Importing Relevant Packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.graphics.tsaplots as sgt
import statsmodels.tsa.stattools as sts
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima_model import ARIMA
from scipy.stats.distributions import chi2
from math import sqrt
import seaborn as sns
sns.set()
```

Importing the Data and Pre-processing

```
raw_csv_data= pd.read_csv("COVID-19_Diagnostic_Laboratory_Testing__PCR_Testing__Time_Series (3).csv")
df_comp = raw_csv_data.copy()
df_comp.date = pd.to_datetime(df_comp.date, dayfirst = True)
df_comp.set_index("date", inplace = True)
df_comp= df_comp.fillna(method= 'ffill')
```

Double-click (or enter) to edit

Examining the Data

```
df_comp.head()
```

	state	state_name	state_fips	fema_region	overall_outcome	new_results_reported	total_results_repo
date							
2020-03-01	AL	Alabama	1	Region 4	Negative	96	
2020-03-01	AL	Alabama	1	Region 4	Positive	16	
2020-03-02	AL	Alabama	1	Region 4	Negative	72	
2020-03-02	AL	Alabama	1	Region 4	Positive	6	
2020-03-03	AL	Alabama	1	Region 4	Negative	94	

COVID-19_Diagnostic_Laboratory_Testing__PCR_Testing__Time_Series (3

File is too large to display. Download

```
#data- values recorded
# analyze time series in cosecutive chunks of data
# dates are used as indexes/indices for time series
# next 8 columns - time series data of state, state_name, region and numerical values for new results reported and to
# new results reported and total results reported - number of daily PCR tests conducted
```

```
#check data types
df_comp.dtypes
```

```
state                      object
state_name                 object
state_fips                  int64
fema_region                object
overall_outcome            object
new_results_reported        int64
total_results_reported      int64
geocoded_state            float64
dtype: object
```

```
df_comp.shape
```

```
(156969, 8)
```

```
#Check columns
df_comp.columns
```

```
Index(['state', 'state_name', 'state_fips', 'fema_region', 'overall_outcome',
       'new_results_reported', 'total_results_reported', 'geocoded_state'],
      dtype='object')
```

```
#Check for NA values
df_comp.isnull().sum()
```

```
state                          0
state_name                     0
state_fips                     0
fema_region                    0
overall_outcome                0
new_results_reported           0
total_results_reported         0
geocoded_state            156969
dtype: int64
```

```
df_time = df_comp[['new_results_reported', 'total_results_reported']].dropna()
df_time.head()
```

new_results_reported total_results_reported

```
df_time.loc['2020-03-01':'2020-12-31'].head(20)
```

date	new_results_reported	total_results_reported
2020-03-01	96	96
2020-03-01	16	16
2020-03-02	72	168
2020-03-02	6	22
2020-03-03	94	262
2020-03-03	9	31
2020-03-04	0	262
2020-03-04	2	33
2020-03-05	61	323
2020-03-05	6	39
2020-03-06	12	335
2020-03-06	4	43
2020-03-07	20	355
2020-03-07	4	47
2020-03-08	94	449
2020-03-08	17	64
2020-03-09	58	507
2020-03-09	6	70
2020-03-10	84	591
2020-03-10	9	79

```
df_time.loc['2020-03-01':'2020-12-31'].count()
```

```
new_results_reported      48402
total_results_reported    48402
dtype: int64
```

```
df_time.loc['2021-01-01': '2021-12-31'].head(20)
```

	new_results_reported	total_results_reported
date		
2021-01-01	86	7650
2021-01-01	10774	2875592
2021-01-01	2549	407775
2021-01-02	42	7692
2021-01-02	6118	2881710
2021-01-02	2395	410170
2021-01-03	25	7717
2021-01-03	4580	2886290
2021-01-03	2034	412204
2021-01-04	23	7740
2021-01-04	6746	2893036
2021-01-04	3161	415365
2021-01-05	25	7765
2021-01-05	11789	2904825
2021-01-05	2513	417878
2021-01-06	48	7813

```
df_time.loc['2021-01-01': '2021-12-31'].count()
```

```
new_results_reported      60694
total_results_reported    60694
dtype: int64
```

2021-01-07 19217 2942323

```
df_time.loc['2022-01-01': '2022-10-27'].head(20)
```

date	new_results_reported	total_results_reported
2022-01-01	12	13797
2022-01-01	4587	5785926
2022-01-01	2813	851838
2022-01-02	17	13814
2022-01-02	4899	5790825
2022-01-02	3062	854900
2022-01-03	14	13828
2022-01-03	7385	5798210

```
df_time.loc['2022-01-01': '2022-10-27'].count()
```

```
new_results_reported      47873
total_results_reported    47873
dtype: int64
```

```
df_time.loc['2020-03-01':'2020-12-31'].describe()
```

	new_results_reported	total_results_reported
count	48402.000000	4.840200e+04
mean	5325.361886	5.246650e+05
std	15330.792390	1.678293e+06
min	-7.000000	0.000000e+00
25%	16.000000	1.161000e+03
50%	369.000000	2.240200e+04
75%	3525.750000	2.695125e+05
max	295601.000000	2.750374e+07

```
df_time.loc['2021-01-01': '2021-12-31'].describe()
```

	new_results_reported	total_results_reported

