This article can be cited as P. Jomsri and W. Choochaiwattana, Machine Learning Mechanism for Adaptive Tourist Recommendation Using Bayesian Algorithm, International Journal of Artificial Intelligence, vol. 19, no. 1, pp. 109-122, 2021.

Machine Learning Mechanism for Adaptive Tourist Recommendation Using Bayesian Algorithm

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ABSTRACT

Currently, recommender systems are available in many daily activities such as online shopping search, and social networks. Due to the increasing demand of the tourism industry through information technology, the recommender systems are integrated into the tourism website. This research aims at exploiting user data to recommend tourist attractions by arranging the attractions together with tourism-related information and making recommendations based on information relevant to the needs of each user. The proposed mechanism has an advantage as it can suggest information at the beginning of use without the need for usage history, rankings, and other special knowledge. Thus, new travelers can get recommendations when start using the recommender system. This research focuses on recommending tourist destinations in Thailand using machine learning methods based on Bayesian Personalized Ranking to predict tourist attraction rankings by comparing four methods: 1) Collaborative Filtering Only, 2) Demographic Filtering Only, 3) Collaborative Filtering and Demographic Filtering, and 4) Hybrid Method of Demographic Filtering and Demographic Filtering Combining with Tourist Attraction Category. The experimental results show that the hybrid method of collaborative filtering and demographic filtering combining with the ranking of tourist attractions recommends tourist attractions better than other methods. Therefore, this hybrid model can be used as a model to support the Recommender system of tourism.

Keywords: Machine Learning, Bayesian Personalized Ranking, Tourist Recommendation, Recommender System.

Mathematics Subject Classification: 97R40, 97R50

Computing Classification System: H.5

1. INTRODUCTION

Nowadays, with the advancement of internet-based applications and widespread communication technology, users can share travel experiences and display reviews online. In addition, those online reviews are important and have an impact on the decision of other travel users. Also, the development of web technology and information retrieval are the main influences on the behavior of both tourists and the tourism industry.

According to Google's statistics (Reyes-Menendez et al., 2019), the data show that people visit many websites and spend about two hours searching for tourist attractions. However, too much information is available to provide search results so as to match the needs of each user. In this regard, Recommender system is considered as an alternative tool to web services which helps users get information that is tailored to their needs. Recommender system is created by collecting user's information such as user interest, which is adjusted and applied to tourists. Although the tourist recommendation system is a form of suggesting tourist destinations based solely on search terms, the previous system still lacks the form of necessary suggestion, and only has tourist destinations according to the needs of the users. The goal of the research focuses on providing suggested places based on the preferences of each user, whether those places are not popular or are the top places to attract tourists. Highlighted places are places that are highly rated.

This study covers reviews and location scores and this vast amount of information is used along with online user profile data. The use and analysis of effective tourist destinations are based on various factors assisted other tourists to make more informed decisions related to their destinations. The challenge for this study is the amount of online information that is available in many different platforms which cause tourists to spend a considerable amount of time deciding and making travel plans. Besides, the growing and advanced technology allows users themselves to use social media, share, and reviews travel experiences like TripAdvisor, for instance.

There are several recommendation systems that focus on the movement of tourists by suggesting tourist destinations from reviews and history (Menk et al., 2019). Although, those suggestion systems only suggest places which are popular or important, mainly. Such recommendation systems seem to miss out on location recommendations that travelers should have visited, or places that should not have been missed. This study proposes recommendation systems which system goals are to use user history data and learns ranking to recommend the top attraction places according to tourist needs and suggested places that are not under-emphasized by learning from the relevant location map table from tourist information by categories, related topics from tourism information of Thailand.

The objective of this research is to apply personalization techniques, which create recommendations tailored to the user's preferences and interests to support tourist recommendations. The system offers content that has filtered tourist forms to each user including natural tourism, community, and community products. The developed system learns the user's location via mobile devices. This research proposes hybrid model for recommending tourist attractions by considering the user's own data, a group of tourist attractions, and the popularity among friends--who use to travel to that place--including the introduction of machine learning method, as well as using the Bayesian network theory to apply in tourism for the benefit of suggesting places to tourists. In this paper, Session 2 demonstrates the related works to this research. Session 3 presents the proposed methodology and all the algorithmic. Session 4 presents experimental results for the research proposed and compares with other models. Finally, the last Session discusses the conclusion of recommender system hybrid methods so as to recommend users about tourist attraction.

