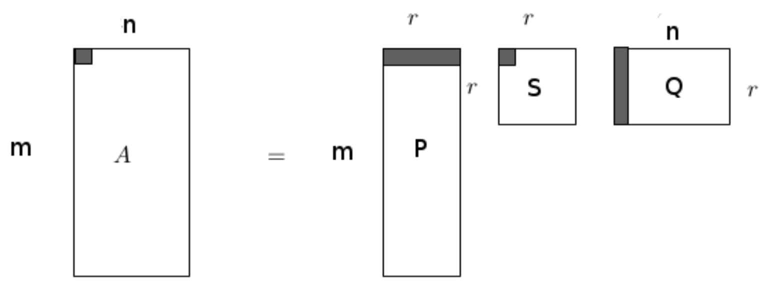
Yaklasiksal SVD ile Tavsiye Sistemleri

SVD, Toplu Tavsiye yazisinda Movielens verisine SVD uygulayarak once boyut azaltmistik. Azaltilmis boyut uzerinden, yeni bir kullanicinin diger mevcut kullanicilara mesafesini hesaplamis, ve boylece en cok benzedigi diger kullaniciyi bulmustuk. Bu kullanicinin bir film icin verdigi notu yeni kullanici icin tahmin olarak baz almistik.

SVD uygulamanin degisik bir yolu daha var. Netflix yarismasinda kullanilan [1] bir yaklasim soyle. Alttaki SVD ayristirmasina bakalim,



1. kullanicini 1. filme verdigi not ustte koyu gosterilen satirlarin carpimi ile oluyor, eger ufak harfler ve kullanici (user) icin u, film icin i indisini kullanirsak, ve q, p vektorlerini Q, P matrislerinin sirasiyla kolon ve satirlarini gostermek icin kullanirsak, ayristirma sonrasi begeni degerinin onemli bir kismi $q_i^T p_u$ carpimindadir. Carpim icinde S'ten gelecek tekil degeri (singular value) ne olacak? Formulasyonu biraz degistirelim dedik, bu degeri carpim disina alarak birkac toplam olarak gosterebiliriz. Bu toplamlar mesela bir kullanicinin ne kadar yanli (bias) not verdigini, ya da bir filmin kabaca, ortalama nasil not almaya meyilli oldugunu modelleyebilirler (ki bu da bir yanlilik olcusu). Bu durumda bir begeni notunu tahmin edecek formul soyle gosterilebilir,

$$\hat{r}_{ui} = \mu + b_i + b_u + q_i^T p_u$$

μ bir skalar, tum filmlere verilen ortalamayi gosteriyor. Bu deger tek bir hesap ile tum begenilerin ortalamasini alarak basitce bulunabilir. $\hat{r}_{ui}$'ya bir tahmin dedik cunku modelimizdeki vektorleri bulduktan sonra (egitim verisiyle hesap sonrasi) bu modeli kullanarak gercek r_{ui}'yi bulmak yaptigimiz bir hesaptir.

$$\min_{b*,q*,p*} \sum_{u,i} (r_{ui} - \mu + b_i + b_u + q_i^T p_u)^2 + \lambda_4 (b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2)$$

$$\min_{b*,q*,p*} \sum_{u,i} (r_{ui} - \hat{r}_{ui})^2 + \lambda_4 (b_i^2 + b_u^2 + ||q_i||^2 + ||p_u||^2)$$

