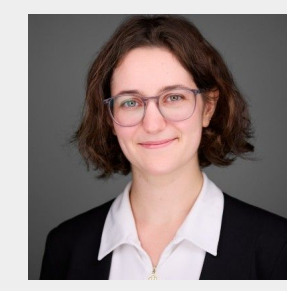


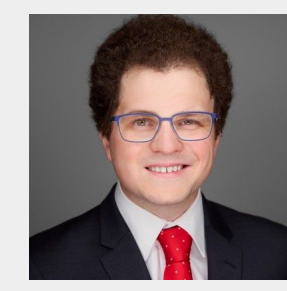


# Making Spam Meat Again

Leveraging Targeted Email Marketing to Reduce Churn



Naomi Keis

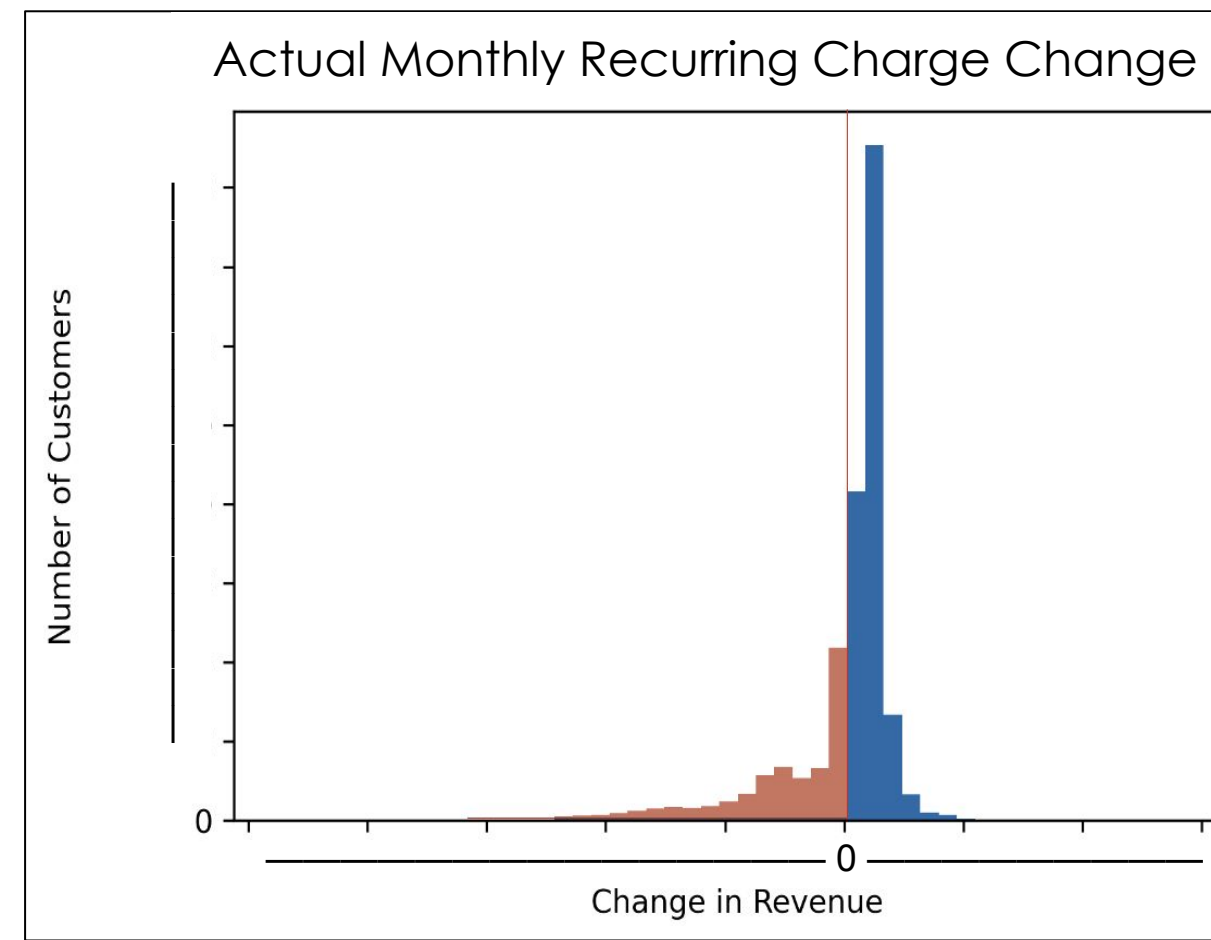


Ian Tong

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## Problem Breakdown



