A Prediction Market Approach to Facilitating Consensus Building among Supply Chain Partners

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ABSTRACT

How to facilitate the process of consensus building among the partners in a supply chain is a crucial issue. As an example of such a problem, this paper takes up perceptual mapping and develops a prediction market system for collectively determining the location of an object on a two-dimensional perceptual map. It introduces a new type of prediction security called SAPS (Square Area Prediction Security) and extends a widely used market making algorithm LMSR (Logarithmic Market Scoring Rule) for handling SAPS in a batch updating environment. This system feeds the location of the object back to the participants as the price distribution of SAPS, which is determined by the number of SAPS sold so far in each square area, and allows them to modify it through transactions of SAPS. The paper further conducts laboratory experiments to see whether the proposed system can support a group of people to build consensus on a perceptual map. As a result, it is observed that the variance of their subjective evaluations on the location of a specified object is reduced through operating the system but that the evolving consensus is not always captured properly by the price distribution. What causes this problem and how to fix it are also discussed.

1. Introduction

In order for a supply chain to compete effectively in today's changing market, the partner companies in the chain should share not only the relevant information on the changing environment but also the policy/strategy on how they compete in the environment. Such a policy/strategy provides a direction along which operational and investment decisions, including those on maintenance, of the companies can be aligned, and it enables the supply chain to function as a unified whole. Forming the shared policy/strategy is a consensus building problem among the partner companies in the chain. It should be deemed as a continual process especially in the changing environment. Further, since the partner companies are geographically, sometimes globally, distributed and their working hours may be different, the consensus building process is characterized by the difficulty and inefficiency of relying wholly on face-to-face communication. Thus, how to facilitate the process is now a crucial issue.

Various consensus building processes have been effectively supported by Delphi method [1][2], which repeats the cycle of obtaining an opinion from each partner separately, aggregating the opinions into a distribution, and feeding the distribution back to each partner. Recently, the prediction market attracts attention as a mechanism that can realize the Delphi-like interaction efficiently and economically. The prediction market is a futures market where participants can buy and sell virtual securities, called prediction securities, whose posterior worth is defined depending on the future outcome of the issue of concern, and outputs a forecast on the issue reflecting the collective knowledge of the participants as the price of the securities [3][4][5]. The prediction market is argued to be helpful for information sharing in a supply chain [6], and it is actually used successfully in industry for aggregating information, for example, on a demand forecast [7][8][9].

The aim of this paper is to investigate whether the prediction market can also support consensus building among the partners in a supply chain. If the prediction market can replace at least some of the

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direct communication necessary for the consensus building process, the efficiency of the process will be improved. The major difference between simple information sharing and consensus building is that the latter needs to ask a question without an objective right answer and thus needs to aggregate subjective evaluations as well as objective information. As a concrete example of such a problem, this paper takes up perceptual mapping. It locates the products or service offerings to be compared on a map so that their relative locations should represent how the market perceives the differences among them. Thus, it can provide an important basis for a shared policy/strategy of a supply chain.

This paper first develops a prediction market system for determining the location of an object on a two-dimensional perceptual map. In order to consider the location of the object, it introduces a new type of prediction security called SAPS (Square Area Prediction Security) and extends a widely used market making algorithm LMSR (Logarithmic Market Scoring Rule) for handling SAPS in a batch updating environment. In the proposed system, the price distribution is determined by the number of SAPS sold so far in each square area, and the distribution represents the agreed location of the object at the time. This system can feed the location of the object back to the participants and allow them to modify the location through securities transactions. It can take the difference and vagueness in their subjective evaluations into consideration, and can update the location of the object accordingly whenever some additional information becomes available.

The paper then conducts laboratory experiments to see whether the proposed prediction market system can support a group of people to build consensus on the location of an object on a perceptual map. In the remainder, the proposed market system is presented first, then the laboratory experiments and their results are described, and they are followed by discussion and conclusions.

2.   Prediction Market System for Perceptual Mapping

2.1.   Perceptual mapping problem

Most methods of drawing a perceptual map, such as factor analysis, principal component analysis, multidimensional scaling, are static in a sense that they determine the locations of the objects of interests on the map based on the data gathered at a time. As a result, the obtained map often fails to satisfy even those who provided the data. Alternatively, this paper deems perceptual mapping as a consensus building problem among the multiple partners in a supply chain.

