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A HYBRID DEMAND FORECASTING AND REINFORCEMENT LEARNING FRAMEWORK FOR DYNAMIC PRICING IN E-COMMERCE

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Abstract
Dynamic pricing is becoming a hot topic these days, most importantly in e-commerce to increase the number of sales and customer satisfaction. This technique is mostly used in developed countries but in developing countries like Pakistan the applications of dynamic pricing are restricted. The main purpose of this research is to scrutinize the implementation of a hybrid dynamic pricing model in developing countries like Pakistan e-commerce sectors by the integration of reinforced learning (RL), demand forecasting, and price prediction methodologies. This study employs Reinforcement Q-Learning and Deep Q-Learning to simulate real-time pricing scenarios. Furthermore, in this study demand forecasting is performed using ARIMA and Prophet models, while Random Forest and XGBoost algorithms are implemented for accurate price prediction based on product-level features. The goal is to create a dynamic pricing structure that is fair, adaptable, and appropriate for the particulars of Pakistan's online marketplace. Dynamic pricing can bring big changes in online marketplace in developing countries. However, its success depends equally on the social and economic conditions as it relies on advances in technology. The ultimate goal of this study is to create a sustainable pricing model that takes into account the preferences of Pakistani consumers and, using data-driven insights and adaptive learning techniques, adapts product prices to shifting market conditions.

INTRODUCTION

Dynamic pricing is basically a technique that adjusts the prices in real-time of different products based on the current conditions in market, demand fluctuations, and customer behavior, which makes it a hot topic in different countries around the world. For instance, multinational companies like Amazon, Uber, and airline booking platforms have integrated dynamic pricing into their daily operations, optimizing their revenue and strengthening customer relationships (Shiller, 2014; Elmaghraby & Keskinocak, 2003). These companies are using an expert level of machine learning models and also doing real-time analysis to adjust prices according to customer behavior.

Dynamic pricing started with the simple idea of supply and demand, but in today's world, it's become a much more complicated game. The business can grow faster if we together use real-time data and AI models, which will help businesses to grow faster and smarter by keeping up with every change in the market. In competitive spaces like online shopping and ride-hailing, those companies that get dynamic pricing right tend to have a major advantage over the other companies in competition (Gallego & Van Ryzin, 1994; Talluri & Van Ryzin, 2004).

However, this strategy has a lot of benefits but still the adoption of dynamic pricing in developing countries like Pakistan is very limited. The delay in adoption of this technology can be caused by a number of factors. First, using these advanced pricing methods is challenging because of the limited access to big data systems and a shortage of AI experts (Huang et al., 2020; Xu & Li, 2020). Another big challenge is that Pakistani consumers are highly sensitive to price. When prices go up or down in Pakistan, many people respond negatively. They often feel the changes are unfair or that sellers are trying to take advantage of them, instead of seeing it as something that happens in a normal market (Misra & Nair, 2019).

There's also a bigger issue that people often don't trust decisions made by algorithms. In our society, there are people who are conscious about clear and fair pricing, and unexpected changes in price can reduce trust, damage the brand, and lead to a loss of customer loyalty (Yang & Shin, 2019; Schlosser et al., 2020). This makes it even more important to keep ethics in mind when designing dynamic pricing systems for such markets.

In light of these challenges, this research presents a hybrid dynamic pricing framework that integrates demand forecasting, price prediction, and reinforcement learning for data-driven
decision making. Demand forecasting was performed with ARIMA and Prophet models to show both short- and long-term trends in prices. Furthermore, I have used XGBoost and Random Forest algorithms to recommend optimal price ranges based on engineered product-level features like order timing, delivery delays, and product weight. Then I used reinforced learning techniques like Q-Learning and Deep Q-Learning agents, which learn the pricing scenarios for multiple products and the agents learned policies that maximize cumulative rewards (Sutton & Barto, 2018; Azar et al., 2022). This approach not only captures market behavior but also ensures adaptability across diverse seasonal and demand-driven scenarios.

