In [ ]:
```
###necessary libaries###
import numpy as np
import pandas as pd
from seglearn.transform import FeatureRep, SegmentXYForecast, last
from subprocess import check_output
from keras.layers import Dense, Activation, Dropout, Input, LSTM, Flatten
from keras.models import Model
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
from numpy import newaxis
import glob
import os
from datetime import datetime
import math
from numpy.random import seed
import tensorflow as tf
import warnings
from sklearn.exceptions import DataConversionWarning

model_seed = 100
# ensure same output results
seed(101)
tf.random.set_seed(model_seed)

# file where csv files lies
path = r'C:\Users\victo\Master_Thesis\merging_data\daimler\hourly\merged_files'
all_files = glob.glob(os.path.join(path, "*.csv"))

# read files to pandas frame
list_of_files = []

for filename in all_files:
    list_of_files.append(pd.read_csv(filename,
                                     sep=',',
                                     )
                         )

# Concatenate all content of files into one DataFrames
concatenate_dataframe = pd.concat(list_of_files,
                                  ignore_index=True,
                                  axis=0,
                                  )

# print(concatenate_dataframe)

### analysis with flair sentiment content
new_df_flair_content = concatenate_dataframe[['Date',
                                              'OPEN',
                                              'HIGH',
                                              'LOW',
                                              'CLOSE',
                                              'VOLUME',
                                              'flair_sentiment_content_score']]

new_df_flair_content['flair_sentiment_content_score'] = new_df_flair_content['flair
_sentiment_content_score'].fillna(0)
# new_df_flair_content[['Date',
#                       'OPEN',
#                       'HIGH',
#                       'LOW',
```

```
#                         'CLOSE',
#                         'VOLUME',
#                         'flair_sentiment_content_score']].astype(np.float64)

new_df_flair_content['Year'] = pd.DatetimeIndex(new_df_flair_content['Date']).year
new_df_flair_content['Month'] = pd.DatetimeIndex(new_df_flair_content['Date']).mont
h
new_df_flair_content['Day'] = pd.DatetimeIndex(new_df_flair_content['Date']).day
new_df_flair_content['Hour'] = pd.DatetimeIndex(new_df_flair_content['Date']).hour
new_df_flair_content['Minute'] = pd.DatetimeIndex(new_df_flair_content['Date']).min
ute
new_df_flair_content['Second'] = pd.DatetimeIndex(new_df_flair_content['Date']).sec
ond

new_df_flair_content = new_df_flair_content.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_flair_content = 0.1

X_train_flair_content, \
X_else_flair_content,\
y_train_flair_content, \
y_else_flair_content = train_test_split(new_df_flair_content,
                                        new_df_flair_content['OPEN'],
                                        test_size=valid_test_size_split_flair_conte
nt*2,
                                        shuffle=False)

X_valid_flair_content, \
X_test_flair_content, \
y_valid_flair_content, \
y_test_flair_content = train_test_split(X_else_flair_content,
                                        y_else_flair_content,
                                        test_size=0.5,
                                        shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_flair_content(df_x, series_y, normalizers_flair_content = None):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'flair_sentiment_content_score']

    if not normalizers_flair_content:
        normalizers_flair_content = {}

    for feat in features_to_minmax:
        if feat not in normalizers_flair_content:
            normalizers_flair_content[feat] = MinMaxScaler()
            normalizers_flair_content[feat].fit(df_x[feat].values.reshape(-1, 1))

        df_x[feat] = normalizers_flair_content[feat].transform(df_x[feat].values.re
shape(-1, 1))
```

```
    series_y = normalizers_flair_content['OPEN'].transform(series_y.values.reshape
(-1, 1))

    return df_x, series_y, normalizers_flair_content

X_train_norm_flair_content, \
y_train_norm_flair_content, \
normalizers_flair_content = minmax_scale_flair_content(X_train_flair_content,
                                                       y_train_flair_content
                                                       )


X_valid_norm_flair_content, \
y_valid_norm_flair_content, \
_ = minmax_scale_flair_content(X_valid_flair_content,
                               y_valid_flair_content,
                               normalizers_flair_content=normalizers_flair_content
                               )

X_test_norm_flair_content, \
y_test_norm_flair_content, \
_ = minmax_scale_flair_content(X_test_flair_content,
                               y_test_flair_content,
                               normalizers_flair_content=normalizers_flair_content
                               )

def encode_cyclicals_flair_content(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x

X_train_norm_flair_content = encode_cyclicals_flair_content(X_train_norm_flair_cont
ent)
X_valid_norm_flair_content = encode_cyclicals_flair_content(X_valid_norm_flair_cont
ent)
X_test_norm_flair_content = encode_cyclicals_flair_content(X_test_norm_flair_conten
t)

# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_flair_content = 45
```

```
FORECAST_DISTANCE_flair_content = 9

segmenter_flair_content = SegmentXYForecast(width=TIME_WINDOW_flair_content,
                                            step=1,
                                            y_func=last,
                                            forecast=FORECAST_DISTANCE_flair_conten
t
                                            )

X_train_rolled_flair_content, \
y_train_rolled_flair_content, \
_ = segmenter_flair_content.fit_transform([X_train_norm_flair_content.values],
                                          [y_train_norm_flair_content.flatten()]
                                          )

X_valid_rolled_flair_content, \
y_valid_rolled_flair_content, \
_ = segmenter_flair_content.fit_transform([X_valid_norm_flair_content.values],
                                          [y_valid_norm_flair_content.flatten()]
                                          )

X_test_rolled_flair_content,\
y_test_rolled_flair_content, \
_ = segmenter_flair_content.fit_transform([X_test_norm_flair_content.values],
                                          [y_test_norm_flair_content.flatten()]
                                          )

# LSTM Model
first_lstm_size_flair_content = 75
second_lstm_size_flair_content = 40
dropout_flair_content = 0.1
EPOCHS_flair_content = 50
BATCH_SIZE_flair_content = 32
column_count_flair_content = len(X_train_norm_flair_content.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_flair_content = Input(shape=(TIME_WINDOW_flair_content, column_count_fl
air_content))
# first LSTM layer
first_lstm_flair_content = LSTM(first_lstm_size_flair_content,
                                return_sequences=True,
                                dropout=dropout_flair_content)(input_layer_flair_co
ntent)
# second LTSM layer
second_lstm_flair_content = LSTM(second_lstm_size_flair_content,
                                 return_sequences=False,
                                 dropout=dropout_flair_content)(first_lstm_flair_co
ntent)
# output layer
output_layer_flair_content = Dense(1)(second_lstm_flair_content)
# creating Model
model_flair_content = Model(inputs=input_layer_flair_content, outputs=output_layer_
flair_content)
# compile model
model_flair_content.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
model_flair_content.summary()
print(' ')
print("---------------------------------------------------------------")
print(' ')
