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A Recommendation Engine to Estimate Housing Values in Real Estate Property Market

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Abstract-A recommendation engine is an automated machine learning technique developed to filter some entities called people, properties or objects, products and movies based on user preference. This can be employed to express recommendation based on user interest determined by its market value. The increasing demand and limited in supply of housing properties limits the existing methods of operation to bear a heavy burden in recommending housing properties. This leads to information overload which made it difficult to search and recommend properties with respect to user's specific interest. These can be affected by its location and condition of property. Therefore; we proposed the use of a recommendation engine with collaborative technique in providing optimal solution to the challenges facing the housing market. This work is aimed at developing an efficient recommendation engine to estimate housing values. This serves to overcome the problem of information overload, help understand what the user wants and recommend properties with the most popular features. The implementation was done using logistic regression and K-nearest neighbor techniques with Python. The performance was improved with some fine-turned hyper-parameter values using the kaggle online dataset. The K-nearest neighbor produced 100% prediction accuracy recorded to be better than the logistic regression with 54.6% accuracy rate.

Keyword- Collaborative Filtering, KNN, Logistic regression, Recommendation Engine

I. INTRODUCTION

A recommendation engine is an automated system developed to extract some entities called items based on user preference[1]. Items are the objects of user interest or distinct things considered as properties/buildings, movies, objects, products and etc[2]. Recommendation techniques have been gaining the interest of professional in the community of research for solving realistic problems using different recommendation techniques. And some of these well-known and widely used approaches includes: logistic regression(LR), K-nearest neighbors(KNN), support vector machine, Clustering techniques, Bayesian network models and etc [3],[4].

The arising demand of housings properties forced the existing methods of practice to bear heavy burden. Unable to recommend properties based on the specific interest of user's. This evidently could not help them search, match and recommend properties to group of users having same interest. The housing property value can be affected by its location, available space, social amenities, and condition, and number of rooms and etc[5],[6]. Most business managers could not understand their customers often time; because customers at times can behave much differently than we think. So it is important to show customers what is relevant with items or properties that they may have interest on by [7],[8]. The aim is to develop an efficient recommendation engine in predicting real estate housing values. Which will serve to overcome the problem of information overload, saves time and help understand what the user really wants. We intend to employ the logistic regression and K-nearest neighbor types of recommendation techniques using the kaggle real estate dataset made available online. And Python (Anaconda: Spider IDE) programming language will be used for the simulation.

This paper is organized in sections as follows: Section two presents a brief review of related literatures to the study area and the knowledge gap in exploring the proposed model; Section three, introduces the materials and methods: which presents the different methods employed and materials used for building the model; Section four, focuses on the results and detailed discussion of results; Section five presents the conclusion to the paper.

