Kabindra Senapati

Project Milestone

DSC 630

Milestone 4:

Note: All updates related to Milestone4 content is added on top of milestone3. Milestone 4 related updates are towards the end.

Data selection :

Data related to Airline industry will be used from Kaggle and related to the safetly trend. Since the project is related Airline industry and analyzing travelling pattern to predict the future airline travel safety trend, I'm attaching the datasets that I will use to build the models for the predictive analytics. The project is to develop accurate demand forecasting model to control the availability in Airline industry.

I'll be using the below models for my predictive analystics

I will be using regession modeling techniques and for this project the below models I might use.

Forecast model

Since Forecast models are one of the most prominent predictive model types. They predict future values based on historical data. In addition, these models manage metric value predictions by estimating the numeric value for new data based on learnings from historical data.

Time series model

A time series model is used to predict future events based on past data ordered in a sequence. It is an econometric technique used to predict future values based on past values. A time series model uses the trends, seasonality and cyclicality of a system, as well as other factors to forecast future behavior.

Both these models will use the past datasets and predict the pricing pattern for the future.

Evaluation:

To evaluate the above models, I might use any one of the below metrics.

To evaluate how good the regression model is, I will or might use below metrics:

- R-squared: it indicates how many variables compared to the total variables the model predicted. R-squared does not take into consideration any biases that might be present in the data.
- Average error: it is the numerical difference between the predicted value and the actual value.
- Median error: the average of all difference between the predicted and the actual values.
- Median absolute error: represents the average of the absolute differences between prediction and actual observation. All individual differences have equal weight, and big outliers can therefore affect the final evaluation of the model.

Learning:

I hope to learn the use and application of predictive modeling on a real life cases.

To start, you need to get clear about what business challenge this model is helping solve. This process will define if you are working with a classification or a regression problem, and ease the process of choosing the right metrics and predictive measures.

Ethical implication:

With The huge amount of data generated is airline industry, it is possible for them to predict flight delays or pricing trend and then provide better services for consumers. However, the application of these big data in the airline industry also results in privacy and ethical issues. Users' information is tracked without permission and several immoral companies overly collect irrelevant personal private data.

Contingency Plan:

I’m confident that I will be able to complete the original project plan but In case I’m not able to execute my original project plan, I will change the dataset and project topic so that I can use the predictive modelling effectively.

Milestone 3 -- Updates

- Will I be able to answer the questions I want to answer with the data I have?

  The data I've chosen for this project , I believe I should be able to answer the questions that I am looking for. The data gives an insight of the flight safety and the type of incidents and the frequency since last 40 years. It gives an overall trend of the incidents in the flight history.

  Used the below datasets to prepare the Dashboard.

  Below steps are followed while preparing the overall presentation and analysing the data.

  1. Overall study of the available dataset and any correlation between different datasets
  2. Choosing the right dataset for the presentation

- Do I need to adjust the data and/or driving questions?

  Based on exploratory data analysis (EDA), visualizations and initial model results, there is a possibility to that it might need some rebalancing of the classes. I plan to employ the machine learning technique SMOTE (Synthetic Minority Oversampling Technique) to overcome this issue if the training data set is imbalanced which usually happens if there are more observations of one categorical variable type and very few for other type.

  Irrespective of this, I should be still using the required tools/techniques and still be able to address the questions with the given dataset.

  The below steps will be used to prep the dataset.

  - The text data is converted into structured data
  - The NA/Null variables are replaced with Median values.

- Do I need to adjust my model/evaluation choices?

  I would need to adjust the models based on the train and test dataset to predict the likeliness of accidents based on the available incident history of airlines from the given dataset (sourced). I would also check and review the train data set before fitting the models to ensure the classes are not imbalanced anywhere in the train data set which incase might need to rebalance them before fitting the actual models for evaluation.

- Are my original expectations still reasonable?

I feel confident that the original expectations are still reasonable to be able to build a predictive model for airline incident likeliness based on the variables available in the given dataset and the model approach I mentioned earlier. While the dataset falls short on the number of features and observations, it is still good enough to address the research questions and build a decent accurate model.

