

PREDICTING CUSTOMER CHURN



CALIFORNIA MARKET

VINAY BEESA GNANESHWAR

“A 5% INCREASE IN CUSTOMER
LOYALTY CAN PRODUCE PROFIT
INCREASES FROM 25% TO 85%”

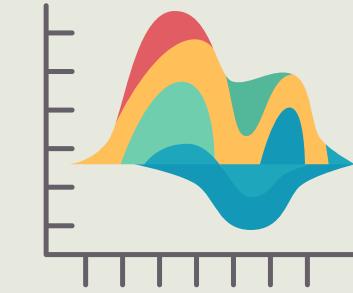
REICHHELD & SASSER (H.B.R)

PROBLEM

26% Churn Rate



DATASET



- Monthly Charges
- Age
- Tenure in Months
- Total Charges.



- Dependents
- Referred a Friend
- Contract type
- Payment Method.



7043

CUSTOMERS

60

UNIQUE VARIABLES

4

MODELS

CHURN

TARGET



VORTEX

DATA CLEANING

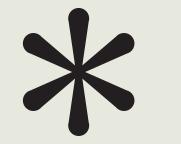
Column names in each DataFrame:

	df1	df2	df3	df4	df5
0	Customer_ID	LoyaltyID_df2	Customer_ID	Service ID_df5	Status ID_df5
1	Count_df1	Customer_ID	Count_df3	Customer_ID	Customer_ID
2	Country_df1	Senior Citizen_df2	Gender_df3	Count_df4	Count_df5
3	State_df1	Partner_df2	Age_df3	Quarter_df4	Quarter_df5
4	City_df1	Dependents_df2	Under 30_df3	Referred a Friend_df4	Satisfaction Score_df5
5	Zip Code_df1	Tenure_df2	Senior Citizen_df3	Number of Referrals_df4	Customer Status_df5
6	Lat Long_df1	Phone Service_df2	Married_df3	Tenure in Months_df4	Churn Label_df5
7	Latitude_df1	Multiple Lines_df2	Dependents_df3	Offer_df4	Churn Value_df5
8	Longitude_df1	Internet Service_df2	Number of Dependents_df3	Phone Service_df4	Churn Score_df5
9	Gender_df1	Online Security_df2	nan	Avg Monthly Long Distance Charges_df4	CLTV_df5
10	Senior Citizen_df1	Online Backup_df2	nan	Multiple Lines_df4	Churn Category_df5
11	Partner_df1	Device Protection_df2	nan	Internet Service_df4	Churn Reason_df5
12	Dependents_df1	Tech Support_df2	nan	Internet Type_df4	nan
13	Tenure Months_df1	Streaming TV_df2	nan	Avg Monthly GB Download_df4	nan
14	Phone Service_df1	Streaming Movies_df2	nan	Online Security_df4	nan
15	Multiple Lines_df1	Contract_df2	nan	Online Backup_df4	nan
16	Internet Service_df1	Paperless Billing_df2	nan	Device Protection Plan_df4	nan
17	Online Security_df1	Payment Method_df2	nan	Premium Tech Support_df4	nan
18	Online Backup_df1	Monthly Charges_df2	nan	Streaming TV_df4	nan
19	Device Protection_df1	Total Charges_df2	nan	Streaming Movies_df4	nan
20	Tech Support_df1	Churn_df2	nan	Streaming Music_df4	nan
21	Streaming TV_df1	nan	nan	Unlimited Data_df4	nan
22	Streaming Movies_df1	nan	nan	Contract_df4	nan
23	Contract_df1	nan	nan	Paperless Billing_df4	nan
24	Paperless Billing_df1	nan	nan	Payment Method_df4	nan
25	Payment Method_df1	nan	nan	Monthly Charge_df4	nan
26	Monthly Charges_df1	nan	nan	Total Charges_df4	nan
27	Total Charges_df1	nan	nan	Total Refunds_df4	nan
28	Churn Label_df1	nan	nan	Total Extra Data Charges_df4	nan
29	Churn Value_df1	nan	nan	Total Long Distance Charges_df4	nan
30	Churn Score_df1	nan	nan	Total Revenue_df4	nan
31	CLTV_df1	nan	nan	nan	nan
32	Churn Reason_df1	nan	nan	nan	nan

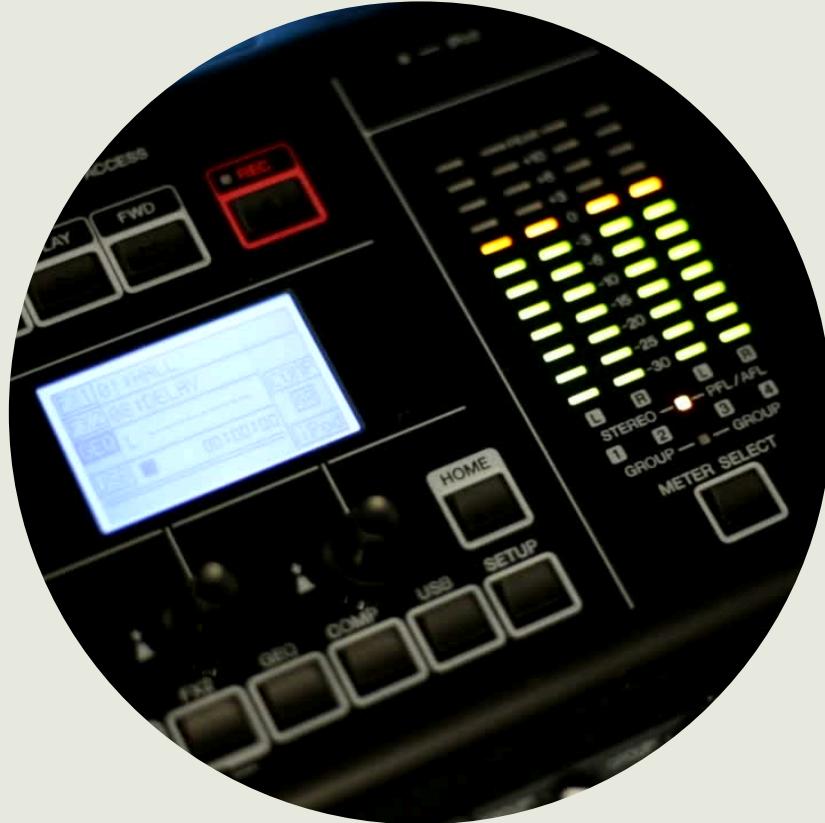
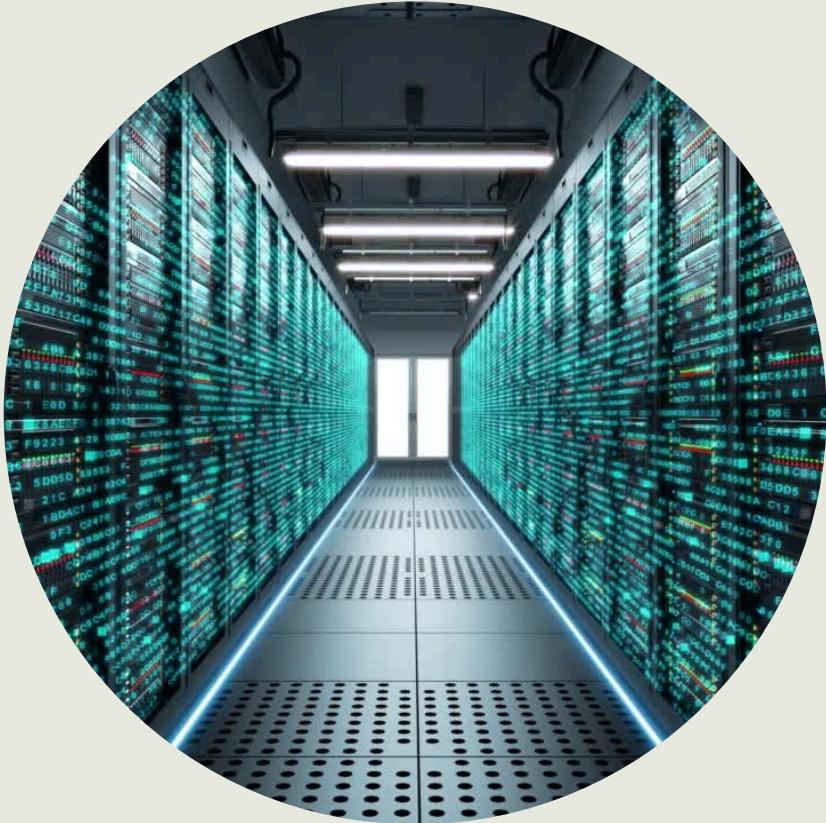


Column names in pre_dummy_df:

	pre_dummy_df
0	Monthly_Charges
1	Dependents
2	Churn
3	Age
4	Under_30
5	Number_of_Dependents
6	Referred_a_Friend
7	Number_of_Referrals
8	Tenure_in_Months
9	Offer
10	Avg_Monthly_Long_Distance_Charges
11	Multiple_Lines
12	Internet_Service
13	Internet_Type
14	Avg_Monthly_GB_Download
15	Online_Security
16	Online_Backup
17	Device_Protection_Plan
18	Premium_Tech_Support
19	Streaming_TV
20	Streaming_Movies
21	Streaming_Music
22	Unlimited_Data
23	Contract
24	Payment_Method
25	Total_Charges
26	Total_Refunds
27	Total_Extra_Data_Charges
28	Total_Long_Distance_Charges
29	Total_Revenue



DATA PREPROCESSING



DROPPING VARIABLES

- 102 to 30 variables
- Handled similar columns.
- Dropping all IDs.

STANDARDIZATION

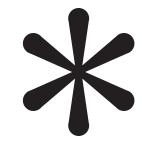
- Homogenization of nomenclature.
- Imputing missing values.
- Association of accurate data type.
- Outlier Detection.

PRE-MODELLING

- Dummy variables - binary.
- Creation of Train & Test dataset.

