Machine Learning Foundation

Course 6, Part a: Pandas TimeSeries LAB

Learning Outcomes

- Understand time series applications for NumPy and Pandas
- Summarize a dataframe with a datetime index
- Generate simple time series plots

Overview: Time Series Data in Python

In this lesson, we will explore some key Time Series-related functionality in the Numpy, Pandas, and Matplotlib packages. We will explore basic data types and summarize a Pandas DataFrame with a DateTime index. We will also explore basic plotting and Time Series visualization. For this lesson, we will use a sample dataset called "Superstore Sales", which includes 4 years of daily Sales data by customer and category. Note: this lesson assumes some basic familiarity with Python and Python data types. References are provided for introductory lessons for each module.

Pandas: has built-in Time Series functionality to work with dates, date ranges, and Time Series data. It is useful for analyzing groups of time series and manipulating data.

Key Data Types for Time Series Data

Key NumPy data types:

> 1. **`Array`** : Array of similarly-typed values, fundamental building block of further analysis. The NumPy **Array** object has several useful built-in methods, including: `shape` , `max` / `min` , `argmax` / `argmin` , `sum` , `cumsum` , `mean` , `var` , `std` , `prod` , `cumprod` , etc.
> 2. **`datetime64`** : is NumPy's datetime format, where each value is a timestamp. It was created to improve on Python's datetime format, and stores timestamps as 64-bit integers. These timestamps often default to nanosecond precision (`datetime64[ns]`), even when working with daily or hourly data, although this can be adjusted.
> 3. **`timedelta64`** : is NumPy's time interval format, which can be thought of as a period of time between two *datetime64* values and uses the same units as *datetime64*. The most common unit values are: **Y**: `year` , **M**: `month` , **W**: `week` , **D**: `day` , **h**: `hour` , **m**: `minute` , **s**: `second` , **ns**: `nanosecond` (default).

Key Pandas data types:

> 1. `Series` : Series is a one-dimensional labeled array that is capable of holding any data type (i.e. `int` , `str` , `float` , etc.), but every element is of this same type. The axis labels of a Series are referred to as the **Index** of the Series, while the Pandas **Series** object is similar to the NumPy **Array**,
> 2. `DataFrame` : Dataframe is a two-dimensional labeled data structure with columns of potentially different types. It largely resembles a spreadsheet or SQL table. The first axis labels of a Dataframe (rows) are referred to as the **Index** of the Series, whereas the second axis labels labels of a Dataframe (columns) are referred to as the **Columns** of the Series
> 3. `Index` : Pandas provides much of its functionality through the **Index** object. Every DataFrame has an attribute: `.index` , which uniquely labels rows and columns and facilitates DataFrame manipulation. The simplest (default) Index type is a RangeIndex, usually a list of integer values. This is often automatically generated when an Index is not set explicitly, or when the Index is reset. Time Series data are usually best represented using the **DatetimeIndex** Index, which is an index of NumPy datetime64 values. However, it is sometimes convenient to use time intervals for the index using the **Timedelta** index, or the **PeriodIndex** when intervals are regular. Pandas supports multiple-level indexing (including hierarchical indexing) via the **MultiIndex**, which accommodates indices of different types and can simplify data exploration.

Dataset Exploration Example

Here we will read in some sample data and explore some key data types and attributes. Our source data is a publicly-available retail sales dataset: **Superstore Sales**, available as a spreadsheet. We begin by importing the libraries and reading in data.

Setup

In [1]:

```
# imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from datetime import datetime
from datetime import timedelta
from dateutil.relativedelta import relativedelta
from IPython.display import display
import os
os.chdir('data')
from colorsetup import colors, palette
sns.set_palette(palette)
# ignore warnings
warnings.filterwarnings('ignore')
```

```
pd.options.display.float_format = '{:,.1f}'.format
%matplotlib inline
plotsize = (13, 5)
```

Read in source data:

It is often easiest to read data in as a Pandas DataFrame. Pandas provides a variety of **Input/Output** options to read files from common (.csv, .json) or proprietary (.xls, .sas7bdat) formats.

In [2]:
```
df = pd.read_excel("Sample - Superstore.xls")
df.columns
```

Out[2]:
```
Index(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'State',
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Sales', 'Quantity', 'Discount', 'Profit'],
      dtype='object')
```

We can see the data have been input and the columns are referenced by a Pandas Index object. There are two Date variables (Order Date and Ship Date), variables for customer and region, product type variables (Category, Sub-Category, Product Name), etc.

Simplify Time Series Data

We will start by simplifying the input data a bit to explore data types. To do so, we will look at Total Sales by Order Date and Category. This allows us to look a Time Series dataset with multiple time series.

In [3]:
```
variables = ['Order Date', 'Category', 'Sales']
group_variables = variables[:2]
outcome_variable = variables[2]
base = df.groupby(group_variables)[outcome_variable].sum().reset_index()
```

Note we reset the index, if we don't, Pandas sets the group variables to the index (more on this later). We can see the result is a Pandas DataFrame with columns for `Order Date`, `Category`, and `Sales`. We can think of this as a `Sales` time series for each `Category`.

In [4]:
```
print("Columns:", base.columns)
print("Index:", base.index)
```

```
Columns: Index(['Order Date', 'Category', 'Sales'], dtype='object')
Index: RangeIndex(start=0, stop=2864, step=1)
```

In [5]:
```
base.head()
```

Out[5]:

	Order Date	Category	Sales
0	2011-01-04	Office Supplies	16.4
1	2011-01-05	Office Supplies	288.1
2	2011-01-06	Office Supplies	19.5
3	2011-01-07	Furniture	2,573.8
4	2011-01-07	Office Supplies	685.3

Individual DataFrame columns are Pandas `Series`, and we can see the `RangeIndex` on the left. This Pandas `DataFrame` is a combination of the `RangeIndex` and Pandas `Series` objects, where each has an underlying data type:

In [6]:
```
base.dtypes
```

Out[6]:
```
Order Date    datetime64[ns]
Category              object
Sales                float64
dtype: object
```

Pandas DataFrame types:

In [7]:
```
for x in base.columns:
    print(x, type(base[x]), base[x].dtype)
```

```
Order Date <class 'pandas.core.series.Series'> datetime64[ns]
Category <class 'pandas.core.series.Series'> object
Sales <class 'pandas.core.series.Series'> float64
```

Working with NumPy Arrays

It isn't always necessary to extract NumPy arrays, as the Pandas Series contains NumPy functionality. However, some applications use NumPy arrays as inputs and can bypass Pandas if desired.

In [8]:
```
order_date = np.array(base['Order Date'])
category = np.array(base['Category'])
sales = np.array (base['Sales'])
```

In [9]:
```
print('Order Date', type(order_date), order_date.dtype)
print('Category', type(category), category.dtype)
print('Sales', type(sales), sales.dtype)
```

```
Order Date <class 'numpy.ndarray'> datetime64[ns]
Category <class 'numpy.ndarray'> object
Sales <class 'numpy.ndarray'> float64
```

If starting from the NumPy arrays, we could build the DataFrame (note dictionary input structure):

In [10]:
```
df_from_numpy = pd.DataFrame({'Order Date':order_date, 'Category':category, 'Sales
```

In [11]:
```
df_from_numpy.dtypes
```

Out[11]:
```
Order Date    datetime64[ns]
Category              object
Sales                float64
dtype: object
```

datetime64 format in Numpy

The NumPy date array is a datetime64 object, with ns (nanosecond) units. We can leave it this way, or specify a unit:

While the Array and Pandas Series are basically the same, we see the Series has an index, and formats the date output somewhat.

In [12]:
```
order_date
```

Out[12]:
```
array(['2011-01-04T00:00:00.000000000', '2011-01-05T00:00:00.000000000',
       '2011-01-06T00:00:00.000000000', ...,
       '2014-12-31T00:00:00.000000000', '2014-12-31T00:00:00.000000000',
       '2014-12-31T00:00:00.000000000'], dtype='datetime64[ns]')
```

In [13]:
```
order_date_daily = np.array(order_date, dtype='datetime64[D]')
```

In [14]:
```
order_date_daily
```

Out[14]:
```
array(['2011-01-04', '2011-01-05', '2011-01-06', ..., '2014-12-31',
       '2014-12-31', '2014-12-31'], dtype='datetime64[D]')
```

The order_date variable now has daily format, although this doesn't change much because we already had one observation per day. In practice, leaving nanosecond precision is usually fine.

