

Scrutinizing Mobile App Recommendation: Identifying Important App-Related Indicators

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Introduction

Basic Recommendation Systems

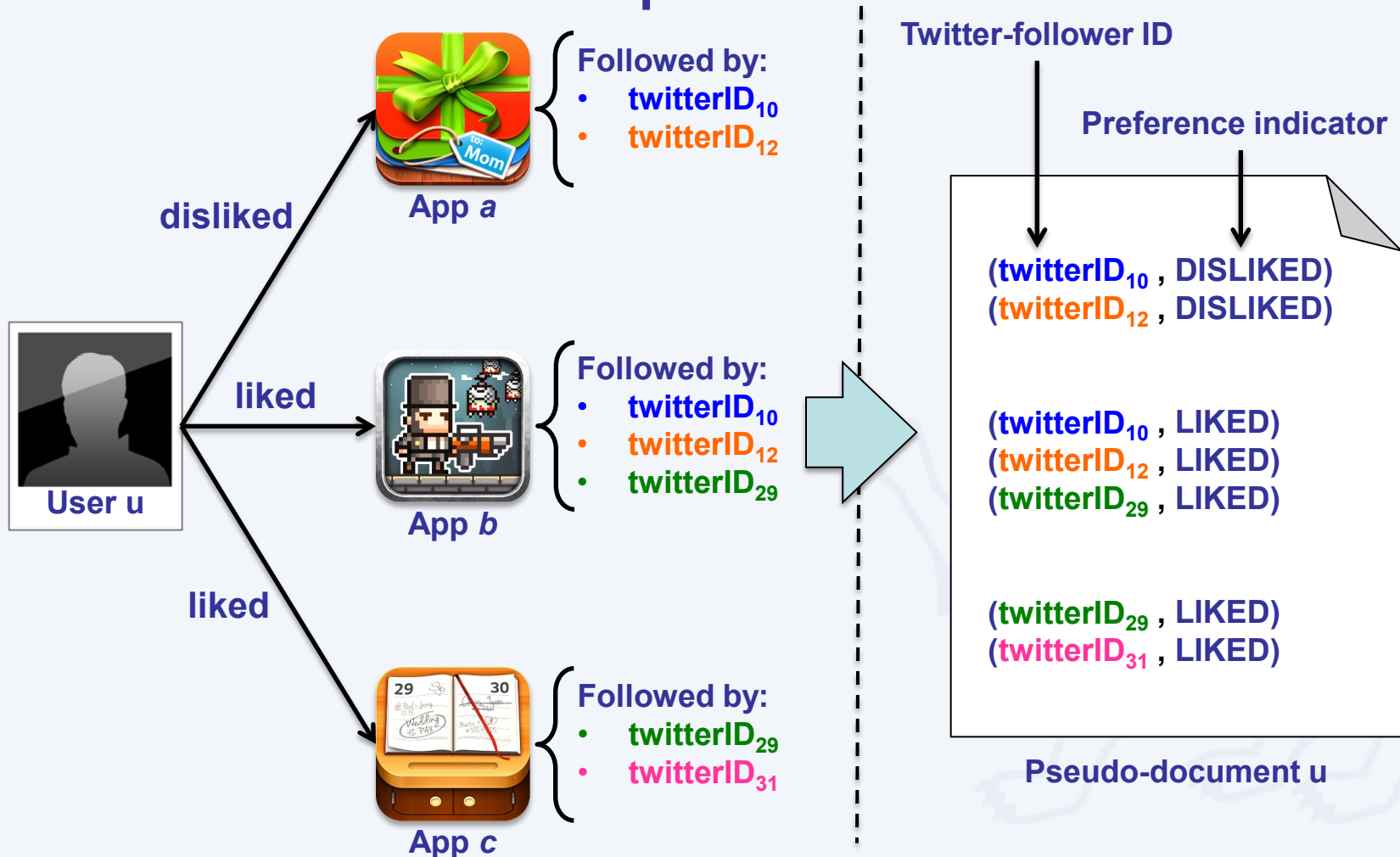
- **Collaborative Filtering (CF)**
 - User's ratings
- **Content-based Filtering (CBF)**
 - Contents of items

We have proposed mobile app recommendation systems:

- **Twitter followers (TWF)** [Lin et al., SIGIR'13]
- **Version sensitive recommendation (VSR)** [Lin et al. SIGIR'14]

Twitter Followers (TWF) [Lin et al., SIGIR'13]

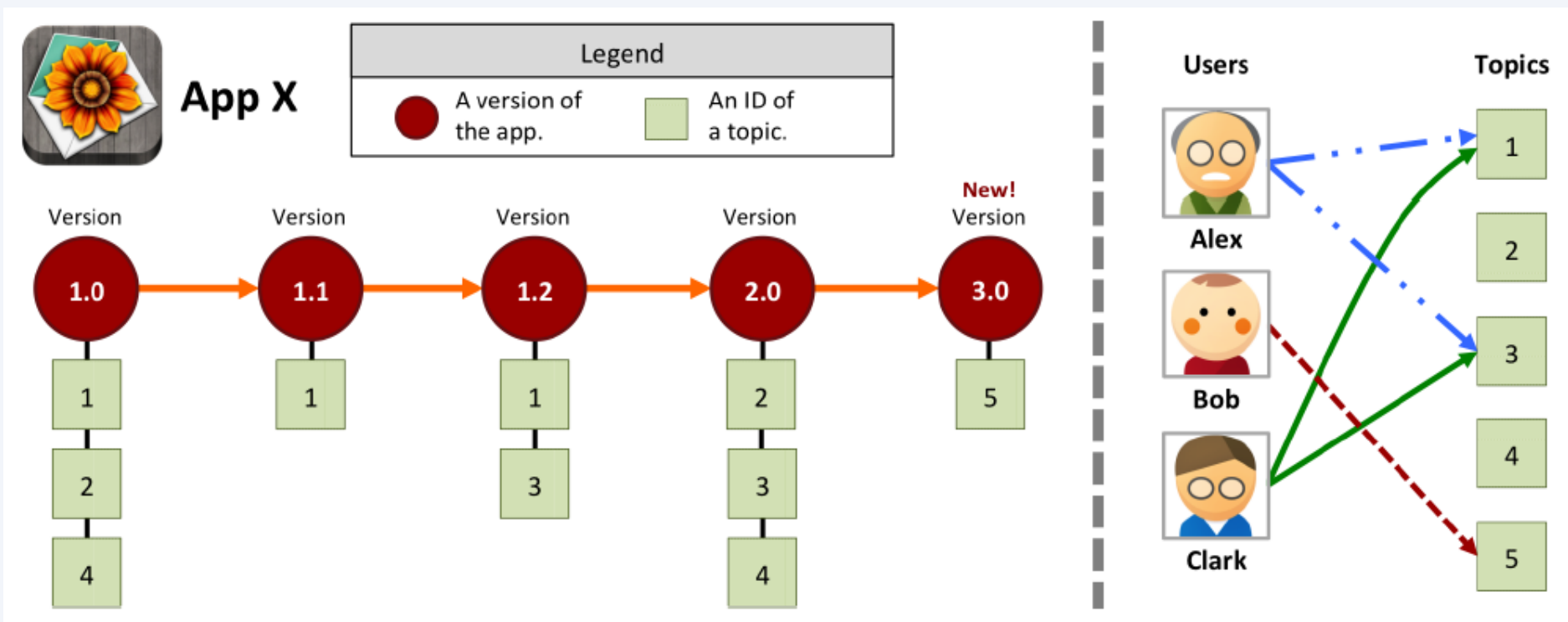
Pseudo-documents and pseudo-words



Version Sensitive Recommendation (VSR)

[Lin et al., SIGIR'14]

Relationship between version of apps and users



Introduction

How about unifying
the followings?

- Collaborative filtering (CF)
- Content-based filtering (CBF)
- Twitter followers (TWF)
- Version sensitive recommendation (VSR)

To achieve this,

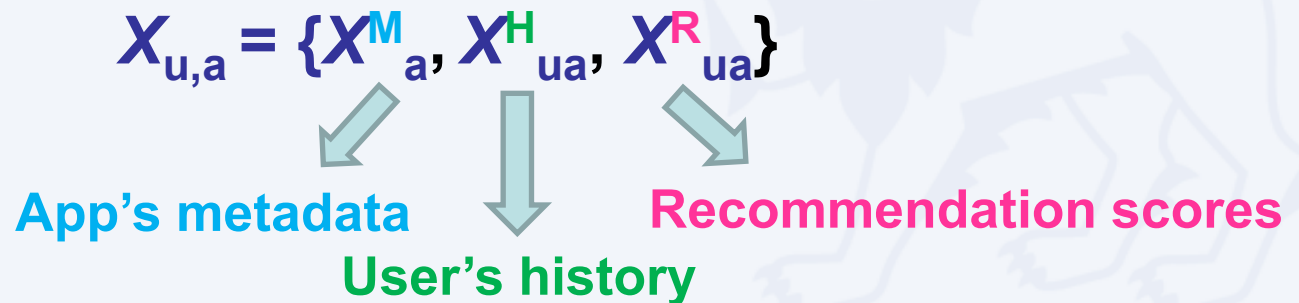
1. **Unify the strengths** of the four recommender techniques.
2. **Propose** a set of specific features (in the app domain) for the unifying framework.
3. **Perform in-depth analysis** of these features and uncover interesting connections.

