Author : Namita Rana

Project Name

Time Series Analysis on Monthly Crime Rates in Seattle.

Data Understanding:

Dataset Details

Dataset Name : SPD Crime Data: 2008-Present

- Source: [https://data.seattle.gov/Public-Safety/SPD-Crime-Data-2008-Present/tazs-3rd5] (https://data.seattle.gov/Public-Safety/SPD-Crime-Data-2008-Present/tazs-3rd5%5D)
- Steps to retrieve dataset:
- Step1: Click on the link provided.
- Step2: Click on export,the file can be save as csv.
- Step3: Read the csv with pandas.
- The data were collected from Seattle Police Department. The data covered the reported offenses and offense categorization coded to simulate the standard reported to the FBI under the National Incident Based Reporting System (NIBRS) in Seattle from February 2010 to February, 2020. In its original form, it had detailed variables including offense ID, sector,offense Parent Group,Precinct, Sector,Offense, and so on. Each row contains the record of a unique event where at least one criminal offense was reported by a member of the community or detected by an officer in the field.

What's in this Dataset? :

- Total : 962145 rows × 17 columns

Repo...	Offe...	Offe...	Offe...	Repo...	Grou...	Crim...	Offe...	Offe...	Offe...	Preci...	Sector	Bea
2020-044...	12605873...	2020 Feb ...		2020 Feb ...	A	SOCIETY	DRUG/NA...	Drug/Nar...	35A	W	Q	Q1
2020-044...	12605598...	2020 Feb ...	2020 Feb ...	2020 Feb ...	A	PROPERTY	LARCENY-...	Theft of ...	23G	N	J	J3
2020-044...	12605567...	2020 Feb ...	2020 Feb ...	2020 Feb ...	A	PROPERTY	ROBBERY	Robbery	120	N	U	U3
2020-044...	12605174...	2020 Feb ...	2020 Feb ...	2020 Feb ...	A	PROPERTY	DESTRUC...	Destructi...	290	W	Q	Q1
2020-044...	12605081...	2020 Feb ...		2020 Feb ...	B	SOCIETY	DRIVING ...	Driving U...	90D	N	B	B2
2020-044...	12605077...	2020 Feb ...		2020 Feb ...	A	PROPERTY	LARCENY-...	Shoplifting	23C	W	M	M1
2020-044...	12605029...	2020 Feb ...	2020 Feb ...	2020 Feb ...	A	PROPERTY	DESTRUC...	Destructi...	290	N	J	J3
2020-043...	12604995...	2020 Feb ...		2020 Feb ...	A	PROPERTY	LARCENY-...	Shoplifting	23C	SW	F	F2
2020-043...	12604963...	2020 Feb ...		2020 Feb ...	B	SOCIETY	DRIVING ...	Driving U...	90D	N	L	L2
2020-044...	12605008...	2020 Feb ...	2020 Feb ...	2020 Feb ...	A	PROPERTY	LARCENY-...	Theft Fro...	23F	E	E	E2
2020-044...	12604928...	2020 Feb ...		2020 Feb ...	A	PROPERTY	LARCENY-...	Shoplifting	23C	E	E	E2

Columns:

- Column Name : Description
- Report Number: Primary key/UID for the overall report. One report can contain multiple offenses, as denoted by the Offense ID.
- Offense ID: Distinct identifier to denote when there are multiple offenses associated with a single report.
- Offense Start DateTime: Start date and time the offense(s) occurred.
- Offense End DateTime: End date and time the offense(s) occurred, when applicable.
- Report DateTime: Date and time the offense(s) was reported. (Can differ from date of occurrence)
- Group A B: Corresponding offense group.
- Crime Against Category: Corresponding offense crime against category.
- Offense Parent Group: Offense_Parent_Group
- Offense: Corresponding offense.
- Offense Code: Corresponding offense code.
- Precinct: Designated police precinct boundary where offense(s) occurred.
- Sector: Designated police sector boundary where offense(s) occurred.
- Beat: Designated police sector boundary where offense(s) occurred.
- MCPP: Designated Micro-Community Policing Plans (MCPP) boundary where offense(s) occurred.
- 100 Block Address: Offense(s) address location blurred to the one hundred block.
- Longitude: Offense(s) spatial coordinate blurred to the one hundred block.
- Latitude: Offense(s) spatial coordinate blurred to the one hundred block.

Business Understanding

Business Problem:

The goal of this modelling is to forecast the crime rates,to figure out which crimes are more frequent,and to make predictions for the number of monthly violent crimes that will occur in future months.

Stakeholder: Seattle Police Department.

Questions that we want to understand.

- Question1: Does the monthly crimes in Seattle from 2008 to 2020 has an increasing trend?
- Question2: Does the monthly crimes in Seattle from 2008 to 2020 has any time-related patterns that could be explained by ARIMA or SARIMA models?

Background:

Seattle is the home place of grunge music, a tech hub and a city that prides itself in progress and innovation. It is a beautiful city that is surrounded by lush landscapes and deserves a place on your itinerary.

According to the most recent data from the FBI, the total crime rate in Seattle is 5,081.0 per 100,000 people. That's 105.15% higher than the national rate of 2,476.7 per 100,000 people and 70.75% higher than the Washington total crime rate of 2,975.8 per 100,000 people.

Seattle saw substantial spikes in the number of aggravated assaults and robberies last year, which were largely responsible for the 20% overall increase in violent crime the city experienced in 2021, according to the Seattle Police Department's year-end crime report.

That report,said the number of aggravated assaults that occurred in Seattle last year — 3,925 — is the most the city has seen in 10 years. It also represents a 24% increase over 2020 totals.

Methods

Cleaning and Feature Engineering

This project uses data cleaning and feature engineering to also addressed the non-stationarity,trend,seasonality in the time series.

Since, the time series was nonstationary which means the status of a time series whose statistical properties are changing through time. We used Statistical test like: Augmented Dickey-Fuller test to check if our series is stationary or not.

Also,we tried to make time series stationary by Differencing.

Models Development

We have implemented ARIMA,SARIMAX model's with different parameters,with automated parameters generated using auto_arima to see how results varies with each change in the parameters.Also performed a gridSeach to find the best paramters with low AIC scores.

We are focussed on finding the best model for our time series in terms of lowest Mean Absolute Percentage as it is unit-free and is safe to use for comparing performances of time series forecast values with different units.

Metrics used:

MAPE(Mean Absolute Percentage Error) MAE(Mean Absolute Error)

Import Packages and Functions We'll make use of the following packages:

numpy and pandas,sklearn is what we'll use to manipulate our data.

matplotlib.pyplot and seaborn will be used to produce plots for visualization.

util will provide the locally defined utility functions that have been provided for this assignment.

Run the next cell to import all the necessary packages.

In [788]:
```
#Importing the generic libraries.
import pandas as pd
import seaborn as sns
from scipy import stats
import numpy as np
from numpy import sqrt
%matplotlib inline
import matplotlib.pyplot as plt
from datetime import datetime

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

In [789]:
```
#Import modelling libraries
import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
import matplotlib.dates as mdates
from datetime import timedelta
from pmdarima import auto_arima
from sklearn.metrics import mean_absolute_error, mean_absolute_percent
```

Loading the dataset.

In [790]:

```
#obtain the data and read the file.
df = pd.read_csv('SPD_Crime_Data__2008-Present.csv', index_col= False)
df
```

Out[790]:

	Report Number	Offense ID	Offense Start DateTime	Offense End DateTime	Report DateTime	Group A B	Crime Against Category	
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	NaN	02/05/2020 11:24:31 AM	A	SOCIETY	
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/04/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/02/2020 09:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 02:21:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTF
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	NaN	02/05/2020 12:51:31 AM	B	SOCIETY	DF
...	...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	NaN	07/13/2013 06:37:00 AM	A	PROPERTY	
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 06:30:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	NaN	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	NaN	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:30:00 AM	02/26/2010 07:54:00 AM	A	PROPERTY	

962145 rows × 17 columns

In [791]:
```
#information about the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 962145 entries, 0 to 962144
Data columns (total 17 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   Report Number           962145 non-null  object 
 1   Offense ID              962145 non-null  int64  
 2   Offense Start DateTime  961188 non-null  object 
 3   Offense End DateTime    530966 non-null  object 
 4   Report DateTime         962145 non-null  object 
 5   Group A B               962145 non-null  object 
 6   Crime Against Category  962145 non-null  object 
 7   Offense Parent Group    962145 non-null  object 
 8   Offense                 962145 non-null  object 
 9   Offense Code            962145 non-null  object 
 10  Precinct                962141 non-null  object 
 11  Sector                  962143 non-null  object 
 12  Beat                    962143 non-null  object 
 13  MCPP                    962142 non-null  object 
 14  100 Block Address       924111 non-null  object 
 15  Longitude               962145 non-null  float64
 16  Latitude                962145 non-null  float64
dtypes: float64(2), int64(1), object(14)
memory usage: 124.8+ MB
```

In [792]:
```
#describe the data
df.describe()
```

Out[792]:

	Offense ID	Longitude	Latitude
count	9.621450e+05	962145.000000	962145.000000
mean	9.973092e+09	-117.492657	45.739128
std	5.590633e+09	23.842952	9.282055
min	7.624429e+09	-122.432252	0.000000
25%	7.652601e+09	-122.347561	47.581983
50%	7.679801e+09	-122.329059	47.614163
75%	7.698945e+09	-122.310168	47.663654
max	3.172592e+10	0.000000	47.774843

Exploratory Data Analysis:

We will look at the time series data in terms of what information is unnique, grouping hte data to get some relevant information.

In [793]:
```
#looking at unique values in offensecode
df['Offense Code'].unique()
```

Out[793]:
```
array(['35A', '23G', '120', '290', '90D', '23C', '23F', '26E', '23D'
,
       '100', '250', '23H', '370', '210', '240', '11B', '280', '26A'
,
       '26B', '270', '26F', '26C', '520', '11D', '26G', '35B', '200'
,
       '64A', '90G', '90A', '23A', '11A', '11C', '40C', '23B', '90F'
,
       '23E', '90B', '720', '09A', '40A', '26D', '90H', '40B', '90E'
,
       '09C', '36A', '36B', '510', '39B', '39A', '09B', '39C', '90J'
,
       '13B', '13A', '13C', '220', '64B'], dtype=object)
```

In [794]:
```
df['Precinct'].unique()
```

Out[794]:
```
array(['W', 'N', 'SW', 'E', 'S', 'UNKNOWN', 'OOJ', nan, '<Null>'],
      dtype=object)
```

In [795]:
```
df['Sector'].unique()
```

Out[795]:
```
array(['Q', 'J', 'U', 'B', 'M', 'F', 'L', 'E', 'R', 'O', 'K', 'C', '
N',
       'G', 'W', 'D', 'S', '99', 'UNKNOWN', '9512', 'SE', 'W2', 'OOJ
',
       nan, '<Null>', '6804', '1700'], dtype=object)
```

In [796]:
```
df['Beat'].unique()
```

Out[796]:
```
array(['Q1', 'J3', 'U3', 'B2', 'M1', 'F2', 'L2', 'E2', 'U2', 'R3', '
R1',
       'E1', 'O3', 'Q3', 'O2', 'K2', 'Q2', 'C3', 'N2', 'G2', 'W2', '
K1',
       'B3', 'M3', 'W3', 'W1', 'D2', 'K3', 'D3', 'G1', 'R2', 'E3', '
F3',
       'N1', 'D1', 'U1', 'F1', 'G3', 'B1', 'N3', 'M2', 'C2', 'S3', '
L1',
       'S1', 'J1', 'J2', 'S2', 'L3', 'C1', 'O1', '99', 'UNKNOWN', 'O
OJ',
       nan, '<Null>'], dtype=object)
```

In [797]:
```
df['Offense ID'].unique()
```

Out[797]:
```
array([12605873663, 12605598696, 12605567653, ...,  7672915592,
        7692227482,  7686420892])
```

In [798]:
```
df.isna().sum()
```

Out[798]:
```
Report Number                 0
Offense ID                    0
Offense Start DateTime      957
Offense End DateTime     431179
Report DateTime               0
Group A B                     0
Crime Against Category        0
Offense Parent Group          0
Offense                       0
Offense Code                  0
Precinct                      4
Sector                        2
Beat                          2
MCPP                          3
100 Block Address         38034
Longitude                     0
Latitude                      0
dtype: int64
```

In [799]:
```
df['Group A B' ].unique()
```

Out[799]:
```
array(['A', 'B'], dtype=object)
```

In [800]:
```
df['Sector'].value_counts()
```

Out[800]:
```
U          75417
B          69518
M          68592
K          67472
E          67455
D          63797
Q          61666
R          59704
L          58680
N          54654
J          50850
W          49162
S          48900
F          46860
C          42899
G          40146
O          29862
UNKNOWN     6404
99            91
OOJ            7
1700           2
6804           1
9512           1
<Null>         1
W2             1
SE             1
Name: Sector, dtype: int64
```

In [801]:
```
df.head()
```

Out[801]:

	Report Number	Offense ID	Offense Start DateTime	Offense End DateTime	Report DateTime	Group A B	Crime Against Category	
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	NaN	02/05/2020 11:24:31 AM	A	SOCIETY	DRU
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/04/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/02/2020 09:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 02:21:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTRUCTI
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	NaN	02/05/2020 12:51:31 AM	B	SOCIETY	DRIVING

In [802]:
```
#convert to datetime
df["date"] = pd.to_datetime(df["Offense Start DateTime"])
df["year"] = df["date"].dt.year
df["month"] = df["date"].dt.month
df["day_of_week"] = df["date"].dt.day_name()
df["hour"] = df["date"].dt.hour
df["Date"] = df["date"].dt.date
df = df.drop("date", axis=1)
df
```

Out[802]:

	Report Number	Offense ID	Offense Start DateTime	Offense End DateTime	Report DateTime	Group A B	Crime Against Category
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	NaN	02/05/2020 11:24:31 AM	A	SOCIETY
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/04/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/02/2020 09:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY

3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 02:21:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTF
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	NaN	02/05/2020 12:51:31 AM	B	SOCIETY	DF
...	...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	NaN	07/13/2013 06:37:00 AM	A	PROPERTY	
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 06:30:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	NaN	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	NaN	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:30:00 AM	02/26/2010 07:54:00 AM	A	PROPERTY	

962145 rows × 22 columns

In [803]:

```
# Map day values to proper strings
dmap1 = {1.0:'January',2.0:'February',3.0:'March',4.0:'April',5.0:'May
df['month'] = df['month'].map(dmap1)
df
```

Out[803]:

	Report Number	Offense ID	Offense Start DateTime	Offense End DateTime	Report DateTime	Group A B	Crime Against Category	
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	NaN	02/05/2020 11:24:31 AM	A	SOCIETY	
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/04/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/02/2020 09:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 02:21:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTF
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	NaN	02/05/2020 12:51:31 AM	B	SOCIETY	DF
...	...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	NaN	07/13/2013 06:37:00 AM	A	PROPERTY	
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 06:30:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	NaN	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	NaN	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:30:00 AM	02/26/2010 07:54:00 AM	A	PROPERTY	

962145 rows × 22 columns

In [804]:
```
#Dropping unncessary columns:
# Will be keeping offence Parent Group and droping offense, offense en
df_new = df.drop(columns =['Offense End DateTime','Offense','100 Block
df_new
```

Out[804]:

	Report Number	Offense ID	Offense Start DateTime	Report DateTime	Group A B	Crime Against Category	Offe
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	02/05/2020 11:24:31 AM	A	SOCIETY	DRUG/NAR
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTRUCTION/DAI
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	02/05/2020 12:51:31 AM	B	SOCIETY	DRIVING UNDEI
...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	07/13/2013 06:37:00 AM	A	PROPERTY	MOTO
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	MOTO
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:54:00 AM	A	PROPERTY	MOTO

962145 rows × 19 columns

In [805]:
```
df_new['Date'].value_counts()
```

Out[805]:
```
2020-05-18    764
2020-05-15    667
2020-03-08    658
2020-05-14    621
2020-05-20    584
             ...
2005-09-13      1
2007-01-07      1
2006-01-25      1
1989-05-14      1
1997-11-01      1
Name: Date, Length: 5865, dtype: int64
```

In [806]:
```
df_new['dt_Year'] = pd.to_datetime(df_new.Date,format='%Y',exact=False
```

In [472]:
```
df_new
```

Out[472]:

	Report Number	Offense ID	Offense Start DateTime	Report DateTime	Group A B	Crime Against Category	Offe
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	02/05/2020 11:24:31 AM	A	SOCIETY	DRUG/NAR
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTRUCTION/DAI
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	02/05/2020 12:51:31 AM	B	SOCIETY	DRIVING UNDEI
...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	07/13/2013 06:37:00 AM	A	PROPERTY	MOTO
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	MOTO
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:54:00 AM	A	PROPERTY	MOTO

962145 rows × 20 columns

In [473]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 962145 entries, 0 to 962144
Data columns (total 20 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   Report Number           962145 non-null  object
 1   Offense ID              962145 non-null  int64
 2   Offense Start DateTime  961188 non-null  object
 3   Report DateTime         962145 non-null  object
 4   Group A B               962145 non-null  object
 5   Crime Against Category  962145 non-null  object
 6   Offense Parent Group    962145 non-null  object
 7   Offense Code            962145 non-null  object
 8   Precinct                962141 non-null  object
 9   Sector                  962143 non-null  object
 10  Beat                    962143 non-null  object
 11  MCPP                    962142 non-null  object
 12  Longitude               962145 non-null  float64
 13  Latitude                962145 non-null  float64
 14  year                    961188 non-null  float64
 15  month                   961188 non-null  object
 16  day_of_week             961188 non-null  object
 17  hour                    961188 non-null  float64
 18  Date                    961188 non-null  object
 19  dt_Year                 961188 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(4), int64(1), object(14)
memory usage: 146.8+ MB
```

In [807]:
```
#Restting the index of the dataframe
df_new.reset_index(drop=True, inplace=True)
df_new
```

Out[807]:

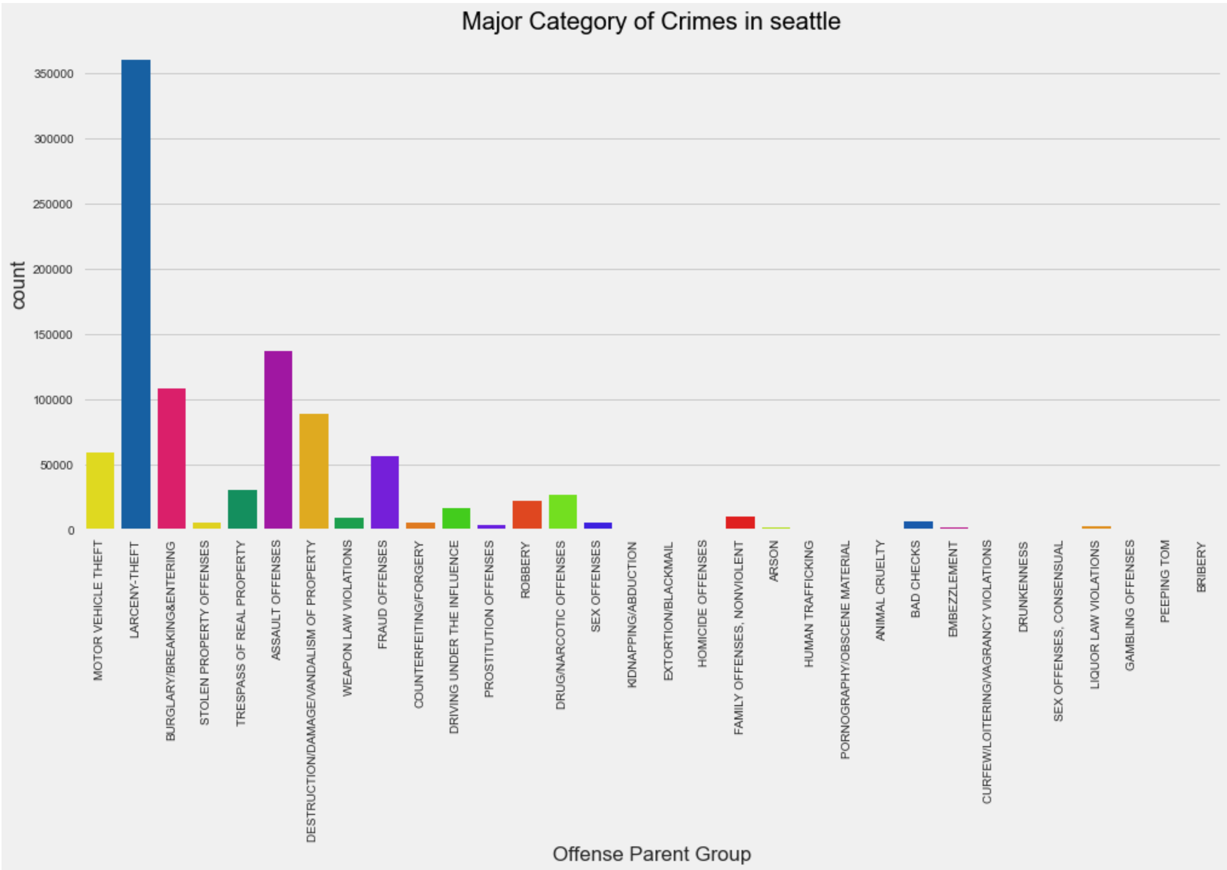
	Report Number	Offense ID	Offense Start DateTime	Report DateTime	Group A B	Crime Against Category	Offe
0	2020-044620	12605873663	02/05/2020 10:10:00 AM	02/05/2020 11:24:31 AM	A	SOCIETY	DRUG/NAR
1	2020-044452	12605598696	02/03/2020 08:00:00 AM	02/05/2020 10:06:28 AM	A	PROPERTY	
2	2020-044465	12605567653	02/02/2020 08:30:00 PM	02/05/2020 09:39:33 AM	A	PROPERTY	
3	2020-044225	12605174036	02/05/2020 01:17:00 AM	02/05/2020 03:30:55 AM	A	PROPERTY	DESTRUCTION/DAI
4	2020-044076	12605081469	02/05/2020 12:51:21 AM	02/05/2020 12:51:31 AM	B	SOCIETY	DRIVING UNDEI
...	...	...	...	...	...	...	
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	07/13/2013 06:37:00 AM	A	PROPERTY	MOTO
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	MOTO
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	02/14/2012 03:04:00 PM	A	PROPERTY	
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	09/19/2010 04:59:00 PM	A	PROPERTY	
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:54:00 AM	A	PROPERTY	MOTO

962145 rows × 20 columns

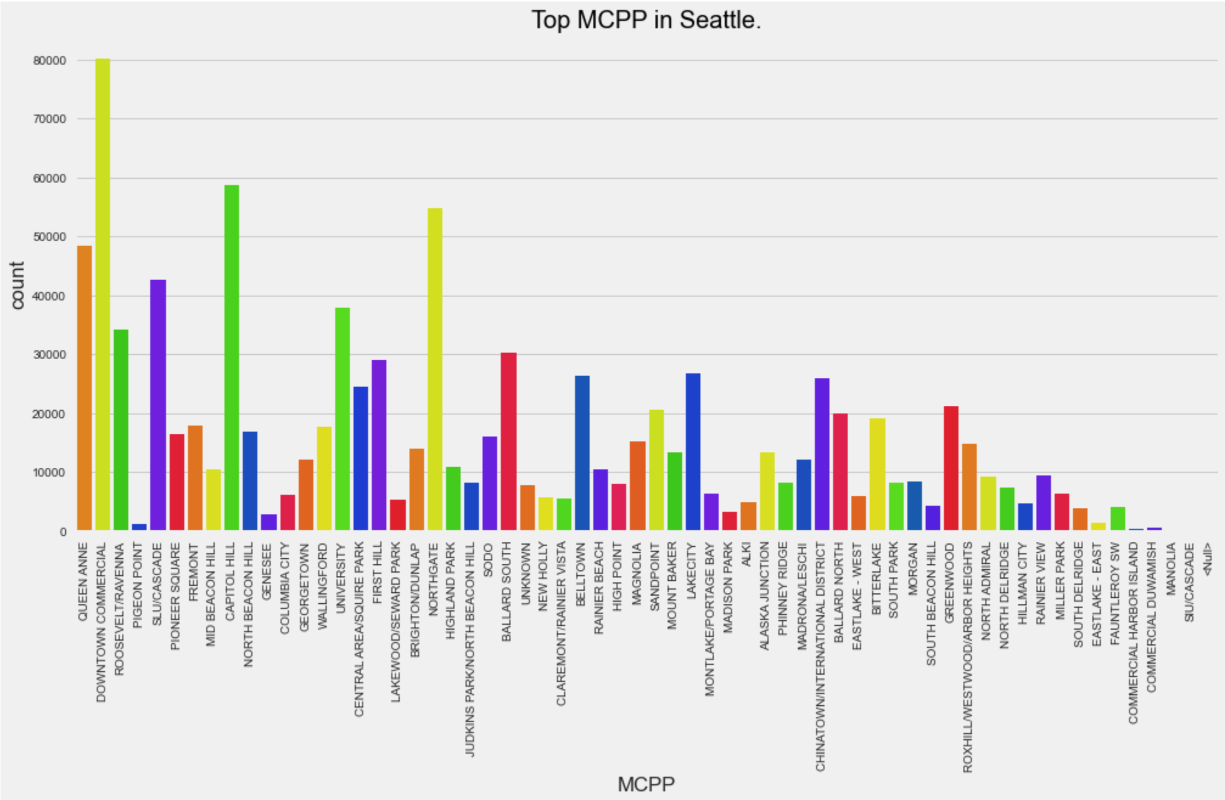
Visualizations to understand the data.

