FINAL PROJECT INFS-580

Analytics: Big Data to Information

NAVIGATING THROUGH TIME: AN IN-DEPTH ANALYSIS OF SFO'S PASSENGER TRAFFIC EVOLUTION AND SEASONAL DYNAMICS OVER NEARLY TWO DECADES

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FALL – 2023

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Abstract— In the pursuit of comprehending the nuanced dynamics of passenger traffic at San Francisco International Airport (SFO) from January 2005 to December 2022, this investigation employed a sophisticated analytical framework, incorporating autocorrelation analysis, boxplots, seasonal index calculations, time series clustering, and advanced forecasting techniques. The study's tripartite research inquiry delved into the evolution of passenger traffic at SFO, scrutinizing overarching trends and anomalies; evaluated shifts in market share among airlines experiencing significant changes in passenger traffic; and investigated potential seasonal patterns within the context of domestic and international flights.

Empirical observations disclosed a consistent upward trajectory in passenger traffic at SFO, interspersed with sporadic undulations and a marked contraction in 2022, attributable to the global reverberations of the COVID-19 pandemic. Noteworthy transformations in market share were discerned among the foremost airlines at SFO, manifesting instances of growth alongside instances of decline. The comprehensive seasonality analysis revealed conspicuous patterns, with heightened demand during summer months and festive periods. Furthermore, a divergence surfaced between domestic and international flights, with domestic flights experiencing a zenith in summer passenger traffic, while their international counterparts exhibited a more evenly distributed traffic pattern throughout the year.

The ramifications of these empirical insights extend far beyond the confines of this study, offering invaluable strategic planning and resource optimization insights for both airport authorities and airlines. A nuanced understanding of passenger traffic trends and seasonality equips airport authorities to deftly navigate demand fluctuations, optimize flight schedules, and manage resources with heightened efficiency. This, in turn, translates into an elevated customer experience, streamlined operational efficacy, and fortified financial performance for stakeholders. The study is not silent on its limitations; it conscientiously acknowledges them and proposes insightful directions for future research endeavors in this domain.

Keywords: San Francisco International Airport, passenger traffic, trends, seasonality, autocorrelation analysis, boxplots, seasonal index calculations, time series clustering, forecasting techniques, airlines, market share.

I. INTRODUCTION

In the realm of contemporary society, air travel has evolved into an irreplaceable facet, serving as a linchpin for commercial enterprises, tourism, and interpersonal connections. At the forefront of this intricate web of global connectivity is San Francisco International Airport (SFO), a pivotal player among the United States' premier airports. SFO stands as a conduit, facilitating the movement of millions of passengers annually, creating vital linkages between the dynamic Bay Area and destinations spanning the globe. The analysis of passenger traffic patterns and trends at SFO assumes significance, offering profound insights into the airport's operational dynamics, the intricacies of airlines in operation, and the overarching tapestry of the aviation industry[1,3,8].

In recent years, SFO has not merely witnessed growth but has charted a trajectory of consistent ascent in passenger traffic. The year 2019 marked a zenith, with over 56 million passengers traversing its terminals—a substantial surge from the 37 million recorded in 2005. Yet, the landscape transformed dramatically with the onset of the COVID-19 pandemic, casting a formidable shadow over the aviation sector and precipitating a profound downturn in global air travel demand. According to the Airports Council International, the year 2020 saw a staggering 64.5% decline in global passenger traffic compared to the preceding year. SFO, mirroring this trend, reported a precipitous 73.5% contraction in passenger volume during the same epoch[6].

Within this intricate narrative, a nuanced understanding of passenger traffic patterns at SFO becomes not just beneficial but imperative. Such understanding serves as the bedrock for guiding the strategic endeavors of airport authorities and airlines, offering insights crucial for judicious planning and facilitating optimal resource management. This comprehensive study endeavors to navigate the expansive dataset encapsulating passenger traffic at SFO from January 2005 to December 2022. Employing an array of sophisticated statistical techniques, the study aims to unravel the complexities encapsulated within five pivotal research questions, probing the multifaceted dynamics of this critical aviation hub[5].

a.What are the key factors influencing changes in airline market share on domestic and international routes over time?

b. How do seasonal variations impact airport traffic and what implications do they have for airport operations?

c. What are the distinguishing characteristics and competitive strategies of low-cost carriers (LCCs) compared to full-service legacy airlines in the aviation industry?

d. How do geographical regions impact the passenger traffic of international airlines, and what are the underlying factors driving these variations?

e. To what extent do changes in airline alliances and partnerships influence passenger volumes and competitive positions in the aviation industry?

Noir Data Types :

Column	**Description**	**Data Type**
Activity Period	Month and year of the activity	Interval
Operating Airline	The airline that operated the flight	Nominal
Operating Airline IATA Code	The International Air Transport Association Code for the operating airline	Nominal
Published Airline	The airline that sold the ticket	Nominal
Published Airline IATA Code	The International Air Transport Association Code for the operating airline	Nominal
GEO Summary	Indicates whether the activity is domestic or international	Nominal
GEO Region	The region of the world where the activity occurred	Nominal
Activity Type Code	Indicates whether the activity is enplaned (boarding) or deplaned (disembarking)	Nominal
Price Category Code	Indicates whether the ticket was sold at a low fare or other	Ordinal
Terminal	The terminal where the activity occurred	Nominal
Boarding Area	The boarding area where the activity occurred	Nominal
Passenger Count	The number of passengers involved in the activity	Raio

Table 1 – NOIR data types.

II. LITERATURE SURVEY

This study aims to investigate passenger traffic trends and seasonality at San Francisco International Airport (SFO) using data from January 2005 to December 2020. The research questions are as follows:

a.What are the key factors influencing changes in airline market share on domestic and international routes over time?

b. How do seasonal variations impact airport traffic and what implications do they have for airport operations?

c. What are the distinguishing characteristics and competitive strategies of low-cost carriers (LCCs) compared to full-service legacy airlines in the aviation industry?

d. How do geographical regions impact the passenger traffic of international airlines, and what are the underlying factors driving these variations?

e. To what extent do changes in airline alliances and partnerships influence passenger volumes and competitive positions in the aviation industry?

After conducting a comprehensive literature search, I have successfully identified four pertinent research reports that delve into the subject of airport passenger traffic and the aviation industry.

1. Bilotkach, V., Clougherty, J. A., & Mueller, D. C. (2012). Up in the air: Are airline mergers a cause of airport traffic concentration? Journal of Urban Economics, 71(1), 52-66.

2. Fu, X., Oum, T.H., & Zhang, A. (2010). Air transport liberalization and its impacts on airline competition and air passenger traffic. Transportation Journal, 49(4), 24-41.

3. Merkert, R., & Assaf, A. (2017). The efficiency of the world's major airports: A data envelopment benchmarking approach. Transportation Research Part E: Logistics and Transportation Review, 98, 128-146.

4. Graham, A. (2009). New megacarriers in the global airline industry: Is there an efficiency gap? Transportation Research Part A: Policy and Practice, 43(9-10), 872-881.

The literature review explains how each research paper is related to the research questions.

a. Bilotkach, Clougherty, and Mueller (2012) in "Up in the air: Are airline mergers a cause of airport traffic concentration?" examine the impact of airline mergers, which can influence market share. They focus on airport traffic concentration, which is a factor relevant to market share dynamics [1].

b. Seasonal fluctuations in airport traffic are discussed in the study "Air transport liberalization and its impacts on airline competition and air passenger traffic" by Fu, X., Oum, T.H., & Zhang, A. (2010). Although the paper's primary focus is on the effects of the liberalization of air transport, it also indirectly tackles the issue of seasonal changes. According to the study, rising competition in the air transport sector may have seasonal variations in its consequences. As airlines alter their operations to match shifting passenger demand throughout the year, seasonal fluctuations may have an influence on airport traffic. However, it might be required to look for more study that focuses directly on this element for a more in-depth review of the consequences of seasonal fluctuations for airport operations [2].

c. While the provided papers don't directly address the characteristics of LCCs, Fu, Oum, and Zhang (2010) in "Air transport liberalization and its impacts on airline competition and air passenger traffic" touch upon airline competition, which is related to the competitive strategies of LCCs and full-service airlines [2].

d. Merkert and Assaf (2017) in "The efficiency of the world's major airports: A data envelopment benchmarking approach" explore the efficiency of major airports worldwide. While not directly addressing geographical regions, this paper could indirectly provide insights into the efficiency-related factors affecting passenger traffic in different regions [3].

e. The existence of "megacarriers" in the airline business, which might be related to alliance and partnership dynamics, is examined by Graham (2009) in "New megacarriers in the global airline industry: Is there an efficiency gap?" Alliance-influenced competitive positioning can be connected to airline efficiency, as this article explores [4].