```
df_time.loc['2022-01-01': '2022-10-27'].describe()
```

	new_results_reported	total_results_reported
count	47873.000000	4.787300e+04
mean	5226.376642	5.428158e+06
std	19210.717437	1.427414e+07
min	0.000000	5.000000e+00
25%	21.000000	3.195000e+04
50%	448.000000	8.574290e+05
75%	3029.000000	4.110616e+06
max	448238.000000	1.500675e+08

```
df_time.resample('M').mean().head(10)
```

	new_results_reported	total_results_reported
date		
2020-03-31	435.070515	3.220299e+03
2020-04-30	1192.319127	2.615304e+04
2020-05-31	2383.923840	7.927454e+04
2020-06-30	3696.434151	1.714075e+05
2020-07-31	5566.151395	3.146443e+05
2020-08-31	5156.828221	4.843928e+05
2020-09-30	5601.700590	6.432566e+05
2020-10-31	7134.728946	8.320530e+05
2020-11-30	9640.622626	1.085906e+06
2020-12-31	10674.158553	1.407529e+06

```
df_time.resample('M').median().head(10)
```

date	new_results_reported	total_results_reported
2020-03-31	18.0	92.0
2020-04-30	153.0	2904.0
2020-05-31	254.5	11548.0
2020-06-30	306.0	21657.5

```
df_time.resample('M').min().head(10)
```

date	new_results_reported	total_results_reported
2020-03-31	0	0
2020-04-30	-2	0
2020-05-31	-2	1
2020-06-30	-3	3
2020-07-31	-3	5
2020-08-31	0	15
2020-09-30	0	1
2020-10-31	0	1
2020-11-30	0	1
2020-12-31	-7	1

```
df_time.resample('M').max().head(10)
```

date	new_results_reported	total_results_reported
2020-03-31	12706	152998
2020-04-30	58081	650900
2020-05-31	72866	1937074
2020-06-30	93075	3991090
2020-07-31	143488	7284903
2020-08-31	131678	10345209
2020-09-30	154518	12957126
2020-10-31	145452	15846282
2020-11-30	233446	20370833
2020-12-31	295601	27503736

```
df_time.resample('M').std().head(10)
```

date	new_results_reported	total_results_reported
2020-03-31	1285.420873	1.152752e+04
2020-04-30	2868.714566	6.193987e+04
2020-05-31	6112.727099	1.835537e+05
2020-06-30	9653.957950	4.113000e+05
2020-07-31	13851.744298	7.594893e+05
2020-08-31	12956.042030	1.163160e+06
2020-09-30	13857.106286	1.537563e+06
2020-10-31	16609.288789	1.955679e+06
2020-11-30	22111.760234	2.499832e+06
2020-12-31	26606.187983	3.232036e+06

```
df_comp.describe()
```

	state_fips	new_results_reported	total_results_reported	geocoded_state
count	156969.000000	156969.000000	1.569690e+05	0.0
mean	31.888163	6230.115781	2.945387e+06	NaN
std	18.561807	20201.091537	9.429461e+06	NaN
min	1.000000	-7.000000	0.000000e+00	NaN
25%	17.000000	20.000000	1.038100e+04	NaN
50%	31.000000	427.000000	1.780100e+05	NaN
75%	46.000000	3877.000000	1.807742e+06	NaN
max	78.000000	448238.000000	1.500675e+08	NaN

```
df_comp["PCR_test"] = df_comp.new_results_reported
```

Splitting the Data

```
del df_comp["state"]
del df_comp["state_name"]
del df_comp["state_fips"]
del df_comp["fema_region"]
del df_comp["overall_outcome"]
del df_comp["geocoded_state"]
del df_comp["total_results_reported"]
```

```
size = int(len(df_comp)*0.8)
df, df_test = df_comp.iloc[:size], df_comp.iloc[size:]
```

```
# int = ensures that size will be an integer and serves as an approximation of the 80% cutoff point of the dataset
# after determining when the train should end and the test should - use the iloc method
# training set  = "df"
# testing set = " df_test"
# df - assign from beginning (start) up to size value
```

```
df =  df_comp.iloc[:size]
```

```
df_test = df_comp.iloc[size:]
```

```
df.tail()
```

	new_results_reported	PCR_test
date		
2022-06-02	1096	1096
2022-06-03	13	13
2022-06-03	5870	5870
2022-06-03	1030	1030
2022-06-04	8	8

```
df_test.head()
```

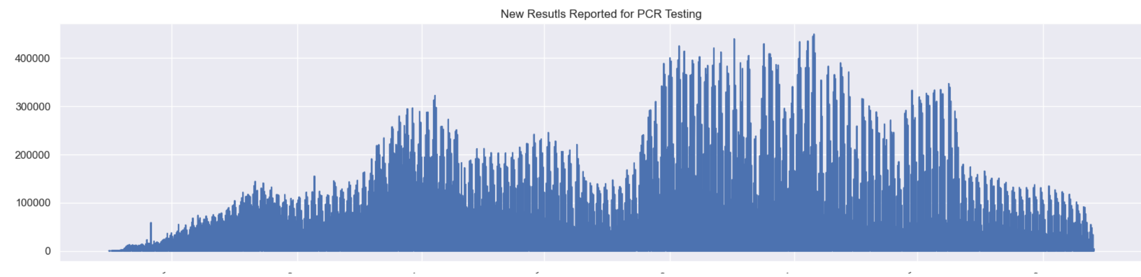
	new_results_reported	PCR_test
date		
2022-06-04	4669	4669
2022-06-04	810	810
2022-06-05	4	4
2022-06-05	3228	3228
2022-06-05	721	721

