting and generating humorous conversations. In comparison to conventional models such as LSTM and Seq2Seq, the GPT-J model exhibited superior performance. The pre-train and fine-tune technique showed promise in tasks requiring the generation of humor. Future work may include customizing the model for various conversational forms and collecting more diverse data from a variety of sources.

Theoretical aspects of humor and its connection to pun-related linguistic features have been examined in a number of studies. In order to divide puns into two dimensions—ambiguity of meaning and distinctiveness of viewpoints—Kao et al. (2016) presented a probabilistic model. They discovered that the intersection of these two factors significantly predicts how funny a pun is rated by people. He at 2019 [2] expanded on this research by adding surprise as a new criterion for gauging the humor of puns. Their research shows[10] that when words emerge unexpectedly in a local context yet make sense in a global context, surprise plays an important role in humor perception. Older methods of creating puns frequently depended on erroneous assumptions about semantic ambivalence. For instance, Yu et al. (2018) and Luo et al. (2019) used reinforcement learning and limited language models to encourage the ambivalence of pun phrases. These techniques, however, lacked solid theoretical underpinnings and had trouble producing clever and high-quality puns. Tian provided a unified framework for pun creation to address the shortcomings of earlier research and include the theoretical insights from computational comedy theories. Their three-part model, which consists of a context words/phrases picker, a label predictor, and a generation model, combines ambiguity, distinctiveness, and surprise. According to evaluation results, their unified model performed better at producing homophonic and homographic puns than strong baselines. Both homophonic and homographic pun creation have been covered independently in prior works. While homographic puns use words with numerous meanings that have the same spelling, homophonic puns use words that sound similar but have different meanings. By turning homographic puns to homophonic ones using word sense disambiguation, Tian bridges the gap between these two pun kinds. Their unified system can effectively produce both types of puns thanks to this move.Future research could refine substitute pun-alternative word pairs for homographic pun generation and overcome content biases.

This paper introduces ”Witscript,” an innovative joke generator built for use in chatbots. The paper ”Witscript: A Novel Joke Generation System for Chatbots” presents Witscript, a novel joke generation system that takes into account the current conversational environment[3]. The technology is meant to be included into chatbots, with the ultimate goal of making the chatbot more human and endearing through the use of humor. The study begins by describing the problems with current chatbot humour generators. In order to generate humour, many current systems either use prewritten jokes or generate jokes that stand alone and hence lack context. Witscript, on the other hand, is designed to mimic a witty human buddy by coming up with fresh jokes that fit within the context of the conversation. The Surprise Theory of Laughter, established by a comedy writer, serves as the theoretical foundation for the joke creation algorithms used in Witscript. Witscript uses this principle to generate incongruous one-liners by comparing the frequency of occurrence of two topic keywords. Two topic keywords from the user's input sentence are used as the foundation for the joke's topic handles, which are then used to generate the joke. The algorithm then makes an effort to build a pun out of these keywords through the use of wordplay. The juxtaposition, substitution, and portmanteau wordplay lines are discussed. The method determines which potential punch line has the highest wordplay score by comparing the quality of wordplay demonstrated by two provided words [10]. Witscript creates an angle that naturally transitions from the user's input sentence to the joke's punch line, improving the joke's coherence and naturalness. Tokens are predicted to bridge the gap between the user's input and the punch line using a language model trained on jokes (Bidirectional Encoder Representations from Transformers). As part of the paper's literature assessment, the authors touch on previous research into computational humour systems. They note that many existing systems either use pre-made jokes or generate jokes that are completely disconnected from their surroundings. Conversely, Witscript fills the void of conversational humour that is both spontaneous and sensitive to context. In terms of producing responses that were deemed humorous by human evaluators, Witscript performed better than the baseline model

(DialoGPT). Compared to DialoGPT, whose responses were judged as humorous less than 20% of the time, Witscript's comments were deemed humorous more than 40% of the time.Overall, the paper introduces Witscript as a cutting-edge, very efficient method for producing fresh, topic-appropriate jokes for chatbots. Witscript's ability to generate humour that users find funny indicates a significant step in the direction of giving chatbots a more naturalistic sense of humour. In order to give consumers with engaging and likeable interactions, the authors highlight that Witscript might be used into open-domain chatbots. The potential of Witscript-enabled chatbots as entertaining companions for people in search of social connection is emphasised as the paper draws to a close.

