Credit Card Cross-Selling Analysis And Prediction

Introduction:

Project Overview

- **Context:** The project targets predicting potential credit card leads for Happy Customer Bank.
- The bank aims to identify customers with a higher likelihood of taking a recommended credit card. Various customer demographics, account details, and engagement metrics are included to support targeted marketing.
- **Dataset Summary:** Key features include Age, Average Account Balance, Occupation, and Credit Product status, with the target variable being Is_Lead.
- **Business Importance:** Accurate prediction can enhance marketing efficiency and customer targeting

Objectives:

Project Objectives

1. **Data Understanding & Cleaning:**
    - Handle missing values.
    - Perform categorical encoding and feature scaling.
2. **Exploratory Data Analysis (EDA):**
    - Analyze customer demographics and financial behavior.
    - Visualize relationships between features and the target variable.
3. **Model Development & Evaluation:**
    - Test and compare different machine learning models.
    - Tune hyperparameters for better performance.
4. **Model Selection:**
    - Choose the best model based on precision, recall, and F1-score.

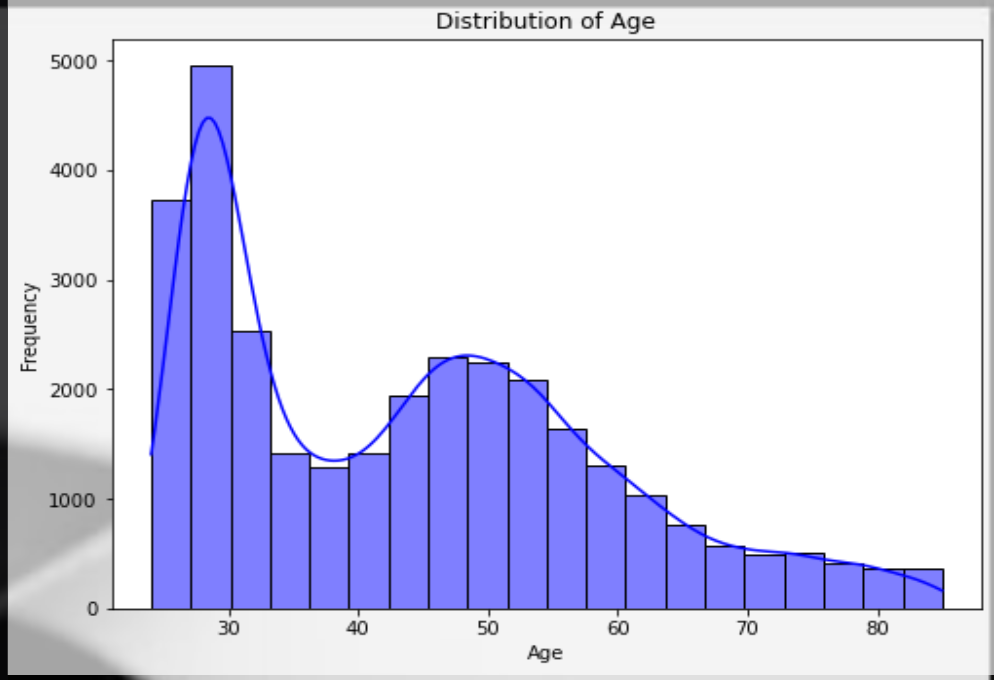
Observations:

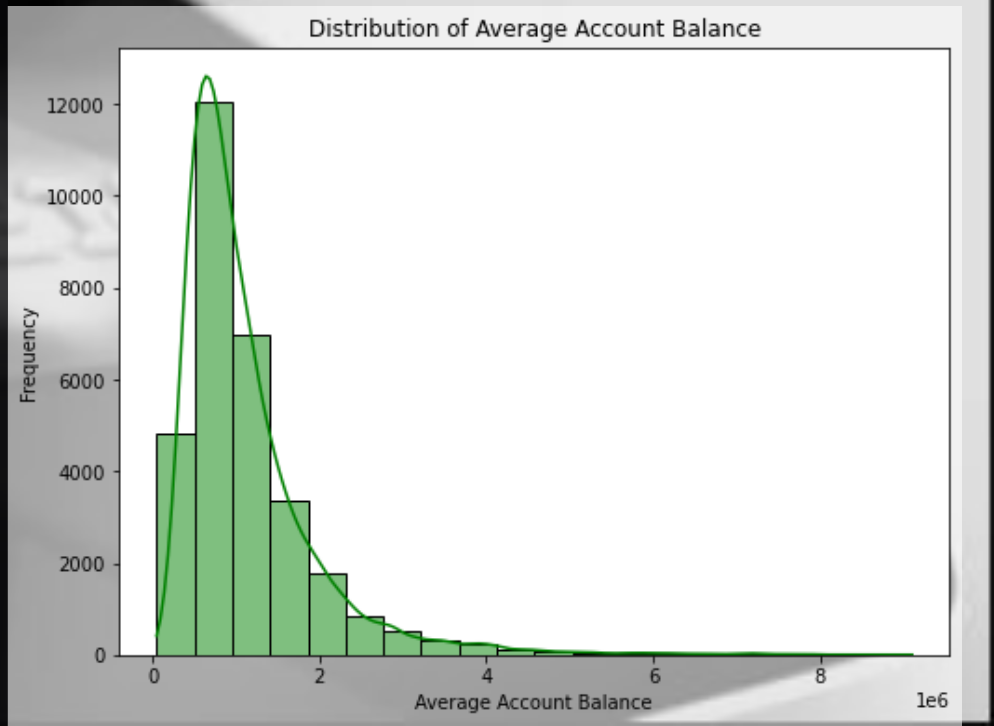
The Age distribution is likely unimodal, with most values concentrated around a specific range (e.g., 25–45 years), depending on the dataset.

Skewness:

Since the distribution is right-skewed it indicates younger customers dominate.

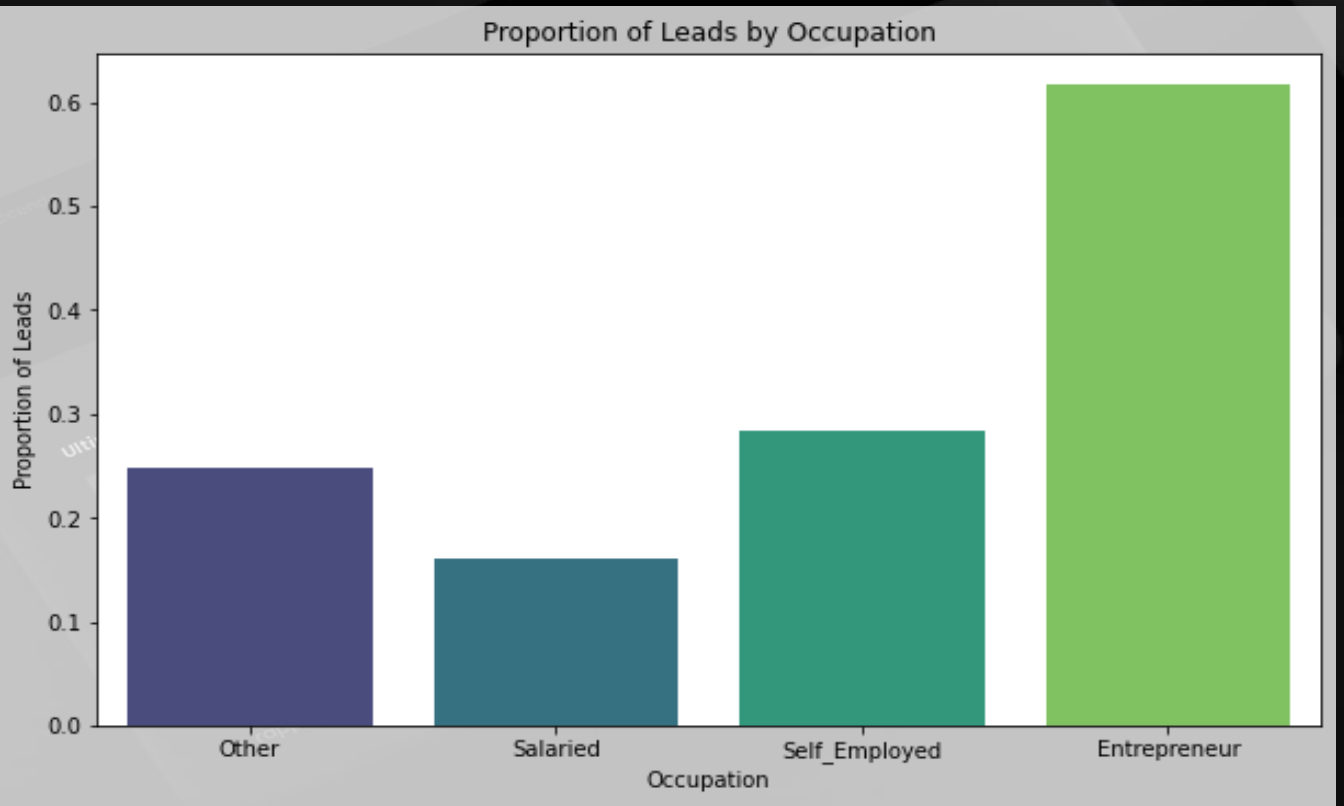
Avg_Account_Balance might show significant right-skewness, meaning most customers have a low balance while a few have very high balances.

