Stock portfolio performance Data Set

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1 Stock portfolio performance Data Set

Data Set Information: There are three disadvantages of weighted scoring stock selection models. First, they cannot identify the relations between weights of stock-picking concepts and performances of portfolios. Second, they cannot systematically discover the optimal combination for weights of concepts to optimize the performances. Third, they are unable to meet various investors preferences. This study aims to more efficiently construct weighted scoring stock selection models to overcome these disadvantages. Since the weights of stock-picking concepts in a weighted scoring stock selection model can be regarded as components in a mixture, we used the simplex centroid mixture design to obtain the experimental sets of weights. These sets of weights are simulated with US stock market historical data to obtain their performances. Performance prediction models were built with the simulated performance data set and artificial neural networks. Furthermore, the optimization models to reflect investors preferences were built up, and the performance prediction models were employed as the kernel of the optimization models so that the optimal solutions can now be solved with optimization techniques. The empirical values of the performances of the optimal weighting combinations generated by the optimization models showed that they can meet various investors preferences and outperform those of S&P 500 not only during the training period but also during the testing period.

Data Access https://archive.ics.uci.edu/ml/datasets/Stock+portfolio+performance

Attribute Information: The inputs are the weights of the stock-picking concepts as follows:
X1=the weight of the Large B/P concept
X2=the weight of the Large ROE concept
X3=the weight of the Large S/P concept
X4=the weight of the Large Return Rate in the last quarter concept
X5=the weight of the Large Market Value concept
X6=the weight of the Small systematic Risk concept
The outputs are the investment performance indicators (normalized) as follows:
Y1=Annual Return
Y2=Excess Return
Y3=Systematic Risk
Y4=Total Risk
Y5=Abs. Win Rate
Y6=Rel. Win Rate

1.0.1 Objective

In this notebook, a neural networks was built using Sklearn MLPRegressor to predict the outcome each investment performances indicators. To optimize the outcome, the model was iterated to determine the best number model performance based on the number of hidden layers.

1.0.2 Libraries to be used

```
In [1]: # Data Setup
        import numpy as np
        import pandas as pd
        import seaborn as sns

        # Linear Regression
        from sklearn.neural_network import MLPRegressor
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import mean_squared_error
```

1.0.3 Data Import

```
In [2]: df = pd.read_excel('stock portfolio performance data set.xlsx', skiprows=[0])
```

1.0.4 EDA, Initial

```
In [3]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63 entries, 0 to 62
Data columns (total 19 columns):
ID                                           63 non-null int64
 Large B/P                                   63 non-null float64
 Large ROE                                   63 non-null float64
 Large S/P                                   63 non-null float64
 Large Return Rate in the last quarter       63 non-null float64
 Large Market Value                          63 non-null float64
 Small systematic Risk                       63 non-null float64
Annual Return                                63 non-null float64
Excess Return                                63 non-null float64
Systematic Risk                              63 non-null float64
Total Risk                                   63 non-null float64
Abs. Win Rate                                63 non-null float64
Rel. Win Rate                                63 non-null float64
Annual Return.1                              63 non-null float64
Excess Return.1                              63 non-null float64
Systematic Risk.1                            63 non-null float64
Total Risk.1                                 63 non-null float64
Abs. Win Rate.1                              63 non-null float64
Rel. Win Rate.1                              63 non-null float64
dtypes: float64(18), int64(1)
```

```
memory usage: 9.4 KB
```

In [4]: df.isnull().any()

```
Out[4]: ID                                          False
         Large B/P                                  False
         Large ROE                                  False
         Large S/P                                  False
         Large Return Rate in the last quarter      False
         Large Market Value                         False
         Small systematic Risk                      False
        Annual Return                               False
        Excess Return                               False
        Systematic Risk                             False
        Total Risk                                  False
        Abs. Win Rate                               False
        Rel. Win Rate                               False
        Annual Return.1                             False
        Excess Return.1                             False
        Systematic Risk.1                           False
        Total Risk.1                                False
        Abs. Win Rate.1                             False
        Rel. Win Rate.1                             False
        dtype: bool
```

