The Progress of Shopping Recommendation System Based on Machine Learning Algorithms

Xiyue Xiong[a]
Data Science and Big Data Technology, University of Reading, Reading, U.K.

Keywords: Machine Learning, Big Data, Random Forest, Recommendation System, Deep Learning Model.

Abstract: The shopping recommendation systems play a crucial role in enhancing the online shopping experience by providing personalized suggestions to users, thereby significantly increasing customer satisfaction and loyalty. This paper discusses the application of machine learning in the context of the commercial shopping field, especially for the shopping recommendation system. The algorithms discussed include random forest, collaborative filtering, deep learning models, deep convolutional networks and other algorithms to elaborate on its application, describing the important role played by machine learning technology in the commercial field. It describes the important role that machine learning technology plays in the commercial field, and makes an outlook assessment of the future development of this technology. Data science and related computer technologies are used frequently and with great importance in the production of recommendation systems when shopping. Different countries are also looking at this as a hot technology and are actively exploring and developing algorithms for it.

1 INTRODUCTION

The rise of e-commerce has changed people's consumption patterns, an increasing number of individuals switch from offline shopping to online shopping, placing orders and making payments through the Internet. Today's Internet users have access to a wealth of information because of the growth and popularisation of the Internet industry, their demands for information are met. However, users have to face the excessive amount of information and they cannot get the information that is really useful for them, the efficiency of the use of information has been reduced. With the increase in the variety and number of products, users will browse a lot of unwanted products. How to help users find the products they need quickly and enhance user viscosity is the focus of many online shopping malls in the face of the globalisation of technology and networking. In this context, personal recommendation system, which recommends information, products, etc. based on the user's information needs, interests, etc. A smart recommendation system not only provides personalised services to users, but also builds a close relationship with them so that they become reliable on the recommendations.

Big data recommendation algorithms first originated in Europe as a systematic optimization of hadoop algorithms. Joldzic worked on large datasets on Hadoop clusters Pessemier started working on recommendation algorithms on Hadoop systems and Mapreduce frameworks in 2011 distributed processing and recommendation modeling research. Currently, research on big data recommender system algorithms in various countries focuses on collaborative filtering algorithms, high-performance computing recommendations, hybrid recommendations, and algorithmic combinations. However, in terms of research areas, the focus varies from country to country. In China, researchers focus on further optimization of the algorithm itself. Such as relationship trustworthiness, user nearest neighbor, matrix analysis, BP neural network, etc. Other countries have focused more on the use of recommender systems. There are a wide range of applications, such as healthcare, online education, social networking services, and recommender systems are particularly popular for e-shopping.

[a] https://orcid.org/0009-0009-5469-1197

Xiong, X.
The Progress of Shopping Recommendation System Based on Machine Learning Algorithms.
DOI: 10.5220/0012910800004508

In *Proceedings of the 1st International Conference on Engineering Management, Information Technology and Intelligence (EMITI 2024)*, pages 110-114
ISBN: 978-989-758-713-9

This paper is dedicated to the application of recommender systems in the field of shopping in a globalized environment, in which in the first part, this article introduces the research background of big data analytics technology and its specific application in the shopping field, the current research status of recommender system algorithms in various countries, and then in the second part, it describes the introduction of various algorithms, such as machine learning, and the way they are applied in shopping recommender systems.

2 METHOD

Machine learning encompasses myriad applications, ranging from high-performance implementations such as artificial neural networks, random forests, to support vector machines. To further elevate the efficacy of these models, advanced deep learning methodologies like deep neural networks, residual neural networks, and deep forests have been concurrently developed and implemented.

2.1 Machine Learning

The realm of machine learning revolves around the exploration of ways computers can imitate or replicate human learning behaviors, enabling them to absorb new knowledge or skills, in addition to reorganizing existing knowledge structures, thereby facilitating improved performance over time. The traditional applicability of machine learning algorithms to small datasets is challenged by the sheer volume and the intricate characteristics of big data. Thus, machine learning algorithms hold immense scholarly significance, being of immense relevance in both the academic and industrial spheres. Consequently, the investigation of machine learning algorithms within the ambit of big data has surged in popularity in both scholastic and commercial domains.

