Smarter Campaigns Start And End With Data Science

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Jane Johnson, Principal Client Strategist
Deluxe Corporation

Presenters

Sushaanth Srirangapathi

» Principal Data Scientist

» Develops strategies utilizing predictive solutions, advanced analytical techniques, and tools to help lenders better acquire and manage customers.

» Supports GenAI Platform Initiatives across Deluxe for various business applications such as Entity Resolution, Data explainability, etc.

Jane Johnson

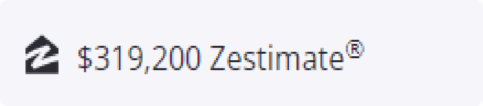
» Principal Client Strategist

» Works with mortgage and banking clients of all sizes, helping them develop and enhance their marketing strategies and maximize the return on their marketing investments.

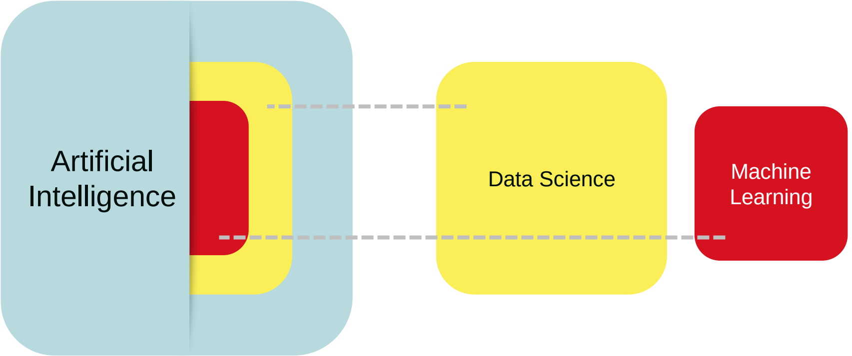
What is Data Science?

Model – What, Why and How

VantageScore FICO AUTO SCORE 9



Connection between data science, AI, and ML



For a successful model, We need:

- Business Case and Supporting Data and Model Building Process

Data Conducive for Data Science

CREDIT

- Tri-Bureau Solutions
- Prescreen Triggers
- ITMA Triggers

BUSINESS

- Demographics
- Business Owner Information
- Credit Data/Business Profiles
- Commercial Real Estate
- UCC filings, SBA & Other Loan Intel
- Import & Export Data

CONSUMER

- 1000s of Demographics & Interests Attributes
- Mortgage & Homeowner Data

TRIGGER

- New to World and Expanding Business
- Businesses Actively Seeking Credit
- Life Events
- New Movers / Pre-Movers

DELUXE PROPRIETARY DATA ASSETS

- ConsumerWealth©
- Consumer Financial Insights Suite (includes Net Assets, Investable Assets and more)
- Consumer Spending Behaviors (ConsumerSpend©)

» Our Deluxe Data Lakes contain data that is specifically curated for marketing and modeling.

Model Types

Input Data

- 1st Party Custom Client Models
- 3rd Party Industry Models

Targeting

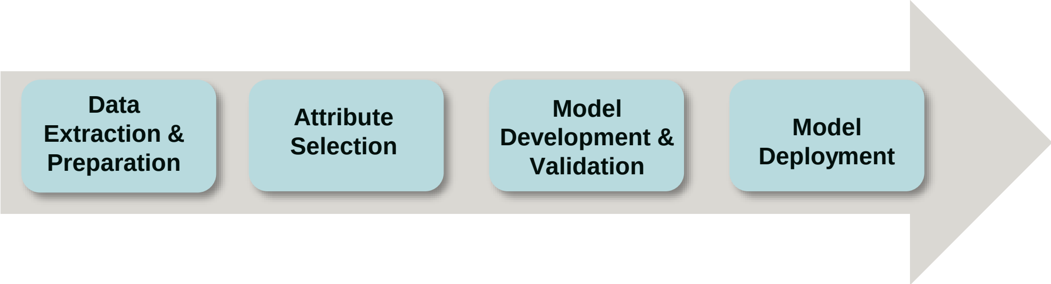
- Individual
- Household
- Household + Branch
- Carrier-Route

Product

- Checking/Savings
- CD and Money Market
- Personal Loans*
- Cards*
- Mortgage and HE Loans*

