IsaziAIChallenge_Case_Study_1

August 16, 2020

Notebook done by: - Name: Yashveer Singh - email: yashveerm8@yahoo.com - contact: 072 217 9781 - role: Senior Data Scientist

1 Isazi Consulting AI Challenge

1.1 Outline

Click on the link to be taken to the relevant section

1.2 Overview of this Notebook

- For the ISAZI AI challenge I have decided to create a Notebook that covers an end-to-end solution rather than optimizing for model performance.
- This notebook places much attention on the modelling section and setting up a Higly optimized data pipeline to run on a TPU and production environment.
- I have decided to do something **unique rather than building the standard timeseries models (ARIMA, SARIMA) that you can find in Kaggle Competion Notebooks** like the Uber Sigma competitions

- I have built a Multivariate-Multi Step Model Data Pipeline optimized to run on the TPU which I have not come across in any time series courses or the web

1. Exploratory Data Analysis

- The purpose of Exploratory Data Analysis is to gain insight into our dataset
- In Exploratory Data Analysis we:
  1. Examine the Distribution of our Data.
  2. Try to find new insights to our Data that will lead to better feature generation.
  3. This new feature generation will lead us to build a model with a higher performance score.
  4. Remember that Data Science is not about creating fancy plots of Data and fitting data to a model, but rather to gain insight from data that will lead to new features and increase overall model performance.
  5. In this notebook I have placed **massive emphasis** on the modelling section and optimization of the data pipeline which has been tested on a TPU for extreme performance rather than spending time on **EDA**
  6. A kaggle link has been provided on how I would have done EDA using wavelet denoising and ARIMA/moving averages

1.1 Loading and Exploring the data

Load Data

First load the dataset which will be used for training and testing the model built in the modelling section.

[102]:
```
!git clone https://github.com/maxbrent/IsaziChallenge.git
```

```
fatal: destination path 'IsaziChallenge' already exists and is not an empty
directory.
```

[103]:
```
import os
import sys
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from IPython.display import Image
```

[104]:
```
pd.set_option("display.max_rows", None)
```

[105]:
```
print(os.listdir("/content/IsaziChallenge"))
```

```
['DS - case study 1 - Sales task.pdf', 'models', 'reports', 'data',
'IsaziAIChallenge_Case_Study_1.ipynb', 'README.md', '.git']
```

[106]:
```
sys.path.insert(0, '/content/IsaziChallenge/')
```

[107]:
```
# from utils import load_data

data = pd.read_csv('/content/IsaziChallenge/data/DS - case study 1 - add␣
 ↪material - sales_volumes.csv', index_col=0)
```

[108]:
```
data.head()
```

[108]:
```
       InvoiceID ProductCode  ...                 Date  UnitPrice
42481     539993       22386  ...  2019-01-04 10:00:00      31.20
42482     539993       21499  ...  2019-01-04 10:00:00       6.72
42483     539993       21498  ...  2019-01-04 10:00:00       6.72
42484     539993       22379  ...  2019-01-04 10:00:00      33.60
42485     539993       20718  ...  2019-01-04 10:00:00      20.00

[5 rows x 6 columns]
```

[109]:
```
len(data)
```

[109]:
```
203422
```

[110]:
```
data.dtypes
```

[110]:
```
InvoiceID       object
ProductCode     object
Description     object
Volume           int64
Date            object
UnitPrice      float64
dtype: object
```

[111]:
```
data.nunique()
```

[111]:
```
InvoiceID      10770
ProductCode     3531
Description     3484
Volume           455
Date            9764
UnitPrice        966
dtype: int64
```

[112]:
```
def convert_data_types(converted):
    """
      Converts data types to the relevant type

      Args:
        converted (dataframe): numpy array with data values.

      Returns:
        converted (dataframe): standardized and normalized numerical variables
    """
    converted['Date'] = pd.to_datetime(converted['Date'])
```

```
    converted['InvoiceID'] = converted['InvoiceID'].astype('category')
    converted['ProductCode'] = converted['ProductCode'].astype('category')
    converted['Description'] = converted['Description'].astype('category')
    return converted
```

[113]:
```
data = convert_data_types(data)
```

View the Dataset

The features (`data`) include the following fields: * InvoiceID: (Categorical) * ProductCode: (Categorical) * Description: (Categorical) * Volume: (Numeric) * UnitPrice: (Numeric)

Analysis From the analysis above we can deduce: - The data is a reasonable size to create a **windowed** dataset at various time points - We have categorical & numerical variables - There is **high cardinality** in each categorical variable - The **Description** feature has multiple word correlations in which we can learn **Embeddings** - We need to **scale** the numerical variables to remove outliers and data skewness

`data` is the Pandas DataFrames that holds the data for 203 , 422 records.

