

Fairway Bank Churn Reduction



Context



- Multinational bank (France, Spain, Germany)
- Worth €2.3B, 1M customers
- Opening branches in Belgium and Holland
- Renovating online banking platform

Problem

- Fairway's churn rate last year: **20%**
- Higher than ideal
 - 19% ¹
 - 15% ²
 - < 5 – 10% ³
- **Goal: reduce churn by 10% in a year**

¹ <https://customergauge.com/blog/average-churn-rate-by-industry>

² <https://www.reviewtrackers.com/blog/bank-customer-retention>

³ <https://uxpressia.com/blog/how-to-approach-customer-churn-measurement-in-banking>

Data Wrangling



- Random sample of Fairway's customers ¹
- 10K observations, 15 features
- Clean data, no duplicates, no missing values

¹ <https://www.kaggle.com/datasets/radheshyamkollipara/bank-customer-churn>
Photo: <https://m.bankingexchange.com/news-feed/item/9336-cfpb-requests-public-input-to-improve-bank-customer-service>

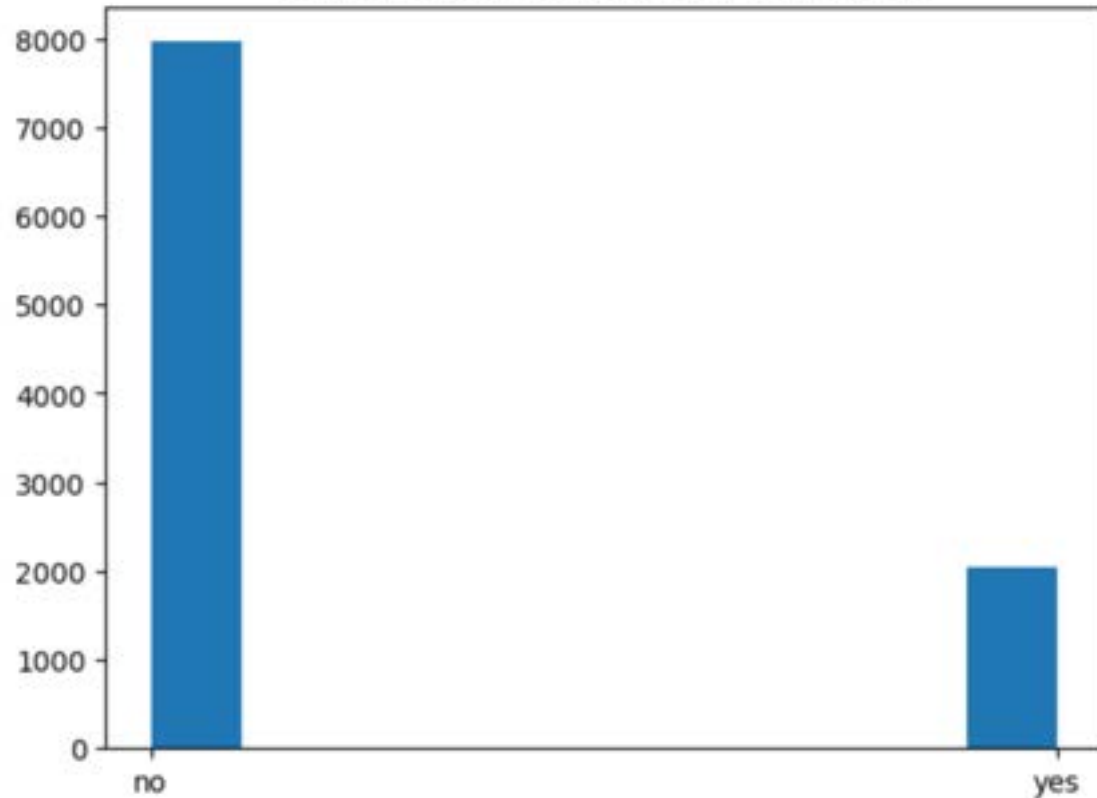
Data Wrangling

Features

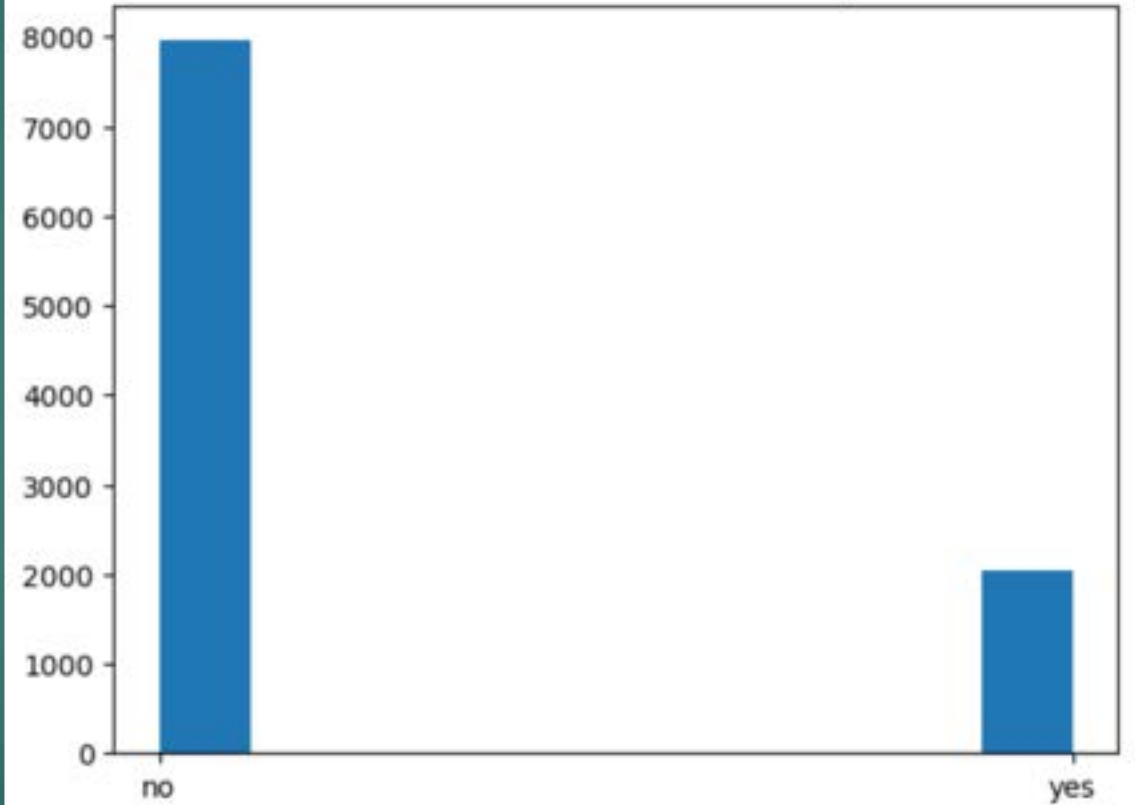
- credit score
- country
- gender
- age
- tenure
- balance
- number of products
- has credit card?
- active?
- salary
- satisfaction (1 – 5)
- card type
- points
- complained?
- **churned?**

