DJI_tSNE_m2_ex4_corrected

October 25, 2018

1 Data visualization with t-SNE

Welcome to your 3-rd assignment in Unsupervised Machine Learning in Finance. This exercise will provide hands-on experience with non-linear models such as KernelPCA and t-SNE.

Instructions: - You will be using Python 3. - Avoid using for-loops and while-loops, unless you are explicitly told to do so. - Do not modify the (# GRADED FUNCTION [function name]) comment in some cells. Your work would not be graded if you change this. Each cell containing that comment should only contain one function. - After coding your function, run the cell right below it to check if your result is correct.

After this assignment you will: - Be able to use KernelPCA to construct eigen-portfolios - Calculate un-expected log-returns - Visualize multi-dimensional data using t-SNE

Let's get started!

1.1 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 [1]: import os
        import numpy as np
        import pandas as pd
        from sklearn import preprocessing
        import datetime
        from sklearn.ensemble import RandomForestClassifier
        from sklearn import neighbors
        from sklearn.ensemble import AdaBoostClassifier
        from sklearn.ensemble import GradientBoostingClassifier
        from sklearn.svm import SVC
        import operator

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

```
import grading

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

from sklearn.decomposition import KernelPCA
```

In [2]:
```
### ONLY FOR GRADING. DO NOT EDIT ###
submissions=dict()
assignment_key="SgjoDxBsEeidDQqwEEcflg"
all_parts=["yzL4C", "B3CHT", "jxlkt","miiAE","VOnND"]
### ONLY FOR GRADING. DO NOT EDIT ###
```

In [65]:
```
# COURSERA_TOKEN = # the key provided to the Student under his/her email on submission
# COURSERA_EMAIL = # the email
COURSERA_TOKEN="ZSuNZOIwAnokeXPF"
COURSERA_EMAIL="cilsya@yahoo.com"
```

In [4]:
```
def check_for_nulls(df):
    """
    Test and report number of NAs in each column of the input data frame
    :param df: pandas.DataFrame
    :return: None
    """
    for col in df.columns.values:
        num_nans = np.sum(df[col].isnull())
        if num_nans > 0:
            print('%d Nans in col %s' % (num_nans, col))
    print('New shape of df: ', df.shape)
```

In [5]:
```
# 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[5]:

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

```
Last column contains SPX index prices:
```

```
Out[6]:               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
```

```
In [7]: check_for_nulls(asset_prices)
```

```
New shape of df:  (3493, 419)
```

Calculate price log-returns

```
In [8]: asset_returns = np.log(asset_prices) - np.log(asset_prices.shift(1))
        asset_returns = asset_returns.iloc[1:, :]
        asset_returns.iloc[:, :n_stocks_show].head()
```

```
Out[8]:                    A        AA      AAPL       ABC       ABT      ADBE  \
        2000-01-28 -0.005495 -0.014286 -0.079188  0.000000  0.033901 -0.085294
        2000-01-31 -0.027934  0.002695  0.020696 -0.033921  0.021340 -0.044402
        2000-02-01  0.070188  0.034380 -0.034317  0.030573  0.009547  0.014654
        2000-02-02  0.074610  0.033236 -0.014460  0.009987  0.005693  0.092861
        2000-02-03  0.016208 -0.031506  0.044531 -0.006639  0.005654  0.119028

                         ADI       ADM       ADP      ADSK       AEE       AEP
        2000-01-28 -0.005874 -0.015751 -0.025222 -0.051287 -0.019158 -0.016902
```

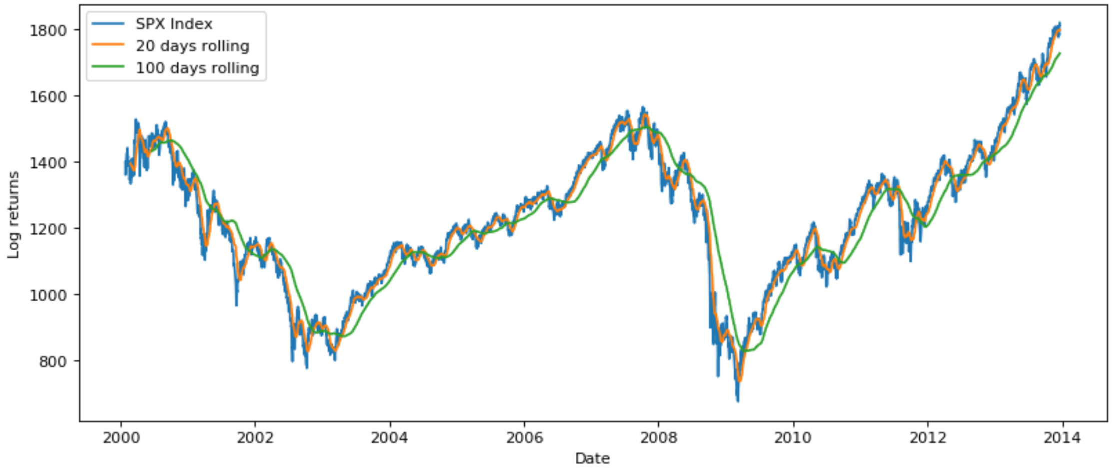
```
2000-01-31 -0.021165 -0.005306 -0.031131 -0.010183  0.007707  0.015038
2000-02-01  0.047006  0.021057  0.015687  0.036155  0.000000  0.005581
2000-02-02 -0.018019 -0.021057 -0.056015  0.005903  0.000000 -0.001857
2000-02-03  0.094129  0.000000  0.065054  0.034679  0.011451  0.032910
```

1.1.1 Part 1 (Calculate Moving Average)

Instructions:

- Calculate 20 and 100-day moving average of SPX Index price based on **spx_index** pd.core.series.Series
- Assign results to **short_rolling_spx** and **long_rolling_spx** respectively

In [23]:
```
# Get the SPX time series. This now returns a Pandas Series object indexed by date.# Ge
spx_index = asset_prices.loc[:, 'SPX']

short_rolling_spx = pd.core.series.Series(np.zeros(len(asset_prices.index)), index=asse
long_rolling_spx = short_rolling_spx

# Calculate the 20 and 100 days moving averages of log-returns
### START CODE HERE ### ( 2 lines of code)
### ...
# Calculate the 20 and 100 days moving averages of the log-returns
short_rolling_spx = asset_prices[['SPX']].rolling(window=20).mean()
long_rolling_spx = asset_prices[['SPX']].rolling(window=100).mean()

