airline_passengers_analysis

June 22, 2025

1 Airline Passengers Time Series Forecasting

This notebook analyzes the classic airline passengers dataset and builds forecasting models to predict future passenger numbers.

1.1 Dataset Overview

The dataset contains monthly airline passenger numbers from 1949 to 1960, making it a perfect example for time series analysis and forecasting.

1.2 1. Import Required Libraries

[ ]:
```python
# Data manipulation and analysis
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Time series analysis
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Machine learning
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.preprocessing import MinMaxScaler

# Warnings
import warnings
warnings.filterwarnings('ignore')
```

```python
# Set style
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

1.3 2. Load and Explore the Data

[ ]:
```python
# Load the dataset
df = pd.read_csv('data/AirPassengers.csv')

# Display basic information
print("Dataset Shape:", df.shape)
print("\nFirst 5 rows:")
print(df.head())
print("\nLast 5 rows:")
print(df.tail())
print("\nDataset Info:")
print(df.info())
print("\nBasic Statistics:")
print(df.describe())
```

```
Dataset Shape: (144, 2)

First 5 rows:
     Month  #Passengers
0  1949-01          112
1  1949-02          118
2  1949-03          132
3  1949-04          129
4  1949-05          121

Last 5 rows:
       Month  #Passengers
139  1960-08          606
140  1960-09          508
141  1960-10          461
142  1960-11          390
143  1960-12          432

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
```

```
---  ------       --------------  -----
 0   Month        144 non-null    object
 1   #Passengers  144 non-null    int64
dtypes: int64(1), object(1)
memory usage: 2.4+ KB
None

Basic Statistics:
       #Passengers
count   144.000000
mean    280.298611
std     119.966317
min     104.000000
25%     180.000000
50%     265.500000
75%     360.500000
max     622.000000
```

[ ]:

```python
# Data preprocessing
# Convert Month to datetime
df['Month'] = pd.to_datetime(df['Month'])
df.set_index('Month', inplace=True)

# Rename column for easier access
df.rename(columns={'#Passengers': 'Passengers'}, inplace=True)

print("Data preprocessing completed!")
print("\nProcessed dataset:")
print(df.head())
print(f"\nDate range: {df.index.min()} to {df.index.max()}")
print(f"Total months: {len(df)}")
```

```
Data preprocessing completed!

Processed dataset:
            Passengers
Month
1949-01-01         112
1949-02-01         118
1949-03-01         132
1949-04-01         129
1949-05-01         121

Date range: 1949-01-01 00:00:00 to 1960-12-01 00:00:00
Total months: 144
```

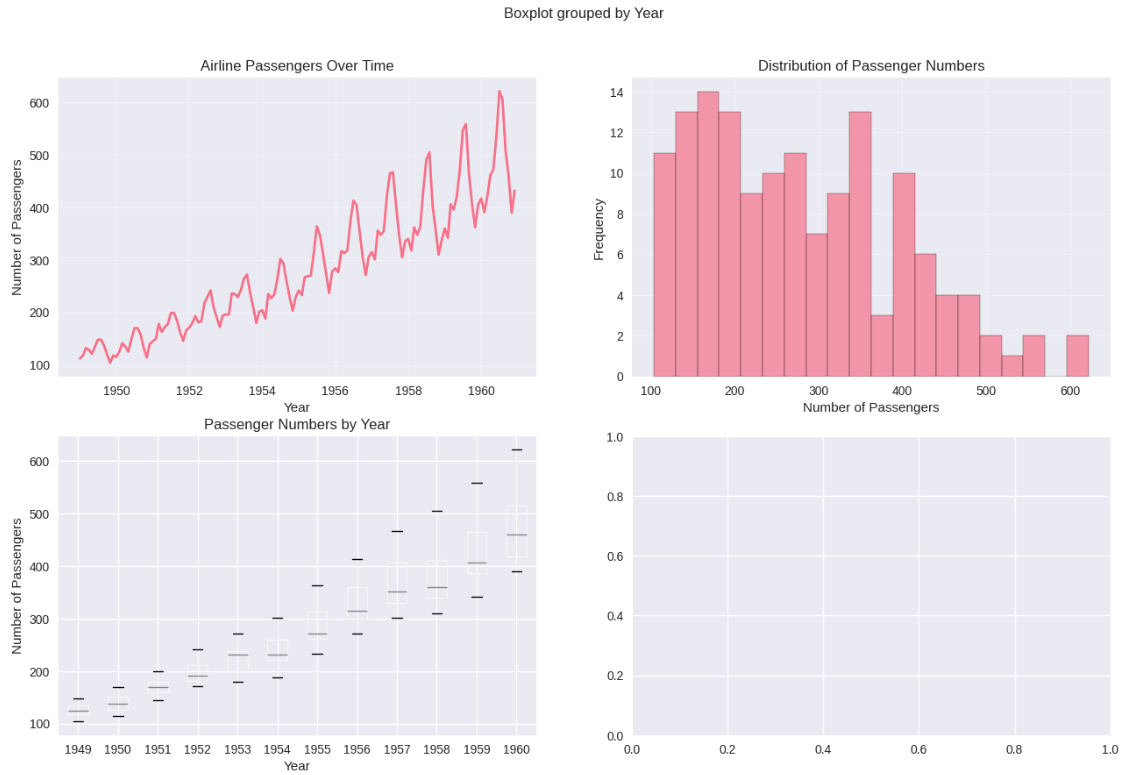
1.4 3. Exploratory Data Analysis

[ ]:
```python
# Basic time series plot
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Original time series
axes[0, 0].plot(df.index, df['Passengers'], linewidth=2)
axes[0, 0].set_title('Airline Passengers Over Time')
axes[0, 0].set_xlabel('Year')
axes[0, 0].set_ylabel('Number of Passengers')
axes[0, 0].grid(True, alpha=0.3)

