Machine Learning Project

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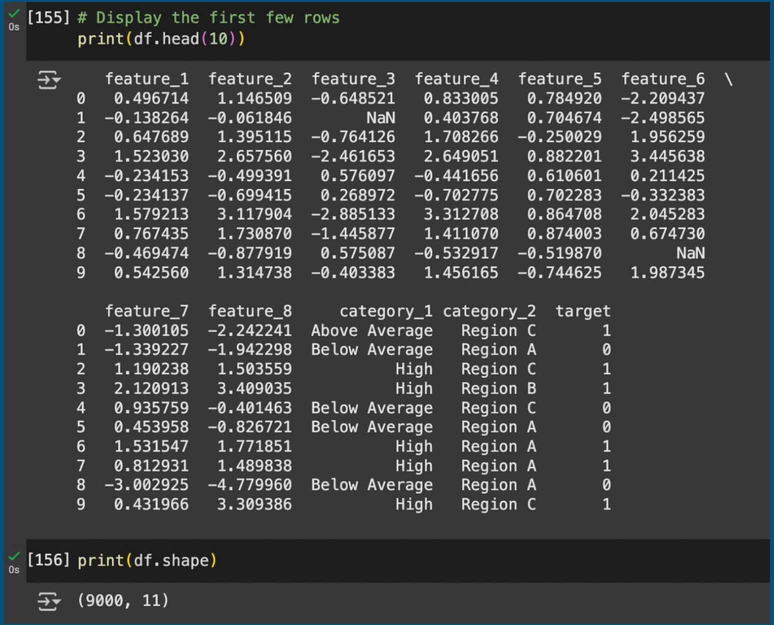
D1.1) Dataset exploration

- 9000 rows × 11 columns
- Binary classification task
- Includes numerical, categorical, and target features



```
[155] # Display the first few rows
      print(df.head(10))

    feature_1  feature_2  feature_3  feature_4  feature_5  feature_6  \
0    0.496714   1.146509  -0.648521   0.833005   0.784920  -2.209437
1   -0.138264  -0.061846        NaN   0.403768   0.704674  -2.498565
2    0.647689   1.395115  -0.764126   1.708266  -0.250029   1.956259
3    1.523030   2.657560  -2.461653   2.649051   0.882201   3.445638
4   -0.234153  -0.499391   0.576097  -0.441656   0.610601   0.211425
5   -0.234137  -0.699415   0.268972  -0.702775   0.702283  -0.332383
6    1.579213   3.117904  -2.885133   3.312708   0.864708   2.045283
7    0.767435   1.730870  -1.445877   1.411070   0.874003   0.674730
8   -0.469474  -0.877919   0.575087  -0.532917  -0.519870        NaN
9    0.542560   1.314738  -0.403383   1.456165  -0.744625   1.987345

    feature_7  feature_8     category_1 category_2  target
0   -1.300105  -2.242241  Above Average   Region C       1
1   -1.339227  -1.942298  Below Average   Region A       0
2    1.190238   1.503559           High   Region C       1
3    2.120913   3.409035           High   Region B       1
4    0.935759  -0.401463  Below Average   Region C       0
5    0.453958  -0.826721  Below Average   Region A       0
6    1.531547   1.771851           High   Region A       1
7    0.812931   1.489838           High   Region A       1
8   -3.002925  -4.779960  Below Average   Region A       0
9    0.431966   3.309386           High   Region C       1

[156] print(df.shape)

(9000, 11)
```

<u>Feature Types</u>

- Numerical Features (8): feature_1 to feature_8
- Categorical Features (2):
- category_1: Ordinal (Low, Below Avg, Above Avg, High)
- category_2: Nominal (Region A, B, C)
- Target: Binary (0 or 1)

<u>Initial Observations</u>

- feature_1 & feature_2: Sharp peaks, long tails → Outliers or high kurtosis
- feature_3, 4, 6, 7, 8: Approximate Gaussian distribution → Good for logistic regression
- Feature_5: Uniform distribution → Limited predictive power

Visual Insights on Feature Distributions

feature_1 & feature_2

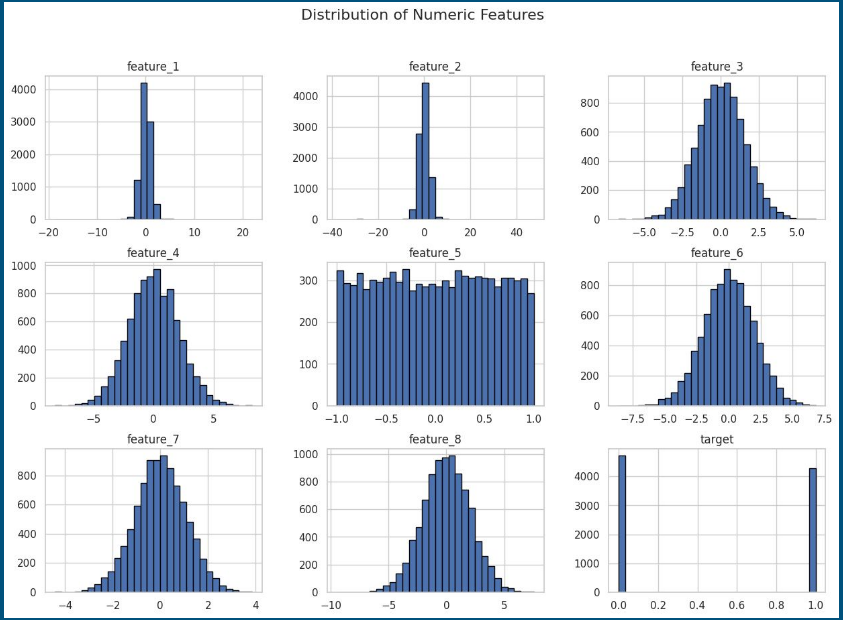
- Sharp central peaks and long tails
- Suggest high kurtosis or outliers
- May require clipping or transformation

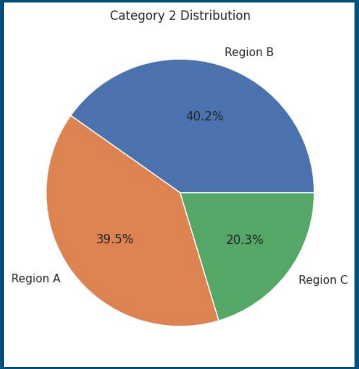
feature_3, 4, 6, 7, 8

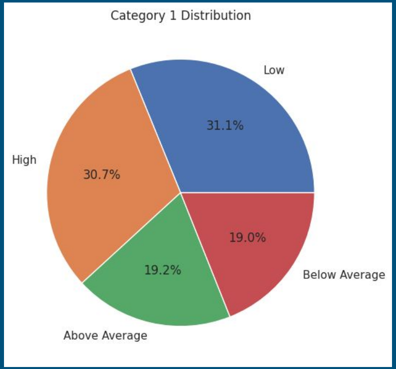
- Approximately Gaussian (bell-shaped) distributions
- Suitable for models assuming normality

feature_5

- Uniformly distributed
- Low individual predictive power
- May help in interaction terms
- Target variable
- Binary (0 and 1)
- Reasonably balanced distribution
- Reduces risk of class imbalance in models







