Building a Recommendation System for EverQuest Landmark's Marketplace

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Motivation

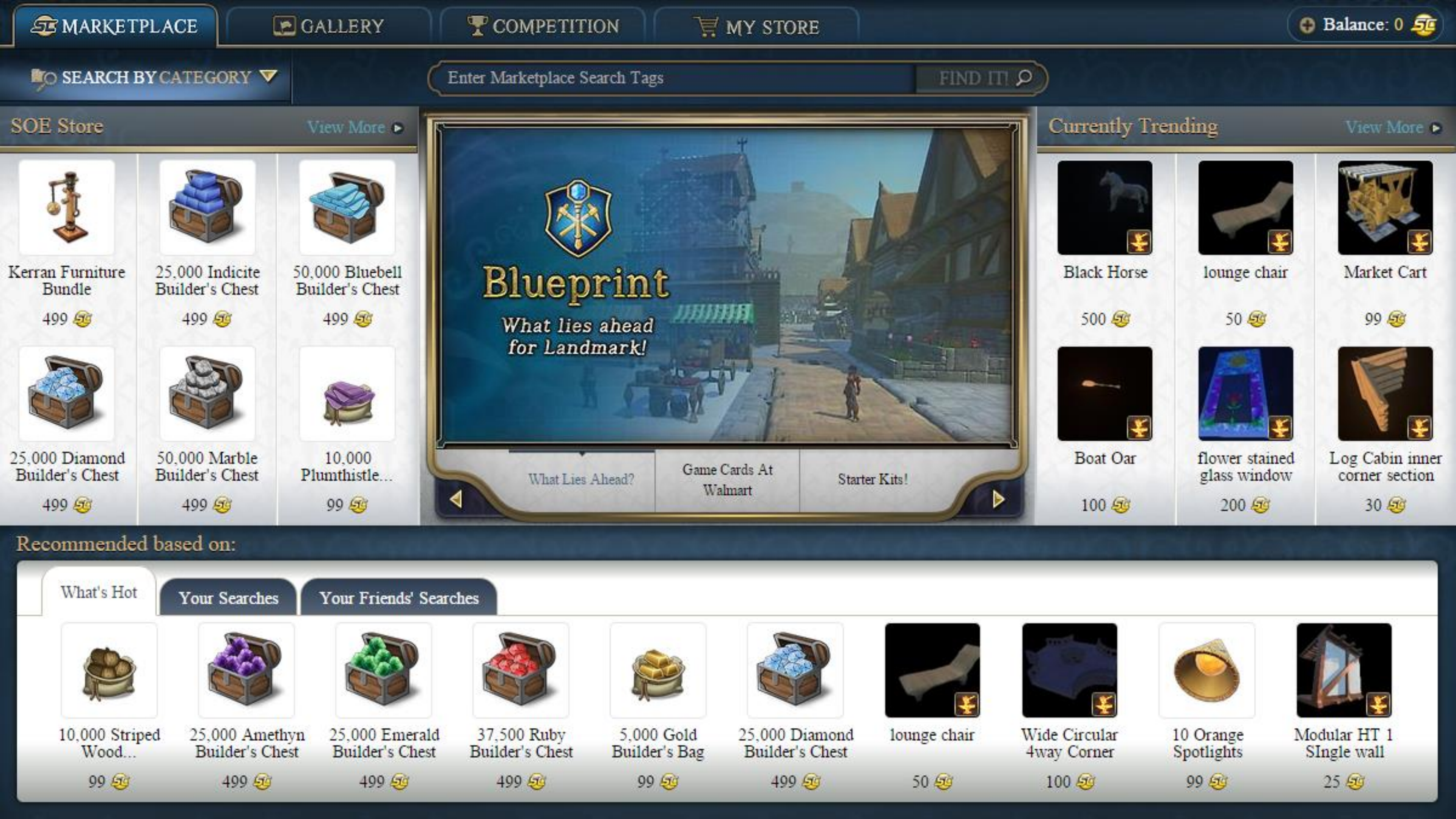
- **Content discovery** is becoming a challenge for players
- **Questions**
  - What **games** to purchase?
  - Which **content** to download?
  - What **items** to purchase?