Methodology

Feature set

1. The app's marketing-related metadata (M)
2. The user's history-related information (H)
3. The recommendation scores of different recommender systems (R)

Each app's feature vector $X_{u,a}$ is composed of the above three types of information.

$$X_{u,a} = \{X_a^M, X_{ua}^H, X_{ua}^R\}$$


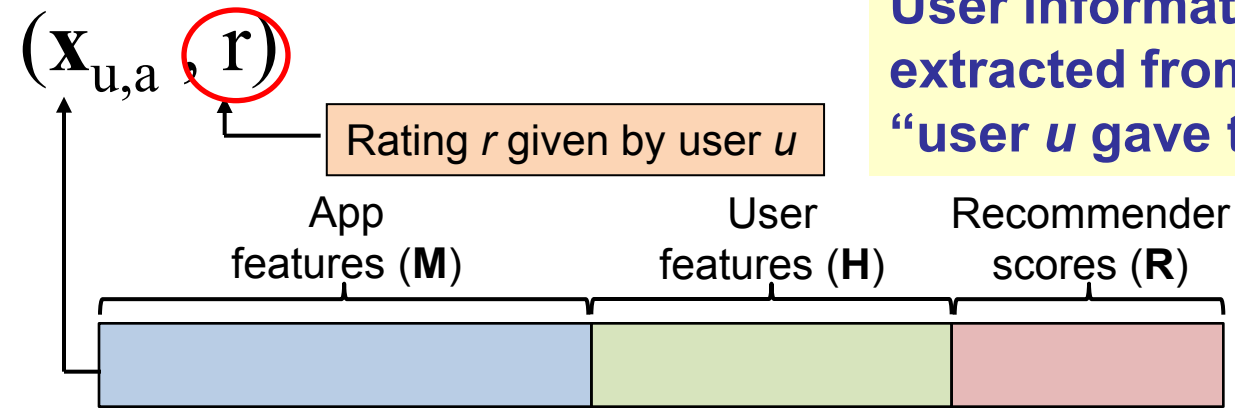
App's metadata

User's history

Recommendation scores

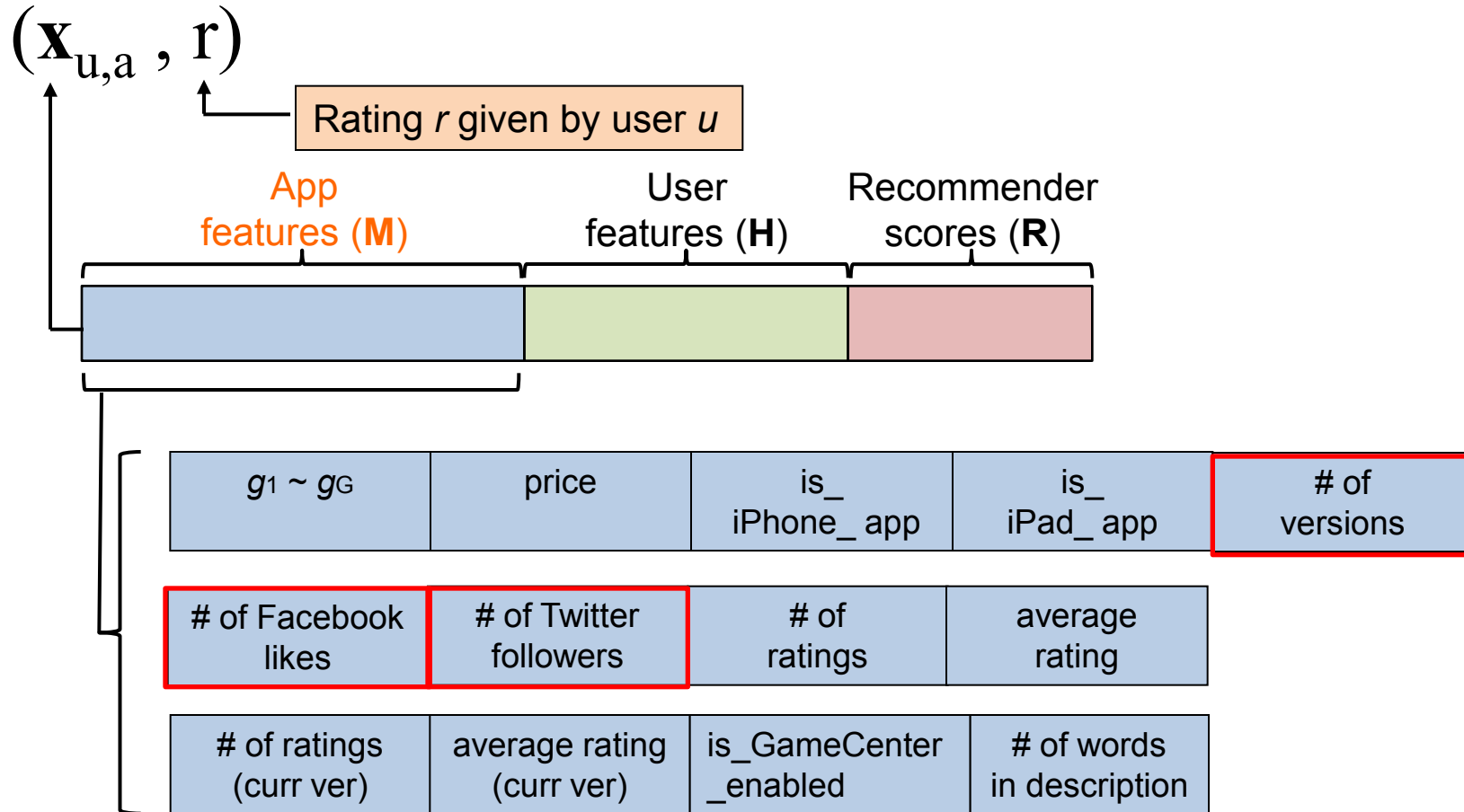
Feature set

User information is extracted from ratings. Namely, "user u gave the rating r to app a ."



Feature set

App's Marketing-Related Metadata (M)

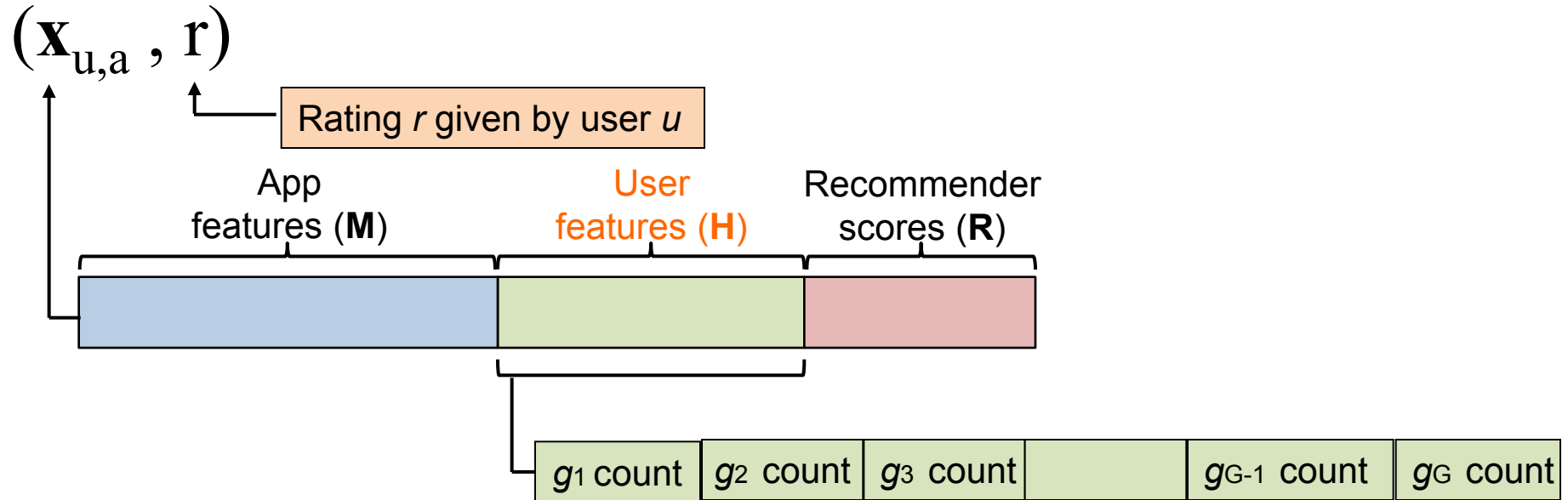


Enrich the app features by including

- # of versions,
- # of Facebook likes,
- # of Twitter followers

Feature set

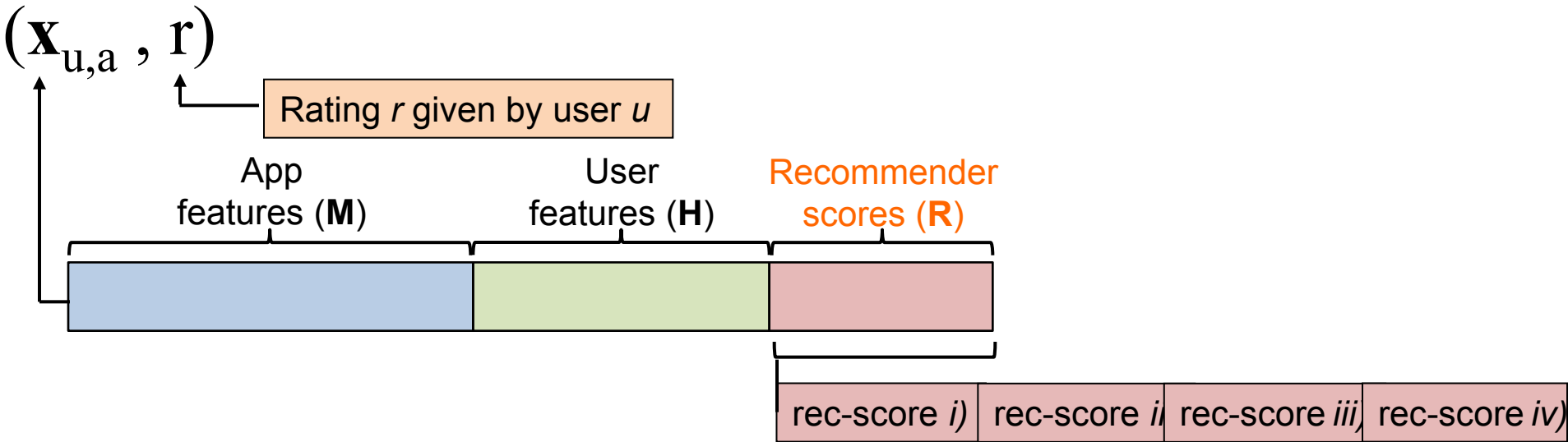
User's History-Related Information (H)



The number of times that apps in genre g were consumed by user u .

