HUDK 4051: LEARNING ANALYTICS PROCESS & THEORY

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Today

- Matching algorithms
- Recommender Systems

Matching

- Common problem
- Assigning medical students to hospitals
- Assigning organ donors to recipients
- Dating websites
- Assigning students to dorms

Characteristics

- Preference measure
- Match two groups together

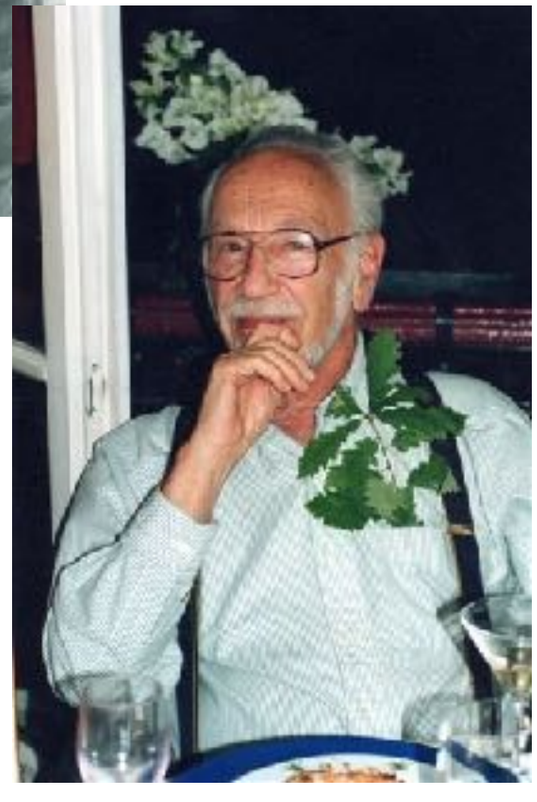
Solution

- 2012 Nobel Prize in Economics

- Gale-Shapley Algorithm (1962)

Lloyd Stowell Shapley

David Gale

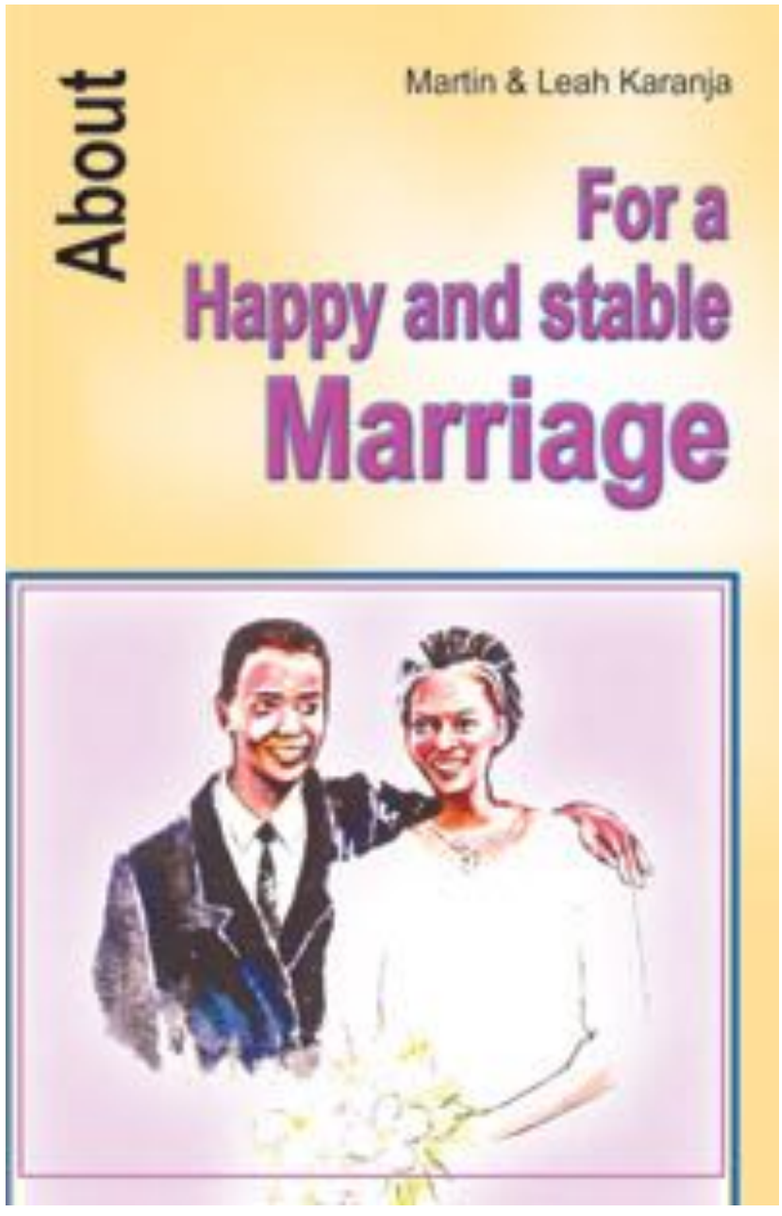


Stable Marriage Problem

Finding a stable matching between two equally sized sets of elements given an ordering of preferences for each element.

