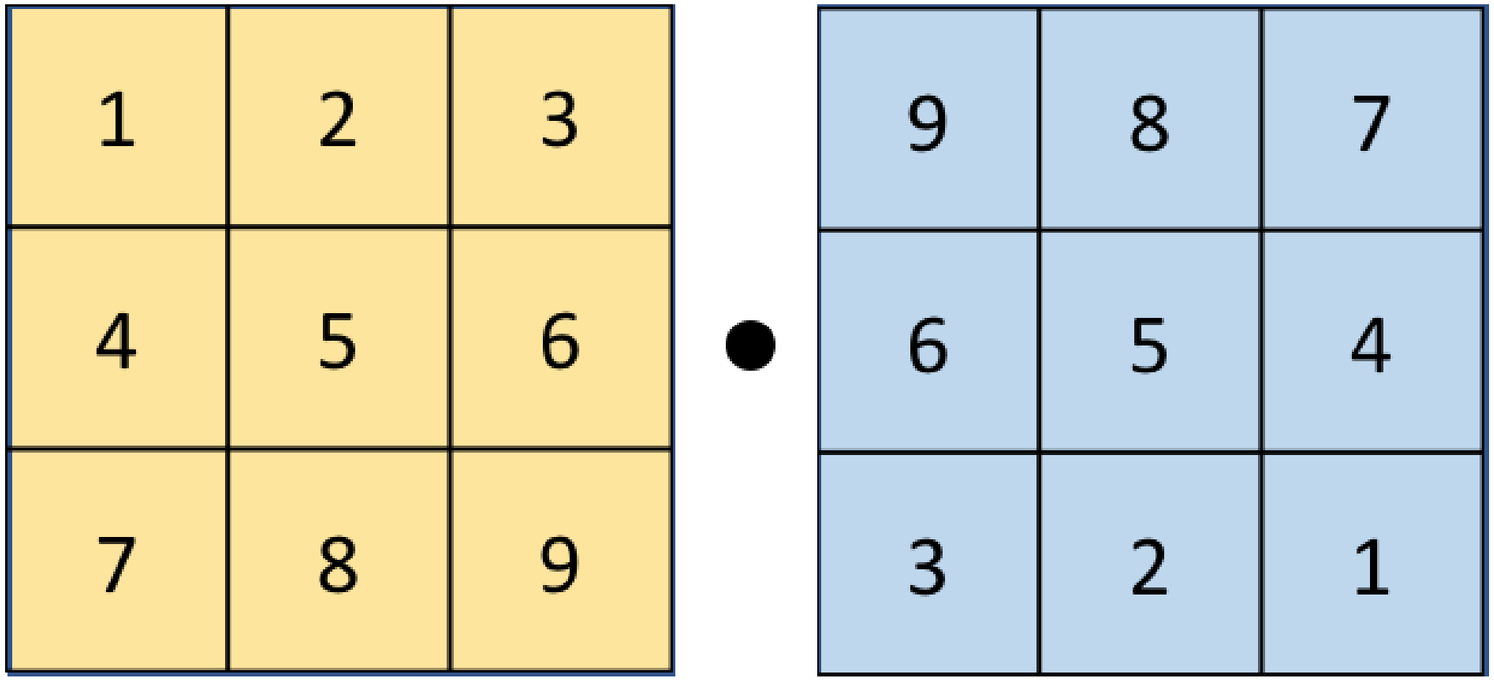
Matrix Multiplication

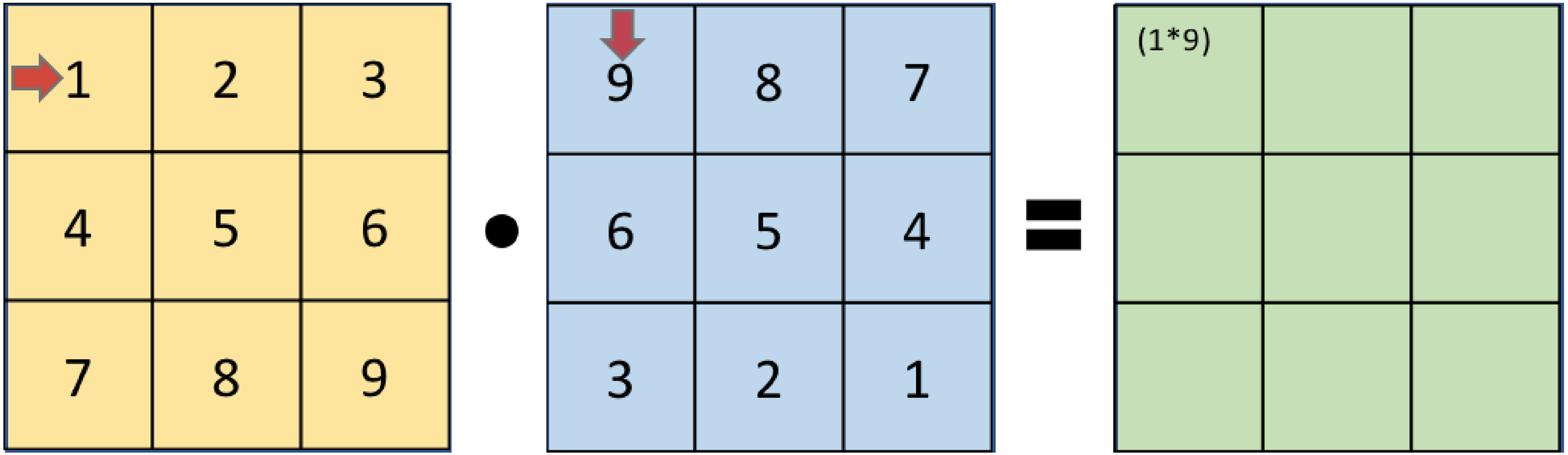
BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Jamen Long
Data Scientist at Nike

