Chapter 8: Forecasting

8.3 Moving Average ¶

8.3.1 Loading and visualizing the time series dataset

```
import warnings
warnings.filterwarnings('ignore')
```

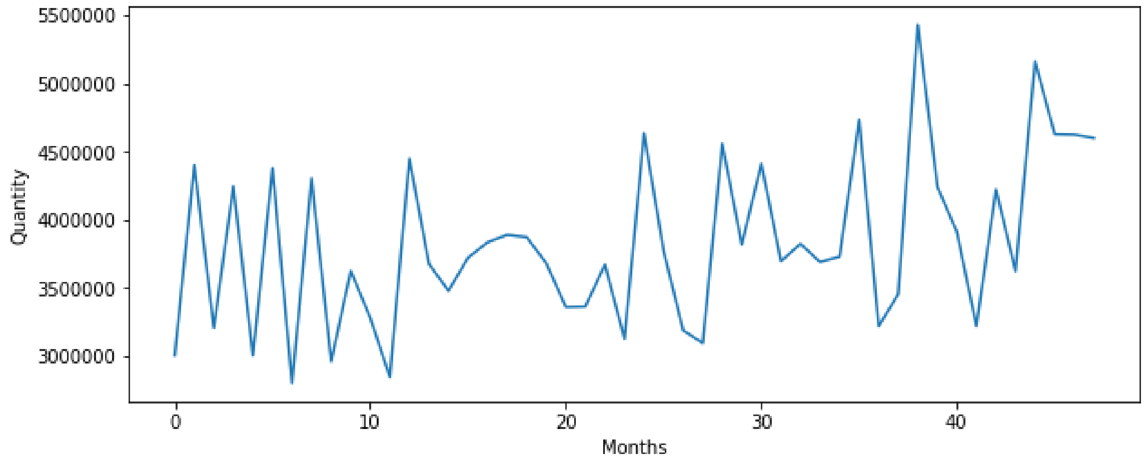
```
import pandas as pd

wsb_df = pd.read_csv( 'wsb.csv' )
wsb_df.head(10)
```

	Month	Sale Quantity	Promotion Expenses	Competition Promotion
0	1	3002666	105	1
1	2	4401553	145	0
2	3	3205279	118	1
3	4	4245349	130	0
4	5	3001940	98	1
5	6	4377766	156	0
6	7	2798343	98	1
7	8	4303668	144	0
8	9	2958185	112	1
9	10	3623386	120	0

```
import matplotlib.pyplot as plt
import seaborn as sn
%matplotlib inline
```

```
plt.figure( figsize=(10,4))
plt.xlabel( "Months" )
plt.ylabel( "Quantity" )
plt.plot( wsb_df['Sale Quantity'] );
```




```
wsb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 4 columns):
Month                    48 non-null int64
Sale Quantity            48 non-null int64
Promotion Expenses       48 non-null int64
Competition Promotion    48 non-null int64
dtypes: int64(4)
memory usage: 1.6 KB
```

8.3.2 Forecasting using Moving Average

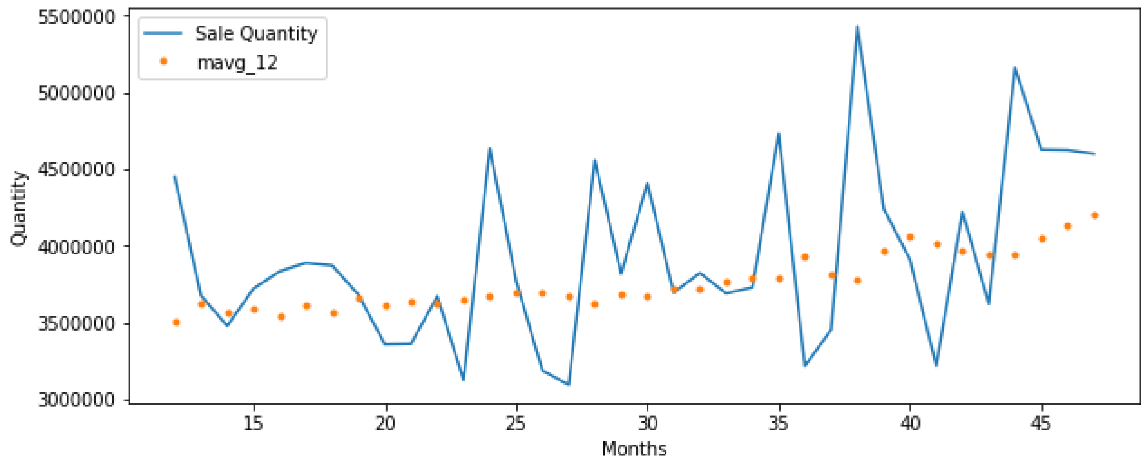
```
wsb_df['mavg_12'] = wsb_df['Sale Quantity'].rolling( window = 12 ).mean().shift(
1)
```

```
pd.set_option('display.float_format', lambda x: '%.2f' % x)
wsb_df[['Sale Quantity', 'mavg_12']][0:]
```

