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Socio-user Context Aware-Based Recommender System: Context Suggestions for A Better Tourism Recommendation

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Abstract

The existing tourism recommender system model is mostly predictive analytics for destination recommendations (item recommendation). Limited research has been conducted in the discussion of a recommender system model, particularly context suggestion. Thus, it is necessary to develop a recommender system model not only to predict tourism destinations but also to suggest contexts appropriate for tourist preferences (context suggestions). A deep learning method was used to create a model of the socio-user context aware-based recommender system for context suggestions. The attribute used as a label to suggest context was uHijos, uCuisine, uAmbience, and uTransport. The accuracy of the socio-user context aware-based recommender system in suggesting the context of uHijos, uAmbience, and uTransport was 100% with an error rate of 0%. It was found that only the level of recognition of the model in suggesting uCuisine was less accurate (below 30%) with a classification error for more than 70%. Performance evaluation of the socio-user model context-based recommender system was considered efficient, particularly for the evaluation of the level of accuracy, completeness (recall/sensitivity), precision, and a harmonic average of precision and recall (F-score), mainly for label/context of uHijos, uAmbience, and uTransport.

Keywords: Context suggestions, recommender system, social context-based, tourism, user context-based

I. Introduction

Information technology (IT) makes it easier for tourism service providers to inform, offer, and recommend tourism products and services (items); or facilitate users (tourists) to access, buy, and share information on tourism products and services [1]. However, this ease produces information overload [2], [3]. This makes it difficult for tourism service providers to present and recommend products and services according to tourist preferences or make it difficult for tourists to find and choose tourism products and services according to user preferences. Therefore, to overcome the excess information, filtering relevant information through a recommender system is proposed.

Tourism is one of the domains of the recommender system that has the most complex and valuable characteristics of products and services that need to be considered as knowledge-dependent information.

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Recommendations for tourism products and services generally only use collaborative filtering (CF), content-based filtering (CB), and hybrid approaches. Otherwise, the recommender system can be combined with additional contextual information in the form of context-aware recommender systems (CARS), such as time information, location, or status, comments, or reviews on social media. Users or travelers are expected to provide personalized recommendations for tourism products and services. Underlying this, CARS can suggest tourism products and services that appropriate for tourists, for example, when tourists are in certain locations, at certain times, and act on social networks by sharing status, comments, and reviews of tourism products and services.

Tourism products and services products are hereinafter referred to as tourism destinations, consisting of tourist objects and attractions, amenities, accessibility, supporting facilities, and institutions and communities [4]. This is an opportunity as well as challenge for tourism entities to attract tourist visits through excellent service. Excellent service is done by recommending personal tourism destinations according to tourist preferences. Personalizing tourism destination recommendations can be realized through a recommender system that aims to reduce the excess information by finding the most relevant information and services from a number of massive and diverse data [3]. In providing recommendations [1], the CF model works on the basis of user and products or services interactions through rating or user behavior in purchasing products and services, while the CB model works on the basis of user attribute information through user profile descriptions and products or services through the keywords of relevant products or services. The hybrid model works based on a combination of several recommender system models. However, the recommender system model faced a number of problems, including cold start problems, limited content analysis, sparsity, and scalability [5]. The issue affects the giving of tourism destination recommendations personally.

The CB model can reduce excess information by filtering based on user profile attributes and tourism destination keywords, but the CB recommender system is constrained by limited content analysis and overspecialization which causes new tourism destinations that are similar to tourism destinations that have never been recommended, making it difficult to personalize destination recommendations tourism. The CB model uses labels to conclude recommendations. Users are recommended items that are similar to those of previous users [6], [7]. This model is limited by labels that are explicitly related to items recommended by the recommender system. Another limitation, if there are two different items represented with the same label, and if there are only a few new users giving an assessment (limited content analysis), then the CB model does not produce accurate recommendations.

The CF model reduces the excess information by filtering based on tourist interactions on the assessment of tourism destinations, but the CF recommender system has limitations if there are new tourists interacting with the recommender system or new tourism destinations added to the catalog have not been assessed (cold-start problems), lack of tourism destination catalog data or tourist reluctance to rate sparseness, and large-scale data processing (scalability) causing the accuracy of the predictions of tourism destinations to be low. The CF model is the most commonly used approach, grouped into memory-based [8], [9] and model-based [10], [11]. The memory-based approach identifies interesting items based on other nearby user opinions obtained from the assessment matrix [8], [9]. This approach is basically a heuristic that predicts assessments based on a whole set of items that were previously assessed by the user. As with the model-based approach, this approach uses a collection of assessments to produce models in predicting judgments [10], [11]. Cold-start problems and scarcity of data are weaknesses of the CF model. The CF model only relies on user preferences to make recommendations. Therefore, the recommender system cannot provide recommendations until new items are valued by a number of users.

The hybrid model is a combination of CF and CB models to produce recommendations [12]. This can overcome the problem-based and collaborative recommender system issues. However, various ways to incorporate content and collaborative based models into hybrid recommender systems produce different recommendations. Underlying this, the CB and CF and hybrid models do not consider additional contextual information. This can affect the provision of personalized tourism destination recommendations according to tourist preferences. In addition, tourism destination recommendations that are less concerned with tourist preferences (contextual information of tourist); lack of understanding of the current situation and conditions of tourists (contextual information of location and time); and less considering tourist activity on social networks (contextual information of status, comments, or reviews).

In recommending products and services, the recommender system is not only based on rating data from various user collaborations, as well as user rating data and description of products and services attributes, but the recommender system needs to use additional contextual information (CARS) [13], such as time [14], location [15], as well as status, comments, or reviews on social media [16], [17]. Personalization is expected to increase the accuracy of tourism destination recommendations [18]. However, the recommendations provided are still general for all tourists and are more accommodating towards explicitly regulating tourist preferences (e.g., filling out preference forms, check-lists, ratings both offline and online) rather than being adaptive to tourist activities on social networks implicitly (e.g., status information, comments, or reviews on social media) [18]. Personalizing tourism destination recommendations can be done through information filtering using a recommender system, both CF and CB. However, personalization through the CF-based recommender system only provides recommendations based on tourist interactions on the rating of tourism destinations, as well as CB-based recommender systems that only provide recommendations based on attributes or keyword information on tourism destinations. In providing this personalization, CF and CB-based recommender systems do not consider additional contextual information in the form of location, time, or status, comments, or reviews on social media. Personalizing tourism destination recommendations underlying tourist preferences is still dominated by homogeneous and structured data usage. Processing online social networking data can generate patterns and trends in tourism that can be used to offer tourism destinations according to tourist preferences [19], [20], thereby creating personalized recommendations on tourism destinations [18].

Context-aware is one of the solutions to respond to each tourist's activities and preferences personally [18]. This is because context-aware can adjust contextual information in providing personalized tourism destination recommendations for tourists [21]. Contextual information is in the form of status, comments, or traveller reviews on social media, locations, entities (people, places, objects) in the surrounding environment, and time [21]–[23]. In addition, providing assistance to guide, inform, and support tourist activities in a personal manner, context-aware can recognize tourist activities through observation of tourist profiles and status, comments, or traveller reviews on social networks [24].