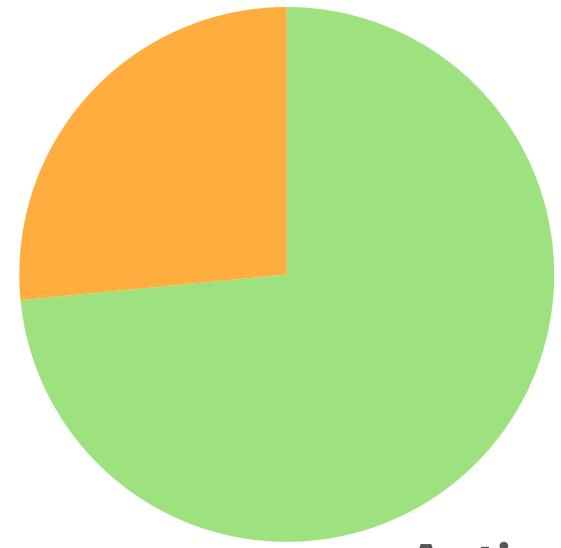


WHAT DOES THE
DATA TELL US?



VORTEX

Churned Customers
26.5%



Active Customers
73.5%

Churn vs Active

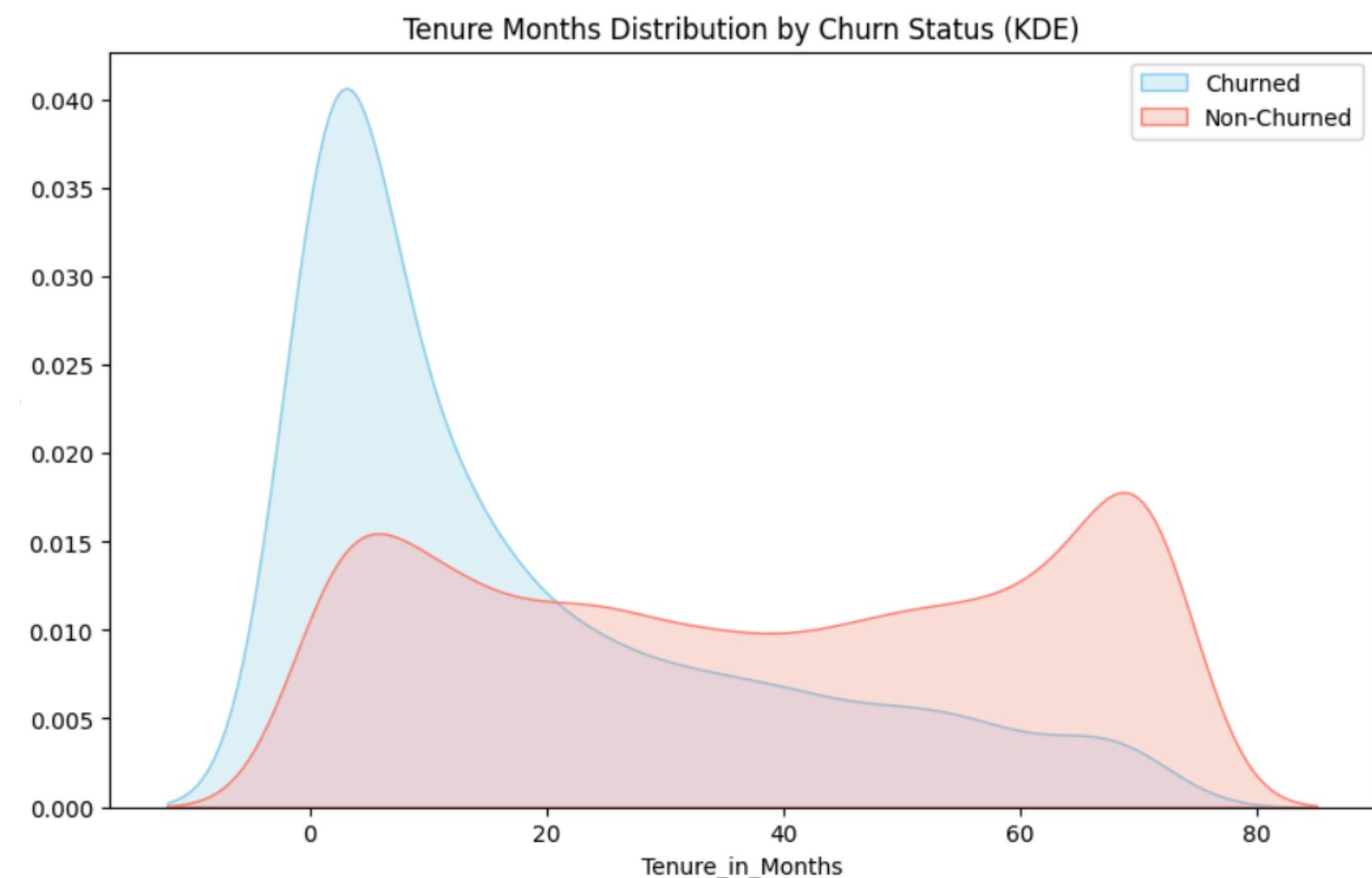
Active - 5174

Churned - 1869

Contract

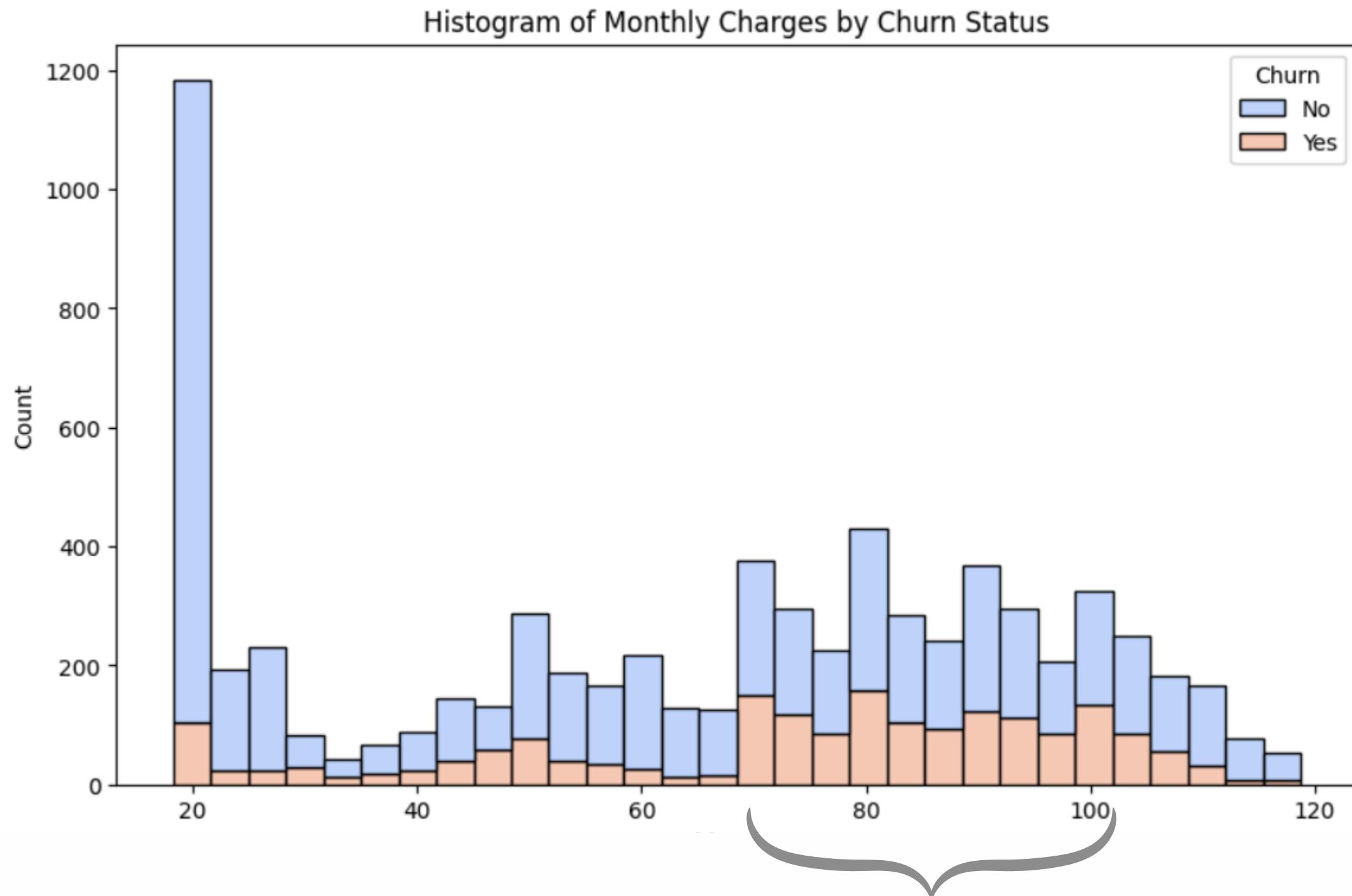
High Churns - 0 to 12 months

Low Churns - 12 onwards





CHURN BY CHARGES

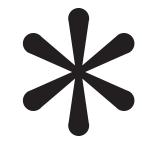


\$20

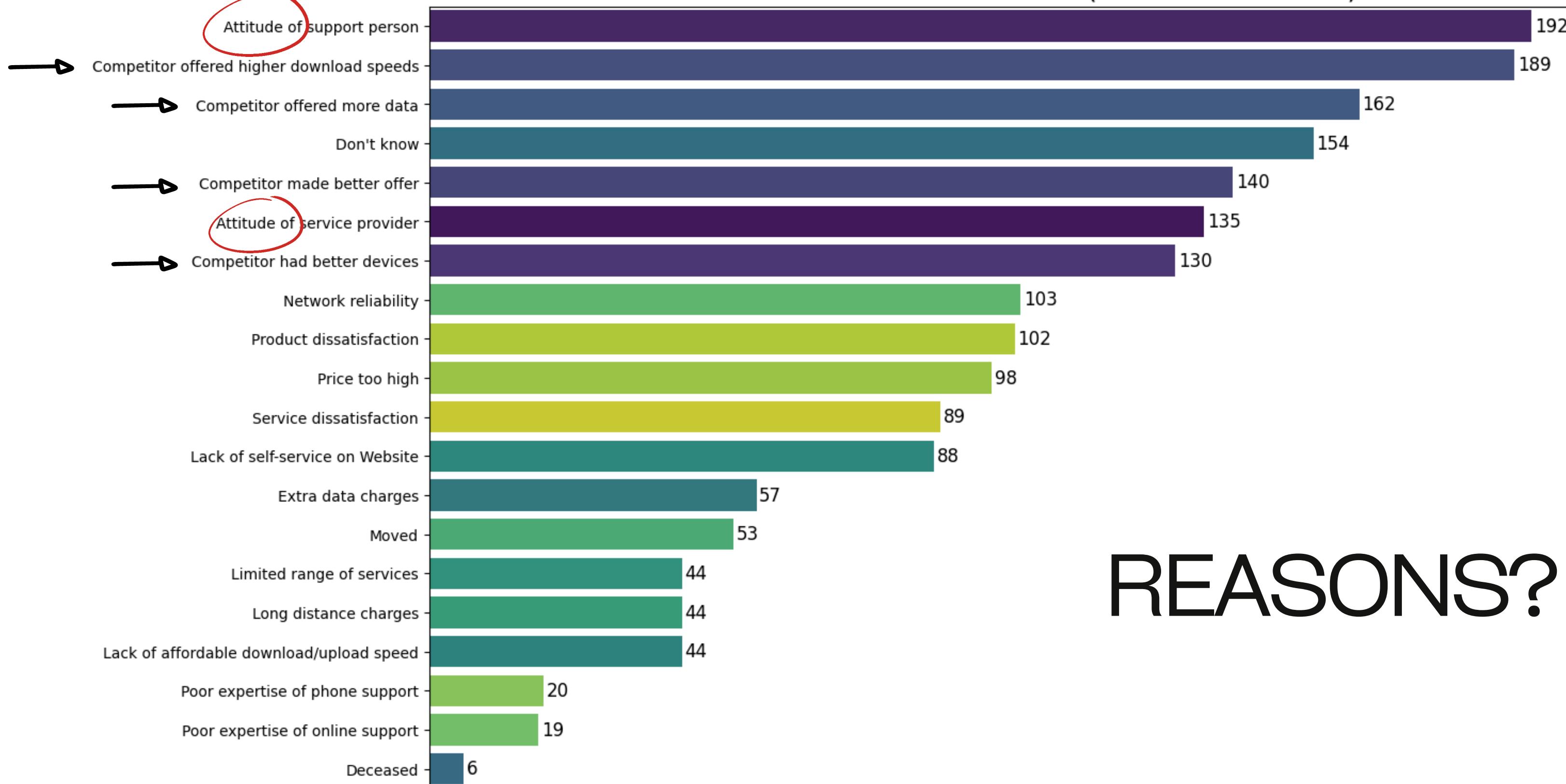
Majority of 'No' Churns

\$70 - \$100

Majority of Churns



Customer Churns & the Reason (Total Churns: 1869)



REASONS?



VORTEX

MODELS



LOGISTIC REGRESSION

Binary Predictor



