Items → Movies.
Users → Netflix users

Recommender Systems

Content Based

10 Feature.

Collaborative Filtering.

User-user Similarity

Item-Item Similarity

Similarity Based Algorithms

Featurize Items & users.

users : Gender, Age, Language, Region, Edu., Income

Items : Genre, Director, Language, Hero, Duration, Music, Awards, Budget, Release

15 Features

← 10 Features → ← 15 Features → Rating watched

100 $u_1 I_1$ 4.0 1

1000 $u_1 I_2$ 2.0 0

0

1

I_{1001}

y

$u_1 I_{1001}$ 4.5 1

$u_2 I_{1001}$ 3.0 0

← X →

$u_{100} I_{1000}$

user id's → Movie Names

$$X = \begin{array}{c|c} & I_1 \; I_2 \; I_3 \; \cdots \; I_m \\ \hline u_1 & R_{11} \; R_{12} \; R_{13} \; \cdots \; R_{1m} \\ u_2 & R_{21} \; R_{22} \; R_{23} \; \cdots \; R_{2m} \\ u_3 & \\ \vdots & \\ u_n & \end{array}$$

⇒ 'sparse Matrix'

$n \times m$

Millions → n; movies → m

Collaborative Filtering

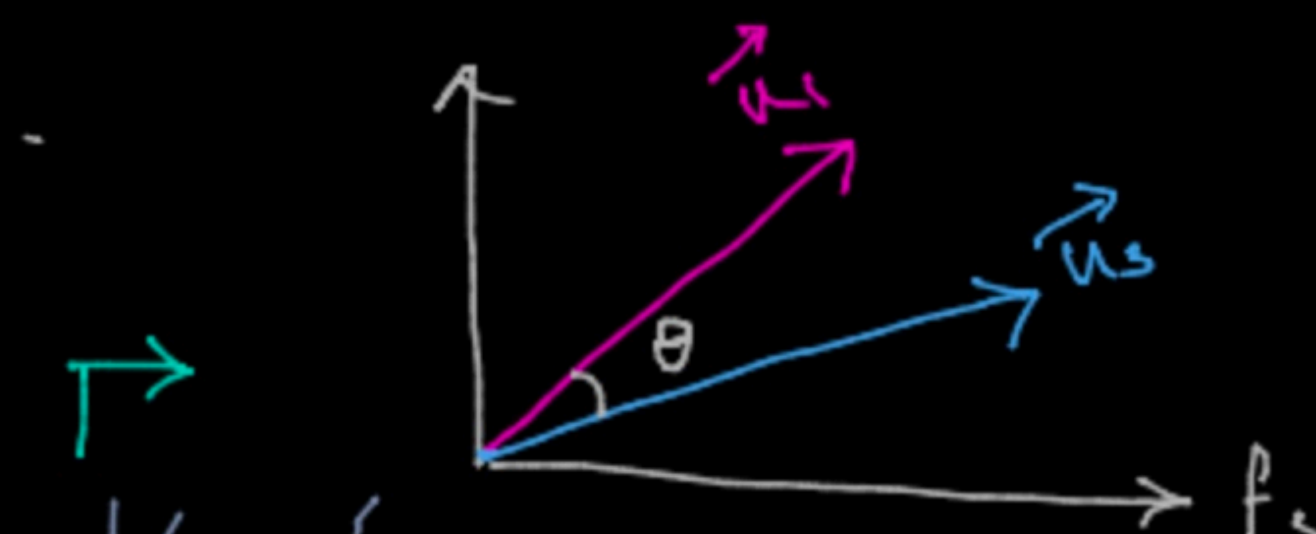
— Similarity Based Algorithm.

⇒ 'Matrix completion problem'

Task in Movie

$$\vec{u_1} = \begin{bmatrix} R_{11} \\ R_{12} \\ R_{13} \\ \vdots \\ R_{1m} \end{bmatrix} \qquad \vec{u_3} = \begin{bmatrix} R_{31} \\ R_{32} \\ R_{33} \\ \vdots \\ R_{3m} \end{bmatrix}$$

Cosine Similarity



$\cos(\theta) \Rightarrow 1$

$\theta = 0;$

user = 11

$u_1 \rightarrow$ Find users sim to u_1

u_7, u_{10}

$\downarrow \quad \downarrow$

$\underbrace{I_{11}, I_{12} \quad I_3, I_{100}}$

User similarity Matrix ✓

$$\begin{array}{c|ccccc} & u_1 & u_2 & u_3 & \cdots & u_n \\ \hline u_1 & 1.0 & S_{12} & S_{13} & \cdots & S_{1n} \\ u_2 & S_{21} & 1.0 & S_{23} & \cdot & S_{2n} \\ u_3 & S_{31} & S_{32} & 1.0 & S_{34} & S_{3n} \\ \vdots & & & & & \\ u_{11} & S_1 & S_2 & S_3 & 1.0 & u_n \end{array}$$

