Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 10, No. 3, 2023

A Novel TCM Prescription Recommendation Method based on Attention Factorization Machines

Wenxuan Xu, Qingtao Wu

School of Information Engineering, Henan University of Science and Technology, Henan 471023, China

Abstract: A prescription recommendation algorithm for attention factorization machines is proposed in this study. This algorithm leverages the pair-wise interaction of factorization machines to capture the multi-category attributes of patients and prescriptions. Additionally, an attention network is incorporated into the factorization machine to assign higher weights to the effective features within the prescription. This enables the algorithm to discern the importance of different combinations of features in the prescription, thereby enhancing the recommendation performance of the model. Through extensive experimentation, it is observed that the prescription recommendation model based on attention factorization machines does not rely on manual features and exhibits commendable recommendation performance. Furthermore, it achieves a certain degree of individualized recommendation effect.

Keywords: Attention Factorization Machines; Factorization Machines; Prescription Recommendation; Attention Network.

1. Introduction

Traditional Chinese Medicine (TCM) is an ancient medical practice that embodies fundamental distinctions in essence, methodology, and philosophy compared to modern medicine. Over the course of millennia, TCM has played an indispensable role in the treatment and prevention of diseases within China and has increasingly garnered attention and utilization in Western countries[1]. Notably, TCM's approach to disease treatment does not conform strictly to the conventional model of matching specific diseases with corresponding remedies. Instead, it employs a system whereby different diseases yielding similar symptoms are addressed with the same TCM prescription. Prescriptions, in this context, denote a compilation of diverse Chinese herb medicines. Throughout our nation's extensive history, numerous treatment prescriptions have been devised and meticulously documented, resulting in a repository of over 100,000 distinct formulations. The transmission and perpetuation of Traditional Chinese Medicine serve as a conduit for the preservation of the cultural and historical heritage of the Chinese nation across millennia. Moreover, TCM boasts an array of distinctive diagnostic and therapeutic methodologies, as well as noteworthy clinical efficacy. The constituent elements of Chinese herb medicines within these prescriptions, alongside their corresponding treatment methodologies, hold paramount importance in terms of clinical outcomes and the development of novel pharmaceutical interventions[2, 3].

In the long history of development, Chinese medicine has amassed an extensive body of literature and treatment records. Among the various forms of Traditional Chinese Medicine (TCM) treatment, the composition of prescriptions using Chinese herb medicine stands out as the most significant. Referred to as "rational prescription medicine," the diagnostic process of TCM holds utmost importance in clinical practice[4, 5]. Rational prescription medicine encompasses principles, methods, prescriptions, and Chinese herb medicines. It delineates the three fundamental steps of diagnosis and treatment: identifying the cause and treatment based on symptoms, and ultimately selecting the appropriate prescription and medicinal materials for treatment. The process of prescription involves the combination of herbs, whereby two or more Chinese herb medicines are harmoniously paired based on the clinical condition and nature of the herbs. By incorporating TCM principles, this combination enhances the therapeutic effect while mitigating potential side effects. An integral aspect of herb combinations lies in herb pairs, which are distinct combinations of two specific herbs and represent the most fundamental and straightforward method of herb coordination[6, 7]. Herb pairs serve as the foundational units in prescription formulation. For instance, as illustrated in Fig.1 from the book Dictionary of Traditional Chinese Medicine Prescriptions, the combination of Chinese Ephedra Herb and Cinnamon Herb induces sweating. Utilizing only one of these herbs would considerably diminish the sweating-inducing effect. Similarly, in numerous prescriptions for repelling cold, the combination of appendages and dried ginger is consistently employed in unison.

Prescription Name:	Ephedra Decoction
Source:	Treatise on Febrile Diseases
Composition herbs & dosage:	Ephedra 9g, Cassia Twig 6g, Apricot seed 6g, Liquorice root 3g.
Usage:	Decocted in water for oral dose
Indication symptoms:	Exogenous wind cold, aversion to cold with fever, headache and body pain, asthma without sweat, white and thin coating of the tongue, floating and tense pulse

Fig. 1 The structure of the model

Throughout the extensive historical trajectory of Traditional Chinese Medicine (TCM), numerous eminent TCM researchers and practitioners have documented diverse treatment methodologies in the TCM classics[8]. In practical applications, TCM physicians frequently consult these revered records while prescribing treatments to patients. This inspired us to propose a model capable of automatically generating prescriptions by acquiring knowledge from these classical texts. In recent years, the burgeoning field of "artificial intelligence + medical treatment" has witnessed remarkable progress, thanks to the convergence of image processing, pattern recognition, deep learning, and other AI technologies[9, 10]. This interdisciplinary approach not only addresses the demands of contemporary societal needs but also serves as a vital conduit for reviving ancient Chinese medicine in the era of scientific and technological advancement.

