IBM Machine learning certificate

Time Series Module project

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Main Objective

How does the changes in daily temperature relate with the amount of violent crimes in Massachusetts state?

Here, we attempt to build a time series models using a dataset on the average temperature in Massachusetts

Then a time series correlation analysis was performed to determine the relationship between crime rate and temperature changes across the state.

In [2]:
```
# Setup
from datetime import datetime
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.api as sm
import seaborn as sns
import sys, os
os.chdir('data')
from colorsetup import colors, palette
sns.set_palette(palette)
import warnings
warnings.simplefilter(action='ignore')
```

Materials and techniques

The daily tempearture dataset was gotten from AWS Marketplace

by [https://theclimatedatafactory.com/ (https://theclimatedatafactory.com/)](https://theclimatedatafactory.com/)

[https://aws.amazon.com/marketplace/pp/prodview-imlqd3epbsufk?sr=0-2&ref_=beagle&applicationId=AWSMPContessa#overview (https://aws.amazon.com/marketplace/pp/prodview-imlqd3epbsufk?sr=0-2&ref_=beagle&applicationId=AWSMPContessa#overview)](https://aws.amazon.com/marketplace/pp/prodview-imlqd3epbsufk?sr=0-2&ref_=beagle&applicationId=AWSMPContessa#overview)

The dataset contains daily temperature data from January 1st, 2018-October 11th, 2020 across major cities, Boston, MA, Chicago, IL, New Orleans, LA, Seattle, WA, Atlanta, GA, and New York, NY,

Here the dataset is loaded as a dataframe and a new dataset is process containily on the data from Boston MA, to represent the temperature data for

In [3]:
```
temp = pd.read_csv('temp20182020.csv')

#data from AWS Marketplace https://theclimatedatafactory.com/
#https://aws.amazon.com/marketplace/pp/prodview-imlqd3epbsufk?sr=0-2&ref_=beag
le&applicationId=AWSMPContessa#overview
```

In [4]:
```
temp.head(5)
```

Out[4]:

	city	date	avgTemp	maxTemp	minTemp	prcp
0	Atlanta	20180101	23.5	29	18	0.0
1	Boston	20180101	6.5	13	0	0.0
2	Atlanta	20180102	24.5	36	13	0.0
3	Boston	20180102	11.5	19	4	0.0
4	Atlanta	20180103	33.0	39	27	0.0

In [5]:
```
temp.shape
```

Out[5]:
```
(6090, 6)
```

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

Out[6]:
```
city        object
date         int64
avgTemp    float64
maxTemp      int64
minTemp      int64
prcp       float64
dtype: object
```

In [7]:
```
#convert temp['date'] to date format

temp['date'] = pd.to_datetime(temp['date'].astype(str), format='%Y%m%d', error
s = 'coerce')
```

In [8]:
```
temp.head(5)
```

Out[8]:

	city	date	avgTemp	maxTemp	minTemp	prcp
0	Atlanta	2018-01-01	23.5	29	18	0.0
1	Boston	2018-01-01	6.5	13	0	0.0
2	Atlanta	2018-01-02	24.5	36	13	0.0
3	Boston	2018-01-02	11.5	19	4	0.0
4	Atlanta	2018-01-03	33.0	39	27	0.0

In [9]:
```
temp.dtypes
```

Out[9]:
```
city                object
date        datetime64[ns]
avgTemp            float64
maxTemp              int64
minTemp              int64
prcp               float64
dtype: object
```

In [10]:
```
temp.describe()
```

Out[10]:

	avgTemp	maxTemp	minTemp	prcp
count	6090.000000	6090.000000	6090.000000	6090.000000
mean	59.667816	67.531856	51.803777	0.138967
std	17.526891	18.506524	17.035435	0.378406
min	-16.500000	-10.000000	-23.000000	0.000000
25%	46.000000	53.000000	39.000000	0.000000
50%	61.000000	70.000000	53.000000	0.000000
75%	74.500000	83.000000	66.000000	0.080000
max	91.500000	100.000000	84.000000	6.240000

In [11]:
```
#find missing data
temp.info
print(temp.isnull().sum())
```

```
city       0
date       0
avgTemp    0
maxTemp    0
minTemp    0
prcp       0
dtype: int64
```

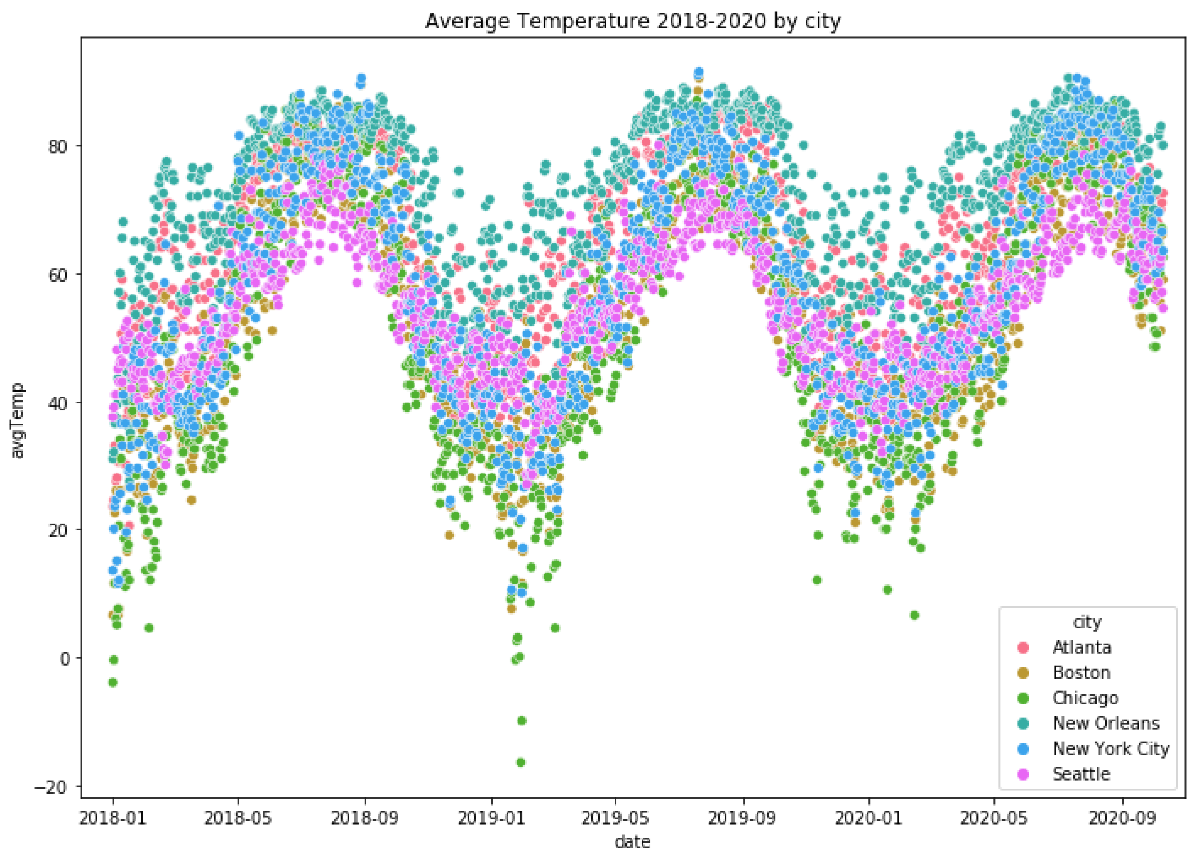
In [12]:
```
print(temp['city'].value_counts())
```

```
New Orleans      1015
Seattle          1015
Boston           1015
New York City    1015
Chicago          1015
Atlanta          1015
Name: city, dtype: int64
```

In [13]:
```
#Lets check out the start and end dates
dates = sorted(temp['date'].unique())
print('Start date is', dates[0], '\n' 'End date is', dates[1014])
```

```
Start date is 2018-01-01T00:00:00.000000000
End date is 2020-10-11T00:00:00.000000000
```

In [14]:
```
#avgTemp over time by city
#plot by city
fig, ax = plt.subplots()
#size of A4 paper
fig.set_size_inches(11.7, 8.27)
sns.scatterplot(data=temp, x="date", y="avgTemp", hue="city", ax=ax)
#set limit of the report date on x axis
ax.set(xlim=('2017-12-01','2020-11-01'))
#setting the title of the figure
ax.set(title=("Average Temperature 2018-2020 by city"))

#save file and image, remember to rename file name otherwise, it will rewrite
#lt.savefig('COVID_19_4.png')
plt.show()
```



In [15]:
```
#Lets create a data set of the temperature data of just Massachusetts state
#Assuming the daily Boston temperature is about the same across the state.
temp_mass=temp[(temp['city'] == 'Boston')]
temp_mass.head()
```