II. RELATED WORKS

A collaborative search algorithm was proposed to match features of real estate properties from an online portal as a source of buying, selling and renting/leasing [9]. This model was able to overcome the problem of privacy to get notification in the search space from an online portal using a database system. But encountered some difficulties where the recommender system could not predict or properties/items that users may have similar interest base on their features. Babu, et al.[10]; developed a recommendation system to predict real estate property values using multiple and polynomial model. This model was able to extract the important features of real estate properties to overcome the error for residual sum of square after training. This leads to the problem of over-fitting; but was reduced by the adoption of ridge regression model in producing an optimal solution. But there was biasness in the process of model fitting which produced low accuracy metrics. Sharma, *et al.*[11], adopted Auto regression and integrated moving average model (ARIMA) with the help of content based linear regression algorithm to predict real estate property values. This was able to solve the problem of stress involving human in the manual computation process and produced 87% metrics of accuracy. The model resulted to low accuracy rate when the predictors are interdependent and not correlated. Kansara, *et al.*[12]; developed an improved machine learning (ML) technique with stacked regression to predict the values of real estate properties. The dataset was split into 80% training and 30% testing set to learn changes in the dependent variable (estimated price) with respect to the independent variable. The root mean square error (RMSE) method was employed as an appropriate tool to fit the model. This model was able to produce new predictions using multiple linear regression (ML), random forest(RF), XBoost algorithm produced a success metrics of 92.66%, 91.19%, and 93.17% respectively[12]. But these models could not work well with large volume of dataset as such required more training time. Erkeh, *et al.*[14]; adopted the collaborative and content-based recommendation system techniques to overcome the increased problem of property listing in Turkey. This model was able to satisfy user's interest with properties that have similar characteristic/features to be recommended. The top-N fraction of the diversification technique was improved; but limited in expressing recommendation on properties below a specific threshold. The scalable model could not handle the arising need of new listing cases which lead to the adoption of diversification techniques to improve system performance. And results to low sensitivity value in terms of price, living space and location. Sing, *et al.*[15], employed linear regression (LR) and random forest model-based collaborative technique to express recommendation on real estate properties that are below the market value. Uzut, *et al.*[16], developed a hybrid model using random forest, gradient boost and linear regression algorithms to predict real estate property values. Both model required more training time to produce a better result and could not work effectively well with large dataset. Manjula, *et al.*[17]; presented a multi-variate regression model to estimate real estate housing values/prices. The model was trained and tested with houses measured and recorded in one-square-feet against property prices or values. The increase in model feature complexity resulted to the problem of over-fitting with low accuracy level as such required more training time. Chen, *et al.*[8]; adopted a model in estimating residential property values using the support vector machine (SVM). Two different samples from neighbouring districts were collected for comparison in terms of property proximity and location. The hit-rate of their proposed system produced 81.8% metrics of accuracy when other adjustable parameters such as the karnel(C) was set to 50(C=50) and gamma variable to 0.5(γ=0.5). The collated training data samples were too small to obtain higher level of accuracy as such required larger data items for the training and testing set classification to efficiently work well. Bahia, *et al.*[18]; presented a neural network model to predict the prices of real estate residential properties using the cascade forward and backward propagation neural-network. The mean square error value was recorded to be 13.583% at 82 iterations (epoch) and produced 96% metrics of accuracy level. The performance of this model was affected by the neural network training time as a result of the increasing mean square error(MSE) value triggered by the sample validation test. Mishra, *et al.*[19]; carried out a research to predict the rating similarity between user-based search patterns on real estate properties with the help of a user-based collaborative-filtering algorithm through a process called isolation. The user-based estimated property values were computed using the weighted sum of different data search patterns on real estate properties. This was able to group highly rated user-based search patterns at the training and testing stage.

III. MATERIAL AND METHODS

From the existing literatures, we were able to build and use a recommendation engine. We adopted the user-based collaborative recommendation algorithm (KNN and LR) to recommend real estate housing properties based on characteristics. The model is developed to classify users into different classes/segments and recommend properties in the order of user preference and the group they belong to [20]. The recommendation engine is employed to make decisions about properties based on item similarity and user interest [21]. The properties are automatically grouped into the following classes: low, average and high class prices. This can be achieved by extracting the lowest and highest housing prices.

Dataset: The dataset used was obtained from the kaggle online repository site containing twenty one thousand six hundred and thirteen (21613) items. And each instance has attributes about real estate housing properties in terms of id, date, price, floors, size, location, number of rooms and bathrooms, grade and etc. The dataset is divided into 80 and 20 percent training and testing set respectively.

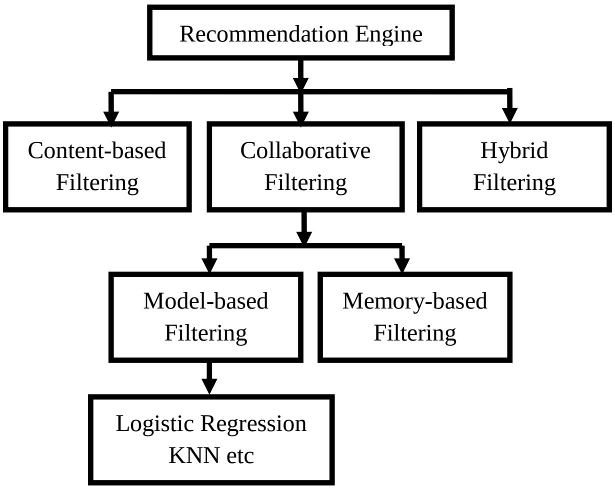

Figure 1: Architecture of Recommendation System,
Source: Mubaraka, et al.[22]

