Bank Marketing Campaign Dataset Analysis Report

I. Dataset Introduction and Task Description

1.1 Dataset Overview

This dataset contains records from a Portuguese bank's direct marketing campaigns, aiming to predict whether clients will subscribe to a term deposit (target variable `y`). The primary dataset (`bank-additional-full.csv`) includes 41,188 records with 20 features, covering client demographics, financial status, and marketing interactions from May 2008 to November 2010.

Key Features:

- **Data Size**: 45,211 samples, 16-20 features.
- **Variables**:
  - **Client Info**: Age, job, marital status, education.
  - **Financial Status**: Credit default, balance, housing/personal loans.
  - **Marketing Data**: Contact method, call duration, previous campaign results.
- **Target**: Subscription to term deposit (`y`: binary `yes`/`no`).
- **Data Quality**: No missing values, but some "unknown" categories require preprocessing.

1.2 Task Objectives

Build a classification model to predict term deposit subscriptions, focusing on:

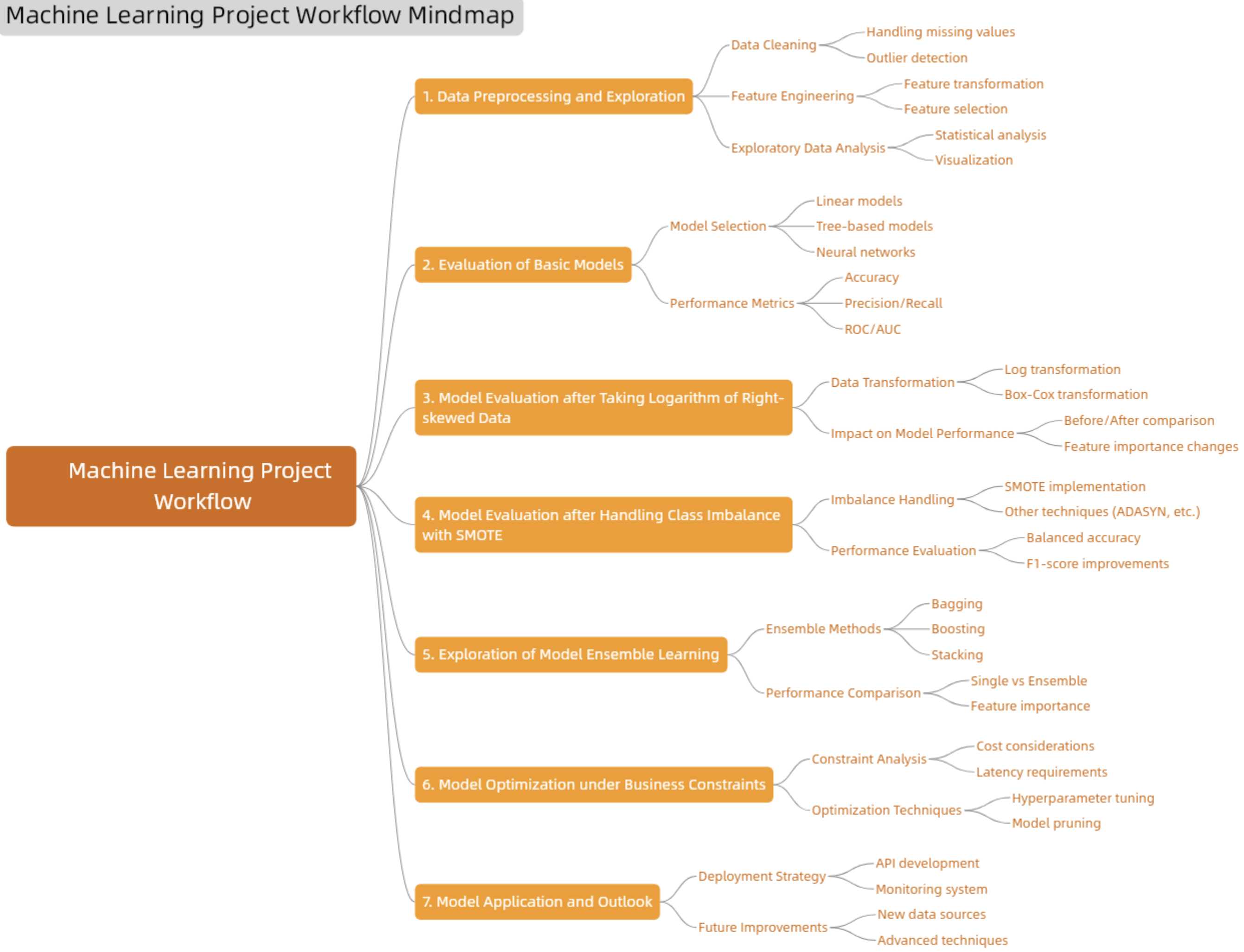
1. **Data Prep**: Handle "unknown" values, skewness, and class imbalance.
2. **Modeling**: Compare logistic regression, random forests, and gradient boosting.
3. **Business Insights**: Analyze key factors to guide marketing strategies.

