Flipkart GRiD 5.0

Problem Statement Title: Personalized Product Recommendations

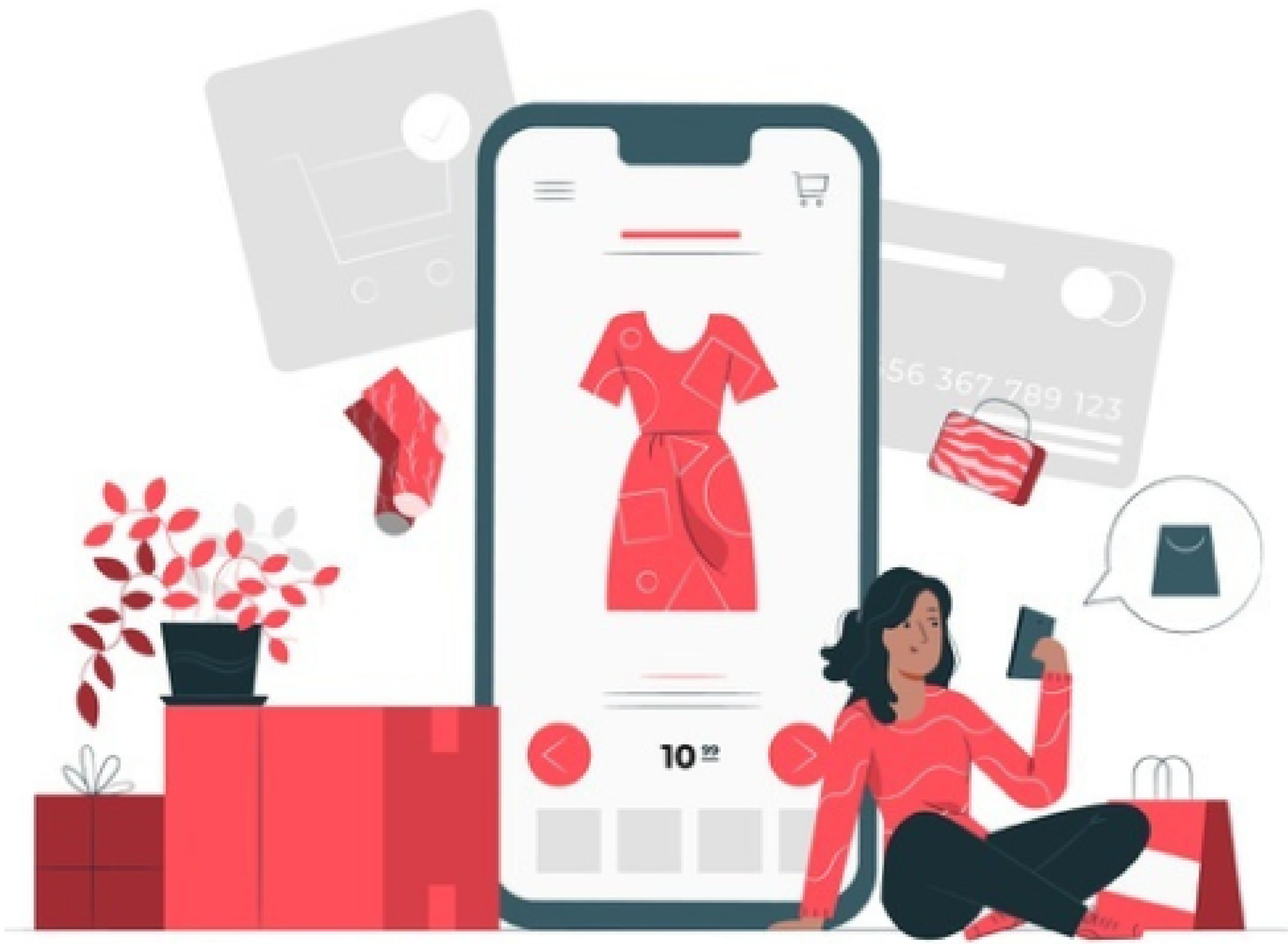
Team Name: Team_Akatsuki

Team members details

Team Name	Team_Akatsuki		
Institute Name/Names	Bundelkhand Institute of Engineering And Technology		
Team Members	1 (Leader)	2	3
Name	Pragya Yadav	Harshit Upadhyay	Vishal Agarwal
Batch	2024	2024	2024

Use-cases

- **Product Recommendations**
- **Cross-selling and Up-selling**
- **Personalized Content and User Retention**
- **Inventory Management**



