Computational Social Science

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Talk Outline

- Part I – Emergence of a new paradigm for social science research
  - Introduction
    - What is computational social science (CSS)?
    - How is it different from social computing (SC)?
  - Why interest in CSS now?
  - Massively Multiplayer Online Games (MMOGs) and Virtual Worlds (VWs) as 'microscopes for social science'
- Part II – New ways of doing social science
  - The Virtual World Exploratorium (VWE) project
  - Specific studies
    - (i) macroeconomic behavior, (ii) trust, reputation and social capital, (iii) **identifying unacceptable behavior (gold farming),** (iv) **social networks and network effects,** (v) **social influence and customer churn**, (vi) **individual and group performance**
- Part III – New challenges for computer science
  - Specific challenges
    - (i) **new computational methods**, (ii) quantification of largely qualitative concepts, e.g. 'group, 'trust', etc.,
- Concluding remarks

Part I – Emergence of a new paradigm for social science research

- Introduction
  - What is computational social science (CSS)?
  - How is it different from social computing (SC)?
- Why interest in CSS now?
- Massively Multiplayer Online Games (MMOGs) and Virtual Worlds (VWs) as ‘microscopes for social science’

Introduction

- Computational Social Science (CSS)
  - Is the emergence of a new paradigm of studying social science that uses computation as an integral part, and not just as a standalone data analysis tool, e.g. ANOVA
  - Has the potential to
    - Further our understanding of human behavior, at the individual and group level, and
    - Help us understand new behaviors emerging as part of the Internet/Web revolution
- Social Computing (SC)
  - Is the creation of tools to enable richer social behavior and experience on the Web
- Success in each enables the other
  - **Great +ve feedback loop!!**

Why Interest in CSS Now?

- In one word (or click)

Multidimensional Networks in Virtual Worlds
Multiple Types of Nodes and Multiple Types of Relationships

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MMOGs and VWs as Microscopes of SS

- 1950s
  - Invention of the electron microscope fundamentally changed chemistry from ‘playing with colored liquids in a lab’ to ‘truly understanding what’s going on’
- 1970s
  - Invention of gene sequencing fundamentally changed biology from a qualitative field to a quantitative field
- 1980s
  - Deployment of the Hubble (and other) Space telescopes has had fundamental impact on astronomy and astrophysics
- 2000s
  - Massive adoption is fundamentally changing social science research
  - Massively Multiplayer Online Games (MMOGs) and Virtual Worlds (VWs) are acting as ‘microscopes of human behavior’
- And the Web Engineering community is building this microscope, without which this would not be possible!!

Part II – New Ways of Doing Social Science

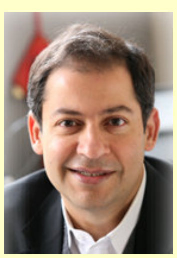
- The Virtual World Exploratorium (VWE) project
- Specific studies
  - macroeconomic behavior
  - social networks and network effects
  - social influence and customer churn
  - individual and group performance
  - identifying unacceptable behavior (gold farming)

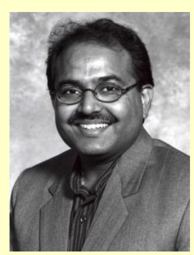
VWE

VIRTUAL WORLDS EXPLORATORIUM

The VWE Project

- Four PIs, 15 PhD students
  - Noshir Contractor, Northwestern: Networks
  - M. Scott Poole, Illinois Urbana-Champaign/NCSA: Groups
  - Jaideep Srivastava, Minnesota: Computer Science
  - Dmitri Williams, USC: Social Psychology
- Collaborators
  - Castronova (Sociology, Indiana), Yee (Xerox PARC), Consalvo, Caplan (Economics, Delaware), Burt (Sociology, U of Chicago), Adamic (Info Sci, Michigan)
- Industry partners
  - Sony (EverQuest 2), Blizzard (World of Warcraft), Linden Labs (2nd Life), Coudera Systems (Hadoop)
- Funding Sources
  - NSF, Army Research Institute, respective institutions, …





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The Minnesota Team

- Faculty Supervisor
  - Jaideep Srivastava
- Post Doctoral Assistant
  - Young Ae Kim
- Ph. D. candidates
  - Nishith Pathak, Muhammad A. Ahmad, Kyong Jin Shim, Jaya Kawale, Colin DeLong
- M.S. candidates
  - Rasik Phalak
- Undergraduate
  - Aarti
- High School students
  - Arjun, Nikhil, Richa, Rashi

Elements of the EQ2 MMOG

- Fantasy based
- Create character
- Never ending quest for advancement and exploration
- Underlying Storyline: Conflict between good and evil factions
- Band with other characters
- Quests to kill monsters
- Craftwork
- Socializing

Some key issues

- The generalizability issue
  - Is one game/world like another? To what degree?
  - Is MMOG behavior similar to VW behavior?
- VW ←→ RW mapping
  - What is the correlation between VW and RW behavior?

=

?

An Example of VW → RW Mapping ☺

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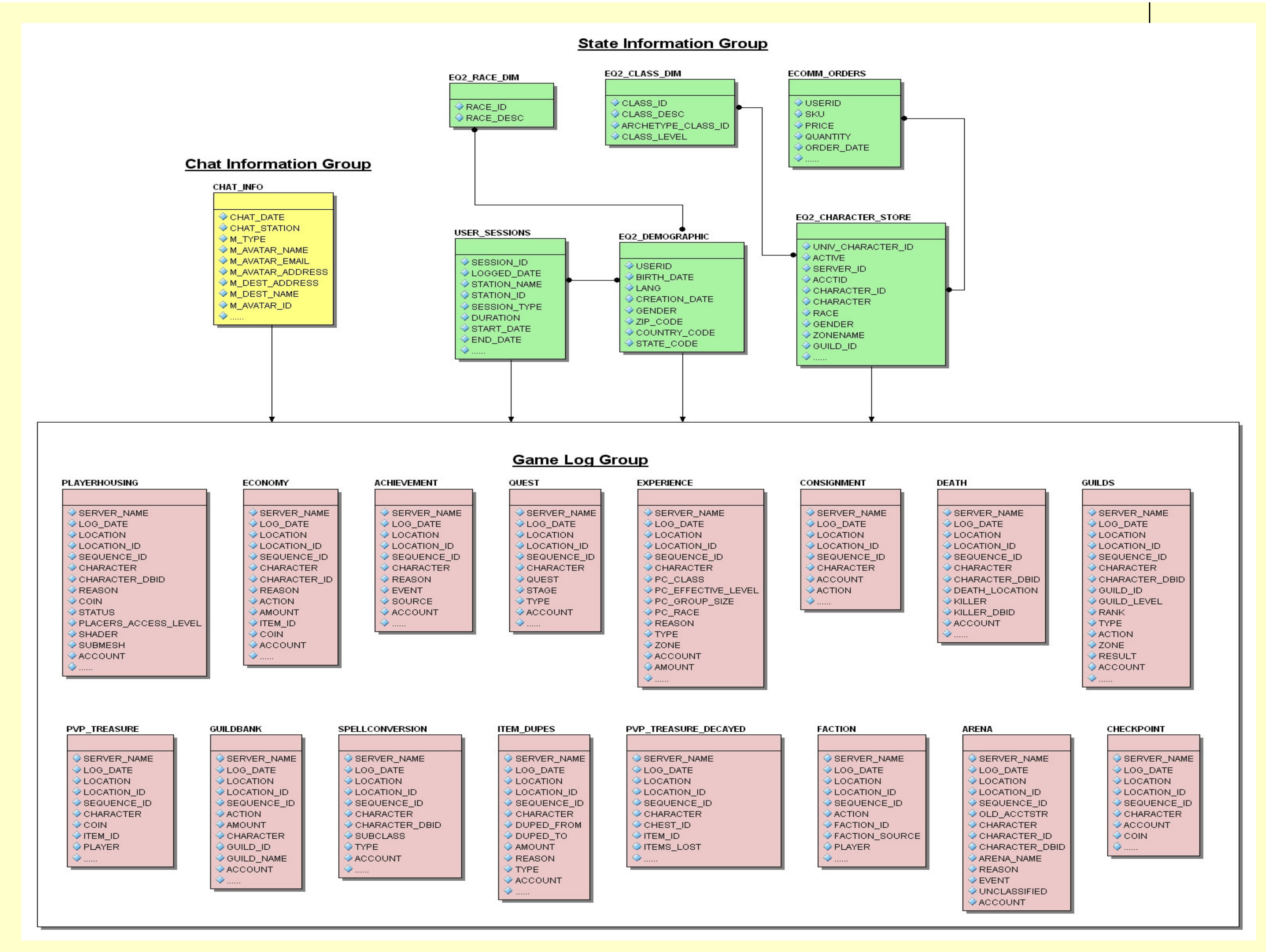
Stats on the Data

- EQ2 basics
  - About 175,000+ players
  - Dozens of servers worldwide
  - Successor to Ever Quest
- Data:
  - 23 tables, 500 classifications of actions
  - 3 Terabytes of data
  - Data captured at the level of actions

http://www.youtube.com/watch?v=G3VamwcAlzs


State Information Group
EQ2_RACE_DIM
RACE_ID
RACE_DESC
EQ2_CLASS_DIM
CLASS_ID
CLASS_DESC
ARCHETYPE_CLASS_ID
CLASS_LEVEL
ECOMM_ORDERS
USERID
SKU
PRICE
QUANTITY
ORDER_DATE
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Chat Information Group
CHAT_INFO
CHAT_DATE
CHAT_STATION
M_TYPE
M_AVATAR_NAME
M_AVATAR_EMAIL
M_AVATAR_ADDRESS
M_DEST_ADDRESS
M_DEST_NAME
M_AVATAR_ID
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USER_SESSIONS
SESSION_ID
LOGGED_DATE
STATION_NAME
STATION_ID
SESSION_TYPE
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EQ2_DEMOGRAPHIC
USERID
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EQ2_CHARACTER_STORE
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Findings from a Player Survey

Who is playing?

- It is not just a bunch of kids
- Average age is 31.16 (US population median is 35)
- More players in their 30s than in their 20s.

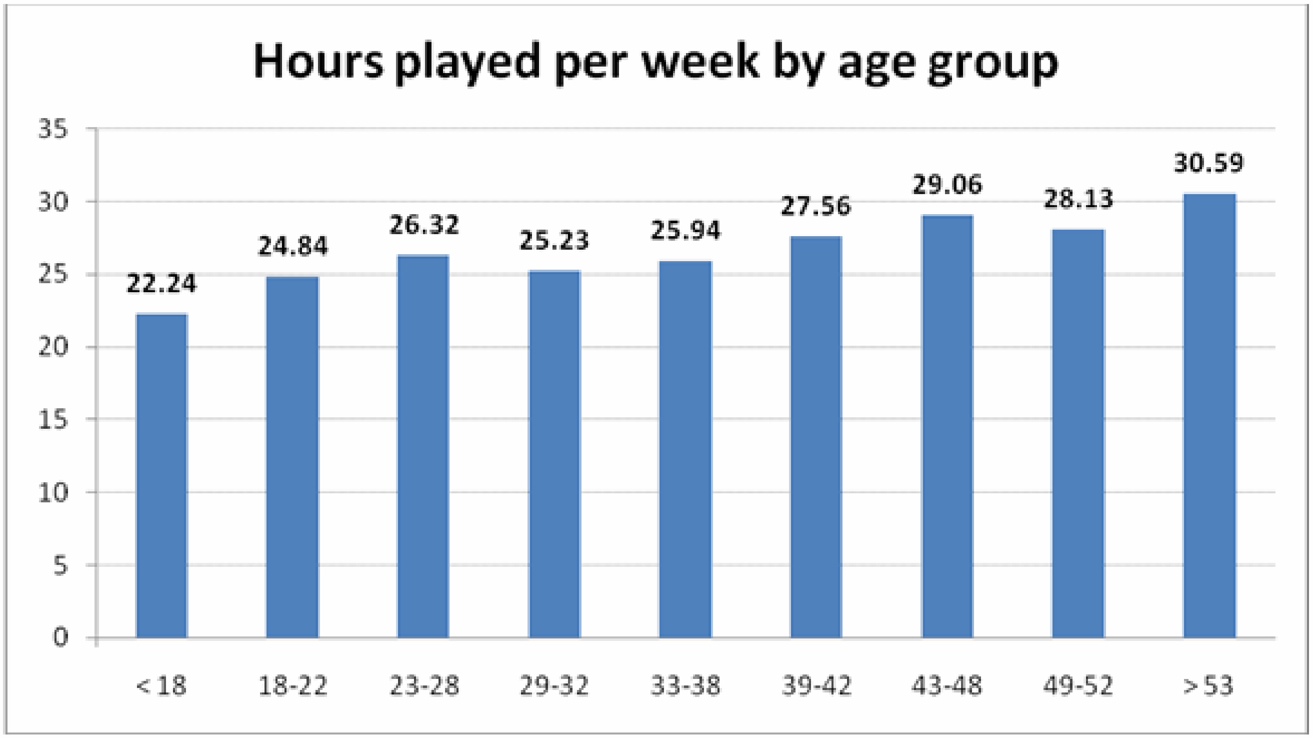
Table 1

Basic age range of EQ2 *players*

Age range	Percentage	Cumulative Percentage
Teens, 12-17	6.58	6.58
College-age, 18-22	12.40	19.09
Young adult, 23-29	26.27	45.61
Thirties, 30-39	36.69	82.64
Forties, 40-49	12.40	95.16
Fifty or older, 50-65	4.80	100.00

How much do they play?

