mtncse8ne

September 7, 2024

1

[ ]:
```
import tensorflow as tf
from scipy.io import loadmat
import matplotlib.pyplot as plt
import numpy as np
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Dense, Flatten, Conv1D, MaxPooling1D,␣
 ↪Dropout, BatchNormalization, LSTM, Reshape
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
import os
import pandas as pd
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from tensorflow.keras.losses import Huber
from tensorflow.keras.regularizers import l2
from tensorflow.keras.initializers import HeNormal
import time
import datetime
from pandas.tseries.offsets import DateOffset
#from sktime.utils.plotting import plot_series
```

[ ]:
```
# Run this cell to connect to your Drive folder

from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

[ ]:
```
#from google.colab import files
#uploaded = files.upload()
```

[ ]:
```
df_forFCST = pd.read_csv(  r'/content/gdrive/MyDrive/DataStore/salesD_smoothed.
 ↪csv' )
```

```
#df_forFCST = pd.read_csv(  r'/content/gdrive/MyDrive/DataStore/   ␣
 ↪salesD_smoothed (1) - salesD_smoothed (1).csv (1).csv')
# Create a BytesIO object from the uploaded file
#file_content = io.BytesIO(uploaded['salesD_smoothed (1).csv'])


df_forFCST.set_index( 'ds', inplace = True )
df_forFCST.index = pd.to_datetime( df_forFCST.index )
df_forFCST.index
print(df_forFCST['y_mix'])
```

```
ds
2019-01-01    135.893037
2019-01-02     45.361847
2019-01-03     74.523035
2019-01-04    108.004398
2019-01-05     71.282903
                 …
2024-07-27    100.898801
2024-07-28     83.893385
2024-07-29    362.231558
2024-07-30    411.531065
2024-07-31    409.263676
Name: y_mix, Length: 2039, dtype: float64
```

[ ]:

```
def windowed_dataset( series, window_size, batch_size ):
    """Generates dataset windows

    Args:
      series (array of float) - contains the values of the time series
      window_size (int) - the number of time steps to include in the feature
      batch_size (int) - the batch size
      shuffle_buffer(int) - buffer size to use for the shuffle method

    Returns:
      dataset (TF Dataset) - TF Dataset containing time windows
    """

    # Generate a TF Dataset from the series values
    dataset = tf.data.Dataset.from_tensor_slices(series)

    # Window the data but only take those with the specified size
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)

    # Flatten the windows by putting its elements in a single batch
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    # Create tuples with features and labels
    dataset = dataset.map(lambda window: (window[:-1], window[-1, 0])) # Extract 'y_mix' as the label

    # Create batches of windows
    # dataset = dataset.batch( batch_size ).prefetch(1)
    dataset = dataset.batch(batch_size, drop_remainder=True).prefetch(1)

    return dataset

# Visualizes time series data
def plot_series(x, y, format="-", start=0, end=None,
                title=None, xlabel=None, ylabel=None, legend=None ):
    """
    Visualizes time series data

    Args:
      x (array of int) - contains values for the x-axis
      y (array of int or tuple of arrays) - contains the values for the y-axis
      format (string) - line style when plotting the graph
      label (string) - tag for the line
      start (int) - first time step to plot
      end (int) - last time step to plot
      title (string) - title of the plot
      xlabel (string) - label for the x-axis
      ylabel (string) - label for the y-axis
      legend (list of strings) - legend for the plot
    """

    # Setup dimensions of the graph figure
    plt.figure(figsize=(8, 4))

    # Check if there are more than two series to plot
    if type(y) is tuple:

      # Loop over the y elements
      for y_curr in y:

        # Plot the x and current y values
        plt.plot(x[start:end], y_curr[start:end], format)

    else:
      # Plot the x and y values
      plt.plot(x[start:end], y[start:end], format)