### END CODE HERE ###

# Plot the index and rolling averages
fig=plt.figure(figsize=(12, 5), dpi= 80, facecolor='w', edgecolor='k')
ax = fig.add_subplot(1, 1, 1)
ax.plot(spx_index.index, spx_index, label='SPX Index')
ax.plot(short_rolling_spx.index, short_rolling_spx, label='20 days rolling')
ax.plot(long_rolling_spx.index, long_rolling_spx, label='100 days rolling')
ax.set_xlabel('Date')
ax.set_ylabel('Log returns')
ax.legend(loc=2)
plt.show()
```




```
In [24]: ### GRADED PART (DO NOT EDIT) ###
         np.random.seed(42)
         idx_test = np.random.randint(low=100, high=len(short_rolling_spx), size=50)
         result = short_rolling_spx.values[idx_test] + long_rolling_spx.values[idx_test]


         ### grading results ###
         part_1 = list(result.squeeze())
         try:
             part1 = " ".join(map(repr, part_1))
         except TypeError:
             part1 = repr(part_1)
         submissions[all_parts[0]]=part1
         grading.submit(COURSERA_EMAIL, COURSERA_TOKEN, assignment_key,all_parts[:1],all_parts,s
         result.squeeze()
         ### GRADED PART (DO NOT EDIT) ###
```

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

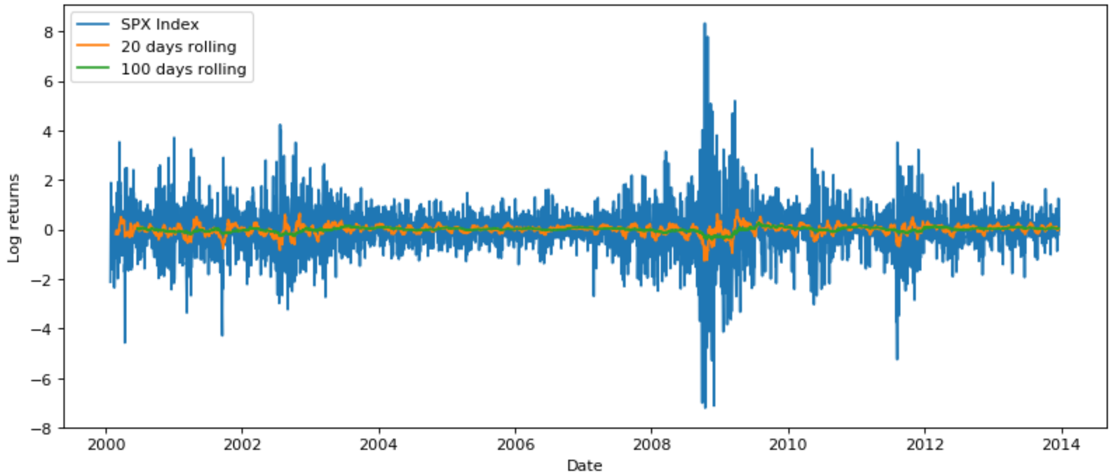
```
Out[24]: array([ 2939.2689,  2065.8155,  2428.6888,  2323.5646,  2228.6512,
                 2832.7891,  2771.952 ,  1765.647 ,  2230.2738,  2360.8532,
                 2222.0255,  2596.199 ,  1932.6528,  2930.1697,  2539.8038,
                 2747.3836,  2834.7257,  3501.9293,  1912.125 ,  2172.2049,
                 2534.7048,  2427.7477,  2187.8932,  2356.6817,  2238.3179,
                 1994.9164,  2388.5834,  2254.9847,  3515.196 ,  2921.5941,
                 1903.9954,  1854.4656,  2468.9543,  2207.0963,  2234.2487,
                 2206.5196,  2610.0842,  2654.0074,  2248.4479,  2950.6151,
                 2534.5414,  2675.5777,  2643.7591,  2675.5777,  1868.7086,
                 2928.2838,  2391.709 ,  2439.4625,  2536.4369,  3004.7813])
```

1.1.2 Apply scikit-learn StandardScaler to stocks log-returns

In [25]:
```
from sklearn.preprocessing import StandardScaler

# Standardize features by removing the mean and scaling to unit variance
# Centering and scaling happen independently on each feature by computing the relevant
# on the samples in the training set. Mean and standard deviation are then stored to be
# data using the transform method.
# http://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler

log_ret_mat_std = StandardScaler().fit_transform(asset_returns.values)
log_ret_df_std = pd.DataFrame(data=log_ret_mat_std,
                              index=asset_returns.index,
                              columns=asset_returns.columns.values)
log_ret_df_std.iloc[:, :10].head()
```

Out[25]:
```
                   A        AA      AAPL       ABC       ABT      ADBE  \
2000-01-28 -0.177095 -0.503576 -2.684641 -0.040166  2.149514 -2.773218
2000-01-31 -0.904935  0.110571  0.665376 -1.782203  1.346264 -1.449596
2000-02-01  2.277787  1.256534 -1.179699  1.529962  0.592079  0.461992
2000-02-02  2.421231  1.215159 -0.513727  0.472721  0.345593  2.993509
2000-02-03  0.526866 -1.126343  1.464752 -0.381145  0.343102  3.840506

                 ADI       ADM       ADP      ADSK
2000-01-28 -0.199237 -0.761249 -1.539968 -1.829376
2000-01-31 -0.716880 -0.268812 -1.898412 -0.377810
2000-02-01  1.590897  0.974079  0.941618  1.258580
2000-02-02 -0.610369 -1.011401 -3.407901  0.190245
2000-02-03  3.186137 -0.018661  3.936335  1.206468
```

In [26]:
```
# Calculate the 20 and 100 days moving averages of the log-returns
short_rolling_spx = log_ret_df_std[['SPX']].rolling(window=20).mean()
long_rolling_spx = log_ret_df_std[['SPX']].rolling(window=100).mean()

# Plot the index and rolling averages
fig=plt.figure(figsize=(12, 5), dpi= 80, facecolor='w', edgecolor='k')
ax = fig.add_subplot(1,1,1)
ax.plot(log_ret_df_std.index, log_ret_df_std[['SPX']], label='SPX Index')
ax.plot(short_rolling_spx.index, short_rolling_spx, label='20 days rolling')
ax.plot(long_rolling_spx.index, long_rolling_spx, label='100 days rolling')
ax.set_xlabel('Date')
ax.set_ylabel('Log returns')
ax.legend(loc=2)
plt.show()
```




