Recommender System Based Tensor Candecomp Parafact Algorithm-ALS to Handle Sparse Data In Food Commerce Information Services

[1] Hanafi

Department of Computer Science
University of Amikom Yogyakarta,
Yogyakarta, 55283, Indonesia
hanafi@amikom.ac.id, hanafi@te.net.id

[2] Nanna Suryana

Faculty of Information and Communication Technology
University Teknikal Malaysia Malaka (UTeM)
Malaka, 76100, Malaysia
nsuryana@utem.edu.my

[3] Abd Samad Hasan Basari

Faculty of Information and Communication Technology
University Teknikal Malaysia Malaka (UTeM)
Malaka, 76100, Malaysia
abdsamad@utem.edu.my

Abstract **- Recommender systems have been widely researched in many applications especially in e-commerce services with the aim to make clear and easy communication between consumer and provider. Simple examples of Recommender systems would include personal and commercial recommendation for the purchase of everyday goods. However, previous studies have not included high order matrix calculation to estimate consumer parameters, e.g., customer behavior, location and their purchase preferences such as those in the field of business online commerce. This study extends the use of Candecomp Parafact algorithm when applied to recommender system to understand consumer preferences. In addition, it is also aimed to produce bilinear models which are constant and stable so that localization can be done to provide more accurate results. As an example the research provides a model based on tensor theory for restaurant and menu selection by analyzing the customer and restaurant parameters.**

Keywords - Recommender system, Candecomp parafact algorithm, tensor, restaurant online

I. INTRODUCTION

Recommender systems have been widely studied to estimate consumer behavior and restaurants parameters to provide recommendation to users. Both parameters are used to predict and recommend menu preferences to customers. Usually customer in recommender system is called user. In this study we used the terms of customer and user interchangeably. In recommendations to consumers the system must predict how customer behave and provide similar preferences [1]. We propose a form of RS configuration that include the time and location of customer as features to improve recommendation accuracy [2]. There are several parameters to guide the system in estimate the consumers and their preferences dynamically.

Sparsity in data mining is referring to situation of incomplete data or there are unresolved action attributes [3]. In restaurant issue, a certain value combination which does not produce an end value, it will result in sparsity data problems [4], [5]. For example, there is no delivery after the menu is ordered, so customer the order and delivery tables. Another example, Restaurant branches and menu types can be ordered by different people with different location spacing. In a database with the sparsity problem, the system lack of information about the customer preferences and locations. Thus, there are multidimensional problems such as incoming call time, different time lag and various transaction records. The issues resulted empty value to be stored in databases [6]. Thus, there is an incomplete attribute problem of order and delivery databases operating as if they were completely filled with both actual data and zero data for all possible combinations of attribute dimension values.

The issues can be solved by certain calculations by defining each attribute as x, y, and z since all data points has specific value attributes [7]. For example, if there is an order, but unexpectedly, then it needs adequate response of providing the menu and delivery to the consumer location. This should be taken as recommendation after the orders are received to send the foods to the location. A good recommendation is based of prediction about the customer order, preferences and delivery location including their combined attribute dimensions [8].

A new studies [9] [10] [11] showed that consumer prediction to minimize such real-time data needs the attributes to be tagged and parsed. In addition, such localization (location determination) requires parameter ratings for the consumer. The attribute analysis will form matrix that can handle the small error level. This approach is called parallel decomposition (Parafact) to reduce the angle of error so that the articulation of the location of the consumer and restaurant site becomes more independent and the matrix can be analyzed with multilinear linkage to produce linear projection of the customer preferences and distances [12] [13] [14]. In some cases research and utilizing locations, such as how to optimize the purpose of medical delivery service [15].

In the field of restaurant business online, restaurant owners are often faced with the problem of providing a very large number of dishes and delivery. This is because the cooked food menu is often not out of order by their customers. In the field of restaurant delivery, sometimes the menu sent to the consumer has issues of distance location and staff's preparation. Thus, there is a dilemma in long distance prediction especially in very busy restaurants. Often the restaurant staffs must calculate consumer location and food recommendation to proceed the consumer order including understand the customer preferences to give menu recommendation. Consumer location and preferences may interfere with the delivery process and consumer location since they have different attributes.

Considering that the existing algorithm has not been able to form prediction of order destination toward restaurant site, therefore, the issues of consumer location and their menu preferences can be resolved with specific recommendation model by attributing their location and favor preferences.

II. THEORETICAL BASIS

Consumer action and item recommendation are important subjects in recommender system field. From marketing perspectives, consumers are the focus of attention in order to provide decision making and influence to buy [16] [17]. Thus, recommender system has role to provide recommendations by understanding consumers preferences, their situation and location [18].

The understanding of consumer attributes such as preferences, location, timing and behavior provide advantages to marketing strategy and recommender system [19] [20]. A good system can estimate and predict the interaction between customer and system and record the attribute involved to provide data record from machine learning [21]. In addition, the prediction of consumer locations is also comparable to dynamic effects and form fluctuated interactions. A good recommender system also can manage the time of service and has benefit of saving time for the users [22] [23]. The aspects of time and location involved multidimensional process.

