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Mining for Gold Farmers: Automatic Detection of Deviant Players in MMOGs

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***Abstract*—Gold farming refers to the illicit practice of gathering and selling virtual goods in online games for real money. Although around one million gold farmers engage in gold farming related activities [14], to date a systematic study of identifying gold farmers has not been done. In this paper we use data from the massively-multiplayer online role-playing game (MMORPG) EverQuest II to identify gold farmers. We perform an exploratory logistic regression analysis to identify salient descriptive statistics followed by a machine learning binary classification problem to identify a set of features for classification purposes. Given the cost associated with investigating gold farmers, we also give criteria for evaluating gold farming detection techniques, and provide suggestions for future testing and evaluation techniques.**

I. Introduction

As information communication technologies have grown more pervasive in social and cultural life, deviant and criminal uses have attracted increasing attention from scholars [12]. Virtual communities in massively-multiplayer online games (MMOGs) such as World of Warcraft and EverQuest II have millions of players engaging in cooperative teams, trade, and communication. These games primarily operate on a monthly subscription basis and have over 45 million subscriptions among Western countries and double that number in Asia [24]. While the in-game economies exhibit characteristics observed in real-world economies [5], a grey market of illicit transactions also exists. Virtual goods like in-game currency, scarce commodities, and weapons require substantial investments of time to accumulate, but these can also be obtained from other players through trade and exchange.

Gold farming refers to a body of practices that involve the sale of virtual in-game resources for real-world money. The name stems from a variety of repetitive practices (”farming”) to accumulate virtual wealth (”gold”) which farmers illicitly sell to other players who lack the time or desire to accumulate their own in-game capital. By repeatedly killing non-player characters (NPCs) and looting their currency, farmers accumulate currency, experience, or other forms of virtual capital which they exchange with other players for real money. Gold buyers then use the purchased resource to obtain powerful weapons, armor, and abilities for their avatars, accelerating them to higher levels, and allowing them to explore and confront more interesting and challenging enemies [3].

Game developers have actively cracked down on the practice by banning farmers' accounts [2]. In-game economies are designed with activities and products that serve as sinks to remove money from circulation and prevent inflation. Farmers inject money into the system disrupting the economic equilibrium and creating inflationary pressures. Additionally, farmers' activities often exclude other players from shared game environments, engaging in theft of account and financial information [16]. Game companies are also motivated to ban farmers to ensure that the game fulfills its role as a meritocratic fantasy space[21]. Because gold farmers are motivated only to accumulate wealth they detract from other players game experience and may drive legitimate players away [20].

The earliest instances of real money trade can be traced back to the terminal-based multi-user dungeons (MUDs) of the 1970s and 80s [14]. Gold farming operations originated in an early MMOG game, Ultima Online, in 1997. The practice grew rapidly with the parallel development of an ecommerce infrastructure in the late 1990s [9]. The complexity of gold trading organizations continued to grow as more games were released into East Asian markets[6], [13]. Gold farming operations now appear to be concentrated in China where the combination of high-speed internet penetration and low labor costs has facilitated it[**?**], [8]. The scale of real money trading has been estimated to be no less than $100 million and upwards of $1 billion annually [4], [19], and the phenomenon has begun to capture popular attention.

II. Related Work

Previous studies of virtual property have focused on the economic impacts [4], user rights and governance [16], [10],

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and legal vagaries [1] rather than the behaviors of the farmers themselves. Surveys of players have measured the extent to which the purchase of farmed gold occurs and how players perceive both producers and consumers of farmed gold [27]. Other research has imputed the scale of the activity based upon proxy measures of price level stabilization and price similarity across agents [18], [19]. No fieldwork beyond journalistic interviews has been done in this domain because of a confluence of factors. Secrecy is highly valued, given the prevalence of competitors as well as the negative repercussions of being discovered [15]. The popular perception of gold farming as an abstract novelty, the rapid pace of innovation and adaption in organizations and technology, the significant language barriers, and the geographic distance likewise conspire against thorough observation or systematic examination [11]. Perhaps the largest barrier has been the lack of availability of data from the game makers themselves.