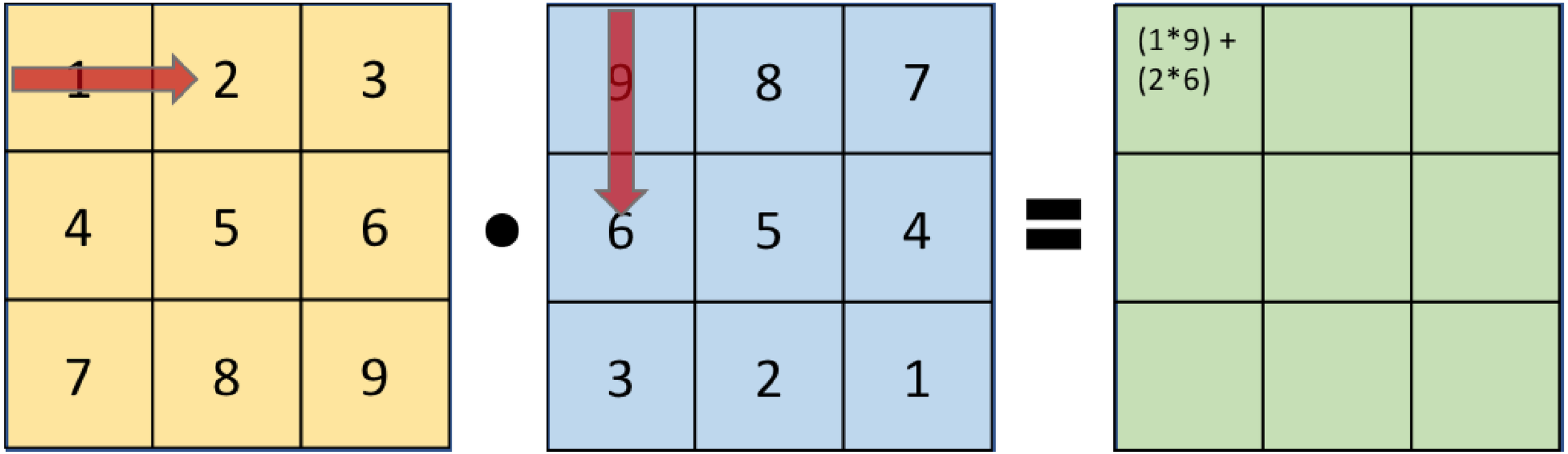
Matrix Multiplication



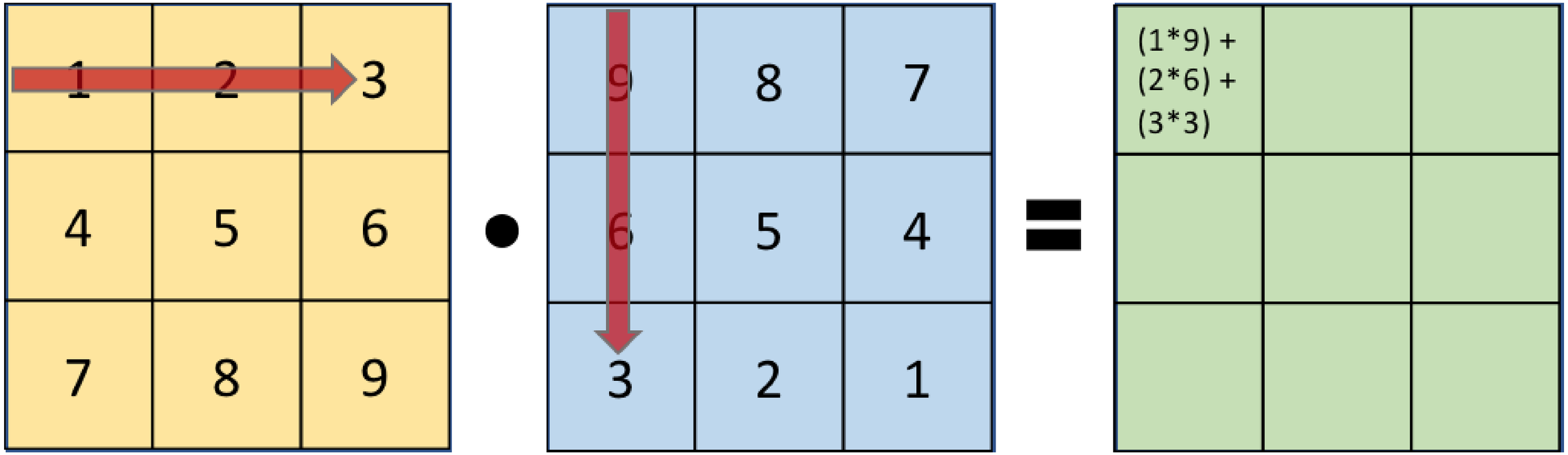
Matrix Multiplication



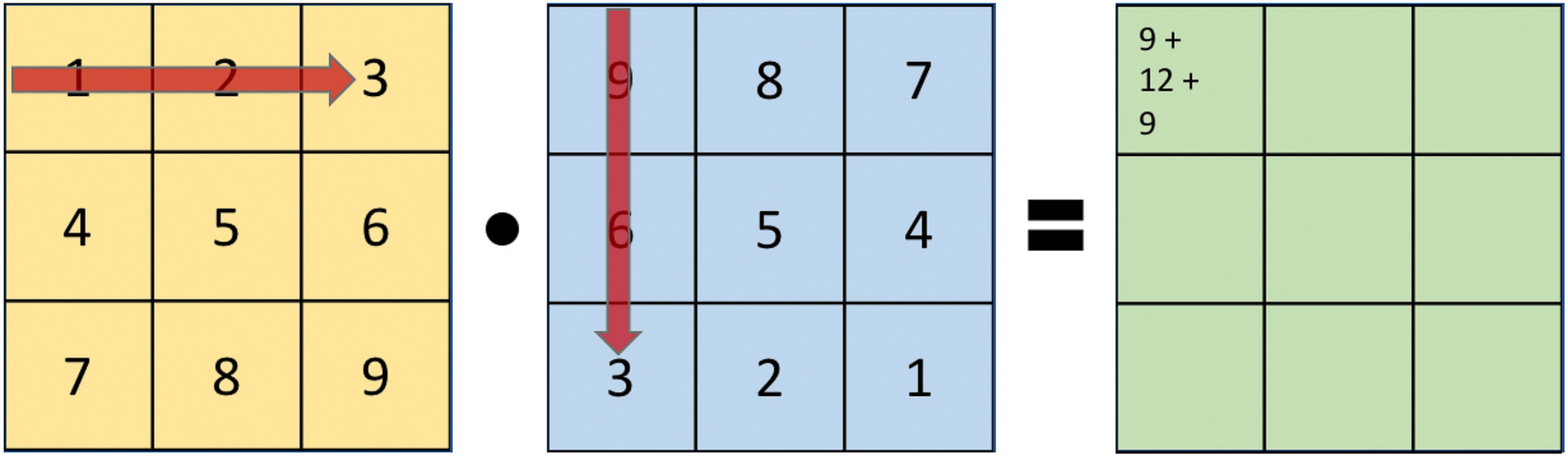
Matrix Multiplication



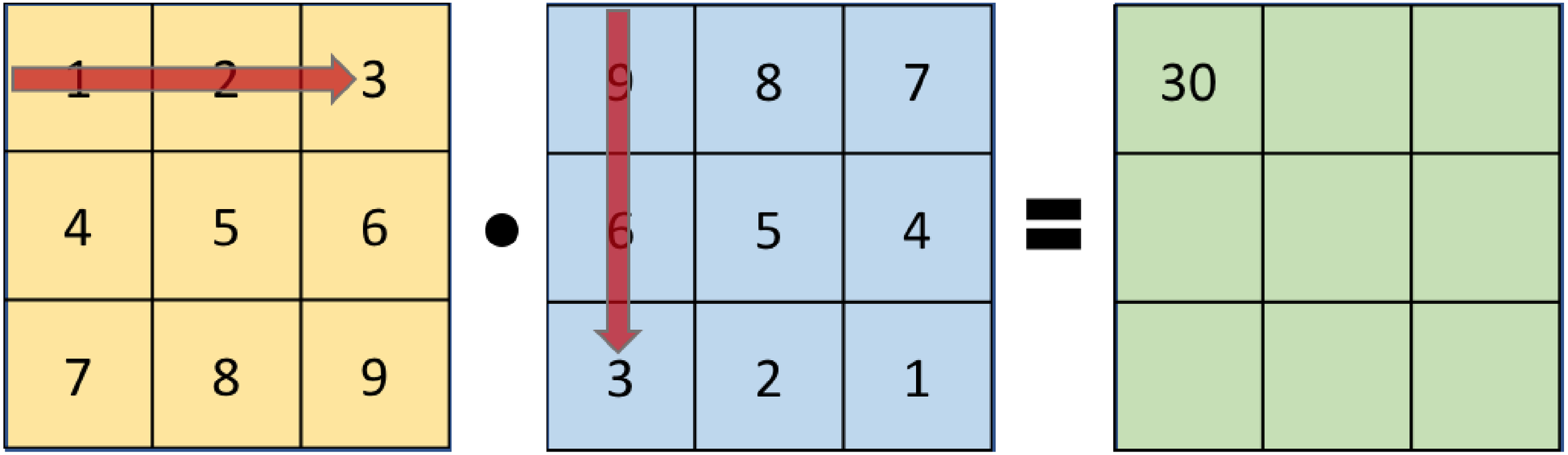
Matrix Multiplication



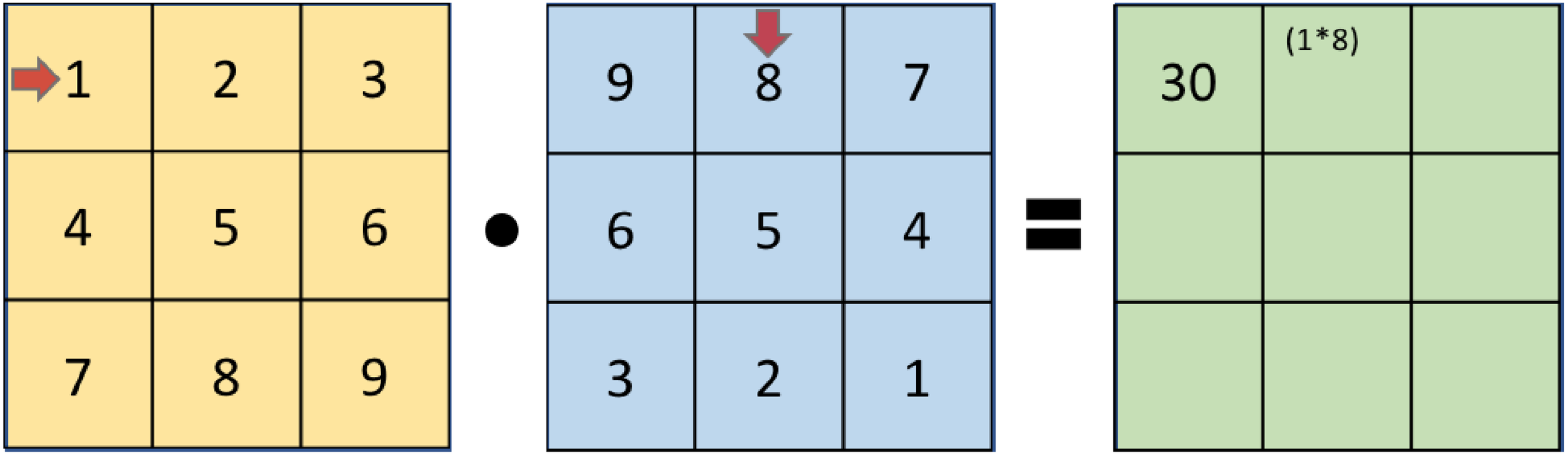
Matrix Multiplication



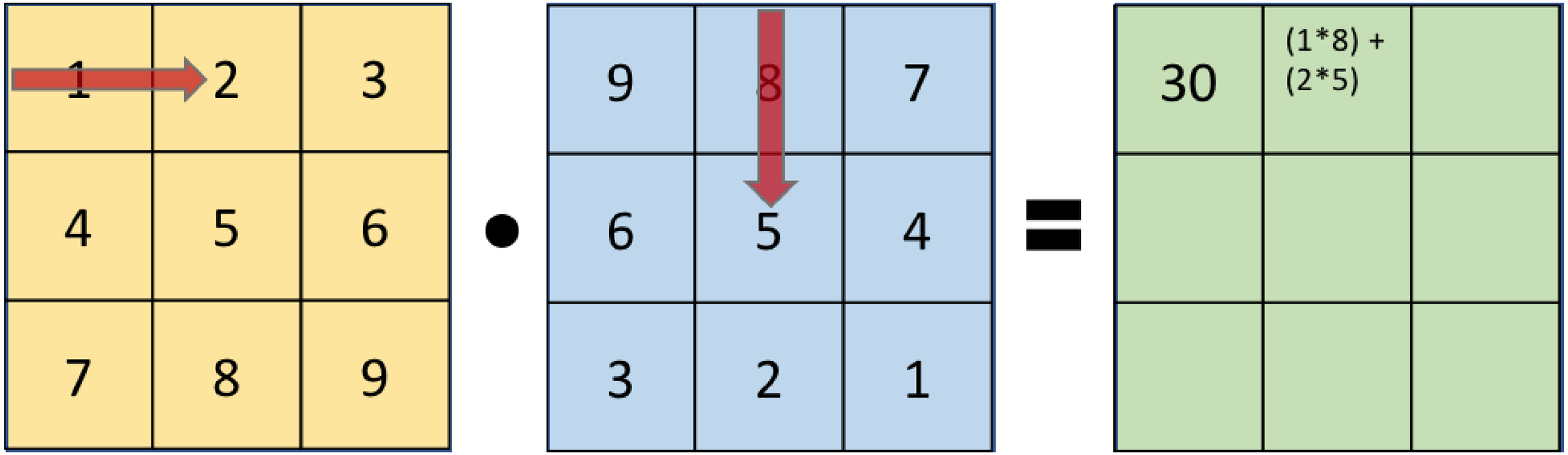
Matrix Multiplication



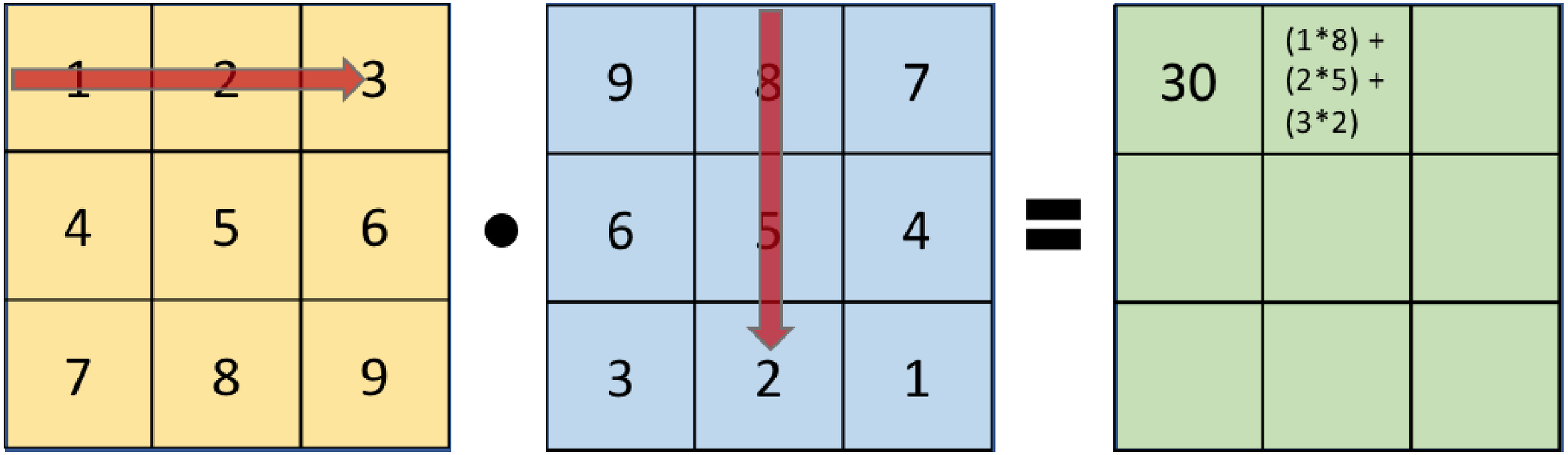
Matrix Multiplication



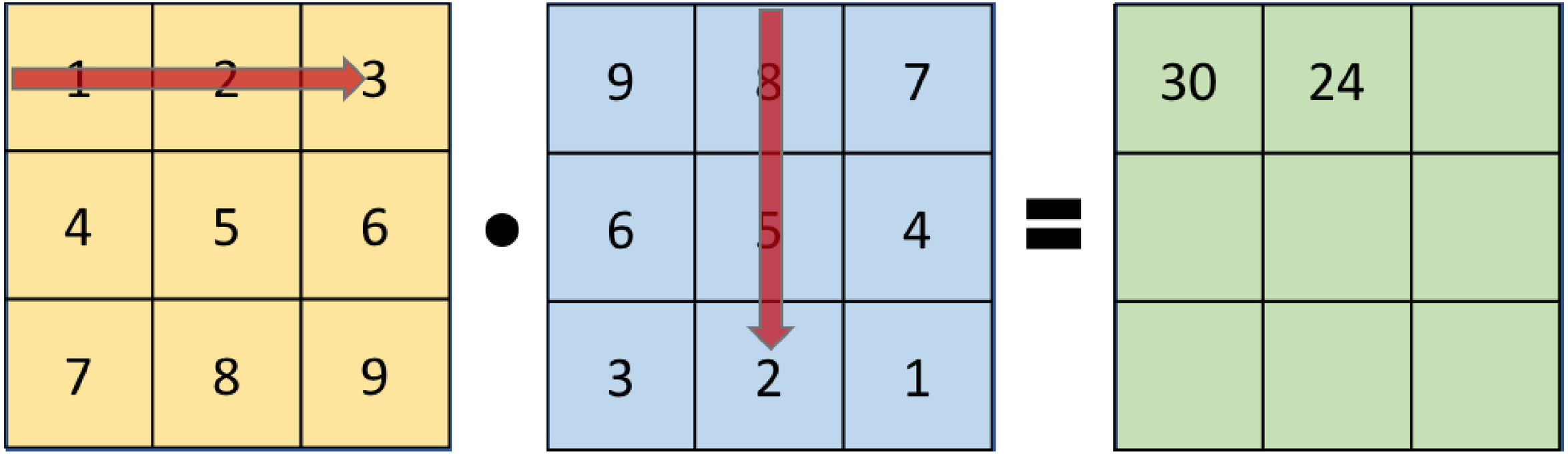