- Mean is 25.86 hours/week
- Compares to US mean of 31.5 for TV (Hu et al, 2001)

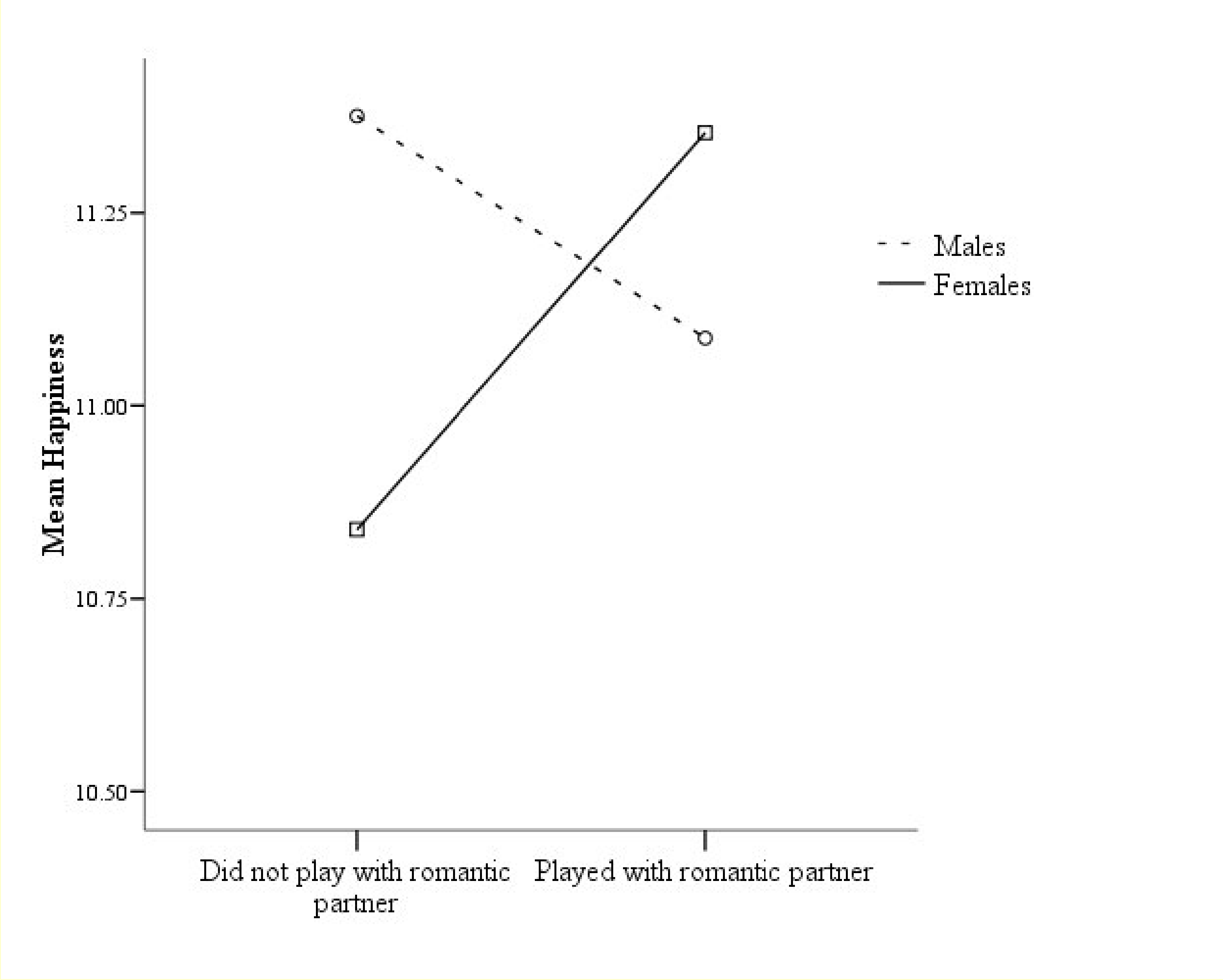


- From prior experimental work, MMO play eats into entertainment TV and going out, not news
- So much for kids being the ones with the free time.

Gender Differences

- Men play more other games, but it was the women who were more satisfied EQ2 players
  - Women: 29.32 hours/week
  - Men: 25.03 hours/week
  - Likelihood of quitting: “no plans to quit”: women 48.66%, men 35.08%
- Gender role theory
  - Boys and girls are socialized early on, and thus have clear role expectations for their behaviors and identities
  - Men indeed were more of the players (80/20%), and played to compete vs. women played to socialize
- Self reported play times
  - Women: 26.03 (3 hours less than actual)
  - Men: 24.10 (1 hour less than actual)

Playing with a partner: Apparently not good for the gander!

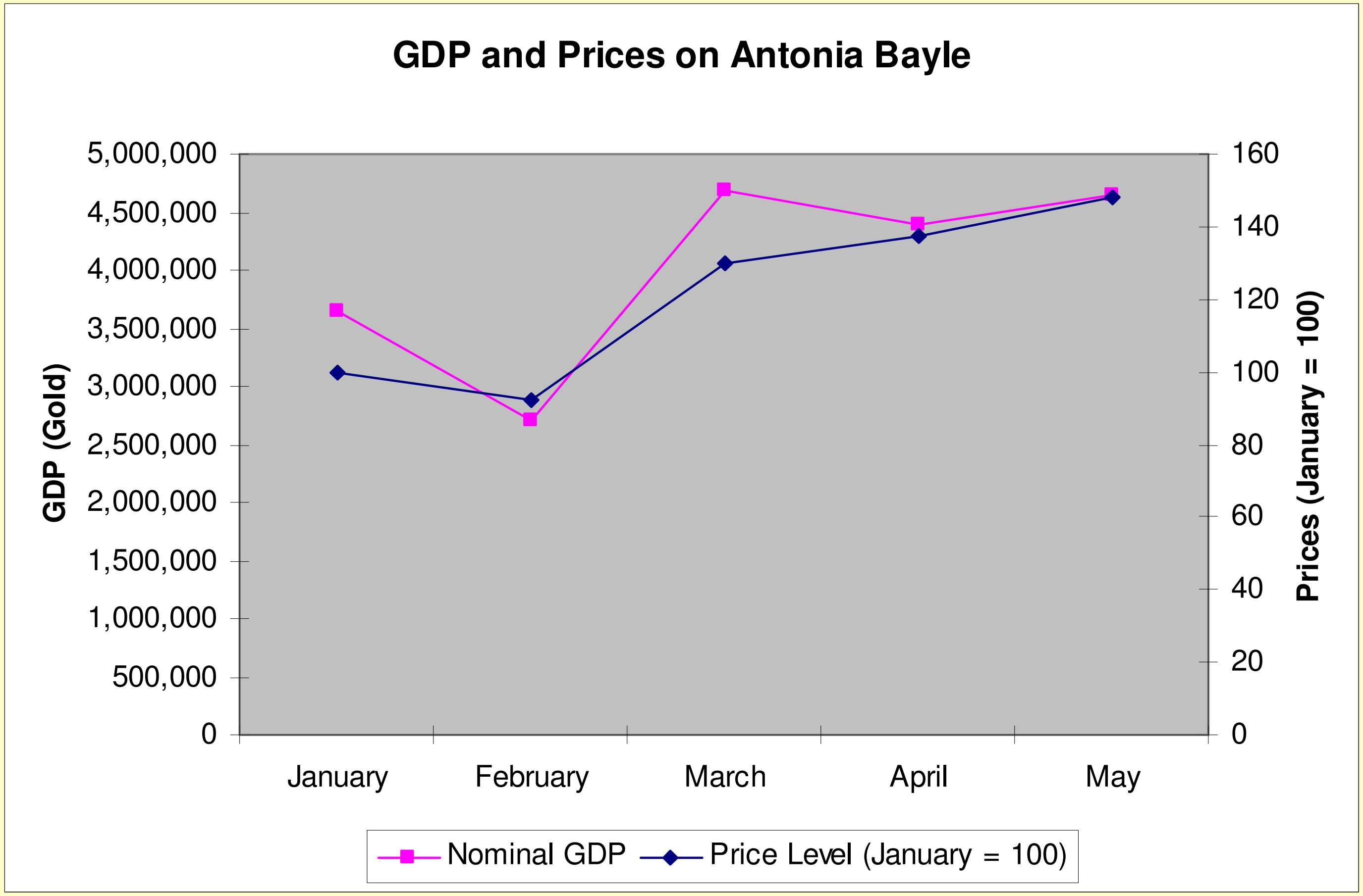


Economics: A test of RW ←→ VW mapping

- Do players behave in virtual worlds as we expect them to in the actual world?
- Economics is an obvious dimension to test
- In the real world, perfect aggregate data are hard to get

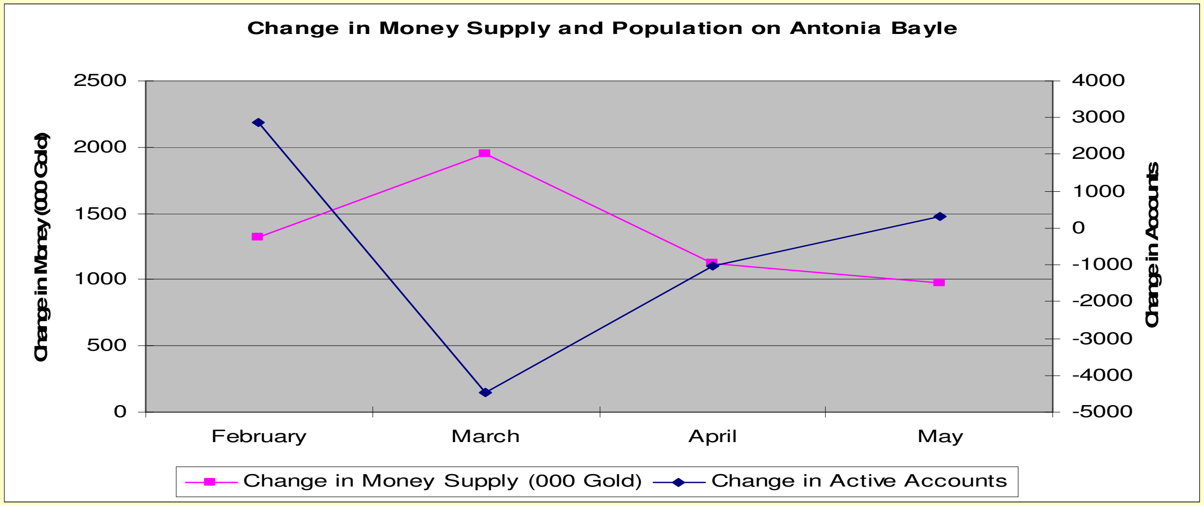
GDP and Price Level

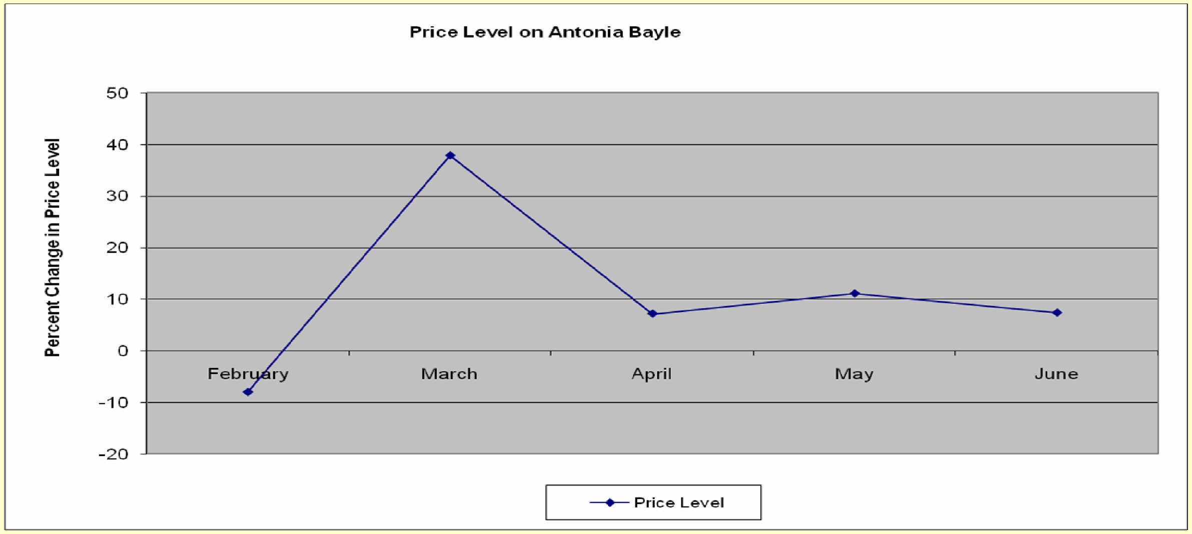
- GDP and price levels are robust but comparatively unstable