Another disadvantage in the prediction of consumer locations and their preferences are the customer behavior has diverse preferences which impact on their consumer location which need representative computing analysis approach [24]. Their behavior has diverse, so it is not fully associated if only using the preferences option only. In addition, it is also considered to have limitations on perspective and requires another stable alternative. Ben-Akiva et al. [25] suggested that other alternatives can be determined by using locational tracking to understand their possible preferences to the food menu.

Zhang, et al., [26] identified the localization by using Support Vector Machines (SVM) computing method. They used SVM as recommender technique with to get attribute of action and order destination. The customer data are processed through a software to process, modify and store consumer location data using LIBSVM [27]. In this system there are 21 identified action-location attributes which provide 84.1% accuracy of action-location prediction. However, after the timing attribute is included, the accuracy of action-location of consumer reached only 69.5%. In addition, tracking consumers action such as preferences and behavior sometimes less efficient if the dataset is getting bigger. Therefore, it needs utilization of matrix analysis to understand the recorded data in order the system can estimate adequate recommendation.

Niehorster, et al., [28] presents a new solution to the problem of position recovery and prediction, orientation and markers taken from the recorded data of the first consumer Location. This is done to determine the optimization level in the search for package model 1 parameters that minimize the difference between package 1 model and the actual 5 packet model. How to do by using package 1 model to be estimated with the recorded data the first consumer location is then displayed as a predicted result. The technique used is Particle Swarm Optimization (PSO) to handle the optimization problem [29]. The results show that the accuracy of packet 1 articulation prediction can be achieved at 15 times the order. Therefore, it shows that the prediction-based model is proven to be feasible in real time.

Other study reported recommender system approach used Hidden Markov (HMM) method to perform consumer analysis and display the consumer preferences [30]. It used training dataset to estimate new consumers by conducting multiple tests using recorded data from the first consumer data records. The study observed consumer behavior to express their characteristics, menu selection and consumer location. The results showed the rate ratios of over 97% for eight of the nine prediction time by using trained system to predict the behavior and preferences of more than one person.

Krueger, et al., [31] Develops a calibration between recorded data from first consumer with stored data by using a tracking route approach which is more important than just the preferences matching approach. The system used locational model to be matched with the associated products (items) and the results are compared with first-time recorded data of consumer location and predicted result. The system recorded first consumer location and preferences to provide prediction. Their study is suitable as menu preferences estimation technique from the first consumer Location (route-to-menu) to track consumer menu preferences and the delivery destinations. As the route-to-menu technique can be an alternative to get low cost, it able to check the accuracy of localization, as well as obtaining new consumers continuously.

III. METHODOLOGY

A. Conceptual Research Model

This study used conceptual model through several steps (1) storing the location of restaurant site and consumers location and mixing with their menu preferences to get a prediction about the consumer behavior, (2) arranging metrics of tensor factors of x, y, z, (3) evaluating the decomposition of the tensor into matrix factor with smallest iteration, (4)) classification, and (5) consumer location optimization.

In this study, it conducted classification of consumer location and preferences menu through 1) Pre-processing, 2) Training, and 3) Testing. Each stage is done in a structured and systematic step. The following is an explanation of each stage to obtain the recommended location and menu which mixed with customer location and menu preferences.

B. Pre-Processing

Restaurant customer data is associated with consumer location and menu preferences. The location of the first consumer is modeled as form of route data and consumer location data are converted into tensor data x, y, z. The consumer location is divided into a scale of 1 to 5 and the menu preferences to be classified will be attributed to packets of 1 to 5 scale.

b. Formulation of consumer location and menu preferences to CP_ALS tensor data Candecomp / Parafact (CP) Alternating least squares (ALS) is a method which worked by updating each matrix factor alternately in each iteration by solving quadratic problems [32]. This method is very important for ranking the recommendation by describing complex data into outer product N vectors. The complex data is called a tensor X with smallest size that can be decomposed into component R, matrix factor and vector weight as below in equation 1.

(1)

Where represent column r^{th} on matrix factor $A(n)$ from size I_n x R.

Grasedyck et al., [33] An X tensor rank at a rank-1 tensor on Candecomp / Parafact (CP) decomposition with $u^{(n)}$ dimensions can be written as an outer product vector with a form as equation 2 in below:

(2)

Zhou et al., [34] on the Candecomp / Parafact (CP) decomposition model with Alternating least squares (ALS) method, a matrix factor with sequential updates. Where the method of Alternating least squares (ALS) served to minimize any error rate (error). Felten, et al., [35] The goal of Alternating least squares (ALS) algorithm is to update each matrix factor alternately in each iteration by solving quadratic problems. Tichavský, et al., [36] Alternating least squares (ALS) algorithm worked as multiple matrices A, B, C which resolved to find a quadratic matrix A, B and C in balanced way. Similarly, when looking for the quadratic form of B, then C and A are equal, and when looking for the quadratic form of C, then A and B are equal. The solution to find matrix A, B, C in [37] are decomposed into first, second and third mode of tensor A. to search for each component of matrices A, B and C, it presented into equation 3, equation 4 and equation 5 as shown on below.