	Sale Quantity	mavg_12
0	3002666	nan
1	4401553	nan
2	3205279	nan
3	4245349	nan
4	3001940	nan
5	4377766	nan
6	2798343	nan
7	4303668	nan
8	2958185	nan
9	3623386	nan
10	3279115	nan
11	2843766	nan
12	4447581	3503418.00
13	3675305	3623827.58
14	3477156	3563306.92
15	3720794	3585963.33
16	3834086	3542250.42
17	3888913	3611595.92
18	3871342	3570858.17
19	3679862	3660274.75
20	3358242	3608290.92
21	3361488	3641629.00
22	3670362	3619804.17
23	3123966	3652408.08
24	4634047	3675758.08
25	3772879	3691296.92
26	3187110	3699428.08
27	3093683	3675257.58
28	4557363	3622998.33
29	3816956	3683271.42
30	4410887	3677275.00
31	3694713	3722237.08
32	3822669	3723474.67
33	3689286	3762176.92

	Sale Quantity	mavg_12
34	3728654	3789493.42
35	4732677	3794351.08
36	3216483	3928410.33
37	3453239	3810280.00
38	5431651	3783643.33
39	4241851	3970688.42
40	3909887	4066369.08
41	3216438	4012412.75
42	4222005	3962369.58
43	3621034	3946629.42
44	5162201	3940489.50
45	4627177	4052117.17
46	4623945	4130274.75
47	4599368	4204882.33

```
plt.figure( figsize=(10,4))
plt.xlabel( "Months" )
plt.ylabel( "Quantity" )
plt.plot( wsb_df['Sale Quantity'][12:] );
plt.plot( wsb_df['mavg_12'][12:], '.' );
plt.legend();
```



8.3.3 Calculating forecast accuracy

8.3.3.2 Root mean square error

```
import numpy as np

def get_mape(actual, predicted):
    y_true, y_pred = np.array(actual), np.array(predicted)
    return np.round( np.mean(np.abs((actual - predicted) / actual)) * 100, 2 )
```

```
get_mape( wsb_df['Sale Quantity'][36:].values,
          wsb_df['mavg_12'][36:].values)
```

```
14.04
```

```
from sklearn.metrics import mean_squared_error

np.sqrt(mean_squared_error( wsb_df['Sale Quantity'][36:].values,
                            wsb_df['mavg_12'][36:].values))
```

```
734725.8359239782
```

8.3.4 Exponential Smoothing

```
wsb_df['ewm'] = wsb_df['Sale Quantity'].ewm( alpha = 0.2 ).mean()
```

```
pd.options.display.float_format = '{:.2f}'.format
```

