Project work

January 8, 2021

[3]:
```
#*****Imports for dataprocessing********
import pandas as pd
import numpy as np
from numpy import array
import math
import pandas_datareader as pdr
import matplotlib.pyplot as plt
from heapq import nsmallest
import scipy.optimize as sco
save_path = '/Users/antonerlandsson/Documents/Models'

#*****Imports for designing the LSTM model.******
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.callbacks import EarlyStopping
```

[51]:
```
plt.style.use('seaborn')
```

The code is splitted into multiple steps

1. Filtering and finding initial stocks for the portfolio.
2. Writing a portfolio class and training a LSTM model with the selected stocks.
3. Calculating returns and covariances
4. Optimizing the portfolio
5. Results

1 Filtering and finding initial stocks for the portfolio.

[26]:
```
# Reading in a list of stocks from the NASDAQ largecap exchange. These are then␣
↪filtered for time on the stoch exchange.
stocks_raw = pd.read_csv('/mnt/c/Users/Anton/Dropbox/PythonProjects/Python␣
↪Projects/Python in Financial Engineering/Project Work/largecap.csv', sep=';
↪', encoding='latin-1', parse_dates = True, infer_datetime_format = True,␣
↪index_col = 'listingdate')
stocks_filtered = stocks_raw[stocks_raw.index <= '2000-01-01'].copy()
stocks_filtered
```

```
[26]:                    company   volume100d       sector  \
listingdate
1999-06-22                  ABB  1411425,625  Industrials
1994-11-08           Assa Abloy  2023678,875  Industrials
1999-04-06          AstraZeneca  501995,8438  Health Care
1973-01-01        Atlas Copco A    1111550,5  Industrials
1994-07-14    Atrium Ljungberg  179766,4063   Financials
…                            …            …            …
1989-07-03               SSAB B    3446860,5    Materials
1997-01-02         Stora Enso A  13966,51953    Materials
1998-08-24              Sweco A  2118,939941  Industrials
1996-05-14              Tele2 A  2005,920044      Telecom
1982-01-01              Volvo A   275950,375  Industrials

                             industry
listingdate
1999-06-22         Industrial Machinery
1994-11-08        Construction Supplies
1999-04-06              Pharmaceuticals
1973-01-01         Industrial Machinery
1994-07-14                  Real Estate
…                                   …
1989-07-03   Mining - Steel & Aluminum
1997-01-02       Forest & Wood Products
1998-08-24         Business Consultants
1996-05-14          Telecommunications
1982-01-01         Industrial Machinery

[77 rows x 4 columns]
```

```
[27]: # Filtering for stocks that have a volume that is higher than the mean. This is
      ↪to only get those stocks that are liquid
      stocks_filtered['volume100d'] = stocks_filtered['volume100d'].str.replace(',',
      ↪'.').astype(float)
      stocks_filtered = stocks_filtered[stocks_filtered['volume100d'] >=
      ↪stocks_filtered['volume100d'].mean()]
      stocks_filtered
```

```
[27]:                    company   volume100d             sector  \
listingdate
1999-06-22                  ABB  1411425.625        Industrials
1994-11-08           Assa Abloy  2023678.875        Industrials
1973-01-01        Atlas Copco A  1111550.500        Industrials
1985-01-01         Electrolux B  1247480.375  Consumer Durables
1994-03-01               Elekta  1535047.875        Health Care
1976-01-01          Ericsson B  7240196.500         Technology
1995-06-08              Getinge  1074312.375        Health Care
```

```
1974-06-17   Hennes & Mauritz  4813372.000  Consumer Durables
1997-12-15        Nordea Bank  7857396.500         Financials
1989-01-01            Sandvik  2624841.500        Industrials
1987-01-01              SCA B  1765903.125          Materials
1975-01-01              SEB A  4364754.000         Financials
1991-07-09          Securitas  1292955.250        Industrials
1987-01-01     Handelsbanken A  5293509.000         Financials
1965-01-01            Skanska  1079145.125        Industrials
1982-01-01              SKF B  1549650.250        Industrials
1989-07-03             SSAB A  4616178.500          Materials
1995-06-09           Swedbank  3557981.500         Financials
1996-05-14            Tele2 B  2666959.500            Telecom
1982-01-01            Volvo B  4372945.000        Industrials
1989-07-03             SSAB B  3446860.500          Materials

                                 industry
listingdate
1999-06-22            Industrial Machinery
1994-11-08           Construction Supplies
1973-01-01            Industrial Machinery
1985-01-01            Consumer Electronics
1994-03-01               Medical Equipment
1976-01-01                  Communications
1995-06-08                Medical Supplies
1974-06-17              Clothing & Footwear
1997-12-15                           Banks
1989-01-01            Industrial Machinery
1987-01-01           Forest & Wood Products
1975-01-01                           Banks
1991-07-09                        Security
1987-01-01                           Banks
1965-01-01   Construction & Infrastructure
1982-01-01           Industrial Components
1989-07-03        Mining - Steel & Aluminum
1995-06-09                           Banks
1996-05-14              Telecommunications
1982-01-01            Industrial Machinery
1989-07-03        Mining - Steel & Aluminum
```

[18]:

```python
# Looking how many unique sectors there are.

print(len(stocks_raw['sector'].unique()))
print(len(stocks_filtered['sector'].unique()))
len(stocks_filtered['sector'].unique()) / len(stocks_raw['sector'].unique())
```

```
9
7
```

[18]: 0.7777777777777778

[22]:
```python
# Dropping the duplicates within industry and sector.

stocks_filtered_industry = stocks_filtered.drop_duplicates('industry')
stocks_filtered_sector = stocks_filtered.drop_duplicates('sector')
print(len(stocks_filtered_industry))
print(len(stocks_filtered_sector))
```

```
14
7
```

[23]:
```python
# Printing the results after removing duplicates.

print(stocks_filtered_industry)
print(stocks_filtered_sector)
```

```
                      company   volume100d            sector  \
listingdate
1999-06-22                ABB  1411425.625       Industrials
1994-11-08         Assa Abloy  2023678.875       Industrials
1985-01-01       Electrolux B  1247480.375  Consumer Durables
1994-03-01             Elekta  1535047.875        Health Care
1976-01-01         Ericsson B  7240196.500         Technology
1995-06-08            Getinge  1074312.375        Health Care
1974-06-17   Hennes & Mauritz  4813372.000  Consumer Durables
1997-12-15        Nordea Bank  7857396.500         Financials
1987-01-01              SCA B  1765903.125          Materials
1991-07-09          Securitas  1292955.250        Industrials
1965-01-01            Skanska  1079145.125        Industrials
1982-01-01              SKF B  1549650.250        Industrials
1989-07-03             SSAB A  4616178.500          Materials
1996-05-14            Tele2 B  2666959.500            Telecom

                                  industry
listingdate
1999-06-22            Industrial Machinery
1994-11-08           Construction Supplies
1985-01-01            Consumer Electronics
1994-03-01               Medical Equipment
1976-01-01                  Communications
1995-06-08                Medical Supplies
1974-06-17              Clothing & Footwear
1997-12-15                           Banks
1987-01-01           Forest & Wood Products
1991-07-09                        Security
1965-01-01   Construction & Infrastructure
1982-01-01           Industrial Components
```

```
1989-07-03       Mining - Steel & Aluminum
1996-05-14               Telecommunications
                     company   volume100d             sector  \
listingdate
1999-06-22               ABB  1411425.625        Industrials
1985-01-01      Electrolux B  1247480.375  Consumer Durables
1994-03-01            Elekta  1535047.875        Health Care
1976-01-01        Ericsson B  7240196.500         Technology
1997-12-15        Nordea Bank  7857396.500         Financials
1987-01-01             SCA B  1765903.125          Materials
1996-05-14           Tele2 B  2666959.500            Telecom

                                 industry
listingdate
1999-06-22        Industrial Machinery
1985-01-01        Consumer Electronics
1994-03-01           Medical Equipment
1976-01-01              Communications
1997-12-15                       Banks
1987-01-01      Forest & Wood Products
1996-05-14          Telecommunications
```

[5]:
```python
# Picking the stocks from the unique industry list as it gives a nice␣
↪diversification.
tickers = ['ABB.ST', 'ASSA-B.ST', 'ELUX-B.ST', 'EKTA-B.ST', 'ERIC-B.ST',␣
↪'GETI-B.ST', 'HM-B.ST', 'NDA-SE.ST', 'SCA-B.ST', 'SECU-B.ST', 'SKA-B.ST',␣
↪'SKF-B.ST', 'SSAB-B.ST', 'TEL2-B.ST']
```

[45]:
```python
df = pdr.get_data_yahoo(tickers, start = '2000-01-01', end =␣
↪'2020-12-10')['Close']
df = df.dropna()
df.head()
```