Matrix Multiplication



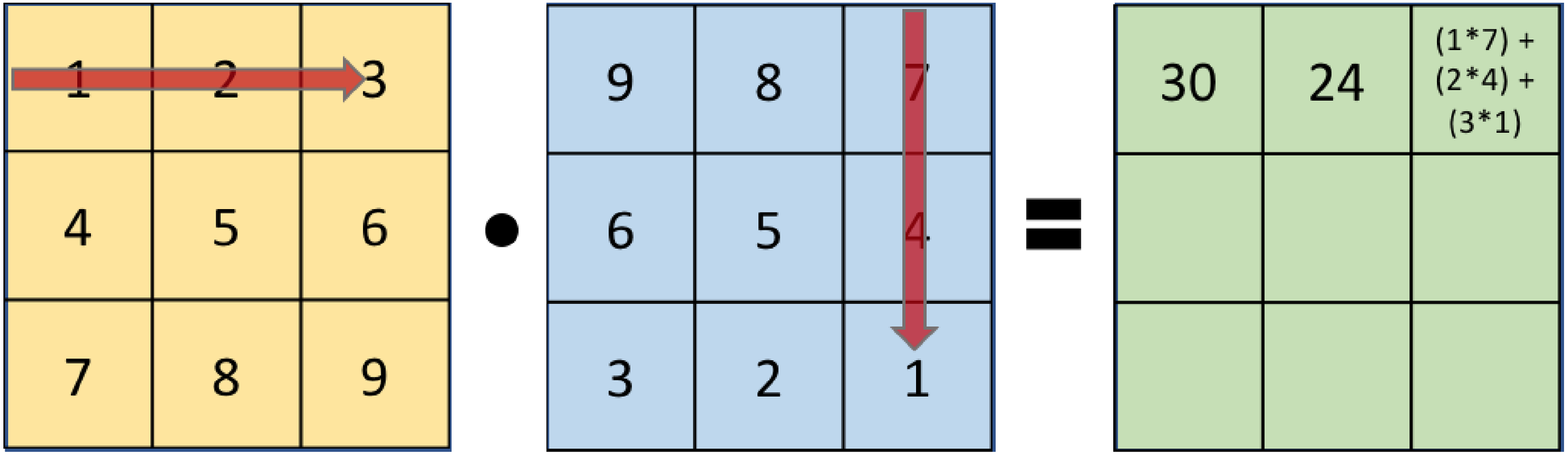
Matrix Multiplication



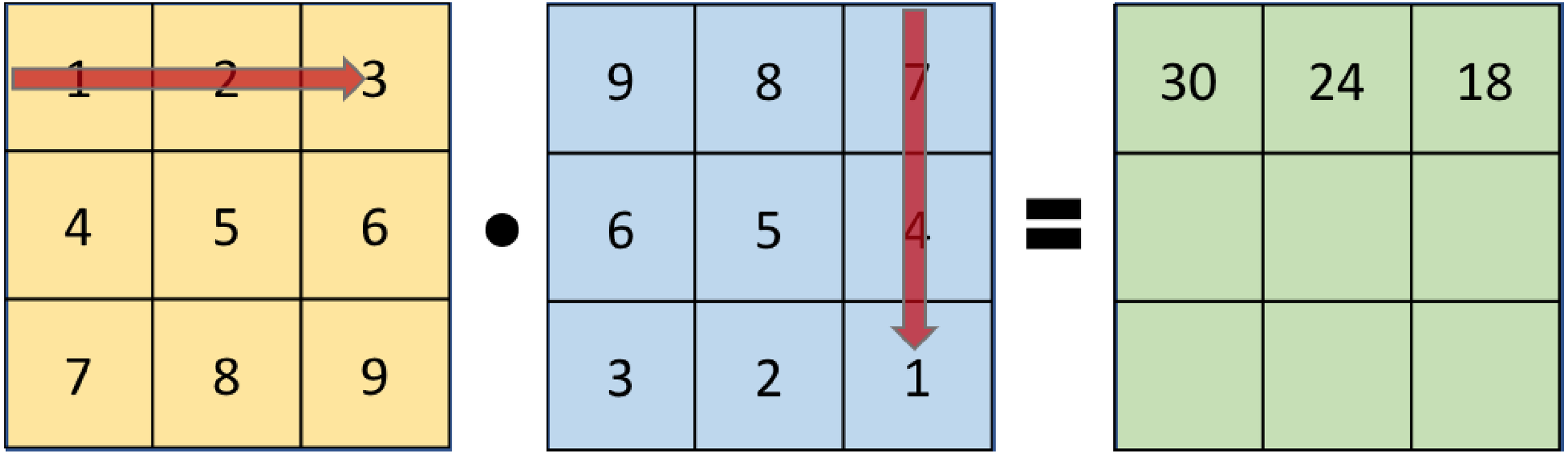
Matrix Multiplication



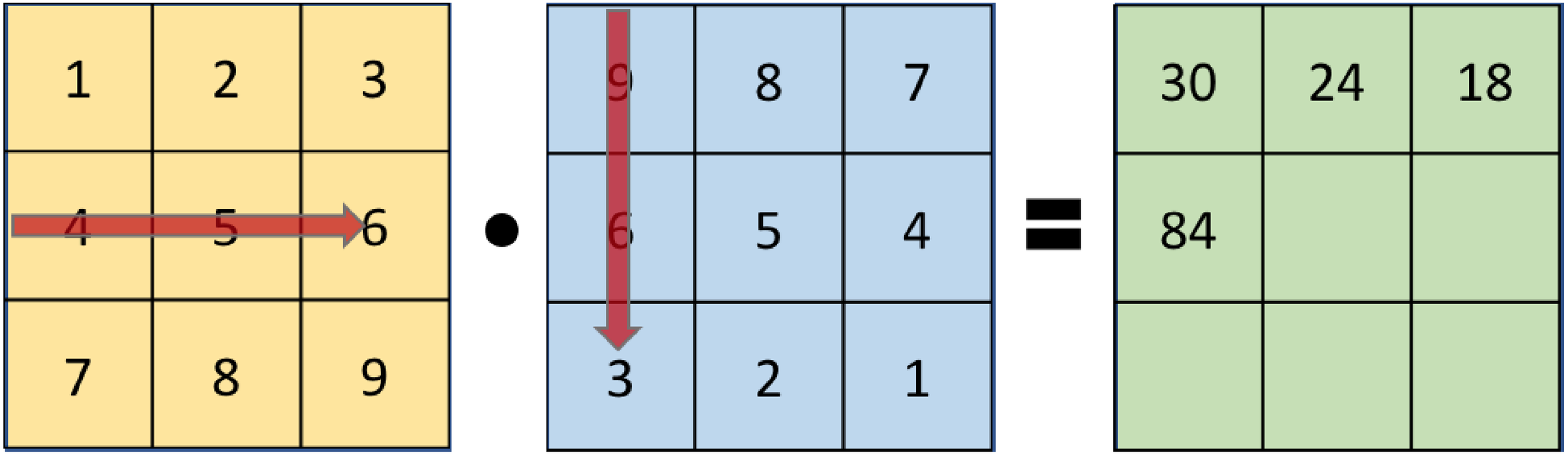
Matrix Multiplication



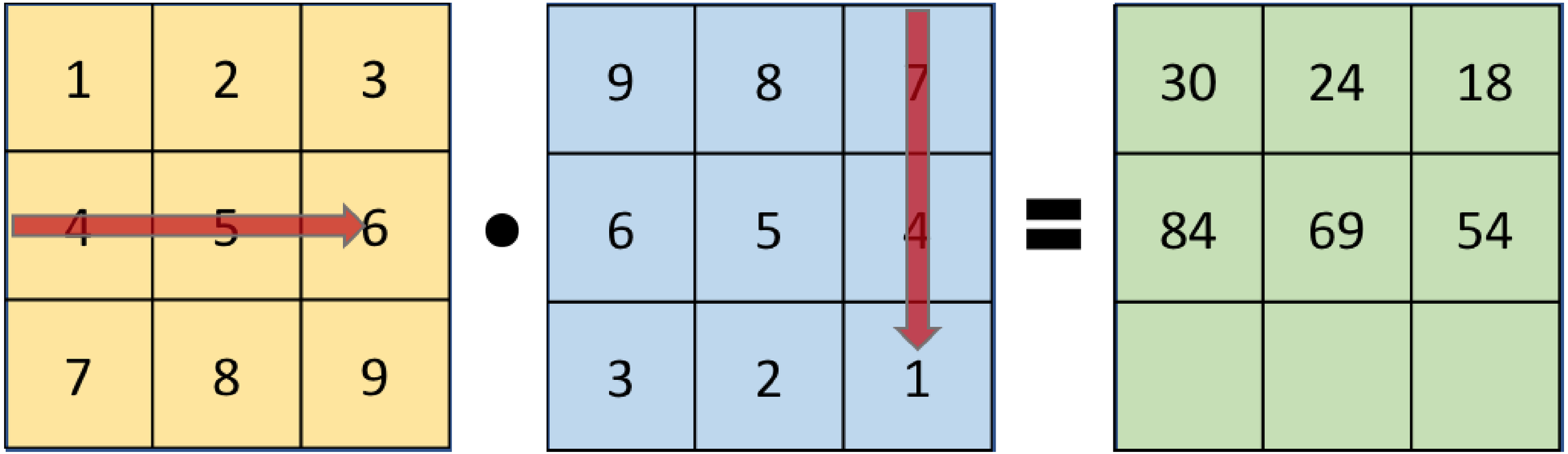
Matrix Multiplication



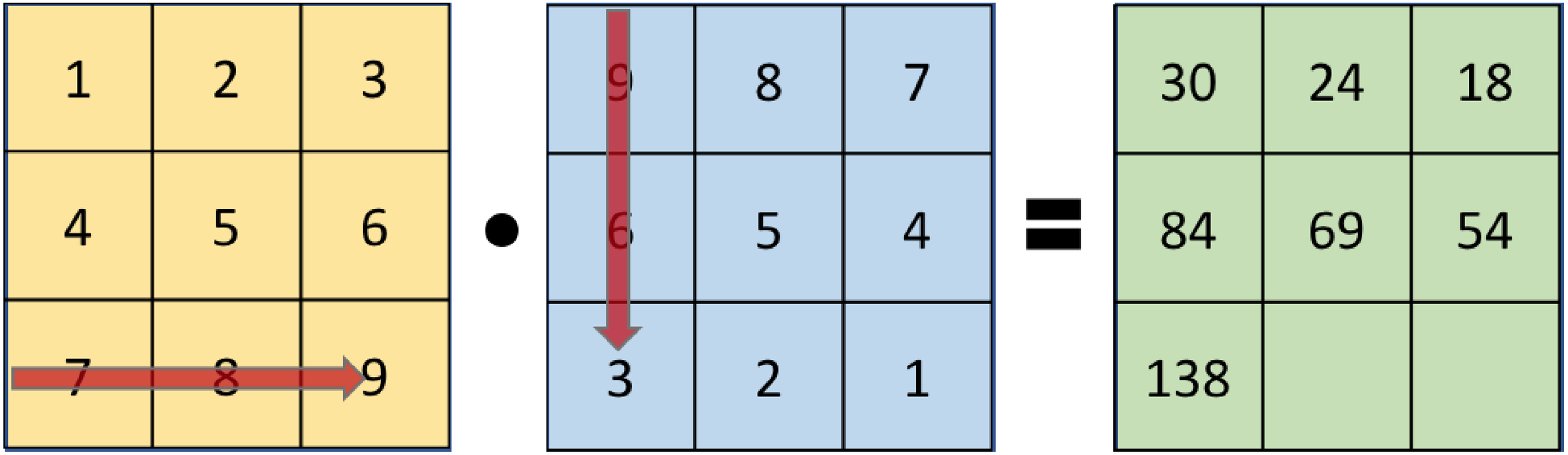
Matrix Multiplication



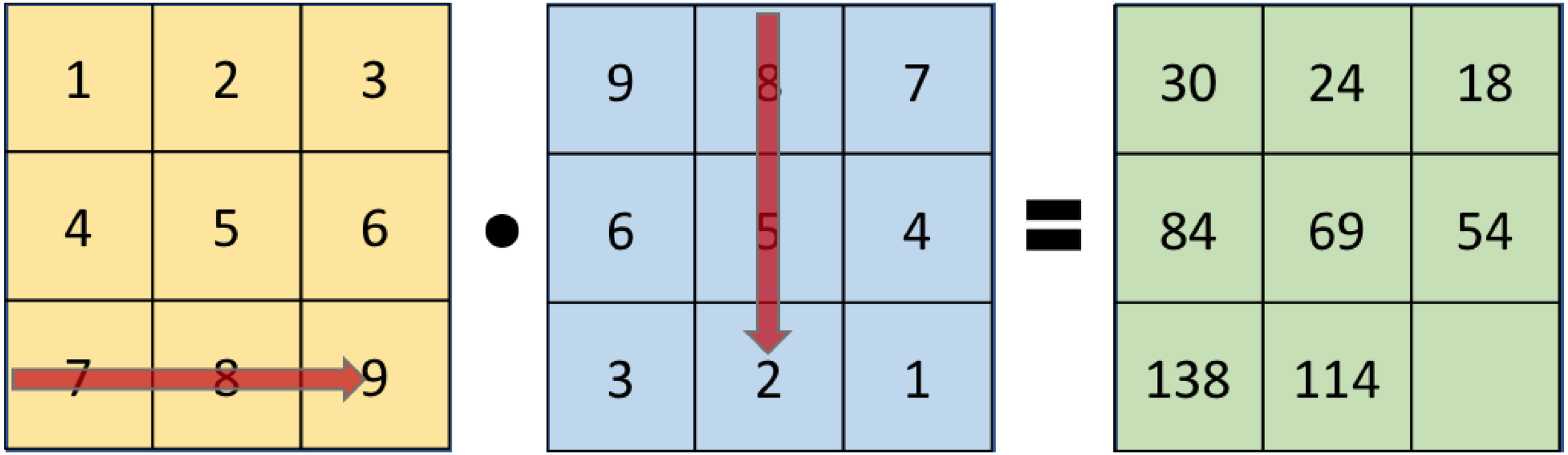
Matrix Multiplication



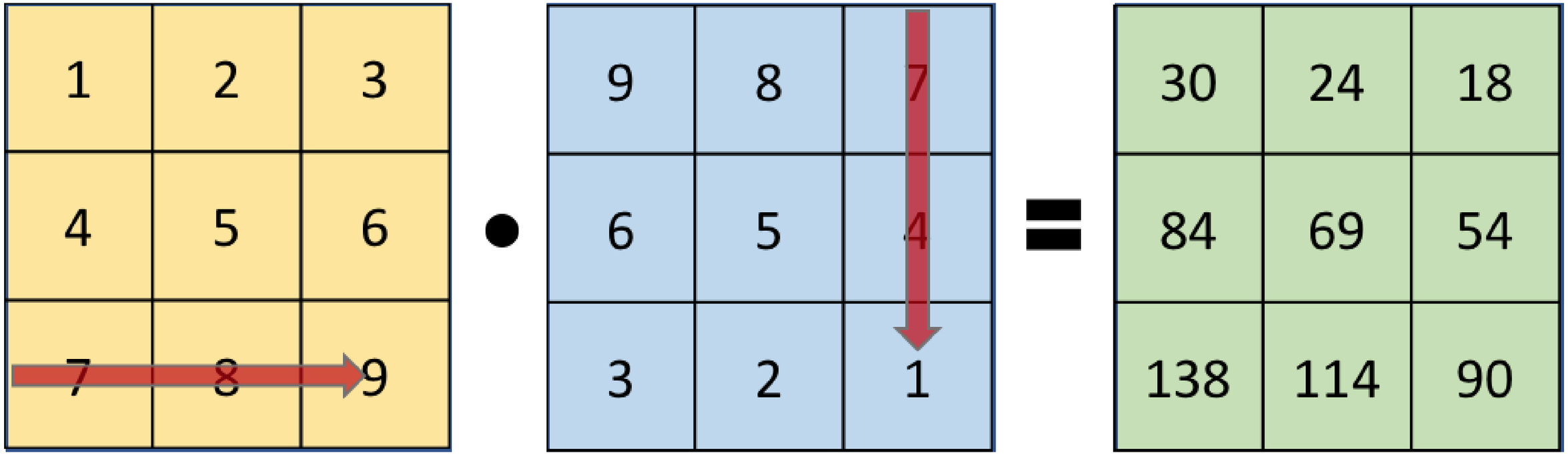
Matrix Multiplication