A Recommendation engine: is an automated machine learning system developed to filter or extract some entities called people, properties or objects, products, movies, songs and etc[23]. There are three main phases involved in building a recommendation engine identified by Isinikage, et al.[24] as: Information collection, learning and recommendation phases.

Information collection phase: is the collection of detailed information about user in building a model for prediction task based on the content of resources the user may want to access by Ghazanfar, et al.[25]. The functionality of a recommendation agent depends mainly on user profile and input in producing accurate and reliable result by Papagelis, & Plexousakis, [26]. The input includes explicit by means of considering user choice in products or items and implicit based on user preference through some observed characteristics by Min & Han, [27]. The success metric of every recommendation model relies mainly on the ability of the developers to represent user's current state of preference/interest about an item.

Learning phase: This employs a learning algorithm to extract/filter notable user characteristics/features obtained from the feedback stage of information collection[28].

Recommendation or prediction phase: in this phase properties(items) are predicted based on what user's may like best using the dataset obtained from the information collection stage. According to Burke,[29]; prediction phase could be memory or model-based through the user observed activities.

(a). Content-based filtering model: This employs series of continuing features about properties put in order to recommend more features with strictly comparable properties. It analyses the content present in the item been recommended and group into user class[30].

(b). Hybrid-Based filtering is based on the concept of both user-based collaborative filtering(UBF) and content-based collaborative filtering(CBF).

(c). Collaborative filtering: The entire intelligence of user-based come into play, but not necessarily taking in account much about what the items is all about, rather who is interested[31],[32].

(i). Memory-based filtering: The model-based filtering learns from previous user ratings to enhance the functionality of the collaborative technique. The likes of model-based algorithms include: regression and clustering techniques, singular value decomposition(SVD) and matrix completion techniques(MCT). These algorithms employs user-item matrix to determine the relations between items.

User-based filtering is the building of a model with respect to user behaviour and similar decisions made by other users. This can be used in predicting housing properties which a user may have specific interest.

Item-based filtering: The item-based CF is built based on the similarity between properties or items. All the user rated items can be filtered to compute the similarity between target items. Considering K having the set of most similar items(k={ n_1, n_2, n_3, . . . n_k } and n_i, n_j assumed to have equal similarity score between the n_i and n_j items. This can be computed using the adjusted cosine similarity given by Sarwar, et al.[32] as follows:

$$S_{n_i n_j} = \frac{\sum_{m \epsilon M_{n_i . n_j}} \hat{r}_{m_i n_i} \; \hat{r}_{m_i n_i}}{\sqrt{\sum_{m \epsilon M_{n_i . n_j}} \left(\hat{r}_{m_i n_j}\right)^2 \sum_{m \epsilon M_{n_i . n_j}} \left(\hat{r}_{m_i n_j}\right)^2}} \qquad (1)$$

The normalizing rating becomes

$$\hat{r}_{m_i n_j} = r_{m\,,n} - \hat{r}_m \qquad (2)$$

Where $\hat{r}_m$is the user average and $r_{m\,,n}$ the user rating. This can overcome the irregularities found in the user's rating scale.

(ii). Model-based recommendation system:
The proposed system model is adopted to extract some useful features/information from the dataset for expressing commendations without having to use the entire items at every time[30]. This is one of the best among other techniques used to solve the problem of over-fitting easily and potentially offers the benefit of speed and scalability. The prediction accuracy of the proposed system depends mainly on the way the model is built[33],[34].

