Modelling market sellers in World of Warcraft

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ABSTRACT

The virtual economy operates like the one in the physical world, which is realized by players with two functions–demand and supply, only using the form as avatars. Only that in virtual worlds, the prices of virtual items is decided by the players instead of by its quality or scarcity, so the player behavior analyses became an important tool to monitor the persistent virtual worlds. In order to achieve the idea of a more balanced virtual market, we analyze the trading behaviors in three points – sellers, prices and items, and expect to figure out the selling motivation, pricing rules and the over/underpricing conditions. In this paper, we use the auction house data in World of Warcraft (WoW) to analyze these seller behaviors. After applying clustering and classification, a market seller model of WoW is presented.

Categories and Subject Descriptors

Design, Economics

General Terms

Design, Economics

Keywords

Virtual Market, Player Behavior, Player modeling, World of Warcraft

1. INTRODUCTION

Like people in the physical world need an economic system, many massively multiplayer online games (MMOG) provide virtual markets for players, utilizing avatars, to trade in the virtual worlds. The economic activities in virtual worlds are adopted from the physical world, such as producing, trading, consuming, etc. [14]. In this marketplace, players could use his/her virtual money, rewarded from the play, to trade with other players for virtual items or services. Some games even allow players to use real money to trade in the market, which means these virtual items and money are not only valuable in virtual worlds but also in the physical world. In addition, some players also spend real money to trade virtual items/money in the auction websites, like ebay or 8591. Examples of using real money to trade will be the US and EU servers of Diablo III, though Blizzard has announced that these trades in old auction house will be soon closed on March 18, 2014.

However, though these markets are considered as one of the best methods of money sinks in the game, it doesn't always serve its best function as designed, just like the Asia servers of Diablo III. While Blizzard only allows real-money trades in US and EU servers, but not in Asia, most gold farmers prefer coming to the Asia servers for their own interest, which caused the inflation of in-game gold after a quarter, according to the aggregation of currency fluctuations between real-money and in-game gold from October 3, 2012 to January 7, 2013, showed in figure 1. Due to this past experience, it is obvious that knowing the trading behaviors among buyers and sellers help creating a more stable virtual market.
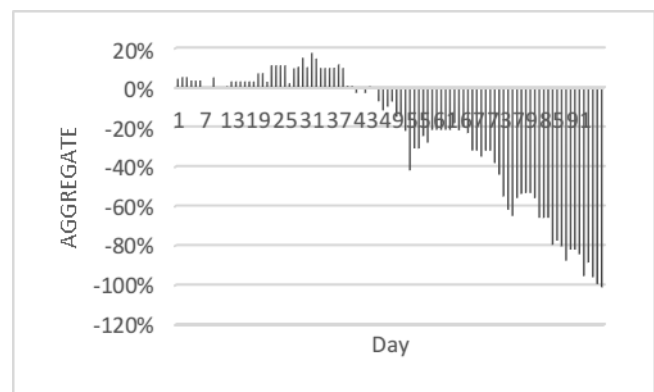

Figure 1. Aggregate of currency fluctuations

(Data from http://www.8591.com.tw/)

Many researchers have suggested that the virtual economy isn't the same as the one in the physical world [5]. E. Castronova pointed out that the prices of virtual items are decided by the players instead of by its quality or scarcity [4], so the player behavior analyses became an important tool to monitor the persistent virtual worlds [8]. With the developments of machine learning and data mining techniques, player behavior analyses could be carried out with player modeling [15, 23], agent modeling [6] or other quantitative methods, which discovers any underlying patterns in the player behaviors and provides an analyzing model for trading behaviors to see the effects of market designs, set by the designers or game managers.

Since player behavior analyses are an important tool to monitor the persistent virtual worlds, it is necessary to know the trading behavior of players to help improving the virtual markets. In this paper, we will use the auction house data in WoW to especially analyze player's selling behaviors. The rest of this paper is organized into 4 parts: research goals, proposed approach, expected achievements, and conclusion.

