```
#necessary imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from \ statsmodels.graphics.tsaplots \ import \ plot\_acf, plot\_pacf
{\tt df=pd.read\_csv('\underline{/content/SBI3Y.csv',index\_col='Date',parse\_dates=True)\#reading~data~to~a~pandas~dataframe}
Start coding or generate with AI.
df.head()
                       0pen
                                   High
                                                                Adj Close
                                                                               Volume
                                                                                        Date
                                                                                        ıl.
      2021-03-24 368.500000 369.049988 358.649994 359.850006 344.386780 42318999
      2021-03-25 360.000000 360.850006 345.200012 355.200012 339.936615 57495003
      2021-03-26 360.000000 362.000000 354.549988 357.200012 341.850647
                                                                           40718848
      2021-03-30 360.100006 364.299988 356.299988 360.799988 345.295959 39405124
      2021-03-31 360,299988 367,850006 357,950012 364,299988 348,645538 38651025
 Next steps: Generate code with df
                                      View recommended plots
# performing the necessary statistics
df.describe()
                  0pen
                                                                                        \blacksquare
                              High
                                                     Close Adj Close
                                                                              Volume
                                           Low
      count 742.000000 742.000000 742.000000 742.000000 742.000000 7.420000e+02
      mean
            530.184502 535.709098 524.120619 529.903370 520.149722 1.989648e+07
             85.002279
                         85.370810 84.655232
                                                 84.969595
                                                             89.607174 1.481146e+07
       std
      min
            326.000000 332.049988 321.299988 328.850006 314.718903 3.692065e+06
            469.012512 475.512497 463.275009 468.399994 455.863212 1.187084e+07
      25%
            530.475006 535.649994 524.200012 530.100006 518.057831 1.578465e+07
      50%
```

Start coding or generate with AI.

75%

max

Data Preprocessing and Exploratory data analysis

Performance of a stock is anly sed base on the daily returns % i.e., valve-prev/prev % . calculating the daily returns for the closed data and the daily returns % i.e., valve-prev/prev % % i.e., valve-prev % i.e., valve

df['daily_returns']=df['Close'].pct_change()

Generate code with df

df.head()

Next steps:

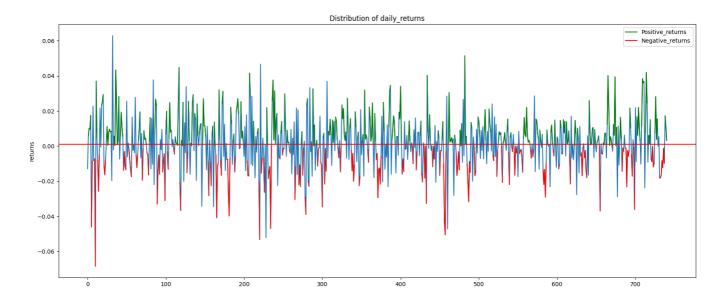
	Open	High	Low	Close	Adj Close	Volume	daily_retu
Date							
2021 03-24	368 SUUUUU	369.049988	358.649994	359.850006	344.386780	42318999	N
2021 03-25	360 000000	360.850006	345.200012	355.200012	339.936615	57495003	-0.0129
2021 03-26	360 000000	362.000000	354.549988	357.200012	341.850647	40718848	0.0056
4)

View recommended plots

586.937500 590.250015 580.662506 585.287476 581.326172 2.245517e+07 790.000000 793.400024 783.000000 788.049988 788.049988 1.928108e+08

```
Volume daily_returns
                                 High
                                                      Close Adj Close
                                                                                                   П
                     Open
                                             Low
         Date
                                                                                                    ılı.
    2021-03-25 360.000000 360.850006 345.200012 355.200012 339.936615 57495003
                                                                                        -0.012922
    2021-03-26 360.000000
                           362.000000 354.549988
                                                 357.200012 341.850647
                                                                        40718848
                                                                                        0.005631
                                                                                        0.010078
    2021-03-30 360.100006
                           364.299988
                                      356.299988
                                                  360.799988
                                                             345.295959
                                                                         39405124
                                                                                         0.009701
    2021-03-31 360 299988
                           367 850006 357 950012 364 299988 348 645538
                                                                         38651025
    2021-04-01
               367.700012
                           371.899994
                                      363.100006 370.649994
                                                             354.722687
                                                                         31883453
                                                                                         0.017431
Next steps:
            Generate code with df
                                    View recommended plots
```

```
# in the above plot the values with positive returns above 0 are shown in green and values with negative returns are shown in red color
fig, ax = plt.subplots(figsize=(20,8))
plt.plot(df['daily_returns'].values)
plt.plot(np.where(df['daily_returns'])>0,df['daily_returns'], None), color="green", label="Positive_returns")
plt.plot(np.where(df['daily_returns'] <= 0,df['daily_returns'], None), color="red", label="Negative_returns")
plt.axhline(df['daily_returns'].mean(), color='red')
plt.legend()
plt.ylabel('returns')
plt.title('Distribution of daily_returns')
plt.show()</pre>
```



df['daily_returns'].describe()

