MUSIC RECOMMENDATIONS

There are quite a few digital music services available these days





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 $PANDORA^*$







Users of these services would be delighted with the huge variety to choose from





But often find it difficult to Sift through the variety and identify things they would like





RECOMMENDATIONS HELP USERS

NAVIGATE THE MAZE OF THE MUSIC CATALOGUES
FIND WHAT THEY ARE LOOKING FOR
FIND ARTISTS THEY MIGHT LIKE, BUT DIDN'T KNOW OF



RECOMMENDATIONS HELP USERS

NAVIGATE THE MAZE OF ONLINE STORES

FIND WHAT THEY ARE LOOKING FOR

FIND ARTISTS THEY MIGHT LIKE, BUT DIDN'T KNOW OF



RECOMMENDATIONS HELP THESE SERVICES

SOLVE THE PROBLEM OF DISCOVERY



HOW?



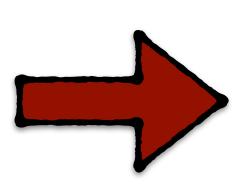
USING PATA

WHAT USERS BOUGHT

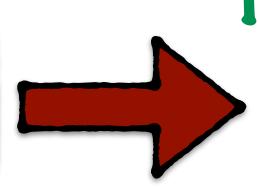
WHAT USERS BROWSED

WHAT USERS LISTENED TO

WHAT USERS RATED



ENGINE



TOP PICKS FOR YOU!!

IF YOU LIKE THIS, YOU'LL LOVE THAT!

RECOMMENDATION ENGINE

FILTER RELEVANT PRODUCTS

PREDICT WHAT RATING THE USER WOULD GIVE A PRODUCT

PREDICT WHETHER A USER WOULD BUY A PRODUCT

RANK PRODUCTS BASED ON THEIR RELEVANCE TO THE USER

TASKS PERFORMED BY RECOMMENDATION ENGINES

MOST RECOMMENDATION ENGINES USE A TECHNIQUE CALLED

COLLABORATIVE FILTERING

COLLABORATIVE FILTERING

HOW POES THAT WORK?

HOW DO YOU NORMALLY FIND

A MOVIE TO WATCH?

A RESTAURANT TO GO TO?

AN ARTIST TO CHECK OUT?

A BOOK TO READ?



THESPHENISHSWIN

COLLABORATIVE FILTERING

HOW POES THAT WORK?

THE BASIC PREMISE IS THAT

IF 2 USERS HAVE THE SAME OPINION ABOUT A BUNCH OF PRODUCTS

THEY ARE LIKELY TO HAVE THE SAME OPINION ABOUT OTHER PRODUCTS TOO

COLLABORATIVE FILTERING IS A GENERAL TERM

FOR ANY ALGORITHM THAT RELIES ONLY ON USER BEHAVIOR (HISTORY, RATINGS, SIMILAR USERS ETC)

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THIS IS AS OPPOSED TO CONTENT BASED FILTERING (WHICH USES PRODUCT ATTRIBUTES LIKE GENRE, DESCRIPTION ETC)

COLLABORATIVE FILTERING IS A GENERAL TERM

FOR ANY ALGORITHM THAT RELIES ONLY ON USER BEHAVIOR (HISTORY, RATINGS, SIMILAR USERS ETC)

CF ALGORITHMS NORMALLY PREDICT USERS' RATINGS FOR PRODUCTS THEY HAVEN'T YET RATED

RATING HERE IS A GENERAL TERM

IT CAN BE A RATING THE USER HAS EXPLICITLY GIVEN

EXPLICIT RATING NETFLIX ASKS USERS TO RATE A MOVIE ONCE THEY HAVE WATCHED IT

IT CAN BE BASED ON A PREFERENCE THE USER HAS SOMEHOW INDICATED

IMPLICIT RATING
TIMES THE USER LISTENED TO AN ARTIST

THERE ARE MANY MANY PIFFERENT ALGORITHMS TO PERFORM COLLABORATIVE FILTERING

1 POPULAR TECHNIQUE IS

LATENT FACTOR ANALYSIS

LATENT FACTOR ANALYSIS

IDENTIFY HIDDEN FACTORS THAT INFLUENCE A USER'S RATING

SOMETIMES THE FACTORS MIGHT TURN OUT TO HAVE MEANING (LIKE GENRE OR OVERALL POPULARITY)