A perceptual map contains multiple objects, and it is their relative locations that need to be agreed upon among the supply chain partners. In this paper, however, only the location of a single object in a two-dimensional perceptual map is considered as the first step, assuming that those of the other objects are given. Thus, the variable of concern in the proposed prediction market system is the absolute location (x, y) of the specified object in a two-dimensional space where the other objects are already located. It is assumed that the feasible region of the location is bounded within a square $(-1 \leq x \leq 1, -1 \leq y \leq 1)$.

2.2.   Square area prediction security

As the prediction security for the two-dimensional variable of concern (x, y), we generalize FIPS (Fixed Interval Prediction Security), which is introduced by Chen and Plott [7] for a scalar variable such as a sales volume, to a two-dimensional vector and call it SAPS (Square Area Prediction Security). In SAPS, the feasible region of x is cut into M equal width slices and each of them is cut again into M equal height pieces along y-axis, as shown in Fig. 1. This divides the whole region of the map into $M \times M$ smaller square areas, and we denote the center of mth square as (x_m, y_m), where m ($\in \{1, 2, \ldots, M \times M\}$) is the index of a square area. Each piece of SAPS is assigned to one of the square areas, and if and only if the resultant location is included in the area, it will be given a prefixed amount of payoff after the market is closed.

The number of slices M should be carefully determined in practice. The higher the number of slices, the more precisely the plausible region of the location can be specified but the more sophisticated user interface and background calculation will be required. In the following laboratory experiments, it is set as $M = 20$. Thus, the whole perceptual map is covered by 400 square areas, and

each participant can choose any combination of them. However, the number of SAPS held is restricted to be equal for all the chosen square areas, so as to reduce the mental workload of the participant.
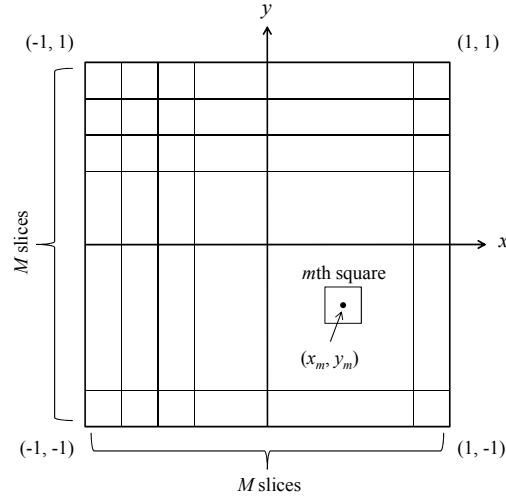
Fig. 1. Definition of square areas for SAPS

2.3. Batch updating market making algorithm

In order to ensure enough liquidity in the market of SAPS even when operated with a small number of participants, a batch updating central market maker is introduced. The market maker offers a price to any bid or ask offer of SAPS. Hence, in extreme cases, even only two participants can interact through the prediction market system. It is for providing the participants a certain length of time between transactions of SAPS exclusively for consideration on the location why batch updating is preferred.

The most popular and widely-used market making algorithm for the prediction market would be LMSR (Logarithmic Market Scoring Rule) proposed by Hanson [10][11]. Suppose that there are N participants and participant n has q_{nm} unites of SAPS assigned to the mth square area, where n ($\in \{1,2,\ldots,N\}$) is the index of a participant. Then, the whole number of the mth SAPS sold so far to all the participants is given by:

$$Q_m = \sum_{n=1}^{N} q_{nm} \tag{1}$$

LMSR defines a cost function based on $\mathbf{Q} = (Q_1, Q_2, \ldots)$ as:

$$C(\mathbf{Q}) = b \cdot \log\left[\sum_{m=1}^{M \times M} \exp(Q_m / b)\right] \tag{2}$$

where b is the sensitivity parameter. When participant n changes her/his asset position from $\mathbf{q}_n = (q_{n1}, q_{n2}, \ldots)$ to $\mathbf{q}_n + \Delta\mathbf{q}_n$, the cost function determines how much to charge as:

$$\text{Cost} = C(\mathbf{Q} + \Delta\mathbf{q}_n) - C(\mathbf{Q}) \tag{3}$$

Thus, the unitary price of SAPS corresponding to the mth square area is given by:

$$P_m = \frac{dC(\mathbf{Q})}{dQ_m} = \frac{\exp(Q_m / b)}{\sum_{i=1}^{M \times M} \exp(Q_i / b)} \tag{4}$$

Since LMSR is a continuous updating market maker, we translate it into a batch updating one to make it more suitable for perceptual mapping. A straightforward way of this translation would be to update the value of $\mathbf{Q}$ in equation (3) only at the beginning of each round and to fix it during the round no matter what transactions are conducted. Hereafter, we denote the fixed value of $\mathbf{Q}$ in round k as $\mathbf{Q}_k$. However, a market maker simply taking this approach can be ripped off easily by a team of participants. That is, obvious arbitrage opportunities against the market maker arise. If these opportunities are taken, the price distribution will not properly reflect the participants' subjective evaluations. Thus, we further introduce two additional functions into the market maker to diminish the problematic arbitrage opportunities.