2. Modelling 1. In this section we will create a Tensorflow **Multivariate Multi-Step Model** 2. We will train a model to predict the volume with **basic features** 3. We will train a model to predict the volume with **generated features** to evaluate change in performance 4. **Discussion** for how to build the Ideal Model for massive **improvement** unsing LSTM Embedding Encoder as the 1st Model and an LSTM Multivariate Multi-Step Model as the second model 5. Instead of focusing on **Moving Average models (SARIMA, ARIMA)** which we can easily find on Kaggle competitions, I have chosen to do something unique which I have not come across on the internet i.e. build a **Multivariate Multistep Model** for High Dimensional Data

NB: My aim is to build a quick end-to-end solution rather than focusing on model performance given time constraints. My data pipeline code is Higly optimized to run on a TPU which I have tested on the Forex Markets with High Dimensional data

2.1 Transform Data for Model

Copying Data to new variable and indexing datetime column - Dropping Description Column because going to create separate embedding model

[114]:
```
features = data.copy()
featuress = data.copy()

def drop_col(df, col_list):
    # df.set_index('Date',inplace=True)
    df.drop(col_list, axis=1, inplace=True)
    return df
```

[115]:
```
features = drop_col(features, col_list=['Description'])
featuress = drop_col(featuress, col_list=['Description'])
```

[116]:
```
features.head()
```

[116]:

	InvoiceID	ProductCode	Volume	Date	UnitPrice
42481	539993	22386	29	2019-01-04 10:00:00	31.20
42482	539993	21499	74	2019-01-04 10:00:00	6.72
42483	539993	21498	74	2019-01-04 10:00:00	6.72
42484	539993	22379	14	2019-01-04 10:00:00	33.60
42485	539993	20718	29	2019-01-04 10:00:00	20.00

[117]:
```python
def basic_transform(ft): # When doing mean, the volume becomes positive, so␣
↪have to use negative volume to identify discount and sum discounts for day␣
↪as feature
    """
      Groups and averages dataframe by day.
      Standardizes numerical feature values of data

      Args:
        ft (dataframe): dataframe with data values.

      Returns:
        ft_npy (numpy array): standardized and normalized numerical variables
    """
    ft = drop_col(ft, col_list=['InvoiceID', 'ProductCode'])
    ft = ft.groupby(pd.Grouper(key='Date',freq='D')).mean()
    ft = ft.fillna(0)
    ft = ft.values

    data_mean = ft[:, :2].mean(axis=0) # Not selecting the categorical features
    data_std = ft[:, :2].std(axis=0)

    ft_npy = (ft[:, :2]-data_mean)/data_std

    return ft_npy
```

[118]:
```python
def generate_ft_transform(ft): # Takes into consideration discounts and returns
    """
      Groups and averages dataframe by day.
      Standardizes numerical feature values of data

      Args:
        ft (dataframe): numpy array with data values.

      Returns:
        ft_npy (numpy array): standardized and normalized numerical variables
    """
    ft = drop_col(ft, col_list=['InvoiceID', 'ProductCode'])
    ft['IsReturns'] = ft['Volume'].apply(lambda x: 1 if x<0 else 0)
    ft['IsDiscount'] = ft['UnitPrice'].apply(lambda x: 1 if x==0 else 0)
    ft['IsWeekDay'] = ft.apply(lambda x: x["Date"].weekday(),axis=1)
    ft['IsWeekDay'] = (ft['IsWeekDay'] < 5).astype(int)
    # print(ft[((ft.Date.dt.month == 4)&(ft.Date.dt.year == 2019)&(ft.Date.dt.day␣
↪== 1))&(ft.IsReturns==1)])
    # print(ft.dtypes)
    ft = ft.groupby(pd.Grouper(key='Date',freq='D')).agg(
        VolumeMean = pd.NamedAgg(column='Volume', aggfunc=np.mean),
        UnitPriceMean = pd.NamedAgg(column='UnitPrice', aggfunc=np.mean),
```

```
        TotReturns = pd.NamedAgg(column='IsReturns', aggfunc=np.sum),
        TotDiscount = pd.NamedAgg(column='IsDiscount', aggfunc=np.sum),
        TotWeekDays = pd.NamedAgg(column='IsWeekDay', aggfunc=np.sum)
    )
    ft = ft.fillna(0)
    ft = ft.values

    global mean_data
    mean_data = ft[:, 0].mean(axis=0) # Used for converting predictions in the␣
↪end
    global std_data
    std_data = ft[:, 0].std(axis=0)

    global data_mean
    data_mean = ft.mean(axis=0) # Not selecting the categorical features
    global data_std
    data_std = ft.std(axis=0)

    ft_npy = (ft-data_mean)/data_std

    return ft_npy
```

[119]:
```
def transform_num_data(npy):
    """
      Standardizes and normalizes our numerical data in
      our numpy array to remove the presence of outliers

      Args:
        npy (numpy array): numpy array with data values.

      Returns:
        npy (numpy array): standardized and normalized numerical variables
    """
    data_mean = npy[:, 3].mean(axis=0)                    # Selecting UnitPrice␣
↪features
    data_std = npy[:, 3].std(axis=0)

    transform_unitP = (npy[:, 3] - data_mean) / data_std # We are standardizing␣
↪the UnitPrice feature
    transform_volume = np.tanh(npy[:, 2])                # Normalize our Volume␣
↪Data

    npy = np.hstack((np.reshape(npy[:, 0], (-1, 1)), np.reshape(npy[:, 1], (-1,␣
↪1)), np.reshape(transform_volume, (-1, 1)), np.reshape(transform_unitP, (-1,␣
↪1))))
    return npy
```

