TATA CONSULTANCY SERVICES

Building on belief

Forecasting of FTSE 100 Index price movements using Quantum Computing approaches

TCS Quantum Computing Challenge

Challenge Sponsor: ***TCS BFSI A&I, Corporate Incubation (Quantum)***

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Problem Statement Overview

Quantum Computing is a new paradigm that promises transformation in the way we approach problems in Quant Finance. It promises improvements to current approaches and brings speed-ups and improves accuracies in AI/ML, Optimisation, and Simulation problems. One of the fundamental building blocks in Finance is to predict the price of an asset that has a dependency on several macro and micro factors, behaviours, and dynamics of the market. Several approaches have been proposed to classically approach price prediction problems using classical methods and we can further enhance the predictions using quantum approaches.

The objective is to effectively predict the price of FTSE 100 index based on historic data using quantum approach and benchmark this against the classical approach.

FTSE 100 is the Financial Times Stock Exchange 100 Index, also called the FTSE 100 Index or informally, the “Footsie". It is a share index of the 100 companies listed on the London Stock Exchange with the highest market capitalisation. Launched in 1984, FTSE 100 is widely used by exchanges for trading in futures, options, and ETFs.

Business Value & Motivation

Why is this problem important for the industry?

Investment managers need to take decisions about entry points and exit points in each window of time. Fund managers often enter and exit at wrong times leading to wealth destruction for their customers. Markets are dynamic, and the behaviour is impacted by policy changes, interest rate movements, currency fluctuations, and many other factors that impact the price daily, adding noise to historic data making the prediction quite challenging. For other set of market participants, price prediction would help in determining the risk exposure, setting margin limits, triggering margin calls, and so on.

Why is this a good problem for exploring a Quantum solution? What metrics are sought to be improved (speed, accuracy, training time, etc.)?

Having a method to predict asset prices accurately through high-end mathematical algorithms and equations without undertaking huge risk (i.e., at the same time not losing on quality of results). While classical methods provide predictions, Quantum computing can enhance the accuracy due to the way in which data is processed using quantum techniques. As the data and independent variables increase, Quantum provides better predictions compared to classical approaches leveraging concepts such as superposition, entanglement, and interference.

With more data and ability to analyse multiple variables, Quantum Computing is expected to provide superior predictions compared to classical approaches.

Further, since price prediction, as a fundamental block, acts as input to many other algorithms, the ability to calculate price faster and more accurately is crucial for Investment banks, funds, and insurance companies.

Which Business KPIs/Measures could possibly be impacted as a result of a Quantum solution?

Accuracy of prediction of asset price would improve profitability. For some stakeholders, it also helps to effectively price the risk, define the margins, or trigger the closing of positions.

Many organisations also make purchase of commodities from open markets and there is a greater chance of increased profitability when the price predictions are accurate.

Current Solution

How is the problem currently being addressed?

In the classical world, the times series predictions are done using methods such as:

1. Autoregressive integrated moving average (ARIMA) is a method that models autocorrelation and seasonality of data in time series.
2. Long Short-Term Memory (LSTM) is a type of neural network that can model the long-term dependencies in the data.
3. Multivariate regression models establish the relationships between multiple predictor variables and the target variable.

Quantum Computing can bring in new methods to estimate/predict the prices speculated on time series. The objective of this challenge is to build quantum algorithms to effectively predict the price of the FTSE 100 index for different time windows.

What are the results of the current solution?

1. **ARIMA**

$$Y(t) = \beta_1 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

Where Y_t is the value of the FTSE index at time t, β_1 is a constant term, ϕ_i and θ_i are parameters of the model (with $\theta_0 = 1$) , and ϵ_t is the error term at time t.

This method generates good predictions understanding the seasonality.

2. **LSTM**

Long Short-Term Memory networks (LSTMs) have been shown to capture long-term dependencies in time-series data and can selectively choose to forget unnecessary information, which might be especially relevant for this use case. The block of equations below, and Fig. (1) cursorily depict the working of LSTMs.

