Sri_Lankan_TourismForecastModel_Prophet

October 16, 2024

```
[1]: import pandas as pd
    df = pd.read_csv('https://raw.githubusercontent.com/dev-achintha/
     Sri_Lanka-Tourism_Forcasting_Model/prophet/dataset/
      →2014-2024-monthly-tourist-arrivals-sl-csv.csv')
    df = df.drop(columns=['PercentageChange'], errors='ignore')
    df['ds'] = pd.to_datetime(df['Year'].astype(str) + '-' + df['Month'],__
      df.rename(columns={'Arrivals': 'y'}, inplace=True)
    df = df[['ds', 'y']]
    df.head()
[1]:
    0 2014-01-01 146575
    1 2014-02-01 141878
    2 2014-03-01 133048
    3 2014-04-01 112631
    4 2014-05-01
                  90046
[2]: # Split data into train and test sets
    train = df[:-24]
    test = df[-24:]
[3]: #prophet
    from prophet import Prophet
    model_prophet = Prophet(yearly_seasonality=True, weekly_seasonality=True,_u
     ⇔daily_seasonality=False,
                            changepoint_prior_scale=0.1, n_changepoints=30)
    model_prophet.add_seasonality(name='monthly', period=30.5, fourier_order=5)
    # changepoints = ['2019-04-21', '2020-03-01', '2022-03-22', '2023-02-25']
           # 2019-04-21 Easter Bombings
           # 2020-03-01 Covid19 Pandemic
           # 2022-03-22 Dollar rate increses
           # 2023-02-25 Dollar rate decreases
     # model = Prophet(changepoints=changepoints)
```

```
model_prophet.fit(train)
    future_prophet = model_prophet.make_future_dataframe(periods=24, freq='ME')
    forecast_prophet = model_prophet.predict(future_prophet)
    06:00:26 - cmdstanpy - INFO - Chain [1] start processing
    06:00:26 - cmdstanpy - INFO - Chain [1] done processing
[4]: # SARIMA
    from statsmodels.tsa.statespace.sarimax import SARIMAX
    model_sarima = SARIMAX(train['y'], order=(1, 1, 1), seasonal_order=(1, 1, 1, 1,
     →12))
    results_sarima = model_sarima.fit()
    forecast_sarima = results_sarima.forecast(steps=24)
    RUNNING THE L-BFGS-B CODE
    Machine precision = 2.220D-16
     N =
                   5
                         M =
                                       10
    At XO
                 O variables are exactly at the bounds
    At iterate
                      f= 1.02766D+01
                                        |proj g|= 1.24216D-01
    At iterate
                      f= 1.02438D+01
                                      |proj g|= 5.17627D-02
                 5
    At iterate
                10
                      f= 1.02372D+01
                                        |proj g|= 1.26834D-03
    At iterate 15
                                       |proj g|= 4.09548D-05
                      f= 1.02372D+01
               * * *
    Tit
        = total number of iterations
         = total number of function evaluations
    Tnint = total number of segments explored during Cauchy searches
    Skip = number of BFGS updates skipped
    Nact = number of active bounds at final generalized Cauchy point
    Projg = norm of the final projected gradient
        = final function value
       N
                   Tnf Tnint Skip Nact
                                              Projg
```

0

1.564D-05

1.024D+01

5

17

20

1

0

F = 10.237194792619087

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH

This problem is unconstrained.

```
[5]: # LSTM Model
     from sklearn.preprocessing import MinMaxScaler
     import numpy as np
     from keras.models import Sequential
     from keras.layers import LSTM, Dense
     scaler = MinMaxScaler()
     scaled_data = scaler.fit_transform(df[['y']])
     def create_sequences(data, seq_length):
         sequences = []
         for i in range(len(data) - seq_length):
             sequences.append(data[i:i+seq_length])
         return np.array(sequences)
     seq length = 12
     X = create_sequences(scaled_data[:-1], seq_length)
     y = scaled_data[seq_length:-1] # Adjust y to have the same number of samples_
      \hookrightarrow a X
     model_lstm = Sequential([
         LSTM(50, activation='relu', input_shape=(seq_length, 1)),
         Dense(1)
     ])
     model_lstm.compile(optimizer='adam', loss='mse')
     model_lstm.fit(X, y, epochs=100, batch_size=32, verbose=0)
     last_sequence = scaled_data[-seq_length:]
     forecast lstm = []
     for in range(24):
         next_pred = model_lstm.predict(last_sequence.reshape(1, seq_length, 1))
         forecast_lstm.append(next_pred[0, 0])
         last_sequence = np.roll(last_sequence, -1)
         last_sequence[-1] = next_pred
     forecast_lstm = scaler.inverse_transform(np.array(forecast_lstm).reshape(-1, 1))
```