The trend of using social networking allows the exchange of content generated by users in the form of publications of comments, opinions, reviews, conversations, ratings, news, community-based questions and answers, relationships and social interactions, and media sharing [25]–[27]. Exchange of content produces data that is large, wide, distributed, unstructured and dynamic. This is a challenge in processing social network data. The data is processed and analysed systematically to obtain valuable information [25], [28]. This is interesting if social networking data is used as a consideration to provide recommendations personally through the social context-based recommender system model [3], [29]. The trend of the recommender system model approach in providing user personalization is to consider the user context. Contextual information related to user-context, including user profiles, locations, and capabilities that are around. The contextual information can be obtained explicitly or implicitly. It is also interesting if additional contextual information is used as a consideration to provide recommendations personally through the user context-based recommender system model. Consideration of the use of status data, comments, or traveller reviews on social networks and tourist context data to be processed further into information that is more valuable in personalizing recommendations for tourism destinations can be synergized through combining models of social context-based recommender systems and user context-based recommender systems be a socio-user context aware-based recommender system.

Underlying this, CARS is generally used to recommend tourism destinations (item recommendation), but in particular, CARS is rarely used to suggest context according to tourist preferences in recommending tourism destinations. For example, suggesting the right time (day, season) for holidays (time context suggestion); right friend advice for visiting destinations (companion/social context suggestion); advice on location, time, right friend to visit destination (location, time, companion/social context suggestion); vacation destination advice (location, time context suggestion); advice of tourists who are right for the night tour (user, time context suggestion); advice when appropriate (e.g., birthday) for tourists visiting special destinations (time context suggestion); appropriate friend advice (e.g., hobbies) for travelers hobby alike (companion/social context suggestion). This can affect the suggested context according to the recommended destination.

Thus, the recommender system is mostly focused only on predictions and recommendations on tourism destinations. The research of recommender system that accommodates additional contextual information and suggests context are still very limited. For this reason, the context suggestion for the socio-user context aware-based tourism destinations recommender system needs to be developed. Based on this background, most recommender systems only predict and recommend tourism destinations, but the recommender system is less considering additional contextual information and context advice that can be chosen for a particular situation. Underlying this, the following problems are formulated: CARS can recommend tourism destinations (item recommendation), but CARS does not suggest a context in accordance with tourist preferences in recommending tourism destinations, so the recommended destination is not in accordance with the suggested context. This research aims to predict context suggestions for recommendations on tourism destinations (item recommendation). This research can contribute significantly to context-based tourism.

II. RELATED WORKS

In using contextual information for the CB approach to the POI (Place of Interest) domain,[30] used a Markov relational network to adjust the POI attributes to the recent context. POI attributes (such as outdoor spaces, waitperson service, dinner) are served as inputs for neural network techniques. The method is used to categorize the proper level of interest of users for the POI taking into account the context of the given situation. Vector results that characterize POI are associated with user vectors using cosine similarity. Meanwhile, Hong et al. [31] offered a framework of relationships among user profiles and services for the same context situation considered to determine user preference rules by means of decision tree algorithms; and Kuo et al. [32] think about context as a weighting factor that affects user suggestion scores for certain items.

In using contextual data for the CF method in hotel and tourism areas, Gao et al. [33] alienated the rating matrix of user-item into sub-matrix according to chronological status, then every sub-matrix was designed taking into account the locality features. Chen & Chen [34] forecasts user preferences by linear regression models as well as values that denote the user's context preferences. This value is considered with three diverse probabilistic techniques, namely reciprocal information-based methods, information-acquisition based methods, and methods based on chi-square statistics. Wu et al. [35] offer a text-based context model. This study observes the recommendations of a context aware-based as a search problem in contextual graphs. This study also includes probabilistic-based post-filtering approaches to increase recommendations that deliver contextual aspects. Xu et al. [36] track the contextual attributes of the user's previous journey to each place. Context-based recommendations are determined by discovery the most related users, calculating scores for each location, and filtering locations that do not encounter contextual necessities.

In using the context for CF in the POI, hotel and tourism fields, Yang et al. [37] combined the locality of access and social networking data into the matrix factorization model; while Zhang & Chow [38] incorporate the social context (interactions) and user locality into the process to measure likenesses between users. In applying the context for CF in the POI area, Dao et al. [39] approved an adjusted Pearson coefficient to estimate similarities between users in dissimilar contexts. This approach describes a similarity context matrix that contains coefficients between the two existing user contexts for using items. This coefficient is entered into the accumulation function to determine the misplaced rating. Khalid et al. [40] endorse eating place by computing projected time in attainment them and allowing for distance, speed, and road surroundings. This method is encompassed in the aggregation task. Meanwhile, Domingues et al. [41] improved the matrix of the preliminary item-users by incorporating contextual aspects as virtual items; and Hong et al. [42] revised the scope of the Jaccard similarity to integrate context. In addition, Ren et al. [43] offered a technique of probabilistic matrix factorization that reflected contextual data occupied from location-based social networks, each POI defined using topic models, geographical and social associations. Next, Ramirez-Garcia & García-Valdez [44] amends the choice to deliver regular contextual recommendations.

In using the context for a hybrid method to the POI area, Valencia Rodríguez & Viktor [45] reflect user demographics, explicitly the geographical distance between the user and the location, and the next time the user desires to reach at the location. This method organises users into clusters, each user has ownership probability in each cluster, and each cluster has a favourite probability distribution on each item. The discriminant filter assesses the utility of items for users and reflects certain contexts.

Determining the relevance of recommendations can be measured by predictive metrics. Predictive metrics are the most frequently used metric for evaluating recommender systems. This metric is based on a comparison of various types between recommended items and items that are accessed and consumed. These metrics are used to appraise predictions, including rating prediction metrics, usage prediction metrics, ranking metrics [46]. Rating prediction metrics measure the correctness of recommendations in terms of errors. The two metrics are the root mean squared error (RMSE) and mean absolute error (MAE) [46]. This metric measures the distance between predictions and real ratings. Lower values of RMSE and MAE show higher predictive model.

Usage prediction metrics are based on various types of proportions between items that are recommended and consumed. These metrics include precision (positive rate), recall (sensitivity), specificity (true negative rate), and F-measure [46]. Precision (true positive rate) measures the proportion of recommended items that produce relevance to the user, which is the recommended item that the user actually accesses or consumes. Recall (sensitivity) measuring the proportion of items accessed or consumed is recommended correctly, i.e., items that are relevant to the user suggested by the recommender system. Recall and precision are usually considered for measuring quality recommendations. Specific (true negative rate) measures the proportion of non-recommended items that are not relevant to the user. The F-measure combines precision and recall which allows for comparison of different recommender systems using a single metric. This metric can be used to compare effects by considering independent context factors (i.e., social, time, and location), or a combination of both when predicting user ratings.

