

pca_eigen_portfolios_m2_ex3

October 25, 2018

0.1 Eigen-portfolio construction using Principal Component Analysis (PCA)

0.1.1 PCA via `sklearn.decomposition` using S&P 500 Index stock data

Welcome to your 2-nd assignment in Unsupervised Machine Learning in Finance.

In this assignment we look in-depth at model-free factor analysis using PCA. By model-free we mean that we do not rely on any factors such as value or momentum to decompose portfolio returns, but instead using Principal Component Analysis (PCA) to deduce structure of portfolio returns.

We work with S&P 500 index stock data.

0.2 About iPython Notebooks

iPython Notebooks are interactive coding environments embedded in a webpage. You will be using iPython notebooks in this class. You only need to write code between the `### START CODE HERE ###` and `### END CODE HERE ###` comments. After writing your code, you can run the cell by either pressing "SHIFT"+"ENTER" or by clicking on "Run Cell" (denoted by a play symbol) in the upper bar of the notebook.

We will often specify "(X lines of code)" in the comments to tell you about how much code you need to write. It is just a rough estimate, so don't feel bad if your code is longer or shorter.

```
In [114]: import os
          import os.path
          import numpy as np
          import datetime

          import sys
          sys.path.append("..")
          import grading

          try:
              import matplotlib.pyplot as plt
              %matplotlib inline
          except:
              pass

          try:
              import pandas as pd
```

```

    print(" pandas: %s"% pd.__version__)
except:
    print("Missing pandas package")

```

pandas: 0.19.2

In [115]: *### ONLY FOR GRADING. DO NOT EDIT ###*

```

submissions=dict()
assignment_key="BBz-XobeEeegARIaPDSa9g"
all_parts=["nvDA9", "ykDlW", "rpYVm", "oWy6l", "MWwt7", "3VyJD"]
### ONLY FOR GRADING. DO NOT EDIT ###

```

In [140]: COURSERA_TOKEN = "HS7Xnr9EQucoKYNu" *# the key provided to the Student under his/her e*
COURSERA_EMAIL = "cilsya@yahoo.com" *# the email*

In [117]: *# load dataset*

```

asset_prices = pd.read_csv(os.getcwd() + '/data/spx_holdings_and_spx_closeprice.csv',
                           date_parser=lambda dt: pd.to_datetime(dt, format='%Y-%m-%d'),
                           index_col = 0).dropna()

n_stocks_show = 12
print('Asset prices shape', asset_prices.shape)
asset_prices.iloc[:, :n_stocks_show].head()

```

Asset prices shape (3493, 419)

```

Out[117]:
          A      AA      AAPL      ABC      ABT      ADBE      ADI  \
2000-01-27  46.1112  78.9443  3.9286  4.5485  13.7898  15.6719  48.0313
2000-01-28  45.8585  77.8245  3.6295  4.5485  14.2653  14.3906  47.7500
2000-01-31  44.5952  78.0345  3.7054  4.3968  14.5730  13.7656  46.7500
2000-02-01  47.8377  80.7640  3.5804  4.5333  14.7128  13.9688  49.0000
2000-02-02  51.5434  83.4934  3.5290  4.5788  14.7968  15.3281  48.1250

          ADM      ADP      ADSK      AEE      AEP
2000-01-27  10.8844  39.5477  8.1250  32.9375  33.5625
2000-01-28  10.7143  38.5627  7.7188  32.3125  33.0000
2000-01-31  10.6576  37.3807  7.6406  32.5625  33.5000
2000-02-01  10.8844  37.9717  7.9219  32.5625  33.6875
2000-02-02  10.6576  35.9032  7.9688  32.5625  33.6250

```

In [118]: print('Last column contains SPX index prices:')
asset_prices.iloc[:, -10:].head()

Last column contains SPX index prices:

```

Out[118]:
          STJ      SVU      SWY      TEG      TER      TGNA      THC  \
2000-01-27  5.5918  86.6178  26.3983  11.3873  65.8677  22.1921  60.9705

```

2000-01-28	5.4520	82.4218	27.4137	11.2230	60.3487	21.7558	62.3032
2000-01-31	5.5499	86.3181	28.2444	11.0862	62.1484	22.0533	60.6373
2000-02-01	5.4240	83.0212	28.7982	11.1683	67.3674	22.2120	60.4708
2000-02-02	5.3541	81.5226	28.6136	11.1956	68.9271	22.6483	62.4698

	X	MAR.1	SPX
2000-01-27	20.7086	12.2457	1398.56
2000-01-28	20.1183	12.0742	1360.16
2000-01-31	19.5772	12.1722	1394.46
2000-02-01	19.5772	12.5151	1409.28
2000-02-02	19.5281	12.3192	1409.12

Part 1 (Asset Returns Calculation) Instructions:

Calculate percent returns, also known as simple returns using `asse_prices`. assign the result to variable `asset_returns`. Keep only not-nan values in the resulting `pandas.DataFrame`

Calculate de-meaned returns and scale them by standard deviation σ . Assign result to `normed_returns` variable

