MATRIX FACTORIZATION TECHNIQUES FOR RECOMMENDER SYSTEMS

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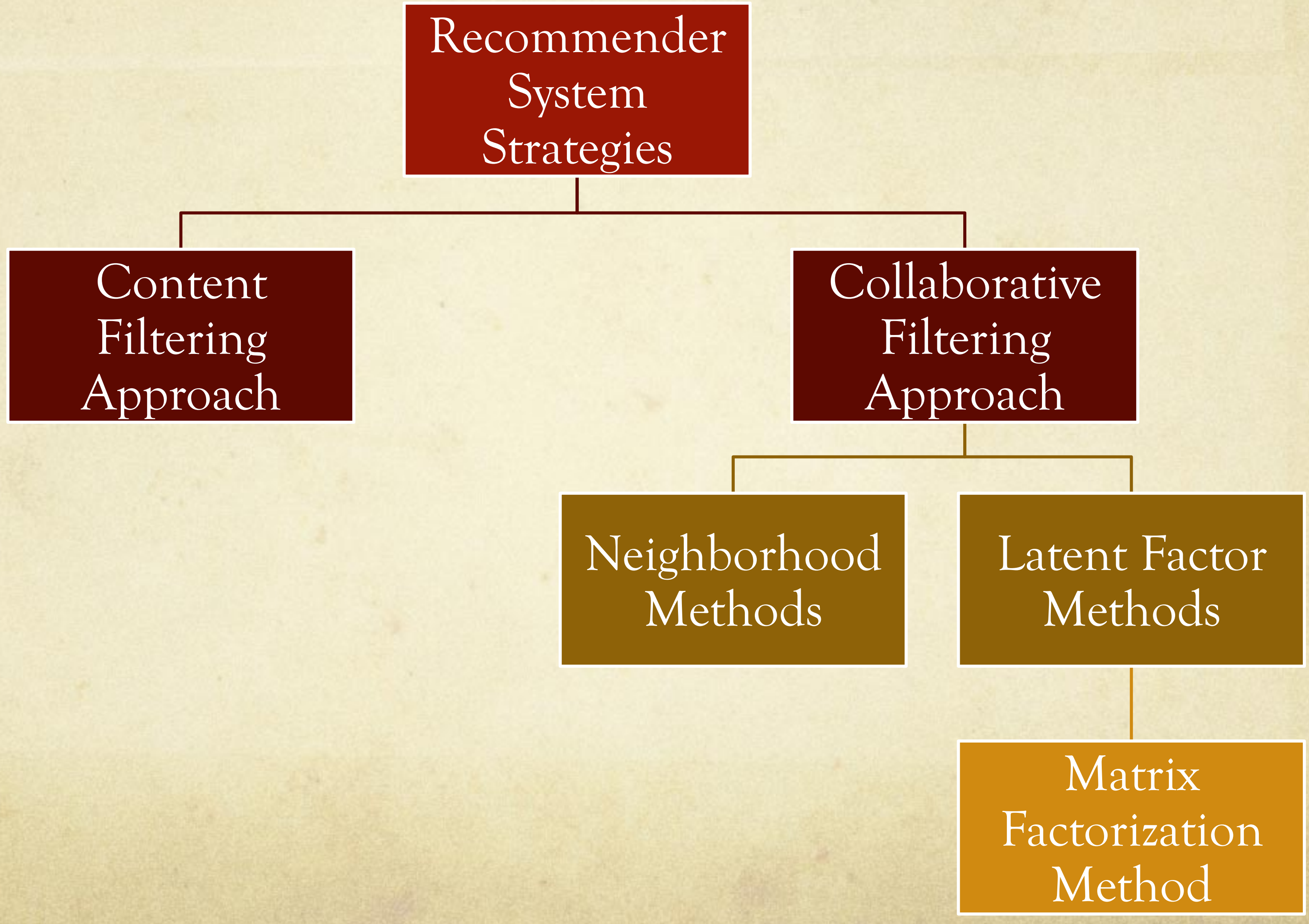
Recommender System Strategies



Content Filtering Approach

Creates a profile for each user or product to characterize its nature

- ▪Eg. Movie profile include attributes regarding its **genre, the participating actors, its box office popularity**…
- ▪Eg. User profile might include **demographic** information or **answers** provided on a suitable questionnaire

