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

A case study of Steam

Pratik Anand   Sanket Lokegaonkar

Outline

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- Standard Matrix Factorization
- Co-occurrence Based Factorization
- Proposed Method
- Empirical Analysis
- Challenges We faced
- Conclusion & Future Work

Big Picture

Given:
Tripartite graph of users, games , communities (Steam)

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

Why is it important:
Few datasets with such a unique-structure (Tripartiteness)
Large real-world dataset unexplored (Sounds like fun!)

Our Technical Framework:
Matrix Factorization shown to work well empirically.
How can we extend matrix factorization methods to this framework?
How can we do better than just applying Matrix Factorization?

Gaming Social Network

- Not as well studied as other social network like Twitter or Facebook
- Unique in representation as centred around video games
- Different kind of relations like friends, followers, fans, publishers, game recommenders etc
- Different kind of gaming networks :

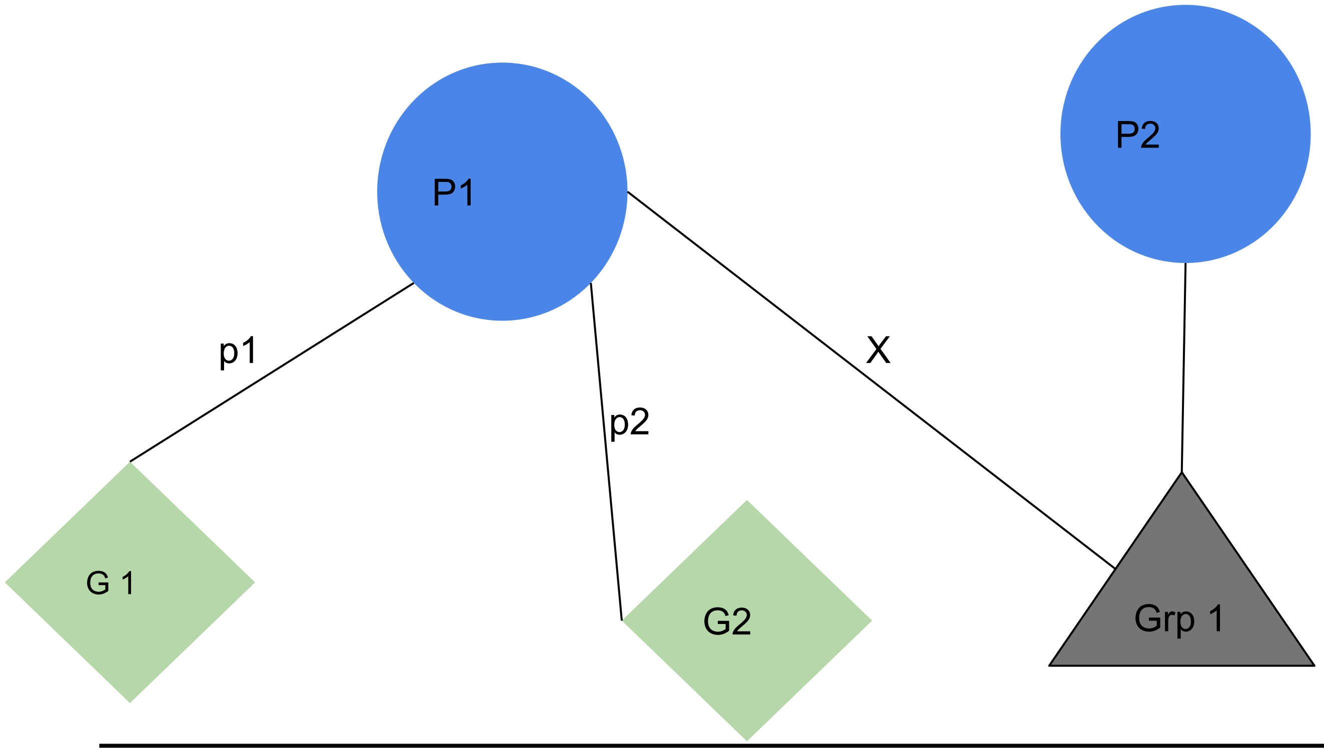
Steam

- 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