However, if we aggregate to monthly:

In [15]:
```
order_date_monthly = np.array(order_date, dtype='datetime64[M]')
```

In [16]:
```
order_date_monthly
```

Out[16]:
```
array(['2011-01', '2011-01', '2011-01', ..., '2014-12', '2014-12',
       '2014-12'], dtype='datetime64[M]')
```

In [17]:
```
np.unique(order_date_monthly)
```

Out[17]:
```
array(['2011-01', '2011-02', '2011-03', '2011-04', '2011-05', '2011-06',
       '2011-07', '2011-08', '2011-09', '2011-10', '2011-11', '2011-12',
       '2012-01', '2012-02', '2012-03', '2012-04', '2012-05', '2012-06',
       '2012-07', '2012-08', '2012-09', '2012-10', '2012-11', '2012-12',
       '2013-01', '2013-02', '2013-03', '2013-04', '2013-05', '2013-06',
       '2013-07', '2013-08', '2013-09', '2013-10', '2013-11', '2013-12',
       '2014-01', '2014-02', '2014-03', '2014-04', '2014-05', '2014-06',
       '2014-07', '2014-08', '2014-09', '2014-10', '2014-11', '2014-12'],
      dtype='datetime64[M]')
```

In [18]:
```
len(np.unique(order_date_monthly))
```

Out[18]:
```
48
```

We can see we have 48 unique months of data.

Working with the Pandas DatetimeIndex

Let's return to our Pandas DataFrame object:

In [19]:
```
print(base.head())
print('\n Unique categories:')
print(base['Category'].unique())
```

```
  Order Date         Category   Sales
0 2011-01-04  Office Supplies    16.4
1 2011-01-05  Office Supplies   288.1
2 2011-01-06  Office Supplies    19.5
3 2011-01-07        Furniture 2,573.8
4 2011-01-07  Office Supplies   685.3

 Unique categories:
['Office Supplies' 'Furniture' 'Technology']
```

Setting Index Using Existing Variable

We often want to set an Index explicitly, or manipulate an Index, for working with Time Series data. The Pandas DateTime Index is useful here, although it is often useful to standardize the index by ensuring all relevant time periods are included only once. Our data violate this condition for two reasons: (1) Multiple values for a given period (due to multiple categories) and (2) Missing days (for daily data). We will fix both of these issues below, and explore some useful Datetime functionality.

In [20]:
```
base.set_index('Order Date', inplace=True)
# Note that without inplace=True, it will output the results without changing the d
```

In [21]:
```
base.head()
```

Out[21]:

	Category	Sales
Order Date		
2011-01-04	Office Supplies	16.4
2011-01-05	Office Supplies	288.1
2011-01-06	Office Supplies	19.5
2011-01-07	Furniture	2,573.8
2011-01-07	Office Supplies	685.3

In [22]:
```
print(base.index)
#print(base.index.unique())
```

```
DatetimeIndex(['2011-01-04', '2011-01-05', '2011-01-06', '2011-01-07',
               '2011-01-07', '2011-01-07', '2011-01-08', '2011-01-08',
               '2011-01-10', '2011-01-10',
               ...
               '2014-12-28', '2014-12-29', '2014-12-29', '2014-12-29',
               '2014-12-30', '2014-12-30', '2014-12-30', '2014-12-31',
               '2014-12-31', '2014-12-31'],
              dtype='datetime64[ns]', name='Order Date', length=2864, freq=None)
```

Subsetting data

We now have a **DatetimeIndex** and we can use it to select data subsets:

In [23]:
```
# Observations in 2014
print(base['2011'].head())
print('\n')
```

```
# Observations in a range of dates, subset of columns:
print(base[base['Category'] == 'Office Supplies']['2011':'2012-02'].head())
```

```
                   Category   Sales
Order Date
2011-01-04  Office Supplies    16.4
2011-01-05  Office Supplies   288.1
2011-01-06  Office Supplies    19.5
2011-01-07        Furniture 2,573.8
2011-01-07  Office Supplies   685.3


                   Category  Sales
Order Date
2011-01-04  Office Supplies   16.4
2011-01-05  Office Supplies  288.1
2011-01-06  Office Supplies   19.5
2011-01-07  Office Supplies  685.3
2011-01-08  Office Supplies   10.4
```

Datetime Components

Pandas Datetime variables have a number of useful **components**. Using the DatetimeIndex, we can extract items like month, year, day of week, quarter, etc.:

In [24]:
```
#base.set_index('Order Date', inplace=True)
print('Day:', base.index.day, '\n')
print('Week:', base.index.week, '\n')
base['DayofWeek'] = base.index.dayofweek # Day of Week: Monday=0, Sunday=6
print(base.head())
# Note: use dt method when the date variable is not part of the index:
# df['Order Date'].dt.dayofweek.head()
del(base['DayofWeek'])
```

```
Day: Int64Index([ 4,  5,  6,  7,  7,  7,  8,  8, 10, 10,
            ...
            28, 29, 29, 29, 30, 30, 30, 31, 31, 31],
           dtype='int64', name='Order Date', length=2864)

Week: Int64Index([ 1,  1,  1,  1,  1,  1,  1,  1,  2,  2,
            ...
            52,  1,  1,  1,  1,  1,  1,  1,  1,  1],
           dtype='int64', name='Order Date', length=2864)

                   Category   Sales  DayofWeek
Order Date
2011-01-04  Office Supplies    16.4          1
2011-01-05  Office Supplies   288.1          2
2011-01-06  Office Supplies    19.5          3
2011-01-07        Furniture 2,573.8          4
2011-01-07  Office Supplies   685.3          4
```

Standardizing the DatetimeIndex

While data from existing variables may be sufficient, some Time Series applications require that data contain all periods and have a Frequency assigned. We can see above that our data do not have a frequency (freq=None). While the data seem daily, there are many types of possible frequencies (business days, weekdays, etc.). If the input data are already standardized, Pandas will infer a Frequency and assign it. Otherwise, we need to ensure there are:

- No duplicate index values
- No missing index values

Setting a Frequency helps ensure the data are standardized and will work in applications, and is also required for functionality like resampling.

Pivoting Data:

Because there are multiple categories, we have multiple Time Series to analyze. As a result, our **DatetimeIndex** does not uniquely identify an observation. To uniquely identify observations, we can either add categorical variables to the Index, or set a Pandas DateTimeIndex with separate columns for each series. There are several ways to accomplish this. The first appraoch uses Pandas' built-in **pivot** method:

Pandas pivot method

In [25]:
```
base.reset_index(inplace=True)
# Note if we didn't reset the index, we could use index=None below
sales_pivot = base.pivot(index='Order Date', columns='Category', values='Sales')
sales_pivot.head()
```

Out[25]:

Category	Furniture	Office Supplies	Technology
Order Date			
2011-01-04	nan	16.4	nan
2011-01-05	nan	288.1	nan
2011-01-06	nan	19.5	nan
2011-01-07	2,573.8	685.3	1,147.9
2011-01-08	76.7	10.4	nan

Note that missing values (`NaN`) are often introduced here, and can be set to 0 easily using the `fillna(0)` method.

Unstacking:

To achieve the same result in Pandas, it is often easier to use the **Index** and **unstack** / **(stack)** methods. The **unstack** method transforms long data into wide data by creating columns by category for levels of the index, while **stack** does the reverse.

Here, we can tell Pandas that the `Date` and `Category` values are part of the **Index** and use the `unstack` function to generate separate columns (this also removes the `Category` column from the Index):

In [26]:
```
sales = base.set_index(['Order Date', 'Category']).unstack('Category').fillna(0)

# Note -- 2 levels of column names, the original variables are in columns.levels[0
```

```
# newly-created category variable names are in columns.levels[1]. This can be reset
# sales.columns = sales.columns.levels[1].rename(None)
# Alternatively, keeping 'Sales' as a level 0 name allows us to refer to the varial
sales.columns = sales.columns.levels[1].rename(None)
sales.head()
```

Out[26]:

Order Date	Furniture	Office Supplies	Technology
2011-01-04	0.0	16.4	0.0
2011-01-05	0.0	288.1	0.0
2011-01-06	0.0	19.5	0.0
2011-01-07	2,573.8	685.3	1,147.9
2011-01-08	76.7	10.4	0.0

In [27]:
```
print(sales.index)
print('\nUnique dates in our data: ', len(sales.index.unique()), 'Days')
```

```
DatetimeIndex(['2011-01-04', '2011-01-05', '2011-01-06', '2011-01-07',
               '2011-01-08', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-14', '2011-01-15',
               ...
               '2014-12-22', '2014-12-23', '2014-12-24', '2014-12-25',
               '2014-12-26', '2014-12-27', '2014-12-28', '2014-12-29',
               '2014-12-30', '2014-12-31'],
              dtype='datetime64[ns]', name='Order Date', length=1238, freq=None)

Unique dates in our data:  1238 Days
```

Since we have now created a column for each category, we can see there no longer repeated values in the Datetime Index.