Feature set

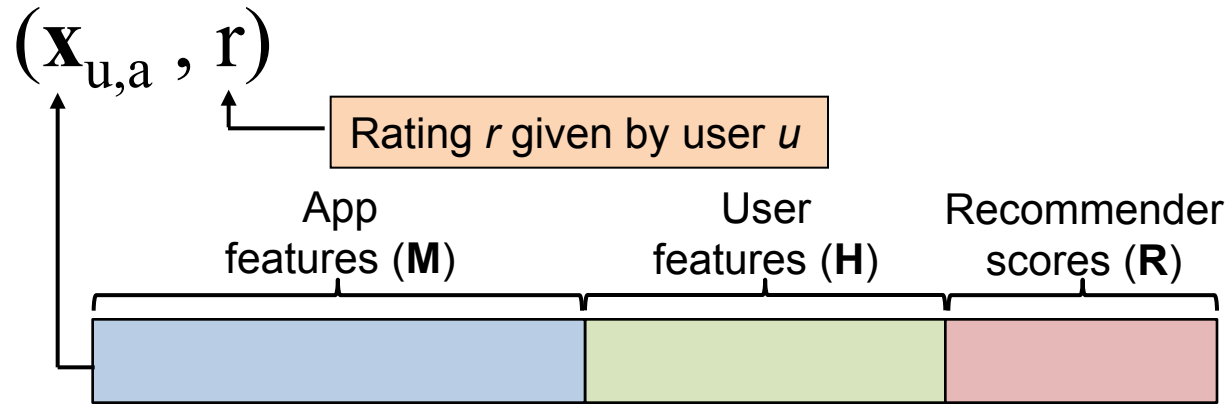
Recommendation Scores from Different Recommender Techniques (R)



Include the recommendation scores from the individual recommendation algorithms:

- i) Collaborative filtering (CF)
- ii) Content-based filtering (CBF)
- iii) Twitter followers (TWF)
- iv) Version sensitive recommendation (VSR)

Combining App Features



Employ **Gradient Tree Boosting (GTB)** to train the model (via “scikit-learn”).

Training Phase:

- Give
 - feature vector “ $\mathbf{X}_{u,a}$ ”
 - rating “ r ”to GTB
- GTB constructs an ensemble of decision tree learners

Test Phase:

- Given a (testing) feature vector (*i.e.*, $\mathbf{X}_{u,a}$), the learned model predicts “ r ”

Experiments

Experimental Data

After retaining only unique users who give at least 30 ratings, we obtain the following data:

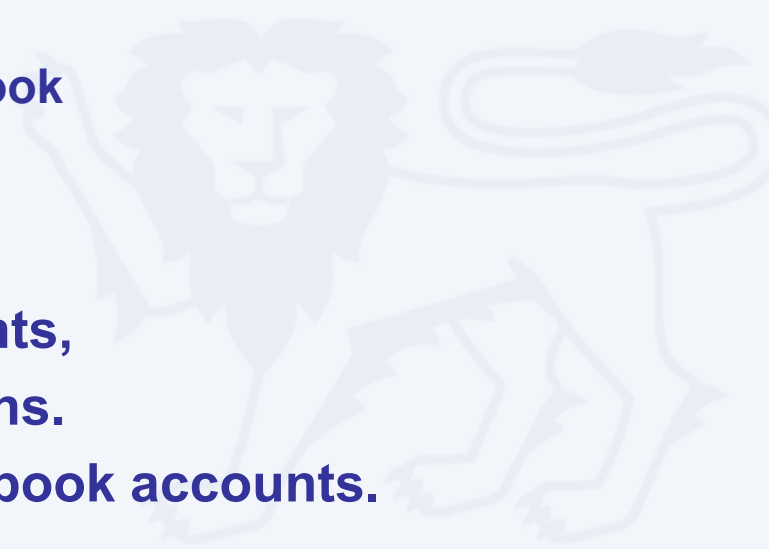
- 33,802 apps
- 16,450 users
- 3,106,759 ratings

Collected from

- iTunes App Store
- App Annie 
- Twitter
- Facebook

Among about 33.8K apps,

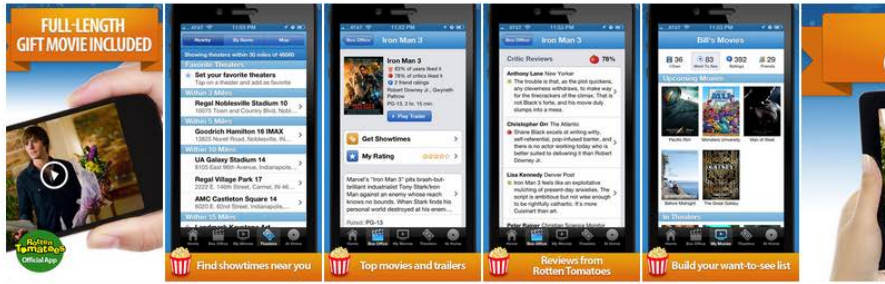
- 7,124 (21.1%) have Twitter accounts
- 9,288 (27.5%) have Facebook accounts,
- 10,520 (31.1%) have at least 5 versions.
- 678 (2%) have both Twitter and Facebook accounts.





Movies by Flixster, with Rotten Tomatoes

Store Price Compatibility Publisher
iTunes Free Universal Flixster



Description

Movies by Flixster. The #1 app for movie reviews, trailers, and showtimes.
- The most downloaded movies app of all time
- Featured in the App Store Essentials Hall of Fame by Apple
- Best showtimes app for iPhone - Lifehacker.com

1. Browse the top box office movies and movies opening soon
2. Look up showtimes at your favorite theater and buy tickets (from participating theaters)
3. Get critic reviews from Rotten Tomatoes
4. Watch high quality trailers
5. Stream and download full-length movies.
6. Create your own "Want to See" list, rate & review movies
7. View and manage your Netflix queue

What's New

Version 6.2 (May 9, 2013)

- 1) We've totally revamped the DVD tab so that you can now use filters to discover movies you want to watch at home.
- 2) The DVD tab has a new addition - Netflix Streaming. Browse through Netflix's streaming catalog and add them to your queue.
- 3) You now have the option of adding a movie to your Netflix queue or launching the Netflix app to stream it.
- 4) Fix for a 'license expired' bug when trying to play downloaded movies.
- 5) You can now see all critic reviews for a movie on iPad
- 6) Fixed errors while redeeming gift movies
- 7) Performance improvements all around

^ Collapse notes

Version 6.1 (Apr 22, 2013)

1. Swipe to the right/left on a movie (in Box Office or DVD screen) to access quick controls - "Want to See" to add the movie to your want to see list, "Add Rating" to add your rating, "Trailer" & "Showtimes" to launch trailer & showtimes for the movie.
2. Movies in your want to see list are now grouped into 3 sections - upcoming movies, movies currently playing in theaters and all other movies available on dvd/streaming
3. Improvements to movie pages on iPad
4. Sort movies in your UltraViolet collection
5. Switching between tabs is now faster

^ Collapse notes

[Flixster Web Site](#)

[Flixster Support](#)

Featured (Jun 12, 2013)

▼ iPhone Market

- Not featured on the iTunes Home Page
- 20 places in iTunes

▼ iPad Market

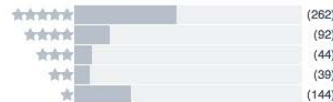
- Not featured on the iTunes Home Page
- 15 places in iTunes

Versions

6.2	May 9, 2013	Current release
6.1	Apr 22, 2013	
6.0	Mar 22, 2013	
...		
3.2 (iPho...		
3.3 (iPho...		First tracked

Average Ratings (United States) More Countries

▼ Current Version - 3.5 - 581 ratings



▶ All Versions - 3.5 - 470,649 ratings

 : App metadata

 : Version information

 : Rating information



Experiments

Comparative Approaches

- **Individual recommendation techniques**

- i) Collaborative filtering (PMF) [Salakhutdinov and Mnih, ICML'08']
- ii) Content-based filtering (LDA) [Blei et al., JMLR'03]
- iii) Twitter followers (TWF) [Lin et al., SIGIR'13]
- iv) Version sensitive recommendation (VSR) [Lin et al., SIGIR'14]

