01_components_and_visualization

June 28, 2025

1 Components and Visualization of Time Series

[1]:
```python
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import os
import plotly.io as pio
pio.templates.default = "plotly_white"
import pandas as pd
from pathlib import Path
from tqdm.autonotebook import tqdm
from IPython.display import display, HTML
# %load_ext autoreload
# %autoreload 2
np.random.seed()
tqdm.pandas()
```

```
/tmp/ipykernel_7717/1114571209.py:9: TqdmWarning: IProgress not found. Please
update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from tqdm.autonotebook import tqdm
```

Components of a time series: 1. Trend 2. Seasonal 3. Cyclical 4. Irregular

$$Y = Trend + Seasonal + Cyclical + Irregular$$

$$Y = Trend * Seasonal * Cyclical * Irregular$$

1.1 Trend Component

- The trend is a long-term change in the mean of a time series.
- It is the smooth and steady movement of a time series in a particular direction.

1.2 Seasonal Component

- The seasonal component is the recurring pattern of a time series that repeats itself every period.
- It is the recurring ups and downs within a period.

1.3 Cyclical Component

- The cyclical component is the recurring pattern of a time series that repeats itself every period.
- It is the recurring ups and downs within a period.

[3]:
```
DATA_FOLDER_PATH = "/home/bilal326/Time_Series/data/london_smart_meters"

block_df = pd.read_parquet(f"{DATA_FOLDER_PATH}/preprocessed/
↪london_smart_meters_merged_block_0-7.parquet")
```

[6]:
```
#Converting to expanded form
from data_utils import compact_to_expanded

exp_block_df = compact_to_expanded(block_df[block_df.file=="block_7"],␣
↪timeseries_col = 'energy_consumption',\
                                   static_cols = ["frequency", "series_length",␣
↪"stdorToU", "Acorn", "Acorn_grouped",\
                                                 "file"],time_varying_cols =␣
↪['holidays', 'visibility', 'windBearing', 'temperature','dewPoint',\
                                                                           ␣
↪'pressure', 'apparentTemperature', 'windSpeed', 'precipType', 'icon',␣
↪'humidity', 'summary'],\
                                                                           ␣
↪    ts_identifier = "LCLid")

# Taking a single time series from the block
ts_df = exp_block_df[exp_block_df.LCLid=="MAC000193"].set_index("timestamp")

ts_df["weekday_name"] = ts_df.index.day_name()
ts_df["weekday"] = ts_df.index.weekday
ts_df["week"] = ts_df.index.isocalendar().week
ts_df["day"] = ts_df.index.day
ts_df["hour"] = ts_df.index.hour
ts_df["date"] = ts_df.index.date
ts_df["month"] = ts_df.index.month
ts_df["month_name"] = ts_df.index.month_name()
ts_df["year"] = ts_df.index.year

#Making ordered categoricals to make for sorted plots
ts_df['month_name'] = pd.Categorical(ts_df['month_name'],␣
↪categories=["January", "February", "March", "April", "May", "June", "July",␣
↪"August", "September", "October", "November", "December"], ordered=True)
ts_df['weekday_name'] = pd.Categorical(ts_df['weekday_name'],␣
↪categories=["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
↪"Saturday", "Sunday"], ordered=True)
```

```
  0%|          | 0/50 [00:00<?, ?it/s]
```

```
100%|     | 50/50 [00:00<00:00, 74.93it/s]
```

[7]:
```
# !wget https://raw.githubusercontent.com/PacktPublishing/
↪Modern-Time-Series-Forecasting-with-Python/refs/heads/main/src/imputation/
↪interpolation.py
```

```
--2025-06-28 18:18:05--
https://raw.githubusercontent.com/PacktPublishing/Modern-Time-Series-
Forecasting-with-Python/refs/heads/main/src/imputation/interpolation.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)…
185.199.109.133, 185.199.110.133, 185.199.111.133, …
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.109.133|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 6820 (6.7K) [text/plain]
Saving to: 'interpolation.py.1'

interpolation.py.1  100%[===================>]   6.66K  --.-KB/s    in 0.001s

2025-06-28 18:18:06 (5.10 MB/s) - 'interpolation.py.1' saved [6820/6820]
```

