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Combining Mobile Intelligence with Formation Mechanism for Group Commerce

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***Abstract*—**The rise of smartphones brings new concept So-Lo-Mo (social-local-mobile) in mobile commerce area in recent years. However, current So-Lo-Mo services only focus on individual users but not a group of users, and the development of group commerce is not enough to satisfy the demand of real-time group buying and less to think about the social relationship between customers. In this research, we integrate mobile intelligence with group commerce and consider customers' preference, real-time context, and social influence as components in the mechanism. With the support of this mechanism, customers are able to gather near customers with the same potential purchase willingness through mobile devices when he/she wants to purchase products or services to have a real-time group-buying. By matching the demand and supply of mobile group-buying market, this research improves the business value of mobile commerce and group commerce further.

***Keywords*—**Group formation, group commerce, mobile commerce, So-Lo-Mo, social influence.

I. Introduction

In recent years, group-buying market has been grown up for several years, making surprising revenues all around the world. In United States, the revenues of the largest group-buying website, Groupon, is $2.573 billion in 2013, and it is still growing. In China, the turnover of group-buying industry reached to $2.29 billion from Q1 to Q2 in 2013 [1].

Forbes [3] issued a report about Groupon's problems and indicated that Groupon has an unsustainable business model for two reasons. First, Groupon is selling other companies' products that have the upper hand in any deal negotiations. Second, Groupon has plenty of competitors. The business model also has a problem that if the minimum number of consumers signed up is not reached, then no one gets the Groupon offer. Group-buying companies cannot get the best use of impulse purchases through this non real-time business model, and about 22% customers have impulse purchases behavior over the Internet [2]. However, group-buying service with mobile computing can create an innovative service that provides real-time group-buying services with higher willingness to impulse purchase. The synchronization between social media and mobile device brings a new opportunity to analyze whether there are friends near the customer or not and utilize the like and check-in data on social media to analyze the purchase preference of customers. Three main research questions are addressed in this paper:

(1) How to improve group commerce from passively waiting for coupons to actively gathering nearby consumers to make a real-time group buying? In the current circumstance, consumers need to wait for more people signing up the coupon. Using mobile technology, it is possible to gather more people actively and quickly by identifying the people nearby.
(2) How to form groups with location-sensitive customers and high cohesion? To identify nearby people nearby and invite them to join a buying group, we need to identify the locations of customers and their travel times. After knowing the nearby customers, it is important to select the people who are suitable to be the group members with high cohesion and to have a better experience of the group buying service.
(3) How to utilize the power of social influence to increase the willingness to purchase? In order to improve the motivation of nearby people to join a group, it is important to consider their preference and social relationships.

In this paper, we present a contextual group formation mechanism to make everyone has the ability to enjoy real-time group buying at anywhere and anytime. Using this mechanism, not only customers but also vendors and shopkeepers can gather several consumers nearby to sell wholesale commodities with group discount. That benefits vendors to save advertising and marketing cost and make revenues.

The remainder of the paper is as follow; we will give a literature review in Section II. The overall system framework will be mentioned in Section III. The experiment and the evaluation of the results will be mentioned in Section IV. Lastly, Section V will cover the conclusion.

II. Related Work

A. Mobile and Group Commerce

Both mobility and broad reach are the two major characteristics of mobile commerce: mobility, e.g., customers can conduct real-time business via mobile devices, and broad reach implies that customers can be reached at any time and place via mobile devices [5]. Various social media have emerged and the research on how to combine mobile commerce and social commerce to generate new knowledge, business model [6]. Group commerce platforms get the largest discount from sellers to attract more customers and sells coupons at a price higher than it got from sellers. However, the business model of group commerce is not sustainable enough. In this paper, considering geographic convenience, social influence

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and customer preference, we propose a contextual group formation mechanism to promote real-time group buying to improve the business model of mobile and group commerce.

B. Context Awareness

Context is any information that can be used to characterize the situation of an entity, where entity is a person, place, or object that is relevant to the interaction between a user and an application, including the user and the application themselves [7]. Ryan et al. [8] proposed that the types of context are location, environment, identity and time. Context awareness is well-known in ubiquitous computing, and context is the key to provide suitable services that are appropriate to the location, identity, activity and time [9]. In this paper considers (1) locations of users, (2) nearby people and (3) the circumstances of group buying as the contextual information to build a contextual group formation mechanism, which has the ability to gather nearby people at anytime and anywhere to enjoy real-time group buying.

