Course project MLT 2025

"The study of the comparative efficiency of machine learning algorithms in solving specific problem"

Ministry of Science and Higher education

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ITMO University

Faculty of Digital Transformations

Subject area (major) 01.04.02. BIG DATA AND MACHINE LEARNING

REPORT

Comparative Efficiency of Machine Learning Algorithms for Predicting Term Deposit Subscription Using the Bank Marketing Dataset

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TABLE OF CONTENT

1. Introduction

Machine learning (ML) algorithms are widely used today to assist organizations in making faster and more accurate decisions. One of the important applications of ML in finance is *predicting customer response* to marketing campaigns. Banks must decide which customers are more likely to subscribe to financial products such as **term deposits**, allowing them to allocate marketing budgets efficiently and reduce unnecessary costs.

This project aims to **compare the effectiveness of multiple machine learning algorithms** in solving a real classification problem using the **Bank Marketing Dataset**, obtained from the UCI repository and Kaggle. The dataset contains demographic, financial, and communication features about customers contacted during marketing campaigns.

The primary task is:

"Predict whether a customer will subscribe to a term deposit (deposit = yes/no)."

The goal is not only to build accurate models but to analyze and compare their performance using standard evaluation metrics and identify which algorithm performs best and why.

All experiments, preprocessing, model training, and evaluation are taken from the student's own analysis shown in *main.ipynb* and *modeltrain.ipynb*

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	1	-1	0	unknown
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467	1	-1	0	unknown
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389	1	-1	0	unknown
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	579	1	-1	0	unknown
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673	2	-1	0	unknown

