Enhanced LSTM Financial Time-Series Forecasting

§1 Project Summary

Equity markets develop prices through the cooperation and competition of millions of independent agents placing bids and asks for small stakes in companies. They are a representation of the faith and hope we place, for instance, in the US financial system and on its ability to innovate against the greatest challenges of our time. Something so abstract is inevitably rife with disagreement and financial markets fluctuate as new information becomes available to investors and speculators. Using statistical tools similar to those used by investment strategists, machines can anticipate market activity by studying the factors which leave the greatest impact on investor sentiment. Using Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs), time-series forecasts can be developed which can motivate an investors decision making.

§2 Historical Context of Engineers in Finance

The general aim of science is to make accurate predictions: gravity works the same way today as it will tomorrow. Unfortunately, for the earnest theoretician, there is a recognition that most natural systems are dynamical and stochastic. Such systems are difficult to predict because they are highly sensitive to either initial conditions, unquantifiable factors, or both. The motivation to produce reliable models of semi-stochastic systems is clear and it is no less clear when financial incentives become involved.

United in their quest for returns on investment, investors and speculators have looked to quantitative finance and statistics to resolve market uncertainty and to understand where particular equities are likely to move. Perhaps the most revolutionary statistical finding of 20th century finance came from Harry Markowitz in 1952. Markowitz found that there are some portfolios which are more efficient than others, and that the efficient portfolio could help investors minimize risk for maximum returns. [1] After diversified efficient portfolios were constructed, however, investors were left to speculate on whether their work will yield financial returns in the near future and by what margins their hopes would be realized.

In 1973, Fischer Black and Myron Scholes created an efficient pricing formula for corporate options. [2] With the advent of computing power, the options market was created in 1973 which allowed speculators to hedge against risk and in some cases seek extra returns in exchange for betting for or against price movements. This emerging financial product gave investors a glimpse into the future of the underlying market that derivatives described, but neither market was immune to collective misunderstanding and folly. As revolutionary as computers were in the 1970's, they were not powerful enough to run the advanced statistical methods that mathematicians had long since described.

In the late 1980's, firms began developing software to run the Vector Autoregression and Value-at-Risk models needed to forecast local price changes. These tools reduced noisy and complicated time-series data into generalized trends which could anticipate business cycles and generate expectations. Portfolio theory collided with the computing power of the early 90's to produce the age of the Quant, a highly trained mathematician who specializes in developing trading strategies and complicated financial products. As the demand grew for more data and more rigorous algorithms with which to study it, neural networks emerged as efficient multidimensional curve fitters, capable of crunching large volumes of data into general trends which could be relied upon.

A large volume of the artificial neural network (ANN) research today is in the primordial stage. The power and sophistication of these models is apparent to everyone but the exact configuration of neurons and weights to guarantee the most optimal results is as of yet unexplained. Rather, species of ANNs have been developed which cater to the needs of a diverse range of computing challenges. One such species, invented in 1997 by Sepp Hochreiter, is the Long Short-Term Memory (LSTM) recurrent neural network (RNN) which recalls previous outputs when studying new inputs. [3] This enables the RNN to more easily discover statistical relationships as it is fed new data.

Although the involvement of engineers in the world of corporate finance might seem obscure to the lay person, there is a clear trend among the worlds foremost financial firms to focus on an increasingly quantitative approach to developing investment strategy.

§3 Project Description

Financial data will be gathered and efficient portfolios will be developed to cater to varying risk-tolerance profiles. The capital asset pricing model (CAPM) will reflect how investors ought to behave with respect to the risk free rate of return and the classes of risk tolerance will be developed with respect to the capital market line (CML). Meanwhile, an LSTM network will generate risk profiles for the market as a whole as well as for the specific portfolios under consideration. The network will not only consider the pricing history of large market indexes but will consider how changes in β, price to equity ratio, dividend yield, CPI, and other quantitative factors have motivated investors to adjust their financial positions.

§3.1 Rationale and Significance

When predicting dynamical systems, most time series approaches consider the value-over-time history in a vacuum.[1] The justification for this approach is clear when there are clearly identifiable trends in the data-set that the machine learning (ML) system is studying. Within the financial context, however, the pricing history is only partly motivational. Investors mostly make financial decisions based on industry and stock specific qualities. For instance, investors may judge whether a particular stock is overpriced by using its price to equity ratio. Or they could study whether an investment is riskier than the market by analyzing its β. It is the thesis of this project that these quantitative factors play a dominant role in

[1] `https://blog.statsbot.co/time-series-prediction-using-recurrent-neural-networks-lstms-807fa6ca7f`

an investors decision making process. Ergo, for an LSTM network to truly garner predictive power, it must develop an intuition about how these ratios and stats affect investor outlook.

