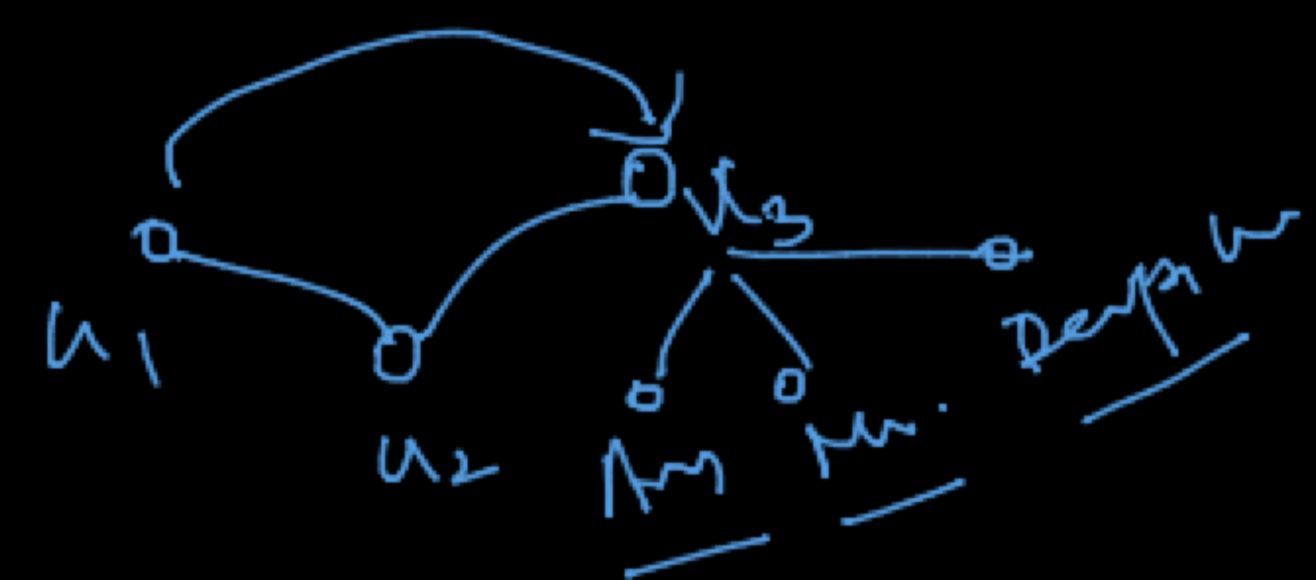
# Recommender System

1. Personal preference - Recommender System ✓
2. Shopping cart → Association Rule. ✓




## Recommendations

**Content Based**

- Regression.
- Classification

**Collaborative Filtering** → Similarity Based Algorithm -

- User-user Similarity
- Item-Item similarity (Amz)

# Netflix.

## Content Based Recommendation:

— Users.
— Movies

10 users ✓ → 50.
5 Movies
✓ . 6th Movies

$U_1 M_6 \rightarrow 1.5$ ✗
$U_2 M_6 \rightarrow 4.0$
$U_3 M_6 \rightarrow 3.8$
→ $M_6$.

Featurize user Info.
Featurize product Info

Gender, Age, Region, language, Area of interest . . . → 10.

✓ user :

lang, genre, Cast, female, Hero, director, writer, year, Rating — 13

✓ Movies :

23 – columns 'y'
Rating ✓

U1M1 :
Gen, Age, Region, lang . . .
Genre, lang . . .
2.5.
4.8 ✓.

U1M2 . . . . . .

→ Regression

Watched ✓
1
0.
→

$U_1 M_6 \rightarrow \boxed{1}$
$U_2 M_6 \rightarrow \boxed{0}$

Model. → 4.2
$U_N M_1$

$(U_1 M_6) \rightarrow$ Mod. — 1 – Recomm
0 – Didn't recommend

X y.

