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CONTEXT-AWARE BASED RESTAURANT RECOMMENDER SYSTEM: A PRESCRIPTIVE ANALYTICS

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Abstract

Providing recommendations for products or services based on users' preferences and current conditions could be more efficient by using a context-based recommender system. It is important and useful to understand the consideration of what should be done by users to visit (prescriptive analytics) based on processed input data optimization. However, discussions and analysis of this system use are still limited. It is noted that prescriptive models can be developed by utilizing or optimizing inputs based on the chosen class rating. In the prediction function, the context-based recommender system can not only be used to predict Good, Neutral, and Bad rating values to produce predictive analytics, but also can be used to optimize input to produce prescriptive analytics. It can be seen that the evaluation of rating predictions using Deep Learning Models showed high accuracy in the performance compared to the Decision Tree and Random Forest. In this model, classification errors were considered the smallest compared to other models. Evaluation of input optimization for prescriptive analytics for class rating predictions showed the highest performance. The research contributes to a better understanding of developing a predictive and prescriptive analytics approach to a context-based recommender system model.

Keywords: Context-aware, Performance, Predictive analytics, Prescriptive analytics, Recommender system.

1. Introduction

The digital technology development has facilitated sellers in recommending products or services and buyers in sharing various kinds of information, including rate and review the products or services [1]. However, the convenience produces information overload. The sellers find it difficult to recommend accurate products or services according to buyers' preferences. At the same time, the users find it hard to search for the products or services that match their preferences. To overcome the information overload, it is necessary to synthesize the information by filtering through a recommender system.

As an information processing system that proactively processes various kinds of data, the recommender system suggests the products or services that can be used by buyers in the decision-making process. The products or services can be the domain of online stores, film, music, tourism, and social networks [2]. The tourism domain presents the products or services of destination, accommodation, transportation, and culinary [3].

In suggesting products or services, the recommender system is created not only based on collaboration by buyer's rating and content by seller's description but also based on contextual information, such as time, location, or social. The information of collaboration and content-based is simple (knowledge-poor), while information of context is more complex (knowledge-dependent) [4]. Therefore, the approach of a recommender system can be categorized into collaborative filtering-based, content-based, hybrid-based, and context-based recommender system.

The domain selection of recommender system in this study is tourism products or services, particularly restaurants (culinary). The restaurant is one of the tourism products or services that has the most complex and valuable or useful characteristics. The restaurant products or services has many attributes, such as cuisine, menu, price, opening hours, feature, popularity, category, location, and facilities. Besides, the restaurant products or services use the contextual information (e.g., time, location, and social network), which is categorized as knowledge-dependent. The context-based recommender system produces not only models predicting the value of some variables in the future based on conditions found in training data but also conditions that will generate expected values (prescriptions) in the future using variable dependencies previously studied in the model prediction [5]. Prescriptive analytic has been recognized as the next advanced analytic generation. The key question in prescriptive analytics is how to benefit from predictive analytics, for example, how to automate complicated decision making with a model of a recommendation system that is empowered using predictions. Predictive analytics produces predictive formulas that reveal the order attached to the data and the estimated value for key performance indicators [6]. The most recommender system research discusses predictive analytics, however, research discussing prescriptive analytics remains scarce. Therefore, a research question was proposed: How to improve the performance of prescriptive analytic accuracy? The performance of prescriptive analytic accuracy is expected to be improved using the deep learning method. The hypothesis proposed is that the performance of prescriptive analytic accuracy would be better if the input was optimized using a deep learning model compared to the decision tree and random forest model.

A context-based recommender system research has been carried out. Based on studies by Sohail et al. [7], the research uses location, temporal and trust context [7].

The context is based on user feedback. The technique used in the study includes artificial intelligence and machine learning techniques [2, 8-13]. However, the research is generally oriented to the prediction function, not exploring the discussion the prescription function. This study aims to produce context-based recommender system models and performances based on predictive and prescriptive analytics. The contribution of this study is to develop a predictive and prescriptive analytics approach to a context-based recommender system model.

2. Related Work

According to Abowd et al. [14], characterization of an entity's situation (e.g., user or item) is information that can affect the user interacting with the application. The context characters can be classified into individual contexts, location contexts, time contexts, activity contexts, and relational contexts [15]. Individual context uses information that is observed from independent entities (e.g., users or items) that can share the same features. This context can be grouped into natural entities (e.g., weather information), human entities (e.g., user payment preferences), artificial entities (for example, hardware and software configurations used in e-commerce platforms), or group entities (e.g., user preferences on the user's social network) [15-20]. Location context refers to a place that is associated with an entity's activity (e.g., the city where the user lives). This context is classified as a physical context (e.g., the coordinates of the user location, address, or road instructions), and virtual context (e.g., the computer's IP address on the network) [15]. Time context utilizes information on hours, days, weeks, months and seasons. The time context can be categorized as a definite context (e.g., a time frame with a starting and ending point) and an uncertain context (e.g., user sessions in e-commerce applications) [15, 21-23]. Activity context refers to the execution of tasks by an entity (e.g., shopping at a certain time) [15]. Relational context refers to the relationship, circumstances, and involvement of entities. Relational context can be defined as a social context (e.g., interpersonal relationships) and functional context (e.g., the use of circumstances and entity involvement) [15, 24-27].

