# 03 – Final evaluation and conclusion

## Telco Customer Churn – Final Evaluation and Conclusion

This notebook performs the final evaluation of the selected churn prediction model on the full dataset (or held-out test set) and translates the results into clear business insights and next steps. It assumes the best model pipeline has already been trained and saved as `best_pipeline.pkl` in the previous notebook.

# 1. Import

```
import pandas as pd
import numpy as np
import pickle

from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    roc_curve,
    precision_recall_curve,
    confusion_matrix,
    classification_report,
)

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")
```

# 2: Load data and model

## Setup: Data and Final Model

In this section:

- Load the cleaned Telco churn dataset (`telco_clean.csv`).
- Recreate the feature matrix `X` and target vector `y`.
- Load the saved **end-to-end pipeline** (`best_pipeline.pkl`) that includes preprocessing (encoders, scalers) and the tuned model.

This mimics a real production scenario: raw-like input features are passed directly into the pipeline to obtain churn predictions.

```
df = pd.read_csv("telco_clean.csv")

if "customerID" in df.columns:
    df = df.drop(columns=["customerID"])

y = df["Churn"].map({"No": 0, "Yes": 1})
X = df.drop(columns=["Churn"])

with open("best_pipeline.pkl", "rb") as f:
    best_model = pickle.load(f)
```

# 3: Final predictions

## Final Model Performance

Here the final model is evaluated using the complete evaluation set:

- **Accuracy** – overall fraction of correct predictions.
- **Precision (churn)** – of the customers predicted as churners, how many actually churned. Important for controlling retention campaign cost.
- **Recall (churn)** – of all real churners, how many the model correctly identified. This is the key metric for retention, because missed churners represent lost revenue.
- **F1-Score** – harmonic mean of precision and recall, useful when classes are imbalanced.
- **ROC-AUC** – measures how well the model ranks customers by churn risk across all thresholds.

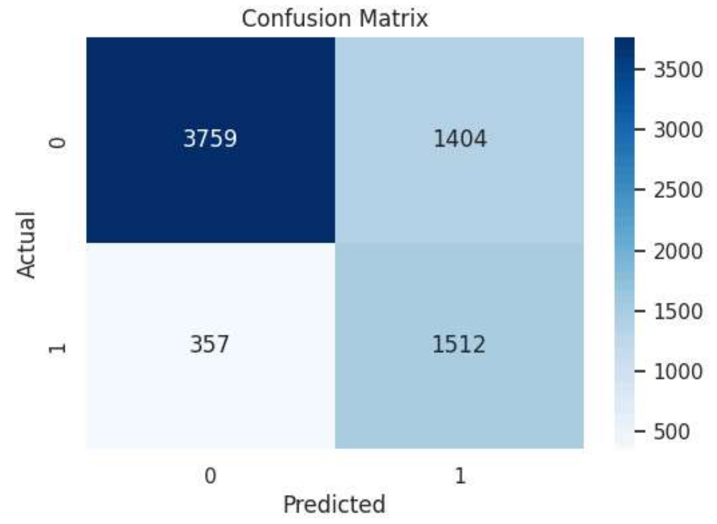
A confusion matrix and classification report are also displayed to show the exact distribution of true positives, false positives, true negatives, and false negatives.

```
y_pred = best_model.predict(X)
y_prob = best_model.predict_proba(X)[:, 1]

acc = accuracy_score(y, y_pred)
prec = precision_score(y, y_pred)
rec = recall_score(y, y_pred)
f1 = f1_score(y, y_pred)
roc = roc_auc_score(y, y_prob)

print("Final Accuracy:", acc)
print("Final Precision:", prec)
print("Final Recall:", rec)
print("Final F1-Score:", f1)
print("Final ROC-AUC:", roc)
print("\nConfusion matrix:\n", confusion_matrix(y, y_pred))
print("\nClassification report:\n", classification_report(y, y_pred))
```

```
Final Accuracy: 0.7495733788395904
Final Precision: 0.5185185185185185
Final Recall: 0.8089887640449438
Final F1-Score: 0.631974921630094
Final ROC-AUC: 0.8474820892411921

Confusion matrix:
 [[3759 1404]
 [ 357 1512]]

Classification report:
               precision    recall  f1-score   support

           0       0.91      0.73      0.81      5163
           1       0.52      0.81      0.63      1869

    accuracy                           0.75      7032
   macro avg       0.72      0.77      0.72      7032
weighted avg       0.81      0.75      0.76      7032
```