*** Lending product models can be response, conversion or underwriting/risk models.**

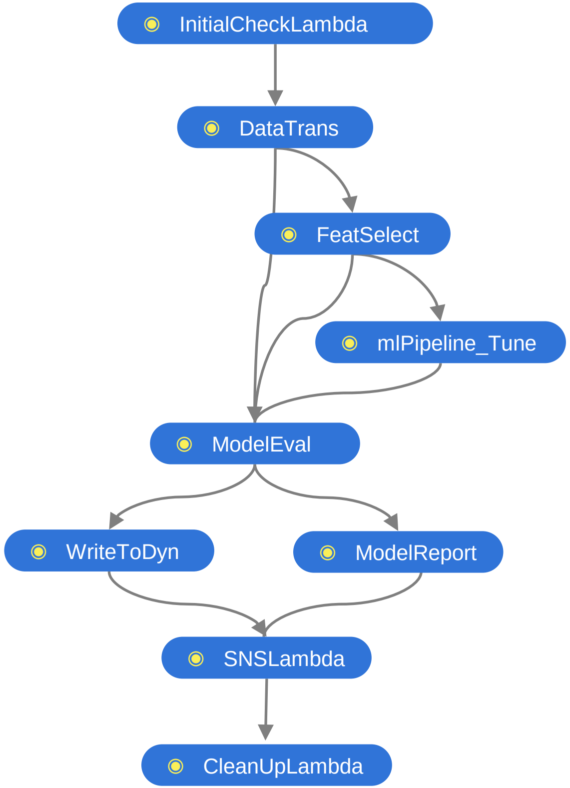
Model – How is it Built



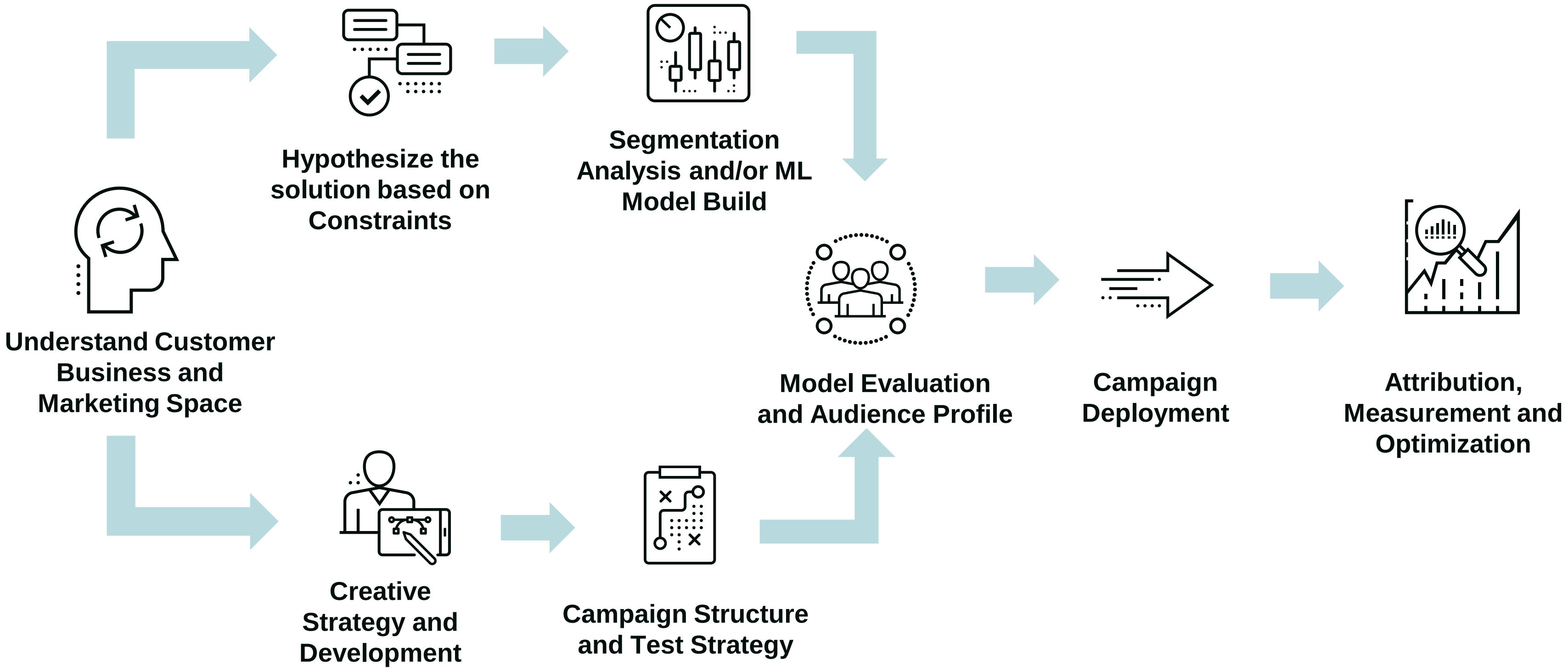
Model Statistics

Max.Lift	Lift.Top.3	AUC	Gini	Linearity	KS
3.95	2.52	0.808	0.617	1	0.46

Attribute	Attr	Definition	Type	Interpretation	Importance	Relationship	AUC
INQ02__SQRT	INQ02	INQUIRIES WITHIN 6 MONTHS-AUTO INQS. IN SAME MONTH WILL COUNT AS ONE	sqrt	square root transformation of inq02	100	positive	0.611
NUMHETRANS__NAI	NUMHETRANS	Number of home equity transactions	nai	Sample mean imputation on NA values for numhetrans	43.1	positive	0.681
AVAILHE__NAD	AVAILHE	Available home equity amount	nad	Dummy indicator on NA values for availhe	43.1	negative	0.585



Typical Marketing Campaign



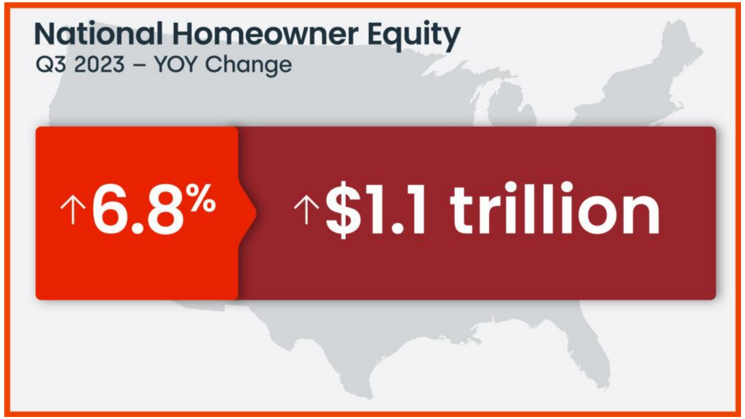
Home Equity Acquisition

Use Case #1

Business Need

» Given rising mortgage interest rates and continued growth in home equity values, this mortgage lender wanted to focus on HELOC acquisitions.

» Deluxe recommended a custom prescreen home equity model to target the most responsive *and* qualified prospects.



Source: CoreLogic, U.S. home equity changes year over year, Q3 2023

Lender's Underwriting Criteria

Global Rejects

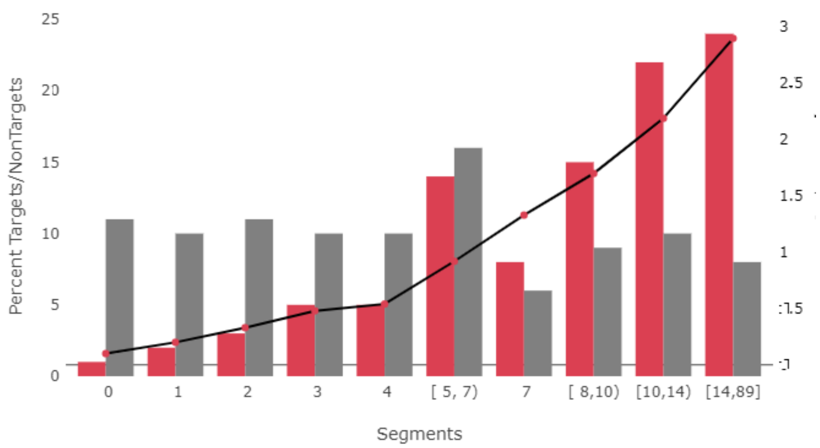
Apartment address:	Target
Public record - number of months since most recent bankruptcy:	= From 1 To 84
Mortgage- Number of 30 DPD w/I 12 mos:	= From 1 To 999
Mortgage- Number of 60 DPD w/I 12 mos:	= From 1 To 999
Mortgage-Number of 90+DPD w/I 12 mos:	= From 1 To 999

Estimated market value:	= From 0 To 249999
FICO risk score (FICO):	= From 200 To 679
Currently derog - currently 30+ DPD:	= From 1 To 999
Mortgage loan type:	VA
Mortgage-Number of 30+DPD w/I 13-24 mos:	= From 1 To 9999
Public record - Months since most recent foreclosure:	= From 1 To 84
Available Home Equity Estimate:	= From 0 To 49999

» In addition to the above exclusions, Deluxe includes only consumers who have available home equity of $50,000 or more based on varying LTV requirements by FICO range and home type.

