Design of Partner Evaluation Model and Intelligent Matching System Based on Multi-Dimensional User Profiling

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Abstract: Aiming at the problems of low matching efficiency of online dating platform and the existing matching mechanism can not meet the needs of high-quality partner evaluation under the background of modern marriage crisis, this study proposes a partner matching framework that integrates multimodal dynamic feature extraction and migration reinforcement learning. By constructing an evaluation model including five core first-level indicators such as physiological quality and personality characteristics and 25 second-level indicators, multi-modal feature engineering is used to process user data, and feature fusion and index mapping are realized by hierarchical dynamic attention fusion network. The matching system combines users' explicit ranking preferences and dynamic behavior feedback, constructs a multi-level weight distribution mechanism, and designs a complete matching process. The simulation results show that the framework is effective to some extent, but there is still room for improvement in training stability, feature processing and matching algorithm optimization. This study provides a scientific and humanistic solution for the matching of marriage, love and friends in the digital age, and has important reference value for the development of related fields.

Keywords: Multi-dimensional user portrait; Partner evaluation model; Intelligent matching system; Multi-modal data fusion; Reinforcement learning

1. Introduction

In recent years, with the economic situation facing multiple uncertainties and challenges, the patterns of marriage and love have been undergoing profound changes globally. Relevant data shows that in China, the number of single people of marriage - able age has exceeded 200 million, and the total fertility rate has dropped to 1.03%, gradually showing the characteristics of "three lows": shortened love cycles, decreased marital stability, and continuously low willingness to have children. This phenomenon, together with the "super - single society" in Japan and the "contractual partnership" model in Northern Europe, constitutes the global picture of modern marriage and love crises.With the continuous popularization of the Internet and the deepening of the fast - paced lifestyle, the social time of young people has become fragmented. A large number of people rely on online socializing and lack face - to - face communication skills, resulting in "social phobia" [1]. Most young people have a solidified social circle and find it difficult to expand their social network. At the same time, the increase in the cost of offline socializing and the higher standards for material conditions further exacerbate the difficulty of finding a suitable partner offline. However, existing online dating and matchmaking platforms have multiple limitations, leading to a low effective matching rate and potentially causing certain impacts on physical and mental health.The relationship models and matching mechanisms in existing research are difficult to meet the needs of high - quality partner evaluation or matching, amplifying ethical risks such as appearance discrimination; the coupling problem of dynamic weight assignment modeling and privacy protection has not been solved, and a more appropriate way to screen ideal partners for contemporary youth remains to be studied.

With the continuous progress of advanced technologies such as machine learning [2] and natural language processing [3], it has gradually become possible to construct user portraits through multimodal data fusion for intelligent partner evaluation and matching [4]. The refined modeling that integrates behavioral, interest, and psychological characteristics improves the matching accuracy. Based on the above - mentioned challenges, this study proposes a partner matching framework that integrates multimodal dynamic feature extraction and transfer reinforcement learning. The aim is to optimize the processing efficiency of user needs through a new paradigm of adaptive multimodal data fusion, break through the dimensional limitations and ethical dilemmas of traditional methods, and provide a scientific and humanistic solution for marriage and love matchmaking in the digital age.

2. Related work

2.1 Online Dating Platforms

Currently, Millennials and Generation Z have become the most active groups using dating apps. Some studies have found that spending quality time with a partner or spouse is regarded as the most happiness - inducing thing [5][6]. In addition, more than half of Generation Z said that the time spent with their partners has no impact on their happiness. With the increasing popularity of Valentine's Day, the traffic to global online dating and marriage websites has shown a significant upward trend, indicating that the path to love is gradually becoming digital [7]. According to recent data from Euromonitor International, a data analysis company, 16% of global Internet consumers visited these platforms at least once a week in 2024, a significant increase from 12% in 2019. Especially in China, this proportion increased from 11% in 2019 to 14%, showing that online love - seeking has become the choice of more and more people. The COVID - 19 pandemic has accelerated this trend, leading to a steady increase in the global usage of online dating platforms.Moreover, even for offline relationship development, the prevalence of "fast - food" love has led to the deterioration of relationship quality, and the number of "one - day - discard" relationships is increasing [8], making it more difficult to sincerely seek a reliable long - term or even lifelong partner. This reflects the dual impact of social atomization and technological alienation on intimate relationships. Before and after the COVID - 19 pandemic, there has been a significant growth trend among consumers of global online dating and matchmaking platforms to varying degrees [9].

Mainstream marriage and love platforms such as Tinder face multiple limitations. First, the data modeling dimension is narrowed, overly relying on location - based services (LBS technology) and static tags, while ignoring deep - level characteristics such as values and personality traits. Second, the dynamic adaptability is insufficient. The user interest drift rate is relatively high, but the platform portrait update cycle is long, resulting in the "static matching fallacy". Third, the ethical mechanism is lacking. A large number of users have experienced data breaches, and the algorithm discrimination coefficient remains high. Users can hardly judge the real comprehensive image of the other party only through self - edited personality tags and descriptions online, which has also led to a large number of fraud cases [10]. In addition, research results show that personality correlations such as neuroticism, social ability, sensation - seeking, and sexual permissiveness are related to more frequent use of online dating services [11], and the increasingly common use of online dating platforms (OPDs) may have an impact on the psychological and sexual health of young people (especially college students) [12].

2.2 Evaluation Models

Researchers have conducted studies on evaluation models in multiple fields. For example, Jennifer M Brinkerhoff proposed a framework for evaluating partnerships based on partnership definitions, characteristics, and added value, which helps to improve relationship performance and project outcomes and can be used to strengthen the theory and practice of partnerships [13]. Eastwick et al. proposed a new comprehensive model based on the interdependence theory. This model emphasizes when and why success or failure occurs to predict relationship outcomes and constructs a new framework for conceptualizing ideal partner preferences in terms of characteristic attractiveness [14]. Omar Ayadi et al. proposed a fuzzy collaborative evaluation method for partner trust evaluation within horizontal collaborative networks, which evaluates the trust level according to the information - sharing attributes of key influencing factors [15]. Birsen Karpak et al. proposed a combined method for effectively evaluating CRM partners, which integrates intuitionistic fuzzy sets (IFS) and group decision - making (GDM). It consists of the intuitionistic fuzzy analytic network process (IF - ANP) for constructing and analyzing standard weights and the intuitionistic fuzzy decision - making trial and evaluation laboratory (IF - DEMATEL) for managing uncertainties to determine the interrelationships between criteria [16]. Hella Abidi et al. established criteria for evaluating strategic partners in the logistics service provider (LSP) network and developed a horizontal LSP partner evaluation model using ANP in LSP1 [17]. However, although these methods have proven to be somewhat effective in practice, they still cannot be well adapted to the comprehensive quality evaluation of ideal partners.

