US Stock Return Prediction using Stock Fundemental Data - HKUST ECON4305 Project (Group 9)

Decription:

We are using US stock fundemental indicator to predict US stock return with various machine learning model.

1) we import the data and clear the data, then we label the features and target variable

2) we reduce the features for regression model

3) we train the model and predict the result by using 70-30 rule to do the data spliting

4) we compare the prediction and the actual result using correlation

5) we repeat the step 2-4 recursively for all models

6) Appendix: explaination of the abandoned model

Table of Content

Set up: Import library & data prepation

In [1]:
```
#Import libraries
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from pandas import read_excel
sns.set(style='whitegrid', palette='muted')
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 14, 8
import time

#Sklearn
from sklearn import metrics
from sklearn.metrics import make_scorer
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split

from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV

from sklearn.decomposition import PCA
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression
from sklearn.feature_selection import RFE
from sklearn.datasets import load_digits
from sklearn.feature_selection import SelectPercentile, chi2

#ensemble learning
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from xgboost import XGBRegressor

#Neural networking
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, SimpleRNN, LSTM, Dropout, R
from sklearn.neural_network import MLPRegressor
from keras.models import Sequential
from keras.layers import Dense, LSTM, SimpleRNN, Dropout
```

```
WARNING:tensorflow:From C:\Users\desti\anaconda3\Lib\site-packages\kera
s\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy i
s deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entro
py instead.
```

Flow:

1. Import data + data clearing
2. Use Grid search to find the optimal hyperparameter that we will be using via PCA
3. Create pipeline to store all ML model that we will be using
4. Test different feature selecting method to run the pipeline

We will using companies' fundemental ratio as the features to do the prediction

First, we select the first column as id of each input, all ratio as features and the last column as target

In [3]:
```
#Import data
DATA = pd.read_excel("US Stock Fundamentals Dataset.xlsx", sheet_name=
DATA=DATA.dropna()
DATA.head(5)
```

Out[3]:

	id_name	roe	rote	roce	roic	roa	ro
6	A_2004	10.918192	14.841590	9.189641	7.162667	5.227290	5.98473
7	A_2005	8.549020	10.827815	9.640000	1.668572	4.736728	5.36197
8	A_2006	85.452196	101.007941	63.836183	8.928691	46.841360	51.16027
9	A_2007	18.511533	25.762164	11.431496	10.975083	8.550560	9.82823
10	A_2008	23.925427	40.208877	13.579938	12.174586	9.245547	10.96085

5 rows × 69 columns

In [4]:
```
shape=DATA.shape
DATA.iloc[:,shape[1]-1].describe()
```

Out[4]:
```
count    11711.000000
mean         7.301829
std         41.753856
min        -98.504249
25%        -14.949400
50%          1.984102
75%         21.487615
max        973.996753
Name: return_adj_12m, dtype: float64
```

In [5]:
```
X_start = 1

# Label, Features and Target
Z, X, y = DATA.iloc[X_start:,0], DATA.iloc[X_start:,1:-1], DATA.iloc[X
```

In [6]:
```
def print_evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r_squared = metrics.r2_score(true, predicted)
    print('MAE:', mae)
    print('RMSE:', rmse)
    print('R-squared', r_squared)
    print('__________________________________')

def evaluate(true, predicted):
    mae = metrics.mean_absolute_error(true, predicted)
    rmse = np.sqrt(metrics.mean_squared_error(true, predicted))
    r_squared = metrics.r2_score(true, predicted)
    return mae, rmse, r_squared
```

Model 1: OLS Linear Regression

Step 1: Grid Search with PCA to reduce the number of features

In [9]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('OLS',LinearRegression())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    #print(' > %.3f' % score_rmse)
    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Out[9]:
```
45
```

Step 2: Train the model with the reduced number of features

In [10]:
```
# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('ols', LinearRegression())
              ]

pipeline_final = Pipeline(steps_final)
```

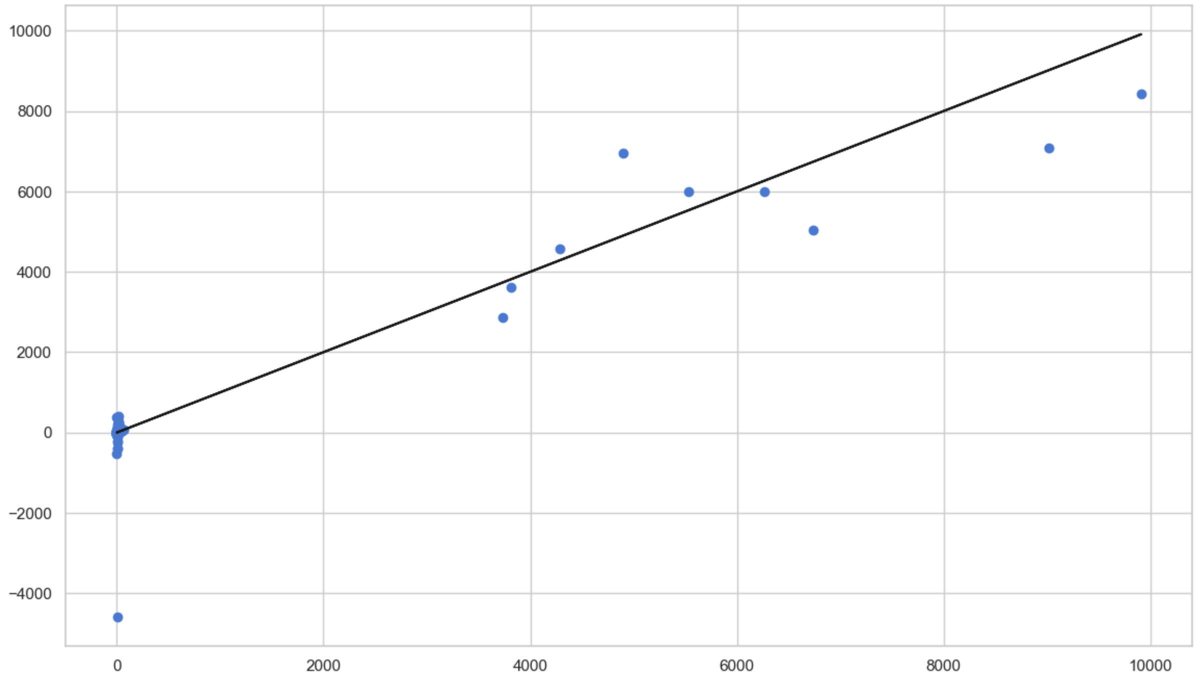
In [11]:
```
n_train = int(0.7 * len(X))

n_forecast = len(X) - n_train

n_records = len(X)
```

```
y_test_list_ols = []

y_pred_list_ols = []

j = 0

for i in range(n_train, n_records):
    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list_ols.extend(y_pred)

    y_test_list_ols.extend(y_test)

    j += 1
```

Step 3: Compare the model with the actual data

In [12]:
```
plt.scatter(y_test_list_ols, y_pred_list_ols)
plt.plot(y_test_list_ols, y_test_list_ols,'k-') # identity line
```

Out[12]:
```
[<matplotlib.lines.Line2D at 0x1e5b59fa690>]
```



In [13]:
```
results_df_ols = pd.DataFrame(data=[["OLS Lineaer Regression", *evalua
                              columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols], axis=0, ignore_index=True)
```

Out[13]:

	Model	MAE	RMSE	R-squared
0	OLS Lineaer Regression	8.759739	102.408536	0.898848

In [ ]:
```
n_forecast = len(X) - n_train
result_ols = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_ols.corr()
```

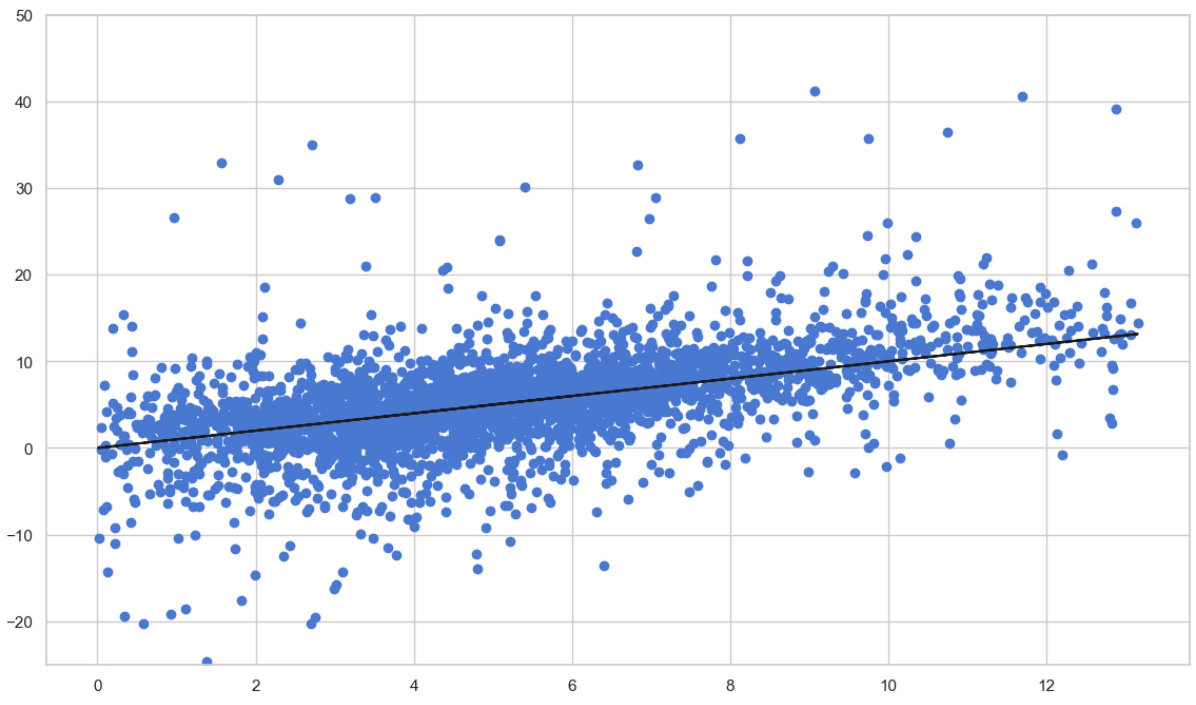
Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045046
Return_Predicted	0.045046	1.000000

Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [14]:
```
predf=pd.DataFrame({'test':y_test_list_ols,'predict':y_pred_list_ols})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [15]:
```
n_forecast = len(X) - n_train
```

```
result_ols = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_ols.corr()
```

Out[15]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.035386
Return_Predicted	0.035386	1.000000

Result for the OLS is poor due to the low correlation.

Since the PCA dimension reduction method only take 1 PCA into account and it is linear project, i.e. we have no idea what happen in the process (e.g. which features used or reduced)

Now we try to apply other feature reduction method to get a more logical approach

bold text# Alternative: SelectKbest

Step 1: Use SelectKBest to select the optimal features

In [17]:
```
model_KBest = SelectKBest(score_func=f_regression, k=10)     #Select k
                                                            #f_regress

model_KBest = model_KBest.fit(X, y)

KBest = model_KBest.get_support()       #Get a mask, or integer index,

data = {"Features":model_KBest.feature_names_in_,"Selection":KBest}
pd.DataFrame(data, columns = ['Features','Selection'])
```

Out[17]:

	Features	Selection
0	roe	False
1	rote	False
2	roce	False
3	roic	False
4	roa	False
...	...	...
62	pocf	False
63	ev_sales	False
64	ev_ebitda	False
65	ev_ebit	False
66	ey	True

67 rows × 2 columns

In [18]:
```
data = {"Features":model_KBest.feature_names_in_,"P-value":model_KBest
df = pd.DataFrame(data, columns = ['Features','P-value'])
df.sort_values(by='P-value', ascending=True).head(model_KBest.k)
```

Out[18]:

	Features	P-value
66	ey	0.000000
57	ebitdaps	0.000000
56	ocfps	0.000000
55	fcfps	0.000000
54	saleps	0.000000
53	bvps	0.000000
52	eps	0.000000
41	F_eq_offer_fs	0.000002
24	cogsr	0.091798
34	rd	0.095488

In [19]:
```
#Identifying the selected features

KBest_feature = []
```

```
for i in range(0,KBest.shape[0]):
    if KBest[i] == True:
        K_feature = X.columns[i]
        KBest_feature.append(K_feature)

KBest_feature
```

Out[19]:
```
['cogsr',
 'rd',
 'F_eq_offer_fs',
 'eps',
 'bvps',
 'saleps',
 'fcfps',
 'ocfps',
 'ebitdaps',
 'ey']
```

Step 2: Train the model with the reduced number of features

In [25]:
```
# Pipeline

# Steps
steps_final = [('SelectKBest', SelectKBest(score_func=f_regression, k=
               ('ols', LinearRegression())
              ]

pipeline_final = Pipeline(steps_final)
```

In [26]:
```
n_train = int(0.7 * len(X))

n_forecast = len(X) - n_train

n_records = len(X)

y_test_list_ols_kbest = []

y_pred_list_ols_kbest = []


j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    y_pred_list_ols_kbest.extend(y_pred)

    y_test_list_ols_kbest.extend(y_test)

    j += 1
```

Step 3: Compare the model with the actual data

In [27]:
```
results_df_ols_kbest = pd.DataFrame(data=[["OLS Lineaer Regression (Se
                                     columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols,results_df_ols_kbest], axis=0, ignore_index=
```

Out[27]:

	Model	MAE	RMSE	R-squared
0	OLS Lineaer Regression	8.759739	102.408536	0.898848
1	OLS Lineaer Regression (SelectKbest)	9.405706	128.891011	0.839769

In [28]:
```
metrics.mean_squared_error(y_test_list_ols_kbest, y_pred_list_ols_kbes
```

Out[28]:
```
128.89101113424496
```

In [29]:
```
n_forecast = len(X) - n_train
result_ols_kbest = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Re
result_ols_kbest.corr()
```

Out[29]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.918277
Return_Predicted	0.918277	1.000000

The result showed that the OLS prediction is terrible as showed in its low correlation

Thus, we can deduct that OLS is not a desireable model for such prediction

Model 2: Random Forest Regression

Step 1: Grid Search to find the optimal hyperparameter

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('RandomForestRegressor',RandomForestRegressor())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    jprint(' > %.3f' % score_rmse)

    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Step 2: Train the model with the reduced number of features

```
In [ ]: def pipeline(config):
            n_comps = config
            steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
                      ('pca', PCA(n_components = n_comps, random_state=1)),
                      ('RandomForestRegressor',RandomForestRegressor())
                     ]
            pipeline = Pipeline(steps)
            return pipeline

        def model_configs():
            n = 25
            n_comps = [i for i in range(1, n+1)]
            configs = list()

            for k in n_comps:
                cfg = k
                configs.append(cfg)

            print('Total configs: %d' % len(configs))
            return configs

        cfg_list = model_configs()
        scores = grid_search(cfg_list)

        #The optimal number of features for OLS from PCA grid search
        optimal_n_pca_comp = int(scores[len(scores)-1][0])

        # Steps
        steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
                        ('pca', PCA(n_components = optimal_n_pca_comp, random_s
                        ('RandomForestRegressor', RandomForestRegressor())
                       ]

        pipeline_final = Pipeline(steps_final)

        n_train = int(0.7 * len(X))
        n_forecast = len(X) - n_train
        n_records = len(X)

        y_test_list_radforest = []
        y_pred_list_radforest = []

        j = 0

        for i in range(n_train, n_records):

            X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i
```

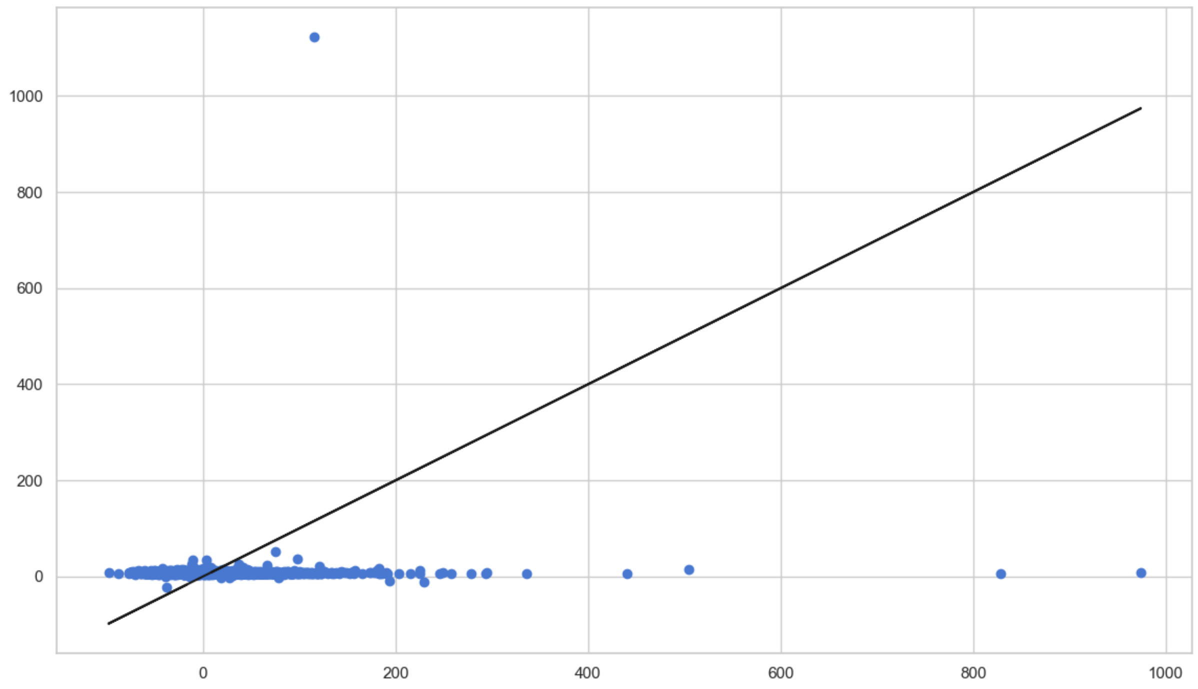
```
    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list_radforest.extend(y_pred)

    y_test_list_radforest.extend(y_test)

    j += 1
```

```
Total configs: 25
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list_radforest, y_pred_list_radforest)
plt.plot(y_test_list_radforest, y_test_list_radforest,'k-') # identity
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045046
Return_Predicted	0.045046	1.000000