This is the right time for this research as there a rapid transformation has been experienced in digital marketing which is because of the growing internet access and the high expend in e- commerce platforms like Daraz and Foodpandas. Beside these all facilities there is still challenges with customer behavior, which is why implementing dynamic pricing strategies is a big opportunity in Pakistan e-commerce market. By building dynamic pricing strategies we can easily get customer trust on changing prices of products and services. This will close the gap between advanced technology and what Pakistani consumers expect.

Additional to this, This study will track the customers behavior, market competition, and economic changes in Pakistan which will help us validate that how fair dynamic pricing strategy is in e- commerce. This main purpose of this study is not only to excel the profit in e-commerce business but also to build a trust worthy, consumer friendly model which will help us to grow the digital marketing in Pakistan while respecting the needs and sensitivities of the local market. In this research, I will merge machine learning algorithms like XGBoost with demand forecasting models like ARIMA and Prophet. I will also use highly effective methods like reinforcement learning (RL). In order to identify the best possible balance between profitability and equity, this research is going to simulate a number of pricing scenarios. For e-commerce companies operating in developing nations around the world, where dynamic pricing is still an untapped potential, the results may offer insightful information.

Literature Review

Dynamic pricing isn't a completely new concept. Its theoretical underpinnings have existed in economics and operations research for a long time. The early inventory-based pricing models emphasized the optimization of selling perishable goods and adjusting prices based on inventory
levels (Gallego & Van Ryzin, 1994). With new technological improvements, more sophisticated approaches have emerged, incorporating real-time adjustments to prices based on rich streams of market and consumer data (Talluri & Van Ryzin, 2004).

On a global scale, there are a variety of industries that have successfully employed dynamic pricing strategies. The airline industry was one of the pioneers who tacitly adopted them, employing yield management practices to gain revenue from available seats and demand forecasts (Bertsimas & Perakis, 2006). Ride-hailing services like Uber introduced the concept of "surge pricing," which balances supply and demand during peak hours (Chen et al., 2019). E-commerce stores like Amazon update prices in real time, adjusting to stock levels, competitors, and consumers' browsing habits (Elmaghraby & Keskinocak, 2003).

The dynamic pricing strategy needs to be implemented in developing countries like Pakistan (Haung et al. 2020). We need to highlight the gaps in existing infrastructure, for instance, there is limited availability of cloud computing infrastructure in Pakistan, also the data storage platforms are very expensive, most importantly there are very few AI-trained professionals available in Pakistan tech industries. Moreover, uneven infrastructure availability between urban and rural areas further complicates efforts to adopt a holistic dynamic-pricing approach (Qureshi et al., 2022).

Dynamic pricing is yet to take off in developing markets like Pakistan. Huang et al. (2020) highlight the infrastructure gaps, for example, the limited availability of cloud computing, expensive data storage, and lack of AI-trained personnel that foster such technologies. Moreover, the urban-rural divide in infrastructure access or availability adds to the problem of a comprehensive approach (Qureshi et al., 2022).

Besides that, there is another most important concern which revolves around the customer behavior on changing prices in market. Several studies on customer behavior suggests that the customers from developing countries like Pakistan are more conscious about the changing prices of products which most probably make them lose their trust on pricing (Yang & Shin, 2019). The instant changes in price are mostly perceived and misinterpreted as manipulative exploitation and this leads the brand image to its downfall (Misra & Niar, 2019). "In digital markets, trust functions as a critical currency pricing approaches that degrade this trust can lead to substantial losses over time.

Merging reinforced learning techniques with traditional machine learning and forecasting models to achieve more accurate and trustworthy dynamic pricing strategies has been the focus of recent studies. A very recent study on hybrid models in dynamic pricing illustrated that using hybrid models like combining ARIMA with Q-Learning enhances long-term revenue outcomes in retail context (Azar et al (2022). Similarly, other researchers have explored the use of Prophet for short- term demand forecasting, which improves the responsiveness of RL agents in dynamic pricing environments (Tian et al., 2021). At the same time, machine learning models like Random Forest and XGBoost have shown very strong performance in predicting product prices which helped the reinforcement learning models like Q-Learning and Deep Q-Learning agents about the pricing ranges and the potential outcomes (Zhao et al., 2020). The integration of these traditional machine learning models and the reinforced models gives very flexible and data driven approach for dynamic pricing which supports instinct decision making in real time changing markets.