K NEIGHBOUR CLASSIFIER

Neighbor Voting



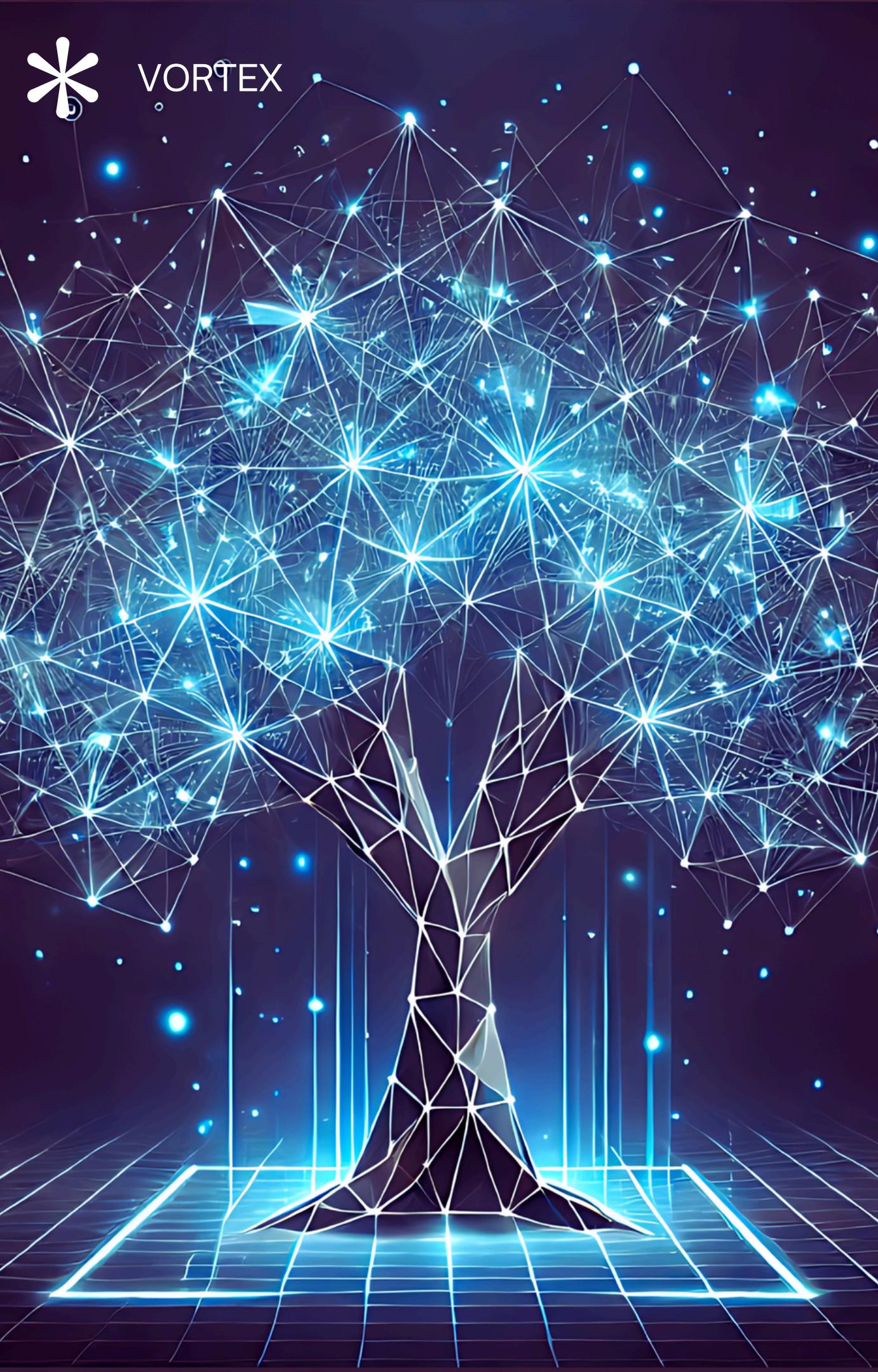
NEURAL NETWORK

Deep Learning



RANDOM FOREST

Tree Ensemble



VORTEX

RANDOM FOREST

01

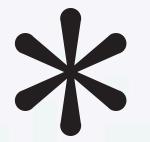
Ensemble Learning Method

02

Prediction & Accuracy

03

Robustness to Noise

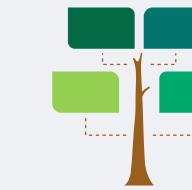


VORTEX

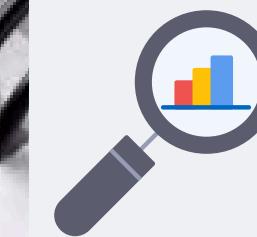
WHAT DOES IT DO?



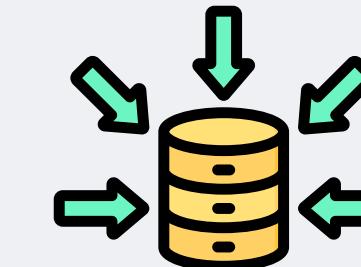
Bootstrapping



Growing Decision Trees



Predictions



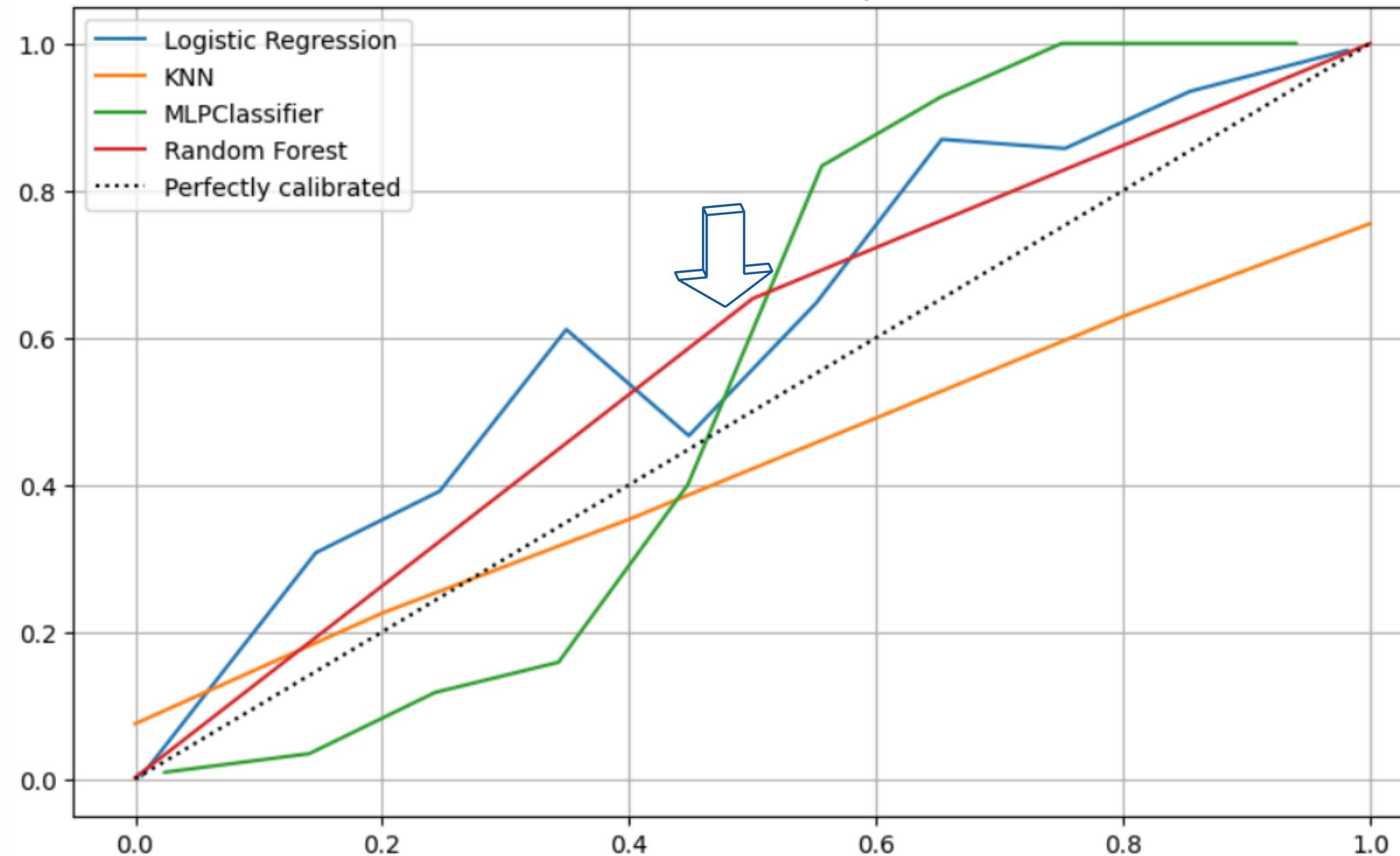
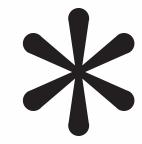
Aggregating Results