^ Fig 1: Distribution of Roll Revenue Change

Average expected MRC increase/customer:

**21%**

Assuming no churn

churn

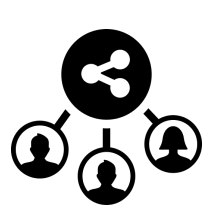
Actual Average MRC increase per customer post-churn:

**2%**

## Churn Rate Investigation

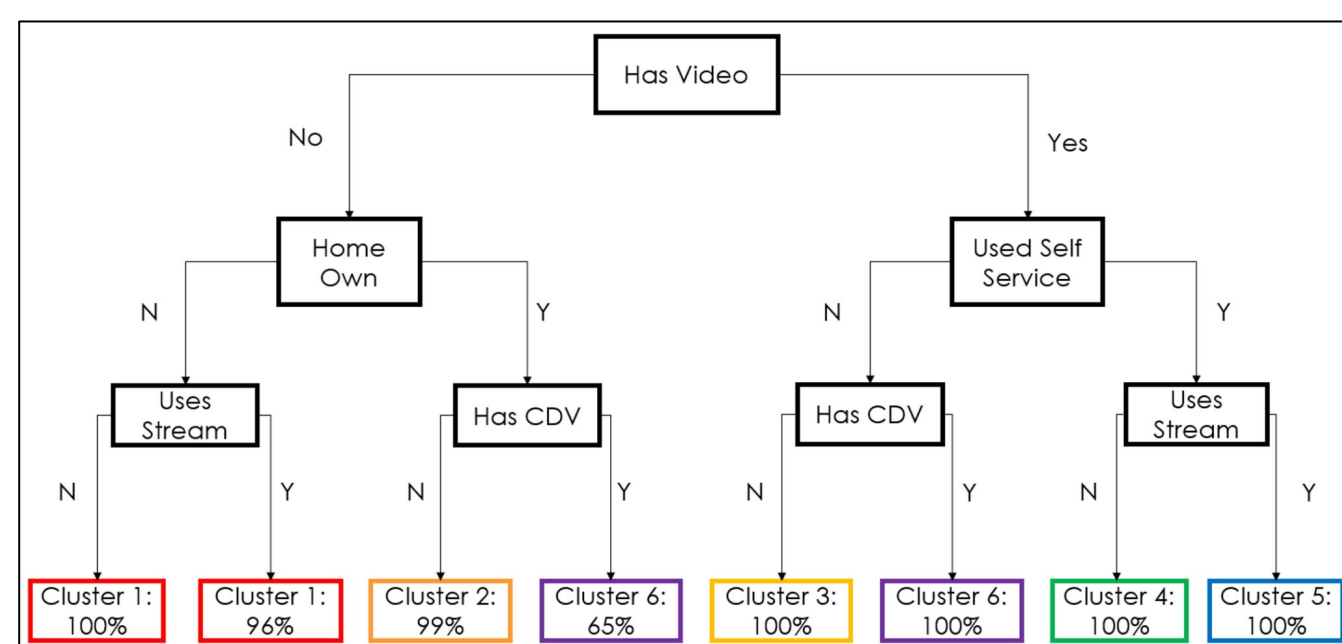
### Customer Segmentation:

Cluster	Churn Δ
1	+13.7%
2	-0.9%
3	-2.2%
4	-2.4%
5	-4.1%
6	-6.3%



Segmentation via Clustering was performed to isolate important sub-groups within the client base

- K-means with Silhouette Score was used to develop the clusters and select the correct amount
- Churn was omitted to avoid data leakage
- A decision tree was overlaid for interpretability



^ Fig 2: Cluster Churn Rate

> Fig 3: Decision Tree for each Cluster and the assigned purity and size of each leaf

### Promo Roll Churn Prediction:



Predictive Modelling was conducted to assess the impact of various factors on churn, and aid in the development of a prescriptive framework

#### Data Includes:

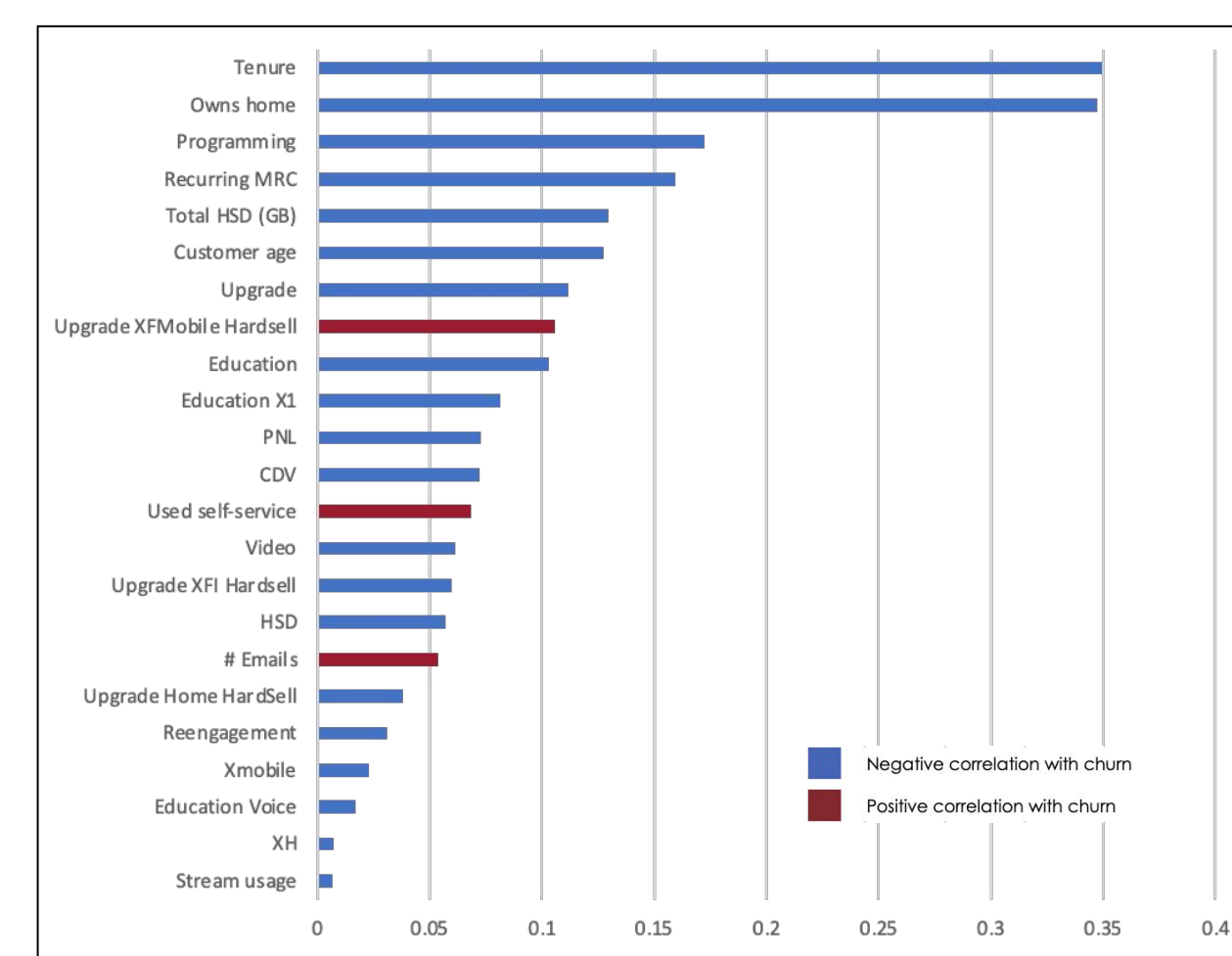
- Emails by key Email Program
- Number of total Emails Sent
- Selected Demographic Features

