



KOSPI 증권 포트폴리오 수익률의 GARCH, GJR-GARCH, E-GARCH 모형 모형 적합, 진단, 최적의 모형 선택

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포트폴리오 종목

Portfolio

포트폴리오 종목

포트폴리오 구성 종목

















2018/01/02 ~ 2019/12/28 (2년)

1. SK하이닉스
2. 기아차
3. 맥쿼리인프라
4. 삼성SDI

5. 엔씨소프트
6. 유한양행
7. 카카오
8. 하이트진로

포트폴리오 종목

주가데이터 불러오기

 SK하이닉스2018.csv
 SK하이닉스2019.csv
 기아차2018.csv
 기아차2019.csv
 맥쿼리인프라2018.csv
 맥쿼리인프라2019.csv
 삼성SDI2018.csv
 삼성SDI2019.csv
 엔씨소프트2018.csv
 엔씨소프트2019.csv
 유한양행2018.csv
 유한양행2019.csv
 카카오2018.csv
 카카오2019.csv
 하이트진로2018.csv
 하이트진로2019.csv

데이터 출처 : [한국거래소]

```

import pandas as pd
import numpy as np
import os
import matplotlib
import matplotlib.font_manager as fm
import matplotlib.pyplot as plt
from tqdm import tqdm

path = "C:/Users/ad/Desktop/강의자료3-2/금융통계/종목Data/"
files = os.listdir(path)
df_list = []
for i in range(8):
    df1 = pd.read_csv(path+files[2*i])
    df2 = pd.read_csv(path+files[2*i+1])
    df = pd.concat([df2, df1])[["년/월/일", "종가"]]
    df["종가"] = df["종가"].apply(lambda x: x.replace(", ", ""))
    df.columns = ["날짜/종가", files[2*i][:-8]]
    df = df.set_index("날짜/종가")
    df_list.append(df)
price = pd.concat(df_list, axis=1)
price = price.apply(pd.to_numeric)
price = price[::-1]
price
    
```

종목별로
2018년 데이터와
2019년 데이터를
불러와서 결합하여
List형태로 저장

모든 종목을 하나의
데이터프레임으로 결합한 후
숫자형으로 변환

	SK하이닉스	기아차	맥쿼리인프라	삼성SDI	엔씨소프트	유한양행	카카오	하이트진로
날짜/종가								
2018/01/02	76600	32800	8220	212000	446500	217000	146500	24400
2018/01/03	77700	32600	8230	207500	435000	215500	149000	24800
2018/01/04	77100	31550	8180	208500	422500	212500	156000	24550
2018/01/05	79300	31950	8170	220500	422000	217500	156000	24400
2018/01/08	78200	32400	8140	225500	420000	215000	159500	23850
...
2019/12/23	94600	44750	11850	228000	540000	243500	148500	27800
2019/12/24	93800	44700	11900	225000	533000	242000	146500	28100
2019/12/26	94800	45100	11900	222500	537000	246000	148000	27900
2019/12/27	96000	44350	11650	233000	541000	236500	153500	28750
2019/12/30	94100	44300	11600	236000	541000	236500	153500	29000

490 rows × 8 columns <8개 종목의 2018/01/02부터 2019/12/30 까지 총 490일의 종가 데이터>

포트폴리오 종목

추세

- 시작일(2018/1/2)을 기준(100)으로 했을 때의 주가 변화 추세

```
▶ (price/price.iloc[0]*100).plot(figsize=(20,10),grid = True)  
plt.legend(loc=2, prop={'size':18})  
plt.show()
```



포트폴리오 종목

일별 로그 수익률

- Daily Log Return : $R_{t+1} = \ln\left(\frac{s_{t+1}}{s_t}\right)$

▶ `log_return = np.log(price/price.shift(1)).dropna()` ← 2018년 첫날(1월2일)의 경우
`log_return.index.name = "날짜/로그수익률"` 전일 증가가 없기 때문에 NaN -> 제거
`log_return = log_return*100` ← Fitting할 때 값이 너무 작아서 생기는 문제를 예방하기 위해
`log_return` 100을 곱함

	SK하이닉스	기아차	맥쿼리인프라	삼성SDI	엔씨소프트	유한양행	카카오	하이트진로
날짜/로그수익률								
2018/01/03	1.425818	-0.611623	0.121581	-2.145494	-2.609337	-0.693644	1.692088	1.626052
2018/01/04	-0.775198	-3.273870	-0.609386	0.480770	-2.915658	-1.401892	4.590970	-1.013180
2018/01/05	2.813485	1.259859	-0.122324	5.595865	-0.118413	2.325686	0.000000	-0.612872
2018/01/08	-1.396848	1.398624	-0.367873	2.242246	-0.475060	-1.156082	2.218791	-2.279891
2018/01/09	-1.676377	0.308167	-0.122926	-2.696793	0.829880	2.525967	-1.579812	2.688890
...
2019/12/23	-0.421942	0.111794	1.273903	-0.219058	0.185357	0.824747	-1.005034	0.722025
2019/12/24	-0.849262	-0.111794	0.421053	-1.324523	-1.304772	-0.617922	-1.355953	1.073356
2019/12/26	1.060455	0.890874	0.000000	-1.117330	0.747667	1.639381	1.018685	-0.714289
2019/12/27	1.257878	-1.676954	-2.123222	4.611135	0.742118	-3.938333	3.648829	3.001108
2019/12/30	-1.999014	-0.112803	-0.430108	1.279335	0.000000	0.000000	0.000000	0.865806