2.3 Matching Mechanisms

In addition to the evaluation of individuals, the attraction matching between two people also needs to be considered. As early as last century, Mortensen studied the matching for finding a lifelong partner or other partners and developed a search - theoretic model that takes into account the initial uncertainty of meeting costs and matching values, explaining the separation behavior as a process of purchasing a "good match". These models indicate several possible social inefficiencies in the matching formation and separation processes [18]. Luo's research began with the general patterns and trends of couple similarity observed in a series of fields, including demographic variables, physical/physiological characteristics, abilities, mental health, habitual behaviors, attitudes, values, and personality, and analyzed four mechanisms leading to similarity, including initial active choice, mating market operation, social homogamy, and convergence [19]. Tai Tsou proposed a method for collaborative ability and partner matching to achieve e - service product innovation through a knowledge integration mechanism and studied the relationships among collaborative ability, partner matching, knowledge integration mechanism (KIM), and e - service product innovation [20]. Nicolo et al. proposed a model in which agents are paired to carry out projects. Agents have priorities for both partners and the projects they are assigned to. The preferences for partners and projects are separable and dichotomous. A suitable concept of weak core is defined, and an algorithm, the Minimum Demand Priority Algorithm (MDPA) for generating allocations in the weak core, is proposed [21]. There are also studies in multi - dimensional feature engineering matching. For example, Gesto - Diaz et al. proposed a new Adaptive Pairwise Matching (APM) algorithm for modalities including visible light, thermal, intensity, and depth images to improve the robustness of matching against outliers and tested it in an evaluation framework [22]. The above - mentioned research provides some reference and inspiration for constructing an ideal partner matching mechanism, but it cannot fundamentally solve the existing problems. he development of related fields.

3. Construction of the Evaluation Model

3.1 Determination of Core Indicators

In previous studies, the attraction between the opposite sexes was usually evaluated through facial characteristics [23], similarity, and physical features [24], or an attraction and five - factor model in opposite - sex interactions was constructed [25]. The dimensions involved in these methods are relatively single and cannot fully evaluate a person's comprehensive qualities. In this study, an attempt is made to build an indicator framework around five core first - level indicators, including 25 second - level indicators in total, namely physiological quality, personality traits, comprehensive ability, family background, and character qualities. The relevant characteristics are shown in Table 1.

(1) Physiological Quality: Covers appearance (facial features, affecting social interactions, etc.), height and weight (basic body shape indicators), age (a marker of physiological and psychological development), and health status (body functions and disease conditions, the basis for life and work).

(2) Personality Traits: Includes extraversion (social preference and activity level), positivity (an optimistic and enterprising attitude), humor (related to emotional regulation and interpersonal harmony), stability (degree of emotional fluctuation), and agreeableness (pro - social traits, affecting the quality of interpersonal relationships).

(3) Comprehensive Ability: Includes learning ability (efficiency and effect of knowledge and skill acquisition), talent ability (special expertise in specific fields), social ability (interpersonal communication and relationship maintenance), execution ability (efficiency and quality from plan to goal achievement), and empathy ability (understanding others' emotional needs, beneficial for cooperation).

(4) Family Background: Includes family address (regional resource conditions), economic condition (financial situation, affecting resource investment), members' occupations (related to social resources and atmosphere), family atmosphere (emotional interaction environment, affecting psychology and personality), and family structure (composition form and member relationships, acting on the growth support system).

(5) Character Qualities: Involves sense of responsibility (dutiful attitude, loyalty), ambition (motivation for progress), living habits (work - rest, diet, hygiene, etc., related to a healthy life), integrity (degree of trustworthiness, the basis of trust), and kindness (willingness to care for and help others).

Table 1. Names and Symbol Representations of Core Indicators

Number	First - level Indicator	Symbol	Second - level Indicator	Symbol
1	Physiological Quality	P	Appearance	P_1
2			Height	P_2
3			Weight	P_3
4			Age	P_4
5			Health Status	P_5
6	Personality Traits	T	Extraversion	T_1
7			Positivity	T_2
8			Humor	T_3
9			Stability	T_4
10			Agreeableness	T_5
11	Comprehensive Ability	A	Learning Ability	A_1
12			Talent Ability	A_2

13			Social Ability	A_3
14			Execution Ability	A_4
15			Empathy Ability	A_5
16			Family Address	F_1
17			Economic Condition	F_2
18	Family Background	F	Occupation of Members	F_3
19			Family Atmosphere	F_4
20			Family Structure	F_5
21			Sense of Responsibility	Q_1
22			Ambition	Q_2
23	Personality Qualities	Q	Living Habits	Q_3
24			Credibility	Q_4
25			Goodwill degree	Q_5

3.2 Multimodal Feature Engineering

3.2.1 Definition and Classification of Data Sources

The relevant multimodal data is mainly collected from users' mobile terminal devices, and its types are rich and diverse, covering various data forms such as text, images, videos, and locations. When these data are initially collected, they often present a state of extremely large data volume and lack of rules and order. In order to obtain valuable information from these complex data, it is crucial to preprocess the original data and accurately extract key features.

During the data collection process, we give priority to using the data resources provided by the user behavior statistical analysis module built into the device. By using the morphological, syntactic, and semantic analysis tools in natural language processing technology, we conduct in-depth analysis of text data, so as to excavate the themes and precise semantic information behind user behaviors. In terms of image and video data processing, with the help of advanced image recognition and video analysis technologies, we use face recognition algorithms to determine the identities of people, scene classification algorithms to identify scene types, and action recognition algorithms to clarify the content of actions, and then construct a network structure that can clearly reflect user behaviors. In addition to collecting users' static basic information, after systematic sorting, the multimodal data collected in this study are summarized into the following four categories of behaviors:

(1) Social Behaviors: It covers the interaction data of users on social media, such as chat records, dynamic releases, and picture/video sharing, which are used to analyze emotional tendencies, social activity levels, and the topological structure of

the relationship network.

(2) Cognitive Behaviors: It includes web browsing records, online learning activities, etc., which reflect users' knowledge acquisition paths, preferences in professional fields, and the depth of cognition.

(3) Entertainment Behaviors: It involves game operation logs, music playback records, and short video interaction behaviors (liking/favoriting/commenting), revealing entertainment preferences, the evolution rules of interests, and the content consumption patterns.