[45]:
```
Symbols          ABB.ST  ASSA-B.ST   ELUX-B.ST  EKTA-B.ST  ERIC-B.ST  \
Date
2012-06-18   112.599998  62.400002  127.900002  81.449997  63.299999
2012-06-19   114.900002  62.866699  129.800003  81.050003  64.500000
2012-06-20   115.099998  63.466702  136.300003  81.599998  64.800003
2012-06-21   114.800003  63.366699  137.199997  81.849998  63.599998
2012-06-25   109.900002  62.400002  133.000000  79.500000  62.000000

Symbols        GETI-B.ST      HM-B.ST  NDA-SE.ST   SCA-B.ST  SECU-B.ST  \
Date
2012-06-18   143.835999  226.399994  56.250000  21.233601  53.599998
2012-06-19   143.673996  230.399994  57.799999  21.233601  54.049999
2012-06-20   142.298004  241.500000  58.150002  21.233601  54.349998
2012-06-21   141.246002  246.199997  57.650002  21.090900  53.849998
```

```
2012-06-25  140.113007  242.300003  56.400002  20.601299  52.450001

Symbols       SKA-B.ST    SKF-B.ST  SSAB-B.ST   TEL2-B.ST
Date
2012-06-18   99.699997  132.199997  34.571098  101.084000
2012-06-19  100.500000  134.500000  35.603901  102.625999
2012-06-20  101.900002  137.300003  36.622002  102.722000
2012-06-21  101.400002  135.100006  37.098000   99.734802
2012-06-25   98.900002  129.500000  34.651699   99.445702
```

[62]:

```python
# We compute the log-return correlation matrix.

logReturn = np.log(df/df.shift(1))
corr_matrix = logReturn.corr()
corr_matrix_box_mean = corr_matrix.mean()
print(corr_matrix)
```

```
Symbols      ABB.ST  ASSA-B.ST  ELUX-B.ST  EKTA-B.ST  ERIC-B.ST  GETI-B.ST  \
Symbols
ABB.ST     1.000000   0.551133   0.450056   0.309828   0.408138   0.278441
ASSA-B.ST  0.551133   1.000000   0.412301   0.291934   0.365384   0.330482
ELUX-B.ST  0.450056   0.412301   1.000000   0.230915   0.287909   0.251236
EKTA-B.ST  0.309828   0.291934   0.230915   1.000000   0.215705   0.266704
ERIC-B.ST  0.408138   0.365384   0.287909   0.215705   1.000000   0.250783
GETI-B.ST  0.278441   0.330482   0.251236   0.266704   0.250783   1.000000
HM-B.ST    0.395156   0.406861   0.361358   0.242273   0.270380   0.154107
NDA-SE.ST  0.536900   0.473044   0.415614   0.242199   0.367478   0.229671
SCA-B.ST   0.466167   0.444881   0.380658   0.296256   0.363928   0.288879
SECU-B.ST  0.501598   0.538117   0.391645   0.280789   0.345475   0.254558
SKA-B.ST   0.557000   0.538289   0.413516   0.285710   0.353931   0.256461
SKF-B.ST   0.612646   0.545771   0.447416   0.281339   0.328304   0.264776
SSAB-B.ST  0.483609   0.390880   0.352877   0.235829   0.302891   0.174476
TEL2-B.ST  0.351977   0.336978   0.262719   0.189015   0.335138   0.221433

Symbols     HM-B.ST  NDA-SE.ST  SCA-B.ST  SECU-B.ST  SKA-B.ST  SKF-B.ST  \
Symbols
ABB.ST     0.395156   0.536900  0.466167   0.501598  0.557000  0.612646
ASSA-B.ST  0.406861   0.473044  0.444881   0.538117  0.538289  0.545771
ELUX-B.ST  0.361358   0.415614  0.380658   0.391645  0.413516  0.447416
EKTA-B.ST  0.242273   0.242199  0.296256   0.280789  0.285710  0.281339
ERIC-B.ST  0.270380   0.367478  0.363928   0.345475  0.353931  0.328304
GETI-B.ST  0.154107   0.229671  0.288879   0.254558  0.256461  0.264776
HM-B.ST    1.000000   0.423641  0.388743   0.411571  0.442182  0.367955
NDA-SE.ST  0.423641   1.000000  0.401215   0.450142  0.540480  0.512431
SCA-B.ST   0.388743   0.401215  1.000000   0.412885  0.428717  0.422285
SECU-B.ST  0.411571   0.450142  0.412885   1.000000  0.516212  0.498442
SKA-B.ST   0.442182   0.540480  0.428717   0.516212  1.000000  0.536135
```

```
SKF-B.ST   0.367955   0.512431  0.422285   0.498442  0.536135  1.000000
SSAB-B.ST  0.354173   0.452063  0.350681   0.411119  0.459950  0.512576
TEL2-B.ST  0.263693   0.311428  0.289564   0.317447  0.360949  0.313388

Symbols    SSAB-B.ST  TEL2-B.ST
Symbols
ABB.ST      0.483609   0.351977
ASSA-B.ST   0.390880   0.336978
ELUX-B.ST   0.352877   0.262719
EKTA-B.ST   0.235829   0.189015
ERIC-B.ST   0.302891   0.335138
GETI-B.ST   0.174476   0.221433
HM-B.ST     0.354173   0.263693
NDA-SE.ST   0.452063   0.311428
SCA-B.ST    0.350681   0.289564
SECU-B.ST   0.411119   0.317447
SKA-B.ST    0.459950   0.360949
SKF-B.ST    0.512576   0.313388
SSAB-B.ST   1.000000   0.264081
TEL2-B.ST   0.264081   1.000000
```

[50]:

```
# We look at the mean correlation between the assets
print(corr_matrix_box_mean)
```

```
Symbols
ABB.ST       0.493046
ASSA-B.ST    0.473290
ELUX-B.ST    0.404159
EKTA-B.ST    0.312036
ERIC-B.ST    0.371103
GETI-B.ST    0.301572
HM-B.ST      0.391578
NDA-SE.ST    0.454022
SCA-B.ST     0.423918
SECU-B.ST    0.452143
SKA-B.ST     0.477824
SKF-B.ST     0.474533
SSAB-B.ST    0.410372
TEL2-B.ST    0.344129
dtype: float64
```

[51]:

```
# We look at the assets which had the smallest mean correlation between␣
↪eachother.

print(nsmallest(6, corr_matrix_box_mean))
print('[SKA-B.ST,            EKTA-B.ST,           GETI-B.ST,            ERIC-B.
↪ST,         TEL2-B.ST,          HM-B.st             ]')
```

```
[0.3015719006389189, 0.31203558161164124, 0.344129426140454, 0.3711031739792328,
0.3915780588071901, 0.404158515591401]
[SKA-B.ST,           EKTA-B.ST,          GETI-B.ST,          ERIC-B.ST,
TELE2-B.ST,         HM-B.st             ]
```

[15]:
```
tickers = ['SKA-B.ST', 'EKTA-B.ST', 'GETI-B.ST', 'ERIC-B.ST', 'TEL2-B.ST',␣
↪'HM-B.ST']
#stock_data = ext_datareader(tickers, start='2014-10-01', end='2020-10-01')
```

[474]:
```
stock_data.head()
```

[474]:
```
Asset              SKA       EKTA        GETI       ERIC       TEL2  \
2014-10-01  145.800003  70.550003  146.425995  90.400002  83.064201
2014-10-02  144.600006  71.250000  145.455002  89.250000  81.811501
2014-10-03  147.699997  71.050003  147.559998  90.599998  82.486000
2014-10-06  146.600006  71.000000  148.044998  89.500000  83.256897
2014-10-07  144.800003  70.500000  147.317001  86.849998  82.486000

Asset               HM
2014-10-01  294.500000
2014-10-02  288.399994
2014-10-03  291.000000
2014-10-06  290.500000
2014-10-07  286.200012
```

2 Writing a portfolio class and training a LSTM model with the selected stocks.

We create a class because we need the stock-data from every asset within our portfolio. By storing the dowloaded data within the object, we only need to specify our portfolio once, then we can train a model on every individual asset by iterating over the TrainModel method.