[120]:
```python
def transform_cat_data(ft):
  """
    Transforms data into label encoded values to use
    for creating embeddings

    Args:
      ft (dataframe): unnormalized training data.

    Returns:
      ft (dateframe): label encoded categorical variables
  """
  encoder = LabelEncoder()
  ft['InvoiceID'] = encoder.fit_transform(ft['InvoiceID'])
  ft['ProductCode'] = encoder.fit_transform(ft['ProductCode'])
  # ft['Description'] = encoder.fit_transform(ft['Description']) Need to create␣
↪a separate encoding embedding model for Description
  return ft
```

[121]:
```python
dataset = basic_transform(features)
```

[122]:
```python
datasett = generate_ft_transform(featuress)
```

[123]:
```python
print(dataset.shape)
print(datasett.shape)
```

```
(178, 2)
(178, 5)
```

[124]:
```python
# Print 1st 5 values of numpy array to compare to iterator
print(datasett[:5, :])
```

```
[[-0.26608458 -0.07434636 -0.0441942   0.5995467   0.61714245]
 [ 0.51515506  4.46338948  2.20339654 -0.22966319 -0.94672834]
 [ 0.85494172  0.09084604  1.64149885 -0.06382121 -0.94672834]
 [ 0.23400666 -0.16599746  0.1286974  -0.56134715  1.42285291]
 [-1.55193478 -0.95399623 -1.08154377 -0.56134715 -0.94672834]]
```

2.2 Create Daily Windowed Time Series Data & Model
2.2.1 Windowing for basic Features

[125]:
```python
tf.random.set_seed(0)
```

[126]:
```python
# Window for Training Set. Data Pipeline optimized to run on TPU
def windowed_dataset_train(series, window_size, batch_size, shuffle_buffer,␣
↪step_forecast):
    """
    Standardizes and normalizes our numerical data in
    our numpy array to remove the presence of outliers

    Args:
```

```
      series (numpy array): numpy array with data values.
      window_size (integer): value for sliding window size.
      batch_size (integer): value to batch time windows.
      shuffle_buffer (integer): value to shuffle data from buffer.
      step_forecast (integer): value to forecast how many days ahead.

    Returns:
      ds (tensor): tensorflow tensor with sliding batched window and labels␣
↪forecast
    """
    ds = tf.data.Dataset.from_tensor_slices(series)
    ds = ds.window(window_size + step_forecast, shift=1, drop_remainder=True)
    ds = ds.flat_map(lambda w: w.batch(window_size + step_forecast)).cache()
    ds = ds.map(lambda w: (w[:-step_forecast], [w[i:i+step_forecast, 0]  for i␣
↪in range(1, window_size+1)]), num_parallel_calls=tf.data.experimental.
↪AUTOTUNE)
    ds = ds.shuffle(shuffle_buffer)
    ds = ds.batch(batch_size).prefetch(tf.data.experimental.AUTOTUNE)
    return ds
```

[127]:
```
# Window for Validation Set
def windowed_dataset_valid(series, window_size, batch_size, shuffle_buffer,␣
↪step_forecast):
    """
    Standardizes and normalizes our numerical data in
    our numpy array to remove the presence of outliers

    Args:
      series (numpy array): numpy array with data values.
      window_size (integer): value for sliding window size.
      batch_size (integer): value to batch time windows.
      shuffle_buffer (integer): value to shuffle data from buffer.
      step_forecast (integer): value to forecast how many days ahead.

    Returns:
      ds (tensor): tensorflow tensor with sliding batched window and labels␣
↪forecast
    """
    ds = tf.data.Dataset.from_tensor_slices(series)
    ds = ds.window(window_size + step_forecast, shift=1, drop_remainder=True)
    ds = ds.flat_map(lambda w: w.batch(window_size + step_forecast)).cache()
    ds = ds.map(lambda w: (w[:-step_forecast], [w[i:i+step_forecast, 0]  for i␣
↪in range(1, window_size+1)]), num_parallel_calls=tf.data.experimental.
↪AUTOTUNE)
    ds = ds.batch(batch_size).prefetch(tf.data.experimental.AUTOTUNE)
    return ds
```

[128]:
```
preview_set = windowed_dataset_train(dataset, 10, 1, 60, 2) # 2 timesteps ahead
↪with sliding window contain 10 samples, remove shuffle to preview window
train_set = windowed_dataset_train(dataset[:124, :], 44, 2, 60, 7)
valid_set = windowed_dataset_valid(dataset[124:178, :], 44, 2, 60, 7)
# train_set = windowed_dataset_train(dataset[:700000, :], 64, 1024, 1000, 10) #
↪100 timesteps ahead with 1st 700 000 of data
# valid_set = windowed_dataset_valid(dataset[700001:800000, :], 64, 1024, 1000,
↪10) # 100 timesteps ahead with last 260 000 of data
# test_set = windowed_dataset_test(dataset[800001:900000, :], 64, 1024, 1000,
↪10)
```