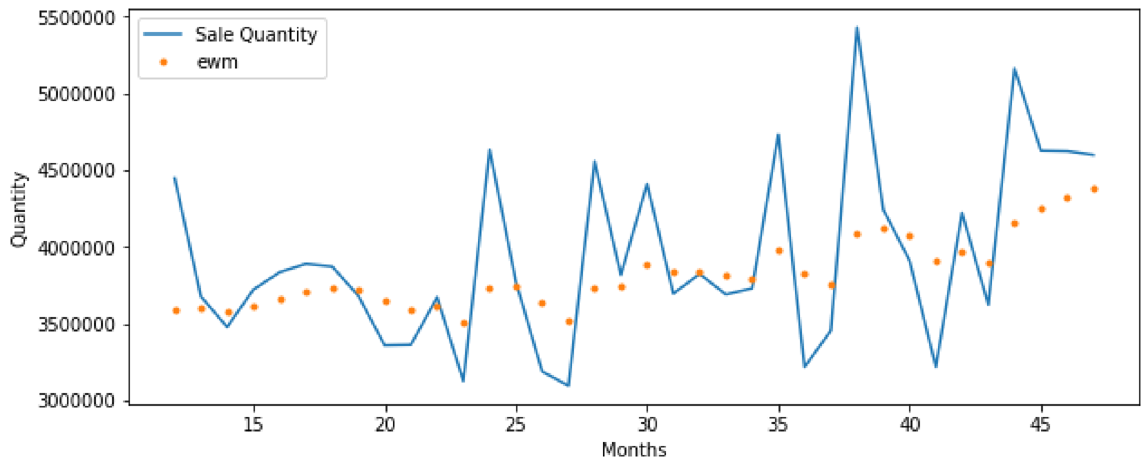
```
wsb_df[36:]
```

	Month	Sale Quantity	Promotion Expenses	Competition Promotion	mavg_12	ewm
36	37	3216483	121	1	3928410.33	3828234.64
37	38	3453239	128	0	3810280.00	3753219.93
38	39	5431651	170	0	3783643.33	4088961.93
39	40	4241851	160	0	3970688.42	4119543.81
40	41	3909887	151	1	4066369.08	4077607.99
41	42	3216438	120	1	4012412.75	3905359.34
42	43	4222005	152	0	3962369.58	3968692.78
43	44	3621034	125	0	3946629.42	3899157.24
44	45	5162201	170	0	3940489.50	4151776.99
45	46	4627177	160	0	4052117.17	4246860.31
46	47	4623945	168	0	4130274.75	4322279.35
47	48	4599368	166	0	4204882.33	4377698.31

```
get_mape( wsb_df[['Sale Quantity']][36:].values,
          wsb_df[['ewm']][36:].values)
```

```
11.15
```

```
plt.figure( figsize=(10,4))
plt.xlabel( "Months" )
plt.ylabel( "Quantity" )
plt.plot( wsb_df['Sale Quantity'][12:] );
plt.plot( wsb_df['ewm'][12:], '.' );
plt.legend();
```

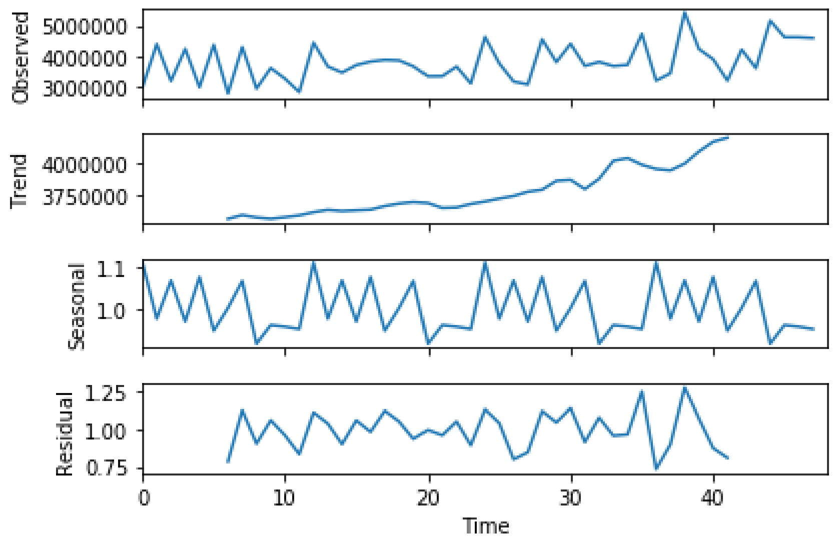


8.4 Decomposing Time Series

```
from statsmodels.tsa.seasonal import seasonal_decompose

ts_decompse = seasonal_decompose( np.array(wsb_df['Sale Quantity']),
                                  model='multiplicative',
                                 freq = 12 )

## Plotting the deocompsed time series components
ts_plot = ts_decompse.plot()
```




```
wsb_df['seasonal'] = ts_decompse.seasonal
wsb_df['trend'] = ts_decompse.trend
```