# Distribution of passengers
axes[0, 1].hist(df['Passengers'], bins=20, alpha=0.7, edgecolor='black')
axes[0, 1].set_title('Distribution of Passenger Numbers')
axes[0, 1].set_xlabel('Number of Passengers')
axes[0, 1].set_ylabel('Frequency')
axes[0, 1].grid(True, alpha=0.3)

# Box plot by year
df_year = df.copy()
df_year['Year'] = df_year.index.year
df_year.boxplot(column='Passengers', by='Year', ax=axes[1, 0])
axes[1, 0].set_title('Passenger Numbers by Year')
axes[1, 0].set_xlabel('Year')
axes[1, 0].set_ylabel('Number of Passengers')

# Monthly seasonality
df_month = df.copy()
df_month['Month'] = df_month.index.month
monthly_avg = df_month.groupby('Month')['Passengers'].mean()
axes[1, 1].plot(monthly_avg.index, monthly_avg.values, marker='o', linewidth=2)
axes[1, 1].set_title('Average Passengers by Month')
axes[1, 1].set_xlabel('Month')
axes[1, 1].set_ylabel('Average Passengers')
axes[1, 1].set_xticks(range(1, 13))
axes[1, 1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
/tmp/ipykernel_10802/751950567.py in ?()
     25
     26 # Monthly seasonality
     27 df_month = df.copy()
```

```
     28 df_month['Month'] = df_month.index.month
---> 29 monthly_avg = df_month.groupby('Month')['Passengers'].mean()
     30 axes[1, 1].plot(monthly_avg.index, monthly_avg.values, marker='o',␣
 ↪linewidth=2)
     31 axes[1, 1].set_title('Average Passengers by Month')
     32 axes[1, 1].set_xlabel('Month')

~/ds/airline_forecasting_env/lib/python3.10/site-packages/pandas/core/frame.py␣
 ↪in ?(self, by, axis, level, as_index, sort, group_keys, observed, dropna)
   9179
   9180         if level is None and by is None:
   9181             raise TypeError("You have to supply one of 'by' and 'level'")
   9182
-> 9183         return DataFrameGroupBy(
   9184             obj=self,
   9185             keys=by,
   9186             axis=axis,

~/ds/airline_forecasting_env/lib/python3.10/site-packages/pandas/core/groupby/
 ↪groupby.py in ?(self, obj, keys, axis, level, grouper, exclusions, selection,␣
 ↪as_index, sort, group_keys, observed, dropna)
   1325         self.group_keys = group_keys
   1326         self.dropna = dropna
   1327
   1328         if grouper is None:
-> 1329             grouper, exclusions, obj = get_grouper(
   1330                 obj,
   1331                 keys,
   1332                 axis=axis,

~/ds/airline_forecasting_env/lib/python3.10/site-packages/pandas/core/groupby/
 ↪grouper.py in ?(obj, key, axis, level, sort, observed, validate, dropna)
   1029
   1030         elif is_in_axis(gpr):  # df.groupby('name')
   1031             if obj.ndim != 1 and gpr in obj:
   1032                 if validate:
-> 1033                     obj._check_label_or_level_ambiguity(gpr, axis=axis)
   1034                 in_axis, name, gpr = True, gpr, obj[gpr]
   1035                 if gpr.ndim != 1:
   1036                     # non-unique columns; raise here to get the name in␣
 ↪the