2. RELATED WORK

The latest innovations of information technology are used by the tourism industry as a solution of recommendation for tourist attractions and user model adaptations in order to improve the recommendation system. Generally, recommendation system has algorithms for recommender information to users. The traditional algorithms are Content Based Filtering (CB), Collaborative Filtering(CF), Demographic Filtering(DF) (Ricci et al.,2011). Since each technique has some disadvantages, the integration of these techniques can be applied such as hybride and weight for recommendation systems to make it become the better system.

Most recommendation systems are based on reliability such as suggesting places by using relevant social networks including the use of techniques in classification and Prediction algorithms for recommendation systems. The systems are generally divided into three categories (Lü et al., 2012 ; Bobadilla et al.,2013) which are CB, CF, and hybrid recommendation systems. The selection of characteristics base on what the user browses is the content-based recommendation system (Wang et al., 2018; Van den Oord ,2013). Therefore, it is necessary to calculate the similarity among the various items. In addition, the collaborative filtering-based recommendation system is accompanied with the consistent recommendations based on ranking predictions. It is widely used in the industry due to its many advantages. For example, an unstructured list can be processed and does not require any domain knowledge to find new user settings. It can create many personalized recommendation results for users. At the same time, hybrid suggestion results can be received based on content and suggestion result collaboration. A mixed referral system can take full advantage of the different types of referral systems and achieve good results. Recommendations from the above categories, modern origin network Generative Adversarial Networks (Goodfellow et al.,2014) and knowledge graphs (KG) are the format for the system recommendation (Wang et al.,2019 and 2018).

The collaborative filtering theory is proposed by Goldberg and his team (Goldberg et al.,2013). And, it, for the first time, is used in Tapestry, a well-known recommendation system. However, Tapestry offers recommended services for special users only. Another famous researcher introduces the system that is called GroupLens, using a collaborative filtering recommendation system (Resnick et al.,1994).

Bayesian personalized ranking (BPR) is another mutual-recommendation system that is proposed by rendering metal (Rendle et al.,2009) and is used in product introduction. The triple-tuple pairwise training method is the first technique of the BPR model. However, the collaborative filtering based recommendation systems face two major problems: 'cold start' and 'data sparseness'. To solve this latter problem, additional information is used (such as text and images) in the system design, suggesting many forms (Li et al.,2019).

Hybrid recommendation systems gain more attention due to their highly efficient and flexible formats (Adomavicius and Tuzhilin ,2005). The topic collaboration topic regression model is a good example of hybrid. Recommendation system provides better recommendation results by using different hybrid model such as early, middle, and late blending (Wangand and Blei ,2011). Since tourism has grown tremendously, the recommendation system for tourist attractions has received a lot of attention. Bayesian network are used to calculate user settings in order to improve pre-detection accuracy and provided optimum tourist spots for users (Hsu et al.,2012). Some researchers have designed a tourist recommendation system based on a multi-step collaboration algorithm, and accuracy has been enhanced by using the Gaussian model (Nilashi et al. ,2015) . Some researcher uses multi agent architecture for single user and group recommendation in the tourism domain (Sebastia et al.,2011).

Moreover, there are many researches that have improved the efficient searching and recommender systems. Some researcher tries to improve local search algorithms by using implicit inverse problems (Nino-Ruiz et al.,2018) and improves Tabu search and simulates annealing methods for nonlinear data assimilation (Nino-Ruiz et al.,2019). Some researches use fuzzy control to improve efficiency of system (Precup et al.,2015 and 2016). In addition, clustering technique and an analytic hierarchy process (AHP) is used for personnalize system recommender system in Thailand which determines the criteria used in determining tourist attractions (Angskun et al.,2014).

Therefore, this paper applies hybride model and use Bayesian network theory for recommendation mechanism by using Tourist Attraction Category, and the traditional recommender algorithm such as CF, DF is compared with proposed model.

3. METHODOLOGY OF MACHINE LEARNING FOR ADAPTIVE TOURIST RECOMMENDATION MECHANISM MODEL

This session presents the proposed framework of machine learning for Adaptive Tourist Recommendation Mechanism Model. Figure 1 shows framework model. The process begins when a tourist searches for top tourist places or tourist attraction from different review sites with such huge data available, the system helps a tourist with efficient search results for user query and then recommends travel places accordingly. Because there is a lot of information for users available, this is absolutely necessary to help tourists with effective search results for their search terms and recommends places respectively. Then, Session 3.1 describes framework of machine learning for adaptive tourist recommendation mechanism Model. The next session suggests recommendation mechanism model using Bayesian Personalized Ranking. The last session is a part of Evaluation Method.