Preview Sliding Windows - As you can see in the code cell below, we have a sample of 2 features in a daily sliding window of 10 days shown in the 1st array - In the 2nd array we have a 2 step forecast - The data that is previewed below seems like multiple labels in the 2nd array, however since we are getting the LSTM to predict a 2 step forecast at each timestep, we will have a 2-step forecast at each of the 10 steps in a slinding window of 10 steps - The **actual windows** that will be **generated** will be a 62 day window, with a 31 day multi-step forecast at each timestep rather than the last timestep

[ ]:
```
iterator = iter(preview)
print(next(iterator))
```

```
(<tf.Tensor: shape=(1, 10, 2), dtype=float64, numpy=
array([[[-2.66084583e-01, -7.43463584e-02],
        [ 5.15155062e-01,  4.46338948e+00],
        [ 8.54941721e-01,  9.08460432e-02],
        [ 2.34006664e-01, -1.65997464e-01],
        [-1.55193478e+00, -9.53996228e-01],
        [-1.41201471e-01, -1.90018046e-01],
        [-6.98642041e-01, -2.86152274e-04],
        [ 2.41860325e+00, -8.88144222e-02],
        [-4.88831291e-01,  5.75793395e-02],
        [-2.06740953e-01, -9.97170061e-03]]])>, <tf.Tensor: shape=(1, 10, 2),
dtype=float64, numpy=
array([[[ 0.51515506,  0.85494172],
        [ 0.85494172,  0.23400666],
        [ 0.23400666, -1.55193478],
        [-1.55193478, -0.14120147],
        [-0.14120147, -0.69864204],
        [-0.69864204,  2.41860325],
        [ 2.41860325, -0.48883129],
        [-0.48883129, -0.20674095],
        [-0.20674095,  1.46673517],
        [ 1.46673517, -1.55193478]]])>)
```

2.2.2 Model Creation for basic features - Usually LSTM models are created just to predict values at the last time step. - There is a major flaw with this, because it prevents the gradients from flowing through each timestep during back propagation causing instability. - I will create an LSTM model to do a multi-step forecast at each timestep rather than just the last timestep

[129]:
```
model = tf.keras.models.Sequential([
    # tf.keras.layers.Conv1D(filters=8, kernel_size=5,
    #                       strides=1, padding="causal",
    #                       activation="relu",
    #                       input_shape=[None, 2]),
    tf.keras.layers.LSTM(7, return_sequences=True, dropout=0.5,␣
 ↪recurrent_dropout=0.5, input_shape=[None, 2]),
    # tf.keras.layers.Dense(31, activation="relu"), # is the same as applying a␣
 ↪TimeDistributed Layer, the only reason we use TimeDistributed is for clarity␣
 ↪to say that it is
    # tf.keras.layers.Dense(31),

  ])
lr_schedule = tf.keras.callbacks.LearningRateScheduler(lambda epoch: 1e-8 *␣
 ↪10**(epoch / 20))
optimizer = tf.keras.optimizers.SGD(lr=1e-8, momentum=0.9)
model.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer,␣
 ↪metrics=["mae"])
```

[130]:
```
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, None, 7)           280
=================================================================
Total params: 280
Trainable params: 280
Non-trainable params: 0
_________________________________________________________________
```

[131]:
```
history = model.fit(train_set, epochs=10, validation_data=valid_set,␣
 ↪callbacks=[lr_schedule])
```

```
Epoch 1/10
37/37 [==============================] - 2s 46ms/step - loss: 0.3876 - mae:
0.7349 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 2/10
37/37 [==============================] - 1s 37ms/step - loss: 0.3877 - mae:
0.7351 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 3/10
37/37 [==============================] - 1s 36ms/step - loss: 0.3878 - mae:
0.7353 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 4/10
37/37 [==============================] - 1s 33ms/step - loss: 0.3879 - mae:
0.7353 - val_loss: 0.4760 - val_mae: 0.8022
```

```
Epoch 5/10
37/37 [==============================] - 1s 33ms/step - loss: 0.3878 - mae:
0.7353 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 6/10
37/37 [==============================] - 1s 36ms/step - loss: 0.3875 - mae:
0.7350 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 7/10
37/37 [==============================] - 1s 36ms/step - loss: 0.3873 - mae:
0.7346 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 8/10
37/37 [==============================] - 1s 35ms/step - loss: 0.3872 - mae:
0.7344 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 9/10
37/37 [==============================] - 1s 37ms/step - loss: 0.3875 - mae:
0.7349 - val_loss: 0.4760 - val_mae: 0.8022
Epoch 10/10
37/37 [==============================] - 1s 35ms/step - loss: 0.3877 - mae:
0.7349 - val_loss: 0.4760 - val_mae: 0.8022
```

