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Recommendation of Healthcare Services Based on an Embedded User Profile Model

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ABSTRACT

In recent years, as the demand for senior care services has further increased, it has become more difficult to obtain matching services from the vast amount of data. Therefore, this paper proposes a service recommendation framework PCE-CF based on an embedded user portrait model. The framework accurately describes the elderly users through four dimensions—population, society, consumption, and health—and constructs the user portrait model by embedding tags. The embedded vector of each older man is learned through the deep learning model, and different feature groups are meaningfully expressed in the transformation space. In addition, location context and dynamic interest model are introduced to process embedded vectors, and users' service preferences are predicted according to their dynamic behaviors. The experiment results show that the PCE-CF framework proposed in this paper can improve the recommendation algorithm's efficiency and have higher feasibility in personalized service recommendations.

KEYWORDS

Multi-Modal Fusion, Neural Network Embedding, Service Recommendation, User Profile

INTRODUCTION

With the explosively increasing global old-age population, elderly care services have gradually become a key industry of social concern. Society's progress, especially the revolution and development of the Internet (Dana et al., 2022; Xiao et al., 2020a) and intelligent software (Xiao et al., 2018), has spawned a range of pension services, which has crucial impacts on older people's service selection. However, due to their particularity, the elderly group has some distinctive characteristics such as health problems, old knowledge structure, and unskilled operation of electronic products when surfing the Internet. Meanwhile, Web service recommendation is now being researched as one of the basic research topics in the SOC sector. Function-based Web service recommendation, social network-based Web service recommendation, and collaborative filtering Web service recommendation are the three categories of research in this field. Therefore, it is of great practical significance compared with other age groups to establish an efficient service recommendation system for the elderly to achieve precise service recommendations.

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A recommendation system (RS) is used to solve the problem of information overload through a large number of Web services (Dang et al., 2021). In particular, it searches for the most relevant content based on the user's specific preferences. Collaborative filtering is one of the most commonly used algorithms in traditional service recommendation systems (Xiao et al., 2020b), with the characteristics of simplicity and intuitiveness (Salhi et al., 2021). With the deepening of services research, recommendation algorithm based on user profiles can recommend services that suit customers requirements and preferences more. User profile builds different models aimed at different customers. Peng et al. (2018) presented a multi-view ensemble framework for constructing user profiles based on the data of grid users to identify the electric-change users accurately. Ahn & Shi (2009) developed a simple and low-cost movie recommendation system harnessing vast cultural metadata about movies existing on the Web and proved the potential of cultural metadata.

The pension industry should seize the opportunity to develop Internet+ and active use of Internet technology (Hairui, 2016; Trapp et al., 2022). However, the pension service recommendation's current development still has problems (Meng et al., 2020). Aiming at the elderly population, their objective conditions, including health status, consumption habits, and economic status, largely determine their demands. Current approaches have a series of difficulties in capturing the needs and interests of senior citizens. Besides this, although recommendation algorithms have had in-depth research in e-commerce, service recommendation in the pension industry is just at the beginning stage. There is an excellent need for pension industry-oriented research to capture the preference of elderly customers and recommend appropriate services for them.

This article proposes an embedded user profile model to mine the characteristics of elder age groups through four dimensions set in the aged service industry. Li & Zhang (2016) analyzed the demand characteristics of the elderly for pension services from the perspective of embedding. Applying deep learning techniques to recommender systems has gained momentum due to their state-of-the-art performances and high-quality recommendations (Huang et al., 2018). The framework the researchers propose builds the user profile model in label design and label embedding (Wang et al., 2021). Label embedding preserves the characteristics of older customers and converses the multi-modal data with complex data types from diverse data sources into unified vectors wisely (Sreevidya et al., 2022). In addition, the embedded user profile model also deals with the tricky problem of matrix sparse, which dramatically improves the efficiency of the service recommendation algorithm.

The main contributions of this paper are summarized as follows:

- Design labels for elder customers in four dimensions including demographic, society, consumption, and health, which expresses their characteristics accurately.
- Propose a PCF-CF framework based on the embedded User Profile Model, which converses the multi-modal data into unified embedded vectors in the way of embedding the designed labels into the neural network.
- Exploit the high dimensional vectors from the neural network and implement recommended top-N services in the data system generated for the elderly according to the statistical rules in the aged service industry.

BACKGROUND

Pension Service

Following the accelerated speed of population aging, there is a natural tendency for pension services to proliferate, which leads to a great amount of research about pension services. Hairui (2016) showed that the pension industry should seize the opportunity for the development of the Internet+ and active use of the Internet technology. Li & Zhang (2016) analyzed the demand characteristics of the elderly for pension services from the perspective of embedding. Hodge et al. (2017) analyzed the importance of online elderly care services in Australia's rural communities based on a case study in Clare, a small rural town in South Australia. Powell (2012) assessed the existing research evidence for personalization and described the conformance of the British community to the requirement of elderly customers.

Deep Learning-Based Recommendation

Deep learning, which is good at mining patterns from large amounts of data (Stylianou et al., 2022), has driven recent research work (Do et al., 2020; Rasmusen et al., 2022). There is also a significant amount of research work on deep learning-based recommendations. In a content-based recommender system, Cheng et al. (2016) proposed a Wide and Deep Learning Model which jointly trained wide linear models and deep neural networks in the use of multi-source heterogeneous data—to combine the benefits of memorization and generalization for recommender systems. Liu & He (2022) put forward a deep learning-based trust-aware recommendation initialization recommendation method, DLIR, which uses deep learning to learn a better vector of potential features of users and items. Li et al. (2021) proposed an effective multi-dimension attention convolutional neural networks (MACNNs) model to analyze customer review texts and predict the pension service quality. He et al. (2017) explored the use of deep neural networks based on collaborative filtering. Embedding models are extensively used in collaborative filtering-based recommendations. Grbovic et al. (2015) leveraged user purchase history determined from e-mail receipts to deliver highly personalized product ads to Yahoo Mail users using distributed representation. Dai et al. (2016) proposed a Recurrent Coevolutionary Feature Embedding Process, which combines a recurrent neural network (RNN) with a multidimensional point process model. Zhang et al. (2016) put forward Collaborative Knowledge Base Embedding (CKE) using hybrid deep learning and probability matrix decomposition model.

