DSO 530 Final Project

Insurance Loss Analytics Project

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Team Members

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Project Background

Current scenario:

Automobile Insurance companies have been using

predictive analytics to:

- Manage Risk
- Forecast Claims
- Identify Fraud
- Optimize Costs

Project Breakdown

LC (Loss Cost)

- Understand how risky a particular segment is
- **High** → high severity of claims, underpriced
- **Low** → lower risk, potential for competitive pricing

HALC (Historical LC)

- Standardized way to compare policy holders, controlling time
- **High** → frequent claims, higher risk
- **Low** →safer drivers, more favorable risk

CS (Claim Status)

- Claim frequency calculation, predicting likelihood of future claims. Important in determining risk.
- **1** → a claim is made
- **0** → no claim

Variable Selection Predictions

Important	Less Important
X.25: Market Value higher value - more expensive claims **X.8: Years with Insurer** more experience = safer behavior	**X.13: Last Payment Method** yearly or half-yearly - do they pay on time **X.26: Number of Doors** redundant to weight

Note:

- Lots of variables account for the same issues
  - X.23-28: Car features
  - X.8-11: Loyalty
- Assumption: Redundant variables can increase noise → LASSO feature selection should be considered

Data Wrangling

Model Preprocessing

Dataset Preparation

Columns Included:

- X.7 - X.14, X.19 - X.29, Age, License_years, Policy_years
- X.27: rows with missing(NA) values were removed

Added columns:

- **Age, License_years, Policy_years**: Derived from date columns by calculating the number of years since birth, license issuance, and policy start

Data Classification:

- Numerical variables: All other continuous variables
- Categorical variables: X.7, X.13, X.19, X.20, X.21, X.27

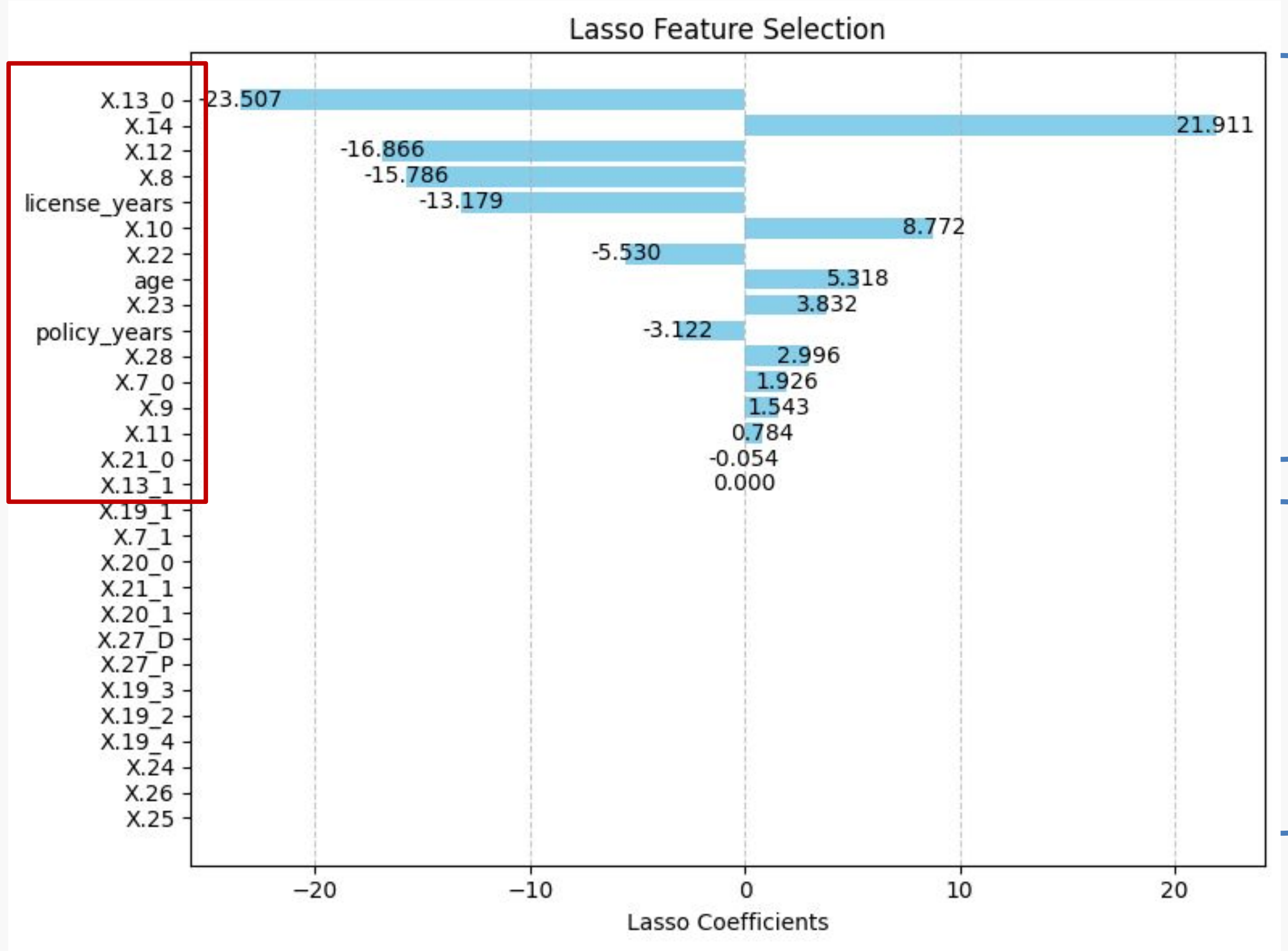
Preprocessing:

- Numerical variables: Standardize with **StandardScaler()** to handle variable magnitude
- Categorical variables: Use **OneHotEncoder(handle_unknown='ignore')** to create dummy variable

Feature Selection – Shrinkage Methods (Lasso)

GridSearchCV for 5-folds
alpha : {0.01, 0.1, 0.05, 5.0, 10.0}

- ***# of Selected Features: 13***
- ***# of Eliminated Features: 16***



Highlights more on Policy and Driver-Related Features

- X.13_0: Last payment method (half-yearly vs. annual)
- X.14: Net premium amount during the current year
- X.12: Number of policies canceled or terminated during the current year
- X.8: Insurance Years
- Driver license years

Shrinkage of Vehicle-Related Features Coefficients

- X.24: Cylinder capacity of the vehicle
- X.25: Market value of the vehicle as of 31/12/2019
- X.26: Number of vehicle doors

Limitation:

- **Linear Assumption Between Y and X**
- **Variance-Bias Trade-Off**

Models Overview

**all features included for model performance*

Predicting LC & HALC (Task 1)

- In the dataset, over 89% of policyholder did not file a claim, making LC and HALC highly **right skewed**; hence **Tweedie regression** is used to predict these variables

- Below are different Tweedie model we tried:
  - TweedieRegressor
  - LightGBM + Tweedie
  - XGBoost + Tweedie
  - Two-step model

Predicting Claim Status (Task 2)

- To predict whether the policyholder filed a claim or not during the year, we used different **classification models** to predict the binary variable

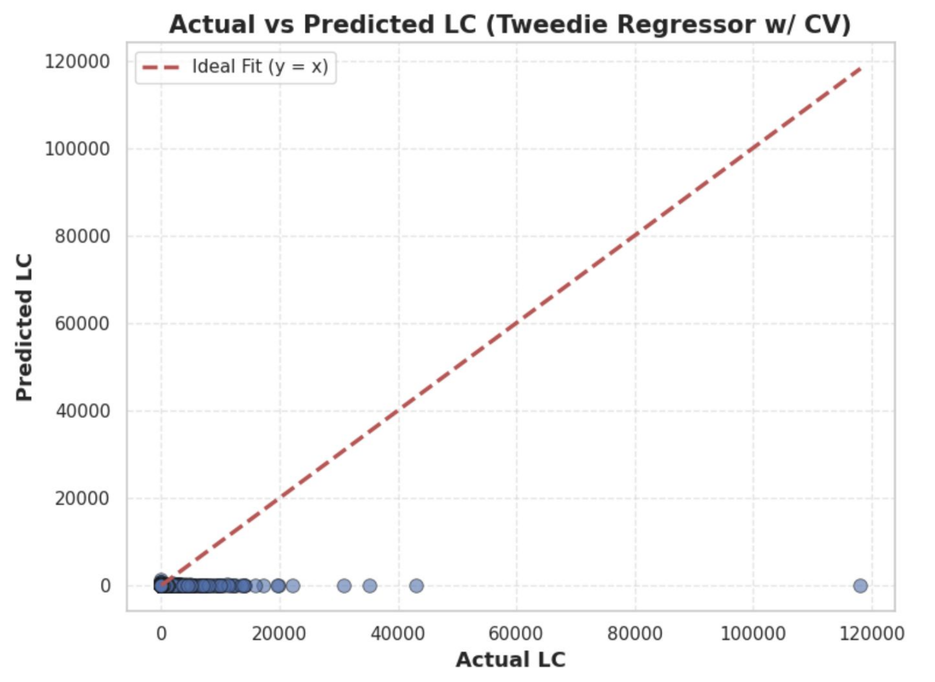
- Below are models we tried:
  - Random Forest
  - LightGBM
  - XGBoost

