Business/Use Case

- Finding the highest growth in 60 days for a specific stock with the intention of expanding functionality to multiple stocks.
- The goal is to streamline the process below on a larger scale and build a stock porfolio of highest forecasted growth.

In Depth Analysis of MongoDB Stock

- Showcasing functions built specifically for EDA and Modeling of stock time series forecasting
- Historical stock data obtained from finance.yahoo.com
- Using ARIMA, Auto Arima and Facebook Prophet models

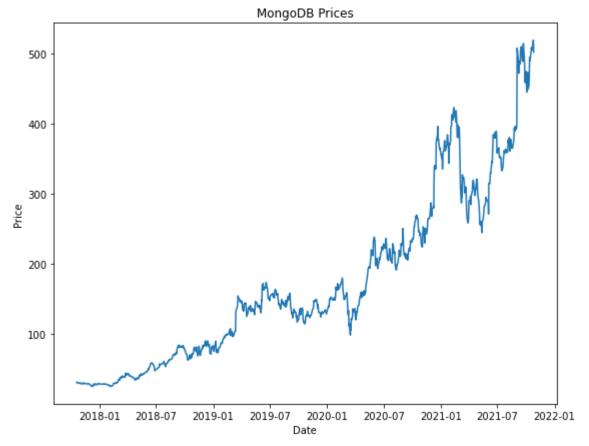
```
from Functions import *
In [2]:
          df = pd.read_csv('Data/MongoDB.csv')
In [3]:
          df.head()
In [4]:
Out[4]:
                                                      Close Adj Close
                                                                         Volume
                  Date
                            Open
                                      High
                                                  Low
           10/19/2017 33.000000 34.000000
                                            29.100000
                                                       32.07
                                                                  32.07
                                                                        11508500
            10/20/2017 33.369999 33.369999
                                            30.100000
                                                       30.68
                                                                  30.68
                                                                         2358700
            10/23/2017 30.510000 31.330000
                                            30.190001
                                                       30.50
                                                                  30.50
                                                                          749400
            10/24/2017 30.459999 30.920000
                                                                  30.57
                                                                          420700
                                            30.438999
                                                       30.57
            10/25/2017 30.500000 31.100000 29.879999
                                                       31.00
                                                                  31.00
                                                                         1219400
```

Preprocessing Function

- From the default stock data provided, we want to look at the change in Adj Close price over time (days)
- The Volume will be our exogenous variable

```
In [10]:
          X, Xvol = preprocess(init_data=df,exog=True)
In [11]:
          X.head()
          Date
Out[11]:
          2017-10-19
                        32.07
          2017-10-20
                        30.68
          2017-10-23
                        30.50
          2017-10-24
                        30.57
          2017-10-25
                        31.00
          Name: Adj Close, dtype: float64
```

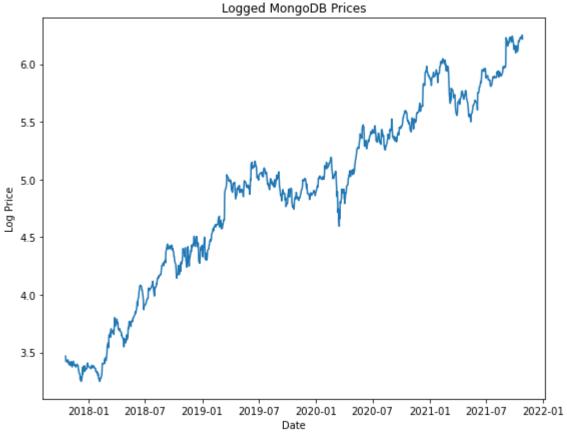
```
Xvol.head()
In [12]:
Out[12]:
         Date
          2017-10-19
                        11508500
          2017-10-20
                         2358700
          2017-10-23
                          749400
          2017-10-24
                          420700
          2017-10-25
                         1219400
         Name: Volume, dtype: int64
          figure = plt.figure(figsize=(9,7))
In [17]:
          plt.plot(X)
          plt.title('MongoDB Prices')
          plt.xlabel('Date')
          plt.ylabel('Price')
           plt.show();
```