OTHER TIMES, THEY MIGHT BE ABSTRACT FACTORS WITH NO REAL LIFE MEANING

LATENT FACTOR ANALYSIS

LET'S SAY YOU WERE POING THIS WITH MOVIES

AND THE HIDDEN FACTORS ARE

1. COMMERCIAL APPEAL
2. DRAMATIC VS COMEDIC NATURE

MOVIES ARE REPRESENTED USING THESE DESCRIPTORS

COMMERCIAL



USERS ARE REPRESENTED USING THE SAME DESCRIPTORS

JANANI WATCHED 10 MOVIES 7 COMMERCIAL, 9 DRAMA

COMEDY

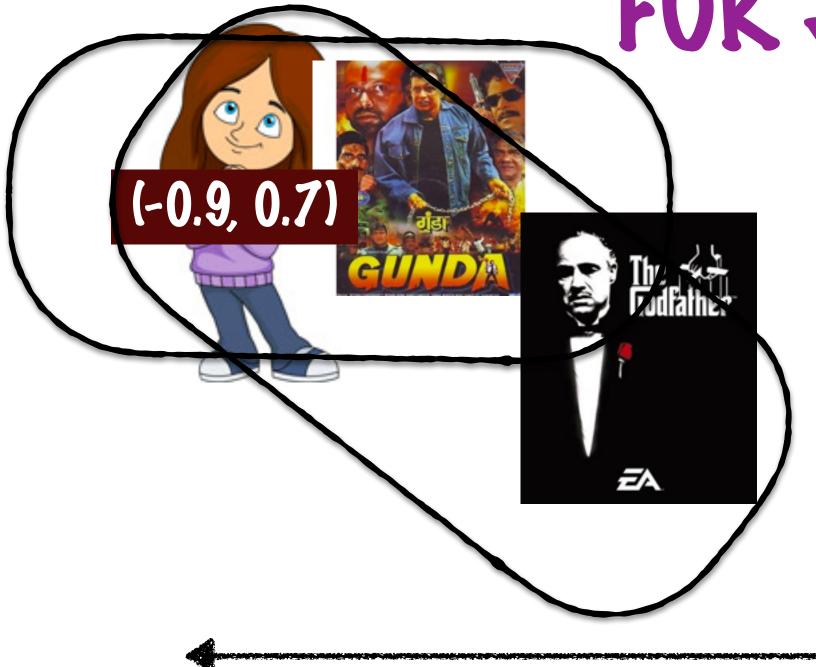


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DRAMA



RECOMMENDATIONS FOR JANANI

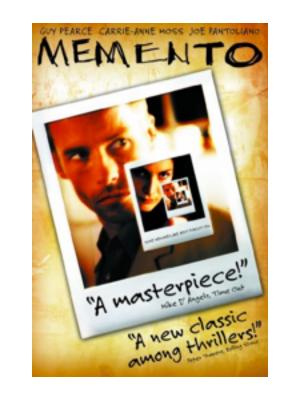


COMMERCIAL



COWEDA

DRAMA



SIEEDER

TO IPENTIFY HIPPEN FACTORS

YOU NEED A USER-PRODUCT-RATING MATRIX

USER 1

USER 2

USER 3

USER 4

••

USER N

PROV 1	PROV 2	PROV	3 PROV	4	PROV V
4	-	4	-	_	-
ı	3	4	-	-	-
5	3	2	~	-	5
2	ı	2	ı	ı	4
ı	į	į	4	-	-
	1	-	-	-	
4	3	4	_	-	5

