Optimization Method of Advertising Texts Based on Generative Models

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Abstract
This article discusses the creation of a new method for optimizing advertising texts using generative models. The authors investigate the role of these models in automatically generating advertising materials, focusing on the use of GPT-like models. The paper thoroughly examines the process of data collection and processing for training these models and developing an algorithm to achieve the best results. This approach can play a pivotal role in marketing and serve as a springboard for future research. Applying this method in a real advertising campaign demonstrated its effectiveness, which manifested in increased impressions, improved CTR, reduced cost-per-click, and heightened view-through rate, underscoring its advantages over traditional advertising techniques. The campaign metrics from March to April 2023 reveal significant improvements across all areas: impressions increased by 2,200; the click-through rate grew by 0.06%; the average cost-per-click decreased from 0.17 UAH to 0.11 UAH; and the view-through rate escalated from 4.27% to 10.8%.

Keywords
Generative models, advertising text optimization, GPT series models, content creation automation, social media marketing.

1. Introduction

Social media has long since evolved from a simple communication tool to a powerful marketing instrument. With deepening digitization and increasing numbers of social media users, these platforms become increasingly competitive, especially in the context of brands vying for user attention. In this environment, the effectiveness of advertising texts becomes a decisive factor determining the success of a marketing campaign. In previous research [15-17], the authors of this study also explored the importance of improving advertising strategies. They presented intelligent methods that use semantic analysis to create targeted advertising content. These methods have demonstrated practical utility by increasing the effectiveness of advertising and reducing costs. The results of these studies provided valuable insights and recommendations for effective marketing campaigns specifically tailored to the higher education sector.

This impact is not limited to social media alone but extends into the realm of search engine advertising, notably on platforms like Google. Google, with its colossal user base and high-frequency usage, provides an advantageous arena for brands to engage potential customers. Google Ads, the platform's advertising service, allows businesses to display ads, product listings, and service offerings in Google's search engine results. This medium is particularly vital due to its ability to reach users at the point of search, where the intent to interact or make a purchase is often high.

As the digital landscape continues to evolve rapidly, businesses are facing the growing need to automate many of their processes in order to remain competitive. This extends to their marketing efforts as well, particularly in the creation and optimization of advertising texts. Brands recognize that compelling ad copy is crucial for capturing audience attention and driving engagement. However, given the scale of operations and the diverse platforms that marketers operate in, manual creation and

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optimization of advertising texts can be time-consuming and less efficient. Therefore, automation in this area could be a game-changer, enabling brands to achieve better marketing results while optimizing their resources.

Generative models, like GPT, present a promising solution for automating the creation of advertising texts. Leveraging machine learning and natural language processing technologies, these models are capable of generating high-quality text based on the data they've been trained on. When provided with a large volume of successful advertising texts, these models can learn the nuances of persuasive and effective ad copy and produce similar texts automatically. This can significantly reduce the time and effort involved in creating advertising texts and enable marketers to focus more on strategic tasks.

This topic is dedicated to the present article, the rest of which is distributed as follows. In section 2, we review an analysis of related works, section 3 introduces the method of optimizing advertising texts based on generative models, in section 4 the implementation of the algorithm itself. Section 5 presents the conclusions of the study.

2. Related Work

In order to fully appreciate the significance of the methodology developed in this research, it is essential to consider the context of related works in the field. Previous research has delved into various aspects of advertising text generation and optimization, providing invaluable insights and laying the groundwork for further exploration. This section presents a review of these related works, outlining their contributions and limitations, and subsequently positioning our research within this existing body of knowledge.

Articles [1, 2, 3] focus on text analysis and processing. Article [1], authored by Li et al., presents a joint semantic topic model designed specifically for processing short texts. This model aims to capture the semantic relationships between topics and words in short texts, enabling more accurate analysis and understanding of their content. In article [2], Qiao et al. propose a method for keyword detection. The method utilizes advanced techniques to identify and extract relevant keywords from texts. This approach aids in improving text categorization, information retrieval, and other text-related tasks. Qian et al., in article [3], focus on predicting content popularity using deep learning techniques. They develop an approach that leverages deep learning algorithms to analyze various factors and predict the popularity of online content. This can be valuable for content creators, marketers, and platforms seeking to optimize their strategies and engage their target audience effectively..