Solution statement/ Proposed approach

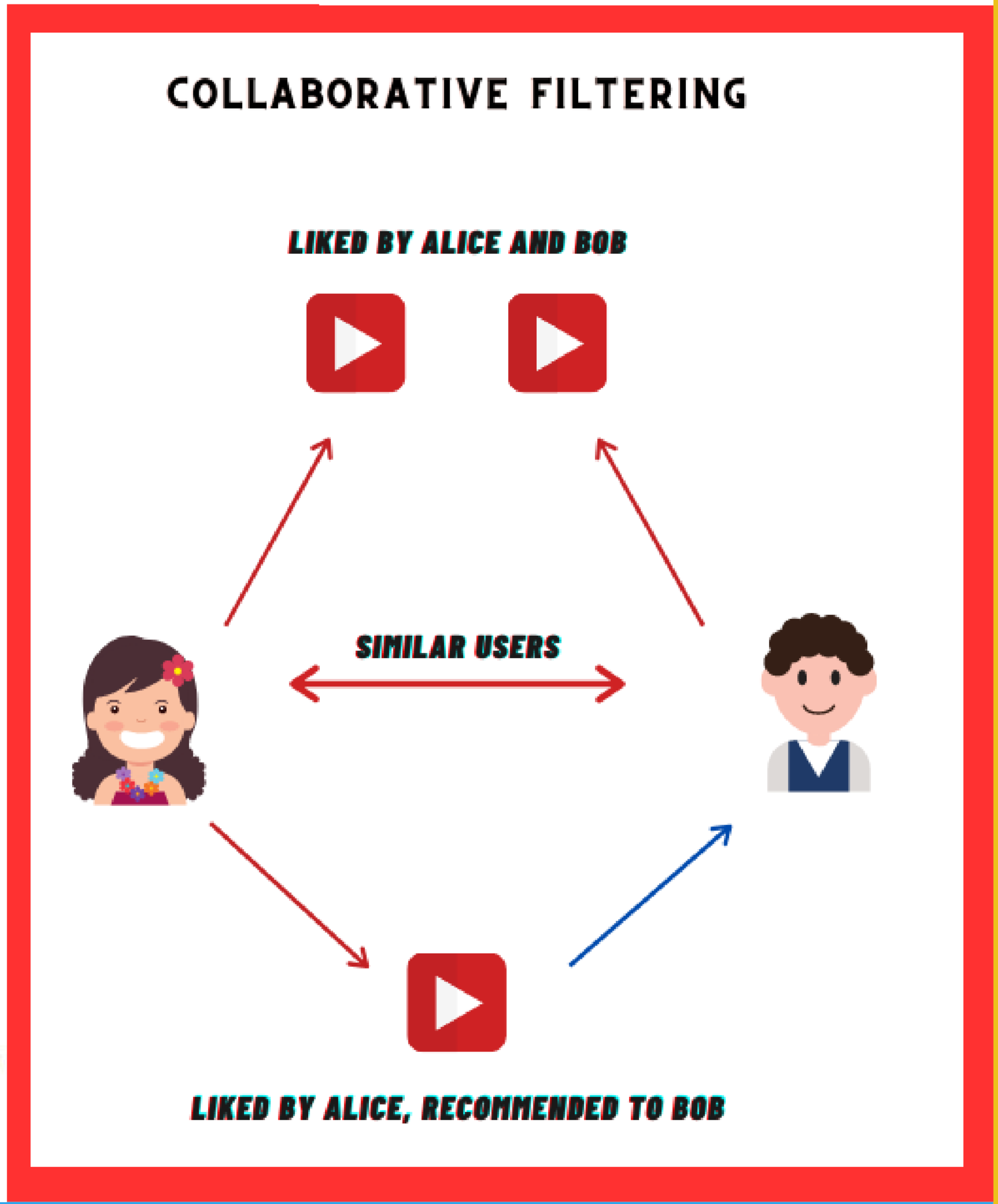
We have two types of datasets

1. Item Dataset <ItemID, Title, Description, Rating, Category, Brand, Cost>

2. User-Item Interaction Dataset <UserID, ItemID, Rating>

CATEGORIZATION OF OUR PROBLEM

- Recommendation based on Rating.
- Colaborative Filtering Recommendation
- Personalized Recommendation.



RECOMMENDATION BASED ON RATING

- This technique is for newly registered users who do not possess any past browser history.
- It is supposed that high rated products will be popular among the users.