Currently, the prevalence of recommended Traditional Chinese Medicine (TCM) prescriptions is observed among TCM practitioners. A proposed method by Li et al.[11] introduces an automated approach to generate TCM prescriptions based on textual testimonials from recommended prescriptions. They employ a sequence-to-sequence model to explore an end-to-end solution for TCM prescription generation. Another study by Zhang et al.[12] presents a prescription recommendation algorithm for lung cancer treatment using a complex network. The algorithm aims to identify core drugs for lung cancer treatment, aiding patients in alleviating their condition. However, both studies deviate from the diagnostic process of TCM prescriptions by solely relying on evidence, leading to a diminishing inheritance of recommended TCM prescriptions. Furthermore, the arrangement of medicinal materials in prescriptions lacks organization, characterized by a "weak order" where the effects of medicinal materials are not influenced by their order. However, the order of herbs in a prescription reflects the mindset during prescription structuring, indicating their interrelation and prioritization. The absence of digitization and standardization has hindered the recognition of Chinese medicine in the artificial intelligence community.

The application of TCM prescription recommendations to the Factor Machine (FM) model enhances the intelligent development of TCM informatization. To advance the automatic generation of TCM prescriptions, this study collected numerous prescriptions and corresponding treatment descriptions from classical TCM data. An Attention Factorization Machine (AFM)[13] was employed to depict the process of TCM prescription production. The prescription recommendation model, using prescriptions from classical TCM books as an example, reflects TCM prescribing patterns, aiding TCM physicians in prescribing and pharmaceutical companies in determining the combination of TCM materials to use. The intelligent technology recommended by TCM prescription holds immense significance for the development and preservation of TCM. By employing artificial intelligence, it investigates the treatment-prescription relationship, accurately extracts its characteristics, and conducts multidimensional quantitative analysis, rendering it more scientific, objective, and systematic. Utilizing deep learning techniques to enhance the accuracy of TCM diagnosis has emerged as a superior and novel approach, making it increasingly favored[14]. However, it is important to note that this study aims to generate candidate prescriptions to promote the intelligence of TCM prescriptions, rather than entirely replacing TCM physicians, considering the real-world context.

2. TCM Prescription Recommendation Model

2.1. Model Application Scenarios

Chinese medicine, with its profound cultural and historical heritage spanning thousands of years, encompasses a diverse range of treatment methods that have consistently exhibited significant clinical efficacy. In the context of today's rapid advancements in artificial intelligence (AI)[15-17], there lies a remarkable opportunity to synergize computer technology with the theoretical knowledge of traditional Chinese medicine. By leveraging this integration, computers can assume the role of eminent physicians, thereby imparting personalized prescriptions to patients through the meticulous selection of legally prescribed remedies. This innovative approach holds tremendous potential to enhance the diagnostic efficiency of traditional Chinese medicine practitioners, as validated by their esteemed certifications. The incorporation of a TCM auxiliary diagnosis and treatment system presents a breakthrough solution that significantly bolsters the diagnostic capabilities of TCM doctors. By doing so, it facilitates the digitization and intelligent preservation of the diagnostic and treatment experiences of venerable and renowned TCM practitioners. This forward-thinking initiative assumes great strategic importance in the pursuit of a healthy China and the establishment of a global community focused on human well-being.

2.2. TCM Prescription Recommendation Model

The Attention Factorization Machine (AFM)-based model for Traditional Chinese Medicine (TCM) prescription recommendation addresses the issue of sparsity in TCM prescription characteristics and treatment diagnostic information following coding. By leveraging the embedding layer and two feature intersection layers, this model enables automatic cross-combination of features, facilitating effective integration of prescription features and the patient's personal information characteristics, all while considering the prescription recommendation task. Consequently, it derives weights for cross-features, determining their significance, and employs an attention network to assign higher weights to valuable cross-characteristics of TCM prescriptions and patients' personal information. Through this approach, the proposed model identifies cross-characteristics that play a prominent role in target prediction, thereby eliminating noise and extraneous information. Given the intricate nature of Chinese medicine prescription drugs and the individual variations observed among patients, the AFM model proves particularly advantageous for intelligent prescription recommendation in Chinese medicine. This advancement contributes to the enhanced intelligence of Chinese medicine diagnosis and treatment.

