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April 29, 2022

1 Correlation and Autocorrelation in Time Series - Lab

1.1 Introduction

In this lab, you'll practice your knowledge of correlation, autocorrelation, and partial autocorrelation by working on three different datasets.

1.2 Objectives

In this lab you will:

- Plot and discuss the autocorrelation function (ACF) for a time series
- Plot and discuss the partial autocorrelation function (PACF) for a time series

1.3 The Exchange Rate Data

We'll be looking at the exchange rates dataset again.

- First, run the following cell to import all the libraries and the functions required for this lab
- Then import the data in `'exch_rates.csv'`
- Change the data type of the `'Frequency'` column
- Set the `'Frequency'` column as the index of the DataFrame

[2]:
```
# Import all packages and functions
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
import seaborn as sns
%matplotlib inline
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from matplotlib.pylab import rcParams
```

[7]:
```
# Import data
xr = pd.read_csv('exch_rates.csv')

# Change the data type of the 'Frequency' column
xr["Frequency"] = pd.to_datetime(xr["Frequency"])

# Set the 'Frequency' column as the index
xr.set_index("Frequency", inplace = True)
```

```
xr.head()
```

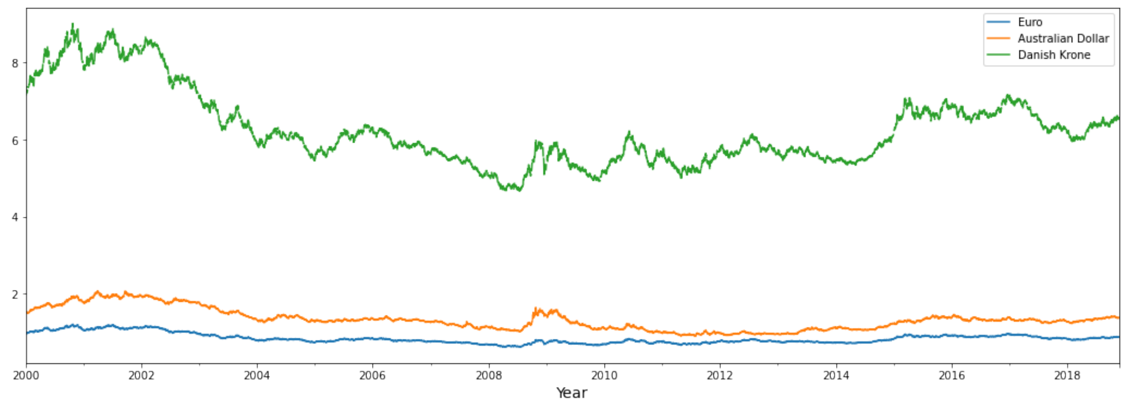
[7]:

	Euro	Australian Dollar	Danish Krone
Frequency			
2000-01-01	NaN	NaN	NaN
2000-01-02	NaN	NaN	NaN
2000-01-03	0.991080	1.520912	7.374034
2000-01-04	0.970403	1.521300	7.222610
2000-01-05	0.964506	1.521316	7.180170

Plot all three exchange rates in one graph:

[14]:

```
# Plot here

xr.plot(figsize = (18, 6));
plt.xlabel("Year", fontsize=14);
```



You can see that the EUR/USD and AUD/USD exchange rates are somewhere between 0.5 and 2, whereas the Danish Krone is somewhere between 4.5 and 9. Now let's look at the correlations between these time series.

[15]:

```
# Correlation
xr.corr()
```

[15]:

	Euro	Australian Dollar	Danish Krone
Euro	1.000000	0.883181	0.999952
Australian Dollar	0.883181	1.000000	0.882513
Danish Krone	0.999952	0.882513	1.000000