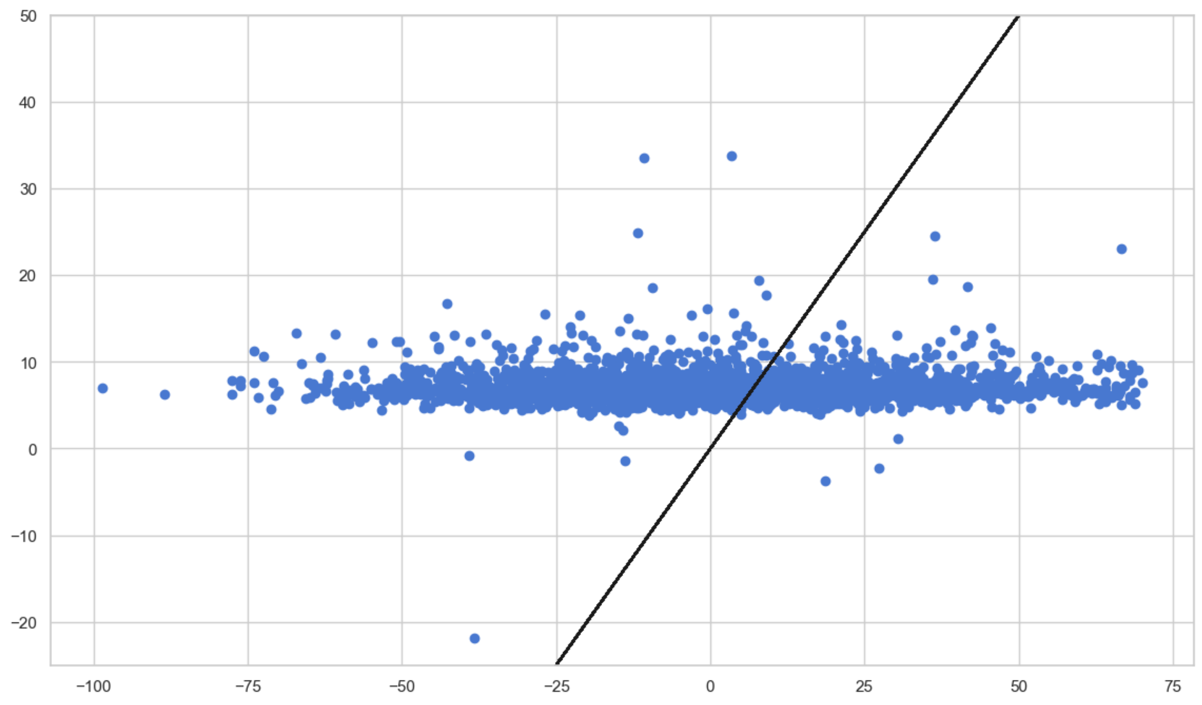


Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:
```
results_df_ran = pd.DataFrame(data=[["Random Forest Regression", *eval
                                      columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols,results_df_ran], axis=0, ignore_index=True)
```

In [ ]:
```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [ ]:

In [ ]:
```
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_rig.corr()
```

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.033939
Return_Predicted	0.033939	1.000000

Result for the OLS is poor due to the low correlation.

Since the PCA dimension reduction method only take 1 PCA into account and it is linear project, i.e. we have no idea what happen in the process (e.g. which features used or reduced)

Now we try to apply other feature reduction method to get a more logical approach

Model 3: XGBoost Regression

Step 1: Grid Search to find the optimal hyperparameter

In [ ]:
```
from xgboost import XGBRegressor
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('xgboost', xgb.XGBRegressor(objective='reg:squarederror'
             ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    #print(' > %.3f' % score_rmse)

    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()
    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Out[ ]:
```
41
```

Note: The optimal number of PCA is 1 for Xgboost

Step 2: Train the model with the reduced number of features

In [31]:
```
n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)
print(n_train,n_forecast,n_records)
```

```
8197 3513 11710
```

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('xgboost', XGBRegressor(objective='reg:squarederror', ra
            ]
    pipeline = Pipeline(steps)
    return pipeline

def model_configs():
    n = 25
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    print('Total configs: %d' % len(configs))
    return configs

#cfg_list = model_configs()
```

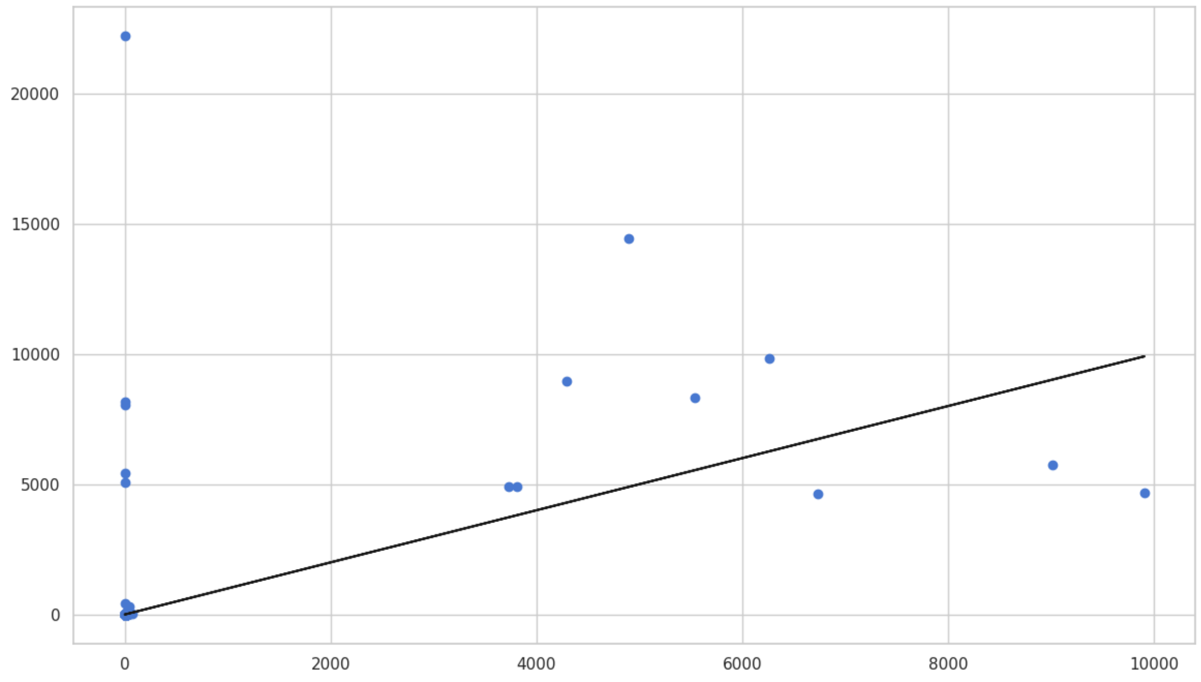
```
#scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
#optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp = 41

# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('xgboost', xgb.XGBRegressor(objective='reg:squarederro
              ]

pipeline_final = Pipeline(steps_final)

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

y_test_list_xgb = []
y_pred_list_xgb = []

j = 0

for i in range(n_train,1,-1):
    print(i)

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list_xgb.extend(y_pred)

    y_test_list_xgb.extend(y_test)

    j += 1
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list_xgb, y_pred_list_xgb)
plt.plot(y_test_list_xgb, y_test_list_xgb,'k-') # identity line
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.563062
Return_Predicted	0.563062	1.000000

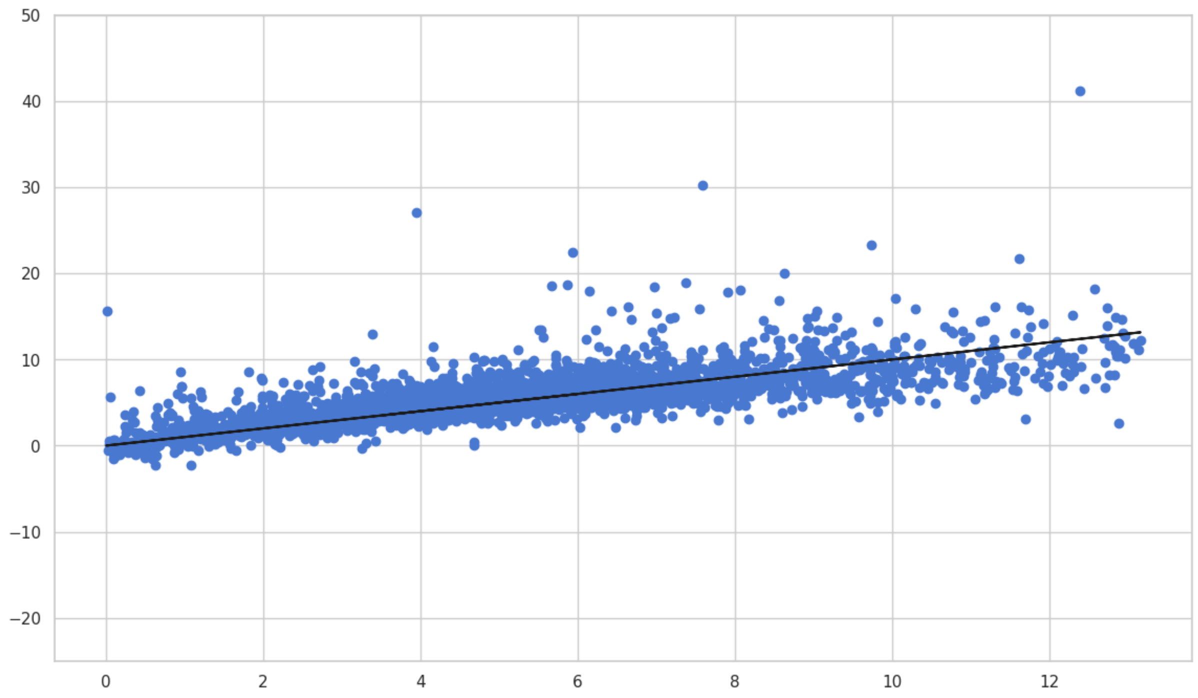


Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:

```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [ ]:
```
results_df_xgb = pd.DataFrame(data=[["XGBoost Regression", *evaluate(y
                                columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols,results_df_ran,results_df_xgb], axis=0, igno
```

In [ ]:
```
```

In [ ]:
```
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.014137
Return_Predicted	0.014137	1.000000

Result for the XGboost is poor due to the low correlation.