3.1. Framework of Machine Learning for Adaptive Tourist Recommendation Mechanism Model

The framework of machine learning for adaptive tourist recommendation mechanism model of this paper is described as follows:

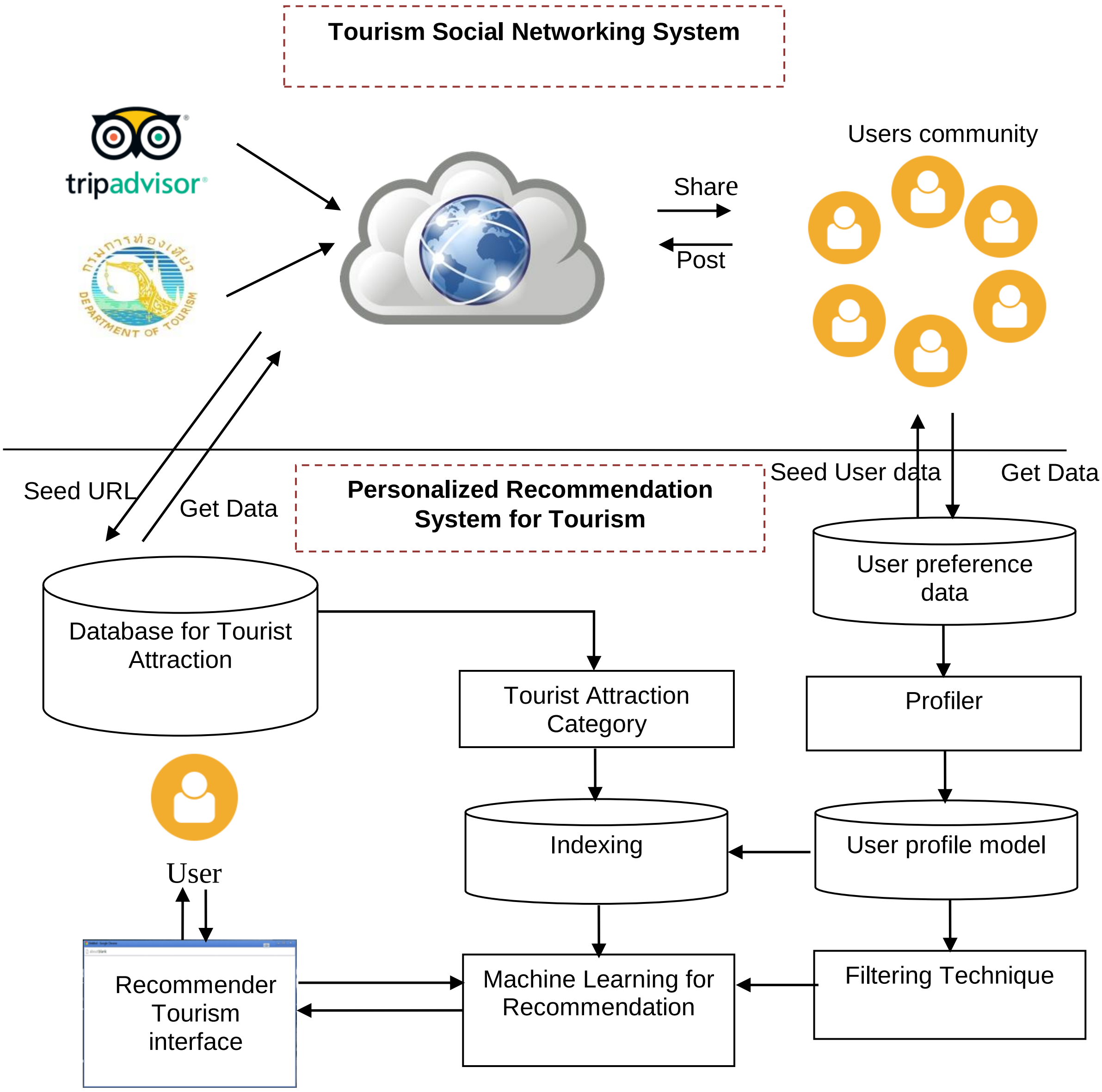

Figure 1. Framework of Machine Learning for Adaptive Tourist Recommendation Mechanism Model