Out[15]:

	city	date	avgTemp	maxTemp	minTemp	prcp
1	Boston	2018-01-01	6.5	13	0	0.00
3	Boston	2018-01-02	11.5	19	4	0.00
5	Boston	2018-01-03	22.5	29	16	0.00
7	Boston	2018-01-04	26.0	30	22	1.35
9	Boston	2018-01-05	15.0	24	6	0.00

In [16]:
```
temp_mass.shape
```
Out[16]:
```
(1015, 6)
```

In [17]:
```
#Lets sort the time in the temp_mass dataset and check the time interval
temp_mass = temp_mass.sort_values(by='date')

# Check time intervals
temp_mass['delta'] = temp_mass['date'] - temp_mass['date'].shift(1)

temp_mass[['date', 'delta']].head()
```
Out[17]:

	date	delta
1	2018-01-01	NaT
3	2018-01-02	1 days
5	2018-01-03	1 days
7	2018-01-04	1 days
9	2018-01-05	1 days

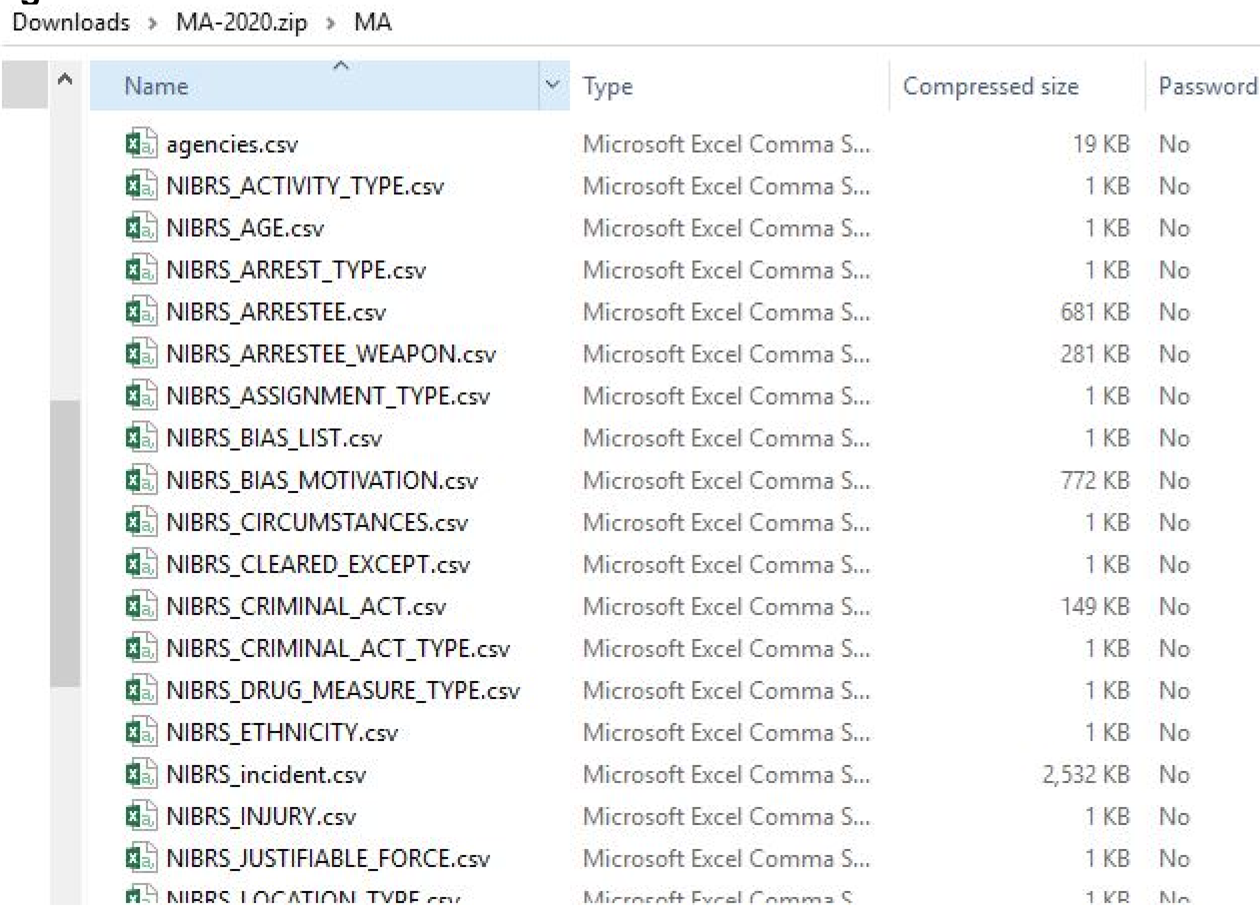
In [18]:
```
temp_mass['delta'].sum(), temp_mass['delta'].count()
```
Out[18]:
```
(Timedelta('1014 days 00:00:00'), 1014)
```

In [19]:
```
temp_mass.head(5)
```
Out[19]:

	city	date	avgTemp	maxTemp	minTemp	prcp	delta
1	Boston	2018-01-01	6.5	13	0	0.00	NaT
3	Boston	2018-01-02	11.5	19	4	0.00	1 days
5	Boston	2018-01-03	22.5	29	16	0.00	1 days
7	Boston	2018-01-04	26.0	30	22	1.35	1 days
9	Boston	2018-01-05	15.0	24	6	0.00	1 days

The crime data for mass from 2018 to 2020 was gotten from the Federal Bureau of Investigation Crime Data Explorer, and Uniform Crime Reporting Program. The compressed file folder was downloaded for each of the year 2018, 2019 and 2020 and the incident.csv files were extracted for each year. It is important to note that only the number or frequency of crime reported will be analysised. Additional data is located in the compressed zip files such as location, type of offense etc.

See image below.



Downloads › MA-2020.zip › MA

Name	Type	Compressed size	Password ...
agencies.csv	Microsoft Excel Comma S...	19 KB	No
NIBRS_ACTIVITY_TYPE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_AGE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_ARREST_TYPE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_ARRESTEE.csv	Microsoft Excel Comma S...	681 KB	No
NIBRS_ARRESTEE_WEAPON.csv	Microsoft Excel Comma S...	281 KB	No
NIBRS_ASSIGNMENT_TYPE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_BIAS_LIST.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_BIAS_MOTIVATION.csv	Microsoft Excel Comma S...	772 KB	No
NIBRS_CIRCUMSTANCES.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_CLEARED_EXCEPT.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_CRIMINAL_ACT.csv	Microsoft Excel Comma S...	149 KB	No
NIBRS_CRIMINAL_ACT_TYPE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_DRUG_MEASURE_TYPE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_ETHNICITY.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_incident.csv	Microsoft Excel Comma S...	2,532 KB	No
NIBRS_INJURY.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_JUSTIFIABLE_FORCE.csv	Microsoft Excel Comma S...	1 KB	No
NIBRS_LOCATION_TYPE.csv	Microsoft Excel Comma S...	1 KB	No

[https://crime-data-explorer.fr.cloud.gov/pages/downloads (https://crime-data-explorer.fr.cloud.gov/pages/downloads)](https://crime-data-explorer.fr.cloud.gov/pages/downloads)

The frequency of crime /incident reported will be computed from the dataset fro each year and the data set from each year 2018 and 2020 will be combined into one dataset.

In [20]:
```
mass_2018 = pd.read_csv('mass_2018.csv', parse_dates=['INCIDENT_DATE'])
mass_2019 = pd.read_csv('mass_2019.csv', parse_dates=['INCIDENT_DATE'])
mass_2020 = pd.read_csv('mass_2020.csv', parse_dates=['INCIDENT_DATE'])
print ('mass_2018 is', mass_2018.shape ,'\n')
print ('mass_2019 is', mass_2019.shape ,'\n')
print ('mass_2020 is', mass_2020.shape)
```

```
mass_2018 is (169343, 15)

mass_2019 is (170461, 15)

mass_2020 is (216195, 15)
```

In [21]:
```
# Combine all the dataframes for 2018 through 2020
crime_Mass = pd.concat([mass_2018, mass_2019, mass_2020], ignore_index=True)
crime_Mass.shape
```

Out[21]: (555999, 15)

In [22]:
```
crime_Mass.head(5)
```

Out[22]:

	DATA_YEAR	AGENCY_ID	INCIDENT_ID	NIBRS_MONTH_ID	CARGO_THEFT_FLAG	SUBMISSIC
0	2018	7676	104967192	8669027	NaN	2
1	2018	7676	104967205	8669027	N	2
2	2018	7676	104967212	8669027	NaN	2
3	2018	7676	104965874	8669027	N	2
4	2018	7676	104965896	8666681	NaN	2

In [23]:
```
#find missing data
crime_Mass.info
print(crime_Mass.isnull().sum())
```

```
DATA_YEAR                 0
AGENCY_ID                 0
INCIDENT_ID               0
NIBRS_MONTH_ID            0
CARGO_THEFT_FLAG     312579
SUBMISSION_DATE           0
INCIDENT_DATE             0
REPORT_DATE_FLAG     508487
INCIDENT_HOUR             0
CLEARED_EXCEPT_ID         0
CLEARED_EXCEPT_DATE  554351
INCIDENT_STATUS           0
DATA_HOME                 0
ORIG_FORMAT               0
DID                       0
dtype: int64
```

