Case Study - Uplift Model to Predict Churn and Deliver Higher Marketing ROI Through Targeted Outreach

What is Churn in a Telco

Churn in simple terms is defined as customers leaving the Telco in given period.

The churn metric is mostly shown as the percentage of customers that cancel a product or service within a given period.

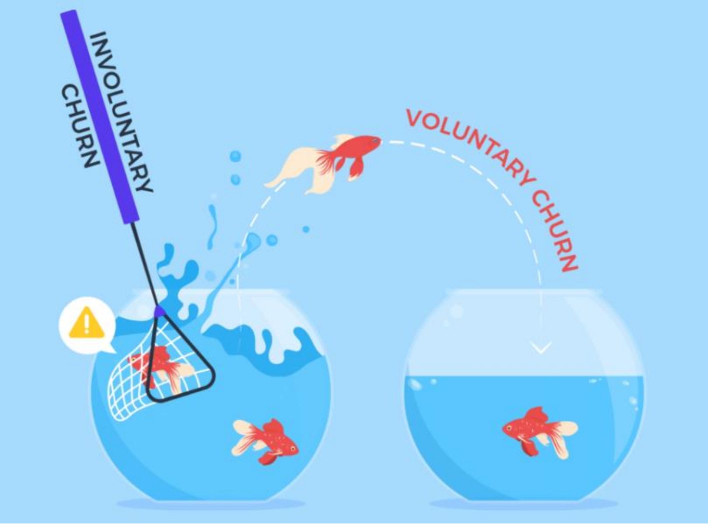
e.g., If a Telco company had 10 Mio. customers on the 1st of January and received 500K contract terminations until the 31st of January the monthly churn for January would be 5%

Voluntary Churn is when a customer actively end or close their account.

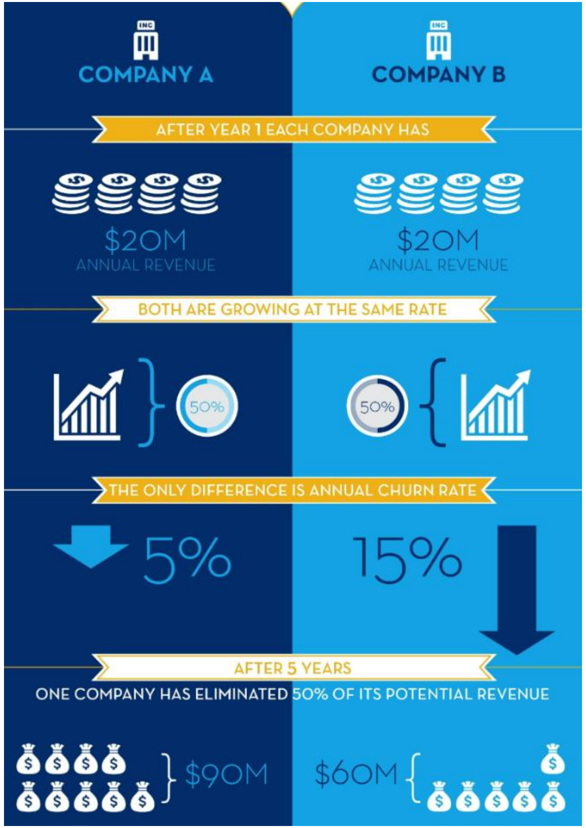
Mainly due to bad experience (network, service) , compelling offer from competition.

Involuntary churn caused due to payment failures, recoveries, lapses from customer end

In most of the cases customers forced to discontinue service or system errors (migrations, upgrades not supported / delete & add operations)



Impact of Churn



Businesses assess rate of churn by customer segments, product categories, lifetime value (LTV), etc.,

The goal of business to reduce churn, increase revenue by targeted marketing campaigns.

Targeted campaigns for retention, upsell, cross sell

The **uplift** of a marketing campaign is usually defined as the difference in response rate between a treated group and a randomized control group.

This allows a marketing team to isolate the effect of a marketing action and measure the effectiveness or otherwise of that individual marketing action.

Churn, Propensity and Uplift

The Problem Statement and the Solution Strategy

- Given a set of customers, the ensemble, how do we take pre-emptive action to prevent churn, prevent them from leaving
- We follow the strategy of:
    - Identify, with as much accuracy as possible, the set to customers who are likely to churn in the immediate future
        - Use analytics and machine learning with past data available to predict a
            - *Propensity Score* for each customer – in the form of the *probability* of that customer to churn
    - Identify possible pre-emptive actions so as to prevent this churn from happening
        - Any such pre-emptive action is called *Treatment*, T
        - Multiple such treatments T are possible – need to choose the right one for the customer – that will retain
            - Such pre-emptive actions could be based on the past experience in understanding customer behaviour
    - Execute the treatment T and try and retain the customer
    - Measure the efficiency of the strategy for further improvements and fine tuning

Churn, Propensity and Uplift

The Showstopper

- How do we "Measure the efficiency of the strategy for further improvements and fine tuning"?
    - We need to know that the treatment T ***caused*** the customer not to churn
    - Assume that C was predicted to churn, was offered the treatment T, and C did not churn
    - *Correlation is not Causation!*
- The usual scores for accuracy of the prediction: Precision, Recall, is not possible to apply in this situation
    - There is no way to assess or conclude that C would not have churned if T was no offered
- The showstopper:
    - Usual prediction methods cannot be tested for accuracy of predicting churn in this context
        - Note that we could have tested the accuracy if customers were NOT offered the Treatment
        - However this defeats the purpose of the entire exercise
- The Solution here is:
    - Model Customer Behaviour so as to predict the impact of T on the *Propensity Score* of C
        - Is C less likely to churn if offered T?

Churn, Propensity and Uplift

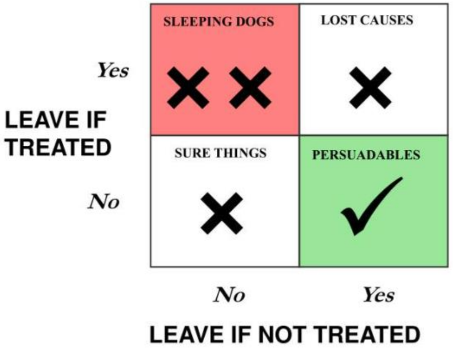
What is Uplift Modelling

- Classic Propensity Model
    - Predict target variable Y given features X
        - $Y = f(X)$
        - $0 \leq Y \leq 1$: $Y = 1: Churn\ ; Y = 0\ No\ churn$
- Uplift Modelling
    - Predict target variable Y given features X and treatment T
        - $Y = f(X, T)$
    - Uplift is then defined as the
        - $U = P(Y|{\sim}T) - P(Y|T)$
        - This measures the difference that the treatment T causes in customer behaviour
- The treatment T is then offered to those customers who have a $U \geq threshold$

Churn, Propensity and Uplift

So, what does it matter – why not offer T to all customers?