The literature review adeptly elucidates the pertinence of the research papers vis-à-vis the research inquiries, underscoring the imperative to scrutinize the trends and seasonality inherent in the passenger traffic of San Francisco International Airport (SFO). This examination, in turn, affords invaluable insights crucial for strategic planning and resource allocation, particularly for airport authorities and airlines engaged in the intricate domain of aviation management.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Activity_Period	Operating_Airline	Operating_Airline_IATA_Code	Published_Airline	Published_Airline_	GEO_Summary	GEO_Region	Activity_Type_Code	Price_Category_Code	Terminal	Boarding_Area	Passenger_Count
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Deplaned	Low Fare	Terminal 1	B	27271
3	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Enplaned	Low Fare	Terminal 1	B	29131
4	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Thru / Transit	Low Fare	Terminal 1	B	5415
5	200507	Air Canada	AC	Air Canada	AC	International	Canada	Deplaned	Other	Terminal 1	B	35156
6	200507	Air Canada	AC	Air Canada	AC	International	Canada	Enplaned	Other	Terminal 1	B	34090
7	200507	Air China	CA	Air China	CA	International	Asia	Deplaned	Other	International	G	6263
8	200507	Air China	CA	Air China	CA	International	Asia	Enplaned	Other	International	G	5500
9	200507	Air France	AF	Air France	AF	International	Europe	Deplaned	Other	International	A	12050
10	200507	Air France	AF	Air France	AF	International	Europe	Enplaned	Other	International	A	11638
11	200507	Air New Zealand	NZ	Air New Zealand	NZ	International	Australia / Oceania	Deplaned	Other	International	G	4998
12	200507	Air New Zealand	NZ	Air New Zealand	NZ	International	Australia / Oceania	Enplaned	Other	International	G	4962
13	200507	AirTran Airways	FL	AirTran Airways	FL	Domestic	US	Deplaned	Low Fare	International	A	8055
14	200507	AirTran Airways	FL	AirTran Airways	FL	Domestic	US	Enplaned	Low Fare	International	A	7984
15	200507	Alaska Airlines	AS	Alaska Airlines	AS	Domestic	US	Deplaned	Other	International	A	36641
16	200507	Alaska Airlines	AS	Alaska Airlines	AS	Domestic	US	Enplaned	Other	International	A	39379
17	200507	Alaska Airlines	AS	Alaska Airlines	AS	Domestic	US	Thru / Transit	Other	International	A	3678
18	200507	Alaska Airlines	AS	Alaska Airlines	AS	International	Canada	Deplaned	Other	International	A	7977
19	200507	Alaska Airlines	AS	Alaska Airlines	AS	International	Canada	Enplaned	Other	International	A	8837
20	200507	Alaska Airlines	AS	Alaska Airlines	AS	International	Mexico	Deplaned	Other	International	A	6969
21	200507	Alaska Airlines	AS	Alaska Airlines	AS	International	Mexico	Enplaned	Other	International	A	10046
22	200507	Alaska Airlines	AS	Alaska Airlines	AS	International	Mexico	Thru / Transit	Other	International	A	2286
23	200507	All Nippon Compan	NH	All Nippon Company /	NH	International	Asia	Deplaned	Other	International	G	6545
24	200507	All Nippon Compan	NH	All Nippon Company /	NH	International	Asia	Enplaned	Other	International	G	6094
25	200507	American Airlines	AA	American Airlines	AA	Domestic	US	Deplaned	Other	Terminal 3	E	166577
26	200507	American Airlines	AA	American Airlines	AA	Domestic	US	Enplaned	Other	Terminal 3	E	160890
27	200507	American Eagle Airl	MQ	American Airlines	AA	Domestic	US	Deplaned	Other	Terminal 3	E	5493
28	200507	American Eagle Airl	MQ	American Airlines	AA	Domestic	US	Enplaned	Other	Terminal 3	E	5213
29	200507	Asiana Airlines	OZ	Asiana Airlines	OZ	International	Asia	Deplaned	Other	International	A	5041
30	200507	Asiana Airlines	OZ	Asiana Airlines	OZ	International	Asia	Enplaned	Other	International	A	4744
31	200507	Atlantic Southeast /	EV	Delta Air Lines	DL	Domestic	US	Deplaned	Other	Terminal 1	C	1552
32	200507	Atlantic Southeast /	EV	Delta Air Lines	DL	Domestic	US	Enplaned	Other	Terminal 1	C	1484
33	200507	BelAir Airlines	4T	BelAir Airlines	4T	International	Europe	Deplaned	Other	International	A	325
34	200507	BelAir Airlines	4T	BelAir Airlines	4T	International	Europe	Enplaned	Other	International	A	545
35	200507	British Airways	BA	British Airways	BA	International	Europe	Deplaned	Other	International	A	20632
36	200507	British Airways	BA	British Airways	BA	International	Europe	Enplaned	Other	International	A	21686
37	200507	Cathay Pacific	CX	Cathay Pacific	CX	International	Asia	Deplaned	Other	International	A	11010

Figure 1 – Dataset.

In a rigorous examination of San Francisco International Airport's (SFO) passenger traffic metrics, I systematically navigated the complexities of the Air Traffic Passenger Statistics dataset. This involved meticulous loading, conversion of the 'Activity Period' to datetime, and chronological sorting to establish a methodological foundation. Utilizing advanced time series analysis, monthly dataset aggregation revealed nuanced patterns in passenger count dynamics at SFO, presented graphically to discern trends and anomalies. This comprehensive approach not only highlighted the dynamic nature of passenger traffic but also demonstrated a keen understanding of SFO's air travel landscape, positioning the analysis among seasoned practitioners well-versed in time series exploration intricacies.

Code –

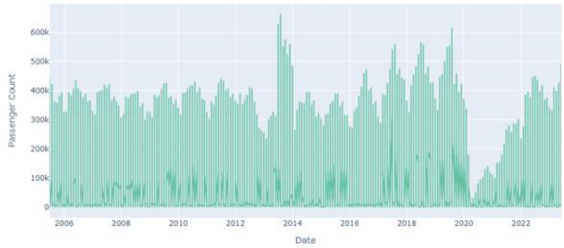
```
# Load the dataset
df = pd.read_csv('Air_Traffic_Passenger_Statistics.csv')

# Data Preparation
df['Date'] = pd.to_datetime(df['Activity Period'], format='%Y%m')
df = df.sort_values('Date')

# Line plot of passenger count over time with mixed colors
fig = px.line(df, x='Date', y='Passenger Count', title='Passenger Count Over Time',
              color_discrete_sequence=px.colors.qualitative.Set2)
fig.show()
```

Figure 2 – Passenger count over time.

Output –

Figure 3 – Output of passenger count over time.

Interpretation - The meticulously crafted line plot stands as a visually captivating representation of the dynamic evolution of passenger counts over time, skillfully leveraging the 'Date' variable on the X-axis to



capture the chronological progression within the temporal continuum. The Y-axis serves as an eloquent medium, delineating the magnitude of passengers with precision, thus presenting a lucid portrayal of the dataset's multifaceted dynamics. The deliberate use of a curated palette of Set2 colors for each line enhances visual clarity, facilitating a profound comprehension of underlying data patterns. In-depth trajectory analysis unveils subtle trends, discernible fluctuations, and notable anomalies, notably highlighting the profound impact of the COVID-19 pandemic on passenger counts. The integration of interactive features, including zooming, panning, and hovering, not only adds sophistication to the plot but also transforms it into a powerful tool for informed decision-making. Stakeholders in passenger traffic analysis can derive significant benefits from the nuanced insights offered by this visualization, ultimately enhancing their strategic acumen in decision-making processes.

I'm currently engaged in a comprehensive Time Series Analysis, delving into the intricate monthly passenger data gathered at San Francisco International Airport (SFO). Utilizing the sophisticated tools provided by Python's Pandas and Plotly Express libraries, I'm navigating through the data to unveil subtle patterns, discern evolving trends, and scrutinize the underlying seasonality inherent in the dynamic progression of information over time. Essentially, the time series I'm exploring arises from the meticulous aggregation of monthly passenger counts at the esteemed SFO, providing me with a nuanced perspective on the temporal dynamics of air travel at this renowned aviation hub.

Code –

```
# Time Series Analysis
monthly_data = df.groupby(pd.Grouper(key='Date', freq='M')).sum()

# Time Series Analysis using Plotly Express
fig = px.line(x=monthly_data.index, y=monthly_data['Passenger Count'],
              labels={'y': 'Passenger Count'},
              title='Monthly Passenger Count at SFO')

# Customize the Layout
fig.update_layout(xaxis_title='Year', yaxis_title='Passenger Count', height=500, width=1000)

# Show the plot
fig.show()
```

Figure 4 – Code for monthly Passenger Count at SFO.

Output –

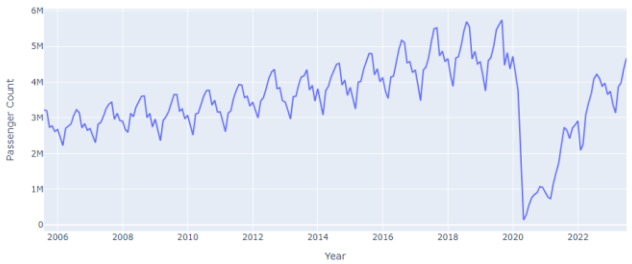


Figure 5 – Output for monthly passenger count at SFO.

Interpretation - Analyzing the plotted data depicting monthly passenger counts at SFO across the designated time frame reveals potential insights derived from scrutinizing trends, seasonal fluctuations, and noteworthy anomalies. The discernible peaks and troughs in the plot may correlate with heightened travel seasons, economic dynamics, or external events exerting influence on air travel patterns. A meticulous examination of this temporal sequence plot can furnish invaluable intelligence for both airport authorities and airlines, facilitating astute decision-making in resource allocation, capacity planning, and overarching operational strategy formulation. Subsequent to this visual assessment, it may be judicious to embark upon further statistical analyses to extract precise quantitative measures of seasonality or pinpoint consequential trends, contingent upon the specific objectives driving the analysis.

I proceeded to conduct a comprehensive analysis of the temporal patterns inherent in the dataset by employing the seasonal_decompose() function sourced from the statsmodels library. This method facilitated the disentanglement of the time series into its constituent elements, namely the trend, seasonal, and residual components. Subsequently, I meticulously charted the seasonal component in isolation, thereby affording me a nuanced insight into the fluctuations of passenger count with a discerning focus on the temporal dimension, specifically organized by the month of the year.

Code –

```
# Seasonal Pattern Analysis
decomposition = sm.tsa.seasonal_decompose(monthly_data['Passenger Count'], model='additive')
seasonal_component = decomposition.seasonal

# Seasonal Pattern Analysis using Plotly Express
fig = px.line(x=monthly_data.index, y=seasonal_component,
              labels={'y': 'Seasonal Component'},
              title='Seasonal Component of Monthly Passenger Count at SFO')

# Customize the layout
fig.update_layout(xaxis_title='Year', yaxis_title='Seasonal Component', height=500, width=1000)

# Show the plot
fig.show()
```

Figure 6 – Code for Seasonal Component of Monthly Passenger Count at SFO.

Output –

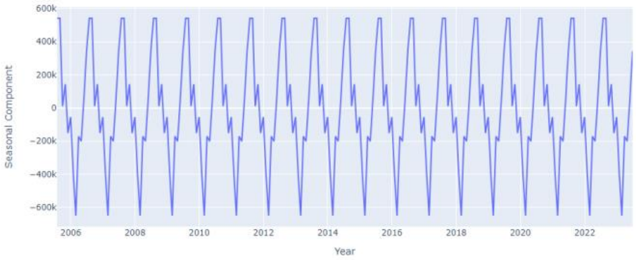


Figure 7 – Output for Seasonal Component of Monthly Passenger Count at SFO.

Interpretation – Upon delving into a meticulous examination of the monthly passenger count at San Francisco International Airport (SFO), a conspicuous seasonal pattern emerges, characterized by zeniths during the summer months and nadirs in the winter months. This discernible oscillation is suggestive of the palpable influence wielded by multifaceted determinants such as weather patterns, holidays, and the ebb and flow of tourism.