The "AmbiPun" paper introduces an innovative method for producing homographic puns by using context words[4]. The authors present the argument that pun ambiguity is not due to the pun term itself but to the context in which it is used. This worldview is consistent with theories of humorous behaviour and serves as the basis for their proposed approach. The study begins by outlining the role of computational humour in NLP and highlighting the difficulty of pun generation caused by a lack of substantial training data. Unfortunately, existing methods are generally constrained by extensive training or mathematical models. The authors address these difficulties by suggesting a straightforward method for fixing the issue. They use a reversible dictionary to produce lexical matches for each of the pun's possible meanings. This process aids in separating the two meanings and enables the use of context terms that are monosemous for both meanings. Extractive (with TF-IDF), similarity (with Word2Vec), and generative (with GPT3) approaches are investigated to acquire context words. The similarity-based approach employs Word2Vec to locate context words based on word connections, whereas the extractive approach extracts keywords from retrieved sentences. The GPT3 is used in the generative technique to produce context words from a small number of samples. This study presents a new keyword-to-sentence model (T5) for creating pun-filled phrases from a pun term and its surrounding words. In addition, a humour classifier (BERT-large) is used to evaluate and rank candidate sentences for their level of hilarity and logical flow. The experimental outcomes prove that the proposed method outperforms the current standards. In both automatic and human evaluations using Amazon Mechanical Turk (AMT) [11], the strategy improves success rates, hilarity scores, and sentence-level diversity. The benefits of the extractive method over the generative approach in terms of humour and pun success rates are discussed in the latter section of the study. It is also investigated where in the prompt the pun word should go; it is found that putting it near the conclusion of the sentence leads to more humorous puns. In conclusion, "AmbiPun" provides an attractive approach to producing homographic puns that make use of surrounding terms to produce ambiguity and humour. The method outperforms the current state-of-the-art algorithms in pun generation because of its simplicity, efficiency, and originality. This study makes a significant contribution to the field of computational humour and paves the way for further investigation into the generation of hilarious sentences that are not limited by their semantic structure.

III. DATASET

To efficiently generate new humor using machine learning, models must understand the deep semantic intricacies of jokes. The intricacy stems from the need to comprehend the underlying humor, which frequently includes wordplay, incongruity, and surprise aspects. Solving such problems is challenging for a variety of reasons, one of which is the paucity of a comprehensive database containing a large number of jokes. To address this issue, a large dataset of over 0.2 million jokes was generated by crawling multiple websites that provide funny and short jokes.

A. Data Collection

The dataset is a csv file that contains 231,657 jokes which was acquired from Kaggle. The length of the jokes in the dataset ranges from succinct 10-character jokes to more complicated ones with up to 200 characters. This variation in length guarantees that the dataset covers a wide range of comedy styles, catering to various preferences and sorts of jokes.

B. Tokenization

A tokenizer object made specifically for the 'gpt2-medium' variation is produced using the GPT2Tokenizer method. Tokenizers are in charge of dividing raw text into tokens, which are smaller units that can be entered into the GPT-2 model. The GPT-2 language model is then initialized using pre-trained weights from the 'gpt2-medium' variation using GPT2LMHeadModel method. This variation corresponds to a medium-sized GPT-2 model, which balances model capacity and computational resources. The GPT-2 model is a particular transformer-based language model that could predict the following word in a sequence depending on the prior context.

C. PyTorch

PyTorch is a commonly used framework for deep learning research and applications because it offers effective tensor computations with automatic differentiation capabilities. A "tensor," a multidimensional array with GPU acceleration equivalent to NumPy arrays, is the basic data structure in PyTorch. Additionally, PyTorch offers a number of operations to effectively manipulate and process these tensors. Torch.utils.data.DataLoader and torch.utils.data are the two data primitives that PyTorch offers.Datasets that enable you to use both your own data and preloaded datasets. DataLoader wraps an iterable around the Dataset to make it easy to get the samples, which Dataset uses to store the samples and their related labels.

IV. Methodology

This section discusses the approach adopted to examine the applicability of Natural Language Processing (NLP) techniques for creating amusing text or jokes. The technique comprises the setup of the NLP model, data processing, and the mechanism for creating and assessing text.