LEt's visualize the data to understand it better.

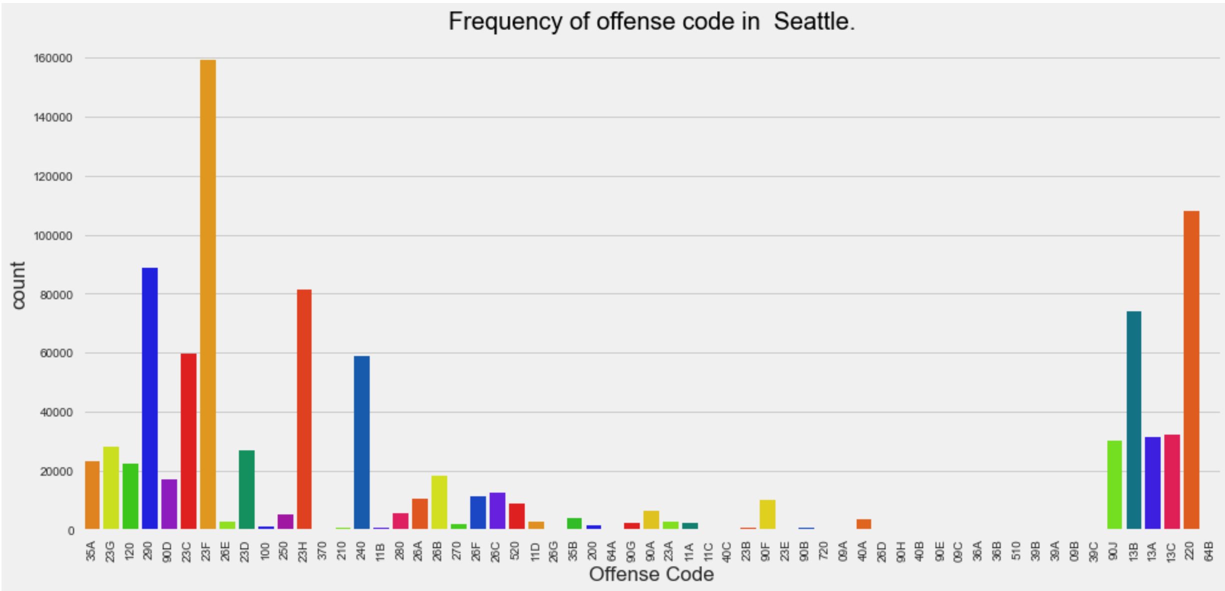
In [808]:
```
#Different categories of crime:
plt.rcParams['figure.figsize'] = (15, 7)
plt.style.use('fivethirtyeight')

sns.countplot(df_new['Offense Parent Group'].sort_index(ascending=Fals
plt.title('Major Category of Crimes in seattle', fontweight = 30, font
plt.xticks(rotation = 90)
plt.show()
```



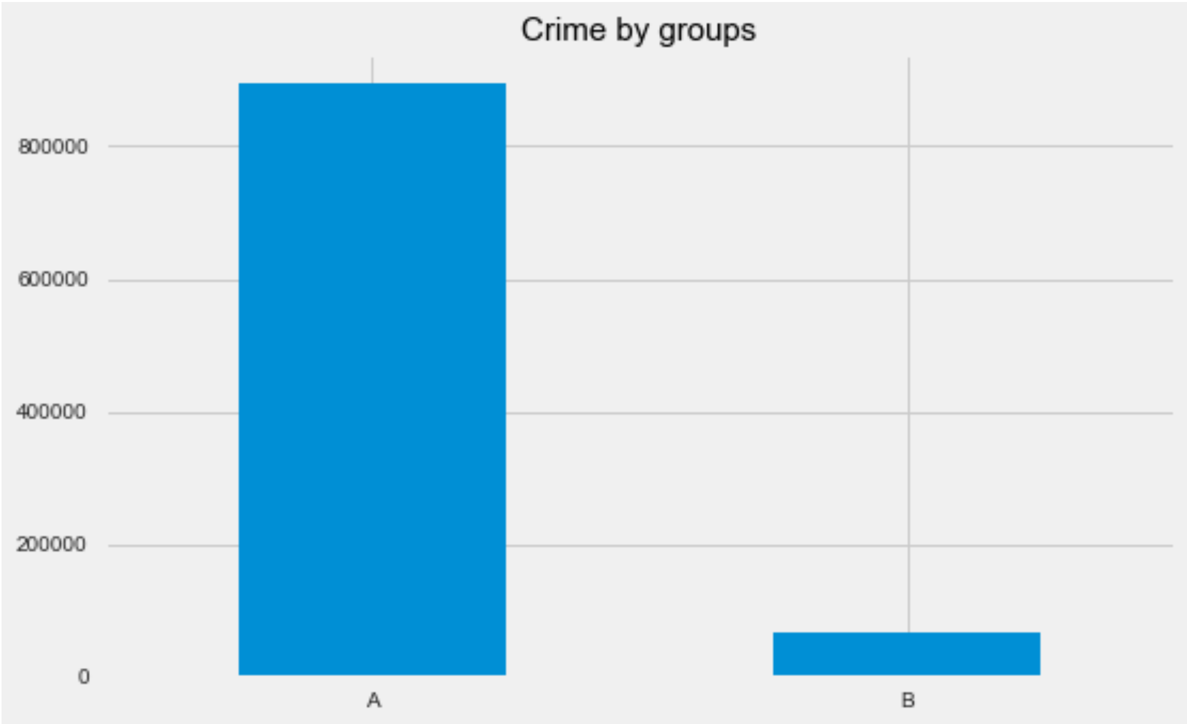
In [809]:
```
#Top MCPP :
plt.rcParams['figure.figsize'] = (15, 7)
plt.style.use('fivethirtyeight')
color = plt.cm.ocean(np.linspace(0, 1, 15))
sns.countplot(df_new['MCPP'].sort_index(ascending=False), palette = 'p
plt.title('Top MCPP in Seattle.', fontweight = 30, fontsize = 20,color
plt.xticks(rotation = 90)
plt.show()
```



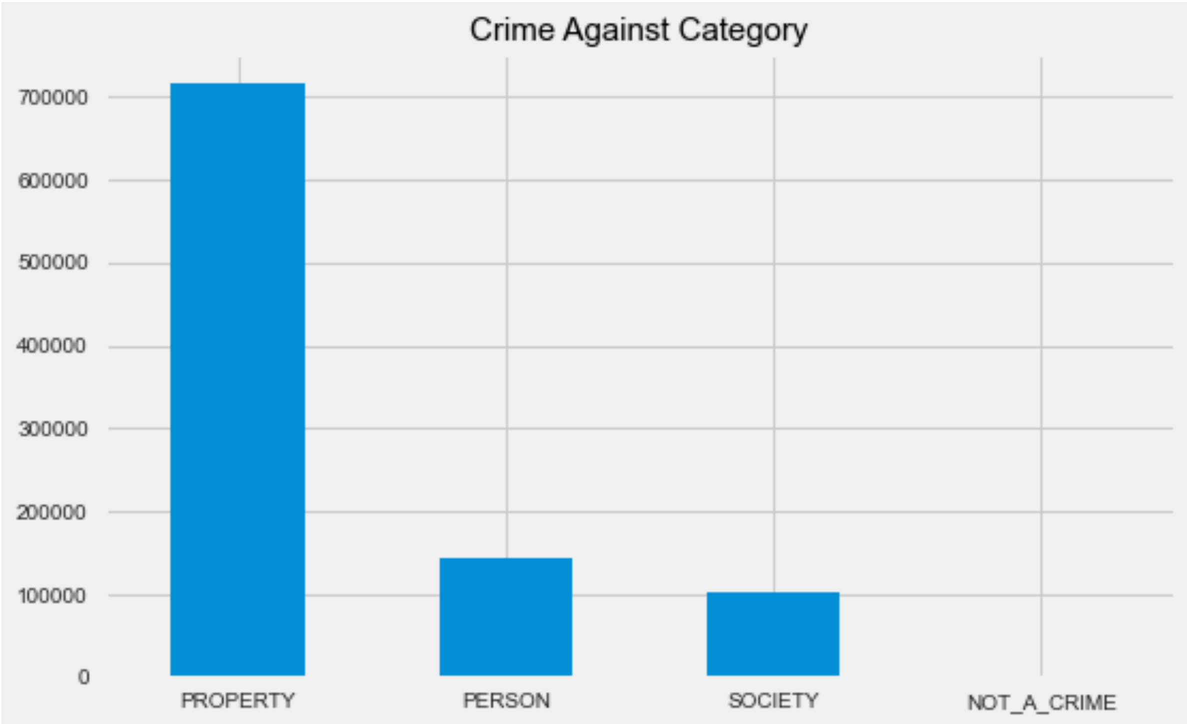
In [810]:
```
#Frequency of offense code::
plt.rcParams['figure.figsize'] = (15, 7)
plt.style.use('fivethirtyeight')
color = plt.cm.ocean(np.linspace(0, 1, 15))
sns.countplot(df_new['Offense Code'].sort_index(ascending=True), palet
plt.title('Frequency of offense code in  Seattle.', fontweight = 30, f
plt.xticks(rotation = 90)
plt.show()
```



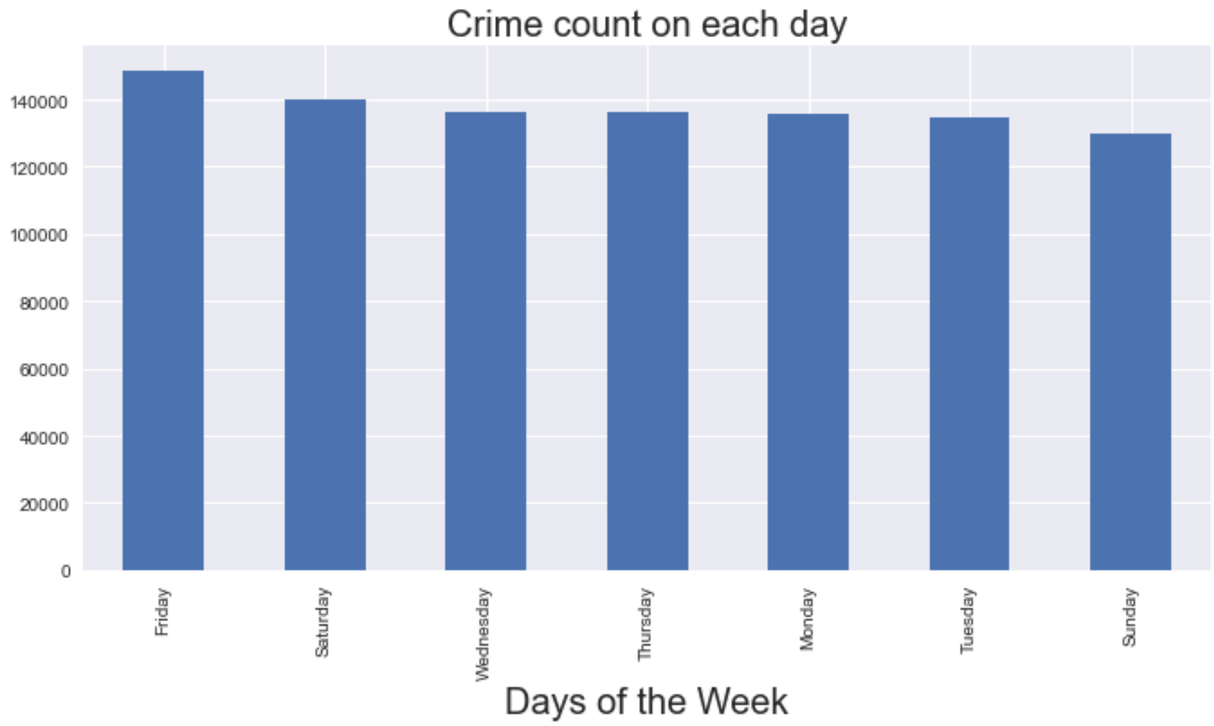
In [811]:
```
#crime by Groups:
plt.rcParams['figure.figsize'] = (8, 5)
plt.style.use('fivethirtyeight')
color = plt.cm.spring(np.linspace(0, 1, 5))
df_new['Group A B'].value_counts().plot.bar()

plt.title('Crime by groups',fontsize =15,color ='Black')
plt.xticks(rotation = 360)
plt.savefig('Crime by groups.png')
plt.show()
```



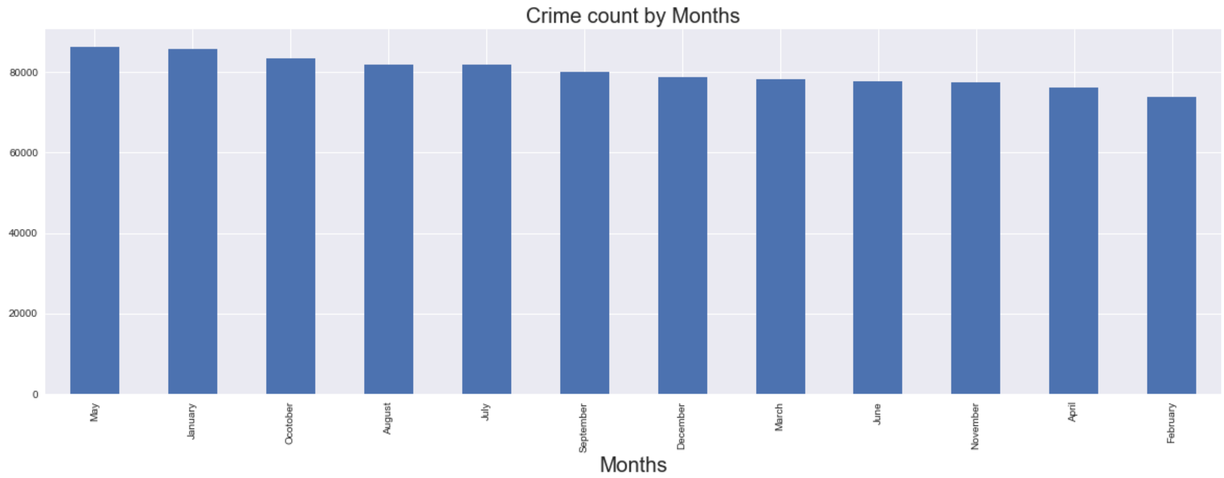
In [812]:
```
#plt.rcParams['figure.figsize'] = (8, 5)
plt.style.use('fivethirtyeight')

color = plt.cm.spring(np.linspace(0, 1, 5))
df_new['Crime Against Category'].value_counts().plot.bar()

plt.title('Crime Against Category',fontsize =15,color ='Black')
plt.xticks(rotation = 360)
plt.show()
```



In [813]:
```
#Crime count by weekdays:
plt.style.use('seaborn')

color = plt.cm.cool(np.linspace(0, 1, 15))
df_new['day_of_week'].value_counts().head(15).plot.bar(figsize = (10,
plt.xlabel("Days of the Week",fontsize=20)
plt.title('Crime count on each day',fontsize = 20)
plt.xticks(rotation = 90)
plt.show()
```

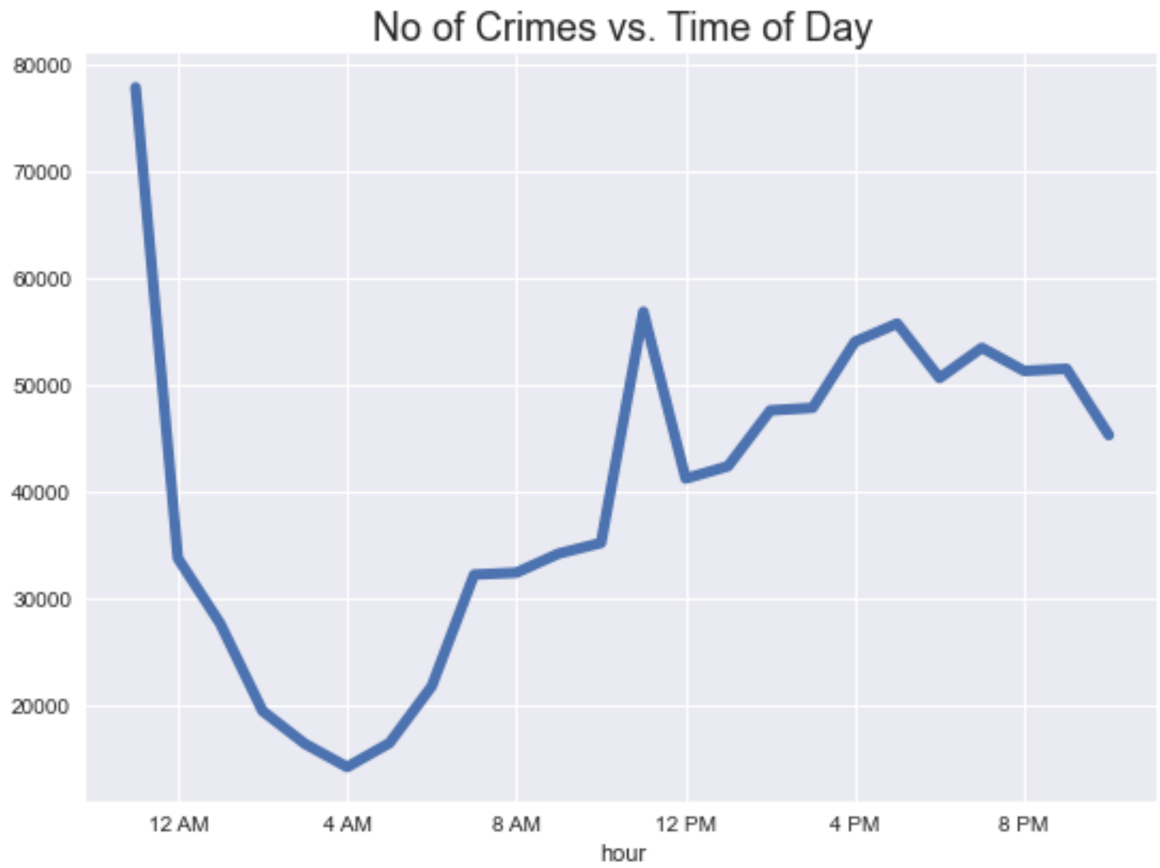


In [814]:
```
#Crime count by Month:
plt.style.use('seaborn')

color = plt.cm.cool(np.linspace(0, 1, 15))
df_new['month'].value_counts().sort_index(ascending=False).sort_values
plt.xlabel("Months",fontsize=20)
plt.title('Crime count by Months',fontsize = 20)
plt.xticks(rotation = 90)
plt.show()
```

