Context-Aware SVM for Context-Dependent Information Recommendation

Kenta Oku, Shinsuke Nakajima, Jun Miyazaki, Shunsuke Uemura
Graduate School of Information Science, Nara Institute of Science and Technology
8916-5, Takayama-cho, Ikoma-shi, Nara, 630-0192, JAPAN
kenta-o@is.naist.jp, shin@is.naist.jp, miyazaki@is.naist.jp, uemura@is.naist.jp

Abstract

The purpose of this study is to propose Context-Aware Support Vector Machine (C-SVM) for application in a context-dependent recommendation system. It is important to consider users' contexts in information recommendation as users' preference change with context. However, currently there are few methods which take into account users' contexts (e.g. time, place, the situation and so on). Thus, we extend the functionality of a Support Vector Machines (SVM), a popular classifier method used between two classes, by adding axes of context to the feature space in order to consider the users' context. We then applied the Context-Aware SVM (C-SVM) and the Collaborative Filtering System with Context-Aware SVM (C-SVM-CF) to a recommendation system for restaurants and then examined the effectiveness of each approach.

1 Introduction

There have been many studies of information recommendation methods which provide users information matching their preferences. In doing so, it is important to consider users' contexts when recommending as users' preferences change with context. In this paper, we define user context as situations or conditions which influence the users' decisions (e.g. time of day, companions, weather, physical condition and so on). However, currently there are few recommendation methods which consider users' contexts. In this study, we propose two methods: Context-Aware Support Vector Machine (C-SVM) and also Collaborative Filtering with Context-Aware Support Vector Machine (C-SVM-CF).

C-SVM extends a Support Vector Machine (SVM), a popular classifier method between two classes, by adding axes of contexts to its feature space. C-SVM is able to learn users' preferences in various contexts.

C-SVM-CF is collaborative filtering using the above mentioned C-SVM. By considering user's contexts in calculating user similarity, we believe that it is possible to more accurately find similar users.

We applied C-SVM and C-SVM-CF to the information recommendation system for restaurants and measured the effectiveness of each approach.

2 Related Work and Method

There have been several studies of recommendation systems using user profiles and collaborative filtering. WebWatcher [1] and WebMate [2] are recommendation systems that use user profiles made from users' access history to the Web pages. GroupLens [3], MovieLens [4] and amazon.com [5] recommends users netnews, movies, books, etc. using collaborative filtering. However, users are not always satisfied with recommended information by these recommendation systems since they do not consider users' contexts. In contrast, C-SVM and C-SVM-CF considering context and thus, can more effectively recommend to users.

A Support Vector Machine (SVM) is one of the major methods for classifying between two classes. It was proposed by Vapnik et al. [6]. Figure 1 illustrates the concept diagram of an SVM. Symbols "○", "●" and "□", "■" correspond to positive and negative training data, respectively. The space containing the training data is called the feature space of the SVM. After receiving training data from a user, a decision model which divides user's training data into two classes, positive and negative, is learned. The decision model can then predict which classes unclassified data belong to. Positive data can then be recommended to the user. In this study, a decision model is called an SVM model.

3 Proposed Methods

C-SVM is an SVM extended by adding axes of contexts to its feature space. Figure 2 illustrates concept diagram of C-SVM. C-SVM learns users' preferences in respect to each context, and thus, C-SVM can achieve context-aware recommendations.

Figure 2 shows a way of recommendation using C-SVM. The axes of x_1, x_2 in Figure 2 denote the parameters of the

Proceedings of the 7th International Conference on Mobile Data Management (MDM'06)
0-7695-2526-1/06 $20.00 © 2006 IEEE