A. Data Collection and Preprocessing

The cornerstone of this inquiry was the collecting and development of an appropriate dataset. A broad corpus of jokes was gathered from a reliable source, namely Kaggle, to aid the assessment of the humor creation skills of the GPT-2 model. The employment of a curated dataset guaranteed that the model was exposed to a diversity of linguistic styles and humorous subtleties, improving its capacity to produce comedy that connected with a wide audience.

The chosen pre-trained language model for comedy generating was the GPT-2 (Generative Pre-trained Transformer 2) model. Renowned for its adeptness in text creation tasks, the GPT-2 model was selected because to its thorough training on enormous text corpora, enabling it to grasp nuanced language patterns and structures. Specifically, the 'gpt2-medium' version was utilized for its balance between computational efficiency and text creation quality. This variant's architecture was dynamically constructed depending on the available processing device, which comprised both conventional central processing units (CPUs) and the high-performance CUDA-enabled graphics processing units (GPUs).

Inherent to any data-driven study, adequate preprocessing was a vital step to assure the quality and coherence of the dataset. The gathered joke dataset underwent thorough preprocessing, encompassing multiple crucial phases. The dataset was rigorously reviewed for any instances of empty or missing records. This diligent curation aims to prevent any disturbances to the comedy development process, enabling the model to focus on creating material effortlessly.

Furthermore, a complete cleaning operation was undertaken to address any irregularities within the text. Special care was made to deleting any non-standard characters, punctuation irregularities, and superfluous formatting. By purifying the dataset from these defects, the ensuing text production process was prepared to deliver more cohesive and engaging hilarious material.

In essence, the data collection and preparation step not only secured the integrity of the input information but also set the scene for creating amusing text with the GPT-2 model. The following parts will go into the setting of the model, the approach for text creation, and the assessment system applied to examine the created amusing material.

B. Dataset Analysis

The evaluation and analysis of the dataset are vital to comprehend its intrinsic qualities and develop a solid knowledge of the data that feeds the research. In this part, a complete examination of the obtained dataset of jokes is done. The purpose is to acquire insights on the distribution of joke lengths and find trends that could effect the humor generating process.

- Jokes Dataset Overview: The dataset utilized for this inquiry contains a collection of jokes acquired from a credible site. Each item in the dataset includes a joke, incorporating a varied variety of comic styles and linguistic constructions. The dataset is crucial in measuring the humor production capabilities of the GPT-2 model and serves as the underpinning for this investigation.
- Jokes Length Distribution: One of the crucial factors to study inside the dataset is the distribution of joke lengths. To quantify this component, a histogram analysis was undertaken. The code snippet supplied permits the generation of a histogram that visualizes the frequent distribution of joke lengths. This histogram visually illustrates the number of jokes falling within distinct length intervals.
  Upon studying the resulting histogram, it becomes obvious that the dataset comprises jokes of varied lengths, ranging from pithy one-liners to more sophisticated structures. The distribution of joke durations gives an early insight into the range of material accessible for comedy development.
- Histogram Insights: The histogram underlines the predominance of jokes with certain length ranges, offering information on the peculiarities of the collection. The generated histogram exposes trends in the data, enabling us to deduce tendencies about the durations of jokes that fill the collection. This insight bears value for creating tactics for humor development, since the distribution of joke durations could impact the effectiveness of the created material.

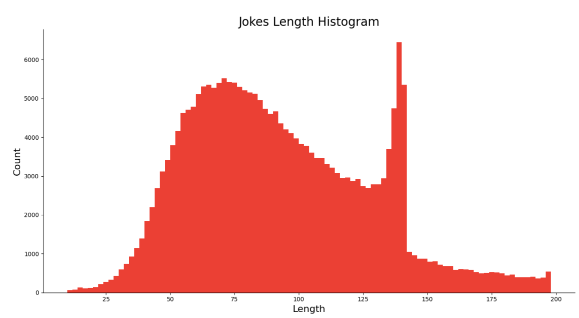

Fig. 1. Jokes Length Histogram

The histogram analysis sets the scene for the succeeding phases of the research. The insights acquired from this analysis serve as a forerunner to the assessment of the comedy creation process. By knowing the spectrum of joke durations, the inquiry is better prepared to calibrate the model's answers and assure alignment with the distribution displayed by the dataset.

