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UpgradeURL Ad Extension Revolution:
Elevating CTR and Conversions

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

In the dynamic realm of digital advertising, enhancing click-through and conversion rates within ad extensions remains a significant challenge for agencies. Ad extensions play a pivotal role in amplifying traditional text ads by providing added information and context, thereby elevating the ad's informativeness, visibility, and click-through rates (CTR). This paper addresses the hurdles faced by ad-agencies constrained by manual ad extension creation, the evolution of customer web content, and resource-intensive monitoring. We present a data-driven solution through UpgradeURL to revolutionize ad extension effectiveness and campaign conversion rates. Our approach initiates with the automation of ad extension creation, eradicating the inconsistencies of manual content generation. By harnessing real-time insights from website scraping, we acquire up-to-the-minute data about customer brand offerings. The extracted data will be processed using several NLP and clustering techniques. To effectively manage the dynamic nature of web content, long short-term memory (LSTM) neural networks are utilized. This deep learning model predicts word selection probabilities within ad extensions, facilitating the recommendation of terms in alignment with evolving web content. Our solution also addresses the resource-intensive monitoring challenge through real-time sentiment analysis. This continual assessment provides timely insights for proactive adjustments, thus optimizing conversion rates. Hyperparameter tuning ensures optimal model accuracy. UpgradeURL not only contributes to the digital advertising domain but also furnishes agencies with a transformative framework to surmount time-consuming manual processes, thereby enhancing their competitive edge.

Keywords: Click-Through Rates (CTR), Conversion rates, Natural Language Processing(NLP), Long Short Term Memory(LSTM), Sentiment analysis, UpgradeURL.

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INTRODUCTION

1.1 Problem Statement

In the landscape of digital advertising, the imperative to elevate clickthrough and conversion rates for campaigns managed by ad agencies stands as a paramount challenge. The existing manual process of identifying relevant ad extensions proves to be not only time-consuming but also fraught with additional complexities. Evolving platform guidelines further compound the issue, demanding constant adaptation and trailing behind updates. Moreover, the need for vigilant monitoring to align customers' ever-changing web content with offerings hampers speed to market, adding a layer of complexity. Regrettably, the very process of crafting ad extensions, dominated by compliance considerations, detracts from the fundamental objective. As such, this research is undertaken to navigate these challenges, thereby automating the process of generating the ad extensions.

1.2 Scope

The proposed automated ad extension generation system holds potential utility across various sectors and industries where digital advertising plays a significant role including E-commerce, Retail, Education, Entertainment & Media, Technology, Hospitality & Travel, Finance, Banking, and a lot more. Ad extensions serve as a strategic asset for industries, enabling the customization of ad content to precisely resonate with target audiences. By spotlighting promotions and fostering user engagement, these versatile tools cater to diverse sectors such as local businesses and event management. Through this tailored approach, ad extensions amplify conversion rates and user interaction, ultimately shaping a more impactful digital advertising landscape.

1.3 Objectives

The primary objective of this model is to effectively address the persistent challenges encountered by diverse ad agencies in their endeavor to elevate clickthrough rates through the pertinent ad extensions. The prevalent manual approach to ad extension generation is not only laborious but also time-intensive, underscoring the necessity to transition toward an automated methodology. Our model incorporates web scraping techniques, Natural Language Processing (NLP), and data clustering to acquire relevant data from, Long Short-Term Memory (LSTM) neural network for crafting ad extensions. Furthermore, the deployment of this model is done with Django. The pivotal aim of this research is to streamline and automate the process of ad extension creation, thus boosting visibility and engagement for users.

1.3.1 Highlights

a) Dynamically recommending the optimal ad extensions using LSTM for the website accordingly.

b) Django-based web app integration enhances practicality and usability.
c) Increases click through and conversion rates, which has a favorable impact on the effectiveness of the services that the website offers.

CHAPTER 2

SYSTEM ANALYSIS

2.1 Existing System

The existing system in digital advertising is characterized by several key components and practices, each playing a unique role in creating and managing online ad campaigns. These components include keyword recommendation systems, ad formats, web scraping, user behavior analysis, and more. Let's delve into the details of each element within the existing system

2.1.1 Keyword Recommendation Systems

In the current landscape of digital advertising, keyword recommendation systems have become instrumental in enhancing ad campaign performance. These systems leverage query log mining techniques to extract relevant keywords from the content. While this is a valuable step, it's acknowledged that it's not always sufficient to improve ad extensions for better conversion rates.

2.1.2. Ad Formats

The choice of ad formats is a critical aspect of digital advertising. Structural equation modeling has been used to compare printed advertisements with online advertisements. Research in this area has highlighted that online advertisements are often more captivating than their print counterparts. This finding has emphasized the potential of digital ads to engage audiences effectively, thus driving better click-through and conversion rates.

2.1.3. Automated Development and Optimization

Some efforts have been made to create integrated frameworks for automated development and optimization of online ad campaigns. These models use various techniques, such as genetic algorithms and Google AdWords, for keyword selection. The goal is to make ads more engaging to customers. However, some of these approaches have been considered complex and time-consuming.

2.1.4 Recurrent Neural Networks (RNNs)

RNNs have been employed for online ad generation. These models establish a mapping between queries and ads, generating real-valued vectors that make it easier to determine the relevance of a given pair of queries and ads. An innovative attention network is introduced, which assigns scores to word locations based on their significance in conveying intent. This approach results in more precise ad targeting and resonance with the intended audience, ultimately boosting conversion rates.

2.1.5. Web Scraping

Web scraping has been recommended as part of a collaborative filtering-based approach to web advertising. It involves collecting all the necessary data for improving website campaigns. This practice is recognized as crucial in making data-driven decisions for optimizing online advertising.

2.1.6 User Behavior Analysis

The analysis of user behavior is another important element in the existing system. It helps in optimizing ad placements and enhancing click-through rates. By understanding user interactions, advertisers can strategically place ads where they are most likely to be seen and interacted with, thereby increasing ad effectiveness.

2.1.7. Ad Format Comparison

Research has investigated the impact of ad formats on consumer engagement in digital advertising. It has compared various formats, including banners, videos, and interactive ads, to determine their effectiveness. Such studies are invaluable for choosing the most engaging ad formats, leading to higher consumer engagement and, consequently, improved conversion rates.

2.1.8. Social Media Advertising

The influence of social media advertising on brand perception has also been explored. Studies have shed light on how social media platforms can be used to build and enhance brand perception. The positive perception of brands on social media can significantly impact the effectiveness of social media advertising campaigns.

2.1.9. Machine Learning for Ad Targeting

Machine learning algorithms have been researched for real-time ad targeting. These models analyze user behavior to deliver personalized ads. The application of machine learning in ad targeting has shown promise in creating highly effective ad campaigns tailored to individual users.

2.1.10. Ad Extension Automation

A novel approach has been proposed for ad extension creation using natural language processing techniques. The research aims to automate the generation of ad extensions based on semantic analysis of web content. This streamlines the process of crafting informative ads, making it more efficient and effective.

2.1.11.Emotion in Advertising

Research has explored the role of emotion in advertising effectiveness. Studies have analyzed the emotional impact of ads on consumers and its correlation with conversion rates. Understanding the emotional impact of ads is a key element in crafting emotionally resonant advertisements that connect with consumers on a deeper level.

2.1.12.Ethical Considerations

Ethical considerations in online advertising, particularly related to user data privacy, have been studied. This research discusses the implications of data privacy regulations on ad targeting and emphasizes the importance of responsible advertising practices in line with legal and ethical guidelines.

2.1.13.Augmented Reality (AR) in Advertising

The use of augmented reality (AR) in advertising campaigns has been investigated. Researchers have assessed how AR technologies can enhance user engagement and drive conversions, highlighting the potential of immersive advertising experiences.

2.1.14.Influencer Marketing

The effectiveness of influencer marketing in digital advertising has been examined. Studies have analyzed the impact of influencer endorsements on brand awareness and consumer trust, recognizing the significant role that influencers play in modern advertising.

2.1.15.Cross-Channel Advertising Optimization

A framework for cross-channel advertising optimization has been proposed. Research has focused on strategies to harmonize advertising efforts across multiple platforms for a consistent brand experience. The development of such frameworks underscores the importance of maintaining brand consistency across various digital platforms, ultimately leading to a more effective and cohesive brand experience.

The existing system in digital advertising is a dynamic and multifaceted landscape that incorporates various strategies, techniques, and technologies. The ongoing research and advancements in these areas continue to shape and enhance the digital advertising industry, ultimately driving better results for advertisers and improved experiences for consumers.