$U_1$ $M_6$

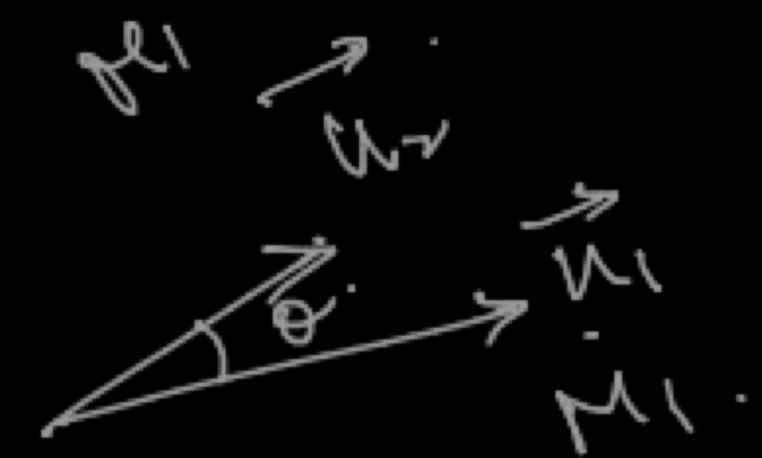
( ... ... ) Rating ? predicting.

✓

( M 18 Eng Bang. SciFic Bg. — — ) → 4.8

( F 63. Eng Ban. SciFic. Bg. - - ) → 2.8

X



# Collaborative Filtering.

— Similarity based Algorithm.

( distance based → Cosine Similarity )

User–User – Similarity

Item – Item. Similarity.

'Matrix Completion Problem'

Input – Data

$$
\begin{array}{c|c}
 & I_1 \quad I_2 \quad I_3 \quad \cdots \quad I_m \\
\hline
\begin{matrix} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_n \end{matrix} &
\begin{bmatrix} R_{11} & \cdot & \cdot\ \cdot & & \\ & & & & \\ \cdot & & R_{33} & & \cdot \\ & \cdot & & \cdot & \\ \cdot & & \cdot & & \end{bmatrix}
\end{array}
\quad \underline{\overline{n \times m}} \rightarrow
$$

n – no. of users on the platform.

m → No. of items.

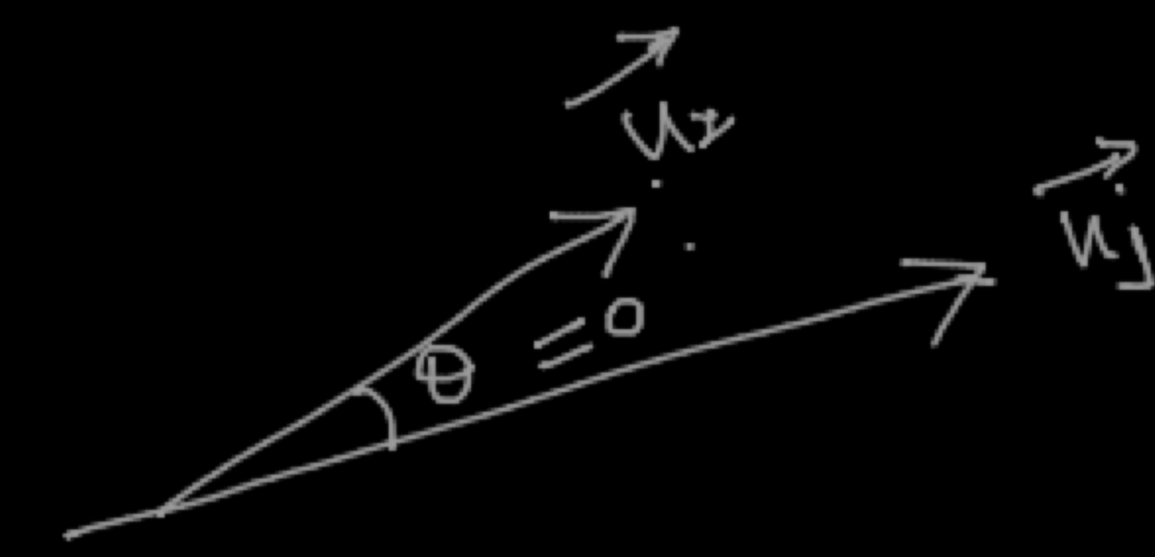
'SPARSE' → Mostly Empty.