Feature Groupings

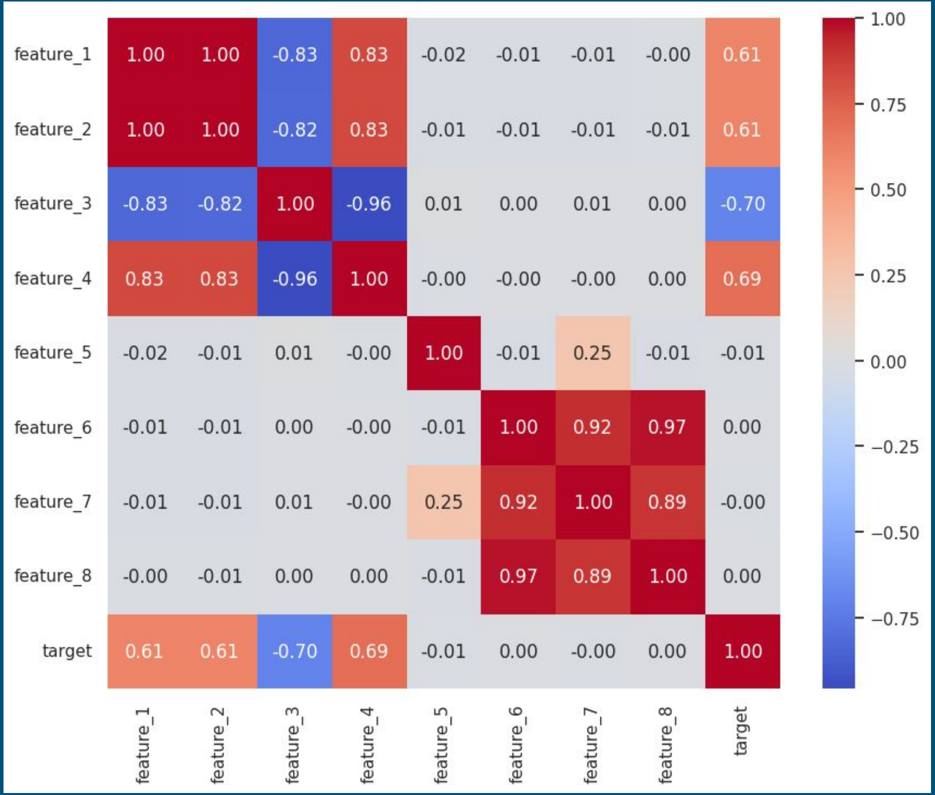
- feature_6, feature_7, feature_8: r = 0.89–0.97
- Highly intercorrelated block → likely redundant or reflect a shared latent factor
- Weak or No Correlation

Strong Negative Correlations

- feature_3 & feature_4: r = –0.96
- feature_3 with feature_1/2: r ≈ –0.83
- Strong opposing trends → ideal for ratios or interaction terms

Interaction Strong Positive Correlations

- feature_1 & feature_2: r = +1.00
- Perfectly correlated → complete redundancy
- One should be dropped to avoid multicollinearity
- feature_1/2 & feature_4: r ≈ +0.83
- Likely share a common source or signal



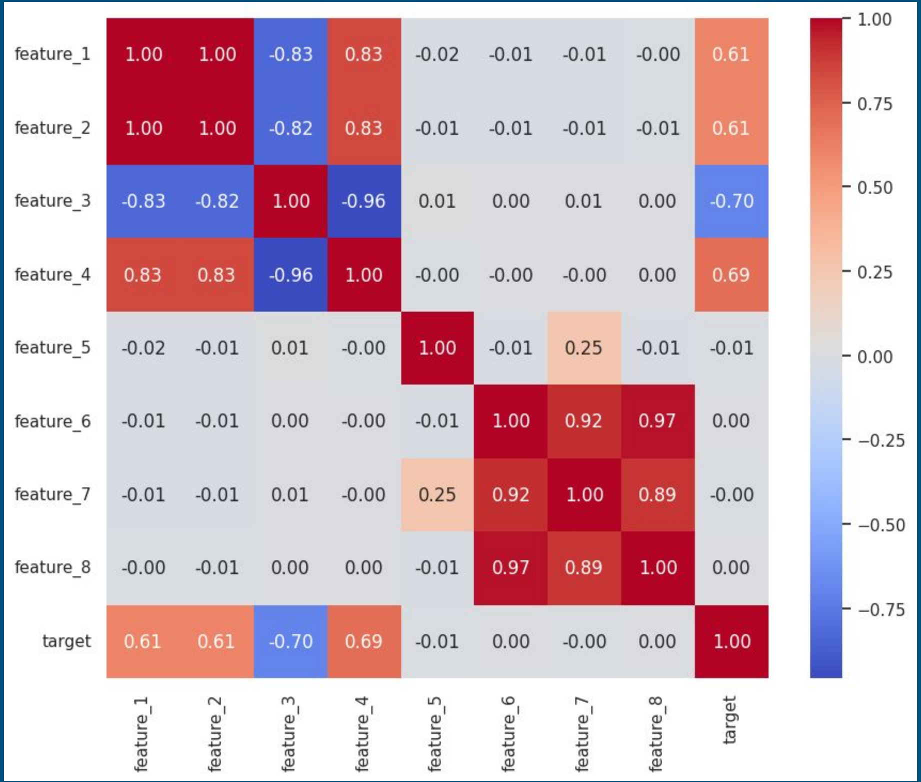
	feature_1	feature_2	feature_3	feature_4	feature_5	feature_6	feature_7	feature_8	target
feature_1	1.00	1.00	-0.83	0.83	-0.02	-0.01	-0.01	-0.00	0.61
feature_2	1.00	1.00	-0.82	0.83	-0.01	-0.01	-0.01	-0.01	0.61
feature_3	-0.83	-0.82	1.00	-0.96	0.01	0.00	0.01	0.00	-0.70
feature_4	0.83	0.83	-0.96	1.00	-0.00	-0.00	-0.00	0.00	0.69
feature_5	-0.02	-0.01	0.01	-0.00	1.00	-0.01	0.25	-0.01	-0.01
feature_6	-0.01	-0.01	0.00	-0.00	-0.01	1.00	0.92	0.97	0.00
feature_7	-0.01	-0.01	0.01	-0.00	0.25	0.92	1.00	0.89	-0.00
feature_8	-0.00	-0.01	0.00	0.00	-0.01	0.97	0.89	1.00	0.00
target	0.61	0.61	-0.70	0.69	-0.01	0.00	-0.00	0.00	1.00

Weak or No Correlation

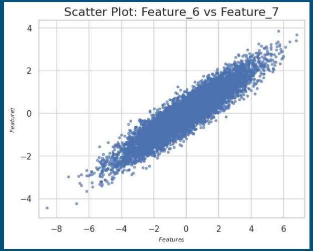
- feature_5:
- No significant correlation with any feature or the target
- Limited individual predictive power
- feature_6–8:
- No direct correlation with target despite being internally consistent

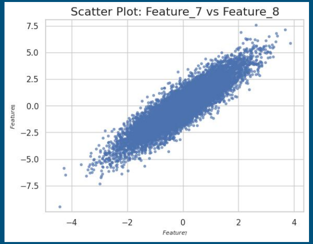
Correlation with Target

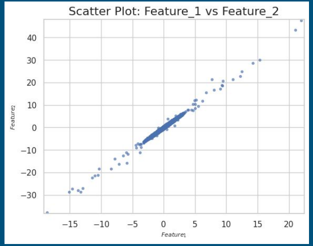
- feature_4: +0.69
- feature_1 & feature_2: +0.61
- feature_3: –0.70
- These features are most predictive and should be prioritized in modeling

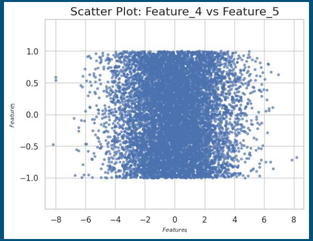


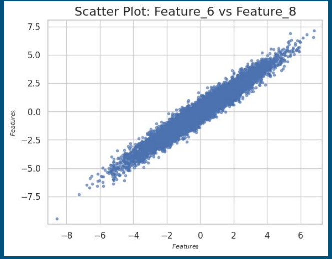
	feature_1	feature_2	feature_3	feature_4	feature_5	feature_6	feature_7	feature_8	target
feature_1	1.00	1.00	-0.83	0.83	-0.02	-0.01	-0.01	-0.00	0.61
feature_2	1.00	1.00	-0.82	0.83	-0.01	-0.01	-0.01	-0.01	0.61
feature_3	-0.83	-0.82	1.00	-0.96	0.01	0.00	0.01	0.00	-0.70
feature_4	0.83	0.83	-0.96	1.00	-0.00	-0.00	-0.00	0.00	0.69
feature_5	-0.02	-0.01	0.01	-0.00	1.00	-0.01	0.25	-0.01	-0.01
feature_6	-0.01	-0.01	0.00	-0.00	-0.01	1.00	0.92	0.97	0.00
feature_7	-0.01	-0.01	0.01	-0.00	0.25	0.92	1.00	0.89	-0.00
feature_8	-0.00	-0.01	0.00	0.00	-0.01	0.97	0.89	1.00	0.00
target	0.61	0.61	-0.70	0.69	-0.01	0.00	-0.00	0.00	1.00