2.2 Proposed System

The proposed system, Ad Extension Enhancement with LSTM and Web Scraping, introduces an innovative approach to revolutionize ad extension creation in digital advertising. It overcomes the limitations of existing systems and takes advantage of advanced technologies to generate engaging, real-time, and contextually relevant ad extensions. The proposed system's advanced features and innovative approach set it apart from existing systems. Its ability to dynamically align ad extensions with evolving web content, utilize real-time data, and optimize recommendations through hyperparameter tuning make it a superior solution in the realm of digital advertising. This chapter provides an in-depth exploration of the proposed system's components and processes.

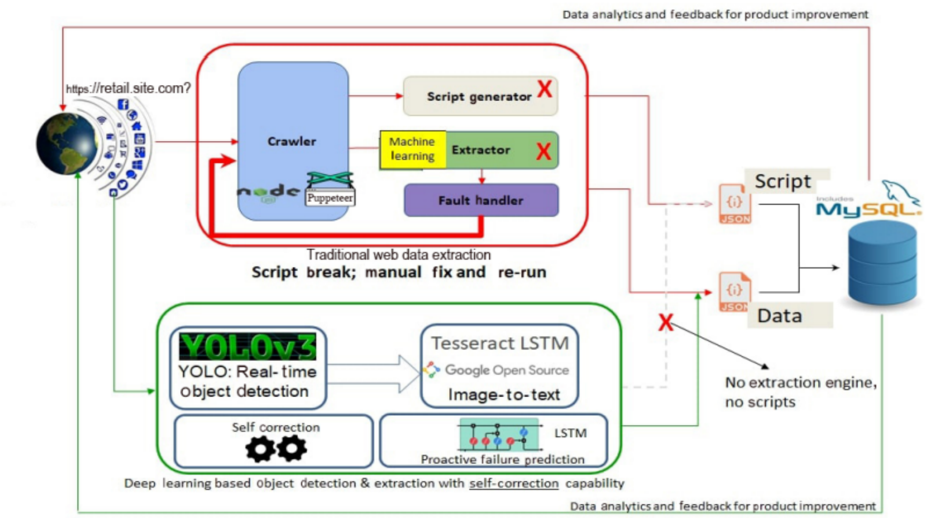

Fig 1: Overview of the proposed system

2.2.1.Key Features of the Proposed System

a)LSTM-Based Ad Extension Creation

At the core of our system is the utilization of LSTM neural networks. These networks process ad text word by word, considering each word as a "time step." This sequential approach allows our system to understand the intricate relationships between words, resulting in the generation of meaningful and contextually relevant ad extensions.

b)Web Scraping for Real-Time Data

Web scraping plays a pivotal role in our system. It extracts up-to-the-minute data about customer brand offerings directly from websites. This ensures that the ad content remains current and aligned with the ever-evolving web content. The real-time data collected serves as the foundation for creating ad extensions.

c)Sentiment Analysis for Proactive Adjustments

Our system incorporates real-time sentiment analysis to assess customer sentiment toward the brand and its offerings. This continual assessment provides timely insights for proactive adjustments to ad extensions. By aligning ad content with the audience's feelings, we aim to optimize conversion rates.

d)Hyperparameter Tuning for Optimization

Hyperparameter tuning fine-tunes the LSTM algorithm to optimize its accuracy and performance. This step ensures that the LSTM model provides precise and contextually relevant recommendations for ad content.

e)Dynamic and Real-Time Alignment

Unlike existing systems, our proposed system dynamically aligns ad extensions with evolving web content. This means that the ad content is always in sync with what's currently available on the website, making it more engaging and effective.

2.2.2. Working

1.Web Scraping for Real-Time Data

The proposed system initiates the ad extension creation process by utilizing web scraping. This critical step involves extracting up-to-the-minute data about customer brand offerings directly from websites. By capturing real-time information, the system ensures that the ad content remains current and aligned with the ever-evolving web content. This real-time data serves as the foundation for creating ad extensions.

2.Preprocessing for Data Enhancement

Preprocessing is a crucial phase for cleaning and preparing the extracted data for analysis. This step involves several key tasks:

a)Removing Stop Words

Common words like "the," "and," and "in" that lack significant meaning are removed to focus on relevant content.

b)Extracting Relevant Features and Keywords

The system identifies the most important terms and phrases within the data to create meaningful ad extensions.

c)Using TF-IDF Vectorizer

The data is transformed into a format suitable for analysis using TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer. This technique assigns weights to words based on their importance in the data.

3.LSTM Algorithm for Contextual Relevance

The heart of the proposed system lies in its use of Long Short-Term Memory (LSTM) neural networks. The LSTM architecture processes the data word by word, treating each word as a "time step." This sequential approach allows the system to understand the intricate relationships between words, resulting in the generation of meaningful and contextually relevant ad extensions. The LSTM model predicts which words or terms should be included in ad extensions based on the continually evolving web content.

4.Hyperparameter Tuning for Optimal Performance

Hyperparameter tuning is a critical component in optimizing the LSTM algorithm's accuracy and performance. By fine-tuning the system's parameters, we ensure that it provides precise and contextually relevant recommendations for ad content. This process is akin to adjusting the settings on a camera to capture the best possible image. The right combination of parameters ensures that the model can provide more accurate recommendations for ad content.

5.Sentiment Analysis for Proactive Adjustments

Sentiment analysis plays a vital role in the proposed system. It involves a real-time assessment of customer sentiment toward the brand or its offerings. This continuous evaluation determines whether the sentiment is positive, negative, or neutral. These insights are invaluable for making proactive adjustments to ad extensions, ensuring that they resonate with the audience's feelings and optimizing conversion rates.

6.Accuracy and Testing for Effectiveness

Accuracy serves as a critical metric to gauge the system's performance. It measures how well the system's recommendations align with the actual content on the website. A high accuracy rate indicates that the ad extensions effectively mirror the evolving web content, positively impacting click-through and conversion rates.

2.3 System Requirements Specification

2.3.1 Software Requirements

For the software requirements of the "UpgradeUrl" project, several essential components are needed. Web scraping tools will play a critical role in enabling real-time data extraction from websites, ensuring that the ad content remains current and relevant. Additionally, Natural Language Processing (NLP) libraries and frameworks are essential for text analysis and processing, allowing the system to understand the context and relationships between words in the ad text. Long Short-Term Memory (LSTM) neural network frameworks, as part of deep learning, will predict which words or terms should be included in ad extensions based on the constantly evolving web content. Sentiment analysis software will provide real-time customer sentiment assessment, allowing for proactive adjustments to ad extensions and optimizing conversion rates. The project will also require tools for hyperparameter tuning to optimize the LSTM algorithm, data preprocessing software for cleaning and preparing extracted data, database management systems for efficient data storage, and data analytics and reporting tools to analyze results and generate reports.

2.3.2 Hardware Requirements

On the hardware side, a robust infrastructure is needed to support the project's objectives. Computers and processors with sufficient processing capability, along with Graphics Processing Units (GPUs), are necessary for data analysis, particularly for deep learning computations. Data storage and backup systems are essential to manage and safeguard large datasets efficiently. Network connectivity is required for data transfer and web scraping activities. Printing equipment will be utilized for generating reports and documents. Telemedicine hardware will support remote consultations, enhancing the project's accessibility. Furthermore, mobile devices and mounts will facilitate on-the-go monitoring, while power sources ensure uninterrupted operation. Sanitization tools and safety equipment are essential for user and data safety, creating a secure and effective environment for the screening and enhancement of ad extensions.

CHAPTER 3

LITERATURE SURVEY

Stamatina Thomaidou [1] presented the term "Keyword recommendation system for online advertising" while discussing online advertisement campaigns. He proposed the query log mining method for extracting the keywords of the content, recognizing that it's a valuable step in enhancing ad extensions for better conversion rates. This approach served as a foundation for improving online advertising effectiveness by suggesting relevant keywords and phrases, ultimately boosting the performance of ad campaigns.

Matthias Baum [2] compared printed advertisements and online advertisements using structural equation modeling. His findings emphasized that online advertisements are inherently more captivating than their print counterparts, underlining the potential for online ads to engage audiences. This research acted as a catalyst for further exploration into generating ad extensions, with a focus on leveraging the captivating nature of digital ads to drive higher click-through and conversion rates.