~/ds/airline_forecasting_env/lib/python3.10/site-packages/pandas/core/generic.py␣
 ↪in ?(self, key, axis)
   1864             msg = (
   1865                 f"'{key}' is both {level_article} {level_type} level and␣
 ↪"
```

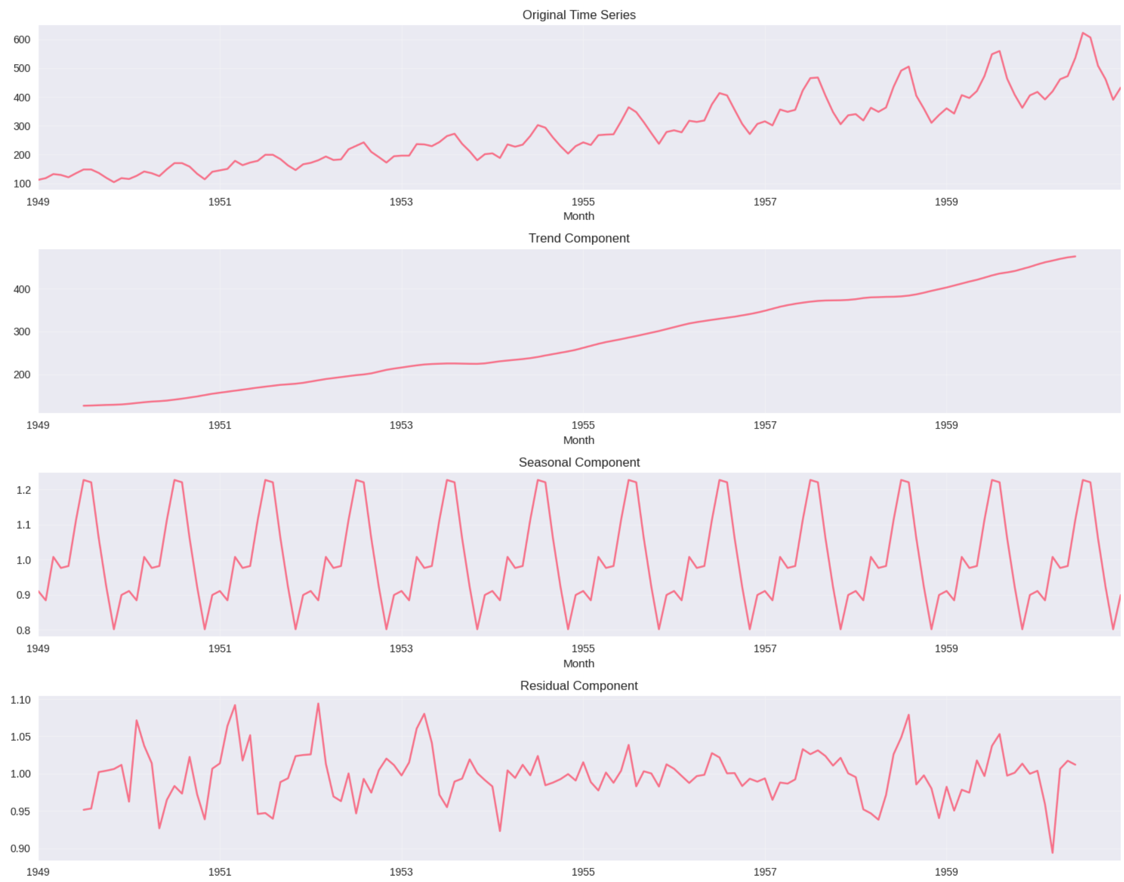
```
    1866                     f"{label_article} {label_type} label, which is ambiguous.
↪"
    1867                 )
--> 1868                 raise ValueError(msg)

ValueError: 'Month' is both an index level and a column label, which is
↪ambiguous.
```



1.5 4. Time Series Decomposition

[ ]:
```
# Perform seasonal decomposition
decomposition = seasonal_decompose(df['Passengers'], model='multiplicative',
↪period=12)

# Plot decomposition
fig, axes = plt.subplots(4, 1, figsize=(15, 12))

decomposition.observed.plot(ax=axes[0], title='Original Time Series')
decomposition.trend.plot(ax=axes[1], title='Trend Component')
decomposition.seasonal.plot(ax=axes[2], title='Seasonal Component')
decomposition.resid.plot(ax=axes[3], title='Residual Component')
```