$$\text{'Sparsity'} = \frac{\#\ \text{Empty Cells}}{\text{Total no. cells}} \approx 1.$$

$$X = \begin{array}{c|c} & I_1 \; I_2 \; I_3 \; \cdots \; I_m \\ \hline \begin{array}{c} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_j \\ \vdots \\ u_n \end{array} & \begin{bmatrix} & \\ \cdots & \cdots \\ & \\ & \\ \cdots & \cdots \\ & \\ & \end{bmatrix} \end{array}$$

User-user similarity

$$u_2 = \begin{bmatrix} R_{21} \\ R_{22} \\ R_{23} \\ \vdots \\ R_{2m} \end{bmatrix}_{m \times 1} \qquad u_j = \begin{bmatrix} R_{j1} \\ R_{j2} \\ \vdots \\ R_{jm} \end{bmatrix}$$




$$\text{Similarity} = \frac{1}{\text{distance}}$$

5.0    2

$\boxed{u_2}$ : $M_1$ $M_3$

$u_j$ : $M_1$ $M_3$ $M_7$ ×

4.5    1.0    4.5    1.0

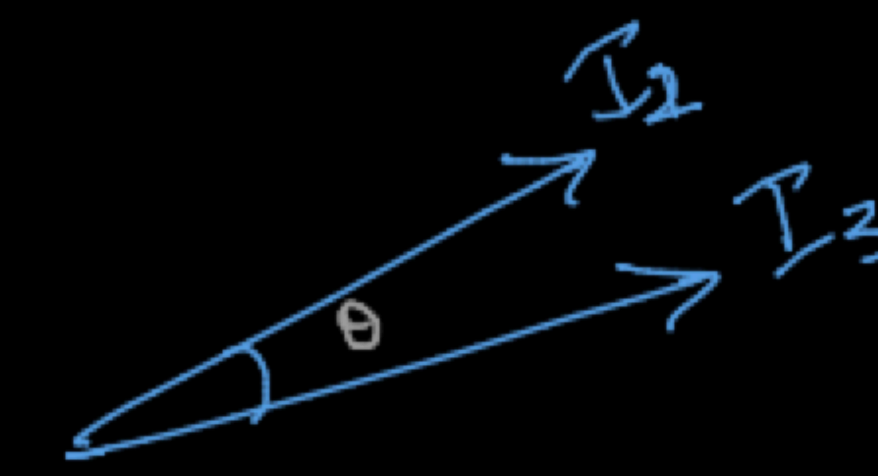
$u_1 \longrightarrow u_2 \;\; u_7 \;\; u_{102}$

'users who have agreed in the past are likely to agree in the future' →

Item - Item Similarity → amzn

$$
\begin{array}{c|c}
 & I_1 \quad I_2 \quad I_3 \quad \cdots \quad I_m \\
\hline
\begin{array}{c} u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_n \end{array} &
\begin{bmatrix} \; & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \end{bmatrix}
\end{array}
\Rightarrow
\quad
I_2 = \begin{bmatrix} R_{12} \\ R_{22} \\ R_{32} \\ R_{42} \\ \vdots \\ R_{n2} \end{bmatrix}
\quad
I_3 = \begin{bmatrix} R_{13} \\ R_{23} \\ \vdots \\ R_{n3} \end{bmatrix}
$$