$$A \leftarrow A_1(C \odot B)(C^t C * B^t B)^{-1} \ldots \quad (3)$$

$$B \leftarrow A_2(C \odot A)(C^t C * A^t A)^{-1} \ldots \quad (4)$$

$$C \leftarrow A_3(B \odot A)(B^t B * A^t A)^{-1} \ldots \quad (5)$$

The results of the feature decomposition / extract feature data are grouped into two classes, namely, (1) preferred food consumer class and (2) not-preferred food consumer class. CP_ALS method has two parameters, namely variables X and R. where variable X represented tensor data, and R variable represented tensor rank [38]. At the stage of data processing, the restaurant site and consumers location are variable input of distance X to be extracted into normalized data. The next iteration for the whole tensor mode shaped the dimensional matrix. therefore, it is re-matrixed the process of reshaping, followed by calculating the normalized locational data of restaurant and consumers as reshaping tensor.

B. Processing CP_ALS Methods into Matlab

```
a=dir('e:¥hmmtensor¥latih');
A={};
GT={'sn sb ' 'cl jgtn '};
for i=1:size(a,1)
 if findstr(a(i).name,GT{1})
 A=[A a(i).name];
 elseif findstr(a(i).name,GT{2})
 A=[A a(i).name];
 end
end
B={};
for i=1:numel(A)
 B=[B ;['e:¥hmmtensor¥latih¥' A{i}]];
end
XYZ1=preproses(B);
save data XYZ1 B
load data
clear X
F=[];
% algoritma dekomposisi CP parafac, parafac ALS
% CP decomposisi : candecomp/parafac = canonic
% decomposition/paralel factor analys
for i=1:10
 f=1;
 X(:,:,:)=XYZ1(i,:,:,:);
 X=tensor(X);
 O=1; %rank -1
 %
 P = parafac_als(X,O,struct('dimorder',[1 2 3])) %X data tensor, O
rank
 F=[F ;[P.U{1}(:,1); P.U{3}(:,1)]'];
end
F=[F [ones(1,5) 2*ones(1,5)]'];
save 'e:¥hmmtensor¥AG Standar1¥data2.mat' F
save 'e:¥hmmtensor¥data2.mat' F
ans =
 10 60 3 3
```

2. *C. Data Uses*

This study used data of restaurant delivery and literature studies according to the consumers location, restaurant sites and menu preferences. The data is processed with Matlab R2015a version for the process of featuring and characterization to classify the consumer into location and menu preferences.

IV. EXPERIMENTAL RESULTS

The main topic of this research is to find methods for prediction in restaurant, consumers and menu preferences and then classify the recommended menu for the customers. It synchronized between the position of the first consumer location of other consumers as recommended by the system. It started from the calibration of the first consumer location to classify based of distance parameters specially to recommend food and menu to customers.

C1. Setting First Consumer Location and Food Menu

Our proposed model seeks to bridge the location settings of consumers and restaurant which can provide the menu they have as potential order. In this case, the preferred distant is analyzed to provide predicted preferences. The first consumer location is associated with the actual consumer location. The first consumer location uses an algorithm that can be processed into Matlab data. We therefore proceed the data processed in the first consumer location data to Matlab. From matlab we will do estimation and decomposition with tensor rule.

C2. Location Synchronization with Food Menu Data

Consumer location data were adapted to the recommended menu data to support the system to perform synchronization process. It used recommender system model using matlab application with the intention to estimate the menu preferences and customer location. Synchronization results in the form of distance data and recommended menus must be consistent with consumer location and menu preferences.

C3. Tensor Decomposition

Tensor decomposition is the tensor-CUR decomposition is most relevant as a data analysis tool when the data consist of one mode that is qualitatively different than the others. In this case, the tensor-CUR decomposition approximately expresses the original data tensor in terms of a basis consisting of underlying sub tensors that are actual data elements and thus that have natural interpretation in terms of the processes generating the data. In order to demonstrate the general applicability of this tensor decomposition, we apply it to problems in two diverse domains of data analysis: hyperspectral medical image analysis and consumer recommendation system analysis [39].

Data obtained from consumer location is then processed by matlab using certain tensor rules. The data in matlab is decomposed into a matrix representing the distance and coordinate which dynamically change in size and numbers of the customer and their location. It is also so-called real time tensor. Thus, tensor concept is considered appropriate for use in this study. The data from tensor calculation is combined into a standard form of formula which typed in the Matlab compiler device platform. The matlab processing flow which combined with the tensor is given in Figure 1 below.

C4. Consumer Classification and Menu Recommendation

The classification of consumer location and menu preferences are adjusted through three stages, e.g., pre-processing, dataset training, and dataset testing. Each stage is done in a structured and systematic step. The classification result of the recommended menu and the consumer location estimation is given in table 1.