Data Set, The data base compiles information from the government agencies in Thailand, namely the Department of Tourism and Tourism of Thailand; as well as, collecting data from the online tourist community from the TripAdvisor website (www.tripadvisor.com) via the web crawler. This research collects online reviews on TripAdvisor, the most well-known platform among tourists and millions of users (Baka, 2016; Simeon et al., 2017). The web crawler collects travel information such as name, tags, places to go, and more. This useful information helps the system to identify user interests and helps the system to create an index for each location. Java programming is used to develop data collection software for this research. The scope of the study and the data sets are collected from 8 provinces in Thailand, namely Bangkok, Ayutthaya, Samut Songkhram, Ratchaburi, Nakhon Pathom, Suphan Buri, Chon Buri, and Phetchaburi. However, the department stores, entertainment venues, zoos, and sanctuaries are separated from the study in this research because they are mostly conducted by the private sector. General places of interest are stored in the system. The researcher conducts a survey of tourist attractions of 8 provinces in November 2019. Overall, 36,478 online reviews from TripAdvisor are included in the research.

Tourist Attraction Category: This research is divided by interest groups of tourist attraction into 6 categories by improving from the main category of the Tourism Authority of Thailand (tourismthailand.org) including:

1) The cultural tourist attraction is where the visitors learned about the ways of life, cultures and livelihood of local people in the exhibition venue, which shows the story of art and craft of people in the community, such as the tradition, the cultural performances, and local product expo.

2) Historical attractions refer to the important places of tourism that represent traces of the past prosperity in various places. Some of them are selected as World heritage sites such as ancient remains, historical park, temple, religious place, construction that are rich in art and architecture.

3) Entertainment Attractions refers to the various recreation tourist attractions and entertainments such as zoos, amusement parks, entertainment district, parks, and buildings.

4) The natural attractions refer to the variety of natural attractions, such as mountains, forest, waterfalls, caves, lakes, wild flowers, and hot springs.

5) Educational Attractions refer to the academic attractions for those who are interested in learning such as libraries, museums, and training centers.

6) Community-based Attractions refer to the places where tourists are able to learn the life of local people such as homestay, fresh markets, floating markets as all of them are filled of Thai traditional ways of life and rich in Thai food.

The information of user review travel place or attraction score is collected from TripAdvisor which is divided into 5 level: Excellent, Very good, Average, Poor, Terrible.

Indexing: Term frequency–inverse document frequency or TF-IDF is used for indexing which is a weight value for being used in information retrieval and search engine. This is a statistical measure used to assess the importance of and words in documents database or big data. However, it is adjusted by the frequency of words in the documents database. All Users in a social networking system can post the detail of travel attraction. In the experiments, an indexer is developed from tourist attraction (Jomsri, 2016).

Table 1: Algorithm of indexing Method.

Index Algorithm

1. Initialization:
    Step1: create an index for a single document
    Step2: merge a set of indices
2. incremental algorithm:
- maintain a stack of segment indices
- create index for each document
- push new indexes onto the stack
- let $b = Z$ be the merge factor; $M = \infty$

  for (*size* = 1; *size* < M; *size* *= b) **{**
    if (there are b indexes with *size* docs on top of the stack) **{**
      pop them off the stack;
      merge them into a single index;
      push the merged index onto the stack;
    } else {
      break;}
  }
- optimization: keep indexes

User profile, Collecting personal information related to a particular user profiles are clearly digital representation of an individual's identity. Users' profiles could have been considered as computer displays of user models that present personal information. Therefore, the prototype of the system and the initial results are presented. Profiler is a mechanism that make use of user-defined tags. For example, the type of travel that users are interested in from the user's total post time to create user profiles. Creating user profiles is to simulate user features or settings guidelines for user profiles profiling with the word vector used in our system to create accurate user profile in tagging behavior. At this stage, there is a process for assessing the suitability of the user profile. In addition, the privacy data of each user is allowed by all user which related to experiment in this paper.

Filtering Technique, This step uses filtering technique. Our propose of this paper is hybrid filtering by using CF , DF and combines with the ranking of tourist attractions. The filtering contains in four types as follows:

1) Collaborative Filtering : This technique is based mainly on the opinions of many users. Similar groups of target members are searched for, regardless of the right or wrong of the recommendations. This user-based filtering has 4 steps : 1) Calculation of similarity computation between two users. There are two methods: Correlation Based and Cosine-based. 2) Selection of

members (neighbor selection) is selected from all users in the system to predict. The main technique for selecting neighboring members is created by the similarity threshold. 3) Prediction is to identify user satisfaction per items based on customer satisfaction and the similarity among several items which bring a group of neighboring members who already select the information to be calculated in order to create further recommendations, and 4) creating recommendations (recommendation) by taking the forecasted values in each item in sequence starting from the list with the most forecast values to the list with the least predictions. The number of recommended items to be displayed is selected according to user needs on how many recommendations are displayed.