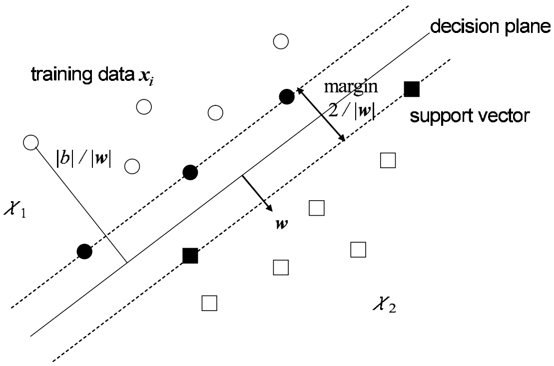

Figure 1. Concept Diagram of an SVM

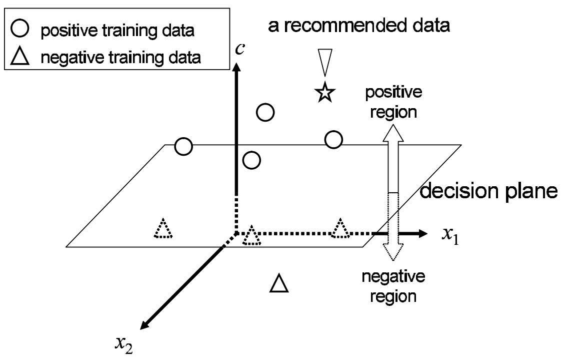

Figure 2. Concept Diagram of C-SVM

features of the training data. Then we add the axes of c to represent the axes of context. Hence, the training data set is now classified positively or negatively within the additional axes of contexts. The data ("☆" in Figure 2) exists in the positive region in the user's current context and thus, represents a recommendation candidate for the user.

C-SVM-CF is collaborative filtering considering the user's contexts. Collaborative filtering is based on the assumption that users who have similar preferences are interested in the same things. User similarity between two users in C-SVM-CF is calculated as similarity between decision planes in their own respective C-SVM model. We believe that it is possible to more accurately find similar users by considering users' contexts.

User similarity between user u and user v in C-SVM-CF $sim(u, v)$ is calculated by Formula (1):

$$sim(u, v) = \frac{1}{2}\left(\frac{M_{v\to u}}{N_u} + \frac{M_{u\to v}}{N_v}\right) \times 100(\%) \qquad (1)$$

whereas, N_u is the amount of user u 's training data, $M_{v\to u}$ is number of user u 's training data points whose class, positive or negative, match the class in user v 's C-SVM model.

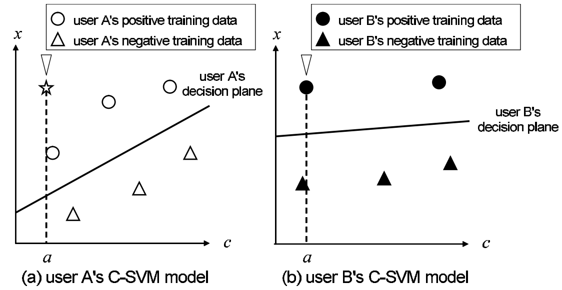

Figure 3. C-SVM Models of User A and User B

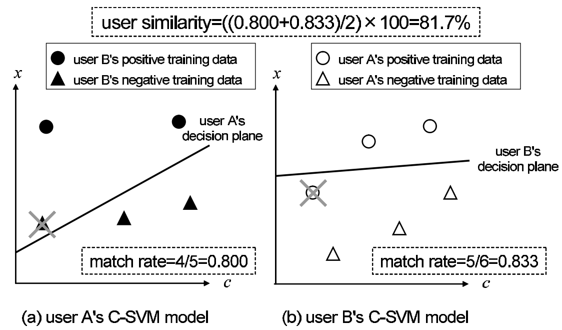

Figure 4. Calculating of User Similarity

Two users whose user similarity is over a certain threshold are regarded as similar users.

Figure 3 illustrates C-SVM models of user A and user B. Symbols "◯", "△","●", "▲" denote the training data, whereas they represent the positive data and the negative data for user A, and the positive data and the negative data for user B, respectively. In Figure 4, the user similarity between user A and user B, *sim*(A, B), is $((5/6 + 4/5)/2) \times 100 = 81.7(\%)$. If the threshold were to be 80%, user A and user B are considered similar users.

Figure 3 shows an example recommendation process using C-SVM-CF. We consider whether to recommend the data point denoted by "☆" in the context a to user A, given user A is similar to user B. User B is positive for the data in context a (▽ in Figure 3 (b)). The data also exists the positive region in user A's C-SVM model ("☆" in Figure 3 (a)). Thus, the data ("☆") represents a recommendation candidate for user A at context a.

4 Experiment

We did experiments applying C-SVM and C-SVM-CF to the recommendation system for restaurants to examine the effectiveness of considering user's contexts.