Since the PCA dimension reduction method only take 1 PCA into account and it is linear project, i.e. we have no idea what happen in the process (e.g. which features used or reduced)

Model 4: SVM Regression

Step 1: Grid Search to find the optimal hyperparameter

In [ ]:
```
from sklearn.svm import SVR

def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('SVM Regression',SVR(kernel='rbf'))
            ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    #print(' > %.3f' % score_rmse)

    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
```

```
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Step 2: Train the model with the reduced number of features

In [ ]:

```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('SVM Regression',SVR(kernel='rbf'))
            ]
    pipeline = Pipeline(steps)
    return pipeline

def model_configs():
    n = 25
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    print('Total configs: %d' % len(configs))
    return configs

#cfg_list = model_configs()
#scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
#optimal_n_pca_comp = int(scores[len(scores)-1][0])

# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('SVM Regression',SVR(kernel='rbf'))
              ]

pipeline_final = Pipeline(steps_final)

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

y_test_list_svm = []
y_pred_list_svm = []
```

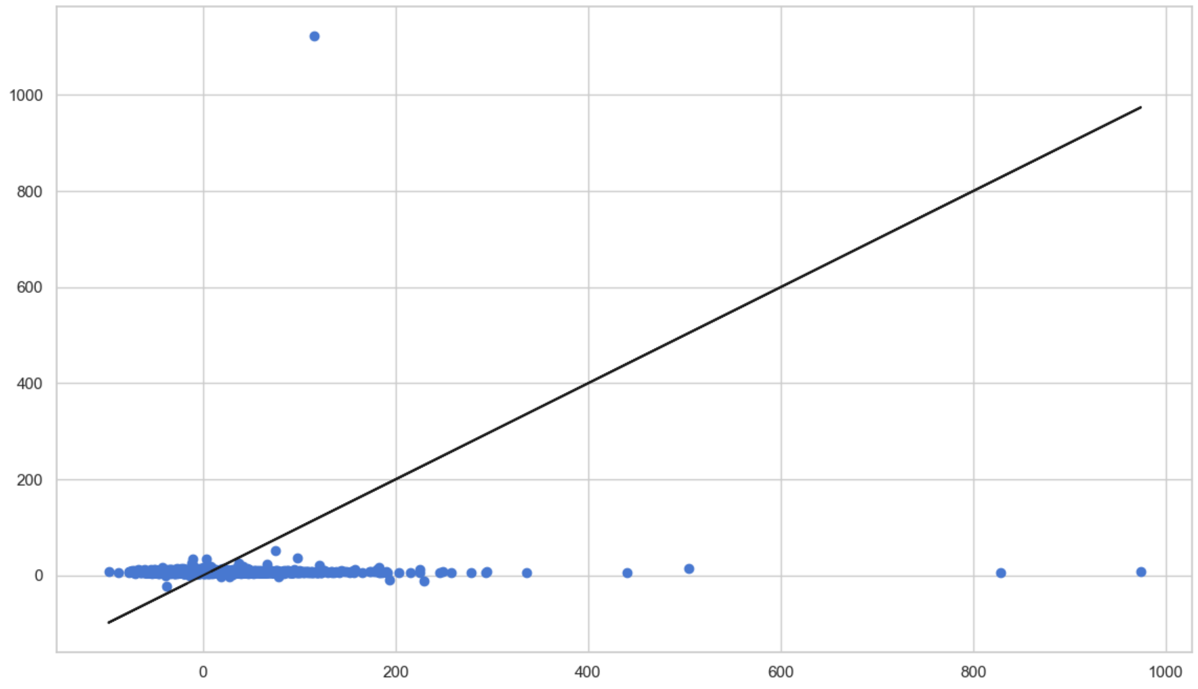
```
j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list_svm.extend(y_pred)

    y_test_list_svm.extend(y_test)

    j += 1
```

```
Total configs: 25
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list_svm, y_pred_list_svm)
plt.plot(y_test_list_svm, y_test_list_svm,'k-') # identity line
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045046
Return_Predicted	0.045046	1.000000



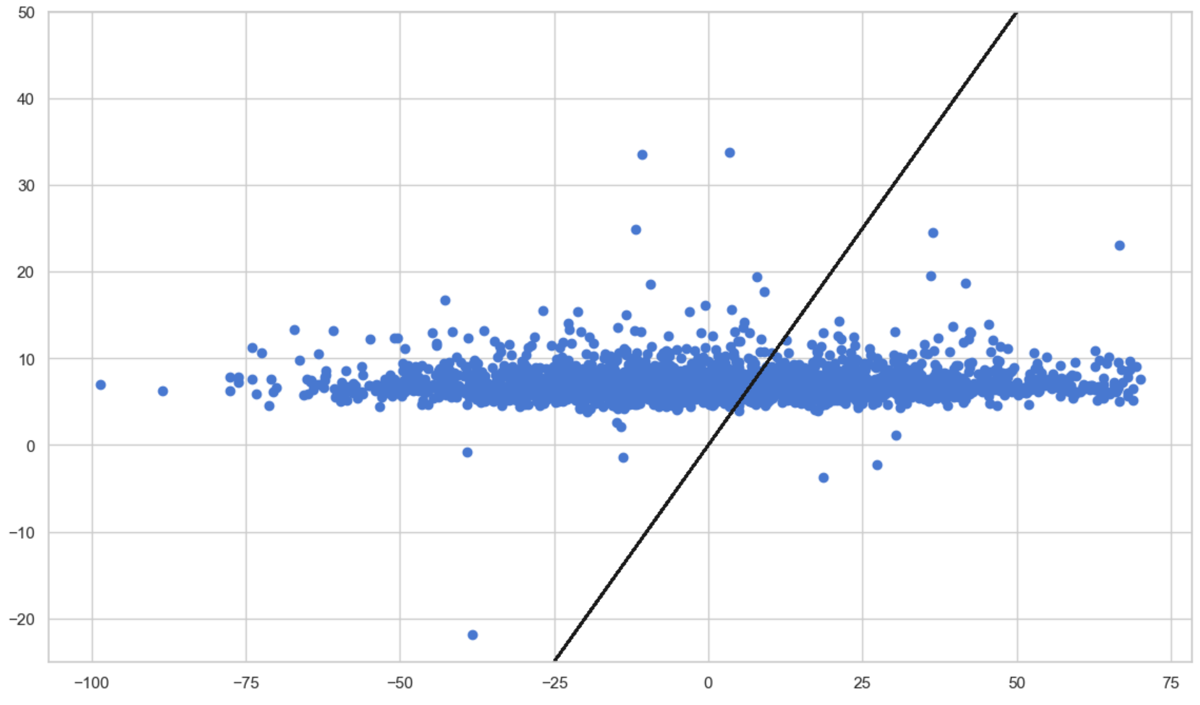
In [ ]:
```
results_df_svm = pd.DataFrame(data=[["Random Forest Regression", *eval
                                    columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols,results_df_ran,results_df_xgb,results_df_svm
```

In [ ]:
```
```

Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:
```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [ ]:
```
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_rig.corr()
```

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.033939
Return_Predicted	0.033939	1.000000

Result for the OLS is poor due to the low correlation.

Since the PCA dimension reduction method only take 1 PCA into account and it is linear project, i.e. we have no idea what happen in the process (e.g. which features used or reduced)

Now we try to apply other feature reduction method to get a more logical approach

Model 5: RNN Neural Networking Model

In [ ]:
```
from sklearn.metrics import mean_squared_error as mse

n_steps = 20
n_features = 66

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

n = n_forecast

# split a multivariate sequence into samples
def split_sequences(X, n_steps):
    X_seq = list()
    for i in range(len(X)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the dataset
        if end_ix > len(X):
            break
        # gather input and output parts of the pattern
        seq_x = X.iloc[i:end_ix, :]
        X_seq.append(seq_x)
    return np.array(X_seq)


X_train = split_sequences(X.iloc[:-n], n_steps)
for i in range(X_train.shape[1]):
  for j in range(X_train.shape[2]):
    X_train[:,i,j] = (X_train[:,i,j]-X_train[:,i,j].mean())/(X_train[:
y_train = y.iloc[n_steps:-n+1].values
print(X_train.shape, y_train.shape)
```

```
X_test = split_sequences(X.iloc[-n-n_steps+1:], n_steps)
for i in range(X_test.shape[1]):
  for j in range(X_test.shape[2]):
    X_test[:,i,j] = (X_test[:,i,j]-X_test[:,i,j].mean())/(X_test[:,i,j
y_test = y.iloc[-n:].values
print(X_test.shape, y_test.shape)
```

```
(8178, 20, 66) (8178,)
(3513, 20, 66) (3513,)
```

In [ ]:

```
#RNN model
model = Sequential()
model.add(SimpleRNN(128, activation='relu', input_shape=(n_steps, n_fe
model.add(Dropout(0.2))
model.add(Dense(1, activation='linear'))

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['m
```

```
WARNING:tensorflow:From C:\Users\desti\anaconda3\Lib\site-packages\kera
s\src\backend.py:873: The name tf.get_default_graph is deprecated. Plea
se use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\desti\anaconda3\Lib\site-packages\kera
s\src\optimizers\__init__.py:309: The name tf.train.Optimizer is deprec
ated. Please use tf.compat.v1.train.Optimizer instead.
```

In [ ]:

```
#Set Seed
np.random.seed(1)
tf.random.set_seed(2)

model_rnn = model.fit(X_train, y_train, batch_size=60, epochs=60, shuf
RNN_pred = model.predict(X_test)
RNN_pred
```

```
WARNING:tensorflow:From C:\Users\desti\anaconda3\Lib\site-packages\kera
s\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is de
precated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\desti\anaconda3\Lib\site-packages\kera
s\src\engine\base_layer_utils.py:384: The name tf.executing_eagerly_out
side_functions is deprecated. Please use tf.compat.v1.executing_eagerly
_outside_functions instead.