Mapping from the elements of one set to the elements of the other set.

Stable: No element of set *A* prefers a different match when *B* also prefers *A* over the element to which *B* is already matched



Stability

The Heirs (왕관을 쓰려는 자, 그 무게를 견뎌라 – 상속자들)

Kim Tan

Choi Young-do

Yoon Chae-young

Rachael Yoo

Cha Eun-sang

Lee Bo-na

Rachel	Cha	Lee	Kim	Kim	Yoon
Lee	Rachel	Rachel	Yoon	Yoon	Kim
Cha	Lee	Cha	Choi	Choi	Choi

Gale-Shapley Algorithm

- Solves for stability
- Two steps:
  - 1. A “proposes” to B and B accepts their preference to create provisional “engagements”
  - 2. Each rejected A proposes to their second preference B and B can “trade up” or not
  - Repeat until all matched

Kim Tan

Choi Young-do

Yoon Chan-young

Rachael Yoo

Cha Eun-sang

Lee Bo-na

Rachel	Cha	Lee	Kim	Kim	Yoon
Lee	Rachel	Rachel	Yoon	Yoon	Kim
Cha	Lee	Cha	Choi	Choi	Choi

Gale-Shapley Algorithm

- Two libraries in R: matchingMarkets & matchingR
- Runs the algorithm
- Checks for stability

Matching students to podcast dates

- Different problem: only have one set of preferences
- How do we solve this?
  - Randomize date preferences?
  - Randomize only those that double up?
  - Distance strategy?
- How do we judge fairness?

Adaptive Systems

Recommender Systems

Collaborative filter: build a model from a user's past behavior + similar decisions made by other users

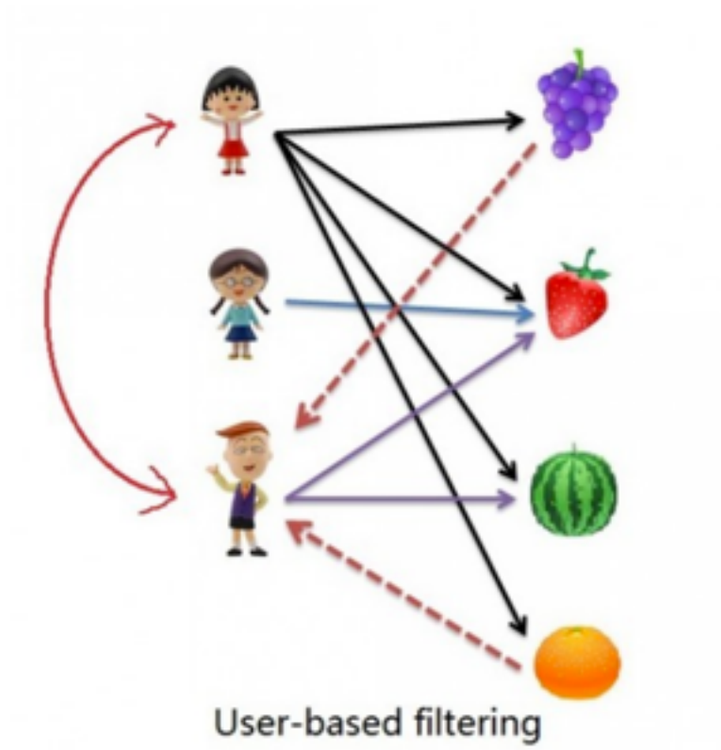
Content filter: utilize a series of discrete characteristics of an item in order to recommend additional items with similar properties

Cold Start Problem

The system cannot draw any inferences for users or items about which it has not yet gathered sufficient information.