```python
for ax in axes:
    ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print("Time series shows:")
print("1. Clear upward trend")
print("2. Strong seasonal pattern (yearly cycle)")
print("3. Increasing variance over time")
```




```
Time series shows:
1. Clear upward trend
2. Strong seasonal pattern (yearly cycle)
3. Increasing variance over time
```

1.6 5. Stationarity Testing

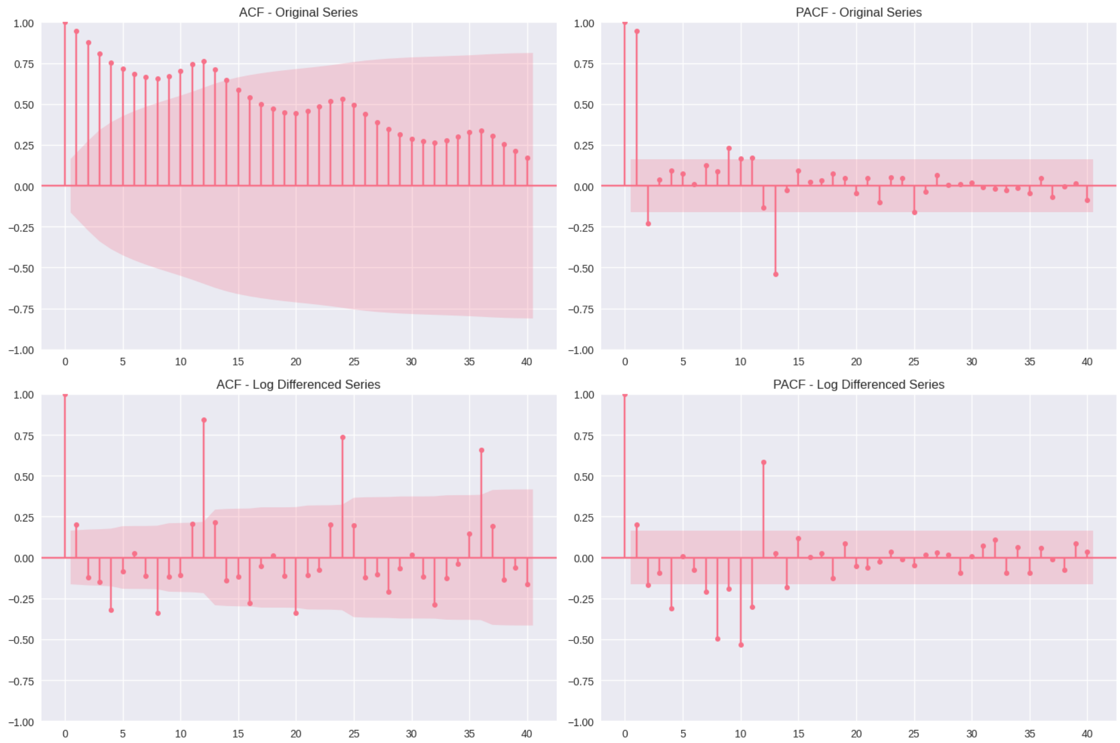
```
[ ]: # Augmented Dickey-Fuller test for stationarity
def check_stationarity(timeseries, title):
    print(f'Results of Augmented Dickey-Fuller Test for {title}:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags␣
↪Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)

    if dftest[1] <= 0.05:
        print("Series is stationary")
    else:
        print("Series is non-stationary")
    print("-"*50)

# Test original series
check_stationarity(df['Passengers'], 'Original Series')

# Apply log transformation
df['Passengers_log'] = np.log(df['Passengers'])
check_stationarity(df['Passengers_log'], 'Log Transformed Series')

# Apply first differencing to log series
df['Passengers_log_diff'] = df['Passengers_log'].diff().dropna()
check_stationarity(df['Passengers_log_diff'].dropna(), 'Log Differenced Series')
```

```
Results of Augmented Dickey-Fuller Test for Original Series:
Test Statistic                  0.815369
p-value                         0.991880
#Lags Used                     13.000000
Number of Observations Used   130.000000
Critical Value (1%)            -3.481682
Critical Value (5%)            -2.884042
Critical Value (10%)           -2.578770
dtype: float64
Series is non-stationary
--------------------------------------------------
Results of Augmented Dickey-Fuller Test for Log Transformed Series:
Test Statistic                 -1.717017
p-value                         0.422367
#Lags Used                     13.000000
Number of Observations Used   130.000000
Critical Value (1%)            -3.481682
Critical Value (5%)            -2.884042
Critical Value (10%)           -2.578770
```