Approach:

- **Input**: Client attributes and marketing history.
- **Output**: Binary prediction (precision/recall emphasis).

Process:

Machine Learning Project Workflow Mindmap



II. Exploratory Data Analysis (EDA)

2.1 Missing Value Analysis

The dataset contains missing values (coded as "unknown") in categorical variables:

- `job` **(288)**, `education` **(1,857)**, `contact` **(13,020)**, and `poutcome` **(36,959)**.

Key Observations:

- `poutcome` exhibits an 81.75% missing rate, suggesting most clients were first-time contacts.
- `contact` has a 28.79% missing rate, warranting further investigation into its relationship with client responses.

2.2 Numerical Feature Analysis

Skewness & Outliers:

- Features like `age`, `balance`, and `duration` display right-skewed distributions (see Figure 1).
- **Implications**: May bias models sensitive to feature scales (e.g., linear models).

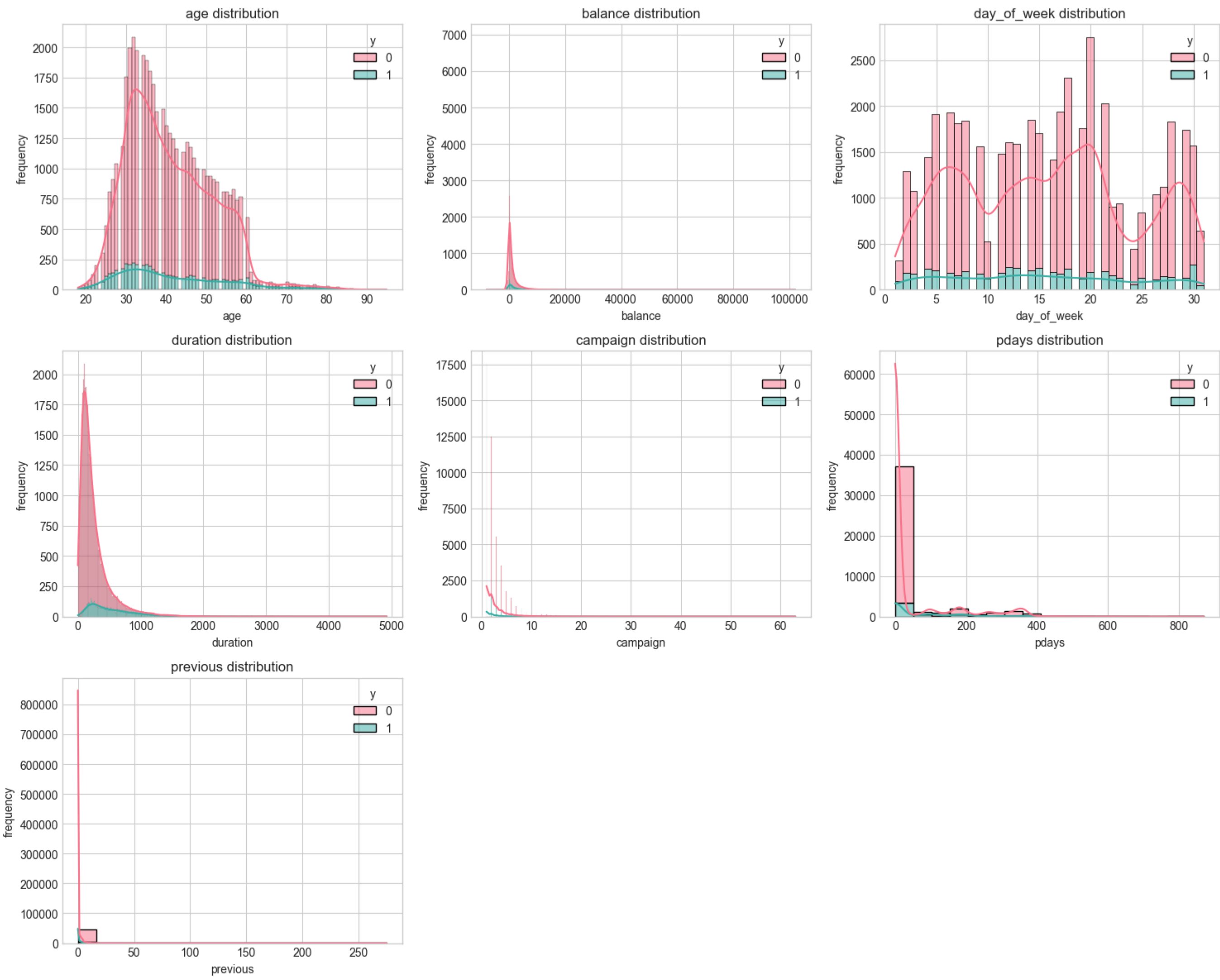


Figure 1: Skewed distributions of key numerical features.

2.3 Class Imbalance

The target variable `y` is highly imbalanced:

- **Negative class (`y=0`)**: 87.5%
- **Positive class (`y=1`)**: 12.5% (7:1 ratio)

Mitigation Strategies:

- **Algorithmic**: Weighted loss functions (e.g., XGBoost's `scale_pos_weight`).
- **Resampling**: SMOTE oversampling or informed undersampling.
- **Evaluation**: Prioritize **F1-score** and **AUC-ROC** over accuracy.

