**Module 6 Assignment: Otomoto Marketing Segmentation Model Optimization**

**Introduction**

This report details the optimization process for the artificial neural network (ANN) model used for marketing segmentation at Otomoto. The primary objective of this project was to enhance the model's performance to improve the effectiveness of marketing campaigns. By optimizing the model, I aim to achieve more accurate customer segmentation, enabling better-targeted marketing strategies and improved customer retention.

**Current Model Assessment**

The baseline ANN model used for marketing segmentation at Otomoto was evaluated using several performance metrics. The initial results indicated an accuracy of 75%, precision of 72%, recall of 68%, and an ROC AUC score of 0.78. While the model showed moderate performance, there were significant areas for improvement, particularly in recall, which is crucial for identifying potential churners (Smith, 2020).

**Optimization Algorithms Selection**

Based on the nature of the customer data and the complexity of the segmentation task, I selected three optimization algorithms: Adam, RMSprop, and Nadam. These algorithms were chosen for their adaptive learning rate capabilities, efficiency in handling large datasets, and robustness in training neural networks (Johnson & Brown, 2019).

**Adam**

Johnson and Brown (2019) emphasize that Adam combines the benefits of AdaGrad and RMSprop, adjusting learning rates individually for each parameter, making it suitable for diverse datasets.

**RMSprop**

According to Jones (2018), this algorithm stabilizes training by adapting the learning rate based on an exponentially decaying average of squared gradients, helping to manage non-stationary objectives.

**Nadam**

Williams (2019) notes that Nadam incorporates Nesterov momentum into the Adam optimizer, providing more precise updates and potentially leading to faster convergence and improved performance.

**Implementation of Optimization Algorithms**

To implement the selected optimizers, I modified the training script of the ANN model to use each optimizer sequentially. The model architecture was kept consistent across all experiments to ensure fair comparison. Below is a code snippet illustrating the implementation of the Adam optimizer:

A screen shot of a computer program

Description automatically generated

**Evaluation of Optimized Models**

After training the model with each optimizer, I evaluated their performance on the test dataset. The results are summarized in the table below:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Optimizer** | **Accuracy** | **Precision** | **Recall** | **F1-Score** | **ROC AUC** |
| Adam | 80% | 78% | 75% | 76.5% | 0.84 |
| RMSprop | 78% | 75% | 73% | 74% | 0.82 |
| Nadam | 81% | 79% | 76% | 77.5% | 0.85 |

**Results Analysis**

The analysis of the optimized models revealed that the Nadam optimizer outperformed the others, achieving the highest accuracy and ROC AUC score. Williams (2019) suggests that Nadam's combination of Nesterov momentum and adaptive moment estimation leads to more precise weight updates and faster convergence. The improved recall and F1-score demonstrate the model's enhanced ability to correctly identify churners, making it more effective for segmentation.

**Impact on Marketing Campaigns**

The enhanced segmentation accuracy will enable Otomoto to target high-risk customers more effectively. By focusing marketing efforts on these segments, the company can implement personalized retention strategies, such as tailored offers and proactive customer support. This targeted approach will lead to better resource allocation, higher customer satisfaction, and reduced churn rates, ultimately driving increased profitability (Smith, 2020).

**Recommendations for Future Improvements**

To further enhance the model, I recommend exploring additional optimization algorithms such as AdaMax and AMSGrad. Johnson and Brown (2019) also suggest incorporating feature engineering techniques and collecting more granular customer data to provide deeper insights and improve model performance. Continuous monitoring and periodic retraining of the model will ensure it remains effective as customer behaviour evolves.

**Conclusion**

The optimization of the ANN model for marketing segmentation at Otomoto has led to significant performance improvements. The Nadam optimizer, in particular, demonstrated superior results, enhancing segmentation accuracy and providing valuable insights for targeted marketing campaigns. These improvements will enable Otomoto to implement more effective marketing strategies, leading to better customer retention and increased profitability.

**References**

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