In [24]:
```
crime_Mass.dtypes
```

Out[24]:
```
DATA_YEAR                          int64
AGENCY_ID                          int64
INCIDENT_ID                        int64
NIBRS_MONTH_ID                     int64
CARGO_THEFT_FLAG                  object
SUBMISSION_DATE                   object
INCIDENT_DATE             datetime64[ns]
REPORT_DATE_FLAG                  object
INCIDENT_HOUR                      int64
CLEARED_EXCEPT_ID                  int64
CLEARED_EXCEPT_DATE               object
INCIDENT_STATUS                    int64
DATA_HOME                         object
ORIG_FORMAT                       object
DID                                int64
dtype: object
```

In [25]:
```
#Create a new df by dropping all the columns except 'INCIDENT_DATE'
crime_Mass_freq = crime_Mass[['INCIDENT_DATE']]
#to keep header and index please use double square brackets.
crime_Mass_freq.columns = ['INCIDENT_DATE']
crime_Mass_freq.shape
```

Out[25]:
```
(555999, 1)
```

In [26]:
```
crime_Mass_freq.head(5)
```

Out[26]:

	INCIDENT_DATE
0	2018-09-05
1	2018-09-09
2	2018-09-16
3	2018-09-20
4	2018-10-02

In [27]:
```
crime_Mass_freq['INCIDENT_DATE'].value_counts()
```

Out[27]:
```
2020-11-20    1283
2020-11-09    1241
2020-11-16    1239
2020-10-26    1192
2020-10-23    1160
              ...
2018-03-13     243
2019-01-20     236
2018-12-25     226
2018-11-22     217
2018-01-04     205
Name: INCIDENT_DATE, Length: 1096, dtype: int64
```

In [28]:
```
crime_Mass_freq['frequency'] =crime_Mass_freq.groupby('INCIDENT_DATE')['INCIDE
NT_DATE'].transform('count')
crime_Mass_freq.head(5)
```

Out[28]:

	INCIDENT_DATE	frequency
0	2018-09-05	523
1	2018-09-09	395
2	2018-09-16	453
3	2018-09-20	543
4	2018-10-02	478

In [29]:
```
crime_Mass_freq.shape
```

Out[29]:
```
(555999, 2)
```

In [30]:
```
# drop duplicate rows
crime_Mass_freq = crime_Mass_freq.drop_duplicates()
crime_Mass_freq.shape
```

Out[30]:
```
(1096, 2)
```

In [31]:
```
#Just to check ^.^
crime_Mass_freq['frequency'].sum()
```

Out[31]:
```
555999
```

In [32]:
```
crime_Mass_freq.describe()
```

Out[32]:

	frequency
count	1096.000000
mean	507.298358
std	129.668891
min	205.000000
25%	437.000000
50%	486.500000
75%	544.250000
max	1283.000000

In [33]:
```
dates1 = sorted(crime_Mass_freq['INCIDENT_DATE'].unique())
print('Start date is', dates1[0], '\n' 'End date is', dates1[1095])
```

```
Start date is 2018-01-01T00:00:00.000000000
End date is 2020-12-31T00:00:00.000000000
```

In [34]:
```
#Lets sort the time in the temp_mass dataset and check the time interval
crime_Mass_freq = crime_Mass_freq.sort_values(by='INCIDENT_DATE')

# Check time intervals
crime_Mass_freq['delta'] = crime_Mass_freq['INCIDENT_DATE'] - crime_Mass_freq[
'INCIDENT_DATE'].shift(1)

crime_Mass_freq[['INCIDENT_DATE', 'delta']].head()
```

Out[34]:

	INCIDENT_DATE	delta
557	2018-01-01	NaT
905	2018-01-02	1 days
975	2018-01-03	1 days
446	2018-01-04	1 days
458	2018-01-05	1 days

In [35]:
```
crime_Mass_freq.head(5)
```

Out[35]:

	INCIDENT_DATE	frequency	delta
557	2018-01-01	363	NaT
905	2018-01-02	384	1 days
975	2018-01-03	405	1 days
446	2018-01-04	205	1 days
458	2018-01-05	289	1 days

In [36]:
```
crime_Mass_freq.drop('delta', axis=1)
```

Out[36]:

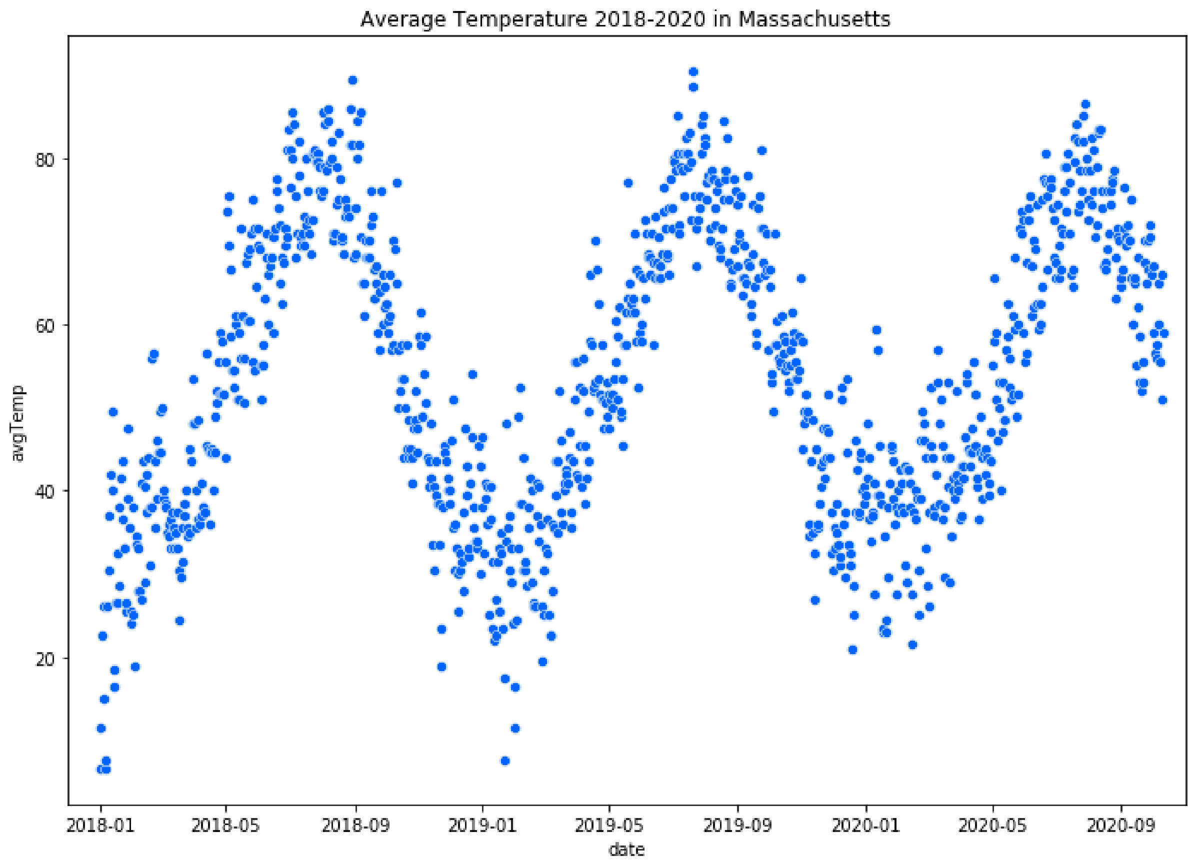
	INCIDENT_DATE	frequency
557	2018-01-01	363
905	2018-01-02	384
975	2018-01-03	405
446	2018-01-04	205
458	2018-01-05	289
...	...	...
340822	2020-12-27	393
340035	2020-12-28	531
340297	2020-12-29	520
340853	2020-12-30	482
340821	2020-12-31	472