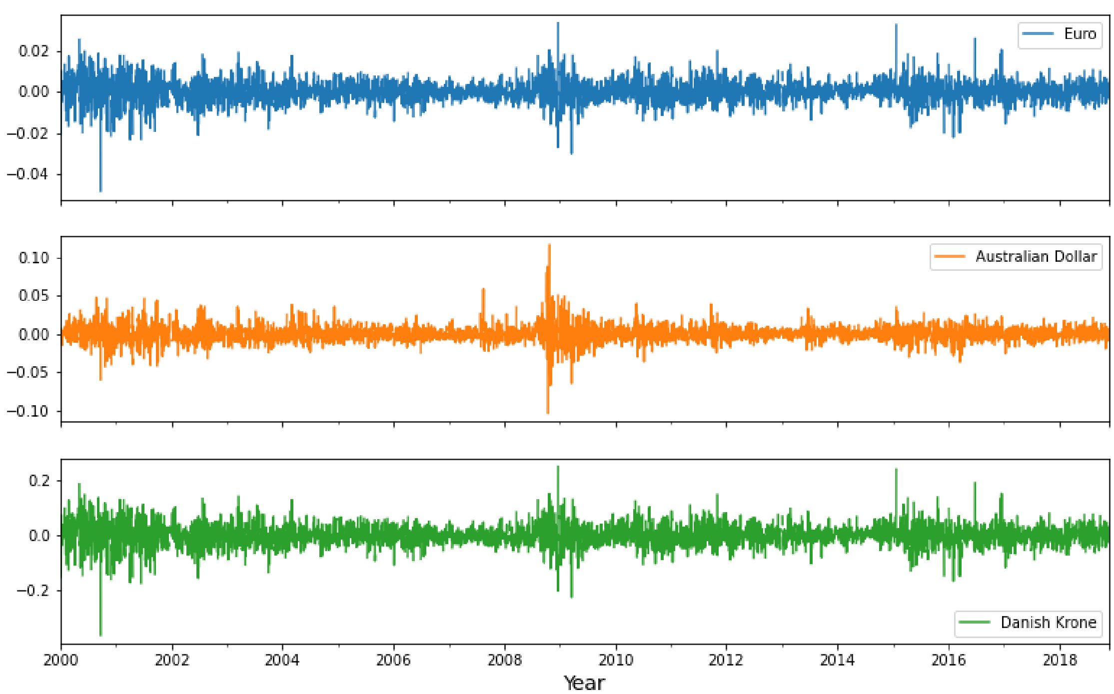
1.3.1 What is your conclusion here? You might want to use outside resources to understand what's going on.

[19]:
```
### G

# The exchange rates for Euro and the Australian dollar are highly correlated,
# but there are differences. The Euro and the Danish Krone, however, is
↪perfectly correlated.
# If you do further research you'll notice that the Danish Krone is pegged to
↪the Euro,
# which means that they are basically designed to perfectly correlate together!
# The fact that the value is just very, very close to 1 is due to rounding
↪errors.
# Usually when the correlation is so close to 1 (or -1), it's too good to be
↪true.
# So make sure you always dig deeper to correctly understand and interpret
↪these numbers.
```

Next, look at the plots of the differenced (1-lag) series. Use subplots to plot them rather than creating just one plot.

[20]:
```
# 1-lag differenced series
xr_diff = xr.diff(periods = 1)
```

[24]:
```
# Plot
xr_diff.plot(figsize = (13, 8), subplots = True, legend=True);
plt.xlabel("Year", fontsize=14);
```



Calculate the correlation of this differenced time series.

[25]:
```
# Correlation
xr_diff.corr()
```

[25]:

	Euro	Australian Dollar	Danish Krone
Euro	1.000000	0.545369	0.999667
Australian Dollar	0.545369	1.000000	0.545133
Danish Krone	0.999667	0.545133	1.000000

1.3.2 Explain what's going on

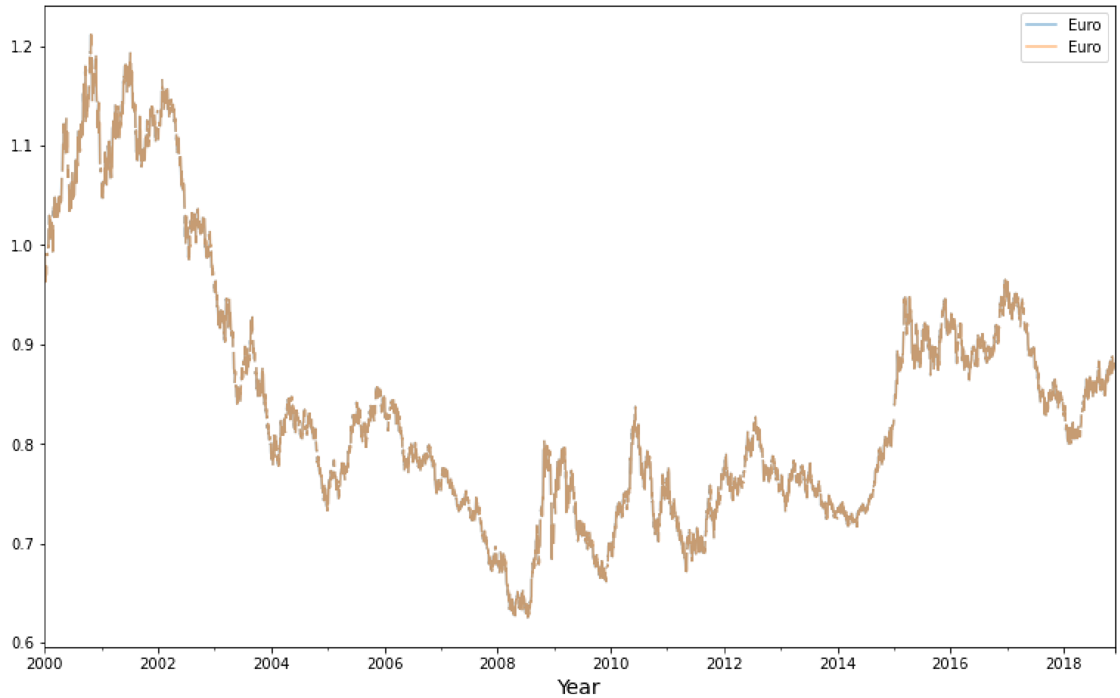
[26]:
```
## G

# Differencing the series here led to a decrease
# in correlation between the EUR/USD and AUD/USD series.
# If you think a little further, this makes sense: in the previous lesson,
# the high correlation was a result of seasonality.
# Differencing led to an increase in correlation between series,
# here the series are moving in (more or less) the same direction
# on a day-to-day basis and seasonality is not present, hence this result.
```