We now compute stock returns and normalize stock returns data by subtracting the mean and dividing by standard diviation. This normalization is required by PCA.

```
In [119]: asset_returns = pd.DataFrame(data=np.zeros(shape=(len(asset_prices.index), asset_prices.columns.values),
                                                    columns=asset_prices.columns.values,
                                                    index=asset_prices.index)

normed_returns = asset_returns
### START CODE HERE ### ( 4 lines of code)
# normed_returns is pandas.DataFrame that should contain normalized returns

# Calculate percent returns, also known as simple returns using asse_prices.
# Assign the result to variable asset_returns.
asset_returns = asset_prices.pct_change()
#
# Keep only not-nan values in the resulting pandas.DataFrame
asset_returns = asset_returns.replace(np.nan, 0, regex=True)

# Calculate de-meaned returns and scale them by standard deviation.
# Assign result to normed_returns variable
# We now compute stock returns and normalize stock returns data by subtracting
# the mean and dividing by standard diviation. This normalization is required by PCA.
normed_returns = (asset_returns - asset_returns.mean(axis=0)) / asset_returns.std(axis=0)
normed_returns = pd.DataFrame(normed_returns)

# Drop the first row
normed_returns = normed_returns.iloc[1:]

### END CODE HERE ###

normed_returns.iloc[-5:, -10:].head()
```

```

Out[119]:
          STJ          SVU          SWY          TEG          TER          TGNA  \
2013-12-16  0.852856  0.965359 -1.169049  0.884888  0.095880  0.656736
2013-12-17  0.275224  0.517383 -0.086115 -0.306246  0.589775 -0.118625
2013-12-18  0.864621  0.509511  0.600804  1.210789 -0.190049  0.925596
2013-12-19  0.210112  0.399634 -0.100170 -0.757517 -0.208051  0.304959
2013-12-20  0.827436  0.748530  0.372500  1.048274  0.264086  0.436939

          THC          X          MAR.1          SPX
2013-12-16  0.180044 -0.238526  0.465122  0.468002
2013-12-17 -0.549598  0.025277 -0.260042 -0.247953
2013-12-18  0.757110  0.058442  0.952602  1.252886
2013-12-19 -0.772312  1.544455 -0.167791 -0.056362
2013-12-20  0.320691 -0.740955  0.373779  0.353914

```

```

In [120]: ### GRADED PART (DO NOT EDIT) ###
part_1=list(normed_returns.iloc[0,: 100].as_matrix().squeeze())
try:
    part1 = " ".join(map(repr, part_1))
except TypeError:
    part1 = repr(part_1)
submissions[all_parts[0]]=part1
grading.submit(COURSE_EMAIL, COURSE_TOKEN, assignment_key,all_parts[:1],all_parts,
normed_returns.iloc[0,: 100].as_matrix().squeeze())
### GRADED PART (DO NOT EDIT) ###

```

Submission successful, please check on the coursera grader page for the status

```

Out[120]: array([-0.19007752, -0.51378354, -2.71508377, -0.04977229,  2.18325301,
-2.68450702, -0.21248702, -0.76709776, -1.54094625, -1.80419545,
-1.37318536, -0.99430738,  0.16138837,  0.72991552,  0.63495564,
-0.72142213, -0.0130274 , -0.8080893 ,  0.39929293, -0.75903493,
-1.43464957, -1.12799754, -1.29403324, -0.44808611, -2.14003095,
 0.58959236, -0.87837898,  0.31433656, -1.0807495 , -0.31371438,
 0.11821896, -1.86893679, -1.87300855, -0.22610904, -0.0418852 ,
-0.02135839, -0.60466587, -1.43107734, -1.16695823, -1.65616404,
-0.50499727, -1.51986323, -0.36364509, -0.58867176, -0.7329979 ,
 0.87668379, -3.12454362, -1.33995546, -1.33884528, -0.53058613,
-1.28327282, -2.21743433,  1.75810464,  0.22819369, -0.48099914,
-0.21162737, -1.39183296, -1.89106681, -1.26540917, -0.90802631,
 1.20025673, -1.13799044, -1.06749907, -1.49050331,  1.65215907,
-0.94853884,  3.36986014, -0.82355183,  1.76617483,  0.04145153,
-2.73724874, -0.93557347,  0.02500748, -0.5273333 , -0.34697322,
-3.31791296, -1.10547323, -0.79767652, -0.4545626 ,  1.58060226,
-1.05550235, -0.19734035, -0.85232869, -3.09491117, -2.41233778,
-0.93938364, -1.88393008, -2.73747984, -2.97119678, -0.52327684,
-0.71140214,  2.02611986, -1.26177708, -3.24599972, -1.04376025,
-0.21377559,  0.86667266, -0.53482316,  0.92667422, -0.51031526])

```

```

In [121]: train_end = datetime.datetime(2012, 3, 26)

df_train = None
df_test = None
df_raw_train = None
df_raw_test = None

df_train = normed_returns[normed_returns.index <= train_end].copy()
df_test = normed_returns[normed_returns.index > train_end].copy()

df_raw_train = asset_returns[asset_returns.index <= train_end].copy()
df_raw_test = asset_returns[asset_returns.index > train_end].copy()

print('Train dataset:', df_train.shape)
print('Test dataset:', df_test.shape)

```

```

Train dataset: (3055, 419)
Test dataset: (437, 419)

```

Now we compute PCA using all available data. Once we do have PCA computed we fix variance explained at some number and see what is the smallest number of components needed to explain this variance.

