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| RESEARCH ARTICLE

Linear Classifiers for Context-aware Place Suggestions Implemented on Google Map

Athitaya Nitchot
Prince of Songkla University International College Hatyai Campus, Prince of Songkla University, Hatyai, Thailand 90110
Corresponding Author: Athitaya Nitchot, **E-mail**: athitaya.n@psu.ac.th

| ABSTRACT
Mobile applications such as Google Maps can provide suggestions for nearby locations. However, some issues with personalized presentation and recommendations and suggested locations are not ordered. This paper proposes context-awareness on place types using linear classifiers. The context-aware ubiquitous support is concerned with recommending nearby locations based on rating and distance. We use the scenario of types of places to process the recommendation. Two experiment studies were conducted, and the results showed that our approach is significantly better than a normal Google places search. Overall, the users were satisfied with our approach.

| KEYWORDS

Location-based Suggestion; Recommendation; Linear Classifiers.

| ARTICLE INFORMATION

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1. Introduction
Given the popularity of using mobile as a place searching platform as an anytime, anywhere approach, we propose context-aware ubiquitous support. A similar study by Hwang, Tsai, and Yang (2008) suggested nearby places related to the currently visited contents. The types of places are determined by an experimental study in which the learners' opinions on the locations, distance, and ratings under consideration are solicited. These variables vary according to the type of location. The application incorporates an API. The inputs are the latitude and longitude of the current user's point and place types as a search term to the Google Map JavaScript API. A linear algorithm is then used to classify the results (Zhang, Iyengar, & Kaelbling, 2002). This is done by changing the place lists so that they can be matched with various types of locations. In the future, we plan to collect the browsing and visiting suggestion history in order to improve the suggestion algorithm.

Section 2 discusses the linear classifiers algorithm applied in context awareness computing, including an experimental study plan to collect learners' opinions on the place distance and ratings against the types of places. Section 3 explains two experimental studies which determine the significant difference between our approach and normal Google places search and another experiment to see the overall usability and accessibility of our approach. The final section 4 acknowledges some of the study's limitations and suggests future research directions to address them.

2. Contextualized Recommendation Using Linear Classifier Approach
2.1 Context of Work
Despite the fact that the literature discusses various aspects of context, this concept remains very defined. De Jong (2007) defines context as identity, location, time, environment, and relation. Job, occupations, function, life outcome, situation, and task are all examples of context, according to Sampson and Fytros (2008). However, context classifications differ. The majority of context-aware computing works regard context terms as the location of uses (Abowd et al., 1999; Dey, 2001). This study takes the user's physical location into account. Personalized location-based recommendations are proposed using the ability of mobile platforms (particularly Androids) to detect the user's location.

The development of learning systems that can provide adaptive support based on the location of users is referred to as context-aware ubiquitous learning (Hwang et al., 2008). Mobile learning and ubiquitous learning are related but not mutually exclusive concepts. Mobile learning, on the other hand, is concerned with the general use of mobile devices in learning. The context may be ignored. When it comes to the use of adaptation supports, ubiquitous learning is more concerned with the context (time, location) that a mobile device can provide. In our research, we use the concept of context awareness to consider the user's location and suggest nearby places that may pique the user's rating and distance.

Initially, the experiment was designed to pique users' interest in searching for locations related to the place they were currently looking at. This focuses on user opinions on either rating or distance. In the early stages of development, the fundamental places are considered. Fundamental places are divided into five content categories. There are 60 people in the survey, and the majority of their responses are the same. Table 1 shows the different related search terms to the place categories.

Place Category	Related Search Terms
Sport	Gymnasium, fitness centre, sport shop
Food	restaurant, food goods, dining, supermarket, fresh market
Education	Nursery, primary school, elementary school, high school, college, university
Gardening	Home decoration, garden, and home shop
Salon	hairdressing school, salon, hairdressing materials shop

Table 1. Categories and Related Key Terms

2.2 The Design of Places Recommendation

Table 1 shows how the experimental results are used in the recommendation process. We search for nearby places based on each place category using the Google Map JavaScript API. Search queries are listed from the search terms in table 1 by showing the list of suggested places based on the search terms. For example, if the users are looking for places under the education category, the search terms can be a nursery, primary school, elementary school, high school, college, or university. In order to locate the suggested primary school, the search query 'primary school' is passed to Google Map JavaScript API. By default, the API will return the closest places first, with the search terms from table 1. The ordering of places in lists, on the other hand, is unrelated to distance or ratings. While these two factors are important in location selection, they differ depending on the type of location.