110/110 [==============================] - 1s 3ms/step
```

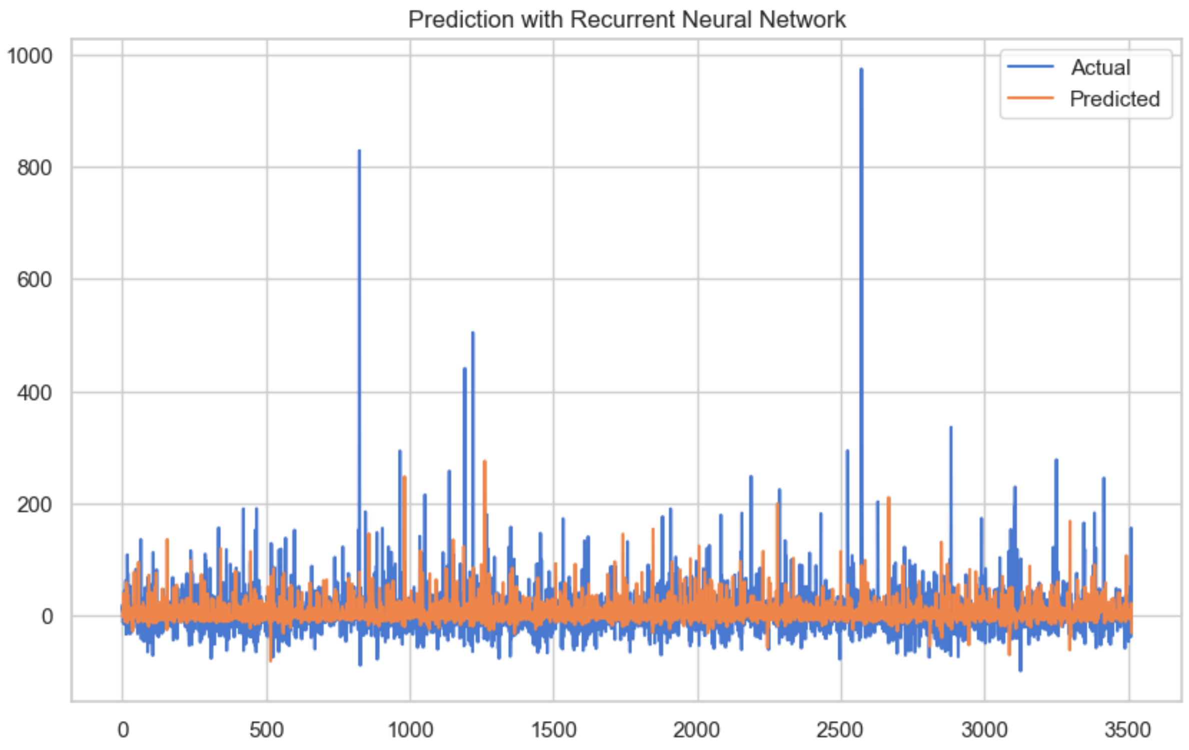
Out[ ]:

```
array([[ -1.3783128 ],
       [  0.73436826],
       [  9.985776  ],
       ...,
       [  0.44443434],
       [ 22.494768  ],
       [-30.334585  ]], dtype=float32)
```

In [ ]:
```
rmse_rnn = np.sqrt(mse(y_test, RNN_pred))
print('The RMSE value of RNN model {:.4f}'.format(rmse_rnn))
```

```
The RMSE value of RNN model 48.3231
```

In [ ]:
```
plt.figure(figsize=(10, 6))
plt.plot(y_test, label='Actual')
plt.plot(RNN_pred, label='Predicted')
plt.title('Prediction with Recurrent Neural Network', fontsize=12)
plt.legend()
plt.show()
```



In [ ]:
```
results_df_rnn = pd.DataFrame(data=[["Random Forest Regression", *eval
                                    columns=['Model', 'MAE', 'RMSE', 'R-square

pd.concat([results_df_ols,results_df_ran,results_df_xgb,results_df_svm
```

Model 6: LSTM Neural Networking Model

In [ ]:
```
#LSTM model
model = Sequential()
model.add(LSTM(128, activation='relu', input_shape=(n_steps, n_feature
model.add(Dropout(0.2))
model.add(Dense(1, activation='linear'))

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['m
```

In [ ]:
```
#Set Seed
```

```
np.random.seed(1)
tf.random.set_seed(2)

model_lstm = model.fit(X_train, y_train, batch_size=60, epochs=60, shu
LSTM_pred = model.predict(X_test)
LSTM_pred
```

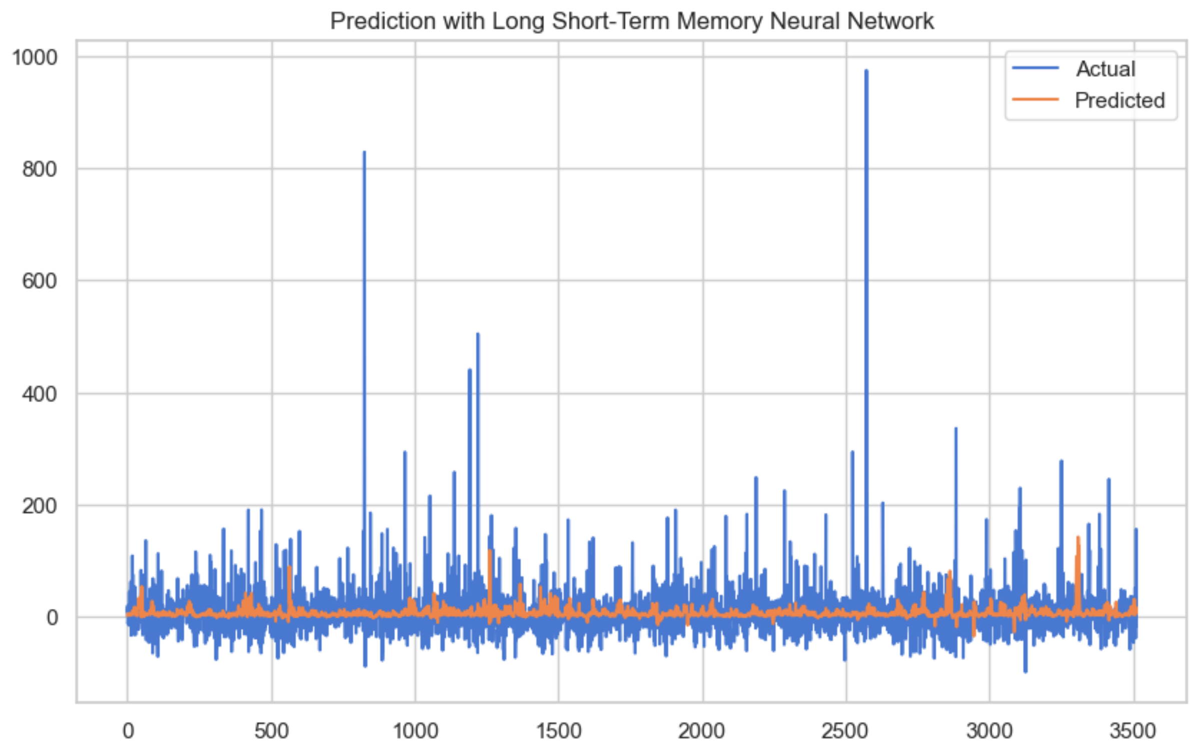
```
110/110 [==============================] - 1s 8ms/step
```

Out[ ]:
```
array([[ 2.0437646],
       [ 4.6970973],
       [ 3.9098842],
       ...,
       [ 7.7866735],
       [16.541145 ],
       [ 7.3832784]], dtype=float32)
```

In [ ]:
```
rmse_lstm = np.sqrt(mse(y_test, LSTM_pred))
print('The RMSE value of LSTM model {:.4f}'.format(rmse_lstm))
```

```
The RMSE value of LSTM model 44.9098
```

In [ ]:
```
plt.figure(figsize=(10, 6))
plt.plot(y_test, label='Actual')
plt.plot(LSTM_pred, label='Predicted')
plt.title('Prediction with Long Short-Term Memory Neural Network', fon
plt.legend()
plt.show()
```



In [ ]:
```
results_df_lstm = pd.DataFrame(data=[["Random Forest Regression", *eva
                            columns=['Model', 'MAE', 'RMSE', 'R-square
```

```
pd.concat([results_df_ols,results_df_ran,results_df_xgb,results_df_svm
```

Comment

By graph, we can clearly see that the RNN model is over-estimating the result whereas LSTM model underestimating it

Since their RMSE are both larger than 40, meaning their prediction are at least 40 units away from the actual value, meaning that the model is not reliable

Comment on Improvement

The result above showed that all the model are not effective in prediction, and the regression plot showed the regression line is suffering the problem of outliers.

Therefore, we assume the data exist significant outlier that impact the result.

Solution: We will use outlier detection model to spot and remove those outliners, then we re-train the data

1) Outlier Detection

Outlier Detection Model 1: Local Outlier Factor (LOF)

In [ ]:
```
from sklearn.neighbors import LocalOutlierFactor

# Part 1: Use randomized search to find the optimal number of neighbor
param_dist = {'n_neighbors': [5, 10, 20, 30, 40]}
lof = LocalOutlierFactor(contamination='auto')
random_search = RandomizedSearchCV(lof, param_distributions=param_dist
random_search.fit(X)
best_n_neighbors = random_search.best_params_['n_neighbors']
print('Best n_neighbors:', best_n_neighbors)

# Part 2: Print out the Z value of the outliers
lof = LocalOutlierFactor(n_neighbors=best_n_neighbors, contamination='
y_pred = lof.fit_predict(X)
outliers = X[y_pred == -1]
```