97%

Predicting Churn

98%

Accuracy



WHY?



Confidence & Accuracy

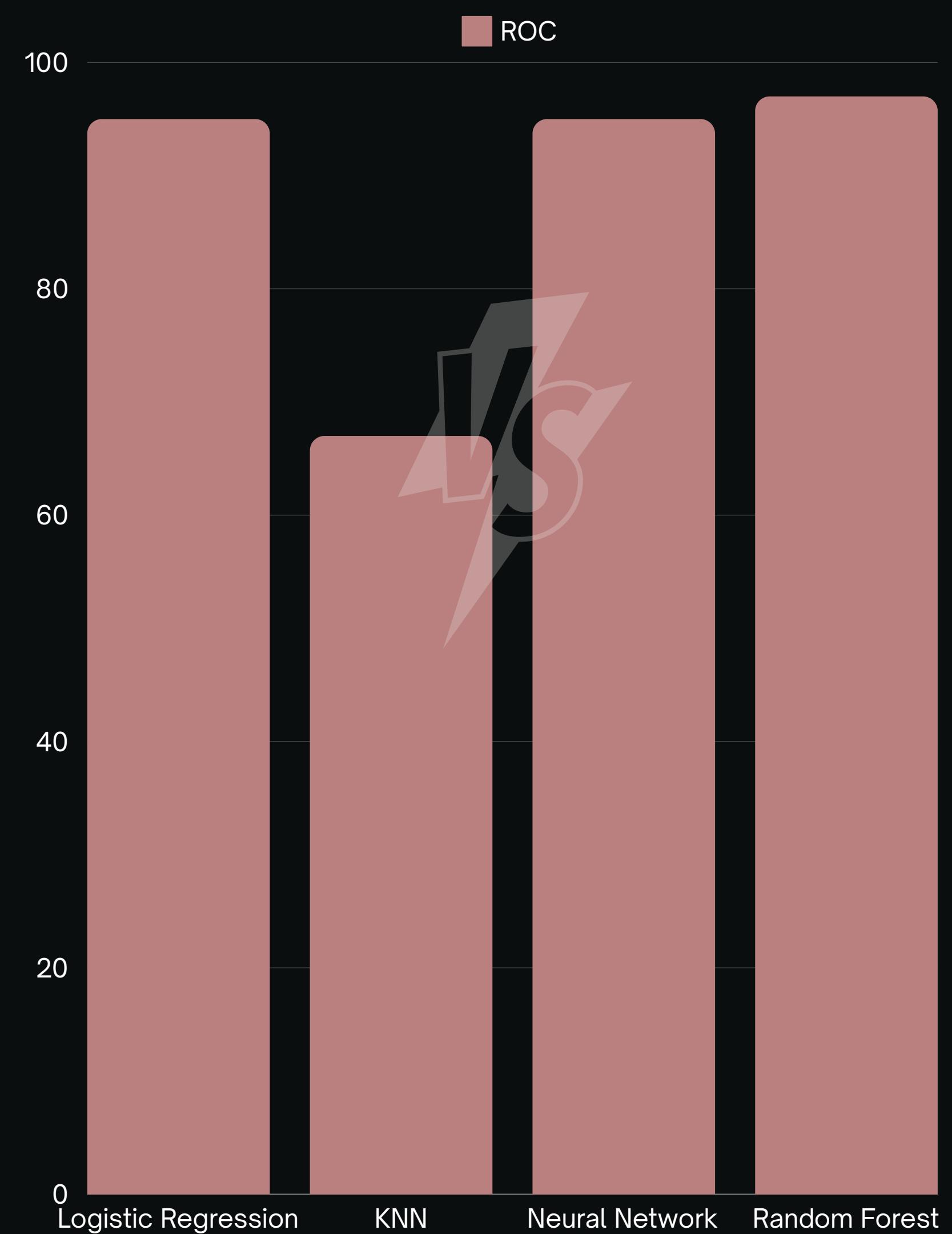


Handles Overfitting



VORTEX

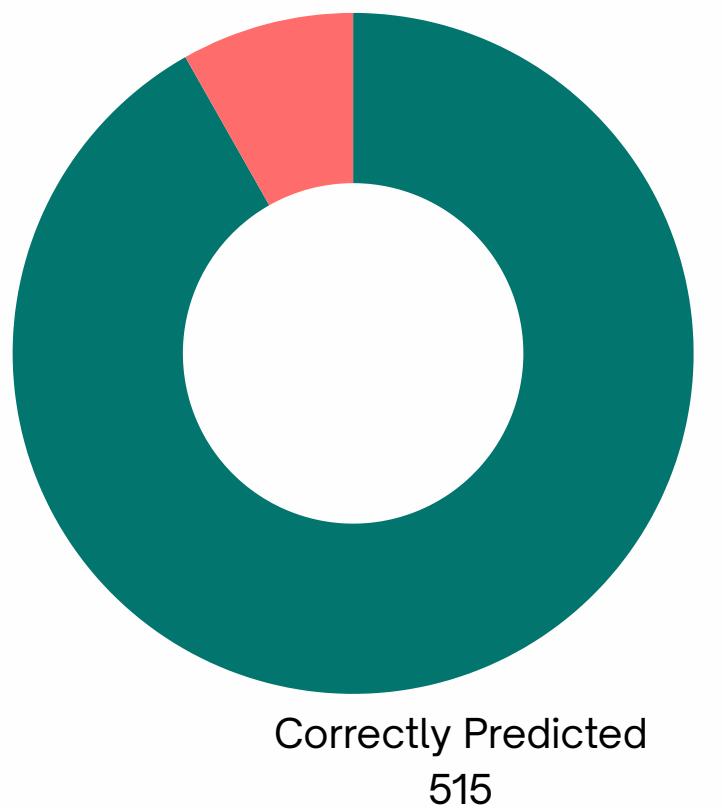
HOW DO THEY COMPARE?



Logistic Regression

Incorrectly Predicted

46



K-Nearest Neighbour

incorrectly Predicted
292

92



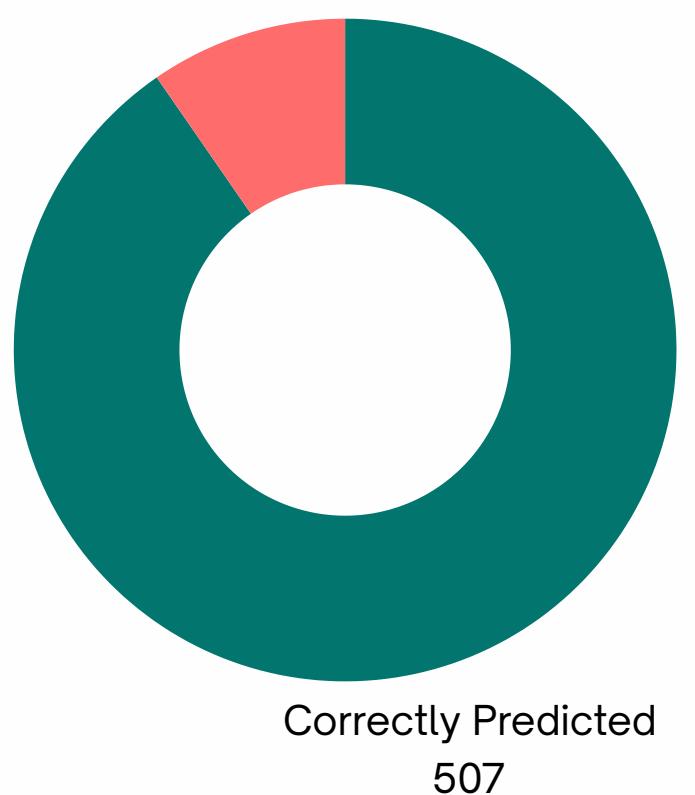
Correctly Predicted

269

Neual Network

Incorrectly Predicted

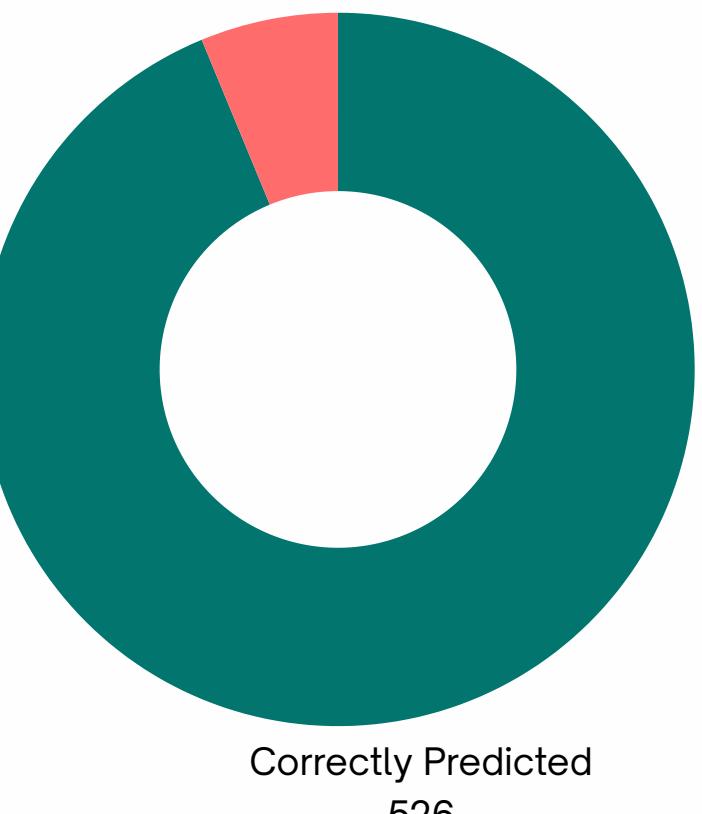
54



Random Forest

incorrectly Predicted

5



The image features a large, bold, black sans-serif font where the words "CONFUSION" and "MATRIX" are stacked vertically. The background is a grid of binary digits (0s and 1s) in a light gray color. At the bottom of the image, there is a smaller photograph of a man in a dark suit and glasses, looking down at a computer monitor. The monitor displays a 2D matrix of numerical data.