1. Line Charts

[8]:
```
#Interpolating Missing values
# from src.imputation.interpolation import SeasonalInterpolation


ts_df['energy_consumption'] = ts_df['energy_consumption'].
↪interpolate(method='linear')
```

[9]:
```
fig = px.line(ts_df, y="energy_consumption", title="Energy Consumption for␣
↪MAC000193")
# fig = format_plot(fig, ylabel="Energy Consumption")
fig.show()
```

2. Rolling Average Plot (rolling avg)

When you have a long time series with high variation, as we have, the line plot can get a bit chaotic. One of the options to get a macro view of the time series in terms of trends and movement is to plot a smoothed version of the time series.

[10]:
```
ts_df["rolling_monthly_avg"] = ts_df["energy_consumption"].
↪rolling(window=48*30).mean()

fig = px.line(ts_df, y="rolling_monthly_avg", title="Rolling Monthly Average␣
↪Energy Consumption for MAC000193")
fig.show()
```

Another use for the line chart is to visualize two or more time series together and investigate any correlations between them.

[11]:
```python
import plotly.graph_objects as go

fig = go.Figure()

# Add first y-axis (Energy Consumption)
fig.add_trace(go.Scatter(
    x=ts_df.index,
    y=ts_df['energy_consumption'],
    name='Energy Consumption',
    yaxis='y1',
    line=dict(color='blue')
))

# Add second y-axis (Temperature)
fig.add_trace(go.Scatter(
    x=ts_df.index,
    y=ts_df['temperature'],
    name='Temperature',
    yaxis='y2',
    line=dict(color='red', dash='dash')
))

# Set layout with dual y-axes
fig.update_layout(
    title='Temperature and Energy Consumption',
    xaxis=dict(title='Time'),
    yaxis=dict(
        title=dict(text='Energy Consumption', font=dict(color='blue')),
        tickfont=dict(color='blue')
    ),
    yaxis2=dict(
        title=dict(text='Temperature', font=dict(color='red')),
        tickfont=dict(color='red'),
        anchor='x',
        overlaying='y',
        side='right'
    ),
    legend=dict(x=0.01, y=0.99),
    width=900,
    height=500
)


fig.show()
```

[12]:
```
import plotly.graph_objects as go

# Create rolling averages (e.g., 48*30 for ~monthly)
ts_df['energy_rolling'] = ts_df['energy_consumption'].rolling(window=48*30).
↪mean()
ts_df['temp_rolling'] = ts_df['temperature'].rolling(window=48*30).mean()

fig = go.Figure()

# Rolling Energy Consumption (y-axis 1)
fig.add_trace(go.Scatter(
    x=ts_df.index,
    y=ts_df['energy_rolling'],
    name='Energy Consumption (Rolling Avg)',
    yaxis='y1',
    line=dict(color='blue')
))

# Rolling Temperature (y-axis 2)
fig.add_trace(go.Scatter(
    x=ts_df.index,
    y=ts_df['temp_rolling'],
    name='Temperature (Rolling Avg)',
    yaxis='y2',
    line=dict(color='red', dash='dash')
))

# Layout with dual axes
fig.update_layout(
    title='Rolling Monthly Averages: Temperature and Energy Consumption',
    xaxis=dict(title='Time'),
    yaxis=dict(
        title=dict(text='Energy Consumption (Rolling Avg)',␣
↪font=dict(color='blue')),
        tickfont=dict(color='blue')
    ),
    yaxis2=dict(
        title=dict(text='Temperature (Rolling Avg)', font=dict(color='red')),
        tickfont=dict(color='red'),
        anchor='x',
        overlaying='y',
        side='right'
    ),
    legend=dict(x=0.01, y=0.99),
    width=900,
    height=500
)
```

```
fig.show()
```