If the data were present machine learning techniques exist to explore the phenomenon. These have received considerable attention in the context of combating cybercrime [22], [7]. Other studies employing social network analysis, entity detection, and anomaly detection techniques have been used extensively in this context [17]. The current research is the first to take advantage of these techniques by virtue of cooperation with a major game developer, Sony Online Entertainment. As outlined below, the current research is the first scholarly attempt to employ data mining and machine learning to detect and identify gold farmers in a data corpus drawn from a live MMOG.

III. Background

A. Game Mechanics

The study uses anonymized data archived from the massively-multiplayer online game Everquest II. In this fantasy role-playing world, a user controls a character to interact with other players in the game world as well as NPCs. Users complete quests, slay NPCs, and explore new areas of the game to earn experience points as well as currency that allows them to purchase more powerful equipment. As levels increase getting powerful weapons, armor, and spells becomes more expensive. Players can shortcut to more exciting content by purchasing the requisite weapons, armor, and skills rather than engaging in the more tedious aspects of accumulating the resources to sell or exchange for these items. Thus being able to obtain a large reserve of game currency from another character reduces the time investment necessary to progress.

B. Gold Farming

Gold farmers repeatedly kill in-game NPCs and collect the currency they carry. The tedious nature of this activity is somewhat lessened by the use of automated programs called bots which simulate user input. These operators have adapted to being banned by employing a highly-specialized value chain that both minimizes the amount of effort and time required to procure gold as well as reducing the likelihood of being detected and attendant issues of losing inventory. Discussions with game administrators have revealed that accounts engaged in gold farming operations within the game fulfill five possible archetypes [25]:

- Gatherers: Accounts accumulating resources.
- Bankers: Low-activity accounts that hold some gold in reserve in the event that a confederate is banned.
- Mules and dealers: One-time characters that interact with the customer to distance the customer from the operation, and complicate administrator back-tracing.
- Marketers: One-time accounts that are ”barkers”, ”peddlers”, or ”spammers” of the company’s services.

The roles are not necessarily exclusive nor proscriptive, but these descriptions of behavioral signatures will inform subsequent methods. The highly specialized roles of gold farmers also suggests that they differ from typical players along several potential salient and latent dimensions. Where players are largely motivated to explore the game and storyline as they gain experience and level up, gold farmers may follow highly optimized paths that allow them to level quickly without engaging in these sideshows. Currently gold farmers are caught in a number of ways such as heuristic-based methods which would indicate illegitimate activity in the game, reporting of gold farmers by other players, peculiar behavior of players like making a large number of transactions over a very short span of time, and ”sting” operations. In all the above cases after being potentially flagged as a gold farmer the activities of the player in the past, present and the future have to be analyzed by a human expert before it can be ascertained that the player is indeed a gold farmer and not a legitimate player. These administrators are the ultimate arbiters of which users are banned.

IV. Data Description

Anonymized EverQuest II database dumps were collected from Sony Online Entertainment. Five distinct types of data were extracted for analysis: activities form experience logs, transaction logs, character attributes like race (human, orc, elf etc)character sex, etc., demographic attributes, and cancelled accounts. The data is already anonymized so that it is not possible to link the player back to a real-world person. Examples of activities include but are not limited to mentoring other players, leveling up, killing monsters, completing a recipe for a potion, etc. The cancelled accounts contained dates, account IDs, and rationales for an administrator cancelling an account including abusive language, credit card fraud, and gold farming. These players were either caught by the game developer’s staff or were identified for investigation by other players. Players and developers recognize that is by no means a comprehensive list, and some unknown gold farmers elude capture. However, our starting point was a simple list of those who were captured. The rationales were manually parsed to identify cases with rationales pertaining to gold farming and real money trade and extracted to generate a master list of accounts banned for gold farming. There were a total of 2,122,600 unique characters out of which 9,179 were gold farmers, or 0.43% of the population.