#### Models Examined:

- Gradient Boosting
  - XGBoost
  - LightGBM
- Variety of Logistic Regression
- Random Forest

#### Final Model: Logistic Regression

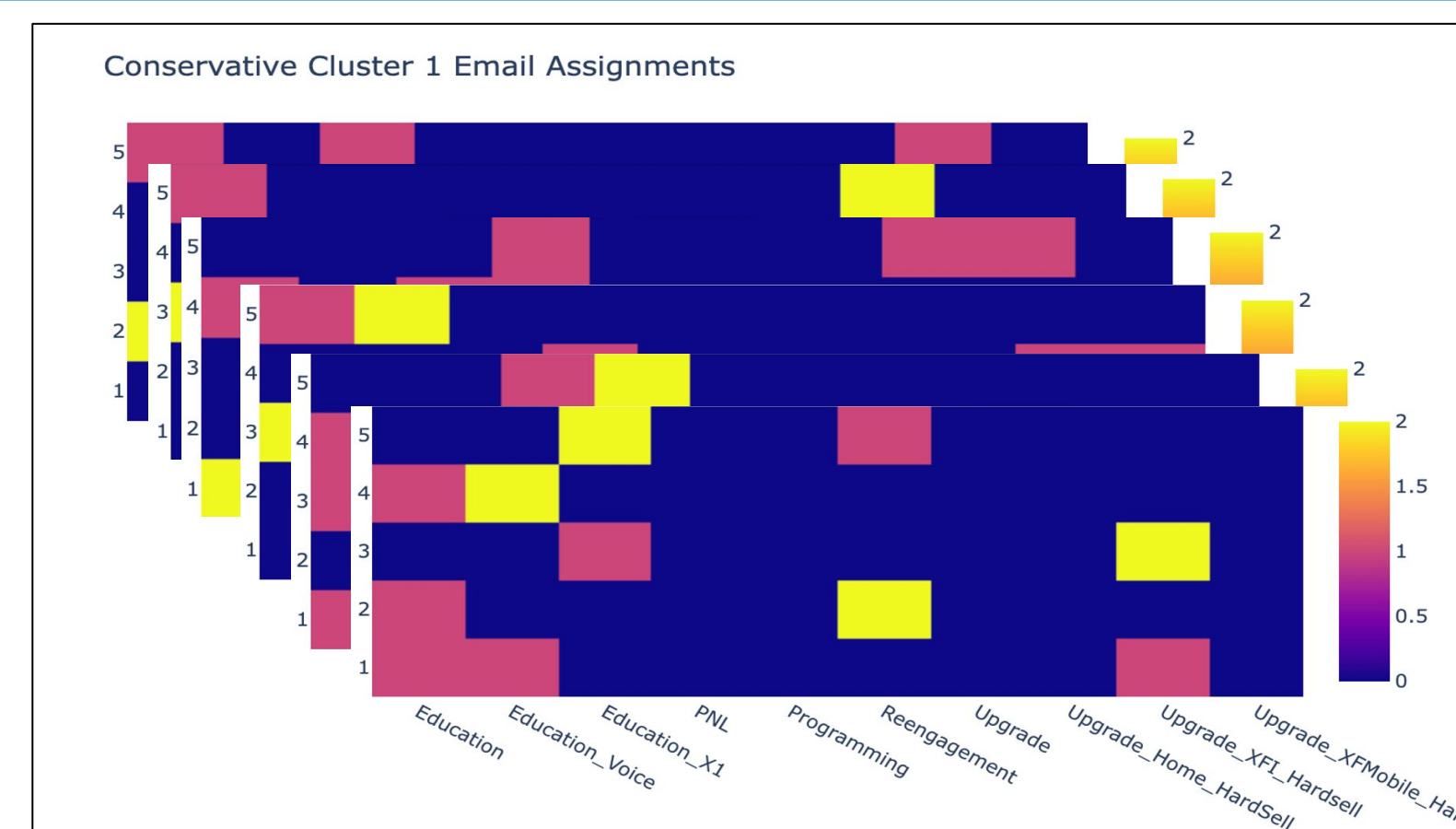
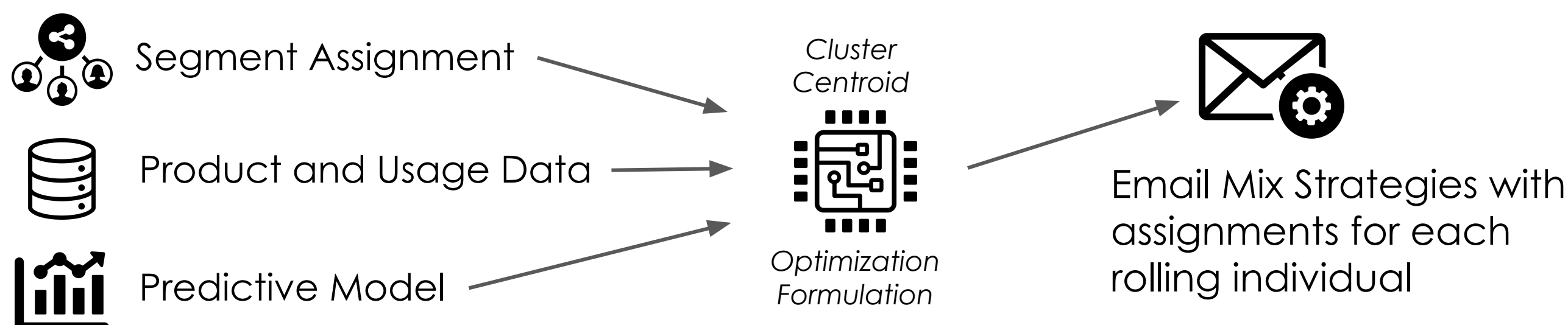
- AUC: 0.726
- Accuracy: 89.3%



