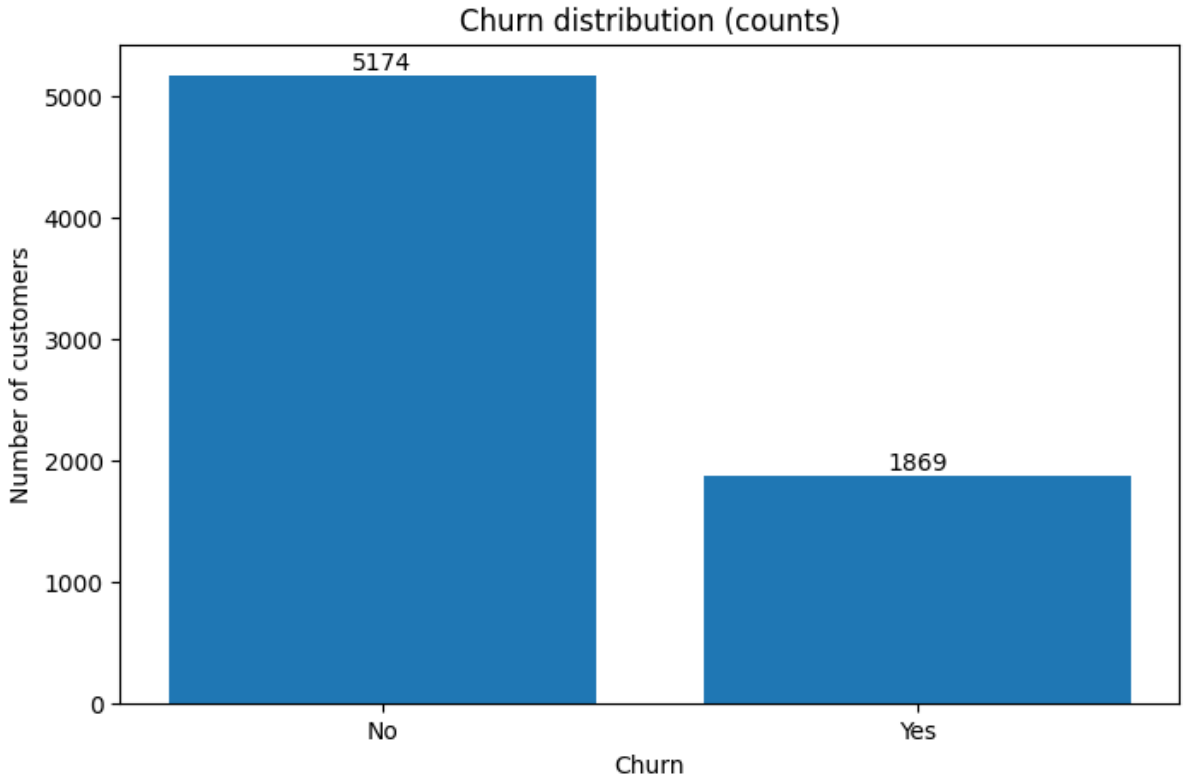
Customer Churn Prediction

1. Project goal

I built an end-to-end churn prediction pipeline to identify customers likely to leave so the business can run targeted retention actions.

2. Dataset summary

- **Raw rows:** 7,043 customers.
- **Key columns:** demographics, service flags, account info, MonthlyCharges, TotalCharges, tenure, and target Churn.
- **Churn distribution:** No = 5,174, Yes = 1,869 (≈ 73.5% No, 26.5% Yes).
- **Data issues found:** TotalCharges initially read as object; after coercion to numeric there were 11 NaNs (all had tenure == 0).