In [5]: df.describe()

```
Out[5]:               ID   Large B/P    Large ROE    Large S/P   \
        count  63.000000   63.000000    63.000000    63.000000
        mean   32.000000    0.166619     0.166619     0.166619
        std    18.330303    0.199304     0.199304     0.199304
        min     1.000000    0.000000     0.000000     0.000000
        25%    16.500000    0.000000     0.000000     0.000000
        50%    32.000000    0.167000     0.167000     0.167000
        75%    47.500000    0.291500     0.291500     0.291500
        max    63.000000    1.000000     1.000000     1.000000

                Large Return Rate in the last quarter    Large Market Value   \
        count                               63.000000             63.000000
        mean                                 0.166619              0.166619
        std                                  0.199304              0.199304
        min                                  0.000000              0.000000
        25%                                  0.000000              0.000000
        50%                                  0.167000              0.167000
        75%                                  0.291500              0.291500
        max                                  1.000000              1.000000

                Small systematic Risk  Annual Return  Excess Return  Systematic Risk  \
```

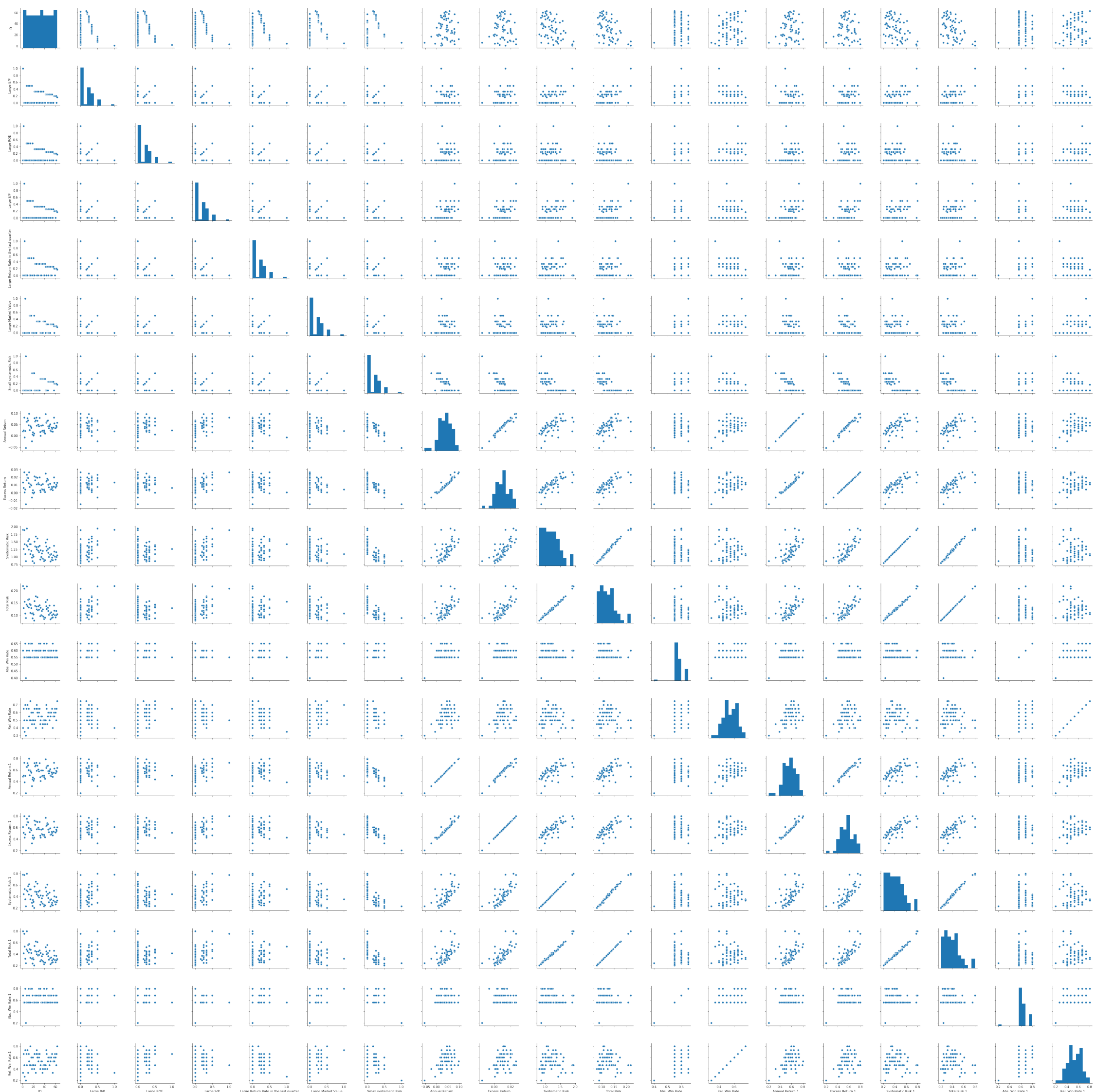
```
count             63.000000    63.000000    63.000000      63.000000
mean               0.166619     0.040384     0.010196       1.206636
std                0.199304     0.028337     0.007972       0.271843
min                0.000000    -0.053382    -0.014856       0.800792