2) Demographic Filtering : In this research, the relationship between users and lists based on past ratings leads to the construction of neighborhoods. Relationship between two users are determined by the similarity of the reference vector which are calculated from the dot-product of two vectors.

3) Combination between CF with DF: The most important task of recommender systems is rating prediction. The rating is combined from two recommender algorithms, described previously--collaborative and demographic filtering. To take into the contribution of each method in the final rating score, a parameter is created for each predictor by the following formulas:

$$r_{u,t} = \frac{\alpha DF_{u,t} + \beta CF_{u,t}}{\alpha + \beta}$$

The value of each paramete is a function Ψ(n) that gives value 1 for big values of user's ratings n and a small value for small values of n. The sigmoid function satisfies these constraints for Ψ(n). Therefore, the parameters α and β are computed as follows:

$$\begin{Bmatrix} \alpha = 1 - \dfrac{1}{1 + e^{\frac{-n}{2}}} \\ \beta = \dfrac{1}{1 + e^{\frac{-n}{2}}} \end{Bmatrix}$$

4) Hybrid between CF , DF and combined with the ranking of tourist attractions: in the final rating score a parameter is created for each predictor by the following formula:

$$H_{u,t} = (r_{u,t} \times 0.5) + (TAscore \times (1 - 0.5)$$

The Combination method of Hybrid are applied in this step. From the initial experiment by defining the weight where $\{w_c$ =0.25, 0.5, 0.75$\}$. The optimal weight is equal proportion value.

3.2. Recommendation Mechanism Model Using Bayesian algorithm

Bayesian Personalized Ranking (BPR) is a process after Filtering Technique process. BPR involved a pair of items (Two user specific commands) to get a more personalized ranking for each user (Rendle et al., 2009). Let U be a set of users and T be the set of items.

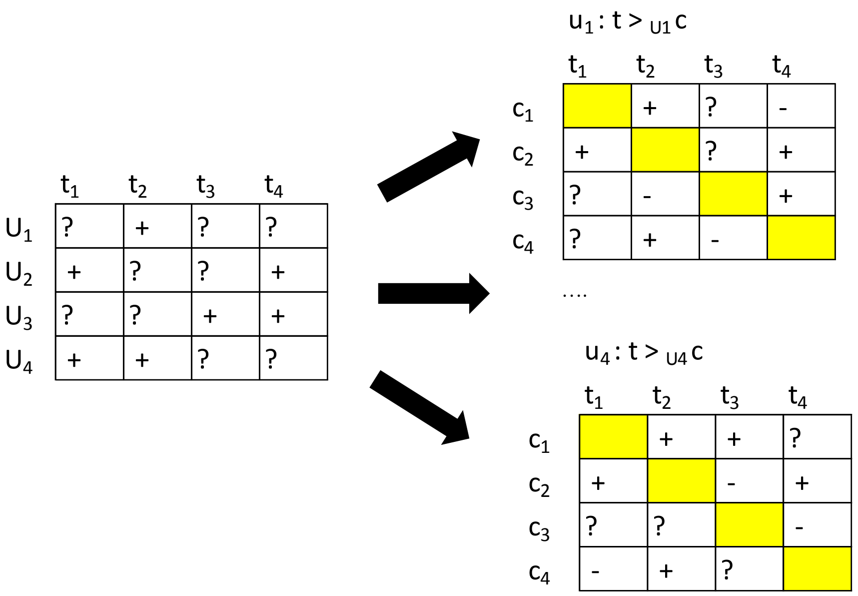

Figure 2. The triplets generated for training data.

Bayesian Personalized Ranking uses pairs item for training data. Optimization is based on the ranking of these user items, instead of simply rating the interaction between user lists. The data set, considered by $(u, t, c) \in DS$, is that user u is assumed to prefer t over c. as follows:

$$(u, t, c) \in DS$$

Figure 2, user u_1 has viewed item t_2 but not item t_1, so the algorithm assumes that this user prefers item t_2 over t_1 or means that $t_2 > t_1$ and gives a positive signal, and could not have made inferences about the settings for items that users see both and is shown as "?" mark.