Generating a complete Index and Setting Frequency

Since we are using daily data, we would like to set a daily frequency. We see our data has a length of 1238 days. By subtracting the smallest date from the largest date, we can tell there are some days missing:

In [28]:
```
print('\nUnique dates in our data: ', len(sales.index.unique()), 'Days')
our_date_range = sales.index.max() - sales.index.min()

# Calculate number of days in date range
print('Total days in our date range:', our_date_range.days, 'Days')
#date_range = pd.date_range(min(sales.index), max(sales.index))
```

```
Unique dates in our data:  1238 Days
Total days in our date range: 1457 Days
```

We can generate a complete index using Pandas' **date_range** function:

In [29]:
```
new_index = pd.date_range(sales.index.min(), sales.index.max())
print(new_index)
```

```
DatetimeIndex(['2011-01-04', '2011-01-05', '2011-01-06', '2011-01-07',
               '2011-01-08', '2011-01-09', '2011-01-10', '2011-01-11',
               '2011-01-12', '2011-01-13',
               ...
               '2014-12-22', '2014-12-23', '2014-12-24', '2014-12-25',
               '2014-12-26', '2014-12-27', '2014-12-28', '2014-12-29',
               '2014-12-30', '2014-12-31'],
              dtype='datetime64[ns]', length=1458, freq='D')
```

To use this index, we need to tell Pandas how to treat missing values. In this case, we want to use zero for days without sales data.

In [30]:
```
sales_new = sales.reindex(new_index, fill_value=0)
```

In [31]:
```
sales_new.index
```

Out[31]:
```
DatetimeIndex(['2011-01-04', '2011-01-05', '2011-01-06', '2011-01-07',
               '2011-01-08', '2011-01-09', '2011-01-10', '2011-01-11',
               '2011-01-12', '2011-01-13',
               ...
               '2014-12-22', '2014-12-23', '2014-12-24', '2014-12-25',
               '2014-12-26', '2014-12-27', '2014-12-28', '2014-12-29',
               '2014-12-30', '2014-12-31'],
              dtype='datetime64[ns]', length=1458, freq='D')
```

We can see the result now has a daily frequency. While some Time Seriods models will work without an explicit frequency, many will not. It is also helps to ensure we aren't missing important dates when summarizing and plotting the data.

Resampling

We can now easily Resample our data at any desired frequency, using either the `asfreq` method or the `resample` method. The `asfreq` method assumes a default fill approach (which can be dangerous). The `resample` method allows this to be specified directly. which generates a **resampler** object. To get to values, we need to specify an aggregation function if upsampling (moving to a lower frequency), or fill function if downsampling (moving to a higher frequency). This typically the sum or mean for upsampling, or interpolate for downsampling. We generate results for some common frequencies below:

Upsampling (Moving to a longer period)

In [32]:
```
sales_weekly = sales_new.resample('W').sum()
print('Weekly Sales')
print(sales_weekly.head(), '\n')

sales_monthly = sales_new.resample('M').sum()
print('Monthly Sales')
print(sales_monthly.head(), '\n')

sales_quarterly = sales_new.resample('Q').sum()
print('Quarterly Sales')
print(sales_quarterly.head(), '\n')

sales_annual = sales_new.resample('Y').sum()
print('Annual Sales')
print(sales_annual.head())
```

```
Weekly Sales
            Furniture  Office Supplies  Technology
2011-01-09    2,650.5          1,019.8     1,147.9
2011-01-16    1,003.8          2,039.4       827.9
2011-01-23    1,747.3            871.1       824.1
2011-01-30      550.2            680.3       343.3
2011-02-06      290.7            502.7       649.9

Monthly Sales
            Furniture  Office Supplies  Technology
2011-01-31    5,951.9          4,851.1     3,143.3
2011-02-28    2,130.3          1,071.7     1,608.5
2011-03-31   14,574.0          8,605.9    32,511.2
2011-04-30    7,944.8         11,155.1     9,195.4
2011-05-31    6,912.8          7,135.6     9,599.9

Quarterly Sales
            Furniture  Office Supplies  Technology
2011-03-31   22,656.1         14,528.7    37,263.0
2011-06-30   28,063.7         31,243.7    27,231.3
2011-09-30   41,957.9         53,924.0    47,751.4
2011-12-31   64,515.1         52,080.0    63,032.6
2012-03-31   27,374.1         23,059.4    18,418.2

Annual Sales
            Furniture  Office Supplies  Technology
2011-12-31  157,192.9        151,776.4   175,278.2
2012-12-31  170,518.2        137,233.5   162,780.8
2013-12-31  198,901.4        183,510.6   226,061.8
2014-12-31  215,387.3        246,526.6   272,033.2
```

Downsampling (moving to a shorter period)

Just as upsampling (moving to a larger period) requires an aggregation function, downsampling (moving from Annual to Monthly, for example) requires an option to fill in missing values. A common approach is the **interpolate** method, which allows various types of interpolation (linear, spline, etc.). Other options (ffill forward fill, bfill backward fill) are also supported.

In [33]:

```
# Note that downsampling (from Annual to Monthly for example) produces missing valu
sales_monthly_from_annual = sales_annual.resample('M')
#print('Monthly from Annual Sales')
#sales_monthly_from_annual.interpolate(method='linear').head()
print(sales_monthly_from_annual.interpolate(method='spline', order=3).head())
```

```
            Furniture  Office Supplies  Technology
2011-12-31  157,192.9        151,776.4   175,278.2
2012-01-31  157,062.6        147,084.7   168,957.8
2012-02-29  157,200.9        143,355.5   164,096.2
2012-03-31  157,611.1        140,049.0   159,969.0
2012-04-30  158,251.0        137,493.3   156,975.1
```

Resampling by changing frequency directly

Another way to achieve this is to use the `asfreq` method:

In [34]:

```
sales_daily = sales.asfreq('D')
sales_businessday = sales.asfreq('B')
sales_hourly = sales.asfreq('h')
```

```
# This will generate missing values:
sales_hourly.head()
```

Out[34]:

Order Date	Furniture	Office Supplies	Technology
2011-01-04 00:00:00	0.0	16.4	0.0
2011-01-04 01:00:00	nan	nan	nan
2011-01-04 02:00:00	nan	nan	nan
2011-01-04 03:00:00	nan	nan	nan
2011-01-04 04:00:00	nan	nan	nan

Variable Transformations

For Time Series models, we may want to use transformed variables (log, difference, growth rate, etc). The example below illustrates how we might generate these variables in Pandas, using the Monthly Sales dataset.

Stationarity Transformations

Concerns about Stationarity often lead to considering variable transformations. Some commonly-used transformation methods (Variable Differencing, Percentage Change, and Log) are implemented below. Because of Index has several levels here, these transformations can be done for each outcome variable with one line (the results could be joined together using the Pandas **concat** method).