```
In [27]: # Assign a label 'regime' to each date:
         # 'regime' = 'benign' for all points except two intervals
         # 'regime' = 'crisis_2001_2002', or
         # 'regime = ', 'crisis_2007-2009'

         # first assign the default value for all rows
         log_ret_df_std['regime'] = 'benign'
         dt_start = np.datetime64('2000-03-24T00:00:00.000000000')
         dt_end = np.datetime64('2002-10-09T00:00:00.000000000')
         flag_crisis_2001_2002 = np.logical_and(log_ret_df_std.index > dt_start, log_ret_df_std.

         dt_start = np.datetime64('2007-10-09T00:00:00.000000000')
         dt_end = np.datetime64('2009-03-09T00:00:00.000000000')
         flag_crisis_2007_2009 = np.logical_and(log_ret_df_std.index > dt_start, log_ret_df_std.

         log_ret_df_std.loc[flag_crisis_2001_2002,'regime'] = 'crisis_2001_2002'
         log_ret_df_std.loc[flag_crisis_2007_2009, 'regime'] = 'crisis_2007_2009'

         print('crisis_2001_2002', log_ret_df_std[log_ret_df_std.regime == 'crisis_2001_2002'].s
         print('crisis_2007_2009', log_ret_df_std[log_ret_df_std.regime == 'crisis_2007_2009'].s
         print(log_ret_df_std.shape)

         print('Last N days of the dataset:')
         log_ret_df_std.iloc[:, :10].tail()
```

```
crisis_2001_2002 635
crisis_2007_2009 354
(3492, 420)
Last N days of the dataset:
```

```
Out[27]:                    A        AA      AAPL       ABC       ABT      ADBE  \
         2013-12-16  0.048156  0.240452  0.156457 -0.040166  0.209504 -1.308457
         2013-12-17  0.657942  0.501195 -0.180108 -0.115249  0.121412 -0.474871
         2013-12-18  0.864258  0.494531 -0.284769  0.897945  2.566273  0.747634
         2013-12-19 -0.285876  0.524670 -0.415206 -0.025413 -0.169652 -0.515127
         2013-12-20 -0.237193 -0.095901  0.250960  0.099780 -0.338791  0.610861

                          ADI       ADM       ADP      ADSK
         2013-12-16  0.229593  0.353842  0.378619 -0.431163
         2013-12-17  0.138236  0.922656 -0.217628  0.216760
         2013-12-18  0.575724  1.831260  1.417926  0.549664
         2013-12-19 -0.082096  0.686380  0.246457 -0.183206
         2013-12-20  0.237364 -0.483890  0.404861  0.813525
```

```
In [28]: # use data before 2012-03-26 for training, and data after it for testing

         train_end = datetime.datetime(2012, 3, 26)
         df_train = log_ret_df_std[log_ret_df_std.index <= train_end].copy()
         df_test = log_ret_df_std[log_ret_df_std.index > train_end].copy()
         print('Train dataset:', df_train.shape)
         print('Test dataset:', df_test.shape)
```

```
Train dataset: (3055, 420)
Test dataset: (437, 420)
```

1.1.3 Part 2 (Returns regression on SPX Index)

Instructions:

- Compute R^2, α, and β for in-sample and out-of-sample regressing each stock returns on SPX returns. Use df_train and df_test data.
- Store in-sample R^2 in **R2_in_sample** list
- Store out-of-sample R^2 in **R2_out_sample** list

```
In [29]: # regress each individual stock on the market

         from sklearn.linear_model import LinearRegression

         # create a Linear Regression object
         lm = LinearRegression()
         stock_tickers = asset_returns.columns.values[:-1] # exclude SPX

         # compute betas for all stocks in the dataset
         R2_in_sample = [0.] * len(stock_tickers)
         R2_out_sample = [0.] * len(stock_tickers)
         betas = [0.] * len(stock_tickers)
         alphas = [0.] * len(stock_tickers)
```

```
### START CODE HERE ### ( 10-12 lines of code)
### ...
# Train the model using the training sets

x=df_train["SPX"]
x=x.reshape(x.shape[0],1)
x2=df_test["SPX"]
x2=x2.reshape(x2.shape[0],1)

j=0
for i in stock_tickers:
    y=df_train[i]
    y=y.reshape(y.shape[0],1)

    lm.fit(x,y)
    alphas[j] = lm.intercept_[0]
    betas[j]= lm.coef_[0][0]

    y2= df_test[i]
    y2=y2.reshape(y2.shape[0],1)

    R2_in_sample[j]=lm.score(x,y)
    R2_out_sample[j]=lm.score(x2,y2)

    j=j+1

### END CODE HERE ###
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:20: FutureWarning: reshape is depre
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:22: FutureWarning: reshape is depre
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:27: FutureWarning: reshape is depre
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:34: FutureWarning: reshape is depre
```

In [30]:
```
df_lr = pd.DataFrame({'R2 in-sample': R2_in_sample, 'R2 out-sample': R2_out_sample, 'Al
                        index=stock_tickers)
df_lr.head(10)
```

Out[30]:

	Alpha	Beta	R2 in-sample	R2 out-sample
A	0.000448	0.575501	0.328228	0.424779
AA	0.002176	0.690469	0.476366	0.388624
AAPL	0.007923	0.502159	0.253775	0.143598
ABC	-0.001616	0.402682	0.160497	0.235728
ABT	-0.000489	0.427570	0.186837	0.253681
ADBE	-0.000820	0.589522	0.343281	0.316982
ADI	0.000891	0.591461	0.342065	0.573918
ADM	0.000758	0.511483	0.263903	0.313796
ADP	-0.002394	0.621857	0.384923	0.562737
ADSK	0.003927	0.565112	0.328240	0.277875

```
In [31]: ### GRADED PART (DO NOT EDIT) ###

         np.random.seed(42)
         idx = np.random.randint(low=0, high=df_lr.shape[0], size=50)
         ### grading results ###
         part_2 = list(df_lr.as_matrix()[idx, :].flatten())
         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,s

         df_lr.as_matrix()[idx, :].flatten()
         ### GRADED PART (DO NOT EDIT) ###
```

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