Ratings given by different users for this movie




$I_2 \quad I_3 \rightarrow$

$(u_1 \quad u_7 \quad u_8)$

$u_1 \quad \cancel{u_2} \rightarrow$

$u_1$

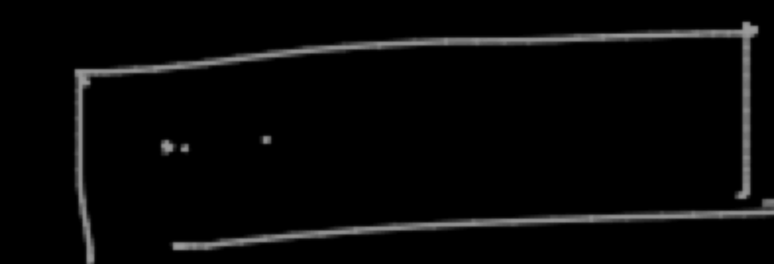
→ (6 months)

pop ✗

Jazz →

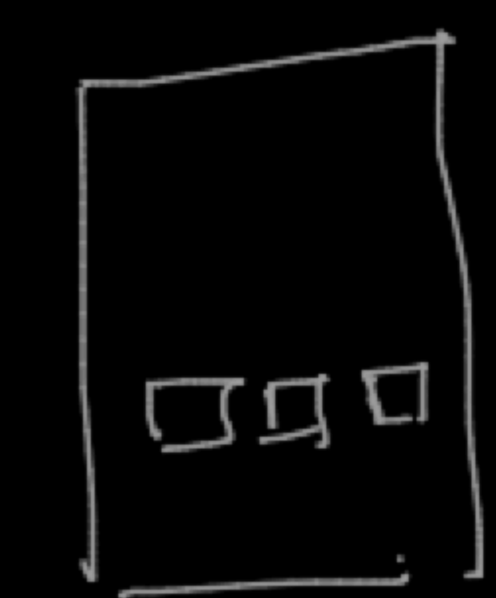
1. Association Rules
2. Users Similarity
3. Item Similarity

Search history ←
Social Media profile ←



1. Realtime Recommendations
   →
2. Late Recommendation
   → offline — msgs
   mails

User ↗
↑



10 Million → $\boxed{1000}$ →
Tree

100 Col → 10 Column
→

→ localized data
→ low rated / Highly popular
→ →
→ clustering

Opera File Edit View History Bookmarks Developer Window Help

10.20 am.

# ← Cold start →

— New user ?

→ New product ?

