Social & Behavioral Analytics

Mining Behaviors of a Connected World

ASONAM 2013

August 25, 2013

Niagara Falls, Canada

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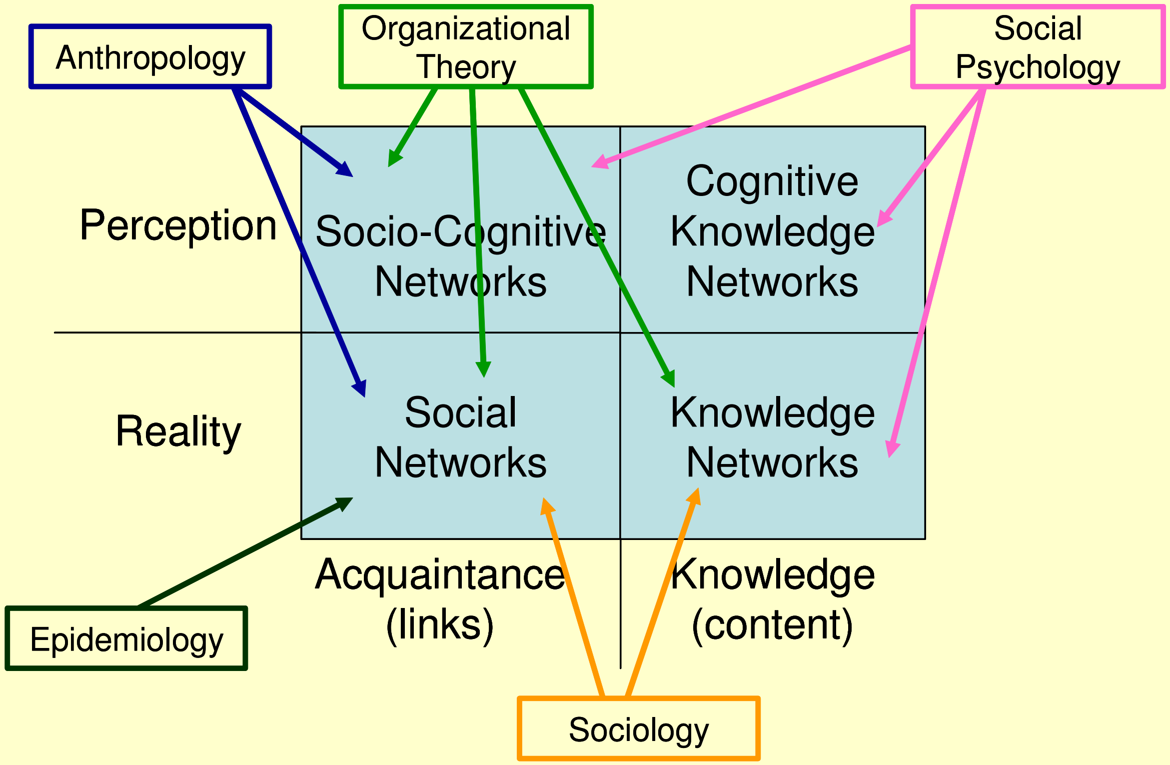
Tutorial Outline

- Part I: Background
  - Emerging types of socialization and behaviors
  - New types of data and its potential
- Part II: Impact on science
  - Some key findings about the population
  - Understanding the nature of inter-personal trust
  - Understanding the nature of team performance
- Part III: Impact on business
  - Churn prediction for subscription services
  - Loyalty and influence in retail
- Conclusion

Part I: Background

Social Network Analysis



- Social science networks have widespread application in various fields
- Most of the analyses techniques have come from Sociology, Statistics and Mathematics
- See (Wasserman and Faust, 1994) for a comprehensive introduction to social network analysis

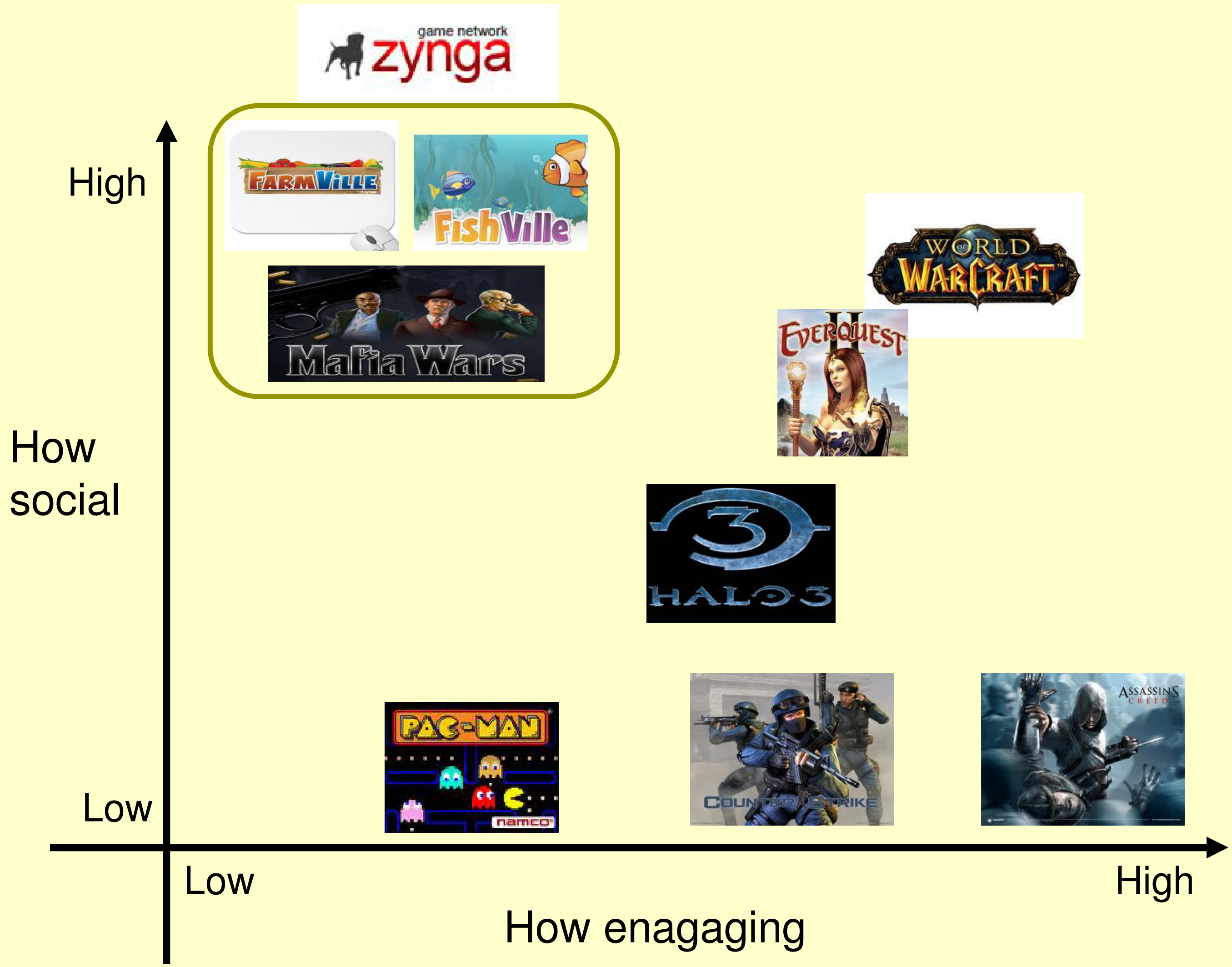
What have been it’s key scientific successes?

- In classical social sciences numerous results
  - ‘Six degree of separation’ [Milgram]
    - Popularized by the ‘Kevin Bacon game’
  - ‘The strength of weak ties’ [Granovetter]
  - ‘Online networks as social networks’ [Wellman, Krackhardt]
  - ‘Dunbar Number’
  - Various types of centrality measures
  - Etc.
- In the Web era
  - ‘The Bow-Tie model of the Web’ [Raghavan]
  - ‘Preferential attachment model’ [Barabasi] (Yes and No)
  - ‘Powerlaw of degree distribution’ [Lots of people] (NO!)
  - Etc.

Application successes

- Numerous in social sciences
- Google – PageRank
- LinkedIn – expanding your Cognitive Social Network
  - making you aware that ‘you’re more connected and closer than you think you are’
- Expertise discovery in organizations
  - Knowledge experts, ‘authorities’
  - Well-connected individuals, ‘hubs’
- Rapid-response teams in emergency management
- Information flow in organizations
- Twitter – real time information dissemination
- Etc.

Online (Multiplayer) Games



Player Behavior & Revenue Model

- Blizzard (subscription)
  - World of Warcraft
  - 12 million subscribers
  - Revenue model
    - $15/month
    - Approx $3billion annual revenue
  - 4 hours a day, 7 days a week!

Hard core gamers

Less socially acceptable

Like Cocaine

- Zynga (free2play)
  - Farmville, Fishville, Mafia Wars, etc.
  - 180 million players
  - Revenue model
    - Virtual goods
    - $700 million in 2010
  - 0.5 hrs a day, 7 days a week

Everyone

More socially acceptable

Like Caffeine

Implications of this ‘addiction’

- 3 billion hours a week are being spent playing online games
  - Jane McGonigal in “Reality is Broken”
- Labor economics
  - What is the impact of so much labor being removed from the pool [Castranova]
- Entertainment economics
  - If MMO players can get 100 hrs/month of entertainment by spending $25 or so, what will happen to other entertainment industries?
- Psychological/Sociological
  - Is it an addiction – the prevailing view (Chinese government’s ‘detox centers’ for kids)
  - Are they fulfilling a deeper need that real world is not (McGonigal)
- Societal
  - **A trend far too important to not be taken seriously!**

Business Example

Levis' – Example of Social Retail

- Levis' leverages its brand to ensure customers **provide** their social network
- Levis' can leverage predictive social analytics technology to **understand the value** of the customer's social network

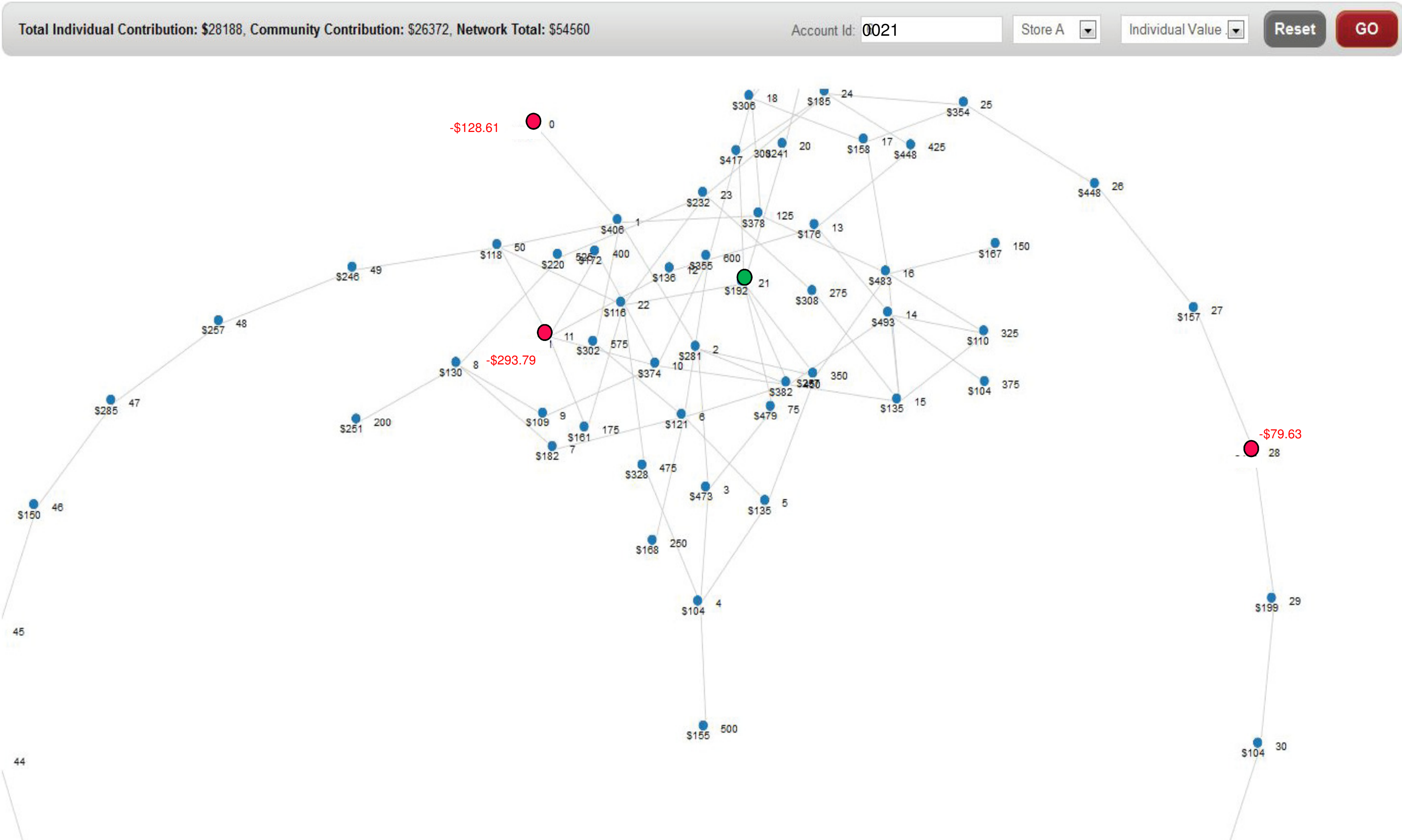
Opportunity, Innovation, Impact

- Companies do not understand the social graph of their customers
- It's not **just** about how they relate to their customers, but **also** about how customers relate to each other

vs.

- Understanding these relationships unlocks immense value
  - **<u>Innovation:</u> Understanding the social network of customers**
    - **Key influencers, relationship strength, …**
  - **<u>Impact:</u> Deriving actionable insights from this understanding**
    - **Customer acquisition, retention, customer care, …**
    - **Social recommendation, influence-based marketing, identifying trend-setters, …**

Unlocking true value by product, category, or store



True Value of each customer

- True value = individual value + social value
- Who really matters, and to what degree
- Some empirical facts
  - 31% activity due to socialization
  - 23% more individual + 8% more social activity

The individual's lifetime value

their social influence

and their true total

Action 1

Export

Account	Individual Value(A)	Social Value(B)	Total value (A+B)
155589	41	61	102
155591	23	33	56
155593	32	56	88
155595	37	10	47
155597	56	22	78
155599	24	22	46

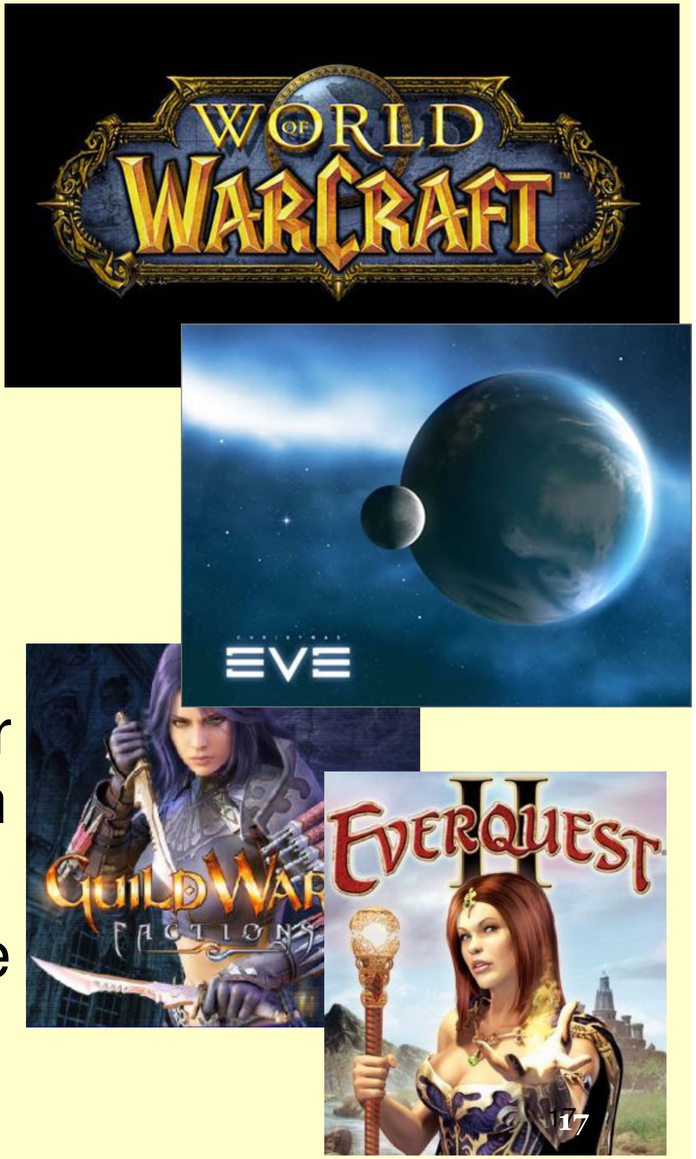
Impact of New Instrumentation on Science

- 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 ‘macroscopes of human behavior’

Rich Social & Behavioral Data Sets

Virtual Worlds & Massive Online Games

- Massively Multiplayer Online Role Playing Games (MMORPGs/MMOs)
- Simulated Environments like SecondLife
- Millions of people can interact with one another is shared virtual environment
- People can engage in a large number of activities with one another and with the environment
- Many of the observed behaviors have offline analogs

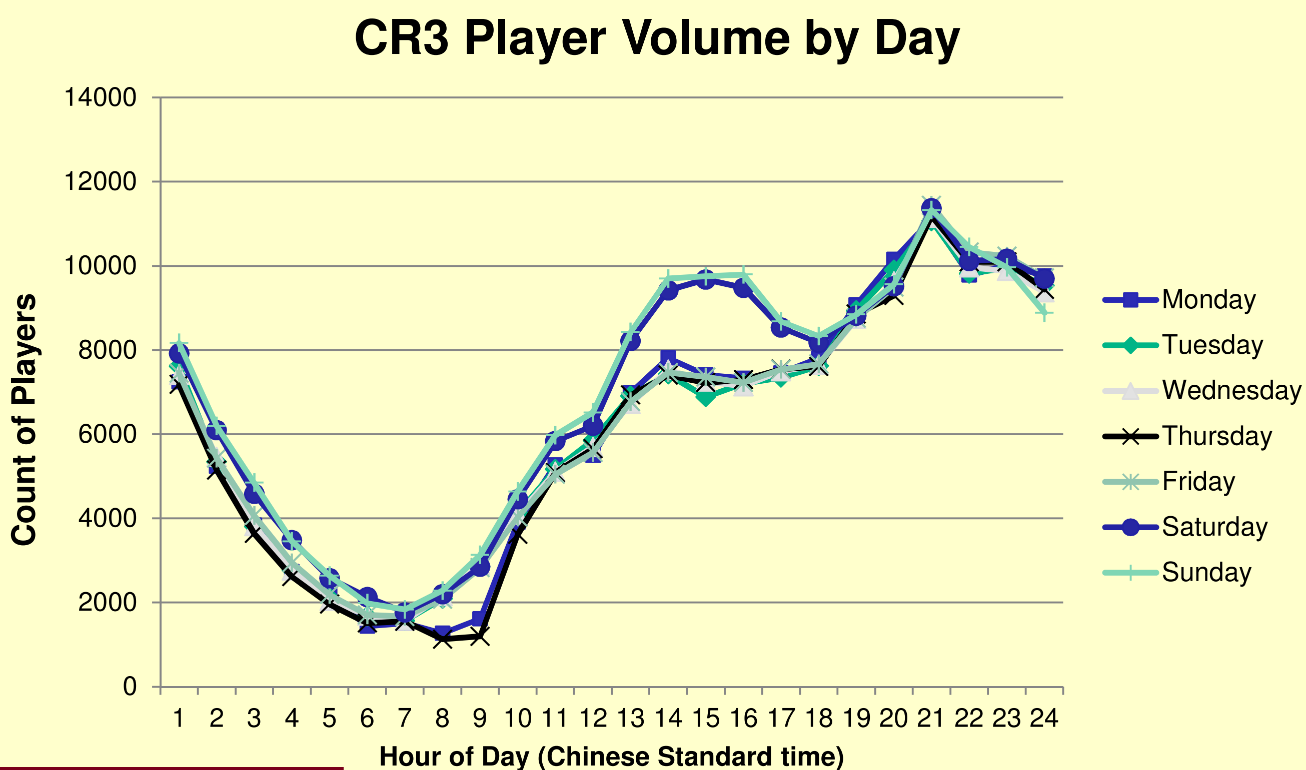


MMORPG – Observatory for Human Behavior

- MMORPG: **M**assively **M**ultiplayer **O**nline **R**ole **P**laying **G**ames
- People assume characters in a fantasy world
- On average, each players spend 25 hours a week
- World-of-Warcraft has 10 million subscribers as of Feb 2012
- MMORPG is $20 Billion industry
- Several in-game relationships: chat, trade, mentor, and housing.
- Helpful in understanding social processes

CR3 and EQ2 Data – Basic Stats

	EQ2	CR3
Size	2.3TB	251GB
Players Country	US	China
Number of Players	675,296	410,725
Period Covered	9 Months (01-JAN-2006 to 11-SEP-2006)	5 Months (08-MAY-2010 to 30-SEP-2010)



Activities and Relationships in EQ2

- Chat – means to communicate in-game messages and invitations with other players
  - Nodes – 349,654; Edges – 86,948,748; Period – 1 Month
- Trade – means to exchange, buy or sell weapons, and other in-game items
  - Nodes – 295,055   Edges –28,594,929; Period – 9 Months
- Mentoring – means to assist lower level players to increase mentors experience points
  - Nodes – 86,495   Edges – 11,913,994; Period – 9 Months
- Housing Trust – means to accumulate and store in-game items; share house with the in-game partner to allow the storing of in-game items
  - Nodes – 63,918   Edges – 128,048; Period – 9 Months