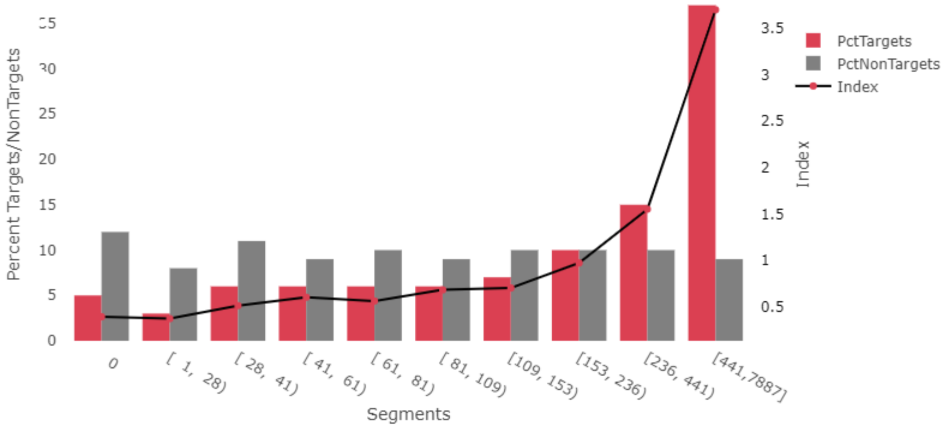
Attribute Segmentation Analysis

Profile Chart - INSTAL01 - installment - number of installment trade



Segments <fctr>	TargetCount <int>	PctTargets <dbl>	NonTargetCount <int>	PctNonTargets <dbl>	Index <dbl>
0	24	1	10989	11	0.10
1	46	2	10411	10	0.20
2	77	3	10716	11	0.33
3	110	5	10401	10	0.48
4	116	5	9724	10	0.54
[5, 7)	320	14	15778	16	0.92
7	178	8	6018	6	1.33
[8,10)	342	15	8954	9	1.70
[10,14)	484	22	9723	10	2.19
[14,89]	531	24	7926	8	2.90

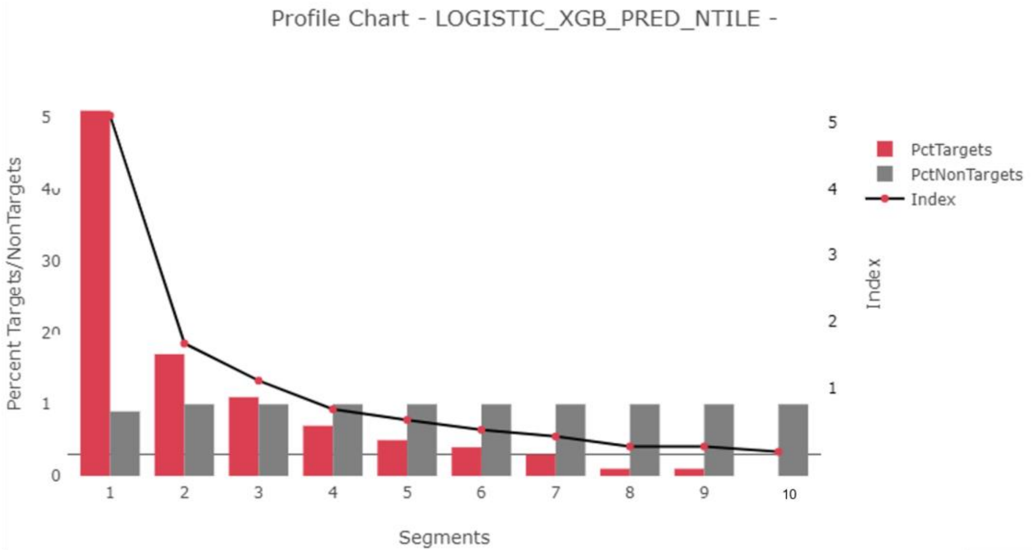
Profile Chart - REV24 - revolving - aggregate monthly payment for balances greater than 0



Segments <fctr>	TargetCount <int>	PctTargets <dbl>	NonTargetCount <int>	PctNonTargets <dbl>	Index <dbl>
0	108	5	12574	12	0.39
[1, 28)	65	3	8044	8	0.37
[28, 41)	127	6	11452	11	0.51
[41, 61)	124	6	9466	9	0.60
[61, 81)	124	6	10091	10	0.56
[81, 109)	141	6	9413	9	0.68
[109, 153)	158	7	10246	10	0.70
[153, 236)	213	10	9955	10	0.97
[236, 441)	345	15	9943	10	1.55
[441,7887]	823	37	9456	9	3.70

HELOC Model Training Performance

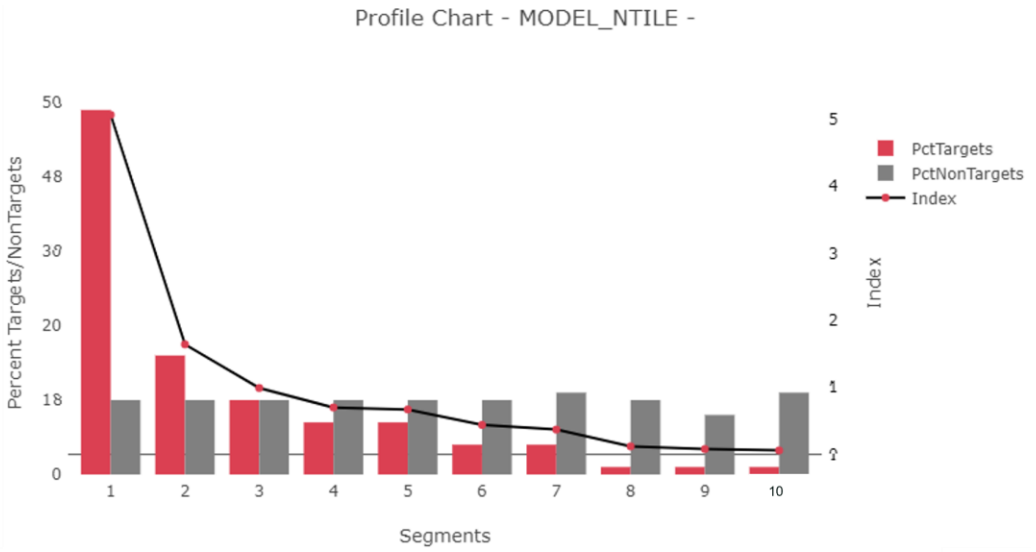
Model
Performance



Segments <fctr>	TargetCount <int>	PctTargets <dbl>	NonTargetCount <int>	PctNonTargets <dbl>	Index <dbl>
1	1136	51	9150	9	5.10
2	371	17	9916	10	1.67
3	247	11	10040	10	1.11
4	152	7	10136	10	0.68
5	116	5	10171	10	0.52
6	82	4	10203	10	0.37
7	60	3	10228	10	0.27
8	27	1	10260	10	0.12
9	27	1	10259	10	0.12
10	10	0	10277	10	0.04