- One could argue that we just go and offer T to all customers instead of going through this rigmarole!
- Cost
    - Suppose: T=Call the customer and explain an attractive new discount scheme on his current plan and persuade to sign up
    - For a telco with 10 million customer base, this is a very expensive and time consuming proposition
- It may be good NOT to offer T to some customers – this is the insight from customer buying behaviour studies
    - Customer Classification
        - *Sure Things*: will anyway buy without being offered T
        - *Lost Causes*: will anyway churn independent of T being offered
        - *Sleeping Dogs*: will get irritated and churn if offered T
        - *Persuadables*: will decide not to churn when persuaded with T
- *The optimal strategy then is to approach only the Persuadables*
    - $Persuadables: Uplift > threshold$

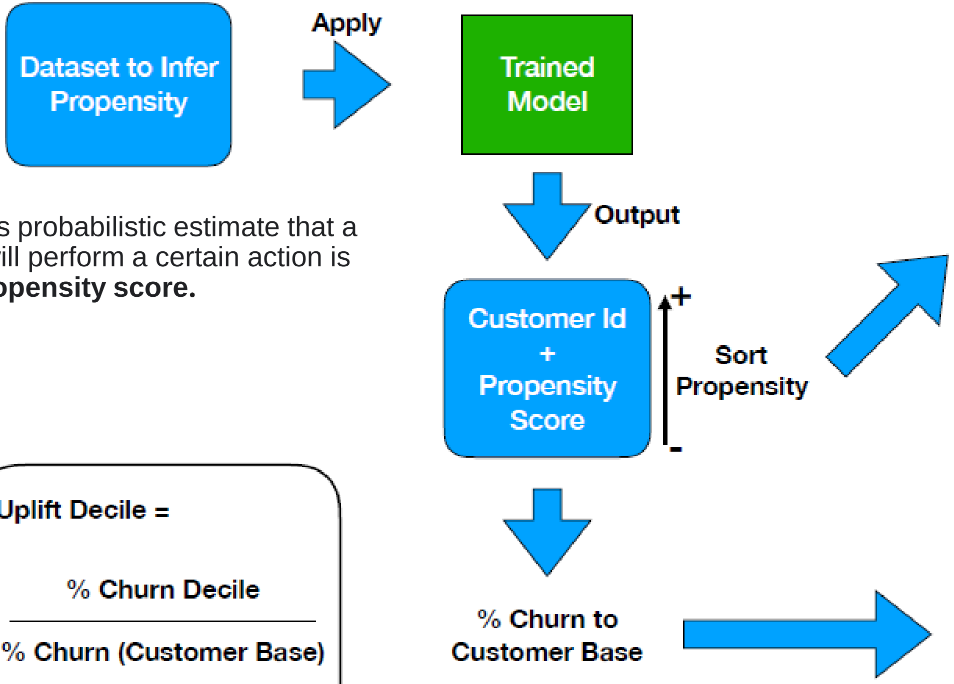


LEAVE IF TREATED

	No	Yes
Yes	SLEEPING DOGS ✗✗	LOST CAUSES ✗
No	SURE THINGS ✗	PERSUADABLES ✓

LEAVE IF NOT TREATED

Calculating Uplift Deciles



Dataset to Infer Propensity

Apply

Trained Model

Output

Customer Id + Propensity Score

Sort Propensity

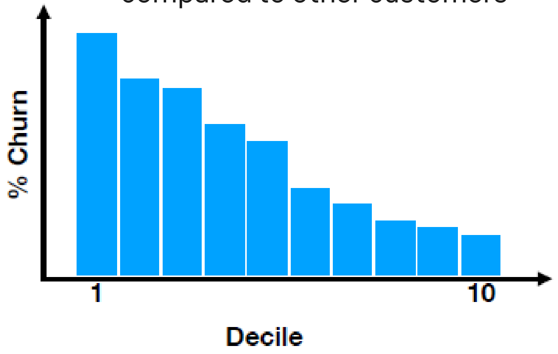
% Churn to Customer Base

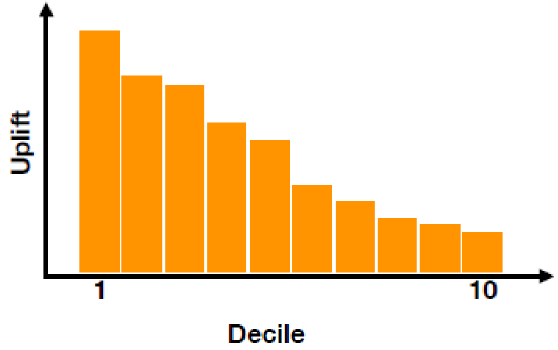
The model's probabilistic estimate that a customer will perform a certain action is called a **propensity score.**

Uplift Decile =

$$\frac{\text{\% Churn Decile}}{\text{\% Churn (Customer Base)}}$$

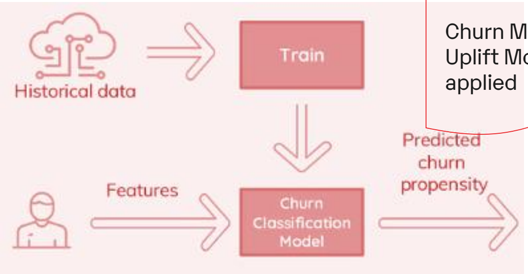
How likely a customer is to churn when compared to other customers





Let us understand how business use ML models

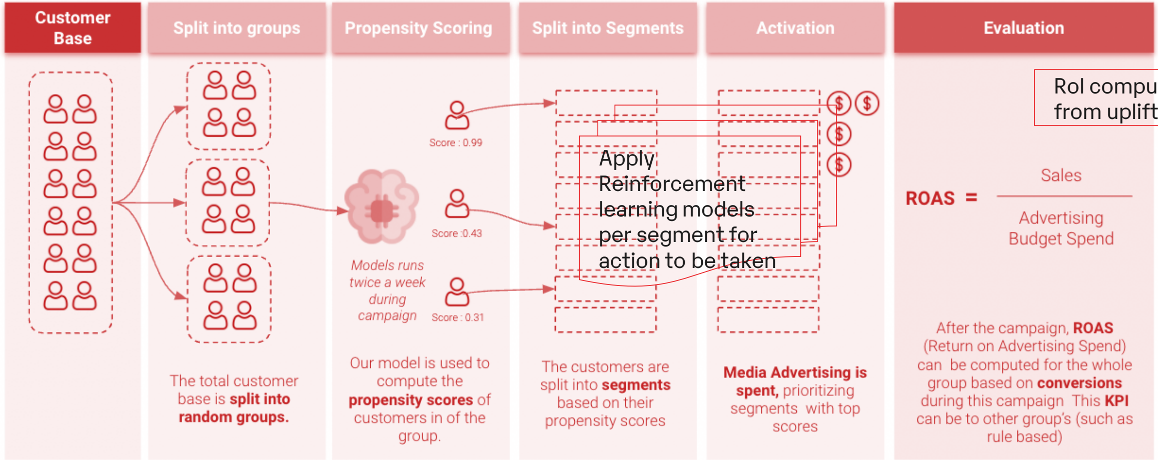
For all customers



Churn Models and Uplift Modelling applied

What do we do now

- Send email or Telemarket or D2D ?
- What should we offer ?
- Which offer will make maximum impact ?
- How do I calculate cost and RoI ?



The total customer base is **split into random groups.**

Our model is used to compute the **propensity scores** of customers in of the group.

The customers are split into **segments** based on their propensity scores

Media Advertising is spent, prioritizing segments with top scores

After the campaign, **ROAS** (Return on Advertising Spend) can be computed for the whole group based on **conversions** during this campaign This **KPI** can be to other group's (such as rule based)

Apply Reinforcement learning models per segment for action to be taken

RoI computed from uplift scores

Modelling to find impact of offers to per customer segment !!!