The context involvement as knowledge of the recommender system is needed to understand the preferences of buyers, both explicitly and implicitly. The location and temporal context is the context that affects buyers and sellers in providing recommendations [7]. A location-based recommender system can use location ratings, especially non-spatial items-based spatial ratings and spatial items-based spatial and non-spatial ratings to produce quality recommendations through user partitioning and travel penalty technique [12]. The temporal recommender system can be used to recommend cafes based on buyers' satisfaction and consumption through neural networks technique [28]. In exploiting the context for collaborative filtering in the POI, hotel and tourism domains, Yang et al. [29] integrated the location of access and social networking information into the matrix factorization model; while Zang and Chow [30] integrate the social context (relationships) and user location into the process to measure similarities between users. These studies are more oriented to predictive analytics.

Other studies related to social network-based recommender system has also been conducted. Research involving user labels, item keywords, and social networks was synthesized using the KNN approach, social regularization, content-based, and collaborative based [31, 32]. Research on user and item information has also been comprehensively conducted. One study used Movielens public datasets with collaborative filtering approach, the similarity of content, and popularity predictions using the KNN technique [33]. Other studies, enhancing user and item information based on rank, classification, and classification of learning was conducted by using Naive Bayes to recommend the product of Netflix and Flixter [34]. These papers also discuss predictive models.

Underlying this, in general, related work discusses item recommendations with various considerations, such as rating, location, time, and other context. The study mainly discusses predictive analytics in the form of product or services recommendations. The recommender system model that is oriented towards prescriptive analytics through input optimization for recommended destination predictions is still very limited. For this reason, the paper aims to develop a recommender system model that not only discuss predictive analytics but also suggests the best actions that can be chosen in prescriptive analytics.

In evaluating the recommender system, accuracy metrics are used to assess the accuracy of predictions and evaluate user ratings and item ratings predicted by the system. The most commonly used recommender system evaluations are MAE, RMSE, Recall, and Precision, [35]. In addition, the metrics are used to evaluate predictive models are grouped into rating prediction metrics, usage prediction metrics, and ranking metrics [3, 15]. The rating prediction metrics cover aspects such as RMSE and MAE. The usage prediction metrics include Precision (true positive rate) and Recall (sensitivity).

3. Modeling Process

Vargas-Govea et al. [36] commented that this research uses public datasets entitled "restaurant and consumer data set" available in Machine Learning Repository, University of California, Irvine [37]. The nine data files are combined using the inner join parameter. Then, replace the missing value using the average value. This research does not use low-quality attributes or many values (e.g., latitude, longitude, address) and the attributes that are not needed are also deleted (e.g., weight, height, color). The dataset used consists of various restaurants (e.g., cuisine, opening hours, price), consumers (e.g., ambience, interest, budget) and overall rating attributes. The number of the dataset is 26,409 rows with 30 attributes. The dataset is used to predict, which restaurants are most visited based on the rating given by visitors. The dataset attribute is also used to search for prescriptions of the current contextual situation through simulations using the machine learning method, including Deep Learning, Decison Tree, and Random Forest.

Deep learning is chosen because this method has feature engineering capabilities that can manipulate features automatically so there is no need to build complex feature extraction models. This method also has the ability to provide increased accuracy that is proportional to the addition of the amount of data. The decision tree was chosen because this method has the ability to construct a classification rule representation with a hierarchical sequential structure by partitioning the set of training data recursively. The reason for choosing random forest, such as this method can be used in the classification of data in large numbers and can be used to influence accuracy to be better if the tree used is increasing. Prediction of rating attributes from sample restaurant and consumer datasets using the H2O deep learning algorithm [38]. The attribute labeled as polynomial can be classified. The quality of the model can be seen through the use of the split validation operator to produce training and testing datasets. Split data uses a type of stratified sampling with 80% training and 20% testing data. The Deep Learning parameter used is activation using a rectifier, the size of the layer is 50:50, reproducible using 1 thread, the local random seed is 1992 with epochs 10.0, the adaptive rate using epsilon 1.0E-8 and rho 0.99, standardize using L1 1.0E-5, L2 0.0, max w2 10.0, and an automatic loss function.