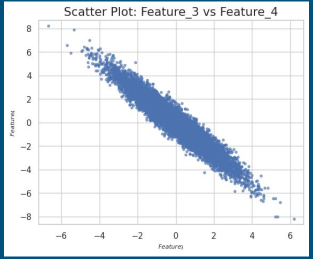












Strong Positive Correlation

feature_1 vs feature_2

- Forms a perfect diagonal line
- Confirms they are functionally identical (r = 1.00)

feature_6 vs feature_7 vs feature_8

- Tight linear clustering
- r > 0.89 → likely the same latent structure

No Correlation / No Pattern:feature_5 with others

- Appears as pure scatter
- Evenly spread, no trend → matches its uniform distribution

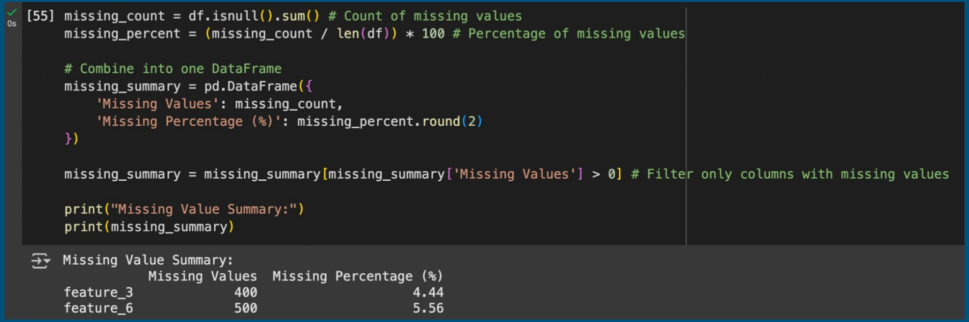
Target Relationships:feature_1, 2, 3, 4 vs target

- Show weak vertical clustering .Some class separation (0 vs 1)
- Other features vs target
- No visible pattern → suggest low predictive power

D2.1) Data Preprocessing

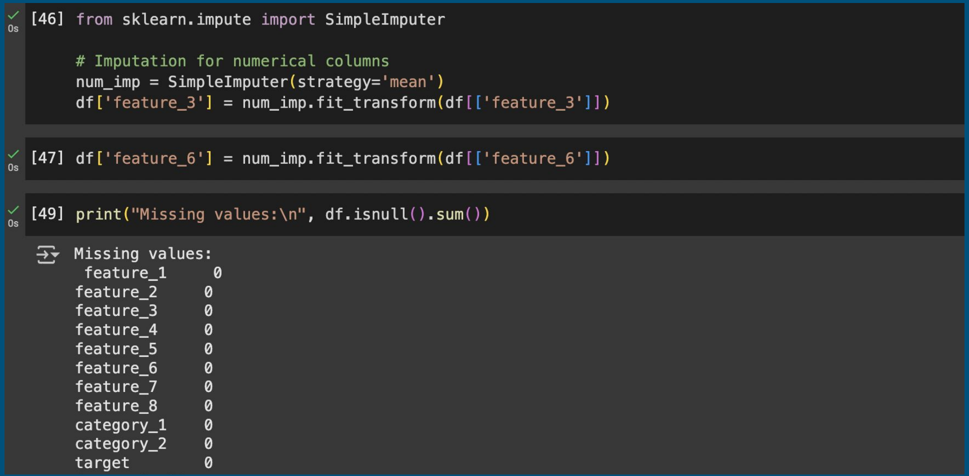
Mean imputation for missing values: feature_3 and feature_6 had **4.44%** and **5.56%** missing values, respectively. Since both are **numerical** and their distributions are **approximately normal** (not skewed), we applied **mean imputation**. This method was chosen because:

1. It aligns well with normal distributions (median for skewed)
2. The data is numerical (mode used for categorical values)
3. It retains all rows, preserving dataset size
4. The missing percentage is low (less than 6%)



```
[55] missing_count = df.isnull().sum() # Count of missing values
     missing_percent = (missing_count / len(df)) * 100 # Percentage of missing values

     # Combine into one DataFrame
     missing_summary = pd.DataFrame({
         'Missing Values': missing_count,
         'Missing Percentage (%)': missing_percent.round(2)
     })

     missing_summary = missing_summary[missing_summary['Missing Values'] > 0] # Filter only columns with missing values

     print("Missing Value Summary:")
     print(missing_summary)
```

```
Missing Value Summary:
           Missing Values  Missing Percentage (%)
feature_3             400                    4.44
feature_6             500                    5.56
```



```
[46] from sklearn.impute import SimpleImputer

     # Imputation for numerical columns
     num_imp = SimpleImputer(strategy='mean')
     df['feature_3'] = num_imp.fit_transform(df[['feature_3']])
```

```
[47] df['feature_6'] = num_imp.fit_transform(df[['feature_6']])
```

```
[49] print("Missing values:\n", df.isnull().sum())
```

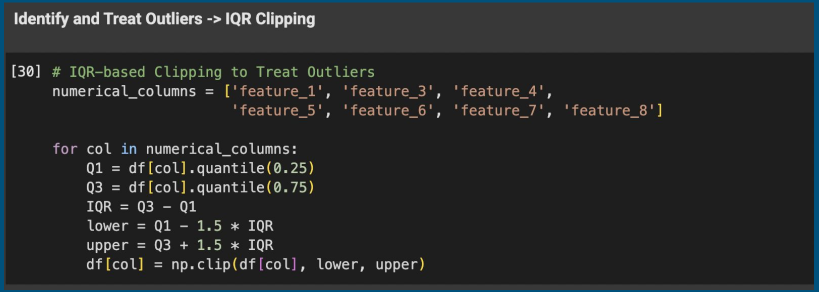
```
Missing values:
 feature_1     0
feature_2     0
feature_3     0
feature_4     0
feature_5     0
feature_6     0
feature_7     0
feature_8     0
category_1    0
category_2    0
target        0
```

Outlier Treatment with IQR Clipping

Applied IQR-based clipping to treat extreme outliers in numerical features.Method is robust and preserves data distribution.Reduces the influence of extreme values without deleting data. Detects values far outside the normal range. Replaces (clips) extreme values to the nearest acceptable boundary. Avoids row deletion → all records retained. Maintains the overall shape and integrity of the data.

