Recommending Games, Communities and Estimating Gameplay time in Gaming Social Network

A case study of Steam

Pratik Anand   Sanket Lokegaonkar

Outline

- Introduction
  - Gaming Social Networks
  - Steam
  - Dataset Sampling
- Graph of interaction
  - Modelling the relations
  - Graph Analysis
- Standard Matrix Factorization
- Co-occurrence Based Factorization
- Proposed Method
- Empirical Results

Gaming Social Network

- Less studied social network than Facebook or twitter network
- Unique in representation as centred around video games
- Different kind of relations like friends, followers, fans, publishers, game recommenders etc
- Multiple kinds of networks : each with its diffferent goal

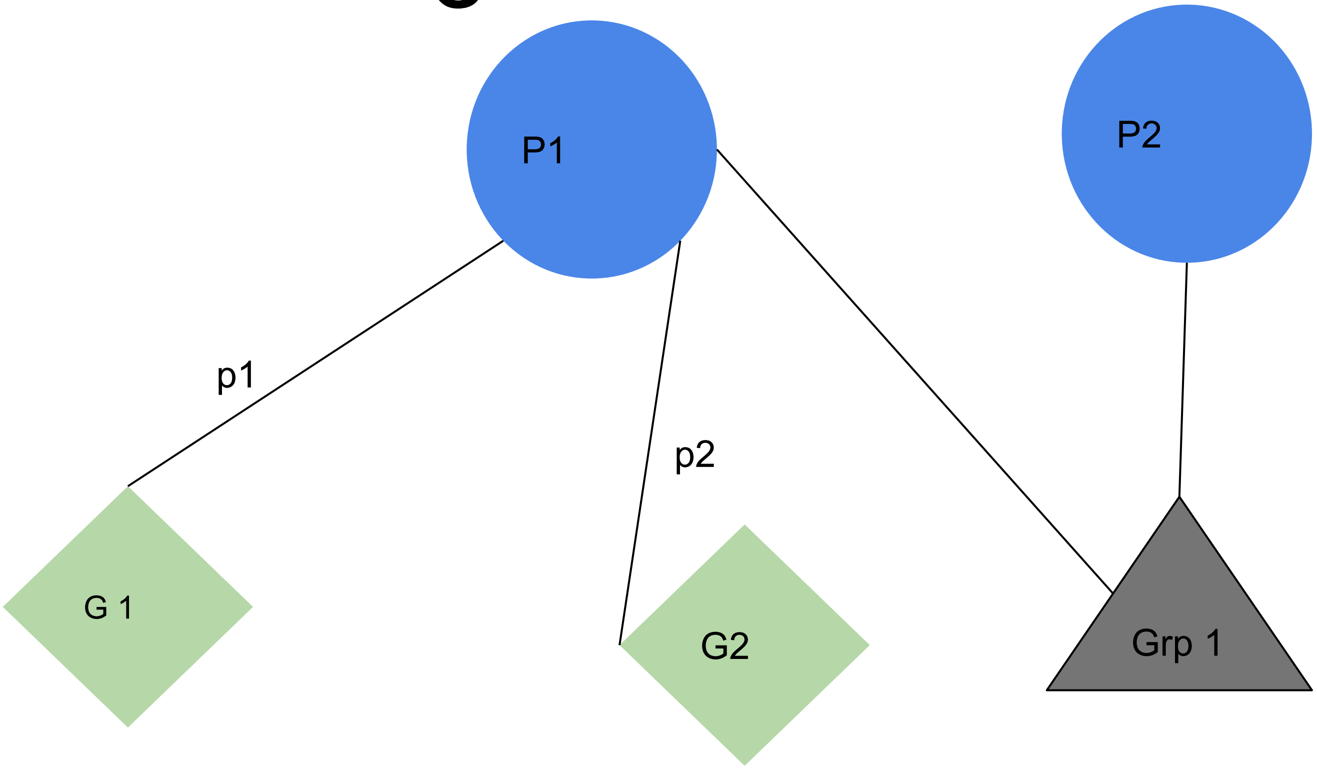
Steam

- Largest online gaming marketplace and social network
- 108.7 million user accounts and 384.3 million owned games
- Different social features :
  - Friendships
  - Communities
  - Clans
  - Steam Workshop
- Tracks user playtime session