MILESTONE 4: - UPDATES

In [3]:

```
import matplotlib.pyplot as plt
from datetime import datetime, timedelta
from matplotlib import dates as mpl_dates
import pandas as pd
import seaborn as sns
```

In [5]:

```
data = pd.read_csv('ICAO_accidents.csv')
```

In [6]:

```
data.head()
```

Out[6]:

	Unnamed: 0	Date	StateOfOccurrence	Location	Model	Registration	Operator
0	0	"2008-01-02T00:00:00.000Z"	PHL	Masbate Airport (MBT)	NAMC YS11 A	RP-C3592	Philippines Asian Spirit
1	1	"2008-01-02T00:00:00.000Z"	IRN	Tehran-Mehrabad Airport (THR)	FOKKER F27 100	EP-IDB	Iran, Islamic Republic Of Iran National Airlin...
2	2	"2008-01-03T00:00:00.000Z"	USA	Oklahoma City	PILATUS PC12	N398J	NaN
3	3	"2008-01-04T00:00:00.000Z"	VEN	A 20 NM del VOR del Gran Roque	LET L410 UVP	YV2081	Venezuela
4	4	"2008-01-05T00:00:00.000Z"	USA	Kodiak	PIPER PA31P 350	N509FN	NaN

5 rows × 25 columns

In [7]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6109 entries, 0 to 6108
Data columns (total 25 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         6109 non-null   int64
 1   Date               6109 non-null   object
 2   StateOfOccurrence  5307 non-null   object
 3   Location           5758 non-null   object
 4   Model              5866 non-null   object
 5   Registration       6109 non-null   object
 6   Operator           4184 non-null   object
 7   StateOfOperator    1391 non-null   object
 8   StateOfRegistry    6107 non-null   object
 9   FlightPhase        5175 non-null   object
 10  Class              6109 non-null   object
```

```
 11  Fatalities            4968 non-null   float64
 12  Over2250              6109 non-null   bool
 13  Over5700              6085 non-null   object
 14  ScheduledCommercial   3277 non-null   object
 15  InjuryLevel           4154 non-null   object
 16  TypeDesignator        6109 non-null   object
 17  Helicopter            4881 non-null   object
 18  Airplane              6109 non-null   bool
 19  Engines               6109 non-null   int64
 20  EngineType            6109 non-null   object
 21  Official              1344 non-null   object
 22  OccCats               6109 non-null   object
 23  Risk                  5359 non-null   object
 24  Year                  6109 non-null   int64
dtypes: bool(2), float64(1), int64(3), object(19)
memory usage: 1.1+ MB
```

Data Prep Steps

In [8]:
```
##Drop Unwanted columns
data.columns
```

Out[8]:
```
Index(['Unnamed: 0', 'Date', 'StateOfOccurrence', 'Location', 'Model',
       'Registration', 'Operator', 'StateOfOperator', 'StateOfRegistry',
       'FlightPhase', 'Class', 'Fatalities', 'Over2250', 'Over5700',
       'ScheduledCommercial', 'InjuryLevel', 'TypeDesignator', 'Helicopter',
       'Airplane', 'Engines', 'EngineType', 'Official', 'OccCats', 'Risk',
       'Year'],
      dtype='object')
```

In [9]:
```
data = data.drop(columns= ['Date','StateOfOccurrence','Location','Model',
                           'Registration','Operator','StateOfOperator','StateOfR
                           'Over2250','Over5700','Class','ScheduledCommercial','
                           'Helicopter',
                           'Airplane','Engines','EngineType','Official','OccCats
```

In [10]:
```
data.head()
```

Out[10]:

	Unnamed: 0	FlightPhase	Fatalities	InjuryLevel	Risk	Year
0	0	Landing	0.0	None	RS	2008
1	1	Take-off	0.0	None	OTH	2008
2	2	Standing	1.0	Fatal	RS	2008
3	3	En route	14.0	Fatal	SCF	2008
4	4	Take-off	6.0	Fatal	LOC-I	2008

In [14]:
```
df = data.groupby(['Year']).size().reset_index(name='Total_accidents')
print(df)
```

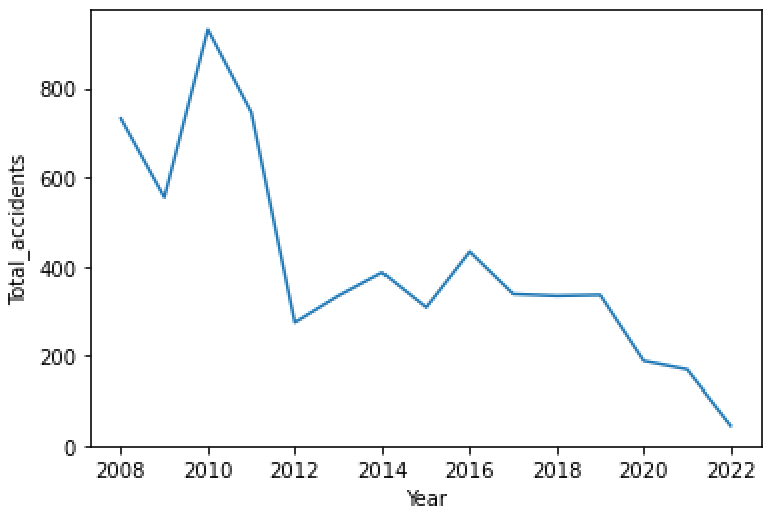
```
   Year  Total_accidents
0  2008              732
1  2009              555
```