In herb medicine prescribing recommendations, the dataset comprises patient information, treatment data, and prescription data, which are utilized for model training. Traditional Chinese Medicine (TCM) prescribing data encompass various types of features, including multi-feature category disordered features (e.g., treatment), binary features (e.g., gender), and continuous features (e.g., age). These features, once one-hot encoded, result in high sparsity and dimensionality. Consequently, learning the interactions between key features and training models becomes challenging. To address this issue, a feature domain structure is introduced wherein different features are allocated to specific domains. For instance, the rule of law is assigned to one domain, while age is assigned to another domain. By employing this approach, the weighted interactions between each feature can be effectively learned without the need for feature engineering.

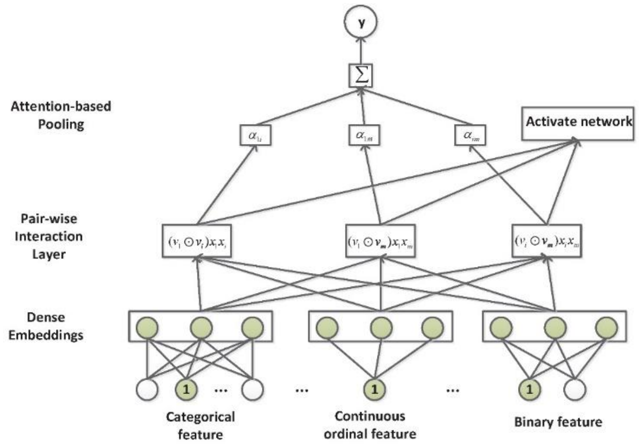

Fig.2 The structure of the model

As depicted in Fig.2, the prescription recommendation text dataset is inputted into the square recommendation model. This model represents the recommended feature category associated with the prescription. Upon passing through the embedding layer, the embedded feature vector for each feature domain is obtained, ensuring consistent vector dimensions. The second-order feature vectors undergo processing in two two-feature interaction layers, where the feature vectors are crossed in pairs to generate second-order feature terms. Simultaneously, each second-order feature vector is incorporated into the attention network's pooling layer, resulting in the output of weight values for each feature vector. These weight values are then used to compute the synthesis of all feature information through the weighted pooling layer. Finally, the synthesized feature vector is inputted into the fully connected layer.

In the embedding layer, data undergoes vector transformations. The training set consists of n data samples. The original feature vector x encompasses m categories, including disordered features (e.g., treatment), binary features (e.g., gender), and continuous features (e.g., age). In the case of Chinese medicine prescription recommendation data, the multi-field classification approach is commonly employed. Each original prescription feature is treated as a separate field, and the original input prescription dataset is uniquely encoded. Binary classification features, such as gender, are encoded using one-hot coding. Unordered feature fields are encoded using a combination of one-hot coding and concatenation, which avoids intermittent feature cross within the same domain and reduces irrelevant interactions. Continuous features are represented by their respective values. For instance, consider the following example: [gender = female, age = 28, treatment = Li Qi and Zhong, prescription = Xiang Su San, medicinal herb one: Su Ye 120g, medicinal herb two: Xiang Fu 120g, herb three: tangerine peel 60g, medicinal herb FOUR: licorice 30g, ...]. This paper converts TCM prescription information into high-dimensional sparse features using a unique one-hot encoding method.

Given the dataset's diverse nature in the prescription of traditional Chinese medicine, consisting of multiple categories such as classification, binary, and other multi-feature categories, several steps are taken to process the data. After applying one-hot encoding to thousands of medicinal material names and assigning unique codes to their corresponding material IDs, an embedding layer treatment follows. It is observed that simple splicing fails to capture sufficient information. To address this, the Factorization Machine (FM) incorporates pairwise interactions into the linear model. This enables automatic pairwise interactions between prescription characteristics and the patient's personal information, essential for the prescription recommendation task. FM calculates the weights of these cross-characteristics, which are expressed discretely as follows:

$$y_{FM}(x) = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} w_{ij} x_i x_j$$