As a result, a survey was carried out in which users were asked about their decisions regarding the reliance on two factors when selecting locations. As shown in table 2, the survey results show the frequency of opinions from participants in favor of distance or rating according to place types.

Place Types	Frequency		Ratio (m : r)
	Distance (m)	Rating (r)	
Sport	27	57	(0.32 : 0.68)
Food	33	51	(0.39 : 0.61)
Education	74	10	(0.88 : 0.12)
Gardening	24	60	(0.32 : 0.68)
Salon	44	40	(0.52 : 0.48)

Table 2 Places Types and Related Ratio

The survey frequencies are converted to a ratio, as indicated in table 2. The addition of the ratio should be equal to 1. in this example. These ratio numbers were considered while computing the place suggestion list, as detailed in the next section.

2.3 Linear Classifiers on Contextualization

One of the strategies utilized in the machine learning approach is linear classifiers (Zhang et al., 2002). To classify data based on numerous factors, several recommender systems have employed linear classifier approaches. The technique, for example, is used to filter websites based on geolocation and user history (Gravano, Hatzivassiloglou, & Lichtenstein, 2003). Algorithms such as the least square method (Yang & Chute, 1994) and the simplest linear method (Pazzani & Billsus, 2007). The simplest linear method is used in this paper to list places based on two factors: rating and distance.

We refer to the following equation $w(l_j) = w(m_j) + w(r_j)$ where j ranges from 0 to n. $w(l_j)$ indicates the total weight of each place's location (this value ranges from 0 to 10). $w(m_j)$ indicates the weight of each place's adjusted distance (this value ranges from 0 to 5). $w(r_j)$ indicates the weight of each place's rating (this value ranges from 0 to 5). Figure 3 shows how we compute the final weight under each place for the suggestion algorithm.

