Assignment 1

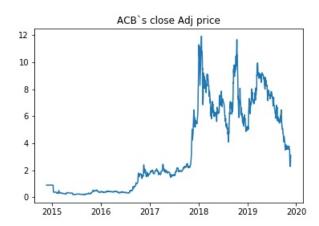
We use the daily data of Aurora Cannabis Inc(ACB) and First Trust Global Wind Energy(FAN) stocks from 2014-11-25 to 2019-11-21 which are captured from Yahoo Finance. The dataset contains Open prices, High prices, Low prices, Close prices, Adjusted Close prices and Volume of stocks. We have checked that there is no NAN or omitted data.

Some of the data from below:

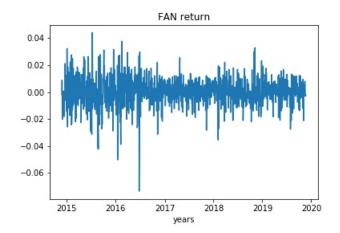
	Date	Open	High	Low	Close	Adj Close	Volume
1254	2019-11-15	2.76	3.17	2.70	2.73	2.73	57222500
1255	2019-11-18	2.72	2.76	2.26	2.28	2.28	64738600
1256	2019-11-19	2.18	2.45	2.14	2.34	2.34	55797000
1257	2019-11-20	2.41	2.73	2.36	2.64	2.64	78398000
1258	2019-11-21	2.79	3.25	2.70	3.12	3.12	107502348

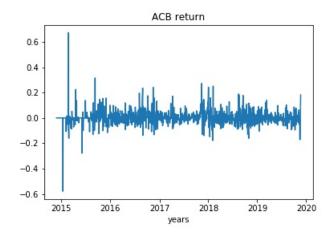
We plot adjusted close price v.s. time and here we get 1257 observations.





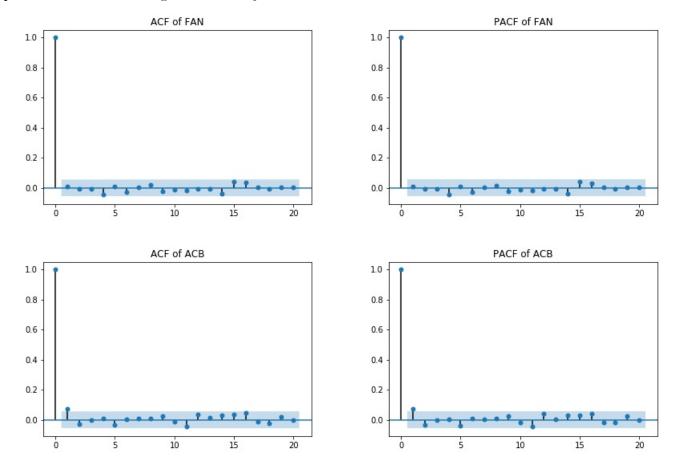
From the plot of Adj.Close against time, we can find that stock prices have a trend over time. We analyze returns instead of prices, for the purpose of detrend. Then we will get time series data which is closed to stationary data:





We can see that the mean of return is almost zero.

We plot ACF and PACF figures for analysis:



From the ACF and PACF plots we can see that for ACB first lag is significant (today's daily return depend on yesterday's value). For FAN is not. But both figures are similar to ACF of White Noise Process (which is weakly stationary process).

We estimate AR(1) model using OLS:

FAN stock

	(LS Regress	ion Results			
Dep. Variable: Daily_return Model: OLS Method: Least Squares Date: Sun, 24 Nov 2019 Time: 18:47:58 No. Observations: 1257 Df Residuals: 1255 Df Model: 1 Covariance Type: nonrobust		Adj. R-squar F-statistic: Prob (F-stat	istic):	0.000 -0.001 0.2015 0.654 3961.2 -7918.		
	coef	std err	t	P> t	[0.025	0.975]
Daily_return_lag			0.449 0.707		-0.043 -0.000	0.068 0.001
Omnibus: Prob(Omnibus): Skew: Kurtosis:		158.451 0.000 -0.494 6.641	Prob(JB):		2.000 745.481 1.32e-162 96.5	

ACB stock

OLS Regression Results							
Method: Least Squares Date: Tue, 26 Nov 2019			Adj. R-squar F-statistic: Prob (F-stat Log-Likeliho	istic):	0. 6. 0.00 182 -36	0.005 0.005 6.812 0.00916 1823.2 -3642. -3632.	
	coef	std err	t	P> t	[0.025	0.975]	
Daily_return_lag const			2.610 1.514	0.009 0.130	0.018 -0.001	0.129 0.006	
Omnibus: Prob(Omnibus): Skew: Kurtosis:		523.432 0.000 1.057 29.268	Jarque-Bera (JB): Prob(JB):		1.988 36373.736 0.00 17.6		

For FAN stock we got insignificant coefficients for parameters of AR(1) and significant but small values of coefficients for ACB stock. This is corresponded to results of previous exercise of assignment.