[6]:
```
class Portfolio(object):
    def __init__(self, tickers, start, end):
        self.tickers = tickers
        self.start = start
        self.end = end
        self._data = self.ext_datareader() # Runs the ext_datareader when we␣
↪initialize the data_reader


    def ext_datareader(self):
        """Converts pandas-datareader yahoo data to a cleaner format.
        Parameters
        ----------
        raw_data : pd.DataFrame
```

```
            Rows represents different timestamps stored in index. Note that␣
↪there can be gaps. Columns are pd.MultiIndex
            with the zero level being assets and the first level indicator.
        Returns
        -------
        df : pd.DataFrame
            A cleaned pd.DataFrame.

        """
        df = pdr.get_data_yahoo(self.tickers, self.start, self.end)
        df = df.drop(['High', 'Low', 'Open', 'Volume'], axis=1, level=0) #␣
↪drops the columns we don't need
        df.index.name = None # removes the date index
        df = df.swaplevel(0, 1, axis=1) # swaps the multiindex
        df.columns.rename(names = ['Asset', 'Channel'], inplace = True)

        df.replace(0, np.nan, inplace=True)
        df.to_csv('/mnt/c/Users/Anton/Documents/Models/portfolio.csv')
        print('Tickers read...')
        print(f'You have {df.columns.levels[0].tolist()} in your portfolio')
        return df.interpolate().dropna()

    def TrainModel(self, stock, split_ratio = 0.8, batch_size = 5, look_back =␣
↪40, epochs = 50, save_graph=True):
        """Trains a univariate LSTM model with the input given.
        Parameters
        ----------
        stock : pd.DataFrame
            Pandas DataFrame containing stock prices ["Close"] and ['Adj␣
↪Close'].
        split_ratio : float
            How the data should be splitted for testing and training. Default␣
↪is 80 % training and 20 % testing.
        batch_size : integer
            How many batches the model should be trained with.
        look_back : integer
            How many days in the past the model should use to predict the next␣
↪days stock price.
        epochs : integer
            How many times the model will iterate every batch_size.
        save_graph : bool
            True if we want to save the loss and validation graphs for every␣
↪trained model. False if we don't want to save.

        Returns
        -------
```

```
        model : tf.keras.Model
            Returns a tf/keras object which has been trained and can be used␣
↪for predictions.
        X_test : ndarray shape (Sample,Timestep,Features)
            Contains the test data for prediction.
        y_test : ndarray shape (Sample,Timestep,Features)
            Validation data
        scaler : sklearn.MinMaxScaler object
            A scaler that is unique for every inputted stock. Used to reverse␣
↪MinMax scaling after prediction.
        """

        # Load the data from the pd.DataFrame
        data = self._data[stock].filter(['Adj Close'])
        dataset = data.values
        training_data_len = math.ceil(len(dataset) * split_ratio)
        scaler = MinMaxScaler(feature_range=(0, 1)) # Transforms features by␣
↪scaling each feature to a given range
        scaled_data = scaler.fit_transform(dataset)

        # Divide the data into training and testing data. Default split ratio␣
↪is 0.8
        X, y = self.processData(scaled_data, look_back)
        X_train, X_test = X[:int(X.shape[0] * split_ratio)], X[int(X.shape[0] *␣
↪split_ratio):]
        y_train, y_test = y[:int(y.shape[0] * split_ratio)], y[int(y.shape[0] *␣
↪split_ratio):]
        pd.DataFrame(X_train).to_csv(f'/mnt/c/Users/Anton/Documents/Models/
↪Train Data/{stock}-X_train.csv', index=False)
        pd.DataFrame(X_test).to_csv(f'/mnt/c/Users/Anton/Documents/Models/Test␣
↪Data/{stock}-X_test.csv', index=False)
        pd.DataFrame(y_train).to_csv(f'/mnt/c/Users/Anton/Documents/Models/
↪Train Data/{stock}-y_train.csv', index=False)
        pd.DataFrame(y_test).to_csv(f'/mnt/c/Users/Anton/Documents/Models/Test␣
↪Data/{stock}-y_test.csv', index=False)

        #Reshape data for (Sample,Timestep,Features) Has to be done because the␣
↪models are very sensitive to input-shape
        X_train = X_train.reshape((X_train.shape[0], X_train.shape[1] ,1))
        X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

        # Create the model
        callback = EarlyStopping(monitor='loss', patience=3) # specifying that␣
↪the training should early stop when the loss has not decreased in three␣
↪ephocs.
        model = self.model(look_back = look_back)
```

```
        history = model.fit(X_train, y_train, epochs=epochs,
                            validation_data = (X_test,y_test),
                            shuffle=True, batch_size = batch_size, callbacks =␣
↪[callback]) # training/fitting the model with the previous data

        # ** Saving model-data **
        model.save(f'/mnt/c/Users/Anton/Documents/Models/{stock}')

        if save_graph == True:
            fig = plt.figure()
            plt.title(f'Loss of {stock}')
            plt.xlabel('Epochs', fontsize=14)
            plt.ylabel('Loss', fontsize=14)
            plt.plot(history.history['loss'])
            plt.plot(history.history['val_loss'])
            plt.legend(['loss', 'val_loss'], loc='upper right')
            plt.savefig(f'/mnt/c/Users/Anton/Documents/Models/{stock}/
↪{stock}-loss.png')
            plt.close(fig)
        return model, X_test, y_test, scaler

        #           ** Creating the LSTM network that is used for training. **

    def model(self, look_back):
        """Builds a model for every single stock. Gives the possibility to␣
↪tweak the architecture of the model for indivudual assets.

        LAYER 1 : LSTM: 52 neurons
        LAYER 2 : LSTM: 52 neurons
        LAYER 3 : DENSE : 25 neurons
        LAYER 4 ( OUTPUT ) : 1 neuron

        Optimizer for gradient decent is adam.
        Loss is measured with Mean Squared Error.

        Parameters
        ----------
        look_back : pd.DataFrame
            How many days in the past the model should use to predict the next␣
↪days stock price.
        Returns
        -------
        _model : tf.keras.Model
            An LSTM model that can be trained on given a certain look_back␣
↪period.
        """
```

```
        _model = Sequential() # calls on the basemodel Sequential() from the␣
↪keras library. Used for one input one output models.
        _model.add(LSTM(52, return_sequences=True, input_shape=(look_back ,␣
↪1))) # return_sequence has to be true when using multiple LSTM layers
        _model.add(LSTM(52, input_shape=(look_back , 1)))
        _model.add(Dense(25))
        _model.add(Dense(1))
        _model.compile(optimizer='adam', loss='mse')
        return _model

    def processData(self, data, look_back):
        """ Method that processes/splits data into according shape/size.
        Parameters
        ----------
        data : pd.DataFrame
            Cointains stockdata that has been MinMax scaled

        Returns
        -------
        array(X) : ndarray shape (Scaled data, look_back, 0)
            Array of data that has been splitted.
        array(Y) : ndarray shape (Scaled data, look_back, 0)
            Array of data that has been splitted.
        """
        X , Y = [] , []
        for i in range(len(data) - look_back - 1): # the range of the data that␣
↪will be used for the model. -look_back and -1 for offsetting it.
            X.append(data[i:(i + look_back),0])
            Y.append(data[(i + look_back),0])
        return array(X) , array(Y)

    @staticmethod
    def plotter(stock, model, x_test, y_test, scaler):
        """ Method that saves the loss-plots

        """
        Xt = model.predict(x_test)
        fig = plt.figure(figsize=(16,8))
        plt.title(f'LSTM model for {stock}')
        plt.xlabel('Date', fontsize=18)
        plt.ylabel('Adj Close Price SEK', fontsize=18)
        plt.plot(scaler.inverse_transform(y_test.reshape(-1,1)))
        plt.plot(scaler.inverse_transform(Xt))
        plt.legend(['Val', 'Predictions'], loc='lower right')
        plt.savefig(f'/mnt/c/Users/Anton/Documents/Models/{stock}/
↪{stock}-model_graph.png')
        plt.close(fig)
```

```python
    @staticmethod
    def pred_act(x_test, scaler, y_test, model):
        """Method that saves the predicted and actual stockprices into csv␣
↪files. Index [-1] is the "real" predicted price.
        """
        act = []
        pred = []
        for i in range(294):
            Xt = model.predict(x_test[i].reshape(1,40,1)) # predict the␣
↪stockprices at every i
            pred.append(scaler.inverse_transform(Xt)) # using scaler.inverse to␣
↪reverse the previous scaled data back to stock prices
            act.append(scaler.inverse_transform(y_test[i].reshape(-1,1))) #␣
↪using scaler.inverse to reverse the previous scaled data back to stock prices
        pred = np.array(pred).flatten() # flattening the array to be␣
↪1-dimension.
        act = np.array(act).flatten()
        df_pred = pd.DataFrame(columns = tickers) # creating a pandas DataFrame␣
↪that has tickers as column-names.
        df_act = pd.DataFrame(columns = tickers)
        df_pred[stock] = pred # appending data to the given stock.
        df_act[stock] = act
        df_pred.to_csv(f'/mnt/c/Users/Anton/Documents/Models/{stock}/
↪{stock}-pred.csv', index=False)
        df_act.to_csv(f'/mnt/c/Users/Anton/Documents/Models/{stock}/
↪{stock}-actual.csv', index=False)
        return act, pred
```

[304]:
```python
# constructs/initialize the portfolio. this loads all the data for the stocks␣
↪within the portfolio. tickers are given since before.
portfolio = Portfolio(tickers, start = '2013-10-01', end = '2020-10-01')
```

```
Tickers read…
You have ['SKA-B.ST', 'EKTA-B.ST', 'GETI-B.ST', 'ERIC-B.ST', 'TEL2-B.ST',
'HM-B.ST'] in your portfolio
```

