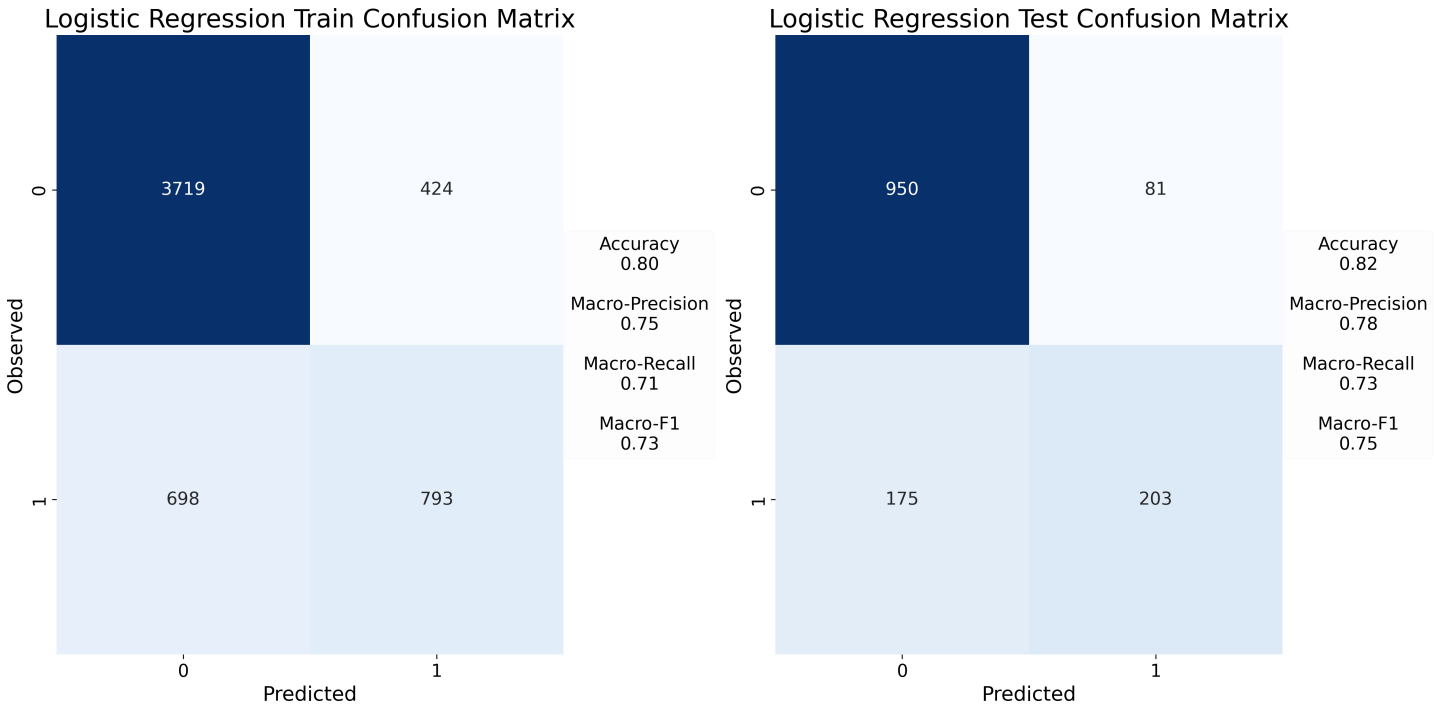
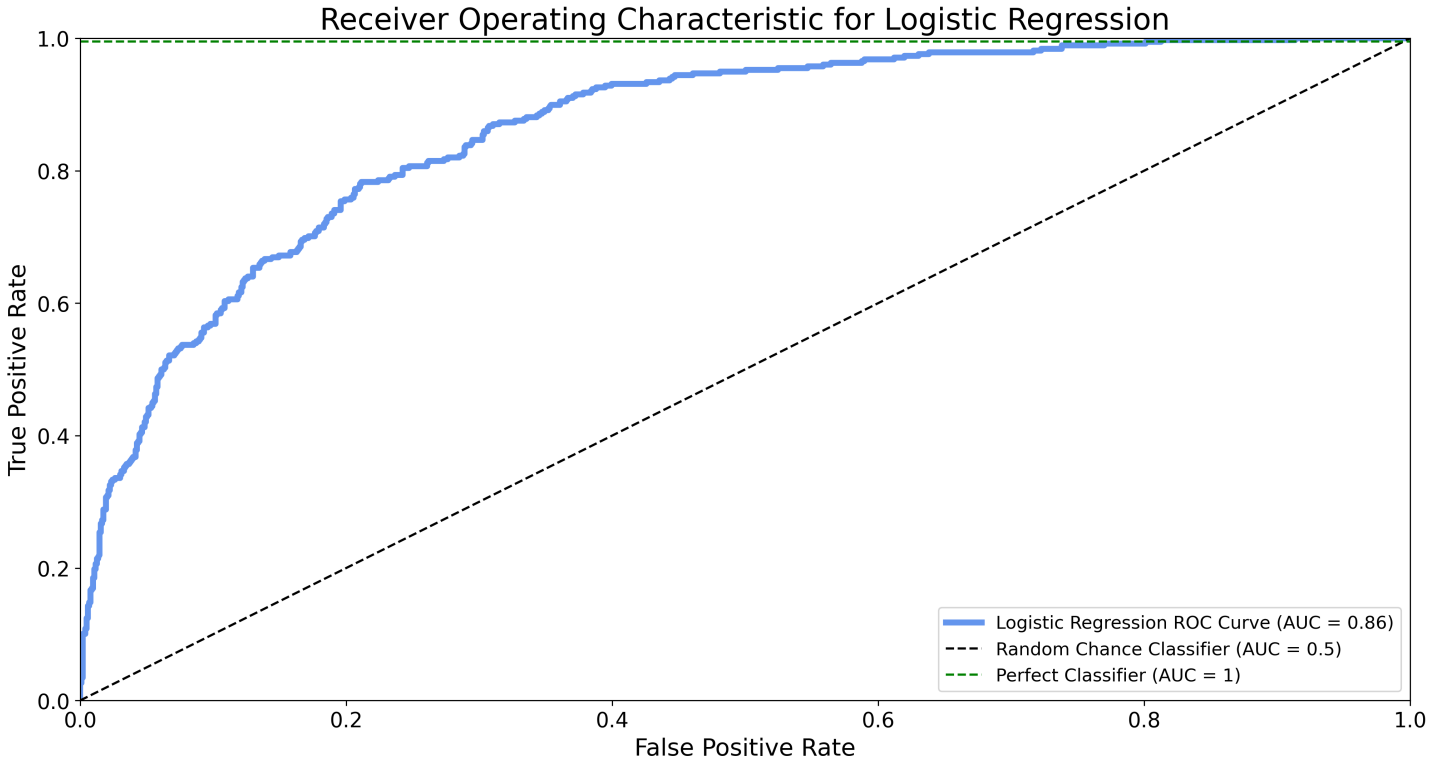
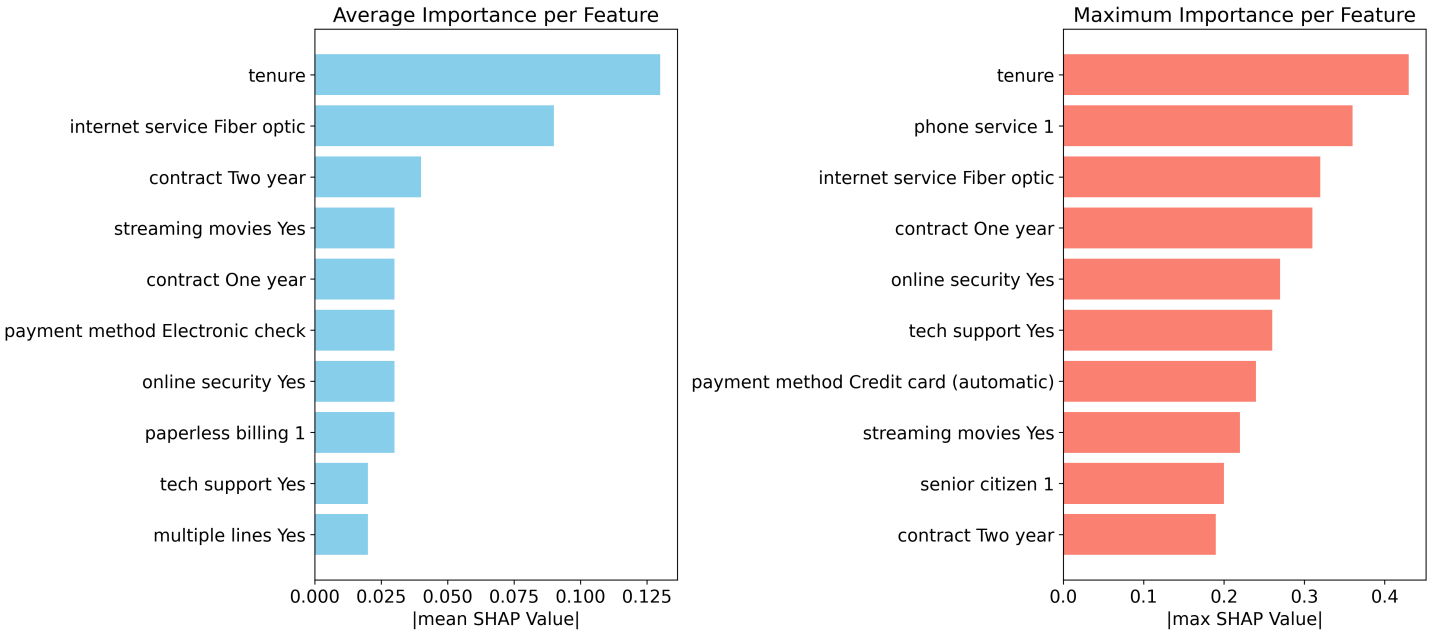
This model and explanation were generated by ModelBot, an agent designed to help non-technical users perform basic machine learning modeling, powered by Llama 3. It is not a replacement for a human data scientist, and there may be discrepancies and inaccuracies within this report.