2. RESEARCH GOALS

Until now, many research papers have mentioned the importance of consumer behaviors in virtual markets, in which we see what the drive of purchase decisions is [3]. However, since players are also sellers in virtual markets, the analysis of its behaviors is also essential for seeing the whole picture of player trading behaviors. Moreover, since all transactions will finally be completed by both sides of a buyer and a seller, which consist of two players, it is necessary to also know the intention of sellers besides the drive of purchase decisions.

First of all, the relationship between the seller and the item tells us the motivation of a seller. For instance, why would a player place an item in a virtual market if it is truly rare and valuable? On the other hand, as the game system charges players for selling a commodity, how would a seller choose certain items to sell for fulfilling his/her own interest? Through analyzing these seller behaviors, we can see how a provider acts and what they consider behind the behaviors in MMOG.

Secondly, by seeing the relationship between the seller and his/her pricing rule, we can see some points as below. Since selling is a mean of making money in MMOG, plus the limitations of costs of playing time and money, the primary concerns between a competitive price and a profit are crucial in the selling behaviors. Also, analyzing the consideration of how much an item should cost also tells us how these players actually regard the value of his/her efforts in the game, for the item (s)he chose to sell is rewarded from their play, like completing quests/dungeons. By knowing this, we can figure out a refined player behavior model to help game designers defining the "value" in the game.

Thirdly, the relationship between the items and prices reflects the situations of a price in the markets, which are overpricing, underpricing and somewhere in between. For instance, when an item has much less value than usual, it could indicate an underpring of the price. By observing and analyzing the change of the price-item relationship, the game designer can sense the current economic system in the game and adjust accordingly for maintaining the balance.

By combining all these three analyses among seller, item and pricing rules, we hope to present a seller model to see its behaviors in the virtual markets. To analyze the points above, we have chosen WoW as our analyzing subject, since WoW is not only played by numerous people, renews its patch every three months for a updated version, provides tools to fetch data for analysis, but most of all, an active trading market.

3. PROPOSED APPROACH

The research is divided into 2 steps: 1.) Collecting the data from the auction house in each capital city of WoW, and 2.) Modeling the seller behaviors with techniques of clustering and classification. The details are described as follows.

To model the market sellers, we collect 3 types of data: snapshots in the auction house, seller profile, and item details. Through the results of the bids, we can find the relationships between sellers and items. First, we use AuctionMaster, a WoW Application Programming Interfaces (API), to collect snapshots in the WoW auction house. We collected 3 months of hourly data from each auction house in Taiwan faction of WoW, in which each realm is divided into 2 separate factions (groups), Horde and Alliance. Since avatars in different groups can't talk, trade, or

exchange, 90 independent data sets are gathered. A record fetched by AuctoinMaster includes name (item name), count (volumes), min bid (starting price), buyout (price of buyout), level, quality (rarity), min increment, bid amount (current highest bidding price), high bidder, time left and owner (seller) [1].

To obtain the complete list of each seller in the data collecting duration, the recorded bids are split up by its seller. With the selling list, we compare successive snapshots and determine the difference between them to find the transactions occurring between market snapshots. Therefore, if a bid disappears between snapshots it is assumed that the bid has been dealt. On the other hand, when a new bid has appeared in the second snapshot it is assumed that a new bid has been placed during the interval [18].

Although WoW doesn't provide the exact result of each bid, the average successful rate of auction houses must be high enough, because WoW charges fees when a seller places a bid. In the beginning, a deposit is paid immediately when a seller lists an item in the auction hall. Then, the deposit will be confiscated when a bid failed or got withdrawn by the seller. The amount of a deposit is based on the Merchant Sell Value (Starting bid price) for both the item and the on-shelf duration, which are 12 hours, 24 hours or 48hours. The longer the duration is, the higher the deposit becomes. Meanwhile, WoW will take a percentage of the winning bid as its cut and return the deposit when the bidding succeeds [10]. In this way, an item owner would rather cash items in the bank than selling them in the auction house, if he has no confidence in selling out this item.

Furthermore, we use WoW Community Web API [21] to collect the seller profile and item details. The seller profile consists of level, class, race, achievement point and honorable kill. Meanwhile, if the seller joins a guild, the guild level, guild members and the achievement point of the guild will also be collected for further processing. In addition, the item level, rarity, and class will also be gathered in the item details. At last, all the final collected data will be saved with the form of comma separated values (CSV) and will be divided into three categories: seller data, item data and transaction list, as listed in table 1.