3. Exploratory Data Analysis (EDA)

3.1 Missing values & problematic rows

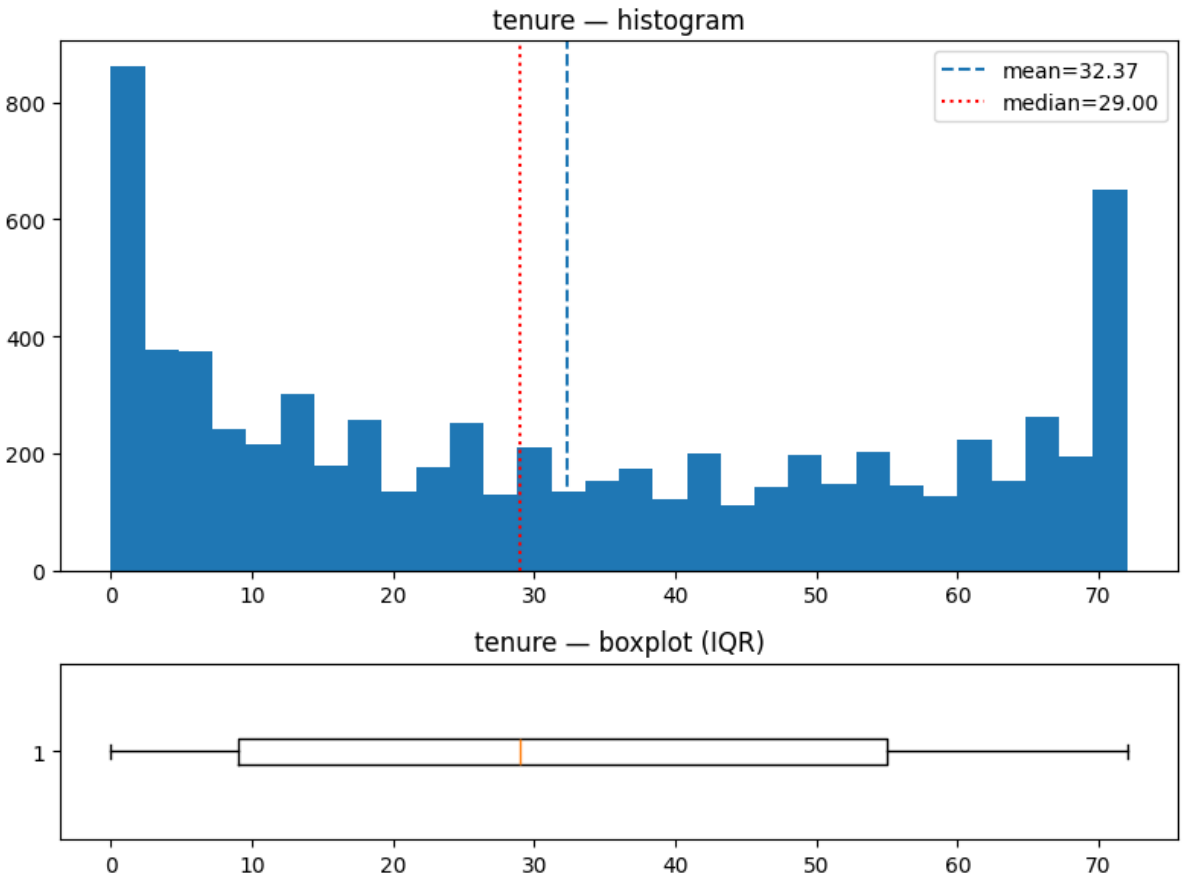
- TotalCharges converted to numeric produced 11 NaN values; all these rows had tenure == 0. I kept them and treated them as new-customer cases (impute or handle explicitly).