Unordered

Item_ID	Rating
01	1
02	2
03	3
04	4
05	1
06	2
07	3
08	4

Group by Rating

Item_ID	Rating
01	1
05	1
03	3
07	3
02	2
06	2
04	4
08	4

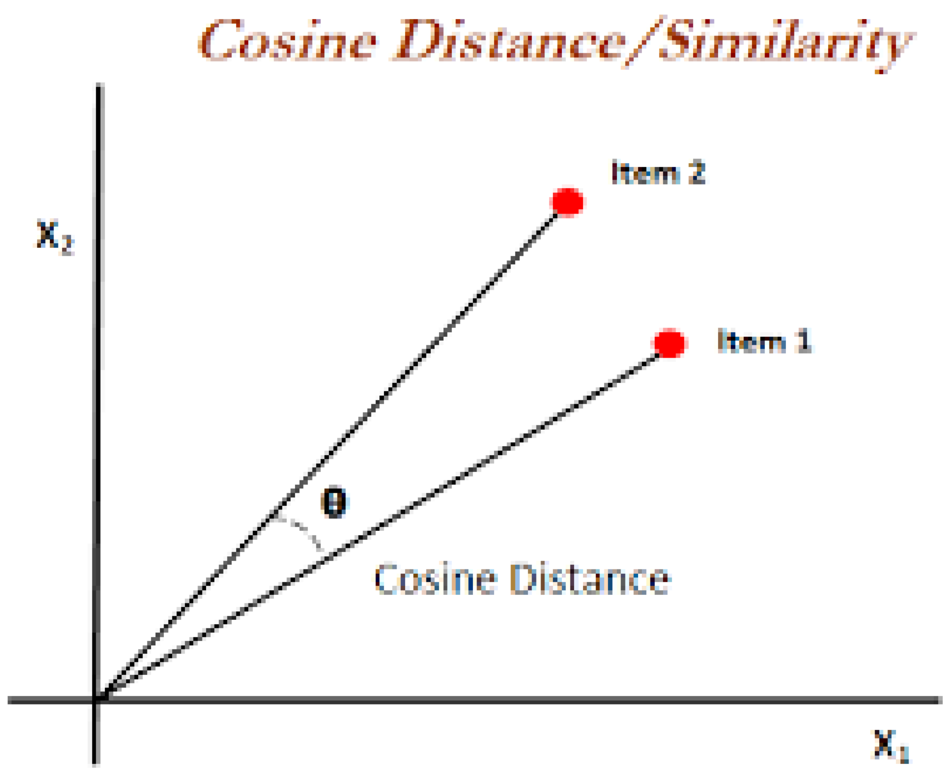
Sorted w.r.t. Rating

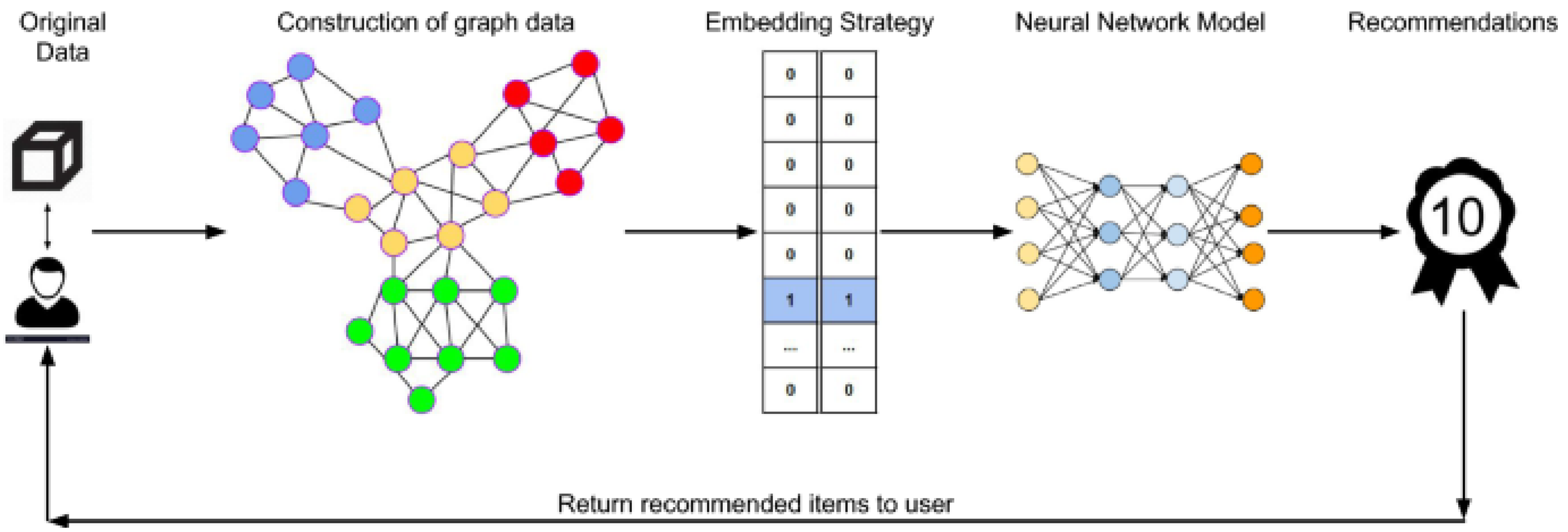
Item_ID	Rating
04	4
08	4
03	3
07	3
02	2
06	2
01	1
05	1

