

Churn Modeling

Banking Sector





**It costs five times more to
acquire a new customer than
keep an existing one**

—Bain & Company



Introduction

GOAL

- Predict likelihood a customer will churn before they do
- Increase profitability through customer retention

SOLUTION

- Construct a classification model
 - Exited vs. Retained





Background

DATA

- Kaggle dataset
 - 14 features with 10,000 rows
- Key features:
 - Age, Balance, # of Products, Is Active

MAXIMIZE CUSTOMER RETENTION

- Maximize recall
- Assumptions:
 - 5:1 Ratio for customer acquisition vs retention
 - \$750 to acquire customer
 - \$150 to retain customer





Baseline Model

DO NOTHING

- Lose 400 customers
- Lose \$300,000

		Predicted	
		Retained	Exited
Actual	Retained	1600	0
	Exited	400	0

False Negative: $400 * \$750 = \$300,000$ Lost



Baseline Model

RETAIN ALL

- Overspend on 1600 customers
- Save 400 customers
- Break even

		Predicted	
		Retained	Exited
Actual	Retained	0	1600
	Exited	0	400

True Pos + False Pos:
 $2,000 * \$150 =$
\$300,000 Spent

True Positives: $400 * \$750 = \$300,000$ Saved

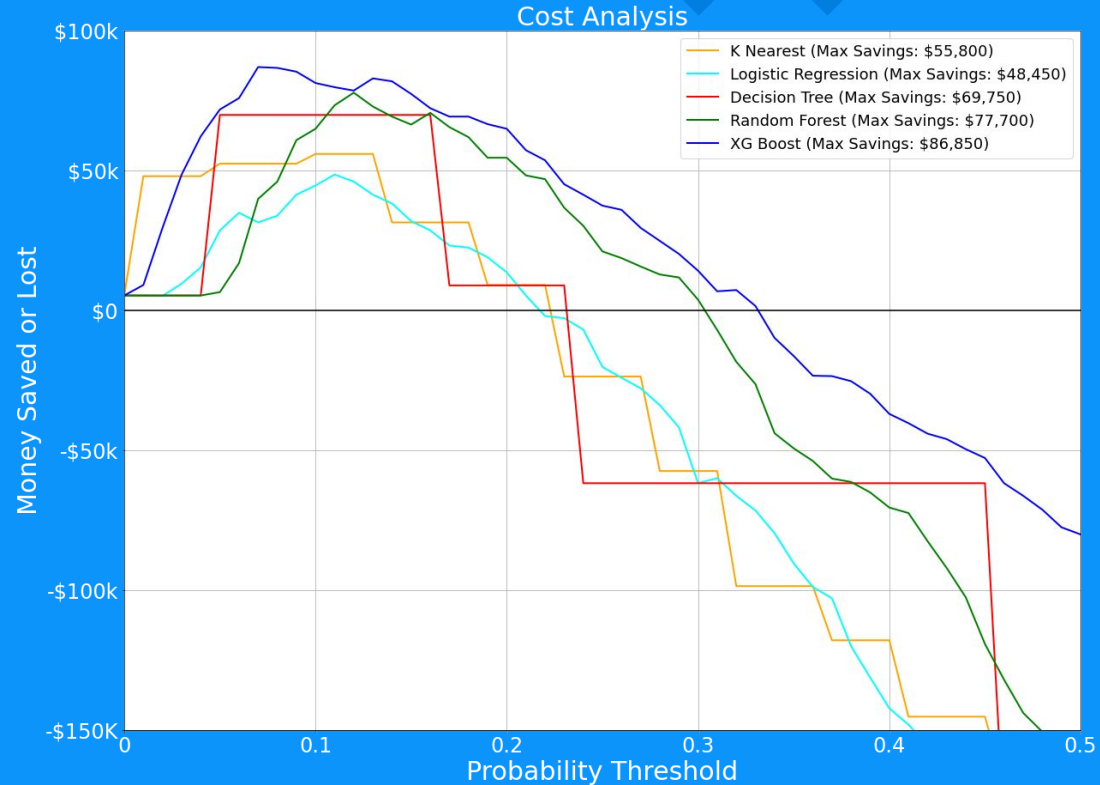


Results

MODEL SELECTION

XG Boost Classifier

- \$86,850 Savings





Results

XG BOOST MODEL

- Overspend on 797 customers
- Save 379 customers
- Loss 28 customers
- \$86,850 Savings

		Predicted	
		Retained	Exited
Actual	Retained	796	797
	Exited	28	379

False Neg: $28 * \$750 = \$21,000$ Lost

True Pos: $379 * \$750 = \$284,250$ Saved

True Pos + False Pos:
 $1,176 * \$150 =$
\$176,400 Spent



Future Work

TARGET PROFITABLE CUSTOMERS

- Maximize precision
- Customer's lifetime value
- Assumptions:
 - Profit margins on saving/checking 5%-20%
 - Higher account balance = more profit





Thanks!

Do You Have Any
Questions?



