Introduction to Recommendation Engine

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2018/05/12

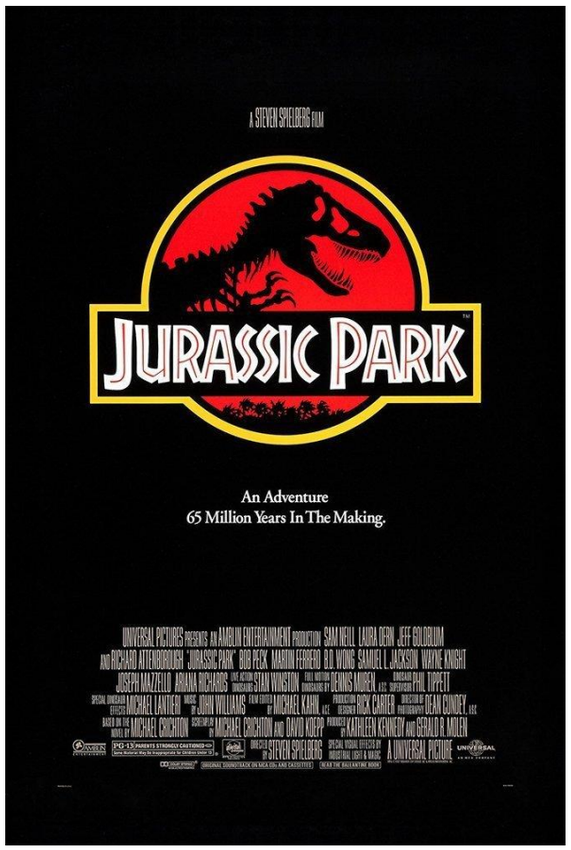
Prologue

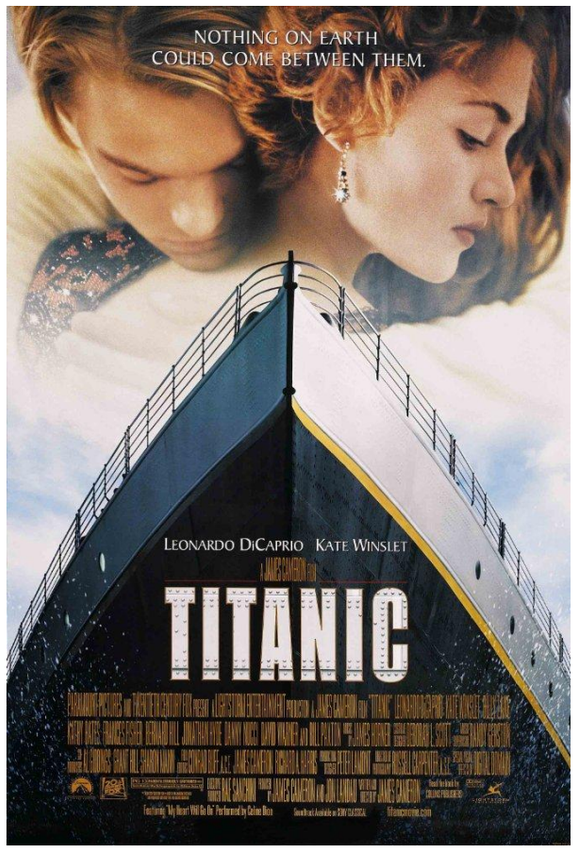
- People are increasing the reliance on conveniences such as e-commerce store or streaming entertainment.

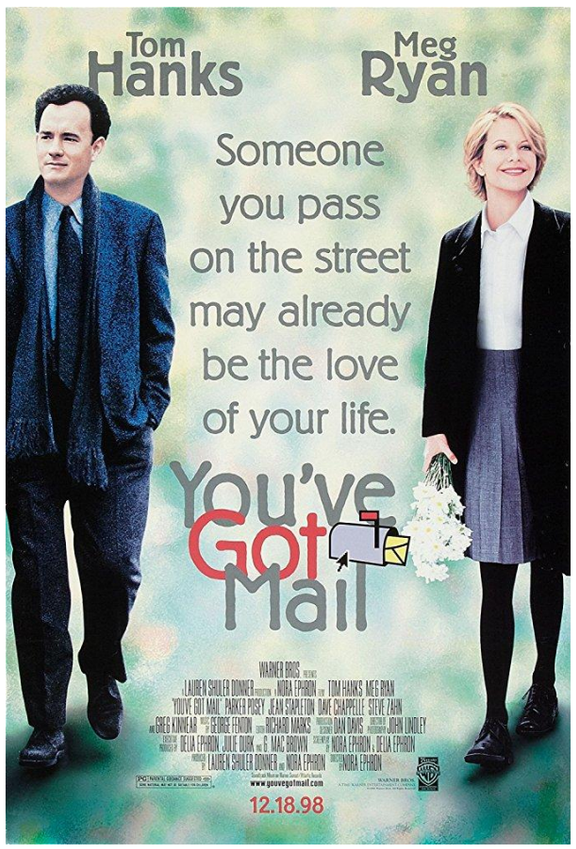
- “Guess” what the customers may like in advance, so to promote more things to sell and in turn generate more revenue.

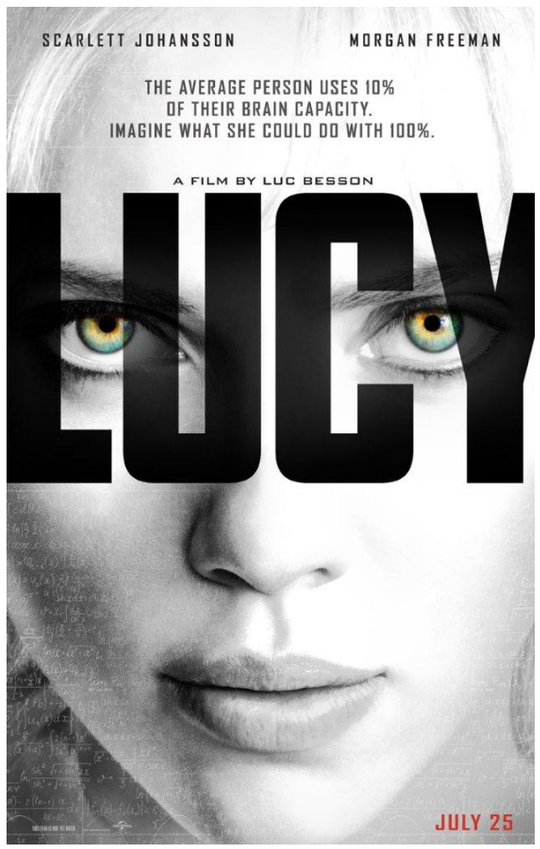
- A *recommendation engine (RE)* is any kind of model that can infer the relationship between users/items and make proper prediction for the users.

Gender	Male
Age	30
Prefer genre	Sci-fi, comedy, action
Prefer director	Steven Spielberg, Christopher Nolan, Michael Bay, James Cameron
Prefer actor/actress	Tom Hanks, Leonardo DiCaprio, Anne Hathaway, Scarlet Johansson









Content Filtering

- What we have just conducted is essentially one way of doing recommendation: *content filtering*.

- By building profiles for both the users and movies, we can provide recommendation by matching the *content* between the two groups, hence the name.

- Take a lot of efforts to build such profiles and many conditional settings to fit a person's taste. 