# fitting model
hist_flair_content = model_flair_content.fit(x=X_train_rolled_flair_content,
                                             y=y_train_rolled_flair_content,
                                             batch_size=BATCH_SIZE_flair_content,
```

```
                                              validation_data=(X_valid_rolled_flair_
content,
                                                                y_valid_rolled_flair_
content
                                                                ),
                                              epochs=EPOCHS_flair_content,
                                              verbose=1,
                                              shuffle=False
                                              )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_flair_content.history['loss'], label='train_flair_content')
plt.plot(hist_flair_content.history['val_loss'], label='test_flair_content')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_flair_content = math.sqrt(min(hist_flair_content.history['val_loss']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_flair_content = model_flair_content.predict(X_test_rolled_fla
ir_content)

predicted_stock_price_flair_content = normalizers_flair_content['OPEN']\
                                      .inverse_transform(predicted_stock_price_flai
r_content).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_flair_content)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_flair_content["OPEN"].inverse_transform(np.array([rms_LSTM_flair_
content]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_flair_content)

### analysis with flair header
new_df_flair_header = concatenate_dataframe[['Date',
                                              'OPEN',
                                              'HIGH',
                                              'LOW',
                                              'CLOSE',
                                              'VOLUME',
                                              'flair_sentiment_header_score']]

new_df_flair_header['flair_sentiment_header_score'] = new_df_flair_header['flair_se
ntiment_header_score'].fillna(0)
# new_df_flair_header[['Date',
#                       'OPEN',
#                       'HIGH',
#                       'LOW',
#                       'CLOSE',
#                       'VOLUME',
#                       'flair_sentiment_header_score']].astype(np.float64)

new_df_flair_header['Year'] = pd.DatetimeIndex(new_df_flair_header['Date']).year
```

```
new_df_flair_header['Month'] = pd.DatetimeIndex(new_df_flair_header['Date']).month
new_df_flair_header['Day'] = pd.DatetimeIndex(new_df_flair_header['Date']).day
new_df_flair_header['Hour'] = pd.DatetimeIndex(new_df_flair_header['Date']).hour
new_df_flair_header['Minute'] = pd.DatetimeIndex(new_df_flair_header['Date']).minut
e
new_df_flair_header['Second'] = pd.DatetimeIndex(new_df_flair_header['Date']).secon
d

new_df_flair_header = new_df_flair_header.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_flair_header = 0.1

X_train_flair_header, \
X_else_flair_header,\
y_train_flair_header, \
y_else_flair_header = train_test_split(new_df_flair_header,
                                       new_df_flair_header['OPEN'],
                                       test_size=valid_test_size_split_flair_header
*2,
                                       shuffle=False)

X_valid_flair_header, \
X_test_flair_header, \
y_valid_flair_header, \
y_test_flair_header = train_test_split(X_else_flair_header,
                                       y_else_flair_header,
                                       test_size=0.5,
                                       shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_flair_header(df_x, series_y, normalizers_flair_header = None):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'flair_sentiment_header_score']

    if not normalizers_flair_header:
        normalizers_flair_header = {}

    for feat in features_to_minmax:
        if feat not in normalizers_flair_header:
            normalizers_flair_header[feat] = MinMaxScaler()
            normalizers_flair_header[feat].fit(df_x[feat].values.reshape(-1, 1))

        df_x[feat] = normalizers_flair_header[feat].transform(df_x[feat].values.res
hape(-1, 1))

    series_y = normalizers_flair_header['OPEN'].transform(series_y.values.reshape(-
1, 1))

    return df_x, series_y, normalizers_flair_header
```

```
X_train_norm_flair_header, \
y_train_norm_flair_header, \
normalizers_flair_header = minmax_scale_flair_header(X_train_flair_header,
                                                     y_train_flair_header
                                                     )

X_valid_norm_flair_header, \
y_valid_norm_flair_header, \
_ = minmax_scale_flair_header(X_valid_flair_header,
                              y_valid_flair_header,
                              normalizers_flair_header=normalizers_flair_header
                              )

X_test_norm_flair_header, \
y_test_norm_flair_header, \
_ = minmax_scale_flair_header(X_test_flair_header,
                              y_test_flair_header,
                              normalizers_flair_header=normalizers_flair_header
                              )

def encode_cyclicals_flair_header(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x

X_train_norm_flair_header = encode_cyclicals_flair_header(X_train_norm_flair_heade
r)
X_valid_norm_flair_header = encode_cyclicals_flair_header(X_valid_norm_flair_heade
r)
X_test_norm_flair_header = encode_cyclicals_flair_header(X_test_norm_flair_header)


# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_flair_header = 45
FORECAST_DISTANCE_flair_header = 9

segmenter_flair_header = SegmentXYForecast(width=TIME_WINDOW_flair_header,
                                           step=1,
                                           y_func=last,
                                           forecast=FORECAST_DISTANCE_flair_header
```

```
                                            )

X_train_rolled_flair_header, \
y_train_rolled_flair_header, \
_ = segmenter_flair_header.fit_transform([X_train_norm_flair_header.values],
                                          [y_train_norm_flair_header.flatten()]
                                          )

X_valid_rolled_flair_header, \
y_valid_rolled_flair_header, \
_ = segmenter_flair_header.fit_transform([X_valid_norm_flair_header.values],
                             [y_valid_norm_flair_header.flatten()]
                             )

X_test_rolled_flair_header,\
y_test_rolled_flair_header, \
_ = segmenter_flair_header.fit_transform([X_test_norm_flair_header.values],
                                          [y_test_norm_flair_header.flatten()]
                                          )

# LSTM Model
first_lstm_size_flair_header = 75
second_lstm_size_flair_header = 40
dropout_flair_header = 0.1
EPOCHS_flair_header = 50
BATCH_SIZE_flair_header = 32
column_count_flair_header = len(X_train_norm_flair_header.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_flair_header = Input(shape=(TIME_WINDOW_flair_header, column_count_flai
r_header))
# first LSTM layer
first_lstm_flair_header = LSTM(first_lstm_size_flair_header,
                               return_sequences=True,
                               dropout=dropout_flair_header)(input_layer_flair_head
er)
# second LTSM layer
second_lstm_flair_header = LSTM(second_lstm_size_flair_header,
                                 return_sequences=False,
                                 dropout=dropout_flair_header)(first_lstm_flair_hea
der)
# output layer
output_layer_flair_header = Dense(1)(second_lstm_flair_header)
# creating Model
model_flair_header = Model(inputs=input_layer_flair_header, outputs=output_layer_fl
air_header)
# compile model
model_flair_header.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