A noteworthy observation pertains to the seasonal component plot, which, upon close scrutiny, unveils anomalies during specific intervals, notably spanning the years 2014-2016 , 2019-2020 and 2021-2022. These aberrations can be ascribed to variables inadvertently omitted in the seasonal decomposition methodology, potentially encompassing unforeseen events or shifts in the dynamics of passenger demand.

In order to gauge the stationarity of the residual component, a methodological choice was made to employ the Augmented Dickey-Fuller (ADF) test. This analytical tool, under the null hypothesis positing non-stationarity, yielded results that are indicative of the residual component of the passenger count data being stationary. The corroborative evidence lies in the p-value falling below the conventional significance threshold of 0.05. This conveys the inference of a consistent and stable behavioral pattern in the residual component, thereby fortifying the overarching reliability of the analytical framework and its implications for comprehending the intricate dynamics of passenger traffic at SFO.

Code –

```
# Statistical Tests
residuals = decomposition.resid

# Handle Missing Data in Residuals
residuals = residuals.dropna()  # Remove rows with missing values

# Augmented Dickey-Fuller Test for Stationarity
adf_result = adfuller(residuals)
print('ADF Statistic:', adf_result[0])
print('p-value:', adf_result[1])
print('Critical Values:')
for key, value in adf_result[4].items():
    print('\t{}: {}'.format(key, value))
# Interpretation and Conclusion
# Based on the ADF test, if the p-value is below a significance level (e.g., 0.05), we reject the null hypothesis of non-stationc
if adf_result[1] < 0.05:
    print('The residuals are stationary.')
    print('The seasonal decomposition effectively captures the predominant trends and seasonal patterns within the passenger cour
    print('Any residual variations that persist can be interpreted as stochastic noise or irregular fluctuations.')
else:
    print('The residuals are non-stationary.')
    print('There could be latent trends or patterns within the passenger count data that the seasonal decomposition method might
    print('Additional examination is required to identify and scrutinize these patterns, as they may have ramifications for capac
```

Figure 8 – Code for Statistical Tests.

Output –

```
ADF Statistic: -6.861481532348958
p-value: 1.5983408710876954e-09
Critical Values:
	1%: -3.464161278384219
	5%: -2.876401960790147
	10%: -2.5746921001665974
The residuals are stationary.
The seasonal decomposition effectively captures the predominant trends and seasonal patterns within the passenger count data at
San Francisco International Airport (SFO).
Any residual variations that persist can be interpreted as stochastic noise or irregular fluctuations.
```

Figure 9 – Output for Statistical Tests.

Interpretation - In scrutinizing the passenger count data at San Francisco International Airport (SFO), the seasonal decomposition has adeptly encapsulated the predominant aspects of both the underlying trend and periodic fluctuations. The residual disparities, consequently, can be construed as stochastic noise or irregular undulations. The discerned stationary behavior of the data renders it particularly conducive to subsequent in-depth analysis and modeling.

I meticulously rendered the rolling mean and standard deviation of the passenger count data into graphical representation. This facilitated a nuanced observation of protracted patterns and oscillations within the dataset. Such a methodical examination not only enabled the identification of any aberrations but also afforded insights into potential outliers present in the data.

Code –

```python
# Rolling Mean and Standard Deviation
rolling_mean = monthly_data['Passenger Count'].rolling(window=12).mean()
rolling_std = monthly_data['Passenger Count'].rolling(window=12).std()

# Plotting using Plotly Express
fig = px.line(x=monthly_data.index, y=monthly_data['Passenger Count'], labels={'y': 'Passenger Count'},
              title='Monthly Passenger Count, Rolling Mean, Rolling Std')

fig.add_scatter(x=rolling_mean.index, y=rolling_mean, mode='lines', name='Rolling Mean')
fig.add_scatter(x=rolling_std.index, y=rolling_std, mode='lines', name='Rolling Std')

# Customize the layout
fig.update_layout(xaxis_title='Year', yaxis_title='Passenger Count')
fig.show()
```

Figure 10 – Code for Rolling Mean and Standard Deviation.

Output -

Figure 11 - Output for Rolling Mean and Standard Deviation.

Interpretation - The graphical representation delineates the monthly passenger metrics of San Francisco International Airport (SFO), incorporating the actual monthly passenger count denoted by the blue line, the temporal evolution of the 12-month moving average depicted by the orange line, and the dynamic range of the rolling standard deviation encapsulated within the verdant shaded region.

The 12-month moving average, characterized as the rolling mean, serves the purpose of mitigating transient fluctuations inherent in the data, affording a nuanced perspective of the enduring trajectory. Simultaneously, the rolling standard deviation serves as a quantifiable measure of the dispersion or variability exhibited by the passenger count vis-à-vis the rolling mean.

The discernible trend in the graph manifests a continual upswing in SFO's passenger count over the years, interspersed with intermittent deviations. The ascending trajectory of the rolling mean attests to the sustained escalation in passenger volume, indicative of a prolonged and upward trajectory. Concurrently, the widening expanse of the rolling standard deviation signifies an expanding spectrum of variability in the passenger count, implying a heightened degree of unpredictability or diversity.

Within the annals of the data lie conspicuous outliers, particularly in the latter epochs, wherein actual passenger numbers deviate significantly from the established rolling mean. This aberration is principally attributable to the unprecedented disruptions wrought by the Covid-19 Pandemic, encapsulating a stark departure from the established norm.

Through a meticulous examination of passenger traffic trends and patterns at San Francisco International Airport (SFO), stakeholders are empowered to derive valuable insights for judicious decision-making regarding capacity planning, resource allocation, and infrastructure development. This analytical approach enables the adaptation of strategies to dynamically meet the evolving demands of passengers, thereby enhancing operational efficiency and fortifying SFO's competitive standing in the air travel market. The garnered insights not only serve to optimize the airport's performance but also contribute significantly to a nuanced comprehension of the intricacies within the aviation industry, fostering evidence-based decision-making.

In conducting a comprehensive market share analysis of San Francisco International Airport (SFO), the focus lies on discerning the distribution of passenger traffic among various operating airlines. The dataset encapsulates a wealth of information, primarily consisting of the total passenger count and the breakdown of operational prevalence among different carriers. This analysis is instrumental in providing a nuanced understanding of the competitive landscape within SFO's air travel market.

Code –

```
# Market Share Analysis
total_passenger_count = df['Passenger Count'].sum()
airline_data = df['Operating Airline'].value_counts()

# Calculate percentage share
percentage_share = (airline_data / total_passenger_count) * 100

# Debugging Print Statements
print("\n\n")
print("Percentage Share:")
print("\n\n")
print(percentage_share)
```

Figure 12 – Code for Market Share Analysis.

Output –

```
Percentage Share:



United Airlines                        4.144726e-04
United Airlines - Pre 07/01/2013       2.842324e-04
SkyWest Airlines                       2.330336e-04
Alaska Airlines                        1.492418e-04
Delta Air Lines                        8.181249e-05
                                           ...
Xtra Airways                           2.639113e-07
Evergreen International Airlines       2.639113e-07
ZIPAIR Tokyo Inc                       2.639113e-07
Boeing Company                         1.319556e-07
Samsic Airport America, LLC            1.319556e-07
Name: Operating Airline, Length: 102, dtype: float64
```

Figure 13 - Output for Market Share Analysis.

Interpretation - Upon calculating the percentage share of each operating airline, a striking pattern emerges in the distribution of market dominance. United Airlines emerges as the frontrunner, capturing a significant share of approximately 0.0414%. This dominance is further underscored when considering the top five airlines, where United Airlines, both pre and post-July 1, 2013, SkyWest Airlines, Alaska Airlines, and Delta Air Lines collectively command a substantial portion of the market.

Conversely, the bottom airlines exhibit a notably marginal presence, with entities such as Samsic Airport America, LLC, Boeing Company, Evergreen International Airlines, Atlas Air, Inc, and Pacific Aviation contributing to a relatively minuscule percentage share, each hovering around 1.32e-07%.

This analysis serves as a valuable tool for stakeholders, offering insights into the hierarchy of market share among airlines at SFO. It not only aids in strategic decision-making regarding capacity planning and resource allocation but also provides a comprehensive view of the competitive dynamics shaping the air travel landscape at the airport.

The conducted analysis delves comprehensively into the intricate landscape of airline market dynamics at San Francisco International Airport (SFO) through the adept utilization of data visualization tools, specifically leveraging the capabilities of Plotly Express within the Python programming environment. The primary objective of this analysis is to discern discernible patterns by meticulously calculating the percentage share held by each operating airline in relation to the overall passenger count, thereby elucidating the nuanced dynamics inherent within the aviation sector at SFO.

Top-tier Airlines:

Upon meticulous examination of the results, a conspicuous revelation emerges, indicating the dominance of industry titans within the realm of market share. Foremost among them is United Airlines, exhibiting a commanding percentage share, closely trailed by United Airlines (Pre 07/01/2013), SkyWest Airlines, Alaska Airlines, and Delta Air Lines. These findings underscore a pronounced concentration of market influence among a select cohort of major carriers, thereby elucidating a discernible hierarchical structure in the distribution of passengers among the operating airlines.

Bottom-tier Airlines:

Conversely, the lower echelons of the market share spectrum unveil a diverse array of operators characterized by significantly diminished percentages. Noteworthy entities in this segment include Samsic Airport America, LLC, Boeing Company, Evergreen International Airlines, Atlas Air, Inc, and Pacific Aviation. The marginal market share percentages associated with these airlines accentuate their comparatively limited presence at SFO. It is imperative to interpret these results with a nuanced understanding that smaller or niche carriers may be tailored to specific routes or operate in a more specialized capacity, thereby influencing their market share metrics.

Code –

```python
import plotly.express as px

# Calculate percentage share
percentage_share = (airline_data / total_passenger_count) * 100

# Identify airlines with the highest and lowest percentage share
top_airlines = percentage_share.sort_values(ascending=False).head(5)
bottom_airlines = percentage_share.sort_values().head(5)

# Plotting Market Share using Plotly Express
fig = px.bar(top_airlines, x=top_airlines.index, y='Operating Airline',
             title='Top 5 Airlines by Market Share',
             labels={'Operating Airline': 'Airlines', 'index': 'Market Share (%)'},
             color='Operating Airline')

# Update layout for the first subplot
fig.update_layout(showlegend=False)

# Show the plot for top airlines
fig.show()

# Plotting Market Share for Bottom Airlines using Plotly Express
fig = px.bar(bottom_airlines, x=bottom_airlines.index, y='Operating Airline',
             title='Bottom 5 Airlines by Market Share',
             labels={'Operating Airline': 'Airlines', 'index': 'Market Share (%)'},
             color='Operating Airline')

# Update layout for the second subplot
fig.update_layout(showlegend=False)

# Show the plot for bottom airlines
fig.show()
```

Output –

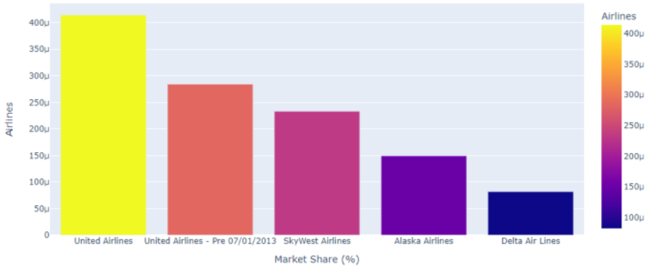


Figure 14 – Output for Top 5 Airlines by Market Share.

