

Optimizing Bank Marketing: A Predictive Model for Customer Subscription

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The Challenge: Moving from Mass Marketing to Intelligent Targeting



The Business Problem

Direct marketing campaigns are expensive and can fatigue customers if poorly targeted.

Goal: Identify clients most likely to subscribe to a term deposit to optimize marketing efforts.



Why This Matters

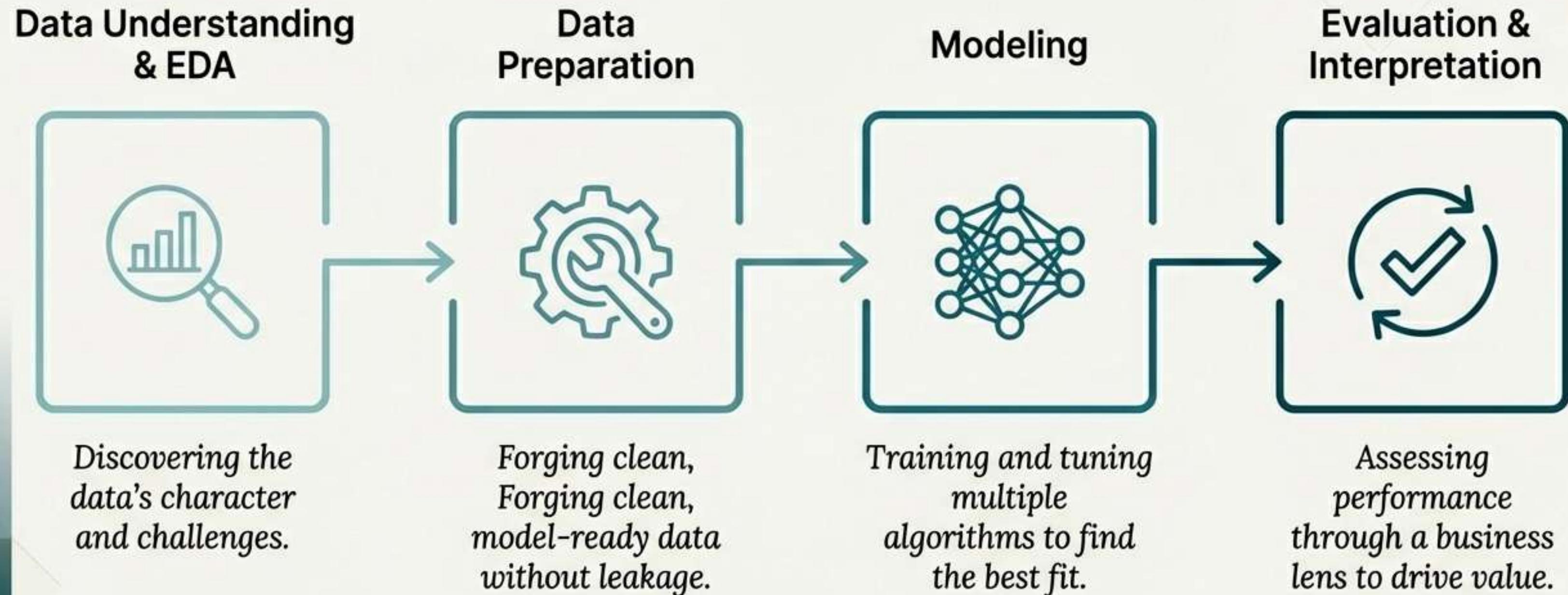
- **Reduce Marketing Costs:** Focus budget on high-potential leads.
- **Improve Campaign Effectiveness:** Increase the subscription rate per contact.



The Data Science Goal

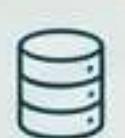
- Build a robust predictive model that ranks clients by their likelihood of subscribing.
- The model should serve as a decision-support tool, not an automated system.

