10만 전자 가즈아

6팀 PL 정기호 김명근 김혜진 신문혁



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리서치 요약

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모델링 / 튜닝 / 검증 [Prophet / ARIMA] 2

탐색적 데이터 분석

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시사점 및 결론



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1. 리서치 요약: SAMSUNG Word_Cloud



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1. 리서치 요약

삼성전자 사업보고서/2021.03.09

(단위 : 억원)

누	<u> </u> 문	매출유형	품 목		제[52기	제51기	제[50기
CE	[부문	제 • 상품, 용역 및 기타매출	TV, 모니터, 냉장고, 세탁기, 에어컨 등	계	481,733	453,228	426,498
IM	부문	제 • 상품, 용역 및 기타매출	HHP, 네트워크시스템, 컴퓨터 등	계	995,875	1,072,662	1,006,777
	반도체 사업	제 • 상품, 용역 및 기타매출	DRAM, NAND Flash, 모바일AP 등	계	728,578	649,391	862,910
DS 부문	DP 사업	제 • 상품, 용역 및 기타매출	스마트폰용 OLED, TV • 모니터용 LCD 패널 등	계	305,857	310,539	324,650
	기타	_	_	계	△4,074	△4,750	△1,904
		부	문 계		1,030,361	955,180	1,185,656
Harman 부문		제 • 상품, 용역 및 기타매출	디지털 콕핏, 텔레매틱스, 스피커 등	계	91,837	100,771	88,437
기	타	_	_	계	△231,736	△277,832	△269,654
		합	계		2,368,070	2,304,009	2,437,714

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2. 탐색적 데이터 분석

[Data]

df = yf.download('005930.KS', start='2016-01-01', end='2021-08-31')
df

	0pen	High	Low	Close	Adj Close	Volume
Date						
2016-01-04	25200.0	25200.0	24100.0	24100.0	20770.701172	15346950
2016-01-05	24040.0	24360.0	23720.0	24160.0	20822.406250	10800100
2016-01-06	24160.0	24160.0	23360.0	23500.0	20253.585938	18337600
2016-01-07	23320.0	23660.0	23020.0	23260.0	20046.742188	14119400
2016-01-08	23260.0	23720.0	23260.0	23420.0	20184.638672	12888150
2021-08-25	76200.0	76600.0	74900.0	75700.0	75700.000000	22319664
2021-08-26	76100.0	76200.0	74600.0	74600.0	74600.000000	16671494
2021-08-27	74300.0	75000.0	73800.0	74300.0	74300.000000	15172748
2021-08-30	75400.0	75500.0	74200.0	74600.0	74600.000000	12686999
2021-08-31	74900.0	76700.0	74300.0	76700.0	76700.000000	24630370
1384 rows × 6	columns					

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2. 탐색적 데이터 분석

[Data]

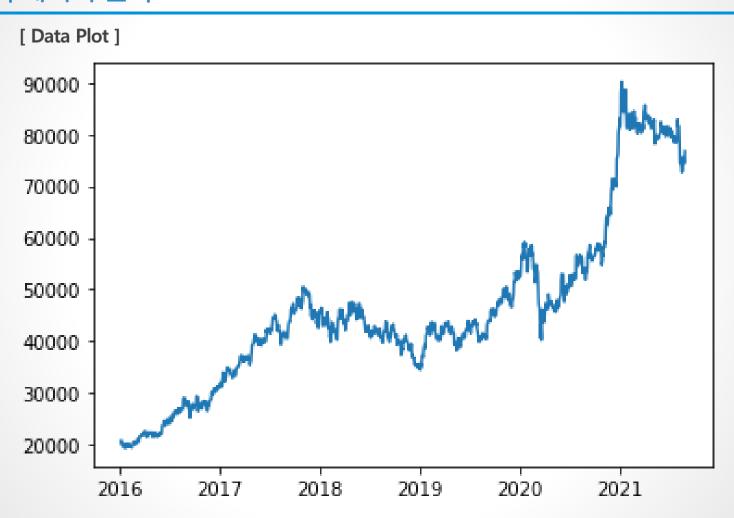
df.describe() # 삼성 주가

	0pen	High	Low	Close	Adj Close	Volume
count	1384.000000	1384.000000	1384.000000	1384.000000	1384.000000	1.384000e+03
mean	49500.585260	49998.945087	49020.223988	49504.855491	46008.932914	1.463016e+07
std	15467.569951	15604.234335	15329.013050	15438.383127	16483.025364	8.280080e+06
min	21760.000000	22660.000000	21760.000000	22520.000000	19408.968750	0.000000e+00
25%	41770.000000	42100.000000	41487.500000	41840.000000	37275.034180	9.350674e+06
50%	47270.000000	47610.000000	46760.000000	47250.000000	43033.273438	1.247097e+07
75 %	54855.000000	55500.000000	54300.000000	54925.000000	51502.114258	1.711926e+07
max	90300.000000	96800.000000	89500.000000	91000.000000	90198.078125	9.030618e+07

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2. 탐색적 데이터 분석



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3. Prophet

[열 변환]

	ds	У			
0	2016-01-04	20770.701172			
1	2016-01-05	20822.406250			
2	2016-01-06	20253.585938			
3	2016-01-07	20046.742188			
4	2016-01-08	20184.638672			
1379	2021-08-25	75700.000000			
1380	2021-08-26	74600.000000			
1381	2021-08-27	74300.000000			
1382	2021-08-30	74600.000000			
1383	2021-08-31	76700.000000			
1384 rows × 2 columns					