Ranking metrics assume that the utility of the item recommended is proportional to its position in the list of recommendations ordered by the recommender system. These metrics include normalized discounted cumulative gain (NDCG) and hit ratio [46]. NDCG considers items that have high ratings to give more satisfaction than those with poor ratings, while the hit ratio measures whether the choice of target users appears on the list of top-K recommendations. Generally denoted as Hit @ K, where K indicates the number of items recommended. Regarding predictive metrics, the accommodation of the context in the recommender system is evaluated using various metrics described above, presented in Table 1.

TABLE I
EVALUATION OF RECOMMENDER SYSTEM

Context	Domain	Evaluation	References
Social, Location	POI, Hotel & Tourism	MAE 22% RMSE 35%	[37]
Social, Location	POI, Hotel & Tourism	Precision 15% Recall 10%	[38]
Time, Location	POI	Precision 5%-33% Recall 5%-33% F-Measure 5%-33%	[41]
Time, Location	POI	Precision 1,7%-3,1% MAE 9% RMSE 4%	[42]
Social, Location	POI	MAE 12.6% RMSE 14.5%	[43]
Location, Time, Activity	POI	Hit ratio 25%	[47]
Time, Location, Weather, Social	Hotel & Tourism	Precision 16%-103%	[35]

III. METHODS

The study uses a quantitative approach to develop a model of socio-user context aware-based recommender system. The model used to predict the context suggestions. The research methodology uses experiments through the development and evaluation of a socio-user context aware-based recommender system to measure the accuracy of personalized tourism destination recommendations, especially context suggestions. The use of datasets to evaluate the recommender system model can be done through a synthetic dataset [50].

The existing public datasets do not exist that can be used according to variables or attributes that reflect the incorporation of social context-based and user context-based recommender system models. For this reason, it is necessary to compile a synthetic dataset with the context obtained from a combination of user context data; social context-based text, specifically status, comments, or reviews; and tourism destination data are taken from several public datasets [51]–[53] and access to Twitter and TripAdvisor social media data tailored to the needs. The synthetic datasets compiled are a combination of tourism destination datasets (restaurants), social contexts-based text (status, comments, reviews), user context (tourist profile), and rating. Ratings that are accommodated include an overall rating, multi rating, and reviews rating. Text-based social contexts are also obtained from combining datasets of status, comments, or reviews on TripAdvisor as well as access to Twitter data which analyzed their sentiments, such as positive, neutral, or negative.

Predicted context suggestions are expected to provide consideration of contextual advice that is appropriate for tourists. The modeling of socio-user context aware-based recommender system uses a machine learning approach with the deep learning method. This method is able to extract the required feature to improve the accuracy. To evaluate context suggestion for socio-user context aware-based recommender system model, the performance measured by accuracy, error, precision, recall, F-score, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) [29], [46], [54]. The evaluation of the model uses performance measurement of model classification [55].

Context suggestion through a recommender system requires data input, data processing, and presentation of results, including evaluation of the recommender system model. Data input in the form of the synthetic dataset is a combination of several public datasets and text-based data on social media that reflect contextual information needed by a context-based recommender system model. Data processing begins with pre-processing, including handling data from missing values and discretizing data, selecting features or attributes needed. Missing values are handled by replacing missing values with frequently occurring values, average values, or certain values. Data discretization converts data types according to the attribute characteristics needed by the recommender system model for further data processing. Selection of features or attributes is done automatically or manually. Automatically, attributes that have a lot of value or high stability can be ignored, but in this study, these attributes are still accommodated. This is done to consider destination recommendations based on diverse attributes, the flexibility of contextual data, and scalability of data. Manually, attributes that are not needed for processing data can be removed, such as identity, name, address, city, zip code, URL, and so on.

The cleared data is used to test the recommender system model based on the socio-user context. The recommender system modeling in this study uses a contextual modeling approach. Contextual modeling incorporates all existing attributes to be modeled. Contextual modeling uses machine learning methods, namely deep learning. Consideration of using this method is based on the ability of engineering features automatically without the need to build a feature extraction model and the ability to provide improved predictive accuracy that is proportional to the addition of the amount of data. Recommender system modeling based on socio-user context uses a classification or supervised learning approach that uses nominal type labels or targets used to predict contexts based on dataset attributes, both numerical and nominal. Evaluate the socio-user model context aware-based recommender system using performance accuracy, error rate, sensitivity, and precision [55]. Besides measuring the error rate, the performance of the model is measured by MAE and RMSE.

The dataset of 44 nominal type attributes and 8 numerical type attributes (52 attributes) are used as inputs to be processed using a contextual modeling approach (socio-user context-based) so as to produce output in the form of context advice. Each context suggestion is processed based on the tourist type attribute, menu preferences, interests, personality, atmosphere, and transportation preferences as labels. Processing of the destination recommendations uses a classification approach with the deep learning method. The use of these methods for socio-user modeling context aware-based recommender systems begins with attribute mapping, feature selection (attributes), attribute labeling, and data separation, then modeling and evaluation. Most features are chosen for modeling, except for rName, rAddress, rCity, rCountry, rState, rZIP, rURL, rFax, and reviews. Review features are not selected because they have been further processed into sentiment and ratingReviews features.

For suggested contexts, advice on who tourists should use the uHijos attribute as a label; what menu suggestions should be ordered by travelers using the uCuisne attribute as a label; favorite suggestions that are in accordance with tourist interests use the uInterest attribute as a label; advice traveled according to the type of traveler using the uPersonality attribute as a label; the atmosphere of a restaurant that should be recommended to tourists using the uAmbience attribute as a label; and what transportation should be recommended using the uTransport attribute as a label. The userID and restaurantID attributes are specified as attributes specific to the user's identity and restaurant identity that are not processed. The dataset is 45,369 lines of data separated into training data of 95% or 43,101 lines of data and testing data as much as 5% or 2,268 lines of data with the type of stratified sampling data submission. The modeling of socio-user context aware-based recommender system uses the deep learning method presented in Fig. 1.

RapidMiner Studio Version 9.0 used to process the datasets in order to predict context suggestion (predictive analytics). The process runs 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.

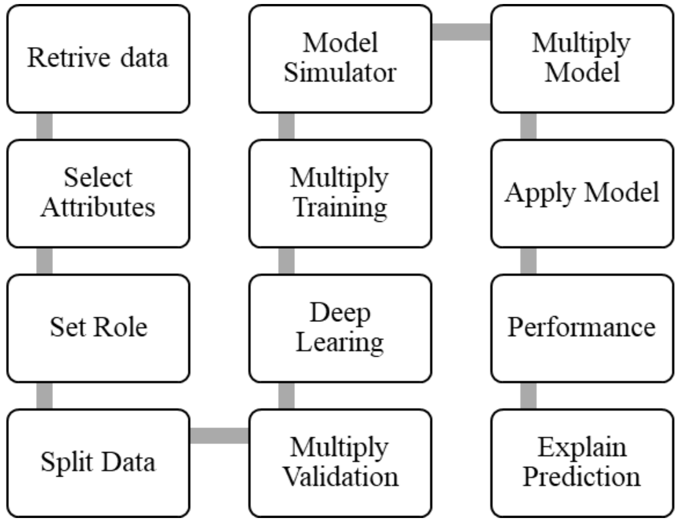

Fig. 1 Context suggestion process.