[132]:
```
history.history.keys()
```

[132]:
```
dict_keys(['loss', 'mae', 'val_loss', 'val_mae', 'lr'])
```

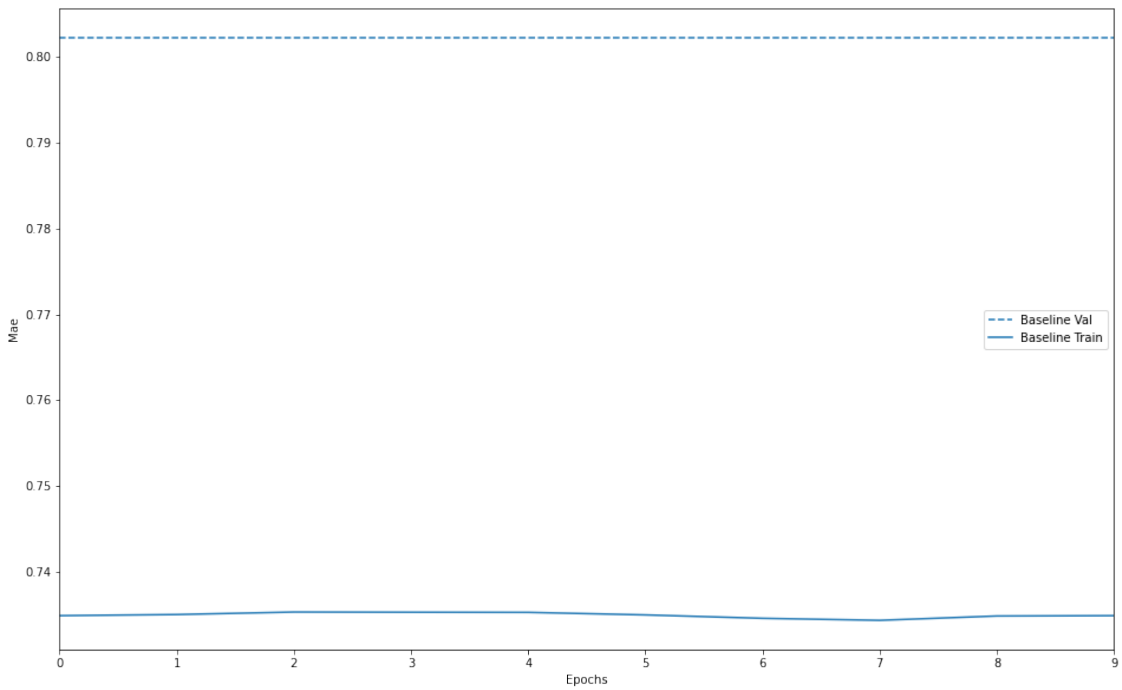
[133]:
```
def plot_history(histories, key='mae'):
  plt.figure(figsize=(16,10))

  for name, history in histories:
    val = plt.plot(history.epoch, history.history['val_'+key],
                   '--', label=name.title()+' Val')
    plt.plot(history.epoch, history.history[key], color=val[0].get_color(),
             label=name.title()+' Train')

  plt.xlabel('Epochs')
  plt.ylabel(key.replace('_',' ').title())
  plt.legend()

  plt.xlim([0,max(history.epoch)])


plot_history([('baseline', history)])
```



2.2.3 Model Creation for Generated Features

```
[ ]: train_sett = windowed_dataset_train(datasett[:124, :], 44, 2, 60, 7)
     valid_sett = windowed_dataset_valid(datasett[124:178, :], 44, 2, 60, 7)
```

```
[ ]: modell = tf.keras.models.Sequential([
         # tf.keras.layers.Conv1D(filters=8, kernel_size=5,
         #                      strides=1, padding="causal",
         #                      activation="relu",
         #                      input_shape=[None, 2]),
         tf.keras.layers.LSTM(7, return_sequences=True, dropout=0.5,␣
      ↪recurrent_dropout=0.5, input_shape=[None, 5]),
         # tf.keras.layers.Dense(31, activation="relu"), # is the same as applying a␣
      ↪TimeDistributed Layer, the only reason we use TimeDistributed is for clarity␣
      ↪to say that it is
         # tf.keras.layers.Dense(31),

       ])
     lr_schedule = tf.keras.callbacks.LearningRateScheduler(lambda epoch: 1e-8 *␣
      ↪10**(epoch / 20))
     optimizer = tf.keras.optimizers.SGD(lr=1e-8, momentum=0.9)
     modell.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer,␣
      ↪metrics=["mae"])
```

```
[ ]: modell.summary()
```

```
Model: "sequential_1"
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, None, 7)           364
=================================================================
Total params: 364
Trainable params: 364
Non-trainable params: 0
_________________________________________________________________
```

Loading Model from Checkpoints

[134]:
```
# Comment 2 lines below if you want to retrain the model
checkpoint_path = "/content/IsaziChallenge/models/checkpoint_path/cp.ckpt"
modell.load_weights(checkpoint_path) # Loads model weights from checkpoints
```

[134]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at
0x7efdfb32e208>
```

[ ]:
```
# Code used to save checkpoints, uncomment if training model
# checkpoint_path = "/content/IsaziChallenge/models/checkpoint_path/cp.ckpt"
# checkpoint_dir = os.path.dirname(checkpoint_path)