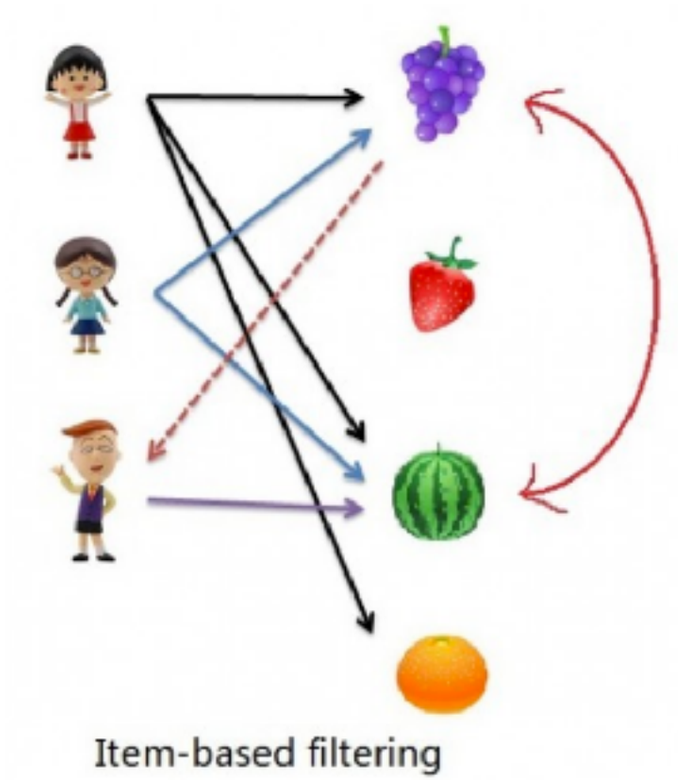
User Based Collaborative Filter

	student A	**student B**	**student C**
podcast	score improved = yes	yes	no
game	yes	no	no
quiz	yes	yes	no



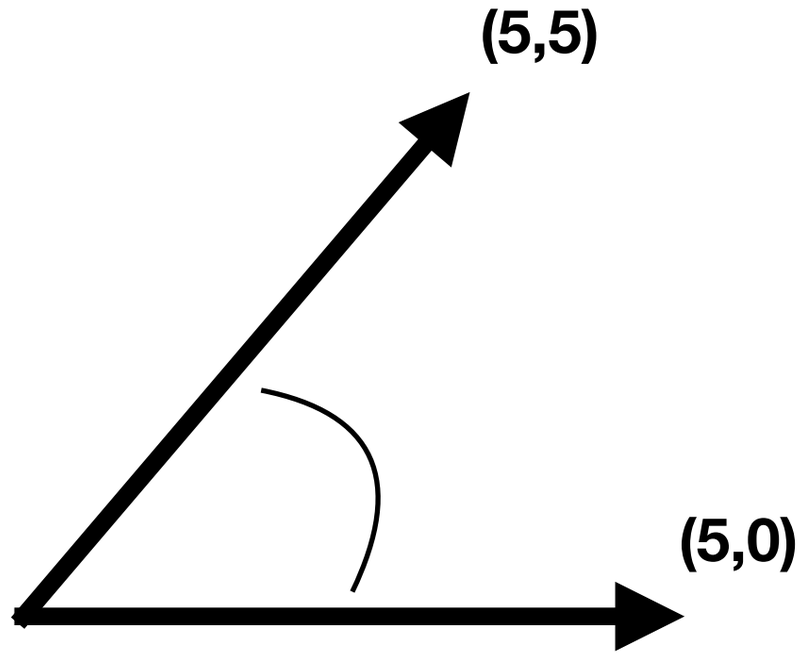
Item Based Collaborative Filter

	student A	**student B**	**student C**
podcast	score improved = yes	yes	no
game	yes	no	no
quiz	yes	yes	no



Similarity

- Many different ways to calculate
- Cosine similarity:
  - Calculate the angle between two vectors
  - Same direction = 1
  - Opposite direction = -1



Item Based Collaborative Filter

	student A	**student B**	**student C**
podcast	score improved = yes	yes	no
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quiz	yes	yes	yes

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

A = c(1,1,1)

B = c(1,0,1)

$$\mathbf{sim_{AB}} = \frac{\mathbf{(1 \times 1 + 1 \times 0 + 1 \times 1)}}{\mathbf{sqrt((1x1 + 1x1 + 1x1)) \times sqrt((1x1 + 0x0 + 1x1))}}$$

sim_{AB} = 0.816

Similarity Matrix

	student A	**student B**	**student C**
student A	1	0.82	0.58
student B	0.82	1	0.71
student C	0.58	0.71	1

	podcast	**game**	**quiz**
podcast	1	0.71	0.82
game	0.71	1	0.58
quiz	0.82	0.58	1

Which to use?

- Depends what you are trying to do?
- There are usually more users than items, therefore more variation
  - Scaling issues (bigger matrix)
  - Items more likely to converge (once converged don’t have to calculate)
- Often an extra step in user-based
  - Find neighborhood of similar individuals
  - Then recommend