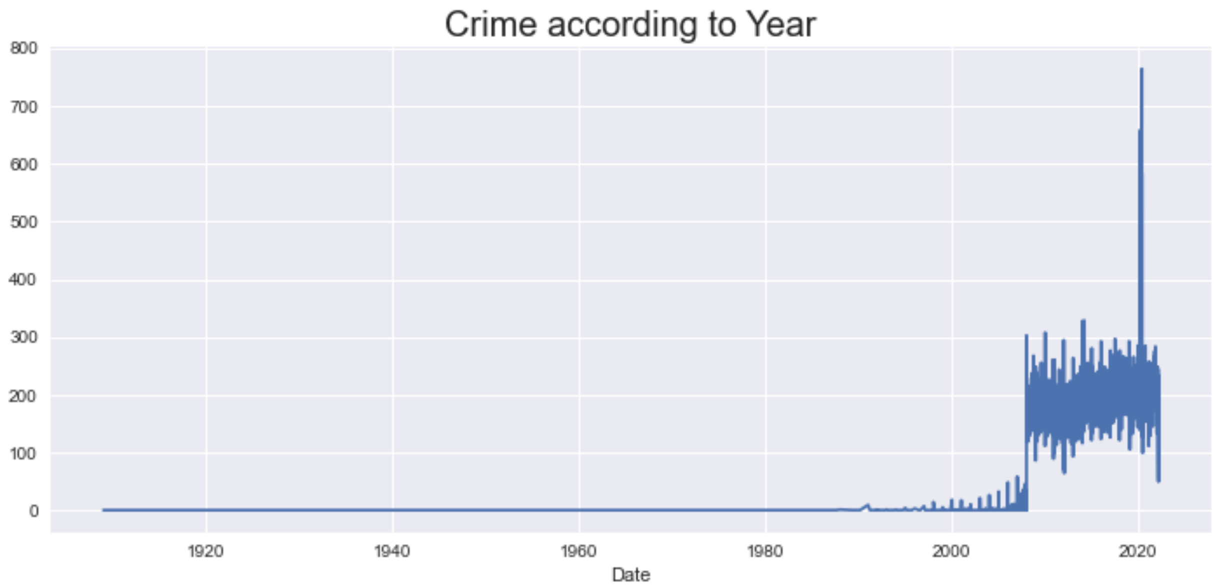


In [815]:
```
#Create line plot of crimes per hour
crime_per_hour = df_new.groupby("hour").count()
plt.title("No of Crimes vs. Time of Day",fontsize=18)
plt.xticks(np.arange(1,24,4),['12 AM','4 AM','8 AM','12 PM','4 PM','8
crime_per_hour['Offense Parent Group'].plot(figsize=(8,6),label='Total
```

Out[815]:
```
<AxesSubplot:title={'center':'No of Crimes vs. Time of Day'}, xlabel
='hour'>
```



In [816]:
```
#Lets plot a line plot to plot crimes accoriding to date
plt.figure(figsize=(10,5))
df_new.groupby('Date').count()['Offense Parent Group'].plot();
plt.title('Crime according to Year', fontsize=20)
plt.tight_layout()
```

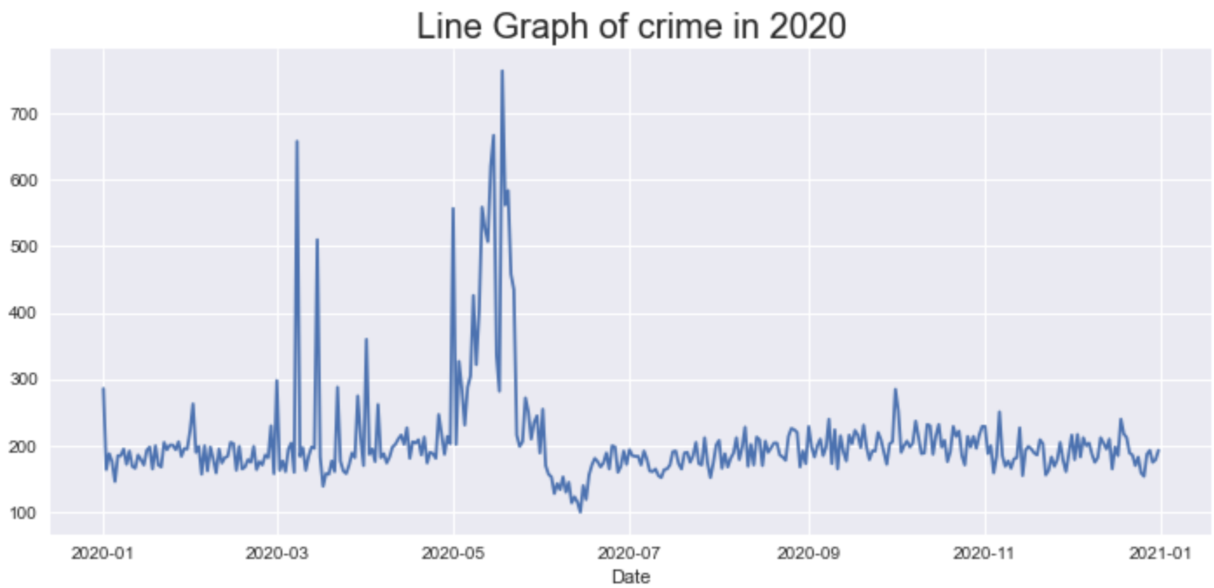


In [817]:
```
#Lets create a table with the highest no of crimes in Seattle.
crime_dates = df_new[df_new["year"] == 2020]
top_10_days = pd.DataFrame(crime_dates["dt_Year"].value_counts().head(
top_10_days.reset_index(inplace=True)
top_10_days.columns=['Date','Count']
top_10_days.head(10)
```

Out[817]:

	Date	Count
0	2020-01-01	76060

In [818]:
```
#Plot crimes according to days in 2020
crime_rate = df_new[df_new["year"] == 2020]
plt.figure(figsize=(10,5))
crime_rate.groupby('Date').count()['Offense Parent Group'].plot();
plt.title("Line Graph of crime in 2020",fontsize=20)
plt.tight_layout()
```

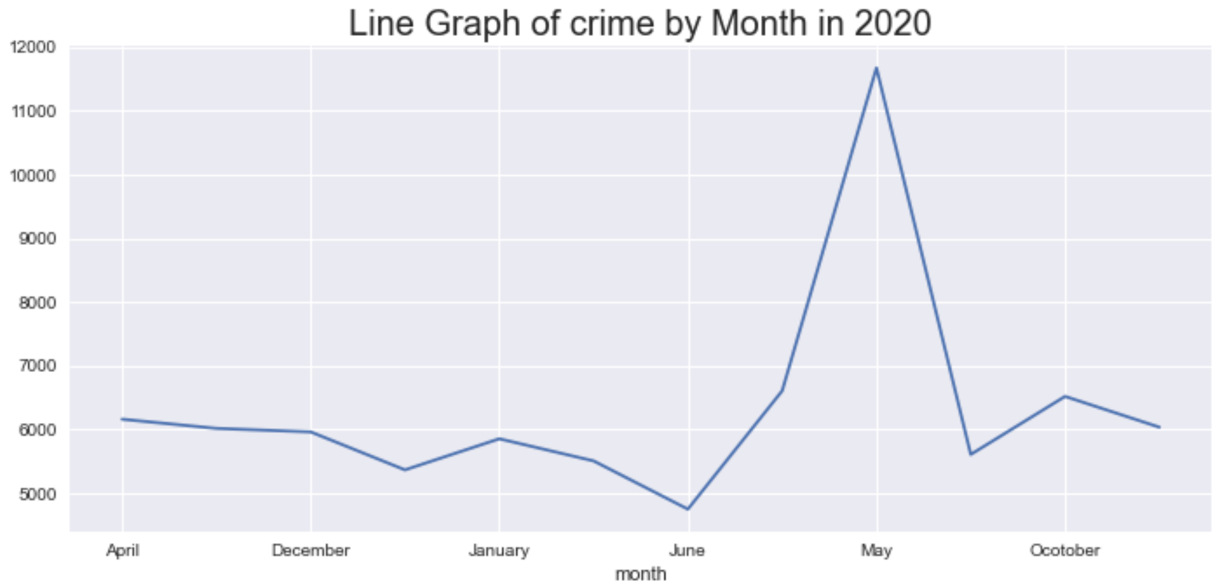


In [819]:
```
#counts by month:
crime_by_month = df_new[df_new["year"] ==2020]
top_10_counts =pd.DataFrame(crime_by_month["month"].value_counts().hea
top_10_counts.reset_index(inplace=True)
top_10_counts.columns = ['Month','Count']
top_10_counts.head(20)
```

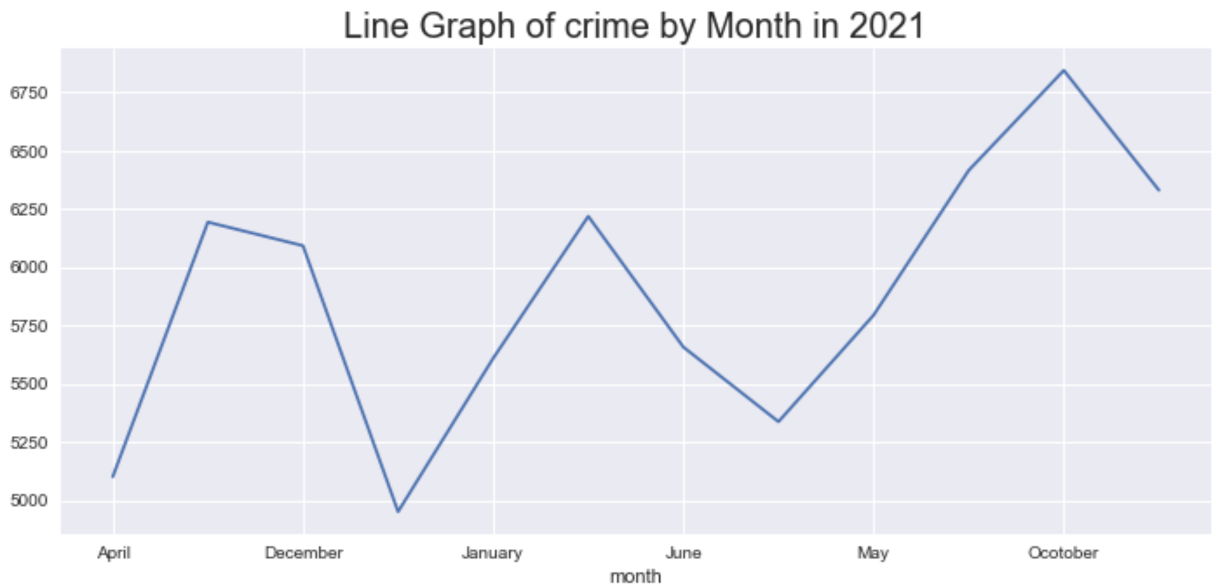
Out[819]:

	Month	Count
0	May	11673
1	March	6607
2	Ocotober	6519
3	April	6161
4	September	6036
5	August	6017
6	December	5962
7	January	5854
8	November	5608
9	July	5507

In [820]:
```
#Plot crimes according to month in 2020
crime_rate = df_new[df_new["year"] == 2020]

plt.figure(figsize=(10,5))
crime_rate.groupby('month').count()['Offense Parent Group'].plot();
plt.title("Line Graph of crime by Month in 2020",fontsize=20)
plt.tight_layout()
```



In [821]:
```
#Plot crimes according to days in 2021
crime_rate = df_new[df_new["year"] == 2021]

plt.figure(figsize=(10,5))
crime_rate.groupby('month').count()['Offense Parent Group'].plot();
plt.title("Line Graph of crime by Month in 2021",fontsize=20)
plt.tight_layout()
```



In [822]:
```
df_new.tail()
```

Out[822]:

	Report Number	Offense ID	Offense Start DateTime	Report DateTime	Group A B	Crime Against Category	Offense Parent Group	Offense Code
962140	2013-247888	7687554356	07/13/2013 01:00:00 AM	07/13/2013 06:37:00 AM	A	PROPERTY	MOTOR VEHICLE THEFT	240
962141	2013-227022	7682354808	06/26/2013 11:00:00 AM	06/29/2013 09:43:00 AM	A	PROPERTY	MOTOR VEHICLE THEFT	240
962142	2012-045494	7672915592	02/14/2012 03:04:00 PM	02/14/2012 03:04:00 PM	A	PROPERTY	LARCENY-THEFT	23C
962143	2010-328592	7692227482	09/19/2010 04:59:00 PM	09/19/2010 04:59:00 PM	A	PROPERTY	LARCENY-THEFT	23C
962144	2010-064656	7686420892	02/25/2010 06:00:00 PM	02/26/2010 07:54:00 AM	A	PROPERTY	MOTOR VEHICLE THEFT	240

In [823]:
```
eep only the cloumns we need:
 = df_new.drop(columns =['Report Number','Crime Against Category','Bea
```

Out[823]:

	Offense Parent Group	year	month	day_of_week	Date	dt_Year
0	DRUG/NARCOTIC OFFENSES	2020.0	February	Wednesday	2020-02-05	2020-01-01
1	LARCENY-THEFT	2020.0	February	Monday	2020-02-03	2020-01-01
2	ROBBERY	2020.0	February	Sunday	2020-02-02	2020-01-01
3	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	2020.0	February	Wednesday	2020-02-05	2020-01-01
4	DRIVING UNDER THE INFLUENCE	2020.0	February	Wednesday	2020-02-05	2020-01-01
...	...	...	...	...	...	...
962140	MOTOR VEHICLE THEFT	2013.0	July	Saturday	2013-07-13	2013-01-01
962141	MOTOR VEHICLE THEFT	2013.0	June	Wednesday	2013-06-26	2013-01-01
962142	LARCENY-THEFT	2012.0	February	Tuesday	2012-02-14	2012-01-01
962143	LARCENY-THEFT	2010.0	September	Sunday	2010-09-19	2010-01-01
962144	MOTOR VEHICLE THEFT	2010.0	February	Thursday	2010-02-25	2010-01-01

962145 rows × 6 columns

In [826]:
```
#checking the nulls.
df_crime.isna().sum()
```

Out[826]:
```
Offense Parent Group    0
year                    0
month                   0
day_of_week             0
Date                    0
dt_Year                 0
dtype: int64
```

In [827]:
```
df_crime= df_crime.dropna(axis=0, how='any')
df_crime
```

Out[827]:

	Offense Parent Group	year	month	day_of_week	Date	dt_Year
0	DRUG/NARCOTIC OFFENSES	2020.0	February	Wednesday	2020-02-05	2020-01-01
1	LARCENY-THEFT	2020.0	February	Monday	2020-02-03	2020-01-01
2	ROBBERY	2020.0	February	Sunday	2020-02-02	2020-01-01
3	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	2020.0	February	Wednesday	2020-02-05	2020-01-01
4	DRIVING UNDER THE INFLUENCE	2020.0	February	Wednesday	2020-02-05	2020-01-01
...	...	...	...	...	...	...
962140	MOTOR VEHICLE THEFT	2013.0	July	Saturday	2013-07-13	2013-01-01
962141	MOTOR VEHICLE THEFT	2013.0	June	Wednesday	2013-06-26	2013-01-01
962142	LARCENY-THEFT	2012.0	February	Tuesday	2012-02-14	2012-01-01
962143	LARCENY-THEFT	2010.0	September	Sunday	2010-09-19	2010-01-01
962144	MOTOR VEHICLE THEFT	2010.0	February	Thursday	2010-02-25	2010-01-01

961188 rows × 6 columns

In [829]:
```
#Converting float year to int:
df_crime.year = df_crime.year.astype(int)
```

In [831]:
```
df_crime['offense_counts'] = df_crime['Offense Parent Group']
```

In [832]:
```
crime_rate
```

Out[832]:

	Report Number	Offense ID	Offense Start DateTime	Report DateTime	Group A B	Crime Against Category	Offe
855961	2021-002024	19260363069	01/03/2021 07:50:00 PM	01/03/2021 09:17:54 PM	A	PROPERTY	STOLEN PROI
857680	2021-032356	20409706356	02/07/2021 06:38:00 PM	02/07/2021 07:37:11 PM	A	PROPERTY	DESTRUCTION/DAI
857826	2021-045588	21421289970	02/15/2021 11:59:00 PM	02/23/2021 05:27:31 PM	A	PROPERTY	MOTO
858055	2021-039062	20881878784	02/16/2021 07:46:00 AM	02/16/2021 09:54:58 AM	A	PROPERTY	STOLEN PROI
858273	2021-054304	21681081028	03/05/2021 04:16:00 AM	03/05/2021 05:05:24 AM	A	PROPERTY	STOLEN PROI
...	...	...	...	...	...	...	
962123	2021-210204	26937951561	08/13/2021 08:28:00 PM	08/13/2021 09:12:43 PM	A	PROPERTY	DESTRUCTION/DAI
962124	2021-210204	26938167902	08/13/2021 08:28:00 PM	08/13/2021 09:12:43 PM	A	SOCIETY	WEAPON
962125	2021-209603	31723041119	08/13/2021 09:11:00 AM	08/13/2021 10:23:44 AM	A	PERSON	AS
962126	2021-206747	31721990307	08/10/2021 03:05:00 PM	08/10/2021 06:24:31 PM	A	PROPERTY	DESTRUCTION/DAI
962127	2021-206747	31722010130	08/10/2021 03:05:00 PM	08/10/2021 06:24:31 PM	A	PERSON	AS

70553 rows × 20 columns

In [834]:
```
#grouping by Date
crime_rate.groupby('Date').count()['Offense Parent Group']
```

Out[834]:
```
Date
2021-01-01    238
2021-01-02    164
2021-01-03    179
2021-01-04    203
2021-01-05    158
             ...
2021-12-27    134
2021-12-28    139
2021-12-29    162
2021-12-30    178
2021-12-31    190
Name: Offense Parent Group, Length: 365, dtype: int64
```

In [835]:
```
crime_rate.groupby('Date').count()['Offense Parent Group']
```

Out[835]:
```
Date
2021-01-01    238
2021-01-02    164
2021-01-03    179
2021-01-04    203
2021-01-05    158
             ...
2021-12-27    134
2021-12-28    139
2021-12-29    162
2021-12-30    178
2021-12-31    190
Name: Offense Parent Group, Length: 365, dtype: int64
```

In [836]:
```
df_crime_new =df_crime.groupby('Date').count()['Offense Parent Group']
```

In [837]:
```
df_crime_new
```

Out[837]:

	Date	count
0	1908-12-13	1
1	1915-12-14	1
2	1920-09-23	1
3	1929-06-06	1
4	1953-04-20	1
...	...	...
5860	2022-02-23	162
5861	2022-02-24	145
5862	2022-02-25	145
5863	2022-02-26	111
5864	2022-02-27	51

5865 rows × 2 columns

Feature Engineering

Prepping our data for modelling.

In [838]:
```
#Prepping our final dataframe.
finalDataFrame = pd.DataFrame()
years =[2010,2011,2012,2013,2014,2015,2016,2017,2018,2019,2020,2021]

for year in years:
    #print(year)
    crime_rate = df_crime[df_crime["year"]== year]
    #monthly_count = pd.concat([monthly_count, crime_rate.groupby(['ye
    df2 = crime_rate.groupby(['year', 'month']).count()['Offense Paren
    if finalDataFrame.empty:
        finalDataFrame = df2
    else:
        finalDataFrame = finalDataFrame.append(df2, ignore_index=True)
print(finalDataFrame)
```

```
     year      month  count
0    2010      April   5199
1    2010     August   5292
2    2010   December   4992
3    2010   February   4680
4    2010    January   6059
..    ...        ...    ...
139  2021      March   5338
140  2021        May   5795
141  2021   November   6416
142  2021    Ocotober   6845
143  2021  September   6331

[144 rows x 3 columns]
```

In [839]:
```
#Our finaldataframe
finalDataFrame
```

Out[839]:

	year	month	count
0	2010	April	5199
1	2010	August	5292
2	2010	December	4992
3	2010	February	4680
4	2010	January	6059
...	...	...	...
139	2021	March	5338
140	2021	May	5795
141	2021	November	6416
142	2021	Ocotober	6845
143	2021	September	6331

144 rows × 3 columns

In [840]:
```
#max value in finalDataFrame
finalDataFrame.max()
```

Out[840]:
```
year           2021
month     September
count         11673
dtype: object
```

In [842]:
```
#Mapping Months to numbers.
d = {'January':'01', 'February':'02', 'March':'03', 'April':'04', 'May
''
finalDataFrame['yearMonth'] = pd.to_datetime(finalDataFrame['year'].as
finalDataFrame
```

Out[842]:

	year	month	count	yearMonth
0	2010	April	5199	2010-04-01
1	2010	August	5292	2010-08-01
2	2010	December	4992	2010-12-01
3	2010	February	4680	2010-02-01
4	2010	January	6059	2010-01-01
...	...	...	...	...
139	2021	March	5338	2021-03-01
140	2021	May	5795	2021-05-01
141	2021	November	6416	2021-11-01
142	2021	Ocotober	6845	2021-10-01
143	2021	September	6331	2021-09-01

144 rows × 4 columns

In [843]:
```
#Creating our final Dtataframe and set_index as Year/Month.
finalDataFrame['Year/Month'] = pd.to_datetime(finalDataFrame['yearMont
finalDataFrame.set_index('Year/Month', inplace=True)
finalDataFrame = finalDataFrame.drop(columns=['year','month','yearMont
finalDataFrame
```

Out[843]:

	count
Year/Month	
2010-04-01	5199
2010-08-01	5292
2010-12-01	4992
2010-02-01	4680
2010-01-01	6059
...	...
2021-03-01	5338
2021-05-01	5795
2021-11-01	6416
2021-10-01	6845
2021-09-01	6331

144 rows × 1 columns

In [844]:

```
#our final dataframe:
finalDataFrame= finalDataFrame.sort_values(by="Year/Month")
finalDataFrame
```

2010-01-01	6059
2010-02-01	4680
2010-03-01	5116
2010-04-01	5199
2010-05-01	5526
...	...
2021-08-01	6194
2021-09-01	6331
2021-10-01	6845
2021-11-01	6416
2021-12-01	6093

144 rows × 1 columns

In [845]:

```
finalDataFrame_monthly = finalDataFrame.resample('Q')
month_mean= finalDataFrame_monthly.mean()
```