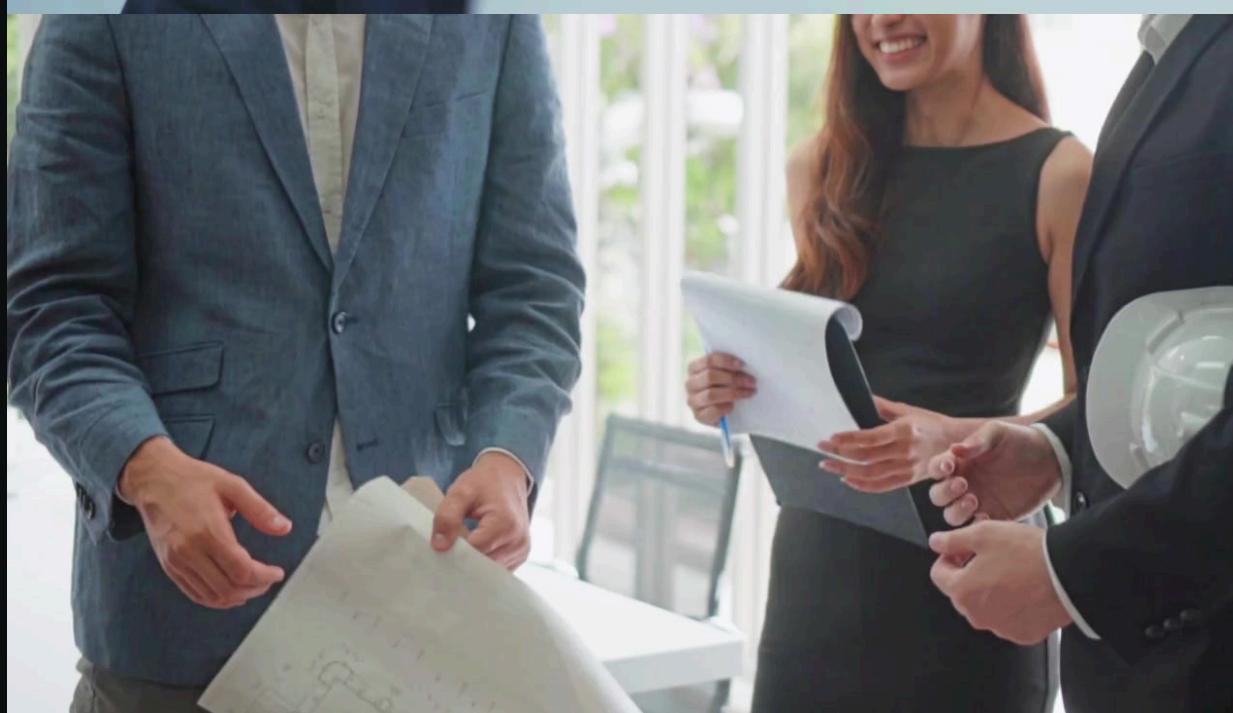
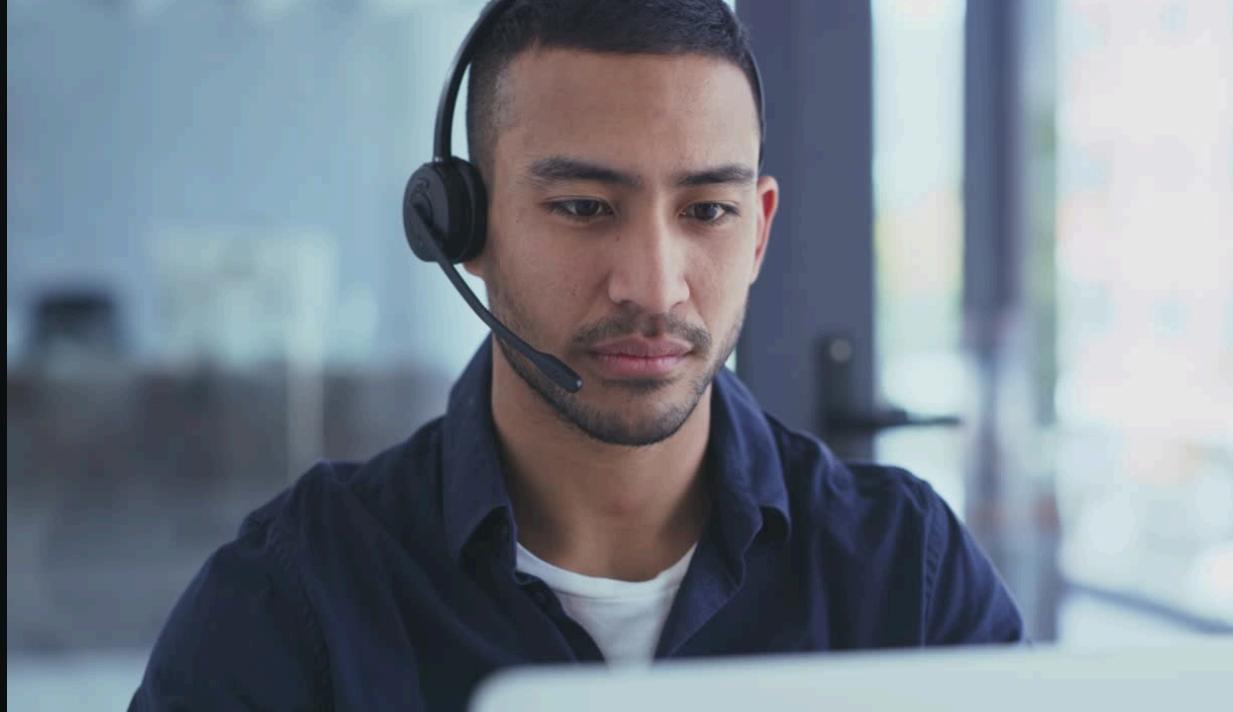
CONFUSION MATRIX

Contract_Month-to-Month
Numerical
Internet_Type_Fiber_Optic
Multiple_Lines_No
Avg_Monthly_GB_Download
Payment_Method_Credit_Card
Method_Bank_Withdrawal
Tenure_in_Months
Monthly_Charges
Internet_Service_Yes
Internet_Type_Cable
Age
Premium_Tech_Support_Yes
Only_Long_Distance_Charges
Dependents_No
Offer_Offer_E
Number_of_Dependents
Online_Security_Yes
Premium_Tech_Support_No
Streaming_Movies_No
Under_30_No
Under_30_Yes
Internet_Type_DSL
Unlimited_Data_No
Contract_One_Year
Streaming_Music_No
Device_Protection_Plan_Yes
Offer_Offer_B
Unlimited_Data_Yes
Referred_a_Friend_Yes
Payment_Method_Mailed_Check
Streaming_Movies_Yes
Multiple_Lines_Yes
Streaming_TV_No

WHAT DO
WE FOCUS
ON?