Relationships

CHAT

Period of interaction: Instantaneous
Familiarity threshold: low

TRADE

Period of interaction: Instantaneous
Familiarity threshold: medium

MENTORING

Period of interaction: long
Familiarity threshold: high

HOUSING

Period of interaction: long
Familiarity threshold: very high

Graph Density

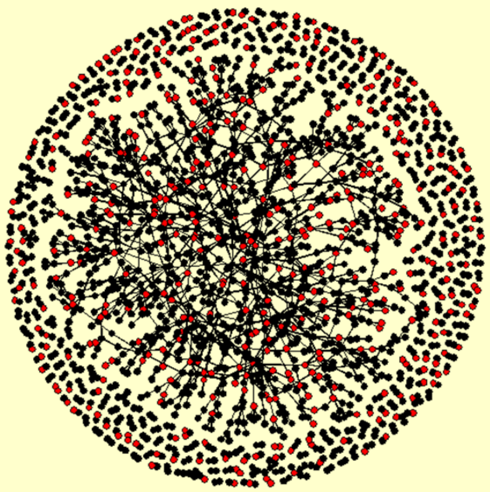
- Node participation
- No of edges

High

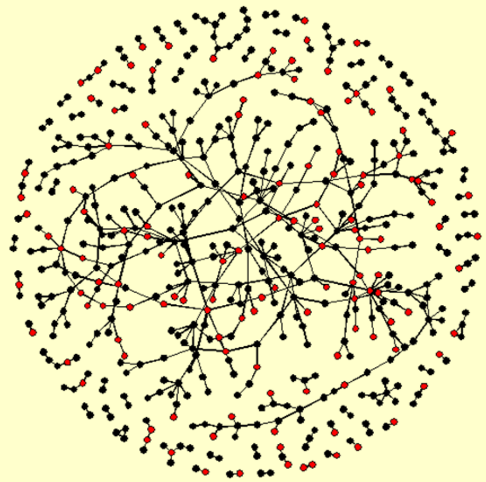
Low

Activity and Relationship Networks in EQ2

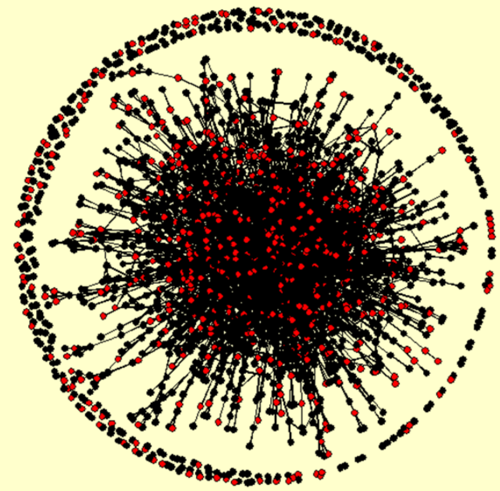
Black: male
Red: female



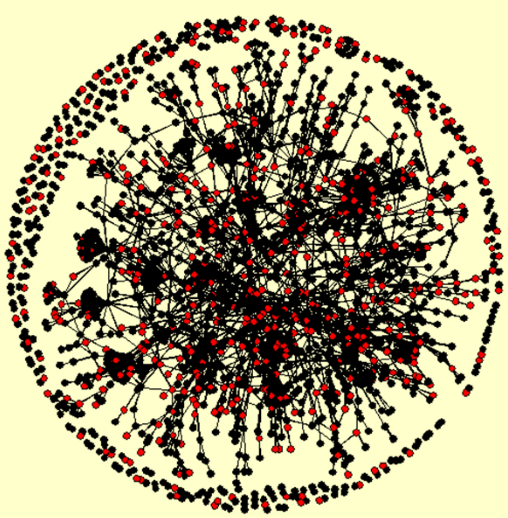
Partnership



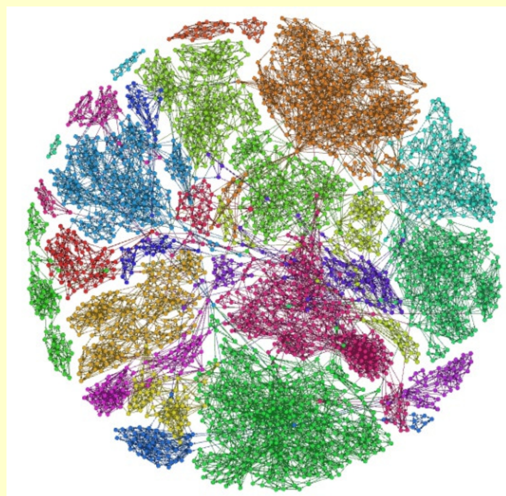
Instant messaging



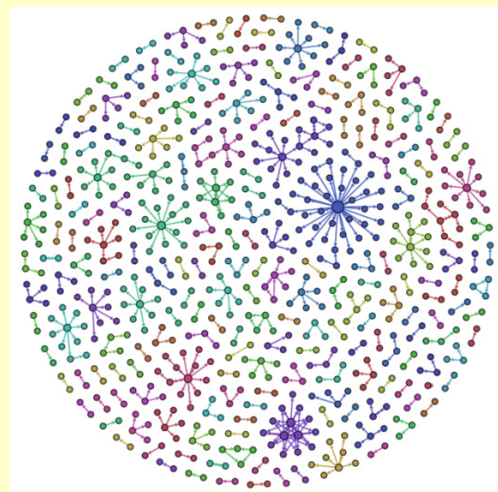
Trade



Mail

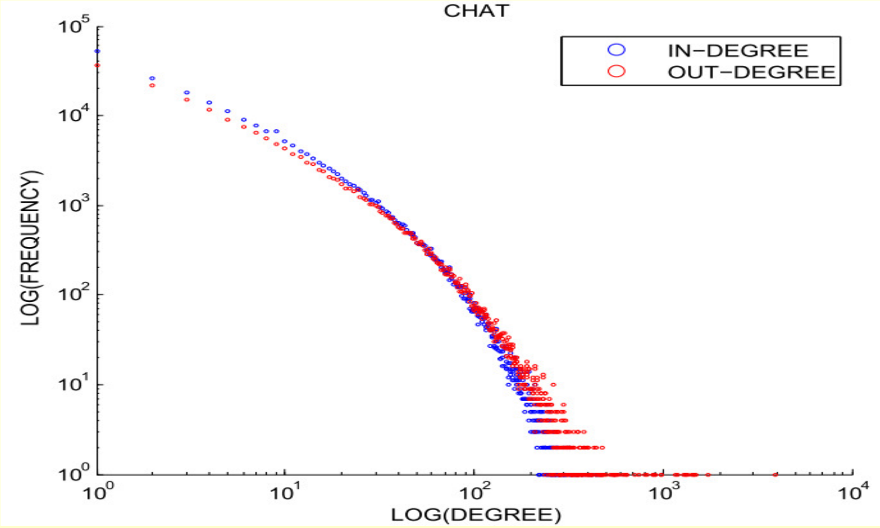


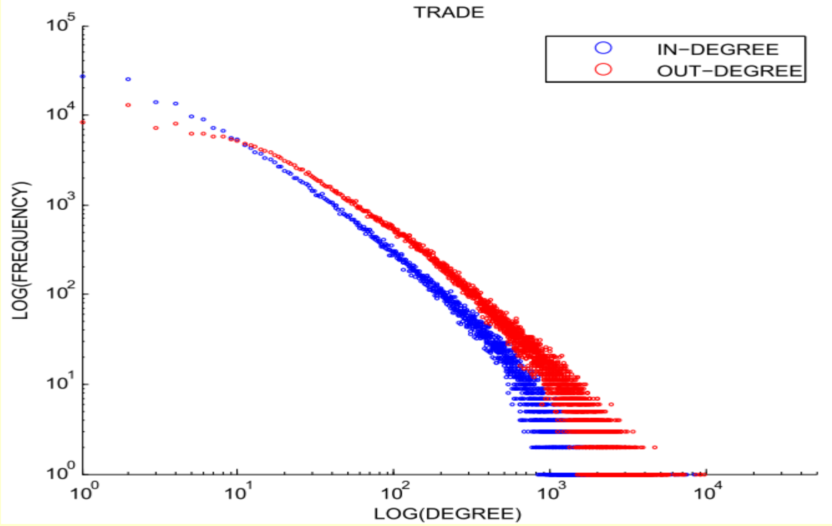
Chat

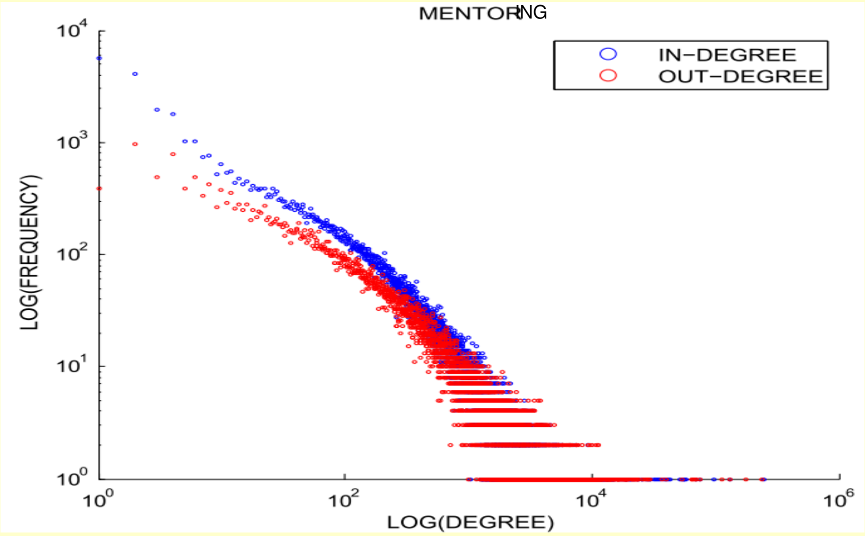


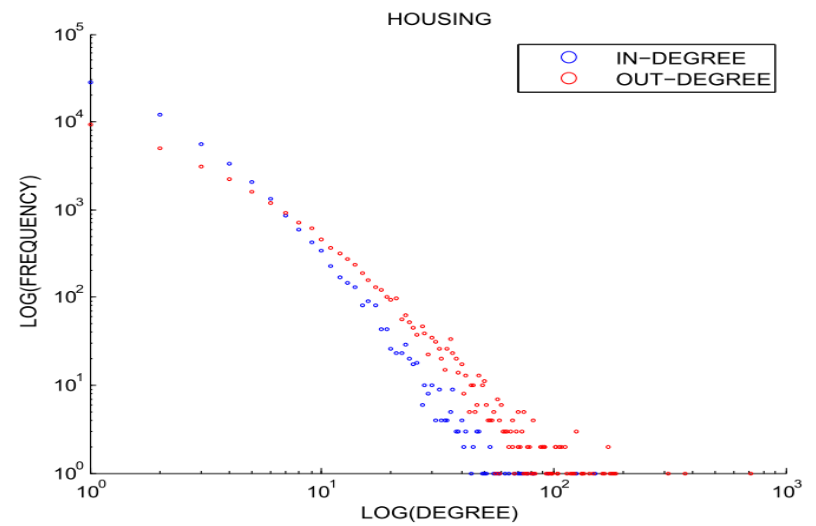
Housing Trust

Degree Distribution for Various Networks









Part II – Impact on Science

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.

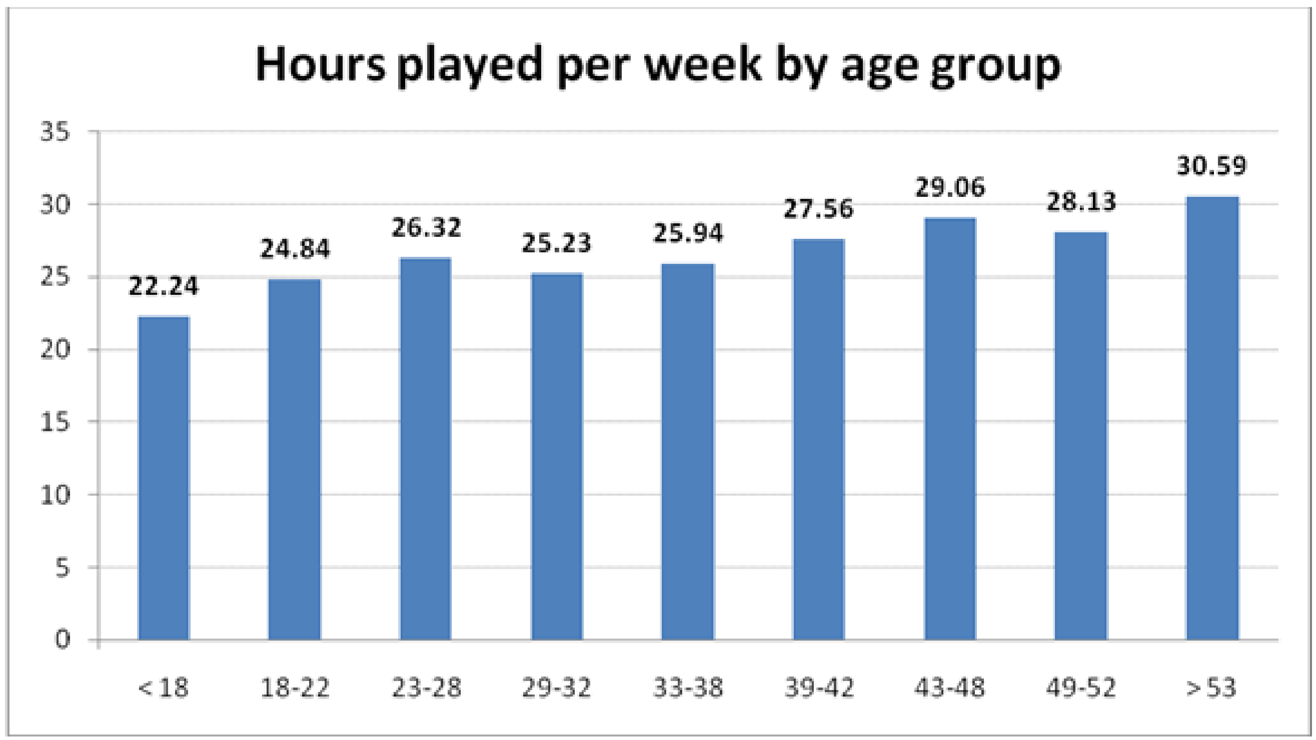
Table 1

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)

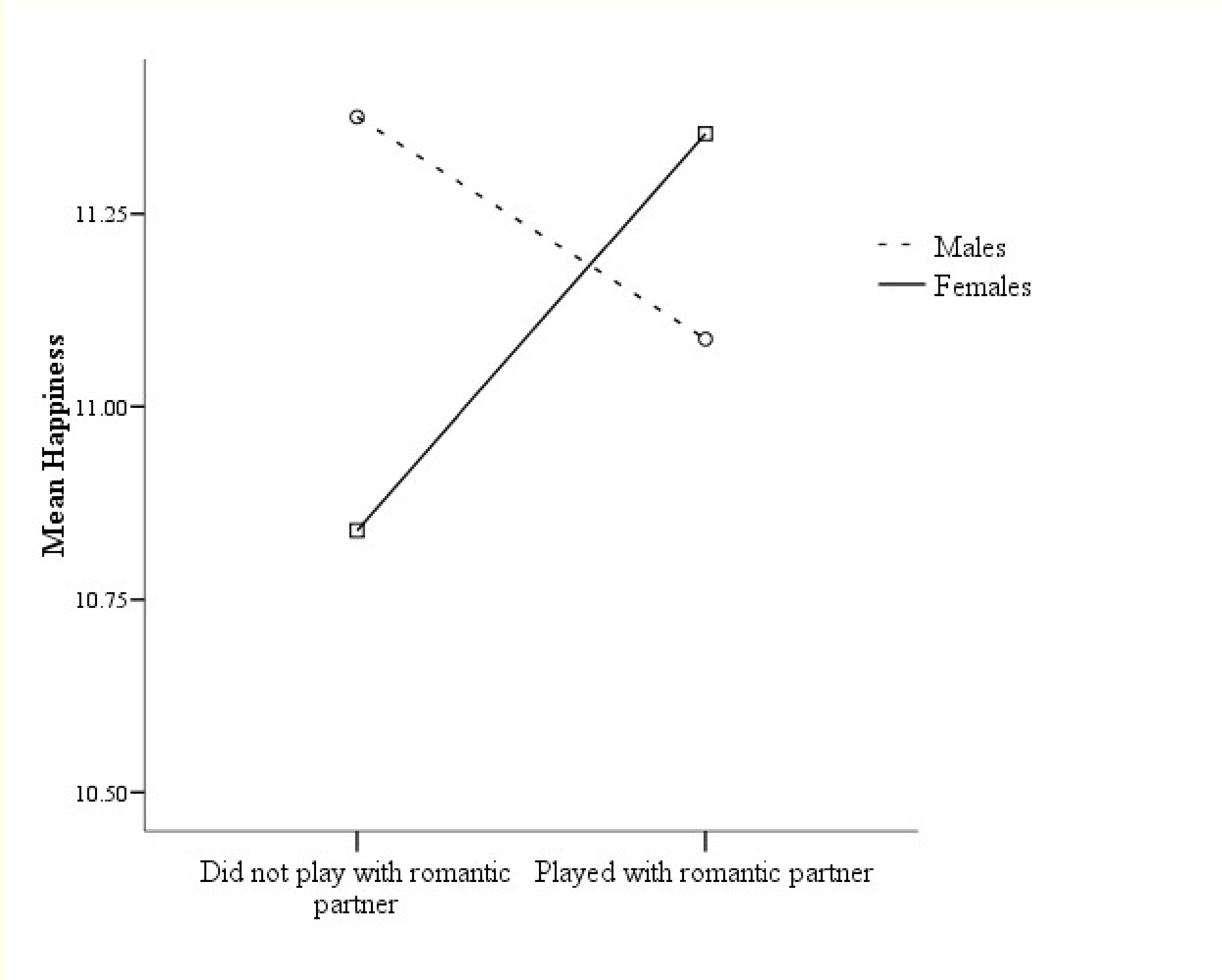


- From prior experimental work, MMO play eats into entertainment TV and going out, not news
- So much for kids being the ones with the free time.

Gender Differences

- More men players (78/22%)
- Men played to compete , and women played to socialize
- 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%
- Self reported play times
  - Women: 26.03 (3 hours less than actual)
  - Men: 24.10 (1 hour less than actual)
  - Boys and girls are socialized early on, and thus have clear role expectations for their behaviors and identities (*Gender Role Theory in action!!*)

Playing with a partner



Inferring RW gender from VW data

Goal

What virtual world behaviors and characteristics predict real world gender?

Data:

- Survey Data n=7119
- Survey Character Store
- EQ2 Character Store

Variables

- *Avatar Characteristics:*
  - Gender, Race, Class, Experience, Guild Rank, Alignment, Archetypes
- *Game play Behaviors:*
  - Total Deaths & Quests, PvP Kills & Deaths, Achievement Points, Number of Characters, Time played, Communication patterns

Gender prediction results

- Close to 95% prediction accuracy
  - Decision trees work rather well
- Character Gender, Race and Class are significant predictors to real life gender.
- Gender swapping is rarer, but systematically different by real gender
- Players tend to choose:
  - character gender based on their real life gender
  - character races that are gendered: women play elves/men play barbarians
  - classes that are gendered: women play priests/men play fighters

Gender swapping behavior

Game Character Gender	Real Gender					
	Male		Female		Total	
Male	4065	82.6%	98	8.2%	4163	68.0%
Female	855	17.4%	1104	91.8%	1959	32.0%
Total	4920	100.0%	1202	100.0%	6122	100.0%

Observation

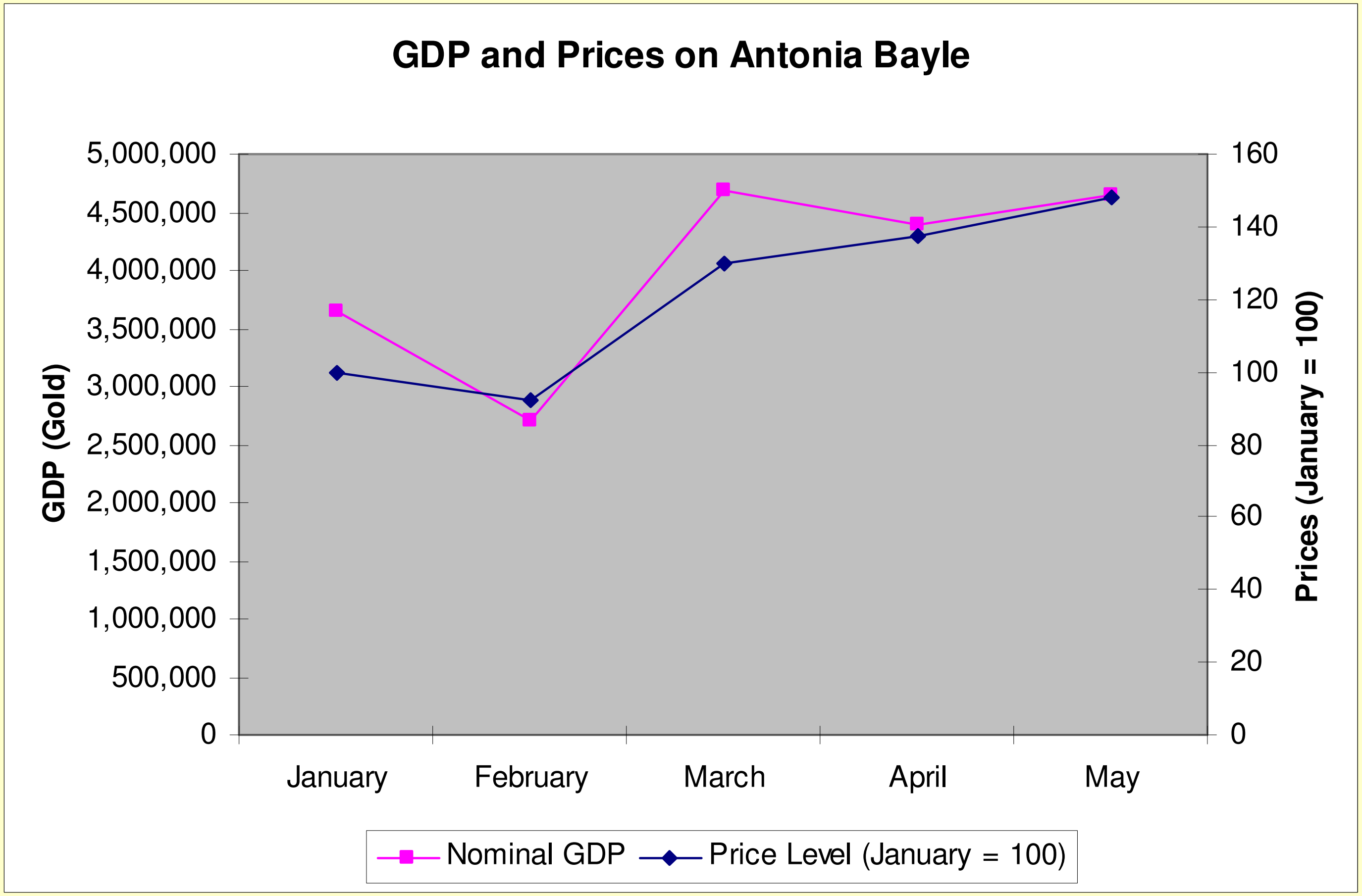
- Far more males gender swap than females
- Why?
  - Men are more creative?
  - Women have less identity confusion?
  - Women get their ‘fill of gender swapping in real life’ ☺

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

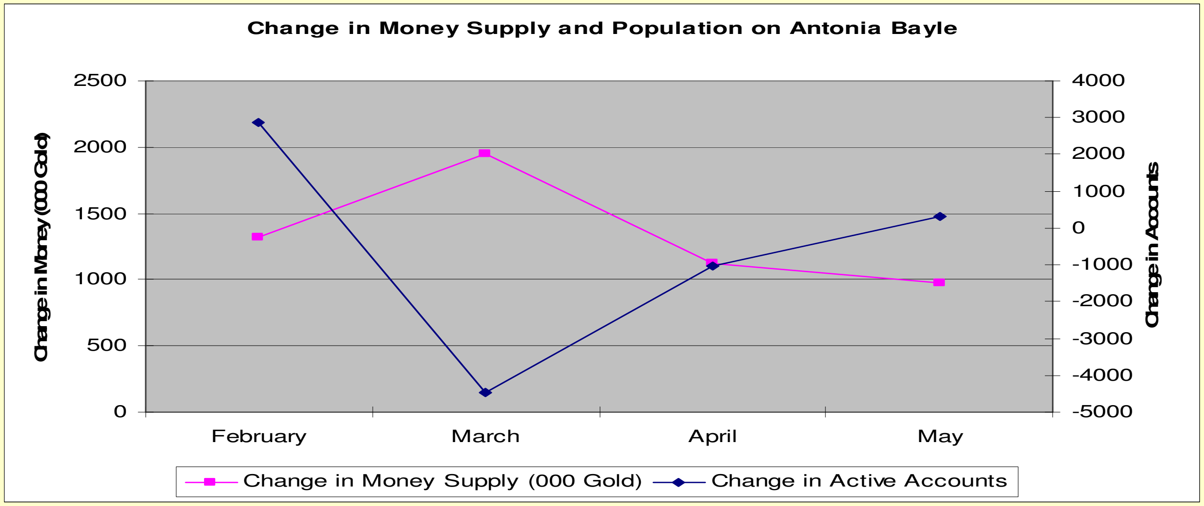
GDP and Price Level

- GDP and price levels are robust but comparatively unstable

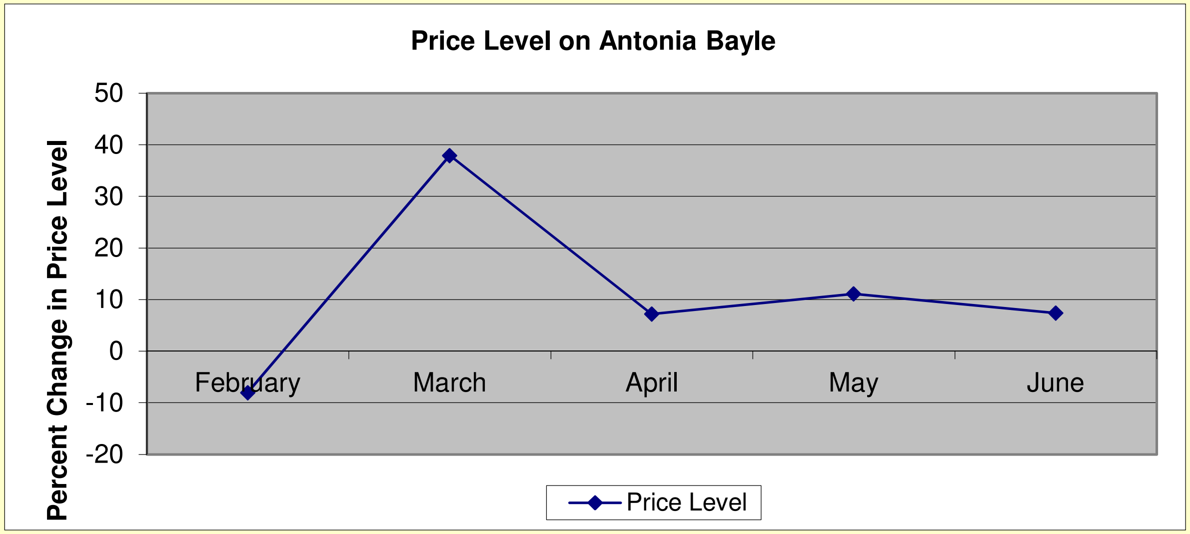


Money Supply and Price

- 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

Networks in Virtual Worlds

Why do we create and sustain networks?