```
Out[31]: array([ -9.67049922e-04,   7.40733288e-01,   5.55857450e-01,
                  5.09490225e-01,   4.59373236e-03,   6.46428603e-01,
                  4.12381016e-01,   4.13343769e-01,  -1.67079795e-04,
                  4.60162705e-01,   2.11584248e-01,   3.03661286e-01,
                  3.32009347e-03,   3.29359405e-01,   1.08648285e-01,
                  1.63064268e-01,  -1.95361484e-03,   4.41668666e-01,
                  1.96621050e-01,   3.51790739e-01,   3.38885382e-03,
                  6.61776832e-01,   4.37066392e-01,   5.46250050e-01,
                 -7.10945228e-04,   6.21759216e-01,   3.82730461e-01,
                  4.26154221e-01,  -9.67049922e-04,   7.40733288e-01,
                  5.55857450e-01,   5.09490225e-01,   4.19833772e-03,
                  4.55076530e-01,   2.07650024e-01,   1.80616581e-01,
                  5.39919913e-03,   6.75964478e-01,   4.63362524e-01,
                  4.76733296e-01,  -1.02424453e-03,   6.57285848e-01,
                  4.26053714e-01,   4.07380380e-01,  -1.54726545e-03,
                  6.51225662e-01,   4.17266938e-01,   4.40535223e-01,
                 -1.62644359e-04,   5.74333145e-01,   3.34997377e-01,
                  2.77833480e-01,  -2.63649732e-03,   6.99704033e-01,
                  4.87191539e-01,   4.56059709e-01,   8.81927867e-04,
                  5.37629469e-01,   2.86701737e-01,   3.49547464e-01,
                 -1.92892721e-03,   5.10956044e-01,   2.63389391e-01,
                  2.12686873e-01,   3.29892655e-03,   4.24035403e-01,
                  1.82665207e-01,   8.22965688e-02,  -2.38301557e-04,
                  5.16165939e-01,   2.62089005e-01,   2.96347564e-01,
                  5.72863544e-03,   6.39927220e-01,   4.01888033e-01,
                  3.44709394e-01,  -1.22176662e-03,   6.56137722e-01,
                  4.29269976e-01,   4.55331628e-01,   5.31173257e-03,
                  4.74834641e-01,   2.31862122e-01,   2.08063899e-01,
```

```
 1.88434062e-03,   6.04344224e-01,   3.61820998e-01,
 4.92241434e-01,   2.86425234e-03,   6.46641786e-01,
 4.15468364e-01,   5.25525022e-01,   8.17977888e-03,
 4.76382046e-01,   2.41829346e-01,   6.12615351e-02,
 1.53725875e-03,   7.56056309e-01,   5.68348952e-01,
 4.21971100e-01,  -1.08893532e-03,   5.03048373e-01,
 2.52032070e-01,   3.73373611e-01,   6.11153160e-03,
 5.82854929e-01,   3.41935023e-01,   2.35067569e-01,
 4.95608399e-03,   6.13766261e-01,   3.71266989e-01,
 2.57858955e-01,   7.53681997e-03,   5.07728304e-01,
 2.70669808e-01,   1.65371515e-01,   3.50495507e-03,
 6.39653605e-01,   4.04117336e-01,   4.48424733e-01,
-5.61751322e-03,   5.59612449e-01,   3.16017683e-01,
 2.61630578e-01,  -4.69884826e-04,   5.79041054e-01,
 3.41425648e-01,   2.79446943e-01,   1.66000347e-03,
 5.53728334e-01,   3.07801071e-01,   3.61175969e-01,
-2.42895389e-03,   3.67945453e-01,   1.38583711e-01,
 1.69949082e-01,   4.96732937e-04,   5.74477868e-01,
 3.55711804e-01,   1.24058731e-01,  -1.95567930e-03,
 5.15308019e-01,   2.61068993e-01,   4.60257693e-01,
-1.67079795e-04,   4.60162705e-01,   2.11584248e-01,
 3.03661286e-01,  -3.51825087e-03,   5.12857306e-01,
 2.63072385e-01,   3.94367557e-01,  -3.56153507e-03,
 3.85281990e-01,   1.49195152e-01,   2.63746494e-01,
-3.50263092e-04,   7.31059905e-01,   5.30089940e-01,
 6.42118528e-01,  -5.21189219e-04,   5.83053992e-01,
 3.29664353e-01,   3.22211480e-01,  -5.96690873e-03,
 4.53327854e-01,   2.09235336e-01,   2.20794268e-01,
 1.19732349e-02,   1.94066487e-01,   3.97743312e-02,
 3.49458130e-02,   5.16573911e-04,   5.16478832e-01,
 2.65254927e-01,   5.06742176e-01,   3.29892655e-03,
 4.24035403e-01,   1.82665207e-01,   8.22965688e-02,
 8.89936998e-04,   4.90192634e-01,   2.36559487e-01,
 2.78653662e-01,   1.67892060e-03,   5.93522136e-01,
 3.50724296e-01,   3.99906367e-01,  -7.10945228e-04,
 6.21759216e-01,   3.82730461e-01,   4.26154221e-01,
-2.91111923e-03,   5.99124121e-01,   3.63653751e-01,
 4.25779252e-01,  -6.42132511e-04,   6.78114978e-01,
 4.56388085e-01,   6.00665929e-01])
```

Part 3 (Calculation of unexpected log-returns) **Instructions:** - Use **df_train** and calculated in Part 2 **df_lr** with β and α to compute unexpected log returns - Calculate unexplained log-returns as difference between the stock return and its value, "predicted" by the index return.

$$\epsilon_t^i = R_t^i - \alpha_i - \beta_i R_t^M$$

- Store unexplained log-returns in df_unexplained pnadas.DataFrame

In [52]:
```python
df_unexplained = df_train.loc[:, stock_tickers]

### START CODE HERE ### ( 4-10 lines of code)
### ...
#
# https://www.coursera.org/learn/fundamentals-machine-learning-in-finance/discussions/u
np_alphas = np.array(alphas)
#df_alphas = pd.DataFrame(np_alphas)
np_betas = np.array(betas)
#df_betas = pd.DataFrame(np_betas)
df_unexplained = df_unexplained - np_alphas - np_betas.reshape(1,418) * df_train["SPX"]