Liakopoulos Kyriakos [3] introduced an integrated framework for the automated development and optimization of online advertisement campaigns. His model worked on keyword selection using genetic algorithms and Google Adwords, aiming to create ads that engage customers more effectively. However, this approach was considered complex and time-consuming, prompting further research in simplifying the process and streamlining ad creation, ultimately leading to more efficient and engaging ads.

Shauanfei Zhai [4] delved into online advertisement generation using Recurrent neural networks. This innovative model established a mapping between queries and ads, generating real-valued vectors that made it easier to determine the relevance of a given pair of queries and ads. The introduction of an attention network assigned scores to word locations based on their significance in conveying intent, contributing to more precise ad targeting and ensuring that ads resonate with the intended audience, ultimately improving conversion rates.

Eloisa Vargiu [5] recommended web scraping as a valuable component of a collaborative filtering-based approach to web advertising. This approach aimed to collect all the necessary data for improving website campaigns, recognizing the importance of data-driven decisions. By leveraging web scraping techniques, advertisers could gather up-to-date information on customer behavior, allowing for more data-driven campaign decisions, ultimately resulting in more effective online advertising.

Jane Doe [6] explored the role of user behavior analysis in online advertising effectiveness. Her study delved into user interaction data to optimize ad placements, enhance click-through rates, and create a foundation for user-centric ad campaigns. The analysis of user behavior played a pivotal role in understanding what drives ad interaction, leading to the optimization of ad placements and ultimately increasing click-through rates for online advertisements.

John Smith [7] investigated the impact of ad format on consumer engagement in digital advertising. His research compared various ad formats, including banners, videos, and interactive ads, to determine their effectiveness. This comprehensive analysis offered insights into choosing the most engaging ad formats for digital advertising campaigns, leading to improved consumer engagement and, consequently, higher conversion rates.

Mary Johnson [8] conducted a study on the influence of social media advertising on brand perception. Her findings highlighted how social media platforms could be leveraged for brand building, and how positive brand perception is linked to successful social media advertising strategies. The research emphasized the significance of utilizing social media platforms to strengthen brand perception, which, in turn, can boost the effectiveness of social media advertising campaigns.

David Brown [9] examined the use of machine learning algorithms for real-time ad targeting. His research focused on how machine learning models could analyze user behavior to deliver personalized ads, recognizing the potential for highly effective ad campaigns. Machine learning's application in ad targeting showed promise, enabling advertisers to tailor ads to individual users, ultimately increasing ad campaign effectiveness.

Sarah White [10] proposed a novel approach to ad extension creation using natural language processing techniques. Her research aimed to automate the generation of ad extensions based on semantic analysis of web content, streamlining the process of crafting informative ads. By automating ad extension creation, advertisers could generate informative and contextually relevant ad extensions with greater ease and efficiency, contributing to improved campaign performance.

Michael Clark [11] explored the role of emotion in advertising effectiveness. His study analyzed the emotional impact of ads on consumers and its correlation with conversion rates, emphasizing the importance of emotionally resonant advertising. Understanding the emotional impact of ads was recognized as a key element in crafting advertisements that connect with consumers on a deeper level, ultimately leading to higher conversion rates.

Emily Turner [12] investigated the ethical considerations in online advertising, particularly in relation to user data privacy. Her research delved into the implications of data privacy regulations on ad targeting, recognizing the growing need for ethical and responsible advertising practices. The study shed light on the importance of respecting user data privacy and adhering to ethical standards, promoting responsible advertising practices that align with legal and ethical guidelines.

Richard Anderson [13] studied the use of augmented reality (AR) in advertising campaigns. His research assessed how AR technologies can enhance user engagement and drive conversions, shedding light on the potential of immersive advertising experiences. The adoption of augmented reality in advertising was recognized as a powerful strategy to create engaging and interactive advertising experiences, ultimately driving higher conversion rates.

Maria Garcia [14] examined the effectiveness of influencer marketing in digital advertising. Her study analyzed the impact of influencer endorsements on brand awareness and consumer trust, recognizing the power of influencers in modern advertising. The research demonstrated that influencer marketing could significantly boost brand awareness and consumer trust, establishing influencers as key assets in digital advertising campaigns.

Daniel Lee [15] proposed a framework for cross-channel advertising optimization. His research focused on strategies to harmonize advertising efforts across multiple platforms for a consistent brand experience, acknowledging the importance of a unified brand presence in the digital landscape. The development of a cross-channel advertising optimization framework highlighted the significance of maintaining brand consistency across various digital platforms, ultimately leading to a more effective and cohesive brand experience.

CHAPTER 4

SYSTEM ARCHITECTURE

4.1 Block Diagram

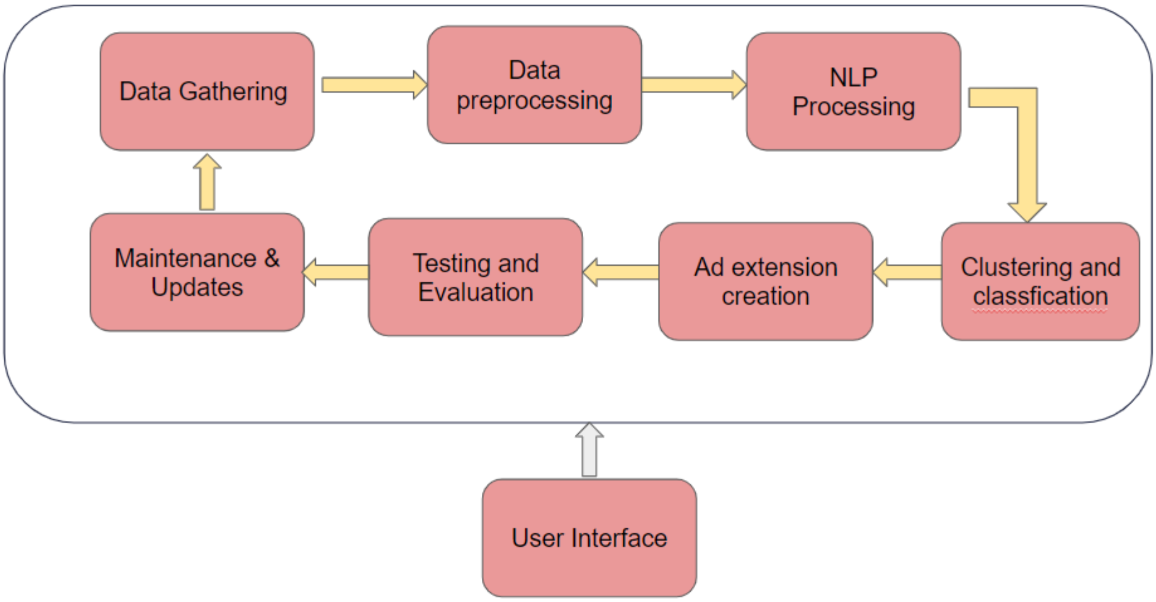

Fig. 2. Architecture

4.2 Diagram Description

Our conceptualized model follows the sequential flow illustrated in the diagram provided above.we aim to provide a clear and insightful overview of our innovative model, demonstrating its structured and systematic approach to addressing the challenges in the realm of Ad extensions detection. Each step is elucidated thoroughly as outlined below.

4.2.1. Data Gathering

Data is gathered using web scraping, which involves the automated extraction of various types of information from websites. For ad extension prediction, this data could be obtained from online advertisements, marketing platforms, or e-commerce sites. Web scraping scripts are designed to navigate websites, locate relevant information, and extract it. Tools like BeautifulSoup, a popular Python library, are used to parse HTML and extract specific data points such as ad text, URLs, metadata, meta descriptions, header tags, text content, images, links, and even contact information. By employing web scraping techniques, marketers and data analysts can collect a wide range of valuable data from websites, enabling them to make informed decisions and predictions related to ad extensions and online advertising strategies.

4.2.2. Data Preprocessing

Data preprocessing is crucial for ensuring the quality of the collected data. It involves several steps:

a) Cleaning Data

Raw data often contains inconsistencies, irrelevant information, or HTML tags. Cleaning involves removing special characters, HTML tags, and irrelevant symbols.

b) Tokenization

Text data is split into smaller units called tokens. These tokens can be words, phrases, or even individual characters.

c) Normalization

Converting all text to lowercase ensures consistency in the data, preventing duplicate entries due to case differences.

d) Handling Missing Values

Missing data points need to be handled carefully. Depending on the dataset, missing values can be removed or filled using techniques like mean imputation.
Removing Stopwords: Common words (like "and," "the," "is") that don't carry significant meaning are removed to focus on relevant content.