Task 1

Model Selection – LC

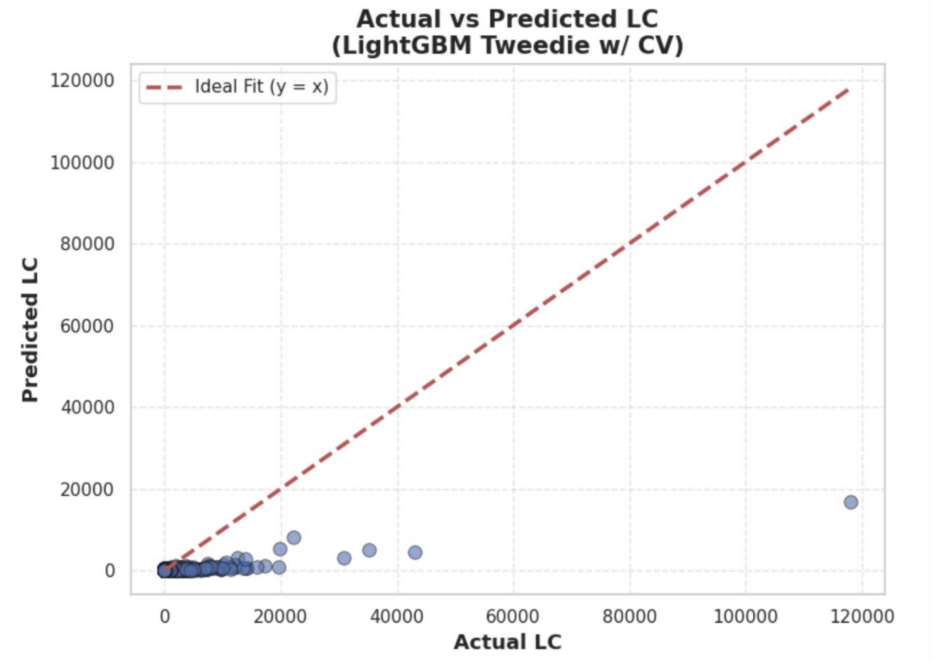
*all LC model parameters are tuned with **5-fold Cross Validation**

Tweedie Regressor



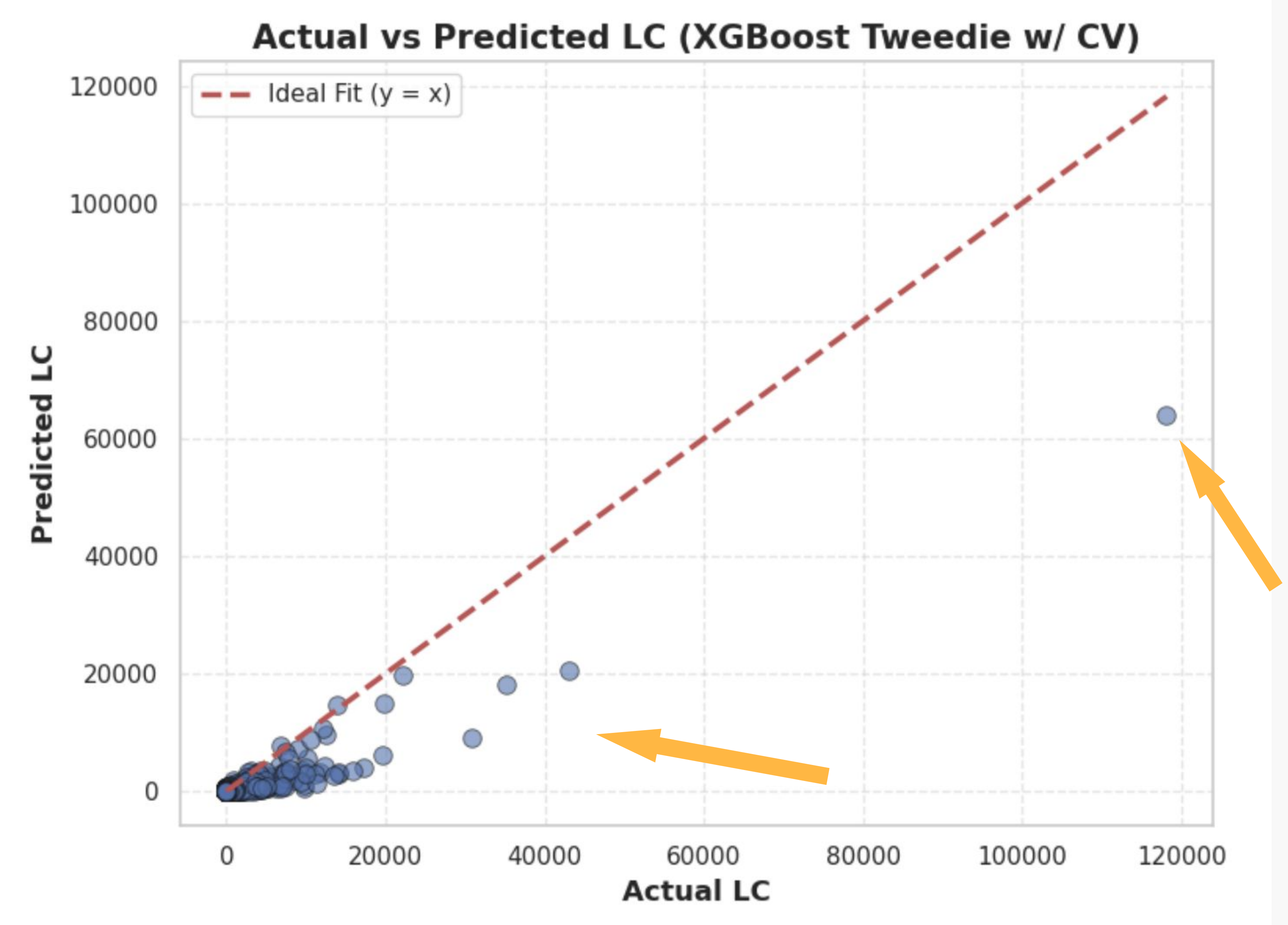
- **MSE**: 712,989
- Overestimates zero-claim losses
- Struggles due to lack of model complexity

LightGBM Tweedie



- **MSE**: 549,996
- Better fit than linear Tweedie
- Still underperforms on high-loss cases

