

Product Concept Evaluation System Applying Preference Market

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Abstract

A product concept evaluation system combining conjoint analysis with prediction markets is developed. It is also proposed how to determine the payoff for each prediction security corresponding to a product concept, so as to have participants to behave truthfully in the market. Further, how the proposed system works is investigated by evolutionary game simulation.

Introduction

Prediction markets are a speculative market for predicting the future using collective intelligence (Wolfers and Zitzewitz 2003). Recently, they have been also used for estimating the preferences of potential consumers on some product concepts (Dahan et al. 2010, Dahan et al. 2011). When applied to this area, the markets are called preference markets. The main difference between preference markets and traditional prediction markets comes from the availability of the correct result. In the traditional prediction markets, the correct result will be known at some point in the future and the payoff can be determined according to it, whereas in the preference markets, the correct result will remain unknown and the payoff should be determined somehow based on the status of the markets themselves (Slamka et al. 2012). Thus, how to induce participants to behave truthfully in the market is a critical issue. Further, the number of prediction securities, and hence that of product concepts, to be compared in a preference market will be limited in the naive approach taken in Dahan et al. (2010, 2011).

This paper, therefore, develops a new product concept evaluation system by combining conjoint analysis with preference markets, and proposes three approaches of payoff determination for incentivizing participants to behave truthfully. In the proposed system, each of the product concepts compared in a market corresponds to a subset of a set of pre-specified attributes, and the attractiveness of each attribute is estimated by conjoint analysis based on the price data obtained from the preference market. Thus, the consumer preference can be estimated even on a product concept which is not directly compared in the market.

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Proposed System

Product Concepts and Attributes

There are N candidate attributes, B_1, B_2, \dots, B_N , which can be incorporated into the new product under consideration. Each possible product concept can be denoted as;

$$\mathbf{x} = (x_1, x_2, \dots, x_N)^T \quad (1)$$

where $x_n = 1$ represents that the attribute B_n is included in the concept and $x_n = 0$ indicates that it is not.

The more attractive the product concept \mathbf{x} is, the higher the market share the product will achieve if it is actually launched into the target market. According to the logit market share model, the market share can be expressed as:

$$SA(\mathbf{x}) = \frac{A(\mathbf{x})}{A(\mathbf{x}) + \sum_{i \in Others} A_i} \quad (2)$$

where $SA(\mathbf{x})$ and $A(\mathbf{x})$ represent the expected market share and the attractiveness of the new product concept \mathbf{x} respectively, and $Others$ expresses the set of competing products in the target market and the attractiveness of the i th product in the set is denoted by A_i . The product attractiveness $A(\mathbf{x})$ is defined as:

$$A(\mathbf{x}) = \exp(\mathbf{a}^T \mathbf{x}) \quad (3)$$

where the attractiveness of the baseline concept is taken as a unit; a_n represents the partial attractiveness added by including the attribute B_n ; the vector \mathbf{a} is defined as $\mathbf{a} = (a_1, a_2, \dots, a_N)^T$.

Prediction Security and Market Maker

The experimental design method is applied to narrow down a set of product concepts comparing in a preference market. In order to compare the relative market share among those product concepts, vote-share type prediction securities are used whose values are proportional to the share of the corresponding product concepts.

We employ CMM (Central Market Maker) in order to ensure the liquidity of the prediction securities and use LMSR (Logarithmic Market Scoring Rule) as the algorithm for CMM (Hanson 2003, Hanson 2007).

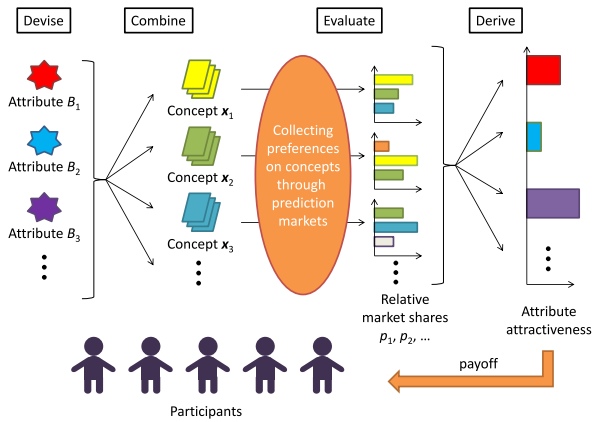


Figure 1: Overview of proposed approach

How to Determine the Payoff

The following three approaches for determining the payoff are proposed.

1. Define the payoff indirectly by the estimated attribute attractiveness rather than the price data themselves, and thereby reduce the influence of outliers in the price data.
2. Run several preference markets in parallel and determine the payoff in each market by using the price data obtained from all of them, and thereby offset the possible bias in the price data of a market.
3. Use the smoothed values, such as VWAP (volume-weighted average price over a period of time) and Average Price (average prices over a period of time), instead of Last Price (market closing price) for estimating the attribute attractiveness, and thereby reduce the impact of the transactions just before the closure.

Evolutionary Game Simulation

Models of Market Participants

We modeled three types of participants. First is fundamental player (FP), who predicts the payoff of a security based on the preference model of its own. Hence, it is expected that the higher the parentage of FP, the higher the accuracy of the preference market. Second is concentration player (CP), who predicts the payoff such that the highest priced security will get 100% share. Third is technical player (TP), who predicts the payoff with exponential smoothing. Each player trades prediction securities to maximize their expected wealth. CP and TP are noise traders in the sense that they may introduce noise and bias into the price data.

Simulation Procedure

- There are 30 players in each market.
- A player chooses an action from buy, sell, or do nothing at a trading turn.
- There are 500 trading turns and they are given randomly to the players.

- Margin buying and short selling are allowed.

A hypothetical five attribute preference model is defined as the correct model, and a slightly modified model by adding some errors is given to each FP. We run 20 market sessions for each setting and compared the final wealth among the player types. We also measured the correlation between the attribute attractiveness in the correct model and the estimated model as the accuracy of the preference market.

Experimental Result

1. If the proposed payoff determination approaches are not used, the final wealth of noise traders is higher than that of FP. However, when the proposed approaches are used, the wealth of FP becomes the highest.
2. The accuracy of preference market improves as the ratio of FP increases. Further, the accuracy also improves along with the number of markets even when the ratio of FP is low. However, the accuracy becomes low when smoothed values are used.

Conclusion

According to the simulation experiments, the proposed system is effective to improve and maintain the accuracy of the preference market in the long term. In order to increase the proportion of FP, determining the payoff based on VWAP and running some markets in parallel are effective. Further, in order to increase the accuracy, using Average Price and running parallel markets are helpful.

Interesting future directions include advancing the model of the attractiveness of attributes and product concept, verifying the optimal number of parallel markets run, and devising a method for designing the set of prediction securities to be introduced to the parallel markets simultaneously. In addition, it is required to demonstrate the utility of the system through laboratory and field experiments.

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