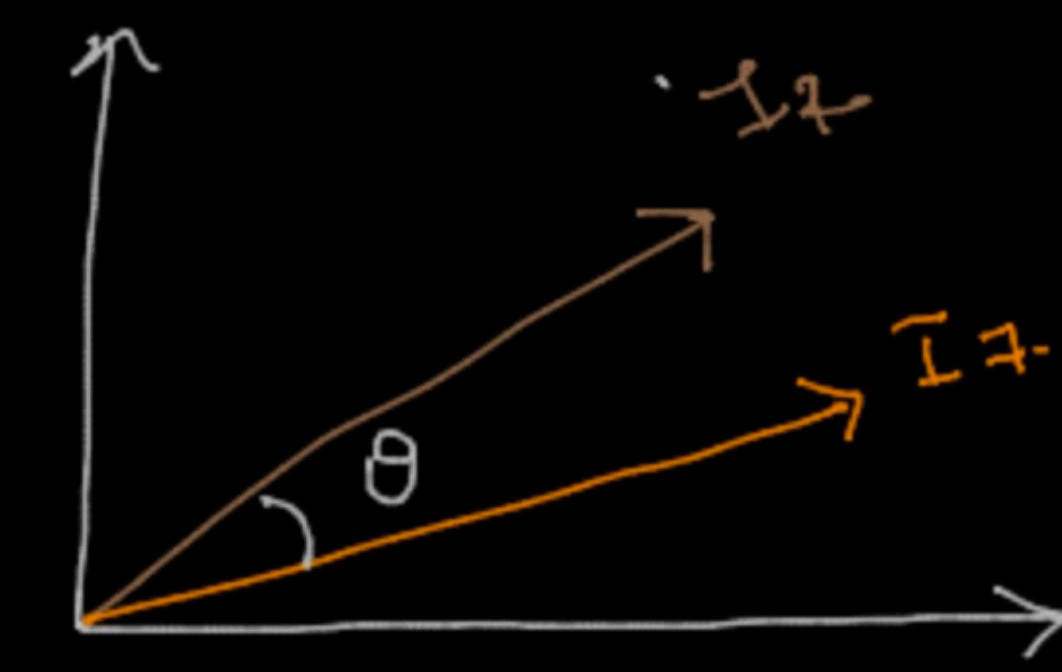
⇒ Find users who are most similar to u_{11}

⇒ Find the movies the similar users have rated.

Item-Item Similarity

$$X = \begin{array}{cc} & \begin{array}{ccccc} I_1 & I_2 & I_3 & \cdots & I_m \end{array} \\ \begin{array}{c} \to u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_n \end{array} & \begin{bmatrix} R_{11} & R_{12} & R_{13} & \cdots & R_{1m} \\ R_{21} & R_{22} & R_{13} & \cdots & R_{2m} \\ & & & & \\ & & & & \\ & & & & \end{bmatrix} \end{array}$$

$$\vec{I_2} = \begin{bmatrix} R_{12} \\ R_{22} \\ R_{32} \\ R_{32} \\ \vdots \\ R_{n2} \end{bmatrix} \qquad \vec{I_7} = \begin{bmatrix} R_{17} \\ R_{27} \\ \vdots \\ R_{n7} \end{bmatrix}$$



Item-Item similarity

$$\begin{array}{cc} & \begin{array}{ccccc} I_1 & I_2 & I_3 & \cdots & I_m \end{array} \\ \begin{array}{c} I_1 \\ I_2 \\ I_3 \\ \vdots \\ I_m \end{array} & \begin{bmatrix} \to 1.0 & S_{12} & S_{13} & \cdots & S_{1m} \\ S_{21} & 1.0 & S_{23} & \cdots & S_{2m} \\ \vdots & & & & \\ & & & & \\ & & & & \end{bmatrix} \end{array} \Rightarrow$$

Comedy I_{10} → I_4, I_7

Horror I_{20} → I_{40}, I_{50}

$$\vec{u_1} \Rightarrow I_{10}, I_{20}$$

$$\begin{array}{cc} & \begin{array}{cc} u_1 & u_2 \end{array} \\ \begin{array}{c} I_1 \\ I_2 \\ I_3 \end{array} & \begin{bmatrix} [\quad] \\ [\quad] \\ \\ \end{bmatrix} \end{array}$$

Blackboard

Wacom Center   Tue 26 Dec 6:32 PM

You are screen sharing   Stop Share

(1) When to recommend?

→ High dimensional Data

Real time Recommendations

→   ↳ Very Popular, Very unpopular

Late Recommendation → local users

— Cluster

(2) Cold Start → Trending

Newly released

Influencers →