In today's rapidly evolving economic landscape, the markets need to be stabilized for which dynamic pricing could be a powerful tool. During the downfall in economic and supply chain distribution, dynamic pricing can help the market by balancing the market forces more effectively than static pricing (Narayanan et al., 2021). However, we need careful ethical design and customer education to make this strategy successful.

In conclusion, the above literature highlights that there are many benefits by using a dynamic pricing strategy which changes prices based on demand, time, or other factors which are controlled by models like reinforced agents which learn by trial and error to make the best pricing decisions. This strategy also identifies the most significant barriers which need to be resolved in developing markets. Pakistan markets are facing many challenges, but it also has a great potential for these infrastructures, as long as the models respect cultural values, technology limits, and ethical rules.

Methodology

To know that how dynamic pricing can help Pakistan's e-commerce market, this study followed a quantitative research approach. I have suggested a custom hybrid approach which will be combining the demand forecasting, price prediction, and dynamic pricing guided by reinforcement learning to make smarter, data-driven pricing decisions.

Dataset

For this study, I choose and Olist E-Commerce Dataset (2017–2018) as a reference point. This data set contain real transaction records from a Brazilian online marketplace; it has detailed and diverse information which make it suitable data set to understand the dynamics of developing e-commerce markets like Pakistan. We selected key features from data set before building models such as order dates, product identifiers, customer types, pricing information, shipping durations, and customer interaction history, all of which were essential for training and testing the dynamic pricing framework.

Demand Forecasting

The monthly product demand was forecasted using two time series models ARIMA and Prophet. The order timestamps were first transformed into monthly aggregates to capture long-term seasonality and short-term demand shifts. Forecast accuracy was evaluated using RMSE and MSE.

Price Prediction

Two supervised machine learning algorithms, Random Forest and XGBoost, were implemented to estimate optimal product pricing. These models were trained on engineered features from the dataset, such as delivery delays, product weight, ordering weekday and hour, and promotional activity. Model performance was evaluated using standard regression metrics.

Reinforcement Learning for Dynamic Pricing

Q-Learning and Deep Q-Learning algorithms were employed to simulate the dynamic pricing environment. These agents learned to modify prices based on the time of order, anticipated demand, and other relevant attributes of the product. Revenue-centric adaptive seasonal behavior along with demand-responsive trends formed the basis for the learning environment reward systems. The performance metrics of standard Q-Learning and Deep Q-Learning demonstrated that the latter outperformed the former in both cumulative reward and adaptability.

Implementation and Results

ARIMA and Prophet for Demand Forecasting

This part illustrates the results of implementing demand forecasting models ARIMA and Prophet to predict future product demand through analyzing historical sales data. Evaluation criteria for these models are based on two industry standard benchmarks, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

The following table summarizes the evaluation scores obtained for the ARIMA and Prophet models on the test dataset:

Table 1: Forecasting Model Performance

Model	**Test MSE**	**Test RMSE**
ARIMA	522,194.97	722.63
Prophet	10,697,673.87	1,034.25

As indicated in Table 1, the ARIMA model dramatically outperformed the Prophet model in both MSE and RMSE. The ARIMA model gave test results of 522,194.97 for MSE and 722.63 for RMSE, demonstrating greater accuracy in capturing the demand trend and seasonal fluctuations within the data set versus the Prophet model which returned much higher test results of 10,697,673.87 for MSE and 1,034.25 for RMSE giving evidence to its relative ineffectiveness in capturing the data's underlying dynamics.

Further model evaluation could be done using the graphical comparison of ARIMA vs Prophet demand forecasting. The ARIMA forecast appears to track actual demand values precisely, especially in periods of peak demand. In figure 4, the output from the Prophet model is shown, and it seems that the smoother curve does not depict the sharp changes well.