XGBoost Tweedie - Tuned



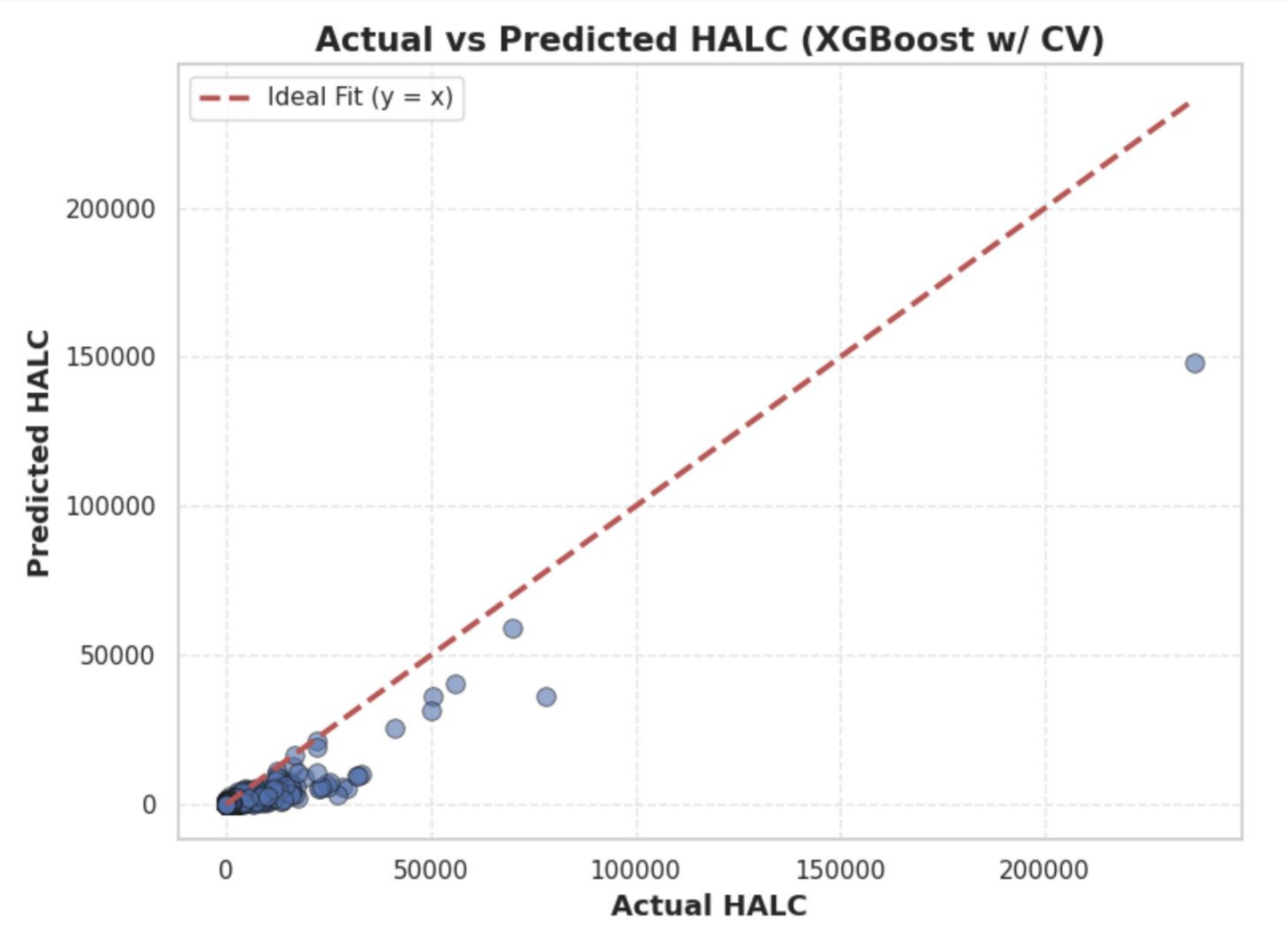
- **MSE**: 217,392
- Best fit across full LC range
- ~**60%** improvement over LightGBM Tweedie
- Best params: α = 1.0, variance power = 1.5

Task 1

Model Selection – HALC

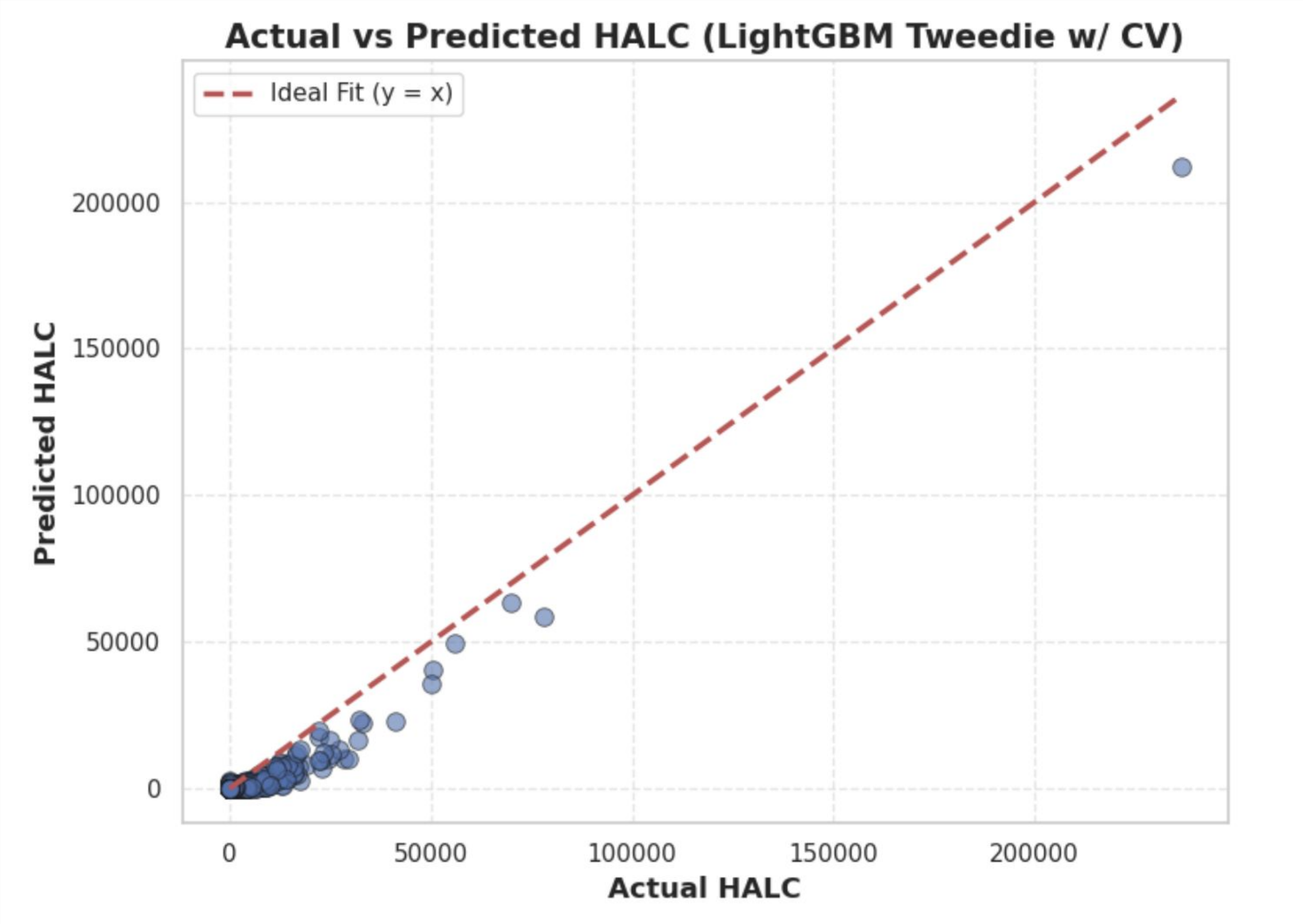
**all HALC model parameters are tuned with 5-fold Cross Validation*

XGBoost Tweedie - Tuned



- **MSE**: 653,948
- Less consistent fit across the full HALC spectrum

LightGBM Tweedie - Tuned



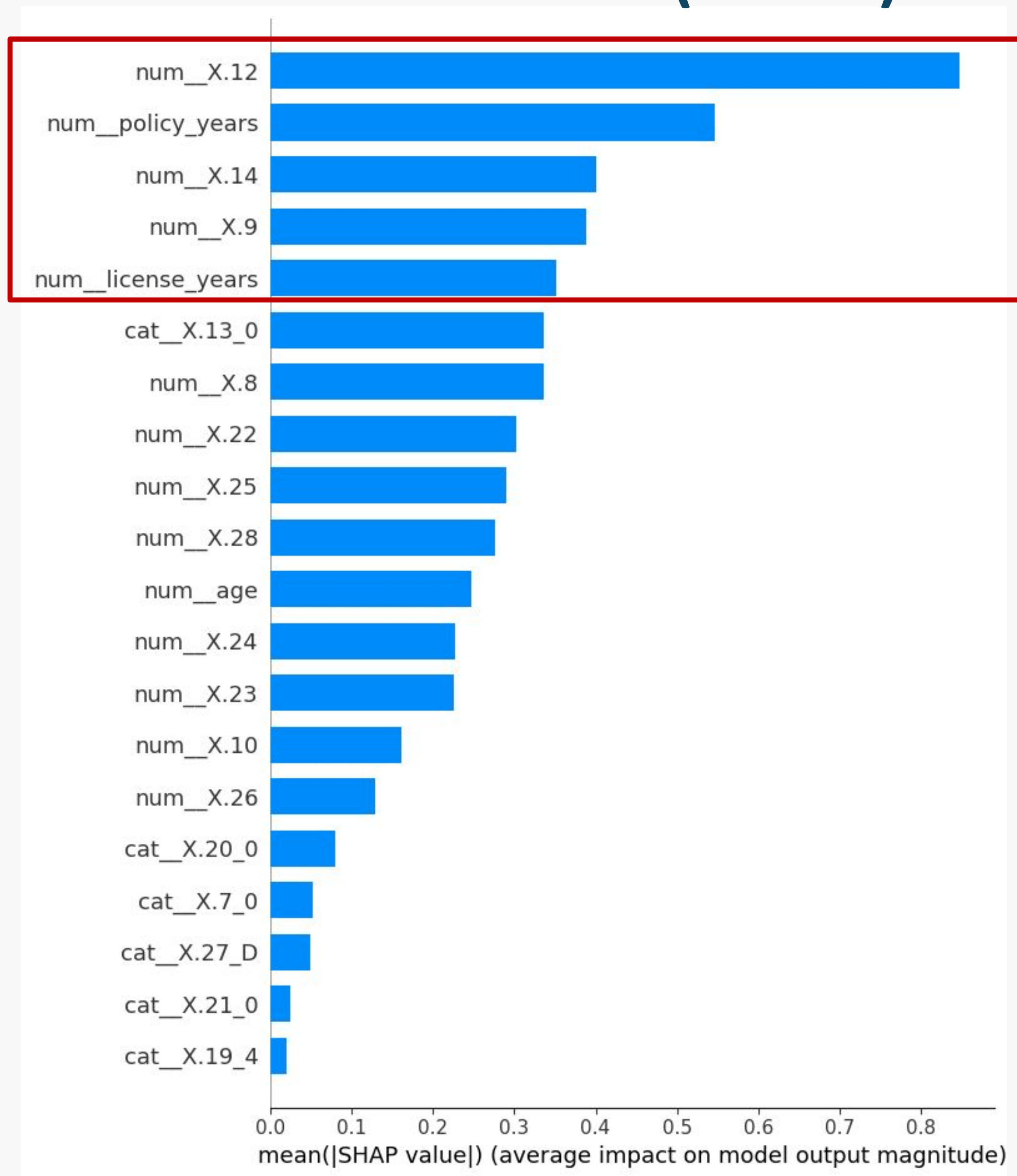
- **MSE**: 360,881
- Best fit across full HALC range
- Performs well across both low and moderately high HALC values
- Best params: α = 0.5, variance power = 1.1