489 rows × 8 columns

Weight

weight

Weight

Weight 배정

• Weight 배정

```
weight = np.array([0.2, 0.2, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1])
```

SK 하이닉스	기아차	맥쿼리 인프라	삼성SDI	엔씨 소프트	유한양행	카카오	하이트 진로
0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1

Weight

Result

• Result

```
mu_p = np.dot(log_return, weight.T)
return_pf = pd.DataFrame({"Portfolio_Return": mu_p}, index = log_return.index.tolist())

vol_pf = pd.DataFrame(return_pf**2, index = log_return.index.tolist())
vol_pf.columns = ["Portfolio_Volatility"]
```

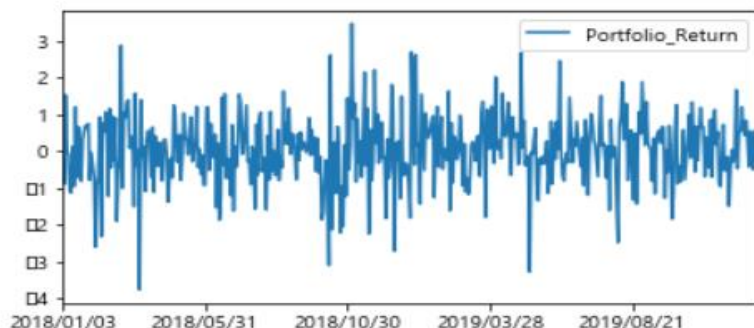
Portfolio 수익률

return_pf

Portfolio_Return	
2018/01/03	-0.038036
2018/01/04	-0.896651
2018/01/05	1.521463
2018/01/08	0.018568
2018/01/09	-0.109121
2019/12/23	0.116164
2019/12/24	-0.503087
2019/12/26	0.547677
2019/12/27	0.510348
2019/12/30	-0.250860

489 rows × 1 columns

```
return_pf.plot()
plt.rcParams['figure.figsize']=[6,3]
plt.show()
```



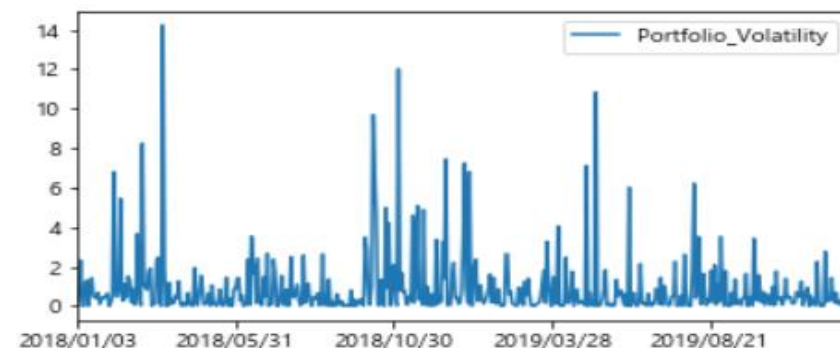
Portfolio Volatility

vol_pf

Portfolio_Volatility	
2018/01/03	0.001447
2018/01/04	0.803983
2018/01/05	2.314850
2018/01/08	0.000345
2018/01/09	0.011907
2019/12/23	0.013494
2019/12/24	0.253097
2019/12/26	0.299950
2019/12/27	0.260456
2019/12/30	0.062931

489 rows × 1 columns

```
vol_pf.plot()
plt.show()
```



모형 적합

Model fitting

GARCH 모형

```
from arch import arch_model
```

```
am = arch_model(return_pf, mean="constant", vol="Garch", p=1, o=0, q=1, dist="normal")  
res_garch = am.fit()
```

```
Iteration: 1, Func. Count: 6, Neg. LLF: 656.672197556883  
Iteration: 2, Func. Count: 15, Neg. LLF: 656.6385626614021  
Iteration: 3, Func. Count: 22, Neg. LLF: 656.294153950011  
Iteration: 4, Func. Count: 29, Neg. LLF: 656.0292161125747  
Iteration: 5, Func. Count: 38, Neg. LLF: 656.0277900150882  
Iteration: 6, Func. Count: 45, Neg. LLF: 655.9500931868131  
Iteration: 7, Func. Count: 52, Neg. LLF: 655.8427539171087  
Iteration: 8, Func. Count: 59, Neg. LLF: 655.8157502957483  
Iteration: 9, Func. Count: 65, Neg. LLF: 655.8105153547926  
Iteration: 10, Func. Count: 71, Neg. LLF: 655.8097986160137  
Iteration: 11, Func. Count: 77, Neg. LLF: 655.8097803635014
```

Optimization terminated successfully. (Exit mode 0)