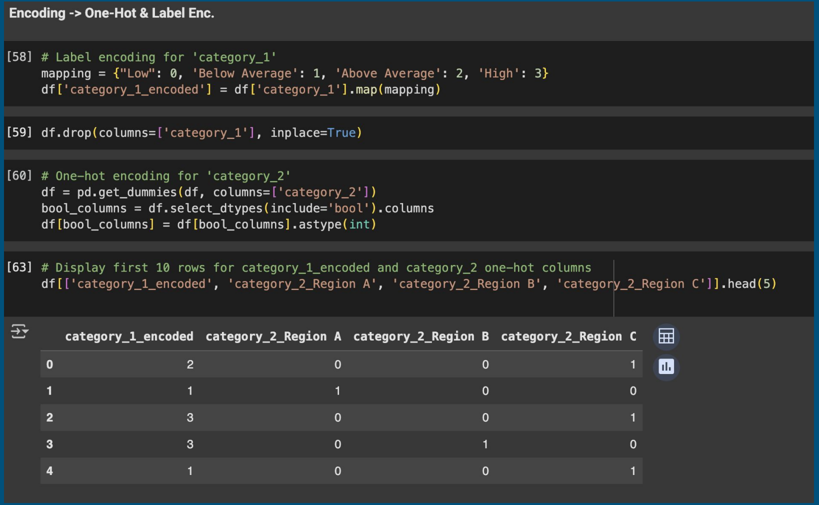
Label Encoding – category_1

Values: "Low", "Below Average", "Above Average", "High" Mapped to integers: 0 → 3.Preserves ordinal structure.Suitable for models that benefit from ranked relationships.One-Hot Encoding – category_2.Values: "Region A", "Region B", "Region C".Transformed into separate binary columns Handles nominal categories (no inherent order) Avoids false ranking.



Identify and Treat Outliers -> IQR Clipping

```
[30] # IQR-based Clipping to Treat Outliers
     numerical_columns = ['feature_1', 'feature_3', 'feature_4',
                          'feature_5', 'feature_6', 'feature_7', 'feature_8']

     for col in numerical_columns:
         Q1 = df[col].quantile(0.25)
         Q3 = df[col].quantile(0.75)
         IQR = Q3 - Q1
         lower = Q1 - 1.5 * IQR
         upper = Q3 + 1.5 * IQR
         df[col] = np.clip(df[col], lower, upper)
```



Encoding -> One-Hot & Label Enc.

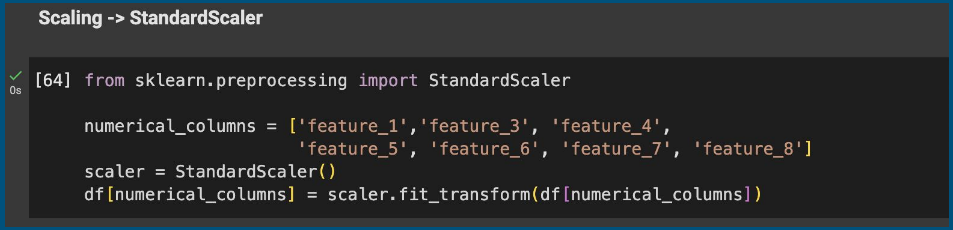
```
[58] # Label encoding for 'category_1'
     mapping = {"Low": 0, 'Below Average': 1, 'Above Average': 2, 'High': 3}
     df['category_1_encoded'] = df['category_1'].map(mapping)
```

```
[59] df.drop(columns=['category_1'], inplace=True)
```

```
[60] # One-hot encoding for 'category_2'
     df = pd.get_dummies(df, columns=['category_2'])
     bool_columns = df.select_dtypes(include='bool').columns
     df[bool_columns] = df[bool_columns].astype(int)
```

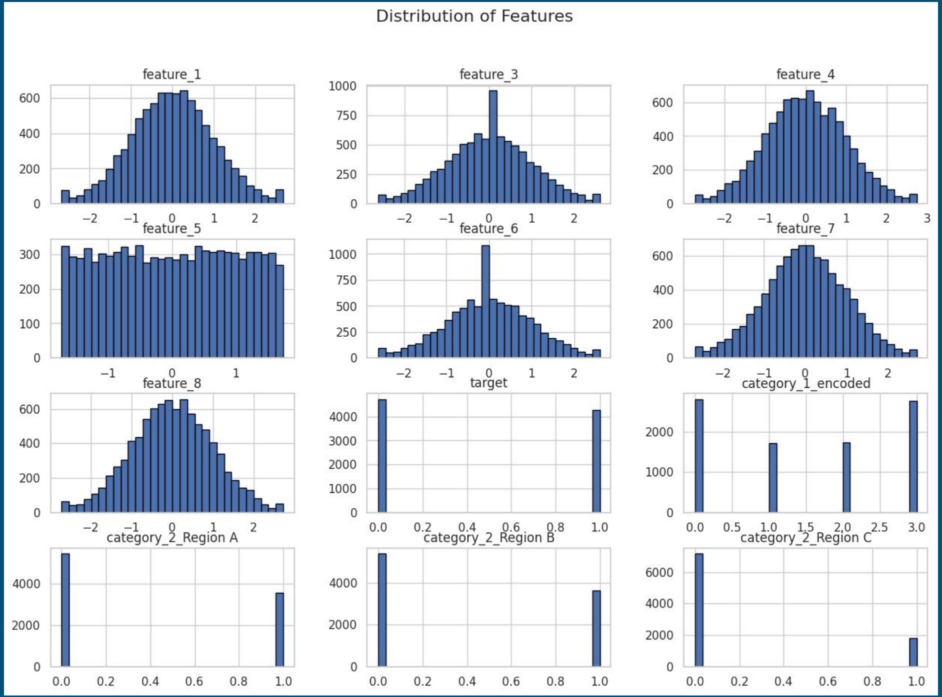
```
[63] # Display first 10 rows for category_1_encoded and category_2 one-hot columns
     df[['category_1_encoded', 'category_2_Region A', 'category_2_Region B', 'category_2_Region C']].head(5)
```

	category_1_encoded	category_2_Region A	category_2_Region B	category_2_Region C
0	2	0	0	1
1	1	1	0	0
2	3	0	0	1
3	3	0	1	0
4	1	0	0	1



Scaling -> StandardScaler

```
[64] from sklearn.preprocessing import StandardScaler

     numerical_columns = ['feature_1','feature_3', 'feature_4',
                          'feature_5', 'feature_6', 'feature_7', 'feature_8']
     scaler = StandardScaler()
     df[numerical_columns] = scaler.fit_transform(df[numerical_columns])
```



Scaling

Rescales features to:Mean = 0.Standard Deviation = 1,Makes features comparable in: Magnitude,Unit

Especially Important For:Support Vector Machines (SVM).Logistic Regression.K-Nearest Neighbors (KNN).Models relying on distance or geometric space

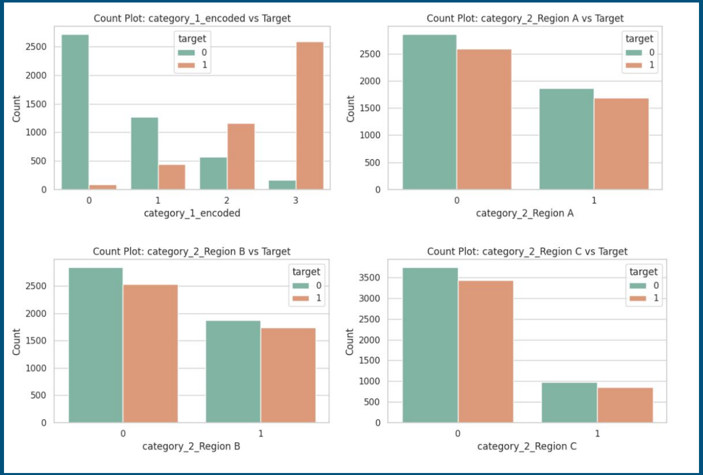
Applied After:Mean Imputation (for missing values),IQR-based Outlier Clipping

Distribution Improvements (Post-Processing):Features like feature_1, feature_3, feature_4, and feature_6 now show:Centered, bell-shaped curves.Tighter, more compact tails

Outlier-prone features now appear more symmetrical and controlled

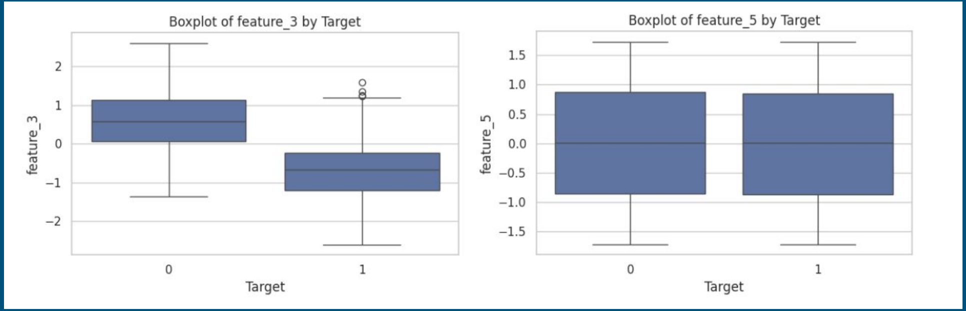
D3.1) Exploratory Data Analysis

- **category_1_encoded** shows strong separation: 0 ("Low") is mostly associated with **target = 0,** 3 ("High") is mostly associated with **target = 1,** 1 ("Below Average") and 2 ("Above Average") are more balanced, showing weaker correlation
- **category_2 (Regions A, B, C)** are more evenly distributed across target classes, suggesting **weaker predictive value**, though minor skews are present in all regions.