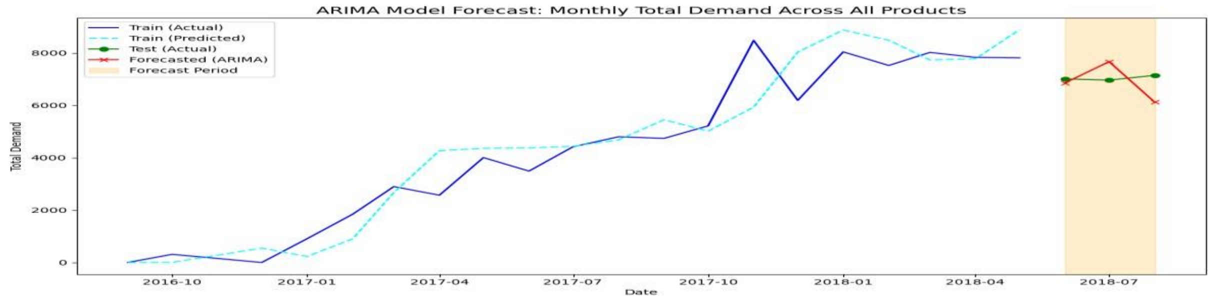

Figure 1: Arima Model Forecast

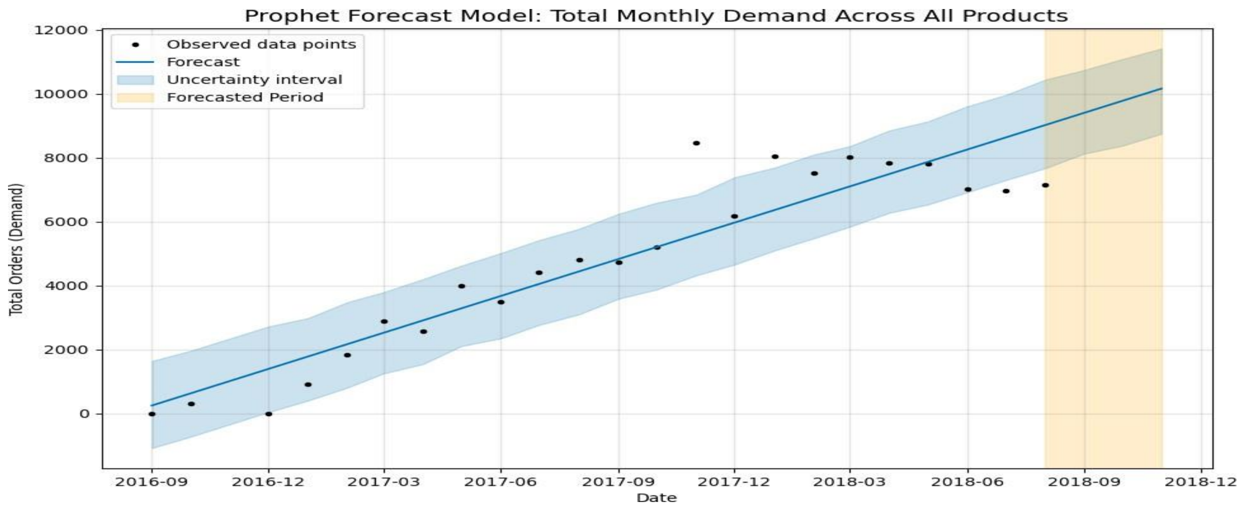

Figure 2: Prophet Model Forecast

These plots confirm that ARIMA adapts more responsively to short-term shifts and seasonal patterns, while Prophet, though robust for many business cases, may require extensive hyperparameter tuning or additional regressors for datasets like this.

Price Prediction Using Machine Learning Models

This part discusses the results obtained from leveraging machine learning algorithms XGBoost Regressor and Random Forest Regressor for optimal product pricing. The models were evaluated on the primary regression evaluation methods: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. In addition, training time was measured to evaluate the efficiency of each model.

Table 2: Machine Learning Models Performance

Model	MAE	MSE	RMSE	R^2 Score	Training Time (s)
XGBoost Regressor	5.32	824.73	28.72	0.9751	0.96
Random Forest Regressor	5.61	1010.29	31.79	0.9695	99.26

As shown in Table 2, it is clear that XGBoost Regressor outperformed Random Forest Regressor in each one of the evaluation metrics. From the results, it is easy to see that diagnosis given by XGBoost provided a higher R^2 score of 0.9751, which is better than the Random Forest R^2 of 0.9695, showing better generalization and fitting to the training data. In addition, XGBoost also had a lower MAE (5.32) and a lower RMSE (28.72) which also supports the claim of better performance given by XGBoost.

