THE HARTFORD

Final PROJECT presentation

Hartford GROUP 3

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PRESENTATION AGENDA

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PROJECT OVERVIEW

The primary objective

- Analyze factors influencing customer retention

- Develop predictive models that can help identify at-risk customers

- Set strategies ideas to improve retention rates.

BUSINESS PROBLEM

Can the likelihood of a customer canceling their auto insurance be estimated?

Additionally, can we determine the specific type of cancellation they will choose, such as midterm or flat cancellation?

KEY INSIGHTS

MODEL

Performance: LightGBM showed the highest accuracy on Test set.
Precision = 0.84 for renewals
0.82 for cancellations
AUC = 0.70

Feature Engineering : Created 5 new features for step 1 model that and reduce dimensionality for improved model performance.

AS BUSINESS

Customer Segmentation: Identified four distinct customer segments with varying loyalty levels and retention needs.

Targeted Retention Strategies: Developed tailored strategies for each segment to improve retention rates and customer satisfaction.

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DATA OVERVIEW AND MODEL CHALLENGES

1. Data Cleaning and Enhancement
- Before Cleaning: 264,963 rows by 54 Columns (strategy) (based needs)
- After Cleaning: 264,963 rows by 57 Columns
  - Removed 2 variables, created 5 variables

2.Preparing for Modeling
- Label Encoding (categorical-numerical)
- Checking correlation between best predictors variables
- Checking correlation with STATUS

- Keep a good Varience = imputation, transformed categ to num and creation of variable

3.imbalanced Classes:
- STATUS:
  - 0 = Not Cancelling - 84.6%
  - 1 = Mid-Term Cancellation - 8.2%
  - 2 = End-Term Cancellation - 7.3%

To try model Imb enviroment

4.Balancing Techniques
- SMOTE
- Downsampling

TWO STEP MODELING APPROACH

Divide the target into two steps

Model in 2 ways

STEP 1: Predict customer cancellation (Class 0 or Class 1 and 2)

STEP 2: Predict mid-term and end-of-term cancellations probabilities (Class 1 or Class 2)

Metrics: We focused on precision because it helps accurately identify real cancellations and minimize false positives in predicting customer cancellations. ROC-AUC was used too as the data imbalance was severe.

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CHOOSING OUR FEATURE SELECTION METHOD FOR STEP 1

- Recursive Feature Elimination
- Principal Component Analysis
- Feature Importance ranking
- No classifier Feature selection
  - Correlation with STATUS thresholds and correlations with other variables

The best method for feature selection that we found was **Feature Importance Ranking**

FINDING THE BEST MODEL TYPE: STEP 1

We tested different models on the full dataset to choose the best model

- Random Forest
- XGBoost
- LightGBM

We found that **LightGBM** had overall higher accuracy and better predictive power than the other models