The first function is cancellation. When participant n sells some pieces of SAPS, their current price and purchase price are compared and, if the current price is higher, the transaction will be treated as a cancellation and only as much as the purchase price will be refunded. If the purchase price is higher, on the other hand, it will be treated as a normal selling at the current price. When the pieces of SAPS to be sold are composed of several parts which have been purchased separately, their purchase price is evaluated on a last in first out basis. Once this function is introduced, the participants can increase their wealth only through the posterior payoff to their SAPS. Although this function has a side effect of slightly decreasing the sensitivity of the price distribution, this makes it difficult for the participants to rip off the market maker by selling it SAPS at an intentionally raised price.

The second function is stepwise transaction. When participant n wants to change her/his asset position by $\Delta\mathbf{q}_n$ and it contains a part to be sold, then the sold part $\Delta\mathbf{q}_n^S$ is first processed separately as described above. Then, this function distinguishes *increasing amount* and *expanding area* and divides the remaining purchased part $\Delta\mathbf{q}_n - \Delta\mathbf{q}_n^S$ into two parts $\Delta\mathbf{q}_n^I$ and $\Delta\mathbf{q}_n^E$ corresponding to these two actions as:

$$\Delta\mathbf{q}_n = \Delta\mathbf{q}_n^S + \Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E \tag{5}$$

Increasing amount means the action of buying some additional pieces of SAPS for the square areas for which she/he already owns SAPS. Whereas, *expanding area* indicates the action of buying SAPS for some other square areas for which she/he has no SAPS at the beginning of the round. The stepwise transaction function determines the price $c(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E)$ of these parts in round k by the following equations:

$$c_{IE}(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E) = \max\left\{[C(\mathbf{Q}_k + \Delta\mathbf{q}_n^I) - C(\mathbf{Q}_k)], [C(\mathbf{Q}_1 + \Delta\mathbf{q}_n^I) - C(\mathbf{Q}_1)]\right\}$$
$$+ \max\left\{[C(\mathbf{Q}_k + \Delta\mathbf{q}_n) - C(\mathbf{Q}_k + \Delta\mathbf{q}_n^I)], [C(\mathbf{Q}_1 + \Delta\mathbf{q}_n^E) - C(\mathbf{Q}_1)]\right\} \tag{6}$$

$$c_{EI}(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E) = \max\left\{[C(\mathbf{Q}_k + \Delta\mathbf{q}_n^E) - C(\mathbf{Q}_k)], [C(\mathbf{Q}_1 + \Delta\mathbf{q}_n^E) - C(\mathbf{Q}_1)]\right\}$$
$$+ \max\left\{[C(\mathbf{Q}_k + \Delta\mathbf{q}_n) - C(\mathbf{Q}_k + \Delta\mathbf{q}_n^E)], [C(\mathbf{Q}_1 + \Delta\mathbf{q}_n^I) - C(\mathbf{Q}_1)]\right\} \tag{7}$$

$$c(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E) = \max[c_{IE}(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E), c_{EI}(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E)] \tag{8}$$

The first term on the right hand side of equation (6) calculates the price for the part of *increasing amount*, which is defined as the higher one between the costs calculated under the value of $\mathbf{Q}$ in the current round and the initial round. The second term calculates the price for the part of *expanding area* similarly, assuming that *increasing amount* has already been processed. Thus, equation (6)

evaluates the price of $\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E$ in two-steps, where the first step determines the price of $\Delta\mathbf{q}_n^I$ and the second step calculates that of $\Delta\mathbf{q}_n^E$. As is obvious, equation (7) conducts the same evaluation by reversing the order of the two parts. Finally, equation (8) determines the price $c(\Delta\mathbf{q}_n^I + \Delta\mathbf{q}_n^E)$ as the higher one between those calculated by the equations (6) and (7). This stepwise transaction function also makes the price distribution slightly insensitive, but it makes it difficult for the participants to intentionally compress the price of SAPS in some square areas, for example, by buying it in other areas beforehand.