[305]:
```python
# Iterating through all of our stocks we have in our portfolio. each loop␣
↪trains the model and validates
# it to it's corresponding test-set. Loss, validation and fit is plotted in␣
↪graphs and saved in a
# directory. RMSE is also computed and saved as a text file.

for stock in tickers:
    model, x_test, y_test, scaler = portfolio.TrainModel(stock) # trains the␣
↪model for the specific stock.
```

```
    portfolio.plotter(stock, model, x_test, y_test, scaler) # calls on the␣
↪plotter method to save graohs
    act, prediction = portfolio.pred_act(x_test, scaler, y_test, model) # calls␣
↪on the pred_act method which saves the predicted and actual price into csv
    rmse = np.sqrt(np.mean(((prediction - act)**2))) # computes the rmse of␣
↪every validated model
    with open (f'/mnt/c/Users/Anton/Documents/Models/{stock}/{stock}-rmse.
↪txt','w') as f: # saves the rmse into .txt file.
            f.write(str(rmse)+'\n')
```

```
Epoch 1/50
275/275 [==============================] - 8s 27ms/step - loss: 0.0018 -
val_loss: 0.0033
Epoch 2/50
275/275 [==============================] - 7s 24ms/step - loss: 9.3786e-04 -
val_loss: 0.0039
Epoch 3/50
275/275 [==============================] - 7s 25ms/step - loss: 6.9316e-04 -
val_loss: 0.0025
Epoch 4/50
275/275 [==============================] - 7s 25ms/step - loss: 6.2064e-04 -
val_loss: 0.0016
Epoch 5/50
275/275 [==============================] - 7s 25ms/step - loss: 5.4043e-04 -
val_loss: 0.0013
Epoch 6/50
275/275 [==============================] - 7s 24ms/step - loss: 4.7188e-04 -
val_loss: 0.0012
Epoch 7/50
275/275 [==============================] - 7s 24ms/step - loss: 4.8699e-04 -
val_loss: 0.0014
Epoch 8/50
275/275 [==============================] - 7s 25ms/step - loss: 3.7723e-04 -
val_loss: 8.4694e-04
Epoch 9/50
275/275 [==============================] - 7s 25ms/step - loss: 3.6925e-04 -
val_loss: 0.0012
Epoch 10/50
275/275 [==============================] - 7s 25ms/step - loss: 3.0187e-04 -
val_loss: 7.7443e-04
Epoch 11/50
275/275 [==============================] - 7s 25ms/step - loss: 2.7186e-04 -
val_loss: 7.4171e-04
Epoch 12/50
275/275 [==============================] - 7s 24ms/step - loss: 3.2268e-04 -
val_loss: 7.3508e-04
Epoch 13/50
```

```
275/275 [==============================] - 7s 24ms/step - loss: 2.9433e-04 -
val_loss: 6.8587e-04
Epoch 14/50
275/275 [==============================] - 7s 25ms/step - loss: 2.8191e-04 -
val_loss: 6.6141e-04
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/SKA-B.ST/assets
Epoch 1/50
275/275 [==============================] - 10s 35ms/step - loss: 0.0028 -
val_loss: 0.0058
Epoch 2/50
275/275 [==============================] - 8s 29ms/step - loss: 0.0012 -
val_loss: 0.0031
Epoch 3/50
275/275 [==============================] - 8s 29ms/step - loss: 0.0010 -
val_loss: 0.0037
Epoch 4/50
275/275 [==============================] - 8s 28ms/step - loss: 8.1207e-04 -
val_loss: 0.0017
Epoch 5/50
275/275 [==============================] - 7s 26ms/step - loss: 6.6704e-04 -
val_loss: 0.0014
Epoch 6/50
275/275 [==============================] - 7s 27ms/step - loss: 6.5178e-04 -
val_loss: 0.0013
Epoch 7/50
275/275 [==============================] - 7s 27ms/step - loss: 5.3898e-04 -
val_loss: 0.0012
Epoch 8/50
275/275 [==============================] - 7s 26ms/step - loss: 4.6598e-04 -
val_loss: 0.0012
Epoch 9/50
275/275 [==============================] - 7s 26ms/step - loss: 4.6264e-04 -
val_loss: 0.0012
Epoch 10/50
275/275 [==============================] - 7s 25ms/step - loss: 4.9310e-04 -
val_loss: 0.0013
Epoch 11/50
275/275 [==============================] - 7s 25ms/step - loss: 5.1214e-04 -
val_loss: 0.0012
Epoch 12/50
275/275 [==============================] - 7s 26ms/step - loss: 4.0919e-04 -
val_loss: 0.0012
Epoch 13/50
275/275 [==============================] - 7s 27ms/step - loss: 4.1809e-04 -
val_loss: 0.0012
Epoch 14/50
275/275 [==============================] - 7s 27ms/step - loss: 4.7701e-04 -
```

```
val_loss: 0.0013
Epoch 15/50
275/275 [==============================] - 7s 26ms/step - loss: 3.8519e-04 -
val_loss: 0.0012
Epoch 16/50
275/275 [==============================] - 7s 26ms/step - loss: 4.2742e-04 -
val_loss: 0.0017
Epoch 17/50
275/275 [==============================] - 7s 26ms/step - loss: 4.1189e-04 -
val_loss: 0.0020
Epoch 18/50
275/275 [==============================] - 7s 26ms/step - loss: 3.8857e-04 -
val_loss: 0.0014
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/EKTA-B.ST/assets
Epoch 1/50
275/275 [==============================] - 8s 30ms/step - loss: 0.0051 -
val_loss: 0.0025
Epoch 2/50
275/275 [==============================] - 9s 32ms/step - loss: 0.0013 -
val_loss: 0.0044
Epoch 3/50
275/275 [==============================] - 8s 28ms/step - loss: 0.0011 -
val_loss: 0.0028
Epoch 4/50
275/275 [==============================] - 8s 27ms/step - loss: 9.0557e-04 -
val_loss: 0.0016
Epoch 5/50
275/275 [==============================] - 8s 28ms/step - loss: 7.0457e-04 -
val_loss: 0.0016
Epoch 6/50
275/275 [==============================] - 7s 27ms/step - loss: 6.6411e-04 -
val_loss: 0.0015
Epoch 7/50
275/275 [==============================] - 7s 26ms/step - loss: 6.1096e-04 -
val_loss: 0.0012
Epoch 8/50
275/275 [==============================] - 7s 25ms/step - loss: 5.7832e-04 -
val_loss: 0.0016
Epoch 9/50
275/275 [==============================] - 8s 27ms/step - loss: 6.1342e-04 -
val_loss: 0.0012
Epoch 10/50
275/275 [==============================] - 7s 26ms/step - loss: 5.8724e-04 -
val_loss: 9.3653e-04
Epoch 11/50
275/275 [==============================] - 7s 26ms/step - loss: 5.2465e-04 -
val_loss: 9.8365e-04
```

```
Epoch 12/50
275/275 [==============================] - 7s 26ms/step - loss: 5.1100e-04 -
val_loss: 0.0014
Epoch 13/50
275/275 [==============================] - 7s 25ms/step - loss: 4.9335e-04 -
val_loss: 9.4255e-04
Epoch 14/50
275/275 [==============================] - 8s 29ms/step - loss: 4.5666e-04 -
val_loss: 8.2874e-04
Epoch 15/50
275/275 [==============================] - 8s 28ms/step - loss: 4.2140e-04 -
val_loss: 0.0010
Epoch 16/50
275/275 [==============================] - 9s 33ms/step - loss: 4.5728e-04 -
val_loss: 9.8850e-04
Epoch 17/50
275/275 [==============================] - 10s 36ms/step - loss: 4.4245e-04 -
val_loss: 8.4596e-04
Epoch 18/50
275/275 [==============================] - 9s 32ms/step - loss: 4.2183e-04 -
val_loss: 8.4633e-04
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/GETI-B.ST/assets
Epoch 1/50
275/275 [==============================] - 8s 29ms/step - loss: 0.0057 -
val_loss: 0.0034
Epoch 2/50
275/275 [==============================] - 7s 27ms/step - loss: 0.0017 -
val_loss: 0.0058
Epoch 3/50
275/275 [==============================] - 8s 28ms/step - loss: 0.0013 -
val_loss: 0.0025
Epoch 4/50
275/275 [==============================] - 8s 28ms/step - loss: 0.0011 -
val_loss: 0.0016
Epoch 5/50
275/275 [==============================] - 8s 29ms/step - loss: 9.2067e-04 -
val_loss: 0.0015
Epoch 6/50
275/275 [==============================] - 7s 27ms/step - loss: 7.9414e-04 -
val_loss: 0.0028
Epoch 7/50
275/275 [==============================] - 7s 26ms/step - loss: 7.0193e-04 -
val_loss: 0.0024
Epoch 8/50
275/275 [==============================] - 7s 27ms/step - loss: 7.1975e-04 -
val_loss: 0.0015
Epoch 9/50
```

```
275/275 [==============================] - 8s 29ms/step - loss: 6.6426e-04 -
val_loss: 0.0017
Epoch 10/50
275/275 [==============================] - 7s 27ms/step - loss: 6.4111e-04 -
val_loss: 0.0011
Epoch 11/50
275/275 [==============================] - 7s 27ms/step - loss: 5.7573e-04 -
val_loss: 0.0017
Epoch 12/50
275/275 [==============================] - 7s 26ms/step - loss: 5.3531e-04 -
val_loss: 0.0018
Epoch 13/50
275/275 [==============================] - 7s 27ms/step - loss: 5.6650e-04 -
val_loss: 9.3250e-04
Epoch 14/50
275/275 [==============================] - 7s 26ms/step - loss: 5.1804e-04 -
val_loss: 9.3375e-04
Epoch 15/50
275/275 [==============================] - 7s 26ms/step - loss: 5.5759e-04 -
val_loss: 9.2727e-04
Epoch 16/50
275/275 [==============================] - 7s 26ms/step - loss: 6.6714e-04 -
val_loss: 9.4876e-04
Epoch 17/50
275/275 [==============================] - 7s 26ms/step - loss: 5.3791e-04 -
val_loss: 9.1310e-04
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/ERIC-B.ST/assets
Epoch 1/50
275/275 [==============================] - 8s 28ms/step - loss: 0.0022 -
val_loss: 0.0040
Epoch 2/50
275/275 [==============================] - 8s 28ms/step - loss: 5.6583e-04 -
val_loss: 0.0025
Epoch 3/50
275/275 [==============================] - 8s 28ms/step - loss: 4.8780e-04 -
val_loss: 0.0022
Epoch 4/50
275/275 [==============================] - 7s 26ms/step - loss: 4.0940e-04 -
val_loss: 0.0015
Epoch 5/50
275/275 [==============================] - 7s 26ms/step - loss: 4.1855e-04 -
val_loss: 0.0018
Epoch 6/50
275/275 [==============================] - 7s 26ms/step - loss: 3.3062e-04 -
val_loss: 0.0011
Epoch 7/50
275/275 [==============================] - 7s 25ms/step - loss: 3.3786e-04 -
```

```
val_loss: 9.3202e-04
Epoch 8/50
275/275 [==============================] - 7s 25ms/step - loss: 2.8845e-04 -
val_loss: 0.0011
Epoch 9/50
275/275 [==============================] - 7s 25ms/step - loss: 2.4722e-04 -
val_loss: 0.0019
Epoch 10/50
275/275 [==============================] - 7s 25ms/step - loss: 2.6036e-04 -
val_loss: 5.2858e-04
Epoch 11/50
275/275 [==============================] - 7s 25ms/step - loss: 2.1735e-04 -
val_loss: 4.5902e-04
Epoch 12/50
275/275 [==============================] - 8s 29ms/step - loss: 2.1232e-04 -
val_loss: 5.6423e-04
Epoch 13/50
275/275 [==============================] - 8s 30ms/step - loss: 2.5864e-04 -
val_loss: 4.3635e-04
Epoch 14/50
275/275 [==============================] - 9s 31ms/step - loss: 1.7878e-04 -
val_loss: 0.0016
Epoch 15/50
275/275 [==============================] - 8s 28ms/step - loss: 2.6403e-04 -
val_loss: 5.1601e-04
Epoch 16/50
275/275 [==============================] - 8s 28ms/step - loss: 1.6488e-04 -
val_loss: 7.5435e-04
Epoch 17/50
275/275 [==============================] - 9s 32ms/step - loss: 1.7594e-04 -
val_loss: 4.3220e-04
Epoch 18/50
275/275 [==============================] - 8s 28ms/step - loss: 1.7323e-04 -
val_loss: 8.2670e-04
Epoch 19/50
275/275 [==============================] - 9s 33ms/step - loss: 1.7044e-04 -
val_loss: 7.6830e-04
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/TEL2-B.ST/assets
Epoch 1/50
275/275 [==============================] - 8s 30ms/step - loss: 0.0063 -
val_loss: 0.0029
Epoch 2/50
275/275 [==============================] - 7s 26ms/step - loss: 0.0014 -
val_loss: 0.0021
Epoch 3/50
275/275 [==============================] - 7s 25ms/step - loss: 0.0011 -
val_loss: 0.0017
```

```
Epoch 4/50
275/275 [==============================] - 7s 25ms/step - loss: 8.9597e-04 -
val_loss: 0.0016
Epoch 5/50
275/275 [==============================] - 8s 29ms/step - loss: 9.1881e-04 -
val_loss: 0.0021
Epoch 6/50
275/275 [==============================] - 8s 30ms/step - loss: 8.0175e-04 -
val_loss: 0.0013
Epoch 7/50
275/275 [==============================] - 8s 28ms/step - loss: 5.9578e-04 -
val_loss: 0.0011
Epoch 8/50
275/275 [==============================] - 8s 27ms/step - loss: 6.2568e-04 -
val_loss: 9.5404e-04
Epoch 9/50
275/275 [==============================] - 8s 27ms/step - loss: 5.8060e-04 -
val_loss: 8.9010e-04
Epoch 10/50
275/275 [==============================] - 7s 26ms/step - loss: 5.1552e-04 -
val_loss: 8.0673e-04
Epoch 11/50
275/275 [==============================] - 7s 26ms/step - loss: 5.9435e-04 -
val_loss: 9.4311e-04
Epoch 12/50
275/275 [==============================] - 7s 26ms/step - loss: 4.8592e-04 -
val_loss: 8.0744e-04
Epoch 13/50
275/275 [==============================] - 8s 28ms/step - loss: 3.9887e-04 -
val_loss: 6.7193e-04
Epoch 14/50
275/275 [==============================] - 8s 27ms/step - loss: 4.3029e-04 -
val_loss: 6.6171e-04
Epoch 15/50
275/275 [==============================] - 8s 29ms/step - loss: 3.9004e-04 -
val_loss: 6.6326e-04
Epoch 16/50
275/275 [==============================] - 10s 35ms/step - loss: 4.4947e-04 -
val_loss: 7.3528e-04
Epoch 17/50
275/275 [==============================] - 8s 30ms/step - loss: 4.3551e-04 -
val_loss: 6.1346e-04
Epoch 18/50
275/275 [==============================] - 8s 29ms/step - loss: 3.9355e-04 -
val_loss: 6.0655e-04
INFO:tensorflow:Assets written to:
/mnt/c/Users/Anton/Documents/Models/HM-B.ST/assets
```