User-based collaborative recommendation Algorithm
Step 1: Start
Step 2: Look for group of user's with common/similar interest/taste
Step 3: Algorithm search at different features and likes of the users(location, size, house floor and

condition) and combine them to make suggestions(Choices)

Step 4: Select an algorithm to measure the user property similarity(KNN and LR)

Step 5: Stop

Logistic Regression Technique(LRT):

The Logistic_Regression class and accuracy score was invoked from the sklearn linear_model and metrics embedded in Python library. The LR model was fitted using the training and test split dataset with attributes of id, housing price and number of bathrooms and etc. The test size was set to 0.2 and random state set to 2 to learn from data patterns. The LR model was able to learn and make predictions that required scaling data represented with labels(low=1, Average=2 and high=3).

K-nearest neighbor technique:

The KNeighbors classifier and accuracy score was invoked from the sklearn neighbors and metrics embedded in Python library respectively. The KNN model was fitted using the training and test split dataset using the attributes of housing price, no. of rooms, bathrooms and etc. The test size was set to 0.2 and random state set to 2. This model was trained and tested to learn from the classified data pattern in predicting the target values. The KNN was able to make accurate predictions using the housing prices as input after training without data scaling.

IV. RESULTS AND DISCUSSIONS

We adopted the KNN and LR to recommend housing properties based on features that are common. This made it easier to find properties with similar features/characteristics.

Figure 2: The total number of dataset tested

Figure 2 depicts the total number of trained and tested dataset obtained from the proposed system model. The housing prices are categorized into three different classes; namely: low, average and high class prices represented with blue, green and black respectively. The average price is recorded to be the highest(9147), followed by the High class(6506) and low class as (5960) prices to form the total shown as (9147+6506+5960)=21613 items.

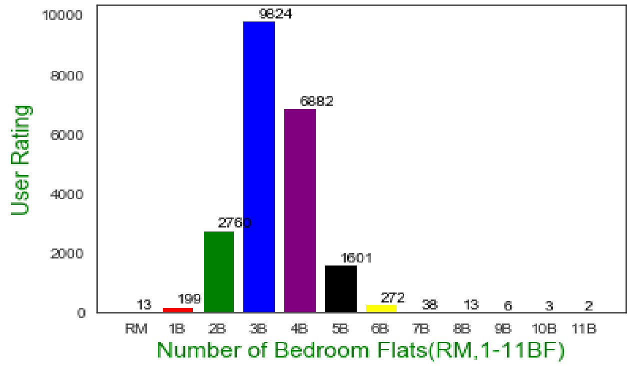

Figure 3: Rated housing properties values based on user interest

The model recommended 3-bedroom flats to be of higher rate of user's interest followed by 4, 2, 6, 1, 6, 7, self-contain/1-room apartment and etc. Therefore, 3 and 4-bedroom flats are predicted to have the highest rate by the recommendation system based on user-preference obtained from the proposed system dataset.

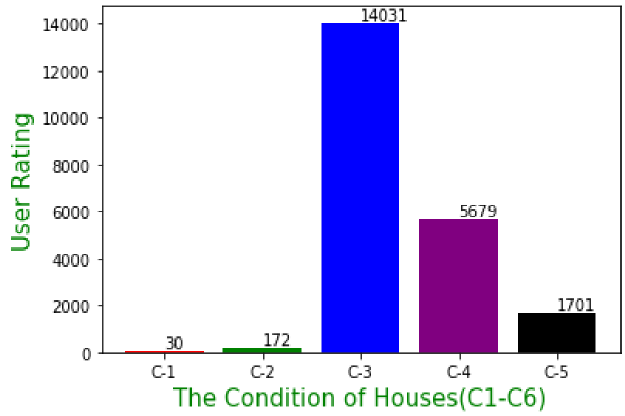

Figure 4: The Condition of housing properties

Figure 4 shows the condition of housing properties and how it affects property value based on user preference or interest. C.1, C.2, C.3, C.4 and C.5 are variables used in representing the condition of housing properties. But C4 is recommended by the engine to have the highest user rating value with similarity interest followed by C.4 and C.5 obtained from the dataset.