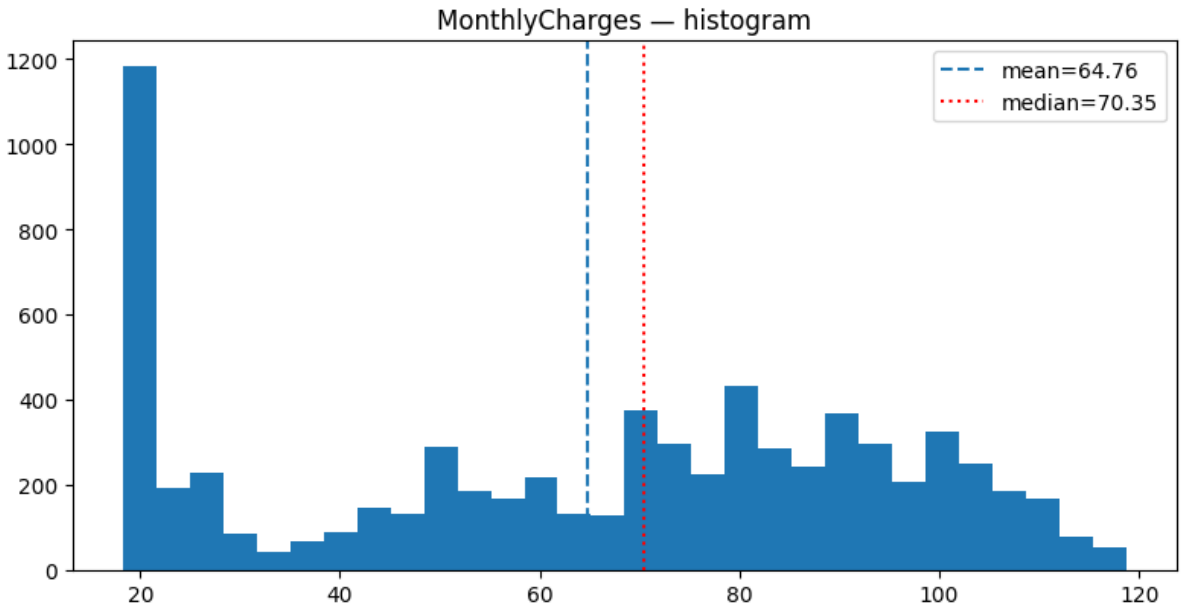
3.2 Numeric summary

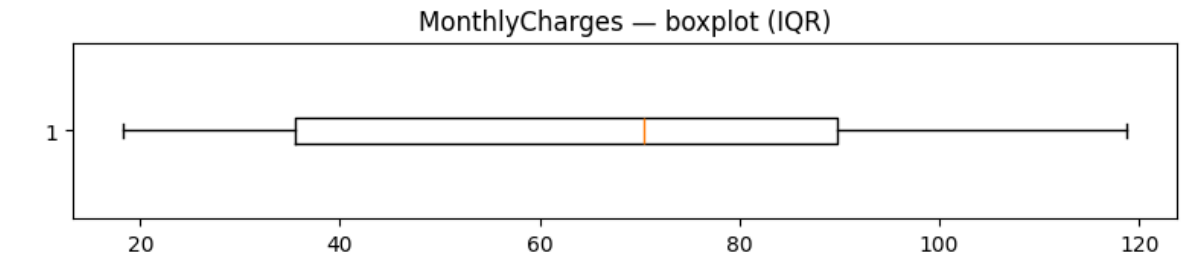
- Numeric columns used in analysis: SeniorCitizen (binary), tenure, MonthlyCharges, TotalCharges (converted to numeric).

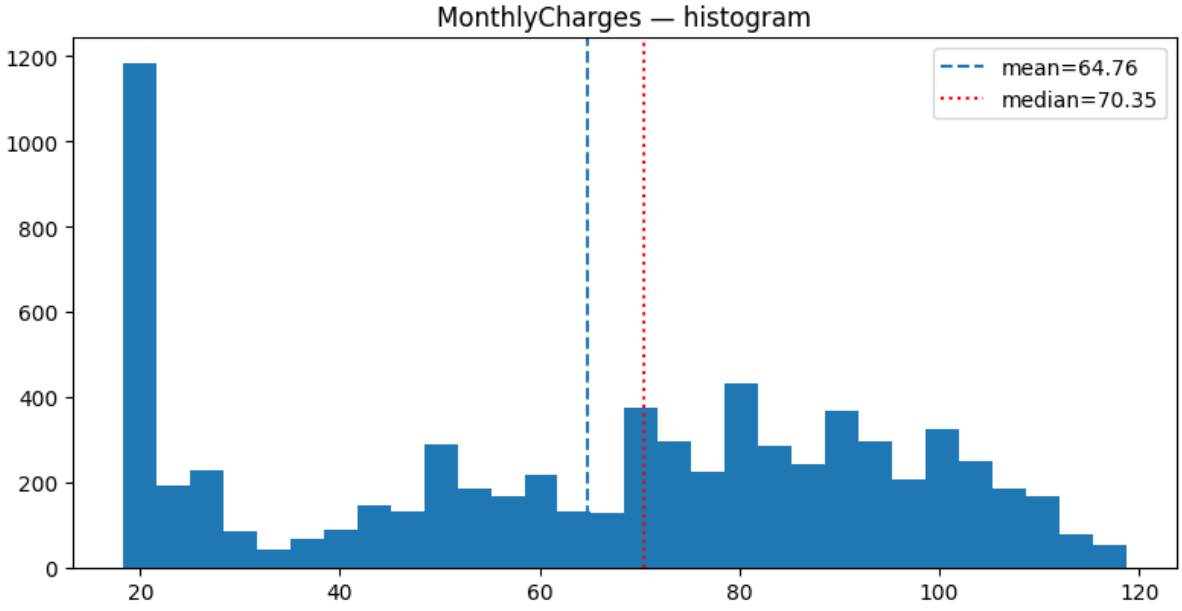
3.3 Distributions & boxplots

- **Tenure:** many customers with low tenure, right tail to 72 months. No extreme outliers detected by IQR rule.
- **MonthlyCharges:** multi-modal distribution (distinct plan clusters). No extreme outliers detected by IQR rule.
- **TotalCharges:** skewed, wide range (explained by tenure × monthly); visually consistent with business logic.