Table 1. Restaurant Parameters

Category	Parameter
is equipped with ...	Car Parking, Non-smoking Section, Single Room, Karaoke, Live Concerts
has services of ...	Lunch, Takeout, All You Can Eat, Coupon, Open Late at Night
recommended for ...	Business Receptions, Banquets, Parties, Dates, Family
environment includes ...	Night View, Ocean View

Table 2. Context Parameters

Category	Parameter	Value
Time	Month	1=Jan. to 12=Dec.
	Hour	0 to 23
	Week	0=Monday to 6=Sunday
Schedule	Area Type	None, Entertainment District, Near Station, Tourist Resort
	Budget (Yen)	0 to 10000
	Holiday	None, A Day OFF, Recess, Before Holiday
Partner	Num. of Male	0 to 10
	Num. of Female	0 to 10
	Lowest Age	0 to 100
	Highest Age	0 to 100
	Relation	None, Family, Boy/Girlfriend, Friend, Boss, Subordinate
	Status	None, Student, Working
External Factor	Weather	Fine, Cloudy, Rainy
	Temperature	-5 to 40

4.1 Experimental Environment

In this experiment, we prepared a database for restaurants extracted from the Japanese gourmet site “Yahoo! Gourmet” [7]. We confined the restaurants to those in the “Shinsaibashi, Namba” area in Osaka. The number of registered restaurants was 938. We used 17 restaurant environment parameters, all shown in table 1, and extracted their values from “Yahoo! Gourmet”. The characteristic of each restaurant is represented by these parameters. The restaurant parameters are given by a binary value $\{0, 1\}$ The number of participants in this experiment was 8. Everyone was acquainted with the “Shinsaibashi, Namba” area; however, they were not familiar with every restaurant in the area. We used 14 parameters listed in table 2 as context parameters in this experiment. The value of context parameters was normalized to $\{0 \text{ to } 1\}$. In future research, we need more consideration in choosing better context parameters for restaurants recommendation.

4.2 Experiment Procedure

The experiment procedure has two main stages: 1) training data registration and decision model generation. 2) recommendation using the generated decision model and the subsequent user feedback of the recommendation.

In the first stage, an SVM model is generated from the training data set. An SVM model is needed in order to decide recommendations for the user. To do so, each testee’s training data set was first recorded using the following procedure: 1) A testee prepares five context patterns chosen by themselves. 2) For each context pattern, the testee evaluates 20 restaurants showed to them at random, giving each positive or negative evaluation for displayed restaurants. In total, the testee evaluates 100 times.

After the data is recorded, an SVM model and C-SVM model are generated from a testee’s training data set. User similarity is needed in order to recommend restaurant information to testees by C-SVM-CF, thus, users’ similarities are calculated from each testee’s C-SVM model.

In the second main stage, restaurants are recommended to each testee and the testee gives satisfaction feedback on those recommendations: 1) Ten context patterns are chosen. 2) In each context pattern, twenty restaurants are recommended, to which each is evaluated positively or negatively by the user. The testee evaluates 200 times in total.

Restaurants are recommended in each context patterns by the following four methods: a) Random, b) SVM, c) C-SVM, d) C-SVM-CF. We examine the effectiveness of C-SVM and C-SVM-CF by comparing satisfaction of the testees between the four methods.

4.3 Result and Examination

4.3.1 Evaluation of C-SVM Model Accuracy

We evaluated C-SVM model accuracy in comparison with SVM model accuracy. We used the training data set used to generate the SVM model and C-SVM model as the test data set. It is desirable that the SVM model accuracy and C-SVM model accuracy are 100 %.

Figure 5 shows the comparisons between SVM model accuracy and C-SVM model accuracy by testee. We see from Figure 5 that C-SVM model accuracy reaches nearly 100 %, while the SVM model accuracy is not able to surpass 70 % on average. This result suggests that it is possible to classify user’s preferences their respective contexts accurately by using the C-SVM model.