Suggestions for context are to produce context predictions that can be suggested to tourists on culinary tourism. The context that can be suggested is by who should travel with tourists, what food menu should be ordered by tourists, the preferences that match the interests of tourists, travel according to tourist personalities, what kind of restaurant atmosphere should be visited, and what transportation should be used. The context with which tourists should travel is suggested based on the uHijos role attribute set as a label. The context of what food menu should be ordered by tourists is suggested based on uCuisne's role set as a label. The context of the restaurant atmosphere that should be visited by tourists is suggested based on uAmbience's set role attribute as a label. What transportation context should be used by tourists is suggested based on uTransport's set of role attributes as a label.

Performance measurement of the classification model is used to evaluate the model of the socio-user context aware-based recommender system. Evaluation of the model uses a measure of accuracy, error rate, recall (sensitivity), and precision. Accuracy or recognition level states that the socio-user context aware-based recommender system correctly classifies a number of tuples in the test data (percentage). The error level or error classification is stated as 1 – accuracy. If the classification of data with classes is balanced (the amount of data in each class is relatively the same), then the measurement of accuracy and error rates are used. However, if the classification of data with classes is not balanced, then the measurement of recall (sensitivity) and precision is used. Recall (sensitivity) or size of completeness states the percentage of positive tuples labeled as positive. Precision or measure of certain states that the percentage of tuples labeled as positive is in fact true. To analyze the quality of the classification model in recognizing tuples from existing classes, a confusion matrix is used. Besides that, the other performance used is Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

IV. RESULTS

The socio-user context aware-based recommender model is not only used to predict rating (rating prediction) and recommend tourism destinations (item recommendation), but the model can also be used to suggest context according to tourist preferences. The suggested context is the context of users (tourists) as a reflection of tourist preferences, including menus of food, time, clothing, or companion that should be recommended to tourists in traveling. To model the suggested context, synthetic datasets are used, which consist of user contextual data, social contextual data, tourism destination data (restaurants), destination rating data. Suggestions context uses context attributes as labels. In this study, context suggestions are modeled based on user contextual data attributes that can be justified as contexts. The attributes of user contextual data that are labeled, among others are preferences for travel, cuisine, atmosphere, and transportation. The dataset is processed through a contextual modeling approach by entering all attributes as input and defining labels that are used as predictions. The contextual modeling process uses the deep learning method. The process begins with mapping attributes, selecting attributes, setting target attributes, and separating data, then modeling and evaluating the context suggestion for the socio-user context aware-based recommender system model. The dataset of 45,369 data lines was separated into training data totaling 95% lines of data and testing data as much as 5% of lines of data with the type of stratified sampling data submission. Socio-user context aware-based recommender systems modeling use the deep learning method, and the evaluation uses measures of performance accuracy, error rates, and so on. In this study, the attribute used as a label to suggest context is uHijos, uCuisine, uAmbience, and uTransport.

A. *Context Suggestion: uHijos*

The uHijos attribute that is used as a label has an independent value (solo traveler), kids (family), and dependent (group). U1045 (userID = U1045) travelers are advised to go to restaurant 135052 (restaurantID = 135052) with family (uHijos = kids), U1091 tourists are advised to go to restaurant 132875 by themselves (uHijos = independent), and userID U1023 travelers are recommended to 132715 with friends (uHijos = dependent). Culinary advice with family is influenced by attribute values uTransport = on foot (confidence level 0.464), uPersonality = hunter-ostentatious (confidence level 0.383), uColor = purple (confidence level 0.329); culinary advice alone is supported by attribute values uTransport = public (confidence level 0.432), uPersonality = thrifty-protector (confidence level 0.231), uMaritalSatus = single (confidence level 0.226); and the group's culinary suggestions are supported by the value of uWeight = 108 (confidence level 0.210), uBudget = medium (confidence level 0.167), uTransport = car owner (trust level 0.127) as Table II.

TABLE II
RESULTS OF CONTEXT SUGGESTION: UHIJOS

Attributes	Suggest uHijos #1	Suggest uHijos #2	Suggest uHijos #3
rPayment	VISA	American Express	cash
rCuisine	Bar	Japanese	Mexican
rHours	08:00-23:30	00:00-00:00	09:00-16:00
rDays	Sun	Mon-Fri	Sun
rParkingLot	none	valet parking	none
rLatitude	22.151	22.150	23.732
rLongitude	-100.977	-100.994	-99.159
rAlcohol	Full Bar	Wine-Beer	No Alcohol Served
rSmokingArea	none	section	none
rDressCode	informal	informal	informal
rAccessibility	no accessibility	no accessibility	no accessibility
rPrice	high	high	low
rAmbience	familiar	familiar	quiet
rFranchise	no	yes	no
rArea	closed	open	open
rOtherServices	none	Internet	none
rating	Average	Average	Poor
foodRating	Good	Good	Poor
serviceRating	Good	Good	Poor
sentiment	Negative	Neutral	Negative
reviewsRating	Poor	Average	Poor
uLatitude	22.170	22.142	23.731
uLongitude	-100.950	-100.949	-99.172

Attributes	Suggest uHijos #1	Suggest uHijos #2	Suggest uHijos #3
uSmoker	false	false	false
uDrinkLevel	casual drinker	abstemious	social drinker
uDressPreference	informal	no preference	no preference
uAmbience	family	family	family
uTransport	on foot	public	car owner
uMaritalSatus	single	single	single
uBirthYear	1988	1992	1984
uInterest	variety	retro	none
uPersonality	hunter-ostentatious	thrifty-protector	hard-worker
uReligion	Catholic	Catholic	Catholic
uActivity	student	student	student
uColor	purple	purple	purple
uWeight	66	60	108
uBudget	low	medium	medium
uHeight	1.54	1.63	1.62
uCuisine	Tibetan	American	Pizzeria
uPayment	cash	cash	cash
uHijos	?	?	?
restaurantID	135052	132875	132715
userID	U1045	U1091	U1023
confidence (kids)	1.000	0.000	0.003
confidence (independent)	0.000	1.000	0.002
confidence (dependent)	0.000	0.000	0.995
prediction (uHijos)	kids	independent	dependent
Support Prediction	uTransport = on foot (0.464); uPersonality = hunter-ostentatious (0.383); uColor = purple (0.329)	uTransport = public (0.432); uPersonality = thrifty-protector (0.231); uMaritalSatus = single (0.226)	uWeight = 108 (0.210); uBudget = medium (0.167); uTransport = car owner (0.127)
Contradict Prediction	uMaritalSatus = single (-0.233); uDrinkLevel = casual drinker (-0.159); rCuisine = Bar (-0.068)	uColor = purple (-0.341); uSmoker = false (-0.137); serviceRating = Good (-0.131)	uHeight = 1.620 (-0.165); uAmbience = family (-0.136); rLatitude = 23.732 (-0.105)

TABLE III
CONFUSION MATRIX OF CONTEXT SUGGESTION: UHIJOS

	true independent	true kids	true dependent	class precision
pred. independent	1179	0	0	100%
pred. kids	0	1080	0	100%
pred. dependent	0	0	9	100%
class recall	100%	100%	100%	

The quality of the socio-user context aware-based recommender system for predicting the context of uHijos in recognizing tuples from the class or the value of the uHijos attribute is contained in confusion matrix Table 3. Based on Table 3, tuples labeled as independent, kids and dependent must be true. The suggested independent context, kids and dependents by tourists are also predicted to be independent, kids and dependent by the model of the socio-user context aware-based recommender system. The model succeeded in rediscovering information about uHijos = kids as much as 1080 from the test data or 100% tuple kids labeled as kids (recall/sensitivity). The accuracy of the socio-user context aware-based recommender system in suggesting the context of uHijos is 100% with an error rate of 0% as presented in Table IV.