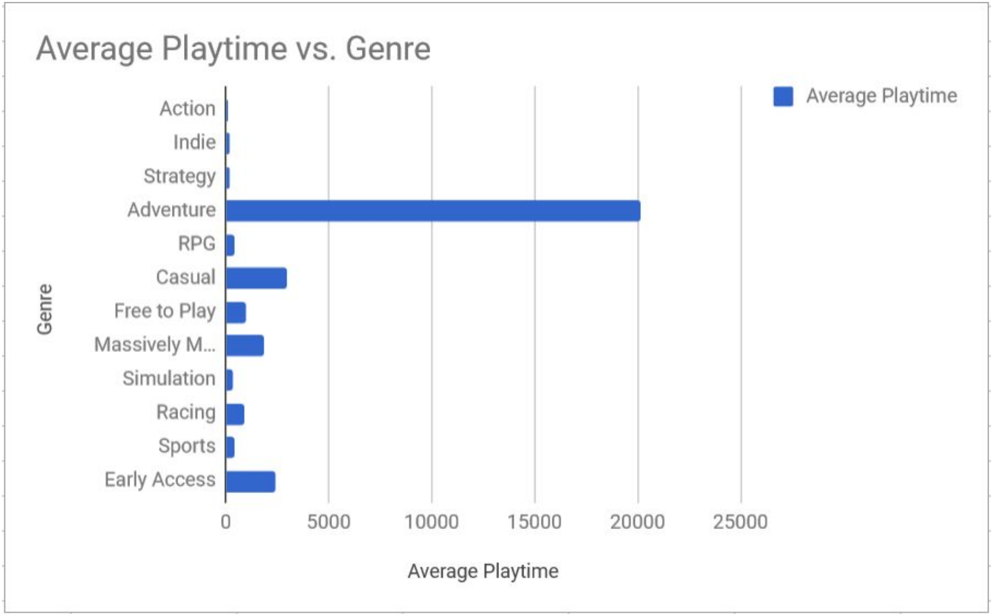
Dataset Sampling

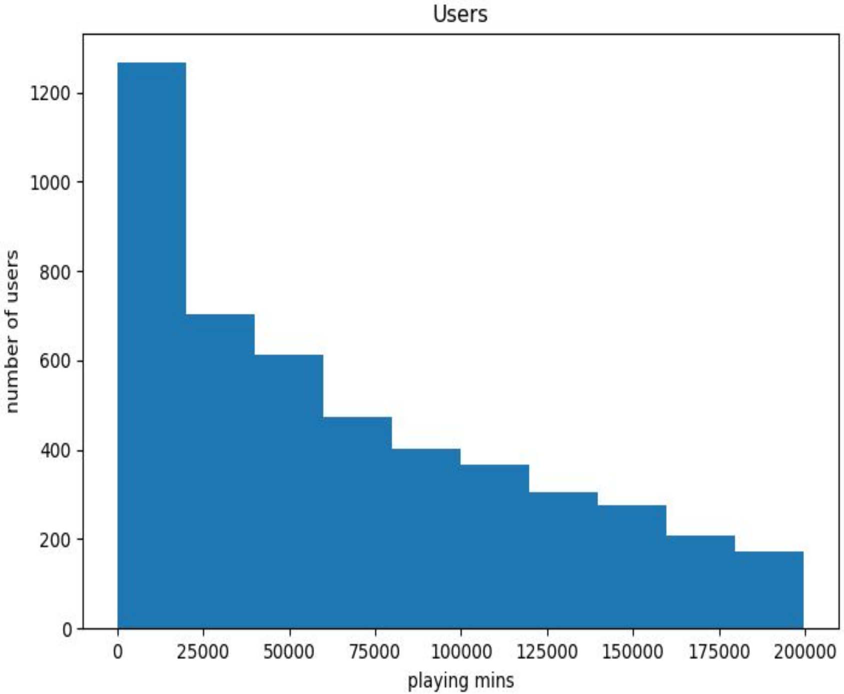
- 170GB Steam dataset compiled by http://steam.internet.byu.edu/ (Condensing Steam: Distilling the Diversity of Gamer Behavior)
- 11 tables with user data retrieved in period of 2 weeks
- Data consisted of friendship, game ownership, playtime as well as community membership
- Gameplay time recorded over the course of two weeks
- Sampled two data sets : 10,000 users and 100,000 users

Modelling the relations



Analyzing Steam





Standard Matrix Factorization

- Given Users U and Items I and User-Item Interaction Matrix
- Find latent features for U and I which reconstruct the matrix
- Solve Least Squares Optimization

Joint Matrix Factorization

- Given 3 interacting entities: Users U, Items I and Communities C
- Interaction Matrices:
    - User-Community Matrix
    - User-Game Matrix
    - User-User Matrix*
- Alternating Least-Squares Optimization
- Solving jointly, might have a synergistic effect improving the performance on both,

Co-occurrence Based Matrix Factorization

- Proposed by Liang et.al RecSys'16
- Given Users U and Items 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 (Proposed Method)