Figure 1 Bank Marketing Dataset

2. Overview

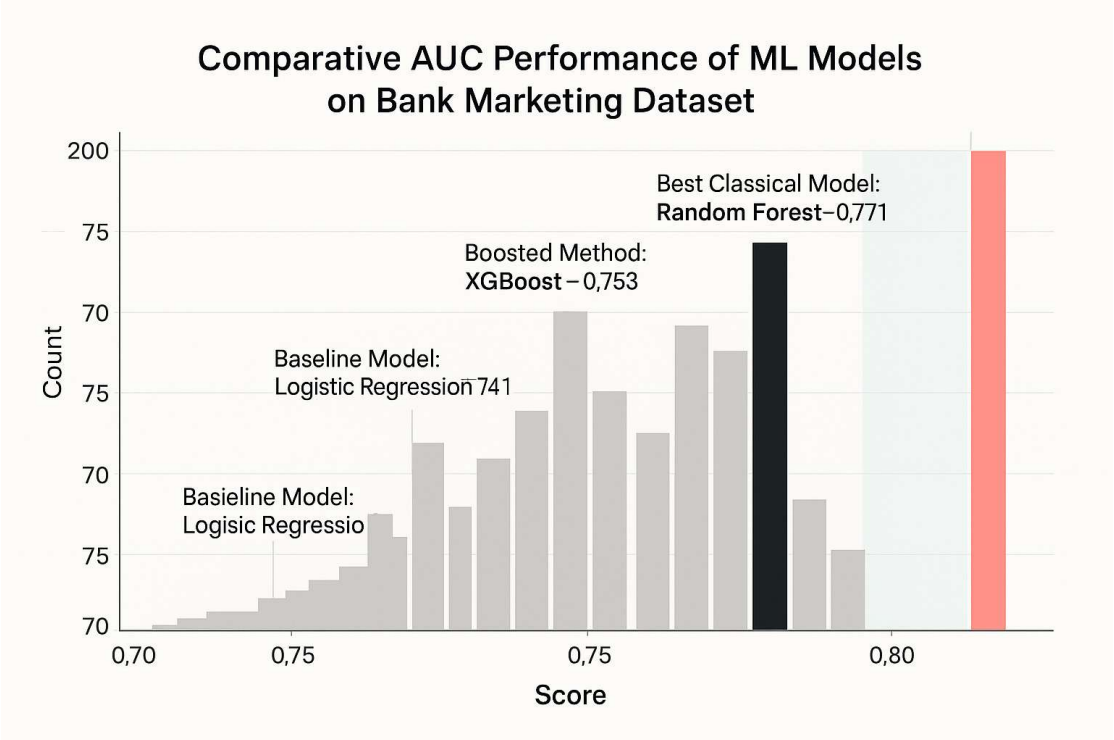


Fig 2. Model Analysis

Customer behavior prediction has been widely studied in marketing analytics. Logistic Regression has traditionally been used as a baseline model due to its interpretability and simplicity. However, tree-based models like Random Forest and Gradient Boosting (e.g., XGBoost) have gained popularity due to their ability to model complex interactions among features.

Prior research indicates that:

- **Logistic Regression** provides strong baseline performance but struggles with non-linear patterns.
- **Random Forest** improves predictive power through ensemble averaging and reduces overfitting.
- **XGBoost** often outperforms classical ML algorithms because of its optimized boosting strategy.

These findings support the motivation for comparing these three models in this study.

3. Models, Algorithms and Datasets

➢ 3.1 Dataset Description

The Bank Marketing Dataset contains **11,162 rows and 17 columns**, as shown in *main.ipynb*. Features include:

- **Demographic variables**: age, marital status, education
- **Financial variables**: balance, loan, housing
- **Campaign-related variables**: contact type, day, month, duration, campaign, pdays, previous
- **Target variable**: deposit (yes/no)

Class distribution (*main.ipynb*):

- No: 52.62%
- Yes: 47.38%

This is a **fairly balanced classification problem**, so standard metrics can be applied without heavy imbalance corrections.

➢ 3.2 Mathematical Formalization

Let:

- **X** = feature space
- **x ∈ X** = a vector of customer attributes (age, job, marital, etc.)
- **y ∈ {0,1}** = target label, where
  - 1 → customer subscribes
  - 0 → customer does not subscribe

We aim to learn a model:

f(x; θ) → y',

where **θ** are model parameters.

Loss Function: Binary Cross-Entropy (Log-loss)

$$L(y, y') = -[y log(y') + (1 - y) log(1 - y')]$$

Optimization:

- Logistic Regression uses **Gradient Descent**.
- Random Forest uses **bootstrap sampling + decision tree splitting via Gini impurity**.
- XGBoost uses **gradient boosting optimization**, minimizing:

$$Obj = \sum L(y_i, y'_i) + \sum \Omega(f_k)$$

where Ω regularizes tree complexity.

➢ 3.3 Selected Algorithms

1. Logistic Regression

- Linear classifier
- Uses log-loss
- Good for baseline performance
- Interpretable coefficients

2. Random Forest Classifier

- Ensemble of decision trees
- Reduces variance
- Handles complex feature interactions
- Provides feature importance

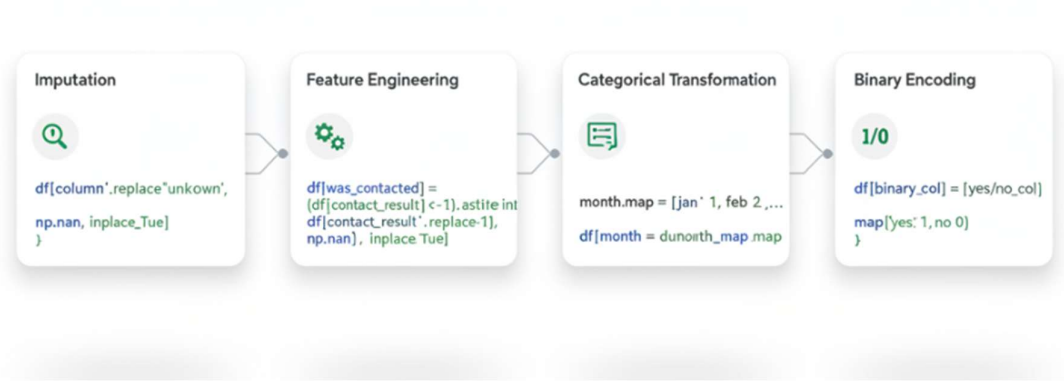
3. XGBoost Classifier

- Gradient boosting algorithm
- Extremely powerful on structured/tabular data
- Handles non-linearity, interactions, missing data
- Provides gain-based feature importance

