Predicting Ethereum's cryptocurrency prices using Recurrent Neural Network (RNN)

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Our Dataset

	Date	Open	High	Low	Close	Volume	Market Cap
0	22-Apr-18	606.12	640.77	593.87	621.86	2,426,270,000	59,985,500,000
1	21-Apr-18	616	621.89	578.55	605.4	2,612,460,000	60,951,100,000
2	20-Apr-18	567.99	618.72	560.28	615.72	2,849,470,000	56,188,700,000
3	19-Apr-18	524.04	567.89	523.26	567.89	2,256,870,000	51,829,900,000
4	18-Apr-18	503.31	525.09	503.05	524.79	1,762,940,000	49,769,600,000
5	17-Apr-18	511.15	518.03	502.56	502.89	1,760,360,000	50,534,000,000
6	16-Apr-18	532.07	534.2	500.25	511.15	1,758,980,000	52,592,200,000
7	15-Apr-18	502.88	531.7	502.88	531.7	1,726,090,000	49,696,300,000
8	14-Apr-18	492.58	512.02	488.28	501.48	1,519,080,000	48,668,400,000
9	13-Apr-18	493.16	526.47	482.66	492.74	2,419,250,000	48,715,400,000
10	12-Apr-18	430.16	493.06	417.41	492.94	2,519,360,000	42,483,600,000
11	11-Apr-18	415.02	430.54	412.47	430.54	1,439,040,000	40,980,200,000
12	10-Apr-18	399.41	415.89	393.88	414.24	1,196,000,000	39,430,400,000
13	9-Apr-18	400.86	429.25	390.61	398.53	1,478,390,000	39,565,100,000
14	8-Apr-18	385.74	402.59	385.6	400.51	948,488,000	38,065,400,000
15	7-Apr-18	370.38	393.06	369.94	385.31	951,475,000	36,541,900,000
16	6-Apr-18	382.73	385.2	366.91	370.29	967,106,000	37,752,600,000
17	5-Apr-18	379.95	387.72	369.82	383.23	1,210,680,000	37,470,200,000
18	4-Apr-18	416.49	417.47	375.31	380.54	1,287,730,000	41,065,100,000
19	3-Apr-18	387.31	418.97	383.53	416.89	1,363,400,000	38,180,800,000
20	2-Apr-18	379.7	395.17	377.59	386.43	1,102,260,000	37,422,500,000
21	1-Apr-18	397.25	400.53	363.81	379.61	1,256,930,000	39,144,700,000
22	31-Mar-18	395	418.47	392.95	396.46	1,323,920,000	38,914,900,000
23	30-Mar-18	385.91	409.93	368.63	394.65	1,878,130,000	38,010,600,000
24	29-Mar-18	448.08	450.81	385.81	385.97	1,970,230,000	44,125,000,000
25	28-Mar-18	450.29	466.21	444.86	446.28	1,514,180,000	44,334,000,000
26	27-Mar-18	489.59	491.46	449.97	450.12	1,617,940,000	48,193,300,000

We are interested in the closing value of each day because dealing with RNN involves sequence dependence data (time-series prediction problem)

Ethereum Charts (Jan. 2016 ~ April 2018)

Building our neural network

```
In [53]: print("Price for last 5 days: ")
         print(testPredict[-5:])
         print("Ethereum price for tomorrow: ", futurePredict)
         # calculate root mean squared error
         trainScore = math.sqrt(mean_squared_error(trainY[:,0], trainPredict[:,0]))
         print('Train Score: %.2f RMSE' % (trainScore))
         testScore = math.sqrt(mean_squared_error(testY[:,0], testPredict[:,0]))
         print('Test Score: %.2f RMSE' % (testScore))

         Price for last 5 days:
         [[525.2916 ]
          [549.16296]
          [596.03516]
          [647.7931 ]
          [636.6541 ]]
         Ethereum price for tomorrow:  [[670.3338]]
         Train Score: 9.81 RMSE
         Test Score: 60.63 RMSE
```

- The network has 1 input layer, a hidden layer with 4 LSTM blocks or neurons, and an output layer that makes a single value prediction.
- After building our network and fitting our model, we were able to predict Ethereum's price tomorrow based off of its' closing values in the last 5 days.