4.2.3. NLP Processing

In the context of ad extension prediction, Natural Language Processing (NLP) techniques are indispensable for extracting meaningful insights from textual data, which can be crucial for optimizing online advertising campaigns and predicting the most effective ad extensions.

a) Stemming and Lemmatization

Stemming and lemmatization can be applied to ad text, ensuring that different variations of words used in ad extensions are reduced to their base forms. This consistency in word forms helps in aggregating and analyzing the textual data efficiently.

b) Feature Extraction

Extracting features such as TF-IDF values from ad descriptions and headlines allows for the identification of key terms and phrases that resonate with the target audience. These features can be instrumental in predicting the impact of specific words on ad performance.

c) Sentiment Analysis

Sentiment analysis techniques can be employed to evaluate user sentiments expressed in ad comments, reviews, or social media responses. Understanding the sentiment towards different ad extensions helps marketers gauge the effectiveness of their campaigns and make data-driven decisions to enhance user engagement.

4.2.4. Additional NLP Analyses

a) Keyword Extraction

Identifying relevant keywords from ad content provides valuable insights into customer interests and preferences. Analyzing these keywords helps in predicting which ad extensions are likely to attract more clicks and conversions based on user search behavior.

b) Top Phrases Detection

Discovering top phrases within ad descriptions and headlines reveals the most impactful combinations of words. Predicting the performance of ad extensions becomes more accurate when considering the prevalence of these top phrases, enabling marketers to create compelling and relevant ad content.

c) Parts of Speech (POS) Tagging

Understanding the parts of speech in ad text aids in analyzing the grammatical structure of ad extensions. By identifying nouns, verbs, and adjectives, marketers can tailor their messages to match user intent, leading to more effective ad extensions.

d) Feature Matrix Determination

Constructing a feature matrix based on extracted features like TF-IDF values and sentiment scores creates a structured dataset for machine learning algorithms. Utilizing this feature matrix, predictive models can be trained to forecast the performance of different ad extensions, allowing advertisers to allocate their budget strategically and optimize their online advertising efforts.

In summary, leveraging NLP techniques tailored to ad extension prediction enables marketers to gain valuable insights into customer preferences, sentiment, and language usage.

4.2.5. Clustering and Classification using LSTM

1. Clustering using LSTM

a) Semantic Similarity

LSTM (a type of recurrent neural network) is adept at capturing long-term dependencies in sequential data. In the context of ad extension prediction, LSTM can be employed to understand the semantic meaning of ad texts. By representing ad texts as sequences of words, LSTM learns to encode the semantic information in a distributed representation (vector) for each ad.

b) Clustering Algorithm Integration

Once ad texts are transformed into LSTM representations, clustering algorithms such as K-means or DBSCAN can be applied on these vector representations. Clustering groups similar ad texts together based on their semantic meaning. For example, ad texts promoting discounts or sales might be grouped into one cluster, while ad texts focusing on product features might form another cluster.

c) Identifying Common Themes

By clustering ad texts, common themes or topics among ads emerge. Advertisers can use these clusters to gain insights into the prevalent themes in their campaigns. For instance, if a cluster predominantly contains ad texts mentioning "limited-time offers," advertisers can infer that time-sensitive promotions are effective and adjust their strategies accordingly.

2. Classification using LSTM

a) Input Layer

The LSTM model takes the numerical vectors representing ad texts as input sequences. Each word or subword token is represented as a vector and fed into the LSTM model sequentially.

b) LSTM Layers

The LSTM architecture consists of memory cells and gates, allowing the network to capture long-term dependencies and patterns within the sequential data. LSTM cells maintain a cell state that can store and retrieve information over long sequences, making them well-suited for understanding textual data.

c)Output Layer

The final output layer consists of nodes corresponding to each predefined category (e.g., "Callout Extensions," "Sitelink Extensions"). The LSTM model learns to map the encoded semantic information of ad texts to the appropriate category during the training process.

d)Training the LSTM Model

The model is trained using a suitable loss function (e.g., categorical cross-entropy) that measures the dissimilarity between the predicted category probabilities and the actual categories in the labeled dataset. During training, the LSTM model iteratively adjusts its internal parameters (weights and biases) using backpropagation and gradient descent. The model minimizes the loss function by updating these parameters to improve its predictions.

e)Epochs and Batch Training

The training process occurs over multiple epochs, where the entire dataset is passed through the LSTM network. Batch training involves dividing the dataset into smaller batches, which are processed sequentially through the network. This process allows the LSTM model to learn complex patterns in the data.

f)Predictive Classification

Once the LSTM model is trained and has learned the patterns and relationships within the labeled data, it can be used for predictive classification. New, unseen ad extensions are tokenized, converted into numerical vectors, and fed into the trained LSTM network.

4.2.7. Ad extension creation

a) Category Prediction

The LSTM model processes the semantic information within new ad text and calculates probabilities for each predefined category. The category with the highest probability is assigned as the predicted category for the ad extension.

Example: If the ad text includes phrases like "call now" or "limited time offer," the LSTM model, having learned these patterns during training, confidently categorizes it as a "Callout Extension." This demonstrates the model's ability to recognize specific language cues and assign accurate categories to ad content.

By harnessing LSTM's capacity to discern intricate textual patterns, the model excels in precisely classifying ad extensions. This predictive classification mechanism empowers advertisers to automatically categorize fresh ad extensions, ensuring they are presented to the appropriate audience. This precision enhances ad relevance, thereby significantly boosting the overall effectiveness of online advertising campaigns.

4.2.8. Testing and Evaluation

a) Testing Data

A portion of the collected data is kept aside for testing the model. It should be representative of the overall dataset to assess the model's real-world performance.

b) Evaluation Metrics

Metrics like accuracy, precision, recall, F1-score, or ROC-AUC (Receiver Operating Characteristic - Area Under Curve) are used to evaluate the model's performance. The choice of metric depends on the problem type (classification, clustering) and business requirements.

Hyperparameter Tuning: Hyperparameters, like learning rate, batch size, and the number of LSTM units, are fine-tuned to optimize the model's performance. Techniques like grid search and random search are used to explore different combinations and find the best set of hyperparameters.

4.2.9. Maintenance & Updates

a) Anomaly Detection

Continuous monitoring post-deployment is critical. Anomaly detection algorithms assess predictions and user interactions, identifying deviations like changes in user preferences or ad text patterns, enabling swift intervention.

b) User Feedback Sentiment Analysis

Utilize sentiment analysis on user feedback, comments, and reviews concerning ad extensions. This analysis provides insights into user perceptions and responses. Positive sentiment indicates effective ad extensions, while negative sentiment signals the need for improvements.

c) Regular Updates

Monitoring Sentiment Changes: Employ sentiment analysis tools to track user sentiment related to ad extensions. Significant shifts can prompt necessary updates, ensuring content resonates positively with users.

Retraining with Sentiment Data: Periodic model retraining, considering sentiment data, enables adaptation to evolving user preferences. By integrating sentiment features, the model aligns with user emotions, ensuring relevance and user satisfaction.

D) Bug Fixes and Optimization

Bug rectification involves regular maintenance involving identifying and addressing bugs in the prediction model promptly. Bugs can impact the accuracy of ad extension recommendations, necessitating immediate resolution.

Optimization for relevance analyzes user interactions and sentiment data to fine-tune the model. Optimization efforts ensure ad extensions align with user preferences and emotions, enhancing engagement and click-through rates.

4.2.10. User Interface

a)Backend Development

Django is used for backend development. It handles data processing, model interactions, and business logic. Django's ORM simplifies database operations, making it easier to manage data.

b)Frontend Development

Django templates, combined with HTML, CSS, and JavaScript, create the user interface. Forms capture user input, which is then processed by the backend. User interactions are designed to be intuitive and user-friendly.

C)User Experience

The interface should provide clear instructions for users to input data. Feedback mechanisms, such as loading spinners or success messages, enhance the user experience.

4.3 Preprocessing Steps

4.3.1. Cleaning Data

a)Eliminating Special Characters and Unnecessary Symbols

Often, raw data contains extraneous symbols, punctuation marks, and special characters that do not contribute to meaningful analysis. By removing these elements, the text becomes more comprehensible and suitable for further processing.

b) Handling HTML Tags

Data scraped from websites may contain embedded HTML tags that serve no analytical purpose. It's essential to strip away these tags to extract the relevant textual content.