Gender	Male
Age	30
Prefer genre	Sci-fi, comedy, action
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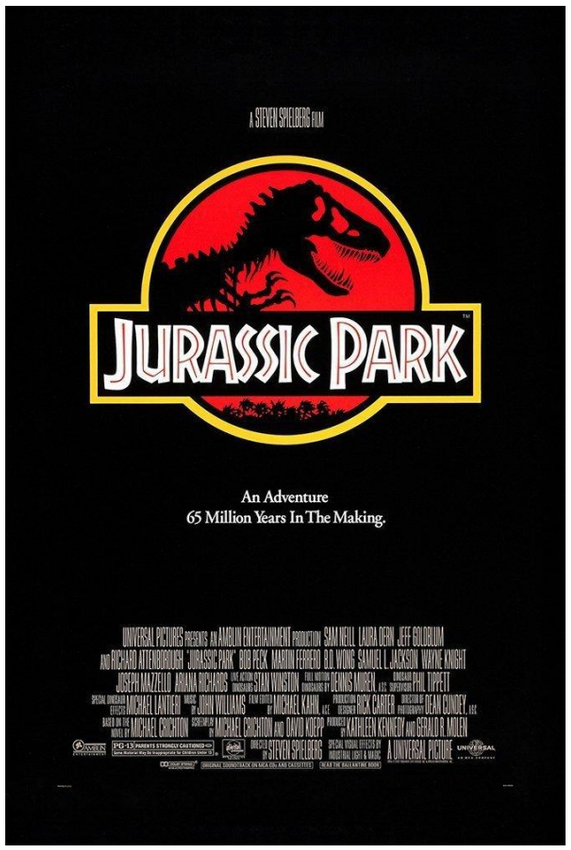
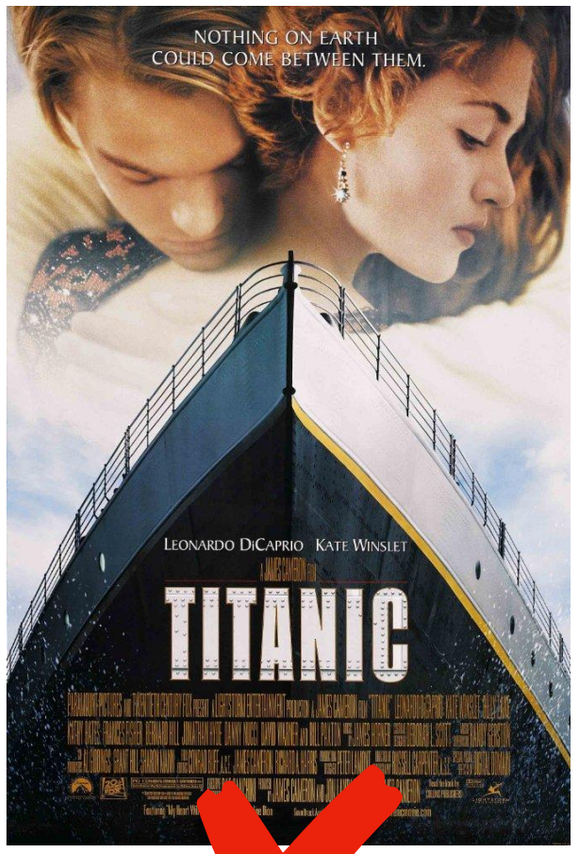
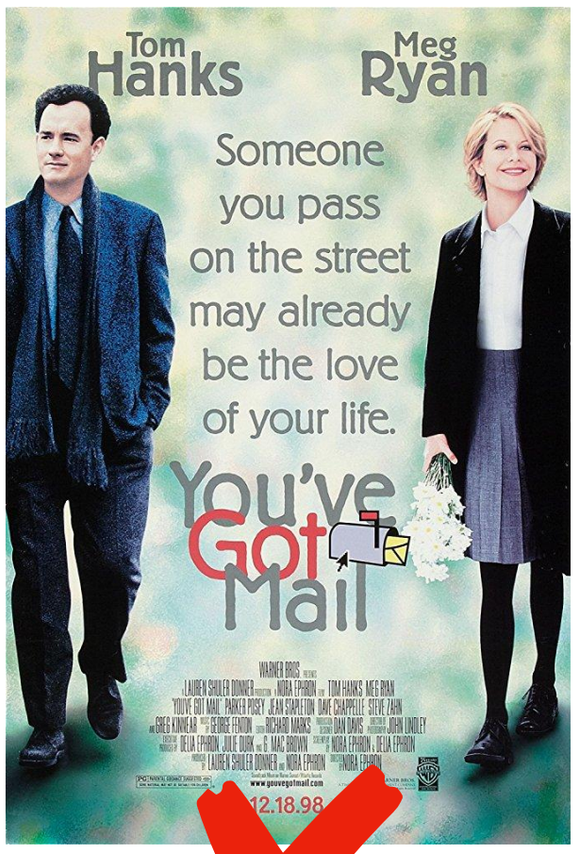
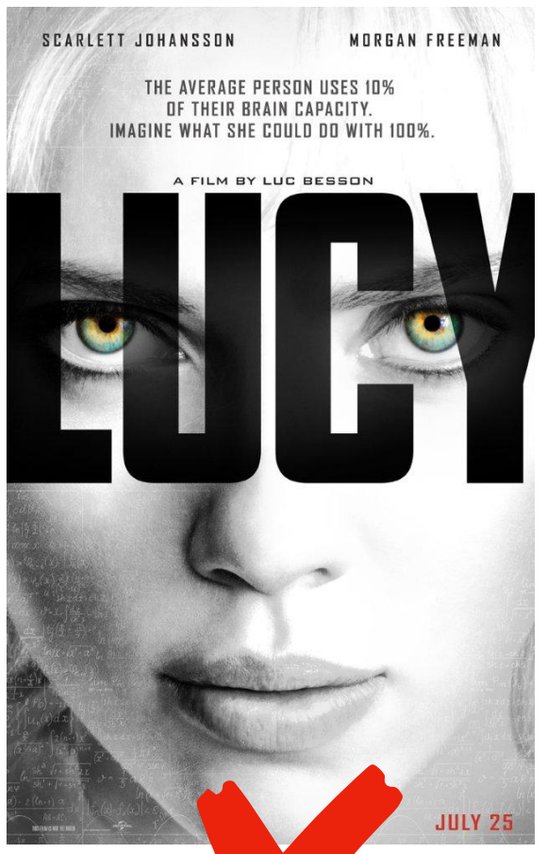








Strategies for Recommendation

- Beside *content filtering* we had just mentioned, there is another method called *collaborative filtering (CF)*.

- *CF* relies on past user behavior among a group of users (hence *collaborative*), so we aren't required to create profiles explicitly.

- The two primary areas of *CF* are the *neighborhood methods* (*memory-based*) and *latent factor models*.

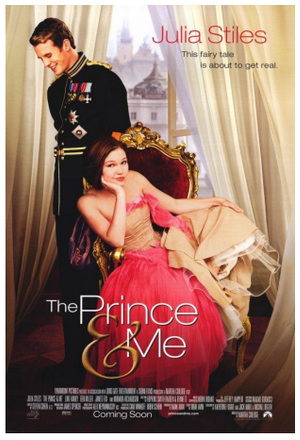

FROM THE DIRECTOR OF "BATMAN BEGINS" and "MEMENTO"
HUGH JACKMAN
CHRISTIAN BALE
SCARLETT JOHANSSON
MICHAEL CAINE
ARE YOU WATCHING CLOSELY?
THE PRESTIGE
OCTOBER 20


WELCOME TO A WORLD WITHOUT RULES.
BALE CAINE LEDGER OLDMAN ECKHART GYLLENHAAL FREEMAN
THE DARK KNIGHT
JULY 18


LEONARDO DICAPRIO
YOUR MIND IS THE SCENE OF THE CRIME.
INCEPTION
EXPERIENCE IT JULY 16 IN THEATERS AND IMAX

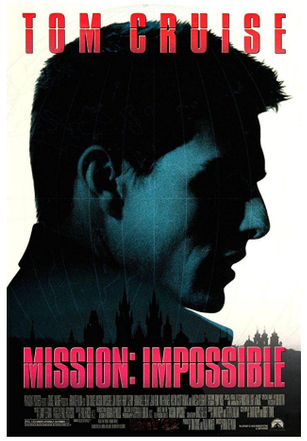

McCONAUGHEY HATHAWAY CHASTAIN CAINE
THE END OF EARTH WILL NOT BE THE END OF US.
INTERSTELLAR
NOVEMBER 7

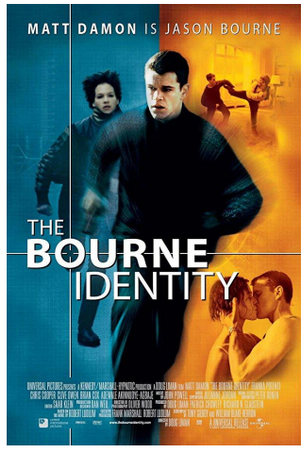

FROM THE DIRECTOR OF "PRETTY WOMAN" & "RUNAWAY BRIDE"
JULIE ANDREWS ANNE HATHAWAY
THE PRINCESS DIARIES
SHE ROCKS. SHE RULES. SHE REIGNS.
SUMMER 2001


Julia Stiles
This fairy tale is about to get real.
The Prince & Me
Coming Soon


RICHARD GERE
JULIA ROBERTS
PRETTY WOMAN
She walked off the street, into his life and stole his heart.