Where n is the number of sample features encoded by one-hot, x_i is the value of the i feature, and x_j is the value of the first j feature. In this study, the second-order parameter w_{ij} of Chinese medicine prescription is decomposed by matrix decomposition, and for each user treatment information and prescription, a hidden vector can be used to represent it. Thus the implicit vector corresponding to x_i corresponds to the implicit vector v_i, the inner product of v_j is equal to the cross term coefficients of x_i and x_j, represents the length of the hidden vector, and the sparse w_{ij} is the second-order cross term diluted by matrix decomposition as:

$$w_{ij} = < v_i, v_j > = \sum_{f=1}^{k} v_{if} v_{jf}$$

Therefore, by training the model to obtain the coefficient of interactive feature terms of traditional Chinese medicine treatment information and prescription information, the expression of FM can be rewritten as:

$$y_{FM}(x) = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} < v_i, v_j > x_i x_j$$

This paper uses an embedding layer to convert it into a dense vector and then feed it into a neural network for training. The advantage of using the embedding layer is that you can get the weights corresponding to the non-zero elements according to the form of the lookup table, and add them together, which will work better. The weight obtained by embedding the layer is the weight corresponding to a position in the single heat vector. The sum of the non-zero feature sets in the input eigenvector x is χ , and the output of the TCM prescription recommendation model embedding layer is:

$$a = [e_1, \cdots, e_m] e = \{v_i x_i\}_{i \in \chi}$$

This model inputs the output result of the embedding layer a into the two feature intersection layers of AFM, and this study uses two feature interaction layers to compress n feature vectors to $n(n-1)/2$ cross vectors, any two cross vectors are the elemental product between the two vectors of patient information and prescription, which is used to encode the interaction of chinese medicine prescription features.

AFM model adds attention networks to learn the weighted characteristics of user information and medicinal material information in prescriptions, and learns the weight scores of the weighted features for recommendation. Because in actual recommendations, not all feature interactions contribute equal value to recommendations, attention mechanisms are introduced to capture the significant structure of the data, thereby extracting feature crossovers that are important to the recommendation model. Attention models can also be thought of as weighted averages of output. The TCM prescription recommendation model takes the patient information and prescription information output vector of the two-two interaction layer as shown in Fig.2. $< v_i, v_m > x_i x_m$ as the attention unit input vector, and returns a vector based on the attention score, which is the input vector weighted arithmetic average, and selects the weight according to the importance of each element in the vector. α_{ij} is the feature interaction weight processed by the attention network, which indicates the degree to which different combinations of features contribute to the final prediction? Therefore, this model retains only the important parts of the feature interaction. The TCM prescription recommendation model lacks the ability to estimate the attention value of cross-features that were not present during training. To address this issue, the model employs perceptrons to parameterize attention, thereby constructing an attention network. The Attention Network learns weights through the utilization of the following formula in its formula:

$$a_{ij1} \leftarrow h^T \sigma(W(v_i \odot v_j)x_i x_j + b)$$

$$a_{ij} \leftarrow \frac{\exp(a_{ij1})}{\sum\limits_{i=1}^{m}\sum\limits_{j=i+1}^{m}\exp(a_{ij1})}$$

Where σ represents the activation function Relu, $W \in R^{t*k}, b \in R^t, h \in R^t$ is the parameter of the model, and t represents the number of attention hidden layer neurons, which is obtained through network optimization.

$$y_{AFM}(x) = w_0 + \sum_{i=1}^{m} w_i x_i + P^T(\sum_{i=1}^{m}\sum_{j=i+1}^{m} \alpha_{ij} < v_i \odot v_j > x_i x_j)$$

The aforementioned algorithm successfully concludes the training process for the Chinese medicine prescription recommendation model, resulting in the generation of a probability set representing the best recommended prescription. Subsequently, the healthcare professional is responsible for carefully selecting the prescription that best suits the needs of the patient.

Drawing upon the Attention Factorization Machine technique within the framework of the Traditional Chinese Medicine (TCM) prescription recommendation model, the input data undergoes preprocessing through the utilization of unique thermal coding in the embedding layer. This preprocessing step facilitates the grouping of features with similar characteristics into coherent scenes, guided by the incorporation of the concept of a scene domain. Consequently, this approach effectively mitigates the issue of feature overlap and the convergence of irrelevant features during subsequent stages. Consequently, the problem of disorderly features during the recommendation process is significantly alleviated, resulting in a notable reduction in the time complexity of the TCM prescription recommendation model. Furthermore, this enhancement also contributes to an improvement in the accuracy of prescription recommendations.

2.3. Model Design and Analysis

The procedural flow of the algorithm for recommending traditional Chinese medicine prescriptions based on deep crossed neural network is presented in the table below. The algorithm's output comprises the prescription for traditional Chinese medicine treatment, encompassing medicinal materials and dosages. This approach transforms high-dimensional sparse features of prescriptions and medical records into lower-dimensional consistent features. These features are then combined and inputted into the residual layer for residual operation, maximizing the utilization and preservation of the original features. Ultimately, the fully connected layer is employed to calculate the probability of prescription recommendation.