    # Label the x-axis
    plt.xlabel(xlabel)
    # Label the y-axis
    plt.ylabel(ylabel)

    # Set the legend
    if legend:
      plt.legend(legend)

    # Set the title
    plt.title(title)

    # Overlay a grid on the graph
    plt.grid(True)

    # Draw the graph on screen
    plt.show()

# Feature engineering after split
def add_time_features( df, max_mix ):
  df = df.copy()
  # max_mix = df.y_mix.max()
  df['y_mix'] = df.y_mix / max_mix
  df['month_number'] = df.index.month / df.index.month.max()
  df['day_of_week'] = df.index.dayofweek / df.index.dayofweek.max()
  df['day_of_month'] = df.index.day / df.index.day.max()
  return df
```

[ ]:

```
def get_model(input_shape, wd = 5e-3, dp = 0.5):
    model = Sequential([
        tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                      activation="relu",
                      input_shape=input_shape, kernel_initializer=HeNormal()),
  tf.keras.layers.LSTM(64, return_sequences=True, kernel_regularizer=l2(wd)),
        Dropout(dp),
  tf.keras.layers.LSTM(64, return_sequences=True, kernel_regularizer=l2(wd)),
        Dropout(dp),
  tf.keras.layers.LSTM(64, return_sequences=True, kernel_regularizer=l2(wd)),
  tf.keras.layers.LSTM(64, kernel_regularizer=l2(wd)),
  tf.keras.layers.Dense(1)
    ])
    return model
```

[ ]:

```
def get_compile(model, lrate = 3e-4):
    optimizer = tf.keras.optimizers.SGD(momentum=0.9, learning_rate=lrate)

    model.compile(optimizer=optimizer,
              #loss='huber',
                loss = 'mae',
                  metrics = ['mae', 'mse'])

def get_checkpoint_every_epoch():
    return ModelCheckpoint(
        filepath='/content/gdrive/MyDrive/var/FTryModel/checkpoints_every_epoch/
 ↪checkpoint_{epoch:03d}.weights.h5',
        save_weights_only=True,
        save_freq='epoch',
    )

def get_checkpoint_best_only():
    return ModelCheckpoint(
        filepath='/content/gdrive/MyDrive/var/FTryModel/checkpoints_best_only/
 ↪checkpoint.weights.h5',
        save_weights_only=True,
        monitor='loss',
        save_best_only=True,
        mode='min',
    )

def get_early_stopping():
    return EarlyStopping(monitor='loss', patience=5, mode='min', min_delta=0.
 ↪005)

def get_lr_schedule():
    lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-9 * 10**(epoch / 15))
    return lr_schedule
```

[ ]:

```
# Split data first
split_dateSm = pd.to_datetime( '2024-04-30' )
train_dfSm = df_forFCST[ df_forFCST.index <= split_dateSm ]
# valid_dfSm = df_forFCST[ df_forFCST.index > split_dateSm ]


max_mix = df_forFCST[ df_forFCST.index <= split_dateSm ]['y_mix'].max()
train_dfSm = add_time_features( train_dfSm, max_mix )
# valid_dfSm = add_time_features( valid_dfSm, max_mix )

# Form numpy arrays
time_trainSm = np.array( train_dfSm.reset_index()['ds'] )
x_trainSm = np.array( train_dfSm[['y_mix', 'month_number', 'day_of_week',␣
 ↪'day_of_month']] )

# time_validSm = np.array( valid_dfSm.reset_index()['ds'])
# x_validSm = np.array( valid_dfSm[['y_mix', 'month_number', 'day_of_week',␣
 ↪'day_of_month']] )
print(len(x_trainSm))
```

```
1947
```

[ ]:
```
checkpoint_every_epoch = get_checkpoint_every_epoch()
checkpoint_best_only = get_checkpoint_best_only()
early_stopping = get_early_stopping()
lr_shed = get_lr_schedule()
callbacks = [checkpoint_every_epoch, checkpoint_best_only, early_stopping]
callbacks = [lr_shed]
```

[ ]:
```
batchs = 64
window_size = 360
input_shape = (window_size, x_trainSm.shape[1])
tf.keras.backend.clear_session()

model = get_model(input_shape)
get_compile(model)
#model.summary()