Our Structured Approach: From Raw Data to Actionable Insights



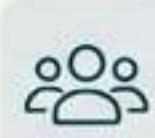
Understanding the Landscape: The Bank Marketing Dataset

Key Metrics



Source

UCI Machine Learning Repository



Observations

41,188 client contacts



Input Features

20



Time Period

2008-2010

A Critical Note on Data Leakage

The `duration` feature (call length) is a powerful predictor but is only known *after* the call.

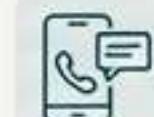
Decision: It was excluded from all predictive models to ensure a realistic, deployable solution.

Feature Categories Breakdown



Client Attributes

`age`, `job`, `education`, `marital`, `default`,
 `housing`, `loan`



Campaign Contact Data

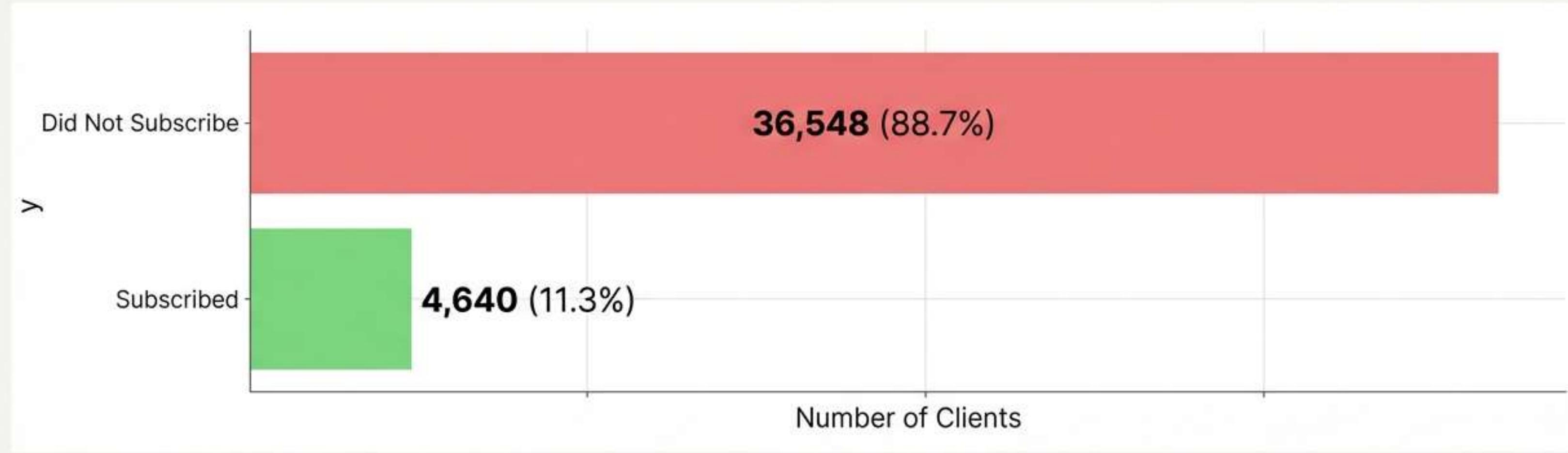
`contact`, `month`, `campaign`, `pdays`,
 `previous`, `poutcome`