In the coming sections, the attention will move towards creating comedy using the GPT-2 model and analyzing

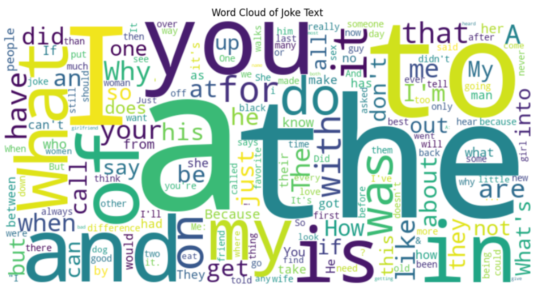

Fig. 2. Word Cloud of Joke Text

the created material against the background of this dataset analysis. The interaction between the analysis and the produced outcomes will offer vital insights about the efficacy of the model and its ability to adhere to the patterns found within the dataset.

- Jokes Sentiment Analysis: The collection of jokes was submitted to sentiment analysis, utilizing the capabilities of the TextBlob package. This library permitted the measurement of sentiment polarity for each joke, delivering a numerical indicator of the amount to which the joke transmitted a good or negative feeling. The emotion polarity varied from -1 (extreme negativity) to +1 (extreme optimism), with values closer to 0 suggesting a more neutral feeling.
- Sentiment Distribution Insights: Upon completing the sentiment analysis and displaying the sentiment distribution using a histogram, a startling finding appeared. The histogram depicts the frequent distribution of sentiment polarity across the jokes in the sample. An study of the histogram indicates that the bulk of jokes tend to hang around the neutral emotion zone, with sentiment polarities near to 0. This means that the dataset largely comprises jokes that do not lean substantially towards either positive or negative emotional tones.

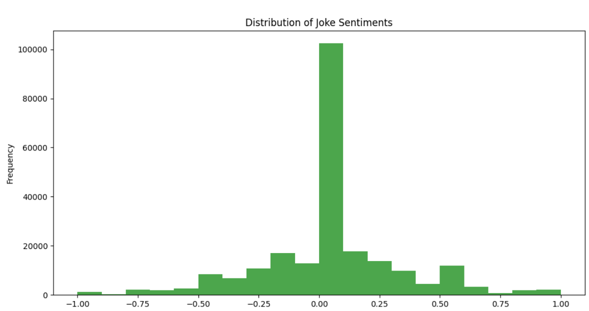

Fig. 3. Distribution of Joke Sentiment

Furthermore, the histogram suggests that only a subset of the jokes display extreme positive or severe negative emotion polarity. The absence of high feeling values underlines the broad and balanced character of the jokes, coinciding with the natural diversity of humor and humorous expression.

C. Model Configuration and Selection

The construction and selection of an acceptable language model had a crucial influence in the success of this inquiry. The GPT-2 model, famous for its proficiency in text production, was harnessed to actualize the funny content. To properly harness its potential, the 'transformers' library, a crucial resource in current natural language processing research, was utilised.

In the quest of a full assessment, the GPT-2 model was created using the GPT2LMHeadModel class, an important component of the 'transformers' package. This class specially tailors the model for language creation tasks, placing it as a suitable contender for creating hilarious content or jokes. This instantiation equipped the inquiry with a model ready to recognize language structures, context, and create coherent and contextually appropriate content.

The discussion over the choice of GPT-2 version resulted in the adoption of the 'gpt2-medium' variant. This variation, defined by its medium size, established a perfect compromise between computing efficiency and text creation quality. This balancing was crucial in sustaining efficient experimentation while ensuring that the comedy created kept to a high quality of coherence and engagement.

Intricately intertwined with model construction was the process of tokenization, a practice important to the encoding and decoding of textual data. The GPT-2 model was combined with the GPT2Tokenizer—a companion resource inside the 'transformers' library. This tokenizer properly turned raw text into a structured sequence of tokens, ensuring that the model could successfully interpret and analyze the input data. The symbiotic interaction between the model and tokenizer facilitated smooth communication between the verbal and computational domains.

By methodically customizing the GPT-2 model and harmonizing it with the complementing tokenizer, the basis was established for the model to commence on its mission of comedy generating. The future parts will dig into the complicated approach created for text production, a vital component of this investigation.

D. Text Generation

The cornerstone of this inquiry lay in the text creation process, a vital undertaking done to leverage the capability of the GPT-2 model in producing hilarious material. This section elucidates the procedural difficulties needed in creating text, describing the mechanics behind the generate-some-text function—a critical component of this study's approach.