Character attributes are the stored attributes of every character at their most recent log-out such as level, experience, class type, damage resistance, and so forth. The player demographic table included self-reported characteristics such as player birthday, account creation date, country, state, ZIP code, language, and gender. The popular stereotype of gold farmers being Chinese men appears to be borne out in the descriptive analysis as 77.6% of players banned for gold farming speak Chinese while only 16.8% of users speaking Chinese have been banned for farming. The experience and transaction tables are longitudinal records of every event in the game that awards experience points to a player or results in an item being exchanged between players, respectively. Given the large size of these datasets, the analysis was limited to the month of June 2006 and contains 24,328,017 records related to experience and 10,085,943 records related to user transactions. Out of the 23,444 players with behavioral data for June 2006, only 147 were subsequently identified as gold farmers.

V. Methods

One of the most important tasks in data mining and machine learning is selecting the features to be used in the classifier. This approach uses data mining and machine learning to identify gold farmers by using an analysis in two phases. The first phase is a deductive logistic multiple regression model that describes the characteristics of gold farmers that differentiate them from a random sample of the population. The second phase is inductive and evaluates a cross-section of well-known classifiers like Naive-Bayes, KNN, Bayesian Networks, and Decision Trees (J48) to correctly identify gold farmers. We propose to study the problem of identifying gold farming as a binary classification problem. One of the motivations for doing so was that class labels for gold farmers were readily available.

A. *Phase I: Deductive logit model*

Because a single account can potentially control several characters, the master list of banned characters was collapsed by character level to generate a list of the highest-level character on 12,134 banned accounts. The banned table was joined with the character and demographic attribute tables by account number. A random sample of non-banned accounts matched by server population was added as a control. The total sample was 24,267 unique account-characters.

Based upon previous accounts of the behavior of gold farmers, we identified sets of demographic and character attributes to use as independent variables and controls in the sequential logistic regression against the binary banned/not-banned outcome. Player demographics (Model 1): Player demographics: Players banned for gold farming should be younger, more male, speak more Chinese, and have more recently-established accounts than typical players. Salient gold farming behavioral characteristics (Model 2): Players banned for gold farming should play for more extended periods of time, have more recorded adventuring time, a greater number of NPC kills, and greater overall wealth than typical players. Non-salient gold farming behavioral characteristics (Model 3): Players banned for gold farming should have lower levels of quests completed, active quests, tradeskill knowledge, tradeskill manufacturing, and deaths than typical players. Model 4 integrates the variables of models 2 and 3 to analyze identified behavioral characteristics and model 5 integrates model 1 and model 4 to control and analyze for both demographic and behavioral variables. The complete model (5) has a very good fit to the observed data (r^2 = 0.677) and logistic regression diagnostics indicate no substantial multicollinearity or specification errors. With respect to other behavioral characteristics, the large standardized coefficients for character age, number of NPCs killed, number of deaths, and experience gained from completing quests suggest these be employed for classification.

B. *Phase II: Inductive machine learning models*

Each set of features can be used separately to build classifiers or alternatively different types of features can be combined in the same classifier. The main intuition behind posing this problem as a classification problem is that gold farmers possess certain demographic and behavioral characteristics that can be exploited. We also extracted Activity Sequence Features which are the number of times the player was engaged in that activity e.g., the number of monsters killed, the number of potion recipes completed etc.

The behavioral data of any given player can be captured by looking into the sequence of activities performed by a player in a given session. We define a session is as a chunk of time in which the player was continuously playing the game with no gaps less than 30 minutes e.g., if a player played the game for two hours in the morning and one hour in the evening on the same day then the game play for that day is said to constitute two different sessions of game. Thus consider the following example of a sequence in a session: KKKDdKdEKdKD where K is killed a monster, D is player died, d is damage points and E is points earned. This sequence implies that the player killed three monsters before being killed, after resurrection the player suffered some damage followed by killing the monster but sustained further damage, and so on. The experiments were performed on the open source Data Mining software Weka which has implementations of many well-known data mining algorithms [26].