Money Supply and Price

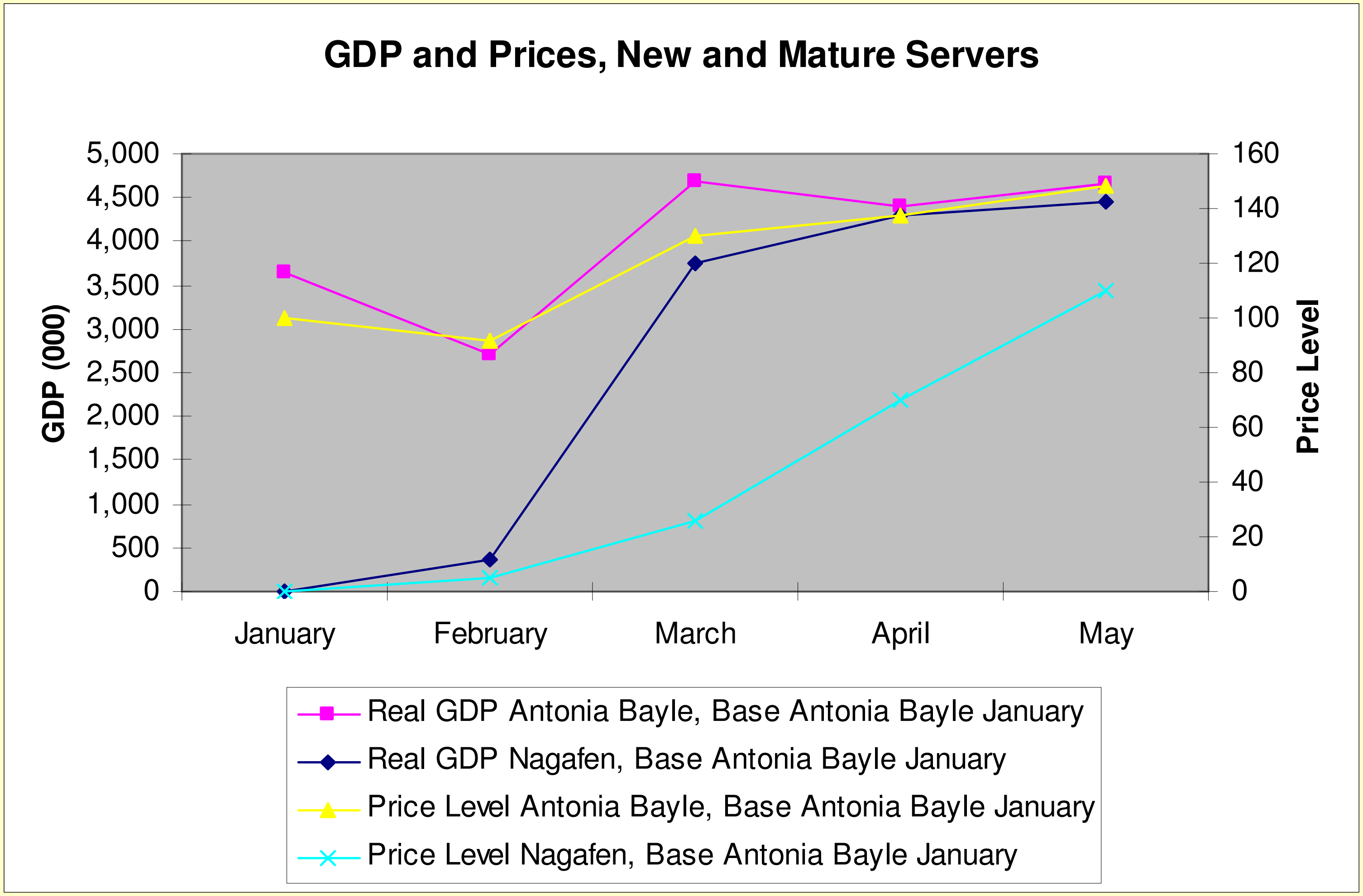
- The instability is explicable through the Quantity Theory of Money
  - a rapid influx of money . . .
  - . . . dramatically boosted prices
- More evidence that this behaves like a real economy





Introduction of Competition

- A new server's GDP and price level rapidly converge to those of an existing server (replicability)



Networks in Virtual Worlds

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Why do we create and sustain networks?

- Theories of self-interest
- Theories of social and resource exchange
- Theories of mutual interest and collective action
- Theories of contagion
- Theories of balance
- Theories of homophily
- Theories of proximity
- Theories of co-evolution

Sources:

Contractor, N. S., Wasserman, S. & Faust, K. (2006). Testing multi-theoretical multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of Management Review*.

Monge, P. R. & Contractor, N. S. (2003). *Theories of Communication Networks*. New York: Oxford University Press.

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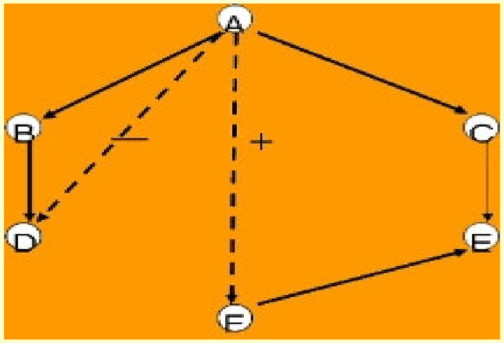
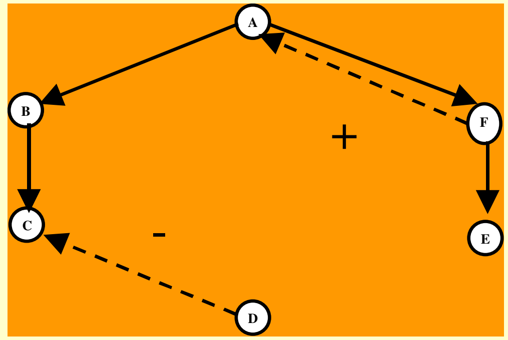
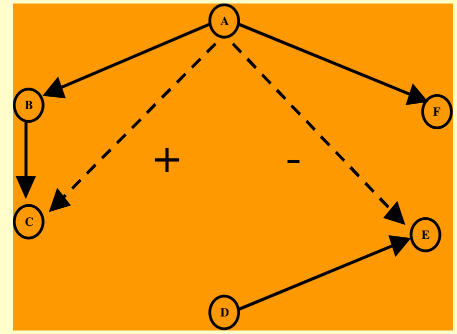
“Structural signatures” of Social Theories



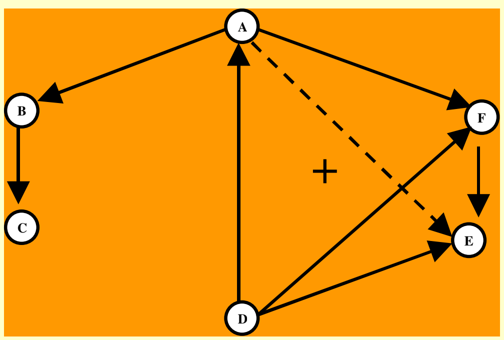
Self interest



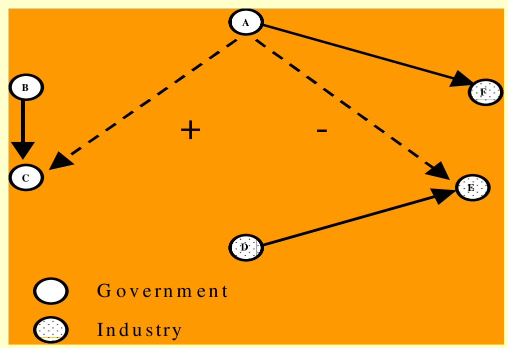
Exchange



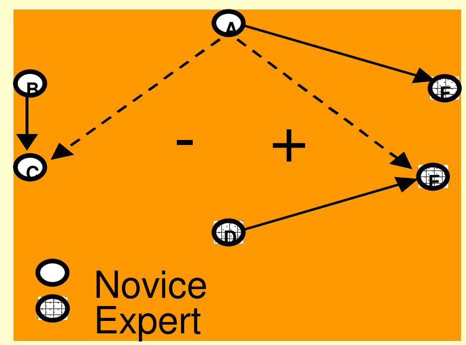
Balance



Collective Action



Homophily



Contagion

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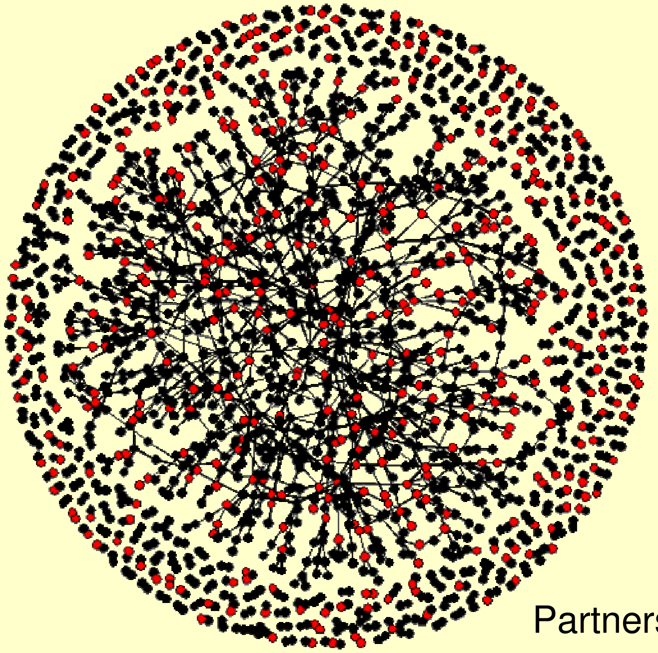
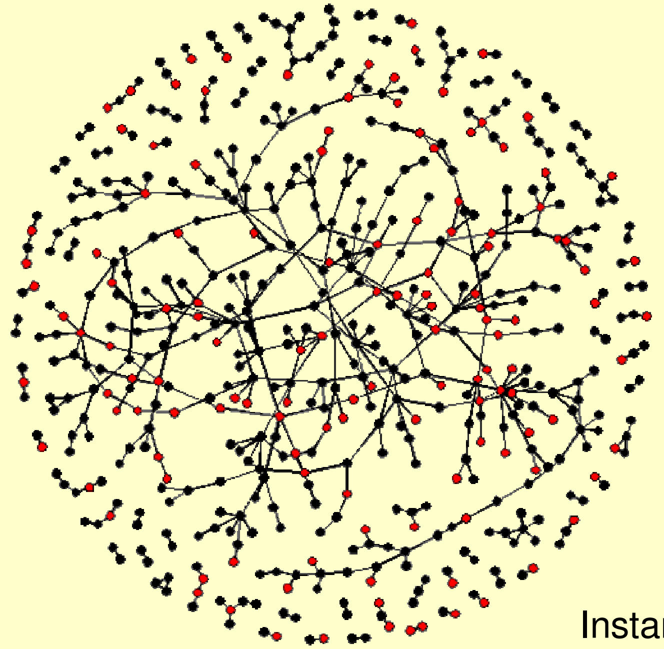
Four Types of Relations in EQ2

