TELCO CUSTOMER CHURN PREDICTION

PREDICTIVE MODELING PROJECT SUMMARY

OVERVIEW

1. This project aims to predict customer churn using the Telco Customer Churn dataset. This project emphasizes predictive modeling to uncover patterns and provide actionable business recommendations. It predicts which telecom customers are likely to leave the service and it provides insights to help retain them.

OBJECTIVE

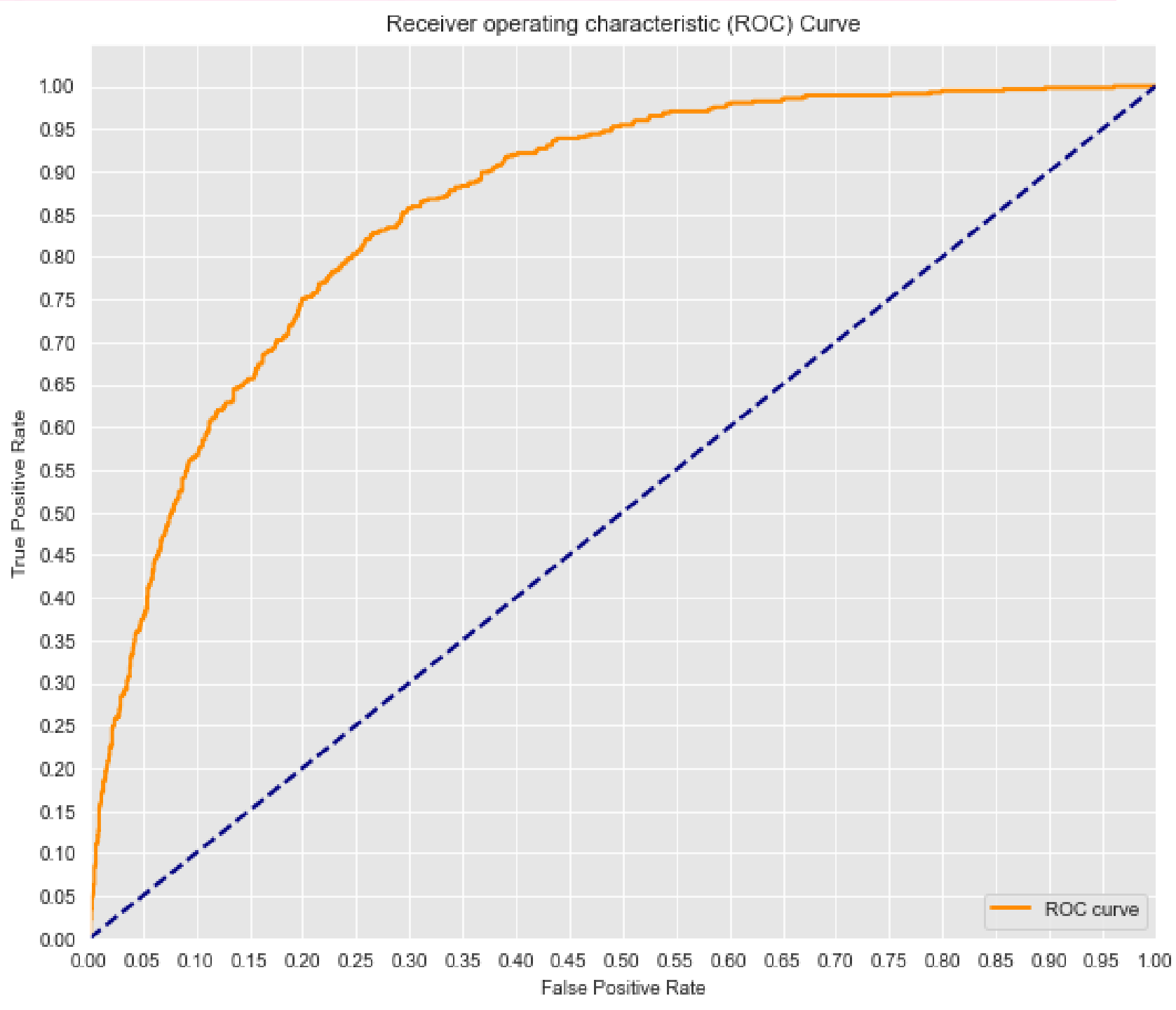
1. Can we accurately predict which customers are likely to churn?
2. What are the most important factors driving customer churn?
3. Can we improve business decisions using these predictions?
4. Where does the model perform well – and where does it struggle?
5. How should the business intervene to reduce churn?

