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Recommendation of Personalised English Learning Resources Based on Transfer Learning and Semantic Analysis

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Abstract. *Personalised learning recommender system has become a research hotspot in the field of education, especially in language learning, how to recommend the most suitable learning resources depending on the learners' personalised needs is a key issue to improve the learning effect given the fast development of information technology. Aiming to provide English learners accurate and personalised learning resource recommendations, so enhancing learning efficiency and learning effect, in this paper we propose a personalised English learning resource recommendation system TL-SAR based on Transfer Learning (TL) and Semantic Analysis (SA). While semantic analysis digs further into the semantic information in the learning resources, and understands the content and context of the resources, so as to match the learners' interests and needs more precisely; transfer learning is used in TL-SAR to solve the data sparsity and cold-start problems and make up for the shortcomings of insufficient data in the target domain by transferring the knowledge from the existing domain to the target domain. Extensive experimental validation on two public datasets (MovieLens and ELDS) is also performed in this work under which the experimental results show that the recommender system based on the fusion of TL and SA has a notable advantage over conventional collaborative filtering recommender methods in terms of evaluation metrics, such as accuracy, recall, and F1 value. Furthermore supporting the distinct contributions of migration learning and semantic analysis to recommendation performance as well as their combined effects are the ablation studies. The suggested personalised recommendation system still has certain difficulties, like high computing resource requirements and model generalisation capabilities to be improved even if it shows better results. Future studies will help to improve the method and expand it to different teaching environments for more general uses.*
Keywords: personalised recommendation system; TL; SA; English language learning

1. **Introduction.** As information technology develops quickly, digital learning and intelligent education have progressively taken front stage in contemporary education [1]. Particularly in the sphere of language education, conventional teaching strategies are confronted with increased difficulties [2]. Although English is a global language and learning it is clearly popular and important, the conventional "one-size-fits-all" teaching approach usually fails to adequately meet the particular needs of every student because of the variations in learners' interests, ability, cultural background and need [3]. Thus, a hot issue in present educational technology research is how to offer suitable learning resources and customised learning paths depending on learners' personality traits, interest preferences and degree of learning progress.

Emerging to address this issue are tailored learning recommender systems. Using data mining, machine learning, and other technologies, personalised recommendation systems promote information most suited for consumers depending on their past behaviour, interests, and requirements. The conventional collaborative filtering-based and content-based recommendation systems have progressively revealed various issues, particularly the challenges of cold start and data sparsity, as learner behavioural data accumulates and the quantity of learning resources becomes evident [4]. Therefore, especially in the field of personalized learning where resources are numerous but data is few, how to mix several approaches to improve the performance of recommender systems remains an essential concern [5].

1.1. **Related work.** Personalised recommender systems have grown rather popular in many disciplines recently, among which education—especially in English learning—has become a hot issue for research [6]. Collaborative filtering, content-based recommendation, hybrid recommendation, etc. are the several ways one may generally divide the research on recommender systems [7].

Originally one of the first techniques used in recommender systems, collaborative filtering bases recommendations on past behavior of users [8]. By assessing users' ratings, clicks or browsing history, collaborative filtering techniques based on user behaviour discover similar users or similar resources and then generate recommendations. Even while collaborative filtering systems have some success, they still have issues including data sparsity and cold start, particularly in tailored English learning resources selection, how to properly handle these concerns is still a difficulty [9].

Content-based recommendation systems generate recommendations by means of content analysis—that is, text, video, graphics, etc.—of learning materials. Content-based recommendation systems concentrate more on the qualities of the learning materials themselves than do cooperative filtering techniques [10]. For instance, we examine keywords, subjects, and classification of learning materials to suggest materials for users based on their interests. Semantic analysis has been one of the main technologies of content-based recommendation systems since natural language processing technology developed recently. Deeply mining the semantic level of text helps one to match user needs and learning resources more exactly [11].

Aiming to offset the limitations of each, hybrid recommendation systems mix content-based techniques with collaborative filtering. Combining many recommendation techniques helps hybrid recommendation systems to sufficiently increase the diversity and accuracy of recommendations. Hybrid recommendation systems are extensively applied in personalized learning resource recommendation in the field of education to increase the accuracy and diversity of recommendations.

Transfer learning (TL), a method able to address the small sample learning challenge, has lately started to be used in recommender systems [12]. TL efficiently enhances the performance of recommender systems in the situation of data scarcity by extending the knowledge of current domains to the target domain. Migration learning can enable models acquire knowledge from related domains (e.g., other language learning or general education domains), therefore compensating for the issue of insufficient personalized data in English learning resources recommendation.

The in-depth knowledge of learning resources and user needs reflects mostly the application of semantic analysis (SA) in customized recommender systems [13]. SA may find deep semantic information from learning materials—such as subjects, emotions, intents, etc.—and match it with users' interests and needs by use of natural language processing technology. SA methods grounded in deep learning (e.g., BERT, GPT, etc.) have tremendously enhanced the accuracy of semantic understanding and given strong technical support for tailored recommendations in recent years.

Overall, personalised recommendation systems still have issues including data sparsity, cold start and suggestion accuracy even if they have made considerable development in the field of English learning [14]. Especially in the context of customised English learning resource selection, the performance of recommender systems can be sufficiently improved by including migrating learning and semantic analysis approaches. To better meet students' individualised demands, future studies can investigate the deep integration of these two and optimise them for certain educational environments.