The method Bayesian personalized ranking (BPR) has two fundamental presumption s:

Presumption of individual pairwise preference, over two items. this assumes that user u prefers an item t to c, $(u, t)\ \alpha\ (u, j)$, if the (u, t) is observed and (u,c) is not observed. Where $t \in \tau$ is (u, t) is observed and $c \in \tau \backslash \tau_u$ is (u,c) is not observed (Rendle et al., 2009).

$$BPR(u) = \prod_{t \in \tau} \prod_{c \epsilon \tau \backslash \tau_u} \Pr(\hat{r}_{ut} > \hat{r}_{uc}) [1 - \Pr(\hat{r}_{uc} > \hat{r}_{ut})]$$

Presumption of independence among users, this assumes that the joint likelihood of pairwise preferences of two users, u_1 and u_2, could have been separated as BPR(u_1, u_2) = BPR(u_1)BPR(u_2), which means that the likelihood of pairwise preferences of user u_1 is independent of that of user u_2 (Pan and Chen, 2016).

$$BPR = \prod_{u \in U} BPR(u)$$

3.3. Evaluation Method

On the one hand, this research considers Mean Absolute Error (MAE) uses the absolute value of the difference between actual rating $r_{u,t}$ instead of the square and difference predicted rating $r*_{u,t}$. The MAE is more tolerant against individual outliers than the RMSE (Shani and Gunawardana, 2011).

$$MAE = \sqrt{\frac{1}{|n|} \sum_{(u,t)} \exists n \left| r*_{u,t} - r_{u,t} \right|}$$

The four different algorithms with Bayesian Personalized Ranking and without Bayesian Personalized Ranking are evaluated by MAE. The first method is CF only. The second method is only DF so as to study which formats are suitable for giving advice (recommendations). The third method is combination of CF with DF. And, the fourth method is the hybrid between CF and DF for each user combine with Tourist Attraction Category. The result of the experiment is a measure of the Mean Absolute Error from the user evaluation and setting the threshold set. The experiment data are collected from 50 users and traveller. The subject tests are given a list of 90 locations in 8 provinces to evaluation. Moreover, assessment of satisfaction from questionnaires to evaluate the algorithms in terms of individual quality metrics concentrated in four topics: Match interests, Novelty, Diversity and Helpful. The five-point scale for assessment as follows: score 5 is excellent, score 4 is good, score 3 is acceptable, score 2 is below average and score 1 is poor.

4. EXPERIMENTAL RESULTS

In this section, the researcher presents the experimental results of using Machine Learning approaches in the recommender system. The examined and conducted experiments are used for recommender system. Additional comparisons of other techniques are tested. The efficiency of hybrid model has an accuracy that is higher when combining many different properties as shown.

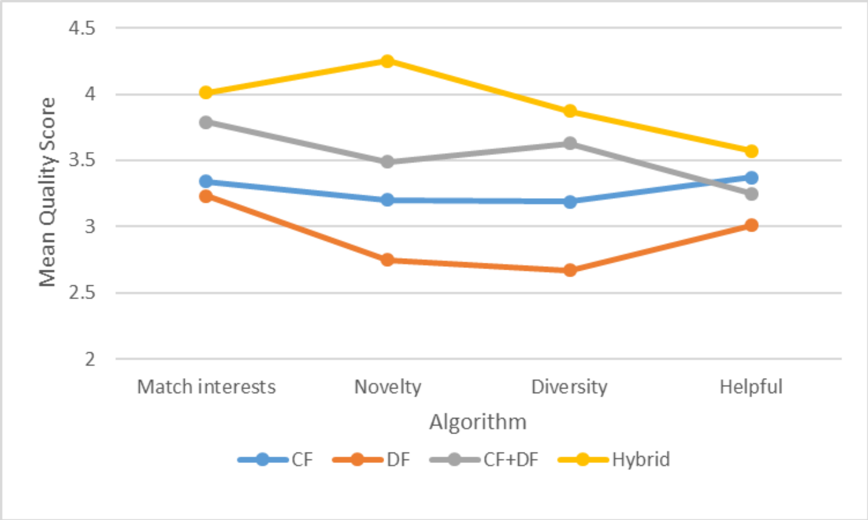

Figure 3. The mean values of the results scores of the four algorithms in terms of different quality score.

The subject test users are asked to rank these five lists based on their items according to the suitability of the recommendations. This ranking helps users assess how they perceive the value of recommendations. In other words, this question evaluates the users' experience with each recommender algorithm. Figure 3 shows the evaluation of the algorithms in terms of individual quality metrics.

In addition, the Table 2 shows the average MAE. All machine learning methods are better than the basic methods. The hybrid introduction techniques between collaborative filtering (CF) and demographic filtering (DF) of each user combined with ranking of tourist attractions outperforms another method. With the threshold set to T=10, the pattern of MAE is in accordance with each other for K=1-10.

