

```
In [ ]: ###necessary libraries###
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\bmw\minutely\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 = new_df_flair_content.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']).month
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']).minute
new_df_flair_content['Second'] = pd.DatetimeIndex(new_df_flair_content['Date']).second

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_content*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.reshape(-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 = 60
FORECAST_DISTANCE_flair_content = 30

```

```

segmenter_flair_content = SegmentXYForecast(width=TIME_WINDOW_flair_content,
                                             step=1,
                                             y_func=last,
                                             forecast=FORECAST_DISTANCE_flair_content
                                             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 = 10
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_flair_content))
# first LSTM layer
first_lstm_flair_content = LSTM(first_lstm_size_flair_content,
                                return_sequences=True,
                                dropout=dropout_flair_content)(input_layer_flair_content)
# second LSTM layer
second_lstm_flair_content = LSTM(second_lstm_size_flair_content,
                                return_sequences=False,
                                dropout=dropout_flair_content)(first_lstm_flair_content)
# 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,

```

```

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_flair_content)

predicted_stock_price_flair_content = normalizers_flair_content['OPEN']\
                                    .inverse_transform(predicted_stock_price_flair_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 = new_df_flair_header.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']).minute
new_df_flair_header['Second'] = pd.DatetimeIndex(new_df_flair_header['Date']).second

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.reshape(-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_header)
X_valid_norm_flair_header = encode_cyclicals_flair_header(X_valid_norm_flair_header)
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 = 60
FORECAST_DISTANCE_flair_header = 30

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 = 10
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_flair_header))
# first LSTM layer
first_lstm_flair_header = LSTM(first_lstm_size_flair_header,
                               return_sequences=True,
                               dropout=dropout_flair_header)(input_layer_flair_header)
# second LSTM layer
second_lstm_flair_header = LSTM(second_lstm_size_flair_header,
                                return_sequences=False,
                                dropout=dropout_flair_header)(first_lstm_flair_header)
# 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_flair_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_header,
                                                             y_valid_rolled_flair_header),
                                           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 = new_df_textblob_content.fillna(0)
# new_df_textblob_content[['Date',
#                          'OPEN',
#                          'HIGH',
#                          'LOW',
#                          'CLOSE',
#                          'VOLUME',
#                          'polarity_textblob_sentiment_content']].astype(np.float64)

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

```

```

    ')).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_content,
                                                             y_train_textblob_content)

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_textblob_content)
X_valid_norm_textblob_content = encode_cyclicals_textblob_content(X_valid_norm_textblob_content)
X_test_norm_textblob_content = encode_cyclicals_textblob_content(X_test_norm_textblob_content)

# Creating target (y) and "windows" (X) for modeling
TIME_WINDOW_textblob_content = 60
FORECAST_DISTANCE_textblob_content = 30

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 = 10
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,

```

```

t,
content,
textblob_content,
textblob_content

y=y_train_rolled_textblob_content
batch_size=BATCH_SIZE_textblob_content
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_rolled_textblob_content)

predicted_stock_price_textblob_content = normalizers_textblob_content['OPEN']\
.inverse_transform(predicted_stock_price_textblob_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_textblob_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']).year
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']).day
new_df_textblob_header['Hour'] = pd.DatetimeIndex(new_df_textblob_header['Date']).hour
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 = None):
    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.reshape(-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 = 60
FORECAST_DISTANCE_textblob_header = 30

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

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 = 10
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_count_textblob_header))
# first LSTM layer
first_lstm_textblob_header = LSTM(first_lstm_size_textblob_header,
                                  return_sequences=True,
                                  dropout=dropout_textblob_header)(input_layer_textblob_header)
# second LTSM layer
second_lstm_textblob_header = LSTM(second_lstm_size_textblob_header,
                                   return_sequences=False,
                                   dropout=dropout_textblob_header)(first_lstm_textblob_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_layer_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_header,
                                                  validation_data=(X_valid_rolled_textblob_header,
                                                                y_valid_rolled_textblob_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_textblob_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_textblob_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 = new_df_vader_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']).month
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']).minute
new_df_vader_content['Second'] = pd.DatetimeIndex(new_df_vader_content['Date']).second

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_content*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 = 60
FORECAST_DISTANCE_vader_content = 30

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

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 = 10
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_vader_content))
# first LSTM layer
first_lstm_vader_content = LSTM(first_lstm_size_vader_content,
                                return_sequences=True,
                                dropout=dropout_vader_content)(input_layer_vader_content)
# second LSTM layer
second_lstm_vader_content = LSTM(second_lstm_size_vader_content,
                                return_sequences=False,
                                dropout=dropout_vader_content)(first_lstm_vader_content)
# 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']).minute
new_df_vader_header['Second'] = pd.DatetimeIndex(new_df_vader_header['Date']).second

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.reshape(-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_header)
X_valid_norm_vader_header = encode_cyclicals_vader_header(X_valid_norm_vader_header)
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 = 60
FORECAST_DISTANCE_vader_header = 30

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 = 10
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_vader_header))
# first LSTM layer
first_lstm_vader_header = LSTM(first_lstm_size_vader_header,
                                return_sequences=True,
                                dropout=dropout_vader_header)(input_layer_vader_header)
# second LSTM layer
second_lstm_vader_header = LSTM(second_lstm_size_vader_header,
                                return_sequences=False,
                                dropout=dropout_vader_header)(first_lstm_vader_header)
# 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_vader_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_header,
                                                             y_valid_rolled_vader_header))

```



```

        ),
        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_vader_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_header]).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['Date']).minute
new_df_without_semantics['Second'] = pd.DatetimeIndex(new_df_without_semantics['Date']).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.res
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 = 60
FORECAST_DISTANCE_without_semantics = 30

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 = 10
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 LSTM 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=output_
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_semantics,
                                                    y=y_train_rolled_without_semantics,
                                                    batch_size=BATCH_SIZE_without_semantics,
                                                    validation_data=(X_valid_rolled_without_semantics,
                                                                    y_valid_rolled_without_semantics),
                                                    epochs=EPOCHS_without_semantics,
                                                    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_rolled_without_semantics)

predicted_stock_price_without_semantics = normalizers_without_semantics['OPEN']\
                                          .inverse_transform(predicted_stock_price_without_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_without_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='bmw Stock Price')
plt.plot(predicted_stock_price_flair_content, color='green', label='Predicted BMW Stock Price with flair content analysis')
plt.plot(predicted_stock_price_flair_header, color='red', label='Predicted BMW Stock Price with flair header analysis')
plt.plot(predicted_stock_price_textblob_header, color='yellow', label='Predicted BMW Stock Price with textblob header analysis')
plt.plot(predicted_stock_price_textblob_content, color='blue', label='Predicted BMW Stock Price with textblob content analysis')

```

```
plt.plot(predicted_stock_price_vader_content, color='cyan', label='Predicted BMW Stock Price with vader content analysis')
plt.plot(predicted_stock_price_vader_header, color='magenta', label='Predicted BMW Stock Price with vader header analysis')
plt.plot(predicted_stock_price_without_semantics, color='orange', label='Predicted BMW Stock Price without semantics analysis')
#plt.rcParams['figure.facecolor'] = 'salmon'
plt.title('BMW Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('BMW 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\bmw\minutely\prediction_bmw_' + date_today + '.png',
            bbox_inches="tight",
            dpi=100,
            pad_inches=1.5)

plt.show()

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