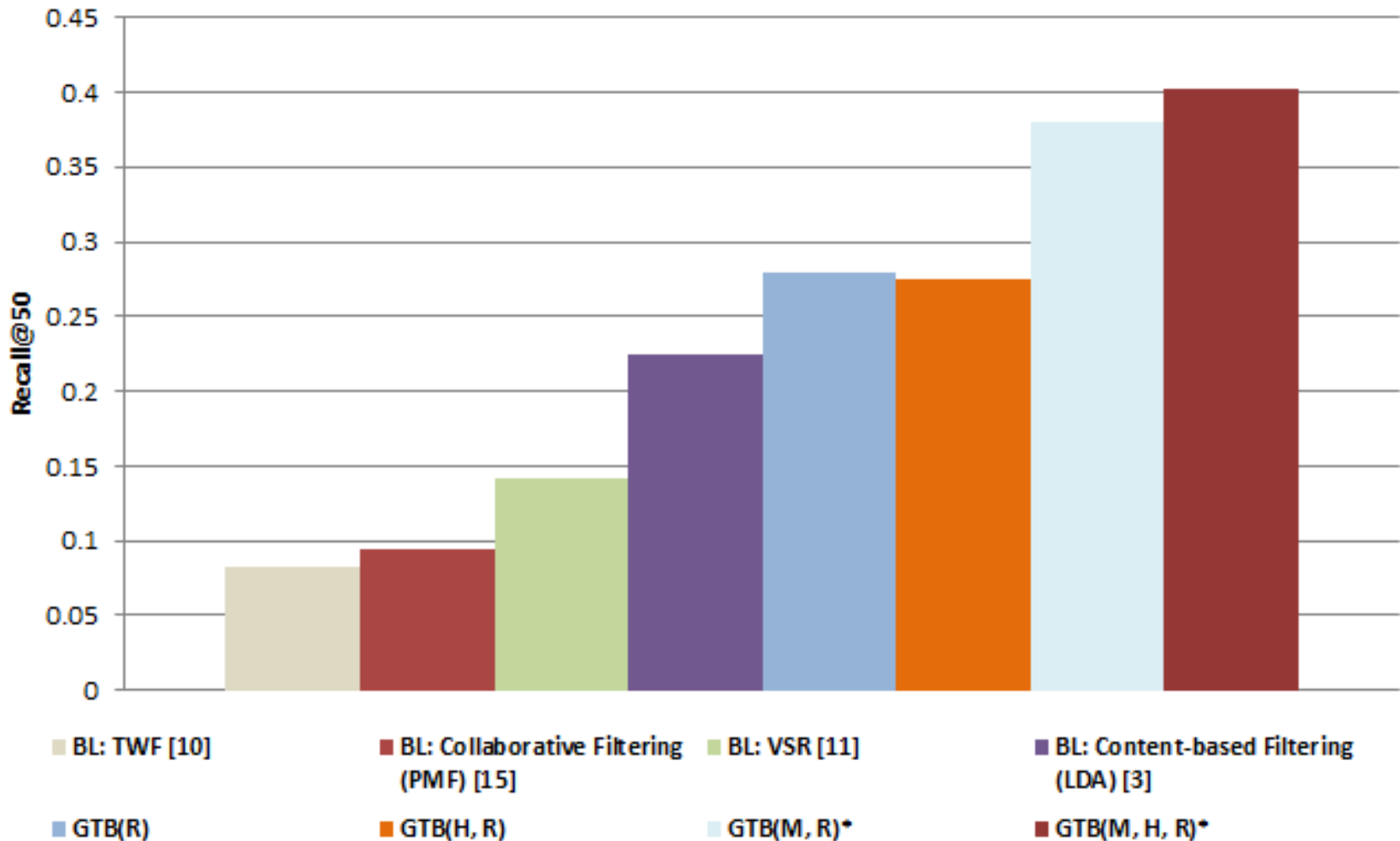
with $X_{u,a} = \{X_{ua}^H\}$

- **Hybrid recommendation techniques**

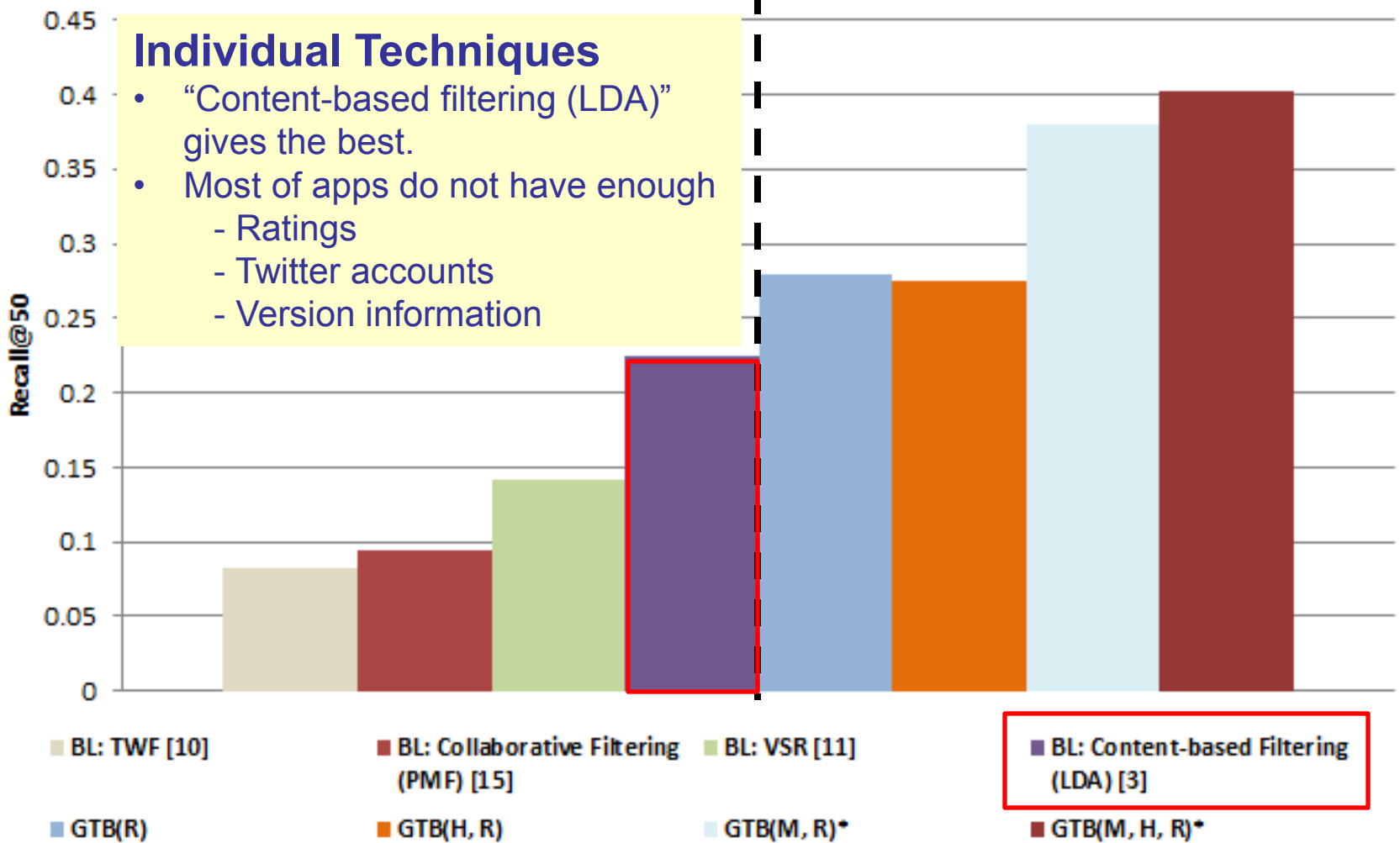
- GTB(R)
- GTB(H, R) M: App's Marketing-related metadata
- GTB(M, R) H: User's history-related information
- GTB(M, H, R) R: Recommendation score

- **Evaluation measure: Recall@50**

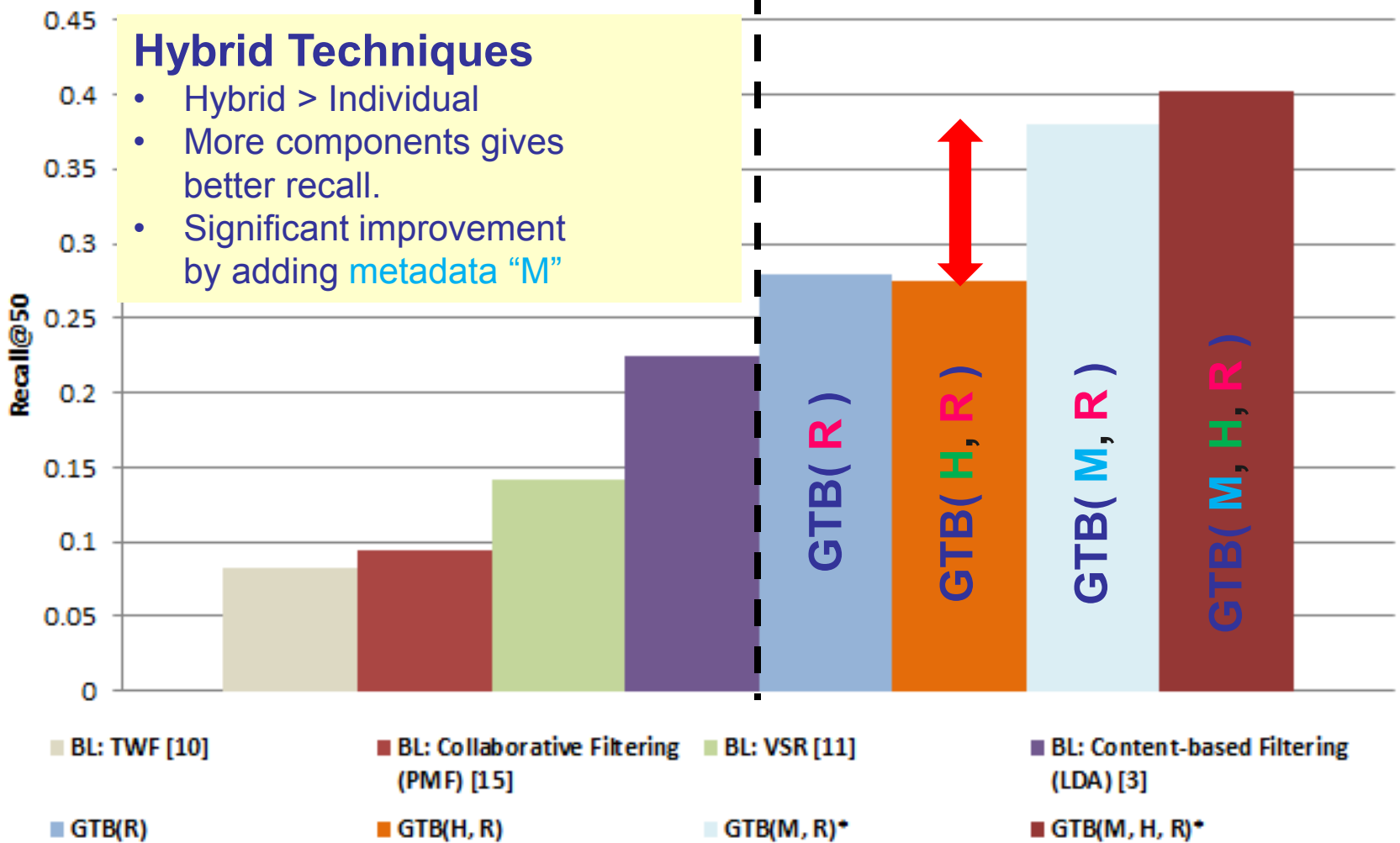
Comparison of Individual and Hybrid Systems