Service Recommendation

Previous work about personalized service recommendations (Yang et al., 2021) can be mainly classified into three types, user modeling, content modeling, and Filtering recommendation. Cai & Li (2010) obtained users' tags and used collaborative tagging to build a user profile model. The representations of user modeling are many and varied. Zhu et al. (2010) expatiated on the relation between user interest and access behavior based on vector space model and document vectorization and then introduced a user interest modeling algorithm. Yao et al. (2015) proposed UPPPCF, which builds a user model based on user preferences and project properties. In content modeling, ASWR extracted the user's functional interests and QoS preferences from their usage history (Kang et al., 2012), and many researchers extracted feature words of service content by natural language processing (Ahmet & Mattila, 2012; Meissa et al., 2021). The filtering recommendation mainly contains rule-based filtering, content-based filtering, collaborative filtering, and hybrid filtering.

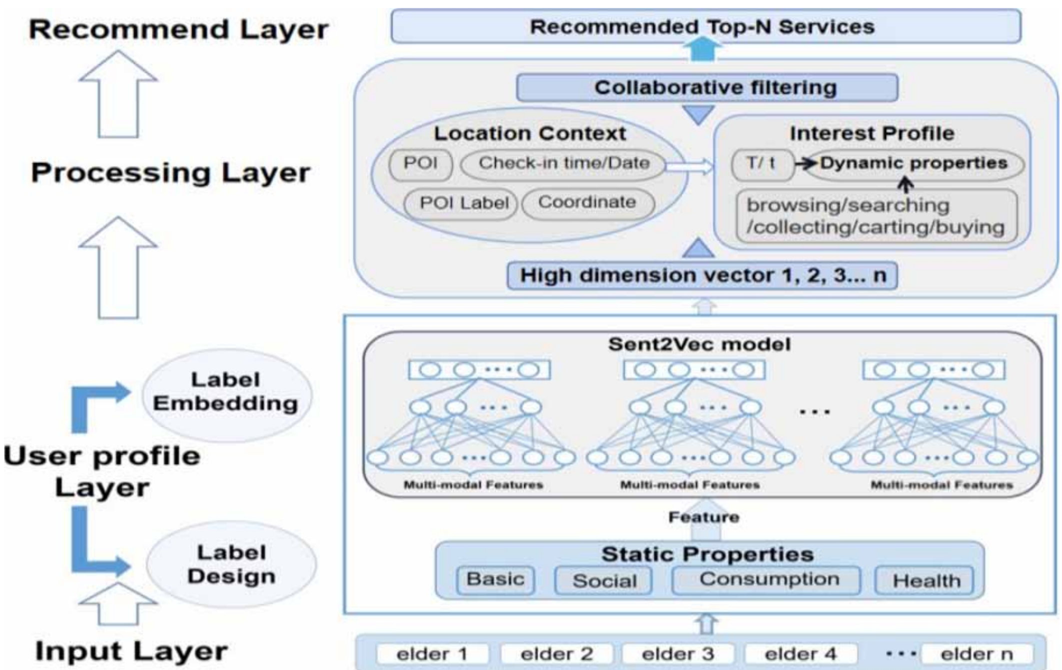
SERVICE RECOMMENDATION FRAMEWORK

Under the aged service industry background, the researchers chose the elderly population as the research object. The framework is based on the embedded user profile model, and the ultimate goal is to recommend suitable services for older customers among massive service data. The objective conditions of the elderly such as health status, consumption habits, and family information, all have a significant impact on their preferences.

Therefore, considering the feature preference of the elderly, this framework characterizes older people from four aspects: demographic characteristics, social characteristics, health characteristics, and consumption characteristics. Secondly, the authors embed the designed label with older customers' features into the neural network space and map multi-modal data into continuous digital vectors according to different characteristic groups.

The service recommendation framework of PCE-CF is shown in Figure 1. In order to show the whole structure clearly, the authors adopt a multi-layer representation which divides the framework into three layers: Input Layer, User Profile Layer, and Recommend layer, and the User Profile Layer contains label design and label embedding.

Figure 1. PCE-CF framework



Input Layer

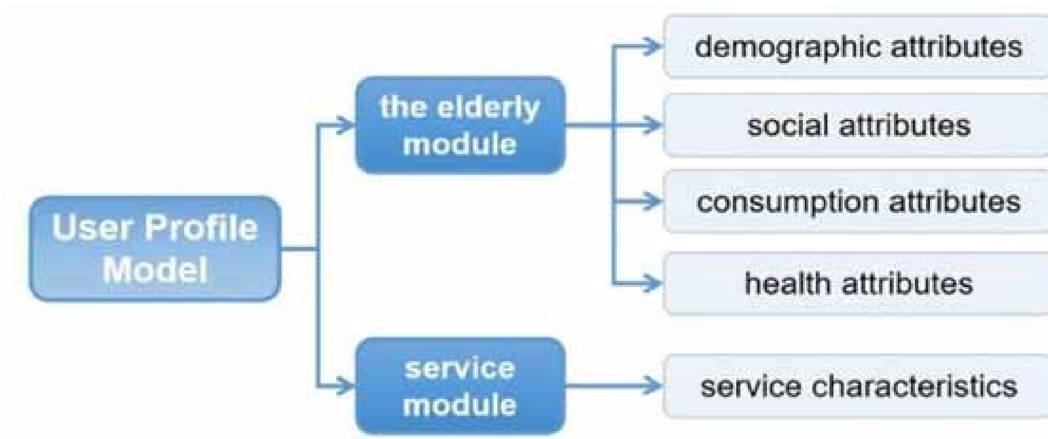
The recommendation model the authors propose is a continuous model, and each layer is arranged in order. The first layer is the data input layer. The purpose of this layer is to collect various information related to the service objects. The input data of this layer is mainly divided into two aspects: elder people's basic attributes and older people's historical information. The basic attributes include personal data, social relations, life preferences, etc. And historical information includes historical service usage records and historical service scoring information.