3 Calculating returns and covariances

[7]:
```
# creates a function that loops over the stocks in the portfolio and reads in␣
↪the stocks actual / predicted data.
tickers = ['SKA-B.ST', 'EKTA-B.ST', 'GETI-B.ST', 'ERIC-B.ST', 'TEL2-B.ST',␣
↪'HM-B.ST']
def concat_df(type_ = ''):
    df = pd.DataFrame(columns = tickers)
    for stock in tickers:
        df[stock] = pd.read_csv(f'{save_path}/{stock}/{stock}-{type_}.
↪csv')[stock]
    return df
```

[8]:
```
actual = concat_df(type_ = 'actual') # saves the portfolio stocks actual stock␣
↪price in a dataframe
unknown_price = actual.iloc[-1] # allocates the real price that is unknown to␣
↪the model into a variable. comparable price
actual = actual[:-1] # all the real stock prices to day t
actual_last = actual.iloc[-1] # getting the time t stock price.
```

[9]:
```
actual_ret = (unknown_price - actual_last) / actual_last
```

[10]:
```
predicted = concat_df(type_='pred') # saves the potfolio stocks predicted stock␣
↪price in a dataframe
pred_price = predicted.iloc[-1] # the t+1 stock price
```

[11]:
```
# the returns should probably be calculated as log_return. it however␣
↪complicates the caluculation of the return for t+1 thus normal return has␣
↪been calculated.
# just showing below how the log returns and covariance matrix with log can be␣
↪calulated.

#log_actual = np.log(actual / actual.shift(1))
#log_actual_price = log_actual.iloc[-2]
#test_cov = log_actual.cov() # testing cov of actual
#log_pred = np.log(predicted / predicted.shift(1))
#log_pred_price = log_pred.iloc[-1]
```

3.0.1 Calulating the return for t –> t+1 with the predicted price at t+1

$E(R_A)_{t+1} = \frac{PP^A_{t+1} - P^A_t}{P^A_t}$

$E(R_A)_{t+1}$ = unweighted expected return of a single asset at time t+1

PP^A_{t+1} = predicted for a specific asset price at t+1

P^A_t = real price of asset at time t

```
[12]: # calculating the returns of all the stocks in our portfolio. this is done with␣
      ↪the do

      def calc_return():
          returns = []

          for stock in tickers:
              returns.append((pred_price[stock] - actual_last[stock]) /␣
      ↪actual_last[stock])

          df = pd.Series(returns, index = tickers, name = 'Predicted returns')
          return df
```

```
[13]: pred_ret = calc_return()
```

```
[14]: # the means/expected returns for t+1
      pred_ret
```

```
[14]: SKA-B.ST      0.003109
      EKTA-B.ST     0.016434
      GETI-B.ST    -0.005667
      ERIC-B.ST    -0.000773
      TEL2-B.ST     0.017092
      HM-B.ST       0.006105
      Name: Predicted returns, dtype: float64
```

3.0.2 Calculating covariance matrix of portfolio

$cov(X, Y) = \sum_{i=0}^{N} = \frac{(R_{X_i} - \bar{R}_X) - (R_{Y_i} - \bar{R}_Y)}{N-1}$

```
[15]: # defining a function that returns the covariance matrix of all the assets.

      def covariance_matrix(bias = False):
          matrix = np.zeros([len(tickers), len(actual) - 1])
          i = 0
          for stocks in tickers: # iterating over both the stocks and the created␣
      ↪matrix.
              numerator = actual[stocks].pct_change().dropna() - pred_ret[stocks] #␣
      ↪calculating the numerator of the function. subtracting the predicted mean/
      ↪return.
              matrix[i] = numerator # adding the numerator to the previos created␣
      ↪matrix.
              i += 1
          daily_cov = np.cov(matrix, bias = bias) # using np.cov to compute the␣
      ↪coveriance matrix of the whole portfolio. bias is used for N - 1.
          print('Daily covariance for the portfolio stocks are: ')
```

```
    print('')
    print(pd.DataFrame(daily_cov, columns=[tickers], index=[tickers]))
    return daily_cov
```

[16]:
```
daily_cov = covariance_matrix()
```

```
Daily covariance for the portfolio stocks are:

           SKA-B.ST EKTA-B.ST GETI-B.ST ERIC-B.ST TEL2-B.ST   HM-B.ST
SKA-B.ST   0.000451  0.000248  0.000096  0.000221  0.000157  0.000355
EKTA-B.ST  0.000248  0.000879  0.000184  0.000216  0.000113  0.000349
GETI-B.ST  0.000096  0.000184  0.000626  0.000200  0.000142  0.000026
ERIC-B.ST  0.000221  0.000216  0.000200  0.000591  0.000185  0.000252
TEL2-B.ST  0.000157  0.000113  0.000142  0.000185  0.000316  0.000165
HM-B.ST    0.000355  0.000349  0.000026  0.000252  0.000165  0.000823
```

4 Optimizing the portfolio

We create a class that will be used for optimizing the portfolio. The class has methods that can be used to optimize the portfolio for maximum sharpe ratio and minimum variance. There are also methods for benchmarking the predicted returns from the LSTM model.