LightGBM
had 68% precision for cancellations on the full model

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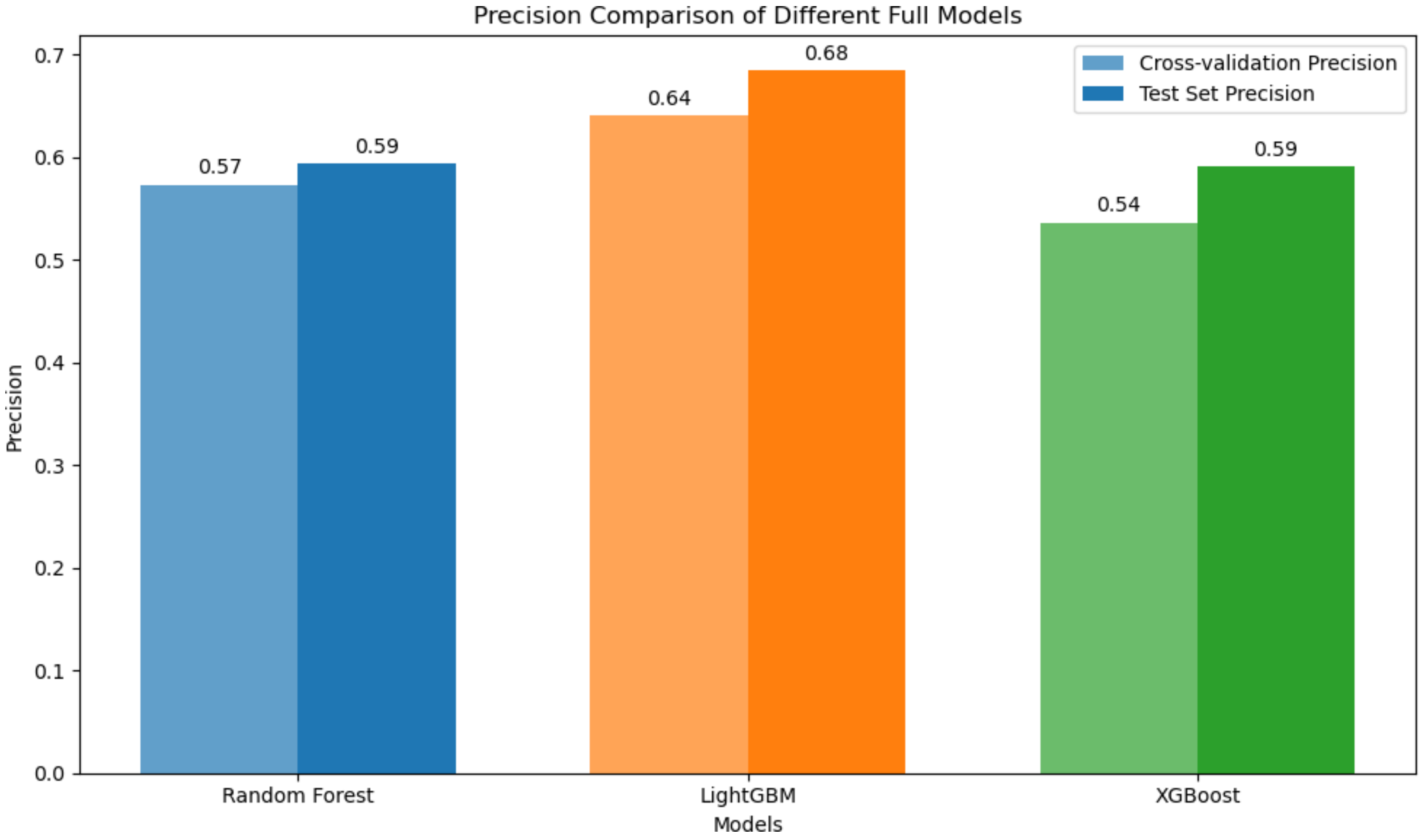
COMPARISON OF DIFFERENT STEP 1 MODELS ON THE FULL DATASET



LightGBM had a better performance using all variables.

CV = 0.64
Test = 0.68

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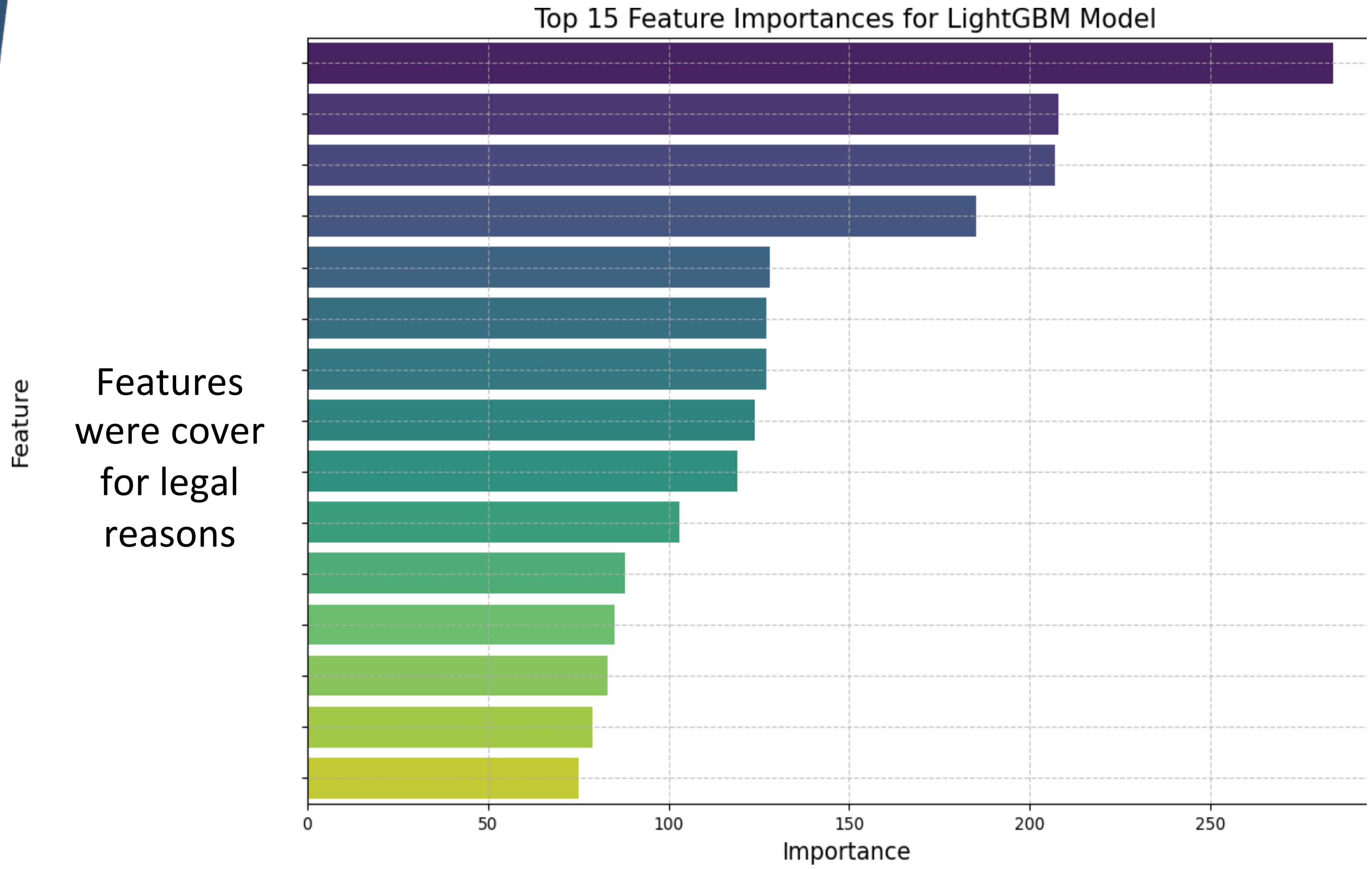
FEATURE IMPORTANCES



