hw7

November 7, 2021

[49]:
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#imported from hw1
import pandas as pd
from statsmodels.tsa.stattools import adfuller
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf

#basic correlation function
df = pd.read_csv('EE627A_HW1_Data.csv', header=0)
data = df.iloc[:, 1::]
data.corr()

#first four-factor correlation & RF
dc = df[['Mkt-RF', 'SMB', 'HML','RF', 'Mom' ]]
dc.corr()



#convert data to series
MKTRF_Series = data['Mkt-RF'].squeeze()
SMB_Series = data['SMB'].squeeze()
HML_Series = data['HML'].squeeze()
RF_Series = data['RF'].squeeze()
Mom_Series = data['Mom'].squeeze()

#new dataframe for first 5 col
new_df = pd.DataFrame(data = {
    'Mkt-RF': [],
    'SMB': [],
    'HML': [],
    'RF': [],
    'Mom': []
})

#compute autocorr and append to new df using series conversion
for i in range(11):
     new_df = new_df.append({
         'Mkt-RF': MKTRF_Series.autocorr(lag=i),
         'SMB': SMB_Series.autocorr(lag=i),
         'HML': HML_Series.autocorr(lag=i),
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            'RF': RF_Series.autocorr(lag=i),
            'Mom': Mom_Series.autocorr(lag=i)
        },
            ignore_index = True)

#print(dc)
#pd.plotting.autocorrelation_plot(new_df)
#print (new_df)
#print('\nFor the four-factor model, Mkt-RF correlates most highly with every␣
 ↪industry. Mom correlates negatively with each industry')
#print('\nRF does not correlate highly with the 30 industry time series. It is␣
 ↪close to uncorrelated for most of them')

#plot_acf(MKTRF_series, alpha=1, lags=20)
df_stationarityTest = adfuller(df['Mkt-RF'], autolag='AIC')
#print("P-value: ", df_stationarityTest[1])
new_df
#print('\n based on the P-value above, the first column is stationary (<0.05),␣
 ↪and since the plot below follows an exponential decay, there is an AR(1) model␣
 ↪in the series')
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[49]:

	Mkt-RF	SMB	HML	RF	Mom
0	1.000000	1.000000	1.000000	1.000000	1.000000
1	0.538767	0.181205	0.078444	0.385678	0.076150
2	0.311438	-0.138087	-0.566225	0.379039	0.190134
3	0.192926	-0.237403	-0.091411	0.079919	0.160320
4	-0.038368	-0.227750	0.001836	0.572369	-0.048704
5	0.079526	0.028412	0.027075	0.001376	0.012745
6	-0.066185	-0.270374	0.074835	0.273039	0.189619
7	-0.207892	-0.140559	-0.094099	-0.012596	-0.314257
8	-0.091080	0.046298	-0.039770	0.007937	0.145516
9	-0.203056	-0.120721	0.135602	0.220136	-0.031519
10	-0.129402	0.051306	-0.330988	-0.147054	-0.218290

[50]:

```
#make each column a PC by transforming using Standard Scaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data_transform = scaler.fit_transform(new_df)
#this standardizes the data
data_transform
```

[50]:

```
array([[ 2.47516309,  2.8964102 ,  2.68113867,  2.39199797,  2.7637021 ],
       [ 1.1688614 ,  0.48710048,  0.16565816,  0.43038046, -0.09103398],
       [ 0.52502393, -0.45241996, -1.59403105,  0.40918234,  0.26118213],
       [ 0.18937257, -0.74465858, -0.29797894, -0.54595043,  0.16905562],
       [-0.46569669, -0.71625314, -0.04344974,  1.02651203, -0.47683806],
       [-0.13179649,  0.0375049 ,  0.02544067, -0.79674952, -0.2869574 ],
```

```
 [-0.54447929, -0.84167591,  0.1558078 ,  0.07070895,  0.25959047],
 [-0.94582037, -0.4596933 , -0.30531526, -0.8413623 , -1.29740914],
 [-0.61498491,  0.09013346, -0.15701939, -0.77579688,  0.12331057],
 [-0.93212247, -0.40131956,  0.32167693, -0.09821738, -0.42373623],
 [-0.72352077,  0.1048714 , -0.95192784, -1.27070525, -1.00086608]])
```

[51]:

```
from sklearn.decomposition import PCA
#instantiate the PCA class with 2 components
pca = PCA(n_components = 2)
pca_transform = pca.fit_transform(data_transform)
```

[52]:

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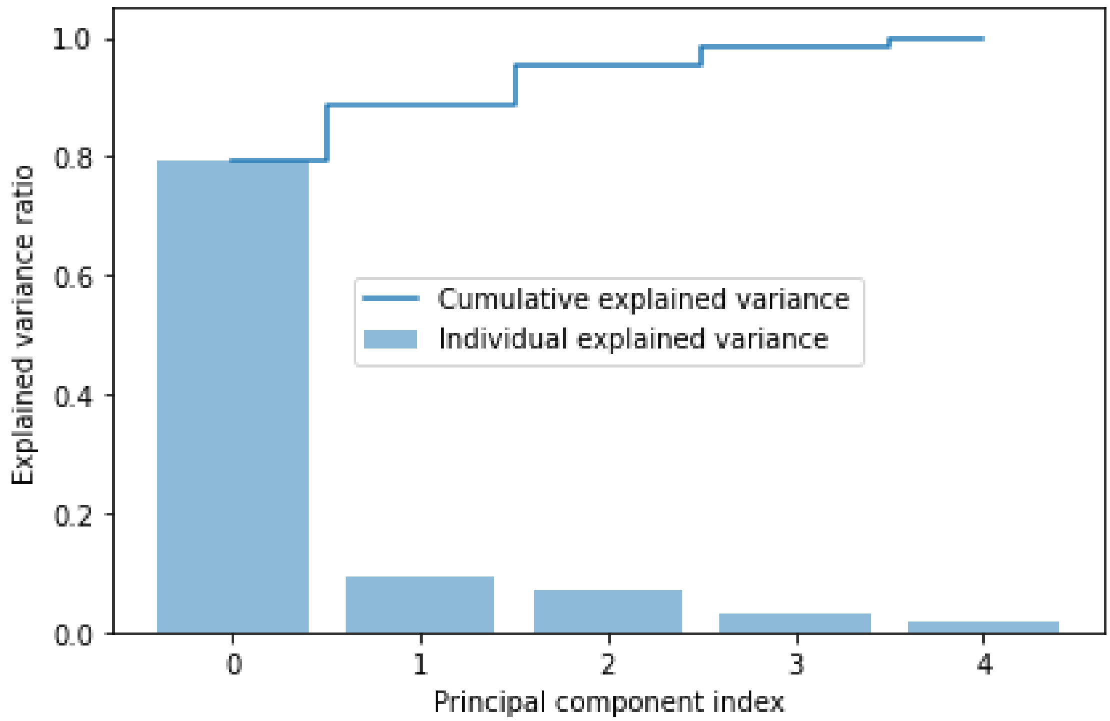
print(pca_transform.shape)
print(data_transform.shape)
#reduced columns from 5 to 2
```

```
(11, 2)
(11, 5)
```

[53]:

```
#total variance explained = (lambda1 + lambda 2) / (lambda1...lambdaN)
import numpy as np
pca = PCA().fit(new_df)
exp_var_pca = pca.explained_variance_ratio_ #can only use␣
 ↪explained_variance_ratio_ with .fit
cum_sum_eigenvalues = np.cumsum(exp_var_pca)
plt.bar(range(0,len(exp_var_pca)), exp_var_pca, alpha=0.5, align='center',␣
 ↪label='Individual explained variance')
plt.step(range(0,len(cum_sum_eigenvalues)), cum_sum_eigenvalues,␣
 ↪where='mid',label='Cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal component index')
plt.legend(loc='center')
plt.tight_layout()
plt.show()
```



[54]:
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print("PC1: ", exp_var_pca[0])
print("PC2: ", exp_var_pca[1])
print("As it can be seen above, PC1 accounts for 75% of the covariance matrix,␣
↪which makes sense since its variance should be maximal")
```
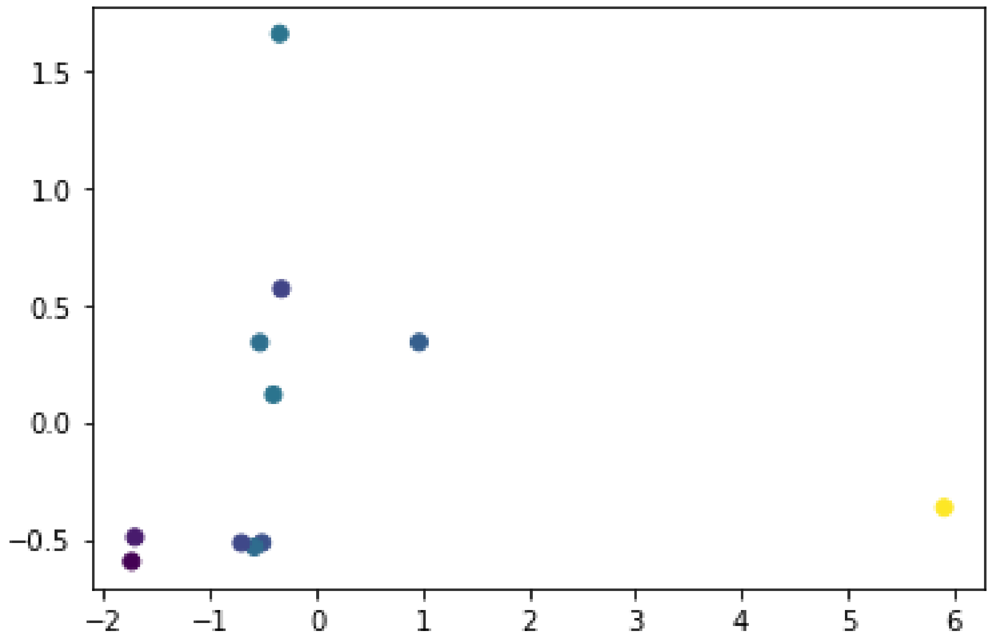

```
PC1:  0.7912284453682369
PC2:  0.0946958946488332
As it can be seen above, PC1 accounts for 75% of the covariance matrix, which
makes sense since its variance should be maximal
```

[55]:
```
plt.scatter(pca_transform[:,0], pca_transform[:,1], c=new_df['Mom']) #Principal␣
↪1 & 2 plotted
#Not enough data points
```

[55]:
```
<matplotlib.collections.PathCollection at 0x16b376121c0>
```



[56]:
```
#Sources:
#https://vitalflux.com/pca-explained-variance-concept-python-example/
#https://inst.eecs.berkeley.edu/~ee127/sp21/livebook/l_sym_pca.html
#https://nickmccullum.com/python-machine-learning/
 ↪principal-component-analysis-python/
```