Task 1

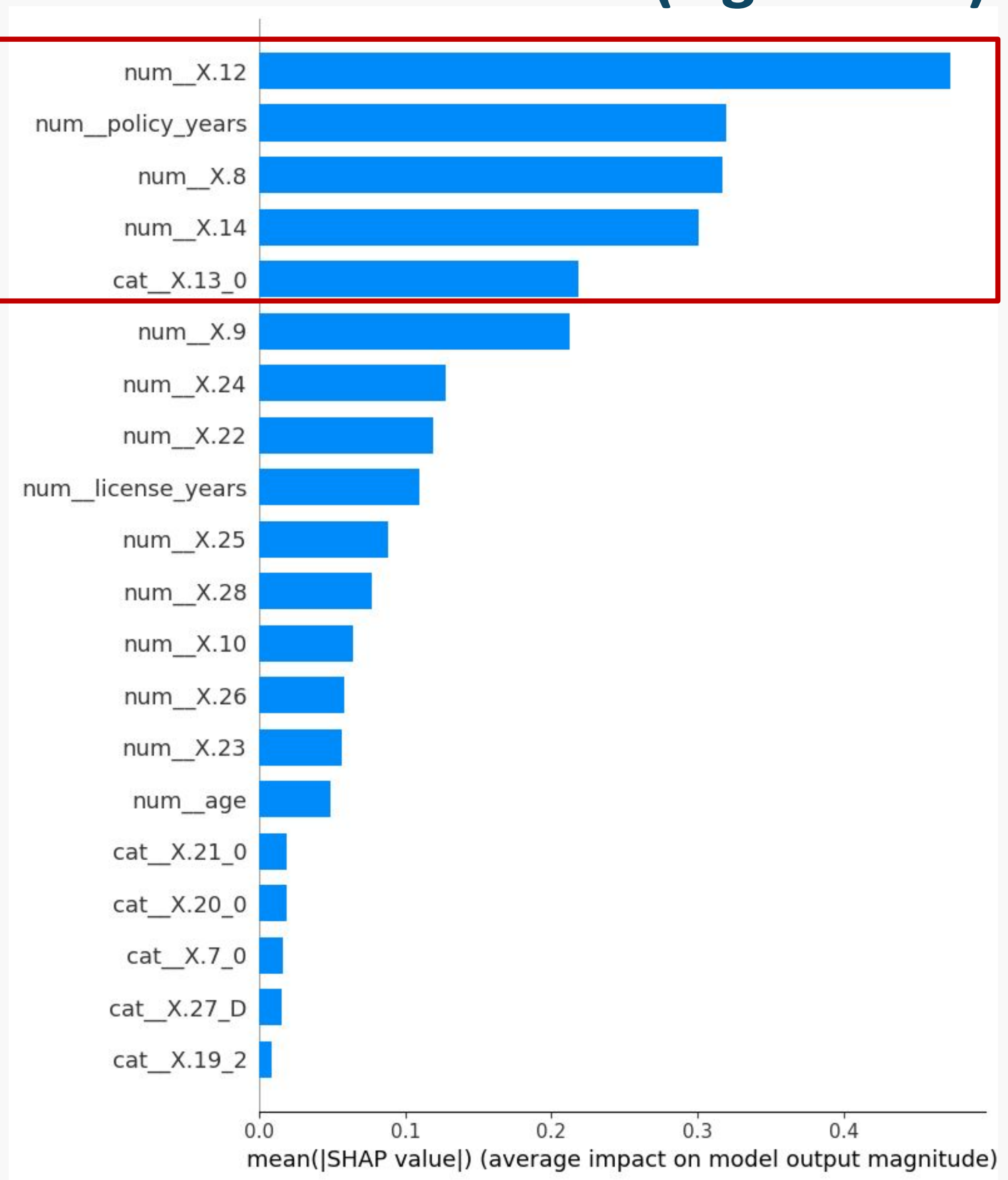
Model Interpretation – LC vs. HALC

Magnitude of Feature Impact on Prediction

SHAP Value for LC (XGBM)



SHAP Value for HALC (LightGBM)



Top Features for Predicting LC

- X.12: # of policies canceled or terminated
- Policy years
- X.14: Net premium amount
- X.9: # of policies held during the current year
- Driver license years

Top Features for Predicting HALC

- X.12: # of policies canceled or terminated
- Policy years
- X.8: Insurance years
- X.14: Net premium amount
- X.13_0: Last payment method (half-yearly vs. annual)

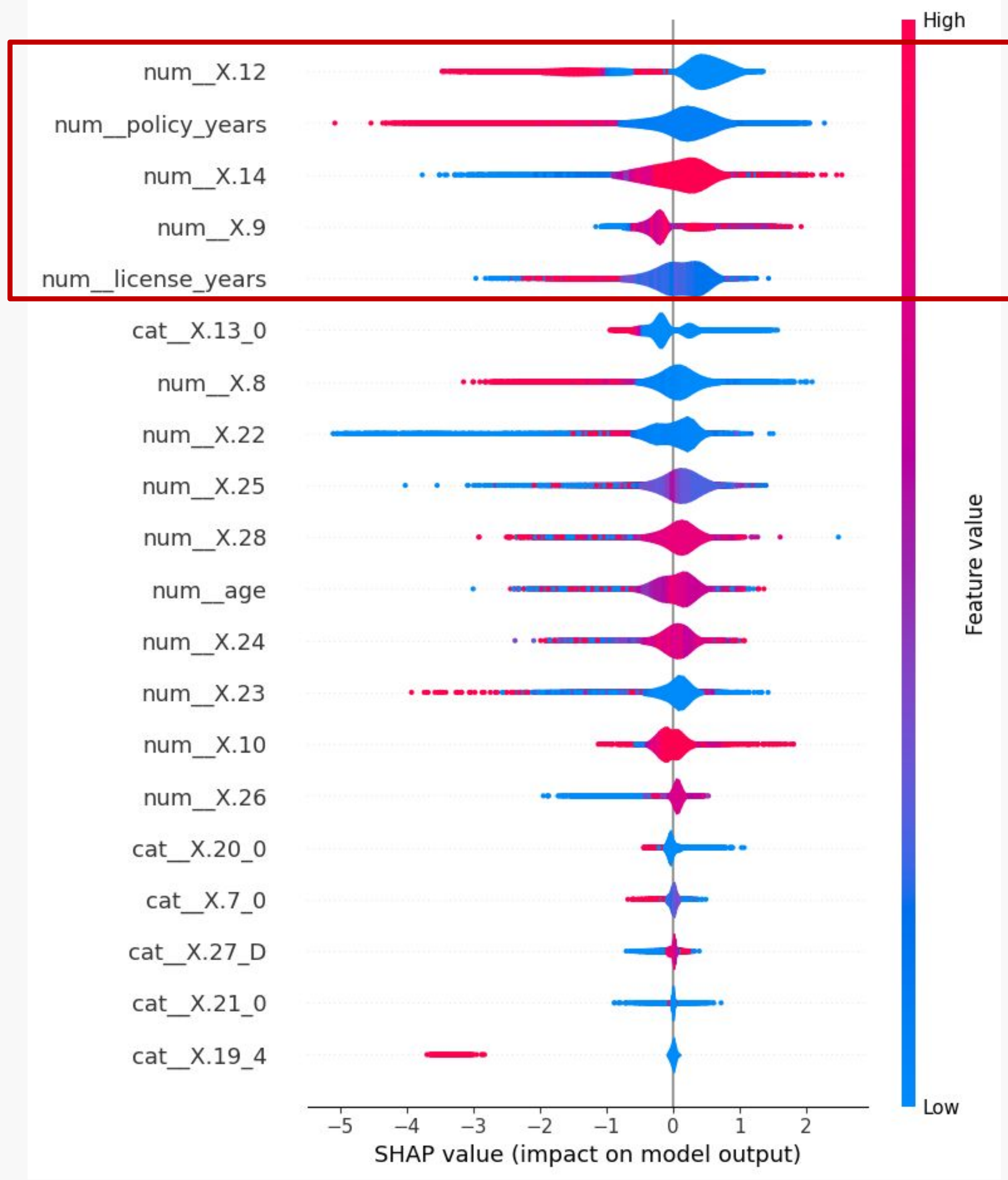
- **Model for LC is focused on short-term risk exposure related to drivers**
- **Model for HALC is more affected by long-term factors**