TOOLS & TECHNIQUES

1. Python, Pandas, Scikit-learn
2. Logistic Regression, Random Forest
3. Feature importance, ROC Curve, Confusion Matrix

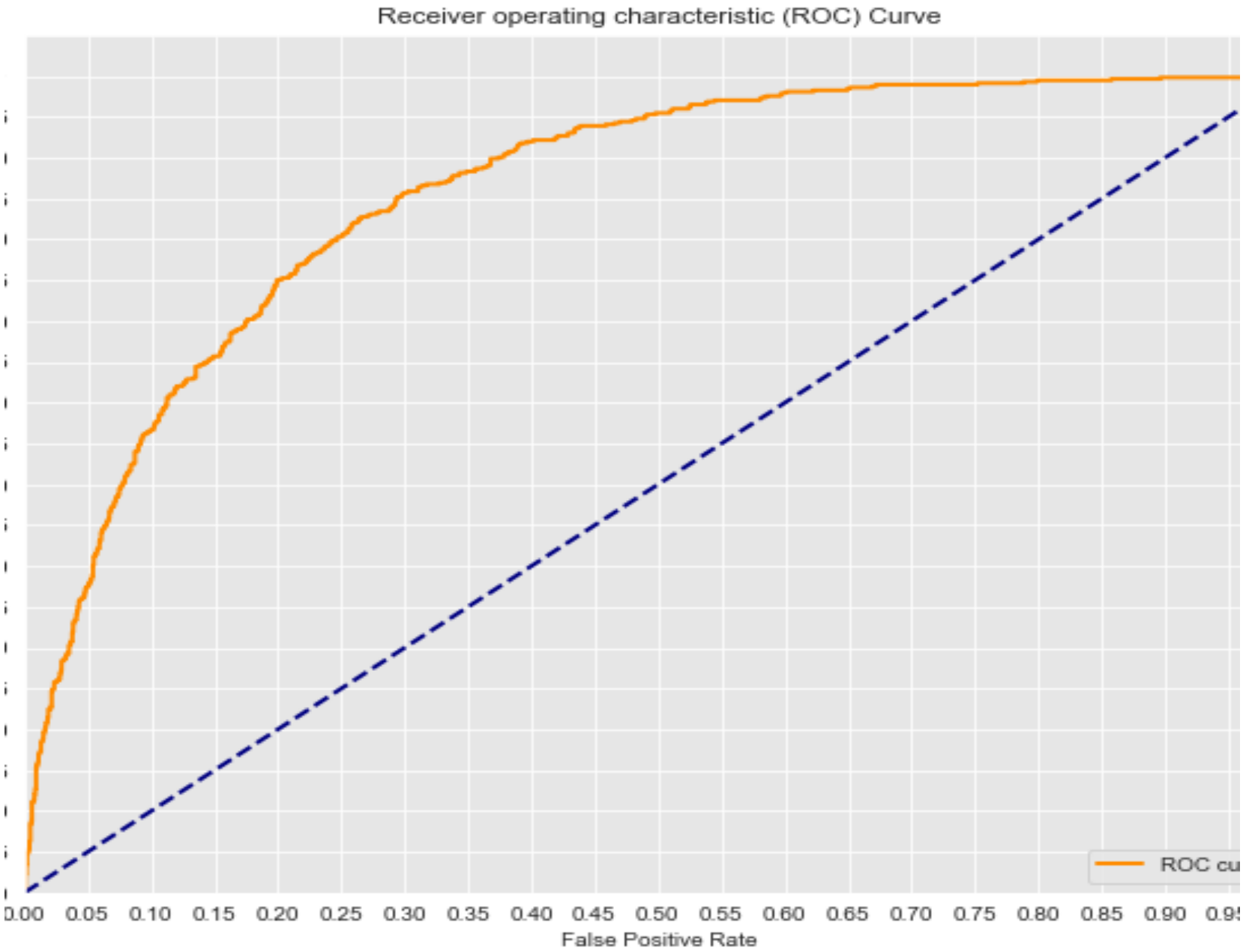
MODEL PERFORMANCE (LOGISTIC REGRESSION)

1. Accuracy: ~81%
2. Precision (Churn): 69%
3. Recall (Churn): 56%
4. F1 Score: 62%
5. AUC: Model performs well above random guessing



ROC Curve for the simple logistic model

- The ROC curve is well above the diagonal baseline which indicates that the model is performing better than random guessing



