Reference

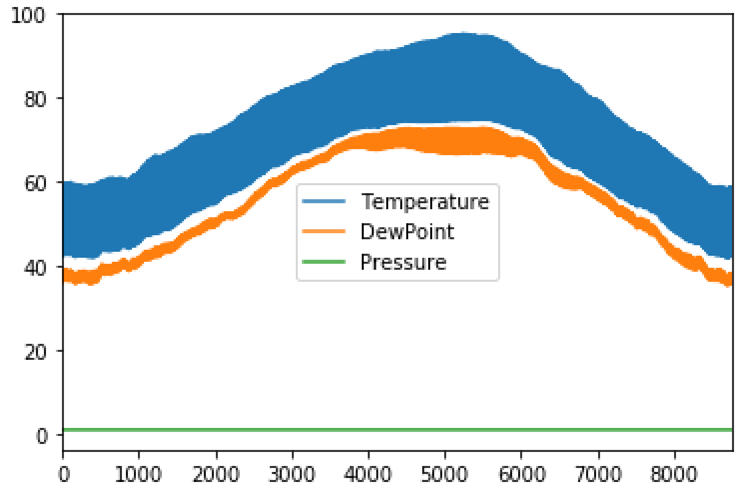
DataCamp course

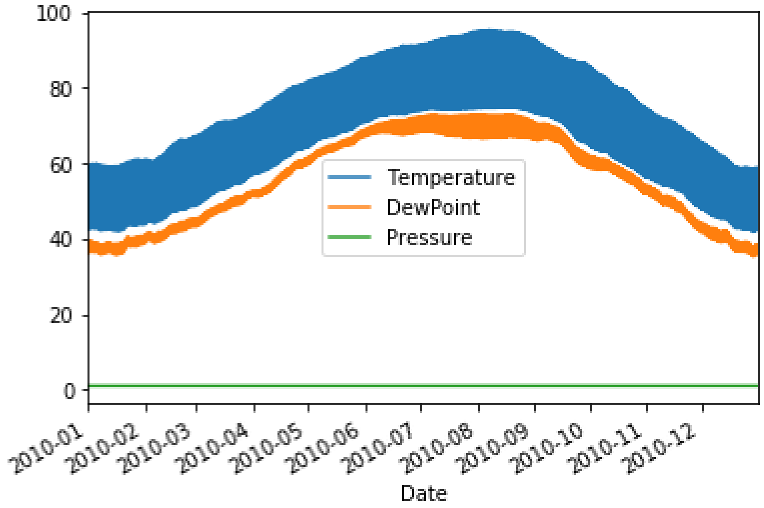
From Introduction to Data Visualization in Python

Plotting time series, datetime indexing

Pandas handles datetimes not only in your data, but also in your plotting.

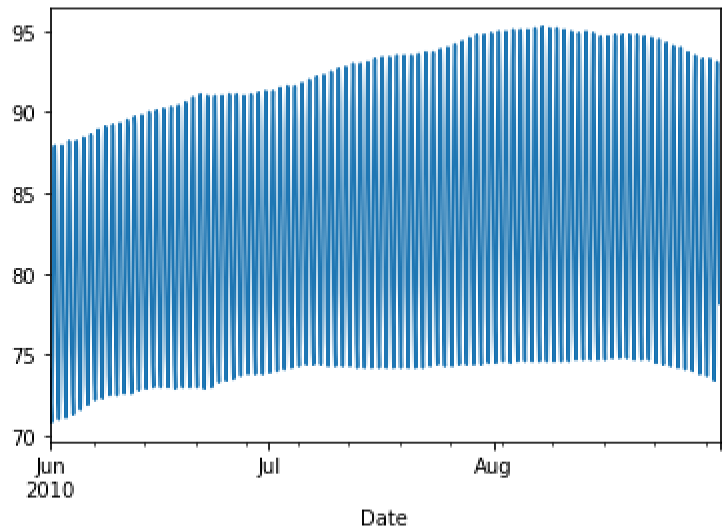
In [2]:
```
import matplotlib.pyplot as plt
import pandas as pd
df = pd.read_csv('weather_data_austin_2010.csv')
# Plot the raw data before setting the datetime index
df.plot()
plt.show()

df.Date = pd.to_datetime(df.Date)
df.set_index('Date', inplace=True)

df.plot()
plt.show()
```

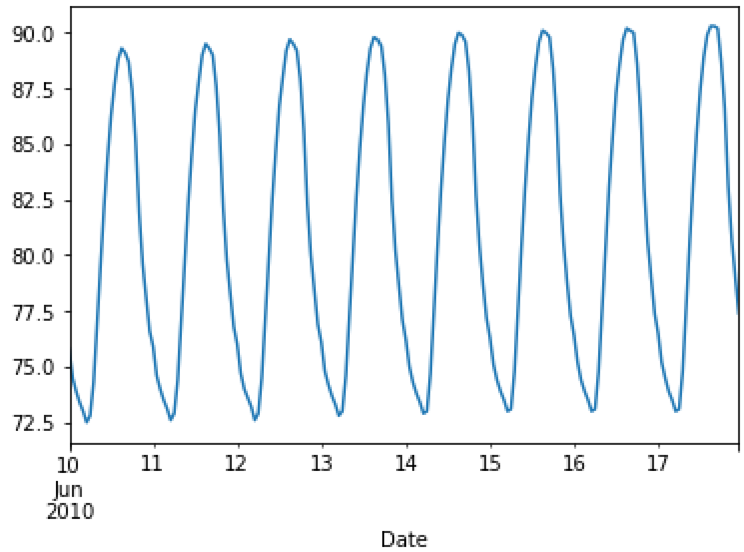




Plotting date ranges, partial indexing

In [3]:
```python
import matplotlib.pyplot as plt
import pandas as pd
df = pd.read_csv('weather_data_austin_2010.csv',index_col='Date', parse_dates=True )

#df.head()
# Plot the summer data
df.Temperature['2010-Jun':'2010-Aug'].plot()
#unsmoothed = df.loc['2010-Aug-01':'2010-Aug-15','Temperature']
plt.show()
plt.clf()

# Plot the one week data
df.Temperature['2010-06-10':'2010-06-17'].plot()
plt.show()
plt.clf()
```

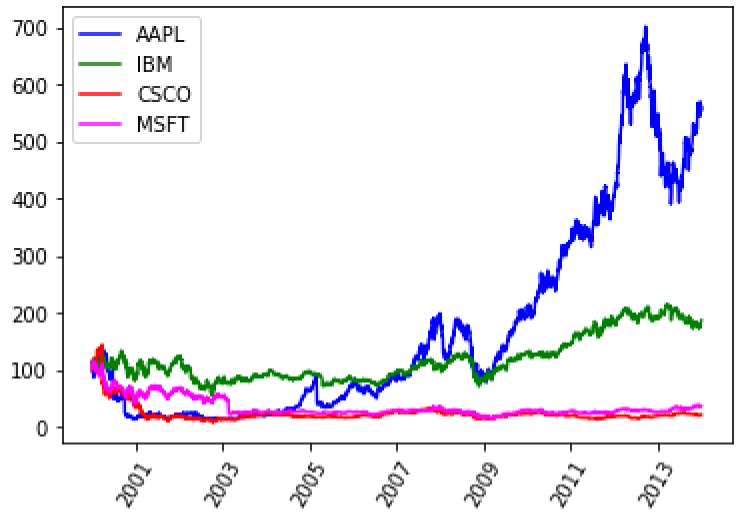




<Figure size 432x288 with 0 Axes>

Plotting multiple stock prices on same graph

In [4]:
```
# A time-series plot with timedate data type as index.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

df_stocks = pd.read_csv("stocks.csv", index_col = 0)
aapl = df_stocks['AAPL']
ibm = df_stocks['IBM']
csco = df_stocks['CSCO']
msft = df_stocks['MSFT']

aapl.index = pd.to_datetime(aapl.index)
ibm.index = pd.to_datetime(ibm.index)
csco.index = pd.to_datetime(csco.index)
msft.index = pd.to_datetime(msft.index)

#****In plt.plot(), only Y-coordiantes are provided. Therefore, X coordiates will use default: the dataFrame inde
#****In the index is not read-in as datetime type, then it will give very congested x-axis.
plt.plot(aapl, color ='blue', label ='AAPL')
plt.plot(ibm, color ='green', label ='IBM')
plt.plot(csco, color ='red', label ='CSCO')
plt.plot(msft, color = 'magenta', label = 'MSFT')
plt.legend(loc='upper left')
plt.xticks(rotation=60)
plt.show()
```



From Visualizing Time Series Data in Python

Introduction

Load your time series data

In [4]:
```
# Import pandas
import pandas as pd

discoveries = pd.read_csv('ch1_discoveries.csv')

# Display the first five lines of the DataFrame
discoveries.head()
discoveries.info()
discoveries.describe()
print(discoveries.dtypes) #Check data types of each column. Alternative way is using info().
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 2 columns):
date    100 non-null object
Y       100 non-null int64
dtypes: int64(1), object(1)
memory usage: 1.6+ KB
date    object
Y        int64
dtype: object
```

Test whether your data is of the correct type

In [5]:
```python
# Convert the date column to a datestamp type
discoveries['date'] = pd.to_datetime(discoveries['date'])
print(discoveries.dtypes)
print(discoveries.info())
discoveries.head()
```

```
date    datetime64[ns]
Y                int64
dtype: object
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 2 columns):
date    100 non-null datetime64[ns]
Y       100 non-null int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 1.6 KB
None
```

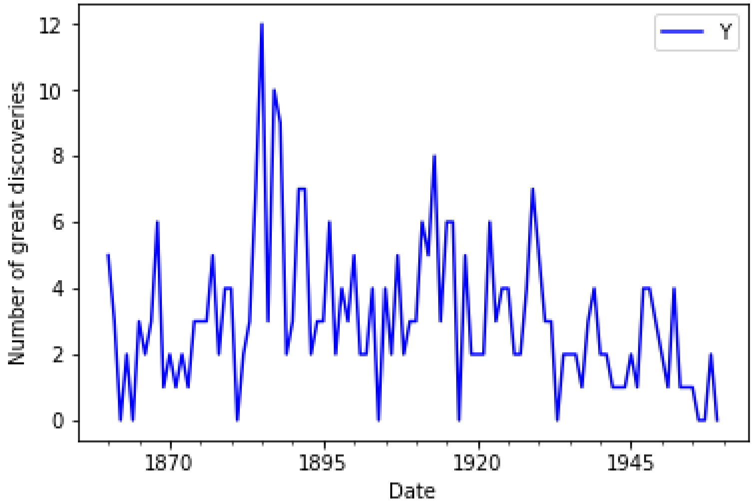
Out[5]:

	date	Y
0	1860-01-01	5
1	1861-01-01	3
2	1862-01-01	0
3	1863-01-01	2
4	1864-01-01	0

Your first plot!

matplotlib is the most widely used plotting library in Python, and would be the most appropriate tool for this job. Fortunately for us, the pandas library has implemented a .plot() method on Series and DataFrame objects that is a wrapper around matplotlib.pyplot.plot(), which makes it easier to produce plots.

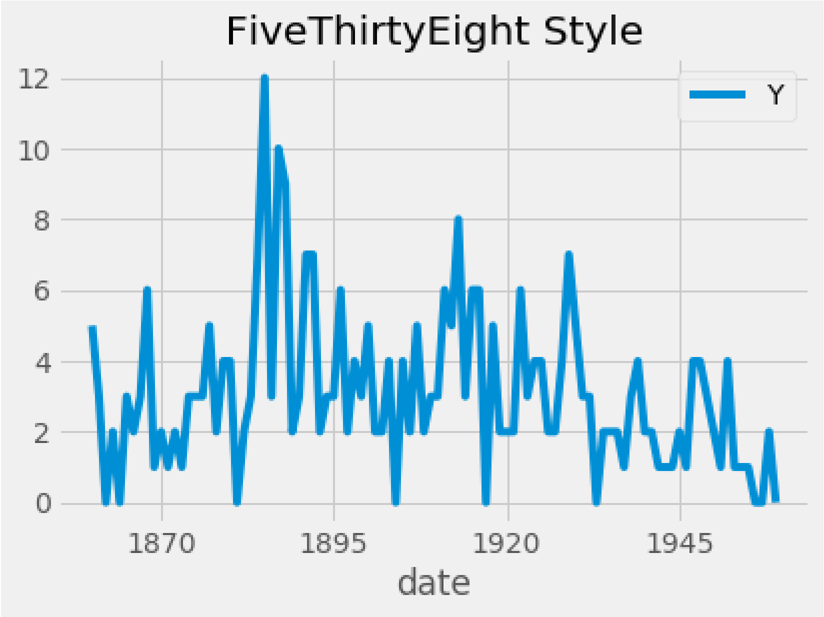
In [6]:
```python
import matplotlib.pyplot as plt
discoveries = discoveries.set_index('date')
ax = discoveries.plot(color='blue')
ax.set_xlabel('Date')
ax.set_ylabel('Number of great discoveries')
plt.show()
```



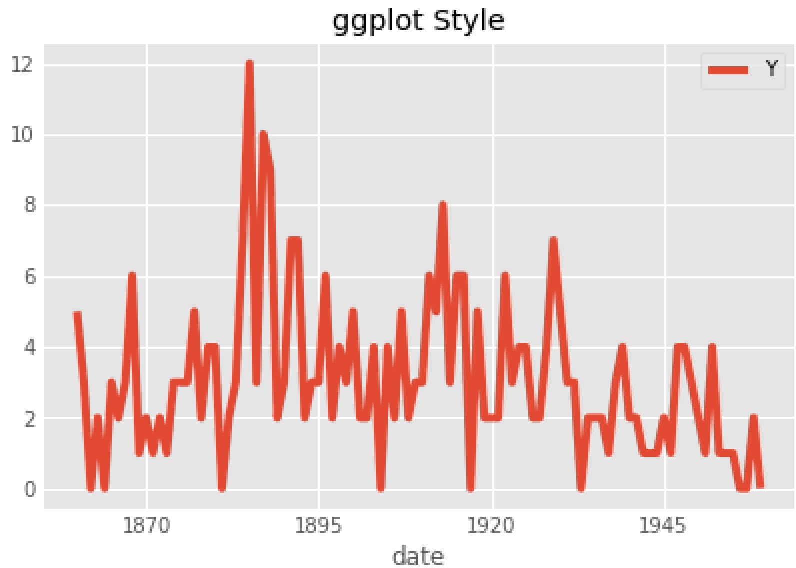
Specify plot styles

See other types in the general python visualization write up.