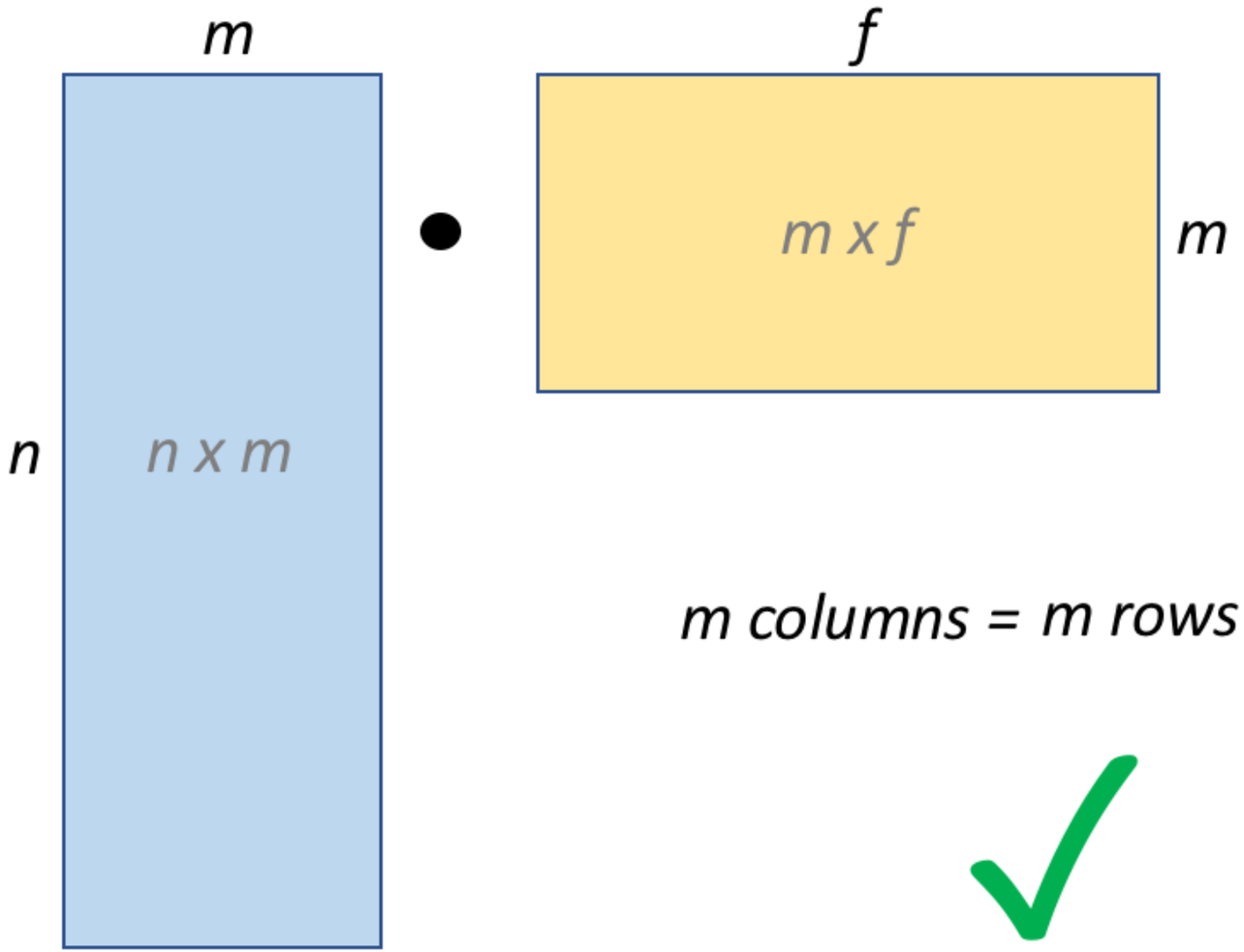
Matrix Multiplication



Matrix Multiplication

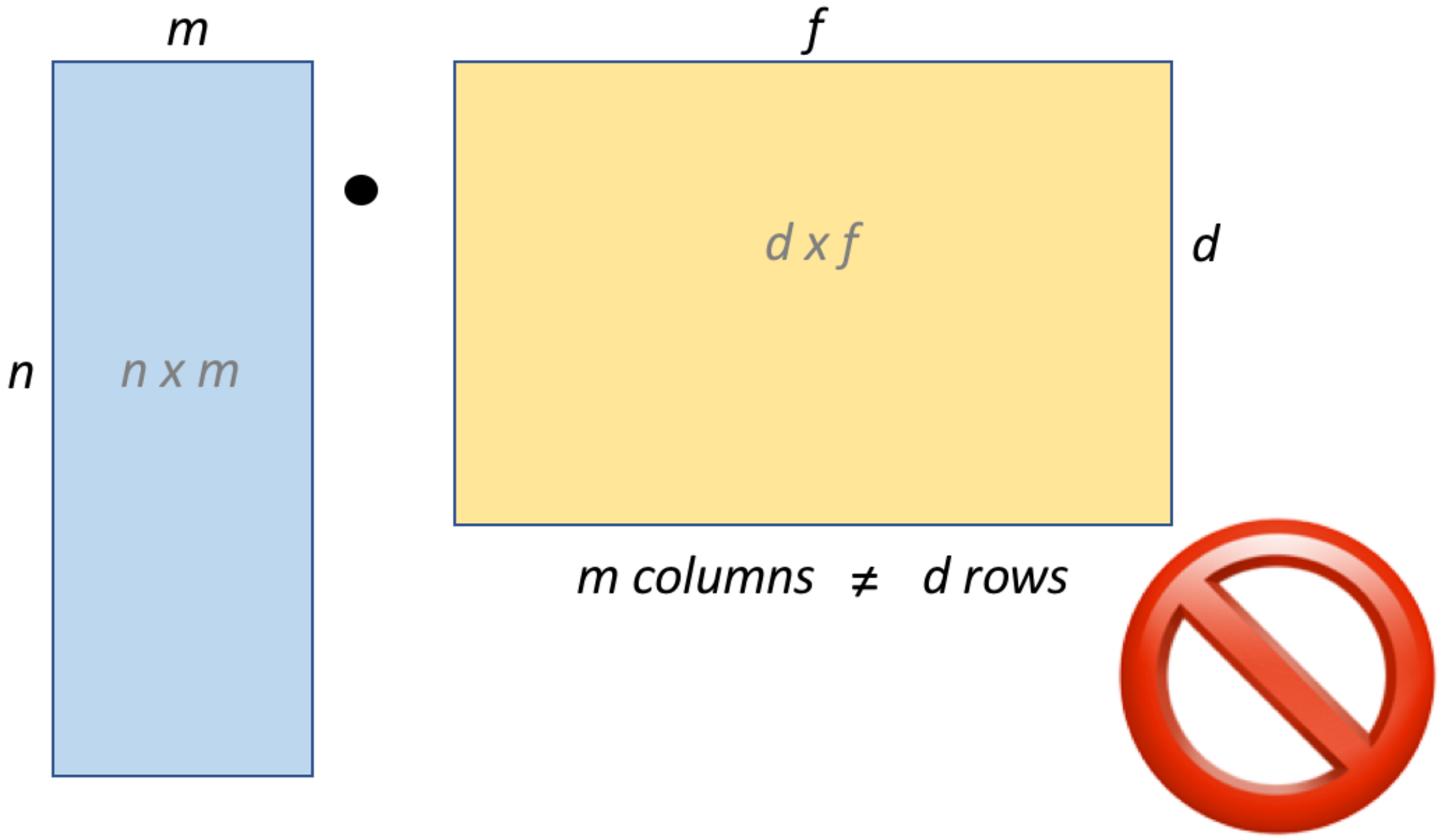


Matrix Multiplication



m columns = m rows

Matrix Multiplication



Let's practice!

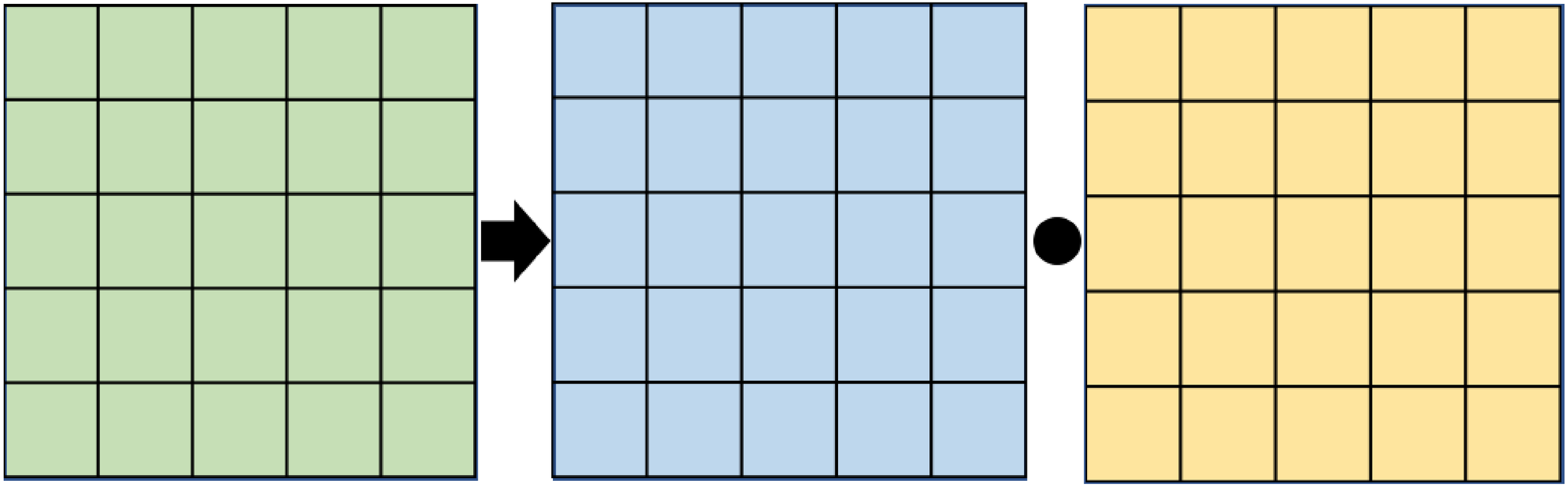
BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Overview of matrix factorization

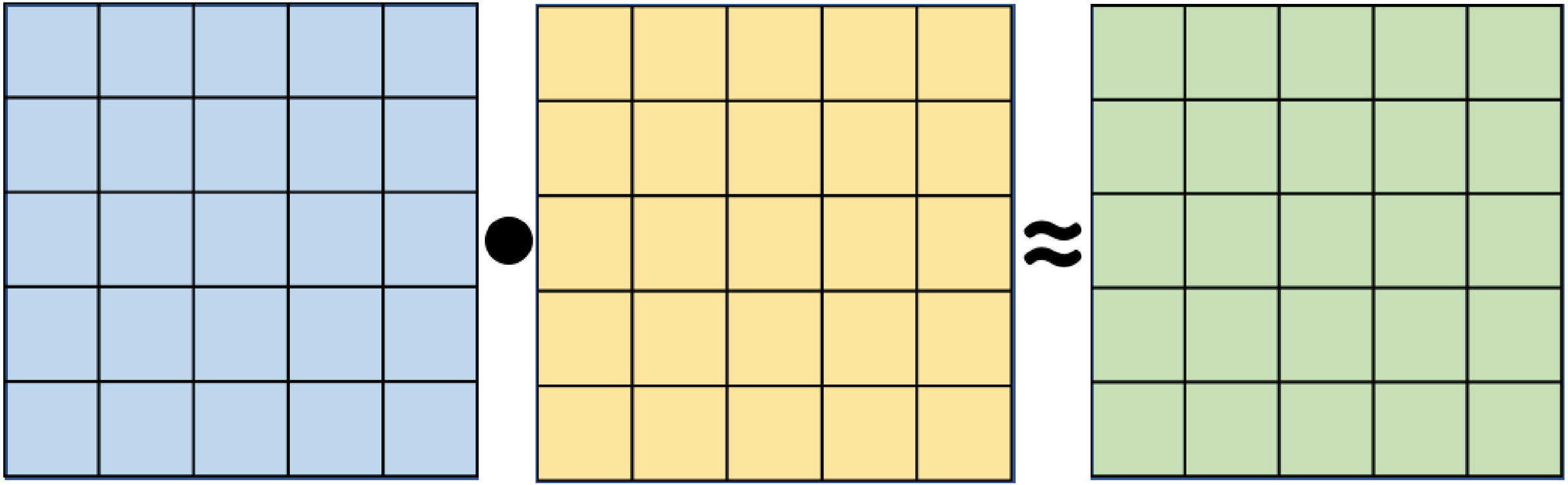
BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Jamen Long
Data Scientist at Nike