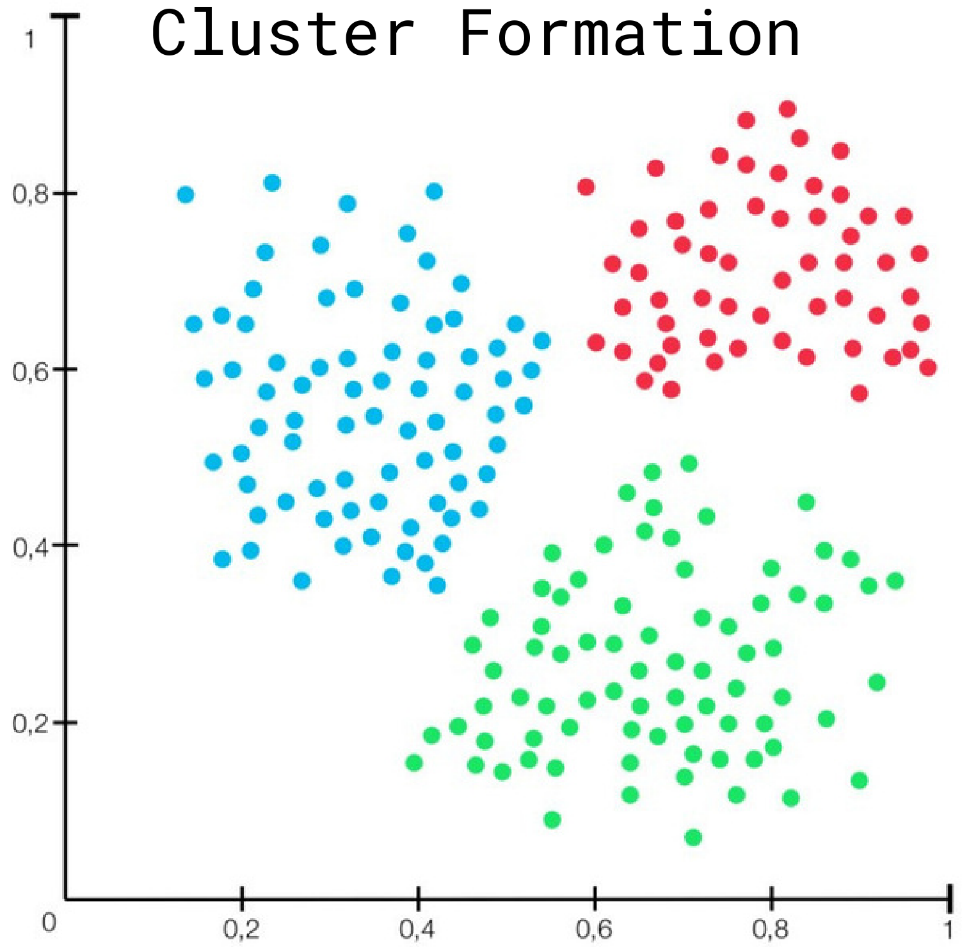
Item ID having 3,5,8,6 will be recommended

