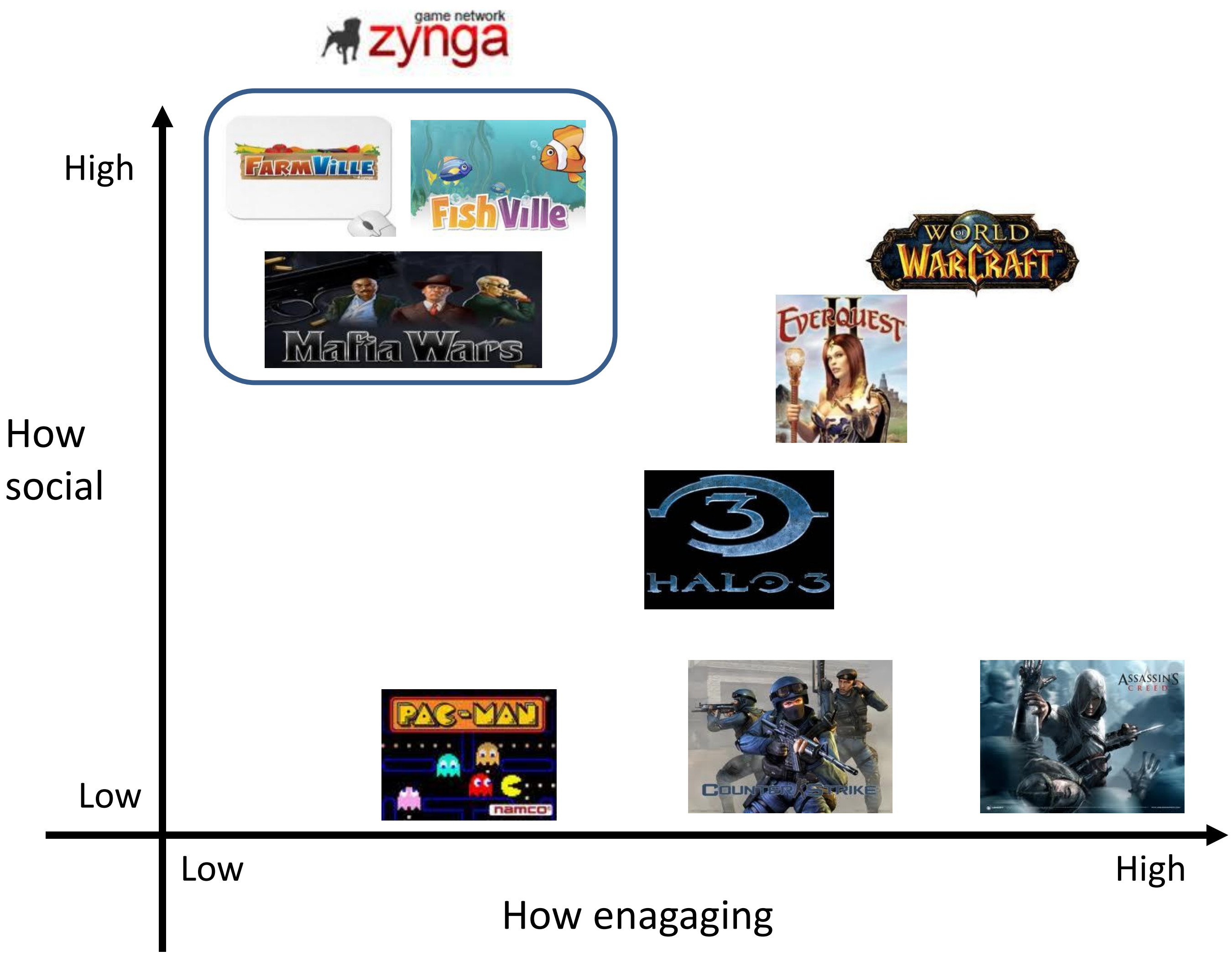
Two Papers from the VWE Project

The Space of Games



Economics & Player Behavior

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

- Zynga (free2play)
  - Farmville, Fishville, Mafia Wars, etc.
  - 160 million players
  - Revenue model
    - Virtual goods
    - $600 million in 2009
  - 0.5 hrs a day, 7 days a week

Hard core gamers

Less socially acceptable

Like Cocaine

Everyone

More socially acceptable

Like Caffeine

[Virtual Worlds Observatory] (www.vwobservatory.com)

Research on MMOs, social networks and more…

Who We Are

VWE team consists of experienced social scientists and computer scientists from Northwestern University, University of Southern California, University of Illinois, and University of Minnesota.

What We Do

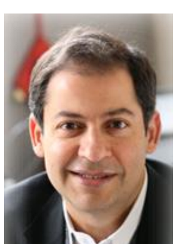
Our team studies various kinds of online communities and video games. We seek to uncover and model the intricacies of human behaviors and interactions.

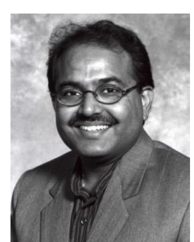
How We Do It

In collaboration with our industry and government sponsors and partners, our team conducts systematic studies of human behaviors by using social network analysis and data mining techniques.