The attributes of a polynomial labeled Rating from a restaurant and consumer sample dataset can be predicted using Decison Tree for classification. Parameters used by Decison Tree are criteria using gain ratio with maximal depth 10, using pruning with confidence 0.1, using pre-pruning with minimum gain 0.01, minimum leaf size 2, the minimum size for split 4, number of pre-pruning 3. The use of Random Forest for classification can predict the attributes of a polynomial labeled rating from a sample of restaurant and consumer datasets. The Random Forest parameter used is a number of trees 100, the criterion uses the gain ratio with maximum depth 10, guess subset ratio with the voting strategy using confidence vote, and parallel execution enabled.

Processing datasets to predict rating labels and simulate attributes to get optimal class rating results (prescriptive analytics) was conducted by using RapidMiner Studio Version 9.0 with the support of computer specifications: Processor Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz 2.81GHz, NVIDIA GeForce GTX 1050 GDDR5 @ 4.0GB, RAM 16.0GB. The process is presented in Fig. 1. Figure 1 shows a simulator model, performance, model, and predicted data. The simulator model used the selection of model input to predict the class rating data and the optimization of input to optimize the class of rating data for each model, namely Deep Learning, Decison Tree, and Random Forest. The optimization used in the model is a Rating attribute as a label or target by maximizing confidence for certain confidence for a class, for example Good value. The input model attribute is determined through a global constraint to stay within 2 standard deviations around the average, stay above all attribute minimum values and it finds the optimal input (no limit). The performance of all predictive model was measured by the accuracy, classification error, weighted mean recall, weighted mean precision, several emerged errors (absolute, relative, root mean squared, and squared), correlation, and squared correlation.

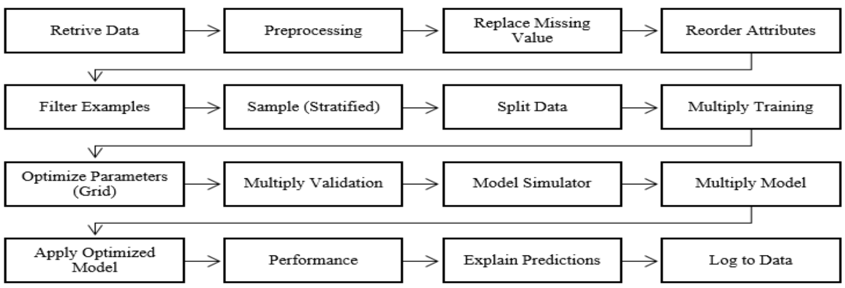


Fig. 1. Predictive modeling process.

4. Results and Discussions

The dataset is 26,409 lines of data separated into training data of 80% or 21,127 rows of data and testing data as much as 20% or 5,282 rows of data with the type of stratified sampling data submission. The dataset of 30 attributes is used as inputs to be processed using a contextual modeling approach (context-based) so as to produce output in the form of rating predictions of restaurant recommendations. The input of restaurant recommendations can be optimized to produce the prescriptive analysis. This study produces the predictions of accuracy, runtime and various performance measurement based on Deep Learning, Decison Tree, and Random Forest. In addition, this study also produces a simulation model for prescription analytics, which optimizes input to get the expected results. This study discusses the simulation of Deep Learning, Decison Tree, and Random Forest along with their performance, including accuracy, sensitivity, and precision for each model. In this predictive modeling, the simulation model is not only used to predict the future but also to figure out the best choice of action.

4.1. Results

4.1.1. Deep Learning

The Deep Learning Model is not only used to predict the rating but also discover the best option of action. This is also known as prescriptive analytics. The outcome of this process is a prescription for the contextual existing situation. To specify the preferred outcome, the model is simulated in Table 1.

Table 1. Deep learning model simulation.

Attributes	Model input	Optimal input
Accessibility	No_accessibility	No_accessibility
Activity	Student	Working-class
Alcohol	Wine-beer	Full_bar
Ambience	Family	Solitary
Area	Closed	Closed
Birth_year	1983	1966
Budget	Low	Medium
Days	Sunday	Monday - Friday
Dress_code	Informal	Formal
Dress_preference	Informal	Elegant
Drink_level	Casual drinker	Abstemious
Franchise	F	T
Hijos	Independent	Dependent
Hours	07:00-23:30;	18:00-11:00;
Interest	Variety	Eco-friendly
Marital_status	Single	Widow
Name	Cafeteria y Restaurant El Pacifico	Restaurant pueblo bonito
Other_services	None	Internet
Parking_lot	None	None
Personality	Hunter-ostentatious	Hunter-ostentatious
Price	Medium	High
Restaurant ambience	Familiar	Quiet
Restaurant cuisine	Mexican	Bar
Religion	Catholic	Catholic
Restaurant payment	Cash	Carte_blanche
Smoker	False	True
Smoking_area	None	Section
Transport	Public	On foot
User payment	Cash	Cash
Prediction	**Bad**	**Good**
Confidence distribution	90.65%	100.00%
Accuracy	99.62%	99.62%
Sensitivity	99.65%	99.60%
Precision	99.74%	99.60%