In studies [4, 5, 8, 9, 11, 12], various approaches to text generation are considered. Yang et al. [4] introduce an approach to text-based steganography using recurrent neural networks. Their work focuses on embedding hidden information within text, demonstrating the potential of utilizing neural networks for covert communication. Iqbal and Qureshi [5] provide a comprehensive review of deep learning models for text generation. They analyze various techniques, including recurrent neural networks (RNNs), generative adversarial networks (GANs), and transformers, highlighting their strengths and limitations in generating coherent and meaningful text. Lipa-Urbina et al. [8] propose the use of SentiGAN, a sentiment-aware generative adversarial network, for generating persuasive messages. Their research aims to enhance the persuasive impact of generated texts by incorporating sentiment analysis. Fan et al. [9] investigate text-based game world generation, exploring the use of deep learning techniques to automatically generate game environments and narratives. Their work focuses on the application of text generation in the context of interactive storytelling. Tang et al. [11] and Heidar and Rezagholizadeh [12] contribute to improving text generation using generative adversarial networks (GANs). They explore techniques to enhance the quality, coherence, and diversity of generated text through the utilization of GAN architectures.

The works of Habib et al. [6] and Huang and Zha [7] utilize NLP technologies and deep learning to improve writing processes in specific areas: medical recommendations and text resumes respectively.

In the study conducted by Kabra et al. [10], the main objective is to automate content generation by utilizing keywords to generate meaningful and relevant content. This approach aims to streamline the content creation process and ensure that the generated content aligns with the desired objectives and messaging.

Bulut and Mahmoud [13] have employed the GPT-2 model for generating advertising texts and keywords. Their research showcases promising results in real advertising campaigns, highlighting the potential of using advanced language models for advertising purposes. Their work is closely related to our research as they also focus on advertising content generation.

Floridi & Chiriatti [14] analyze the limits of GPT-3 and claim that its capabilities to solve mathematical, semantic, and ethical issues are limited. This is important for our research as you use GPT models, but your work is focused on specific applications where these limitations may be less significant.

Although the studies by Kabra et al. [10] and Bulut & Mahmoud [13] have made significant contributions to the understanding of ad text generation and optimization, our study takes a more comprehensive approach by analyzing the overall ad content. This goes beyond the simple keyword-based analysis that was central to their study.

A key advancement in our research is the use of more sophisticated and powerful generative models. By leveraging the capabilities of these advanced AI tools, we can create more relevant and engaging ad copy, which ultimately leads to more effective advertising campaigns. Another distinctive feature of our research is the attention we pay to the quality of the input data. We carefully select and pre-process the data to ensure that our model is trained on the most successful advertising texts. This ensures that the generated texts are not only grammatically correct, but also effective in terms of achieving marketing goals.

Although our study builds on the foundations laid by Kabra et al. [10] and Bulut & Mahmoud [13], it extends their work by offering a more detailed analysis of advertising content and providing a practical, proven methodology for using advanced generative models in advertising.

3. Materials and methods

Optimizing advertising texts using generative models is a complex process, involving data collection, model training, and experimentation. This aids in the creation of effective advertising messages. The developed method for optimizing advertising texts based on generative models broadens marketing possibilities.

Thus, the method for optimizing advertising texts based on generative models can be conducted structurally (Fig.1) and comprises several stages:

Stage 1. Data collection. Gather a large number of advertising texts from various sources that you deem successful. Success can be measured using metrics such as the:

- Impressions: This is a measure of the number of times an ad is displayed, regardless of whether it is clicked on or not. It is an indicator of the reach or exposure of an advertisement. This metric is usually represented as an absolute number. The higher the number of impressions, the greater the exposure of the ad.
- CTR (Click-Through Rate): This is the ratio of users who click on a specific link to the number of total users who view a page, email, or advertisement. It is often used to measure the success of an online advertising campaign for a particular website as well as the effectiveness of email campaigns. It is calculated by dividing the number of clicks an ad receives by the number of impressions and is usually expressed as a percentage. A higher CTR indicates a more effective ad.

$$CTR = \left(\frac{Number\ of\ clicks}{Number\ of\ impressions}\right) * 100\%$$

- Average Cost Per Click (CPC): This is a measure of the price paid for each click in a pay-per-click (PPC) marketing campaign. It's an important metric as it determines the financial success of your paid advertising campaigns and how much ROI they generate. It's calculated by dividing the total cost of your clicks by the total number of clicks.