1.2. **Contribution.** The innovations in this paper are mainly in the following areas:

First, this work suggests a personalised English learning resource recommendation system based on TL and SA's combination. TL-SAR is thus By means of these two approaches, the integration helps the recommendation system to overcome the typical issues of data sparsity and cold start and more precisely grasp the demands of the learners compared with conventional recommendation systems.

Second, first of its kind in current research, this article uses TL and SA in a customized recommender system in the English learning domain. Semantic analysis allows one to delve deeper into the possible information in the learning resources, such as the topic, context, and sentiment of the resources, so more precisely reflecting the learners' needs, while most of the conventional recommender systems concentrate on using user behavioral data to make recommendations.

At last, this work uses two public datasets - MovieLens and ELDS - to perform adequate experimental validation of the efficacy of the proposed strategy in personalized English learning resources suggestion. The possibilities and benefits of the recommender system combining migration learning and semantic analysis are shown by the experimental results showing good performance in several assessment criteria, including accuracy, recall, and F1 score, so indicating their practical relevance.

This paper presents a unique personalised English learning resource recommendation method based on thorough integration of migration learning and semantic analysis, which not only solves several problems in the conventional method but also improves the accuracy and intelligence level of the recommendation system and offers fresh ideas and methods for the research in the field of personalised learning recommendation.

2. Theoretical analysis.

2.1. **Transfer Learning.** TL is a learning technique meant to address the issues of inadequate labeled data and unequal distribution of training data confronted by conventional machine learning models [15]. While conventional machine learning approaches depend on a lot of labelled data for training, the fundamental idea of TL is to migrate the knowledge learnt from one domain (source domain) to another (target domain) in order to help achieve better learning performance in the target domain. Especially in data-scarce environments, effective application of TL can significantly raise the performance of models on small datasets [16].

TL's major objective is to use the knowledge of the source domain to assist with the task in the target domain so lowering the necessary data requirements for training in the target domain. Usually, the main ideas of TL are Domain, Task and Mapping. The chores in the target and source domains could be similar or different [17]. Effective migration depends on a good migration plan developed to overcome the variations between the source and target domains.

Usually, TL follows these guidelines: Initially specify the target domain D_t and the source domain D_s; subsequently:

$$D_s = \{X_s, Y_s\} \tag{1}$$

$$D_t = \{X_t, Y_t\} \tag{2}$$

where X serves the feature space and Y the label space. Either the source and target domains may be different or they may share the same feature space $X_s = X_t$. The labels Y_s and Y_t vary not always in meaning.

Extraction of accurate information from the knowledge in the source domain and application of it to the tasks in the target domain constitute TL's major responsibilities. Two varieties of TL are Task Transfer (TT) and Domain Adaptation (DA). Domain adaptation involves sharing the same task in the source and target domains but with differing data distribution. By adjusting the data distribution of the source and target domains, one hopes to have the learning algorithm generalize better in the target domain. Conversely, task migration is the situation in which the tasks in the source and target domains differ yet the knowledge of the tasks in the source domain facilitates the tasks in the target domain. For instance, going from picture categorization to object detection.

Commonly used approaches in TL are model-based, feature-based, and instance-based migration [18]. Among them, model-based migration is most often utilized in which the source domain model's parameters are changed to match the destination domain's job.

Quantifying the distribution difference between the target and source domains is a crucial responsibility of TL. Using the Kullback-Leibler (KL) scatter with the following formula will help one frequently evaluate distributional difference [19]:

$$D_{KL}(P_s \| P_t) = \sum_{x \in X} P_s(x) \log \frac{P_s(x)}{P_t(x)} \tag{3}$$

where $D_{KL}(P_s \| P_t)$ denotes the KL dispersion between the source and $P_s(x)$ and $P_t(x)$ respectively reflect the probability distributions of the source and target domains respectively.

The function can be stated as assuming that the goal of training on the source domain D_s is to minimise the loss function L_s, thus:

$$L_s(\theta) = \frac{1}{n_s} \sum_{i=1}^{n_s} \ell(f_\theta(x_i^s), y_i^s) \tag{4}$$

where $\ell(\cdot, \cdot)$ is the loss function; f_θ is the learning algorithm's prediction function; θ is a model parameter when x_i^s and y_i^s are samples and labels from the source domain.

Usually aiming to minimise the target domain loss function L_t, TL on the target domain D_t can be shown as:

$$L_t(\theta) = \frac{1}{n_t} \sum_{i=1}^{n_t} \ell(f_\theta(x_i^t), y_i^t) \tag{5}$$

where x_i^t and y_i^t are the target domain's samples and labels respectively.

A popular method in TL is to minimise the weighted loss function of the source and destination domain tasks, therefore attaining knowledge migration:

$$L_{\text{total}} = L_s(\theta) + \lambda L_t(\theta) \tag{6}$$

where λ is the weight coefficient regulating the equilibrium between the target and source domain losses.

Source and target domains in model-based TL can share some of the model parameters. By jointly optimizing the following objective functions assuming the common parameters are θ_s and θ_t:

$$L_{\text{joint}} = L_s(\theta_s) + L_t(\theta_t) + \gamma \|\theta_s - \theta_t\|^2 \tag{7}$$

where $\|\theta_s - \theta_t\|$ is the distance between the source and target domain parameters and γ is the regularisation factor.