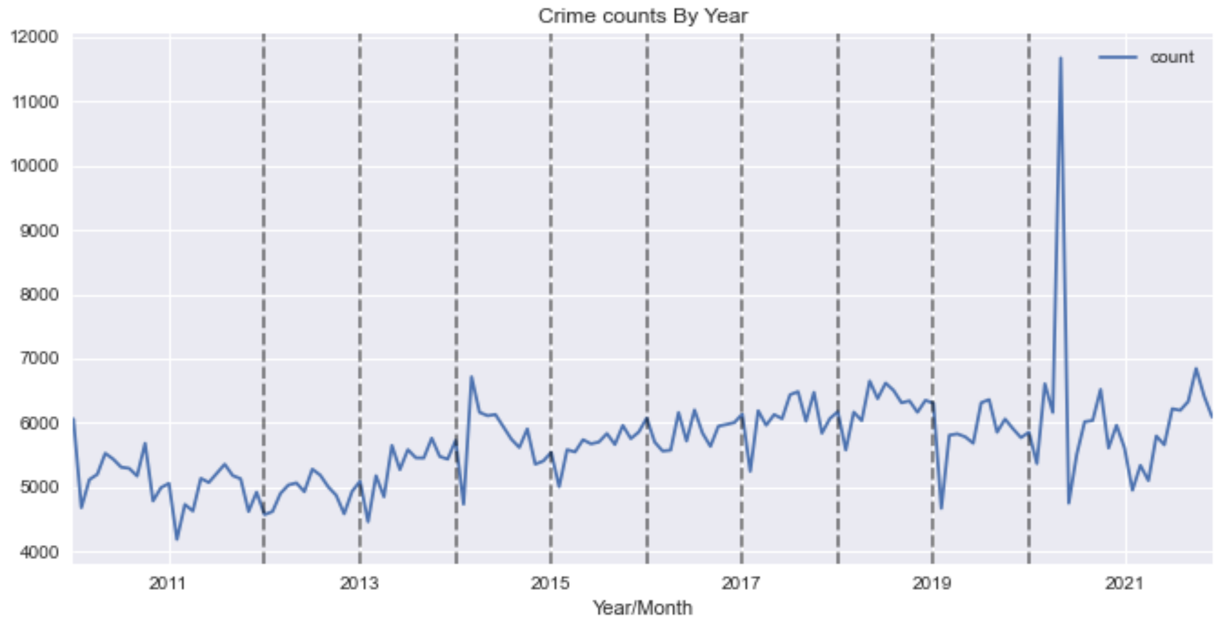
In [846]:

```
month_mean.head()
```

Out[846]:

	count
Year/Month	
2010-03-31	5285.000000
2010-06-30	5386.666667
2010-09-30	5258.333333
2010-12-31	5152.666667
2011-03-31	4658.333333

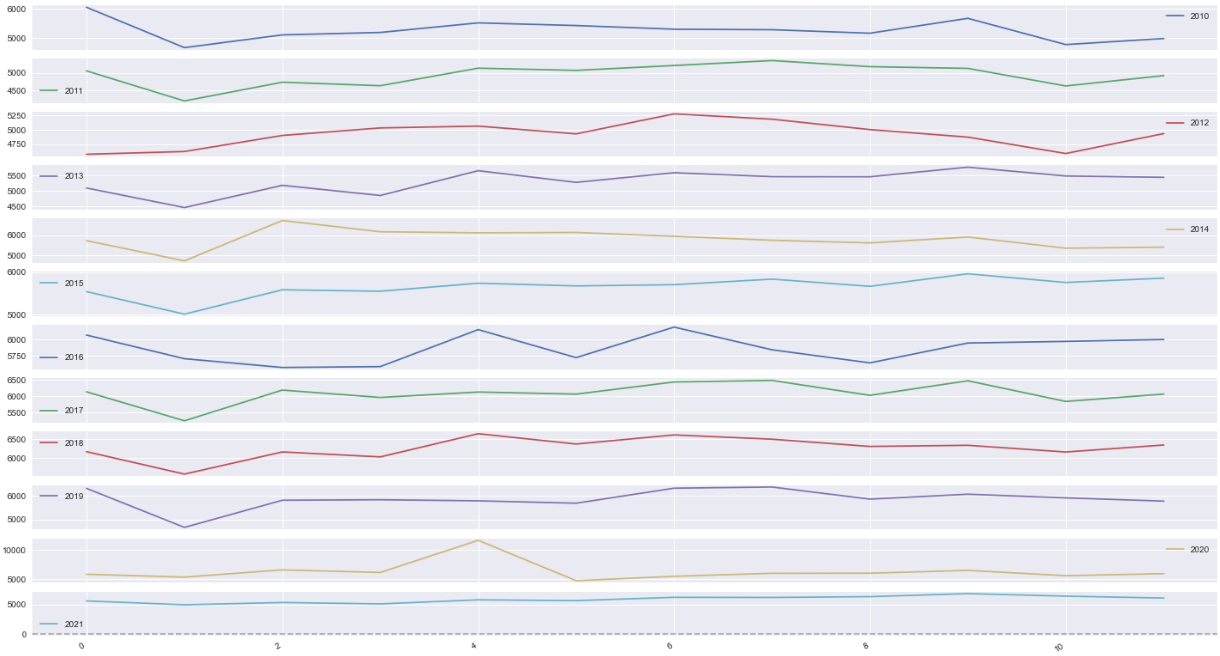
In [847]:
```
# Create a time series line plot for finalDataFrame
finalDataFrame.plot(figsize = (10,5))
for year in range(2012,2021):
    plt.axvline(datetime(year,1,1),linestyle='--',color ='k',alpha= 0.
plt.title("Crime counts By Year")
plt.show()
```



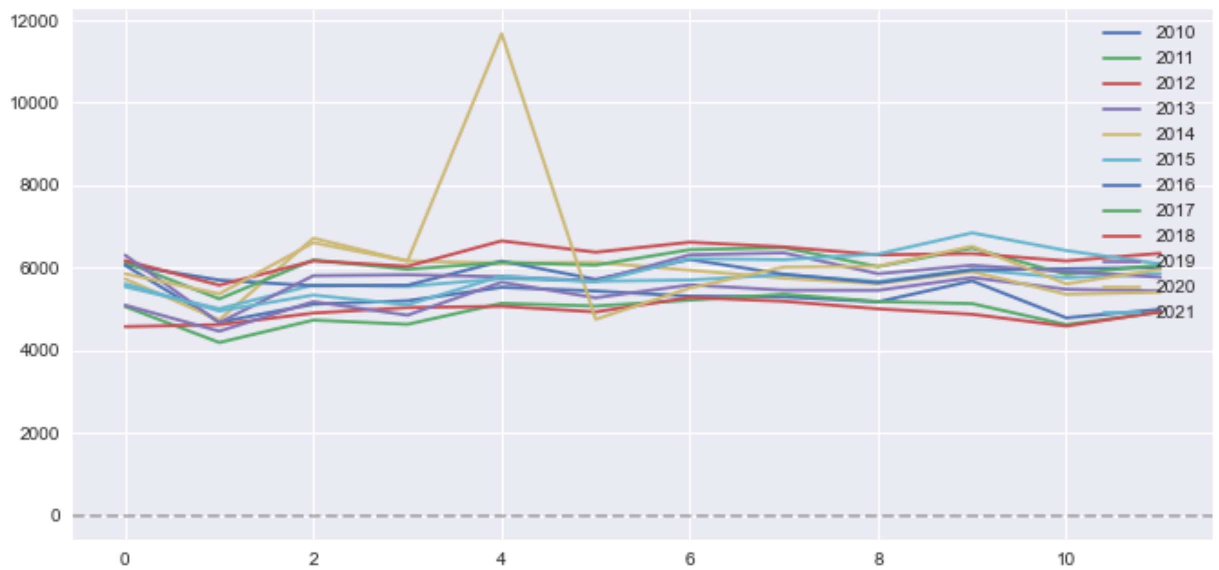
Grouping and Visualizing time series data

In [848]:
```
#let's group the data by year and create a line plot for each year for
year_groups = finalDataFrame.groupby(pd.Grouper(freq ='A'))
```

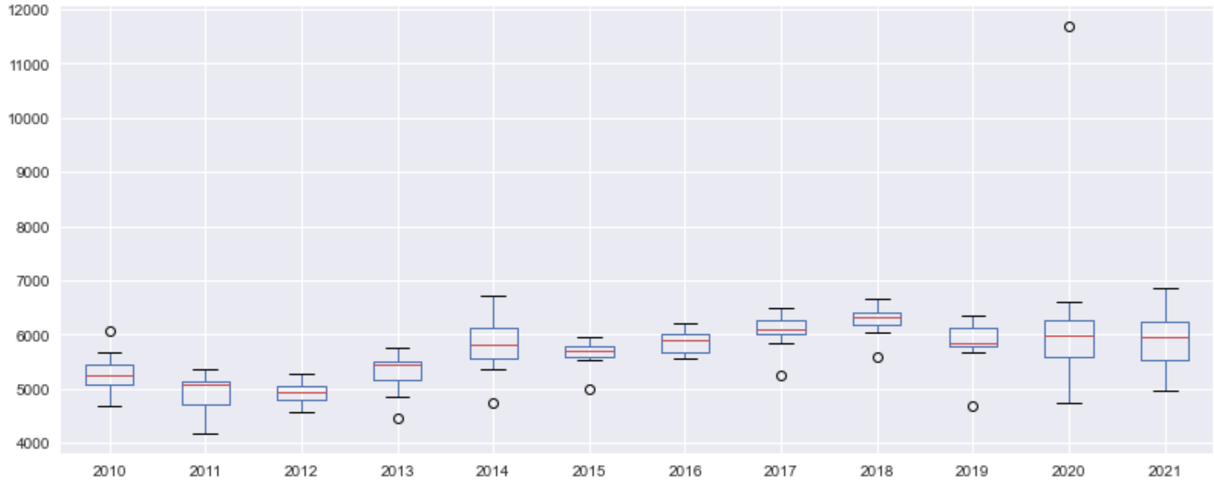
In [849]:
```
# Create a new DataFrame and store yearly values in columns
crime_annual = pd.DataFrame()

for yr, group in year_groups:
    crime_annual[yr.year] = group.values.ravel()

# Plot the yearly groups as subplots
crime_annual.plot(figsize = (22,15), subplots=True, legend=True)
plt.axhline(0,linestyle='--',color ='k',alpha= 0.3)
plt.show()
```



In [850]:
```
# Plot all years on the same graph
crime_annual.plot(figsize = (10,5), subplots=False, legend=True)
plt.axhline(0,linestyle='--',color ='k',alpha= 0.3)
plt.show()
```



In [851]:
```
# Generate a box and whiskers plot for finalDataFrame
crime_annual.boxplot(figsize = (12,5))
plt.show()
```



Step 1: Visualizing the time series:

Seasonal Decomposition

Trends - What is the overall trend in the data?

Seasonality - How does crimes fluctuate between seasons?

Residuals - When removing trends and seasonality what does the data look like?

Time Series Decomposition

Time series decomposition is a mathematical procedure that transforms a time series into multiple different time series. The original time series is often split into three component series:

- Seasonal:
- Trend:
- Random:

Since the time series doesn't seems to have a linear trend we will used model as 'Multiplicable.

By visualization, if the time series is having exponential growth or decrement with time then the time series can be considered as the multiplicative time series.

Source: [https://towardsdatascience.com/time-series-from-scratch-decomposing-time-series-data-7b7ad0c30fe7] (https://towardsdatascience.com/time-series-from-scratch-decomposing-time-series-data-7b7ad0c30fe7%5D)

In [853]:
```
#Seasonal decomposing the series to see trend, seasonality,and residua
from statsmodels.tsa.seasonal import seasonal_decompose
plt.rcParams['figure.figsize'] = 11, 9
decomposition = seasonal_decompose(finalDataFrame,model='multiplicable
decomposition.plot()
plt.show()
```

Trends - An almost linear incline in the number of monthly violent crimes,with declining rate for some months.

Seasonality - It looks like there correlation with seasons with a peak in the summer months and a trough in the winter months

Residuals - This mostly looks like noise, however we can improve on this,

Create a stationarity check function:

- Augmented Dickey-Fuller (ADF) Test

ADF test is used to determine the presence of unit root in the series, and hence helps in understanding if the series is stationary or not. The null and alternate hypothesis of this test are:

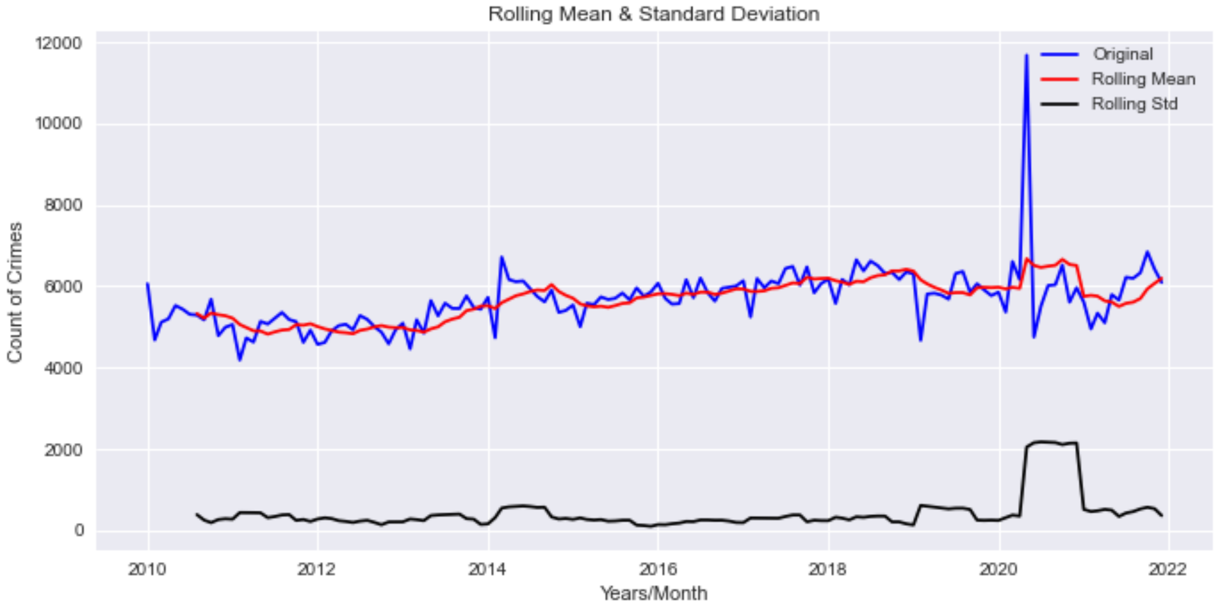
Null Hypothesis(Ho): The series has a unit root, meaning it is non-stationary. It has some time dependent structure.

Alternate Hypothesis(HA): The series has no unit root, meaning it is stationary. It does not have time-dependent structure.

Source: [https://machinelearningmastery.com/time-series-data-stationary-python/](https://machinelearningmastery.com/time-series-data-stationary-python/%5D)

In [854]:
```
# Create a function to check for the stationarity of a given time seri
#When the test statistic is lower than the critical value shown, you r

def stationarity_check(series):
    # Calculate rolling statistics
    roll_mean = series.rolling(window=8, center=False).mean()
    roll_std = series.rolling(window=8, center=False).std()

    # Perform the Dickey Fuller Test
    dftest = adfuller(series,autolag='AIC')

    # Plot rolling statistics:
    fig = plt.figure(figsize=(10,5))
    plt.xlabel("Years/Month")
    plt.ylabel("Count of Crimes")
    plt.plot(series, color='blue',label='Original')
    plt.plot(roll_mean, color='red', label='Rolling Mean')
    plt.plot(roll_std, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    # Print Dickey-Fuller test results
    print('Results of Dickey-Fuller Test: \n')

    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-valu
                                             '#Lags Used', 'Number of
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    #print(dfoutput)

    return dfoutput
```

In [855]:
```
stationarity_check(finalDataFrame)
```




```
Results of Dickey-Fuller Test:
```

Out[855]:
```
Test Statistic                  -2.529663
p-value                          0.108423
#Lags Used                       4.000000
Number of Observations Used    139.000000
Critical Value (1%)             -3.478294
Critical Value (5%)             -2.882568
Critical Value (10%)            -2.577983
dtype: float64
```

Unsurprisingly the data fails the augmeneted Dickey-Fuller Test as T-statisticis greater than Critical value,hence not being able to reject the null hypothesis(T-Statistic > Critical value 1%),which concludes:

- series is non-stationary.

Step 2: Make Time Series stationary.

In [856]:
```
#Let's try to normalise data by getting average and standard deviation
avg, dev = finalDataFrame.mean() ,finalDataFrame.std()
```

In [857]:
```
finalDataFrame1 =(finalDataFrame - avg)/dev
```

In [858]:
```
#plotting the DataFrame1:
finalDataFrame1.plot(figsize = (10,3))
for year in range(2012,2021):
    plt.axvline(datetime(year,1,1),linestyle='--',color ='k',alpha= 0.
plt.show()
```

In [863]:
```
finalDataFrame1.head()
```

Out[863]:

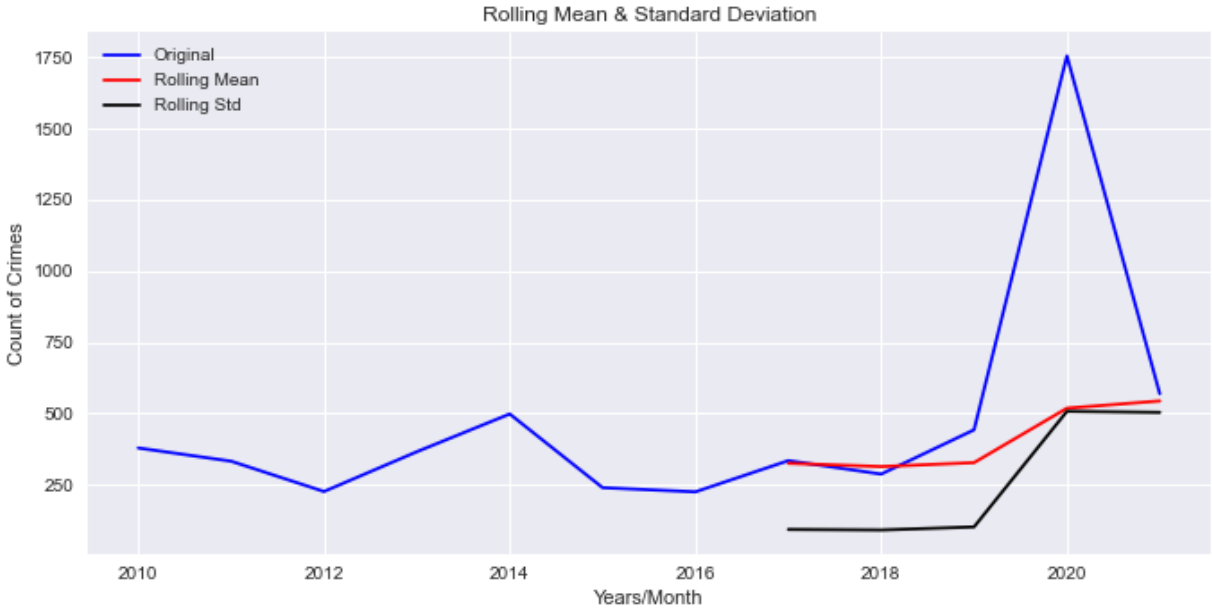
	count
Year/Month	
2010-01-01	0.502006
2010-02-01	-1.333264
2010-03-01	-0.753004
2010-04-01	-0.642542
2010-05-01	-0.207348

This doesn't show any change compared tot he original plot.Let's try another method.

In [864]:
```
#Let's try grouping
#groupby_index = finalDataFrame.groupby(finalDataFrame.index.year).stc
```

In [865]:
```
#groupby_index
```

In [866]:
```
stationarity_check(groupby_index['count'])
```




```
Results of Dickey-Fuller Test:
```

Out[866]:
```
Test Statistic                 -4.087169
p-value                         0.001017
#Lags Used                      4.000000
Number of Observations Used     7.000000
Critical Value (1%)            -4.938690
Critical Value (5%)            -3.477583
Critical Value (10%)           -2.843868
dtype: float64
```

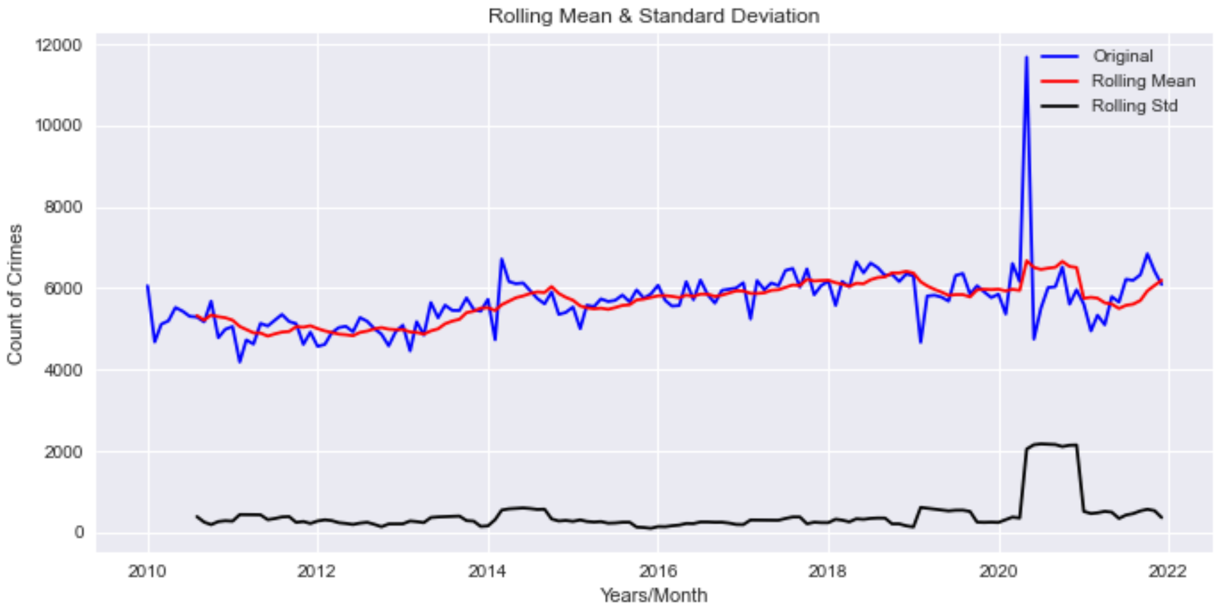
T-statistic > Critical Value, hence unable to reject the null hypothesis.Fails ADF test.Hence,is non-stationary.