The recommended menu and consumer location are also synchronized with restaurant distance. For dataset it also compared with menu preferences derived from social media data mining using the first consumer location analysis which modified to tensor data x, y, z. the consumer location and menu preferences are classified according to the preferred food menu and preferred food. Consumer preferences about the menu are associated with a certain restaurant distance based on large packages and small packages menu.

In long-distance prediction to food, there are preferably 10 large distance-to-packet distances, ie: long, medium, and close. The same applies for food prediction about their favorable and unfavorable food menu consisted three large distance-to-packet groupings, eg, 1 packet distance, medium range, and close range.

Grouping the large distance-to-packet (large package) can be considered as coordinate location points from the initial point of delivery and destination end point. When the prediction of these large packets is connected, they will form a route. The more accurate the location of the coordinates, the better the shape of the route and represents the consumer location prediction. To improve the accuracy, it added Alternating Least Square (ALS) algorithm which will be discussed in the next section [40].

C5. Calculations by Tensor Alternating Least Squares (ALS)

Tensor data is conventionally still needed to estimate the filtering about the data mismatch and estimation error. In this study, they are implemented together with other algorithms [36].Therefore, we added Alternating Least Squares (ALS) as an embedded algorithm capable of calculating customer and menu matrices that are considered not sequential and have many negative values that must be converted to quadratic form without eliminating back and forth mode. Previous studies [40] [36] [35] reported that ALS is useful for overcoming convexity or bulging coordinates towards the middle or to the edge of void values.

Thus, the combination of CP and ALS is an advantage to change the shape of the matrix to become flatter and more convenient in generating and fulfill sparse matrices as a standardized matrix and represents the standard form of distance-menu matrices representing better recommendation matrices.

C6. Width-Range estimation of food menu and customer preference with CP

In the long-distance prediction of food, it is preferably repeated three times to obtain the best results and then SR is required to provide a final fit recommendation with a value of 9.650109e-01. The complete results of the long-range prediction with food preferably with CP are given in figure. 1.

Figure 1 estimated the positional possibility of location and possible menu that form the delivery route in standard position without background. The long-range prediction of food is preferably based on the new distance recognizable by SR which is then connected by CP-ALS and give more accurate route. However, there is noisy result from the deviation of menu preferences and delivery minutes which may cause constraint of comparison process so that it could be a mismatch delivery route that located the consumer different from their real location. This is caused by the consumer location which estimated from their first orders, menu type, menu preferences, and size of the ordered packet (ie x, y, z values) that make the distance menu can be overlapped or skewed from their normalized delivery. Therefore, to do long-range prediction of food preferences and consumer location, it preferably needs to find the restaurant distance and their coordination format by estimating the standardized menu preferences matrices and joint identification as sequential key location until the entire distance of consumer tensor can be extracted.

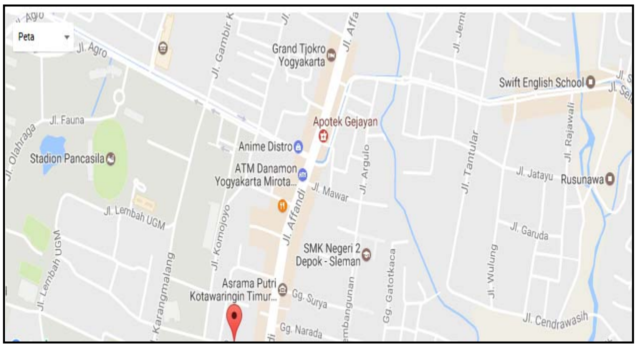

Figure 1. Position possible locations and possible menus from CP-ALS estimation

Furthermore, after the consumer can be associated and recognized, it is necessary to monitor the performance of the entire SR system in order to know its effectiveness in associating the position of the distance to the menu, especially in finding the nearest Iterative point as a reference coordinate point of distance to the menu. When the distance to the menu has been all associated, it will be possible to obtain a long-distance prediction of the overall preferred food menu. The results of the prediction are given in the form of route drawings as given in figure 2 for long-distance prediction of preferred food and long-range prediction to preferred food preferences matrices.

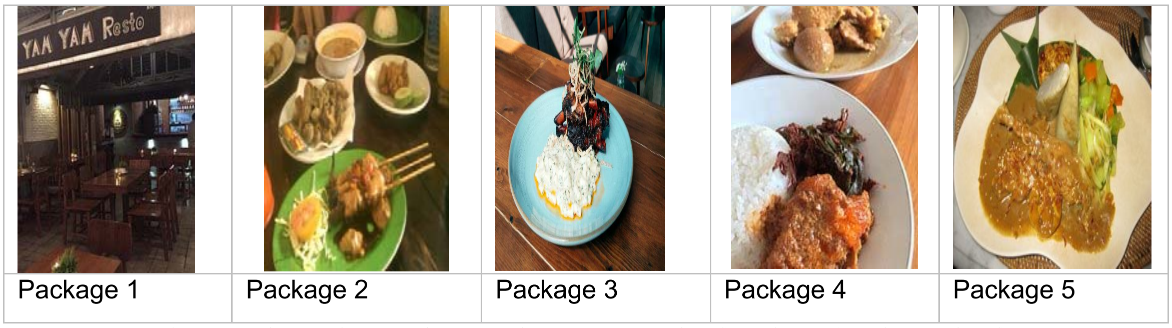

Figure 2. package scale 1 to package 5. Package 1 (= most preferred). Package 5 (= At least preferred).