In [8]:
```
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
ax1 = discoveries.plot()
ax1.set_title('FiveThirtyEight Style')
plt.show()
```



In [9]:
```
import matplotlib.pyplot as plt
plt.style.use('ggplot')
ax2 = discoveries.plot()
ax2.set_title('ggplot Style')
plt.show()
```



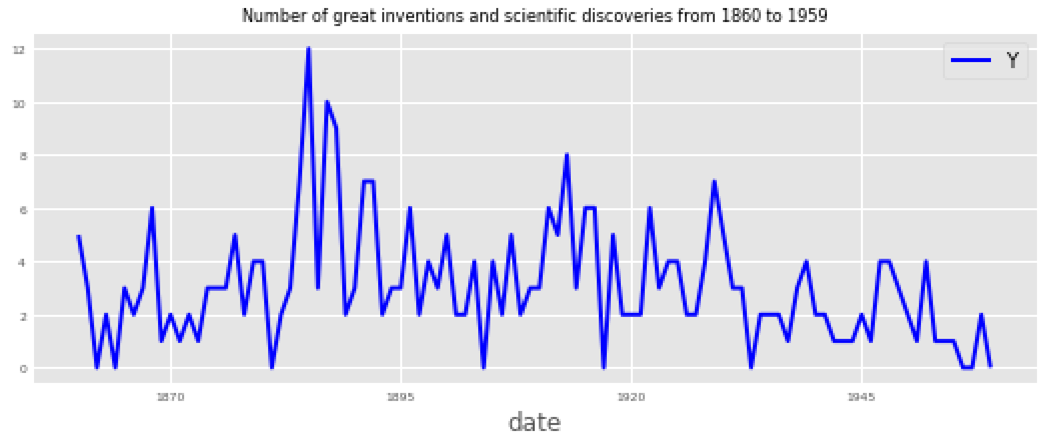
In [10]:
```
print(plt.style.available)
```

```
['bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn-bright', 'seab
orn-colorblind', 'seaborn-dark-palette', 'seaborn-dark', 'seaborn-darkgrid', 'seaborn-deep', 'seaborn-muted',
'seaborn-notebook', 'seaborn-paper', 'seaborn-pastel', 'seaborn-poster', 'seaborn-talk', 'seaborn-ticks', 'seab
orn-white', 'seaborn-whitegrid', 'seaborn', 'Solarize_Light2', '_classic_test']
```

Display and label plots

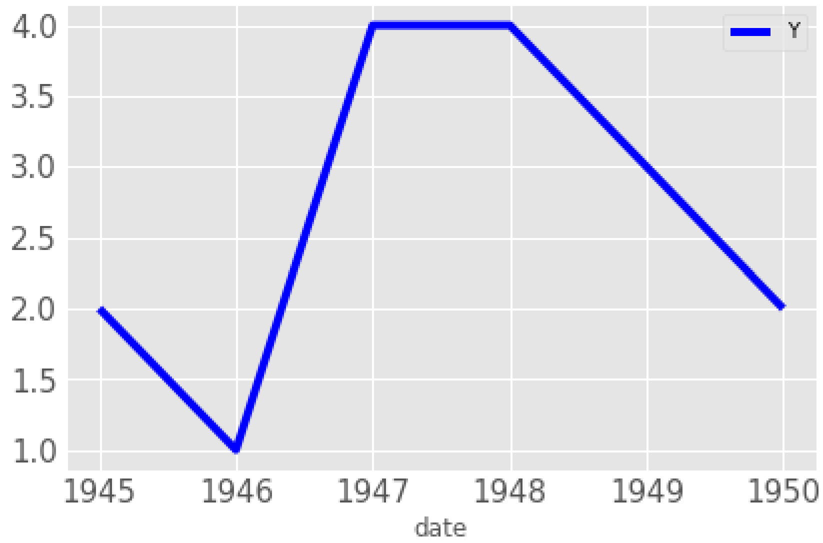
Here using plot() built on data frame object is nice to specify size directly in site.

In [11]:
```
ax = discoveries.plot(color='blue', figsize=(8, 3), linewidth=2, fontsize=6)
ax.set_title('Number of great inventions and scientific discoveries from 1860 to 1959', fontsize=8)
plt.show()
```

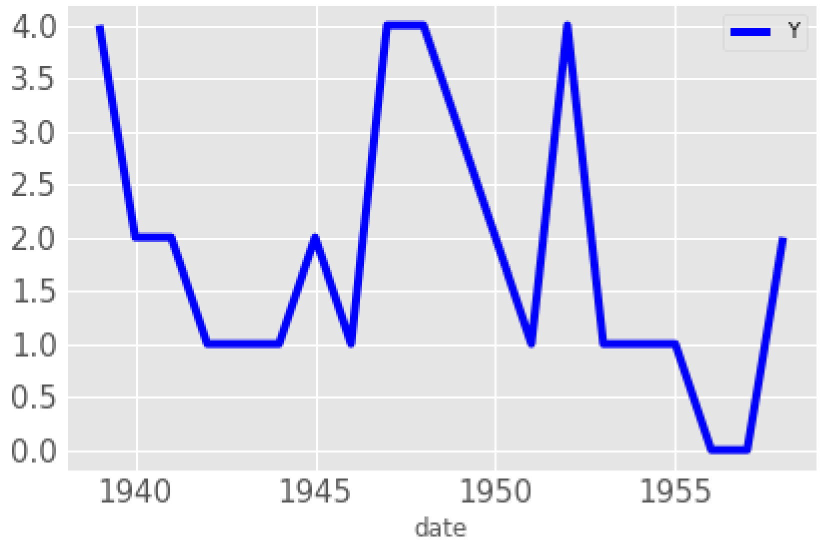


Subset time series data

In [12]:
```
discoveries_subset_1 = discoveries['1945-01':'1950-01']
ax = discoveries_subset_1.plot(color='blue', fontsize=15)
plt.show()
```

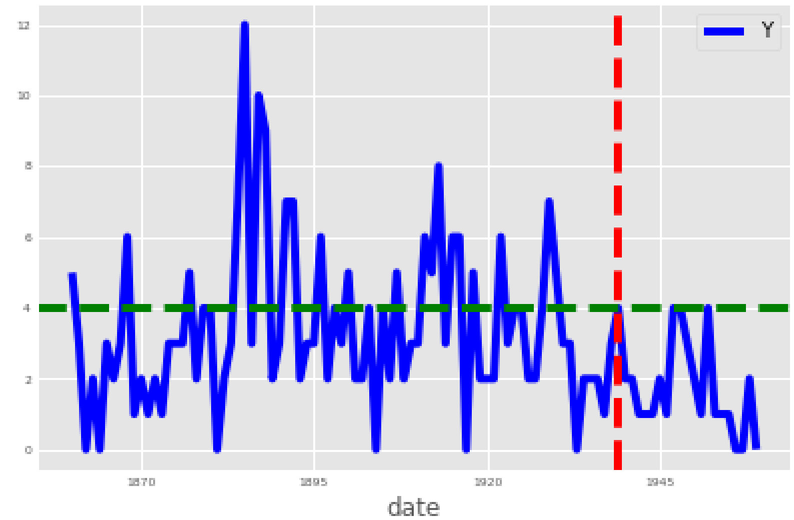


```
In [13]: discoveries_subset_2 = discoveries['1939-01':'1958-01']
         ax = discoveries_subset_2.plot(color='blue', fontsize=15)
         plt.show()
```



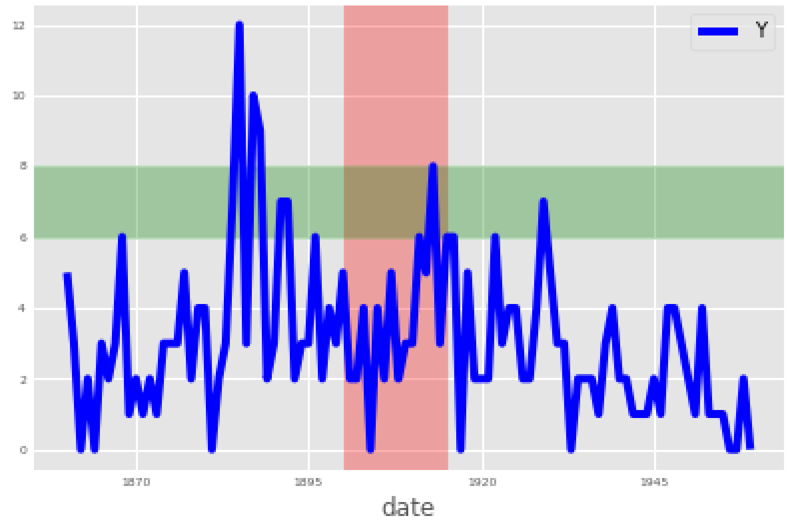
Add vertical and horizontal markers

In [14]:
```
ax = discoveries.plot(color='blue', fontsize=6)
ax.axvline('1939-01-01', color='red', linestyle='--')
ax.axhline(4, color='green', linestyle='--')
plt.show()
```



Add shaded regions to your plot

In [16]:
```python
ax = discoveries.plot(color='blue', fontsize=6)
ax.axvspan('1900-01-01', '1915-01-01', color='red', alpha=0.3)
ax.axhspan(6, 8, color='green', alpha=0.3)
plt.show()
```



Summary Statistics and Diagnostics

In this chapter, you will gain a deeper understanding of your time series data by computing summary statistics and plotting aggregated views of your data.

Find missing values

In [21]:
```python
import pandas as pd
co2_levels = pd.read_csv('ch2_co2_levels.csv')
co2_levels = co2_levels.set_index('datestamp')
print(co2_levels.isnull().sum())
```

```
co2    59
dtype: int64
```

Handle missing values

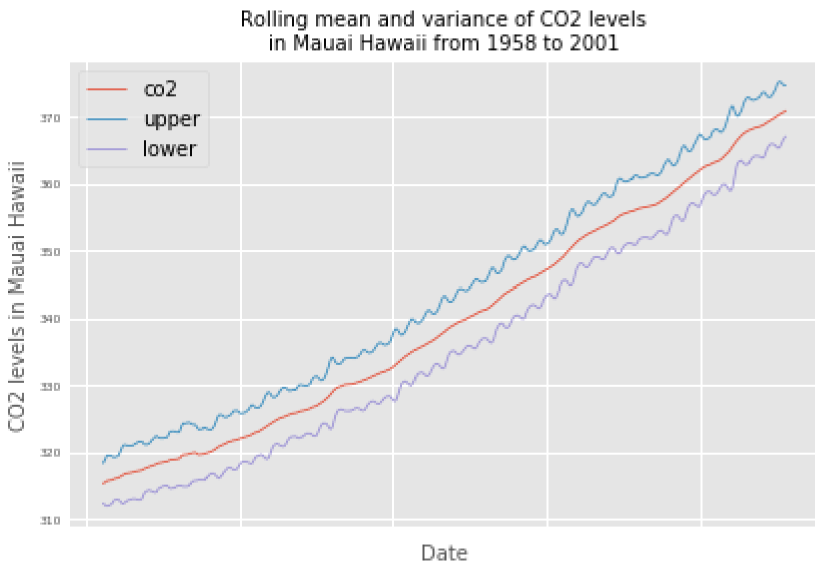
In order to replace missing values in your time series data, you can use the command:
df = df.fillna(method="ffill") where the argument specifies the type of method you want to use. For example, specifying bfill (i.e backfilling) will ensure that missing values are replaced using the next valid observation, while ffill (i.e. forward-filling) ensures that missing values are replaced using the last valid observation.