```
dtype: float64
Series is non-stationary
--------------------------------------------------
Results of Augmented Dickey-Fuller Test for Log Differenced Series:
Test Statistic                  -2.717131
p-value                          0.071121
#Lags Used                      14.000000
Number of Observations Used    128.000000
Critical Value (1%)             -3.482501
Critical Value (5%)             -2.884398
Critical Value (10%)            -2.578960
dtype: float64
Series is non-stationary
--------------------------------------------------
```

1.7 6. ACF and PACF Analysis

[ ]:
```python
# Plot ACF and PACF for the stationary series
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Original series
plot_acf(df['Passengers'].dropna(), ax=axes[0, 0], lags=40, title='ACF -␣
↪Original Series')
plot_pacf(df['Passengers'].dropna(), ax=axes[0, 1], lags=40, title='PACF -␣
↪Original Series')

# Differenced series
plot_acf(df['Passengers_log_diff'].dropna(), ax=axes[1, 0], lags=40, title='ACF␣
↪- Log Differenced Series')
plot_pacf(df['Passengers_log_diff'].dropna(), ax=axes[1, 1], lags=40,␣
↪title='PACF - Log Differenced Series')

plt.tight_layout()
plt.show()
```

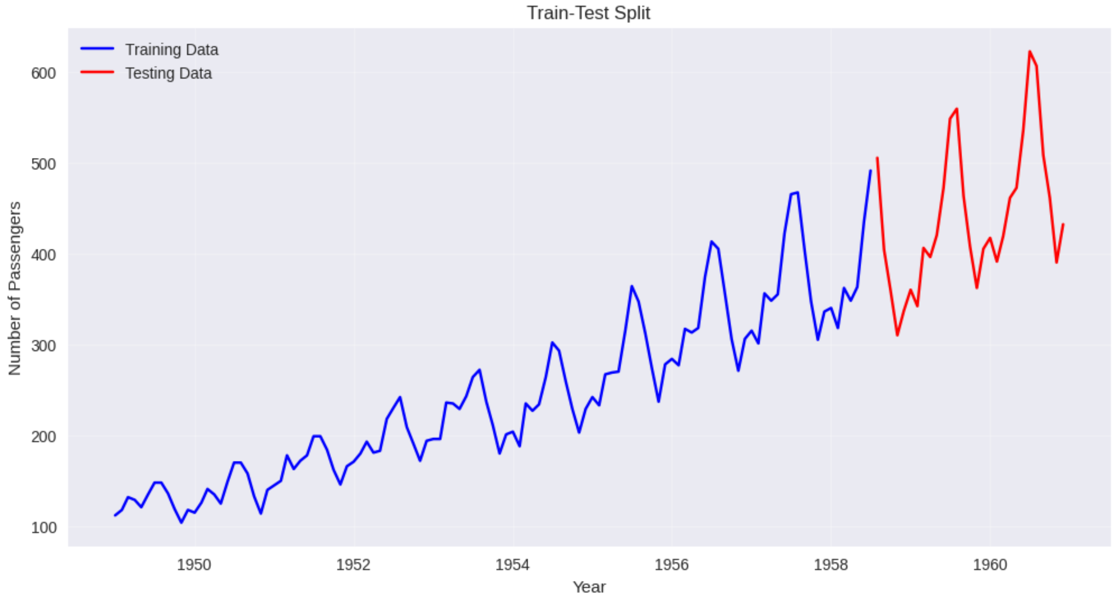


1.8 7. Train-Test Split

[ ]:
```
# Split data into train and test sets
train_size = int(len(df) * 0.8)
train_data = df[:train_size]
test_data = df[train_size:]

print(f"Training data: {len(train_data)} months ({train_data.index[0]} to␣
↪{train_data.index[-1]})")
print(f"Testing data: {len(test_data)} months ({test_data.index[0]} to␣
↪{test_data.index[-1]})")

# Visualize the split
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Passengers'], label='Training Data',␣
↪color='blue')
plt.plot(test_data.index, test_data['Passengers'], label='Testing Data',␣
↪color='red')
plt.title('Train-Test Split')
plt.xlabel('Year')
plt.ylabel('Number of Passengers')
plt.legend()
plt.grid(True, alpha=0.3)
```