DOI 10.5013/IJSSST.a.19.06.60 ISSN: 1473-804x online, 1473-8031 print

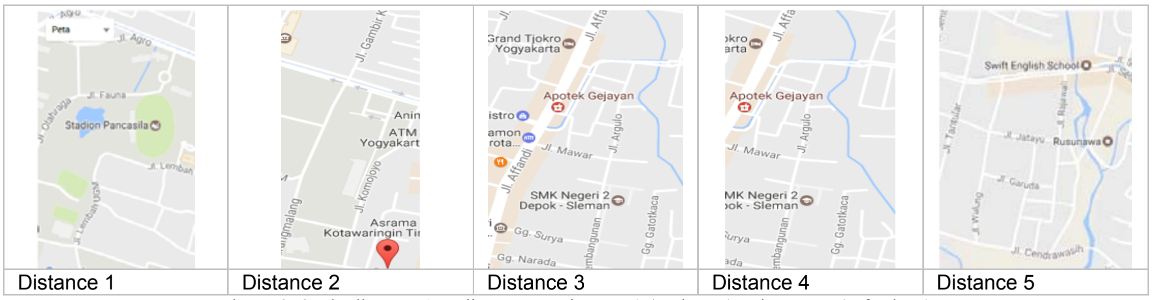

Figure 3. Scale distance 1 to distance 5. Distance 1 (= closest), Distance 5 (= furthest)

C7. Width-Range Estimation of Food Menu and Customer Preferences with CP

Candecomp parafact (CP) algorithm is applied to consumer prediction with the aim to minimize real-time data in order the consumer features can be tagged and parsed [32]. In addition, it is also aimed to produce bilinear models with constant and stable so that their localization can be done (as location determination) in more accurate manner. However, CP has a weakness in reading the location of coordinates due to angular shift that requires parameter ratings for the consumer, so it needs to be done factor analysis to form a matrix that has a small error level [41]. This process is called parallel decomposition (Parafact) which aims to reduce the angle of error from deviated customer location and restaurant distance. The articulation of the customer location becomes more independent from the restaurant distance and the matrix can be analyzed with multilinear approach to produce linear projection result of these distances. The result of linear projection data is given in Table I.

From table I, it showed the estimation result of the food package 1, package 2, package 3, package 4, and package 5, and combined package. The value varies indicating that the negative sign means the customer location which closer to the restaurant location will have smaller distance, whereas the positive sign means that the customer location is further away from the menu preferences. This means that the customer location is independent from restaurant distance. From table III it can be seen that only at unexpected distances there are positive value due to the prediction of long-distance locations to the food menu is still provide sparse data problem, in this case is especially in joint portions.

TABLE I. RESULTS OF ANALYSIS AND CONSUMERS PREDICTION AT CLOSE RANGE TO FOOD IS PREFERRED WITH CP_ALS (IN METERS)

Pkg 1	**Round**	**Pkg 2**	**Round**	**Pkg 3**	**Round**	**Pkg 4**	**Round**	**Pkg 5**	**Round**
306	**1**	**24**	**1**	**24**	**1**	**24**	**1**	**940**	**1**
24	1	24	1	2890	2	230	1	23	1
23	1	23	1	88	1	84	1	84	1
84	1	2084	2	8	1	720	1	78	1
78	1	78	1	82	1	82	1	82	1
82	1	24	1	250	1	280	1	300	1
300	1	300	1	300	1	771	1	2600	2
Iter 1, fit = 2.641084e01, fitdelta = 2.6e01, Iter 2: fit = 2.650102e01, fitdelta = 2.0e04 Iter 3: fit = 2.650102e01, fitdelta = 1.7e02 Final fit = 2.650102e01, P.lambda = [6302.0763]									

Notes:
A. Result iter 1, iter, 2, iter 3 showed that simulation is repeated three times to get the most stable value displayed by the computer
B. Fit is the fitness value of the feasibility of the distance to be used as raw data
C. Fitdelta is a fitness rounding value of up to one decimal in decimal value
D. The location of the first consumer is counted as the reference number given number 1 means that the order is received, and the menu is sent to the location, whereas the value of zero means that the order is rejected, and the menu is not sent.

C8. Analysis result of consumer prediction on long distance to favored food with CP-ALS.

The association of long distances with favored food is estimated with CP_ALS and provide quantitative vector and local searches results. It configured customer location, restaurant distance, and menu preferences as tensor features that allow linear discriminant transformation from original feature with the tensor rule. Given that there is a variation of the three variables on each menu delivery, it is necessary to obtain a standardized linear discriminant to identify and differentiate each feature to form the first, second, and sixth layers so that segmentation can be done for the determination of distances from number one to number six. Briefly the CP-ALS prediction results are given in the table below.