$$\boldsymbol{f_t = \sigma\left(W_f\ [h_{t-1}, x_t] + b_f\right)}$$

$$i_t = \sigma\left(\boldsymbol{W_f\ [h_{t-1}, x_t] + b_i}\right)$$

$$\boldsymbol{C_t = tanh\ (W_c\ [h_{t-1}, x_t] + b_c)}$$

$$\boldsymbol{C_t = \ f_t * C_{t-1} + i_t * Ct}$$

$$\boldsymbol{o_t = \sigma\ (W_o\ [h_{t-1}, x_t] + b_o)}$$

$$\boldsymbol{h_t = o_t * tanh(C_t)}$$

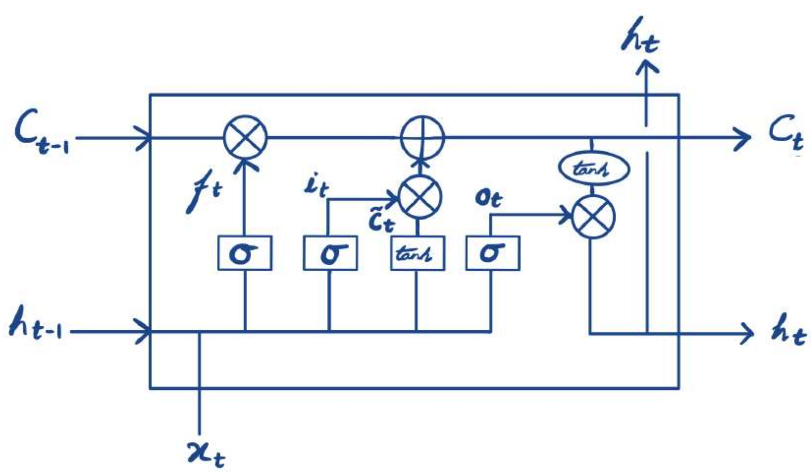

Figure 1: A single LSTM block

3. Multivariate Regression Models

$$Y(t) = \beta_0 + \sum_{i=1}^{k} \beta_i X_{t,i} + \ \epsilon_t$$

Where Y_t is the value of the FTSE index at time t, β_i are regression coefficients, $X_{t,i}$ are the continuous response values of the predictor variables at time t , and ϵ_t is the error term at time t.

Are the current results satisfactory? What are the limitations of the current solution?

Time series computations are heavy, not path driven, impacted by seasonality, and external noise which makes it difficult to predict the price. As we increase the variables, establishing the correlations between different variables is expected to be better with quantum computing compared to classical approaches. Therefore quantum computing approaches are expected to generate better results than classical methods.

Problem Definition for the Quantum Challenge

Redefined scope of the problem for the purpose of the Challenge

Classical Machine learning and statistical models are widely used in price predictions. This challenge would like to explore usage of quantum algorithms for making prediction of FTSE 100 price based on the historic data for last 10 years.

The FTSE 100 (Financial Times Stock Exchange 100) is one of the most widely used measures of the performance of the UK stock market. The stock prices of companies listed on the FTSE are subject to fluctuations due to a wide range of factors, such as changes in interest rates, economic growth, currency exchange rates, LIBOR, and other events. Developing accurate models to predict the future prices of the FTSE index or individual stocks is crucial for effective investment decision making.

The goal of this challenge is to develop a quantum algorithm that can accurately predict the future prices of the FTSE index. The algorithm should be able to handle a large number of variables and incorporate quantum parallelism to speed up the computations and improve the accuracy of predictions. The algorithm should be able to handle noisy data and be robust to handle changes (due to the underlying dynamics of the stock market) as much as possible.

Participants are expected to develop and implement a quantum algorithm using a suitable quantum programming language, such as Qiskit, PennyLane, or Cirq. The algorithm will be evaluated based on its accuracy in predicting the future prices of the FTSE index using a test dataset. The participants can access dataset of historical FTSE prices and predictor variables related to interest rates, GDP growth, inflation, VIX, LIBOR, Currency exchange rate and any other data.

The winning solution will be the one that achieves the highest accuracy in predicting the prices of the FTSE 100 index. The results of this challenge could provide new methods in the field of finance and investment decision making using quantum computing.

Description of the data/datasets provided

- Historical FTSE prices dataset: This dataset can be obtained from Yahoo or LSE. The data has historical prices of the FTSE index along with other relevant information such as volume, opening and closing prices. Last 10 years data is considered for meaningful training and testing of the quantum algorithms.

- Other predictor datasets: This dataset contains predictor variables that are known to influence the prices of the FTSE index, such as interest rates, GDP growth, inflation, and events. The dataset covers the same 10-year period as the historical prices dataset and is of sufficient quality to allow for accurate prediction of prices.

Examples of predictor datasets: Currency, LIBOR, Inflation, unemployment, VIX, and other parameters.

Participants can however be creative and are encouraged to choose their own variables to build better models for this challenge.