In one particularly interesting approach to time-series forecasting, Ryo Akita et. al. develop an LSTM to process news articles about particular companies and to estimate investor sentiment using the frequency of positive and negative mentions. [4] This approach contrasts sharply against the strict time-series value approach documented above. My strategy is similar: enhance an LSTM time-series analysis by including external factors.

§3.2 Plan of Work

In the following sections, I will describe the field of study for this project along with the methodologies employed and the milestones which must be completed in a timely manner for this research to be completed.

§3.2.1 Scope

I have higher ambitions for creating a trading platform which automatically balances portfolios and estimates market risk. However, I must deconstruct this project into its constituent parts before I proceed. First I would like to test whether market trends can be forecasted using what statistics are known about individual stock or portfolio. This project is not attempting to fundamentally improve quantitative financial maths nor is it proposing to improve the architecture of LSTM networks generally. Rather, it is looking to apply both techniques together in a way that hasn't yet been well documented.

§3.2.2 Methods

Essentially, the financial component to this project involves the formation of efficient portfolios and quantifying the relationship between acceptable risk and return. For this, Markowitz's efficient portfolio theory and the CAPM will allow us to quickly generate the portfolios we are looking for. Additionally, we can calculate the normalized moving window β to motivate the LSTM by $\Delta\beta$ and not by the explicit values of β itself. These quantifiable components have already been developed over the last 6 months of independent research and they simply have to be applied to the project.

The most challenging component in this project will be the development of the neural network. The architecture of the LSTM-RNN is particularly challenging and most scholars are unsure how to optimize them. To this end, the attributed of the LSTM could be fed to a genetic algorithm to determine the most optimal configuration. Such a genetic approach should be considered an absolute last resort as it would take an enormous amount of time and research to develop. However, should I exhaust my alternative approaches to LSTM optimization, the genetic algorithm might be the only remaining option.

After the system is developed fully, it can be served from a raspberry pi which is connected to the internet. This will allow for real time evaluation of financial data. The Twitter APIs offer a promising opportunity for feedback but the best results might come from serving a small website from the device which can only be accessed securely. This security is less for privacy reasons, as the device has no access to the users financial data, just a simulation, but mostly to handle against buffer overflow. A blacklist of data-requests could mitigate against a server crash.

§3.2.3 Task Breakdown

This research project relies on the fusion of several distinct programming functions. Primarily, the successful implementation of LSTM software to judge market conditions and the financial front-end to support the LSTM analysis. Additionally, there are several improvements to the Raspbian-Linux OS which could make this software more efficient but I will mostly rely upon CHRON tables and reduced software packages to ensure efficient operation.

The first stage of research ought to be the compilation of all financial analysis software that I have developed thus far. The LSTM system cannot take input data before the synthesis of financial data is reliable and salable. This stage of the project ought not take longer than a few days.

After the financial base of the project is reliable developed, the research into LSTM can begin. I have found several promising leads for financial time series analysis LSTM systems and I can begin following their advice immediately to develop example projects before starting on my own.

Once the LSTM network is working properly it can be served within a larger ecosystem of software packages on the Raspberry Pi. Alternatively, a lower level system such as the MicroPython could be employed considering that the native language for this project will be Python, but this would present more challenges as the packages and software are updated.

Below, Figure 1 represents the work-flow which is to completed by this research project. Each item represents a function of subsystem which must be completed before the system can expected to produce reliable results.