Next, let's look at the "lag-1 autocorrelation" for the EUR/USD exchange rate.

- Create a "lag-1 autocorrelation" series
- Combine both the original and the shifted ("lag-1 autocorrelation") series into a DataFrame
- Plot these time series, and look at the correlation coefficient

[27]:
```
# Isolate the EUR/USD exchange rate
eur = xr[['Euro']]

# "Shift" the time series by one period
eur_shift_1 = eur.shift(periods = 1)
```

[33]:
```
# Combine the original and shifted time series
lag_1 = pd.concat([eur, eur_shift_1], axis = 1)

# Plot
lag_1.plot(figsize = (13, 8), subplots = False, legend=True, alpha = 0.5);
plt.xlabel("Year", fontsize=14);
```

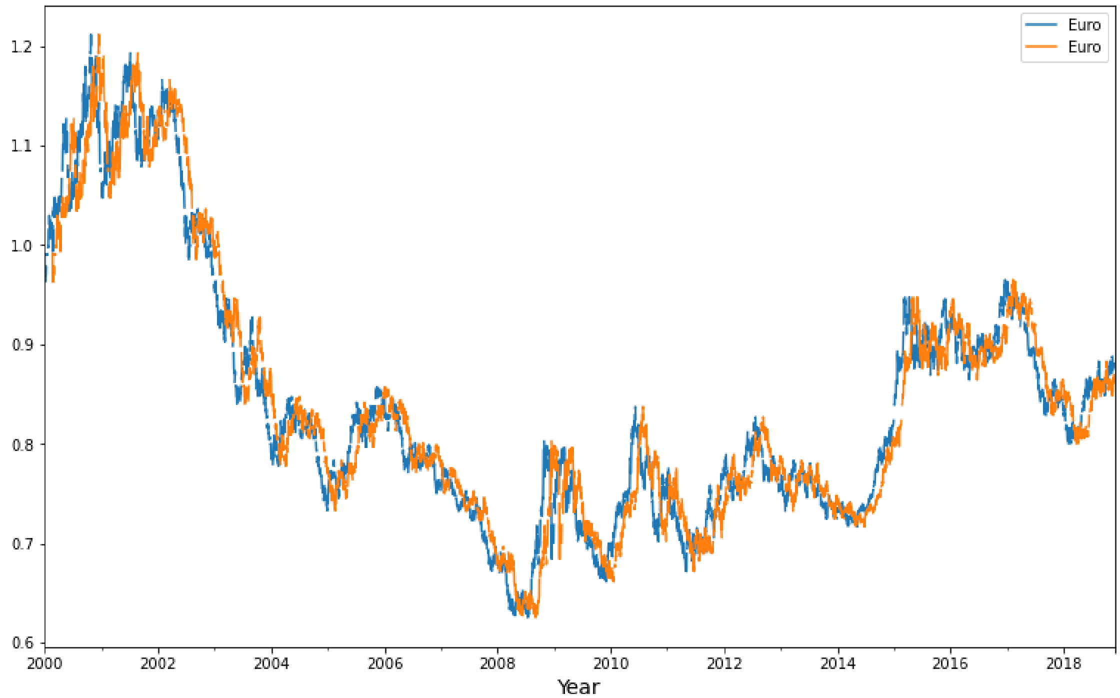


[34]:
```python
# Correlation
lag_1.corr()
```

[34]:
```
          Euro      Euro
Euro  1.000000  0.999146
Euro  0.999146  1.000000
```

Repeat this for a “lag-50 autocorrelation”.

