In [2]:	<pre>import warnings import itertools import numpy as np import matplotlib.pyplot as plt warnings.filterwarnings("ignore") plt.style.use('fivethirtyeight') import pandas as pd import statsmodels.api as sm import matplotlib.pyplot as plt</pre>
In [3]: Out[3]:	<pre>df = pd.read_excel("Sample - Superstore.xls") df</pre>
	1 2 CA-2016-11-08 11-11 2016-11-08 2016-2016-11-08 CG-12520 Claire Gute Consumer States United States Henderson 42420 South FUR-CH-10000454 Furniture Furniture Hon Deluxe Fabric Upholstered Stacking Chairs, 731.9400 3 0.00 2 CA-152156 CA-2016-11-08 2016-11-08 CA-2016-11-08 CA-2016-11-08 DV-13045 Darrin Van Huff Corporate States Los Angeles 90036 West OFF-LA-10000240 Office Supplies Labels Address Labels for Typewriters b 14.6200 2 0.00
	3 4 2015- 108966 2015- 2015- 2015- Class So-20335 Sean O'Donnell Consumer United States Lauderdale 33311 South FUR-TA- 10000577 Furniture Tables Series Slim Rectangular Table 4 5 2015- 2015- 2015- 2015- 10-11 10-18 Class SO-20335 Sean O'Donnell Consumer United States Lauderdale 33311 South OFF-ST- 10000760 Supplies Storage
	9989 9990 CA- 2014- 2014- 01-21 01-23 Second Class TB-21400 Boeckenhauer Consumer United States Miami 33180 South FUR-FU- 10001889 Furniture Furnishings Ultra Door Pull Handle 25.2480 3 0.20 P9990 9991 CA- 2017- 121258 20
	9992 9993 CA- 2017- 121258 2017- 2017- 02-26 03-03 Standard Olass DB-13060 Dave Brooks Consumer United States Costa Mesa 92627 West OFF-PA- 10004041 Supplies Paper Books with Stickers, 2 3/4" x 5" 29.6000 4 0.00 Cass Power Center, Withtou
In [4]:	<pre>9994 rows × 21 columns furniture = df.loc[df['Category'] == 'Furniture'] furniture['Order Date'].min(), furniture['Order Date'].max() (Timestamp('2014-01-06 00:00:00'), Timestamp('2017-12-30 00:00:00')) cols = ['Row ID', 'Order ID', 'Ship Date', 'Ship Mode', 'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'State', 'Postal Code', 'Region', 'Produ furniture.drop(cols, axis=1, inplace=True)</pre>
Out[5]: In [6]:	<pre>furniture = furniture.sort_values('Order Date') furniture.isnull().sum() Order Date</pre>
Out[6]:	Order Date Sales 0 2014-01-06 2573.8200 1 2014-01-07 76.7280 2 2014-01-10 51.9400 3 2014-01-11 9.9400 4 2014-01-13 879.9390
	884 2017-12-24 1393.4940 885 2017-12-25 832.4540 886 2017-12-28 551.2568 887 2017-12-29 2330.7180 888 2017-12-30 323.1360
In [7]: Out[7]:	<pre>furniture = furniture.set_index('Order Date') furniture.index DatetimeIndex(['2014-01-06', '2014-01-07', '2014-01-10', '2014-01-11',</pre>
In [8]: Out[8]:	<pre>y_useful = furniture['Sales'].resample('MS').mean() y_useful['2015':] Order Date 2015-01-01 978.328467 2015-02-01 522.395667 2015-03-01 781.236437 2015-04-01 805.822962 2015-05-01 624.996700 2015-06-01 428.565500</pre>
	2015-08-01 602.412012 2015-09-01 1382.790684 2015-10-01 632.980184 2015-11-01 1286.701354 2015-12-01 1049.355418 2016-01-01 508.182867 2016-02-01 356.868273 2016-03-01 609.575810 2016-04-01 695.373158 2016-05-01 687.265227 2016-06-01 816.910750
	2016-07-01 768.736412 2016-08-01 734.307782 2016-10-01 624.872474 2016-11-01 1271.345152 2016-12-01 1410.719808 2017-01-01 397.602133 2017-02-01 528.179800 2017-03-01 544.672240 2017-04-01 453.297905 2017-05-01 678.302328 2017-06-01 826.460291
In [9]:	2017-07-01 562.524857 2017-08-01 857.881889 2017-09-01 1209.508583 2017-10-01 875.362728 2017-11-01 1277.817759 2017-12-01 1256.298672 Freq: MS, Name: Sales, dtype: float64 y_useful.plot(figsize=(15, 6)) plt.show()
	1200
	800 600 Jan Jul Jan Jul Jan Jul Jan Jul 2014 2015 2016 2017