- *Partnership*: Two players play together in combat activities;
- *Instant messaging*: Two players exchange messages through Sony universal chat system
- *Player trade*: Players meet “face-to-face” in EQ2 and one gives items to another;
- *Mail*: One player sends a message and/or items to others by in-game mail

	Synchronous	Asynchronous
Interpersonal interaction	Partnership, Instant messaging	
Transactional interaction	Player trade	Mail

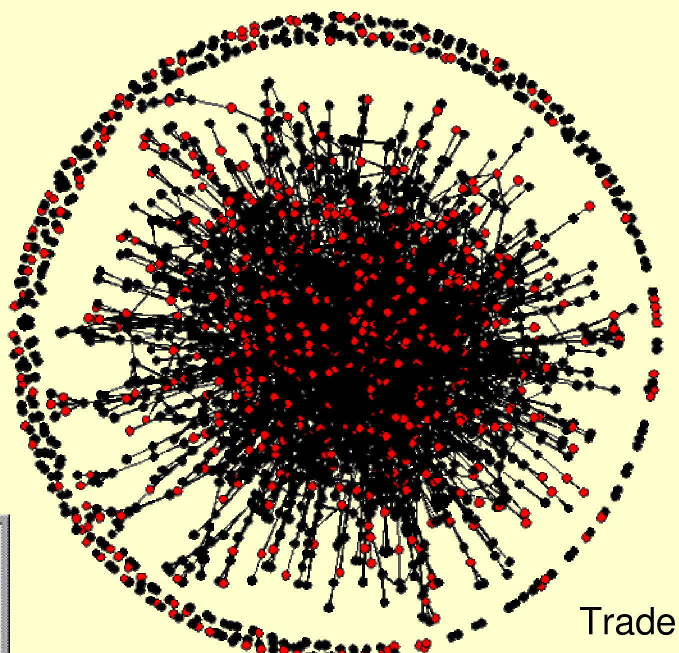


Partnership

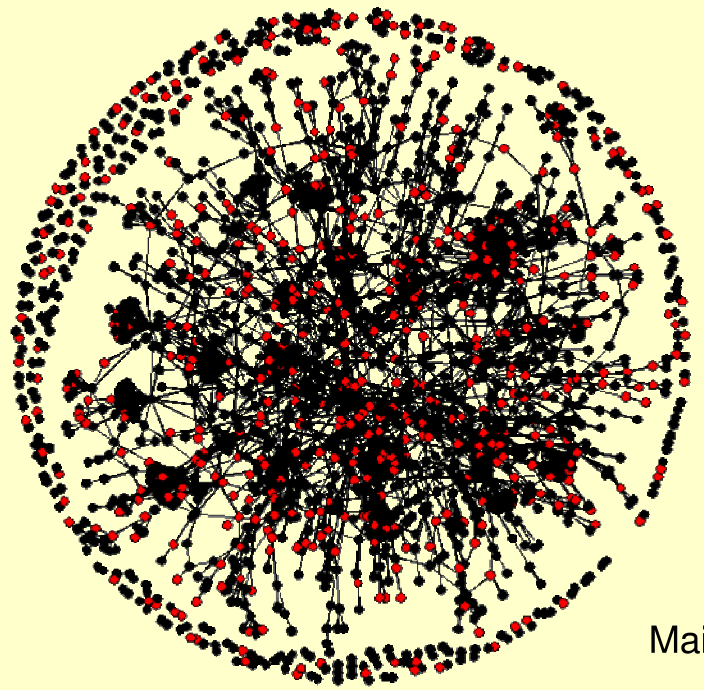


Instant messaging

Black: male
Red: female



Trade



Mail

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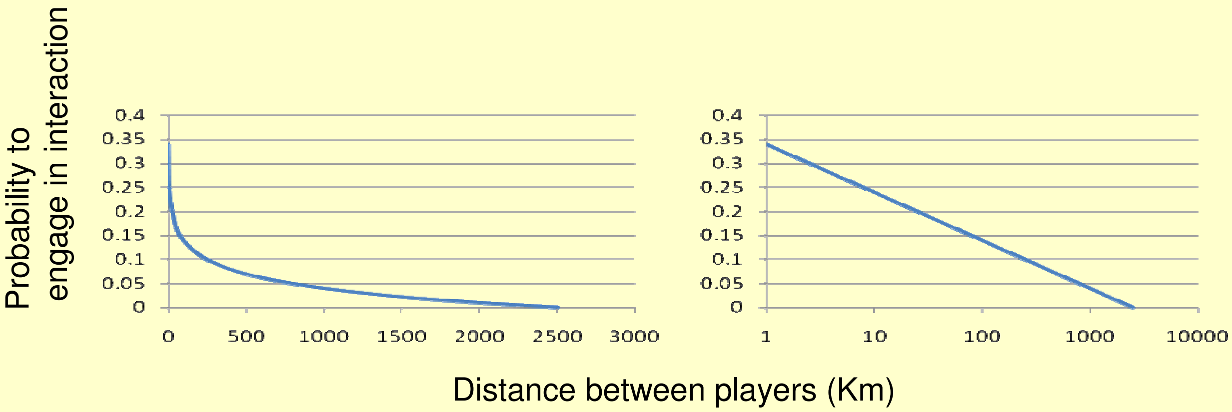
Hypotheses

- Network
  - **H1: (Sparsity) Individuals are not likely to engage in interaction randomly in a virtual world.**
  - **H2: (Popularity) Individuals with many interactions are more likely to engage in interaction than those have a few interactions.**
  - **H3: (Transitivity) Two individuals who both interact with the third parties are more likely to engage in interaction than those do not have common parties between them.**
- Proximity
  - **H4: (Geographical) Individuals who are proximate in *geographical distance* are more likely to engage in interaction than those who are not proximate.**
  - **H4a: (Short distance) Individuals who are in *close proximity* are substantially more likely to engage in interaction than those who are at medium or low proximity.**

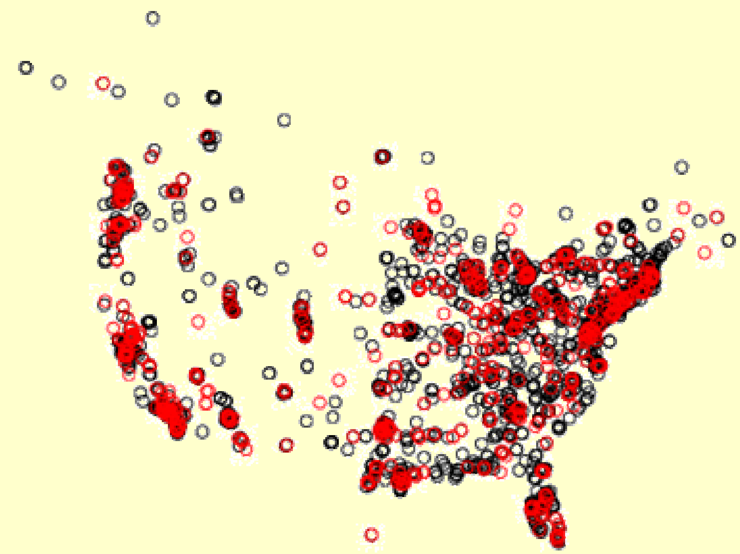


Hypotheses

- Temporal
  - H5: (Temporal) Individuals who are proximate in *time zone* are more likely to engage in interaction than those who have bigger time differences.
  - H6: (Synchronization) Individuals who are proximate in time zone are more likely to engage in synchronous interactions than asynchronous interactions.
- Homophily
  - H7: (Gender) Individuals of the same gender are more likely to engage in interaction than those of opposite genders.
  - H8: (Age) Individuals who have smaller age differences are more likely to engage in interaction than those who have bigger differences.
  - H9: (Experience) Players who have similar years of game experience are more likely to engage in interaction than those who have bigger differences.

Data Description

- 3140 players from Aug 25 to Aug 31 2006, in Antonia Bayle
  - 2998 US, 142 CA ; 2447 male, 693 female
- Demographic information
  - Gender, age, and account age (years played Sony games)
  - Zip code, state, and country



1: hily Model

Not supported: Individuals of the same gender are NOT likely to engage in interaction.

heses	Variables	Partner Model P1	IM Model I1	Trade Model T1	Mail Model M1
Sparsity	Edges	-8.587***(.28)	-6.687***(.20)	-5.780***(.03)	-5.525***(.03)
2: Popularity	GWDegree	1.253***(.18)	1.407***(.20)	-0.905***(.06)	-1.145***(.06)
H3: Transitivity	GWESP	1.454***(.04)	1.237***(.04)		
H7: Gender homophily	Same Gender	-0.152***(.02)	-0.148***(.03)	-0.061***(.01)	-0.059***(.01)
H8: Age homophily	Age Difference	-0.035***(.001)	-0.026***(.002)	-0.025***(.0007)	-0.031***(.001)
H9: Experience homophily	AcctAge Difference	-0.115***(.005)	-0.063***(.01)	-0.144***(.003)	-0.086***(.003)
H4,4a,4b: Geographical proximity	Log(Distance)				
H5,6: Temporal proximity	Timezone difference				
Control	Female	-0.201***(.02)	-0.080* (.04)	-0.041***(.01)	0.024** (.009)
	Age	0.005***(.0002)	-0.002***(.0005)		
	AcctAge	0.007** (.002)	0.038***(.005)	0.032***(.001)	
	Log likelihood	-13547.59	-3123.28	-29001.57	-23386.54
	Degeneracy value	0.478	0.672	2.120	5.013

Supported: Individuals with similar age and experience are more likely to engage in interaction.

Signif. codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < + < 0.1

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Special behavior in MMORPG: Females have a strong tendency to interact with male partners

1a: Detail

heses	Variables	Partner Model P1a	IM Model I1a	Trade Model T1a	Mail Model M1a
Sparsity	Edges	-8.716***(.28)	-6.837***(.21)	-5.820***(.03)	-5.478***(.03)
Popularity	GWDegree	1.223***(.18)	1.381***(.21)	-0.901***(.05)	-1.154***(.06)
3: Transitivity	GWESP	1.481***(.05)	1.172***(.04)		
H7: Gender homophily	Male-male match	0.041* (.02)	-0.067^{+} (.03)	-0.019* (.009)	-0.114***(.01)
	Female-female match	-0.369***(.06)	-0.209* (.10)	-0.115** (.04)	-0.038 (.04)
H8: Age homophily	Age Difference	-0.035***(.001)	-0.025***(.002)	-0.025***(.001)	-0.030***(.0006)
H9: Experience homophily	AcctAge Difference	-0.115***(.006)	-0.057***(.01)	-0.144***(.003)	-0.085***(.003)
H4,4a,4b: Geographical proximity	Log(Distance)				
H5,6: Temporal proximity	Timezone difference				
Control	Female				
	Age	0.005***(.0002)	-0.002** (.0005)		
	AcctAge	0.007** (.002)	0.037***(.005)	0.033***(.001)	
	Log likelihood	-13547.45	-3122.35	-29001.21	-23387.15
	Degeneracy value	1.370	1.503	2.520	6.672

Signif. codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < $^{+}$ < 0.1

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Hypotheses Tested

	Hypotheses	Partnership	IM	Trade	Mail
H1	Sparsity	Yes	Yes	Yes	Yes
H2	Popularity	Yes	Yes	No	No
H3	Transitivity	Yes	Yes	N/A	N/A
H4	Geographic proximity	Yes	Yes	Yes	Yes
H4a	Short distance	Yes	Yes	Yes	Yes
H4b	Interaction types	High	Low	Medium	Medium
H5	Temporal proximity	Yes	Yes	Yes	Yes
H6	Synchronization	High	Low	Medium	Medium
H7	Gender homophily	No	No	No	No
H8	Age homophily	Yes	Yes	Yes	Yes
H9	Experience homophily	Yes	Yes	Yes	Yes

