COMPUTER PROGRAMMING AND
ARTIFICIAL INTELLIGENCE

Telecom Churn Prediction

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Final Presentation

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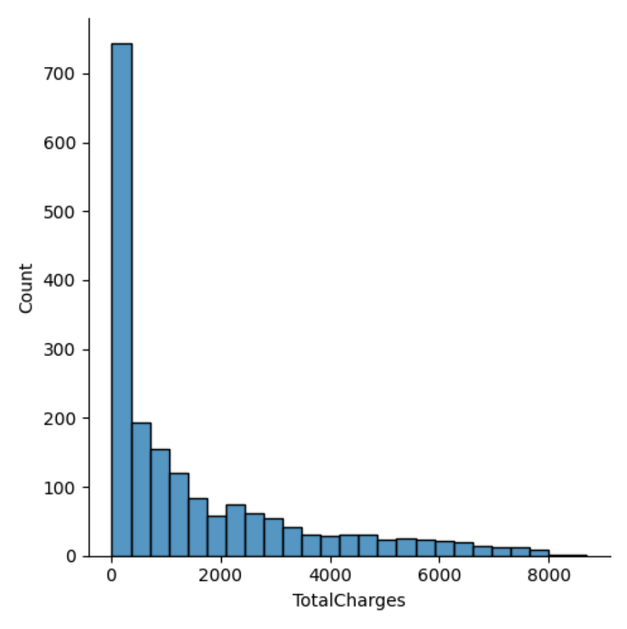
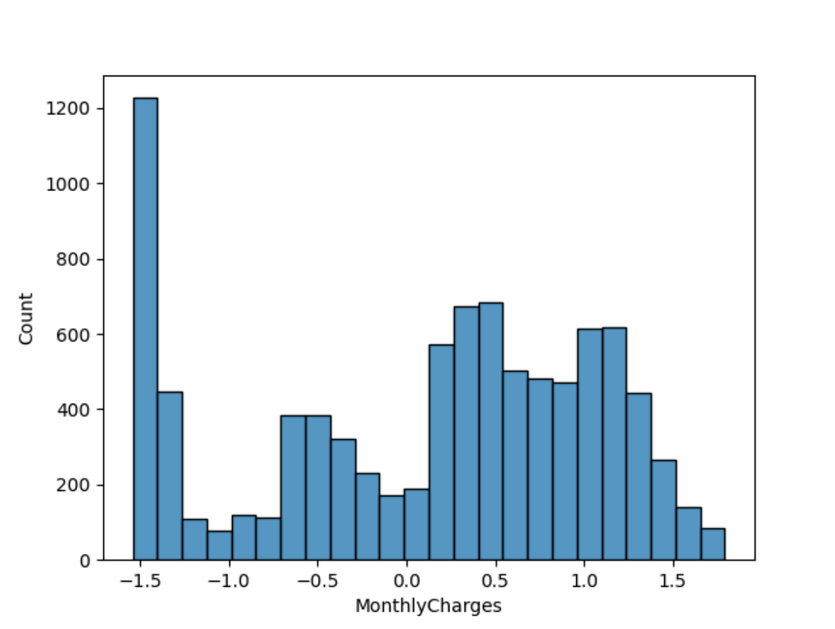
Methodology

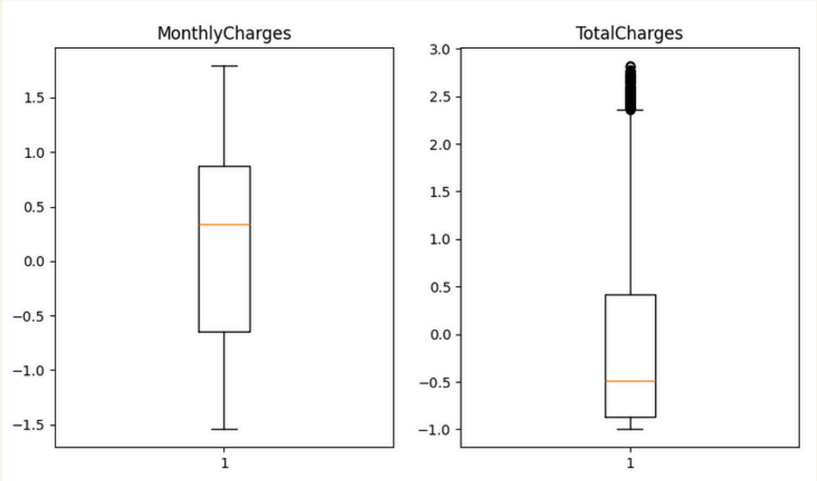
The methodology for this project encompasses exploratory data analysis (EDA), preprocessing, machine learning model and Pipeline with a focus on aligning predictive outcomes with business goals.