HELOC Model Performance on HELOC Targets

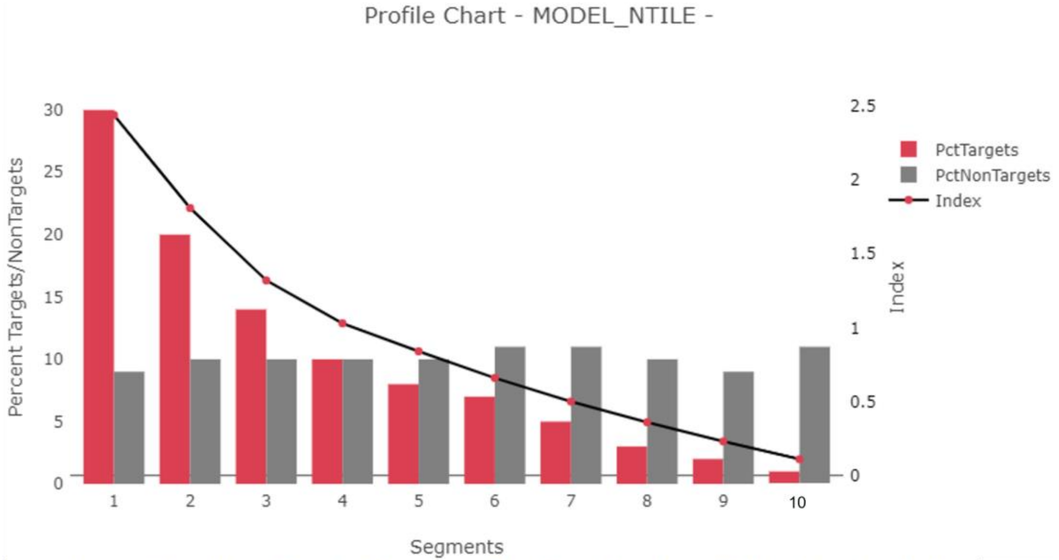
Out-of-Time
Holdout
Performance



Segments <fctr>	TargetCount <int>	PctTargets <dbl>	NonTargetCount <int>	PctNonTargets <dbl>	Index <dbl>
1	440	49	13706	10	5.06
2	144	16	14136	10	1.64
3	87	10	14247	10	0.99
4	61	7	14125	10	0.70
5	60	7	14519	10	0.67
6	40	4	14718	10	0.44
7	37	4	16017	11	0.37
8	11	1	14921	10	0.12
9	6	1	11907	8	0.08
10	6	1	15801	11	0.06

HELOC Model Performance on MTG Targets

Holdout Performance on **Mortgage Product**



Segments <fctr>	TargetCount <int>	PctTargets <dbl>	NonTargetCount <int>	PctNonTargets <dbl>	Index <dbl>
1	5196	30	9076	9	2.44
2	3581	20	9662	10	1.81
3	2372	14	9654	10	1.32
4	1775	10	9746	10	1.03
5	1447	8	10086	10	0.84
6	1150	7	10566	11	0.66
7	902	5	11269	11	0.50
8	584	3	10388	10	0.36
9	299	2	8488	9	0.23
10	178	1	10837	11	0.11

Campaign Strategy and Deployment

» We applied the underwriting criteria before building the model.

» During deployment,

- Underwriting + suppression + NCOA criteria
- Score and choose top N% Model score up to the desired mail quantity with a random control

Performance

- » Based on the success of Deluxe models in this lender’s credit trigger program, we recently moved forward with this batch Demand Gen program.
- » We expect our first results in the upcoming month but given we were able to analyze the data and validate the model upfront, we are confident in the program’s success.

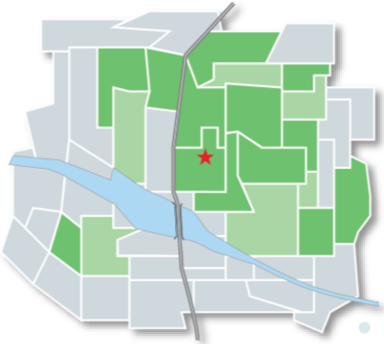
Checking Acquisition

Use Case #2

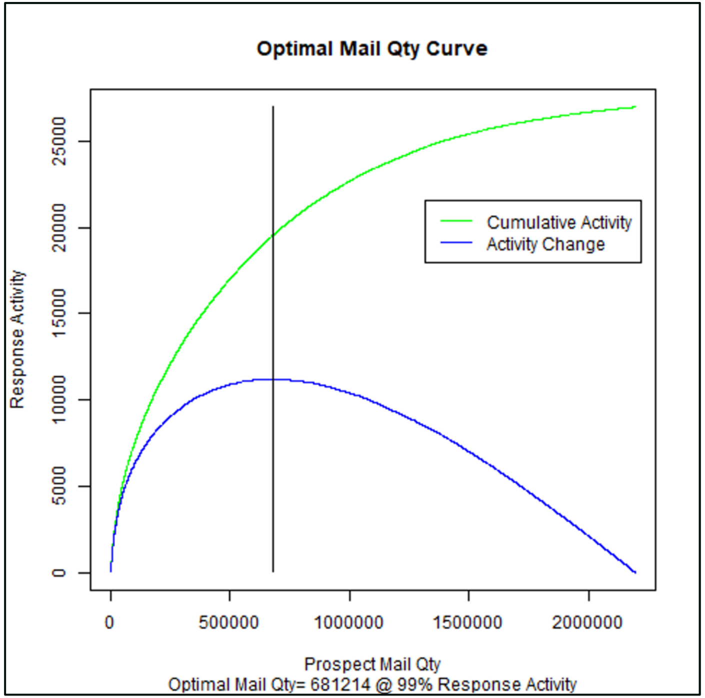
Business Need

- This Financial Institution wanted to acquire checking customers at the lowest possible cost.
- Deluxe recommended targeting prospects most likely to open checking accounts at the most economical cost using our Carrier Route Checking Model.