Log Transformations and FB Prophet Prep

- Preprocessing can perform log transformations on the data
- Can also shape the data in the format used by Prophet

```
2017-10-23
                         3.417727
          2017-10-24
                         3.420019
          2017-10-25
                         3.433987
          Name: Adj Close, dtype: float64
In [21]:
           Xfb.head()
Out[21]:
                    ds
                           у
             2017-10-19 32.07
             2017-10-20
                       30.68
             2017-10-23
                       30.50
             2017-10-24
                        30.57
             2017-10-25 31.00
           figure2 = plt.figure(figsize=(9,7))
In [23]:
           plt.plot(Xlog)
           plt.title('Logged MongoDB Prices')
           plt.xlabel('Date')
           plt.ylabel('Log Price')
           plt.show();
```



Train Test Split for Time Series

• Instead of taking random samples of the data, train test split sets a cutoff date for training and testing data

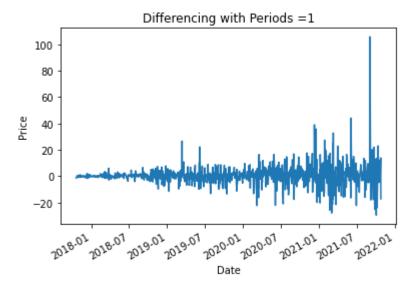
- The same preprocessing above is built in to the split, along with log transform and prophet set up
- Default split is 75% Train, 25% Test

```
Xtrain,Xtrainvol,Xtest,Xtestvol = train_test(df,exog=True)
In [10]:
          Xtrain.head()
In [11]:
Out[11]: Date
         2017-10-19
                       32.07
         2017-10-20
                       30.68
                       30.50
         2017-10-23
         2017-10-24
                       30.57
         2017-10-25
                       31.00
         Name: Adj Close, dtype: float64
          Xtest.head()
In [12]:
         Date
Out[12]:
         2020-10-26
                       240.100006
         2020-10-27
                       244.009995
         2020-10-28
                       240.039993
                       235.690002
         2020-10-29
         2020-10-30
                       228.470001
         Name: Adj Close, dtype: float64
          length data = len(df)
In [13]:
          length train = len(Xtrain)
          length_test = len(Xtest)
          print('Total Data Length:',length_data)
          print('Train Length:', length_train, length_train/length_data*100,"%")
          print('Test Length:', length_test, length_test/length_data*100,"%")
         Total Data Length: 1012
         Train Length: 759 75.0 %
         Test Length: 253 25.0 %
```

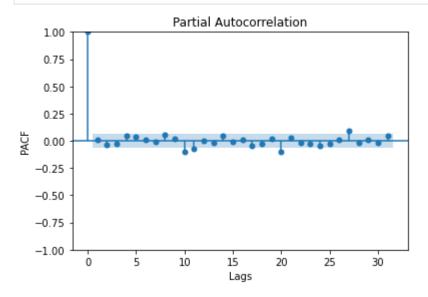
ARIMA Order Parameters

• These functions provide intial p,d,q values from ACF, PACF and Dickey-Fuller tests

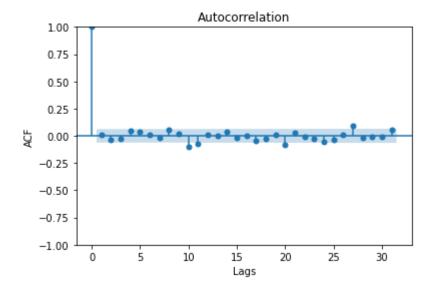
```
In [14]: d = return_d(data=X,plotting=True)
```



In [15]: p = return_p(data=X,plotting=True) # Uses differenced data to calculate PACF



In [16]: q = return_q(data=X,plotting=True) # Uses differenced data to calculate ACF



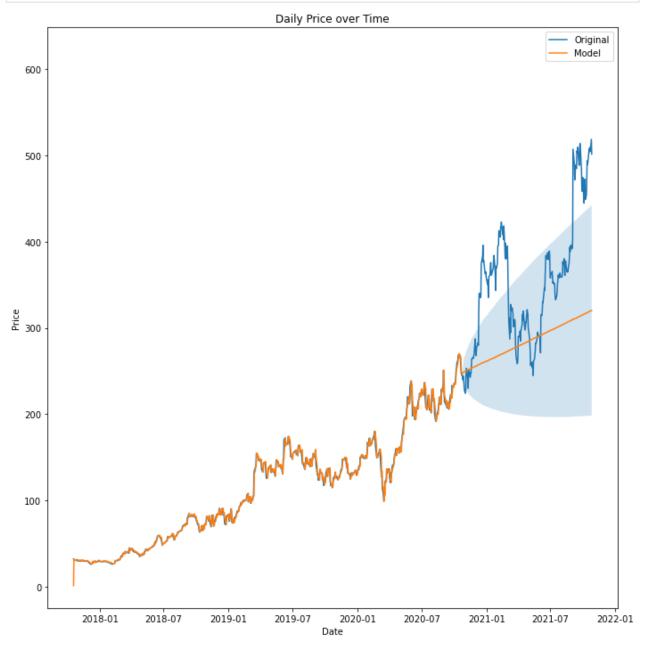
```
print("d = ",d)
print("q = ",q)

p = 0
d = 1
a = 0
```