Impact of Social Influence on Player Churn

Player Churn

- Propensity of a player to quit
- Crucial for subscriber based systems as retaining existing players is much cheaper than getting new ones
- Churn prediction helps in identifying players who are likely to churn so that marketing activities can be targeted on that player
- Churn management techniques cannot focus across the entire player base because
  - Player retention efforts cost money
- The revenue generation was $2 billion in 2006 and is expected to explode to a staggering $11.5 billion by 2011 [1]
- The number of active subscriptions in 2008 was over 16 million, out of which that of WoW alone is 10 million
- There are a number of key players battling for the market share in the intense competition and some of the key ones are WoW, Lineage, Final Fantasy, Eve Online and Everquest

[1] Ars technica

Dataset

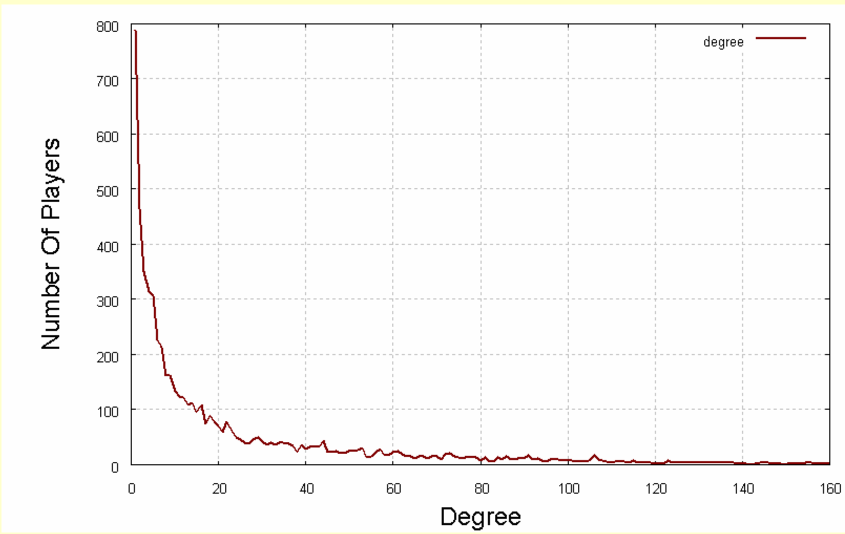
- Group data of players grouping used to build social network
- Edges are defined by the cumulative experience points shared by the players in Aug 06.

Graph Characteristic	Value
Number of Nodes	6213
Number of Edges	153983
Average degree	24.78
Average experience points shared	210897

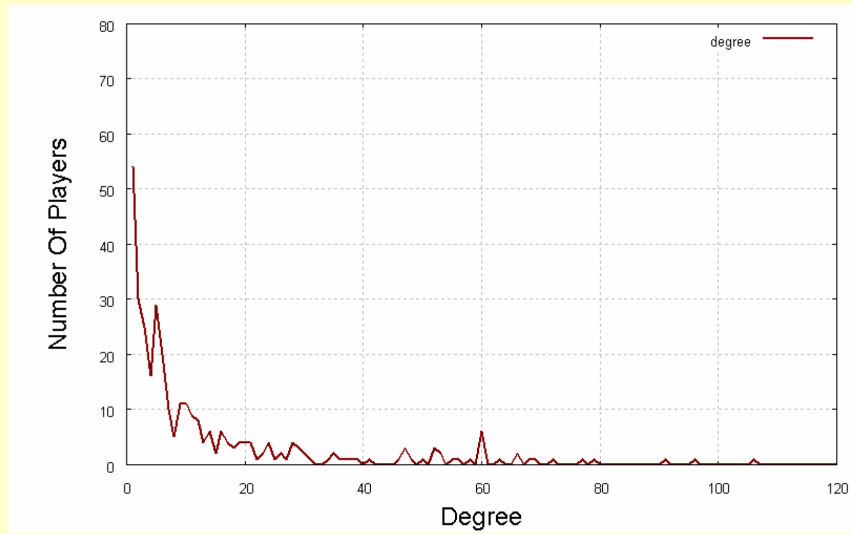
Month	Churners
August	334
September	414
October	380
November	277
December	230

Socialization Behavior

Degree distribution of Non churners and Churners



Non churners



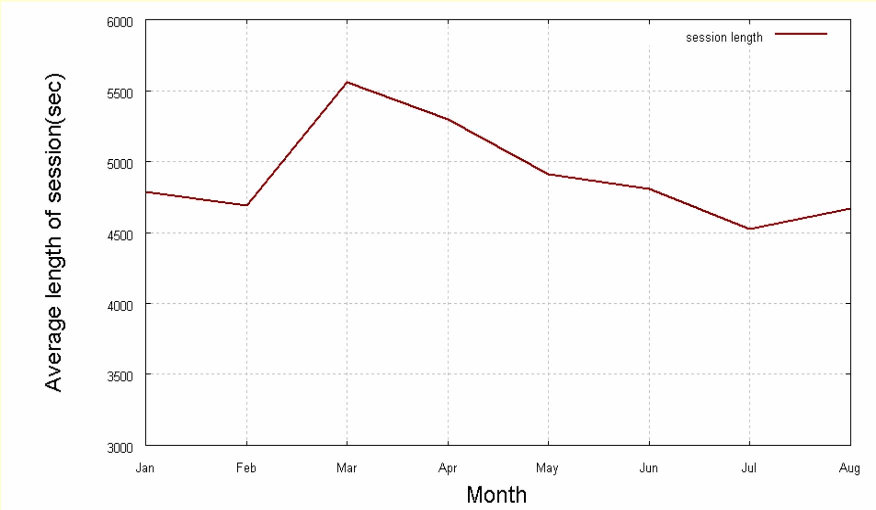
Churners

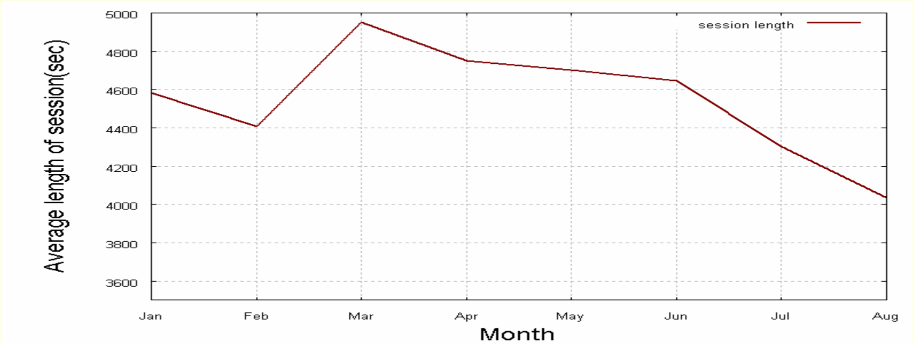
Degree distribution follows a power law for both non churners and churners

➔ No significant difference

Session Length

Average session lengths of Non churners and Churners





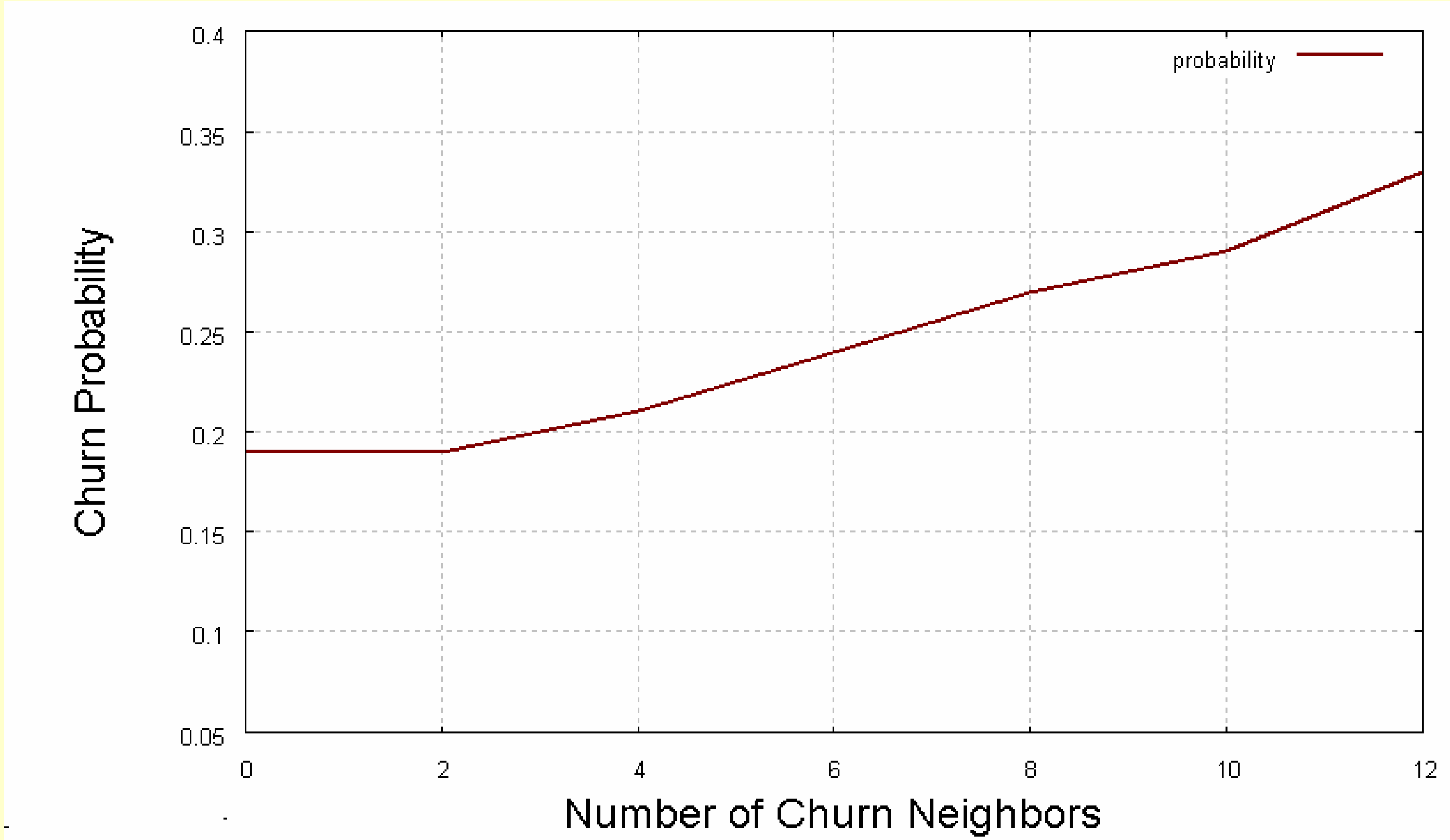
Non churners

Churners

Average length of sessions for churners (in Aug) goes down from Jun to Aug as compared to non churners

➔ **There is a difference**

Neighborhood Effects



Churn probability increases with increase in number of churners in the neighborhood

➔ **Neighbors do have an impact**

Results

Training Set : 4026 (includes Aug churners)

Testing Set : 2187 (includes Sept + Oct churners)

Total churners in Training set : 334

Total churners in Test set : 764

Baseline model – no social influence

Method	Precision	Recall	Correct Predictions	Total Predictions	F score
Simple Diffusion Model	**17.9**	**11.2**	**77**	**430**	**13.77**

Incorporating social influence

Method	Precision	Recall	Correct Predictions	Total Predictions	F-score
AdaBoost M1	**50.1**	**29.8**	**205**	**409**	**37.37**
ADTree	**46.5**	**41.3**	**284**	**611**	**43.74**
JRip	**43.1**	**18.8**	**129**	**299**	**26.18**
J48	**38.5**	**21.5**	**148**	**384**	**27.59**
NaiveBayes	**49.7**	**23.3**	**160**	**322**	**31.72**

Inferring Player Progress/Learning from Performance Data

Background - Learning

- Educational Psychology, Learning Sciences
- Learning is
  - Transformation of an individual from legitimate peripheral participant (Lave & Wenger, 1991) to a <u>central member</u> of a community
- Learning depends on
  - How individual interacts with
    - Materials
    - Social contexts
  - How interactions change over time (i.e. grouping behavior)
  - How individual constructs knowledge (i.e. apprenticeship, completing tasks)
- Learning can be inferred from
  - Trajectory of participation (Greeno, 1997)
  - Growth of identity within community (Gee, 1999)

Performance Metrics

- Long studied in Industrial Engineering & Operations Research
- Performance = Productivity + Quality + Inventory
- Performance Metrics
  - Assembly line balancing problem
    - maximize efficiency through minimization of idle time
    - → Maximum possible productivity in a given time duration
  - Can we leverage this for measuring online player's performance?
  - Being able to measure player's performance over time across difficulty levels
  - → Allow for individual/group learning patterns

Impact of Groups on Performance

- Operations Research
  - Recent trend in manufacturing plants to adopt formation of work teams as a practice
  - Goal: Increase performance, especially quality
- MMORPGs
  - Nature of games encourage group formations (quests)
  - Homogeneous vs. Heterogeneous group formations
    - Monster raids vs. Quests
  - How does group formation affect individual player performance?