EDA

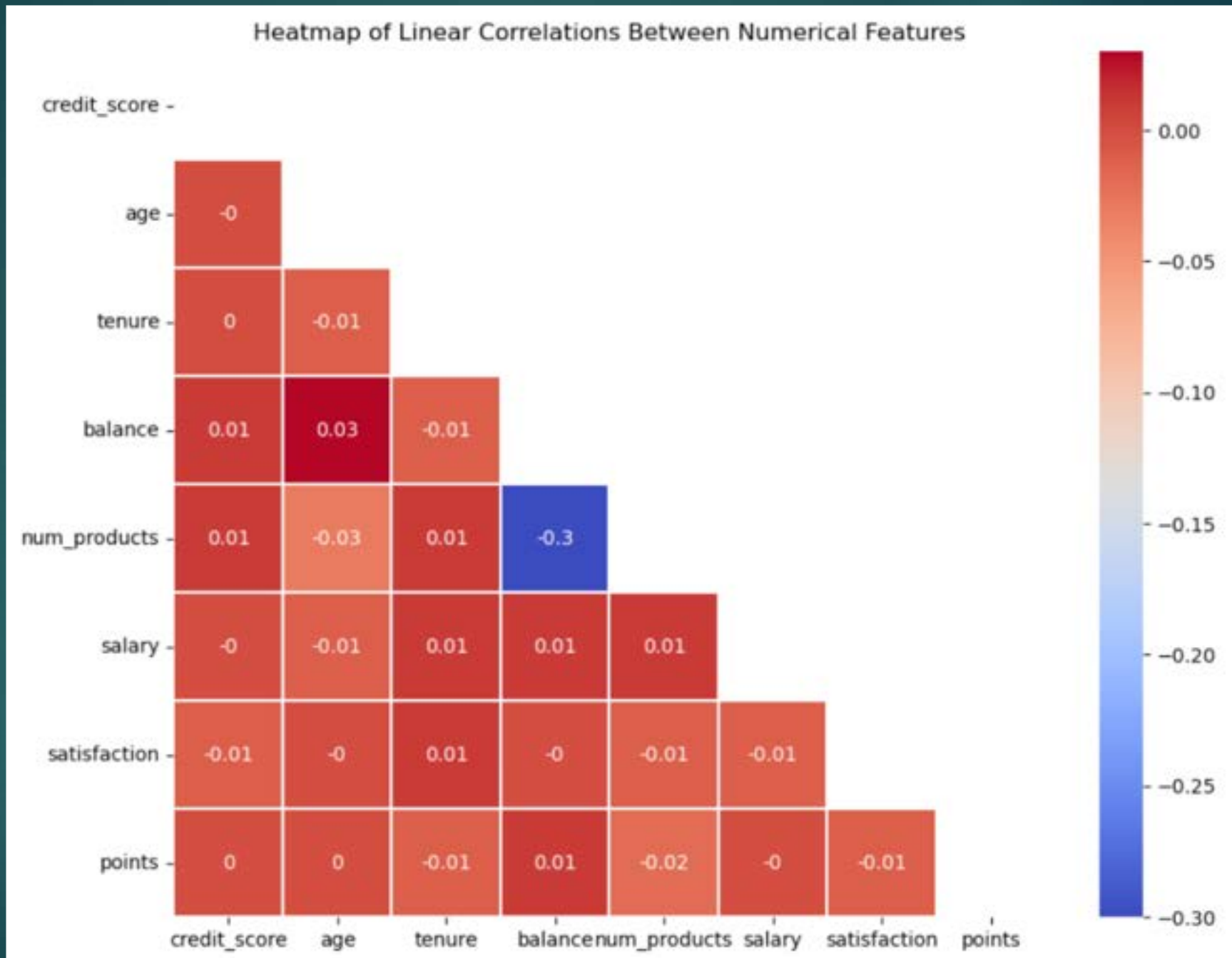
Distribution of customers who churned



Distribution of customers who complained



EDA



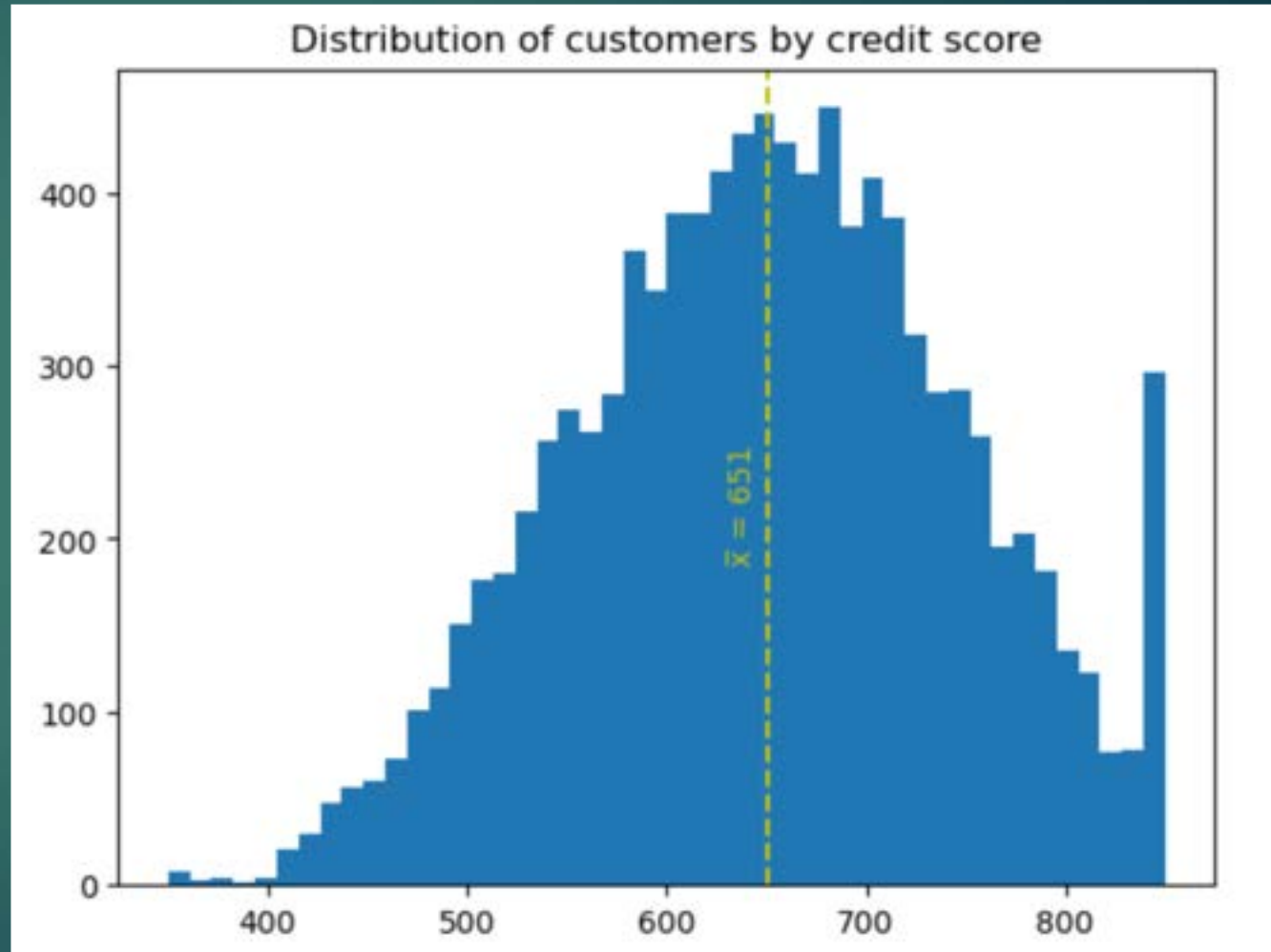
Preprocessing

- Dummy encoding (0's and 1's)
 - 19 total input features
- Bin numerical features
 - credit score
 - age
 - balance
 - salary
 - points
- Dimensionality reduction, cluster analysis

Preprocessing

credit score ¹

- 300 – 579
- 580 – 669
- 670 – 799
- 800 - 850

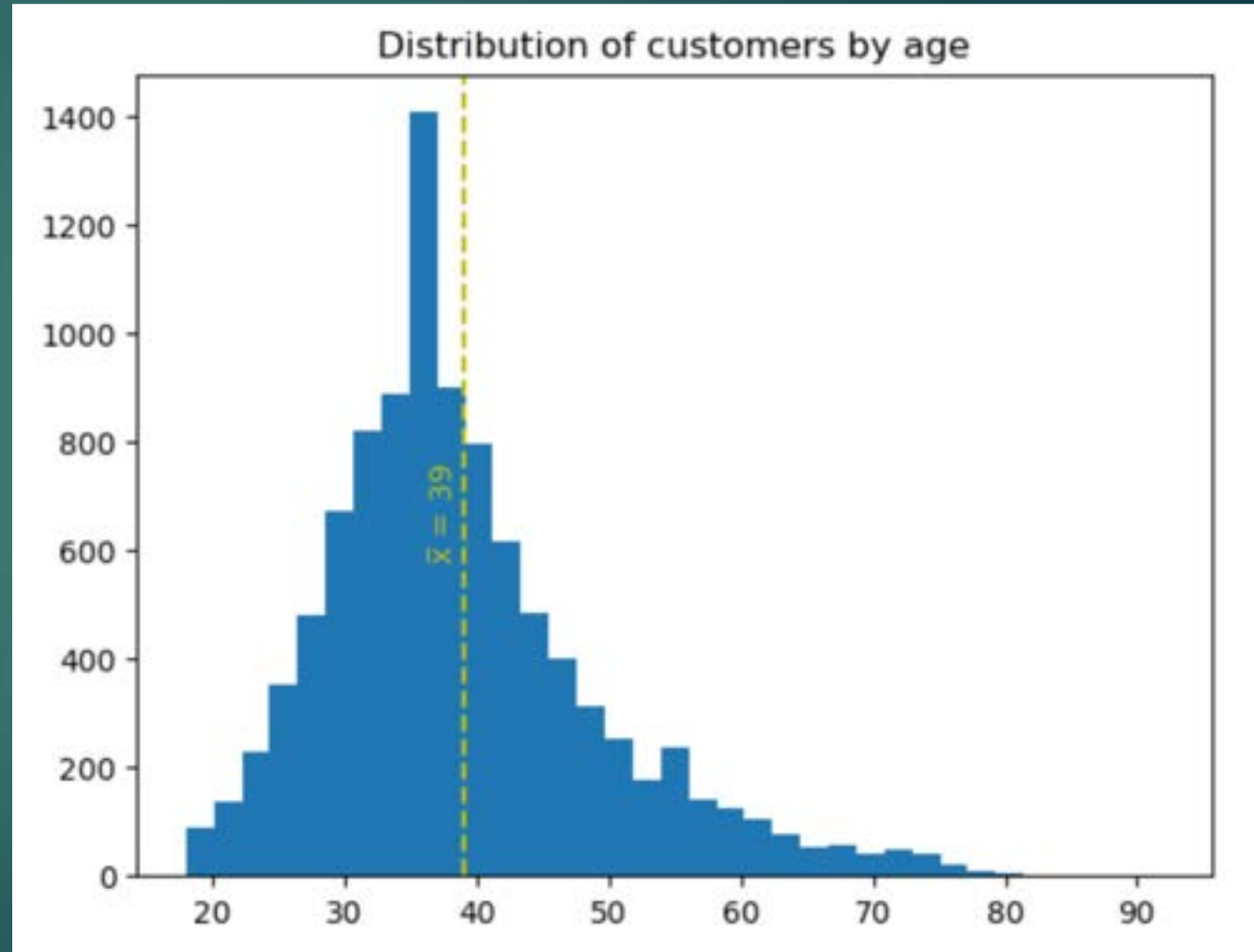


¹ <https://time.com/personal-finance/article/different-credit-scoring-ranges/>

Preprocessing

age ¹

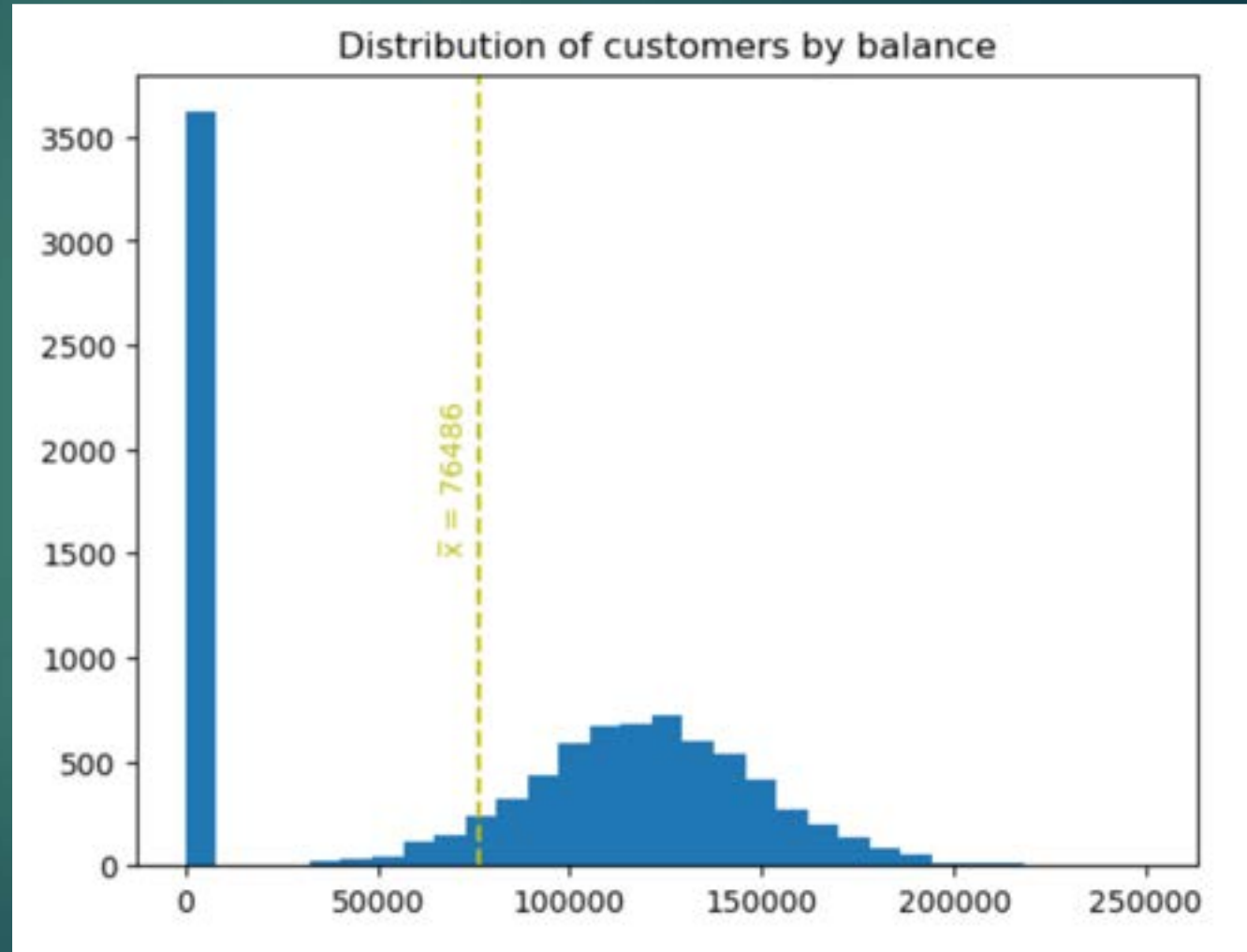
- 18 – 24
- 25 – 34
- 35 – 44
- 45 – 54
- 55 – 64
- 65+