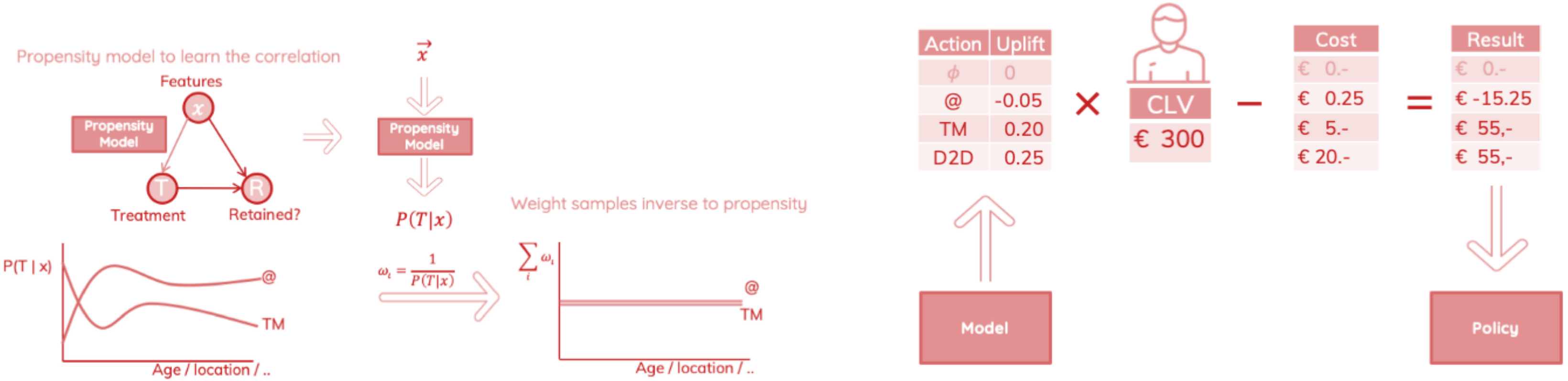
Applying Reinforcement learning to target group of customers

Reinforcement Learnings is about learning the optimal behavior in an environment to obtain maximum reward.

e.g., Should I send a mail or call the customer ? What amount of discount is good - $10 or $15 ?

State of the customer
(Usage, plans, top-up)