Part 2 (PCA fitting) Instructions: - Calculate covariance matrix using training data set, i.e. **df_train** for all assets. Assign results to **cov_matrix**. - Calculate covariance matrix using training data set, i.e. **df_raw_train** for all assets. Assign results to **cov_matrix_raw**. - Use scikit-learn PCA to fit PCA model to **cov_matrix**. Assign fitted model to **pca**

```

In [122]: import sklearn.decomposition
import seaborn as sns

stock_tickers = normed_returns.columns.values[:-1]
assert 'SPX' not in stock_tickers, "By accident included SPX index"

n_tickers = len(stock_tickers)
pca = None
cov_matrix = pd.DataFrame(data=np.ones(shape=(n_tickers, n_tickers)), columns=stock_tickers)
cov_matrix_raw = cov_matrix

if df_train is not None and df_raw_train is not None:
    stock_tickers = asset_returns.columns.values[:-1]
    assert 'SPX' not in stock_tickers, "By accident included SPX index"

    ### START CODE HERE ### ( 2-3 lines of code)

    # computing PCA on S&P 500 stocks

```

```

# Calculate covariance matrix using training data set,
# i.e. df_train for all assets. Assign results to cov_matrix.
#cov_matrix=df_train.cov()
cov_matrix = df_train[stock_tickers].cov()

# Calculate covariance matrix using training data set,
# i.e. df_raw_train for all assets. Assign results to cov_matrix_raw.
cov_matrix_raw=df_raw_train[stock_tickers].cov()

# Use scikit-learn PCA to fit PCA model to cov_matrix. Assign fitted model to pca
clf = sklearn.decomposition.PCA()
pca = clf.fit(cov_matrix)

# not normed covariance matrix

### END CODE HERE ###

cov_raw_df = pd.DataFrame({'Variance': np.diag(cov_matrix_raw)}, index=stock_tickers)
# cumulative variance explained
var_threshold = 0.8
var_explained = np.cumsum(pca.explained_variance_ratio_)
num_comp = np.where(np.logical_not(var_explained < var_threshold))[0][0] + 1 # +1
print('%d components explain %.2f%% of variance' %(num_comp, 100* var_threshold))

```

4 components explain 80.00% of variance

```

In [123]: ### GRADED PART (DO NOT EDIT) ###
part_2 = np.diag(cov_matrix[: 100])
try:
    part2 = " ".join(map(repr, part_2))
except TypeError:
    part2 = repr(part_2)
submissions[all_parts[1]]=part2
grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:2],all_parts,
### GRADED PART (DO NOT EDIT) ###
np.diag(cov_matrix[: 100])

```

Submission successful, please check on the coursera grader page for the status

```

Out[123]: array([ 1.10478242,  1.09455432,  1.08221062,  1.10548586,  1.06972085,
                  1.10629519,  1.11901325,  1.08425013,  1.09834527,  1.06621229,
                  1.07829579,  1.10771015,  1.12450535,  1.10444381,  1.07751955,
                  1.11984646,  1.11539247,  1.1071917 ,  1.04857046,  1.10832658,
                  1.1051169 ,  1.04327362,  1.07497386,  1.12542467,  1.10863228,
                  1.09149441,  1.08449312,  1.02697733,  1.09840268,  1.08537602,
                  1.0805351 ,  1.08147741,  1.0962246 ,  0.99836261,  1.11100475,
                  1.01462408,  1.10392495,  1.06629289,  1.11035646,  1.08830348,

```

```

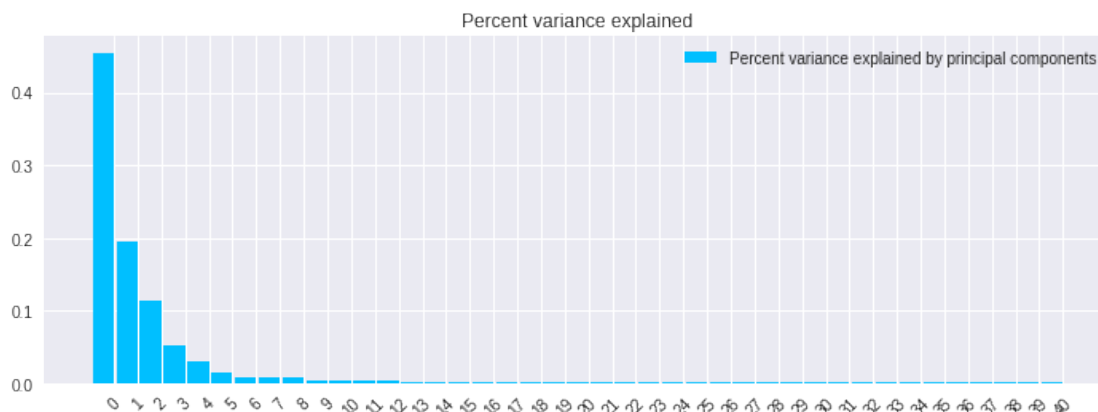
1.08267576, 1.0942163 , 1.08520176, 1.10535237, 0.99878741,
1.08378042, 1.10224712, 1.08963727, 1.08908082, 1.09592188,
1.10310166, 1.09182003, 1.07098094, 1.11227998, 1.07335399,
1.10657054, 1.10486349, 1.11563753, 1.06738213, 1.08956209,
1.07238537, 1.08182671, 1.11571354, 1.09594673, 1.0994683 ,
1.10130047, 1.09801796, 1.05345536, 1.08266256, 1.1045181 ,
1.10797538, 1.08555709, 1.02560735, 1.10627165, 1.10368709,
1.10945548, 1.08744706, 1.11857364, 1.1185181 , 1.08153319,
1.11718141, 1.05624895, 1.09646017, 1.10243721, 1.06202598,
1.09049077, 1.09369544, 1.11218236, 1.04809318, 1.09233857,
1.09220974, 1.10276995, 1.09400944, 1.09430711, 1.09951659,
0.92383279, 1.0996432 , 1.05928944, 1.08108677, 1.09932206])