```
wn = np.random.normal(loc= df.PCR_test.mean(), scale = df.PCR_test.std(), size = len(df))
```

```
df.describe()
```

	new_results_reported	PCR_test
count	125575.000000	125575.000000
mean	6675.576158	6675.576158
std	21825.835003	21825.835003
min	0.000000	0.000000

```
df_comp.new_results_reported.plot(figsize =(20,5),title = "New Resutls Reported for PCR Testing")
plt.show()
```




```
# White noise in Time series (TS)
# def white nose is a special type of time-series, where the data doesn't follow a pattern
# no patterns found - unpredictable
# 1. constant mean
# 2. constant variance
# 3. no autocorrelation in any period
# autocorrelation measures how correlated a series is with past versions of itself
# NO autocorrelation = NO clear relationship between past and present value
```

```
df["wn"]= wn
```

```
C:\Users\lisad\AppData\Local\Temp\ipykernel_14372\2477116740.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retu
  df["wn"]= wn
```

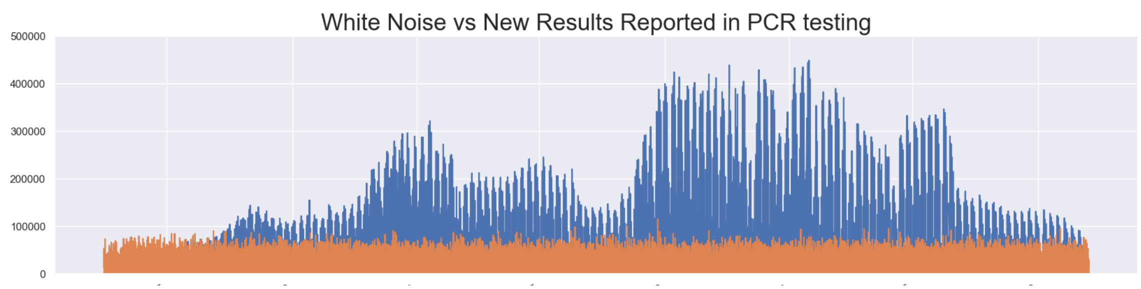
```
df.describe()
```

	new_results_reported	PCR_test	wn
count	125575.000000	125575.000000	125575.000000
mean	6675.576158	6675.576158	6592.621230

```
df.wn.plot(figsize = (20,5))
plt.title("White Noise in Time Series", size = 24)
plt.show()
```


```
# no clear pattern in data except for most values forming around the mean
# see how many values are within some proximity of the mean of PCR_test
```

```
df.PCR_test.plot(figsize= (20,5))
df.wn.plot(figsize = (20,5))
plt.title("White Noise vs New Results Reported in PCR testing", size = 24)
plt.ylim(0, 500000)
plt.show()
```




```
sts.adfuller(df.PCR_test)
```

```
(-7.408732170618658,
 7.228139124737943e-11,
 72,
 125502,
 {'1%': -3.4304021062115018,
  '5%': -2.861563030180707,
  '10%': -2.566782258150325},
 2417073.7975664325)
```

```
#Output of Dickey Fuller test
# 1. test statistic (-354.47)- compare it to certain critical values to determine if we have significant proof of sta
```

```
# python provides us with the 1%, 5% and 10% critical values for the dickey fuller table
# use any of them as level of significance in our analysis
# t-stat is less than any of the critical values
# for all of these levels of significance, we find sufficient evidence of stationarity in the dataset
# 2. p-value -  associated with t-stat (0.0)
# rejecting the null hypothesis- data is stationary
# 3. # of lags in the regression when determining t-stat  (0)- autocorrelation used to determine proper model
# 4. number of observations used in the analysis (125574)- depends on the number of lags used in the regression - two
# 5. maximized information criteria provided- there is some autocorrelation
# higher values, the more difficult it is to make predictions for the future
```

```
sts.adfuller(df.wn)
```

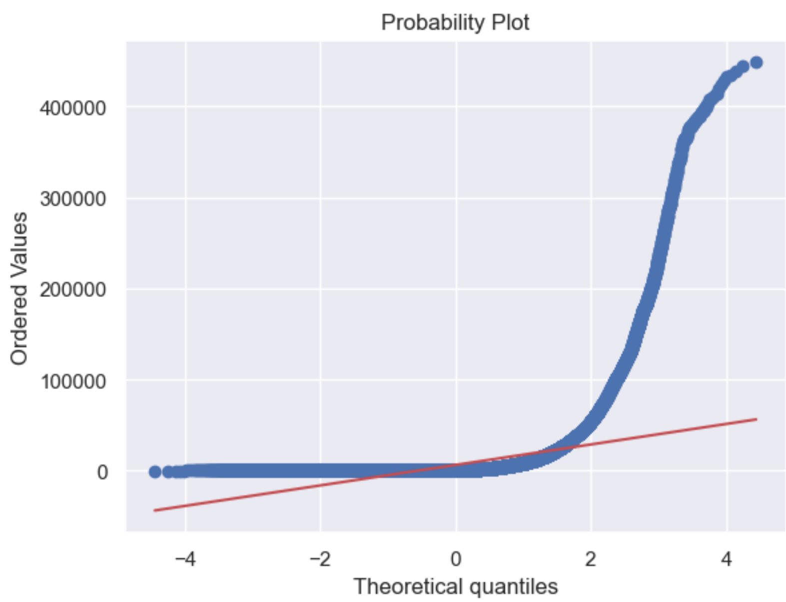
```
(-354.4702952804052,
 0.0,
 0,
 125574,
 {'1%': -3.4304020763349037,
  '5%': -2.861563016975805,
  '10%': -2.566782251121803},
 2863271.987938293)
```