EDA (Exploratory Data analysis)

- Most features are categorical and need encoding; only three numerical features: **tenure, monthly charges, and total charges.**
- Most features are free from missing values.
- Distribution analysis (using histograms and boxplots) shows a class imbalance

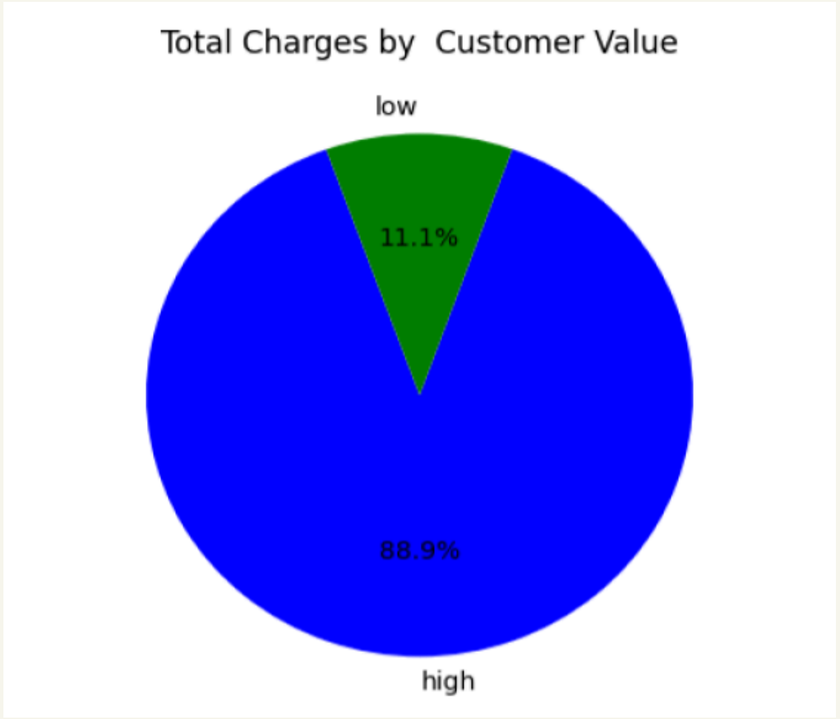






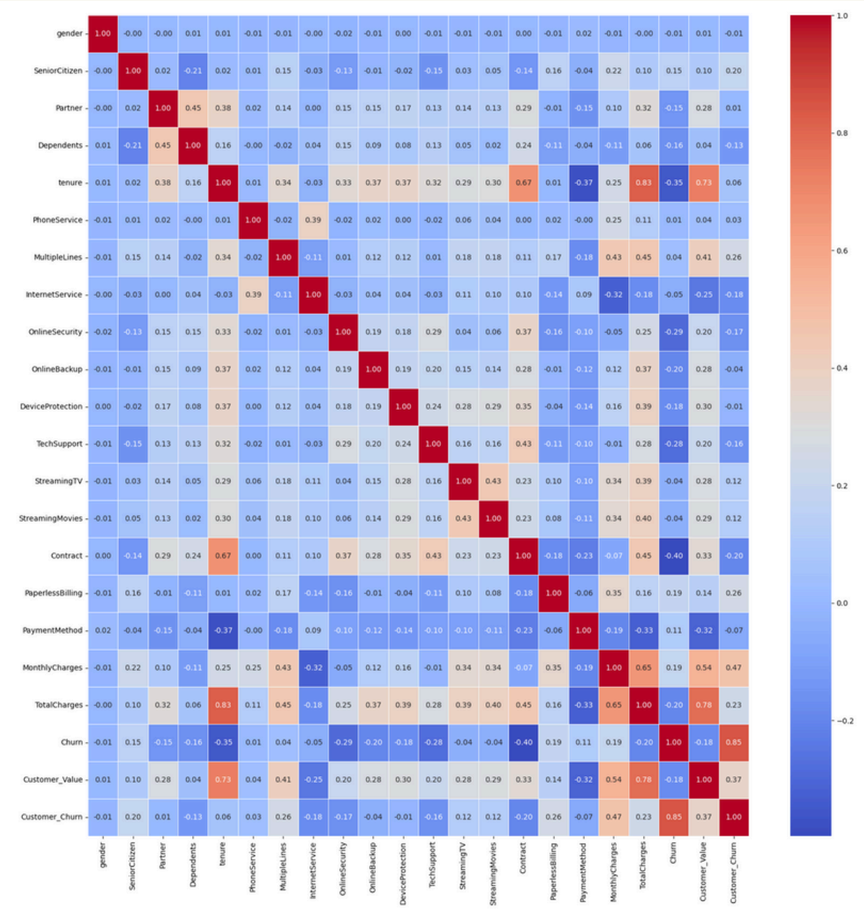
EDA (Exploratory Data analysis)