In [22]:
```
co2_levels = co2_levels.fillna(method='bfill')
print(co2_levels.isnull().sum())
```

```
co2    0
dtype: int64
```

Display rolling averages

In [23]:
```
ma = co2_levels.rolling(window=52).mean()
mstd = co2_levels.rolling(window=52).std()
ma['upper'] = ma['co2'] + (mstd['co2'] * 2)
ma['lower'] = ma['co2'] - (mstd['co2'] * 2)
ax = ma.plot(linewidth=0.8, fontsize=6)
ax.set_xlabel('Date', fontsize=10)
ax.set_ylabel('CO2 levels in Mauai Hawaii', fontsize=10)
ax.set_title('Rolling mean and variance of CO2 levels\nin Mauai Hawaii from 1958 to 2001', fontsize=10)
plt.show()
```



Display aggregated values

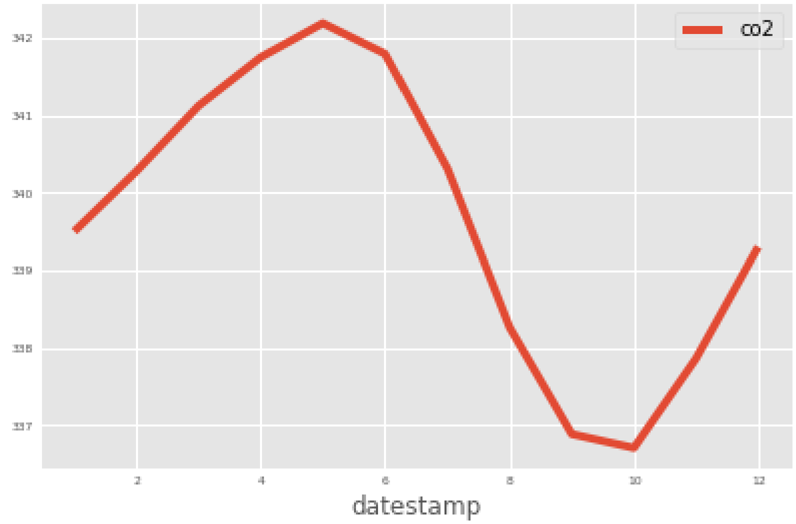
You may sometimes be required to display your data in a more aggregated form. For example, the co2_levels data contains weekly data, but you may need to display its values aggregated by month of year. In datasets such as the co2_levels DataFrame where the index is a datetime type, you can extract the year of each dates in the index:

extract of the year in each dates of the df DataFrame

index_year = df.index.year To extract the month or day of the dates in the indices of the df DataFrame, you would use df.index.month and df.index.day, respectively. You can then use the extracted year of each indices in the co2_levels DataFrame and the groupby function to compute the mean CO2 levels by year:

df_by_year = df.groupby(index_year).mean()

In [33]:
```
co2_levels.index = pd.to_datetime(co2_levels.index)
# This sentence is newly added. Otherwise the code below will not work.

index_month = co2_levels.index.month
mean_co2_levels_by_month = co2_levels.groupby(index_month).mean()
mean_co2_levels_by_month.plot(fontsize=6)
plt.legend(fontsize=10)
plt.show()
```



Compute numerical summaries

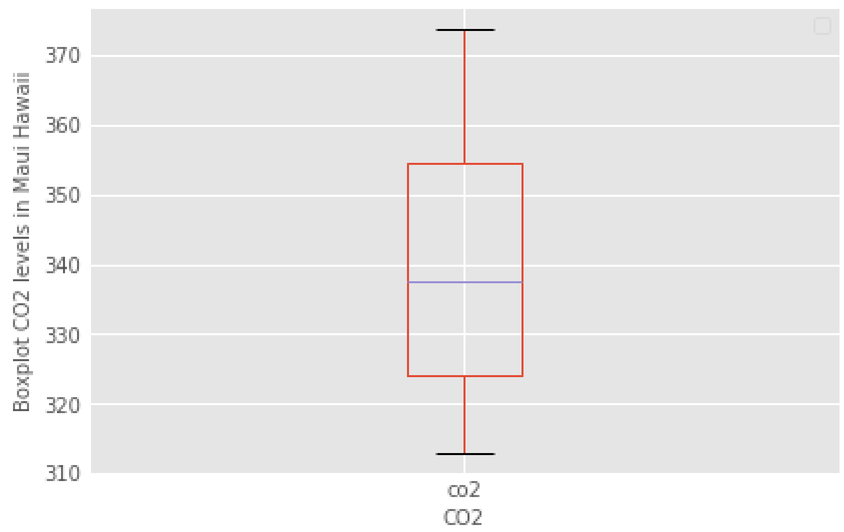
In [35]:
```python
print(co2_levels.describe())
```

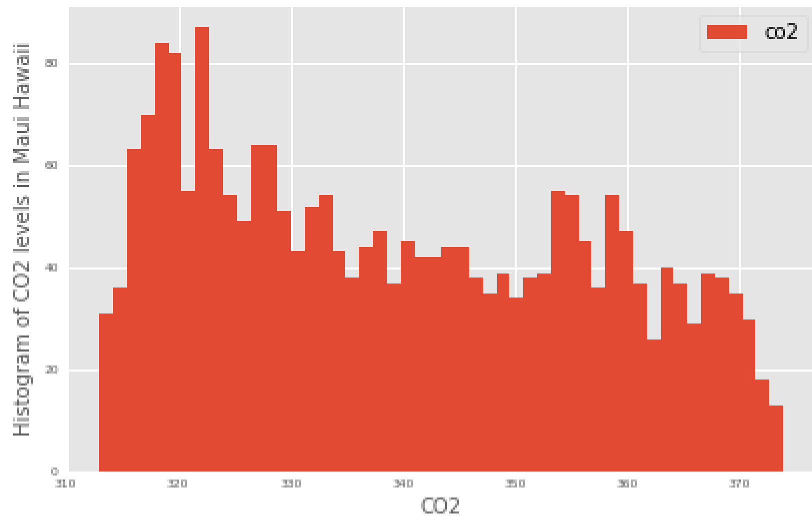
```
                co2
count  2284.000000
mean    339.657750
std      17.100899
min     313.000000
25%     323.975000
50%     337.700000
75%     354.500000
max     373.900000
```

Boxplots and Histograms

In [38]:
```
ax = co2_levels.boxplot()
ax.set_xlabel('CO2', fontsize=10)
ax.set_ylabel('Boxplot CO2 levels in Maui Hawaii', fontsize=10)
plt.legend(fontsize=10)
plt.show()
ax = co2_levels.plot(kind='hist', bins=50, fontsize=6)

ax.set_xlabel('CO2', fontsize=10)
ax.set_ylabel('Histogram of CO2 levels in Maui Hawaii', fontsize=10)
plt.legend(fontsize=10)
plt.show()
```

```
No handles with labels found to put in legend.
```

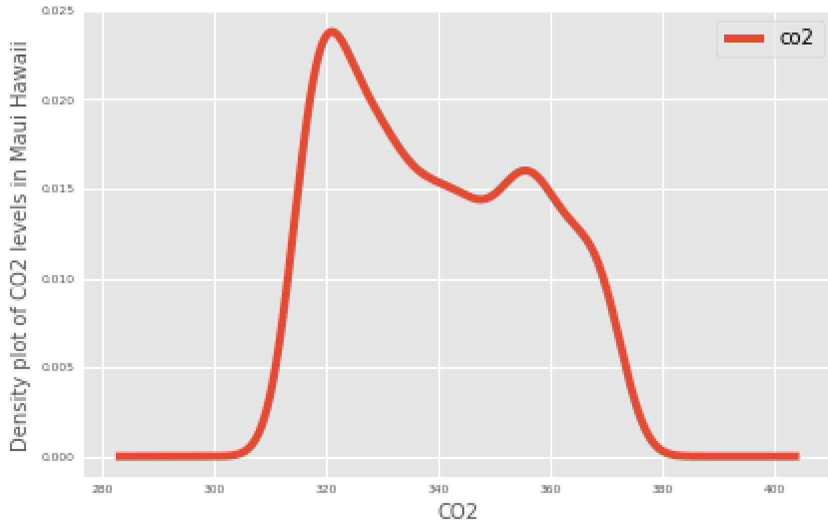




Density plots

In practice, histograms can be a substandard method for assessing the distribution of your data because they can be strongly affected by the number of bins that have been specified. Instead, kernel density plots represent a more effective way to view the distribution of your data. An example of how to generate a density plot of is shown below:

In [39]:
```
ax = co2_levels.plot(kind='density', linewidth=4, fontsize=6)
ax.set_xlabel('CO2', fontsize=10)
ax.set_ylabel('Density plot of CO2 levels in Maui Hawaii', fontsize=10)
plt.show()
```



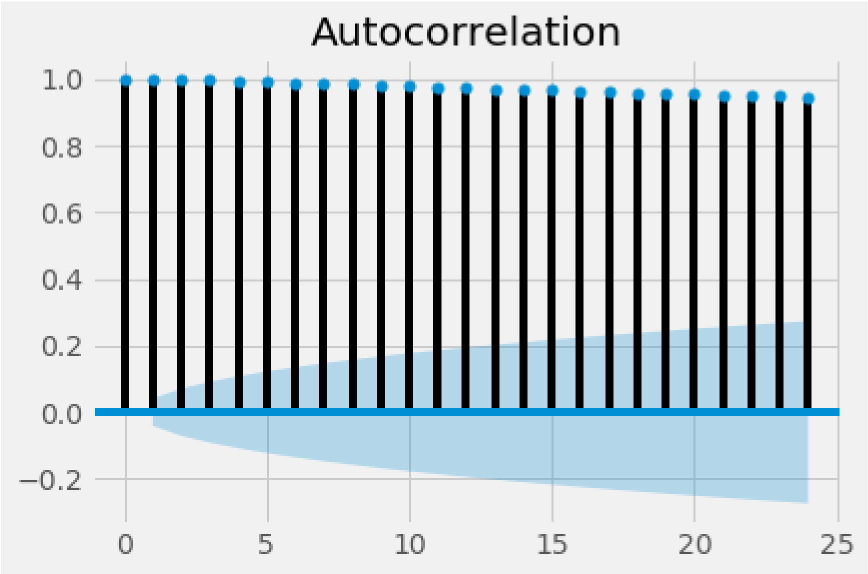
Seasonality, Trend and Noise

You will **go beyond summary statistics by learning about autocorrelation and partial autocorrelation plots**. You will also learn how to automatically detect seasonality, trend and noise in your time series data.

Autocorrelation in time series data

In [40]:
```
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
from statsmodels.graphics import tsaplots
fig = tsaplots.plot_acf(co2_levels['co2'], lags=24)
plt.show()
```

```
C:\Users\ljyan\Anaconda3\lib\site-packages\statsmodels\compat\pandas.py:56: FutureWarning: The pandas.core.date
tools module is deprecated and will be removed in a future version. Please use the pandas.tseries module instea
d.
  from pandas.core import datetools
```



Interpret autocorrelation plots

If autocorrelation values are close to 0, then values between consecutive observations are not correlated with one another. Inversely, autocorrelations values close to 1 or -1 indicate that there exists strong positive or negative correlations between consecutive observations, respectively. In order to help you asses how trustworthy these autocorrelation values are, the plot_acf() function also returns confidence intervals (represented as blue shaded regions). **If an autocorrelation value goes beyond the confidence interval region, you can assume that the observed autocorrelation value is statistically significant**. In other words, this value is not due to the volatility in measurement.

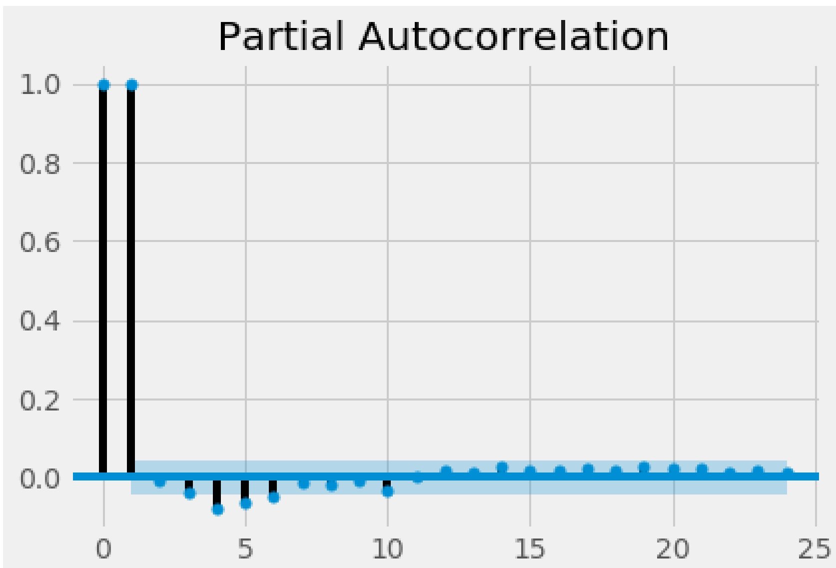
In the autocorrelation plot above, the consecutive observations are highly correlated (i.e superior to 0.5) and statistically significant.