COLABORATIVE FILTERING RECOMMENDATION

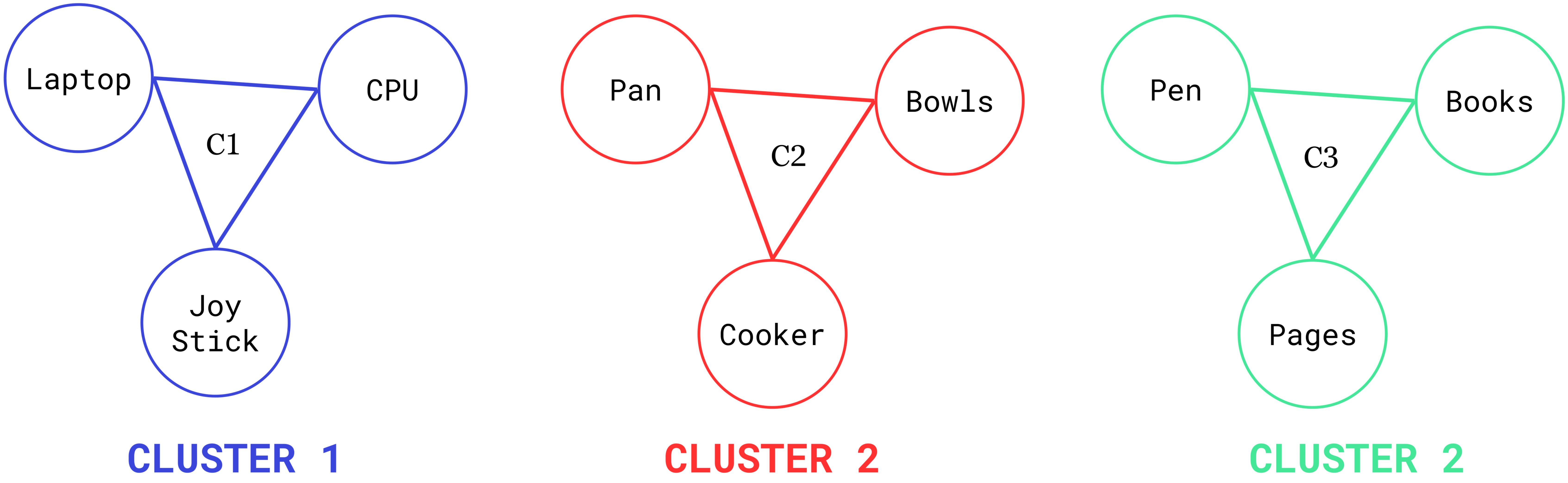
- Conversion of Dataset to Graph
- Featurization of Item Entity
- Embeding features into Single Feature and Vectorization
- Cosine-Similarity between Items
- Graph Neural Network







Item Dataset Graph Formation(Undirected and Homogenous)



- **<u>Cluster Formation within Item Dataset-</u>**We will <u>make clusters within Item dataset with K-means</u> algorithm of unsupervised learning. and labeling each ItemID as cluster ID in Item dataset.

Unordered Item Dataset

Id	Item	Category	Brand	Cost
1	Laptop	Electronics	Dell	60000
2	Oil Painting	Art	Camel	500
3	Shirt	Outfit	Nykaa	2000
4	Brush	Art	Camel	100
5	Skirt	Outfit	Gucci	10000
6	Headphones	Electronics	Zebronic	600

Unordered dataset having Item_name, category, brand cost as key features.

Cluster formation

Id	Item	Category	Brand	Cost
1	Laptop	Electronics	Dell	60000
6	Headphones	Electronics	Zebronic	600
2	Oil Painting	Art	Camel	500
4	Brush	Art	Camel	100
3	Shirt	Outfit	Nykaa	2000
5	Skirt	Outfit	Gucci	10000

Cluster-1

Cluster-2

Cluster-3

Cluster formation on the basis of key features.

Manipulation with User-Item Interaction Dataset

UserID	ItemID	Rating	ClusterID
U1	1	4	1
U2	4	5	2
U3	2	3	3
U4	5	1	1
U5	3	2	2
U6	6	5	3

UserID	ItemID	Rating	ClusterID
U1	1	4	1
U4	5	1	1
U5	3	2	2
U2	4	5	2
U3	2	3	3
U6	6	5	3