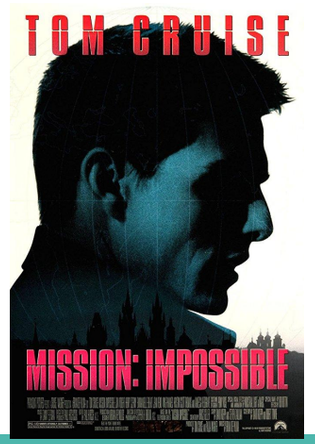

jennifer lopez
ralph fiennes
maid in manhattan
December 13... love checks in

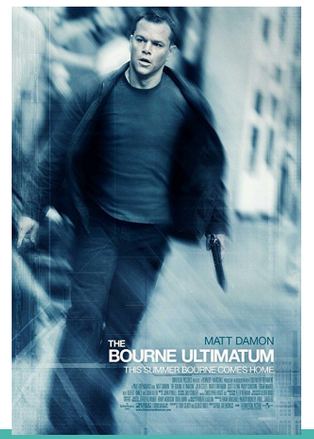

TOM CRUISE
MISSION: IMPOSSIBLE


MATT DAMON IS JASON BOURNE
THE BOURNE IDENTITY


CASINO ROYALE
NOVEMBER 17

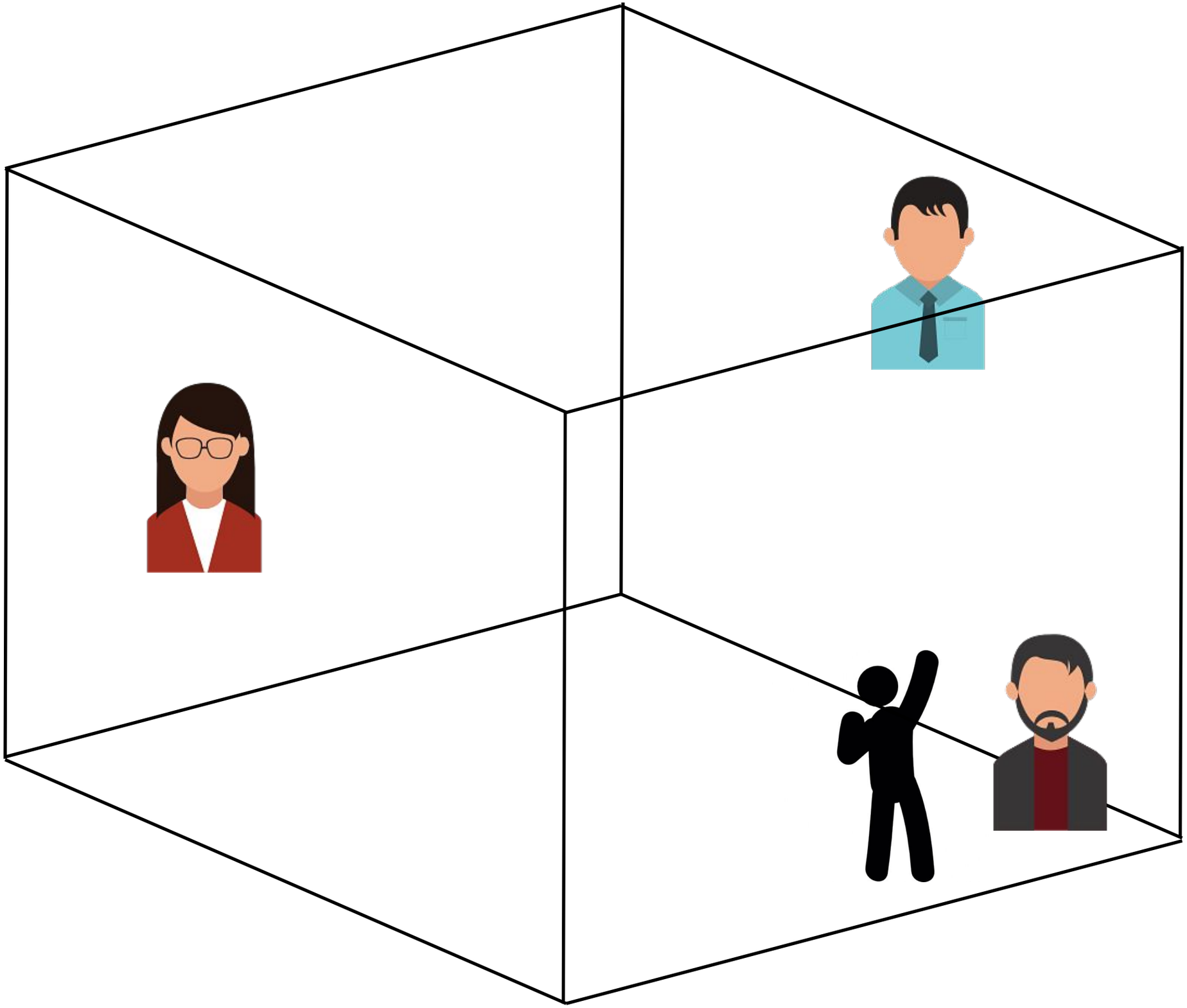

COLIN FIRTH SAMUEL L. JACKSON MICHAEL CAINE
FROM THE DIRECTOR OF X-MEN: FIRST CLASS
Kingsman
THE SECRET SERVICE
FEBRUARY 13


TOM CRUISE
MISSION: IMPOSSIBLE


MATT DAMON
THE BOURNE ULTIMATUM
THIS SUMMER BOURNE COMES HOME


CASINO ROYALE
NOVEMBER 17


TOM CRUISE
MISSION: IMPOSSIBLE
ROGUE NATION
IN THEATERS AND IMAX JULY 31



User-based and Item-based CF

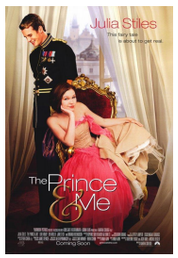
- For neighborhood methods, we have two primary types of algorithms: user-based and item-based.

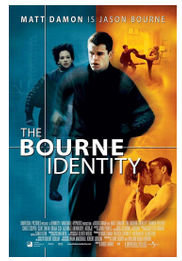
- In *user-based CF*, we group together users who gave similar ratings to the same set of items, whereby we could later use the ratings of a specific users to predict those of his/her peers.

- For *item-based CF*, we group the items instead.