PLAYERSTUDIO™

Daybreak's **revenue-sharing** program for **user-created content**

Infantry Gear in PlanetSide 2

Housing Items in Landmark


MARKETPLACE
GALLERY
COMPETITION
MY STORE
Balance: 0
SEARCH BY CATEGORY
Enter Marketplace Search Tags
FIND IT!
SOE Store
View More
Kerran Furniture Bundle
499
25,000 Indicite Builder's Chest
499
50,000 Bluebell Builder's Chest
499
25,000 Diamond Builder's Chest
499
50,000 Marble Builder's Chest
499
10,000 Plumthistle...
99
Blueprint
What lies ahead for Landmark!
What Lies Ahead?
Game Cards At Walmart
Starter Kits!
Currently Trending
View More
Black Horse
500
lounge chair
50
Market Cart
99
Boat Oar
100
flower stained glass window
200
Log Cabin inner corner section
30
Recommended based on:
What's Hot
Your Searches
Your Friends' Searches
10,000 Striped Wood...
99
25,000 Amethyn Builder's Chest
499
25,000 Emerald Builder's Chest
499
37,500 Ruby Builder's Chest
499
5,000 Gold Builder's Bag
99
25,000 Diamond Builder's Chest
499
lounge chair
50
Wide Circular 4way Corner
100
10 Orange Spotlights
99
Modular HT 1 SIngle wall
25

Recommender Goals

- Make **relevant content** easier to discover
- Recommend content based on **gameplay style**, **friends**, and **prior purchases**
- Improve conversion and **monetization metrics**

Recommender Results

- **Offline Experiments**
  - 80% increase in recall rate over a top sellers list
- **Marketplace Results**
  - Recommendations drive over 10% of item sales
  - Used by 20% of purchasers
  - Lifetime value of users that purchased recommendations is 10% higher than other purchasers

Types of Recommendations

- **Item Ratings**
  - The recommender provides a rating for an item the player has not yet rated
- **Item Rankings**
  - The recommender provides a list of the most relevant items for a player

Recommendation Algorithms

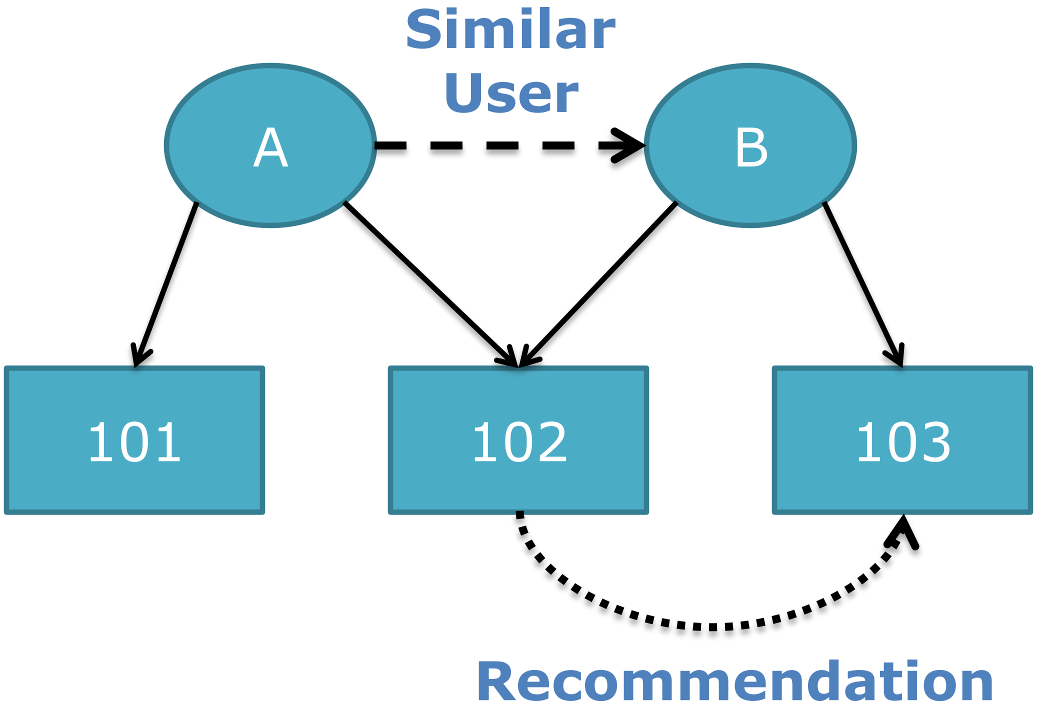
- **Content-Based Filtering**
- **Collaborative Filtering**
  - Item-to-Item
  - User-to-User

Collaborative Filtering

- Rates items for a player based on the player's **similarity** to **other players**
- Does not require **meta-data** to be maintained
- Can use **explicit** and **implicit** data collection
- Challenges include **scalability** and **cold starts**

User-Based Collaborative Filtering

- Users
- Items



Algorithm Overview

Computing a recommendation for a user, U:

For every other user, **V**

Compute the similarity, **S**, between **U** and **V**

For every item, **I**, rated by **V**

Add **V**’s rating for **I**, weighted by **S** to a running average of **I**

Return the top rated items

Choosing an Algorithm

- **How big** is the item catalog? Is it **curated**?
- What is the target **number of users**?
- What **player context** will be used to provide item recommendations?