1096 rows × 2 columns

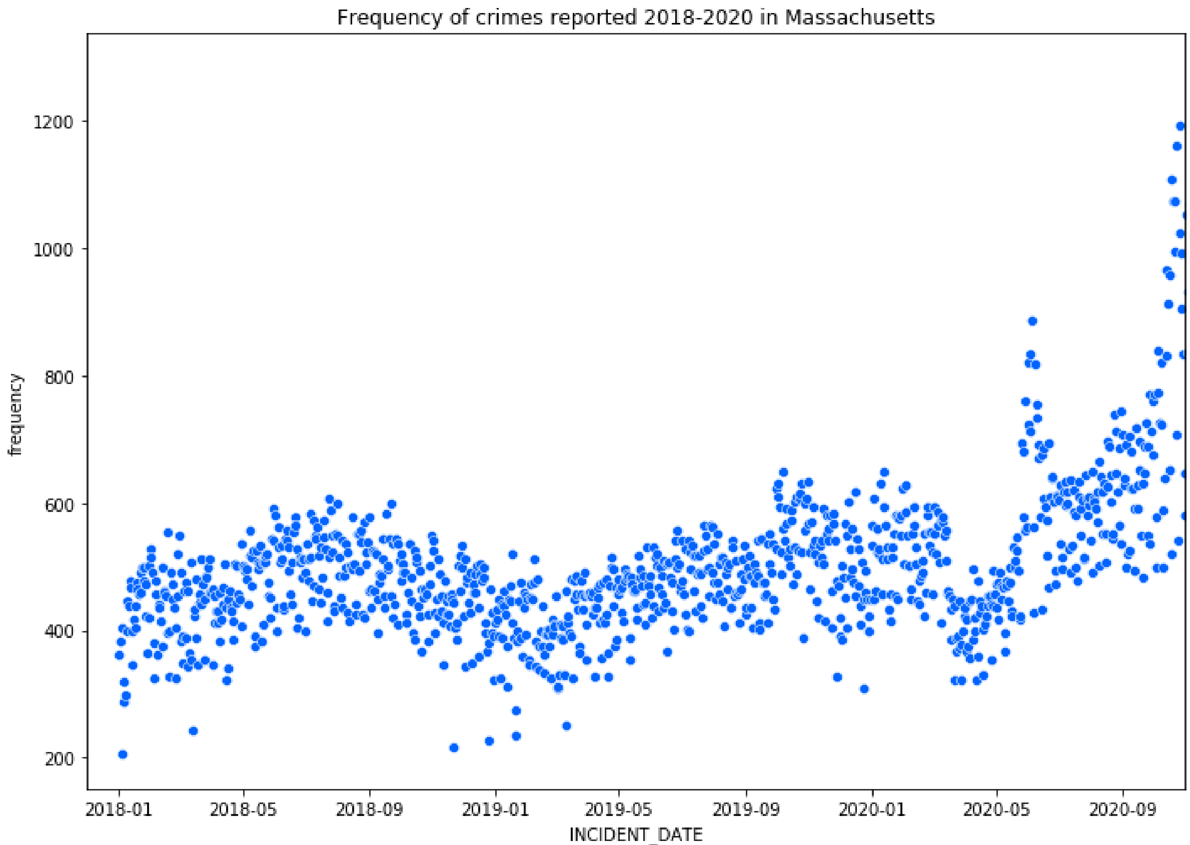
Data visualization and analysis

In [38]:

```
fig, ax = plt.subplots()
#size of A4 paper
fig.set_size_inches(11.7, 8.27)
sns.scatterplot(data=temp_mass, x="date", y="avgTemp", ax=ax)
ax.set(xlim=('2017-12-01','2020-11-01'))
ax.set(title=("Average Temperature 2018-2020 in Massachusetts"))
plt.show()
```



In [37]:
```
fig, ax = plt.subplots()
#size of A4 paper
fig.set_size_inches(11.7, 8.27)
sns.scatterplot(data=crime_Mass_freq, x="INCIDENT_DATE", y="frequency", ax=ax)
ax.set(xlim=('2017-12-01','2020-11-01'))
ax.set(title=("Frequency of crimes reported 2018-2020 in Massachusetts"))
plt.show()
```



Checking for patterns in the Massachusetts temperature dataset for stationarity, Irregularity and trends of this timeseries data

In [39]:
```
#Augmented Dickey-fuller test
from statsmodels.tsa.stattools import adfuller
print("Observations of Dickey-fuller test")
dftest = adfuller(temp_mass['avgTemp'],autolag='AIC')
dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#lags used',
'number of observations used'])
for key,value in dftest[4].items():
    dfoutput['critical value (%s)'%key]= value
print(dfoutput)
```

```
Observations of Dickey-fuller test
Test Statistic                   -2.501154
p-value                           0.115194
#lags used                        9.000000
number of observations used    1005.000000
critical value (1%)              -3.436873
critical value (5%)              -2.864420
critical value (10%)             -2.568304
dtype: float64
```

Since the p value is more than 0.05, we will fail to reject the Null hypothesis: that the series is nonstationary.

In addition the test statistic ADF value (-2.5) is not less than the critical values (-3.44 , -2.86 , -2.57) at different percentages . In this case, we cannot reject our null hypothesis and conclude that the temp_mass dataset is nonstationary.

In [40]:
```
#Augmented Dickey-fuller test
from statsmodels.tsa.stattools import adfuller
print("Observations of Dickey-fuller test")
dftest1 = adfuller(crime_Mass_freq['frequency'],autolag='AIC')
dfoutput1=pd.Series(dftest1[0:4],index=['Test Statistic','p-value','#lags use
d','number of observations used'])
for key,value in dftest[4].items():
    dfoutput1['critical value (%s)'%key]= value
print(dfoutput1)
```

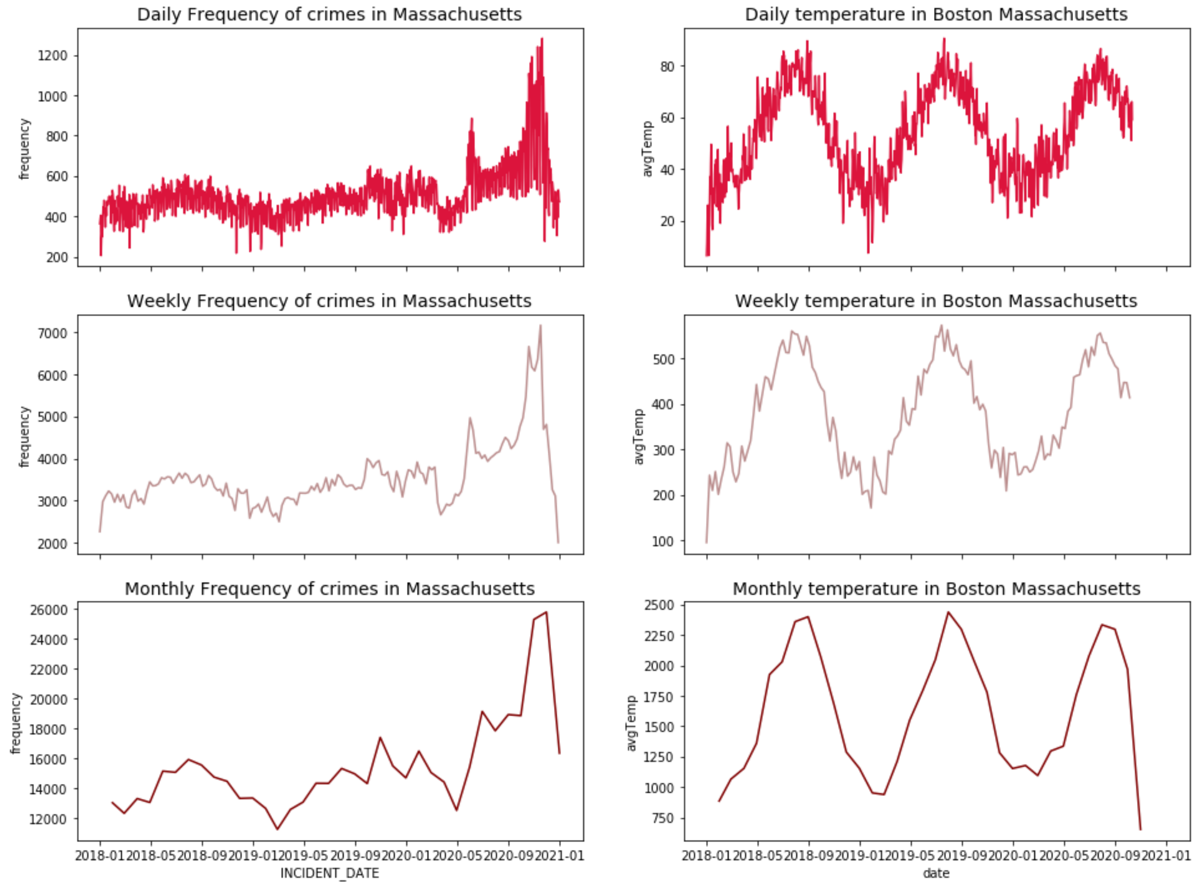
```
Observations of Dickey-fuller test
Test Statistic                   -2.445794
p-value                           0.129226
#lags used                       21.000000
number of observations used    1074.000000
critical value (1%)              -3.436873
critical value (5%)              -2.864420
critical value (10%)             -2.568304
dtype: float64
```

Since the p value is 0.13, we will fail to reject the Null hypothesis: that the series is nonstationary.

In addition the test statistic ADF value (-2.4) is not less than the critical values (-3.44 , -2.86 , -2.57) at different percentages . In this case, we cannot reject our null hypothesis and conclude that the temp_mass dataset is nonstationary.

Both data sets will have to be transformed.