MonthlyCharges — histogram
mean=64.76
median=70.35
0
200
400
600
800
1000
1200
20
40
60
80
100
120


MonthlyCharges — boxplot (IQR)
1
20
40
60
80
100
120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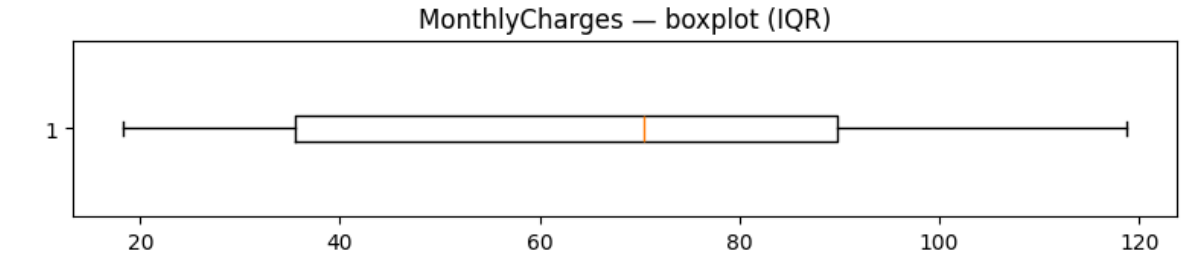

MonthlyCharges — boxplot (IQR)
1
20
40
60
80
100
120

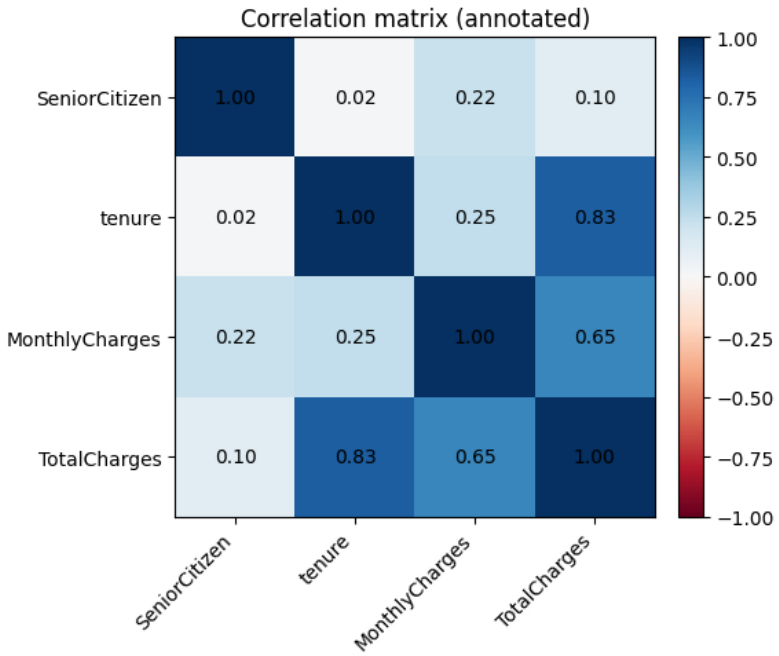
3.4 Outlier check (IQR rule)

- I computed outlier counts using the IQR rule:
    - **SeniorCitizen:** flagged (binary behavior causes IQR rule to misreport)
    - **tenure:** 0 outliers
    - **MonthlyCharges:** 0 outliers

3.5 Correlation analysis

- Correlation (numeric features):
    - **tenure ↔ TotalCharges:** strong positive correlation (≈ 0.83)
    - **MonthlyCharges ↔ TotalCharges:** moderate positive correlation (≈ 0.65)
    - **tenure ↔ MonthlyCharges:** weak correlation (≈ 0.25)

Interpretation: TotalCharges is largely redundant with tenure and MonthlyCharges (expected since TotalCharges ≈ tenure × MonthlyCharges). I kept TotalCharges but treated its scaling cautiously.