Economic Context

`emp.var.rate`, `cons.price.idx`, `euribor3m`,
 `nr.employed`

The Core Challenge: Subscriptions are a Rare Event

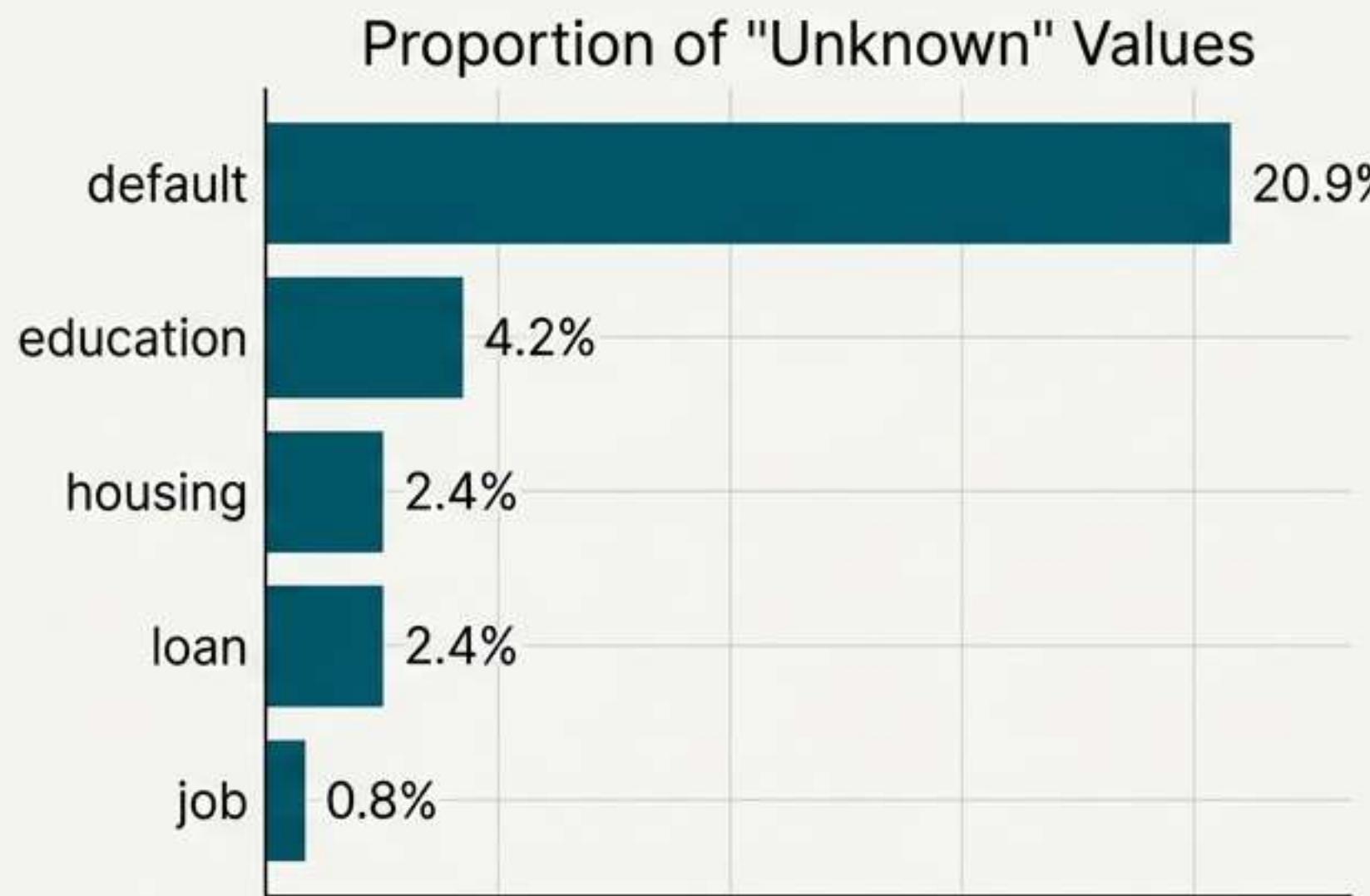


Implications for Modeling

- 📊 The dataset is highly imbalanced.
- 📊 Standard accuracy is a misleading metric. A model that always predicts 'No' would be ~89% accurate but commercially useless.
- 🎯 **Our Focus:** Evaluation will prioritize metrics like ROC-AUC, Recall, and Precision that are robust to imbalance.

Uncovering Signal in Missing Information

The dataset contains no standard null values, but “unknown” appears in several categorical columns.