C. Social Influence

Individual decision making is to maximize the decision effectiveness in the condition of being given limited resources. However, there are three factors which will influence people when making a decision: influential people, utility improvement from the options, and people's social network. Social influence is the process in which individuals will change their feelings, thinking or behavior when interacting with someone with similar experience or expert. In the past, traditional social behavior is realized through physical interactions, such as face-to-face communication. But now, there have a lot of powerful social network platforms which allow us to interact with each other on the Internet. As the quick development of social media, consumers can much easily get information (people's preference and relationship) from on-line sources and make a decision with the support of their social network [4], [10]. In this research, we propose a social decision support mechanism according to human behaviors on and information extracted from the social networks.

III. System Framework

The proposed contextual group formation mechanism is an innovative service model that customers can gather other nearby customers with certain social relations and similar preference at anywhere and anytime when they want to enjoy group buying. The system framework is illustrated in Fig. 1.

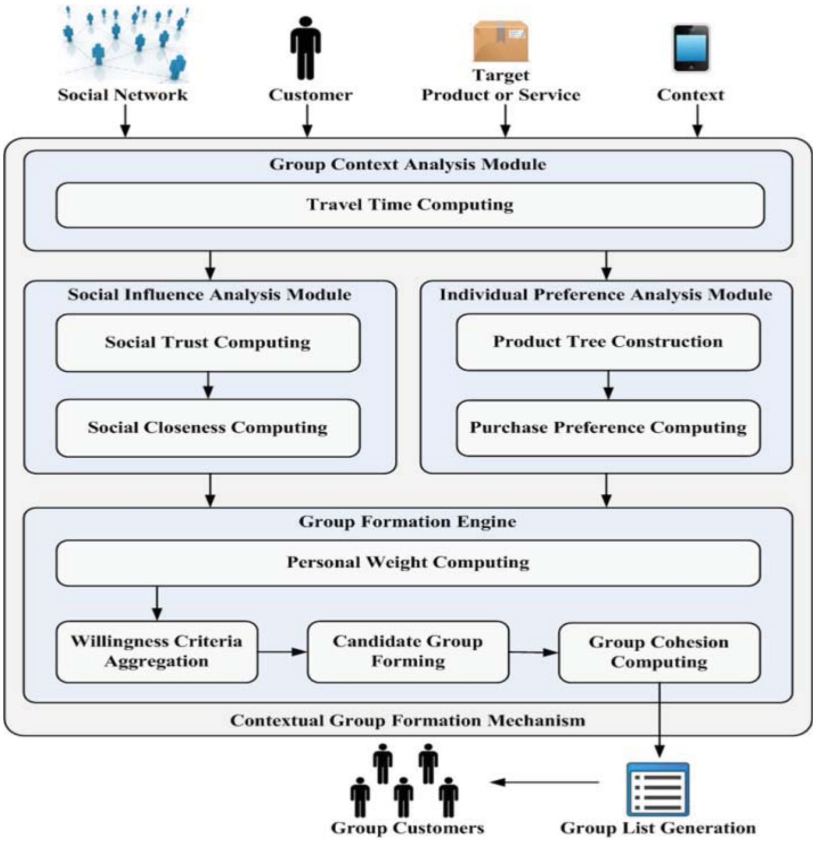


Fig. 1 Contextual Group Formation Mechanism

A. Group Context Analysis Module

To get locations of mobile users, we use GPS (Global Positioning System) in mobile devices to receive longitude and latitude data of users. We consider the travel time but not distance between locations because distance cannot represent the real time spent that users may move by walking, driving or other methods. Let *TravelTime*(i,j) be the travel time from the user j (origin location) to the group leader i (destination location) in particular travel mode.

To detect nearby people, we set the default maximum constraint of travel time to be 15 minutes, because we think if the user requires more than 15 minutes to go to the place, that is too long to be the real-time group-buying service that we want to provide. Users can change the default limit of travel time if needed. After getting the travel times of users and filter out users far away from the group leader, we denote a set of people near the group leader i as J(i). Every person j in set $J(i)$ has his/her own *TravelTime*(i,j), and we rank $j_n(i)$ according to *TravelTime*(i,j) in ascending order. We denote *Rank*($j_n(i)$) as the rank of person $j_n(i)$ in $J(i)$ and then compute the score of this module for the group leader i and each nearby person j is represented as:

$$GroupContext(i,j) = \frac{n - Rank(j_n(i)) + 1}{n}, \forall j_n(i) \in J(i)$$

B. Social Influence Analysis Modul

This module is to measure the degree of trust and closeness between two users. We denote *SocialInfluence*(i,j) as the degree of social influence between the person j and the group leader i.