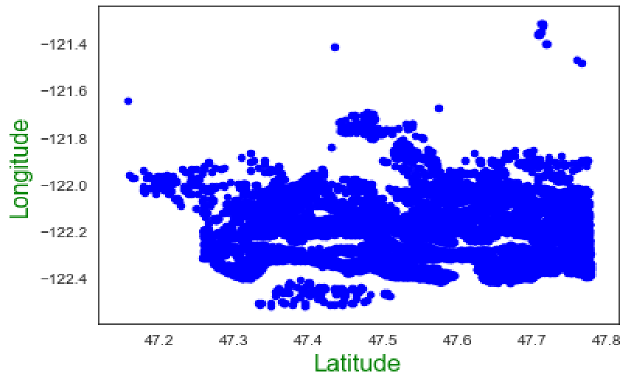

Figure 5: Location of housing properties

Figure 5 depicts the location of real estate properties and how it affects property values obtained from the proposed system dataset. There are several housing properties located and highly concentrated within the latitude of 47.3 and 48.8 and longitude -122.0 to -122.4.

Table 1: Number of bedrooms against price

Bedrooms	Average Price	User Rating
0	4.102231e+05	13
1	3.176580e+05	199
2	4.013877e+05	2760
3	4.662524e+05	9828
4	6.355611e+05	6883
5	7.873442e+05	1602
6	8.258535e+05	272
7	9.514478e+05	38
8	1.105077e+06	13
9	8.939998e+05	6
10	8.200000e+05	3
11	5.200000e+05	2
12	6.400000e+05	1

Table 2: Condition of Housing against Price

Condition	Average price	User Rating
1	334431.666667	30
2	327316.215116	172
3	542134.512289	14031
4	521300.705230	5679
5	612577.742504	1701

Table 3: Housing grades against Price

Grade	Average Price	User Rating
1	1.420000e+05	1
3	2.056667e+05	3
4	2.143810e+0	29
5	2.485240e+05	242
6	3.018784e+05	2039
7	4.025933e+05	8981
8	5.428584e+05	6071
9	7.736759e+05	1616
10	1.072347e+06	1134
11	1.497898e+06	400
12	2.192500e+06	50
13	3.710769e+06	13

The model was able to search and classify users into 13, 5 and 12 groups as shown in figure 1, 2 and 3 having same interest based on the no. of bedrooms, house condition and grades obtained from the dataset. The attributes and average prices are mapped to group of similar users with same characteristics/features.

Table 4: The classification report of KNN

	precision	recall	f1-score	support
Average_p	1.0	1.0	1.0	9147
High_P	1.0	1.0	1.0	6506
Low_P	1.0	1.0	1.0	5960
accuracy			1.0	21613
macro_avg	1.0	1.0	1.0	21613
weighted_avg	1.0	1.0	1.0	21613

Table 5: The classification report for logistic regression

	Precision	Recall	F1-score	Support
Average_p	0.76	0.39	0.52	5960
High_P	0.53	0.49	0.51	9147
Low_P	0.46	0.70	0.55	6506
accuracy			0.53	21613
macro_avg	0.58	0.53	0.52	21613
weighted_avg	0.57	0.53	0.52	21613

The accuracy rate was measured using different parameters or metrics but depends on the filtering method. According to Sarwar et al.(2001) there are two major ways of measuring the performance of recommender systems: viz; the statistical and decision support metrics of accuracy(DSMA). The DSMA is used to extract quality data from the available set of items using: Recall, F-score and precision as shown in table 4 and 5. This can be computed as follows:

$$\text{Precision(P)} = \frac{\text{Correctly recommeded properties}}{\text{Total recommended properties}} \quad (2)$$

$$\text{Recall(R)} = \frac{\text{Correctly recommended properties}}{\text{Total useful recommended properties}} \quad (3)$$