4. Feature engineering & preprocessing

4.1 Column grouping and transformers

- **Numeric (StandardScaler):** tenure, MonthlyCharges
    - **Rationale:** these columns are on different scales; StandardScaler (z-score) centers and scales for models that are scale-sensitive.
- **Numeric (RobustScaler):** TotalCharges
    - **Rationale:** TotalCharges has wide spread; RobustScaler (median & IQR) reduces sensitivity to possible extreme values.
- **Binary passthrough:** SeniorCitizen (0/1) — no scaling applied.
- **Categorical → OneHotEncoder(drop='first', handle_unknown='ignore'):** gender, Partner, Dependents, PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling, PaymentMethod.
    - drop='first' reduces redundancy. handle_unknown='ignore' avoids crashes at inference when unseen categories appear.

4.2 Pipeline & output

- Implemented ColumnTransformer inside an sklearn.Pipeline.
- X_processed shape: (7,043, 23) features after scaling + one-hot encoding.
- Saved artifacts:
    - preprocessor.joblib (the fitted ColumnTransformer pipeline)
    - preprocessor_raw_columns.json (raw input column order expected by the preprocessor)
    - preprocessor_output_columns.json (final processed feature names)

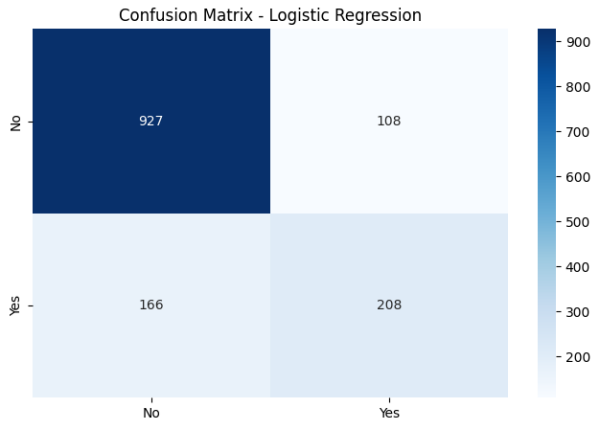
5. Dataset splits & SageMaker formatting

- Locally for sklearn experiments: I used 80% train / 20% test (stratified by y).
- For SageMaker XGBoost HPO: I created 70% train / 15% validation / 15% test CSVs in the format expected by SageMaker XGBoost (label as the first column, no header).
- Saved processed data files:
  - churn_processed.csv (final processed dataset)
  - SageMaker CSVs: train_for_sagemaker.csv, validation_for_sagemaker.csv, test_for_sagemaker.csv (label-first format).

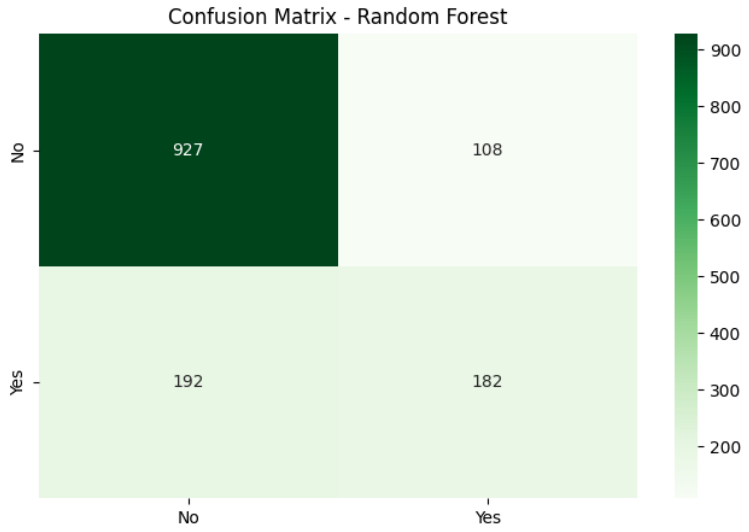
6. Modeling — models trained, tuning, and evaluation

6.1 Baseline models (local)

- Logistic Regression (baseline)
  - Test set (n ≈ 1,409):
    - Class 0 (No): precision 0.85, recall 0.90, f1 0.87 (support 1,035)
    - Class 1 (Yes): precision 0.66, recall 0.56, f1 0.60 (support 374)
    - Accuracy: 0.81, ROC-AUC: ≈ 0.8422
    - Confusion matrix:



- Random Forest (baseline)
  - Test set (n ≈ 1,409):
    - Class 0: precision 0.83, recall 0.90, f1 0.86
    - Class 1: precision 0.63, recall 0.49, f1 0.55
    - Accuracy: 0.79, ROC-AUC: ≈ 0.8258
    - Confusion matrix:



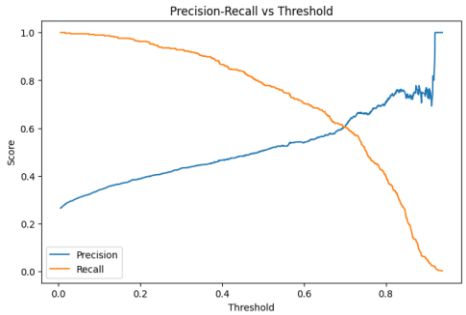
6.2 Hyperparameter tuning (sklearn)

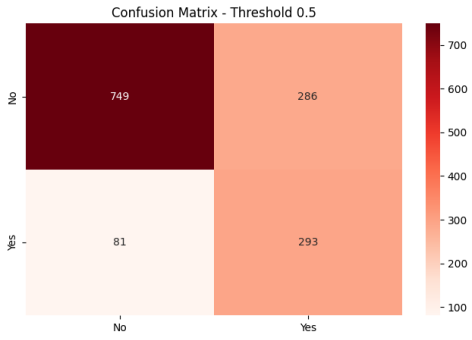
- Logistic Regression (GridSearchCV, scoring='recall', cv=5): best params C=1, penalty='l2', solver='lbfgs' — CV recall ≈ 0.548.
- Random Forest (RandomizedSearchCV, scoring='recall', cv=5): best params n_estimators=200, max_depth=10, min_samples_split=5, min_samples_leaf=1 — CV recall ≈ 0.495.
- After tuning, test set metrics were similar; logistic remained stronger on recall under this objective.

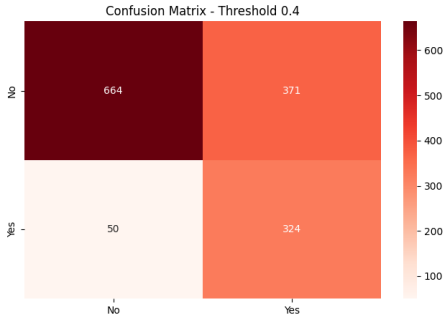
6.3 Addressing imbalance (class weight & threshold tuning)

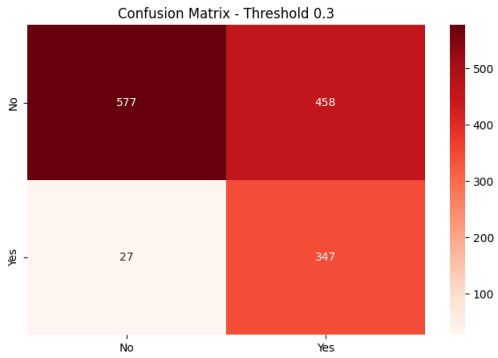
- LogisticRegression with class_weight='balanced':
  - At default threshold 0.5:
    - Class 1 recall increased to ~0.78, precision decreased to ~0.51, accuracy ≈ 0.74, ROC-AUC ≈ 0.842.

- Precision–Recall vs Threshold: lowering threshold improves recall and reduces precision. Example results:
  - threshold 0.5 → recall ≈ 0.78, precision ≈ 0.51
  - threshold 0.4 → recall ≈ 0.87, precision ≈ 0.47
  - threshold 0.3 → recall ≈ 0.93, precision ≈ 0.43









6.4 SageMaker XGBoost with Automatic Model Tuning (HPO)

- **Estimator:** SageMaker XGBoost built-in container. Fixed hyperparams: objective="binary:logistic", eval_metric="auc", num_round=200.
- **Hyperparameter search space (Bayesian):**
  - eta (0.01–0.3), max_depth (3–10), min_child_weight (1–10), subsample (0.5–1.0), colsample_bytree (0.5–1.0).
- **Tuner configuration:** objective_metric_name="validation:auc", max_jobs=12, max_parallel_jobs=2, strategy="Bayesian".
- **Important fix made:** SageMaker XGBoost requires label as the first column and labels in {0,1}; I updated CSVs accordingly.