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

θ = User Latent Features

β = Game Latent Features

α = Community Latent Features

JFactor : Combined Optimization Model

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

In a gist, Joint Factor + Co-occurrence = JFactor
Implemented in TensorLab

Notation:

- L_{mf} = Joint Matrix Factorization Objective ;
- U_{ij} = Co-occurrence Matrix for Games ;
- W_{ij} = Co-occurrence Matrix for Communities
- p_i = Context features of Users
- q_j = Latent features of Communities

Empirical Analysis: Evaluation Metrics

Absolute Error:

- Mean Square Error:

Ranking Metrics:

- Recall @ M
- NDCG @ M
- MAP @ M

Empirical Analysis: Ablation Study

Settings we compare:

- Trained on Games Only (G)
- Trained on Communities Only (C)
- Trained on Games + Games Co-occurrence Matrix (G + Embedding G)
- Trained on Community + Community Co-occurrence Matrix (C + Embedding C)
- Games + Community (Joint Factorization)
- Games + Community + Community Co-occurrence Matrix + Game Co-Occurrence Matrix (All Combined)

Empirical Analysis: Ablation Study

10K Users , 1.9K Communities, 3.1K Games

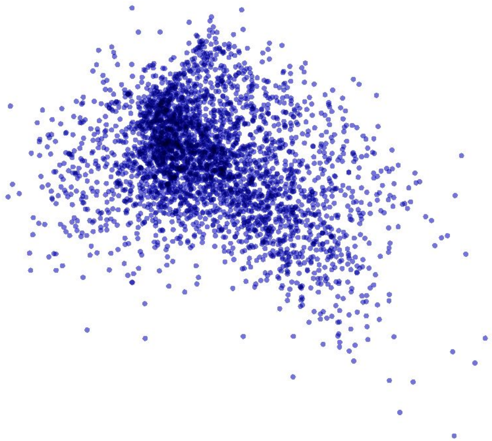
	User-Game Matrix					User-Community Matrix				
	Recall@20	Recall@50	NDCG@100	MAP@100	MSE	Recall@20	Recall@50	NDCG@100	MAP@100	MSE
Games Only Factorization	0.242547	0.322987	1.675945	0.117363	0.4953	-	-	-	-	
Communities Only Factorization	-	-	-	-		0.151137	0.186248	0.092616	0.055346	0.95
G+C (Joint Factorization)	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

Empirical Analysis: Ablation Study

100K Users , 15K Communities, 3.9K Games

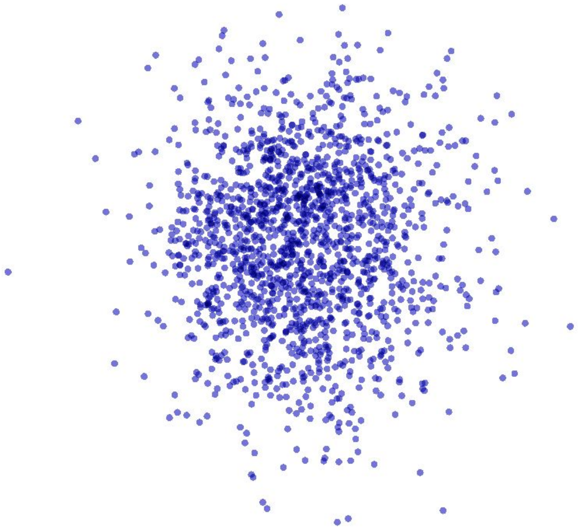
	User-Game Matrix					User-Community Matrix				
	Recall@20	Recall@50	NDCG@100	MAP@100	MSE	Recall@20	Recall@50	NDCG@100	MAP@100	MSE
Games Only Factorization	0.047	0.129	0.5624	0.012	0.3374	-	-	-		
Communities Only Factorization	-	-	-	-		0.0108	0.015	0.005	0.002612	2.2618
G+C (Joint Factorization)	0.009180	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
    - Users who hoard/or are addicted clustered together.
- Visualizing the latent features(PCA)
    - PCA- Games

Empirical Study: Qualitative



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Critical Analysis: What went wrong?

- No strong synergistic signal between User-Community and User-Games
- Sparsity of User-Community
- Joint optimization ?
- Over-constrained System
- Longer training times?

Challenges We faced

- Lots of changes to the core idea:
    - Initially , planned to do tensor factorization-based approach
- Lots of changes towards the end
    - Did not explore details on why the results are weird
- Tried integrating User-User Friendship Graph.
    - Got worse performance.
- Tried our own implementation in Python.
    - Had bugs. Was not working as expected.

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
  - Incorporating User-Friendship Graph

Thanks!
Questions?