VORTEX



CONTRACT LENGTH

BETTER SERVICE

REFERRALS

Incentives



Early Renewal Options



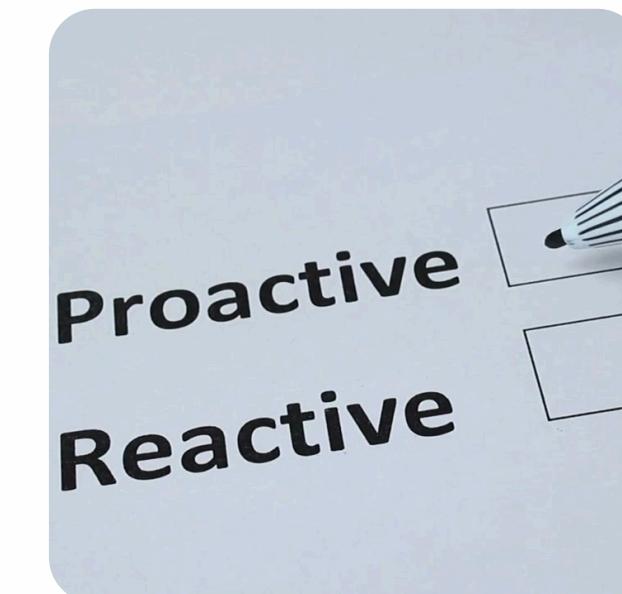
Engage Customers

**IMPLEMENTATION-
CONTRACT LENGTH**

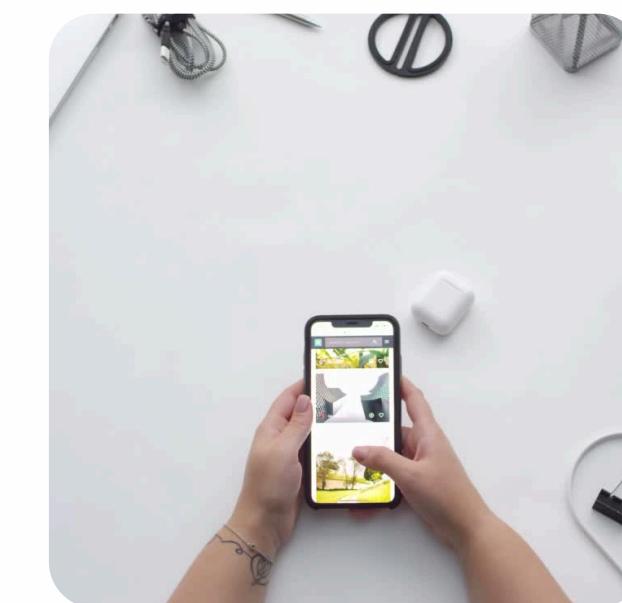
IMPLEMENTATION- BETTER SERVICE



Enhance Customer
Support



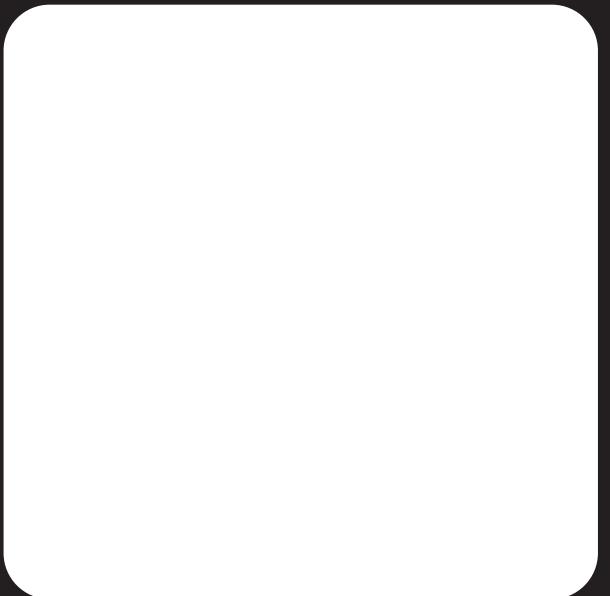
Proactive



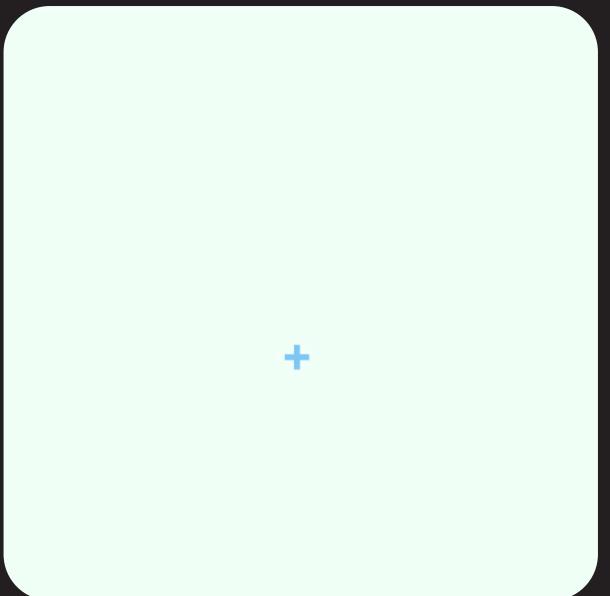
Personalized
Communication



Targeted
Referral

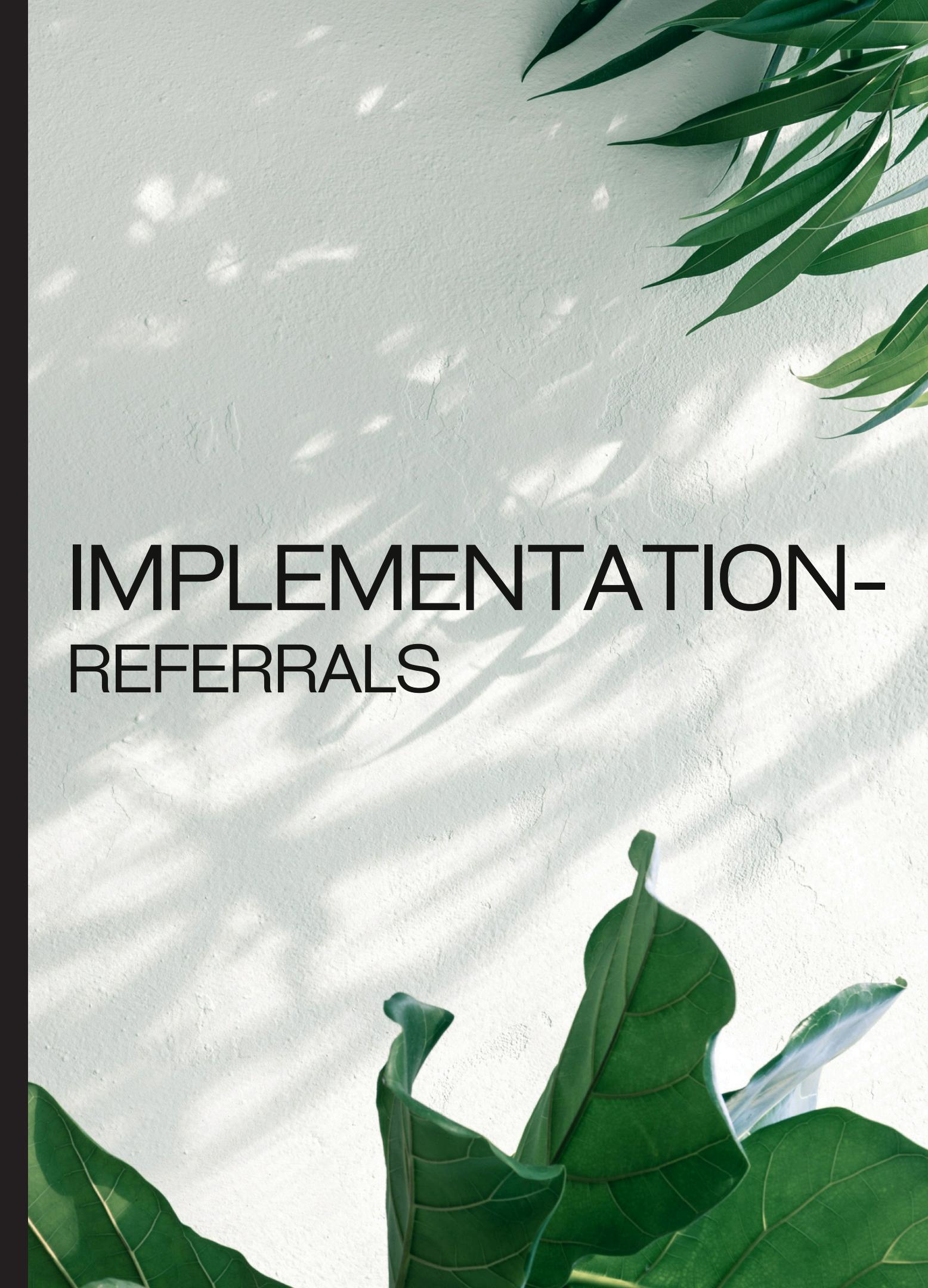


Reward
Retention

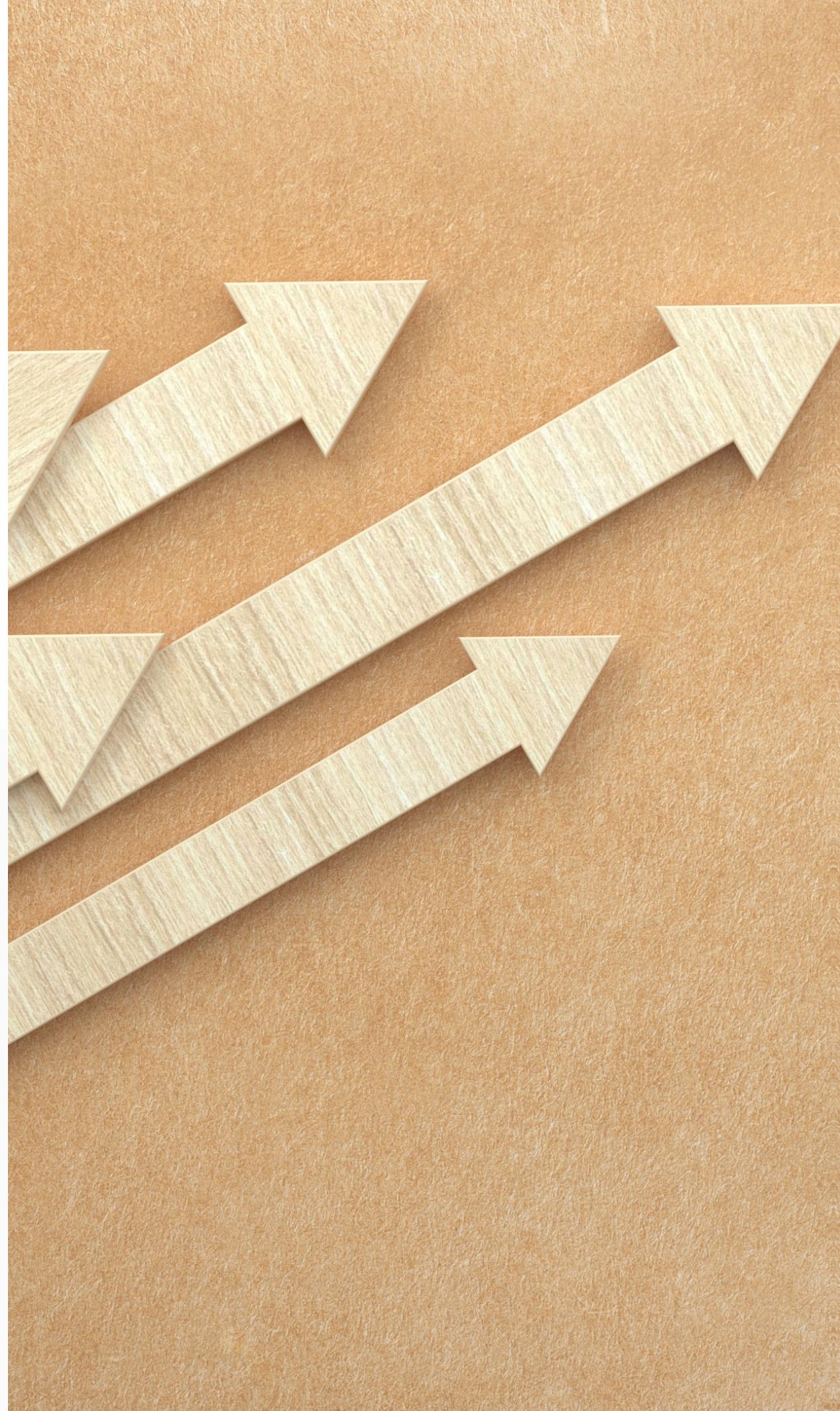


Optimize
Effectiveness

IMPLEMENTATION- REFERRALS



FINAL WORDS



- Working on these implementations.
- Work on better service thereafter.
- Further fine-tune prediction model.
- Continuous Customer Feedback Integration.