# # Create a callback that saves the model's weights
# cp_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
#                                                  save_weights_only=True,
#                                                  verbose=1)
```

[ ]:
```
# Uncomment to keep training model. Model is loaded in the cells below
# historyy = modell.fit(train_sett, epochs=10, validation_data=valid_sett,␣
↪callbacks=[lr_schedule, cp_callback])
```

```
Epoch 1/10
     37/Unknown - 1s 25ms/step - loss: 0.3950 - mae: 0.7471
Epoch 00001: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 30ms/step - loss: 0.3950 - mae:
0.7471 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 2/10
36/37 [============================>.] - ETA: 0s - loss: 0.3937 - mae: 0.7459
Epoch 00002: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3937 - mae:
0.7461 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 3/10
36/37 [============================>.] - ETA: 0s - loss: 0.3941 - mae: 0.7465
Epoch 00003: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 31ms/step - loss: 0.3949 - mae:
```

```
0.7473 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 4/10
36/37 [============================>.] - ETA: 0s - loss: 0.3928 - mae: 0.7451
Epoch 00004: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3945 - mae:
0.7468 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 5/10
36/37 [============================>.] - ETA: 0s - loss: 0.3946 - mae: 0.7471
Epoch 00005: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 31ms/step - loss: 0.3944 - mae:
0.7469 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 6/10
36/37 [============================>.] - ETA: 0s - loss: 0.3947 - mae: 0.7469
Epoch 00006: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3946 - mae:
0.7470 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 7/10
36/37 [============================>.] - ETA: 0s - loss: 0.3956 - mae: 0.7482
Epoch 00007: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 30ms/step - loss: 0.3954 - mae:
0.7476 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 8/10
35/37 [===========================>..] - ETA: 0s - loss: 0.3949 - mae: 0.7471
Epoch 00008: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3945 - mae:
0.7466 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 9/10
36/37 [============================>.] - ETA: 0s - loss: 0.3954 - mae: 0.7474
Epoch 00009: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3947 - mae:
0.7469 - val_loss: 0.4891 - val_mae: 0.8252
Epoch 10/10
36/37 [============================>.] - ETA: 0s - loss: 0.3939 - mae: 0.7464
Epoch 00010: saving model to
/content/IsaziChallenge/models/checkpoint_path/cp.ckpt
37/37 [==============================] - 1s 29ms/step - loss: 0.3946 - mae:
0.7469 - val_loss: 0.4891 - val_mae: 0.8252
```

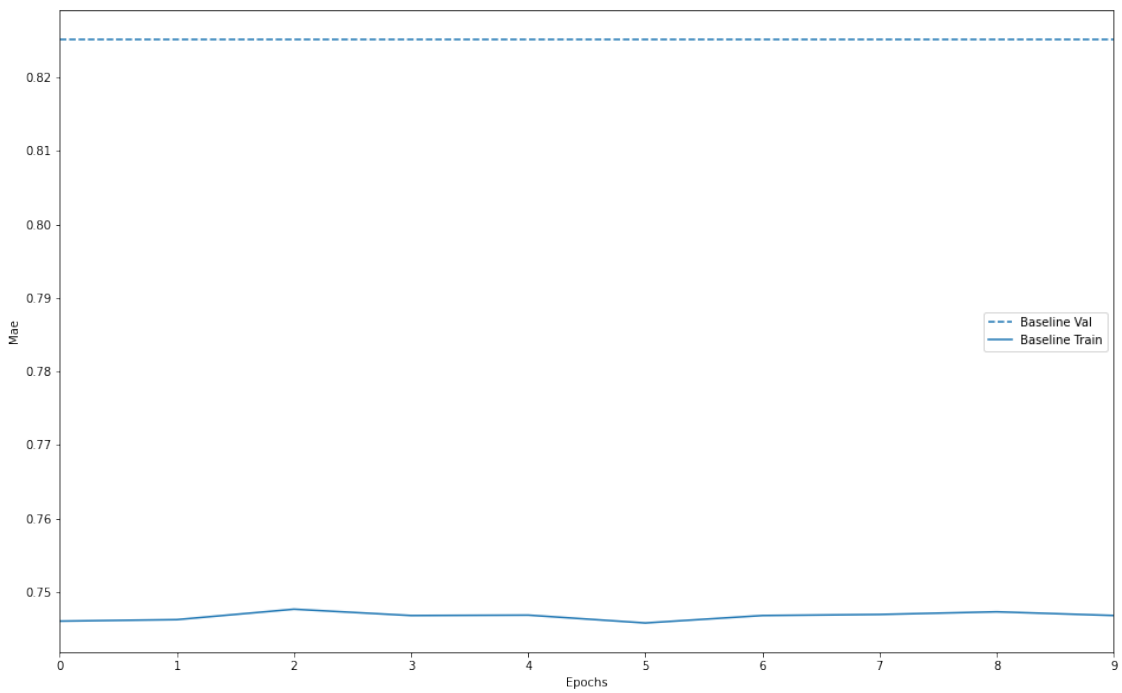
[ ]:
```
# def plot_history(histories, key='mae'):
#   plt.figure(figsize=(16,10))
```