2.1.1 Random Forest

Random Forest (RF), a central pillar of statistical learning theory, utilizes the bootstrap resampling method that extracts multiple specimens from the original data sample. Subsequently, decision tree modeling is employed on each bootstrap sample. The predictions derived from various decision trees are aggregated to generate a final prognosis through a voting mechanism. In the context of the independent variable X, each decision tree classification model nominates the optimal classification outcome. Thereby, the RF model comprises a composite classification model, assembled from a multitude of decision tree classification models. In the arena of economic management, RF finds substantial utility, particularly in forecasting potential customer attrition. For instance, when employed in the domain of customer relationship management, RF demonstrated superior efficacy (Lariviere, 2005). Further research suggested that Weighted Random Forests eclipse standard RF in terms of predictive capabilities, especially in the context of AUC metrics (Burez, 2009). Beyond customer churn predictions, RF has been deployed successfully in customer loyalty forecasting. For example, Buckinx et al. advocated the integration of customer loyalty predictive values within a customer transaction database, and evaluated the predictive capacities of multiple linear regression, RF, and ANN (Buckinx, 2007).

2.1.2 Collaborative Filtering

The concept of "collaborative filtering" found its origin in the mid-1990s when Goldberg and his associates coined the term during the development of their recommendation system, Tapestry (David, 1992). Since then, this method has been the subject of extensive research and wide-ranging applications. Collaborative filtering is founded on the basic assumption that users A and B, who exhibit similar historical annotation patterns or behavioral habits (such as purchasing habits, reading preferences, film choices, etc.), are likely to share similar interests on other items. Generally, collaborative filtering techniques employ a database to record users' historical annotations, which is then leveraged to predict user interests and offer personalized recommendations. Amazon, a pioneering online bookstore with no physical storefront, exemplifies excellent use of collaborative filtering. It offers an extensive database and a sophisticated search system that allows users to conveniently look up book information online. Users can add chosen books to a virtual shopping basket, review their selected products, choose their preferred service, and place their order, thereby receiving their purchases at home within a few days. Amazon's advanced personalized recommendation function stands out, enabling it to suggest books attuned to the diverse interests and preferences of its users. This recommendation software examines the books purchased by a reader, as well as their evaluation of other books, to suggest new books that the reader might like. Amazon's system can analyze past purchases to make tailored suggestions, saving customer information to allow for more personalized suggestions during future visits. Furthermore, Amazon's stellar post-sales service adds to its appeal. Within 30 days of purchase, customers can return their purchases in good condition to Amazon for a full refund of the original price. Upon return visits to the site, Amazon greets customers by name, enhancing their online shopping experience.

2.2 Deep Learning

Deep learning, within the realm of signal processing, has wide-ranging applicability, extending beyond sounds, images, and videos to encompass text, language, and the transmission of semantically enriched information that humans can interpret. In the domain of voice recognition, traditional Multilayer Perceptrons (MLPs) have been utilised for an extended period. However, standalone MLPs significantly underperform compared to systems that employ the Gaussian Mixture Model-Hidden Markov Model (GMM-HMM). A breakthrough has been observed in the challenge of large vocabulary continuous speech recognition (LVC-SR) with the innovative application of deep learning techniques. This evolutionary leap is attributable to the amalgamation of Hidden Markov Models (HMMs) leveraging sequence modeling expertise, and Deep Belief Networks (DBNs) offering robust discriminative capabilities (Dahl, 2011). Further advancements were signaled by the efficient binary coding of speech spectrograms using a deep auto-encoder (Deng, 2010). This development further emphasizes the extensive possibilities of deep learning in signal processing.