As a group leader uses this mechanism to gather nearby people to join his/her group buying, it is important to know whether the person is trustable or not. We denote *SocialTrust*(i,j) as a value that represents how nearby person j is trustable to the group leader i. We use four kinds of social data to analyze it: (1) the number of successful transactions of nearby person j denotes as *STrans*(j), (2) the number of reports of nearby person j denotes as *Reported*(j), (3) the total number of transactions of nearby person j denotes as *Trans*(j) and (4) the number of good reviews given by the group leader i and i's friends to the person j nearby denotes as *FriendsReviews*(i,j). We consider the number of good reviews of nearby people base on friend referrals. That is to say, nearby candidate users who have received more good reviews will receive a higher score, and thus more likely to be recommended to a group leader for group formation. The good reviews of friends can be formulated as:

$$Friends\,\mathrm{Re}views(i,j) = \sum_{f_n(i) \in Friends(i)} \mathrm{Re}views(i, f_n(i), j)$$

where *Friends*(i) is a set of all friends, and *Reviews*(i,$f_n(i)$,j) is the number of good reviews given by the group leader i and i's friend $f_n(i)$ to the person j. The value of *SocialTrust*(i,j) is defined as:

$$SocialTrust(i,j) = \frac{STrans(j) - \mathrm{Re}\,ported(j)}{Trans(j)} \times Friends\,\mathrm{Re}views(i,j)$$

It is usual that customers want to purchase something together with friends more than with strangers, so we consider the social relations between two users into this mechanism. We compute the degree of closeness between two users by using their social data collected from Facebook. In order to compute the degree of closeness between the group leaders to any person nearby, the interaction between users who are in the social network of the group leader is required on social media. The interaction between two users, who are denoted as u_1 and u_2 on social media is measured by: (1) *Tag*(u_1,u_2) is the number of the two users be tagged together in comments and posts, including status, check-ins and photos, (2) *Comment*(u_1,u_2) is the number of comments written by the two users under a same post which is created by them and we denote it as and (3) *Like*(u_1,u_2) is the number of likes given by the two users in comments and posts, including status, check-ins and photos which they own. The interaction between two users, u_1 and u_2, can be quantified as:

$$Interaction(u_1,u_2) = Tag(u_1,u_2) + Comment(u_1,u_2) + Like(u_1,u_2)$$

The social closeness between the group leader i and the nearby person j can be formulated as:

$$SocialClosness(i,j) = Max(\frac{1}{LenPath(Path_n(i,j))}$$
$$\times \sum \frac{Interaction(u_1,u_2)}{Degree(i, Link_n(u_1,u_2))},$$
$$\forall Link_n(u_1,u_2) \in Links\ (u_1,u_2) \in Path_n(i,j) \in Paths(i,j)$$

where *Paths*(i,j) as a set which contains all the social paths which are the routes to connect the group leader i with the nearby person j, *Links*(u_1,u_2) denotes each social path which has a set of links, which connects two users in the particular social path and has its *Interaction*(u_1,u_2) value, *LenPath*($Path_n(i,j)$) represents length of a social path, and *Degree*(i, $Link_n(u_1,u_2)$) denotes the social degree from the group leader i to the particular link. Finally, we have done social trust computing and social closeness computing, and then we combine them to calculate the social influence between the group leader i and nearby person j as:

$$SocialInfluence(i,j) = SocialTrust(i,j) \times SocialCloseness(i,j)$$

C. Individual Preference Analysis Module

This module analyzes how a user wants to purchase the target product with his/her preference. To measure individual preference, we denote IndividualPreference(j,p) to compute the similarity between the preference of person j near the group leader and the target product p. Before computing the similarity between user preference and target product, we should identify the target product at first. A tree structure is built to classify the target product. Products are hierarchical structures in the real world.

In order to enhance the relationship and synchronization between products and places, we refer to the hierarchical categories of places on Facebook in order to construct a tree structure for the place tree and match the products to the categories which it belongs to. We name the special tree "ProductPlace" tree and mark the index of each node to identify each category.

We measure the purchase preference of a user by two kinds of social data: (1) pages and (2) check-ins. We transform the the two kinds of data to match the ProductPlace tree. Pages on Facebook has its own categories, and we can use its categories to match the ProductPlace tree. We modify the Cosine Similarity method to create a new similarity equation because Cosine Similarity method has two defects and cannot be used into this mechanism: (1) if a user has many check-ins of different categories, the value of similarity will be reduced because the denominator of Cosine Similarity will be larger and cause distortion and (2) the value of Cosine Similarity will be normalized and make the value between 0 and 1 because of it denominator, but this neglects the influence of many pages liked and check-ins posted on the same category.