6.5 Final XGBoost results (best model from SageMaker HPO, evaluated locally on test.csv)

- **Test set (n = 1,057):**
  - ROC-AUC (test): 0.8552514248942821
  - Classification report:
    - Class 0: precision 0.92, recall 0.72, f1 0.81 (support 777)
    - Class 1: precision 0.51, recall 0.82, f1 0.63 (support 280)
- **Confusion matrix:**

```
[[561 216]
 [ 51 229]]
```

  - TN = 561, FP = 216, FN = 51, TP = 229

7. Comparative summary

Model	Test rows	ROC-AUC	Precision (churn)	Recall (churn)	F1 (churn)	Key observation
Logistic (baseline)	1,409	0.8422	0.66	0.56	0.60	Interpretable baseline
Random Forest (baseline)	1,409	0.8258	0.63	0.49	0.55	Slightly lower recall
Logistic (class_weight='balanced')	1,409	0.8419	0.51	0.78	0.61	Higher recall via weighting
Logistic (threshold 0.4)	1,409	—	0.47	0.87	0.61	Threshold tuned for recall
XGBoost (SageMaker HPO, best)	1,057	**0.8553**	0.51	**0.82**	0.63	Best ROC-AUC and high recall

8. Artifacts & files produced

- preprocessor.joblib — saved sklearn ColumnTransformer pipeline (use for inference).
- preprocessor_raw_columns.json — raw column order expected by the preprocessor (must be used to build input rows).
- preprocessor_output_columns.json — final processed feature names (for debugging).
- churn_processed.csv — processed dataset (features + label) used in experiments.
- SageMaker artifacts: train.csv, validation.csv, test.csv (label-first format for XGBoost).
- model.tar.gz in S3 (best model path printed by tuner) — contains the XGBoost model file; I downloaded and loaded it locally for evaluation.
- Notebook files: fe.ipynb (feature engineering notebook), SageMaker notebook (HPO + training notebook).

9. Inference & deployment approach

- Implemented a local Streamlit app (app.py) to perform inference using the saved preprocessing pipeline and the downloaded XGBoost model. The app loads three artifacts that must be placed next to app.py: preprocessor.joblib, preprocessor_raw_columns.json, and the extracted XGBoost model file (xgboost-model). If any of these files are missing the app stops and reports the missing files.

- The Streamlit app workflow (what the app does):

  - Presents an input form for all raw customer fields (categoricals as selectboxes, numerics as number inputs).

  - Uses preprocessor_raw_columns.json to reindex the user input DataFrame into the exact raw column order expected by the preprocessor.