These are 1overN which is a simple weight allocation of 1 / number of assets, giving a equal distribution of weights between the assets.

The other one is a random optimizer which only takes random weights from a normal distribution which has to add up to one and allocates these weights to the different assets in the portfolio.

There is also a method for plotting the efficient frontier of the different allocations. This is based on Monte-Carlo simulation. It's only used for visualization.

Unfortunately, we didn't manage to compute a minimum variance portfolio. No matter what we did, the weights were always the same as the initial guess. It might have something to do with that the portfolio volatility and returns is not scaled to 256 days(1 year). This makes the covariances extremely small and there is probably a very small difference in volatility between different portfolios.

[360]:
```
class portfolio_optimizer(object):
    def __init__(self, mean, daily_cov, log_ret = False):
        self.cons = ({'type': 'eq', 'fun': lambda x:  np.sum(x) - 1}) # setting␣
 ↪up the constraint for the opmitization. total sum of weights can only be 1
        self.bnds = tuple((0, 1) for x in range(len(tickers)))
        self.initialGuess = np.ones(len(tickers))*(1./len(tickers)) # intital␣
 ↪guess of weights for the optimizer to start from
        self.mean = mean # the calculated means/returns from the assets between␣
 ↪t --> t+1
        self.daily_cov = daily_cov # the calculated covariance from the␣
 ↪portfolio
```

```
    # method that returns the portfolio returns, volatility and sharpe-ratio␣
↪given inputted weights.
    def portfolio_stats(self, weights):
        weights = np.array(weights)
        pret = np.sum(self.mean * weights) # portfolio returns
        pvol = np.sqrt(np.dot(weights.T, np.dot(self.daily_cov, weights))) #␣
↪portfolio volatility
        return np.array([pret, pvol, pret / pvol])

    # function that returns weights for a minimized negative sharpe ratio
    def min_func_sharpe(self, weights):
        return -self.portfolio_stats(weights)[2]

    # function that returns weights for a minimized variance
    def min_func_variance(self, weights):
        return self.portfolio_stats(weights)[1] ** 2

    # function that return weights for portfolios with least standard devation
    def min_func_port(self, weights):
        return self.portfolio_stats(weights)[1]

    # method that minimizes the negative sharpe and variance.
    def optimizer(self, no_info = False):
        max_sharpe = sco.minimize(self.min_func_sharpe, self.initialGuess,␣
↪method='SLSQP',
                            bounds=self.bnds, constraints=self.cons)
        min_variance = sco.minimize(self.min_func_variance, self.initialGuess,␣
↪method='SLSQP',
                            bounds=self.bnds, constraints=self.cons)

        if no_info == False:
            print(f"Max Sharpe {max_sharpe['message']}")
            print('')
            print('The return, volatility and Sharpe-Ratio are:', self.
↪portfolio_stats(max_sharpe['x']).round(3))
            print('')
            print(pd.DataFrame(max_sharpe['x'].round(3), index=[tickers],␣
↪columns = ['Maximum Sharpe Weights']))
            print('')
            print(f"Min Variance {min_variance['message']}")
            print('')
            print('The return, volatility and Sharpe-Ratio are:', self.
↪portfolio_stats(min_variance['x']).round(3))
            print('')
            print(pd.DataFrame(min_variance['x'].round(3), index=[tickers],␣
↪columns = ['Minimum Variance Weights']))
```

```
        else:
            pass
        return self.portfolio_stats(max_sharpe['x'].round(3))

    def one_over_n(self, no_info = False):
        """
        Simple N over 1 allocation to benchmark the deep-learning performance␣
↪with

        Returns: return, volatility and sharpe ratio
        """
        weights = np.ones(len(tickers)) * (1./len(tickers))
        if no_info == False:
            print('The return, volatility and Sharpe-Ratio are:', self.
↪portfolio_stats(weights.round(3)))
            print('')
        else:
            pass
        return self.portfolio_stats(weights)

    def random_optimizer(self, no_info = False):
        """
        Creates a random weight allocation of the portfolio without any␣
↪knowledge about the past, present
        or future. Returns the return, volatity and sharpe ratio.
        """
        np.random.seed(200)
        weights = np.random.random(len(tickers))
        weights /= np.sum(weights)
        if no_info == False:
            print('The return, volatility and Sharpe-Ratio are:', self.
↪portfolio_stats(weights.round(3)))
            print('')
        else:
            pass
        return self.portfolio_stats(weights)


    def graph_efficient_frontier(self):
        """
        Monte Carlo Simulation in order to produce a efficient frontier. The␣
↪same structure as above
        methods.

        """
```

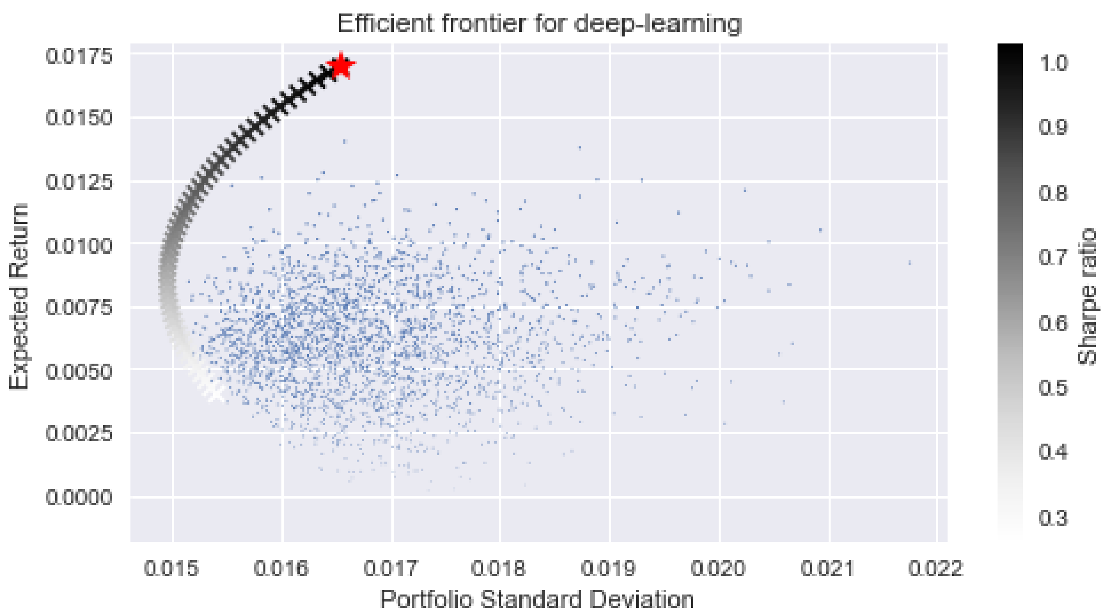
```
        max_sharpe = sco.minimize(self.min_func_sharpe, self.initialGuess, method='SLSQP',
                       bounds=self.bnds, constraints=self.cons)
        max_ret = self.portfolio_stats(max_sharpe['x'])[0]
        trets = np.linspace(0.004, max_ret, 50)
        tvols = []
        for tret in trets:
            cons = ({'type': 'eq', 'fun': lambda x:  self.portfolio_stats(x)[0] - tret},
            {'type': 'eq', 'fun': lambda x:  np.sum(x) - 1})
            res = sco.minimize(self.min_func_port, self.initialGuess, method='SLSQP',
                       bounds=self.bnds, constraints=cons)

            tvols.append(res['fun']) #the value of the objective, i.e. standard deviation of portfolio returns
        tvols = np.array(tvols)

        # prepare lists for portfolio returns and volatilities
        prets = []
        pvols = []
        pSharpe =[]

        # randomly generate 2500 portfolios
        for p in range (2500):
            weights = np.random.random(len(tickers))
            weights /= np.sum(weights)

            # portfolio return
            ret = np.sum(self.mean * weights)
            #portfolio volatility
            vol = np.sqrt(np.dot(weights,
                        np.dot(self.daily_cov, weights.T)))

            prets.append(ret)
            pvols.append(vol)
            #portfolio Sharpe ratio
            sharpe = ret/vol
            pSharpe.append(sharpe)

        plt.figure(figsize=(8, 4))
        plt.scatter(pvols, prets, pSharpe, marker='o')
            # random portfolio composition
        plt.scatter(tvols, trets, c = trets/tvols, marker='x')
            # efficient frontier
        plt.plot(self.portfolio_stats(max_sharpe['x'])[1], self.portfolio_stats(max_sharpe['x'])[0],'r*', markersize=15.0)
```

```
            # portfolio with highest Sharpe ratio
        #plt.plot(portfolio_stats(optv['x'])[1], portfolio_stats(optv['x'])[0],
        #          'y*', markersize=15.0)
            # minimum variance portfolio
        #plt.grid(True)
        plt.xlabel('Portfolio Standard Deviation')
        plt.ylabel('Expected Return')
        plt.colorbar(label='Sharpe ratio')
        plt.title('Efficient frontier for deep-learning')
```