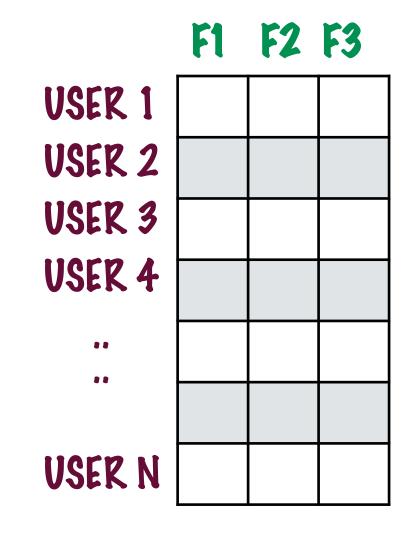
IT REPRESENTS USERS BY THEIR RATINGS FOR DIFFERENT PRODUCTS

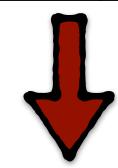
IT REPRESENTS USERS BY THEIR RATINGS FOR DIFFERENT PRODUCTS

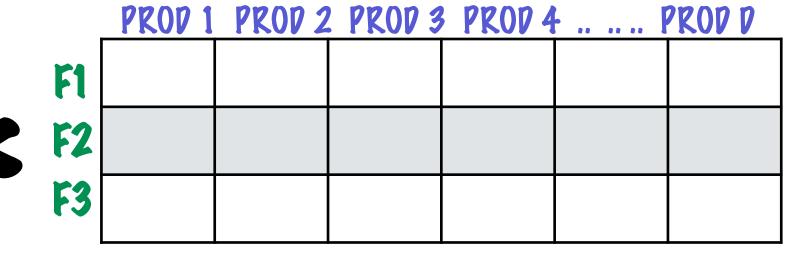
	IROVI	INVIZ	IKUV	IROVI		KUV V
JSER 1	4	-	4	-	-	-
JSER 2	ı	3	4	•	-	-
JSER 3	5	3	2	ı	ı	5
JSER 4	2	ı	2	ı	ı	4
••	ı	ı	ı	4	ı	ı
	-	1	-	-	ı	-
JSER N	4	3	4	•	ı	5