```
outlier_ids = Z[y_pred == -1]
print('Outlier IDs:', outlier_ids)

# Part 3: Define new X such that it removes all the outliers that it d
X_new = X[y_pred == 1]
y_new = y[y_pred == 1]
```

Outlier Detection Model 2: Isolation Forest

In [ ]:
```
isof = isof.fit(X)

# Part 1: Use randomized search to find the optimal number of nu
param_dist = {'n_estimators': [60, 80, 100, 120, 140]}
isof = IsolationForest(n_estimators=100, max_samples=len(X), contamina
random_search = RandomizedSearchCV(isof, param_distributions=param_dis
random_search.fit(X)
best_n_estimators = random_search.best_params_['n_estimators']
print('best n_estimators:', best_n_estimators)

# Part 2: Print out the Z value of the outliers
isof = IsolationForest(n_estimators=best_n_estimators, max_samples=len
isof = isof.fit(X)
y_pred = isof.predict(X)
outliers = X[y_pred == -1]
outlier_ids = Z[y_pred == -1]
print('Outlier IDs:', outlier_ids)

# Part 3: Define new X such that it removes all the outliers that it d
X_new = X[y_pred == 1]
y_new = y[y_pred == 1]
```

Outlier Detection Model 3: One-class SVM

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import classification_report

# Part 1: Use randomized search to find the optimal number of nu
param_dist = {'nu': [0.01, 0.05, 0.1, 0.15, 0.2]}
svm = OneClassSVM(kernel='linear')
random_search = RandomizedSearchCV(svm, param_distributions=param_dist
random_search = random_search.fit(X)
best_nu = random_search.best_params_['nu']
print('Best nu:', best_nu)

# Part 2: Print out the Z value of the outliers
svm = OneClassSVM(nu=best_nu, kernel='linear')
svm = svm.fit(X)
y_pred = svm.predict(X)
outliers = X[y_pred == -1]
```

```
outlier_ids = Z[y_pred == -1]
print('Outlier IDs:', outlier_ids)

# Part 3: Define new X such that it removes all the outliers that it d
X_new = X[y_pred == 1]
y_new = y[y_pred == 1]
```

Result of outliers detection

2) Alternative Model

Alternative Model 1: Ridge Regression

Step 1: Grid Search to find the optimal hyperparameter

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('Ridge',Ridge())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    #print(' > %.3f' % score_rmse)

    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Out[ ]:
```
1
```

Note: The optimal number of PCA is 1 for OLS

Step 2: Train the model with the reduced number of features

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('Ridge',Ridge())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def model_configs():
    n = 25
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)
    print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])

# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('Ridge', Ridge())
              ]

pipeline_final = Pipeline(steps_final)

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

y_test_list = []
y_pred_list = []

j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list.extend(y_pred)

    y_test_list.extend(y_test)

    j += 1
```

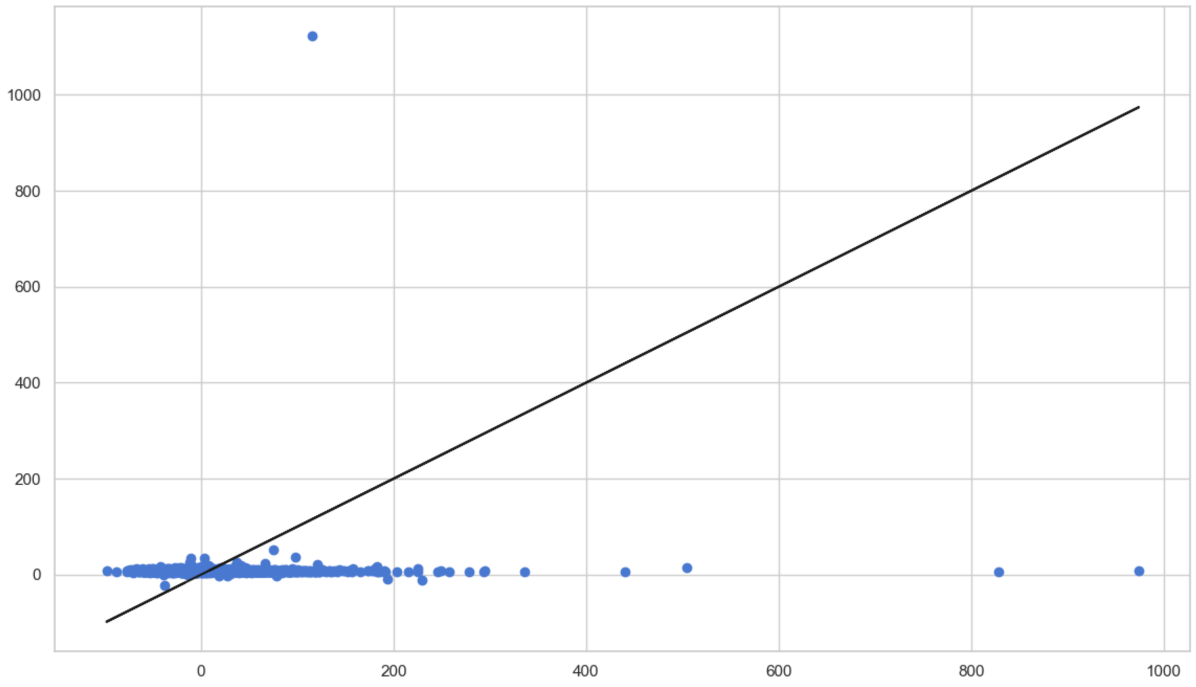
```
Total configs: 25
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list, y_pred_list)
plt.plot(y_test_list, y_test_list,'k-') # identity line
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045046
Return_Predicted	0.045046	1.000000

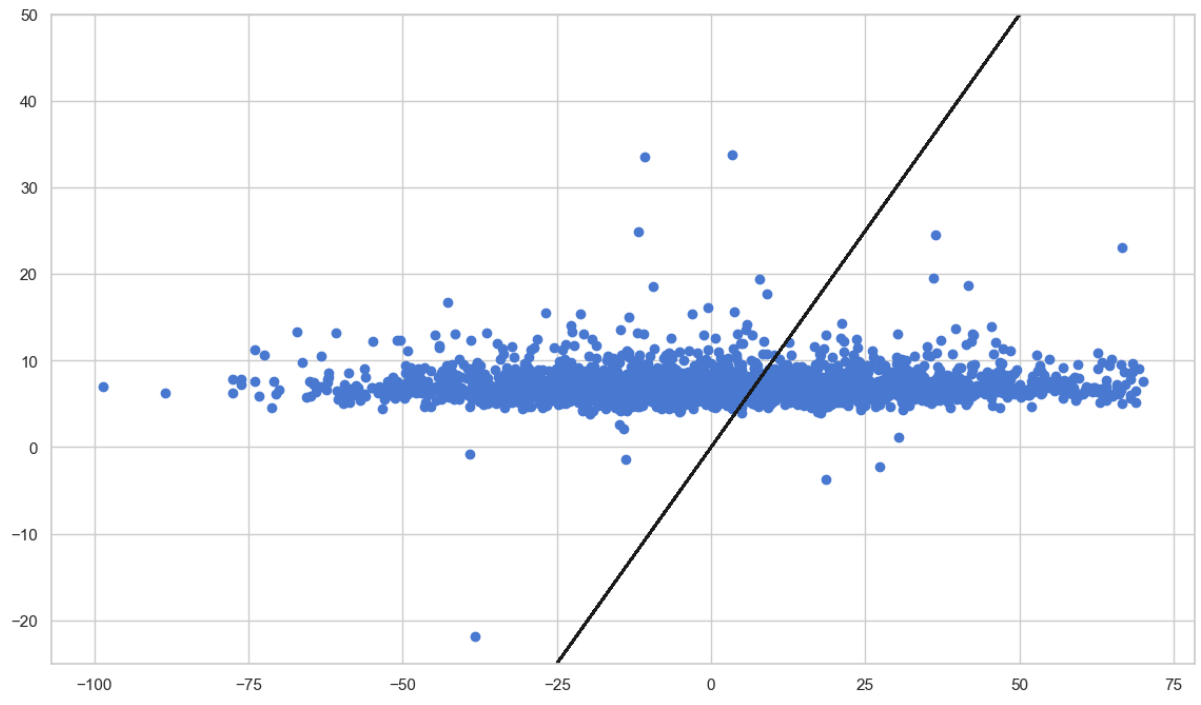


Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:

```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [ ]:
```
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.033939
Return_Predicted	0.033939	1.000000

Result for the OLS is poor due to the low correlation.