Why “Unknown” is a Feature, Not a Flaw

- ◆ **Hypothesis:** "Unknown" is not random missing data. It represents meaningful information (e.g., a client's refusal to answer).
- ◆ **Decision:** Treat "unknown" as a distinct category during encoding.
- ◆ **Benefit:** This allows the model to learn if the absence of information is itself a predictive signal, preserving valuable data that would otherwise be dropped.

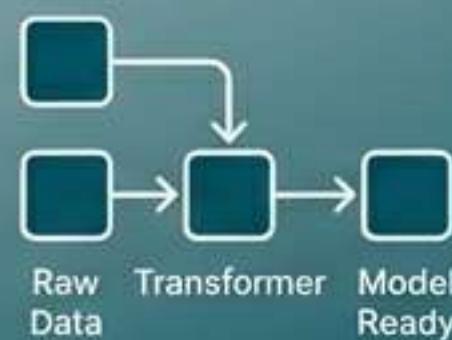
Engineering a Model-Ready and Leak-Proof Dataset

Domain-Informed Feature Engineering

-  **pdays_transformed:** Converted 999 (never contacted) to -1 to treat it as a special case, not a large number.
-  **contacted_before:** Created a binary flag from pdays to clearly separate new vs. existing contacts.
-  **total_contacts:** Combined campaign and previous to capture a client's total exposure to marketing.

Systematic Preprocessing

-  **Categorical Features:** One-Hot Encoded to convert text into numerical format.
-  **Numerical Features:** Standard Scaled to normalize ranges and prevent feature dominance.



Ensuring Reproducibility and Preventing Leakage

All steps were encapsulated in a scikit-learn ColumnTransformer and Pipeline.

Benefit: This guarantees that the same transformations are applied consistently to training and testing data, preventing data leakage and making the entire workflow reproducible.

Selecting the Right Tool: A Multi-Model Approach

We trained and compared four distinct models to cover a range of behaviors and complexities.

1. **Logistic Regression:** A powerful and interpretable baseline.
2. **Decision Tree:** To capture non-linear rules and interactions.
3. **Random Forest:** An ensemble model for high performance and robustness against overfitting.
4. **Weighted Random Forest:** A specialized version of Random Forest with '`class_weight='balanced'`' to explicitly address the **class imbalance** identified in our EDA.

Training and Tuning Strategy

- **Data Split:** Used a stratified train-test split to maintain the target distribution in both sets.
- **Tuning:** Employed GridSearchCV with 5-fold cross-validation to systematically find the best hyperparameters for each model.
- **Scoring Metric:** Optimized for **ROC-AUC**, as it effectively measures a model's ability to discriminate between classes, which is crucial for our ranking goal.

