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User Interest Prediction Using Deep Learning on Advertisement

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Abstract. Online advertising has drawn considerable interest from a variety of platforms, including search engines, third-party websites, social media, and mobile apps. The success of online campaigns is a problem for online marketing and is typically measured by user response via various indicators, such as clicks on advertisement (ad) creatives, product subscriptions, item purchases, or explicit customer input via online surveys. There participants in the digital advertising eco-systems of the internet. There are kinds of data are accessible for predicting user response. It can user behavior be predicted in a transparent and/or trustworthy manner. We give a thorough analysis of user response prediction in online advertising and related recommender applications in this survey. A crucial element in online digital advertising is user interest and behavior modelling. On the one hand, user interests have a direct bearing on how they react to and use the advertisement that is displayed (Ad). The likelihood that a viewer of an advertisement will make a purchase, however, can also be determined by the user's interests. The majority of the time, click-through rate prediction techniques use static feature sets to represent users and train machine learning classifiers to predict clicks. Such methods just use the pre-given features for learning, disregarding temporal variance and changes in user actions. In this article, we provide two deep learning-based frameworks, LSTMcp and LSTMip, for modelling user interest and predicting user clicks. Our intention is too precisely.

Keywords: prediction models; online advertising, SNS; personalized ads; deep learning.

1. Introduction

Internet advertising offers a standard marketing experience when customers access online services using electronic devices, such as desktop computers, smartphones, tablets, etc. In order to reach users through a variety of platforms, including search engines, news websites, and social networks, various stakeholders use the Internet as a means of advertising. These platforms have designated spots or areas where advertisements (ads) are displayed alongside search results, posts, or page content. A section of internet services and websites are loaded with clickable links, much like the traditional media, such as print magazines and newspapers, where specific spots are assigned to be sold for ads. In such cases, either the ads to be pre-sold (i.e., negotiated) by sellers (publishers) to buyers (advertisers) or they are dynamically selected through a real-time bidding (or auction) process are displayed to audience (i.e., users). Online advertisers compete for ad opportunities by bidding, but only the winner will be able to show their adverts to users (so only the winner needs to pay to the publisher for the purchase of the auctioned ad opportunity). The main focus of computational advertising is on applying computational methods to deliver, show, and serve adverts (Ads) to audiences (i.e., users) who are interested in the Ad at the appropriate moment. For many digital advertising and recommendation systems, predicting a click—the first quantifiable user response— is a crucial step in capturing the user tendency to take other actions, including making a purchase or signing up for a service. These systems are customized for user preferences to determine the order in which adverts should be displayed to users based on the feedback that has been observed. Companies like Google launch paid search advertising based on user intents identified through the query terms in the age of search engines and social media platforms. Platforms like Face book offer advertisers user demographic data from user-generated content for viral marketing in social media marketing. Monitoring the effectiveness of advertisements in traditional media, such as TV or printed newspapers, is challenging. The ability to deliver advertisements to specific target groups based on self-disclosed information found on public profiles, such as age and gender, is one of the benefits of advertising on SNS. There is a dearth of study on social media photographs as well as research on categorizing SNS users' interests through image analysis. According to earlier studies, raising perceived relevance causes consumers to react more favorably.

2. Related works

Click- through rate (ctr) prediction: Predicting click-through rates for online advertising is one of the most crucial tasks whose accuracy affects the income of companies in this industry [5]. For example, key features like landing page URL, keywords, Ad title, Ad text, etc. can be extracted from search advertising and then help train logistic regression model to predict whether a search advertisement will be clicked. The fact that data are typically presented in a categorical format presents one of the main challenges in CTR and user response (such as click) prediction. The sparsity problem is caused by the method used to convert them into high dimensional binary feature representation. Previous works onPersonalized advertising Potential customers are now identified using cutting-edge recommender systems and artificial intelligence technology [1]. The degree of resemblance between customer and product content profiles is examined by Mooney and Roy using the content-based approach. Additionally, gathering behavioral data from users' likes, comments, searches, and tweets aids in drawing conclusions about their preferences. SNS users not only upload photos, but also self-identify in the descriptions of the photos, adding textual and contextual information that improves the photos. Images may communicate a thousand words; therefore picture recognition software can recognize and expose brands and items even when they are not expressly stated. Therefore, to improve the accuracy of identifying consumers' preferences, the current study evaluates both photos and sentences from SNS users. User interest modeling: Because the main objective of advertising is to identify the best match between audiences (users) and adverts, understanding user interests is one of the biggest issues in online digital advertising [3]. Introduced a novel rank-aware block-oriented inverted index to match news feed as a query to get the k most pertinent Ads for real-time news stream advertising calls. We need a model to anticipate user interest and explain their portable preference because users' interactions with systems are restricted to the history of categories of Web sites they have visited in the e-commerce area and the simple phrases they have used in search engines.