```
2    2010                 932
3    2011                 746
4    2012                 274
5    2013                 334
6    2014                 386
7    2015                 308
8    2016                 433
9    2017                 338
10   2018                 334
11   2019                 336
12   2020                 188
13   2021                 169
14   2022                  44
```

In [15]:

```
sns.lineplot(data=df,x=df.Year,y=df.Total_accidents)
```

Out[15]: <AxesSubplot:xlabel='Year', ylabel='Total_accidents'>



In [16]:

```
newdf = df.dropna()
```

In [17]:

```
newdf.head()
```

Out[17]:

	Year	Total_accidents
0	2008	732
1	2009	555
2	2010	932
3	2011	746
4	2012	274

In [42]:

```
len(newdf)
```

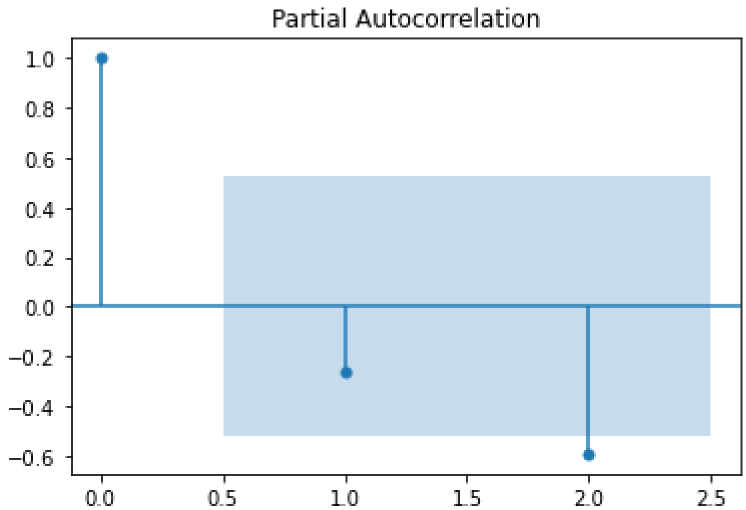
Out[42]: 15

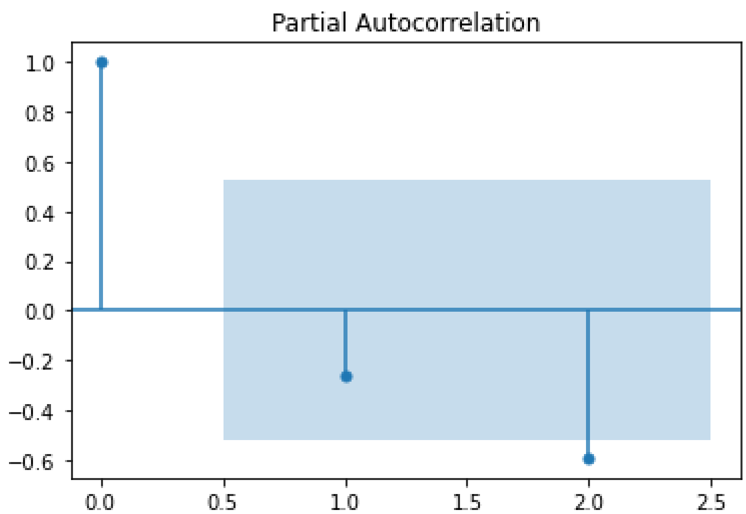
In [1]:
```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