Moreover connected to the selected model design is the influence of TL. Assuming the target model is θ_t^*, the ideal model parameters after transfer learning need to minimise the loss function of the target domain while considering the impact of source domain knowledge:

$$\theta_t^* = \arg\min_{\theta_t} L_t(\theta_t) + \alpha R(\theta_t) \tag{8}$$

where α is a hyperparameter to control the weight of the regularisation term and $R(\theta_t)$ is the regularisation term.

By means of knowledge migration from the source domain, TL addresses the issues of generalizing ability in the target domain and data scarcity. By means of knowledge migration from the source domain to the target user group, TL can efficiently solve the cold-start issue and enhance the accuracy of recommendation and system resilience in personalized recommender systems. Transfer learning's mathematical foundation gives theoretical basis to enable the building of more effective algorithms.

2.2. **Semantic Analysis.** In the realm of natural language processing, particularly in systems for customized English learning resources, SA is rather essential. SA technology can enable computers to grasp the substance of text and hence offer more accurate recommendation services by parsing the latent semantics of language [20]. In the recommendation system, SA considers semantic links among words, phrases, and contexts in addition to the meaning of individual words.

First of all, one of the fundamental questions of SA is how to translate natural language content into a computer-understandable form. Though basic and easy to use, the old Bag-of-Words (BOW) increasingly substitutes more effective strategies since it ignores the order and contextual information between words. Currently, the mainstream approaches for processing SA include Word Embeddings (WEB) and pre-trained models based on deep learning, notably BERT.

Word embeddings are among the most often applied methods in SA. Word embeddings are fundamentally a means of mapping words into a continuous low-dimensional vector space such that related words are closer in that space. FastText, GloVe, and Word2Vec are common word embedding systems [21]. These systems maximise the similarity of context words to learn word vectors. Skip-grams are extensively applied in Word2Vec to produce word vectors. Predicting the context word w_o given a central word w_c is the aim, hence the procedure may be shown by the following equation:

$$P(w_o|w_c) = \frac{\exp(v_{w_o}^T v_{w_c})}{\sum_{w \in V} \exp(v_w^T v_{w_c})} \tag{9}$$

where V is the vocabulary; v_{w_c} and v_{w_o} are the word vectors of the center and context words respectively; $P(w_o|w_c)$ is the likelihood of predicting the context word w_o given the center word w_c.

Pre-trained language models based on Transformers, including Bidirectional Encoder Representations from Transformers (BERT), have made major advancement in SA recently to improve the context understanding capacity of the model [22]. By means of the bi-directional encoder, BERT captures the context dependency relationship between the previous and previous contexts in the sentence, so producing contextually relevant word vectors. The training aim of BERT is to forecast the masked words (Masked Language Model), with an objective function as follows:

$$L_{MLM} = -\log P(w_t|H_t) \tag{10}$$

where H_t is the hidden layer output; w_t is the word vector of the target word; $P(w_t|H_t)$ is the probability of the masked word.

Apart from word-level semantic representation, SA has to handle sentence-level semantic comprehension as well, particularly for uses in information retrieval and recommender systems. One often used method is to get semantic information of complete sentences by means of sentence embeddings [23]. Usually, sentence embeddings result by aggregating word vectors of individual words in a sentence. Assume a sentence has n words $w_1, w_2, \ldots, w_n$; its sentence embedding can be stated as:

$$v_{\text{sentence}} = \frac{1}{n}\sum_{i=1}^{n} v_{w_i} \tag{11}$$

where v_{sentence} is the general semantic representation of the sentence; v_{w_i} is the word vector of the i-th word.

Moreover, sentence similarity calculation can be applied for recommendation in order to grasp more intricate semantic links between texts. Given two sentences S_1 and S_2 whose sentence embeddings are v_{S_1} and v_{S_2} respectively, then the cosine similarity between them may be calculated with this formula:

$$\text{similarity}(S_1, S_2) = \frac{v_{S_1} \cdot v_{S_2}}{\|v_{S_1}\| \cdot \|v_{S_2}\|} \tag{12}$$

where the relevant vectors have modulus lengths $\|v_{S_1}\|$ and $\|v_{S_2}\|$.

In tailored recommender systems, SA depends not only on phrase and word embedding but also on user interest modeling to raise suggestion accuracy. Assuming that the user's previous behavior may be expressed as a sequence of sentences $\{S_1, S_2, \ldots, S_k\}$, weighted average of these sentence embeddings generates the user's interest vectors.

$$v_{\text{user}} = \sum_{i=1}^{k} \alpha_i v_{S_i} \tag{13}$$

where α_i reflects the user's degree of sentence interest by being the weight connected with the sentence S_i. This allows the recommender system to match the user's interest vector with the semantic representation of the learning resource, therefore generating personalized learning resource recommendations.

All things considered, tailored English learning materials recommendations depend much on SA. The recommender system can better find the matching relationship between user demands and learning materials by means of deep semantic comprehension of text, thereby enhancing the accuracy and customization degree of recommendation.

3. **Personalised English learning resource recommendation system based on transfer learning and semantic analysis: TL-SAR.** This chapter presents a personalised English learning resource recommendation system (TL-SAR) grounded on TL and SA. See Figure 1; by combining migrating learning and semantic analysis approaches, the system can intelligibly suggest tailored English learning resources depending on users' interests and needs. Six primary modules make up the TL-SAR system: user model construction module; resource representation module; semantic matching module; migration learning module; recommendation generating module; system evaluation module.