PREDICTION GOAL

The model is predicting the likelihood of a customer churning (leaving) their service. Accurate predictions are crucial to identify high-risk customers and take proactive measures to retain them, reducing revenue loss and improving customer satisfaction.

OVERFITTING OR UNDERFITTING

The model's training accuracy is 0.80, and testing accuracy is 0.82, indicating a slight improvement in generalization. The training precision is 0.75, and testing precision is 0.78, suggesting that the model is performing well in terms of correctly identifying positive predictions. The training recall is 0.71, and testing recall is 0.73, indicating that the model is capturing most of the positive cases. The training F1 score is 0.73, and testing F1 score is 0.75, showing a moderate level of accuracy.

Based on these metrics, the model appears to be performing well in generalization, with only a minor difference between training and testing accuracy. This suggests that the model is not overfitting or underfitting significantly.

CONFUSION MATRIX INTERPRETATION

The confusion matrix is: [[950 81] [175 203]] True positives (TP) are correctly predicted churn cases (203), while false positives (FP) are incorrectly predicted churn cases (81). True negatives (TN) are correctly predicted non-churn cases (950), while false negatives (FN) are incorrectly predicted non-churn cases (175).

The model tends to favor the non-churn class, as there are more true negatives than true positives. This could be due to class imbalance, where the non-churn class has a larger proportion of instances. False negatives (incorrectly predicting non-churn) might be more critical in this context, as they could lead to missed opportunities to retain high-risk customers.

ROC CURVE & AUC SCORE

The ROC curve represents the model's ability to distinguish between classes based on different thresholds. The AUC score (0.86) measures the model's overall performance, with higher values indicating better separation between classes.

The AUC score of 0.86 indicates that the model is able to accurately distinguish between churn and non-churn classes, with a high level of precision. This suggests that the model is effective in identifying high-risk customers.

SHAP VALUE INTERPRETATION

SHAP values measure the contribution of each feature to the predicted outcome. The average SHAP value for each feature indicates the overall importance of that feature across all predictions.

- Average SHAP values: tenure (0.13), internet service Fiber optic (0.09), contract Two year (0.04), streaming movies Yes (0.03), and multiple lines Yes (0.02) are the top features by average SHAP value.
- Maximum SHAP values: tenure (0.43), phone service 1 (0.36), and internet service Fiber optic (0.32) are the top features by maximum SHAP value.

The top features by SHAP values are likely to be influential in predicting churn. Tenure, in particular, appears to be a strong indicator of churn, with a maximum SHAP value of 0.43. This suggests that customers with longer tenure are more likely to churn.

KEY INSIGHTS & RECOMMENDATIONS

The model is performing well in generalization, with a moderate level of accuracy. However, the class imbalance and tendency to favor the non-churn class might require attention. The model's reliance on tenure as a key feature could be beneficial, but it's essential to consider other factors that might influence churn.

Recommendations:

- Collect more data to rebalance the classes and improve the model's performance.
- Consider incorporating additional features that might be relevant to churn prediction.
- Tune the model's thresholds to optimize the trade-off between precision and recall.

MODEL RATING

Rating: 8/10

The model's generalization performance is moderate, and its interpretability is good, with SHAP values providing insight into feature importance. However, the class imbalance and reliance on a single feature (tenure) might require attention to improve the model's overall performance.