$$Average\ CPC = \frac{Total\ cost\ of\ clicks}{Total\ number\ of\ clicks}$$

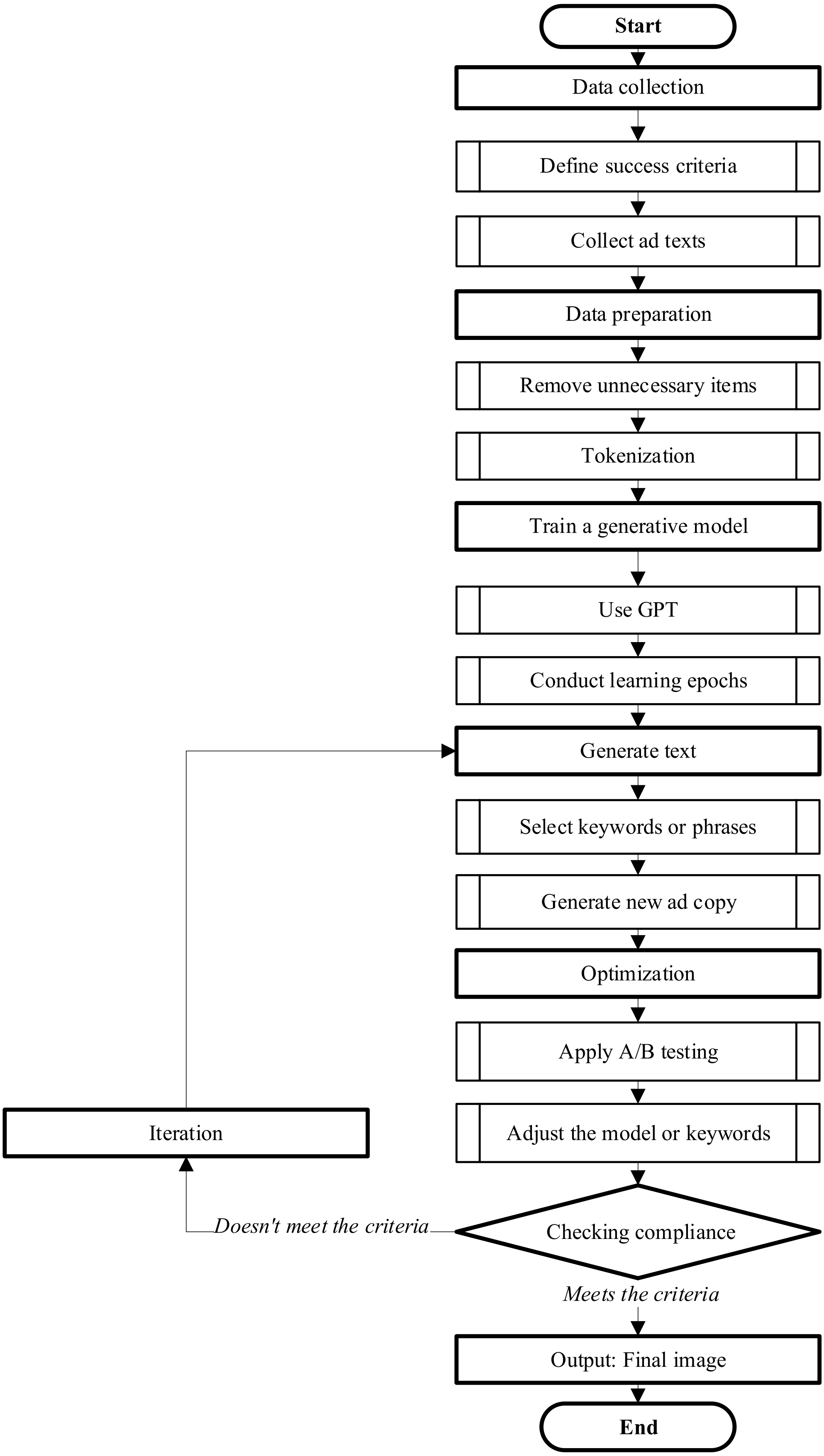


Fig. 1. Algorithm for optimizing advertising texts based on a generative model

- View-through rate (VTR): This measures the number of completed views of a video ad to the number of initial impressions. It's often used in digital advertising to measure the effectiveness of a video campaign. Like CTR, it is calculated by dividing the number of complete views by the number of impressions and is usually expressed as a percentage. A higher VTR indicates that users were interested enough to watch your video until the end.

$$VTR = \left(\frac{Number\ of\ completed\ views}{Number\ of\ impressions}\right) * 100\%$$

By tracking these metrics, it's possible to evaluate the effectiveness of different advertising texts. This helps in identifying patterns and trends that can be used to optimize future marketing efforts.