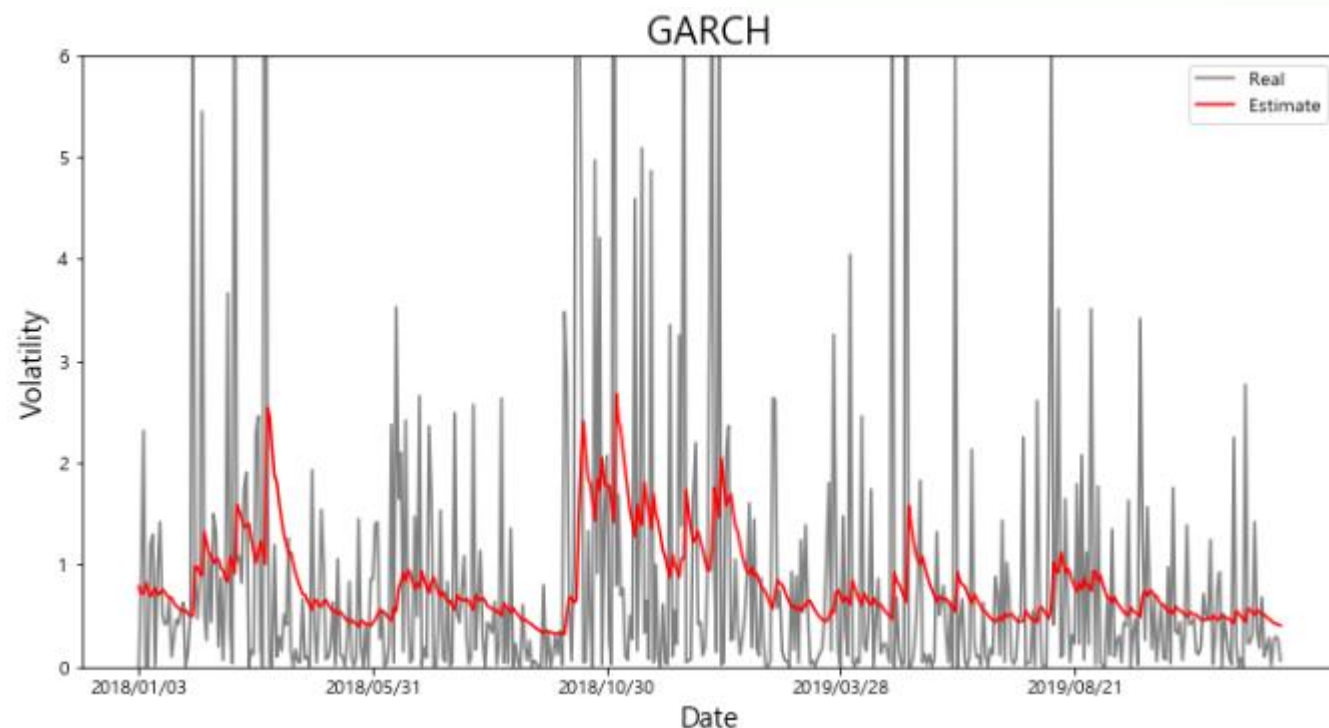
Current function value: 655.8097796522372

Iterations: 11

Function evaluations: 78

Gradient evaluations: 11

```
plt.plot(vol_pf, color="gray")  
plt.plot(res_garch.conditional_volatility**2, color="r")  
plt.title("GARCH", fontsize=20)  
plt.ylabel("Volatility", fontsize = 15)  
plt.xlabel("Date", fontsize = 15)  
plt.legend(["Real", "Estimate"])  
plt.xticks(["2018/01/03", "2018/05/31", "2018/10/30", "2019/03/28", "2019/08/21"])  
plt.rcParams['figure.figsize']=[12,6]  
plt.ylim(0,6)  
plt.show()
```



GJR-GARCH 모형

```
am = arch_model(return_pf, mean="constant", vol="Garch", p=1, o=1, q=1)  
gjr_garch = am.fit()
```

Iteration:	1,	Func. Count:	7,	Neg. LLF:	654.6068965714094
Iteration:	2,	Func. Count:	18,	Neg. LLF:	654.6060086146795
Iteration:	3,	Func. Count:	28,	Neg. LLF:	654.5957153916952
Iteration:	4,	Func. Count:	36,	Neg. LLF:	654.3021153370714
Iteration:	5,	Func. Count:	44,	Neg. LLF:	654.1683394141695
Iteration:	6,	Func. Count:	52,	Neg. LLF:	653.9833448561546
Iteration:	7,	Func. Count:	60,	Neg. LLF:	653.9161705694946
Iteration:	8,	Func. Count:	68,	Neg. LLF:	653.8212920090908
Iteration:	9,	Func. Count:	76,	Neg. LLF:	653.8027332856387
Iteration:	10,	Func. Count:	84,	Neg. LLF:	653.7937900826537
Iteration:	11,	Func. Count:	91,	Neg. LLF:	653.7911191022504
Iteration:	12,	Func. Count:	98,	Neg. LLF:	653.7873497541331
Iteration:	13,	Func. Count:	105,	Neg. LLF:	653.7872817134091
Iteration:	14,	Func. Count:	112,	Neg. LLF:	653.787268324651

Optimization terminated successfully. (Exit mode 0)