[ADF Test]

adf_test(df_samsung.y)	
Test Statistic p-value # of Lags Used # of Observations Used Critical Value (1%) Critical Value (5%) Critical Value (10%) dtype: float64	-0.765326 0.829096 18.000000 1365.000000 -3.435150 -2.863660 -2.567899
L KDCC To at 1	

>>> [KPSS Test]

kpss_test(df_samsung.y)	
Test Statistic p-value # of Lags Critical Value (10%) Critical Value (5%) Critical Value (2.5%) Critical Value (1%) dtype: float64	4.190858 0.010000 24.000000 0.347000 0.463000 0.574000 0.739000

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3. Prophet

[Data Set 설정]

```
df_samsung_train = df_samsung[df_samsung['ds']<='2021-07-31']
df_samsung_test = df_samsung[df_samsung['ds']>'2021-07-31']
```

[Prophet Model 설정]

```
model = Prophet(seasonality_mode='multiplicative')
model.fit(df_samsung_train)
```

[1 Month 예측]

```
df_future1 = model.make_future_dataframe(periods=21, freq='d')
df_forecast1 = model.predict(df_future1)
```

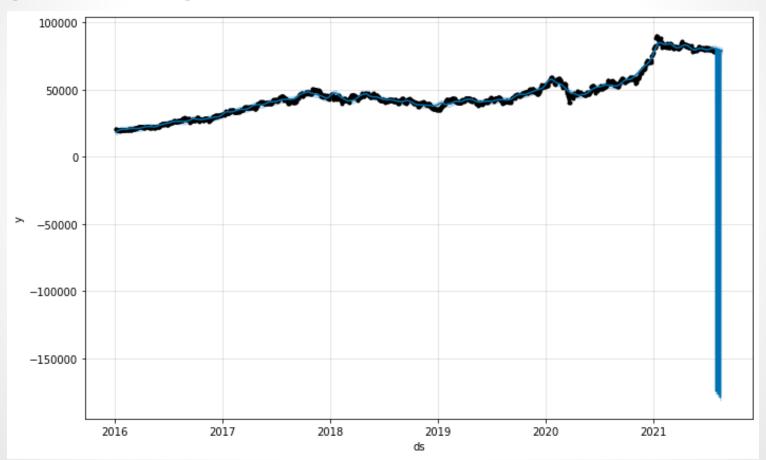
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3. Prophet

[1 Month 예측 결과]

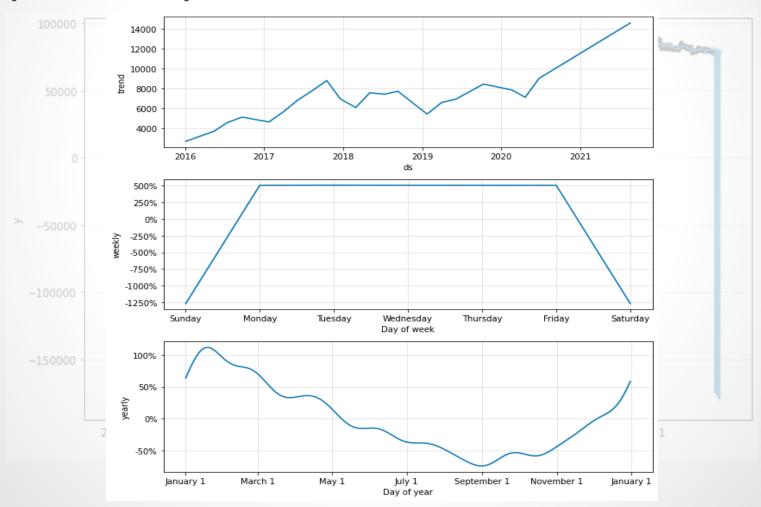


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3. Prophet

[1 Month 예측 결과]



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3. Prophet

[weekly seasonality False 로 Prophet Model 설정]

```
df_future = prophet.make_future_dataframe(periods=21, freq='d')
df_forecast = prophet.predict(df_future)
model.plot(df_forecast)
plt.tight_layout()
plt.show()
```

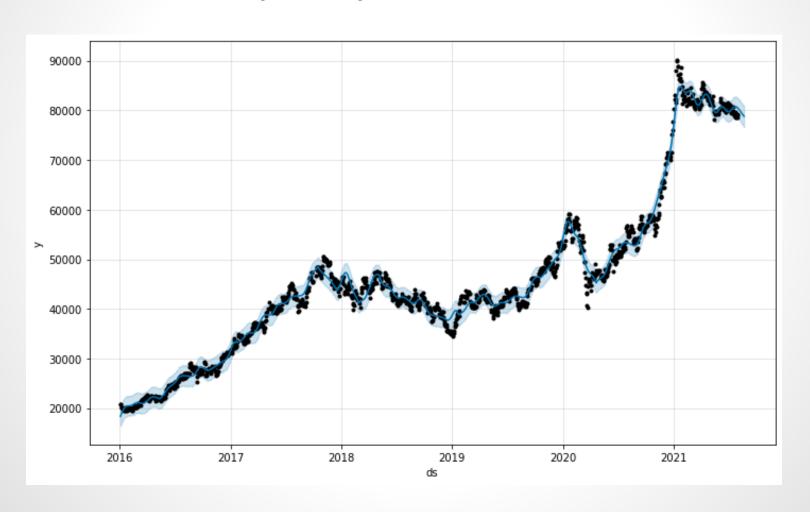
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3. Prophet