Stage 2. Data preparation. In this stage, the raw advertising texts are processed into a suitable format that the model can understand and learn from.

2.1. Data Cleaning. The first step is to remove all unnecessary elements from the texts. These could include URLs, special characters [18], non-relevant hashtags, etc. This helps to ensure that the model focuses on the meaningful content of the texts. This process can be performed using various text preprocessing techniques available in libraries like NLTK or spaCy in Python.

2.2. Tokenization. After the data is cleaned, it needs to be tokenized. Tokenization is the process of splitting the text into individual words or tokens. These tokens serve as the input for the model. Tokenization can be done at different levels - you can choose to tokenize at the word level, sentence level, or even at the character level. The choice of tokenization level would depend on your model and the problem at hand. In Python, tokenization can be easily done using libraries like NLTK, spaCy, or even the built-in split() function.

2.3. Numerical Encoding. After tokenization, each token is assigned a unique integer. This transforms the text data into numerical data that the model can process. This step often involves building a vocabulary of all unique tokens and assigning each token a unique integer. The result would be sequences of integers representing your advertising texts.

2.4. Padding. When training a model, all input sequences should be of the same length. But since texts can vary in length, we perform a process called padding. Padding involves adding zeros to the shorter sequences until they are the same length as the longest sequence. The resulting sequences form a matrix that can be fed into the model.

Stage 3. Model training. Model training is the phase where the generative model, such as GPT, learns from the processed advertising texts. Here's how it works:

3.1. Initialization. Before the training begins, the model is initialized with random weights. These weights are the parameters that the model will adjust to learn the relationships in the data. In the case of GPT and other transformer models, there could be millions of these parameters.

3.2. Feed-forward. During training, the model takes in the input data (i.e., the sequences of integers from the data preparation stage) and performs a series of mathematical operations defined by its architecture (such as attention mechanisms, activation functions, etc.). At the end of this feed-forward process, the model generates a sequence of outputs, which, at the start of training, are likely quite different from the desired advertising texts.

3.3. Backpropagation and optimization. The difference between the model's outputs and the actual data is calculated using a loss function. This loss is then used to adjust the model's weights via a process called backpropagation, where the gradient of the loss is calculated with respect to each weight, and the weights are adjusted in the direction that minimizes the loss.

3.4. Iteration: Steps 3.2 and 3.3 are repeated for a large number of iterations (or epochs), gradually improving the model's ability to generate advertising texts similar to those in the input data. During this process, it is common to split the data into a training set and a validation set. The training set is used to adjust the weights, while the validation set is used to gauge the model's performance on unseen data and prevent overfitting.

3.5. Model selection: After training, it might be useful to test several models or model configurations to find the best performing one. This is typically done using metrics such as precision, recall, F1-score, etc., on a separate test set not used during training.

The result of this training process is a model that can generate new sequences of tokens similar to the advertising texts it was trained on.

Stage 4. Text generation. After successful training of the model, it's time to generate new advertising texts. The process generally involves feeding the model with some seed text or keywords related to the product or service being advertised. The model uses this input to generate contextually relevant text. Mathematically, this corresponds to feeding the model's input layer with a sequence of integers (tokens), and the model produces a probability distribution over the possible next tokens.

Stage 5. Optimization: To ensure the quality and effectiveness of generated texts, optimization techniques are applied. A common method is A/B testing, where two versions of the ad (A and B) are shown to different subsets of users. The ad that achieves a better response, as measured by metrics such as click-through rate (CTR), conversions, or user interactions, is selected. In mathematical terms, if p_A and p_B represent the probability of success (e.g., a click or a conversion) for ads A and B, we would choose ad A if p_A > p_B, and ad B otherwise. Further tuning of the model might also be performed based on these tests, which could involve adjusting the model's hyperparameters or re-training it with new data.