User Profile Layer

Label Design

This part mainly processes the data from the input layer. The main work is to match the collected data into corresponding labels the authors designed. In view of the collected data being various, the models from different labels are also different. In this part, the authors organize the older people's features and then embed these features into the neural network. The label design of the user profile model involves two modules: the elderly module and the service module. The corresponding structure is presented in Figure 2. In the elderly module, the authors focus on analyzing the characteristics of elderly users. Therefore, the demographic, social, consumption, and health attributes are selected as entry points to describe the elderly groups. And in the service module, the authors consider service characteristics such as influence factors and service satisfaction.

Figure 2. User Profile Model Structure



The current mainstream labeling system is hierarchical and needs to be subdivided layer by layer. As for the labels of elderly users, first-level labels are an abstraction of the set of lower-layer labels. During the construction process, the lowermost third-level labels are mainly constructed owing to upper-level labels being only statistically significant but have no practical significance. The third-level labels can be mapped to the upper two-level labels. The requirements for the underlying label are as follows:

1. As it is necessary to avoid duplication and conflicts among the labels, each label can only represent one meaning.
2. Labels must have certain semantic to facilitate the understanding of each label.

On the basis of the above principles, the details of each dimension in the label design are put forward.

- **Demographic Attributes:** The demographic attributes mainly contain the basic attributes of the elderly, and the specific label categories are shown in Table 1. In the design of the demographic attribute labels, the secondary labels mainly involve the gender, age, place of residence, city level, political outlook, education level, personality traits, and occupation of the elderly users. The main purpose is to grasp the basic information of the elderly to better predict and evaluate their needs and preferences in service selection based on these characteristics. In the data storage, the data type of each label is also shown in the following table.
- **Social Attributes:** Among the social attribute labels, the first level labels of the PCE-CF model are divided into family structure attributes and affordability attributes of elderly users. Considering the influence of family environment and social network circle on the emotion and psychology of the elderly, in addition, financial ability also largely influences which type and level of service the user chooses in the service recommendation process. Therefore, in the design of the social attributes label, the family structure of the elderly takes into account whether there is a spouse,

who lives with them or lives alone, the number of children in the family and whether the family atmosphere is harmonious.

Table 1. Demographic attributes

First-Level Label	Second-Level Label	Third-Level Label
Demographic Attributes	gender	male, female
	age	younger, middle, elderly
	residence	rural registration, else
	city level	first-tier, second-tier, third-tier
	political status	masses, league member, party member
	culture level	lower, junior, mid, higher
	character	intellect, mood, will
	profession	enterprises and public institutions, professional, office staff, service worker, production staff, operator, soldier, other

Under the elderly financial ability label, we mainly consider their current income, whether they have a regular monthly income, whether they are subsidized by others and belong to the poor group, and what level the financial ability of this user belongs. The detailed label design of the social attributes label and the data types corresponding to the three levels of labels are shown in Table 2.

Table 2. Social attributes

First-Level Label	Second-Level Label	Third-Level Label
Family Structure	spouse	yes, no, others
	living conditions	live alone, live with a spouse, live with children
	number of children	1, 2, 3, over three
	family atmosphere	harmonious, reasonably, general, less, disharmony
Economic Ability	income	low, middle, higher
	stable income	yes, no
	assistance from others	yes, no
	economic degree	tight, general, comfortable, rich

- **Consumption Attributes:** Existing research shows that the elderly are more susceptible to surroundings compared with youth and middle-aged groups. They present features of purchase together in the consumption process (Hu et al., 2020). According to the consumption characteristics of the elderly, the consumption attributes labels of the User Profile Model are divided into the following six consumption patterns:
    - **Habitual Consumption:** The elderly have formed an inherent consumption attitude in the long-term process of consumption. It is not easy for them to change their habit of purchasing a certain product or service.
    - **Hedonic Consumption:** Some elderly people in wealthy conditions are biased toward flashy spending and focus on quality.
    - **Realistic Consumption:** Some elderly people are accustomed to traditional consumption and pay more attention to utility. They purchase some rigid demands and consume sensibly.
    - **Convenient Consumption:** The elderly pay more attention to the convenience of purchase and use but are not willing to spend a lot of time in the selection process.
    - **Blind Consumption:** A small number of elderly households are too blind to consumption. It leads to inappropriate purchases and spawns economic loss.
    - **Compensatory Consumption:** A lot of elderly people present powerful psychology of consumption compensation. They begin to balance their consumption.
- **Health Attributes:** According to the elderly health classification model, the elderly are divided into the following health levels:
    - Level 1 represents the poorest health status. The old people at this level are too unhealthy to take care of themselves.
    - Level 2 represents poor health. This level contains the elderly who suffers from serious illnesses and cannot take care of themselves completely.
    - Level 3 generally represents health status. The elderly in this level are able to exercise properly though their bodies are weak due to old age or some diseases.
    - Level 4 represents good health. Although there may be some problems in their physiology or psychology, their overall condition is good. And they belong to the healthiest group of the elderly.

