

# Final Project Report

#### Bank Marketing (Campaign)

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**Specialization:** Data Science

Github: <a href="https://github.com/asat94/Data-Glacier-Internship">https://github.com/asat94/Data-Glacier-Internship</a>

# Agenda

PROBLEM STATEMENT BUSINESS UNDERSTANDING DATA EXPLORATION MODELLING DASHBOARD SUMMARY



Your Deep Learning Partner

#### **Problem Statement**

 ABC Bank wants to sell its term deposit product to customers. Before launching the product, the bank aims to develop a model to understand whether a particular customer will buy their product or not, based on the customer's past interaction with the bank or other financial institutions.







### **Business Understanding**

**Objective:** Use Machine Learning to predict customers likely to subscribe to term deposits.

**Goal:** Optimize marketing efforts, focusing resources on high-probability customers.

#### **Benefits:**

Increased conversion rates

Cost savings by minimizing wasted marketing efforts

#### **Two Model Scenarios:**

With 'Duration' Feature: Higher accuracy, but complex and not ideal for pre-call campaigns.

Without 'Duration' Feature: Simpler, more practical for operational use.

**Focus:** Balance technical performance and business feasibility for a transparent, effective model aligned with marketing goals.

# Project Lifecycle and Deadlines

Week	Deadline	Assignment
Week 7	2025.03.19	Business Understanding
Week 8	2025.03.26	Data Understanding
Week 9	2025.04.02	Data Cleansing and Transformation
Week 10	2025.04.09	EDA
Week 11	2025.04.16	EDA Presentation and proposed modeling technique
Week 12	2025.04.23	Model Selection and Model Building/Dashboard
Week 13	2025.04.30	Final Project Report and Code

### **Data Exploration**

Bank-full data

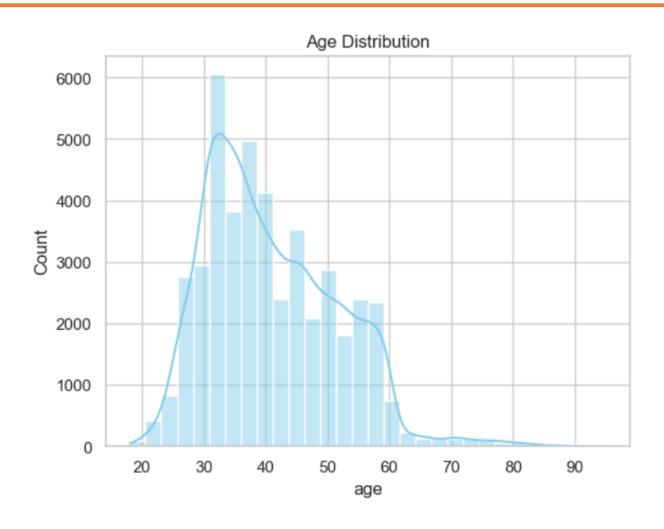
**Total Data** 

- 45,211 rows
- 17 columns

- Data Cleaned & Formatted
- Checked Missing Values & Outliers

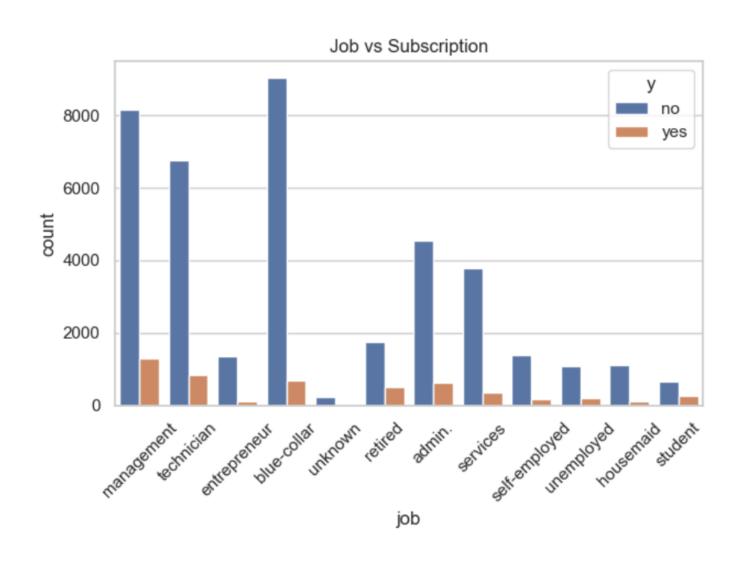
#	Column	Non-Null Count	Dtype
0	age	45211 non-null	int64
1	job	45211 non-null	object
2	marital	45211 non-null	object
3	education	45211 non-null	object
4	default	45211 non-null	object
5	balance	45211 non-null	int64
6	housing	45211 non-null	object
7	loan	45211 non-null	object
8	contact	45211 non-null	object
9	day	45211 non-null	int64
10	month	45211 non-null	object
11	duration	45211 non-null	int64
12	campaign	45211 non-null	int64
13	pdays	45211 non-null	int64
14	previous	45211 non-null	int64
15	poutcome	45211 non-null	object
16	У	45211 non-null	object

