Datasets-Used-In-This-Course

October 19, 2022

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1 Datasets Used In This Course

In no particular order these are the datasets used throughout the course. In most cases we have modified the source data to build .csv files with selected columns, records, and a DateTime index.

CO2 Levels atop Mauna Loa, HI US Macroeconomic Data Starbucks Stock Data Energy Production US Population Data Temperature Data - Mt. Washington, NH Temperature Data - Mauna Loa, HI Airline Passengers Daily Total Female Births Monthly Milk Production Danube River Discharge Rhine River Discharge Price of Ground Chuck Real Manufacturing and Trade Inventories California Publishing Industry Employees California Hospitality Industry Employees RideAustin Value of Manufacturers' Shipments M2 Money Stock Personal Spending US Population by County

Additional Resources:

Federal Reserve Bank of St. Louis Federal Reserve Economic Data (FRED)

NOAA National Centers for Environmental Information (NCEI) (formerly NCDC) Statsmodels Datasets Package U.S. Census Bureau Business and Industry; Time Series/Trend Charts U.S. Dept. of Labor Bureau of Labor Statistics

NOTE: As of April 15th, 2019 DataMarket.com is no longer available. DataMarket has been acquired by Qlik.

1.0.1 Perform Standard Imports

[1]:
```
import numpy as np
import pandas as pd
import statsmodels.api as sm
%matplotlib inline
```

1.1 CO2 Levels atop Mauna Loa, HI

Atmospheric CO levels from air samples collected at Mauna Loa Observatory, Hawaii, USA from March 1958 to November 2018. This dataset lacks a DateTime index, and instead relies on a decimal_date value supplied by the provider. Also, missing data is handled with an interpolated values column. Source: https://www.esrl.noaa.gov/gmd/ccgg/trends/data.html

[2]:
```
df1 = pd.read_csv('../Data/co2_mm_mlo.csv')
df1.head()
```

[2]:

	year	month	decimal_date	average	interpolated
0	1958	3	1958.208	315.71	315.71
1	1958	4	1958.292	317.45	317.45
2	1958	5	1958.375	317.50	317.50
3	1958	6	1958.458	NaN	317.10
4	1958	7	1958.542	315.86	315.86

[3]:
```
# To create a DatetimeIndex
df1['date']=pd.to_datetime(dict(year=df1['year'], month=df1['month'], day=1))
df1.set_index('date',inplace=True)
df1.index.freq = 'MS'
df1.head()
```

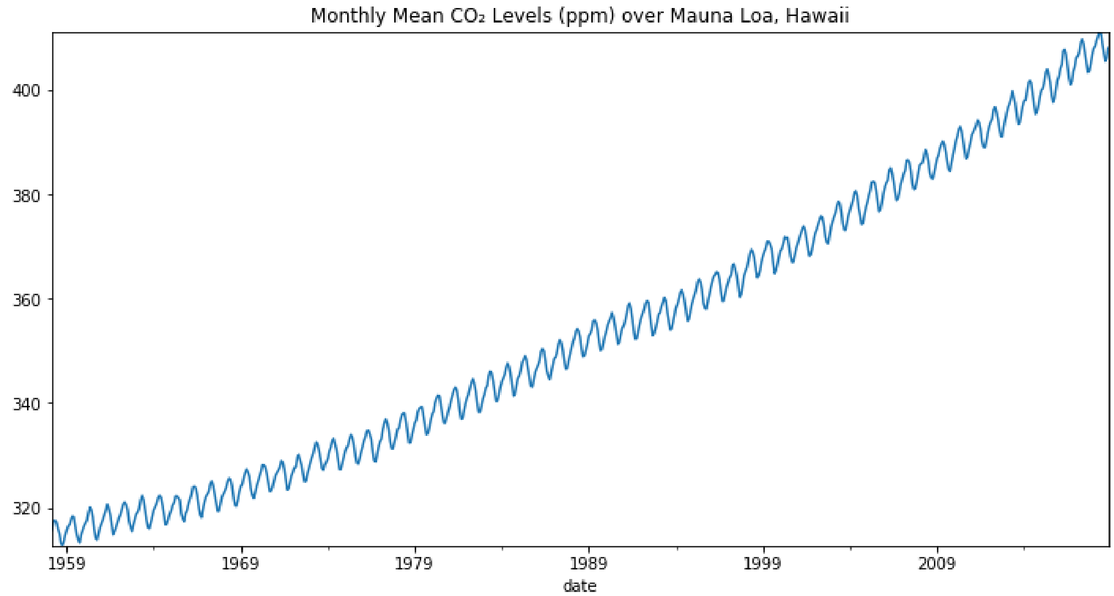
[3]:

	year	month	decimal_date	average	interpolated
date					
1958-03-01	1958	3	1958.208	315.71	315.71
1958-04-01	1958	4	1958.292	317.45	317.45
1958-05-01	1958	5	1958.375	317.50	317.50
1958-06-01	1958	6	1958.458	NaN	317.10
1958-07-01	1958	7	1958.542	315.86	315.86

1.1.1 Alternatively, load from statsmodels built-in datasets

NOTE: At the time of this writing the statsmodels co2 dataset has a known issue with pandas. df = sm.datasets.co2.load_pandas().data raises TypeError: **new**() got an unexpected keyword argument 'format' This is due to be fixed in an upcoming release.

[4]:
```
title = 'Monthly Mean CO  Levels (ppm) over Mauna Loa, Hawaii'
#df1.plot('decimal_date','interpolated',figsize=(12,6),title=title).
↪autoscale(axis='both',tight=True);
df1['interpolated'].plot(figsize=(12,6),title=title).
↪autoscale(axis='both',tight=True);
```



1.2 US Macroeconomic Data

Contains U.S. Macroeconomic Data from Q1 1959 to Q3 2009.

[6]:

```
df2 = pd.read_csv('../Data/macrodata.csv',index_col=0,parse_dates=True)
df2.head()
```

[6]:

```
            year  quarter   realgdp  realcons  realinv  realgovt  realdpi  \
1959-03-31  1959        1  2710.349    1707.4  286.898   470.045   1886.9
1959-06-30  1959        2  2778.801    1733.7  310.859   481.301   1919.7
1959-09-30  1959        3  2775.488    1751.8  289.226   491.260   1916.4
1959-12-31  1959        4  2785.204    1753.7  299.356   484.052   1931.3
1960-03-31  1960        1  2847.699    1770.5  331.722   462.199   1955.5

              cpi     m1  tbilrate  unemp      pop  infl  realint
1959-03-31  28.98  139.7      2.82    5.8  177.146  0.00     0.00
1959-06-30  29.15  141.7      3.08    5.1  177.830  2.34     0.74
1959-09-30  29.35  140.5      3.82    5.3  178.657  2.74     1.09
1959-12-31  29.37  140.0      4.33    5.6  179.386  0.27     4.06
1960-03-31  29.54  139.6      3.50    5.2  180.007  2.31     1.19
```