Performance Matrix

	T1 (L = 5, SL = 2)	T2 (L = 6, SL = 10)	T3 (L = 7, SL = 1)	T4 (L = 9, SL = 2)	T5 (L = 11, SL = 8)
P1 (L = 30)	80 1/1	126 ½	135 1/4	173 1/4	199 1/10
P2 (L = 25)	140 1/2	200 1/3	x	320 1/3	273 1/16
P3 (L = 25)	140 1/4	200 1/6	260 1/8	x	x
P4 (L = 15)	250 1/10	357 1/10	400 1/16	x	x

Experience Points

Success Ratio

T = task (monster). Each monster has 1) Level and 2) Sub-level
P = player. Each player has a Level (i.e. L = 25)

Performance Index #1
Performance = F (Productivity)

$$Performance_k = \frac{\sum_{i=1}^{N} XP_i}{\sum_{j=1}^{M} ST_j}$$

where

XP = Experience points

N = Total number of tasks completed by Player K

ST = Session time

M = Total number of session times during which Player K completed tasks

Performance of player K at a certain Level

Performance Index #2

Performance = F (Productivity, Quality)

$$Performance_k = \frac{\displaystyle\sum_{i=1}^{N} \frac{XP_i + (XP_i \times Q_i)}{2}}{\displaystyle\sum_{j=1}^{M} ST_j}$$

where

XP = Experience points

N = Total number of tasks completed by Player K

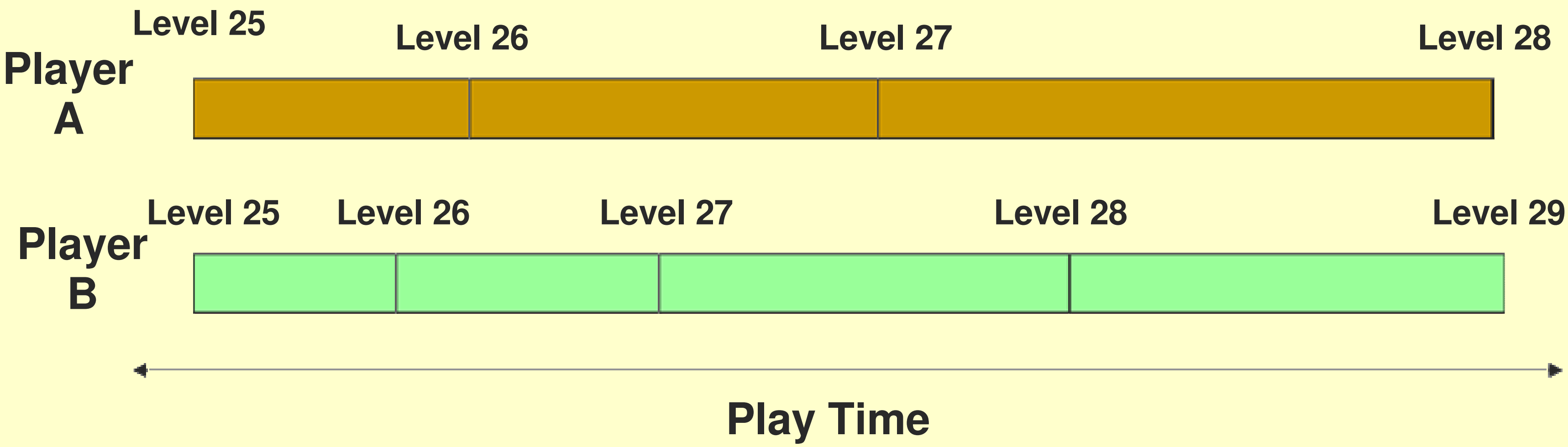
ST = Session time

M = Total number of session times during which Player K completed tasks

Q = Quality or success ratio associated with completing Task i

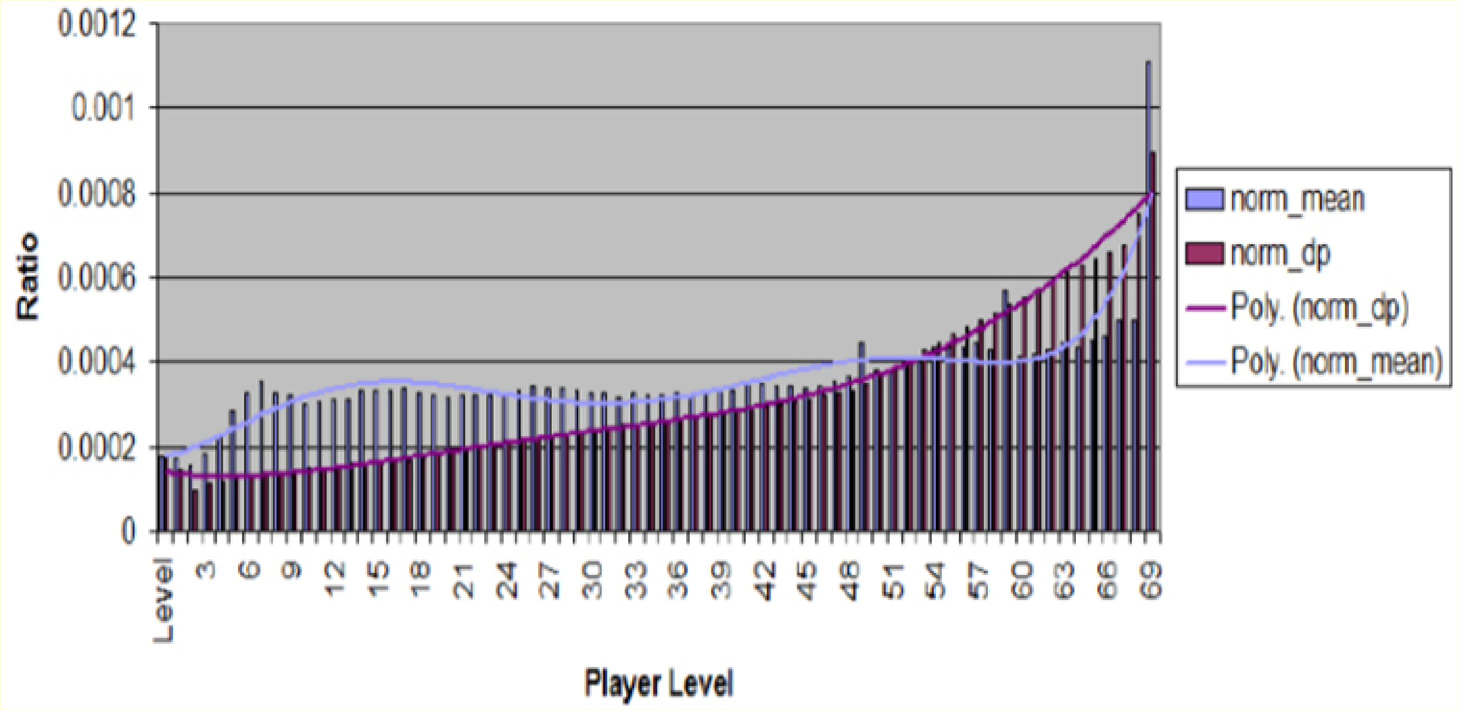
Is Performance Predictable?

Is past performance a good predictor of a player's future performance?



- Per definition of Performance Metrics methods #1 and #2, Player B is a better player
  - **Takes lesser time to advance between levels**
- Caveat
  - **Past is a good predictor of future performance. But, how far back do we go?**
  - **Is Player A's performance between Level 25 and Level 26 a good predictor of his performance down the road, say to advance to Level 70?**

Performance data reveals …



- **Tasks performed by players up until Level 49 were more challenging than expected as time spent increases with an increasing level of task difficulty**
- **Between Levels 50 and 55, the actual time spent is well in accordance with what is expected.**
- **Beyond Level 55 up until Level 68, the actual time spent is well below what is expected.**
- **Tasks performed were not challenging enough as time spent decreases with a decreasing level of task difficulty.**

Performance Metric 1 – Evaluation

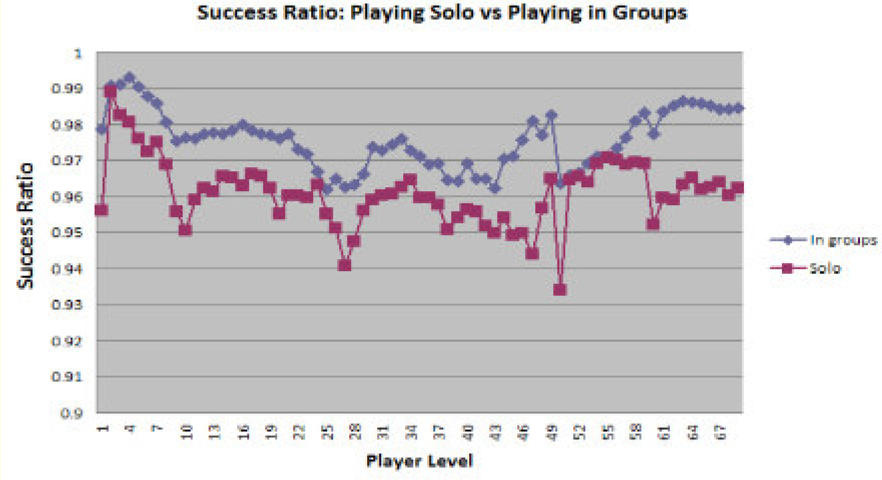


Fig. 3. Success Ratio - Playing Solo vs. Playing in Groups

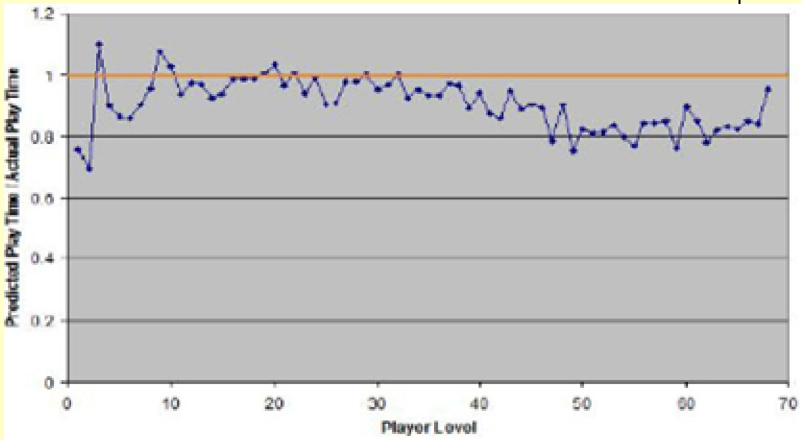


Fig. 5. Ratio of Predicted Play Time and Actual Play Time by Player Level

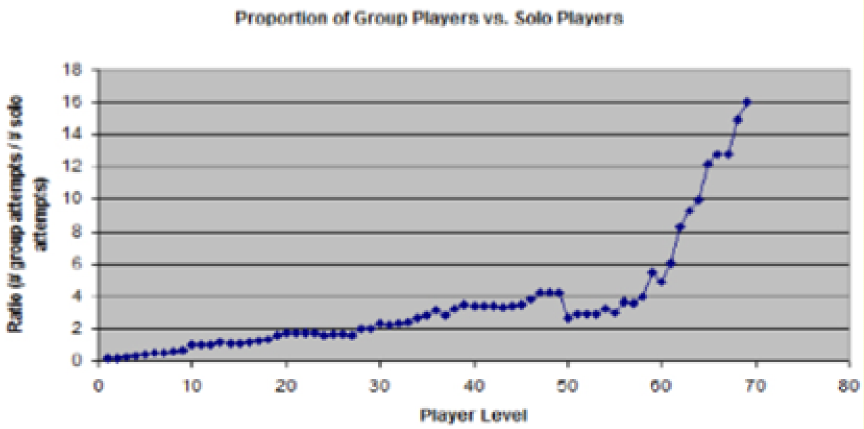


Fig. 4. Proportion of Group Players versus Solo Players

- **As the player level increases, group formation becomes a more common occurrence**
- **Playing in groups leads to higher success ratio at the individual player's level.**
  - **There is a tradeoff between playing solo versus playing in groups. From timing perspective, playing solo allows a given player to advance faster than it would if he were to play in groups.**
  - **From the perspective of successful task completion and success ratio, playing in groups serves as an advantage in that the chance of getting a given task done is higher for a given individual player in this setting.**

Identifying Undesirable Behavior (Gold Farming)

Background

- Goldfarming:
  - Performing the same in-game activities to gain valuable items that can be sold to other players
- Goldfarmers can be of different types
  - Automated Bots
  - Human players that perform the same activities again and again
- Issues
  - Unfair to other players
  - Ruins the gaming experience for legitimate players

The Economics of Gold Farming

- MyMMOShop.com sold for $10 million in 2008
- Currently $100 million - $1billion dollar industry and growing
- Almost 1 million Gold Farmers in China
- Many Gold Farmers make 30cents/hour
- On average players spend as much money on buying items as they spend money on game subscription.