The tag system involves the lifestyle of the elderly mainly includes some exercise conditions such as exercise frequency, exercise mode, exercise time, diet, whether to smoke and drink, and other habit issues; in terms of physical examination items include the oral condition, vision, hearing, skin condition, sclera condition, etc. of elderly users. The specific label design and the data types corresponding to the three-level label data are shown in Table 3.

Table 3. Health attributes

First-Level Label	Second-Level Label	Third-Level Label
Health Indicators	number of chronic diseases	1, 2, 3, over three
	medication	yes, no
	health level	1, 2, 3, 4
	symptom description	asymptomatic, headache, chest tightness, chronic cough, tinnitus, dazzling ...
	general situation	height, weight, pulse, body temperature, respiratory rate
Lifestyle	physical exercise	exercise frequency, exercise method, exercise time
	eating habits	balanced, meat, oil and salt
	smoking	never smoke, smoking, have quit smoking
	drinking	never, occasionally, regular, daily
Checkpoints	oral cavity sclera	lips, dentition, pharynx
	vision	left eye, right eye
	hearing	hear, can't hear clearly, can't hear
	skin	normal, flushing, pale, yellow staining, pigmentation
	sclera	normal, yellow stain, congestion, other

Label Embedding

The next part of the User Profile Model layer is label embedding. The main goal of this part is to learn a high-dimensional vector for each old customer that could summarize their portrait features. In this part, the authors take the feature information depicted by the designed label as input and then use the pre-trained Sent2Vec model (Pagliardini et al., 2017) to generate bigram embeddings based on 16GB of English Wikipedia text. The Wikipedia text contains about 69 million English sentences and about 1.7 billion words. The embedding of feature labels for elderly users is obtained as 700 dimensional vectors:

- Selection of the embedding model:
    - **One-Hot Encoding:** Although the one-hot encoding vector is relatively intuitive and easy to construct, the length of each dimension is the same as the whole dictionary, which results in high-dimensional sparseness, and causes a lot of wasted space. On the other hand, one-hot encoding couldn't reflect the relationship among the adjacent data because it is just a simple representation similar to numbering. Thus, it is impossible to judge the similarity among different elderly customers in the situation of this article. In addition, the position of the one-hot encoding in the column vector can only be represented by 0 or 1. For the labels the authors designed in the first part of the User Profile layer, most of them are not expressed by only two third-level labels. In conclusion, one-hot encoding is inapplicable for this model.
    - **Sen2vec Model:** Goldberg & Levy (2014) published a paper in 2014 and open-sourced Word2vec, a tool for calculating word vectors. It considers the cooccurrence among words, and the word vectors corresponding to synonyms would be closer in a multidimensional space. Based on that, Arora et al. (2016) explored the Sen2vec model, which concatenated words into sentences and mapped them into high-dimensional space. The characteristic information from the designed label is presented in the form of words, phrases, sentences, and numbers; therefore, the embedding model is further extended on the basis of the Sen2vec

model. It represents the multi-modal data in joint representation and maps complex data to specific high-dimensional vectors uniformly.

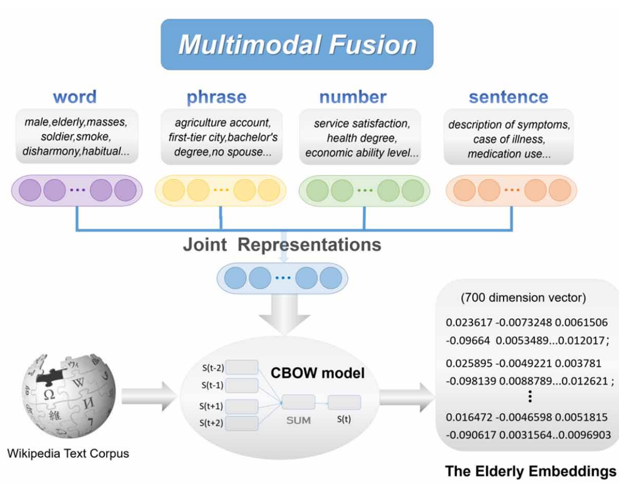
- Design

The approach the authors propose depicts the elderly through four dimensions of population, society, consumption, and health in the User Profile Layer. The elderly data have different sources or forms in each dimension, and the samples may also come from data collection in different periods. Thus, based on the previous part, the authors divide the data of the elderly into four different modes: words, phrases, numbers, and long or short sentences to describe the characteristics of older customers. The corresponding analysis is as follows:

- **Words:** Some specific content information such as gender, occupation, city, and political status could be expressed as words in the characteristic data from the User Profile Layer. The form of words is mainly concentrated in the dimension of demographic attributes.
- **Phrases:** As a single word cannot accurately describe some data information, the authors present them in the form of phrases. For example, living with a spouse, never smoking, and family harmony.
- **Numbers:** The satisfaction degrees of the services are reflected by the service scores in historical service data of the elderly. Therefore, the form of numbers must be considered in this embedding model due to some information that need to be expressed by numbers, such as the health degree index and economic ability index.
- **Long or Short Sentences:** The authors need to describe different labels in more detail to express exact characteristics. As far as older adults are concerned, the researchers should pay more attention to the health attributes in service recommendations. That is, sentences are required to describe further information like case history and symptom description.

By means of multi-modal fusion and utilizing complementarity, the label embedding part learns new fusion features from original data in different modes. The researchers get a multi-modal vector for each old customer by transferring the fusion features into a Continuous Bag of Words (CBOW) (Kenter et al., 2016). The embedding diagram is shown in Figure 3.