The present study introduces an algorithm, denoted as Algorithm 1, for recommending Traditional Chinese Medicine (TCM) prescriptions based on the Attention Factorization Machine. In order to perform an effective evaluation, the name set of TCM treatment methods is divided into two sets: the training set and the test set. These sets primarily consist of patient personal information data and treatment names. The labeling of prescription information corresponding to the Chinese medicine treatment method is carried out based on the diagnosis results provided by Chinese medicine practitioners. The labeled data is further divided into the training label set and the test label set.

To begin, a vector representation of a sample is extracted from the Chinese medicine prescription dataset. The second-order cross-term of the factor decomposition machine is employed to perform a cross-combination of the patient's multi-category attributes and the prescription attributes. Notably, the attention network assigns higher weights to the effective features within the prescription. This process helps to discern the relative importance of different combination features in the prescription. By utilizing gradient descent optimization, a convolutional neural network is trained to obtain the final structure of the TCM prescription recommendation network. Similarly, the accuracy of the TCM prescription recommendation algorithm is evaluated by utilizing the TCM prescribing test set and the corresponding diagnostic results of TCM prescriptions.

Algorithm 1 TCM prescription recommendation algorithm

Input: TCM Therapeutic name *x*
Output: Therapeutic prescription corresponding to Therapeutic name
1: **while** *input Therapeutic name vector* **do**
2: *one-hot coding was used to process the input text of TCM therapeutic*
3: *The input feature of the prescription recommenda model embedding layer is* $e \leftarrow \{v_i x_i\}$
4: **if** e not null **then**
5: *FM algorithm is used for further feature processing of feature set*
6: $y_{FM}(x) \leftarrow w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} < v_i, v_j > x_i x_j$
7: **end if**
8: *Matria decomposition is used to transform treatm to – prescription features into low - dimensional dense features*
9: $w_{ij} \leftarrow < v_i, v_j >$
10: *The attention mechanism extracts the cross - features of the recommendatio -n model and calculates the attention weight* $a_{i,j}$
11: **for** i < Number of interaction vectors **do**
12: $a_{ij1} \leftarrow h^T \sigma\left(W\left(v_i \odot v_j\right) x_i x_j + b\right)$
13: **end for**
14: $a_{ij} \leftarrow \frac{\exp\left(a_{ij1}\right)}{\sum_{i=1}^{m}\sum_{j=i+1}^{m}\exp\left(a_{ij1}\right)}$
15: *The recommended prescription information was obtained by converting the recommendation results into probability output.*
16: *The cross-entropy loss function with a L2 regularizationt term is regarded as the network optimization function.*
17: **end while**

3. Experiments and analysis

3.1. Experimental Data

This study conducts experiments on Traditional Chinese Medicine (TCM) prescription datasets. Classical books are utilized to train prescription datasets, evaluating the accuracy of the algorithm and comparing the results with experimental findings. The aforementioned classical books consist of 23 treatment methods, over 400 treatment sub-categories, and a total of 4174 commonly used Chinese medicine material names, doses, sources, and related information. Moreover, more than 900 classic formulas are included. The training and testing datasets encompass 21 categories of TCM prescription information characteristics, such as the patient's age, gender, pregnancy status, treatment details, prescription name, and medicinal materials. The ultimate objective is to provide prescription recommendations for patients. Additionally, the 11990 TCM samples, classified as positive and negative, are partitioned into training and test sets based on a predetermined ratio.

Prescription sentences containing "missing values" have an impact on the effectiveness of model recommendations. Consequently, it is crucial to reconstruct these features. In this study, the missing values of multi-category features are interpolated as -1, enabling their incorporation into the model by creating a new category.

The prescription recommendation model transforms the high-dimensional sparse features of Traditional Chinese Medicine (TCM) treatments into dense features by mapping the original features of the treatment name, prescription information, and patient's personal information data into an embedding vector. The embedding layer consists of a single neural network layer. TCM prescribing data includes disordered features from multiple categories (e.g., treatment), binary features (e.g., sex), and continuous features (e.g., age). This study distinguishes and encodes the TCM data features of each category. For instance, continuous data like patient age can be used directly with normalization treatment, while binary features like sex are encoded as [0,1] for female and [1,0] for male. The pre-processing of TCM prescription experiment data involves data cleaning, data conversion, and category coding. A list of numerical and categorical features is constructed, marking the corresponding features in the dataset. An input layer dictionary is created, which is returned as dense and sparse dictionaries. The sparse features are embedded and combined, and the resulting input layer and corresponding embedding layer are obtained. If the embedding list is directly imported into the fully connected layer, it needs to be flattened; otherwise, flattening is not required. Finally, the input data is converted into dictionary format, and the input model is prepared for use.