PROD 1 PROD 2 PROD 3 PROD 4

BREAK THIS POWN TO IDENTIFY THE HIPPEN FACTORS





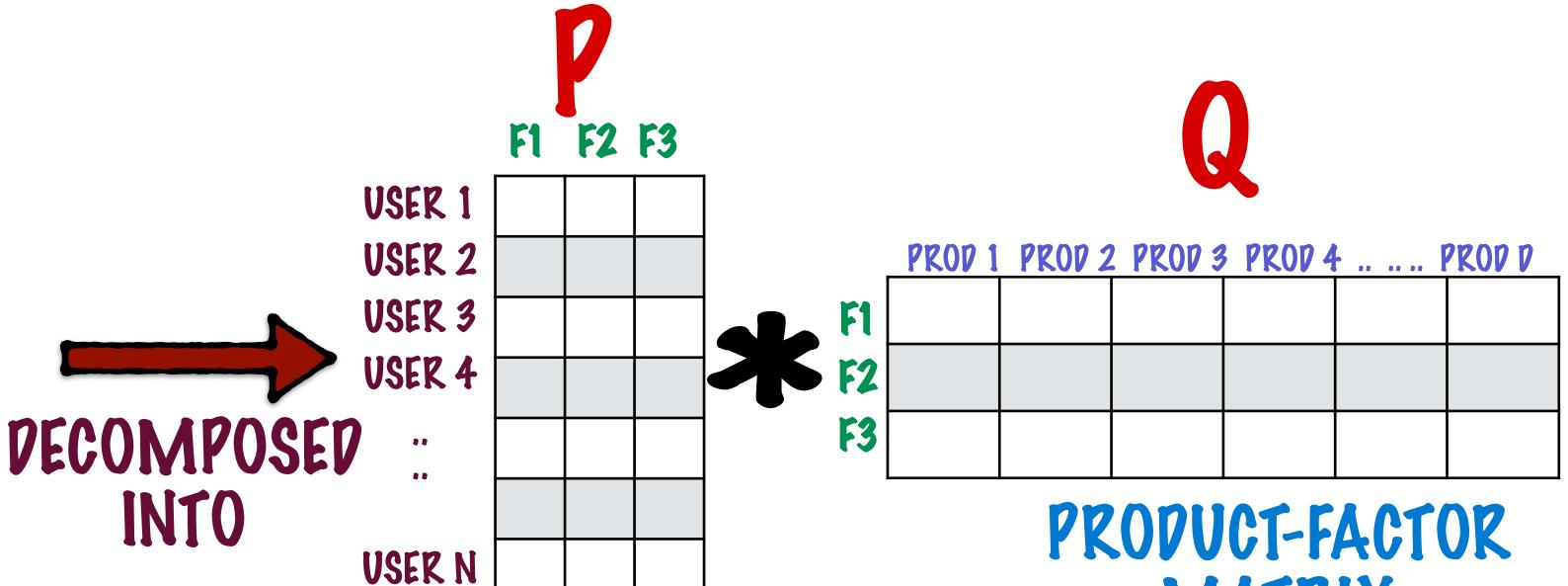


PRODD

USER-PROP RATING MATRIX

PROD 1 PROD 2 PROD 3 PROD 4 PROD D

_						
USER 1	4	ı	4	ı	ı	ı
USER 2	ı	3	4	1	ı	-
USER 3	5	3	2	•	•	5
USER 4	2	ı	2		-	4
••	1	•	•	4	1	-
•	1	1	ı	1	ı	ı
USER N	4	3	4	•	•	5