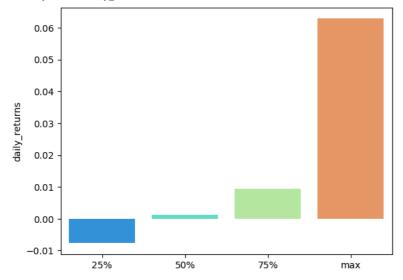
```
741.000000
count
mean
           0.001112
std
           0.015902
min
          -0.068414
25%
           -0.007700
50%
           0.001243
75%
           0.009498
           0.062838
max
Name: daily_returns, dtype: float64
```

returns_quantiles= df['daily_returns'].describe()[['25%','50%','75%','max']]

 $\verb|sns.barplot(returns_quantiles,palette='rainbow')| # plotting the returns quatilels \\$

<ipython-input-11-1843fd361d7d>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le sns.barplot(returns_quantiles,palette='rainbow') # plotting the returns quatilels <Axes: ylabel='daily_returns'>



#calculating outliers Q1= -0.009777 Q3= 0.011454 IQR= Q3-Q1 upper_bound=Q3+1.5*IQR lower_bound=Q1-1.5*IQR $outliers \ = df[(df['daily_returns'] > upper_bound) \ | \ (df['daily_returns'] < lower_bound)]$

outliers

	0pen	High	Low	Close	Adj Close	Volume	daily_returns	
Date								
2021-04-05	367.500000	369.200012	349.049988	353.549988	338.357483	51743981	-0.046135	t
2021-04-12	344.000000	344.000000	322.549988	328.850006	314.718903	75501713	-0.068414	•
2021-05-17	364.399994	385.200012	363.649994	383.100006	366.637695	106555796	0.062838	
2021-09-16	444.850006	466.100006	442.750000	463.700012	447.871368	42637448	0.044722	
2022-02-14	515.000000	515.599976	499.700012	501.399994	484.284454	26153332	-0.053248	
2022-02-15	502.000000	526.849976	497.100006	524.799988	506.885651	23842951	0.046669	
2022-02-24	480.000000	487.950012	468.000000	472.649994	456.515869	32356037	-0.052236	
2022-03-07	447.500000	453.950012	433.450012	440.299988	425.270142	33720472	-0.046867	
2023-01-25	595.849976	595.849976	567.400024	568.700012	557.859375	25686294	-0.043156	
2023-01-27	568.000000	568.549988	532.250000	539.950012	529.657410	40163464	-0.050554	
2023-02-01	561.400024	565.000000	499.350006	527.349976	517.297546	38218810	-0.047245	
2023-03-03	542.000000	564.299988	541.750000	561.200012	550.502380	27656538	0.051429	

Generate code with outliers View recommended plots Next steps:

outliers=outliers.sort_values('daily_returns',ascending=False)

outliers

	0pen	High	Low	Close	Adj Close	Volume	daily_returns	#
Date								11.
2021-05-17	364.399994	385.200012	363.649994	383.100006	366.637695	106555796	0.062838	*/
2023-03-03	542.000000	564.299988	541.750000	561.200012	550.502380	27656538	0.051429	
2022-02-15	502.000000	526.849976	497.100006	524.799988	506.885651	23842951	0.046669	
2021-09-16	444.850006	466.100006	442.750000	463.700012	447.871368	42637448	0.044722	
2023-01-25	595.849976	595.849976	567.400024	568.700012	557.859375	25686294	-0.043156	
2021-04-05	367.500000	369.200012	349.049988	353.549988	338.357483	51743981	-0.046135	
2022-03-07	447.500000	453.950012	433.450012	440.299988	425.270142	33720472	-0.046867	
2023-02-01	561.400024	565.000000	499.350006	527.349976	517.297546	38218810	-0.047245	
2023-01-27	568.000000	568.549988	532.250000	539.950012	529.657410	40163464	-0.050554	
2022-02-24	480.000000	487.950012	468.000000	472.649994	456.515869	32356037	-0.052236	
2022-02-14	515.000000	515.599976	499.700012	501.399994	484.284454	26153332	-0.053248	
2021-04-12	344.000000	344.000000	322.549988	328.850006	314.718903	75501713	-0.068414	

Next steps:

Generate code with outliers

View recommended plots

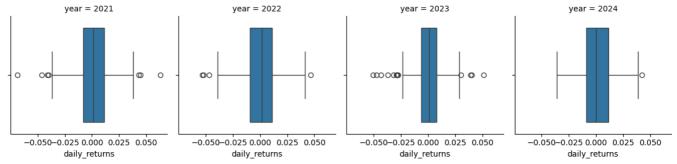
Here further see the reason for particular outliers. For example on May5 2021 stok market has rose due to psu etc

```
df['year'] = pd.DatetimeIndex(df.index).year
```

```
# outliers identified based on year
```