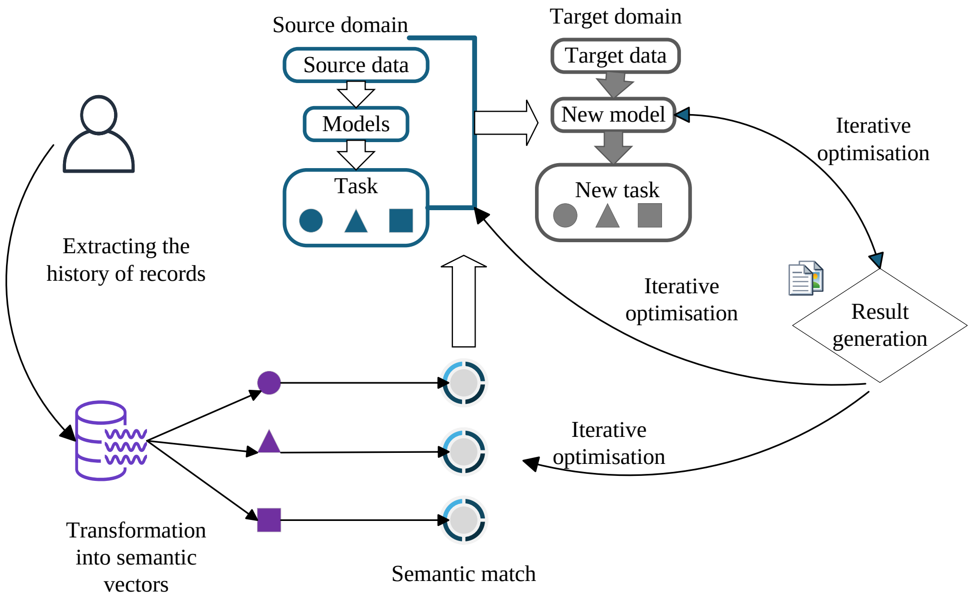

Figure 1. A TL-SAR model

(1) User model building module. The user model building module mostly helps to extract from the user's learning behavior, past, and interaction data their interests and preferences. This module can provide a tailored user feature vector reflecting the learning needs and interests of the user by means of the SA of user data.

Assuming u_i to be the feature vector of user i, it is built by weighted averaging the semantic representation of every resource in the user's learning past:

$$u_i = \frac{1}{k}\sum_{j=1}^{k} \alpha_j r_j \tag{14}$$

where r_j is the semantic representation of the jth learning resource and α_j is its weight.

(2) Resource representation module. The Resource Representation Module's job is to create semantic vectors out of all English learning materials. The system generates a low-dimensional vector representation from the content of every resource—articles, movies, glossaries, etc.—by means of SA. A TF-IDF technique or a deep learning-based model (e.g., Word2Vec, BERT) can be used to create the representation of every resource thereby catching its semantic content.

Adopting the TF-IDF method allows one to acquire the semantic representation r_r of a resource r by computing the weight of every word:

$$r_r = \sum_{i=1}^{n} \mathrm{TF}(w_i) \cdot \mathrm{IDF}(w_i) \cdot v_{w_i} \tag{15}$$

where $\mathrm{IDF}(w_i)$ is the inverse document frequency of vocabulary w_i over all resources; $\mathrm{TF}(w_i)$ is the word frequency of vocabulary w_i in resource r; n is the total number of words in the resource. This means that the way resources are portrayed shows the value of every word in the overall collection of papers.

(3) Semantic matching module. Compute the similarity between the user model and the learning resources and suggest the most pertinent learning resources for the user depending on the similarity is the aim of the semantic matching module. Usually, computing the distance or similarity between the user model and the semantic representation of the resource helps one to identify the resource that most satisfies the needs of the user.

We employ the Euclidean distance in this system to quantify the user model u_i's and the resource r_r's similarity. More specifically, the Euclidean distance $d(u_i, r_r)$ between user model and resource is computed as follows: u_i, and r_r respectively are semantic representations of them:

$$d(u_i, r_r) = \sqrt{\sum_{k=1}^{d} (u_{i,k} - r_{r,k})^2} \tag{16}$$

where $u_{i,k}$ and $r_{r,k}$ indicate the values of the user model and the semantic representation of the resource in the kth dimension correspondingly; d is the dimension of the vector. The user and the resource have more semantic similarity the smaller their Euclidean distance; so, the resource is more relevant to the individual needs of the user. Calculation of this distance helps the system to filter the learning materials most suited for the user's needs.

(4) Migration learning module. Using expertise from many fields, the migrating learning module maximizes the efficacy of tailored recommendations. To increase the accuracy and generality of the recommendation system, the system combines learning resources from other comparable domains with data from the target domain (English learning resources) using TL.

The TL process may be obtained with the following formula assuming M_s is the model of the source domain and M_t is the model of the target domain:

$$M_t = f(M_s, r_t) \tag{17}$$

where $f(\cdot)$ is a migration function that moves knowledge from the source domain to the target domain, therefore enhancing the recommendation of the target task.

(5) Recommendation generation module. Combining the data of the Semantic Matching Module and the Migration Learning Module, the Recommendation Generation Module offers users tailored learning resource recommendations. Based on the user's interests, actions, and the match between the resources and the user computed by the system, the module creates a recommendation list.

The formula determines the suggested results:

$$\hat{R}_i = \sum_{r \in R} \lambda_r \cdot \mathrm{CosineSimilarity}(u_i, r_r) \tag{18}$$

where R is the set of all recommended resources; λ_r is the weight coefficient of resource r; so, the final recommendation list $\hat{R}_i$ is produced depending on the degree of semantic matching between the resources and the user as well as the outcomes of the migrating learning optimisation.