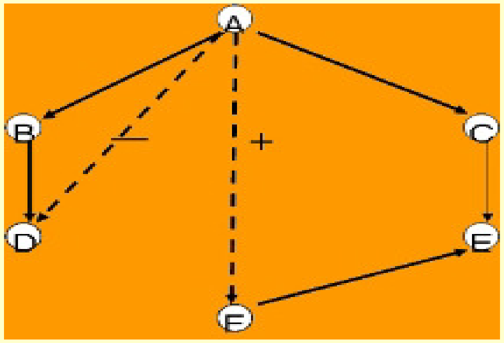
- Theories of self-interest
- Theories of social and resource exchange
- Theories of mutual interest and collective action
- Theories of contagion
- Theories of balance
- Theories of homophily
- Theories of proximity
- Theories of co-evolution

Sources:

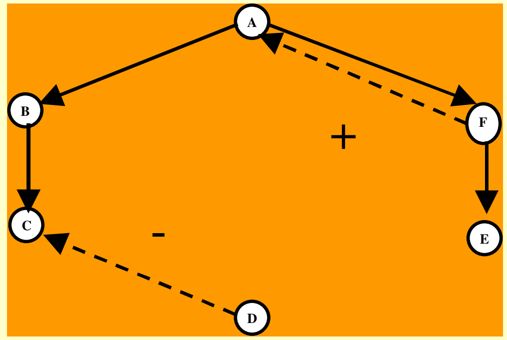
Contractor, N. S., Wasserman, S. & Faust, K. (2006). Testing multi-theoretical multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of Management Review*.

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

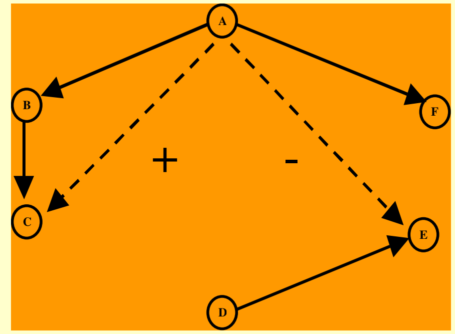
“Structural signatures” of Social Theories



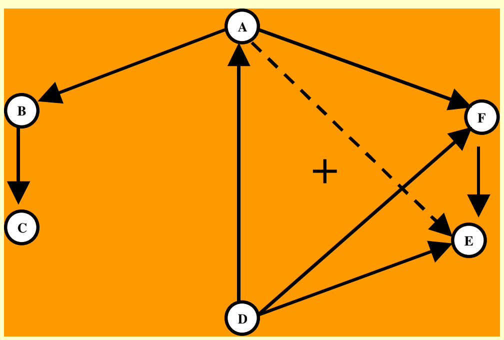
Self interest



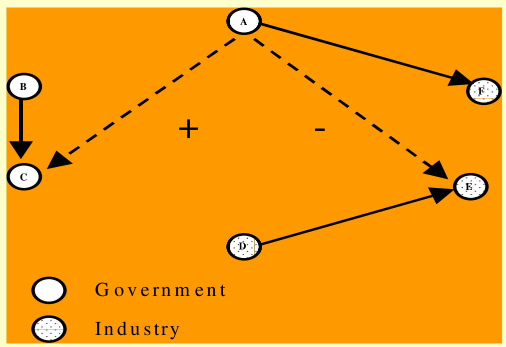
Exchange



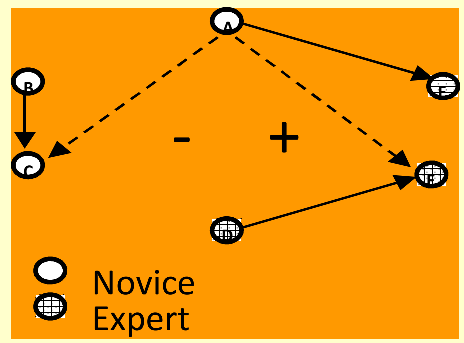
Balance



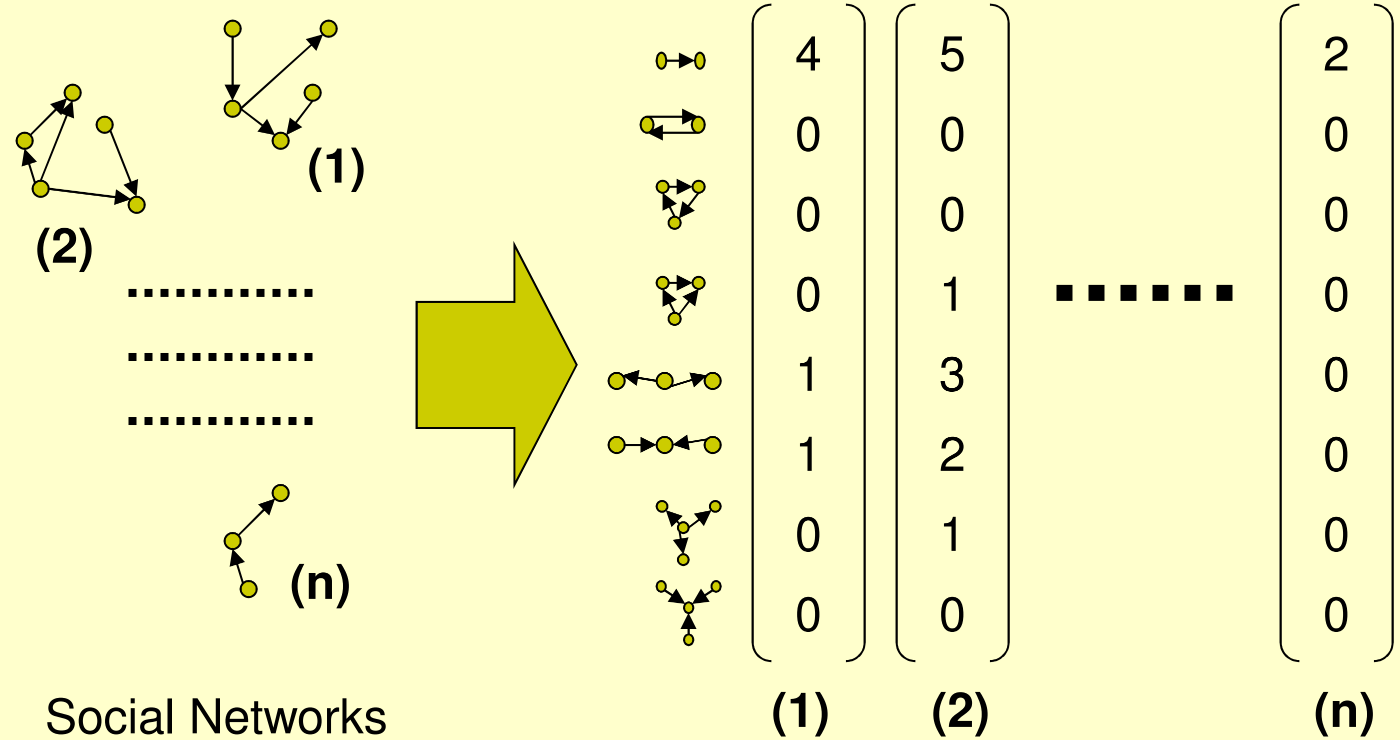
Collective Action



Homophily



Contagion



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

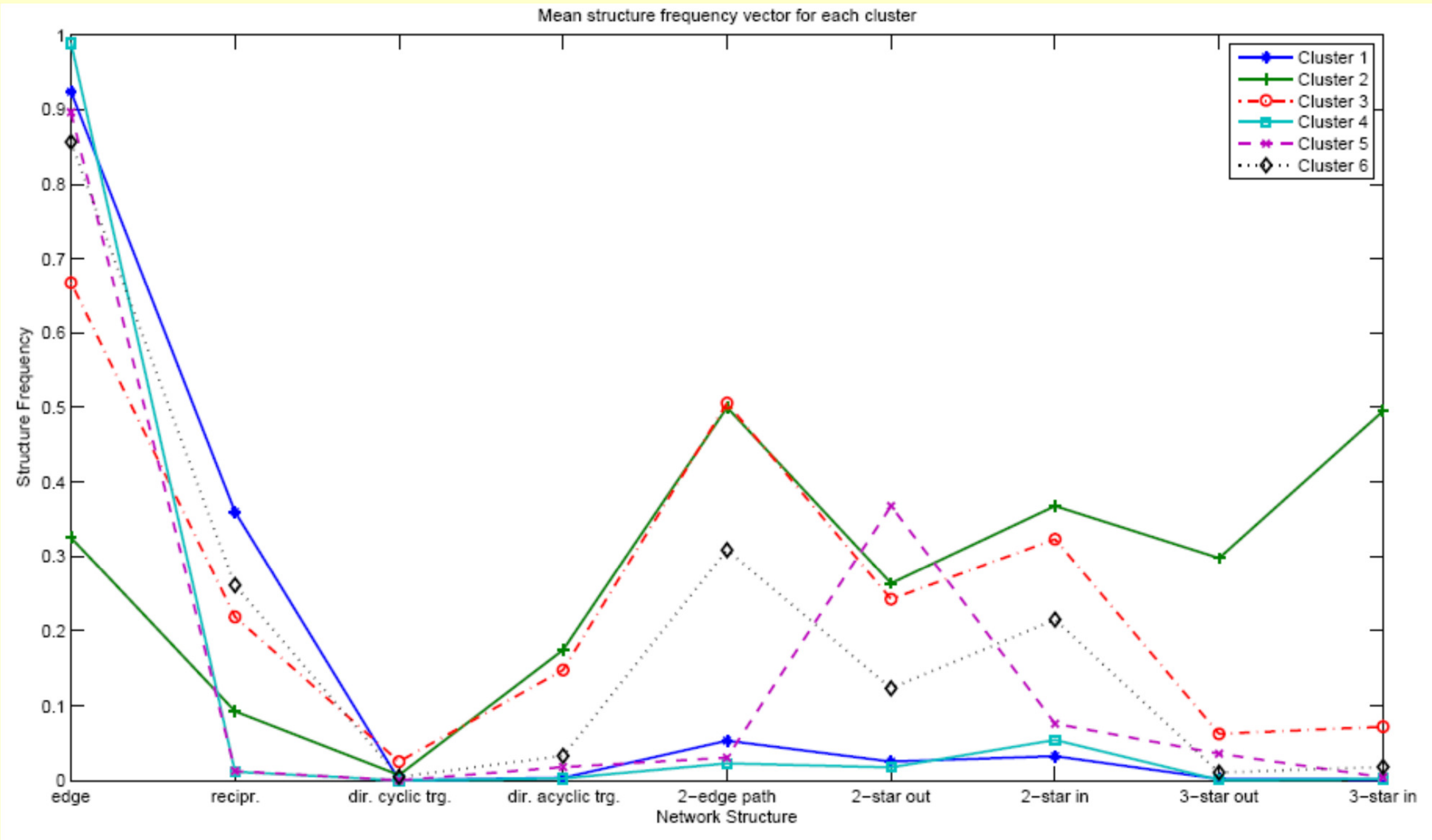
Cluster Structure
Vectors using
Text clustering
methods

Social theory + IR based network analysis

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 – normalized network structure vector means for all clusters



Results

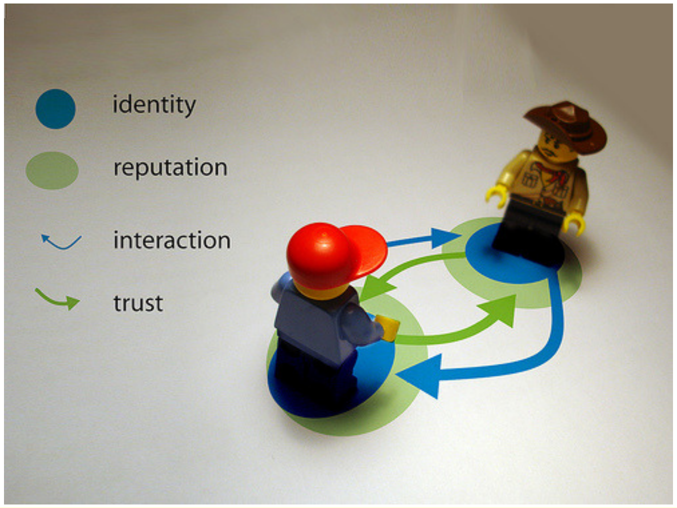
- Clusters 1 and 4 are similar
  - Groups kill fewer monsters
  - Group members in cluster 4 do not communicate much
  - Group members in cluster 1 generally limit their communication to just one other person in the group
  - Most people belong to these two clusters
  - Consistent with previous research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

Some Open Questions

- How similar/dissimilar are online social networks from real-world social networks?
- Is online socialization
  - Only a sustainability activity of real-world networks?
  - Causing new social networks to be formed?
  - Is fundamentally a different type of networking activity?
- A fundamental tenet of socialization has been "geography/proximity drives socialization"
  - How is this being impacted by online socialization?

Understanding the nature of trust networks



“If you want to go fast walk alone, if you want to go far then walk with a group.”

- Proverb from Ghana

Big Picture Questions

- How is trust expressed differently in different social contexts?
  - Cooperative (PvE), Adversarial (PvP), …
- How is trust expressed in different types of social networks?
  - Housing, Mentoring, Trade, Group, …
- What are the characteristics of trust and related networks in MMOs?
  - Similarities and differences with social networks in other domains e.g., citation networks, co-authorship networks
- What role can features derived from the trust network play in prediction tasks e.g., link prediction (formation, breakage, change), trust propensity, success prediction

EQ2 Trust Relationship

- All players can carry only limited number of items at a time
- Player buys a house to store excess in-game items
- House is shared with a in-game partner until the owner revokes the permission to house
- There are several levels of permission of access
  - TRUSTEE – The partner can enter, store and move items in and out of the house
  - FRIEND – The partner can enter, store and move his items only
  - VISITOR – The partner can enter and see the house
  - NONE – The partner can see the house from outside
  - REMOVE – The partner cannot see the house

Do players prefer a specific trust level? Is there any stable trust level? Do players express higher trust level quickly compared to lower?

Homophily and Trust

- **Homophily:** Birds of a feather flock together
- There is no one form of homophily and homophily in general is described in multiple ways: Status vs. Value Homophily
- Each of these homophiles are in turn defined in multiple ways themselves
- Previous literature instantiates homophily in MMOs in terms of player characteristics and behavior in the game

Network Models, Homophily and Trust Networks in MMOs

- **RQ1:** Does homophily in MMOs operate in ways similar to homophily in the offline world?
- **RQ2:** How do we map characteristics that define homophily in the offline world to online settings?

Mapping Homophily in MMOs

TABLE I THE TOPOLOGY OF HOMOPHILY IN MMOs

Homophily Types	Sub-category	Variables	Description
Status	Ascribed characteristics	gender	Player gender
		age	Player age
	Acquired characteristics	Class*	MMO professional class
		Guild membership	
		Location	
		Player level	
		Race*	Character race
		* Though class and race are ascribed characteristics in the real world, it is a matter of choice in MMOs – therefore, labeled as acquired characteristics.	
Value		Time needed for level change	Average time of a player to climb up "Player level" - support "aspiration" idea of value Homophily – hypothesis is that players will like to see similarity in climbing up levels among their peers (mentor- mentee relationships as exceptions)
		Quest difficulty level	Explain the idea of "challenge" a person like to take in the game – hypothesis is that players like challenge are more likely to group together.

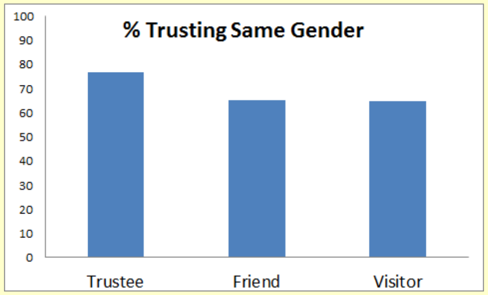
- In general, studies of homophily in MMOs assume only one type of homophily and generalize based on that type
- Even in the offline world homophily is of different types
- Hence the necessity of Mapping Homophily which we address here
- Mapping and *Proteus Effect*

Trust and Homophily in MMOs

	Homophily Type	Hypothesis	Observation
H1	Gender Homophily	Players trust other players who are of the same gender	?
H2	Age Homophily	Players trust other players who are of the same age cohorts	?
H3	Class Homophily	Players trust other players who are of the same class	?
H4	Race Homophily	Players trust other players who are of the same race	?
H5	Guild Homophily	Players trust other players who belong to the same guild	?
H6	Level Homophily	Players trust other players who are at a similar level	?
H7	Challenge Homophily	Players trust other players who like similar types of challenges	?

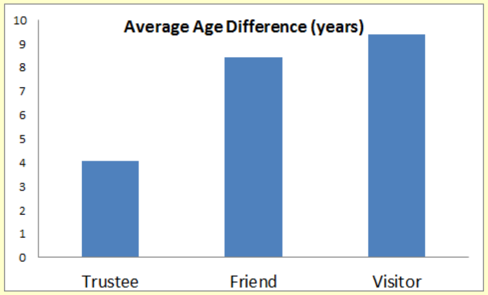
Key Observations

H1: Players trust other players who are of the same gender?



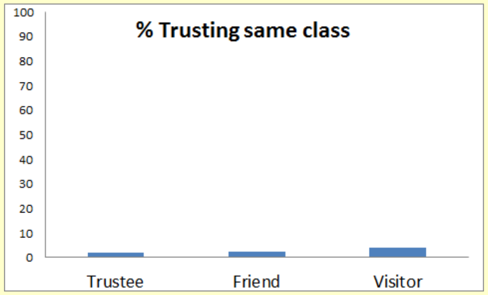
In general players trust other players who are of the same gender

H2: Players trust other players who are of similar age?



The stronger the type of trust the lesser is the age difference between the people specifying trust

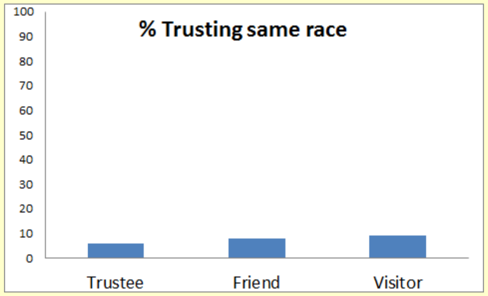
H3: Players trust other players who are of the same class?



Class does not seem to effect the choice of trusting others

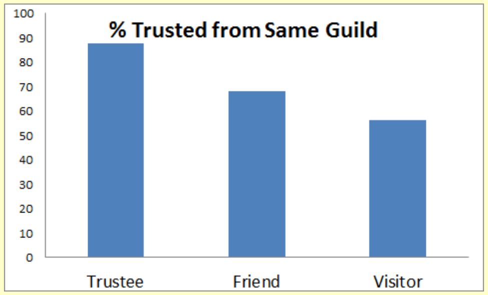
Key Observations

H4: Players trust other players who are of the same race?



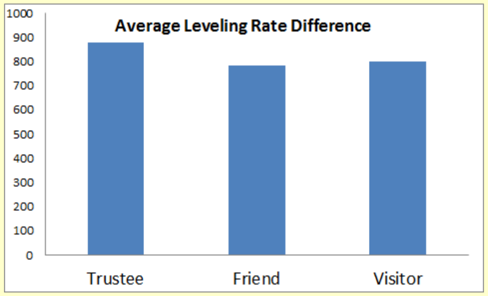
Race does not seem to effect the choice of trusting others

H5: Players trust other players who are of the same guild?



In general, the stronger the type of trust, the greater is the percentage of the people who trust people in their own guilds

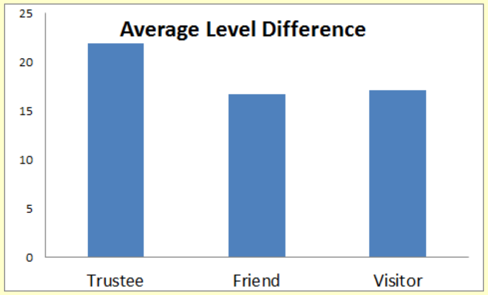
H6: Players trust other players more who are level at a similar rate?

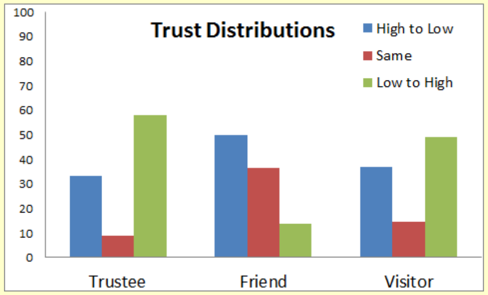


Leveling at the same rate does not seem to greatly effect trust amongst players

Key Observations

H7: Players trust other players who are of the same level?