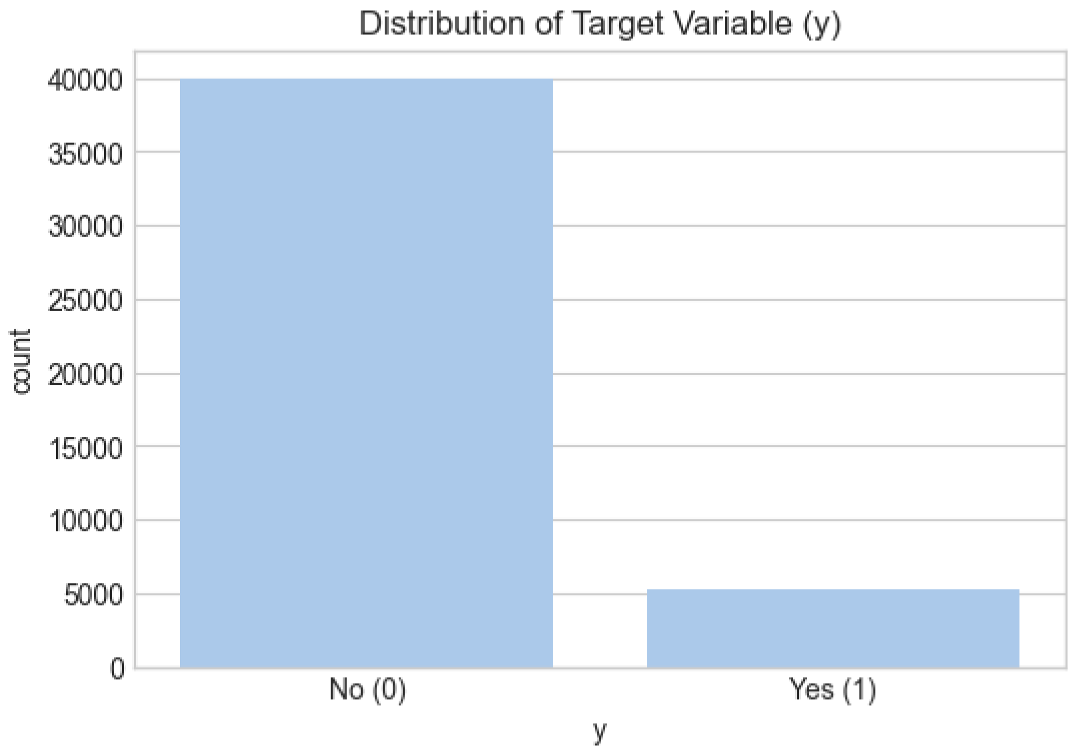


Figure 2: Severe class imbalance in the target variable.

III. Model Training, Evaluation Criteria, and Preliminary Results

3.1 Model Selection and Theoretical Analysis

Table 3.1: Theoretical Comparison of Selected Models

Model	Key Characteristics	Strengths	Limitations	Selection Rationale
Logistic Regression	Linear classification via sigmoid function	Interpretable, efficient computation	Linear decision boundary only	Baseline for linear separability analysis
Decision Tree	Hierarchical splitting via information gain/Gini	Handles nonlinearity, visualizable	Prone to overfitting	Exploratory analysis of feature hierarchies
Random Forest	Ensemble of decorrelated decision trees	Robust to overfitting, parallelizable	Computationally expensive	Improves generalizability over single trees
SVM (Linear Kernel)	Maximizes margin with regularization	Effective in high dimensions	Sensitive to class imbalance	Validates linear separability hypothesis

Model	Key Characteristics	Strengths	Limitations	Selection Rationale
Gaussian Naive Bayes	Bayesian approach with feature independence assumption	Fast training, low variance	Strong independence assumptions	Benchmark for generative approach
XGBoost	Gradient boosting with regularization	State-of-art performance, handles missing data	Hyperparameter-sensitive	Optimal for imbalanced classification
CatBoost	Ordered boosting with categorical handling	Robust to categorical features	Slower training	Specialized for categorical data
MLP	Multilayer neural network with nonlinear activation	Captures complex patterns	Data-hungry, prone to overfitting	Tests deep learning potential