HIGHEST PROBABILITY LOCATIONS



Analyses and Validations



Carrier Route Model Validation

Model Decile	Volume	Accounts Opened	Account Response Rate
1	278,034	1,190	0.428%
2	325,956	1,067	0.327%
3	338,703	990	0.292%
4	301,526	734	0.243%
5+	731,901	1,493	0.204%
Total	1,976,120	5,474	0.277%

Campaign Strategy and Deployment

» Our strategy was to not only select highly responsive CRRTs per region, but also select an appropriate percentage of ***Low and Moderate Income (LMI)*** and ***Minority (MN)*** populations based on the FI's requirements.

Region	Projected_LMI	Target_LMI	Delta
Region 1	35.20%	13.04%	**22.20%**
Region 2	31.58%	17.39%	**14.20%**
Region 3	59.34%	18.42%	**40.90%**
Region 4	37.51%	37.14%	**0.40%**
Region 5	48.56%	35.66%	**12.90%**
Region 6	42.80%	23.08%	**19.70%**
Region 7	55.03%	29.73%	**25.30%**
Region 8	49.52%	20.41%	**29.10%**
Region 9	42.40%	32.26%	**10.10%**
Region 10	30.98%	23.49%	**7.50%**
Region 11	59.42%	30.77%	**28.70%**
Region 12	63.88%	52.17%	**11.70%**
Region 13	73.60%	24.24%	**49.40%**
Region 14	61.80%	31.94%	**29.90%**

Region	Projecte_MN	Target_MN	Delta
Region 1	37.10%	13.04%	**24.10%**
Region 2	0.00%	0.00%	**0.00%**
Region 3	27.84%	5.26%	**22.60%**
Region 4	3.14%	0.00%	**3.10%**
Region 5	36.74%	24.72%	**12.00%**
Region 6	17.78%	1.28%	**16.50%**
Region 7	52.74%	26.12%	**26.60%**
Region 8	41.84%	4.08%	**37.80%**
Region 9	27.61%	25.81%	**1.80%**
Region 10	0.00%	0.00%	**0.00%**
Region 11	32.92%	23.08%	**9.80%**
Region 12	62.54%	52.17%	**10.40%**
Region 13	65.72%	27.27%	**38.40%**
Region 14	55.68%	23.03%	**32.60%**

Note: LMI/MN minimum validation: all Delta are higher than 0, meaning we reached our targeted LMI/MN population percentage.

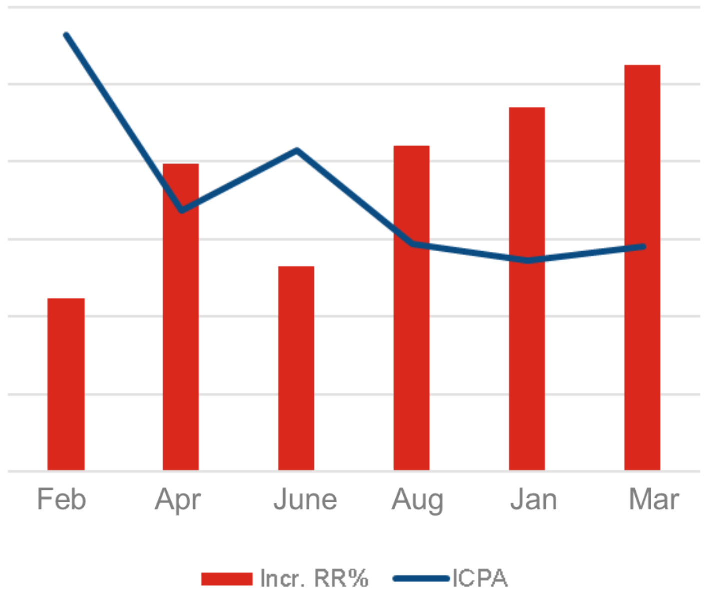
Combining Household & Carrier Route Targeting

» Deluxe has developed Postal Select, a hybrid approach that blends carrier route and household-level targeting to yield the lowest possible acquisition cost.

Household (HH) Targeting
• Extensive consumer, household, property and geo-level data assets for targeting • Separate, effective targeting approaches for basic vs. premium checking • Increased investment in data and postage • Addresses mailers to consumer names

Carrier Route (CR-RT) Targeting
• Geo-level data for targeting • More effective for basic checking • Lower cost / lower investment in data; more economical postage rates • Usually addresses mailers to "our neighbor"

Case Study: Transition to Hybrid Approach



Unsecured Loan Acquisition

Use Case #3

14.8% Increase

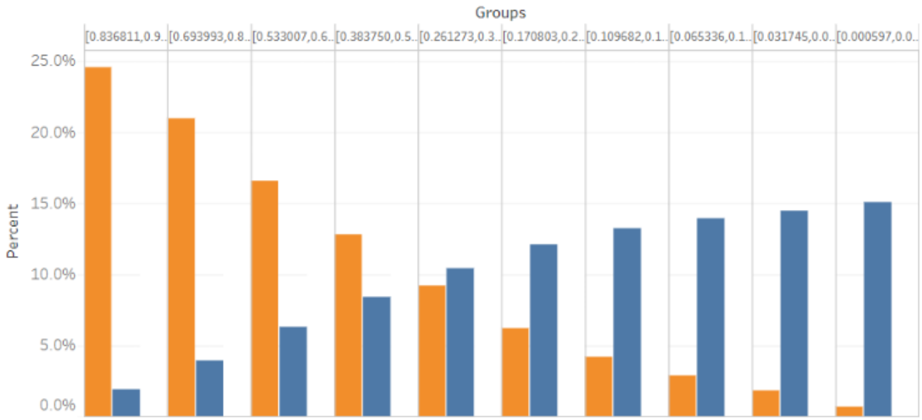
in unsecured personal loan balances year-over-year, the eighth consecutive quarterly record.

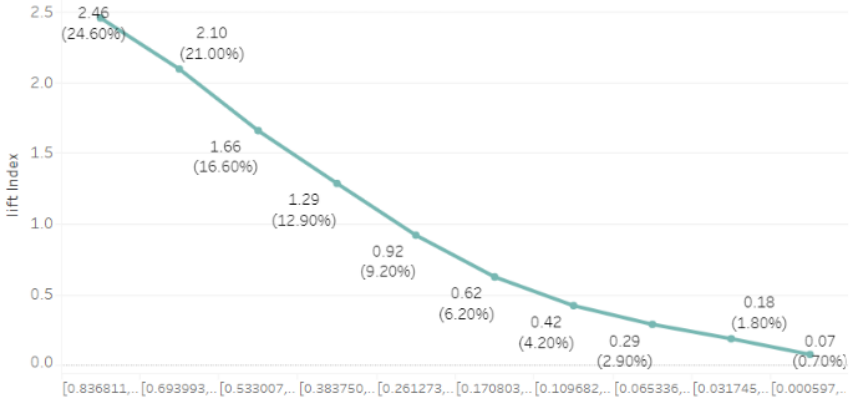
TransUnion Q3 2023 Credit Industry Insights Report

Business Need

- This lender wanted to expand their business in the growing unsecured loan market.
- Deluxe recommended optimization across three different categories: Response, Conversion and Denials, using an ensemble model approach.
- The lender shared first-party data including applications, funds, and approval and denial flags.