Seasonal plots

A seasonal plot is very similar to a line plot, but the key difference here is that the x-axis denotes the “seasons,” the y-axis denotes the time series value

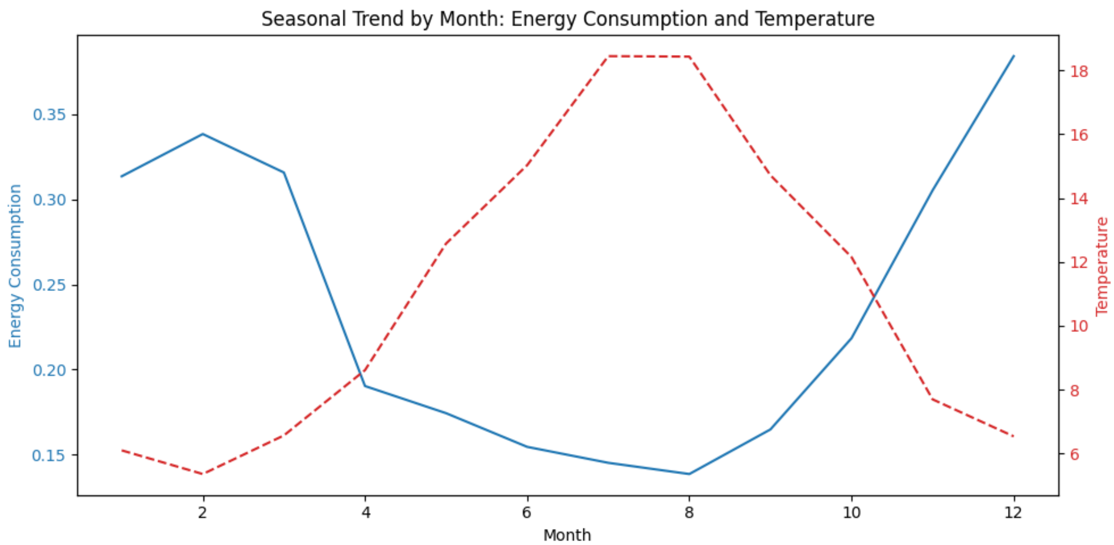
And the different seasonal cycles are represented in different colors or line types.

[13]:
```
plot_df = ts_df[~ts_df.year.isin([2011, 2014])].groupby(["year",␣
↪"month_name"])[['energy_consumption',"temperature"]].mean().reset_index()



fig = px.line(plot_df, x="month_name", y='energy_consumption', color="year",␣
↪line_dash="year", title="Seasonal Plot - Monthly")
# fig = format_plot(fig, ylabel="Energy Consumption", xlabel="Month")
fig.show()
```

```
/tmp/ipykernel_7717/3793814189.py:1: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
```