Generate offer

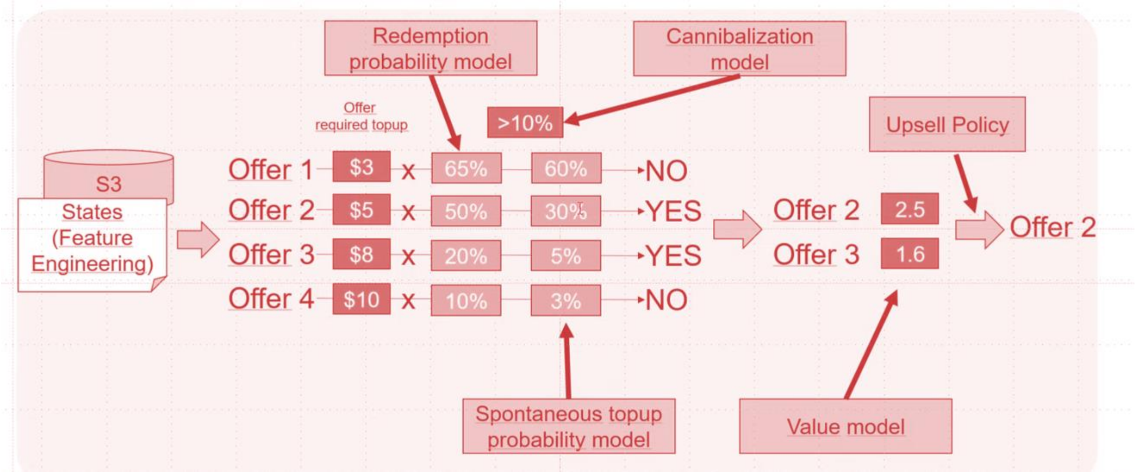


Action	Uplift
ϕ	0
@	-0.05
TM	0.20
D2D	0.25

Cost
€ 0.-
€ 0.25
€ 5.-
€ 20.-

Result
€ 0.-
€ -15.25
€ 55,-
€ 55,-

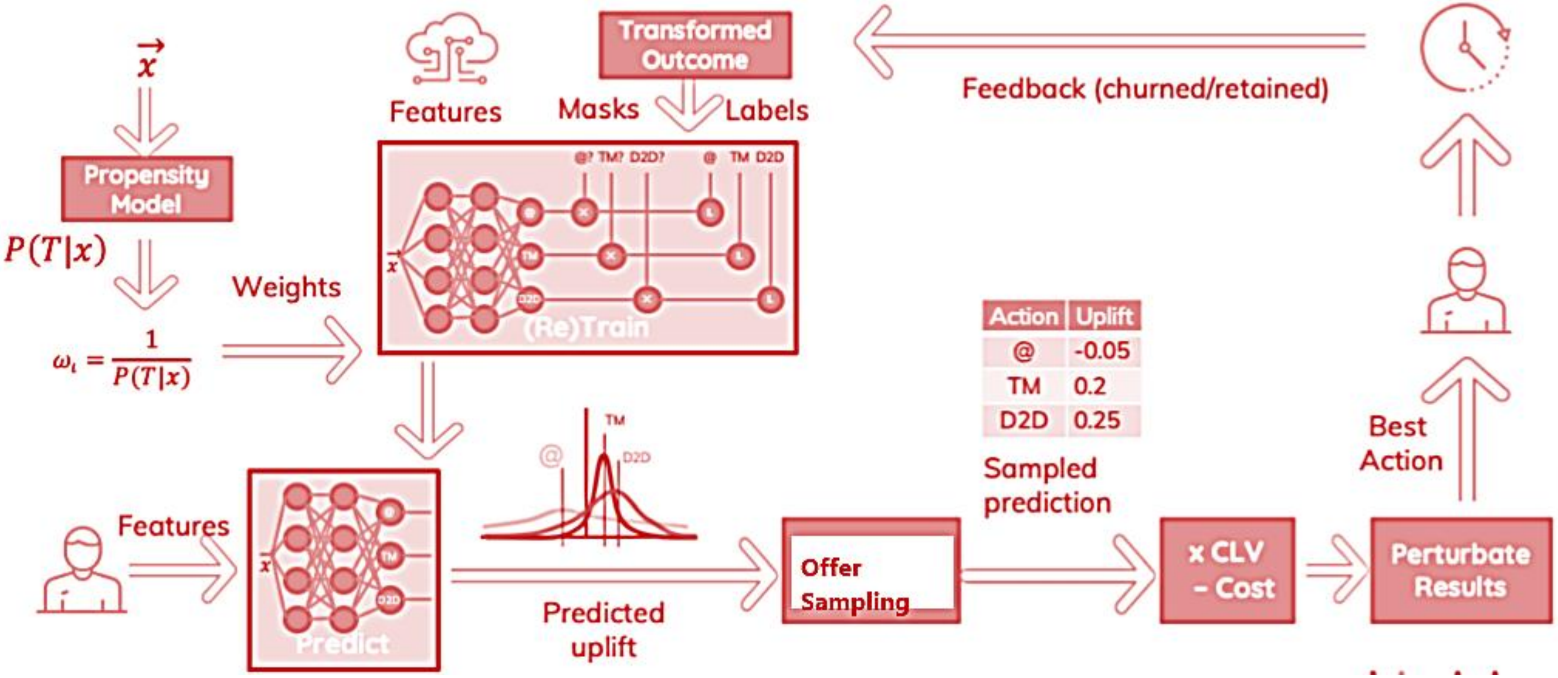
Selecting targeted offers using RL



- States of each customer is given to RandomForest based Redemption probability model
  - Generates probability values **(1)** for different offers
- States and topup rates are fed into Spontaneous topup probability model which is also RandomForest based.
  - Generates probability values **(2)** whether the customer can take up that offer.
- Rule based cannibalization model is defined by BI team. It gives a constant threshold value **(3)** as output.
  - Offers that satisfy the constrain abs(**(1)** – **(2)**) > **(3)** is further passed to next step in the pipeline.

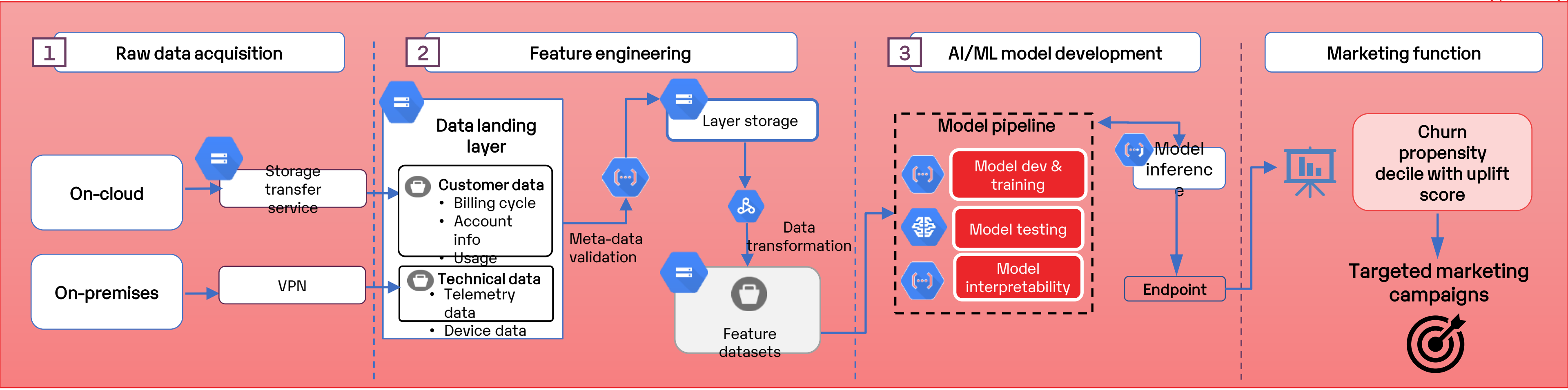
- Rule based Value model and Selection policy defined by BI team filters and allows only set offers that satisfies the constraints defined by those policies/models.

The machine learning landscape – full picture



Action	Uplift
@	-0.05
TM	0.2
D2D	0.25

Implementing 3 key enablers of the uplift model to achieve excellence in targeted marketing



1 Raw data acquisition

2 Feature engineering

3 AI/ML model development

Marketing function

On-cloud

Storage transfer service

On-premises

VPN

Data landing layer

Customer data
- Billing cycle
- Account info
- Usage

Technical data
- Telemetry data
- Device data

Meta-data validation

Layer storage

Data transformation

Feature datasets

Model pipeline

Model dev & training

Model testing

Model interpretability

Model inference

Endpoint

Churn propensity decile with uplift score

Targeted marketing campaigns

1

Raw data acquisition

Determining the right type of data input to get the right features and eventually an accurate churn propensity

2

Feature engineering

Selecting the best feature datasets from a wide range of raw data, resulting in enhanced AI/ML model accuracy

3

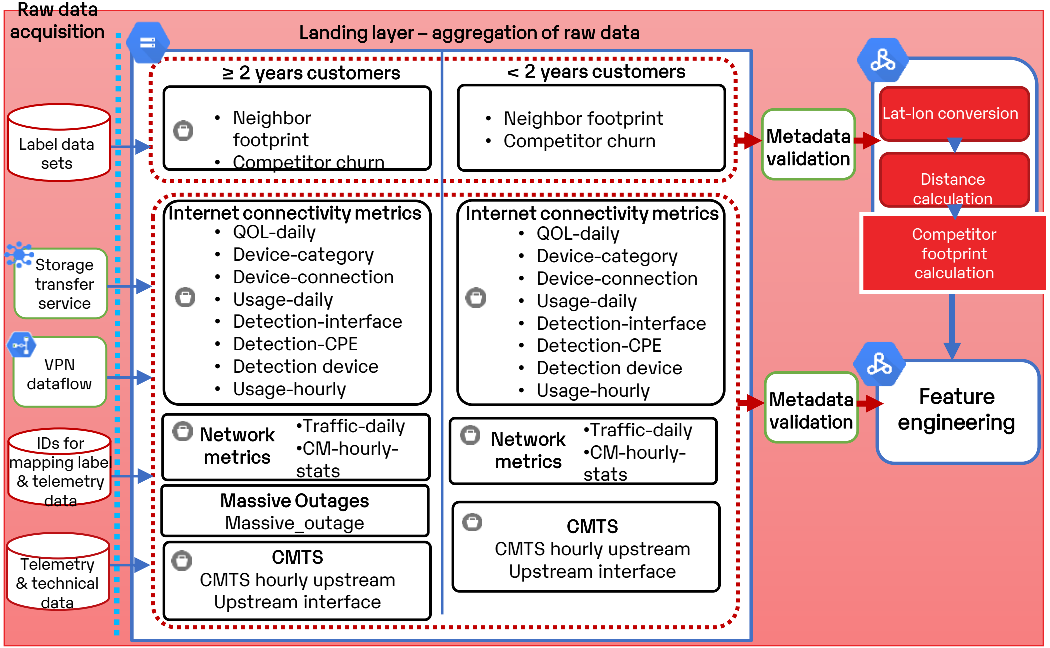
AI/ML model development

Developing an AI/ML engine to increase the uplift and predict the churn propensity

With these 3 key enablers, DSPs can achieve an increase of 10%-18% in the uplift score. Furthermore, the return on marketing investment for DSPs would increase drastically.

Raw data acquisition: Selecting the best raw data to achieve accurate churn propensity and improved uplift

It is critical to **prioritize only the most relevant and the best raw data** input, to achieve an accurate churn propensity output and uplift score.