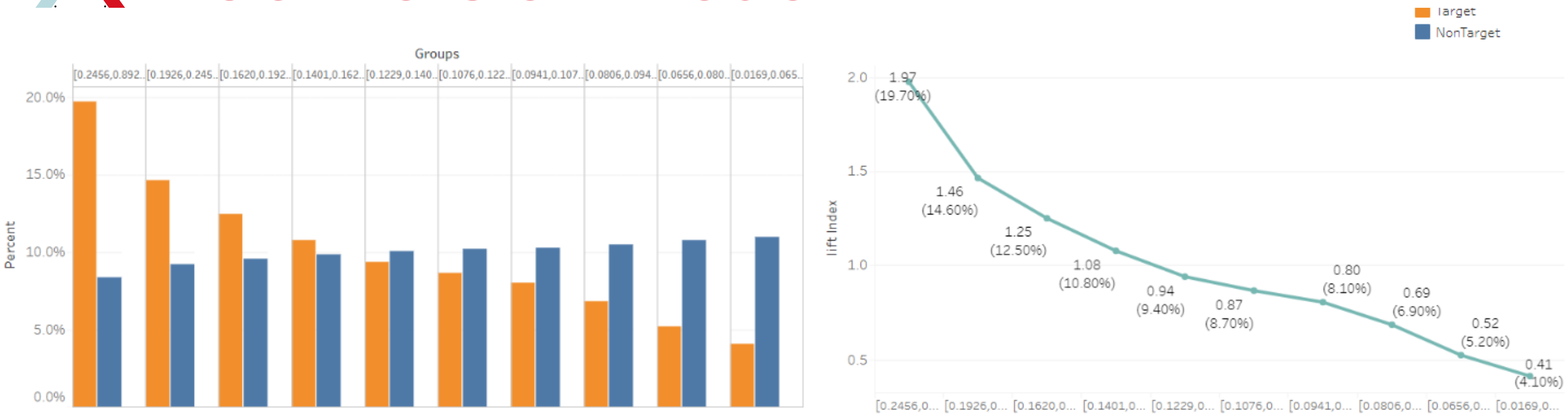
Response Model





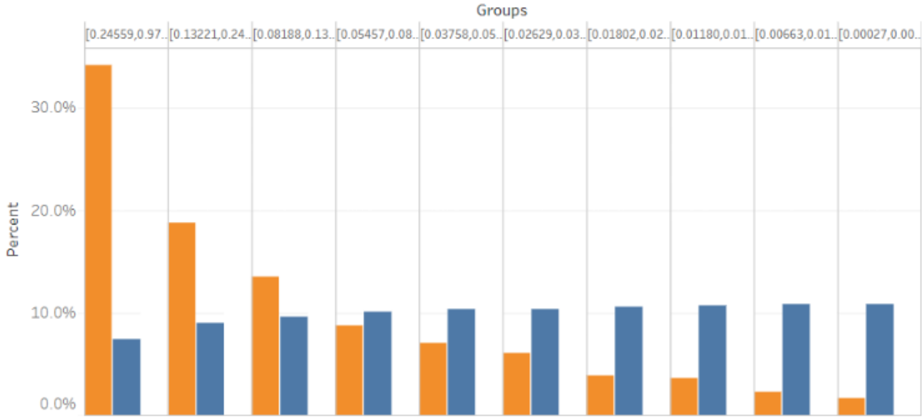
Attribute	Groups	N	Target	Target Rate	Target Per	Non Target	Non-Target Per	lift Index	KS
Response_Model_score	[0.836811,0.9909]	7,759	6,790	87.5%	24.60%	969	1.90%	2.46	22.7%
	[0.693993,0.8368)	7,760	5,791	74.6%	21.00%	1,969	3.90%	2.10	39.8%
	[0.533007,0.6940)	7,759	4,583	59.1%	16.60%	3,176	6.40%	1.66	50.0%
	[0.383750,0.5330)	7,760	3,550	45.7%	12.90%	4,210	8.40%	1.29	54.5%
	[0.261273,0.3838)	7,760	2,536	32.7%	9.20%	5,224	10.50%	0.92	53.2%
	[0.170803,0.2613)	7,759	1,718	22.1%	6.20%	6,041	12.10%	0.62	47.3%
	[0.109682,0.1708)	7,760	1,156	14.9%	4.20%	6,604	13.20%	0.42	38.3%
	[0.065336,0.1097)	7,759	789	10.2%	2.90%	6,970	13.90%	0.29	27.3%
	[0.031745,0.0653)	7,760	508	6.5%	1.80%	7,252	14.50%	0.18	14.6%
	[0.000597,0.0317)	7,760	199	2.6%	0.70%	7,561	15.10%	0.07	0.2%
	Overall	77,596	27,620	35.6%	100.00%	49,976	100.00%	1.00	54.5%

