TCS Quantum Challenge

Quantum Computing & Simulation Hub

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Introduction

Challenge Introduction

Large retailers have problems for replenishing stores with right products, quantities,etc., in the right time (restock), requiring precision while also finding the right balance between stock and availability.

Importance of the problem

Currently, for a retailer with over a thousand stores and tens of thousands of different SKUs, granularity is traded off against speed of calculation and hence, SKUs are grouped, this results in a sub-optimal solution.

So for a better optimization in cost-benefit is important not to trade that much of granularity and also being able to cover the demand needed.

Understanding the problem

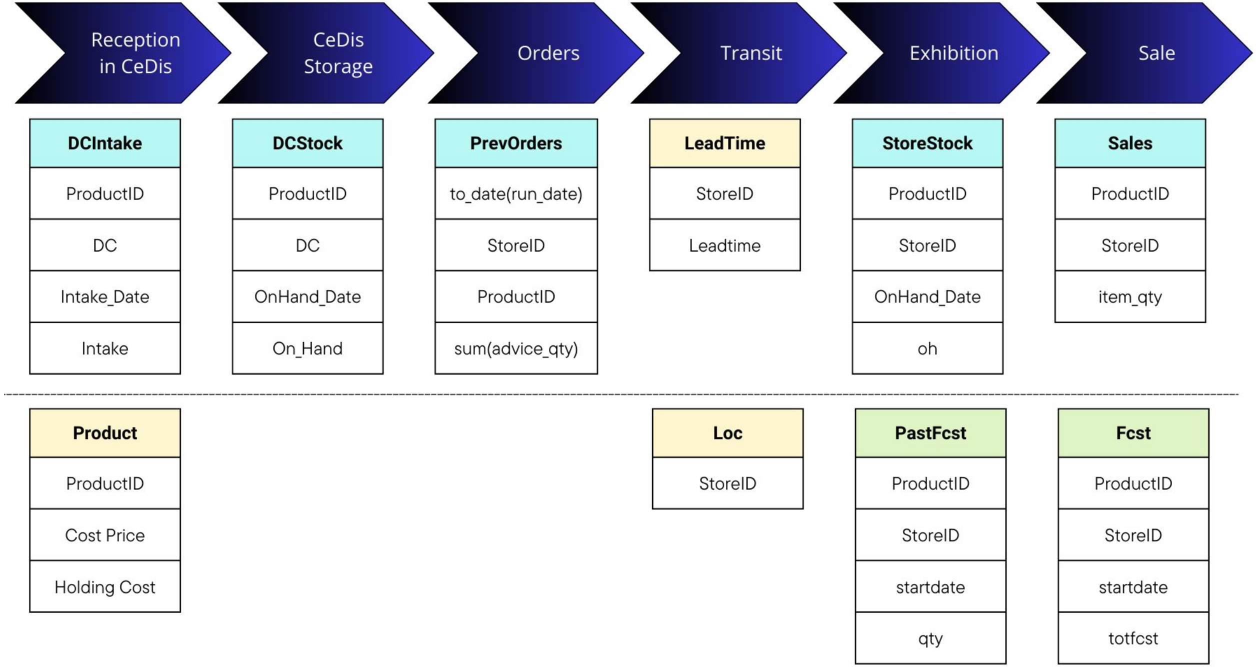
Interpretation

Identify a quantum-based solution approach to solve the need of SKU optimizing capital and cost

Highlights

- Granularity
- Seasonality
- Speed
- Precision
- Forecast
- Demand

Dataset Overview



- Briefly introduce the data provided

- Highlight important characteristics and how they fit into your approach

Some Classic ML Models for Retail Optimization

- Demand Forecasting with Long Short-Term Memory (LSTM) Networks:

  Why: LSTMs are well-suited for capturing sequential patterns and are effective in modeling time-series data, making them suitable for forecasting demand. By considering factors like rate of sale, seasonality, and sales forecast accuracy, LSTM networks can provide more accurate predictions compared to traditional methods.

- Optimization with Reinforcement Learning (RL):

  Why: Reinforcement Learning can be applied to optimize the supply chain decisions, considering factors such as delivery frequency, pack sizes, and distribution center capacity. RL models can adapt to changing conditions and learn optimal strategies over time, enabling the system to find better solutions for the dynamic and complex challenges in replenishing stock.

- Random Forests for Inventory Optimization:

  Why: Random Forests are robust and can handle a large number of features. They can be employed for inventory optimization, taking into account multiple dimensions like range, physical variations between stores, and store access limitations. Random Forests can provide insights into feature importance, helping identify critical factors influencing the stock replenishment process.

Some Quantum ML models

- Quantum Support Vector Machine (QSVM):

  Purpose: Used for classification tasks in quantum machine learning.

  Key Feature: Utilizes quantum parallelism to enhance the efficiency of support vector machine algorithms.

- **Quantum Neural Networks:**

  Purpose: Applies quantum principles to neural networks, potentially providing advantages in certain tasks.

  Key Feature: Leverages quantum entanglement and superposition for computations.

- Quantum K-Means Clustering:

  Purpose: Used for clustering data points into groups.

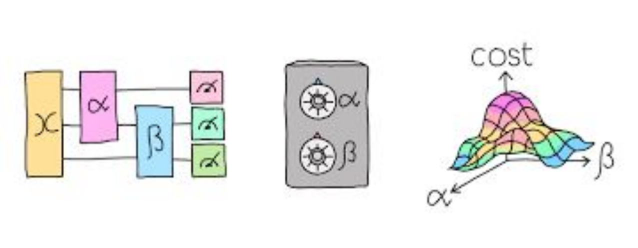
  Key Feature: Exploits quantum parallelism to speed up the clustering process.