[37]:
```python
# "Shift" the time series by 50 periods
eur_shift_50 = eur.shift(periods = 50)

# Combine the original and shifted time series
lag_50 = pd.concat([eur, eur_shift_50], axis = 1)

# Plot
lag_50.plot(figsize = (13, 8), subplots = False, legend=True, alpha = 1);
plt.xlabel("Year", fontsize=14);
```



[38]:
```
# Correlation
lag_50.corr()
```

[38]:

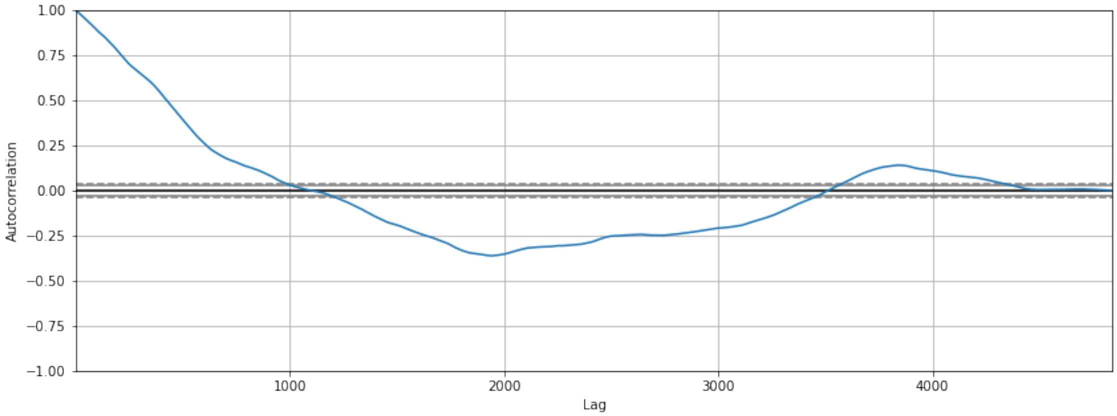
	Euro	Euro
Euro	1.000000	0.968321
Euro	0.968321	1.000000

1.3.3 What's your conclusion here?

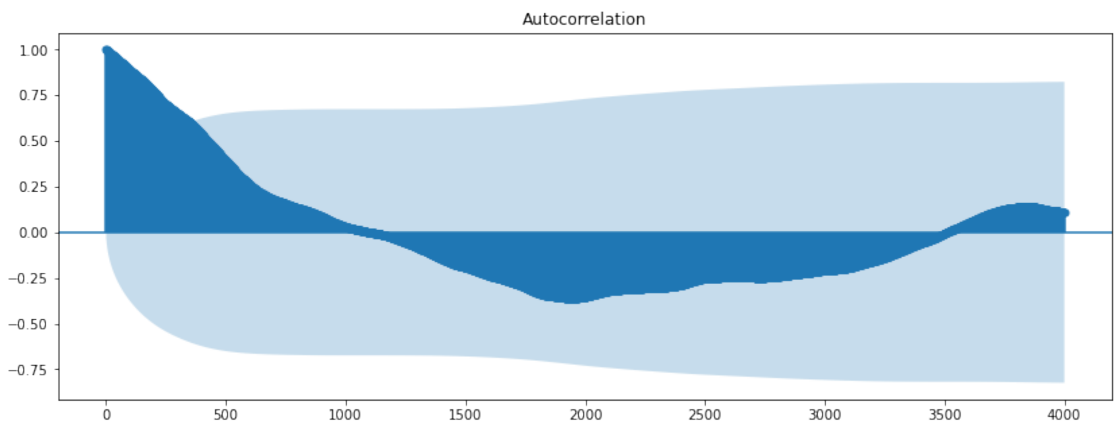
[39]:
```
### G

# Autocorrelation is very high in these time series, even up to a lag as big as␣
↪50!
# This is no big surprise though: remember that these are random walk series,
# which are highly recursive, as each value depends heavily on the previous one!
```

Knowing this, let's plot the ACF now.

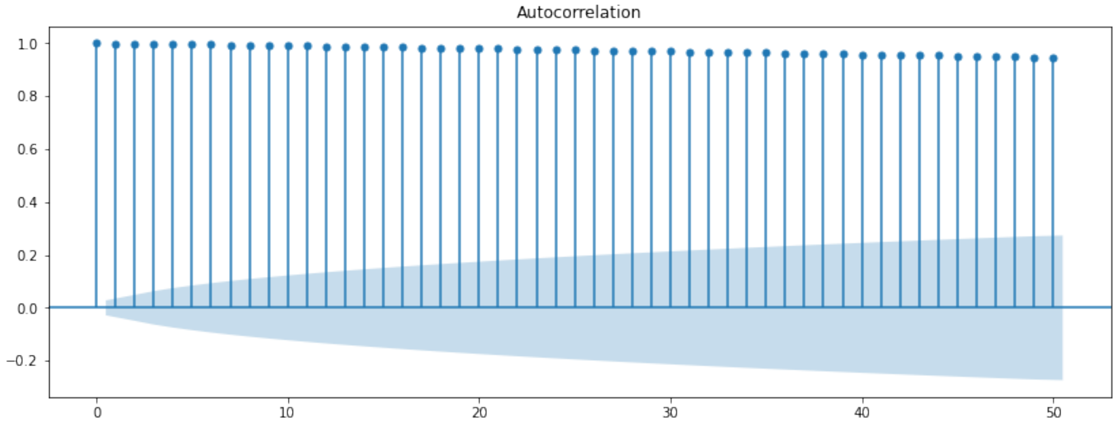
[62]:
```
# Plot ACF
# rcParams['figure.figsize'] = 14, 5
fig, ax = plt.subplots(figsize = (14, 5))
pd.plotting.autocorrelation_plot(eur.dropna());
```