[361]:
```
pred_portfolio = portfolio_optimizer(pred_ret, daily_cov)
```

5 Results

[362]:
```
pred_portfolio.graph_efficient_frontier()
```



[363]:
```
deep_learning = pred_portfolio.optimizer()
```

```
Max Sharpe Optimization terminated successfully

The return, volatility and Sharpe-Ratio are: [0.017 0.017 1.025]

           Maximum Sharpe Weights
SKA-B.ST                    0.000
EKTA-B.ST                   0.199
GETI-B.ST                   0.000
```

```
ERIC-B.ST                    0.000
TEL2-B.ST                    0.801
HM-B.ST                      0.000

Min Variance Optimization terminated successfully

The return, volatility and Sharpe-Ratio are: [0.006 0.016 0.372]

           Minimum Variance Weights
SKA-B.ST                      0.167
EKTA-B.ST                     0.167
GETI-B.ST                     0.167
ERIC-B.ST                     0.167
TEL2-B.ST                     0.167
HM-B.ST                       0.167
```

5.0.1 Graphs of the performance of the LSTM prediction when applied with portfolio optimization

[364]:
```
deeplearning = pred_portfolio.optimizer(no_info=True)
```

[365]:
```
one_over_n = pred_portfolio.one_over_n(no_info=False)
```

```
The return, volatility and Sharpe-Ratio are: [0.00606205 0.01628103 0.37233783]
```

[366]:
```
random_weights = pred_portfolio.random_optimizer(no_info=False)
```

```
The return, volatility and Sharpe-Ratio are: [0.00540843 0.01537108 0.35185777]
```

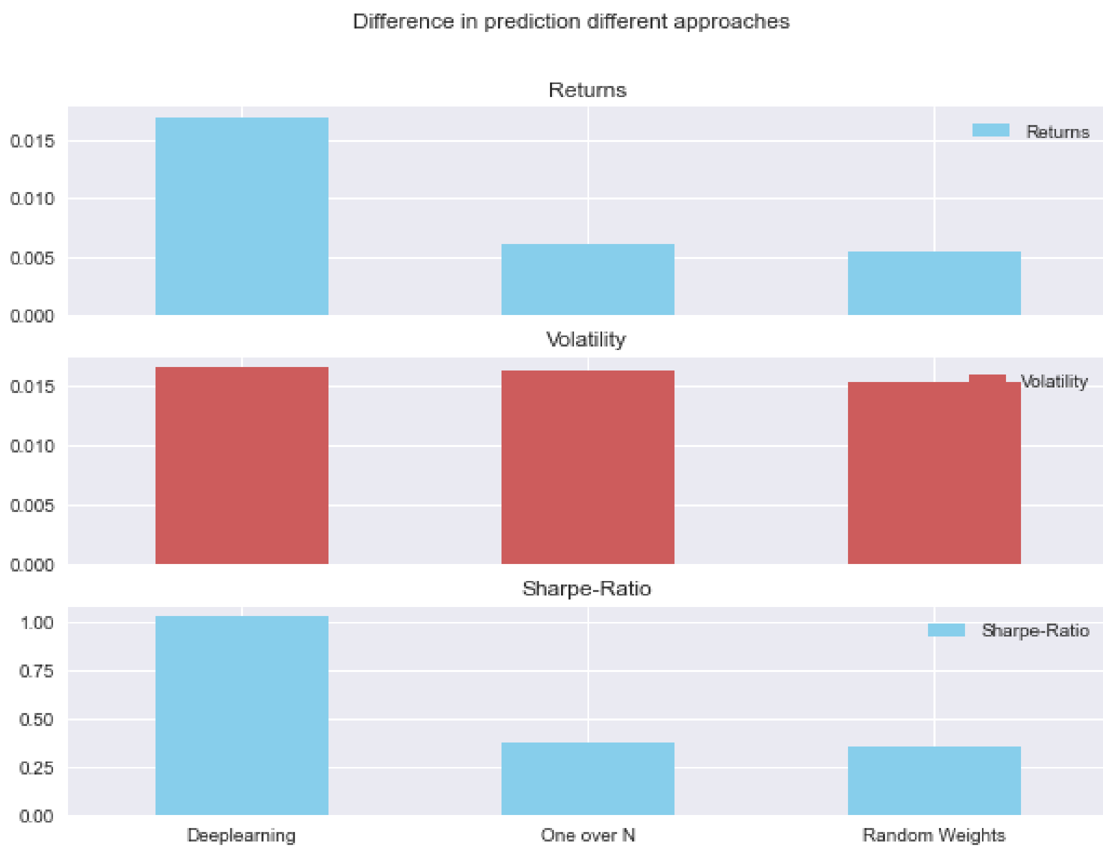
[367]:
```
df1 = pd.DataFrame([deeplearning, one_over_n, random_weights],
                   columns = ['Returns', 'Volatility', 'Sharpe-Ratio'],
                   index = ['Deeplearning', 'One over N', 'Random Weights'])
```

[368]:
```
df1
```

[368]:

	Returns	Volatility	Sharpe-Ratio
Deeplearning	0.016961	0.016542	1.025279
One over N	0.006050	0.016249	0.372338
Random Weights	0.005414	0.015355	0.352599

[369]:
```
ax = df1.plot.bar(color=["SkyBlue","IndianRed"], rot=0,
                  title="Difference in prediction different approaches",␣
 ↪subplots = True, figsize = (10, 7))
plt.show()
```



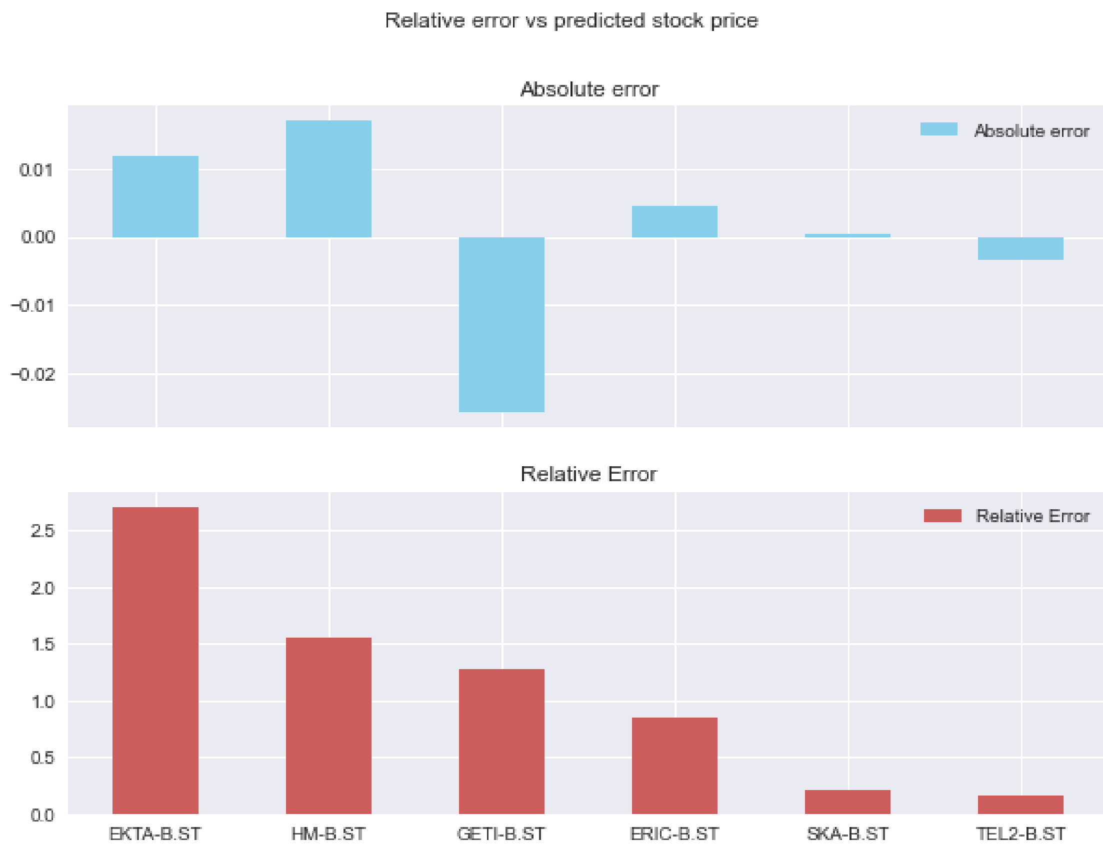
[370]:
```python
# Error in price prediction

abs_error = pred_ret - actual_ret
print("Absolute error: ")
print(abs_error)
print("")
rel_error = abs(abs_error / actual_ret)
print("Relative error: ")
print(rel_error)
```

```
Absolute error:
SKA-B.ST      0.000530
EKTA-B.ST     0.011994
GETI-B.ST    -0.025894
ERIC-B.ST     0.004508
TEL2-B.ST    -0.003427
HM-B.ST       0.017062
dtype: float64

Relative error:
SKA-B.ST      0.205601
```

```
EKTA-B.ST    2.701826
GETI-B.ST    1.280165
ERIC-B.ST    0.853649
TEL2-B.ST    0.167029
HM-B.ST      1.557211
dtype: float64
```