3. Proposed Models

Methodologies: deep learning based methods: In order to capture non-linear feature interaction in sparse input data, the majority of earlier work using deep network structures is primarily built on two components: embedding and interaction [5]. The purpose of the embedding component is to convert the sparse input data into a dense, low-dimensional latent space. An aggregation procedure is then used to process the embedding vectors and create a fixed length vector for the deep component. By injecting a fixed-length vector into the deep neural network component, which is often implemented by the multi-layer perceptron, the high-order interactions between features are handled [5]. To discover the non-linear link between user attributes and user responses, gradient-based training is used. Recurrent neural network based methods: Neurons in deep neural networks are often connected in multiple layers. The independent features incorporate the data that pass through multi-layer perceptron’s to produce the output without backward linkages, similar to how neurons have a stateless structure. With relation to predicting user responses, taking into account independently visited or clicked adverts fails to effectively extract valuable user interests. Based on rnn algorithm: The RNN-based model is a deep learning model that is applied to time-series data that changes over time, such as natural language. It attempts to continually retain information on inputs that change over time and provide the most suitable outputs that can appear from one point in time to the next. A suggested solution to RNN's long-term dependency issues is the LSTM. The issue of losing information from a very distant past exists because RNNs have a straightforward structure that continuously repeats information from the past and present in the same way Bidirectional LSTM is a model that adds a backward state layer for learning future information to increase future predictive performance. RNN, LSTM, and GRU are models for learning exclusively from the past and predicting the future through current-time information. Similar to image classification, the best performance model based on accuracy was chosen. These models, which also include RNN, LSTM, GRU, and bidirectional LSTM. As a hybrid NN model for user interest classification, these chosen CNN model and RNN model were utilized RNN, LSTM, GRU, and bidirectional LSTM are some of the models used for text classification. As with image classification, the top performance model based on accuracy was chosen. Next, a hybrid NN model for user interest classification was developed using the chosen CNN and RNN models. This makes it possible to customize advertising and recommendations using our suggested approach. Bidirectional LSTM is a model that adds a backward state layer for learning future information to increase future predictive performance. RNN, LSTM, and GRU are models for learning exclusively from the past and predicting the future through current-time information. For instance, existing RNN-based models learn the phrase "I am a boy" in the same way as forwarding state layers and also "boy an am I" in the backward state layer of bidirectional LSTM when the phrase is present. This will make it easier to forecast the future and maintain past and future knowledge simultaneously. RNN: Recurrent Neural Network (RNN) are a type ofNeuralNetworkwhere the output from previous step are fed as input to the current step [3]. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases like when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is Hidden state, which remembers.

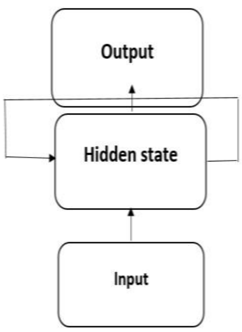

FIGURE 1. Vanilla recurrent networks (RNN) model

LSTM:Long Short Term Memory is a kind of recurrent neural network. In RNN output from the last step is fed as input in the current step. LSTM was designed by Hoch Reiter &Schmidhuber. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. LSTM can by default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data.