Partial autocorrelation in time series data

Like autocorrelation, the partial autocorrelation function (PACF) measures the correlation coefficient between a time-series and lagged versions of itself. However, it extends upon this idea by also removing the effect of previous time points. For example, a partial autocorrelation function of order 3 returns the correlation between our time series (t_1, t_2, t_3, ...) and its own values lagged by 3 time points (t_4, t_5, t_6, ...), but only after removing all effects attributable to lags 1 and 2. **Figure this out in the future**

The plot_pacf() function in the statsmodels library can be used to measure and plot the partial autocorrelation of a time series.

In [41]:
```
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
from statsmodels.graphics import tsaplots
fig = tsaplots.plot_pacf(co2_levels['co2'], lags=24)
plt.show()
```



Just like autocorrelation, partial autocorrelation plots can be tricky to interpret, so let's test your understanding of those!

Interpret partial autocorrelation plots

If partial autocorrelation values are close to 0, then values between observations and lagged observations are not correlated with one another. Inversely, partial autocorrelations with values close to 1 or -1 indicate that there exists strong positive or negative correlations between the lagged observations of the time series.

The .plot_pacf() function also returns confidence intervals, which are represented as blue shaded regions. If partial autocorrelation values are beyond this confidence interval regions, then you can assume that the observed partial autocorrelation values are statistically significant.

In the partial autocorrelation plot below, at which lag values do we have statistically significant partial autocorrelations?
Answer: 0, 1, 4, 5, 6

Time series decomposition

When visualizing time series data, you should look out for some distinguishable patterns:

seasonality: does the data display a clear periodic pattern?
trend: does the data follow a consistent upwards or downward slope?
noise: are there any outlier points or missing values that are not consistent with the rest of the data?

You can rely on a method known as time-series decomposition to automatically extract and quantify the structure of time-series data. The statsmodels library provides the seasonal_decompose() function to perform time series decomposition out of the box.

In [42]:
```python
import statsmodels.api as sm
decomposition = sm.tsa.seasonal_decompose(co2_levels)
print(decomposition.seasonal)
```

```
                 co2
datestamp
1958-03-29  1.028042
1958-04-05  1.235242
1958-04-12  1.412344
1958-04-19  1.701186
1958-04-26  1.950694
1958-05-03  2.032939
1958-05-10  2.445506
1958-05-17  2.535041
1958-05-24  2.662031
1958-05-31  2.837948
1958-06-07  2.786137
1958-06-14  2.897139
1958-06-21  2.700962
1958-06-28  2.637389
1958-07-05  2.499487
1958-07-12  2.328869
1958-07-19  2.016146
1958-07-26  1.696378
1958-08-02  1.320640
1958-08-09  0.900761
1958-08-16  0.515989
1958-08-23  0.086897
1958-08-30 -0.474590
1958-09-06 -0.810900
1958-09-13 -1.287685
1958-09-20 -1.805108
1958-09-27 -2.068716
1958-10-04 -2.560531
1958-10-11 -2.856752
1958-10-18 -3.108765
...              ...
2001-06-09  1.320640
2001-06-16  0.900761
2001-06-23  0.515989
2001-06-30  0.086897
2001-07-07 -0.474590
```

```
2001-07-14 -0.810900
2001-07-21 -1.287685
2001-07-28 -1.805108
2001-08-04 -2.068716
2001-08-11 -2.560531
2001-08-18 -2.856752
2001-08-25 -3.108765
2001-09-01 -3.170460
2001-09-08 -3.267396
2001-09-15 -3.194297
2001-09-22 -3.016323
2001-09-29 -2.812656
2001-10-06 -2.588640
2001-10-13 -2.351296
2001-10-20 -2.072159
2001-10-27 -1.802325
2001-11-03 -1.509391
2001-11-10 -1.284167
2001-11-17 -1.024060
2001-11-24 -0.791949
2001-12-01 -0.525044
2001-12-08 -0.392799
2001-12-15 -0.134838
2001-12-22  0.116056
2001-12-29  0.285354

[2284 rows x 1 columns]
```

Time series decomposition is a powerful method to reveal the structure of your time series. Now let's visualize these components.

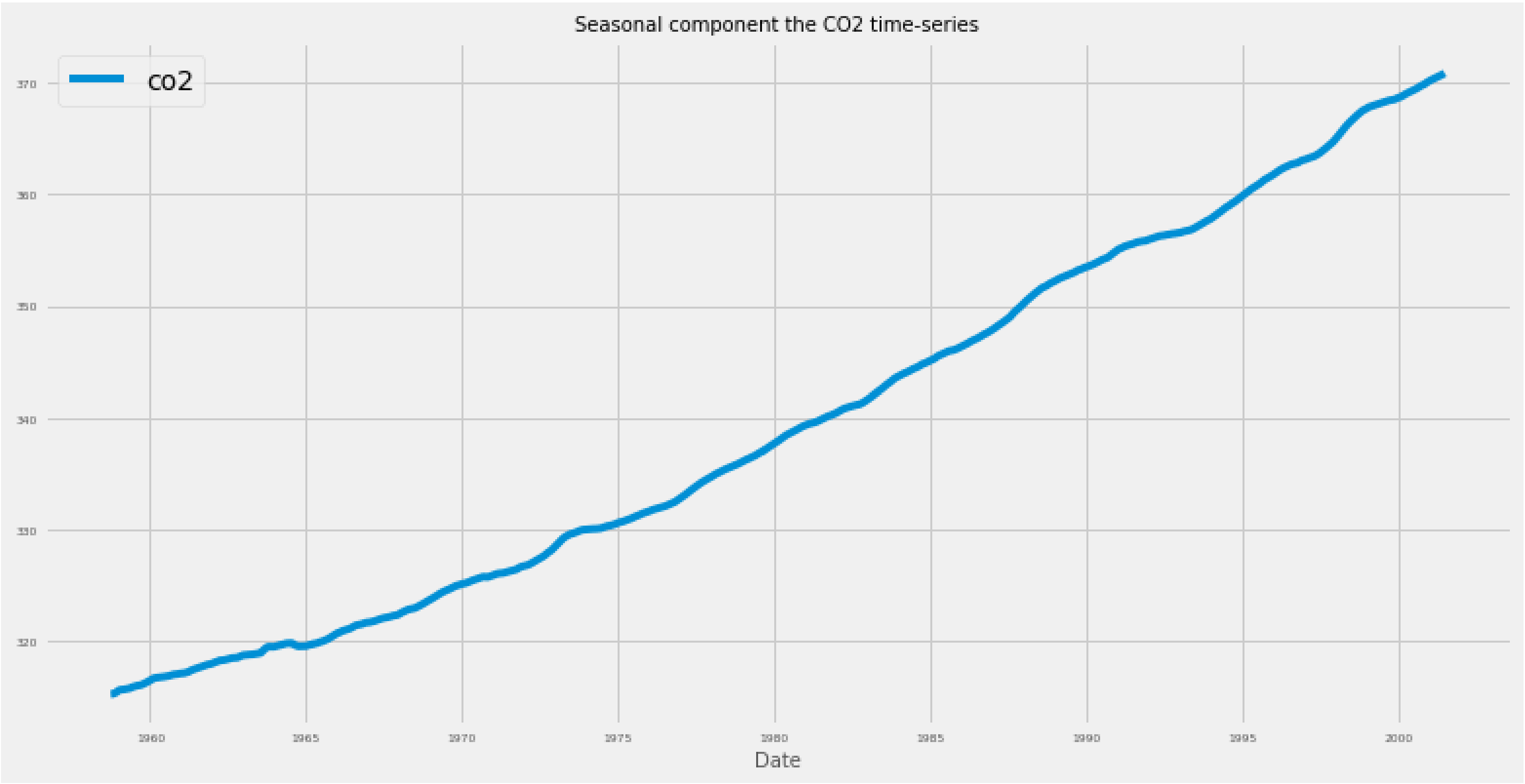
Plot individual components

It is also possible to extract other inferred quantities from your time-series decomposition object. The following code shows you how to extract the observed, trend and noise (or residual, resid) components.

observed = decomposition.observed
trend = decomposition.trend
residuals = decomposition.resid
You can then use the extracted components and plot them individually.

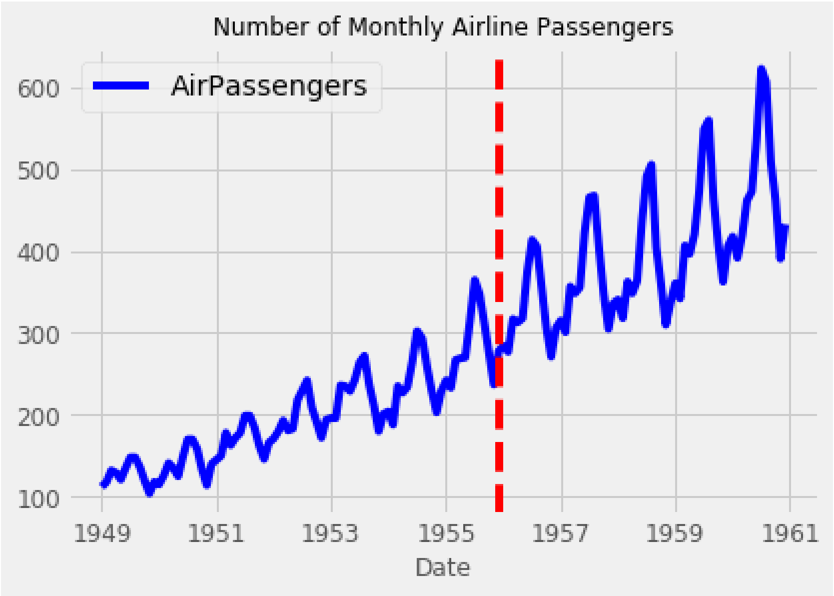
In [43]:

```
trend = decomposition.trend
ax = trend.plot(figsize=(12, 6), fontsize=6)
ax.set_xlabel('Date', fontsize=10)
ax.set_title('Seasonal component the CO2 time-series', fontsize=10)
plt.show()
```



Visualize the airline dataset

In [47]:
```
import pandas as pd
airline = pd.read_csv('ch3_airline_passengers.csv', index_col = 'Month', parse_dates = True)
ax = airline.plot(color='blue', fontsize=12)
ax.axvline('1955-12-01', color='red', linestyle='--')
ax.set_xlabel('Date', fontsize=12)
ax.set_title('Number of Monthly Airline Passengers', fontsize=12)
plt.show()
```

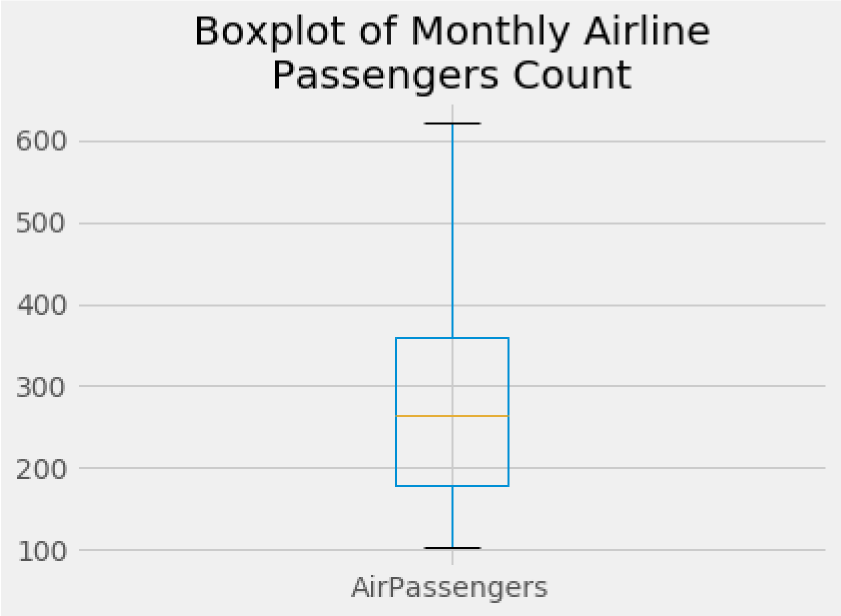


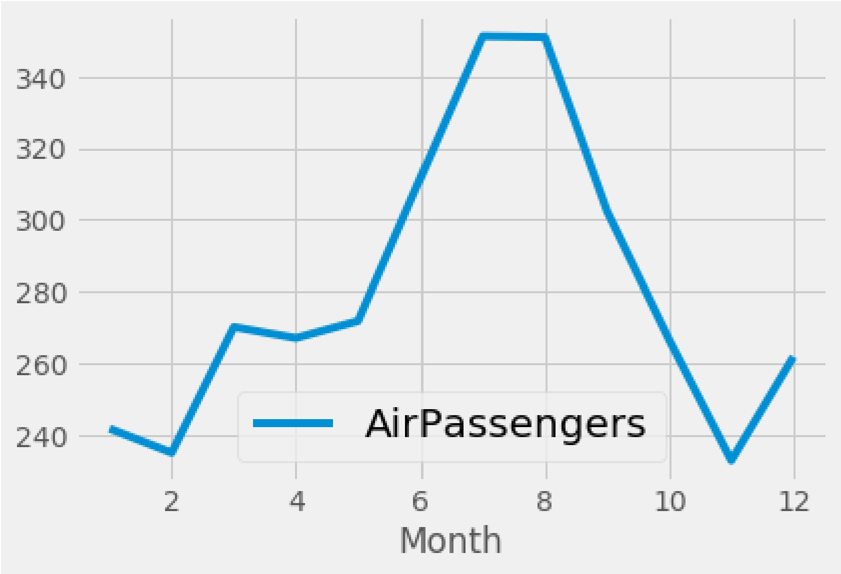
Analyze the airline dataset

- How to check for the presence of missing values, and how to collect summary statistics of time series data contained in a pandas DataFrame.
- To generate boxplots of your data to quickly gain insight in your data.
- Display aggregate statistics of your data using groupby().