Features were cover for legal reasons

LightGBM feature selection technique was used for selecting the best 15

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COREELATION AND VIF

15 Best Variables Cleaning

- One was removed for correlation.
- 2 Removed for VIF and high correlation.

Feature

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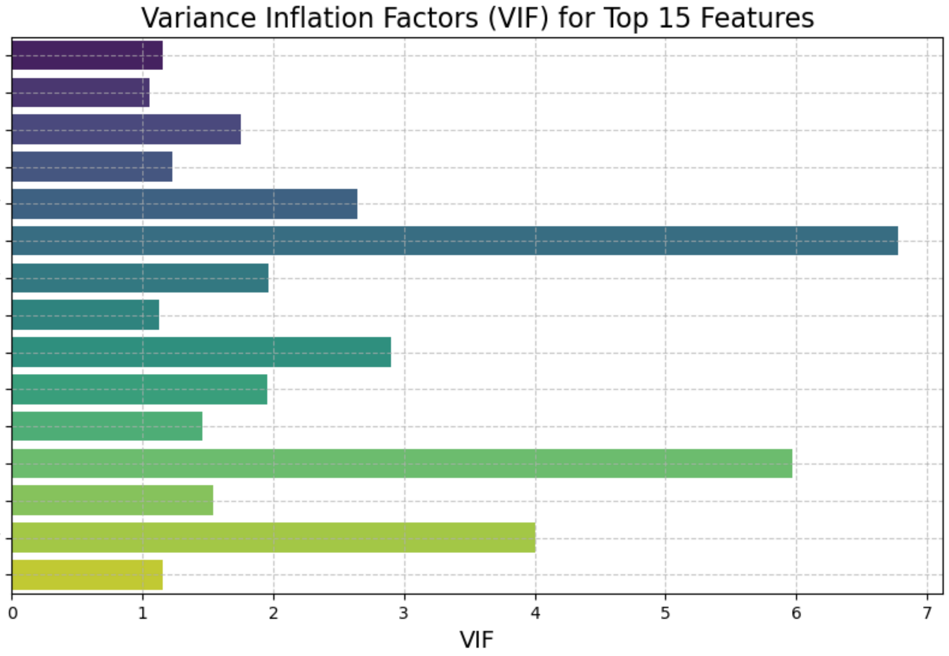