model_flair_header.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
# fitting model
hist_flair_header = model_flair_header.fit(x=X_train_rolled_flair_header,
                                           y=y_train_rolled_flair_header,
                                           batch_size=BATCH_SIZE_flair_header,
                                           validation_data=(X_valid_rolled_flair_he
ader,
                                                            y_valid_rolled_flair_he
ader
                                                            ),
                                           epochs=EPOCHS_flair_header,
                                           verbose=1,
```

```
                                            shuffle=False
                                            )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_flair_header.history['loss'], label='train_flair_header')
plt.plot(hist_flair_header.history['val_loss'], label='test_flair_header')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_flair_header = math.sqrt(min(hist_flair_header.history['val_loss']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_flair_header = model_flair_header.predict(X_test_rolled_flair
_header)

predicted_stock_price_flair_header = normalizers_flair_header['OPEN']\
                                      .inverse_transform(predicted_stock_price_flai
r_header).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_flair_header)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_flair_header["OPEN"].inverse_transform(np.array([rms_LSTM_flair_h
eader]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_flair_header)

### analysis with textblob sentiment content
new_df_textblob_content = concatenate_dataframe[['Date',
                                                 'OPEN',
                                                 'HIGH',
                                                 'LOW',
                                                 'CLOSE',
                                                 'VOLUME',
                                                 'polarity_textblob_sentiment_conte
nt']]

new_df_textblob_content['polarity_textblob_sentiment_content'] = new_df_textblob_co
ntent['polarity_textblob_sentiment_content'].fillna(0)
# new_df_textblob_content[['Date',
#                           'OPEN',
#                           'HIGH',
#                           'LOW',
#                           'CLOSE',
#                           'VOLUME',
#                           'polarity_textblob_sentiment_content']].astype(np.float6
4)

new_df_textblob_content['Year'] = pd.DatetimeIndex(new_df_textblob_content['Date
']).year
new_df_textblob_content['Month'] = pd.DatetimeIndex(new_df_textblob_content['Date
']).month
new_df_textblob_content['Day'] = pd.DatetimeIndex(new_df_textblob_content['Date']).
day
```

```
new_df_textblob_content['Hour'] = pd.DatetimeIndex(new_df_textblob_content['Date
']).hour
new_df_textblob_content['Minute'] = pd.DatetimeIndex(new_df_textblob_content['Date
']).minute
new_df_textblob_content['Second'] = pd.DatetimeIndex(new_df_textblob_content['Date
']).second

new_df_textblob_content = new_df_textblob_content.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_textblob_content = 0.1

X_train_textblob_content, \
X_else_textblob_content,\
y_train_textblob_content, \
y_else_textblob_content = train_test_split(new_df_textblob_content,
                                           new_df_textblob_content['OPEN'],
                                           test_size=valid_test_size_split_textblob
_content*2,
                                           shuffle=False)

X_valid_textblob_content, \
X_test_textblob_content, \
y_valid_textblob_content, \
y_test_textblob_content = train_test_split(X_else_textblob_content,
                                           y_else_textblob_content,
                                           test_size=0.5,
                                           shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_textblob_content(df_x, series_y, normalizers_textblob_content = No
ne):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'polarity_textblob_sentiment_content']

    if not normalizers_textblob_content:
        normalizers_textblob_content = {}

    for feat in features_to_minmax:
        if feat not in normalizers_textblob_content:
            normalizers_textblob_content[feat] = MinMaxScaler()
            normalizers_textblob_content[feat].fit(df_x[feat].values.reshape(-1,
1))

        df_x[feat] = normalizers_textblob_content[feat].transform(df_x[feat].value
s.reshape(-1, 1))

    series_y = normalizers_textblob_content['OPEN'].transform(series_y.values.resha
pe(-1, 1))

    return df_x, series_y, normalizers_textblob_content
```

```
X_train_norm_textblob_content, \
y_train_norm_textblob_content, \
normalizers_textblob_content = minmax_scale_textblob_content(X_train_textblob_conte
nt,
                                                              y_train_textblob_conte
nt
                                                              )

X_valid_norm_textblob_content, \
y_valid_norm_textblob_content, \
_ = minmax_scale_textblob_content(X_valid_textblob_content,
                                  y_valid_textblob_content,
                                  normalizers_textblob_content=normalizers_textblob
_content
                                  )

X_test_norm_textblob_content, \
y_test_norm_textblob_content, \
_ = minmax_scale_textblob_content(X_test_textblob_content,
                                  y_test_textblob_content,
                                  normalizers_textblob_content=normalizers_textblob
_content
                                  )

def encode_cyclicals_textblob_content(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x

X_train_norm_textblob_content = encode_cyclicals_textblob_content(X_train_norm_text
blob_content)
X_valid_norm_textblob_content = encode_cyclicals_textblob_content(X_valid_norm_text
blob_content)
X_test_norm_textblob_content = encode_cyclicals_textblob_content(X_test_norm_textbl
ob_content)

# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_textblob_content = 45
FORECAST_DISTANCE_textblob_content = 9
```

```
segmenter_textblob_content = SegmentXYForecast(width=TIME_WINDOW_textblob_content,
                                               step=1,
                                               y_func=last,
                                               forecast=FORECAST_DISTANCE_textblob_
content
                                               )

X_train_rolled_textblob_content, \
y_train_rolled_textblob_content, \
_ = segmenter_textblob_content.fit_transform([X_train_norm_textblob_content.value
s],
                                             [y_train_norm_textblob_content.flatten
()]
                                             )

X_valid_rolled_textblob_content, \
y_valid_rolled_textblob_content, \
_ = segmenter_textblob_content.fit_transform([X_valid_norm_textblob_content.value
s],
                                             [y_valid_norm_textblob_content.flatten
()]
                                             )

X_test_rolled_textblob_content,\
y_test_rolled_textblob_content, \
_ = segmenter_textblob_content.fit_transform([X_test_norm_textblob_content.values],
                                             [y_test_norm_textblob_content.flatten
()]
                                             )

# LSTM Model
first_lstm_size_textblob_content = 75
second_lstm_size_textblob_content = 40
dropout_textblob_content = 0.1
EPOCHS_textblob_content = 50
BATCH_SIZE_textblob_content = 32
column_count_textblob_content = len(X_train_norm_textblob_content.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_textblob_content = Input(shape=(TIME_WINDOW_textblob_content, column_co
unt_textblob_content))