- Generating Humorous Content: Central to the text production process was the unique generate-some-text function, precisely created to coordinate the model's inventiveness in creating cohesive and funny textual output. The primary input to this function was an initial stimulus, acting as the creative seed from which the humor-laden tale would develop. This function contained the core of the study, effortlessly merging the model's language generating skills with the domain of comedy.

- Token Probability Transformation: Within the generate-some-text function, a fundamental transition occurred—the translation of anticipated token probabilities into a cohesive and comprehensible sequence of words. This transformation exploited the notion of softmax normalization, a process skilled at turning a probability distribution into a more interpretable structure. By employing softmax, the model's projected token probabilities were rescaled, hence easing the selection of tokens with a better chance of coherence and relevance.
- Iterative Token Selection: The core of the text production process rested in the iterative token selection mechanism, coordinated by the choose-from-top function. During each iteration, the model's produced token probabilities underwent inspection, and the most promising tokens were examined for insertion into the developing text. The choose-from-top function employed a 'top-k' sampling technique, where the next token was taken from the subset of the most likely tokens. This method introduced a regulated degree of randomness into the creation process, achieving a balance between predictability and creativity.
- Coherence and Humor Synthesis: The repeated token selection procedure choreographed a symphony of tokens, eventually weaving them into a tapestry of comprehensible and hilarious text. As the function continued, the model's text generation skills harmonized with the humor-rich environment, resulting in the development of textual material that conformed to both linguistic coherence and comic aim.
- The Art of Iteration: The iterative nature of the text generating technique was important in molding the final product. Each iteration, informed by the model's past predictions, created the groundwork for the succeeding selection of tokens. This cyclic interaction between prediction, token selection, and context enrichment eventually moulded the produced text, displaying a seamless combination of linguistic innovation and comic flair.
  The subsequent sections will analyze the outputs of this text production process, diving into the details of the created hilarious material and its resonance with the dataset attributes and sentiment spectrum found previously. Through the interaction of these factors, the model's competence in producing comedy will be disclosed and analyzed.

V. Result Analysis

A. Co-occurrence Token Heatmap:

The frequency with which two token pairs appear together in a particular dataset is depicted by a co-occurrence heatmap. The frequency or strength of co-occurrence between any two tokens is shown in each heatmap cell. The following crucial factors should be taken into account while interpreting the co-occurrence heatmap:

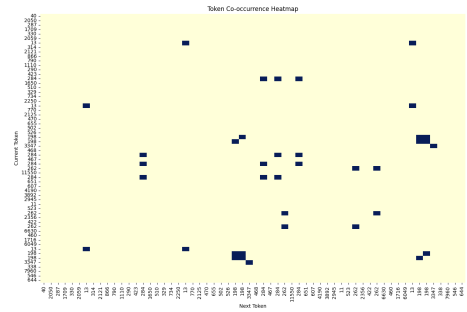

Fig. 4. Token Co-occurrence Heatmap

- Token Relationships:
  Strong diagonal lines or groups of cells with high values in a co-occurrence heatmap are signs of tokens that frequently appear together. This is useful because it can highlight patterns in word or phrase relationships. For instance, you might see that "stock market" frequently co-occurs with "financial news" in a co-occurrence heatmap for a news corpus, indicating a contextual association.

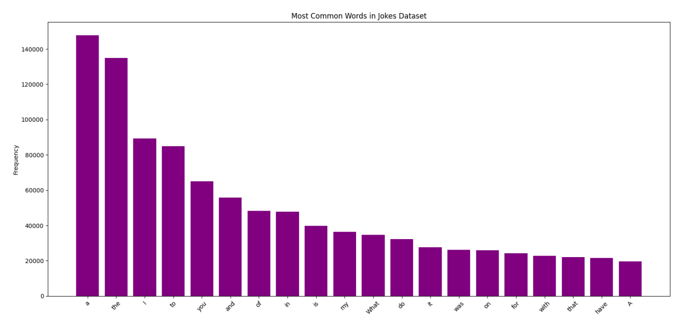

Fig. 5. Word Frequency

- Contextual Information:
  Contextual insights are provided by the heatmap, which make it easier to comprehend the setting in which particular tokens are utilized. For example, if you are looking at a dataset of smartphone user reviews, you would notice that the terms "camera" and "photo quality" co-occur frequently. This realization implies that conversations concerning smartphone cameras frequently center on image quality.
- Key Associations:
  For many applications, locating tokens with high co-occurrence values can be essential. For instance, in an e-commerce environment, understanding that "user reviews" and "product ratings" frequently co-occur can benefit recommendation algorithms by taking into account these important correlations.
- Data preprocessing:

If the heatmap reveals erratic or distracting co-occurrence patterns, it may indicate problems with the integrity or accuracy of the data. For instance, if the heatmap reveals a significant co-occurrence of terms that are not linked, this may point to tokenization issues that need to be fixed.