/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:718: UserWarning: Using the boxplot function without specifying `order` warnings.warn(warning)

<seaborn.axisgrid.FacetGrid at 0x7bd6ef3fd480>

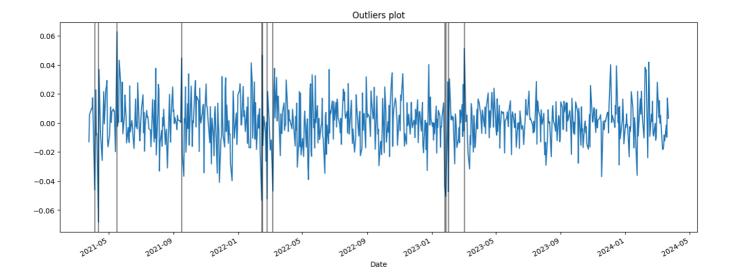


Start coding or $\underline{\text{generate}}$ with AI.

ax=df['daily_returns'].plot(figsize=(16,6),title='Outliers plot') for i in outliers.index: ax.axvline(i,color='black',alpha=0.5)

g = sns.FacetGrid(df, col="year")

g.map(sns.boxplot, "daily_returns")

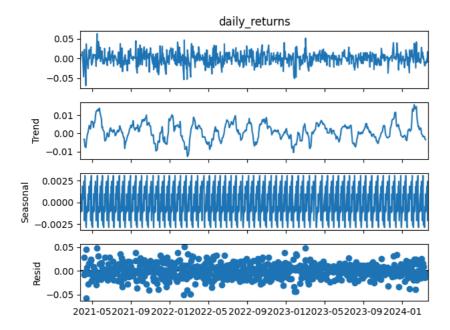


Start coding or $\underline{\text{generate}}$ with AI.

Understanding the ETS(error, trend and seasonality of the stock by using ETS decomposition method of statsmodels library)

from statsmodels.tsa.seasonal import seasonal decompose

result=seasonal_decompose(df['daily_returns'],model='additive',period=12) # there are two modes for trend analysis either additive or multiplicati result.plot();



- from the above we can make following inference
 - · Residuals are very high which shows uncertainity of data
 - · Data follows a cyclic pattern which have to be obtained by using forecasting models and find the seasonal components

We have taken 1d, 3d and 5d simple moving averages in order to analyze the trend or seasonality

df['sma1d']=df['daily_returns'].rolling(window=1).mean()
df['sma3d']=df['daily_returns'].rolling(window=3).mean()

```
df['sma5d']=df['daily_returns'].rolling(window=5).mean()
```

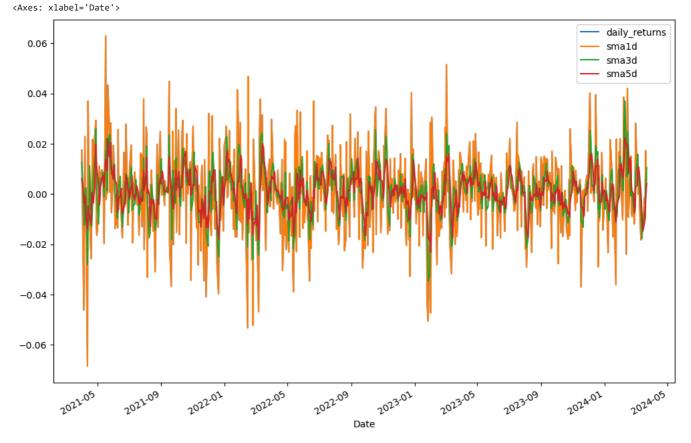
df=df.dropna()

df.head()

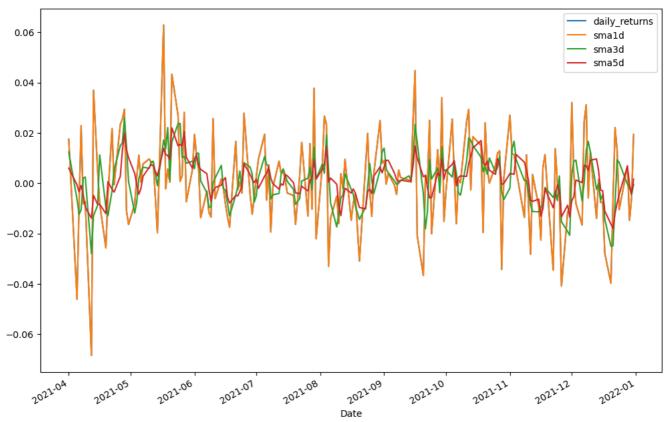
		Open	High	Low	Close	Adj Close	Volume	daily_returns	year	sma1d	sma3d	sma5d	
D	ate												ıl.
20: 04:	21- -01	367.700012	371.899994	363.100006	370.649994	354.722687	31883453	0.017431	2021	0.017431	0.012403	0.005984	
	21- -05	367.500000	369.200012	349.049988	353.549988	338.357483	51743981	-0.046135	2021	-0.046135	-0.006335	-0.000659	
	21- -06	355.700012	357.000000	349.299988	350.549988	335.486420	44147709	-0.008485	2021	-0.008485	-0.012397	-0.003482	
20	21-	054 050000	000 0000 10	-0.47.000000	050-540000	-040 440000 -	1000000			- 0-000004-	- 0 0 40000		
Next step	ps:	Generate coo	le with df	View re	ecommended	plots							