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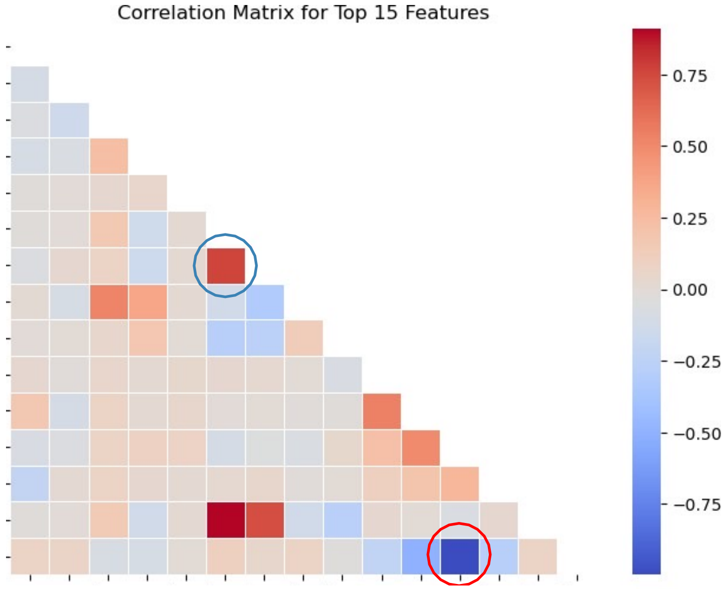

Features were cover for legal reasons

DATA ENHANCEMENT

- Create new variables that show important business statistics.
- Increased robustness
- Reduce the complexity of models and improve efficiency
- Ensure model accuracy

FEATURE ENGINEERING FOR ENHANCED MODEL PERFORMANCE

NEW FEATURES

PREMIUM_CHANGE: Absolute change in renewal premium over two terms.

DRVR_AGE_DIFF: Difference between the oldest and youngest drivers on the policy.

BILL_PREM_DIFF: Difference between the total annual bill premium amount and the average term premium.

AVG_COMP_BI_RTNG_SYM: Average of comprehensive and bodily injury rating symbols.

VEHICLE_AGE: Age of the vehicle calculated from the model year.

Variables used to create new features were combined to form new ones to avoid multicollinearity and higher prediction power.

STEP 1 FINAL MODEL FEATURE SELECTION

Original Features

New Features

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CHECKING SHAP VALUES FOR THE FIRST MODEL RESULTS

Positive SHAP values indicate an increase in the probability of cancellation and vice-versa.

SHAP Values best features for predicting cancellations: BILL_PREM_DIFF, VEHICLE_AGE and YEARS_WITH_HIG