Matrix Factorization



Matrix Factorization



Matrix Factorization

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

Matrix Factorization

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

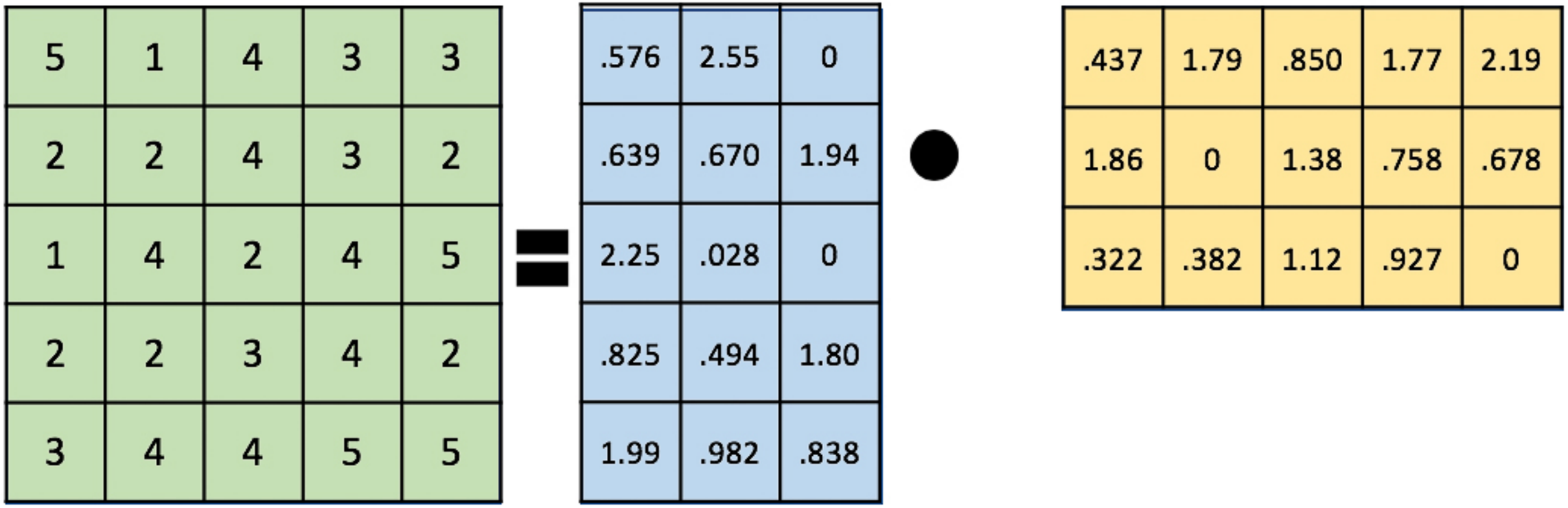
=

1	0	0	0	0
2/5	1	0	0	0
1/5	19/8	1	0	0
2/5	1	2/9	1	0
3/5	17/8	7/9	2/43	1

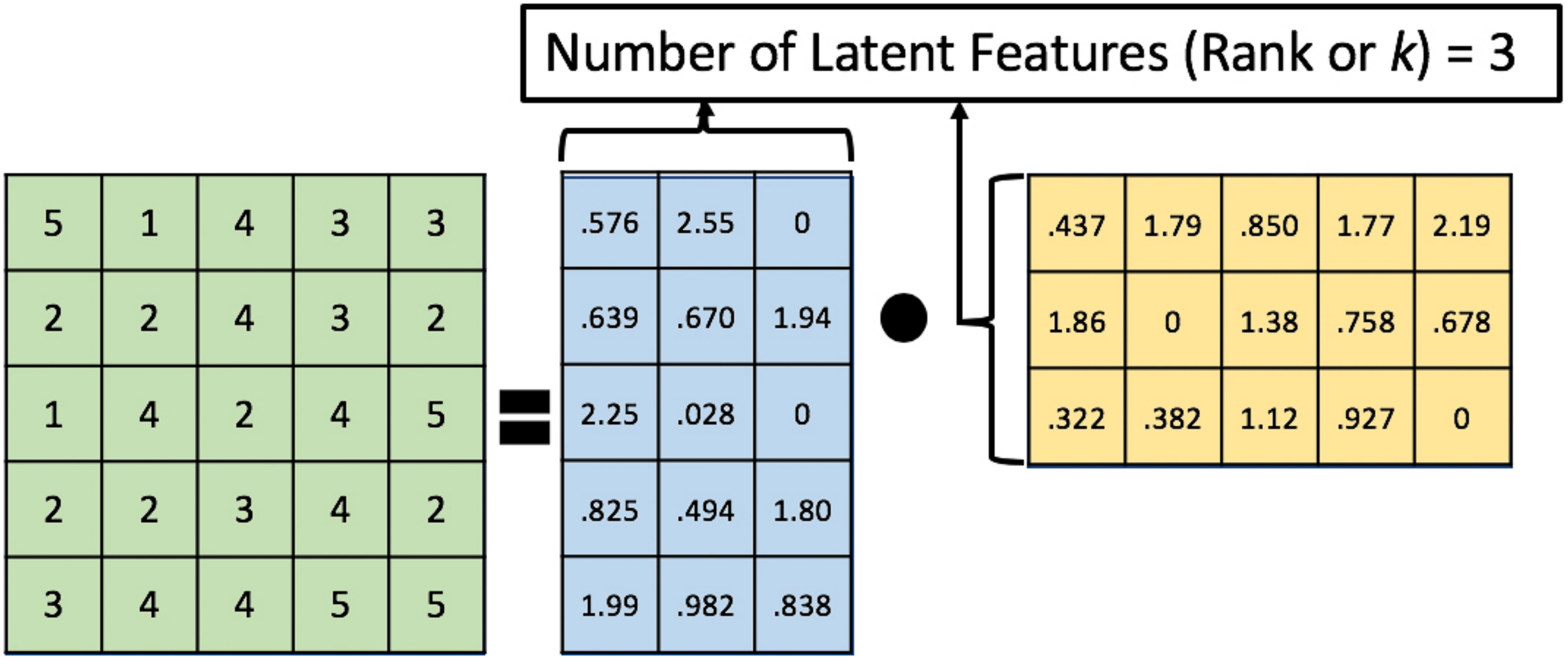
•

5	1	4	3	3
0	8/5	12/5	9/5	4/5
0	0	-9/2	-7/8	5/2
0	0	0	43/36	-5/9
0	0	0	0	-18/43

Matrix Factorization



Rank of Factor Matrices



84	-	48	-
-	50	-	-
-	-	51	-
91	-	-	107

Filling in the Blanks

84	-	48	-
-	50	-	-
-	-	51	-
91	-	-	107

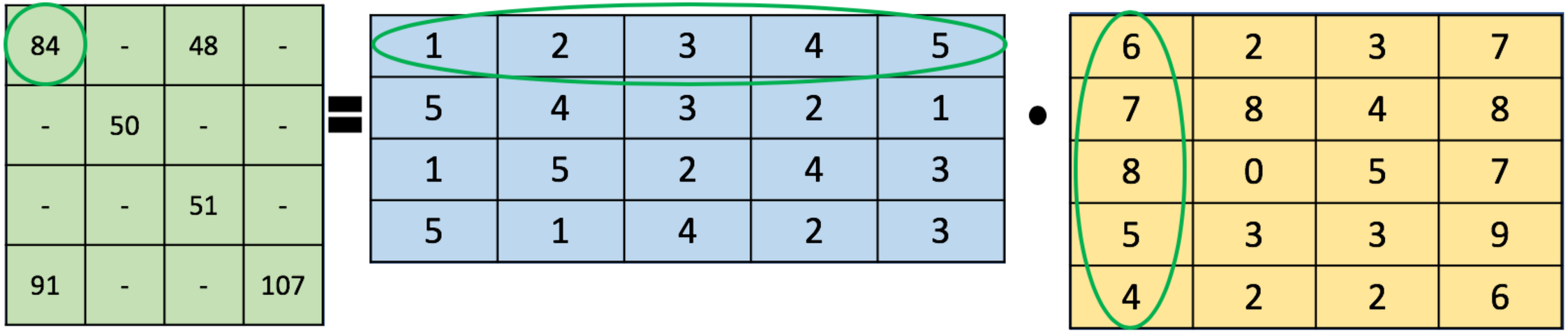
=

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

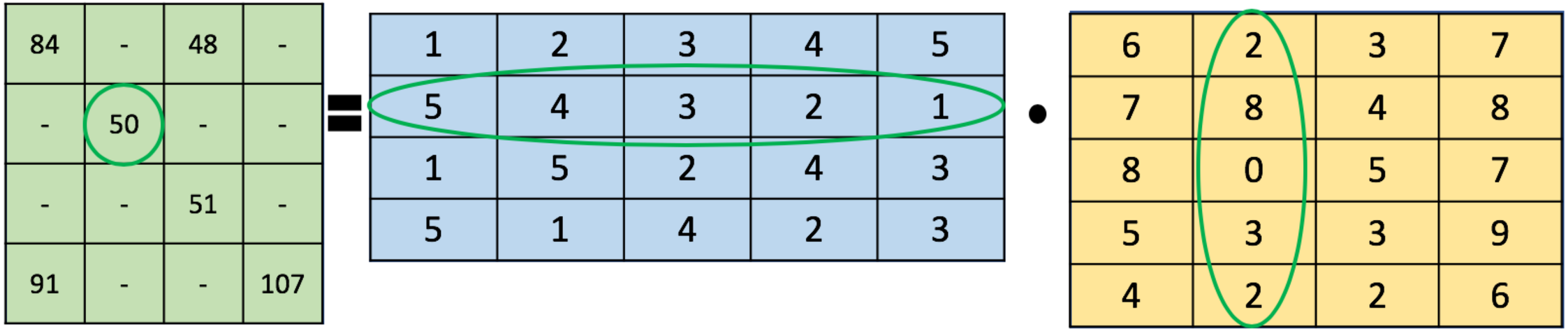
•

6	2	3	7
7	8	4	8
8	0	5	7
5	3	3	9
4	2	2	6

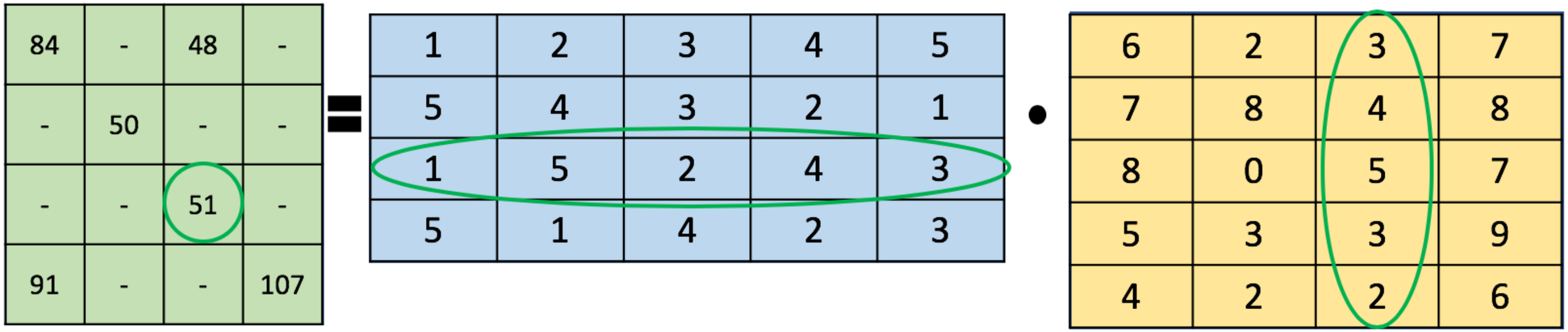
Filling In the Blanks



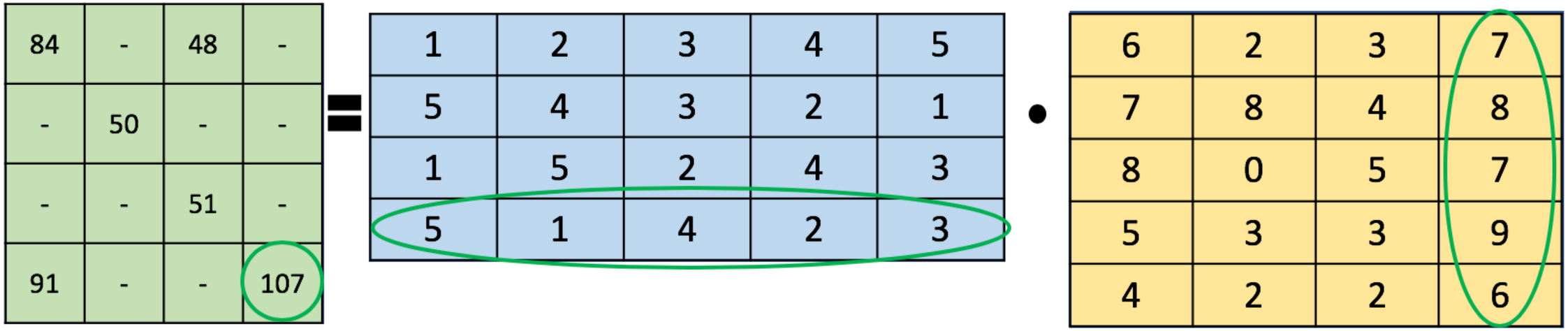
Filling In the Blanks



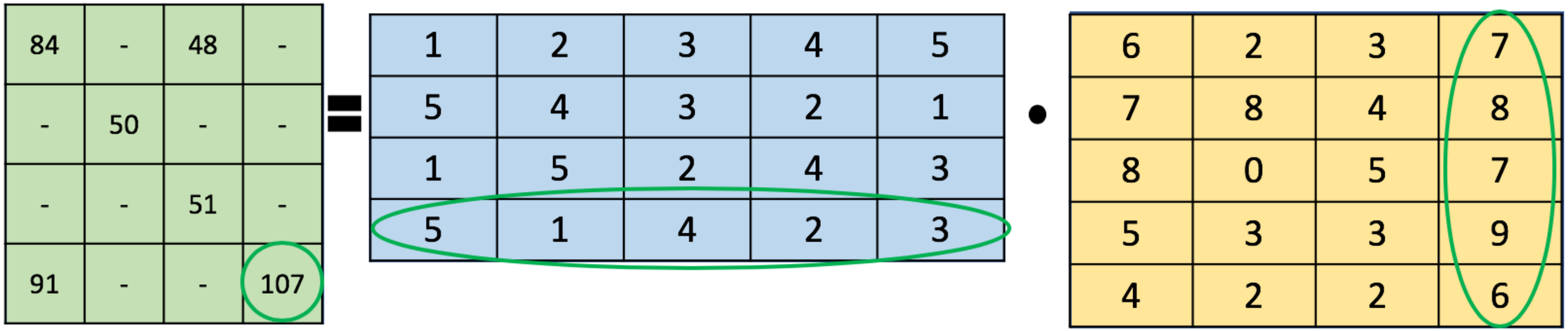
Filling In the Blanks

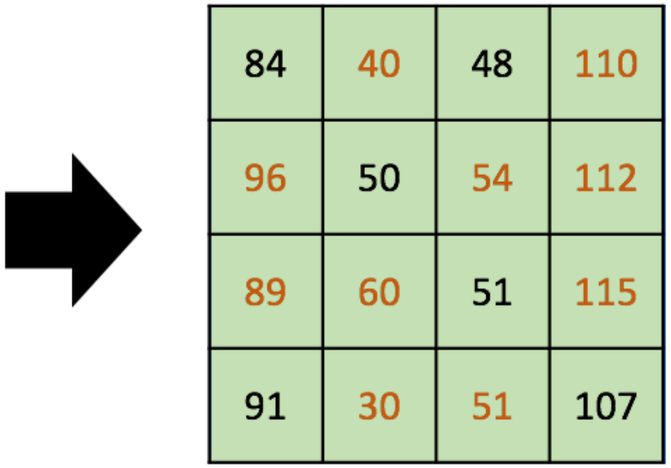


Filling In the Blanks



Filling In the Blanks





Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

How ALS alternates to generate predictions

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Jamen Long
Data Scientist at Nike

movieId	1	2	3	4	5	6
userId						
1		-	-	-	-	-
2		-	-	-	-	-
3		-	-	-	-	-
4		-	-	-	-	-
5		-	-	4	-	-
6		-	-	-	-	-
7		3	-	-	-	-
8		-	-	-	-	-
9		4	-	-	-	-
10		-	-	-	-	-
11		-	-	-	-	-
12		-	-	-	-	-

movieId	1	2	3	4	5	6
userId						
1		-	-	-	-	-
2		-	-	-	-	-
3		-	-	-	-	-
4		-	-	-	-	-
5		-	-	4	-	-
6		-	-	-	-	-
7		3	-	-	-	-
8		-	-	-	-	-
9		4	-	-	-	-
10		-	-	-	-	-
11		-	-	-	-	-
12		-	-	-	-	-

R =

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074063	1.332295
User_4	0.495512	0.075752	0.529940
User_5	0.219477	0.124221	0.000000
User_6	0.022552	0.162423	1.088869
User_7	0.999537	0.109175	0.372134
User_8	0.124147	0.180746	0.276849
User_9	0.144918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

X

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.008054	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.980059	0.471187	0.096935	0.465978	0.687785	0.419522

P

movieId	1	2	3	4	5	6
userId						
1	-	-	-	-	-	
2	-	-	-	-	-	
3	-	-	-	-	-	
4	-	-	-	-	-	
5	-	-	-	-	-	
6	-	-	-	-	-	
7	3	-	-	-	-	
8	-	-	-	-	-	
9	4	-	-	-	-	
10	-	-	-	-	-	
11	-	-	-	-	-	
12	-	-	-	-	-	

Constant

=

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074065	1.332295
User_4	0.495522	0.077752	0.529940
User_5	0.219477	0.127221	0.000000