# first LSTM layer
first_lstm_textblob_content = LSTM(first_lstm_size_textblob_content,
                                   return_sequences=True,
                                   dropout=dropout_textblob_content)(input_layer_te
xtblob_content)
# second LTSM layer
second_lstm_textblob_content = LSTM(second_lstm_size_textblob_content,
                                    return_sequences=False,
                                    dropout=dropout_textblob_content)(first_lstm_te
xtblob_content)
# output layer
output_layer_textblob_content = Dense(1)(second_lstm_textblob_content)
# creating Model
model_textblob_content = Model(inputs=input_layer_textblob_content, outputs=output_
layer_textblob_content)
# compile model
model_textblob_content.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
model_textblob_content.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
```

```
# fitting model
hist_textblob_content = model_textblob_content.fit(x=X_train_rolled_textblob_conten
t,
                                                    y=y_train_rolled_textblob_conten
t,
                                                    batch_size=BATCH_SIZE_textblob_c
ontent,
                                                    validation_data=(X_valid_rolled_
textblob_content,
                                                                     y_valid_rolled_
textblob_content
                                                                     ),
                                                    epochs=EPOCHS_textblob_content,
                                                    verbose=1,
                                                    shuffle=False
                                                    )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_textblob_content.history['loss'], label='train_textblob_content')
plt.plot(hist_textblob_content.history['val_loss'], label='test_textblob_content')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_textblob_content = math.sqrt(min(hist_textblob_content.history['val_loss
']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_textblob_content = model_textblob_content.predict(X_test_roll
ed_textblob_content)

predicted_stock_price_textblob_content = normalizers_textblob_content['OPEN']\
                                      .inverse_transform(predicted_stock_price_text
blob_content).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_textblob_content)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_textblob_content["OPEN"].inverse_transform(np.array([rms_LSTM_tex
tblob_content]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_textblob_content)

### analysis with textblob header
new_df_textblob_header = concatenate_dataframe[['Date',
                                                'OPEN',
                                                'HIGH',
                                                'LOW',
                                                'CLOSE',
                                                'VOLUME',
                                                'polarity_textblob_sentiment_header
']]

new_df_textblob_header = new_df_textblob_header.fillna(0)
# new_df_textblob_header[['Date',
```

```
#                          'OPEN',
#                          'HIGH',
#                          'LOW',
#                          'CLOSE',
#                          'VOLUME',
#                          'polarity_textblob_sentiment_header']].astype(np.float64)

new_df_textblob_header['Year'] = pd.DatetimeIndex(new_df_textblob_header['Date']).y
ear
new_df_textblob_header['Month'] = pd.DatetimeIndex(new_df_textblob_header['Date']).
month
new_df_textblob_header['Day'] = pd.DatetimeIndex(new_df_textblob_header['Date']).da
y
new_df_textblob_header['Hour'] = pd.DatetimeIndex(new_df_textblob_header['Date']).h
our
new_df_textblob_header['Minute'] = pd.DatetimeIndex(new_df_textblob_header['Date
']).minute
new_df_textblob_header['Second'] = pd.DatetimeIndex(new_df_textblob_header['Date
']).second

new_df_textblob_header = new_df_textblob_header.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_textblob_header = 0.1

X_train_textblob_header, \
X_else_textblob_header,\
y_train_textblob_header, \
y_else_textblob_header = train_test_split(new_df_textblob_header,
                                          new_df_textblob_header['OPEN'],
                                          test_size=valid_test_size_split_textblob_
header*2,
                                          shuffle=False)

X_valid_textblob_header, \
X_test_textblob_header, \
y_valid_textblob_header, \
y_test_textblob_header = train_test_split(X_else_textblob_header,
                                          y_else_textblob_header,
                                          test_size=0.5,
                                          shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_textblob_header(df_x, series_y, normalizers_textblob_header = Non
e):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'polarity_textblob_sentiment_header']

    if not normalizers_textblob_header:
        normalizers_textblob_header = {}
```

```
    for feat in features_to_minmax:
        if feat not in normalizers_textblob_header:
            normalizers_textblob_header[feat] = MinMaxScaler()
            normalizers_textblob_header[feat].fit(df_x[feat].values.reshape(-1, 1))

        df_x[feat] = normalizers_textblob_header[feat].transform(df_x[feat].values.
reshape(-1, 1))

    series_y = normalizers_textblob_header['OPEN'].transform(series_y.values.reshap
e(-1, 1))

    return df_x, series_y, normalizers_textblob_header

X_train_norm_textblob_header, \
y_train_norm_textblob_header, \
normalizers_textblob_header = minmax_scale_textblob_header(X_train_textblob_header,
                                                           y_train_textblob_header
                                                           )

X_valid_norm_textblob_header, \
y_valid_norm_textblob_header, \
_ = minmax_scale_textblob_header(X_valid_textblob_header,
                                 y_valid_textblob_header,
                                 normalizers_textblob_header=normalizers_textblob_h
eader
                                 )

X_test_norm_textblob_header, \
y_test_norm_textblob_header, \
_ = minmax_scale_textblob_header(X_test_textblob_header,
                                 y_test_textblob_header,
                                 normalizers_textblob_header=normalizers_textblob_h
eader
                                 )

def encode_cyclicals_textblob_header(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x
```

```
X_train_norm_textblob_header = encode_cyclicals_textblob_header(X_train_norm_textbl
ob_header)
X_valid_norm_textblob_header = encode_cyclicals_textblob_header(X_valid_norm_textbl
ob_header)
X_test_norm_textblob_header = encode_cyclicals_textblob_header(X_test_norm_textblob
_header)


# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_textblob_header = 45
FORECAST_DISTANCE_textblob_header = 9

segmenter_textblob_header = SegmentXYForecast(width=TIME_WINDOW_textblob_header,
                                              step=1,
                                              y_func=last,
                                              forecast=FORECAST_DISTANCE_textblob_h
eader
                                              )

X_train_rolled_textblob_header, \
y_train_rolled_textblob_header, \
_ = segmenter_textblob_header.fit_transform([X_train_norm_textblob_header.values],
                                            [y_train_norm_textblob_header.flatten
()]
                                            )

X_valid_rolled_textblob_header, \
y_valid_rolled_textblob_header, \
_ = segmenter_textblob_header.fit_transform([X_valid_norm_textblob_header.values],
                                            [y_valid_norm_textblob_header.flatten
()]
                                            )