1.2.1 Alternatively, load from statsmodels built-in datasets

[14]:
```
df2sm = sm.datasets.macrodata.load_pandas().data
df2sm.index = pd.Index(sm.tsa.datetools.dates_from_range('1959Q1', '2009Q3'))
print(sm.datasets.macrodata.NOTE)
df2sm.head()
```

```
::
    Number of Observations - 203

    Number of Variables - 14

    Variable name definitions::

        year      - 1959q1 - 2009q3
        quarter   - 1-4
        realgdp   - Real gross domestic product (Bil. of chained 2005 US$,
                    seasonally adjusted annual rate)
        realcons  - Real personal consumption expenditures (Bil. of chained
                    2005 US$, seasonally adjusted annual rate)
        realinv   - Real gross private domestic investment (Bil. of chained
                    2005 US$, seasonally adjusted annual rate)
        realgovt  - Real federal consumption expenditures & gross investment
                    (Bil. of chained 2005 US$, seasonally adjusted annual rate)
        realdpi   - Real private disposable income (Bil. of chained 2005
                    US$, seasonally adjusted annual rate)
        cpi       - End of the quarter consumer price index for all urban
                    consumers: all items (1982-84 = 100, seasonally adjusted).
        m1        - End of the quarter M1 nominal money stock (Seasonally
                    adjusted)
        tbilrate  - Quarterly monthly average of the monthly 3-month
                    treasury bill: secondary market rate
        unemp     - Seasonally adjusted unemployment rate (%)
        pop       - End of the quarter total population: all ages incl. armed
                    forces over seas
        infl      - Inflation rate (ln(cpi_{t}/cpi_{t-1}) * 400)
        realint   - Real interest rate (tbilrate - infl)
```

[14]:

	year	quarter	realgdp	realcons	realinv	realgovt	realdpi \
1959-03-31	1959.0	1.0	2710.349	1707.4	286.898	470.045	1886.9
1959-06-30	1959.0	2.0	2778.801	1733.7	310.859	481.301	1919.7
1959-09-30	1959.0	3.0	2775.488	1751.8	289.226	491.260	1916.4
1959-12-31	1959.0	4.0	2785.204	1753.7	299.356	484.052	1931.3
1960-03-31	1960.0	1.0	2847.699	1770.5	331.722	462.199	1955.5

	cpi	m1	tbilrate	unemp	pop	infl	realint

1959-03-31	28.98	139.7	2.82	5.8	177.146	0.00	0.00
1959-06-30	29.15	141.7	3.08	5.1	177.830	2.34	0.74
1959-09-30	29.35	140.5	3.82	5.3	178.657	2.74	1.09
1959-12-31	29.37	140.0	4.33	5.6	179.386	0.27	4.06
1960-03-31	29.54	139.6	3.50	5.2	180.007	2.31	1.19

1.3 Starbucks Stock Data

Contains daily closing prices and daily trading volumes for Starbucks stock from 2015 to 2018.

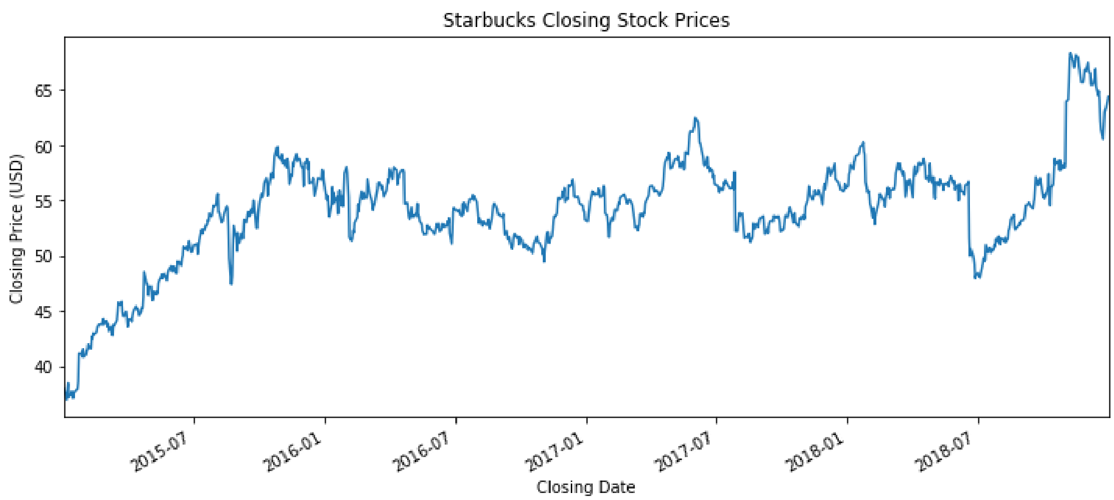
[4]:
```
df3 = pd.read_csv('../Data/starbucks.csv', index_col='Date', parse_dates=True)
df3.head()
```

[4]:

	Close	Volume
Date		
2015-01-02	38.0061	6906098
2015-01-05	37.2781	11623796
2015-01-06	36.9748	7664340
2015-01-07	37.8848	9732554
2015-01-08	38.4961	13170548

[8]:
```
title='Starbucks Closing Stock Prices'
ylabel='Closing Price (USD)'
xlabel='Closing Date'

ax = df3['Close'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.4 Energy Production

Contains data from the Federal Reserve Economic Database (FRED) concerning the Industrial Production Index for Electricity and Gas Utilities from January 1970 to December 1989. Source: https://fred.stlouisfed.org/series/IPG2211A2N

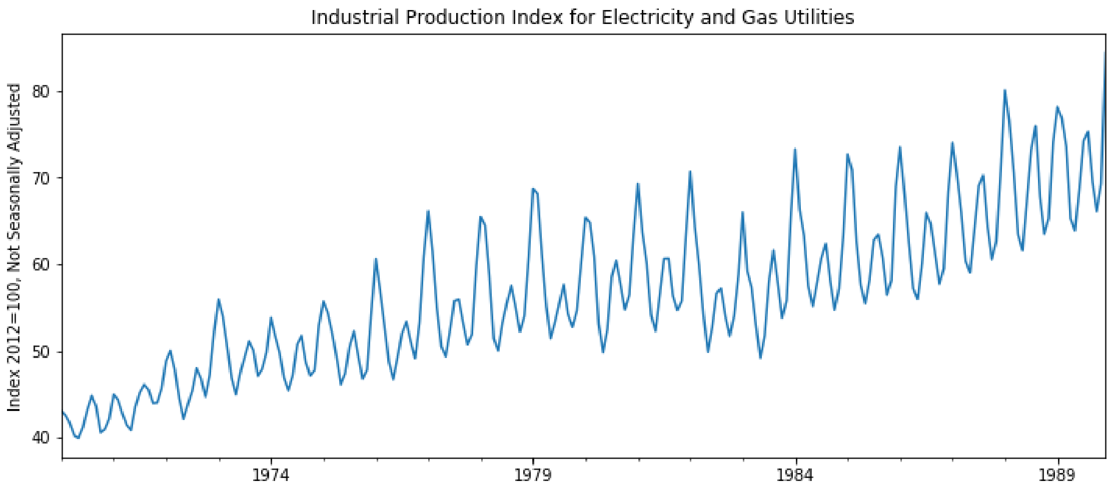
[3]:
```
df4 = pd.read_csv('../Data/EnergyProduction.csv',index_col=0,parse_dates=True)
df4.head()
```

[3]:

DATE	EnergyIndex
1970-01-01	43.0869
1970-02-01	42.5577
1970-03-01	41.6215
1970-04-01	40.1982
1970-05-01	39.9321

[4]:
```
title='Industrial Production Index for Electricity and Gas Utilities'
ylabel='Index 2012=100, Not Seasonally Adjusted'
xlabel=''

ax = df4['EnergyIndex'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.5 U.S. Population Data