Table 2: Average MAE results

Algorithm	**MAE**	
	Without BPR	**With BPR**
Collaborative filtering	0.89	0.78
Demographic filtering	0.92	0.89
CF+DF	0.78	0.56
Hybrid approche	0.60	0.55

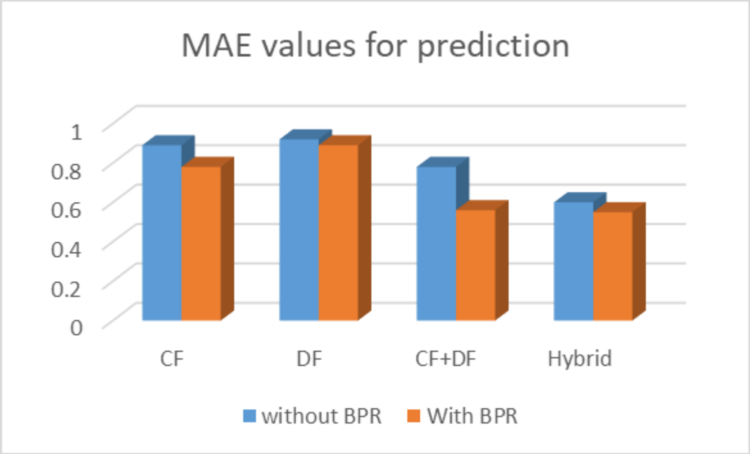

Figure 4. MAE values for tourist recommender system.

Figure 4 compare of information between with and without machine learning using BPR. This implies that machine learning model improves the efficient of tourist recommender system.

5. DISCUSSION AND CONCLUSION

This research develops a recommender system by integrating machine leaning techniques with the Bayesian Network to provide recommendations for tourist destinations. The results show that Hybrid methods, combined with collaborative filtering (CF) and demographic filtering (DF) including ranking of tourist attractions, are better than basic methods, and the demographic filtering (DF) alone is not enough to predict accurate scoring, even if a thorough test is needed to confirm the results. It concludes that some places that are not recommended by users on social networks are combined with demographic filtering (DF) and ranking using tourist information resulted in places with increased interest and the recommender system is more effective.

6. ACKNOWLEDGMENT

The authors would like to thank Thailand Science Research and Innovation (TSRI) and Office of the Higher Education Commission for scholarship support. (Scholarship ID:MRG6280233)

7. REFERENCES

Adomavicius, G., Tuzhilin A., 2005, Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Trans. Knowl. Data Eng.* **17**, 734–749.

Angskun, T., Angskun,J., 2014, A Personalized System for Travel Attraction Recommendation Using a Clustering Technique and an Analytic Hierarchy Process. *Suranaree J. Soc. Sci.* ,**8**(**2**), 87-109.

Baka, V. ,2016, The becoming of user-generated reviews: Looking at the past to understand the future of managing reputation in the travel sector. *Tourism Management*, **53**,148–162.

Bobadilla, J., Ortega, F., Hernando, A., Gutierrez, A., 2013, Recommender systems survey. Knowl. *Syst.,* 46,109-132.

Goldberg, D., Nichols, D., Terry, D., and Oki, B. M., 2013, Using collaborative filtering to weave an information tapestry. *Commun. ACM.* **35**, 61–70.

Goodfellow, I. J., Pouget-Abadie, J., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., and Mirza, M., Generative adversarial nets. *Proc. Neural Inf. Process. Syst. (NIPS).* 2872-2680.

Hsu, F.-M., Lin, Y.-T., Ho, T.-K.,2012, Design and implementation of an intelligent recommendation system for tourist attractions: The integration of EBM model, Bayesian network and Google Maps, *Expert Syst. Appl.* **39**, 3257–3264.

Jomsri, P., 2016, A combination indexing for image social bookmarking system to improve search results, *Journal of Digital Information Management* .**14(6),** 423-431.

Li,G., Zhu, T., Hua. J., Yuan, T., Niu Zheng, u., Li, T., Zhang, H..,2019, Asking Images: Hybrid Recommendation System for Tourist Spots by Hierarchical Sampling Statistics and Multimodal Visual Bayesian Personalized Ranking. *IEEE Access*, **7**, 126539- 126560.

Lü, L., Medo, M., Yeung, C. H., Zhang, Y.-C., Zhang, Z.-K., and Zhou, T., 2012, Recommender systems. Phys. Rep. 519, 49.