From the plots we can observe:

- **feature_3** shows strong class separation. The **median for target = 0 is around 0.75**, while for **target = 1 it's below –0.5**. This indicates a clear difference in distribution, making it a **strongly discriminative feature**.
- **feature_5**, however, shows nearly identical boxplots for both classes, suggesting **low predictive value** as the distributions overlap heavily.



T-Tests for Feature Significance

To evaluate feature relevance, we performed Independent Two-Sample T-Tests comparing numeric feature distributions between target classes (0 vs. 1).

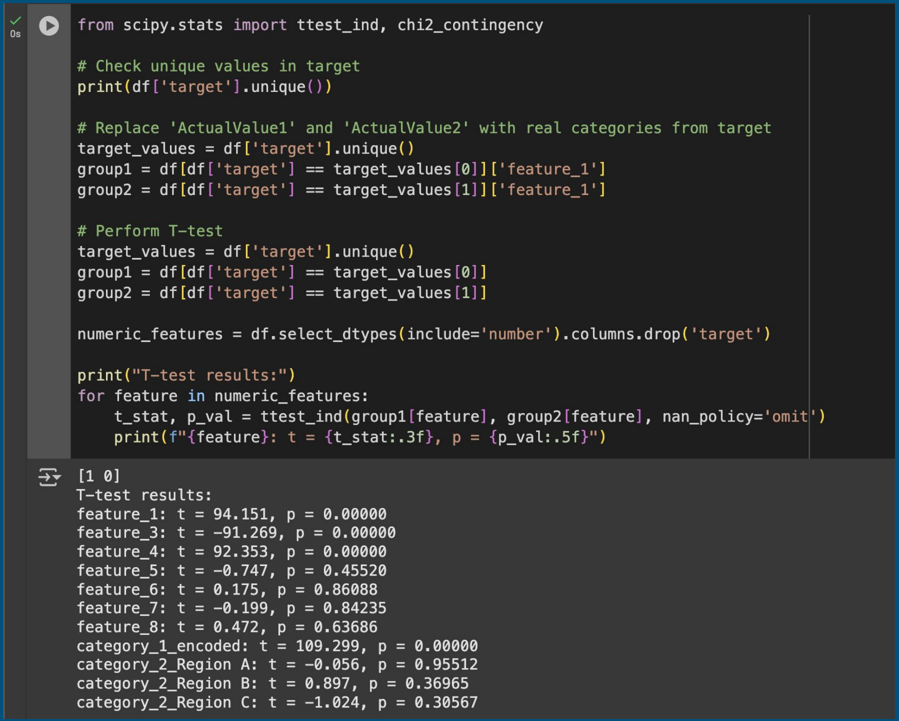
Method: Used scipy.stats.ttest_ind on all numeric features (excluding target).

Key Metrics:

- **t-statistic**: Measures group difference
- **p-value**: Significance of difference (threshold: **$p < 0.05$**)

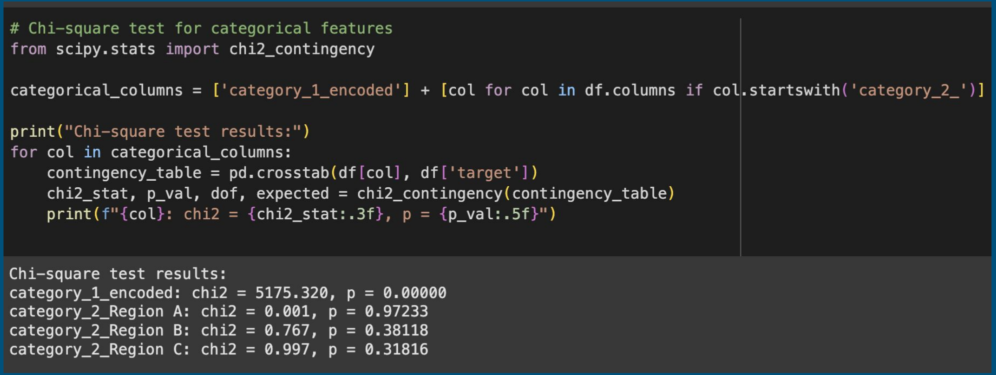
Results

- **Significant Features** ($p < 0.05$):
  feature_1, feature_3, feature_4, category_1_encoded
  → Strongly differentiate between classes; retain for modeling.
- **Not Significant** ($p > 0.05$):
  feature_5 to feature_8, one-hot category_2
  → Weak class separation; consider removal or further analysis.



```python
from scipy.stats import ttest_ind, chi2_contingency

# Check unique values in target
print(df['target'].unique())

# Replace 'ActualValue1' and 'ActualValue2' with real categories from target
target_values = df['target'].unique()
group1 = df[df['target'] == target_values[0]]['feature_1']
group2 = df[df['target'] == target_values[1]]['feature_1']

# Perform T-test
target_values = df['target'].unique()
group1 = df[df['target'] == target_values[0]]
group2 = df[df['target'] == target_values[1]]

numeric_features = df.select_dtypes(include='number').columns.drop('target')

print("T-test results:")
for feature in numeric_features:
    t_stat, p_val = ttest_ind(group1[feature], group2[feature], nan_policy='omit')
    print(f"{feature}: t = {t_stat:.3f}, p = {p_val:.5f}")
```

```
[1 0]
T-test results:
feature_1: t = 94.151, p = 0.00000
feature_3: t = -91.269, p = 0.00000
feature_4: t = 92.353, p = 0.00000
feature_5: t = -0.747, p = 0.45520
feature_6: t = 0.175, p = 0.86088
feature_7: t = -0.199, p = 0.84235
feature_8: t = 0.472, p = 0.63686
category_1_encoded: t = 109.299, p = 0.00000
category_2_Region A: t = -0.056, p = 0.95512
category_2_Region B: t = 0.897, p = 0.36965
category_2_Region C: t = -1.024, p = 0.30567
```



```
# Chi-square test for categorical features
from scipy.stats import chi2_contingency

categorical_columns = ['category_1_encoded'] + [col for col in df.columns if col.startswith('category_2_')]

print("Chi-square test results:")
for col in categorical_columns:
    contingency_table = pd.crosstab(df[col], df['target'])
    chi2_stat, p_val, dof, expected = chi2_contingency(contingency_table)
    print(f"{col}: chi2 = {chi2_stat:.3f}, p = {p_val:.5f}")
```

```
Chi-square test results:
category_1_encoded: chi2 = 5175.320, p = 0.00000
category_2_Region A: chi2 = 0.001, p = 0.97233
category_2_Region B: chi2 = 0.767, p = 0.38118
category_2_Region C: chi2 = 0.997, p = 0.31816
```

Chi-square test: To evaluate whether categorical variables are significantly associated with the target variable, we applied the Chi-Square Test of Independence. The Chi-Square Test is used only for categorical features because it evaluates relationships based on frequency counts in discrete groups, which is not applicable to continuous numerical variables. This statistical test is ideal for determining if there is a relationship between two categorical variables which are the encoded features and the binary target.