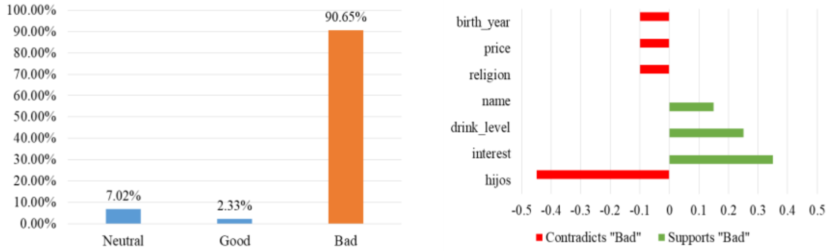
In predictive analytics, based on Bad rating predictions (Table 1) recommended Cafeteria y Restaurant El Pacifico restaurant. This recommendation is given to consumers who like a family atmosphere (ambience: family), like soft drinks (drink_level: casual drinker), like to pay in cash (User Payment: cash), non-smokers (smoker: false), dress casually (dress_preference: informal), using public transportation (transport: public), unmarried (marital_status: single), independent consumer type (hijos: independent), born in 1983 (birth_year: 1983), interested in many things (interest: variety), arrogant (personality: hunter-ostentatious), Catholic (religion: Catholic), student status (activity: student), and limited financial (budget: low). The recommended restaurant serves a menu of Mexican food (Restaurant Cuisine: Mexican), accepts unofficially dressed consumers (dress_code: informal), atmosphere full of intimacy (Restaurant Ambience: familiar), space closed (area: closed), accept cash payments (Restaurant Payment: cash), but provides liquor (alcohol: Wine-Beer), open weekends (days: Sunday) in the morning to night (hours: 7:00-23:30), price is quite expensive (price: medium), not franchise (franchise: f), does not have parking facilities (parking_lot: none), does not provide a smoking room (smoking_area: none), is not easy to find (accessibility: no_accessibility), not supported other services (other_services: none).

Restaurant predictions based on Good rating values (Table 1) provide foresight in the form of Restaurant Pueblo Bonito recommendations (predictive analytics). The recommendation prediction can provide new insights on how consumers should go on a culinary tour in the restaurant (prescriptive analytics). If consumers visit the restaurant, these consumers should order a restaurant food menu (Restaurant Cuisine: Bar), use public transportation (parking_lot: none), wear formal attire (dress_code: formal), pay by check (Restaurant Payment: Carte_Blanche), may not be noisy (Restaurant Ambience: quiet), use the free hotspot access service (other_services: Internet), order alcohol (alcohol: Full_Bar), bring a lot of money (price: high), visit at night or during the day (hours: 18:00-11:00) on weekdays (days: Monday to Friday), may smoke (smoking_area: section), use guide map of restaurant location (accessibility: no_accessibility), no need to wear a hat (area: closed), and like franchise (franchise: *t*). However, these consumers should also consider their preferences, namely consumers should walk (transport: on foot), like an atmosphere full of privacy (ambience: solitary), wear good clothes (dress_preference: elegant), have enough finances (budget: medium), pay cash (User payment: cash), invite other people (hijos: dependent), and save on consumption of drinks (drink_level: abstemious). These consumers are usually eco-friendly (interest: eco-friendly), true smokers (smoker: true), workers (activity: working-class), born in 1966 (birth_year: 1966), widowed (marital_status: widow), Catholic (religion: Catholic), and a hunter and show-off personality (personality: hunter-ostentatious).

Table 1 showed the prediction of Bad was as accurate as Good. Nevertheless, the Bad prediction is performed well in sensitivity and precision than the Good one. The input choice for the model related to the confidence distribution, important factors, and accuracy is presented in Fig. 2 (Bad rating expectation) and Fig. 3 (Good rating prediction). The inputs for Deep Learning Model in Table 1 is designated to see the model’s response to the rating prediction. Based on Fig. 2, the model showed the confidence for this decision was 90.65%. The value of hijos, religion, price, and birth_year does not support this decision. The accuracy indicates that 99.62% of all predictions prepared by this model were correct. When the model said Bad, it covered 99.65% of those cases.