```

```

In [124]: if pca is not None:
    bar_width = 0.9
    n_asset = int((1 / 10) * normed_returns.shape[1])
    x_indx = np.arange(n_asset)
    fig, ax = plt.subplots()
    fig.set_size_inches(12, 4)
    # Eigenvalues are measured as percentage of explained variance.
    rects = ax.bar(x_indx, pca.explained_variance_ratio_[:n_asset], bar_width, color='
    ax.set_xticks(x_indx + bar_width / 2)
    ax.set_xticklabels(list(range(n_asset)), rotation=45)
    ax.set_title('Percent variance explained')
    ax.legend((rects[0],), ('Percent variance explained by principal components',))

```



```

In [125]: if pca is not None:
    projected = pca.fit_transform(cov_matrix)

```

Part 3 (Eigen-portfolios construction) Instructions:

We now look at the first two eigen portfolios. We use definition of eigen portfolios as provided by Avellaneda <http://math.nyu.edu/faculty/avellane/AvellanedaLeeStatArb20090616.pdf>

Following Avellaneda we define eigen portfolio weights as:

$$Q_i^{(j)} = \frac{v_i^{(j)}}{\sigma_i}$$

where j is the index of eigen portfolio and v_i is the i -th element of j -th eigen vector.

In the code the `pca.components_` are the Principal axes in feature space, representing the directions of maximum variance in the data. The components are sorted by `explained_variance_`.

Hint: do not forget to normalize portfolio weights such they sum up to 1.

Assign `pc_w` to be weights of the first eigen portfolio.

```
In [126]: # the first two eigen-portfolio weights# the fi
# first component
# get the Principal components
pc_w = np.zeros(len(stock_tickers))
eigen_prtf1 = pd.DataFrame(data ={'weights': pc_w.squeeze()*100}, index = stock_tickers)
if pca is not None:
    pcs = pca.components_

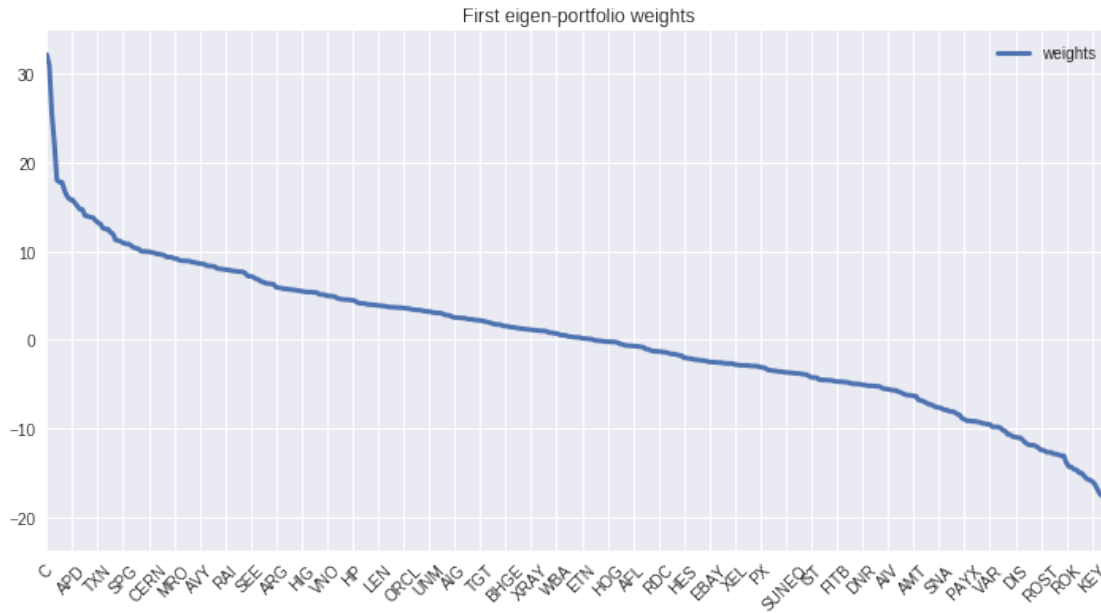
    ### START CODE HERE ### ( 1-2 lines of code)
    # normalized to 1

    # NOTE: You use 0 because it is the first portfolio
    pc_w = pcs[:,0] / np.sum(pcs[:,0])

    ### END CODE HERE ###

eigen_prtf1 = pd.DataFrame(data ={'weights': pc_w.squeeze()*100}, index = stock_tickers)
eigen_prtf1.sort_values(by=['weights'], ascending=False, inplace=True)
print('Sum of weights of first eigen-portfolio: %.2f' % np.sum(eigen_prtf1))
eigen_prtf1.plot(title='First eigen-portfolio weights',
                 figsize=(12,6),
                 xticks=range(0, len(stock_tickers),10),
                 rot=45,
                 linewidth=3)
```