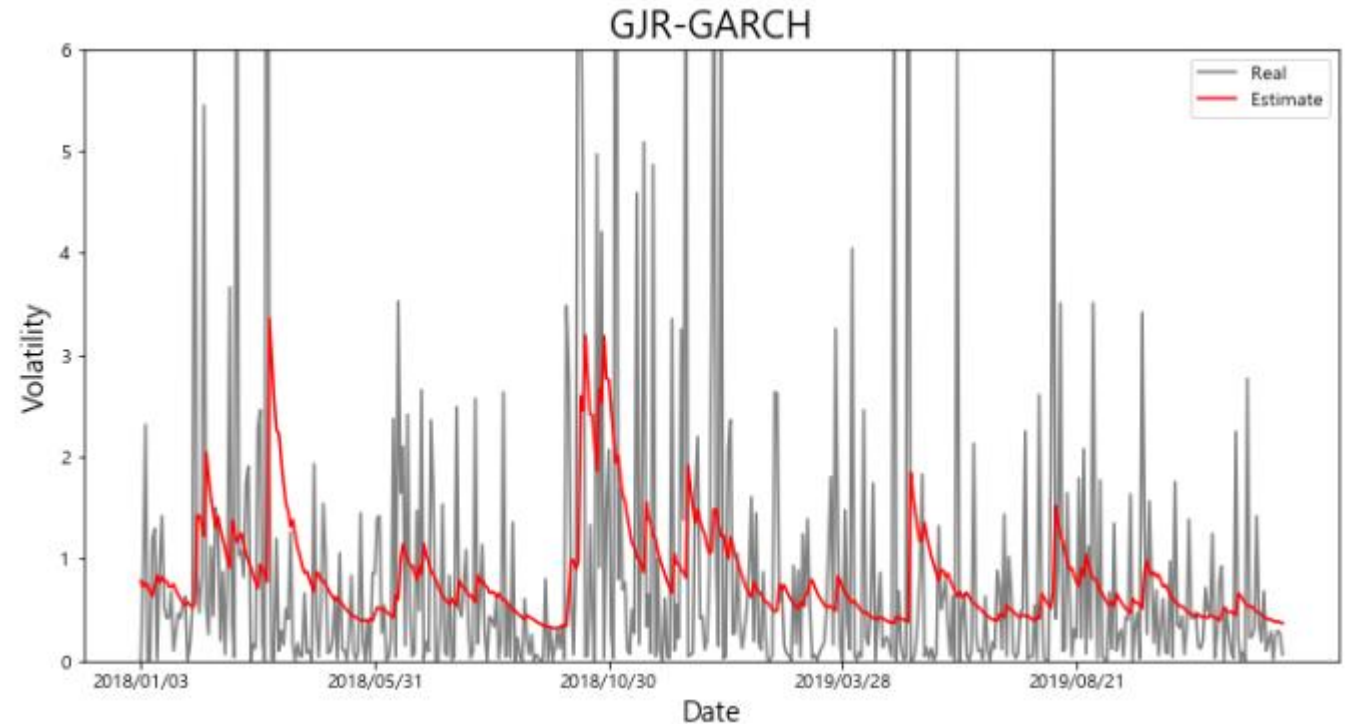
Current function value: 653.7872676075299

Iterations: 14

Function evaluations: 113

Gradient evaluations: 14

```
plt.plot(vol_pf, color="gray")  
plt.plot(gjr_garch.conditional_volatility**2, color="r")  
plt.title("GJR-GARCH", fontsize=20)  
plt.ylabel("Volatility", fontsize=15)  
plt.xlabel("Date", fontsize=15)  
plt.legend(["Real", "Estimate"])  
plt.xticks(["2018/01/03", "2018/05/31", "2018/10/30", "2019/03/28", "2019/08/21"])  
plt.rcParams['figure.figsize']=[12,6]  
plt.ylim(0,6)  
plt.show()
```



E-GARCH 모형

```
am = arch_model(return_pf, mean="constant", vol="EGarch", p=1, o=1, q=1,)  
E_garch = am.fit()
```

```
Iteration: 1, Func. Count: 7, Neg. LLF: 653.1580620359164  
Iteration: 2, Func. Count: 17, Neg. LLF: 652.9693107815815  
Iteration: 3, Func. Count: 28, Neg. LLF: 652.9534021394346  
Iteration: 4, Func. Count: 38, Neg. LLF: 652.9212263047164  
Iteration: 5, Func. Count: 47, Neg. LLF: 652.9159655097517  
Iteration: 6, Func. Count: 57, Neg. LLF: 652.9157884137567  
Iteration: 7, Func. Count: 64, Neg. LLF: 652.9003497213128  
Iteration: 8, Func. Count: 71, Neg. LLF: 652.8982621022044  
Iteration: 9, Func. Count: 78, Neg. LLF: 652.898257593473
```

Optimization terminated successfully. (Exit mode 0)