8.5 Auto Regressive Integrated Moving Average Models (ARIMA)

8.5.1 Auto Regression (AR) Models

```
vimana_df = pd.read_csv('vimana.csv')

vimana_df.head(5)
```

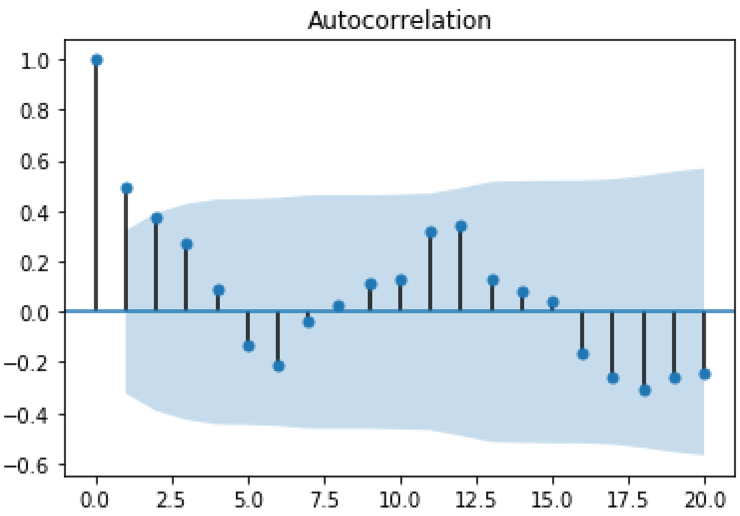
	Month	demand
0	1	457
1	2	439
2	3	404
3	4	392
4	5	403

```
vimana_df.info()
```

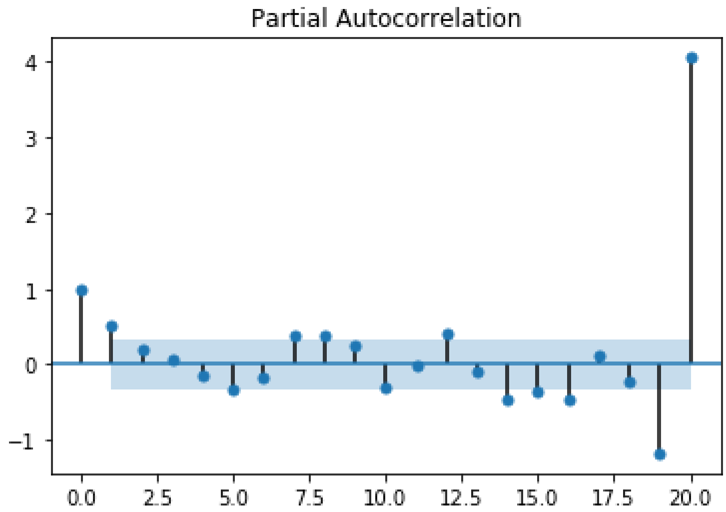
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 37 entries, 0 to 36
Data columns (total 2 columns):
Month     37 non-null int64
demand    37 non-null int64
dtypes: int64(2)
memory usage: 672.0 bytes
```

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Show autocorrelation upto lag 10
acf_plot = plot_acf( vimana_df.demand,
                     lags=20)
```



```
pacf_plot = plot_pacf( vimana_df.demand,
                       lags=20 )
```



Building AR Model

```
from statsmodels.tsa.arima_model import ARIMA
```

```
arima = ARIMA( vimana_df.demand[0:30].astype(np.float64).as_matrix(),
              order = (1,0,0))
ar_model = arima.fit()
```

```
ar_model.summary2()
```