The Verdict: Performance Across Key Business Metrics

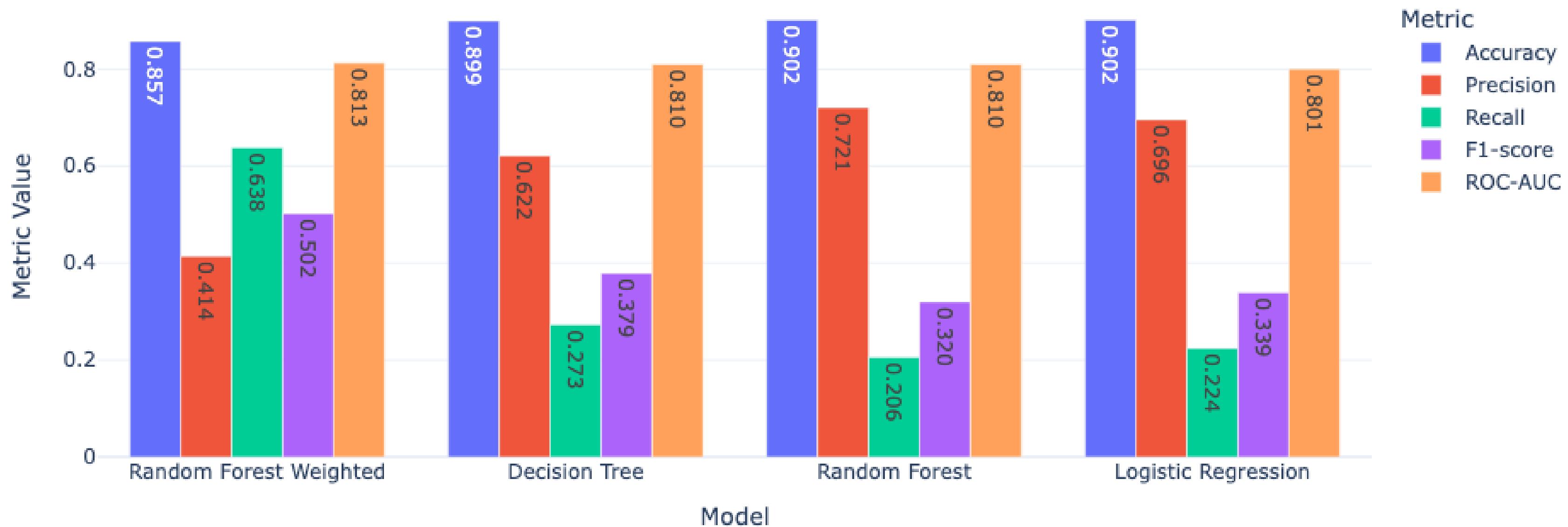
Model	ROC-AUC	Recall	Precision	F1-score	Accuracy
Random Forest Weighted	0.813	0.638	0.414	0.502	0.857
Decision Tree	0.810	0.273	0.622	0.379	0.899
Random Forest	0.810	0.206	0.721	0.320	0.902
Logistic Regression	0.801	0.224	0.696	0.339	0.902

Highest ROC-AUC: The Weighted Random Forest is best at ranking clients by subscription likelihood.

Misleading Accuracy: The non-weighted models show higher accuracy (~90%) by defaulting to the majority "No" class, but they fail to identify most actual subscribers (low Recall).

The Critical Trade-Off: Notice the inverse relationship between Recall and Precision. We will explore this next.