In [45]:
```
fig, ax = plt.subplots(ncols=2, nrows=3, sharex=True, figsize=(16,12))

#Crime frequency in MA

sns.lineplot(crime_Mass_freq['INCIDENT_DATE'], crime_Mass_freq['frequency'], c
olor='crimson', ax=ax[0, 0])
ax[0, 0].set_title('Daily Frequency of crimes in Massachusetts', fontsize=14)

resamp_crime_Mass_freq = crime_Mass_freq[['INCIDENT_DATE','frequency']].resamp
le('7D', on='INCIDENT_DATE').sum().reset_index(drop=False)
sns.lineplot(resamp_crime_Mass_freq['INCIDENT_DATE'], resamp_crime_Mass_freq[
'frequency'], color='rosybrown', ax=ax[1, 0])
ax[1, 0].set_title('Weekly Frequency of crimes in Massachusetts', fontsize=14)

resamp_crime_Mass_freq = crime_Mass_freq[['INCIDENT_DATE','frequency']].resamp
le('M', on='INCIDENT_DATE').sum().reset_index(drop=False)
sns.lineplot(resamp_crime_Mass_freq['INCIDENT_DATE'], resamp_crime_Mass_freq[
'frequency'], color='maroon', ax=ax[2, 0])
ax[2, 0].set_title('Monthly Frequency of crimes in Massachusetts', fontsize=14
)

#Temperature in MA

sns.lineplot(temp_mass['date'], temp_mass['avgTemp'], color='crimson', ax=ax[0
, 1])
ax[0, 1].set_title('Daily temperature in Boston Massachusetts', fontsize=14)

resamp_temp_mass = temp_mass[['date','avgTemp']].resample('7D', on='date').sum
().reset_index(drop=False)
sns.lineplot(resamp_temp_mass['date'], resamp_temp_mass['avgTemp'], color='ros
ybrown', ax=ax[1, 1])
ax[1, 1].set_title('Weekly temperature in Boston Massachusetts', fontsize=14)

resamp_temp_mass = temp_mass[['date','avgTemp']].resample('M', on='date').sum
().reset_index(drop=False)
sns.lineplot(resamp_temp_mass['date'], resamp_temp_mass['avgTemp'], color='mar
oon', ax=ax[2, 1])
ax[2, 1].set_title('Monthly temperature in Boston Massachusetts', fontsize=14)


plt.show()
```



The weekly date looks better/smoother. The two dataframes temp_mass and crime_Mass_freq will be combined and set at weekly time interval by downsampling.

In [47]:
```
#rename crime_Mass_freq column to match
crime_Mass_freq=crime_Mass_freq.rename(columns={"INCIDENT_DATE": "date"})
crime_Mass_freq.head(5)
```

Out[47]:

	date	frequency	delta
557	2018-01-01	363	NaT
905	2018-01-02	384	1 days
975	2018-01-03	405	1 days
446	2018-01-04	205	1 days
458	2018-01-05	289	1 days

In [48]:
```
#combine the dfs
merged_Mass = pd.merge(crime_Mass_freq, temp_mass, on="date")
merged_Mass.shape
```

Out[48]: (1015, 9)

In [49]:
```
#find missing data
merged_Mass.info
print(merged_Mass.isnull().sum())
```

```
date         0
frequency    0
delta_x      1
city         0
avgTemp      0
maxTemp      0
minTemp      0
prcp         0
delta_y      1
dtype: int64
```

In [51]:
```
#delete the other columns not needed
merged_Mass=merged_Mass[['date','frequency','avgTemp']]
merged_Mass.head(5)
```

Out[51]:

	date	frequency	avgTemp
0	2018-01-01	363	6.5
1	2018-01-02	384	11.5
2	2018-01-03	405	22.5
3	2018-01-04	205	26.0
4	2018-01-05	289	15.0

In [52]:
```
dates2 = sorted(merged_Mass['date'].unique())
print('Start date is', dates2[0], '\n' 'End date is', dates2[1014])
```

```
Start date is 2018-01-01T00:00:00.000000000
End date is 2020-10-11T00:00:00.000000000
```

In [53]:
```
#donwsample to the weekly dataset
downsample = merged_Mass[['date',
                 'frequency',
                 'avgTemp',
                ]].resample('7D', on='date').mean().reset_index(drop=False)
merged_Mass2= downsample.copy()
merged_Mass2.shape
```

Out[53]: (145, 3)

In [54]:
```
merged_Mass2.head(5)
```

Out[54]:

	date	frequency	avgTemp
0	2018-01-01	323.428571	13.642857
1	2018-01-08	425.285714	34.785714
2	2018-01-15	445.428571	30.000000
3	2018-01-22	461.142857	35.928571
4	2018-01-29	451.428571	28.785714

Let's repeat the stationarity test after smoothing the dataset to the weekly time-interval...

In [57]:
```
from statsmodels.tsa.stattools import adfuller

print("Observations of Dickey-fuller test")
dftest = adfuller(merged_Mass2['frequency'],autolag='AIC')
dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#lags used',
'number of observations used'])
for key,value in dftest[4].items():
    dfoutput['critical value (%s)'%key]= value
print(dfoutput)
```

```
Observations of Dickey-fuller test
Test Statistic                  -2.607564
p-value                          0.091444
#lags used                       0.000000
number of observations used    144.000000
critical value (1%)             -3.476598
critical value (5%)             -2.881829
critical value (10%)            -2.577589
dtype: float64
```

In [58]:
```
from statsmodels.tsa.stattools import adfuller

print("Observations of Dickey-fuller test")
dftest = adfuller(merged_Mass2['avgTemp'],autolag='AIC')
dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#lags used',
'number of observations used'])
for key,value in dftest[4].items():
    dfoutput['critical value (%s)'%key]= value
print(dfoutput)
```

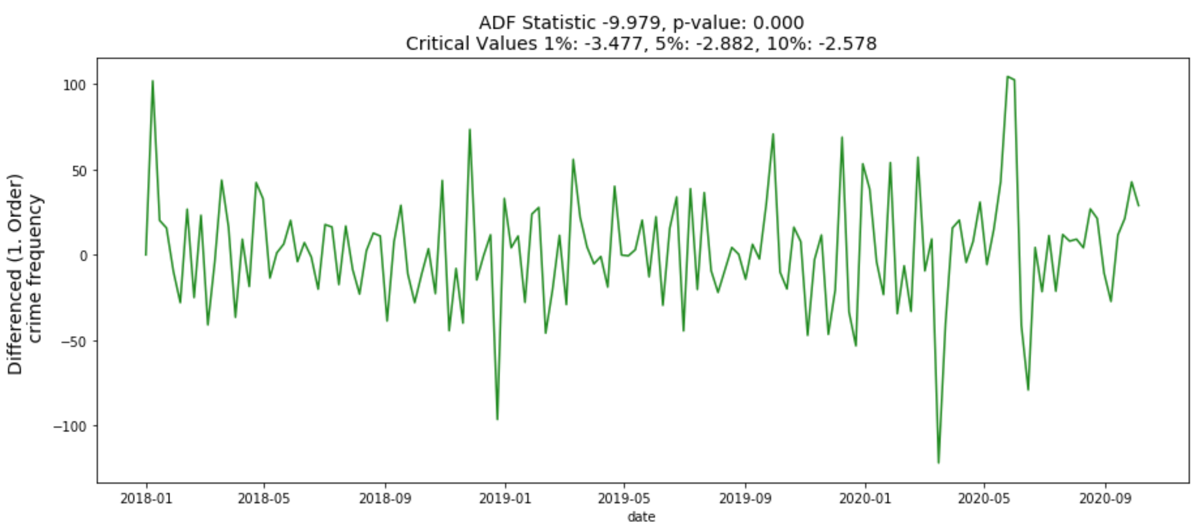
```
Observations of Dickey-fuller test
Test Statistic                  -5.822793e+00
p-value                          4.145246e-07
#lags used                       1.100000e+01
number of observations used      1.330000e+02
critical value (1%)             -3.480500e+00
critical value (5%)             -2.883528e+00
critical value (10%)            -2.578496e+00
dtype: float64
```

The smoothed temperature variable is stationary as p-value is 4.15 X 10^-7, the test statistic ADF value (-5.82) is not less than the critical values (-3.48 , -2.88 , -2.58) at different percentages. However the frequency of crime data is not as p-value is 0.09 the test statistic ADF value (-2.6) is not less than the critical values (-3.48 , -2.88 , -2.58) at different percentages.

The crime data series has to be transformed into stationarity ones.