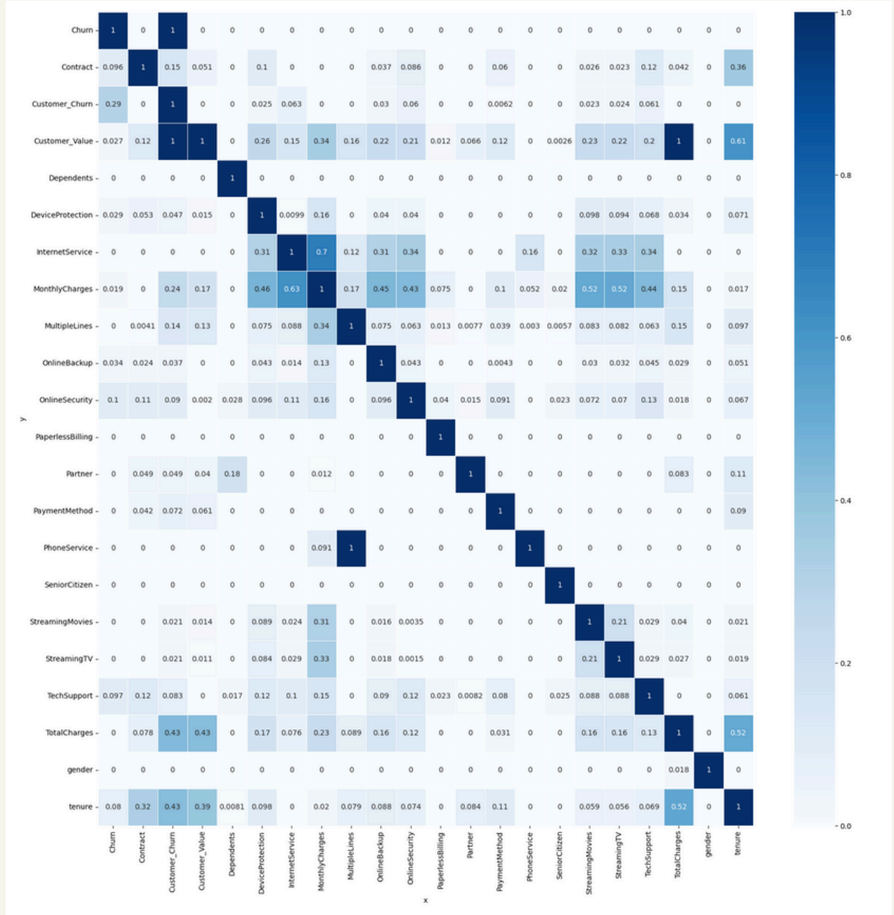
- The model will be evaluated using business-oriented metrics derived from total customer revenue.
- Analysis of total charges reveals
  - Median total charges: 1394.55
  - Over 80% of total revenue comes from customers with total charges above the median.