Method 2:

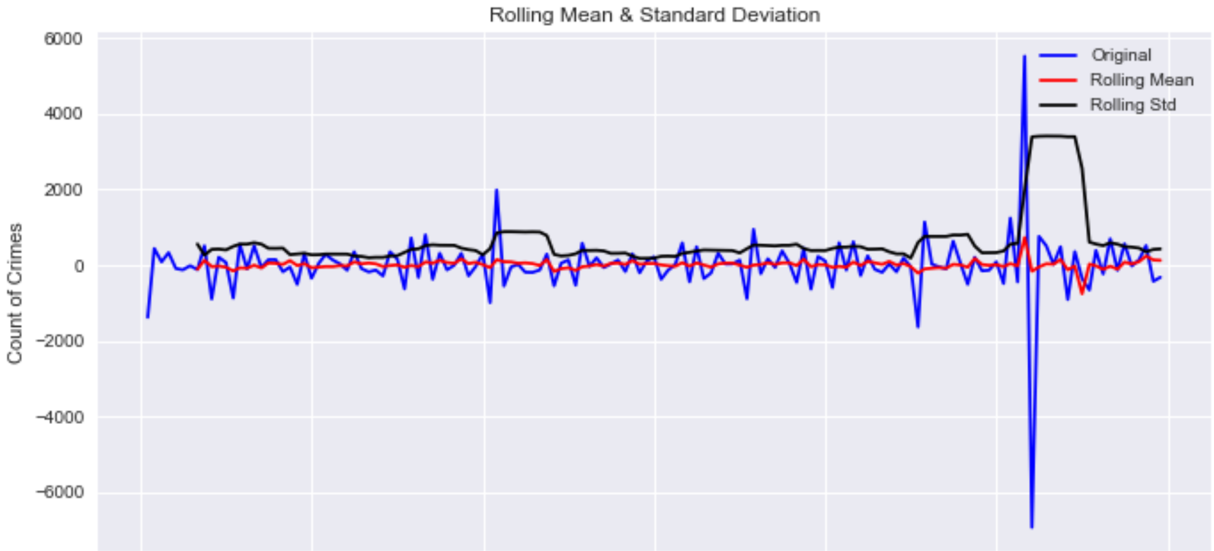
A very common way to make a time series stationary is differencing: from each value in our time series, we subtract the previous value.

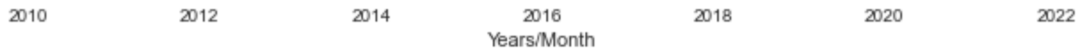
In [867]:
```
eate afunction to check if our series is stationary by differencing whi
rence_test(series, max_d):
ts =[]
ndex in range(max_d):
dfuller_result=  stationarity_check(series)
eries = series.diff().dropna()
f adfuller_result[1] <= 0.05:
   series_stationary = True
lse:
   series_stationary =False
esults.append((index,adfuller_result[1],series_stationary))
ts_df = pd.DataFrame(results,columns=['diff','p-value','series_stationa
n results_df
```

In [868]:
```
difference_test(finalDataFrame['count'],3)
```

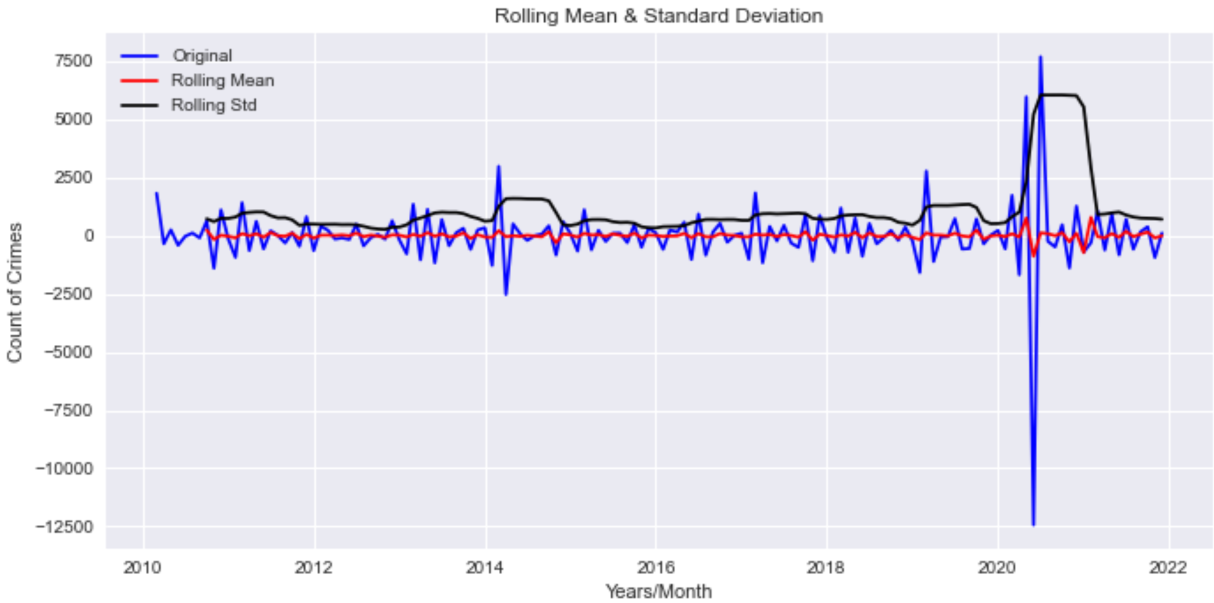


Results of Dickey-Fuller Test:






```
Results of Dickey-Fuller Test:
```

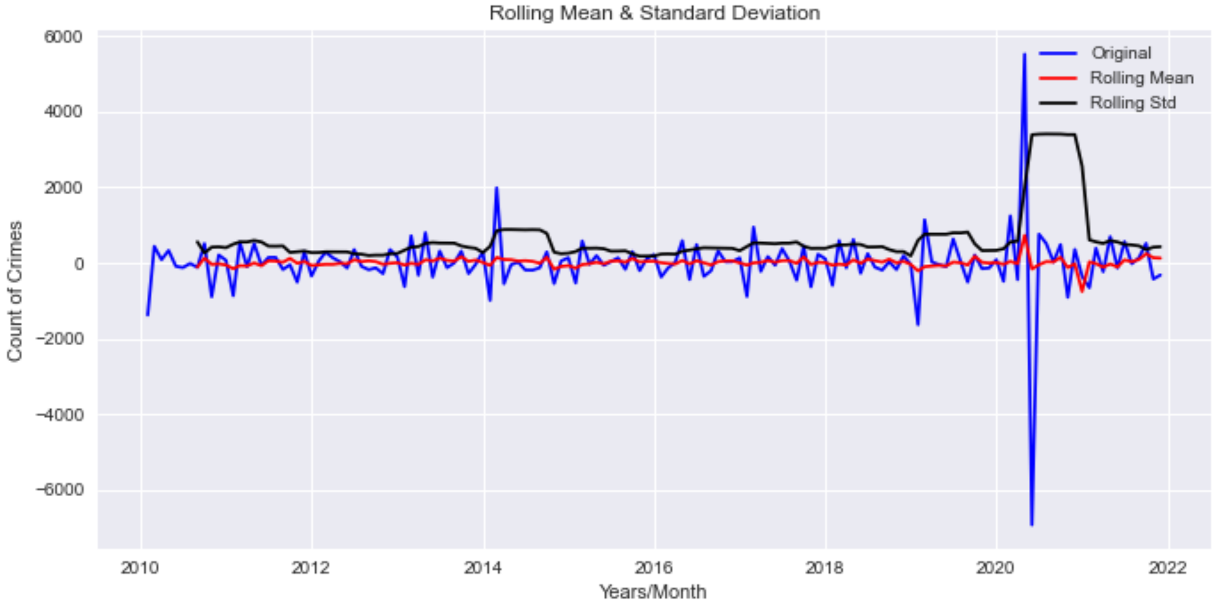



```
Results of Dickey-Fuller Test:
```

Out[868]:

	diff	p-value	series_stationary
0	0	1.084228e-01	False
1	1	3.569738e-17	True
2	2	1.457723e-09	True

In [869]:
```
#Lets see the results of dickey fuller test of differencing by 1:
stationarity_check(finalDataFrame['count'].diff().dropna())
```



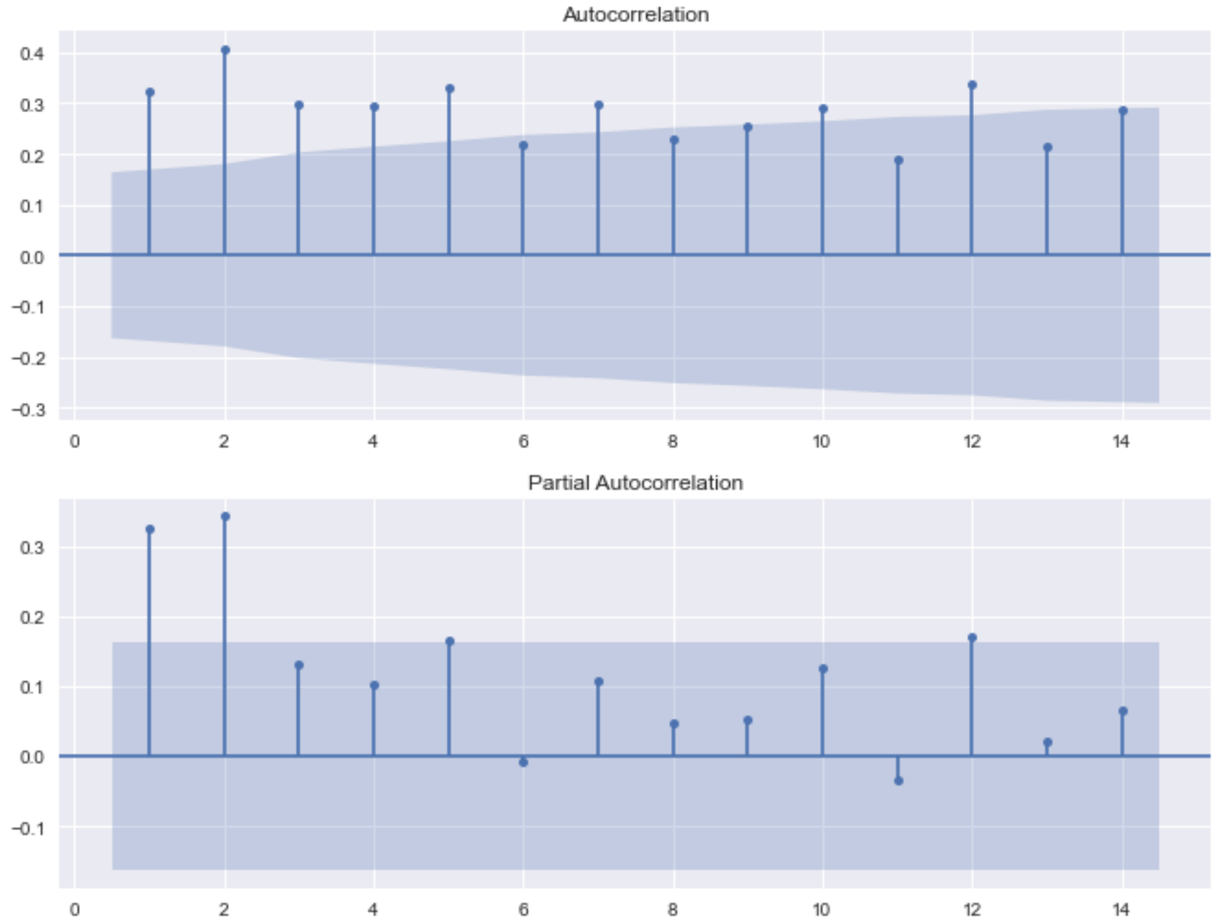

```
Results of Dickey-Fuller Test:
```

Out[869]:
```
Test Statistic                 -9.890444e+00
p-value                         3.569738e-17
#Lags Used                      3.000000e+00
Number of Observations Used     1.390000e+02
Critical Value (1%)            -3.478294e+00
Critical Value (5%)            -2.882568e+00
Critical Value (10%)           -2.577983e+00
dtype: float64
```

Above results of differencing once shows p-value <0.05, and Tstatistics < Critical Value,which rejects the null hypothesis and confirms our alternate hypothesis that time series is stationary.

Results: Differencing by 1& 2 makes our time series stationary.

In [870]:
```
# Create figure
fig, (ax1, ax2) = plt.subplots(2,1, figsize=(10,8))

# Plot the ACF of df_store_2_item_28_timeon ax1
plot_acf(finalDataFrame,lags=14, zero=False, ax=ax1)

# Plot the PACF of df_store_2_item_28_timeon ax2
plot_pacf(finalDataFrame,lags=14, zero=False, ax=ax2)

plt.show()
```



Estimating p,q: From the above ACF and PACF plot we can identify p=1,q=1.

In [872]:
```
#Fitting our Arima model: with d=1
model = ARIMA(finalDataFrame, order=(1,1,1))
results = model.fit()
# statistics of the model
results.summary()
```

Out[872]:

ARIMA Model Results

Dep. Variable:	D.count	**No. Observations:**	143
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-1128.678
Method:	css-mle	**S.D. of innovations**	643.720
Date:	Wed, 09 Mar 2022	**AIC**	2265.357
Time:	14:11:03	**BIC**	2277.208
Sample:	02-01-2010	**HQIC**	2270.172
	- 12-01-2021		

	coef	std err	z	P>|z|	[0.025	0.975]
const	7.4761	4.749	1.574	0.115	-1.831	16.783
ar.L1.D.count	0.0038	0.099	0.039	0.969	-0.190	0.198
ma.L1.D.count	-0.9230	0.057	-16.057	0.000	-1.036	-0.810

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	261.0163	+0.0000j	261.0163	0.0000
MA.1	1.0835	+0.0000j	1.0835	0.0000

Let's find best P,q for our model with help of aic,bic scores.

In [875]:
```
# Create empty list to store search results
order_aic_bic=[]

# Loop over p values from 0-6
for p in range(7):
  # Loop over q values from 0-6
    for q in range(7):
      # create and fit ARMA(p,q) model
        model = SARIMAX(finalDataFrame, order=(p,1,q)) #because adf te
        results = model.fit()

        # Append order and results tuple
        order_aic_bic.append((p,q,results.aic, results.bic))
```

In [876]:
```
# Construct DataFrame from order aic bic
```

```
order_df = pd.DataFrame(order_aic_bic,
                        columns=['p','q','AIC','BIC'])

# Print order_df in order of increasing AIC
order_df.sort_values('AIC')
```

Out[876]:

	p	q	AIC	BIC
1	0	1	2260.800696	2266.726385
15	2	1	2261.666461	2273.517839
3	0	3	2261.725954	2273.577332
18	2	4	2262.512984	2283.252897
8	1	1	2262.767814	2271.656348
2	0	2	2262.776367	2271.664901
22	3	1	2263.662483	2278.476706
25	3	4	2263.678209	2287.380966
19	2	5	2263.692639	2287.395396
10	1	3	2263.694717	2278.508940
4	0	4	2263.705925	2278.520148
31	4	3	2263.711047	2287.413804
23	3	2	2264.121811	2281.898879
9	1	2	2264.126725	2275.978104
16	2	2	2264.427459	2279.241683
33	4	5	2265.367790	2294.996237
5	0	5	2265.531073	2283.308140
29	4	1	2265.633663	2283.410731
38	5	3	2265.644302	2292.309903
17	2	3	2265.653613	2283.430680
26	3	5	2265.676233	2292.341835
11	1	4	2265.692388	2283.469456
32	4	4	2265.966256	2292.631858
30	4	2	2266.035147	2286.775060
39	5	4	2266.207207	2295.835653
20	2	6	2266.332617	2292.998219
12	1	5	2266.676326	2287.416239
6	0	6	2267.047021	2287.786933

36	5	1	2267.132957	2287.872869
40	5	5	2267.590901	2300.182192
43	6	1	2267.783704	2291.486461
46	6	4	2268.225890	2300.817181
37	5	2	2268.383197	2292.085954
13	1	6	2268.512486	2292.215243
24	3	3	2268.760084	2289.499996
44	6	2	2268.892401	2295.558003
47	6	5	2270.199111	2305.753247
45	6	3	2270.408993	2300.037439
34	4	6	2270.716276	2303.307567
27	3	6	2271.792971	2301.421418
41	5	6	2272.219767	2307.773903
48	6	6	2272.378713	2310.895693
28	4	0	2273.108173	2287.922396
42	6	0	2274.228506	2294.968419
35	5	0	2274.890913	2292.667980
21	3	0	2277.765076	2289.616454
14	2	0	2281.007221	2289.895755
7	1	0	2289.316139	2295.241828
0	0	0	2344.701215	2347.664060

In [877]:

```
# Print order_df in order of increasing BIC
order_df.sort_values('BIC')
```

Out[877]:

	p	q	AIC	BIC
1	0	1	2260.800696	2266.726385
8	1	1	2262.767814	2271.656348
2	0	2	2262.776367	2271.664901
15	2	1	2261.666461	2273.517839
3	0	3	2261.725954	2273.577332
9	1	2	2264.126725	2275.978104
22	3	1	2263.662483	2278.476706
10	1	3	2263.694717	2278.508940
4	0	4	2263.705925	2278.520148

16	2	2	2264.427459	2279.241683
23	3	2	2264.121811	2281.898879
18	2	4	2262.512984	2283.252897
5	0	5	2265.531073	2283.308140
29	4	1	2265.633663	2283.410731
17	2	3	2265.653613	2283.430680
11	1	4	2265.692388	2283.469456
30	4	2	2266.035147	2286.775060
25	3	4	2263.678209	2287.380966
19	2	5	2263.692639	2287.395396
31	4	3	2263.711047	2287.413804
12	1	5	2266.676326	2287.416239
6	0	6	2267.047021	2287.786933
36	5	1	2267.132957	2287.872869
28	4	0	2273.108173	2287.922396
24	3	3	2268.760084	2289.499996
21	3	0	2277.765076	2289.616454
14	2	0	2281.007221	2289.895755
43	6	1	2267.783704	2291.486461
37	5	2	2268.383197	2292.085954
13	1	6	2268.512486	2292.215243
38	5	3	2265.644302	2292.309903
26	3	5	2265.676233	2292.341835
32	4	4	2265.966256	2292.631858
35	5	0	2274.890913	2292.667980
20	2	6	2266.332617	2292.998219
42	6	0	2274.228506	2294.968419
33	4	5	2265.367790	2294.996237
7	1	0	2289.316139	2295.241828
44	6	2	2268.892401	2295.558003
39	5	4	2266.207207	2295.835653
45	6	3	2270.408993	2300.037439
40	5	5	2267.590901	2300.182192
46	6	4	2268.225890	2300.817181

27	3	6	2271.792971	2301.421418
34	4	6	2270.716276	2303.307567
47	6	5	2270.199111	2305.753247
41	5	6	2272.219767	2307.773903
48	6	6	2272.378713	2310.895693
0	0	0	2344.701215	2347.664060

Both AIC and BIC agree that the best model in this case should be ARIMA(0,1,1).

Step 3: Implementing Models:

BaseLine Model:

- For our baseline Model we will be implementing ARIMA:
- Find optimal parameters for ARIMA

About ARIMA model

- ARIMA stands for Autoregressive Integreted Moving Average
- ARIMA models are denoted with the notation ARIMA(p, d, q)

These three parameters account for seasonality, trend, and noise in data ARIMA Model ARIMA as a feature:

- Autoregressive Integrated Moving Average (ARIMA) — This was one of the most popular techniques for predicting future values of time series data (in the pre-neural networks ages). Let's add it and see if it comes off as an important predictive feature.

ARIMA is a technique for predicting time series data. We will show how to use it, and all though ARIMA will not serve as our final prediction, we will use it as a technique to denoise the stock a little and to (possibly) extract some new patters or features.

ARIMA is an acronym. This acronym is descriptive, capturing the key aspects of the model itself. Briefly, they are:

AR: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations.

I: Integrated. The use of differencing of raw observations (e.g. subtracting an observation from an observation at the previous time step) in order to make the time series stationary.

MA: Moving Average. A model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The parameters of the ARIMA model are defined as follows:

```
p: The number of lag observations included in the model, also
called the lag order.

d: The number of times that the raw observations are differenc
ed, also called the degree of differencing.

q: The size of the moving average window, also called the orde
r of moving average.
```

STEPS FOR ARIMA

1. Define the model by calling ARIMA() and passing in the p, d, and q parameters.
2. The model is prepared on the training data by calling the fit() function.
3. Predictions can be made by calling the predict() function and specifying the index of the time or times to be predicted.

Metrics Choosen to compare Models:

- MAPE(Mean ABsolute Percentage Error)
- MAE(Mean Absolute Error)

Auto Regressive Model

- The autocorrelation function is a function that represents autocorrelation of a time series as a function of the time lag.
- Creating an autocorrelation function for our "finalDataFrame", we have the lag on the x-axis and the correlation value for each respective lag value on the y-axis.