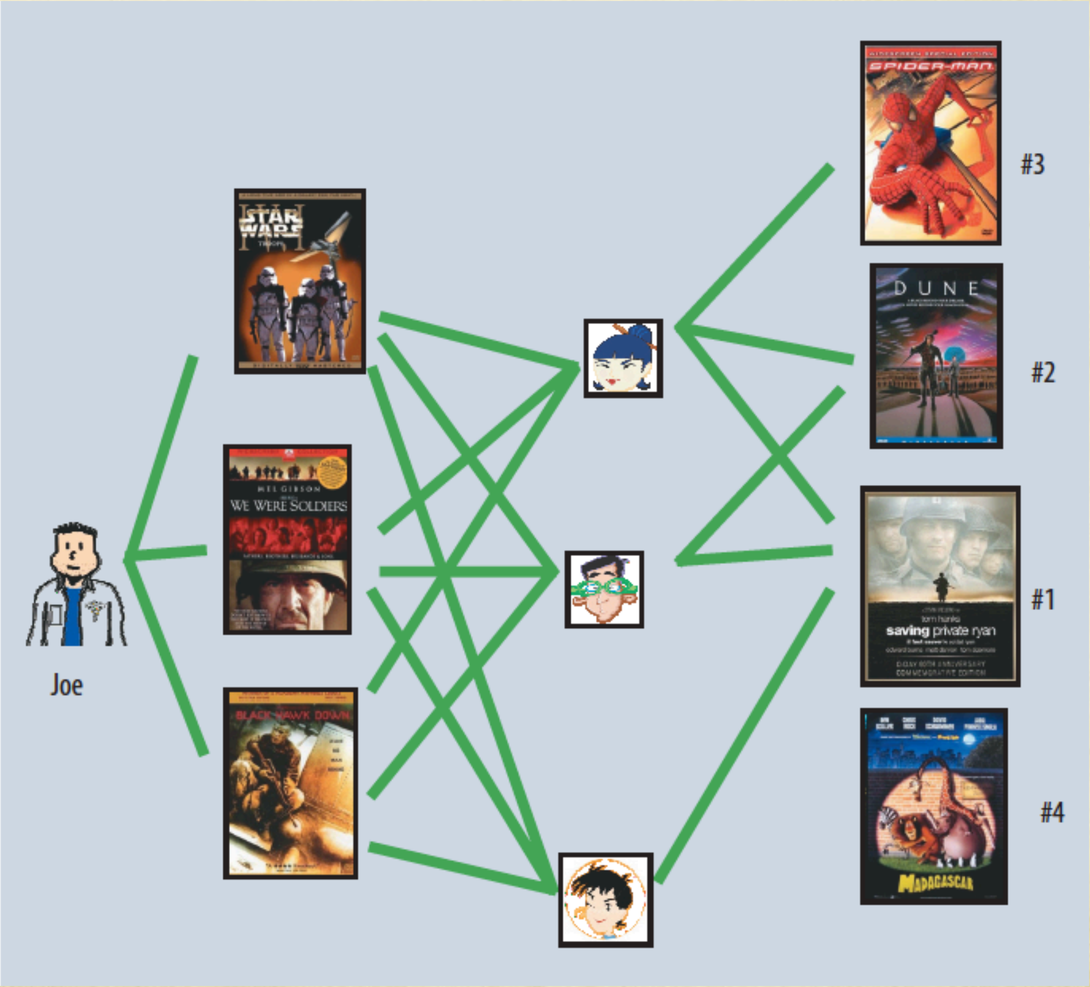
Collaborative Filtering Approach

Relies only on past user behavior (eg. Previous transactions or product ratings)