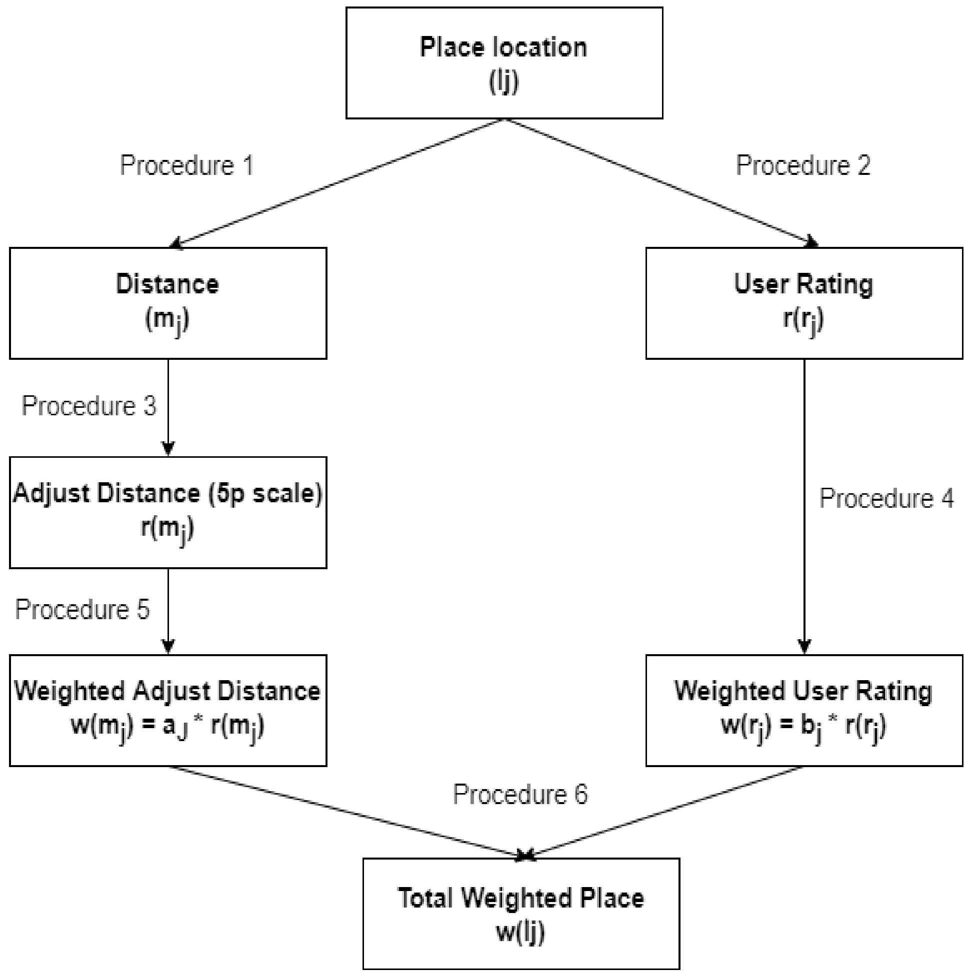

Figure 1 Overall Procedure (Total Weight of Each Place)

Six procedures make up the overall process. Procedure 1 calculates the distance between the user's point and each location (m_j) using the Map JavaScript API from Google (Google Inc., 2022). Procedure 2 is to obtain the rating of places (r(r_j)) from the Google Map JavaScript API. Procedure 3 is to use m_j and adjust it to be ranging from 0 to 5 using formula $r(m_j) = \frac{5000 - m_j}{5000} * 5$. Procedure 4 involves adjusting the weight of place rating based on the ratio in table 2 as $w(u_j) = b_{j*}[r(u_j)]$. Procedure 5 refers to a formula $w(m_j) = a_j * r(m_j)$, to compute the weight of distance for each location based on the opinion ratio (as computed in table 2). The last procedure calculates the final weight value of the suggested place by referring to the summation of $w(m_j) + w(r_j)$. Each place's total weight will be sorted and suggested as the list of places. The preliminary prototype was implemented with embedded Google API. The prototype screenshots are shown in Figures 2, 3, and 4. Figure 2 shows the page allowing the user to choose the types of places they would like to get the list of suggestions. Figure 3 shows the locations with the highest total weight that will be listed first. Each location indicates the rating and distance value. In figure 4, the blue map pin refers to the top five recommended places.

Figure 2 Prototype Screenshot (Choose Types of Place Page)

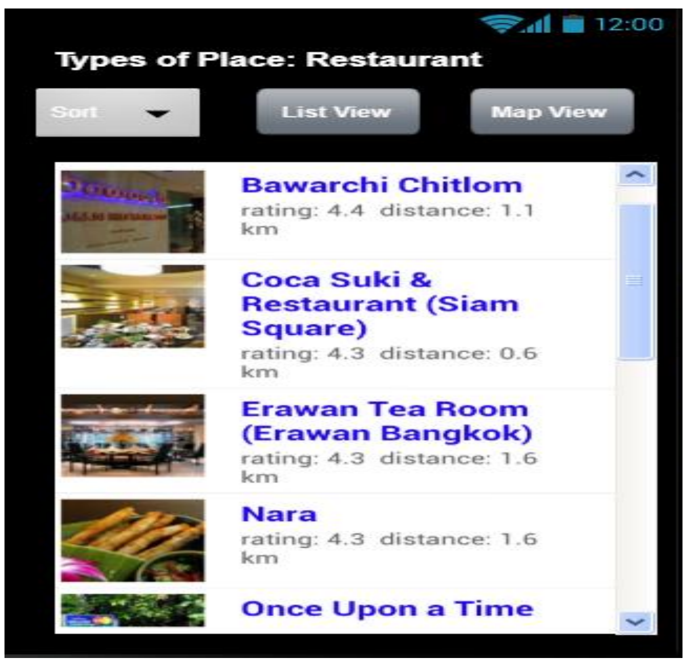

Figure 3 Prototype Screenshot (List of Place Suggestions as "Restaurant")

Figure 4 Prototype Screenshot (Map Display Place Suggestions as "Restaurant")

3. Experimental Studies

This section outlines the experimental tests that were carried out to assess the efficacy and usability of our approach as a preliminary prototype. There are two experimental studies: one to see whether our approach is significantly better than the default suggestion by Google Maps, and the other to measure users' general satisfaction with our approach and usability.