$$\text{F-score} = \frac{2PR}{P+R} \quad (4)$$

Figure 6: Predicted classes of housing prices

S/N	Price	Target	LR_Pred	KNN_Pred
0	221900.0	Low.P	Low.P	Low.P
1	538000.0	Average.P	Average.P	Average.P
2	180000.0	Low.P	Low.P	Low.P
3	604000.0	HighP	High.P	High.P
4	510000.0	Average.P	High.P	Average.P
...	...	...	...	...
21608	21610.0	Average.P	High.P	Average.P
21609	400000.0	Average.P	Average.P	Average.P
21610	402101.0	Average.P	High.P	Average.P
21611	400000.0	Average.P	High.P	Average,P
21612	325000.0	Low.P	High.P	Low.P

Figure 6 depicts the predicted target values of KNN and LR. The exact solution is recorded under the target variable used to check mate the functionality of both models against housing prices. The predicted KNN was same the target while logistic regression produced a lot of wrongly values. The prediction made by KNN in serial number 4 was Average.p and target recorded Average.p but logistic predicted High.P using the housing price.

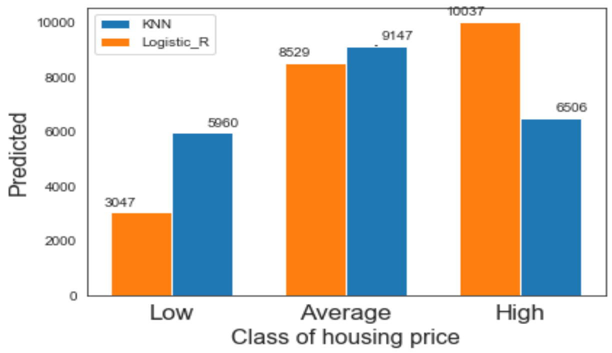

Figure 6: The total number of predicted housing values based on user rating

Figure 6 depicts the total number of predicted housing values in the order of user preference. The KNN produced the best and exactly as the target shown in figure 2 above. While LR produced the least with some variations in predicting correctly as the target.

Table 7: Metrics of comparison

Model Complexity	KNN	Logistic Regression
Prediction Accuracy	100%	52.60%
Training time	0.211s	3.94s
Prediction time	1.59s	0.52s

Table 7 shows the model complexity in terms of accuracy, prediction and training time variation. The KNN produce 100% prediction accuracy and training time 0.211 second which performed better compared to LR with 52.60% and 3.94 seconds. The LR prediction time was faster than the KNN recorded to be 1.59 and 0.52 seconds respectively.

V. CONCLUSION

The model is useful to professionals, brokers and investors in recommending housing properties to users based on price, location, grade and etc as an order of preference. The KNN produced 100% metrics of accuracy which was better than the logistic regression model with adjusted nearest neighbor value. The logistic regression required data scaling in producing 54.7% accuracy rate with some fine-tuned hyper-parameter values. The model performed well in predicting new born housing properties and less prone to over-fitting. The training time complexity of KNN was faster but higher in prediction time than logistic regression model.

REFERENCES

[1]. T. D. Minh-Phung, V. N. Dung, and L. Nguyen, "Model-based Approach for Collaborative Filtering," *The 6th international Conference on Information Technology for Education(IT@EDU), Ho Chi City, Veitna,* **2018**

[2]. X. Su, and T. M. Khoshgoftaar, "Collaborative Filtering for Multi-class Data Using Belief Nets Algorithm," *in The 18th IEEE International Conference on Tools with Artificial Intelligence(ICTAI), Arlington, VA, USA, **2006***

[3]. G. Shani, D. Heckerman, and R. I. Brafman, "An MDP-based Recommender System," *Journal of Machine Learning Research,* **Vol. 6, Issue. 2, pp.1265-1265, 2005.**

[4]. P. Patil, D. Shah, H. Rajput, and J. Chheda, "Housing Prediction Using Machine Learning and RPA," *International Research Journal of Engineering and Technology(IRJET),* **Vol. 7, Issue. 3, pp.5560-5563, 2020.**