Modeling

Base ARIMA Model

In [18]: arima = base_model(df,exog=True,logged=False,plotting=True,summary=True,mse=True)



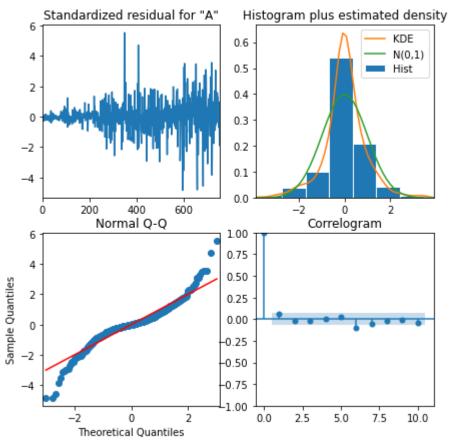
SARIMAX Results

Dep. Variable: Adj Close No. Observations: 759 Model: SARIMAX(0, 1, 0)Log Likelihood -2241.718 4489.435 Date: Mon, 15 Nov 2021 AIC Time: BIC 4503.327 20:36:09

Sample:		-	0 HQIC 759			4494.785	
Covariance	Type:		opg				
	coef	std err	Z	P> z	[0.025	0.975]	
intercept Volume sigma2	0.2859 7.089e-08 21.6920	0.183 9.42e-08 0.620	1.566 0.752 35.009	0.117 0.452 0.000	-0.072 -1.14e-07 20.478	0.644 2.56e-07 22.906	
Ljung-Box (L1) (Q): Prob(Q): Heteroskedasticity (H): Prob(H) (two-sided):		2.51 0.11 18.00 0.00	Jarque-Bera Prob(JB): Skew: Kurtosis:	а (ЈВ):	0 -0	.00 .00 .14	

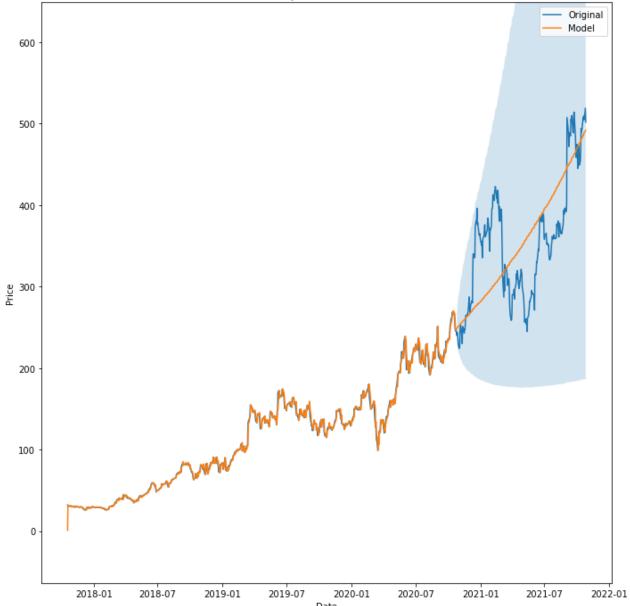
Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step). ARIMA Test RMSE: 92.10970700146592



In [19]: arima_logged = base_model(df,exog=True,logged=True,plotting=True,summary=True,mse=True)





SARIMAX Results

===========			==============
Dep. Variable:	Adj Close	No. Observations:	759
Model:	SARIMAX(0, 1, 0)	Log Likelihood	1423.479
Date:	Mon, 15 Nov 2021	AIC	-2840.958
Time:	20:36:10	BIC	-2827.065
Sample:	0	HQIC	-2835.607
	- 759		