```
# no autocorrelation in white noise - no lags involved in the regression
# a p-value close to 0 and no lags being part of the regression
```

```
import scipy.stats
import pylab
```

```
scipy.stats.probplot(df_comp.new_results_reported, plot= pylab)
pylab.show
```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```

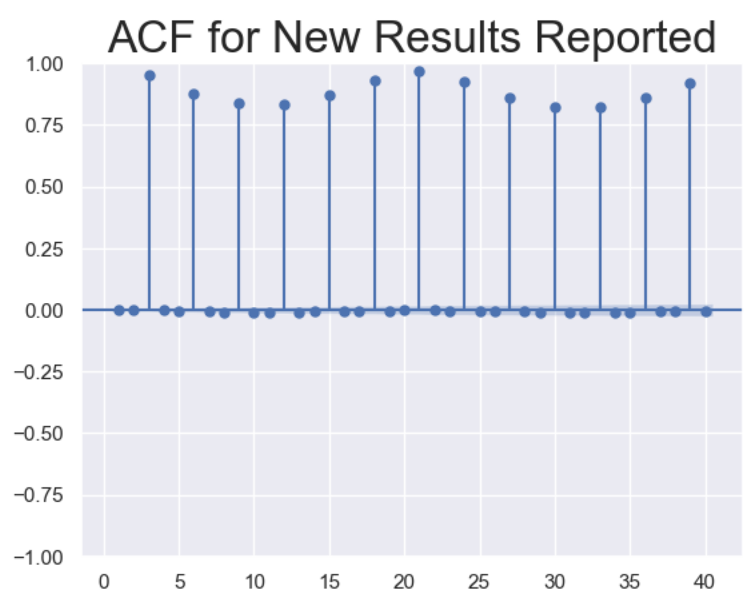


```
#test, then explore plot
# QQ plot takes all the values a variable can take and arranges them in ascending order
# y axis- New Results Reported
# x axis- Theoretical Quantile - how many standard deviations away from the mean these values are
# red diagonal line- what the data points should follow if they are normally distributed
# not normally distributed - more values on 500 mark
# data is trending upwards
# split data into training and test set to use machine learning to forecast the future
```

```
df.PCR_test.dropna()
```

```
date
2020-03-01      96
2020-03-01      16
2020-03-02      72
2020-03-02       6
2020-03-03      94
              ...
2022-06-02    1096
2022-06-03      13
2022-06-03    5870
2022-06-03    1030
2022-06-04       8
Name: PCR_test, Length: 125575, dtype: int64
```

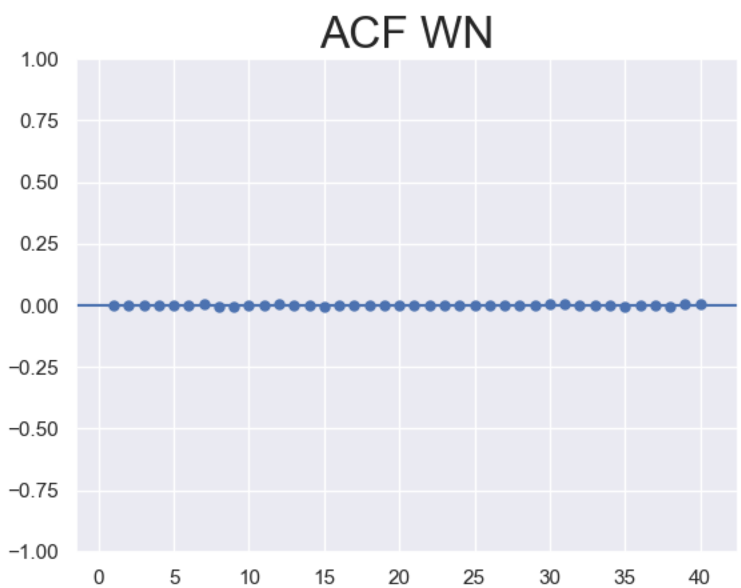
```
sgt.plot_acf(df.PCR_test, lags = 40, zero = False)
plt.title("ACF for New Results Reported", size = 24)
plt.show()
```