Figure 3. The Embedding Model diagram



The authors exploit the expansion of the CBOW model to represent the text information of different modes with fusion features and use the unsupervised target to train the distributed representation from a large number of test data sets.

The similarity between different older adults can be expressed visually from the distance in high-dimensional space. This approach avoids the dimensional disaster in feature representation and reflects the correlation among different older adults, thus improving the accuracy of similarity calculation.

Recommend Layer

The last layer of the framework is the service recommendation output layer. The main goal of this layer is to select the nearest neighbor for target users by using the embedded vectors in the previous layer and then recommend top-N services that best match them:

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_h - y_h)^2} = \sqrt{\sum_{i=1}^{h} (x_i - y_i)^2} \tag{1}$$

According to the elderly similarity, the authors find K elders more similar to the target elderly u and represent the set S(U, K). The authors extract the services that the elderly like in S and remove the services that u has used. For each candidate service I, the degree of interest of the target elderly u is calculated by the following formula:

$$p\left(u,i\right) = \sum\nolimits_{v \in S\left(u,K\right) \cap N\left(i\right)} w_{uv} \times r_{vi} \tag{2}$$

where r_{vi} is the degree of user V's preference for i, that is service score. uv represents the similarity between the target old man u and the similar old man v. The prediction score formula of target elderly u for service i is as follows:

$$G\left(u,i\right) = \frac{\sum\nolimits_{v \in S\left(u,K\right)} \left(r_{vi} - \overline{r}_{v}\right) \times w_{uv}}{\sum\nolimits_{v \in S\left(u,K\right)} w_{uv}} \tag{3}$$

$\overline{r}_v$ is the average service score of the elderly. The researchers select the first-N services as the output through the degree of interest of the elderly and get the top-N services that more match the target elderly.

EXPERIMENT AND RESULT

Generation of Data Sets

The available real data sets related to the research of pension services the authors can get include:

- www.BestShan.com contains old people's information, their browsing records, and scoring records for different types of elderly care services.
- www.keai99.com contains 2315 pieces of the elderly's basic information, including 25 characteristics such as name, gender, birthday, place of residence, education, occupation, etc.

- The data set provided by Alibaba in the Alibaba Cloud Tianchi competition contains the estimated click-through rate of Taobao display ads, including advertising information, user information, and user behavior log data.

However, the above data sets have the following two problems:

- The elderly feature data is not comprehensive enough to be accurately described.
- The correspondence between elderly data and elderly care services cannot be achieved.

Since it is not currently possible to obtain information containing all the characteristics of the elderly, the authors consult much information on aged people services. The following constraints and data generation rules are set based on the correlation among different attributes to ensure the authenticity and reliability of the data.

Consumption Attributes Constraints

Extensive studies have shown that gender, personality, previous occupation, and education level have a significant impact on the consumption characteristics of the elderly. Intellectual, emotional, and willful personalities are divided by psychological functions that directly affect consumption patterns. Occupations with higher rigor would be considered more thoroughly when consuming. The higher the education level, the stronger the judgment ability. The elderly who have higher degrees restrain unreasonable consumption better, and are biased towards realistic and hedonic consumption. The consumption attribute constraint rules are shown in Figure 4.

Health Attribute Constraints

High education level and satisfactory social support are the protective factors of the elderly's health behaviors while spouse-free, chronic diseases, the use of walking aids, loneliness, and depression are the risk factors for the elderly's health behaviors. Besides this, age, mental health, education, economic ability, the number of chronic diseases, long-term medication, smoking, and alcohol consumption can have an impact on health status. Elderly living alone without a spouse, lower education, and lower-income result in poor health. Based on this, the health degree constraint rules are set, as shown in Figure 5.

Figure 4. Consumption Attributes Constraints

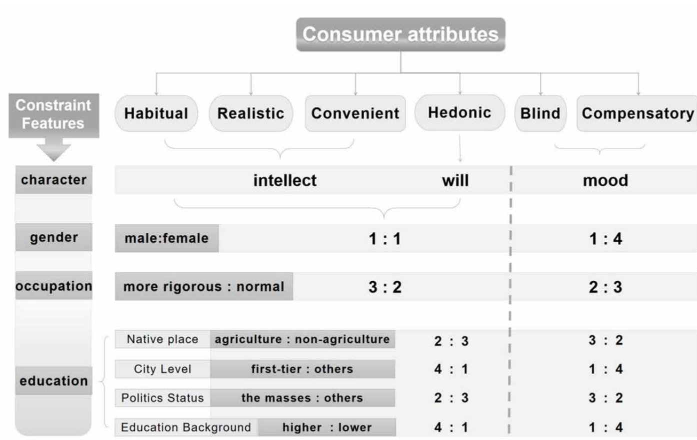
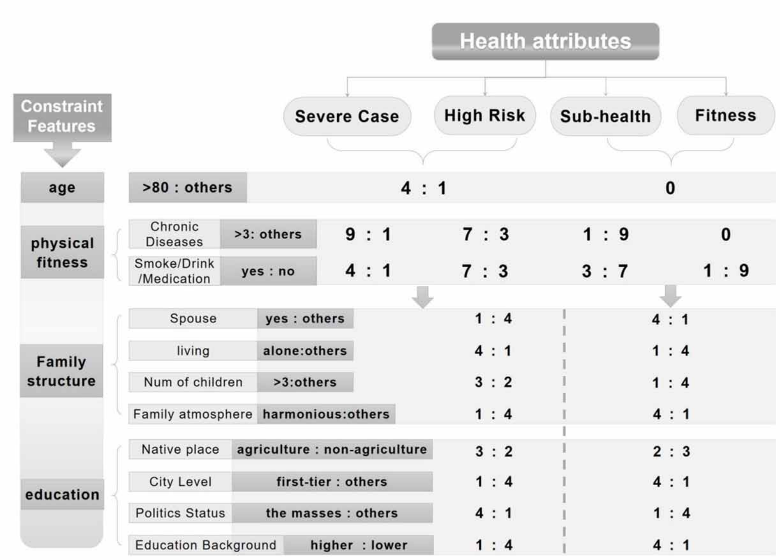