In [35]:

```
# Variable First Difference
print('Monthly Sales, First Difference \n', sales_monthly.diff().head())

# Variable Percent Change
print('\nMonthly Sales % Change \n', sales_monthly.pct_change().head())

# Log Sales
print('\nlog(1+Monthly Sales) \n', np.log(1 +  sales_monthly).head())

# Add % change to original data:
sales_monthly.join(sales_monthly.pct_change().add_suffix('_%_Change')).head()
```

```
Monthly Sales, First Difference
            Furniture  Office Supplies  Technology
2011-01-31        nan              nan         nan
2011-02-28   -3,821.5         -3,779.4    -1,534.8
2011-03-31   12,443.6          7,534.2    30,902.7
2011-04-30   -6,629.1          2,549.2   -23,315.7
2011-05-31   -1,032.1         -4,019.4       404.4

Monthly Sales % Change
            Furniture  Office Supplies  Technology
2011-01-31        nan              nan         nan
2011-02-28       -0.6             -0.8        -0.5
2011-03-31        5.8              7.0        19.2
2011-04-30       -0.5              0.3        -0.7
2011-05-31       -0.1             -0.4         0.0

log(1+Monthly Sales)
            Furniture  Office Supplies  Technology
2011-01-31        8.7              8.5         8.1
2011-02-28        7.7              7.0         7.4
2011-03-31        9.6              9.1        10.4
2011-04-30        9.0              9.3         9.1
2011-05-31        8.8              8.9         9.2
```

Out[35]:

	Furniture	Office Supplies	Technology	Furniture_%_Change	Office Supplies_%_Change	Technology_%_Cl
2011-01-31	5,951.9	4,851.1	3,143.3	nan	nan	
2011-02-28	2,130.3	1,071.7	1,608.5	-0.6	-0.8	
2011-03-31	14,574.0	8,605.9	32,511.2	5.8	7.0	
2011-04-30	7,944.8	11,155.1	9,195.4	-0.5	0.3	
2011-05-31	6,912.8	7,135.6	9,599.9	-0.1	-0.4	

Rolling Averages and Windows

Another approach to transforming data involves looking at rolling averages. We will discuss this further in the Smoothing lessons. Here we set up rolling calculations for Mean and Standard Deviation, with variable window size. We will plot these a bit later.

In [36]:

```
window_size = 7
rolling_window = sales_new.rolling(window_size)
print('Rolling Mean')
print(rolling_window.mean().dropna().head())
print('\nRolling St. Dev')
print(rolling_window.std().dropna().head())
print('\nCumulative Sales')
print(sales_new.cumsum().dropna().head())
```

```
Rolling Mean
            Furniture  Office Supplies  Technology
2011-01-10      378.6            147.0       168.4
2011-01-11      386.1            145.1       168.4
2011-01-12      387.5            103.9       168.4
2011-01-13      387.5            101.1       168.4
2011-01-14      145.5            292.8        96.8

Rolling St. Dev
            Furniture  Office Supplies  Technology
2011-01-10      968.4            258.9       432.1
2011-01-11      965.2            260.1       432.1
2011-01-12      964.6            256.5       432.1
2011-01-13      964.6            257.6       432.1
2011-01-14      325.3            764.8       242.8

Cumulative Sales
            Furniture  Office Supplies  Technology
2011-01-04        0.0             16.4         0.0
2011-01-05        0.0            304.5         0.0
2011-01-06        0.0            324.0         0.0
2011-01-07    2,573.8          1,009.4     1,147.9
2011-01-08    2,650.5          1,019.8     1,147.9
```

Visualization

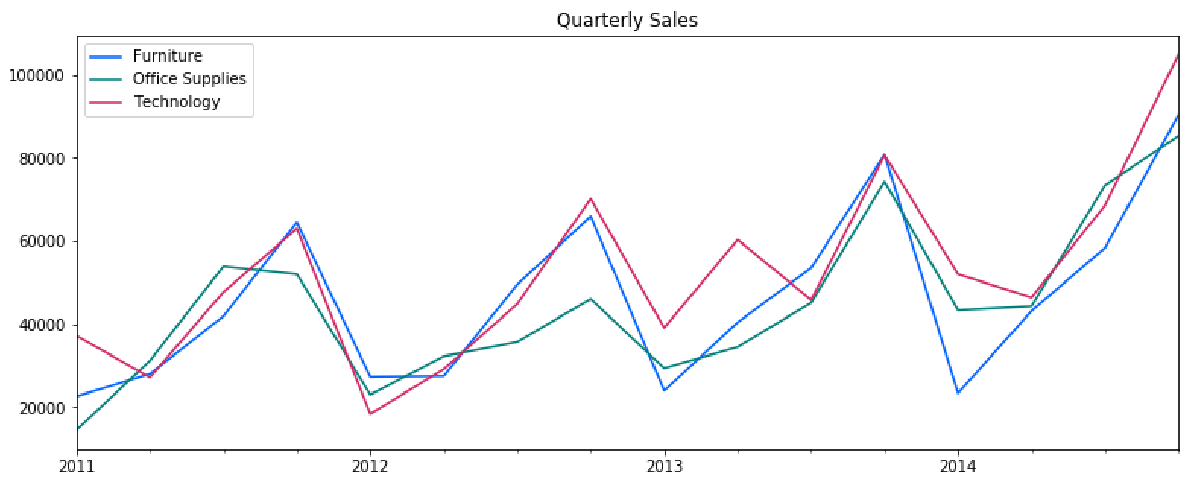
Here we explore methods for plotting Time Series Data. Most of these packages use **Matplotlib's pyplot** library, although it may not be called directly. This means it is possible to adjust plot features, like the title, using **pyplot** commands.

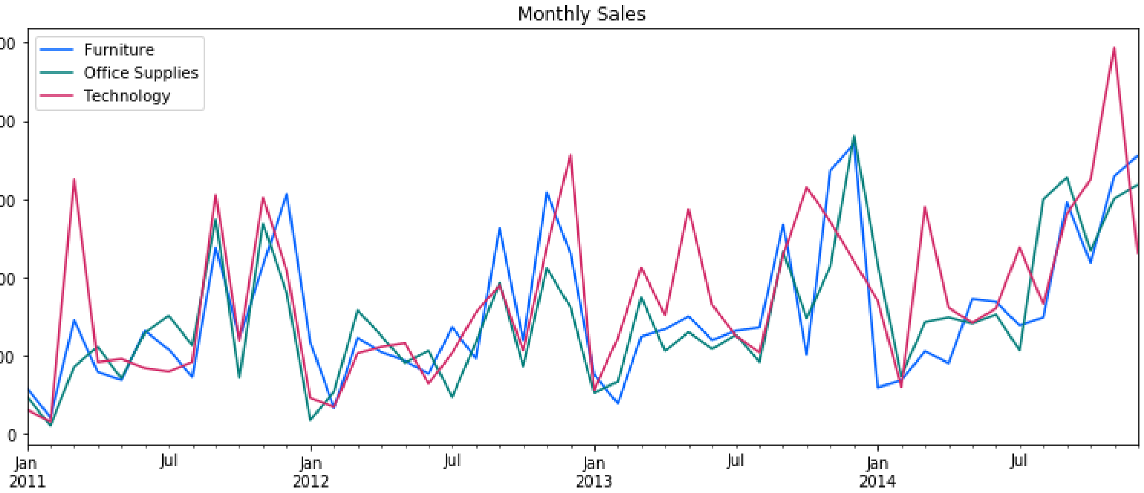
Pandas Built-in Plotting

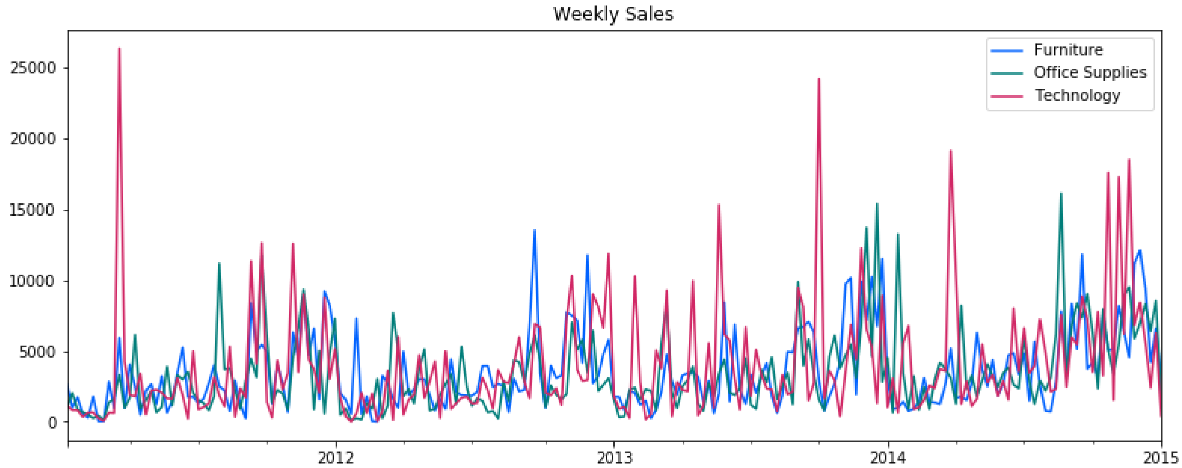
Pandas DataFrames have a built-in **plot** method which, by default, plots columns against the index:

In [37]:
```
sales_quarterly.plot(figsize=plotsize, title='Quarterly Sales')
#plt.title('Monthly Sales')
sales_monthly.plot(figsize=plotsize, title='Monthly Sales')
#plt.title('Monthly Sales')
sales_weekly.plot(figsize=plotsize, title='Weekly Sales')
#plt.title('Monthly Sales')
```

Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f85ce28dcd0>
```



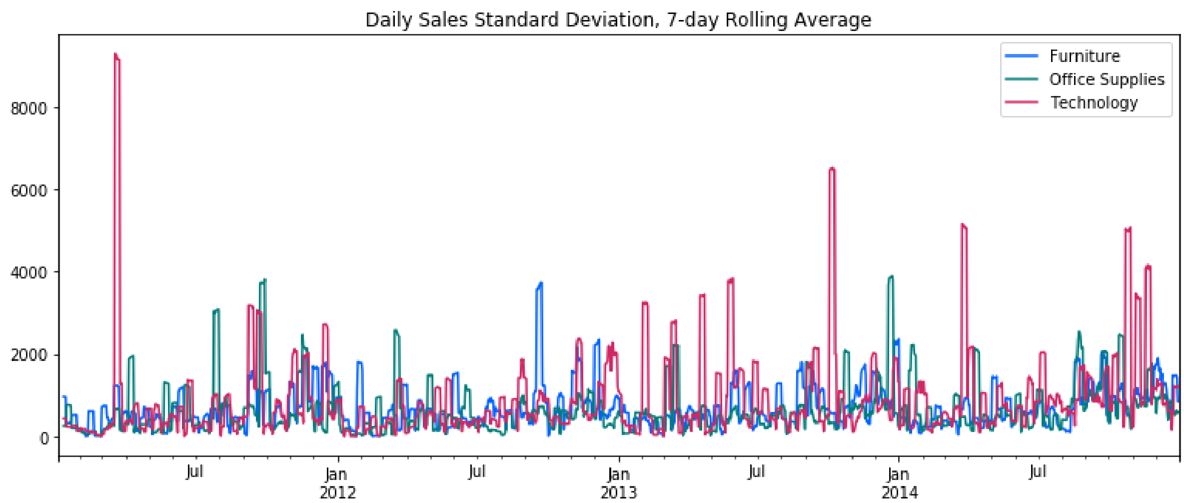


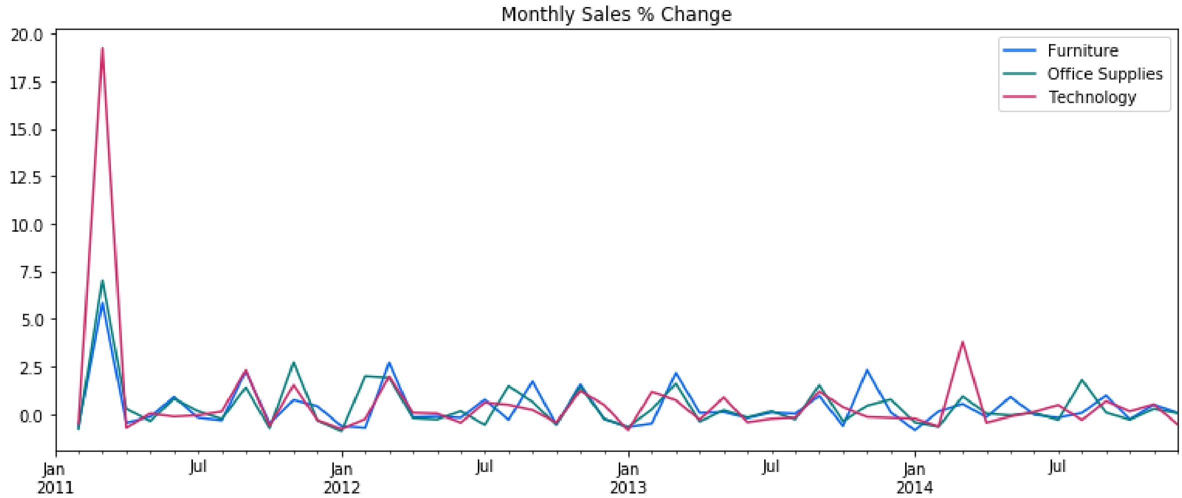


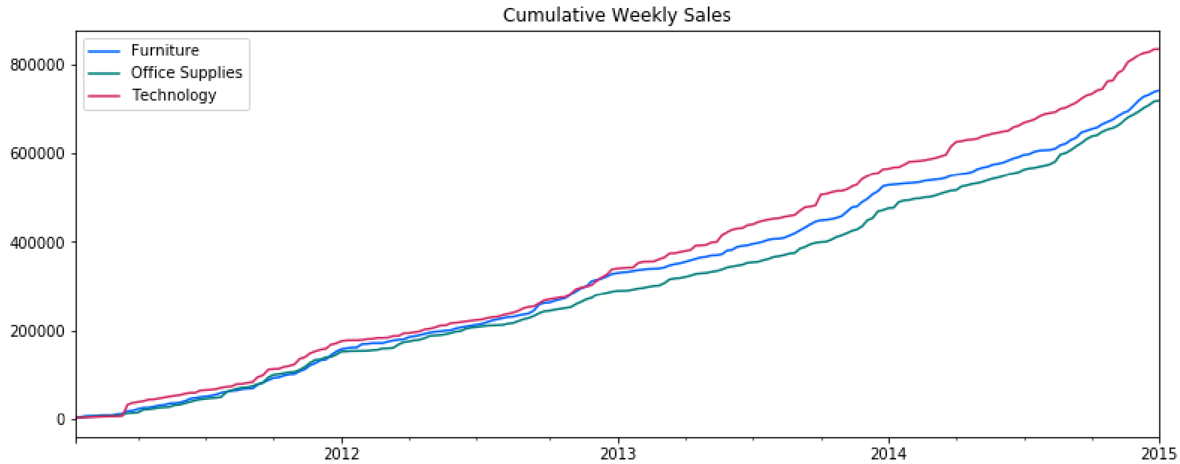
Here, we plot functions like rolling averages and cumulative Sales calculated above:

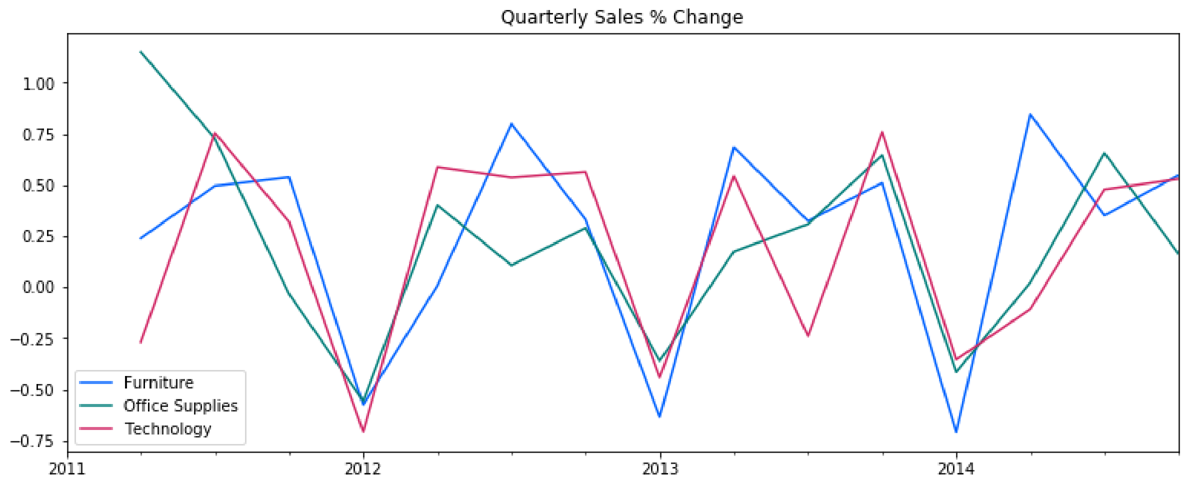
In [38]:
```
#rolling_window.mean().plot(figsize=plotsize, title='Daily Sales, 7-day Rolling Ave
rolling_window.std().plot(figsize=plotsize, title='Daily Sales Standard Deviation, 

# Monthly Sales Percent Change
sales_monthly.pct_change().plot(figsize=plotsize, title='Monthly Sales % Change')

# Cumulative Weekly Sales
sales_weekly.cumsum().plot(figsize=plotsize, title='Cumulative Weekly Sales')

# Quarterly Sales Growth
sales_quarterly.pct_change().plot(figsize=plotsize, title='Quarterly Sales % Chang
```

Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f85ceaa5b50>
```









