The Experiment Report of Machine Learning

SCHOOL: SCHOOL OF SOFTWARE ENGINEERING

SUBJECT: SOFTWARE ENGINEERING

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Recommender System Based on Matrix Decomposition

Abstract—The recommender system is a research issue that is getting hotter and hotter now, Matrix decomposition is a more effective and fast way to implement the recommender system. High dimensional user-item scoring matrix is decomposed into two low-dimensional user factor matrices and item factor matrices. Use the product of these two low-dimensional matrices to fit the scoring matrix to predict the user's rating of the item, in order to recommend users with higher ratings of the item.

I. Introduction

The emergence and popularization of the internet bring a great deal of information to the users and satisfy the user's demand for information in the information age. However, with the rapid development of the network, the substantial increase of the amount of information on the Internet makes the users face a great deal of information When you can not get from that part of the information that is really useful to yourself, but the efficiency of the use of information but reduced, and this is the so-called information overload problem.

A very potential solution to the information overload problem is the recommendation system, which is based on the user's information needs, interests, etc., will be interested in the user information, products, etc. to recommend to the user's personalized information recommendation system. Compared with the search engine recommendation system through the study of the user's interest preferences, personalized calculations, the system found that the user's point of interest, so as to guide the user to find their own information needs.

Currently recommended system is the most used matrix decomposition method. Matrix factorization predicts missing values in the scoring matrix and then recommends the user somehow based on the predicted value. Common matrix decomposition methods include basic MF, Regularized MF, probability-based matrix factorization (PMF), etc

Basic MF is the most basic decomposition method. The score matrix R is decomposed into the user matrix U and the item matrix S, and the product of U and S gets closer and closer to the real matrix through continuous iterative training.Projections close to the true value is to minimize the difference, which is our objective function, and then iteratively calculate U and S using a gradient descent, which is the matrix that is decomposed when they converge.

II. Methods and Theory

In this experiment, we will use Stochastic Gradient Descent to matrix decomposition algorithm.

1. Matrix Factorization

Decompose high dimensional rating matrix R $\in \mathbb{R}^{m\times n}$ into two low dimensional user factor and item feature matrices.P $\in \mathbb{R}^{m\times k}$ and $Q \in \mathbb{R}^{k\times n}$.We will use the product of two low-rank feature matrices to predict the rating which users don't score. We chose the squared error loss as the objective function

$$\text{Squared error loss:} \mathcal{L}(r_{u,i}, \hat{r}_{u,i}) = (r_{u,i} - \hat{r}_{u,i})^2$$

2. Stochastic Gradient Descent

We use stochastic gradient descent to get the two low-rank feature matrices. Randomly select an observed sample $r_{u,i}$ from observed set Ω, calculate the gradient to the objective function and update the feature matrices P and Q.

SGD is to minimize the objective function

$$\mathcal{L} = \sum_{u,i\in\Omega} (r_{u,i} - p_u^T q_i)^2 + \lambda_p ||p_u||^2 + \lambda_q ||q_i||^2$$

$$\text{Prediction error: } E_{u,i} = r_{u,i} - p_u{}^T q_i$$

$$\text{Gradient: } \frac{\partial \mathcal{L}}{\partial p_u} = E_{u,i}(-q_i) + \lambda_p p_u$$

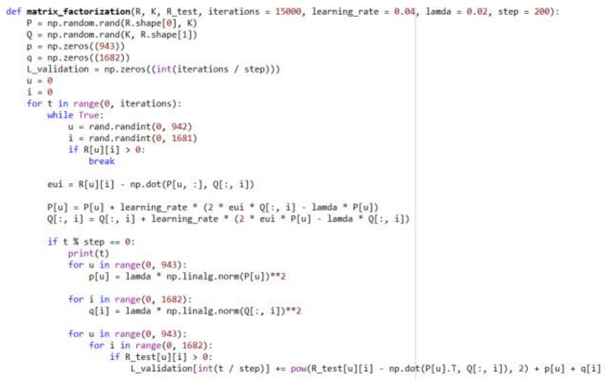
$$\frac{\partial \mathcal{L}}{\partial q_i} = E_{u,i}(-p_u) + \lambda_q q_i$$