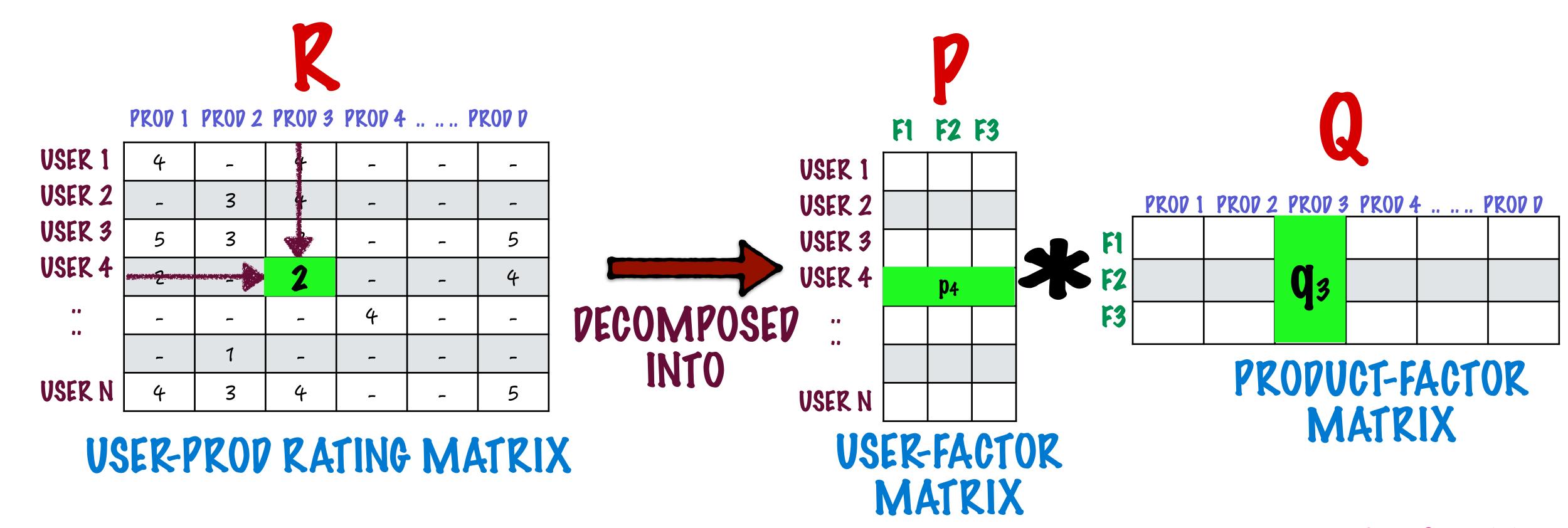


USER-FACTOR MATRIX

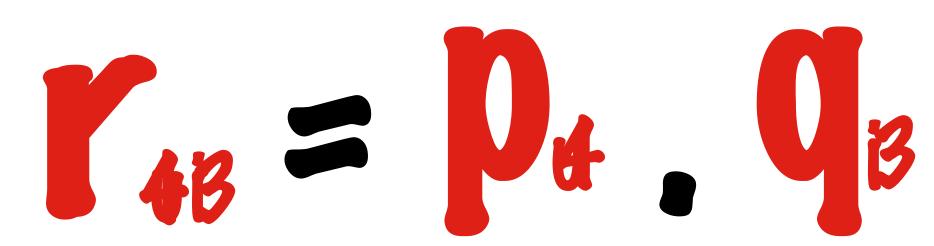
EACH ROW IS A USER DESCRIBED BY THEIR INTEREST IN THE HIDDEN FACTORS

PRODUCT-FACTOR MATRIX

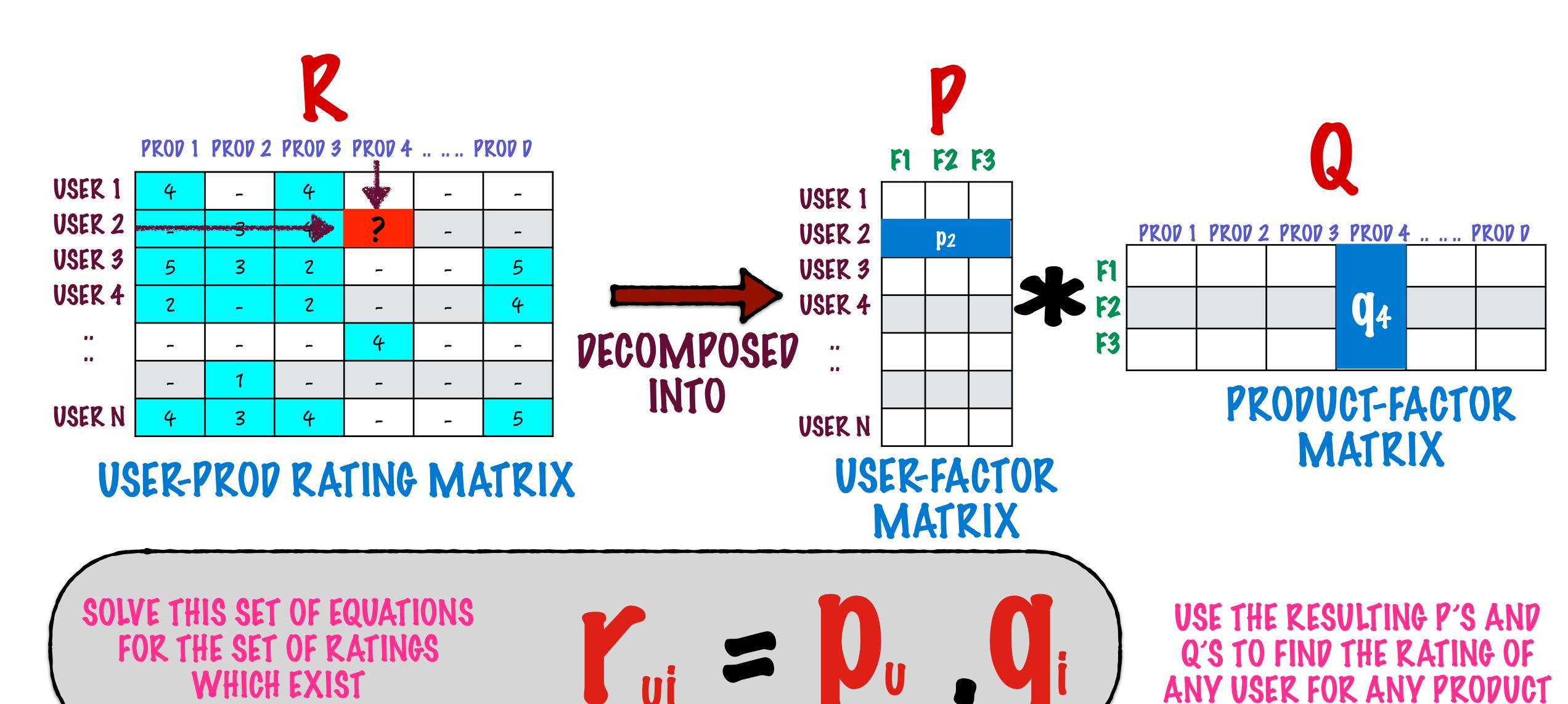
EACH COLUMN IS A PRODUCT DESCRIBED BY ITS RELEVANCE TO THE HIDDEN FACTORS



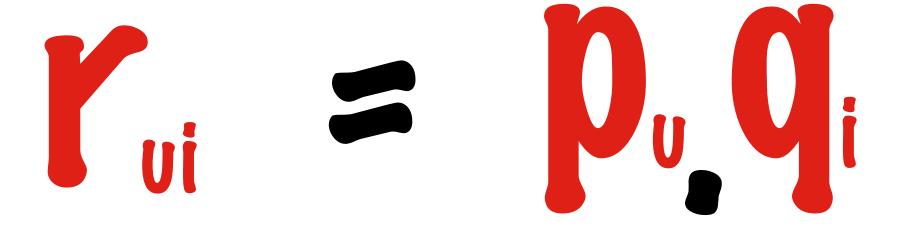
EACH RATING HAS TO BE DECOMPOSED INTO 2 VECTORS



YOU CAN WRITE SUCH AN EQUATION FOR EACH RATING OF AN PROD i BY USER u



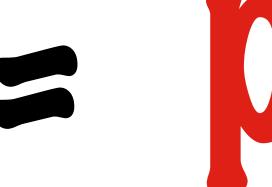
SOLVE THIS SET OF EQUATIONS FOR THE SET OF RATINGS WHICH EXIST (TRAINING SET)



ONCE WE'VE SOLVED THIS SET OF EQUATIONS WE CAN PREDICT WHAT RATING THE USER WOULD GIVE TO ANY PRODUCT