User_6	0.022552	0.162423	1.088869
User_7	0.999547	0.109175	0.372134
User_8	0.134157	0.180746	0.276849
User_9	0.144918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

Constant

×

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.008534	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.080059	0.471181	0.096935	0.465978	0.687785	0.419522

Adjusted

movieId	1	2	3	4	5	6
userId						
1	-	-	-	-	-	
2	-	-	-	-	-	
3	-	-	-	-	-	
4	-	-	-	-	-	
5	-	-	-	-	-	
6	-	-	-	-	-	
7	3	-	-	-	-	
8	-	-	-	-	-	
9	4	-	-	-	-	
10	-	-	-	-	-	
11	-	-	-	-	-	
12	-	-	-	-	-	

Constant

$R = U \times M$

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074063	1.332295
User_4	0.495512	0.077752	0.529940
User_5	0.219477	0.121721	0.000000
User_6	0.022552	0.162423	1.088869
User_7	0.999557	0.101175	0.372134
User_8	0.114117	0.180746	0.276849
User_9	0.144918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

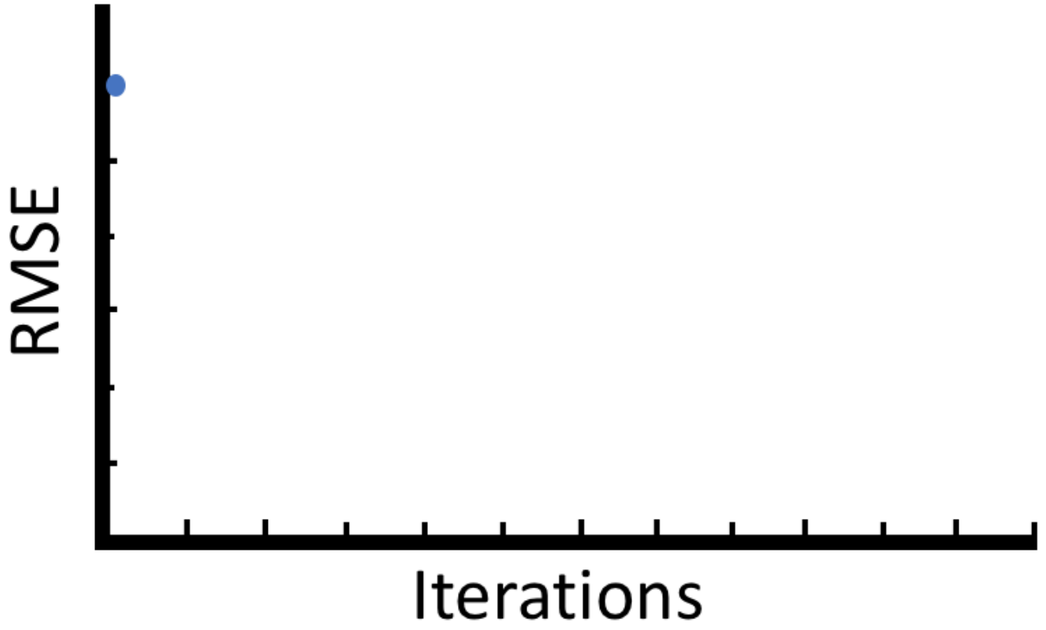
Constant

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.008354	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.980059	0.471181	0.096935	0.465978	0.687785	0.419522

Adjusted

Iteration: 1

RMSE = 12,000



movieId	1	2	3	4	5	6
userId						
1	-	-	-	-	-	
2	-	-	-	-	-	
3	-	-	-	-	-	
4	-	-	-	-	-	
5	-	-	-	-	-	
6	-	-	-	-	-	
7	3	-	-	-	-	
8	-	-	-	-	-	
9	4	-	-	-	-	
10	-	-	-	-	-	
11	-	-	-	-	-	
12	-	-	-	-	-	

Constant

=

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074063	0.332295
User_4	0.495522	0.075152	0.529940
User_5	0.219477	0.172221	0.000000
User_6	0.022552	0.262423	1.088869
User_7	0.995631	0.109175	0.372134
User_8	0.124147	0.180746	0.276849
User_9	0.244918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

Adjusted

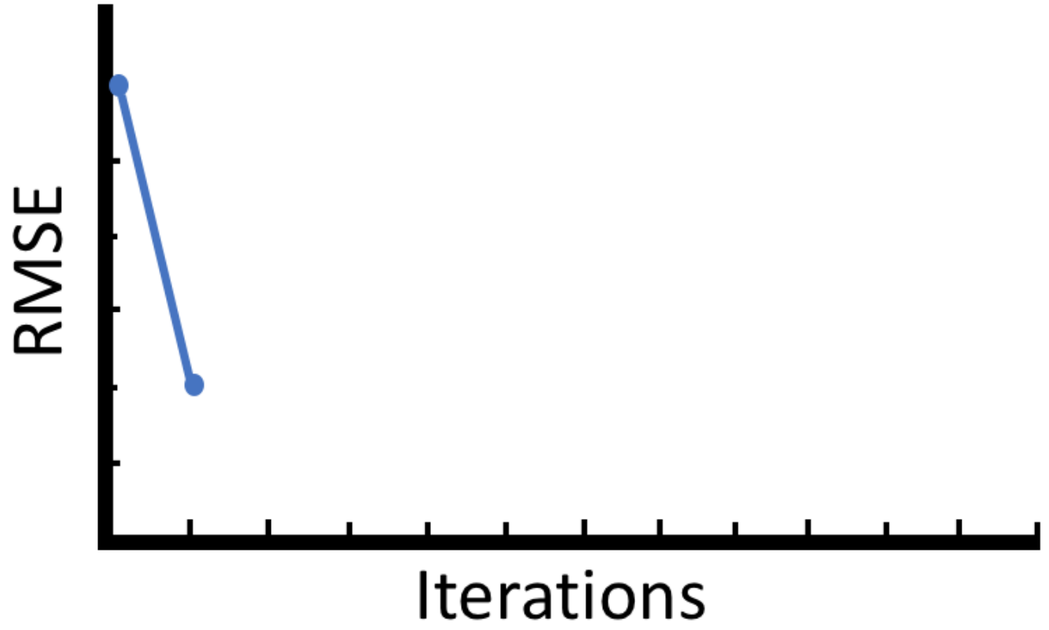
X

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.005646	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.980059	0.471818	0.096935	0.465978	0.687785	0.419522

Constant

Iteration: 2

RMSE = 4,000



movieId	1	2	3	4	5	6
userId						
1	-	-	-	-	-	
2	-	-	-	-	-	
3	-	-	-	-	-	
4	-	-	-	-	-	
5	-	-	-	-	-	
6	-	-	-	-	-	
7	3	-	-	-	-	
8	-	-	-	-	-	
9	4	-	-	-	-	
10	-	-	-	-	-	
11	-	-	-	-	-	
12	-	-	-	-	-	

Constant

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074003	1.332295
User_4	0.495512	0.077752	0.529940
User_5	0.219477	0.127221	0.000000
User_6	0.022552	0.162423	1.088869
User_7	0.999557	0.100175	0.372134
User_8	0.114157	0.180746	0.276849
User_9	0.144918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