2.2.1 CNN

A Convolutional Neural Network (CNN) is a specialized artificial neural network designed to process two-dimensional input data. Within a CNN, each layer comprises numerous two-dimensional planes, with each plane consisting of multiple independent neurons. Neurons in two adjacent layers are interconnected, while there are no connections among neurons within the same layer. By employing fewer network linkages and weight parameters compared to fully connected networks of comparable dimensions, CNNs effectively reduce the learning complexity of network models, rendering them simpler to train. A significant application of CNNs can be seen in YOLO (You Only Look Once), which approaches object detection as a regression problem (Redmon, 2015). The YOLO model uses a CNN structure with 24 convolutional layers and two fully connected layers. It inputs the entire image and divides it into 7*7 grids, predicting encapsulating boxes and their class probabilities via CNN. YOLO has the advantage of minimal background error and high detection speed, capable of processing 45 images per second on a Titan GPU. Another intriguing application of CNNs is in the Faster R-CNN (Ren, 2016). It combines the Fast R-CNN (Girshick, 2015) with a region proposal network, sharing a convolutional layer feature network, thereby improving object detection speed and accuracy. Furthermore, CNNs have been employed for image fusion (Li, 2016), short text clustering (Xu, 2015) and in numerous other domains.

3 DISCUSSION

3.1 Feature Extraction

While techniques for automatic feature extraction for text information are fairly advanced, the extensive amount of information available on the internet is shared in multimedia formats. Recommending solely textual information falls short in satisfying user needs. Progress in multimedia information recommendation research has been gradual, primarily due to the constraints of automatic feature extraction technology for such information. Presently, multimedia information recommendations are often generated based on manual annotations by users, a process that also faces the issue of overfitting when recommending text-based information. Hybrid recommendation methods can bolster the diversity of content-based recommendations, addressing these challenges.

3.2 Scalability Problems

When user numbers for a commercial recommender system escalate into millions or even tens of millions, scalability problems pose a significant challenge for the recommendation algorithm. Many online recommendation platforms necessitate swift provision of recommendation results to users, which imposes stringent expectations for the timeliness of recommendations. Regrettably, most extant recommendation algorithms lack scalability. Some relief from scalability challenges can be achieved by employing strategies such as dimensionality reduction, clustering, and classification. For instance, dimensionality reduction techniques like Singular

Value Decomposition (SVD) can compress matrices and yield improved recommendation results. However, matrix decomposition is time-consuming. Algorithms like the nearest-neighbor-based KNN (Deshpande, 2004), which considers only the closest neighbors exhibiting the highest similarity to a target user, can somewhat decrease the time overhead of the recommendation process. Users are categorized based on their preferences, allowing for recommendations to be based predominantly on users sharing similar preferences with the target user. Model-based collaborative filtering (CF) algorithms, like clustering collaborative filtering algorithms categorize users by their preferences (Conno, 1999; Sarwar, 2002), factoring in only users from the same category as the target user during the recommendation process. These methods can navigate scalability issues, bolstering the performance and utility of recommender systems.

3.3 Data Sparsity Problem

Data sparsity poses a major challenge for effective recommender systems. Collaborative filtering recommendation algorithms rely heavily on user-item rating matrices, but these matrices are typically sparse, leading to potential inaccuracies in generated recommendations. This problem is compounded when new users enter the system. Due to a lack of rating data for such users, the generation of personalized recommendations becomes challenging, a predicament known as the cold start problem. Dimensionality reduction techniques offer a common solution to this issue (Bilus, 1998). These methods compress matrices - for instance, through the use of singular value decomposition to eliminate unimportant or noisy users and items, thereby reducing the dimensionality of user-item rating matrices. Latent indexing techniques are also used to project users' dimensions into a lower latitude space, facilitating the calculation of user similarities. Another viable solution to mitigate data sparsity is to generate recommendations based on social data. This approach leverages existing data, thereby enabling fuller and more accurate user profiles for recommendation generation (Bilus, 1998; Canny J, 2022)

3.4 Other Issues

Besides the central challenges, recommender systems grapple with additional issues such as privacy concerns (Feng, 2006). Many users are hesitant to share their ratings or historical browsing data. The resolution to this issue lies in enhancing the trustworthiness of recommender systems and designing systems that safeguard users' private data. Furthermore, when introducing recommendations to users, it's crucial to provide a justification for the recommended product (Herlocker, 2000). For instance, Amazon furnishes users with reasons like "recommended for you because you browsed/bought this". However, a significant number of present recommendation algorithms fall short in providing satisfactory rationales for their recommendations.