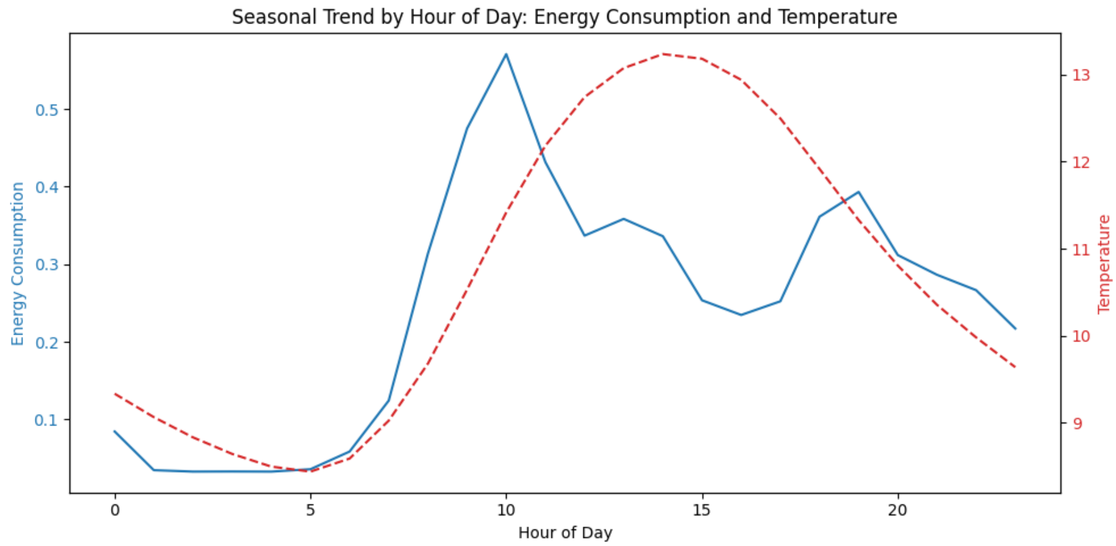
[14]:
```
import matplotlib.pyplot as plt
import pandas as pd

# Make sure datetime index
ts_df['month'] = ts_df.index.month
ts_df['hour'] = ts_df.index.hour

# Monthly averages
monthly_avg = ts_df.groupby('month')[['energy_consumption', 'temperature']].
↪mean()

# Plot
fig, ax1 = plt.subplots(figsize=(10, 5))

color = 'tab:blue'
ax1.set_xlabel('Month')
ax1.set_ylabel('Energy Consumption', color=color)
ax1.plot(monthly_avg.index, monthly_avg['energy_consumption'], color=color,␣
↪label='Energy Consumption')
ax1.tick_params(axis='y', labelcolor=color)

# Second y-axis
```

```
ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Temperature', color=color)
ax2.plot(monthly_avg.index, monthly_avg['temperature'], color=color,␣
 ↪linestyle='--', label='Temperature')
ax2.tick_params(axis='y', labelcolor=color)

plt.title('Seasonal Trend by Month: Energy Consumption and Temperature')
fig.tight_layout()
plt.show()
```



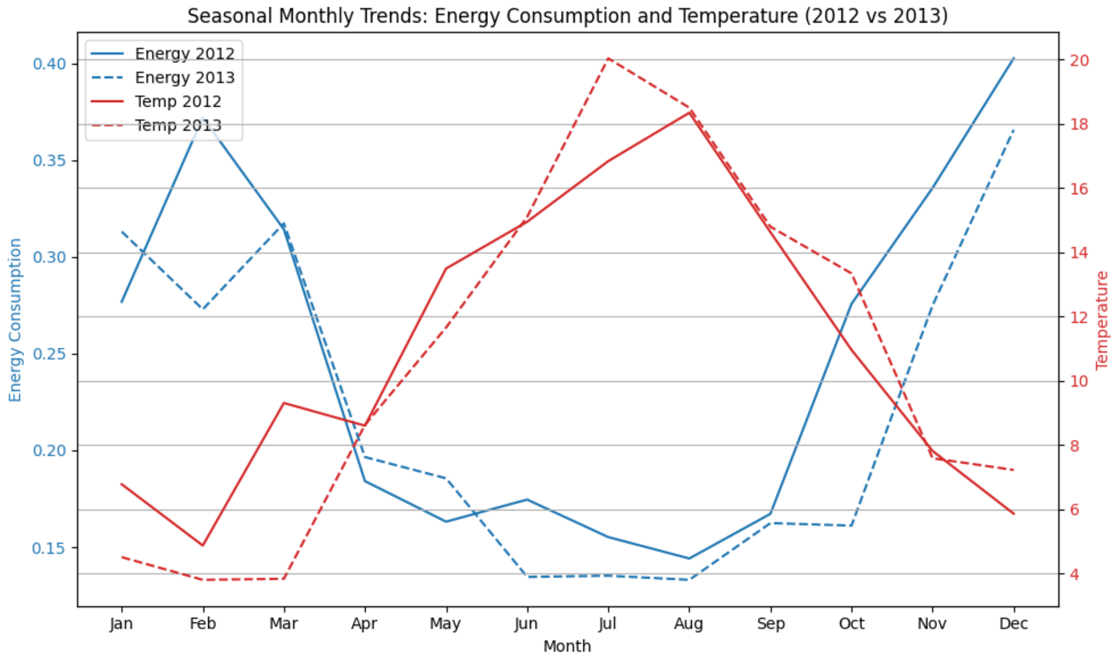
[15]:
```
# Hourly averages
hourly_avg = ts_df.groupby('hour')[['energy_consumption', 'temperature']].mean()

fig, ax1 = plt.subplots(figsize=(10, 5))

color = 'tab:blue'
ax1.set_xlabel('Hour of Day')
ax1.set_ylabel('Energy Consumption', color=color)
ax1.plot(hourly_avg.index, hourly_avg['energy_consumption'], color=color)
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Temperature', color=color)
ax2.plot(hourly_avg.index, hourly_avg['temperature'], color=color,␣
 ↪linestyle='--')
ax2.tick_params(axis='y', labelcolor=color)
```

```
plt.title('Seasonal Trend by Hour of Day: Energy Consumption and Temperature')
fig.tight_layout()
plt.show()
```