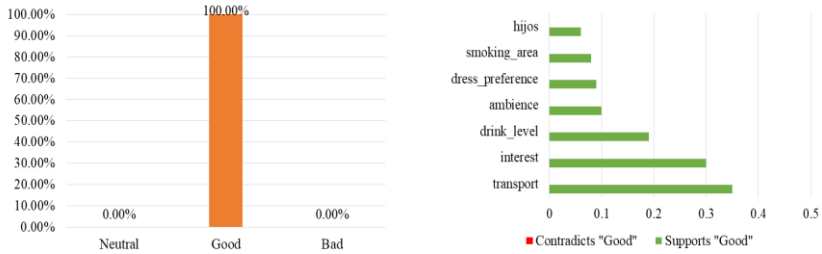
The inputs for the model in Table 1 was optimized to understand the model's feedback to the Good rating prediction. Based on Fig. 3, the model was super-confident that the exact prediction is Good. The confidence for this judgment is high with 100%. The main support for this decision included transport, interest, drink_level, ambience, dress_preference, smoking_area, and hijos. The accuracy illustrates that 99.62% of all predictions completed by this model are correct. When the model states Good, it covered 99.60% of those cases as well as with all predictions.

The Deep Learning Model is accomplished with more than 90% accuracy and 0.38% classification error and the model's performance of precision and recall is presented in Table 2.



(a) Most likely prediction: Bad. **(b) Important factors for Bad.**

Fig. 2. Result of deep learning model prediction: Bad.



(a) Most likely prediction: Good. **(b) Important factors for Good.**

Fig. 3. Optimal input result of deep learning model prediction: Good.

Table 2. Deep learning performance.

	True good	True neutral	True bad	Class precision
Prediction good	1757	2	5	99.60%
Prediction neutral	4	1244	3	99.44%
Prediction bad	3	3	2261	99.74%
Class recall	99.60%	99.60%	99.65%	-

4.1.1. Decision tree

In modeling prediction, the Decision Tree was used to predict an outcome and prescribe an optimized input. The optimization aims to find the optimal blend of inputs for the model so that the desired outcome is achieved, as shown in Table 3.

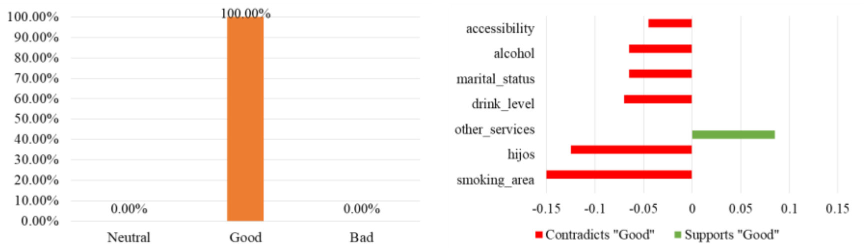
Underlying the Table 3, the prediction based on Good rating recommends Cafeteria y Restaurant El Pacifico, which is open on weekends in the morning until evening, accepts cash payments, serves Mexican dishes, serves beer, has a menu of moderate fare, not franchises, family atmosphere, room closed, accepts consumers dressed informally, but does not provide parking spaces, smoking rooms, map guides, and other services. The restaurant is recommended for consumers who are students, like the family atmosphere, born in 1983, preference for casual dress, love to pay in cash, like to ride public transportation, single, non-smoker, Catholic, have little money, show off, like a lot of things, and independent.

Still underlying Table 3, input optimization based on Neutral rating predictions produces Luna Cafe. The prescriptions that can be given to consumers who visit the restaurant, among others, order Sushi, pay with non-cash money, visit in the morning, afternoon or evening on weekdays, dress neatly, invite families, can use the free Internet, and do not need to carry money a lot.

Table 3. Decision tree model simulation.