Task 1

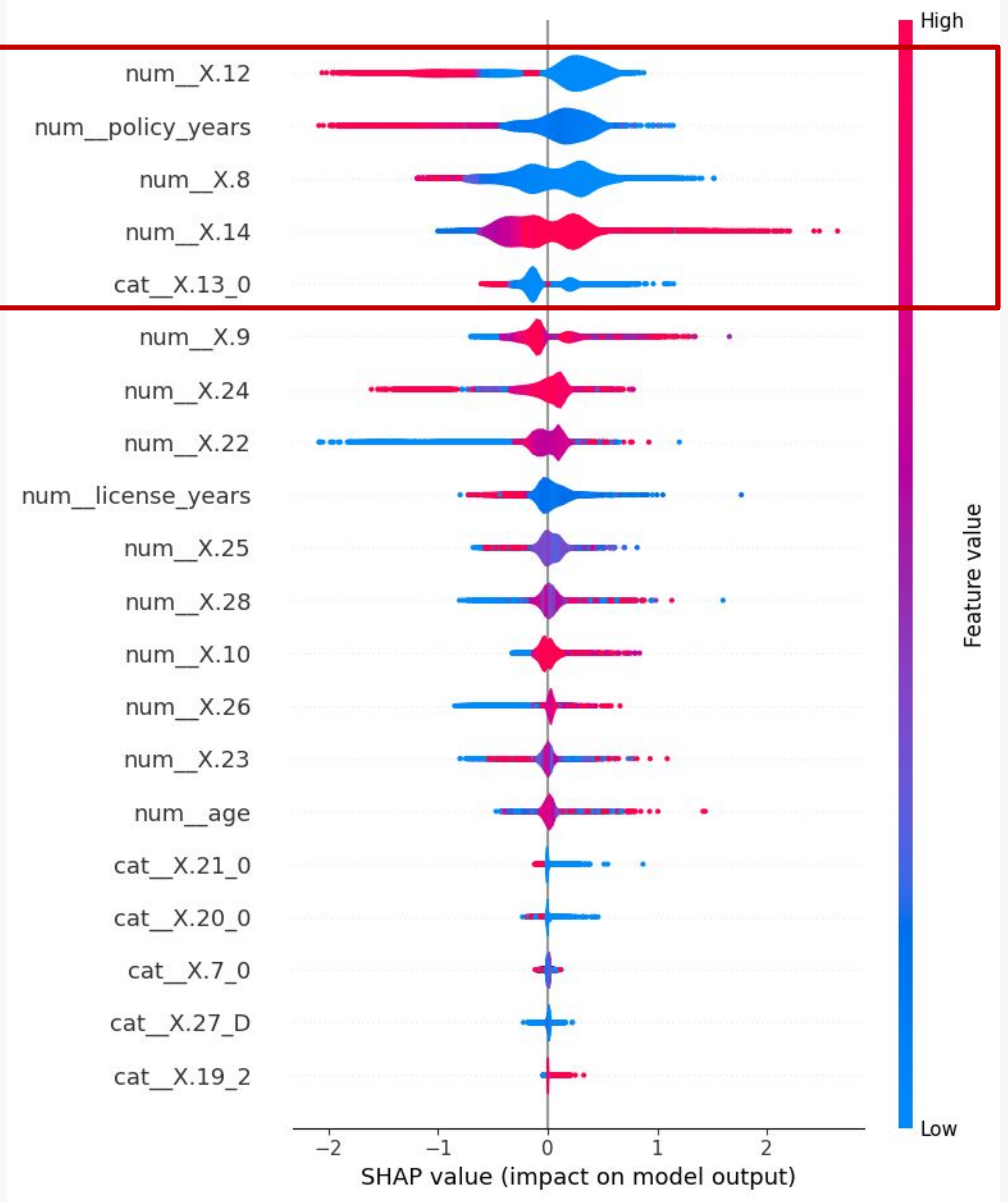
Model Interpretation – LC vs. HALC

Direction of Feature Impact on Prediction

Violin Chart for LC (XGBM)



Violin Chart for HALC (LightGBM)



Top Features for Predicting LC

X.12: # of policies canceled or terminated	Negative
Policy Years	Negative
X.14: Net premium amount	Positive
X.9: # of policies held during the current year	Positive
Driver license years	Negative

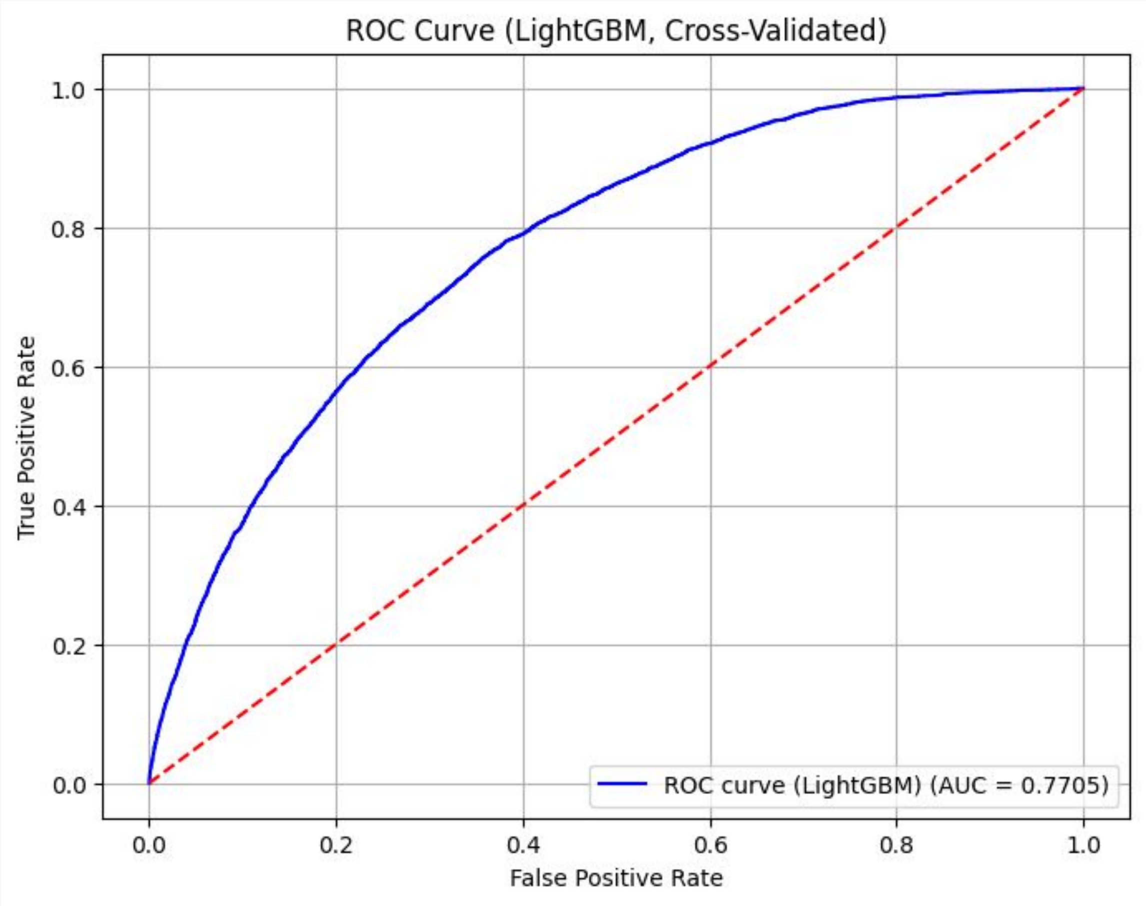
Top Features for Predicting HALC

X.12: # of policies canceled or terminated	Negative
Policy Years	Negative
X.8: Insurance years	Negative
X.14: Net premium amount	Positive
X.13_0: Last payment method (half-yearly vs. annual)	Negative