(6) System evaluation module. The objective of the module on system evaluation is to validate the recommendation efficacy of the TL-SAR recommender system by means of quantitative analysis of its performance. To completely assess the recommendation system, the module runs on Precision, Recall, and F1-score.

Precision in the context of recommendation results refers to the percentage of accurate recommendations:

$$\text{Precision} = \frac{|R_{\text{relevant}} \cap R_{\text{recommended}}|}{|R_{\text{recommended}}|} \tag{19}$$

Recall is a gauge of the percentage of all pertinent materials that are effectively advised:

$$\text{Recall} = \frac{|R_{\text{relevant}} \cap R_{\text{recommended}}|}{|R_{\text{relevant}}|} \tag{20}$$

The F1-score is the mean of recall and precision corrected:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{21}$$

Furthermore, depending on user comments and online testing, the module of system assessment modulates the recommendation algorithm and maximizes system performance. Performance evaluation of the system helps engineers to always enhance TL-SAR to raise its user happiness and suggestion accuracy.

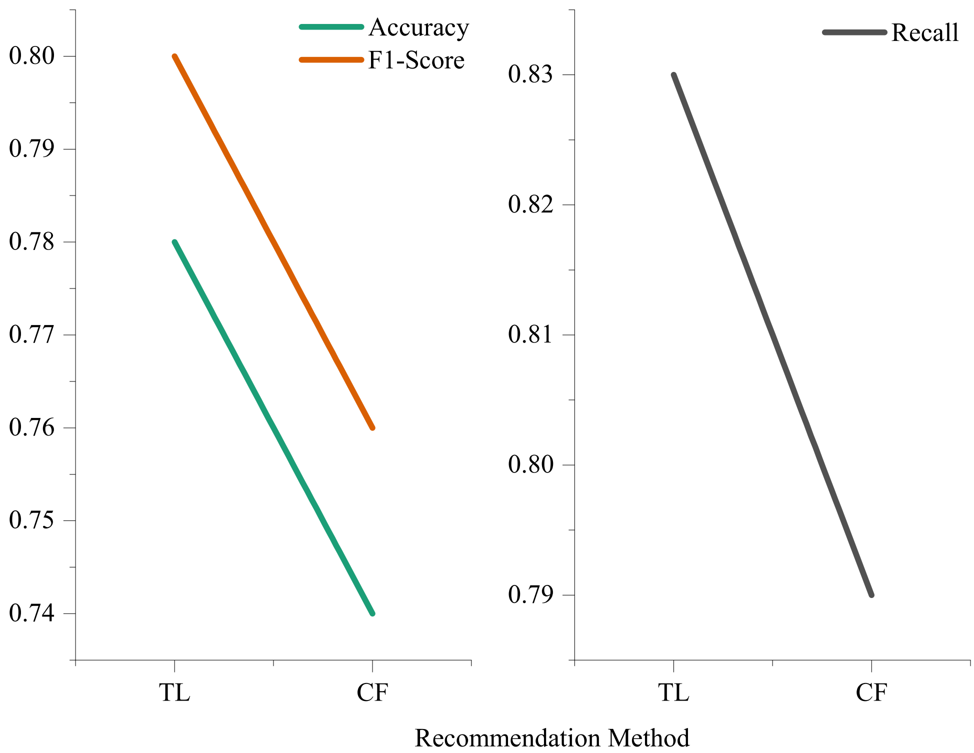

Figure 2. System performance comparison

4. Performance testing and analysis.

4.1. **Data sources.** Two particular datasets were selected to assist the experimental component of this work: the English Learning Dataset (ELDS) and the MovieLens Dataset. These two datasets can efficiently assess the effectiveness of recommender systems depending on transfer learning and semantic analysis; they respectively cover the tasks of recommender systems and personalised suggestion of English learning resources.

Table 1 offers a quick overview of the two sets:

From the angles of recommender systems and personalised learning resource recommendation respectively, these two datasets offer rich experimental data for this research.

Table 1. Comparison of MovieLens dataset and ELDS

Dataset Name	**MovieLens Dataset**	**ELDS**
Sample Size	20,000+ movies, 138,000+ ratings	10,000 students' learning records
Resource Type	Movies	English learning resources (videos, articles, exercises)
User Behavior Data	User ratings, movie tags, timestamps	Student learning records, ratings, progress
Applicable Field	Recommendation systems, Transfer Learning	Personalized learning resource recommendation, Semantic Analysis

Particularly with comprehensive data on user preferences and resource ratings, the MovieLens dataset offers a suitable base for the transfer learning investigations. Particularly in the English learning environment, the ELDS dataset is able to directly assist the process of tailored suggestion based on semantic analysis.

4.2. **Experiments in TL.** Aiming at comparing the effectiveness of TL-based recommender systems with conventional collaborative filtering (CF)-based methods in personalized recommendation tasks, we assessed using the MovieLens dataset and the ELDS dataset respectively in migration learning experiments. While traditional CF depends on user-item interaction information and usually performs better when the amount of data is large and the domains are similar, TL is expected to effectively improve the generalisation ability of the recommender system by migrating the knowledge from the existing domain (source domain) to the new domain (target domain), especially in data-scarce or cold-start circumstances. In order to thus fully assess the recommendation efficacy, we examine the performance of TL and CF on two datasets using three evaluation metrics: Accuracy, Recall, and F1-Score.