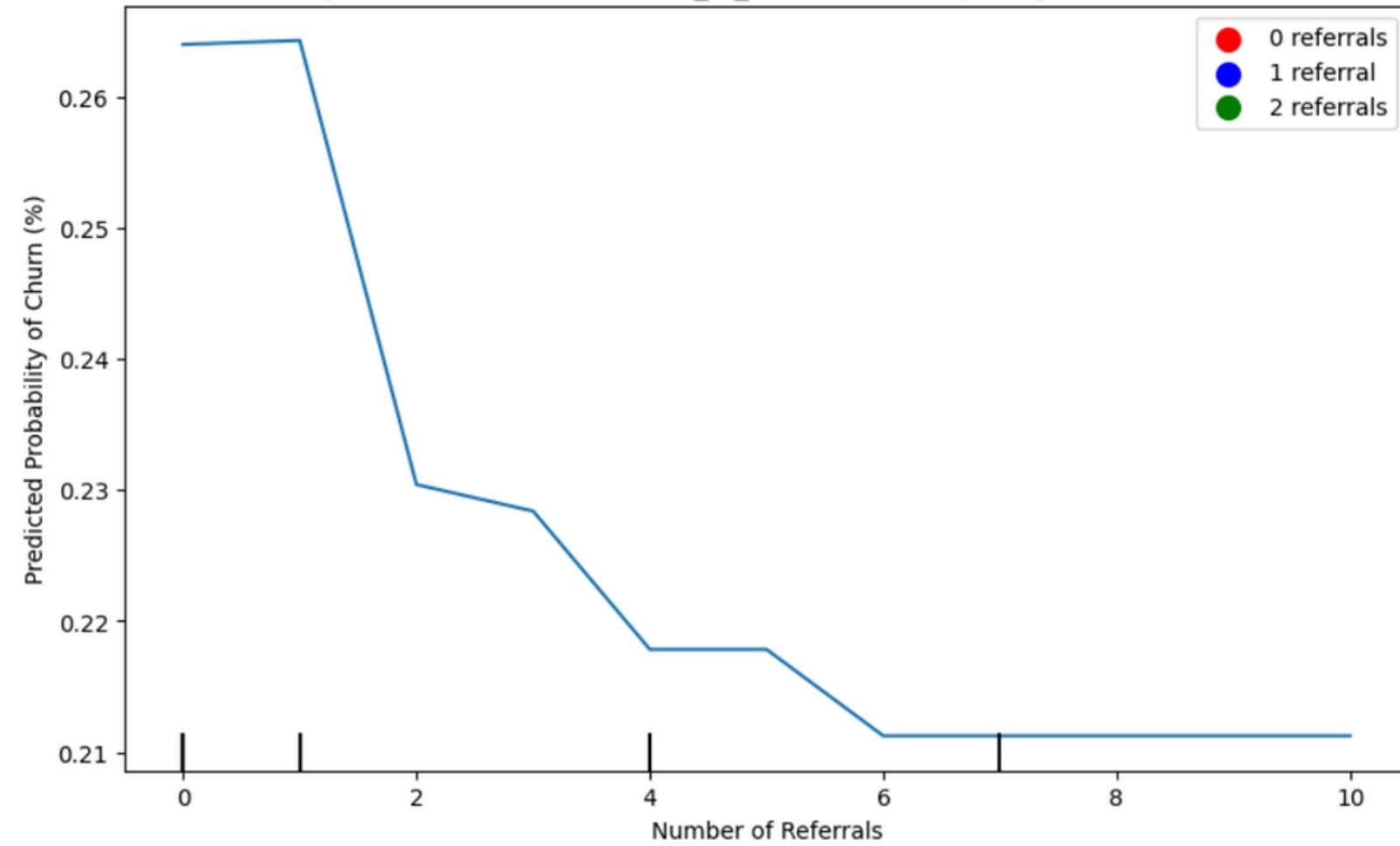


*Thank
you.*





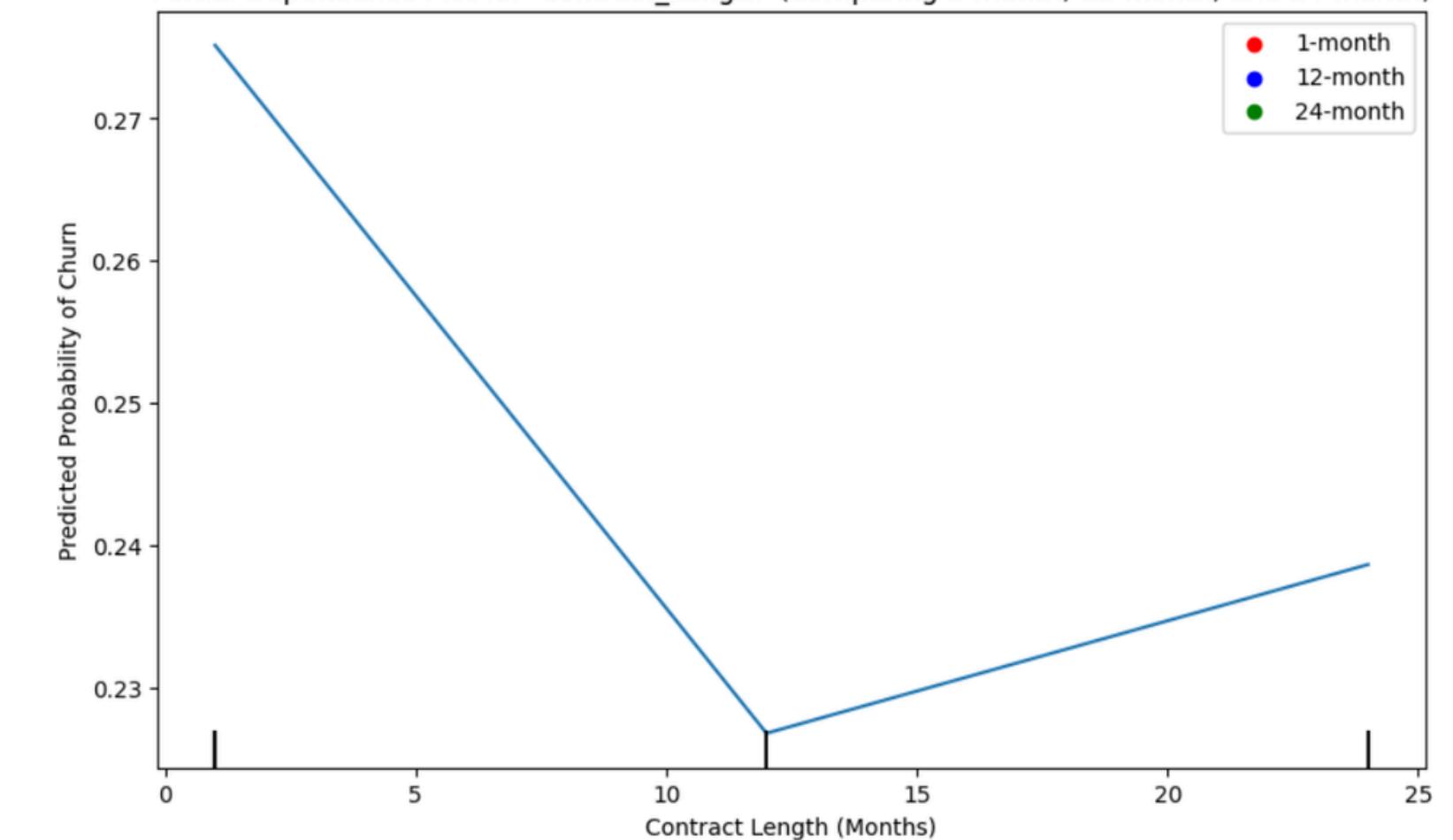
Partial Dependence Plot for 'Number_of_Referrals' (Comparing 0, 1, and 2 referrals)