X_test_rolled_textblob_header,\
y_test_rolled_textblob_header, \
_ = segmenter_textblob_header.fit_transform([X_test_norm_textblob_header.values],
                                            [y_test_norm_textblob_header.flatten()]
                                            )

# LSTM Model
first_lstm_size_textblob_header = 75
second_lstm_size_textblob_header = 40
dropout_textblob_header = 0.1
EPOCHS_textblob_header = 50
BATCH_SIZE_textblob_header = 32
column_count_textblob_header = len(X_train_norm_textblob_header.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_textblob_header = Input(shape=(TIME_WINDOW_textblob_header, column_coun
t_textblob_header))
# first LSTM layer
first_lstm_textblob_header = LSTM(first_lstm_size_textblob_header,
                                  return_sequences=True,
                                  dropout=dropout_textblob_header)(input_layer_text
blob_header)
# second LTSM layer
second_lstm_textblob_header = LSTM(second_lstm_size_textblob_header,
                                   return_sequences=False,
                                   dropout=dropout_textblob_header)(first_lstm_text
blob_header)
# output layer
output_layer_textblob_header = Dense(1)(second_lstm_textblob_header)
# creating Model
model_textblob_header = Model(inputs=input_layer_textblob_header, outputs=output_la
```

```
yer_textblob_header)
# compile model
model_textblob_header.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
model_textblob_header.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
# fitting model
hist_textblob_header = model_textblob_header.fit(x=X_train_rolled_textblob_header,
                                                 y=y_train_rolled_textblob_header,
                                                 batch_size=BATCH_SIZE_textblob_hea
der,
                                                 validation_data=(X_valid_rolled_te
xtblob_header,
                                                                  y_valid_rolled_te
xtblob_header
                                                                  ),
                                                 epochs=EPOCHS_textblob_header,
                                                 verbose=1,
                                                 shuffle=False
                                                 )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_textblob_header.history['loss'], label='train_textblob_header')
plt.plot(hist_textblob_header.history['val_loss'], label='test_textblob_header')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_textblob_header = math.sqrt(min(hist_textblob_header.history['val_loss']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_textblob_header = model_textblob_header.predict(X_test_rolled
_textblob_header)

predicted_stock_price_textblob_header = normalizers_textblob_header['OPEN']\
                                      .inverse_transform(predicted_stock_price_text
blob_header).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_textblob_header)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_textblob_header["OPEN"].inverse_transform(np.array([rms_LSTM_text
blob_header]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_textblob_header)

### analysis with vader sentiment content
new_df_vader_content = concatenate_dataframe[['Date',
                                              'OPEN',
                                              'HIGH',
                                              'LOW',
                                              'CLOSE',
                                              'VOLUME',
```

```
                                               'compound_vader_articel_content']]

new_df_vader_content['compound_vader_articel_content'] = new_df_vader_content['comp
ound_vader_articel_content'].fillna(0)
# new_df_vader_content[['Date',
#                        'OPEN',
#                        'HIGH',
#                        'LOW',
#                        'CLOSE',
#                        'VOLUME',
#                        'compound_vader_articel_content']].astype(np.float64)

new_df_vader_content['Year'] = pd.DatetimeIndex(new_df_vader_content['Date']).year
new_df_vader_content['Month'] = pd.DatetimeIndex(new_df_vader_content['Date']).mont
h
new_df_vader_content['Day'] = pd.DatetimeIndex(new_df_vader_content['Date']).day
new_df_vader_content['Hour'] = pd.DatetimeIndex(new_df_vader_content['Date']).hour
new_df_vader_content['Minute'] = pd.DatetimeIndex(new_df_vader_content['Date']).min
ute
new_df_vader_content['Second'] = pd.DatetimeIndex(new_df_vader_content['Date']).sec
ond

new_df_vader_content = new_df_vader_content.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_vader_content = 0.1

X_train_vader_content, \
X_else_vader_content,\
y_train_vader_content, \
y_else_vader_content = train_test_split(new_df_vader_content,
                                        new_df_vader_content['OPEN'],
                                        test_size=valid_test_size_split_vader_conte
nt*2,
                                        shuffle=False)

X_valid_vader_content, \
X_test_vader_content, \
y_valid_vader_content, \
y_test_vader_content = train_test_split(X_else_vader_content,
                                        y_else_vader_content,
                                        test_size=0.5,
                                        shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_vader_content(df_x, series_y, normalizers_vader_content = None):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'compound_vader_articel_content']

    if not normalizers_vader_content:
        normalizers_vader_content = {}
```

```
    for feat in features_to_minmax:
        if feat not in normalizers_vader_content:
            normalizers_vader_content[feat] = MinMaxScaler()
            normalizers_vader_content[feat].fit(df_x[feat].values.reshape(-1, 1))

        df_x[feat] = normalizers_vader_content[feat].transform(df_x[feat].values.re
shape(-1, 1))

    series_y = normalizers_vader_content['OPEN'].transform(series_y.values.reshape
(-1, 1))

    return df_x, series_y, normalizers_vader_content

X_train_norm_vader_content, \
y_train_norm_vader_content, \
normalizers_vader_content = minmax_scale_vader_content(X_train_vader_content,
                                                       y_train_vader_content
                                                       )

X_valid_norm_vader_content, \
y_valid_norm_vader_content, \
_ = minmax_scale_vader_content(X_valid_vader_content,
                               y_valid_vader_content,
                               normalizers_vader_content=normalizers_vader_content
                               )

X_test_norm_vader_content, \
y_test_norm_vader_content, \
_ = minmax_scale_vader_content(X_test_vader_content,
                               y_test_vader_content,
                               normalizers_vader_content=normalizers_vader_content
                               )

def encode_cyclicals_vader_content(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x

X_train_norm_vader_content = encode_cyclicals_vader_content(X_train_norm_vader_cont
```

```
ent)
X_valid_norm_vader_content = encode_cyclicals_vader_content(X_valid_norm_vader_cont
ent)
X_test_norm_vader_content = encode_cyclicals_vader_content(X_test_norm_vader_conten
t)


# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_vader_content = 45
FORECAST_DISTANCE_vader_content = 9

segmenter_vader_content = SegmentXYForecast(width=TIME_WINDOW_vader_content,
                                            step=1,
                                            y_func=last,
                                            forecast=FORECAST_DISTANCE_vader_conten
t
                                            )

X_train_rolled_vader_content, \
y_train_rolled_vader_content, \
