Modeling Player Performance in Massively Multiplayer Online Role-Playing Games: The Effects of Diversity in Mentoring Network

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***Abstract*—This study investigates and reports preliminary findings on player performance prediction approaches which model player's past performance and social diversity in mentoring network in EverQuest II, a popular massively multiplayer online role-playing game (MMORPG) developed by Sony Online Entertainment. Our contributions include a better understanding of performance metrics used in the game and a foundation of recommendation systems for mentors and apprentices. We examined three different game servers from the EverQuest II game logs. In all three servers, the results from our analyses suggest that increase in social diversity in terms of characters and classes encountered moderately negatively correlates with player performance. Based on this finding, we built predictive models to predict player's future performance based on past performance and social diversity in terms of mentoring activities. Our results indicate that 1) models employing past performance and social diversity perform better and 2) prediction for mentors is generally better than that for apprentices.**

Keywords-video games; massively multiplayer online games; player performance; mentoring

I. Introduction

A. Background

Massively Multiplayer Online Role-Playing Games (MMORPGs) are personal computer or console-based digital games where thousands of players can simultaneously sign on to the same online, persistent virtual world to interact and collaborate with each other through their in-game characters. Recent years have seen an explosive growth in digital game sales including MMORPGs. As people spend more time in virtual environments, researchers have recently taken notice that virtual environments such as EverQuest II, developed by Sony Online Entertainment, serve as a major mechanism for socialization [1,2].

While many games today provide in-game "how to started" guides to help newcomers ramp up quickly in the early stage of the game as well as in-game assistants throughout the game to help identify tasks to perform to gain rewards, it lacks accurate player performance prediction systems which can model not only player's past performance but social interactions which can influence player performance. In this study, we focus on statistical analysis of player performance prediction models based on player's past performance and social diversity in mentoring network. We use operational data of game players in EverQuest II. Our findings provide a foundation for a customized performance management system and mentor/apprentice recommendation system during game play where its primary objective is to evaluate and suggest mentoring-based social interactions in order to optimize player performance.

Furthermore, educational research has found virtual environments to be a sound venue for studying learning, collaboration, social participation, literacy in online space, and learning trajectory at the individual level as well as at the group level. The approach and the results presented in this paper also contribute to a better understanding of learners in virtual environments for educational research (i.e. E-learning, education games) with potential applications in student performance assessment, course and curriculum recommendation, and dynamic monitoring of and instant feedback on student performance.

B. Mentoring Network

In this study, we analyze the mentoring network in EverQuest II where we focus on combat-oriented activities where the skill assessment and projection models have already been built [1,3]. This network consists of two or more players teaming up together to kill monsters where one or more team members (of higher level) can mentor a team member (of lower level).

In mentor system, higher level players act as mentors to lower level players. Mentors level down to the level of their apprentices in order to teach them combat skills, transmit knowledge about different aspects of the game, and perform one or more tasks with the apprentices. This is almost analogous to an in-class one-on-one teaching between a teacher and a student. Mentors gain achievement points from successfully completing tasks with their apprentices. Apprentices also gain experience (XP) points (plus bonus XP for participating in mentoring) from, for instance, killing monsters but more importantly, they attain valuable lessons and experience by interacting with their mentors. A skilled

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and knowledgeable mentor will help his apprentice pick up the game quickly and efficiently. A given player can have multiple mentors in a session. He can interact with one mentor at a time. When the mentor levels down, his abilities will also scale down to that level.

C. Research Problems

While there are numerous studies on the effects of mentoring on mentors and mentees [9-12], little is understood about the effects of mentoring on player performance in highly social-driven games such as MMORPGs. In this study, we focus on building player performance prediction models which incorporate information about player's past performance and social diversity in mentoring interactions in the game.

II. DATASET

A. Game Logs: In-game Behavior Data

The study uses nine months worth of player and team activity data on 'Guk' server (Player-versus-Environment or PvE), 'Antonia Bayle' server (Role-Playing or RP), and 'Nagafen' server (Player-versus-Player or PvP), between January 2006 and September 2006.

	Guk	Antonia Bayle	Nagafen
Total # characters	64,102	102,177	130,472
Total # characters as mentors (%)	18.4%	14.2%	9.2%
Total # characters as apprentices (%)	28.4%	23.7%	18.0%

Table 1 – Dataset Overview

The dataset contains at the minimum the following information about game players and their characters: class, race, task, timestamp of task completion, group size (whether a given character grouped with one or more other characters in completing a task), average group level (if a given character played with one or more other characters, this value represents the average of player levels of all characters involved in that group), XP points, location (location in which the task was completed), and mentoring and apprenticeship activities. Details of the game's point-scaling system, task types, combat team formation, and character selection are described in [1,3-5]. A previous study [1] defines player performance in EverQuest II as a function of XP point gain and play time (referred to as session time). We refer to this measure as player Efficiency Index. Given two players, the one with a larger point gain, given the same amount of time as the other player, is considered more efficient. This study uses Efficiency Index as the player performance metric.