```
#   for name, history in histories:
#     val = plt.plot(history.epoch, history.history['val_'+key],
#                    '--', label=name.title()+' Val')
#     plt.plot(history.epoch, history.history[key], color=val[0].get_color(),
#              label=name.title()+' Train')

#   plt.xlabel('Epochs')
#   plt.ylabel(key.replace('_',' ').title())
#   plt.legend()

#   plt.xlim([0,max(history.epoch)])


# plot_history([('baseline', historyy)])
```



2.2.4 Running Predicitions

[143]:
```
data.dtypes
```

[143]:
```
InvoiceID             category
ProductCode           category
Description           category
Volume                   int64
Date            datetime64[ns]
UnitPrice              float64
dtype: object
```

[144]:
```
print(len(data))
```

```
203422
```

[145]:
```
def generate_predict_ft(ft): # Takes into consideration discounts and returns
    """
    Groups and averages dataframe by day.
    Standardizes numerical feature values of data

    Args:
      ft (dataframe): numpy array with data values.

    Returns:
      ft_npy (numpy array): standardized and normalized numerical variables
    """
    ft = drop_col(ft, col_list=['InvoiceID', 'ProductCode'])
    ft['IsReturns'] = ft['Volume'].apply(lambda x: 1 if x<0 else 0)
    ft['IsDiscount'] = ft['UnitPrice'].apply(lambda x: 1 if x==0 else 0)
    ft['IsWeekDay'] = ft.apply(lambda x: x["Date"].weekday(),axis=1)
    ft['IsWeekDay'] = (ft['IsWeekDay'] < 5).astype(int)
    ft = ft.groupby(pd.Grouper(key='Date',freq='D')).agg(
        VolumeMean = pd.NamedAgg(column='Volume', aggfunc=np.mean),
        UnitPriceMean = pd.NamedAgg(column='UnitPrice', aggfunc=np.mean),
        TotReturns = pd.NamedAgg(column='IsReturns', aggfunc=np.sum),
        TotDiscount = pd.NamedAgg(column='IsDiscount', aggfunc=np.sum),
        TotWeekDays = pd.NamedAgg(column='IsWeekDay', aggfunc=np.sum)
    )
    ft = ft.fillna(0)
    ft = ft.values

    ft_npy = (ft-data_mean)/data_std

    return ft_npy
```

[146]:
```
def predict_transform(df_to_predict):
    # Might have to create a read csv to pass from command line
    convert_data_types(df_to_predict)
    fts = df_to_predict.copy()
    fts = drop_col(fts, col_list=['Description'])
    data_set = generate_predict_ft(fts)
    predict_set = windowed_dataset_valid(data_set, 44, 2, 60, 7)
    return predict_set
```

[147]:
```
prediction_set = predict_transform(data.iloc[:-60000, :]) # Create an argument␣
 ↪parser to parse prediction dataframe file through command line
npyz = (modell.predict(prediction_set) * std_data) + mean_data
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:11:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  # This is added back by InteractiveShellApp.init_path()
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:12:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  if sys.path[0] == '':
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:13:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  del sys.path[0]
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:14:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[148]:
```
print(npyz[0, 0, :])
print(npyz[0, 1, :])
print(npyz[0, 2, :])
```

```
[22.040794 22.30324  23.162722 22.696892 22.49132  22.508926 23.424372]
[24.176308 17.695864 27.374987 23.159117 20.47332  24.464855 26.995945]
[22.31354  19.729282 25.651539 24.928905 22.528397 23.286795 24.758812]
```

2.3 Close to Perfect Model - Thus far I have kept the model simple by building the first **Multivariate Multi-Step** model with just the **Volume** and **UnitPrice** features - The **second** model that was built was a result of generating more features such as **discounts, returns(negative volumes), weekends/weekdays**. We could also include exponential moving averages as features to improve performance - The **IDEAL** way to build a model for the best performance is to do the following: 1. Firstly there is a **massive correlation** for the **"Description"** feature, so we need to train an encoder to learn embeddings for the Description feature. I have written some sample code for this, however due to time constraints I am just explaining my thought process rather than building this complex model. 2. Once we have **learnt the embeddings for the Description feature**, we can then

train a **second model**, using the first model to generate embeddings for the Description feature. 3. The second model will be the same as the model that I have built for the generated features, however this time I will include the **"ProductID"** and **"InvoiceID"** as embedding features.