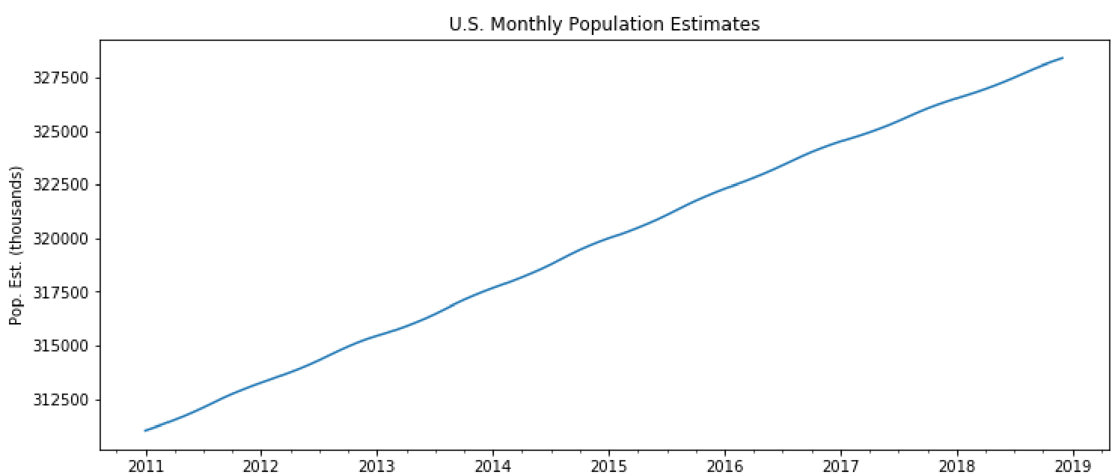
Contains monthly U.S. population estimates in thousands from January 2011 to December 2018 (96 records, or 8 years of data). Population includes resident population plus armed forces overseas. The monthly estimate is the average of estimates for the first of the month and the first of the following month. Source: https://fred.stlouisfed.org/series/POPTHM

[14]:
```
df5 = pd.read_csv('../Data/uspopulation.csv',index_col=0,parse_dates=True)
df5.head()
```

[14]:
```
            PopEst
DATE
2011-01-01  311037
2011-02-01  311189
2011-03-01  311351
2011-04-01  311522
2011-05-01  311699
```

[16]:
```
title='U.S. Monthly Population Estimates'
ylabel='Pop. Est. (thousands)'
xlabel='' # we don't really need a label here

ax = df5['PopEst'].plot(figsize=(12,5),title=title);
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.6 Temperature Data - Mt. Washington, NH

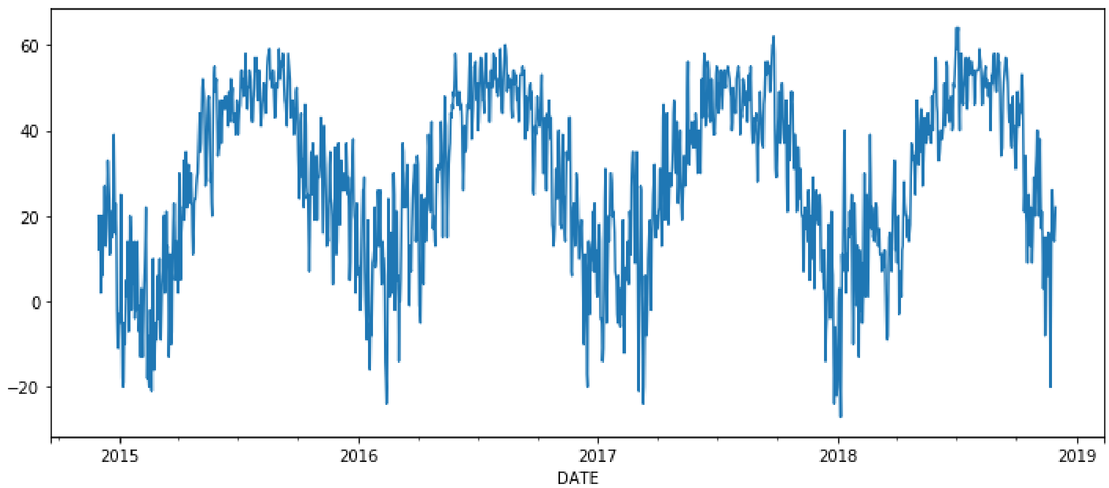
Contains Daily Minimum Dry Bulb Temperatures (°F) recorded on the summit of Mt. Washington in New Hampshire from December 1, 2014 to November 30, 2018. The dataset contains four years of temperature data. (1461 records, 7 columns) Source: https://www.ncdc.noaa.gov/data-access

[12]:
```
df6 = pd.read_csv('../Data/MtWashingtonDailyTemps.
 ↪csv',index_col='DATE',parse_dates=True)
df6.index.freq = 'D'
df6.head()
```

[12]:

	MinTemp	MaxTemp	AvgTemp	AvgWindSpeed	Sunrise	Sunset
DATE						
2014-12-01	3	36	20	65.1	700	1608
2014-12-02	1	22	12	34.7	702	1607
2014-12-03	8	32	20	53.0	703	1607
2014-12-04	-5	9	2	60.2	704	1607
2014-12-05	6	17	12	30.5	705	1607

[13]:
```
df6['AvgTemp'].plot(figsize=(12,5));
```



1.7 Temperature Data - Mauna Loa, HI

Contains Daily Minimum Dry Bulb Temperatures (°F) recorded at Mauna Loa in Hawaii from January 1, 2014 to December 30, 2018. The dataset contains five years of temperature data. (1825 records, 6 columns) Source: https://www.ncdc.noaa.gov/data-access

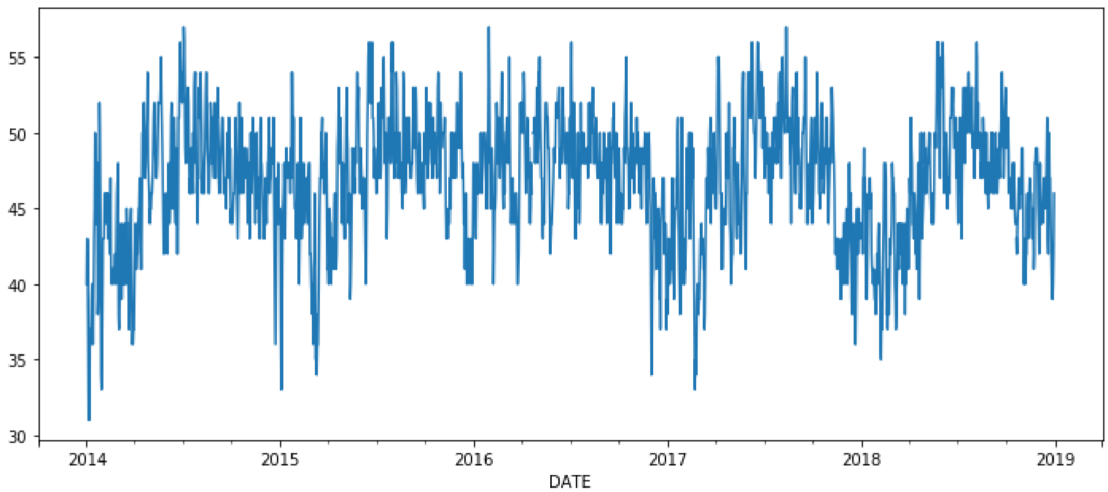
[7]:
```
df7 = pd.read_csv('../Data/MaunaLoaDailyTemps.
 ↪csv',index_col='DATE',parse_dates=True)
df7.index.freq = 'D'
df7.head()
```

[7]:

	MinTemp	MaxTemp	AvgTemp	Sunrise	Sunset
DATE					
2014-01-01	33.0	46.0	40.0	657	1756
2014-01-02	35.0	50.0	43.0	657	1756
2014-01-03	36.0	45.0	41.0	657	1757
2014-01-04	32.0	41.0	37.0	658	1757
2014-01-05	24.0	38.0	31.0	658	1758

[8]:

```
df7['AvgTemp'].plot(figsize=(12,5));
```



1.8 Airline Passengers

[5]:

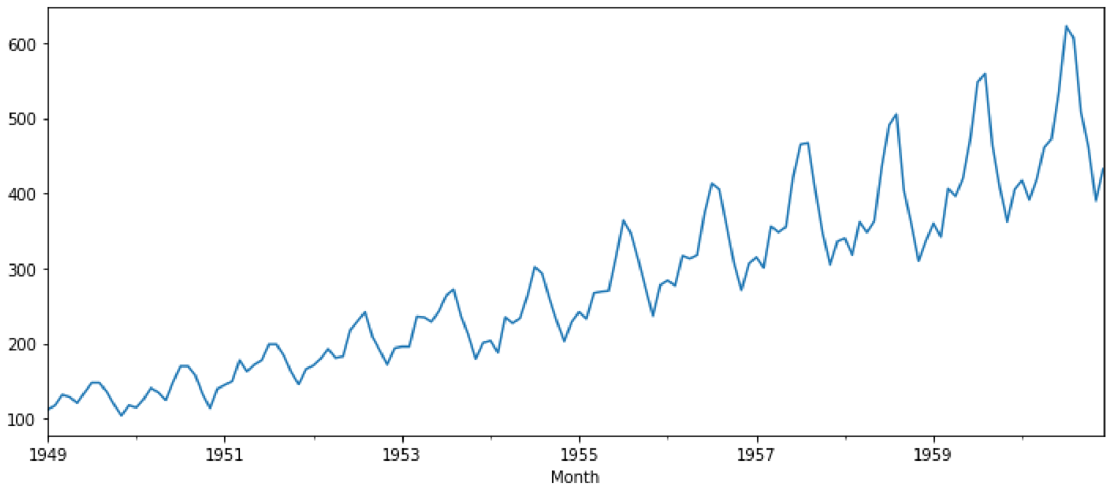
```
df8 = pd.read_csv('../Data/airline_passengers.
↪csv',index_col='Month',parse_dates=True)
df8.index.freq = 'MS'
df8.head()
```

[5]:

	Thousands of Passengers
Month	
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121

[6]:

```
df8['Thousands of Passengers'].plot(figsize=(12,5)).
↪autoscale(axis='x',tight=True);
```



1.9 Daily Total Female Births

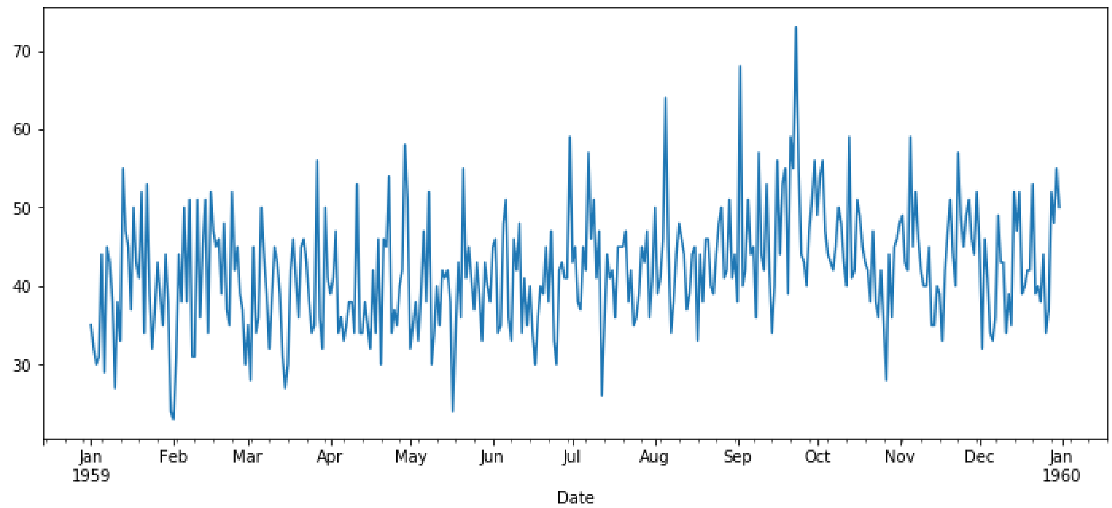
Contains Daily Total Female Births in California during 1959. The dataset contains 365 records. Source: https://datamarket.com/data/set/235k/daily-total-female-births-in-california-1959

[10]:
```
df9 = pd.read_csv('../Data/DailyTotalFemaleBirths.
↪csv',index_col='Date',parse_dates=True)
df9.index.freq = 'D'
df9.head()
```

[10]:

	Births
Date	
1959-01-01	35
1959-01-02	32
1959-01-03	30
1959-01-04	31
1959-01-05	44

[11]:
```
df9['Births'].plot(figsize=(12,5));
```



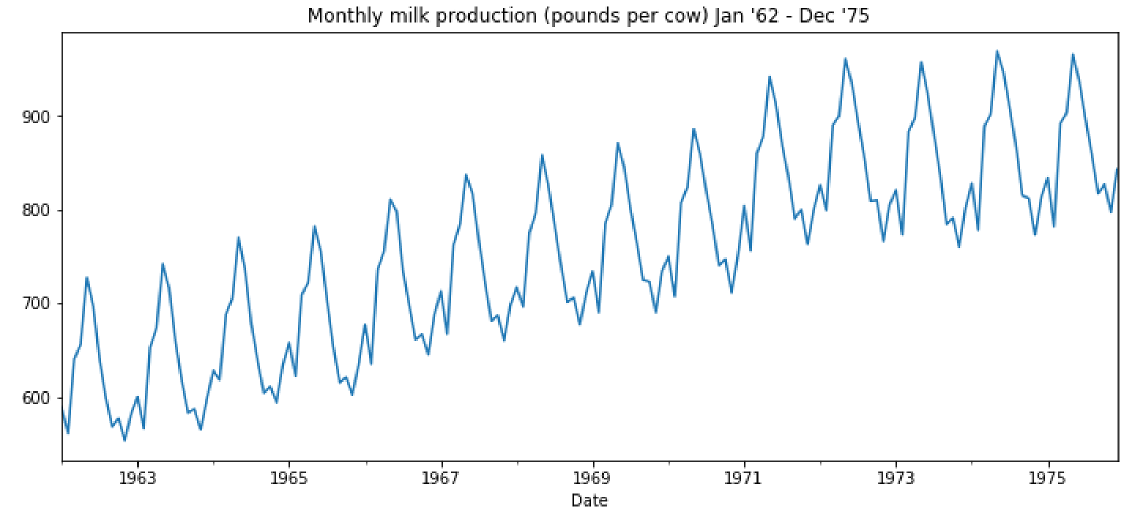
1.10 Monthly Milk Production

Contains monthly milk production values in pounds per cow from January 1962 to December 1975. (168 records, 2 columns) Source: https://datamarket.com/data/set/22ox/monthly-milk-production-pounds-per-cow-jan-62-dec-75

[2]:
```
df10 = pd.read_csv('../Data/monthly_milk_production.
↪csv',index_col='Date',parse_dates=True)
df10.index.freq = 'MS'
df10.head()
```

[2]:
```
            Production
Date
1962-01-01         589
1962-02-01         561
1962-03-01         640
1962-04-01         656
1962-05-01         727
```

[6]:
```
title = "Monthly milk production (pounds per cow) Jan '62 - Dec '75"
df10['Production'].plot(title=title,figsize=(12,5)).autoscale(axis='x',␣
↪tight=True);
```



[7]:
```
df10.describe().transpose()
```

[7]:

	count	mean	std	min	25%	50%	75%	max
Production	168.0	754.708333	102.204524	553.0	677.75	761.0	824.5	969.0

1.11 Danube River Discharge

Mean annual discharge (m^3/s) of the Danube River at Orshava, Romania, 1837–1957 (120 records)Source: https://datamarket.com/data/set/22qc/danube-river-at-orshava-romania-1837-1957

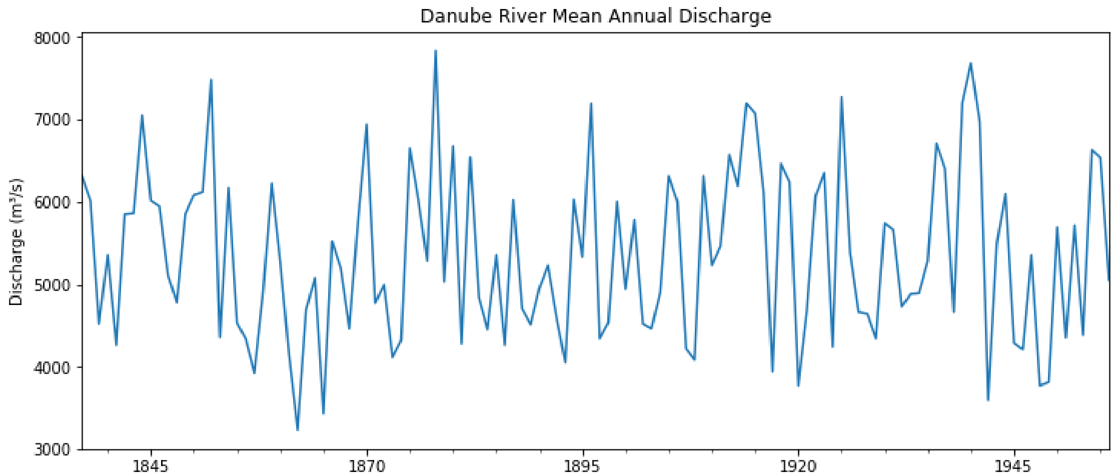
[4]:
```
df11 = pd.read_csv('../Data/danube_river_discharge.
↪csv',index_col='Year',parse_dates=True)
df11.index.freq = 'AS'
df11.head()
```

[4]:

	Discharge
Year	
1837-01-01	6315.937
1838-01-01	6015.683
1839-01-01	4525.167
1840-01-01	5361.574
1841-01-01	4267.812

[10]:
```
title = 'Danube River Mean Annual Discharge'
ylabel='Discharge (m³/s)'
xlabel='' # we don't really need a label here
```