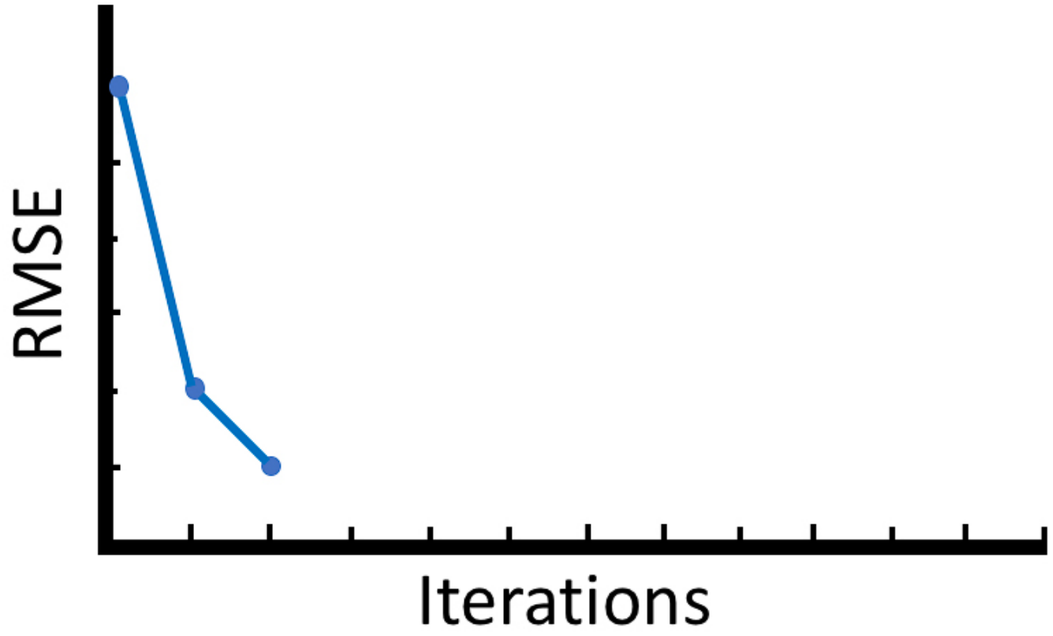
Constant

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.008514	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.980059	0.477181	0.096935	0.465978	0.687785	0.419522

Adjusted

Iteration: 3

RMSE = 2,000



movieId	1	2	3	4	5	6
userId						
1	–	–	–	–	–	
2	–	–	–	–	–	
3	–	–	–	–	–	
4	–	–	–	–	–	
5	–	–	–	–	–	
6	–	–	–	–	–	
7	3	–	–	–	–	
8	–	–	–	–	–	
9	4	–	–	–	–	
10	–	–	–	–	–	
11	–	–	–	–	–	
12	–	–	–	–	–	

Constant

=

	U_LF_0	U_LF_1	U_LF_2
User_0	0.000000	0.092497	0.007393
User_1	0.000000	0.000000	1.322806
User_2	0.293443	0.000000	0.362894
User_3	0.140157	1.074063	0.332295
User_4	0.495512	0.015152	0.529940
User_5	0.219477	0.121221	0.000000
User_6	0.022552	0.202423	1.088869
User_7	0.999531	0.109175	0.372134
User_8	0.124147	0.180746	0.276849
User_9	0.244918	0.154747	0.196846
User_10	0.177815	0.025850	0.015767
User_11	0.066618	0.117502	0.064694
User_12	0.367768	0.000000	0.322991

Adjusted

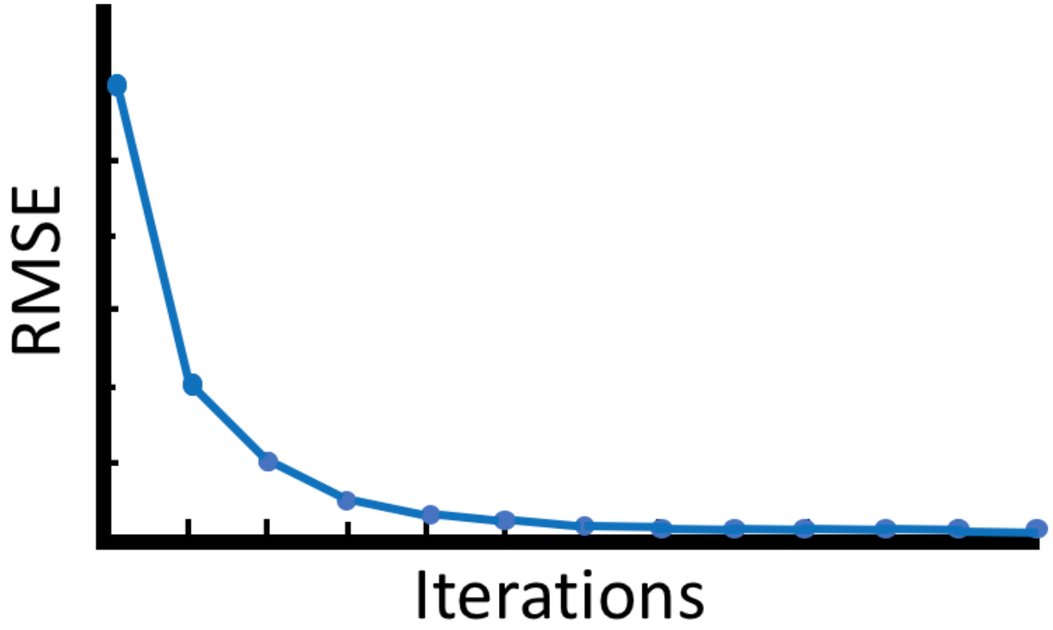
X

	Movie_0	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
M_LF_0	1.296350	0.290096	0.000000	0.000000	0.044772	0.372374	0.000000
M_LF_1	0.297598	0.000000	0.000000	0.005646	0.036239	0.296742	0.172025
M_LF_2	1.265775	0.080059	0.047182	0.096935	0.465978	0.687785	0.419522

Constant

Iteration: n

RMSE = 0.6



movieId	1	2	3	4	5	6
userId						
1		-	-	-	-	-
2		-	-	-	-	-
3		-	-	-	-	-
4		-	-	-	-	-
5		-	-	4	-	-
6		-	-	-	-	-
7		3	-	-	-	-
8		-	-	-	-	-
9		4	-	-	-	-
10		-	-	-	-	-
11		-	-	-	-	-
12		-	-	-	-	-

Original Sparse Matrix

ALS

	Movie_1	Movie_2	Movie_3	Movie_4	Movie_5	Movie_6
User_1	1.296428	3.937481	0.128226	0.616399	0.909806	0.554946
User_2	0.440784	0.170991	0.035177	0.182239	0.358864	2.782786
User_3	1.346387	0.636410	0.135210	3.421250	1.287243	0.743692
User_4	0.663118	0.250311	0.051797	0.271871	2.867512	0.235352
User_5	0.063669	0.001000	4.000000	0.014328	0.118589	0.021369
User_6	1.073698	1.343627	0.106466	0.514285	0.805503	0.484745
User_7	3.000000	0.176224	0.036689	0.222114	0.660547	0.174899
User_8	0.307343	0.131904	0.027857	0.141114	3.989767	0.147237
User_9	4.000000	0.093997	0.019955	0.103822	0.235271	0.109201
User_10	0.067036	0.007638	1.452647	0.016245	0.084729	0.011062
User_11	0.082730	0.031429	0.006935	0.037387	0.104170	2.039812
User_12	0.423238	0.152189	0.031309	0.166972	4.001211	0.135502

Completed Prediction Matrix

	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

R

	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

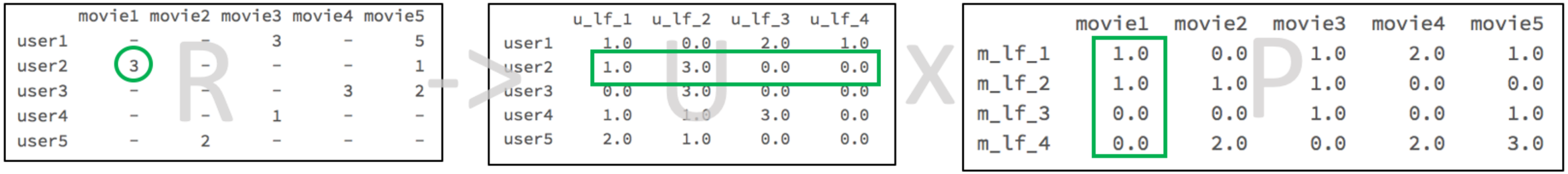
R ->

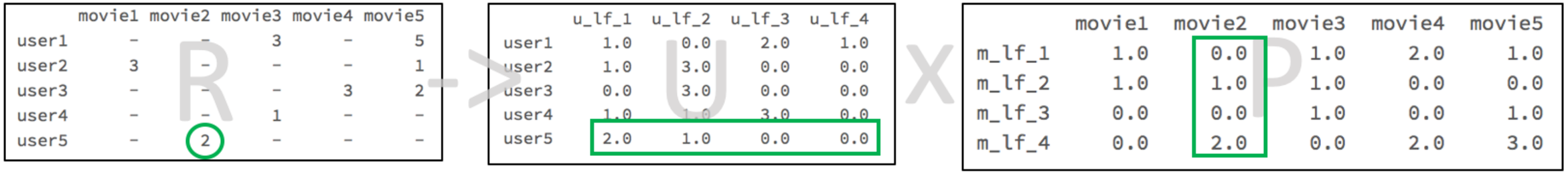
	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

U x

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

P


movie1 movie2 movie3 movie4 movie5
user1 - - 3 - 5
user2 3 - - - 1
user3 - - - 3 2
user4 - - 1 - -
user5 - 2 - - -
R
->
u_lf_1 u_lf_2 u_lf_3 u_lf_4
user1 1.0 0.0 2.0 1.0
user2 1.0 3.0 0.0 0.0
user3 0.0 3.0 0.0 0.0
user4 1.0 1.0 3.0 0.0
user5 2.0 1.0 0.0 0.0
U
X
movie1 movie2 movie3 movie4 movie5
m_lf_1 1.0 0.0 1.0 2.0 1.0
m_lf_2 1.0 1.0 1.0 0.0 0.0
m_lf_3 0.0 0.0 1.0 0.0 1.0
m_lf_4 0.0 2.0 0.0 2.0 3.0
P



	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

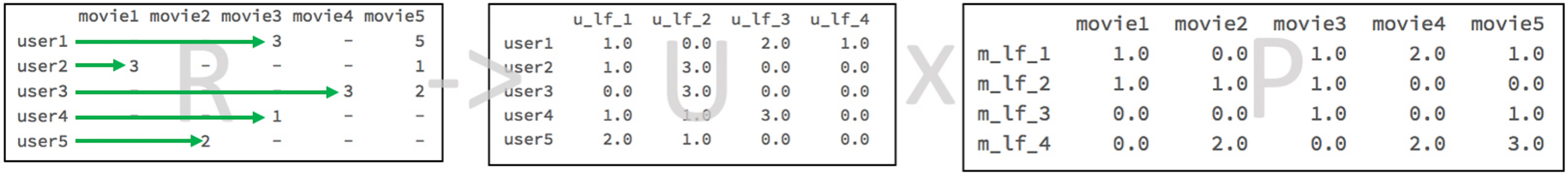
R ->

	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

U x

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

P



	movie1	movie2	movie3	movie4	movie5
user1			3	-	5
user2	3	-	-	-	1
user3				3	2
user4			1	-	-
user5	2	-	-	-	-

R

->

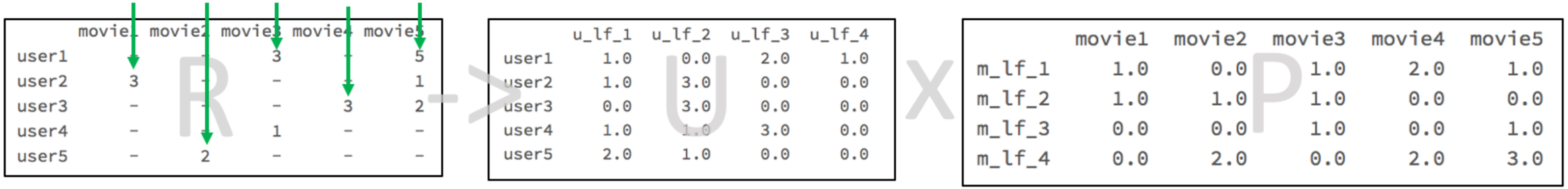
	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

U

X

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

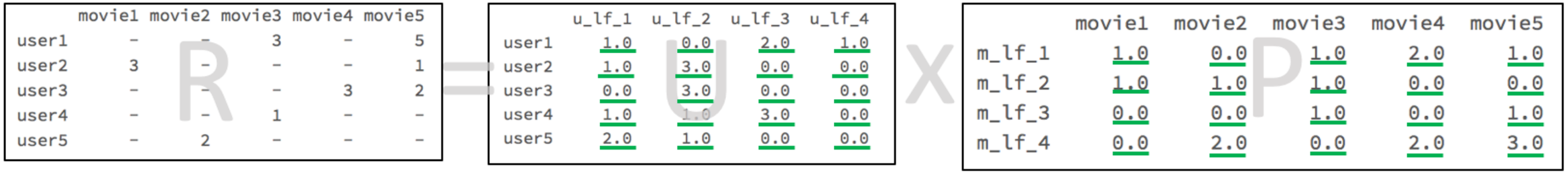
P



	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0


movie1 movie2 movie3 movie4 movie5
user1 - - 3 - 5
user2 3 - - - 1
user3 - - - 3 2
user4 - - 1 - -
user5 - 2 - - -
R
=
u_lf_1 u_lf_2 u_lf_3 u_lf_4
user1 1.0 0.0 2.0 1.0
user2 1.0 3.0 0.0 0.0
user3 0.0 3.0 0.0 0.0
user4 1.0 1.0 3.0 0.0
user5 2.0 1.0 0.0 0.0
U
x
movie1 movie2 movie3 movie4 movie5
m_lf_1 1.0 0.0 1.0 2.0 1.0
m_lf_2 1.0 1.0 1.0 0.0 0.0
m_lf_3 0.0 0.0 1.0 0.0 1.0
m_lf_4 0.0 2.0 0.0 2.0 3.0
P