Comparison of Individual and Hybrid Systems



Comparison of Individual and Hybrid Systems



Ablation Testing for Hybrid Recommendation

Feature	Recall@50
GTB(M, H, R)	0.403
GTB(M, H, R), excluding TWF	0.363
GTB(M, H, R), excluding VSR	0.346
GTB(M, H, R), excluding collaborative filtering (PMF)	0.292
GTB(M, H, R), excluding content-based filtering (LDA)	0.237
TWF	0.082
VSR	0.141
Collaborative filtering (PMF)	0.094
Content-based filtering (LDA)	0.225

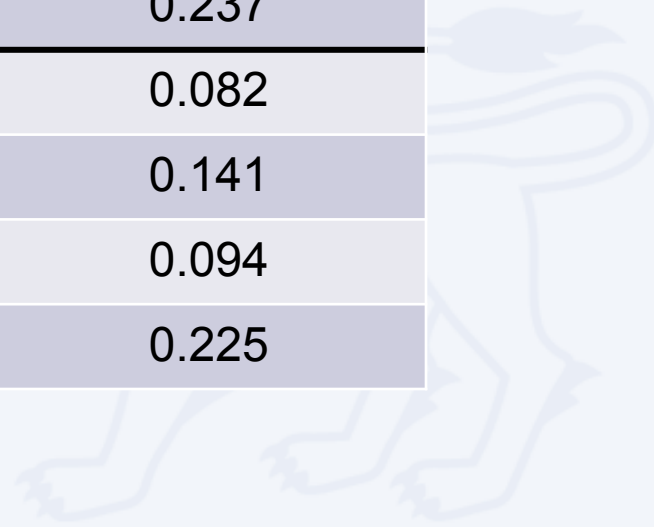
Improve by
16.5%



Ablation Testing for Hybrid Recommendation

Feature	Recall@50
GTB(M, H, R)	0.403
GTB(M, H, R), excluding TWF	0.363
GTB(M, H, R), excluding VSR	0.346
GTB(M, H, R), excluding collaborative filtering (PMF)	0.292
GTB(M, H, R), excluding content-based filtering (LDA)	0.237
TWF	0.082
VSR	0.141
Collaborative filtering (PMF)	0.094
Content-based filtering (LDA)	0.225

Improve by 11.0%

Ablation Testing Using Sufficient Twitter Information

Feature	Recall@50
GTB _{TWF} (M, H, R)	0.446
GTB _{TWF} (M, H, R), excluding VSR	0.412
GTB _{TWF} (M, H, R), excluding collaborative filtering (PMF)	0.390
GTB _{TWF} (M, H, R), excluding content-based filtering (LDA)	0.386
GTB _{TWF} (M, H, R), excluding TWF	0.338

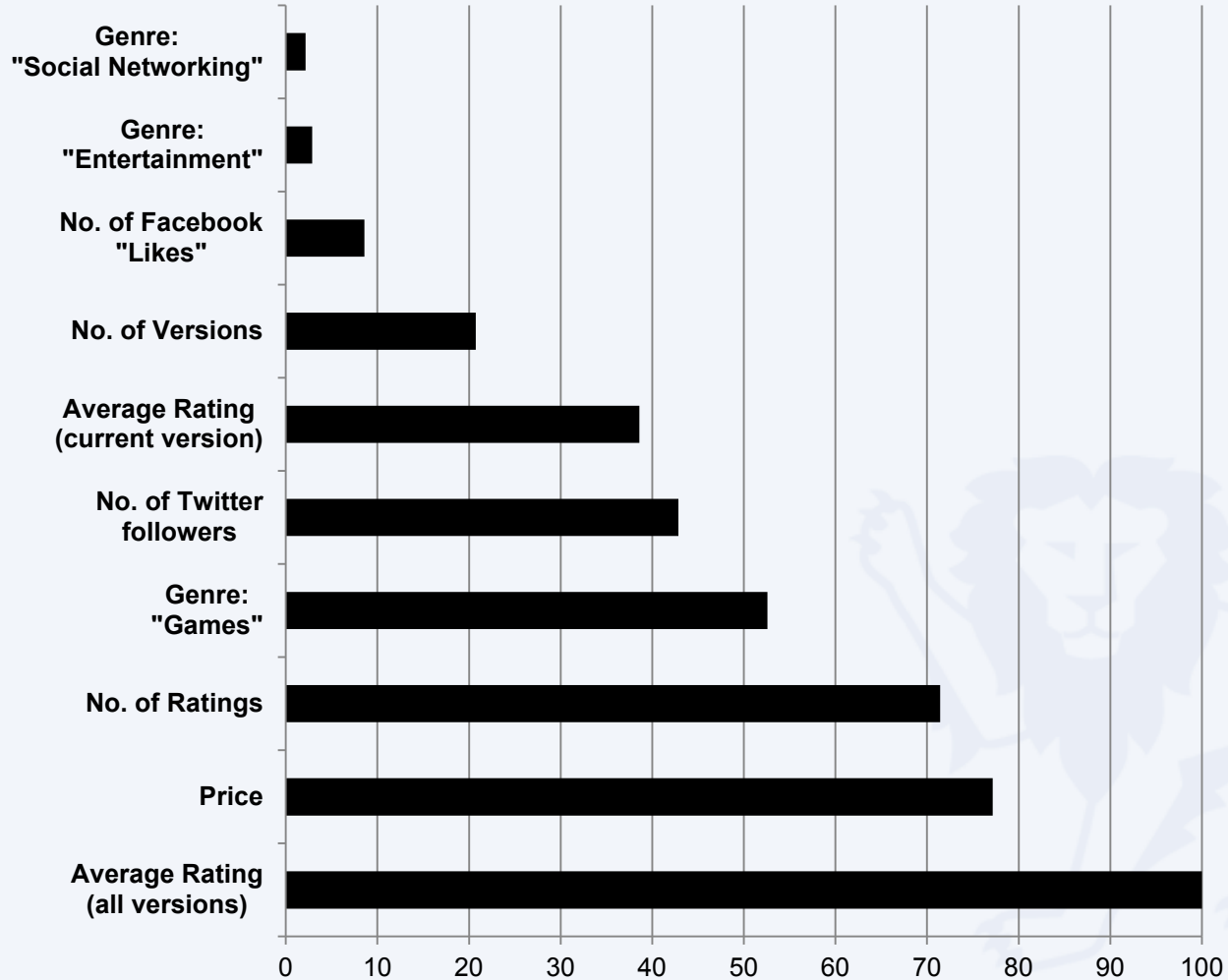
Ablating Twitter information results in largest dip, indicating Twitter followers are important by using full twitter information.

Ablation Testing Using Sufficient Version Information

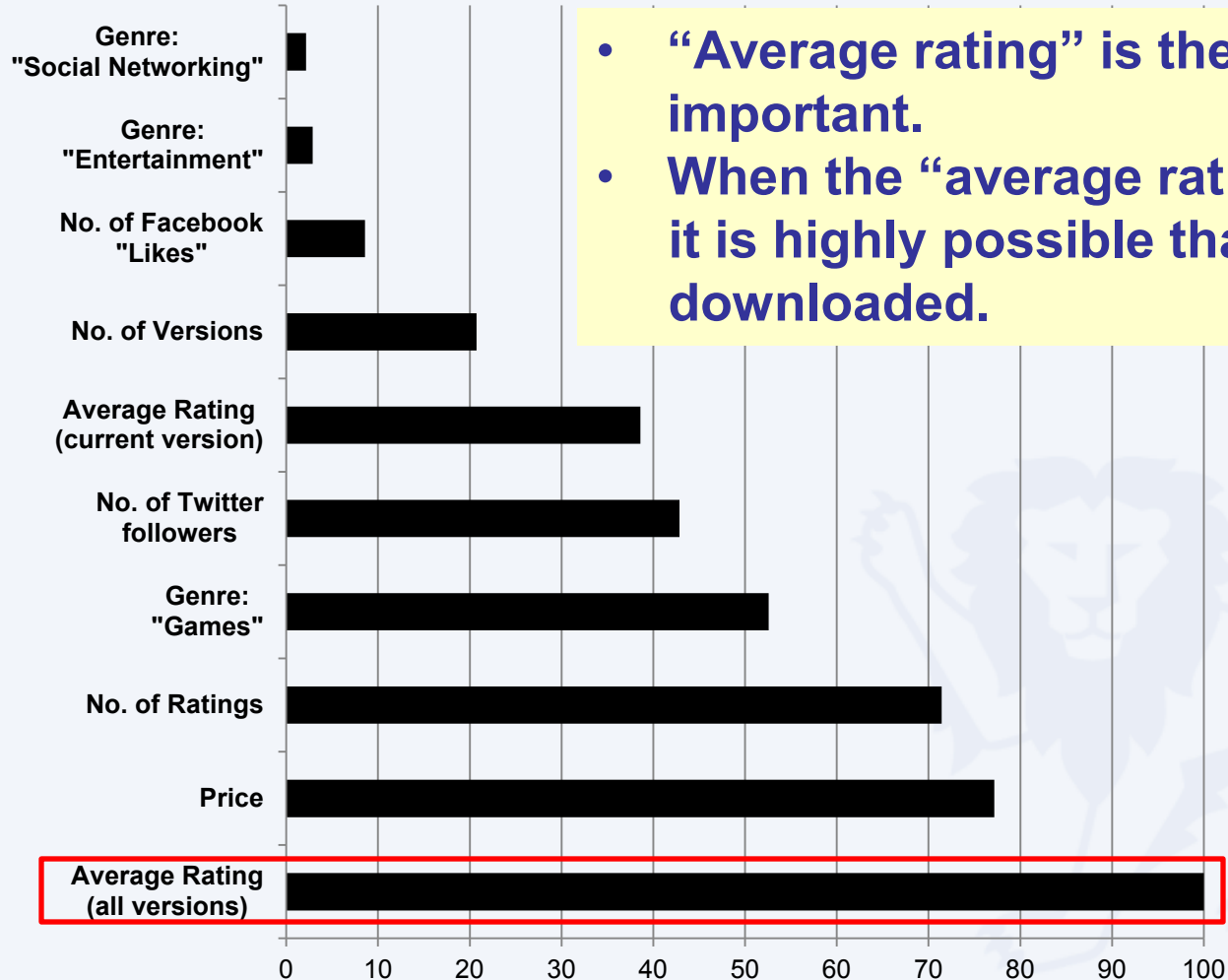
Feature	Recall@50
$GTB_{VSR}(M, H, R)$	0.418
$GTB_{VSR}(M, H, R)$, excluding TWF	0.396
$GTB_{VSR}(M, H, R)$, excluding content-based filtering (PMF)	0.361
$GTB_{VSR}(M, H, R)$, excluding VSR	0.344
$GTB_{VSR}(M, H, R)$, excluding collaborative filtering (PMF)	0.335