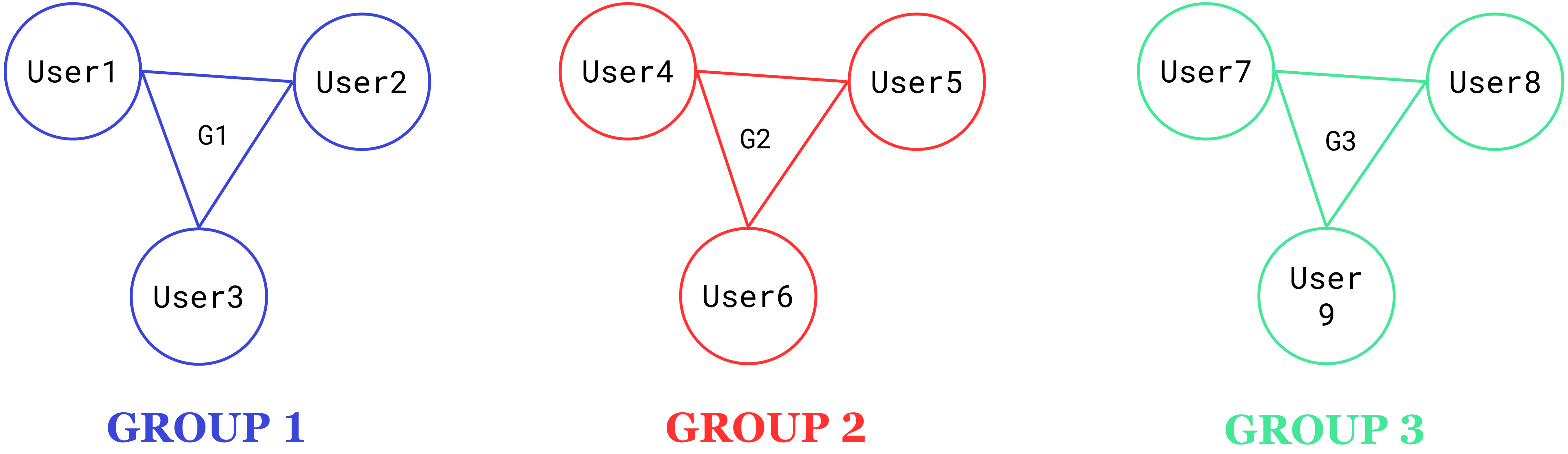
Group-1

Group-2

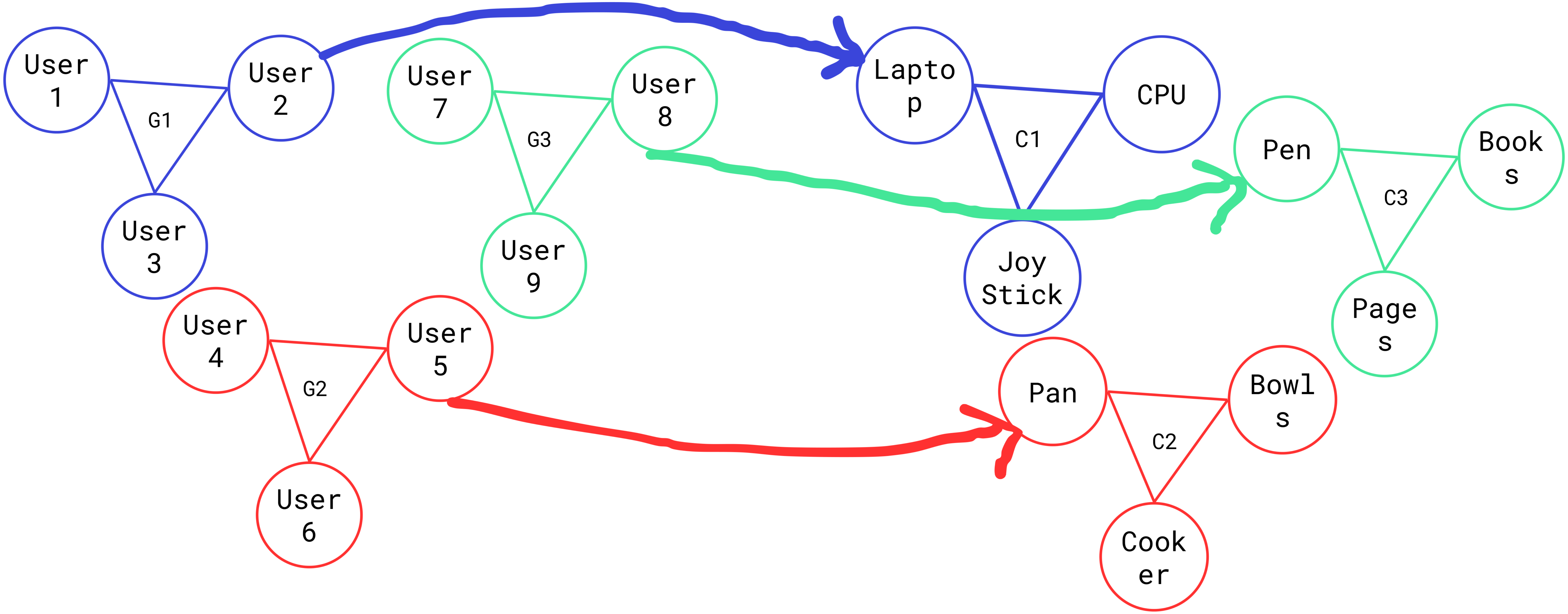
Group-3

User Co-relation Graph (Undirected Homogenous)

- **<u>User Corelation Graph Formation-</u>**We will make user co-relation graph, where each node will represent a single user and edges between the graphs will show co-relation among them on basis of their common purchase preferences and patterns.