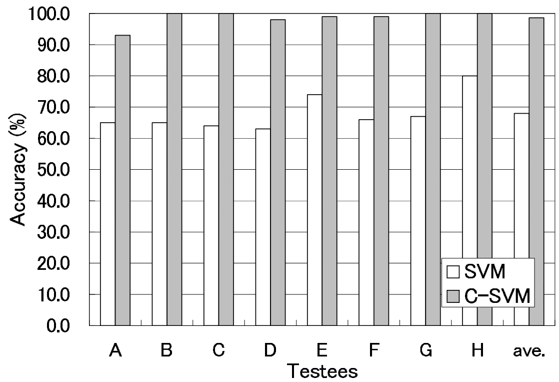

Figure 5. Accuracy of an SVM Model and C-SVM model

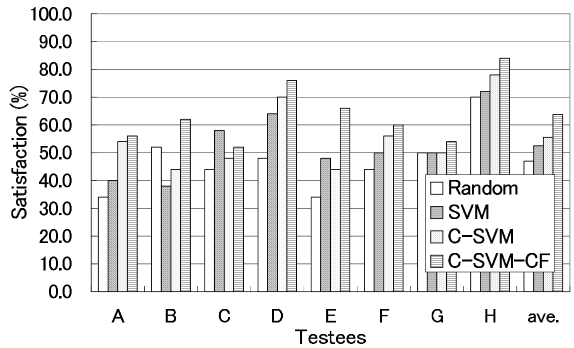

Figure 6. Testee's Satisfaction to Recommendation

4.3.2 Examination of Effectiveness of C-SVM and C-SVM-CF

We examined the effectiveness of C-SVM and C-SVM-CF by comparing the testees' satisfaction with the recommendations given by following four methods: a) Random, b) SVM, c) C-SVM, d) C-SVM-CF. User similarity between each testee calculated from C-SVM model ranged from 42.5% to 62.5% In this experiment, we chose 50% user similarity as the threshold to determine similar users.

Figure 6 shows the comparison of testees' satisfaction to the recommendations given by each of the four methods. We see from Figure 6 that the testees' satisfaction for C-SVM-CF was the highest on average among four methods. Following C-SVM-CF, the testees' satisfaction for C-SVM was the next highest. This experiment was done on the condition that all testees were familiar with the "Shinsaibashi, Namba" area. This result suggests that C-SVM-CF works effectively on the condition that similar users know the target contexts.

5 Conclusion

In this study, we proposed Context-Aware SVM (C-SVM) and Collaborative Filtering System with Context-Aware SVM (C-SVM-CF). We applied C-SVM and C-SVM-CF to our recommendation system for restaurants. We then examined the effectiveness of C-SVM and C-SVM-CF approaches from the results of our experiments.

The result of our experiments suggested that it is possible to classify users' preferences in their respective contexts accurately by using C-SVM model. The result also suggested that C-SVM-CF works effectively on the condition that similar users know the target contexts.

In future works, we would like to define contexts in detail more (e.g. users' history, distance, surrounding restaurants, partners' preferences and so on). Further, we would like to examine orthogonality of context parameters.

Acknowledgments

This research is partly supported by a Grant of Scientific Research (15200010 and 17700132) from the Ministry of Education, Culture, Sports, Science and Technology of Japan and Core Research for Evolutional Science and Technology (CREST) Program "Advanced Media Technology for Everyday Living" of Japan Science and Technology Agency (JST).

References

[1] T. Joachims, D. Freitag and T. Mitchell: "WebWatcher: A Tour Guide for the World Wide Web", *Proc. of IJCAI'97* (1997).

[2] L. Chen and K. Sycara: "WebMate: A Personal Agent for Browsing and Searching", *Proc. of the 2nd International Conference on Autonomous Agent (Agent'98)*, pp. 132-139 (1998).

[3] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom and J. Riedl: "GroupLens: An Open Architecture for Collaborative Filtering of Netnews", *Proc. of ACM 1994 Conference on Computer Supported Cooperative Work (CSCW'94)*, pp. 175-186 (1994).

[4] GroupLens Research, "movielens", http://movielens.umn.edu/login

[5] amazon, "amazon.com", http://www.amazon.com/

[6] C. Cortes and V. Vapnik: "Support-Vector Networks", *Machine Learning* Vol. 20, No. 3, pp. 273-297 (1995).

[7] Yahoo Japan, "Yahoo! Gourmet (Japan)", http://gourmet.yahoo.co.jp/gourmet/