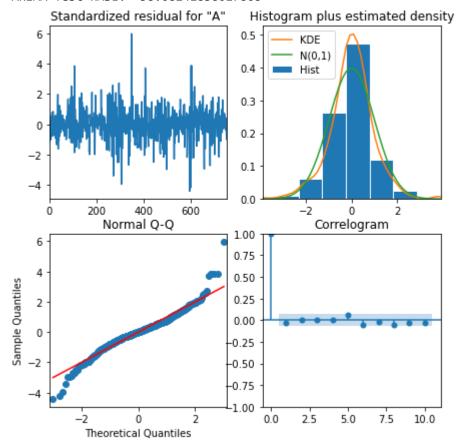
Covariance Type: opg

	coef	std err	z	P> z	[0.025	0.975]
intercept	0.0027	0.002	1.764	0.078	-0.000	0.006
Volume	0.0023	0.002	1.003	0.316	-0.002	0.007
sigma2	0.0014	4.21e-05	32.481	0.000	0.001	0.001

Ljung-Box (L1) (Q):	0.73	Jarque-Bera (JB):	414.68
<pre>Prob(Q):</pre>	0.39	Prob(JB):	0.00
Heteroskedasticity (H):	1.53	Skew:	0.05
<pre>Prob(H) (two-sided):</pre>	0.00	Kurtosis:	6.62

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step). ARIMA Test RMSE: 58.08241838017868



Base Model Findings

- Base ARIMA model has an AIC of 4489 and RMSE of 92
- Base ARIMA model with log transformed data has an AIC of -2840 and RMSE of 58
- In both metrics and visualization, the model with log transformed data performed better
- In both cases, it appears the Volume variable is insignificant

Auto Arima Model

```
Performing stepwise search to minimize aic
ARIMA(2,1,2)(0,0,0)[0] intercept
                                    : AIC=4478.800, Time=0.62 sec
                                    : AIC=4487.592, Time=0.06 sec
ARIMA(0,1,0)(0,0,0)[0] intercept
                                    : AIC=4487.080, Time=0.05 sec
ARIMA(1,1,0)(0,0,0)[0] intercept
                                    : AIC=4486.999, Time=0.05 sec
ARIMA(0,1,1)(0,0,0)[0] intercept
ARIMA(0,1,0)(0,0,0)[0]
                                    : AIC=4488.422, Time=0.02 sec
                                    : AIC=inf, Time=0.59 sec
ARIMA(1,1,2)(0,0,0)[0] intercept
ARIMA(2,1,1)(0,0,0)[0] intercept
                                    : AIC=inf, Time=0.58 sec
ARIMA(3,1,2)(0,0,0)[0] intercept
                                    : AIC=4480.460, Time=0.76 sec
ARIMA(2,1,3)(0,0,0)[0] intercept
                                    : AIC=4480.513, Time=0.84 sec
                                    : AIC=4488.916, Time=0.13 sec
ARIMA(1,1,1)(0,0,0)[0] intercept
                                    : AIC=4492.609, Time=0.26 sec
ARIMA(1,1,3)(0,0,0)[0] intercept
ARIMA(3,1,1)(0,0,0)[0] intercept
                                    : AIC=4492.633, Time=0.26 sec
ARIMA(3,1,3)(0,0,0)[0] intercept
                                    : AIC=4480.974, Time=0.96 sec
```

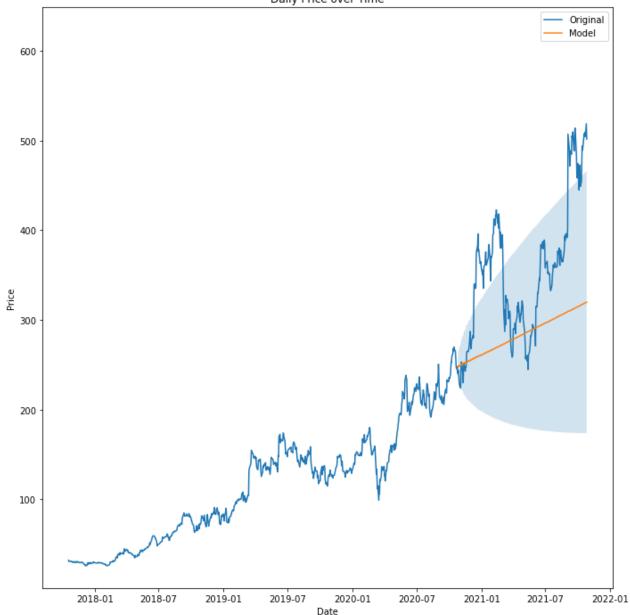
ARIMA(2,1,2)(0,0,0)[0]