df[['daily_returns','sma1d','sma3d','sma5d']].plot(figsize=(12,8))

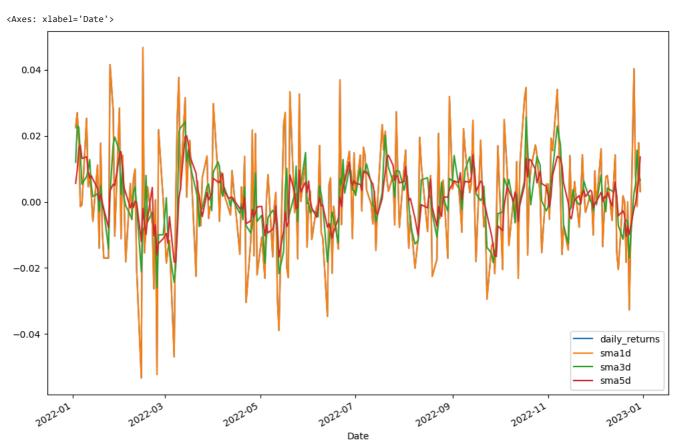
. If the 27 case of 2 case 2 case 32 the case 32 the case 32 c

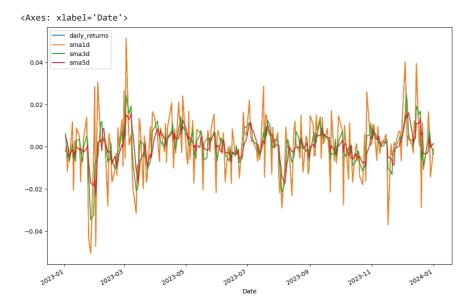


#Distribution for 2021 df[:'2021-12-31'][['daily_returns','sma1d','sma3d','sma5d']].plot(figsize=(12,8))

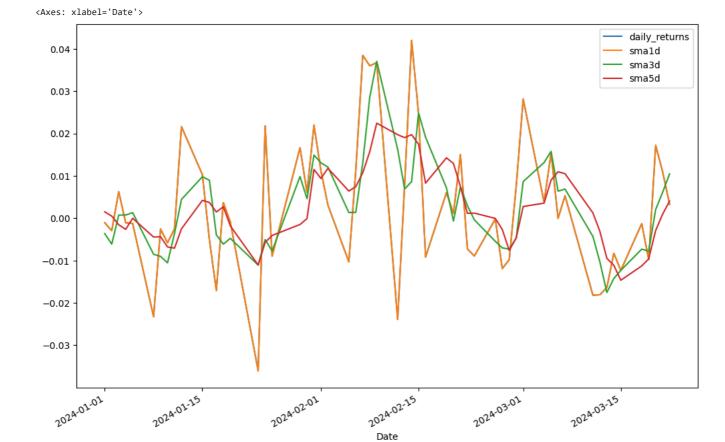


#Distribution for 2022 df['2022-01-01':'2023-01-01'][['daily_returns','sma1d','sma3d','sma5d']].plot(figsize=(12,8))





#distribution for 2024 df['2024-01-01':][['daily_returns','sma1d','sma3d','sma5d']].plot(figsize=(12,8))



Start coding or generate with AI.

Checking if the returs distribution is stationery by using Augumented Dickey fuller test

```
# Using Augumented dickey fuller test
from statsmodels.tsa.stattools import adfuller
def adf_test(series,title=''):
  print('Augmented Dicky fuller test :{title}')
   result=adfuller(series.dropna(),autolag='AIC')
  labels=['ADF test_statistic','p-value','#lags_used','#observations']
  out=pd.Series(result[0:4],index=labels)
   for key,val in result[4].items():
   out[f'Critical value ({key})']=val
  print(out.to_string())
  if result[1]<0.05:
    print('reject null hypothesis')
    print('Data has no unit root and is stationary')
  else:
    print('no evidence to reject null hypothesis')
    print('Data has unit root and is non-stationary')
```

adf_test(df['daily_returns']) #here we can see that as p-value is less that 0.05 it falls in the region of rejection of null hypothesis and the da

```
Augmented Dicky fuller test :{title}
ADF test_statistic
                       -1.224990e+01
p-value
                        9.593358e-23
                        3.000000e+00
#lags_used
#observations
                        7.330000e+02
                       -3,439303e+00
Critical value (1%)
Critical value (5%)
                       -2.865491e+00
Critical value (10%)
                       -2.568874e+00
reject null hypothesis
Data has no unit root and is stationary
```