```
ax = df11['Discharge'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.12 Rhine River Discharge

Mean annual discharge (m^3/s) of the Rhine River near Basel, Switzerland, 1807–1957 (150 records)Source: https://datamarket.com/data/set/22wp/rhine-river-near-basle-switzerland-1807-1957

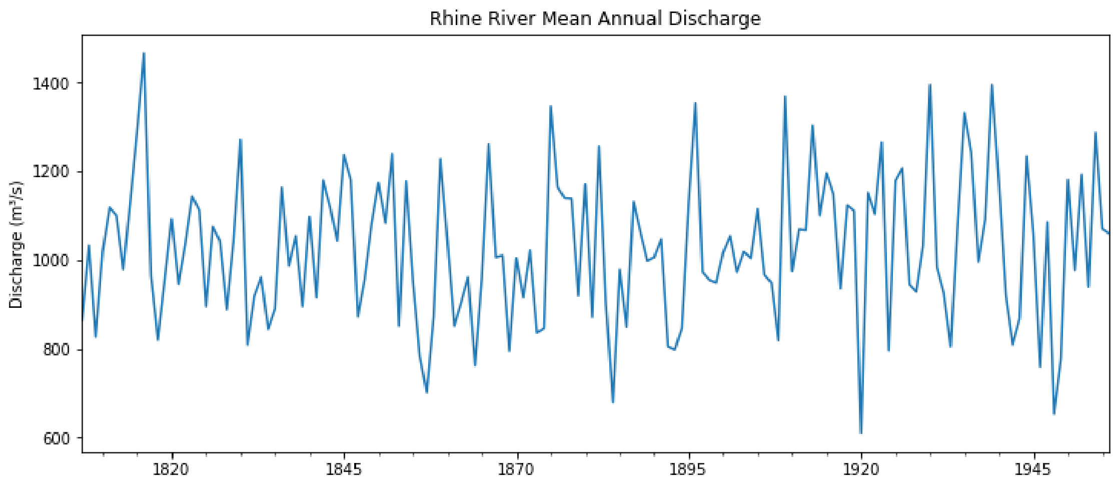
[11]:
```
df12 = pd.read_csv('../Data/rhine_river_discharge.
 ↪csv',index_col='Year',parse_dates=True)
df12.index.freq = 'AS'
df12.head()
```

[11]:

Year	Discharge
1807-01-01	864.884
1808-01-01	1033.141
1809-01-01	826.923
1810-01-01	1018.777
1811-01-01	1118.296

[12]:
```
title = 'Rhine River Mean Annual Discharge'
ylabel='Discharge (m³/s)'
xlabel='' # we don't really need a label here
```

```
ax = df12['Discharge'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.13 Price of Ground Chuck

Average price of ground chuck (100% beef) per pound. Source: U.S. Bureau of Labor Statistics, Consumer Price Index https://www.bls.gov/charts/consumer-price-index/consumer-price-index-average-price-data.htm

[2]:
```
df13 = pd.read_csv('../Data/price_of_ground_chuck.
 ↪csv',index_col='Month',parse_dates=True)
df13.index.freq = 'MS'
df13.head()
```

[2]:

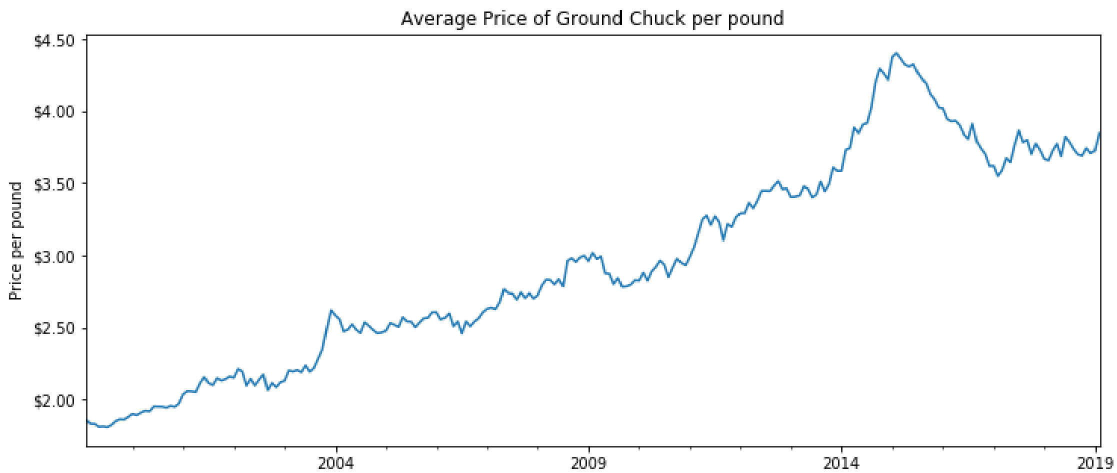
Month	Price
1999-02-01	1.862
1999-03-01	1.834
1999-04-01	1.833
1999-05-01	1.812
1999-06-01	1.815

[6]:
```
# HERE'S A TRICK TO PUT DOLLAR SIGNS ON Y-AXIS TICKS
import matplotlib.ticker as ticker
formatter = ticker.FormatStrFormatter('$%1.2f')