Figure 5. Health Attributes Constraints



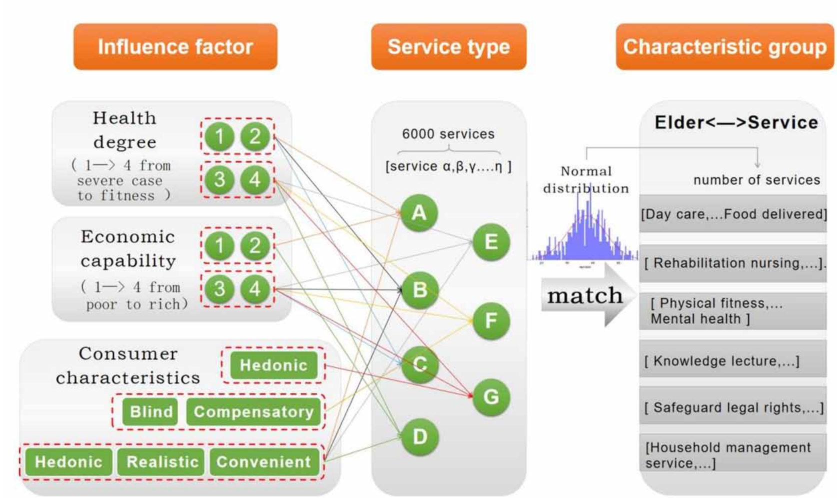
- **Age:** Some studies have concluded that the older the elderly, the worse standard of health promotion. Other studies show that the elderly aged 60-80 years old have a higher total score of healthy lifestyles, and the health behavior level of elderly people over 80 years old is significantly reduced.
- **Educational level:** The results of the study show that the higher the education level of the elderly, the better health and living standards they have.
- **Marital status:** Several studies have shown that the health-promoting lifestyle scores of elderly people living with their spouses are higher than those of widowed, divorced, or unmarried elderly. The reason for the analysis may be that the widowed or divorced elderly are lonely and less willing to receive external health education knowledge and behaviors. However, elderly people with a spouse who communicate more with each other can urge both of them to develop a good lifestyle and healthy behavior together.
- **Number of children:** The survey found that elderly people with fewer children have higher scores on health-promoting lifestyles, which may be related to their subjective independence from child care. And elderly people with many children need to devote more energy and time to taking care of their families but are less concerned about their healthy life behavior.

Description of Service Features

According to the statistical information on senior care services released by Ningbo Municipal Statistics Bureau (2018), the public opinion survey data shows that health conditions and financial ability have become the main factors considered by the elderly when choosing senior care services.

At the level of service profile description, the researchers select health degree, economic capability, and consumer characteristics as the main influencing factors, and further divide the service according to different degrees of service satisfaction. Thus they divide into a total of seven service types and 6000 related elderly care services. The overall matching framework of elderly data and service data is shown in Figure 6.

Figure 6. Description of service features



The researchers matched the old group and the elderly data generated according to the statistics of the pension service field. To ensure the real feasibility of the data, they select the service quantity range and make the number of services allocated to each elderly person fit the normal distribution.

Evaluation Index

Scoring Prediction

Service rating prediction is based on the degree of the elderly interest. The accuracy of score prediction is generally calculated by Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

RMSE (Root Mean Square Error) measures the deviation between the observed value and the true value. It is commonly used as a standard for measuring the prediction results of machine learning models:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(h\left(x_i\right) - y_i)^2} \tag{4}$$

MAE (Mean Absolute Error) is the average of absolute error. It could better reflect the actual situation of the predicted value error:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|\left(h\left(x_i\right) - y_i\right)\right| \tag{5}$$

Top-N Recommendation

The accuracy of the Top-N recommendation is generally measured by precision and recall. Let $R(u)$ be the recommendation list for the elderly based on the elderly' s data on the training set, and $T(u)$ be the elderly' s service list on the test set. The precision of the recommended result and the recall are:

$$precision = \frac{\sum_{u \in U} \left| R\left(u\right) \cap T\left(u\right) \right|}{\sum_{u \in U} R\left(u\right)} \tag{6}$$

$$recall = \frac{\sum_{u \in U} \left| R\left(u\right) \cap T\left(u\right) \right|}{\sum_{u \in U} T\left(u\right)} \tag{7}$$

Experimental Results

Evaluation of the Embedded User Profile Model

It is worth mentioning that similar attribute labels are closer in the semantic space. For example, compared with the profession of a teacher, the older man's political appearance is mass or party member embedded cosine similarity is higher.

In order to prove the expressive ability of embedding, the researchers convert the data generated according to the design of the old user profile system into embedded vectors. There are 3400 pieces of data of seven service types, 4:1 divided into training and test sets, and passed into the KNN model. The researchers assign a range of values from 1 to 30 for K, changing the parameters continuously, and evaluate different parameter models' ability through ten cross-validations. They use the accuracy as the evaluation index, and Figure 7 is obtained.

According to Figure 7, the best K value is obtained. When K = 16, accuracy = 0.9588. When the best K value is transferred into the model for training, the score is 0.9706. At this time, the ability of the model is the best. The researchers reduced the dimension of 3400 pieces of data from the 700 dimensional vector through TSNE, and the visualization results are shown in Figure 8.