### END CODE HERE ###

print('Unexplained log-returns of S&P 500 Index stocks', df_unexplained.shape)
print('Unexplained log-returns of S&P 500 Index stocks:')
df_unexplained.iloc[:, :10].head()
```

```
Unexplained log-returns of S&P 500 Index stocks (3055, 418)
Unexplained log-returns of S&P 500 Index stocks:


/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:11: FutureWarning: reshape is depre
```

Out[52]:

```
                   A        AA      AAPL       ABC       ABT      ADBE  \
2000-01-28  1.042699  0.958259 -1.627829  0.815262  3.056585 -1.522426
2000-01-31 -1.990722 -1.193765 -0.289570 -2.540007  0.540397 -2.560558
2000-02-01  1.818522  0.703883 -1.587967  1.210541  0.251689 -0.007182
2000-02-02  2.429032  1.222879 -0.514452  0.480108  0.352210  3.002779
2000-02-03  0.040778 -1.711177  1.033078 -0.719335 -0.017217  3.343853

                 ADI       ADM       ADP      ADSK
2000-01-28  1.053955  0.322498 -0.219042 -0.635088
2000-01-31 -1.833211 -1.234180 -3.068782 -1.447484
2000-02-01  1.118464  0.565542  0.448237  0.804120
2000-02-02 -0.602783 -1.004828 -3.396594  0.194417
2000-02-03  2.686136 -0.451039  3.413969  0.725667
```

In [53]:
```python
### GRADED PART (DO NOT EDIT) ###
np.random.seed(42)
idx_row = np.random.randint(low=0, high=df_lr.shape[0], size=100)
np.random.seed(42)
idx_col = np.random.randint(low=0, high=df_lr.shape[1], size=100)

# grading
part_3=list(df_unexplained.as_matrix()[idx_row, idx_col])
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,s
    df_unexplained.as_matrix()[idx_row, idx_col]
    ### GRADED PART (DO NOT EDIT) ###
```

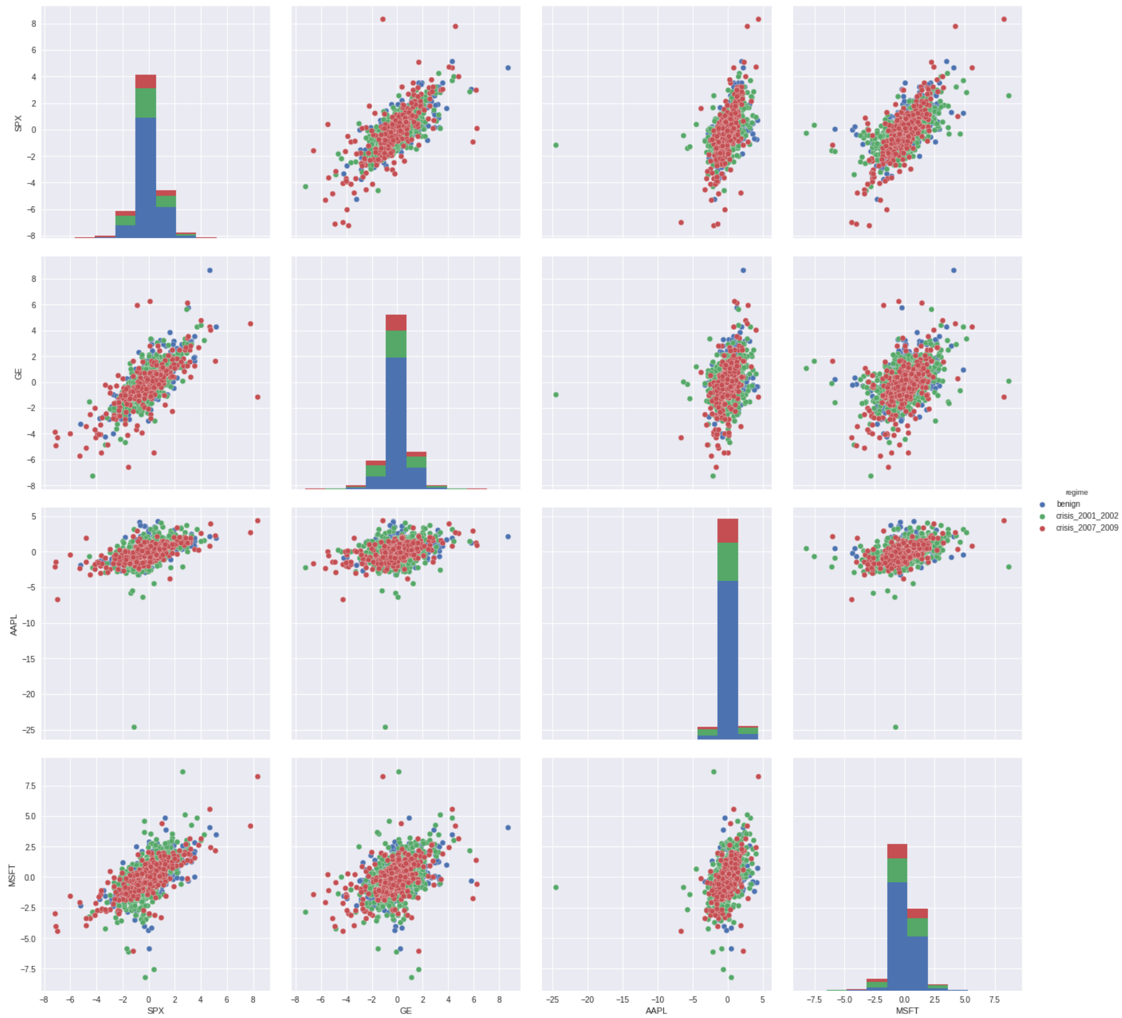
```
Submission successful, please check on the coursera grader page for the status
```