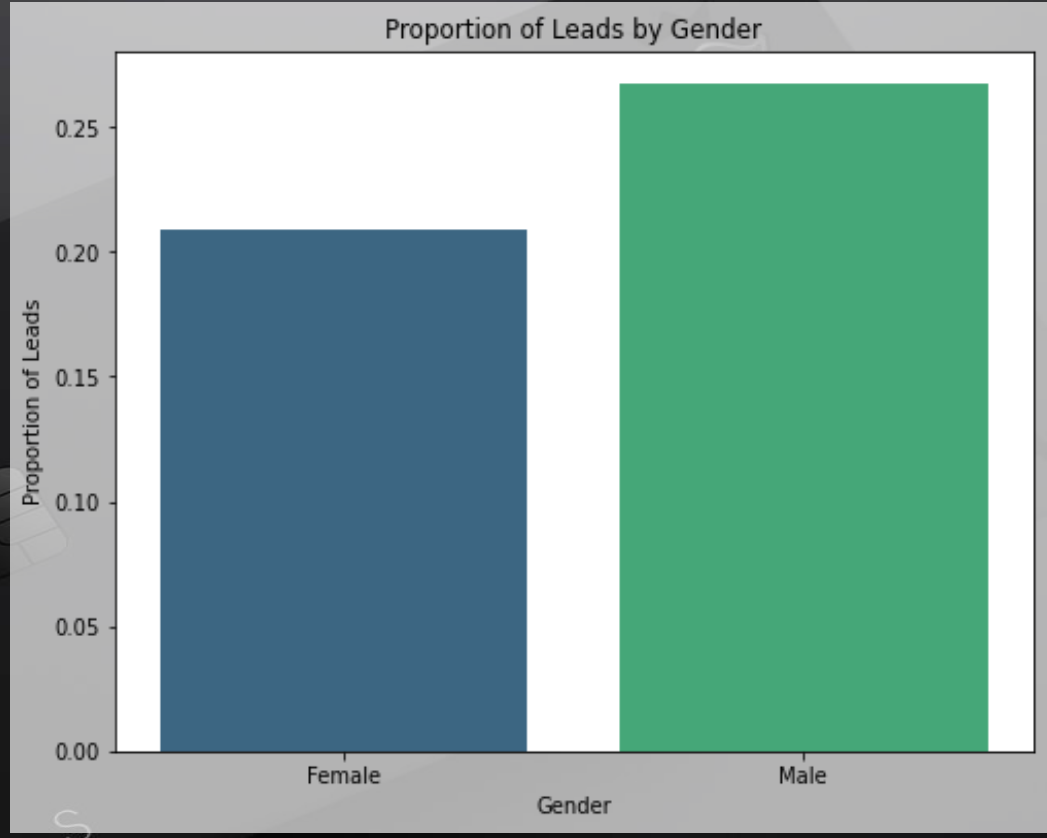




Entrepreneurs stand out as the occupation category with the highest proportion of leads (above 60%).

This suggests that entrepreneurs are highly interested in the financial product or service being offered.





Males seems to dominate the lead conversions

The pairplot reveals some separability between Is_Lead = 0 and Is_Lead = 1 based on features like Age and Avg_Account_Balance.