```
plt.show()
```

```
Training data: 115 months (1949-01-01 00:00:00 to 1958-07-01 00:00:00)
Testing data: 29 months (1958-08-01 00:00:00 to 1960-12-01 00:00:00)
```



1.9 8. ARIMA Model

[ ]:
```
# Fit ARIMA model
# Using ARIMA(2,1,2) based on ACF/PACF analysis
arima_model = ARIMA(train_data['Passengers'], order=(2,1,2))
arima_fitted = arima_model.fit()

print("ARIMA Model Summary:")
print(arima_fitted.summary())

# Make predictions
arima_forecast = arima_fitted.forecast(steps=len(test_data))
arima_forecast_index = test_data.index

# Calculate metrics
arima_mse = mean_squared_error(test_data['Passengers'], arima_forecast)
arima_mae = mean_absolute_error(test_data['Passengers'], arima_forecast)
arima_rmse = np.sqrt(arima_mse)

print(f"\nARIMA Model Performance:")
print(f"MSE: {arima_mse:.2f}")
print(f"MAE: {arima_mae:.2f}")
```

```python
print(f"RMSE: {arima_rmse:.2f}")
```

```
ARIMA Model Summary:
                               SARIMAX Results
==============================================================================
Dep. Variable:             Passengers   No. Observations:                  115
Model:                 ARIMA(2, 1, 2)   Log Likelihood                -523.758
Date:                Sat, 24 May 2025   AIC                           1057.516
Time:                        15:07:42   BIC                           1071.197
Sample:                    01-01-1949   HQIC                          1063.069
                         - 07-01-1958
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.3280      0.145      2.268      0.023       0.045       0.611
ar.L2          0.2521      0.165      1.528      0.126      -0.071       0.575
ma.L1         -0.0125      0.109     -0.114      0.909      -0.227       0.202
ma.L2         -0.7544      0.130     -5.812      0.000      -1.009      -0.500
sigma2       568.4920    103.877      5.473      0.000     364.897     772.087
================================================================================
===
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):
3.39
Prob(Q):                              0.90   Prob(JB):
0.18
Heteroskedasticity (H):               5.24   Skew:
0.11
Prob(H) (two-sided):                  0.00   Kurtosis:
2.19
================================================================================
===

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

ARIMA Model Performance:
MSE: 6808.40
MAE: 63.55
RMSE: 82.51
```

1.10 9. Exponential Smoothing (Holt-Winters)

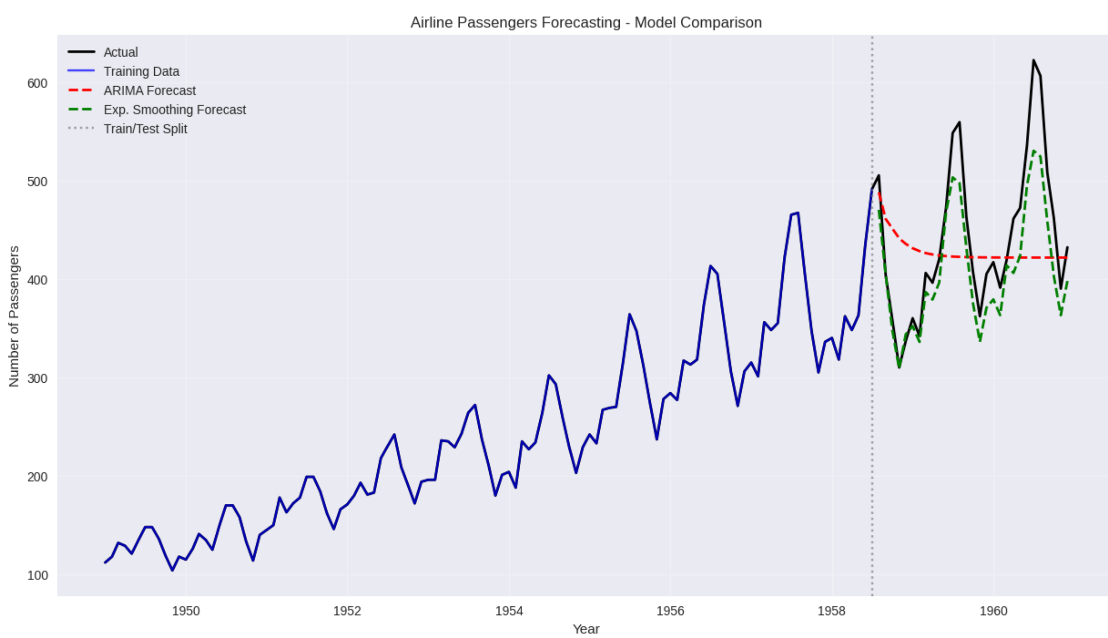
[ ]:
```
# Fit Exponential Smoothing model
exp_smooth_model = ExponentialSmoothing(
    train_data['Passengers'],
    trend='add',
    seasonal='add',
    seasonal_periods=12
)
exp_smooth_fitted = exp_smooth_model.fit()