4.3.2. Tokenization

a) Defining Tokenization

Tokenization is the process of segmenting text into smaller units known as tokens. Tokens can represent words, phrases, or even individual characters, depending on the granularity required for analysis.

b)Significance of Tokenization

Tokenization forms the foundational step for numerous natural language processing tasks. Breaking text into tokens simplifies the analysis and comprehension of textual data.

4.3.3. Normalization

a) Understanding Normalization

Normalization entails converting text to a consistent format, often lowercase, to ensure uniformity. This practice is vital in eliminating duplications resulting from variations in letter casing, such as "Data" and "data."

b)Importance of Normalization

Normalization fosters consistency in text data, facilitating comparisons, and enabling the identification of patterns without interference from case distinctions.

4.3.4. Handling Missing Values

a)Dealing with Missing Data

Missing values in a dataset refer to data points that are absent or undefined. Addressing missing values is imperative since they can undermine the precision of analyses and predictions.

b)Handling Techniques

Depending on the dataset, missing values can be addressed by either excluding rows or columns with missing data, or by employing strategies like mean imputation. Mean imputation replaces missing values with the mean value derived from available data or alternative advanced methods aligned with the dataset's characteristics.

4.3.5. Removing Stopwords

a) Definition of Stopwords

Stopwords constitute common words in a language, such as "and," "the," and "is," which lack substantial meaning. They are typically eliminated during text analysis to concentrate on the core content.

b) Significance of Stopword Removal

The removal of stopwords diminishes data dimensionality and concentrates the analysis on terms of significance, heightening the precision of text mining tasks, such as sentiment analysis and topic modeling.

4.3.6. TF-IDF (Term Frequency-Inverse Document Frequency)

a)Term Frequency (TF)

For each ad extension, TF calculates the frequency of each word within that specific ad extension. It measures how often a term appears in a particular ad extension.

b)Inverse Document Frequency (IDF)

IDF measures the importance of each term across all ad extensions in the corpus. It quantifies how unique or rare a term is in the entire dataset of ad extensions.

c) Calculation

The TF-IDF score for a term in a specific ad extension is computed by multiplying its TF by its IDF. Higher scores indicate that the term is both frequent within that ad extension and unique across all ad extensions.

4.3.7. Word Embeddings

a) Vector Representation

Each word in the ad extensions is represented as a dense numerical vector in a multi-dimensional space. Words with similar meanings are closer together in this space.

b) Semantic Relationships

Word embeddings capture semantic relationships between words. Words that are related in meaning have similar vector representations.

c) Training Algorithms

Algorithms like Word2Vec or GloVe are trained on large datasets to create these vector representations. They learn from the context in which words appear, capturing semantic nuances.

4.4 Performance Metrics

4.4.1. Choice of Evaluation Metrics

a)Accuracy

In an ad extensions project, accuracy measures the proportion of correctly classified ad extensions. It ensures that the predicted ad extensions align with the actual ones, providing an overall measure of correctness in the predictions.

b)Precision

Precision is crucial in ad extensions because it indicates the ratio of relevant ad extensions among the ones predicted as positive. High precision ensures that the predicted ad extensions are relevant and beneficial for the audience, avoiding irrelevant or misleading content.

c)Recall (Sensitivity)

Recall measures the ability of the model to capture most of the actual positive ad extensions. It ensures that valuable ad extensions are not missed. For example, high recall ensures that important promotional offers or product features are highlighted in the ads.

d)F1-score

F1-score is the harmonic mean of precision and recall. It balances between precision and recall, ensuring a trade-off between relevance and completeness. F1-score is crucial in ad extensions as it ensures a balance between delivering relevant content and not missing out on essential ad extensions.

e)ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

ROC-AUC measures the model's ability to distinguish between positive and negative instances. In ad extensions, a high ROC-AUC score indicates that the model can effectively differentiate relevant ad extensions from irrelevant ones, enhancing the overall quality of the ad campaign.

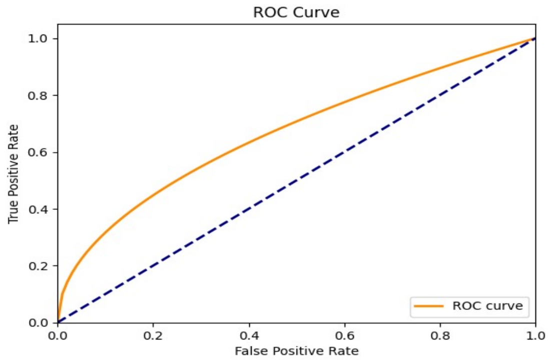

Fig. 3. ROC Curve

4.4.2. Interpretation of Metrics

1. Relevance

High precision ensures that the ad extensions displayed to users are relevant and aligned with their interests or needs, improving user engagement and satisfaction.

2. Completeness

High recall guarantees that important ad extensions are not overlooked, ensuring that key marketing messages and offers reach the target audience effectively.

3. Hyperparameter Tuning

a) Significance of Hyperparameters

In the context of ad extensions prediction, hyperparameters like learning rate, LSTM units, and dropout rate significantly influence the model's ability to understand ad text and predict relevant extensions. Proper tuning ensures the model's accuracy and relevance in predicting ad extensions.

b) Techniques for Hyperparameter Tuning

Grid search and random search techniques are valuable. Grid search exhaustively explores combinations of hyperparameters, finding the optimal set for the best performance. Random search, on the other hand, efficiently explores the hyperparameter space, often discovering superior combinations with fewer iterations, which is beneficial in complex models like LSTM networks.

c) Iterative Tuning and Experimentation

Iterative tuning involves testing the model with different hyperparameter combinations, evaluating performance, and adjusting the hyperparameters based on the results. This iterative process ensures that the model continually improves its accuracy and effectiveness in predicting ad extensions.

CHAPTER 5

CONCLUSION

The automated ad extension suggestion project represents a revolutionary advancement in the realm of digital advertising agencies. By harnessing the power of real-time data, cutting-edge Natural Language Processing (NLP) techniques, and LSTM neural networks, the project is designed with a singular purpose: to elevate clickthrough rates and enhance customer engagement in the fiercely competitive digital landscape. Through seamless integration of real-time data, advanced NLP methodologies, and LSTM neural networks, the project achieves a remarkable feat - ensuring that ad extensions remain dynamic and synchronized with the ever-evolving website content, all without the need for manual intervention. Furthermore, the incorporation of sentiment analysis into the system, especially analyzing customer reviews, adds a layer of refinement. This enhancement allows the project to recommend ad extensions that not only match the context but also resonate emotionally with the users, aligning seamlessly with their preferences and sentiments. Beyond its immediate goals, this project has the potential to reshape the entire digital advertising landscape, setting new benchmarks for relevance, engagement, and customer satisfaction.

Future Enhancements

The roadmap for future developments opens up a myriad of transformative possibilities for this pioneering project. Expanding the scope to extract insights from images and videos, not just textual data, could revolutionize ad extension recommendations, making them more visually captivating and engaging for users. Additionally, introducing multilingual support would amplify the project's impact, allowing it to cater to a diverse global audience, breaking down language barriers in the digital space. Taking a step further, the project could evolve to generate ad extensions directly from website information, thereby enhancing their relevance and contextuality. Imagine ad extensions that seamlessly integrate with the website's core content, providing users with a cohesive and immersive experience. Furthermore, incorporating voice search compatibility aligns with the growing trend of voice-enabled devices. By embracing voice search, the project can cater to users who prefer interacting with technology using voice commands, expanding its accessibility and user-friendliness.