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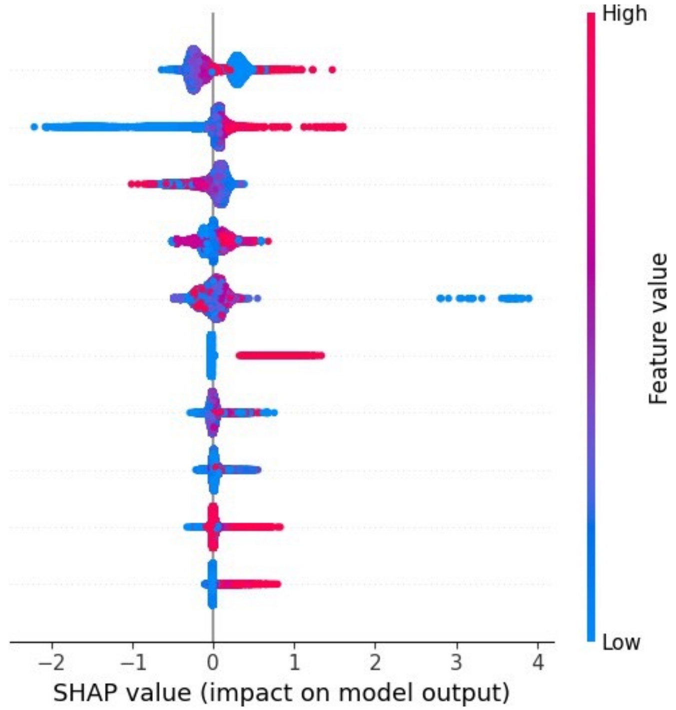
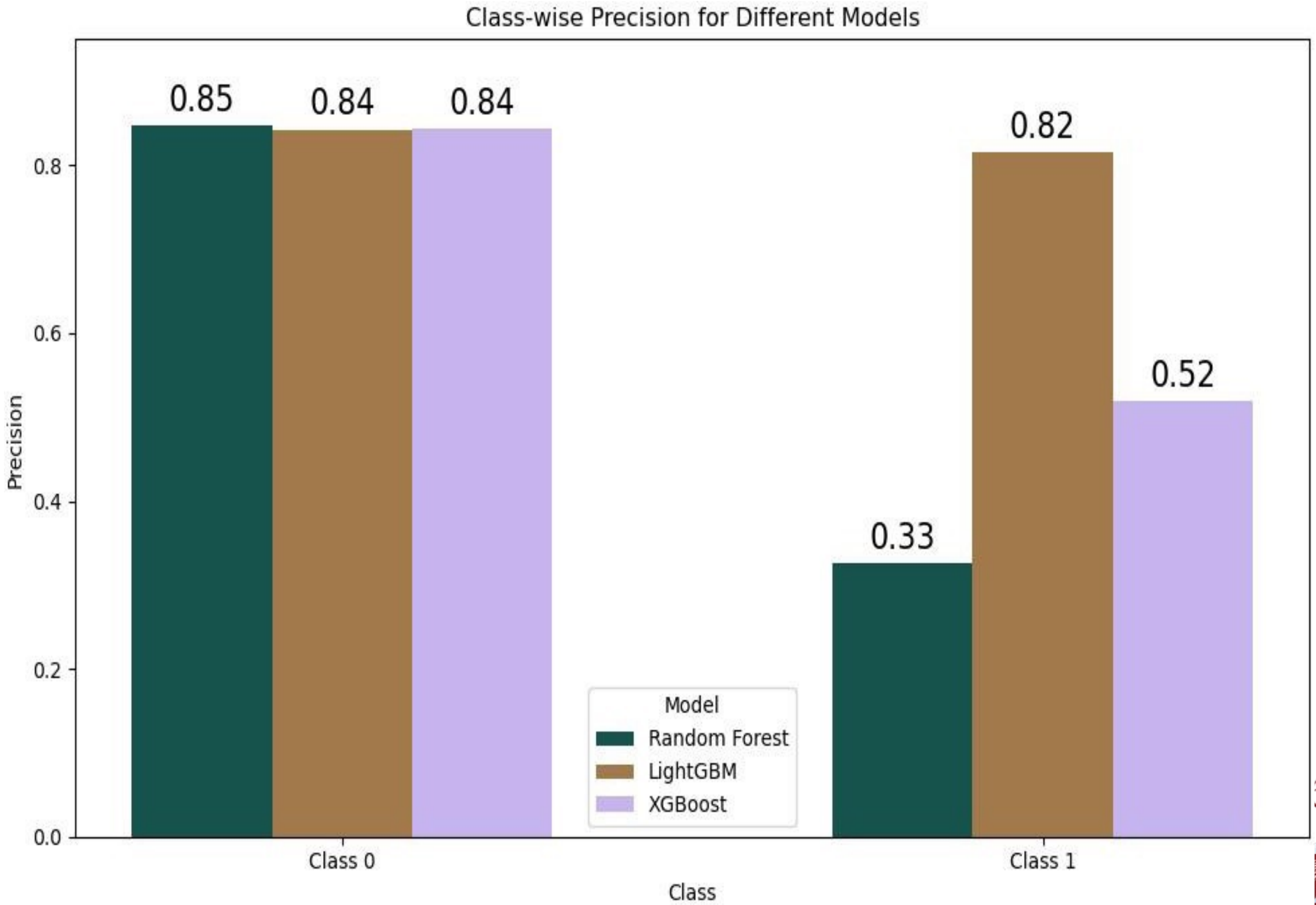


STEP 1 FINAL MODEL PERFORMANCE

Step 1 Final Model Performance comparison of cancellations between models.
Precision class 0 = 84, 1 = 82