Figure 3 and 4 respectively demonstrate the findings of the tests on these two datasets.

It shows that in terms of accuracy, recall, and F1 score, TL beats the conventional collaborative filtering technique. Specifically, the accuracy of TL is 0.78, which is 0.04 higher than the 0.74 of collaborative filtering, the recall is 0.04 higher, and the F1 score is 0.04 higher, which suggests that TL is able to more precisely suggest movies to consumers on this dataset, and also outperforms the recall-related items, with a better balance of recommendation effects.

With an increase of 0.08 in the recall rate and 0.07 in the F1 score, the performance difference in TL over the collaborative filtering strategy is even more noteworthy on the ELDS dataset: TL achieves an accuracy of 0.75, which is 0.07 higher than the 0.68 of the collaborative filtering approach. This difference implies that by efficiently moving knowledge acquired in the source domain (MovieLens) to the target domain, TL is able to increase recommendation performance despite the fact that the ELDS dataset differs from the MovieLens dataset in terms of domains. By use of efficient knowledge migration from the source domain (MovieLens) to the target domain, TL can enhance the recommendation performance. By spreading knowledge across domains and enabling more relevant resource recommendations, TL overcomes the cold-start issue by comparison with conventional collaborative filtering techniques.

On both datasets, TL generally beats conventional CF quite noticeably. TL shows its benefits in the movie recommendation work on the MovieLens dataset by improving