[16]:
```
import matplotlib.pyplot as plt
import pandas as pd

# Make sure datetime index is set
ts_df['month'] = ts_df.index.month
ts_df['year'] = ts_df.index.year

# Filter for 2012 and 2013
season_df = ts_df[ts_df['year'].isin([2012, 2013])]

# Monthly averages
monthly_avg = season_df.groupby(['year', 'month'])[['energy_consumption',␣
↪'temperature']].mean().reset_index()

# Pivot to get separate columns for plotting
energy_pivot = monthly_avg.pivot(index='month', columns='year',␣
↪values='energy_consumption')
temp_pivot = monthly_avg.pivot(index='month', columns='year',␣
↪values='temperature')

# Plot
fig, ax1 = plt.subplots(figsize=(10, 6))
```

```
# Left y-axis (Energy)
color_energy = 'tab:blue'
ax1.set_xlabel('Month')
ax1.set_ylabel('Energy Consumption', color=color_energy)
ax1.plot(energy_pivot.index, energy_pivot[2012], label='Energy 2012',␣
 ↪color=color_energy)
ax1.plot(energy_pivot.index, energy_pivot[2013], label='Energy 2013',␣
 ↪color=color_energy, linestyle='--')
ax1.tick_params(axis='y', labelcolor=color_energy)

# Right y-axis (Temperature)
ax2 = ax1.twinx()
color_temp = 'tab:red'
ax2.set_ylabel('Temperature', color=color_temp)
ax2.plot(temp_pivot.index, temp_pivot[2012], label='Temp 2012',␣
 ↪color=color_temp)
ax2.plot(temp_pivot.index, temp_pivot[2013], label='Temp 2013',␣
 ↪color=color_temp, linestyle='--')
ax2.tick_params(axis='y', labelcolor=color_temp)

# Title and legend
plt.title('Seasonal Monthly Trends: Energy Consumption and Temperature (2012 vs␣
 ↪2013)')

# Combine legends from both axes
lines_1, labels_1 = ax1.get_legend_handles_labels()
lines_2, labels_2 = ax2.get_legend_handles_labels()
ax1.legend(lines_1 + lines_2, labels_1 + labels_2, loc='upper left')

# Month labels
ax1.set_xticks(range(1,13))
ax1.set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                     'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])

plt.grid(True)
fig.tight_layout()
plt.show()
```



But when there are too many seasonal cycles to be plotted, it increases visual clutter. An alternative to a seasonal plot is a seasonal box plot.

[17]:
```
plot_df =  ts_df.groupby(["date","weekday_name", "hour"])["energy_consumption"].
  ↪mean().reset_index().dropna()

fig = px.box(plot_df, y="energy_consumption", x="hour", log_y=True, title="Box␣
  ↪Plot: Day of Month-Hourly Average")
fig.update_layout(height=700)
fig.show()
```

```
/tmp/ipykernel_7717/1998492874.py:1: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
```

- the seasonal box plot is much more informative.
- The horizontal line in the box tells us about the median,
- the box is the interquartile range (IQR), and the points that are marked are the outliers.