[68]:
```
# rcParams['figure.figsize'] = 14, 5
fig, ax = plt.subplots(figsize = (14, 5))
plot_acf(eur.dropna(), lags = 4000, ax = ax);
```



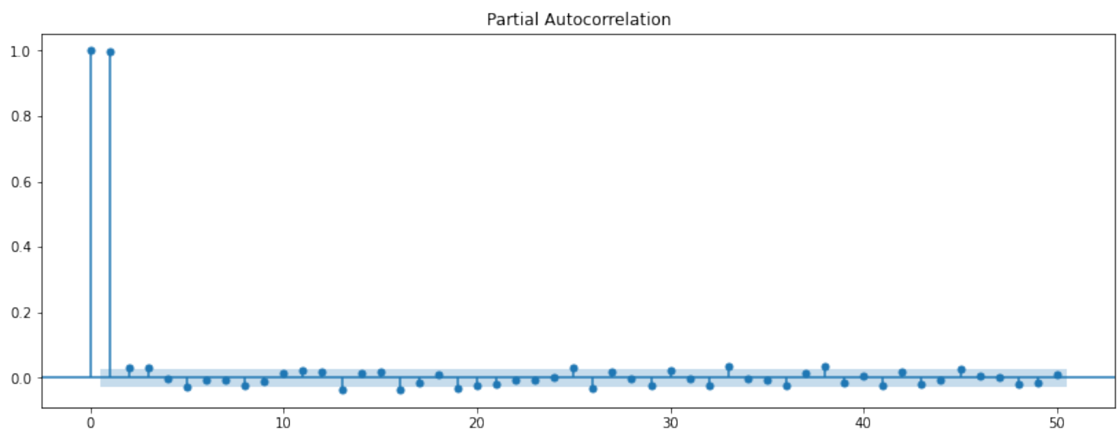
[69]:
```
# rcParams['figure.figsize'] = 14, 5
fig, ax = plt.subplots(figsize = (14, 5))
plot_acf(eur.dropna(), lags = 50, ax = ax);
```



The series is heavily autocorrelated at first, and then there is a decay. This is a typical result for a series that is a random walk, generally you'll see heavy autocorrelations first, slowly tailing off until there is no autocorrelation anymore.

Next, let's look at the partial autocorrelation function plot.

[70]:
```
# Plot PACF
fig, ax = plt.subplots(figsize = (14, 5))
plot_pacf(eur.dropna(), lags = 50, ax = ax);
```



This is interesting! Remember that *Partial Autocorrelation Function* gives the partial correlation of a time series with its own lagged values, controlling for the values of the time series at all shorter lags. When controlling for 1 period, the PACF is only very high for one-period lags, and basically 0 for shorter lags. This is again a typical result for random walk series!

1.4 The Airpassenger Data

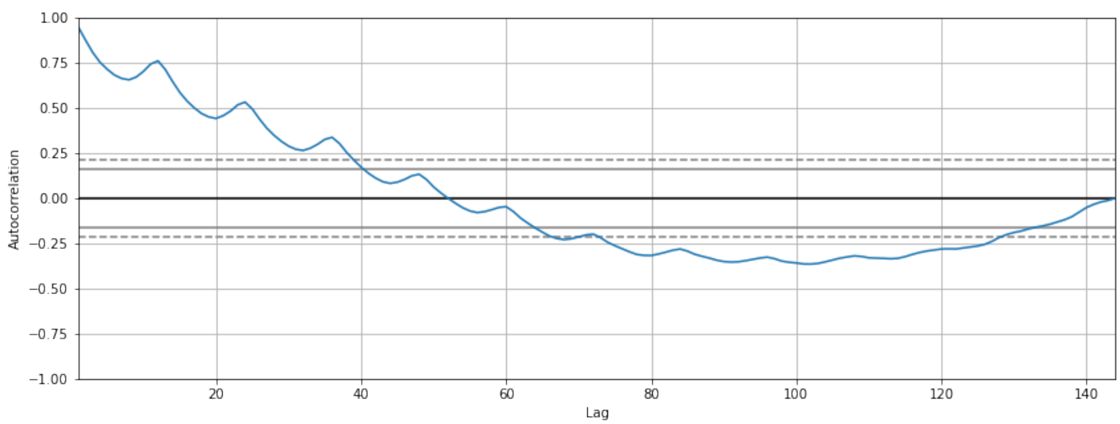
Let's work with the air passenger dataset you have seen before. Plot the ACF and PACF for both the differenced and regular series.