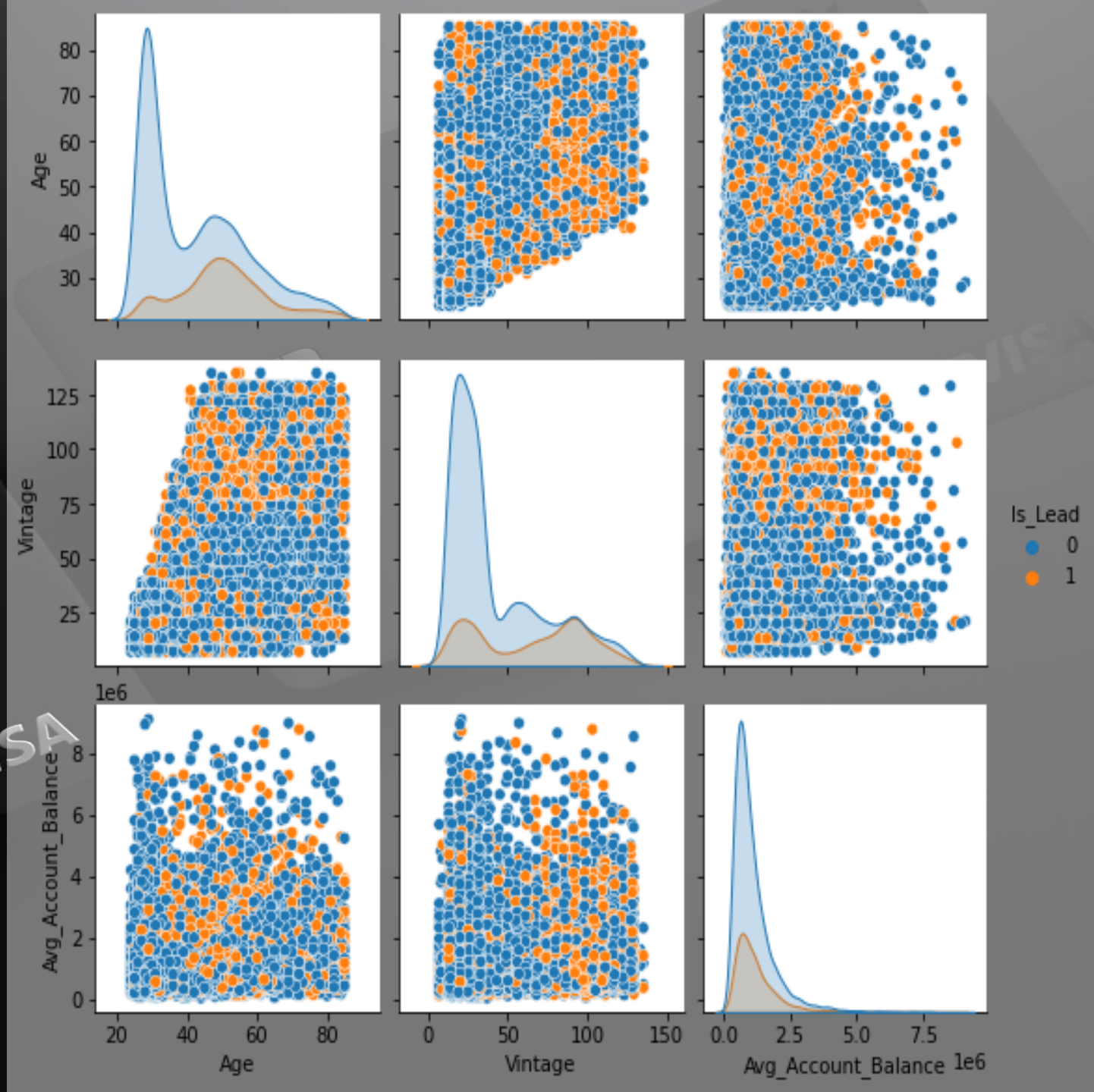
However, there's also overlap, indicating some noise in the data.

Imbalance in Target Variable:

The dataset is highly imbalanced, requiring resampling techniques or model adjustments

Metrics:

Use **Precision**, **Recall**, **F1-Score,** to evaluate the model, rather than accuracy, due to imbalance.



Feature Selection: The most Important Features are Occupation, Vintage, Credit_Product

Best Model Before Tuning:
Logistic Regression and **Gradient Boosting** had the highest precision (0.8496 and 0.8497).