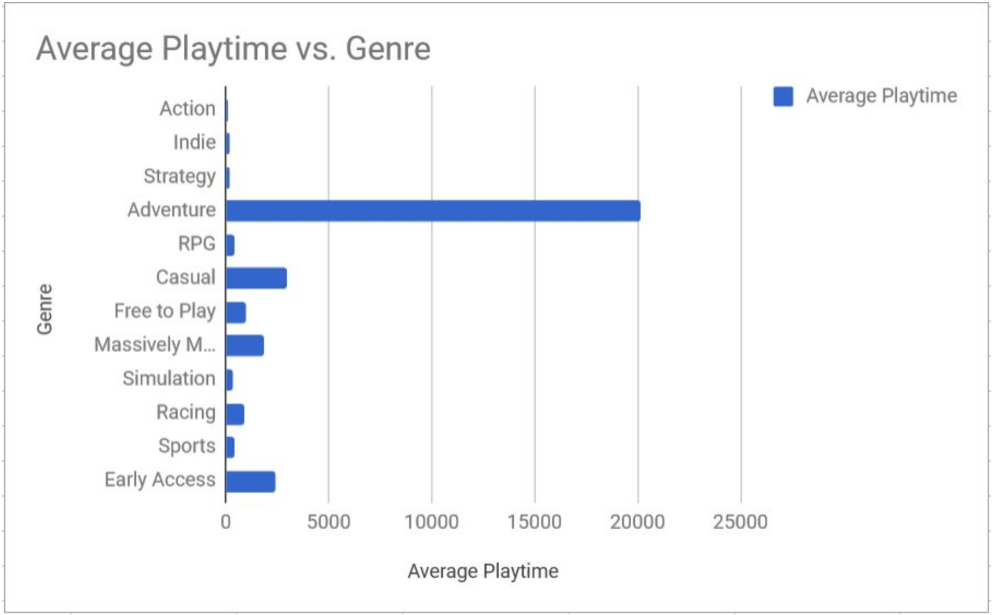
Dataset Sampling

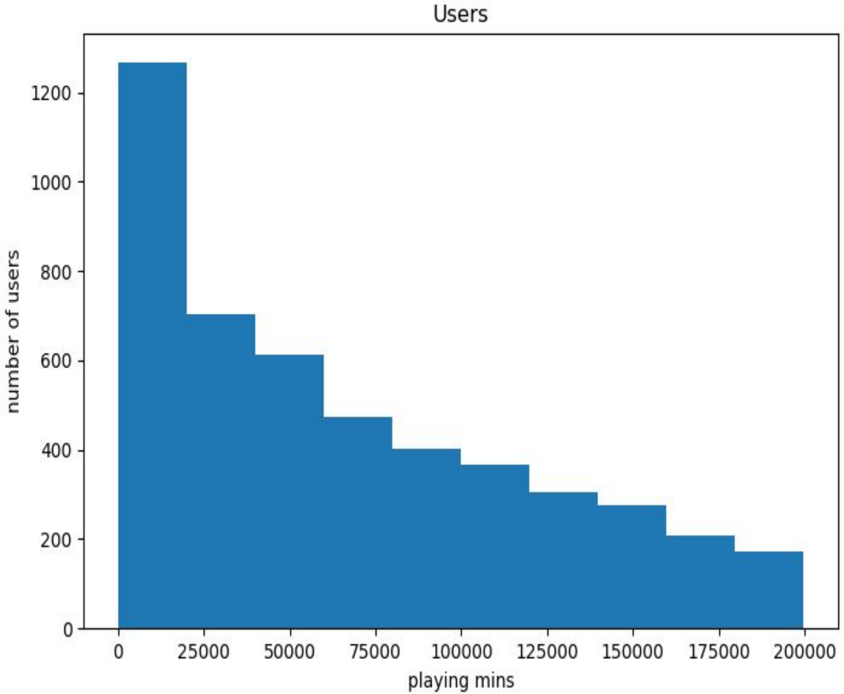
- 170GB Steam dataset compiled by http://steam.internet.byu.edu/
- 11 tables with user data retrieved in period of 2 weeks
- Data consisted of friendship, game ownership, playtime as well as community membership
- Sampled two data sets : 10,000 users and 100,000 users

Modelling the relations



Graph Analysis





Objective : How do we learn a model which can predict games and communities while staying consistent to each other?

