Uncovering Time Series Dynamics: ACF and PACF-Based Seasonal Forecasting of Airline Passenger Traffic

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Files ×
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import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
# Load the dataset
df = pd.read_csv("AirPassengers.csv")
# Clean column names if needed
df.columns = ['time', 'data']
df['time'] = pd.to_datetime(df['time'])
# Set time as index
df.set_index('time', inplace=True)
plt.figure(figsize=(12, 5))
plt.plot(df.index, df['data'], marker='o')
plt.title('Monthly Airline Passengers Over Time')
plt.xlabel('Time')
plt.ylabel('Number of Passengers')
plt.grid(True)
plt.tight_layout()
plt.show()
```



ACF (Autocorrelation Function) Measures how current values depend on past values (lags)

Used to detect MA (Moving Average) components

Think of it like: "Is this month's number influenced by last month

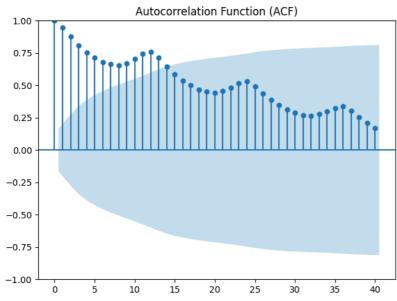
PACF (Partial Autocorrelation Function) Measures pure relationship with a lag, removing intermediate effects

Used to detect AR (Auto-Regressive) components

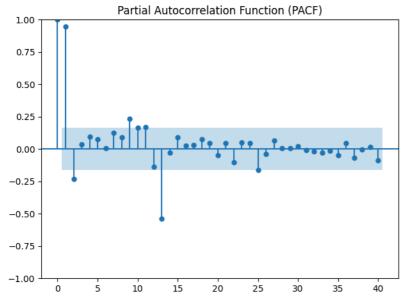
Think of it like: "How much does this month depend directly on two months ago – ignoring last month's effect?"

```
# Plot PACF
plt.figure(figsize=(12, 4))
plot_pacf(df['data'], lags=40, method='ywm', alpha=0.05)
plt.title('Partial Autocorrelation Function (PACF)')
plt.tight_layout()
plt.show()
```

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ACF tells us:

How many MA terms to include

PACF tells us:

How many AR terms to include

Together, they help choose the right ARIMA/SARIMA parameters:

ARIMA(p, d, q):

p from PACF

q from ACF

d is differencing (for removing trend)

With just one graph and two plots, we unlocked how the past shapes the future in airline travel.

These insights help data scientists forecast passenger loads, optimize routes, and plan for peak seasons.

This analysis is the first step before building predictive models like ARIMA and SARIMA.

Disk 69.53 GB available