### **Age Distribution**



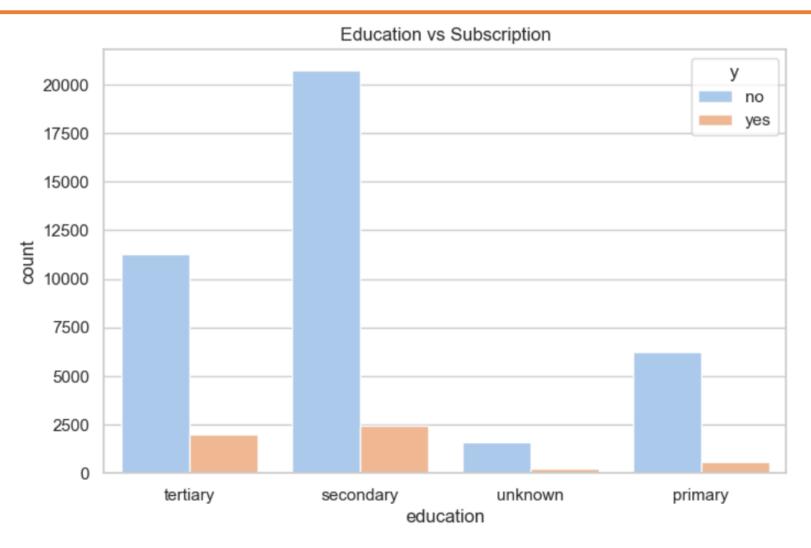
Customers are mainly between 25 to 60 years old, a key demographic for term deposits

#### Job vs Subscription



Management and technician roles show higher subscription rates.

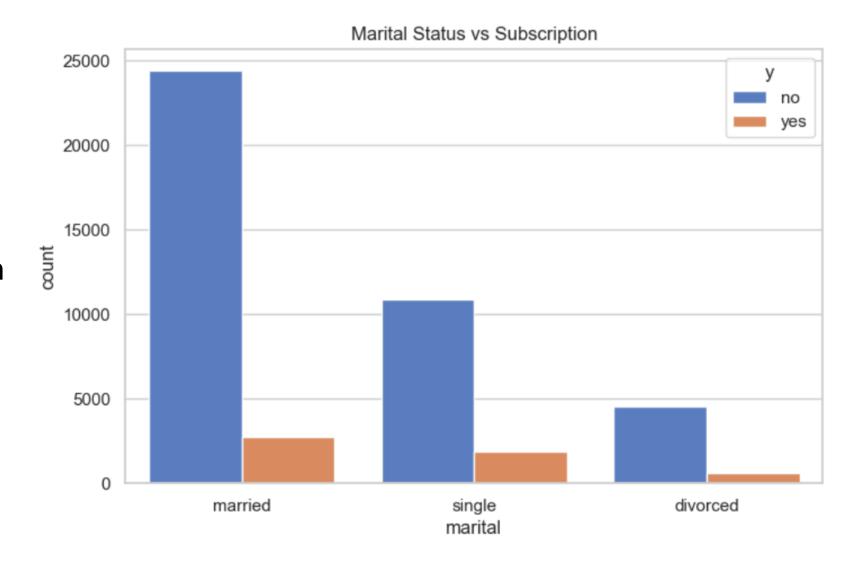
### **Education vs Subscription**



<u>Tertiary</u> educated customers are more likely to subscribe.