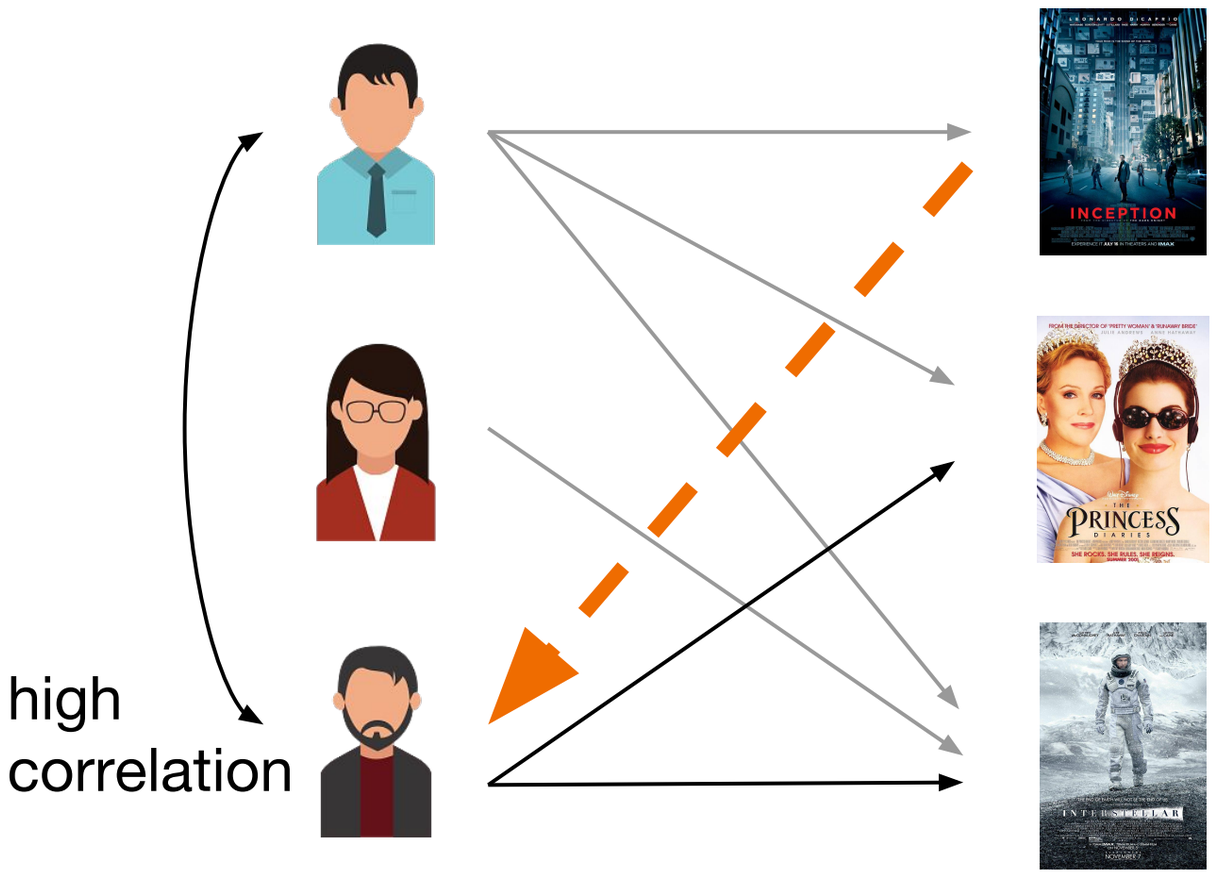





8.7	10	10	9	?	?	?	9	8	8.5
?	?	?	1	10	10	10	?	?	2
8	9	9	9	?	?	5	10	10	9.5

--- User-based CF --- Item-based CF



User-based filtering

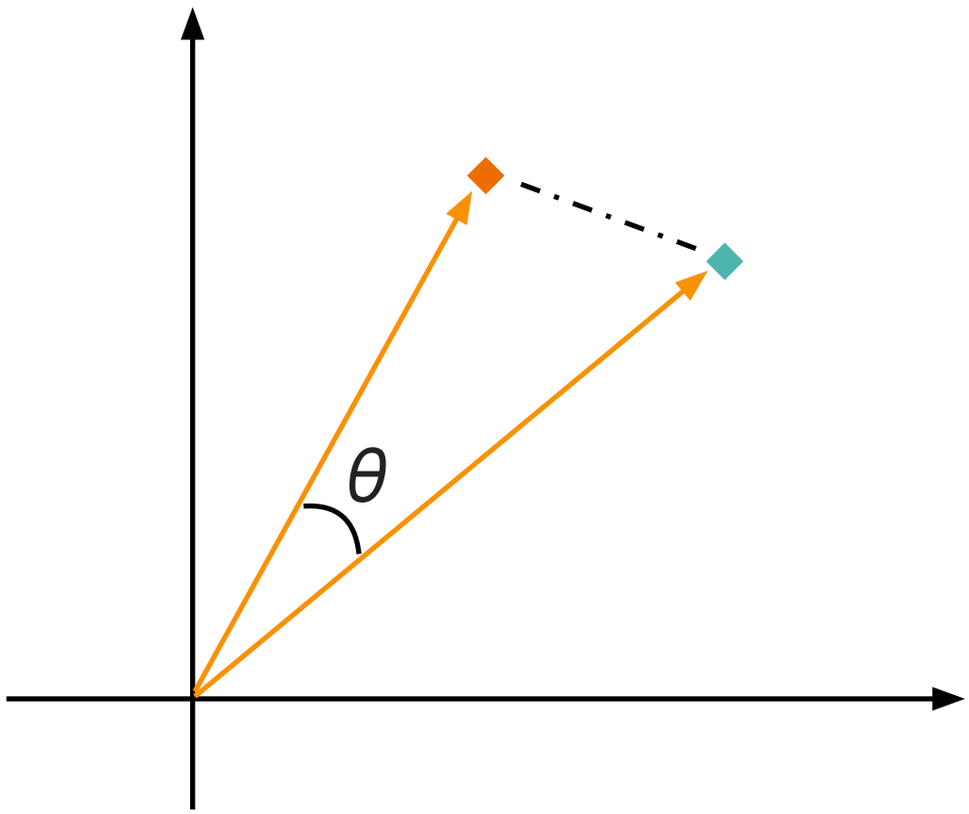
You may like it because your “friends” liked it.

Item-based filtering

You tend to like that item since you have liked those items.

Measuring Similarity

- To measure the similarity between users or items, we can use metrics like Euclidean distance or cosine similarity.



Euclidean distance: distance between points

$$\mathrm{d}(\mathbf{p}, \mathbf{q}) = \mathrm{d}(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

Cosine similarity: angle between vectors

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

Example: User-Based CF

	8.7	10	10	9	?	?	?	9	8	8.5	**23.96**
	?	?	?	1	10	10	10	?	?	?	**17.46**
	8	9	9	9	?	?	5	10	10	9.5	**24.94**