Model:	ARMA	BIC:	375.7336
Dependent Variable:	y	Log-Likelihood:	-182.77
Date:	2019-04-23 22:00	Scale:	1.0000
No. Observations:	30	Method:	css-mle
Df Model:	2	Sample:	0
Df Residuals:	28		0
Converged:	1.0000	S.D. of innovations:	106.593
No. Iterations:	14.0000	HQIC:	372.875
AIC:	371.5300		

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	513.4433	35.9147	14.2962	0.0000	443.0519	583.8348
ar.L1.y	0.4726	0.1576	2.9995	0.0056	0.1638	0.7814

	Real	Imaginary	Modulus	Frequency
AR.1	2.1161	0.0000	2.1161	0.0000

Forecast and Measure Accuracy

```
forecast_31_37 = ar_model.predict(30, 36)
```

```
forecast_31_37
```

```
array([480.15343682, 497.71129378, 506.00873185, 509.92990963,
       511.78296777, 512.65868028, 513.07252181])
```

```
get_mape( vimana_df.demand[30:],
          forecast_31_37 )
```

```
19.12
```

8.5.2 Moving Average (MA) Processes

```
arima = ARIMA( vimana_df.demand[0:30].astype(np.float64).as_matrix(),
               order = (0,0,1))
ma_model = arima.fit()
ma_model.summary2()
```

Model:	ARMA	BIC:	378.7982
Dependent Variable:	y	Log-Likelihood:	-184.30
Date:	2019-04-23 22:00	Scale:	1.0000
No. Observations:	30	Method:	css-mle
Df Model:	2	Sample:	0
Df Residuals:	28		0
Converged:	1.0000	S.D. of innovations:	112.453
No. Iterations:	15.0000	HQIC:	375.939
AIC:	374.5946		

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	516.5440	26.8307	19.2520	0.0000	463.9569	569.1312
ma.L1.y	0.3173	0.1421	2.2327	0.0337	0.0388	0.5958

	Real	**Imaginary**	**Modulus**	**Frequency**
MA.1	-3.1518	0.0000	3.1518	0.5000

```
forecast_31_37 = ma_model.predict(30, 36)
get_mape( vimana_df.demand[30:],
          forecast_31_37 )
```

```
17.8
```

8.5.3 ARMA Model

```
arima = ARIMA( vimana_df.demand[0:30].astype(np.float64).as_matrix(),
               order = (1,0,1))
arma_model = arima.fit()
arma_model.summary2()
```

Model:	ARMA	BIC:	377.2964
Dependent Variable:	y	Log-Likelihood:	-181.85
Date:	2019-04-23 22:00	Scale:	1.0000
No. Observations:	30	Method:	css-mle
Df Model:	3	Sample:	0
Df Residuals:	27		0
Converged:	1.0000	S.D. of innovations:	103.223
No. Iterations:	21.0000	HQIC:	373.485
AIC:	371.6916		

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	508.3995	45.3279	11.2160	0.0000	419.5585	597.2405
ar.L1.y	0.7421	0.1681	4.4158	0.0001	0.4127	1.0715
ma.L1.y	-0.3394	0.2070	-1.6401	0.1126	-0.7451	0.0662

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1	1.3475	0.0000	1.3475	0.0000
MA.1	2.9461	0.0000	2.9461	0.0000

```
forecast_31_37 = arma_model.predict(30, 36)
get_mape( vimana_df.demand[30:],
          forecast_31_37 )
```

```
20.27
```

8.5.4 ARIMA Model

8.5.4.1 What is stationary data?

```
store_df = pd.read_excel('store.xls')
```

```
store_df.head(5)
```

	Date	demand
0	2014-10-01	15
1	2014-10-02	7
2	2014-10-03	8
3	2014-10-04	10
4	2014-10-05	13

```
store_df.info()
```