> Note: When plotting the PACF, make sure you specify `method='ywm'` in order to avoid any warnings.

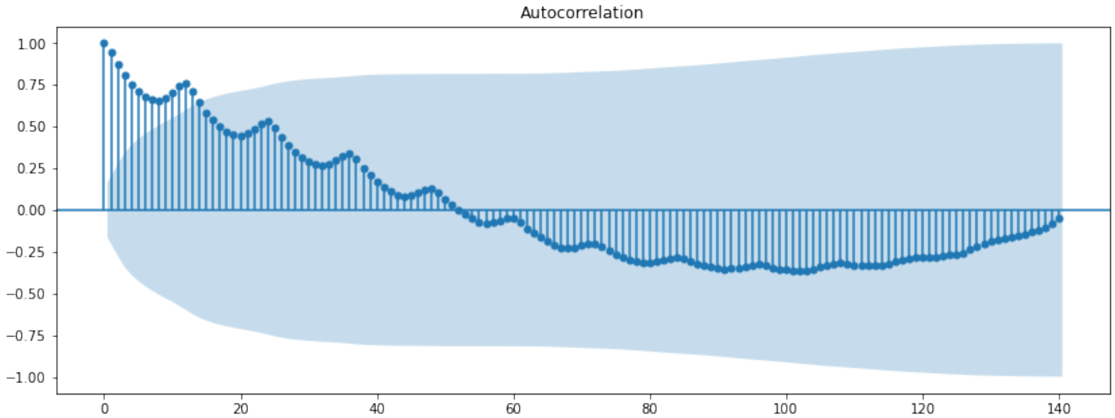
[71]:
```
# Import and process the air passenger data
air = pd.read_csv('passengers.csv')
air['Month'] = pd.to_datetime(air['Month'])
air.set_index('Month', inplace=True)
air.head()
```

[71]:
```
            #Passengers
Month
1949-01-01          112
1949-02-01          118
1949-03-01          132
1949-04-01          129
1949-05-01          121
```

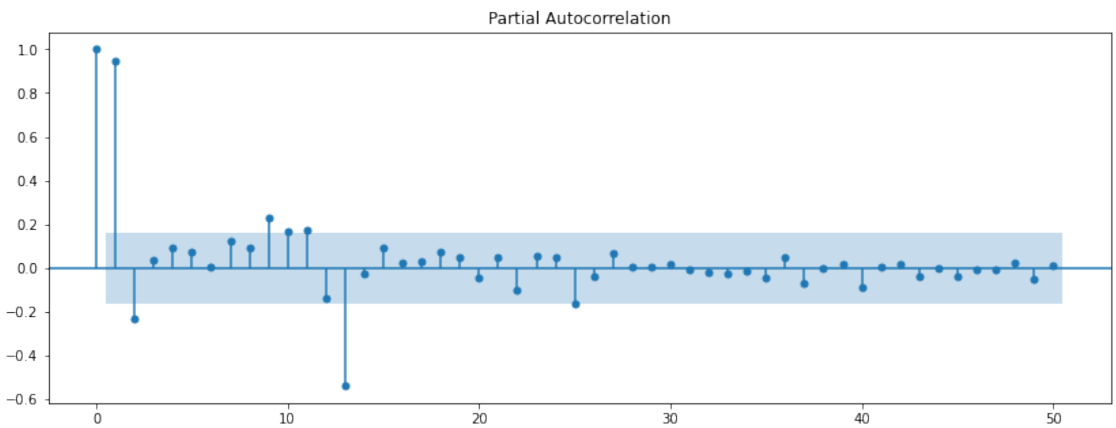
[82]:
```
#  Plot ACF
# rcParams['figure.figsize'] = 14, 5
fig, ax = plt.subplots(figsize = (14, 5))
pd.plotting.autocorrelation_plot(air);
```



[74]:
```
# Plot ACF (regular)
fig, ax = plt.subplots(figsize = (14, 5))
plot_acf(air, lags = 140, ax = ax);
```