```
# bottom = lags; left = values of AC coefficient
# corr - values between 1 and -1
```

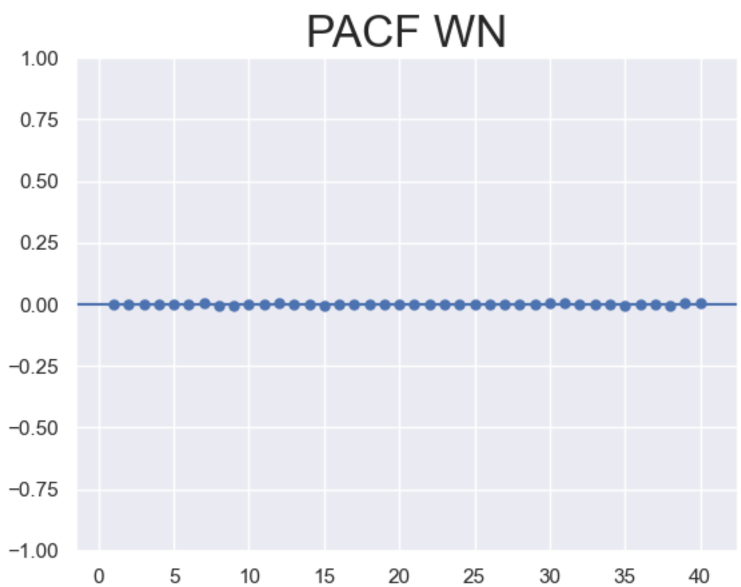
```
# thin line - represents the AC (autocorrelation) from the TS and a lagged copy of itself
# 1st line - AC one time period ago - t-1 etc
# blue area around the x-axis represents significance
# values situated outside are significantly different from 0 suggests the existence of AC
# the greater the distance in time, the more unlikely it is that this AC persists
# e.g. today's PCR test results are more closer to yesterday's PCR test results than PCR test results one month ago
# AC coefficient in higher lags is sufficiently greater to be significantly different from 0
# AC barely diminshes as the lags decrease
# suggests that results from a month back can serve as decent estimators
```

```
sgt.plot_acf(df.wn, lags = 40, zero = False)
plt.title("ACF WN", size = 24)
plt.show()
```




```
sgt.plot_pacf(df.PCR_test, lags =  40, zero = False, method = ("ols") )
# Order of Least Squares - OLS
plt.title("PACF New Results Reported", size = 24)
plt.show()
```


```
sgt.plot_pacf(df.wn, lags = 40, zero = False, method = ("ols"))
plt.title("PACF WN", size = 24)
plt.show()
```



Creating Returns

```
df['returns'] = df.PCR_test.pct_change(1)*100
df= df.iloc[1:]
```

The ARIMA Model

```
# Order - p, d, and q
# P and q reprsent the AR and MA lags respectively
# d order is the integration--> the number of times we need to integrate the timepseries to ensure stationarity
# No integration:
# ARIMA(0, 0 , q) =  MA)(q)
# ARIMA(p, 0, 0) = AR(p)
# ARIMA (p, 0, q) = ARMA (p,q)
# Integration - accounting for the non- seasonal difference between periods
```

```
# AR components= differences between PCR test results
# ARIMA (1, 1, 1)
# lose observations - for any integration we lose a single observation
# no previous period
```

LLR Test

```
def LLR_Test(mod_1, mod_2, DF = 1):
    L1 = mod_1.fit(start_ar_lags = 20).llf
    L2 = mod_2.fit(start_ar_lags = 20).llf
    LR = (2*(L2-L1))
    p =  chi2.sf(LR, DF).round(3)
    return p
```

Creating Returns

```
df['returns']= df.PCR_test.pct_change(1)*100
```

ARIMA(1,1,1)

```
import statsmodels.tsa.stattools as sts
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
```

```
model_ar_1_i_1_ma_1 = sm.tsa.arima.ARIMA(df.PCR_test, order = (1,1,1))
results_ar_1_i_1_ma_1 = model_ar_1_i_1_ma_1.fit()
print(results_ar_1_i_1_ma_1.summary())
```

```
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
                               SARIMAX Results
==============================================================================
Dep. Variable:               PCR_test   No. Observations:               125572
Model:                 ARIMA(1, 1, 1)   Log Likelihood            -1420499.321
Date:                Sun, 29 Jan 2023   AIC                        2841004.643
Time:                        23:43:59   BIC                        2841033.865
Sample:                             0   HQIC                       2841013.421
                             - 125572
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
```

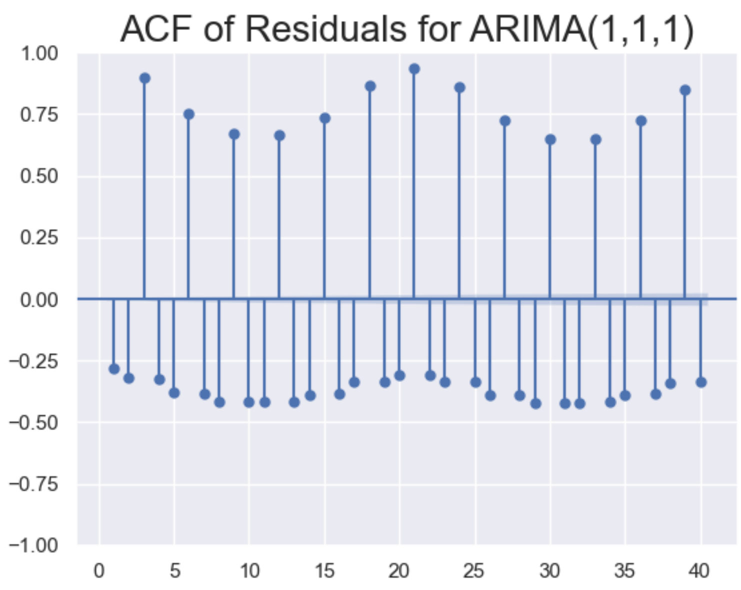
```
------------------------------------------------------------------------------
ar.L1         -0.4073      0.002   -227.546      0.000      -0.411      -0.404
ma.L1         -0.9694      0.000  -2535.794      0.000      -0.970      -0.969
sigma2      7.058e+08   1.11e-12   6.38e+20      0.000    7.06e+08    7.06e+08
===================================================================================
Ljung-Box (L1) (Q):                9976.14   Jarque-Bera (JB):          15790216.16
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               0.35   Skew:                             2.83
Prob(H) (two-sided):                  0.00   Kurtosis:                        57.64
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.65e+34. Standard errors may be unsta
```