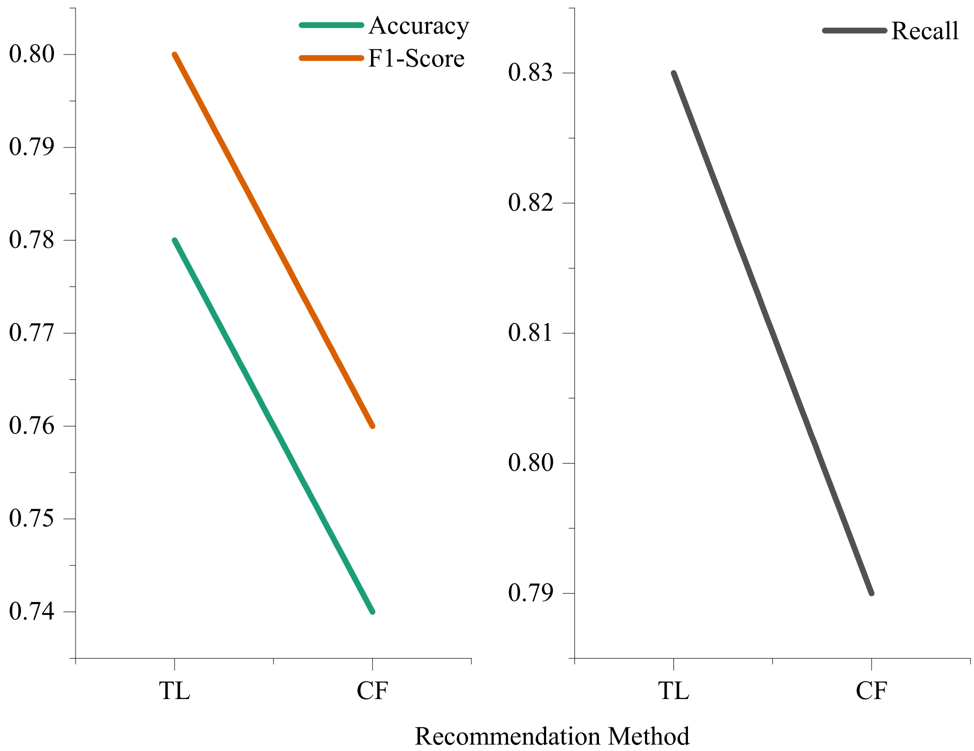

Figure 3. Experimental results on the MovieLens dataset

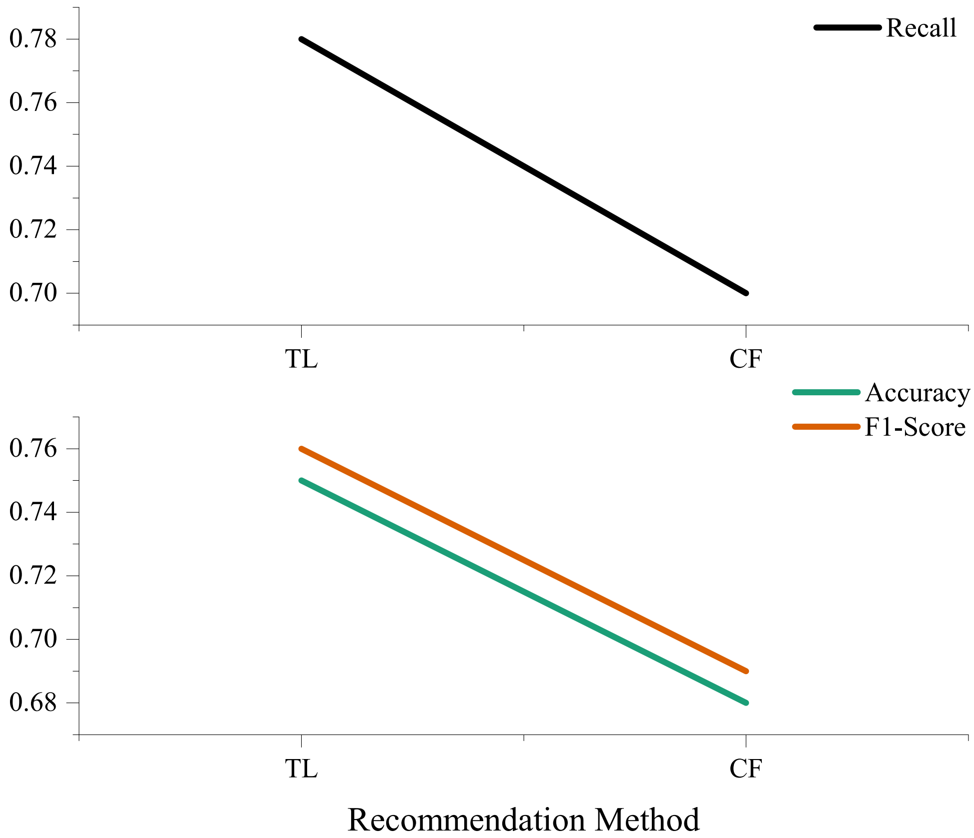

Figure 4. Experimental results on the ELDS dataset

accuracy, recall, and F1 score by 0.04%. With an improvement of 0.07 in accuracy, 0.08

in recall, and 0.07 in F1 score, which shows that TL can efficiently borrow the knowledge of the source domain when dealing with the cross-domain recommendation task, and so improve the recommendation performance in the target domain by fine-tuning the model, on the ELDS dataset the advantages of TL are even more clear.

Particularly on the ELDS dataset, CF performs more generally, most likely due to the dataset including the suggestion of learning materials in several areas and CF is less flexible between domains. Conversely, especially in cases of cold start and data shortage, TL might accomplish superior adaptation and performance in the target domain by use of the features and patterns learnt in the source domain.

4.3. **Ablation experiments.** In this work, we assess TL and SA's respective contributions to a tailored English learning resource recommendation system. Four models make up the experimental design: the baseline model CF, the model employing only TL, the model employing only SA, and the full model TL-SAR employing both TL and SA. Using Accuracy, Recall, and F1-Score as evaluation criteria, we performed the experiments on the MovieLens and ELDS datasets separately.

Figure 5 shows the outcomes of the MovieLens dataset studies.

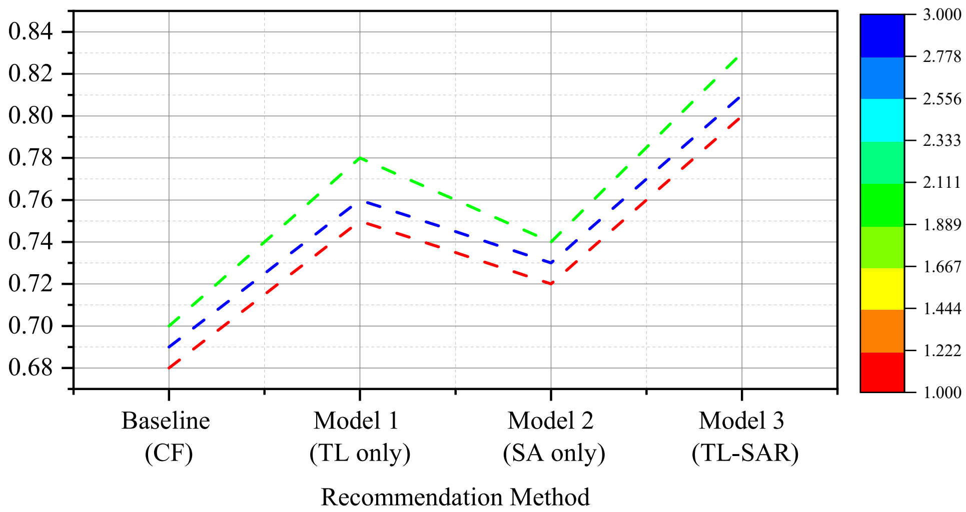

Figure 5. Experimental results on the MovieLens dataset

While the model using only TL (Model 1) shows a notable improvement over CF with 0.75 accuracy, 0.78 recall, and 0.76 F1 score, suggesting that TL is able to efficiently improve the quality of the recommendations on this dataset, the benchmark model CF performs the lowest with 0.68 accuracy, 0.70 recall, and 0.69 F1 score. With an accuracy of 0.72, a recall of 0.74, and an F1 score of 0.73, the SA-only model (Model 2) also beats CF; yet, the improvement is little when compared to the model with TL alone. With an accuracy of 0.80, a recall of 0.83, and an F1 score of 0.81—indicating that the mix of TL and SA can complement each other to improve the performance of the recommender system—the TL-SAR model (Model 3), which combines TL and SA, performs the best on all the evaluation measures.

Figure 6 demonstrate the experimental findings on the ELDS dataset.

With an accuracy of 0.71, a recall of 0.73, and an F1 score of 0.72, the SA-only model (Model 2) similarly beats CF; the improvement is somewhat modest when compared to the TL model. With an accuracy of 0.77, a recall of 0.79, and an F1 score of 0.78, the TL-SAR model (Model 3), which combines TL and SA, finally also shows the ideal performance.