#here we can see that as p-value is less that 0.05 it falls in the region of rejection of null hypothesis and the data is stationery which was observed that data is around the mean

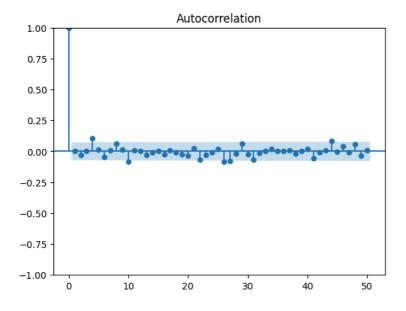
df.tail()

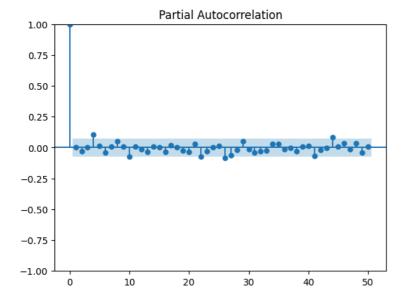
	0pen	High	Low	Close	Adj Close	Volume	daily_returns	year	sma1d	sma3d	sma5d	\blacksquare
Date												ılı
2024- 03-18	727.099976	737.900024	722.099976	730.950012	730.950012	18145126	-0.001298	2024	-0.001298	-0.007314	-0.011285	
2024- 03-19	730.000000	734.349976	721.150024	723.799988	723.799988	15205043	-0.009782	2024	-0.009782	-0.007809	-0.009622	
2024- 03-20	725.150024	738.950012	719.799988	736.250000	736.250000	25405455	0.017201	2024	0.017201	0.002040	-0.002905	
2024-	740 000000	750 500070	740 540000	744 000000	744 000000	15101101	0.040004	0004	0.040004	0.000440	0.000040	

Choosing the appropriate model

from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

```
acf_plot = plot_acf(df['daily_returns'], lags = 50)
```





From pacf plot we can infer that values for p are 1,5,44 whch are outside shaded region

Start coding or <u>generate</u> with AI.

Splitting data set in to training and testing

len(df)

737

train=df[:-30]
test=df[-30:]

ARIMA model

from statsmodels.tsa.arima.model import ARIMA

Start coding or $\underline{\text{generate}}$ with AI.

model = ARIMA(train['daily_returns'],order=(1,0,5))
result=model.fit()
result.summary()

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)
```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist_packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

SARIMAX Results

 Dep. Variable:
 daily_returns
 No. Observations:
 707

 Model:
 ARIMA(1, 0, 5)
 Log Likelihood
 1927.811

 Date:
 Mon, 25 Mar 2024
 AIC
 -3839.622

 Time:
 02:03:55
 BIC
 -3803.134

 Sample:
 0
 HQIC
 -3825.524

Covariance Type: opg

coef std err z P>|z| [0.025 0.975] **const** 0.0010 0.001 1.628 0.104 -0.000 0.002 ar.L1 0.0536 8.474 0.006 0.995 -16.555 16.662 ma.L1 -0.0641 8.479 -0.008 0.994 -16.682 16.554 ma.L2 -0.0304 0.101 -0.302 0.763 -0.228 0.167 ma.L3 0.0008 0.262 0.003 0.998 -0.513 0.514 ma.L4 0.0909 0.039 2.323 0.020 0.014 0.168 ma.L5 -0.0008 0.770 -0.001 0.999 -1.511 1.509 sigma2 0.0003 1.09e-05 23.015 0.000 0.000 0.000 Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 47.82 **Prob(Q):** 0.99 **Prob(JB):** 0.00 Heteroskedasticity (H): 0.49 Skew: -0.14 4.24 Prob(H) (two-sided): 0.00 Kurtosis:

Warnings:

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