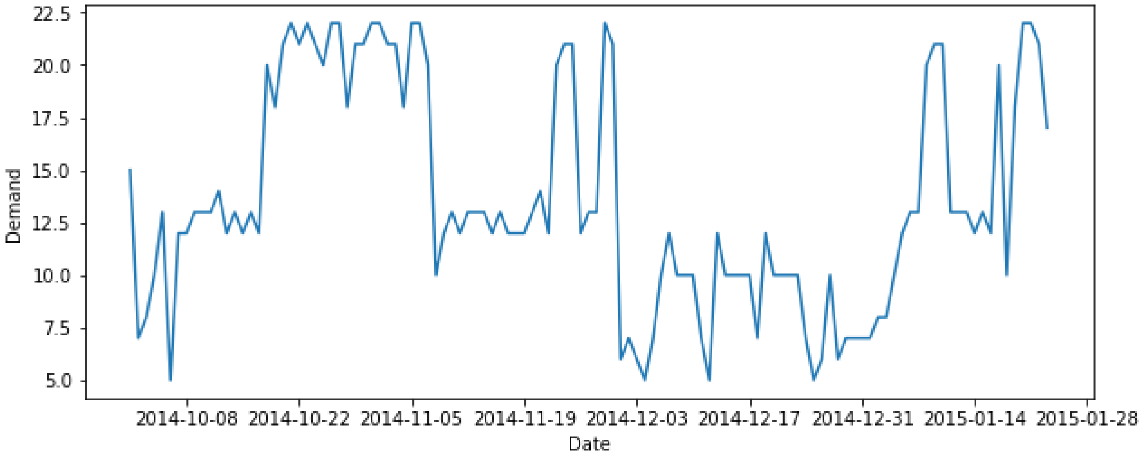
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 115 entries, 0 to 114
Data columns (total 2 columns):
Date      115 non-null datetime64[ns]
demand    115 non-null int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 1.9 KB
```

```
store_df.set_index( pd.to_datetime(store_df.Date), inplace= True)
store_df.drop('Date', axis = 1, inplace = True)
store_df[-5:]
```

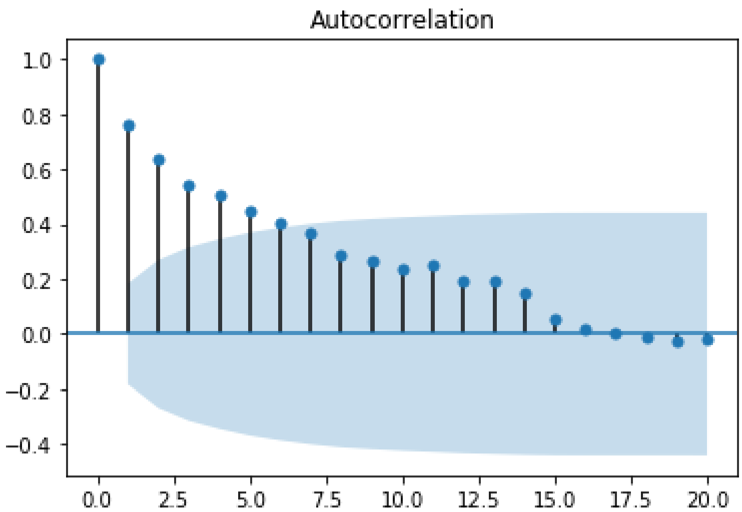
	demand
Date	
2015-01-19	18
2015-01-20	22
2015-01-21	22
2015-01-22	21
2015-01-23	17

Now we will draw the ACF plot to verify stationarity.

```
plt.figure( figsize=(10,4))
plt.xlabel( "Date" )
plt.ylabel( "Demand" )
plt.plot( store_df.demand );
```




```
acf_plot = plot_acf( store_df.demand,
                     lags=20 )
```



8.5.4.2 Dicky-Fuller Test

```
from statsmodels.tsa.stattools import adfuller
```

```
def adfuller_test( ts ):
    adfuller_result = adfuller( ts, autolag=None )
    adfuller_out = pd.Series(adfuller_result[0:4],
                          index=['Test Statistic',
                                 'p-value',
                                 'Lags Used',
                                 'Number of Observations Used'])
    print( adfuller_out )
```