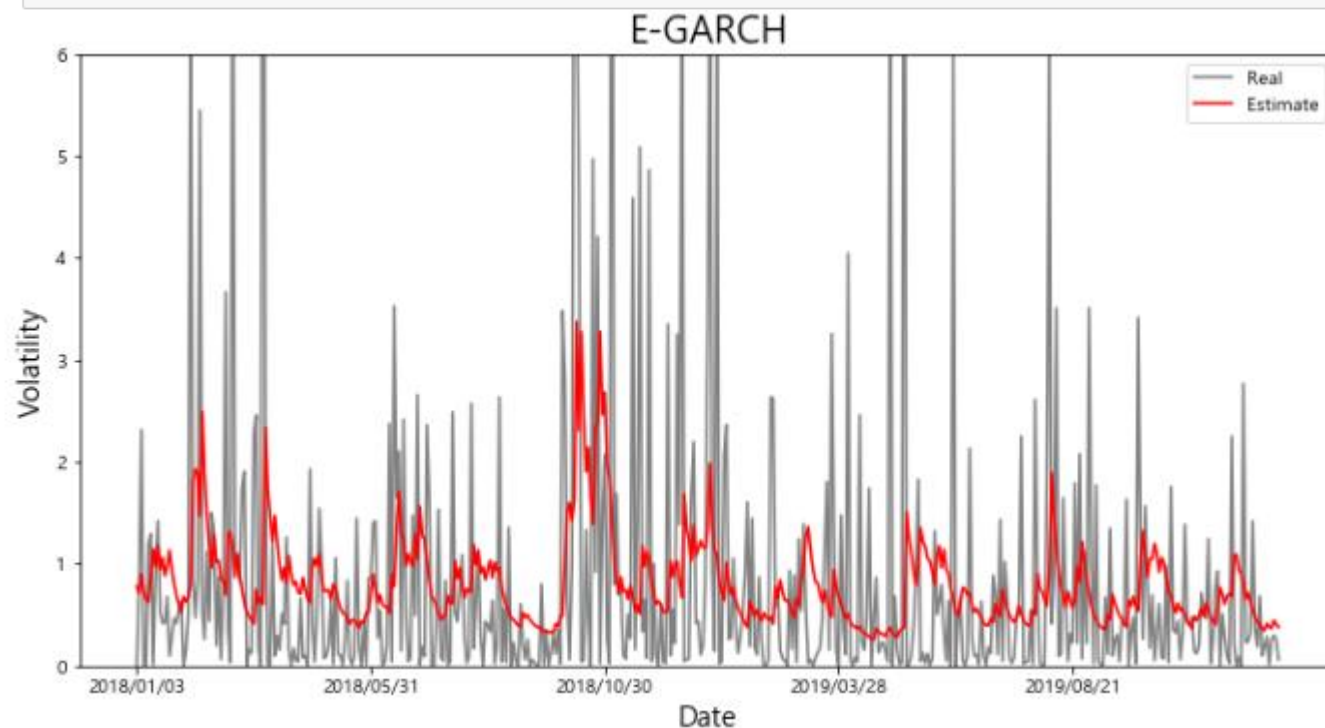
Current function value: 652.8982575934973

Iterations: 9

Function evaluations: 78

Gradient evaluations: 9

```
plt.plot(vol_pf, color="gray")  
plt.plot(E_garch.conditional_volatility**2, color="r")  
plt.title("E-GARCH", fontsize=20)  
plt.ylabel("Volatility", fontsize = 15)  
plt.xlabel("Date", fontsize = 15)  
plt.legend(["Real", "Estimate"])  
plt.xticks(["2018/01/03", "2018/05/31", "2018/10/30", "2019/03/28", "2019/08/21"])  
plt.rcParams['figure.figsize']=[12,6]  
plt.ylim(0,6)  
plt.show()
```



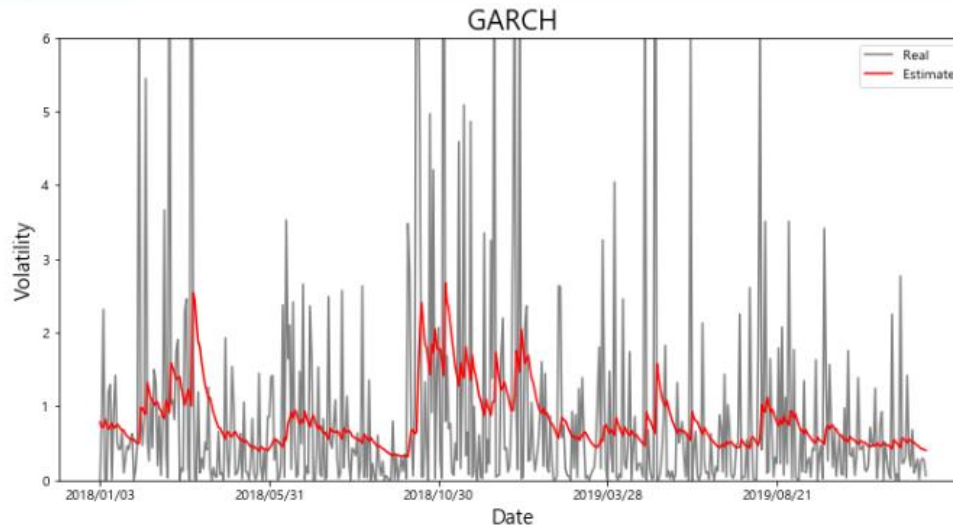
모형 진단

Model Evaluation

모형 진단

GARCH

• GARCH

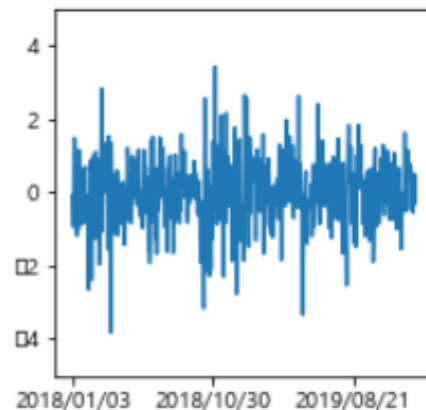


전체적인 추세는 따라가지만
급격한 변화는 잘 따라가지 못함.