Raw data acquisition

Landing layer – aggregation of raw data

Label data sets

Storage transfer service

VPN dataflow

IDs for mapping label & telemetry data

Telemetry & technical data

≥ 2 years customers

- Neighbor footprint
- Competitor churn

< 2 years customers

- Neighbor footprint
- Competitor churn

Internet connectivity metrics

- QOL-daily
- Device-category
- Device-connection
- Usage-daily
- Detection-interface
- Detection-CPE
- Detection device
- Usage-hourly

Internet connectivity metrics

- QOL-daily
- Device-category
- Device-connection
- Usage-daily
- Detection-interface
- Detection-CPE
- Detection device
- Usage-hourly

Network metrics
- Traffic-daily
- CM-hourly-stats

Network metrics
- Traffic-daily
- CM-hourly-stats

Massive Outages
Massive_outage

CMTS
CMTS hourly upstream
Upstream interface

CMTS
CMTS hourly upstream
Upstream interface

Metadata validation

Lat-lon conversion

Distance calculation

Competitor footprint calculation

Metadata validation

Feature engineering

Fig: Raw data acquisition and landing layer

Recommended raw datasets for uplift model

- Device throughput
- Massive outages
- Neighbor data
- Call center
- Churn probability
- Competitor footprint
- Interface status
- Daily traffic
- Tickets
- Socio demographic
- CPE performance
- Hourly stats of CM
- Daily usage
- Hourly usage
- Network health

RECOMMENDATIONS

Aggregation of raw data:

- **Solution architects and domain experts should collaborate** to decide on data aggregation strategies and finalize the type of raw datasets to be used.
- Select the raw data **based on the past 2-3 months trends**. The historical trends depends on
  - Customers churn data
  - Active customers feedback
  - Customer response from marketing campaigns
- **Select the raw data, which has high influencing features** such as distance between an active customer and churner, competitor footprint, hourly broadband usage, etc.

Metadata validation to check the quality of raw data:

- Perform metadata validation daily, as the raw data acquisition is a continuous on-going process.
- Metadata validation tool could be built using Python.

The raw data, once obtained, must be engineered to get the best feature dataset, which would be fed into the AI/ML engine to achieve churn propensity and uplift score.

Feature engineering (FE): Leveraging data science to process raw data and select the best features

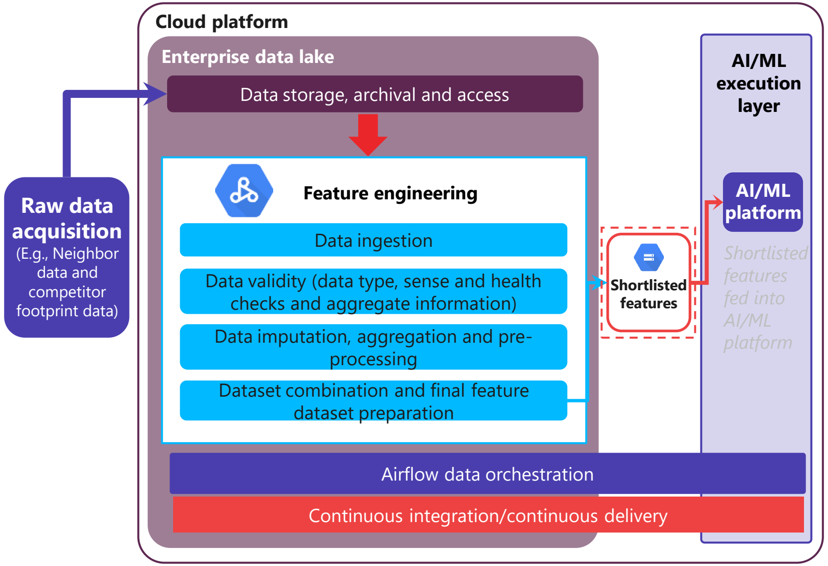


Fig: Feature engineering process

BENEFITS FOR DSPs

The selection of few best features out of more than thousands of features increases the accuracy of churn propensity. This is not achievable in traditional manual churn modeling.
Completely automated engineering allows the processing of any raw data, irrespective of the occurrence of data bias or data shift, which occurs due to customer behaviour shifts. Thus, DSPs do not have to repeat the feature engineering process depending on data variations.

Significance of feature selection:

- With feature engineering, the raw data is transformed into features that better represent the underlying issue to the ML algorithm, resulting in enhanced model accuracy.

RECOMMENDATIONS

Engineer the raw data to determine high-quality features

- Use the FE model to ingest and analyze the raw data to obtain a total of 3,000-11,000 features. (*Note: this number may differ based on raw data*)
- Execute the feature selection process, using the AI/ML platform to select only the best 400-1,000 final features (out of the 3,000-11,000 total features)

The most critical features for an effective uplift model are listed below:

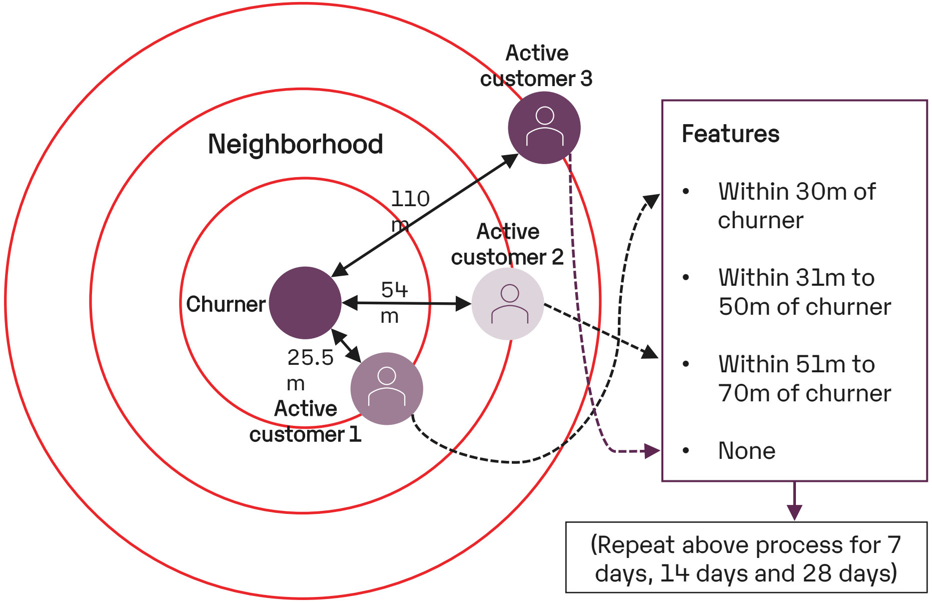
- Active churners who are present within 30 meters from possible churner
- Ratio of competitor networks present closer to 200 meters of churners churned in 30 days
- Active churners who are present within 50 meters from possible churner and churner before last 15 days
- Probability of churning to competitor X
- Probability of churning to unknown competitors
- Downstream hourly broadband usage in MB
- Upstream hourly broadband usage in MB
- Power cycle detection
- Number of stations per interface (hourly)
- Broadband connectivity detection

Use data orchestration platform to automate FE data pipeline

- The whole FE architecture should be managed on a data orchestration and scheduling platform such as **Apache Airflow**, which allows the FE data pipeline to be triggered automatically bi-weekly or monthly

The features, once obtained, must be fed into the AI/ML engine to achieve churn propensity and uplift score.

Example to illustrate feature generation using **neighbor and competitor footprint data**



Features

- Within 30m of churner
- Within 31m to 50m of churner
- Within 51m to 70m of churner
- None

(Repeat above process for 7 days, 14 days and 28 days)

Note: *m represents distance in meters*

The above diagram shows the features generated based on the distance between a churner and active customers, in a particular neighborhood. The features are generated for every 7, 14, and 28 days and fed into the AI/ML model.