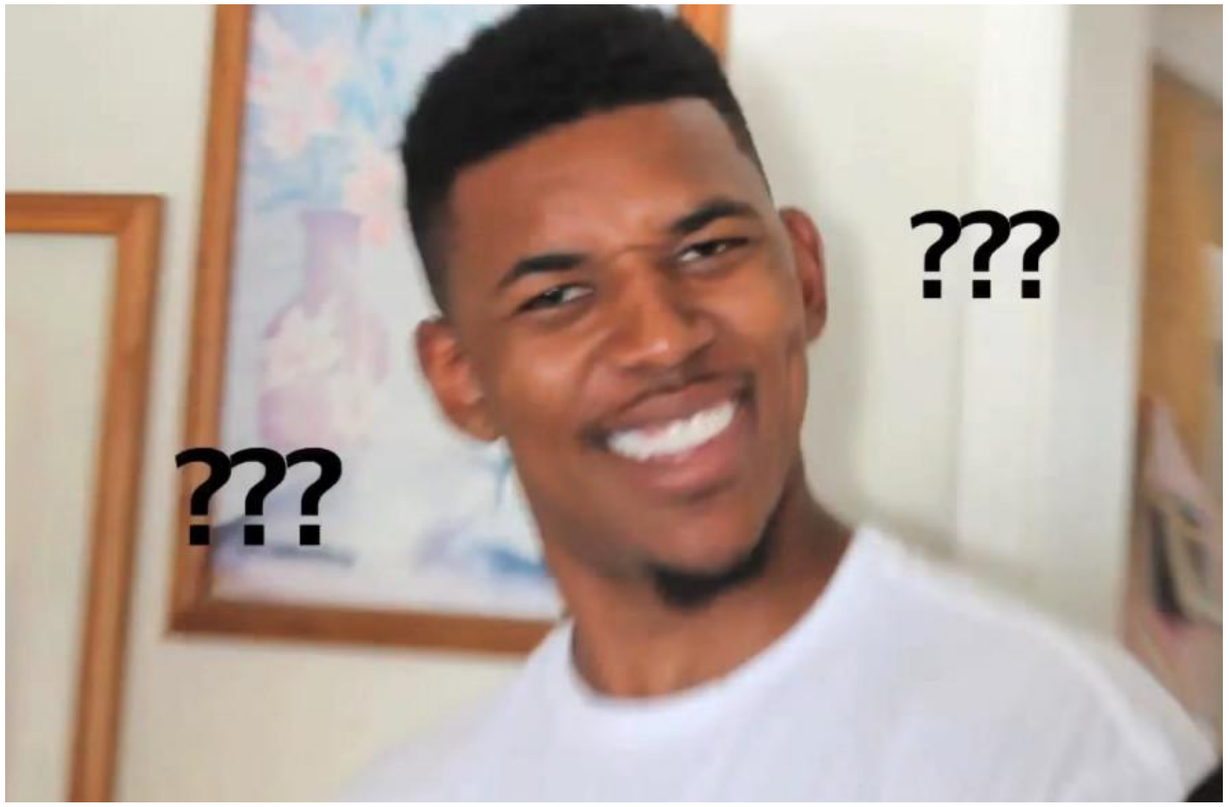
➔ cosine similarity:

$$: \frac{9 * 1 + 8.5 * 2}{23.96 * 17.46} = 0.062$$

$$: \frac{8.7 * 8 + 10 * 9 + 10 * 9 + 9 * 9 + 9 * 10 + 8 * 10 + 8.5 * 9.5}{23.96 * 24.94} = 0.973$$

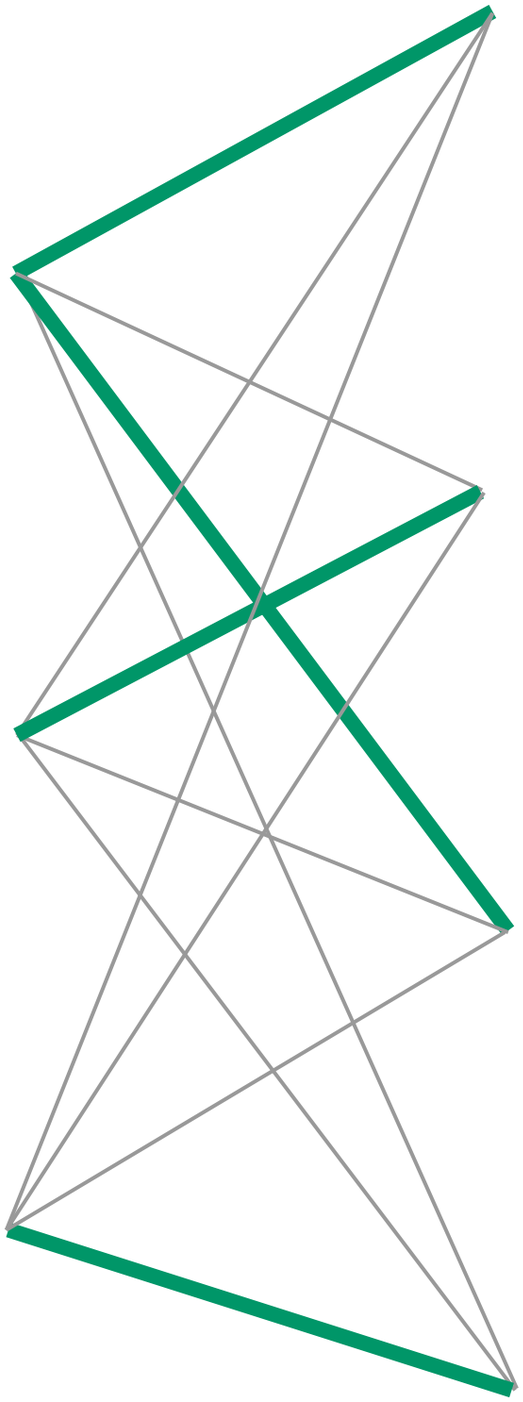
Latent Factor Models

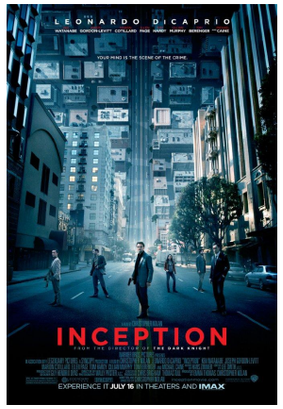
- Explain the rating by characterizing both users and items on a number of *latent factors* inferred from rating patterns.

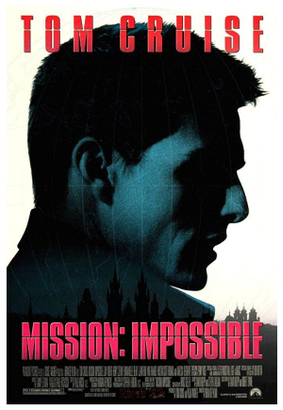


The factors are latent.

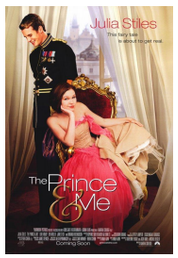
Not directly observable ...