### Marital Status vs Subscription

Single customers tend to have higher subscription rates than married/divorced

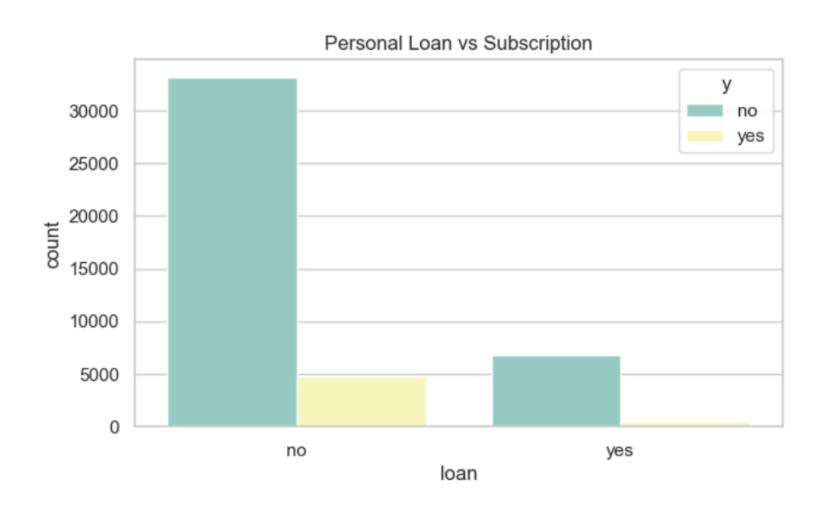


### **Housing Loan Status**



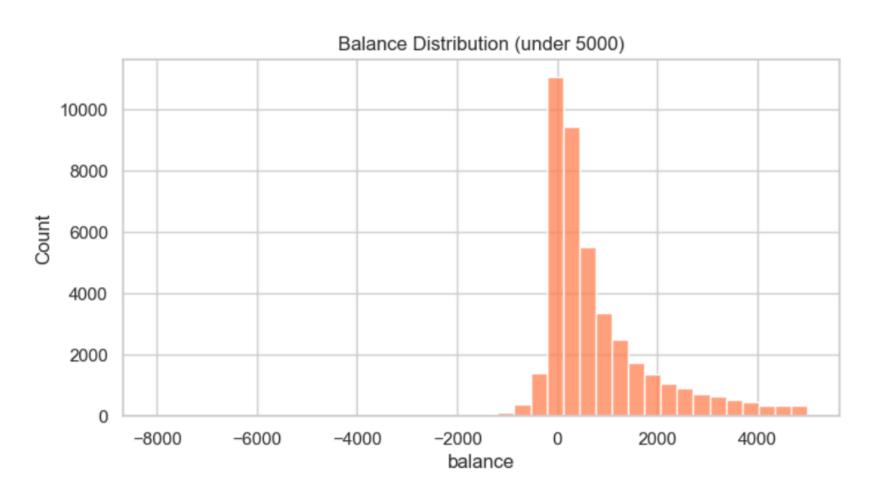
Customers without housing loans appear slightly more likely to subscribe