Preprocessing

balance

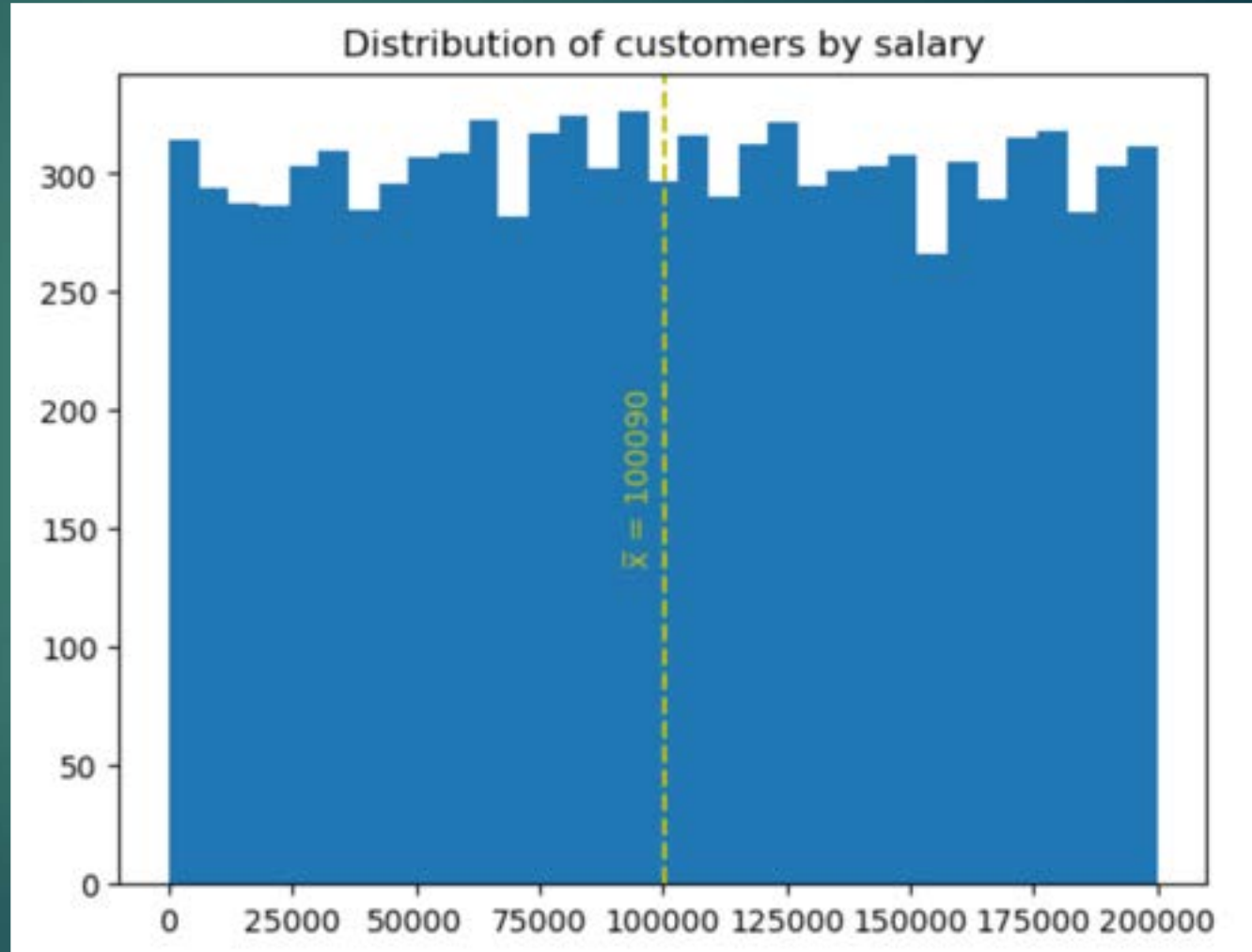
- 0
- 1 – (100K)
- 100K – (150K)
- 150K+



Preprocessing

salary

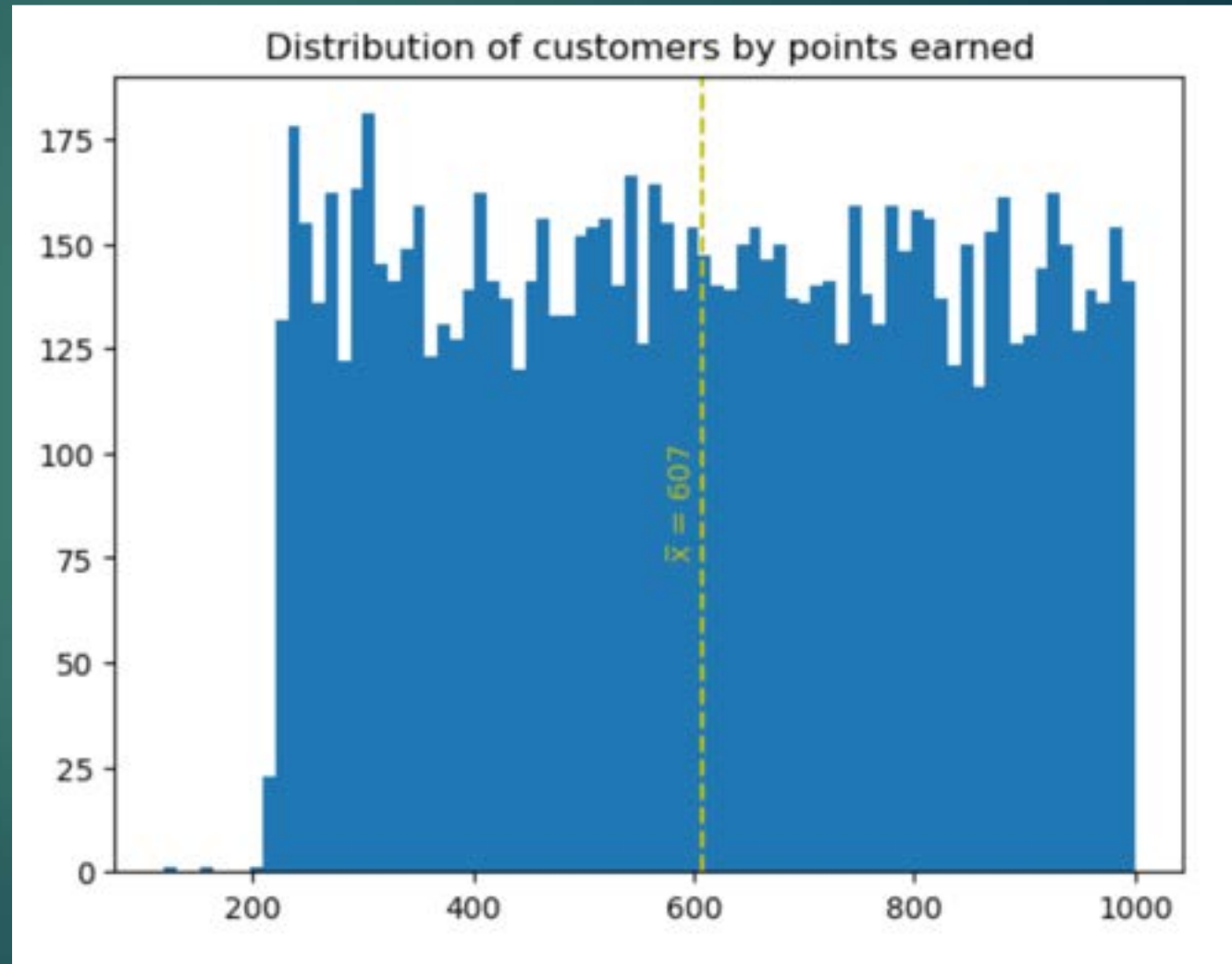
- 0 – (50K)
- 50K – (100K)
- 100K – (150K)
- 150K+



Preprocessing

points

- 0 – 299
- 300 – 399
- 400 – 499
- 500 – 599
- 600 – 699
- 700 – 799
- 800 – 899
- 900+



Modeling

- 80 / 20 train / test split
- 5-Fold stratified K-fold on train set
- Goal: minimize false negatives
- Performance metric: **recall**

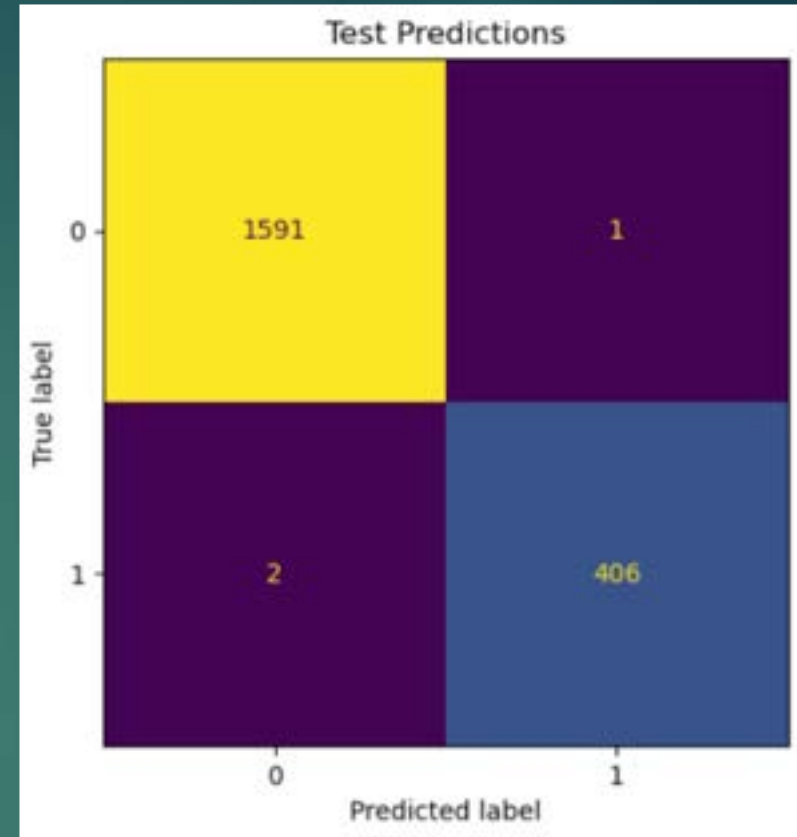
Modeling

Models

- Random Forest
- Extra Trees
- Gradient Boosting
- Hist Gradient Boosting
- AdaBoost
- XGBoost
- LightGBM
- CatBoost
- Logistic Regression
- Support Vector

Modeling

- Initial 99.88% train set recall
- Complain: golden feature
- Only 4 / 2038 customers who churned didn't complain
- Only 10 / 2044 customers who complained didn't churn



Modeling



- Drop 'complain' feature
- Initial median recall: 44.14%
- Lower probability threshold for more positive predictions
- Balance false positive tradeoff by optimizing f1-score
- Improved median recall: 60.50%

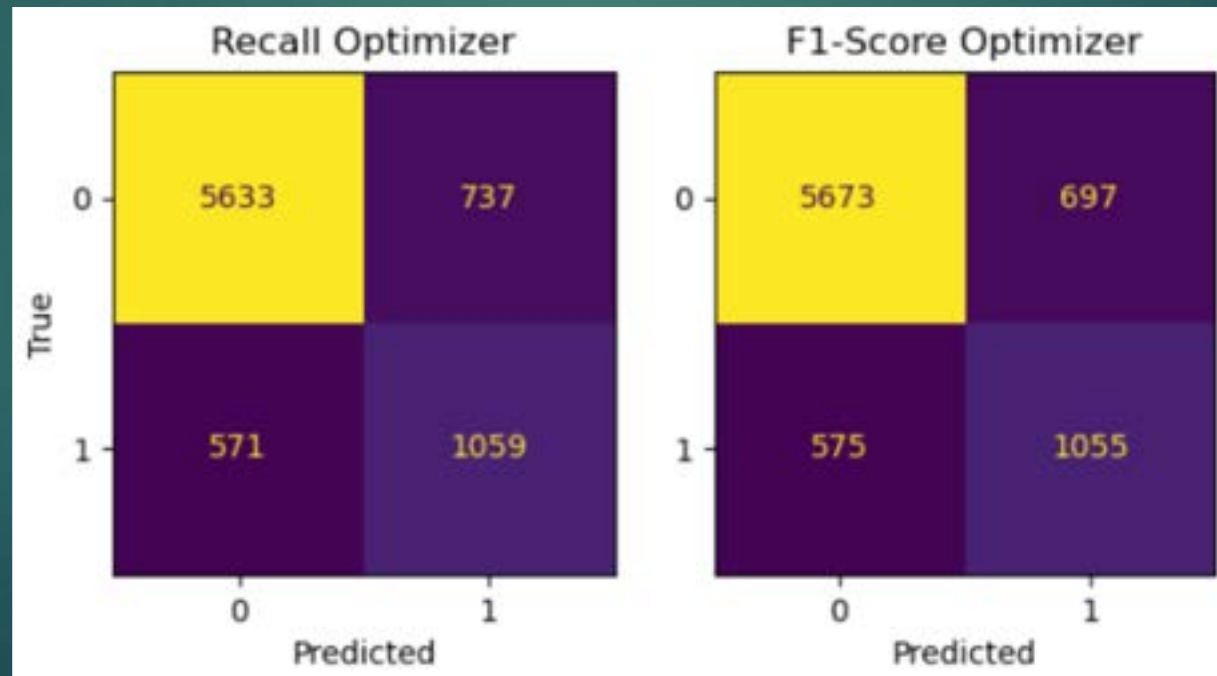
Modeling

Optimum Probability Thresholds

- 0.25 Logistic Regression
- 0.27 Support Vector
- 0.29 CatBoost
- 0.30 XGBoost
- 0.31 Hist Gradient Boosting
- 0.32 Extra Trees
- 0.33 Gradient Boosting
- 0.34 Random Forest, LightGBM
- 0.50 AdaBoost