(4) Consumption Behaviors: It integrates shopping data and payment records from multiple platforms to depict consumption ability, brand preferences, and spatio-temporal consumption habits.

3.2.2 Multimodal data preprocessing

Because the data involved in the above four categories of behaviors come from different modes, their data characteristics and structures are quite different, so before in-depth analysis, the original data must be systematically preprocessed and classified according to different modal characteristics. The basic processing methods and steps of each mode are as follows:

(1)Text data:

① Cleaning and standardization: remove special characters and emoticons, and adopt UTF-8； as the unified coding format;

② Semantic analysis: RoBERTa model is used to extract context-aware word vectors, and the formula is:

$$\mathbf{h}_t = RoBERTa(\mathbf{x}_t) \quad (1)$$

③ Emotional analysis: Based on the multi-task learning framework, jointly predict emotional polarity (positive/negative) and fine-grained emotional categories (such as joy and anger).

(2)Image/video data:

① Normalization of resolution: uniformly adjust to 224 × 224 pixels, and standardize RGB channels.

② Spatio-temporal feature extraction: the global feature of the image is extracted by Vision Transformer(ViT);

$$\mathbf{v}_{image} = ViT(\mathbf{I}) \quad (2)$$

Video Swin Transformer is used to model the inter-frame space-time system;

$$\mathbf{v}_{video} = VideoSwin(\{\mathbf{I}_1, ..., \mathbf{I}_T\} \quad (3)$$

Cross-modal alignment: aligning video content with user comment text through comparative learning.

(3) Time series behavior data:

① Missing value filling: using time series interpolation (such as linear interpolation) to complete breakpoints.

② Periodic coding: the time stamp is converted into sine/cosine periodic features;

$$\mathbf{v}_{time} = [\sin(2\pi t / 24), \cos(2\pi t / 24)] \tag{4}$$

③ Sequence modeling: capturing long-term dependency through Transformer;

$$\mathbf{h}_{seq} = Transformer(\mathbf{x}_1, ..., \mathbf{x}_T) \tag{5}$$

(4)Graph structure data:

① Node feature coding: using graphs to aggregate neighbor information;

$$\mathbf{h}_v = \sigma(\mathbf{W} \cdot CONCAT(\mathbf{h}_v, MEAN(\{\mathbf{h}_u \mid u \in \mathcal{N}(v)\})) \tag{6}$$

② Calculation of edge weight: define edge weight according to interaction frequency or semantic similarity.

③ Subgraph sampling: random walk strategy is adopted to generate training subgraphs.

(5)Privacy protection strategy:

① Local differential privacy: adding Laplace noise to sensitive features (such as consumption amount);

$$\tilde{x} = x + Laplace(0, \Delta f / \epsilon) \tag{7}$$

② Federated feature aggregation: local processing of user data, encrypting and uploading gradient parameters to update the global model.

3.3 Comprehensive model construction

3.3.1 Feature Fusion Network

After multi-modal feature extraction and classification, it is necessary to fuse all kinds of features into 25 core secondary indicators to get corresponding scores, and then get the scores of each primary indicator. In order to effectively map multimodal features to core indicators, a hierarchical dynamic attention fusion network (HDAFN) is proposed, and its structural model is divided into three fusion levels:

（1）Intra-modal feature alignment: realize feature space alignment through cross-modal comparative learning.

① Text-visual alignment:

$$\mathcal{L}_{align} = -\log \frac{\exp(sim\mathbf{v}_{text}, \mathbf{v}_{image} / \tau)}{\sum_{j=1}^{N} \exp(sim\mathbf{v}_{text}, \mathbf{v}_j^{image} / \tau)} \tag{8}$$

Where τ are the temperature parameters and $\mathbf{v}_{text}$ the feature vectors of text and $\mathbf{v}_{image}$ image (including video) respectively.

② Time series-graph structure alignment: Graph attention mechanism (GAT) is used to model the interaction between time series behavior and social network.

$$\alpha_{ij} = softmax(\mathbf{a}^T [\mathbf{Wh}_i \| \mathbf{Wh}_j]) \tag{9}$$

$$h_i' = \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}\mathbf{W}\mathbf{h}_j\right) \quad (10)$$

（2）Cross-modal dynamic weighted fusion: design a dual-channel attention mechanism to dynamically allocate feature weights.

① Modal importance weight:

$$\beta_m = softmax(\mathbf{W}_m[\mathbf{v}_{text};\mathbf{v}_{image};\mathbf{v}_{time};\mathbf{v}_{graph}]) \quad (11)$$

② Index correlation weight:

$$\gamma_k = sigmoid(\mathbf{W}_k \cdot \mathbf{v}_m)(k \in \{P,T,A,F,Q\}) \quad (12)$$

③ Final fusion features:

$$\mathbf{v}_{fused}^{(k)} = \sum_{m=1}^{M} \beta_m \cdot \gamma_k \cdot \mathbf{v}_m \quad (13)$$

（3）Hierarchical indicator mapping: define mapping function based on core indicators.

①Secondary index score:

$$s_{ki} = \sigma(\mathbf{w}_{ki}^T \mathbf{v}_{fused}^{(k)} + b_{ki})(i = 1,...,5) \quad (14)$$

Where is Sigmoid function, which is the first-level indicator category (such as physiological quality) and the second-level indicator serial number. σ refers to the level 1 index category, i refers to the sequence number of a secondary indicator.

② Level 1 indicator aggregation:

$$S_k = \sum_{i=1}^{5} \omega_{ki} \cdot s_{ki}(\sum \omega_{ki} = 1) \quad (15)$$

The weights ω_{ki} are dynamically adjusted through reinforcement learning (Look at the section 4).

③ Comprehensive evaluation model:

$$G = \sum_{i=1}^{5} \lambda_{S_k} \cdot S_k(\sum \lambda_{S_k} = 1) \quad (16)$$

In the same way, the score G is evaluated for the final attractiveness of users, and the weight λ_{S_k} is dynamically adjusted through reinforcement learning(Look at the section 4).

3.3.2 Dynamic update mechanism

(1) Incremental feature learning: adopting Elastic Weight Consolidation, EWC) to prevent the model from forgetting historical features;

$$\mathcal{L}_{total} = \mathcal{L}_{new} + \lambda \sum_i F_i(\theta_i - \theta_{i,old})^2 \quad (17)$$

(2) Federated parameter updating: Under the federated learning framework,

global model parameters are updated by encryption gradient aggregation:

$$\theta_{global}^{(t+1)} = \frac{1}{|\mathcal{C}|}\sum_{c\in\mathcal{C}}\theta_{local}^{(c)} + \mathcal{N}(0,\sigma^2) \quad (18)$$

Where F_i refers the Fisher Information volume of item θ_i , measuring of its importance to historical tasks.