In [10]:	<pre>decomposition = sm.tsa.seasonal_decompose(y_useful, model='additive') trend = decomposition.trend plt.figure(figsize=(12,16)) plt.subplot(411) plt.plot(trend, label="Trend") plt.legend() Seasonal = decomposition.trend</pre>
	<pre>plt.subplot(412) plt.plot(trend,label="Seasonal") plt.legend() Residual = decomposition.trend plt.subplot(413) plt.plot(trend,label="Residual") plt.legend() plt.show()</pre> Trend
	820 800 780 760 740 2014-09 2015-01 2015-05 2015-09 2016-01 2016-05 2016-09 2017-01 2017-05
	840 Seasonal 820 780
	760 740 2014-09 2015-01 2015-05 2016-01 2016-05 2016-09 2017-01 2017-05 840 Residual 820
In [11]:	780 760 740 2014-09 2015-01 2015-05 2015-09 2016-01 2016-05 2016-09 2017-01 2017-05 from statsmodels.tsa.stattools import adfuller y_test = adfuller(y_useful, autolag="AIC")
Out[11]: In [12]:	<pre>y_test (-5.191070187339267, 9.168756655665896e-06, 10, 37, {'1%': -3.6209175221605827, '5%': -2.9435394610388332, '10%': -2.6104002410518627}, 521.9616303121272) from statsmodels.tsa.stattools import acf, pacf</pre>
III [12].	<pre>from statsmodels.graphics.tsaplots import plot_acf, plot_pacf # fig, (ax1,ax2) = plt.subplots(1,2,figsize=(10,5)) # fig = sm.graphics.tsa.plot_acf(y_useful.values.squeeze(),lags=20,ax=ax1) # ax1.axhline(y==-1.96/np.sqrt(len(y_useful))) # ax1.axhline(y==1.96/np.sqrt(len(y_useful))) # fig = sm.graphics.tsa.plot_pacf(y_useful,lags=20,ax=ax2) # ax2.axhline(y==-1.96/np.sqrt(len(y_useful))) # ax2.axhline(y==1.96/np.sqrt(len(y_useful))) fig, axes = plt.subplots(1,2,figsize=(16,3), dpi= 100) plot_acf(y_useful, lags=20, ax=axes[0]) plot_pacf(y_useful, lags=20, ax=axes[1])</pre>
Out[12]:	1.0 0.5
	0.0 -0.5 0.0 O.0 O.0 O.0 O.0 O.0 O.0
	0.5 0.0 -0.5 0 5 10 15 20 0 5 10 15 20
In [13]: Out[13]: In [14]:	<pre>model = sm.tsa.ARIMA(y_useful,order=(2,0,2)) result = model.fit(disp=-1) result <statsmodels.tsa.arima_model.armaresultswrapper 0x211cf4494f0="" at=""> print(result.aic) print(result.bic) 693.5725330243508</statsmodels.tsa.arima_model.armaresultswrapper></pre>
In [15]: Out[15]: In [16]:	<pre>from sklearn import metrics results_pred = result.predict() metrics.mean_absolute_error(y_useful.values, results_pred.values) 231.642903843485 result.summary()</pre>
Out[16]:	Dep. Variable: Sales No. Observations: 48 Model: ARMA(2, 2) Log Likelihood -340.786 Method: css-mle S.D. of innovations 292.913 Date: Sun, 25 Apr 2021 AIC 693.573 Time: 10:30:04 BIC 704.800 Sample: 01-01-2014 HQIC 697.815 - 12-01-2017 - 12-01-2017
	const std err z P> z [0.025] 0.975] const 785.4806 57.423 13.679 0.000 672.933 898.029 ar.L1.Sales -0.0880 0.633 -0.139 0.889 -1.329 1.153 ar.L2.Sales 0.2451 0.311 0.787 0.431 -0.365 0.856 ma.L1.Sales 0.3534 0.618 0.572 0.568 -0.859 1.565 ma.L2.Sales -0.1988 0.309 -0.643 0.520 -0.805 0.408
To [47].	Roots Real Imaginary Modulus Frequency AR.1 -1.8483
	<pre>plt.plot(forc_arima) plt.plot(y_useful)</pre>
	1000 800 600 400 2014 2015 2016 2017 2018 2019 2020 2021 2022
In [18]: Out[18]:	<pre>import statsmodels.api as sm model=sm.tsa.statespace.SARIMAX(y_useful,order=(1, 1, 1),seasonal_order=(1,1,1,12)) results = model.fit() forc_sarima = results.predict(start=36,end=96,dynamic=True) plt.plot(forc_sarima) plt.plot(y_useful) [<matplotlib.lines.line2d 0x211cee76fd0="" at="">]</matplotlib.lines.line2d></pre>
	1200 1000 800 400
In [19]: Out[19]:	2014 2015 2016 2017 2018 2019 2020 2021 2022 results.summary()
	Time: 10:30:18 BIC 494.359 Sample: 01-01-2014 HQIC 489.267 Covariance Type: opg coef std err z P> z [0.025 0.975 ar.L1 0.0854 0.250 0.342 0.732 -0.404 0.575
	ma.L1
	Heteroskedasticity (H): 0.54 Skew: -0.37 Prob(H) (two-sided): 0.30 Kurtosis: 2.05 Warnings: [1] Covariance matrix calculated using the outer product of gradients (complex-step).