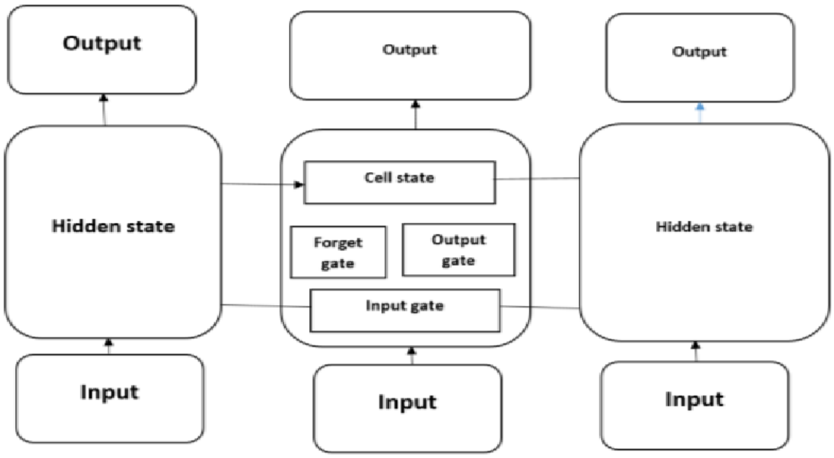

FIGURE 2. (b) Long short-term memory (LSTM) model.

While RNN, LSTM and GRU are models for learning only from the past and predicting the future through current-time information, bidirectional LSTM [4] proposes a model that adds a backward state layer for learning future information to improve future predictive performance. This will help preserve past and future information at the same time and better predict future information.

4. Experiment and analysis

Standard data: To verify user click and user interest, we prepared two datasets using data that we extracted from the DSP of one of our business partners. Dataset For Post-View Clicks The primary purpose of this dataset is to validate binary user click prediction. From 1day log events, we extracted 5.6 million users' request records [2]. These anonymous data contain chronological lists of different request categories, which show how users browsed. When a post-view click occurs at the end of a chain of viewed impressions, there are two types of positive and negative user reactions that can happen. This dataset has a serious class imbalance problem because positive responses (clicks) to digital advertising are very uncommon. As a result, in order to address this problem, we employ random down sampling to create a training set with a class distribution ratio of 10:90%, or positive: negative samples. LSTMip: LSTMip is the proposed method which uses the framework for user interest prediction. Experimental settings and performance metrics: Experimental environment: We put seven strategies for comparisons (including the one we suggested) into practice. All neural network-based models were built using Tensor Flow and CUDA to benefit from GPU computing, and Adam optimization, a variation on gradient descent, was used to train them. The remaining models are created via the Python scikit-learn module [7]. The dataset is divided into training, test, and validation sets for training models using a 70:20:10 ratio. During the data preprocessing stage, sequential data from the input is converted to a binary vector by one-hot encoding with numerous classified campaign IDs and removing the less-frequent ones. So, using a filter to maintain those categories with more than 1000 occurrences in our dataset, we choose the top categorized campaign IDs based on frequency networks. Model Training And Data PreparationSince LSTM demands that input be organized in tensor format, in our experiments, we set m = 70 and d = 153, which are based on the statistical properties of the data [6]. These values are used in our proposed method to represent data as a third order tensor (Rnmd), where n, m, and d correspond to the number of users, the frequent sequence length, and the number of most frequent page category IDs, respectively. For the remaining approaches, their input data are gathered by adding up values in the sequence length dimension and projecting the third-order tensor data (Rnmd) to a second-order tensor Rnd. Therefore, none of the other baselines (including the suggested technique) take into account the timing of the users' requests; instead, they simply aggregate them into a table.

5. User interest prediction results

In order to compare the proposed technique with naive Bayes, random forests (with Deep FM techniques, two versions of SVM with linear and RBF kernels, logistic regression, and 100 tree estimators. Click samples from the prior task's click response prediction are the input data. We summarise the Receiver Operating Characteristic (ROC) curves and AUC values for various approaches to predicting user interest [8]. Further evaluates the effectiveness of several approaches for predicting user interest using other performance data. The AUC values demonstrate the LSTMip network's efficacy in identifying the association between consecutive data and click response. It is highlighted by the fact that neural network methods perform better than linear classifiers like LR and linear SVM.