3.1 Experiment I (Our Approach VS. Google Maps)

Experiment I seeks to determine if our approach is significantly greater than a default Google map platform. Kirkpatrick's (Kirkpatrick, 2007) four stages of assessment are covered in this experiment. Participants will be invited to access both platforms in order to test for a substantial difference between them. The place suggestions are the independent variables, which are based on two platforms. Table 2 shows the list of dependent variables.

Participants are internet users in general. The estimated sample size for each experiment is 10, as determined by the G*Power program (Buchner, Faul, & Erdfelder, 2010). There are a total of 50 participants in the trial.

3.1.1 Experimental Materials

The participants are provided with two kinds of materials: a scenario/instruction and a questionnaire. The questionnaire is intended to ask users to examine and rate each platform on a 5-point Likert scale (Trochim, 2006). There are five options: 'Strongly Disagree,' 'Disagree,' 'Neither Agree Nor Disagree,' 'Agree,' and 'Strongly Agree.' The weighted ratings for each scale are 1, 2, 3, 4, and 5. Table 3 shows the questions depending on the dependent variable. Corresponding Questions with Dependent Variables (Experiment I).

Question No.	Dependent Variables	Actual Questions
1	Relevancy	The suggested places are linked to the search terms
2	Non-relevancy	The suggested places have nothing to do with the search terms
3	Improvement in comprehension	The suggested places aid in boosting users' understanding of the places
4	User's need	The suggested places are relevant to the user's need
5	Lost in hyperspace	The suggested places direct users to non-related places
6	Easy to use	This platform is simple to use

Table 3 Corresponding Questions with Dependent Variables

3.1.2 Results and Suggestions
We use the Manova test to compare the dependent variables gathered from two approaches. There were 50 participants joining the experiment. Multivariate tests are shown in Table 4. Table 5 displays descriptive statistics, standard errors, and p-value.

Effect		Value	F	Error df	Sig.
Dependent Variables	Pillai's Trace	0.91	38.15^{b}	49	<0.05
	Wilks' Lambda	0.21	38.15^{b}	49	<0.05
	Hotelling's Trace	5.94	38.15^{b}	49	<0.05
	Roy's Largest Root	5.94	38.15^{b}	49	<0.05

Table 4 Multivariate Tests

Dependent Variable	Approaches	Mean	SE.	Sig.
Relevancy	Our Approach	4.68	0.15	<0.05
	Google Map API	2.08	0.15	
Non-relevancy	Our Approach	1.52	0.15	<0.05
	Google Map API	3.88	0.15	
Improvement in Comprehension	Our Approach	4.08	0.17	0.01
	Google Map API	3.48	0.17	
User's Need	Our Approach	4.08	0.20	<0.05
	Google Map API	2.96	0.20	
Lost in Hyperspace	Our Approach	2.16	0.19	<0.05
	Google Map API	3.88	0.19	
Easy to Use	Our Approach	3.88	0.18	0.28
	Google Map API	3.60	0.18	

Table 5 Descriptive Statistic and p Values under All Dependent Variables Comparison

The findings indicate that participants can distinguish between the lists of recommended places on two approaches. They are generally pleased with our approach in the following variables: offering relevant places, increasing user understanding, matching with users' needs, and being less lost in hyperspace.

3.2 Experiment II (Overall Rating)
Experiment II will compare Kirkpatrick's level one reaction (Kirkpatrick, 2007) to the recommendation techniques used in our approach. The analysis looks for any significant deviation in the mean rating for each dependent variable from the value '3' on the Likert scale. The dependent variables are based on two kinds of suggestions (interest-based and contextualized). Table 5 displays the dependent variables in relation to the adaptive presentation depending on user interest and the contextualized suggestion using linear classifiers.