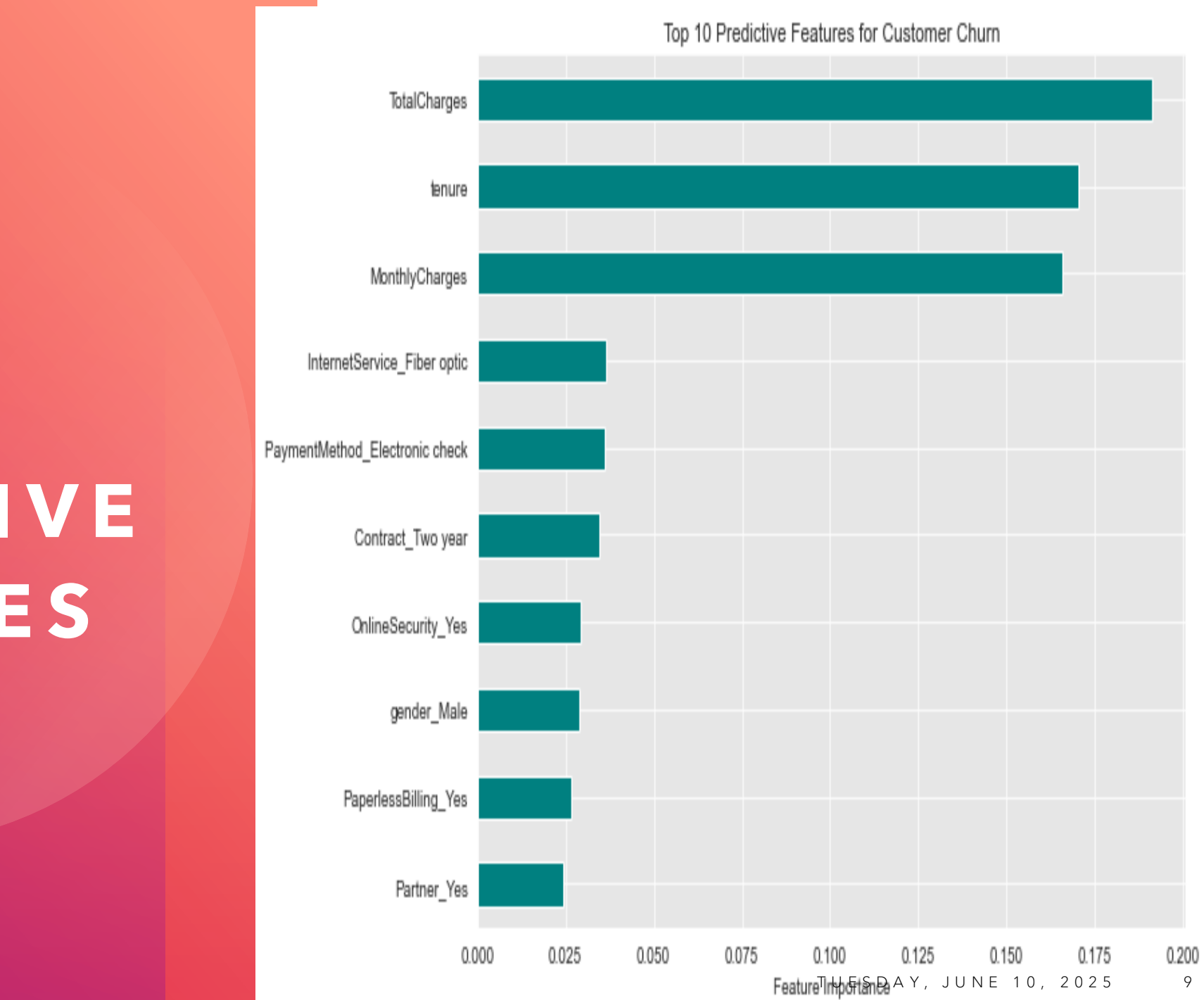
ROC Curve for the hyperparameterized model

- Hyperparameterized model's ROC curve appears to be slightly more "bulged" toward the top-left corner compared to Model 1, which typically indicates better performance.

TOP PREDICTIVE FEATURES (RANDOM FOREST)

1. Tenure (0.170)
2. Monthly Charges (0.166)
3. Fiber Optic Internet (0.036)
4. Electronic Check Payment (0.036)
5. Two-Year Contract (0.035)
6. Online Security (0.029)

TOP PREDICTIVE FEATURES



PREDICTIVE FINDINGS

1. Shorter tenure and higher monthly charges = higher churn.
2. Fiber optic users and electronic check users churn more.
3. Two-year contracts and security features reduce churn.
4. Demographics (partner, gender) have minor effects.

BUSINESS RECOMMENDATIONS

1. Target new customers with retention incentives.
2. Review high-bill customer experience/value.
3. Promote long-term contracts with loyalty benefits.
4. Offer security features as part of bundled plans.
5. Encourage auto-pay over electronic check.

NEXT STEPS

1. Improve recall using class balancing (SMOTE, weighting).
2. Test ensemble models like XGBoost.
3. Deploy dashboard for churn-risk scoring.

CONCLUSIONS

1. Our predictive model successfully identifies customers at high risk of churn with ~81% accuracy.
2. Key risk drivers: **short tenure**, **high monthly charges**, **electronic check payments**, and **fiber optic service**.
3. Key retention factors: **long-term contracts**, **online security features**, and **engagement of new users early**.
4. The business can proactively reduce churn by **targeting vulnerable customer segments** and **adjusting service offerings** based on model insights.

THANK YOU