[5]. O. Aluko, "The Effect of Location and Neighbourhood Attributes on Housing Values In Metropolitan Lagos," *Ethiopian Journal of Environmental Studies and Management(EJESM),* **Vol. 4, Issue. 2, pp.69-81, 2011.**

[6]. A. *S.* Tewari, and A. G. Berman, "Collaborative Recommendation System Using Dynamic Content-Based Filtering, Association Rule Mining and Opinion Mining", *International Journal of Intelligent Engineering and Systems,* **Vol. 10, Issue. 5, pp.70-82, 2017.**

[7]. A. Pasbola, R. Saxena, and R. Anita, "Housing Property Recommendation with Automated Requirement Prediction," *International Journal of Advanced Science and Technology(IJAST),* **Vol. 29, Issue. 6, pp.2479-2485, 2020.**

[8]. J. Chen, C. F. Ong, C. L. Zheng, and Hsu, S. "Forecasting Spatial Dynamics of the Housing Market Using Support Vector Machine," *International Journal of Strategic Property Management,* **Vol. 21, Issue. 3, pp.273–283, 2017.**

[9]. P. Paunikar, P. Modake, S. Wagh, and P. Mishra, "Implementation of User Based Collaborative Algorithm in Real Estate Property," *International Journal of Innovative Research in Computer and Communication Engineering(IJIRCCE),* **Vol. 5, Issue. 1, pp.573- 724, 2017.**

[10]. A. Babu, and A. S. Chandran, "Literature Review on Real Estate Value Prediction Using Machine Learning," *International Journal of Computer Science and Mobile Applications(IJCSMA),* **Vol. 7, Issue. 3, 8-9, pp.2019.**

[11]. A. Sharma, S. Sonawale, D. Ghonasgi, and S. Patankar, (2020). "House Price Prediction Forecasting and Recommendation System Using Machine Learning," *International Research Journal of Engineering and Technology (IRJET), 7(5), 1540-1550*

[12]. D. Kansara, R. Singh, D. Sanghvi, and P. Kanani, "Improving Accuracy of Real Estate Valuation Using Stacked Regression," *International Journal of Engineering Development and Research(IJEDR),* **Vol. 6, Issue. 3, pp.2321-9939, 2018.**

[13]. S. C. Bourassa, E. Cantoni, and M. Hoesli, "Predicting house prices with spatial dependence: a comparison of alternative methods,"*Journal of Real Estate Research,* **Vol. 32, Issue. 2, pp.139–160, 2010.**

[14]. M. Erkeh, K. Cayirh, H. Tas, A. Hepsen, and T. Aytekin, (2020), "Recommendation Systems Applied in Turkish Real Estate Market," *Journal of Computations and Modelling(JCM), Scientific Press International Limited(SPIL),* **Vol. 10, Issue. 1, pp.1792-8850, 2020.**

[15]. S. Sing, and K. J. Monika-Nag, Land Price Prediction using Machine Learning Algorithm, *International Research Journal of Engineering and Technology (IRJET),* **Vol. 7, Issue. 5, pp.1986-1988, 2020.**

[16]. O. G. Uzut, and S. Buyrukoğlu, "Prediction of Real Estate Prices with Data Mining Algorithms, *Euroasia Journal of Mathematics," Engineering, Natural & Medical Sciences,* **Vol. 8, Issue. 9, pp.77-82, 2020.**

[17]. R. Manjula, S. Jain, S. Srivastava, and P. R. Kher, "Real estate value prediction using multivariate regression models," *IOP Conference Series: Materials Science and Engineering,* **Vol. 263, pp1-7, 2017.**

[18]. I. S. H. Bahia, "A Data Mining Model by Using ANN for Predicting Real Estate Market: Comparative Study," *International Journal of Intelligence Science(IJIS),* **Vol. 3, pp.162-169, 2013.**