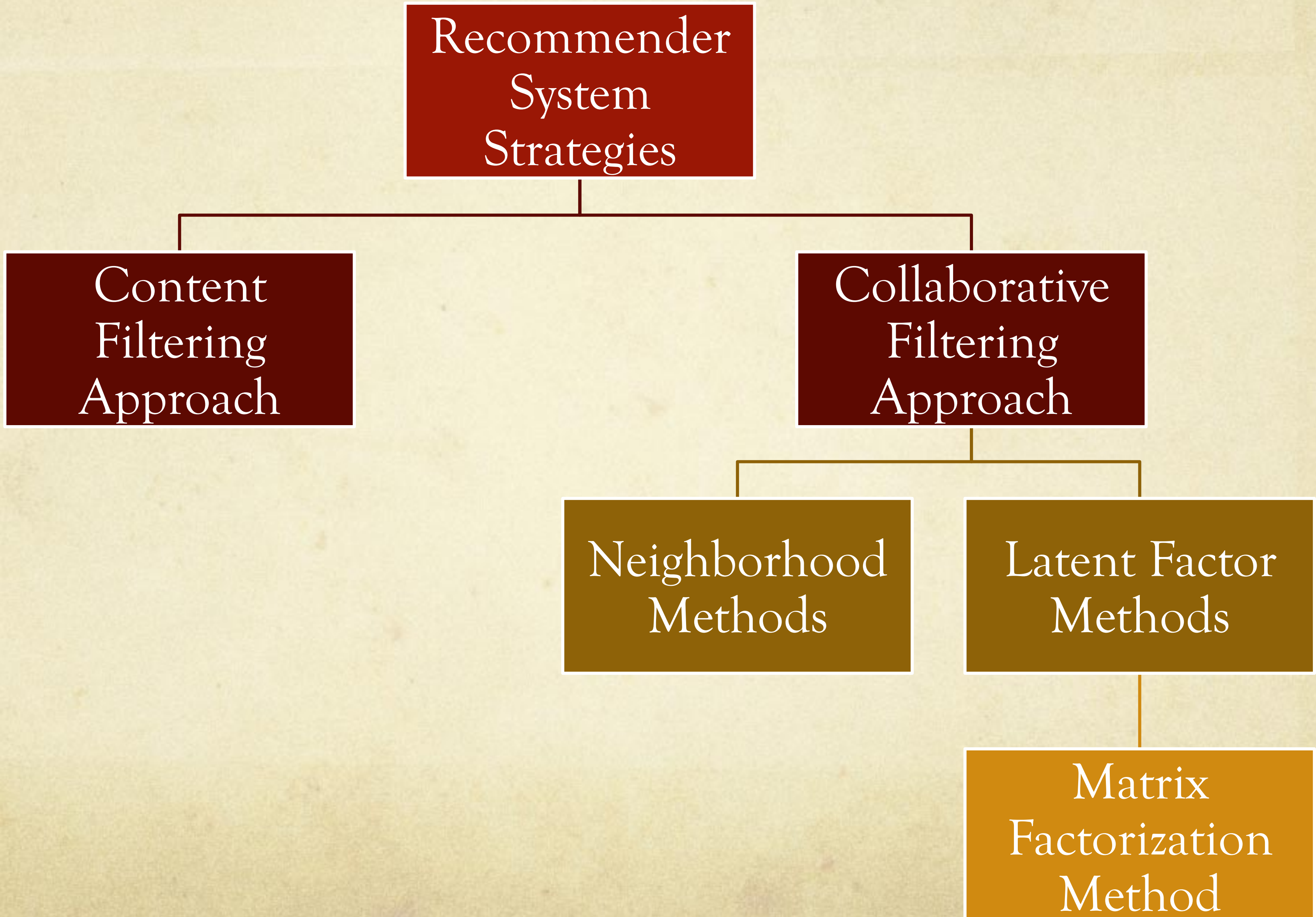
Basic assumption and idea

- Users give ratings to catalog items
- Customers who had similar tastes in the past, will have similar tastes in the future