Model Performance Comparison Across Metrics



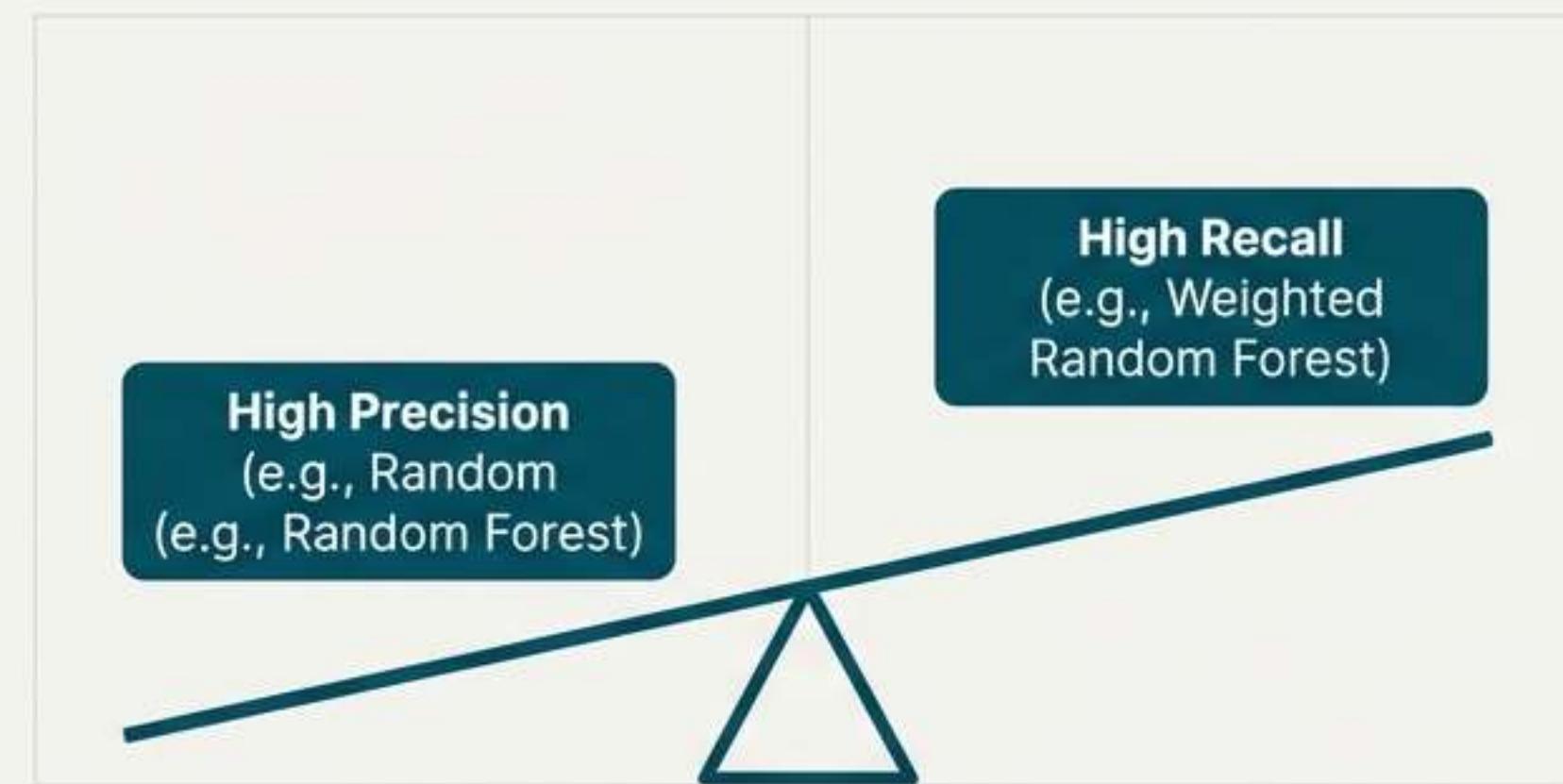
Why the Weighted Random Forest is the Right Business Choice

High Precision

What it means: When the model predicts "Yes", it's very likely to be correct.

Business Cost: We miss a large number of potential subscribers (low Recall).

High cost of missed opportunity.



High Recall

What it means: The model successfully identifies a large portion of all actual subscribers.

Business Cost: We contact some clients who won't subscribe (lower Precision).