Sum of weights of first eigen-portfolio: 100.00



```
In [127]: ### GRADED PART (DO NOT EDIT) ###
part_3 = list(eigen_prtf1.squeeze().values)
try:
    part3 = " ".join(map(repr, part_3))
except TypeError:
    part3 = repr(part_3)
submissions[all_parts[2]]=part3
grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:3],all_parts,
eigen_prtf1.squeeze().values
### GRADED PART (DO NOT EDIT) ###
```

Submission successful, please check on the coursera grader page for the status

```
Out[127]: array([ 32.15547082,  30.93331571,  25.50690946,  22.16692719,
 18.0084551 ,  17.79274279,  17.76739043,  16.81887906,
 16.18044798,  15.83751903,  15.80622057,  15.43514505,
 15.08183151,  14.72599396,  14.69233946,  14.01724021,
 13.94498039,  13.82736864,  13.79893355,  13.50764428,
 13.22700267,  13.07689841,  12.60979677,  12.49351237,
 12.4903706 ,  12.13617091,  11.9322199 ,  11.25764885,
 11.18816081,  11.09465525,  10.92698727,  10.82310861,
 10.81853368,  10.64480777,  10.42272303,  10.32425886,
 10.25665844,   9.99412232,   9.97134908,   9.96661664,
   9.93448604,   9.86862787,   9.80218276,   9.71240557,
   9.65882792,   9.62251218,   9.55778555,   9.33968423,
   9.31616556,   9.29653033,   9.17835941,   9.14977202,
```

8.96821037,	8.9177161 ,	8.91322329,	8.89646924,
8.8799625 ,	8.75396254,	8.73041028,	8.66509701,
8.59805673,	8.56422707,	8.49296757,	8.34200401,
8.31680707,	8.3057816 ,	8.24337229,	8.01697141,
8.01096448,	7.95181494,	7.92632961,	7.89394253,
7.82586628,	7.77922591,	7.73977603,	7.7102848 ,
7.67616568,	7.65502354,	7.46049124,	7.16904627,
7.16499153,	7.07692559,	6.88752121,	6.79697204,
6.57166439,	6.51115034,	6.35907629,	6.34806269,
6.2959234 ,	6.26471226,	5.91766594,	5.87986826,
5.83148134,	5.75485922,	5.75154895,	5.67796318,
5.66518754,	5.63156086,	5.58097947,	5.52810798,
5.48664341,	5.42941712,	5.39066262,	5.38534655,
5.38016212,	5.33456593,	5.32420457,	5.12045453,
5.11200473,	5.08350238,	4.94674916,	4.94186195,
4.89834571,	4.87174841,	4.6964071 ,	4.61284181,
4.55988048,	4.54195027,	4.52345153,	4.50194742,
4.44229078,	4.39519593,	4.18692015,	4.11507943,
4.10315254,	4.07944548,	3.98368565,	3.98232014,
3.95128997,	3.91389828,	3.88748504,	3.84520555,
3.80683415,	3.78278605,	3.70337093,	3.68669643,
3.66231812,	3.64800547,	3.61877551,	3.6156949 ,
3.60230469,	3.53728682,	3.53400538,	3.45089396,
3.41445369,	3.36509603,	3.36246114,	3.31898242,
3.24149733,	3.19563602,	3.18543828,	3.12807285,
3.0586226 ,	3.04506868,	3.0292527 ,	2.98808882,
2.819787 ,	2.77915188,	2.74135916,	2.60589448,
2.521452 ,	2.50983641,	2.47472813,	2.4596093 ,
2.44461919,	2.3367548 ,	2.32204847,	2.2997673 ,
2.22884839,	2.21381473,	2.19521506,	2.13298126,
2.0549353 ,	1.99192831,	1.9118519 ,	1.8125287 ,
1.74306812,	1.71493054,	1.70515543,	1.57693067,
1.54512793,	1.51493463,	1.42282797,	1.42173825,
1.35874791,	1.3038053 ,	1.26817757,	1.22984722,
1.18228405,	1.17452971,	1.11102132,	1.09734363,
1.05287933,	1.0367257 ,	1.0088328 ,	1.00585178,
0.97290835,	0.81703713,	0.81121118,	0.73682225,
0.7274888 ,	0.59832347,	0.52122702,	0.51450865,
0.46007593,	0.36156475,	0.34605725,	0.29243735,
0.26727476,	0.26189998,	0.1773287 ,	0.15123653,
0.10719077,	0.08639683,	0.05970625,	-0.05573653,
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-1.2980971 ,	-1.34253224,	-1.38819411,	-1.41692674,

```

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-15.67342681, -15.7902799 , -15.93650179, -16.22205681,
-16.77748843, -17.31302391, -17.60036091, -17.79534609,
-21.00083593, -21.04153965])