In the second step, features from transaction lists, seller data, and item data are extracted to analyze with the techniques of clustering and classification [8, 9, 17]. Features from the seller data and item data are applied for finding the motivation of selling. And the rules of setting a price are processed with features from seller data and the transaction lists. At last, through the features from item data and the transaction lists, a classifier to tell a competitive price is presented. Combining with these three results from different sets, a market seller model in WoW is introduced.

4. EXPECTED ACHIEVEMENTS

We've collected 45 WoW Asia servers, i.e. 90 data sets, from June 29, 2011 to August 28, 2011. In each transaction, we can see the desire (demand) of players from the angle of consumers. However, we would like to know what this same group of players could supply as sellers in the game at the same time? In other words, what are their seller behaviors? We hope to answer this question through our research and the expected achievements are described as follows.

Table 1. Attributes and descriptions of the collected data

Category: Seller Data	
Attribute	**Description**
Seller name	Seller's name in WoW
Class	Seller's profession in WoW
Race	Seller's race in WoW
Level	Seller's level in WoW
Gender	Seller's gender in WoW
AchievementPoints	Units that accumulates based on different types of achievements
HonorableKills	Number of killing a member from the opposite Faction who is a player or selected NPCs (almost always in battlegrounds)
Guild Level	Level of the seller joined guild
Guild Members	Size of the seller joined guild
Guild Achievement Points	Achievement points of the seller joined guild
Total	Number of the seller's total bids
Sold	Number of the sold bids
Days of work	Days of the seller sells an item
Profit	Profit of the sold items

Category: Item Data	
Attribute	**Description**
Rate of rare item	Percentage of the rare commodities in Sold
Rate of item level below 35	Percentage of the sold commodities with level below 35 in Sold
Rate of item level between 35 and 65	Percentage of the sold commodities with level between 35 and 65 in Sold
Rate of item level more 65	Percentage of the sold commodities with level above 65 in Sold
Item Class Distribution	Item class distribution of Sold (18 classes in total)
Starting Price List	List of min bid in each seller's bid

Category: Transaction List	
Attribute	**Description**
Selling list	Item list of the seller's total bids
Sold list	Item list of the seller's sold bids

First of all, to figure out the motivation of selling an item in a virtual market: we apply the clustering method to find the relationships between features from the seller data and the item data. Based on these relationships, we could discuss the motivation of the seller for selling an item in a virtual market and his/her reason of choosing which item to sell.

Secondly, as for the pricing rules of a seller: based on the features extracted from the sellers and the transaction list, we again apply the method of clustering to find out the considerations of a seller while (s)he sets a price in a virtual market to find out how (s)he regards the value of his/her efforts rewarded in the play.

Finally, the relationships between item and price: based on the features from the item data and the transaction lists, we apply the classification method to distribute the items and prices into three categories—overpricing, reasonable market price and underpricing. Since the relationships can indicate a current economic situation, a classifier is introduced to avoid the case of overpricing or underpricing.

After collecting these three relationships, a market seller model in WoW is presented to explain the seller behaviors in a virtual market.

5. CONCLUSION

Trading behaviors have become an important player behavior in MMOGs, while virtual markets play an important role in virtual economy. Therefore, understanding player behaviors indicates to understand virtual markets, which leads to building a more stable virtual economic environment. In the previous researches, numerous researchers have been discussing consumer behaviors and leave a large space for doing researches in seller behaviors, which this study is mainly about. This research is conducted with data collection, through the technique of machine learning to generate a market seller model for explaining seller behaviors in MMOG. Our finding will assist game designers to build a more balanced virtual market in MMOGs.

6. ACKNOWLEDGMENTS

7. PLANS FOR THE WORK

Table 2. Plan for the work

Time	Work
09/2013 — 12/2013	Literature Review
01/2014 — 03/2014	Data Analyzing
04/2014 — 06/2014	Seller Modeling
06/2014 — 08/2014	Discussion

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