In [22]:
```
newdf['firstdiff'] = newdf['Total_accidents'].diff(1)
```

In [24]:
```
plot_pacf(newdf['firstdiff'].dropna(),lags=2)
```

Out[24]:





In [43]:
```
##Split this data into a training and test set.
##Use the last year of data (July 2020 – June 2021) of data as your test
#set and the rest as your training set.
len(data.index)
df_train=newdf.iloc[:10]
df_test = newdf.iloc[10:]
```

In [44]:
```
##Use the model to predict the monthly retail sales on the last year of data.
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [46]:
```
model= SARIMAX(df_train['Total_accidents'],
 order=(1,1,1),
 enforce_invertibility=False, enforce_stationarity=False)
```

In [47]:
```
result = model.fit()
```

```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            2     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  5.08357D+00    |proj g|=  8.94720D-02

At iterate    5    f=  4.80021D+00    |proj g|=  2.10095D-01

At iterate   10    f=  4.70439D+00    |proj g|=  3.10118D-03
 This problem is unconstrained.
At iterate   15    f=  4.70438D+00    |proj g|=  9.35261D-06

           * * *

Tit   = total number of iterations
Tnf   = 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
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    2     15     21      1     0     0   9.353D-06   4.704D+00
  F =   4.7043816778283993

CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL
```

In [48]:
```
print(result.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:        Total_accidents   No. Observations:                   10
Model:               SARIMAX(0, 1, 1)   Log Likelihood                 -47.044
Date:                Tue, 07 Feb 2023   AIC                             98.088
Time:                        20:15:26   BIC                             97.979
Sample:                             0   HQIC                            96.751
                                 - 10
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.2961      0.804     -0.368      0.713      -1.872       1.280
sigma2      4.021e+04   1.45e+04      2.764      0.006    1.17e+04    6.87e+04
================================================================================
===
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):
2.70
```

```
Prob(Q):                              0.92   Prob(JB):
0.26
Heteroskedasticity (H):               0.06   Skew:                         -
1.42
Prob(H) (two-sided):                  0.11   Kurtosis:
4.09
=================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-s
tep).
```

In [50]:

```
final_predict = pd.DataFrame(result.predict(start=len(df_train),end = len(newdf)
```

In [51]:

```
final_predict.column=['pred']
```

```
/var/folders/jd/05jr366d0jn13pfs71x7v06w0000gn/T/ipykernel_64845/297076127.py:1:
UserWarning: Pandas doesn't allow columns to be created via a new attribute name
- see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-acces
s
  final_predict.column=['pred']
```

In [52]:

```
final_predict
```

Out[52]:

	predicted_mean
10	356.993447
11	356.993447
12	356.993447
13	356.993447
14	356.993447

In [53]:

```
final_data = pd.concat((final_predict,df_test),axis=1)
```

In [54]:

```
final_data.head()
```

Out[54]:

	predicted_mean	Year	Total_accidents
10	356.993447	2018	334
11	356.993447	2019	336
12	356.993447	2020	188
13	356.993447	2021	169
14	356.993447	2022	44

In [56]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt
```

```
rms = sqrt(mean_squared_error(final_predict['predicted_mean'].values,
                              df_test['Total_accidents'].values))
```

In [57]:
```
print(rms)
```

```
180.46309434976877
```

In [ ]:
```
## Outcome and conclusion
```

In [ ]:
```
The dataset had to go through lot of cleaning process and still the dataset
is not a static one. and becasue of that the model outcome for RMS is pretty
high . I believe we need to take other factors into account while building
the model and instead of the taking the actual numbers for the year, we
should have more breakdown of the numbers based on the monthly or daily
data where we could have calculated the moving average and standard deviation
and that could have given a better result.

An RMSE of 100 and more indicates that the model has a large discrepancy
between its predictions and the actual values.

A high RMSE can indicate a few things, such as:

Overfitting: The model may have memorized the training data too well and
is not generalizing well to new data.
Outliers: There may be some outliers in the data that are affecting the
model's performance.


In conclusion, if the RMSE of a predictive model is 100 and more,
it's important to analyze the causes and make adjustments to improve the
model's performance. This may involve collecting more data, using a
different model, or using a combination of models. The goal is to achieve
a lower RMSE that indicates a closer match between the predicted and actual
values.
```