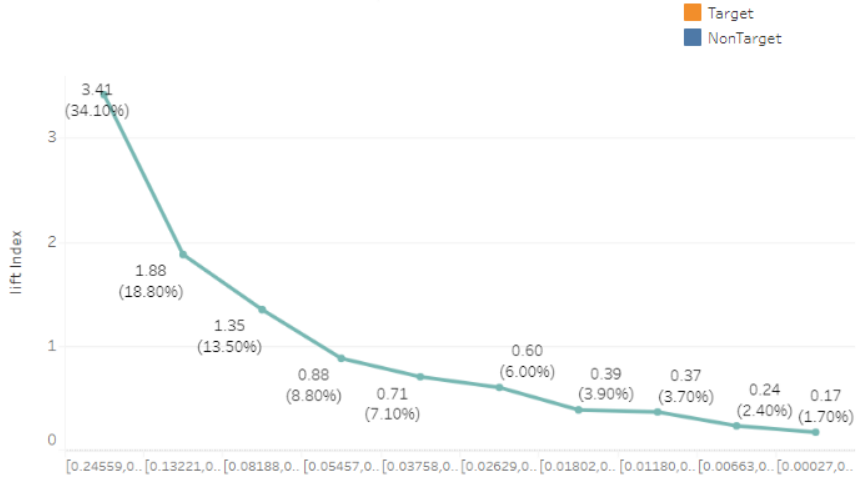
Conversion Model



Attribute	Groups	N	Target	Target Rate	Target Per	Non Target	Non-Target Per	lift Index	KS
Conversion_Model_score	[0.2456,0.8925]	3,220	905	28.1%	19.70%	2,315	8.40%	1.97	11.3%
	[0.1926,0.2456)	3,220	671	20.8%	14.60%	2,549	9.20%	1.46	16.7%
	[0.1620,0.1926)	3,220	573	17.8%	12.50%	2,647	9.60%	1.25	19.6%
	[0.1401,0.1620)	3,221	494	15.3%	10.80%	2,727	9.90%	1.08	20.5%
	[0.1229,0.1401)	3,220	431	13.4%	9.40%	2,789	10.10%	0.94	19.8%
	[0.1076,0.1229)	3,220	397	12.3%	8.70%	2,823	10.20%	0.87	18.3%
	[0.0941,0.1076)	3,221	369	11.5%	8.10%	2,852	10.30%	0.80	16.1%
	[0.0806,0.0941)	3,220	314	9.8%	6.90%	2,906	10.50%	0.69	12.5%
	[0.0656,0.0806)	3,220	240	7.5%	5.20%	2,980	10.80%	0.52	6.9%
	[0.0169,0.0656)	3,221	189	5.9%	4.10%	3,032	11.00%	0.41	0.0%
	Overall	32,203	4,583	14.2%	100.00%	27,620	100.00%	1.00	20.5%

Denial Model





Attribute	Groups	N	Target	Target Rate	Target Per	Non Target	Non-Target Per	lift Index	KS
Denial_Model_score	[0.24559,0.97889]	3,055	1,001	32.8%	34.10%	2,054	7.40%	3.41	26.7%
	[0.13221,0.24559)	3,055	551	18.0%	18.80%	2,504	9.10%	1.88	36.4%
	[0.08188,0.13221)	3,055	396	13.0%	13.50%	2,659	9.60%	1.35	40.3%
	[0.05457,0.08188)	3,056	259	8.5%	8.80%	2,797	10.10%	0.88	39.0%
	[0.03758,0.05457)	3,055	207	6.8%	7.10%	2,848	10.30%	0.71	35.8%
	[0.02629,0.03758)	3,055	177	5.8%	6.00%	2,878	10.40%	0.60	31.4%
	[0.01802,0.02629)	3,056	114	3.7%	3.90%	2,942	10.70%	0.39	24.6%
	[0.01180,0.01802)	3,055	108	3.5%	3.70%	2,947	10.70%	0.37	17.6%
	[0.00663,0.01180)	3,055	69	2.3%	2.40%	2,986	10.80%	0.24	9.2%
	[0.00027,0.00663)	3,056	51	1.7%	1.70%	3,005	10.90%	0.17	0.0%
	Overall	30,553	2,933	9.6%	100.00%	27,620	100.00%	1.00	40.3%

Ensemble Approach

Response Model

+

Conversion Model

-

Denial Model

Campaign Strategy and Deployment

- We applied the underwriting criteria before building the 3 models. We used first-party data from the lender as our target universe to build these models.
- During deployment,
  - Underwriting + suppression + NCOA criteria
  - Ensemble score calculated using the conversion and response model score
  - Remove Top 2 deciles of the Denial model from the above universe.
  - Select Top N records using Ensemble Score based on mail volume required

Performance

Initial campaign results:

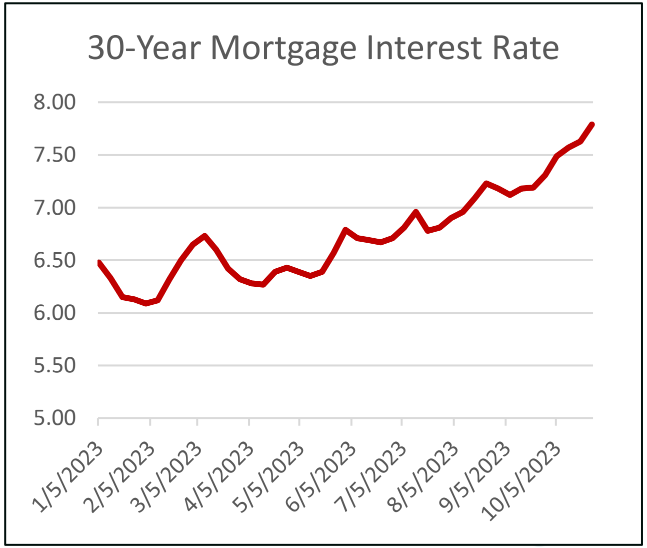
Creative	Creative 1	Creative 2	Creative 3	Total
Mail Application Response Rate	0.86%	0.87%	0.86%	0.86%
Application Decline Rate	51%	55%	52%	53%
Application to Fund Rate	8.2%	8.6%	7.4%	8.0%
Funded Loan Response Rate	0.070%	0.075%	0.063%	0.070%
Mail Loan Balance	$694,000	$705,000	$605,000	$2,004,000
Average Mail Loan Balance	$14,800	$14,100	$14,400	$14,400
NOC Response Rate	0.043%	0.047%	0.036%	0.042%
NOC Loan Balance	$380,042	$391,132	$290,836	$1,062,010

Mortgage Retention

Use Case #4

Business Need

- A national mortgage lender wanted to retain customers during period of increasing interest rates.
- Rather than randomly market to all customers, Deluxe recommended targeting customers most likely to be in the market for a mortgage product using two of our Deluxe Proprietary Industry Models:
  1. Mortgage In-the-Market Model
  2. Home Equity Conversion Model



Source: Freddie Mac

Analyses and Validations

Credit MTG In-The-Market Model

Month of Fi..	1	2	3	4	5	6	7	8	9	10	Grand T..
June	37.41%	20.05%	12.42%	9.68%	8.20%	6.22%	3.55%	1.78%	0.49%	0.19%	100.00%
July	33.35%	19.98%	13.13%	10.74%	9.05%	6.79%	4.12%	1.95%	0.64%	0.25%	100.00%
August	27.98%	20.04%	14.17%	11.89%	10.28%	7.83%	4.48%	2.35%	0.71%	0.28%	100.00%
September	25.31%	19.96%	14.71%	12.54%	10.74%	7.98%	5.02%	2.62%	0.81%	0.31%	100.00%
October	24.06%	19.82%	14.71%	12.57%	11.11%	8.28%	5.29%	2.84%	0.90%	0.43%	100.00%
November	22.59%	18.94%	14.39%	12.67%	11.20%	8.79%	5.89%	3.67%	1.29%	0.58%	100.00%
December	21.94%	18.22%	14.53%	12.66%	11.19%	8.70%	6.05%	4.36%	1.59%	0.76%	100.00%
Grand Total	28.39%	19.68%	13.90%	11.66%	10.08%	7.66%	4.76%	2.64%	0.85%	0.37%	100.00%