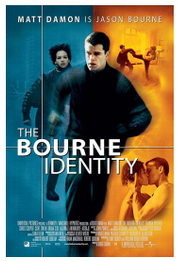






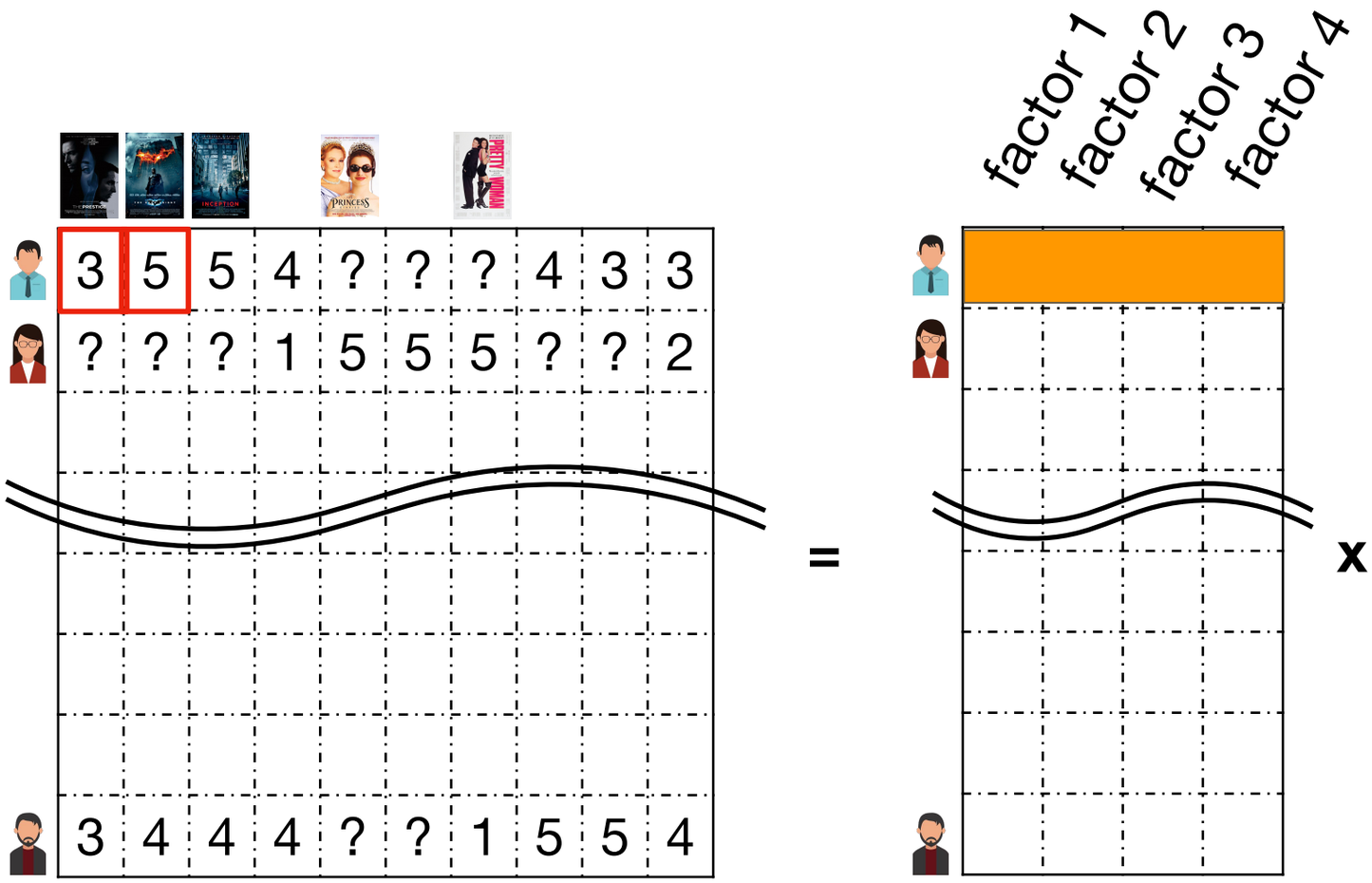
Not directly observable ...



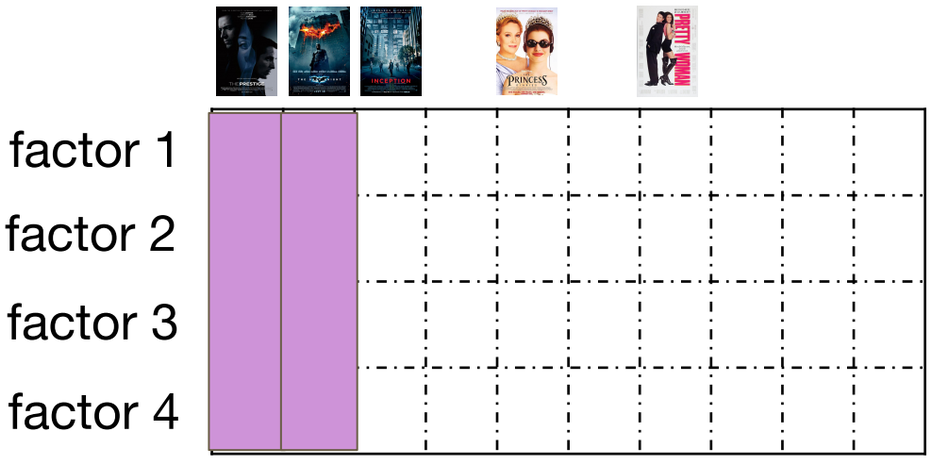


3	5	5	4	?	?	?	4	3	3
?	?	?	1	5	5	5	?	?	2
3	4	4	4	?	?	1	5	5	4

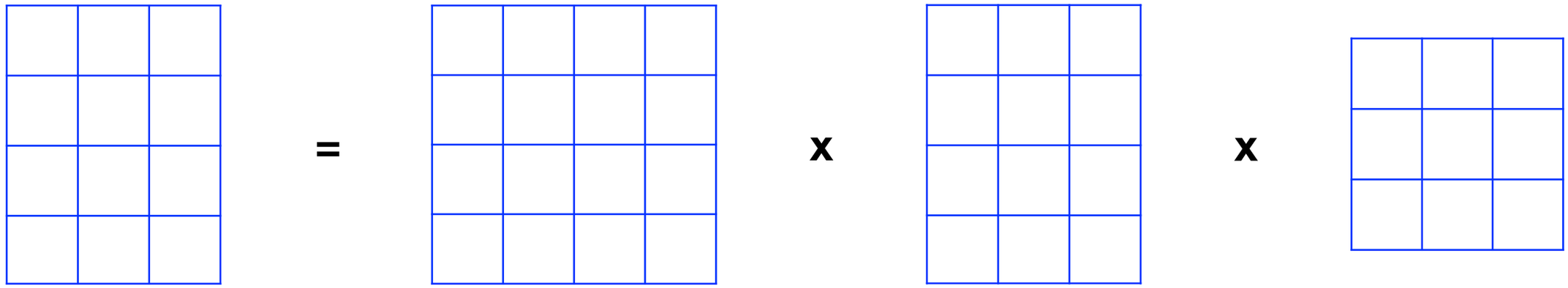
What is latent factor anyway?



x



Singular Value Decomposition (SVD)



$$A \quad U \quad \Sigma \quad V^T$$

That is (kind of) what SVD is

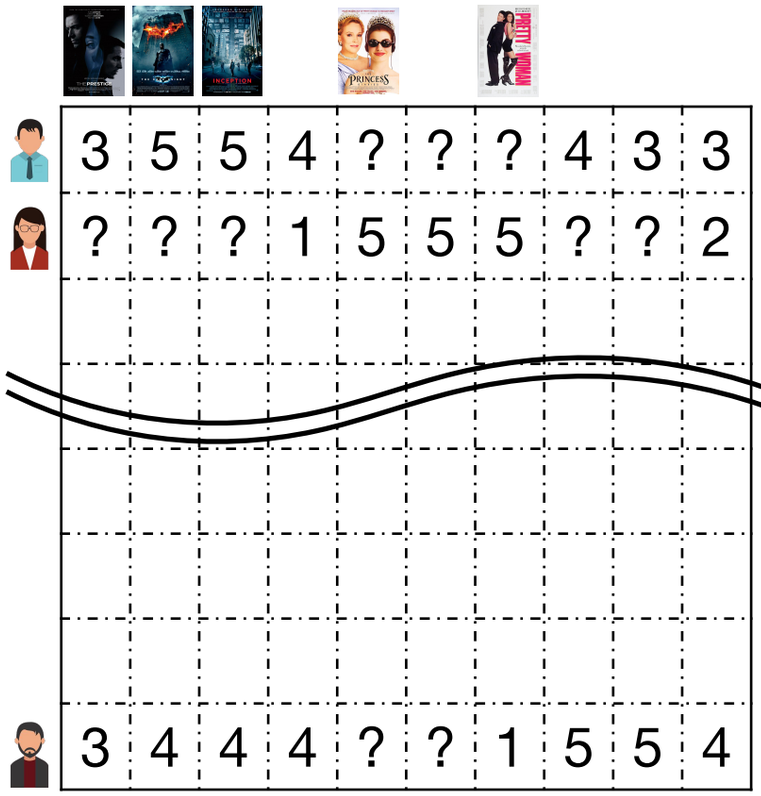
3	5	5	4	?	?	?	4	3	3
?	?	?	1	5	5	5	?	?	2
3	4	4	4	?	?	1	5	5	4