_ = segmenter_vader_content.fit_transform([X_train_norm_vader_content.values],
                                          [y_train_norm_vader_content.flatten()]
                                          )

X_valid_rolled_vader_content, \
y_valid_rolled_vader_content, \
_ = segmenter_vader_content.fit_transform([X_valid_norm_vader_content.values],
                                          [y_valid_norm_vader_content.flatten()]
                                          )

X_test_rolled_vader_content,\
y_test_rolled_vader_content, \
_ = segmenter_vader_content.fit_transform([X_test_norm_vader_content.values],
                                          [y_test_norm_vader_content.flatten()]
                                          )

# LSTM Model
first_lstm_size_vader_content = 75
second_lstm_size_vader_content = 40
dropout_vader_content = 0.1
EPOCHS_vader_content = 50
BATCH_SIZE_vader_content = 32
column_count_vader_content = len(X_train_norm_vader_content.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_vader_content = Input(shape=(TIME_WINDOW_vader_content, column_count_va
der_content))
# first LSTM layer
first_lstm_vader_content = LSTM(first_lstm_size_vader_content,
                                return_sequences=True,
                                dropout=dropout_vader_content)(input_layer_vader_co
ntent)
# second LTSM layer
second_lstm_vader_content = LSTM(second_lstm_size_vader_content,
                                 return_sequences=False,
                                 dropout=dropout_vader_content)(first_lstm_vader_co
ntent)
# output layer
output_layer_vader_content = Dense(1)(second_lstm_vader_content)
# creating Model
model_vader_content = Model(inputs=input_layer_vader_content, outputs=output_layer_
vader_content)
# compile model
model_vader_content.compile(optimizer='adam', loss='mean_absolute_error')
```

```
# model summary
model_vader_content.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
# fitting model
hist_vader_content = model_vader_content.fit(x=X_train_rolled_vader_content,
                                             y=y_train_rolled_vader_content,
                                             batch_size=BATCH_SIZE_vader_content,
                                             validation_data=(X_valid_rolled_vader_
content,
                                                              y_valid_rolled_vader_
content
                                                              ),
                                             epochs=EPOCHS_vader_content,
                                             verbose=1,
                                             shuffle=False
                                             )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_vader_content.history['loss'], label='train_vader_content')
plt.plot(hist_vader_content.history['val_loss'], label='test_vader_content')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_vader_content = math.sqrt(min(hist_vader_content.history['val_loss']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_vader_content = model_vader_content.predict(X_test_rolled_vad
er_content)

predicted_stock_price_vader_content = normalizers_vader_content['OPEN']\
                                      .inverse_transform(predicted_stock_price_vade
r_content).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_vader_content)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_vader_content["OPEN"].inverse_transform(np.array([rms_LSTM_vader_
content]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_vader_content)

### analysis with vader header
new_df_vader_header = concatenate_dataframe[['Date',
                                             'OPEN',
                                             'HIGH',
                                             'LOW',
                                             'CLOSE',
                                             'VOLUME',
                                             'compound_vader_header']]

new_df_vader_header = new_df_vader_header.fillna(0)
# new_df_vader_header[['Date',
```

```
#                        'OPEN',
#                        'HIGH',
#                        'LOW',
#                        'CLOSE',
#                        'VOLUME',
#                        'compound_vader_header']].astype(np.float64)

new_df_vader_header['Year'] = pd.DatetimeIndex(new_df_vader_header['Date']).year
new_df_vader_header['Month'] = pd.DatetimeIndex(new_df_vader_header['Date']).month
new_df_vader_header['Day'] = pd.DatetimeIndex(new_df_vader_header['Date']).day
new_df_vader_header['Hour'] = pd.DatetimeIndex(new_df_vader_header['Date']).hour
new_df_vader_header['Minute'] = pd.DatetimeIndex(new_df_vader_header['Date']).minut
e
new_df_vader_header['Second'] = pd.DatetimeIndex(new_df_vader_header['Date']).secon
d

new_df_vader_header = new_df_vader_header.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_vader_header = 0.1

X_train_vader_header, \
X_else_vader_header,\
y_train_vader_header, \
y_else_vader_header = train_test_split(new_df_vader_header,
                                       new_df_vader_header['OPEN'],
                                       test_size=valid_test_size_split_vader_header
*2,
                                       shuffle=False)

X_valid_vader_header, \
X_test_vader_header, \
y_valid_vader_header, \
y_test_vader_header = train_test_split(X_else_vader_header,
                                       y_else_vader_header,
                                       test_size=0.5,
                                       shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_vader_header(df_x, series_y, normalizers_vader_header = None):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME',
                          'compound_vader_header']

    if not normalizers_vader_header:
        normalizers_vader_header = {}

    for feat in features_to_minmax:
        if feat not in normalizers_vader_header:
            normalizers_vader_header[feat] = MinMaxScaler()
            normalizers_vader_header[feat].fit(df_x[feat].values.reshape(-1, 1))
```

```
        df_x[feat] = normalizers_vader_header[feat].transform(df_x[feat].values.res
hape(-1, 1))

    series_y = normalizers_vader_header['OPEN'].transform(series_y.values.reshape(-
1, 1))

    return df_x, series_y, normalizers_vader_header

X_train_norm_vader_header, \
y_train_norm_vader_header, \
normalizers_vader_header = minmax_scale_vader_header(X_train_vader_header,
                                                     y_train_vader_header
                                                     )

X_valid_norm_vader_header, \
y_valid_norm_vader_header, \
_ = minmax_scale_vader_header(X_valid_vader_header,
                              y_valid_vader_header,
                              normalizers_vader_header=normalizers_vader_header
                              )

X_test_norm_vader_header, \
y_test_norm_vader_header, \
_ = minmax_scale_vader_header(X_test_vader_header,
                              y_test_vader_header,
                              normalizers_vader_header=normalizers_vader_header
                              )

def encode_cyclicals_vader_header(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)

    return df_x

X_train_norm_vader_header = encode_cyclicals_vader_header(X_train_norm_vader_heade
r)
X_valid_norm_vader_header = encode_cyclicals_vader_header(X_valid_norm_vader_heade
r)
X_test_norm_vader_header = encode_cyclicals_vader_header(X_test_norm_vader_header)


# Creating target (y) and "windows" (X) for modeling
```

```
TIME_WINDOW_vader_header = 45
FORECAST_DISTANCE_vader_header = 9

segmenter_vader_header = SegmentXYForecast(width=TIME_WINDOW_vader_header,
                                           step=1,
                                           y_func=last,
                                           forecast=FORECAST_DISTANCE_vader_header