Modeling

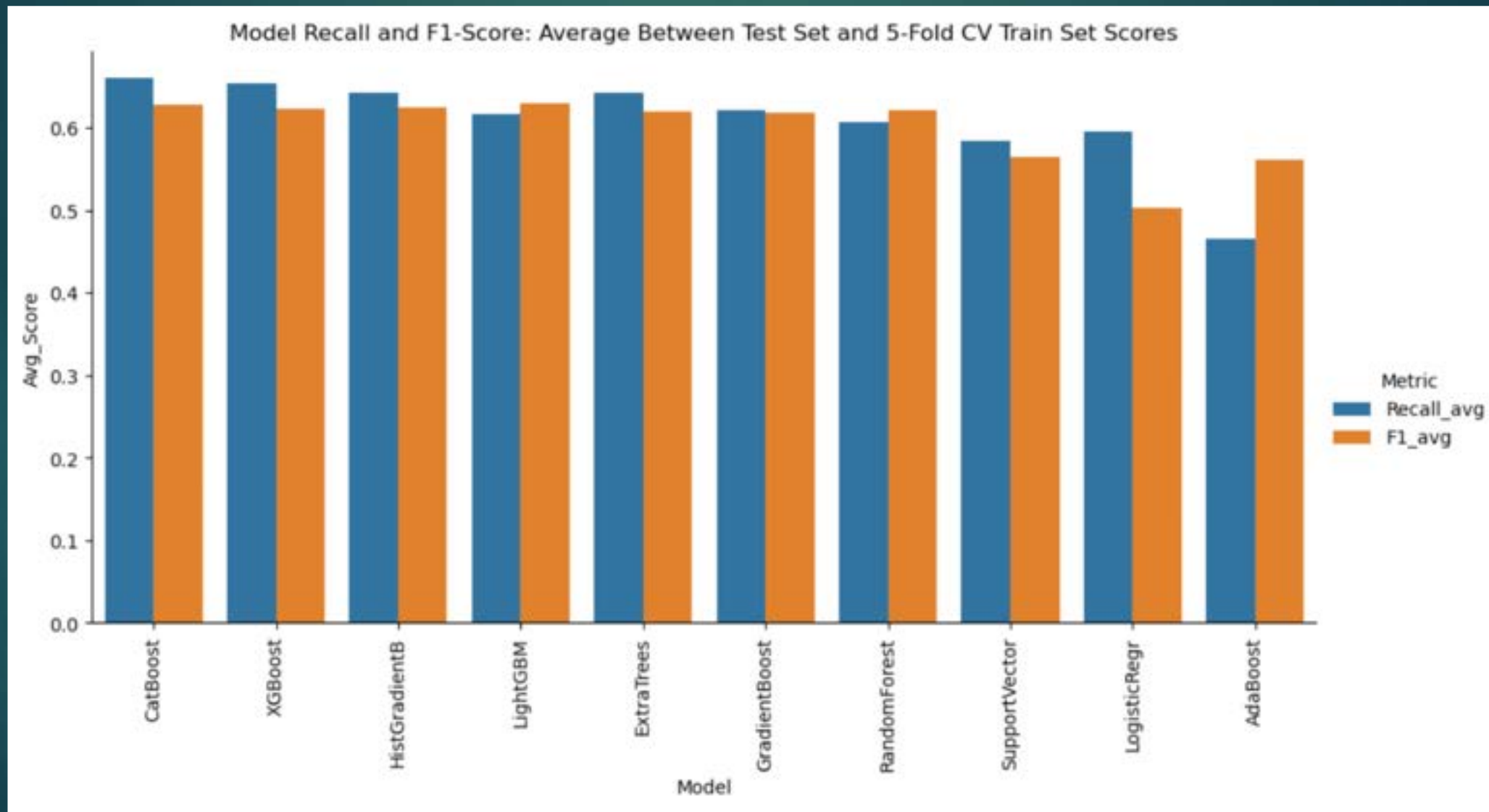
- Hyperparameter tuning - Optuna
- F1-score best optimizer metric



Modeling

- Aggregate score (per model, 5 metrics)
 - Train set: mean 5-fold cross-validation score
 - Average with test set score
 - Subtract train set standard deviation
- Metric weights
 - 40% recall
 - 30% f1-score
 - 20% ROC AUC
 - 5% precision
 - 5% accuracy

Modeling



Modeling

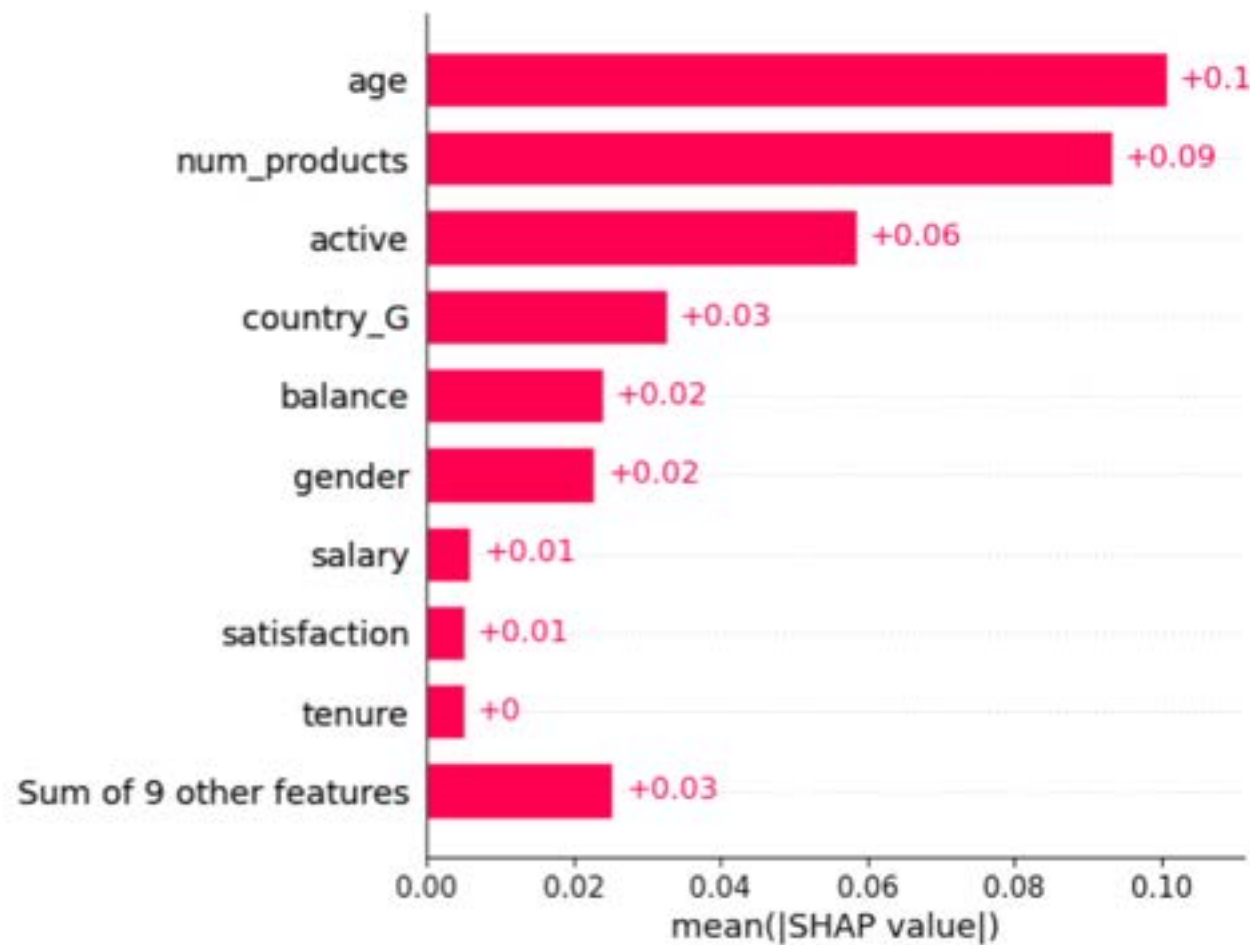
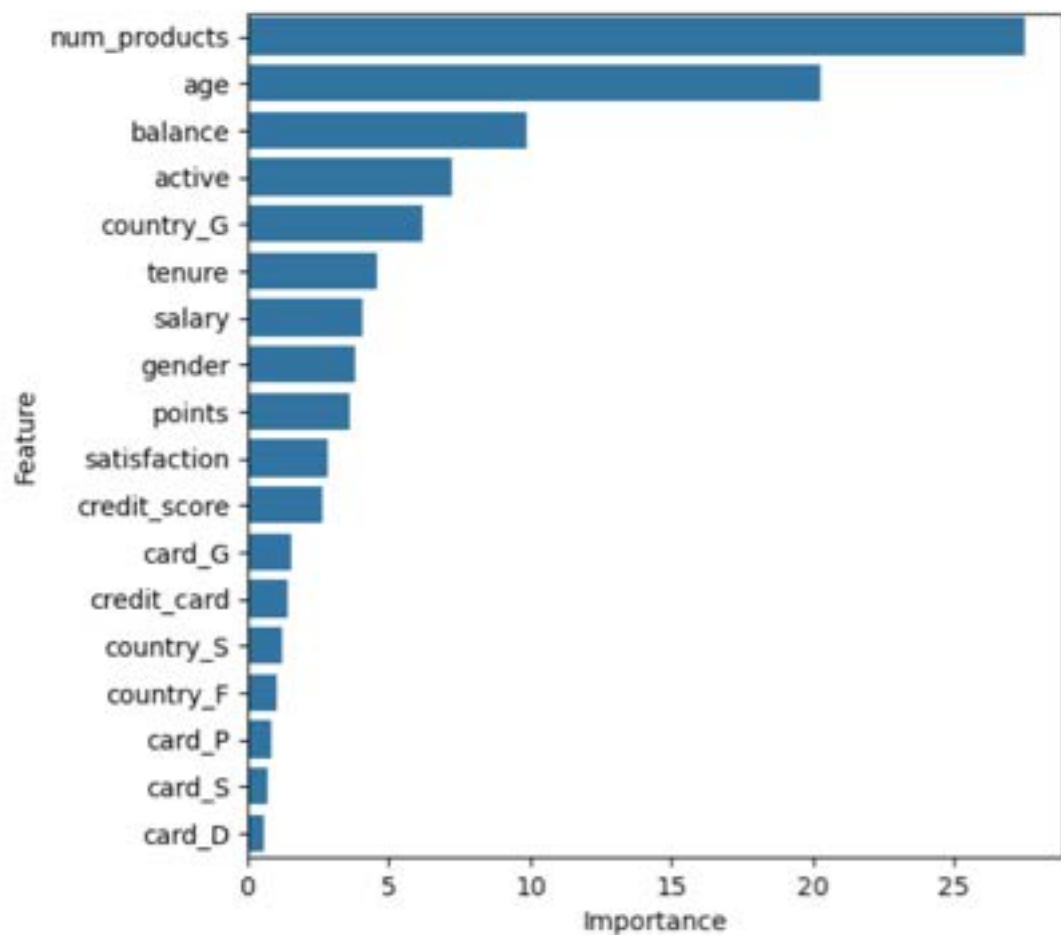
Best model: CatBoost Classifier

