```
In [2]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import warnings
         warnings.filterwarnings('ignore')
         import yfinance as yf
In [48]: # Extraccioón de datos historicos con un rango especifico
         dis = yf.download(tickers = 'DIS', start = '2023-01-01', end = '2023-04-01', rounding = True)
dis.columns = dis.columns.droplevel(1)
         dis.index = pd.to_datetime(dis.index).strftime('%Y-%m-%d')
         [********* 100%********** 1 of 1 completed
Out[48]:
             Price Adj Close Close High Low Open Volume
              Date
         2023-01-03 88.27 88.97 89.97 87.83 88.98 14997100
         2023-01-04
                    91.26 91.98 92.75 89.36 90.00 14957200
         2023-01-05 91.20 91.92 92.48 90.51 91.66 11622600
         2023-01-06
                     93.18 93.92 94.69 91.32 92.66 9828100
         2023-01-09 94.03 94.77 95.70 93.45 94.43 11675800
         2023-03-27 94.87 95.62 96.02 94.38 94.78 7487900
         2023-03-28 94.08 94.82 96.00 94.59 95.51 5426100
         2023-03-29 96.11 96.87 96.91 95.35 96.08 5889100
         2023-03-30 97.33 98.10 98.92 97.67 98.73 7669500
         2023-03-31 99.35 100.13 100.20 98.50 98.89 8920000
In [49]: dis = dis['Close']
          dis
Out[49]: Date
          2023-01-03
                          88.97
          2023-01-04
                          91.98
                         91.92
          2023-01-05
          2023-01-06
                          93.92
          2023-01-09
                           94.77
          2023-03-27
                          95.62
                          94.82
          2023-03-28
          2023-03-29
                         96.87
          2023-03-30
                           98.10
          2023-03-31 100.13
          Name: Close, Length: 62, dtype: float64
In [50]: # utilizamos el 70% de la base para la base de entrenamiento
          dis.index = pd.to_datetime(dis.index)
len_train = int(len(dis)* .7)
          len_train
Out[50]: 43
In [51]: # utilizamos el 30% de la base para la base de pruebas
           len_test = int(len(dis) * .3)
          len_test
Out[51]: 18
```

```
In [52]: # definimos grupos de puerba y entrenamiento
           train = dis[0:len_train]
           train
  Out[52]: Date
           2023-01-03
                        88.97
           2023-01-04
                         91.98
           2023-01-05
                         91.92
           2023-01-06
                         93.92
           2023-01-09
                         94.77
           2023-01-10
                        95.56
           2023-01-11
                        96.33
           2023-01-12
                        99.81
           2023-01-13
                        99.40
           2023-01-17
                        99.91
           2023-01-18
                        99.04
           2023-01-19
                        99.08
           2023-01-20 103.48
In [53]: test = dis[len_train:]
         test
Out[53]: Date
         2023-03-07
                     99.06
         2023-03-08
                     99.30
                      96.14
         2023-03-09
                      93.57
         2023-03-10
         2023-03-13
                      92.60
         2023-03-14
                       93.36
         2023-03-15
                       93.10
         2023-03-16
                       94.29
         2023-03-17
                      93.20
         2023-03-20
                       94.22
                      96.54
         2023-03-21
                      94.90
         2023-03-22
         2023-03-23
                      95.83
         2023-03-24
                      94.08
         2023-03-27
                      95.62
         2023-03-28
                      94.82
         2023-03-29
                      96.87
                      98.10
         2023-03-30
         2023-03-31
                     100.13
        Name: Close, dtype: float64
```

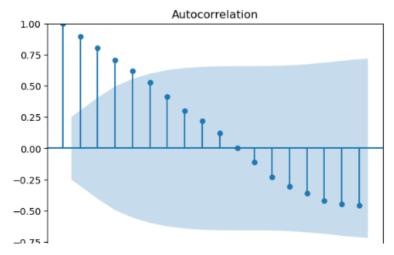
```
In [54]: # obtenemos los valores para la grafica de autocorrelacion, funcion de autorcorrelacion(acf)
from statsmodels.tsa.stattools import acf
from statsmodels.graphics.tsaplots import plot_acf

acf_array = acf(train)
print(acf_array)

# grafico de nivel de confianza del 90%

plot_acf(train, alpha = 0.10)
plt.show()

[ 1.000000000+00 8.93676862e-01 8.05243892e-01 7.06909430e-01
6.22030380e-01 5.25234900e-01 4.15450780e-01 3.00150124e-01
2.19430750e-01 1.20838146e-01 4.18616085e-04 -1.11289565e-01
-2.28961906e-01 -3.03417271e-01 -3.62183951e-01 -4.20839262e-01
```



```
In [55]: # hacemos el ajuste con ARIMA
from statsmodels.tsa.arima.model import ARIMA

model = ARIMA(train, order = (1,0,0))
result = model.fit()

C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
but it has no associated frequency information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
but it has no associated frequency information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarnin
but it has no associated frequency information and so will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
```