- By looking at the medians, we can see that the peak consumption occurs from 9 A.M. onward.
- But the variability is also higher from 9 A.M.
- But the variability is also higher from 9 A.M.

[23]:

```python
import plotly.express as px

# Group by date, weekday name, and hour, then take the mean
plot_df2 = ts_df.groupby(["date", "weekday_name",␣
 ↪"hour"])["energy_consumption"].mean().reset_index().dropna()

# Create pivot table: weekday as rows, hour as columns
pivot_table = plot_df2.pivot_table(index="weekday_name", columns="hour",␣
 ↪values="energy_consumption", aggfunc='mean')

# Optional: order weekdays correctly
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday']
pivot_table = pivot_table.reindex(weekday_order)

# Plot heatmap
fig = px.imshow(
    pivot_table,
    labels=dict(x="Hour of Day", y="Day of Week", color="Energy Consumption"),
    aspect="auto",
    color_continuous_scale="bluered",
    title="Heatmap: Hourly Energy Consumption by Day of Week"
)

fig.update_layout(xaxis_title="Hour", yaxis_title="Weekday")
fig.show()
```

```
/tmp/ipykernel_7717/3335086085.py:4: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.

/tmp/ipykernel_7717/3335086085.py:7: FutureWarning:

The default value of observed=False is deprecated and will change to
observed=True in a future version of pandas. Specify observed=False to silence
this warning and retain the current behavior
```

1.4 Autocorrelation plot

- Correlation means the strength of the relationship between two variables.
- Autocorrelation is the correlation between a time series and itself at different lags.
- Autocorrelation measures how a time series value at time t is **related to** its own **past values** (e.g., $t-1, t-2, \ldots$).
- It tells you whether past values can help **predict** future ones and **how** they're related.

Positive Autocorrelation **Definition:** Positive autocorrelation means that if a value is **high**, the next value (at some lag k) is also **likely to be high**, and if it's low, the next value is likely to be low too.

Interpretation:

- The series has a **momentum**-like behavior.
- Patterns **persist** — high follows high, low follows low.

Example: Imagine daily temperature. If today is warm, tomorrow is also likely to be warm.

Visual:

High → High → High → … Low → Low → Low → …

Negative Autocorrelation **Definition:** Negative autocorrelation means that if a value is **high**, the next value is more likely to be **low**, and vice versa.

Interpretation:

- The series shows **alternating** or **mean-reverting** behavior.
- A high value is followed by a dip and then a rise again.

Example: Think of a bouncing ball: every bounce goes up and then down.

Visual: High → Low → High → Low → …

[22]:
```
plot_df.head()
```

[22]:

	date	weekday_name	hour	energy_consumption
144	2012-01-01	Sunday	0	0.3770
145	2012-01-01	Sunday	1	0.0955
146	2012-01-01	Sunday	2	0.0380
147	2012-01-01	Sunday	3	0.0285
148	2012-01-01	Sunday	4	0.0360

1.4.1 Partial Autocorrelation

Partial Autocorrelation (PACF)

Definition: **Partial autocorrelation** measures the **direct effect** of a time series' past value at lag k on its current value, **after removing the effects of all shorter lags** (1 through $k-1$).

In simpler terms:

> It tells you how much **extra predictive power** lag k adds **after accounting for** lags 1 to $k-1$.

Why is this useful? In time series (especially AR models), just looking at autocorrelation (ACF) can be misleading — you might see high correlation at lag 3, but it might just be because lag 3 is indirectly related via lag 1 and 2.

Partial autocorrelation tells you:

- Does lag k have a **direct influence** on the current value?
- Or is its effect just due to its correlation with earlier lags?

Example: Autocorrelation vs Partial Autocorrelation Let's say we have a time series X_t, and:

- Lag 1 affects X_t directly.
- Lag 2 affects X_t **only because** it's correlated with Lag 1.