2.4. Market session flow

Accordingly, the flow of a market session can be summarized as follows:

Step 0. Set $k = 0$ and $\Delta\mathbf{q}_n = (0,0,\ldots)$ $(n = 1,2,\ldots,N)$. Initialize $\mathbf{Q}_k$ so that it should represent an appropriate prior distribution.

Step 1. Add one to k and update $\mathbf{Q}_k$ with the following equation:

$$\mathbf{Q}_k = \mathbf{Q}_{k-1} + \sum_{n=1}^{N} \Delta\mathbf{q}_n \qquad (9)$$

Step 2. Apply the stepwise transaction function to any request of SIPS transaction submitted from the participants. When round k finishes, go to **Step 3**.

Step 3. If the value of k has reached the predetermined round limit, end the procedure. Otherwise, go back to **Step 1**.

3. Laboratory Experiments

3.1. Experimental objectives

The primary objective of the laboratory experiments is to see whether the proposed system can support participants to build consensus on the location of an object on a perceptual map. If this supporting function is confirmed, it is also studied whether the function is affected by the number of rounds and the availability of chatting function. Since the proposed system is a batch updating system, each experimental term consists of several rounds and the price distribution is renewed after every round. The number of rounds specifies how many times the price updating cycle is repeated until the supporting function is evaluated. The effect of the number of rounds on the supporting function is related to the efficiency of the function. Whereas, when chatting function is available, the participants can exchange comments through it. Thus, the effect of its availability on the supporting function investigates whether the proposed system encourages constructive or disruptive discussion among the participants.

3.2. Experimental outline

The perceptual map dealt with in each experimental term is concerned with a certain product category and includes ten currently available products in the category. Since the proposed system at the moment can deal with the location of only one of the products, those of the other nine products should have been set in advance. Thus, we rely on principal component analysis for locating the nine products as a last resort. The participants are given a same table which shows some technical specifications of the ten products as related information[1], and they are requested to evaluate the products in several aspects using a five level likert scale before starting the market session on the products. The obtained evaluation scores are averaged over the participants and principal component analysis is applied to the averaged scores. Then, the scores of the first and second principal

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[1] The technical specifications on the table can be deemed as an example of the objective information. All the participants have been provided the same objective information in the experiment.

components are used to determine the locations of the nine products on the map.

In the corresponding market session, the location of the remaining one product is speculated on by the participants. Here, what we are interested in is whether the participants can agree on the location rather than whether they can find the predefined answer of it. Hence, the resultant location of the remaining product is determined independently of its principal component scores as follows: In each experimental term, two parallel markets, Market 1 and Market 2, are run on the same theme. The participants are randomly assigned to one of the markets and they cannot see any information on the other market during the market session. After a final round of the term, the resultant location of the object in a market is defined by the expected value taken with respect to the price distribution of the other market.

This parallel market approach can mitigate the problem of Keynesian beauty contest, which appears whenever applying the prediction market to an issue without an objective right answer.

3.3. Experimental design

The laboratory experiments are composed of eight terms. The profiles of the terms are shown below in Table 1. The experiments include two control factors, Round and Chatting. Round specifies the number of rounds and its levels are two and five. Chatting distinguishes whether the participants can exchange comments through chatting function during the corresponding market session. When its level is on, chatting function is activated, and otherwise, it is not. The experimental terms are conducted in the order of the term number shown in the table. Since it was not clear before starting the experiments whether all of the eight terms and a couple of testing terms can be finished within the limited time, we determined to conduct the five round terms first so that at least the data on these terms can be obtained. This means that Round is confounded with the potential learning effect. So the four terms of five rounds, and those of two rounds as well, are divided into halves, and whether the term is included in the first half or the second one is treated as a block factor in order to handle the possible learning effect.