Catching Gold Farmers Today

- Systematic studies have not been done
- Most Gold farmers are caught by
  - Reporting by other players
  - Solicitation for selling “gold”
  - ‘String operations’ by the game developer
  - Heuristic Based Approaches

Types of Gold Farmers

- **Gatherers:** Accounts accumulating gold or other resources.
- **Bankers:** Distributed, low-activity accounts that hold some gold in reserve in the event that any one gatherer or other banker is banned.
- **Mules and dealers:** One-time characters that interact with the customer, act as a chain to distance the customer from the operation, and complicate administrator back-tracing.
- **Marketers:** One-time accounts that are ”barkers”, ”peddlers”, or ”spammers.”

What clues exist?

- Demographic Features*
- Performance Features
- Task distributions
  - set of tasks performed
- Sequence of activities performed by gold farmers
  - Examples: KKKdDKdEESSKD, SSSEKdKdDD
  - Where
    - K= Killed Monster, d = damage points, D = Character Death, S = Completed a recipe e.g., spell

*** All information is anonymized.**

Patterns of Suspicious Behavior

TABLE V
SEQUENCE PATTERNS FOR PLAYER ACTIVITIES

Sequence	Explanation
KKKKKKKKKK+	10 or more kills in a row
d+K+	One or more damage followed by one or more kills
d+[a-z,A-Z]*K+	Damage followed by other activities and then by one or more kills
E+[a-z,A-Z]*K+	Pattern 4: Earned payment followed by other activities and then by one or more kills
M+S+	One or more mentoring instances followed by successful completion of recipes
M+[a-z,A-Z]*K+	Damage followed by other activities and then by kills
K+D	One or more kills followed by the death of the character
E+D	One or more earned payments followed by the death of the character
M+[a-z,A-Z]*q	Mentoring followed by other activities and then by quest points
M+[a-z,A-Z]*K+	Mentoring followed by other activities and then by one or more kills
M+E+	One or more instances of mentoring followed by one or more instances of earned payments
MMMMMMMMMM+	Ten mentoring instances in a row

Machine Learning Approach

- Gold Farmer Identification as a binary classification problem
- Highly Skewed Distribution ➔ ‘rare class problem’
  - 9,178 Gold Farmer Characters out of a total of 2.1 million characters
- Tried various combinations of classifiers and features e.g., Decision Trees, Rule Based Classifiers, Bayes Nets, NaiveBayes, etc.

Results

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	.0125	0.291	.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	0.19	0.223	0.293	0.19	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

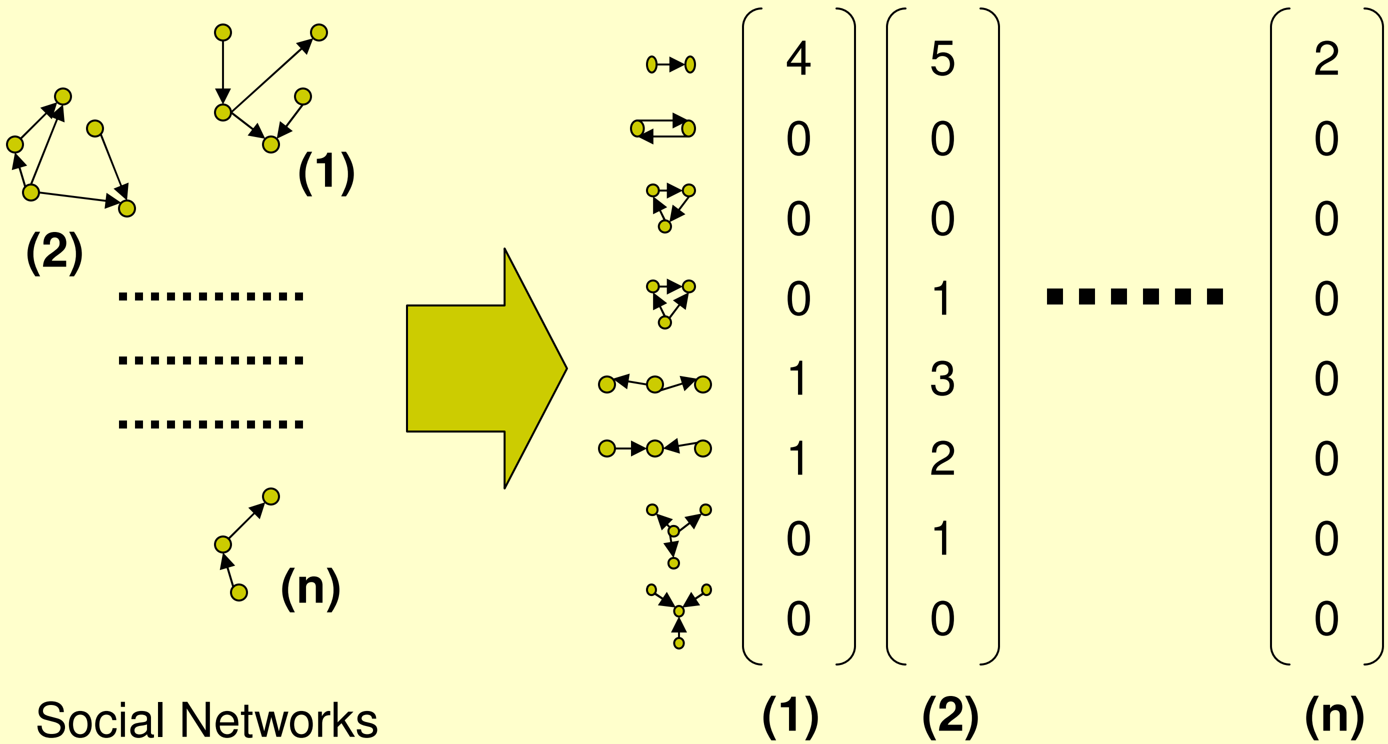
Result Interpretation

- Characters predicted as Gold Farmers have to be investigated by a human
- Classifiers have different performance with respect to precision and recall
- Greater Precision translates into more Gold Farmers being Identified
- Greater Recall translates into investigating more players
- ROC cannot be used because FP Rate is extremely small
- Evaluation
  - F-Measure

Part III – New Challenges for Computer Science

- Specific challenges
  - new computational methods
  - quantification of largely qualitative concepts, e.g. ‘group, ‘trust’, etc.,

IR based Approach for Large Scale Network Analysis



Social Networks
as network structure frequency
vectors in a bag-of-words model

Cluster Structure
Vectors using
Text clustering
methods

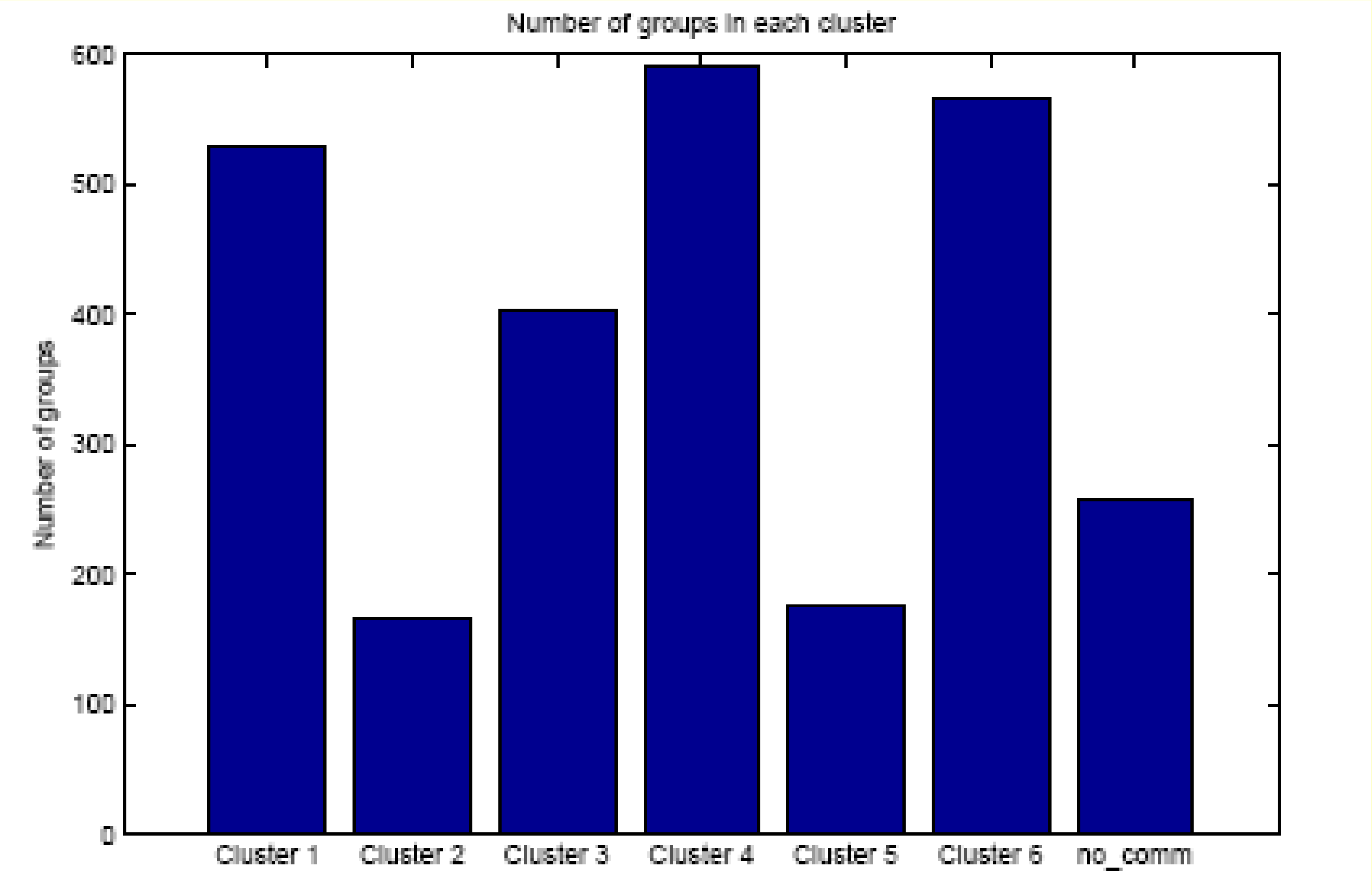
Cluster means provide
modes of network
structure configurations
Making up all the
social networks

Attribute values for
each cluster can be
used to discover
trends between network
structures and attributes