[1 Month 예측 결과 : weekly seasonality False]



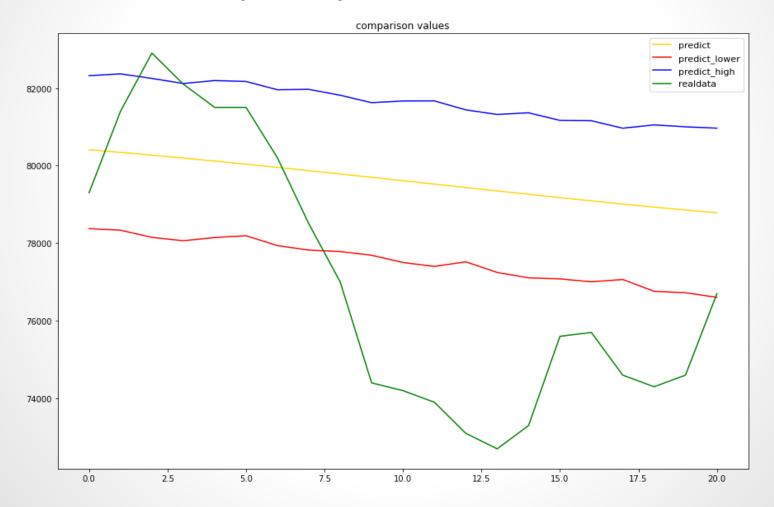
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3. Prophet

[1 Month 예측 결과 : weekly seasonality False]



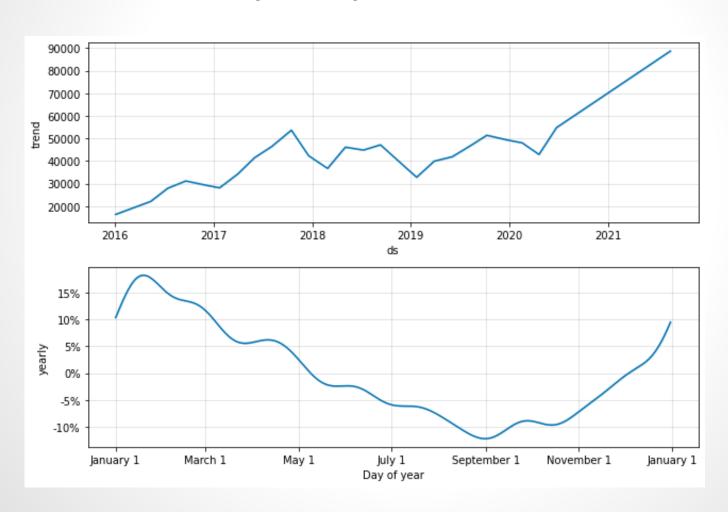
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3. Prophet

[1 Month 예측 결과 : weekly seasonality False]



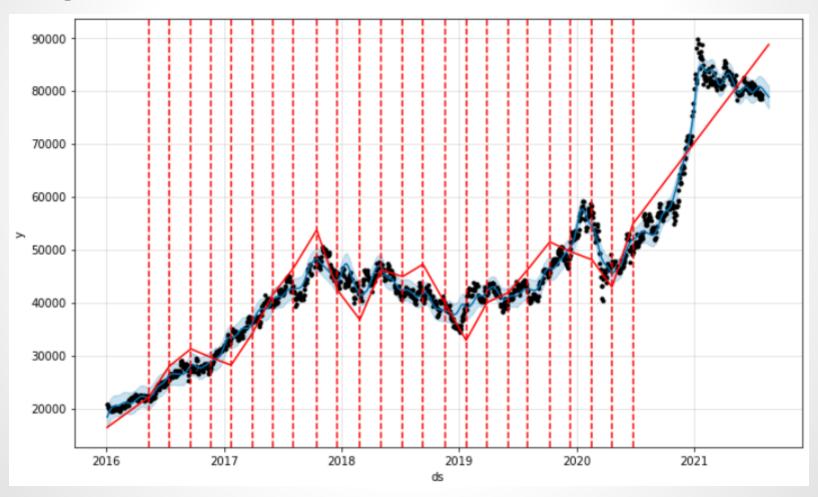
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3. Prophet

[Change Point]



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3. Prophet

[결과치 조정 – 상한가 및 하한가 설정]

```
# 상한가 설정
df samsung train['cap'] = 90000
#하한가 설정
df_samsung_train['floor'] = 10000
# 상한가 적용을 위한 파라미터를 다음과 같이 설정
re_prophet = Prophet(seasonality_mode = 'multiplicative',
               growth = 'logistic',
               yearly_seasonality = True,
               weekly_seasonality = False,
               daily_seasonality = False,
               changepoint prior scale = 0.5)
re_prophet.fit(df_samsung_train)
# 21일 기간 예측
df_future2 = re_prophet.make_future_dataframe(periods = 21, freq = 'd')
# 상한가 하한가 설정
df_future2['cap'] = 90000
df_future2['floor'] = 10000
```

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3. Prophet

[상한선 하한선 데이터 제거]

```
df_del_samsung = df_samsung_train
df del samsung.loc[df samsung train['y'] > 90000, 'y'] = None
df del samsung.loc[df samsung train['y'] < 10000, 'y'] = None
# prophet 모델 학습
rere_prophet = Prophet(seasonality_mode = 'multiplicative',
                      growth = 'logistic',
                yearly_seasonality = True,
                weekly seasonality = False.
                daily seasonality = False.
                changepoint prior scale = 0.5)
rere_prophet.fit(df_del_samsung)
# 21일 예측
df future3 = rere prophet.make future dataframe(periods = 21, freq = 'd')
# 상한가 하한가 설정
df_future3['cap'] = 90000
df future3['floor'] = 10000
```

