Game Project

Overview of Collaborative Filtering

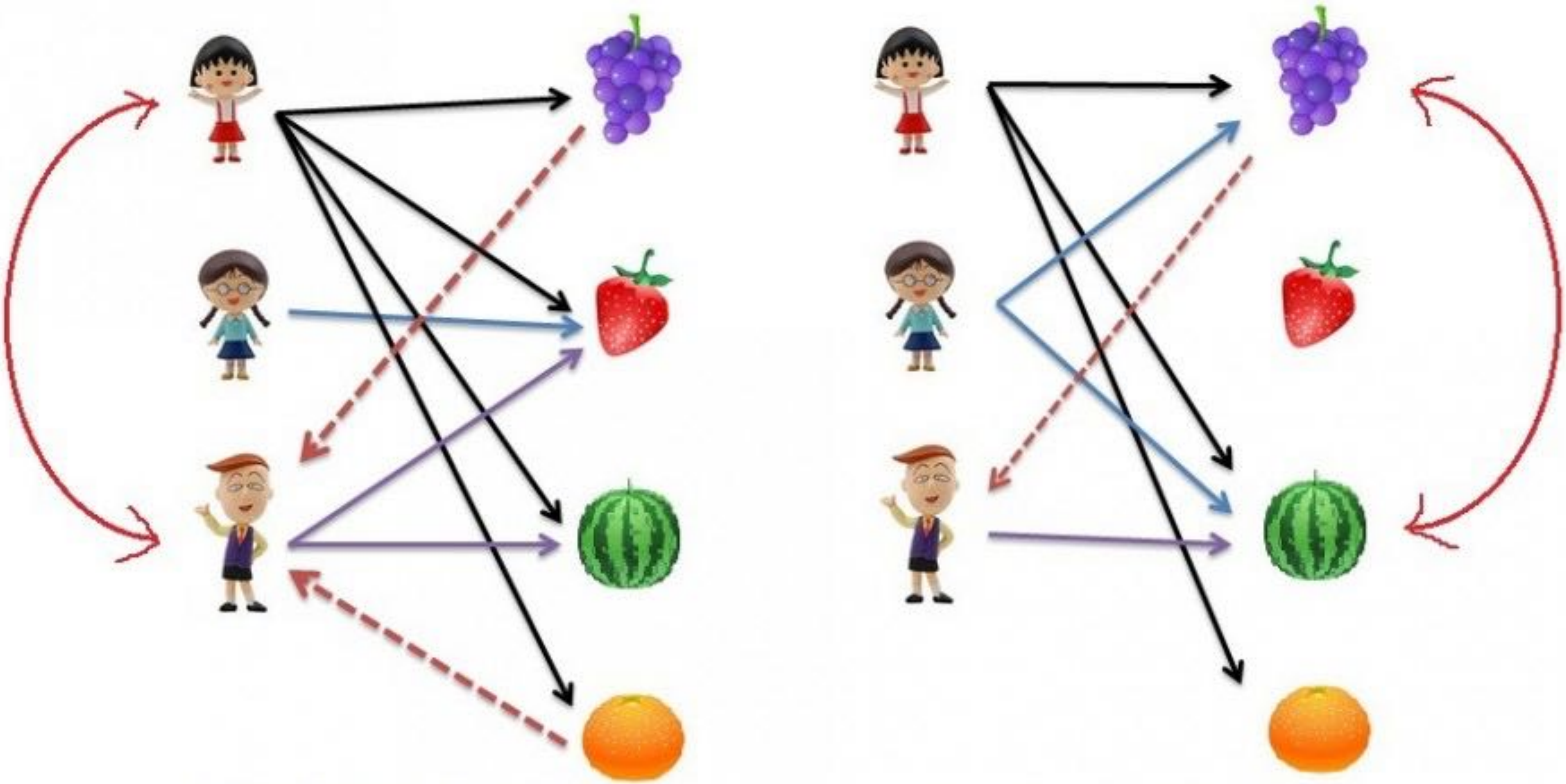
Collaborative filtering looks for patterns in the user activity to produce user specific recommendations.

Input: depends only on usage data (e.g. ratings, purchases, downloads, user preferences).

Types:

- Neighbourhood-based CF (user-based, item-based)
- Model-based CF (matrix factorisation, restricted boltzmann machines, bayesian networks, etc)

Pros	**Cons**
• Minimal domain knowledge required • User and item features are not required • Produces good enough results in most cases	• Cold start problem • Needs standardised products • Requires high user:item ratio (1:10) • Popularity bias (doesn't play well with the long tail) • Can be difficult to provide explanations



User-based filtering

Item-based filtering

Refresher: Matrix Decomposition

r
5 x 6 matrix

X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
X_{21}	X_{22}	X_{12}	X_{24}	X_{25}	X_{26}
X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}
X_{41}	X_{42}	X_{43}	X_{44}	X_{45}	X_{46}
X_{51}	X_{52}	X_{53}	X_{54}	X_{55}	X_{56}