In [48]:
```python
print(airline.isnull().sum())
print(airline.describe())

ax = airline.boxplot()
ax.set_title('Boxplot of Monthly Airline\nPassengers Count', fontsize=20)
plt.show()

index_month = airline.index.month
mean_airline_by_month = airline.groupby(index_month).mean()
mean_airline_by_month.plot()
plt.legend(fontsize=20)
plt.show()
```

```
AirPassengers    0
dtype: int64
       AirPassengers
count     144.000000
mean      280.298611
std       119.966317
min       104.000000
25%       180.000000
50%       265.500000
75%       360.500000
max       622.000000
```





Time series decomposition of the airline dataset

In [ ]:

```
import statsmodels.api as sm
decomposition = sm.tsa.seasonal_decompose(airline)
trend = decomposition.trend
seasonal = decomposition.seasonal

#To print, I need put trend and seasonal above into the airline_decomposed below
print(airline_decomposed.head(5))
ax = airline_decomposed.plot(figsize=(12, 6), fontsize=15)
ax.set_xlabel('Date', fontsize=15)
plt.legend(fontsize=15)
plt.show()
```

Work with Multiple Time Series

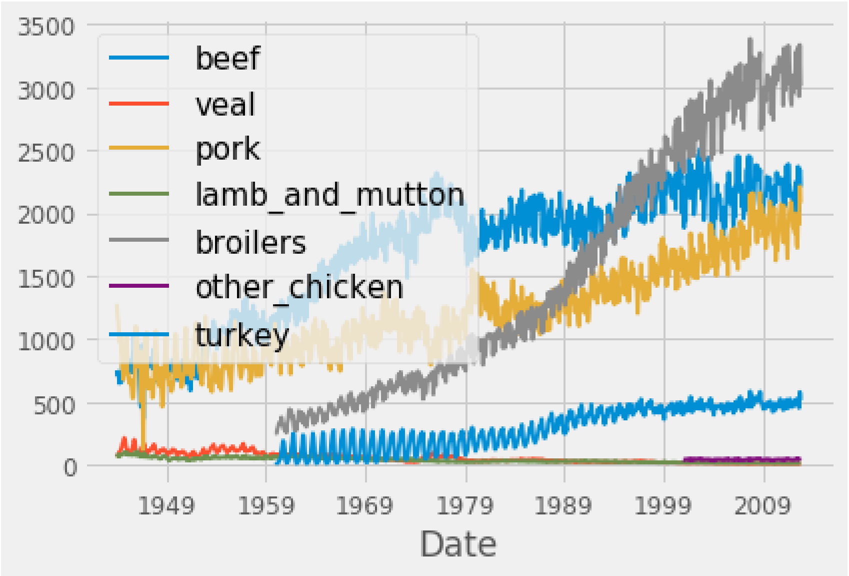
Load multiple time series

In [52]:
```python
meat = pd.read_csv('ch4_meat.csv',index_col = 'date', parse_dates = True)
#The above sentence replace the following sentences.
print(meat.head(5))
# meat['date'] = pd.to_datetime(meat['date'])
# meat = meat.set_index('date')
print(meat.describe())
```

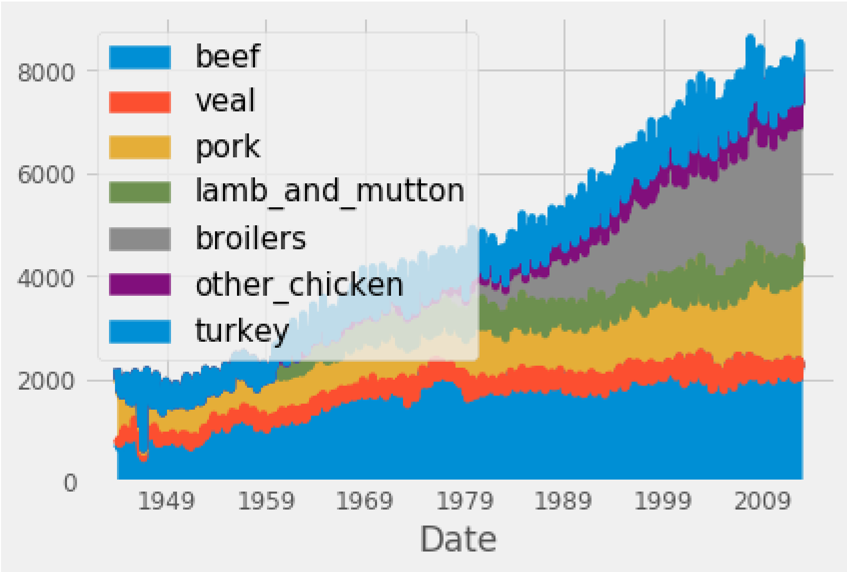
```
             beef   veal    pork  lamb_and_mutton  broilers  other_chicken  \
date
1944-01-01  751.0   85.0  1280.0             89.0       NaN            NaN
1944-02-01  713.0   77.0  1169.0             72.0       NaN            NaN
1944-03-01  741.0   90.0  1128.0             75.0       NaN            NaN
1944-04-01  650.0   89.0   978.0             66.0       NaN            NaN
1944-05-01  681.0  106.0  1029.0             78.0       NaN            NaN

            turkey
date
1944-01-01     NaN
1944-02-01     NaN
1944-03-01     NaN
1944-04-01     NaN
1944-05-01     NaN
              beef        veal         pork  lamb_and_mutton     broilers  \
count   827.000000  827.000000   827.000000       827.000000   635.000000
mean   1683.463362   54.198549  1211.683797        38.360701  1516.582520
std     501.698480   39.062804   371.311802        19.624340   963.012101
min     366.000000    8.800000   124.000000        10.900000   250.900000
25%    1231.500000   24.000000   934.500000        23.000000   636.350000
50%    1853.000000   40.000000  1156.000000        31.000000  1211.300000
75%    2070.000000   79.000000  1466.000000        55.000000  2426.650000
max    2512.000000  215.000000  2210.400000       109.000000  3383.800000

       other_chicken      turkey
count     143.000000  635.000000
mean       43.033566  292.814646
std         3.867141  162.482638
min        32.300000   12.400000
25%        40.200000  154.150000
50%        43.400000  278.300000
75%        45.650000  449.150000
max        51.100000  585.100000
```

Visualize multiple time series

In [53]:
```
ax = meat.plot(linewidth=2, fontsize=12)
ax.set_xlabel('Date')
ax.legend(fontsize=15)
plt.show()
```



In [54]:
```
# Plot an area chart
ax = meat.plot.area(fontsize=12)
ax.set_xlabel('Date')
ax.legend(fontsize=15)
plt.show()
```

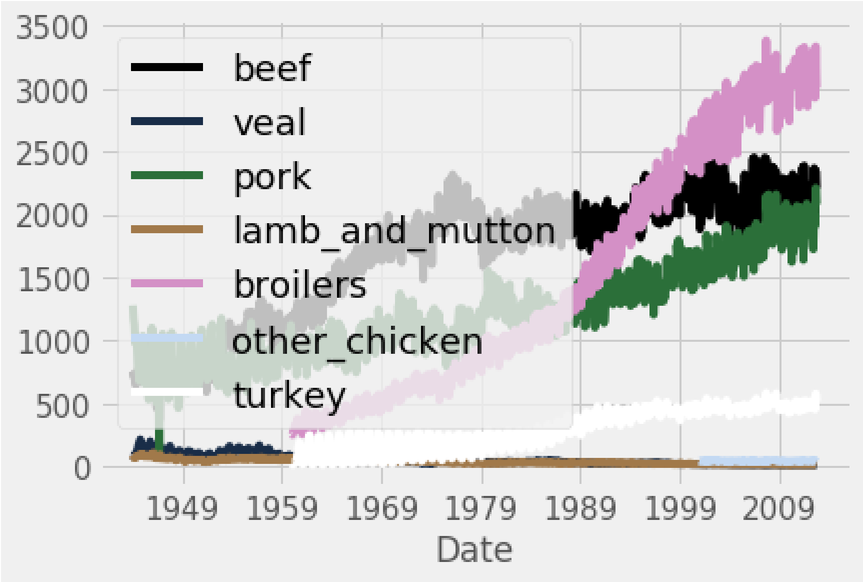


Define the color palette of your plots

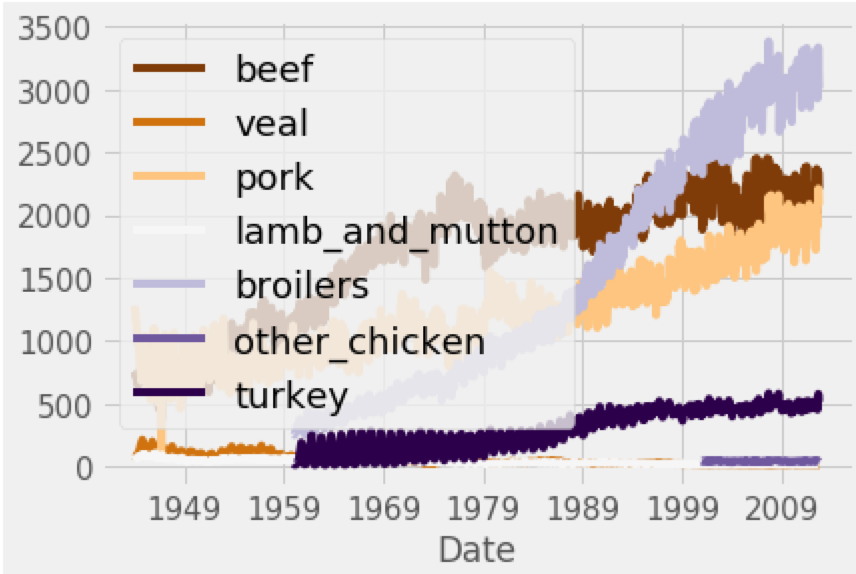
When visualizing multiple time series, it can be difficult to differentiate between various colors in the default color scheme.

To remedy this, you can define each color manually, but this may be time-consuming. Fortunately, it is possible to leverage the colormap argument to .plot() to automatically assign specific color palettes with varying contrasts. You can either provide a matplotlib colormap as an input to this parameter, or provide one of the default strings that is available in the colormap() function available in matplotlib (all of which are available here).

In [55]:
```
ax = meat.plot(colormap='cubehelix', fontsize=15)
ax.set_xlabel('Date')
ax.legend(fontsize=18)
plt.show()
```



In [56]:
```
ax = meat.plot(colormap='PuOr', fontsize=15)
ax.set_xlabel('Date')
ax.legend(fontsize=18)
plt.show()
```



Add summary statistics to your time series plot

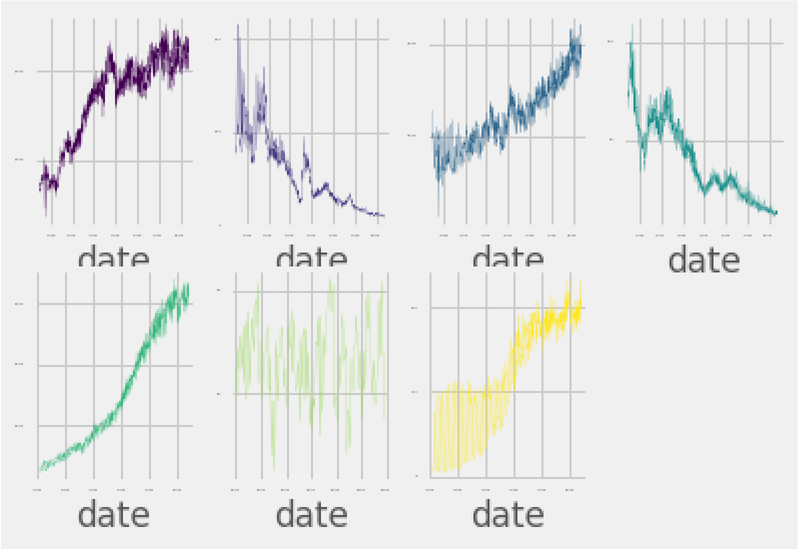
It is possible to visualize time series plots and numerical summaries on one single graph by using the pandas API to matplotlib along with the table method:

In [ ]:

```
ax = meat.plot(fontsize=6, linewidth=1)
ax.set_xlabel('Date', fontsize=6)

# Add summary table information to the plot
ax.table(cellText=meat_mean.values,
         colWidths = [0.15]*len(meat_mean.columns),
         rowLabels=meat_mean.index,
         colLabels=meat_mean.columns,
         loc='top')

ax.legend(loc='upper center', bbox_to_anchor=(0.5, 0.95), ncol=3, fontsize=6)

plt.show()
```