In [56]: print(result.summary())

-4.48296465e-01]

		SARI	[MAX Resu]	lts			
========							
Dep. Varia				Observations:		43	
Model:		ARIMA(1, 0,	 Log 	Likelihood		-86.541	
Date:	We	d, 06 Nov 20	324 AIC			179.083	
Time:		14:00:	17 BIC			184.367	
Sample:			0 HQIC			181.031	
		-	43				
Covariance	Type:		opg				
	coef	std err	Z	P> Z	[0.025	0.975]	
const	98.0216	5.257	18.645	0.000	87.717	108.326	
ar.L1	0.9717	0.031	30.960	0.000	0.910	1.033	
sigma2	3.0655	0.663	4.624	0.000	1.766	4.365	
Ljung-Box	(L1) (Q):		0.03	Jarque-Bera	(JB):	=======	0.56
Prob(0):		0.87	Prob(JB):			0.76	
Heterosked	dasticity (H):		0.56	Skew:			0.27
Prob(H) (two-sided):		0.28	Kurtosis:			2.88	

```
In [57]: # realizamos Las predicciones
           predicciones = result.forecast(len(test))
           predicciones
           C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_m
           e. Prediction results will be given with an integer index beginning a
             return get_prediction_index(
  Out[57]: 43 100.585304
           44
                 100.512722
           45
                 100.442195
           46
                 100.373665
           47
                 100.307075
               100.242371
           48
In [59]: # pronosticamos con un intervalode confianza de 90%
         conf = result.get_forecast(len(test)).conf_int(alpha = .10)
         conf
         C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa
         e. Prediction results will be given with an integer index beginning
           return get_prediction_index(
Out[59]:
             lower Close upper Close
          43 97.705423 103.465184
          44 96.497195 104.528249
              95.592651 105.291740
```

46 94.851077 105.898254 94.216903 106.397248

49 93.165983 107.193013

93.661072 106.823669

47

48

```
In [60]: fcast_result = result.get_forecast(len(test))
         print(fcast_result.summary_frame(alpha = .10))
         Close
                     mean mean_se mean_ci_lower mean_ci_upper
                100.585304 1.750843
         43
                                          97.705423
                                                         103.465184
         44
                100.512722 2.441267
                                           96.497195
                                                         104.528249
         45
                100.442195 2.948314
                                           95.592651
                                                         105.291740
                100.373665 3.357495
                                          94.851077
         46
                                                         105.896254
                100.307075 3.702562
         47
                                          94.216903
                                                         106.397248
                                          93.661072
         48
                100.242371 4.001145
                                                         106.823669
         49
                100.179498 4.263914
                                          93.165983
                                                         107.193013
         50
                100.118405 4.497947
                                          92.719940
                                                         107.516870
         51
                100.059042 4.708251
                                           92.314658
                                                         107.803426
                                                         108.058735
               100.001360 4.898536
                                          91.943984
         52
         53
                 99.945310 5.071651
                                          91.603187
                                                         108.287433
                 99.890848 5.229845
                                                         108.493177
                                          91.288519
         54
                                          90.996943
         55
                 99.837927 5.374937
                                                         108.678911
         56
                 99.786505 5.508423
                                          90.725956
                                                         108.847054
         57
                 99.736538 5.631554
                                          90.473456
                                                         108,999620
         58
                 99.687986 5.745391
                                           90.237659
                                                         109.138313
                 99.640809 5.850840
                                          90.017033
         59
                                                         109.264585
                 99.594967 5.948688
                                          89.810246
                                                         109.379688
         60
                 99.550423 6.039619
                                          89.616134
                                                         109.484713
         61
         C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa_base\tsa_model.py:836: ValueWarning: No suppor
         e. Prediction results will be given with an integer index beginning at 'start'.
           return get_prediction_index(
In [61]: # Convertimos test a DataFrame
         test = pd.DataFrame(test)
test = test.reset_index()
In [62]: # Convertimos test a DataFrame
         predicciones = pd.DataFrame(predicciones)
predicciones = predicciones.reset_index()
In [73]: test
Out[73]:
                       Date Close
              0 2023-03-07
                              99.06
              1 2023-03-08 99.30
              2 2023-03-09 96.14
              3 2023-03-10 93.57
              4 2023-03-13 92.60
```