```
# 2 coefficients
# integration order has no effect on the number of parameters we need to estimate
# Integration - we a re transforming the underlyuing data while no modellin is performed
```

Residuals of ARIMA(1,1,1)

```
df['res_ar_1_i_1_ma_1'] = results_ar_1_i_1_ma_1.resid
sgt.plot_acf(df.res_ar_1_i_1_ma_1, zero= False, lags = 40)
plt.title("ACF of Residuals for ARIMA(1,1,1)", size = 20)
plt.show()
```




```
# 3, 21 and 38 lags are highly significant
# incorporating lags into model might significantly improve performance
```

```
# residuals follow the same pattern as ACF - no significant time period to use
# try and see how the models that contain them perform
```

Higher- Lag ARIMA Model

```
model_ar_1_i_1_ma_2 = sm.tsa.arima.ARIMA(df.PCR_test, order = (1,1,2))
results_ar_1_i_1_ma_2 = model_ar_1_i_1_ma_2.fit()
model_ar_1_i_1_ma_3 = sm.tsa.arima.ARIMA(df.PCR_test, order = (1,1,3))
results_ar_1_i_1_ma_3 = model_ar_1_i_1_ma_3.fit()
model_ar_1_i_1_ma_1 = sm.tsa.arima.ARIMA(df.PCR_test, order = (2,1,1))
results_ar_1_i_1_ma_1 = model_ar_1_i_1_ma_1.fit()
model_ar_1_i_1_ma_1 = sm.tsa.arima.ARIMA(df.PCR_test, order = (3,1,1))
results_ar_1_i_1_ma_1 = model_ar_1_i_1_ma_1.fit()
model_ar_1_i_1_ma_2 = sm.tsa.arima.ARIMA(df.PCR_test, order = (3,1,2))
results_ar_1_i_1_ma_2 = model_ar_1_i_1_ma_2.fit()
```

```
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index
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  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-inver
  warn('Non-invertible starting MA parameters found.'
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index
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```

```
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C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index
  self._init_dates(dates, freq)
```

```
start_ar_lags=  5
```

```
# provide enough starting AR lags for each model to allow for the execution of the fit model
#.fit(start_ar_lags=  number)
#print the ".llf" and ".aic" store the log-likelihood and the AIC values for each model
```