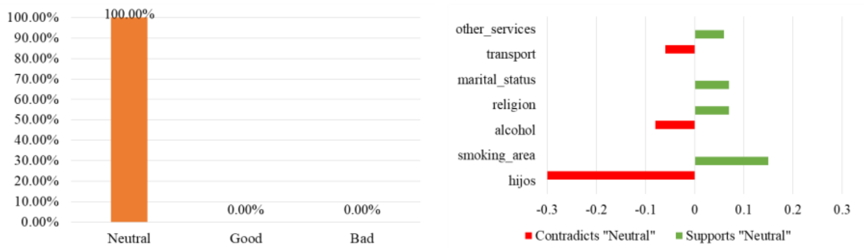
Attributes	Model input	Optimal input
Accessibility	No_Accessibility	Completely
Activity	Student	Working-class
Alcohol	Wine-Beer	Wine-beer
Ambience	Family	Solitary
Area	Closed	Open
Birth_year	1983	1983
Budget	Low	High
Days	Sun;	Mon;tue;wed; thu;fri;
Dress_code	Informal	Formal
Dress_preference	Informal	Elegant
Drink_level	Casual Drinker	Social drinker
Franchise	*F*	*F*
Hijos	Independent	Kids
Hours	07:00-23:30;	11:00-01:00;
Interest	Variety	Retro
Marital_status	Single	Single
Name	Cafeteria Y Restaurant El Pacifico	Luna cafe
Other_services	None	Internet
Parking_lot	None	Public
Personality	Hunter-Ostentatious	Hunter-ostentatious
Price	Medium	Low
Restaurant ambience	Familiar	Familiar
Restaurant cuisine	Mexican	Sushi
Religion	Catholic	Jewish
Restaurant payment	Cash	Visa
Smoker	False	False
Smoking_area	None	None
Transport	Public	On foot
User payment	Cash	MasterCard-Eurocard
Prediction	**Good**	**Neutral**
Confidence distribution	100.00%	100.00%
Accuracy	98.20%	98.20%
Sensitivity	97.34%	97.44%
Precision	98.17%	95.98%

Table 3 showed the prediction of Good is as accurate as Neutral. However, the Neutral prediction is performed better in sensitivity and precision than the Good one. The input selection for the model resulted in the confidence distribution, important factors, and accuracy as presented in Fig. 4 for Good rating prediction and Fig. 5 for Neutral rating prediction. To know the Decision Tree Model's reaction on Table 3, the input for the model was selected. Based on Fig. 4, the model was super-confident that the correct prediction was Good. The confidence for this decision was high with 100%. The value of smoking_area, hijos, other_services, drink_level, marital_status, alcohol, and accessibility did not support this decision. The accuracy presented that 98.20% of all predictions prepared by this model were correct. When the model said Good, it covered 97.34% of those cases. Then, it was correct with 98.17% of all predictions for class Good.



(a) Most likely prediction: Good. **(b) Important factors for Good.**

Fig. 4. Result of decision tree model prediction: Good.



(a) Most likely prediction: Neutral. **(b) Important factors for Neutral.**

Fig. 5. Optimal input result of decision tree model prediction: Neutral.

To see the Decision Tree Model's reaction to Table 3, the optimal input is selected. Based on Fig. 5, the model is super-confident that the correct prediction is Neutral. The confidence for this decision is high with 100%. The value of hijos does not support this decision though. The accuracy shows that 98.20% of all predictions done by this model are correct. When the model says Neutral, it covers 97.44% of those cases and it is correct with 95.98% of all predictions for class Neutral.

The Decision Tree Model performs that the accuracy is 98.20% and the classification error is 1.80%. However, the model's performance of precision and recall showed in Table 4.

Table 4. Decision tree model performance.

	True good	True neutral	True bad	Class precision
Prediction good	1717	24	8	98.17%
Prediction neutral	43	1217	8	95.98%
Prediction bad	4	8	2253	99.47%
Class recall	97.34%	97.44%	99.29%	-

4.1.2. Random Forest

The simulation of Random Forest Model did not only forecast the rating but also presented the prescription for the contextual recent situations. The model was used to predict a rating based on the given input to succeed the desired output and to prescribe the optimized input to reach the preferred outcome. The model simulation is shown in Table 5.

Table 5. Random forest model simulation.

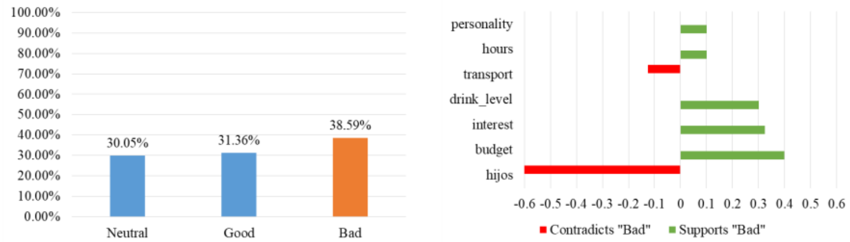
Attributes	Model input	Optimal input
Accessibility	No_accessibility	Partially
Activity	Student	Professional
Alcohol	Wine-beer	No_alcohol_ served
Ambience	Family	Friends
Area	Closed	Closed
Birth_year	1983	1985
Budget	Low	Medium
Days	Sun;	Sat;
Dress_code	Informal	Casual
Dress_preference	Informal	No preference
Drink_level	Casual drinker	Abstemious
Franchise	F	T
Hijos	Independent	Independent
Hours	07:00-23:30;	11:00-19:30;
Interest	Variety	Eco-friendly
Marital_status	Single	Married
Name	Cafeteria y Restaurant El Pacifico	Restaurant wu zhuo yi
Other_services	None	None
Parking_lot	None	None
Personality	Hunter-ostentatious	Hunter-ostentatious
Price	Medium	Medium
Restaurant ambience	Familiar	Familiar
Restaurant cuisine	Mexican	Family
Religion	Catholic	Catholic
Restaurant payment	Cash	Bank_debit_ cards
Smoker	False	False
Smoking_area	None	Not permitted
Transport	Public	On foot
User payment	Cash	Bank_debit_ cards
Prediction	**Bad**	**Good**
Confidence Distribution	38.59%	94.44%
Accuracy	95.87%	95.87%
Sensitivity	95.99%	97.62%
Precision	99.95%	91.50%