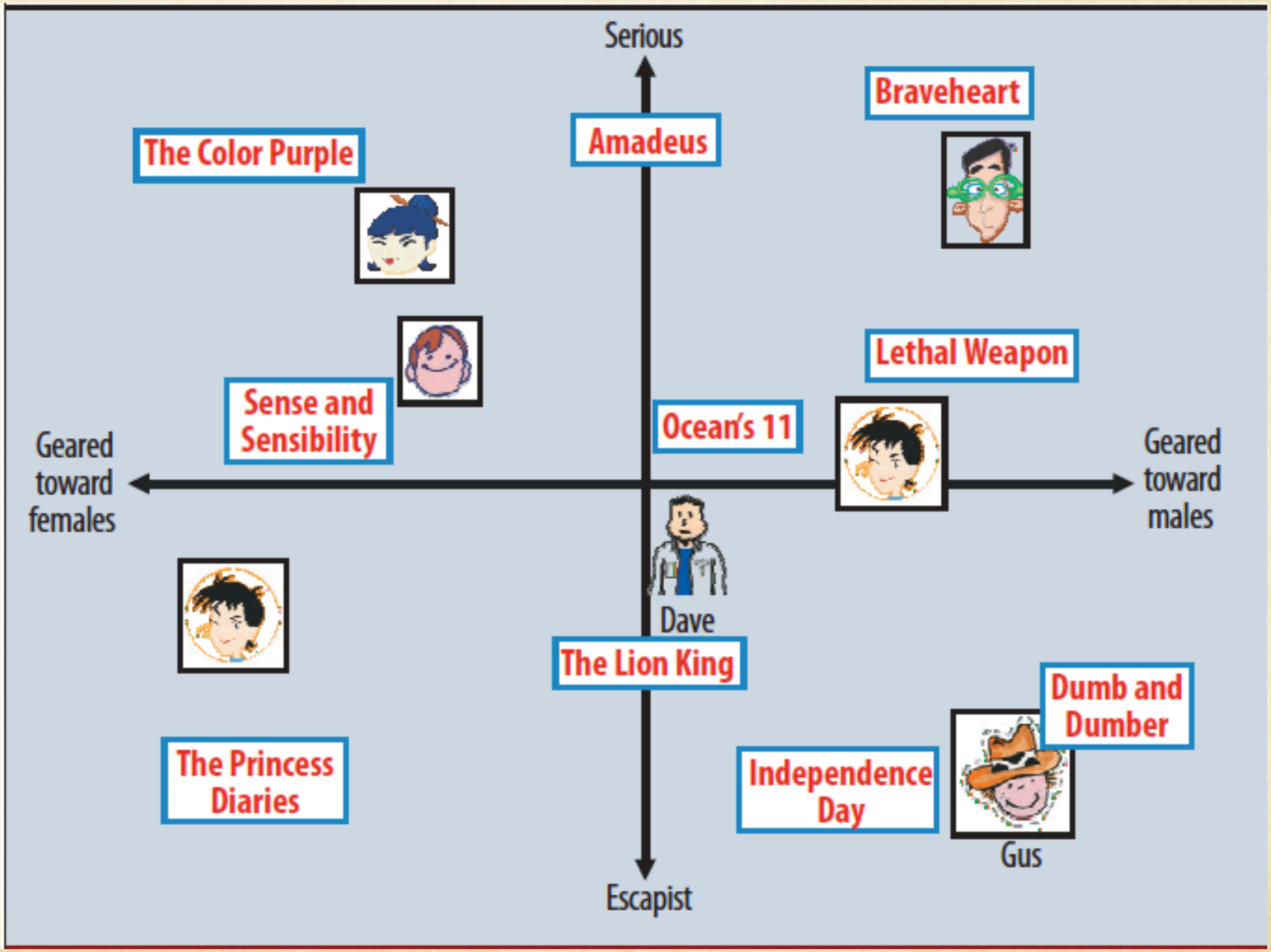
User Oriented Neighborhood Method



Recommender System Strategies



Latent Factor Method



Matrix Factorization Methods

Characteristic

- Characterizes both items and users by vectors of factors inferred from item rating patterns

Rely on matrix types of input data

- One dimension representing user
- The other representing items

Two data types

- High-quality explicit feedback
  - Includes explicit input by users regarding their interest in products
  - We refer to explicit user feedback as ratings
  - Usually sparse matrix, since any single user is likely to have rated only a small percentage of possible items

Matrix Factorization Methods

Implicit feedback

Which indirectly reflects option by observing user behavior

- Purchase history, browsing history, search patterns, mouse movements

–Usually denotes the presence or absence of an event

–Typically represented by a densely filled matrix

Matrix Factorization Methods

Difficulties

- High portion of missing values caused by sparseness in the user-item rating matrix

Matrix Factorization Methods

1. Adding Biases

Typical collaborative filtering data exhibits large systematic tendencies for some users to give higher ratings than others

- And for some items to receive higher ratings than others

–Some products are widely perceived as better(or worse) than others

- Its unwise to explain the full rating value in this form
- We should identify the user and item bias

Matrix Factorization Methods

Adding Biases

For example:

- Suppose we want to estimate user john's rating of the movie Titanic
- And the average rating over all movies is 3.7 stars
- Titanic is better than an average movie, so it tends to be rated 0.5 starts above the average movie
- John is a critical user, who tends to rate 0.3 stars lower than the average
- Thus, the estimate for Titanic's rating by John would be (3.7+0.5-0.3)

Matrix Factorization Methods

2. Additional Input Sources

A system must deal with cold start problem, wherein many users supply very few ratings

- We need to incorporate additional sources to relieve this problem
- Using implicit feedback to gain insight into user preferences
- Eg: Demographics, such as gender, age group, zip code, income level.

Matrix Factorization Methods

3. Temporal Dynamics

Time-drifting nature

- So far, the presented models have been static
- In reality, product perception and popularity constantly change as new selections emerge
- Similarly, customer's inclinations evolve, leading them to redefine their taste
- The system should account for the temporal effects

Matrix Factorization Methods

Temporal Dynamics

Multiple sources of temporal dynamics

- **Item-side effects:**

–Product perception and popularity are constantly changing

–Seasonal patterns influence items' popularity

- **User-side effects:**

–Customers ever redefine their taste

–Drifting rating scale

–Change of rater within household

Matrix Factorization Methods

4. Inputs With Varying Confidence Levels

- **Are all observed ratings deserve the same weight or confidence?**

–For example, massive advertising might influence votes for certain items, which do not aptly reflect longer-term characteristics

- **The user might be unaware of the existence of the item, or unable to consume it due to its price**

–Consuming an item can also be the result of factors different from preferring it

▪a user may watch a TV show just because he/she is staying on the channel of the previously watched show

▪a consumer may buy an item as gift for someone else, despite not liking the item for himself

Conclusion

- Matrix Factorization techniques have become a dominant methodology within collaborative filtering recommenders.
- At the same time, they offer a compact memory-efficient model that systems can learn relatively easily.
- What makes these techniques even more convenient is that models can integrate naturally many crucial aspects of the data, such as multiple forms of feedback, temporal dynamics, and confidence levels.