- Variational Quantum Eigensolver (VQE):

  Purpose: Used for solving optimization problems, including those in chemistry and materials science.

  Key Feature: Applies a variational approach to find the minimum eigenvalue of a given Hamiltonian.

Choosing the right model



Classic Neural Network:

Framework: Classical neural networks operate in a classical computing framework, using classical bits for information representation.

Processing: Computation is based on classical binary logic, involving weighted sums and activation functions in a layer-wise fashion.

Superposition and Entanglement: Lacks the inherent ability for quantum superposition and entanglement, limiting parallelism and potential computational speedup.

Training Algorithm: Typically trained using classical optimization algorithms like gradient descent.

Memory: Stores and processes information using classical bits with well-defined states (0 or 1).

Quantum Neural Network:

Framework: Operates within a quantum computing framework, utilizing quantum bits or qubits for information representation.

Processing: Leverages quantum principles, such as superposition and entanglement, to perform parallel computations across multiple states simultaneously.

Superposition and Entanglement: Can exploit quantum superposition and entanglement, potentially offering advantages in certain computational tasks.

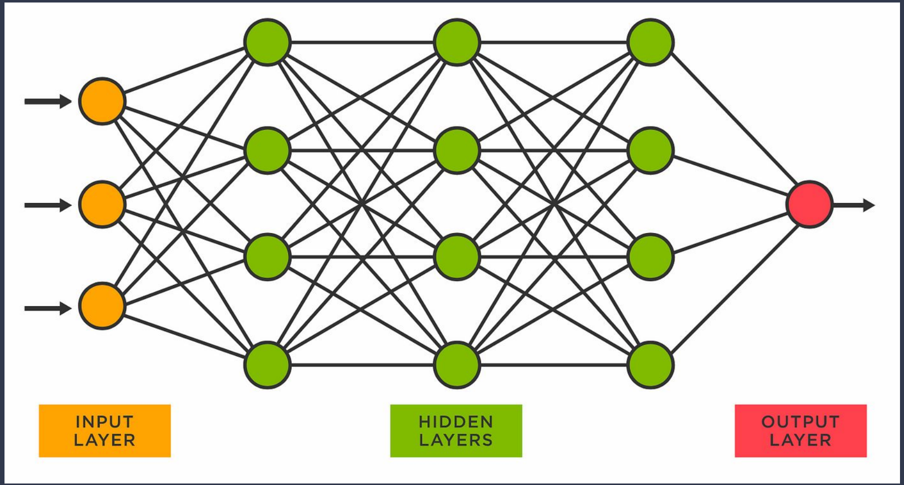
Training Algorithm: May involve quantum algorithms like quantum gradient descent or variational quantum circuits for optimization.

Memory: Uses qubits, which can exist in a superposition of states, allowing for richer and more complex representations.

Proposed Solution

Why will it work?

Selecting a Model:
Quantum Neural Network



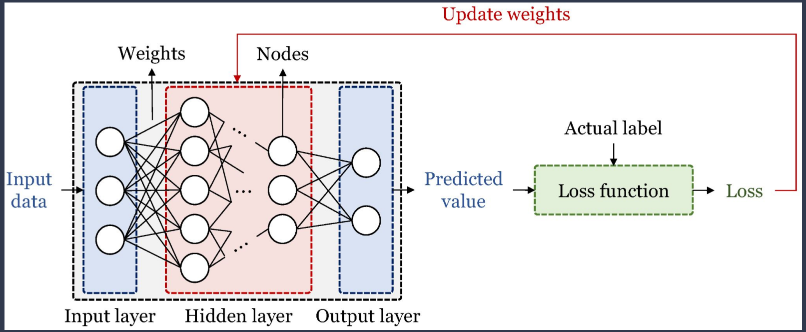
Neural Networks (particularly LSTM) are well-suited for capturing sequential patterns and are effective in modeling time-series data, making them suitable for forecasting demand.

By considering factors like rate of sale, seasonality, and sales forecast accuracy, LSTM networks can provide more accurate predictions compared to traditional methods.

Based on this description and the previous research for Quantum ML models, we opted for this solution.

Why will it work?

Quantum vs Classical Neural Networks



We will be doing a comparison between the LSTM neural network and the Quantum Neural Network, this is because:

a) We want to use a model that can be in “similar conditions”
b) Having a similar methodology, compare the results
c) Explore also if there’s a significant change between models and also having a challenge model
d) Compare results

Innovation Quotient

- Discuss the innovativeness of your solution

- Explain its originality and novelty

Deep dive into Proposed Solution

We've harnessed both classic and quantum modeling to revamp the replenishment system, creating an optimized, data-driven approach for increased efficiency and accuracy.

- Utilization of deep and quantum neural networks for individualized forecasting and precise predictions.
- SKU-based replenishment enables a detailed understanding of each product's needs.
- Historical sales data and variables such as seasonality guide accurate future demand predictions.
- Lead time predictions ensure no understock or overstock scenarios, optimizing costs.
- The ultimate goal is a harmonious balance between stock availability and supply chain costs.

Early Experiments

- Share early results from your solution

- Interpret these results and what it means for your project

Roadmap for Phase II

- Address any potential challenges and how you plan to overcome these
- Outline what steps you plan to take in phase II
- Highlight key milestones and goals

Conclusions

- Summarize your proposal
- Reinforce why it is innovative and promising
- Highlight the potential benefits of the solution

Thanks

Time for Q&A

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