4. Matching system design

4.1 Matching mechanism design

This system combines users' explicit ranking preferences and dynamic behavior feedback to construct a multi-level weight distribution mechanism to realize the collaborative optimization of users' subjective needs and objective behavior data. The specific design is as follows:

4.1.1Weight initialization based on sorting

(1) Sorting quantization rules

Because each user's degree of care about each index is different, it is necessary for users to set their own ranking to determine the initial weight. Users rank the five core first-level indicators in order of importance: physiological quality (P), personality characteristics (T), comprehensive ability (A), family background (F) and personality quality (Q). Assign initial weight according to ordinal position:

$$\lambda_k^{(0)} = \frac{2(N - r_k + 1)}{N(N+1)}(k \in \{P,T,A,F,Q\}) \quad (19)$$

Where $N = 5$ as the total number of indicators, $r_k \in \{1,2,3,4,5\}$ is the ordinal number of the user's ranking (1 is the highest priority) $Q > T > A > F > P$, then the weight is:

$$\lambda_Q^{(0)} = \frac{2(5-1+1)}{5\times 6} = 0.333, \lambda_T^{(0)} = 0.267, \lambda_A^{(0)} = 0.200, \lambda_F^{(0)} = 0.133, \lambda_P^{(0)} = 0.067$$

In addition, a manual correction interface is added to allow users to manually fine-tune the automatically generated weights to ensure the accurate expression of initial preferences.

（2）Weight distribution of secondary indicators

Users sort the secondary indicators internally under each primary indicator (such as face value P1 and height P2 under physiological quality (P)). Using the same ordinal number method to calculate the weight:

$$\omega_{ki}^{(0)} = \frac{2(M - r_{ki} + 1)}{M(M+1)}(k \in \{P,T,A,F,Q\}; i = 1,2,\ldots,5) \quad (20)$$

Where $M = 5$ is the number of secondary indicators， r_{ki} is the ranking of the secondary indicators in the primary category.If the user is ranked in the physiological quality (P) is $P_5 > P_2 > P_1 > P_4 > P_3$， then the weight is:

$$\omega_{P_5} = 0.333, \omega_{P_2} = 0.267, \omega_{P_1} = 0.200, \omega_{P_4} = 0.133, \omega_{P_3} = 0.067$$

Similarly, manual weight adjustment is also added to reduce system deviation.

4.1.2 Dynamic weight optimization mechanism

Considering that some users may collect limited data in the system, which leads to inaccurate evaluation and matching, users can change the comprehensive score and matching degree of evaluation by changing some aspects of their own characteristics, in-depth contact with corresponding users and other behaviors within a period of time, so it is necessary to increase the dynamic weight optimization mechanism.

（1）Weight Adjustment Based on Reinforcement Learning

In addition to updating the collected data after a certain period of time, the system can also update the weight through the feedback mechanism, in which positive feedback includes users' actions such as initiating a chat, exchanging contact information, marking "interested" and expressing their likes; Negative feedback includes users ignoring recommendations, not returning messages for a long time, marking "not interested" or terminating interaction after matching. Modeling users' implicit preferences through Policy Network, and adjusting weights according to feedback:

$$\nabla_\theta J(\theta) = \mathbb{E}\left[\nabla_\theta \log \pi_\theta(a \mid s) \cdot R(s,a)\right] \tag{21}$$

Where π_θ is the weight adjustment strategy， $R(s,a)$ is the immediate rewards calculated based on user feedback.

（2）Cross-level weight collaboration

Cross-level weight collaboration mainly includes two aspects: the linkage between primary and secondary weights and conflict resolution rules. If a secondary indicator (such as health status (P5) frequently triggers positive feedback, the global weight of its primary indicator (physical quality (P)) will be raised simultaneously. When users' explicit ranking weights contradict implicit behavior feedback (for example, users claim to attach importance to personality quality, but the actual data display pays more attention to face value), a dialogue confirmation process is started to guide users to recalibrate or accept system optimization suggestions. λ_P .When the user's explicit sorting weight is in conflict with the implicit behavioral feedback (such as the user claims to value personality quality but the actual data shows that he or she pays more attention to appearance), the dialog confirmation process is activated to guide the user to recalibrate or accept the system optimization suggestions.

4.1.3 Weight constraint and fairness guarantee

（1）Ethical boundary constraint

① Limit of sensitive indicators: set the upper limit of weight for indicators that are easy to cause discrimination (such as physical quality (P)) to prevent the matching deviation of appearance orientation. $\lambda_P^{\max} \leq 0.3$, preventing appearance-oriented matching bias.

② Diversity enhancement: Shannon entropy constraint is introduced to ensure that the weight distribution of each first-level index meets the minimum diversity threshold;

$$H(\boldsymbol{\lambda}) = -\sum_{k=1}^{5} \lambda_k \log \lambda_k \geq H_{\min} \tag{22}$$

（2）Cold start optimization: considering group preference transfer. For new users, similar user groups are matched based on clustering algorithm, and the initialization weights are:

$$\lambda_k^{(0)} = \beta \cdot \lambda_k^{user} + (1-\beta) \cdot \lambda_k^{group} \tag{23}$$

Which $\beta \in [0,1]$ reflects the user's personalized input integrity（If all sorted then $\beta = 1$） .

4.2 User matching process

4.2.1Whole process stage division

The matching process designed in this study mainly includes the following four stages:

（1）Registration and portrait generation stage

①Multi-modal data collection: Users voluntarily authorize to obtain multi-modal data such as social behavior, cognitive behavior, entertainment behavior, consumption behavior and physiological data (the lack of which will affect their own evaluation scores). Localize sensitive data (such as income and address) through federated feature extractor, and upload only encrypted feature vectors;

②System self-evaluation: after uploading data, the system will default that all indicators of users have the same weight, and get the original score. Users can see the advantages and disadvantages of their own indicators. When others match themselves, they will dynamically adjust the weight and score according to the weight of other indicators to get the score from others' perspective. If the system score is lower than 60 (converted into a 100-point scale), they can't directly match others, but can only match by means of account number, nickname or code scanning.

③Initial weight setting: When matching other users, you should first sort the indicators you value step by step. The first is the first-level indicator sorting interface: the user sorts the five core indicators (physiology, personality, ability, family and quality) through drag-and-drop interaction, and the system automatically calculates the initial weight; Then the second-level indicators are refined: under each first-level indicator, users further sort the second-level indicators (such as face value, health and sense of responsibility) to generate segmentation weights; Finally, the manual correction module provides a visual weight distribution map, which supports users to manually adjust the weight ratio (allowing 15% deviation).