[19]. P. Mishra, "Implementation of User Based Collaborative Algorithm in Real Estate Property," *International Journal of Innovative Research in Computer and Communication Engineering(IJIRCCE),* **Vol. 5, Issue. 1, pp.717-724, 2017.**

[20]. Y. Koren, R. M. Bell, and C. Volinsky, "Matrix factorization Techniques for Recommender Systems," *IEEE Computer,* **Vol. 42, Issue. 8, pp.30-37, 2009.**

[21]. M. Deshpande, and G. Karypis, "Item-Based Top-N Recommendation Algorithms," *ACM Transactions on Information Systems,* **Vol. 22, Issue. 1, pp.145-177, 2014.**

[22]. S. I. Mubaraka, and I. S. Charles, "Recommendation System: Algorithms, Evaluation and Limitations," *Journal of Advances in Mathematics and Computer Science(JAMCS),* **Vol. 35, Issue. 2, pp.121-137, 2020.**

[23]. G. Adomavicius, and A. Tuzhilin, "Toward the Nest Generation of Recommender System: A Survey of the State-of-the-art and Possible Extension," *IEEE Transactions Knowledge Data Engineering,* **Vol. 17, Issue. 6, pp.49-734, 2009.**

[24]. *F. O.* Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, "Recommendation systems: Principles, methods and evaluation," *Cairo University: Egyptian Informatics Journal, Elsevier* **Vol. 16, pp.261-273, 2015.**

[25].A. M. Ghazanfar, and A. Priigel-Bennett, "Building Switching Hybrid Recommender System Using Machine Learning Classifiers and Collaborative Filtering," *IAENG International Journal of Computer Science(IJCS),* **Vol. 37, Issue. 3, pp.67-89, 2010.**

[26]. M. Papagelis, and D. Plexousakis, "Quantitative Analysis of User-based and Item-based prediction Algorithm for Recommendation Agents," *International Journal of Engineering Application and Artificial Intelligence(IJEAAI),* **Vol. 18, Issue. 4, pp.9-781, 2005.**

[27]. S. H. Min, and I. Han, "Detection of the Customer Time-variation Pattern for Improving Recommender System," *Expert System Application(ESA),* **Vol. 37, Issue. 4. pp.46-56, 2010.**

[28]. S. Kodali, M. Dabbiru, and T. Tao, "A Cuisine Based Recommender System Using K-NN and Mapreduce Approach," *International Journal of Innovative Technology and Exploring Engineering(IJITEE),* **Vol. 8, Issue. 7, pp.32-36, 2019.**

[29]. R. Burke, "Hybrid Recommender System: Survey and Experiments," *User Modeling and User-Adapted Interaction(UMUAI),* **Vol. 12, Issue. 4, pp.331-370, 2002.**

[30]. M. Vozalis, and K. Margaritis, "Using SVD and Demographic Data for the Enhancement of generalized Collaborative Filtering," *Information Sciences(IS),* **Vol. 177, Issue. 5, pp.3017-3037, 2007**

[31]. L. G. T. Jonathan, L. Herlocker, A. Konstan, and J. T. Riedl, (2004). "Evaluating Collaborative Filtering Recommendation Systems," *ACM Transactions on Information System(TOIS) archive,* **Vol. 22, pp.734-749, 2014.**

[32]. B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-based Collaborative Filtering Recommendation Algorithms," *In: Proceedings of the 10th International Conference on World Wide Web, ACM, Hong Kong, China,* **pp.295, 2001.**

[33]. M. Y. H. Al-Shamri, and K. K. Bharadway, "Fuzzy-generic Approach to Recommender Systems Based on a Novel Hybrid User Model," *Expert System Application(ESA),* **Vol. 35, Issue. 3, pp.99-1386, 2008.**

[34]. H. R. Singh, S. Maurya, T. Tripathi, T. Narula, and G. Srivastav, "Movie Recommendation System using Cosine Similarity and KNN," *International Journal of Engineering and Advanced Technology (IJEAT),* **Vol. 9, Issue. 5, pp.45-78, 2020.**

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