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), …**
- **Data and technology partners**
  - **Sony (EverQuest 2), 38Studios (Copernicus), Linden Labs (2nd Life), Bungie (Halo3), Kingsoft (Chevalier's Romance), …**
  - **Cloudera Systems (Hadoop), Microsoft (Azure), Weka, …**






Item Recommendations in Multiple Overlapping Social Networks in MMOs

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Outline

- Introduction
- Item Recommendation in Multiple Networks
- Data Set: EverQuest II
- Coextensive Networks in EverQuest II
- Experiments
- Interpretation of Results
- Conclusion

Introduction

- Recommendation is a well studied problem
- Recommendation can be described as a prediction task where the goal is to maximize correct prediction
- Commonly used techniques include collaborative filtering, similarity based techniques and techniques based on social networks

Social Network in Recommendation

- Scalability issues in similarity based and collaborative filtering based techniques
- Social Network based techniques have been employed to greatly reduce the search space
- Examples of Trust Network Based Recommendation: FilmTrust (Golbeck), ePinions

Recommendation in Multiple Social Networks

- To the best of our knowledge the problem of recommendation in multiple social networks has not been explored before mainly because of lack of datasets
- We explore this problem in the context of coextensive (multiple over lapping) social networks in Massively Multiplayer Online Role Playing Games (MMORPGs)
- **Problem:** Given Coextensive Social Networks determine, use the various subnets to make recommendations. The relative efficacy of each network can thus be determined by how well each network does in the prediction task

Dataset: EverQuest II

- EverQuest II (EQ2): A massively multiplayer online role playing game where millions of players can interact with one another
- The goal is to complete various tasks which may be cooperative or adversarial in nature
- We use data from February 2006 to June 2006 with 25,870,200 transactions (after data clean up)

(Image Source: Game Spy)

The Coextensive Network in EQ2

- **Trust:** Trust is described in terms of explicitly granting trust access to another player within the game to one's virtual house within the game.
- **Trade:** Trade corresponds to virtual face to face trade between characters within the game. (Different from Consignment)
- **Mentoring:** A mentoring relationship is established within the game when a player explicitly mentors another player within the game.
- **Adversarial:** An adversarial relationship refers to player vs. player combat within the game which results in the death of one of the players.
- **Consignment:** Alternative trade mechanism (used for testing in this paper)

Experiments

- The recommendation problem is set up as a classification problem where the classes are: Buy Item and do not buy item
- 10,000 instances (randomly sampled from the data) for the over all prediction task and 3,000 instances for predicting for high-end and low-end items
- Equally divided between positive and negative examples (buy, vs. do not buy)
- Item data from the consignment network is used

Experiments: Feature Set

- **Acquired Characteristics Features:**
  In-game age, in-game gender, level, activities count, monsters killed, number of the items bought for the players which have similar characteristics
- **Network Based Features**
  Number of friends who bought the item, fraction of total items bought by friends, Number of FoFs who bought the items, fraction of total items bought by friends

Experiments: Feature Set

- **Ascribed Features:**
  Age, Gender, Location, Number of people with the same age who bought the item, Number of people with the same gender who bought the item, Number of people with the same location who bought the item

Results (For All The Items)

Table 1: Prediction results when all items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.50	0.50	**0.50**
Acscribed	N	0.27	0.06	0.09
Acquired	Y	0.80	0.40	**0.53**
Trust	Y	0.43	0.19	0.26
Mentoring	Y	0.41	0.20	0.27
Trade	Y	0.66	0.29	0.40
Adversarial	Y	0.83	0.40	**0.54**
Multi-Net	Y	0.22	0.10	0.13

Results: Key Observations

- Predictions based on ascribed (real world) characteristics do quite poorly.
- In general the network based approaches do not perform well (worse than random). A possible explanation is that this is because friendship in other social interactions is not an indicative of trade.
- The predictions based on the adversarial network and the acquired (in-game) characteristics performs the best.

Results (For Low-End Items)

Table 2: Prediction results when only low-end items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.5	0.5	0.5
Acscribed	N	0.07	0.12	0.08
Acquired	Y	0.45	0.80	**0.57**
Trust	Y	0.40	0.67	**0.50**
Mentoring	Y	0.37	0.65	**0.47**
Trade	Y	0.24	0.38	0.20
Adversarial	Y	0.38	0.53	0.44
Multi-Net	Y	0.47	0.49	0.53

Results: Key Observations (Low End)

- The Network based approaches perform much better as compared to before.
- The ascribed characteristics based approach again does poorly.
- The trade network based approach does poorly. This could be because partners of the players in the trade network are engaging in trading of different types of items.

Results (For High-End Items)

Table 3: Prediction results when only high-end items are used

Approach	**Network**	**Precision**	**Recall**	**F-Score**
Random	N	0.5	0.5	0.5
Acscribed	N	0.50	0.59	0.54
Acquired	Y	0.62	0.67	0.65
Trust	Y	0.55	0.63	0.58
Mentoring	Y	0.64	0.74	**0.69**
Trade	Y	0.67	0.80	**0.73**
Adversarial	Y	0.65	0.76	**0.70**
Multi-Net	Y	0.59	0.67	0.63

Results: Key Observations (High End)

- Significant improvement in results is obtained as compared to the previous instances.
- This is because if a *friend* buys an item then that is a strong indicator that the person also buy it. However the same applies for a *foe*.
- The Trade network based approach performs the best. The hypothesis about different trading types from the low-end items is thus validated.

Interpretation of Results

- Overall poor performance when predicting items in general.
- The Adversarial network is surprisingly a good predictor for overall prediction as well as for high end items but not for low end items. We think this is the case because adversaries may buy similar items in order to keep up with one another in an *arms race*.
- The trust network which represents the strongest type of *friendship* in the coextensive networks is not as useful for prediction as one may expect beforehand.

Conclusion

- Considered the problem of recommendations in coextensive social networks and compared the efficacy of different networks in the prediction task
- The choice of network for prediction depends upon what type of items one has to predict
- Future work involves replicating these results in different servers since those servers have a different social environment. Additionally replicate results in the trade network as well.