TABLE II. RESULTS ANALYSIS AND CONSUMER PREDICTION ON LONG DISTANCE TO FOOD IS PREFERRED WITH CP_ALS (IN METERS

Pkg1	Round	Pkg 2	Round	Pkg 3	Round	Pkg 4	Round	Pkg 5	Round
1,303	1	1,303	1	1,303	1	1,303	1	1,303	1
1,303	1	1,303	1	1,303	1	1,303	1	1,302	1
1,093	1	1,093	1	1,093	1	1,083	1	1,076	1
1,077	1	1,079	1	1,081	1	1,080	1	1,082	1
1,080	1	1,079	1	1,080	1	1,078	1	1,081,	1
1,085	1	1,090	1	1,090	1	1,097	1	1,097	1
Iter 1: fit = 9.656474e-01 fitdelta = 9.7e-01 Iter 2: fit = 9.666737e-01 fitdelta = 1.0e-03 Iter 3: fit = 9.666738e-01 fitdelta = 1.1e-08 Final fit = 9.666738e-01 P.lambda = [6297.0662]									

C9. Analysis Result of Consumer Preferences Prediction from Restaurant Distance and Unflavored Food With CP-ALS

Candecomp parafact algorithms are used to estimate the menu preferences prediction. It also minimized the dynamic real-time sparsity, so customer features can be tagged and parsed. In addition, it produced bilinear models with constant and stable segmentation so that accurate location determination is reached. A smaller distance sixe between restaurant and customer location will predict their frequency of order and therefore, higher delivery frequency. A smaller customer numbers group with unflavored food means that there is higher possibility that the food will be ordered and tasted and even be liked by customers. Therefore, the variables of distance and unflavored food menu are used and analyzed in this part. Their prediction result and the unflavored food estimation by using CP are given in table III.

TABLE III. CONSUMER PREFERENCES PREDICTION FROM RESTAURANT DISTANCE AND UNFLAVORED FOOD WITH CP-ALS

Pkg 1	Round	Pkg 2	Round	Pkg 3	Round	Pkg 4	Round	Pkg 5	Round
1,095	**1**	**1,093**	**1**	**1,092**	**1**	**1,092**	**1**	**1,092**	**1**
1,092	1	1,092	1	1,091	1	1,091	1	1,090	1
1,090	1	1,090	1	1,091	1	1,088	1	1,086	1
1,088	1	1,090	1	1,090	1	1,091	1	1,092	1
1,092	1	1,092	1	1,092	1	1,092	1	1,092	1
1,093	1	1,092	1	1,091	1	1,091	1	1,091	1
1,089	1	1,089	1	278	0	578	0	5,732	6
Iter 1: fit = 9.635099e-01 fitdelta = 9.6e-01 Iter 2: fit = 9.646898e-01 fitdelta = 1.2e-03 Iter 3: fit = 9.646898e-01 fitdelta = 4.5e-09 Final fit = 9.646898e-01 P.lambda = [6158.3347]									

From the above results it showed that (after rounding estimation values), it obtained mismatch on third sixth row package where route distance which shorter than the limit of 1000 meters as the most possible that customer will stay to order the food menu even though the menu are not favored.

IV. CONCLUSION AND FUTURE WORK

This research was carried out through the stages of tensor formulation accordance with the tensor rules of. Starting from location record of consumer and extraction of consumer location data, classification of location of consumer of restaurant until testing phase. Based on this, it can be concluded in this study.

From the above results, it can be seen that after the rounding, it obtained some error on the third sixth row package where the restaurants and customer location is below the limit of 1000 meters. In addition, the recommended menus are predicted accurately from location determination but not menu favors. This means that distance is the main factors that impact on the customer preferences. Finally, recording of consumer locations and menu preferences is quicker and easier but should still pay attention to the quality of the tensor data estimation as well as the tensor rules analysis to estimate the customer food favors, their menu preferences and the restaurant-customer location (distance). Our simulation of the customer location and restaurant distance showed that customer location can predict better the menu preferences as the simulation results showed.

Suggestions: The results of this study can still be refined into food menu preferences and distance effects. The consumer location simulation with recorded data showed that after normalization, the consumer considers their location as more important than their menu food favors. It means that customer tends to search the food menu from

the distance. There is similarity of smaller distance with type of package quantity, number of delivery and route conditions. The accuracy of the recommendation and classification are impacted from the tensor application to the customer data, in addition, CP-ALS also improve the quality of recommendation result based on the consumer menu favors and their preferences.

Research Limitation: The data is recorded in the form of a simulation as comparison only so that there may be variations of distance and consumer menu favors. The tensor theories used in this research need to be developed further in terms of application and algorithms so that it can determine the impact of customer trust and their social networking other than consumer location to provide better recommendation and prediction.