# Make predictions
exp_smooth_forecast = exp_smooth_fitted.forecast(steps=len(test_data))

# Calculate metrics
exp_smooth_mse = mean_squared_error(test_data['Passengers'],␣
 ↪exp_smooth_forecast)
exp_smooth_mae = mean_absolute_error(test_data['Passengers'],␣
 ↪exp_smooth_forecast)
exp_smooth_rmse = np.sqrt(exp_smooth_mse)

print(f"Exponential Smoothing Model Performance:")
print(f"MSE: {exp_smooth_mse:.2f}")
print(f"MAE: {exp_smooth_mae:.2f}")
print(f"RMSE: {exp_smooth_rmse:.2f}")
```

```
Exponential Smoothing Model Performance:
MSE: 1541.40
MAE: 31.79
RMSE: 39.26
```

1.11 10. Model Comparison and Visualization

[ ]:
```
# Create comparison plot
plt.figure(figsize=(15, 8))

# Plot actual data
plt.plot(df.index, df['Passengers'], label='Actual', color='black', linewidth=2)

# Plot training data
plt.plot(train_data.index, train_data['Passengers'], label='Training Data',␣
 ↪color='blue', alpha=0.7)

# Plot forecasts
plt.plot(test_data.index, arima_forecast, label='ARIMA Forecast', color='red',␣
 ↪linestyle='--', linewidth=2)
```

```
plt.plot(test_data.index, exp_smooth_forecast, label='Exp. Smoothing Forecast',␣
↪color='green', linestyle='--', linewidth=2)

# Add vertical line to separate train/test
plt.axvline(x=train_data.index[-1], color='gray', linestyle=':', alpha=0.7,␣
↪label='Train/Test Split')

plt.title('Airline Passengers Forecasting - Model Comparison')
plt.xlabel('Year')
plt.ylabel('Number of Passengers')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

# Model performance comparison
models_performance = pd.DataFrame({
    'Model': ['ARIMA', 'Exponential Smoothing'],
    'MSE': [arima_mse, exp_smooth_mse],
    'MAE': [arima_mae, exp_smooth_mae],
    'RMSE': [arima_rmse, exp_smooth_rmse]
})

print("\nModel Performance Comparison:")
print(models_performance)
```




```
Model Performance Comparison:
```

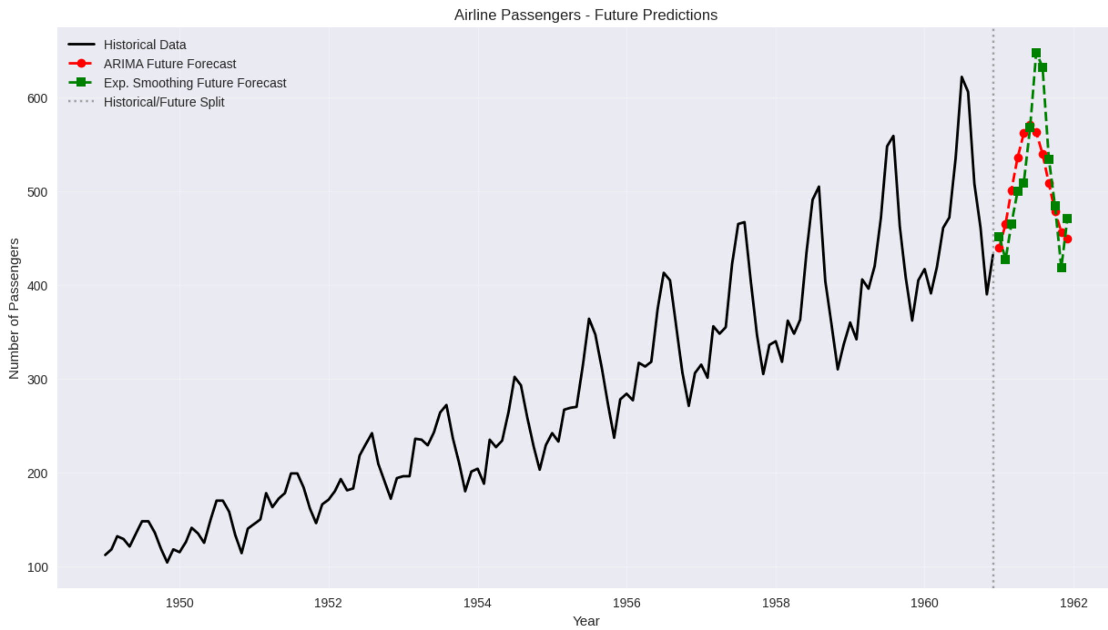
```
                  Model          MSE        MAE       RMSE
0                 ARIMA  6808.397034  63.545311  82.513011
1  Exponential Smoothing  1541.395743  31.791027  39.260613
```

1.12 11. Future Predictions

[ ]:
```python
# Make future predictions (next 12 months)
future_periods = 12