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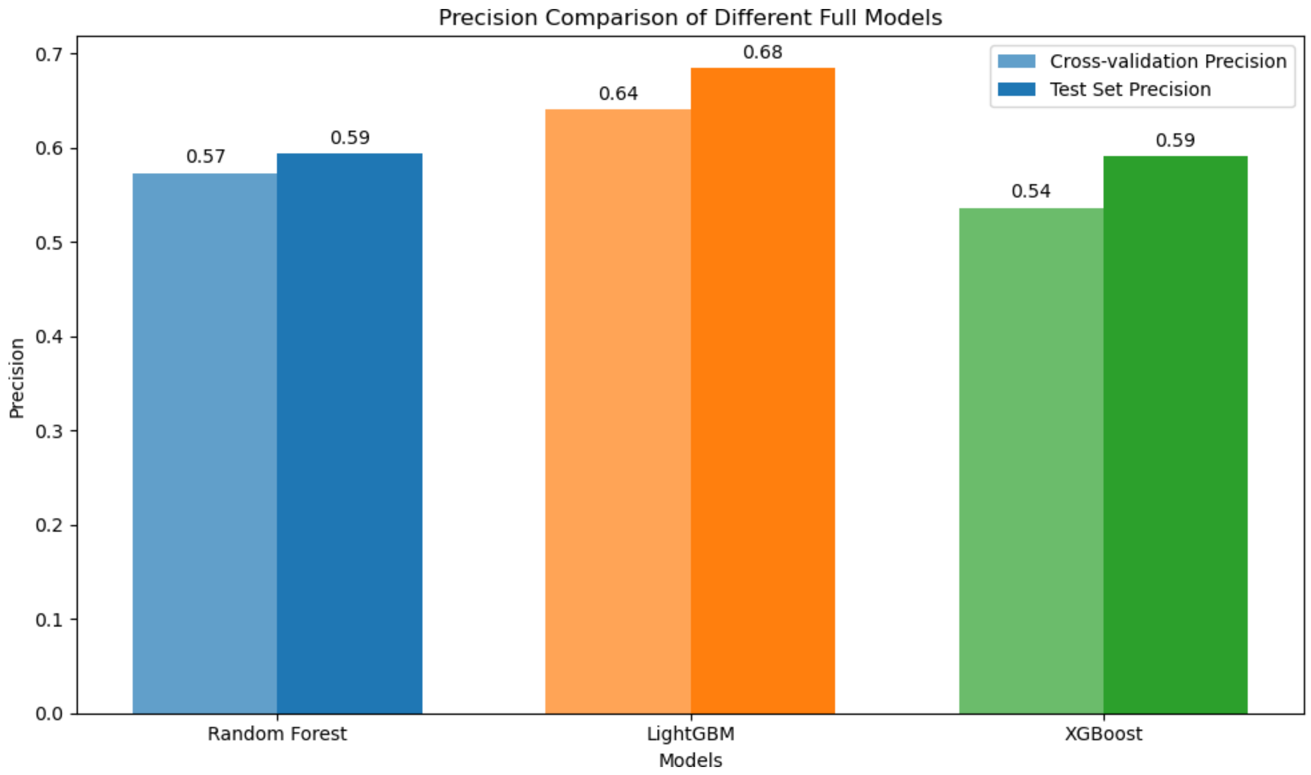
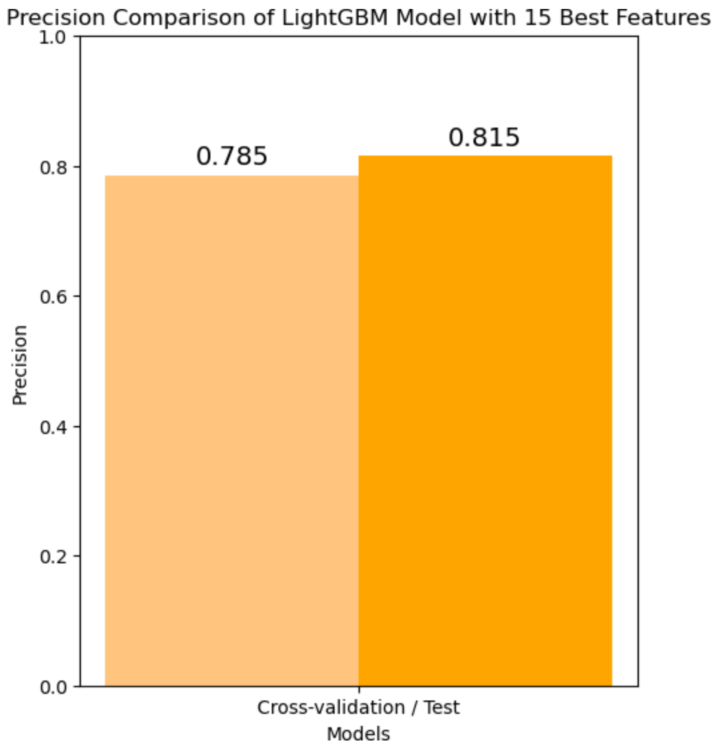
STEP 1 MODEL RESULTS ON THE TEST SET