The difference observed in training time is remarkable as well, with XGBoost completing training in under 1 second opposed to over 100 seconds for the Random Forest ensemble. This difference highlights XGBoost's computational efficiency, which is a benefit when pricing needs to be done on large scale or in real-time.

Further model prediction insights can be gathered from the graphical comparison of predicted to prices.

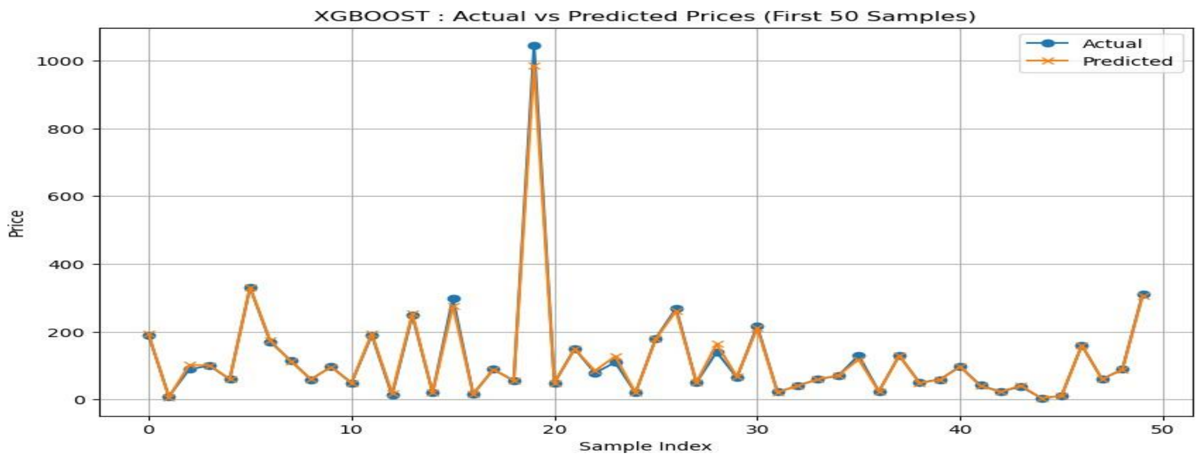

Figure 3: XGBOOST Price Prediction

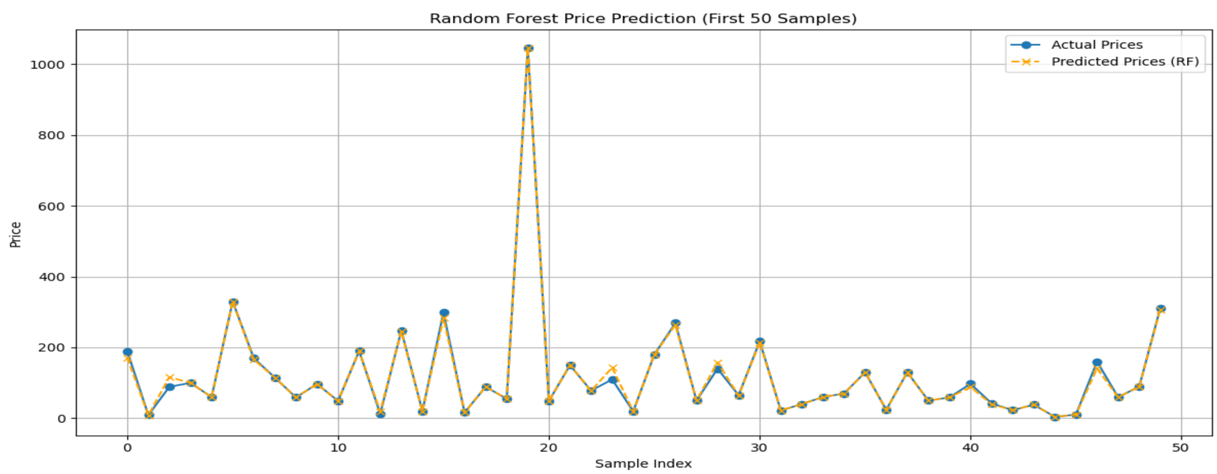

Figure 4 : Random Forest Price Prediction

As shown in Figure 3, the XGBoost model predictions which were done on the actual prices were nearly spot on showing very little deviation throughout the distribution. Figure 4, however, shows that the Random Forest predictions show to be a bit more off the mark in comparison to the actual prices, particularly at the higher and lower extremes.