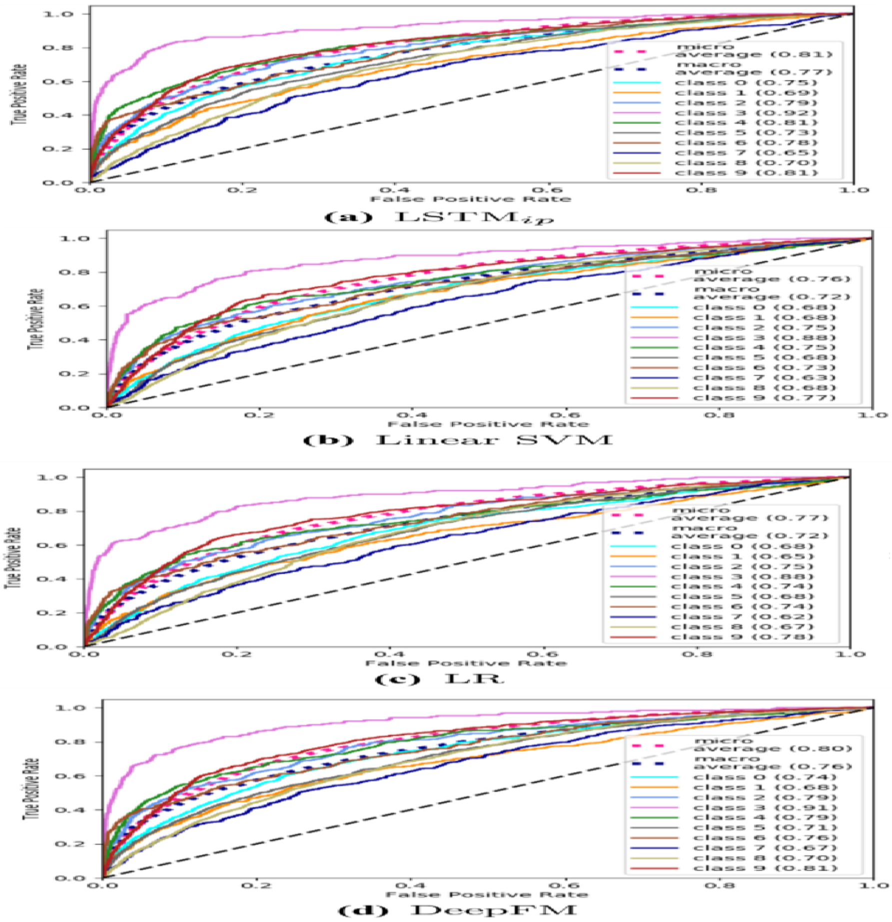

FIGURE 3. Sensitivity study of the proposed framework (LSTMip) with respect to the ensemble size (*n*) for user interest prediction.

6. Conclusion

One of the most crucial phases of real-time bidding for computational advertising is CTR estimate. In this paper, we concentrate on the task of creating a novel framework for LSTM-based deep neural networks that anticipate user interest and click reaction. Our method allows sequences to have varying lengths and different numbers of dimensions and can fully utilize temporal information in user sequences for learning. We employ padding and bucketing to learn binary user click prediction and multi-class user interest prediction. Our method can embed useful latent temporal information in request sequences to anticipate users' responses and interests in online digital advertising, according to experiments and comparisons on real-world data obtained from our industry partner.

7. Future Enhancement

Combining machine learning models based on images and text should be explored in future study. Image data should be used by researchers to forecast user interaction. Additionally, image-based models excelled at handling complex data. One such statistic is comment sentiment. For comment sentiment, image-based models performed more than 40% better than text-based models. Share counts cause a repetition of the phenomenon. By a factor of 3.5, the imagebased model performed noticeably better than the text-based model. The performance of text- and image-based models on simple data, such as comment count, was comparable. Word2Vec uses substantially smaller word vectors for NLP. The goal of this study was to predict comment sentiment using Word2Vec. To train Word2Vec models, additional comment 67sentiment data should be gathered in future studies. Future study may solve the issues with Facebook API scraping. The researchers could be gathering feedback.

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