EDA (Exploratory Data analysis)

- Feature selection was performed **using correlations** and **predictive power score**.
- Heatmaps were plotted to identify relationships among features.
  - The **tenure feature** was excluded due to high correlation with other features.
  - **All other features were retained.**





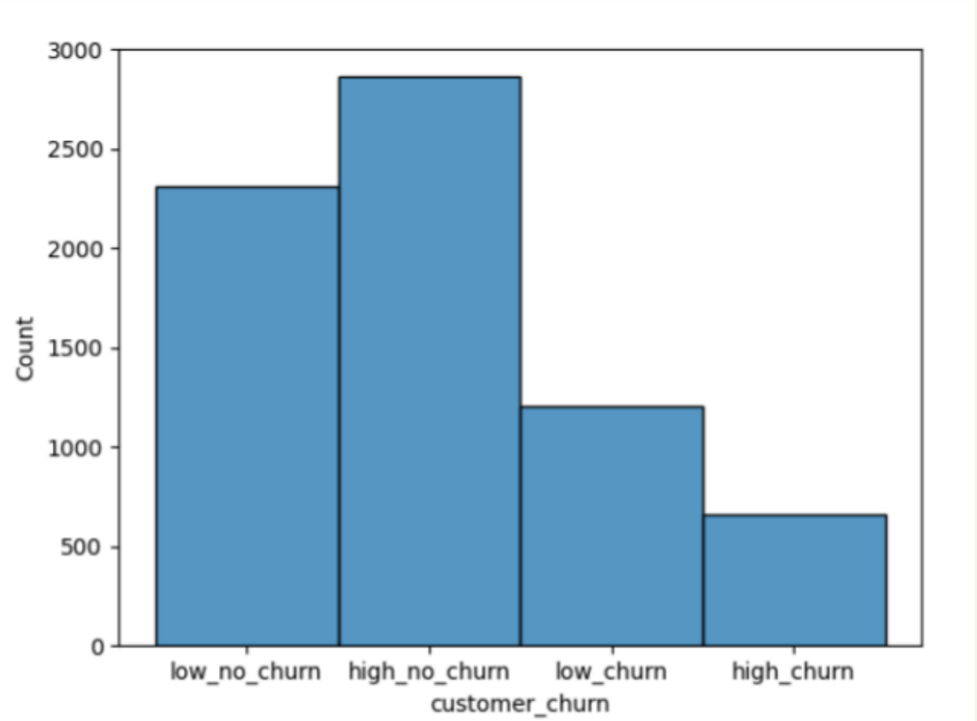
Pre-Processing

Imputing missing values

- Missing values in total charges were imputed using values from the **monthly charges** feature, assuming these customers have not been charged yet.
- All other features are free from missing values.

Feature Engineering

- Created two new columns for model evaluation
  a. **Customer_value**: Categorized as "high" (above median) or "low" (below median).
  b. **Customer_churn**: Derived from Customer_value and churn, forming four classes: low_churn, high_churn, low_no_churn, high_no_churn



Pre-Processing

Train-Test Split

- Used 10% of data for the test set **(~800 samples)**.

Scaling

- Applied StandardScaler() to scale numerical features, as charges are unbounded despite right-skewed distributions.

Encoding

- Used **label encoding** for categorical features with 2-3 unique values instead of one-hot encoding.

Modeling

- **Model Selection**
- **Upsampling with SMOTE**
- **Hyperparameter Tuning**
- **Experiment Class Weights**

Cross_val with four classes training data

1. Logistic Regression
2. Support Vector Classifier
3. Decision Tree Classifier
4. Random Forest Classifier
5. AdaBoost Classifier
6. **Gradient Boosting Classifier**

Modeling

- Model Selection
- Upsampling with SMOTE
- Hyperparameter Tuning
- Experiment Class Weights

```
from imblearn.over_sampling import SMOTEN
smote = SMOTEN(random_state=0)

X_train_up,y_train_up = smote.fit_resample(X_train,y_train)
```

Modeling

- Model Selection
- Upsampling with SMOTE
- Hyperparameter Tuning
- Experiment Class Weights