Menk, A., Sebastia, L., 2019,Ferreira,R., Recommendation Systems for Tourism Based on Social Networks: ASurvey. *arXiv 2019*, arXiv:1903.12099, 1-23.

Nilashi, M., bin Ibrahim, O., Ithnin, N., Sarmin, N. H., 2015, A multi-criteria collaborative filtering recommender system for the tourism domain using expectation maximization (EM) and PCA–ANFIS Electron. *Commerce Res. Appl.,* **14**, no. 6, 542–562.

Nino-Ruiz, E. D., & Yang, X. S. 2019. Improved Tabu Search and Simulated Annealing methods for nonlinear data assimilation. *Applied Soft Computing*, 83, 105624.

Nino-Ruiz, E. D., Ardila, C., & Capacho, R. 2018. Local search methods for the solution of implicit inverse problems. *Soft Computing*, **22(14)**, 4819-4832.

Precup, R. E. and Tomescu, M. L., 2015. Stable fuzzy logic control of a general class of chaotic systems, *Neural Computing and Applications,* 26(3), 541-550.

Precup, R.E., David, R.C., Petriu, E. M., Szedlak-Stinean, A.I. and Bojan-Dragos, C.-A., 2016. Grey wolf optimizer-based approach to the tuning of PI-fuzzy controllers with a reduced process parametric sensitivity. *IFAC- PapersO Line,* **49(5)**, 55-60.

Rendle, S. Freudenthaler, C., Gantner Z., Schmidt-Thieme, 2009, L.,Bpr: Bayesian personalized ranking from implicit feedback. *Proceedings of the 25th conference on uncertainty in artificial intelligence*, UAI '09, Arlington, Virginia, United States, 452–461.

Rendle, S., Freudenthaler, C.C., Gantner, Z., Schmidt-Thieme, L.,2009, BPR: Bayesian personalized ranking from implicit feedback. *Proc. Conf. Uncertainty Artif. Intell.*, 452–461.

Resnick, P., Iacovou, N., Suchak, M., Riedl, J., Bergstrom, P., 1994, GroupLens: An open architecture for collaborative filtering of netnews. *Proc. ACM Conf. Comput. Supported Cooperat.* Work, New York, NY, USA,175–186.

Reyes-Menendez, A., Saura, J.R., Martinez-Navalon, J.G, 2019, The impact of e-WOM on Hotels Management Reputation: ExploringTrip Advisor Review Credibility withthe ELM model. IEEE Access 7,68868–68877.

Ricci, F., Rokach, L., Shapira B. ,2011, Introduction to Recommender Systems Handbook. Recommender Systems Handbook. Springer, Boston, MA.

Shani, G., Gunawardana, A.,2011, Evaluating recommendation systems. *Recommender systems handbook*. Springer US, 257-297.

Sebastia, L., Giret, A., Garcia, I. ,2011, A Multi Agent Architecture for Single User and Group Recommendation in the Tourism Domain. *International Journal of Artificial Intelligence™.* **6(s11),**161-182.

Simeon, M. I., Buonincontri, P., Cinquegrani, F., & Martone, A.,2017, Exploring tourists' cultural experiences in Naples through online reviews. *Journal of Hospitality and Tourism Technology*, **8**(**2**), 220–238.

Van den Oord, A., Dieleman, S., and Schrauwen, B., 2013, Deep content-based music recommendation. *Proc. Conf. Workshop Neural Inf. Process. Syst.* (NIPS). Lake Tahoe, CA, USA.

Wang, C. Blei, D.M., 2011, Collaborative to pic modeling for recommending scientific articles. *Proc. ACM Conf. Knowl. Discovery Data Mining (KDD).* New York, NY, USA, 448–456.

Wang, D., Liang, Y., Xu, D., Feng, X.,Guan, R., 2018, A content-based recommender system for computer science publications. *Knowl.-Based Syst.* **157**, 1-9.

Wang, H. W., Zhang, F. Z., Li, W., Xie, X., Guo, M., and Zhao, M.,2019, Multitask feature learning for knowledge graph enhanced recommendation. *Proc. Int. Conf. World Wide Web (WWW).* 2000-2010.

Wang, H., Zhang, F, Xie, X., Guo, M., 2018, DKN: Deep knowledge-aware network for news recommendation. *Proc. Int. Conf. World Wide Web (WWW).* Lyon, France. 1835–1844.

Weike, P., Chen, L.,2016, Group Bayesian personalized ranking with rich interactions for one-class collaborative filtering, *Neurocomputing*, **207**, 501-510.