```

We sort the first two eigen portfolio weights and plot the results.

```

In [128]: pc_w = np.zeros(len(stock_tickers))
          eigen_prtf2 = pd.DataFrame(data ={'weights': pc_w.squeeze()*100}, index = stock_ticker

```

```

if pca is not None:
    pcs = pca.components_

    ### START CODE HERE ### ( 1-2 lines of code)
    # normalized to 1

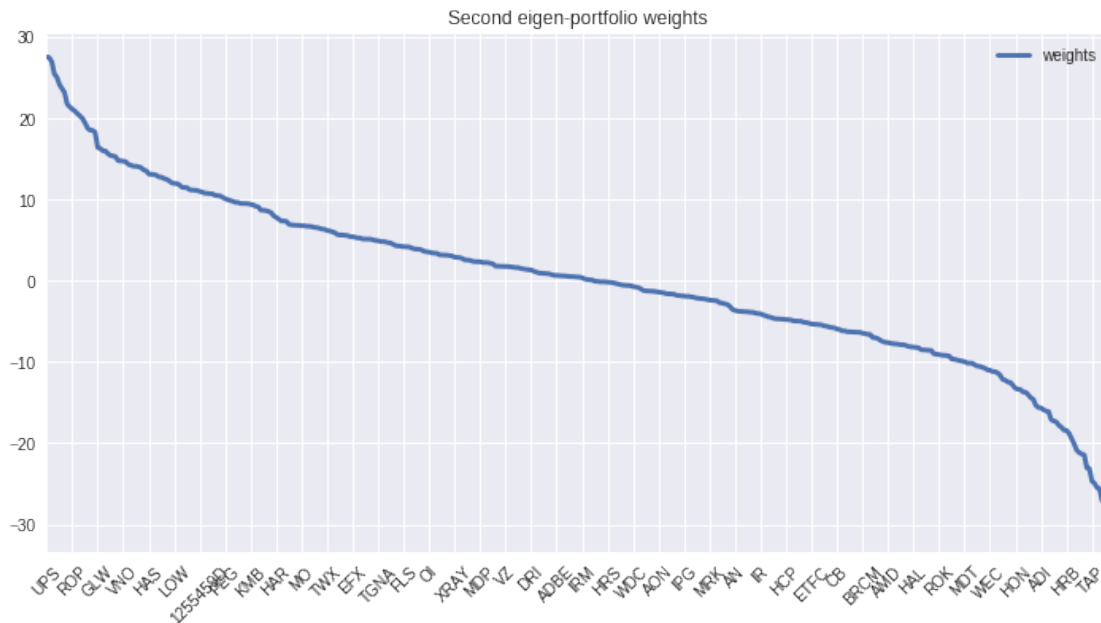
    # NOTE: You use 1 because it is the second portfolio
    pc_w = pcs[:,1] / np.sum(pcs[:,1])

    ### END CODE HERE ###

eigen_prtf2 = pd.DataFrame(data={'weights': pc_w.squeeze()*100}, index = stock_tickers)
eigen_prtf2.sort_values(by=['weights'], ascending=False, inplace=True)
print('Sum of weights of second eigen-portfolio: %.2f' % np.sum(eigen_prtf2))
eigen_prtf2.plot(title='Second eigen-portfolio weights',
                  figsize=(12,6),
                  xticks=range(0, len(stock_tickers),10),
                  rot=45,
                  linewidth=3)

```

Sum of weights of second eigen-portfolio: 100.00



```

In [129]: ### GRADED PART (DO NOT EDIT) ###
          part_4 = list(eigen_prtf2.as_matrix().squeeze())

```

```

try:
    part4 = " ".join(map(repr, part_4))
except TypeError:
    part4 = repr(part_4)
submissions[all_parts[3]]=part4
grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:4],all_parts,
eigen_prtf2.as_matrix()).squeeze()
### GRADED PART (DO NOT EDIT) ###

```

Submission successful, please check on the coursera grader page for the status

```

Out[129]: array([ 27.52926321,  27.44201015,  26.91912098,  25.43007608,
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```

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```

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-28.39394627, -30.44830912])

```

Part 4 (Compute performance of several eigen portfolios) Instructions: - Implement `sharpe_ratio()` function. The function takes `ts_returns` argument of type `pd.Series` and returns a tuple of annualized return, annualized vol, and annualized sharpe ratio, where sharpe ratio is defined as annualized return divided by annualized volatility - find portfolio (an index into `sharpe_metric`) that has the highest sharpe ratio

```

In [130]: def sharpe_ratio(ts_returns, periods_per_year=252):
    """
    sharpe_ratio - Calculates annualized return, annualized vol, and annualized sharpe ratio
                   where sharpe ratio is defined as annualized return divided by annualized volatility

    Arguments:
    ts_returns - pd.Series of returns of a single eigen portfolio

    Return:
    a tuple of three doubles: annualized return, volatility, and sharpe ratio
    """

    annualized_return = 0.
    annualized_vol = 0.
    annualized_sharpe = 0.

    ### START CODE HERE ### ( 4-5 lines of code)
    ### ...
    n_years = ts_returns.shape[0]/periods_per_year
    annualized_return = np.power(np.prod(1+ts_returns), (1/n_years))-1