Since the PCA dimension reduction method only take 1 PCA into account and it is linear project, i.e. we have no idea what happen in the process (e.g. which features used or reduced)

Now we try to apply other feature reduction method to get a more logical approach

Alternative: SelectKbest

In [ ]:
```
model_KBest = SelectKBest(score_func=f_regression, k=20)     #Select k
                                                            #f_regress
model_KBest = model_KBest.fit(X, y)

KBest = model_KBest.get_support()       #Get a mask, or integer index,

data = {"Features":model_KBest.feature_names_in_,"Selection":KBest}
pd.DataFrame(data, columns = ['Features','Selection'])
```

Out[ ]:

	Features	Selection
0	rote	False
1	roce	False
2	roic	False
3	roa	True
4	rota	True
...	...	...
61	pocf	False
62	ev_sales	False
63	ev_ebitda	False
64	ev_ebit	True
65	ey	True

66 rows × 2 columns

In [ ]:

```
data = {"Features":model_KBest.feature_names_in_,"P-value":model_KBest
df = pd.DataFrame(data, columns = ['Features','P-value'])
df.sort_values(by='P-value', ascending=True).head(model_KBest.k)
```

Out[ ]:

	Features	P-value
6	roa_gp	5.489549e-24
18	turn	7.344450e-23
38	F_lever_chg	3.193096e-19
45	sloan	3.711740e-08
46	price_eop	1.241251e-07
33	rd	8.475292e-07
5	roa_cfo	3.586505e-06
10	roa_fcf	2.377100e-05
43	F_score	3.060555e-05
17	lever	3.063435e-05
65	ey	3.997741e-05
32	rd_ocf	5.354625e-05
31	rd_oi	1.815889e-04
3	roa	7.597853e-04
30	rd_sale	1.538491e-03
48	bv_eop	2.314929e-03
64	ev_ebit	2.816677e-03
40	F_eq_offer_fs	2.835076e-03
4	rota	6.349536e-03
53	saleps	9.977031e-03

In [ ]:

```
#Identifying the selected features

KBest_feature = []

for i in range(0,KBest.shape[0]):
    if KBest[i] == True:
        K_feature = X.columns[i]
        KBest_feature.append(K_feature)

print("Below is the features that we will be selected to train the mod
KBest_feature
```

```
Below is the features that we will be selected to train the model
```

Out[ ]:
```
['roa',
 'rota',
 'roa_cfo',
 'roa_gp',
 'roa_fcf',
 'lever',
 'turn',
 'rd_sale',
 'rd_oi',
 'rd_ocf',
 'rd',
 'F_lever_chg',
 'F_eq_offer_fs',
 'F_score',
 'sloan',
 'price_eop',
 'bv_eop',
 'saleps',
 'ev_ebit',
 'ey']
```

In [ ]:
```python
# Pipeline

# Steps
steps_final = [('SelectKBest', SelectKBest(score_func=f_regression, k=
               ('rig', Ridge())
              ]

pipeline_final = Pipeline(steps_final)
```

In [ ]:
```python
n_train = 334

n_records = len(X)

y_test_list = []

y_pred_list = []

j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list.extend(y_pred)

    y_test_list.extend(y_test)
    j += 1
```

In [ ]:
```
metrics.mean_squared_error(y_test_list, y_pred_list, squared=False)
```

Out[ ]:
```
8788.462056864635
```

In [ ]:
```
n_forecast = len(X) - n_train
result_rig_kbest = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Re
result_rig_kbest.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	-0.000417
Return_Predicted	-0.000417	1.000000

Alternative Model 2: Lasso Regression

Step 1: Grid Search to find the optimal hyperparameter

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('Lasso',Lasso())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def split(cfg):

    for i in np.arange(0.1, 1, 0.1):

        X_train, X_test, y_train, y_test = train_test_split(X, y, test

        model = pipeline(cfg).fit(X_train, y_train)

        y_pred = model.predict(X_test)

    score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

    #print(' > %.3f' % score_rmse)

    return score_rmse

def repeat_evaluate(config):
    key = str(config)
    scores = [split(config)]
    result = np.mean(scores)
    #print('> Model[%s] %.3f' % (key, result))
    return (key, result)

def grid_search(cfg_list):
    scores = [repeat_evaluate(cfg) for cfg in cfg_list]
    scores.sort(key=lambda tup: tup[1], reverse=True)
    return scores

def model_configs():
    n = 50
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    #print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])
optimal_n_pca_comp
```

Out[ ]:
```
1
```

Note: The optimal number of PCA is 1 for OLS

Step 2: Train the model with the reduced number of features

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
             ('pca', PCA(n_components = n_comps, random_state=1)),
             ('Lasso',Lasso())
            ]
    pipeline = Pipeline(steps)
    return pipeline

def model_configs():
    n = 25
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
```

```
            configs.append(cfg)

    print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])

# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('Lasso', Lasso())
              ]

pipeline_final = Pipeline(steps_final)

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

y_test_list = []
y_pred_list = []

j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list.extend(y_pred)

    y_test_list.extend(y_test)

    j += 1
```

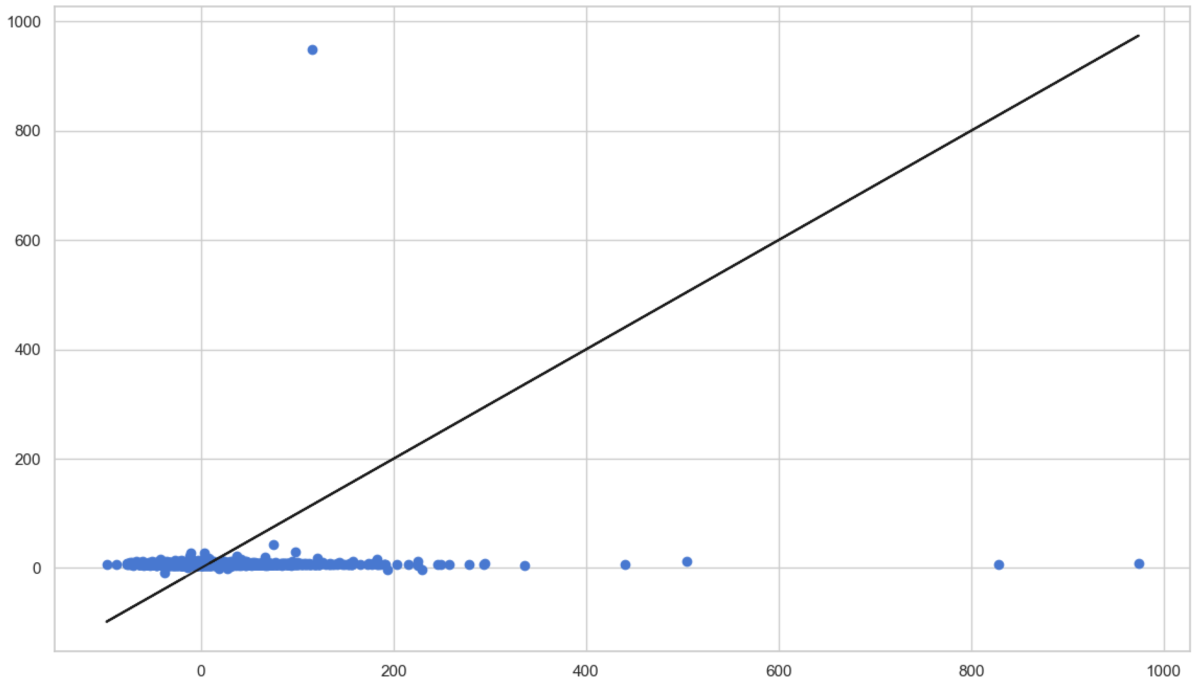
```
Total configs: 25
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list, y_pred_list)
plt.plot(y_test_list, y_test_list,'k-') # identity line
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045281
Return_Predicted	0.045281	1.000000

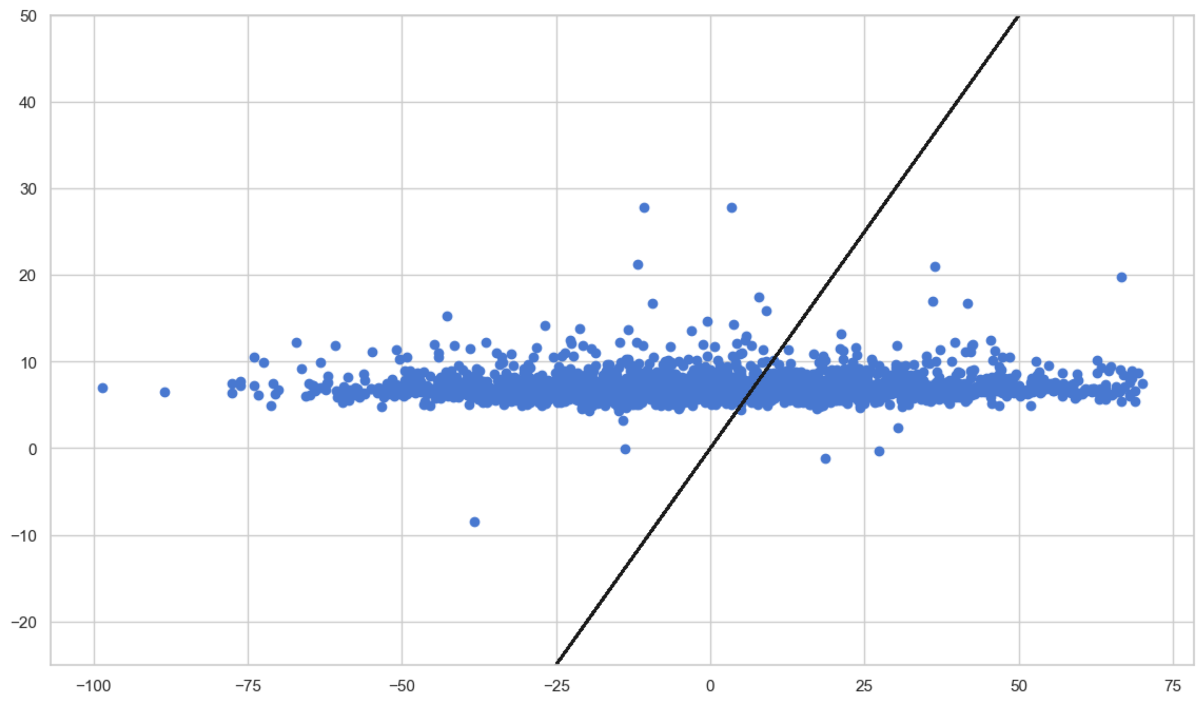


Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:

```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



```
In [ ]: n_forecast = len(X) - n_train
        result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
        result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.030881
Return_Predicted	0.030881	1.000000

