The Impact of Artificial Intelligence on Internet Advertising: Advertising Recommendation System Based on Deep Learning Technology

Xiaoying Lin

Communication University of China, No.1, Dingfuzhuang Street(E), Chaoyang District, Beijing, P.R. China.

linxy06@cuc.edu.cn

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Abstract: Internet online advertising has developed rapidly in recent years, showing great market value. Deep learning is a technology that extracts low-level simple features through multi-layer neural networks to form high-level abstract and difficult-to-change features. In recent years, the field of machine learning and artificial intelligence has attracted great attention and made breakthroughs. Deep learning technology can predict the click-through rate of advertisement more accurately. It can directly extract the complex dependence and non-linear relationship between users and items to be recommended from large-scale data sets, achieve more accurate recommendation, and effectively enhance the personalized effect and optimize user experience.

Introduction

Since the 1990s, Internet advertising has developed rapidly. According to the annual monitoring report of China's online market in 2018, the scale of China's online advertising market reached 375.01 billion yuan in 2017, an increase of 32.9% over the previous year. Among them, the mobile advertising market has reached 254.96 billion yuan, which is the absolute mainstream of the market; the advertising share of e-commerce websites exceeds 30%, which exceeds search advertising. Primary advertising, mainly in the form of information flow advertising, has developed rapidly, with a total scale of 68.88 billion yuan, accounting for 18.4% of the total amount of online advertising. [1]

In the era of information explosion, in order to alleviate the confusion of choice caused by information overload, recommendation system came into being. It is widely used in e-commerce, computing advertisement, information distribution, project suggestion, search engine, network news and social media, which brings great convenience to people's lives. It also promotes the rapid development of the economy. Overstock, a well-known online retailer in the United States, claims that after the initial introduction of personalized advertising recommendation system, "advertising click-through rate is twice as high as before, and sales growth is as high as 20% to 30%.

Surveys show that 35% of Amazon's total sales come from recommendation systems; 60% of YouTube's video clicks come from home page recommendation; 80% of Netflix's movies come from company recommendation systems; as early as 2012, Google earned $42 billion through advertising recommendation systems; Baidu and Taobao's. Advertising recommendation system can bring more than 10 billion yuan of revenue to the company every year. Today's headline was created in 2012, and the recommendation system has also contributed to the rapid development in a few years. [2]

Advertising Recommendation and Artificial Intelligence

Advertising is to match the needs of the audience. Because of the diversity of the audience's needs, how to accurately segment the audience's needs is the key problem to be solved in advertising. In traditional media advertising, advertisers can only indirectly infer the audience's needs through the different types of media, layout and channels, such as Mercedes-Benz car advertisements in automobile magazines and women's toiletries advertisements in front of soap operas. However, there is a problem of low precision in this way of advertising: media has tens of millions of audiences, but they face the same advertising. However, with the development of computer technology, especially the development and maturity of artificial intelligence technology, Internet advertising could solve the problem of inaccurate delivery, and to put advertising information in appropriate scenarios to the appropriate users.

Advertising recommendation system is mainly based on user's needs, interests, purchase characteristics, etc. It simulates sales personnel to provide users with project information and suggestions (including commodities, pictures, news, etc.) to help users decide which items to choose or buy, in order to use traffic efficiently, distribute information efficiently, and promote users. Experience and long tail mining play a key role. Traditional recommendation systems mainly use the nearest neighbor method, collaborative filtering, content-based and multiple combinations to recommend. They mainly model explicit feedback (such as purchase, rating or comment) between users and projects, while complex implicit feedback (such as browsing records, watching advertising videos, clicking and viewing) is involved. There are few problems, such as sparse data, cold start, poor recommendation effect and poor user experience.

Artificial intelligence (AI) has become a field with many practical applications and active research topics, and is developing vigorously. Intelligent system can automatically process daily work, understand voice or image, help medical diagnosis, and support basic scientific research. In recent years, in-depth learning has been the most respected technology in the field of artificial intelligence. Deep learning is a technology that extracts low-level simple features through multi-layer neural networks to form high-level abstract and difficult-to-change features. [3]

Advertising recommendation system based on deep recommendation can be composed of neural network structure (mainly composed of input layer, several hidden layer and output layer). There are several neurons in each layer. There are connection weights between neurons. Each neuron imitates human nerve cells, and the connections between nodes imitate the connections between nerve cells and non-linear excitation functions. It automatically learns the complex combination relationship between users and features of items (including commodities, news, video, music, etc.) and solves the problem of artificial design features in traditional recommendation systems. Questions, skills to improve efficiency, but also more accurately put forward personalized suggestions. After the Internet giants such as Google, Amazon, Facebook and Twitter, Alibaba, Tencent, Baidu and Jingdong have also established their own artificial intelligence research institutions.