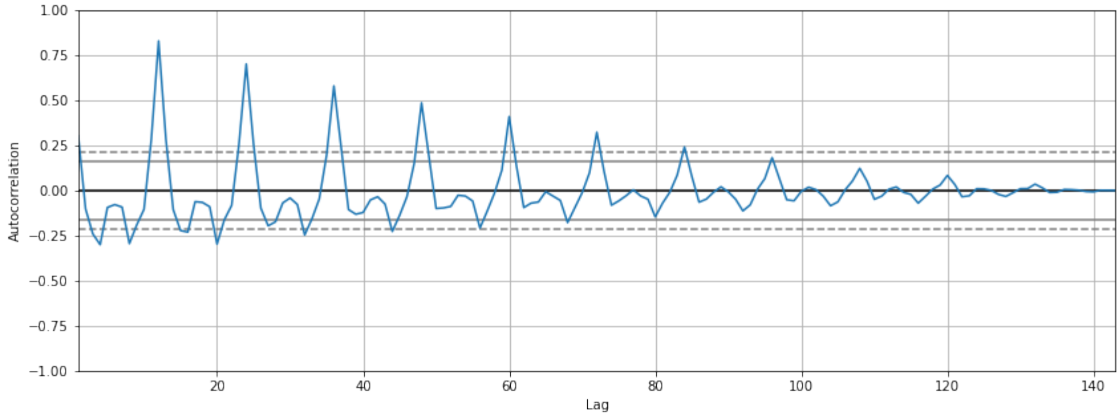


[78]:
```
# Plot PACF (regular)
fig, ax = plt.subplots(figsize = (14, 5))
plot_pacf(air, lags = 50, ax = ax, method='ywm');
```

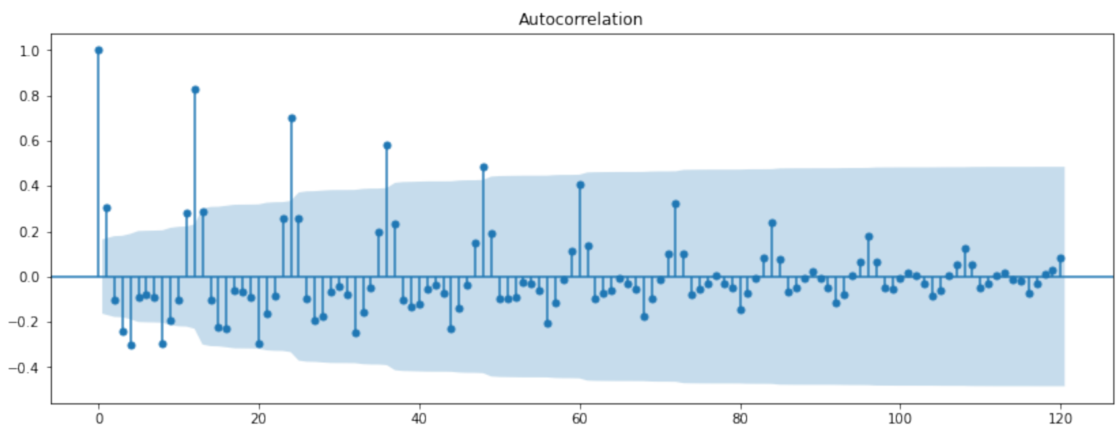


[85]:
```
# Generate a differenced series
air_diff = air.diff(periods = 1)
```

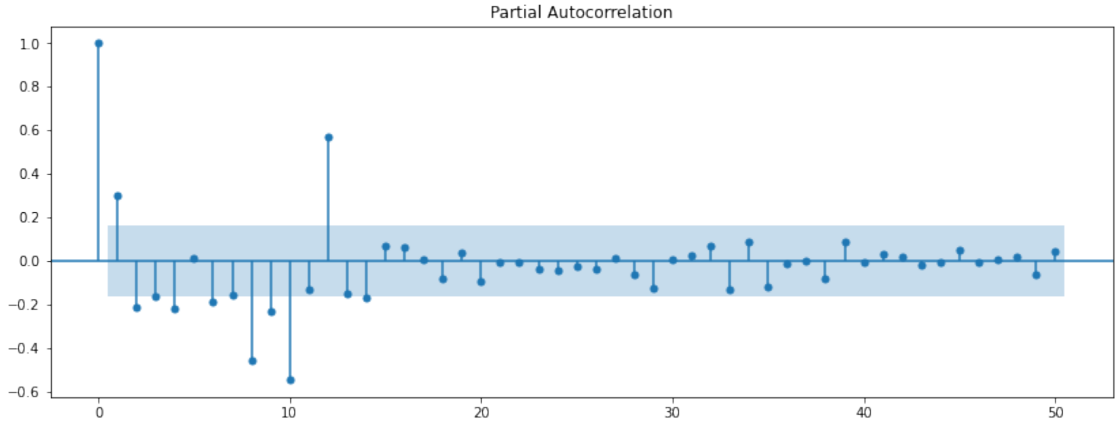
[88]:
```
#  Plot ACF
# rcParams['figure.figsize'] = 14, 5
fig, ax = plt.subplots(figsize = (14, 5))
pd.plotting.autocorrelation_plot(air_diff.dropna());
```



[93]:
```
# Plot ACF (differenced)
fig, ax = plt.subplots(figsize = (14, 5))
plot_acf(air_diff.dropna(), lags = 120, ax = ax);
```



[89]:
```
# Plot PACF (differenced)
# Plot PACF (regular)
fig, ax = plt.subplots(figsize = (14, 5))
plot_pacf(air_diff.dropna(), lags = 50, ax = ax, method='ywm');
```



1.4.1 Your conclusion here

[ ]:
```
### G

# The result reminds us a lot of the google trends data.
# The seasonality is much more clear in the differenced time series.
# The PACF has just one very strong correlation, right at 12 months.
```

1.5 The NYSE data

Are you getting the hang of interpreting ACF and PACF plots? For one final time, plot the ACF and PACF for both the NYSE time series.