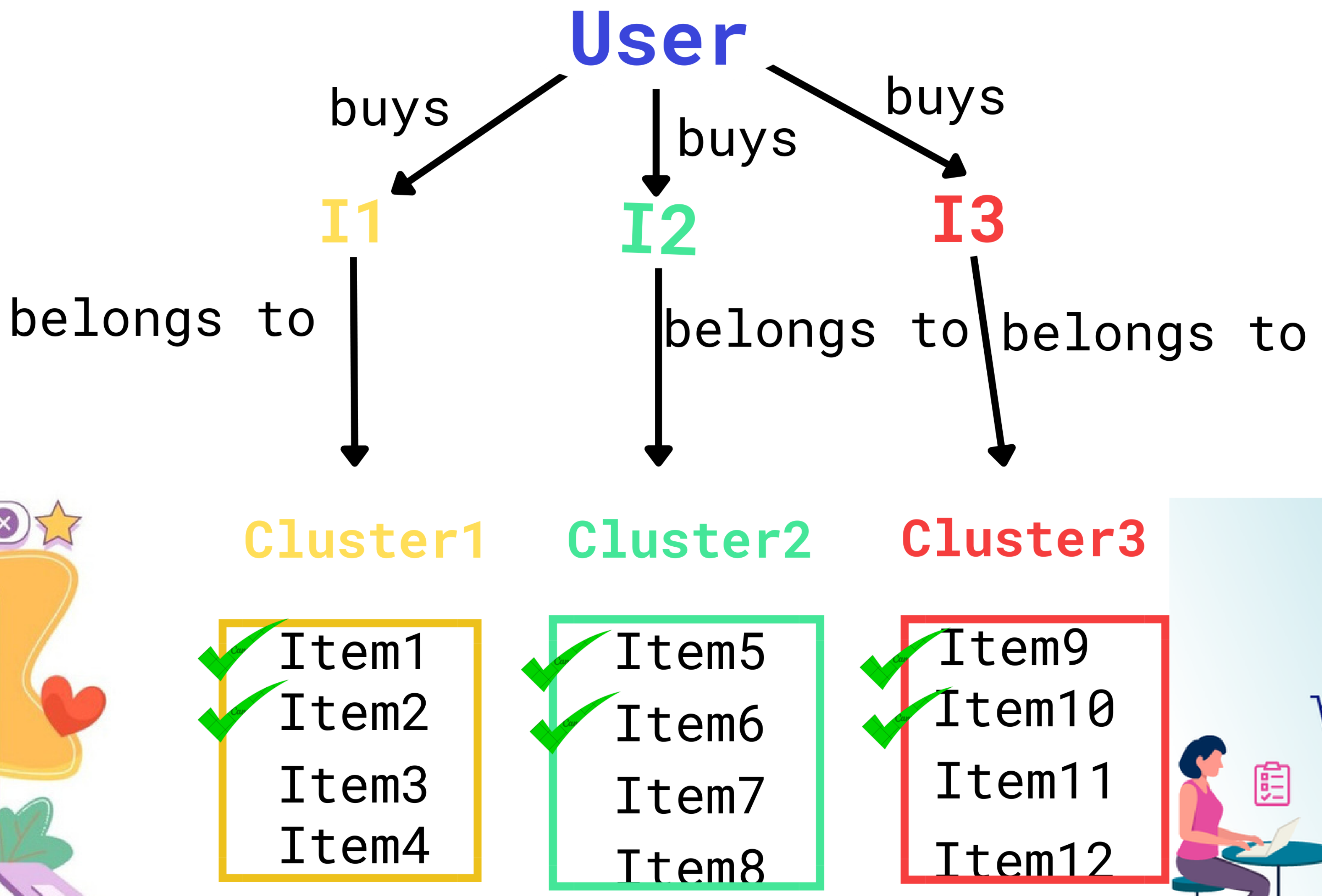


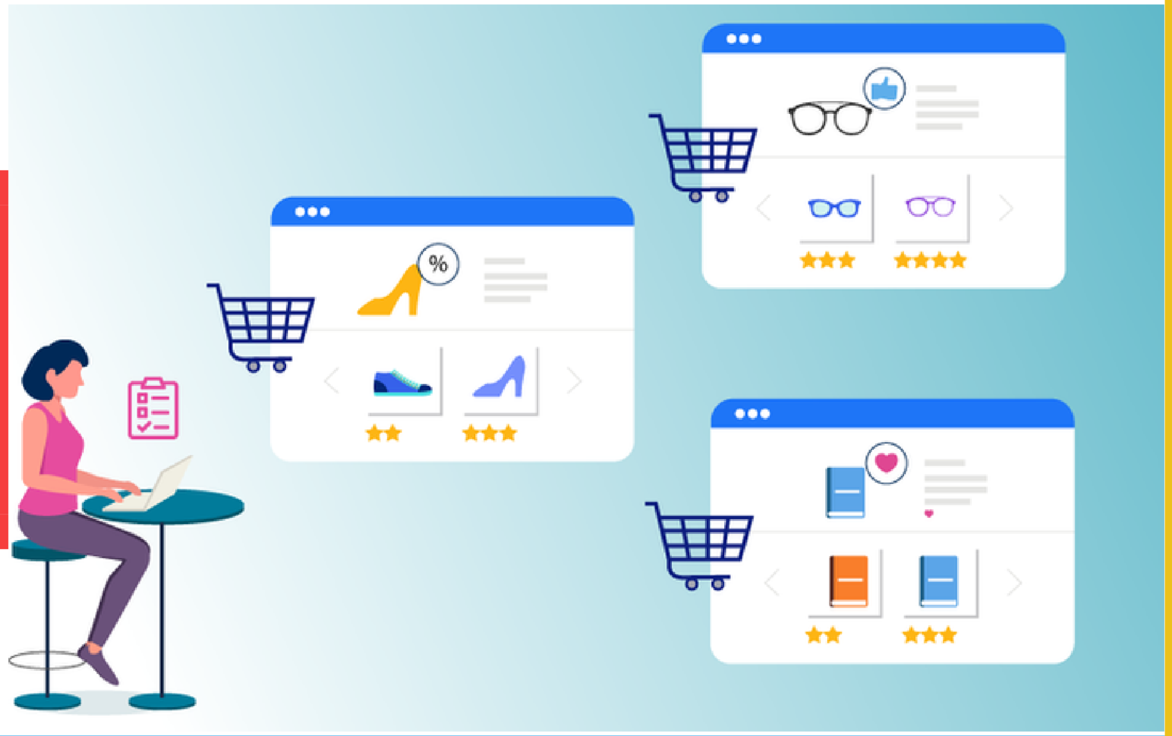
User-Item Interaction Graph(Bipartite and Hetrogenous)



Personalized Recommendation

- **If there is a user who purchases item1,item2,item3 from different clusters. We will recommend him a combine catelogue of items which will be formed by merging top rated items of each cluster.**





Limitations

- **Data Sparsity:** In many cases, user-item interactions are sparse, for ex- users have interacted with only a small fraction of available items. This can lead to challenges in finding meaningful patterns and making accurate recommendations.

- **Popularity Bias:** Recommendation systems tend to recommend popular items more frequently, which can lead to a "rich get richer" scenario where already popular items receive more exposure while niche items are overlooked.

- **Changing Preferences:** User preferences can change over time due to various factors. Recommendation systems need to adapt quickly to these changes to remain effective.

- **Limited Diversity:** Algorithms might prioritize accuracy and user preferences, leading to recommendations that are similar and lacking diversity.

- **Misinterpretation of Actions:** User interactions might not always accurately reflect preferences. For instance, clicks might not always indicate genuine interest. they could be accidental or exploratory.

- **Cold Start Problem:** When a new user or item enters the system with limited data, it's challenging to provide accurate recommendations. The system lacks sufficient information to make personalized suggestions.

Future Scope

- **Personalization at Scale:** As more user data becomes available, recommendation systems will become even more personalized, considering not only explicit user actions but also implicit signals from various sources to provide highly individualized recommendations.

- **Context-Aware Recommendations**: Recommendation systems will increasingly leverage contextual information such as location, time of day, and user behavior to provide recommendations that are relevant to the current context.

- **Multimodal Recommendations**: With the increasing availability of data in various formats (images, text, audio), recommendation systems will need to adapt to provide recommendations based on a combination of modalities.

- **Explainable Recommendations**: Users are becoming more concerned about the "black box" nature of recommendation algorithms. Future systems will likely focus on providing transparent explanations for why certain recommendations are made.

- **Enhanced User Interfaces**: The user interface for recommendations will evolve to seamlessly integrate with various platforms, from e-commerce websites to mobile apps and voice assistants.

Flipkart GRiD 5.0

Thank You