Results from different sets of features are given in Table III. Since the current problem is a rare class problem we only report the classification results for the rare class as the precision and recall for the dominant class is more than 99% in almost all the cases. From the domain experts point of view the goal of any gold farmer-detecting technique should be to increase the number of true positives (correctly identified gold farmers) while at the same time decreasing the number of false positives (legitimate players labeled as gold farmers). It is essential for these classifications to have high precision to minimize the number of false positive since any positive match has to be investigated by an administrator. Recall captures the other aspect of performance i.e., capturing as many gold farmers as possible but requires the actual number of positives

TABLE I
STANDARDIZED BETA COEFFICIENTS; T STATISTICS IN PARENTHESES * P <.05, ** P <.01, *** P <.001, N=24267

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Player age	0.097* (-2.54)				-0.174*** (-3.78)
Account age	-1.713*** (-25.81)				-0.747*** (-10.83)
Chinese	4.410*** (-64.06)				3.846*** (-48.23)
Female	0.028 (-0.65)				-0.102 (-1.95)
Character age		1.481*** (-17.69)		3.585*** (-28.46)	3.405*** (-23.39)
Time adventuring		3.031*** (-53.69)		1.326*** (-20.17)	0.553*** (-7.01)
NPC kills		-1.792*** (-24.22)		-3.011*** (-20.67)	-3.759*** (-20.89)
Bank wealth		-0.175*** (-5.36)		-0.025 (-0.50)	-0.008 (-0.13)
Personal wealth		0.095** (-2.89)		0.488*** (-9.57)	0.763*** (-12.73)
Rare items collected		-0.615*** (-16.98)		0.882*** (-12.88)	0.868*** (-9.3)
Quests completed			-5.375*** (-54.71)	-5.352*** (-45.52)	-3.045*** (-20.72)
Quests active			-0.566*** (-6.62)	-0.424*** (-4.59)	-0.162 (-1.37)
Recipes known			-1.337*** (-15.46)	-1.366*** (-14.83)	-0.752*** (-6.31)
Items crafted			1.454*** (-19.27)	0.312*** (-3.87)	0.267** (-2.65)
Total deaths			6.644*** (-69.92)	4.983*** (-34.74)	3.359*** (-19.14)
Total PVP deaths			-0.289*** (-6.31)	-0.318*** (-5.94)	-0.447*** (-6.14)
Psuedo-R^2	0.550	0.214	0.430	0.530	0.677

in the dataset. While the records in the data are all labeled as gold farmers and are assumed to certain gold farmers, there are likely to be players in the dataset who are gold farmers but were not identified or banned.

VI. RESULTS

A. Phase I: Deductive logit model

The results for various models from Phase I are given in Table I. The analysis from Phase I demonstrated that non-salient behavioral characteristics (model 3) accounted for substantially more variance than the salient behavioral characteristics (model 2). This suggests that along these salient characteristics (wealth, time played, rare items acquired), gold farmers may not differ substantially from other (elite) players but are significantly different along more latent characteristics such as how many quests they complete, how often they die, and their tradeskill expertise. It is likewise telling that even with 12 distinct predictive variables of gold farming activity in model 4, the 4-variable demographic-only model (model 1) still accounted for more of the variance among players identified as gold farmers. The analysis also bears out the intuition that players with old and well-established accounts are not as likely to be gold farmers.

Other than Chinese language (a dummy variable), player demographic attributes have a small effect compared to other variables. High levels of NPC kills, quests completed, and tradeskill recipe knowledge all strongly decreased the likelihood of being identified as a gold farmer in the model. This combination of variables suggests that farmers exhibit low levels of expertise across a variety of metrics. High levels of time played, time spent adventuring, and high total deaths are all factors associated with gold farming activity which also implies a low level of expertise within the game itself. While the accumulation of wealth in a bank was not significantly associated with gold farming activity which suggests that farmers have possibly adapted their behavior on this count to avoid detection the model does predict that gold farmers carry more coins on their character.

B. Phase II: Inductive machine learning models

As described in the previous section, different sets of features were used for different classifiers. Features used for classification include gender, language, location, character race, class, experience, wealth, age, deaths, player-versus-player activity, number of economic transaction, and anonymized social interaction data. The set of features used for each set of models are given in Table III. Table IV gives the corresponding results in terms of precision, recall and the F-Score for the various classifiers that we used. Using only the players' self-reported demographic characteristics for classification should have strongly predicted the identification of gold farmers given their skewed language distribution, but as seen in Model 1, two classifiers (JRIP and J48) misclassified every instance of the "farmer" class. By F-score, the KNN algorithm is the best metric for demographic features. Examining only features of the character played within the game, model 2 reveals that the algorithms identify gold farmers with much lower precision and recall than the demographic model alone.