Although VSR does not displace CF, it still results in the second largest dip in recall scores.

Feature Importance

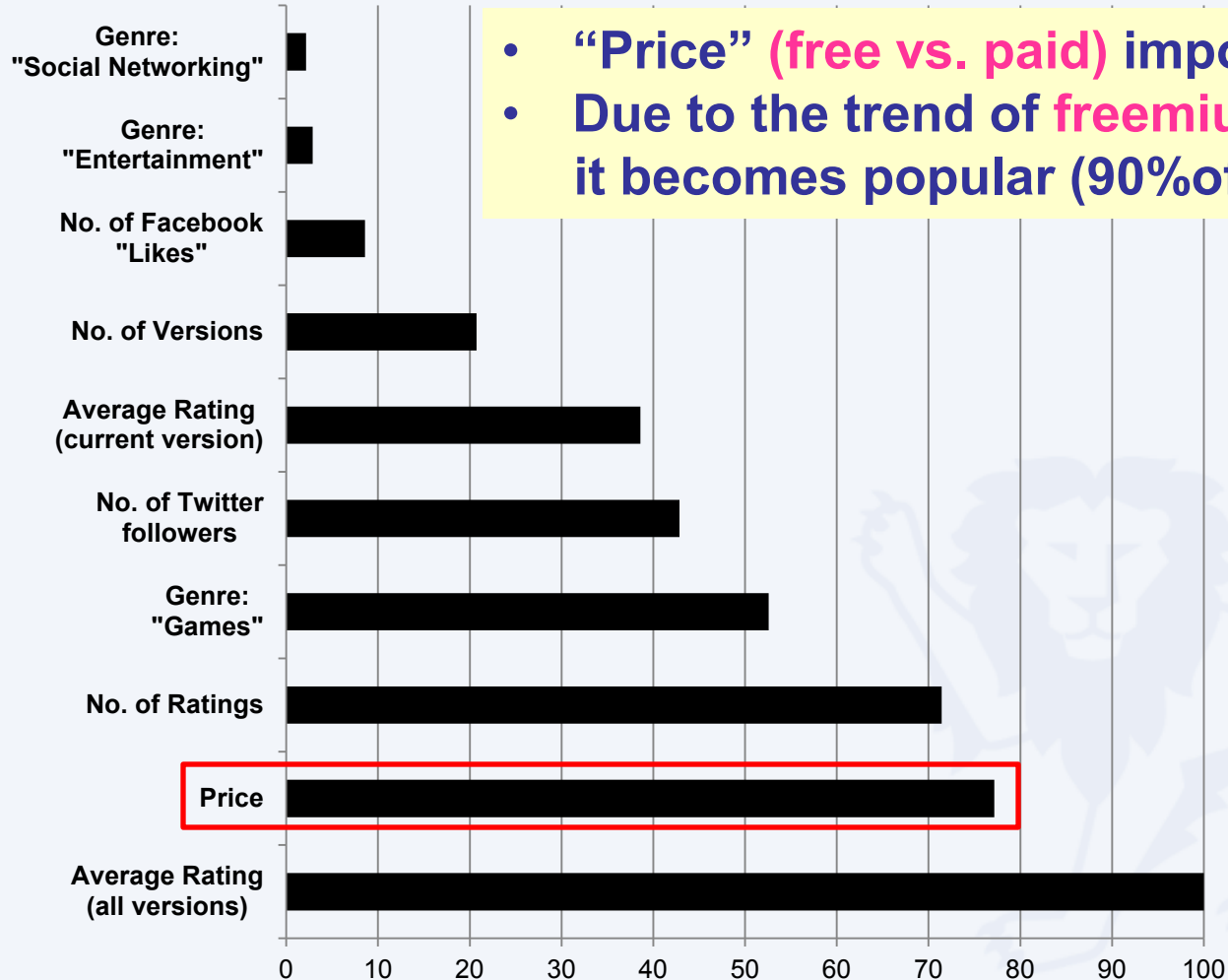


Feature Importance



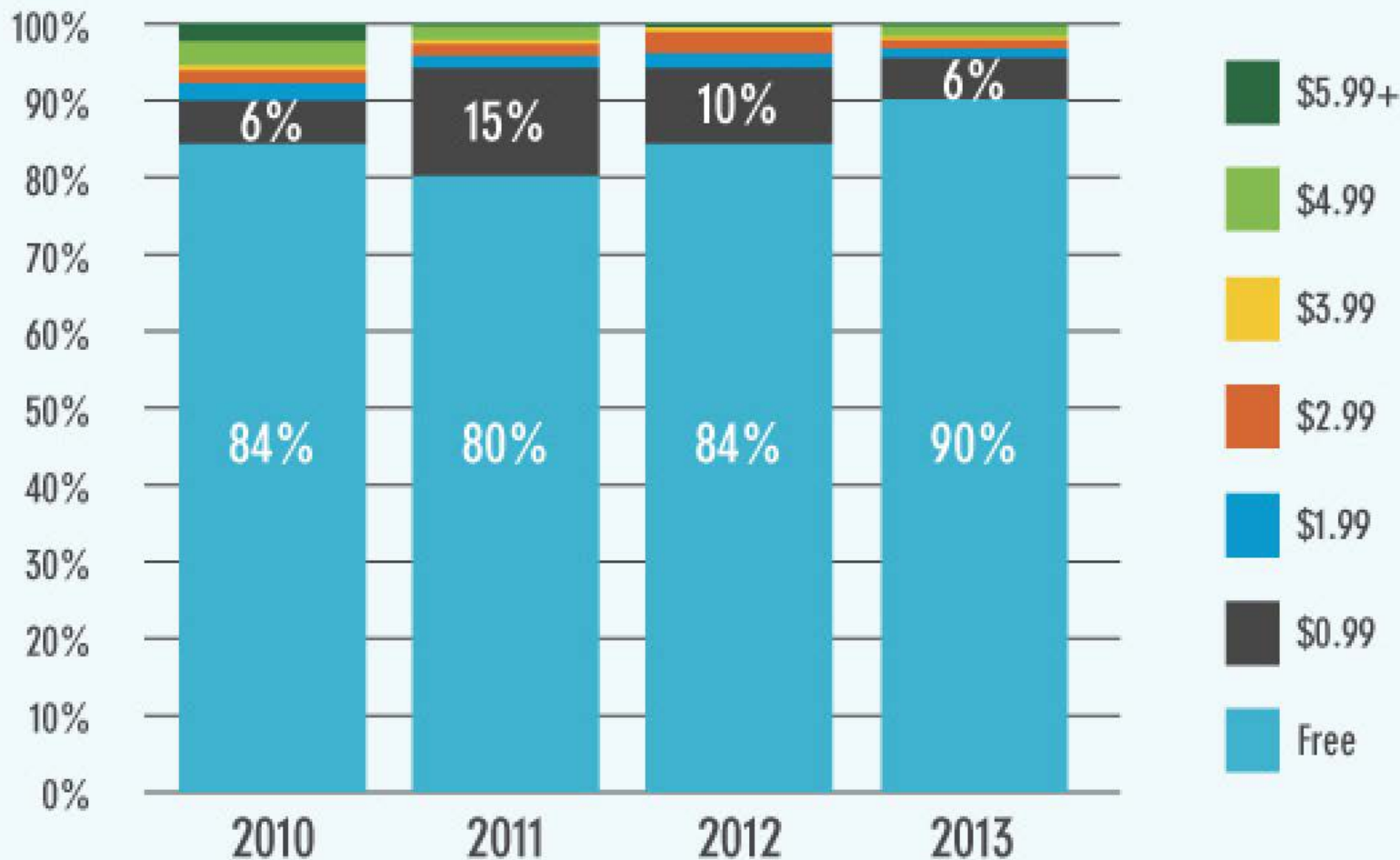
- “Average rating” is the most important.
- When the “average rating” is high, it is highly possible that the app is downloaded.