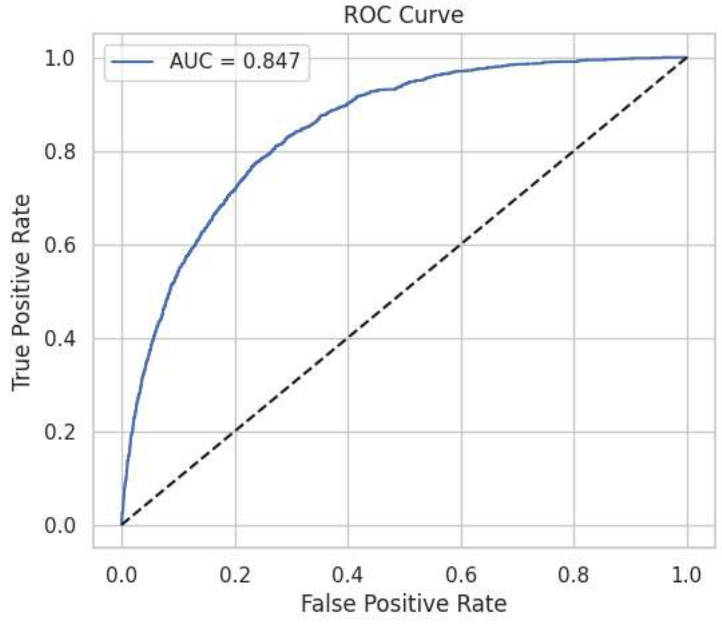
## 4: Confusion matrix heatmap

```
cm = confusion_matrix(y, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



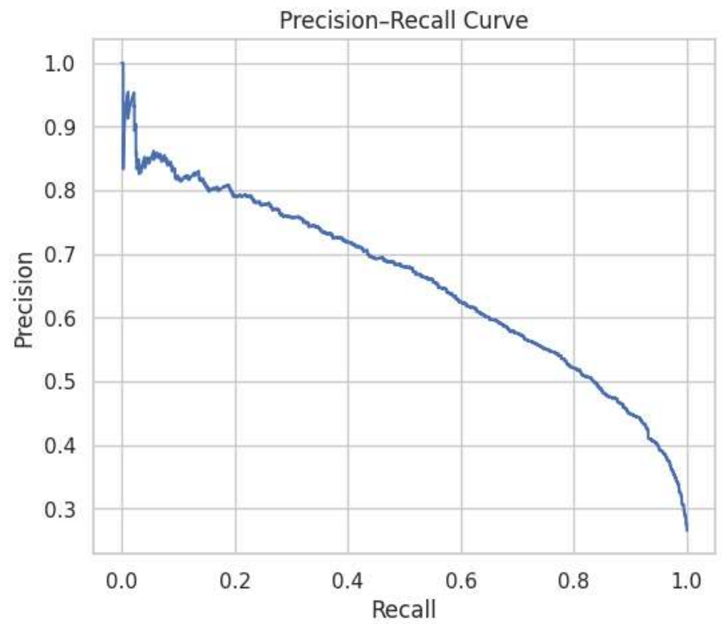

## 5: ROC curve

```
fpr, tpr, _ = roc_curve(y, y_prob)
plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, label=f"AUC = {roc:.3f}")
plt.plot([0, 1], [0, 1], "k--")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid(True)
plt.show()
```




## 6: Precision–Recall curve (optional but nice)

```
precisions, recalls, thresholds = precision_recall_curve(y, y_prob)
plt.figure(figsize=(6, 5))
plt.plot(recalls, precisions)
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.grid(True)
plt.show()
```




## 7: Example of threshold tuning (business point)

```
threshold = 0.35  # choose after looking at PR curve

y_pred_custom = (y_prob >= threshold).astype(int)

print("=== With threshold =", threshold, "===")
print("Accuracy:", accuracy_score(y, y_pred_custom))
print("Precision:", precision_score(y, y_pred_custom))
print("Recall:", recall_score(y, y_pred_custom))
print("F1-Score:", f1_score(y, y_pred_custom))
print("Confusion matrix:\n", confusion_matrix(y, y_pred_custom))
```

```
=== With threshold = 0.35 ===
Accuracy: 0.675910125142207
Precision: 0.4461376773515502
Recall: 0.9085072231139647
F1-Score: 0.5984140969162995
Confusion matrix:
 [[3055 2108]
```

```
 [ 171 1698]]
```

## 8. Ready for Deployment

The final deliverable from this notebook is a **single serialized pipeline** (`best_pipeline.pkl`) that:

- Accepts raw-like customer features as input (same schema as the original dataset).
- Applies all preprocessing steps (encoding, scaling) consistently.
- Outputs churn probability and class label.

This artifact can now be:

- Exposed via a **Flask or FastAPI service** for real-time scoring.
- Integrated into batch jobs to generate daily churn-risk lists for retention teams.
- Deployed in the cloud using Docker and a simple API layer.

This closes the modeling loop and prepares the churn prediction system for real-world use in production.