The findings for activity distribution in model 3 are marginally better than the previous model employing character features classifiers but the KNN algorithm has markedly inferior precision and recall as compared to the demographic model. These predictive machine learning findings corroborate our earlier descriptive regression results that the salient behavioral characteristics on which we expect gold farmers to be differentiated from other players (wealth, time played, etc.) are not reliable features. The inability to distinguish farmers suggests that they are able to cloak their behavior given their similarity to highly-skilled players along the variables included in these models.

Next, we incorporated both the previous demographic features with cumulative statistics of how much experience and money characters had. As shown in Table III, the performance

TABLE II
DESCRIPTION OF MODELS

Model name	Classifier features
Model 1	Demographic features only
Model 2	Character features only
Model 3	Activity distribution features
Model 4	Demographic and accumulation features
Model 5	Sequence activity features
Model 6	Model 3 plus economic transactions
Model 7	Model 6 but for a sub-class

TABLE IV
F-MEASURES FOR GOLD FARMERS (DEMOGRAPHIC & STAT FEATURES)

Classifier	F_1-Score	$F_{0.8}$-Score	F_2-Score	$F_{0.5}$-Score
BayesNet	**0.371**	0.350	**0.445**	0.318
NaiveBayes	0.213	0.211	0.218	0.207
Logistic Reg.	0.294	0.333	0.223	**0.432**
AdaBoost	0.218	0.228	0.195	0.247
J48	0	0	0	0
JRIP	0.102	0.123	0.068	0.196
KNN	0.353	**0.351**	0.357	0.348

of all algorithms increased substantially across the board with the BayesNet exhibiting the strongest recall performance and KNN being an accurate predictor of gold farming activity. We next used our alphabet of 22 activities captured in the experience and transaction logs to perform two analyses incorporating activity sequences alone and the distribution of activity with economic transactions. We define a set of 10 patterns As seen in Table III, this sequence approach alone has poor precision and recall across all algorithms compared to previous methods. For model 6 we removed all instances where the number of activities associated with gold farmers was less than six, the number of gold farmers was reduced to 83. We then reran the same set of classifier for this new dataset for the activity distribution features. The performance of most of the classifiers improves in terms of both precision and recall. This confirms our earlier hypothesis that the various subclasses within the gold farmer class could be a source of confusion for the classifiers.

VII. CLASSIFIER SELECTION

The trade-offs between precision and recall are to be expected in classification problems. The best F-Score was obtained by using demographic features with KNN, yet BayesNet gives the highest value for recall if both the demographic and the character statistics are used. An alternative would be to use the ROC curve to decide which classifier to use. However, this cannot be used in our case since the false positive rate is extremely low for all the cases of classifiers and features that we have investigated.

However, we can address the problem of selecting a consistent classifier by referring to the domain. There are two main constraints that we are trying to satisfy: increasing the number of gold farmers who are caught and reducing the number of false positives as this would translate into work that has to be done by humans. Thus, given scarce human resources, precision should be given a high priority. One the other hand, if enough human resources are available, then more false positives can be tolerated if the number of true positives are likely to increase. This trade-off can be captured by using the generalized version of van Rijsbergens [23] F-measure as the metric for decision making. It can be described as follows:

$$F_\beta = (1+\beta^2)\cdot(precision\cdot recall)/(\beta^2\cdot precision + recall)$$

where β is a scaling factor that describes the relative importance of recall with respect to precision. This criteria can be illustrated as follows. Consider the results of various algorithms from Table IV. If equal weight is given to both precision and recall then Bayes not should be used as the classifier of choice. The same would occur if recall is given twice as important as precision. However if precision is given twice as importance as recall then Logistic Regression will be chosen, similarly if recall is said to be only 80% as important as precision then KNN would be chosen. The choice of values for β would depend upon the domain expert while taking into account the resources available.