B. Character Social Diversity

For each player, we compute social diversity score with respect to different characters he/she socializes with in mentoring network. We term this "Character Diversity," and it is computed as the following:

$$\log_2 \frac{(\#\, unique\ apprentices)}{(\#\, mentoring\ sessions)}$$

Likewise, for apprentices, we compute Character Diversity as:

$$\log_2 \frac{(\#\, unique\ mentors)}{(\#\, apprenticing\ sessions)}$$

C. Class Social Diversity

For each player, we compute social diversity score with respect to different classes [8] he/she socializes with in mentoring network. We term this "Class Diversity," and it is computed as the following:

$$\log_2 \frac{(\#\, unique\ apprentice\ classes)}{(\#\, mentoring\ sessions)}$$

Likewise, for apprentices, we compute social diversity score as:

$$\log_2 \frac{(\#\, unique\ mentor\ classes)}{(\#\, apprenticing\ sessions)}$$

III. PLAYER PERFORMANCE AND SOCIAL DIVERSITY

First, we report our preliminary findings on the relationship between player performance and social diversity.

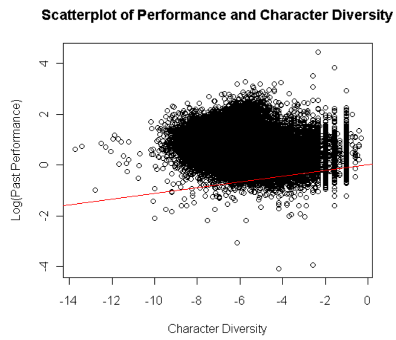

Figure 1 - Correlation between Player Performance and Character Diversity ('Guk' server, mentors) Adjusted R-squared: 0.538, P-value < 2.2e-16

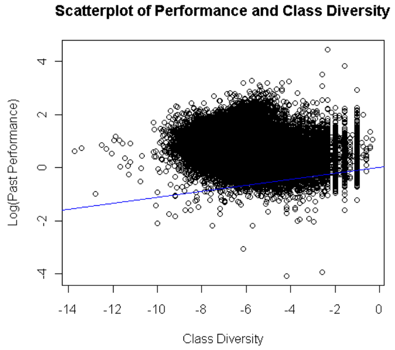

Figure 2 - Correlation between Player Performance and Class Diversity ('Guk' server, mentors) Adjusted R-squared: 0.5387, P-value < 2.2e-16

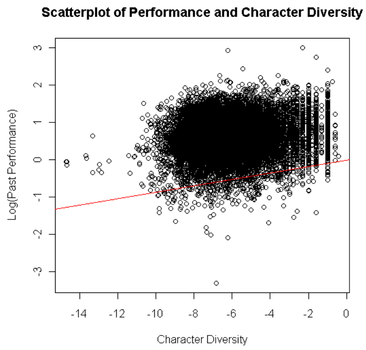

Figure 3 - Correlation between Player Performance and Character Diversity ('Guk' server, apprentices) Adjusted R-squared: 0.4367, P-value < 2.2e-16

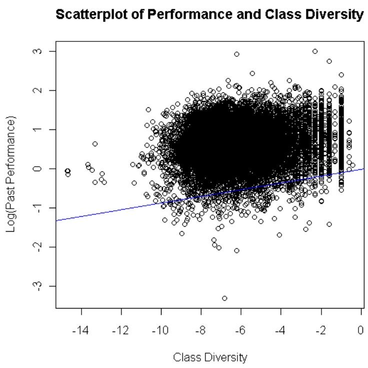

Figure 4 - Correlation between Player Performance and Class Diversity ('Guk' server, apprentices) Adjusted R-squared: 0.4371, P-value < 2.2e-16

Figure 1 shows that player performance is moderately negatively correlated with player performance. As the Character Diversity value decreases, player performance moderately increases. Figure 2 shows that player performance is moderately negatively correlated with player performance. As the Class Diversity value decreases, player performance moderately increases. Figures 3 through 4 are showing a similar trend of moderate correlation.

For 'Antonia Bayle' server, we report Adjusted R-squared and P-value below:

- [Mentors, Character Diversity] R-squared: 0.394
- [Mentors, Class Diversity] R-squared: 0.3934
- [Apprentice, Character Diversity] R-squared: 0.4915
- [Apprentice, Class Diversity] R-squared: 0.4923
- In all of the above cases, P-value < 2.2e-16.

For 'Nagafen' server, we report Adjusted R-squared and P-value below:

- [Mentors, Character Diversity] R-squared: 0.4663
- [Mentors, Class Diversity] R-squared: 0.4662
- [Apprentice, Character Diversity] R-squared: 0.1217
- [Apprentice, Class Diversity] R-squared: 0.1215
- In all of the above cases, P-value < 2.2e-16.