Figure 7. Accuracy of the KNN model

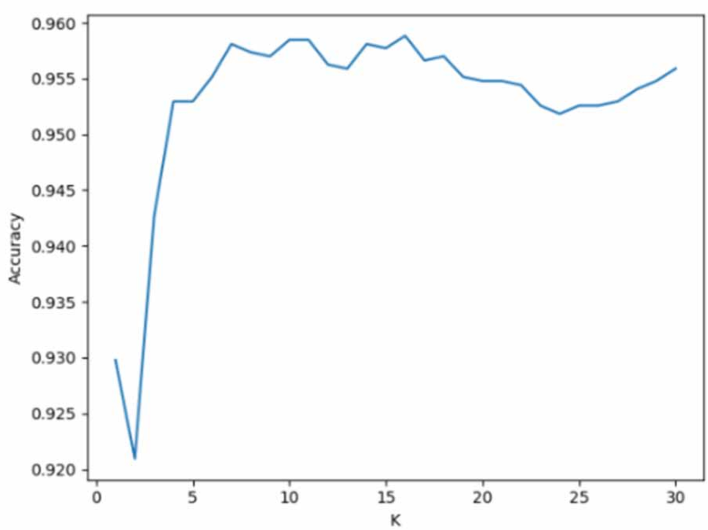


Figure 8. TSNE visualization

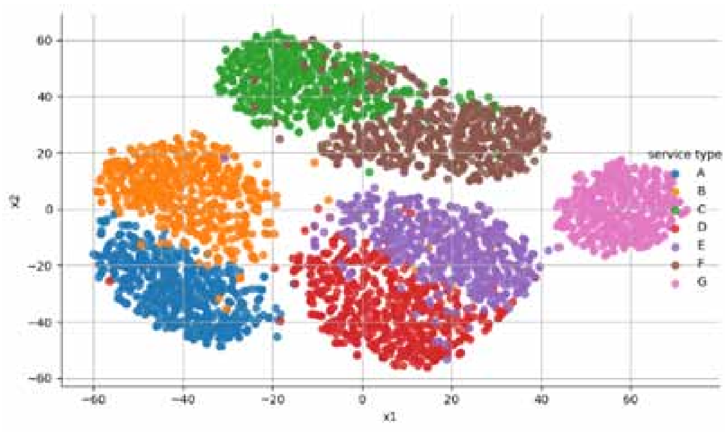


Figure 8 shows that the elderly groups with similar characteristics are closer in the embedding space. Therefore, based on this kind of language embedding, the researchers can better judge the similarity between the two sentences of the elderly and then achieve more accurate predictions to recommend services more precisely.

Results

Algorithm Performance

Set top-N = 10, and the nearest K value is 10~30, that is, 10 best services are recommended for the target user. When K value is 28, the performance is best. At this time, precision=0.7792 and recall = 0.7125.

In the case of N = 11, the authors change the K value, and calculate the value of MAE and RMSE, which is consistent with the best K value for calculation of precision and recall. When K is 28, the value is the lowest, MAE = 0.4937, and RMSE = 0.5659. The results are shown in Figure 9.

Comparative Experiment of the User Profile Model

The researchers propose four dimensions of population, society, consumption, and health in the label design of the user profile layer to describe the elderly service objects. Owing to the generated data system is the division of service types based on the economic ability, health degree, and consumption characteristics as the main influencing factors, the researchers control them separately and test the algorithm's performance. The experimental results are shown in Figure 10.

It can be seen from the results that each dimension set by the User Profile Layer has an impact on the overall performance of the algorithm, and the algorithm performance is the best when considering four dimensions comprehensively.

Comparative Experiment

The researchers conducted the comparative experiment in the same data set:

- **User Profile:** Build the User Profile Model through feature extraction, create document vectors for each service to represent its property, and then implement service recommendations by calculating similarity.
- **LFM:** This approach decomposes the user-service matrix into two-factor matrices connected by latent factors and calculates the element in factor matrices through the optimization method.

- **User-Based CF:** The similarity between the elderly is calculated based on their service scores, and the satisfaction degree of the target elderly with the target service is predicted according to the similarity and their historical behavior.
- **Service-Based CF:** The similarity between services is calculated by the elderly's rating of services, and a recommendation list is generated for them according to the similarity of services and their historical behavior.

Figure 9. Results

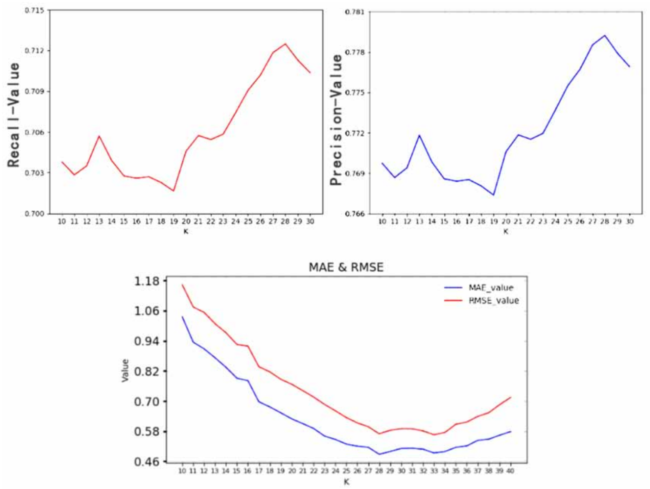
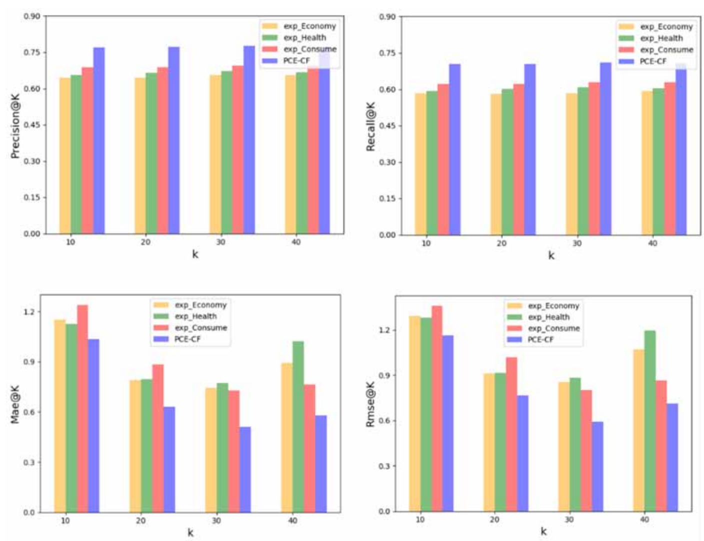