```
Out[53]: array([ -1.06384099e+00,   2.46332604e+00,  -3.98137854e-01,
                 -1.73038638e+00,  -1.24664956e+00,  -3.21817166e+00,
                 -2.68605112e+00,   5.85249927e-02,  -6.03871994e-01,
                  1.03144668e+00,  -6.01130305e-01,   4.94079044e-01,
                  1.30232663e-01,   1.79332853e+00,  -1.80093157e-02,
                  3.77015908e-01,   1.13280607e+00,   9.63269929e-01,
                 -1.59153487e-01,  -8.88290688e-01,   9.21991730e-02,
                 -2.31988629e+00,   5.36111856e-01,   7.33048310e-04,
                  2.15086376e+00,   7.49150157e-01,  -6.54042167e-01,
                  1.16224382e+00,  -2.30230439e-01,   1.44999689e+00,
                  1.05277023e+00,  -7.98942377e-01,   2.02227271e+00,
                  9.92660502e-01,   1.83791224e-01,  -2.03348972e+00,
                  1.19212702e-02,   1.04849661e+00,  -1.63479730e+00,
                 -1.49765433e+00,   7.08336754e-01,   1.68044925e+00,
                  1.62131811e+00,   4.70785893e-01,   1.13280607e+00,
                  2.48876285e-01,  -9.46299873e-01,   4.10043306e-01,
                  7.48012073e-02,  -1.48831729e+00,  -1.48892790e+00,
                  8.28865986e-01,  -2.39932634e-01,   1.08907282e+00,
                 -1.04344925e+00,  -2.12259066e+00,  -1.28603637e-01,
                 -5.01361862e-01,  -2.16458853e+00,  -1.48243566e+00,
                 -5.98827164e-01,  -3.95188258e-01,   3.34495330e+00,
                 -2.08734894e+00,   7.45087779e-01,  -1.04352780e+00,
                  2.85174202e+00,   4.43656482e+00,  -1.80093157e-02,
                  8.28865986e-01,  -1.19376469e+00,   1.07507937e-03,
                  2.28021800e+00,  -4.90196977e-01,  -1.59536385e-01,
                  1.29023038e+00,  -9.05798264e-01,  -5.52918964e-02,
                 -5.10496686e+00,  -1.35687103e+00,   3.66516263e+00,
                 -1.16934288e+00,  -8.35486859e-01,  -5.33908733e-01,
                 -3.20885886e-01,   1.78669043e-01,   1.03144668e+00,
                 -2.82513305e-01,   1.74373734e+00,   3.69283021e-01,
                 -4.27066683e-01,  -2.76930876e-01,   1.72809911e+00,
                  3.58955938e-01,   4.30931745e-01,   1.16396725e+00,
                 -3.71384036e-01,   6.39617491e-02,  -1.40889830e+00,
                 -2.82513305e-01])
```

Part 4 (Kernel PCA of Covariance Matrix of Returns) **Instructions:** - Perform Kernel PCA with 1 component using returns data **df_test** for all stocks in df_test - Transform original mapping in the coordinates of the first principal component - Assign tranformed returns to PCA_1 in **** DataFrame

```
In [54]: import seaborn as sns
         sns.pairplot(df_train.loc[:, ['SPX', 'GE', 'AAPL', 'MSFT', 'regime']],
                      vars=['SPX', 'GE', 'AAPL', 'MSFT'], hue="regime", size=4.5)
```

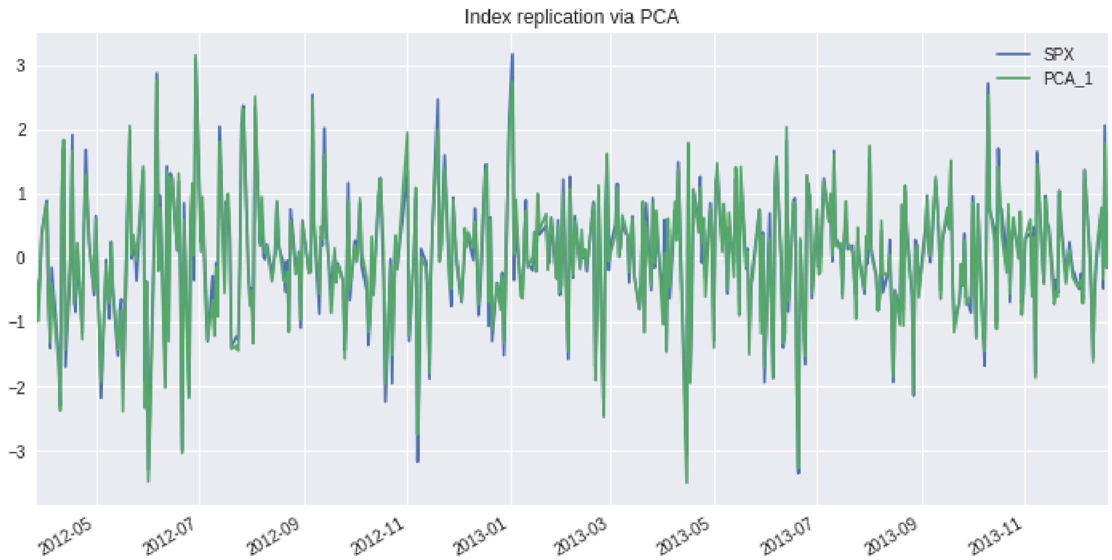
```
Out[54]: <seaborn.axisgrid.PairGrid at 0x7fd2cf28a128>
```




```
In [75]: stock_tickers = asset_returns.columns.values[:-1]
         assert 'SPX' not in stock_tickers, "By accident included SPX index"
         data = df_test[stock_tickers].values

         df_index_test = pd.DataFrame(data=df_test['SPX'].values, index=df_test.index, columns=[
         df_index_test['PCA_1'] = np.ones(len(df_test.index))
```

```
### START CODE HERE ### ( 2-3 lines of code)
# please set random_state=42 when initializing Kernel PCA
kernel_pca_model = KernelPCA(n_components=1, random_state=42)
projected = kernel_pca_model.fit_transform(data) #df_test[stock_tickers].values
#pca = Kmodel.fit(data) #df_test[stock_tickers].values
df_index_test['PCA_1'] = projected

### GRADED PART (DO NOT EDIT) ###

# draw the two plots
df_plot = df_index_test[['SPX', 'PCA_1']].apply(lambda x: (x - x.mean()) / x.std())
df_plot.plot(figsize=(12, 6), title='Index replication via PCA')
```

Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd2cccd52e8>



In [76]:
```
### GRADED PART (DO NOT EDIT) ###
np.random.seed(42)
transformed_first_pc = df_index_test['PCA_1'].values
idx_test = np.random.randint(low=0, high=len(transformed_first_pc), size=100)

#grading
part_4=list(np.absolute(transformed_first_pc[idx_test]))
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,s
```

```
        np.absolute(transformed_first_pc[idx_test]) # because PCA results match down to a sign
        ### GRADED PART (DO NOT EDIT) ###
```

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

