Towards market seller modeling in World of Warcraft

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***Abstract*—This short paper describes work in progress on modeling market sellers in World of Warcraft. We describe the motivations for modeling market sellers, the method of collecting the data, our method for clustering sellers and some preliminary results.**

I. Introduction

The market design in massively multiplayer online games (MMOG) is double-sided. On the positive side, it's basically the best way to sink (remove) virtual items or currency from the players to avoid economic inflation, which is inconvenient and always a threat since a MMOG is persistent. On the other side, it increases the difficulty to maintain the economic balance and the game designs. In Guild Wars 2 (GW2), a global market is easily implemented for all players, but the prices in it are sensitive to the invisible hand. Some prices of the crafted items were even less than the cost of the ingredients. When this situation happens, players begin to craft for nothing in return and the fun reduces due to the competitions between players. Furthermore, the introduction of auction house ruins the original game design, which occurs in Diablo III. One of the major reasons why Diablo II succeeded is finding random gears in the game, which could not apply in Diablo III, since the feature is destroyed through the auction house.

Every player plays a producer and a consumer in the game at the same time. Many researchers covered the angle from the consumers [1]–[3], but seldom cover the structure and models of the supply. In the physical world, when manufacturers find out the demand is under the supply, they either reduce the amount of the products. However, in the virtual world, players do not have such mechanisms to make adjustments accordingly, which discourages players to stay in the game. For this reason, it is crucial to analyze player behavior to monitor game environments [4], [5]; the trading behavior of players is directly provided through analyaing the in-game market/auction house (AH) data.

Also, we want to develop a cross-server data-driven methodology for building player models. Games like MMOG run in different servers, while each server serves different players under the same game environment. Each server has its own scenario after running a while; therefore, to model these player behavioral patterns from the cross-server data, we started to design the methodology and chose World of Warcraft (WoW) as our target. 8 different factions in WoW are selected to understand the structure of market sellers: which types of players there are and what we can cater to each. In the end, a set of predictive agent-based models of the economy [3] would be generated. To get there, we need to know which types of sellers we need to model and finding families of agents we need to create. With the predictive models, we could find imbalances and rectify in the commodity system. The rest of this paper is organized into 4 parts: Data collection and preprocessing, Methods, Preliminary results, and conclusion.

II. Data collection and preprocessing

The auction house (AH) in WoW is a place where players can trade with each other. The auction list in AH and detailed item information were collected to analyze the market seller models. The auction list is collected hourly from June 29 to August 28, 2011 (which is before the WoW Patch 5.4 of the connected realms) with a WoW application programming interface (API), AuctionMaster2. The fetched data consists item name, volumes, starting bidding price, the price of buyout, level, quality, etc.

WoW provides two types of game servers: player vs player (PvP) and player vs environment (PvE). Each realm (server) in WoW is divided into 2 separate factions (groups), Horde and Alliance, and avatars in different groups can't talk, trade, or exchange. Due to the faction scales and the balance between PvP and PvE, 8 Taiwan factions are picked and listed as follow: the alliance (1912 avatars) & horde of Arygos (1331 avatars), the alliance (1145 avatars) & horde of Dreadmist Peak (2441 avatars) , the alliance (1867 avatars) & horde of Icecrown (1331 avatars), the alliance of Lights hope (2435 avatars) and the horde of World tree (1011 avatars).

After obtaining the auction lists from AH, each seller's total selling list and the success transaction list are generated. The success transactions are determined by comparing the successive items in the total selling list. Through each seller's success transaction list, each single seller's item class distribution of total volume are generated with the item classes, defined by WoW item classification. But since over 90% of the items on the shelf is in the class of trade good, the items of trade goods were further classified with the subclasses of trade goods. Therefore, the class distribution of single seller's item is composed with 8 features: seven subclasses of trade goods and others, including every item class except trading goods.