```

```

annualized_vol = ts_returns.std() * np.sqrt(periods_per_year)
annualized_sharpe = annualized_return / annualized_vol

```

```

### END CODE HERE ###

```

```

return annualized_return, annualized_vol, annualized_sharpe

```

We compute the annualized return, volatility, and Sharpe ratio of the first two eigen portfolios.

```

In [131]: if df_raw_test is not None:
    eigen_ptrf1_returns = np.dot(df_raw_test.loc[:, eigen_ptrf1.index], eigen_ptrf1 /
    eigen_ptrf1_returns = pd.Series(eigen_ptrf1_returns.squeeze(), index=df_test.index
er, vol, sharpe = sharpe_ratio(eigen_ptrf1_returns)
    print('First eigen-portfolio:\nReturn = %.2f%%\nVolatility = %.2f%%\nSharpe = %.2f
    year_frac = (eigen_ptrf1_returns.index[-1] - eigen_ptrf1_returns.index[0]).days /

    df_plot = pd.DataFrame({'PC1': eigen_ptrf1_returns, 'SPX': df_raw_test.loc[:, 'SPX
    np.cumprod(df_plot + 1).plot(title='Returns of the market-cap weighted index vs. F
    figsize=(12,6), linewidth=3)

```

First eigen-portfolio:

Return = 41.39%

Volatility = 31.50%

Sharpe = 1.31



```

In [132]: if df_raw_test is not None:
    eigen_ptrf2_returns = np.dot(df_raw_test.loc[:, eigen_ptrf2.index], eigen_ptrf2 /
    eigen_ptrf2_returns = pd.Series(eigen_ptrf2_returns.squeeze(), index=df_test.index
er, vol, sharpe = sharpe_ratio(eigen_ptrf2_returns)
    print('Second eigen-portfolio:\nReturn = %.2f%%\nVolatility = %.2f%%\nSharpe = %.2

```


Second eigen-portfolio:
Return = 15.76%
Volatility = 42.84%
Sharpe = 0.37

We repeat the exercise of computing Sharpe ratio for the first N portfolios and select portfolio with the highest positive Sharpe ratio.

```
In [133]: n_portfolios = 120
          annualized_ret = np.array([0.] * n_portfolios)
          sharpe_metric = np.array([0.] * n_portfolios)
          annualized_vol = np.array([0.] * n_portfolios)
          idx_highest_sharpe = 0 # index into sharpe_metric which identifies a portfolio with rh

          if pca is not None:
              for ix in range(n_portfolios):

                  ### START CODE HERE ### ( 4-5 lines of code)
                  pc_w = pcs[:,ix] / np.sum(pcs[:,ix])

                  eigen_prtf = pd.DataFrame(data={'weights': pc_w}, index = stock_tickers)
                  eigen_returns = np.dot(df_raw_test.loc[:, eigen_prtf.index], eigen_prtf )
                  eigen_returns = pd.Series(eigen_returns.squeeze(), index=df_test.index)
                  annualized_ret[ix], annualized_vol[ix], sharpe_metric[ix] = sharpe_ratio( eige

                  ### END CODE HERE ###

                  # find portfolio with the highest Sharpe ratio
                  ### START CODE HERE ### ( 2-3 lines of code)
                  ### ...
                  results = pd.DataFrame(data={'Return': annualized_ret, 'Vol': annualized_vol, 'Sha
                  results.sort_values(by=['Sharpe'], ascending=False, inplace=True)
                  idx_highest_sharpe = results.index[0]

                  ### END CODE HERE ###

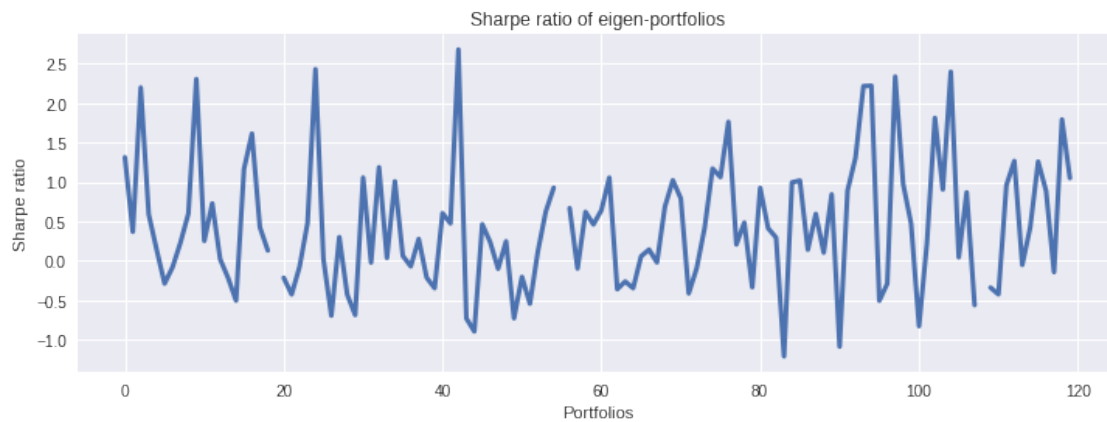
          print('Eigen portfolio #%d with the highest Sharpe. Return %.2f%%, vol = %.2f%%, S
                (idx_highest_sharpe,
                 annualized_ret[idx_highest_sharpe]*100,
                 annualized_vol[idx_highest_sharpe]*100,
                 sharpe_metric[idx_highest_sharpe]))

          fig, ax = plt.subplots()
          fig.set_size_inches(12, 4)
          ax.plot(sharpe_metric, linewidth=3)
          ax.set_title('Sharpe ratio of eigen-portfolios')
```

```
ax.set_ylabel('Sharpe ratio')
ax.set_xlabel('Portfolios')
```