=

x

1	1	1	0	0	0	0	0	0	0
0	0	0	0	1	1	1	1	0	0
1	1	1	1	0	0	0	0	0	0
0	1	0	0	0	0	0	1	1	1

But in practice…



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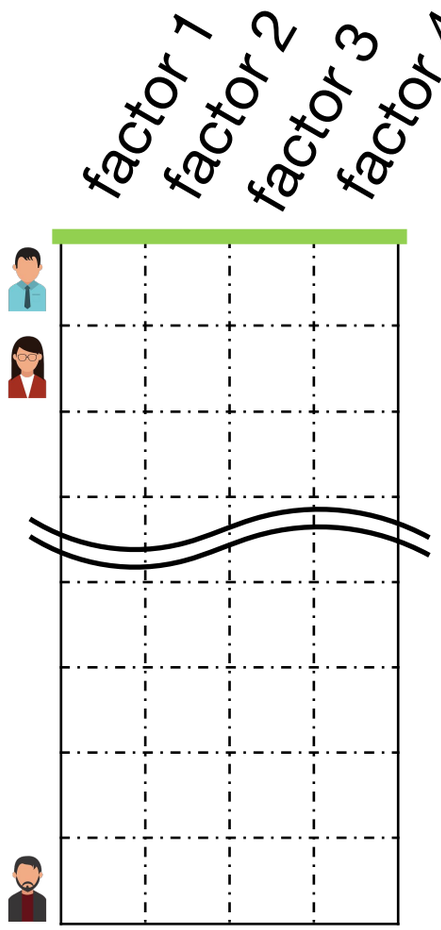
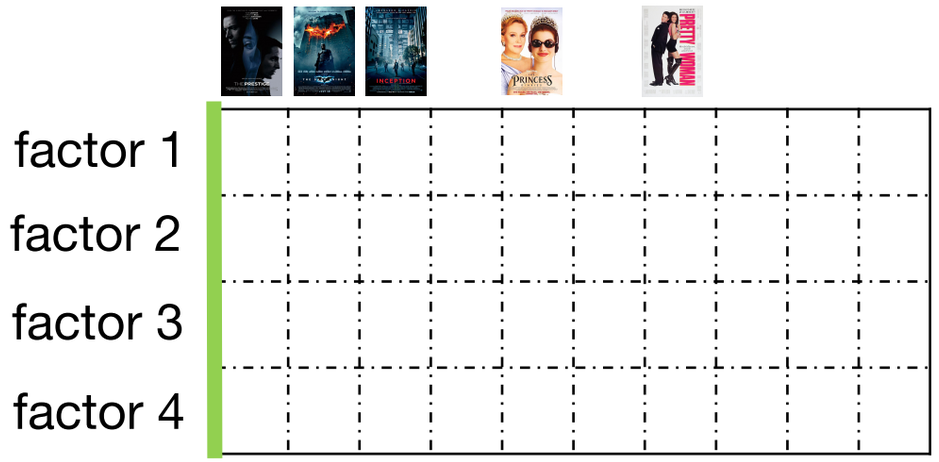


x



“Full of holes”

Can’t change the length of “contact”

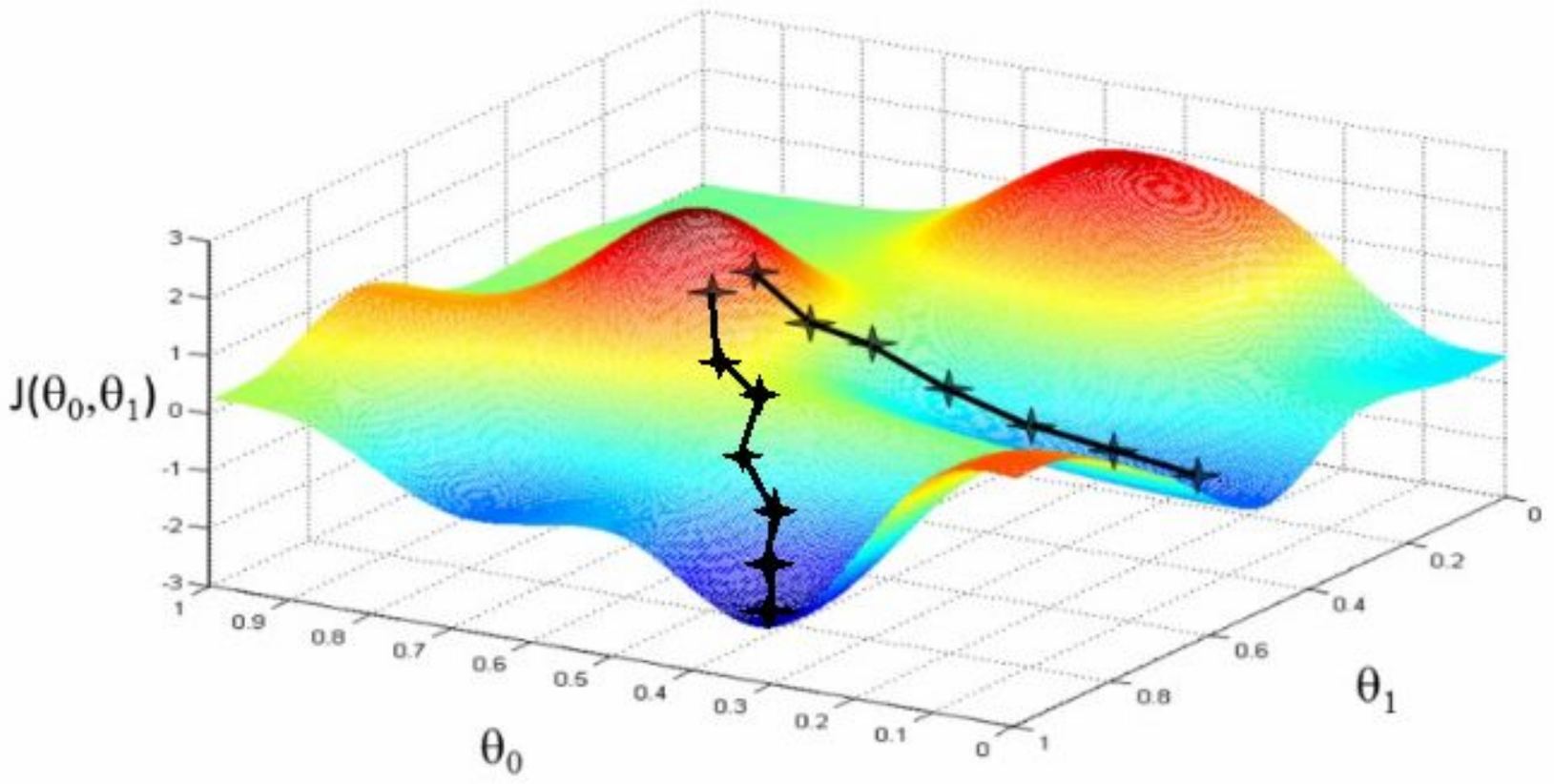
How to factor the matrix

- To perform matrix factorization for large matrices, we learn the entries through optimization methods such as *stochastic gradient descent* (SGD).

- Methods like *alternating least square* (ALS) are also used when computation can be parallelized.

- We are going to briefly introduce SGD for its popularity.