```
start=len(train)
end=len(train)+len(test)-1

df['forecast']=result.predict(start = start, end = end)
df[['daily_returns','forecast']].plot(figsize=(12,8))
```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: ValueWarning: No supported index is available. Prediction_index(

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836: FutureWarning: No supported index is available. In the return get_prediction_index(

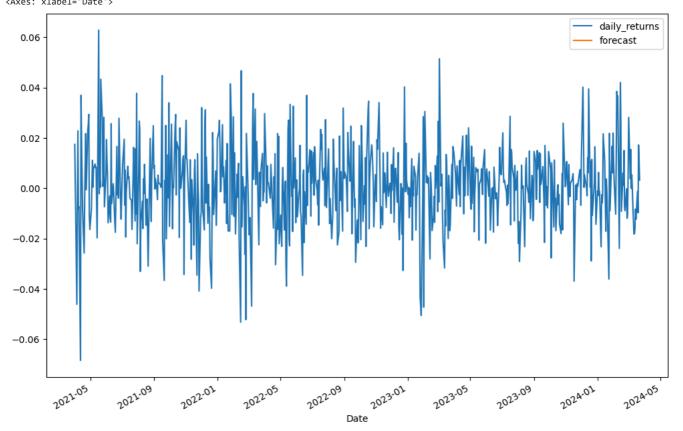
<ipython-input-51-dda93fc59791>:4: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

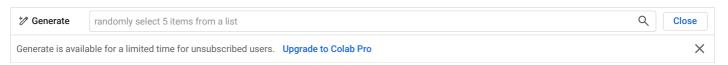
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus df['forecast']=result.predict(start = start, end = end)

<Axes: xlabel='Date'>



SARIMAMODEL



from statsmodels.tsa.statespace.sarimax import SARIMAX model_S = SARIMAX(df['daily_returns'],order=(2, 0, 0),seasonal_order=(1,0,1,44)) result_S = model_S.fit() result_S.summary()

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

SARIMAX Results

 Dep. Variable:
 daily_returns
 No. Observations: 737

 Model:
 SARIMAX(2, 0, 0)x(1, 0, [1], 44)
 Log Likelihood
 2007.067

df['forecast_s']=result_S.predict(start= start, end =end)
df['2024-01-01':][['daily_returns','forecast_s']].plot(figsize=(12,8))

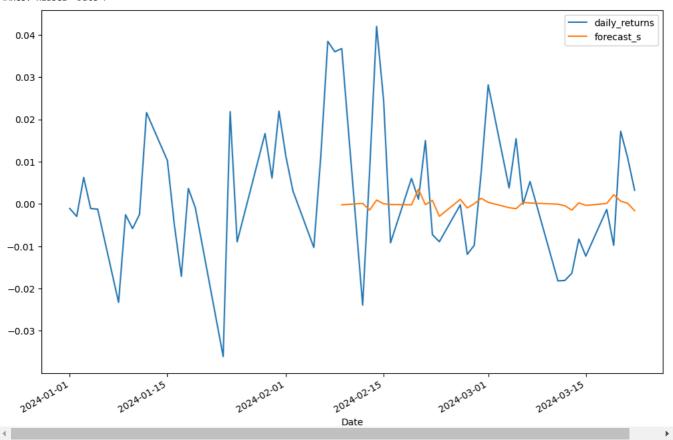
<ipython-input-58-ca9f0ce5183b>:1: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a $\mathsf{DataFrame}$.

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#returning-a-view-versus df['forecast_s']=result_S.predict(start= start, end =end)

<Axes: xlabel='Date'>



performing similar analysis for simple moving averages

```
adf_test(df['sma1d'])
```

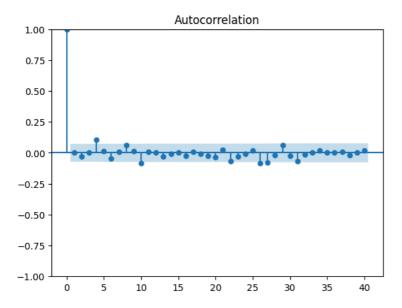
Augmented Dicky fuller test :{title} -1.224990e+01 ADF test_statistic p-value 9.593358e-23 3.000000e+00 #lags used 7.330000e+02 #observations -3,439303e+00 Critical value (1%) Critical value (5%) -2.865491e+00 Critical value (10%) -2.568874e+00 reject null hypothesis Data has no unit root and is stationary

adf_test(df['sma3d'])

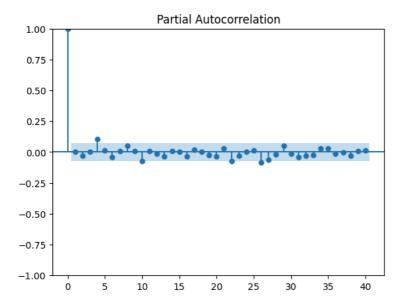
Augmented Dicky fuller test :{title} ADF test statistic -6.653637e+00 5.047662e-09 p-value 2.000000e+01 #lags_used 7.160000e+02 #observations Critical value (1%) -3.439516e+00 Critical value (5%) -2.865585e+00 Critical value (10%) -2.568924e+00 ${\tt reject\ null\ hypothesis}$ Data has no unit root and is stationary