Task 2

Model Selection – Claim Status

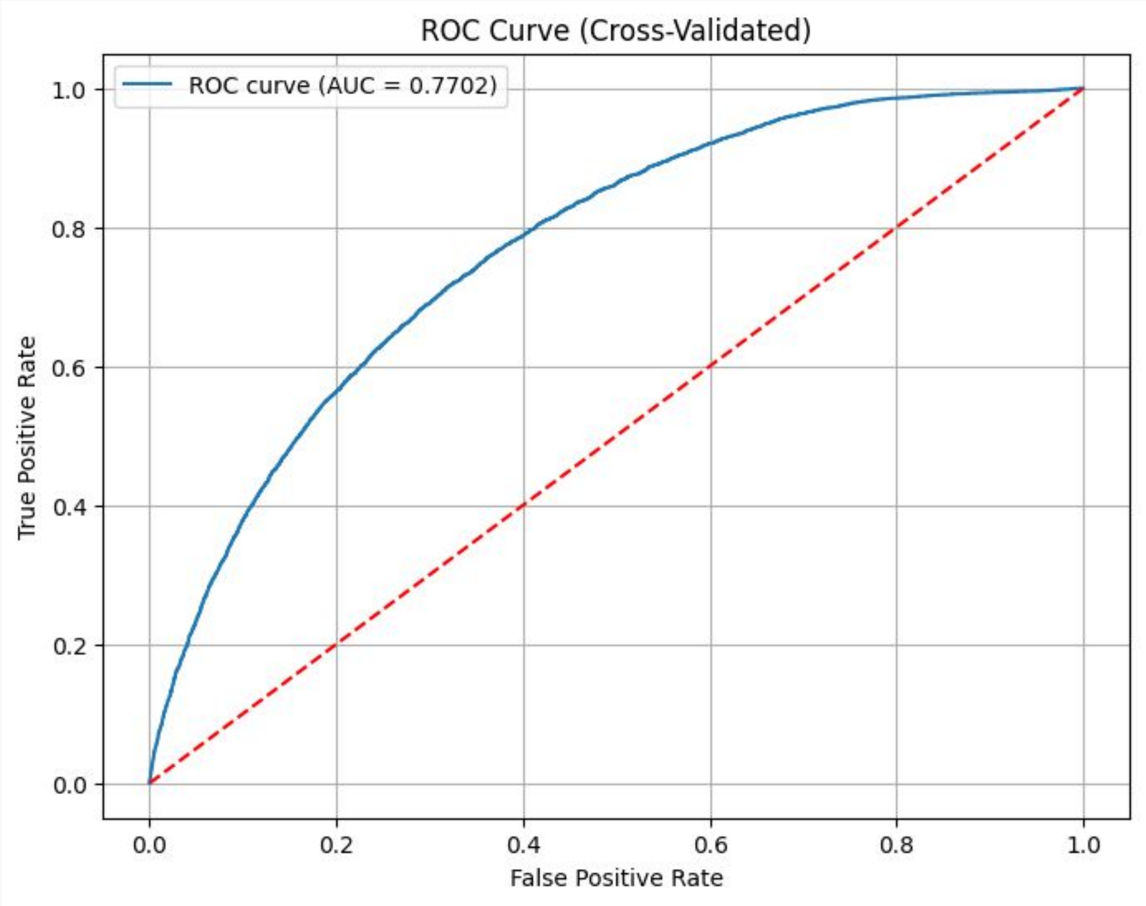
Light Gradient Boosting Machine (LightGBM)



Best Parameters:

- learning_rate = 0.05
- max_depth = -1
- n_estimators = 100
- num_leaves = 31

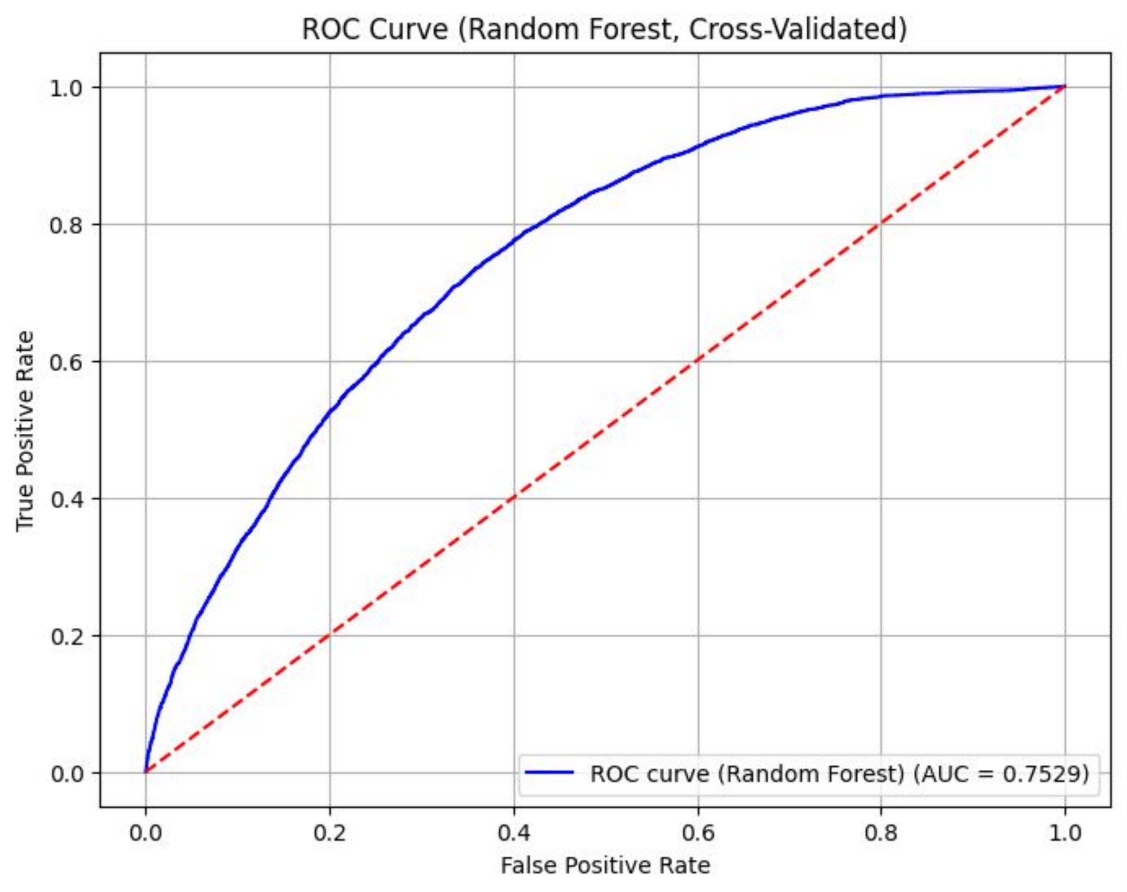
Extreme Gradient Boosting (XGBoost)



Best Parameters:

- gamma = 0.1
- learning_rate = 0.05
- max_depth = 5
- n_estimators = 200

Random Forest Classifier



Best Parameters:

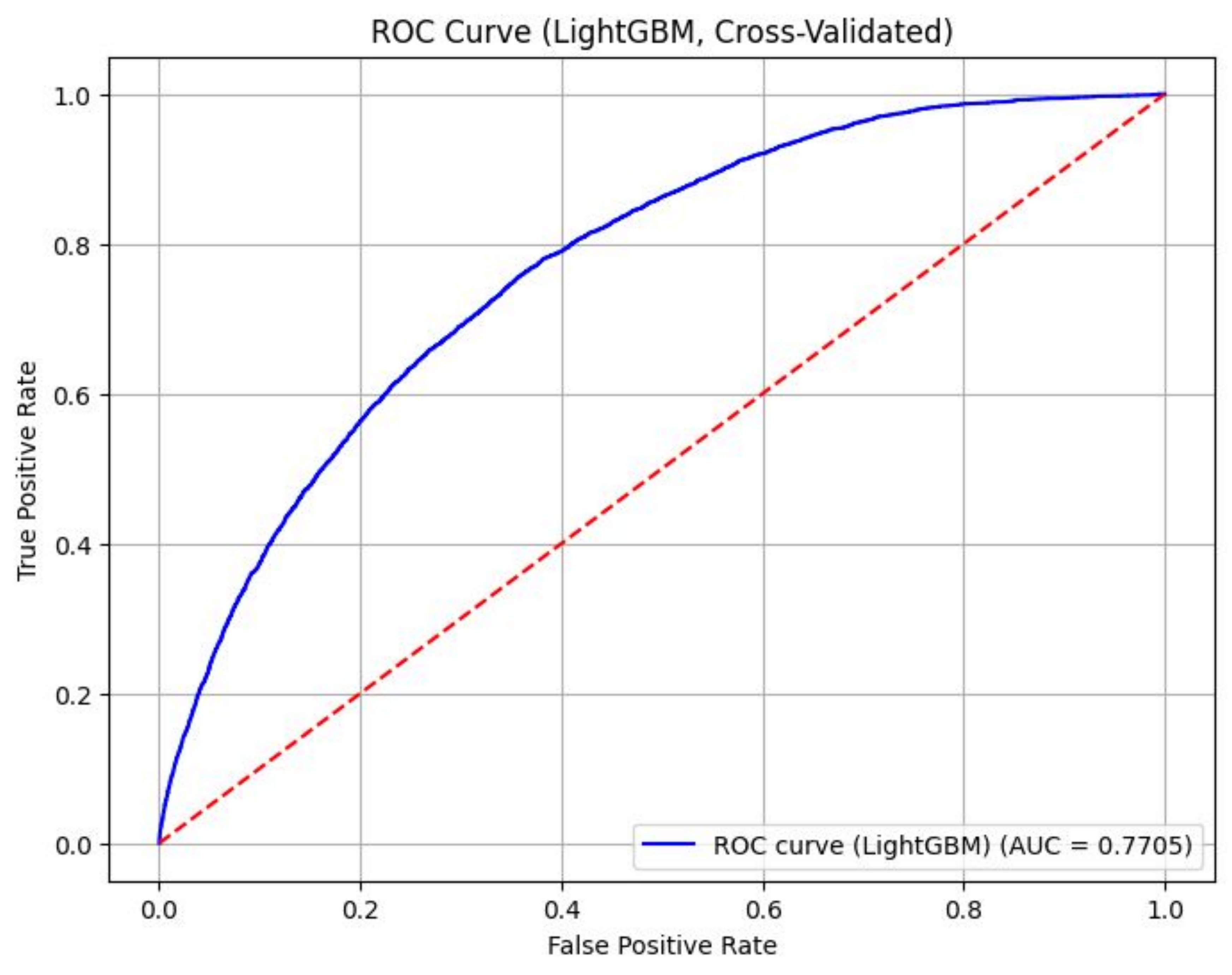
- bootstrap = False
- max_depth = 10
- min_samples_leaf = 2
- min_samples_split = 5
- n_estimators = 200

*all results are tuned

Task 2

Model Evaluation – Claim Status

Light Gradient Boosting Machine (LightGBM)



Best Parameters:
- learning_rate: 0.05
- max_depth: -1
- n_estimators: 100
- num_leaves: 31

Validation method:

For each model, we've used 5-fold cross-validation to find out the best parameters for each model

Evaluation method:

By comparing the ROC AUC score across each models' best tuned version, we see that LightGBM has the highest AUC (0.7705)

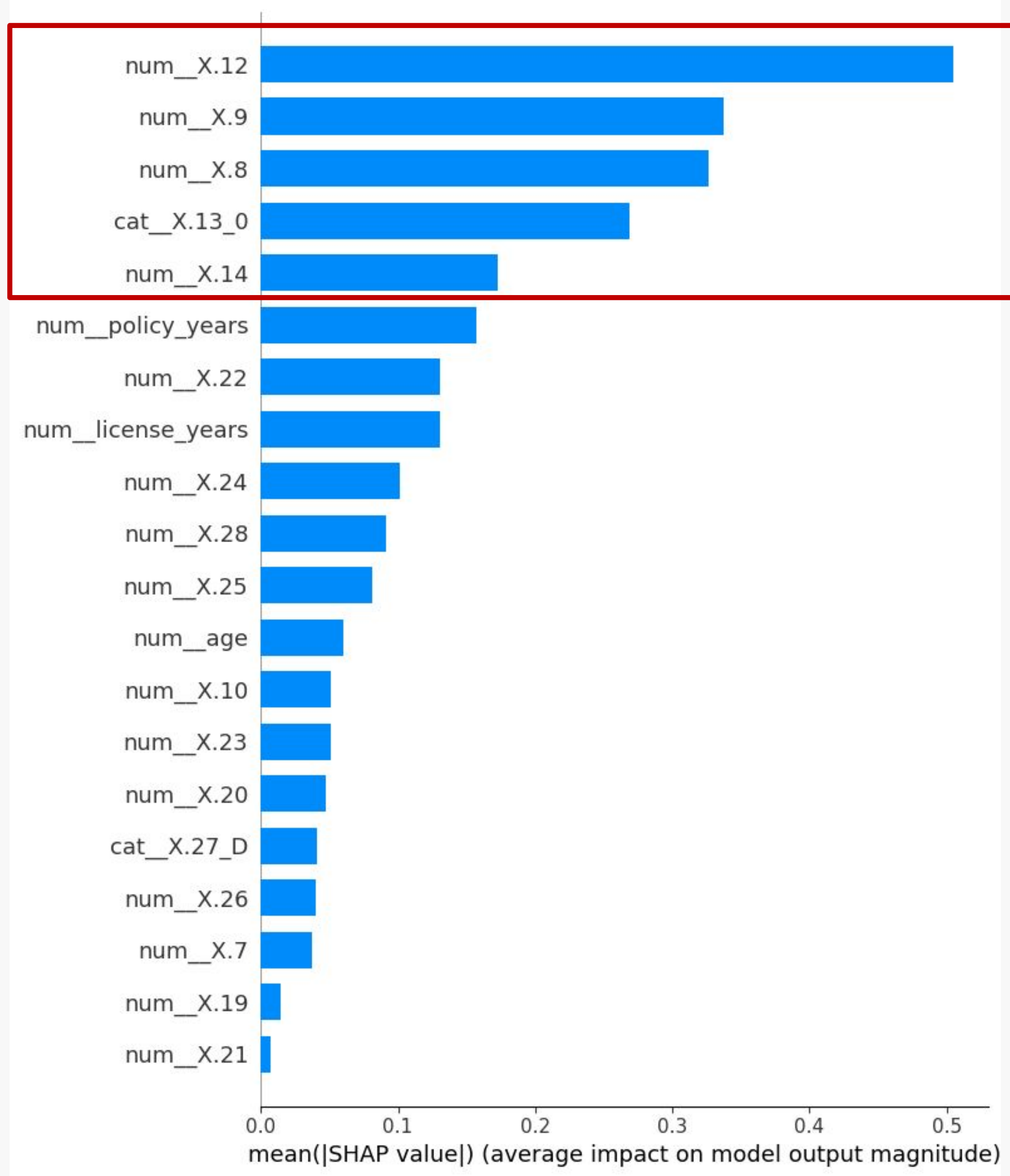
➔ ***LightGBM offers an excellent trade-off between training efficiency and prediction accuracy***