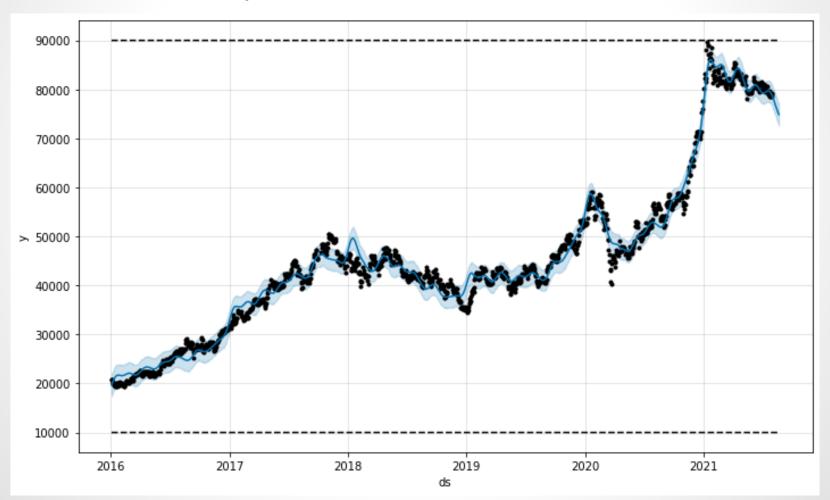
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3. Prophet

[상한선 하한선 데이터 제거 plot]



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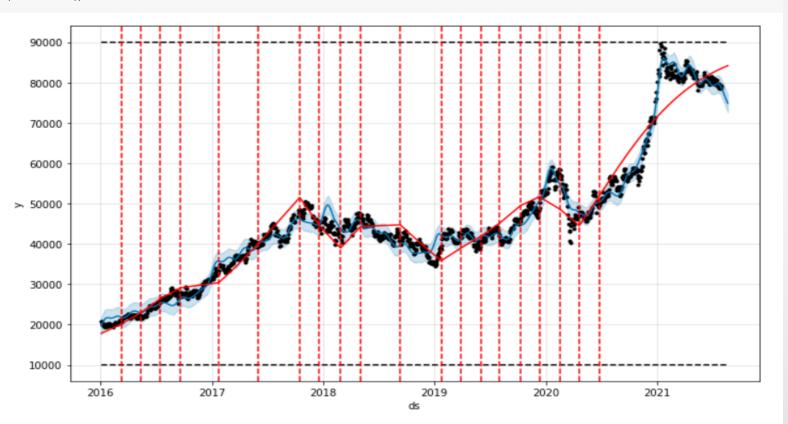
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3. Prophet

[Outlier 설정 후 Changepoint 설정]

```
fig = rere_prophet.plot(df_forecast3)
add_changepoints_to_plot(fig.gca(), rere_prophet, df_forecast3)
plt.show()
```



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3. Prophet

[1 Month 예측 결과 : 상한선 하한선 데이터 제거]

```
df_forecast3[['ds','yhat', 'yhat_lower', 'yhat_upper']].tail(5)
```

	ds	yhat	yhat_lower	yhat_upper
1379	2021-08-16	75525.958015	73345.741464	77663.499368
1380	2021-08-17	75350.012784	73294.413443	77502.606011
1381	2021-08-18	75182.379422	73124.931138	77377.627010
1382	2021-08-19	75024.159061	72697.490991	77107.833837
1383	2021-08-20	74876.470098	72603.623330	77179.442031

pred_fbprophet_y_1 = df_forecast3.yhat.values[-21:]

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3. Prophet

[결과 비교 분석]

df_test.tail(5)

	FBprophet predict	FBprophet predict	remove outlier	real data
16	79069.492181		75525.958015	75700.0
17	78984.675650		75350.012784	74600.0
18	78902.163800		75182.379422	74300.0
19	78822.781641		75024.159061	74600.0
20	78747.471330		74876.470098	76700.0

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3. Prophet

[RMSE 검증]

```
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt

plt.figure(figsize=(20, 15))

# fbprophet 모델의 rmse
rmse_fbprophet = sqrt(mean_squared_error(pred_fbprophet_y, test_y))

# 전처리 진행한 fbprophet 모델의 rmse
rmse_fbprophet_1 = sqrt(mean_squared_error(pred_fbprophet_y_1, test_y))
```

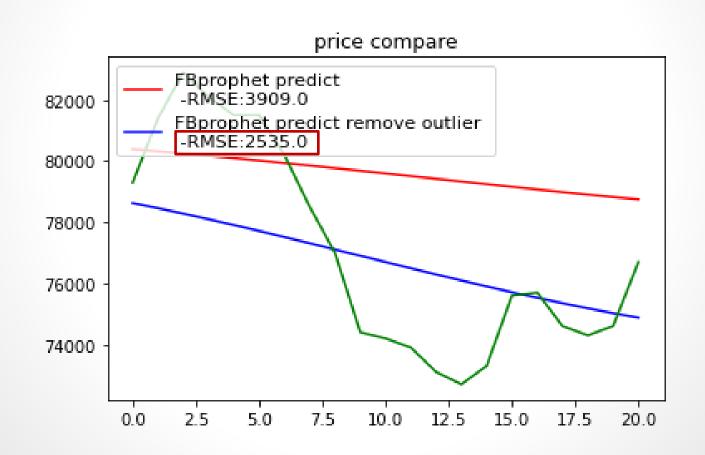
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3. Prophet