Neighbor and competitor footprint data provide higher number of influencing features, which are useful to achieve an accurate churn propensity and higher uplift score.

RECOMMENDATIONS

Use the neighbor and competitor footprint data to determine the following:

- Density of active and churned users in a neighborhood
- Competitor footprint in the same neighborhood
- Number of churners for every 7 days, 14 days, and 28 days
- Period of churn: date and time of a customer churn
- Distance between a churner and active customer/subscriber

AI/ML model development: AI/ML engine increases the uplift score and enables DSPs to target the right set of customers

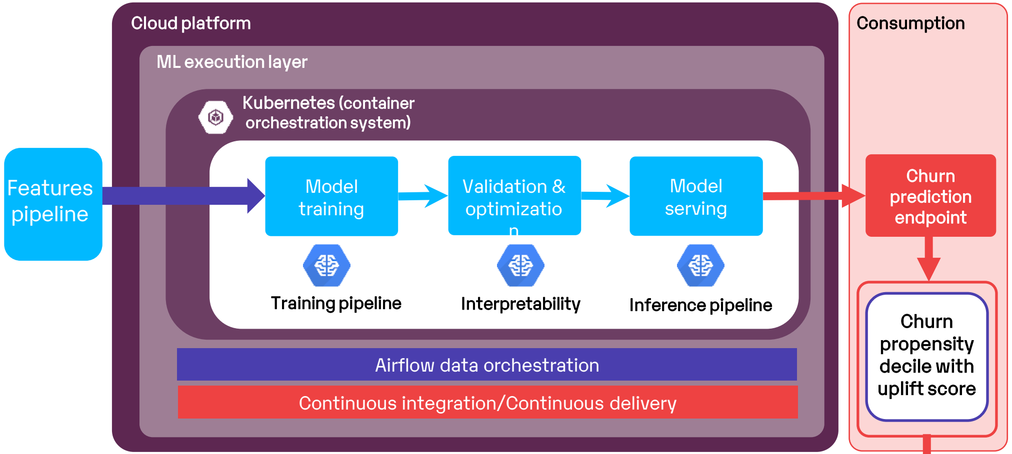
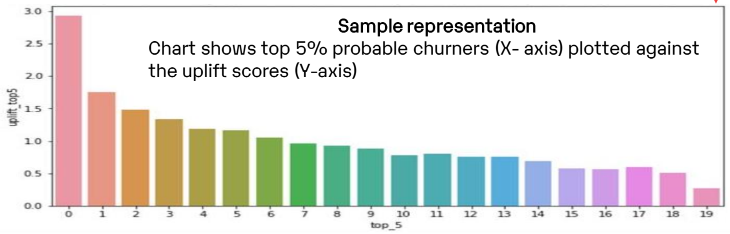


Fig: AI/ML engine to predict churn propensity



Sample representation

Chart shows top 5% probable churners (X- axis) plotted against the uplift scores (Y-axis)

	top_5	sum_volChurn	count_volChurn	pct_volChurn_fivepct	pct_customer_base_churn	uplift_top5
0	0	1114.0	12904	0.086330	0.029445	2.931885
1	1	668.0	12904	0.051767	0.029445	1.758078
2	2	565.0	12903	0.043788	0.029445	1.487113
3	3	507.0	12904	0.039290	0.029445	1.334350
4	4	451.0	12904	0.034950	0.029445	1.186966

The AI/ML engine uses the best features, from the feature engineering pipeline, to predict the probability scores of the churners.

RECOMMENDATIONS

- Adopt **multiclass classification**-based AI/ML model, as a variety of features are analysed to predict the churn
- Implement custom **hyperparameter tuning** before the ML process begins, as it helps in testing different configurations when training the ML model
- Implement **Kubernetes, an open-source container-orchestration system,** to automate the deployment and management of ML model

---

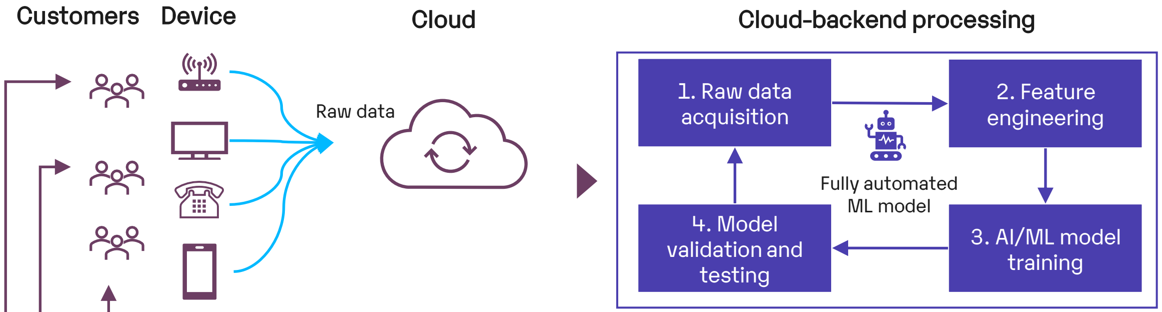
Run supervised ML algorithm on the engineered features

- Run the engineered features through three ML algorithms – i) Variance inflation factor, ii) Random forest algorithm, iii) XGBoost model
- These algorithms analyze and select the top features, which is required to predict the churn propensity and increase the uplift

BENEFITS

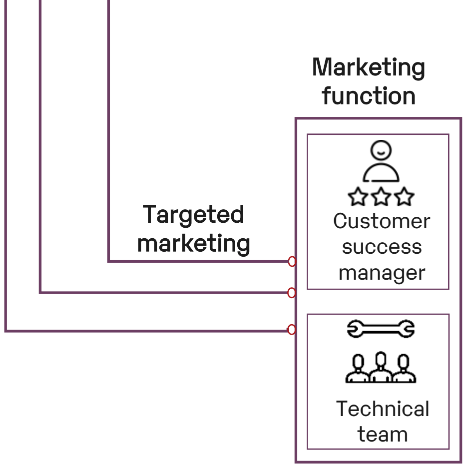
- The model sorts the probable churners into deciles, with the corresponding uplift score
- A high uplift score determines the customer's likelihood to respond to marketing campaigns

A leading DSP in the Americas implemented the ML-based uplift model to achieve excellence in targeted marketing



The output is a .csv file which is used in the coding script to determine the churn propensity decile with uplift score

```
[1]: # Load the libraries
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns

     import warnings
     warnings.filterwarnings('ignore')

[2]: # Loading preducted file per experiments
     _predicted_customer = pd.read_csv(r"_predicted_  _ _xgboost_new_data_may_11.csv")

[3]: print("This is the valu count for volChurn", _predicted_customer['volChurn'].value_counts())
     print("shape of the customer base", _predicted_customer.shape)

     This is the valu count for volChurn 0.0    250474
     1.0      7599
     Name: volChurn, dtype: int64
     shape of the customer base (258073, 10)

[4]:  _predicted_customer['volChurn'] =  _predicted_customer['volChurn'].fillna(0)
```



Sample results

Output can be downloaded as an Excel spreadsheet (representative data)