The Impact of Deep Learning Technology on Internet Advertising

Better prediction of advertising click-through rate. Search Engine Advertising (SEA) refers to the advertisement that an advertiser determines the relevant keywords, titles or product descriptions of a product based on the characteristics of its products or services, and makes his own bids and delivers them. When the content searched by the user is related to the keywords purchased by the advertiser, the advertisement media will display its advertisement on the search results page. After clicking, the user charges the advertiser according to the charging rules. The key technology to support search engine advertising is to predict the click-through rate of advertising. With the development of Internet recommendation system technology, precision advertising based on artificial intelligence technology has become the mainstream trend of online advertising recommendation. Advertisers should first evaluate users' preferences for advertising, and then make procedural purchases and put search engine advertisements on the advertising platform. At this time, the click-through rate of advertisements has become a key indicator to evaluate users' preferences.

In the past, there were two main techniques for evaluating click-through rates: one was to design feature extraction schemes to obtain features, the other was to model user click behavior. Because of the high dimensional sparsity of advertising data and the highly non-linear relationship between various features, there are many shortcomings in previous technical schemes. For example, the sparsity of advertising data can not be effectively reduced, and hiding rules in advertising data can not be found. In-depth learning technology can solve this problem by describing the non-linear correlation in the data to solve the feature learning problem of high-dimensional sparse advertising data.

Some scholars have carried out relevant research on Feature-based learning of advertising click-through rate prediction technology, and studied feature-based learning method from the experimental point of view. Firstly, the feature composition of input layer is analyzed, and the higher-order combination feature between learning features of stack self-coding network algorithm is used as the training object of click prediction model. The experimental results show that this method can effectively improve the estimation accuracy of advertisement click-through rate. [4]

Recommendations are more accurate. Deep learning can directly extract complex dependencies and non-linear relationships between users and projects to be recommended from large-scale data sets, and achieve more accurate recommendation effect. YouTube is the world's largest platform for creating, sharing and discovering video content, with more than 1 billion users worldwide uploading video in hours per second. YouTube's recommendation system is responsible for timely and accurate recommendation of videos that users may be interested in, making it one of the largest and most complex recommendation systems in the world. Traditional recommendation algorithms can't analyze YouTube video in time, and can't provide accurate suggestions for independent users.

YouTube engineers apply multilayer perceptron (MLP) to YouTube recommendations. Compared with other commercial recommendation systems, the system needs to deal with such problems as huge data volume, constantly updating and changing video libraries, and the non-observability of user behavior. The deep network configuration of the whole model may require learning billions of parameters and training with hundreds of billions of data. The system consists of two neural networks: the first one is to retrieve from all video libraries to generate a broad set of personalized recommendation candidate videos for users; the second one is to distinguish and refine the candidate videos based on the candidate video sets (not only the output of the first neural network, but also the candidate videos generated from other sources). To recommend the top ranked videos to users. Actual online effects show that YouTube's in-depth learning-based recommendation system is fully capable of real-time processing of massive (million-scale) videos and recommending personalized or attractive videos to users. The whole process only takes tens of microseconds. [5]

Improving the personalized effect of recommendation. Deep learning technology can obtain useful data from different heterogeneous data sources (such as text, image, music, video and other unstructured data), which effectively improves the personalization effect. In social media, in order to enhance user experience and facilitate users to edit, organize, categorize and search for pictures, audio and video resources, it is usually done by tagging related tags for resources. Since tags represent the user's understanding of their resources, the user's recommended tag list is a personalized list containing their "favorite" keywords. People usually choose words related to content or context, such as location or time, to annotate images. Most traditional image tag recommendation systems do not consider the additional information provided by uploaded images, but rely only on text information, or use simple low-level image features (based on users, suggestions between items and tags, or only on tag-related information). For new images without historical information, the traditional recommendation based on personalized tags is not efficient. Image label recommendation system based on depth learning can be used in convolutional neural networks with excellent performance in image recognition and classification to obtain visual features from images by supervised learning. The experimental data show that compared with the traditional visual features or the most advanced personalized tag recommendation model based on tag history information, the image features selected in this way will greatly improve the accuracy of the recommendation.