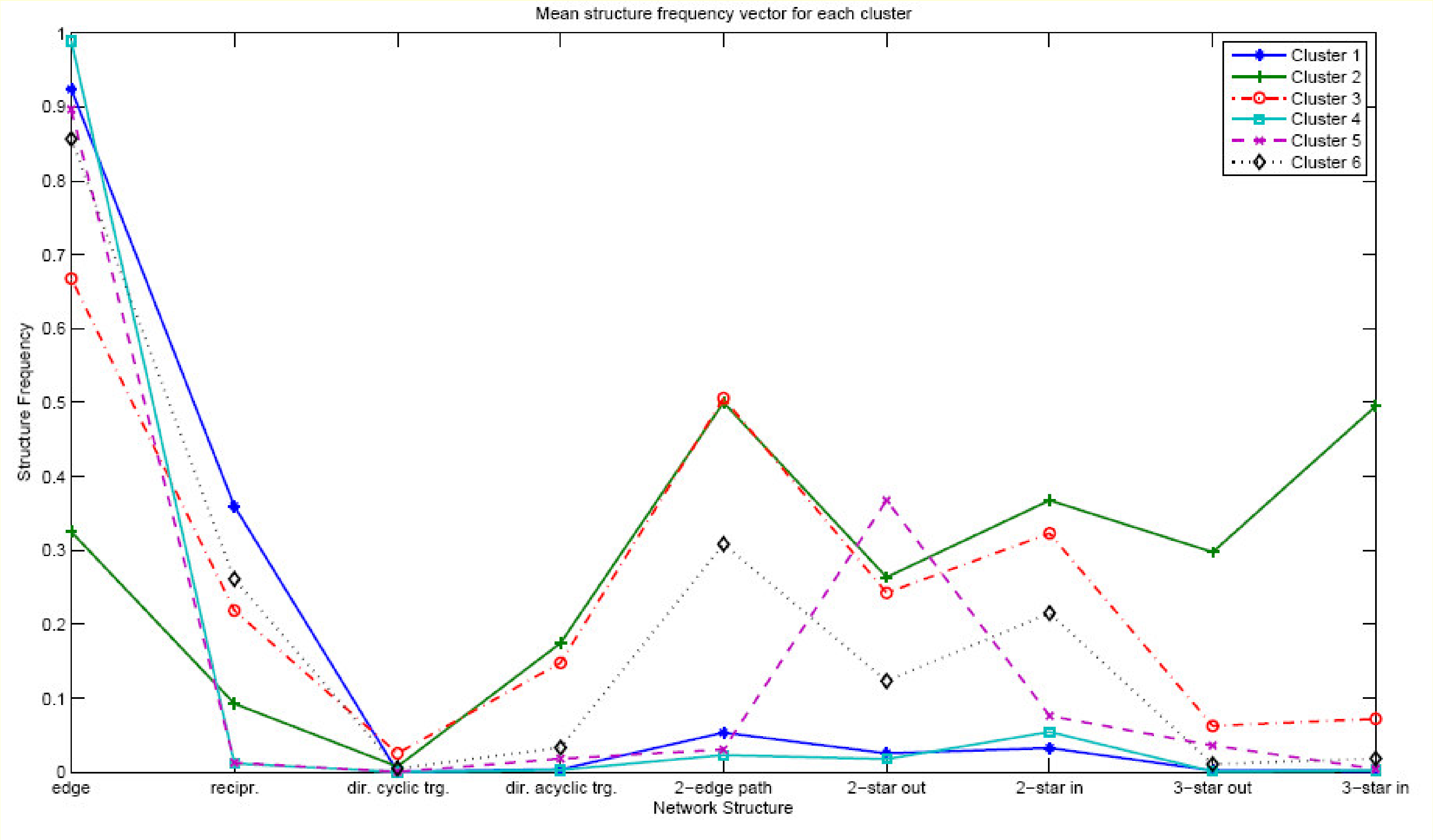
Results

- Experiments done on EQ2 groups between 5th and 9th Sept. 2006 on the Guk server
- Total of 2688 groups
- Groups of sizes >4 were considered
- Network structure-vectors for all groups were clustered using K-means with cosine distance
- 6 Clusters detected

Results – Strength of each cluster



Results – normalized network structure vector means for all clusters



Results

- Clusters 1 and 4 are similar
  - Groups kill fewer monsters
  - Group members in cluster 4 do not communicate much
  - Group members in cluster 1 generally limit their communication to just one other person in the group
  - Most people belong to these two clusters
  - Consistent with previous research - users in virtual environments are less likely to interact with strangers

    [N. Ducheneaut, N. Yee, E. Nickell and R. Moore, "Alone Together?" Exploring the social dynamics of massively multiplayer online games, *Proceedings CHI06*, ACM Press, New York, 407-416.]
- Cluster 5 groups have many 1-edge and 2-out stars
  - Most of the communication is one way possibly indicating presence of central people
  - Maximum number of monsters killed out of all clusters
  - Performance of the groups is very good
  - Minimal communication
  - It is possible that cluster 5 consists of groups more focused on playing and performing well in the game and less on socializing

Results

- Cluster 3 and 6
  - Groups kill more monsters together, higher communication activity and relatively poorer performance [more deaths]
  - Data suggests that group members are likely to socialize with each other as compared to all other clusters
- Cluster 2 consists of Raid Groups
  - Large groups fighting very challenging monsters
  - High communication activity as lots of co-ordination and planning is involved

Trust in Virtual Worlds

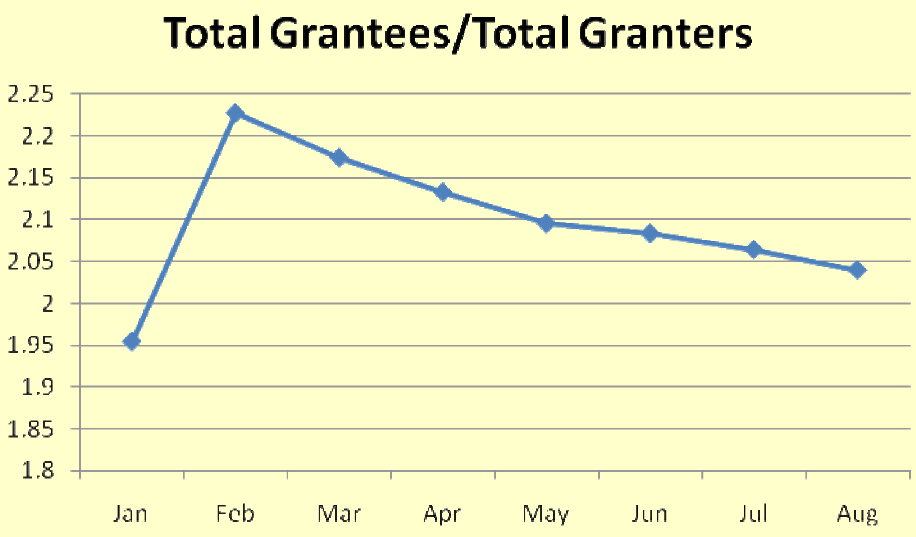
Trust in Virtual Worlds

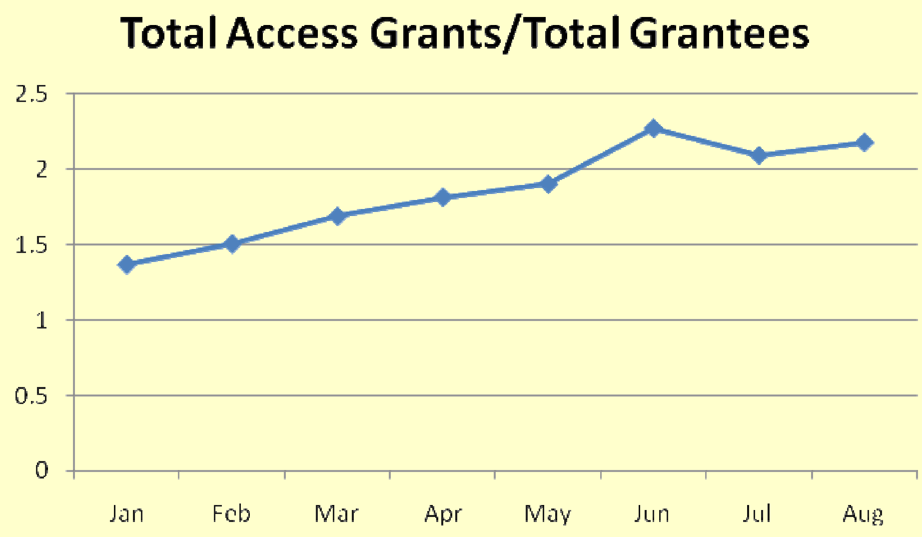
- Trust has become problematic in the late 20^{th} and early 21^{st} centuries
  - Modernity and Self Identity (Giddens): Institutions that once provided foundation for trust are changing rapidly and creating a sense of discontinuity that creates a sense of insecurity
  - Bowling Alone (Putnam and Oldenberg): Sense of civil society and community that provided basis for trust has eroded
  - No Sense of Place (Meyrowitz): Media connect us to others not part of our communities—can we trust them?
- Online worlds offer potential for community
  - Community depends on trustworthiness of online worlds
  - Do participants have a sense of trust in EQ2?
  - Does trust work the same way in EQ2 as in RL?

Housing Trust in EverQuest II

- Houses vary in sizes and amenities reflected in the price of the house
- Unique ownership is enforced
- Players have to pay a rent for upkeep
- Various levels of access allowed to houses which are reflective of trust between players
- A player at any level can grant access rights to another player at the same level or a level below it
    - The only exception is ownership
- Levels of trust
    - Owner (Exclusive)
    - Trustee
    - Friend
    - Visitor
    - None

Data Description





- The diameter of the trust network(s) is shrinking
- The trust network(s) become dense over time

Logic Models for Trust

- **Trust:** Given agent *i* and agent *j*, i trusts j to do α with respect to her goal Φ if and only if I wants Φ to be true in the future and *i* believes the following:
  - Doing α by j will result in Φ AND j has the capacity to do α AND j has the intention of doing α
  - Formally
    - Trust (i, j, α, Φ) def = $Goal_i Φ$ ^ $Bel_i(After_{j:α} Φ$ ^ $Can_j α$ ^ $Int_j α)$
- **Breach of Trust:** Given agent *i* and agent *j*, i trusts j to do α with respect to her goal Φ then breach of trust (BoT) is defined as follows:
  - i trusts j to do α but j does not intend to do α even though j has the capability to do α
  - Formally
    - $BoT_{j,i}$ def= Trust (i, j, α, Φ) ^ ¬$Int_j α$

Logic Models for Trust

- **Misperception:** Given agent *i* and agent *j*, i misperceives the capability of j and trusts j to do α with respect to her goal Φ if and only if i wants Φ to be true in the future, the following two cases are possible
- **Misperception I:** The following holds:
  - (i belives that Doing α by j will result in Φ AND j has the capacity to do α AND j has the intention of doing α) AND (j does not have the capability to do α.)
  - Formally
    - Misp1 (i, j, α, Φ) def = $Goal_i Φ$ ^ $Bel_i(After_{j:α} Φ$ ^ $Can_j α$ ^ $Int_j α)$ ^ $¬Can_j α$, which can be rewritten as
    - Misp1 (i, j, α, Φ) def= Trust (i, j, α, Φ) ^ $¬Can_j α$
- **Misperception II:** The following holds:
  - (i belives that Doing α by j will result in ¬Φ AND j has the capacity to do α AND j does not have the intention of doing α) AND (j does have the intention to do α.)
  - Formally
    - Misp2 (i, j, α, Φ) def = $Goal_i Φ$ ^ $Bel_i(After_{j:α} Φ$ ^ $Can_j α$ ^ $¬Int_j α)$ ^ $Int_j α$

Key Observations

- Trust in online world exhibits similar patterns of result to what would be expected in RL
- Institutions like guilds serve an important function in MMOs in that they provide a basis for trust
- MMOGs engender trust and may be a basis for community
- Communication has a role in generating trust in online worlds

Concluding Remarks

Converging Technology Trends

- Rapid increase in the usage of the Internet/Web
  - ➔ increased amount of interactions on line
  - ➔ huge amount of socialization on line
- Increase in resolution and deployment of data collection 'probes', e.g. GPS, cell phone/PDA, wireless enabled laptop, RFID tags, …
  - ➔ increased ability to monitor and record interactions at a really fine granularity
- Dramatic increase in storage capacity and decrease in storage costs
  - ➔ feasible to store all the data collected
- Fundamental advances in computational methods for data analytics

Becoming possible to <u>really</u> understand individual and group behavior at a fine granularity

The microscopes have been trained on human behavior

So, why not look through it!

What about privacy you say

– but that’s another talk ☺

And Last, but not the Least

mucha ¡gracias!

mila esker

For your fantastic hospitality!