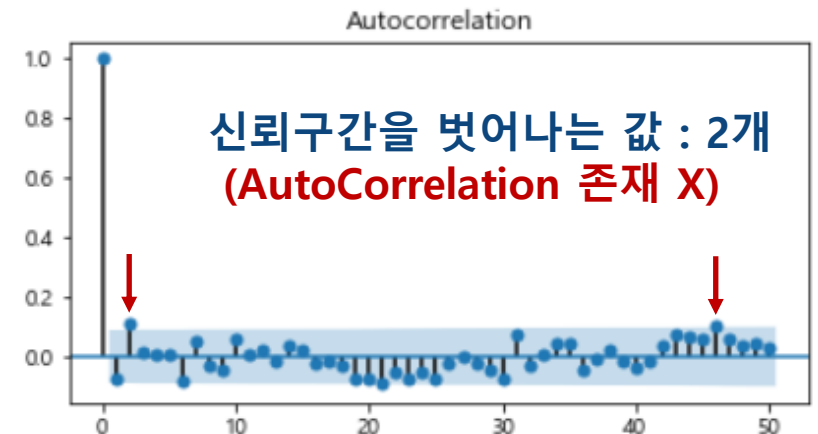
```
plt.plot(garch.resid)
plt.rcParams['figure.figsize']=[3,3]
plt.xticks(["2018/01/03","2018/10/30","2019/08/21"])
plt.ylim(-5,5)
plt.show()
```

▶ `from statsmodels.graphics.tsaplots import plot_acf`

▶ `plot_acf(garch.resid, lags=50)`
`plt.rcParams['figure.figsize']=[6,3]`
`plt.show()`



Volatility
clustering이
약하게 존재

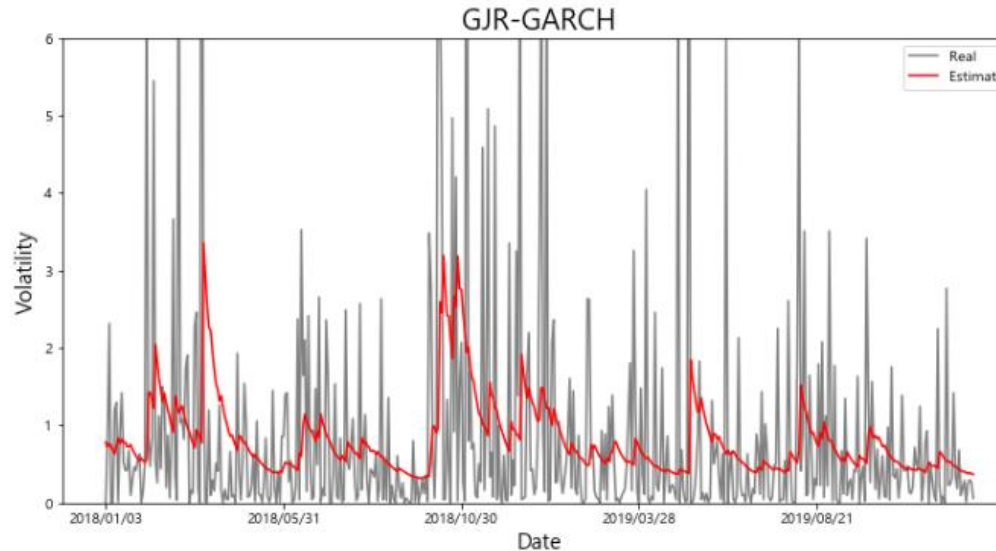


신뢰구간을 벗어나는 값 : 2개
(AutoCorrelation 존재 X)