SOLVE THIS SET OF EQUATIONS FOR THE SET OF RATINGS WHICH EXIST (TRAINING SET)

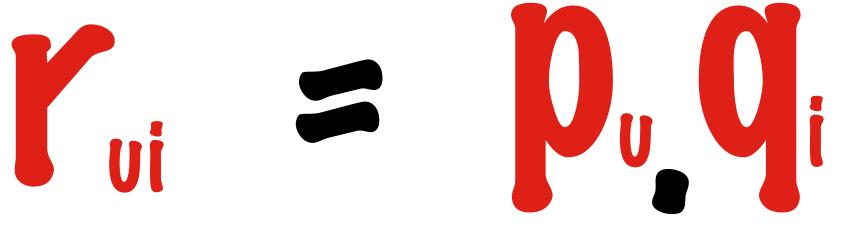




SORT THE PREDICTED RATINGS IN PESCENDING ORDER TO FIND THE TOP RECOMMENDATIONS FOR A USER

SOLVE THIS SET OF EQUATIONS FOR THE SET OF RATINGS WHICH EXIST (TRAINING SET)





ALTERNATING LEAST SQUARES

IS A TECHNIQUE TO SOLVE THIS SET OF EQUATIONS

ALTERNATING LEAST SQUARES

ALS IS A STANDARD OPTIMIZATION TECHNIQUE THAT CAN BE APPLIED TO MANY PROBLEMS

SPARK'S MILIB HAS A BUILT-IN CLASS FOR APPLYING ALS ON ANY USER-PRODUCT-RATING MATRIX

MLLIB COMPLETELY ABSTRACTS AWAY THE TECHNICAL IMPLEMENTATION PETAILS OF ALS