Challenge Evaluation Criteria

The entries will be evaluated by a Jury panel consisting of experts from the Industry and Academia. A representative list of criteria that would be considered by the Jury while evaluating the Phase-I and Phase-II submissions is given below. Please note that there are no specific weightages assigned to any of the criteria, and this should not be interpreted as a comprehensive list. The criteria listed below are indicative, and the Jury panel would be free to use their expertise, experience, and judgement to evaluate the entries.

Phase I:

- **Background work done:** Quality of background work done to understand the use case and the state of the art.
- **Innovation Quotient:** The overall innovation quotient in terms of originality and novelty seen in the approach, concept, and the algorithm.
- **Comprehensiveness:** Level of detail, coverage of the tasks towards the targeted goal of the challenge.
- **Promise:** As reflected through the results from any early experimentation done. Promise of the planned approach for Phase II.
- **Technical soundness:** Ability of the team to defend their work during presentation/ interaction with the Jury. Capability of the team to carry forward the work.

Phase II:

- **Innovation Quotient:** The overall innovation quotient in terms of originality and novelty seen in the approach, concept, and the algorithm.
- **Comprehensiveness:** Level of detail, coverage of the tasks towards the targeted goal of the challenge.
- **Technical completeness:** Quality and completeness of the code/solution and its ability to execute and produce results as documented.
- **Comparison with internal benchmarks:** How well the solution compares with any benchmark results that may have been achieved by the organisers.
- **Impact:** Value impact of the solution on current quantum hardware (any benefits shown in terms of improved optimisation, speed, and accuracy vis-à-vis classical approaches).
- **Extensibility:** Ease of adapting/modifying the solution to address variants of the use case (especially additional complexities).

- **Resource requirements & Scalability:** Any resource estimation provided for the solution to indicate the potential future scaling of the solution.
- **Technical soundness:** Ability of the team to defend their work during presentation/ interaction with the Jury. Capability of the team to carry forward the work.
- **Pitch:** Clarity, demonstration, and structure of the overall pitch.

Solution KPI

Participants are requested to submit entries that are comprehensible and backed up with mathematical foundations.

Evaluation criteria will be primarily based on following parameters in general:

- Accuracy: Correct 80 per cent of the times within the MAE benchmark for a given time window
- Mean Absolute Error (MAE): The MAE measures the average absolute difference between the predicted and actual prices.
- Root Mean Squared Error (RMSE): The RMSE measures the square root of the average squared difference between the predicted and actual prices.
- Coefficient of Determination (R-squared): The R-squared measures the proportion of the variance in the actual prices that is explained by the predicted prices.

Outline of some relevant work done in this area

There are several quantum regression approaches proposed. IBM has VQR which is a quantum version of the regression model. However, participants are encouraged to propose any new quantum algorithms for time series prediction models.

Marquee banks are doing significant work in this area. The concepts are also useful for Insurance, banking, energy, and utility companies.

Suggestions or pointers to the participants for attempting the solution

Suggested Approach

1. Problem formulation
2. Data preparation and Cleansing
3. Data instrumentation
4. Algorithm selection using classical and quantum approaches
5. Quantum circuit design
6. Quantum simulation
7. Result analysis
8. Iterative improvement and Benchmarking

Recommendations

Quantum is an evolving technology and researchers are coming up with new algorithms and methods to solve the classical problems effectively. There are several quantum algorithms that could potentially be used for stock price or FTSE stock price prediction problems such as Variational Quantum Regression (VQR), VQLS and so on. Participants are encouraged to consider exploring other methods such as Quantum Amplitude Estimation (QAE) or Quantum Support Vector Machine (QSVM) or Quantum Neural Networks (QNN) or any other methods.

References

1. **Variational Quantum Linear Solver**
   Carlos Bravo-Prieto, Ryan LaRose, M. Cerezo, Yigit Subasi, Lukasz Cincio, Patrick J. Coles
   https://arxiv.org/abs/1909.05820

2. **Qiskit – Variational Quantum Regressor Implementation**
   https://qiskit.org/documentation/machine-learning/stubs/qiskit_machine_learning.algorithms.VQR.html

3. **Stock Price Prediction model for Netflix**
   Vivek Chaudhary
   https://towardsai.net/p/machine-learning/netflix-stock-prediction-model-a-comparative-study-of-linear-regression-k-nearest-neighbor-knn-4527ff17939b

4. **Predicting Stock Prices using Quantum Long-Short Term Memory ML**
   https://github.com/XanaduAI/QHack/issues/37

5. **One-Step Time Series Forecasting Using Variational Quantum Circuits**
   (P. Kaushik, S. Pramanik, M.G. Chandra, C. V. Sridhar)
   https://arxiv.org/abs/2207.07982