In [69]:

```
# First Order Differencing
#since we are using a open source function let define df
df=merged_Mass2
ts_diff = np.diff(merged_Mass2['frequency'])
merged_Mass2['frequency_diff'] = np.append([0], ts_diff)

                                #***************
    # Thanks to https://www.kaggle.com/iamleonie for this function!

def visualize_adfuller_results(series, title, ax):
    result = adfuller(series)
    significance_level = 0.05
    adf_stat = result[0]
    p_val = result[1]
    crit_val_1 = result[4]['1%']
    crit_val_5 = result[4]['5%']
    crit_val_10 = result[4]['10%']

    if (p_val < significance_level) & ((adf_stat < crit_val_1)):
        linecolor = 'forestgreen'
    elif (p_val < significance_level) & (adf_stat < crit_val_5):
        linecolor = 'orange'
    elif (p_val < significance_level) & (adf_stat < crit_val_10):
        linecolor = 'red'
    else:
        linecolor = 'purple'
    sns.lineplot(x=df['date'], y=series, ax=ax, color=linecolor)
    ax.set_title(f'ADF Statistic {adf_stat:0.3f}, p-value: {p_val:0.3f}\nCriti
cal Values 1%: {crit_val_1:0.3f}, 5%: {crit_val_5:0.3f}, 10%: {crit_val_10:0.3
f}', fontsize=14)
    ax.set_ylabel(ylabel=title, fontsize=14)

                                      #***************


f, ax = plt.subplots(nrows=1, ncols=1, figsize=(15, 6))
visualize_adfuller_results(merged_Mass2['frequency_diff'], 'Differenced (1. Or
der) \n crime frequency', ax)
```



Times series decomposition

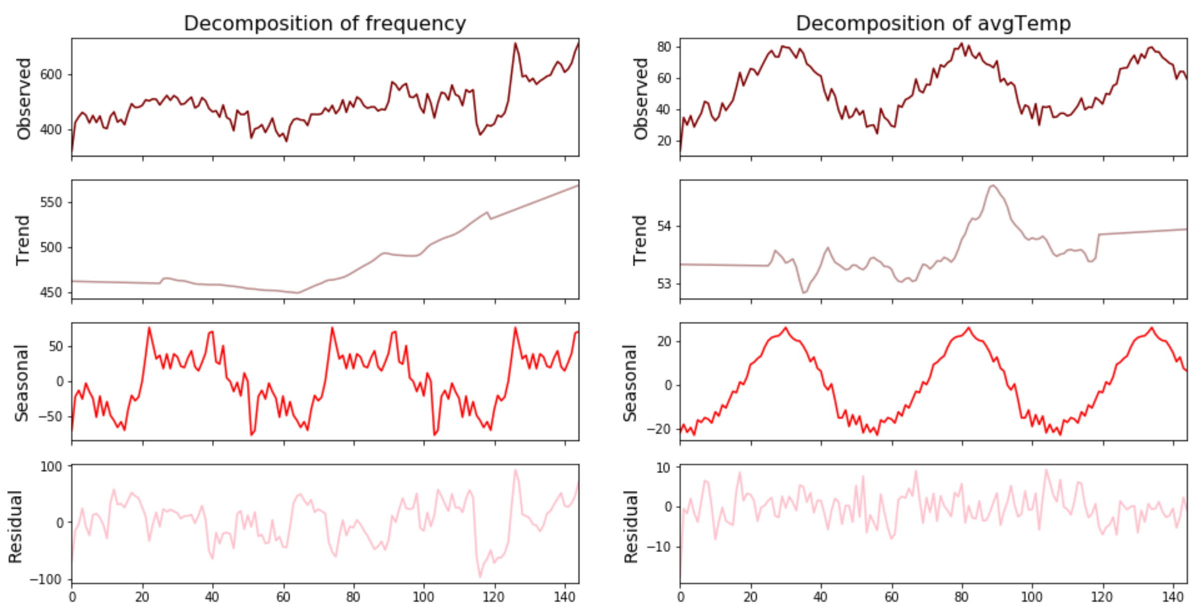
In [64]:
```
#feture engineering
merged_Mass2['year'] = pd.DatetimeIndex(merged_Mass2['date']).year
merged_Mass2['month'] = pd.DatetimeIndex(merged_Mass2['date']).month
merged_Mass2['day'] = pd.DatetimeIndex(merged_Mass2['date']).day
merged_Mass2['day_of_year'] = pd.DatetimeIndex(merged_Mass2['date']).dayofyear
merged_Mass2['week_of_year'] = pd.DatetimeIndex(merged_Mass2['date']).weekofye
ar
merged_Mass2['quarter'] = pd.DatetimeIndex(merged_Mass2['date']).quarter
merged_Mass2['season'] = merged_Mass2['month'] % 12 // 3 + 1

merged_Mass2[['date', 'year', 'month', 'day', 'day_of_year', 'week_of_year',
'quarter', 'season']].head()
```

Out[64]:

	date	year	month	day	day_of_year	week_of_year	quarter	season
0	2018-01-01	2018	1	1	1	1	1	1
1	2018-01-08	2018	1	8	8	2	1	1
2	2018-01-15	2018	1	15	15	3	1	1
3	2018-01-22	2018	1	22	22	4	1	1
4	2018-01-29	2018	1	29	29	5	1	1

In [66]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

columns =  ['frequency', 'avgTemp']

for column in columns:
    decomp = seasonal_decompose(merged_Mass2[column], freq=52, model='additiv
e', extrapolate_trend='freq')
    merged_Mass2[f"{column}_trend"] = decomp.trend
    merged_Mass2[f"{column}_seasonal"] = decomp.seasonal
```

In [70]:
```
fig, ax = plt.subplots(ncols=2, nrows=4, sharex=True, figsize=(16,8))

for i, column in enumerate(['frequency', 'avgTemp']):

    res = seasonal_decompose(merged_Mass2[column], freq=52, model='additive',
extrapolate_trend='freq')

    ax[0,i].set_title('Decomposition of {}'.format(column), fontsize=16)
    res.observed.plot(ax=ax[0,i], legend=False, color='maroon')
    ax[0,i].set_ylabel('Observed', fontsize=14)

    res.trend.plot(ax=ax[1,i], legend=False, color='rosybrown')
    ax[1,i].set_ylabel('Trend', fontsize=14)

    res.seasonal.plot(ax=ax[2,i], legend=False, color='red')
    ax[2,i].set_ylabel('Seasonal', fontsize=14)

    res.resid.plot(ax=ax[3,i], legend=False, color='pink')
    ax[3,i].set_ylabel('Residual', fontsize=14)

plt.show()
```



Correlation analysis

In [81]:
```
corr1 = merged_Mass[columns].corr()

corr1
```

Out[81]:

	frequency	avgTemp
frequency	1.000000	0.446341
avgTemp	0.446341	1.000000

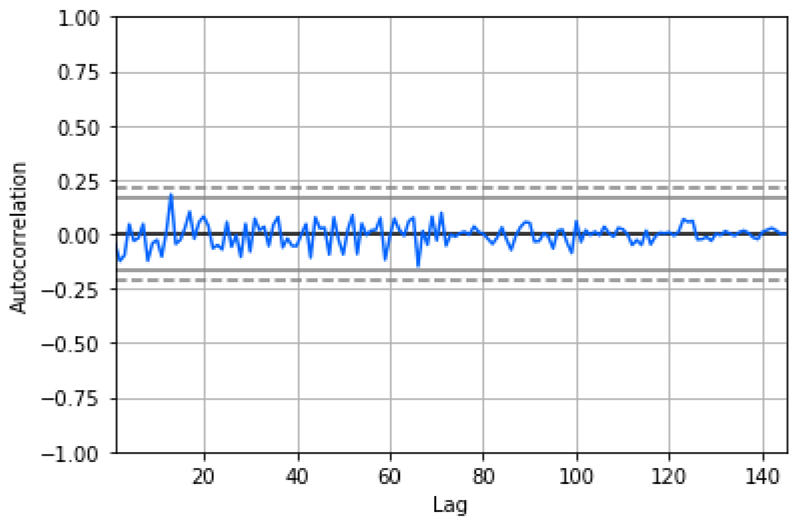
In [82]:
```
corr2 = merged_Mass2[columns].corr()