[RMSE 검증 결과 Plot]



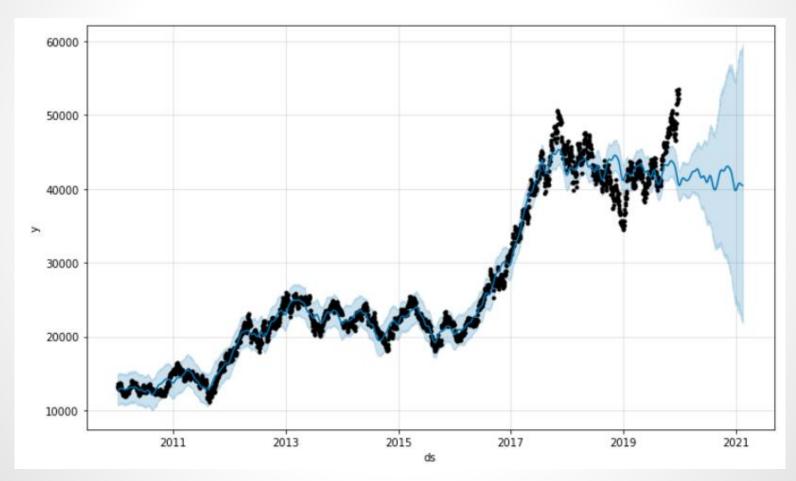
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3. Prophet

[2010~2021 Data / 1Year 예측]



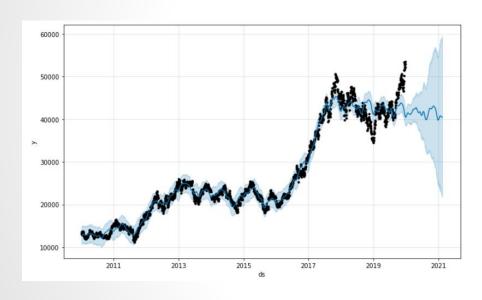
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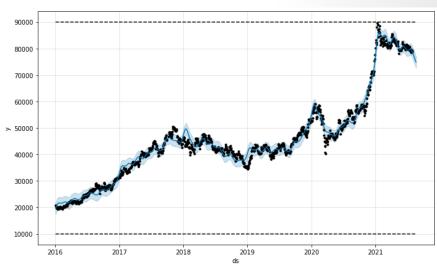
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3. Prophet

[Prophet Model 비교]





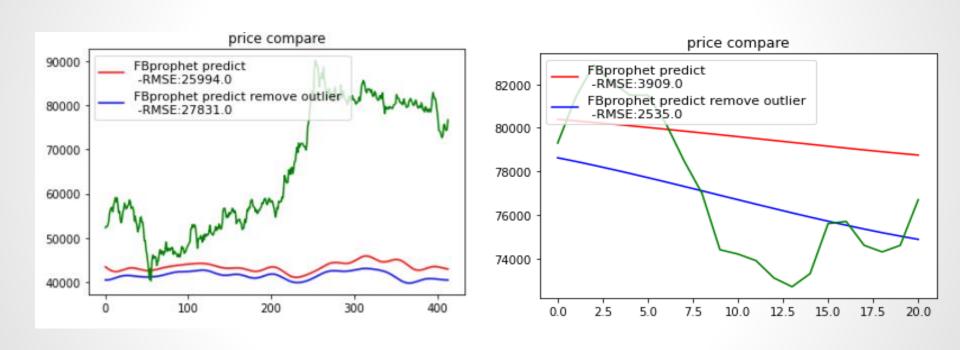
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3. Prophet

[Prophet Model 비교]



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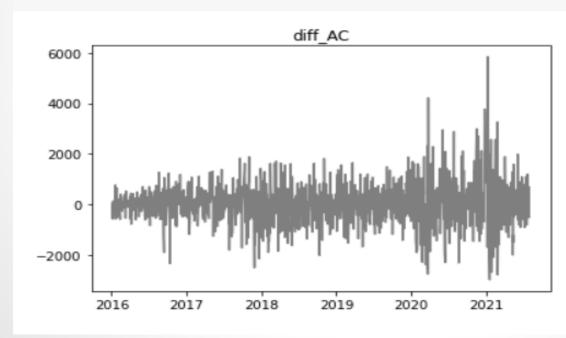
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3. ARIMA

[Differencing]

```
diff_ACm = df_samsung['Adj Close'].diff(1)
diff_AC = diff_ACm.fillna(0)
plt.plot(diff_AC, color='black', alpha=0.5)
plt.title('diff_AC')
plt.show()
```



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3. ARIMA

[Differencing한 결과로 adf_test / kpss_test]

```
adf_test(diff_AC)
Results of Dickey-Fuller Test:
Test Statistic
                              -8.169455e+00
p-value
                               8.701976e-13
#Lags Used
                               1.700000e+01
Number of Observations Used
                              1.345000e+03
Critical Value (1%)
                              -3.435221e+00
Critical Value (5%)
                              -2.863691e+00
Critical Value (10%)
                              -2.567915e+00
dtype: float64
kpss_test(diff_AC)
Results of KPSS Test:
Test Statistic
                         0.096151
p-value
                         0.100000
Lags Used
                         3.000000
Critical Value (10%)
                         0.347000
Critical Value (5%)
                         0.463000
Critical Value (2.5%)
                         0.574000
Critical Value (1%)
                         0.739000
dtype: float64
```