Stage 6. Iteration: The process doesn't end after a single cycle. As marketing campaigns progress, new data can be collected, and the model can be updated or fine-tuned with this data. The input keywords or seed texts can also be modified to align with the changing marketing strategies. By repeating this process, businesses can ensure continual improvement in the quality of the generated advertising texts, leading to better user engagement and higher returns from advertising campaigns.

The algorithm (see Fig. 1) begins with the data collection phase, where criteria are defined and texts are gathered. Following this is the data preparation phase, where unwanted elements are removed and tokenization is conducted. The next step is to train the model, using models such as GPT, and conducting training epochs. Afterwards, text generation occurs, selecting keywords for generating the texts. Optimization involves the application of A/B testing and model tuning. Finally, the generation process is iterated, repeating the steps for further optimization and model improvement.

4. Experimental Results and Discussion

To implement the developed algorithm (Fig. 1) for optimizing advertising texts based on generative models, we have chosen the free programming language Python and open libraries such as LangChain, OpenAI, Streamlit, and FAISS. The LangChain library is needed to connect the GPT-3.5 language model with our data. OpenAI, in turn, is used to convert part of the SCV file into vectors. The powerful FAISS library is used to create a vector store that stores vector representations of CSV data. And the Streamlit library provides tools for creating a user interface for the chatbot. It allows users to input and send their queries to the chatbot.

Next, we will briefly demonstrate the steps of our chatbot operation (Fig. 2). First, the user enters the OpenAI API key, after which he uploads the CSV file, on the basis of which the chatbot will be based. If the user has uploaded a CSV file, it is processed using the CSVLoader class from LangChain. The CSV file is broken down into unique lines.

Parts of the CSV file obtained after splitting are converted into vectors using OpenAI embeddings. These vectors then represent an index based on the content of each line of the given file. A vector storage (FAISS) is created from the documents obtained after embedding.

Next, a ConversationalRetrievalChain is added, providing it with the necessary chat model (e.g., gpt-3.5-turbo) and FAISS vector storage that stores our file converted into vectors via OpenAIEmbeddings(). This chain allows for a chatbot with memory, using the vector storage to find relevant information from our dataset.

This all operates within a previously created user interface using Streamlit. When a user enters a query, it is passed to the conversational_chat function, which generates the chatbot's response. This function feeds the user's query and conversation history into the ConversationalRetrievalChain, which generates the chatbot's response. The chatbot's responses and the user's messages are displayed in the user interface.