Likelihood to respond to marketing campaigns	Top 5% probable churners			
	Uplift score	Customer name	Customer contact details	
			Phone no.	Email
High	2.93	Customer 1	112233445	customer1@xyz.com
	2.93	Customer 2	112233445	customer2@xyz.com
	2.93	Customer 3	112233445	customer3@xyz.com
Medium	1.76	Customer 4	112233445	customer4@xyz.com
	1.76	Customer 5	112233445	Customer5@xyz.com
Low	1.49	Customer 6	112233445	customer6@xyz.com

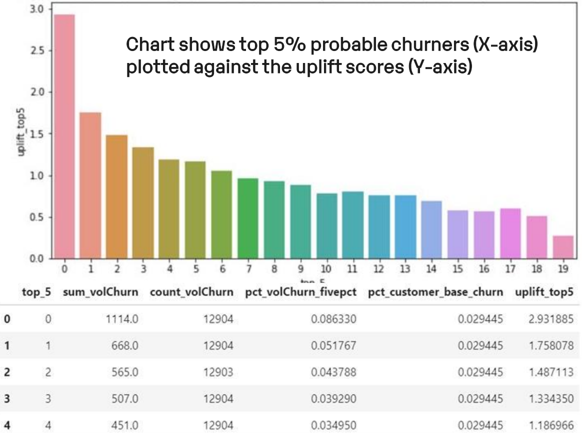
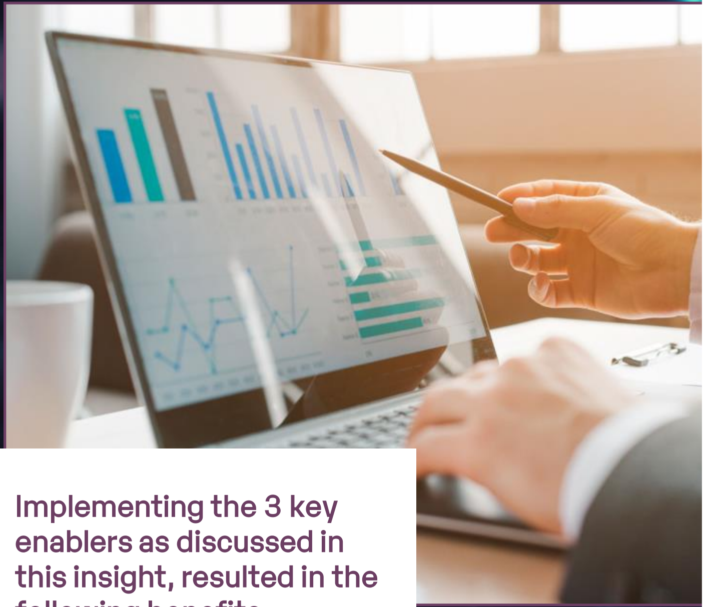


Chart shows top 5% probable churners (X-axis) plotted against the uplift scores (Y-axis)

	top_5	sum_volChurn	count_volChurn	pct_volChurn_fivepct	pct_customer_base_churn	uplift_top5
0	0	1114.0	12904	0.086330	0.029445	2.931885
1	1	668.0	12904	0.051767	0.029445	1.758078
2	2	565.0	12903	0.043788	0.029445	1.487113
3	3	507.0	12904	0.039290	0.029445	1.334350
4	4	451.0	12904	0.034950	0.029445	1.186966

Benefits achieved by the DSP after implementing the ML-based uplift model



Implementing the 3 key enablers as discussed in this insight, resulted in the following benefits.

10%-18% increase in uplift score resulted in targeting the right set of customers, who would respond positively to the marketing campaigns

	Uplift score of top 10,000 probable churners
Traditional/manual approach	3.47
ML-based uplift modelling	4.1
% increase in uplift score	**18.2%**

Improved customer retention due to personalized marketing campaigns

Improved targeted marketing
- Increase in marketing ROI
- Reduction in time-to-market for targeted campaigns

Used Google Cloud Platform (GCP) for end-to-end execution of the ML-based uplift model, which drastically reduced the architecture setup time

Prodapt enables powerful technologies that accelerate connectedness

Singularly focused on **Connectedness** aka Telecommunications, Media, & Technology (TMT) vertical

We are obsessed with the future of Connectedness

We combine deep domain expertise and digital-by-default skills to enable transformations using Cloud, Network, AI, Robotics and CX

Prodapt's customers today help more than a **billion people,** and **five billion devices** stay connected

Great Place To Work®
Certified
APR 2021-MAR 2022
INDIA

Part of the Jhaver Group
Privately Owned

$3.0 B in revenues
22,000 Employees worldwide
64+ global locations

THE JHAVER GROUP

Customers

Americ
as

verizon
facebook
CenturyLink
AT&T
LIBERTY LATIN AMERICA
Frontier
amazon
windstream.
TELUS
Google
ROGERS.

Europe

kpn
LIBERTY GLOBAL
BT
Virgin media
colt
proximus
vodafone Ziggo
T · ·
TELE2
upc
T · ·Mobile·
Magenta

Africa

Telkom
MTN

OEM/ISV

ASPIDER-NGI
FEDEROS
SMART/RG An ADTRAN Company
mycomOSI
cisco
VeriSat
SEAGATE
CLEARACCESS
ORACLE
ADTRAN

Recognized by

tmforum
Everest Group®
ISG imagine your future
zinnov ZONES
Gartner
Deloitte. Technology Fast50

Ecosystem Partners

salesforce
FEDEROS
headspin
nuagenetworks
Lanner
Atrinet
intel
ADVANTECH Enabling an Intelligent Planet
Vlocity
flexiWAN
celonis
Microsoft Azure
RESOLVE
casa systems
aws

Internship opportunities @ Prodapt

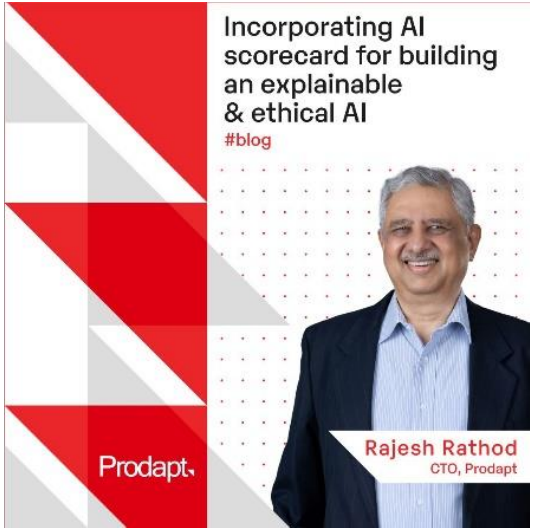
The various opportunities to engage with Prodapt

You can actively be a part of the various Platform and software engineering services work @ Prodapt

- As on roll employees
- As full-time interns (M. Tech, M.S, Final year internship) for 6 to 9 months
- As part of your semester internship / short time internship
- Part time support to dedicated outcome initiatives / PoC / Technical paper research groups
- Tech bytes – present your thoughts to industry audience

Be a part of tech domains in Cloud, AIML, Intent Based Networks, Blockchains, Quantum computing, Metaverse, Cybersecurity, ASIC design, Agile software development and a lot more …..