Alternative Model 3: Elastic Net Regression

Step 1: Grid Search to find the optimal hyperparameter

```
In [ ]: def pipeline(config):
            n_comps = config
            steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
                     ('pca', PCA(n_components = n_comps, random_state=1)),
                     ('ElasticNet',ElasticNet())
                    ]
            pipeline = Pipeline(steps)
            return pipeline

        def split(cfg):

            for i in np.arange(0.1, 1, 0.1):

                X_train, X_test, y_train, y_test = train_test_split(X, y, test
                model = pipeline(cfg).fit(X_train, y_train)

                y_pred = model.predict(X_test)

            score_rmse = metrics.mean_squared_error(y_test, y_pred, squared=Fa

            #print(' > %.3f' % score_rmse)

            return score_rmse

        def repeat_evaluate(config):
            key = str(config)
            scores = [split(config)]
            result = np.mean(scores)
            #print('> Model[%s] %.3f' % (key, result))
            return (key, result)

        def grid_search(cfg_list):
            scores = [repeat_evaluate(cfg) for cfg in cfg_list]
            scores.sort(key=lambda tup: tup[1], reverse=True)
            return scores

        def model_configs():
            n = 50
            n_comps = [i for i in range(1, n+1)]
            configs = list()

            for k in n_comps:
                cfg = k
                configs.append(cfg)

            #print('Total configs: %d' % len(configs))
            return configs

        cfg_list = model_configs()
        scores = grid_search(cfg_list)

        #The optimal number of features for OLS from PCA grid search
        optimal_n_pca_comp = int(scores[len(scores)-1][0])
        optimal_n_pca_comp
```

Out[ ]:
```
1
```

Note: The optimal number of PCA is 1 for OLS

Step 2: Train the model with the reduced number of features

In [ ]:
```
def pipeline(config):
    n_comps = config
    steps = [('scaler', StandardScaler(copy=True, with_mean=True, with
              ('pca', PCA(n_components = n_comps, random_state=1)),
              ('ElasticNet',ElasticNet())
             ]
    pipeline = Pipeline(steps)
    return pipeline

def model_configs():
    n = 25
    n_comps = [i for i in range(1, n+1)]
    configs = list()

    for k in n_comps:
        cfg = k
        configs.append(cfg)

    print('Total configs: %d' % len(configs))
    return configs

cfg_list = model_configs()
scores = grid_search(cfg_list)

#The optimal number of features for OLS from PCA grid search
optimal_n_pca_comp = int(scores[len(scores)-1][0])

# Steps
steps_final = [('scaler', StandardScaler(copy=True, with_mean=True, wi
               ('pca', PCA(n_components = optimal_n_pca_comp, random_s
               ('ElasticNet', ElasticNet())
              ]

pipeline_final = Pipeline(steps_final)

n_train = int(0.7 * len(X))
n_forecast = len(X) - n_train
n_records = len(X)

y_test_list = []
y_pred_list = []

j = 0

for i in range(n_train, n_records):

    X_train, X_test, y_train, y_test = X[j:i], X[i:i+1], y[j:i], y[i:i

    model = pipeline_final.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    y_pred_list.extend(y_pred)
    y_test_list.extend(y_test)

    j += 1
```

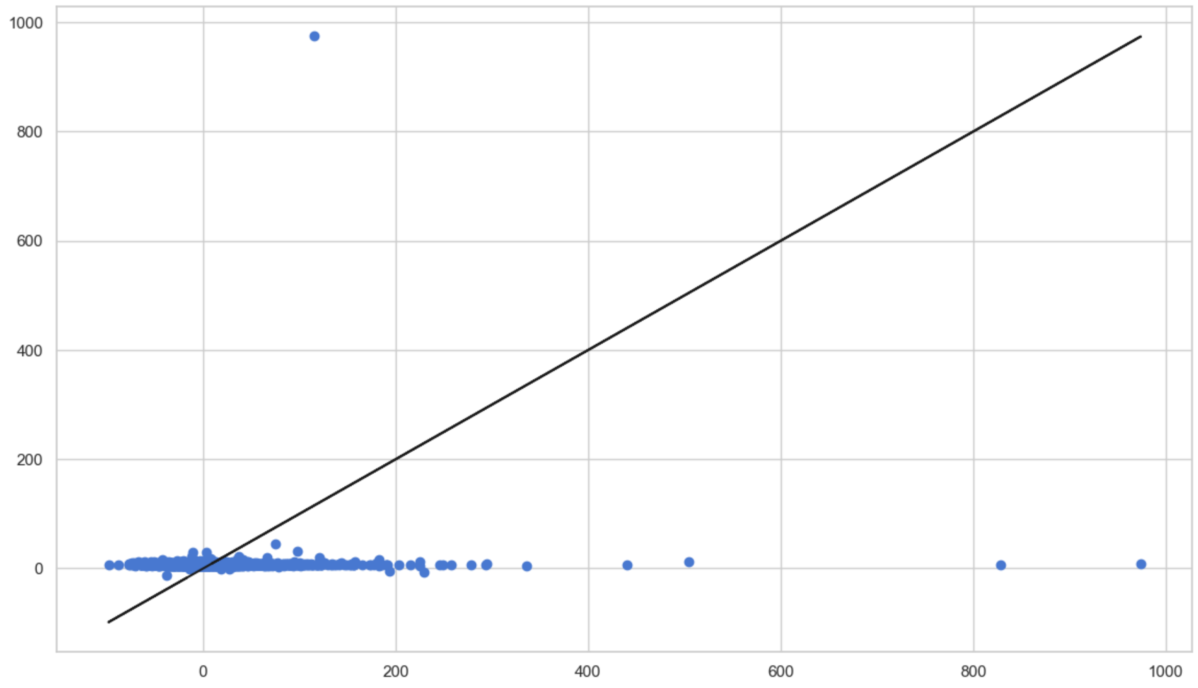
```
Total configs: 25
```

Step 3: Compare the model with the actual data

In [ ]:
```
plt.scatter(y_test_list, y_pred_list)
plt.plot(y_test_list, y_test_list,'k-') # identity line
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': y[-n_forecast:], 'Return_P
result_rig.corr()
```

Out[ ]:

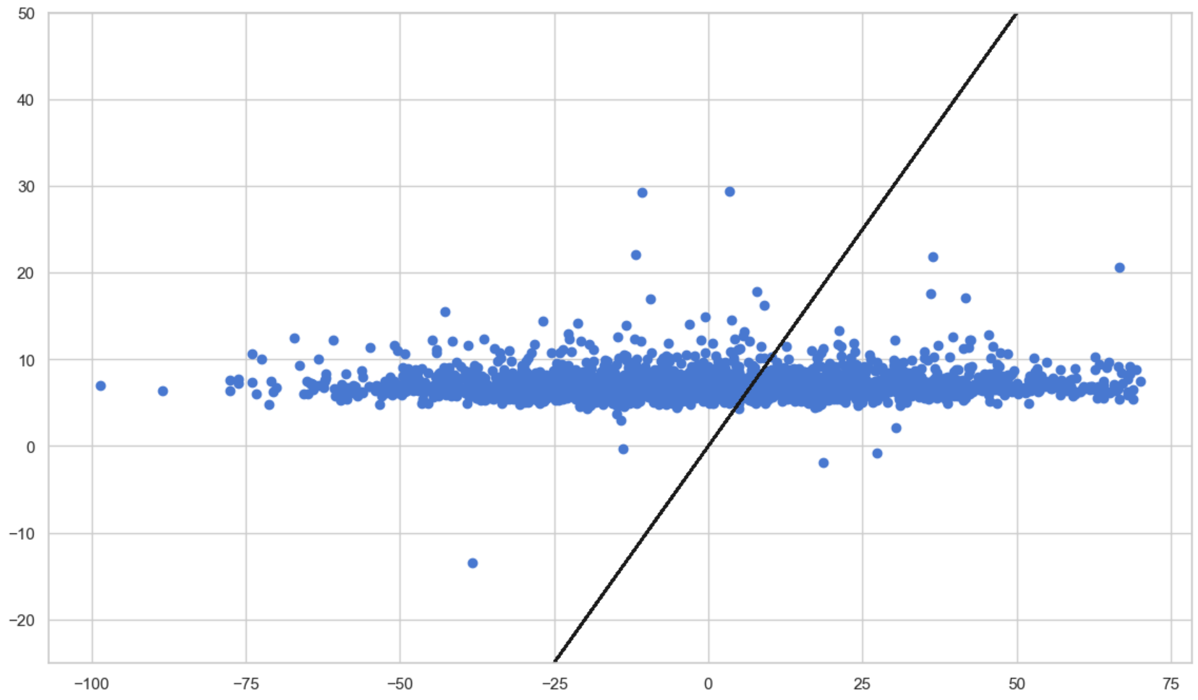
	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.045166
Return_Predicted	0.045166	1.000000



Since the result seems to be influened by the outliers significantly

We try to do the comparsion after removing the outlier

In [ ]:
```
predf=pd.DataFrame({'test':y_test_list,'predict':y_pred_list})
non_outliner_df=predf[predf['predict'] <= predf['predict'].quantile(0.
non_outliner_df=predf[predf['test'] <= predf['test'].quantile(0.95)]
# non_outliner_df=predf[predf['predict'] <= 600]
plt.scatter(non_outliner_df['test'], non_outliner_df['predict'])
plt.plot(non_outliner_df['test'],non_outliner_df['test'],'k-') # ident
plt.ylim(-25,50)
plt.show()
```



In [ ]:
```
n_forecast = len(X) - n_train
result_rig = pd.DataFrame({'Return_Actual': non_outliner_df['test'], '
result_rig.corr()
```

Out[ ]:

	Return_Actual	Return_Predicted
Return_Actual	1.000000	0.031683
Return_Predicted	0.031683	1.000000