/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:20: RuntimeWarning: invalid value e

Eigen portfolio #42 with the highest Sharpe. Return 61.14%, vol = 22.80%, Sharpe = 2.68



```
In [135]: results = pd.DataFrame(data={'Return': annualized_ret, 'Vol': annualized_vol, 'Sharpe':
results.sort_values(by=['Sharpe'], ascending=False, inplace=True)
results.head(10)
```

```
Out[135]:
```

	Return	Sharpe	Vol
42	0.611434	2.681348	0.228032
24	1.032188	2.431337	0.424535
104	0.512464	2.398724	0.213640
97	1.425566	2.337932	0.609755
9	0.753551	2.306594	0.326694
94	0.502024	2.221589	0.225975
93	0.601081	2.216771	0.271152
2	0.453435	2.198514	0.206246
102	0.274141	1.813004	0.151208
118	0.874385	1.793424	0.487551

```
In [138]: # https://www.coursera.org/learn/fundamentals-machine-learning-in-finance/discussions/
# 1) Use the COLUMNS in the pcs matrix to get the weights for the eigenportfolios, alt
# 2) Calculate annualized returns in the function sharpe_ratio() using the GEOMETRIC M
# 3) You will get NaN's in the results array (most likely for 3 eigenportfolios). Ther
# If you want to read the detailed discussion that led up to these insights:
# https://www.coursera.org/learn/fundamentals-machine-learning-in-finance/discussions/
results.dropna(inplace=True)
```

```

In [141]: ### GRADED PART (DO NOT EDIT) ###
part_5 = list(results.iloc[:, 1].values.squeeze())
try:
    part5 = " ".join(map(repr, part_5))
except TypeError:
    part5 = repr(part_5)
submissions[all_parts[4]]=part5
grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:5],all_parts,
results.iloc[:, 1].values.squeeze())
### GRADED PART (DO NOT EDIT) ###

```

Submission successful, please check on the coursera grader page for the status

```

Out[141]: array([ 2.6813484 ,  2.43133729,  2.39872441,  2.33793196,  2.30659408,
                  2.2215888 ,  2.21677072,  2.19851392,  1.81300448,  1.79342355,
                  1.76312102,  1.61425529,  1.31396078,  1.30787333,  1.26660644,
                  1.25886217,  1.18686551,  1.17035236,  1.16468931,  1.06187955,
                  1.05578097,  1.05505619,  1.04882183,  1.02165311,  1.01830017,
                  1.00828466,  0.9950413 ,  0.97529078,  0.95814138,  0.92726174,
                  0.92483908,  0.9041755 ,  0.892538 ,  0.88642444,  0.86855357,
                  0.84287489,  0.79154656,  0.72805392,  0.68482588,  0.66836196,
                  0.6409441 ,  0.62474111,  0.62004933,  0.60334582,  0.60023437,
                  0.59475285,  0.59099198,  0.48426658,  0.47799353,  0.4744462 ,
                  0.47279402,  0.4633251 ,  0.46119895,  0.42591032,  0.42364012,
                  0.4154465 ,  0.41216641,  0.36782358,  0.30061062,  0.29467349,
                  0.27701825,  0.25218297,  0.24688822,  0.23702365,  0.23110684,
                  0.22909072,  0.20739045,  0.14233782,  0.14092441,  0.14041398,
                  0.12992884,  0.11645889,  0.10386647,  0.06261485,  0.05660946,
                  0.04381496,  0.03628373,  0.02335065,  0.0196972 , -0.02080937,
                 -0.02324732, -0.05237539, -0.07090431, -0.07540448, -0.08175437,
                 -0.09488243, -0.09824429, -0.10093641, -0.14388952, -0.20466851,
                 -0.21334344, -0.21533153, -0.21828648, -0.26267369, -0.2892743 ,
                 -0.29044642, -0.33643461, -0.33996271, -0.34752596, -0.34790642,
                 -0.36088246, -0.41386509, -0.42601372, -0.4260432 , -0.42930941,
                 -0.50531452, -0.50667305, -0.54441457, -0.56360898, -0.68829319,
                 -0.6969187 , -0.72947431, -0.73094077, -0.82976763, -0.89658443,
                 -1.0902614 , -1.21303801])

```

```

In [142]: ### GRADED PART (DO NOT EDIT) ###
part6 = str(idx_highest_sharpe)
submissions[all_parts[5]]=part6
grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:6],all_parts,
idx_highest_sharpe)
### GRADED PART (DO NOT EDIT) ###

```

Submission successful, please check on the coursera grader page for the status

```

Out[142]: 42

```