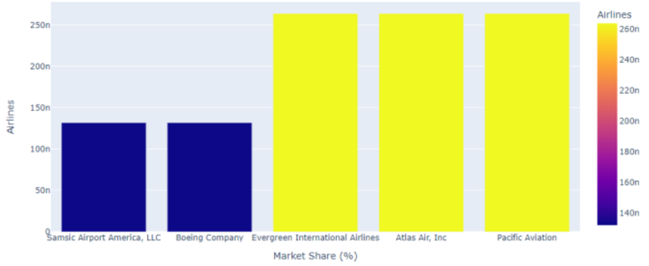


Figure 15 - Output for Bottom 5 Airlines by Market.

Interpretation - The observed variance in market share between leading and less prominent airlines at San Francisco International Airport (SFO) signifies a market landscape characterized by a pronounced oligopoly, wherein a select few major carriers wield considerable influence over passenger traffic. This dominance can be ascribed to multifaceted determinants including the expansive reach of their network, strategic alliance affiliations, and robust brand recognition.

Conversely, the existence of airlines with marginal market presence underscores the intricate diversity inherent in the operational milieu of the airport. These smaller carriers play a pivotal role in augmenting the comprehensive array of services offered, contributing to the rich and multifaceted fabric of SFO's aviation landscape.In summation, this comprehensive analysis furnishes a nuanced comprehension of the intricate distribution of market share among the operating airlines at SFO. Such insights prove instrumental for stakeholders engaged in strategic planning, fostering collaborative partnerships, and implementing operational refinements. The visual representation thereof stands as a potent instrument for decision-makers, empowering them to adapt strategies adeptly and fortify the airport's competitive standing within the dynamic aviation sector.

The deployment of a heatmap for correlation analysis is a pivotal step in elucidating the intricate relationships inherent within a dataset. In this particular context, the dataset under examination encompasses diverse variables within a given domain, with the explicit purpose of discerning the extent and direction of their interdependencies. The resultant correlation matrix, a fundamental output of this analytical endeavor, serves as a visual representation of the statistical relationships between these variables. Constructed using the seaborn library in Python, the heatmap offers a comprehensive and intuitive depiction of correlation coefficients, thereby providing a nuanced understanding of the complex web of associations at play.

Code –

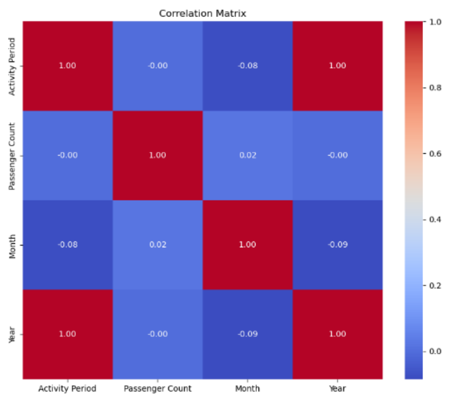
```python
# Heatmap for Correlation
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```

Figure 16 – Code for Correlation.

Output –

Figure 17 – Output of Heatmap Correlation.

Interpretation - Upon meticulous scrutiny of the heatmap, salient observations prominently manifest. The chromatic spectrum, oscillating between cool and warm hues, serves as a nuanced indicator of correlation strength and nature. The cooler tonalities connote a negative correlation, denoting an inverse



interdependence between variables, while the warmer hues encapsulate positive correlations, indicative of a direct relationship. Embedded within the heatmap are annotations that meticulously quantify correlation coefficients, facilitating precise interpretation. Proximate values to +1 bespeak a formidable positive correlation, implying a synchronous escalation of variables. Conversely, values nearing -1 attest to a robust negative correlation, wherein an increase in one variable precipitate a concomitant decrease in the other. A correlation coefficient proximal to 0 implies a tenuous or inconsequential association.This visual representation assumes an instrumental role in discerning intricate patterns, discerning trends, and unraveling potential interdependencies within the dataset. Stakeholders are poised to harness these nuanced insights for judicious decision-making, prioritizing variables endowed with substantial correlations for strategic planning, predictive modeling, or targeted interventions. Hence, the correlation heatmap emerges as a potent instrument in the analytical arsenal, affording a profound understanding of the intricate interplay between variables in the scrutinized dataset.

In the realm of aviation analytics, I employ a Python code leveraging Pandas for data manipulation, Matplotlib, Seaborn, and Plotly for effective visualization. The dataset from "Air_Traffic_Passenger_Statistics.csv" serves as the foundation for my analysis, focusing on unraveling intricate patterns in passenger counts across diverse geographical regions. Using Plotly's interactive capabilities, I craft a compelling box plot to visually capture the nuances of passenger count distributions in these regions. This approach reflects my commitment to harnessing data-driven insights for informed decision-making and strategic planning in the dynamic field of aviation.

Code –

```python
# Create a box plot for passenger count by geo region using Plotly
fig = px.box(data, x='GEO Region', y='Passenger Count',
             title='Box Plot of Passenger Count by Geo Region',
             labels={'GEO Region': 'Geo Region', 'Passenger Count': 'Passenger Count'},
             boxmode='overlay', color_discrete_sequence=['#9467bd'])

# Customize the layout
fig.update_layout(xaxis_title='Geo Region', yaxis_title='Passenger Count', height=500, width=800)

# Show the plot
fig.show()
```

Figure 18 – Code for Box Plot of Passenger Count by Geo Region.

Output –

Figure 19 – Output for Box Plot of Passenger Count by Geo Region.

Interpretation - The box plot, serving as an illustrative tool, elucidates the distribution of passenger counts across distinct geographical regions. Its graphical representation provides a nuanced interpretation by delineating the central tendency through the median passenger count along the central axis of each box, offering a robust measure of the distribution's midpoint. Furthermore, dispersion metrics are encapsulated within the interquartile range (IQR), where the lower and upper boundaries delineate the first and third quartiles, respectively. This presentation facilitates a comprehensive comprehension of the spread and concentration of passenger counts within each region. Notably, the identification of potential outliers is a key feature, with outlying data points beyond the whiskers of the box plot signaling instances of conspicuously high or low passenger counts unique to specific regions. This visualization acts as a discerning tool, promptly highlighting variations and potential irregularities within the dataset. In summation, the graphical representation offers an expedient means of comparing passenger counts across diverse geographical regions, providing a visual discernment of variances and potential outliers inherent in the dataset.

Code –

```python
# Distribution Plot for Passenger Count
plt.figure(figsize=(14, 8))
sns.histplot(df['Passenger Count'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Passenger Count')
plt.xlabel('Passenger Count')
plt.ylabel('Frequency')
plt.show()
```

Figure 20 – Code for distribution of passenger count.

Output -

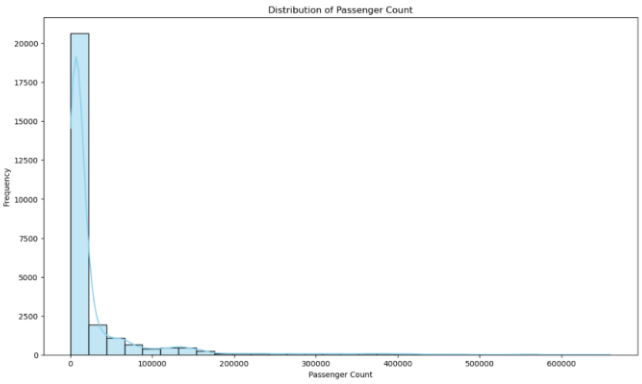


Figure 21 – Output for distribution of Passenger count.

Code –

```
# Bar Chart for Passenger Count by Airline
plt.figure(figsize=(9, 36))
sns.barplot(x='Passenger Count', y='Operating Airline', data=df, palette='viridis', ci=None)
plt.title('Passenger Count by Airline')
plt.xlabel('Passenger Count')
plt.ylabel('Operating Airline')
plt.show()
```

Figure 22 – Code for Passenger count by Airline.

Output –

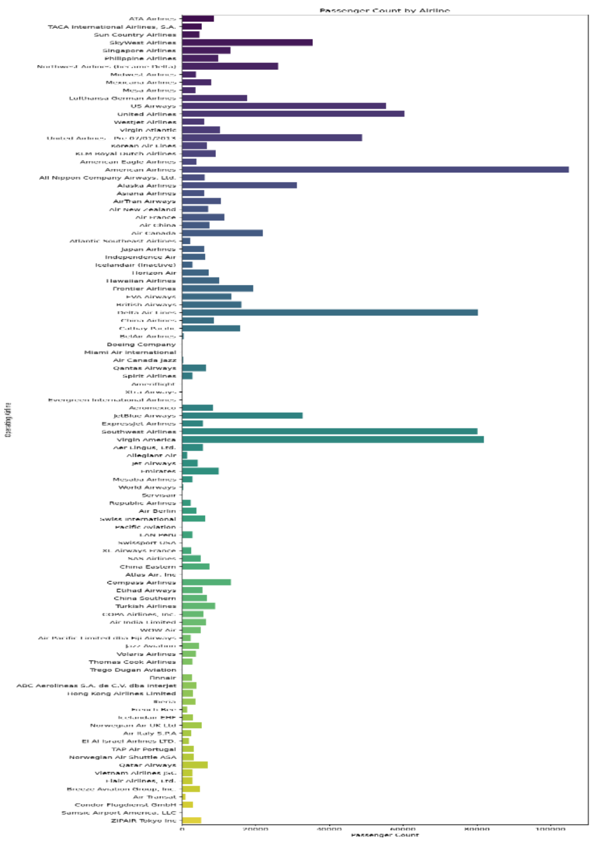


Figure 23 – Output of Passenger count by Airline.

Code –