	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

R =

	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

U x

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

P

	movie1	movie2	movie3	movie4	movie5
user1	-	-	3	-	5
user2	3	-	-	-	1
user3	-	-	-	3	2
user4	-	-	1	-	-
user5	-	2	-	-	-

R ->

	u_lf_1	u_lf_2	u_lf_3	u_lf_4
user1	1.0	0.0	2.0	1.0
user2	1.0	3.0	0.0	0.0
user3	0.0	3.0	0.0	0.0
user4	1.0	1.0	3.0	0.0
user5	2.0	1.0	0.0	0.0

U x

	movie1	movie2	movie3	movie4	movie5
m_lf_1	1.0	0.0	1.0	2.0	1.0
m_lf_2	1.0	1.0	1.0	0.0	0.0
m_lf_3	0.0	0.0	1.0	0.0	1.0
m_lf_4	0.0	2.0	0.0	2.0	3.0

P

=

	movie1	movie2	movie3	movie4	movie5
user1	1.0	2.0	3.0	4.0	6.0
user2	4.0	3.0	4.0	2.0	1.0
user3	3.0	3.0	3.0	1.0	1.0
user4	2.0	1.0	5.0	1.0	4.0
user5	3.0	1.0	3.0	4.0	2.0

$\hat{R}$

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Data preparation for Spark ALS

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Jamen Long
Data Scientist at Nike

Conventional Dataframe

userId	Good Will H...	Batman For...	Incredibles	Shawshank Redemption	Coco
z097s3	2	3	null	4	4
z176c4	1	null	4	3	4
m821i6	3	4	null	3	5
t872c7	1	2	4	5	null
b728q0	2	null	5	2	null
f540n1	2	1	null	3	1
w066f1	5	null	5	2	5
v081u6	1	null	5	1	1
j197o6	3	2	2	4	null
n202j1	2	null	2	null	2

Row-based data format

```
+------+--------------------+------+
|userId|            variable|rating|
+------+--------------------+------+
|z097s3|   Good Will Hunting|     2|
|z097s3|      Batman Forever|     3|
|z097s3|The Shawshank Red...|     4|
|z097s3|                Coco|     4|
|z176c4|   Good Will Hunting|     1|
|z176c4|     The Incredibles|     4|
|z176c4|The Shawshank Red...|     3|
|z176c4|                Coco|     4|
|m821i6|   Good Will Hunting|     3|
|m821i6|      Batman Forever|     4|
```

Row-based data format (cont.)

```
         +------+--------------------+------+
         |userId|            variable|rating|
         +------+--------------------+------+
z097s3   |z097s3|   Good Will Hunting|     2|
 |-----> |z097s3|      Batman Forever|     3|
 |-----> |z097s3|The Shawshank Red...|     4|
 |-----> |z097s3|                Coco|     4|
z176c4   |z176c4|   Good Will Hunting|     1|
 |-----> |z176c4|     The Incredibles|     4|
 |-----> |z176c4|The Shawshank Red...|     3|
 |-----> |z176c4|                Coco|     4|
m821i6   |m821i6|   Good Will Hunting|     3|
 |-----> |m821i6|      Batman Forever|     4|
```

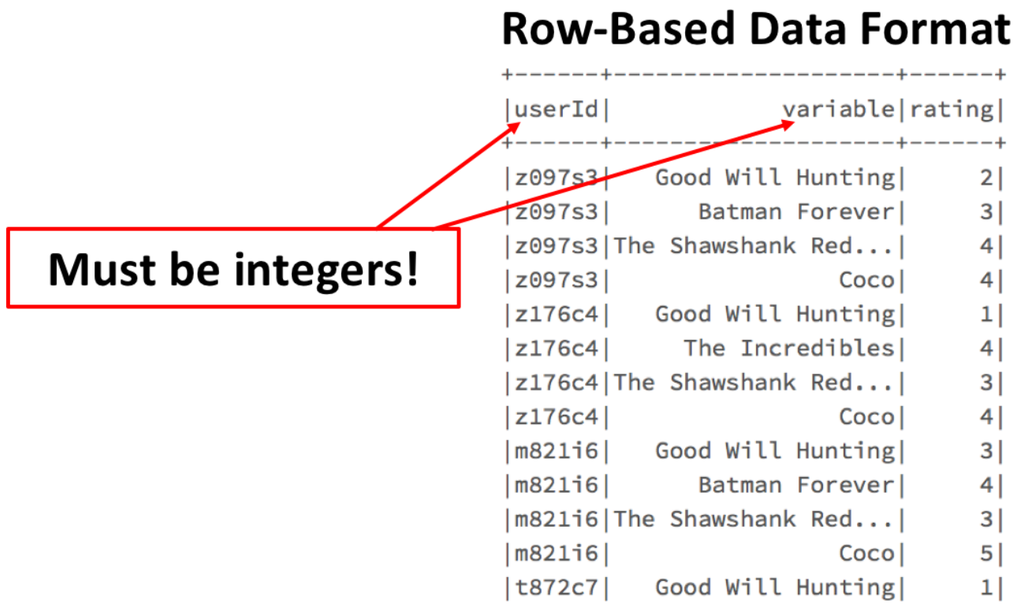
```
df.printSchema()
```

```
root
 |-- userId: string (nullable = true)
 |-- variable: string (nullable = false)
 |-- rating: long (nullable = true)
```

Must be integers

```
df.printSchema()
```

```
root
 |-- userId: string (nullable = true)
 |-- variable: string (nullable = false)
 |-- rating: long (nullable = true)
```



Conventional Dataframe

```
ratings.show()
```

```
+------+--------------+-------------+----------+--------------------+----+
|userId|Good Will H...|Batman For...|Incredibles|Shawshank Redemption|Coco|
+------+--------------+-------------+----------+--------------------+----+
|z097s3|             2|            3|      null|                   4|   4|
|z176c4|             1|         null|         4|                   3|   4|
|m821i6|             3|            4|      null|                   3|   5|
|t872c7|             1|            2|         4|                   5|null|
|b728q0|             2|         null|         5|                   2|null|
|f540n1|             2|            1|      null|                   3|   1|
|w066f1|             5|         null|         5|                   2|   5|
|v081u6|             1|         null|         5|                   1|   1|
```

Wide to long function

```
# Function to convert conventional datafame into row-based ("long") dataframe
wide_to_long
```

```
<function __main__.to_long>
```

```
# Function to convert conventional datafame into row-based ("long") dataframe
long_ratings = wide_to_long(ratings)
long_ratings.show()
```

```
+------+--------------------+------+
|userId|            variable|rating|
+------+--------------------+------+
|z097s3|   Good Will Hunting|     2|
|z097s3|      Batman Forever|     3|
|z097s3|The Shawshank Red...|     4|
|z097s3|                Coco|     4|
|z176c4|   Good Will Hunting|     1|
|z176c4|     The Incredibles|     4|
|z176c4|The Shawshank Red...|     3|
|z176c4|                Coco|     4|
```

Steps to get integer ID's

1. Extract unique `userIds` and `movieIds`
2. Assign unique integers to each id
3. Rejoin unique integer id's back to the ratings data

Extracting distinct user IDs

```
users = long_ratings.select('userId').distinct()
users.show()
```

```
+------+
|userId|
+------+
|j197o6|
|m821i6|
|g025o2|
|z176c4|
|a610z0|
|c460j6|
|w066f1|
|v081u6|
|t791a0|
```

Monotonically increasing ID

```
from pyspark.sql.functions import monotonically_increasing_id
```

Coalesce method

```
from pyspark.sql.functions import monotonically_increasing_id
users = users.coalesce(1)
```

Persist method

```
from pyspark.sql.functions import monotonically_increasing_id
users = users.coalesce(1)
users = users.withColumn(
    "userIntId", monotonically_increasing_id()).persist()
users.show()
```

```
+------+---------+
|userId|userIntId|
+------+---------+
|j197o6|        0|
|m821i6|        1|
|g025o2|        2|
|z176c4|        3|
|a610z0|        4|
|c460j6|        5|
|w066f1|        6|
```

Movie integer IDs

```
movies = long_ratings.select("variable").distinct()
movies = movies.coalesce(1)
movies = movies.withColumn(
    "movieId", monotonically_increasing_id()).persist()
movies.show()
```

```
+--------------------+-------+
|            variable|movieId|
+--------------------+-------+
|     The Incredibles|      0|
|                Coco|      1|
|The Shawshank Red...|      2|
|   Good Will Hunting|      3|
|      Batman Forever|      4|
+--------------------+-------+
```

Joining UserIds and MovieIds

```
ratings_w_int_ids = long_ratings.join(
    users, "userId", "left").join(movies, "variable", "left")

ratings_w_int_ids.show()
```

```
+--------------------+------+------+---------+-------+
|            variable|userId|rating|userIntId|movieId|
+--------------------+------+------+---------+-------+
|   Good Will Hunting|z097s3|     2|       16|      3|
|      Batman Forever|z097s3|     3|       16|      4|
|The Shawshank Red...|z097s3|     4|       16|      2|
|                Coco|z097s3|     4|       16|      1|
|   Good Will Hunting|z176c4|     1|        3|      3|
|     The Incredibles|z176c4|     4|        3|      0|
|The Shawshank Red...|z176c4|     3|        3|      2|
|                Coco|z176c4|     4|        3|      1|
```

```
from pyspark.ml.functions import col

ratings_data = ratings_w_int_ids.select(
                                        col("userIntId").alias("userid"),
                                        col("variable").alias("movieId"),
                                        col("rating"))

ratings_data.show()
```

```
+------+-------+------+
|userId|movieId|rating|
+------+-------+------+
|    16|      3|     2|
|    16|      4|     3|
|    16|      2|     4|
|    16|      1|     4|
|     3|      3|     1|
|     3|      0|     4|
```

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

ALS parameters and hyperparameters

BUILDING RECOMMENDATION ENGINES WITH PYSPARK

Jamen Long
Data Scientist at Nike

Example ALS model code

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Column names

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Arguments

- `userCol` : Name of column that contains user id's
- `itemCol` : Name of column that contains item id's
- `ratingCol` : Name of column that contains ratings

Original Ratings Matrix

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7	Movie …	Movie *n*
User 1									
User 2									
User 3									
User 4									
User 5									
User…									
User *m*									

ALS

Factor Matrices

	LF1	LF…	LF k
User 1			
User 2			
User 3			
User 4			
User 5			
User..			
User *m*			

U

X

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie…	Movie *n*
LF1							
LF…							
LF k							

P

Original Ratings Matrix

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7	Movie ...	Movie *n*
User 1									
User 2									
User 3									
User 4									
User 5									
User...									
User *m*									

ALS

Factor Matrices

	LF1	LF...	LF k
User 1			
User 2			
User 3			
User 4			
User 5			
User..			
User *m*			

U

X

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie ...	Movie *n*
LF1							
LF ...							
LF k							

P

Movie Latent Features

User Latent Features

Rank

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Hyperparameters

- `rank` , k: number of latent features

MaxIter

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Hyperparameters

- `rank` , k: number of latent features
- `maxIter` : number of iterations

RegParam

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Hyperparameters

- `rank` , k: number of latent features
- `maxIter` : number of iterations
- `regParam` : Lambda

Alpha

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Hyperparameters

- `rank` , k: number of latent features
- `maxIter` : number of iterations
- `regParam` : Lambda
- `alpha` : Discussed later. Only used with implicit ratings.

Non-negative

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Additional Arguments

- `nonnegative = True` : Ensures positive numbers

Cold start strategy

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Additional Arguments

- `nonnegative = True` : Ensures positive numbers
- `coldStartStrategy = "drop"` : Addresses issues with test/train split

Implicit preferences

```
als_model = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
                rank=25, maxIter=100, regParam=.05, alpha=40,
                nonnegative=True,
                coldStartStrategy="drop",
                implicitPrefs=False)
```

Additional Arguments

- `nonnegative = True` : Ensures positive numbers
- `coldStartStrategy = "drop"` : Addresses issues with test/train split
- `implicitPrefs = True` : True/False depending on ratings type

Sample ALS model build

```
als = ALS(userCol="userId", itemCol="movieId", ratingCol="rating",
          rank=25, maxIter=100, regParam=.05,
          nonnegative=True,
          coldStartStrategy="drop",
          implicitPrefs=False)
```

Fit and transform methods

```
# Fit ALS to training dataset
model = als.fit(training_data)

# Generate predictions on test dataset
predictions = model.transform(test_data)
```

Let's practice!

BUILDING RECOMMENDATION ENGINES WITH PYSPARK