모형 진단

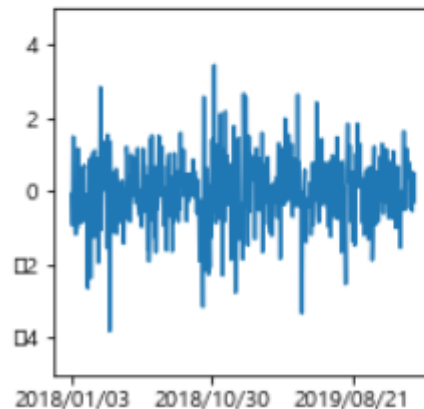
GJR-GARCH

• GJR-GARCH



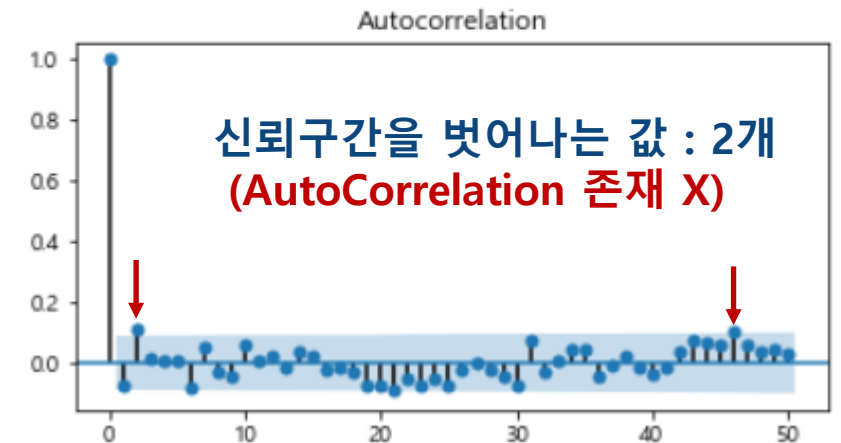
GARCH보다는 약간 개선되었지만
→ 여전히 급격한 변화는 잘 따라가지
못함.

```
plt.plot(gjr_garch.resid)
plt.ylim(-5,5)
plt.rcParams['figure.figsize']=[3,3]
plt.xticks(["2018/01/03","2018/10/30","2019/08/21"])
plt.show()
```



Volatility
clustering이
약하게 존재

```
plot_acf(gjr_garch.resid, lags=50)
plt.rcParams['figure.figsize']=[6,3]
plt.show()
```

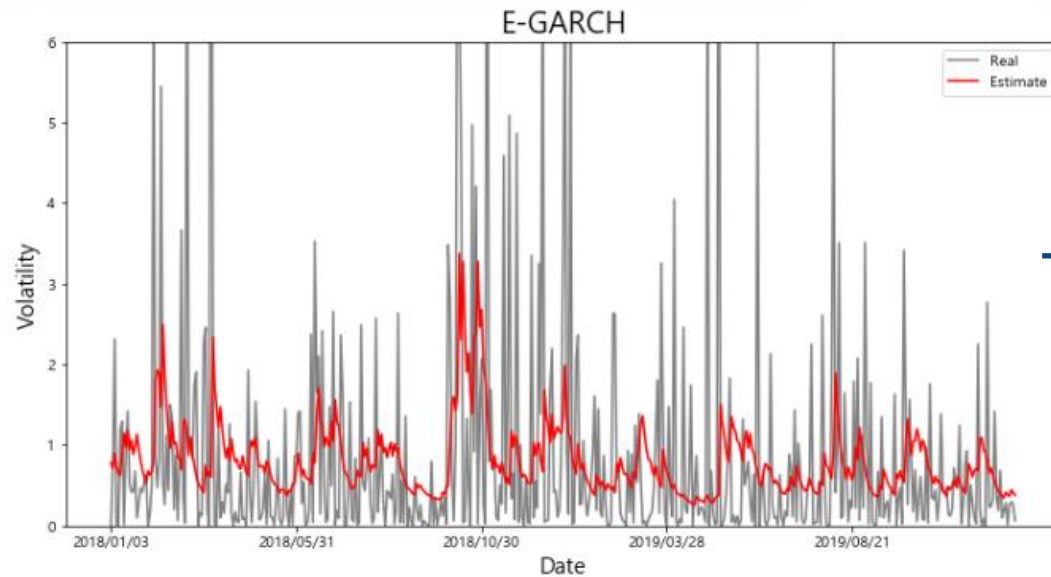


신뢰구간을 벗어나는 값 : 2개
(AutoCorrelation 존재 X)

모형 진단

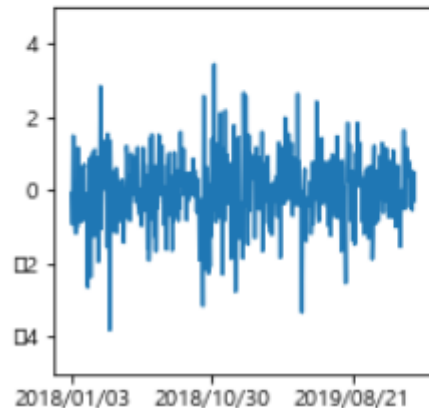
GJR-GARCH

● E-GARCH



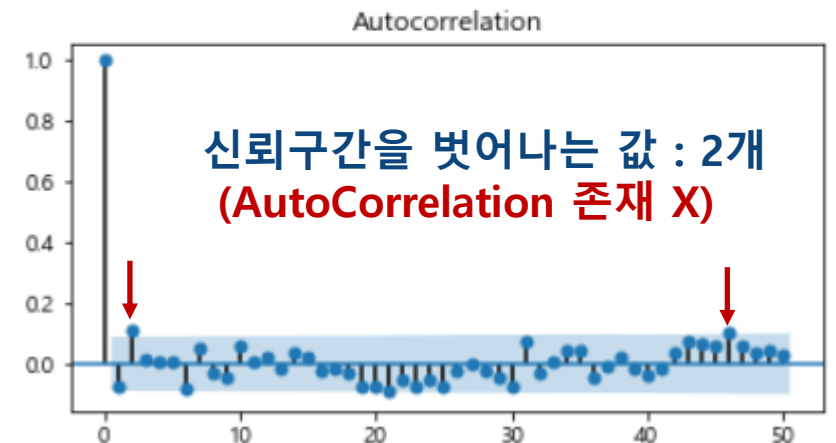
→ GARCH나 GJR-GARCH보다는
조금 더 올라가야 할 때 잘 올라감.

```
plt.plot(E_garch.resid)
plt.ylim(-5,5)
plt.rcParams['figure.figsize']=[3,3]
plt.xticks(["2018/01/03","2018/10/30","2019/08/21"])
plt.show()
```