#### **Personal Loan Status**



Those without personal loans show better subscription interest

## Balance Distribution (Zoomed In)



Most customers have balances under 5000, indicating a middle-income audience

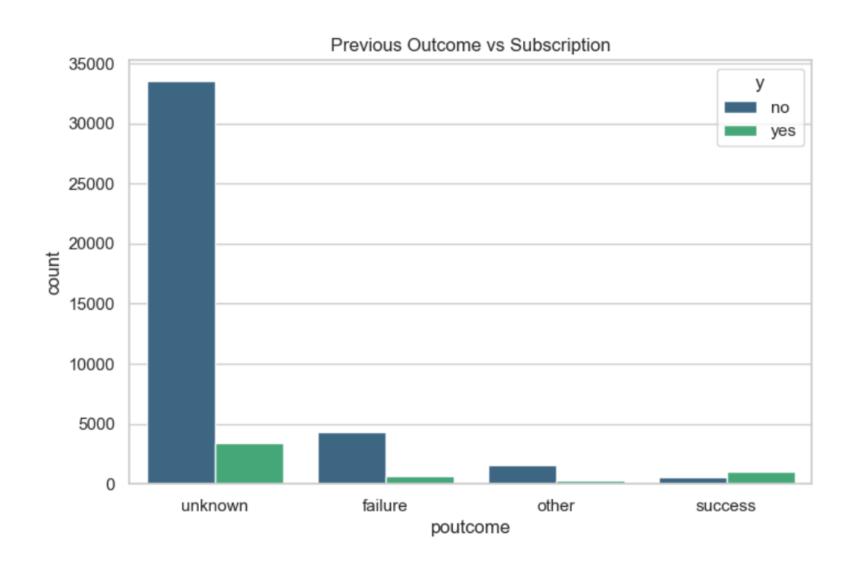
## Contact Method vs Subscription



Customers contacted via cellular show better subscription rates

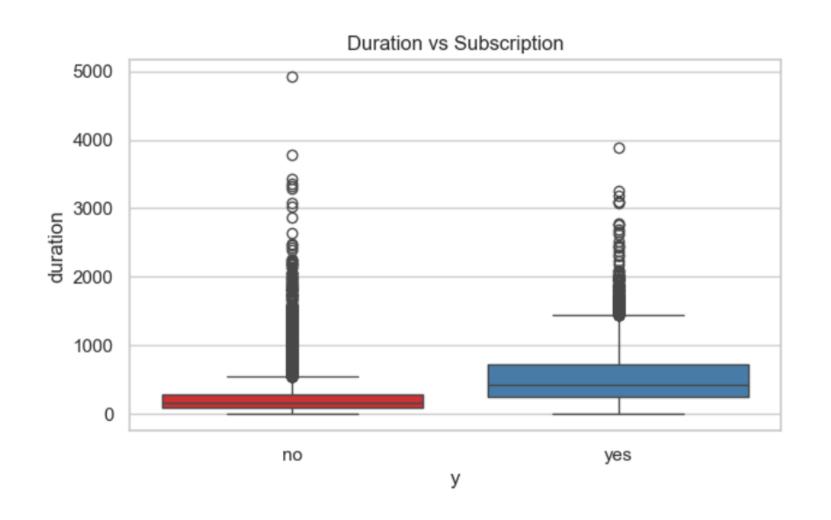


### Previous outcome vs Subscription



Successful outcomes in prior campaigns drastically improve subscription chances

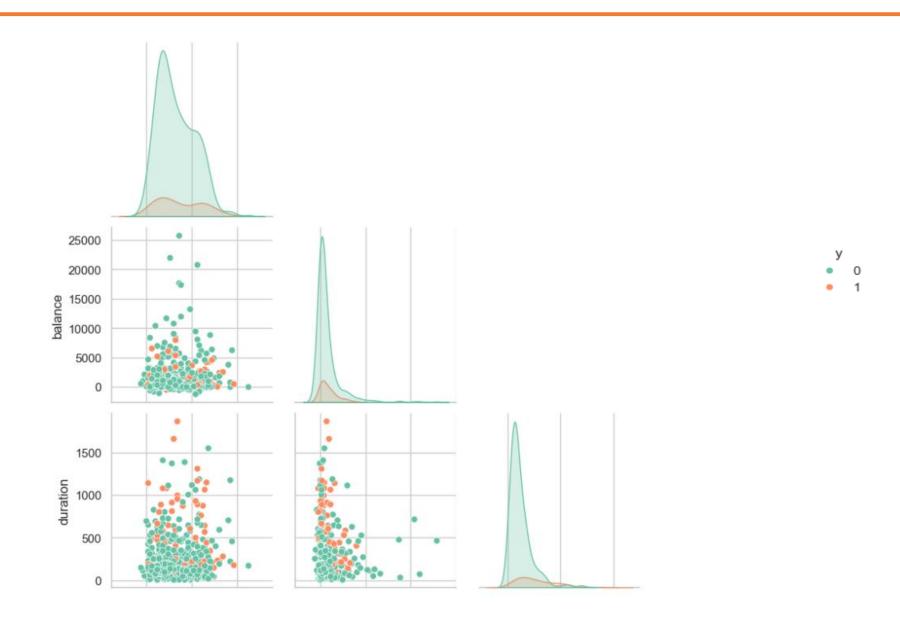
### **Duration vs Subscription**



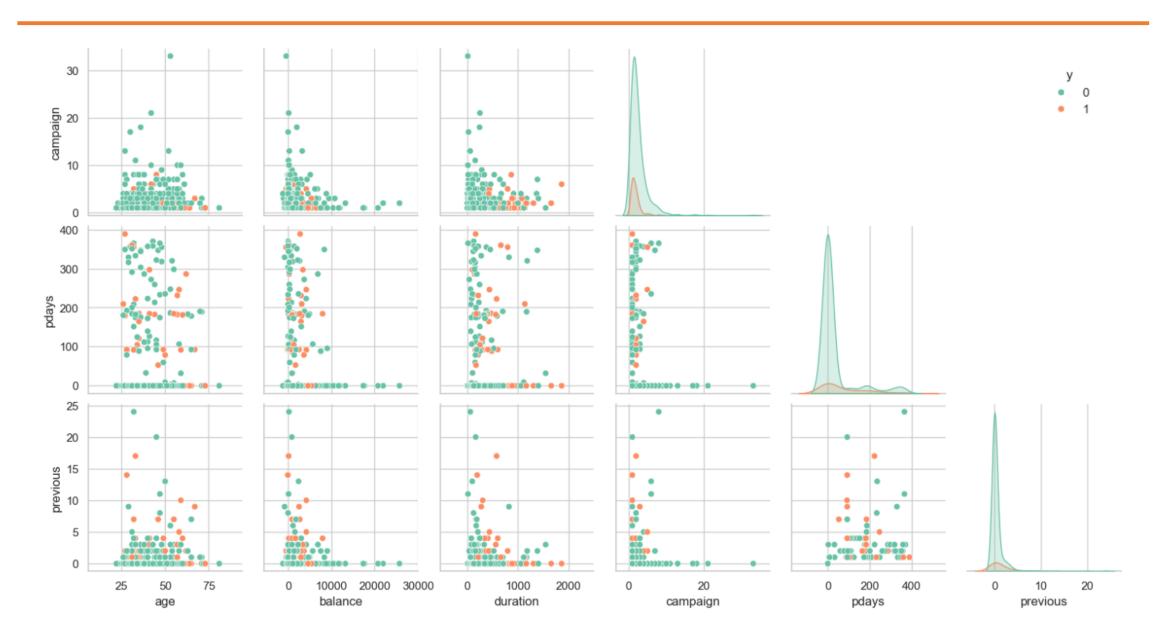
Longer call durations often lead to a 'yes' decision — indicating interest builds over time.



# Pair Plot (Scatter Matrix)



## Pair Plot (Scatter Matrix)



## Modelling

=== LR with o	duration === precision	recall	f1-score	support	=== LR w/o dur	ration === precision	recall	f1-score	support
0	0.91	0.98	0.94	7952	0	0.90	0.99	0.94	7952
1	0.64	0.30	0.41	1091	1	0.70	0.16	0.26	1091
accuracy			0.90	9043	accuracy			0.89	9043
macro avg	0.78	0.64	0.68	9043	macro avg	0.80	0.57	0.60	9043
weighted avg	0.88	0.90	0.88	9043	weighted avg	0.87	0.89	0.86	9043
=== RF with duration ===									
=== RF with o	duration ===				=== RF w/o dur	ration ===			
=== RF with o	duration === precision	recall	f1-score	support	=== RF w/o dur	ration === precision	recall	f1-score	support
=== RF with 0		recall 0.97	f1-score	support 7952	=== RF w/o dur		recall 0.99		
	precision					precision		f1-score 0.94 0.31	support 7952 1091
0	precision 0.92	0.97	0.94	7952	0 1	precision 0.90	0.99	0.94 0.31	7952 1091
ø 1	precision 0.92	0.97	0.94 0.49	7952 1091	0	precision 0.90	0.99	0.94	7952

- Including the duration variable significantly improves performance across all models.
- Random Forest with duration achieves the best overall performance