Used chi2_contingency from scipy.stats.Created contingency tables between:Each categorical feature The target variable.Metrics Computed Chi-Square Statistic (χ^2):

- Small (O ≈ E): Observed ≈ Expected → likely no relationship
- Large (O ≠ E): Observed ≠ Expected → likely significant relationship

p-value:

- $p < 0.05$ → Significant association with target
- $p \geq 0.05$ → Likely independent of target

Observations

category_1_encoded:Shows a strong statistical relationship with the targetClass distribution varies significantly between target = 0 and 1.Useful predictor for classification.category_2_Region A, B, C:p-values > 0.05No significant distribution differences across target classes. Less predictive

D4.1) Feature Engineering

1 New Feature: feature_1_5_mean:

- Combines feature_1 to feature_5 into a single averaged feature
- Captures the central tendency of a group of strongly correlated variables
- Derived based on:Correlation heatmapT-test results

Reasoning & Purpose: All five features are: Highly correlated with each other Statistically significant predictors of the target Averaging these features amplifies shared predictive patterns

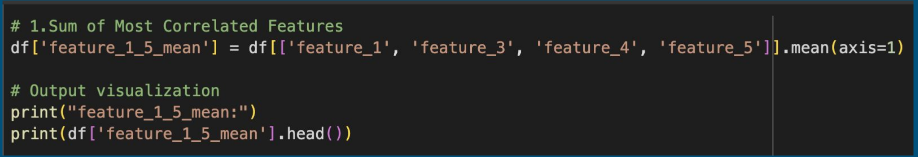
Potential Impact: Enhances signal strength by combining aligned predictors.Alone, it has moderate predictive value.Performs best when used alongside the original features Offers a compact behavioral summary for model interpretability

Feature 2:

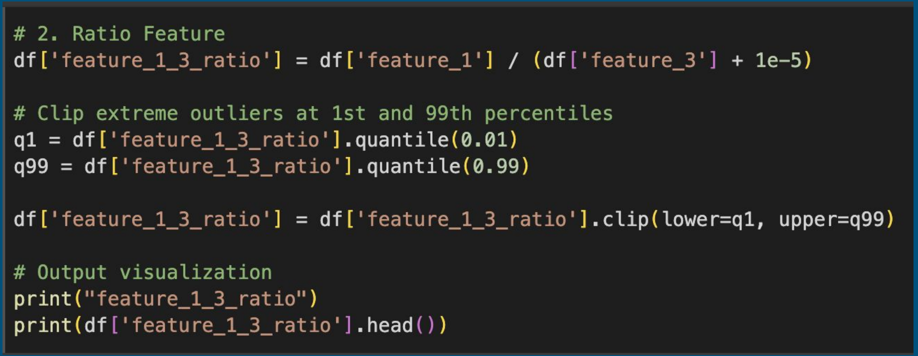
feature_1 / feature_3Engineered by dividing:feature_1 (strong positive correlation with target) by feature_3 (strong negative correlation with target)

Combines two predictive signals with opposing directions Reasoning & Purpose Captures a contrasting signal.Amplifies separation between classes: When numerator and denominator move in opposite directions Potential Impact Enhances discriminative power Highlights class differences more strongly

Potential Impact. Enhances discriminative power.highlights class differences more strongly.Outlier control: Values clipped at 1st and 99th percentiles to improve robustness .Improves performance in:SVM,Logistic Regression,models that benefit from high contrast and variance



```python
# 1.Sum of Most Correlated Features
df['feature_1_5_mean'] = df[['feature_1', 'feature_3', 'feature_4', 'feature_5']].mean(axis=1)

# Output visualization
print("feature_1_5_mean:")
print(df['feature_1_5_mean'].head())
```



```python
# 2. Ratio Feature
df['feature_1_3_ratio'] = df['feature_1'] / (df['feature_3'] + 1e-5)

# Clip extreme outliers at 1st and 99th percentiles
q1 = df['feature_1_3_ratio'].quantile(0.01)
q99 = df['feature_1_3_ratio'].quantile(0.99)

df['feature_1_3_ratio'] = df['feature_1_3_ratio'].clip(lower=q1, upper=q99)

# Output visualization
print("feature_1_3_ratio")
print(df['feature_1_3_ratio'].head())
```

Feature 4: total_service_usage

Created by summing all standardized numerical features.Represents the overall magnitude of user activity or behavior Captures total engagement across multiple dimensions .

Reasoning & Purpose Provides an aggregate representation of user behavior.Acts as a proxy for overall service usage or customer activity Reduces complexity by summarizing 8 features into one metric

Improves interpretability:High-level signal of general usage intensity

Potential Impact

Helps models detect general behavioral patterns.Reduces risk of overfitting on individual features.Offers a single interpretable signal for usage strength.Preprocessing for Engineered Features.Confirmed: No missing values in new features.Applied StandardScaler() to all four engineered features Ensures:Normalized influence in models.Prevents bias from scale differences.Maintains consistency with original numerical feature

Feature3: Interaction term

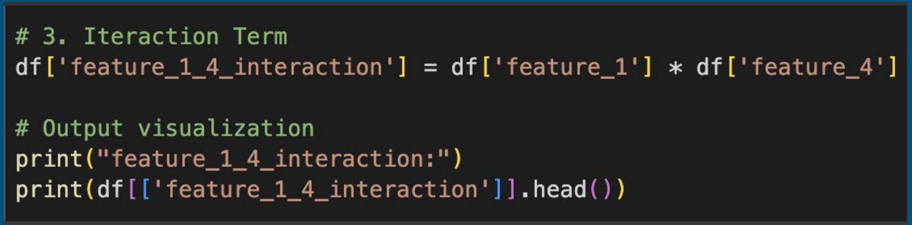
New Feature: feature_1 × feature_4

Created by multiplying two strongly predictive and positively correlated features:Feature_1 & Feature_4 both identified as important via correlation and t-test analysis Reasoning & Purpose

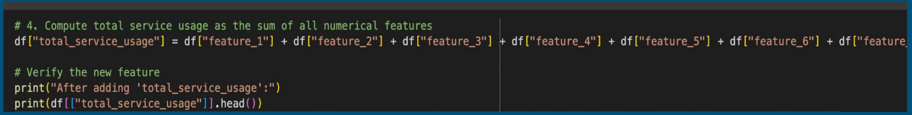
Aligned with correlation structure: Both features increase with target = 1.Their product intensifies the trend.Adds non-linearity to the dataset:.Helps linear models capture complex interactions

Potential Impact

Boosts performance in models that do not detect interactions natively, such as: Logistic Regression Linear SVM Improves class separability



```
# 3. Iteraction Term
df['feature_1_4_interaction'] = df['feature_1'] * df['feature_4']

# Output visualization
print("feature_1_4_interaction:")
print(df[['feature_1_4_interaction']].head())
```



```
# 4. Compute total service usage as the sum of all numerical features
df["total_service_usage"] = df["feature_1"] + df["feature_2"] + df["feature_3"] + df["feature_4"] + df["feature_5"] + df["feature_6"] + df["feature_

# Verify the new feature
print("After adding 'total_service_usage':")
print(df[["total_service_usage"]].head())
```

D5.1) Comparing model performances.