Volatility
clustering이
약하게 존재

```
plot_acf(E_garch.resid, lags=50)
plt.rcParams['figure.figsize']=[6,3]
plt.show()
```



신뢰구간을 벗어나는 값 : 2개
(AutoCorrelation 존재 X)

모형 진단

LR, AIC/BIC

• LR, AIC/BIC

```
garch.summary()
```

1. GARCH

Constant Mean - GARCH Model Results

Dep. Variable:	Portfolio_Return	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	GARCH	Log-Likelihood:	-655.810
Distribution:	Normal	AIC:	1319.62
Method:	Maximum Likelihood	BIC:	1336.39
		No. Observations:	489
Date:	Wed, Jun 03 2020	Df Residuals:	485
Time:	21:52:45	Df Model:	4

```
E_garch.summary()
```

3. E-GARCH

Constant Mean - EGARCH Model Results

Dep. Variable:	Portfolio_Return	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	EGARCH	Log-Likelihood:	-652.898
Distribution:	Normal	AIC:	1315.80
Method:	Maximum Likelihood	BIC:	1336.76
		No. Observations:	489
Date:	Wed, Jun 03 2020	Df Residuals:	484
Time:	22:27:44	Df Model:	5

```
gjr_garch.summary()
```

2. GJR-GARCH

Constant Mean - GJR-GARCH Model Results

Dep. Variable:	Portfolio_Return	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	GJR-GARCH	Log-Likelihood:	-653.787
Distribution:	Normal	AIC:	1317.57
Method:	Maximum Likelihood	BIC:	1338.54
		No. Observations:	489
Date:	Wed, Jun 03 2020	Df Residuals:	484
Time:	21:53:27	Df Model:	5

$$LR = 2 \log \left(\frac{L_1}{L_0} \right) = 2(\log(L_1) - \log(L_0))$$

H_0 : GARCH vs H_1 : GJR-GARCH
 $LR = 4.046 < \chi^2(1) \rightarrow H_0$

모형 진단

MSE, QLIKE

• MSE, QLIKE

MSE

GARCH

```
from sklearn.metrics import mean_squared_error
```

```
mse = mean_squared_error(vol_pf, garch.conditional_volatility**2)  
mse
```

2.5206

2.520604494359118

GJR-GARCH

```
mse = mean_squared_error(vol_pf, gjr_garch.conditional_volatility**2)  
mse
```

2.5013

2.5013742212669716

E-GARCH

```
mse = mean_squared_error(vol_pf, E_garch.conditional_volatility**2)  
mse
```

2.4861

2.4861506899405983

QLIKE

GARCH

```
qlike(vol_pf, garch.conditional_volatility**2)
```

Portfolio_Volatility 671.004682
dtype: float64

671.0046

GJR-GARCH

```
qlike(vol_pf, gjr_garch.conditional_volatility**2)
```

Portfolio_Volatility 668.237748
dtype: float64

668.2377

E-GARCH

```
qlike(vol_pf, E_garch.conditional_volatility**2)
```

Portfolio_Volatility 661.589472
dtype: float64

661.5894

```
def qlike(obs, fore):  
    a = []  
    for i in range(len(obs)):   
        div = obs.iloc[i]/fore.iloc[i]  
        b = div - 1 - np.log(div)  
        a.append(b)  
    return sum(a)
```


모형 진단

표

- 표

	GARCH	GJR-GARCH	E-GARCH
MSE	2.5206	2.5013	2.4816
QLIKE	671.0046	668.2377	661.5894
AIC	1319.62	1317.52	1315.58
BIC	1336.39	1338.54	1336.76

위 표의 통계량에 따라서, E-GARCH 모형이 최적의 모형이다.

결론

Conclusion

결론

세 모형 모두 미세하게 volatility clustering이 존재하지만 뚜렷이 나타난다고 할 수는 없어 보이고 AutoCorrelation이 존재하지 않는다. 따라서 모두 잔차(ε_t)들이 독립인 random variable 이라고 할 수 있다. 따라서 모든 모형이 타당합니다.

LR 테스트에 따르면 검정 통계량이 모두 자유도가 1인 카이제곱 통계량보다 작게 나오므로 GARCH 모형이 셋 중에 제일 나은 모형이라는 결과가 나온다.

하지만 여러 가지 통계량들(MSE, QLIKE, AIC, BIC)과 Volatility 그래프를 종합하여 판단한다면 E-GARCH가 가장 나은 모형이다. (하지만 거의 유사하다)

참고

Reference

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감사합니다

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