: AIC=4479.588, Time=0.31 sec

Best model: ARIMA(2,1,2)(0,0,0)[0] intercept

Total fit time: 5.480 seconds





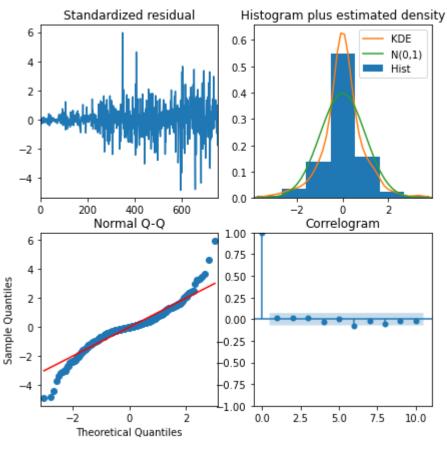
SARIMAX Results

	S, WE DO NESSEE								
========	========	=======	=======			========			
Dep. Variab	le:		y No.	Observations	5:	759			
Model:	SA	RIMAX(2, 1,	2) Log	Likelihood		-2233.400			
Date:	Mo	n, 15 Nov 2	021 AIC			4478.800			
Time:		20:36	:17 BIC			4506.584			
Sample:			0 HQIC	2		4489.500			
·		_	759						
Covariance ⁻	Туре:		opg						
=========	========	=======	=======			========			
	coef	std err	Z	P> z	[0.025	0.975]			
intercept	0.5848	0.352	1.663	0.096	-0.105	1.274			
ar.L1	-0.0882	0.023	-3.814	0.000	-0.134	-0.043			
ar.L2	-0.9625	0.024	-40.573	0.000	-1.009	-0.916			
ma.L1	0.1284	0.026	4.958	0.000	0.078	0.179			
ma.L2	0.9579	0.024	40.280	0.000	0.911	1.004			
sigma2	21.2140	0.586	36.223	0.000	20.066	22.362			

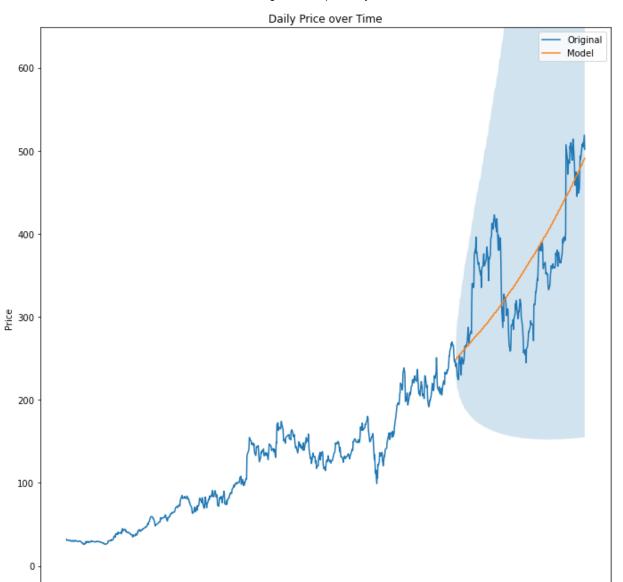
Ljung-Box (L1) (Q): 0.30 Jarque-Bera (JB): 796.26 Prob(Q): 0.59 Prob(JB): 0.00 Heteroskedasticity (H): 16.58 Skew: -0.07 Prob(H) (two-sided): 0.00 Kurtosis: 8.02

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step). Auto Arima Test RMSE: 92.40403475573405



Best model: ARIMA(0,1,0)(0,0,0)[0] intercept Total fit time: 0.858 seconds



SARIMAX Results

2019-07

2019-01

2020-01

2020-07

2021-01

2021-07

2022-01

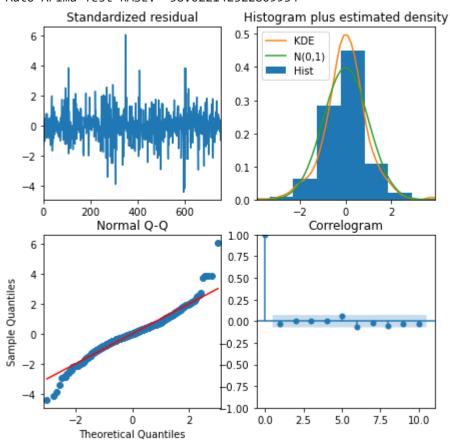
===========	======	=========	======	========		========
Dep. Variable:		<u>'</u>	y No.	Observations:	:	759
Model:	SAR	IMAX(0, 1, 0) Log	Likelihood		1423.106
Date:	Mon	, 15 Nov 202	1 AIC			-2842.212
Time:		20:36:19	9 BIC			-2832.951
Sample:		(0 HQIC			-2838.645
		- 759	9			
Covariance Type:		op	g			
=======================================	======	:=======:	======	========		=======
	coef	std err	Z	P> z	[0.025	0.975]
intercept 0.0	 0027	0.001	2.005	0.045	6.07e-05	0.005
sigma2 0.0	0014	4.19e-05	32.714	0.000	0.001	0.001
Ljung-Box (L1) (Q) ·	:=======:	====== 0.70	========= Jarque-Bera	 (1B)·	424.23
Prob(Q):	, •		0.40	Prob(JB):	(35).	0.00
Heteroskedasticity	v (H):		1.52	Skew:		0.11
Prob(H) (two-side			0.00	Kurtosis:		6.66