Table 1 Profiles of experimental terms

Term	Product	Round	Chatting	Block
1	Range	5	On	1st
2	Note PC	5	Off	1st
3	Clothes washer	5	On	2nd
4	Air conditioner	5	Off	2nd
6	Cell-phone	2	On	1st
5	Blu-ray recorder	2	Off	1st
8	Desktop PC	2	On	2nd
7	Video camera	2	Off	2nd

The number of participants was twelve until term 6 and it was reduced to eleven in terms 7 and 8, but all the terms have been conducted. The participants are endowed with P\$2000 (Prediction Dollars) at the beginning of each experimental term and they are supposed to trade SAPS with this virtual money. They are prohibited from short selling SAPS as well as the virtual money. Each round lasts two minutes. After the final round, the proposed system determined the square area including the resultant location as described earlier. If a participant has SAPS corresponding to this square area, she/he will be given P\$1000 per share as the payoff, otherwise, the payoff will be nothing. The actual fee paid to each participant for each term is set proportional to her/his posterior wealth of the term with preset upper and lower bounds.

The value of the sensitivity parameter of LMSR is set as $b = 100$ according to some preliminary experiments.

3.4. Evaluation measures

Before and after the market session of every experimental term, each of the participants is requested to identify a square area which, she/he thinks, will include the resultant location. The

answers are hidden to the other participants. If the proposed market system actually supported the participants to built consensus on the location, the variance of the answered locations will be reduced through the market session. Thus, we define a measure F_1 for evaluating the supporting function as:

$$F_1 = \frac{\sum_{n=1}^{N}\left[\left(x_{1,n} - \bar{x}_1\right)^2 + \left(y_{1,n} - \bar{y}_1\right)^2\right]}{\sum_{n=1}^{N}\left[\left(x_{0,n} - \bar{x}_0\right)^2 + \left(y_{0,n} - \bar{y}_0\right)^2\right]} \tag{9}$$

where N is the number of participants in the corresponding market, $(x_{0,n}, y_{0,n})$ and $(x_{1,n}, y_{1,n})$ are the center of the square area that participant n choose before and after the market session, and $(\bar{x}_0, \bar{y}_0)$ and $(\bar{x}_1, \bar{y}_1)$ are the averages of them taken over the participants, respectively. When F_1 is smaller than 1.0, we can see that the variance of the answered locations is reduced through the market session.

We also define another evaluation measure F_2 based on the price distribution, because the variance of the price distribution will be decreased through rounds if the supporting function of the proposed system gradually leads the participants to a consensus. We define this measure as:

$$F_2 = \frac{\sum_{m=1}^{M \times M} P_{F,m}\left[\left(x_m - \bar{x}_F\right)^2 + \left(y_m - \bar{y}_F\right)^2\right]}{\sum_{m=1}^{M \times M} P_{I,m}\left[\left(x_m - \bar{x}_I\right)^2 + \left(y_m - \bar{y}_I\right)^2\right]} \tag{10}$$

where $P_{I,m}$ and $P_{F,m}$ are the price distributions after the initial round and the final round, and $(\bar{x}_I, \bar{y}_I)$ and $(\bar{x}_F, \bar{y}_F)$ are the expectations of (x, y) with respect to the distributions, respectively. When F_2 is smaller than 1.0, we can see that the variance of the price distribution is reduced through rounds.