This study did not measure the frequency of menu or mismatch of customer order and delivered food menu when the restaurant's closed. That's because it used data of online restaurant which open for 24-hours services. This This study can produce food recommendation effectively consider collaborative filtering and distance of location restaurant. Enhance tensor and Parafact to calculate several data variable successful to generate recommendation. Even though, this study does not suitable the criteria of long-distance order delivery which longer than 5000 meters. For next research better to calculate further long distance of restaurant venue.

REFERENCE

[1] Y. Jiang, J. Shang, and Y. Liu, "Maximizing customer satisfaction through an online recommendation system: A novel associative classification model," Decis. Support Syst., vol. 48, no. 3, pp. 470–479, 2010.

[2] L. Coyle and P. Cunningham, "Improving Recommendation Ranking by Learning Personal Feature Weights," Adv. Case-based Reason., vol. 3155, no. 02, pp. 560–572, 2004.

[3] S. Goil and A. Choudhary, "PARSIMONY: An Infrastructure for Parallel Multidimensional Analysis and Data Mining," J. Parallel Distrib. Comput., vol. 61, no. 3, pp. 285–321, 2001.

[4] M. Papagelis, D. Plexousakis, and T. Kutsuras, "Alleviating the sparsity problem of collaborative filtering using trust inferences," Trust Manag., vol. 3477, pp. 224–239, 2005.

[5] B. Jafarpour, V. K. Goyal, D. B. McLaughlin, and W. T. Freeman, "Compressed History Matching: Exploiting Transform-Domain Sparsity for Regularization of Nonlinear Dynamic Data Integration Problems," Math. Geosci., vol. 42, no. 1, pp. 1–27, 2010.

[6] D. R. Tobergte and S. Curtis, Data Mining know it all, vol. 53, no. 9. 2013.

[7] Z. Huang, "Extensions to the k-Means Algorithm for Clustering Large Data Sets with Categorical Values," Data Min. Knowl. Discov., vol. 2, no. 3, pp. 283–304, 1998.

[8] S. Sivapalan, A. Sadeghian, H. Rahnama, and A. M. Madni, "Recommender systems in e-commerce," World Autom. Congr. Proc., 2014.

[9] I. Christopher et al., "METHOD AND APPARATUS FOR CORRELATING AND VEWING DSPARATE DATA," vol. 2, no. 12, 2015.

[10] B. Us et al., "PANGENETIC WEB SATISFACTION PREDICTION SYSTEM," vol. 2, no. 12, 2012.

[11] I. Christopher et al., "WEB SERVER AND METHOD FOR HOSTING AWEB PAGE FOR PRESENTING LOCATION BASED USER QUALITY DATA RELATED TO A COMMUNICATION NETWORK," vol. 2, no. 12, 2015.

[12] S. Pouryazdian, S. Beheshti, and S. Krishnan, "CANDECOMP/PARAFAC model order selection based on Reconstruction Error in the presence of Kronecker structured colored noise," Digit. Signal Process. A Rev. J., vol. 48, pp. 12–26, 2016.

[13] S. Pouryazdian, A. Chang, D. J. Bosnyak, L. J. Trainor, S. Beheshti, and S. Krishnan, "Multi-domain feature selection in auditory MisMatch Negativity via PARAFAC-based template matching approach," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, vol. 2016–October, pp. 1603–1607, 2016.

[14] A. Rouijel, K. Minaoui, P. Comon, and D. Aboutajdine, "CP decomposition approach to blind separation for DS-CDMA system using a new performance index," EURASIP J. Adv. Signal Process., vol. 2014, no. 1, pp. 1–12, 2014.

[15] M. H. Azizan, T. L. Go, W. A. L. W.M. Hatta, C. S. Lim, and S. S. Teoh, "Comparison of Emergency Medical Services Delivery Performance Using Maximal Covering Location and Gradual Cover Location Problems," Int. J. Electr. Comput. Eng., vol. 7, no. 5, p. 2791, 2017.

[16] J. Martínez, L. I. Esteban, M. A. A. F. Rejón, and Guardia, "Consumers' psychological outcomes linked to the use of an online store's recommendation system," emeraldinsight.com, 2015.

[17] P. S. Wei and H. P. Lu, "An examination of the celebrity endorsements and online customer reviews influence female

consumers' shopping behavior," Comput. Human Behav., vol. 29, no. 1, pp. 193–201, 2013.

[18] Y. Y. Wang, A. Luse, A. M. Townsend, and B. E. Mennecke, Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems, vol. 13, no. 4. Springer Berlin Heidelberg, 2015.

[19] Hanafi, N. Suryana, A. Samad, and B. I. N. Hasan, "PAPER SURVEY AND EXAMPLE OF COLLABORATIVE FILTERING IMPLEMENTATION IN RECOMMENDER," J. Theor. Appl. Inf. Technol., vol. 95, no. 16, 2017.

[20] J. Peppard and J. Ward, THE STRATEGIC OF MANAGEMENT INFORMATION SYSTEM: Building a Digital Strategy, Fouth. wiley.

[21] I. H. Witten, E. Frank, and M. a Hall, Data Mining: Practical Machine Learning Tools and Techniques, vol. 54, no. 2. 2011.