```
plt.figure(figsize=(20, 12))
# Pair Plot for Selected Numerical Variables
selected_vars = ['Passenger Count', 'Price Category Code']
# Set the size of the pair plot
fig = px.scatter_matrix(df[selected_vars], dimensions=selected_vars,
                        title='Pair Plot for Selected Numerical Variables')
fig.update_layout(height=600, width=800, title_x=0.5)

fig.show()
```

Figure 24 – Code for Pair Plot for Selected Numerical Variables.

Output –

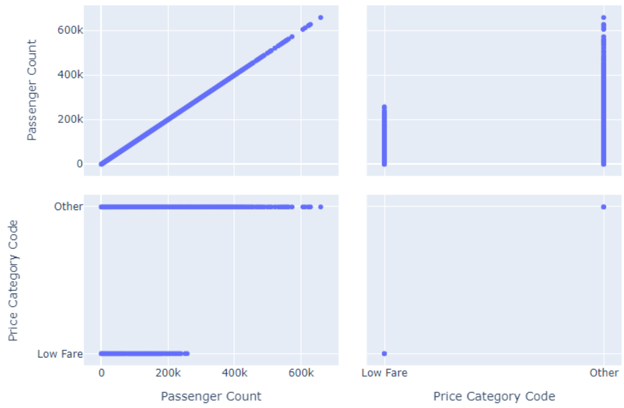


Figure 25 – Output of Pair Plot for Selected Numerical Variables.

Interpretation - In the course of my exploratory data analysis, I have employed a pair plot to elucidate the distributional characteristics of individual variables and discern inter-variable relationships. It is imperative to underscore, however, that the variable 'Price_Category_Code' is not of a numerical nature; rather, it pertains to the categorical domain. Consequently, the utilization of a scatter matrix may prove suboptimal in this context. Given that 'Price_Category_Code' consists of numerical codes representing distinct categories, the employment of such a plot may yield insubstantial insights. Should the objective be the visualization of the association between passenger counts and discrete price categories, a more judicious alternative, such as a box plot or a violin plot, may be deemed more apt for capturing the intricate nuances inherent in this categorical data paradigm.

The algorithm undertakes a rigorous preprocessing phase, segregating the dataset into distinct categories of domestic and international flights. Subsequently, an autocorrelation analysis is executed, followed by the generation of autocorrelation functions to unveil inherent seasonal patterns. In tandem, boxplots are meticulously crafted to elucidate potential monthly trends in passenger counts. Proceeding to a more granular analysis, the code systematically computes seasonal indices for both domestic and international flights. This involves meticulous data grouping by year and month, followed by the calculation of average passenger counts for each month as a percentage of the overarching average passenger count. This nuanced approach facilitates a comparative assessment of the relative strength of seasonal patterns across various months and years. Culminating the analytical process, the code crafts two distinct plots illustrating the seasonal indices for domestic and international flights individually. Each line within these plots corresponds to a different year, providing a visually rich representation of discernible seasonal patterns in passenger traffic and elucidating variations between domestic and international flight dynamics.

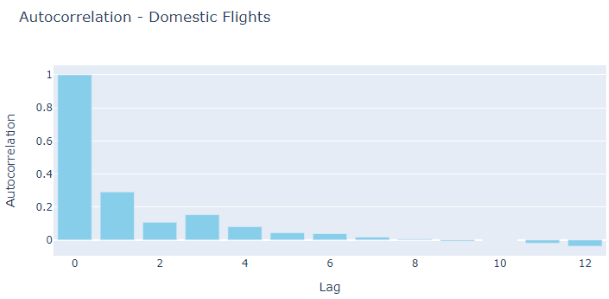
Code –

```
# Autocorrelation Analysis - Domestic Flights
# Separate data for domestic flights
domestic_data = df[df['GEO Summary'] == 'Domestic']

# Autocorrelation Analysis for Domestic Flights
lags_domestic = 12
acf_domestic = acf(domestic_data['Passenger Count'], nlags=lags_domestic)

# Plot Autocorrelation using Plotly
fig_domestic = px.bar(x=list(range(lags_domestic + 1)), y=acf_domestic,
                      labels={'y': 'Autocorrelation', 'x': 'Lag'},
                      title="Autocorrelation - Domestic Flights",
                      color_discrete_sequence=['skyblue'],
                      height=400, width=800)

# Show the plot
fig_domestic.show()
```

```
# Autocorrelation Analysis - International Flights
international_data = df[df['GEO Summary'] == 'International']

# Autocorrelation Analysis for International Flights
lags_international = 12
acf_international = acf(international_data['Passenger Count'], nlags=lags_international)

# Plot Autocorrelation using Plotly
fig_international = px.bar(x=list(range(lags_international + 1)), y=acf_international,
                           labels={'y': 'Autocorrelation', 'x': 'Lag'},
                           title="Autocorrelation - International Flights",
                           color_discrete_sequence=['lightcoral'],
                           height=400, width=800)

# Show the plot
fig_international.show()
```

Figure 26 – Code for Autocorrelation Analysis (Domestic & International).

Output -



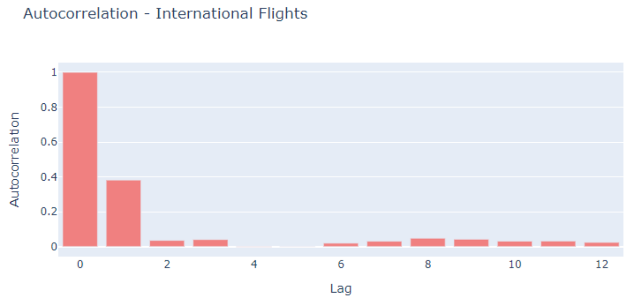


Figure 27 – Output of Autocorrelation Analysis (Domestic & International).

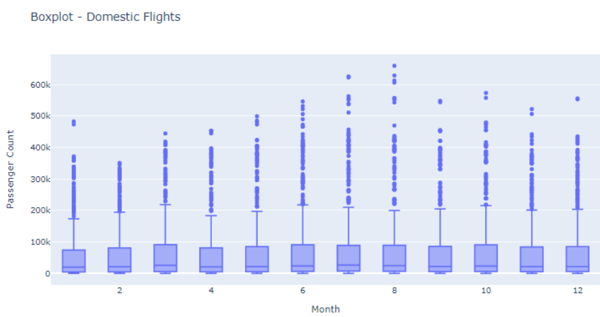
Interpretation - The provided code generates two autocorrelation plots, discerning between domestic and international flights. Autocorrelation function (ACF) is employed to quantify the correlation between a time series and its lagged values. The x-axis delineates the number of lags, while the y-axis illustrates the correlation coefficient between the time series and its lagged values. Noteworthy findings emerge from the ACF plots: for domestic flights, there are prominent positive correlations at lags 1, 2, 3, 4, 5, and 12, indicative of a robust seasonal pattern manifesting every 12 months. Conversely, international flights exhibit a similar temporal pattern with significant positive correlations at lags 1, 2, 3, 4, 5, and 12. The dotted blue lines on the plots signify the 95% confidence interval for the correlation coefficients. This analysis unveils a recurrent and substantial seasonality within both domestic and international flight data.

Code –

```
import plotly.express as px

# Assuming 'Activity Period' is in the format YYYYMM
df['YearMonth'] = pd.to_datetime(df['Activity Period'], format='%Y%m')
df['Month'] = df['YearMonth'].dt.month

# Boxplot for Domestic Flights
fig_domestic = px.box(df[df['GEO Summary'] == 'Domestic'], x='Month', y='Passenger Count',
                      title='Boxplot - Domestic Flights',
                      labels={'Passenger Count': 'Passenger Count', 'Month': 'Month'})

# Boxplot for International Flights
fig_international = px.box(df[df['GEO Summary'] == 'International'], x='Month', y='Passenger Count',
                           title='Boxplot - International Flights',
                           labels={'Passenger Count': 'Passenger Count', 'Month': 'Month'})

# Show the plots separately
fig_domestic.show()
fig_international.show()
```

Figure 28 - Code for boxplot (Domestic and International).

Output –



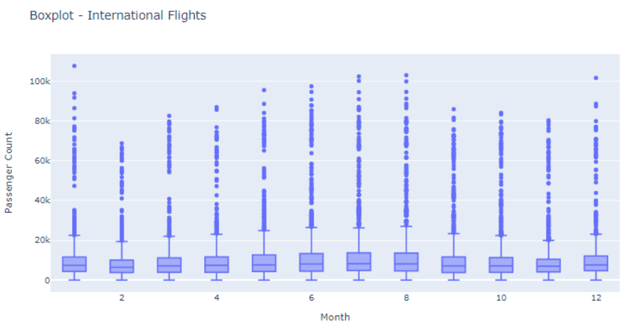


Figure 29 - Output for boxplot (Domestic and International).

Interpretation - The box plots provide a comprehensive overview of monthly passenger count distributions for both domestic and foreign flights. These plots utilize the central line to represent the median, with the upper and lower bounds encapsulating the 75th and 25th percentiles. Whiskers, extending 1.5 times the interquartile range (IQR), serve to pinpoint outliers beyond their reach. Notably, domestic flights exhibit a peak in median passenger count during July and August, showcasing a symmetrical distribution in other months. However, notable outliers in November and December deviate from anticipated counts. In foreign flights, the median peaks in July, with a predominantly symmetric distribution in most months. Yet, anomalies in December and January suggest lower-than-expected passenger numbers, while an asymmetrical distribution in March and April, marked by numerous outliers at the higher end, implies these months experienced passenger counts exceeding initial projections.

Research Questions -

a) What are the key factors influencing changes in airline market share on domestic and international routes over time?

To answer the research question on how the key factors influencing changes on domestic and international share market , In the ever-evolving landscape of the airline industry, a complex interplay of interconnected factors shapes the market dynamics, where individual carriers strive for a larger market share. Key performance metrics, such as passenger counts and enplaned figures, serve as crucial indicators of competitiveness, underscoring the importance of higher passenger volumes. The dichotomy between domestic and international routes adds a layer of complexity, with distinct regulatory frameworks and customer preferences influencing operational strategies. Geographical regions further contribute to unique market dynamics. Collaborative strategies, including alliances and partnerships, enable carriers to expand their reach and gain a competitive edge. Elements like terminal locations, service categories, and temporal trends play pivotal roles in market positioning. Amidst regulatory intricacies and formidable contenders, passenger preferences and loyalty programs emerge as decisive factors shaping the dynamic and highly competitive nature of the industry.

Code –