1. Recommend popular item /

Cooking / Songs / Dance. ↗

politics / sports / Racing. ↘

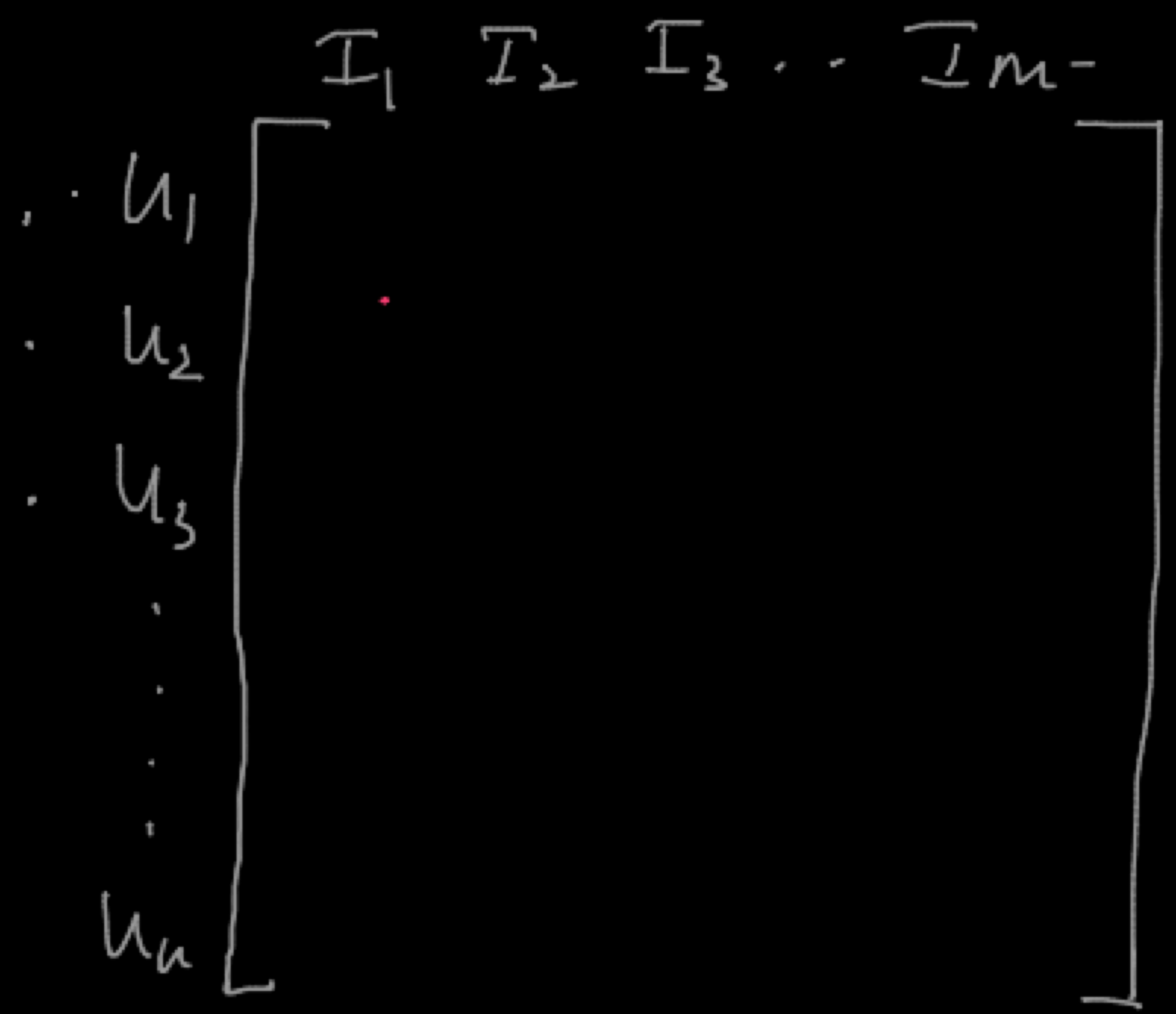
