

Quantitative Trading Strategies using Deep Learning: Pairs Trading Simerjot Kaur (sk3391)

Introduction

- · Pairs Trading is a widely used quantitative trading strategy.
- It involves two key aspects:
- · Identify co-integrated pairs of financial assets.
- Forecast spread between the paired assets.
- Forecasted spread is then used to make trading decisions
- However, forecasting spread between the paired assets is a non-trivial exercise, and requires deep domain expertise to create predictive models.

Problem Statement

- Current state-of-the-art spread forecasting methods include statistical methods such as Kalman Filters, ARIMA models, and VAR.
- We aim to explore LSTM/RNNs as a means to forecast spread
- Formally, given a time series of spread (S_1,\ldots,S_t) predict the value of spread 1-time step (S₁₊₁), 5-time step (S_{t+5}) , and 15-time steps (S_{t+15}) in the future.

Dataset and Features

- Dataset Used
 - 10 year (10.01.2008 10.01.2018) daily 'close', 'open', 'high', 'low' price and 'volume traded' for various exchange traded funds (ETFs) were extracted from Yahoo! Finance and used as dataset

Snapshot: Sample Data

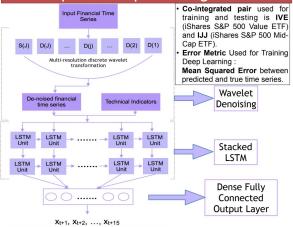
	Close	High		Open	Volume					
2008-10-01	35.860001	37.200001	34.939999	35.410000	569600.0					
2008-10-02	33.700001	34.990002	33.529999	34.860001	751900.0					
2008-10-03	33.299999	35.080002	33.200001	34.099998	853100.0					

- **Data Preprocessing Steps**
- Data Cleaning
- · Pre-processed data to discard any dead ETFs
- Wavelet Denoising
 Multi-resolution discrete wavelet transform to perform de-noising.
- Feature Extraction:
- · Extracted various technical indicators (TI) such as 'Momentum', 'Volatility' and 'Trend' indicators from raw time series data that can be used as feature inputs for LSTM

End-to-end System Pipeline



Proposed Deep Learning Model



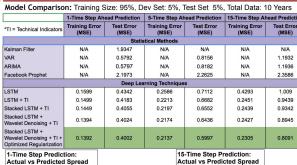
Discussions and Conclusions

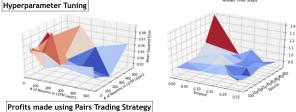
- Deep learning based methods outperform statistical techniques in predicting spread for pairs trading.
- Additional features, like technical indicators, and Wavelet de-noising that eliminates market data noise, improve performance significantly.
- Prediction of St+1 is performing significantly better than [1]. Additionally, we have been able to predict spread at 15-time steps ahead.
- Profits made using deep learning based methods are significantly more than the traditional statistical techniques.

References

[1] Wei Bao, Jun Yue2, Yulei Rao. A deep learning framework for financial time series using stacked autoencoders and long short term memory.

Results





-3.25

-4.00

-4.50

Profits made using Pairs Trading Strategy									
	Ground Truth	Kalman Filter	VAR	ARIMA	Facebook Prophet	Deep Learning Method			
Profit Made	\$91,965	\$29,960	\$64,448	\$64,580	\$49,317	\$75,689			

Future W<u>o</u>rk

- Add more information from other sources, such as current news, twitter feeds etc. via NLP to help improve long term predictive power of model.
- Replace current statistical methods with deep learning methods for identifying co-integrated pairs.

YouTube Link: https://youtu.be/KMWc5jAcnOA