TABLE IV
EVALUATION OF CONTEXT SUGGESTION: UHIJOS

Evaluation	Performance
Accuracy	100%
Classification error	0%
Sensitivity (Prediction: independent)	100%
Precision (Prediction: independent)	100%
F-score	100%
MAE	0.000 +/- 0.001
RMSE	0.001 +/- 0.000

B. Context Suggestion: uCusine

The value of uCuisine attribute can be seen in Table 5. The uCuisine attribute is used as a label in suggesting the context of the preferences of tourists' cuisine. userID U1081 is recommended to order Mexican cuisine (uCuisine = Mexican) if a culinary tourism at restaurantID 135043 with the support of the attribute value uPersonality = hard-worker (confidence level 0.428); uBudget = low (confidence level 0.276); and uLatitude = 22,192 (confidence level 0.150). Fast food (uCuisine = Fast Food) is recommended for userID U1046 when visiting restaurantID 135085 with the role of the attribute value uDrinkLevel = abstemious (confidence level 0.339); uBudget = medium (confidence level 0.258); and uHeight = 1.810 (confidence level 0.161). Suggestions for café-style cuisine (uCuisine = Cafe-Coffee Shop) at restaurantID 135032 are given to userID U1018 with the support of the attribute value uAmbience = friends (confidence level 0.279); u Personality = hunter-ostentatious (confidence level 0.185); and uHeight = 1.690 (confidence level 0.183). Suggestions The uCuisine context is presented in Table 5.

TABLE V
RESULTS OF CONTEXT SUGGESTION: UCUSINE

Attributes	Suggest uCuisine #1	Suggest uCuisine #2	Suggest uCuisine #3
rPayment	cash	cash	cash
rCuisine	Fast Food	Fast Food	Cafeteria
rHours	00:00-00:00	00:00-00:00	07:00-23:30
rDays	Sat	Mon-Fri	Sat
rParkingLot	none	public	public
rLatitude	22.186	22.151	22.152
rLongitude	-100.945	-100.983	-100.973
rAlcohol	No Alcohol Served	No Alcohol Served	Wine-Beer
rSmokingArea	none	not permitted	section
rDressCode	informal	informal	informal
rAccessibility	no accessibility	no accessibility	no accessibility
rPrice	medium	medium	medium
rAmbience	familiar	familiar	familiar

Attributes	Suggest uCuisine #1	Suggest uCuisine #2	Suggest uCuisine #3
rFranchise	no	no	no
rArea	closed	closed	closed
rOtherServices	none	none	none
rating	Poor	Average	Average
foodRating	Poor	Good	Average
serviceRating	Average	Average	Average
sentiment	Negative	Neutral	Neutral
reviewsRating	Terrible	Average	Average
uLatitude	22.192	22.144	22.151
uLongitude	-100.957	-100.988	-100.975
uSmoker	false	false	false
uDrinkLevel	casual drinker	abstemious	casual drinker
uDressPreference	formal	informal	no preference
uAmbience	friends	solitary	friends
uTransport	public	public	car owner
uMaritalSatus	single	single	single
uHijos	independent	independent	independent
uBirthYear	1990	1983	1988
uInterest	technology	technology	eco-friendly
uPersonality	hard-worker	thrifty-protector	hunter-ostentatious
uReligion	Catholic	Catholic	Catholic
uActivity	student	student	student
uColor	white	blue	white
uWeight	57	76	50
uBudget	low	medium	low
uHeight	1.67	1.81	1.69
uPayment	cash	cash	cash
uCuisine	?	?	?
restaurantID	135043	135085	135032
userID	U1081	U1046	U1018
confidence(Mexican)	1.000	0.070	0.060
confidence(African)	0.000	0.000	0.000
confidence(Barbecue)	0.000	0.000	0.000
confidence(Bakery)	0.000	0.000	0.000
confidence(Deli-Sandwiches)	0.000	0.061	0.001
confidence(Dessert-Ice Cream)	0.000	0.073	0.000
confidence(Soup)	0.000	0.000	0.000
confidence(Cafeteria)	0.000	0.047	0.073
confidence(Polish)	0.000	0.000	0.000
confidence(Family)	0.000	0.052	0.066
confidence(Hot Dogs)	0.000	0.053	0.046

Attributes	Suggest uCuisine #1	Suggest uCuisine #2	Suggest uCuisine #3
confidence(Ethiopian)	0.000	0.000	0.000
confidence(Italian)	0.000	0.000	0.035
confidence(Burgers)	0.000	0.054	0.100
confidence(Japanese)	0.000	0.065	0.000
confidence(Irish)	0.000	0.000	0.000
confidence(Fast Food)	0.000	0.116	0.000
confidence(Indian-Pakistani)	0.000	0.000	0.000
confidence(Tibetan)	0.000	0.000	0.000
confidence(Russian-Ukrainian)	0.000	0.000	0.000
confidence(American)	0.000	0.052	0.000
confidence(Chinese)	0.000	0.046	0.058
confidence(Seafood)	0.000	0.056	0.000
confidence(Cuban)	0.000	0.000	0.000
confidence(Cafe-Coffee Shop)	0.000	0.035	0.112
confidence (Contemporary)	0.000	0.000	0.069
confidence(Mediterranean)	0.000	0.000	0.000
confidence(Regional)	0.000	0.000	0.000
confidence(Latin American)	0.000	0.052	0.093
confidence(Brazilian)	0.000	0.000	0.000
confidence(Pizzeria)	0.000	0.048	0.000
confidence (Australian)	0.000	0.000	0.051
confidence(Dutch-Belgian)	0.000	0.000	0.000
confidence (Indonesian)	0.000	0.000	0.000
confidence(Pacific Northwest)	0.000	0.000	0.000
confidence(Lebanese)	0.000	0.000	0.000
confidence(Moroccan)	0.000	0.000	0.001
confidence(Korean)	0.000	0.000	0.000
confidence(Fine Dining)	0.000	0.000	0.000
confidence(Armenian)	0.000	0.000	0.000
confidence(Pacific Rim)	0.000	0.000	0.000
confidence(Israeli)	0.000	0.000	0.000
confidence(Eastern-European)	0.000	0.000	0.000
confidence(Southern)	0.000	0.000	0.000
confidence(Tunisian)	0.000	0.000	0.000
confidence(Eclectic)	0.000	0.000	0.000
confidence(Dim Sum)	0.000	0.000	0.000
confidence(Asian)	0.000	0.056	0.000
confidence(Diner)	0.000	0.000	0.061