```
Augmented Dicky fuller test :{title}
ADF test_statistic
                         -5.623599
p-value
                          0.000001
#lags_used
                         20.000000
#observations
                        716.000000
Critical value (1%)
                         -3.439516
Critical value (5%)
                         -2.865585
Critical value (10%)
                         -2.568924
reject null hypothesis
Data has no unit root and is stationary
```

plot_acf(df['sma1d'],lags=40);



plot_pacf(df['sma1d'],lags=40);



wecan see that 1,5 are values for p

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model_1d = SARIMAX(df['smald'],order=(2, 0, 0),seasonal_order=(1,0,1,44))
result_1d = model_1d.fit()
result_1d.summary()
```

```
/usr/local/lib/python 3.10/dist-packages/stats models/tsa/base/tsa\_model.py: 473: \ Value Ward of the following the property of the property
      self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueW
     self._init_dates(dates, freq)
                                                                                         SARIMAX Results
     Dep. Variable: sma1d
                                                                                                                                              No. Observations: 737
                                                      SARIMAX(2, 0, 0)x(1, 0, [1], 44) Log Likelihood 2007.067
               Model:
                  Date:
                                                     Mon, 25 Mar 2024
                                                                                                                                                                    AIC
                                                                                                                                                                                                      -4004.135
                                                     02:42:31
                                                                                                                                                                   BIC
                                                                                                                                                                                                      -3981.122
                 Time:
              Sample:
                                                     0
                                                                                                                                                                 HQIC
                                                                                                                                                                                                      -3995.260
                                                     - 737
 Covariance Type: opg
                                 coef std err
                                                                                     z P>|z| [0.025 0.975]
      ar.L1 0.0131 0.031 0.417 0.677 -0.048 0.075
      ar.L2 -0.0273 0.037
                                                                            -0.740 0.459 -0.100 0.045
  ar.S.L44 0.3035 0.444
                                                                        0.683 0.495 -0.567 1.174
 ma.S.L44 -0.2204 0.452
                                                                           -0.488 0.625 -1.105 0.665
   sigma2 0.0003 1.04e-05 24.320 0.000 0.000 0.000
     Ljung-Box (L1) (Q): 0.05 Jarque-Bera (JB): 53.97
                     Prob(Q):
                                                                     0.82
                                                                                              Prob(JB):
                                                                                                                                        0.00
Heteroskedasticity (H): 0.48
                                                                                                   Skew:
                                                                                                                                         -0.12
                                                                                                                                         4.31
    Prob(H) (two-sided): 0.00
                                                                                                Kurtosis:
```

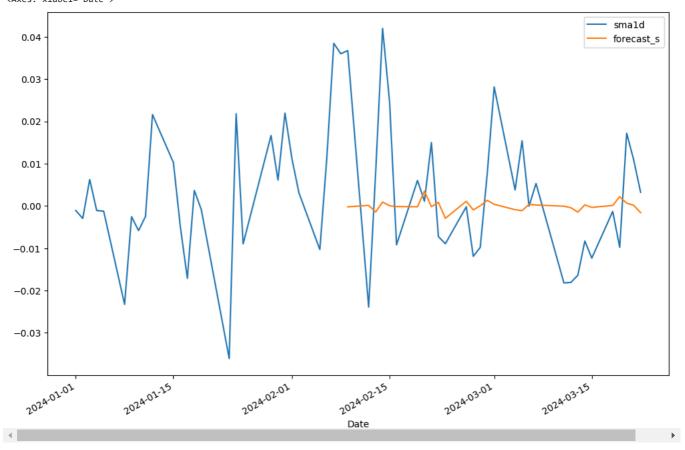
Warnings:

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

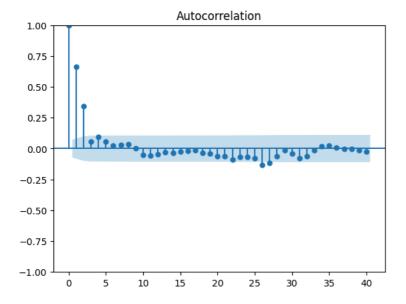
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus

df['forecast_1d']=result_1d.predict(start= start, end =end)

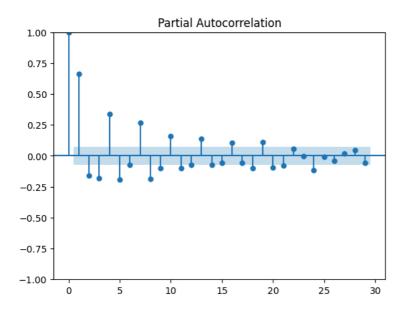
<Axes: xlabel='Date'>



for sma3d
acf_plot=plot_acf(df['sma3d'],lags=40)



pacf_plot=plot_pacf(df['sma3d'])