corr2
```

Out[82]:

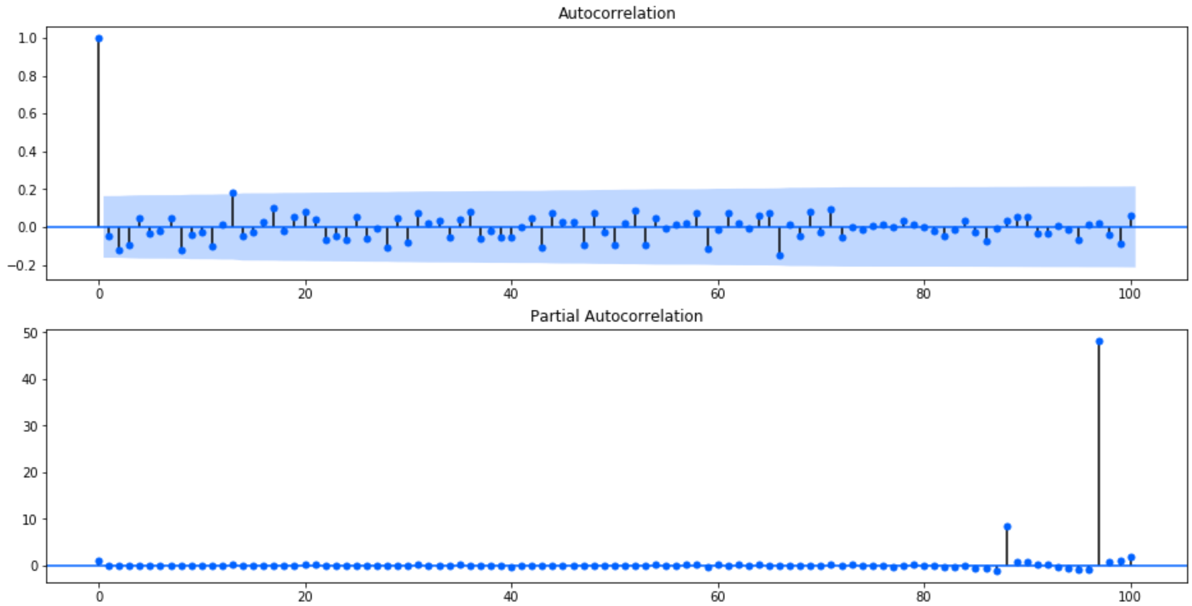
	frequency	avgTemp
frequency	1.000000	0.555592
avgTemp	0.555592	1.000000

About 45% of the regular dataset on frequency of crime and average temperature correlate compared with 56% in the downsampled dataset.

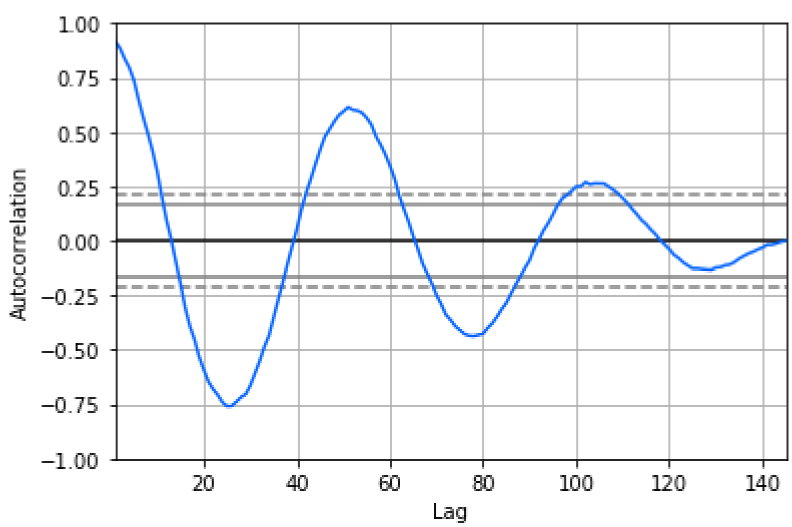
In [84]:
```
#ACF Plot of differenced frequency of crime time series

from pandas.plotting import autocorrelation_plot

autocorrelation_plot(merged_Mass2['frequency_diff'])
plt.show()
```



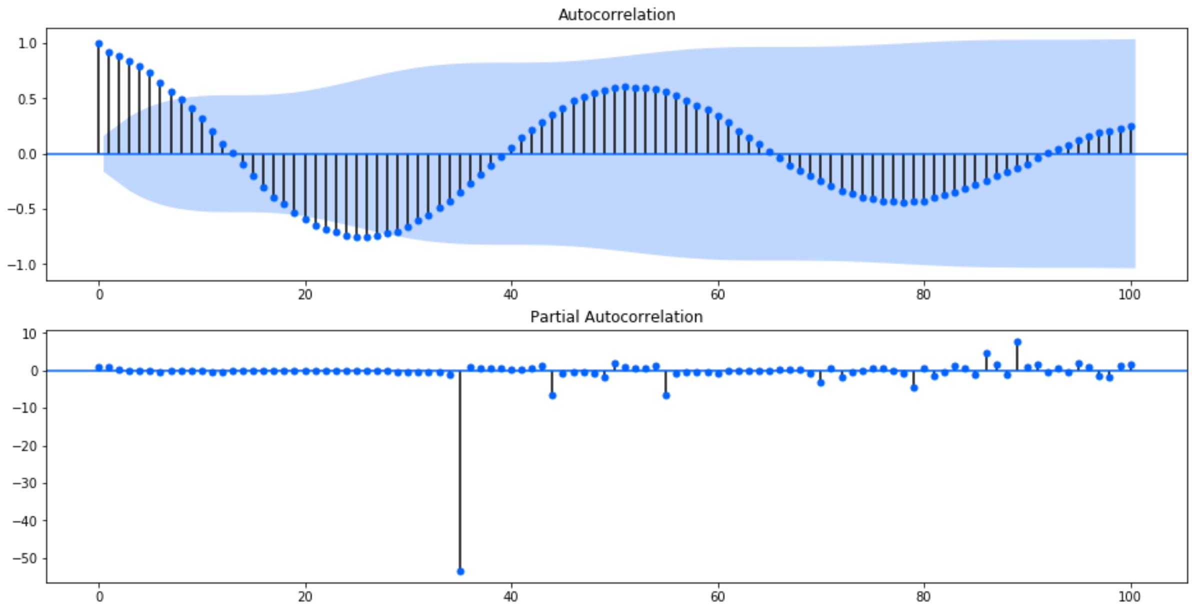
In [85]:
```python
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

f, ax = plt.subplots(nrows=2, ncols=1, figsize=(16, 8))

plot_acf(merged_Mass2['frequency_diff'], lags=100, ax=ax[0])
plot_pacf(merged_Mass2['frequency_diff'], lags=100, ax=ax[1])

plt.show()
```



In [87]:
```python
#ACF Plot of differenced frequency of crime time series

from pandas.plotting import autocorrelation_plot

autocorrelation_plot(merged_Mass2['avgTemp'])
plt.show()
```



In [86]:
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

f, ax = plt.subplots(nrows=2, ncols=1, figsize=(16, 8))

plot_acf(merged_Mass2['avgTemp'], lags=100, ax=ax[0])
plot_pacf(merged_Mass2['avgTemp'], lags=100, ax=ax[1])

plt.show()
```



Time-series Modeling

SARIMA

In [131]:
```
sar = sm.tsa.statespace.SARIMAX(merged_Mass2.avgTemp,
                                order=(1,0,0),
                                seasonal_order=(0,1,1,12),
                                trend='c').fit()
sar.summary()
```

Out[131]:

Statespace Model Results

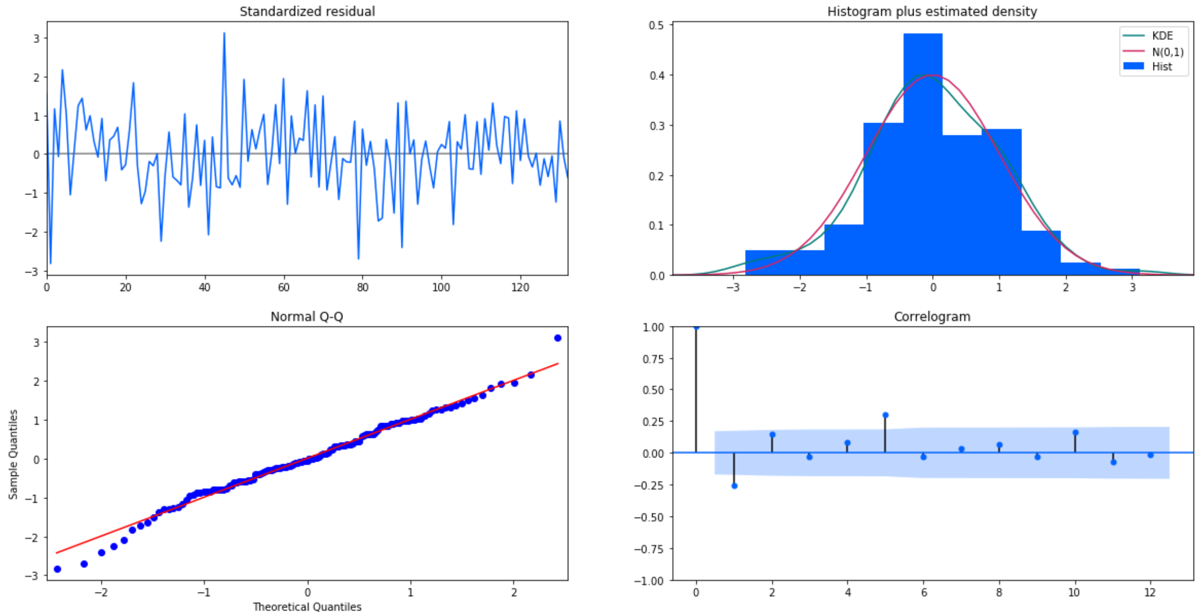
Dep. Variable:	avgTemp	**No. Observations:**	145
Model:	SARIMAX(1, 0, 0)x(0, 1, 1, 12)	**Log Likelihood**	-437.372
Date:	Sun, 06 Feb 2022	**AIC**	882.745
Time:	02:31:41	**BIC**	894.306
Sample:	0	**HQIC**	887.443
	- 145		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.1147	0.114	1.006	0.314	-0.109	0.338
ar.L1	0.9527	0.032	29.803	0.000	0.890	1.015
ma.S.L12	-0.9992	24.725	-0.040	0.968	-49.459	47.461
sigma2	33.3910	824.306	0.041	0.968	-1582.218	1649.000