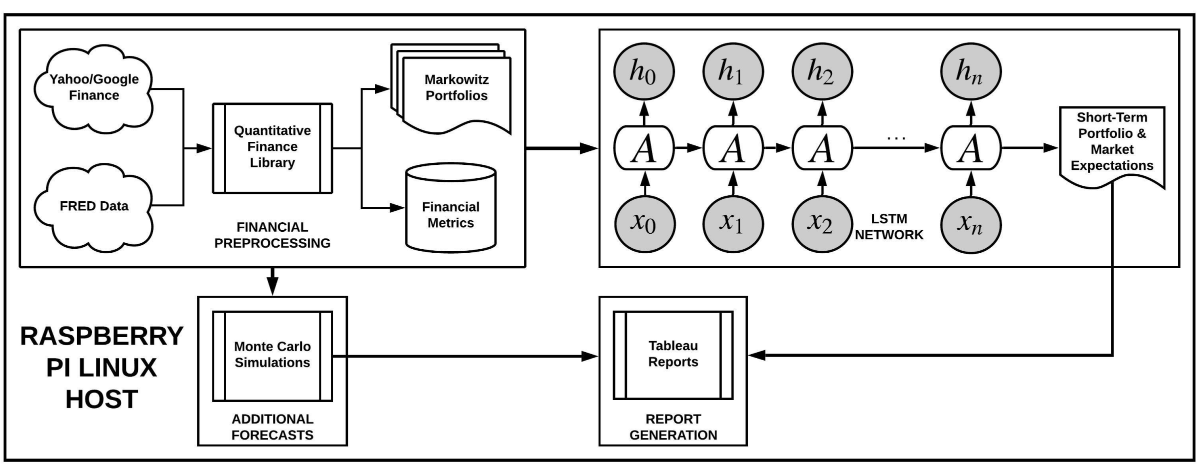

Figure 1: Diagram of system tasks.

In terms of the time-table for this research, the priority must be the development of the LSTM RNNs. With respect to these realities, this research task has been given the greatest share of the time. Figure 1 details the processes which must be completed, by which date and what must have be accomplished before the task can be considered completed.

Process	**Completion Date**	**Success Criteria**
Financial Preprocessing	4/7/2019	When, in a single file or function, a set of stock tickers can be sent in and the efficient portfolios and risk analytics are returned automatically.
Additional Forecasts	4/10/2019	Automatically generates the Monte-Carlo spread plots given a portfolio or market-index input.
LSTM Network	5/01/2019	The time-series analysis is working to the best of its ability and strategies to optimize it further have been exhausted.
Report Generation	5/05/2019	Automatic reports are generated from a database of portfolios, risks, and LSTM guidance.
Linux Host Machine	5/10/2019	The ecosystem of python functions works without supervision and can be configured remotely.

Table 1: Schedule of tasks.

These time-frames are realistic if the software approaches are direct and without IT incident. In other words, if work proceeds linearly then these tasks can be achieved with 5 hours per week over the course of this semester. However, projects rarely proceed in a linear fashion and I expect delays which may exceed the time allotted for this semester.

§4 Conclusion

The knowledge and experience gained from this project will vastly improve upon my ability to both apply neural networks to complicated problems as well as to understand how financial risk is estimated and how its conclusions are acted upon. This is a unique approach to financial time-series analysis, possibly offering future developers the opportunity to program more accurate and reliable forecasting tools.

§5 Personal Statement

It is important for me to personally express both my excitement to develop a time-series approach as well as my general disdain for the financial speculation proposed by this project. When it comes to managing wealth, it is wise to focus on risk mitigation and fee minimization. To these ends, investors are wise to avoid unnecessary complexities in their investment strategy as well as to reduce their active management role so as to lower their fee structure. The methods and sciences which this project glorifies ought only to be explored by corporate wealth managers and market makers. As for the lay person, I subscribe to Benjamin Graham's *Intelligent Investor* which outlines a strategy of index funds, dollar cost averaging, and the strict avoidance of market timing. Avoiding local sell-offs and corrections by liquidating your investments, moving to more secure investments for a time, and then finding an appropriate time to reenter the market, is foolish. If one were to genuinely follow the speculative approach outlined in this paper, I would suggest that they avoid speculating with anything they are not completely willing to lose. Neural networks have captured our imagination since emerging from obscurity in 2006, but they cannot predict the future. I earnestly implore you to keep an open mind but not to believe the hype.

References

[1] H. Markowitz, "Portfolio selection," *The Journal of Finance*, vol. 7, pp. 77–91, 1952.

[2] F. Black, "The pricing of options and corporate liabilities," *Journal of Political Economy*, vol. 81, pp. 637–654, 1973.

[3] S. Hochreiter, "Long short-term memory," *Neural Computation*, vol. 9, pp. 1735–1780, 11 1997.

[4] R. Akita et al., "Deep learning for stock prediction using numerical and textual information," 2016.