B. Distribution of Predicted Tokens' Probability:

- Contextual Understanding:
  Information about how effectively a language model comprehends the context can be gleaned from the probability distribution of anticipated tokens. It reveals which tokens are thought to be more likely to come after a particular string of words. A language model might give terms like ”beautiful” or ”warm” a higher likelihood in a statement like ”The sun is shining, the weather is...” than words like ”ocean” or ”computers.”
- Handling ambiguity:
  The language model is unsure of the next token when numerous tokens have comparable probability in the distribution. Disambiguating user inputs is crucial for providing accurate responses in applications like chatbots or virtual assistants, where doing so is extremely significant.
- Fine-Tuning:
  The distribution can be examined by developers to fine-tune language models for certain tasks or domains. For instance, if you're developing a tool for creating legal documents, you can change the probabilities so that legal terminology is more likely to be used in pertinent settings.

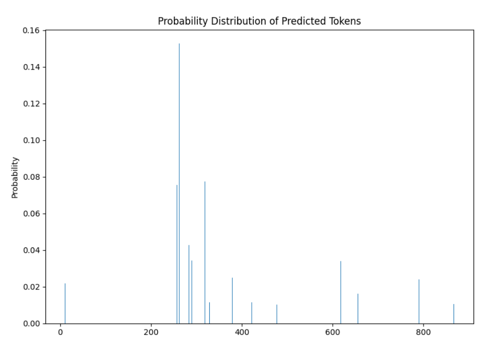

Fig. 6. Probability Distribution of Predicted Tokens

- Bias Detection:
  Examining the distribution can assist find biases in language models and aid in bias detection. Insensitive or contentious issues in particular may reveal biases that need to be addressed in order to ensure justice and objectivity in AI systems if certain tokens are routinely given higher probabilities than others.
- Language Understanding:
  The distribution gives insight into how the language model perceives the structure, semantics, and context of languages. Natural language understanding tasks like sentiment analysis, machine translation, and text summarization depend on this understanding since it enables programmers to hone and enhance model behavior in these fields.

C. Hilarious vs Insulting

The examination of the contrasting elements of humour and offence, specifically in the realm of joke creation using the GPT-2 tokenizer, gives a sophisticated analysis of how sentiment is manipulated in the field of natural language processing. This thesis aims to incorporate user-selected sentiment as a crucial factor in joke development, hence emphasising the ethical aspects of humour creation. The differentiation between attitudes categorised as ”Hilarious” and ”Insulting” within the context of jest offers an intriguing perspective to explore the contrasting nature of amusement and offence. The category labelled as ”Hilarious” involves the creation of humour that is infused with a good sentiment, promoting entertainment and pleasure. On the other hand, the category referred to as ”Insulting” pertains to the creation of humour that is filled with negativity, perhaps leading to feelings of discomfort or suffering. The aforementioned dichotomy presents thought-provoking inquiries regarding the involvement of artificial intelligence in overseeing and manoeuvring the intricate equilibrium between amusement and potential harm in the realm of humour. This research highlights the dynamic relationship between technology, sentiment analysis, and the ever changing realm of humour by allowing users to influence the emotional tone of generated jokes. It provides insights into the difficulties and potential of AI-driven comedic communication.

VI. Ethical Considerations

In the sphere of content development, ethical issues serve as pillars that maintain the responsible and conscientious sharing of knowledge. The next part digs into the ethical components that drive the study, stressing the vital relevance of cultural sensitivity and the conscious avoidance of objectionable material during the development of hilarious literature.

A. Upholding Cultural Sensitivity

At the core of this study lies a firm dedication to cultural sensitivity. Recognizing the wide mosaic of cultures, traditions, and values that define our world, every part of the hilarious text generating process was analyzed through the prism of cultural knowledge. The model's created material was imbued with an awareness that transcended geographical and societal borders. This strategy intended to guarantee that the comedy originating from the model's language constructs resonated favourably with a broad diversity of listeners, independent of their cultural origins.