Predictive analytics analyses what will happen (foresight), while prescriptive analytics analyses how to optimize what happened (insight). The recommendation system not only predicts what restaurants are recommended (predictive analytics), namely Bad rating prediction, but the recommendation system can also describe how consumers should visit recommended restaurants (prescriptive analytics) through input optimization through Good rating prediction as shown Table 5.

Table 5 revealed the prediction of Bad was as accurate as Good. However, the Good prediction was implemented better in sensitivity than the Neutral one, but not in precision. The input collection for the model resulted in the confidence distribution, important factors, and accuracy is presented in Fig. 6 (for Bad rating prediction) and Fig. 7 (for Good rating prediction).

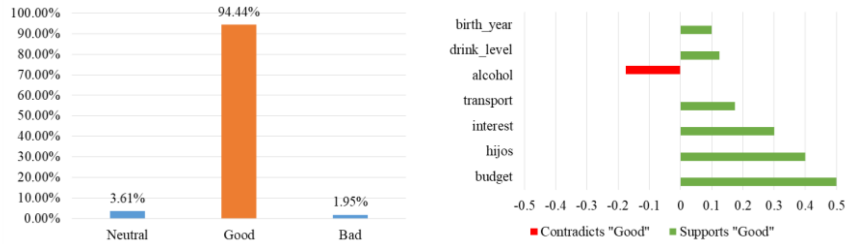
The inputs for the model in Table 5 showed the Random Forest model's reaction to the rating prediction. Figure 6 shows a coin toss, however, the model's prediction was Bad. The confidence for this decision was very low at only 38.59%. It seems that the value of hijos and transport did not support this decision. The accuracy approved that 95.87% of all predictions finished by this model were correct. When the model said Bad, it covered more than 90% of those cases and the prediction.The inputs for the model in Table 5 showed the Random Forest model's response to the rating prediction. Figure 7 shows a case of Good with more than 90% of the confidence and accuracy. The leading support for this decision ranges from budget, hijos, interest, transport, alcohol, drink_level, and birth_year.

The Random Forest Model executes that the accuracy showed 95.87% with the classification error for around 4.13%. The model's performance of precision and recall is displayed in Table 6.



(a) Most likely prediction: Bad. **(b) Important factors for Bad.**

Fig. 6. Result of random forest model prediction: Bad.



(a) Most likely prediction: Good. **(b) Important factors for Good.**

Fig. 7. Optimal input result of random forest model prediction: Good.

Table 6. Random forest performance.

	True good	True neutral	True bad	Class precision
Prediction good	1722	85	75	91.50%
Prediction neutral	41	1164	16	95.33%
Prediction bad	1	0	2178	99.95%
Class recall	97.62%	93.19%	95.99%	

4.2. Discussion

Based on the level of accuracy, Deep Learning Model is more accurate than the other two models (Decision Tree and Random Forest). However, the runtime required by the Deep Learning Model is longer than the Decision Tree Model but is faster than Random Forest. Moreover, based on classification error, Deep Learning Model showed the smallest error compared to the other models. The model is able to produce the highest level of accuracy with the smallest error. The accuracy, classification error, and runtime of the models can be seen in Table 7.

Table 7. Accuracy, classification error, and runtime.

Model	Accuracy	Classification error	Runtime
Deep learning	99.6%	0.4%	19 s
Decision tree	98.2%	1.8%	1 s
Random forest	95.9%	4.1%	46 s

Based on Table 7, the results of the performance accuracy test between deep learning, decision trees, and random forest models in prescriptive analytics showed that deep learning models produce the best accuracy performance compared to the decision tree and random forest model. Thus, the hypothesis, which states that the accuracy of prescriptive analytics will be better if the input is optimized using a deep learning model compared to the decision tree and random forest model accepted. Based on other performance measurements the Deep Learning Model produces the best performance, followed by the Decision Tree and Random Forest, as presented in Table 8.

