PCA Index | Replicating Dow Index

```
import os
import numpy as np
import pandas as pd
import pandas_datareader.data as web
from sklearn.decomposition import PCA as sklearnPCA

from pylab import plt, mpl
plt.style.use('seaborn-v0_8')
mpl.rcParams['savefig.dpi'] = 300
mpl.rcParams['font.family'] = 'serif'
pd.set_option('mode.chained_assignment', None)
pd.set_option('display.float_format', '{:.4f}'.format)
np.set_printoptions(suppress=True, precision=4)
os.environ['PYTHONHASHSEED'] = '0'
```

Constructing a PCA Index

Principal Component Analysis (PCA) is a statistical procedure that employs an orthogonal transformation to convert a set of observations of potentially correlated variables into a set of values of linearly uncorrelated variables known as principal components. The number of principal components is either equal to or less than the number of original variables. This transformation is defined in a manner that ensures the first principal component exhibits the maximum possible variance, effectively accounting for as much of the variability in the data as possible. Subsequent components, while being orthogonal (i.e., uncorrelated) to the preceding components, strive to possess the highest variance achievable under this constraint.

In this section, we present an illustrative example showcasing the application of Principal Component Analysis (PCA) in a specific context. We gather data for both the German DAX index and all the individual stocks comprising the index. Subsequently, we employ PCA to extract the principal components, which we utilize to construct a composite index referred to as the PCA_index.