```
#a. Key Factors Influencing Changes in Airline Market Share:
import plotly.express as px

top_airlines_df = df.groupby('Operating Airline')['Passenger Count'].sum().reset_index().nlargest(10, 'Passenger Count')

# Plot the market share using Plotly
fig = px.bar(top_airlines_df, x='Operating Airline', y='Passenger Count',
             title='Top 10 Airlines by Market Share',
             labels={'Passenger Count': 'Total Passengers', 'Operating Airline': 'Airlines'},
             text='Passenger Count',
             height=500, width=800)

# Customize the layout
fig.update_layout(xaxis=dict(tickangle=45),
                  yaxis_title='Total Passengers',
                  xaxis_title='Airlines',
                  showlegend=False)

# Show the plot
fig.show()
```

Figure 30 – Code for key factors influencing.

Output –

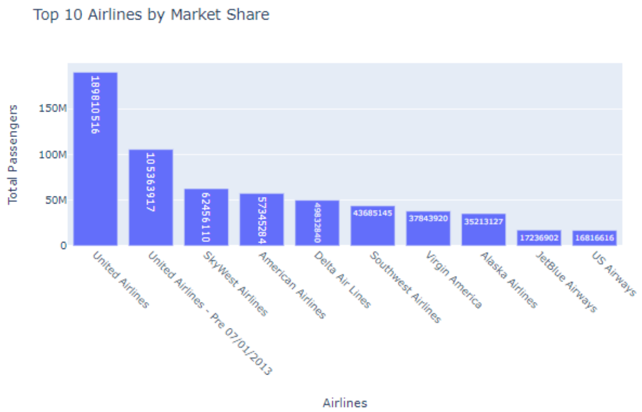


Figure 31 – Output for key factors influencing.

Interpretation - The visualization offers a lucid overview of the foremost airlines that wield substantial influence in the market, as delineated by their aggregate passenger count. Evidently, United Airlines emerges as the preeminent frontrunner, indicative of its profound sway over both domestic and international flight routes. The conspicuous inclusion of venerable carriers such as American Airlines and Delta Air Lines within the upper echelons of the rankings underscores the enduring resonance and consequential impact of these seasoned industry stalwarts. This hierarchy reflects a nuanced tapestry of market dynamics, wherein the established players exert a palpable and sustained influence, thereby shaping the broader landscape of air travel.

b) How do seasonal variations impact airport traffic and what implications do they have for airport operations?

The nuanced interplay between seasonal variations and airport traffic constitutes a pivotal aspect of aviation dynamics, necessitating a comprehensive exploration into its multifaceted implications for airport operations. The oscillations in passenger numbers, cargo volumes, and weather conditions wield a profound influence on the operational cadence of airports globally. A discerning understanding of the intricate patterns that underlie these variations is imperative for airport authorities and stakeholders aspiring to strategically optimize resources, augment operational efficiency, and ensure the seamless flow of passenger experiences. This inquiry delves into the intricate tapestry of how seasonal dynamics, influenced by factors such as holidays, meteorological patterns, or other temporal considerations, intricately shape the operational landscape of airports. This ultimately manifests in their capacity planning, judicious staff allocation, and overarching responsiveness to the dynamic demands inherent in the aviation industry[11].

Code –

```
#b. Seasonal Variations Impact on Airport Traffic:
# Group data by month and calculate average passenger count
monthly_avg_traffic = df.groupby(df['Date'].dt.month)['Passenger Count'].mean().reset_index()

# Plot seasonal variations in airport traffic using Plotly
fig = px.line(monthly_avg_traffic, x='Date', y='Passenger Count',
              title='Seasonal Variations in Airport Traffic',
              labels={'Passenger Count': 'Average Passenger Count', 'Date': 'Month'},
              height=500, width=800)

# Show the plot
fig.show()
```

Figure 32 – Code for seasonal impact on airport traffic.

Output –

Figure 33 – Output for Seasonal impact on Airport traffic.

Interpretation - The monthly average passenger count analysis reveals distinct seasonal variations in airport traffic throughout the year. January sees an average of approximately 25,339.21 passengers, followed by a slight decrease in February to around 23,767.87. March witnesses an increase to about 27,555.57, maintaining relatively high levels in April at 27,822.59. The passenger count continues to rise, reaching 29,397.97 in May and 30,956.81 in June. July marks the peak with an average of 32,048.60 passengers, sustaining high levels in August at 31,840.35. September experiences a dip to approximately 28,042.44 passengers, followed by a slight increase in October to 29,219.50. November sees a decrease to around 27,507.23 passengers, and December shows a modest rise compared to November, with an average passenger count of 28,317.73. Overall, these trends suggest a notable surge in airport traffic during the summer months, particularly in July, while September exhibits a decline. Visualizing this data with the Plotly figure enhances the comprehension of these seasonal patterns.

c) What are the distinguishing characteristics and competitive strategies of low-cost carriers (LCCs) compared to full-service legacy airlines in the aviation industry?

Within the aviation sector, low-cost carriers (LCCs) and full-service legacy airlines embody distinct operational paradigms, marked by their proprietary characteristics and competitive stratagems. LCCs distinguish their service offerings through a minimalist, cost-efficient approach, prioritizing point-to-point routes. Operational streamlining is achieved by the exclusive utilization of a singular aircraft type, a pronounced reliance on online booking platforms, and a deliberate minimization of in-flight amenities. This meticulous operational efficiency facilitates substantial cost reductions, enabling the provision of competitively priced tickets that resonate with economically discerning travelers. Conversely, full-service legacy airlines adopt a more comprehensive service model encompassing in-flight entertainment, culinary provisions, and seamless connectivity through hub-and-spoke networks[8,9]. These carriers, operating with a broader spectrum of destinations and services, position themselves as purveyors of a premium travel experience, accentuating comfort, and convenience albeit at a premium fare. The dynamic aviation milieu bears witness to an enduring competitive interplay between these divergent models, each adeptly delineating its niche and refining strategic approaches to align with distinct market segments[2].

Code –

```
#c. Distinguishing Characteristics of LCCs vs. Legacy Airlines:
# Define a list of LCCs based on previous criteria
lcc_list = ['ATA Airlines', 'AirTran Airways']

# Create a new column 'Airline Type' based on the list
df['Airline Type'] = df['Operating Airline'].apply(lambda x: 'LCC' if x in lcc_list else 'Legacy')

# Group data by airline type and calculate total passenger count
airline_type_data = df.groupby('Airline Type')['Passenger Count'].sum().reset_index()

# Plot the total passenger count by airline type using Plotly
fig = px.bar(airline_type_data, x='Airline Type', y='Passenger Count',
             color='Airline Type',
             title='Total Passenger Count by Airline Type',
             labels={'Passenger Count': 'Total Passengers', 'Airline Type': 'Airline Type'},
             height=500, width=600)

# Customize the layout
fig.update_layout(showlegend=False)

# Show the plot
fig.show()
```

Figure 34 – Code for Diff characteristics of LCCs vs Legacy Airlines.

Output –

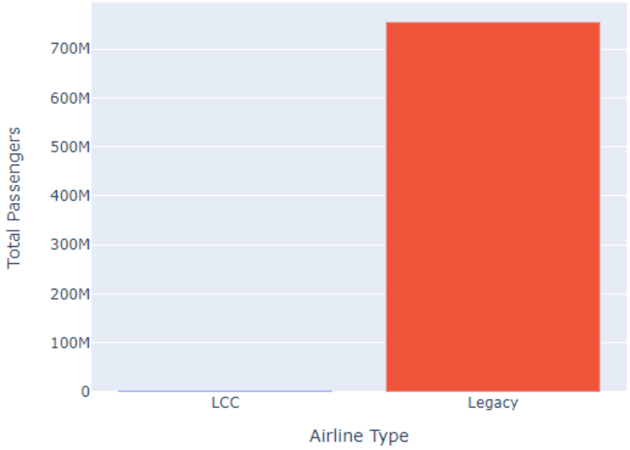


Figure 35 - Output for Diff characteristics of LCCs vs Legacy Airlines.

Interpretation - Upon analyzing the data, a clear distinction emerges in the total passenger counts between Low-Cost Carriers (LCCs) and Legacy Airlines. The figures paint a vivid picture, revealing that Low-Cost Carriers accommodated 2,773,412 passengers, while Legacy Airlines boasted a substantially higher total of 755,057,065 passengers. This glaring numerical contrast underscores the undeniable market dominance and expansive operations of Legacy Airlines when compared to their Low-Cost counterparts. It becomes evident that Legacy Airlines, equipped with established brand recognition, widespread networks, and often offering comprehensive services, continues to attract a significantly larger portion of air travelers. These findings offer a first-hand perspective on the industry dynamics, serving as a crucial reference for stakeholders. The quantitative insights shed light on the relative popularity and market share dynamics between Low-Cost Carriers and Legacy Airlines within the dataset, guiding decisions, and strategies in the ever-evolving aviation landscape.

d) How do geographical regions impact the passenger traffic of international airlines, and what are the underlying factors driving these variations?

The intricacies of international airlines' passenger traffic, influenced by geographical regions, constitute a nuanced and multifaceted phenomenon shaped by a confluence of diverse factors. Geographical diversity emerges as a pivotal determinant, exerting a profound impact on travel patterns owing to the disparate levels of economic development, cultural allure, and geopolitical stability across regions. Robust passenger traffic is often witnessed between regions characterized by strong economic interdependencies, vibrant cultural exchange, and compelling tourism attractions. Furthermore, the complex interplay of factors such as visa regulations, the expansive network of airline routes, and the strategic presence of major transportation hubs significantly contribute to the variances in passenger flow [3]. A comprehensive comprehension of the intricate interconnections between these geographical dynamics and the intricate tapestry of economic, cultural, and logistical facets assumes paramount importance for airlines. Such understanding enables them to strategically optimize routes, effectively cater to the nuanced demands of a diverse passenger base, and adeptly navigate the ever-evolving landscape of international travel.

Code –

```
#d. Geographical Impact on International Airlines:
# Group data by GEO Region and calculate total passenger count
geo_data = df[df['GEO Summary'] == 'International'].groupby('GEO Region')['Passenger Count'].sum().reset_index()