Attributes	Suggest uCuisine #1	Suggest uCuisine #2	Suggest uCuisine #3
confidence(Bagels)	0.000	0.000	0.000
confidence(Southeast Asian)	0.000	0.000	0.000
confidence (Vietnamese)	0.000	0.000	0.000
confidence(Sushi)	0.000	0.064	0.000
confidence(Cajun-Creole)	0.000	0.000	0.000
confidence(Kosher)	0.000	0.000	0.000
confidence (Continental-European)	0.000	0.000	0.000
confidence (Vegetarian)	0.000	0.000	0.000
confidence(Doughnuts)	0.000	0.000	0.043
confidence(Greek)	0.000	0.000	0.000
confidence(Turkish)	0.000	0.000	0.000
confidence(Caribbean)	0.000	0.000	0.000
confidence(Fusion)	0.000	0.000	0.000
confidence(Tex-Mex)	0.000	0.000	0.001
confidence(Tapas)	0.000	0.000	0.000
confidence(Jamaican)	0.000	0.000	0.000
confidence(Spanish)	0.000	0.000	0.000
confidence(Romanian)	0.000	0.000	0.000
confidence(Breakfast-Brunch)	0.000	0.000	0.001
confidence(Mongolian)	0.000	0.000	0.001
confidence (Portuguese)	0.000	0.000	0.000
confidence(Persian)	0.000	0.000	0.000
confidence (International)	0.000	0.000	0.000
confidence(German)	0.000	0.000	0.000
confidence(Juice)	0.000	0.000	0.000
confidence (Polynesian)	0.000	0.000	0.000
confidence(Thai)	0.000	0.000	0.000
confidence (North_African)	0.000	0.000	0.000
confidence(Hungarian)	0.000	0.000	0.000
confidence(Filipino)	0.000	0.000	0.000
confidence(Afghan)	0.000	0.000	0.057
confidence(Austrian)	0.000	0.000	0.000
confidence (Southwestern)	0.000	0.000	0.000
confidence(Middle Eastern)	0.000	0.000	0.001
confidence(Burmese)	0.000	0.000	0.000
confidence(Malaysian)	0.000	0.000	0.000
confidence(French)	0.000	0.000	0.000
confidence(Chilean)	0.000	0.000	0.000

Attributes	Suggest uCuisine #1	Suggest uCuisine #2	Suggest uCuisine #3
confidence(Cambodian)	0.000	0.000	0.000
confidence (Indigenous)	0.000	0.000	0.000
confidence (California)	0.000	0.000	0.000
confidence(Bar)	0.000	0.000	0.068
confidence(Canadian)	0.000	0.000	0.000
confidence(Peruvian)	0.000	0.000	0.000
confidence(Basque)	0.000	0.000	0.000
confidence(Swiss)	0.000	0.000	0.000
confidence(Hawaiian)	0.000	0.000	0.000
confidence(Bar Pub Brewery)	0.000	0.000	0.000
confidence(Steaks)	0.000	0.000	0.000
confidence(Organic-Healthy)	0.000	0.000	0.000
confidence(Tea_House)	0.000	0.000	0.000
confidence (Scandinavian)	0.000	0.000	0.000
confidence(British)	0.000	0.000	0.000
prediction(uCuisine)	Mexican	Fast Food	Cafe-Coffee Shop
Support Prediction	uPersonality = hard-worker (0.428); uBudget = low (0.276); uLatitude = 22.192 (0.150)	uDrinkLevel = abstemious (0.339); uBudget = medium (0.258); uHeight = 1.810 (0.161)	uAmbience = friends (0.279); uPersonality = hunter-ostentatious (0.185); uHeight = 1.690 (0.183)
Contradict Prediction	uWeight = 57 (-0.314); uAmbience = friends (-0.143); uDrinkLevel = casual drinker (-0.119)	uHijos = independent (-0.233); rDressCode = informal (-0.175); uInterest = technology (-0.117)	uBudget = low (-0.337); uLatitude = 22.151 (-0.125); uTransport = car owner (-0.122)

Based on Table VI, 91.13% of tuples labeled as Mexican must be true. Mexican-recommended cuisine by tourists is also predictable by Mexican by the model of a socio-user context aware-based recommender system. The model also managed to recover information about uCuisine = Mexican as much as 80.32% Mexican tuples labeled Mexican (recall/sensitivity). However, the level of introduction of the socio-user context aware-based recommender system in suggesting uCuisine is less accurate with more than 70% classification errors.

TABLE VI
EVALUATION OF CONTEXT SUGGESTION: UCUSINE

Evaluation	Performance
Accuracy	23.84%
Classification error	76.16%
Sensitivity (Prediction: Mexican)	80.32%
Precision (Prediction: Mexican)	91.13%
F-score	85.38%
MAE	0.778 +/- 0.371
RMSE	0.862 +/- 0.000

C. Context Suggestion: uAmbience

Suggestions for culinary traveling atmosphere can also be given to tourists according to the expected preferences. For this reason, the atmosphere context used as a label is uAmbience. The value of uAmbience attributes includes family, friends, and solitary. The results of the suggested context can be seen in Table 7. A solitary atmosphere (like being alone or just pairing) (uAmbience = solitary) is recommended for tourists user U1108 who have a culinary tour at restaurantID 135058 just to drink, use public transportation, and are interested in technological developments. This is reflected in the support of the attribute value uDrinkLevel = abstemious (confidence level 0.301); uTransport = public (confidence level 0.217); and uInterest = technology (confidence level 0.155). Family atmosphere (uAmbience = family) is recommended for tourists userID U1089 who has a culinary tour at restaurantID 135058 with family or children, likes purple, and is interested in many things. This can be seen in the role of attribute values in supporting uAmbience's prediction, namely uHijos = kids (confidence level 0.478); uColor = purple (confidence level 0.254); uInterest = variety (confidence level 0.175). Suggestions for an atmosphere suitable for culinary tours with friends (uAmbience = friends) can be given to tourists userID U1013 when visiting restaurantID 135060 with the support of uHijos = independent attribute values (confidence level 0.425); uDrinkLevel = casual drinker (0.284); and uInterest = technology (confidence level 0.135).