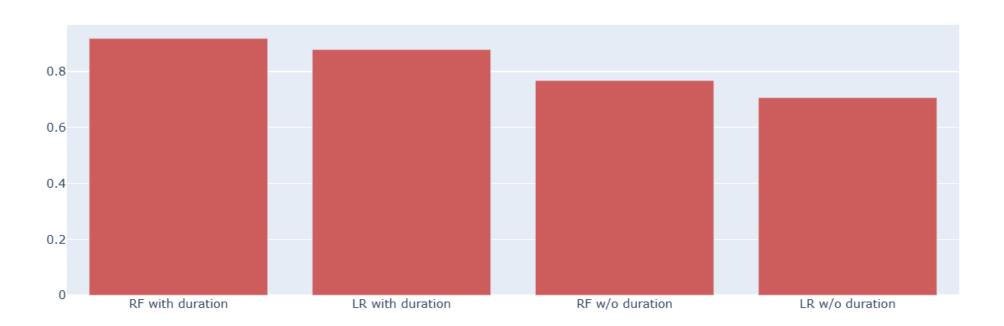
#### **ABC Bank Term Deposit Prediction Dashboard**

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Model AUC Scores

**AUC Comparison Across Models** 

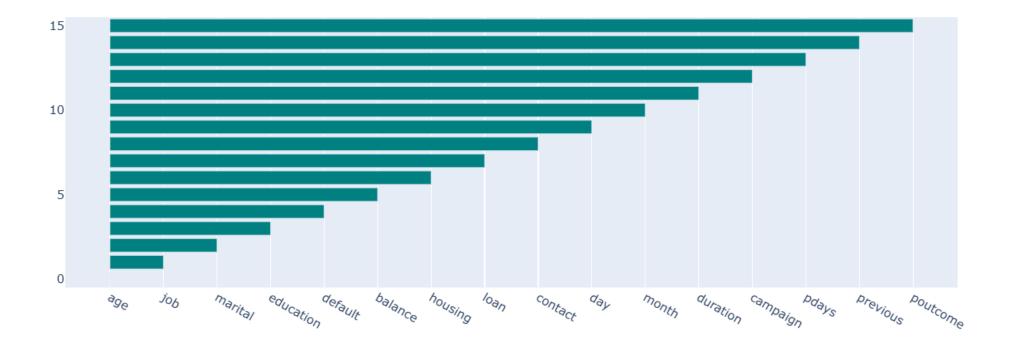




#### Random Forest with Duration

#### **Random Forest (with Duration) - Feature Importances**

Top Predictive Features

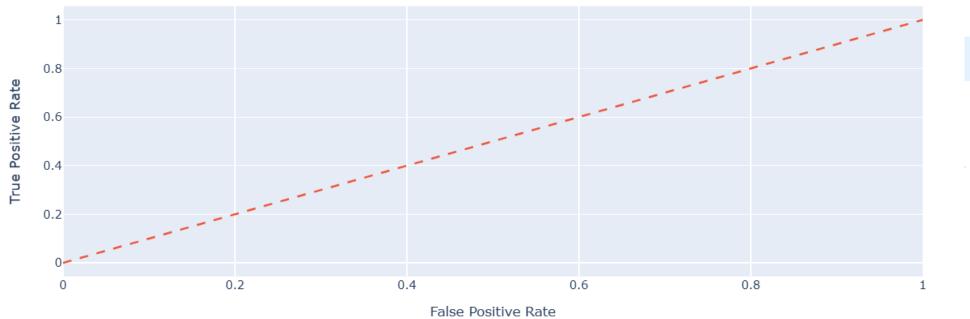


#### Select Model for ROC Curve

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RF with duration × 🔻

ROC Curve: RF with duration



LR with duration

RF with duration

LR w/o duration

RF w/o duration

### Summary

Objective: Predict customer subscription using past interaction data.

#### **Key Findings:**

- Higher subscription rates among management/technician roles and tertiaryeducated customers.
- Longer call duration and positive past outcomes strongly linked to subscriptions.
- Subscribed customers often have higher balances.

#### **Model Performance:**

Random Forest with 'duration' achieved top ROC-AUC (0.918).

#### Conclusion:

ABC Bank can enhance targeting and maximize marketing ROI using the Random Forest model with key customer insights.

# THANK YOU