In recommendation system, we often need to deal with various text data, such as product description, news information, user messages and so on. Compared with structured information (such as attributes of commodities, etc.), textual data has the following characteristics: firstly, the amount of structured information is very small, and the amount of information is also uncertain. For example, different users may have different descriptions of the same product in terms of words, text length and so on. Secondly, although the information is timely, it is easy to cause ambiguity and difficult to automate the analysis. After the emergence of some new nouns and things, microblogs and circles of friends are usually the first places to reflect changes, and most of these are pure text data. The analysis of these data can get the information that structured and predefined data cannot get as quickly as possible.

Tencent Effect Advertising Platform uses a series of Neural Language Model (NLM) and neural networks based on word embedding to extract user semantic features (user's search, shopping, browsing records and other text descriptions) and advertising semantic features, such as advertisement title and login page (la). Linking page and other text descriptions are matched semantically to achieve the purpose of personalized recommendation. Text Semantic Model is widely used in Tencent's various businesses, such as text semantic understanding, QQ group recommendation, user business interest mining, similar to user expansion, advertising click-through rate and conversion rate prediction, and has achieved good results and performance.

Enhancing User Experience. In-depth learning can use context information to adjust the services and products to be recommended for different scenarios and users' locations, so as to enhance the user experience. For example, as China's largest life service platform, the company's business covers eating, drinking, playing, entertainment, travel and other fields, with hundreds of millions of users and various user behavior.

Due to the diversity of its own business, the recommendation system of the group review is quite different from most other recommendation systems: the first is the diversity of business forms. In addition to recommending outdoors to users, users can also make real-time judgments according to different scenarios in order to recommend different forms of business, such as group buying, hotels, attractions and overlord meals. The second is the diversity of consumer scenarios. If the user is at home, he can choose takeaway service. If the user is out of town, he can shop or travel, such as booking a hotel. With the change of user's interest, location, environment and time, the recommended scenario may change.

According to the extensive in-depth learning model proposed by Google in 2016, the technical team of Metro has developed a set of comment recommendation system according to the needs and characteristics of its own business. In this system, the data of application scenarios are divided into the following categories: the first category is user portrait: gender, location, price preference, project preference, etc; the second category is project portrait: merchants, takeout, group orders and other projects. Among them, the characteristics of the merchant include the merchant price, the merchant's high praise rate and the merchant's geographical location. The characteristics of takeout include the average price, delivery time and takeout sales volume. The third category is scene portrait: user's current location, time, business circle near location and user-based context scene information. The experimental results show that the accuracy of the system is improved by 2.96 compared with the previous recommendation system. At the same time, some more innovative projects will be recommended according to the current scenario, which will better improve the user experience effect.

Summary

In the era of big data, the increase of data volume challenges the practical application. Facts have proved that in-depth learning is very effective in large data analysis, but there are also problems in adjusting parameters and optimizing models. In addition, most of the current in-depth learning-based advertising recommendation systems focus on the accuracy and personalization of recommendation, but it is obviously not enough to focus on this point. In addition to accuracy, other evaluation criteria, such as diversity, novelty, surprise, privacy protection and interpretability, are equally important.

By encouraging diversity, novelty and surprise, recommendation systems bring more value to customers whose intentions are not clearly defined. The increasing privacy protection and enhancing customer trust will reduce users' concerns and allow them to use projects they are interested in more freely. Good interpretability provides evidence for each recommendation. recommendation systems show users more reliable results. In order to provide users with a better user experience, future advertising recommendation systems based on in-depth learning should not only accurately model historical data, but also explore the following issues: incremental learning of non-stationary stream data, such as sudden influx of users or projects; high-dimensional tensor and multimedia data Computing efficiency of source; Through the extensive combination of different models, the application of in-depth learning in other evaluation scales of advertising recommendation system is fully explored. In addition, some advertising experts and scholars criticize the recommendation system based on artificial intelligence from the ethical point of view. They believe that the precise push under the guidance of artificial intelligence does not give push to individuals who do not match the consumption scenario, which is a kind of discrimination.

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