Landmark's Approach

- **User-to-user collaborative filtering**
- **Motivation**
  - Large item catalog with limited annotations
  - Rich game telemetry to alleviate cold starts
  - Scales to millions of users

Prototyping a Recommender

- **Apache Mahout**
  - Free & scalable Java machine learning library

- **Functionality**
  - User-based and item-based collaborative filtering
  - Single machine and cluster implementations
  - Built-in evaluation methods

Getting Started with Mahout

1. Choose what to recommend: ratings or rankings
2. Select a recommendation algorithm
3. Select a similarity measure
4. Encode your data into Mahout’s format
5. Evaluate the results
6. Encode additional features and iterate

Similarity Measures

- **Item Rankings**
  - Jaccard Index (Tanimoto)
  - Log Likelihood
- **Item Ratings**
  - Cosine Similarity
  - Euclidean Distance

Mahout's Data Format

- **Item Associations**

User ID,	Item ID
1,	101
1,	102
2,	102
2,	103
3,	104

- **Item Ratings**

User ID,	Item ID,	Rating
1,	101,	5.0
1,	102,	4.0
2,	102,	2.5
2,	103,	5.0
3,	104,	1.0

Encoding Commerce Data

SQL Query

```
select u.UserID, s.ItemID
from SampleUsers u
Join Sales s
    on u.UserID = s.UserID
group by u.UserID, s.ItemID
```

Result Set

User ID	Item ID
1	101
1	102
2	102
2	103
3	104

Generating Recommendations

Building the Recommender

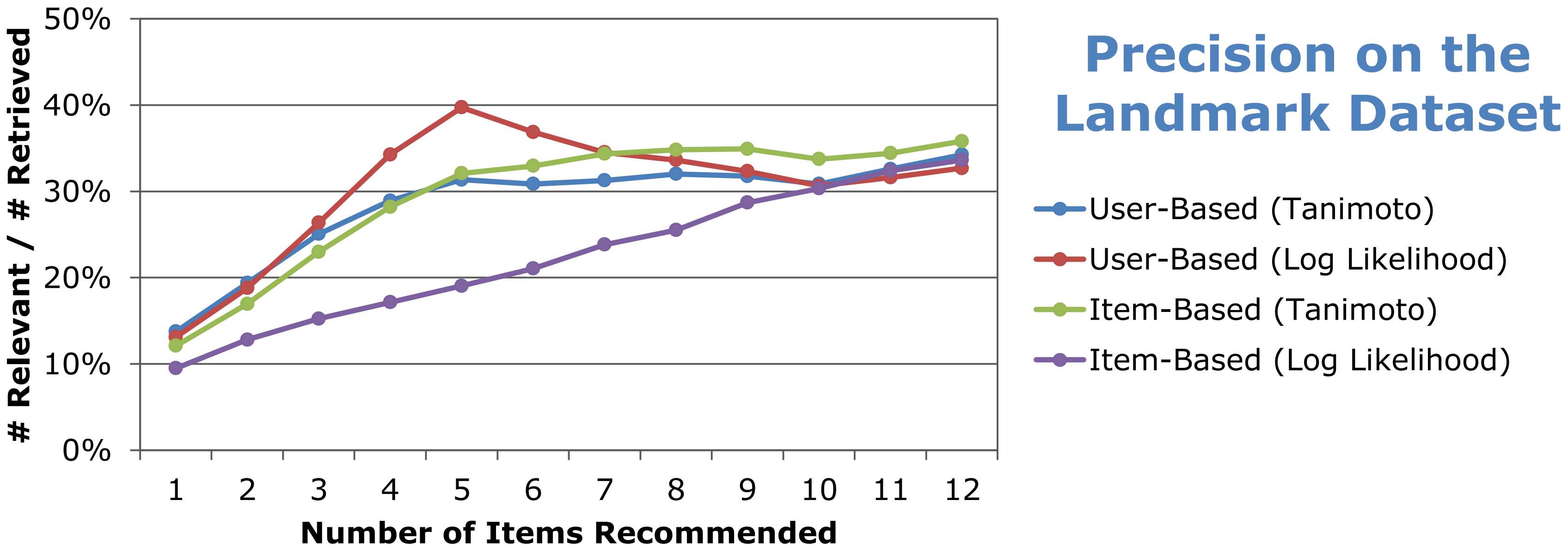
```
model = new DataModel(new File("SalesData.csv"));
similarity = new TanimotoSimilarity(model);
recommender  = new UserBasedRecommender(model, similarity);
```