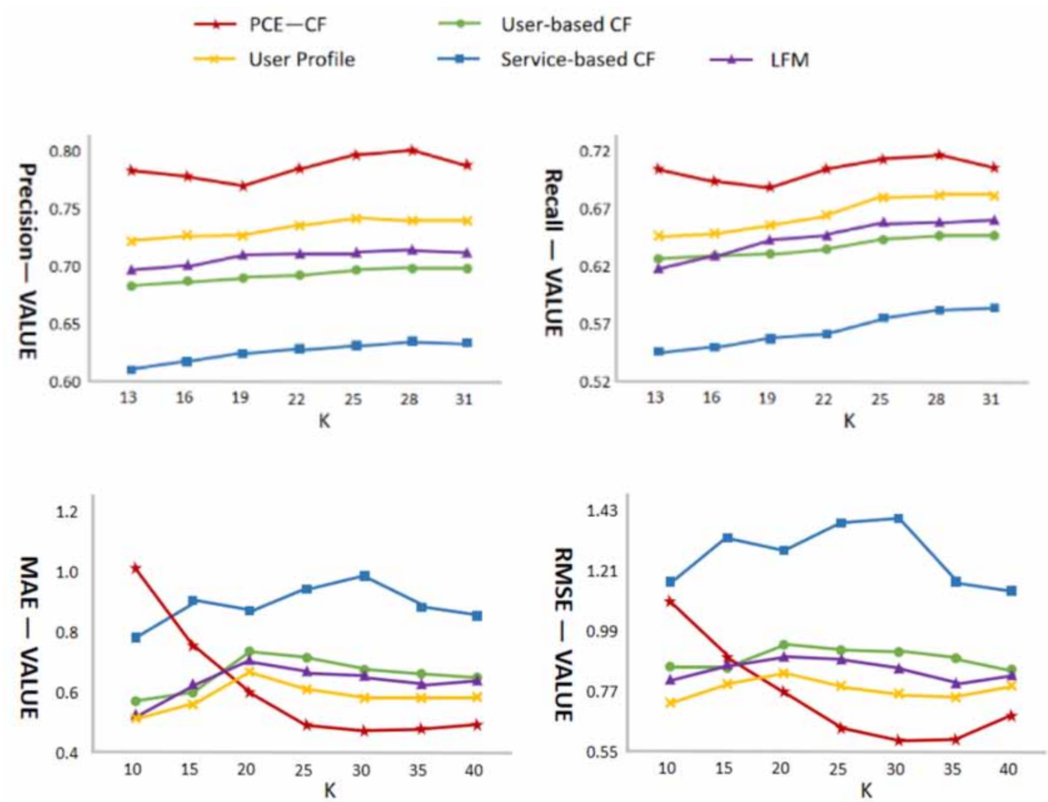
Figure 10. Results of Comparison



The researchers control the number of recommended services, select the nearest neighbor as a variable, and compare evaluation indexes of the five algorithms. It can be seen from Figure11 that the index of MAE and RMSE are greatly affected by the nearest neighbor K. When the value of K is 20~40, the approach PCE the researchers propose has greater advantages.

As a result of the comparison of precision and recall with other competitive methods, it is pretty obvious that the proposed model PCE-CF has better performance. Service-based CF always performs worst while the user profile method behaves much better. And the result shows that the top-N recommendation is less affected by the value K.

Figure 11. Results of Comparison



CONCLUSION

This article proposes a collaborative filtering service recommendation framework of PCECF based on the embedded User Profile Model. The researchers designed labels for older customers to sort out their characteristics through complex multi-modal data and then embedded the labels into a neural network to obtain a unified vector. By means of label embedding, the researchers extract the preference of older customers by multi-modal fusion to make better the performance of recommendations. To illustrate better, the framework is divided into three layers: Data Input Layer, User Profile Layer, and Service Recommended Layer.

The results of extensive experiments show that the labels of the User Profile Model this article designed further enhance the effectiveness of the traditional recommender systems approaches, and embedding the designed labels into neutral network spaces effectively ameliorates the problem during the conversion of complex data with high dimensions. This article demonstrates that this approach can significantly outperform the existing service recommendation algorithm. In future work, the researchers will enrich the modes of the User Profile Model and continue to optimize the recommendation model by considering the dynamic behavior attributes of the elderly. At the same time, the data processing will be further optimized, and the data will be collected and cleaned by existing techniques so that they can be compatible with the user portrait model proposed in this paper. Enhancing the inclusiveness of the model and increasing the generality of the model also need further research.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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