Overview of Model Evaluation Process

Model Evaluation Approach

Dataset split: 80% training, 20% testing

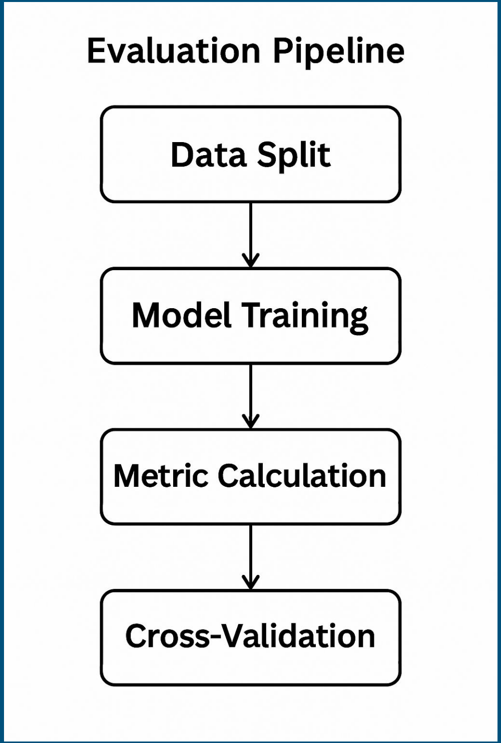
Models evaluated:

- Logistic Regression
- Random Forest
- Support Vector Machine (SVM)

Evaluation Metrics:

- Accuracy, Precision, Recall, F1-Score, ROC-AUC

5-Fold Cross-Validation: For more robust performance



Model Performance Summary (With Engineered Features)

Model Performance with Engineered Features

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
Logistic Regression	87.83%	87.38%	87.01%	87.18%	95.35%
Random Forest	**88.53%**	**88.89%**	85.42%	87.10%	**95.35%**
SVM	88.03%	87.5%	86.3%	86.9%	94.46%

Key Insights and Model Selection

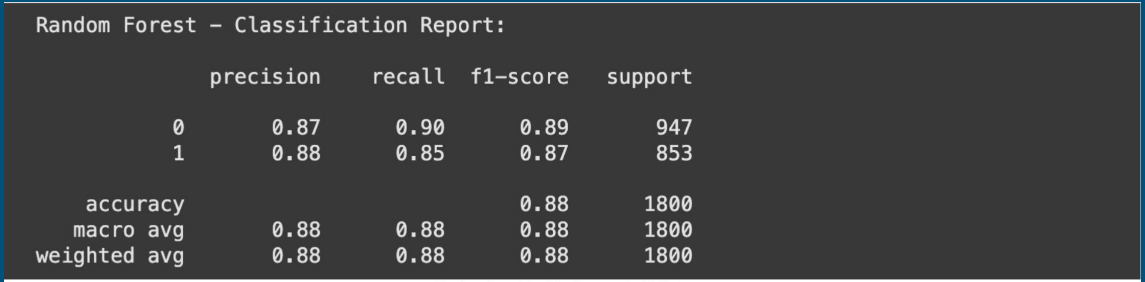
Best Model: Random Forest

Best accuracy & ROC-AUC with engineered features

Balanced precision & recall

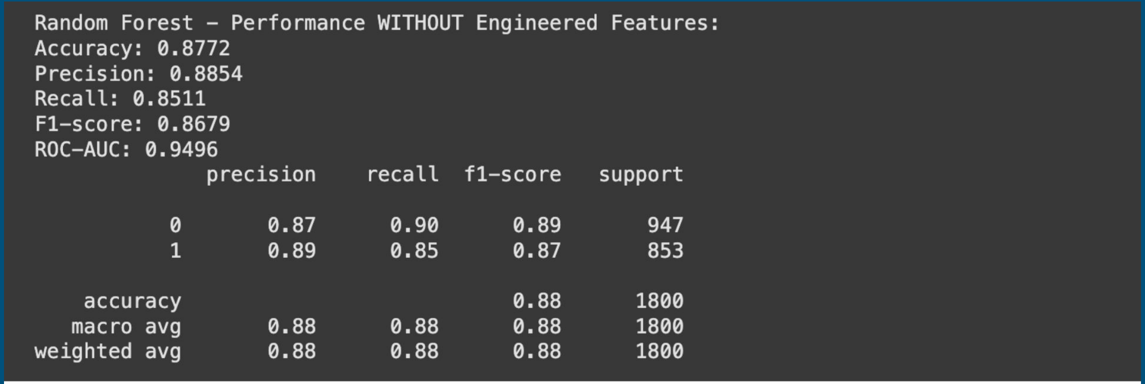
Robust with or without engineered features

Conclusion: Random Forest is optimal for deployment



```
Random Forest - Classification Report:

              precision    recall  f1-score   support

           0       0.87      0.90      0.89       947
           1       0.88      0.85      0.87       853

    accuracy                           0.88      1800
   macro avg       0.88      0.88      0.88      1800
weighted avg       0.88      0.88      0.88      1800
```

Random Forest classification report with features



```
Random Forest - Performance WITHOUT Engineered Features:
Accuracy: 0.8772
Precision: 0.8854
Recall: 0.8511
F1-score: 0.8679
ROC-AUC: 0.9496
              precision    recall  f1-score   support

           0       0.87      0.90      0.89       947
           1       0.89      0.85      0.87       853

    accuracy                           0.88      1800
   macro avg       0.88      0.88      0.88      1800
weighted avg       0.88      0.88      0.88      1800
```

Random Forest classification report without features

D6.1) Hyperparameter tuning

Hyperparameter Tuning Strategy

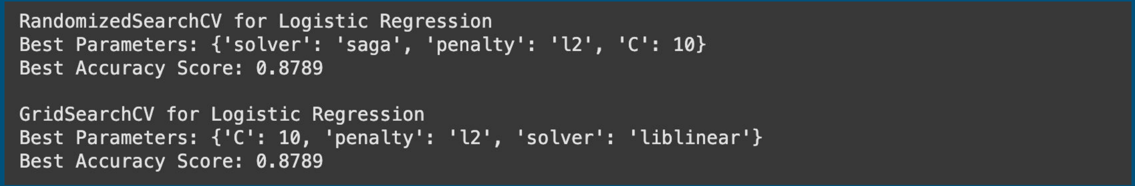
Tuning Methods Used

RandomizedSearchCV: Efficient, broad search

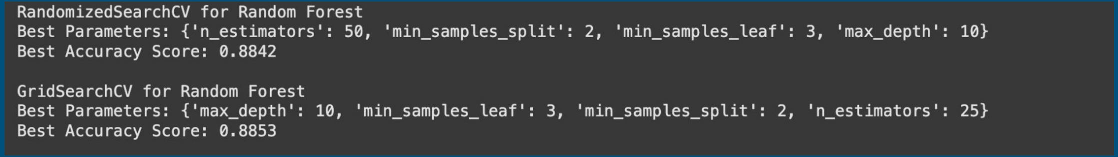
GridSearchCV: Exhaustive, precise tuning

Applied to all 3 models

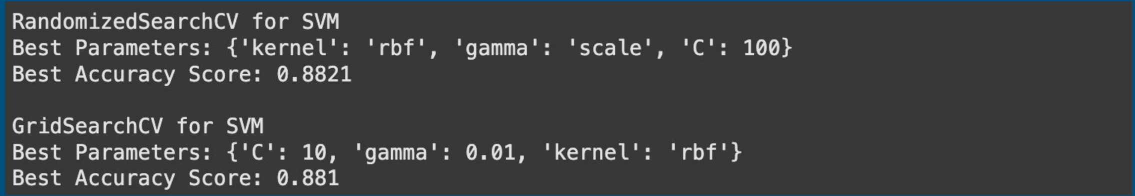
Evaluated with cross-validation



```
RandomizedSearchCV for Logistic Regression
Best Parameters: {'solver': 'saga', 'penalty': 'l2', 'C': 10}
Best Accuracy Score: 0.8789

GridSearchCV for Logistic Regression
Best Parameters: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear'}
Best Accuracy Score: 0.8789
```



```
RandomizedSearchCV for Random Forest
Best Parameters: {'n_estimators': 50, 'min_samples_split': 2, 'min_samples_leaf': 3, 'max_depth': 10}
Best Accuracy Score: 0.8842

GridSearchCV for Random Forest
Best Parameters: {'max_depth': 10, 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 25}
Best Accuracy Score: 0.8853
```



```
RandomizedSearchCV for SVM
Best Parameters: {'kernel': 'rbf', 'gamma': 'scale', 'C': 100}
Best Accuracy Score: 0.8821

GridSearchCV for SVM
Best Parameters: {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
Best Accuracy Score: 0.881
```

Tuning Results Summary

Best Hyperparameters & Scores

Model	**Method**	**Best Params (shortened)**	**Accuracy**
Logistic Regression	GridSearchCV	C=10, penalty=L2, solver=liblinear	87.89%
Random Forest	GridSearchCV	n=25, depth=10, leaf=3	**88.53%**
SVM	GridSearchCV	C=10, kernel=rbf, gamma=scale	88.03%

D6.2) Best-tuned models.