3.5. Results and discussion

3.5.1. Results overview

Figure 2 a) and b) show how the variance of the participants' evaluations changes over market rounds. The prior and posterior evaluations are directly asked to each participant as described earlier, but her/his evaluation in each round itself is not clear. Hence, the center point of her/his whole chosen square areas is treated as a surrogate. There are four two-round terms as well as five-round terms, and each term has two markets. Thus, eight values are obtained for each variance, and they are represented by a box plot. We can visually confirm that each figure shows a decreasing trend. Further, it is also interesting that the variance seems to reach its minimum value in the second or third round and the minimum value seems to be smaller than the variance of the posterior evaluations, and that the process seems to exhibit not only the decreasing trend but also a slight fluctuation. However, since further data will be required to properly study these points, this paper does not go into them in the remainder.
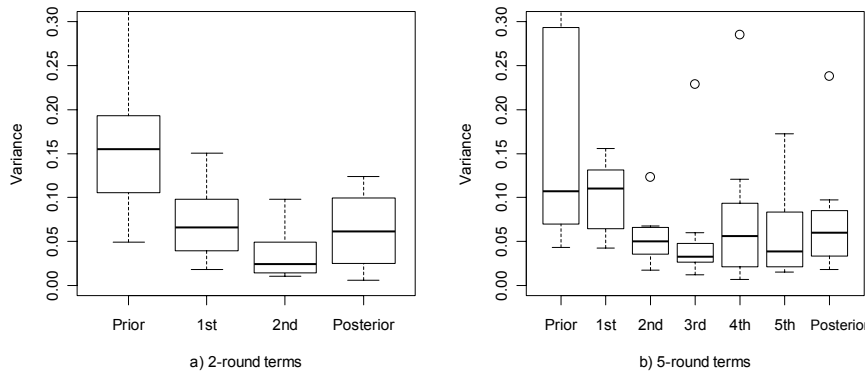
**Fig. 2. How variance of evaluations changes over rounds**
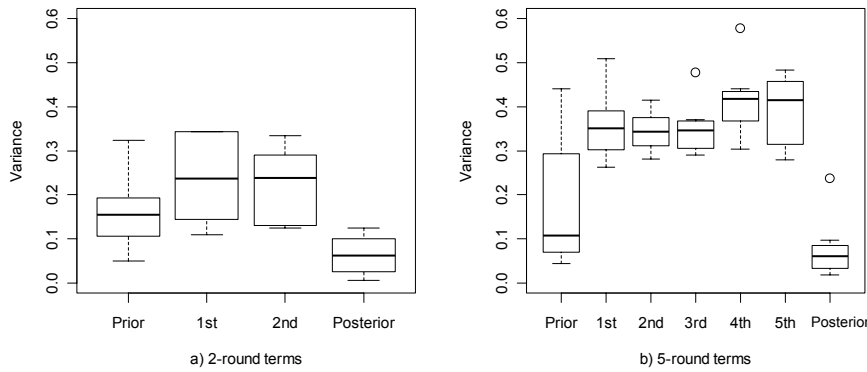
Fig. 3. How variance of price distribution changes over rounds

Figure 3 a) and b) are intended to represent the same process in terms of the price distribution. It is understandable that the variance of the price distribution tends to take a higher value than that of the prior or posterior evaluations, because the former contains not only the variation among the participants but also that within each participant. However, it cannot be overlooked that no clear decreasing trend can be observed for the variance of the price distribution over rounds in the figures. This point is revisited in 3.5.2 quantitatively through examining evaluation measure F_2.

Figure 4 shows the trajectory of the equally-weighted mean of the participants' evaluations, which are defined above, for each market of every term. It seems from the figure that the interaction among the participants through the proposed prediction market system not only reduces the variance of their subjective evaluations but also moves the mean of them, that is, what the interaction does is not just averaging the evaluations.

Figure 5 represents the trajectory of the mean of the price distribution for each market of every term. Although each trajectory in figure 5 is similar to the corresponding one in figure 4, the former is, in general, more winding than the latter. Further, the intermediate points of each trajectory in figure 5 seem to be dragged toward the center of the map (0, 0). This is found to be due to the exponential function appears in equation (4). It assigns a non-zero price to even a square area for which no SAPS has been sold so far, and its effect drags the mean to the center. Further, when used in a batch updating environment, the exponential function sometimes drastically changes the price distribution between rounds, and it also makes the trajectory sensitive.
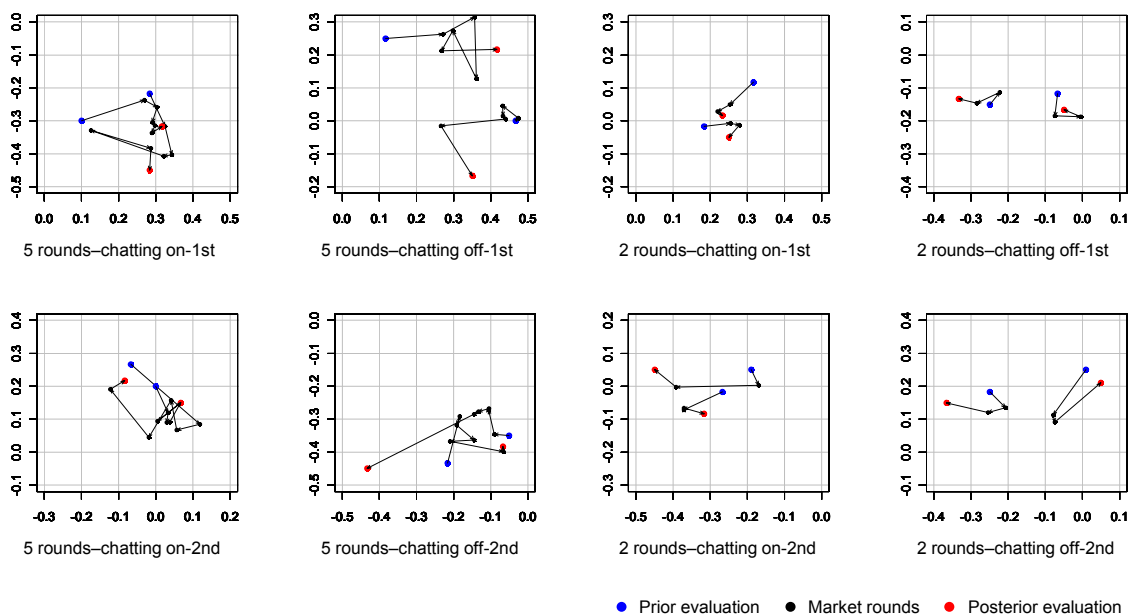
Fig. 4. How mean of evaluations moves over rounds