Plot your time series on individual plots

In [58]:
```python
# Create a facetted graph with 2 rows and 4 columns
meat.plot(subplots=True,
          layout=(2, 4),
          sharex=False,
          sharey=False,
          colormap='viridis',
          fontsize=2,
          legend=False,
          linewidth=0.2)

plt.show()
```



Compute correlations between time series

Correlation coefficients can be computed with the pearson, kendall and spearman methods. A full discussion of these different methods is outside the scope of this course, but the pearson method should be used when relationships between your variables are thought to be linear, while the kendall and spearman methods should be used when relationships between your variables are **thought to be non-linear.**

In [60]:
```
print(meat[['beef', 'pork']].corr(method='spearman'))
```

```
          beef      pork
beef  1.000000  0.827587
pork  0.827587  1.000000
```

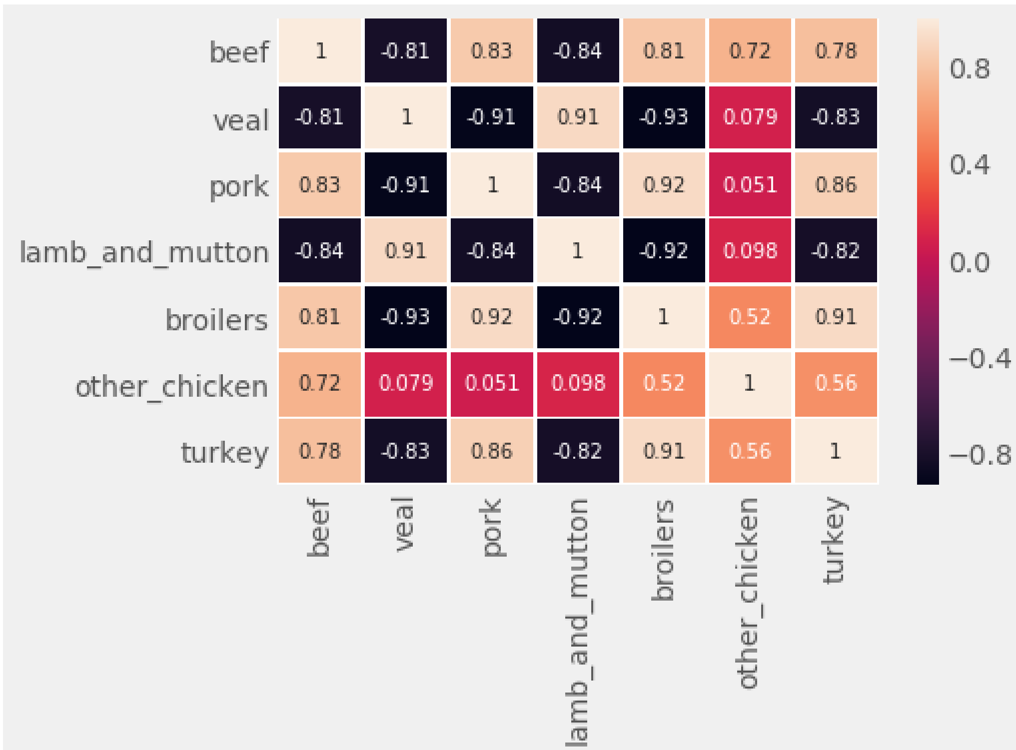
In [61]:
```
print(meat[['pork', 'veal', 'turkey']].corr(method='pearson'))
```

```
            pork      veal    turkey
pork    1.000000 -0.808834  0.835215
veal   -0.808834  1.000000 -0.768366
turkey  0.835215 -0.768366  1.000000
```

Visualize correlation matrices

The correlation matrix generated in the previous exercise can be plotted using a heatmap. To do so, you can leverage the heatmap() function from the seaborn library which contains several arguments to tailor the look of your heatmap.

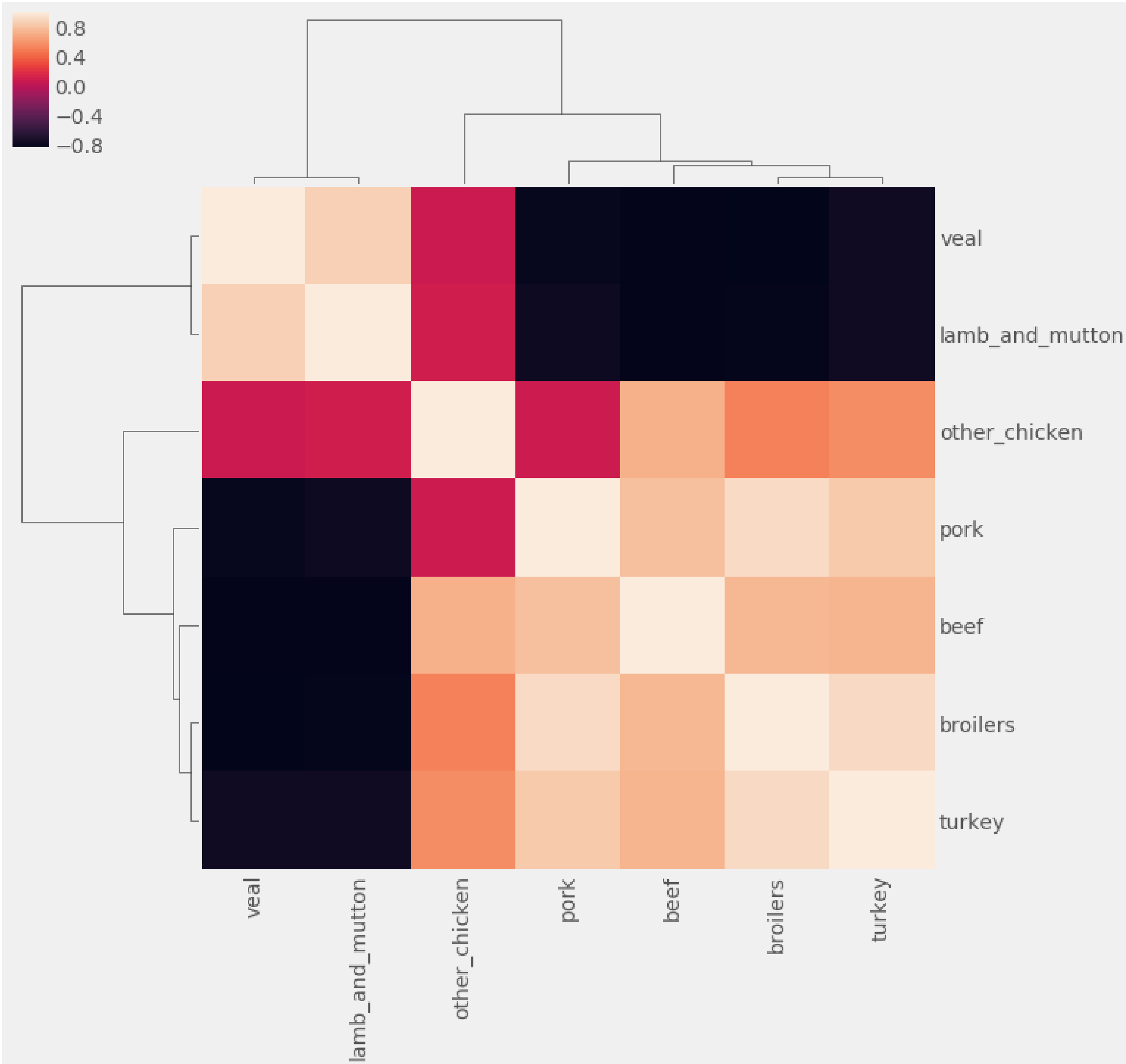
In [62]:
```
import seaborn as sns
corr_meat = meat.corr(method='spearman')
sns.heatmap(corr_meat,
            annot=True,
            linewidths=0.4,
            annot_kws={"size": 10})

plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.show()
```



Clustered heatmaps

Heatmaps are extremely useful to visualize a correlation matrix, but clustermaps are better. A Clustermap allows to uncover structure in a correlation matrix by producing a hierarchically-clustered heatmap:

In [63]:
```
import seaborn as sns
corr_meat = meat.corr(method='pearson')

# Customize the heatmap of the corr_meat correlation matrix and rotate the x-axis labels
fig = sns.clustermap(corr_meat,
                     row_cluster=True,
                     col_cluster=True,
                     figsize=(10, 10))

plt.setp(fig.ax_heatmap.xaxis.get_majorticklabels(), rotation=90)
plt.setp(fig.ax_heatmap.yaxis.get_majorticklabels(), rotation=0)
plt.show()
```


0.8
0.4
0.0
−0.4
−0.8
veal
lamb_and_mutton
other_chicken
pork
beef
broilers
turkey

Case Study

This chapter will give you a chance to practice all the concepts covered in the course. You will visualize the unemployment rate in the US from 2000 to 2010.

In [65]:
```python
import pandas as pd
jobs = pd.read_csv('ch5_employment.csv')

print(jobs.head(5))
print(jobs.dtypes)
jobs['datestamp'] = pd.to_datetime(jobs['datestamp'])
jobs = jobs.set_index('datestamp')
print(jobs.isnull().sum())
```

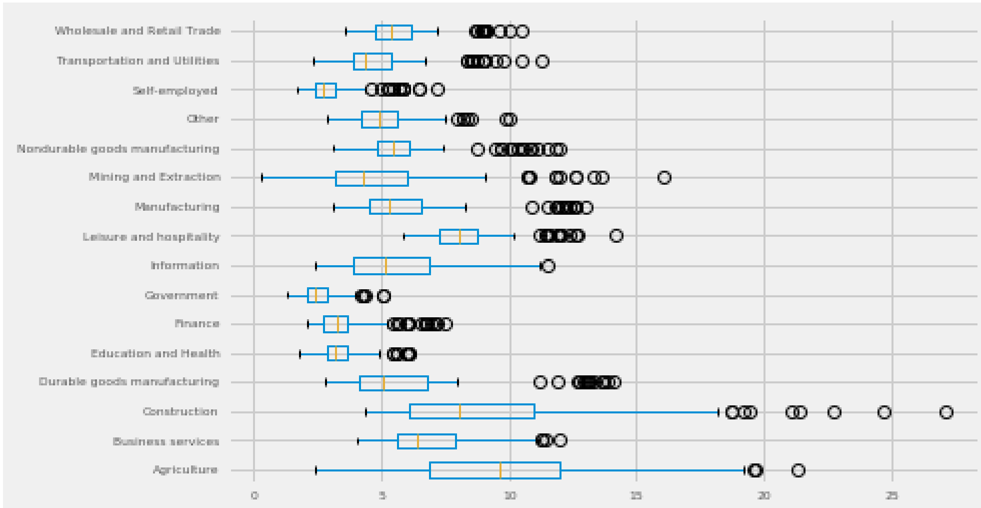
```
    datestamp  Agriculture  Business services  Construction  \
0  2000-01-01         10.3                5.7           9.7   
1  2000-02-01         11.5                5.2          10.6   
2  2000-03-01         10.4                5.4           8.7   
3  2000-04-01          8.9                4.5           5.8   
4  2000-05-01          5.1                4.7           5.0   

   Durable goods manufacturing  Education and Health  Finance  Government  \
0                          3.2                   2.3      2.7         2.1   
1                          2.9                   2.2      2.8         2.0   
2                          2.8                   2.5      2.6         1.5   
3                          3.4                   2.1      2.3         1.3   
4                          3.4                   2.7      2.2         1.9   

   Information  Leisure and hospitality  Manufacturing  Mining and Extraction  \
0          3.4                      7.5            3.6                    3.9   
1          2.9                      7.5            3.4                    5.5   
2          3.6                      7.4            3.6                    3.7   
3          2.4                      6.1            3.7                    4.1   
4          3.5                      6.2            3.4                    5.3   

   Nondurable goods manufacturing  Other  Self-employed  \
0                             4.4    4.9            2.3   
1                             4.2    4.1            2.5   
2                             5.1    4.3            2.0   
3                             4.0    4.2            2.0   
4                             3.6    4.5            1.9   

   Transportation and Utilities  Wholesale and Retail Trade  
0                           4.3                         5.0  
1                           4.0                         5.2  
2                           3.5                         5.1  
3                           3.4                         4.1  
```

```
4                           3.4                           4.3
datestamp                          object
Agriculture                       float64
Business services                 float64
Construction                      float64
Durable goods manufacturing       float64
Education and Health              float64
Finance                           float64
Government                        float64
Information                       float64
Leisure and hospitality           float64
Manufacturing                     float64
Mining and Extraction             float64
Nondurable goods manufacturing    float64
Other                             float64
Self-employed                     float64
Transportation and Utilities      float64
Wholesale and Retail Trade        float64
dtype: object
Agriculture                       0
Business services                 0
Construction                      0
Durable goods manufacturing       0
Education and Health              0
Finance                           0
Government                        0
Information                       0
Leisure and hospitality           0
Manufacturing                     0
Mining and Extraction             0
Nondurable goods manufacturing    0
Other                             0
Self-employed                     0
Transportation and Utilities      0
Wholesale and Retail Trade        0
dtype: int64
```