Feature Importance



- **“Price” (free vs. paid) important.**
- **Due to the trend of freemium apps, it becomes popular (90% of app store).**

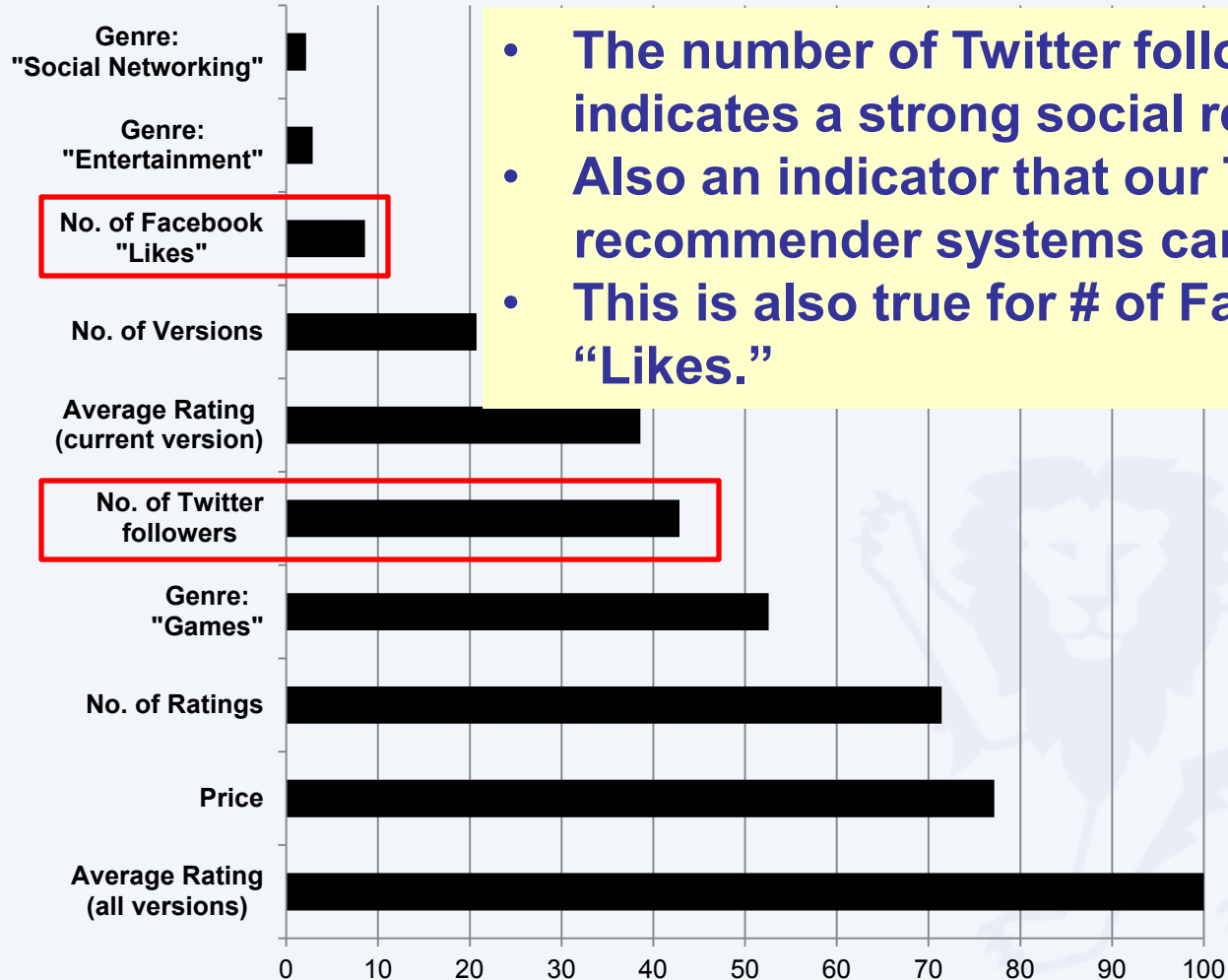
Increasingly the Price of Apps is Free



Source: Flurry Analytics and the Apple App Store.

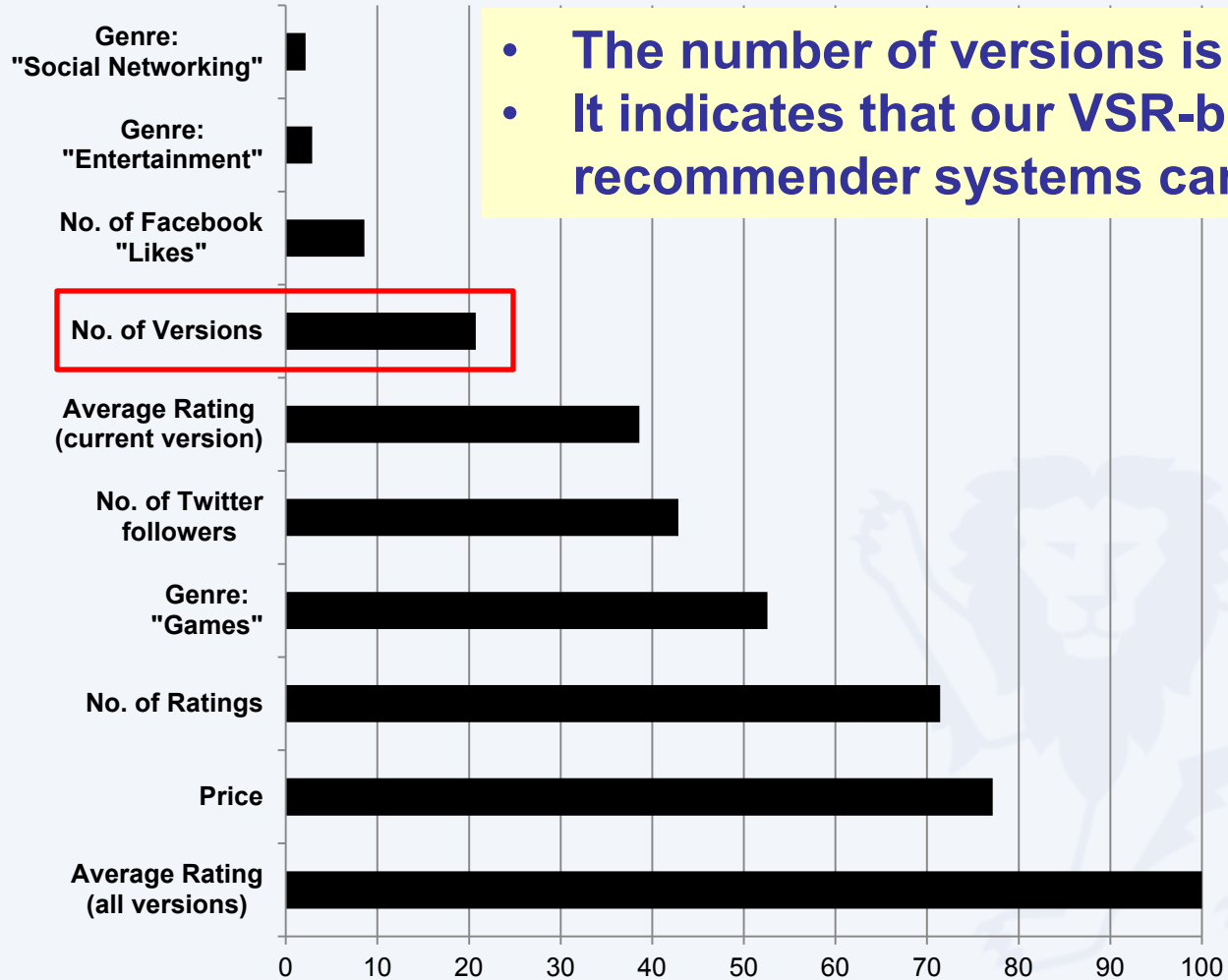
Data is for iOS apps using Flurry Analytics in April of each year, and is weighted by monthly average users.

Feature Importance



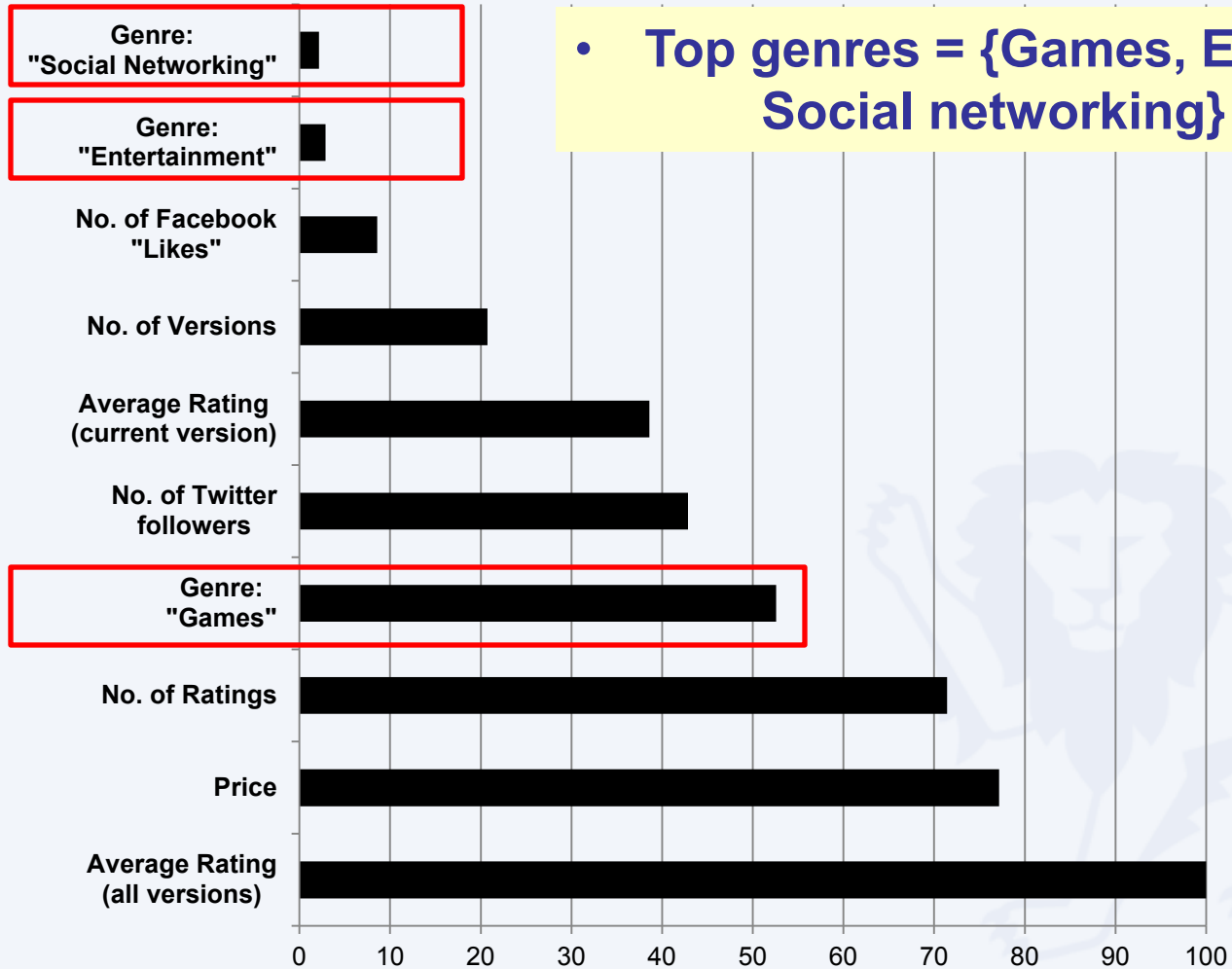
- The number of Twitter followers (TWF) indicates a strong social reach.
- Also an indicator that our TWF-based recommender systems can be helpful.
- This is also true for # of Facebook "Likes."