Time Series Visualizations

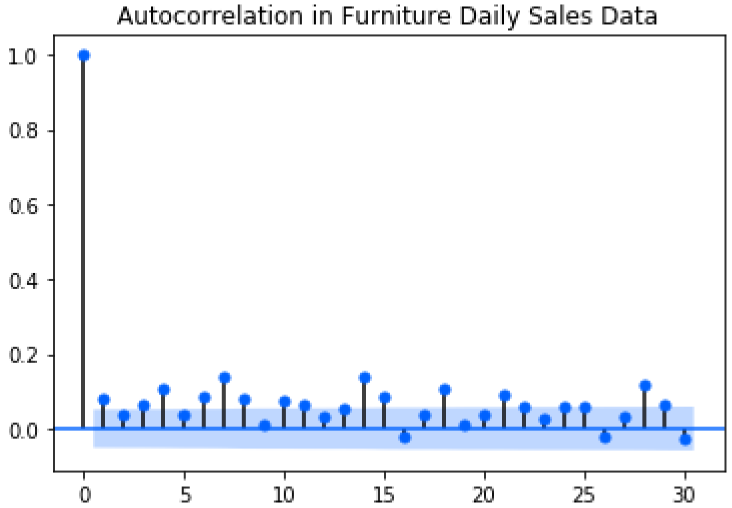
There are a number of packages to help analyze Time Series data and create relevant plots. One example is **statsmodels**, which includes a number of methods for plotting Time Series-specific visualizations:

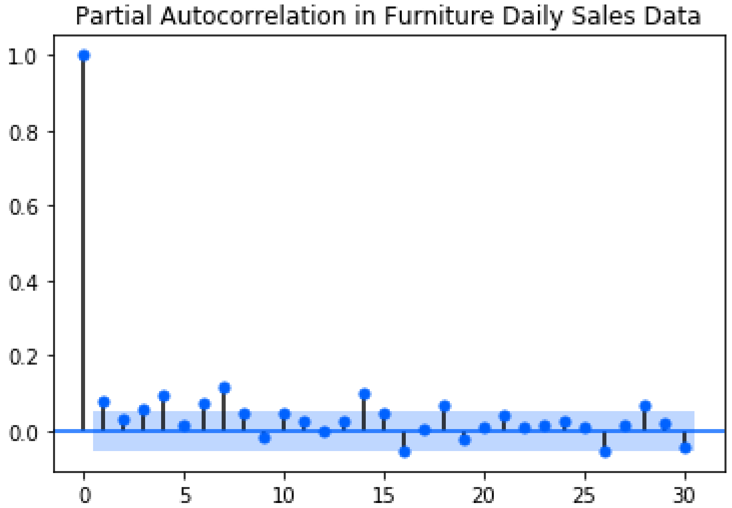
- **plot_acf**: Plot of the Autocorrelation Function
- **plot_pacf**: Plot of the Partial Autocorrelation Function
- **month_plot**: Seasonal Plot for Monthly Data
- **quarter_plot**: Seasonal Plot for Quarterly Data

Some examples are illustrated below:

In [39]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf, month_plot, quarter_