IV. PLAYER PERFORMANCE PREDICTION

This section describes our prediction of player performance, which models player's past performance and social diversity. We use Weka [13], an open-source data mining suite, to evaluate various classification algorithms on our dataset. We use 10-fold cross-validation. Player's future performance is the dependent variable and the independent variables are different in the following settings:

1. [Experiment 1] Past player performance only
2. [Experiment 2] Past player performance, Character Diversity, and Class Diversity

We performed logarithmic nonlinear transformation on the independent variable. Below, we report prediction results, and here is the legend: 1) CC = Correlation Coefficient, 2) MAE = Mean Absolute Error, 3) RMSE = Root Mean Squared Error, 4) RAE = Relative Absolute Error, 5) RRSE = Root Relative Squared Error.

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.713	0.124	0.164	66.65	70.13
	REP Tree	0.752	0.120	0.157	62.80	66.29
	Bagging (REP Tree)	0.772	0.116	0.151	60.32	63.65
Exp2	Linear Regression	0.715	0.124	0.164	66.46	69.92
	REP Tree	0.752	0.115	0.155	61.86	66.55
	Bagging (REP Tree)	0.800	0.105	0.140	56.15	60.04

Table 2 - Prediction Results ('Guk' server, mentors)

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.567	0.145	0.193	79.41	82.41
	REP Tree	0.524	0.157	0.213	81.07	85.78
	Bagging (REP Tree)	0.547	0.153	0.208	79.34	84.07
Exp2	Linear	0.572	0.144	0.192	78.99	82.00

	Regression					
	REP Tree	0.590	0.136	0.191	74.50	81.69
	Bagging (REP Tree)	0.639	0.128	0.180	69.88	77.10

Table 3 - Prediction Results ('Guk' server, apprentices)

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.752	0.120	0.156	62.85	65.92
	REP Tree	0.752	0.120	0.157	62.80	66.29
	Bagging (REP Tree)	0.772	0.116	0.151	60.32	63.65
Exp2	Linear Regression	0.754	0.120	0.156	62.62	65.68
	REP Tree	0.758	0.118	0.156	61.61	65.78
	Bagging (REP Tree)	0.802	0.108	0.142	56.10	59.75

Table 4 - Prediction Results ('Antonia Bayle' server, mentors)

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.575	0.150	0.203	77.63	81.85
	REP Tree	0.524	0.157	0.213	81.07	85.78
	Bagging (REP Tree)	0.547	0.153	0.208	79.34	84.07
Exp2	Linear Regression	0.581	0.149	0.202	77.32	81.42
	REP Tree	0.531	0.155	0.212	80.13	85.41
	Bagging (REP Tree)	0.562	0.150	0.206	77.39	82.97

Table 5 - Prediction Results ('Antonia Bayle' server, apprentices)

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.805	0.117	0.152	55.72	59.34
	REP Tree	0.810	0.115	0.151	54.59	58.92
	Bagging (REP Tree)	0.825	0.111	0.145	52.56	56.59
Exp2	Linear Regression	0.807	0.117	0.151	55.52	59.10
	REP Tree	0.822	0.110	0.147	52.27	57.24
	Bagging (REP Tree)	0.854	0.100	0.133	47.58	52.06

Table 6 - Prediction Results ('Nagafen' server, mentors)

	Algorithm	CC	MAE	RMSE	RAE (%)	RRSE (%)
Exp1	Linear Regression	0.591	0.152	0.202	76.39	80.70
	REP Tree	0.561	0.154	0.209	77.32	83.50
	Bagging (REP Tree)	0.592	0.149	0.203	74.71	80.90
Exp2	Linear Regression	0.613	0.149	0.198	74.86	79.02
	REP Tree	0.581	0.149	0.206	74.94	82.39
	Bagging (REP Tree)	0.638	0.138	0.193	69.55	77.09

Table 7 - Prediction Results ('Nagafen' server, apprentices)

In Tables 2 through 7, we compare the prediction results between Experiment 1 (not including social diversity as part of feature representation) and Experiment 2 (including social diversity). Overall, across all three game servers, for both mentors and apprentices, the coefficient correlation is higher in Experiment 2. Additionally, MAE's, RMSE's, RAE's, and RRSE's are slightly smaller in Experiment 2. Overall, the results indicate that the predictive models built on both past performance and social diversity better fit the data across all three game servers for both mentors and apprentices. Also, prediction for mentors is overall better than that for apprentices.

V. CONCLUSIONS

This research investigates and reports preliminary findings on the effects of social diversity in mentoring network on player performance. We examined three different game servers from the EverQuest II game logs. In all three servers, the results from our analyses suggest that increase in social diversity in terms of characters and classes encountered moderately negatively correlates with player performance. Based on this finding, we built predictive models to predict player's future performance based on past performance and social diversity in terms of mentoring activities. Future directions include exploring more prediction algorithms, building predictive models for different player population segments (i.e. class, race, gender), and investigating other in-game variables that can potentially improve the current models for apprentices.

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