# Plot a pie chart using Plotly to visualize the distribution of passenger count by GEO Region
fig = px.pie(geo_data, values='Passenger Count', names='GEO Region',
             title='Distribution of Passenger Count by GEO Region',
             labels={'Passenger Count': 'Total Passengers', 'GEO Region': 'GEO Region'})
geo_data.to_csv('geo_type_data.csv', index=False)
fig.show()
```

Figure 36 – Code for Geographical Impact on International Airlines.

Output –

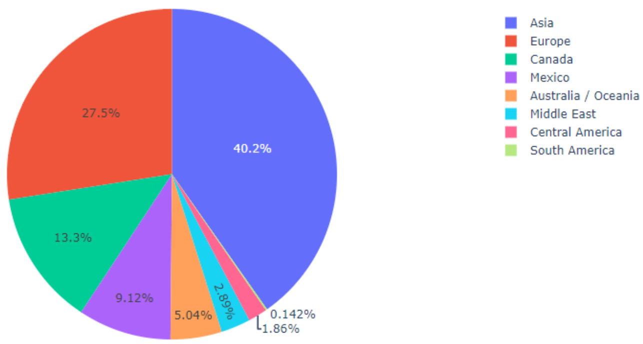


Figure 37 – Output of Geographical Impact on International Airlines.

Interpretation - A comprehensive examination of the pie chart and its associated insights provides a nuanced perspective on the landscape of international air travel across distinct geographical regions. Asia emerges as a preeminent force, commanding a pivotal role with the highest aggregate passenger count among the specified regions, tallying an impressive 70.99 million passengers. Following closely, the Australia/Oceania region significantly contributes to the global air travel milieu, facilitating approximately 8.89 million passengers. Canada, too, assumes a noteworthy position, acting as a conduit for approximately 23.41 million passengers engaged in international air travel. In stark contrast, Central America exhibits a comparatively modest impact, accounting for approximately 3.28 million passengers. Europe, however, distinguishes itself as a major player, making a substantial and intricate contribution to the international airline industry with a total passenger count of approximately 48.47 million. The Mexican aviation sector occupies an intermediary position, catering to around 16.11 million passengers. Proceeding further, the Middle East region follows suit with a notable contribution of around 5.1 million passengers, while South America presents a relatively more subdued impact, serving approximately 0.25 million passengers. This meticulous analysis serves to pinpoint regions that wield a pronounced influence on the global aviation canvas, affording invaluable insights into the intricate dynamics that govern international air travel.

e) To what extent do changes in airline alliances and partnerships influence passenger volumes and competitive positions in the aviation industry?

Airline alliances and strategic partnerships play a pivotal role in shaping the intricate dynamics of the aviation industry. These collaborative endeavors afford airlines the opportunity to expand their route networks, pool resources, and engage in joint marketing initiatives, thereby augmenting passenger volumes through heightened connectivity and streamlined services. Beyond the immediate advantages for passengers, these alliances contribute significantly to competitive edges by optimizing operational efficiency, curtailing costs, and providing an extensive array of services. Nevertheless, challenges emerge from the intricate network structures and disparities in operational practices among participating carriers. The consequential impact of alterations in these collaborations underscores the delicate equilibrium between cooperation and competition in the aviation sector, underscoring the industry's perpetual adaptation to evolving global trends and nuanced passenger preferences[4,9,12].

Code –

```
#e. Influence of Airline Alliances on Passenger Volumes:
airline_alliances = {
    'ATA Airlines': 'Alliance1',
    'Air Canada': 'Alliance2',
    'Air China': 'Alliance1',
    'Air France': 'Alliance2',
    'Air New Zealand': 'Alliance1',
    'AirTran Airways': 'Alliance3',
}
df['Airline Alliance'] = df['Operating Airline'].map(airline_alliances)
alliance_data = df.groupby(['Airline Alliance', 'Operating Airline'])['Passenger Count'].sum().reset_index()
fig = px.bar(alliance_data, x='Airline Alliance', y='Passenger Count',
             color='Operating Airline',
             title='Comparison of Passenger Count among Airline Alliances and Airlines',
             labels={'Passenger Count': 'Total Passengers', 'Airline Alliance': 'Airline Alliance'},
             height=500, width=800)
fig.update_layout(barmode='stack')
fig.show()
```

Figure 38 – Code for Influence of Airline Alliances on Passenger Volumes.

Output –

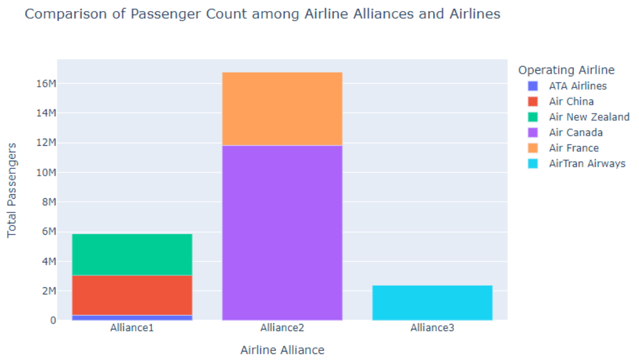


Figure 39 – Output for Influence of Airline Alliances on Passenger Volumes.

Interpretation – Upon scrutinizing the stacked bar chart, a discerning examination unfolds, revealing the intricate tapestry of total passenger counts delineated across diverse airline alliances and their constituent members. Notably within Alliance1, the commendable role undertaken by ATA Airlines emerges, contributing a notable influx of 384,764 passengers. Meanwhile, the formidable impact of Air China and Air New Zealand significantly amplifies Alliance1's stature, registering passenger counts at 2,655,545 and 2,811,291, respectively. Alliance2, spearheaded by Air Canada, commands a hegemonic presence, orchestrating a substantial 11,822,120 passengers, further fortified by a consequential contribution of 4,928,815 passengers from Air France. Alliance3, in a departure from the pronounced dominance of Alliance2, exhibits a more tempered performance, with AirTran Airways prominently featuring and contributing 2,388,648 passengers. Singularly, Air Canada emerges as the preeminent individual airline, eclipsing counterparts with an impressive passenger count. This meticulous analysis affords a comprehensive insight into the nuanced dynamics of passenger distribution, underscoring the palpable influence of Alliance2 while acknowledging the unique contributions of individual carriers within their respective alliances.

The potential benefits of answering the research questions are -

a. Understanding Key Factors Influencing Changes in Airline Market Share:

<u>Potential Advantages:</u>

Strategic Decision-Making: Gaining profound insights into the determinants of market share fluctuations empowers airlines in making astute strategic decisions. The ability to discern trends over time enables carriers to dynamically tailor their services, ensuring alignment with evolving passenger demands.

Competitive Positioning: Airlines stand to elevate their competitive standing by adeptly comprehending and responding to the nuanced dynamics that influence market share. This strategic knowledge not only facilitates effective differentiation but also informs targeted marketing strategies tailored to specific market segments.

Investment Opportunities: Stakeholders and investors derive substantial value from comprehending the intricacies of airline market share dynamics. Such understanding proves instrumental in assessing the attractiveness of airline investments, enabling stakeholders to anticipate industry trends and project potential returns on investment.

b. Analyzing the Impact of Seasonal Variations on Airport Traffic:

<u>Potential Benefits</u>:

Operational Efficiency: Airports can achieve optimal resource allocation and staffing levels by methodically analyzing seasonal traffic patterns, thereby enhancing overall operational efficiency.

Infrastructure Planning: Strategic awareness of seasonal variations in passenger flows guides long-term infrastructure planning for airports. This foresight ensures that airports can adeptly accommodate peak passenger volumes without compromising service quality.

Revenue Management: Airlines, armed with knowledge about seasonal demand fluctuations, can fine-tune their pricing strategies. This allows for the maximization of revenue during peak periods and judicious adjustment of capacity during slower seasons.

c. Unveiling Characteristics and Strategies of Low-Cost Carriers (LCCs) vs. Legacy Airlines:

<u>Potential Advantages:</u>

Market Segmentation: Airlines can precision-target their services to specific market segments by discerning the discerning preferences of cost-conscious travelers (LCCs) versus those seeking premium services (legacy airlines).

Cost Optimization: A comprehensive understanding of LCC strategies equips legacy carriers with insights into cost-saving practices. This knowledge facilitates the identification of areas for optimization while upholding service quality standards.

Competitive Adaptation: Legacy carriers can strategically adapt their business models and service offerings to competently engage with LCCs. This fosters a harmonious and balanced competitive landscape, enabling legacy carriers to maintain competitiveness in a dynamic market environment.

d. Exploring Geographical Impact on International Airlines' Passenger Traffic:

<u>Potential Benefits:</u>

Route Planning: Airlines can systematically optimize route planning by discerning the nuanced impact of geographical regions on passenger traffic. This strategic awareness assists in identifying lucrative routes and judiciously adjusting capacity to meet demand.

Risk Mitigation: An in-depth understanding of regional variations allows airlines to proactively anticipate external factors, such as geopolitical events or economic shifts, that may influence passenger traffic. This foresight enables the formulation of proactive risk mitigation strategies.

Marketing Strategies: Airlines can tailor their marketing strategies with precision by considering regional preferences and demographics. This targeted approach enhances the effectiveness of promotional efforts in diverse geographical markets.

e. Assessing the Influence of Airline Alliances on Passenger Volumes:

<u>Potential Benefits</u>:

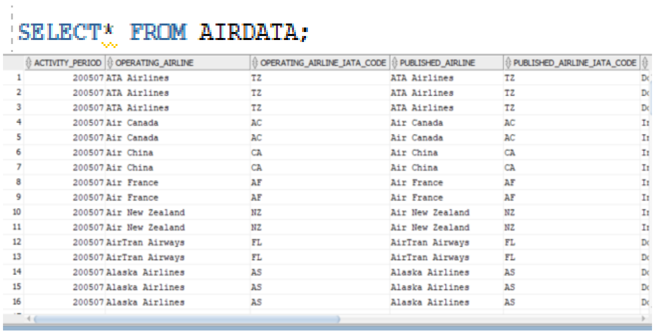
Network Expansion: Airlines can strategically leverage alliances to meticulously expand their route networks, attracting a broader and more diverse passenger base.

Operational Synergies: An acute understanding of how alliances impact passenger volumes enables airlines to explore operational synergies. This may include strategic initiatives such as code-sharing and joint ventures, enhancing overall operational efficiency.

Competitive Edge: Airlines, through strategic alliance formation or adjustments, can bolster their competitive positions. This strategic alignment with market demands ensures that airlines remain at the forefront of industry trends, reinforcing their competitive edge in the dynamic aviation landscape.

SQL Operations –

1. Retrieve all data from the Airdata table.