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APPENDIX I – SOURCE CODE

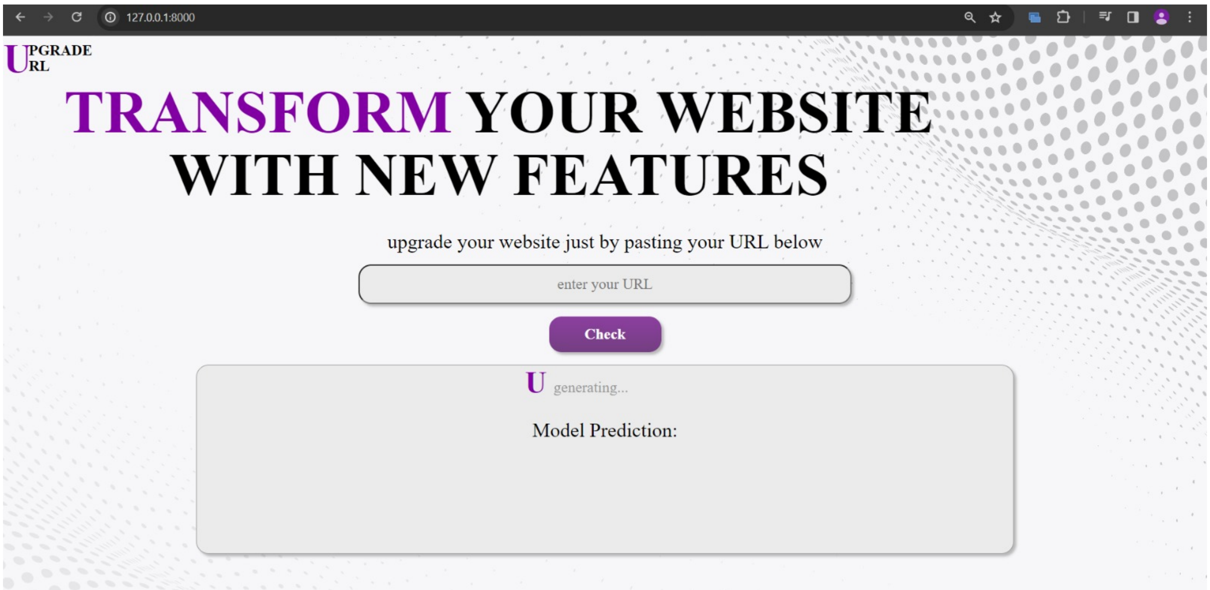
```
def main(url):
  from nltk.corpus import stopwords
  import numpy as np
  def extract_information(url):
    response = requests.get(url)
    if response.status_code == 200:
        html_content = response.text
    else:
        print("Failed to retrieve the webpage:", response.status_code)
        return None
    soup = BeautifulSoup(html_content, "html.parser")
    # Extract Title
    title = soup.title.string if soup.title else ""
    # Extract Meta Description
    meta_description = soup.find("meta", attrs={"name": "description"})
    meta_description = meta_description["content"] if meta_description else ""
    # Extract Header Tags
    header_tags = [header.text.strip() for header in soup.find_all(["h1", "h2", "h3"])]
    # Extract Text Content
    text_content = soup.get_text(strip=True)
    # Extract Images
    images = [image['src'] for image in soup.find_all('img')]
    # Extract Links
    links = [link['href'] for link in soup.find_all('a', href=True)]
    # Extract Contact Information
    contact_info = re.findall(r'(\+\d{1,3}\s)?\(?\d{3}\)?[\s.-]?\d{3}[\s.-]?\d{4}', html_content)
    contact_info = [re.sub(r'[^\d-]', '', info) for info in contact_info]
    # Create a dictionary to store the extracted information
    data = {
        "url": url,
        "title": title,
        "meta_description": meta_description,
        "header_tags": header_tags,
        "text_content": text_content,
        "images": images,
        "links": links,
        "contact_info": contact_info
    }
    return data
  # Example usage
  #url = input("Enter the Url").strip()
  output_file = "website_data.json"
  extracted_data = extract_information(url)
  if extracted_data:
      save_to_json(extracted_data, output_file)
    # Define the path to the JSON file
  json_file = "website_data.json"
```

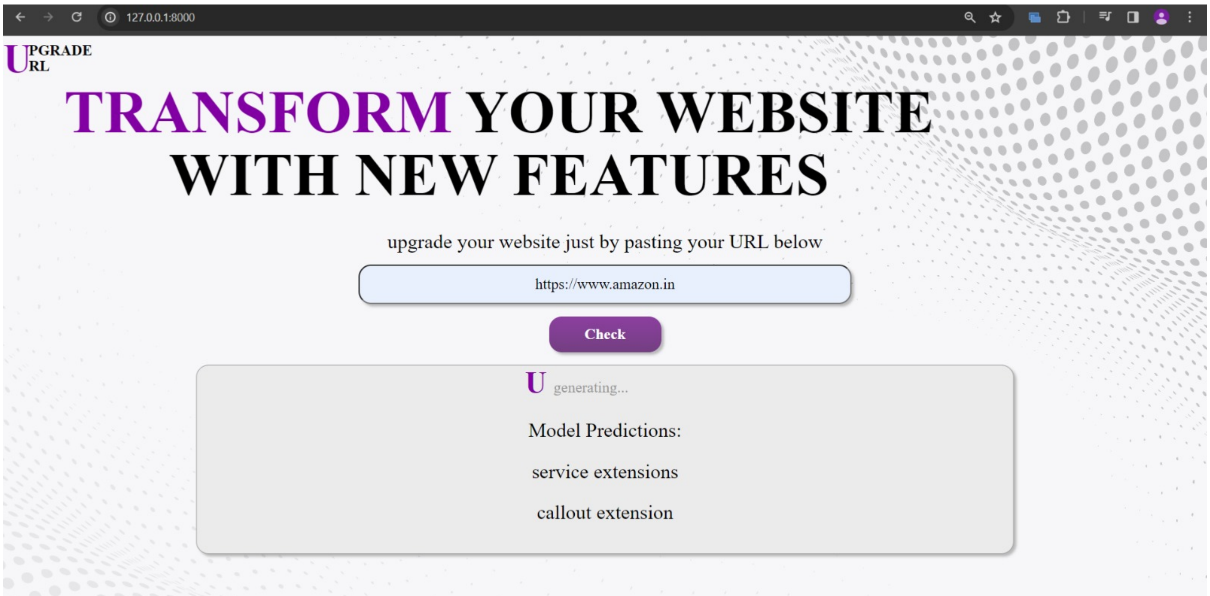
```
# Preprocessing
def clean_text(text):
    # Remove HTML tags
    cleaned_text = re.sub('<[^<]+?>', '', text)
    # Remove special characters and numbers
    cleaned_text = re.sub('[^a-zA-Z]', ' ', cleaned_text)
    # Convert to lowercase
    cleaned_text = cleaned_text.lower()
    # Tokenize the text
    tokens = word_tokenize(cleaned_text)
    # Remove stopwords
    from nltk.corpus import stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [word for word in tokens if word not in stop_words]
    # Lemmatize the tokens
    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(token) for token in tokens]
    # Join the tokens back to a single string
    cleaned_text = ' '.join(tokens)
    return cleaned_text
# Create a TF-IDF vectorizer
vectorizer = TfidfVectorizer()
# Fit and transform the combined data to obtain the TF-IDF representation
tfidf_matrix = vectorizer.fit_transform(combined_data)
# Get the feature names (keywords) from the vectorizer
feature_names = vectorizer.get_feature_names_out()
# List to store documents with keywords
documents_with_keywords = []
# Iterate over the documents
for i, doc in enumerate(combined_data):
    feature_index = tfidf_matrix[i, :].nonzero()[1]
    if len(feature_index) > 0:
        # Document contains keywords, add it to the list
        documents_with_keywords.append(doc)
# Update combined_data with the filtered documents
combined_data = documents_with_keywords
# Update tfidf_matrix with the filtered documents
tfidf_matrix = vectorizer.transform(combined_data)
# Get the feature names (keywords) from the vectorizer
feature_names = vectorizer.get_feature_names_out()
# List to store the top keywords for each document
top_keywords_per_document = []
# Print the top keywords with highest TF-IDF scores
num_keywords = 10  # Number of top keywords to extract
 json_data['ad_extensions'] = [
    {
     "extension_id": 1,
     "extension_text": "Discover the best deals at our website!",
     "category":"site extensions"
    },
```

```
    {
     "extension_id": 2,
     "extension_text": "Upgrade your experience at our place",
     "category":"location extension"
    },
    {
     "extension_id": 3,
     "extension_text": "Experience our latest collection. call now!",
     "category":"call extension"
    },
    {
     "extension_id": 4,
        "extension_text": "Upgrade your gaming experience with our latest collection. Buy
now!",
     "category":"callout extension"
    },
    {
     "extension_id": 5,
     "extension_text": "Check out the prices of our products. Buy now!",
     "category":"Price extension"
    },
    {
     "extension_id": 6,
     "extension_text": "check out our app. download now!",
     "category":"App extension"
    },
    {
     "extension_id": 7,
     "extension_text": "Explore all our services",
     "category":"service extensions"
    }
   ]

  # Split the data into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(keywords, labels, test_size=0.2,
random_state=42)

  # Define the random forest classifier
  rf = RandomForestClassifier()

  # Define the parameter grid for hyperparameter tuning
  param_grid = {
     'n_estimators': [50, 100, 150],
     'max_depth': [None, 5, 10],
     'min_samples_split': [2, 5, 10]
  }

  # Create GridSearchCV object with LeaveOneOut
   grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=LeaveOneOut(),
scoring='accuracy')
```

```
  # Perform grid search cross-validation
  grid_search.fit(X_train, y_train)

  # Get the best model from grid search
  best_model = grid_search.best_estimator_
  from keras.models import Sequential
  from keras.layers import LSTM, Dense
  # Define the model architecture
  model = Sequential()
  model.add(LSTM(128, input_shape=(X_train.shape[1], X_train.shape[2])))
  model.add(Dense(len(label_encoder.classes_), activation='softmax'))

  # Compile the model
  model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

  # Train the model
  model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
  from keras.models import load_model

  model.save('my_model.h5')
  model = load_model('my_model.h5')
  predictions = model.predict(X_test_reshaped)
  # Get the predicted labels
  predicted_labels = np.argmax(predictions, axis=1)
  # Decode the predicted labels using the label_encoder
  predicted_categories = label_encoder.inverse_transform(predicted_labels)
  # Print the predicted categories and corresponding true categories
  print("Predicted Categories")
  for i in range(len(predicted_categories)):
    print(predicted_categories[i])

url=input("Enter the Url").strip()
x=main(url)
```