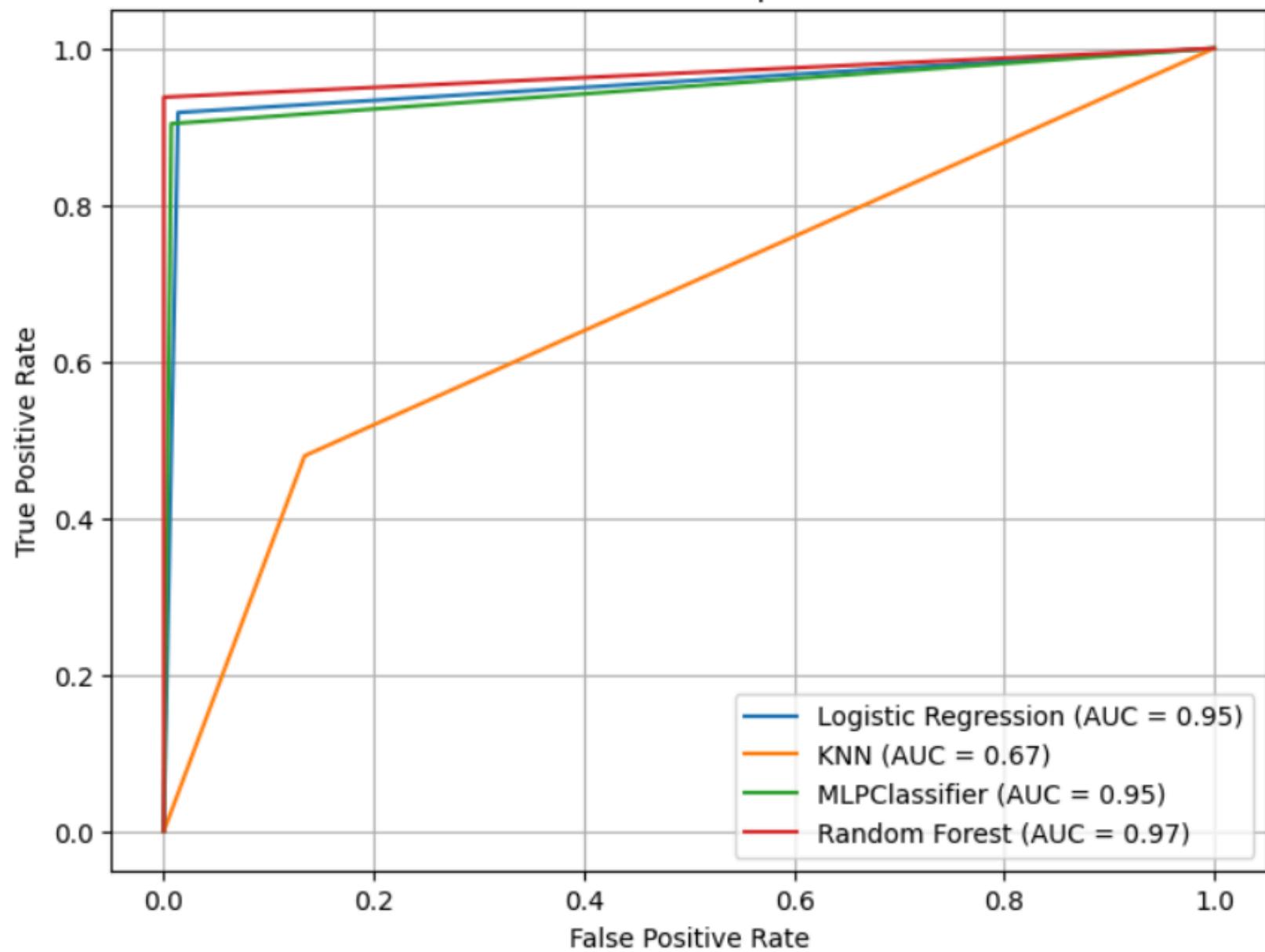
Impact on Churn with increase
in Referrals

Impact on Churn with change in Contract Length

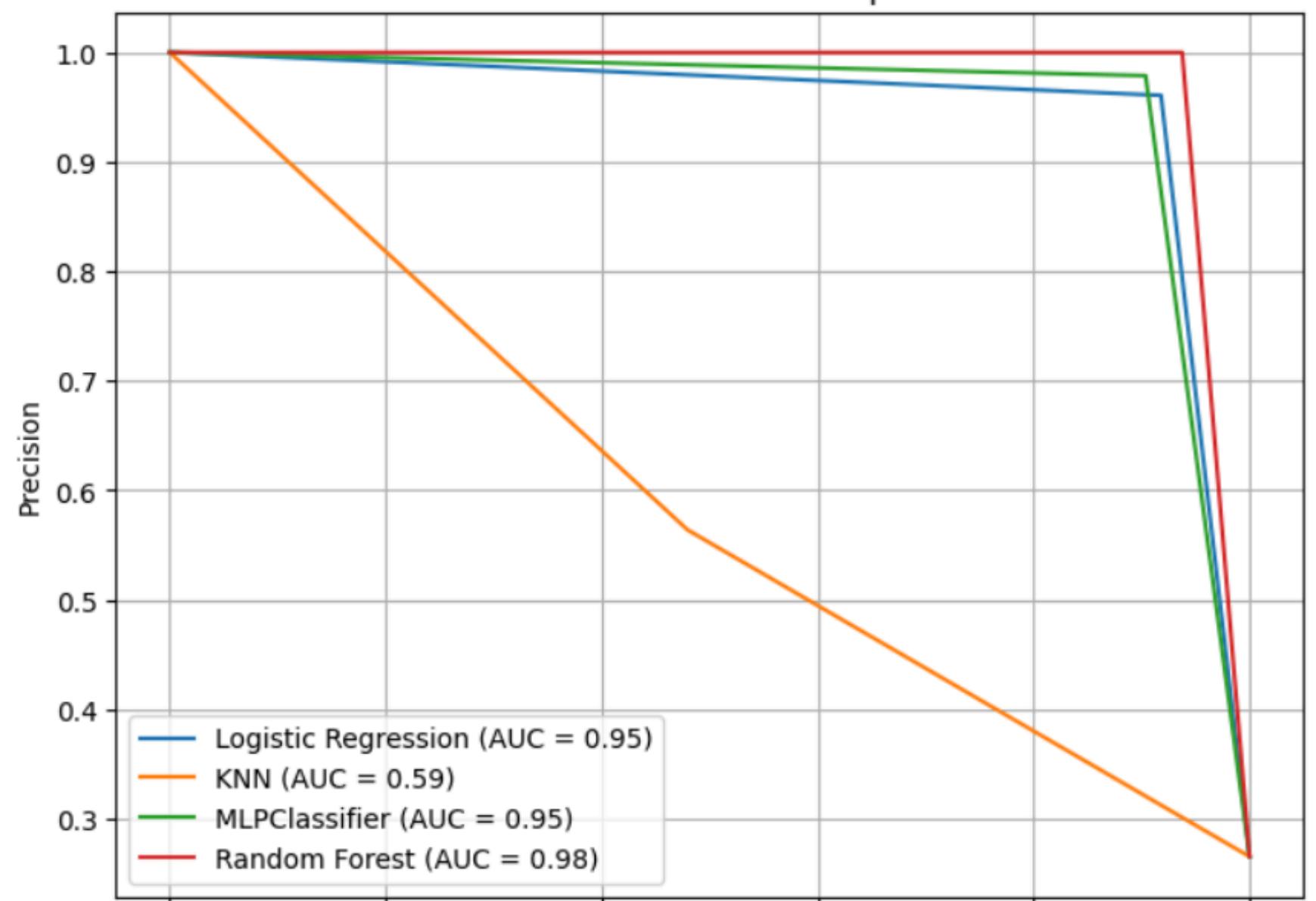
Partial Dependence Plot for 'Contract_Length' (Comparing 1-month, 12-month, and 24-month)



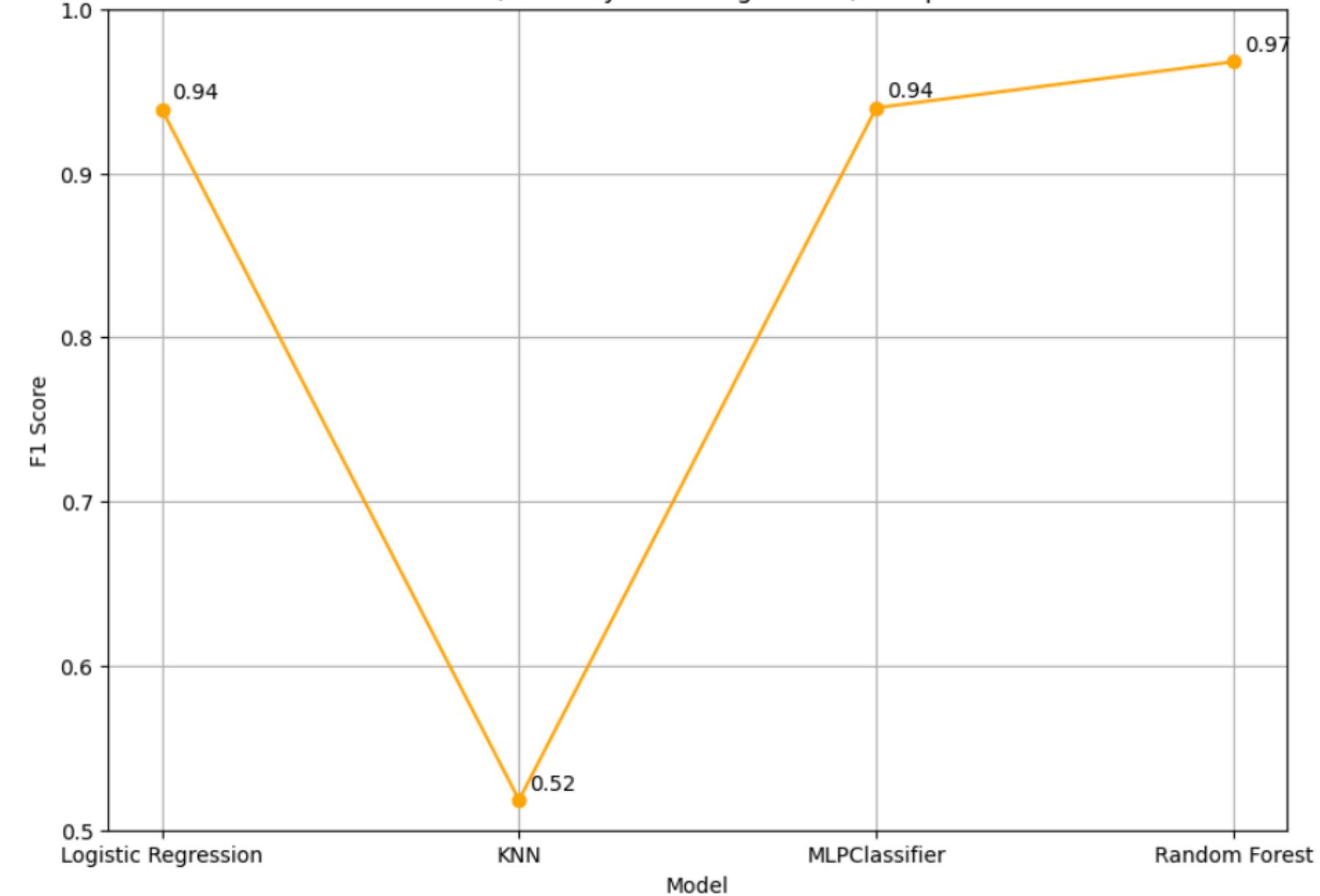
ROC Curve Comparison



Precision-Recall Curve Comparison



F1 Score (Correctly Predicting Churns) Comparison



Accuracy Comparison