These results support our previous understanding that in the context of this e-commerce application, XGBoost proves to be a far more accurate and efficient model for price prediction. His performance results can be tied to the successful application of ensemble learning bias and variance reduction capabilities stemming from the gradient boosting method.

It does seem that both models handled the tasks quite well, evidenced by the high R^2 values and strong explanatory power. Work for the future could include adding feature selection, hyperparameter tuning, or even ensemble stacking to improve model resilience. Moreover, others may further investigate the incorporation of machine and reinforcement learning into a hybrid decision framework to dynamically modulate price adjustments based on demand and predictive pricing models.

Reinforcement Learning-Based Pricing

In this research, two concepts of reinforcement learning were used for dynamically optimizing product pricing: classical Q-Learning and its derivative, Deep Q-Learning or DQN. The outcomes of these methods were evaluated

based on the cumulative rewards obtained over episodes, which
acted as profit indicators or the success level of the simulated pricing environment strategy performance.
Q-Learning Performance

In the case of Q-Learning model, the training was done over 1000 episodes, each containing a cycle of state-action-reward feedback. The agent focused on improving popular Ev(tiona gaps) benefiting "action-value (Q)" av Q-table strategy to reach long-term cumulative reward objectives.

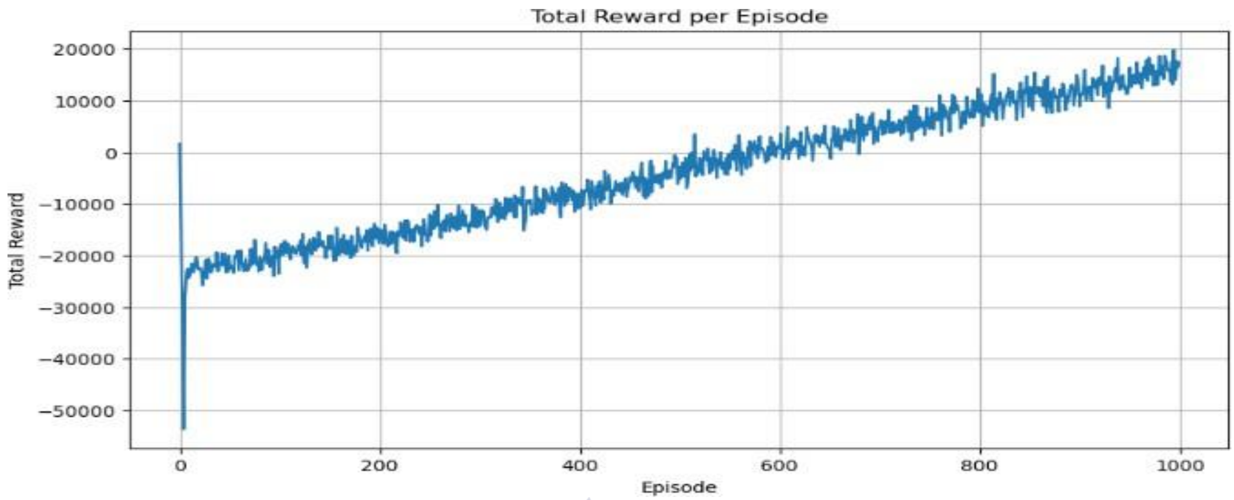

Figure 5: Q-Learning Model Performance

It can be seen from the graph that the early episodes tend to be negative or low in reward and this The graph illustrates that the initial episodes typically show negative rewards. This reflects the early stage of random exploration, where rewards are low. With further training, model learns effective pricing strategies, resulting in improved rewards. Despite the aforementioned fluctuations, the overall trend describes stable learning and convergence with robust improvement, ultimately earning over $20,000 in rewards, indicating significant learning.
Q-Learning proved effective for this problem because the state and action spaces were DQN was trained for only 75 appropriately discretized, allowing the agent to map pricing decisions to positive outcomes reliably. This method, despite its simplicity, learned from long-term interactions and was less computationally demanding compared to DQN.