Tuning one hyperparameter at a time

```
# gradeint boosting parameters
gbc_parameters = {'loss': 'log_loss',
'learning_rate': 0.1,
'min_samples_split': 0.17272727272727273,
'min_samples_leaf': 0.17272727272727273,
'max_depth': 3,
'max_features': 'log2',
'criterion': 'friedman_mse',
'subsample': 0.95,
'n_estimators': 50}

# histogram-based gradeint boosting parameters
hgc_parameters = {'learning_rate': 0.1,
        'min_samples_leaf': 10,
        'max_depth': None,
        'max_features': 0.5,
        'l2_regularization': 0.1,
        'max_iter': 130}
```

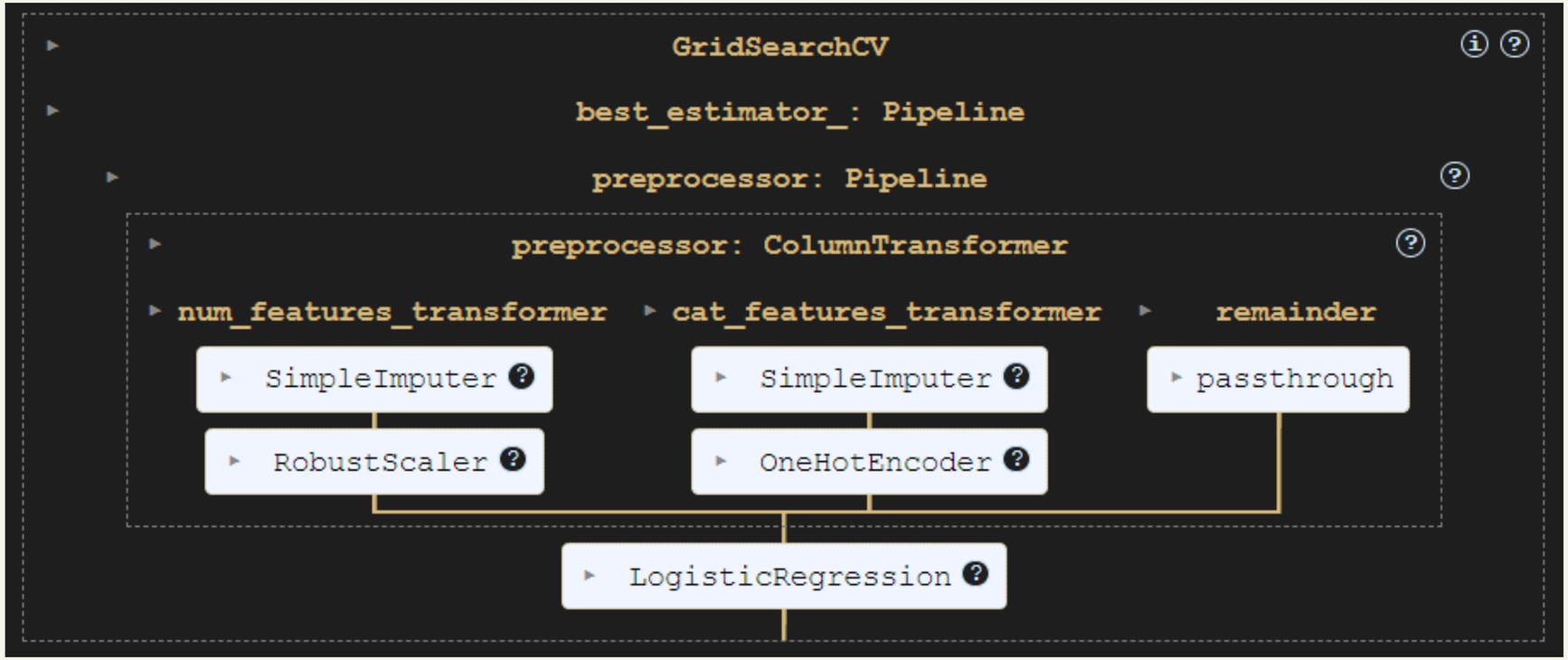
Modeling

- Model Selection
- Upsampling with SMOTE
- Hyperparameter Tuning
- Experiment Class Weights

Train HGboost with class weights

```
cls_weights1 = {0 : 2, 1 : 1, 2 : 1, 3 : 1}
cls_weights2 = {0 : 3, 1 : 1, 2 : 2, 3 : 1}
cls_weights3 = {0 : 4, 1 : 1, 2 : 1, 3 : 1}
cls_weights4 = {0 : 4, 1 : 1, 2 : 1, 3 : 1}
```

Pipeline


GridSearchCV
best_estimator_: Pipeline
preprocessor: Pipeline
preprocessor: ColumnTransformer
num_features_transformer
cat_features_transformer
remainder
SimpleImputer
SimpleImputer
passthrough
RobustScaler
OneHotEncoder
LogisticRegression

Model Evaluation Results

The model evaluation focuses on minimizing potential revenue losses from false negatives (misclassified non-churners), especially among high-value customers, whose departure poses a significant financial risk.