Feature Importance



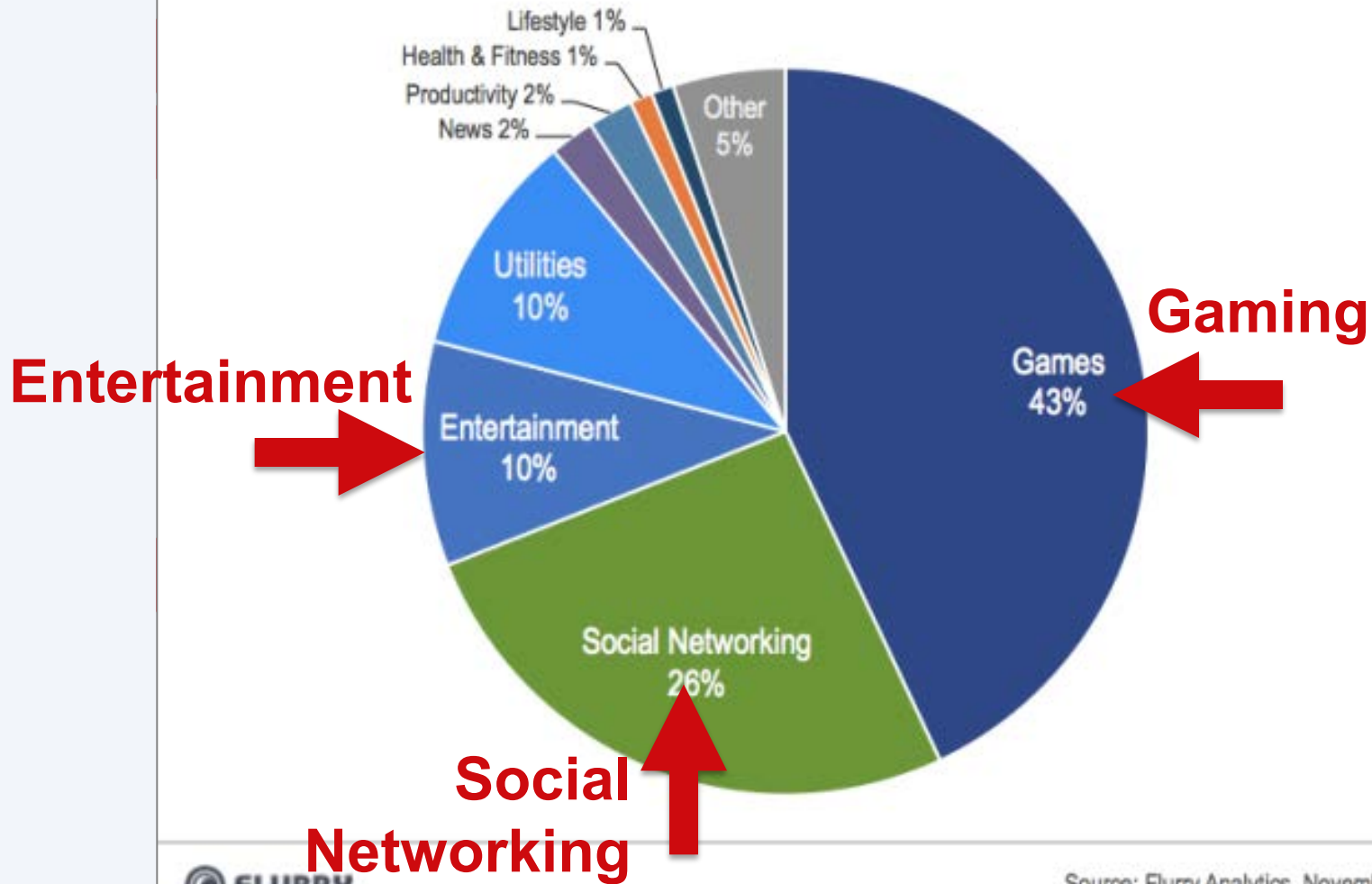
- The number of versions is important.
- It indicates that our VSR-based recommender systems can be helpful.

Feature Importance



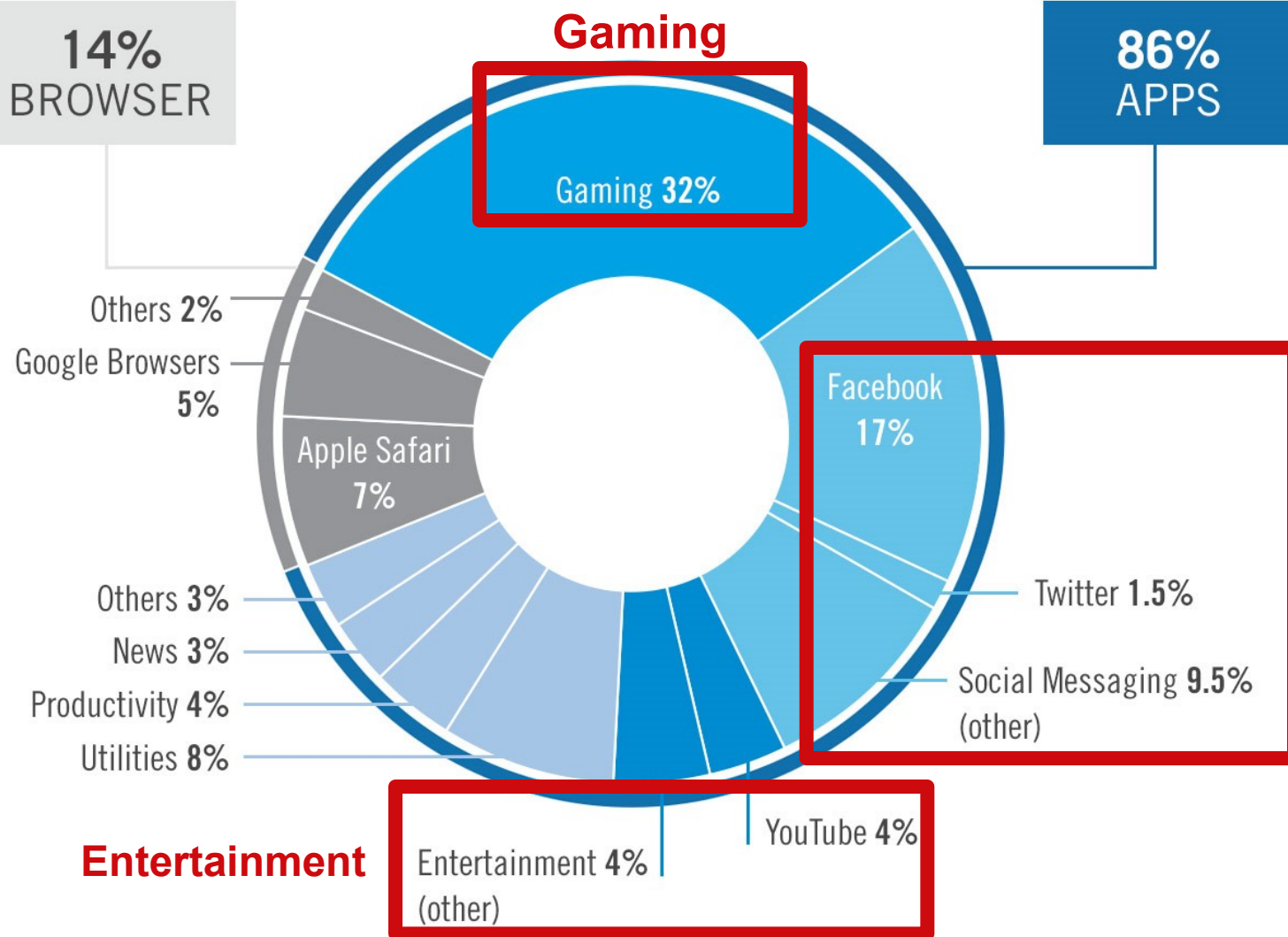
Fea

WW iOS & Android Smart Device Time Spent per App Category



ment,

Time Spent on iOS and Android Connected Devices



Social Networking

Conclusion

- Employ GTB to integrate the features for the unifying recommendation techniques.
- Observe interesting correlations between important feature components and studies from third-party app analytics
- Our studies indicate that mobile app recommendation systems need to
 - Further focus on user and trend analysis in social networks
 - Treat genre information with more importance

Thank you very much!