title = 'Average Price of Ground Chuck per pound'
```

```
ylabel='Price per pound'
xlabel='' # we don't really need a label here

ax = df13['Price'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
ax.yaxis.set_major_formatter(formatter);
```



1.14 Real Manufacturing and Trade Inventories

Real Manufacturing and Trade Inventory Estimates in Chained 2012 Dollars, Seasonally Adjusted, Jan 1997-Dec 2018 (264 records)For information on how these estimates are obtained visit https://apps.bea.gov/scb/pdf/2009/10%20October/1009_isr.pdf Source: https://fred.stlouisfed.org/series/INVCMRMT

[3]:
```
df14 = pd.read_csv('../Data/TradeInventories.
 ↪csv',index_col='Date',parse_dates=True)
df14.index.freq = 'MS'
df14.head()
```

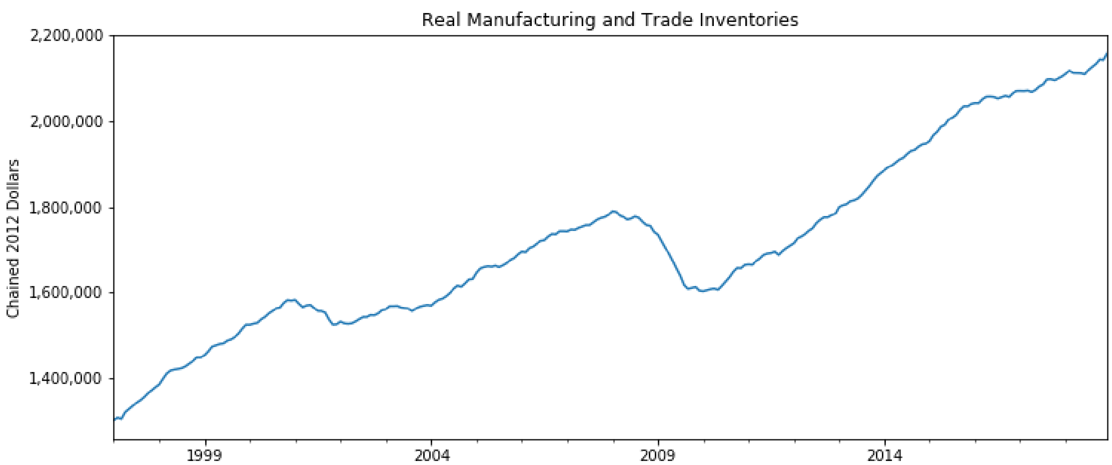
[3]:

	Inventories
Date	
1997-01-01	1301161
1997-02-01	1307080
1997-03-01	1303978
1997-04-01	1319740
1997-05-01	1327294

[11]:
```
# HERE'S A TRICK TO ADD COMMAS TO Y-AXIS TICK VALUES
import matplotlib.ticker as ticker
formatter = ticker.StrMethodFormatter('{x:,.0f}')

title='Real Manufacturing and Trade Inventories'
ylabel='Chained 2012 Dollars'
xlabel='' # we don't really need a label here

ax = df14['Inventories'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
ax.yaxis.set_major_formatter(formatter);
```



1.15 California Publishing Industry Employees

All Employees: Information: Newspaper, Periodical, Book, and Directory Publishers in California in Thousands of Persons, Not Seasonally Adjusted, from Jan 1990-Dec 2018 (348 records) Source: https://fred.stlouisfed.org/series/SMU06000005051110001

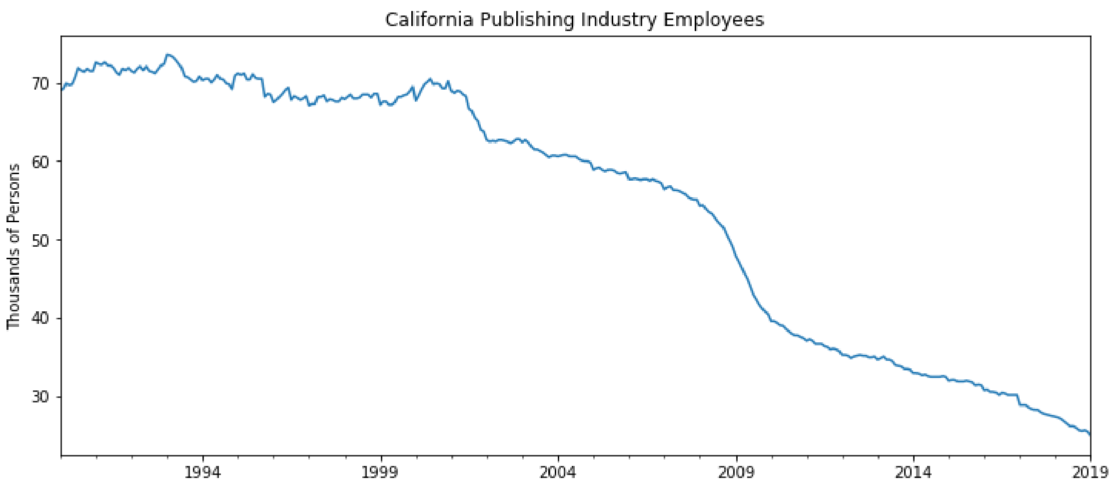
[12]:
```
df15 = pd.read_csv('../Data/PublishingEmployees.
 ↪csv',index_col='Date',parse_dates=True)
df15.index.freq = 'MS'
df15.head()
```

[12]:
```
            Employees
Date
1990-01-01       69.1
1990-02-01       69.2
```

```
1990-03-01        69.9
1990-04-01        69.7
1990-05-01        69.8
```

[15]:
```
title='California Publishing Industry Employees'
ylabel='Thousands of Persons'
xlabel='' # we don't really need a label here

ax = df15['Employees'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.16 California Hospitality Industry Employees

All Employees: Leisure and Hospitality in California in Thousands of Persons, Not Seasonally Adjusted, from Jan 1990-Dec 2018 (348 records) Source: https://fred.stlouisfed.org/series/CALEIHN

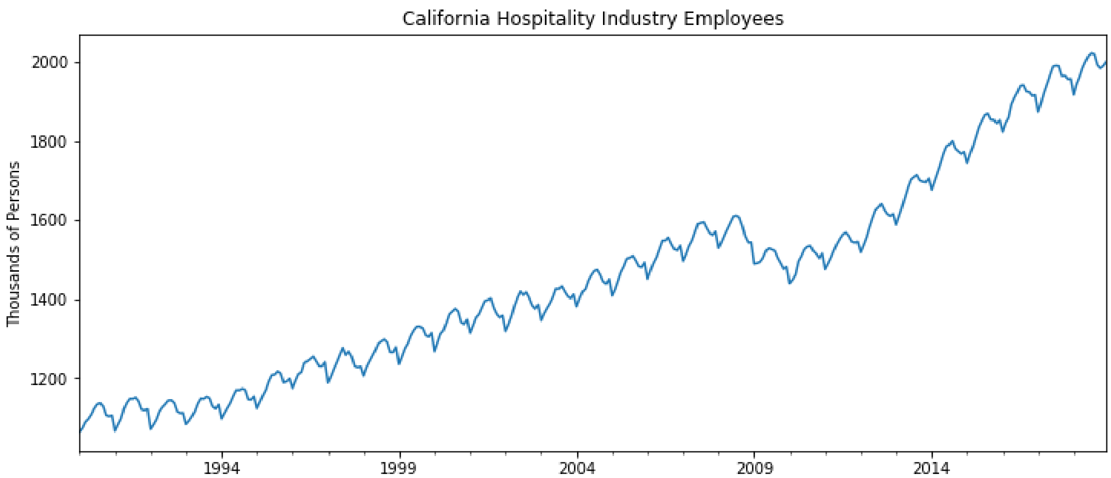
[7]:
```
df16 = pd.read_csv('../Data/HospitalityEmployees.
↪csv',index_col='Date',parse_dates=True)
df16.index.freq = 'MS'
df16.head()
```