About the presenter



Rajesh Rathod, CTO Prodapt

As the Chief Technology Officer, Rajesh Rathod assists the CEO & the Board in building strategic growth drivers focused on next-generation technology and capability development. Rajesh is also responsible for scaling Prodapt labs, building next-gen technology offerings and IP frameworks to boost future growth, in addition to driving the M&A technology strategy. As part of the role, he also oversees the learning & development function to prepare Prodaptians for the next phase of growth.

Rajesh Rathod completed his B. Tech in Electrical Engineering from the Indian Institute of Technology, Bombay, and his Master's in Electrical Engineering at the Indian Institute of Science, Bangalore. Outside his professional engagements, Rajesh is an active member of Shri Ram Chandra Mission, a spiritual organization, where he volunteers for several initiatives.

Get in touch

USA

Prodapt North America, Inc.
Oregon: 10260 SW Greenburg Road, Portland
Phone: +1 503 636 3737

Dallas: 1333, Corporate Dr., Suite 101, Irving
Phone: +1 972 201 9009

New York: 1 Bridge Street, Irvington
Phone: +1 646 403 8161

CANADA

Prodapt Canada, Inc.
Vancouver: 777, Hornby Street,
Suite 600, BC V6Z 1S4
Phone: +1 503 210 0107

PANAMA

Prodapt Panama, Inc.
Panama Pacifico: Suite No 206, Building 3815
Phone: +1 503 636 3737

CHILE

Prodapt Chile SPA
Las Condes: Avenida Amperico Vespucio Sur
100, 11th Floor, Santiago de Chile

UK

Prodapt (UK) Limited
Reading: Suite 277, 200 Brook Drive,
Green Park, RG2 6UB
Phone: +44 (0) 11 8900 1068

IRELAND

Prodapt Ireland Limited
Dublin: Suite 3, One earlsfort centre,
lower hatch street
Phone: +44 (0) 11 8900 1068

EUROPE

Prodapt Solutions Europe &
Prodapt Consulting B.V.
Rijswijk: De Bruyn Kopsstraat 14
Phone: +31 (0) 70 4140722

Prodapt Germany GmbH
Münich: Brienner Straße 12, 80333
Phone: +31 (0) 70 4140722

Prodapt Digital Solution LLC
Zagreb: Grand Centar,
Hektorovićeva ulica 2, 10 000

Prodapt Switzerland GmbH
Zurich: Muhlebachstrasse 54,
8008 Zürich

Prodapt Austria GmbH
Vienna: Karlsplatz 3/19 1010
Phone: +31 (0) 70 4140722

Prodapt Slovakia j.s.a
Bratislava: Plynárenská 7/A, 821 09

SOUTH AFRICA

Prodapt SA (Pty) Ltd.
Johannesburg: No. 3, 3rd Avenue, Rivonia
Phone: +27 (0) 11 259 4000

INDIA

Prodapt Solutions Pvt. Ltd.
Chennai: Prince Infocity II, OMR
Phone: +91 44 4903 3000

"Chennai One" SEZ, Thoraipakkam
Phone: +91 44 4230 2300

IIT Madras Research Park II,
3rd floor, Kanagam Road, Taramani
Phone: +91 44 4903 3020

Bangalore: "CareerNet Campus"
2nd floor, No. 53, Devarabisana Halli,
Phone: +91 80 4655 7008

Hyderabad: Workafella Cyber Crown 4th Floor,
Sec II Village, HUDA Techno, Madhapur

THANK YOU!

Chase
Extraordinary

info@prodapt.com | www.prodapt.com

Prodapt

Personalized marketing strategy of DSPs (Digital Service Providers) relies upon the ability to determine the **propensity to churn and target the right set of customers**

DSPs have been **increasing their investments in strategic marketing to** retain customers. However, it is critical to justify the investments by **targeting the right set of customers, who are most likely to respond** to the marketing campaigns.

Focusing on a **personalized marketing approach** will retain active customers and active subscriptions

The key to personalized marketing is to first **identify the most probable churners** and their corresponding **uplift metric**, which determines their **likelihood to respond to the marketing campaigns**

Thus, the **uplift metric enables DSPs to target** the right set of customers with personalized campaigns and maximize marketing return on investment (ROI).

Personalized outreach is a key lever for DSPs to retain customers and increase revenue

Engagement	Levers	Upside
Drive customer value	Reduce churn and grow advocacy	15-40% absolute churn reduction
	Personalize outreach and cross-sell	15-30% increase in revenue from cross-sell

DSPs' marketing strategy should be based on four key criteria

1. Identify customers who are most likely to churn voluntarily
2. Determine the propensity to churn
3. Identify customers with a higher probability to respond positively to marketing campaigns
4. Target those customers with personalized marketing campaigns

Different approaches to **determine the right set of target customers** for achieving **higher marketing ROI**

Types of customers based on their buying response to marketing campaigns

Persuadables

Customers who buy only when a marketing campaign is served

Targeting them will generate incremental value

Sure things

Customers who buy with or without a marketing campaign

Lost cause

Customers who would not buy irrespective of a marketing campaign is sent to them or not

Sleeping dogs

Customers who buy without marketing campaign. But would stop buying when a campaign is targeted at them

Different types of approaches to determine the right set of target customers

Manual spreadsheet based statistical modelling

- The model provides a **randomized and inaccurate list** of target customers, which may include all four types of buyers. This results in targeting the wrong customers
- Results in **low return** on marketing investment

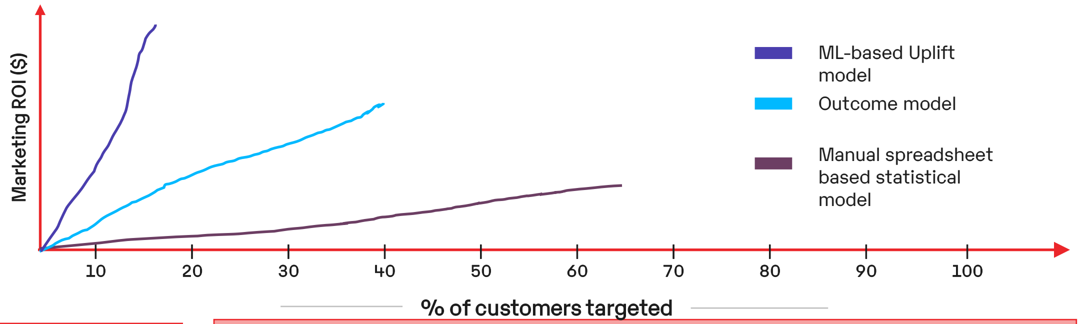
Outcome modelling

- The model identifies the list of buyers and non-buyers. The model lacks granularity in terms of categorizing the buyers into persuadable and sure things
- Results in **medium return** on marketing investment

ML-based uplift modelling

- The model identifies the list of buyers and non-buyers and **provides granularity** in terms of which buyers are persuadables. This results in targeting only one type of customer – persuadables, thereby improving marketing efficiency and drive higher incremental revenue
- Results in **high return** on marketing investment

Customers targeted vs marketing ROI achieved using different types of approaches



Recommendation

ML-based uplift model promises to deliver higher return on marketing investment. The successful implementation of the model requires right set of enablers such as raw data acquisition, data engineering, and lifecycle management using ML Ops. These enablers are presented in upcoming slides.

Final outcome of ML-based uplift model

Increase in uplift score: An increased uplift score determines which decile of customers has high probability to respond positively to marketing campaigns.