2024-10-16 06:00:37.674733: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32] Could not find cuda drivers on your machine, GPU will not be used. 2024-10-16 06:00:37.678098: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32] Could not find cuda drivers on your machine, GPU will not be used.

2024-10-16 06:00:37.687433: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:485] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered 2024-10-16 06:00:37.701333: E

external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:8454] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered

2024-10-16 06:00:37.705542: E

external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1452] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered

2024-10-16 06:00:37.719201: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.

To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

2024-10-16 06:00:38.945013: W

tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT

/usr/local/python/3.12.1/lib/python3.12/site-

packages/keras/src/layers/rnn/rnn.py:204: 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__(**kwargs)

1/1 Os 107ms/step 1/1 Os 12ms/step 1/1 0s 12ms/step 1/1 0s 12ms/step 1/1 0s 14ms/step 1/1 0s 13ms/step 1/1 0s 13ms/step 1/1 0s 12ms/step 1/1 Os 12ms/step 1/1 0s 12ms/step 1/1 Os 12ms/step 1/1 0s 15ms/step 1/1 Os 12ms/step 1/1 0s 12ms/step 1/1 0s 12ms/step 1/1 Os 19ms/step 1/1 Os 22ms/step 1/1 Os 19ms/step 1/1 0s 14ms/step 1/1 0s 12ms/step 1/1 0s 12ms/step

Os 21ms/step

1/1

```
import warnings
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tools.sm_exceptions import ConvergenceWarning

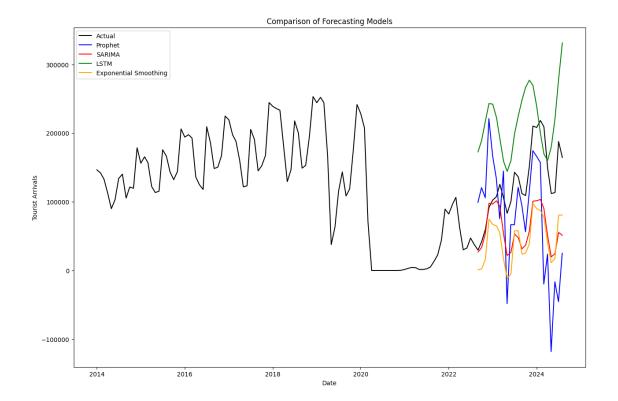
# Suppress the ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)

# Define and fit the Exponential Smoothing model
model_es = ExponentialSmoothing(train['y'], seasonal_periods=12, trend='add',
seasonal='add')
results_es = model_es.fit(optimized=True, remove_bias=True)

# Forecast using the fitted model
forecast_es = results_es.forecast(24)
```

1/1

Os 31ms/step



```
[12]: # Calculate MAE for each mode!
from sklearn.metrics import mean_absolute_error

mae_prophet = mean_absolute_error(test['y'], forecast_prophet['yhat'][-24:])
mae_sarima = mean_absolute_error(test['y'], forecast_sarima)
mae_lstm = mean_absolute_error(test['y'], forecast_lstm)
mae_es = mean_absolute_error(test['y'], forecast_es)

print(f"MAE Prophet: {mae_prophet}")
print(f"MAE SARIMA: {mae_sarima}")
print(f"MAE LSTM: {mae_lstm}")
print(f"MAE Exponential Smoothing: {mae_es}")
```

MAE Prophet: 87229.15375560976 MAE SARIMA: 68969.09074247057 MAE LSTM: 93762.59440104167

MAE Exponential Smoothing: 83541.2909200419

```
!jupyter nbconvert --to pdf /workspaces/
Sri_Lanka-Tourism_Forcasting_Model_SARIMA/notebooks/
Sri_Lankan_TourismForecastModel_Prophet.ipynb
```