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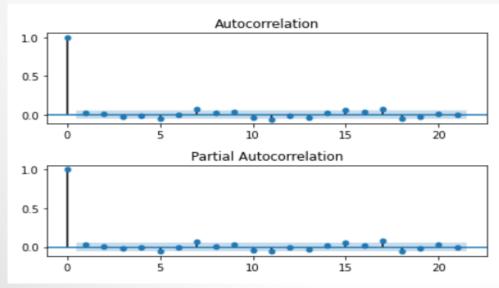
3. ARIMA

[Data ACF / PACF]

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

N_LAGS = 21
SIGNIFICANCE_LEVEL = 0.05

fig, ax = plt.subplots(2, 1)
plot_acf(diff_AC, ax=ax[0], lags=N_LAGS, alpha=SIGNIFICANCE_LEVEL)
plot_pacf(diff_AC, ax=ax[1], lags=N_LAGS, alpha=SIGNIFICANCE_LEVEL)
plt.tight_layout()
```



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3. ARIMA

[ACF, PACF TEST for diagnosis ARIMA(p,d,q)]

	coef	std err	z	P> z	[0.025	0.975]
ar.L1.D.Adj Close ma.L1.D.Adj Close	0.1931 -0.1616	0.480 0.482	0.402 -0.335	0.688 0.738	-0.748 -1.107	1.134 0.784
=======================================	coef	std err	Z	P> z	 [0.025	0.975]
ar.L1.D.Adj Close ma.L1.D.Adj Close ma.L2.D.Adj Close	-0.5563 0.5876 0.0371	0.409 0.409 0.028	-1.359 1.435 1.307	0.174 0.152 0.191	-1.359 -0.215 -0.019	0.246 1.390 0.093
	coef	std err	Z	P> z	[0.025	0.975]
ar.L1.D.Adj Close ar.L2.D.Adj Close ma.L1.D.Adj Close	-0.5195 0.0357 0.5501	0.429 0.028 0.429	-1.210 1.276 1.283	0.227 0.202 0.200	-1.361 -0.019 -0.291	0.322 0.090 1.391
=======================================	coef	std err	Z	P> z	[0.025	0.975]
ar.L1.D.Adj Close ar.L2.D.Adj Close ma.L1.D.Adj Close ma.L2.D.Adj Close	1.2928 -0.9307 -1.2556 0.8925	0.057 0.035 0.069 0.041	22.592 -26.453 -18.103 21.749	0.000 0.000 0.000 0.000	1.181 -1.000 -1.391 0.812	1.405 -0.862 -1.120 0.973

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3. ARIMA

[ARIMA Model : Data Differencing]

```
model = ARIMA(df_samsung['Adj Close'], order=(2,1,2))
model_fit1 = model.fit(trend='nc',full_output=True, disp=True, start_ar_lags=4)
print(model_fit1.summary())
```

[ARIMA Model: Data 차분 _ Summary]

ARIMA Model Results							
Dep. Variable: Model: Method: Date: Time: Sample:	ARIMA(2, 1, 2) css-mle Fri, 03 Sep 2021	No. Observations: Log Likelihood S.D. of innovations AIC BIC HQIC	1362 -11016 . 419 787 . 948 22042 . 839 22068 . 922 22052 . 603				
Sample:	1	HQIC	22052 . 603				

						=======
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.D.Adj Close ar.L2.D.Adj Close ma.L1.D.Adj Close ma.L2.D.Adj Close	1.2928 -0.9307 -1.2556 0.8925	0.057 0.035 0.069 0.041	22.592 -26.453 -18.103 21.749	0.000 0.000 0.000 0.000	1.181 -1.000 -1.391 0.812	1.405 -0.862 -1.120 0.973
		Roots				

	Rea I	Imaginary	Modulus	Frequency
AR.1	0.6945	-0.7695j	1.0365	-0.1331
AR.2	0.6945	+0.7695j	1.0365	0.1331
MA.1	0.7034	-0.7910j	1.0585	-0.1343
MA.2	0.7034	+0.7910j	1.0585	0.1343

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3. ARIMA

[ARIMA Model : Data Differencing]

```
# 마지막 21일의 예측 데이터 (2021-08-01 ~ 2021-08-31)
pred_arima_AC1 = forecast_data1[0].tolist()
# 해당 forecast의 [0]번째 array에 예측된 가격이 나옴.
# 실제 21일의 데이터 (2021-08-01 ~ 2021-08-31)
test_samsung = yf.download('005930.KS', '2021-08-01', '2021-08-31')['Adj Close']
test AC1 = pd.DataFrame(test samsung)
# 마지막 21일의 예측 데이터 최소값
pred_AC1_lower = []
# 마지막 21일의 예측 데이터 최대값
pred AC1 upper = []
for lower_upper in forecast_data[2]:
   lower = lower_upper[0]
   upper = lower upper[1]
   pred_AC1_lower.append(lower)
   pred_AC1_upper.append(upper)
```