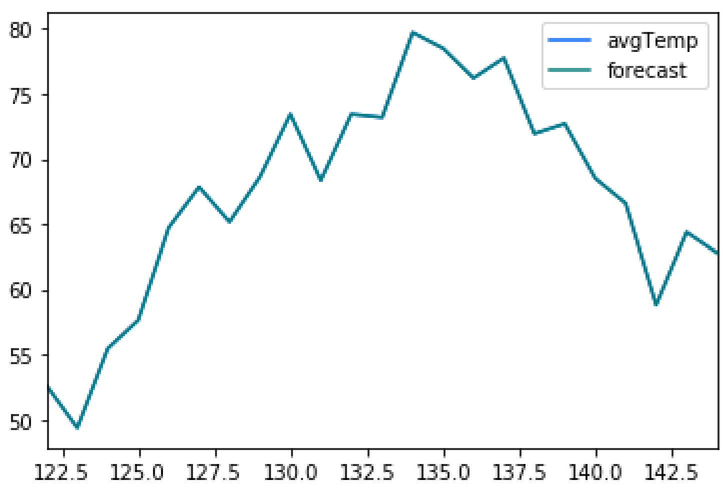
Ljung-Box (Q):	78.61	**Jarque-Bera (JB):**	1.65
Prob(Q):	0.00	**Prob(JB):**	0.44
Heteroskedasticity (H):	0.60	**Skew:**	-0.12
Prob(H) (two-sided):	0.09	**Kurtosis:**	3.48

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

In [134]:
```
# plot residual diagnostics
sar.plot_diagnostics(lags=12,figsize = (20,10),);
```



In [98]:
```
# plot predictions
pd.plotting.register_matplotlib_converters()
#use model.predict() start and end in relation to series
merged_Mass2['forecast'] = sar.predict(start = 100, end= 144)
merged_Mass2[122:][['avgTemp', 'forecast']].plot();
```



In [91]:
```
sar1 = sm.tsa.statespace.SARIMAX(merged_Mass2.frequency,
                                order=(1,0,0),
                                seasonal_order=(0,1,1,12),
                                trend='c').fit()
sar1.summary()
```

Out[91]:

Statespace Model Results

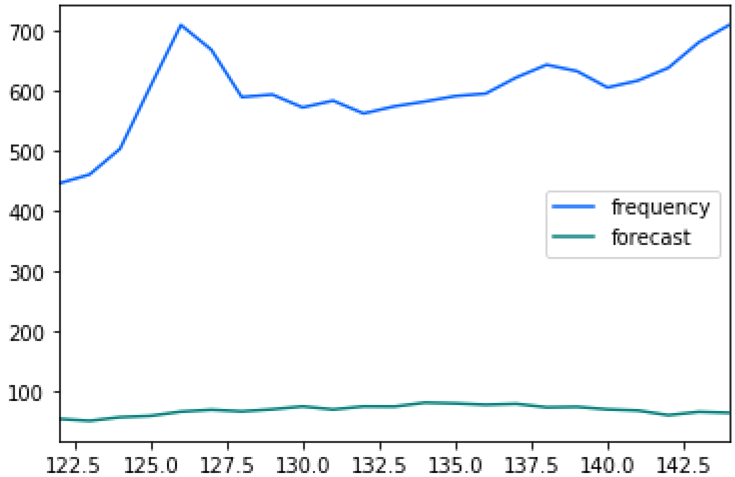
Dep. Variable:	frequency	**No. Observations:**	145
Model:	SARIMAX(1, 0, 0)x(0, 1, 1, 12)	**Log Likelihood**	-665.576
Date:	Sat, 05 Feb 2022	**AIC**	1339.151
Time:	02:56:53	**BIC**	1350.713
Sample:	0	**HQIC**	1343.849
	- 145		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	2.1398	0.922	2.322	0.020	0.333	3.946
ar.L1	0.8719	0.050	17.464	0.000	0.774	0.970
ma.S.L12	-0.9966	6.115	-0.163	0.871	-12.981	10.988
sigma2	1038.3264	6266.280	0.166	0.868	-1.12e+04	1.33e+04

Ljung-Box (Q):	35.19	**Jarque-Bera (JB):**	12.46
Prob(Q):	0.69	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.56	**Skew:**	-0.09
Prob(H) (two-sided):	0.14	**Kurtosis:**	4.49

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

In [99]:
```
# plot predictions
pd.plotting.register_matplotlib_converters()
#use model.predict() start and end in relation to series
merged_Mass2['forecast'] = sar.predict(start = 100, end= 144)
merged_Mass2[122:][['frequency', 'forecast']].plot();
```



In [92]:
```
sar2 = sm.tsa.statespace.SARIMAX(merged_Mass2.frequency_diff,
                                 order=(1,0,0),
                                 seasonal_order=(0,1,1,12),
                                 trend='c').fit()
sar2.summary()
```

Out[92]:

Statespace Model Results

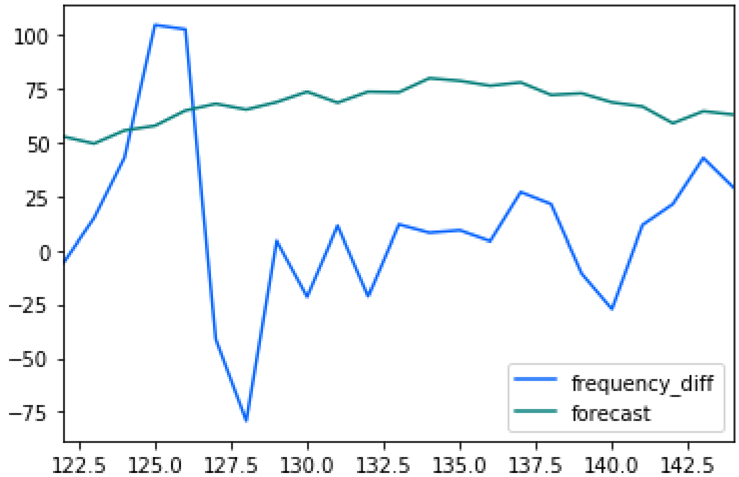
Dep. Variable:	frequency_diff	**No. Observations:**	145
Model:	SARIMAX(1, 0, 0)x(0, 1, 1, 12)	**Log Likelihood**	-668.858
Date:	Sat, 05 Feb 2022	**AIC**	1345.717
Time:	02:57:02	**BIC**	1357.278
Sample:	0	**HQIC**	1350.415
	- 145		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	0.2332	0.764	0.305	0.760	-1.265	1.731
ar.L1	-0.0421	0.079	-0.534	0.593	-0.196	0.112
ma.S.L12	-0.9968	5.835	-0.171	0.864	-12.433	10.439
sigma2	1095.0564	6311.467	0.174	0.862	-1.13e+04	1.35e+04

Ljung-Box (Q):	35.29	**Jarque-Bera (JB):**	12.11
Prob(Q):	0.68	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.59	**Skew:**	-0.11
Prob(H) (two-sided):	0.13	**Kurtosis:**	4.46

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

In [100]:
```
# plot predictions
pd.plotting.register_matplotlib_converters()
#use model.predict() start and end in relation to series
merged_Mass2['forecast'] = sar.predict(start = 100, end= 144)
merged_Mass2[122:][['frequency_diff', 'forecast']].plot();
```



SARIMA forecast doesn't have for the frequency of crime variant.

Since, the main aim of this project is to determine the relationship between crime and temperature. A multivariant time series modelling approach would be best to compare the two variables of frequency of crime and average temperature. Also, I based on the correlations results above, there's is moderate correlation between the variables.

Next, let's use a multi-layered LSTM recurrent neural network to predict the sequence of values.

Conclusion and next steps

A longer timeseries dataset would provide better insights from the dataset. There was some observed trends in the frequency crime begin highest in the warmer months. About 55% of the frequency of crime and temperature data are correlated. There were technical issues installing keras (tensorflow), pmdarima and prophet. However, using SARIMA, forecasting the temperature variable show the seasonality of temerature changes throughout the year. However, forecasting the frequency of crime variable does not captures seasonality with the SARIMA model. Ideally, the objective of this project would be to use prophet to analysis how they two variable are related over time. Also, there was a spike in crime in 2020 after the COVID-19 pandemic began. This is an event to consider for anlaysis lookig at how the variable was before and after the pandemic.

In [ ]:
```

```

```
In [ ]:
```

```
In [ ]:
```