In [880]:
```
#Baseline Model.
arima_model_01 = ARIMA(finalDataFrame, order=(0,1,1))
# fit model
arima_results = arima_model_01.fit()

# Calculate the mean absolute error from residuals
mae = np.mean(np.abs(arima_results.resid))

# Print mean absolute error
print('MAE: %.3f' % mae)

#Print results summary
arima_results.summary()
```

```
MAE: 360.750
```

Out[880]:

ARIMA Model Results

Dep. Variable:	D.count	**No. Observations:**	143
Model:	ARIMA(0, 1, 1)	**Log Likelihood**	-1128.679
Method:	css-mle	**S.D. of innovations**	643.740
Date:	Wed, 09 Mar 2022	**AIC**	2263.358
Time:	14:13:37	**BIC**	2272.247
Sample:	02-01-2010	**HQIC**	2266.970
	- 12-01-2021		

	coef	std err	z	P>|z|	[0.025	0.975]
const	7.4514	4.746	1.570	0.116	-1.850	16.753
ma.L1.D.count	-0.9218	0.049	-18.685	0.000	-1.018	-0.825

Roots

	Real	Imaginary	Modulus	Frequency
MA.1	1.0848	+0.0000j	1.0848	0.0000

In [881]:
```
#Baseline Model without differencing.
arima_model_01 = ARIMA(finalDataFrame, order=(0,0,1))
# fit model
arima_results = arima_model_01.fit()

# Calculate the mean absolute error from residuals
mae = np.mean(np.abs(arima_results.resid))

# Print mean absolute error
print('MAE: %.3f' % mae)

#Print results summary
arima_results.summary()
```

```
MAE: 456.760
```

Out[881]:

ARMA Model Results

Dep. Variable:	count	**No. Observations:**	144
Model:	ARMA(0, 1)	**Log Likelihood**	-1152.701
Method:	css-mle	**S.D. of innovations**	724.719
Date:	Wed, 09 Mar 2022	**AIC**	2311.401
Time:	14:13:39	**BIC**	2320.311
Sample:	01-01-2010	**HQIC**	2315.021
	- 12-01-2021		

	coef	std err	z	P>|z|	[0.025	0.975]
const	5683.1083	72.426	78.468	0.000	5541.157	5825.060
ma.L1.count	0.2006	0.065	3.095	0.002	0.074	0.328

Roots

	Real	Imaginary	Modulus	Frequency
MA.1	-4.9850	+0.0000j	4.9850	0.5000

In [882]:
```
finalDataFrame.describe()
```

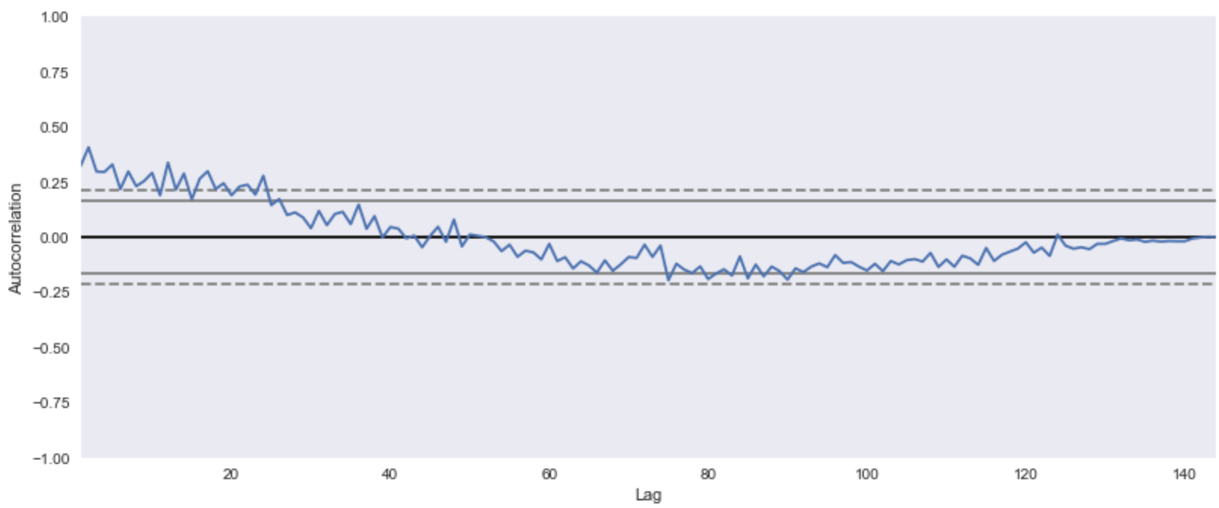
Out[882]:

	count
count	144.000000
mean	5681.798611
std	751.388203
min	4187.000000
25%	5195.750000
50%	5691.500000
75%	6068.000000
max	11673.000000

Autocorrelation plots :

Are a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero.Source [https://www.itl.nist.gov/div898/handbook/eda/section3/autocopl.htm] (https://www.itl.nist.gov/div898/handbook/eda/section3/autocopl.htm%5D)

In [884]:
```
#plotting the autocorelation_plot
#from pandas.tools.plotting import autocorrelation_plot
plt.figure(figsize=(12,5))
pd.plotting.autocorrelation_plot(finalDataFrame['count']);
```



In [885]:
```
finalDataFrame.head()
```

Out[885]:

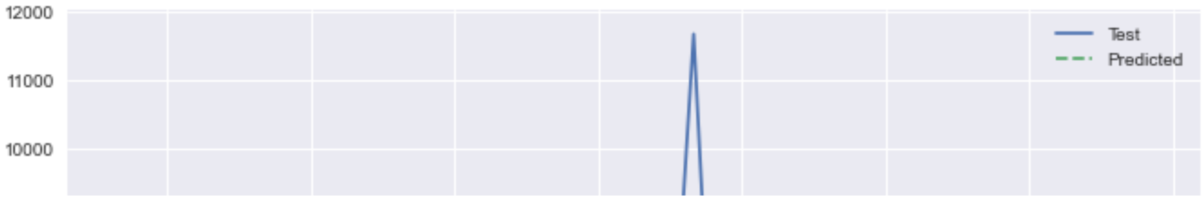
	count
Year/Month	
2010-01-01	6059
2010-02-01	4680
2010-03-01	5116
2010-04-01	5199
2010-05-01	5526

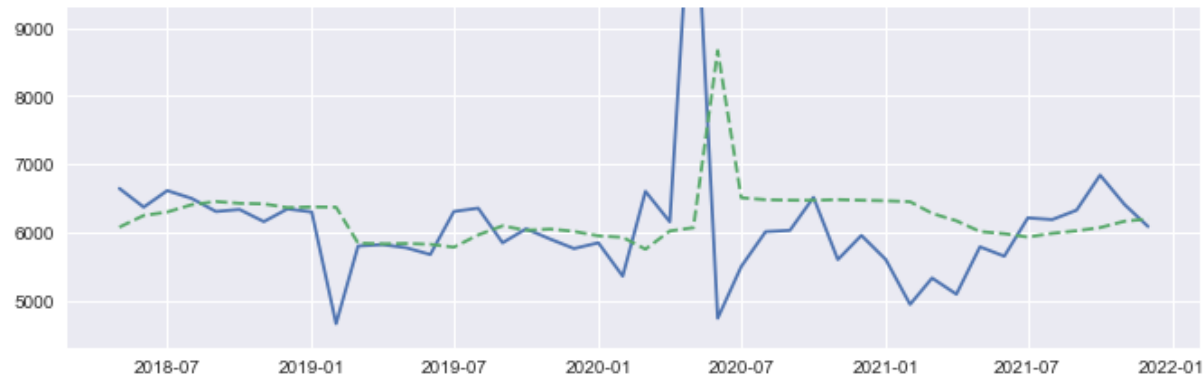
In [887]:
```
#Functions to implement ARIMA
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
import matplotlib.dates as mdates
from datetime import timedelta
from numpy import sqrt

def evaluate_arima_models(data,order,forecast_periods):
    """ This function evaluates arima models.
    Args:
        data: timseries
        order: order of the model
        forecast_periods = number of periods
    Return:
        returns summary of evaluated model, and MAE,MAPE.
    """

    #preparing training dataset
    val = int(len(data)* 0.1)
    size = int(len(data) * 0.7)
    validation_set = data[0:val]
    train,test = data[val:size],data[size:len(data)]

    data_series =[x for x in train]

    #making predictions
    arima_results =[]
    predictions = []
    for i in range(len(test)):
        model = ARIMA(data_series,order = order)
        arima_results = model.fit(dis=0)
        yhat = arima_results.forecast()[0]
        predictions.append(yhat)
        data_series.append(test[i])

    #Calculating future_forecast.
```

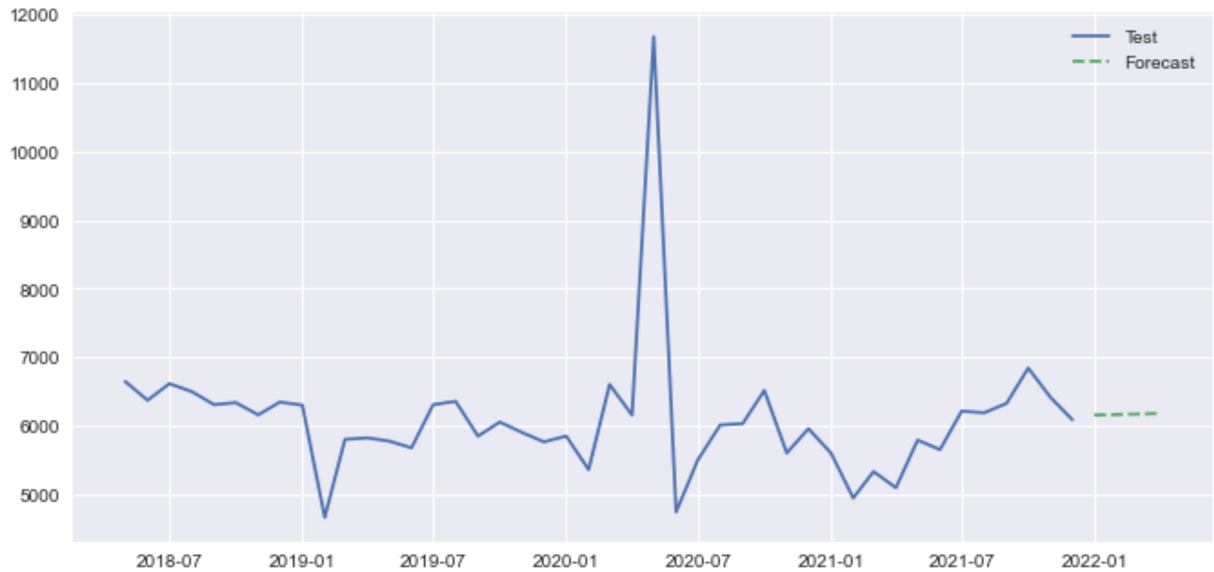
```
    future_forecast = model_fit.forecast(forecast_periods)[0]
    future_dates = [test.index[-1] + timedelta(i*365/12) for i in rang
    test_dates = test.index

    # creates pandas series with datetime index for the predictions ar
    forecast = pd.Series(future_forecast, index=future_dates)
    predictions = pd.Series(predictions, index=test_dates)

    # Plotting predictions with test data:
    fig = plt.figure(figsize=(10,5))
    plt.plot(test, label='Test')
    plt.plot(predictions ,linestyle="--" ,label = 'Predicted')
    plt.legend(loc='best')
    plt.show()
    #plotting predicted with forecast
    fig = plt.figure(figsize=(10,5))
    plt.plot(test , label = 'Test')
    plt.plot(forecast,linestyle="--", label='Forecast')
    plt.legend(loc='best')
    plt.show()

    print("-----------------------------------------------------")
    print("Values for test",test[:10])
    print("----------------------------------------------------")
    print("Values for Predictions",predictions[:10])
    print("----------------------------------------------------")

    #calculate the mean absolute error from residuals
    mae = np.mean(np.abs(arima_results.resid))
    print('The Mean absolute Error of our forecasts is {}'.format(rour

    MAPE= mean_absolute_percentage_error(test, predictions)
    print('The Mean absolute Percentage Error of our forecasts is {}'.

    # calculate out of sample error
    rmse = sqrt(mean_squared_error(test, predictions))
    #Normalized rmse values
    norm_rmse = rmse/(data.max()-data.min())
    print('The Normalized RMSE value is {}'.format(round(norm_rmse, 4)
    return arima_results
```

In [888]:

```
#for order of p,d,q
#ARIMA(1) for order of 0,1,1
order=(0,1,1)
periods=4
arima_results1= evaluate_arima_models(finalDataFrame['count'],order,pe
print(arima_results1.summary())
```








```
----------------------------------------------------
Values for test Year/Month
2018-05-01    6650
2018-06-01    6376
2018-07-01    6618
2018-08-01    6504
2018-09-01    6312
2018-10-01    6342
2018-11-01    6164
2018-12-01    6350
2019-01-01    6305
2019-02-01    4670

Name: count, dtype: int64
----------------------------------------------------
Values for Predictions Year/Month
2018-05-01    [6083.172686061763]
2018-06-01     [6254.36869765279]
2018-07-01    [6303.997666549675]
2018-08-01    [6411.791518938847]
2018-09-01    [6457.853159051223]
2018-10-01    [6431.940019241249]
2018-11-01    [6423.823310875957]
2018-12-01    [6369.230409781989]
2019-01-01    [6380.059268233501]
2019-02-01     [6375.32347926553]
```

```
dtype: object
----------------------------------------------------
The Mean absolute Error of our forecasts is 361.786
The Mean absolute Percentage Error of our forecasts is 0.0983
The Normalized RMSE value is 0.1565
                             ARIMA Model Results
===================================================================
==========
Dep. Variable:                    D.y   No. Observations:
128
Model:                 ARIMA(0, 1, 1)   Log Likelihood
-1013.615
Method:                       css-mle   S.D. of innovations
659.896
Date:                Wed, 09 Mar 2022   AIC
2033.230
Time:                        14:23:39   BIC
2041.786
Sample:                             1   HQIC
2036.706

===================================================================
==========
                 coef    std err          z      P>|z|      [0.025
0.975]
-------------------------------------------------------------------
----------
const          9.8638      4.561      2.163      0.031       0.925
18.803
ma.L1.D.y     -0.9305      0.041    -22.852      0.000      -1.010
-0.851
                                    Roots
===================================================================
=========
                  Real          Imaginary           Modulus
Frequency
-------------------------------------------------------------------
---------
MA.1            1.0747           +0.0000j            1.0747
0.0000

-------------------------------------------------------------------
---------
```

GridSearch ARIMA hyperparamters.

In [889]:
```
# evaluate combinations of p, d and q values for an ARIMA model
def evaluate_models(dataset, p_values, d_values, q_values):
    dataset = dataset.astype('float32')
    best_score, best_cfg = float("inf"), None
    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                try:
                    mse = evaluate_arima_models(dataset, order,periods
                    if mse < best_score:
                        best_score, best_cfg = mse, order
                    print('ARIMA%s MSE=%.3f' % (order,mse))
                except:
                    continue
    print('Best ARIMA%s MSE=%.3f' % (best_cfg, best_score))
```

Since, this is doing a gridSearch it takes a little longer time to execute.

In [890]:
```
#p_values = [0, 1, 2, 4, 6, 8, 10]
#d_values = range(0, 3)
#q_values = range(0, 3)
#evaluate_models(finalDataFrame.values, p_values, d_values, q_values)
```

Fitting ARIMA using combinations of p,d,q is a tedious task.To reduce this time we will make use of an open source Python library: PMDArima

Automated Model Selection:

PMDArima is an open-source Python library that is used for time series forecasting and also helps in creating time series plots. It is easy to use and generates time-series forecast on the ARIMA model.

- Installing required libraries We will start by installing a PMDArima library by using pip.

Diagnostic Plots:

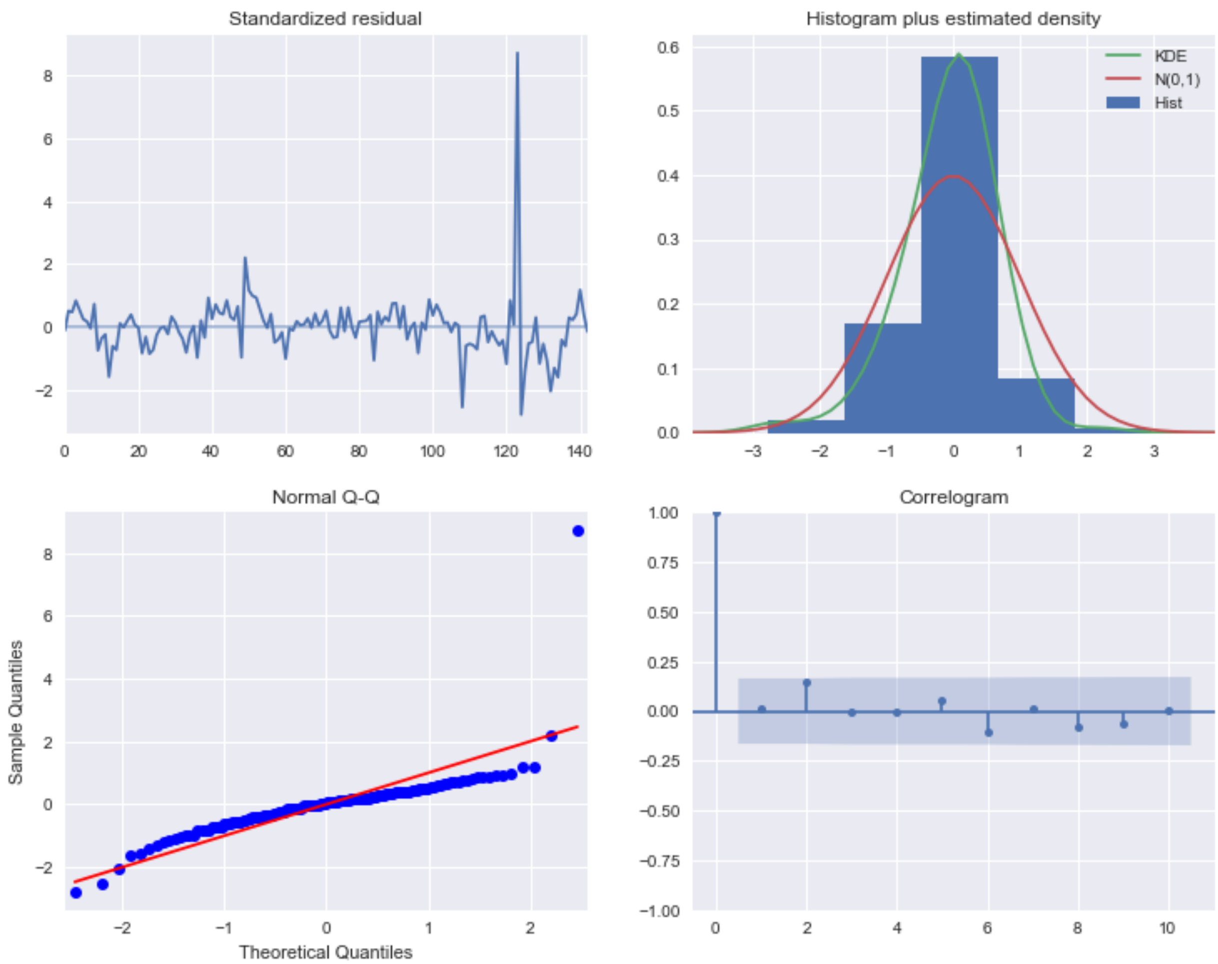
The diagnostic plots show residuals in four different ways Source: [https://data.library.virginia.edu/diagnostic-plots/](https://data.library.virginia.edu/diagnostic-plots/%5D)

In [891]:
```
#pip install pmdarima
```

In [892]:
```
#To iteratively clculate the best scores for p,d,q we have isntalled p
#We will pass our data to the function to get the best paramaters for
def arimamodel(data):
    automodel = pm.auto_arima(data,_p =1,
                              d=1,
                              start_q=1,
                              test='adf',
                              max_q=3,
                              m =12,
                             trace=True)
    return automodel
```

In [893]:
```
results  = arimamodel(finalDataFrame['count'])
results.plot_diagnostics()
plt.show()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,1)(1,0,1)[12] intercept   : AIC=inf, Time=1.13 sec
 ARIMA(0,1,0)(0,0,0)[12] intercept   : AIC=2346.698, Time=0.01 sec
 ARIMA(1,1,0)(1,0,0)[12] intercept   : AIC=2291.961, Time=0.08 sec
 ARIMA(0,1,1)(0,0,1)[12] intercept   : AIC=2261.794, Time=0.47 sec
 ARIMA(0,1,0)(0,0,0)[12]             : AIC=2344.701, Time=0.01 sec
 ARIMA(0,1,1)(0,0,0)[12] intercept   : AIC=2260.542, Time=0.12 sec
 ARIMA(0,1,1)(1,0,0)[12] intercept   : AIC=2261.581, Time=0.40 sec
 ARIMA(0,1,1)(1,0,1)[12] intercept   : AIC=inf, Time=0.49 sec
 ARIMA(1,1,1)(0,0,0)[12] intercept   : AIC=2262.511, Time=0.58 sec
 ARIMA(0,1,2)(0,0,0)[12] intercept   : AIC=2262.520, Time=0.42 sec
 ARIMA(1,1,0)(0,0,0)[12] intercept   : AIC=2291.279, Time=0.06 sec
 ARIMA(1,1,2)(0,0,0)[12] intercept   : AIC=inf, Time=0.45 sec
 ARIMA(0,1,1)(0,0,0)[12]             : AIC=2260.801, Time=0.07 sec

Best model:  ARIMA(0,1,1)(0,0,0)[12] intercept
Total fit time: 4.325 seconds
```



Above Q-Q plots show no boious patterns in the residuals,normal distribution of the residuals. ACF plot are all inside the blue are which means lag greater than 1 should not be significant.Overall seems a good model.

In [894]:
```
mae = np.mean(np.abs(model_fit.resid))
print('Mae: %.3f' % mae)
```

```
Mae: 360.750
```

Implementing SARIMA:

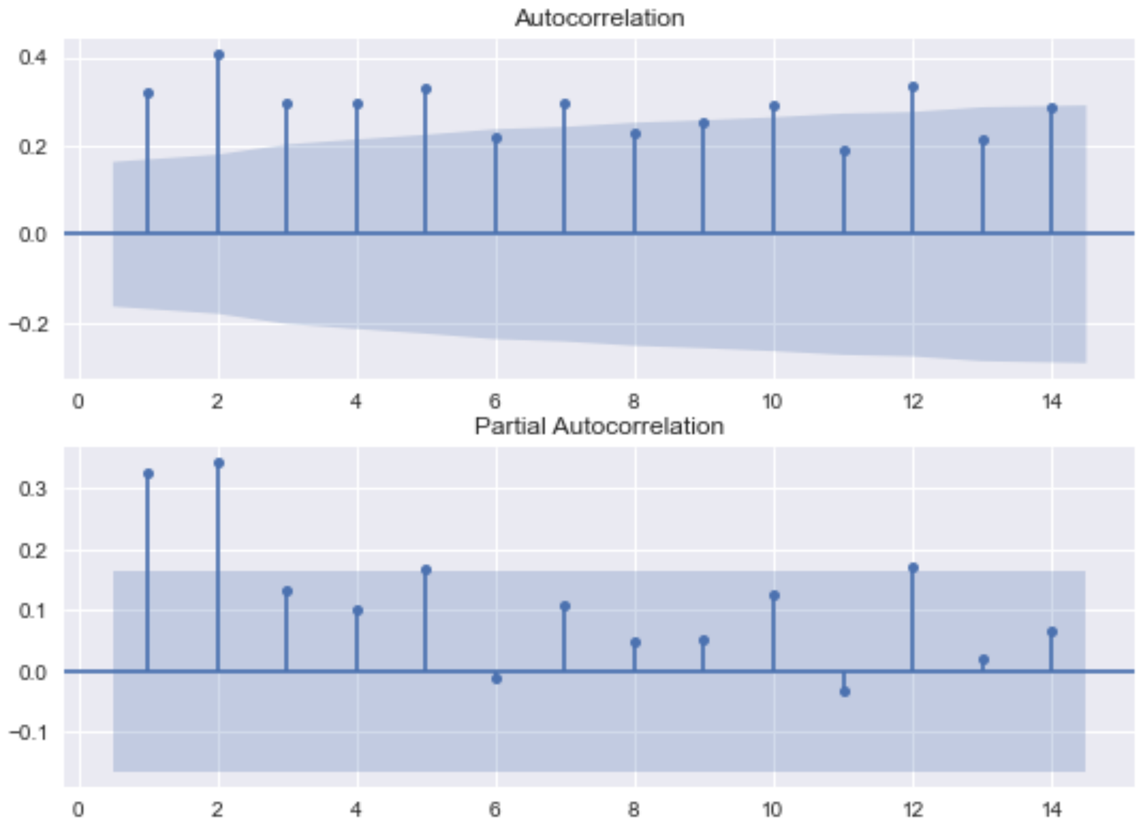
Seasonal Autoregressive Integrated Moving Average, SARIMA or Seasonal ARIMA, is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component.