● Prior evaluation ● Market rounds ● Posterior evaluation
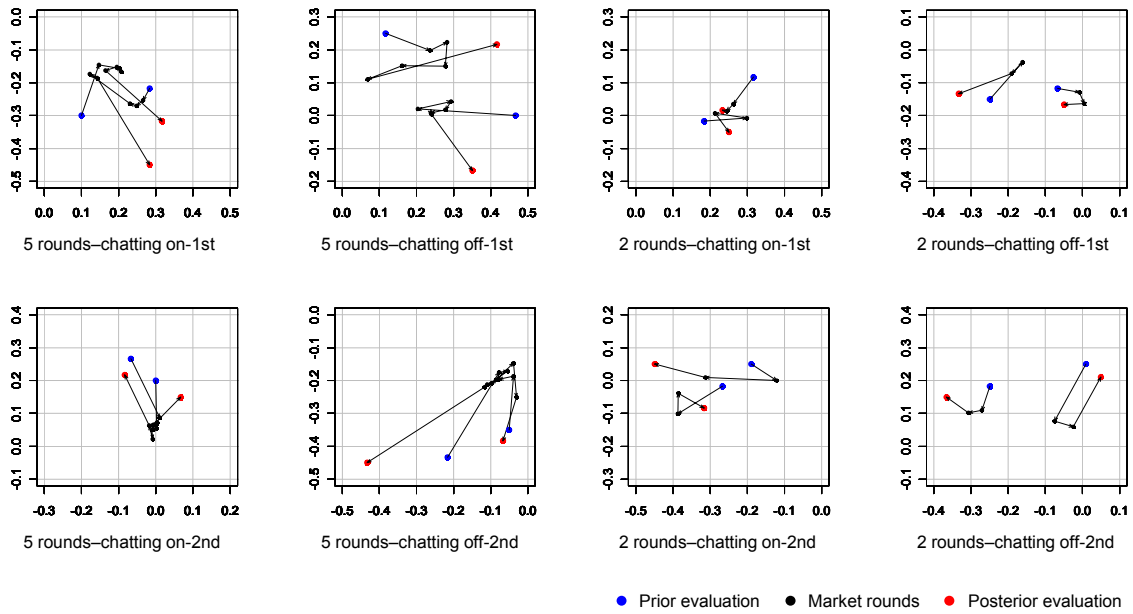
Fig. 5. How mean of price distribution moves over rounds

3.5.2. Resultant values of evaluation measures

The obtained values of F_1 are shown in Table 2. The values in the table are smaller than 1.0 excepting that of Market 1 of term 3 treating cloth washers. Further, the null hypothesis that the population value of F_1 is equal to or greater than 1.0 is rejected with a p value of 0.26×10^{-4}. Thus, we can judge that the proposed system has a significant supporting function in terms of F_1, that is, the system supports the participants to built consensus on the location at least inside of their minds. As an outlier, the value of F_1 of Market 1 of term 3 was abnormally higher than those of the other cases. Studying the comments exchanged through chatting function in the market reveals that this was caused by a participant's proposal to the other members to intentionally sell all SAPS at hand in the fourth round. This might be intended to find some arbitrage opportunities, but it seems to have failed in vain and the same proposal was not seen after this term.