Search history / Social Media profile →

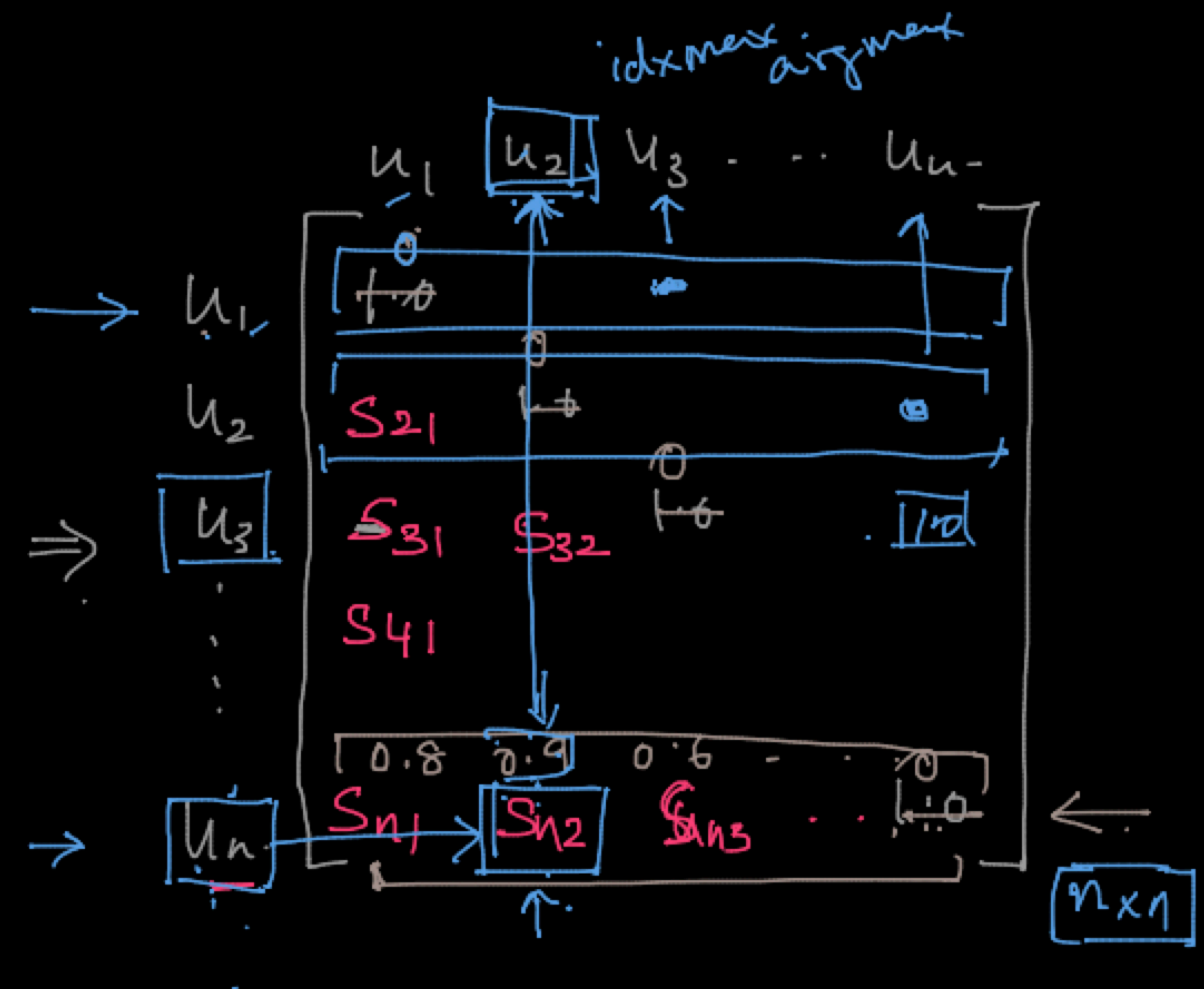
2. New product → ?