Full Dataset Prediction



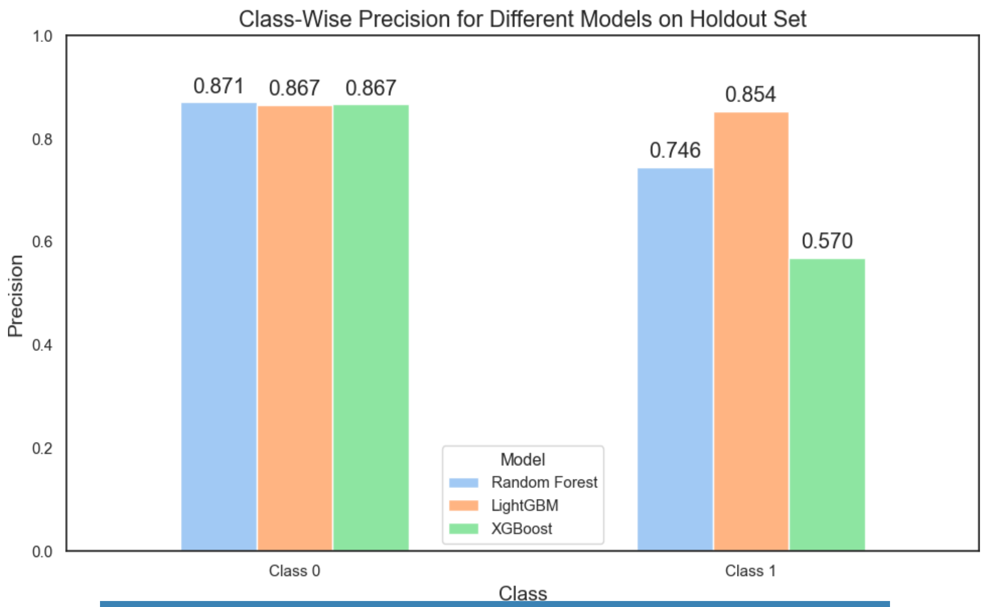
Step 1 Final Model Prediction



LightGBM had a better performance using all variables and reached 0.82 on Test set using the 10 best variables for prediction.

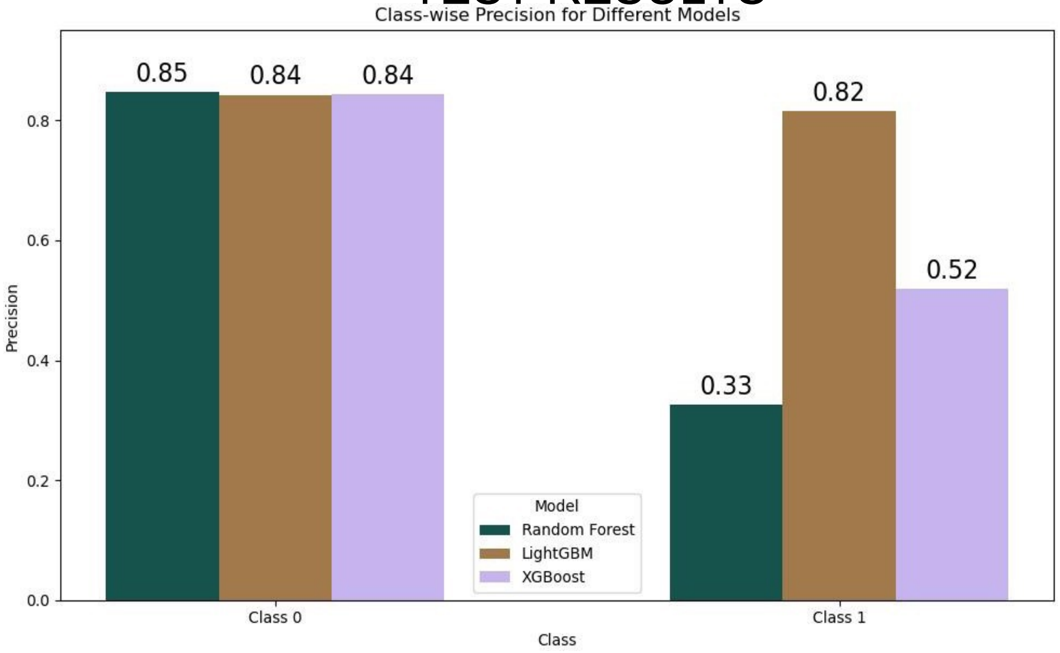
STEP 1 MODEL - HOLDOUT SET VS TEST SET

HOLDOUT RESULTS



The consistent performance across the test set and holdout set indicates that the model is not overfitting

TEST RESULTS



The model showed a slightly better performance on the holdout set.