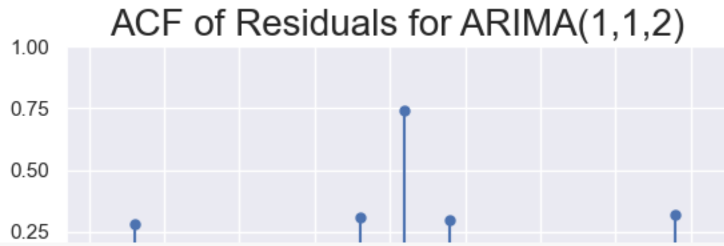
```
print("ARIMA(1,1,1):  \t LL = " , results_ar_1_i_1_ma_1.llf, "\t AIC = ", results_ar_1_i_1_ma_1.aic)
print("ARIMA(1,1,2):  \t LL = " , results_ar_1_i_1_ma_2.llf, "\t AIC = ", results_ar_1_i_1_ma_2.aic)
print("ARIMA(1,1,3):  \t LL = " ,results_ar_1_i_1_ma_3.llf,  "\t AIC = ",  results_ar_1_i_1_ma_3.aic)
print("ARIMA(2,1,1):  \t LL = " , results_ar_1_i_1_ma_1.llf, "\t AIC = ", results_ar_1_i_1_ma_1.aic)
print("ARIMA(3,1,1):  \t LL = " , results_ar_1_i_1_ma_1.llf, "\t AIC = ", results_ar_1_i_1_ma_1.aic)
print("ARIMA(1,1,2):  \t LL = ", results_ar_1_i_1_ma_1.llf,  "\t AIC = ",  results_ar_1_i_1_ma_1.aic)
```

```
ARIMA(1,1,1):    LL =  -1285534.291750092       AIC =  2571078.583500184
ARIMA(1,1,2):    LL =  -1282673.515205816       AIC =  2565359.030411632
ARIMA(1,1,3):    LL =  -1404408.0991085828      AIC =  2808826.1982171657
ARIMA(2,1,1):    LL =  -1285534.291750092       AIC =  2571078.583500184
ARIMA(3,1,1):    LL =  -1285534.291750092       AIC =  2571078.583500184
ARIMA(1,1,2):    LL =  -1285534.291750092       AIC =  2571078.583500184
```

```
# highest log likelihood and the lowest AIC - model 2
```

```
#Examining the ACF of residuals
```

```
df['res_ar_1_i_1_ma_2'] = results_ar_1_i_1_ma_2.resid
sgt.plot_acf(df.res_ar_1_i_1_ma_2, zero= False, lags = 40)
plt.title("ACF of Residuals for ARIMA(1,1,2)", size = 20)
plt.show()
```




```
model_ar_5_i_1_ma_1 = sm.tsa.arima.ARIMA(df.PCR_test, order = (5,1,1))
results_ar_5_i_1_ma_1 = model_ar_5_i_1_ma_1.fit()
model_ar_6_i_1_ma_3 = sm.tsa.arima.ARIMA(df.PCR_test, order = (6,1,3))
results_ar_6_i_1_ma_3 = model_ar_6_i_1_ma_3.fit()
```

```
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
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C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
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  self._init_dates(dates, freq)
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  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary s
  warn('Non-stationary starting autoregressive parameters'
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible s
  warn('Non-invertible starting MA parameters found.'
C:\Users\lisad\.conda\lib\site-packages\statsmodels\base\model.py:604: ConvergenceWarning: Maximum Likelihood op
  warnings.warn("Maximum Likelihood optimization failed to "
```
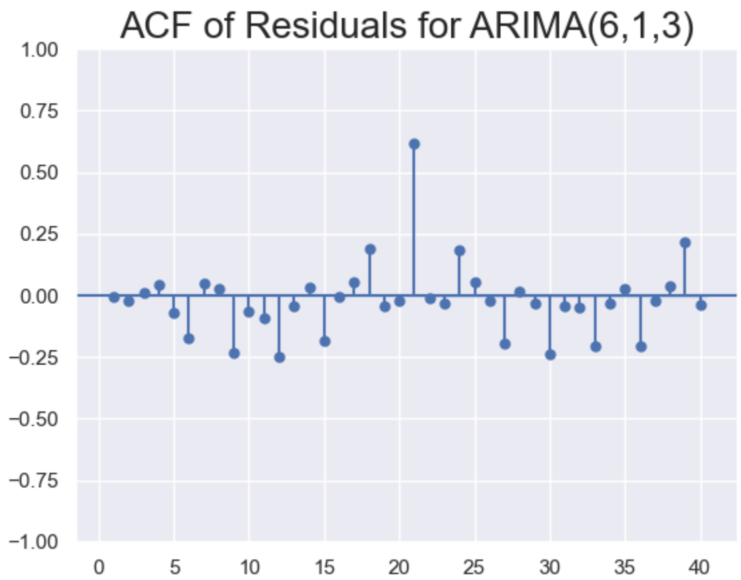

```
print("ARIMA(1,1,3):  \t  LL = ", results_ar_1_i_1_ma_3.llf, "\t AIC = ", results_ar_1_i_1_ma_3.aic)
print("ARIMA(5,1,1):  \t  LL = " , results_ar_5_i_1_ma_1.llf, "\t AIC = ", results_ar_5_i_1_ma_1.aic)
print("ARIMA(6,1,3):  \t  LL = " , results_ar_6_i_1_ma_3.llf, "\t AIC = ", results_ar_6_i_1_ma_3.aic)
```

```
ARIMA(1,1,3):     LL =  -1404408.0991085828      AIC =  2808826.1982171657
ARIMA(5,1,1):     LL =  -1280610.6724858566      AIC =  2561235.344971713
ARIMA(6,1,3):     LL =  -1276548.826927627       AIC =  2553117.653855254
```

```
# AIC (6, 1, 3) is preferred
# The ARIMA(1,1,3) and ARIMA (5,1,1) are nested in the ARIMA (6,1,3)
#ARIMA(1,1,3) - 4 degrees of freedom
#ARIMA(6,1,3) - 9 degrees of freedom
```

```
df['res_ar_6_i_1_ma_3'] = results_ar_6_i_1_ma_3.resid
sgt.plot_acf(df.res_ar_6_i_1_ma_3, zero= False, lags = 40)
plt.title("ACF of Residuals for ARIMA(6,1,3)", size = 20)
plt.show()
```