Describe time series data with boxplots

In [66]:

```python
jobs.boxplot(fontsize=6, vert=False)
plt.show()
print(jobs.describe())
print('Agriculture')
print('Construction')
```




```
       Agriculture  Business services  Construction  \
count   122.000000         122.000000    122.000000
mean      9.840984           6.919672      9.426230
std       3.962067           1.862534      4.587619
min       2.400000           4.100000      4.400000
25%       6.900000           5.600000      6.100000
50%       9.600000           6.450000      8.100000
75%      11.950000           7.875000     10.975000
max      21.300000          12.000000     27.100000

       Durable goods manufacturing  Education and Health     Finance  \
count                   122.000000            122.000000  122.000000
mean                      6.025410              3.420492    3.540164
std                       2.854475              0.877538    1.235405
min                       2.800000              1.800000    2.100000
25%                       4.125000              2.900000    2.700000
50%                       5.100000              3.200000    3.300000
75%                       6.775000              3.700000    3.700000
max                      14.100000              6.100000    7.500000
```

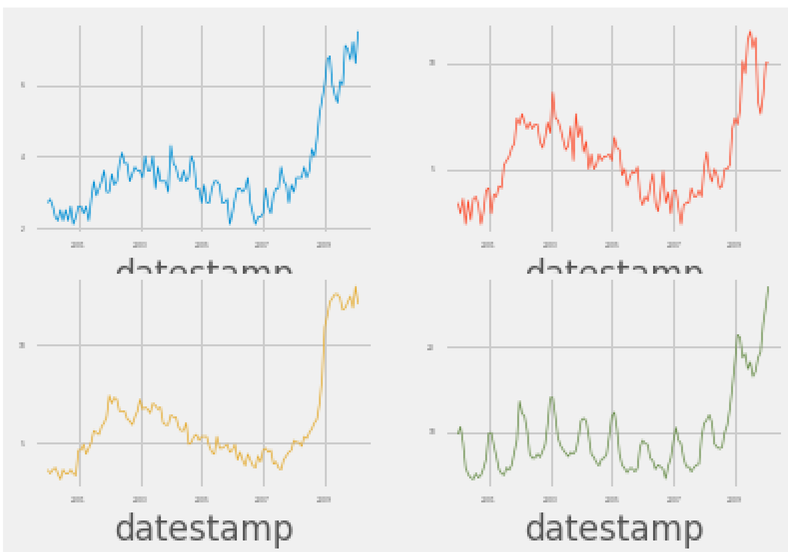
```
       Government  Information  Leisure and hospitality  Manufacturing  \
count  122.000000   122.000000               122.000000     122.000000   
mean     2.581148     5.486885                 8.315574       5.982787   
std      0.686750     2.016582                 1.605570       2.484221   
min      1.300000     2.400000                 5.900000       3.100000   
25%      2.100000     3.900000                 7.300000       4.500000   
50%      2.400000     5.150000                 8.050000       5.300000   
75%      2.875000     6.900000                 8.800000       6.600000   
max      5.100000    11.500000                14.200000      13.000000   

       Mining and Extraction  Nondurable goods manufacturing       Other  \
count             122.000000                      122.000000  122.000000   
mean                5.088525                        5.930328    5.096721   
std                 2.942428                        1.922330    1.317457   
min                 0.300000                        3.100000    2.900000   
25%                 3.200000                        4.825000    4.200000   
50%                 4.300000                        5.500000    4.900000   
75%                 6.050000                        6.100000    5.600000   
max                16.100000                       12.000000   10.000000   

       Self-employed  Transportation and Utilities  Wholesale and Retail Trade  
count     122.000000                    122.000000                  122.000000  
mean        3.031967                      4.935246                    5.766393  
std         1.124429                      1.753340                    1.463417  
min         1.700000                      2.300000                    3.600000  
25%         2.400000                      3.900000                    4.800000  
50%         2.700000                      4.400000                    5.400000  
75%         3.200000                      5.400000                    6.200000  
max         7.200000                     11.300000                   10.500000  
Agriculture
Construction
```

Plot all the time series in your dataset

The jobs DataFrame contains 16 time series representing the unemployment rate of various industries between 2001 and 2010. This may seem like a large amount of time series to visualize at the same time, but Chapter 4 introduced you to facetted plots. In this exercise, you will explore some of the time series in the jobs DataFrame and look to extract some meaningful information from these plots.

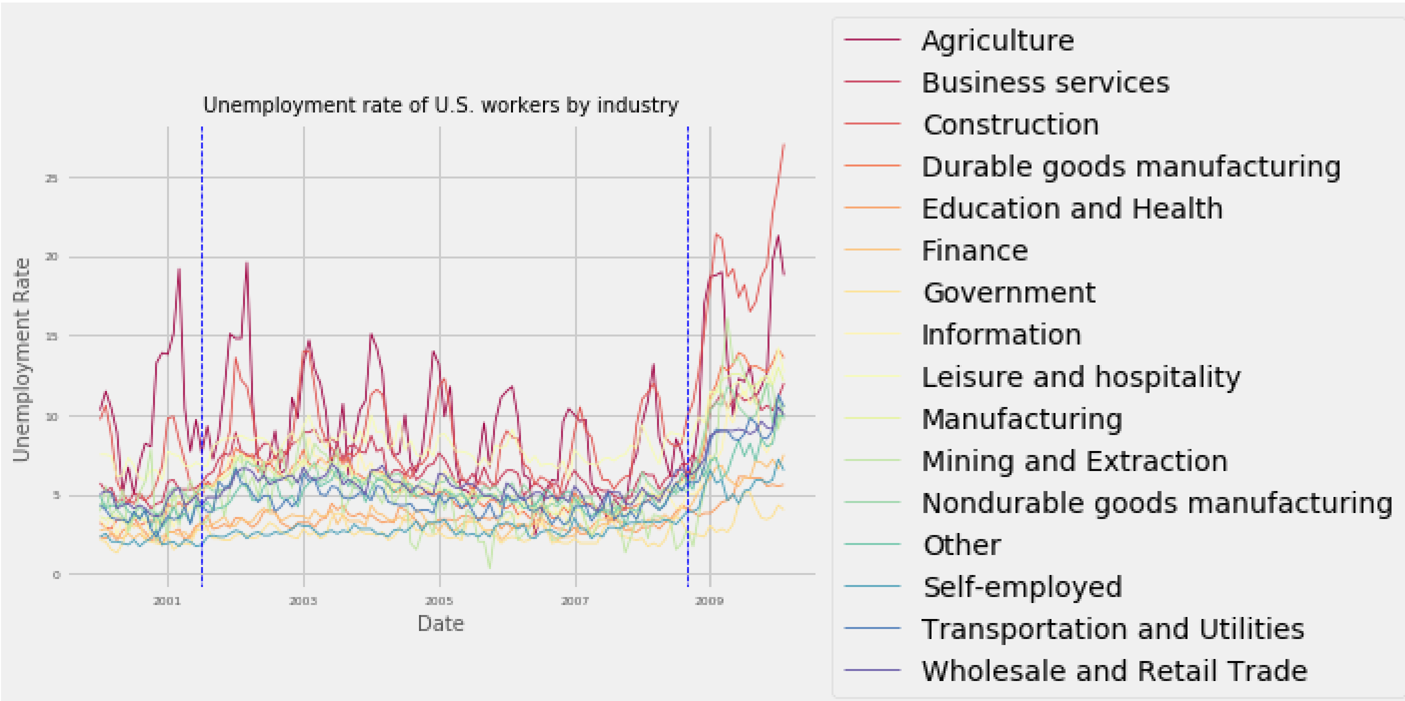
In [68]:
```python
jobs_subset = jobs[['Finance', 'Information', 'Manufacturing', 'Construction']]
print(jobs_subset.head(5))
ax = jobs_subset.plot(subplots=True,
                      layout=(2, 2),
                      sharex=False,
                      sharey=False,
                      linewidth=0.7,
                      fontsize=3,
                      legend=False)

plt.show()
```

```
            Finance  Information  Manufacturing  Construction
datestamp
2000-01-01      2.7          3.4            3.6           9.7
2000-02-01      2.8          2.9            3.4          10.6
2000-03-01      2.6          3.6            3.6           8.7
2000-04-01      2.3          2.4            3.7           5.8
2000-05-01      2.2          3.5            3.4           5.0
```



Annotate significant events in time series data

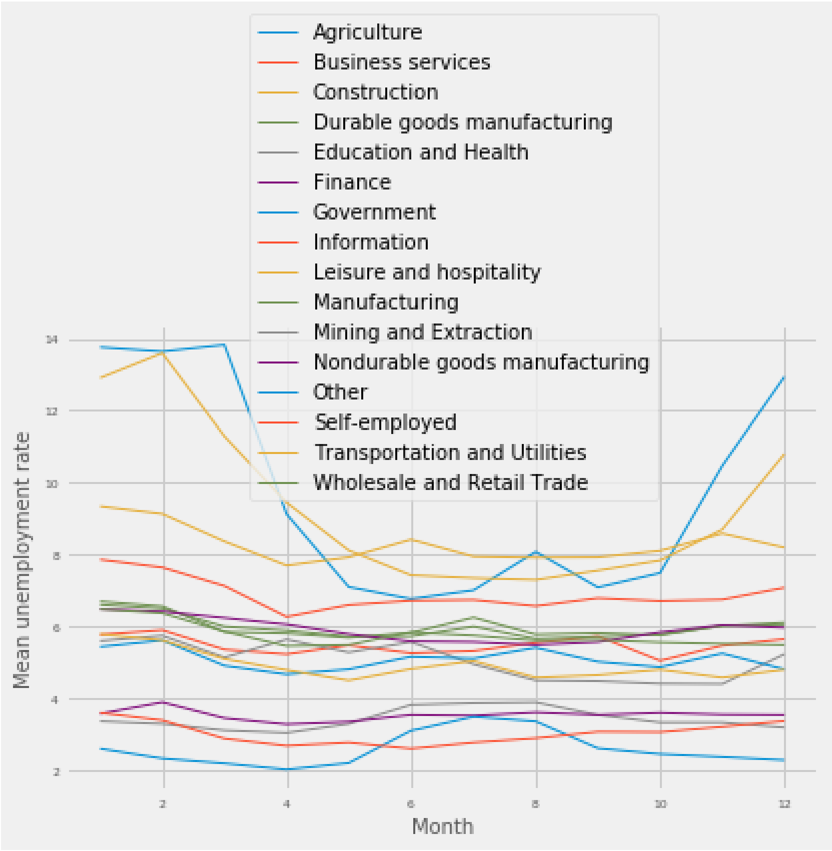
In [69]:
```
ax = jobs.plot(colormap='Spectral', fontsize=6, linewidth=0.8)
ax.set_xlabel('Date', fontsize=10)
ax.set_ylabel('Unemployment Rate', fontsize=10)
ax.set_title('Unemployment rate of U.S. workers by industry', fontsize=10)
ax.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

ax.axvline('2001-07-01', color='blue', linestyle='--', linewidth=0.8)
ax.axvline('2008-09-01', color='blue', linestyle='--', linewidth=0.8)

plt.show()
```



Plot monthly and yearly trends

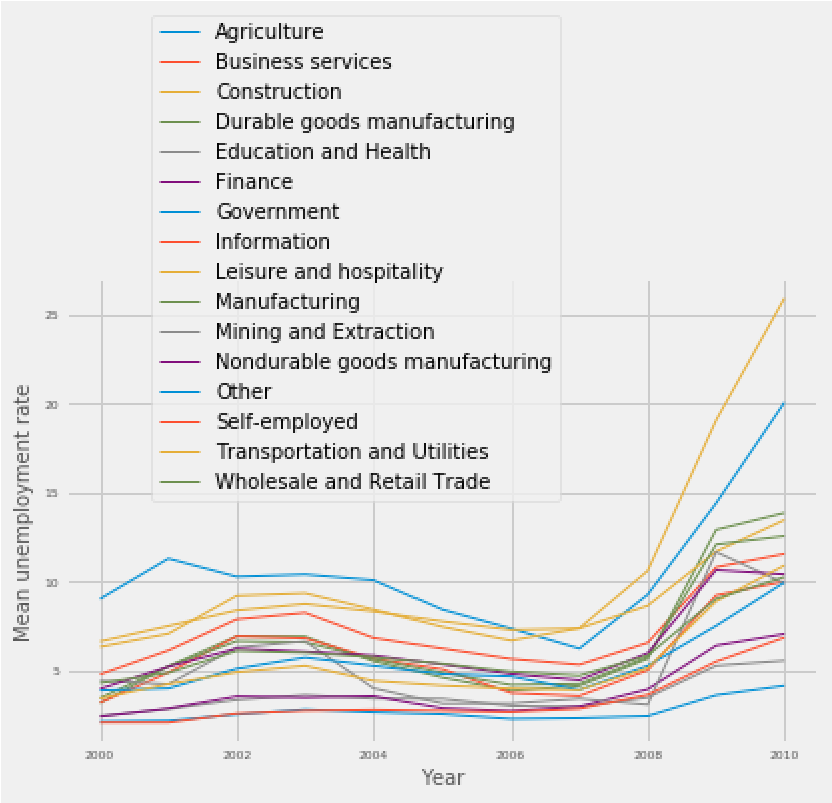
In [70]:

```
index_month = jobs.index.month
jobs_by_month = jobs.groupby(index_month).mean()

# Plot the mean unemployment rate for each month
ax = jobs_by_month.plot(fontsize=6, linewidth=1)
ax.set_xlabel('Month', fontsize=10)
ax.set_ylabel('Mean unemployment rate', fontsize=10)
ax.legend(bbox_to_anchor=(0.8, 0.6), fontsize=10)
plt.show()
```



Plot monthly and yearly trends

In [71]:
```
index_year = jobs.index.year
jobs_by_year = jobs.groupby(index_year).mean()

ax = jobs_by_year.plot(fontsize=6, linewidth=1)
ax.set_xlabel('Year', fontsize=10)
ax.set_ylabel('Mean unemployment rate', fontsize=10)
ax.legend(bbox_to_anchor=(0.1, 0.5), fontsize=10)
plt.show()
```



Apply time series decomposition to your dataset

You will now perform time series decomposition on multiple time series. You can achieve this by leveraging the Python dictionary to store the results of each time series decomposition.