[7]:
```
            Employees
Date
1990-01-01     1064.5
1990-02-01     1074.5
1990-03-01     1090.0
1990-04-01     1097.4
```

```
1990-05-01     1108.7
```

[8]:
```
title='California Hospitality Industry Employees'
ylabel='Thousands of Persons'
xlabel='' # we don't really need a label here

ax = df16['Employees'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.17 RideAustin

RideAustin is a non-profit, municipal ridesharing service based in Austin, Texas, with a model comparing directly to that of Uber. The data covers rides requested from June 4, 2016 to February 7, 2017 (249 days), just over 35 weeks. It shows a clear weekly cycle, with peak ride demand typically on Saturday. Data was made available by CEO Andy Tryba, at https://data.world/andytryba/rideaustin

[3]:
```
df17 = pd.read_csv('../Data/RideAustin.csv',index_col='Date',parse_dates=True)
df17.index.freq = 'D'
df17.head()
```

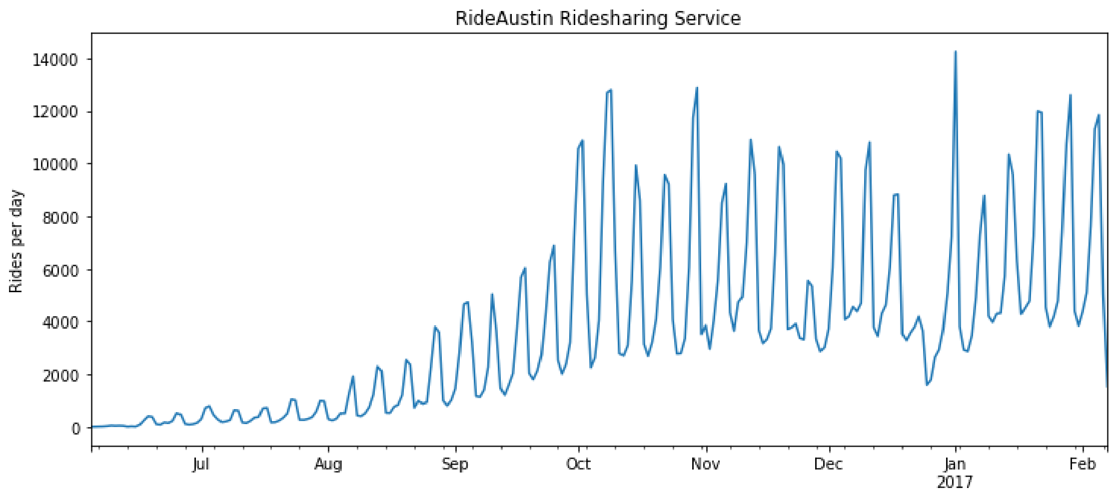
[3]:

	Rides	PRCP	TMAX	TMIN	AWND	GustSpeed2	Fog	HeavyFog	Thunder
Date									
2016-06-04	7	0.1	86	67	4.9	13.0	1	0	0
2016-06-05	12	0.0	88	68	5.8	14.1	0	0	0
2016-06-06	19	0.0	90	70	4.3	13.0	0	0	0
2016-06-07	22	0.0	92	69	2.0	8.1	0	0	0

2016-06-08	35	0.0	92	70	2.7	12.1	1	0	0

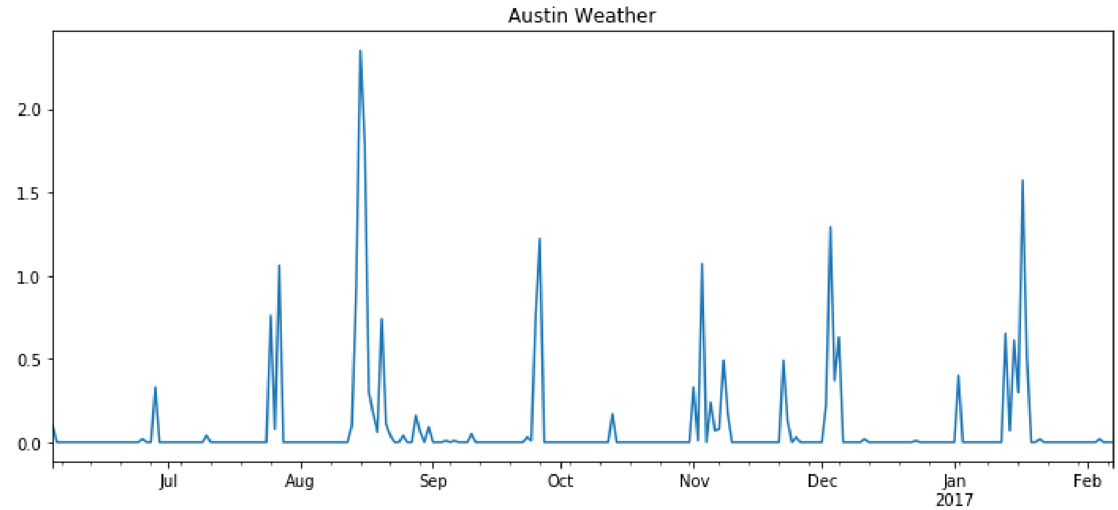
[4]:
```
title='RideAustin Ridesharing Service'
ylabel='Rides per day'
xlabel='' # we don't really need a label here

ax = df17['Rides'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



[7]:
```
title = 'Austin Weather'
ylabel=''
xlabel=''

ax = df17['PRCP'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.18 Value of Manufacturers' Shipments

Value of Manufacturers' Shipments for All Manufacturing Industries in millions of dollars, not seasonally adjusted. Monthly data, January 1992 to January 2019 (325 records). Source: https://fred.stlouisfed.org/series/UMTMVS

[3]:
```
df18 = pd.read_csv('../Data/UMTMVS.csv',index_col='DATE',parse_dates=True)
df18.index.freq = 'MS'
df18.head()
```

[3]:

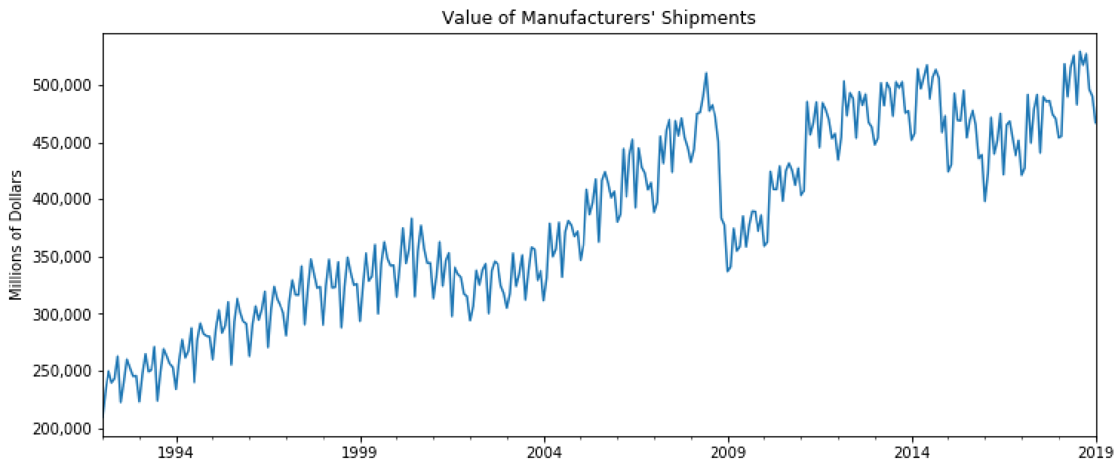
DATE	UMTMVS
1992-01-01	209438.0
1992-02-01	232679.0
1992-03-01	249673.0
1992-04-01	239666.0
1992-05-01	243231.0

[5]:
```
# HERE'S A TRICK TO ADD COMMAS TO Y-AXIS TICK VALUES
import matplotlib.ticker as ticker
formatter = ticker.StrMethodFormatter('{x:,.0f}')