Participants are internet users who want to learn how to utilize e-Learning systems. The estimated sample size for this experiment is 8, as determined by the G*Power program (Buchner et al., 2010). There are a total of 50 participants in the trial.

3.2.1 Experimental Materials
As in experiment I, two sets of materials will be provided: a scenario/instruction and a questionnaire. As shown in table 6, the questions are based on the dependent variable.

Question No.	Recommendation Techniques	Dependent Variables	Actual Questions
1	Adaptation (User's interest)	Match with user's interest	The suggested places are relevant to the user's interests
2	Adaptation (User's interest)	Beneficial in uses	The places suggested are useful
3	Adaptation (User's interest)	User's need	The suggested places are relevant to the user's requirements

Question No.	Recommendation Techniques	Dependent Variables	Actual Questions
5	Contextualization (Linear Classifiers)	Useful (In general)	The suggested places are useful
6	Contextualization (Linear Classifiers)	Wide range types	The places advised are of various categories
7	Contextualization (Linear Classifiers)	Location relevancy	The suggested places are connected to the current place categories
8	Contextualization (Linear Classifiers)	Reasonably Listed	The suggested places are properly mentioned

Table 6 Corresponding Questions with Dependent Variables

3.2.2 Results and Discussion

All dependent variables are examined to see the significant difference from the '3' value using a one-sample t-test. The number of tests of significance m for this experiment is 7. The Bonferroni adjustment yields a threshold of 0.05/m = 0.0071. As a result, our significance criteria was 0.0071. Table 7 displays the means and t-test findings for one sample.

Dependent Variables	N	$\bar{x}$	t	P Value
Matching with Interest of users	50	4.89	13.02	< 0.05
Benefit to use	50	4.62	11.88	< 0.05
Reasonably Listed	50	4.22	10.01	< 0.05
Wide Range Types	50	4.43	11.23	< 0.05
Matching with user's Satisfaction	50	4.26	7.98	< 0.05
Location Relevancy	50	4.64	9.02	< 0.05
Matching with user's Need	50	4.77	12.56	< 0.05

Table 7. One Sample t-test under All Dependent Variables Results (Test Value = 3).

According to the findings, users are generally quite happy with the adaptive strategies based on user interest and contextualization. In terms of adaptive strategies based on user interest, participants believed that the recommended places were relevant to their interests, needs, and satisfaction. Furthermore, they believed that the advice might increase the usability of our approach. The participants thought the contextual suggestion (places) was beneficial since the approach gives a wide variety of sorts of places and the recommended destinations are fairly connected and suitably described.

4. Conclusion, Limitations and Further Studies

This study proposes adaptive and context-aware approaches to the places' suggestions. This encourages us to improve the current map API's mobility, display, and contextualization. Improving the display means tailoring the material to the user's interests and relevance. The goal is to deliver resources that meet the demands of the user and to dynamically adapt the presentation depending on various users. This study takes into account both adaptive display and navigation help. The adaptive presentation approach is utilized on the application homepage to provide suggested places depending on the user's interests. This is done to keep visitors from becoming lost in hyperspace and to provide them with more relevant content. When the user chooses the place category, the contextual suggestion retrieves the user's location and suggests nearby similar locations. These helpful strategies will be tested in experimental investigations (adaptation and contextualization). According to the results of the trials, consumers are pleased with our approach's display and suggestion approaches. Furthermore, users consider the adaptive and context-aware capabilities as more advantageous than the Google map.

Our study continues to have certain limitations. Because there is still a preliminary prototype, so we plan to include better design and usability in the future. Another drawback of our approach is it limits only certain types of places. The ratios of other places must be investigated in future studies. Furthermore, we want to expand the usage by providing varied route assistance and recommending relevant places to learners based on the current selected place. We will begin by releasing our developed mobile application via the Android operating system first. Other platforms (iOS, Windows Phone) will be examined after the Android version is stable and extensively used.

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