```
pred_arima_AC1 = pd.DataFrame(np.array(pred_arima_AC1).astype(int))
pred_AC1_lower = np.array(pred_AC1_lower).astype(int)
pred_AC1_upper = np.array(pred_AC1_upper).astype(int)
test_AC1 = test_AC1.values
```

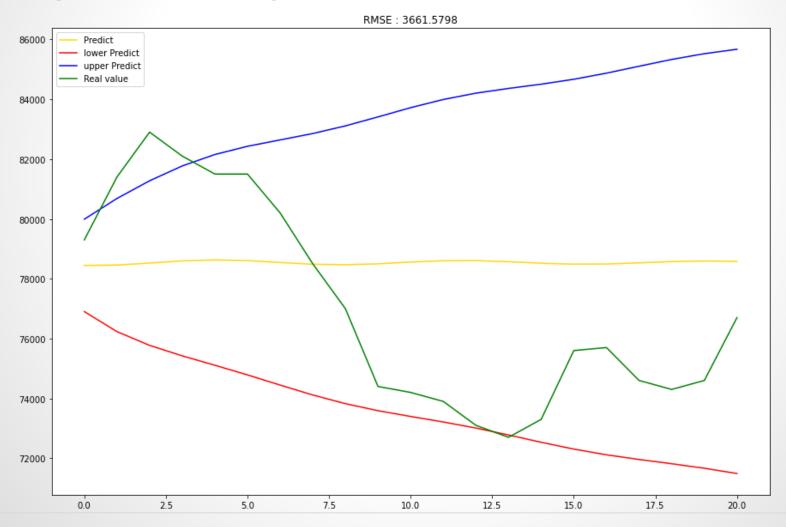
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3. ARIMA

[ARIMA Model 결과 Plot]



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3. ARIMA

[Data log, Differencing 시행]

```
In_AC = np.log(df_samsung['Adj Close'])
plt.plot(ln_AC, color='black', alpha=0.5)
plt.title('logscale_AC')
plt.show()
```

```
In_diff_ACm = In_AC.diff(1)
In_diff_AC = In_diff_ACm.fillna(0)
In_diff_AC
```

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3. ARIMA

[Data log, Differencing ADF / KPSS Test]

adf_test(In_diff_AC)		kpss_test(In_diff_AC)	
Results of Dickey-Fuller Test: Test Statistic p-value #Lags Used Number of Observations Used Critical Value (1%) Critical Value (5%) Critical Value (10%) dtype: float64	-22.044447 0.000000 2.000000 1360.000000 -3.435167 -2.863668 -2.567903	Results of KPSS Test: Test Statistic p-value Lags Used Critical Value (10%) Critical Value (5%) Critical Value (2.5%) Critical Value (1%) dtype: float64	0.091651 0.100000 8.000000 0.347000 0.463000 0.574000 0.739000

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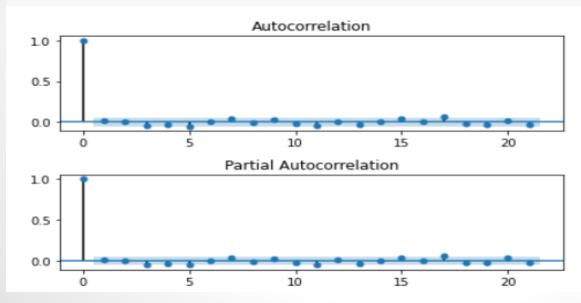
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3. ARIMA

[Data log, Differencing ACF / PACF]

```
N_LAGS = 21
SIGNIFICANCE_LEVEL = 0.05 #음영값임....

fig, ax = plt.subplots(2, 1)
plot_acf(In_diff_AC, ax=ax[0], lags=N_LAGS, alpha=SIGNIFICANCE_LEVEL)
plot_pacf(In_diff_AC, ax=ax[1], lags=N_LAGS, alpha=SIGNIFICANCE_LEVEL)
plt.tight_layout()
```



SAMSUNG

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3. ARIMA

[ACF, PACF TEST for diagnosis ARIMA(p,d,q)]

=======================================	coef	std err	z	P> z	[0.025	0.975]
const	0.0010	0.000	2.147	0.032	8.5e-05	0.002
ar.L1.D.Adj Close	-0.9921	0.012	-79.680	0.000	-1.017	-0.968
ma.L1.D.Adj Close	0.9950	0.010	102.521	0.000	0.976	1.014

	coef	std err	z	P> z	[0.025	0.975]
const ar.L1.D.Adj Close ar.L2.D.Adj Close ma.L1.D.Adj Close	0.0010 1.2023 -0.9665 -1.1822	0.000 0.026 0.024 0.028	2.125 45.933 -40.233 -42.497	0.034 0.000 0.000 0.000	7.61e-05 1.151 -1.014 -1.237	0.002 1.254 -0.919 -1.128
ma.L2.D.Adj Close	0.9585	0.027	34.985	0.000	0.905	1.012

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3. ARIMA

[ARIMA Model : Data log, Differencing]

```
model = ARIMA(In_AC, order=(1,1,1))
model_fit2 = model.fit(trend='c',full_output=True, disp=True, start_ar_lags=2)
```

[ARIMA Model: Data 로그, 차분 _ Summary]

		A	RIMA Mode	l Results			_
Dep. Variable: Model: Method: Date: Time: Sample:		D.Adj Close ARIMA(1, 1, 1) css-mle Fri, 03 Sep 2021 06:31:23		No. Observations: Log Likelihood S.D. of innovations AIC BIC HQIC		 1362 3635.981 0.017 -7263.962 -7243.095 -7256.150	
		coef	std err	z	P> z	[0.025	0.975]
const ar.L1.D.Adj ma.L1.D.Adj		0.0010 -0.9921 0.9950		-79.680 102.521		8.5e-05 -1.017 0.976	0.002 -0.968 1.014
Rea I		 Imagina	 ry	Modulus	Frequency		
AR.1 MA.1	-1.0080 -1.0051		+0.000		1.0080 1.0051	0.5000 0.5000	

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3. ARIMA

[1Month 예측: ARIMA Model (Data log, Differencing)]