                                           )

X_train_rolled_vader_header, \
y_train_rolled_vader_header, \
_ = segmenter_vader_header.fit_transform([X_train_norm_vader_header.values],
                                         [y_train_norm_vader_header.flatten()]
                                         )

X_valid_rolled_vader_header, \
y_valid_rolled_vader_header, \
_ = segmenter_vader_header.fit_transform([X_valid_norm_vader_header.values],
                                         [y_valid_norm_vader_header.flatten()]
                                         )

X_test_rolled_vader_header,\
y_test_rolled_vader_header, \
_ = segmenter_vader_header.fit_transform([X_test_norm_vader_header.values],
                                         [y_test_norm_vader_header.flatten()]
                                         )

# LSTM Model
first_lstm_size_vader_header = 75
second_lstm_size_vader_header = 40
dropout_vader_header = 0.1
EPOCHS_vader_header = 50
BATCH_SIZE_vader_header = 32
column_count_vader_header = len(X_train_norm_vader_header.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_vader_header = Input(shape=(TIME_WINDOW_vader_header, column_count_vade
r_header))
# first LSTM layer
first_lstm_vader_header = LSTM(first_lstm_size_vader_header,
                               return_sequences=True,
                               dropout=dropout_vader_header)(input_layer_vader_head
er)
# second LTSM layer
second_lstm_vader_header = LSTM(second_lstm_size_vader_header,
                                return_sequences=False,
                                dropout=dropout_vader_header)(first_lstm_vader_head
er)
# output layer
output_layer_vader_header = Dense(1)(second_lstm_vader_header)
# creating Model
model_vader_header = Model(inputs=input_layer_vader_header, outputs=output_layer_va
der_header)
# compile model
model_vader_header.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
model_vader_header.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
# fitting model
hist_vader_header = model_vader_header.fit(x=X_train_rolled_vader_header,
                                           y=y_train_rolled_vader_header,
                                           batch_size=BATCH_SIZE_vader_header,
```

```
                                          validation_data=(X_valid_rolled_vader_he
ader,
                                                           y_valid_rolled_vader_he
ader
                                                           ),
                                          epochs=EPOCHS_vader_header,
                                          verbose=1,
                                          shuffle=False
                                          )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_vader_header.history['loss'], label='train_vader_header')
plt.plot(hist_vader_header.history['val_loss'], label='test_vader_header')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_vader_header = math.sqrt(min(hist_vader_header.history['val_loss']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_vader_header = model_vader_header.predict(X_test_rolled_vader
_header)

predicted_stock_price_vader_header = normalizers_vader_header['OPEN']\
                                     .inverse_transform(predicted_stock_price_vade
r_header).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_vader_header)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_vader_header["OPEN"].inverse_transform(np.array([rms_LSTM_vader_h
eader]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_vader_header)

### analysis with without semantics
new_df_without_semantics = concatenate_dataframe[['Date',
                                                  'OPEN',
                                                  'HIGH',
                                                  'LOW',
                                                  'CLOSE',
                                                  'VOLUME']]

new_df_without_semantics = new_df_without_semantics.fillna(0)
# new_df_without_semantics[['Date',
#                            'OPEN',
#                            'HIGH',
#                            'LOW',
#                            'CLOSE',
#                            'VOLUME']].astype(np.float64)

new_df_without_semantics['Year'] = pd.DatetimeIndex(new_df_without_semantics['Date
']).year
new_df_without_semantics['Month'] = pd.DatetimeIndex(new_df_without_semantics['Date
']).month
```

```
new_df_without_semantics['Day'] = pd.DatetimeIndex(new_df_without_semantics['Date
']).day
new_df_without_semantics['Hour'] = pd.DatetimeIndex(new_df_without_semantics['Date
']).hour
new_df_without_semantics['Minute'] = pd.DatetimeIndex(new_df_without_semantics['Dat
e']).minute
new_df_without_semantics['Second'] = pd.DatetimeIndex(new_df_without_semantics['Dat
e']).second

new_df_without_semantics = new_df_without_semantics.drop(['Date'], axis=1)

# train, valid, test split
valid_test_size_split_without_semantics = 0.1

X_train_without_semantics, \
X_else_without_semantics,\
y_train_without_semantics, \
y_else_without_semantics = train_test_split(new_df_without_semantics,
                                            new_df_without_semantics['OPEN'],
                                            test_size=valid_test_size_split_without
_semantics*2,
                                            shuffle=False)

X_valid_without_semantics, \
X_test_without_semantics, \
y_valid_without_semantics, \
y_test_without_semantics = train_test_split(X_else_without_semantics,
                                            y_else_without_semantics,
                                            test_size=0.5,
                                            shuffle=False)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)


# normalize data
def minmax_scale_without_semantics(df_x, series_y, normalizers_without_semantics =
None):
    features_to_minmax = ['Year',
                          'Month',
                          'Day',
                          'Hour',
                          'Minute',
                          'Second',
                          'OPEN',
                          'HIGH',
                          'LOW',
                          'CLOSE',
                          'VOLUME']

    if not normalizers_without_semantics:
        normalizers_without_semantics = {}

    for feat in features_to_minmax:
        if feat not in normalizers_without_semantics:
            normalizers_without_semantics[feat] = MinMaxScaler()
            normalizers_without_semantics[feat].fit(df_x[feat].values.reshape(-1,
1))

        df_x[feat] = normalizers_without_semantics[feat].transform(df_x[feat].value
s.reshape(-1, 1))

    series_y = normalizers_without_semantics['OPEN'].transform(series_y.values.resh
ape(-1, 1))
```

```
    return df_x, series_y, normalizers_without_semantics

X_train_norm_without_semantics, \
y_train_norm_without_semantics, \
normalizers_without_semantics = minmax_scale_without_semantics(X_train_without_sema
ntics,
                                                                y_train_without_sema
ntics
                                                                )

X_valid_norm_without_semantics, \
y_valid_norm_without_semantics, \
_ = minmax_scale_without_semantics(X_valid_without_semantics,
                                   y_valid_without_semantics,
                                   normalizers_without_semantics=normalizers_withou
t_semantics
                                   )

X_test_norm_without_semantics, \
y_test_norm_without_semantics, \
_ = minmax_scale_without_semantics(X_test_without_semantics,
                                   y_test_without_semantics,
                                   normalizers_without_semantics=normalizers_withou
t_semantics
                                   )

def encode_cyclicals_without_semantics(df_x):
    # "month","day","hour", "cdbw", "dayofweek"