4. Experimental Settings

The hyperparameters of the network are typically adjusted based on the specific data. To optimize the performance of each model, a thorough investigation of the parameters was conducted. In this study, the TCM prescription recommendation model underwent supervised training with minimized prediction error. Since the TCM prescription recommendation model is a binary model, the logarithmic loss function serves as the commonly employed objective function.

Consequently, the logarithmic loss function recommended by TCM prescriptions was adopted as the objective function in this study. Furthermore, both the prescription recommendation model and the comparison model employed the same set of hyperparameters. The TCM prescription recommendation model utilized the rectified linear unit (Relu) as its activation function, set the dropout rate at 0.5, employed L2 regularization and dropout techniques to prevent overfitting, and employed Adam as an optimizer to adaptively adjust the learning rate. The primary experimental parameters are presented in the following Tab.1.

Tab.1 Main experimental parameters

Parameter Name	Parameter Value
batch-size	64
Dropout	0.5
rate	0.001
L2	0.01
Optimizer	Adam

5. Results and Discussion

In this paper, presents a comparative analysis between the TCM prescribing recommendation model proposed herein and two existing models, namely, Factorization-Machine based Neural Network (DeepFM) and Neural Factorization Machine (NFM), utilizing the TCM prescribing recommendation dataset. The objective is to evaluate the performance and effectiveness of the recommended models for TCM prescription. In order to facilitate a comprehensive understanding of the experimental outcomes, Fig.3 to Fig.6 display the results derived from the comparative analysis of the aforementioned models in terms of their TCM prescription recommendations. These figures provide valuable insights into the comparative evaluation, enabling a thorough assessment of the proposed TCM prescribing recommendation model in relation to the DeepFM and NFM models.

Fig.3 and Fig.4 present the training and test accuracies of three distinct methods. Upon examination of these figures, it becomes evident that the prescription recommendation model exhibits the most favorable performance. In comparison to the other two models, this study's model achieves a higher accuracy rate. Specifically, in the test set, the comparison models lack the ability to reflect category and level information as all features possess equal importance. It should be noted that not all feature interactions yield positive gains, and the inclusion of noisy features may even compromise the model's accuracy. In contrast, the AFM model assigns attention weights to individual features, allowing for the filtration of significant crossover features. Consequently, the model proposed in this study outperforms the other two comparison algorithms.