Task 2

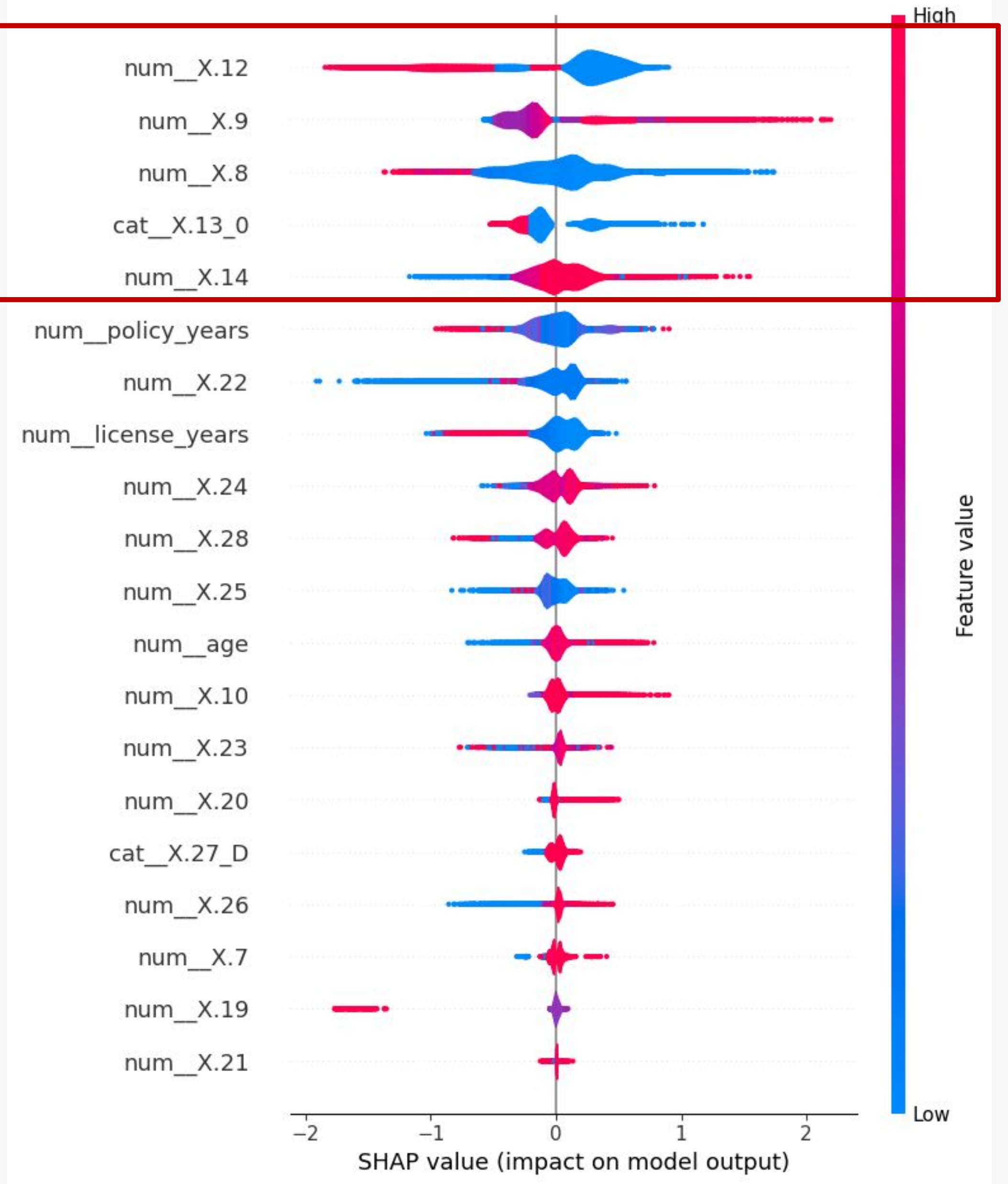
Model Interpretation – Claim Status

Magnitude & Direction of Feature Impact on Prediction

SHAP Value for CS (LightGBM)



Violin Chart for CS (LightGBM)



Top Features for Predicting Claim Status

X.12: # of policies canceled or terminated	Negative
X.9: # of policies held during the current year	Positive
X.8: Insurance years	Negative
X.13_0: Last payment method (half-yearly vs. annual)	Negative
X.14: Net premium amount	Positive

- The number of policies becomes 2nd important feature for predicting claim status

Innovation: Adversarial Validation

What is Adversarial Validation?

- A technique used to check **whether your training and test datasets come from the same distribution**
  - avoid overfitting

Steps:

1. Label training data as **0**, test data as **1**
2. Combine both datasets and shuffle
3. Train a **classifier** (like XGBoost or Logistic Regression) to predict the label

Why is it relevant?

- Issues that may lead to performance gap
  - data **leakage**
  - **distribution shift** between training and test sets
  - **non-representative** test data
- Adversarial Validation helps test this hypothesis

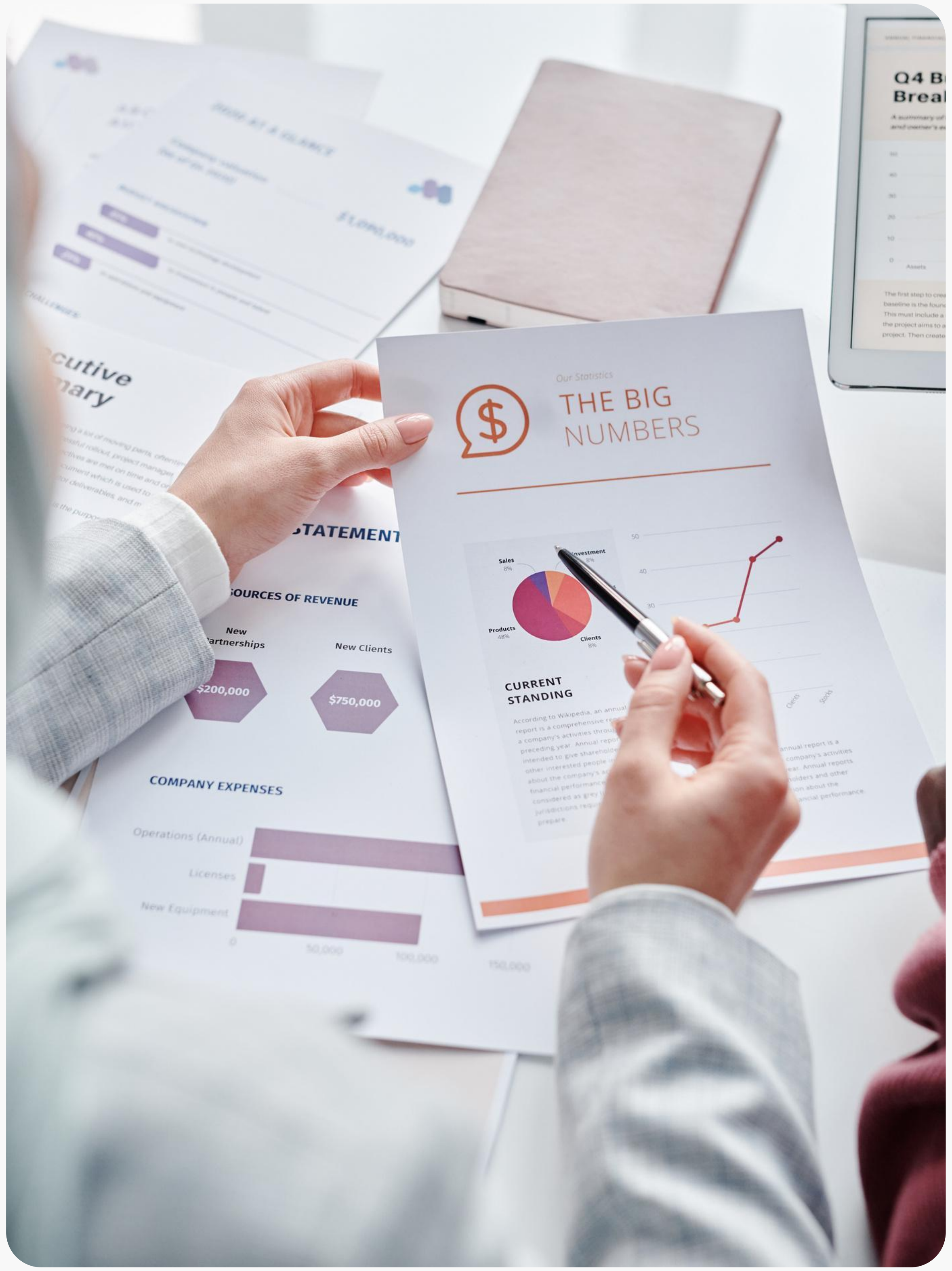
Our findings

Logistic Regression	LightGBM Classifier
AUC ≈ 0.51 → model could not distinguish between train and test sets	Train AUC = 0.78, but Validation AUC = 0.51 → model overfit, no real separation

Interpretation:

- **Train and test sets share similar distributions**
- **No strong evidence of data leakage or distribution shift**

Business Questions



Accuracy or Interpretation?

- **Prediction accuracy is slightly more important**, especially for predicting *Claim Status (CS)*
  - Accurate CS predictions help flag high-risk policyholders → Enables risk-adjusted pricing
- However, **interpretation is still critical** in regulated industries like insurance.
- **Balance is key.** We optimized accuracy **without sacrificing explainability**.

Using our model to directly predict loss cost for car insurance policies?

- **Caution is warranted.**
- **89%** of policyholders had **zero claims** → Highly imbalanced and skewed data.
- Tweedie regression helps but doesn't eliminate rare-event risk.

Thank you