In this exercise, you will initialize an empty dictionary with a set of curly braces, {}, use a for loop to iterate through the columns of the DataFrame and apply time series decomposition to each time series. After each time series decomposition, you place the results in the dictionary by using the command my_dict[key] = value, where my_dict is your dictionary, key is the name of the column/time series, and value is the decomposition object of that time series.

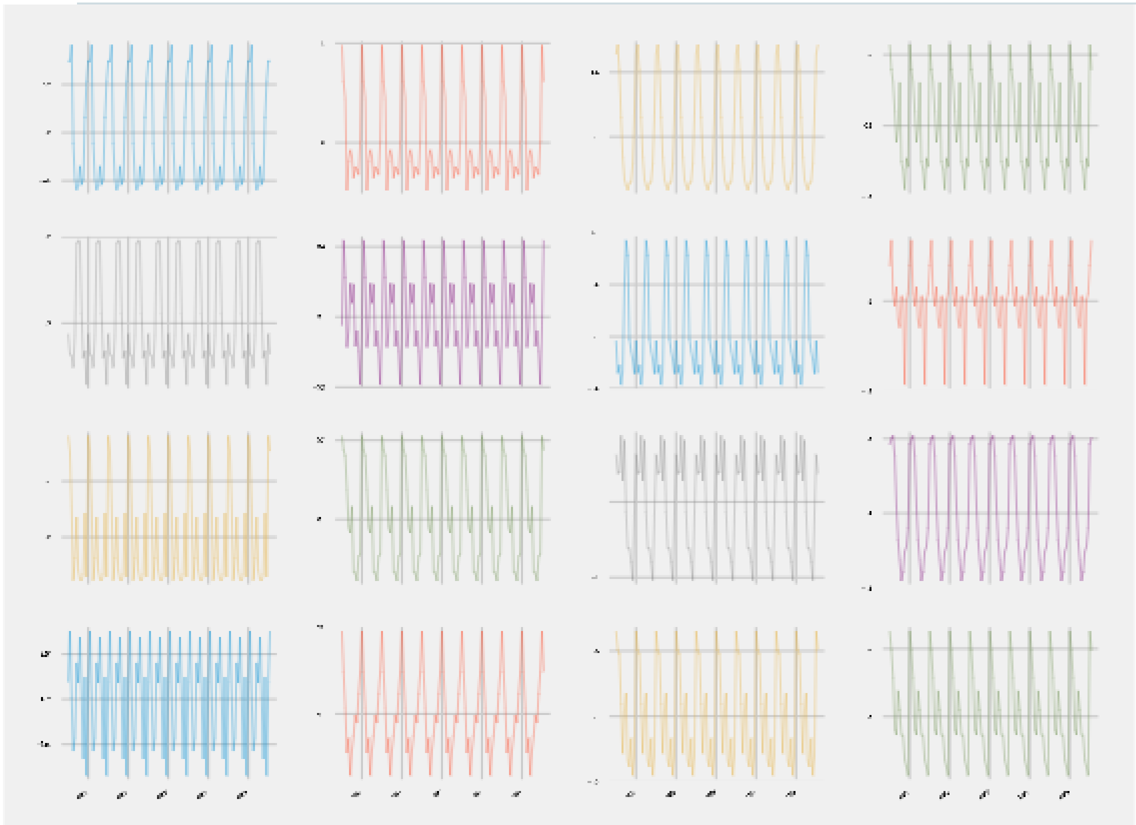
In [80]:
```
jobs_decomp = {}
jobs_names = jobs.columns

for ts in jobs_names:
    ts_decomposition = sm.tsa.seasonal_decompose(jobs[ts])
    jobs_decomp[ts] = ts_decomposition
```

Visualize the seasonality of multiple time series

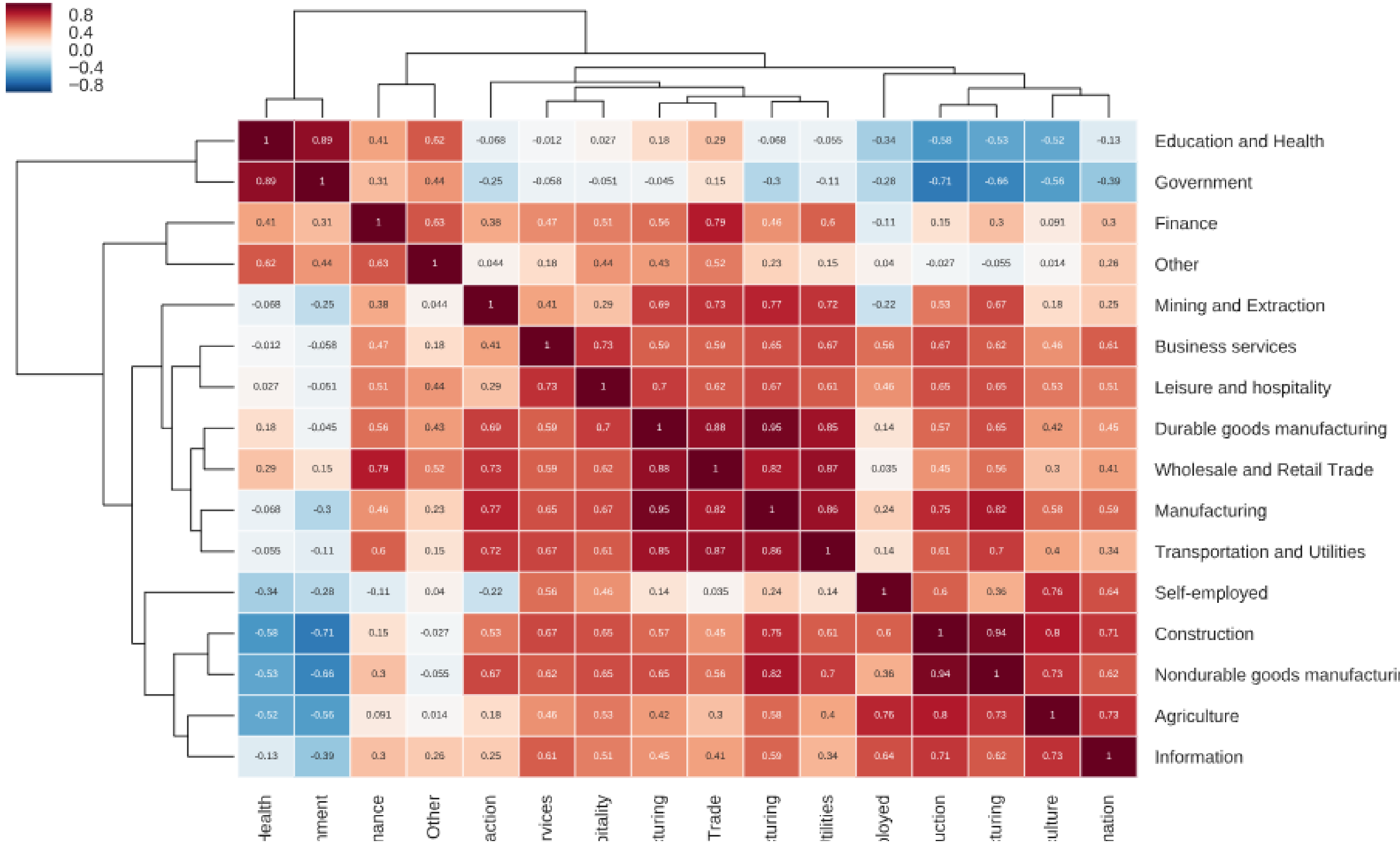
You will now extract the seasonality component of jobs_decomp to visualize the seasonality in these time series. Note that before plotting, you will have to convert the dictionary of seasonality components into a DataFrame using the pd.DataFrame.from_dict() function.

An empty dictionary jobs_seasonal and the time series decompisiton object jobs_decomp from the previous exercise are available in your workspace.

In [ ]:
```
# Extract the seasonal values for the decomposition of each time series
for ts in jobs_names:
    jobs_seasonal[ts] = jobs_decomp[ts].seasonal

# Create a DataFrame from the jobs_seasonal dictionnary
seasonality_df = pd.DataFrame.from_dict(jobs_seasonal)

# Remove the label for the index
seasonality_df.index.name = None

# Create a faceted plot of the seasonality_df DataFrame
seasonality_df.plot(subplots=True,
                   layout=(4, 4),
                   sharey=False,
                   fontsize=2,
                   linewidth=0.3,
                   legend=False)

# Show plot
plt.show()
```



In [ ]:
```
# Get correlation matrix of the seasonality_df DataFrame
seasonality_corr = seasonality_df.corr(method='spearman')

# Customize the clustermap of the seasonality_corr correlation matrix
fig = sns.clustermap(seasonality_corr, annot=True, annot_kws={"size": 4}, linewidths=.4, figsize=(15, 10))
plt.setp(fig.ax_heatmap.yaxis.get_majorticklabels(), rotation=0)
plt.setp(fig.ax_heatmap.xaxis.get_majorticklabels(), rotation=90)
plt.show()

# Print the correlation between the seasonalities of the Government and Education & Health industries
print(0.89)
```



0.8
0.4
0.0
−0.4
−0.8
Education and Health
Government
Finance
Other
Mining and Extraction
Business services
Leisure and hospitality
Durable goods manufacturing
Wholesale and Retail Trade
Manufacturing
Transportation and Utilities
Self-employed
Construction
Nondurable goods manufacturin
Agriculture
Information
1 0.89 0.41 0.62 -0.068 -0.012 0.027 0.18 0.29 -0.068 -0.055 -0.34 -0.58 -0.53 -0.52 -0.13
0.89 1 0.31 0.44 -0.25 -0.058 -0.051 -0.045 0.15 -0.3 -0.11 -0.28 -0.71 -0.66 -0.56 -0.39
0.41 0.31 1 0.63 0.38 0.47 0.51 0.56 0.79 0.46 0.6 -0.11 0.15 0.3 0.091 0.3
0.62 0.44 0.63 1 0.044 0.18 0.44 0.43 0.52 0.23 0.15 0.04 -0.027 -0.055 0.014 0.26
-0.068 -0.25 0.38 0.044 1 0.41 0.29 0.69 0.73 0.77 0.72 -0.22 0.53 0.67 0.18 0.25
-0.012 -0.058 0.47 0.18 0.41 1 0.73 0.59 0.59 0.65 0.67 0.56 0.67 0.62 0.46 0.61
0.027 -0.051 0.51 0.44 0.29 0.73 1 0.7 0.62 0.67 0.61 0.46 0.65 0.65 0.53 0.51
0.18 -0.045 0.56 0.43 0.69 0.59 0.7 1 0.88 0.95 0.85 0.14 0.57 0.65 0.42 0.45
0.29 0.15 0.79 0.52 0.73 0.59 0.62 0.88 1 0.82 0.87 0.035 0.45 0.56 0.3 0.41
-0.068 -0.3 0.46 0.23 0.77 0.65 0.67 0.95 0.82 1 0.86 0.24 0.75 0.82 0.58 0.59
-0.055 -0.11 0.6 0.15 0.72 0.67 0.61 0.85 0.87 0.86 1 0.14 0.61 0.7 0.4 0.34
-0.34 -0.28 -0.11 0.04 -0.22 0.56 0.46 0.14 0.035 0.24 0.14 1 0.6 0.36 0.76 0.64
-0.58 -0.71 0.15 -0.027 0.53 0.67 0.65 0.57 0.45 0.75 0.61 0.6 1 0.94 0.8 0.71
-0.53 -0.66 0.3 -0.055 0.67 0.62 0.65 0.65 0.56 0.82 0.7 0.36 0.94 1 0.73 0.62
-0.52 -0.56 0.091 0.014 0.18 0.46 0.53 0.42 0.3 0.58 0.4 0.76 0.8 0.73 1 0.73
-0.13 -0.39 0.3 0.26 0.25 0.61 0.51 0.45 0.41 0.59 0.34 0.64 0.71 0.62 0.73 1
Other
Trade