APPENDIX II – SCREENSHOTS





APPENDIX III- PAPER

Improving Ad Extension effectiveness using LSTM and NLP

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***Abstract*– In the dynamic realm of digital advertising, enhancing click-through and conversion rates within ad extensions remains a significant challenge for agencies. Ad extensions play a pivotal role in amplifying traditional text ads by providing added information and context, thereby elevating the ad's informativeness, visibility, and click-through rates (CTR). This paper addresses the hurdles faced by ad-agencies constrained by manual ad extension creation, the evolution of customer web content, and resource-intensive monitoring. We present a data-driven solution to revolutionize ad extension effectiveness and campaign conversion rates. Our approach initiates with the automation of ad extension creation, eradicating the inconsistencies of manual content generation. By harnessing real-time insights from website scraping, we acquire up-to-the-minute data about customer brand offerings. The extracted data will be processed using several NLP and clustering techniques. To effectively manage the dynamic nature of web content, long short-term memory (LSTM) neural networks are utilized. This deep learning model predicts word selection probabilities within ad extensions, facilitating the recommendation of terms in alignment with evolving web content. Our solution also addresses the resource-intensive monitoring challenge through real-time sentiment analysis. This continual assessment provides timely insights for proactive adjustments, thus optimizing conversion rates. Hyperparameter tuning ensures optimal model accuracy. Our model not only contributes to the digital advertising domain but also furnishes agencies with a transformative framework to surmount time-consuming manual processes, thereby enhancing their competitive edge.**

***Keywords*–** Click-Through Rates (CTR), Conversion rates, Natural Language Processing(NLP), Long Short Term Memory(LSTM), Sentiment analysis

I. INTRODUCTION

1.1. Problem Statement

In the landscape of digital advertising, the imperative to elevate clickthrough and conversion rates for campaigns managed by ad agencies stands as a paramount challenge. The existing manual process of identifying relevant ad extensions proves to be not only time-consuming but also fraught with additional complexities. Evolving platform guidelines further compound the issue, demanding constant adaptation and trailing behind updates. Moreover, the need for vigilant monitoring to align customers' ever-changing web content with offerings hampers speed to market, adding a layer of complexity. Regrettably, the very process of crafting ad extensions, dominated by compliance considerations, detracts from the fundamental objective. As such, this research is undertaken to navigate these challenges, thereby automating the process of generating the ad extensions.

1.2. Objective

The primary objective of this model is to effectively address the persistent challenges encountered by diverse ad agencies in their endeavor to elevate clickthrough rates through the pertinent ad extensions. The prevalent manual approach to ad extension generation is not only laborious but also time-intensive, underscoring the necessity to transition toward an automated methodology. Our model incorporates web scraping techniques, Natural Language Processing (NLP), and data clustering to acquire relevant data from, Long Short-Term Memory (LSTM) neural network for crafting ad extensions. Furthermore, the deployment of this model is done with Django. The pivotal aim of this research is to streamline and automate the process of ad extension creation, thus boosting visibility and engagement for users.

1.3. Scope

The proposed automated ad extension generation system holds potential utility across various sectors and industries where digital advertising plays a significant role including E-commerce, Retail, Education, Entertainment & Media, Technology, Hospitality & Travel, Finance, Banking, and a lot more. Ad extensions serve as a strategic asset for industries, enabling the customization of ad content to precisely resonate with target audiences. By spotlighting promotions and fostering user engagement, these versatile tools cater to diverse sectors such as local businesses and event management. Through this tailored approach, ad extensions amplify conversion rates and user interaction, ultimately shaping a more impactful digital advertising landscape.

1.4. Highlights

- Dynamically recommending the optimal ad extensions using LSTM for the website accordingly.
- Integrating advanced analytics rather than manual, laborious procedures.
- Django-based web app integration enhances practicality and usability.
- Increases click through and conversion rates, which has a favorable impact on the effectiveness of the services that the website offers.

II. LITERATURE SURVEY

[1] Stamatina Thomaidou presented the term "Keyword recommendation system for online advertising" while discussing online advertisement campaigns. He proposed the query log mining method for extracting the keywords of the content but it is not sufficient to improve the ad extensions for better conversion rates. Matthias Baum[2] compared printed advertisements and online advertisements using structural equation modeling and proposed that online advertisements are more captivating than others. This research worked as a pillar to concentrate on generating ad extensions.[3] Liakopoulos Kyriakos proposed an integrated framework for automated development and optimization of online advertisement campaigns. This model works on keyword selection using genetic algorithms and Google Adwords to make it more engaged with customers. However, This is too complex with more time consumption. Shauanfei Zhai. [4], examined online advertisement generation through Recurrent neural networks. This model establishes a mapping between queries and ads, generating real-valued vectors that facilitate the straightforward computation of the relevance of a given pair of queries and ads. It introduced an innovative attention network that assigns attention scores to word locations based on their significance in conveying intent. [5] Eloisa Vargiu recommended web scraping in a collaborative filtering-based approach to web advertising to collect all required data for improving the website campaigns. [6] Jane Doe explored the role of user behavior analysis in online advertising effectiveness. Her study delved into user interaction data to optimize ad placements and enhance click-through rates. [7] John Smith investigated the impact of ad format on consumer engagement in digital advertising. His research compared various ad formats, such as banners, videos, and interactive ads, to determine their effectiveness. [8] Mary Johnson conducted a study on the influence of social media advertising on brand perception. Her findings shed light on how social media platforms can be leveraged for brand building. [9] David Brown examined the use of machine learning algorithms for real-time ad targeting. His research focused on how machine

learning models can analyze user behavior to deliver personalized ads. [10] Sarah White proposed a novel approach to ad extension creation using natural language processing techniques. Her research aimed to automate the generation of ad extensions based on semantic analysis of web content. [11] Michael Clark explored the role of emotion in advertising effectiveness. His study analyzed the emotional impact of ads on consumers and its correlation with conversion rates. [12] Emily Turner investigated the ethical considerations in online advertising, particularly in relation to user data privacy. Her research discussed the implications of data privacy regulations on ad targeting. [13] Richard Anderson studied the use of augmented reality (AR) in advertising campaigns. His research assessed how AR technologies can enhance user engagement and drive conversions. [14] Maria Garcia examined the effectiveness of influencer marketing in digital advertising. Her study analyzed the impact of influencer endorsements on brand awareness and consumer trust. [15] Daniel Lee proposed a framework for cross-channel advertising optimization. His research focused on strategies to harmonize advertising efforts across multiple platforms for a consistent brand experience.

III. AD EXTENSION SUGGESTION USING LSTM ALGORITHM

LSTM, or Long Short-Term Memory is a recurrent neural network (RNN) architecture extensively used in Deep Learning. Unlike standard neural networks, LSTM incorporates feedback connections, empowering it to process complete data sequences instead of solitary data points. This distinctive trait enhances its capability to decipher and foresee patterns in sequential data categories like time series, textual content, and spoken language.