Warnings:

2018-01

2018-07

[1] Covariance matrix calculated using the outer product of gradients (complex-step). Auto Arima Test RMSE: 58.022142322809934



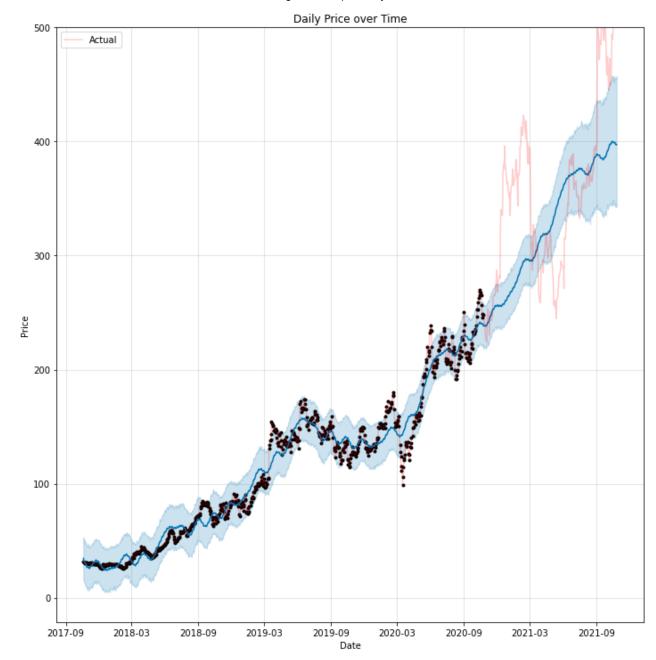
Auto ARIMA Findings

- The auto ARIMA model with untransformed data performed almost the same as the base ARIMA model. AIC = 4478 and RMSE = 92.4
- The auto ARIMA model with log transformed data also performed better with similar results to base ARIMA with transformed data. AIC = -2842 and RMSE = 58
- Visually, the log transformed data appears to be better fit as well

Facebook Prophet Model

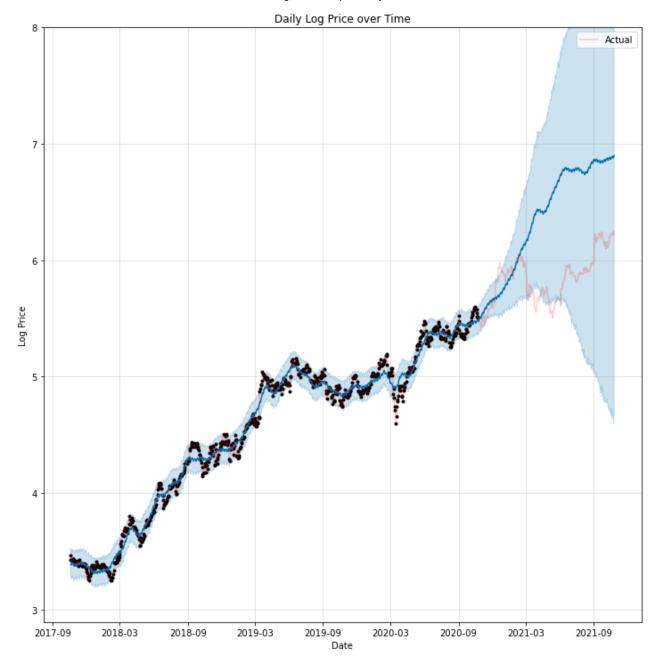
In [22]:

fb = create_prophet(data=df,logged=False,plotting=True,mse=True)



Prophet Test RMSE: 65.78887755293908

In [23]: fb_logged = create_prophet(data=df,logged=True,plotting=True,mse=True)