4 CONCLUSIONS

The study reviews pertinent algorithms, scrutinizes their strengths and weaknesses, delves deeper into commonly employed strategies for scoring and similarity computations in recommendation algorithms, and encapsulates the evaluation criteria and methodologies typically used for assessing recommendation algorithms. Though recommendation technology has seen substantial advancements over the last two decades, it still falls short of an all-encompassing resolution to the core issue. As the scope of application domains expands, recommender systems will grapple with fresh demands and challenges. Investigations in intelligent information processing realms, such as information retrieval, remain focused on devising recommender solutions for the aforementioned problems. This is because the evolution of recommender systems and the challenges they face remain inherently intertwined.

REFERENCES

Bilus D, Pazzani M, 1998, Learning collaborative information filters. Process of International Conference on Machine Learning, 46-54.

Buckinx W, Vverstraeten G, Poel D V D, 2007, Predicting customer loyalty using the internal transactional database. Expert Systems with Applications, 32(1).

Burez J, Poel DV D, 2009, Handling class imbalance in customer churn prediction. Expert Systems with Applications, 36(3).

Canny J, 2022, Collaborative filtering with privacy via factor analysis. Process of the 25th International ACM SIGIR Conference on Research and Development in Information Retrieval, 238-245.

Connor M O, Herlocker J L, 1999, Clustering items for collaborative filtering. Process of the ACM SIGIR Workshop on Recommender Systems.

Dahl G E, et al., 2011, Large vocabulary continuous speech recognition with context-dependent DBN-HMMs. Proc of IEEE International Conference on Acoustics, Speech and Signal Processing, 4688-4691.

Deng L, et al., 2010, Binary coding of speech spectrograms using a deep auto-encoder. Proc of the 11th Annual Conference of International Speech Communication Association, 1692-1695.

Deshpande M, Karypis G, 2004, Item-based top-N recommendation algorithms. ACM Transaction on Information Systems, 22(1): 143-177.

Feng Z, Huiyou C, 2006, A study on privacy preserving collaborative filtering recommendation based on distributed data. Journal of Computing, 29(8): 1487-1495.

Girshick R, 2015, Fast R-CNN. Proceedings of the 2015 IEEE International Conference on Computer Vision. Santiago, Chile.

Goldberg D, Nichols D, Oki BM, Terry D, 1992, Using collaborative filtering to weave an information tapestry. Communications of the ACM, 12.

Herlocker JL, Konstan JA, Riedl J, 2000, Explaining collaborative filtering recommendations. Process of the ACM Conference on Computer Supported Cooperative Work.

Lariviere B, Poel DVD, 2005, Predicting customer retention and profitability by using random forests and regression forests techniques. Expert Systems with Applications, 29(2).

Li H, Liu F, Yang S Y, et al., 2016, Remote sensing image fusion based on deep support value learning networks. Computers, 39(8): 1583-1596 (in Chinese).

Redmon J, Divval S, Girshick R, et al., 2015, You only look once: Unified, real-time object detection. arXiv:1506.02640v5.

Ren S Q, et al., 2016, Faster R-CNN: Towards real-time object detection with region proposal networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, doi:10.1109/TPAMI.2016.2577031.

Sarwar B M, Karypis G, Konstan J A, et al., 2002, Recommender systems for large-scale e-commerce: Scalable neighborhood formation using clustering. Process of the 5th International Conference on Computer and Information Technology.

Xu J M, et al., 2015, Short text clustering via convolutional neural networks. Proceedings of the NAACL-HLT 2015. Denver, USA, 62-69.