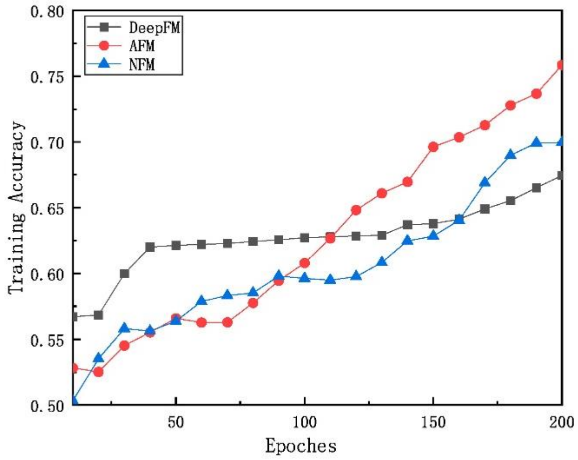

Fig.3 Accuracy of medical record training set

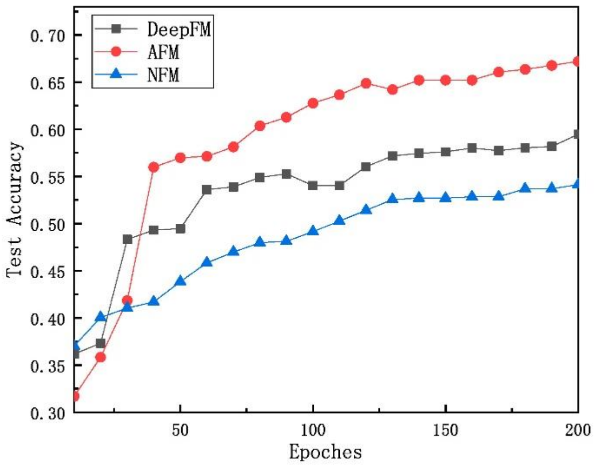

Fig.4 Accuracy of medical record test set

Fig.5 and Fig.6 display the training and test losses for three distinct recommendation methods, respectively. Setting the dropout rate to 0.5 enhances the generalization capability of both the model and the two alternative algorithms. Notably, the Attention Factorization Machine model outperforms the other contrasting algorithms. Furthermore, even without employing dropout, the recommended algorithm model proposed by this institution surpasses the factorization machine model, thereby highlighting the significance of the attention network in capturing feature intersections. These findings underscore the broader decomposition capability of the Attention Factorization Machine for handling unseen data.

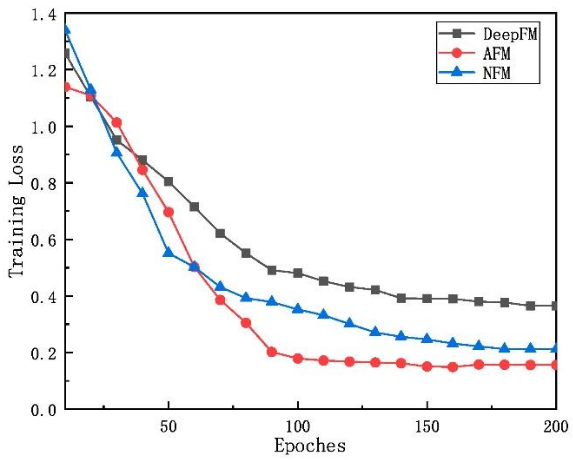

Fig.5 Loss of medical record training set

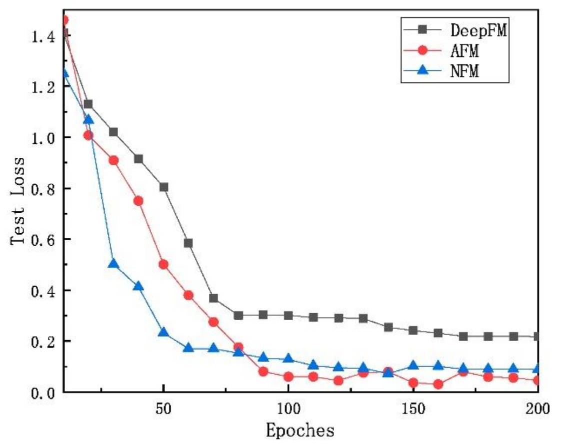

Fig.6 Loss of medical record test set

6. Conclusion

At present, as a result of significant advancements in data acquisition technology, algorithms, and integration techniques, the field of artificial intelligence (AI) in China has witnessed remarkable progress. However, when dealing with multidimensional data comprising continuous, categorical, and binary attributes, the task of feature engineering and training recommendation models becomes challenging. To address this issue, our research proposes a prescription recommendation model based on Attention Factorization Machine (AFM), which effectively applies AFM to local recommendation tasks and achieves promising outcomes. This model facilitates the recommendation of appropriate Chinese medicine treatments to patients. Nevertheless, AFM, being a complex neural network model, tends to exhibit overfitting and over reactivity when trained on specific datasets, thereby resulting in suboptimal performance. Despite incorporating L2 regularization and dropout techniques to mitigate these problems, experimental results demonstrate the persistence of overfitting issues. Therefore, the subsequent objective of this paper revolves around devising strategies to effectively resolve the overfitting problem encountered by the AFM model.

Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Data available statements

We establish medical record and clinical record dataset based on classical books. The dataset contains 6996 data items and 343 categories of diseases. There are more than 900 kinds of classic prescriptions, whose information consists of names, doses, sources and others of 4,174 commonly used Chinese medicinal materials.

The relative data sets and main code used to support the findings of this study have been deposited in the Github repository [https://github.com/lin-haust/TCM-prescription-datasets.git].

Acknowledgements

This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grants No. 62002102 and No. 62102134, and in part by the Key Technologies R\&D Program of Henan Province under

Grants Nos. 222102310565, 212102210088, No.212102210083, and in part by Henan Postdoctoral Foundation, and Foundation from the Postdoctoral Research Station of Control Science and Engineering at Henan University of Science and Technology, and in part by the Luoyang Major Scientic and Technological Innovation Projects under Grants No. 2101017A.