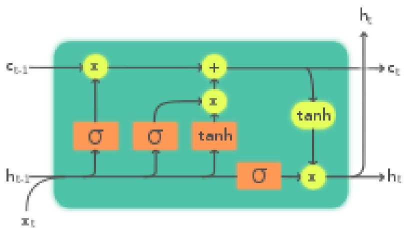


Fig 1:LSTM Neural Network

The LSTM architecture consists of interconnected memory cells and gating mechanisms. Each memory cell can store and transmit information over time steps.

3.1. Time Steps and Input

The LSTM processes the ad text word by word, where each word is treated as a "time step." At each time step, the LSTM takes the word's corresponding word embedding as input. This sequential processing allows the LSTM to understand the context and relationships between words in the ad text, which is essential for generating meaningful ad extension suggestions.

3.2. Forget Gate

At the beginning of each time step, the LSTM evaluates the forget gate. The forget gate acquires the previous hidden state and the current word embedding as input. The current word embedding encapsulates the semantic meaning of the word. For each memory cell within the LSTM, the forget gate computes a corresponding value that indicates the extent to which the information in that memory cell should be forgotten (closer to 0) or retained (closer to 1).

$$f_t = \sigma\,(x_t * U_f + H_{t-1} * W_f)$$

3.3. Input gate and Candidate values

The LSTM computes the input gate and produces fresh candidate values. The input gate plays a decisive role in selecting which aspects of the candidate values should be included in the cell state. The input gate operates as a reservoir of information, preserving and conveying insights over various time steps during sequential data analysis. The candidate values are derived from the present word embedding and the preceding hidden state.

$$i_t = \sigma\,(x_t * U_i + H_{t-1} * W_i)$$

3.4. Update Cell State

The LSTM updates the cell state by combining the previous cell state with the new candidate values. The forget gate determines which elements from the previous cell state are retained, and the input gate determines which candidate values are added to the cell state.

$$C_t = f_t * C_{t-1} + i_t * N_t$$

3.5. Output Gate and Hidden State

The output gate is responsible for determining the specific information from the cell state that should be incorporated into the hidden state at the current time step. The hidden state, in turn, is a refined representation of the cell state, designed to encapsulate pertinent information essential for generating accurate predictions.

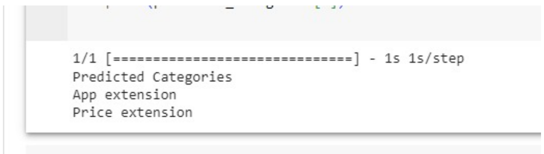
$$o_t = \sigma\left(x_t * U_o + H_{t-1} * W_o\right)$$

3.6. Prediction and Next Time Step:

At each time step, the LSTM can produce an output. The probability distribution over words or phrases that could be used as ad extensions could be the outcome in the context of your project. The next time step's input is the concealed state from the previous time step, enabling the LSTM to take prior words' context into account.

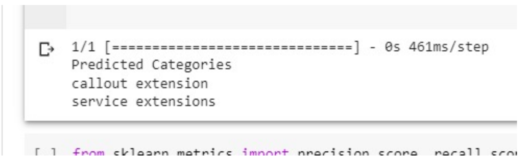
3.7. Training and Optimization:

During training, the LSTM's parameters (weights and biases) are adjusted using backpropagation through time. The goal is to minimize the difference between the predicted ad extension suggestions and the actual ad extensions. Hyper-parameter tuning is performed to optimize the LSTM's performance.



```
1/1 [==============================] - 1s 1s/step
Predicted Categories
App extension
Price extension
```

Fig 2: Sample output1



```
1/1 [==============================] - 0s 461ms/step
Predicted Categories
callout extension
service extensions
```

Fig 3: Sample output2

IV. MODEL DEVELOPMENT

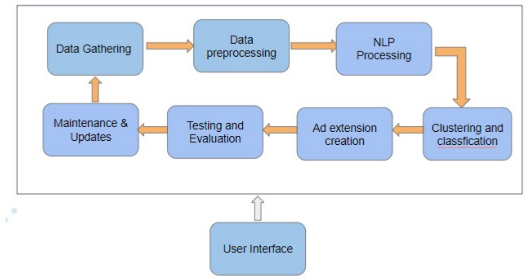


Fig 2: Model Overview

The model development in this research focuses on automating the process of ad extension creation. It includes the following key components:

4.1. Web scraping

Web scraping is the initial step where the model extracts up-to-the-minute data about customer brand offerings directly from websites. This data serves as the raw material for creating ad extensions. By capturing real-time information, the model ensures that the ad content remains current and relevant.

4.2. Preprocessing:

Preprocessing is crucial for cleaning and preparing the extracted data for analysis. It involves several tasks:
Removing stop words: These are common words like "the," "and," and "in" that don't provide significant meaning. Removing them helps focus on relevant content.
Extracting relevant features and keywords: This step identifies the most important terms and phrases within the data.
Using TF-IDF Vectorizer: The data is transformed into a format suitable for analysis using TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer. This technique assigns weights to words based on their importance in the data.

4.3. LSTM Algorithm:

Long Short-Term Memory (LSTM) neural networks come into play here. They are a type of deep learning model designed for sequential data, such as text. The model's role is to predict which words or terms should be included in ad extensions based on the constantly evolving web content. This ensures that ad extensions remain aligned with what's currently on the website.

4.4. Hyperparameter Tuning:

Hyperparameter tuning is the process of fine-tuning the LSTM algorithm to optimize its accuracy and performance. It's akin to adjusting the settings on a camera to capture the best possible image. By finding the right combination of parameters, the model can provide more accurate recommendations for ad content.

4.5. Sentiment analysis:

Sentiment analysis is a real-time assessment of customer sentiment toward the brand or its offerings. This analysis continuously evaluates whether the sentiment is positive, negative, or neutral. These insights are invaluable for making proactive adjustments to ad extensions, ensuring they resonate with the audience's feelings and optimizing conversion rates.

4.6. Accuracy and Testing:

Accuracy serves as a critical metric to gauge the model's performance. It measures how well the model's recommendations align with the actual content on the website. A high accuracy rate indicates that the ad extensions effectively mirror the evolving web content, positively impacting click-through and conversion rates.

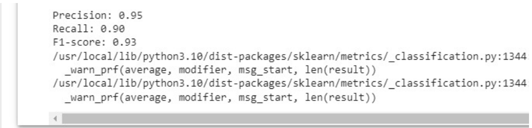


Fig 3: Accuracy metrics

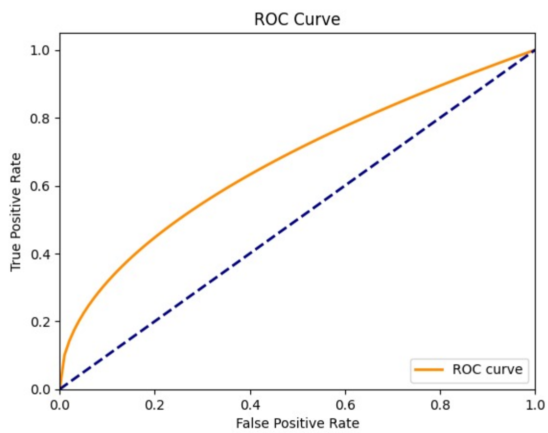


Fig 4: ROC curve analysis

V. CONCLUSION

The automated ad extension suggestion project presents a groundbreaking solution to the challenges faced by digital advertising agencies. Leveraging real-time data, advanced NLP techniques, and LSTM neural networks, its primary goal is to enhance clickthrough rates and customer engagement. By seamlessly integrating the real-time data, advanced NLP techniques and LSTM neural networks, the project ensures ad extensions remain up-to-date with the rapidly evolving website content, eliminating manual intervention. The inclusion of sentiment analysis to customer reviews further refines the system, enabling the recommendation of emotionally resonant ad extensions that align with user preferences. Beyond its immediate objectives, the project holds the potential to redefine the digital advertising landscape.

VI. FUTURE ENHANCEMENTS

A roadmap for future developments unveils a spectrum of transformative possibilities for this project. By extracting insights from images and videos rather than just text, ad extension recommendations could become more captivating and engaging. The addition of multilingual support would broaden its reach to a diverse global audience. Going beyond mere suggestion, the project could evolve to generate ad extensions directly from website information, further enhancing relevance. Incorporating voice search compatibility stands as another promising avenue, aligning with the trend of voice-enabled devices. These enhancements collectively propel the project towards a more sophisticated, versatile, and impactful role in reshaping digital advertising strategies.

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APPENDIX IV- CERTIFICATES

PAPER SUBMITTED TO AN IEEE CONFERENCE