3

We take 10 stocks: ACB, CELG, SIRI, STNE, FAN, SPLK, PSTG, CGC, AMD, UBER and run Unit-Root test on them. The unit root test is a common procedure to determine whether a time series is random walk or not. So we consider the simple AR(1) model: $y_t = \phi y_{t-1} + \varepsilon_t$, where $\varepsilon_t \sim WN(0, \sigma^2)$ and the hypotheses of interest are:

$$H_0: \phi = 1$$

 $H_1: |\phi| < 1$

t 5% t_10% t_1% ACB -32.758382 0.000000e+00 -3.435567 -2.863844 -2.567997CELG -34.158777 0.000000e+00 -3.435571-2.863846 -2.567998-37.321282 0.000000e+00 -3.435567-2.863844-2.567997-15.314434 4.144185e-28 -3.454896 -2.872345 -2.572528 -34.961655 0.000000e+00 -3.435567-2.863844-2.567997 SPLK -33.623594 0.000000e+00 -3.435567 -2.863844-2.567997-20.537250 0.000000e+00 -3.436666 -2.864328 -2.568255 -3.435601 -10.359171 2.421749e-18 -2.863859 -2.568004-21.208868 0.000000e+00 -3.435575-2.863848-2.567999UBER -11.366601 9.194109e-21 -3.479743 -2.883198 -2.578320

Table shows the result of unit root tests using the ADF unit root test. The null hypothesis of existence of unit-root isn't performed at the 1%, 5%, 10% significance levels. The result of the ADF test illustrates that all the stocks are stationary at any significance level.

We expected such results, because we saw on ACF plots for FAN and ACB stocks that autoorrelation coefficients for lag1 significantly less than one. It's expected that for another stock we will get the same results.

4

Assume the two stocks from 1 are Random Walks with 0 unconditional mean:

$$y_t = y_{t-1} + \varepsilon_t$$
, where $\varepsilon_t \sim IWN(0, \sigma^2)$.

We can estimate σ^2 from our data

$$z_t = y_t - y_{t-1} = \varepsilon_t$$

$$\sigma^2 = Var(\varepsilon_t) = Var(z_t).$$

So we take lag from daily return and calculate variation of this lag.

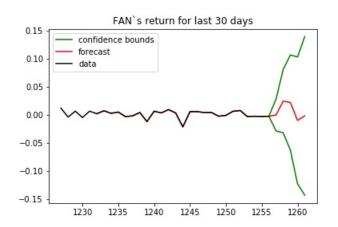
Generate 5 random variables $(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5)$ with Gauss distribution $(0, \sigma^2)$ to produce 5-day forecast. Then 5 forecasting varibles:

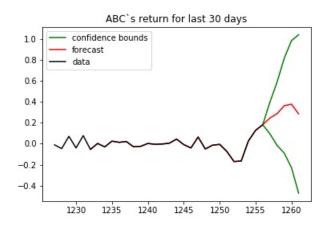
$$\hat{y}_{t+i} = \hat{y}_t + \sum_{j=1}^{i} \varepsilon_j, \ i = (1, 2, 3, 4, 5)$$

and 95-confidence interval for them:

$$(y_{t+i} - 1.96 * i * \sigma; y_{t+i} + 1.96 * i * \sigma).$$

We got plots with 5-days forecast for FAN and ACB stocks:





Our forecast shows that FAN stock will decrease in 5 days and ACB stock will increase in average. But we can't give some investment advice, because random walk forecast is unexpected (it changes every time you run the code). We have wide confidence interval and out of five random values ε_i , we can obtain a forecast of an increase in the value and a fall or value may remain unchanged.

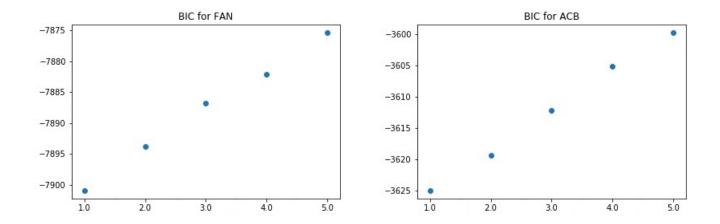
5

There are two techniques to identify the order of AR model:

- 1. Partial Autocorrelation Function
- 2. Information criteria.
- 1) We can define the order p of AR(p) by using PACF plot. Because partial autocorrelation is the amount of correlation between a variable and a lag of itself that is not explained by correlations at all lower-order-lags. So if for example only first partial autocorrelation at lag1 significant, it means that all the higher-order autocorrelations are effectively explained by the lag1 autocorrelation. In this case we should choose p equal 1 (AR(1)).

We saw above that in the PACF plot for FAN stock there aren't significant lags, so AR model can't explain our data. PACF plot for ACB stock has significant lag1, so we choose AR(1) model

2) Bayesian information criterion (BIC) is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function. It is possible to increase the likelihood by adding parameters, but it can lead to overfitting. The BIC resolves this problem by introducing a penalty term for the number of parameters in the model. We test the models AR(p) using corresponding BIC values:



Than lower BIC value than lower penalty terms. And as a result an additive lag make model worse. It means that AR(1) is better than models with higher order.

We got different results for FAN using PACF and BIC because with the help of BIC we can understand only the best order of the AR(p) model, but we can't understand whether we need AR model or not in general.