```
# 마지막 21일의 예측 데이터 (2021-08-01 ~ 2021-08-31)
pred arima AC2 = np.exp(forecast data2[0].tolist())
# 실제 21일의 데이터 (2021-08-01 ~ 2021-08-31)
test_samsung = yf.download('005930.KS', '2021-08-01', '2021-08-31')['Adj Close']
test AC2 = pd.DataFrame(test samsung)
# 마지막 21일의 예측 데이터 최소값
pred_AC2_lower = []
# 마지막 21일의 예측 데이터 최대값
pred_AC2_upper = []
for lower_upper in np.exp(forecast_data2[2]):
   lower = lower_upper[0]
   upper = lower_upper[1]
   pred AC2 lower.append(lower)
   pred_AC2_upper.append(upper)
```

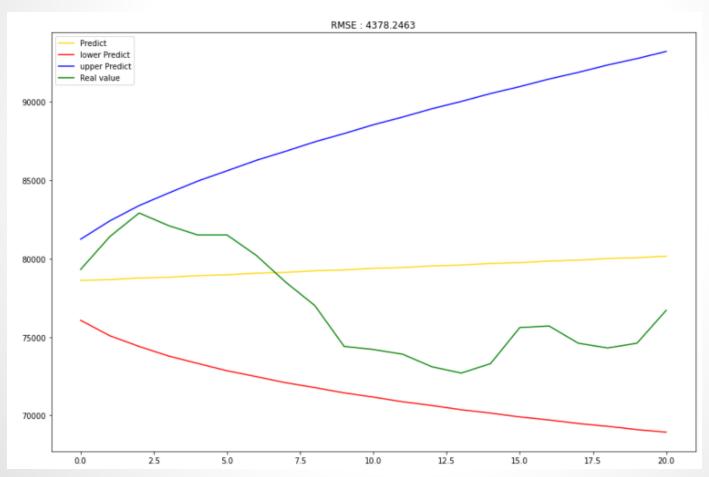
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3. ARIMA

[1Month 예측: ARIMA Model (Data 로그, 차분)]



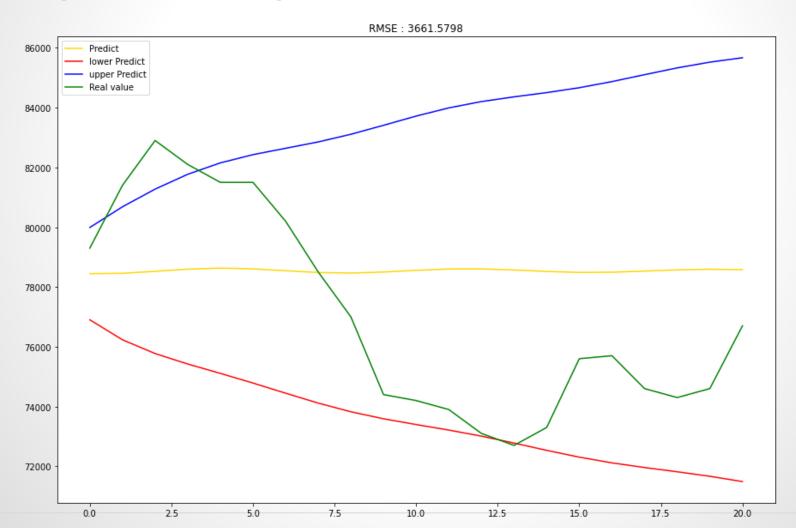
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3. ARIMA

[ARIMA Model 결과 Plot]



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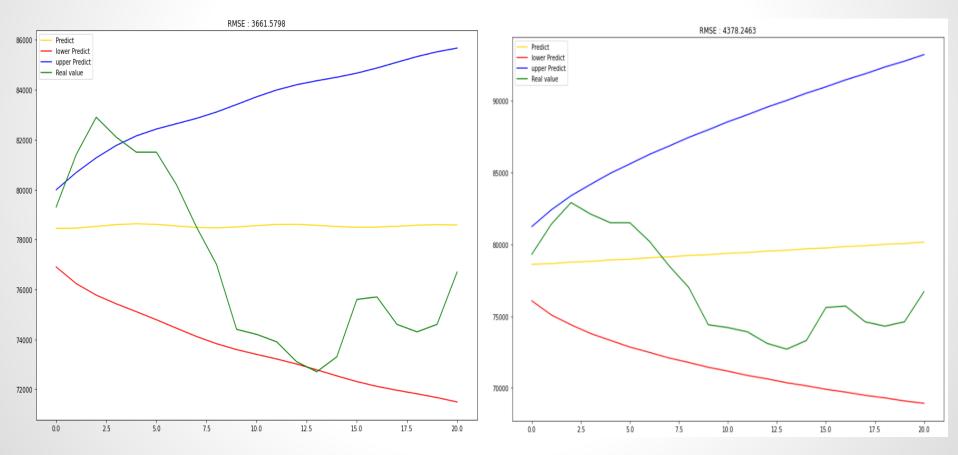
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3. ARIMA

[ARIMA Model 결과 Plot]

[1Month 예측: ARIMA Model (Data 로그, 차분)]



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4. 시사점 및 결론