```
Out[76]: array([ 2.81264873,  1.0212579 ,  3.82280109,  4.45800988,
                 1.89638074,  4.93135654,  2.11776577,  9.60493421,
                 2.81264873,  3.28584703,  7.92116124,  1.6025791 ,
                 5.53281157,  8.55828773,  6.56407882,  2.52749704,
                 8.96373405,  1.35828487,  1.22531481, 24.23713855,
                 2.00760752,  1.93619077,  5.35570067,  2.60219962,
                 0.34785633, 20.37301703,  0.72409454,  1.31006507,
                 7.22057714,  6.16790594,  0.57324629,  1.66213893,
                 1.76561837,  6.75294026,  9.73804903,  2.83802785,
                 5.97808944,  4.45800988,  9.75209914,  1.30664976,
                 1.47305523,  9.36604765,  9.58799909,  3.33895779,
                 4.19472424,  1.35828487,  6.19673548,  0.59907927,
                 9.60493421,  1.68347838,  3.05861624, 10.30909458,
                 5.70803648,  3.88782753,  5.5758476 ,  0.1458809 ,
                 2.01257801,  4.51134676,  0.41091121, 14.92772154,
                 0.34785633,  2.19444128,  1.43233492,  4.72156492,
                 0.29730135, 14.36085461,  2.91241258,  7.27412575,
                 1.35005297, 10.48378192,  0.27945052, 20.4816482 ,
                 2.52749704,  5.70803648,  7.30869214,  8.19327029,
                 9.98519242,  4.30588102,  3.74692129,  2.24040025,
                14.61628141,  3.20228466,  4.2461602 , 10.5305691 ,
                 4.09021724,  1.57582128,  4.59217942,  6.12701792,
                15.08979599,  4.45800988,  7.92116124,  7.64854209,
                 9.75209914,  2.19495232,  7.44010145,  4.60921436,
                 4.95089776, 12.94147928,  4.72156492, 14.92772154])
```

1.1.4 Part 5 (Visualization with t-SNE)

Lets turn attention to a popular dimensonality reduction algorithm: t-distributed stochastic neighbor embedding (t-SNE). Developed by Laurens van der Maaten and Geoffrey Hinton (see the original paper here), this algorithm has been successfully applied to many real-world datasets.

The t-SNE algorithm provides an effective method to visualize a complex dataset. It successfully uncovers hidden structures in the data, exposing natural clusters and smooth nonlinear variations along the dimensions. It has been implemented in many languages, including Python, and it can be easily used thanks to the scikit-learn library.

Instructions: - Fit TSNE with 2 components, 300 iterations. Set perplexity to 50. - Use **log_ret_df_std** dataset for stock tickers only - Store the results of fitting in **tsne_results** np.array

```
In [77]: import time
         from sklearn.manifold import TSNE

         np.random.seed(42)
```

```
tsne_results = np.zeros((log_ret_df_std[stock_tickers].shape[0], 2))
perplexity = 50
n_iter = 300
time_start = time.time()
### START CODE HERE ### ( 2-3 lines of code)
#... please set random_state=42 when initializing TSNE
tsne_results = TSNE( n_components=2,
                     perplexity=50.0,
                     n_iter=300,
                     random_state=42 ).fit_transform( log_ret_df_std[stock_tickers] )


### GRADED PART (DO NOT EDIT) ###
```

In [78]:
```
df_tsne = pd.DataFrame({'regime': log_ret_df_std.regime.values,
                        'x-tsne': tsne_results[:,0],
                        'y-tsne': tsne_results[:,1]},
                       index=log_ret_df_std.index)
print('t-SNE (perplexity=%.0f) data:' % perplexity)
df_tsne.head(10)
```

```
t-SNE (perplexity=50) data:
```

Out[78]:

	regime	x-tsne	y-tsne
2000-01-28	benign	-3.038673	-5.316556
2000-01-31	benign	-8.765260	3.094646
2000-02-01	benign	-8.244621	0.480547
2000-02-02	benign	-8.708703	-2.338986
2000-02-03	benign	-6.688275	3.085631
2000-02-04	benign	-7.527815	-4.522123
2000-02-07	benign	-7.912331	-5.846404
2000-02-08	benign	-5.841453	0.052098
2000-02-09	benign	-3.304428	-5.064686
2000-02-10	benign	-5.084796	-1.647474

In [79]:
```
### GRADED PART (DO NOT EDIT) ###
np.random.seed(42)
idx_row = np.random.randint(low=0, high=tsne_results.shape[0], size=100)
np.random.seed(42)
idx_col = np.random.randint(low=0, high=tsne_results.shape[1], size=100)

#grading
part_5 = list(tsne_results[idx_row, idx_col]) # because PCA results match down to a sig
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,s