- iterations: 545
- learning_rate: 0.013560631530876574
- depth: 6
- l2_leaf_reg: 2.548492629309027
- random_strength: 0.3660344916841721
- bagging_temperature: 0.2722303737601264
- probability threshold: 0.29

CatBoost									
Train Report					Test Report				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	0.91	0.89	0.90	6370	0	0.91	0.88	0.90	1592
1	0.60	0.65	0.62	1630	1	0.60	0.67	0.63	408
accuracy			0.84	8000	accuracy			0.84	2000
macro avg	0.76	0.77	0.76	8000	macro avg	0.76	0.78	0.77	2000
weighted avg	0.85	0.84	0.84	8000	weighted avg	0.85	0.84	0.84	2000

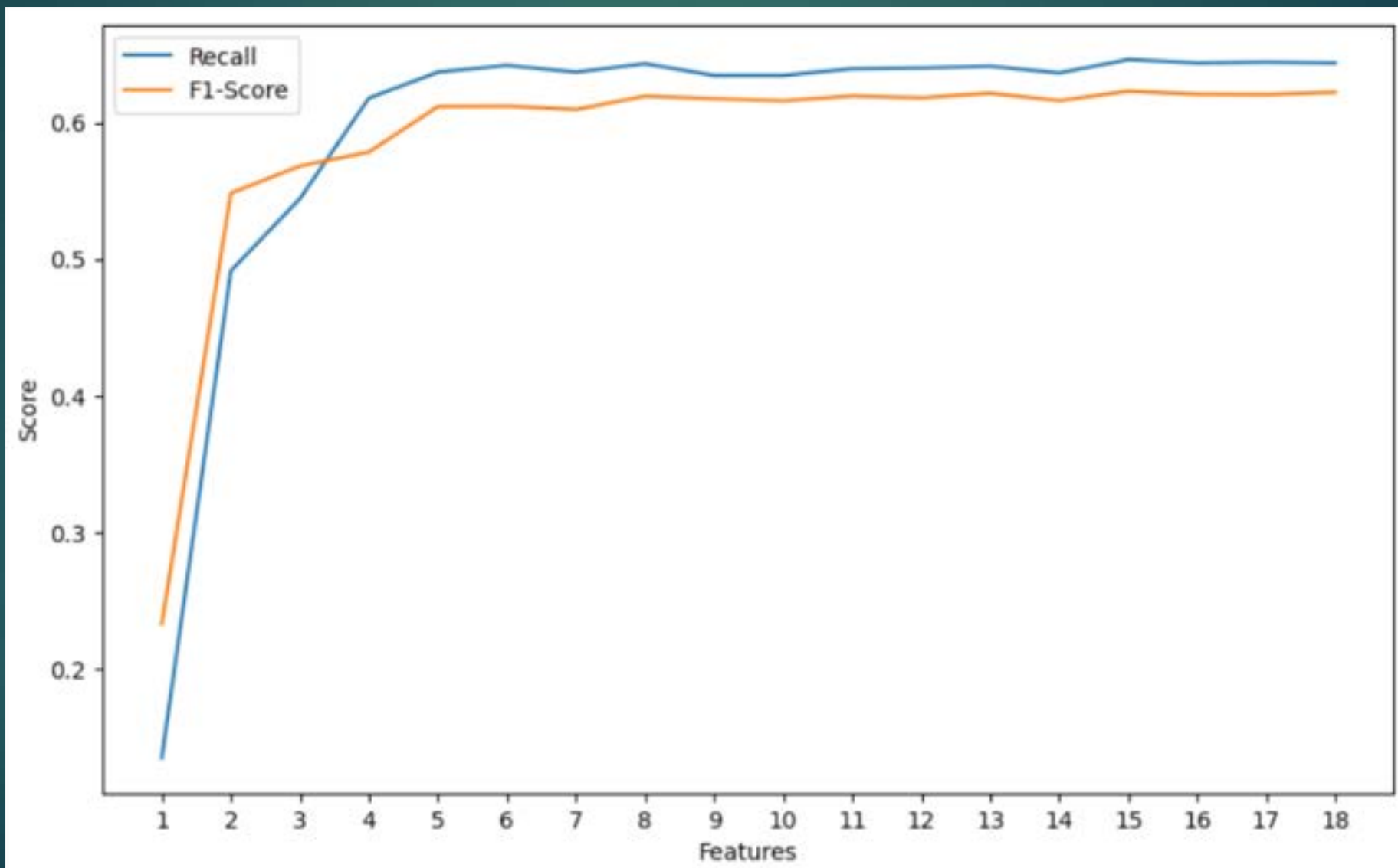
Modeling

CatBoost Feature Importances vs. SHAP Values



Modeling

CatBoost Feature Reduction: Recall and F1-Scores on Cross-Validated Train Set



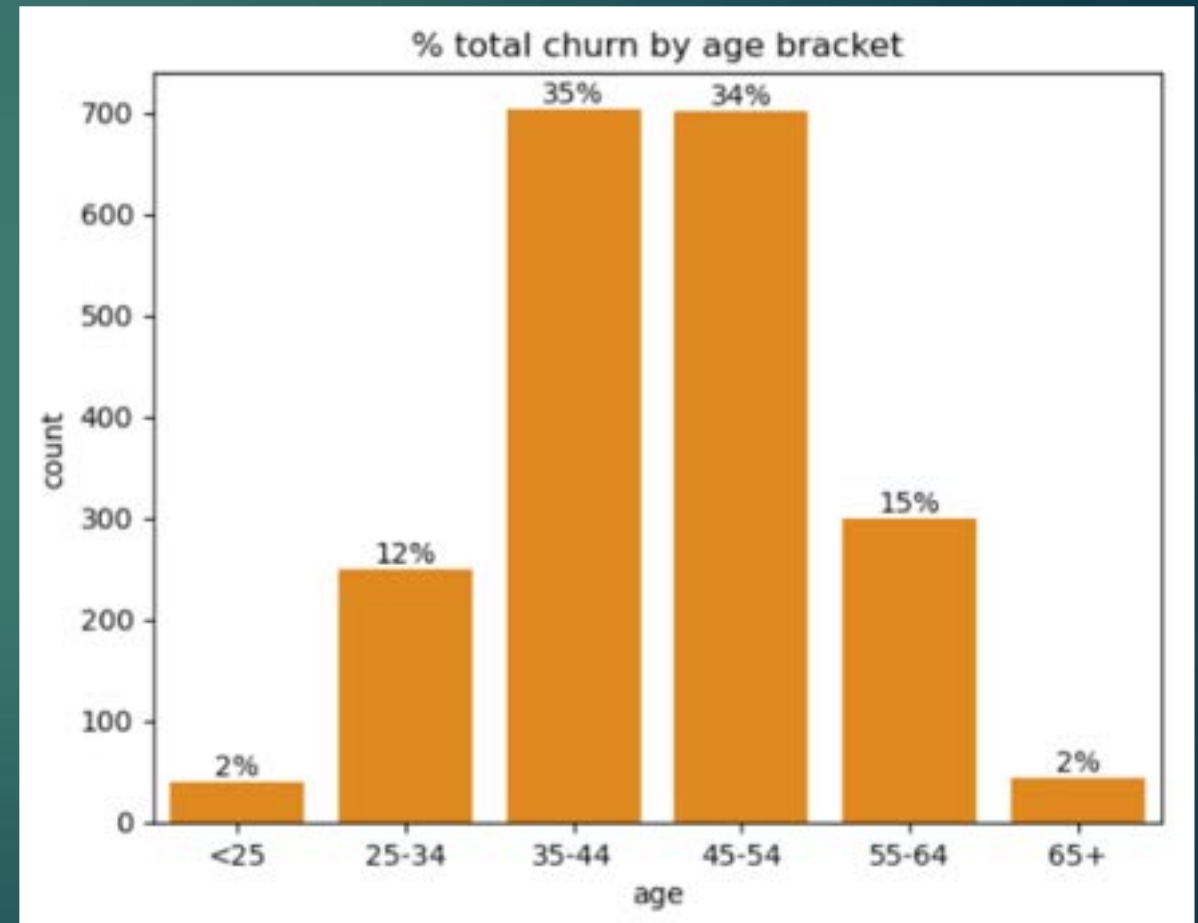
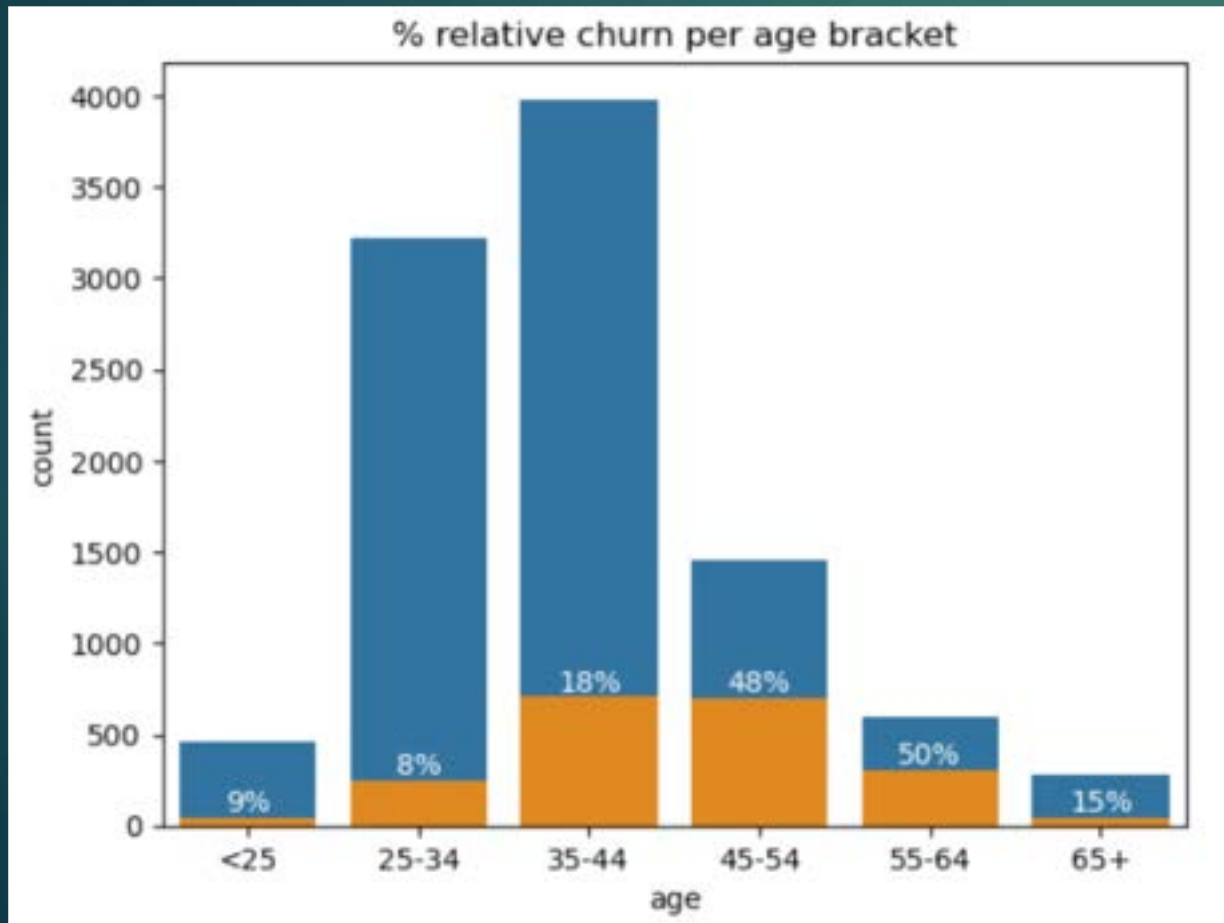
Additional EDA