NB: I have written sample code to show that I am capable of building this complex model, however the first 2 models are fully functional

Windowing for including Embeddings for Categorical Features

[ ]:
```
# Test Window
def windowed_dataset(series, window_size, batch_size, shuffle_buffer,␣
↪step_forecast):
    ds = tf.data.Dataset.from_tensor_slices(({'input_x': series[:, 2:],␣
↪'input_embed': series[:, :-2].astype(int)}))
    ds_all = ds.window(window_size + step_forecast, shift=1,␣
↪drop_remainder=True)
    ds = ds_all.flat_map(lambda w: w['input_x'].batch(window_size +␣
↪step_forecast))

    ds = ds.map(lambda w: w[:-step_forecast])
    ds = ds.batch(batch_size).prefetch(1)

    ds2 = ds_all.flat_map(lambda w: w['input_embed'].batch(window_size +␣
↪step_forecast))

    ds2 = ds2.map(lambda w: w[:-step_forecast])
    ds2 = ds2.batch(batch_size).prefetch(1)

    ds3 = ds_all.flat_map(lambda w: w['input_x'].batch(window_size +␣
↪step_forecast))

    ds3 = ds3.map(lambda w: tf.stack([w[i:i+step_forecast, 0]  for i in␣
↪range(1, window_size+1)], axis=0))
    ds3 = ds3.batch(batch_size).prefetch(1)

    # Both Methods Work
    ds_final = tf.data.Dataset.zip(({'input_main': ds, 'input_embed': ds2},␣
↪ds3))
    # ds_final = tf.data.Dataset.zip(((ds, ds2), ds3))

    return ds_final # iter(ds_final)

    # return ds, ds2, ds3
```

[ ]:
```
iterator = iter(windowed_dataset(dataset, 20, 1, 1000, 5))
```

[ ]:
```
train_set = next(iterator)
```

[ ]:
```
print(train_set)
```

```
({'input_main': <tf.Tensor: shape=(1, 20, 2), dtype=float64, numpy=
```

```
array([[[ 1.        , -0.02575347],
        [ 1.        , -0.03921155],
        [ 1.        , -0.03921155],
        [ 1.        , -0.02443406],
        [ 1.        , -0.03191076],
        [ 1.        , -0.02575347],
        [ 1.        , -0.01431851],
        [ 1.        , -0.03015154],
        [ 1.        , -0.01695735],
        [ 1.        , -0.02575347],
        [ 1.        , -0.0204758 ],
        [ 1.        , -0.0204758 ],
        [ 1.        , -0.0204758 ],
        [ 1.        , -0.01695735],
        [ 1.        , -0.01695735],
        [ 1.        , -0.0204758 ],
        [ 1.        , -0.00552238],
        [-0.9993293 , -0.04290592],
        [-1.        , -0.04290592],
        [-1.        , -0.04290592]]])>, 'input_embed': <tf.Tensor: shape=(1, 20,
2), dtype=int64, numpy=
array([[[   0, 1270],
        [   0,  622],
        [   0,  621],
        [   0, 1263],
        [   0,  167],
        [   0, 3048],
        [   0,  144],
        [   0, 1814],
        [   0, 1530],
        [   0, 1754],
        [   0, 1752],
        [   0, 1194],
        [   0, 1193],
        [   0, 3067],
        [   0, 1667],
        [   0, 1335],
        [   0, 1719],
        [   1, 1689],
        [   2, 3027],
        [   3,  797]]])>}, <tf.Tensor: shape=(1, 20, 5), dtype=float64, numpy=
array([[[ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
        [ 1.       ,  1.       ,  1.       ,  1.       ,  1.       ],
```

```
[ 1.        ,  1.        ,  1.        ,  1.        ,  1.        ],
[ 1.        ,  1.        ,  1.        ,  1.        ,  1.        ],
[ 1.        ,  1.        ,  1.        ,  1.        ,  1.        ],
[ 1.        ,  1.        ,  1.        ,  1.        ,  1.        ],
[ 1.        ,  1.        ,  1.        ,  1.        ,  1.        ],
[ 1.        ,  1.        ,  1.        ,  1.        , -0.9993293],
[ 1.        ,  1.        ,  1.        , -0.9993293, -1.        ],
[ 1.        ,  1.        , -0.9993293, -1.        , -1.        ],
[ 1.        , -0.9993293, -1.        , -1.        ,  1.        ],
[-0.9993293, -1.        , -1.        ,  1.        ,  0.9999092],
[-1.        , -1.        ,  1.        ,  0.9999092, -0.9993293],
[-1.        ,  1.        ,  0.9999092, -0.9993293, -1.        ],
[ 1.        ,  0.9999092, -0.9993293, -1.        ,  1.        ]]])>)
```

3. Conclusion - This is a notebook to get Data Scientists started and covers all of the necessary techniques - However due to my time constraints I could not include everything that I wanted to include - So instead I have attached my unstructured notes on these topics in the github repository provided. - This is located in the "Raw" folder in my github repository. - For future use the following content will be added: - Evaluating Model Performance with Multiple Metrics(TP, TN, FP, FN, Precision, Recall, F1 Score, AUC, ROC) - Scaling our Models to Production in Google Cloud Platform - Advanced Statistics such as Gaussian Processes, Multivariate Distributions, Likelihood, Out-of-Distribution models, etc.

4. References

[1] Géron, A., 2019. Hands-On Machine Learning With Scikit-Learn, Keras And Tensorflow. 2nd ed. Sebastopol: O'Reilly Media. Book

[2] Tensorflow Timeseries Prediction Deeplearning.AI

[3] Kaggle M5 Competition Timeseries (DENOISING WAVELETS, ARIMA, MOVING AVERAGES)