[371]:

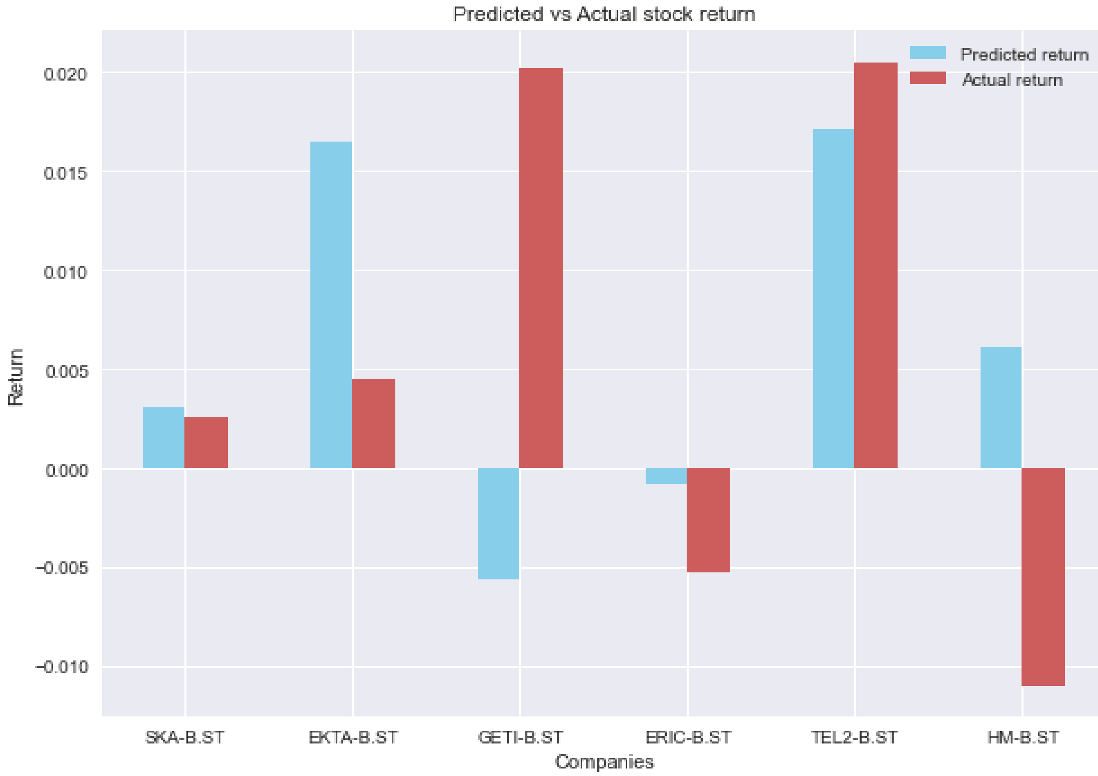
```
df = pd.DataFrame({"Absolute error":abs_error, "Relative Error":rel_error})
sorted_df = df.sort_values(by = ['Relative Error'], ascending=False)
ax = sorted_df.plot.bar(color=["SkyBlue","IndianRed", "Blueviolet",␣
↪"Darkcyan"], rot=0, title="Relative error vs predicted stock price",␣
↪subplots = True, figsize = (10, 7))
plt.show()
```



[372]:

```
df = pd.DataFrame({"Predicted return":pred_ret,"Actual return":actual_ret})
sorted_df = df.sort_values(by = ['Predicted return'], ascending=False)
ax = df.plot.bar(color=["SkyBlue","IndianRed"], rot=0, title="Predicted vs␣
↪Actual stock return", figsize = (10, 7))
ax.set_xlabel("Companies")
ax.set_ylabel("Return")
```

```
plt.show()
```



5.0.2 Optimizing with the real stock return to compare the predicted performance with the real

[373]:
```
actual_ret = (unknown_price - actual_last) / actual_last
```

[374]:
```
actual_portfolio = portfolio_optimizer(actual_ret, daily_cov)
```

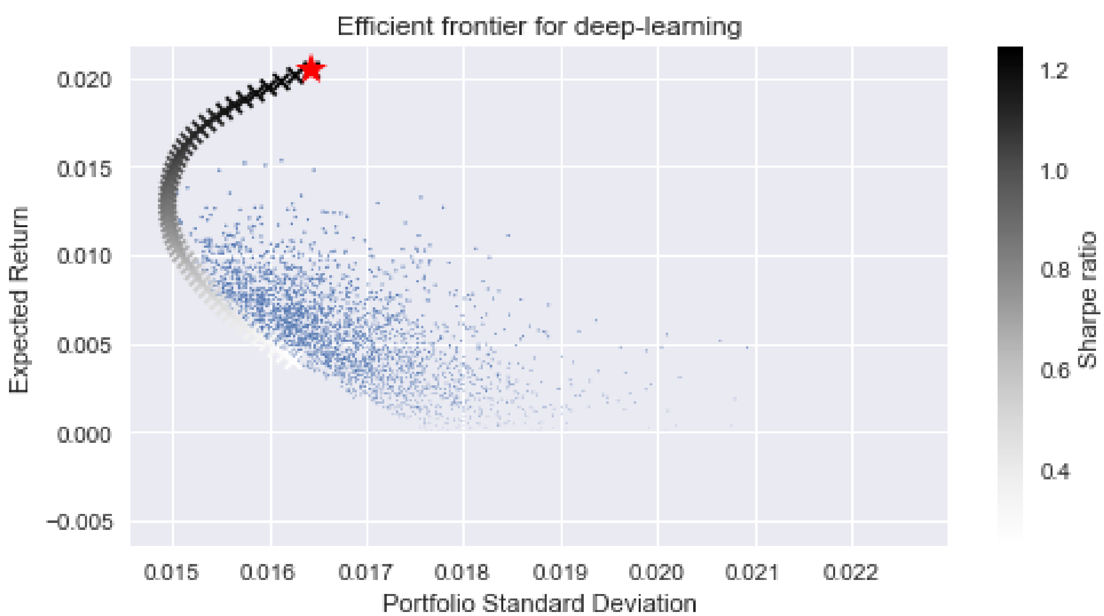
[375]:
```
no_pred = actual_portfolio.optimizer()
```

```
Max Sharpe Optimization terminated successfully

The return, volatility and Sharpe-Ratio are: [0.02  0.016 1.244]

           Maximum Sharpe Weights
SKA-B.ST                    0.000
EKTA-B.ST                   0.000
GETI-B.ST                   0.259
ERIC-B.ST                   0.000
TEL2-B.ST                   0.741
HM-B.ST                     0.000
```

```
Min Variance Optimization terminated successfully

The return, volatility and Sharpe-Ratio are: [0.005 0.016 0.323]

           Minimum Variance Weights
SKA-B.ST                      0.167
EKTA-B.ST                     0.167
GETI-B.ST                     0.167
ERIC-B.ST                     0.167
TEL2-B.ST                     0.167
HM-B.ST                       0.167
```

[376]:
```
actual_portfolio.graph_efficient_frontier()
```

```
/Users/antonerlandsson/.local/lib/python3.8/site-
packages/matplotlib/collections.py:922: RuntimeWarning: invalid value
encountered in sqrt
  scale = np.sqrt(self._sizes) * dpi / 72.0 * self._factor
```



[377]:
```
no_pred = actual_portfolio.optimizer(no_info=True)
```

[378]:
```
one_over_n_nopred = actual_portfolio.one_over_n(no_info=False)
```

```
The return, volatility and Sharpe-Ratio are: [0.00526486 0.01628103 0.32337356]
```

[379]:
```python
random_weights_nopred = actual_portfolio.random_optimizer(no_info=False)
```

```
The return, volatility and Sharpe-Ratio are: [0.00974538 0.01537108 0.63400753]
```

[380]:
```python
df2 = pd.DataFrame([no_pred, one_over_n_nopred, random_weights_nopred],
                   columns = ['Returns', 'Volatility', 'Sharpe-Ratio'],
                   index = ['Known prices', 'One over N', 'Random Weights'])
```

[381]:
```python
ax = df2.plot.bar(color=["SkyBlue","IndianRed", "Blueviolet"], rot=0,
                  title="Difference in returns, volatility and sharpe by␣
↪different approaches", subplots = True, figsize = (10, 7))

plt.show()
```

5.0.3 Showing the difference between "approaches"

[382]:
```
df3 = pd.DataFrame([no_pred, one_over_n_nopred, random_weights_nopred,␣
↪deep_learning, one_over_n, random_weights],
                  columns = ['Returns', 'Volatility', 'Sharpe-Ratio'],
                  index = ['Optimized weights Known Price', '1overN Known␣
↪Prices', 'Random Weights Known Prices', 'Optimized Weights LSTM', '1overN␣
↪LSTM', 'Random Weights LSTM'])
```

[383]:
```
test = df3.sort_values(by = ['Sharpe-Ratio'], axis = 0, ascending = True)

ax = test['Sharpe-Ratio'].plot.barh(rot=0,
                 title="Difference in Sharpe-Ratio by method", figsize = (10,␣
↪7))
```