#validation_data = (X_val, y_val)

dataset = windowed_dataset(x_trainSm, window_size, batchs)
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Model: "sequential"



 Layer (type)                          Output Shape                        ␣
↪Param #

 conv1d (Conv1D)                       (None, 358, 64)                       ␣
↪832

 lstm (LSTM)                           (None, 358, 64)                     ␣
↪33,024

 lstm_1 (LSTM)                         (None, 358, 64)                     ␣
↪33,024
```

```
lstm_2 (LSTM)                        (None, 358, 64)                      ␣
↪33,024

lstm_3 (LSTM)                        (None, 64)                           ␣
↪33,024

dropout (Dropout)                    (None, 64)                             ␣
↪  0

dense (Dense)                        (None, 1)                              ␣
↪ 65
```

```
Total params: 132,993 (519.50 KB)

Trainable params: 132,993 (519.50 KB)

Non-trainable params: 0 (0.00 B)
```

2

[ ]:

```
# Train the model

history = model.fit(dataset, epochs = 7, verbose = 2, shuffle = False)
```

```
Epoch 1/7
24/24 - 33s - 1s/step - loss: 0.2711 - mae: 0.2602 - mse: 0.1005
Epoch 2/7
```

```
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can generate at
least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()`
function when building your dataset.
  self.gen.throw(typ, value, traceback)
```

```
24/24 - 37s - 2s/step - loss: 0.1588 - mae: 0.1525 - mse: 0.0366
Epoch 3/7
24/24 - 41s - 2s/step - loss: 0.1535 - mae: 0.1473 - mse: 0.0331
Epoch 4/7
24/24 - 41s - 2s/step - loss: 0.1546 - mae: 0.1484 - mse: 0.0332
Epoch 5/7
24/24 - 41s - 2s/step - loss: 0.1541 - mae: 0.1480 - mse: 0.0336
Epoch 6/7
24/24 - 41s - 2s/step - loss: 0.1543 - mae: 0.1482 - mse: 0.0335
```

```
Epoch 7/7
24/24 - 41s - 2s/step - loss: 0.1539 - mae: 0.1478 - mse: 0.0332
```

[ ]:

```
# TEST PREDICTION

# Split data first
split_dateSm = pd.to_datetime( '2024-04-30' )
upper_boundary = pd.to_datetime( '2024-07-31' )
train_dfSm = df_forFCST[ df_forFCST.index <= split_dateSm ]
valid_dfSm = df_forFCST[ ( df_forFCST.index > split_dateSm ) & ( df_forFCST.
 ↪index <= upper_boundary ) ]

# max_mix = df_forFCST[ df_forFCST.index <= split_dateSm ]['y_mix'].max()
max_mix = 679.8297498652444
train_dfSm = add_time_features( train_dfSm, max_mix )
valid_dfSm = add_time_features( valid_dfSm, max_mix )

# Form numpy arrays
time_trainSm = np.array( train_dfSm.reset_index()['ds'] )
x_trainSm = np.array( train_dfSm[['y_mix', 'month_number', 'day_of_week',␣
 ↪'day_of_month']] )