III. Methods

Efficiency is the major concern when dealing with big datasets, especially when investigating multiple servers. Based on the efficiency and the convincibility, K-means and Silhouette algorithm are our best suggestions after trying hierarchical clustering and self-organizing networks, for which we have too limited space to demonstrate in the paper. Moreover, K-means can give us intuitively interpretable behavioral profiles. Also, although the Silhouette coefficients are higher for convex clusters. Since every evaluation is

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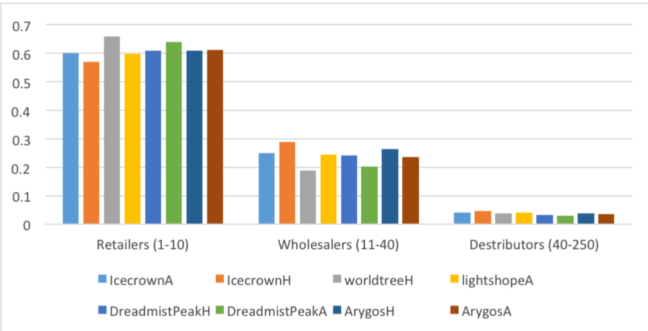

Fig. 1. Histograms of normalized average supply per transaction of the alliance & horde of Dreadmist Peak (DreadmistPeakA & DreadmistPeakH), the alliance & horde of Icecrown (IcecrownA & IcecrownH), the alliance of Light's hope (Light'shopeA), the horde of World tree (World treeA), and the alliance & horde of Arygos (ArygosA & ArygosH)

running under the same situation, a higher value does not affect the evaluation results.

Meanwhile, we introduced the normal average supply per transaction (the ratio of the total volume and the total transactions) for omitting the outliers and dividing the sellers into 3 categories: retailers, wholesalers and distributors. The histograms of the normalized average supply per transaction in the 8 servers are shown in figure 1.

A. *For one server: clustering, finding k with silhouette.*

The biggest dataset, the horde in Dreadmist Peak, is clustered with k-means algorithm for all k values that are less than or equal to 20. The Euclidean distances (quantization errors) between each player instance and its corresponding cluster centroid are calculated for all 20 trials. And then, Silhouette algorithm [6] is applied to identify which k could be a proper value for k-means algorithm. The higher the Silhouette Coefficient scores are, the better the defined clusters are.

B. *Between servers: comparing number of clusters and cluster centroids.*

We apply the same method mentioned in previos section, k-means algorithm and the Silhouette coefficients, to cluster other 7 factions. After clustering the other 7 factions, we use the quantization error to check the stablity of the clustering results. Every distance between the cluster centroid of the horde in Dreadmist Peak and the centroid of the corresponding cluster among the other 7 clustering results is further calculated.

IV. Preliminary results

The description in this section is the results observed from retailers. In the future work, we will cluster the other two categories (wholesalers and distributors) with the same setup.

Through the clustering results of the 8 factions, we classified the retailers in AH into 3 types: (1) Retailers with only one major class of items, (2) Retailers with one major and one minor classes or with two minor classes, and (3) Retailers with one major and two minor classes. The terms of "major" and "minor" used here are observed from the centroids of clusters. The first and second types of players exist in every faction, and the third type of players exists in the factions over 10,000 avatars. The bigger the population of the faction is, the higher the chances of players selling multiple classes are.

The 8 datasets cover the two different types (PvP and PvE) of playing patterns and our findings showed that selling patterns are similar in the two types of servers. The majority of the sellers in the market tend to sell one major class of items and some also sell one or two minor classes. In addition, we applied the same setting to analyze every dataset to check the feasibility of the proposed method. Although the proposed approach is relatively ad-hoc and leaning on the domain knowledge, we found the results generated by the proposed method are considerably consistent and stable between servers.

V. Conclusion

In this paper, market seller models are proposed to explain seller behaviors in MMOG. We use data collection, clustering through k-means algorithm, and Silhouette algorithm to find clusters of sellers. According to the item classes in WoW, 8 features extracted from transactions in AH are used for clustering. Through the quantization errors between the centroids of the corresponding clusters among the 8 factions in WoW, we find that the selling patterns of the retailers, which means sellers with the average supply per transaction from 1 to 10, in different servers are consistent. The retailers tend to sell chiefly one class of items, but in servers with high player population, some retailers sell multiple classes of items. In sum, our findings could help to understand the structure of the markets and develop a cross-server data-driven methodology for building player models from cross-server data.

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