    #DIRECTIONS = {"N": 1.0, "NE": 2.0, "E": 3.0, "SE": 4.0, "S": 5.0, "SW": 6.0, "
W": 7.0, "NW": 8.0, "cv": np.nan}

    df_x['month_sin'] = np.sin(2 * np.pi * df_x.Month / 12)
    df_x['month_cos'] = np.cos(2 * np.pi * df_x.Month / 12)
    df_x.drop('Month', axis=1, inplace=True)

    df_x['day_sin'] = np.sin(2 * np.pi * df_x.Day / 31)
    df_x['day_cos'] = np.cos(2 * np.pi * df_x.Day / 31)
    df_x.drop('Day', axis=1, inplace=True)

    df_x['hour_sin'] = np.sin(2 * np.pi * df_x.Hour / 24)
    df_x['hour_cos'] = np.cos(2 * np.pi * df_x.Hour / 24)
    df_x.drop('Hour', axis=1, inplace=True)

    df_x['min_sin'] = np.sin(2 * np.pi * df_x.Minute / 60)
    df_x['min_cos'] = np.cos(2 * np.pi * df_x.Minute / 60)
    df_x.drop('Minute', axis=1, inplace=True)

    df_x['sec_sin'] = np.sin(2 * np.pi * df_x.Second / 60)
    df_x['sec_cos'] = np.cos(2 * np.pi * df_x.Second / 60)
    df_x.drop('Second', axis=1, inplace=True)


    return df_x

X_train_norm_without_semantics = encode_cyclicals_without_semantics(X_train_norm_wi
thout_semantics)
X_valid_norm_without_semantics = encode_cyclicals_without_semantics(X_valid_norm_wi
thout_semantics)
X_test_norm_without_semantics = encode_cyclicals_without_semantics(X_test_norm_with
out_semantics)


# Creating target (y) and "windows" (X) for modeling
```

```
TIME_WINDOW_without_semantics = 45
FORECAST_DISTANCE_without_semantics = 9

segmenter_without_semantics = SegmentXYForecast(width=TIME_WINDOW_without_semantic
s,
                                                step=1,
                                                y_func=last,
                                                forecast=FORECAST_DISTANCE_without_
semantics
                                                )

X_train_rolled_without_semantics, \
y_train_rolled_without_semantics, \
_ = segmenter_without_semantics.fit_transform([X_train_norm_without_semantics.value
s],
                                              [y_train_norm_without_semantics.flatt
en()]
                                              )

X_valid_rolled_without_semantics, \
y_valid_rolled_without_semantics, \
_ = segmenter_without_semantics.fit_transform([X_valid_norm_without_semantics.value
s],
                                              [y_valid_norm_without_semantics.flatt
en()]
                                              )

X_test_rolled_without_semantics,\
y_test_rolled_without_semantics, \
_ = segmenter_without_semantics.fit_transform([X_test_norm_without_semantics.value
s],
                                              [y_test_norm_without_semantics.flatte
n()]
                                              )

# LSTM Model
first_lstm_size_without_semantics = 75
second_lstm_size_without_semantics = 40
dropout_without_semantics = 0.1
EPOCHS_without_semantics = 50
BATCH_SIZE_without_semantics = 32
column_count_without_semantics = len(X_train_norm_without_semantics.columns)
# model with use of Funcational API of Keras
# input layer
input_layer_without_semantics = Input(shape=(TIME_WINDOW_without_semantics, column_
count_without_semantics))
# first LSTM layer
first_lstm_without_semantics = LSTM(first_lstm_size_without_semantics,
                                    return_sequences=True,
                                    dropout=dropout_without_semantics)(input_layer_
without_semantics)
# second LTSM layer
second_lstm_without_semantics = LSTM(second_lstm_size_without_semantics,
                                     return_sequences=False,
                                     dropout=dropout_without_semantics)(first_lstm_
without_semantics)
# output layer
output_layer_without_semantics = Dense(1)(second_lstm_without_semantics)
# creating Model
model_without_semantics = Model(inputs=input_layer_without_semantics, outputs=outpu
t_layer_without_semantics)
# compile model
model_without_semantics.compile(optimizer='adam', loss='mean_absolute_error')
# model summary
```

```
model_without_semantics.summary()
print(' ')
print("----------------------------------------------------------------")
print(' ')
# fitting model
hist_without_semantics = model_without_semantics.fit(x=X_train_rolled_without_seman
tics,
                                                     y=y_train_rolled_without_seman
tics,
                                                     batch_size=BATCH_SIZE_without_
semantics,
                                                     validation_data=(X_valid_rolle
d_without_semantics,
                                                                      y_valid_rolle
d_without_semantics
                                                                      ),
                                                     epochs=EPOCHS_without_semantic
s,
                                                     verbose=1,
                                                     shuffle=False
                                                     )
print(' ')
print("----------------------------------------------------------------")
print(' ')

plt.plot(hist_without_semantics.history['loss'], label='train_without_semantics')
plt.plot(hist_without_semantics.history['val_loss'], label='test_without_semantics
')
plt.legend()
plt.show()
print(' ')
print("----------------------------------------------------------------")
print(' ')
rms_LSTM_without_semantics = math.sqrt(min(hist_without_semantics.history['val_loss
']))
print(' ')
print("----------------------------------------------------------------")
print(' ')
# predicting stock prices
predicted_stock_price_without_semantics = model_without_semantics.predict(X_test_ro
lled_without_semantics)

predicted_stock_price_without_semantics = normalizers_without_semantics['OPEN']\
                                      .inverse_transform(predicted_stock_price_with
out_semantics).reshape(-1, 1)
print(' ')
print("Root mean squared error on valid:", rms_LSTM_without_semantics)
print(' ')
print("----------------------------------------------------------------")
print(' ')
print("Root mean squared error on valid inverse transformed from normalization:",
      normalizers_without_semantics["OPEN"].inverse_transform(np.array([rms_LSTM_wi
thout_semantics]).reshape(1, -1)))
print(' ')
print("----------------------------------------------------------------")
print(' ')
print(predicted_stock_price_without_semantics)

plt.figure(figsize=(10,5))
#plt.plot(X_test, color='black', label='daimler Stock Price')
plt.plot(predicted_stock_price_flair_content, color='green', label='Predicted Daiml
er Stock Price with flair content analysis')
plt.plot(predicted_stock_price_flair_header, color='red', label='Predicted Daimler
Stock Price with flair header analysis')
```

```
plt.plot(predicted_stock_price_textblob_header, color='yellow', label='Predicted Da
imler Stock Price with textblob header analysis')
plt.plot(predicted_stock_price_textblob_content, color='blue', label='Predicted Dai
mler Stock Price with textblob content analysis')
plt.plot(predicted_stock_price_vader_content, color='cyan', label='Predicted Daimle
r Stock Price with vader content analysis')
plt.plot(predicted_stock_price_vader_header, color='magenta', label='Predicted Daim
ler Stock Price with vader header analysis')
plt.plot(predicted_stock_price_without_semantics, color='orange', label='Predicted
Daimler Stock Price without semantics analysis')
#plt.rcParams['figure.facecolor'] = 'salmon'
plt.title('Daimler Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Daimler Stock Price')
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.005), borderaxespad=8)
date_today = str(datetime.now().strftime("%Y%m%d"))
plt.savefig(r'C:\Users\victo\Master_Thesis\stockprice_prediction\LSTM\daimler\hourl
y\prediction_daimler_' + date_today + '.png',
            bbox_inches="tight",
            dpi=100,
            pad_inches=1.5)
plt.show()


print('Run is finished and plot is saved!')
```