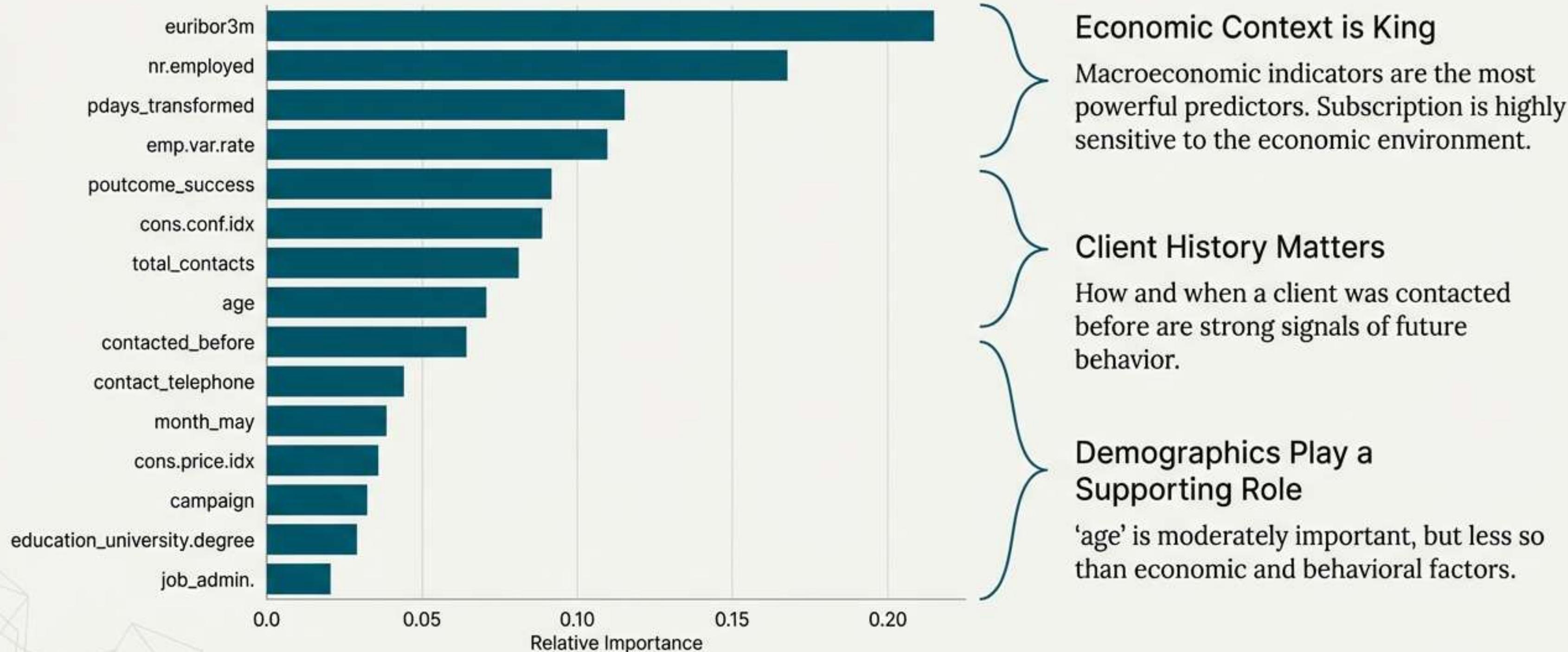
Acceptable cost of marketing spend.

For a growth-oriented marketing campaign, **missing a potential customer (False Negative) is more costly than contacting a non-subscribing one (False Positive)**.

The Weighted Random Forest's high Recall (0.638) makes it the superior model for maximizing lead generation.

Decoding the Model: What Factors Drive Subscription?

Top 15 Feature Importances (Weighted Random Forest)



Quantifying the Impact: A Look at Predicted vs. Actual Outcomes

		Predicted	
		No	Yes
Actual	No	6463	843
	Correctly ignored non-subscribers	Cost of unnecessary marketing contacts	
Yes	No	337	595
	Cost of missed opportunities	Successfully identified subscribers	

The model successfully identifies **63.8%** of all potential subscribers in the test set.

For every 10 leads the model flags as positive, approximately **4** will convert. This trade-off was deemed acceptable to capture the majority of interested clients.

From Insights to Action: Strategic Recommendations



Target Based on Economic Climate

Insight:

Macroeconomic features are dominant predictors.

Action:

Prioritize and potentially increase marketing spend during periods with favorable indicators (e.g., lower 'euribor3m', higher 'nr.employed').



Cultivate and Re-engage Past Contacts

Insight:

Previous campaign outcomes and contact history are highly predictive.

Action:

Develop targeted follow-up campaigns for clients with a 'poutcome' of 'success' and re-engage previously contacted clients.



Implement a Ranked-Lead System

Insight:

The model excels at ranking clients by subscription probability.

Action:

Use the model's probability scores to create a tiered contact list. Focus top-tier marketing efforts (e.g., experienced agents) on the highest-probability leads to maximize ROI.

Thank You!



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