> Note: When plotting the PACF, make sure you specify `method='ywm'` in order to avoid any warnings.

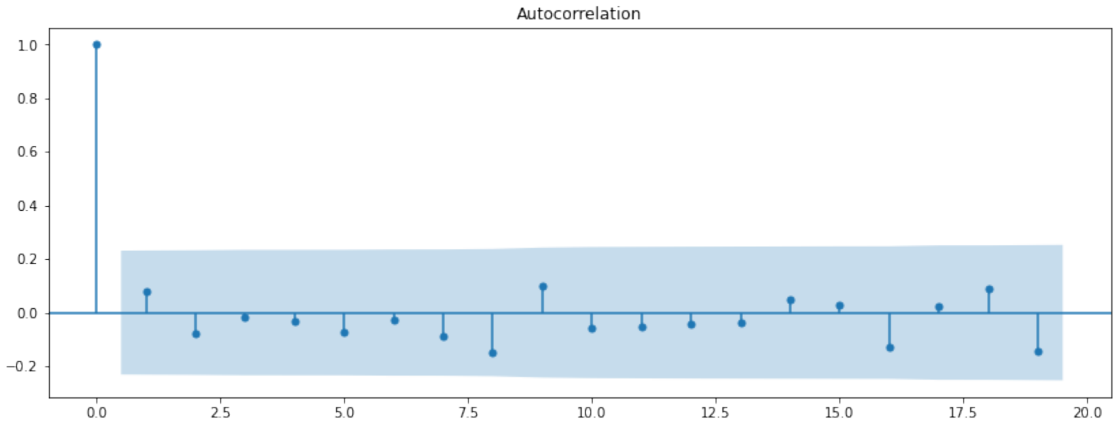
[97]:
```
# Import and process the NYSE data
nyse = pd.read_csv('NYSE_monthly.csv')
nyse['Month'] = pd.to_datetime(nyse['Month'])
nyse.set_index('Month', inplace=True)
nyse.head()
```

[97]:

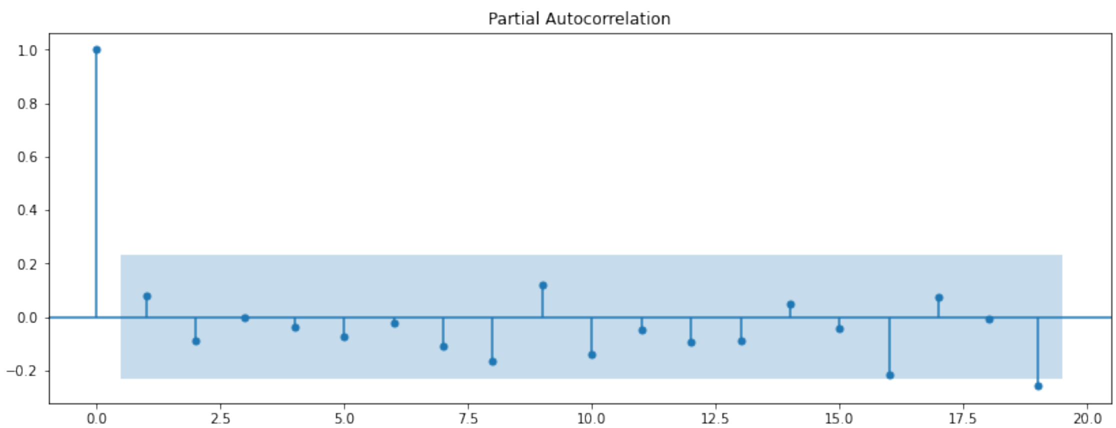
	monthly_return
Month	
1961-01-01	0.082
1961-02-01	0.059
1961-03-01	0.050
1961-04-01	0.008
1961-05-01	0.042

[98]:
```
# Plot ACF
# Plot ACF (differenced)
```

```
fig, ax = plt.subplots(figsize = (14, 5))
plot_acf(nyse, ax = ax);
```



[99]:
```
# Plot PACF
# Plot ACF (differenced)
fig, ax = plt.subplots(figsize = (14, 5))
plot_pacf(nyse, ax = ax);
```



1.6 Your conclusion here

[100]:
```
### G

# Autocorrelations and partial autocorrelations are virtually 0 for any lag.
# This is no surprise! The NYSE series was a white noise series, meaning there
# is no trend or no seasonality! This is, again, a typical result for these␣
↪kind of series.
```

1.7 Summary

Great, you've now been introduced to ACF and PACF. Let's move into more serious modeling with autoregressive and moving average models!