Model Evaluation Metrics

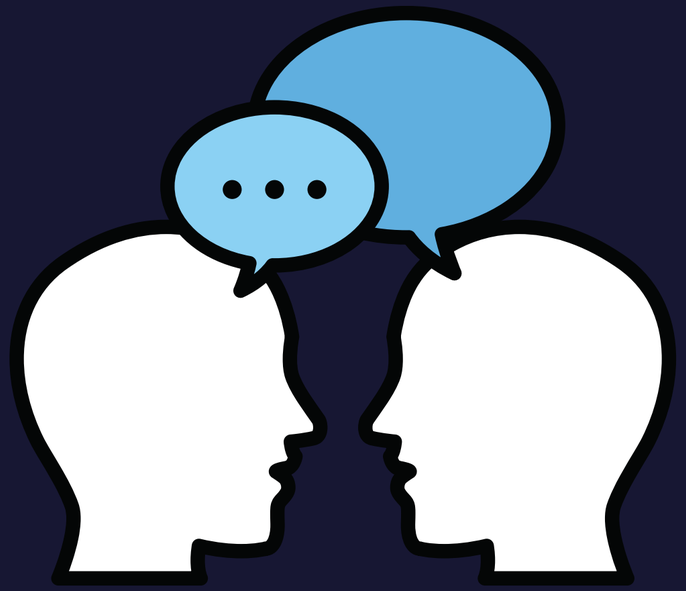
$$Potential\ Risk\ in\ Currency\ = \sum_{i=0}^{m} (TC)\ if\ FN$$

$$Risk\ Factor\ = \frac{Potential\ Risk\ in\ Currency}{\sum_{i=0}^{m} (TC)\ where\ target = "churn"}$$

	Models	Potential Risk in Currency	Risk Factor	Number of wrong predictions	False Negatives
0	gbc_4class_upsample	168376.30	0.520904	191	64
1	hgbc_4class_upsample_class_weight4	185005.20	0.572349	190	77
2	hgbc_4class_upsample_class_weight3	186503.45	0.576984	193	69
3	hgbc_4class_upsample_class_weight1	187950.35	0.581460	168	76
4	hgbc_4class_upsample_class_weight2	188011.10	0.581648	197	65
5	gbc_2class_upsample	190178.70	0.588354	178	63
6	hgbc_4class_upsample	236796.05	0.732573	167	90
7	hgbc_4class	246049.50	0.761201	157	89
8	gbc_2class	247608.90	0.766025	147	100
9	gbc_4class	277095.30	0.857247	145	105

Evaluation Results

- Variations of Gradient Boosting Classifier (GBC) and Histogram-Based Gradient Boosting Classifier (HGBC) were assessed.
- Upsampling techniques enhance performance by reducing revenue loss, e.g., gbc_4class_upsample shows a lower risk factor (0.5209) compared to gbc_4class (0.8572).
- Class weight adjustments improve outcomes, as seen in hgbc_4class_upsample_class_weight1, achieving a lower risk factor (0.5814) and potential risk (187950.34).
- Trade-offs include increased false negatives and risk factors in models like gbc_2class (0.7660), highlighting the need to balance accuracy with financial impact.



Discussion

EVALUATION METRIC

Risk factor shows how well the model predicts on the high-valued customer churns

PERFOMANCE

Risk factor - improvement (0.5)

Reduce the risk of potential loss of revenue

RECATEGORIZING AND UPSAMPLING

Effective for unbalanced data and the interest is in least dominant class

Conclusion

- A MORE ROBUST MODEL
- EVALUATION METRIC
- A GENERAL APPROCH FOR UMBALANCED DATA