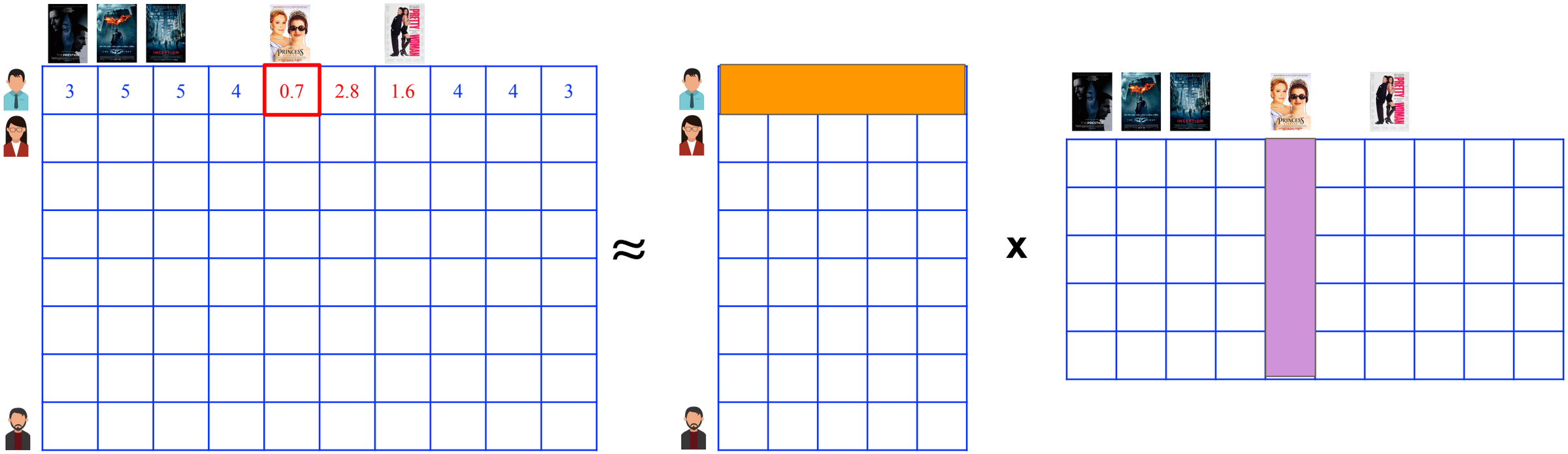
Goal:



Initialize these and tune the numbers!

x

Ok, I've got the matrices. Then what?



➔ Key points:

1. The approximate matrix will not be identical to the original.
2. The factor matrices will keep changing as long as there are users changing the rating (even if *you* stay inactive for a while).

Evaluating a model

- To evaluate how a machine learning model did, we use metrics such as *precision* and *recall*.

Predicted value \ Actual value	True	False
True	True positive (TP)	False positive (FP)
False	False negative (FN)	True negative (TN)

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP + FP}}$$

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP + FN}}$$

Scenario 1:

Predicted value \ Actual value	Have cancer	Safe
Have cancer	45	5
Safe	190	1000

$$\text{Precision} = \frac{45}{45 + 5} = 90\%$$

$$\text{Recall} = \frac{45}{45 + 190} = 19.15\%$$

Scenario 2:

Predicted value \ Actual value	Have cancer	Safe
Have cancer	200	800
Safe	35	205

$$\text{Precision} = \frac{200}{200 + 800} = 20\%$$

$$\text{Recall} = \frac{200}{200 + 35} = 85.11\%$$

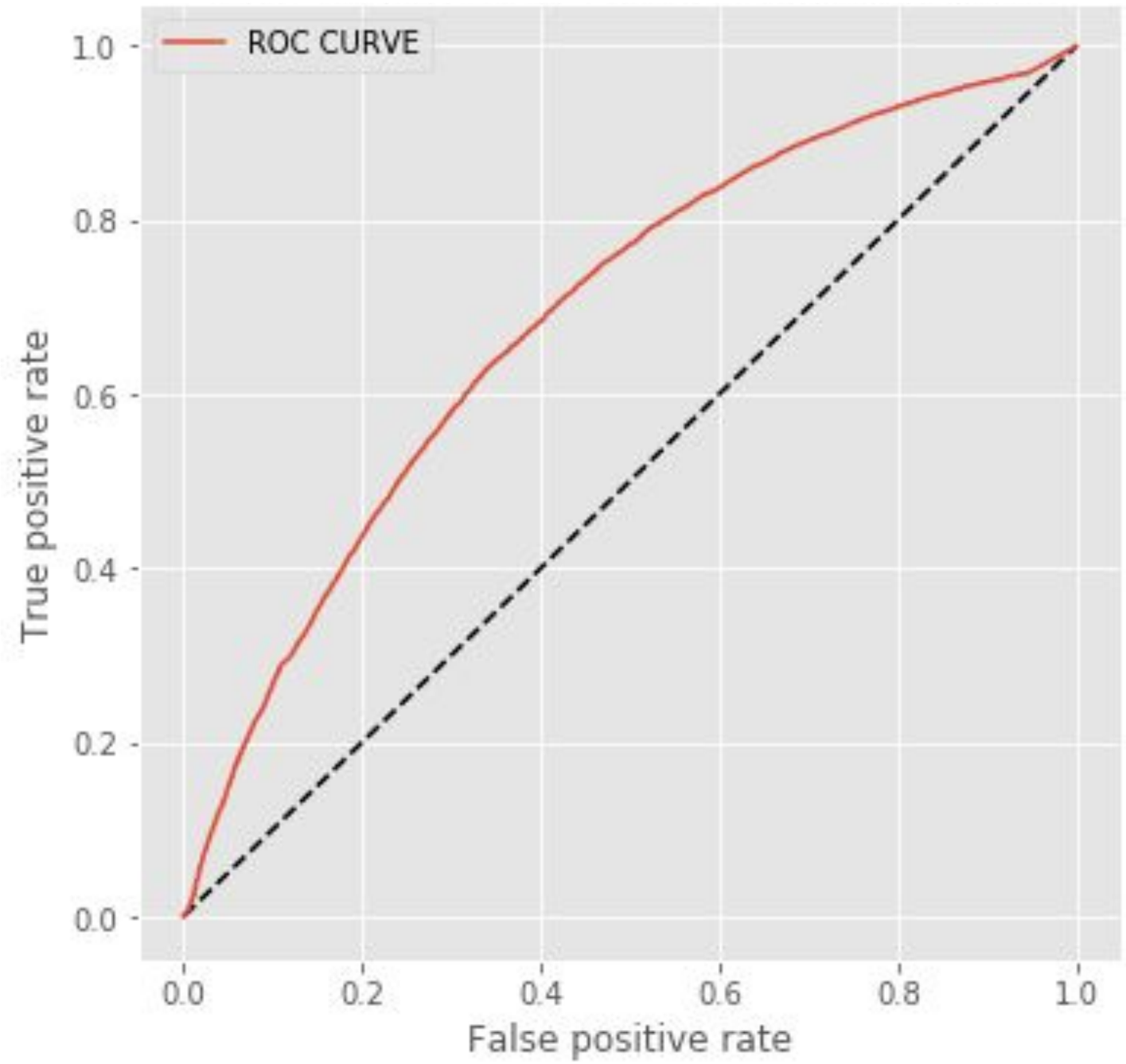
That's why we have F1-score

- F1-score (or F-score) is the harmonic mean between precision and recall:

$$F1 = 2 * \frac{1}{\frac{1}{Precision} + \frac{1}{Recall}} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Also, the ROC curve

Receiver Operating Characteristic (ROC) curve



Area Under Curve (AUC) = 0.6876

Let's evaluate the ranking as well

- A RE often delivers numerous outputs, while only a portion of them is most relevant to what the user really wants.

- We **rank our results** for the users, so the entries that the user would most likely selected would be near the top.

- How do we evaluate the *ranking* of results? 

鍾欣怡

Search

（鍾欣桐）

1

2

3

（鍾欣凌）

4

Relevance (0-3 scale):

1

Cumulative Gain: 1 + 3 + 3 + 1 = 10
(@ rank 4)

Discounted Cumulative Gain (DCG):
(@ rank *p*)

$$\sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)}$$

3

$$\frac{1}{\log_2(1+1)} + \frac{3}{\log_2(2+1)} + \frac{3}{\log_2(3+1)} + \frac{1}{\log_2(4+1)} = 4.824$$

3

$$\frac{3}{\log_2(1+1)} + \frac{3}{\log_2(2+1)} + \frac{1}{\log_2(3+1)} + \frac{1}{\log_2(4+1)} = 5.824$$

1

Normalized DCG:
(@ rank *p*)

$$\frac{DCG_p}{IDCG_p}, \quad \mathrm{IDCG_p} = \sum_{i=1}^{|REL|} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$