Most relevant features across top 5 models

- age
- number of products
- active
- Germany
- balance
- gender

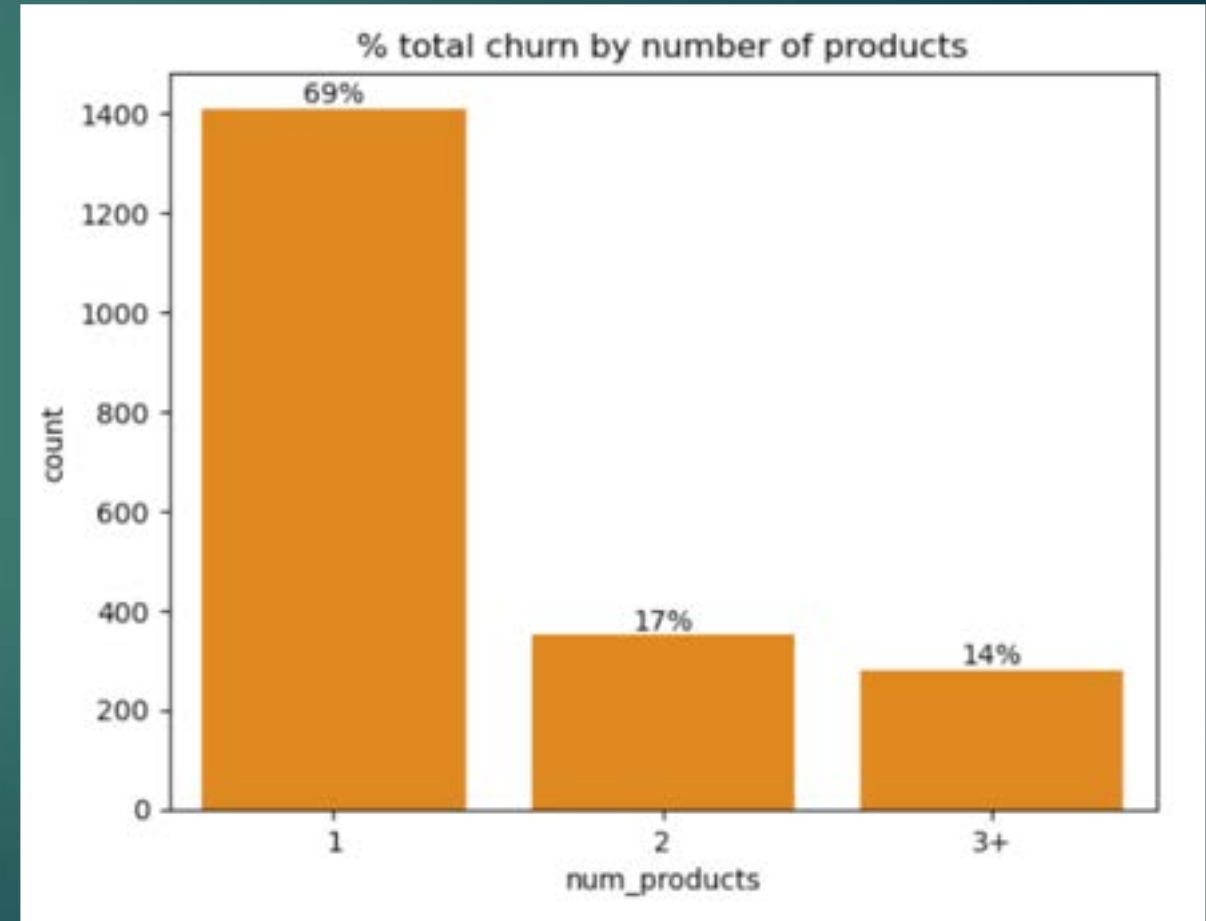
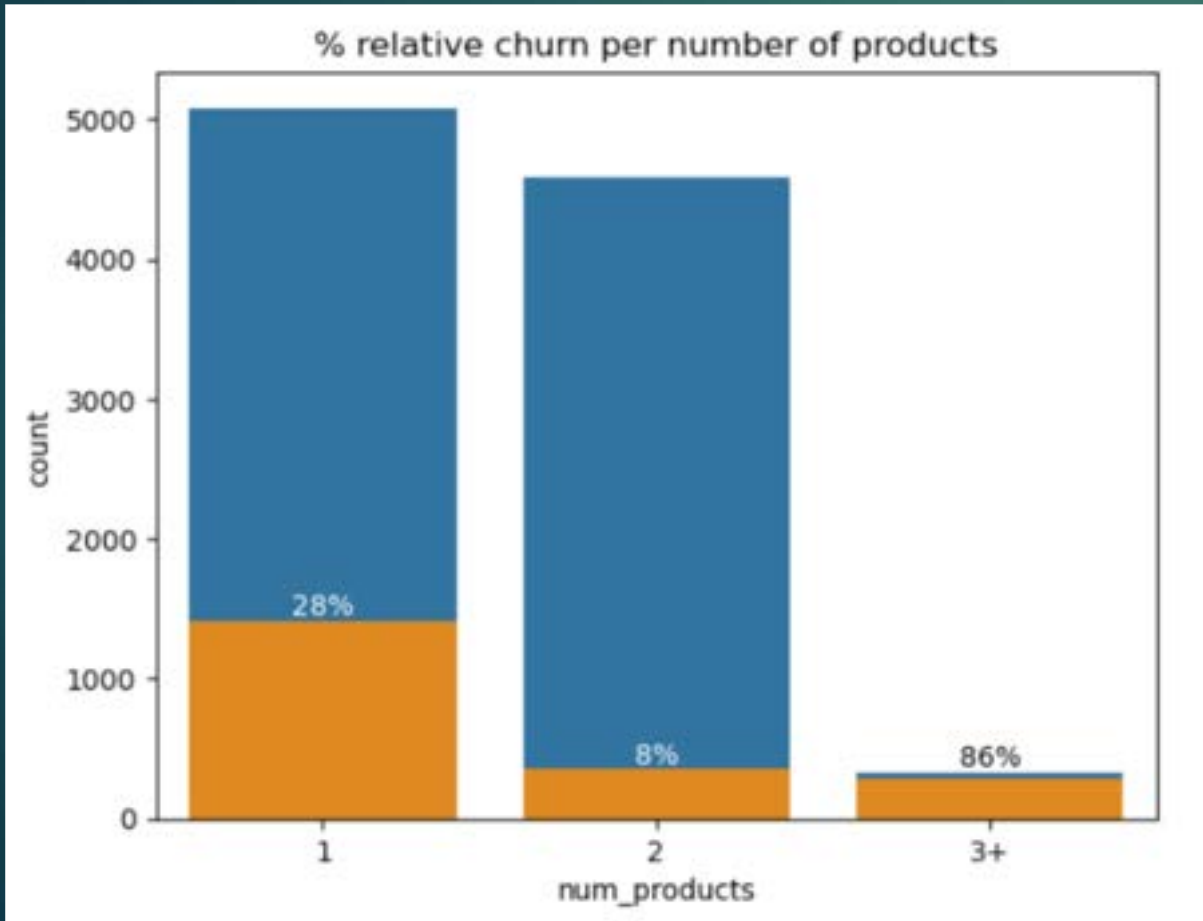
Additional EDA

Countplots of Age Bracket and Churn Cases



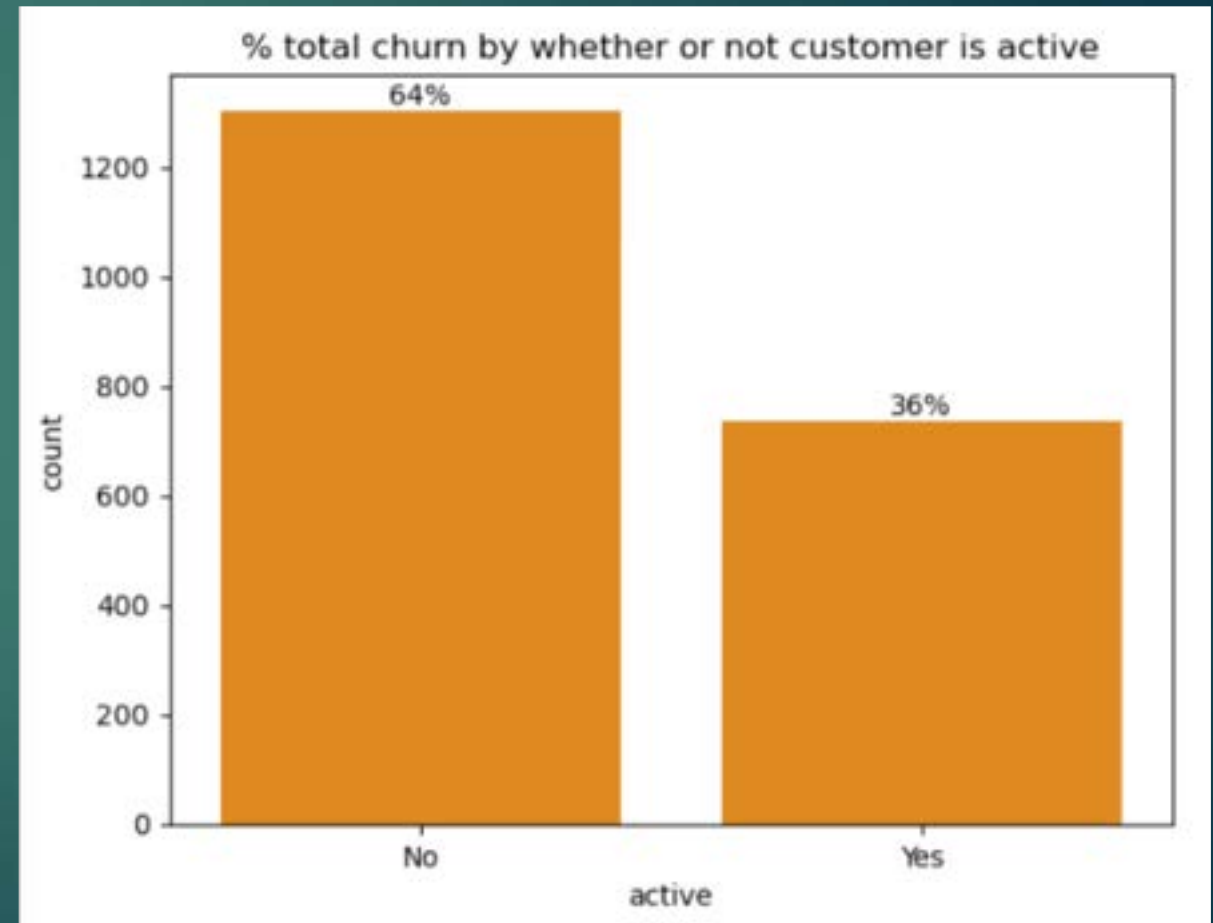
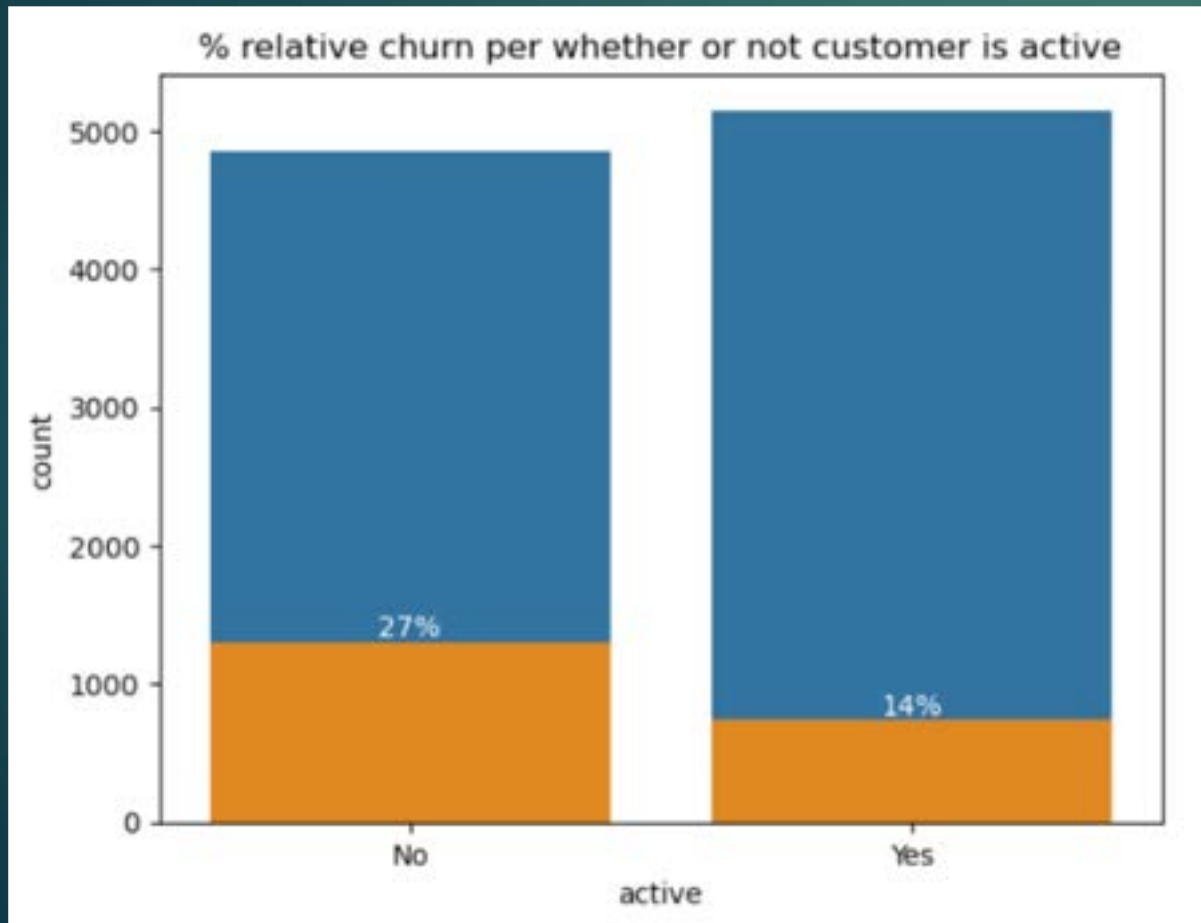
Additional EDA