Deep Q-Learning Performance
The application of a neural network in approximating the Q-function allows an agent to process multi-dimensional and continuous states within a DQN. Due to limited computational resources,

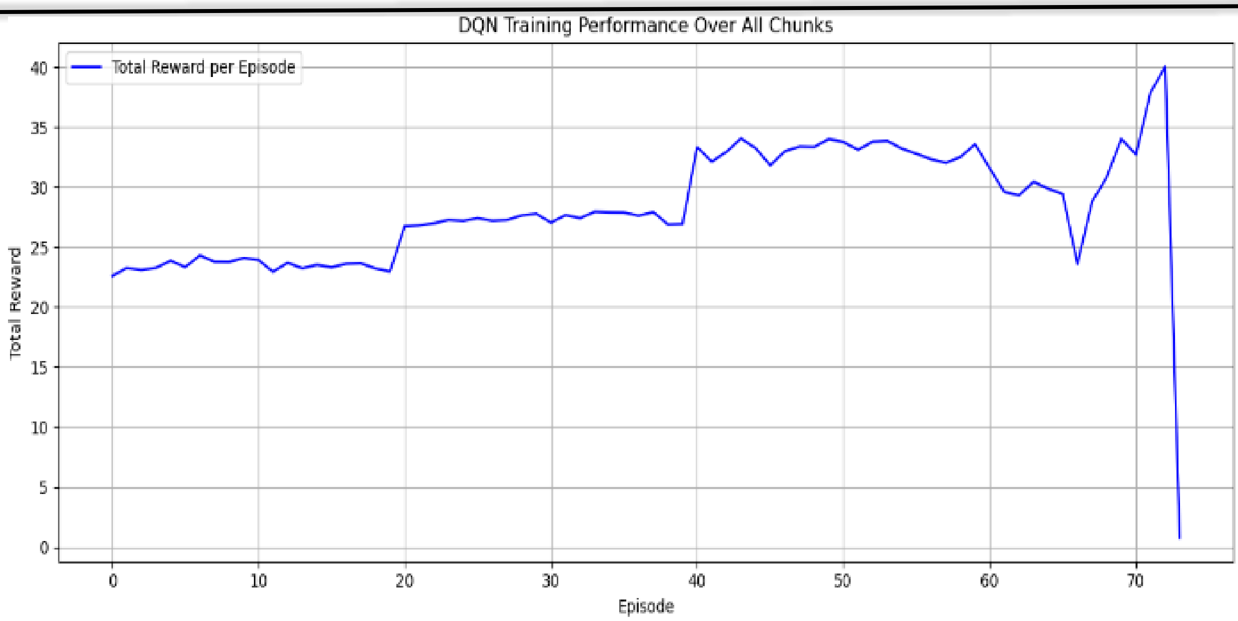

Figure 6: Deep Q-Learning Model Performance

At the beginning of the training process the reward values for DQN were low, starting at a value of 23. This suggests the agent's learning during the early phases was extremely limited. However, by the 40th epoch, the model was able to achieve total rewards of 40, indicating some improvements, albeit inconsistent relative to the prior stage of the model. As much as some improvement could be discerned relative to prior stages of training, this improvement fed the impression that there was no convergence to a stable point. Over the entire period of training, the model displayed a lot of oscillations in performance leading to sharp declines and not reaching any stabilized level even after 70 epochs. Unlike Q-Learning, which eventually reached some form of performance plateau, the DQN curve overall exhibited complete lack of convergence.

The underperformance of Deep Q-Networks in this study is likely due to multiple interrelated reasons. To begin with, 75 training episodes is far too low considering how deep and complex the model is. Furthermore, the high variance in the observed training rewards suggests that the ratio between exploration and exploitation is suboptimal, pointing towards unstable learning dynamics. Also, the model's architecture may need some adjustments as explorative boosting by adding layers with regularization and tweaking learning rates could yield better performance. Finally, the implementation of advanced methods like Double DQN, Target Networks, and Experience Replay may have been sub-optimized, calibrating more thoroughly these methods could improve performance significantly.