- Level difference seems to have some effect on trust
- For Trustee (strongest) and the Visitor (weakest) form of trust, the lower level players are more likely to trust players who are at a higher level

Summary:

- Homophily is observed for a subset of types in MMOs as compared to what it is observed for in the offline world
- The types of homophily which are not observed in MMOs are the ones which are greatly effected by game mechanics

Modeling Trust Dynamics

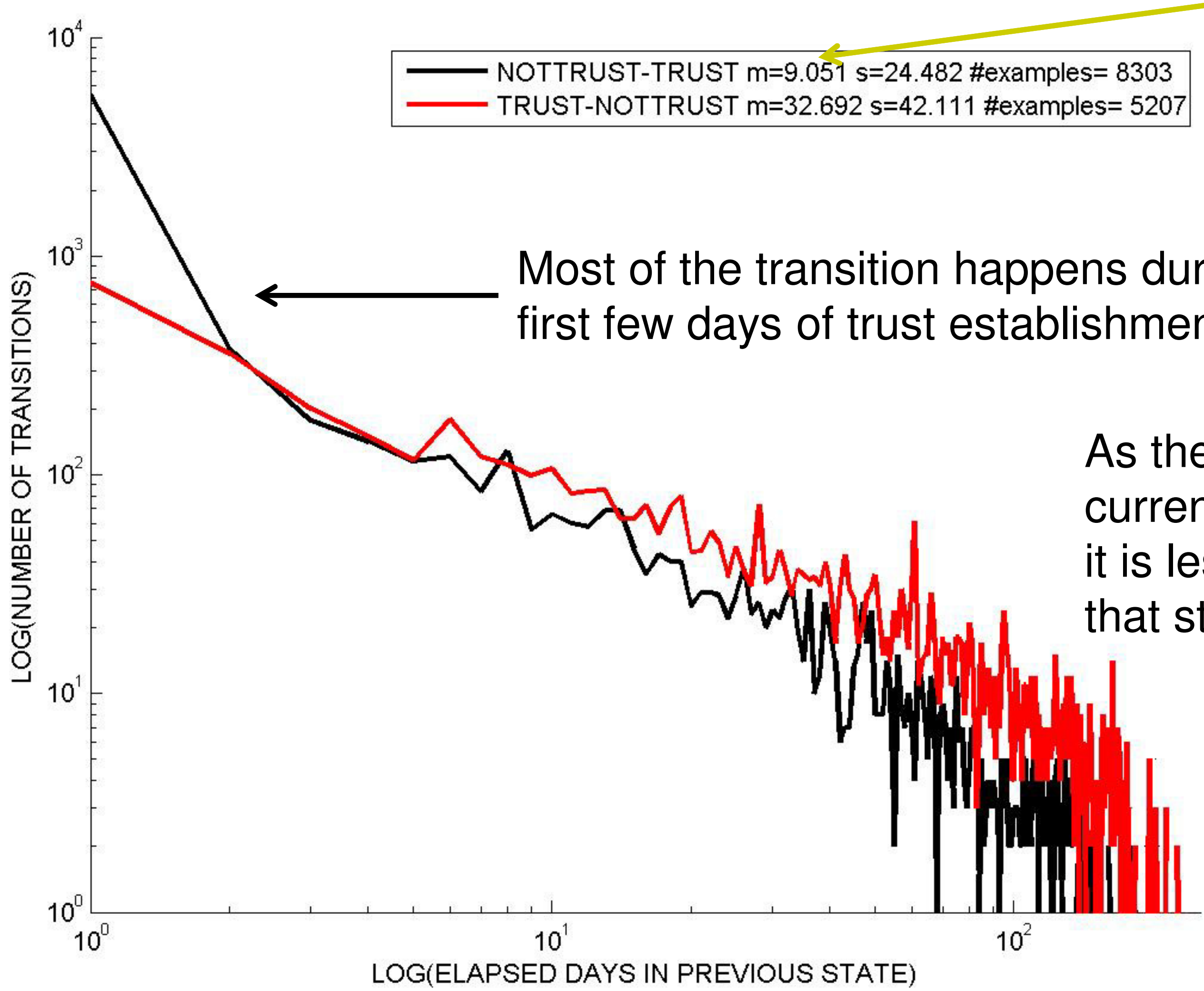
EQ2 Trust Dynamics

	BEG	REMOVE	NONE	VISITOR	FRIEND	TRUSTEE	END
BEG	0	4956	2576	6733	26728	64142	0
REMOVE	0	0	45	759	257	2024	8518
NONE	0	712	0	473	148	1617	1339
VISITOR	0	1185	161	0	641	459	8010
FRIEND	0	2383	1241	1398	0	4203	20030
TRUSTEE	0	2367	266	1093	1481	0	67238
END	0	0	0	0	0	0	0

Key Observations:

- Frequency of Expression: People express stronger relationships more often than weaker relationships. See total count of the upper triangular part compared to the lower.
- Stability of Trust: Trustee state is predominantly preferred and stable state compared to all other states. See BEG->TRUSTEE and TRUSTEE->EOD.
- Reduction of Trust: People reduce their trust level to REMOVE compared to any other state. Compare REMOVE column with other columns.

Time-to-Revoke

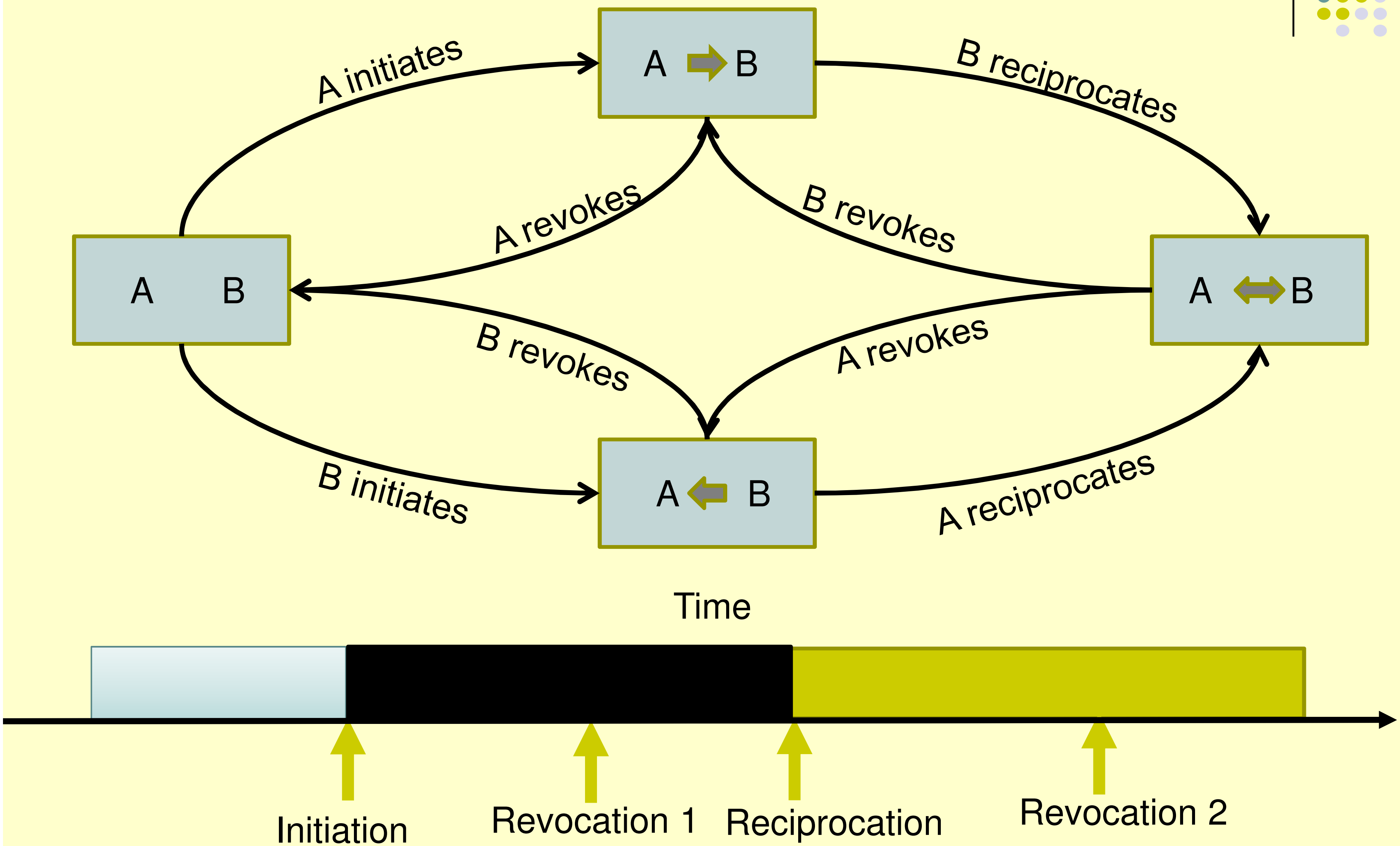


People switch to trust state much more quickly

Most of the transition happens during first few days of trust establishment

As the relationship stays in current state for longer period it is less likely to move out of that state

Modeling Dynamics of Dyadic Trust



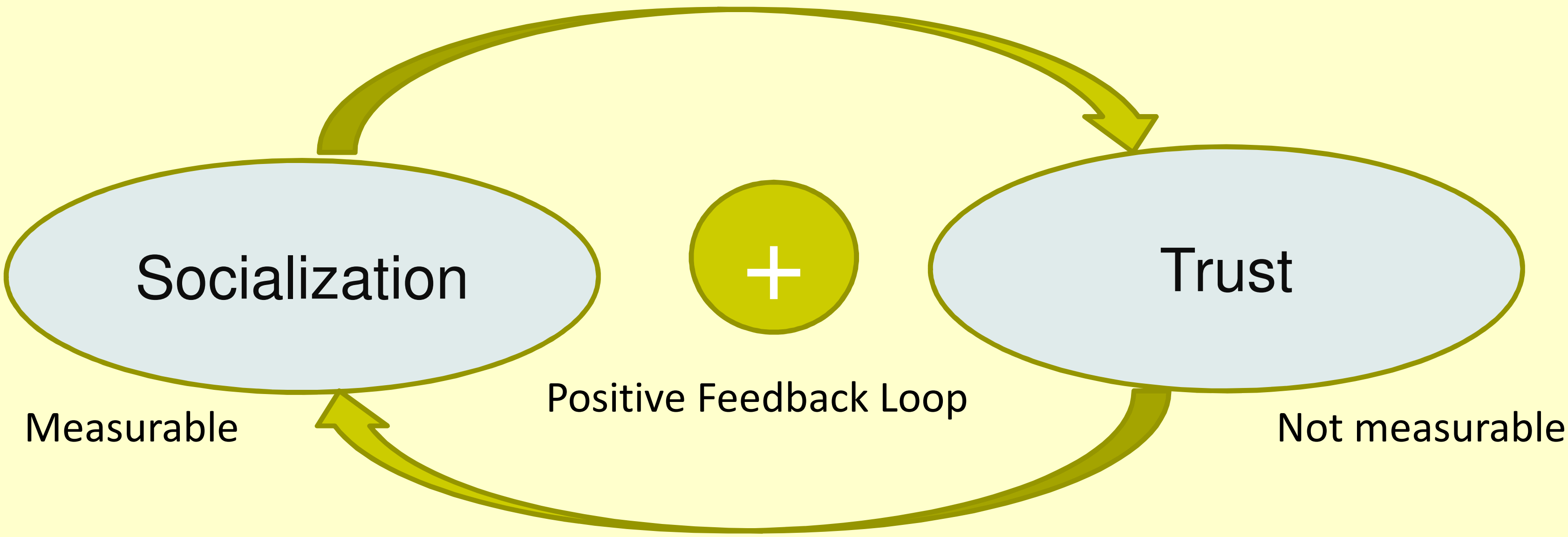
Questions of Interest in Trust Dynamics

- **Socialization and Trust**
- What role does socialization play in trust formation?
- What role does trust play in socialization?
- **Trust Reciprocation**
- When is trust reciprocated?
- What role do other relationships/activities play in trust reciprocation?
- Can we predict if reciprocation will happen?
- **Trust Revocation**
- What causes trust revocation?
- Can revocation be predicted?
- Is revocation an indicator of distrust?
- Revocation cascades and the 'scarlet lettering effect'

Socialization and Trust Formation

Trust and Socialization

- Trust is a hidden variable
- Measurable indirectly through observable proxies
- Social activities strongly correlated with trust



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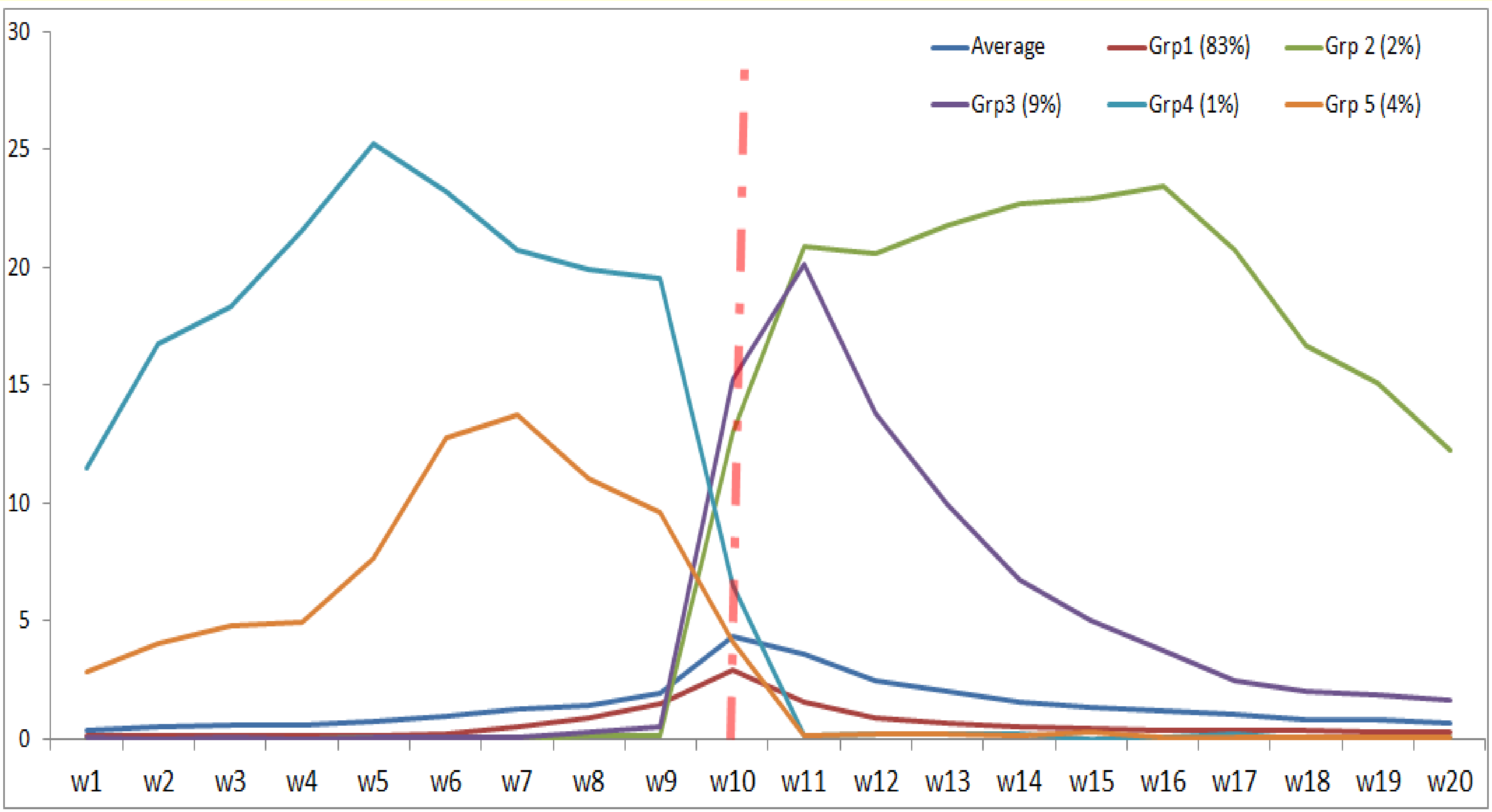
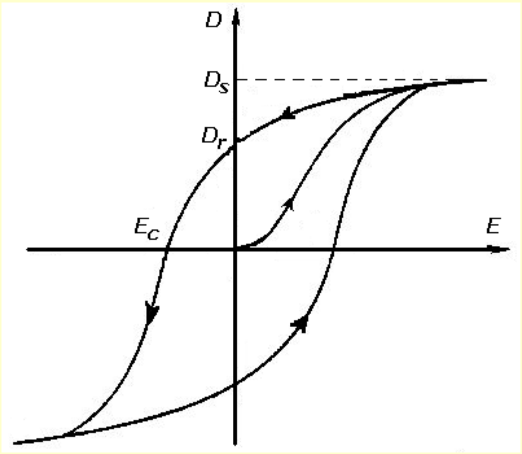
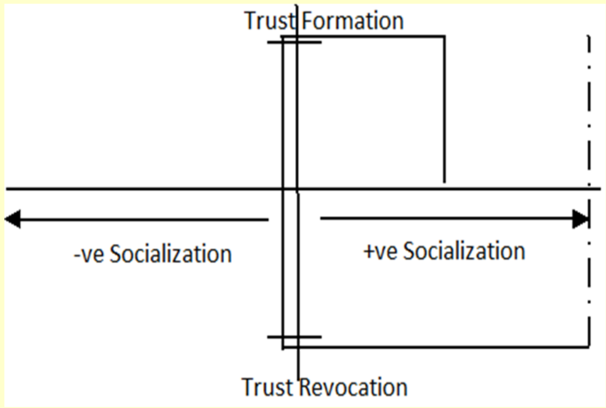
Socialization and Trust Granting



Does trust exhibit a social hysteresis?





Magnetic Hysteresis	Social Hysteresis
Polarity changes requires equal effort	Trust is harder to build than distrust
Ease of magnetization depends on the magnetic material	Ease of trust formation depends on the characters of the persons involved
Depends on the strength of magnetic field	Depends on the type of social interaction

Trust Reciprocation

Reciprocation in Granting Trust

	Responses received	No Response	Second or more Interaction
Trust Forward Link	16904/72445 = 23.3%	54273/72445 =74.9%	1268/72445 =1.75%

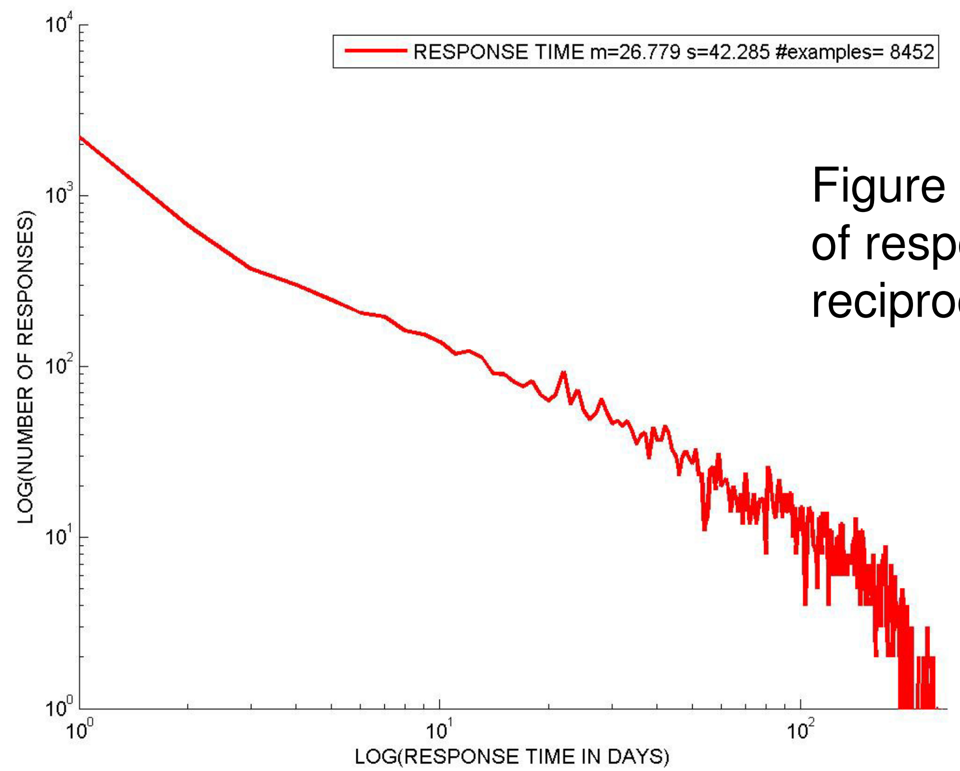
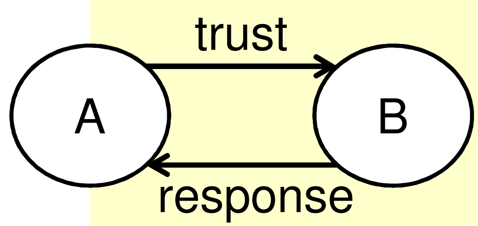


Figure shows the distribution of response times for trust reciprocation



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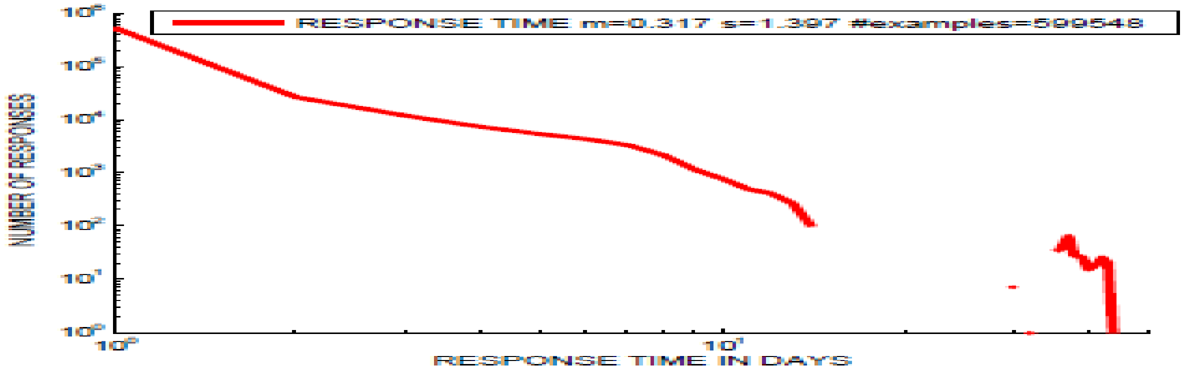
Reciprocation in Chat, Trade and Trust

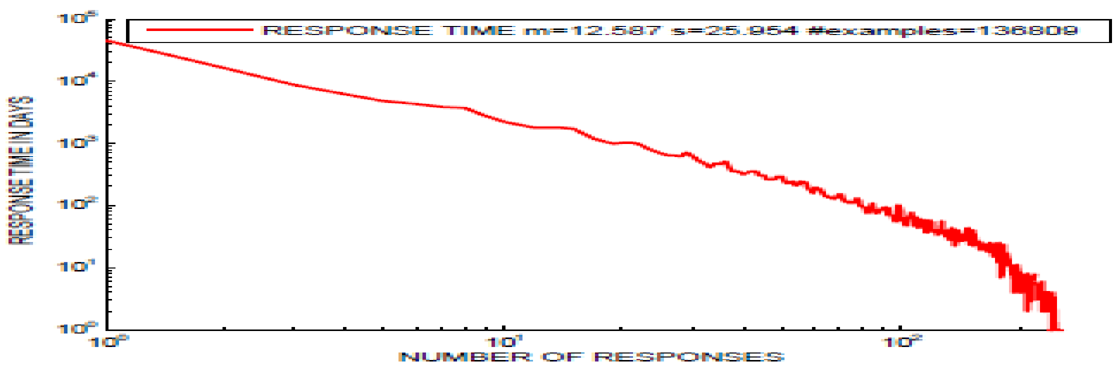
Network Type (period)	All Forward edges	First reciprocation	Second reciprocation	Third Reciprocation	All other reciprocation	Total reciprocation
Chat (1 month)	1840492	441039(23.9%)	79412(4.3%)	32128(1.7%)	46969(2.6%)	599548(32.6%)
Trade (9 months)	520861	74137(14.23%)	11850(2.3%)	3766(0.72%)	47056(9.0%)	136809(26.3%)
Trust (9 months)	62674	8452 (13.5%)	351 (0.56%)	0(0.0%)	0(0.0%)	8083 (14.0%)

- Chat is a low barrier relationship
- Trade is a medium barrier relationship
- Trust is a high barrier relationship

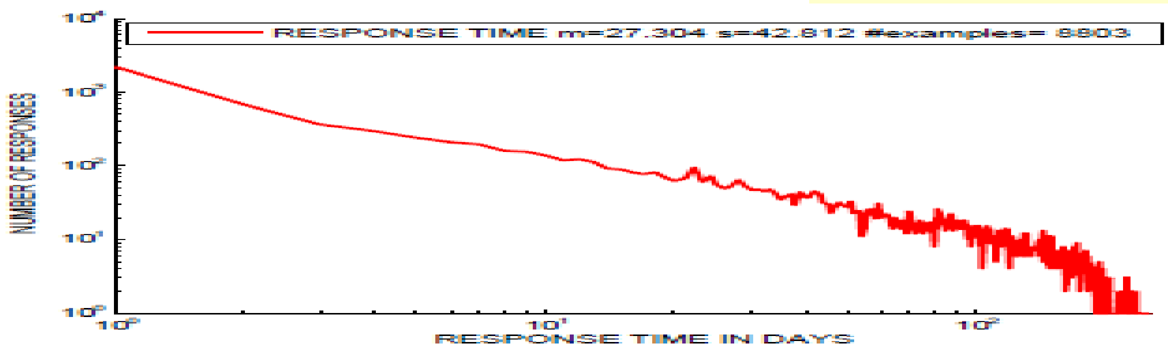
Response time distribution in Chat, Trade and Trust