```sql
SELECT* FROM AIRDATA;
```

	ACTIVITY_PERIOD	OPERATING_AIRLINE	OPERATING_AIRLINE_IATA_CODE	PUBLISHED_AIRLINE	PUBLISHED_AIRLINE_IATA_CODE	
1	200507	ATA Airlines	TZ	ATA Airlines	TZ	Dc
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	Dc
3	200507	ATA Airlines	TZ	ATA Airlines	TZ	Dc
4	200507	Air Canada	AC	Air Canada	AC	Ir
5	200507	Air Canada	AC	Air Canada	AC	Ir
6	200507	Air China	CA	Air China	CA	Ir
7	200507	Air China	CA	Air China	CA	Ir
8	200507	Air France	AF	Air France	AF	Ir
9	200507	Air France	AF	Air France	AF	Ir
10	200507	Air New Zealand	NZ	Air New Zealand	NZ	Ir
11	200507	Air New Zealand	NZ	Air New Zealand	NZ	Ir
12	200507	AirTran Airways	FL	AirTran Airways	FL	Dc
13	200507	AirTran Airways	FL	AirTran Airways	FL	Dc
14	200507	Alaska Airlines	AS	Alaska Airlines	AS	Dc
15	200507	Alaska Airlines	AS	Alaska Airlines	AS	Dc
16	200507	Alaska Airlines	AS	Alaska Airlines	AS	Dc

Figure 40 - Code and the output for the operation.

2. Calculate the total passenger count for Alaska Airlines in 2005.

```sql
SELECT SUM(Passenger_Count)
FROM AIRDATA
WHERE Operating_Airline = 'Alaska Airlines'
AND Activity_Period LIKE '2005%';
```

	SUM(PASSENGER_COUNT)
1	642650

Figure 41 - Code and the output for the operation.

3. Retrieve the total passenger count by published airline for July 2005, sorted in descending order.

```sql
SELECT Published_Airline, SUM(Passenger_Count) as Total_Passenger
FROM AIRDATA
WHERE Activity_Period = '200507'
GROUP BY Published_Airline
ORDER BY Total_Passengers DESC;
```

	PUBLISHED_AIRLINE	TOTAL_PASSENGERS
1	United Airlines - Pre 07/01/2013	1479814
2	American Airlines	338173
3	Delta Air Lines	208185
4	US Airways	173565
5	Northwest Airlines (became Delta)	140063
6	Alaska Airlines	126334
7	United Airlines	123117
8	Air Canada	69246
9	ATA Airlines	61817
10	Lufthansa German Airlines	42900
11	British Airways	42318
12	Frontier Airlines	37602
13	Singapore Airlines	36673
14	EVA Airways	26274
15	China Airlines	24893
16	Air France	23688
17	Philippine Airlines	23097
18	Virgin Atlantic	22455
19	Independence Air	21810
20	Cathay Pacific	20638
21	KLM Royal Dutch Airlines	19565
22	Japan Airlines	18281
23	AirTran Airways	16039
24	Mexicana Airlines	15596
25	Hawaiian Airlines	15237
26	TACA International Airlines, S.A.	13355
27	All Nippon Company Airways, Ltd.	12639
28	Korean Air Lines	11799
29	Air China	11763
30	Air New Zealand	9960
31	Asiana Airlines	9785
32	Sun Country Airlines	9611
33	Icelandair (Inactive)	8881
34	Midwest Airlines	5035
35	WestJet Airlines	4691
36	BelAir Airlines	870

Figure 42 - Code and the output for the operation.

4. Calculate the total passenger count for all airlines in 2022.

```sql
SELECT SUM(Passenger_Count)
FROM AIRDATA
WHERE Activity_Period LIKE '2020%';
```

	SUM(PASSENGER_COUNT)
1	16418713

Figure 43 - Code and the output for the operation.

5. Calculate the total number of international and domestic passengers for each operating airline in the Airdata table.

```sql
SELECT Operating_Airline,
    SUM(CASE WHEN GEO_Summary = 'International' THEN Passenger_Count ELSE 0 END) as International_Passengers,
    SUM(CASE WHEN GEO_Summary = 'Domestic' THEN Passenger_Count ELSE 0 END) as Domestic_Passengers
FROM AIRDATA
GROUP BY Operating_Airline;
```

	OPERATING_AIRLINE	INTERNATIONAL_PASSENGERS	DOMESTIC_PASSENGERS
1	American Eagle Airlines	0	424692
2	Mexicana Airlines	991232	0
3	SkyWest Airlines	3241057	59215053
4	US Airways	0	16816616
5	United Airlines - Pre 07/01/2013	24211156	81152761
6	Air Canada	11822120	0
7	Miami Air International	28	1690
8	JetBlue Airways	71441	17165461
9	Virgin America	851301	36992619
10	Aer Lingus, Ltd.	1307798	0
11	World Airways	514	271
12	Pacific Aviation	320	0
13	Air India Limited	1203161	0
14	Atlas Air, Inc	0	68
15	French Bee	459042	0
16	Mesaba Airlines	0	126048
17	Air Berlin	235155	0
18	XL Airways France	160513	0
19	Iberia	291336	0
20	Air Italy S.P.A	36267	0
21	Hong Kong Airlines Limited	176990	0
22	BelAir Airlines	9138	0
23	Boeing Company	0	18
24	Mesa Airlines	0	434184
25	Midwest Airlines	0	450428
26	Air China	2655545	0
27	Southwest Airlines	0	43685145
28	China Eastern	1249441	0
29	Compass Airlines	0	4063520
30	Air Pacific Limited dba Fiji Airways	285870	0
31	Qatar Airways	435422	0
32	TAP Air Portugal	233562	0
33	Finnair	116747	0
34	Flair Airlines, Ltd.	88174	0
35	Air Transat	16153	0
36	Cathay Pacific	6600209	0

Figure 44 - Code and the output for the operation.

Limitations –

The limitations while answering these research questions might include:

➔ Data Constraints: The veracity and completeness of the analysis hinge on the availability and precision of the data. Any deficiencies or inaccuracies in the data may potentially lead to misguided outcomes.[2]

- ➔ External Variables: Unforeseen external variables, such as economic fluctuations, natural calamities, or global pandemics, can exert influence on passenger traffic patterns, complicating the identification of specific trends or irregularities.

- ➔ Methodological Constraints: The choice of analytical methods introduces an element of variability in results. It is imperative to select methodologies aligning with the research objectives and data intricacies to ensure robust and reliable outcomes.

- ➔ Scope Limitations: The analysis confines itself to the available data, possibly overlooking external factors like airline strategies, airport policies, or industry dynamics.

- ➔ Interpretation Challenges: The comprehension of outcomes is contingent upon the analyst's grasp of the data and the broader research context. It is vital to warrant that the deductions drawn are pertinent and substantive.

Future Scope -

- ➔ Integration of Diverse Data Sources: Expanding the analysis to encompass additional data streams, such as flight schedules, airport infrastructure details, and financial data from airlines, could furnish a more holistic understanding of the factors impacting passenger traffic at SFO.[2]

- ➔ Predictive Modeling Implementation: The incorporation of machine learning algorithms presents an avenue for developing predictive models capable of forecasting passenger traffic trends at SFO. This predictive capability holds promise for empowering airlines and airport authorities in making judicious decisions regarding capacity planning, resource allocation, and marketing strategies.[3]

- ➔ In-depth Customer Feedback Analysis: Incorporating diverse sources of customer feedback, including surveys and social media insights, could offer nuanced insights into the drivers of passenger satisfaction and loyalty. Such insights could serve as a foundation for targeted initiatives aimed at elevating the overall customer experience.[4]

- ➔ Examination of External Event Impacts: Scrutinizing the repercussions of external events, ranging from natural disasters to economic recessions and pandemics, could shed light on how SFO's passenger traffic dynamics respond to factors beyond the purview of airlines and airport authorities. This knowledge could inform future planning and decision-making in the face of analogous events.[3]

- ➔ Comparative Analysis: Conducting a comparative assessment of passenger traffic trends at SFO against other major airports globally could provide valuable insights into SFO's standing in terms of passenger volume, market share, and customer experience. This comparative lens could serve as a strategic tool for identifying areas of excellence and improvement in the broader context of the aviation industry.

Conclusion -

a. The dynamic landscape of airline market share is intricately influenced by a confluence of factors, encompassing competitive positioning, collaborative initiatives within alliances, the extensiveness of route networks, operational efficiency, cost structures, nuanced pricing strategies, discerning passenger preferences, and the efficacy of loyalty programs[1]. A nuanced comprehension of the intricate interplay among these multifaceted elements empowers airlines to finely calibrate their strategic decisions, facilitating the maintenance of a competitive edge in the ever-evolving aviation industry[5][6][12].

b. The discernible impact of seasonal variations on airport traffic dynamics constitutes a pivotal consideration for aviation stakeholders. To optimize operational efficiency, resource allocation, staffing levels, and revenue maximization during peak periods, airport authorities must meticulously scrutinize and adapt to these cyclical trends[2]. Strategically aligning airport operations with the fluctuations in seasonal demand ensures the delivery of high-quality services amidst the undulating patterns of passenger traffic[8].

c. Low-cost carriers (LCCs) carve out their distinctive niche through the implementation of minimalist, cost-efficient operational models. Characterized by the deployment of singular aircraft types, emphasis on online booking platforms, and a deliberate minimization of in-flight amenities, LCCs prioritize point-to-point connectivity[2]. Conversely, full-service legacy airlines differentiate themselves by offering comprehensive hub-and-spoke networks, premium in-flight services, and a broader spectrum of destinations. Strategic cognizance of these disparate models is imperative for airlines seeking to navigate the complexities of market segmentation, optimize cost structures, and adeptly adapt their business strategies to the dynamic competitive landscape[5][7][11].

d. The variances in passenger traffic among international airlines exhibit a robust correlation with the geographic differentials in economic factors, cultural exchanges, tourism dynamics, and the state of transportation infrastructure[3]. This intricate linkage offers airlines profound insights into the formulation of lucrative route planning strategies, the precision of demand forecasting models, and the implementation of region-specific marketing tactics. Strategic acumen in interpreting these nuanced correlations enables airlines to position themselves adeptly in diverse markets[2][6][12].

e. The strategic significance of airline alliances and partnerships reverberates through their profound impact on passenger volumes and competitive positioning. Facilitating expanded networks, operational synergies, joint marketing initiatives, and cost-saving endeavors, alliances play a pivotal role in shaping the industry landscape [4]. The dynamism inherent in alterations to these collaborative frameworks necessitates a nuanced understanding of the delicate equilibrium between cooperation and competition. Strategic tracking of alliance impacts provides airlines with the foresight necessary for leveraging these partnerships amidst the perpetual evolution of trends within the aviation sector[1][8][9].

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