time_validSm = np.array( valid_dfSm.reset_index()['ds'])
x_validSm = np.array( valid_dfSm[['y_mix', 'month_number', 'day_of_week',␣
 ↪'day_of_month']] )
```

[ ]:

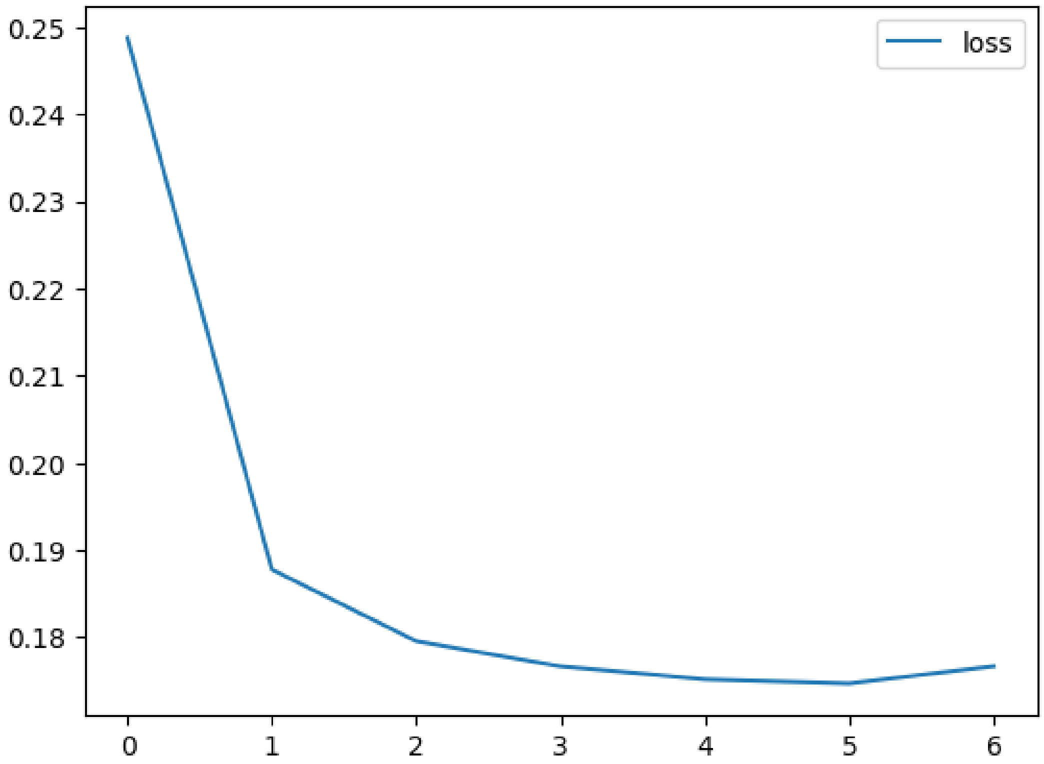
```
# Reduce the original series
forecast_series = x_trainSm[-window_size:]


forecast_period = ( pd.to_datetime( time_validSm[-1] ) - pd.to_datetime(␣
 ↪time_validSm[0] ) ).days + 1
final_result = np.empty( shape = (1, 1) )

for period in range( forecast_period ):

    forecast = model.predict( forecast_series[np.newaxis], verbose=0 )
    results = forecast.squeeze()

    forecast_date = time_validSm[0] + pd.Timedelta(days=period)
    month_num = forecast_date.month / 12
    day_of_week = forecast_date.dayofweek / 6
    day_of_month = forecast_date.day / 31

    # Append the new prediction and features
    forecast_series = np.append( forecast_series,
                                   [[ results, month_num, day_of_week,␣
 ↪day_of_month ]], axis=0)
    final_result = np.append( final_result, results )

    # Remove the oldest data point
    forecast_series = forecast_series[1:]


final_result = final_result[ 1 : ] # extract only the predicted sales for␣
 ↪plotting and grouping
#print(x_validSm[ : forecast_period, 0 ] * max_mix, final_result * max_mix)
#print(x_validSm[ : forecast_period, 0 ] * max_mix, final_result * max_mix)

# Plot the results
#plot_series( time_validSm[ : forecast_period ], \
#             ( x_validSm[ : forecast_period, 0 ] * max_mix, final_result *␣
 ↪max_mix ), legend = ['x_valid', 'prediction']  )

