EE219 Project 3

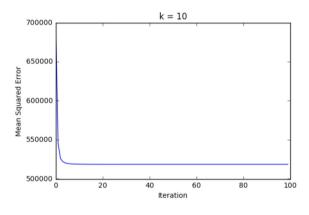
304743326 Andrew Lin, 004587761 Wei-Ting Chen

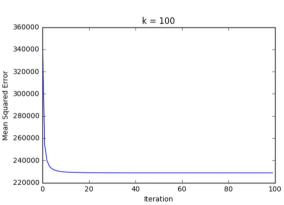
Part 1

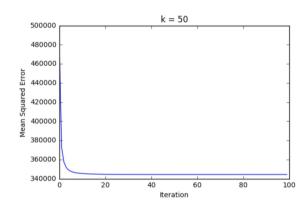
By using collaborative filtering, we get the prediction matrix of movie rating. The total least squared errors in different k are shown below. We use an additional k=500 to build the matrix. As we can see for the table, the total error decreases as k grows because larger k allows the model to be more complex, but the computational time also grows with k.

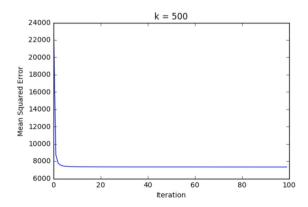
k	Total Least Squared Error
10	518677.53742
50	344355.418277
100	228794.691722
500	7332.39135187

Since we're finding a set of matrix factorization that has the minimum error, the error of each iteration should decrease and finally converge as shown below.









We randomly choose 10% of the raw data read from file as test data, and the rest 90% as training data and build the rating matrix for cross validation. We take 100 iterations of factorization, and generate the initial U and V as randomly generated matrices.

The average absolute error of each test for different k is shown below. It is calculated as the total error of a test divided by the number of test entries.

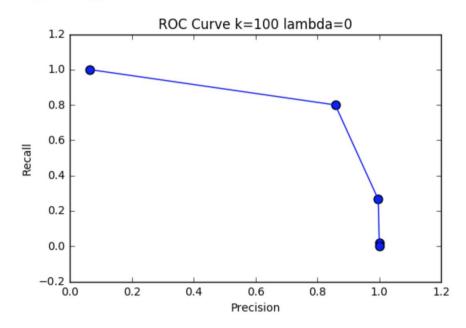
Validation Test	k=10	k=50	k=100	k=500
1	1.779193	1.260250	1.141260	0.247676
2	1.783527	1.222235	1.176608	0.258433
3	1.772448	1.204210	1.183285	0.253079
4	1.784322	1.218771	1.268180	0.261518
5	1.780508	1.207648	1.146087	0.257994
6	1.762604	1.205965	1.181372	0.256614
7	1.777819	1.213634	1.140929	0.261418
8	1.797829	1.229649	1.206965	0.277199
9	1.761902	1.263216	1.131555	0.254955
10	1.816251	1.237786	1.185611	0.268044

The average absolute error of different k among each test is shown below. It is calculated as the total error of all test of a particular k divided by 10.

	k=10	k=50	k=100	k=500
Average Absolute Error	17816.404551	12263.363667	11761.851387	2596.929652

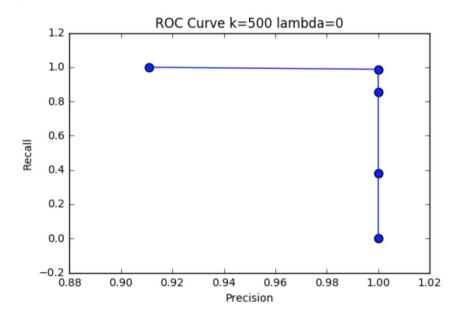
We calculate the precision and recall using the model and the test data that give the minimum validation error with k=100. We get the result and the ROC curve as below:

Precision: 0.986564 Recall: 0.018016



This shows that our model can retrieve more accurate predictions than incorrectly predicted ones, but it fails to evaluate most of the movie preferences. This also happens with k=500 as shown below:

Precision: 0.999981 Recall: 0.149102

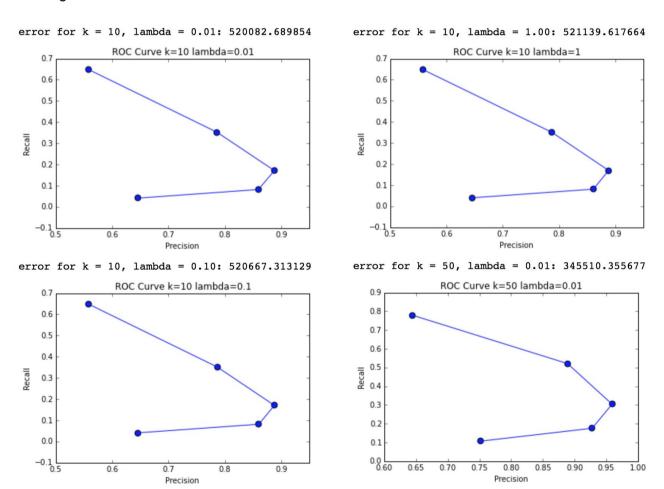


We interpret this as a tradeoff of precision and recall.

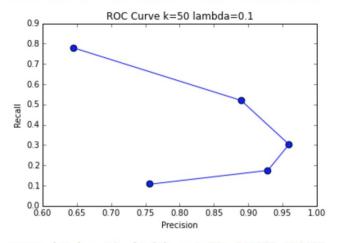
We apply the same matrix factorization function with K=10, 50, 100 on reversed R and W, and obtain the total squared error as shown below:

К	Least Squared error
10	128481.586294
50	86853.134640
100	59135.867432

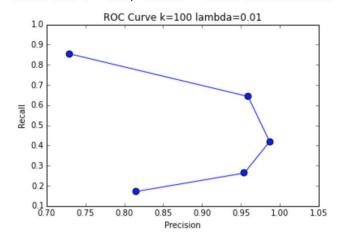
We then add a regularization term λ to the cost function, and run matrix factorization again, with K=10, 50, 100 and λ =0.01, 0.1, 1. We plotted the ROC curve and calculated the least square errors. It is seen in the plotted graphs that the result improves as K and λ becomes larger.



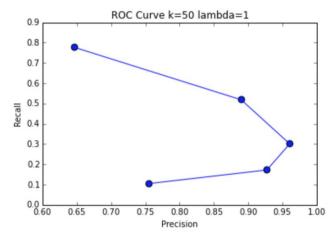
error for k = 50, lambda = 0.10: 346093.448286



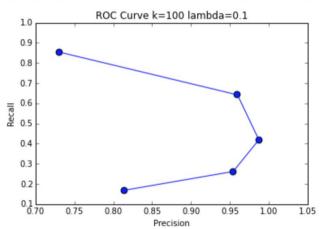
error for k = 100, lambda = 0.01: 229884.253657



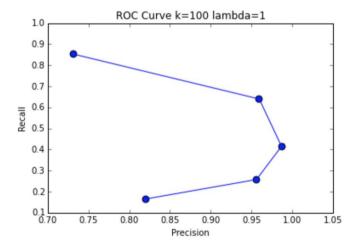
error for k = 50, lambda = 1.00: 347389.179082



error for k = 100, lambda = 0.10: 230289.832031



error for k = 100, lambda = 1.00: 232216.165217



Average precision on all folds for L = 5 is 0.69838939.

We calculated the hit rate by counting the number of movies in L that are liked by the users and also recommended by our system. On the other hand, the false-alarm rate is the number of movies in L that are not actually liked by the users.

L	Precision
1	0.72301666
2	0.71028271
3	0.70406829
4	0.70301212
5	0.69838939