from pacf we can use 1,2,5,8,11,14,17,20,23 for autoreggression

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model_3d = SARIMAX(df['sma3d'],order=(2, 0,2),seasonal_order=(1,0,1,20))
result_3d = model_3d.fit()
result_3d.summary()
```

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueW self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueW self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:607: ConvergenceWar warnings.warn("Maximum Likelihood optimization failed to "

SARIMAX Results

Dep. Variable: sma3d No. Observations: 737 SARIMAX(2, 0, 2)x(1, 0, [1], 20) Log Likelihood 2800.868 Model: Mon, 25 Mar 2024 AIC -5587.737 Date: Time: 02:42:59 BIC -5555.519 Sample: HQIC -5575.312 - 737

Covariance Type: opg

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.0726	0.031	2.340	0.019	0.012	0.133
ar.L2	-0.0373	0.038	-0.976	0.329	-0.112	0.038
ma.L1	0.9737	0.013	76.324	0.000	0.949	0.999
ma.L2	0.9732	0.013	72.185	0.000	0.947	1.000
ar.S.L20	-0.1239	0.292	-0.425	0.671	-0.696	0.448
ma.S.L20	-0.0148	0.291	-0.051	0.960	-0.586	0.556
sigma2	2.889e-05	1.18e-06	24.544	0.000	2.66e-05	3.12e-05

 Ljung-Box (L1) (Q):
 1.92 Jarque-Bera (JB):
 62.33

 Prob(Q):
 0.17
 Prob(JB):
 0.00

 Heteroskedasticity (H):
 0.48
 Skew:
 -0.08

 Prob(H) (two-sided):
 0.00
 Kurtosis:
 4.41

Warnings:

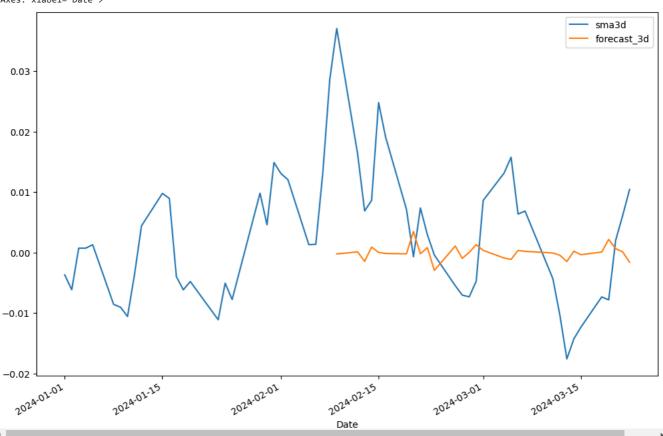
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

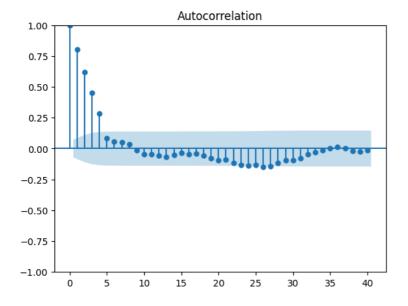
```
df['forecast_3d']=result_1d.predict(start= start, end =end)
df['2024-01-01':][['sma3d','forecast_3d']].plot(figsize=(12,8))
```

<ipython-input-82-84960f4f556d>: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

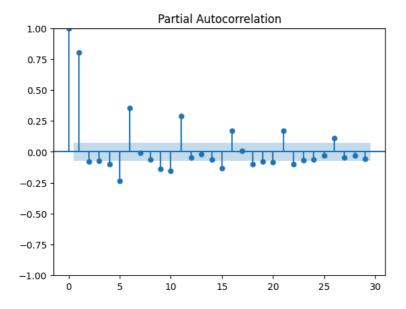
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus df['forecast_3d']=result_1d.predict(start= start, end =end)

<Axes: xlabel='Date'>





pacf=plot_pacf(df['sma5d'])



p value can be 1,6,11,16,21,26

from statsmodels.tsa.statespace.sarimax import SARIMAX
model_5d = SARIMAX(df['sma3d'],order=(1, 0,5),seasonal_order=(1,0,5,20))
result_5d = model_3d.fit()
result_5d.summary()

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it self._init_dates(dates, freq)

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to warnings.warn("Maximum Likelihood optimization failed to "

SARIMAX Results

 Dep. Variable:
 sma3d
 No. Observations:
 737

 Model:
 SARIMAX(2, 0, 2)x(1, 0, [1], 20)
 Log Likelihood
 2800.868

 Date:
 Mon, 25 Mar 2024
 AIC
 -5587.737

df['forecast_5d']=result_1d.predict(start= start, end =end)
df['2024-01-01':][['sma5d','forecast_5d']].plot(figsize=(12,8))

<ipython-input-86-7286b4942a1a>: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#returning-a-view-versus df['forecast_5d']=result_1d.predict(start= start, end =end)

<Axes: xlabel='Date'>

