On risk evaluation for cryptocurrency markets using an LSTM artificial neural network.

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Cryptocurrencies

Over the past few years, "cryptocurrency" has become a well-used term in financial circles and news headlines.

General notes

- We make no difference between cryptocurrencies and "normal" stock prices.
- Cryptocurrency dynamics is unique in a sense that we can see high volatility and high liquidity at the same time.
- Arbitrage opportunities on cryptocurrency markets are not easy to exploit.

Problem

- We try to predict the probability of crossing a certain barrier using some historical information.

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Academic interest

Table: Number of papers with "cryptocurrency" keyword.

Engine	Publications (papers) found
Google Scholar	11 900
Researchgate	837
Springer link	722
Ssrn	454
ScienceDirect	268
BlockchainLibrary	190
ArXiv	189
Econbiz	167
Jstor	76

What are cryptocurrencies

General notes

- We make no difference between cryptocurrencies and “normal” stock prices.
- Cryptocurrency dynamics is unique in a sense that we can see high volatility and high liquidity at the same time.
- Arbitrage opportunities on cryptocurrency markets are not easy to exploit.

How to acquire the data?

Sources

- Coinmarketcap.
- Poloniex API
- Kaggle datasets
- Custom data collectors

What top cryptocurrencies are (Coinmarketcap)

Position	Name	calitalization	avg price
1	Bitcoin (BTC)	$93,334,631,518	$5,285.70
2	Ethereum (ETH)	$17,848,982,526	$168.78
3	Ripple (XRP)	$13,436,161,868	$0.320132
4	Bitcoin Cash	$5,031,673,483	$283.62
5	EOS	$4,684,726,701	$5.17
6	Litecoin	$4,658,710,175	$75.83
7	Binance	$3,412,916,505	$24.17
8	Tether	$2,602,196,817	$1.01
9	Stellar	$2,157,410,101	$0.111416
10	Cardano	$1,875,473,273	$0.072336
11	TRON	$1,643,117,501	$0.024641
12	Monero	$1,157,920,100	$68.38
13	Dash	$1,055,288,634	$120.43
14	Bitcoin SV	$1,008,523,963	$56.85
15	Tezos	$873,571,780	$1.32

Top cryptocurrencies shares

Position	Name	Share	Cumulative share
1	Bitcoin Bitcoin	52.78%	52.78%
2	Ethereum Ethereum	10.09%	62.88%
3	XRP XRP	07.60%	70.48%
4	Bitcoin Cash	02.85%	73.32%
5	EOS EOS	02.65%	75.97%
6	Litecoin	02.63%	78.61%
7	Binance	01.93%	80.54%
8	Tether	01.47%	82.01%
9	Stellar	01.22%	83.23%
10	Cardano	01.06%	84.29%
11	TRON	00.93%	85.22%
12	Monero	00.65%	85.87%
13	Dash	00.60%	86.47%
14	Bitcoin SV	00.57%	87.04%
15	Tezos	00.49%	87.53%

Top cryptocurrencies shares

Cryptocurrency market vs MOEX

Total Russian stock market capitalization (MOEX): $645,233,992,728
Total cryptocurrency market cap: $176,822,984,800 (27.4%)

Cryptocurrency market summary

More than 50% of total the market capitalization is focused in Bitcoin

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LSTM networks

The idea of LSTM

- Primitive neural networks started thinking from scratch.
- To add a concept of memory, recurrent networks emerged.
- To make RNN learn faster, LSTMs were invented.

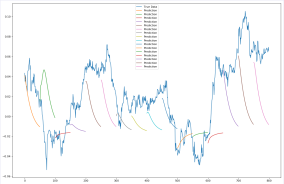
Descriptions and samples

- Hochreiter S. and Schmidhuber J. Long short-term memory, Neural Computation. 1997.
- Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data. PLoS ONE. 2019.
- https://github.com/jaungiers/Multidimensional-LSTM-BitCoin-Time-Series