→ Random recommend → Exer →

↘ Makeup →

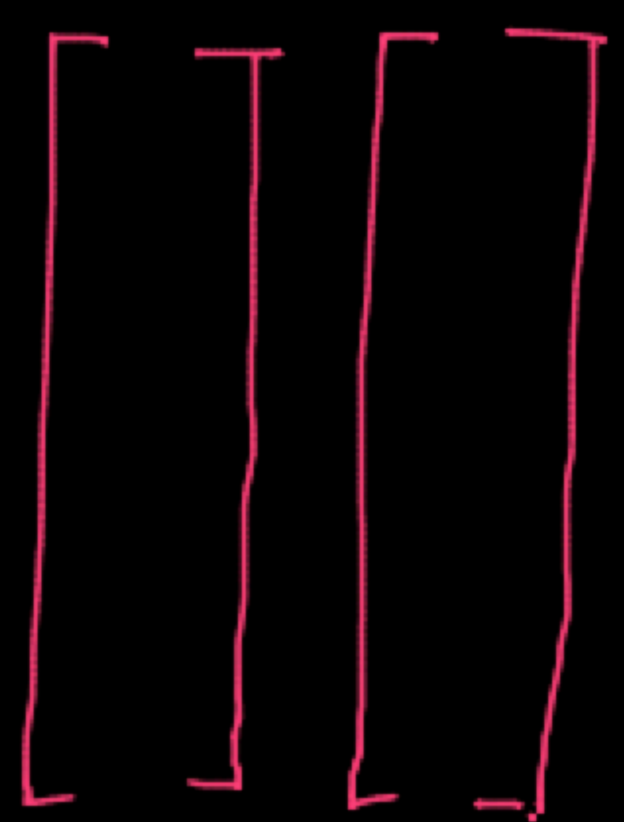
→ Influencers ⇉ —



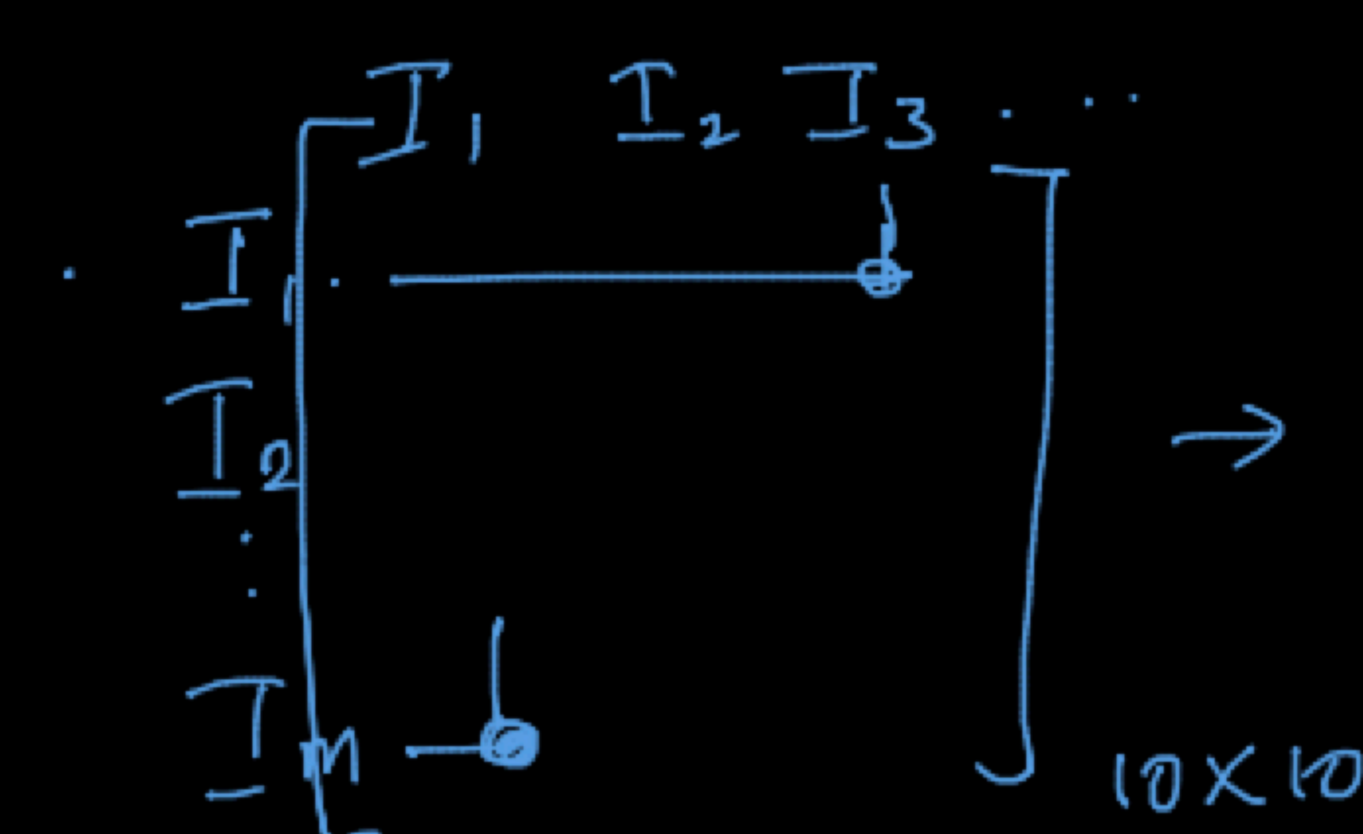

User-user similarity Matrix.

$\vec{u_1} \rightarrow \vec{u_2} \rightarrow$ distance



$S_{12} = 1 - \underline{\text{distance}}$

$=$




$\rightarrow$ Item-Item.

→ across columns find the max number

$$
\begin{array}{c|ccc}
 & u_1 & u_2 & u_3 \\
\hline
u_1 & 0 & \boxed{0.8} & 0.7 \\
u_2 & 0.8 & 0 & 0.9 \\
u_3 & 0.7 & 0.9 & 0
\end{array}
$$

$u_{68}$ — index corresponding to max

~~768~~ $\boxed{0.98}$

$u_1 \rightarrow u_{768}$

idx max

axis = 1

Pandas dataframe