VIII. CONCLUSION AND FUTURE WORK

Using an anonymized dataset extracted from the massively-multiplayer online game EverQuest II, we used several machine learning binary classification techniques to identify gold farmers within the game world. A number of feature types were explored for classification and various combinations of classifiers and features gave a wide range of results in terms of precision and recall. Despite the strong, significant effects observed across five logistic regression models for exploratory analysis, classifier algorithms operating on seven different combinations of behavioral data were not able to precisely identify gold farmers. We attribute the difficulty in discriminating between gold farmers and legitimate players to farmers specialization into distinct roles that exhibit very different behavioral signatures. From a domain expertise point of view, given the trade-off between identifying gold farmers and amount of effort required in investigating we proposed that the generalized F-Measure should be used to select which classifier and feature set combination should be used in which context. We note, however, that our evaluation is likely to be conservative. Since we cannot know the true number and identity of gold farmers within the data, it is possible - perhaps likely that a number of our false positives were farmers who had yet to be caught. Thus the precision rates here should be seen as a minimum baseline. If these cases could be investigated more closely, some may translate into true positives, further validating the approach.

Our future work will explore how to incorporate the behavioral signatures of each distinct gold farming role. These behavioral signatures will inform the development of different hierarchical regression models as well as building different classifiers. In this paper we have simply looked at the overall performance of the classifiers in detecting gold farmers. Given the applicability of this line of research to identifying other

TABLE III
CLASSIFIER PERFORMANCE FOR ALL GOLD FARMERS (BY MODEL)

Classifier	Measure	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
BayesNet	Prec.	0.208	0.033	0.0125	0.291	0.131	0.134	0.109
	Recall	0.225	0.186	0.102	0.513	0.131	0.102	0.265
	F-Score	0.216	0.057	0.112	0.371	0.131	0.116	0.155
NaiveBayes	Prec.	0.211	0.051	0.042	0.204	0.052	0.037	0.038
	Recall	0.223	0.136	0.190	0.223	0.293	0.190	0.313
	F-Score	0.216	0.074	0.069	0.213	0.088	0.061	0.068
LogisticReg.	Prec.	0.636	0.182	0.333	0.630	0.091	0.300	0.273
	Recall	0.192	0.017	0.020	0.192	0.010	0.020	0.036
	F-Score	0.294	0.031	0.038	0.294	0.018	0.038	0.064
AdaBoost	Prec.	0.412	0.051	0.042	0.271	0.052	0.037	0.038
	Recall	0.138	0.136	0.190	0.183	0.293	0.190	0.313
	F-Score	0.207	0.074	0.069	0.218	0.088	0.061	0.068
J48	Prec.	0	0.75	0.286	0	0.143	0.353	0.300
	Recall	0	0.025	0.027	0	0.010	0.041	0.036
	F-Score	0	0.049	0.050	0	0.019	0.073	0.065
JRIP	Prec.	0	0.333	0.286	0.526	0.250	0	0.250
	Recall	0	0.068	0.014	0.056	0.020	0	0.060
	F-Score	0	0.113	0.026	0.102	0.037	0	0.097
KNN	Prec.	0.493	0.050	0.086	0.345	0.112	0.122	0.176
	Recall	0.304	0.017	0.061	0.361	0.111	0.082	0.157
	F-Score	0.376	0.025	0.071	0.353	0.112	0.098	0.166

forms of cybercrime such as credit card fraud and money laundering as well as national security applications, we anticipate that the methods we develop for detecting gold farming could potentially be applied to these other datasets for validation.