$$e_{ui} := r_{ui} - \hat{r}_{ui}$$

$$b_u \leftarrow b_u + \gamma(e_{ui} - \lambda \cdot b_u)$$

$$b_i \leftarrow b_i + \gamma(e_{ui} - \lambda \cdot b_i)$$

$$q_i \leftarrow q_i + \gamma(e_{ui} \cdot p_u - \lambda \cdot q_i)$$

$$p_u \leftarrow p_u + \gamma(e_{ui} \cdot q_i - \lambda \cdot p_u)$$

```
from numpy.linalg import linalg as la
import numpy as np
import random
import pandas as pd, os

def create_training_test(df,collim=2,rowlim=200):
    test_data = []
    df_train = df.copy()
    for u in range(df.shape[0]):
        row = df.ix[u]; idxs = row.index[row.notnull()]
        if len(idxs) > collim:
            i = random.choice(idxs); val = df.ix[u,i]
            test_data.append([u,i,val])
            df_train.ix[u,i] = np.nan
        if len(test_data) > rowlim: break
    return df_train, test_data

def ssvd(df_train,rank):
    print 'rank',rank
    gamma = 0.02 # regularization
    lam = 0.05

    mu = df_train.mean().mean()
    m,n = df_train.shape
    c = 0.03
    b_u = np.ones(m) * c
    b_i = np.ones(n) * c
    p_u = np.ones((m, rank)) * c
    q_i = np.ones((rank, n)) * c
    r_ui = np.array(df_train)
    for u in range(m):
        #print "user", u
        row = df_train.ix[u]; idxs = row.index[row.notnull()]
        for i in idxs:
            i = int(i)
            r_ui_hat = mu + b_i[i] + b_u[u] + np.dot(q_i[:,i].T,p_u[u,:])
            e_ui = r_ui[u,i] - r_ui_hat
            b_u[u] = b_u[u] + gamma * (e_ui - lam*b_u[u])
            b_i[i] = b_i[i] + gamma * (e_ui - lam*b_i[i])
            q_i[:,i] = q_i[:,i] + gamma * (e_ui*p_u[u,:].T - lam*q_i[:,i])
            p_u[u,:] = p_u[u,:] + gamma * (e_ui*q_i[:,i].T - lam*p_u[u,:])
```

```
    return mu,b_u,b_i,q_i,p_u
```

```
import pandas as pd
import ssvd
d =  np.array(
[[  5.,   5.,   3.,  nan,   5.,   5.],
 [  5.,  nan,   4.,  nan,   4.,   4.],
 [ nan,   3.,  nan,   5.,   4.,   5.],
 [  5.,   4.,   3.,   3.,   5.,   5.],
 [  5.,   5.,  nan,  nan,  nan,   5.]
])
data = pd.DataFrame (d,
    columns=['0','1','2','3','4','5'],
    index=['Ben','Tom','John','Fred','Bob'])
mu,b_u,b_i,q_i,p_u = ssvd.ssvd(data,rank=3)
print mu
print 'b_u',b_u
print 'b_i',b_i
print 'q_i',q_i
print 'p_u',p_u
u = 4; i = 2
r_ui_hat = mu + b_i[i] + b_u[u] + np.dot(q_i[:,i].T,p_u[u,:])
print r_ui_hat
```

```
3
5 6
4.31388888889
b_u [ 0.05129388  0.01927226  0.0206893   0.0065487   0.06568321]
b_i [ 0.07820389  0.01958841 -0.03217881  0.01561187  0.04071886  0.07140383]
q_i [[ 0.03132989  0.02957741  0.02802317  0.02951804  0.0301854   0.03108419]
 [ 0.03132989  0.02957741  0.02802317  0.02951804  0.0301854   0.03108419]
 [ 0.03132989  0.02957741  0.02802317  0.02951804  0.0301854   0.03108419]]
p_u [[ 0.03053543  0.03053543  0.03053543]
 [ 0.0295772   0.0295772   0.0295772 ]
 [ 0.02963018  0.02963018  0.02963018]
 [ 0.02921864  0.02921864  0.02921864]
 [ 0.03100583  0.03100583  0.03100583]]
4.34999993855
```

```
import pandas as pd, os
df = pd.read_csv("%s/Downloads/movielens.csv" % os.environ['HOME'] ,sep=';')
print df.shape
df = df.ix[:,1:3700] # id kolonunu atla,
df.columns = range(3699)
print df.shape
```

```
(6040, 3731)
(6040, 3699)
```

```
import ssvd
df_train, test_data = ssvd.create_training_test(df,300)
print len(test_data)
```

```
201
```

```python
import ssvd; reload(ssvd)
mu,b_u,b_i,q_i,p_u = ssvd.ssvd(df_train,rank=25)
print 'mu',mu
```

```
rank 25
mu 3.23808578394
```

```python
rmse = 0; n = 0
for u,i,real in test_data:
    r_ui_hat = mu + b_i[i] + b_u[u] + np.dot(q_i[:,i].T,p_u[u,:])
    rmse += (real-r_ui_hat)**2
    n += 1
    #print u,i,real, r_ui_hat
print "rmse", np.sqrt(rmse / n)
```

```
rmse 0.91
```

Kaynaklar

http://sifter.org/~simon/journal/20061211.html

Koren, Bell, *Recommender Systems Handbook*, http://www.cs.bme.hu/nagyadat/Recommender_systems_handbook.pdf

http://www2.research.att.com/~volinsky/papers/ieeecomputer.pdf

http://www.cs.nyu.edu/~yann/talks/lecun-20071207-nonconvex.pdf

http://courses.cs.washington.edu/courses/cse528/09sp/sanger_pca_nn.pdf

http://users.ics.aalto.fi/oja/Oja1982.pdf

http://arxiv.org/pdf/1308.3509

http://www.maths.qmul.ac.uk/~wj/MTH5110/notes/MAS235_lecturenotes1.pdf

http://heim.ifi.uio.no/~tom/powerandqrslides.pdf

http://math.stackexchange.com/questions/649701/gradient-descent-on-non-convex-function-works-but-how