（2）Candidate matching pool construction stage

① Dynamic filtering rules: First, hard condition filtering: quickly eliminate mismatched objects according to uncompromising conditions set by users (such as age range and geographical location).

② Soft Conditional Scoring: Calculate the comprehensive attraction score of the candidate based on the user's weight (λ_k, ω_{ki}) :

$$G_j = \sum_{k=1}^{5} \lambda_k \left(\sum_{i=1}^{5} \omega_{ki} \cdot s_{ki}^{(j)} \right) \tag{24}$$

Where $s_{ki}^{(j)}$ is the standardized score of the candidate j in the secondary index ki.

③ Social graph enhancement: Using Graph Embedding technology to explore the potential associations of users' social networks (such as common interest communities and indirect friendship), and give priority to recommending candidates in three-dimensional space.

（3）Real-time matching recommendation stage

Adopt mixed recommendation strategy:

① Active search mode: the user sets the filtering conditions (such as "degree ⩾ master's degree" and "monthly consumption ⩾ 10,000 yuan"), and triggers the real-time matching engine to generate a Top-K list (K=50).

② Passive recommendation mode: a. Context-aware collaborative filtering: dynamically adjust the recommendation strategy according to the user's current scene (working day/weekend, morning and evening time) (such as focusing on ability matching on working day and interest matching on weekend); B. Apply Bandit algorithm of reinforcement learning: balance between exploration (recommending long-tail candidates) and utilization (recommending high-scoring candidates), and the formula is:

$$a_t = \arg\max_j \left(\hat{G}_j + c\sqrt{\frac{\ln t}{n_j}} \right) \tag{25}$$

$\hat{G}_j$ refers to the estimated score， n_j is candidation j history exposure times， c refers to the exploration coefficient.

（4）Two-way matching verification stage

① Gale-Shapley stable matching improvement: two-way preference list generation: the system generates a preference list for each user, and reversely calculates the interest score $G_{j \to i}$ of the current user for the candidate; Mutual selection verification protocol: only when both parties put each other on the Top-N preference list (N=20) can the matching be triggered successfully, so as to avoid one-way interest deviation.

② Dynamic threshold adjustment: according to user activity (daily average login times) and historical matching success rate, the mutual selection threshold is adjusted adaptively:

$$\theta_i^{(t)} = \theta_{base} + \alpha \cdot \left(1 - \frac{S}{T}\right) \tag{26}$$

Among them, $\theta_{base} = 0.7$, S refers to the number of successful tables, T refers to the total exposure, α refers to the attenuation coefficient.

4.2.2 Interactive feedback and model iteration

（1）Negative feedback learning mechanism:

① Explicit feedback processing: when the user clicks "not interested", the system records the reasons for rejection (such as "conflict of values" and "communication style mismatch", etc.), and locates the abnormal weights of related indicators through the attention mechanism.

(2) Trigger local weight correction:

$$\Delta\lambda_k = -\eta \cdot \frac{\partial \mathcal{L}_{reject}}{\partial \lambda_k}, \mathcal{L}_{reject} = \sum_{j \in \mathcal{D}_{reject}} \left\| G_j - G_{threshold} \right\|^2 \tag{27}$$

③ Implicit feedback analysis: monitoring user behavior sequence (such as skipping recommended page speed, chat reply delay), and predicting potential dissatisfaction factors through LSTM time series model.

（2）Distilling knowledge from successful cases: building a high-quality matching feature library.

① Store the weight distribution and interaction patterns of long-term relationship users (⩾6 months) and construct a positive sample set. $\{\lambda_k^*, \omega_{ki}^*\}$ with the interaction patterns, constructing the positive sample collection $\mathcal{D}_{success}$.

② Enhance model discrimination by comparing learning loss;

$$\mathcal{L}_{contrast} = -\log \frac{\exp(sim(v_i, v_j^+)/\tau)}{\exp(sim(v_i, v_j^+)/\tau) + \sum_{j^-} \exp(sim(v_i, v_j^-)/\tau)} \tag{28}$$

Among them, v_j^+ refers characteristic of successful cases, v_j^- refers to the characteristics of failed cases.

4.2.3 Ethical interactive design

（1）Progressive information disclosure protocol;

① Three-stage information unlocking rules:

A. Initial screening period: only insensitive indicators (interest labels, statement of values) and evaluation scores (I don't know the specific scores) are displayed.

B. Interactive period: After the two parties have chatted for more than 10 times, they will unlock data such as family background and consumption level (knowing each specific score).

C. Trust period: After the contact information is exchanged, in-depth information such as health report and education certificate will be released.

② Privacy sandbox mechanism: sensitive data (such as income certificate and medical examination report) are stored in local encrypted containers, and the authenticity is only verified by Zero-Knowledge Proof to avoid the original data leakage.

（2）Anti-fast-food relationship strategy;

① Deep interactive encouragement and feedback:

A. Give priority to users who have been chatting for more than 7 days and the two-way ratio of messages is ⩾40%.

B. Enable the relationship quality evaluation model, prompt the users of "high-frequency matching-quick termination" for behavior correction, and reduce their matching priority.

C. Evaluate the users who are reported to be dishonest and lower their scores. In severe cases, directly block the account for a certain period, and after unlocking, re-import the data for evaluation and match to restore a certain score.

② Time decay factor: users' short-term (within 24 hours) repeated matching requests will trigger the cooling mechanism, and the matching threshold will increase with time:

$$\theta_i^{(t)} \leftarrow \theta_i^{(t)} + \gamma \cdot (1 - e^{-t/\xi}) \qquad (29)$$

Where $\gamma = 0.1$ is the decay rate, $\xi = 24$ is the time constant.

5. Simulation experiment

In order to comprehensively evaluate the performance and effectiveness of partner evaluation model and intelligent matching system based on federated learning, a series of simulation experiments were carried out in virtual environment. Considering that it is difficult to obtain the actual multi-modal user data, this experiment uses virtual user data for simulation test, and initially realizes the above design content.