# group by months and estimate errors
data = np.array( [ x_validSm[  : forecast_period, 0 ] * max_mix, final_result *␣
 ↪max_mix ] ).T

df_result = pd.DataFrame( data = data, index = time_validSm[ : forecast_period␣
 ↪],
                          columns = [ "x_valid", "prediction"] )

df_resultGR = df_result.groupby( pd.Grouper( freq = "M" ) ).sum()
p_error = np.abs( np.array( df_resultGR["x_valid"] ) - ( np.array(␣
 ↪df_resultGR['prediction'] ) ) ) \
    / np.array( df_resultGR["x_valid"] )

df_resultGR = df_result.groupby( pd.Grouper( freq = "M" ) ).sum()
df_resultGR['a_error'] = np.abs( np.round( \
    np.array( df_resultGR["x_valid"] ) \
    - np.array( df_resultGR['prediction'] ), 0 ) )
df_resultGR['p_error'] = np.round( ( np.array( df_resultGR["x_valid"] ) \
    -  np.array( df_resultGR['prediction'] ) ) \
    / np.array( df_resultGR["x_valid"] ), 2 )

df_resultGR
```

```
[ ]:            x_valid   prediction  a_error  p_error
     2024-05-31   9284.0  8358.277478    926.0     0.10
     2024-06-30   9035.0  8192.796052    842.0     0.09
     2024-07-31   9152.0  8590.570777    561.0     0.06
```

[ ]:

```
df = pd.DataFrame(history.history)
df = df
df.plot(y=['loss'])
```

[ ]: <Axes: >



3 Now we start final training, here are 5 models setups, train each of them from the scratch and choose median

#may repeat this 3 times and choose average result

[ ]:

```
batchsi = [64]
lratesi = [1e-4, 1e-4, 3e-4, 3e-4, 8e-4]
weedi  =  [8e-4, 2e-3, 3e-4, 5e-3, 5e-3]
dpi = [0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5]
bests = []
```

[ ]:

```
for i in range(len(lratesi)):
                weed = weedi[i]
                dp = dpi[i]
```

```
            lrate = lratesi[i]
            batchs = 64
            window_size = 360
            input_shape = (window_size, x_trainSm.shape[1])

            tf.keras.backend.clear_session()
            model = get_model(input_shape, weed, dp)
            get_compile(model, lrate)
            history = model.fit(dataset, epochs = 10, verbose = 0, shuffle␣
↪= False)

            # Split data first
            split_dateSm = pd.to_datetime( '2024-04-30' )
            upper_boundary = pd.to_datetime( '2024-07-31' )
            train_dfSm = df_forFCST[ df_forFCST.index <= split_dateSm ]
            valid_dfSm = df_forFCST[ ( df_forFCST.index > split_dateSm ) &␣
↪( df_forFCST.index <= upper_boundary ) ]

            # max_mix = df_forFCST[ df_forFCST.index <= split_dateSm␣
↪]['y_mix'].max()
            max_mix = 679.8297498652444
            train_dfSm = add_time_features( train_dfSm, max_mix )
            valid_dfSm = add_time_features( valid_dfSm, max_mix )

            # Form numpy arrays
            time_trainSm = np.array( train_dfSm.reset_index()['ds'] )
            x_trainSm = np.array( train_dfSm[['y_mix', 'month_number',␣
↪'day_of_week', 'day_of_month']] )

            time_validSm = np.array( valid_dfSm.reset_index()['ds'])
            x_validSm = np.array( valid_dfSm[['y_mix', 'month_number',␣
↪'day_of_week', 'day_of_month']] )


            # Reduce the original series
            forecast_series = x_trainSm[-window_size:]


            forecast_period = ( pd.to_datetime( time_validSm[-1] ) - pd.
↪to_datetime( time_validSm[0] ) ).days + 1
            final_result = np.empty( shape = (1, 1) )

            for period in range( forecast_period ):

                forecast = model.predict( forecast_series[np.newaxis],␣
↪verbose=0 )
```

```
                    results = forecast.squeeze()

                    forecast_date = time_validSm[0] + pd.Timedelta(days=period)
                    month_num = forecast_date.month / 12
                    day_of_week = forecast_date.dayofweek / 6
                    day_of_month = forecast_date.day / 31

                    forecast_series = np.append( forecast_series,
                                                [[ results, month_num,␣
↪day_of_week, day_of_month ]], axis=0)
                    final_result = np.append( final_result, results )