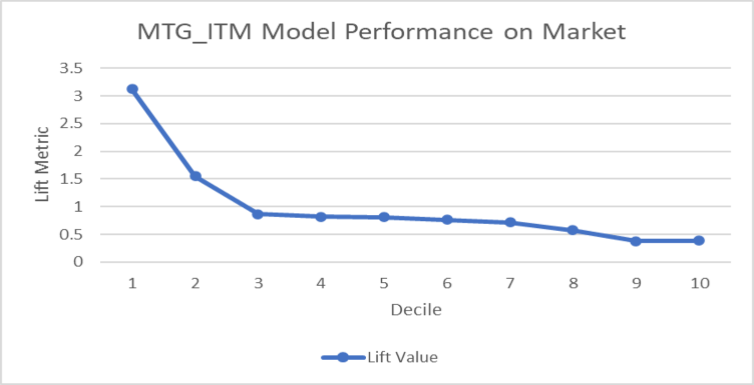
Credit HE Conversion Model

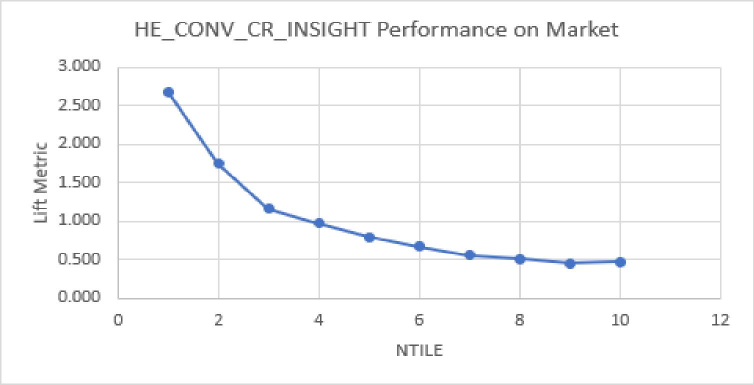
Month of Fi..	1	2	3	4	5	6	7	8	9	10	Total
June	51.79%	18.87%	9.11%	7.44%	5.35%	4.31%	1.75%	1.17%	0.13%	0.08%	100.00%
July	46.50%	20.59%	11.78%	7.48%	6.49%	4.09%	2.01%	0.81%	0.15%	0.09%	100.00%
August	39.26%	21.51%	13.22%	9.96%	7.45%	4.50%	2.47%	1.15%	0.36%	0.12%	100.00%
September	35.83%	23.11%	13.67%	9.75%	8.06%	5.86%	2.28%	0.88%	0.49%	0.07%	100.00%
October	35.64%	21.48%	13.15%	11.57%	8.36%	5.95%	2.68%	0.75%	0.30%	0.11%	100.00%
November	33.92%	20.94%	13.58%	10.54%	9.25%	6.25%	3.77%	1.11%	0.43%	0.21%	100.00%
December	35.68%	21.12%	13.84%	11.07%	8.18%	4.93%	3.43%	1.56%	0.12%	0.06%	100.00%
Total	40.98%	20.98%	12.34%	9.41%	7.37%	5.02%	2.49%	1.04%	0.28%	0.11%	100.00%

Analyses and Validations

Client Targets + MTG ITM + Underwriting			
Deciles	% targets	% nontargets	Lift
1	68%	21%	5.21
2	12%	16%	1.24
3	6%	11%	0.86
4	4%	10%	0.58
5	3%	9%	0.54
6	4%	8%	0.76
7	2%	7%	0.37
8	1%	7%	0.15
9	1%	7%	0.16
10	0%	4%	0.12

Client Targets + HE CONV + Underwriting			
Deciles	% targets	% nontargets	lift
1	66%	20%	5.22
2	14%	16%	1.35
3	7%	12%	0.92
4	2%	10%	0.37
5	3%	9%	0.51
6	4%	8%	0.88
7	1%	7%	0.32
8	1%	7%	0.21
9	1%	7%	0.22
10	0%	4%	0.00





Campaign Strategy and Deployment

» We used Deluxe's Industry Models for the campaign.

» During Deployment:

- Customer portfolio is matched to our credit data assets.
- Underwriting + suppression + NCOA criteria
- **Mortgage Offer**: Top 3 deciles of the Mortgage In-the-Market model
- **HELOC Offer**: Top 4 deciles of the Home Equity Conversion model after Suppression

Performance

This retention program has been **outstanding** over the past 1+ years and the lender continues to mail customers in the top model deciles every other month.

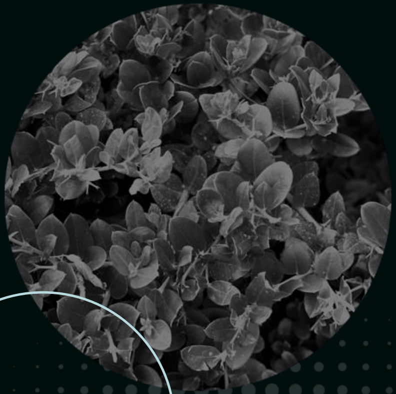
Key Takeaways

Smarter Campaigns Start And End With Data Science

Executive Summary

In this session you learned:

- In marketing, we can predict the likelihood of a consumer purchasing a product with various signals within the disparate Data Assets available about the consumer.
- Having curated data that is conducive for modeling is key to successful Data-Driven Marketing campaigns.
- Data Analysis and Validation are crucial steps in the campaign process if you want to make your campaigns smarter.
- Leading FI’s are incorporating models into their marketing campaigns to improve response and lower cost-per-acquisition.



Thank you for attending!

- This evening: Join us for our CoLab Reception in Sparkle Ballroom
  - 4:00 – 5:00 PM
- Final Night Event tonight on La Côte lawn
  - 7:00 – 10:00 PM
- Consider attending these breakout sessions:
  - **Friend Or Foe: Navigating The Responsible Use Of AI In Marketing**
    - **Today | 3:00 – 3:45 PM | Flicker 2/3**
  - **Strike While the Iron Is Hot With Trigger Marketing**
    - **Tomorrow | 10:45 – 11:30 AM | Flicker 1**