STEP 1: 0THER APPROACHES

Techniques we tried to implement to improve our prediction results

- Weighting
  - Increases other metrics at the cost of precision

- SMOTE
  - No changes on classes precision

- Lasso and Ridge regularization
  Did not change precision

- PCA
  Class 1 was overestimated

- Learning Rate Scheduler

STEP 2 MODEL PREDICTION

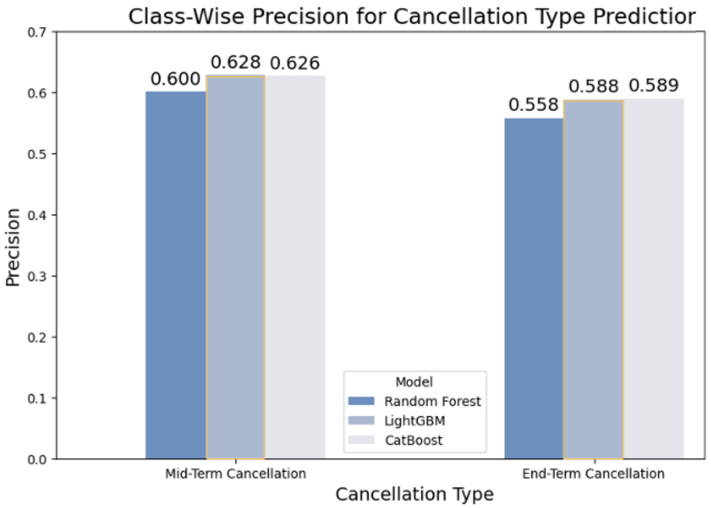
Progress and Challenges

Target Variable Creation: Filtered out non-cancellations and used STATUS column for cancellation type.

Feature Selection: Used LightGBM, identified ZIP Code and Policy Effective Date as top features. Various feature selection techniques were applied, but none significantly improved model performance.

Challenges Faced: Insufficient data for minority classes, impacting performance despite various techniques.

STEP 2 Model Results



Precision didn't meet levels we found acceptable:
Class 1: 63% Class 2: 59%

STEP 2 Cancellation type model: Best results were achieved by 15 top feature importance selection using LightGBM classifier

CUSTOMER SEGMENTATION OVERVIEW

We focused on **3 KEY FEATURES** from the **STEP 1 MODEL** to divide the customers into **4 SEGMENTS**

Features were cover for legal reasons

METHOD USED: KMEANS CLUSTERING

	Premium Difference	Vehicle Age	Avg Years with insurance
SEGMENT 0	Moderate	Older Vehicles	7+
SEGMENT 1	Very Low	Oldest Vehicles	6+
SEGMENT 2	Highest	Newest Vehicles	9+
SEGMENT 3	Relatively High	Relatively New	8+

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SEGMENT CHARACTERISTICS AND STRATEGIES

	SIZE	CUSTOMER LOYALTY	STRATEGIES
SEGMENT 0	100,000+	HIGH (LONG TERM CUTOMERS)	LOYALTY PROGRAMS & CUSTOMER FEEDBACK
SEGMENT 1	100,000+	MODERATE (POTENTIAL FOR GROWTH)	ENGAGEMENT CAMPAIGNS & INCETIVES ON RENEWALS
SEGMENT 3	ABOUT 5,800	VERY HIGH	PREMIUM SERVICES & PERSONALIZED OFFERS
SEGMENT 4	AROUND 40,000	HIGH BUT NEEDS ENGAGEMENT	REGULAR CHECK INS & TARGETED DISCOUNTS

NEXT STEPS (if we had more time)

1.**Gather More Data**: Collect additional information on customers who cancel mid-term to better understand their characteristics and reasons for cancellation.

2.**Integrate External Data Sources**: Incorporate external data sources, such as economic indicators and competitor actions, to enhance the model’s predictive power and provide a more comprehensive view of the factors influencing customer cancellations.

3.**Continue the Development of Step 2 Model**: Find and implement new techniques that could help increase the predictive power of the step 2 model.

4. **Adding both model** : Create a new model adding step one and 2

Thank you

Q\A