High Frequency Exchange Rate Forecasting using Deep Learning on Cryptocurrency Markets

Bernardo Ramos (bramos@stanford.edu), Imanol Arrieta-Ibarra (imanol@stanford.edu)

Stanford University

Objectives

Project Goals:

- Design an exchange rate forecasting system that is better than baseline models.
- Assess when Deep Learning achieves better performance than conventional tools.
- Exploit characteristics of a market with statistical arbitrage opportunities.
- Provide a statistical arbitrage trading strategy.

Data Features

The data was obtained from Binance's API covering September 1, 2017 through October 31, 2018.

Independent Variable

- Y_t represents the difference between the time-weighted average price (TWAP) between Bitcoin and Ethereum at the 1-minute frequency.

Covariates Each type of covariate template is applied to the exhange rates of ETH-BTC, ETH-USDT, BTC-USDT; represented as X_t.

- Open, close, high and low rates for X_t.
- Volume for X_t.
- $X_t - X_{t-1}$
- Hour of the day.
- Time since last trade.

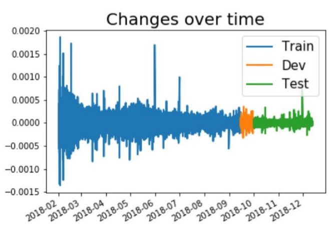

Figure 1: Time Weighted Average Price returns by minute for BTC-ETH

Distribution of Prediction Errors

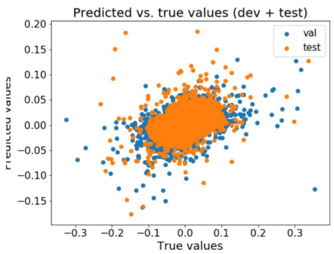

Figure 2: Scatterplot of validation set (true and predicted values).

Trading Strategies

1. Random Strategy (Buy or Sell at Random)
2. Long-Short Strategy (Buy then Sell alternating periods)
3. Threshold Strategy (Buy if above a threshold. Sell if below)

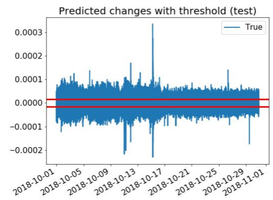

Figure 3: Threshold Strategy.

Architecture

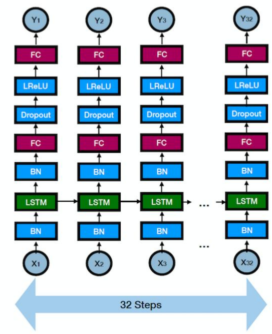

Figure 5: 32 step LSTM with: Dropout: 0.3 , LReLU: $\alpha = 0.3$

Can Deep Learning Beat the Crypto Market?

Despite the widespread belief that the efficient market hypothesis holds, recent state-of-the-art methods have shown there are grounds to have reasonable performance in predicting financial returns. Our exercise confirms these findings for the Crypto Exchange Rate Market.

Prediction Performance

	RMSE	Hit rate	R^2
train	0.07	59.27%	12.4%
dev	0.03	58.63%	12.5%
test	0.02	58.11%	12.1%

Table 1: LSTM performance measures for train, dev and test.

test	RMSE	Hit rate	R^2
Linear	0.0234	**58.59%**	10.37%
LSTM	**0.02319**	58.43%	**12.19%**
ARX(1)*	0.0225	46.58%	16.99%

Table 2: Model performance measures for test set .* ARX(1) were computed in-sample only for reference.

Earnings for Threshold Trading strategy

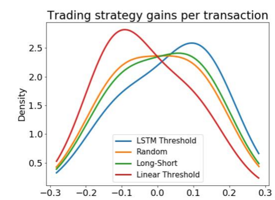

Figure 4: Earnings distribution for diferent strategies.

Summary of Results

- Showed there are grounds for a profitable statistical arbitrage strategy in the Crypto Market.
- With the current features and architectures tried, there was no significant difference in prediction between Deep Learning model that improved on traditional methods for the specific task of regression.
- In the trading strategy simulation, the Deep Learning threshold trading strategy outperformed all traditional methods.