=

q
5 x 3 matrix

a	**b**	**c**

p
3 x 6 matrix

	x				
	y				
	z				

$$\mathbf{X_{32} = (a, b, c) \,.\, (x, y, z) = a * x + b * y + c * z}$$

Rating Prediction

$$\hat{r}_{ui} = q_i^T p_u$$

User Preference Factor Vector

Movie Preference Factor Vector

proprietary material

Item

User

User/ Item	A	B	C	D
Ted		4		3
Carol	3		2	
Bob		5		2
Alice			4	

Ted	1.4	.9
Carol	1.2	1
Bob	1.5	.9
Alice	1.2	.8

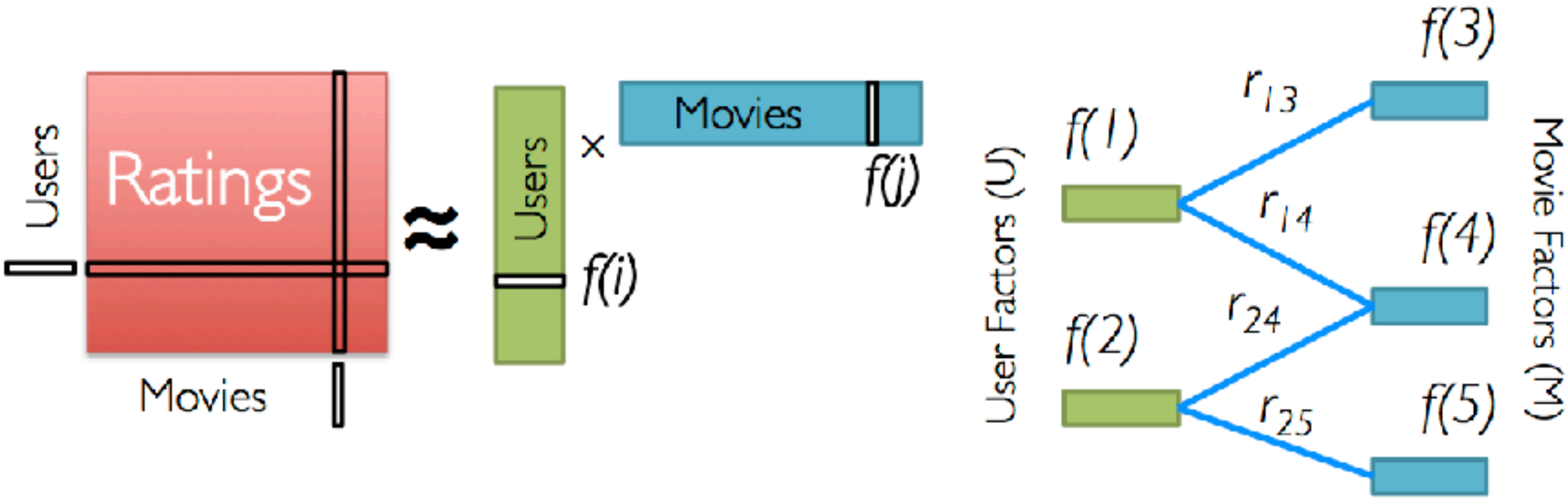
User

*

A	B	C	D
1.4	1.3	.9	1.2
.8	1.1	2	.8

Item

Alternative Least Square



Iterate:

$$f[i] = \arg \min_{w \in \mathbb{R}^d} \sum_{j \in \mathrm{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

Overview of Content-based Filtering

Content-based filtering recommends items with similar content (e.g. metadata, description, topics) to the items the user has liked in the past.

Input: depends only on the content/descriptions of the items and the users (but not usage data).

Types:

- Information Retrieval (e.g. tf-idf, Okapi BM25)
- Machine Learning (e.g. Naive Bayes, support vector machines, decision trees, etc)

Pros	Cons
• No cold start problem • No need for usage data • No popularity bias, can recommend items with rare features • Can user content features to provide explanations	• Item content needs to be machine readable and meaningful • Easy to pigeonhole the user • Difficult to implement serendipity • Difficult to combine multiple item's features together

Overview of Hybrid Approaches

Hybrid Approaches combines collaborative filtering and content-based filtering in order to use the pros of one to address the cons of the other.

Input: uses user and item content features as well as usage data to benefit from both types of data.

Types:

- Weighted
- Switching
- Mixed
- Feature Combination
- Cascade
- Feature augmentation
- Meta-level

Pros	Cons
• Often outperforms CF and CB alone • No cold start problem • No popularity bias, can recommend items with rare features • Can implement serendipity, diversity	• Can be a lot of work to get the right balance

Overview of Popularity

Popularity is an approach where you recommend items that are popular (e.g. most downloaded, watched, high impact).	
Input: uses usage data and item content (e.g. categories).	
Pros	**Cons**
• Relatively easy to implement • Good baseline algorithm • Helps with new user cold start problem	• Needs standardised products • Often needs some type of item categorisation • Won't recommend new items (fewer opportunities to learn) • Recommendation list tends not to change much

Overview of Non-traditional Approaches

Advanced or “Non-traditional” Approaches

- Deep learning
- Learning to rank
- Multi-armed bandits (explore/exploit)
- Context-aware recommendations
  - Tensor Factorisation
  - Factorisation Machines
- Social recommendations
- …..

Pros	**Cons**
• Good for eking out those final performance percentage points • You can say you’re working with cutting edge approaches ;)	• Less well understood • Less supported in recommendation toolkits • Not recommended approaches for your first recommender