D. Group Formation Engine

The group formation engine is to generate the candidate groups and find the group with highest cohesion, which is appropriate to the circumstance of particular group buying, for the group leader.

Each user has his/her own weights of criteria which affect the willingness to participate in a group or not. We compute the personal weights of three criteria which influence the willingness of a user to join a group in a specific situation. We adopt the analytic hierarchy process (AHP) theory to compute the weights of the three willingness criteria: group context, social influence and individual preference towards a particular circumstance. These three weights of three criteria imply how the user *j* makes decision to whether to join a group buying with the invitation from the group leader or not.

Using the weight values of three criteria, this mechanism can have the ability to measure the willingness-to-join that the person *j* who is near the group leader *i* will want to join the group to purchase target product *p* together in a specific circumstance. We denote the willingness-to-join of person *j* as $JoinWillingness(i,j,p)$ and its value is calculated as the aggregation of the weight value of each criterion with the corresponding score of the criterion which is calculated by the group context, social influence and individual preference analysis module. The value of $JoinWillingness(i,j,p)$ is measured as:

$$\begin{aligned}
&JoinWillingness(i, j, p) = W_c(j) \times GroupContext(i, j)\\
&+W_s(j) \times SocialInfluence(i, j)\\
&+W_p(j) \times IndividualPreference(i, j)
\end{aligned}$$

Considering the search range of nearby people and great diversity of the group members, the candidate groups are represented as follows:

$$G(i, N_{re}) = \{G_1(i, N_{re}), G_2(i, N_{re}), ..., G_n(i, N_{re})\}$$

where N_{re} represents the number of people required to the group buying, and n is the number of candidate group.

We measure the cohesion of these groups by three steps: (1) the density of network, (2) the social closeness between group members and (3) the average score of willingness-to-join and social closeness in the network. Measuring the density of each candidate group, this mechanism filters the top groups with highest density to do the next step. The second step is to compute the social closeness between group members as the strength of each tie. The third step is to compare which network is the best one to recommend to the group leader. We use the strength of ties to measure the group cohesion in this step. The type of ties is not all the same because the ties from nearby people to the group leader *i* are measured by willingness-to-join and the other ties between nearby people are measured by social closeness. Due to the different types of ties, we need to calculate separately. The average strength of ties can represent the average cohesion of the network. Then, we aggregate these two average values to compute the cohesion of the whole network by multiplying these two average values because multiplying can make the higher value higher, vice versa. It is useful to show the difference distinctly between each network

E. Group List Generation

The mechanism will provide a group list with highest group cohesion to the group leader and inform the group members to meet themselves. The group list provides five types of information: (1) name, (2) profile picture, (3) relationship with the group leader, (4) location and (5) travel time. The group leader can gather the appropriate and nearby people to enjoy group buying by the group list, and the group members also benefit from group discount.

IV. Experiment Study

In this section, we describe the process and evaluate the proposed mechanism. We select Facebook as the main social data source because it is one of the most popular social network platforms and provides FQL (Facebook Query Language) to collect data conveniently.

A. Data Collection and Preprocessing

We collected 274 users with mobile devices aged from 10 to 60 to do the experiments. The gender distribution was 132 male and 142 female users. Most of the users lived in Taipei and Hsinchu, Taiwan, and the remainder in other cities. The number of tags was 129,538, comments were 196,334, likes was 335,922, check-ins was 6,210, and fan pages liked was 15,248. The average number of friends of users was 536.

There are three scenarios of group buying with different characteristics: (1) buy products with very strong preference and dismiss after a transaction is completed, (2) buy products with essential preference and do something with group members together after a transaction is completed and (3) buy products with weak preference and do something with group members together with close interaction after a transaction is completed. We select "group buying at a wholesale store" as scenario 1, "buying group tickets" as scenario 2 and "eating at a restaurant together with group discounts" as scenario 3 because these three activities of group buying are closer to daily life and have the most of demands. The group leader can choose one of the three scenarios to be the target and then start group buying. After the user has created a group buying event, the app will run the proposed mechanism and invite the people who are appropriate to this group to join the group buying event. The standard of complete group formation is reaching the minimum number of people required and they are all ready for group buying.

B. Results and Evaluation

To evaluate the accuracy of the proposed contextual group formation mechanism in identifying the users with high willingness to participate in the group buying, six approaches of group formation including (1) random, (2) collaborative filtering (CF), (3) CS model (group context and social influence), (4) CP model (group context and individual preference), (5) SP model (social influence and individual preference) and (6) CSP model (group context, social influence and individual preference) was chosen to compare accuracy.

