Optimizing Resource Allocation for Maximum Revenue using 3 propensity models to target

- Credit card buyers
- Consumer loan buyers
- Mutual Fund buyers

Key Considerations for Resource Allocation for maximising revenue from credit card/consumer loan/mutual fund buyers

- Marketing Budget - Higher precision ensures fewer wasted offers, lowering cost per acquisition.
- Revenue per Customer - Capturing high-value customers is more important than just increasing sign-ups.
- Customer Lifetime Value (CLV): Prioritize customers who will actively use the credit card, not just sign up.
- Banks want to target the right customers while minimizing wasted marketing efforts.
- A Weighted Strategy with an optimized balance of Precision and Recall to be considered
- Primary Focus - Precision (to avoid marketing spend on uninterested customers).
- Secondary Focus - Balanced Recall (to ensure enough high-value customers are captured).
- Adjust the probability threshold to optimize for the highest net profit.

Strategy for maximising profit with optimised allocation of resources ie. selecting the customers that contribute to high profit

1. Find the Best Probability Threshold on Validation Data
    a. The threshold that returns the maximum profit is considered the best probability threshold on the validation data
    b. We have sales revenue for each customer corresponding to the product that was purchased, hence use net profit is computed to determine the optimal threshold on validation data.
    c. **Net Profit Computation**

        Net Profit = Total Revenue - Total Marketing Cost where
        Total Revenue = Total Revenue from Actual Buyers basically from all True Positives

        *Sum(Sales revenue per customer for the particular product * True Positives)*

        Marketing Cost = Total Marketing Cost spend on the targeted customers basically all true positives and false positives

        *Sum(Fixed Marketing cost per customer for the particular product *(TruePositives+FalsePositives))*

True Positives are the buyers predicted by the model who actually purchased
False Positives are the buyers predicted by the model but who didn't buy

2. After finding the optimal threshold on validation data, apply it to test data
3. Rank the customers in the test data based on the probabilities and get the predictions based on the optimal threshold. Select top 15% of customers & find profitable ones. (Offers can be targeted to 15% of clients, hence applying this cutoff to all the models and selecting the top best of customers from each model based on the product offers.
4. To identify the profitable customers in the top 15 % of testdata for which we do not have any revenue data. In this case, we can estimate **expected revenue** based on the **predicted probability** of a customer buying and their likelihood of generating revenue. The higher probability customers tend to generate more revenue, hence use predicted probability as a weight for potential revenue.
    1. Estimate the potential revenue per customer based on validation data.
    2. Use predicted probability to weight the revenue contribution of each customer.

In this methodology, validation data acts as a proxy for revenue-based threshold tuning. Even without revenue on test data, the same threshold should still optimize profitability. False positives are thereby reduced(wasted spend) while targeting high-value customers. In this way we can calculate the expected revenue for each customer.

Modeling Strategy

- 3 propensity models have been built to predict customers who will buy credit card, consumer loan and mutual fund.
- XGboost algorithm has been selected based on good predictive power and precision and recall metrics.
- Customer Profiles created based on models
- Assumptions made
    - Avg revenue of customer per product in the validation dataset weighted by the test customer's predictive probability was taken as the expected revenue of each customer in the test dataset.
    - The train and test datasets contained members with age <18, hence removed them to avoid performance reduction of the model
- Ultimately 15% of clients can be given offers to only 1 product. Hence from the 606 members in the testdata, we can target 90 customers. Hence we target 30 customers from each model. Total expected revenue - sum of adjusted expected revenue from the 30 customers of each model.

Customer Profile based on Credit Card Propensity Model

- **Optimised Threshold for maximum profit - 0.38**
- **Metrics based on this threshold**
- **Precision - 26%**
- **Recall - 71%**
- **TP- 57, FP - 166, FN - 23**

- **Confusion Matrix -** `[[118 166]`
- `[ 23  57]]`
- **Adjusted Expected Revenue from Top 15% Customers: 188.29 euro**

Customers in this segment have the following characteristics by which there is a high likelihood of purchasing credit card