III. Experiment

1. Datasets

In this experiment, we use MovieLens-100k dataset. This dataset were collected by the GroupLens Research Project at the University of Minnesota. The data was collected through the MovieLens web site (movielens.umn.edu) during the seven-month period from September 19th, 1997 through April 22nd, 1998. It consists of 100,000 ratings (1-5) from 943 users on 1682 movies, and each user has rated at least 20 movies. We use u1.base and u1.test which are seperated from dataset u.data with proportion of 80% and 20%.

user id	**item id**	**rating**	**timestamp**
196	242	3	881250949
186	302	3	891717742
22	377	1	878887116
244	51	2	880606923
166	346	1	886397596



```
def matrix_factorization(R, K, R_test, iterations = 15000, learning_rate = 0.04, lamda = 0.02, step = 200):
    P = np.random.rand(R.shape[0], K)
    Q = np.random.rand(K, R.shape[1])
    p = np.zeros((943))
    q = np.zeros((1682))
    L_validation = np.zeros((int(iterations / step)))
    u = 0
    i = 0
    for t in range(0, iterations):
        while True:
            u = rand.randint(0, 942)
            i = rand.randint(0, 1681)
            if R[u][i] > 0:
                break

        eui = R[u][i] - np.dot(P[u, :], Q[:, i])

        P[u] = P[u] + learning_rate * (2 * eui * Q[:, i] - lamda * P[u])
        Q[:, i] = Q[:, i] + learning_rate * (2 * eui * P[u] - lamda * Q[:, i])

        if t % step == 0:
            print(t)
            for u in range(0, 943):
                p[u] = lamda * np.linalg.norm(P[u])**2

            for i in range(0, 1682):
                q[i] = lamda * np.linalg.norm(Q[:, i])**2

            for u in range(0, 943):
                for i in range(0, 1682):
                    if R_test[u][i] > 0:
                        L_validation[int(t / step)] += pow(R_test[u][i] - np.dot(P[u].T, Q[:, i]), 2) + p[u] + q[i]
```

Figure 1

2. Experimental Setup

In this experiment, we use SGD to decompose the rating matrix. We calculate the gradient by observed sample selected randomly.

3. Algorithm Implementation

We implementation the algorithm as Figure 1. In this code, we should calculate the loss of validation set, but it takes long time. So we calculate the loss each 200 iterations.

Figure 2 show the loss of validation set has converged

IV. CONCLUSION

Through this experiment, we use the matrix decomposition method to build a recommendation system, and use a method of stochastic gradient descent to update the two low-rank feature matrices.

Because of the use of a stochastic gradient descent method, it takes less time to update the matrix, but calculating loss requires a lot of time, so we calculate a loss every 200 iterations.

In general, the stochastic gradient descent algorithm can better solve the experiment of recommendation system. In the study of parameter k, we found that the greater the k value, the better the convergence effect.

REFERENCES

Albert Au Yeung Matrix Factorization: A Simple Tutorial and Implementation in Python http://www.quuxlabs.com/blog/2010/09/matrix-factorization-a-simple-tutorial-and-implementation-in-python/

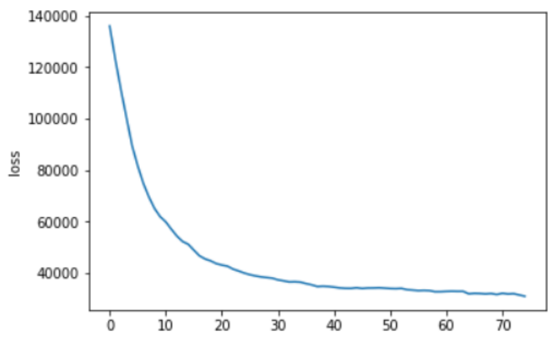


Figure 2