It adds three new hyperparameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality.

In [896]:
```
Functions to implement SARIMA
mport statsmodels.api as sm
rom statsmodels.tsa.statespace.sarimax import SARIMAX

ef evaluate_sarima(data,order,seasonal_order,forecast_periods):

   #preparing training dataset
   val = int(len(data)* 0.1)
   size = int(len(data) * 0.7)
   validation_set = data[0:val]
   train,test = data[val:size],data[size:len(data)]
   #print(validation_set)

   data_series =[x for x in train]

   #making predictions
   sarimax_results = []
   predictions = []
   for i in range(len(test)):
       model = SARIMAX(data_series,order = order)
       sarimax_results = model.fit(dis=0)
       yhat = sarimax_results.forecast()[0]
       predictions.append(yhat)
       data_series.append(test[i])

   #Calculating future_forecast.
   future_forecast = model_fit.forecast(forecast_periods)[0]
   future_dates = [test.index[-1] + timedelta(i*365/12) for i in range
   test_dates = test.index

   # creates pandas series with datetime index for the predictions and
```

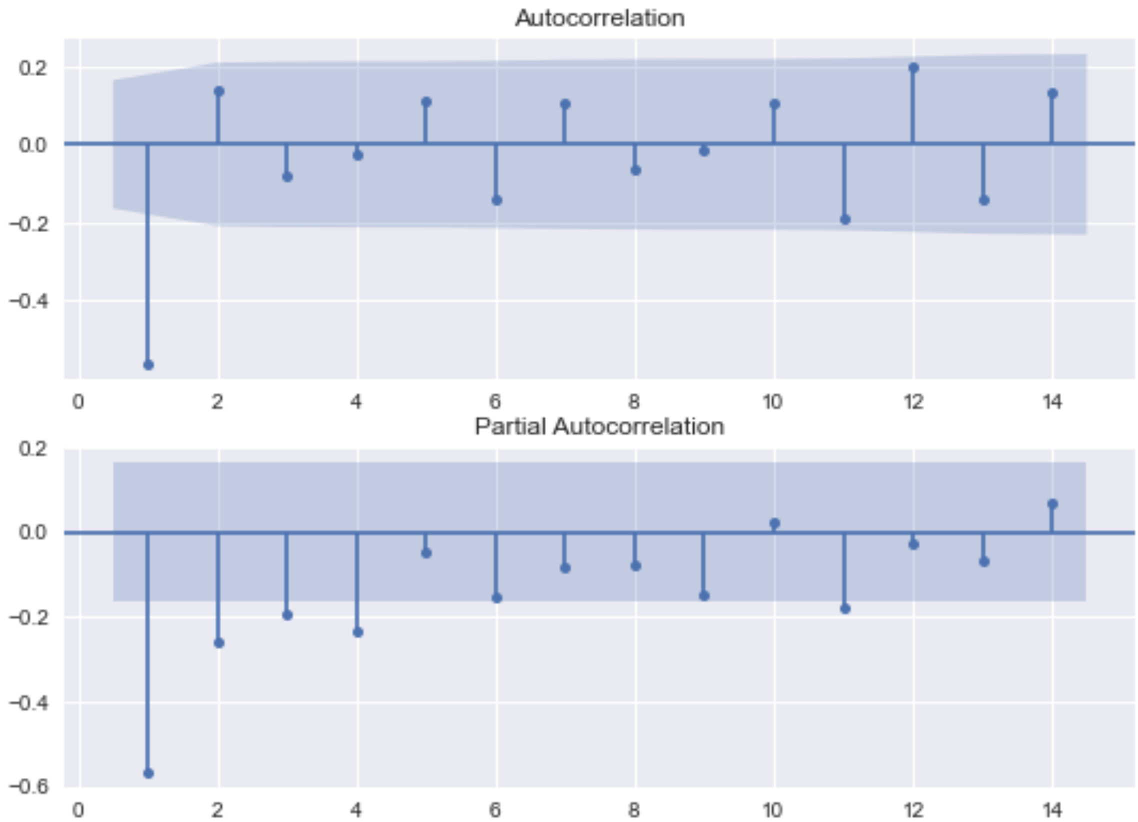
```
forecast = pd.Series(future_forecast, index=future_dates)
predictions = pd.Series(predictions, index=test_dates)

# Plotting predictions with test data:
fig = plt.figure(figsize=(10,5))
plt.plot(test, label='Test')
plt.plot(predictions ,linestyle="--" ,label = 'Predicted')
plt.legend(loc='best')
plt.show()
#plotting predicted with forecast
fig = plt.figure(figsize=(10,5))
plt.plot(test , label = 'Test')
plt.plot(forecast,linestyle="--", label='Forecast')
plt.legend(loc='best')
plt.show()

print("-----------------------------------------------------")
print("Values for test",test[:10])
print("----------------------------------------------------")
print("Values for Predictions",predictions[:10])
print("----------------------------------------------------")

#calculate the mean absolute error from residuals
mae = np.mean(np.abs(sarimax_results.resid))
print('The Mean absolute Error of our forecasts is {}'.format(round

MAPE= mean_absolute_percentage_error(test, predictions)
print('The Mean absolute Percentage Error of our predictions is {}'
# calculate out of sample error
rmse = sqrt(mean_squared_error(test, predictions))
#Normalized rmse values
norm_rmse = rmse/(data.max()-data.min())
print('The Normalized RMSE value is {}'.format(round(norm_rmse, 4))
return sarimax_results
```

In [897]:
```
# Create the figure
fig, (ax1, ax2) = plt.subplots(2,1,figsize=(8,6))

# Plot the ACF on ax1
plot_acf(finalDataFrame['count'], lags=14, zero=False, ax=ax1)

# Plot the PACF on ax2
plot_pacf(finalDataFrame['count'], lags=14, zero=False, ax=ax2)

plt.show()
```

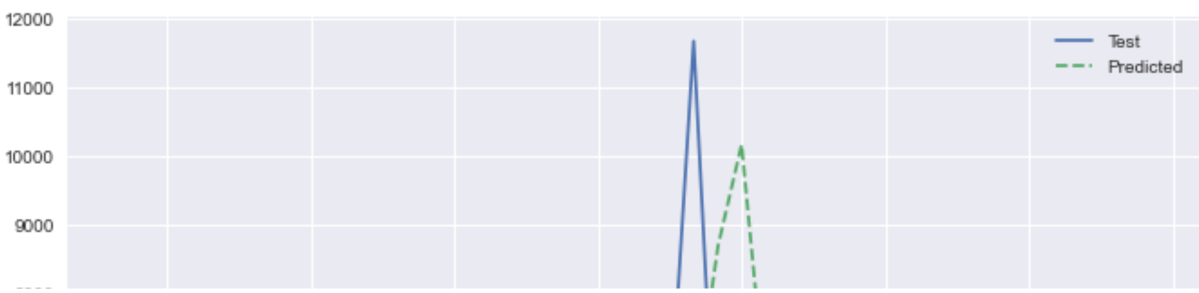


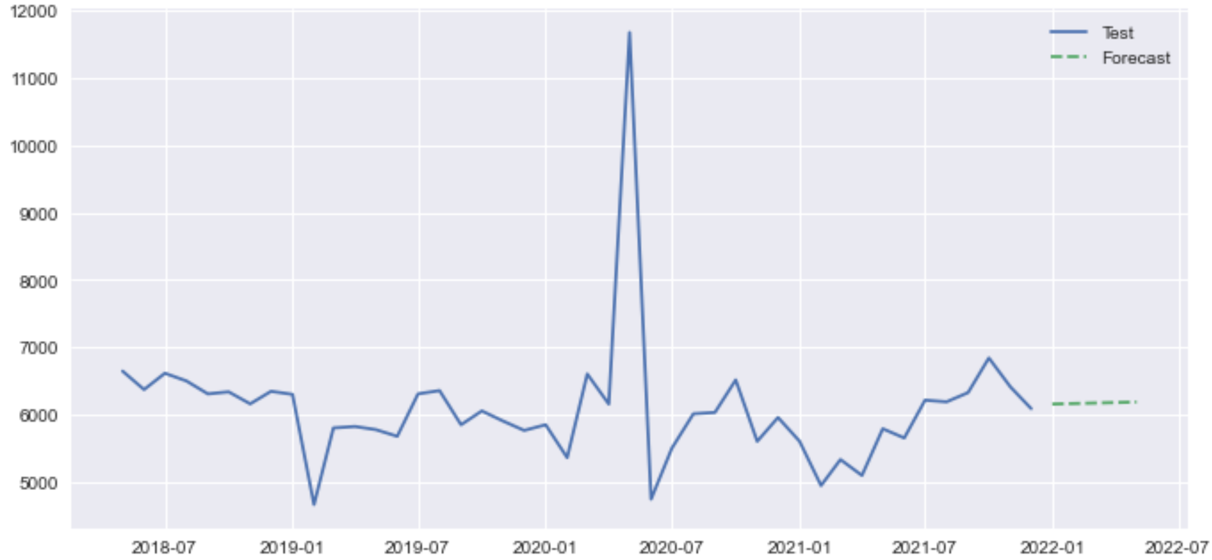
In [898]:
```
# Take the first and seasonal differences (S=7) and drop NaNs
finalDataFrame_diff = finalDataFrame['count'].diff(1).dropna()
```

In [899]:
```
# Create the figure
fig, (ax1, ax2) = plt.subplots(2,1,figsize=(8,6))

# Plot the ACF on ax1
plot_acf(finalDataFrame_diff, lags=14, zero=False, ax=ax1)

# Plot the PACF on ax2
plot_pacf(finalDataFrame_diff, lags=14, zero=False, ax=ax2)

plt.show()
```



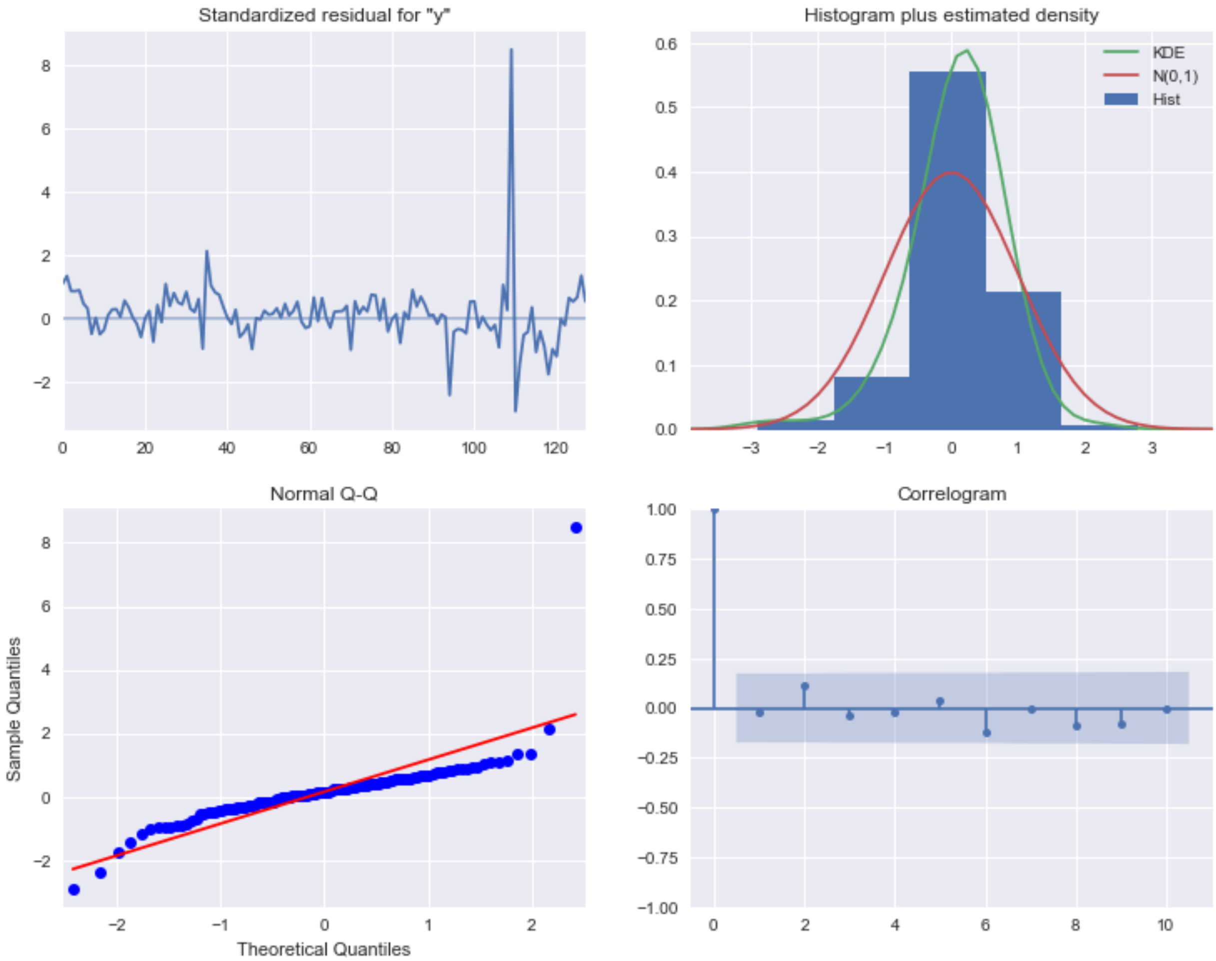
In [900]:
```
#for order of p,d,q
#sARIMA(1) for order of 1,1,1
order=(1,1,1)
seasonal_order =(0,1,1,2)
periods=5
sarimax_results1 = evaluate_sarima(finalDataFrame['count'],order,seaso
sarimax_results1.summary()
sarimax_results1.plot_diagnostics()
plt.show()
```





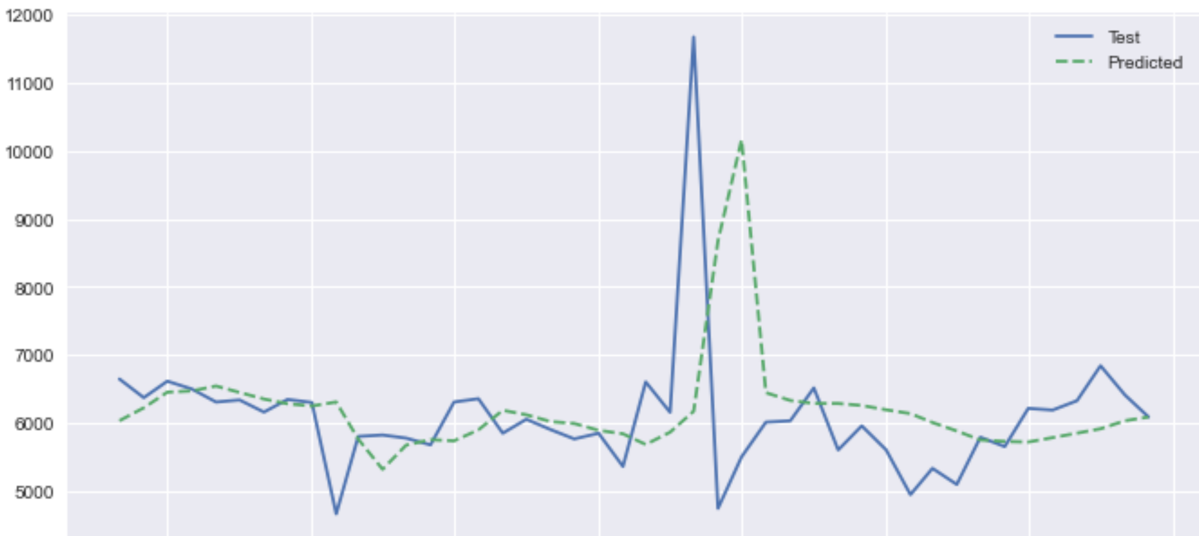

```
-----------------------------------------------------
Values for test Year/Month
2018-05-01    6650
2018-06-01    6376
2018-07-01    6618
2018-08-01    6504
2018-09-01    6312
2018-10-01    6342
2018-11-01    6164
2018-12-01    6350
2019-01-01    6305
2019-02-01    4670
Name: count, dtype: int64
-----------------------------------------------------
Values for Predictions Year/Month
2018-05-01    6037.697179
2018-06-01    6227.130885
2018-07-01    6456.807168
2018-08-01    6474.898062
2018-09-01    6547.275631
2018-10-01    6452.623667
2018-11-01    6355.897607
2018-12-01    6287.062466
2019-01-01    6253.675126
2019-02-01    6312.341274
dtype: float64
-----------------------------------------------------
The Mean absolute Error of our forecasts is 418.2909
```

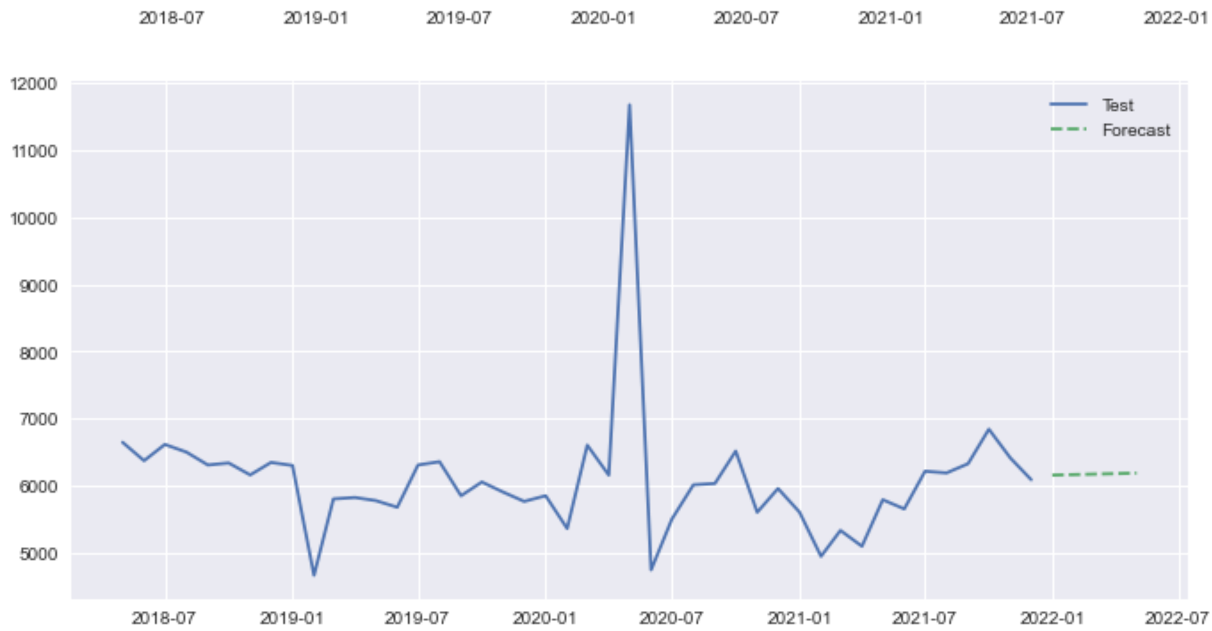
```
The Mean absolute Percentage Error of our predictions is 0.1097
The Normalized RMSE value is 0.1779
```



In [905]:

```
#for order of p,d,q
#SARIMAX(3) for order of 1,1,1
order=(1,1,1)
seasonal_order =(1,1,1,6)
periods=5
Sarimax_results2 = evaluate_sarima(finalDataFrame['count'],order,seasc
Sarimax_results2.summary()
```






```
-----------------------------------------------------
Values for test Year/Month
2018-05-01    6650
2018-06-01    6376
2018-07-01    6618
2018-08-01    6504
2018-09-01    6312
2018-10-01    6342
2018-11-01    6164
2018-12-01    6350
2019-01-01    6305
2019-02-01    4670
Name: count, dtype: int64
----------------------------------------------------
Values for Predictions Year/Month
2018-05-01    6037.697179
2018-06-01    6227.130885
2018-07-01    6456.807168
2018-08-01    6474.898062
2018-09-01    6547.275631
2018-10-01    6452.623667
2018-11-01    6355.897607
2018-12-01    6287.062466
2019-01-01    6253.675126
2019-02-01    6312.341274
dtype: float64
----------------------------------------------------
The Mean absolute Error of our forecasts is 418.2909
The Mean absolute Percentage Error of our predictions is 0.1097
The Normalized RMSE value is 0.1779
```

Out[905]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	129
Model:	SARIMAX(1, 1, 1)	**Log Likelihood**	-1017.168

Date:	Wed, 09 Mar 2022	**AIC**	2040.336
Time:	14:34:55	**BIC**	2048.892
Sample:	0 - 129	**HQIC**	2043.812
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0045	0.071	-0.064	0.949	-0.143	0.134
ma.L1	-0.8737	0.065	-13.526	0.000	-1.000	-0.747
sigma2	4.464e+05	1.26e+04	35.427	0.000	4.22e+05	4.71e+05

Ljung-Box (L1) (Q):	0.07	**Jarque-Bera (JB):**	6987.35
Prob(Q):	0.80	**Prob(JB):**	0.00
Heteroskedasticity (H):	5.19	**Skew:**	4.04
Prob(H) (two-sided):	0.00	**Kurtosis:**	38.28

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

lets' try automated paramter selection for SARIMA.