Final Tuning Takeaways

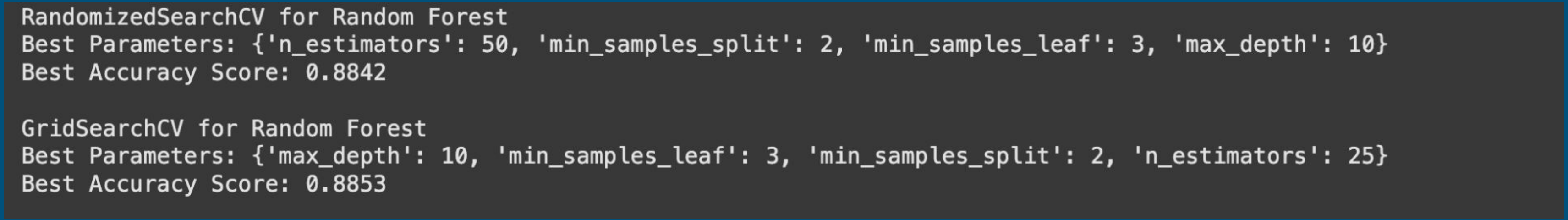
Why Random Forest Wins

Best accuracy (88.53%) and ROC-AUC (~0.953)

Strong generalization and low variance

Consistent across both tuning methods

Feature importance available for interpretation



```
RandomizedSearchCV for Random Forest
Best Parameters: {'n_estimators': 50, 'min_samples_split': 2, 'min_samples_leaf': 3, 'max_depth': 10}
Best Accuracy Score: 0.8842

GridSearchCV for Random Forest
Best Parameters: {'max_depth': 10, 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 25}
Best Accuracy Score: 0.8853
```

D7.1) Model interpretation

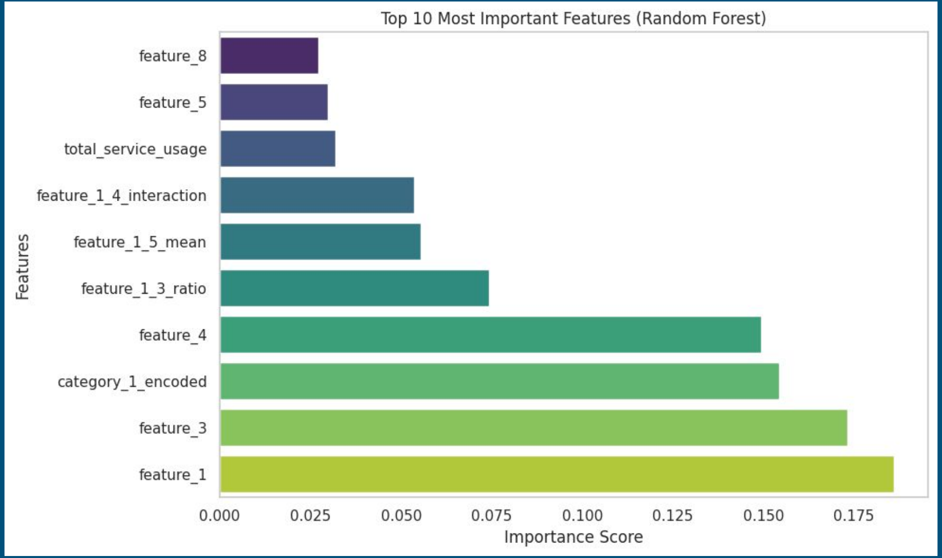
Global Interpretation – Random Forest

Feature Importance (Global View)

Top features: feature_1, feature_3, category_1_encoded

Feature_1 = most predictive in all models

Less important: feature_8, feature_5



Local Interpretation (LIME)

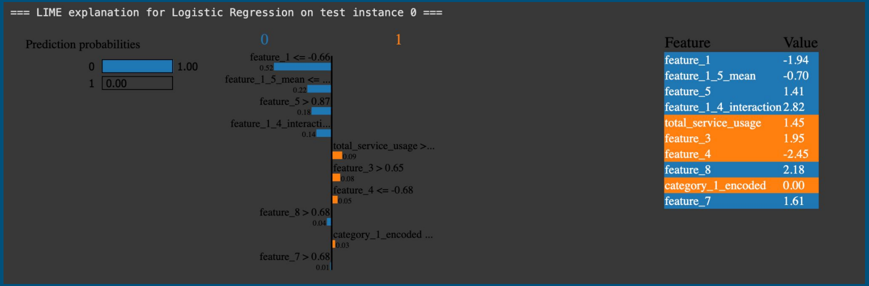
Local Explanations with LIME

Logistic Regression: strong reliance on feature_1

Random Forest: distributed reasoning across features

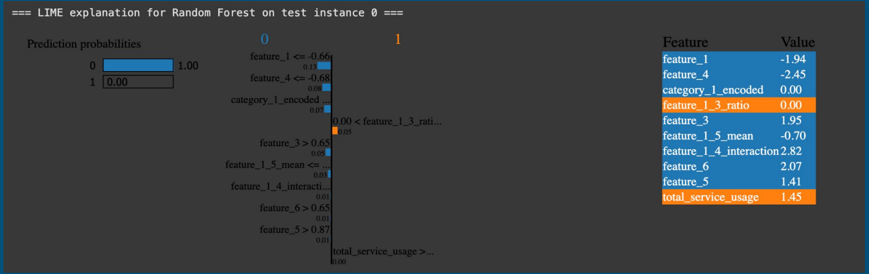
SVM: margin-based logic, lower confidence

All models agreed on prediction for the sample case



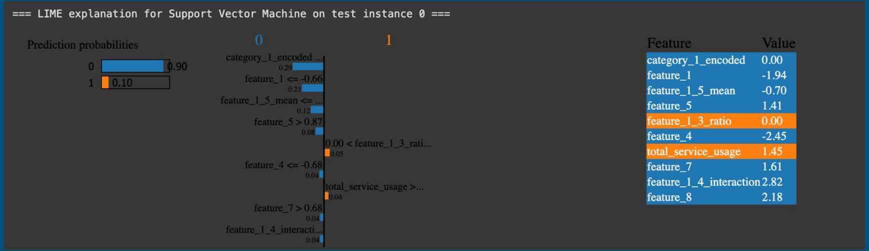
```
=== LIME explanation for Logistic Regression on test instance 0 ===
```

Feature	Value
feature_1	-1.94
feature_1_5_mean	-0.70
feature_5	1.41
feature_1_4_interaction	2.82
total_service_usage	1.45
feature_3	1.95
feature_4	-2.45
feature_8	2.18
category_1_encoded	0.00
feature_7	1.61



```
=== LIME explanation for Random Forest on test instance 0 ===
```

Feature	Value
feature_1	-1.94
feature_4	-2.45
category_1_encoded	0.00
feature_1_3_ratio	0.00
feature_3	1.95
feature_1_5_mean	-0.70
feature_1_4_interaction	2.82
feature_6	2.07
feature_5	1.41
total_service_usage	1.45



```
=== LIME explanation for Support Vector Machine on test instance 0 ===
```

Feature	Value
category_1_encoded	0.00
feature_1	-1.94
feature_1_5_mean	-0.70
feature_5	1.41
feature_1_3_ratio	0.00
feature_4	-2.45
total_service_usage	1.45
feature_7	1.61
feature_1_4_interaction	2.82
feature_8	2.18