tsne_results[idx_row, idx_col]
### GRADED PART (DO NOT EDIT) ###
```

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

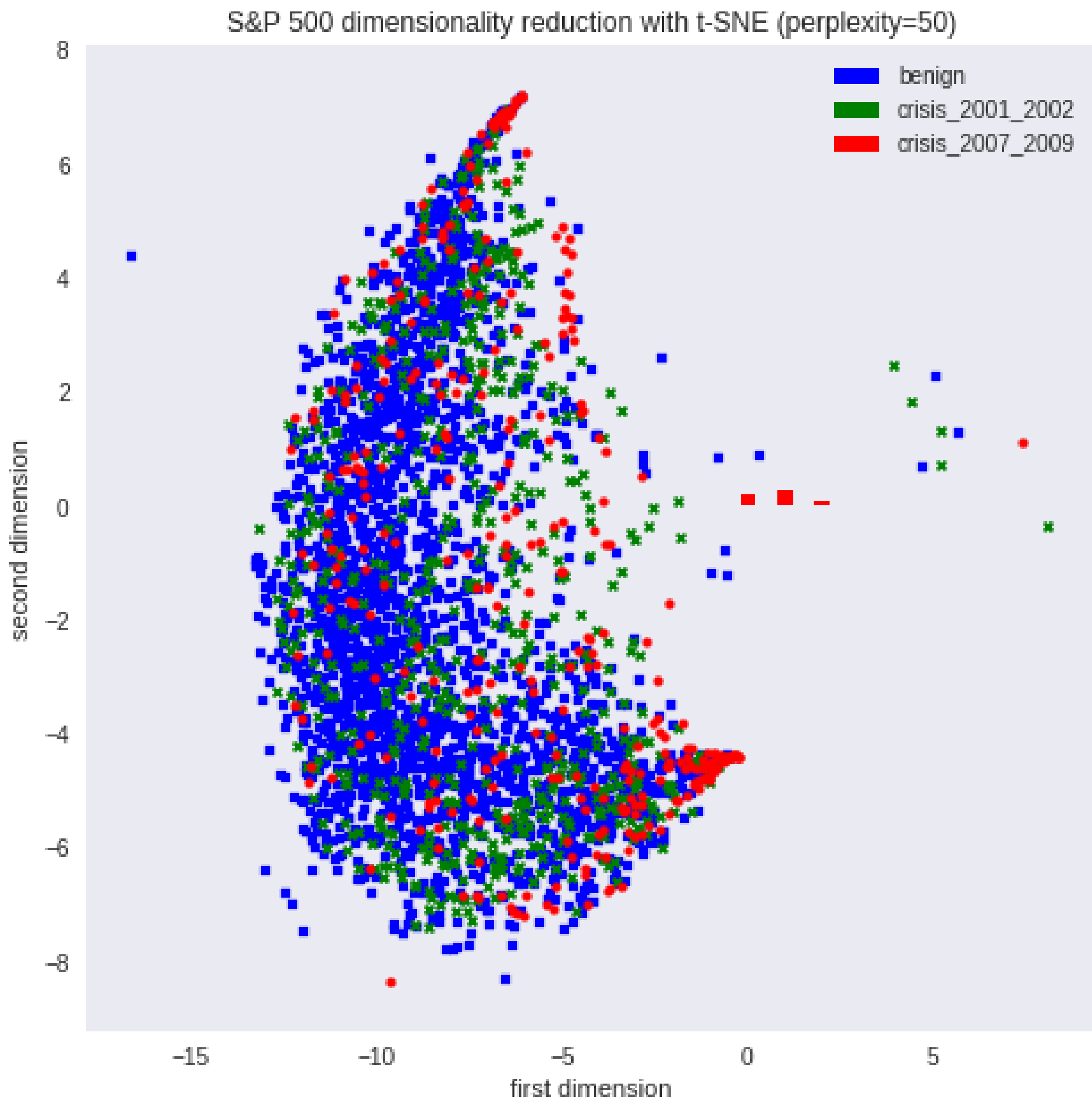
```
Out[79]: array([ -7.27752779,   3.97922194,  -4.95499954, -11.95070426,
               -10.96153847,  -5.59631304,  -7.34812751,  -6.42637253,
                -4.34998945,  -6.89970789,  -6.51875683,  -9.59451548,
                -4.32173727,  -5.61804782,   0.25647417,  -7.91333904,
                 1.84540425,  -1.59525999,  -4.69650804,  -7.82388042,
                -3.52797559, -10.35609149,  -4.82478387,  -5.21829759,
                 4.16881871,   2.75929713,  -6.22412129,   0.71199362,
                -2.38738997,   3.57643448, -10.74498128,  -5.84538947,
                -4.9310639 ,   3.43898344,  -4.14266855,  -6.72443296,
                -0.89687314,  -6.06944889,  -5.1753488 ,  -8.67070395,
               -10.75367228,  -9.50263653,  -0.18979738,  -3.98885135,
                -4.31156161,  -3.98885135,   3.62077396,  -9.31454961,
                -0.86092471,   0.58070048,  -7.06093787,  -4.02564937,
                -3.09743313,   2.89553328,  -7.22889814,  -4.37827015,
                -6.69086267,  -8.95234196,  -8.61584711, -10.58632673,
                -7.53349756,  -6.40884109,  -6.62375233,  -6.60614982,
               -10.89034414,  -4.00172358,   6.30258067,  -6.20732752,
                 0.38678631,  -4.68414978,  -2.34763544,  -3.62741414,
                -8.88872528,   1.14955065,  -4.35723264,  -4.35330341,
                -4.18172544,  -2.56710331,  -7.84590043,  -3.39016821,
                -4.99979225,  -0.62622467,  -3.6905336 ,  -4.66058956,
               -10.42486813,  -3.63615232,   1.762335  ,  -1.96064274,
                -0.69211448,  -3.09711116,  -5.63970741,  -3.51136039,
                -5.28277617,   0.59504166,  -0.95834627,  -5.9675336 ,
                -3.1866327 ,   3.44990257,   1.70706296,  -7.37366448])
```

```
In [81]: def plot_tsne_2D(df_tsne, label_column, plot_title):
             """
             plot_tsne_2D - plots t-SNE as two-dimensional graph
             Arguments:
             label_column - column name where labels data is stored
             df_tsne - pandas.DataFrame with columns x-tsne, y-tsne
             plot_title - string
             """
             unique_labels = df_tsne[label_column].unique()
             print('Data labels:', unique_labels)
             print(df_tsne.shape)

             colors = [ 'b', 'g','r']
```

```
    markers = ['s', 'x', 'o']
    y_train = df_tsne.regime.values

    plt.figure(figsize=(8, 8))
    ix = 0
    bars = [None] * len(unique_labels)
    for label, c, m in zip(unique_labels, colors, markers):
        plt.scatter(df_tsne.loc[df_tsne[label_column]==label, 'x-tsne'],
                    df_tsne.loc[df_tsne[label_column]==label, 'y-tsne'],
                    c=c, label=label, marker=m, s=15)
        bars[ix] = plt.bar([0, 1, 2], [0.2, 0.3, 0.1], width=0.4, align="center", color
        ix += 1

    plt.legend(bars, unique_labels)
    plt.xlabel('first dimension')
    plt.ylabel('second dimension')
    plt.title(plot_title)
    plt.grid()
    plt.show()
```

```
In [82]: plot_tsne_2D(df_tsne, 'regime', 'S&P 500 dimensionality reduction with t-SNE (perplexit
```

```
Data labels: ['benign' 'crisis_2001_2002' 'crisis_2007_2009']
(3492, 3)
```


S&P 500 dimensionality reduction with t-SNE (perplexity=50)
benign
crisis_2001_2002
crisis_2007_2009
second dimension
first dimension
8
6
4
2
0
−2
−4
−6
−8
−15
−10
−5
0
5

```
In [ ]:
```