5 2023-03-14 93.36 6 2023-03-15 93.10 7 2023-03-16 94.29 8 2023-03-17 93.20

```
100.585304
0
     43
1
     44
             100.512722
             100.442195
     45
2
             100.373665
3
     46
     47
             100.307075
     48
             100.242371
5
6
     49
             100.179498
              100 110/06
7
     50
```

```
In [71]: # calculamos el nivel de error cuando comparamos las predicciones con los valores de test

acumulador1 = 0
acumulador2 = 0

for contador in range(0, 18):
    acumulador1 = acumulador1 + (test.iloc[contador][1] - predicciones.iloc[contador][1]) ** 2
    acumulador2 = acumulador2 + np.abs((test.iloc[contador][1] - predicciones.iloc[contador][1]) / test.iloc[contador][1])

mse = acumulador1 / 18
    rmse = np.round(np.sqrt(mse), 2)
    mape = np.round((acumulador2 / 18) * 100, 2)
    print("MSEM = ', rmse, 'Mape = ', mape, '%')

RSEM = 5.14 Mape = 5.02 %

In [74]: # Tambien podemos usar sklearn y obtendriamos resultados parecidos
    from sklearn.metrics import mean_squared_error

# RMSE
    rmse = np.round(np.sqrt(mean_squared_error(test['close'], predicciones['predicted_mean'])), 2)

# MAPE
    mape = np.round(np.mean(np.abs((test['close'] - predicciones['predicted_mean'])) / test['close'])) * 100, 2)

    print('RMSE = ', rmse, 'Mape = ', mape, '%')

RMSE = 5.0 Mape = 4.79 %
```

 * La desvacion media absoluta porcentual es de Mape = 5.0 %, y en promedio nos equivocamos 4.79 dlls al pronosticar

Pronostica los precios diarios por acción para el mes de Abril del 2023, tanto de manera puntual como mediante un intervalo de confianza del 90%, a partir del resultado obtenido en el punto anterior, p.

```
In [76]: # pronostico para el mes de abril
            predicciones = result.forecast(len(test) + 30)
predicciones.tail(30)
            C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported index is availabl e. Prediction results will be given with an integer index beginning at `start`.
return get_prediction_index(
Out[76]: 62 99.507141
                    99.465083
99.424217
            64
            65
                    99.384507
            66
67
                     99.345922
                     99.308429
            68
69
                    99.271997
99.236597
            70
71
72
                     99.202199
                     99.168775
                     99.136297
            73
74
                     99.104739
                     99.074074
            75
76
77
                     99.044278
                     99.015325
                     98.987191
             78
                     98.959854
            79
                     98.933292
            80
                    98.907481
                    98.882401
```

In [77]: # realizamos un pronostico con intervalode confianza del 90% conf = result.get_forecast(len(test) + 30).conf_int(alpha = 0.10) conf.tail(30)

C:\Users\Isaac\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No
e. Prediction results will be given with an integer index beginning at `start`.
return get_prediction_index(

Out[77]:

	lower Close	upper Close
62	89.433670	109.580611
63	89.261943	109.668223
64	89.100140	109.748293
65	88.947531	109.821483
66	88.803458	109.888385
67	88.667326	109.949531
68	88.538593	110.005401
69	88.416767	110.056427
70	88.301396	110.103002
71	88.192067	110.145483
72	88.088400	110.184194

```
In [78]: train = pd.DataFrame(train)
    lista = test['Date']
    lista = pd.DataFrame(lista)
    test.index = test['Date']
    test.drop(columns = ['Date'], inplace = True)
    test
```

Out[78]:

Close

Date	
2023-03-07	99.06
2023-03-08	99.30
2023-03-09	96.14
2023-03-10	93.57
2023-03-13	92.60
2023-03-14	93.36
2023-03-15	93.10
2023-03-16	94.29
2023-03-17	93.20

In [79]: lista

Out[79]:

Date

- 0 2023-03-07
- 1 2023-03-08
- 2 2023-03-09
- 3 2023-03-10
- 4 2023-03-13
- 5 2023-03-14
- 6 2023-03-15
- 7 2023-03-16
- 8 2023-03-17
- 9 2023-03-20
- 10 2023-03-21

```
In [86]: # generamos 30 dias poseteriores (mes de abril) de la ultima fecha '2023-03-31'
          lista2 = []
          for day in range(1, 21):
              fecha = ((pd.to_datetime('2023-03-31') + pd.offsets.BDay(day)).date())
              lista2.append(fecha)
          # convertimos Lista2 en DF
          lista2 = pd.DataFrame(lista2, columns = ['Date'])
          lista2['Date'] = pd.to_datetime(lista2['Date'])
          lista2
Out[86]:
                   Date
           0 2023-04-03
            1 2023-04-04
           2 2023-04-05
            3 2023-04-06
           4 2023-04-07
            5 2023-04-10
           6 2023-04-11
            7 2023-04-12
            8 2023-04-13
            9 2022 04 4A
In [89]: lista3.drop(columns = ['index'], inplace = True)
Out[89]:
                   Date
            0 2023-03-07
            1 2023-03-08
            2 2023-03-09
            3 2023-03-10
            4 2023-03-13
            5 2023-03-14
            6 2023-03-15
            7 2023-03-16
            8 2023-03-17
            9 2023-03-20
           10 2023-03-21
           11 2023-03-22
           12 2023-03-23
           13 2023-03-24
           14 2023-03-27
           15 2023-03-28
```

```
In [90]: # predcciones Lo convertimos en DF, y reseteamos eL indice

predicciones = pd.DataFrame(predicciones)
predicciones = predicciones.reset_index()

predicciones.drop(columns = ['index'], inplace = True)
predicciones
```

Out[90]:

predicted_mean 0 100.585304 1 100.512722 100.442195 2 100.373665 3 4 100.307075 100.242371 100.179498 6 100.118405 7 100.059042

```
In [98]: # concatenamos Lista3 con Las predicciones
frames = [lista3, predicciones]
res = pd.concat(frames, axis = 1, join = 'inner')
# renombramos Las columnas
res.columns = ['Date', 'Predicciones']
res
```

```
20 2020-01-11 88.100770
29 2023-04-17
               99.136297
30 2023-04-18 99.104739
31 2023-04-19
               99.074074
32 2023-04-20 99.044278
33 2023-04-21
              99.015325
34 2023-04-24
              98.987191
35 2023-04-25
              98.959854
36 2023-04-26 98.933292
37 2023-04-27
               98.907481
38 2023-04-28 98.882401
```

```
In [100]: # dejamos como indice el campo 'Date'

res.index = res['Date']
res.drop(columns = ['Date'], inplace = True)
res
```

```
2020-04-11
              66.100261
2023-04-18
              99.104739
2023-04-19
              99.074074
2023-04-20
              99.044278
2023-04-21
              99.015325
2023-04-24
              98.987191
2023-04-25
              98.959854
2023-04-26
              98.933292
2023-04-27
              98.907481
2023-04-28
              98.882401
```

```
In [101]: conf = conf.reset_index()
    conf.drop(columns = ['index'], inplace = True)
    conf
```

Out[101]:

	lower Close	upper Close
0	97.705423	103.465184
1	96.497195	104.528249
2	95.592651	105.291740
3	94.851077	105.896254
4	94.216903	106.397248
5	93.661072	106.823669

```
In [119]: frames = [lista3, conf]
   intervalos = pd.concat(frames, axis = 1, join = 'inner')
   intervalos.tail(10)
```

Out[119]:

Date lower Close upper Close 29 2023-04-17 88.088400 110.184194 30 2023-04-18 87.990046 110.219433 31 2023-04-19 87.896679 110.251469 32 2023-04-20 87.808002 110.280553 33 2023-04-21 87.723737 110.306912 34 2023-04-24 87.643627 110.330755 35 2023-04-25 87.567433 110.352276 36 2023-04-26 87.494931 110.371652 37 2023-04-27 87.425915 110.389047 38 2023-04-28 87.360189 110.404612

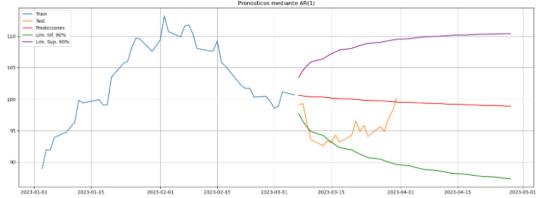
```
In [120]: intervalos.index = intervalos['Date']
  intervalos.drop(columns = ['Date'], inplace = True)
  intervalos.tail(15)
```