Best Model After Tuning:
Decision Tree Classifier achieved the highest tuned precision (0.8567), followed closely by Random Forest Classifier (0.8550).

Thus, **Decision Tree Classifier** is the best model after hyperparameter tuning.

Model	Cross-Val Precision	Best Tuned Precision
Logistic Regression	0.8496 (Test)	0.8009
Random Forest Classifier	0.7429 (Test)	0.855
Gradient Boosting	0.8497 (Test)	0.8417
Decision Tree Classifier	0.7487 (Test)	0.8567

Evaluation of Models Before Tuning:

Logistic Regression (LR)

- **Precision**:
  - Train: **0.8496**, Test: **0.8496**
  - Consistently high precision, indicating the model has a strong ability to correctly identify positive cases when it predicts them.

- **Recall**:
  - Train: **0.4248**, Test: **0.4248**
  - Low recall, meaning the model misses a significant number of true positives.

- **F1-Score**:
  - Train: **0.5664**, Test: **0.5663**
  - Balanced but moderate F1-score, reflecting the trade-off between precision and recall.

- **Conclusion**: Logistic Regression offers high precision but sacrifices recall, which might not be ideal for imbalanced data where identifying true positives is critical.

Random Forest Classifier (RFC)

- **Precision**:
  - Train: **0.8350**, Test: **0.7435**
  - Train precision is good but overfits slightly, as the test precision drops.

- **Recall**:
  - Train: **0.4997**, Test: **0.4464**
  - Higher recall compared to LR, but still not ideal. Overfitting is noticeable.

- **F1-Score**:
  - Train: **0.6225**, Test: **0.5544**
  - Higher than LR on training but drops significantly on testing, again indicating overfitting.

- **Conclusion**: Random Forest improves recall slightly over LR but suffers from overfitting, as evidenced by the precision and F1-score drop on the test set.

Evaluation of Models Before Tuning:

Gradient Boosting (GB)

- **Precision**:
  - Train: **0.8500**, Test: **0.8497**
  - Very consistent between train and test, with minimal overfitting.

- **Recall**:
  - Train: **0.4252**, Test: **0.4251**
  - Similar recall performance to LR, which is relatively low.

- **F1-Score**:
  - Train: **0.5669**, Test: **0.5665**
  - Matches LR almost identically but offers slightly better stability.

- **Conclusion**: Gradient Boosting performs similarly to Logistic Regression but with slightly better generalization. Its precision-recall tradeoff is still an issue for imbalanced data.

Decision Tree Classifier (DTC)

Precision:

Train: **0.8628**, Test: **0.7490**

High train precision but overfits significantly, as test precision is much lower.

Recall:

Train: **0.4748**, Test: **0.4179**

Recall drops significantly on the test set, suggesting overfitting.

F1-Score:

Train: **0.6118**, Test: **0.5351**

Higher than LR and GB on training but lower on testing due to overfitting.

Conclusion: Decision Tree overfits the training data and generalizes poorly compared to other models.

The below table highlights the **precision** and **recall** for each model, including the best values after tuning.

Based on both **precision** and **recall**, the **Decision Tree Classifier (DTC)** stands out as the most reliable model for predicting leads. It provides the highest precision (**0.8567**) and recall (**0.5712**) after tuning, making it an ideal choice for situations where both false positives (predicting non-leads as leads) and false negatives (failing to predict actual leads) need to be minimized.

Model	Precision (Best Score)	Recall (Best Score)
Logistic Regression (LR)	0.8009	0.5277
Decision Tree Classifier (DTC)	0.8567	0.5712
Gradient Boosting Classifier (GBC)	0.8417	0.5597
Random Forest Classifier (RFC)	0.855	0.4804

Recommendation:

For this imbalanced dataset, the goal is to achieve a balance between **precision and recall** while minimizing overfitting. Based on the metrics:

Decision Tree Classifier:

- **Best Model After Tuning:** achieved the highest tuned precision (0.8567), followed closely by Random Forest Classifier (0.8550).
- Highest precision (critical for minimizing false leads).
- Balanced trade-off between precision and recall

Use Case Justification

Precision: DTC performs very well at identifying leads accurately (precision of 0.8567).

Recall: DTC also performs well at capturing all the leads (recall of 0.5712), ensuring that fewer leads are missed.