LightGBM	Gradient boosting with leaf-wise growth	Extremely fast, memory-efficient	May overfit without constraints	Scalability for large datasets

3.2 Evaluation Framework

Core Metrics:

1. **Precision** = TP/(TP+FP)
    - *Business Impact*: Measures marketing efficiency (avoiding wasted outreach)
2. **Recall** = TP/(TP+FN)
    - *Business Impact*: Captures subscriber acquisition capability
3. **F1-score** = 2×(Precision×Recall)/(Precision+Recall)
    - *Optimal for*: Imbalanced class trade-offs
4. **AUC-ROC**
    - *Advantage*: Threshold-independent performance assessment

Business Optimization Strategy:

- **Growth Focus**: Maximize Recall (minimize missed opportunities)
- **Cost Sensitivity**: Maximize Precision (minimize false leads)
- **Balanced Approach**: Optimize F1-score

3.3 Baseline Performance Analysis

Table 3.2: Initial Model Performance (Untreated Data)

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
XGBoost	0.907	0.648	0.457	0.536	0.933
CatBoost	0.909	0.645	0.489	0.556	0.932
MLP	0.907	0.614	0.540	0.575	0.927
Random Forest	0.906	0.665	0.387	0.489	0.926
LightGBM	0.906	0.665	0.397	0.497	0.926
Logistic	0.902	0.645	0.351	0.455	0.906
SVM (RBF)	0.903	0.669	0.335	0.447	0.895
Naive Bayes	0.864	0.427	0.483	0.454	0.809
Decision Tree	0.876	0.470	0.461	0.465	0.696

Key Findings:

1. **Performance Hierarchy**: Tree-based ensembles (XGBoost, CatBoost) lead in AUC-ROC, while MLP achieves best recall
2. **Class Imbalance Impact**: All models show depressed recall (<0.55), indicating difficulty identifying subscribers
3. **Trade-off Analysis**: Higher precision models (SVM, Random Forest) exhibit lower recall