Standard Matrix Factorization

- Given Users U and Items I , find latent features for U and I which reconstruct the matrix
- Classical Technique
- Can work well with different optimizer:
  - SGD
  - BFGS

Joint Matrix Factorization

- Given Users U and Items I and Communities C , find latent features for U , I and C which reconstruct the interaction matrix UI (User-Item) and User-Community(User-Community)

- Alternating Least -Squares based Optimization
- Intuitively , can have a synergistic effect improving the performance on both,

Co-occurrence Based Matrix Factorization

- Given Users U and Items I, find the latent features for U , I.
- Does not utilize core-property of similar items are bought together
- Construct a Co-occurrence Matrix(similar to word2vec)

$$PMI(i, j) = \log \frac{P(i, j)}{P(i)P(j)}$$

- Perform Joint Optimization which conforms with the co-occurrence matrix
- Alternating Least -Squares based Optimization
- Intuitively , can have a synergistic effect improving the performance on both,

JFactor Matrix Factorization

- **Intuition:**
  - Use both ideas for User-Community Matrix and User-Game Matrix
  - Joint Factorization should have a synergistic effect between the User-Game Matrix and User-Community Matrix
- **Math: (Joint Optimization Part)**

$$L_{mf} = \sum_{u,i}(x_{ui} - \theta_u^T \beta_i)^2 + \sum_{u,j}(x_{ui} - \theta_u^T \alpha_j)^2$$
$$+ \sum_{u1,u2}(x_{u1,u2} - \theta_{u1}^T \theta_{u2})^2 + \sum_{u} \|\theta_u\|^2 + \sum_{i} \|\theta_i\|^2 + \sum_{j} \|\alpha_j\|^2$$

$X \in R^{U \times G}$: Sparse User-Game Interaction Matrix from U Users and G Games
$Y \in R^{U \times C}$: Sparse User-Community Interaction Matrix from U Users and C Communities
$Z \in R^{U \times U}$: Sparse User-User Interaction Matrix from U Users

Theta = User Latent Features

Beta = Game Latent Features

alpha = Community Latent Features

JFactor : Combined Optimization Model

$$L_{modified} = L_{mf} + \sum_{ij}(U_{ij} - \beta_i^T p_i) + \sum_{ij}(W_{ij} - \alpha_i^T q_i) + \sum_i \|p_i\|^2 + \sum_j \|q_j\|^2$$

L_mf = Joint Matrix Factorization Objective ;

Uij = Co-occurrence Matrix for Games ; Wij = Co-occurrence Matrix for Communities

Beta = Latent features of Users ; Pi = Context features of Users

alpha = Latent features of Communities qj = Latent features of Communities

JFactor : Combined Optimization Model

$$L_{modified} = L_{mf} + \sum_{ij}(U_{ij} - \beta_i^T p_i) + \sum_{ij}(W_{ij} - \alpha_i^T q_i) + \sum_i \|p_i\|^2 + \sum_j \|q_j\|^2$$

L_mf = Joint Matrix Factorization Objective ;

Uij = Co-occurrence Matrix for Games ; Wij = Co-occurrence Matrix for Communities

Beta = Latent features of Users ; Pi = Context features of Users

alpha = Latent features of Communities qj = Latent features of Communities

Empirical Study

- Model is sound? - At least we believe it.
- Model should work in real life? - Meh!

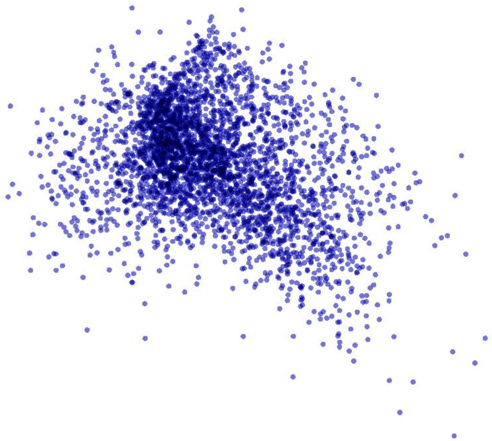
Table 1. Ablation Study comparing effects of different optimizations on the 10K BFS-Sampled dataset. We perform evaluation on 10k dataset