Countplots of Number of Products and Churn Cases



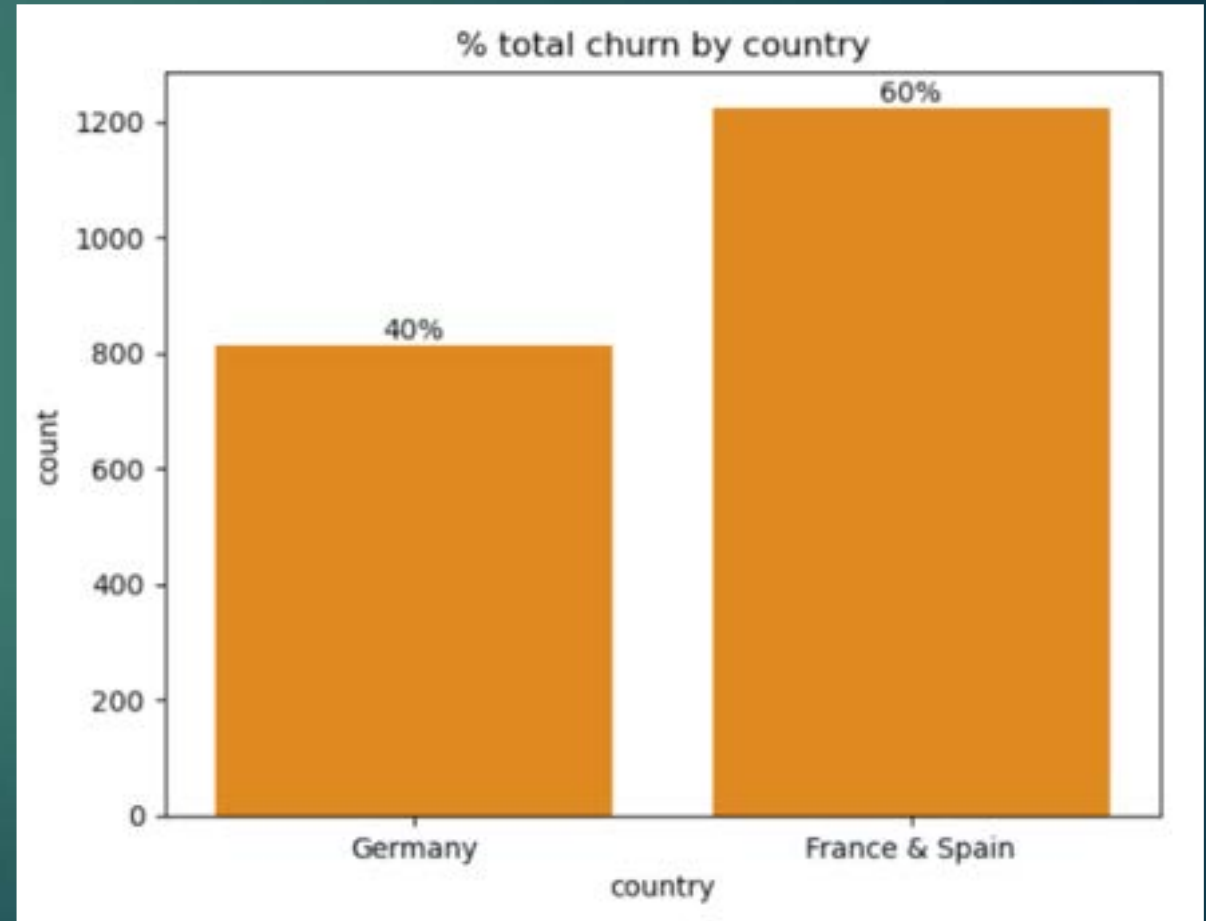
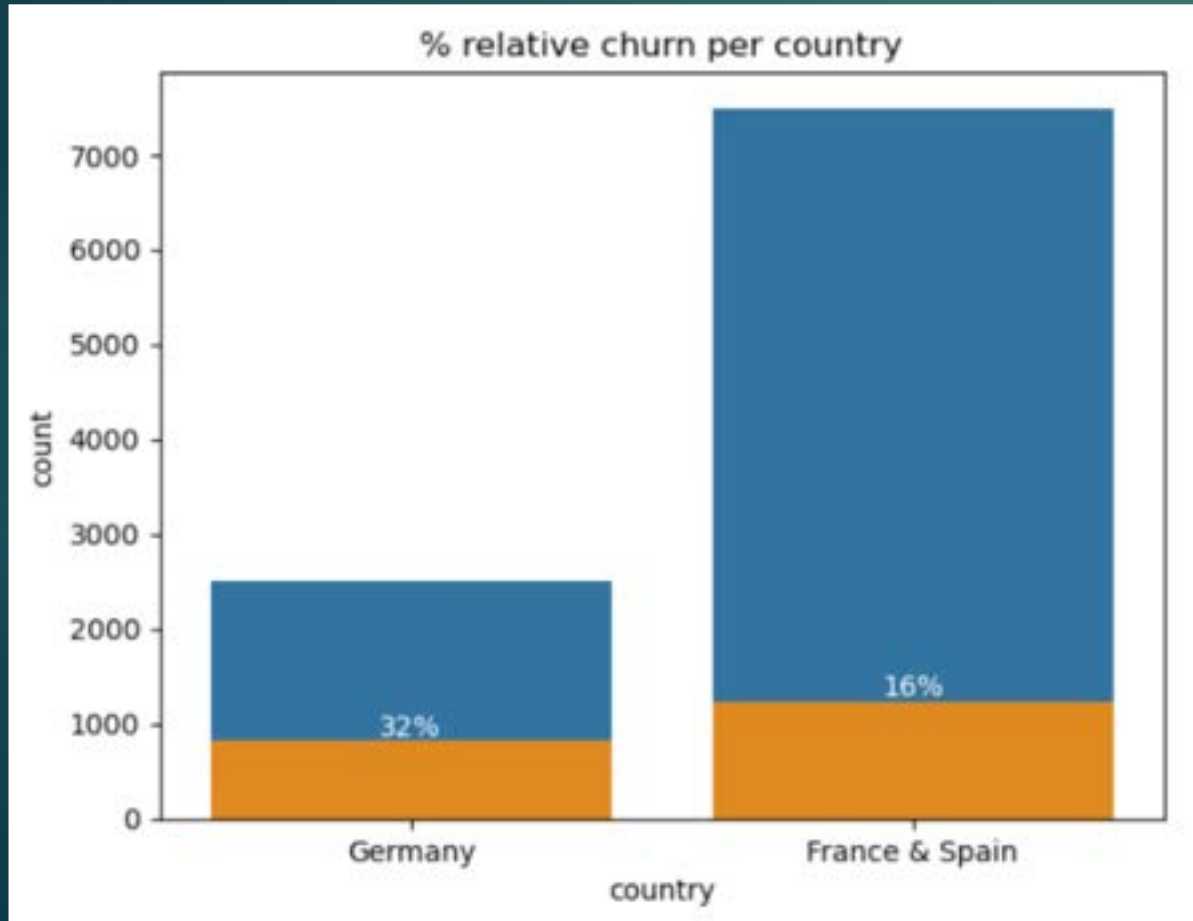
Additional EDA