TABLE VII
RESULTS OF CONTEXT SUGGESTION: UAMBIENCE

Attributes	**Suggest uAmbience #1**	**Suggest uAmbience #2**	**Suggest uAmbience #3**
rPayment	MasterCard-Eurocard	MasterCard-Eurocard	cash
rCuisine	Pizzeria	Pizzeria	Seafood
rHours	13:00-23:00	13:00-23:00	11:30-19:00
rDays	Sat	Sun	Mon-Fri
rParkingLot	public	public	none
rLatitude	22.166	22.166	22.157
rLongitude	-101.001	-101.001	-100.978
rAlcohol	No Alcohol Served	No Alcohol Served	No Alcohol Served
rSmokingArea	none	none	none
rDressCode	informal	informal	informal
rAccessibility	no accessibility	no accessibility	no accessibility
rPrice	medium	medium	medium
rAmbience	familiar	familiar	familiar
rFranchise	yes	yes	no
rArea	closed	closed	closed
rOtherServices	none	none	none
rating	Average	Average	Average
foodRating	Average	Average	Average
serviceRating	Average	Average	Poor
sentiment	Negative	Negative	Neutral
reviewsRating	Poor	Poor	Average
uLatitude	22.144	22.170	22.157
uLongitude	-100.988	-100.950	-100.984
uSmoker	false	false	false
uDrinkLevel	abstemious	casual drinker	casual drinker

Attributes	Suggest uAmbience #1	Suggest uAmbience #2	Suggest uAmbience #3
uDressPreference	informal	informal	elegant
uTransport	public	on foot	car owner
uMaritalSatus	single	single	single
uHijos	independent	kids	independent
uBirthYear	1983	1988	1991
uInterest	technology	variety	technology
uPersonality	thrifty-protector	hunter-ostentatious	thrifty-protector
uReligion	Catholic	Catholic	Mormon
uActivity	student	student	student
uColor	blue	purple	orange
uWeight	76	66	68
uBudget	medium	low	high
uHeight	1.81	1.54	1.60
uCuisine	Hot Dogs	Regional	Mongolian
uPayment	cash	cash	cash
uAmbience	?	?	?
restaurantID	135058	135058	135060
userID	U1108	U1089	U1013
confidence (family)	0.000	1.000	0.000
confidence (friends)	0.000	0.000	1.000
confidence (solitary)	1.000	0.000	0.000
prediction (uAmbience)	solitary	family	friends
Support Prediction	uDrinkLevel = abstemious (0.301); uTransport = public (0.217); uInterest = technology (0.155)	uHijos = kids (0.478); uColor = purple (0.254); uInterest = variety (0.175)	uHijos = independent (0.425); uDrinkLevel = casual drinker (0.284); uInterest = technology (0.135)
Contradict Prediction	uBudget = medium (-0.266); rDays = Sat (-0.116); uReligion = Catholic (-0.088)	uBudget = low (-0.341); uDrinkLevel = casual drinker (-0.156); uWeight = 66 (-0.125)	uMaritalSatus = single (-0.145); uActivity = student (-0.081); rArea = closed (-0.076)

The quality of the socio-user context-based recommender system for predicting the uAmbience context in recognizing tuples from the class or the value of the uAmbience attribute is stated in confusion matrix Table 8.

TABLE VIII
CONFUSION MATRIX OF CONTEXT SUGGESTION: UAMBIENCE

	true family	true friends	true solitary	class precision
pred. family	1393	0	0	100%
pred. friends	0	418	0	100%
pred. solitary	0	0	458	100%
class recall	100%	100%	100%	

According to Table IX, tuples labeled as family, friends, and solitary must be true. The context suggested by family, friends, and solitary by tourists is also predicted by family, friends, and solitary by the model of the socio-user context aware-based recommender system. The model succeeded in rediscovering uAmbience = family of 1393 from the test data or 100% of the tuple family labeled as the family (recall/sensitivity).

TABLE IX
EVALUATION OF CONTEXT SUGGESTION: UAMBIENCE

Evaluation	Performance
Accuracy	100%
Classification error	0%
Sensitivity (Prediction: family)	100%
Precision (Prediction: family)	100%
F-score	100%
MAE	0.000 +/- 0.005
RMSE	0.005 +/- 0.000

D. Reference Context Suggestion: uAmbience

In culinary tourism, tourists can be advised that transportation should be used. Transportation context advice using the uTransport attribute as a label. uTransport attribute values include walking (on foot), public (public) transportation, and riding a private vehicle (car owner). The results of the transport context suggestion are presented in Table 10. Walking (uTransport = on foot) to restaurantID 135060 can be recommended to userID users U1077 who like the atmosphere for culinary tours with friends, middle income, and prefer to pay cash. This can be seen in the support of the attribute value uAmbience = friends (confidence level 0.174); uBudget = medium (confidence level 0.115); uPayment = cash (confidence level 0.103). Tourist userID U1083 who likes to travel alone (solo traveler), height around 180 cm, and likes blue color, it is recommended to have a culinary tour at restaurantID 132723 using public transportation (uTransport = public). The attribute values that play a role in uTransport predictions for advice on transportation contexts are uHijos = independent (confidence level 0.529); uHeight = 1,810 (confidence level 0.233); uColor = blue (confidence level 0.227). When visiting restaurantID 135052, then user10 U1064 tourists who are middle income, free dress preferences, and 75 kg weight are advised to use a private car (uTransport = car owner). The attribute values that play a role in uTransport predictions for the suggestion of the transportation context are uBudget = medium (confidence level 0.170); uDressPreference = no preference (confidence level 0.133); uWeight = 75 (confidence level 0.109).

TABLE X
RESULTS OF CONTEXT SUGGESTION: UTRANSPORT

Attributes	Suggest uTransport #1	Suggest uTransport #2	Suggest uTransport #3
rPayment	cash	VISA	VISA
rCuisine	Seafood	Mexican	Bar
rHours	11:30-19:00	00:00-00:00	08:00-23:30
rDays	Sat	Sat	Mon-Fri
rParkingLot	none	public	none
rLatitude	22.157	22.149	22.151
rLongitude	-100.978	-101.020	-100.977
rAlcohol	No Alcohol Served	Full Bar	Full Bar
rSmokingArea	none	section	none
rDressCode	informal	informal	informal
rAccessibility	no accessibility	completely	no accessibility
rPrice	medium	medium	high
rAmbience	familiar	familiar	familiar