Out[120]:

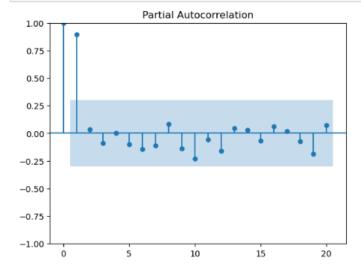
lower Close upper Close

Date		
2023-04-10	88.667326	109.949531
2023-04-11	88.538593	110.005401
2023-04-12	88.416767	110.056427
2023-04-13	88.301396	110.103002
2023-04-14	88.192067	110.145483
2023-04-17	88.088400	110.184194
2023-04-18	87.990046	110.219433
2023-04-19	87.896679	110.251469
2023-04-20	87.808002	110.280553
2023-04-21	87.723737	110.306912
2023-04-24	87.643627	110.330755
2023-04-25	87.567433	110.352276
2023-04-26	87.494931	110.371652
2023-04-27	87.425915	110.389047
2023-04-28	87.360189	110.404612

In [106]: # gráficamos plt.figure(figsize = (20,7)) plt.grid() plt.plot(train, label = 'Train') plt.plot(test, label = 'Test') plt.plot(tres, label = 'Predicciones', color = 'red') plt.plot(intervalos['lower close'], label = 'Lim. Inf. 90%', color = 'green') plt.plot(intervalos['upper close'], label = 'Lim. Sup. 90%', color = 'purple') plt.legend() plt.title('Pronosticos mediante AR(1)') plt.show() Pronosticos mediante AR(1)



In [113]: # Determinación del valor adecuado de p para AR(1) a partir de la función de autocorrelación parcial
 from statsmodels.graphics.tsaplots import plot_pacf
 plot_pacf(train, lags = 20)
 plt.show()



* Conclusión: El modelo AR(1) parace ser el mas adecuado

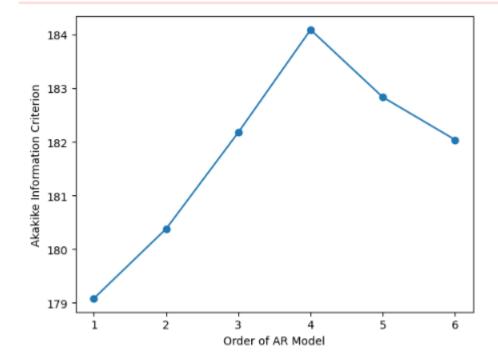
```
In [117]: # Determinación del valor adecuado de p para AR(p), a partir del criterio de de información Akaike
# fit the data to an AR(p) for p = 0,...,6 and save the BIC

AIC = np.zeros(7)
for p in range(7):
    model = ARIMA(train, order = (p,0,0))
    result = model.fit()

# save the BIC for AR(p)
    AIC[p] = result.aic

# graficamos

plt.plot(range(1,7), AIC[1:7], marker = 'o')
plt.xlabel('Order of AR Model')
plt.ylabel('Akakike Information Criterion')
plt.show()
```

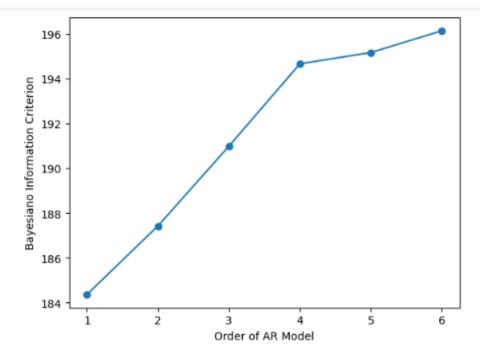


```
In [118]: # Determinación del valor adecuado de p para AR(p), a partir del criterio de de información Bayesiano
# fit the data to an AR(p) for p = 0,...,6 and save the BIC

BIC = np.zeros(7)
for p in range(7):
    mod = ARIMA(train, order = (p,0,0))
    res = mod.fit()

# save the BIC for AR(p)
    BIC[p] = res.bic

# Graficamos
plt.plot(range(1,7), BIC[1:7], marker = 'o')
plt.xlabel('Order of AR Model')
plt.ylabel('Bayesiano Information Criterion')
plt.show()
```



Conclusión: En ambos Indices se tiene el menor valor para p = 1.

· Se recomienda utilizar el modelo AR(1)