Appendix





Target Profitable Customers

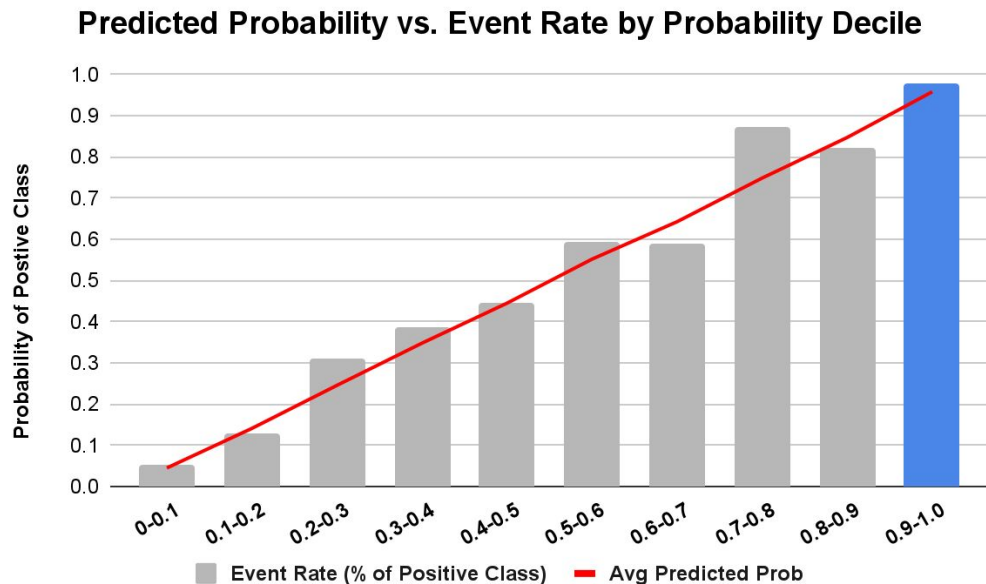
INCREASE THRESHOLD

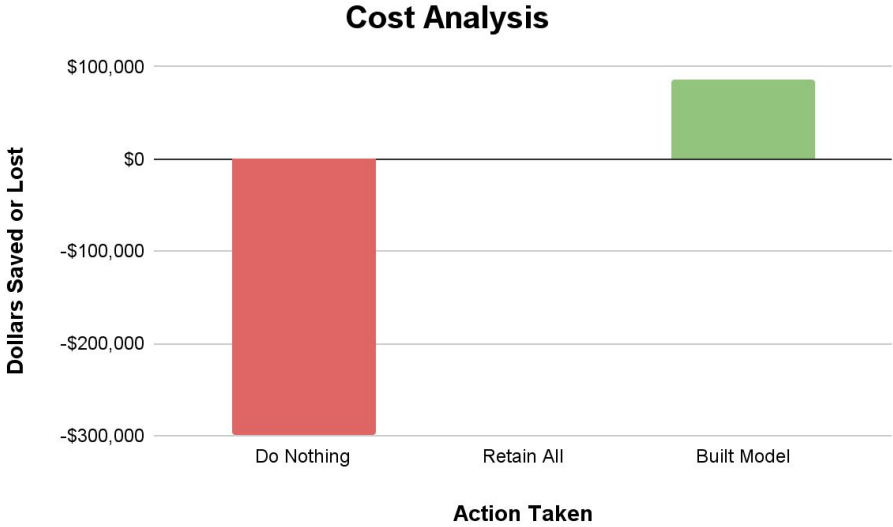
PRO

- More certain in our classifications
- Decreased false positives

CON

- Increase number false negatives







Target Profitable Customers

	Coefficients	Features
3	0.331589	NumOfProducts
5	0.166128	IsActiveMember
1	0.140150	Age
8	0.120134	Germany
7	0.074238	Male
11	0.064423	Zero
0	0.023757	CreditScore
6	0.022050	EstimatedSalary
9	0.021833	Spain
10	0.013632	Mid
2	0.012769	Tenure
4	0.009297	HasCrCard



Target Profitable Customers

CreditScore	Age	Tenure	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Male	Germany	Spain	Mid	Zero	Balance	CustomerId	Pred	Exited	binned
376	29	4	4	1	0	119346.88	0	1	0	1	0	115046.74	15656148	0.998629	1	(0.9, 1.0]
546	58	3	4	1	0	128881.87	0	1	0	1	0	106458.31	15640846	0.997863	1	(0.9, 1.0]
469	52	8	3	0	0	150093.32	0	1	0	0	0	139493.25	15696989	0.994660	1	(0.9, 1.0]
630	51	0	3	0	0	88372.69	0	1	0	1	0	108449.23	15592773	0.994600	1	(0.9, 1.0]
521	52	5	3	0	0	53793.10	1	1	0	1	0	116497.31	15701602	0.993649	1	(0.9, 1.0]
533	49	1	3	1	0	69409.37	0	1	0	1	0	102286.60	15727317	0.993133	1	(0.9, 1.0]
547	55	4	3	1	0	16922.28	1	1	0	1	0	111362.76	15589017	0.992926	1	(0.9, 1.0]



Target Profitable Customers

Customer ID	Age	Number of Products	Is Active Member	Balance	Prediction of Churn
15589017	55	4	0	\$111,362	99.2%
15689341	50	3	0	\$0	99.2%