title="Value of Manufacturers' Shipments" # be careful with quotes here!
ylabel='Millions of Dollars'
xlabel='' # we don't really need a label here

ax = df18['UMTMVS'].plot(figsize=(12,5),title=title)
```

```
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel)
ax.yaxis.set_major_formatter(formatter);
```



1.19 M2 Money Stock

U.S. M2 Money Stock in Billions of Dollars, Monthly, Seasonally Adjusted, 1/1/95-12/1/15 (252 records) Compared to M1, M2 includes a broader set of financial assets held principally by households. M2 consists of M1 plus: (1) savings deposits (which include money market deposit accounts, or MMDAs); (2) small-denomination time deposits (time deposits in amounts of less than $100,000); and (3) balances in retail money market mutual funds (MMMFs). Source: https://fred.stlouisfed.org/series/M2SL

[2]:
```
df19 = pd.read_csv('../Data/M2SLMoneyStock.
 ↪csv',index_col='Date',parse_dates=True)
df19.index.freq = 'MS'
df19.head()
```

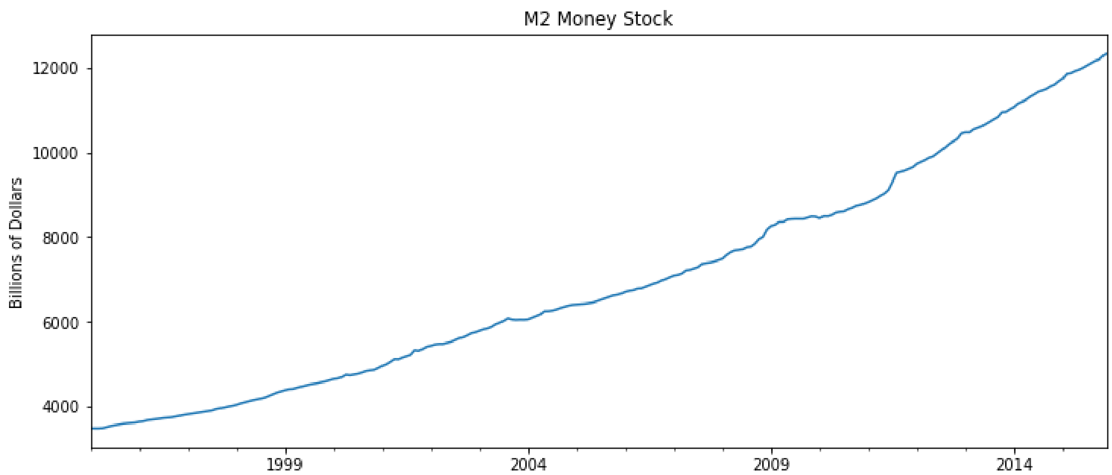
[2]:

Date	Money
1995-01-01	3492.4
1995-02-01	3489.9
1995-03-01	3491.1
1995-04-01	3499.2
1995-05-01	3524.2

[3]:
```
title = 'M2 Money Stock'
ylabel='Billions of Dollars'
```

```
xlabel=''

ax = df19['Money'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.20 Personal Spending

U.S. Personal Consumption Expenditures in Billions of Dollars, Monthly, Seasonally Adjusted, 1/1/95-12/1/15 (252 records) See Bureau of Economic Analysis, BEA Account Code: DPCERC A Guide to the National Income and Product Accounts of the United States (NIPA) - http://www.bea.gov/national/pdf/nipaguid.pdf Source: https://fred.stlouisfed.org/series/PCE

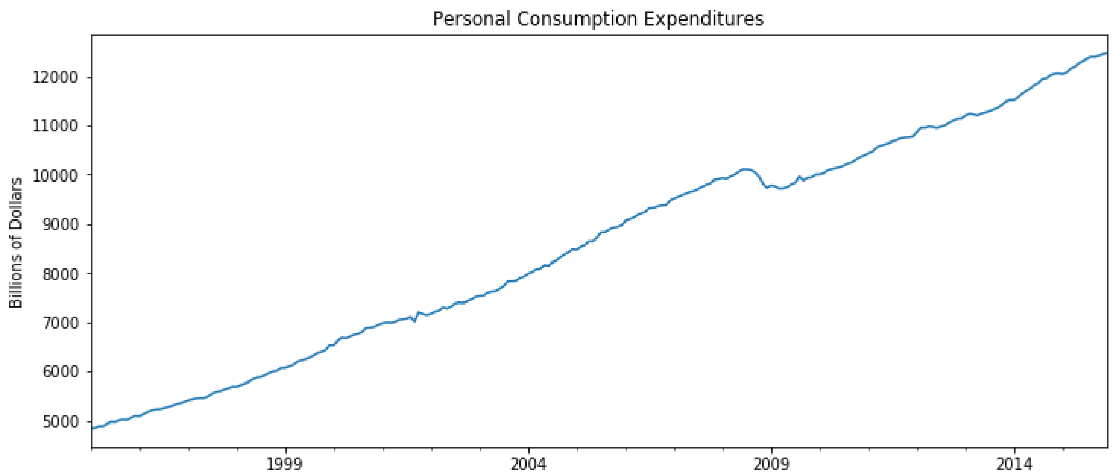
[4]:
```
df20 = pd.read_csv('../Data/PCEPersonalSpending.csv',index_col=0,␣
↪parse_dates=True)
df20.index.freq = 'MS'
df20.head()
```

[4]:
```
            Spending
Date
1995-01-01    4851.2
1995-02-01    4850.8
1995-03-01    4885.4
1995-04-01    4890.2
1995-05-01    4933.1
```

[5]:
```
title = 'Personal Consumption Expenditures'
ylabel='Billions of Dollars'
```

```
xlabel=''

ax = df20['Spending'].plot(figsize=(12,5),title=title)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



1.21 U.S. Population by County

Population data from the 2010 Census and 2017 Estimates for counties in the 50 U.S. States and District of Columbia. Data is used for pandas exercises - it does not contain dates. (3142 records, 4 columns) Source: https://www.census.gov/data/tables/2017/demo/popest/counties-total.html

[5]:
```
dfx = pd.read_csv('../Data/population_by_county.csv')
dfx.head()
```

[5]:

	County	State	2010Census	2017PopEstimate
0	Abbeville County	South Carolina	25417	24722
1	Acadia Parish	Louisiana	61773	62590
2	Accomack County	Virginia	33164	32545
3	Ada County	Idaho	392365	456849
4	Adair County	Iowa	7682	7054

[ ]:
```
```