Attributes	Suggest uTransport #1	Suggest uTransport #2	Suggest uTransport #3
rFranchise	no	no	no
rArea	closed	closed	closed
rOtherServices	none	none	none
rating	Average	Average	Good
foodRating	Good	Average	Poor
serviceRating	Good	Average	Good
sentiment	Neutral	Neutral	Positive
reviewsRating	Average	Average	Very good
uLatitude	22.156	22.144	22.149
uLongitude	-100.977	-100.988	-100.978
uSmoker	false	false	true
uDrinkLevel	casual drinker	abstemious	social drinker
uDressPreference	informal	informal	no preference
uAmbience	friends	solitary	family
uMaritalSatus	single	single	single
uHijos	independent	independent	independent
uBirthYear	1991	1983	1991
uInterest	eco-friendly	technology	technology
uPersonality	thrifty-protector	thrifty-protector	hunter-ostentatious
uReligion	Catholic	Catholic	Catholic
uActivity	student	student	student
uColor	green	blue	blue
uWeight	70	76	75
uBudget	medium	medium	medium
uHeight	1.67	1.81	1.71
uCuisine	Polish	Burgers	Italian
uPayment	cash	MasterCard-Eurocard	VISA
uTransport	?	?	?
restaurantID	135060	132723	135052
userID	U1077	U1083	U1064
confidence (public)	0.000	1.000	0.000
confidence(on foot)	1.000	0.000	0.000
confidence(car owner)	0.000	0.000	1.000
prediction (uTransport)	on foot	public	car owner
Support Prediction	uAmbience = friends (0.174); uBudget = medium (0.115); uPayment = cash (0.103)	uHijos = independent (0.529); uHeight = 1.810 (0.233); uColor = blue (0.227)	uBudget = medium (0.170); uDressPreference = no preference (0.133); uWeight = 75 (0.109)
Contradict Prediction	uHijos = independent (-0.512); uDrinkLevel = casual drinker (-0.188); rLatitude = 22.157 (-0.109)	uBudget = medium (-0.234); uDrinkLevel = abstemious (-0.196); uWeight = 76 (-0.135)	uAmbience = family (-0.414); uColor = blue (-0.160); uActivity = student (-0.095)

The quality of the socio-user context aware-based recommender system for predicting context suggestions uTransport in recognizing tuples from the class or the value of the uTransport attribute is stated in confusion matrix Table XI.

TABLE XI
CONFUSION MATRIX OF CONTEXT SUGGESTION: UTRANSPORT

	true public	**true on foot**	**true car owner**	**class precision**
pred. public	787	0	0	100%
pred. on foot	0	1191	0	100%
pred. car owner	0	0	290	100%
class recall	100%	100%	100%	

Based on Table 11, tuples labeled as public, on foot, and the car owner must be true. The context suggested by the public, on foot, and the car owner by tourists is also predicted to be public, on foot, and the car owner by the model of the socio-user context aware-based recommender system. The model succeeded in rediscovering information about uTransport = on foot by 1191 from the test data or 100% tuple on foot labeled as on foot (recall/sensitivity). The accuracy of the socio-user context aware-based recommender system in suggesting the uTransport context is 100% with a 0% error rate as presented in Table XII.

TABLE XII
EVALUATION OF CONTEXT SUGGESTION: UTRANSPORT

Evaluation	**Performance**
Accuracy	100%
Classification error	0%
Sensitivity (Prediction: public)	100%
Precision (Prediction: public)	100%
F-score	100%
MAE	0.000 +/- 0.001
RMSE	0.001 +/- 0.000

Based on the evaluation of uHijos, uCuisine, uAmbience, and uTransport contexts (Table XIII) it can be seen that only uCuisine's performance has an accuracy of less than 25% and an error rate of more than 75%. This is because the value of the uCuisine attribute is very large and the attribute value is not balanced, so the socio-user context aware-based recommender model is less accurate in suggesting the context of the cuisine that matches preferences. For this reason, evaluations with unbalanced attribute values can be used for other performance measures, namely precision and recall. This can be seen in the performance which states that 91.13% tuples labeled as uCuisine = Mexican must be true. Mexican-recommended cuisine by tourists is also predictable by Mexican by the model of a socio-user context aware-based recommender system. The model also managed to recover information about uCuisine = Mexican as much as 80.32% Mexican tuples labeled Mexican (recall/sensitivity).

TABLE XIII
EVALUATION OF CONTEXT SUGGESTION: UTRANSPORT

Context Suggestion	**Accuracy**	**Sensitivity**	**Precision**	**F-score**	**MAE**	**RMSE**
uHijos	100%	100%	100%	100%	0.000 +/- 0.001	0.001 +/- 0.000
uCuisine	23.84%	80.32%	91.13%	85.38%	0.778 +/- 0.371	0.862 +/- 0.000
uAmbience	100%	100%	100%	100%	0.000 +/- 0.005	0.005 +/- 0.000
uTransport	100%	100%	100%	100%	0.000 +/- 0.001	0.001 +/- 0.000

The performance of evaluating the socio-user context aware-based recommender system model can be compared with the results of other studies as presented in Table XIV.

TABLE XIV
EVALUATION OF CONTEXT SUGGESTION: UTRANSPORT

References	Label/ Context	Domain	Accuracy	Recall	Precision	F-score	MAE	RMSE
[38]	Social, Location	POI, Hotel & Tourism		10%	15%			
[41]	Time, Location	POI		5%-33%	5%-33%	5%-33%		
[37]	Social, Location	POI, Hotel & Tourism					22%	35%
[43]	Social, Location	POI					12.60%	14.50%
[48]	User, Time, Location	Food					9%	9%
[42]	Time, Location	POI			1.7%-3.1%		9%	4%
Proposed system	uHijos	Tourism (Culinary)	100%	100%	100%	100%	0%	0.10%
	uAmbience		100%	100%	100%	100%	0%	0.50%
	uTransport		100%	100%	100%	100%	0%	0.10%
	uCuisine		23.84%	80.32%	91.13%	85.38%	77.80%	86.20%

Table 14 shows that the performance evaluation of a socio-user context-based recommender system model is better than other researchers [37], [38], [41]–[43], [48], especially for level evaluation measures accuracy, completeness (recall/sensitivity), certainty, and harmonic average of precision and recall (F-score), especially for label/context of uHijos, uAmbience, and uTransport. However, most of the MAE and RMSE produced by other researchers [37], [42], [43], [48] are better than performance evaluations of the socio-user context aware-based recommender system, particulary for uCuisine labels/contexts.

V. CONCLUSION

Many tourism destinations are offered on the Internet. The offer was massive by tourism service providers, causing excessive information for tourists. This excess information makes it difficult for tourists to choose destinations according to preference. One solution to overcoming excessive information is information filtering. Information can be filtered using a recommender system. However, the existing tourism recommender system, most still use the content-based filtering (CB), collaborative filtering (CF), and hybrid models. The model has not considered additional contextual information in recommending tourism destinations. Context as additional information, including location context, time context, social context, physical context, modal context, computing context, and other contexts. The list of tourism destinations is mostly given by the recommender system, but the context suggestions recommended by the recommender system are still very limited. For this reason, the recommender system is not only predicting tourism destination recommendations (predictive models) but also suggesting contexts for tourist preferences (context suggestion) suitable to be modeled.

In modeling the socio-user context aware-based recommender system to suggest the context, a contextual modeling approach with deep learning method was applied. The given context suggestion uses the uHijos, uCuisine, uAmbience, and uTransport attributes as label/context. As a result, performance evaluations of accuracy, recall/sensitivity, precision, and F-score for social-user context-based recommender system models for context suggestions show more useful results with various elements including label/context uHijos, uAmbience, and uTransport. However, MAE and RMSE performance evaluations for suggesting contexts with the uCuisine label/context are lower than other researchers. The results of evaluating the prediction of suggesting contexts that can be chosen in a tour need to be followed up with a survey or user study. A user study is used to determine whether the evaluation obtained is based on modeling in accordance with user expectations so that predictions of suggested contexts that can be chosen in the tour can improve the user experience.

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