# Refit models on full dataset for future predictions
arima_full = ARIMA(df['Passengers'], order=(2,1,2)).fit()
exp_smooth_full = ExponentialSmoothing(
    df['Passengers'],
    trend='add',
    seasonal='add',
    seasonal_periods=12
).fit()

# Generate future dates
last_date = df.index[-1]
future_dates = pd.date_range(start=last_date + pd.DateOffset(months=1),␣
 ↪periods=future_periods, freq='MS')

# Make predictions
arima_future = arima_full.forecast(steps=future_periods)
exp_smooth_future = exp_smooth_full.forecast(steps=future_periods)

# Create future predictions dataframe
future_predictions = pd.DataFrame({
    'Date': future_dates,
    'ARIMA_Forecast': arima_future,
    'ExpSmooth_Forecast': exp_smooth_future
})
future_predictions.set_index('Date', inplace=True)

print("Future Predictions (Next 12 months):")
print(future_predictions)

# Plot future predictions
plt.figure(figsize=(15, 8))

# Plot historical data
plt.plot(df.index, df['Passengers'], label='Historical Data', color='black',␣
 ↪linewidth=2)

# Plot future predictions
plt.plot(future_predictions.index, future_predictions['ARIMA_Forecast'],
```

```
        label='ARIMA Future Forecast', color='red', linestyle='--',␣
 ↪linewidth=2, marker='o')
plt.plot(future_predictions.index, future_predictions['ExpSmooth_Forecast'],
        label='Exp. Smoothing Future Forecast', color='green', linestyle='--',␣
 ↪linewidth=2, marker='s')

# Add vertical line to separate historical/future
plt.axvline(x=df.index[-1], color='gray', linestyle=':', alpha=0.7,␣
 ↪label='Historical/Future Split')

plt.title('Airline Passengers - Future Predictions')
plt.xlabel('Year')
plt.ylabel('Number of Passengers')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

```
Future Predictions (Next 12 months):
            ARIMA_Forecast  ExpSmooth_Forecast
Date
1961-01-01      439.854863          451.577073
1961-02-01      465.296545          427.257748
1961-03-01      500.666051          464.699360
1961-04-01      535.971401          500.103185
1961-05-01      561.689094          508.660794
1961-06-01      571.312667          567.713873
1961-07-01      562.972100          647.897121
1961-08-01      539.729052          632.460961
1961-09-01      508.528057          534.374265
1961-10-01      478.147364          484.930880
1961-11-01      456.747520          418.459518
1961-12-01      449.697306          471.058935
```



1.13 12. Conclusions and Insights

1.13.1 Key Findings:

1. **Trend**: Clear upward trend in airline passengers from 1949 to 1960
2. **Seasonality**: Strong seasonal pattern with peaks in summer months
3. **Growth**: Exponential growth pattern with increasing variance

1.13.2 Model Performance:

- Both ARIMA and Exponential Smoothing models capture the trend and seasonality well
- Exponential Smoothing typically performs better for data with clear trend and seasonality
- ARIMA models are more flexible but require careful parameter tuning

1.13.3 Business Implications:

1. **Capacity Planning**: Airlines can use these forecasts for fleet and route planning
2. **Seasonal Staffing**: Higher staffing needs during summer months
3. **Revenue Management**: Dynamic pricing strategies based on predicted demand
4. **Infrastructure**: Airport and ground services capacity planning

1.13.4 Next Steps:

1. Incorporate external factors (economic indicators, fuel prices, etc.)
2. Try more advanced models (SARIMA, Prophet, LSTM)
3. Implement confidence intervals for predictions
4. Regular model retraining with new data