(b) Chat



(c) Trade



(a) Trust

Response time distribution indicates barrier in relationship formation

Reciprocation in Heterogeneous Networks

Forward Type	First Forward Edge	Chat Reciprocation	Trade Reciprocation	Trust Reciprocation
Chat	1645623	435758	1187	105
Trade	74428	7953	11402	335
Trust	10502	907	1016	722

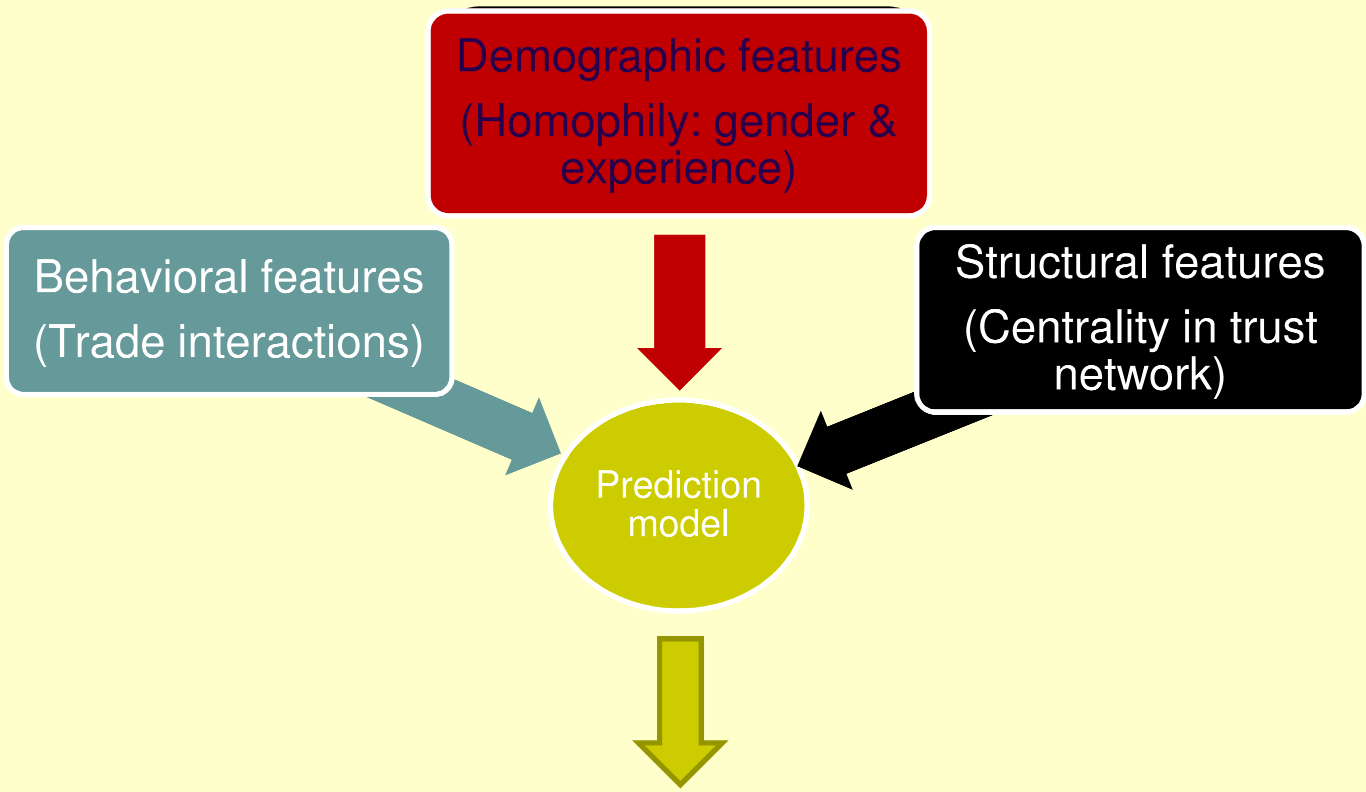
With trust request, chat and trade responses are surprisingly higher
➔ 'feeling the requester out'?

Role of low barrier relationships on Trust reciprocation

Trust type	Forward Edges	CHAT responses	TRADE responses
Complete	743	243(37%)	408(63%)
Incomplete	9145	6962 (75%)	2331(25%)

Reversal behavior of chat and trade for trust reciprocation completion

Predicting Trust Reciprocation



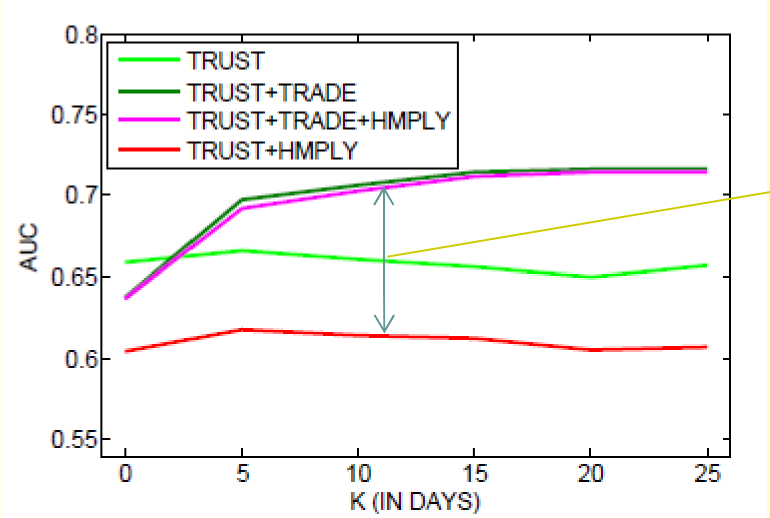
Output: Trust reciprocation (Yes/No)

- (+) class (trust reciprocated=yes)→ 8083 instances
- (-) class (trust reciprocated=no)→ 52574 instances

Reciprocation Prediction Results

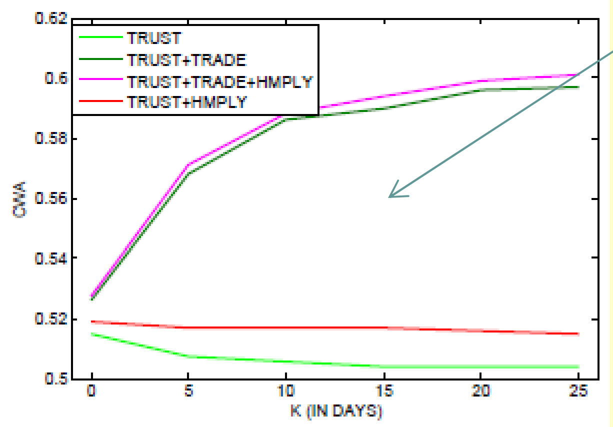
Classifier	CWA	AUC	Avg Precision	Avg recall	F-measure
Trust only	0.515	0.659	0.800	0.863	0.806
Trust+trade(k=0)	0.526	0.637	0.825	0.866	0.816
Trust+homophily	0.519	0.604	0.788	0.849	0.808
Trust+trade(k=0)+homophily	0.527	0.634	0.826	0.866	0.817
Trust+trade(k large)	0.588	0.714	0.871	0.885	0.851

Recirocation Prediction Results

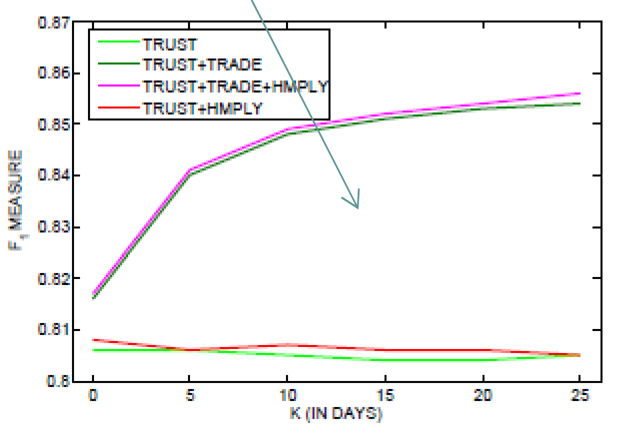


11% AUC boost up by addition of trade interaction features

CWA and F measure improvements

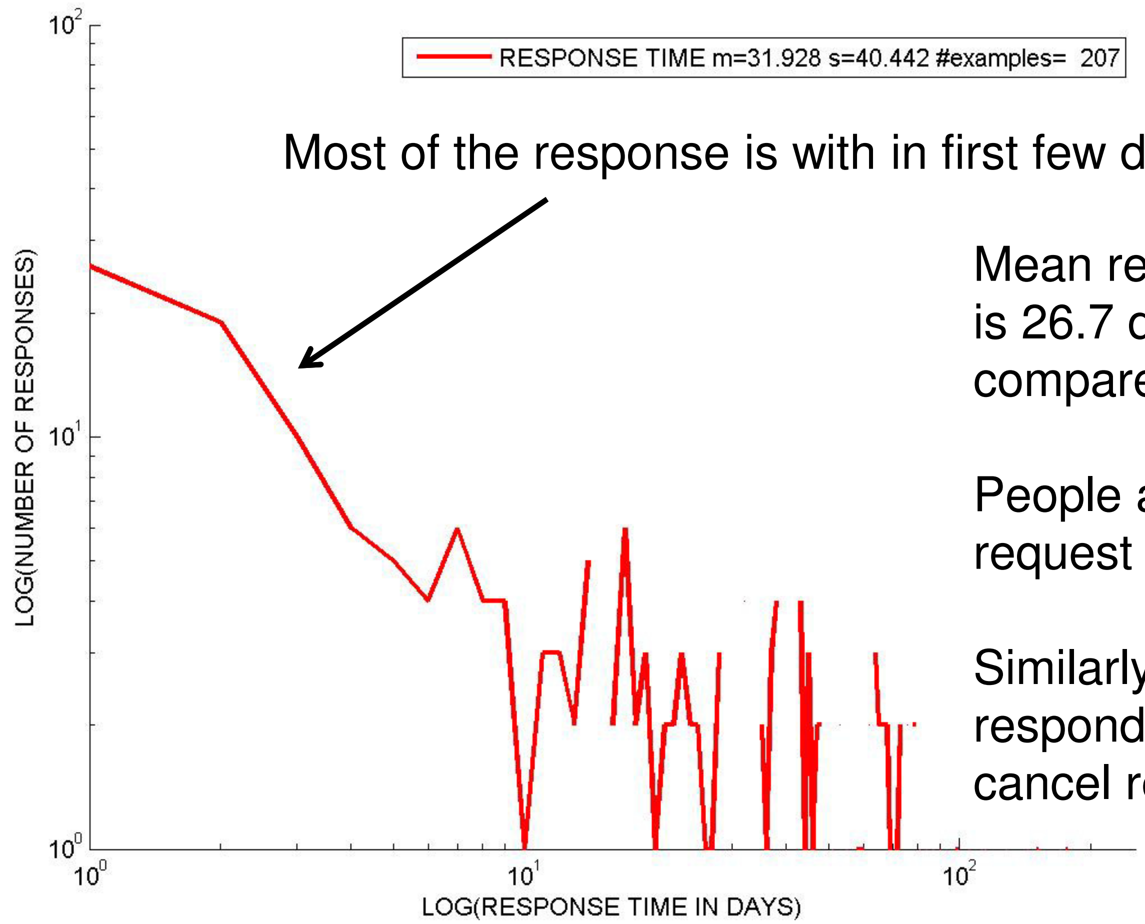


(a) Class weighted accuracy



(b) F_1 measure

Revoking Trust - Response Time Distribution



Mean response time for trust response is 26.7 days which is much lower compared to 31.9 days for cancellation.

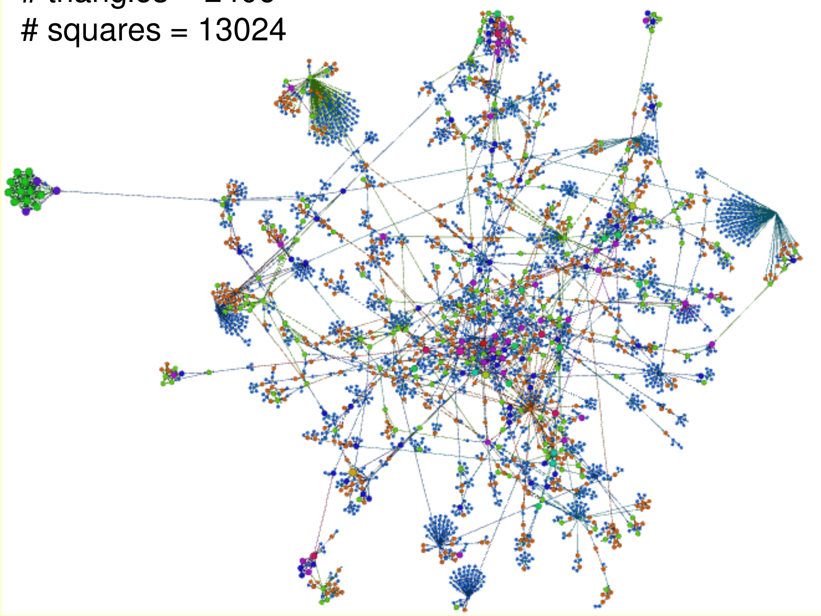
People are more responsive to trust request than its cancel request.

Similarly, 23.3% of trust requests are responded whereas only 19.6% of cancel requests are responded.

Trust Revocation and Distrust

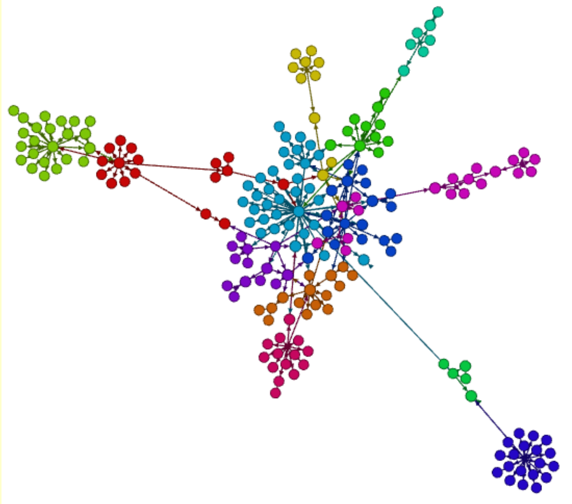
Comparison of trust grant and revocation?

triangles = 2406
squares = 13024



EQ2 Housing Trust Relationships Aug 2006

triangles = 21
squares = 24



EQ2 Housing Distrust Relationships Jul 2006

People grant trust more frequently and across communities compared to revocation

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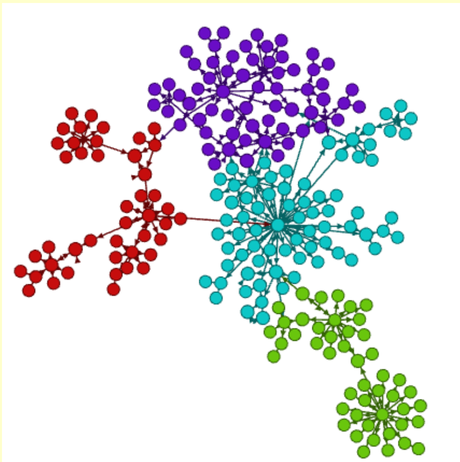
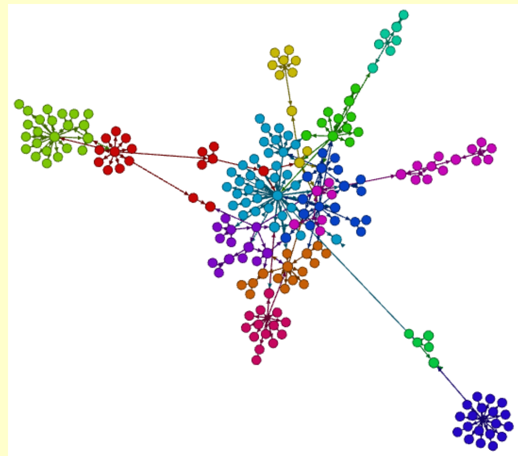
Nature of Trust Revocations



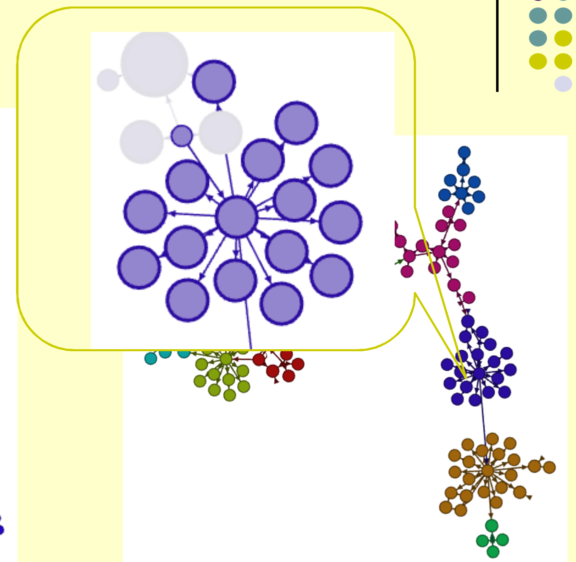
Revocation in Jun 2006

\# triangles = 3
\# squares = 8



Revocation in Jul 2006

\# triangles = 21
\# squares = 24



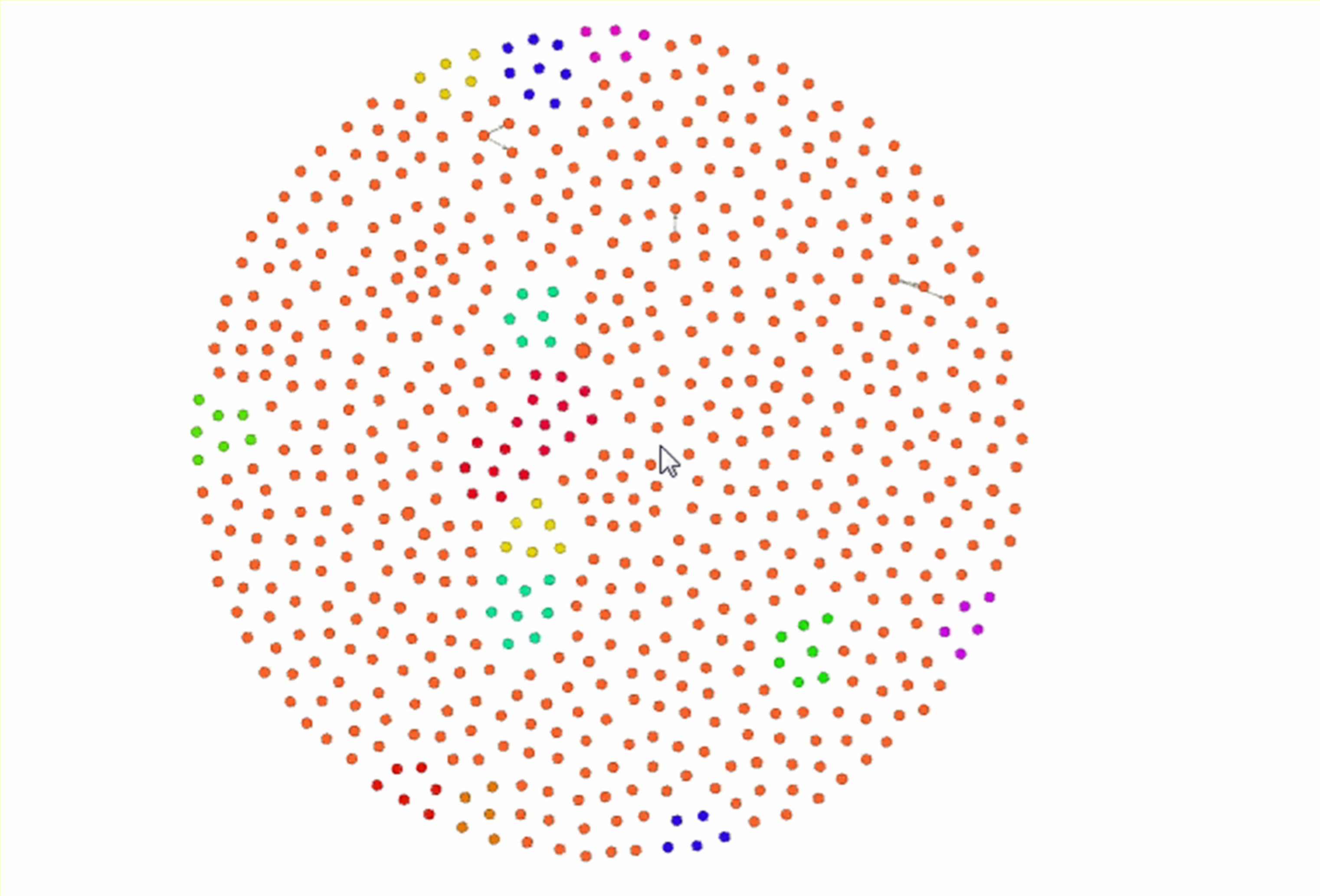
Revocation in Aug 2006

\# triangles = 28
\# squares = 0

- Trust revocation often happens by a single person in a community against several others
- Most *trust revocations* are within a community as opposed to *trust grants* which cuts across several communities
- Is there a *scarlet lettering effect* at play?