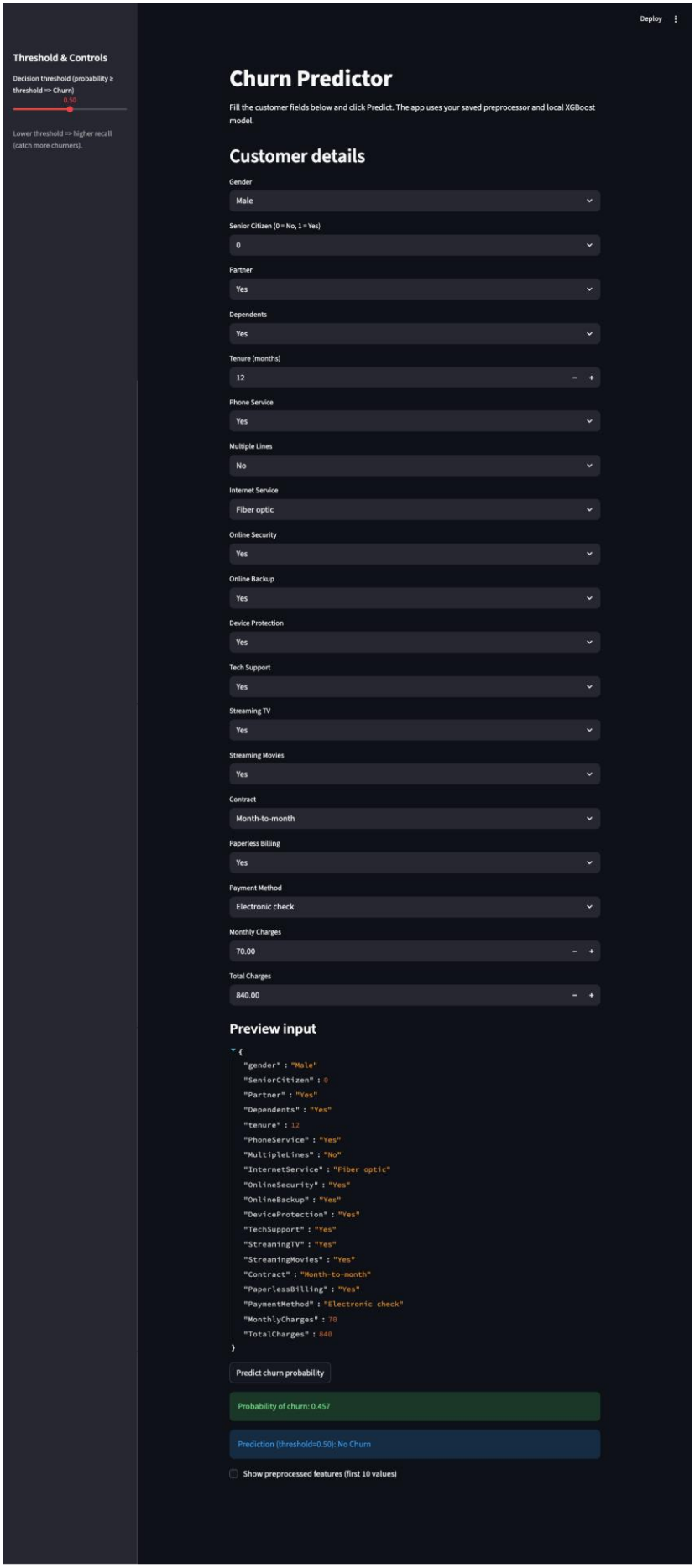
  - Fills any missing numeric values with 0 and missing string values with "No" as a safety measure.

  - Transforms the reindexed raw DataFrame with the loaded preprocessor.joblib to produce the numeric feature vector.

  - Converts the processed vector to an xgboost.DMatrix and calls Booster.predict(...) to obtain a probability of churn.

  - Applies an interactive threshold slider (user-controlled in the sidebar) to convert probability → label (Churn / No Churn), and displays both the probability and the thresholded prediction.

  - Optionally shows the preprocessed feature values for debugging.


Deploy
Threshold & Controls
Decision threshold (probability ≥ threshold => Churn)
0.50
Lower threshold => higher recall (catch more churners).
Churn Predictor
Fill the customer fields below and click Predict. The app uses your saved preprocessor and local XGBoost model.
Customer details
Gender
Male
Senior Citizen (0 = No, 1 = Yes)
0
Partner
Yes
Dependents
Yes
Tenure (months)
12
Phone Service
Yes
Multiple Lines
No
Internet Service
Fiber optic
Online Security
Yes
Online Backup
Yes
Device Protection
Yes
Tech Support
Yes
Streaming TV
Yes
Streaming Movies
Yes
Contract
Month-to-month
Paperless Billing
Yes
Payment Method
Electronic check
Monthly Charges
70.00
Total Charges
840.00
Preview input
{
"gender" : "Male"
"SeniorCitizen" : 0
"Partner" : "Yes"
"Dependents" : "Yes"
"tenure" : 12
"PhoneService" : "Yes"
"MultipleLines" : "No"
"InternetService" : "Fiber optic"
"OnlineSecurity" : "Yes"
"OnlineBackup" : "Yes"
"DeviceProtection" : "Yes"
"TechSupport" : "Yes"
"StreamingTV" : "Yes"
"StreamingMovies" : "Yes"
"Contract" : "Month-to-month"
"PaperlessBilling" : "Yes"
"PaymentMethod" : "Electronic check"
"MonthlyCharges" : 70
"TotalCharges" : 840
}
Predict churn probability
Probability of churn: 0.457
Prediction (threshold=0.50): No Churn
Show preprocessed features (first 10 values)

10. Conclusion

I built and validated a complete churn prediction pipeline—data cleaning, robust preprocessing, baseline models, hyperparameter tuning on SageMaker, and local inference-ready deployment artifacts—resulting in an XGBoost model that achieved the best ROC-AUC (~0.855) and a high churn recall (≈0.82) at the evaluated threshold.

(END OF REPORT)