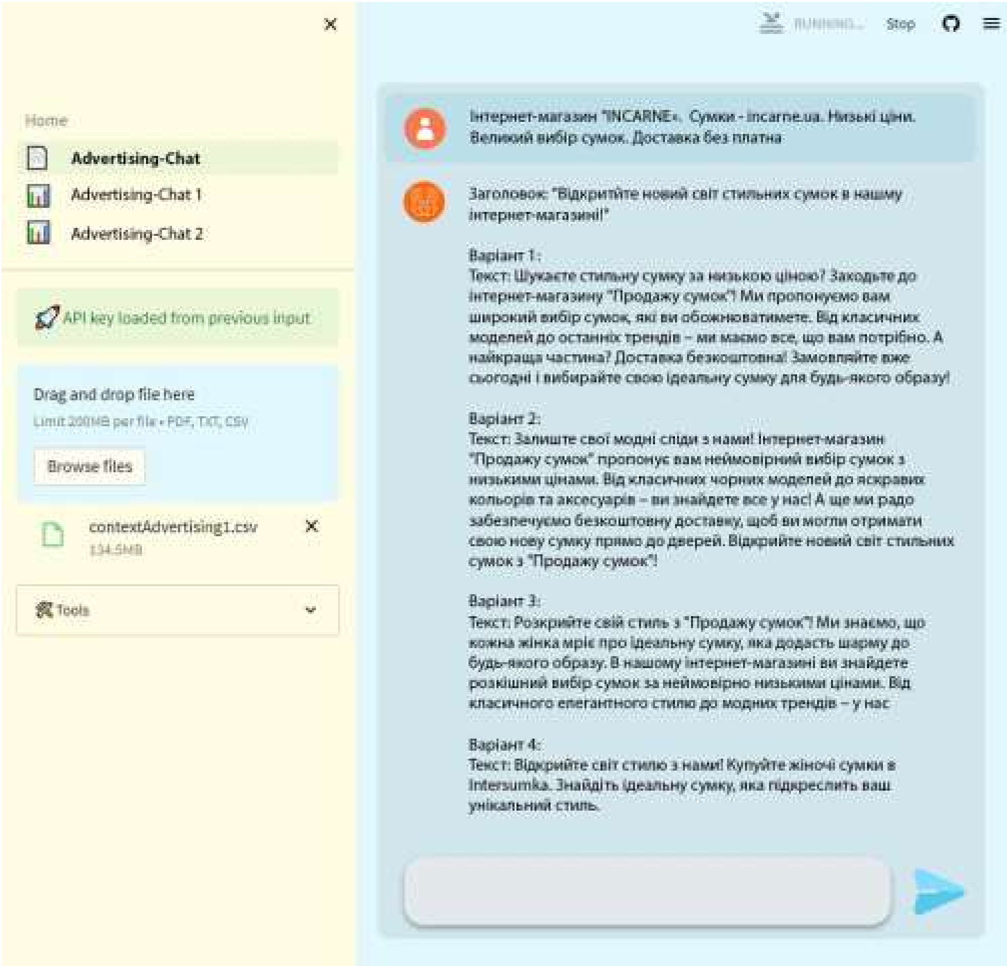
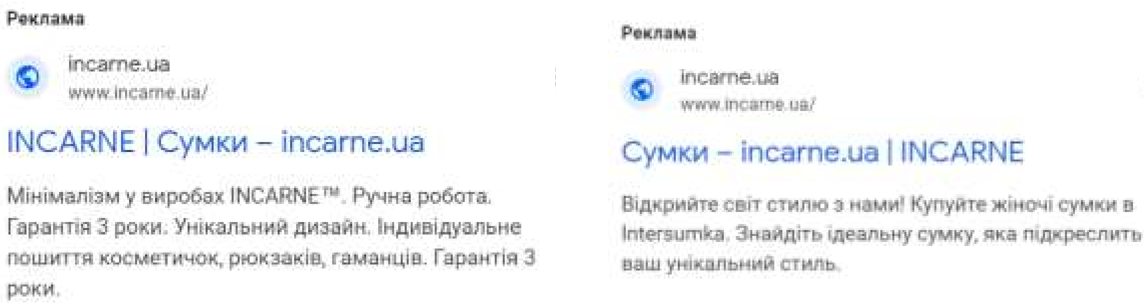


Fig. 2. The process of chatbot operation using OpenAI API and a CSV file

This comparative experiment was designed to assess the effectiveness of the proposed method of text generation in a real-world setting. Google's advertising platform was chosen for the experiment due to its widespread use and significance in the digital advertising sphere.

Variant 4, as presented in Figure 2, was selected for the experiment because it best aligns with Google's character limit for contextual advertising. This decision was based on our aim to ensure that the generated advertisement would be compatible with Google's guidelines and standards.

In this experiment, the first variant of advertising, depicted in Figure 3.A, was created following general rules for crafting advertisements in Google's platform. These rules incorporate a variety of best practices and recommendations in creating engaging and effective advertisements, including relevance to the product or service, compelling call-to-action, usage of keywords, and compliance with Google's editorial guidelines.



A. Попередня версія B. Сформовано на основі методу

Fig. 3. Advertisement for bag sales in Google

Table 1 presents a comparative analysis of the performance indicators of two advertising campaigns - one based on general advertising principles and one developed using the proposed text generation method.

The first advertising campaign with textual content ran from March 1, 2023, to March 31, 2023 (as shown in Figure 3.A). The goal of this campaign was to establish a baseline of performance using traditional advertising methods. During this period, the ads were shown to users and various metrics such as number of impressions, click-through rate (CTR), average cost per click, and viewability were measured to assess the overall effectiveness and efficiency of the campaign, allowing for an overall assessment of the campaign's performance.

Then, from April 1, 2023, to April 30, 2023, an advertising campaign was run using the textual content generated by the proposed method (as shown in Figure 3.B). This campaign was essentially a test run of our proposed method, where advertising text was generated using trained generative models. The effectiveness of this campaign was also evaluated using the same metrics as the previous one.

In the context of our research, we examined several key metrics to evaluate the effectiveness of the proposed method. Let's analyze the changes in these indicators as presented in Table 1:

• Impressions: This metric increased by 2,200 from March to April, indicating an increase in advertisement visibility or traffic. This is a positive trend since more impressions usually lead to a greater number of clicks and potential sales.