A generative model for trust networks

Trust Formation in MMOG



Social Networks: General Observations

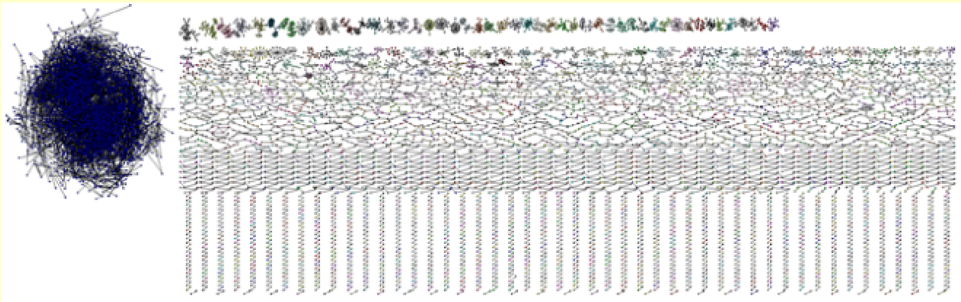
- There is an extensive literature on characteristics of social networks (Leskovec PAKDD 2005, Leskovec ICDM 2005, McGlohon ICDM 2008, McGlohon KDD 2008)
- The network exhibits **monotonically shrinking diameter** over time (Leskovec PAKDD 2005, Leskovec ICDM 2005, McGlohon ICDM 2008)
- At a certain point in time called the **Gelling Point** many smaller connected connect together and become part of the largest connected component (Leskovec PAKDD 2005, Leskovec ICDM 2005, McGlohon ICDM 2008)
- The **largest connected component (LCC)** comprises of the majority of the nodes in the network (>= 80%) (McGlohon ICDM 2008, McGlohon KDD 2008)

Social Networks: General Observations

- The **size of the second and the third largest connected components remain constant** (more or less) even though the identity of these components change over time (Leskovec PAKDD 2005, Leskovec ICDM 2005, McGlohon ICDM 2008, McGlohon KDD 2008)
- Network **isolates** are few in number (<5%) (Leskovec PAKDD 2005, Leskovec ICDM 2005)
- The **number of connected components decreases over time**
  (Leskovec PAKDD 2005, Leskovec ICDM 2005, McGlohon ICDM 2008)
- Relatively fast **growth** of **LCC** close to the **gelling point** (Leskovec PAKDD 2005, Leskovec ICDM 2005)

Trust Networks in MMOs

- Data from 4 servers is available. Results from one server (Player vs. Environment, 'guk') are shown
- The network consists of 15,237 nodes, 30,686 edges and 1,476 connected components
- Dataset spans from January 2006 to August 2006
- Average node degree of 4.03. The size of the three largest connected components are as follows: 9039, 51 and 49. The largest connected component accounts for 59% of all the nodes in the network



The Trust Network on 'guk' on August 31, 2006

Key Observations

- ***Observation 1:*** Preferential Attachment: The rich get richer but not too rich
  Explanation: Social bandwidth is limited, Dunbar Number
- ***Observation 2:*** The growth of the LCC is retarded after the gelling point
  Explanation: The trust network has a *relatively* low growth rate as compared to the other networks
- ***Observation 3:*** Non-monotonic change in the diameter of the largest connected component
  Explanation: Players have different levels of activity at various points in time and can also “drop out” of the network if they churn from the game

Key Observations

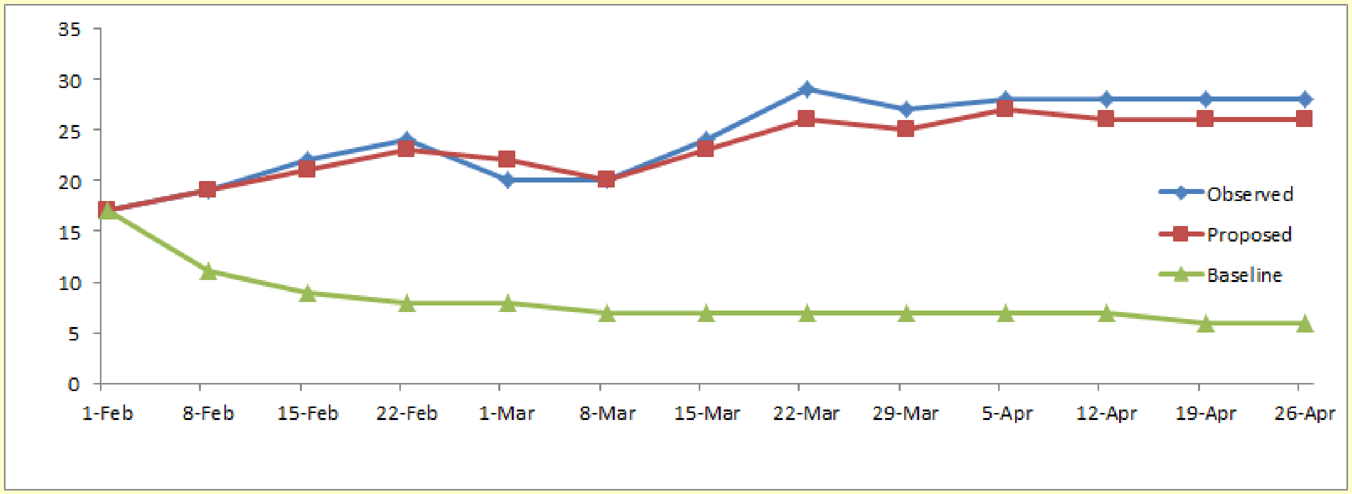
- ***Observation 4:*** A large number of isolate components are observed (> 1000)
  Explanation: People join in groups and spend *all* the time playing with one another instead of interacting with people from the outside
- ***Observation 5:*** The number of isolate components increases monotonically over time
  Explanation: (Same as observation 4)
- ***Observation 6:*** Nodes in the non-LCC constitute a significant portion of the network (41%, 8 months after gelling point)
  Explanation: (Same as observation 4)

Generative Models of Trust Networks

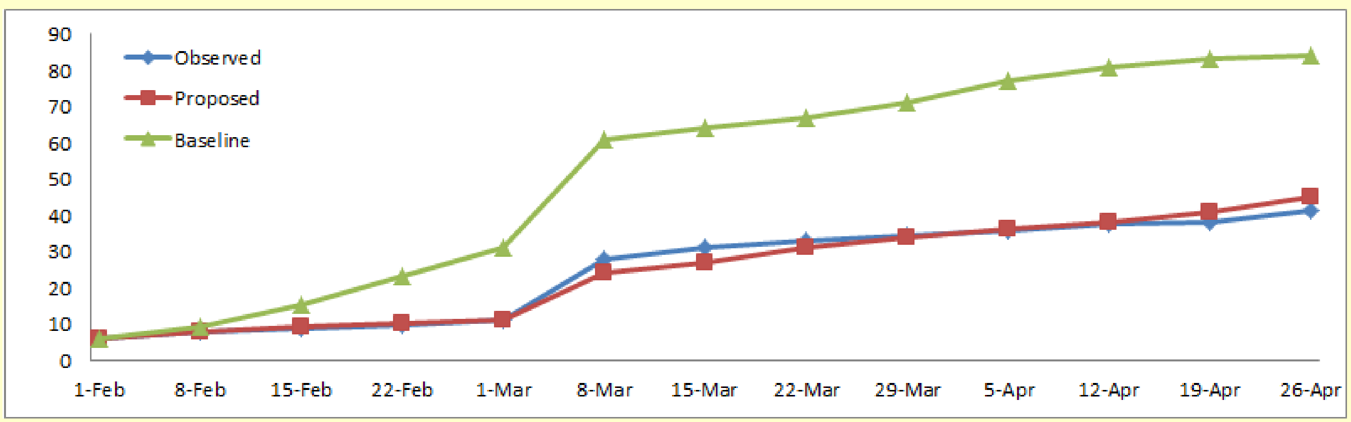
- **Time bound Preferential Attachment:** The rich get rich but not so much after a certain point in time. Edge formation is bound by time
- **Presence of Auxiliary Components:** Isolated nodes are added to the network at an almost constant rate over time
- **Non-Monotonic Decrease in the Diameter:** Nodes become inert after a certain point in time. Sample the lifetime of nodes from a normal distribution
- **Homophily in Edge formation:** Probability of edge formation dependent upon node degree as well as agreement (similarity) in node characteristics

Results

Diameter: Non-Monotonically Changing Diameter

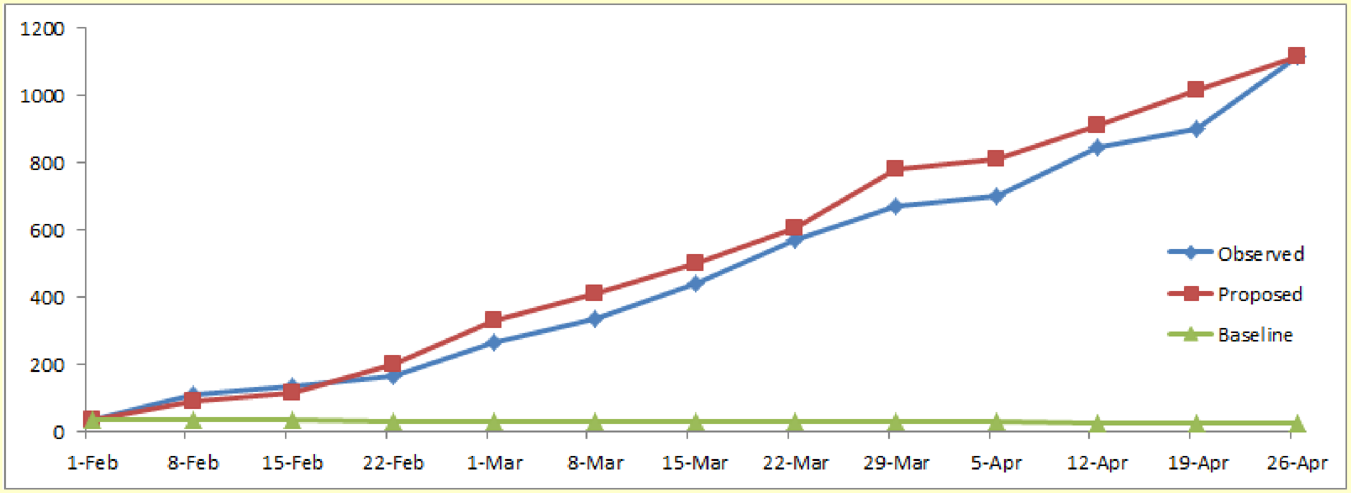


% LCC as being relatively small

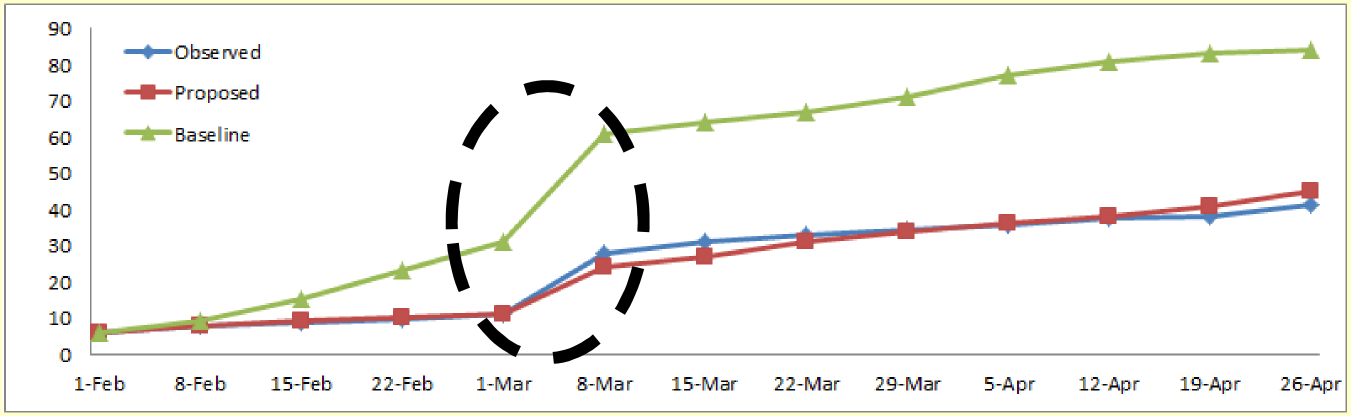


Results

Number of Connected Components



Network growth and the gelling point



Conclusion: Trust Networks

- Trust Networks in MMOs exhibit many properties which are not exhibited by other social networks in most other domains
- Models of social networks should incorporate the peculiarities which are observed in MMOs in general
- Generalization? Similar observations have been made for mentoring networks but not for PvP, Trade and Chat Networks
- Future Directions
  - **Dynamics of trust revocation**
  - **The *scarlet lettering effect***
  - **Trustworthiness vs. Trustingness**
  - **Level of trust in a community**
  - **Trust evolution over time**

How Real is EQ2 Trust?

- Firstly, trust is an immeasurable, like intelligence, influence, etc. ➔ we must work with proxies for trust
- Generally accepted facts about trust
  - *A trusts B if A gives B the power to cause some harm to A*
  - Harm could be financial, reputation, loss of life/property, etc.
  - The *degree of trust* is proportional to the *amount of harm*
  - A risks something when (s)he trusts B, with degree of trust proportional to magnitude of risk
- So, what's at risk in EQ2
  - *Small risk:* real money spent in acquiring virtual items
  - *Big risk:* Hours upon hours of efforts (a staggering 25.86 hrs/week on the average for EQ2 players!) spent in acquiring the goods/status
  - Seems like a pretty decent proxy for trust, since the risk is

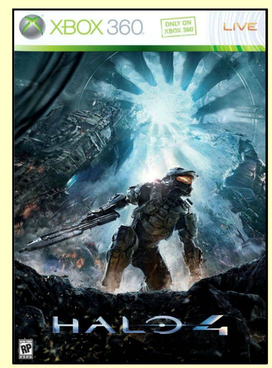
Understanding the dynamics of team performance

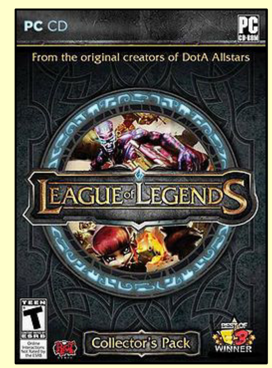
Outline of talk

- Motivation
- Challenges
- Quick review: skill assessment
- My previous work: TeamSkill
  - Initial work
  - Online extensions
  - Game-specific data integration
- The NBA dataset
  - Description
  - Evaluation
- Conclusions

Motivation

- My work is focused on skill assessment and team chemistry
- Skill assessment is an old problem, but pervasive in today's online multiplayer videogames
- We developed several approaches which incorporate team chemistry and evaluated them on data from professional Halo 3 players
- Results were very encouraging
  - ~2-11% increase in predictive accuracy
- The question: ***How might these approaches apply to real-world team sports like basketball?***





Challenges

- But there are challenges (of course)
  - Online requirement – skill ratings must be updated after each game to ensure scalability
  - Generalization potential – ideal systems work with data common across multiple games (wins/losses, composition, etc)
- Due to the above 2 challenges, best known game outcome prediction accuracy between 66-70% (depending on the dataset)

Quick review: skill assessment

Quick review: skill assessment

- An old problem (with different applications in different contexts)
- Paired comparison estimation
  - Foundational work by Thurstone (1927) and Bradley-Terry (1952)
  - Elo (1959), popularized in chess ranking (FIDE, USCF)
  - Glicko (1993) – player-level ratings volatility incorporated (σ^2), addition of rating periods

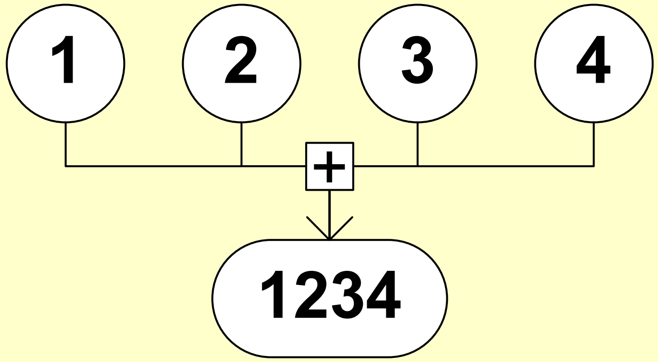
Quick review: skill assessment

- TrueSkill (2006) - factor-graph based approach used in Microsoft's Xbox Live gaming service
  - Used to match players/teams up with each other online
- Other related work
  - Whole History Rating (Coulum, 2008)
  - Group comparisons (Huang et al, 2008)
  - Hierarchical models (Menke et al, 2007)
  - Shapley value (Shapley, 1953)
- My work focuses on Elo, Glicko, and TrueSkill
  - Most widely-used in skill assessment problems
  - Highly cited in field

Previous Work: TeamSkill

C. DeLong, N. Pathak, K. Erickson, E. Perrino, K. Shim, and J. Srivastava, “Teamskill: Modeling team chemistry in online multi-player games.” Shenzhen, China: Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2011.

The problem



- Basic idea
  - Given: skill ratings of each team member, i.e., $s_i \sim N(\mu_i, \sigma_i^2)$
  - Sum across all team members
- <u>Not intuitive</u>: Team chemistry is a well-known concept in team-based competition [Martens 1987, Yukelson 1997] and it is not captured in *any* of these models
  - Can think of it as the overall dynamics of a team resulting from leadership, confidence, relationships, and mutual trust
  - Independence assumption not realistic in teams, especially at high levels of play

More information is available, however…

1 **2** **3** **4** ← k=1

12 **13** **14** **23** **24** **34** ← k=2

123 **124** **134** **234** ← k=3

1234 ← k=4

- **Observation**: We have more information than just the history of individual players – we also know the histories of groups of players
  - Player 1's history ∩ player 2's history → history of {1, 2}
  - Existing approaches only make use of top row
- <u>Main idea</u>: Utilize Elo/Glicko/TrueSkill as 'base learners' (a la boosting), estimate the skills of subgroups of players on a team, combine in some way, and use to produce better estimate of a team's skill
  - Each rating says something about the skill of that particular subgroup

TeamSkill

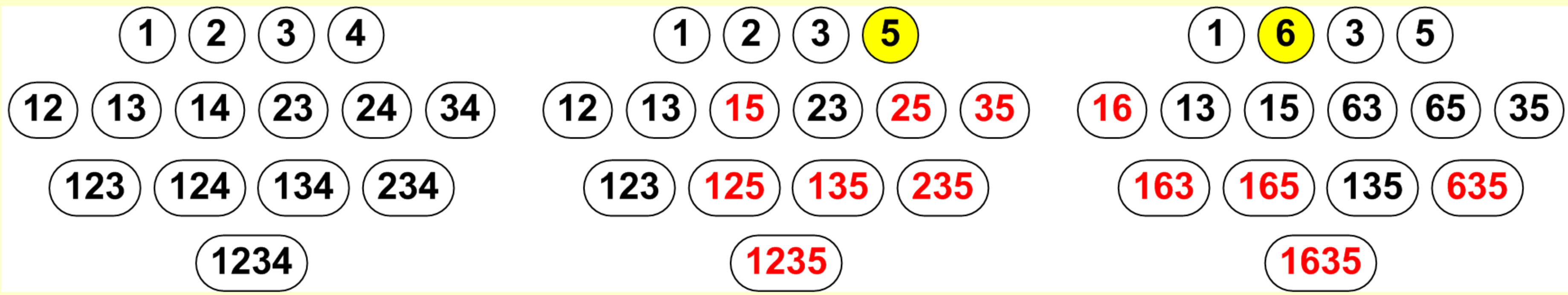
- Introduce four different aggregation approaches:
  - TeamSkill-K
    - Choose a subgroup size k (e.g., k=3 → subgroups of 3 players)
    - Scale the average subgroup skill rating up to size of team
  - TeamSkill-AllK
    - Recurse through lattice induced by power set of team members
    - For each node of group size k, scale child node (size k-1) ratings up to k & combine with parent rating
  - TeamSkill-AllK-EV
    - Loop through each set of ratings for k-sized subgroups, compute average rating, and scale up to size of team
    - Final rating is unweighted average of each scaled average subgroup rating
  - TeamSkill-AllK-LS
    - Only use ratings for largest subgroups covering all members of team
- Result: AllK-EV w/Glicko learner best performer (~64-65% acc.), statistically-significant improvement in “close” games
  - Margin tends to widen over time (as more group level history is observed)

Online extensions

C. DeLong and J. Srivastava, "TeamSkill Evolved: Mixed Classification Schemes for Team-Based Multi-Player Games." Kuala Lumpur, Malaysia: Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2012.

Motivation

black = history available **red** = no history available



time: t = 1 t = 100 t = 200

After 1 game

New player – 5 - who's never played with 1, 2, or 3

New player – 6 – who's played with 3 or 5 (not both)

- Previous TeamSkill approaches were "naïve"
  - Aggregation weights for each subgroup level remained the same throughout the assessment process for AllK and EV, the best performers
  - Potential problem: the feature space is expanding and contracting over time
- Developed three methods to dynamically adjust aggregation weights after each game

TeamSkill-AllK-Ev-OL1

$$1 \leq \beta \leq \infty, w_k^0 = \frac{1}{K}, K' = \min\left(\max_{k \leq K}(|h_i(k)| > 0), \max_{k \leq K}(|h_j(k)| > 0)\right)$$

$$u = \frac{1}{K'} \sum_{k > K'} w_k^t$$

$$w'^t_{(k \leq K')} = w^t_{(k \leq K')} + u$$

$$s_i^* = \sum_{k=1}^{K'} w'^t_k E[h_i(k)]$$

$$w^{t+1}_{(k \leq K')} = w^t_{(k \leq K')} \beta^{\frac{1}{2} + P_k(i > j)}$$

$$w_k^{t+1} = \frac{w_k^{t+1}}{\sum_{l=1}^{K} w_l^{t+1}}$$

- Single weight vector *w*, resize based on available group history, updates proportional to confidence in prediction
- s^*_i is the team skill rating for team *i* used in game *t* with opponent *j*
  - $E[h_i(k)]$ is the average skill rating for subgroups of size *k*

TeamSkill-AllK-Ev-OL2

$$s_i^* = \sum_{k=1}^{K'} w_{(K',k)}^t E[h_i(k)]$$

$$w_{(K',k \le K')}^{t+1} = w_{(K',k \le K')}^t \beta^{\frac{1}{2}+P_k(i>j)}$$

$$w_{(K',k)}^{t+1} = \frac{w_{(K',k)}^{t+1}}{\sum_{l=1}^{K'} w_{(K',l)}^{t+1}}$$

- Maintain weight matrix where the *K'*-th row corresponds to the case where the largest subgroup with available history is of size K'
- Lower triangular used only

TeamSkill-AllK-Ev-OL3

$$s_i^* = \sum_{k=1}^{K'} w_k'^t E[h_i(k)]$$

$$w_{(k \leq K')}^{t+1} = w_{(k \leq K')}^{t} \beta^{\frac{1}{2} + (d - L_{d,k})/d}$$

$$w_k^{t+1} = \frac{w_k^{t+1}}{\sum_{l=1}^{K} w_l^{t+1}}$$

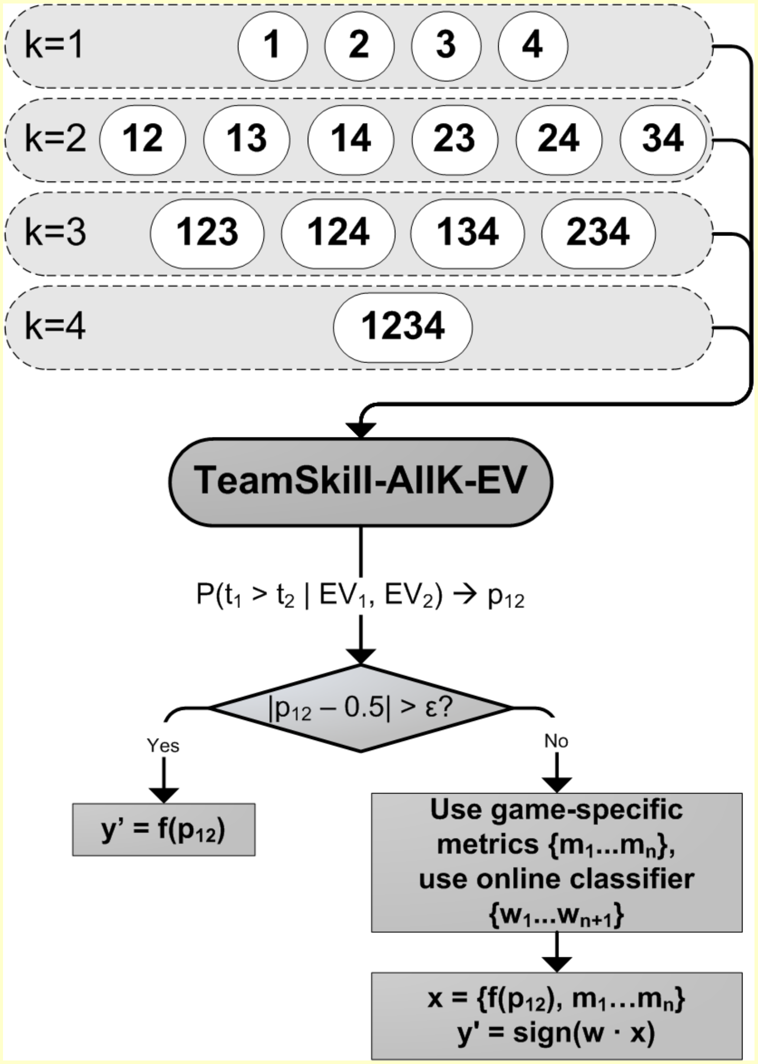
- Similar to OL1, but uses rolling history window of *d* games for *k*-sized groups to compute updates to weight vector given the mistakes made in that window, $L_{d,k}$

Impact of game-specific data

C. DeLong and J. Srivastava, “TeamSkill Evolved: Mixed Classification Schemes for Team-Based Multi-Player Games.” Kuala Lumpur, Malaysia: Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2012.