- **ActBal_CA (Current Account Balance)**
  - Higher ActBal_CA increases the likelihood of buying a credit card.
  - Lower ActBal_CA decreases the likelihood.
- **VolumeDeb_PaymentOrder (Total Debit Volume via Payment Orders)**
  - Lower values negatively impact predictions.
  - Higher values increase the likelihood of credit card adoption.
- **ActBal_SA (Savings Account Balance)**
  - Customers with higher savings balances (red) tend to buy credit cards.
  - Lower values (blue) show no significant impact or reduce propensity.
- **VolumeCred (Total Credited Volume)**
  - Higher incoming funds are associated with a higher propensity to get a credit card.
  - Suggests financially active customers prefer credit products.
- **Age**
  - Higher Age values have mixed effects (some positive, some negative).
  - Younger customers may be less likely to take a credit card with some exceptions
- **Tenure**
  - Longer banking tenure increases the likelihood of credit card adoption.
  - Shows that loyal customers are more engaged.
- **Count_OVD (Number of Overdrafts)**
  - More overdraft occurrences increase the probability of getting a credit card.
  - Suggests financial needs or dependency on credit.

These customers(Client ids) fall into the above profile
19, 1487, 587, 978, 340, 1129, 1222, 1510, 382, 352, 651, 1077, 535, 1280, 1410, 389, 1076, 505, 1447, 1588, 375, 1455, 347, 715, 1120, 330, 541, 532, 1047, 748
Expected revenue from the 30 members is obtained as 73 euro

Key Points

- **High balances (ActBal_CA, ActBal_SA) and high transaction volume (VolumeCred, VolumeDeb) indicate higher credit card adoption.**
- **Customers with frequent overdrafts (Count_OVD) or large payment orders (VolumeDeb_PaymentOrder) are more likely to get a credit card.**
- **Older, long-tenured, and financially active customers have a higher credit card propensity.**

Customer Profile based on Consumer Loan Propensity Model

- **Optimised Threshold for maximum profit - 0.33**
- **Metrics based on this threshold**

- **Precision - 30%**
- **Recall - 76%**
- **TP - 74, FP-169 FN - 23**
- **Confusion Matrix -** `[[ 98 169]`
- `[ 23  74]]`

- **Adjusted Expected Revenue from Top 15% Customers: 193.44 euro**

Customers in this segment have the following characteristics by which there is a high likelihood of purchasing consumer loan

- **Tenure:**
  - Longer tenure increases the probability of getting a loan.
- **Age:**
  - Lower values of Age from young to middle aged have higher consumer loan acceptance. Higher aged customers have less chances but with exceptions.
- **VolumeDeb:**
  - High volume of debit transactions positively impact the likelihood of taking loan.
- **VolumeCred:**
  - Lower credit transaction positively impact the likelihood of taking a loan.
- **TransactionsDebCashless_Card & TransactionsDeb:**
  - High transaction activity can increase the likelihood of a loan approval.
- **ActBal_CA (Current Account Balance):**
  - Higher balance in a current account can push predictions towards a loan approval.
- **Count_CC (Credit Card Count):**
  - A high number of credit cards may slightly reduce loan approval likelihood.

These customers(Client ids) fall into the above profile
41, 852, 231, 886, 710, 403, 677, 1064, 1123, 1349, 342, 1341, 1096, 524, 183, 9, 1597, 1192, 1332, 786, 126, 1295, 760, 94, 1611, 206, 1049, 1356, 975, 889
Expected revenue from the 30 members is obtained as 72 euro

Customer Profile based on Mutual Fund Propensity Model

- **Optimised Threshold for maximum profit - 0.57**
- **Metrics based on this threshold**
  - **Precision - 25%**
  - **Recall - 23%**
  - **TP - 18, FP-55, FN - 60**
  - **Confusion Matrix -** `[[231  55]`
  - `[ 60  18]]`
- **Adjusted Expected Revenue from Top 15% Customers: 160.98 euro**

Customers in this segment have the following characteristics by which there is a high likelihood of purchasing mutual fund

- **VolumeCred & VolumeDeb**
  - Higher transaction volumes (both debit and credit) tend to increase the probability of mutual fund investment.
- **TransactionsDebCashless_Card**
  - Cashless transactions have positive impact on the prediction
- **ActBal_CA & ActBal_CL**
  - Customers with higher account balances show a higher likelihood of investing.
- Demographic variables like age and tenure play a role but are secondary compared to transactional behavior.

These customers(Client ids) fall into the above profile
200, 1553, 353, 766, 1225, 1119, 1516, 1229, 1226, 1008, 124, 1525, 594, 866, 354, 1313, 1148, 1487, 1007, 1088, 340, 697, 769, 521, 1480, 912, 635, 232, 109, 538

Expected revenue from the 30 members is obtained as 60 euro