print('Daily data Autocorrelation Plots')
# Autocorrelation and Partial Autocorrelation Functions for Daily Data
#plot_acf(sales_new['Sales']['Furniture'])
acf_plot = plot_acf(sales_new['Furniture'], lags=30, title='Autocorrelation in Furn
#plot_acf(sales_new['Sales']['Furniture'])
pacf_plot = plot_pacf(sales_new['Furniture'], lags=30, title='Partial Autocorrelati
#plot_acf(sales_new['Sales']['Furniture'])
```

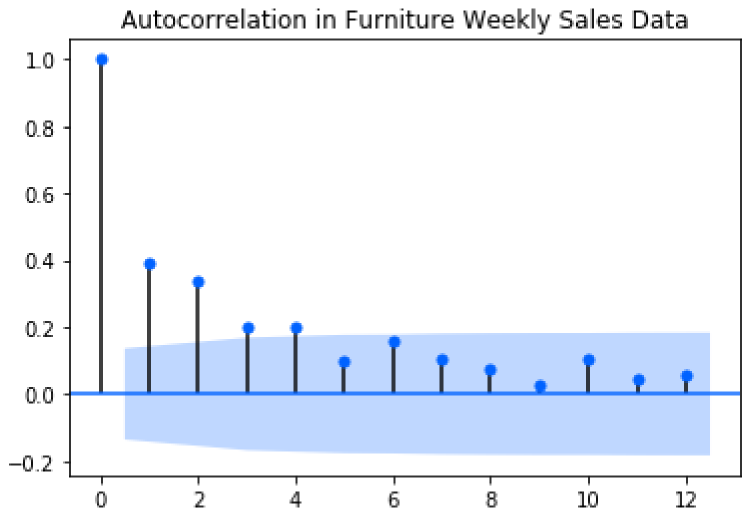
```
Daily data Autocorrelation Plots
```

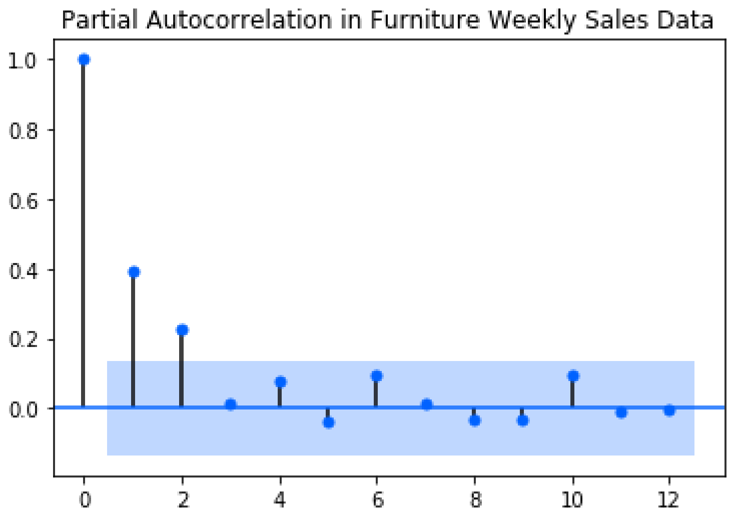




In [40]:
```
print('\nWeekly data Autocorrelation Plots')
# Autocorrelation and Partial Autocorrelation Functions for Daily Data
#plot_acf(sales_new['Sales']['Furniture'])
acf_plot = plot_acf(sales_weekly['Furniture'], lags=12, title='Autocorrelation in F
#plot_acf(sales_new['Sales']['Furniture'])
pacf_plot = plot_pacf(sales_weekly['Furniture'], lags=12, title='Partial Autocorre
#plot_acf(sales_new['Sales']['Furniture'])
```

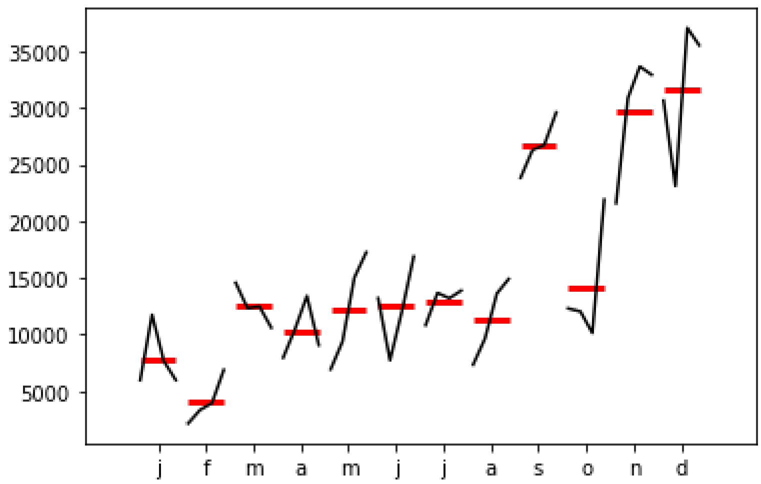
```
Weekly data Autocorrelation Plots
```





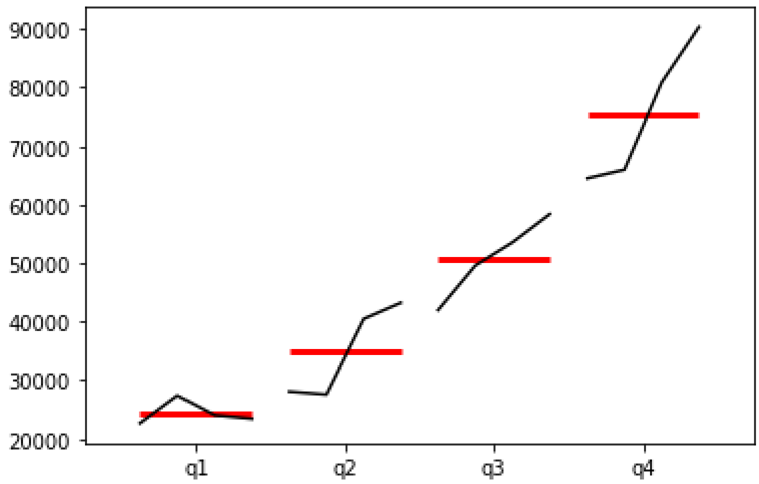
In [41]:
```
print('\nMonthly Data Seasonal Plot')
m_plot = month_plot(sales_monthly['Furniture'])
```

Monthly Data Seasonal Plot



In [42]:
```
print('\nQuarterly Data Seasonal Plot')
q_plot = quarter_plot(sales_quarterly['Furniture'])
```

Quarterly Data Seasonal Plot



Exercises

Exercise 1:

Using the source data, set up Monthly data for Sales and Profit by Segment by either (1) Resampling or (2) Grouping data by Year and Month.

In [43]:
```
### BEGIN SOLUTION
new_vars = ['Segment','Profit','Order Date','Sales']
new_base = df[new_vars].set_index('Order Date')
prof_pivot = new_base.pivot_table(columns='Segment',index = 'Order Date')
prof_month = prof_pivot.resample('M').sum()
prof_month.head()
### END SOLUTION
```

Out[43]:

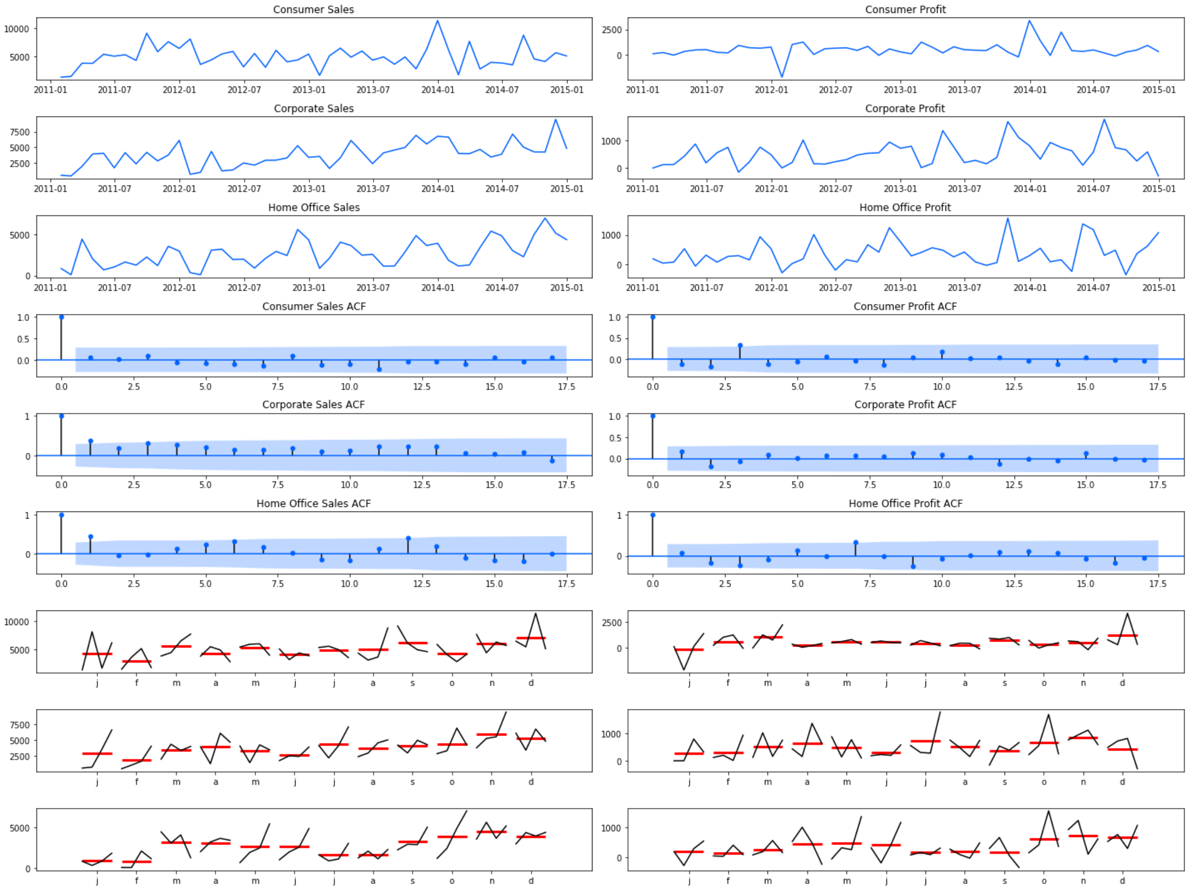
		Profit			Sales	
Segment	**Consumer**	**Corporate**	**Home Office**	**Consumer**	**Corporate**	**Home Office**
Order Date						
2011-01-31	106.5	5.9	185.0	1,304.1	568.0	855.9
2011-02-28	228.3	126.0	37.9	1,442.7	464.1	104.1
2011-03-31	-26.5	131.3	73.7	3,777.8	1,988.4	4,439.9
2011-04-30	336.9	435.6	527.9	3,752.8	3,951.2	2,031.6
2011-05-31	484.0	873.0	-63.3	5,373.2	4,077.7	696.1

Exercise 2:

Analyze the results from the first exercise to determine whether Autocorrelation or Seasonal patterns differ by Segment or whether we are looking at Sales or Profits.

In [44]:
```
### BEGIN SOLUTION
fig,axes = plt.subplots(9,2,figsize=(20,15),)
for i,cat in enumerate(['Consumer','Corporate','Home Office']):
    for j,money in enumerate(['Sales','Profit']):
        axes[i,j].plot(prof_month[money,cat])
        axes[i,j].title.set_text(cat+" "+money)
```

```
        plot_acf(prof_month[money,cat],ax=axes[i+3,j],title = cat+" "+money+" ACF")
        month_plot(prof_month[money,cat],ax=axes[i+6,j])