Ji and Shen [31, 32] mentioned that user labels, item keywords, and social networks was synthesized using the KNN approach, social regularization, content-based, and collaborative based. As a result, the evaluation of the KNN approach and social regularization presented within the performance of MAE 0.1622 and Recall 0.3398, and the evaluation of a content-based and collaborative-based approach resulted in the performance of MAE 0.1412 and Recall 0.3625 [31]. However, research involving only user labels and product keywords using a content-based and collaborative based approach results in the performance of MAE 0.2013 and RMSE 0.3352 [32]. Compared to Table 8, the RMSE and recall of Deep Learning, Decision Tree, and Random Forest show better performance than [31, 32].

A study by Wang and Chen [33] used Movielens public datasets with collaborative filtering approach, the similarity of content, and popularity predictions using the KNN technique with the evaluation results of MAE 0.8085 and RMSE 0.9370. Other studies, enhancing user and item information based on rank, classification and classification of learning was conducted by using Naive Bayes to produce Netflix RMSE 0.862 evaluation and Flixter RMSE 0.898 [34]. Compared to

Table 8, the RMSE of Deep Learning, Decision Tree, and Random Forest show better performance than [33, 34].

Content-based and collaborative filtering approaches in the context aware recommender system have been widely investigated with performance results presented in Table 9. Underlying performance evaluation in Table 9, specifically RMSE, Recall, and Precision demonstrate that the performance of models Deep Learning, Decision Tree, and Random Forest in Table 8 generally show better performance.

Table 8. Performance vector.

	Deep learning	Decision tree	Random forest
Accuracy	99.62%	98.20%	95.87%
Classification error	0.38%	1.80%	4.13%
Weighted mean recall	99.62%, weights: 1, 1, 1	98.02%, weights: 1, 1, 1	95.60%, weights: 1, 1, 1
Weighted mean precision	99.59%, weights: 1, 1, 1	97.87%, weights: 1, 1, 1	95.59%, weights: 1, 1, 1
Root mean squared error	0.056 +/- 0.000	0.124 +/- 0.000	0.247 +/- 0.000
Squared error	0.003 +/- 0.040	0.015 +/- 0.108	0.061 +/- 0.107
Correlation	0.994	0.984	0.945
Squared correlation	0.989	0.967	0.894

Table 9. Recommender system evaluation.

Context	Domain	Evaluation	References
Social, location	POI, hotel and tourism	MAE 22% RMSE 35%	[29]
Social, location	POI, hotel and tourism	Precision 15% Recall 10%	[30]
Time, location	POI	Precision 5%-33% Recall 5%-33% F-Measure 5%-33%	[39]
Time, location	POI	Precision 1, 7%-3, 1% MAE 9% RMSE 4%	[40]
Social, location	POI	MAE 12.6% RMSE 14.5%	[41]
Location, time, activity	POI	Hit ratio 25%	[42]
User, time, location	Food	MAP 15% MAE 9% RMSE 9%	[43]

5. Conclusion

In the prediction model, a context-based recommender system cannot only be used to predict rating values but also to optimize the input based on the choice of class rating. It is significant and valuable to know the concern of what should be done by users to visit (prescriptive analytics) based on managed input data optimization. Evaluation of rating predictions showed high accuracy performance when using Deep Learning Models, but the required runtime was longer than the Decision Tree and Random Forest Model. Deep Learning Model accuracy reached 99.6% with runtime 19s. The error classification of Deep Learning Models was the smallest compared to other models, which was only 0.38%. Meanwhile, evaluation of input optimization for prescriptive analytics using Deep Learning Model for Good rating predictions showed the highest performance, namely accuracy (99.62%), sensitivity (99.60%), and precision (99.60%).

The most important insight in the study is to develop a predictive and prescriptive analytics approach to a context-based recommender system model. Future research should discuss further development by using a variety of machine learning methods with other or various public datasets, particularly to examine prescriptive analytics in a more accurate, sensitive, and precise way.

Nomenclatures

f	False
H2O	An open source, in-memory, distributed, fast, and scalable machine learning and predictive analytics platform
L1	A regularization method that constrains the absolute value of the weights and has the net effect of dropping some weights (setting them to zero) from a model to reduce complexity and avoid overfitting
L2	A regularization method that constrains the sum of the squared weights
max w2	A maximum on the sum of squared incoming weights into any one neuron
t	True

Abbreviations

KNN	K-Nearest Neighbors
MAE	Mean Absolute Error
MAP	Mean Average Precision
POI	Place of Interest
RSME	Root Mean Square Error
URL	Uniform Resource Locator
UserID	User Identification

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