```
adfuller_test( store_df.demand )
```

```
Test Statistic                  -1.65
p-value                          0.46
Lags Used                       13.00
Number of Observations Used    101.00
dtype: float64
```

8.5.4.3 Differencing

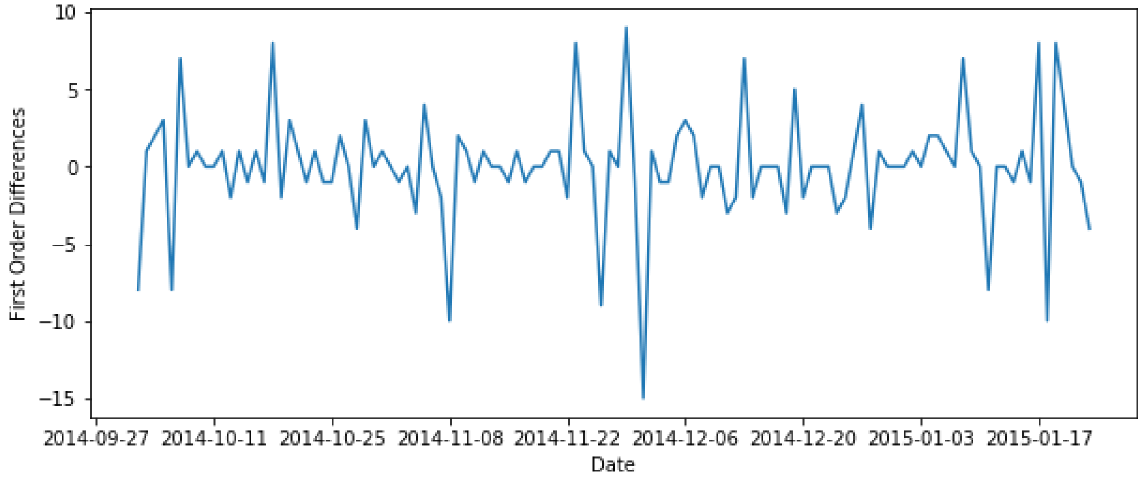
```
store_df['demand_diff'] = store_df.demand - store_df.demand.shift(1)
```

```
store_df.head(5)
```

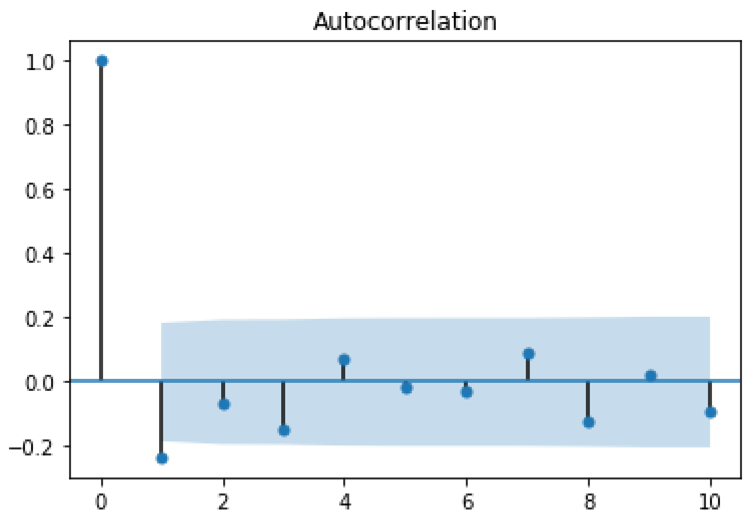
	demand	demand_diff
Date		
2014-10-01	15	nan
2014-10-02	7	-8.00
2014-10-03	8	1.00
2014-10-04	10	2.00
2014-10-05	13	3.00

```
store_diff_df = store_df.dropna()
```

```
plt.figure( figsize=(10,4))
plt.xlabel( "Date" )
plt.ylabel( "First Order Differences" )
plt.plot( store_diff_df.demand_diff );
```




```
pacf_plot = plot_acf( store_df.demand_diff.dropna(),
                      lags=10 )
```