Models with Higher Levels of Integration

```
# captured effects incorporated into the 6th lag without including in model
# the further back in time we go, the less relevant the values become
# include up to 40 lags into the model, we will have WN residuals
# want the model to predict other time-series data as well
# the model parameters will become too dependent on the data set - lead to overfitting (removing predictive power)
# best estimator for PCR tests - ARIMA(6,1,3)
```

```
df['delta_new_results_reported'] = df.PCR_test.diff(1)
```

```
model_delta_ar_1_i_1_ma_1 = sm.tsa.arima.ARIMA(df.delta_new_results_reported[1:], order = (1,0,1))
results_delta_ar_1_i_1_ma_1 = model_delta_ar_1_i_1_ma_1.fit()
print(results_delta_ar_1_i_1_ma_1.summary())
```

```
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
```

```
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
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C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
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C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
                                    SARIMAX Results
=======================================================================================
Dep. Variable:     delta_new_results_reported   No. Observations:             125571
Model:                         ARIMA(1, 0, 1)   Log Likelihood           -1420499.913
Date:                        Mon, 30 Jan 2023   AIC                       2841007.827
Time:                                00:12:46   BIC                       2841046.789
Sample:                                     0   HQIC                      2841019.531
                                     - 125571
Covariance Type:                          opg
===============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
const       5.036e-05      3.531   1.43e-05      1.000      -6.921       6.921
ar.L1         -0.4073      0.002   -164.297      0.000      -0.412      -0.402
ma.L1         -0.9694      0.000  -2521.199      0.000      -0.970      -0.969
sigma2      7.058e+08   9.73e-07   7.26e+14      0.000    7.06e+08    7.06e+08
===================================================================================
Ljung-Box (L1) (Q):                9976.42   Jarque-Bera (JB):         15790611.55
Prob(Q):                              0.00   Prob(JB):                        0.00
Heteroskedasticity (H):               0.35   Skew:                            2.83
Prob(H) (two-sided):                  0.00   Kurtosis:                       57.64
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.49e+28. Standard errors may be unsta
```

```
sts.adfuller(df.delta_new_results_reported[1:])
```

```
(-47.07790204397484,
 0.0,
 71,
 125499,
 {'1%': -3.4304021074571036,
  '5%': -2.86156303073124,
  '10%': -2.5667822584433555},
 2417053.6600029585)
```

```
# test statistic is 14x greater in absolute value and the critical 1% value
# p-value  is 0.0 - confirmation of stationarity
# no need for additional layers of integration
# fitting ARIMA models with d> 1 is not recommended since the series is already stationary
```

```
# Forecasting
# Time series we expect patterns to persist as we progress through time
# 1. find the pattern - selecting the correct model
# 2. predict the future
```

```
size = int(len(df_comp)*0.8)
df, df_test = df_comp.iloc[:size], df_comp.iloc[size:]
```

```
df_comp["ret_new_results_reported"] = df_comp.new_results_reported.pct_change(1).mul(100)
```

```
df_comp.ret_new_results_reported = df_comp.ret_new_results_reported
```

```
df_comp["norm_ret_new_results_reported"] = df_comp.ret_new_results_reported.div(df_comp.ret_new_results_reported[1])*
```

Fitting a Model

```
model_ar = sm.tsa.ARIMA(df.new_results_reported, order =(1, 0, 0))
results_ar = model_ar.fit()
```

```
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
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C:\Users\lisad\.conda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has be
  self._init_dates(dates, freq)
```

Simple Forecasting

```
# Specify a time period
# the starting point of the forecasted period is the first one we do not have values for
# the first day after the end of the training set
```

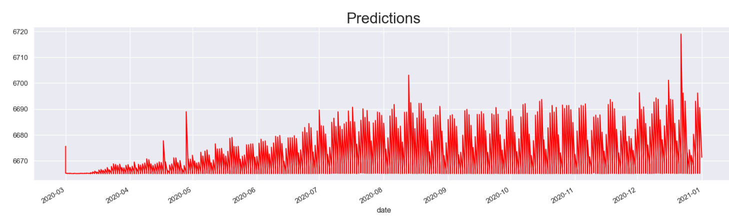
```
df.tail()
```

date	new_results_reported	PCR_test	ret_new_results_reported	norm_ret_new_results_reported
2022-06-02	1096	1096	-77.568563	93.082276
2022-06-03	13	13	-98.813869	118.576642
2022-06-03	5870	5870	45053.846154	-54064.615385

```
# Create variables that will help us change the periods easily instead of typing them up every time
# make sure that the start and end dates are business days, otherwise the code will resilt in an error
start_date = "2020-03-01"
end_date = "2021-01-01"
```

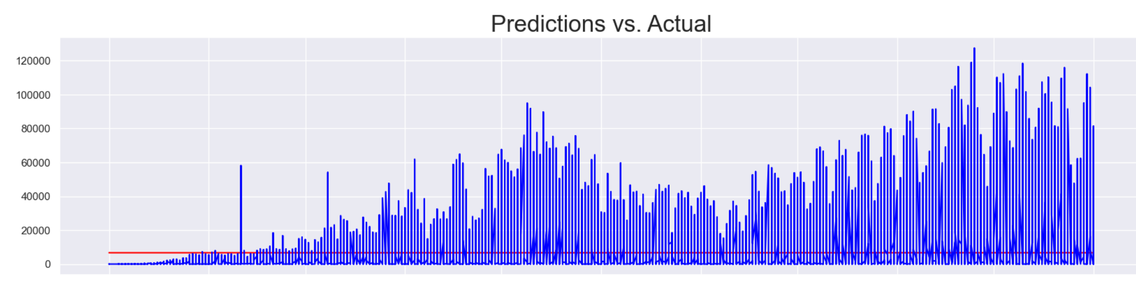
```
df_pred = results_ar.predict(start=start_date, end= end_date)
```

```
df_pred[start_date:end_date].plot(figsize = (20, 5), color = "red")
plt.title("Predictions", size = 24)
plt.show()
```




```
# over the course of the interval actual PCR test results moved cyclically and fluctated u
# upwards trend
# plot is skewed to the right
# 2021-01 as the highest peak of 6720 new results reported
```

```
df_pred[start_date:end_date].plot(figsize = (20, 5), color = "red")
df_test.new_results_reported[start_date:end_date].plot(color ="blue")
plt.title("Predictions vs. Actual", size = 24)
plt.show()
```



```
ons since it assumes all future returns will be 0, or extremely close to it
selves must have low absolute values
er in value with the highest peak being 2020-01 with over 120000 new results reported
```

0s completed at 4:23 PM