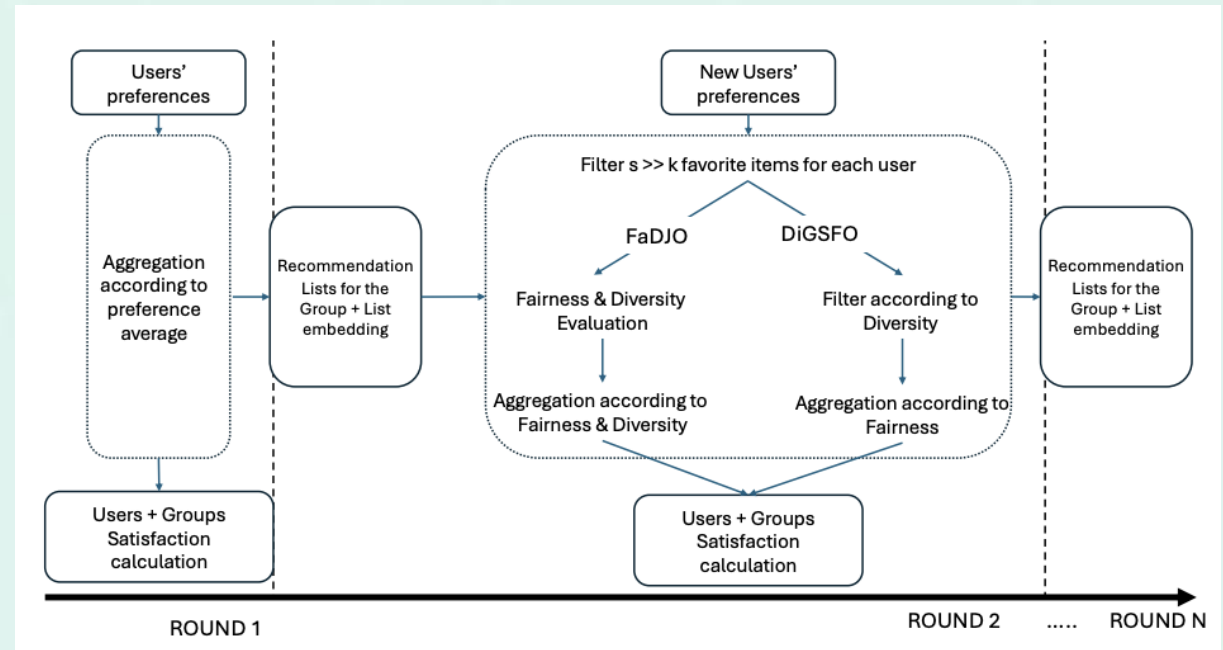


Diverse Sequential Group Recommendation

Diversity-Guided Selection with Fairness Optimization (DiGSFO)

- Students: Oskari Perikangas, Xiaosi Huang
- Course: DATA.ML.360-2025-2026-1
- Date: November 10, 2025



Sequential Group Recommendations

Challenges:

- Filter bubble: Repeatedly suggesting similar genres
- Unfairness: Minority preferences get ignored
- Users only see content matching past behavior

Solution: DiGSFO

(Diversity-Guided Selection with Fairness Optimization)

Core idea:

- Filter by diversity (genre distance)
- Optimize by fairness (weighted satisfaction)
- List-level evaluation (coherent recommendations_more rounds)

DiGSFO Algorithm Flow

Round 1: Average aggregation (no history to compare)

Round 2 onwards:

Step 1: Generate candidates

- Each user: top-100 items
- Create 50 candidate lists (sliding window)

Step 2: Filter by diversity

- Calculate genre distance to history
- Keep only lists with distance $\geq \delta$

Step 3: Score by fairness

- Weighted fairness (considers history)
- Select most fair list

Innovation: Combines diversity + fairness

Tested users example:

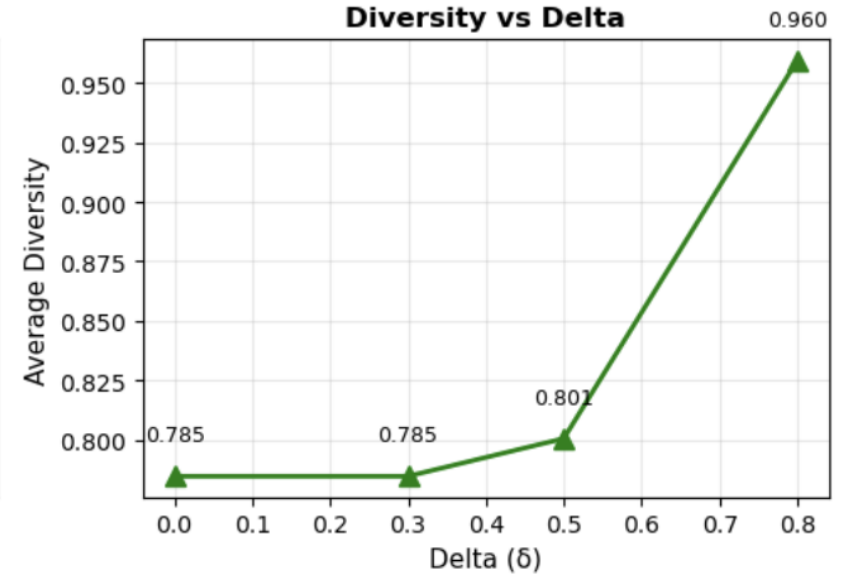
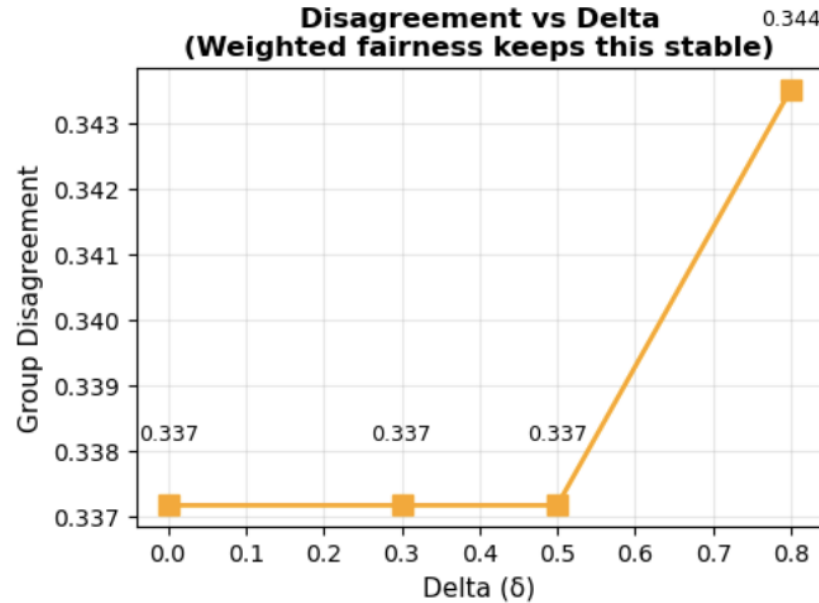
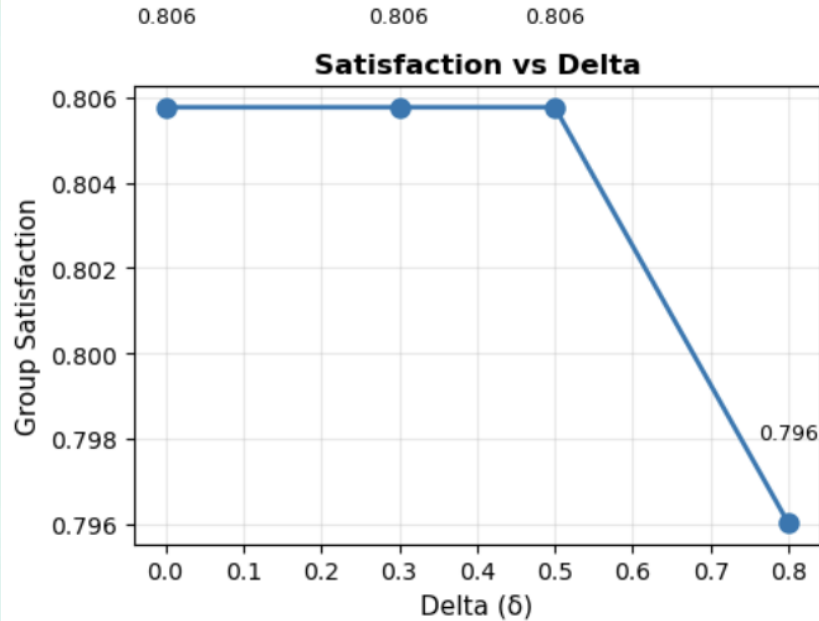
- Group: 3 users (User 1, 414, 599)
- Rounds: 10 sequential recommendation rounds
- Recommendations per round: 5 movies (one list)
- Rating scale: 0.5 to 5.0 (MovieLens dataset)

Process:

- Round 1: Average aggregation selects top-5 movies
- Round 2-10: Generate 50 candidate lists (5 movies each),
select the most fair and diverse list

Total: 50 movies recommended across 10 rounds

Results: Delta Parameter Testing



- Satisfaction: Stable at 0.806 (delta 0.0-0.5)
- Disagreement: Stable at 0.337 (weighted fairness works)
- Diversity: Increases with delta
- 0.785 (no filter) \rightarrow 0.801 (delta=0.5) \rightarrow 0.960 (delta=0.8)

Best configuration: Delta = 0.5

\rightarrow Balances diversity gain with satisfaction maintenance

Why DiGSFO Works Well

1. Prevents repetitive content

Genre-based distance filtering

→ Diversity +2% (0.785 → 0.801)

2. Maintains group fairness

Weighted fairness mechanism

→ Disagreement stable at 0.337

3. List-level optimization

Evaluates 5-movie sets as whole

→ Coherent recommendations

Tested on group [User 1, 414, 599] over 10 rounds

Successfully balanced diversity and fairness

```
=====
Testing different delta values (with weighted fairness)
=====
```

```
Delta=0.0: GroupSat=0.806, GroupDis=0.337, AvgDiv=0.785
```

```
Delta=0.3: GroupSat=0.806, GroupDis=0.337, AvgDiv=0.785
```

```
Delta=0.5: GroupSat=0.806, GroupDis=0.337, AvgDiv=0.801
```

```
Delta=0.8: GroupSat=0.796, GroupDis=0.344, AvgDiv=0.960
```