In [906]:

```
#Automated parameter selection fot SARIMA.
Sarimax_model = auto_arima(finalDataFrame['count'],
                       start_P=1,
                       start_q=1,
                       max_p=6,
                       max_q=6,
                       m=12,
                       seasonal=True,
                       d=1,
                       D=1,
                       trace=True,
                       information_criterion='aic',
                       error_action='ignore',
                       suppress_warnings=True,
                       stepwise=True)
Sarimax_model.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,1)(1,1,1)[12]             : AIC=2078.068, Time=1.42 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=2217.220, Time=0.02 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=2116.398, Time=0.36 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=2077.858, Time=0.94 sec
```

```
 ARIMA(0,1,1)(0,1,0)[12]             : AIC=inf, Time=0.08 sec
 ARIMA(0,1,1)(1,1,1)[12]             : AIC=2074.372, Time=1.74 sec
 ARIMA(0,1,1)(1,1,0)[12]             : AIC=2086.656, Time=0.53 sec
 ARIMA(0,1,1)(2,1,1)[12]             : AIC=2076.304, Time=1.89 sec
 ARIMA(0,1,1)(1,1,2)[12]             : AIC=inf, Time=3.14 sec
 ARIMA(0,1,1)(0,1,2)[12]             : AIC=inf, Time=1.19 sec
 ARIMA(0,1,1)(2,1,0)[12]             : AIC=inf, Time=1.13 sec
 ARIMA(0,1,1)(2,1,2)[12]             : AIC=inf, Time=4.61 sec
 ARIMA(0,1,0)(1,1,1)[12]             : AIC=2144.433, Time=0.53 sec
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=2076.395, Time=1.66 sec
 ARIMA(0,1,2)(1,1,1)[12]             : AIC=2076.363, Time=1.21 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=2107.226, Time=1.37 sec
 ARIMA(1,1,2)(1,1,1)[12]             : AIC=inf, Time=2.01 sec
 ARIMA(0,1,1)(1,1,1)[12] intercept   : AIC=2076.262, Time=1.45 sec

Best model:  ARIMA(0,1,1)(1,1,1)[12]
Total fit time: 25.323 seconds
```

Out[906]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	144
Model:	SARIMAX(0, 1, 1)x(1, 1, 1, 12)	**Log Likelihood**	-1033.186
Date:	Wed, 09 Mar 2022	**AIC**	2074.372
Time:	14:35:31	**BIC**	2085.872
Sample:	0	**HQIC**	2079.045
	- 144		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ma.L1	-0.8708	0.038	-22.944	0.000	-0.945	-0.796
ar.S.L12	-0.3210	0.225	-1.427	0.154	-0.762	0.120
ma.S.L12	-0.6518	0.268	-2.433	0.015	-1.177	-0.127
sigma2	3.731e+05	1.8e+04	20.766	0.000	3.38e+05	4.08e+05

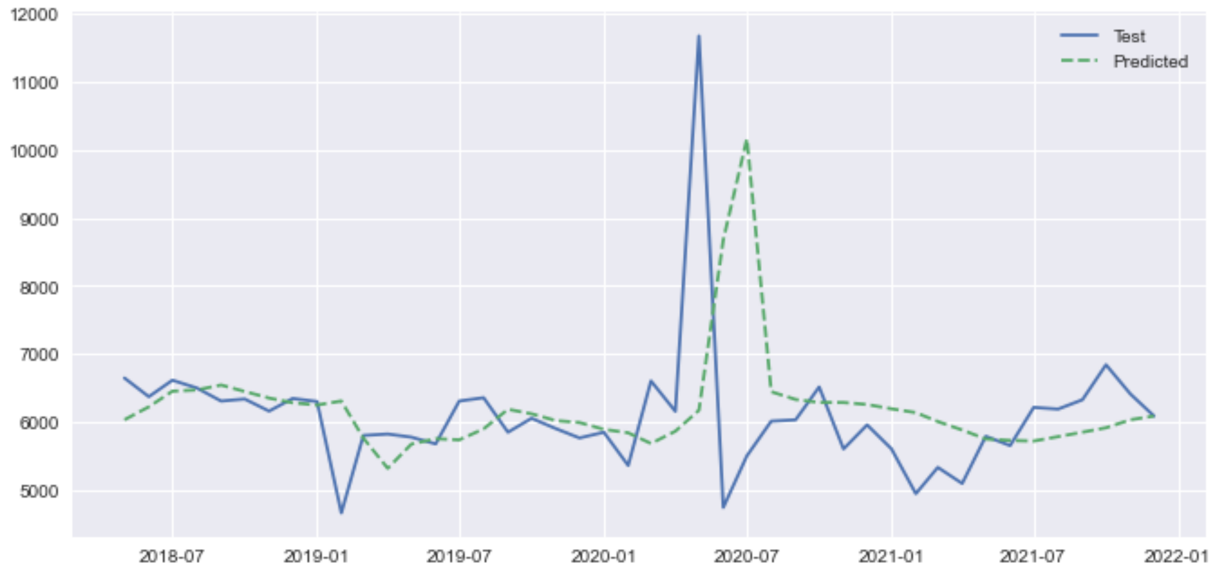
Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	8445.71
Prob(Q):	0.90	**Prob(JB):**	0.00
Heteroskedasticity (H):	5.44	**Skew:**	4.26
Prob(H) (two-sided):	0.00	**Kurtosis:**	41.40

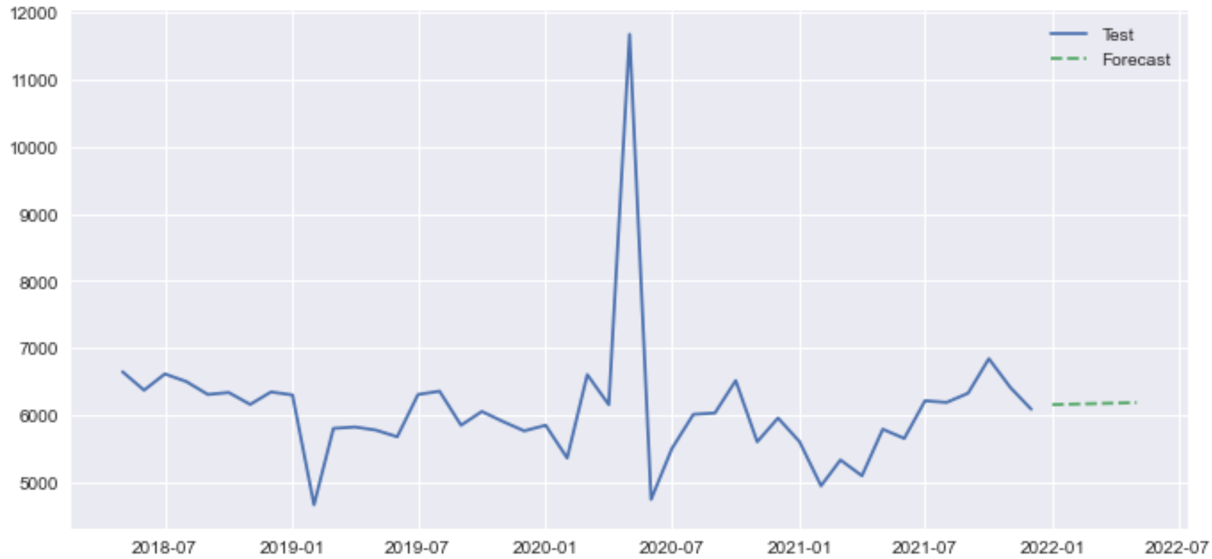
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [914]:

```
#for order of p,d,q
```

```
#SARIMAX(2) for order of 1,1,1
order=(1,1,1)
seasonal_order =(1,1,1,2)
periods=5
Sarimax_results2 = evaluate_sarima(finalDataFrame['count'],order,seaso
Sarimax_results2.summary()
```






```
-----------------------------------------------------
Values for test Year/Month
2018-05-01    6650
2018-06-01    6376
2018-07-01    6618
2018-08-01    6504
2018-09-01    6312
2018-10-01    6342
2018-11-01    6164
2018-12-01    6350
2019-01-01    6305
2019-02-01    4670
Name: count, dtype: int64
```

```
------------------------------------------------------
Values for Predictions Year/Month
2018-05-01    6037.697179
2018-06-01    6227.130885
2018-07-01    6456.807168
2018-08-01    6474.898062
2018-09-01    6547.275631
2018-10-01    6452.623667
2018-11-01    6355.897607
2018-12-01    6287.062466
2019-01-01    6253.675126
2019-02-01    6312.341274
dtype: float64
------------------------------------------------------
The Mean absolute Error of our forecasts is 418.2909
The Mean absolute Percentage Error of our predictions is 0.1097
The Normalized RMSE value is 0.1779
```

Out[914]:

SARIMAX Results

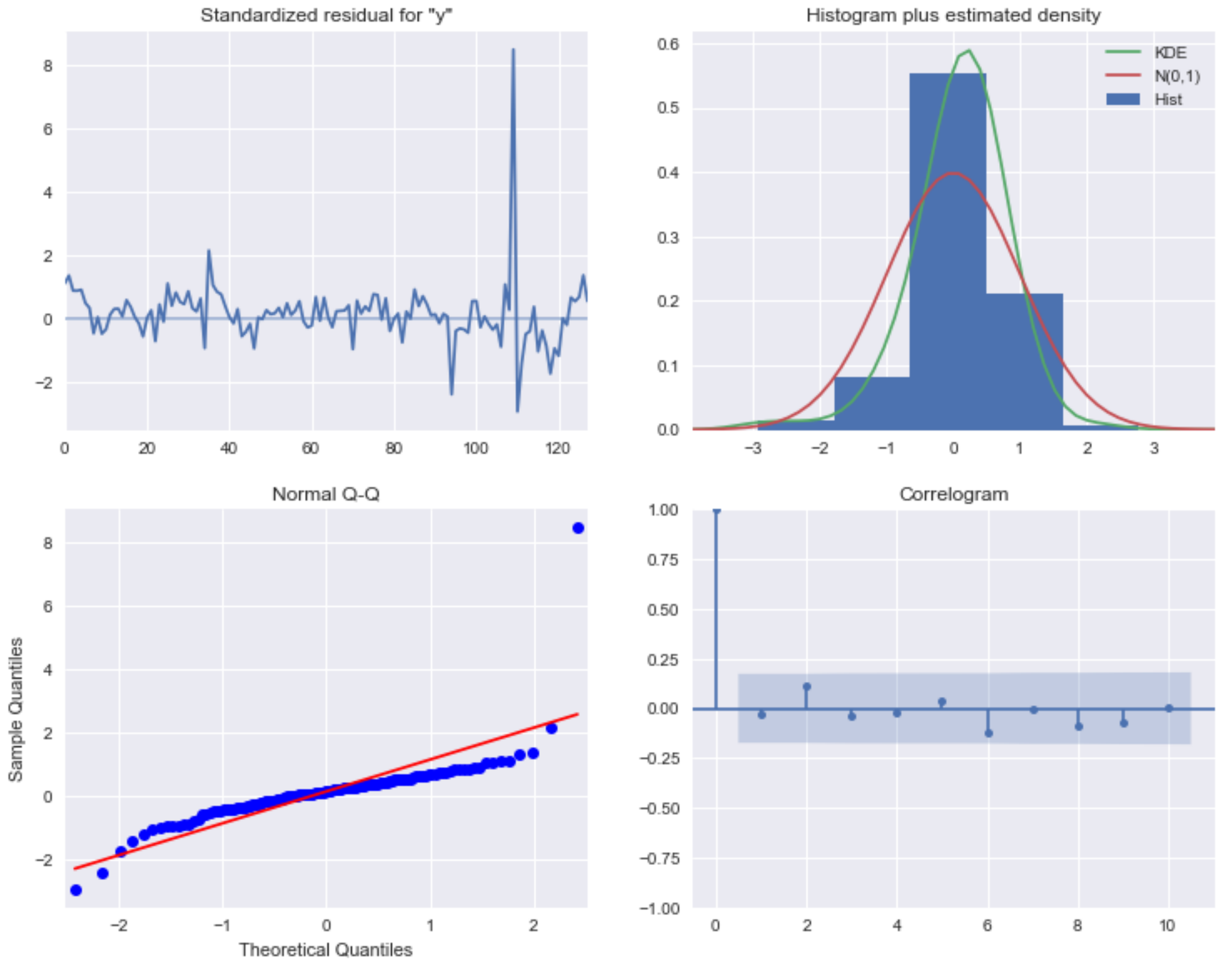
Dep. Variable:	y	**No. Observations:**	129
Model:	SARIMAX(1, 1, 1)	**Log Likelihood**	-1017.168
Date:	Wed, 09 Mar 2022	**AIC**	2040.336
Time:	15:00:45	**BIC**	2048.892
Sample:	0 - 129	**HQIC**	2043.812
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0045	0.071	-0.064	0.949	-0.143	0.134
ma.L1	-0.8737	0.065	-13.526	0.000	-1.000	-0.747
sigma2	4.464e+05	1.26e+04	35.427	0.000	4.22e+05	4.71e+05

Ljung-Box (L1) (Q):	0.07	**Jarque-Bera (JB):**	6987.35
Prob(Q):	0.80	**Prob(JB):**	0.00
Heteroskedasticity (H):	5.19	**Skew:**	4.04
Prob(H) (two-sided):	0.00	**Kurtosis:**	38.28

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [908]:
```
#Let's plot 4 diagnostic plots to see residuals in 4 different ways.
Sarimax_results2.plot_diagnostics()
plt.show()
```



Forecasting ARIMA & SARIMA results:

SARIMA vs ARIMA forecasts:

We compared our 3 SARIMA models to our Baseline ARIMA model and picked up the best 2.

* Forecasting in Sample

To see how good the models are doing we will take 10% of the data as validation data.

- Metrics Used to Compare Models: The models choosen here will be evaluated using MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error). These are popular metrics when evaluating forecasting models. When comparing forecast methods applied to a single time series, or to several time series with the same units, MAE is popular as it is easy to both understand and compute. Percentage errors measures such as MAPE have the advantage of being unit-free, and so are frequently used to compare forecast performances between data sets. Source: [https://sailajakarra.medium.com/time-series-predictions-using-arima-sarimax-e6724844cae0] (https://sailajakarra.medium.com/time-series-predictions-using-arima-sarimax-e6724844cae0%5D)

In [909]:
```
arima_results1.summary()
```

Out[909]:

ARIMA Model Results

Dep. Variable:	D.y	**No. Observations:**	128
Model:	ARIMA(0, 1, 1)	**Log Likelihood**	-1013.615
Method:	css-mle	**S.D. of innovations**	659.896
Date:	Wed, 09 Mar 2022	**AIC**	2033.230
Time:	14:35:36	**BIC**	2041.786
Sample:	1	**HQIC**	2036.706

	coef	std err	z	P>|z|	[0.025	0.975]
const	9.8638	4.561	2.163	0.031	0.925	18.803
ma.L1.D.y	-0.9305	0.041	-22.852	0.000	-1.010	-0.851

Roots

	Real	Imaginary	Modulus	Frequency
MA.1	1.0747	+0.0000j	1.0747	0.0000

In [615]:
```
sarimax_results1.summary()
```

Out[615]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	129
Model:	SARIMAX(1, 1, 1)	**Log Likelihood**	-1017.168
Date:	Wed, 09 Mar 2022	**AIC**	2040.336
Time:	09:24:57	**BIC**	2048.892
Sample:	0	**HQIC**	2043.812
	- 129		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0045	0.071	-0.064	0.949	-0.143	0.134
ma.L1	-0.8737	0.065	-13.526	0.000	-1.000	-0.747
sigma2	4.464e+05	1.26e+04	35.427	0.000	4.22e+05	4.71e+05

Ljung-Box (L1) (Q):	0.07	**Jarque-Bera (JB):**	6987.35
Prob(Q):	0.80	**Prob(JB):**	0.00
Heteroskedasticity (H):	5.19	**Skew:**	4.04
Prob(H) (two-sided):	0.00	**Kurtosis:**	38.28

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Forecasting with our Out of Sample set:

We will be sampling with our Arima01(0,1,1) and SARIMAX(1,1,1)(1,1,1,2) with a period od 24 and see how the models perform.

In [747]:
```
arima_model = ARIMA(finalDataFrame, order=(1,1,1))
# fit model
arima_results = arima_model.fit()

# Calculate the mean absolute error from residuals
mae = np.mean(np.abs(arima_results.resid))

# Print mean absolute error
print('MAE: %.3f' % mae)
```

```
MAE: 360.475
```

In [748]:
```
forecast_arima = arima_results.predict(start = len(finalDataFrame['cou
                           end=len(finalDataFrame['count'])+24,
                           typ='levels').rename('arima(0,1,1)')
```

In [749]:
```
finalDataFrame['count'].plot(figsize=(10,5),legend=True,color='r')
forecast_arima.plot(legend=True)
```

Out[749]: <AxesSubplot:xlabel='Year/Month'>

For sarima

In [772]:
```
sarima_model = SARIMAX(finalDataFrame, order=(1,1,1),seasonal_order =(
# fit model
sarima_results = sarima_model.fit()
# Calculate the mean absolute error from residuals
mae = np.mean(np.abs(sarima_results.resid))
# Print mean absolute error
print('MAE: %.3f' % mae)
```

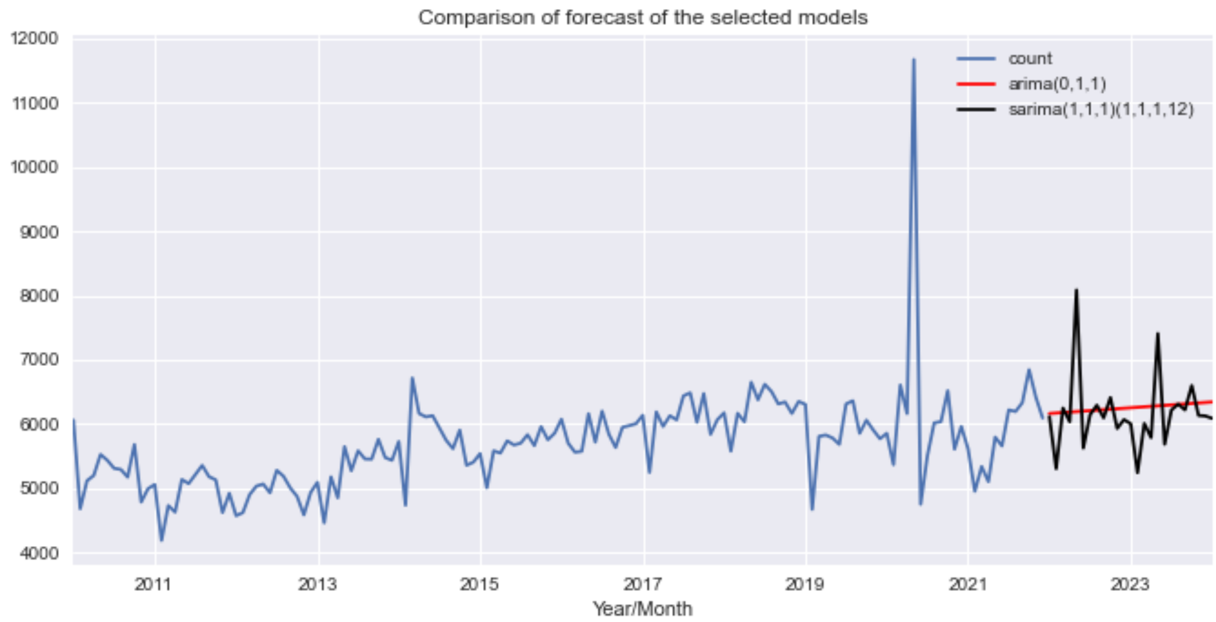
```
MAE: 386.576
```

In [773]:
```
forecast_sarima = sarima_results.predict(start = len(finalDataFrame['c
                                         end=len(finalDataFrame['count'])+24,
                                         typ='levels').rename('sarima(1,1,1)(1,1,1,1
```

In [774]:
```
finalDataFrame['count'].plot(figsize=(10,5),legend=True,color='r')
forecast_arima.plot(legend=True)
```

Out[774]: <AxesSubplot:xlabel='Year/Month'>

In [776]:
```
#ploting the forecast results for arima and sarima:
dates = finalDataFrame.index
finalDataFrame['count'].plot(figsize=(10,5),legend=True)
forecast_arima.plot(legend=True,color ='red')
forecast_sarima.plot(legend=True,color='black')
plt.title("Comparison of forecast of the selected models")
plt.show()
```



In [915]:
```
df_arima_results = pd.DataFrame({'metrics':['MAE'],
                   'ARIMA(0,1,1)': 360.47,
                   'SARIMA(1,1,1)(1,1,1)12': 386.00,
                  })

df_arima_results
```

Out[915]:

	metrics	ARIMA(0,1,1)	SARIMA(1,1,1)(1,1,1)12
0	MAE	360.47	386.0

Our Sarima model follows the time series better. Arima model completely ignored the seasonal information,is not a good representation for the forecast.

Saving the model:

In [782]:
```
# Import pickle
import pickle

# Set model name
filename = "../finalDataFrame.pkl"

# Pickle it
with open('filename.txt','wb') as fh:
    pickle.dump(sarima_model,fh)
```

In [787]:
```
pickle_off = open("filename.txt","rb")
loaded_model = pickle.load(pickle_off)
loaded_model.fit().summary()
```

Out[787]:

SARIMAX Results

Dep. Variable:	count	**No. Observations:**	144
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 12)	**Log Likelihood**	-1033.198
Date:	Wed, 09 Mar 2022	**AIC**	2076.395
Time:	13:42:40	**BIC**	2090.771
Sample:	01-01-2010	**HQIC**	2082.237
	- 12-01-2021		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0574	0.001	-44.538	0.000	-0.060	-0.055
ma.L1	-0.6523	0.000	-3303.519	0.000	-0.653	-0.652
ar.S.L12	-0.8826	0.000	-6046.620	0.000	-0.883	-0.882
ma.S.L12	-0.0359	0.001	-27.870	0.000	-0.038	-0.033
sigma2	8.738e+05	1.47e-10	5.93e+15	0.000	8.74e+05	8.74e+05

Ljung-Box (L1) (Q):	0.07	**Jarque-Bera (JB):**	8473.34
Prob(Q):	0.80	**Prob(JB):**	0.00
Heteroskedasticity (H):	5.49	**Skew:**	4.24
Prob(H) (two-sided):	0.00	**Kurtosis:**	41.48

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.12e+30. Standard errors may be unstable.

Conclusions:

We used ARIMA models and its variants: Seasonal ARIMA (SARIMA) and ARIMAX which uses external data (exogenous inputs) to improve the performance of the ARIMA model. We followed the Box-Jenkins method to find the best model considering a part of our dataset (time series of sales of product 28 of Walmart's store 2). As first step we've identified important characteristics of our time series such as stationarity and seasonality. Then, we also used graphical and statistical methods such as follows to find the best fit model:

- Augmented Dickey-Fuller test,
- ACF and PACF plots analysis,
- Exploring model summary statistics,
- Analyze plots obtained using the statsmodel method plot_diagnostics.

We chose Arima(0,1,1) & Sarima(1,1,1)(1,1,1,12) as our best one's.The MAPE & MAE on both the models were least. Out of these two SARIMAX performed better on the forecast hence we choose this as our final model

Limitations:

Model seems to performing well for forecasting but might be overfitting the data.It can be explored more to understand the time series btter.

Future Work:

Would like to see how the time series iwll perform with more advanced time series models like prophet.

In [ ]:

```

```