                    forecast_series = forecast_series[1:]

                final_result = final_result[ 1 : ]
                data = np.array( [ x_validSm[  : forecast_period, 0 ] *␣
↪max_mix, final_result * max_mix ] ).T

                df_result = pd.DataFrame( data = data, index = time_validSm[ :␣
↪forecast_period ],
                                        columns = [ "x_valid", "prediction"] )

                df_resultGR = df_result.groupby( pd.Grouper( freq = "M" ) ).
↪sum()
                p_error = np.abs( np.array( df_resultGR["x_valid"] ) - ( np.
↪array( df_resultGR['prediction'] ) ) ) \
                    / np.array( df_resultGR["x_valid"] )

                df_resultGR = df_result.groupby( pd.Grouper( freq = "M" ) ).
↪sum()
                df_resultGR['a_error'] = np.abs( np.round( \
                    np.array( df_resultGR["x_valid"] ) \
                    - np.array( df_resultGR['prediction'] ), 0 ) )
                df_resultGR['p_error'] = np.round( ( np.array(␣
↪df_resultGR["x_valid"] ) \
                    -  np.array( df_resultGR['prediction'] ) ) \
                    / np.array( df_resultGR["x_valid"] ), 2 )
                print(df_resultGR['prediction'].values, df_resultGR['x_valid'].
↪values, df_resultGR['p_error'].values)
                bests.append(df_resultGR['prediction'].values)
```

```
[8737.16444758 9381.14716373 9205.48805536] [8855. 8299. 8303.] [ 0.01 -0.13
-0.11]
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
```

```
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can generate at
least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()`
function when building your dataset.
  self.gen.throw(typ, value, traceback)

[8452.35662773 9038.4760699  8789.39684086] [8855. 8299. 8303.] [ 0.05 -0.09
-0.06]

/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can generate at
least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()`
function when building your dataset.
  self.gen.throw(typ, value, traceback)

[7418.02186598 8083.63526496 8000.09271215] [8855. 8299. 8303.] [0.16 0.03 0.04]

/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can generate at
least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()`
function when building your dataset.
  self.gen.throw(typ, value, traceback)

[7944.83941674 8637.26410977 8566.22472004] [8855. 8299. 8303.] [ 0.1  -0.04
-0.03]

/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can generate at
least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()`
function when building your dataset.
```

```
  self.gen.throw(typ, value, traceback)
```

```
[8062.78570565 8711.99538905 8546.35112953] [8855. 8299. 8303.] [ 0.09 -0.05
-0.03]
```

[ ]:

```
print(*bests, sep = '\n')
#360
#64, 0.0001, 0.0003, 0.5, array([-0.01,  0.04,  0.02]) in 2 5 3 ** nos used
#64, 0.0001, 0.0008, 0.5, array([-0.04,  0.03,  0.01]) in 2 3 3 ***
#64, 0.0001, 0.002, 0.5, array([-0.  ,  0.05,  0.03]) in 3 3 2 ***
#64, 0.0003, 0.0003, 0.5, array([-0.03,  0.04,  0.04]) in 2 3 2 ***
#64, 0.0003, 0.005, 0.5, array([-0.01,  0.04,  0.02]) in 3 2 2 ****
#64, 0.0008, 0.0008, 0.5, array([-0.03,  0.04,  0.03]) in 4 3 4 ** noy used
#64, 0.0008, 0.005, 0.5, array([-0.  03,  0.04,  0.03]) in 3 3 3 ***

#we take 5 3 + star models, train them and take the median values for each month
#answer would be [8993, 8798, 9092]
#here result luckily is 3/3/1 % deviation for each month
```

```
[8737.16444758 9381.14716373 9205.48805536]
[8452.35662773 9038.4760699  8789.39684086]
[7418.02186598 8083.63526496 8000.09271215]
[7944.83941674 8637.26410977 8566.22472004]
[8062.78570565 8711.99538905 8546.35112953]
```

End of final test