5.1 Experimental setup

5.1.1 Virtual User Data Generation

Using data generation method to construct virtual user data set. According to the preset experimental parameters, 1000 virtual users are generated. In the feature generation process, each user has a 25-dimensional feature vector, and its generation process comprehensively considers various statistical distributions and correlation modeling. The basic features are randomly generated by truncated normal distribution, and the distribution parameters are set as truncation interval [-2, 2], mean value 0.5, standard deviation 0.2, and generation dimension (1000,5); The related features are obtained by multivariate normal distribution combined with the randomly generated and symmetrical correlation matrix, and then the related features are scaled in the [0, 1] range, and finally the basic features and related features are spliced to form a complete 25-dimensional feature vector. When generating time series behavior data, the time step is set to 30, and the dynamic behavior pattern of users is simulated by integrating random noise, linear trend and other factors. At the same time, metadata including the user's gender (randomly selected as "m" or "f" with a probability of 0.5), age (randomly selected at the age of 18 to 45), place (generated by using the virtual data generation tool) and so on are generated to enrich the user's portrait.

5.1.2 Selection of evaluation indicators

In order to accurately measure the performance of the model and matching system, the following evaluation indicators are selected:

(1) Matching accuracy: it is used to evaluate the degree of matching results and users' real preferences, and calculate the proportion of the number of user pairs that successfully matched and the actual feature fit of both parties is consistent with the predicted fit of the model to the total number of matched user pairs.

(2) Matching success rate: it reflects the proportion of successful matching under a certain number of attempts, that is, the proportion of the number of users who successfully matched to the total number of matching attempts.

(3) Training loss: In the process of federal learning and training, the difference between the predicted value and the real value of the model is quantified by the mean square error loss function, so as to evaluate the fitting effect of the model in the training process. The lower the training loss, the stronger the fitting ability of the model to the data and the better the generalization performance.

5.1.3 Model and system parameter setting

(1) Federated learning model: `The companion evaluation model adopts a specific neural network architecture, including two parts: encoder and predictor. The encoder consists of two layers of linear transformation and ReLU activation function, which sequentially maps the input from 25 dimensions to 64 dimensions, and then from 64 dimensions to 32 dimensions. The predictor is also composed of two layers of linear transformation and ReLU activation function, which further maps 32-dimensional features to 16-dimensional features and finally outputs 5-dimensional vectors. In the federal learning setting, it is determined that the number of clients is 5, the training rounds are 20, and the learning rate is 0.01. When dividing data, the data is sorted according to the first feature to realize non-independent and identically distributed data partition, and then the index is evenly divided into five copies, which are distributed to each client for local training.

(2) Matching system: In the process of dynamic matching, the initial weight of intelligent matching system is set to uniform distribution, that is, the weight of each dimension is 1/5, and the number of matching rounds is set to 10. In the matching process, the similarity between candidate users is measured by calculating the feature-based similarity matrix, and 50 candidates are randomly selected from 1000 users in each cycle to form a candidate pool, and the similarity is calculated according to the dynamically adjusted weights. The weight adjustment strategy is based on

reinforcement learning and optimized according to the historical matching results.

5.2 Evaluation model experiment

5.2.1 Model training

The generated 1000 virtual user data are strictly divided into training set and verification set according to the ratio of 8:2. During the training process, each client independently conducts model training based on locally distributed data. Specifically, the client first converts the training set data into a data format suitable for the deep learning framework, and loads it with a batch size of 32 through the data loader, and at the same time randomly scrambles the data to enhance the generalization ability of the model. The client clones the global model and uses Adam optimizer (learning rate is 0.01) for three rounds of local training. For each batch of data in each round of training, the mean square error loss between the predicted value of the model and the real value (here, the first five-dimensional features are taken) is calculated, and the gradient is calculated by using the back propagation algorithm and the model parameters are updated. After completing the local training, the client collects the gradient information of each parameter and uploads it to the server. By aggregating the gradients uploaded by each client, the server calculates the average gradient and updates the global model parameters accordingly, thus realizing the iterative optimization of the model.

5.2.2 Performance evaluation

The comprehensive performance evaluation of the trained model is made by using the verification set. By calculating the mean square error loss between the predicted value and the real value of the samples in the verification set, the prediction accuracy of the model on user characteristics is accurately measured. At the same time, the prediction deviation of the model in different feature dimensions is deeply analyzed, and whether the model can accurately capture the real situation of users in various dimensions such as physiological quality and personality characteristics is carefully observed, which provides solid data support and theoretical basis for the targeted optimization of the subsequent model.

5.3 Matching system experiment

5.3.1 Simulation of Matching Process

Based on the generated virtual user data, the complete workflow of intelligent matching system is strictly simulated. In the stage of registration and portrait generation, multi-modal data is accurately allocated to each virtual user, and detailed and accurate user portraits are constructed through efficient feature extraction algorithms. In the construction stage of candidate matching pool, according to the pre-set conditions of users (such as age range, personality preference, etc.) and the quantitative evaluation results of users' comprehensive quality by the evaluation model, a screening algorithm is used to screen out eligible candidates, and 50 users are randomly selected at a time to form a candidate pool to ensure that the candidates have certain diversity and representativeness. In the real-time matching and recommendation stage, the mixed recommendation strategy based on dynamic weight is adopted, and the similarity between users is calculated according to the weights of different feature dimensions through a well-designed similarity calculation method, so as to provide personalized matching and recommendation for users. In the two-way matching verification stage, the matching willingness of both parties is verified through a specific verification mechanism. If both parties agree, it is determined as a successful matching, and the matching results are recorded in detail to provide accurate data for subsequent effect evaluation.

5.3.2 Evaluation of Matching Effect

Strictly evaluate the effect of the matching system according to the preset evaluation index. When calculating the matching accuracy, accurately count the number of user pairs successfully matched and the actual feature fit of both parties is consistent with the predicted fit of the model, and divide it by the total number of matched user pairs to get the index value; When counting the success rate of matching, divide the number of users who successfully matched by the total number of matching attempts; When analyzing the stability of matching, the fluctuation of matching results in different experiments is comprehensively observed through repeated experiments, and statistics such as standard deviation of matching results are calculated by statistical methods, so as to scientifically evaluate the stability of matching system under different experimental conditions and provide strong support for the reliability evaluation of the system.

5.4 Experimental Results and Analysis

5.4.1 Presentation of results

（1）Training convergence: As shown in Figure 1, it shows the changes of key indicators in the process of federal learning and training. The blue broken line represents the federated learning loss, and its fluctuation reflects the dynamic adjustment of data fitting in the training process of the model. The red dotted line indicates the Matching Success Rate, which shows the performance of the matching system in the training process.