Fig. 2 presents the evaluation results of users about how they are satisfied with this real-time group buying service in different models and scenarios. The value of each model is average score.

	Random	CF	CS Model	CP Model	SP Model	CSP Model
Scenario 1	2.95	3.48	2.96	3.51	4.00	4.51
Scenario 2	2.89	3.47	3.11	3.52	4.08	4.40
Scenario 3	3.01	3.58	3.56	3.48	4.02	4.50

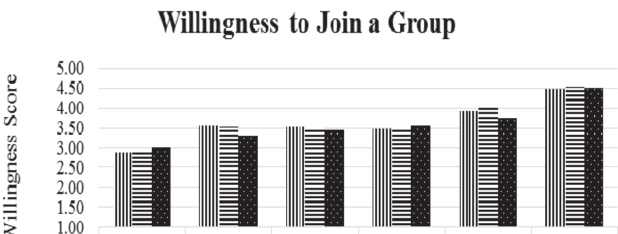
Fig. 2 Evaluation of Satisfaction with Service

TABLE I
STATISTICAL VERIFICATION OF SATISFACTION

Paired Group	Paired Differences				
	Mean	Std. Deviation	Std. Error Mean	t	Sig. (2-tailed)
CSP-Random	2.98	0.72	0.04	68.47	0.000
CSP-CF	0.96	0.73	0.04	21.92	0.000
CSP-CS	1.47	0.96	0.06	25.52	0.000
CSP-CP	0.98	0.70	0.04	23.21	0.000
CSP-SP	0.45	0.95	0.06	7.80	0.000

The results of satisfaction scores show that the factor of social influence is more important. We think that it is because group buying with friends is more joyful than with strangers. The score of CS model is lower than CP model because consumers care about preference more than social influence where the context in the moment of group buying is the same. Due to the increasing importance of social influence, the satisfaction score of CS, SP and CSP models are higher than their likeness score, and the satisfaction score of CSP model is the highest. The result of the two-paired sample t-test is shown in Table I. At the 95% significant level, all the test results show that the proposed CSP approach significantly outperforms the other approaches.

Fig. 3 shows the evaluation results of users about how much they want to participate in the group buying in different models and scenarios. The value of each model is average score.



	Random	CF	CS Model	CP Model	SP Model	CSP Model
Scenario 1	2.88	3.55	3.52	3.48	3.92	4.47
Scenario 2	2.90	3.52	3.51	3.51	4.05	4.52
Scenario 3	2.99	3.29	3.44	3.56	3.75	4.50

Fig. 3 Evaluation of Willingness to Join a Group

The evaluation results of willingness show that users care about individual preference and social influence almost equally. We can know that preference and social influence are the key criteria for users to decide whether to join the group buying or not, so the scores of SP and CSP models are higher than the other models. Considering all the criteria, the willingness score of CSP model is the highest, because it is convenient to users to go to the place, enjoy and interact with friends and buy what they like or want in a group discount. We use the same statistical setting as before to verify the significance as Table II. The statistical verification results also show that CSP model outperforms the other models.

TABLE II
STATISTICAL VERIFICATION OF WILLINGNESS

Paired Group	Paired Differences				
	Mean	Std. Deviation	Std. Error Mean	t	Sig. (2-tailed)
CSP-Random	3.01	0.70	0.42	70.88	0.000
CSP-CF	1.05	0.76	0.46	22.92	0.000
CSP-CS	1.01	0.71	0.43	23.45	0.000
CSP-CP	0.97	0.71	0.43	22.79	0.000
CSP-SP	0.60	0.98	0.06	10.14	0.000

After evaluating satisfaction and willingness in different six models, CSP model which combines group context, social influence and individual preference is the most suitable model for the proposed contextual group formation mechanism by considering all the aspects of the user experience of group buying.

V. Conclusion

In this paper, we proposed a contextual group formation mechanism. The proposed mechanism could assist the local business to increase the revenue and help the consumers to gather nearby people actively who have similar preference and social interaction quickly and then enjoy the experience of group buying. From the perspective of system innovation, we design an efficient and effective group formation system for group buying. From the experimental results, we verify that the system can improve the user willingness to join a group buying. From the methodological perspective, we consider the multi-criteria factors of group context, social influence and individual preference in mobile environment and found that use the three criteria together can bring the most perfect user experience of real-time group. From the business perspective, the proposed mechanism provides more opportunities to group commerce. Not only group-coupon platform on the website can bring the group commerce but also make every consumer has the ability of gathering nearby people to enjoy real-time group buying at anywhere and anytime, and vendors also benefit from selling large amounts of products at once.

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