Table 1. Comparison of the effectiveness of the formed advertising content

Indicator	**March 1, 2023 – March 31, 2023**	**April 1, 2023 – April 30, 2023**	**Change**
Impressions	6 160	8 360	2 200
CTR	0,11%	0,15%	0,06%
Average cost per click	0,17 UAH	0,11 UAH	-0,06 UAH
View-through rate	4,27%	10,8%	6,53%

• CTR (Click-Through Rate): It increased by 0.06%, from 0.11% to 0.17%. This means that more people are clicking on your advertisements when they see them, which is a good sign.

• Average Cost Per Click: The cost per click decreased from 0.17 UAH to 0.11 UAH. This can be positive if this price decrease did not impact the quality of traffic or sales.

• View Rate: The rate has significantly increased - from 4.27% to 10.8%, indicating an increase in the number of people who viewed or interacted with the advertisement. This is a very positive change that shows greater user interaction with the advertisement. Overall, these data point to an improvement in the effectiveness of your advertising campaign in April compared to March.

The dataset gathered during the period of the research provides strong evidence in favor of the proposed method for advertising text optimization. The fact that these improvements were observed in just one month (from March to April) hints at the potential for even greater effectiveness with continued use and refinement of this approach.

Summarizing the results, the method demonstrates its ability to effectively increase ad visibility, with a significant increase of 2,200 impressions. This can directly contribute to better brand recognition, an expanded customer base, and a larger market share. Although a seemingly minor improvement, the 0.06% increase in CTR indicates the content's effectiveness in capturing users' attention and generating interest. Even small increments in this metric can lead to a substantial rise in user engagement levels. The average cost-per-click decreased from 0.17 UAH to 0.11 UAH, highlighting improved economic efficiency. The method not only produces effective content but also does so in a more cost-effective manner. This can directly result in higher return on ad spend (ROAS), a crucial aspect of any successful advertising campaign. Lastly, the view-through rate increased from 4.27% to 10.8%, providing evidence of enhanced interaction and engagement fostered by the new ad texts. This is a critical factor in the marketing domain as it directly influences conversion rates.

The achievements of this work become more evident when compared to related works such as those of Kabra et al. [10] and Bulut & Mahmoud [13]. Unlike these studies, which focus primarily on keyword analysis, our research takes a broader perspective, analyzing the overall ad content. Furthermore, while previous studies have explored the application of machine learning models for advertising, our research employs more advanced generative models. These models are designed to generate high-quality advertising texts, a novel approach that sets our work apart from existing research in the field.

5. Conclusions

During this study, we developed a method for optimizing advertising texts using generative models, specifically leveraging the power of models such as GPT. Our approach centered on the utilization of a large corpus of successful advertising texts, primarily sourced from social networks. These texts provided the training data necessary for the models to learn, understand, and subsequently generate new, high-quality advertising content.

The application of this method in a real-world advertising campaign from March to April 2023 provided evidence of its effectiveness, as reflected in improved metrics across all categories. Impressions: There was an increase of 2,200 impressions, signaling that the advertisements were visible to a larger audience. This increase in visibility is crucial in the digital advertising landscape, as it often corresponds to an increased chance of user interaction and potential conversion. Click-Through Rate (CTR): The CTR, an important indicator of audience engagement, increased by 0.06%. This suggests a higher percentage of individuals were enticed to click on the ad after seeing it, marking an improvement in audience interaction. Average Cost Per Click (CPC): Economically, the method proved to be more efficient as well. The average cost per click decreased from 0.17 UAH to 0.11 UAH, reducing the financial resources required for each user interaction. View-Through Rate (VTR): Finally, the view-through rate saw a significant jump from 4.27% to 10.8%, demonstrating an increased level of user engagement with the advertisement.

The compilation of these indicators points towards the successful implementation of the advertising strategy based on our proposed method. It shows that the usage of generative models in creating and optimizing ad content can enhance advertising efficiency, making ads more visible, engaging, and cost-effective.

Despite these promising results, the research is not yet complete. Future work will focus on developing more precise performance metrics, refining our model, and adapting the method for a more global reach, across various languages and cultural contexts. This will ensure a more comprehensive and versatile approach to optimizing advertising texts using AI-based models.

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