25%                0.000000     0.021405     0.004378       0.997674
50%                0.167000     0.042629     0.010413       1.181784
75%                0.291500     0.061776     0.015840       1.363218
max                1.000000     0.098369     0.026548       1.939118

       Total Risk  Abs. Win Rate  Rel. Win Rate  Annual Return.1  \
count   63.000000      63.000000      63.000000        63.000000
mean     0.124854       0.578571       0.552381         0.570737
std      0.031626       0.043731       0.100975         0.112040
min      0.078831       0.400000       0.300000         0.200000
25%      0.100883       0.550000       0.500000         0.495695
50%      0.119563       0.550000       0.550000         0.579611
75%      0.139269       0.600000       0.650000         0.655315
max      0.218617       0.650000       0.750000         0.800000

       Excess Return.1  Systematic Risk.1  Total Risk.1  Abs. Win Rate.1  \
count        63.000000          63.000000     63.000000        63.000000
mean          0.563039           0.413916      0.397544         0.628571
std           0.115526           0.143286      0.135746         0.104956
min           0.200000           0.200000      0.200000         0.200000
25%           0.478730           0.303774      0.294651         0.560000
50%           0.566175           0.400817      0.374831         0.560000
75%           0.644828           0.496449      0.459415         0.680000
max           0.800000           0.800000      0.800000         0.800000

       Rel. Win Rate.1
count        63.000000
mean          0.536508
std           0.134633
min           0.200000
25%           0.466667
50%           0.533333
75%           0.666667
max           0.800000
```