Data

The DAX Index and Its 30 Stocks

```
[75]: import pandas as pd import yfinance as yf
```

```
# Define the symbols of the Dow Jones Industrial Average
      dow_symbols = ['AAPL', 'AXP', 'BA', 'CAT', 'CSCO', 'CVX', 'DIS', 'GS', __

    'HD','IBM',

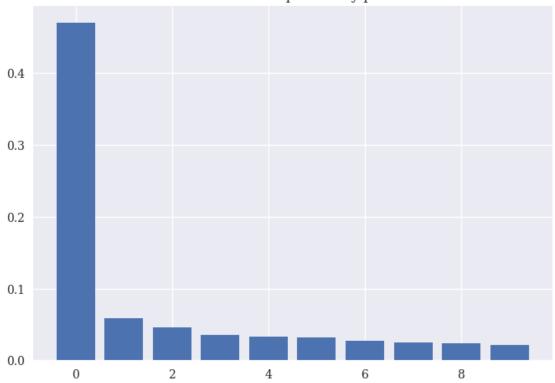
                     'INTC', 'JNJ', 'JPM', 'KO', 'MCD', 'MMM', 'MRK', 'MSFT', L

    'NKE', 'PFE',

                     'PG', 'TRV', 'UNH', 'V', 'VZ', 'WBA', 'WMT', 'XOM', '^DJI']
      data = pd.DataFrame()
      data = yf.download(dow_symbols, start="2010-01-01", end="2023-08-31")["Close"]
      data = data.dropna()
      # Separate the index data
      dow_index = pd.DataFrame(data.pop('^DJI'))
     [******** 29 of 29 completed
     The DataFrame object 'data' now contains data for all DAX stock
[76]: data[data.columns[:10]].head()
[76]:
                   AAPL
                            AXP
                                    BA
                                           CAT
                                                   CSCO
                                                            CVX
                                                                    DIS
                                                                              GS \
      Date
      2010-01-04 7.6432 40.9200 56.1800 58.5500 24.6900 79.0600 32.0700 173.0800
      2010-01-05 7.6564 40.8300 58.0200 59.2500 24.5800 79.6200 31.9900 176.1400
      2010-01-06 7.5346 41.4900 59.7800 59.4300 24.4200 79.6300 31.8200 174.2600
      2010-01-07 7.5207 41.9800 62.2000 59.6700 24.5300 79.3300 31.8300 177.6700
      2010-01-08 7.5707 41.9500 61.6000 60.3400 24.6600 79.4700 31.8800 174.3100
                      HD
                              IBM
     Date
      2010-01-04 28.6700 126.6252
      2010-01-05 28.8800 125.0956
      2010-01-06 28.7800 124.2830
      2010-01-07 29.1200 123.8528
      2010-01-08 28.9800 125.0956
[77]: # dow_index cummulative returns, normalized
      #dow_index_returns = dow_index.pct_change()
      dow_index_returns = np.log(dow_index / dow_index.shift(1))
      dow_index_returns.dropna(inplace=True)
      dow_ret_idx = dow_index_returns.cumsum() + 1
      dow_ret_idx.columns =['dow']
```

```
[78]: #stocks_ret = data.pct_change()
     stocks_ret = np.log(data / data.shift(1))
     stocks_ret.dropna(inplace=True)
     stocks_ret .head()
[78]:
                   AAPL
                           AXP
                                    BA
                                          CAT
                                                CSCO
                                                         CVX
                                                                 DIS
                                                                          GS \
     Date
     2010-01-05 0.0017 -0.0022 0.0322 0.0119 -0.0045 0.0071 -0.0025 0.0175
     2010-01-06 -0.0160 0.0160 0.0299 0.0030 -0.0065 0.0001 -0.0053 -0.0107
     2010-01-07 -0.0019 0.0117 0.0397 0.0040 0.0045 -0.0038 0.0003 0.0194
     2010-01-08 0.0066 -0.0007 -0.0097 0.0112 0.0053 0.0018 0.0016 -0.0191
     2010-01-11 -0.0089 -0.0115 -0.0119 0.0609 -0.0028 0.0176 -0.0164 -0.0159
                           IBM ...
                                      NKE
                                              PFE
                                                      PG
                                                             TRV
                                                                     UNH \
     Date
     2010-01-05 0.0073 -0.0122 ... 0.0040 -0.0144 0.0003 -0.0240 -0.0016
     2010-01-06 -0.0035 -0.0065 ... -0.0061 -0.0032 -0.0048 -0.0143 0.0098
     2010-01-07 0.0117 -0.0035 ... 0.0098 -0.0038 -0.0054 0.0143 0.0377
     2010-01-08 -0.0048 0.0100 ... -0.0020 0.0081 -0.0013 -0.0014 -0.0094
     2010-01-11 -0.0287 -0.0105 ... -0.0124 0.0080 -0.0040 -0.0004 0.0067
                            ٧Z
                                   WBA
                                           WMT
                                                  MOX
     Date
     2010-01-06 -0.0135 -0.0435 -0.0076 -0.0022 0.0086
     2010-01-07 0.0093 -0.0060 0.0060 0.0006 -0.0031
     2010-01-08 0.0028 0.0006 0.0014 -0.0050 -0.0040
     2010-01-11 -0.0029 0.0041 0.0016 0.0164 0.0112
     [5 rows x 28 columns]
[86]: # USING SKLEARN
     sklearn_pca = sklearnPCA(n_components=10) # let's look at the first 20_1
      ⇔components
     pc = sklearn_pca.fit_transform(stocks_ret)
     # plot the variance explained by pcs
     plt.bar(range(10),sklearn_pca.explained_variance_ratio_)
     plt.title('variance explained by pc')
     plt.show()
```





```
[80]: # check the explained variance reatio sklearn_pca.explained_variance_ratio_
```

```
[80]: array([0.4702, 0.0581, 0.0456, 0.0359, 0.0335, 0.0318, 0.0273, 0.0252, 0.0231, 0.0216, 0.0202, 0.0196, 0.0181, 0.018 , 0.0155, 0.0144, 0.0144, 0.0136, 0.0129, 0.012])
```

```
[81]: # get the Principal components
pcs =sklearn_pca.components_

#first component
pc1 = pcs[0,:]

# normalized to 1
pc_w = np.asmatrix(pc1/sum(pc1)).T

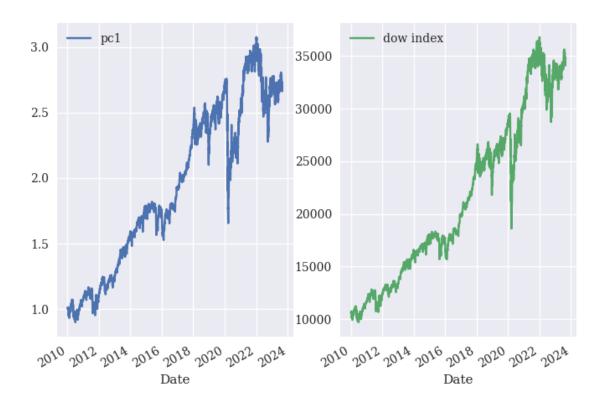
# apply our first component as weight of the stocks
pc1_ret = stocks_ret.values*pc_w

# plot the total return index of the first PC portfolio
pc_ret = pd.DataFrame(data =pc1_ret, index= stocks_ret.index)
```

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pc_ret_idx = pc_ret+1
pc_ret_idx= pc_ret_idx.cumprod()
pc_ret_idx.columns =['pc1']

pc_ret_idx['dow index'] = dow_index[1:]
pc_ret_idx.plot(subplots=True,title ='PC portfolio vs Market',layout =[1,2])
plt.show()
```

PC portfolio vs Market



The weights of the equities in our portfolio are:

```
[82]: # plot the weights in the PC
weights_df = pd.DataFrame(data = pc_w*100,index = data.columns)
weights_df.columns=['weights']
weights_df.plot.bar(title='PCA portfolio weights',rot =45,fontsize =8)
plt.show()
```