```
store_train = store_df[0:100]
store_test = store_df[100:]
```

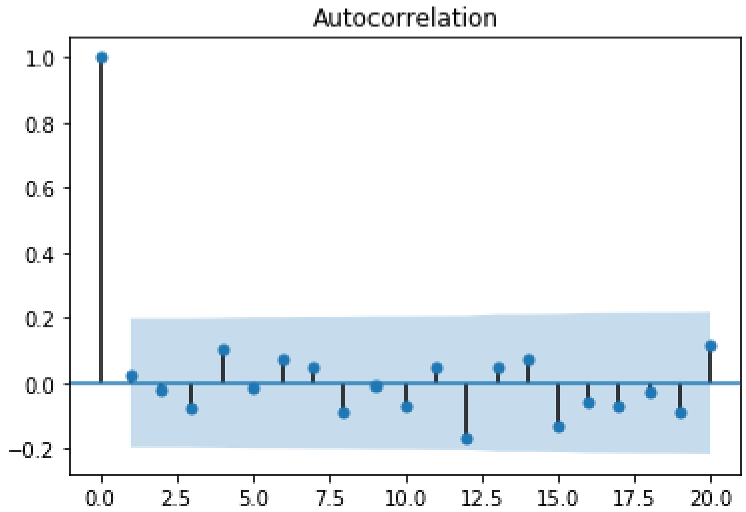
```
arima = ARIMA( store_train.demand.astype(np.float64).as_matrix(),
               order = (1,1,1))
arima_model = arima.fit()
arima_model.summary2()
```

Model:	ARIMA	BIC:	532.1510
Dependent Variable:	D.y	Log-Likelihood:	-256.89
Date:	2019-04-23 22:00	Scale:	1.0000
No. Observations:	99	Method:	css-mle
Df Model:	3	Sample:	1
Df Residuals:	96		0
Converged:	1.0000	S.D. of innovations:	3.237
No. Iterations:	10.0000	HQIC:	525.971
AIC:	521.7706		

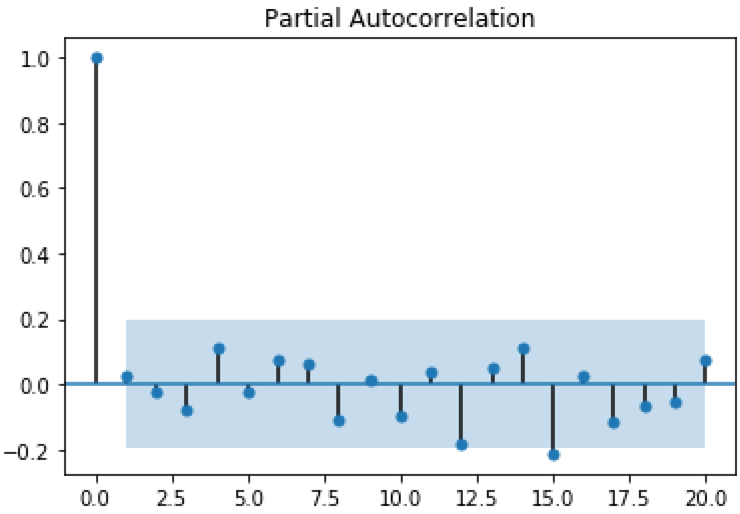
	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0357	0.1599	0.2232	0.8238	-0.2776	0.3490
ar.L1.D.y	0.4058	0.2294	1.7695	0.0800	-0.0437	0.8554
ma.L1.D.y	-0.7155	0.1790	-3.9972	0.0001	-1.0663	-0.3647

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1	2.4641	0.0000	2.4641	0.0000
MA.1	1.3977	0.0000	1.3977	0.0000

```
acf_plot = plot_acf(arima_model.resid,
                    lags = 20)
```



```
pacf_plot = plot_pacf(arima_model.resid,
                      lags = 20)
```



8.5.4.4 Forecast and measure accuracy

```
store_predict, stderr, ci = arima_model.forecast(steps = 15)
```

```
store_predict
```

```
array([17.32364962, 16.2586981 , 15.84770837, 15.70211912, 15.664238
63,
       15.67007012, 15.69364144, 15.7244122 , 15.75810475, 15.792983
07,
       15.8283426 , 15.86389744, 15.89953153, 15.93519779, 15.970877
1 ])
```

```
get_mape( store_df.demand[100:],
          store_predict )
```

```
24.17
```