Adding game-specific data

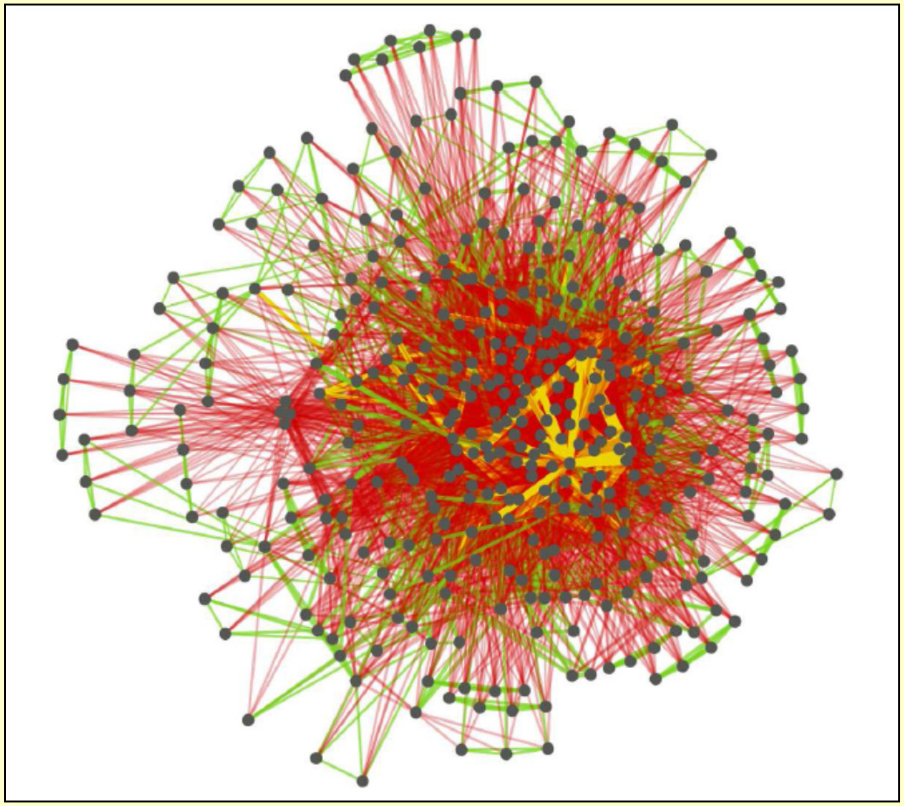
- Perhaps integration of some game-specific data might be helpful - but how?
- Retain label predicted by TeamSkill-AllK-EV, along with game-specific data, as additional features for online classification framework
  - Perceptron (1958)
  - PA/PA-I/PA-II (2006)
  - Confidence-weighted (2009)
  - Best performer – **PA-II**
- Two different methods
  - **EVGen**: make use of extra features for every instance
  - **EVMixed**: if EV is sufficiently confident in its predicted label $f(p_{12})$, then there is no need for additional feature information (shown on right)



Data set overview

- Collected over the course of 2009
- 7,590 games (2,076 from tournaments and 5,514 from Xbox Live scrimmages)
- 448 players on 140 different professional and semi-professional teams
- Games took place during January 2008 through January 2010

- Websites pertaining to this data
  - http://stats.halofit.org - Player/team statistics
  - http://halofit.org – Datasets and related information



“Friend or foe” social network for all tournaments in 2008 and 2009

The NBA dataset

The NBA dataset

- Our data preparation tasks
  - Resolve 2 source data files ("play by play" and "match ups") into single output file with one row per player per team per match up per game
  - Clean source dataset i.e., remove games in one source data file not found in the other, fix underlying sort order of data files, convert text-oriented files into numeric id's, etc
  - Remove match ups where no points were scored

- Extracted from extremely fine-grained source dataset on basketballvalue.com
- All games from 2011-2012 NBA regular season
- For each game
  - One row of data for each *play* in the game e.g., 3pt'er, foul, player substitution, end of period, etc
  - Who was on the court at any point in the game for either team (known as a "match up")

Evaluation

- **Task**: predict outcomes of "match ups" and compare accuracy to unaltered baseline versions (k = 1) of their base learner rating systems - Elo, Glicko, and TrueSkill
- One team "defeats" the other by outscoring the other for a given match up
- Each rating approach was tested on <u>2 types of match ups</u> – all match ups and just those considered "close" (i.e., prior probability of one team outscoring the other close to 50%).
- Minimum match-up lengths tested: 30, 60, 90, 120, 150, 200, 250, 300, 350, 400, 450, and 500 seconds

Results – overall accuracy & close games

Overall accuracy based on maximum observed performance for baseline, team-based approaches, and TeamSkill-AllK-EVMixed

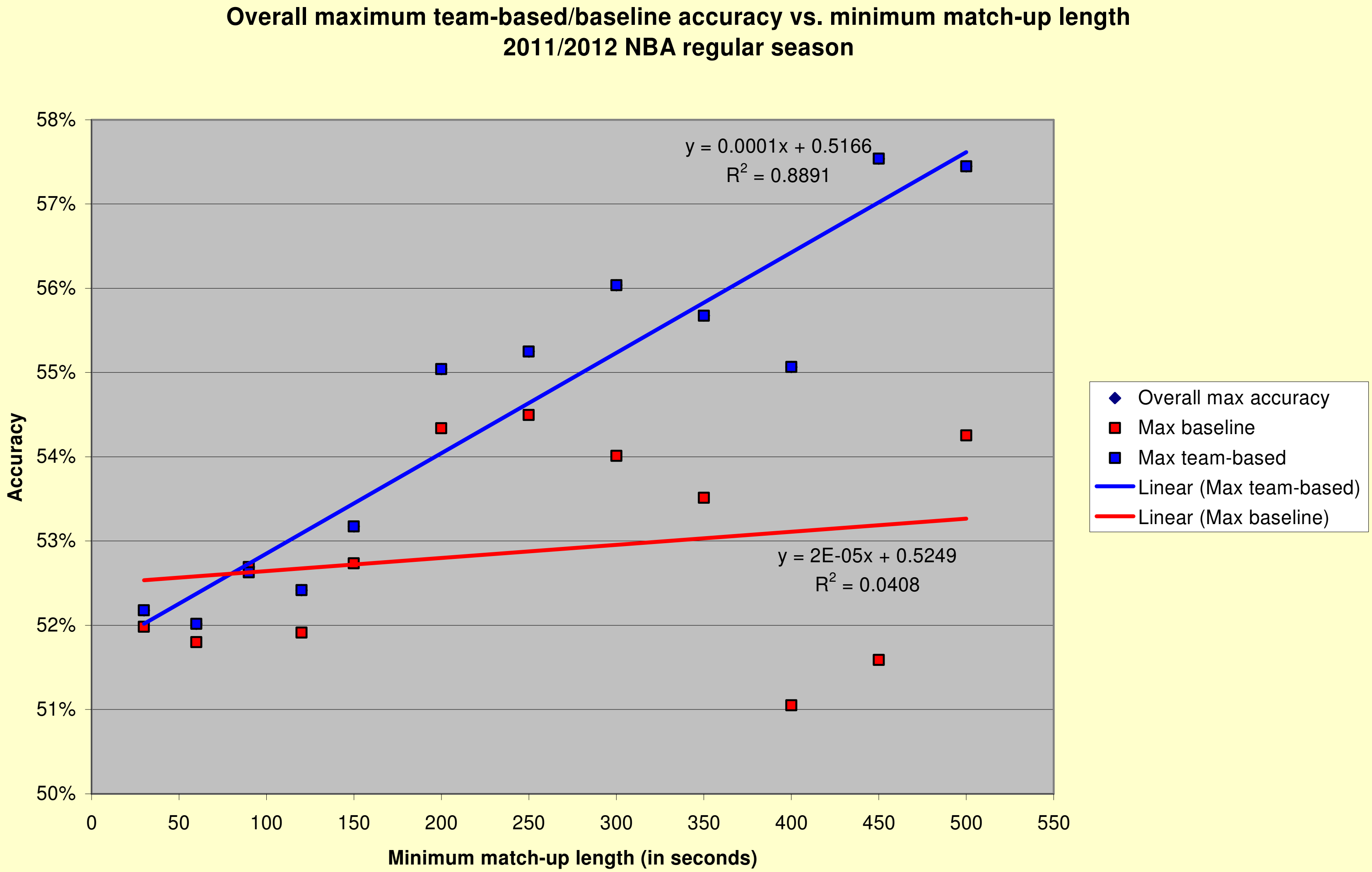
Min. match-up length	N instances	Max. baseline	Max. team-based	Team vs. baseline Δ	$\Theta(Z)$*	Max. EVMixed	EVMixed vs. baseline Δ	$\Theta(Z)$*
30	19,483	51.98%	52.18%	0.20%	0.350	52.08%	0.10%	0.428
60	14,949	51.80%	52.02%	0.20%	0.356	51.58%	-0.20%	0.653
90	10,601	52.69%	52.63%	-0.10%	0.538	51.38%	-1.30%	0.972
120	7,181	51.92%	52.42%	0.50%	0.274	51.87%	0.00%	0.520
150	5,008	52.74%	53.18%	0.40%	0.330	52.72%	0.00%	0.508
200	2,985	54.34%	55.04%	0.70%	0.292	55.04%	0.70%	0.292
250	1,991	54.50%	55.25%	0.80%	0.316	54.04%	-0.50%	0.613
300	1,383	54.01%	56.04%	2.00%	0.142	55.53%	1.50%	0.211
350	925	53.51%	55.68%	2.20%	0.175	55.14%	1.60%	0.242
400	523	51.05%	55.07%	4.00%	0.097	55.07%	4.00%	0.097
450	252	51.59%	57.54%	6.00%	0.090	57.54%	6.00%	0.090
500	94	54.26%	57.45%	3.20%	0.330	57.45%	3.20%	0.330

Accuracy in "close" games based on maximum observed performance for baseline, team-based approaches, and TeamSkill-AllK-EVMixed

Min. match-up length	N instances	Max. baseline	Max. team-based	Team vs. baseline Δ	$\Theta(Z)$*	Max. EVMixed	EVMixed vs. baseline Δ	$\Theta(Z)$*
30	3,897	51.25%	51.48%	0.20%	0.420	51.09%	-0.20%	0.554
60	2,990	50.30%	51.41%	1.10%	0.197	49.16%	-1.10%	0.810
90	2,120	51.93%	52.69%	0.80%	0.311	49.91%	-2.00%	0.907
120	1,436	51.39%	53.97%	2.60%	0.083	50.42%	-1.00%	0.699
150	1,002	51.60%	52.99%	1.40%	0.266	52.50%	0.90%	0.344
200	597	53.10%	53.60%	0.50%	0.431	52.09%	-1.00%	0.636
250	398	53.27%	58.29%	5.00%	0.077	53.77%	0.50%	0.443
300	277	50.18%	54.51%	4.30%	0.154	54.51%	4.30%	0.154
350	185	52.43%	52.97%	0.50%	0.458	52.97%	0.50%	0.458
400	105	45.71%	61.91%	16.20%	0.009	61.91%	16.20%	0.009
450	50	44.00%	62.00%	18.00%	0.036	62.00%	18.00%	0.036
500	19	42.11%	73.68%	31.60%	0.024	73.68%	31.60%	0.024

**One-tailed Z-test of hypothesis that max. team-based/EVMixed accuracy > max. baseline accuracy*

Results – accuracy vs. min. match-up length



Results - detail

- Overall performance of teach TeamSKill method and baseline for each base learner – Elo, Glicko, and TrueSkill – by minimum match-up length
- Main observations
  - As match-up length grows, margin of improvement between best team-based methods and baseline grows
  - Suggests a more fundamental connection between minimum match-up length and strong team-based approaches like EVMixed

		Match-up length (in seconds)					
Learner	TeamSkill method	30s	120s	250s	400s	450s	500s
Elo	Baseline (TS1)	51.81%	51.23%	54.09%	49.90%	51.59%	46.81%
	TS2	51.70%	50.97%	54.80%	50.86%	50.40%	47.87%
	TS3	51.54%	50.84%	53.39%	50.48%	51.59%	48.94%
	TS4	51.13%	50.91%	52.99%	52.20%	50.00%	46.81%
	TS5	50.88%	50.69%	51.58%	50.29%	48.41%	46.81%
	AllK	51.62%	51.55%	54.70%	49.90%	53.57%	50.00%
	AllKEV	51.66%	51.05%	53.79%	50.10%	51.19%	45.74%
	AllKLS	51.39%	49.88%	53.09%	51.24%	51.59%	47.87%
	OL1	51.83%	51.13%	54.09%	49.90%	51.19%	46.81%
	OL2	51.80%	50.90%	54.34%	50.10%	51.59%	45.74%
	OL3	51.63%	50.94%	53.79%	50.10%	51.59%	45.74%
	EVGen (μ)	49.74%	50.70%	50.21%	49.81%	47.92%	55.59%
	EVMixed (μ)	51.07%	51.70%	52.75%	52.05%	52.37%	53.87%
	EVMixed (σ^2)	0.14%	0.16%	0.64%	1.29%	2.18%	1.93%
	EVMixed (min)	50.92%	51.57%	51.78%	49.52%	48.41%	51.06%
	EVGen (max)	51.20%	51.87%	53.74%	55.07%	55.95%	57.45%
Glicko	Baseline (TS1)	51.85%	51.59%	53.44%	49.52%	48.81%	54.26%
	TS2	50.54%	50.52%	50.98%	52.39%	46.03%	51.06%
	TS3	50.53%	49.38%	51.68%	52.77%	46.03%	50.00%
	TS4	50.20%	50.17%	52.13%	51.05%	50.40%	48.94%
	TS5	51.54%	51.61%	52.99%	50.48%	45.63%	44.68%
	AllK	51.58%	52.42%	55.25%	51.43%	50.00%	50.00%
	AllKEV	50.71%	50.70%	51.73%	53.35%	49.21%	51.06%
	AllKLS	49.77%	49.14%	48.82%	47.99%	48.81%	53.19%
	OL1	51.73%	51.68%	53.94%	51.82%	48.41%	54.26%
	OL2	51.67%	51.32%	52.39%	53.54%	49.21%	51.06%
	OL3	50.75%	50.61%	51.68%	53.35%	49.21%	51.06%
	EVGen (μ)	49.58%	50.94%	50.73%	49.76%	49.90%	54.52%
	EVMixed (μ)	50.76%	50.77%	52.50%	54.63%	53.04%	56.79%
	EVMixed (σ^2)	0.01%	0.02%	0.19%	0.17%	0.39%	0.52%
	EVMixed (min)	50.75%	50.76%	52.18%	54.11%	52.38%	56.38%
	EVGen (max)	50.76%	50.80%	52.74%	54.88%	53.57%	57.45%
TrueSkill	Baseline (TS1)	51.98%	51.91%	54.50%	51.05%	50.40%	46.81%
	TS2	51.75%	51.26%	54.85%	50.67%	50.40%	47.87%
	TS3	51.72%	50.81%	53.19%	50.86%	52.78%	52.13%
	TS4	51.43%	50.54%	52.89%	52.39%	50.40%	50.00%
	TS5	51.72%	51.66%	52.79%	51.05%	49.60%	46.81%
	AllK	51.87%	51.97%	54.90%	50.86%	52.78%	51.06%
	AllKEV	52.15%	51.57%	54.14%	51.63%	50.40%	47.87%
	AllKLS	52.00%	51.08%	53.29%	50.48%	51.19%	50.00%
	OL1	51.94%	51.87%	54.50%	50.67%	51.19%	46.81%
	OL2	52.18%	52.30%	54.39%	51.82%	50.00%	47.87%
	OL3	52.13%	51.61%	54.29%	51.63%	50.00%	46.81%
	EVGen (μ)	49.94%	50.83%	50.84%	49.71%	48.21%	54.79%
	EVMixed (μ)	52.04%	51.72%	53.60%	52.82%	54.69%	53.07%
	EVMixed (σ^2)	0.04%	0.16%	0.17%	0.85%	1.45%	2.16%
	EVMixed (min)	52.00%	51.55%	53.39%	51.24%	52.78%	48.94%
	EVGen (max)	52.08%	51.87%	54.04%	54.30%	57.54%	57.45%

Conclusions

- Can TeamSkill be applied to real-world team sports? Yes.
  - To our knowledge, this is the first such instance in which approaches accounting for group cohesion have been shown to positively impact predictive performance in both team-based video games and real-world team sports
- EVMixed stands out again, particularly for "close" games
  - Conditional inclusion of game-specific features critical for predicting outcomes of games where teams are otherwise evenly-matched
- Some of the other approaches also do well (or at least ok)
  - AllK and, to a lesser extent, AllK-EV, OL1, and OL2 with Glicko as base learner
- Suggests a fundamental connection between minimum match-length and EVMixed accuracy for close games
  - Longer match-ups → more opportunity for team chemistry to play a role
  - Ties in with previous work with Halo: typical games ~10 minutes/600s

Thanks!

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Part III: Impact on Business:

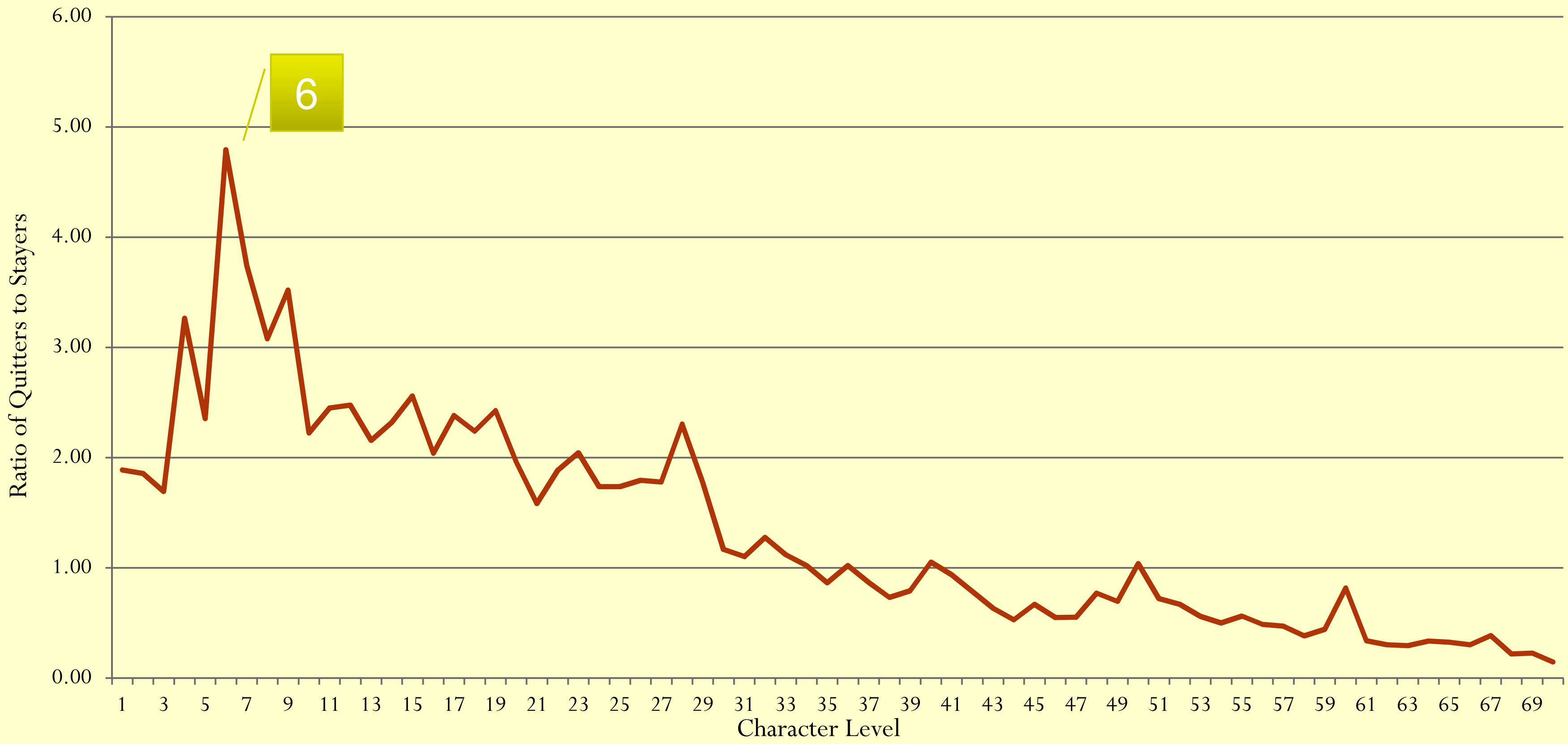
Social Commerce, Churn Analysis, Influence

Levis' – Example of Social Retail

- Levis' leverages its brand to ensure customers **provide** their social network
- Levis' can leverage predictive social analytics technology to **understand the value** of the customer's social network

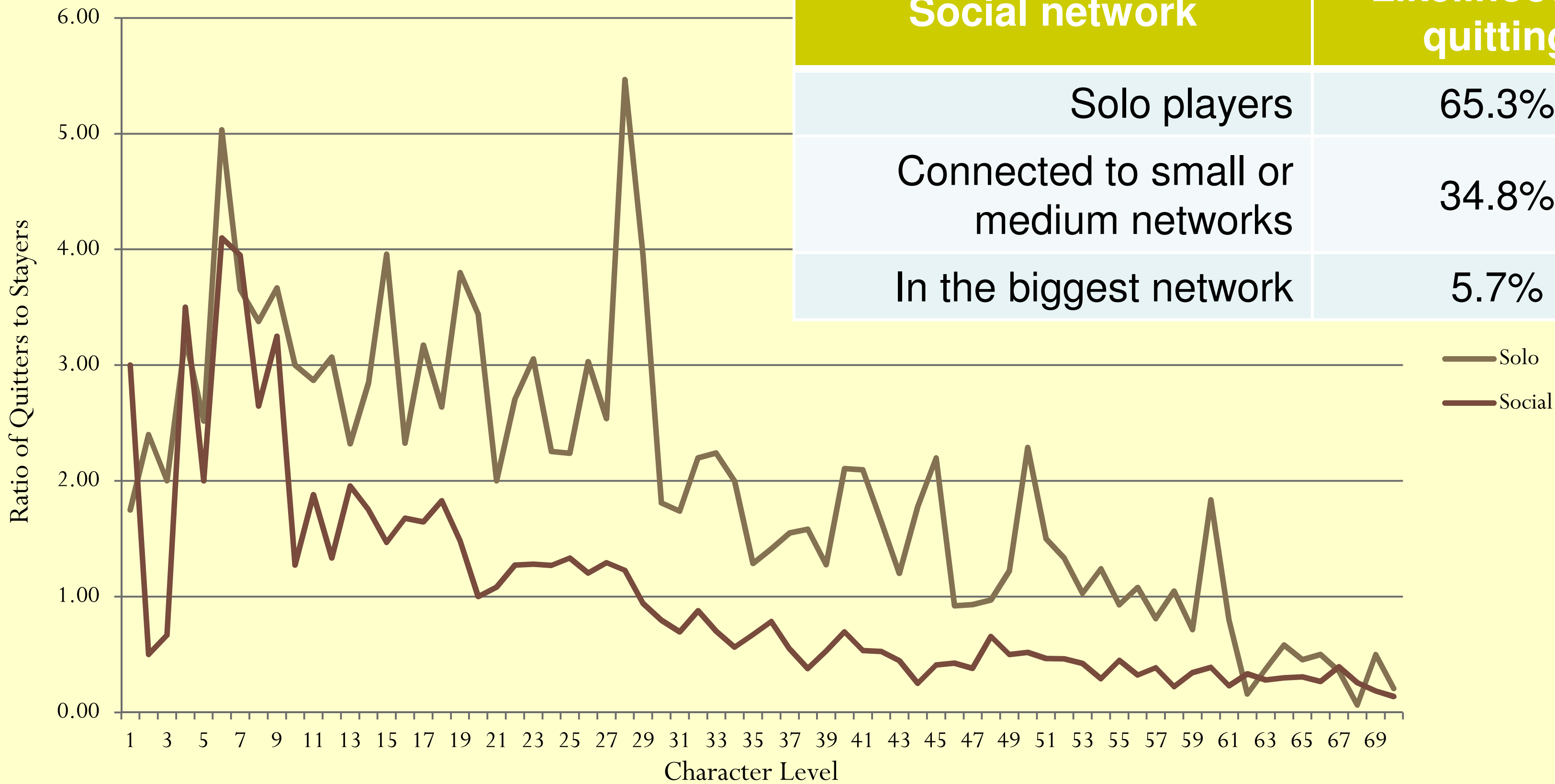
Player Churn Prediction

Time Equals Stickiness



- There are less quitters as the levels go up, and focus should be on the first 20 levels.

Churn in Subscription Games

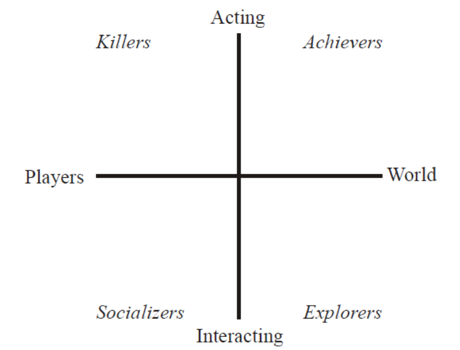


Social network	Likelihood of quitting
Solo players	65.3%
Connected to small or medium networks	34.8%
In the biggest network	5.7%

- Isolated players are 3.5x more likely to quit (B = 1.26, p<.001). Focus design on facilitating social interaction.