References

[1] K. Chen, and X. U. Hao. The integration of traditional Chinese medicine and Western medicine. European Review. Vol. 11 (2003) No. 2, p. 225-235.

[2] Y. Jaiswal, Z. Liang, Z. Zhao. Botanical drugs in Ayurveda and traditional Chinese medicine. Journal of ethnopharmacology. Vol. 194 (2016), p. 245-259.

[3] L. Hua, Y. Gao, J. Zou, et al. Reflections on treatment of COVID-19 with traditional Chinese medicine. Chinese medicine Vol. 15.1 (2020) , p. 94.

[4] S. X. Wang, Y. Wang, Y. B. Lu, et al. Diagnosis and treatment of novel coronavirus pneumonia based on the theory of traditional Chinese medicine. Journal of integrative medicine, Vol. 18 (2020) No. 4, p. 275-283.

[5] J. C. Pan, Y. T. Tsai, J. N. Lai, et al. The traditional Chinese medicine prescription pattern of patients with primary dysmenorrhea in Taiwan: a large-scale cross sectional survey. Journal of ethnopharmacology. Elsevier. Vol. 152 (2014) No. 2, p. 314-319.

[6] S. Wang, Y. Hu, W. Tan, et al. Compatibility art of traditional Chinese medicine: from the perspective of herb pairs. Journal of ethnopharmacology. Vol. 143 (2012) No. 2, p. 412-423.

[7] C. Y. Ung, H. Li, Z. Cao, et al. Are herb-pairs of traditional Chinese medicine distinguishable from others? Pattern analysis and artificial intelligence classification study of traditionally defined herbal properties. Journal of Ethnopharmacology. Vol. 111 (2007) No. 2, p. 371-377.

[8] F. Yu, T. Takahashi, J. Moriya, et al. Traditional Chinese medicine and Kampo: a review from the distant past for the future. Journal of International Medical Research. Vol. 34 (2006) No. 3, p. 231-239.

[9] H. Chen, Y. He. Machine Learning Approaches in Traditional Chinese Medicine: A Systematic Review. The American journal of Chinese medicine. Vol. 50 (2022) No. 01, p. 91-131.

[10] X. Chu, B. Sun, Q. Huang, S. Peng, Y. Zhou, Y. Zhang. Quantitative knowledge presentation models of traditional Chinese medicine (TCM): A review. Artificial intelligence in medicine. Elsevier. Vol. 103 (2020), p. 101810.

[11] W. Li, Z. Yang, X. Sun. Exploration on Generating Traditional Chinese Medicine Prescription from Symptoms with an End-to-End method. In: Natural Language Processing and Chinese Computing: 8th CCF International Conference, NLPCC 2019, Dunhuang, China, October 9–14, 2019, Proceedings, Part I 8. Springer International Publishing, 2019. p. 486-498.

[12] Y. Zhang, K. Hu, T. Yang, et al. Prescription recommendation algorithm for Traditional Chinese Medicine treatment of lung cancer based on complex networks. Journal of Traditional Chinese Medicine and National Medicine. Vol. 30 (2019) No. 5, p. 1257-1260.

[13] J. Xiao, H. Ye, X. He, et al. Attentional factorization machines: Learning the weight of feature interactions via attention networks. arXiv preprint arXiv:1708.04617 (2017).

[14] L. Yao, Y. Zhang, B. Wei, et al. A Topic Modeling Approach for Traditional Chinese Medicine Prescriptions. IEEE Transactions on Knowledge & Data Engineering. 2018, p. 1-1.

[15] X. Dong, Y. Zheng, Z. Shu, et al. TCMPR: TCM Prescription recommendation based on subnetwork term mapping and deep learning. In 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). 2012, p. 3776-3783.

[16] Z. Gong, N. Zhang, J. He. KGRN: Knowledge Graph Relational Path Network for Target Prediction of TCM Prescriptions. In International Conference on Intelligent Computing, 2021, p. 148-161.

[17] T. Liang, L. Zheng, L. Chen, et al. Multi-view factorization machines for mobile app recommendation based on hierarchical attention. Knowledge-Based Systems. Elsevier. Vol. 187 (2020), p. 104821.

[18] P. Wen, W. Yuan, Q. Qin, et al. Neural attention model for recommendation based on factorization machines. Applied Intelligence. Springer. Vol. 51(2021) No. 4, p. 1829-1844.

[19] Z. Wang, J. Ma, Y. Zhang, et al. Attention-over-Attention Field-Aware Factorization Machine. Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34 (2020) No. 04, p. 6323-6330.