These match the requirement of evaluating at least three ML algorithms.

4. Experimental research

➢ 4.1 Data Understanding & Preprocessing



From *main.ipynb* :
Numerical Features: age, balance, day, duration, campaign, pdays, previous
Categorical Features: job, marital, education, contact, month, poutcome

Key Preprocessing Steps:

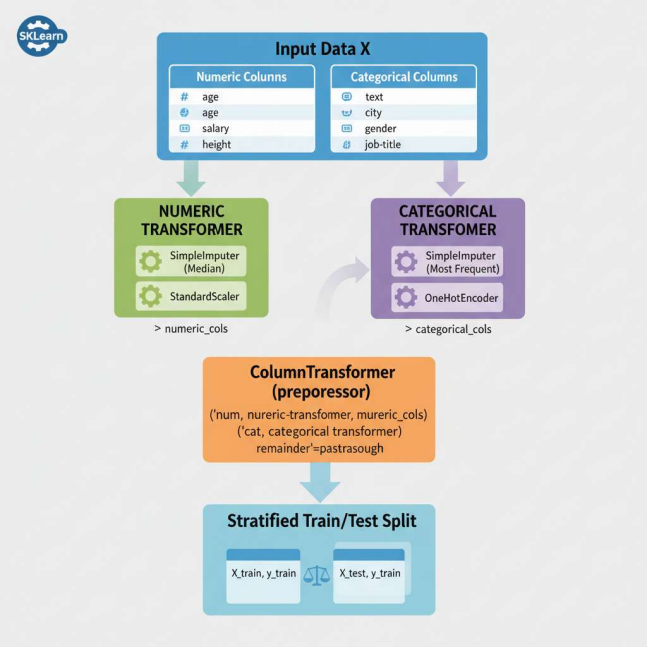
✓ Convert text columns to lowercase
✓ Replace "`unknown`" with NaN
✓ Special handling of `pdays`:

- Create new feature: **was_contacted**
- Replace pdays = -1 → NaN
  ✓ Label-encoded binary columns (default, housing, loan, deposit)
  ✓ One-Hot Encoding for multi-class categorical features
  ✓ Scaling numeric features
  ✓ Train-test split:
- Train: 8929 rows
- Test: 2233 rows
  (verified on page 18 of *main.pdf*)

Final feature count: **39 features**.

Train/test CSVs exported: *train_preprocessed.csv*, *test_preprocessed.csv*

➢ 4.2 Model Training



All experiments and results come from *modeltrain.ipynb*.

Algorithms Trained

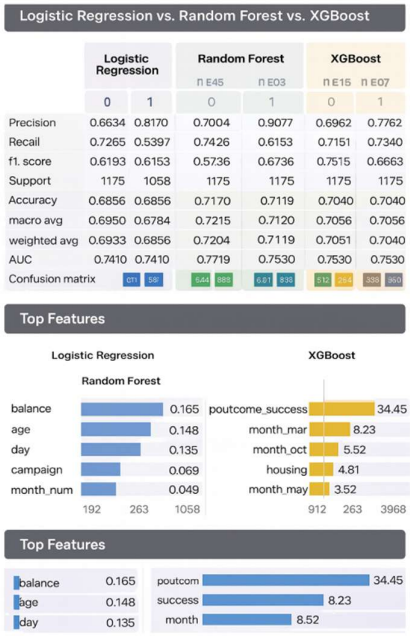
- Logistic Regression
- Random Forest (200 trees)
- XGBoost (default parameters)