USDT/BTC price predictions

One-step-ahead

Multiple-steps-ahead



Data preparation scheme

Data prepatation

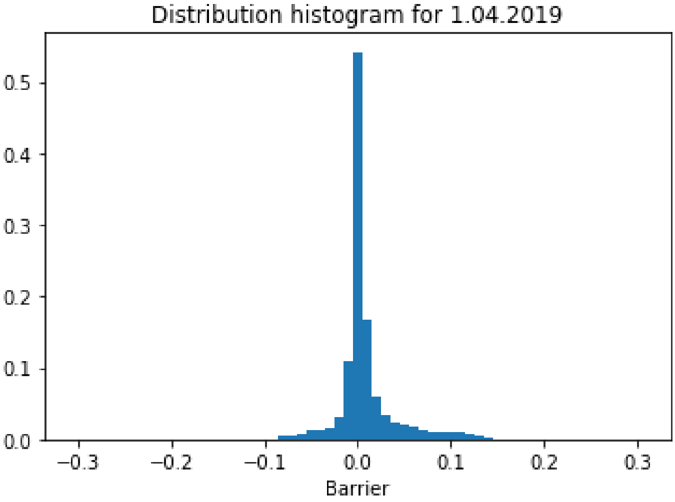
1. Consider logreturns
2. The length of a period is 1 day, ending at 23:59:59 GMT.
3. Consider the first available "open" price for an asset as a starting price and then use a volume-weighted average price for every next time step.
4. For the very first moment observed, set a logarithm of return to zero, whereas for the other open daily prices we compared it to the last available open price.
5. $x_i = \log(S_i/S_0), i = 1, 2, \ldots,$ where S_0 is the open price of a period and S_i is a volume-weighted average for each of the following 5-min periods.
6. On the beginning of a new trading day renew S_0, reset the counter i and continue the process.

Bitcoin dynamics analysis

Data prepatation 2

1. Prepare a set of barriers $H_k = dh \cdot k$ for $k = -30, \dots, -1$ and $k = 1, \dots, 30$, with $dh = 0.01$. So we obtained 30 barriers on each side from 0, which are multiples of 0.01, i.e. 1%: $0.01, 0.02, \dots, 0.3$ and $-0.01, -0.02, \dots, -0.3$. A number of barriers and dh were chosen experimentally so as to reflect the distribution features "well enough".
2. Mark the barrier as H_k "crossed" at moment i if the respective logreturn x_i is greater or equal then H_k if $k > 0$ (or less of equal than H_k for $k < 0$).
3. Collect a statistics on "crossing" events for each barrier.

Histogram sample



On CGMY model

CGMY model

CGMY (The fine structure of asset returns: An empirical investigation. 2002) model has 4 parameters, namely:

- $\nu > 0$,
- $\lambda_- > 0$,
- $\lambda_+ > \lambda_-$,
- $0 < c < 2$

The characteristic exponent of the associated Lévy process is (for $\nu \neq 0, 1, \nu < 2$)as follows:

$$\phi(\xi) = -i\mu\xi + c\Gamma(-\nu)\left[(-\lambda)_-^\nu - (-\lambda_- - i\xi)^\nu + \lambda_+^\nu - (\lambda_+ + i\xi)^\nu\right]$$

Model calibration (CGMY)

- We calculated prices of a first touch digital option.
- The price of this contingent claim with a payoff equals to 1 can be interpreted as a probability of crossing a barrier, for each of H_k under consideration. We used a Wiener-Hopf-factorization based pricing method to evaluate option prices.
- We used Nelder-Mead (NM) algorithm, which started from a predefined set of points and placed additional linear penalties (as the computationally fastest ones), to restrict the set of parameter values it should stop on.
- The penalty implementation added the value $|b_n - p_n|$, $n = 1, .., 4$ where b_n is a boundary condition and p_n is a respective parameter value guess to error function.

Log error

Let sp_k be the statistical probability k-th barrier and mp_k be price of a first-touch digital option for the same barrier (also acting as probability). Then error function e could be calculated as:

$$e = \sum_k d_k,$$

where

$$d_k = \begin{cases} 0, mp_k = sp_k = 0 \\ |mp_k| \log(|mp_k|), sp_k = 0 \\ |sp_k| \log(|sp_k|), mp_k = 0 \\ |mp_k - sp_k| \log(mp_k / sp_k), otherwise \end{cases}$$

We also used a standard deviation of the prices generated by the CGMY / LSTM model from their statistical equivalents.

Learning (LSTM)

- We used a cross-validation technique with 3 sets, which does not intersect
- Sequences of historical probabilities and bitcoin data (OHLC + volume) were used as features.
- Additional penalty was added to prevent replicating the last data available.
- Last n samples were used to predict $(n+1)$ - st

Summary

Results obtained

- The network overfits easily (cross validation + more data)
- The network likes memorizing the very last value (penalty)
- In comparison to CGMY model, the network currently is at best 19% more accurate

Future researches

- Hyperparameter setup
- Activation (dropout) functions analysis

THANK YOU FOR ATTENTION!

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References

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