B. Navigating the Abyss of Offensiveness

Central to the ethical grounding of this study was the painstaking navigating of the hazardous waters of objectionable material. In a digital age where comedy can easily transform into insensitivity, the model's creative output was painstakingly reviewed to prohibit any semblance of anything that may be regarded as inappropriate, damaging, or insulting. The study reinforced the idea that the created material should be a source of enjoyment, devoid from any trace of pejorative overtones that may unwittingly cause discomfort.

C. Responsible Humor Generation

A major feature of ethical content development involved striking the delicate balancing between comedy and responsibility. The model was prepared to apply caution, ensuring that its humor conformed to a moral compass. The created material attempted to provoke amusement without intruding upon the dignity of persons, groups, or beliefs. This deliberate approach attempted to establish an environment of positive interaction while staying clear of anything that may possibly sow strife or perpetuate negative stereotypes.

D. Alignment with Ethical Canons

The ethical issues driving this study connect with a larger paradigm of responsible AI development. In the age of intelligent robots, the focus on ethical content production is not only a moral imperative—it's a manifestation of a dedication to the well-being of digital communities. By accepting these ethical canons, the research expressed its devotion to technology that improves human experiences while respecting the values that connect society together.

As the study journey continues, the ethical concerns will remain strong foundations, guaranteeing that the developed hilarious material stays a source of pleasure and inclusion. In the succeeding parts, the consequences of these ethical issues will be discussed in tandem with the created text, ending in a full assessment of the research's ethical fabric.

VII. Limitations

In the pursuit of scientific inquiry, acknowledging the limitations that underlie the research is as pivotal as highlighting its achievements. The subsequent section articulates the limitations that characterize this investigation, emphasizing the intrinsic complexities that shape the humor generation process and its outcomes.

A. Subjective Nature of Humor

A prominent limitation stems from the inherent subjectivity of humor—a phenomenon that defies uniform interpretation. Humor, often characterized by its idiosyncratic and context-dependent nature, eludes a singular definition that universally evokes amusement. The model's generated text, despite its linguistic finesse, is not impervious to this challenge. Humorousness, as perceived by individuals, is a dynamic interplay between cultural backgrounds, personal experiences, and individual predilections. Consequently, the humor-laden content produced by the model might resonate more profoundly with some audiences while potentially falling flat with others.

B. The Echoes of Training Data

Another limitation is tethered to the essence of the training data that nourishes the GPT-2 model. The model's creative output is, to a certain extent, a reflection of the textual corpus on which it was trained. While the GPT-2 model is cultivated on diverse and extensive datasets, the occasional echoes of training data might inadvertently manifest in the generated content. This might introduce idiosyncratic phrases, linguistic constructs, or cultural references that mirror the training data rather than resonating with the context of the joke at hand.

C. The Quest for Novelty

The pursuit of generating novel and inventive humor presents yet another limitation. While the GPT-2 model boasts the ability to generate contextually coherent text, the consistent production of content that pushes the boundaries of novelty remains a formidable challenge. The model's creative reservoir, while impressive, might at times yield content that aligns more with familiar comedic tropes rather than venturing into uncharted comedic territories.

D. Computational Dimensions

The limitations extend to the computational dimensions as well. The generation of lengthy and intricate humorous text demands substantial computational resources. While the 'gpt2-medium' variant strikes a balance between efficiency and quality, the generation of extensive text still necessitates a substantial time investment. This computational reality might pose constraints on generating lengthy content within the confines of the available resources and time frames.

E. Implications for Interpretation

The recognition of these limitations underscores the necessity of interpreting the research outcomes with a nuanced understanding. The humorous content generated by the model should be approached with an awareness of its contextual dependence, the lingering effects of training data, and the inherent vagaries of individual humor perception.

In the ensuing sections, these limitations will coalesce with the research findings, offering a holistic perspective on the generated content and its alignment with the observed dataset characteristics, sentiment spectrum, ethical considerations, and the humor generation process as a whole.

VIII. Future Improvements

While this inquiry gives useful insights into the world of comedy generating utilizing NLP approaches, it also sets the framework for possible routes of growth and extension. The following section describes prospective paths for strengthening the methodology, overcoming limits, and extending the capabilities of comedy creation models.