Logged Prophet Test RMSE: 369.84401898575334

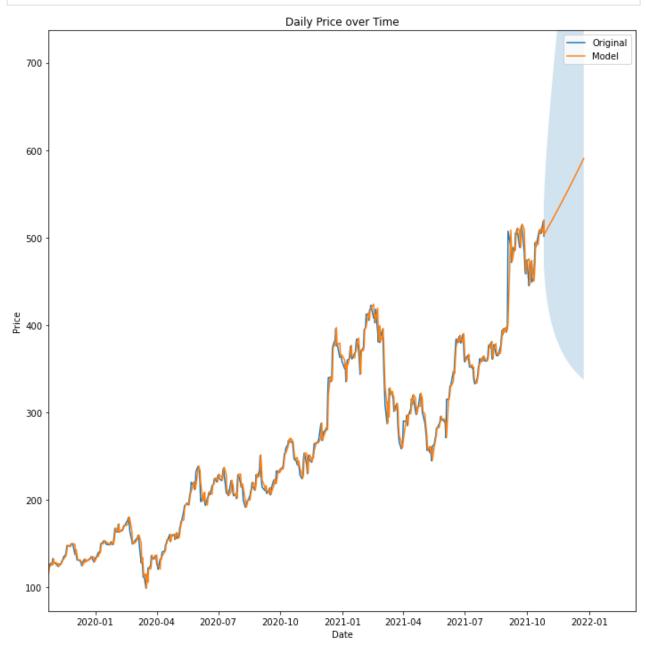
Facebook Prophet Findings

- Model with untransformed data has an RMSE of 65.8
- Model with log transformed data has a worse RMSE of 369.8
- In the vusualizations, the model with untransformed data provided a safe forecasting based on the trend
- However, the log transformed model overvalued the future prices

Highest Growths in 60 Days

• Utilizing the best version of each model above, the models will be refit using the entire data set and forecasting the growth after 60 days

Base Model Growth



SARIMAX Results

=========	=======		=======	========	=========	========	
Dep. Variable	e:	Adj Cl	ose No.	Observation:	s:	1012	
Model:	S	ARIMAX(0, 1,	0) Log	Likelihood		1902.632	
Date:	Me	on, 15 Nov 2	.021 AIC			-3801.265	
Time:		20:36	3:30 BIC			-3791.428	
Sample:			0 HQIC			-3797.528	
		- 1	.012				
Covariance T	ype:		opg				
=========	=======		========	========	=========		
	coef	std err	Z	P> z	[0.025	0.975]	
intercent	0.0027	0.001	2.315	0.021	0.000	0.005	

39.866

0.000

0.001

0.001

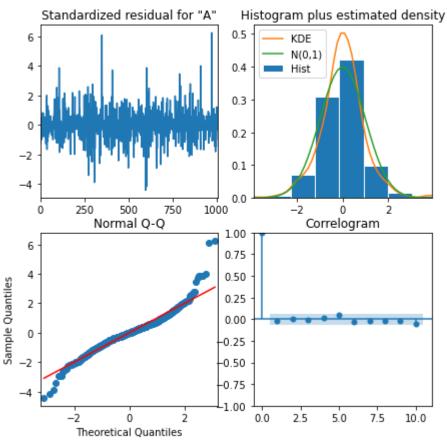
sigma2

0.0014

Ljung-Box (L1) (Q):	0.49	Jarque-Bera (JB):	869.35
<pre>Prob(Q):</pre>	0.48	Prob(JB):	0.00
Heteroskedasticity (H):	0.99	Skew:	0.42
<pre>Prob(H) (two-sided):</pre>	0.92	Kurtosis:	7.46

Warnings:

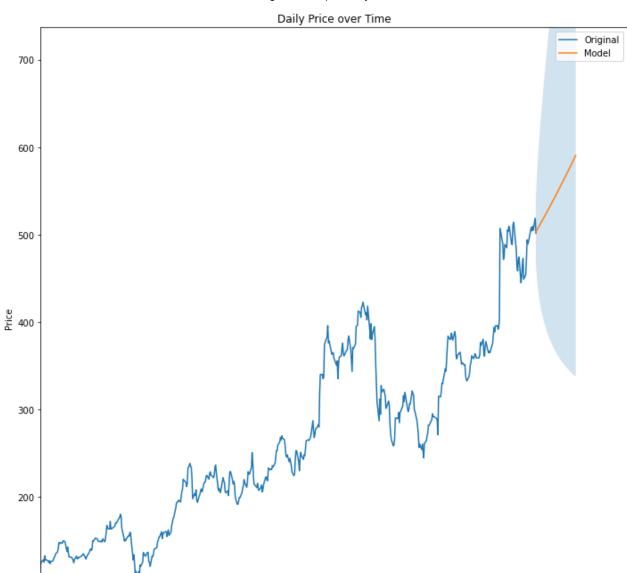
[1] Covariance matrix calculated using the outer product of gradients (complex-step). ROI: $17.41\,\%$