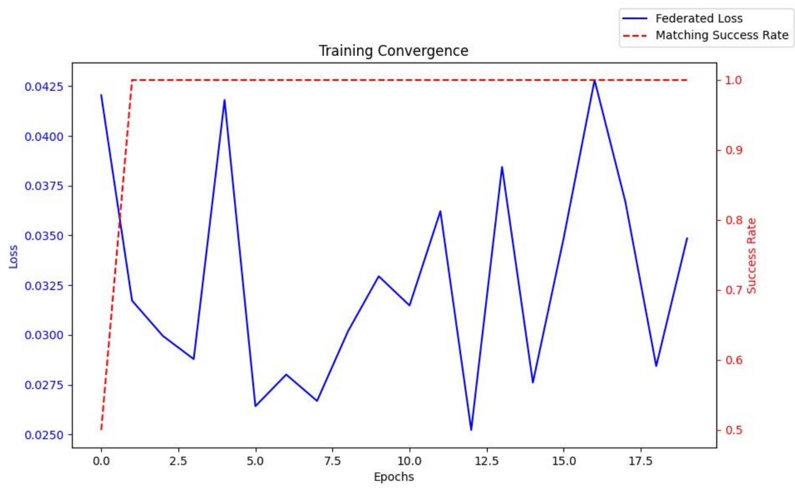

Figure 1. Changes of federal learning process indicators

（2）User embedding visualization: As shown in Figure 2, using t-SNE dimensionality reduction technology, high-dimensional user features are mapped to two-dimensional plane, and the feature values are distinguished by different colors. The distribution of scattered points in the diagram intuitively shows the feature clustering of users in low-dimensional space, which can help to understand the potential similarities and differences between users.

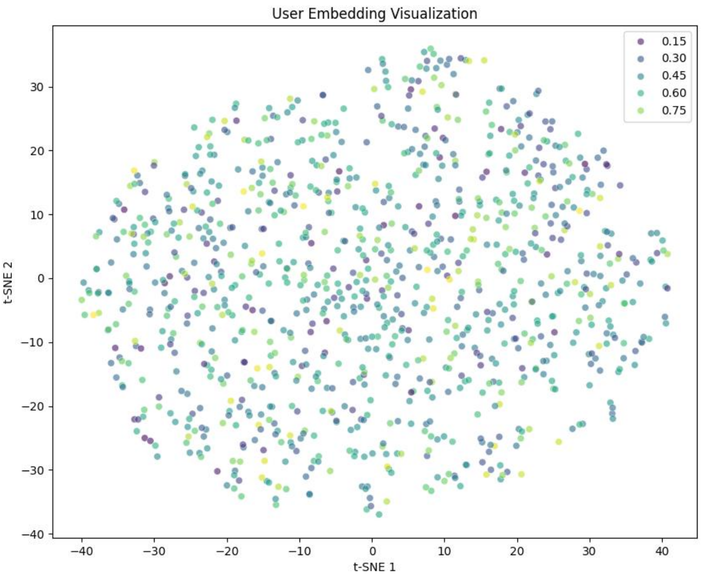

Figure 2. User Embedded Visualization

（3）Feature distribution: Figure 3 shows the distribution of features in different dimensions by kernel density estimation (KDE) curve. Curves with different colors correspond to different dimensions (Dim 0, Dim 5, Dim 10, Dim 15, Dim 20), and the shape and position of curves reflect the concentration trend and dispersion degree of eigenvalues of each dimension.

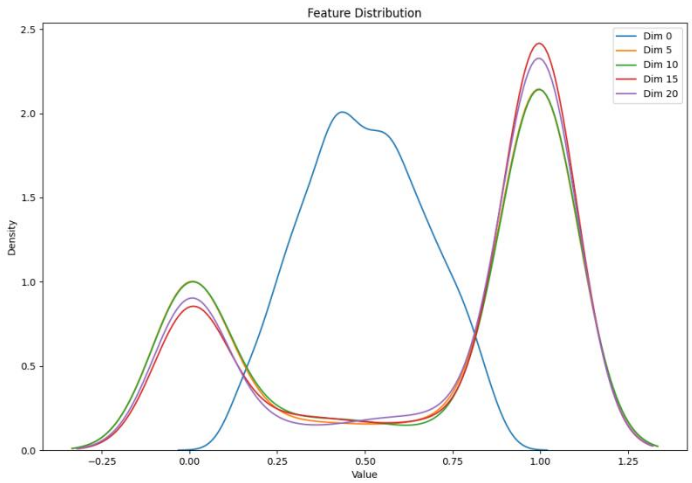

Figure 3. Distribution of user characteristics

（4）User-matching network: Figure 4 constructs a user-matching network structure, in which nodes represent users, the depth of node color reflects a certain characteristic value (identified by the color bar on the right), and the connecting lines between nodes represent the association between users. Through this diagram, we can intuitively observe the topological structure of user matching relationship and the distribution characteristics of features in the matching network (taking physiological quality and personality quality as examples).

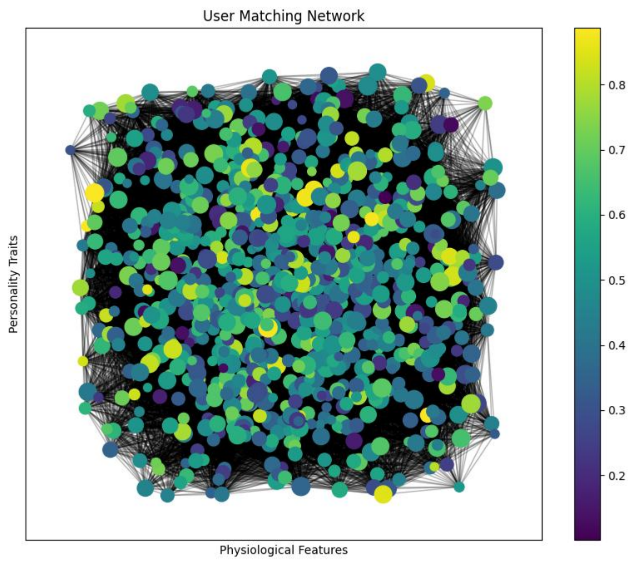

Figure 4. Schematic diagram of user matching network

5.4.2 Analysis of results

（1）Analysis of training convergence: As can be seen from Figure 1, the federal learning loss shows a downward trend of fluctuation, indicating that the model is gradually optimized in the training process, but the fluctuation indicates that the training process may be affected by factors such as the non-independent distribution characteristics of data or the model structure. The matching success rate is relatively stable and maintained at a high level, which shows that the matching system can maintain a certain matching effect in the training process, but there is still room for improvement. We can further explore how to adjust the training parameters or optimize the model structure to make the federal learning loss converge faster and reduce the fluctuation, and further improve the matching success rate.