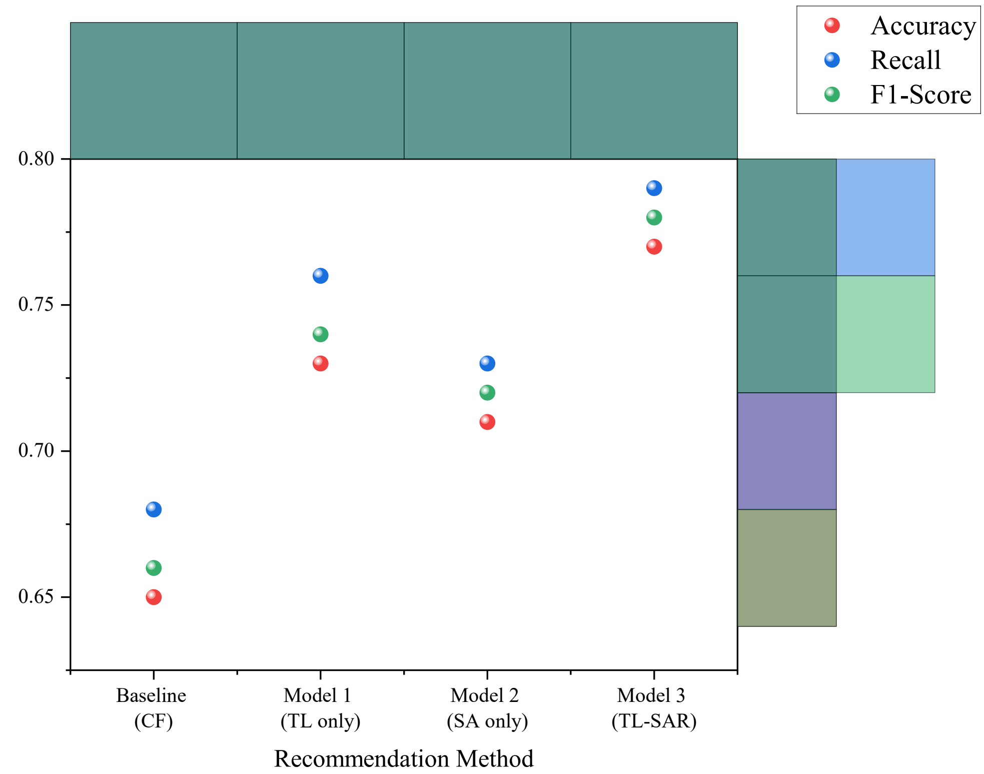

Figure 6. Experimental results on the ELDS dataset

These two sets of experimental results indicate that both TL and SA can considerably enhance the performance of the recommender system; moreover, the TL-SAR model—that is, the combination of TL and SA—show optimal results on both datasets, so demonstrating the complementary character of these two methods in tailored recommender systems. While on the ELDS dataset the TL-SAR model performs also well, especially in the F1 score, on the MovieLens dataset the improvement of the TL-SAR model is clearly clear, especially in the accuracy and recall rates.

5. **Conclusion.** Aiming to increase the accuracy and efficiency of recommendation systems in personalised learning environments by merging TL and SA, we present a personalised English learning resource recommendation system in this work. First we examine relevant research work in this work and then we address the benefits of TL and SA application in recommender systems. Second, this work describes the architecture of the suggested recommender system split into many modules: resource representation module, semantic matching module, suggestion generating module, user personalizing modeling module, and system assessment module. By means of these modules, the complimentary character of migration learning and semantic analysis is completely exploited to improve the recommender system performance.

We performed thorough experimental validation on two public datasets, MovieLens and ELDS, and the experimental findings suggest that the recommender system based on the fusion of TL and SA shows better recommendation outcomes than the conventional collaborative filtering technique. Particularly, the model combining TL and SA shows best in accuracy, recall, and F1 score. We also carried ablation studies to confirm the independent and cooperative effects of TL and SA on the recommender system performance.

Though the tailored recommender system suggested in this work has produced more noteworthy outcomes, it also has some restrictions. First of all, the varied features of the two common datasets we utilized in our experiments could restrict the generalisation capacity of the model even if we conducted two similar tests. Second, whilst the semantic analysis also depends on sophisticated natural language processing techniques, which may lead to a longer model training time, the training of transfer learning calls for more data and computer resources. Furthermore, even if this paper suggests a recommendation approach based on users' historical data and interests, it is still difficult to update the user model in time and accommodate users' dynamic needs in pragmatic applications where users' needs and interests evolve quickly.

Future studies might be conducted in the following lines. Initially, enlarge the dataset to investigate other kinds of learning materials and recommendation scenarios in order to confirm the generalization capacity of the suggested approach. Second, more advanced deep learning models can be tried to maximize the benefit of transfer learning, especially in cross-domain transfer learning, where how to efficiently transfer information is still an issue deserving of in-depth study. Once again, the semantic analysis module can incorporate more sophisticated natural language processing methods, such BERT and other pre-training models, to raise the semantic matching and text representation accuracy even further. Furthermore, given the dynamic character of user interests and wants, more flexible online learning and tailored modeling strategies can be created to accommodate quick changes in user behavior. Combining additional real-time data and user feedback finally allows one to investigate the interaction between recommender systems and practical application scenarios to enhance the real-time and accuracy of the system.

Although this study still has some shortcomings overall, the integration of transfer learning and semantic analysis has shown a better application prospect in the field of personalised English learning resource recommendation. Future research can further optimise the algorithm and extend the application scenarios to provide more theoretical support and technical solutions for intelligent recommendation in the field of education.

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