Comparative Analysis

To provide a clearer overview of the two models, Table 3 presents a side-by-side comparison across key criteria

Criterion	Q-Learning	Deep Q-Learning (DQN)
Training Episodes	1000	75
Performance Trend	Consistent Increase	Fluctuating, Unstable
Max Reward Observed	20,000+	40
Stability	High	Moderate to Low
Scalability	Low (Discrete States)	High (Continuous States)
Training Complexity	Low	High

Table 3: Reinforced Models Comparative Analysis

Despite DQN's theoretical advantages, the Q-Learning model outperformed DQN in this specific implementation. Q-Learning's simplicity and extended training led to more stable convergence and better pricing policies under the current setup.

Recommendations and Future Work

Even though the ARIMA model outperformed others in this study, there is still much that can be done to improve it. Further hybrid ARIMA forecasting models as research topics could be devised that would use ARIMA's strength in capturing linear time dependencies and combine them with more sophisticated nonlinear pattern machine learning algorithms. The robustness of the Prophet model in many applications could be improved by adding more relevant external variables such as predictive promotional campaign analytics, national holidays, or even weather conditions. These contextual factors could help the model better adapt to real-world fluctuations in consumer

demand. Furthermore, the implementation of deep learning approaches, particularly Long Short- Term Memory (LSTM) networks, holds promise for multivariate time series forecasting. LSTM networks are especially effective at learning long-term dependencies and complex temporal dynamics, which could significantly enhance predictive accuracy in more intricate datasets.

In this research, the reinforcement learning part indicates that the Q - learning model was better than the deep Q – Network model. Nevertheless, there is room to improve the performance of DQN. One possibility includes trying to improve the model by letting it train between 500 – 1000 episodes. More advanced variants of DQN like the ones mentioned earlier could be looked into as well since they seem to have the ability to make learning in complex environments more stable and efficient. In addition to this, other changes can be made to the design of DQNs reward function. If the reward criteria for DQNs were adjusted to include actual business objects like increase revenue, improve customer conversion rate and retention would yield treasurable results.

From this point, changes can be made to the input feature set by incorporating behavioral insights alongside appropriate normalizations and time indicators. These improvements will allow the model to learn responsive and adaptive context pricing policies. Looking forward, the inclusion of Multi-Agent Reinforcement Learning (MARL) may enable the capture of more sophisticated simulated market interactions with several competing sellers operating within the same system. This would improve the model's reliability and usefulness in dynamic e-commerce environments. As stated above, LIME and SHAP explainability techniques would strengthen the decision-making transparency of the reinforcement learning agent by incorporating rationale behind its actions to model behaviors using parameters that can be more easily understood. Hence, interpreting agent decisions promotes trust from stakeholders which eases the implementation of smart pricing mechanisms in practice.

Conclusion

The implementation of dynamic pricing systems in Pakistan's evolving e-commerce landscape seemed feasible with the results gained from the investigation, which integrated intelligent pricing systems with demand forecasting. Real-time monitoring coupled with responsive systems automation weighing intelligent reaction strategies with intelligent systems heuristics was able to incorporate market self-adjustment.

Among the examined forecasting models, ARIMA outshined Prophet in accurately capturing and predicting emerging trends as well as seasonal shifts in product demand. In prediction of pricing, XGBoost's performance in comparison to Random Forest showed how critical precision alongside resource responsiveness is in real-time applications.

The classical Q-Learning model was noticeably more efficient than Deep Q-Learning in reinforcement learning owing to the latter's high computational complexity. This affirms the practicality of simpler models in low-resource contexts where constrained budgets drive the need for efficiency and straightforward design.

Pakistan's developing markets can benefit from sophisticated hybrid frameworks that incorporate smart dynamic pricing based on real-time analytics, as this system suggests. There is potential for additional refinement, especially with integration of more sophisticated algorithms towards implementation. It gives us a strong starting point for creating pricing systems that are fair, flexible, and able to scale. In a country where digital transformation is happening fast, solutions like this can help build customer trust and encourage businesses to innovate with confidence.

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