In [6]:
```
df.shape
```

Out[6]:
```
(63, 19)
```

In [7]:
```
sns.pairplot(df)
```

Out[7]:
```
<seaborn.axisgrid.PairGrid at 0x1a1777ea90>
```



1.0.5 Data Setup, EDA Continued

This data set

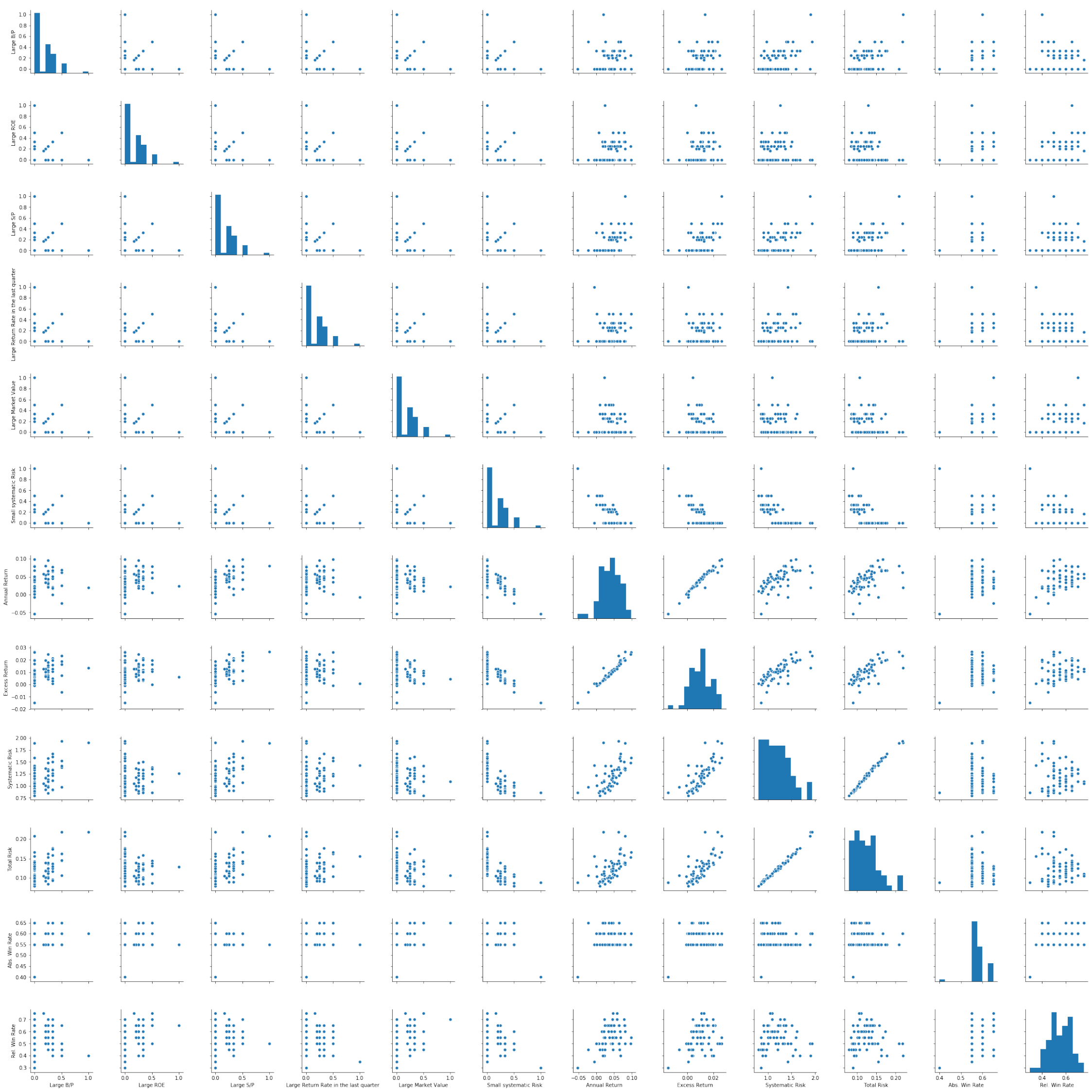
```
In [8]: #Data to be used al filtered as a new data frame.
        df_n = df.iloc[:, 1:13]
        df_n.shape
        print('The shape of the new data frame is: {}'.format(df_n.shape))

        # Data selection
        x = df_n.iloc[:,0:6]
        y = df_n.iloc[:, 6:]
```

```
#y1 = df_n['Annual Return']
#y2 = df_n['Excess Return']
#y3 = df_n['Systematic Risk']
#y4 = df_n['Total Risk']
#y5 = df_n['Abs. Win Rate']
#y6 = df_n['Rel. Win Rate']
print('Shape of x: {}\nShape of y: {}'.format(x.shape, y.shape))
```

```
The shape of the new data frame is: (63, 12)
Shape of x: (63, 6)
Shape of y: (63, 6)
```

In [9]:
```
sns.pairplot(df_n)
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x1a1fc51cc0>



1.0.6 Model Selection

To obtain the best numbers o f hidden layers, the code below iterates different over the model with different hidden layers. For each iteration R Squared and the Mean Squared Error of the model being will be attached to a list. Then, by filtering the maximum R Squared and the minimum Mean Squared Error the best number of hidden layyers was determined.

In [15]:
```
#best_parameters = []
#best_score = []

score_l = []
mse_l = []

x_train, x_test, y_train, y_test = train_test_split(x, y, random_state = 12, test_size
t = range(1, 2010, 10)
for i in t:
    model = MLPRegressor(solver='lbfgs', learning_rate_init=0.019,hidden_layer_sizes=
                         learning_rate='adaptive')
    model.fit(x_train, y_train)

    y_pred = model.predict(x_test)
    score = model.score(x_test, y_test)
    mse = mean_squared_error(y_test, y_pred)
    score_l.append(score)
    mse_l.append(mse)

df_params = pd.DataFrame({'R^2':score_l, 'mse':mse_l }, index=t)
df_params.shape
```

Out[15]:
```
(201, 2)
```

In [16]:
```
# Model Selection
df_params['R^2'].max(), df_params['mse'].min()

maxs = df_params[df_params['R^2']==df_params['R^2'].max()]

mins = df_params[df_params['mse']==df_params['mse'].min()]

print('Maximum R^2: \n{} \n\nMinimum Mean Squared error: \n{} \n \nThe best number of
```

```
Maximum R^2:
          R^2       mse
801   0.782108   0.003329

Minimum Mean Squared error:
          R^2       mse
```

```
801  0.782108  0.003329

The best number of hidden layers:Int64Index([801], dtype='int64')
```