Countplots of Active and Churn Cases



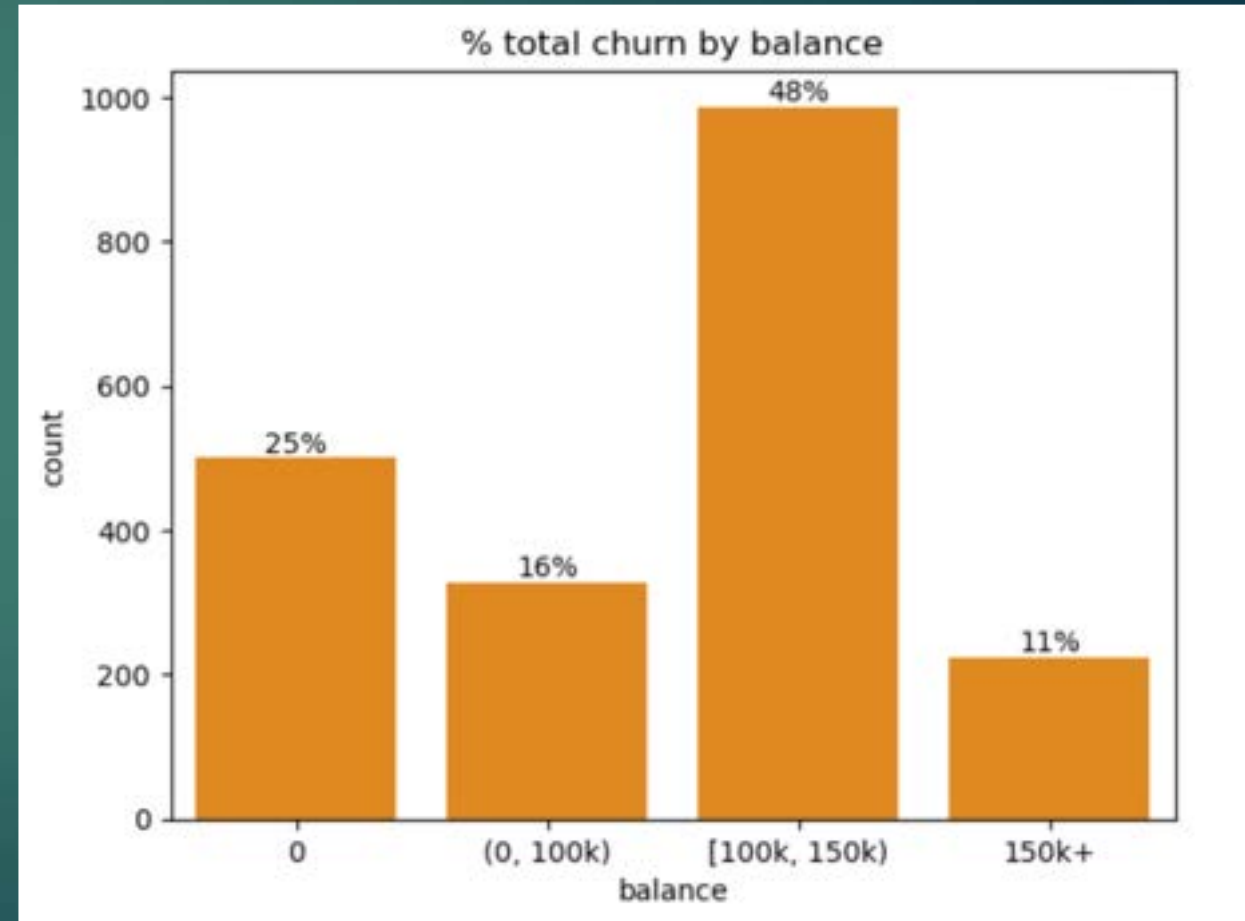
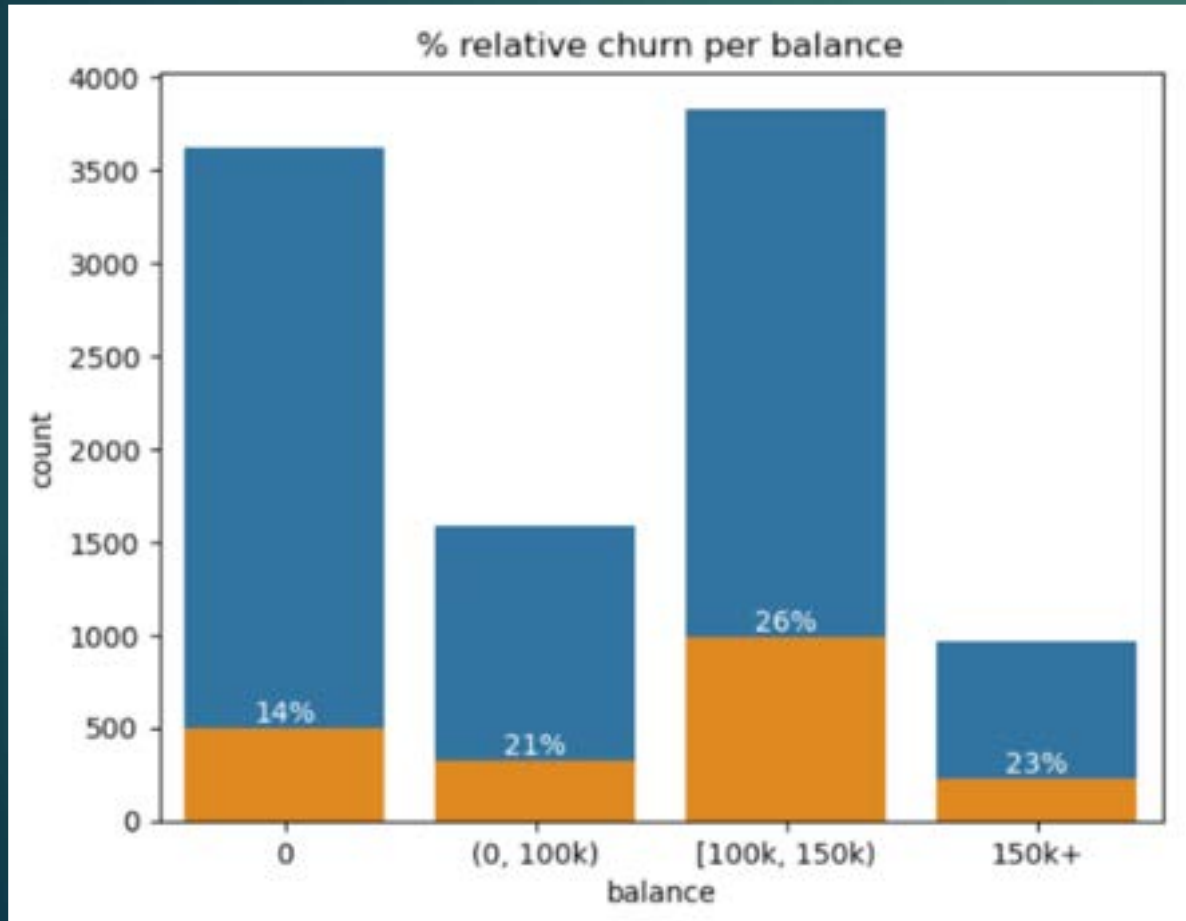
Additional EDA

Countplots of Country and Churn Cases



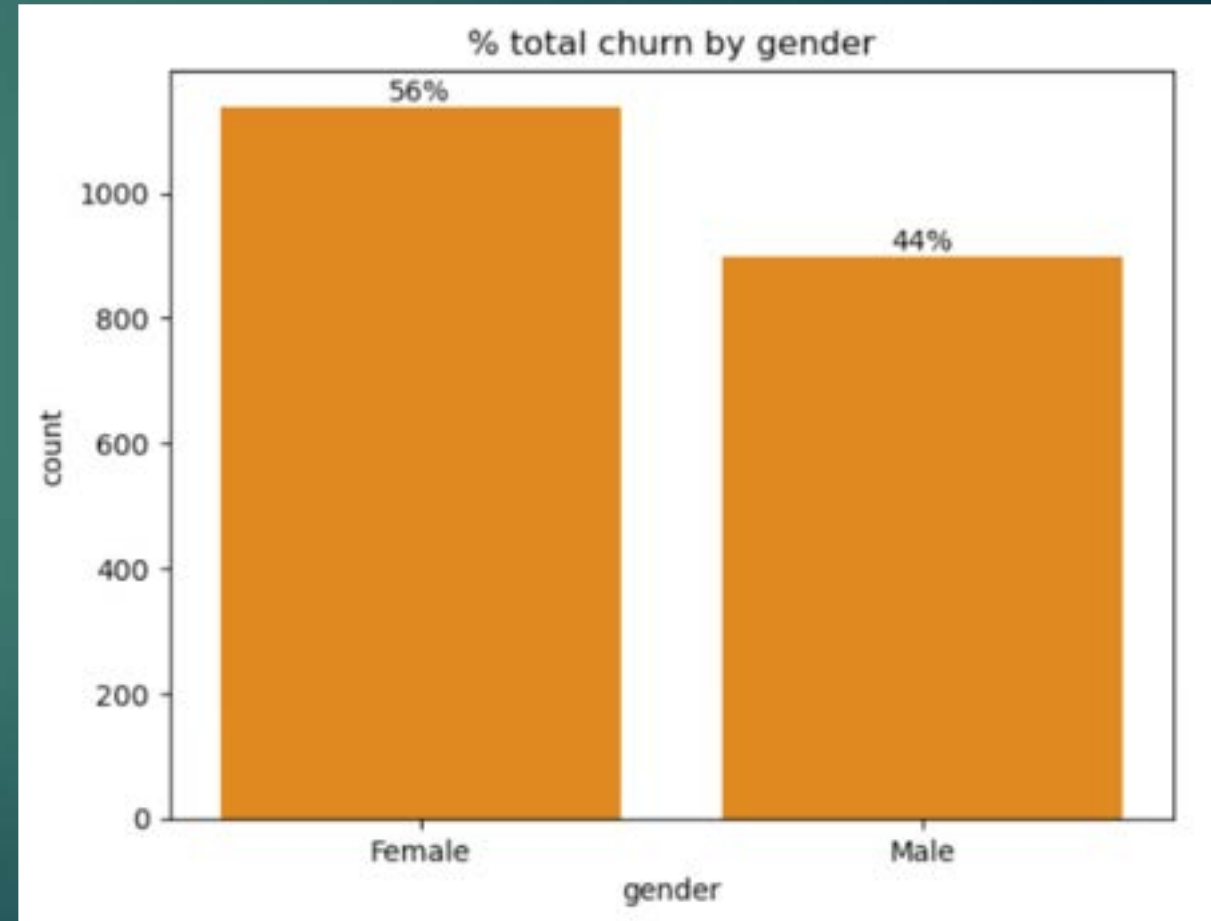
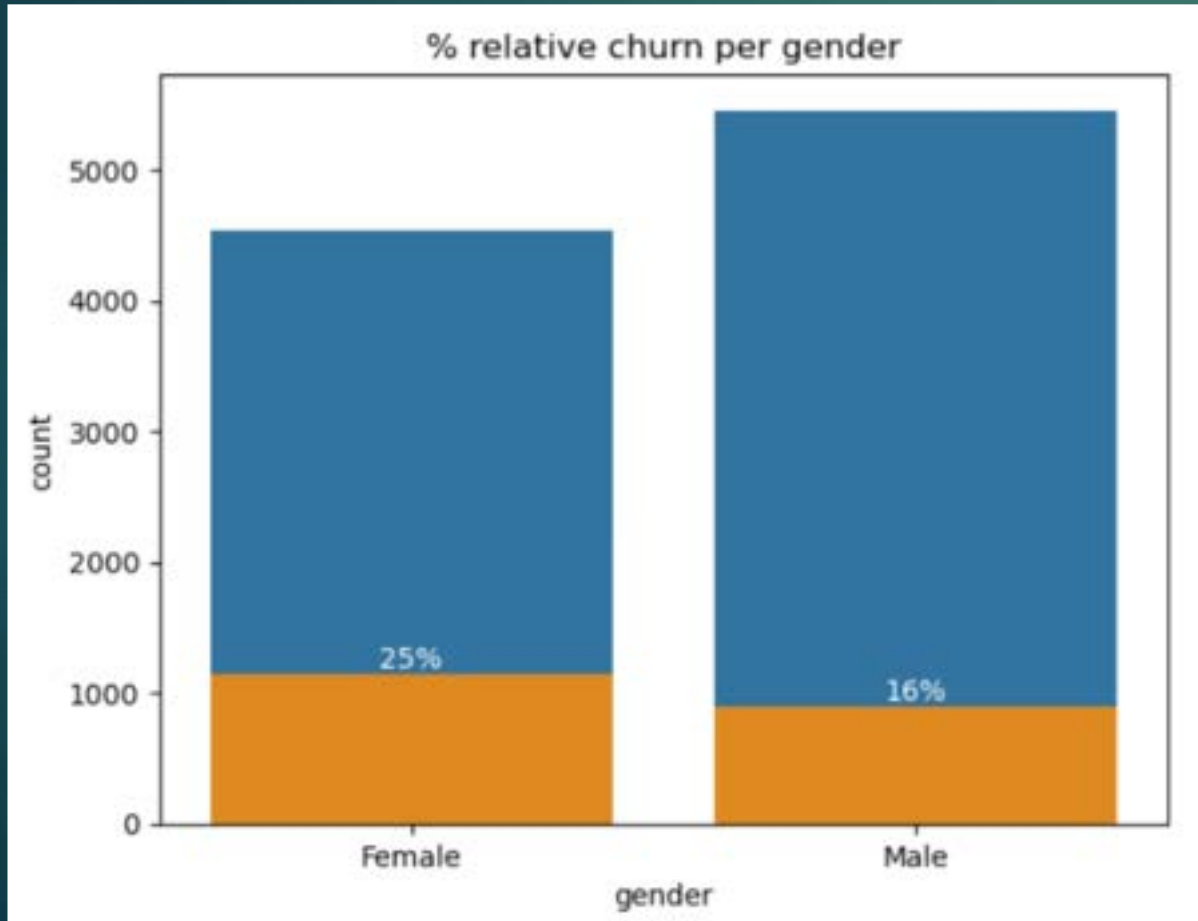
Additional EDA

Countplots of Balance and Churn Cases



Additional EDA

Countplots of Gender and Churn Cases



Future Implications

- Better complaint resolution
- CatBoost Classifier: 67.4% recall (test set)
- Further investigate key features
- Additional features, larger sample, other models
- Customer segmentation – cluster analysis

Thanks

Photo: https://en.wikipedia.org/wiki/Soci%C3%A9t%C3%A9_G%C3%A9n%C3%A9rale