Auto ARIMA Growth

Best model: ARIMA(0,1,0)(0,0,0)[0] intercept

Total fit time: 1.041 seconds



SARIMAX Results

2020-10

2021-01

Date

2021-04

2021-07

2021-10

2022-01

Dep. Variable:			y No.	Observations:	;	1012		
Model:	SA	RIMAX(0, 1, 0) Log	Likelihood		1902.632		
Date:	Мо	n, 15 Nov 202	1 AIC			-3801.265		
Time:		20:36:3	1 BIC			-3791.428		
Sample:			0 HQIC			-3797.528		
·		- 101	2					
Covariance Type: opg								
==========	=======		======	========		:=======		
	coef	std err	Z	P> z	[0.025	0.975]		
intercept	0.0027	0.001	2.315	0.021	0.000	0.005		
sigma2	0.0014	3.41e-05	39.866	0.000	0.001	0.001		
=======================================		========	======		·========		==	
Ljung-Box (L1)	(Q):		0.49		(JB):	869.		
Prob(Q):			0.48	Prob(JB):		0.0		
Heteroskedasticity (H):		0.99	Skew:		0.4			
Prob(H) (two-s	ided):		0.92	Kurtosis:		7.	46	
==========	=======	=========	=======	=========		=========	==	

Warnings:

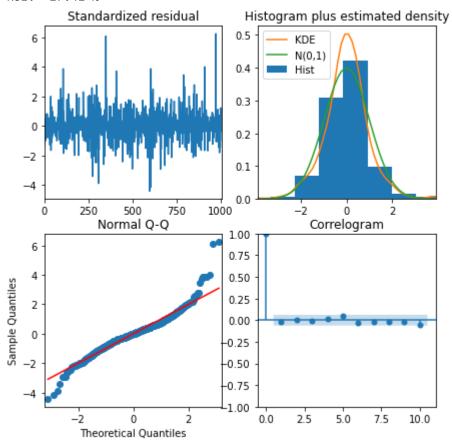
100

2020-01

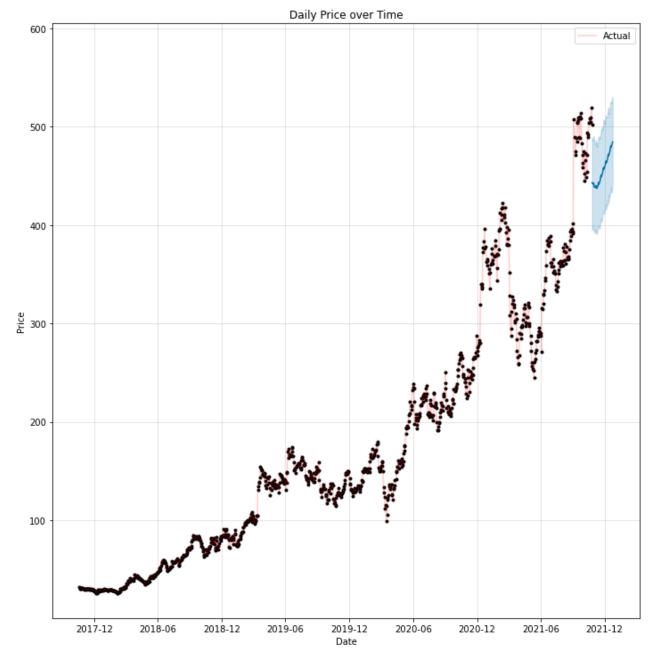
2020-04

2020-07

[1] Covariance matrix calculated using the outer product of gradients (complex-step). ROI: 17.41 %



Facebook Prophet Growth



ROI: -3.42 %

Conclusions

- The ARIMA models expect a growth of ~ 17% after 60 days
- The Facebook Prophet model expects to lose ~3% after 60 days. However, it maintains a positive growth rate over time.
- Based on the models above, it looks like MongoDB would be a safe buy