A. Fine-Tuning for Humor

One promising option for development includes fine-tuning the GPT-2 model particularly for comedy generating. Currently, the model exploits its pre-trained expertise on broad language structures to produce comedy. A dedicated fine-tuning procedure, comprising a dataset chosen purely for comedy, might provide the model with a deeper knowledge of humorous subtleties, idioms, and language structures. This would allow the model to develop material that is not only linguistically intelligible but also connects strongly with the concepts of comedy.

B. Enhanced Sentiment Adaptation

Expanding the sentiment analysis part might provide deeper comedy creation outputs. By adding sentiment adaptation into the text creation process, the model could dynamically alter the created content to coincide with intended sentiment polarity. This would allow the model to design comedy that perfectly correlates to distinct emotional tones, boosting the efficacy of humor delivery for varied audiences.

C. Contextual Humor Calibration

Contextual knowledge is a possible component for future advancement. By enhancing the model with the capacity to absorb and integrate contextual signals, the produced information might be infused with a heightened relevance to the existing dialogue or context. This would promote the development of comedy that is not simply linguistically funny, but also tailored to the situational background, connecting more profoundly with the audience.

D. Bias Mitigation

Addressing possible biases within the comedy creation process stands as a significant area for progress. By rigorously reviewing the training data and improving the model's answers, efforts might be aimed towards avoiding the accidental spread of biases that could be present in the training dataset. This would strengthen the ethical integrity of the created material, ensuring that comedy stays inclusive and courteous.

E. Interactive Humor Generation

Enabling user participation with the humor production process is an approach that offers increased engagement and personalisation. Developing interfaces that let users to contribute real-time input, change created material, and affect the direction of comedy would encourage a collaborative and engaging experience. Such interfaces might include user choices, boosting the model's flexibility to particular comedy types.

F. Multilingual and Multicultural Humor

Expanding the model's skills to create comedy in many languages and across varied cultural situations is a critical frontier. Incorporating multilingual training data and cultural references will widen the comedy generating spectrum, appealing to worldwide audiences with diverse language and cultural sensitivities.

In summation, the road of future progress extends before us, encouraging invention and refinement. By fine-tuning models for humor, enhancing sentiment adaptation, embracing contextual understanding, mitigating biases, fostering user interaction, and catering to diverse linguistic and cultural dimensions, the realm of humor generation can evolve into a more immersive, inclusive, and sophisticated domain. These possible enhancements offer the possibility of enhancing the quality, relevance, and impact of comedy created by NLP approaches.

IX. Conclusion

In the era of natural language processing and artificial intelligence, the marriage of linguistic prowess and computational ingenuity unveils new horizons of creativity and engagement. This investigation embarked on a journey to explore the intersection of language and humor, leveraging the prowess of the GPT-2 model to generate humorous text. The synthesis of linguistic constructs and computational algorithms birthed a realm of amusement that traversed the digital landscape.

Through meticulous data collection, sentiment analysis, and ethical considerations, this study laid the groundwork for humor generation. The GPT-2 model emerged as a proficient partner, demonstrating the capacity to produce coherent and contextually relevant humorous content. The orchestration of sentiment, length distribution, and cultural sensitivity fortified the model's creative output, imbuing it with a balance that resonated across a diverse spectrum of audiences.

However, this journey was not without its challenges and limitations. The inherent subjectivity of humor, the echoes of training data, and the quest for novelty posed complexities that demanded attention. The research remained steadfast in its ethical commitment, upholding cultural sensitivity and eschewing offensive content. The interplay of sentiment analysis, ethical considerations, and humor generation painted a nuanced tapestry that celebrated the artistry of language generation.

As the curtain falls on this exploration, it beckons the unfolding of future improvements. The canvas of possibilities is broad and inviting—fine-tuning for humor, adaptive sentiment calibration, contextual humor refinement, bias mitigation, interactive interfaces, and global multicultural expansion. These horizons hold the promise of further elevating the quality, inclusivity, and impact of humor generation, orchestrating a symphony of linguistic creativity that resonates across cultures, sentiments, and preferences.

In essence, this investigation shines a light on the potential of NLP techniques to weave threads of laughter and joy into the digital tapestry. It accentuates the fusion of linguistics and technology, reminding us that the art of humor transcends beyond mere words—it embodies a connection between minds, cultures, and the timeless human pursuit of mirth.

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