Table 2 Resultant values of F_1

Round	Chatting	Block	Market 1	Market 2
5	On	1st	0.64	0.58
5	Off	1st	0.54	0.27
5	On	2nd	1.51	0.62
5	Off	2nd	0.37	0.08
2	On	1st	0.82	0.73
2	Off	1st	0.63	0.36
2	On	2nd	0.40	0.06
2	Off	2nd	0.06	0.32

Table 3 shows the obtained values of F_2. Some values in the table are greater than 1.0 and the others are smaller than 1.0. This time, the same null hypothesis on F_2 cannot be rejected, since its p value is 0.79. This means that the consensus evolved in the participants' minds is not properly represented by the price distribution. As the outlying case described above implies, the supporting function in terms of F_1 is not independent of the price distribution. Hence, this problem should be resolved in order to further refine the function. In addition to the effect of the exponential function in equation (4) described earlier, we suspects that this problem is also caused by the restriction imposed

on the numbers of SAPS. In the experiments, the participants are not allowed to hold different numbers of SAPS for different square areas. This restriction is aimed at enhancing the operability of the simple prototype GUI for the participants. Thus, sophisticating the GUI as well as the market maker will be necessary. If more degree of freedom can be provided for them to form their assets through the GUI without requiring much mental workload, the price distribution will also become more flexible.

Table 3 Resultant values of F_2

Round	Chatting	Block	Market 1	Market 2
5	On	1st	1.62	1.16
5	Off	1st	0.80	1.32
5	On	2nd	1.56	0.84
5	Off	2nd	0.95	0.86
2	On	1st	1.14	1.41
2	Off	1st	0.98	0.69
2	On	2nd	0.99	0.70
2	Off	2nd	0.85	1.11

3.5.3. Factorial effects on evaluation measures

Next, analysis of variance is applied to F_1 and F_2. Tables 4 and 5 show the results. The main effects of Round on both F_1 and F_2 do not seem so significant. This means that the level of consensus achieved in the experiments can be reached with only two rounds. However, if the problem of GUI described above has been resolved and the price distribution has become more flexible, a higher level of consensus may become achievable and more rounds may be required for it.

Table 4 ANOVA table for F_1

	Df	Sum Sq	Mean Sq	F value	P(>F)
Round	1	0.094	0.094	0.904	0.362
Chatting	1	0.474	0.474	4.557	0.056
Block	1	0.082	0.082	0.790	0.393
R:C	1	0.131	0.131	1.257	0.286
Residuals	11	1.145	0.104		

Table 5 ANOVA table for F_2

	Df	Sum Sq	Mean Sq	F value	P(>F)
Round	1	0.098	0.098	1.313	0.276
Chatting	1	0.219	0.219	2.930	0.115
Block	1	0.099	0.099	1.330	0.273
R:C	1	0.025	0.025	0.337	0.574
Residuals	11	0.820	0.075		

The main effect of Chatting on F_1 is significant at 90% confidence level, and that on F_2 has a relatively small p value. Thus, we can judge that the availability of chatting function has some effects on the level of consensus achieved, and the effects may be intermediated by the price distribution. A significant part of the exchanged comments was found to be related to the SAPS to hold and/or the price distribution. Hence, it seems that the proposed market system provides a shared context for discussion. Studying the main effect of Chatting on F_1 in detail shows that the chatting function was used disruptively in the experiments. A typical example is the outlying case of Market 1 of term 3 described earlier. The participants in a market looked for any arbitrage opportunities against the market maker as a team using the chatting function. This means that, even though it is in an

unfavorable form, cooperation among the participants appeared. When they have fully understood that there are no arbitrage opportunities against the market maker, the form of the cooperation may be changed into a productive one.

The main effects of Block on F_1 and F_2 were also not significant, but again we should not simply conclude that there is no learning effect of the proposed system. Rather, we suspect that the participants are still in the early phase of learning. This is why they are looking for arbitrage opportunities which do not actually exist. However, it is not clear only from the experimental results how many preparatory sessions will be required for first-time uses to become able to properly interact through the system. Further, it will depend on, among others, the GUI design. Thus, ongoing research should deal with these issues.

4. Conclusion

This paper proposed a prediction market system for supporting geographically distributed supply chain partners to collectively determine the location of an object on a perceptual map. It utilizes a newly introduced prediction security called SAPS and an original market making algorithm suitable for the security type. The paper also conducted laboratory experiments to show how the proposed system works. As a result, it is observed that this system can support consensus building on the location, but the price distribution does not always represent the evolving consensus properly. Thus, it is necessary to refine the GUI as well as the market making algorithm in order to resolve the problem. Further, it is also found that the performance of the system was affected by the availability of chatting function, but the function was used disruptively rather than constructively. Hence, how to motivate the participants to use the function constructively should also be studied. It is also important to generalize the system so that it can handle the locations of multiple objects at the same time.

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