（2）User embedding analysis: In Figure 2, users show a certain clustering trend on the two-dimensional plane, indicating that there is similarity aggregation of user features after dimensionality reduction. This shows that the model can effectively capture user features and make a reasonable mapping in the low-dimensional space, which is helpful to understand the characteristics distribution law of user groups and provide an intuitive reference for subsequent matching and recommendation based on user features. However, there are still some scattered points that are scattered, which may mean that these users have unique feature combinations and need to further refine the feature extraction and representation methods.

（3）Feature distribution analysis: Observing Figure 3, the distribution patterns of features in different dimensions are different. Some dimension features show obvious unimodal distribution, which shows that these features have a relatively concentrated range of values in the user population; However, the distribution of some dimension features is relatively flat or there are many peaks, which reflects the diversity and complexity of feature values. By analyzing the distribution of these features, it can provide guidance for feature engineering. For example, the features in the distribution set can be normalized, and the internal structure of complex distribution features can be deeply excavated.

（4）User matching network analysis: Figure 4 shows the complex matching relationship network between users. The color of nodes in some areas is relatively single, which indicates that users in these areas are highly similar in this feature, and may be more likely to form associations in the matching process. The density of connections reflects the closeness of the matching relationship between users. The area with dense lines indicates that there are many matching attempts or successful matching times between these users, which may be due to the high similarity score of these users' feature combinations in the matching algorithm. However, there are also some nodes with sparse connections, which may be because the characteristics of these users are difficult to form effective matching with those of other users, or the matching algorithm has limitations in dealing with these feature combinations. This requires us to further optimize the matching algorithm, for example, by introducing more complex similarity measurement methods or combining feature information of other dimensions to improve the matching situation of these users.

Generally speaking, the partner evaluation model and intelligent matching system in this experiment show certain effectiveness, but there is room for improvement in training stability, feature representation and processing, and matching algorithm optimization. The follow-up research will focus on these problems, and further improve the performance and reliability of the system by adjusting the model structure, optimizing feature engineering and improving matching algorithm, so as to better meet the practical application requirements.

6. Conclusion and prospect

6.1 Discussion

This study focuses on modern dating problems, aiming to build a partner matching framework that integrates multi-modal dynamic feature extraction and migration reinforcement learning to meet many challenges of existing online dating platforms and matching mechanisms. In the research process, through a comprehensive analysis of the status quo of online dating platforms, the problems existing in data modeling, dynamic adaptability and ethical mechanism of mainstream platforms are clarified, which provides a key direction for the subsequent model and system design. At the same time, combing the existing evaluation models and matching mechanisms, it is found that although they have their own achievements, they still have shortcomings in adapting to the complex needs of ideal partner evaluation and matching.

In the construction of evaluation model, this study built a comprehensive index framework around five core first-level indicators and 25 second-level indicators, such as physiological quality, personality characteristics, comprehensive ability, family background and personality quality. Through multi-modal feature engineering, the text, image, video and other data from users' mobile terminals are processed, and the potential information of users is effectively mined. The hierarchical dynamic attention fusion network (HDAFN) has realized the effective mapping from multimodal features to core indicators, and combined with the dynamic updating mechanism, it has improved the adaptability and accuracy of the model.

In the design of matching system, a multi-level weight distribution mechanism is constructed by combining users' explicit ranking preferences and dynamic behavior feedback, which effectively optimizes the collaboration between users' subjective needs and objective behavior data. The whole process design from registration and portrait generation, candidate matching pool construction, real-time matching recommendation to two-way matching verification, and the integration of interactive feedback, model iteration and ethical interactive design make the matching system more suitable for practical application scenarios and enhance the practicability and reliability of the system.

The simulation results show that the partner evaluation model and intelligent matching system proposed in this study have achieved good results to some extent. Although the federal learning loss fluctuates, it shows a downward trend, which shows that the model is gradually optimized in the training process; The matching success rate is relatively stable, which reflects that the matching system has certain effectiveness. However, the experiment also revealed some problems in training stability, feature representation and processing, and optimization of matching algorithm, which provided an improvement direction for the follow-up research.

6.2 Conclusion

Based on the research process and experimental results, this study successfully constructed a set of partner evaluation model and intelligent matching system based on multi-dimensional user portraits. The system has made innovations in multi-modal data fusion, index system construction, matching mechanism design and ethical interaction, which provides new ideas and methods for solving the problems of modern dating. The simulation results show that the system has certain advantages in matching accuracy and success rate, and can achieve more effective partner matching in virtual environment. At the same time, the design concept and method of the system also provide a useful reference for the research and application in related fields, which has certain theoretical and practical value.

6.3 Future work

Although some achievements have been made in this study, there are still many aspects worthy of further exploration and improvement.

(1) Model optimization: In-depth study on the influence mechanism of non-independent and identical distribution of data on model training in the process of federal learning, and explore more effective data division methods and model training strategies to improve the convergence speed and stability of federal learning loss. For example, more advanced federated learning algorithms, such as federated transfer learning and federated reinforcement learning, are tried to improve the adaptability of the model under different data distribution. At the same time, the structure of the evaluation model is further optimized, and more complex neural network architecture, such as the variant model of Transformer, is introduced to enhance the model's ability to extract and express user features and improve the accuracy of evaluation.

(2) Feature engineering improvement: Mining more dimensions and deeper user features, besides the existing behavior, interests and psychological features, taking into account the hidden features such as users' values, life goals and emotional needs, so as to make the constructed user portrait more comprehensive and accurate. Combined with the latest artificial intelligence technology, such as knowledge map and emotion calculation, the method of multi-modal feature extraction and fusion is improved to improve the quality and usability of features and provide more abundant and accurate information for matching algorithm.

(3) Innovation of matching algorithm: Explore a more efficient and intelligent matching algorithm. Besides the matching method based on similarity calculation, introduce technologies such as GAN in deep learning and DQN in reinforcement learning to optimize the matching strategy and improve the accuracy and efficiency of matching. Consider integrating popular algorithms in social network analysis and recommendation system, such as PageRank algorithm and optimized version of collaborative filtering algorithm, into the matching system, so as to tap the potential relationship between users and improve the matching effect.

(4) Practical application expansion: apply the research results to the actual scene, develop the actual application program, collect a large number of real user data for

testing and optimization, and verify the feasibility and effectiveness of the system in practical application. Cooperate with the dating platform, integrate and deploy this system, and continuously improve the function and performance of the system through the feedback of actual users, so as to provide better and more reliable partner matching services for the majority of single users and effectively solve the practical problems in modern dating.

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