[22] Hanafi, N. Suryana, and A. Sammad, "AN UNDERSTANDING AND APPROACH SOLUTION FOR COLD START PROBLEM ASSOCIATED WITH RECOMMENDER SYSTEM : A LITERATURE REVIEW," J. Theor. Appl. Inf. Technol., vol. 96, no. 09, 2018.

[23] D. Gavalas, C. Konstantopoulos, and K. Mastakas, "Mobile recommender systems in tourism Damianos," vol. 39, pp. 319–333, 2014.

[24] W. Engineering, "Different perceptions of online shopping concerning product availability , consumer location , and experience Takashi Okamoto," vol. 11, no. 3, 2016.

[25] M. Ben-Akiva, D. McFadden, and K. Train, "Foundations of Stated Preference Elicitation - Consumer Behavior and Choice-based Conjoint Analysis," vol. 2015, pp. 1–124, 2015.

[26] Y. Zhang, D. Y. Kimberg, H. B. Coslett, M. F. Schwartz, and Z. Wang, "Multivariate lesion-symptom mapping using support vector regression," Hum. Brain Mapp., vol. 35, no. 12, pp. 5861–5876, 2014.

[27] F. C. Chen, M. R. Jahanshahi, R. T. Wu, and C. Joffe, "A texture-Based Video Processing Methodology Using Bayesian Data Fusion for Autonomous Crack Detection on Metallic Surfaces," Comput. Civ. Infrastruct. Eng., vol. 32, no. 4, pp. 271–287, 2017.

[28] D. C. Niehorster, L. Li, and M. Lappe, "The accuracy and precision of position and orientation tracking in the HTC vive virtual reality system for scientific research," Iperception., vol. 8, no. 3, pp. 1–23, 2017.

[29] C. J. Ting, K. C. Wu, and H. Chou, "Particle swarm optimization algorithm for the berth allocation problem," Expert Syst. Appl., vol. 41, no. 4 PART 1, pp. 1543–1550, 2014.

[30] S. Cheung, Y. Shirai, H. Morita, H. Takashima, M. Nakamoto, and E. H. S. Ip, "Application of hidden markov model to analyze enthusiasts' dynamics of a lifestyle brand," Proc. Annu. Hawaii Int. Conf. Syst. Sci., vol. 2016–March, pp. 1557–1566, 2016.

[31] R. Krueger, D. Thom, and T. Ertl, "Visual Analysis of Movement Behavior Using Web Data for Context Enrichment," Pacific Vis. Symp. (PacificVis), 2014 IEEE, pp. 193–200, 2014.

[32] A. Phan and P. Tichavsk, "Tensor Deflation for CANDECOMP / PARAFAC . Part I: Alternating Subspace Update Algorithm," vol. 63, no. November, pp. 5924–5938, 2015.

[33] L. Grasedyck, D. Kressner, and C. Tobler, "A literature survey of low-rank tensor approximation techniques," GAMM Mitteilungen, vol. 36, no. 1, pp. 53–78, 2013.

[34] Y. Zhang, G. Zhou, Q. Zhao, A. Cichocki, and X. Wang, "Fast nonnegative tensor factorization based on accelerated proximal gradient and low-rank approximation," Neurocomputing, vol. 198, pp. 148–154, 2016.

[35] J. Felten, H. Hall, J. Jaumot, R. Tauler, A. De Juan, and A. Gorzsás, "Vibrational spectroscopic image analysis of biological material using multivariate curve resolution-alternating least squares (MCR-ALS)," Nat. Protoc., vol. 10, no. 2, pp. 217–240, 2015.

[36] P. Tichavsky, A. H. Phan, and A. Cichocki, "Partitioned Alternating Least Squares Technique for Canonical Polyadic Tensor Decomposition," IEEE Signal Process. Lett., vol. 23, no. 7, pp. 993–997, 2016.

[37] T. G. Kolda, "Numerical optimization for symmetric tensor decomposition," Math. Program., vol. 151, no. 1, pp. 225–248, 2015.

[38] E. Frolov and I. Oseledets, "Tensor methods and recommender systems," Wiley Interdiscip. Rev. Data Min. Knowl. Discov., vol. 7, no. 3, pp. 1–41, 2017.

[39] G. Perspective, "TENSOR-CUR DECOMPOSITIONS FOR TENSOR-BASED DATA∗," vol. 48, no. 1, pp. 162–186, 2009.

[40] J. B. Ghasemi, M. K. Rofouei, and N. Amiri, "Multivariate curve resolution alternating least squares in the quantitative determination of sulfur using overlapped S(Kα)-Mo(Lα) emission peaks by wavelength dispersive X-ray fluorescence spectrometry," X-Ray Spectrom., vol. 44, no. 2, pp. 75–80, 2015.

[41] K. Liu, J. P. C. L. Da Costa, H. C. So, L. Huang, and J. Ye, "Detection of number of components in CANDECOMP/PARAFAC models via minimum description length," Digit. Signal Process. A Rev. J., vol. 51, pp. 110–123, 2016.