Then:

- ACF might show **high** correlation at both lag 1 and 2.
- **PACF** will show **high** only at lag 1, and **near-zero** at lag 2.

In Practice: How it's used In **AR (AutoRegressive)** models:

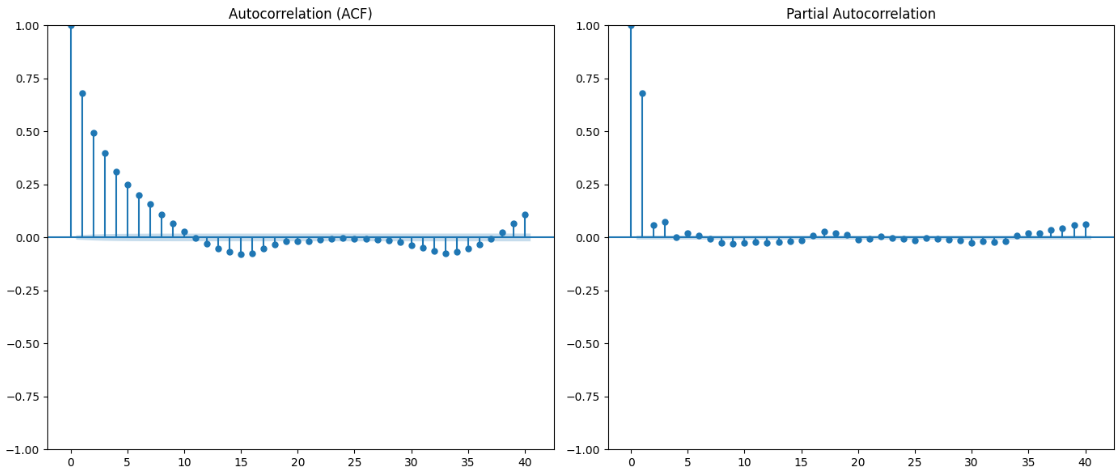
- **PACF plot** helps you choose the order p (how many lags to use).
- You look for the **last significant lag** in the PACF plot → that's often your AR model order.

Quick Summary

Term	What it Measures	Includes Indirect Effects?	Used For
ACF (Autocorrelation Function)	Correlation of current value with past lags	Yes	Identifying MA (moving average) order
PACF (Partial Autocorrelation Function)	Direct correlation of lag k, removing lags 1 to $k-1$	No	Identifying AR (autoregressive) order

[24]:
```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
series = ts_df['energy_consumption'].dropna()


# Set number of lags (how far back you want to check correlation)
num_lags = 40

plt.figure(figsize=(14, 6))

# ACF plot
plt.subplot(1, 2, 1)
plot_acf(series, lags=num_lags, ax=plt.gca())
plt.title('Autocorrelation (ACF)')

# PACF plot
```

```
plt.subplot(1, 2, 2)
plot_pacf(series, lags=num_lags, ax=plt.gca(), method='ywm')  # 'ywm' is a␣
↪stable method

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



1.5 Interpretation

1.5.1 ACF (Left Plot)

- **Lag 1 to ~10**: Gradually decreasing autocorrelation — this is called a **slow decay**.
- This suggests that the time series is **strongly influenced by its recent past**, and those effects **fade over time**.
- This kind of pattern is typical in an **AR (AutoRegressive)** process — especially **AR(1) or AR(2)**.

1.5.2 PACF (Right Plot)

- **Lag 1**: Very strong spike — indicates a **strong direct effect** from lag 1.
- **Lag 2**: Also slightly significant.
- **Lag 3 and beyond**: Mostly within confidence bounds (i.e., not significant).

1.5.3 This tells us:

- **Most of the predictive power comes from the first 1 or 2 lags.**
- After that, past values don't directly contribute much.

1.5.4 Conclusion:

Your time series likely follows an **AR(1)** or **AR(2)** model. Here's why:

Indicator	Observation	Suggestion
ACF	Slowly decays	Autoregressive process
PACF	Big spike at lag 1, possibly lag 2	Likely AR(1) or AR(2)