Generating a List

```
recommendations = recommender.recommend(1, 6);
```

Evaluating Recommendations

Precision computes the ratio of **relevant** recommendations



Holdout Experiment

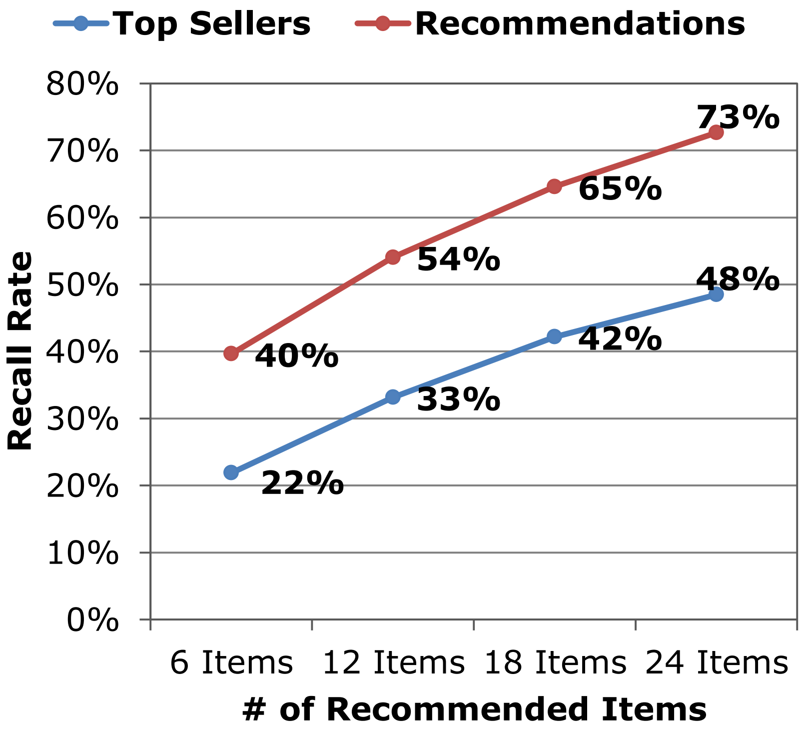
- An experiment that excludes a single item from a player's list of purchases

- **Goals**
  - Generate the smallest list that includes the item
  - Enable offline evaluation of different algorithms
  - Compare recommendations with rule-based approaches

Landmark's Holdout Results

Recommendations significantly outperform a **top sellers** list

80% increase in the holdout **Recall Rate** at 6 items



Integrating Additional Features

- Landmark uses additional features to build item recommendations

Features and Weights

- Item purchased 1.0
- Item liked 0.5
- Item viewed 0.25

Encoding Additional Features

```
select distinct u.UserID, s.ItemID, 1.0 as Value
from SampleUsers u
join Sales s on u.UserID = s.UserID

union select distinct u.UserID, i.ItemID, 0.5 as Value
from SampleUsers u
join ItemLikes i on u.UserID = i.UserID

union select distinct u.UserID, i.ItemID, 0.25 as Value
from SampleUsers u
join ItemViews i on u.UserID = i.UserID
```

Deployment in Landmark

- In-house implementation
- **Current Deployment**
  - Recommendations are generated on the fly and cached
- **Planned Expansion**
  - An offline process builds a user-similarity matrix
  - An online process generates item recommendations in near real-time

Summary

- **Recommendation systems** can be applied to **content discovery** in games
- Libraries enable **rapid prototyping**
- Recommendations can significantly **outperform rule-based** approaches

Thank You

- **Ben G. Weber (@bgweber)**
  - Director of Business Intelligence & Analytics
  - Daybreak Game Company
- **Further Reading**
  - Amazon.com Recommendations: Item-to-Item Collaborative Filtering
  - Mahout in Action