Player Motivation Theories

Player Type	Motivation
Achievers *Diamonds*	Advancement within the game - acquiring gold, killing monsters
Explorers *Spades*	Uncovering intricacies of the game environment
Socializers *Hearts*	Interacting with other players Forming friendships
Killers *Clubs*	Imposition on others Give grief to players



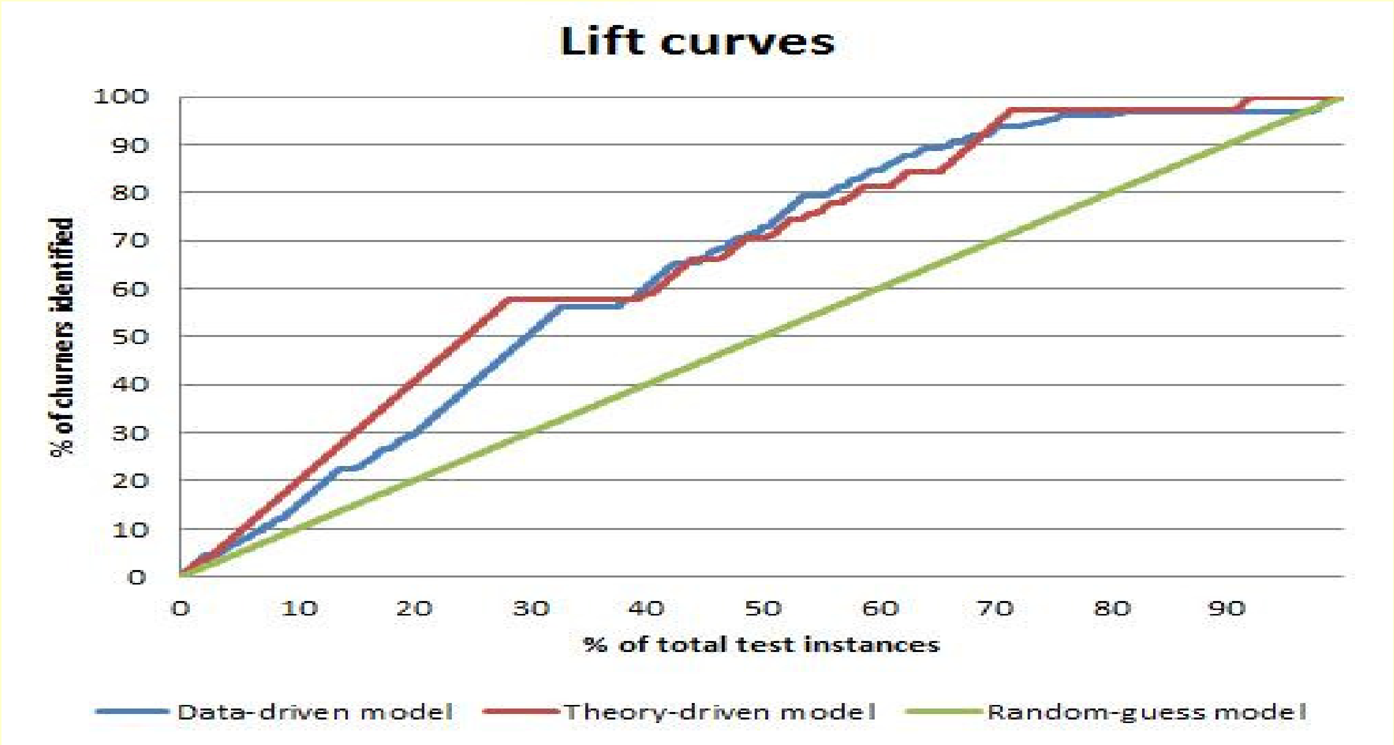
The original player types graph.

Richard Bartle, 1996

Achievement	Social	Immersion
Advancement Progress, Power, Accumulation, Status	***Socializing*** Casual Chat, Helping Others, Making Friends	***Discovery*** Exploration, Lore, Finding Hidden Things
Mechanics Numbers, Optimization, Templating, analysis	***Relationship*** Personal, Self-disclosure, Find and Give, Support	***Role-playing*** Story Line, Character History, Roles, Fantasy
Competition Challenging Others, Provocation, Domination	***Teamwork*** Collaboration, Groups, Group achievement	***Customization*** Appearances, Accessories, Style, Color schemes
		Escapism Relax, Escape from Real Life, Avoid Real Life problems

Nick Yee, 2005

Model Evaluation (Lift Chart)



- Observations
  - TD model does better in predicting top quintile of churners
  - DD model performs better in the 40%-70% range

	Training Set	Test Set	Full dataset	% of total
Churners	5261	2630	7891	47.91
Non-churners	5718	2860	8578	52.09
Total	10979	5490	16469	100

Loyalty & Influence in e-commerce

Loyalty and Influence

- Loyalty
  - *of a customer to an organization*
  - can be category/product specific
  - can vary with time
  - etc.
- Loyalty: **loyalty**(A,c,t)
  - A: customer
  - c: category
  - t: time
- Influence
  - *of a customer on another customer*
  - can be category/product specific
  - can vary with time
  - etc.
- Influence: **influence**(A,B,c,t)
  - A: *influencing customer*
  - B: *influenced customer*
  - c: category
  - t: time

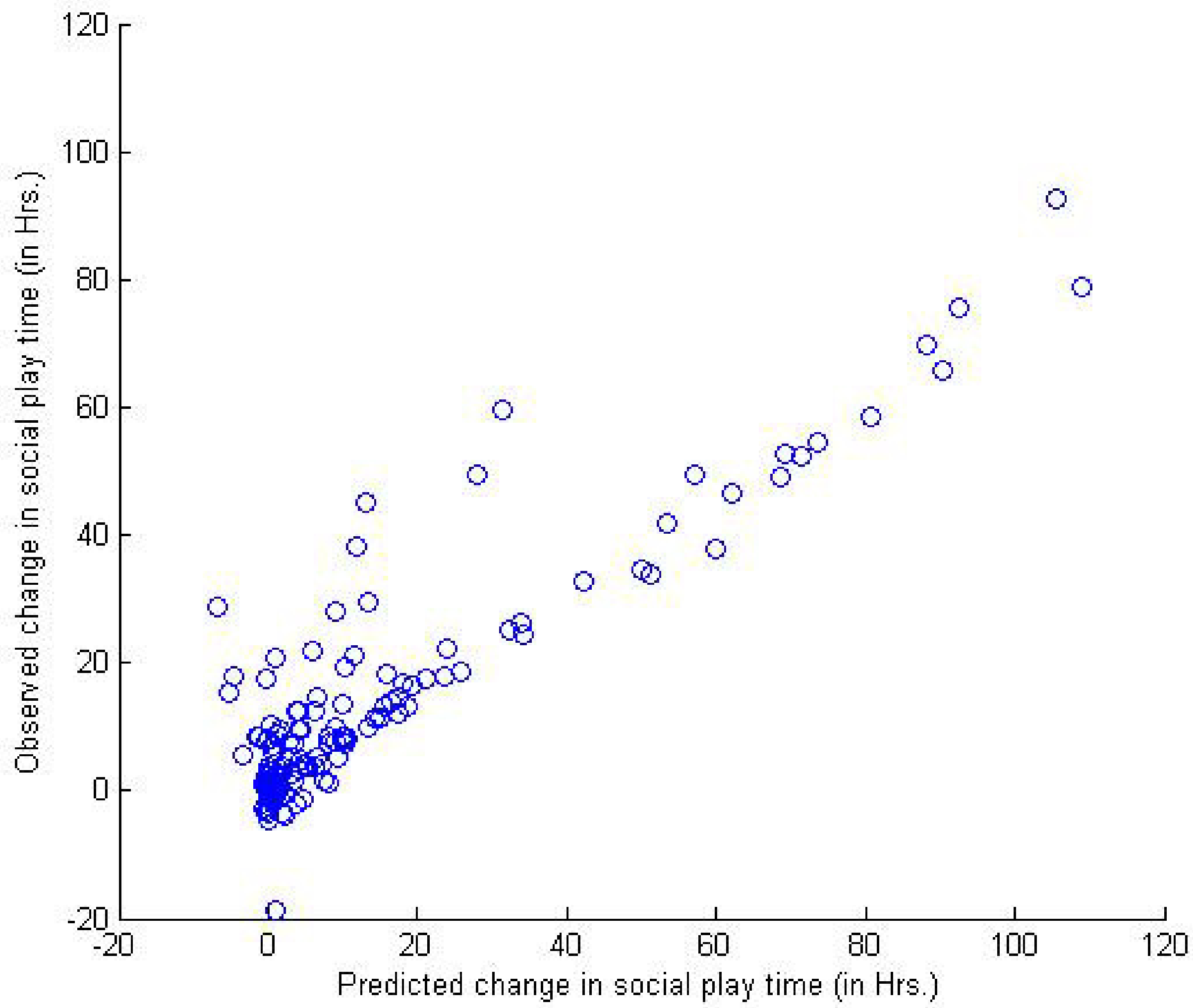
Influence(A,B,c,t) = change in loyalty(B,c,t) caused by the presence of A

Properties of influence(A,B,c,t)

- **influence**(A,B,*,t)
  - Influence of A on B across all categories, at time t
- **influence**(A,*,c,t)
  - Influence of A on all neighbors in category c, at time t
- **influence**(*,B,c,t)
  - Influence of all its neighbors on B, for category c at time t
- **influence**(A,*,*,t)
  - Total influence of A on the network, at time t
- (**influence**(A,B,c,t2) – **influence**(A,B,c,t1))/(t2 – t1)
  - Rate of change of A's influence on B for category c

Influence(A,B,c,t) is truly the atom of influence

Model Validation



True Value of each customer

- True value = individual value + social value
- Who really matters, and to what degree
- Some empirical facts
  - 31% activity due to socialization
  - 23% more individual + 8% more social activity

The individual's lifetime value

their social influence

and their true total

Action 1

Export

Account	Individual Value(A)	Social Value(B)	Total value (A+B)
155589	41	61	102
155591	23	33	56
155593	32	56	88
155595	37	10	47
155597	56	22	78
155599	24	22	46
155601	31	13	44

So what does Ninja Metrics do?

https://dev2katana.ninjametrics.com/html/index.html

Katana Analytics Engine

Welcome to Katana | Settings | Logout

Xicom Tech

- DASHBOARD
- SYSTEM METRICS
- USER METRICS
- BASIC PACKAGE
- NETWORK VALUE

Track which instances lead to quitting, which levels lead to spending, what social events lead to long-term retention & more

Dashboard

The executive summary is based on data through 07/08/2012 for 0 shards and player accounts.

Jump to 07/15/2012

	PER MONTH	THIS WEEK	LAST WEEK	+ / -
Total number of accounts	716,899	716,899	742,390	-25,491
Total value	64.15	64.15	63.83	0.32
Total Solo value	1,685,408	1,685,408	1,742,394	-56,986
Total Influence (Community) value	0.91	0.91	0.73	0.18
Average player value	33,942	33,942	28,297	5,645

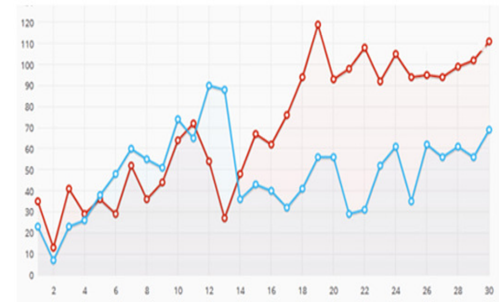
Standouts

HIGH | LOW

LABEL	THIS WEEK	LAST WEEK
Most valuable player	716,899	742,390
Stickiest quest	64.15	63.83
Stickiest item	1,685,408	1,742,394
Stickiest location	0.91	0.73
Stickiest Social event	33,942	28,297
Stickiest NPC	0.56	0.45
Most valuable shard	44,885	37,227
Stickiest location	0.56	28,297

Population Trend

FROM 07/15/2012 TO 07/20/2013 GO

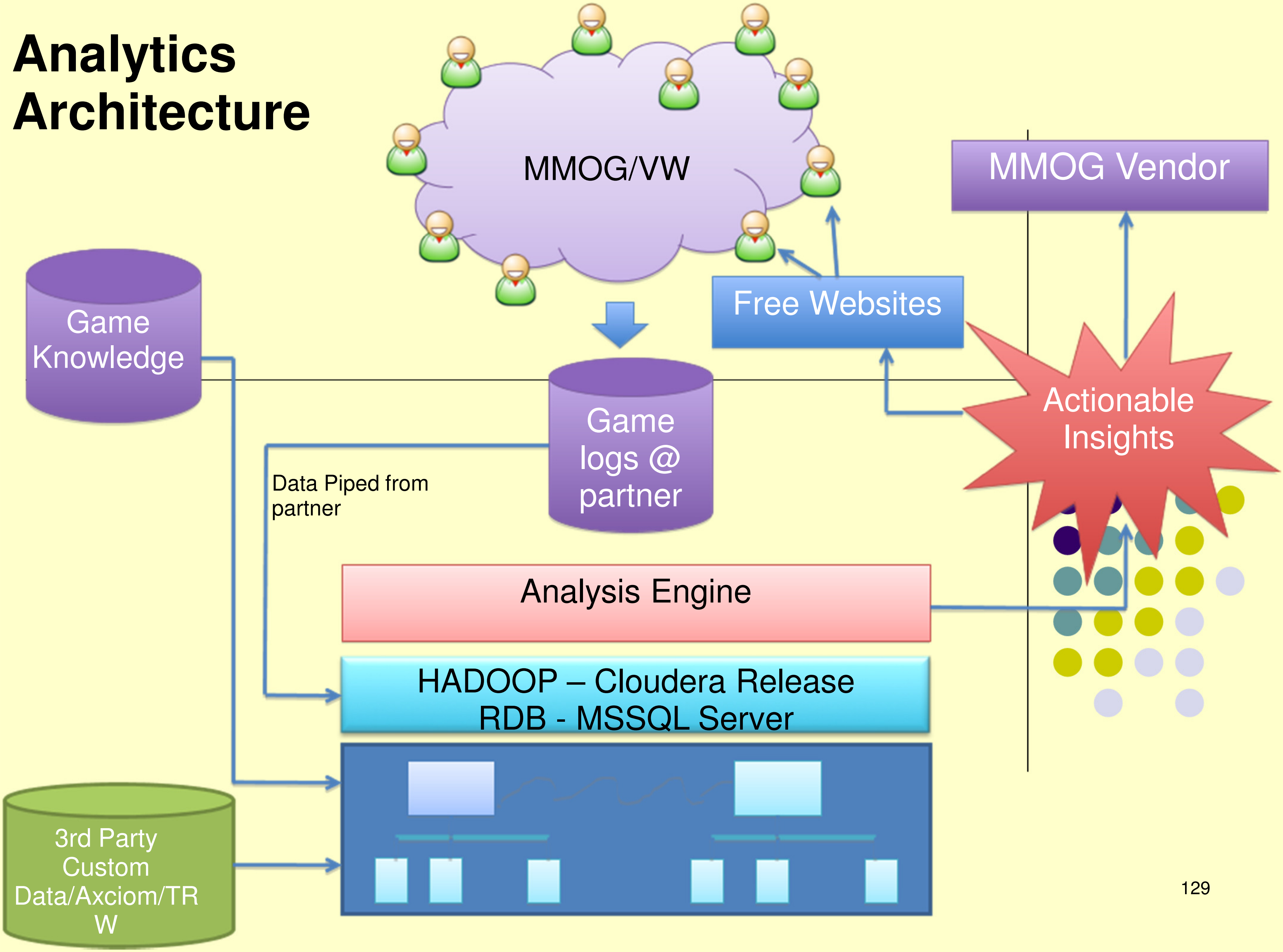


Churn Breakdown

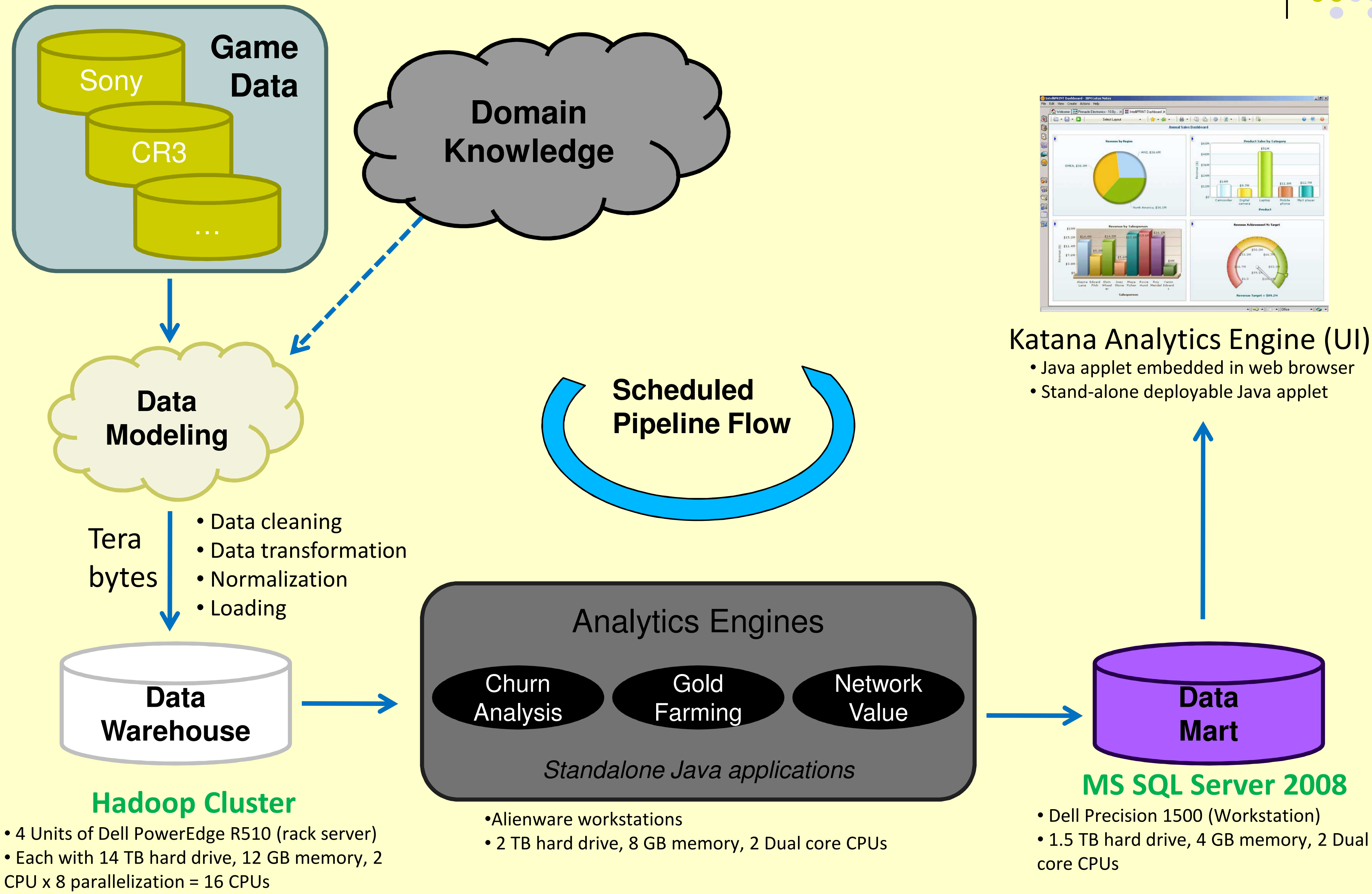
HIGH RISK	$50.00	20%
MODERATE RISK	$30.00	44%
LOW RISK	$20.00	44%
STABLE	$10.00	50%

Powered by Ninja Metrics

Analytics Architecture



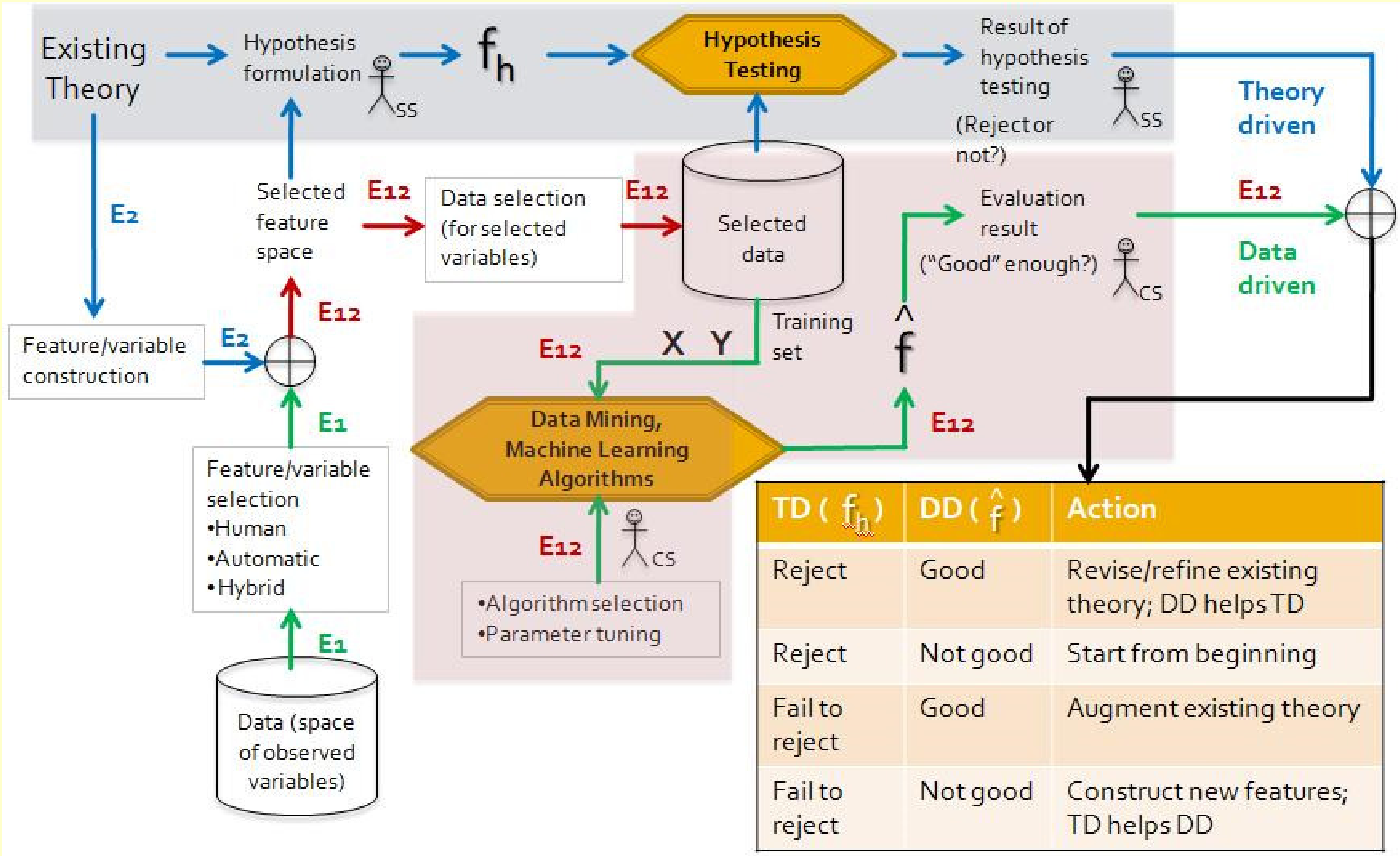
Analytics Pipeline



Summary – The Big Picture

- Converging 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
- Great opportunities for
  - Basic R&D
  - Applied R&D
  - Entrepreneurship
- *But, putting together the right team and partnerships is critical!*

Synthesis of TD and DD approach



TD (f_h)	DD ($\hat{f}$)	Action
Reject	Good	Revise/refine existing theory; DD helps TD
Reject	Not good	Start from beginning
Fail to reject	Good	Augment existing theory
Fail to reject	Not good	Construct new features; TD helps DD

and last,
but certainly not the least

- thank you for your invitation