Why Not Just Recommend Popular Books?

We tested collaborative filtering vs. popularity baseline:

Method	Precision@10
Pure collaborative filtering	2.16%
Improved collaborative (filtered)	2.45%
Popularity baseline	7.56%
Hybrid (50/50)	8.83%

Lesson: Pure collaborative filtering performs worse than just recommending popular books!
Why? 95.75% sparsity - too much missing data
Solution: Hybrid approach works best (8.83% vs 7.56%)

Data Filtering & Scalability

Data Filtering

Started with 1,000 Hardcover users and 45,203 books. Filtered to:

- **Users with $\geq$ 20 ratings:** 246 users
- **Books with $\geq$ 5 users:** 2,547 books
- **Total possible:** $246 \times 2,547 = 626,562$ ratings
- **Actual interactions:** 26,598 (only 4.25%)

Computational Performance

Training time and scalability (300 iterations, 20 features):

- **Current dataset (246 users):** 8.1 seconds
- **Projected 10,000 users:** 32.7 seconds
- **Projected 100,000 users:** 5.2 minutes
- **Time per user:** 33ms (scales linearly)

The Masking Solution

Problem: 95.75% Sparsity

Most entries in the ratings matrix are unknown, not negative ratings. We can't train on missing data!

Solution: Masking Matrix R

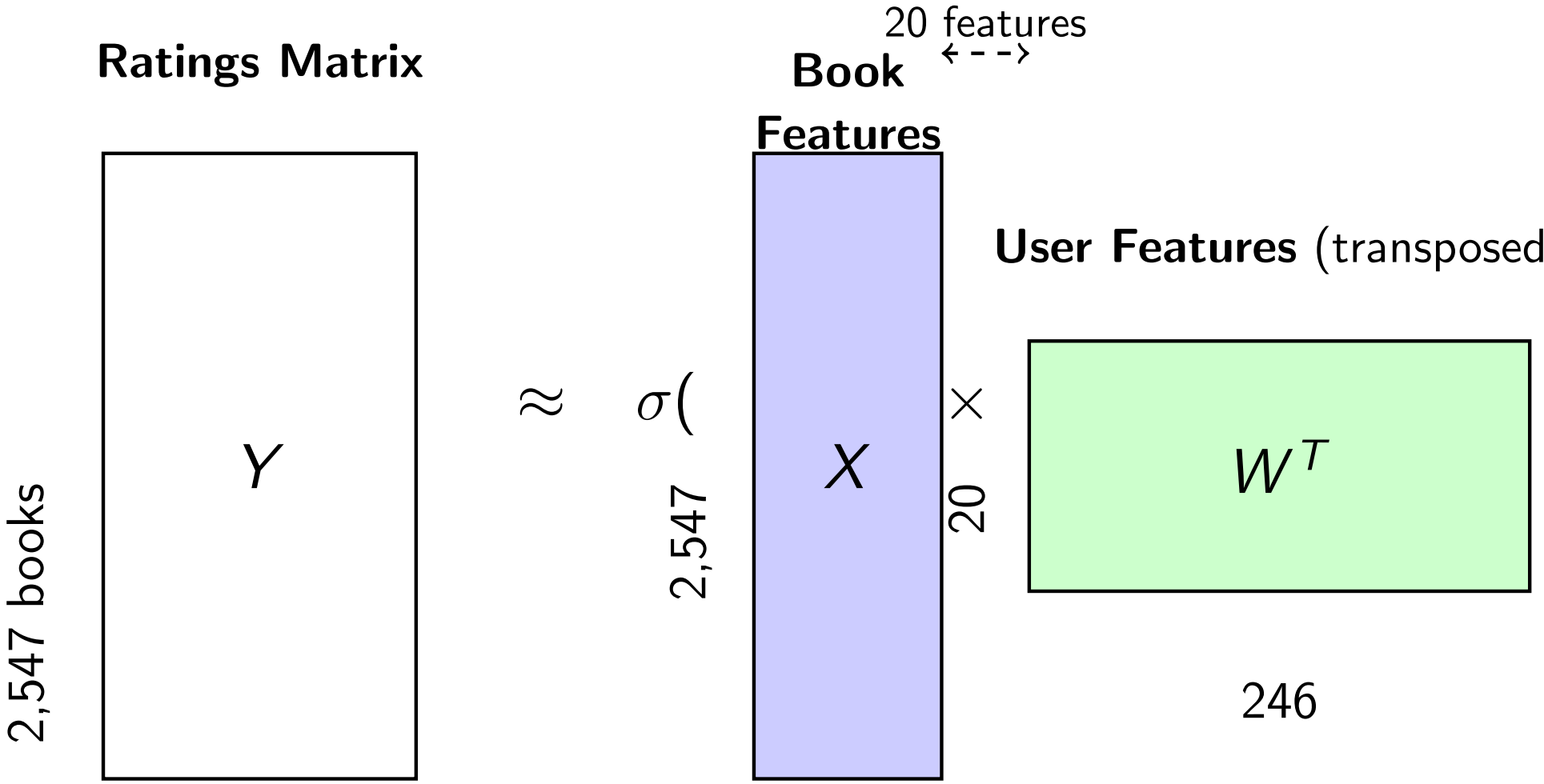
We use a mask matrix R where:

$$R[i,j] = \begin{cases} 1 & \text{if user } i \text{ interacted with book } j \\ 0 & \text{otherwise (unread)} \end{cases}$$

Key insight: Only train on known interactions (4.25%), ignore unread books (95.75%)

This prevents the model from trying to predict missing data and focuses learning on actual user preferences.

Matrix Factorization: Learning User Preferences



The Hybrid Method: Best of Both Worlds

Why Hybrid?

Pure collaborative filtering (2.16%) performed worse than just recommending popular books (7.56%)!

The Solution: 50/50 Hybrid Approach

Combine two recommendation strategies:

$$\text{Final Score} = 0.5 \times \text{Popularity Score} + 0.5 \times \text{Collaborative Score}$$

- **Popularity:** Recommend books many users liked (safe baseline)
- **Collaborative:** Recommend based on user's learned preferences (personalization)

Result

Clustering: Finding Your Reading Tribe

Goal: Group users with similar reading preferences

How It Works

1. Start with each user's 20-dimensional feature vector
2. **Normalize** the vectors (make them unit length)
3. Use K-means clustering to group similar users
4. Tested different cluster counts, found K=13 is optimal

Finding Friends within Your Cluster

- Calculate **dot product** (cosine similarity) with each cluster member
- Higher similarity = better friend match
- Show shared books as conversation starters

Result: 13 distinct reading groups (Fantasy Fans, Sci-Fi Enthusiasts, etc.)