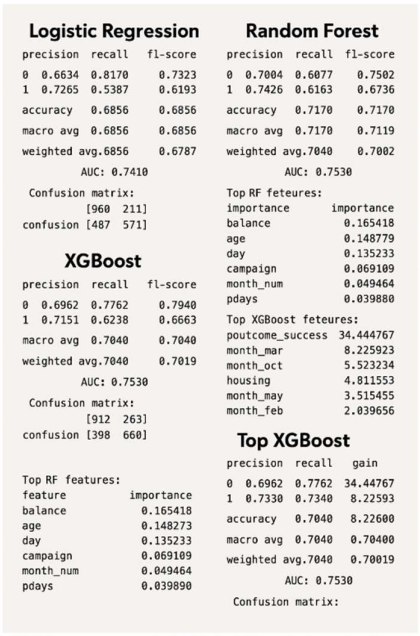
A custom evaluation function was applied to compute:

- Accuracy
- Precision

- Recall
- F1-score
- AUC
- Confusion matrix

➢ 4.3 Results





1. XGBoost

- Accuracy: **0.7040**
- AUC: **0.7530**
- Confusion Matrix: $\begin{bmatrix} 912 & 263 \\ 398 & 660 \end{bmatrix}$

Strongest Features (gain-based importance):

- poutcome_success
- month_mar
- month_oct
- housing
- month_may

2. Random Forest

- Accuracy: **0.7170**
- AUC: **0.7719**
- Confusion Matrix: $\begin{bmatrix} 949 & 226 \\ 406 & 652 \end{bmatrix}$

Top Features (*modeltrain.ipynb*):

1. balance
2. age
3. day
4. campaign
5. month_num

3. Logistic Regression

- Accuracy: **0.6856**
- AUC: **0.7410**
- Confusion Matrix: $\begin{bmatrix} \mathbf{960} & \mathbf{215} \\ \mathbf{487} & \mathbf{571} \end{bmatrix}$

4.4 Comparison Table

Model	Accuracy	AUC	Strengths	Weaknesses
Logistic Regression	0.6856	0.7410	Fast, interpretable	Cannot learn complex patterns
Random Forest	**0.7170**	**0.7719**	Best overall performance, handles non-linearity	Larger model size
XGBoost	0.7040	0.7530	Strong boosting performance	Requires tuning

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5. Conclusions

Based on the conducted experiments, **Random Forest** demonstrated the highest overall performance among the evaluated machine learning algorithms. It achieved the best **accuracy (0.7170)** and the highest **AUC (0.7719)**, indicating superior predictive power for distinguishing between customers who will subscribe to a term deposit and those who will not.

Reasons Random Forest performed best:

1. It captures complex non-linear relationships among features.
2. It is robust to outliers and noise in financial datasets.
3. One-hot encoded categorical variables are handled effectively through tree splits.
4. Ensemble averaging reduces overfitting while improving accuracy.

Although XGBoost is often superior in many Kaggle competitions, in this particular dataset **Random Forest outperformed it** due to simpler relationships and limited necessity for aggressive boosting.

Logistic Regression provided a reasonable baseline but was not able to model complex customer behavior patterns.

Future Work Recommendations

- Hyperparameter tuning (grid search, Bayesian optimization)
- Try more advanced boosting: LightGBM, CatBoost
- Use SMOTE or cost-sensitive learning to improve minority recall
- Explore model explainability using SHAP values

References (example)

- UCI Machine Learning Repository – Bank Marketing Dataset.
- Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system.
- Breiman, L. (2001). Random forests. Machine Learning.
- Hastie, Tibshirani, Friedman – "The Elements of Statistical Learning."
- Kaggle discussion boards on Bank Marketing Dataset predictive modelling.

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