	User-Game Matrix					User-Community Matrix				
	Recall@20	Recall@50	NDCG@100	MAP@100	MSE	Recall@20	Recall@50	NDCG@100	MAP@100	MSE
Games Only Factorization	0.242547	0.322987	1.675945	0.117363	0.4953	-	-	-	-	
Communities Only Factorization	-	-	-	-		0.151137	0.186248	0.092616	0.055346	0.95
G+C (Joint Factorization)	0.190743	0.268247	1.300759	0.085098	0.5153	0.009453	0.021832	0.012558	0.002898	1.622
Games + Game co-occurrence Factorization	0.254986	0.342827	1.747526	0.123401	0.4937					
Community + Community co-occurrence Factorization						0.007765	0.023858	0.010219	0.002573	2.6075
(Joint Factorization + Co-occurence)	0.237249	0.313843	1.674253	0.117684	0.4744	0.069097	0.127842	0.054317	0.023398	0.5032

Table 2. Ablation Study comparing effects of different optimizations on the 100K BFS-Sampled dataset. We perform evaluation on 100k datast

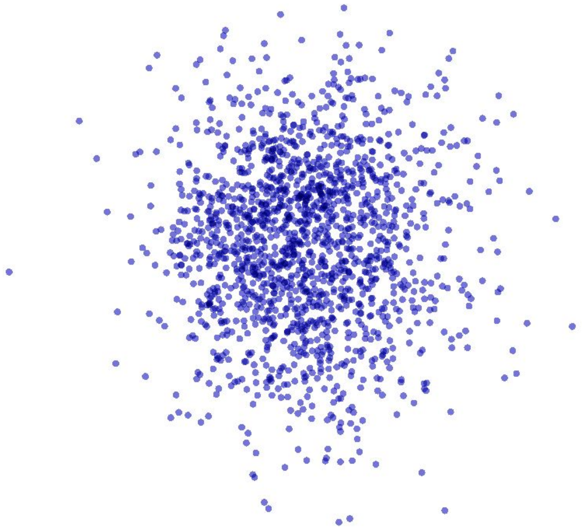
	User-Game Matrix					User-Community Matrix				
	Recall@20	Recall@50	NDCG@100	MAP@100	MSE	Recall@20	Recall@50	NDCG@100	MAP@100	MSE
Games Only Factorization	0.047	0.129	0.5624	0.012	0.3374	-	-	-		
Communities Only Factorization	-	-	-	-		0.0108	0.015	0.005	0.002612	2.2618
G+C (Joint Factorization)	0.009180	0.033939	0.205335	0.002952	0.3461	0.000444	0.001710	0.000701	N/A	3.8844
Games + Game co-occurrence Factorization	0.229253	0.349671	1.511421	0.087371	0.333					
Community + Community co-occurrence Factorization						0.000804	0.002311	0.000905	0.000174	4.49
(Joint Factorization + Co-occurence)	0.000924	0.012138	0.149904	0.001536	0.3615	0.000499	0.001793	0.000683	0.000126	4.30

Empirical Study: Qualitative



- Random Sampling:
  - Games with similar genres are clustered together -
  - Users with high scores are clustered together
- Visualizing the latent features(PCA)
  - PCA- Games

Empirical Study: Qualitative



- Random Sampling:
  - Games with similar genres are clustered together -
  - Users with high scores are clustered together
- Visualizing the latent features(PCA)
  - PCA- Communities

Empirical Study: Qualitative

- Random Sampling:
  - Games with similar genres are clustered together -
  - Users with high scores are clustered together
- Visualizing the latent features(PCA)
  - PCA- Users

In Retrospect

- Model does not work as expected
- Possible issues:
  - Sparsity of the community matrix
  - Difficulty in optimization
  - Longer training times might help.

Conclusion & Future Work

- We developed a model for jointly recommending communities and games together.
- First to explore this unique dataset from the recommendation perspective
- Future Work:
  - Find a way to avoid over-constraining
  - Model sensitive to initialization. Further investigation needed

Thank You

References cited in the paper :
https://github.com/pratikone/steam-addiction-analysis/blob/master/doc/LOKEGAONKAR-ANAND-final.pdf