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REFERENCES

[1] J. Balkin, *Virtual Liberty: Freedom to Design and Freedom to Play in Virtual Worlds.*, Virginia Law Review, vol. 90, no. 8, 2004.
[2] T. Bramwell, *World of Warcraft players banned for selling gold*, Games Industry March 14, 2005
[3] Castronova, E. (2005). *Synthetic worlds: The business and culture of online games.* Chicago: University of Chicago Press.
[4] Castronova, E. (2006) *A cost-benefit analysis of real-money trade in the products of synthetic economies*, Info, 8(6), 51-68
[5] Castronova, T., D. Williams, C. Shen, Y. Huang, B. Keegan, L. Xiong, R. Ratan (2009, in press). *As real as real? Macroeconomic behavior in a large-scale virtual world.* New Media and Society.
[6] D. Chan, *Negotiating intra-Asian games networks: on cultural proximity, East Asian games design, and Chinese farmers*, FibreCulture, vol. 8, 2006.
[7] H. Chen, W. Chung, J.J. Xu, G. Wang, Y. Qin, and M. Chau, *Crime Data Mining: A General Framework and Some Examples*, Computers & Security, vol. 37, no. 4, 2004, pp. 50-56.
[8] R. Davis, *Welcome to the new gold mines*, The Guardian, 2009.
[9] J. Dibbell, *Play Money: Or, How I Quit My Day Job and Made Millions Trading Virtual Loot*, Basic Books, 2006.
[10] Grimmelmann, J. (2006). *Virtual Power Politics. The State of Play: Law, Games, and Virtual Worlds.* J. M. Balkin and B. S. Noveck. New York, New York University Press.
[11] Heeks, Richard *Analysis Current Analysis and Future Research Agenda on "gold farming": Real-World Production in Developing Countries for the Virtual Economies of Online Games* Development Informatics Group IDPM, SED, University of Manchester, UK - 2008
[12] B. Howell, *Real World Problems of Virtual Crime*, Cybercrime: Digital Cops in a Networked Environment, J.M. Balkin, G. Grimmelmann, E. Katz, M. Kozlovski, S. Wagman, and T. Karzky eds., New York University Press, 2007.
[13] J.-S. Huhh, *Culture and Business of PC Bangs in Korea*, Games and Culture, vol. 3, no. 1, 2008, pp. 26.
[14] Hunter, D. *The early history of real money trades*, TerraNova, 13 Jan 2006 http://terranova.blogs.com/terra_nova/2006/01/the_early_histo.html
[15] G. Jin, *Chinese Gold Farmers in the Game World*, Consumers, Commodities, & Consumption, vol. 7, no. 2, 2006.
[16] G. Lastowka, *ID theft, RMT & Lineage*, Terra Nova 2006; http://terranova.blogs.com/terra_nova/2006/07/id_theft_rmt_nc.html.
[17] Aleksandar Lazarevic, Levent Ertz, Vipin Kumar, Aysel Ozgur, Jaideep Srivastava *A Comparative Study of Anomaly Detection Schemes in Network Intrusion Detection*. SDM 2003
[18] V. Lehdonvirta, *Virtual economics: applying economics to the study of game worlds*, Virtual economics: applying economics to the study of game worlds, 2005.
[19] T. Lehtiniemi, *How big is the RMT market anyway*, Virtual Economy Research Network, no. March 2, 2007.
[20] T.M. Malaby, *Anthropology and Play: The Contours of Playful Experience*, SSRN, 2008.
[21] T. Taylor, *Play between worlds: Exploring online game culture*, MIT Press, 2006.
[22] K. Taipale, *How Technology, Security, and Privacy Can Coexist in the Digital Age*, Cybercrime: Digital Cops in a Networked Environment, J.M. Balkin, G. Grimmelmann, E. Katz, N. Kozlovski, S. Wagman, and T. Karzky eds., New York University Press, 2007.
[23] van Rijsbergen, 1979 van Rijsbergen, C. J. (1979). Information Retrieval. Butterworths, London
[24] White, P. (2008). *MMOGData: Charts*. Gloucester, United Kingdom. http://mmogdata.voig.com/
[25] Brian Wilcox, Sony Online Entertainment Personal Communication.
[26] Ian H. Witten and Eibe Frank (2005) *Data Mining: Practical machine learning tools and techniques*, 2nd Edition, Morgan Kaufmann, San Francisco, 2005.
[27] N. Yee, *The labor of fun: how video games blur the boundaries of work and play*, Games and Culture, vol. 1, no. 1, 2006, pp. 68-71.