fig.tight_layout()
plt.show()
### END SOLUTION
```



Seasonal patterns across groups are pretty similar and there is very little autocorrelation.

Exercise 3:

Use the result from Exercise 2 to develop an EDA function to explore other variables (like Region or Sub-Category) that may be of interest.

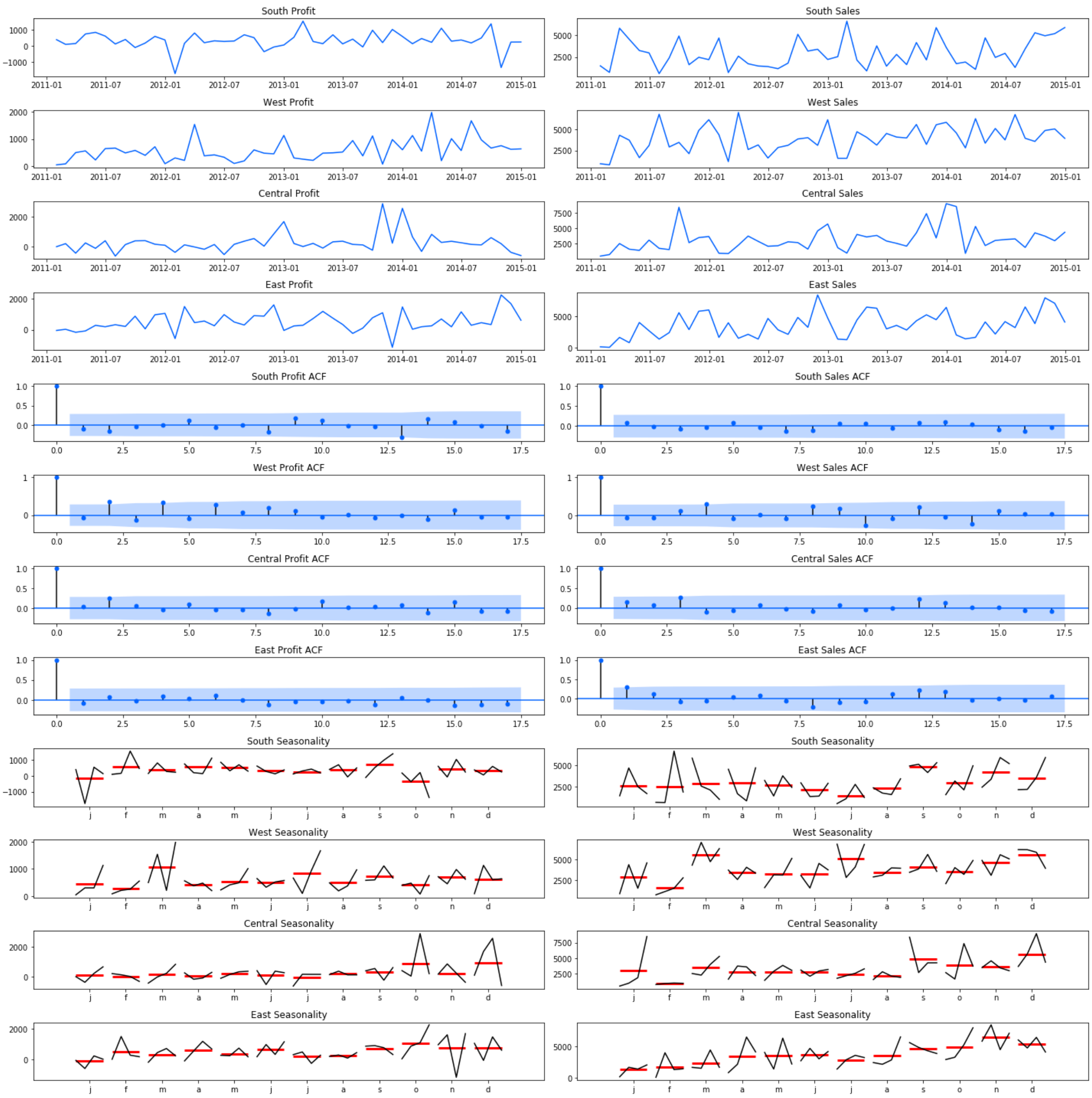
In [45]:

```
### BEGIN SOLUTION
cat_var = 'Region'
date_var = 'Order Date'
money_vars = ['Profit', 'Sales']

def monthly_eda(cat_var=cat_var,
                date_var=date_var,
                money_vars=money_vars):
    new_vars = [cat_var, date_var] + money_vars
    cats = list(df[cat_var].unique())
    num_cats = len(cats)
    new_base = df[new_vars].set_index(date_var)
    prof_pivot = new_base.pivot_table(columns=cat_var,index = date_var)
    prof_month = prof_pivot.resample('M').sum()
    prof_month.head()

    fig,axes = plt.subplots(num_cats*3, 2, figsize=(20, 5*num_cats),)
    for i,cat in enumerate(cats):
        for j,money in enumerate(money_vars):
```

```
            axes[i,j].plot(prof_month[money,cat])
            axes[i,j].title.set_text(cat+" "+money)
            fig = plot_acf(prof_month[money,cat],ax=axes[i+num_cats,j],title = cat
            fig = month_plot(prof_month[money,cat],ax=axes[i+num_cats*2,j])
            axes[i+num_cats*2,j].title.set_text(cat+" Seasonality")

    fig.tight_layout()
    plt.show()
### END SOLUTION
```

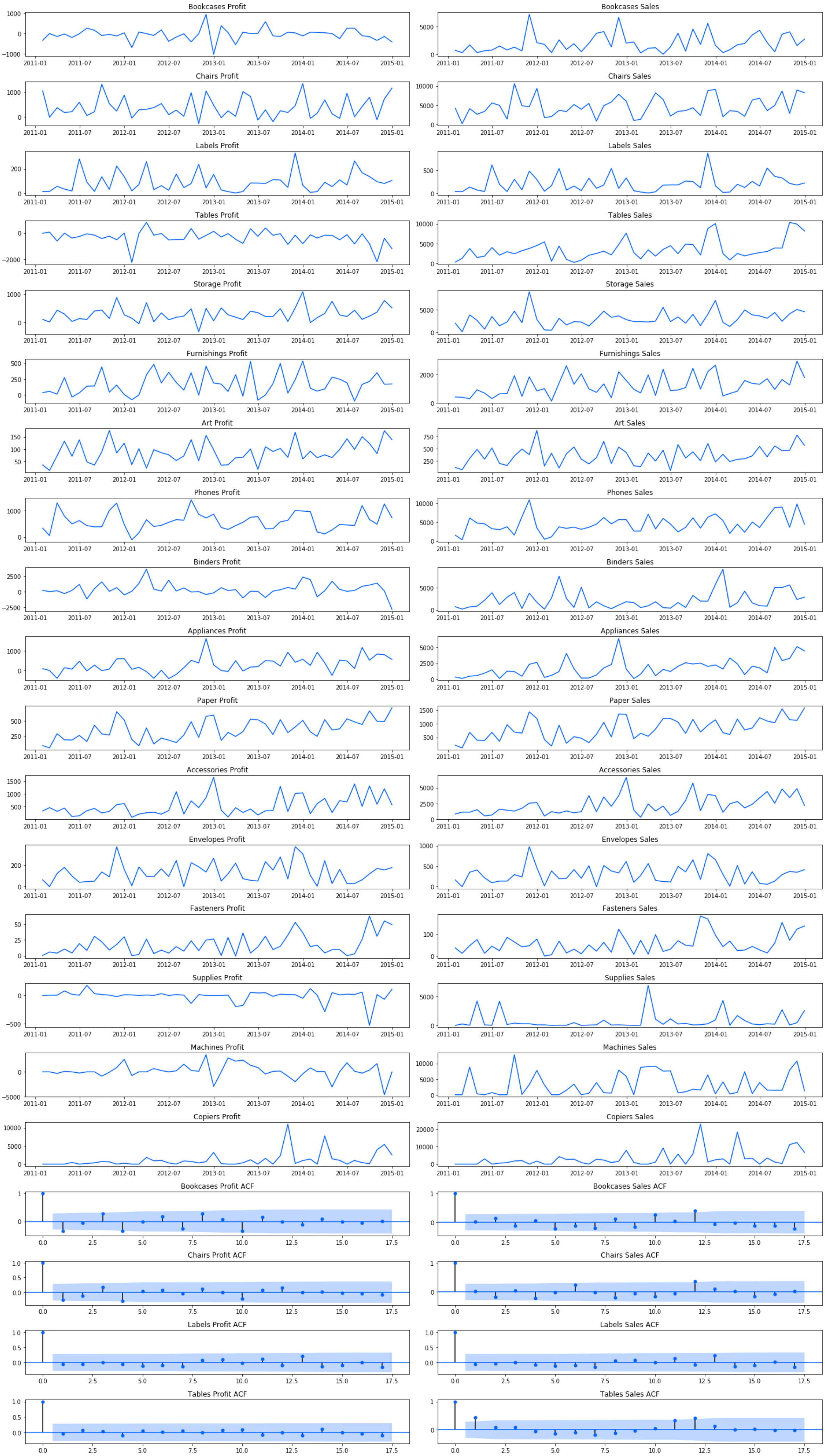
In [46]:

```
monthly_eda(cat_var='Region')
```



In [47]:

```
monthly_eda(cat_var='Sub-Category')
```


Bookcases Profit
Bookcases Sales
Chairs Profit
Chairs Sales
Labels Profit
Labels Sales
Tables Profit
Tables Sales
Storage Profit
Storage Sales
Furnishings Profit
Furnishings Sales
Art Profit
Art Sales
Phones Profit
Phones Sales
Binders Profit
Binders Sales
Appliances Profit
Appliances Sales
Paper Profit
Paper Sales
Accessories Profit
Accessories Sales
Envelopes Profit
Envelopes Sales
Fasteners Profit
Fasteners Sales
Supplies Profit
Supplies Sales
Machines Profit
Machines Sales
Copiers Profit
Copiers Sales
Bookcases Profit ACF
Bookcases Sales ACF
Chairs Profit ACF
Chairs Sales ACF
Labels Profit ACF
Labels Sales ACF
Tables Profit ACF
Tables Sales ACF