^ Fig 4: Feature Importance of Model Factors

## Prescriptive Application

Combining the modelling performed on Churn Prediction and Segmentation we created a decisioning engine through optimization of cluster centroids to assign email mix strategies:



^ Fig 5: Example Email Mix Strategy Set

### Objective Values:

$$\text{Min}_x \sum_c (\beta_c x_c + \gamma_c z_c + \alpha_c (s_c + \sum_j x_{c,j})) + \sum_t \alpha_t x_t$$

[ Log Odds ] [ Timing ]

### Key Variables/Inputs:

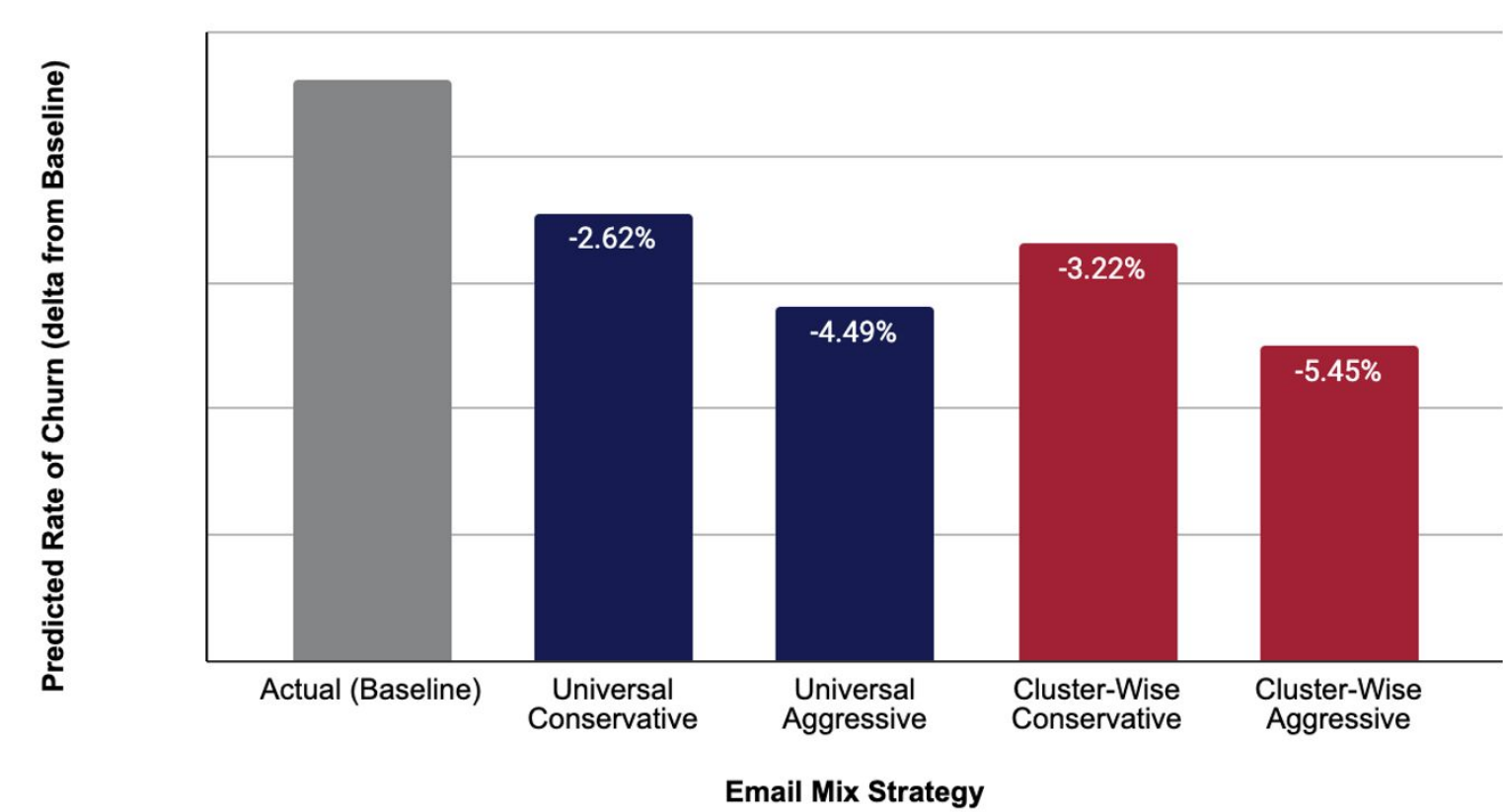
- $x_{cjt}$  - sending an email  $j$  to cluster  $c$  in week  $t$
- $z_j$  - known centroid demographic value  $j$  for cluster  $c$
- $\beta_{c,j}$  - coefficient for cluster  $c$  for email category  $j$
- $\gamma_{c,k}$  - coefficient for cluster  $c$  for demographic  $k$
- $\alpha_t$  - coefficient for emails in week  $t$

### Constraints:

- Restrict the total number of emails that can be sent in any one week
- Restrict the total number of emails sent in any one category
- Restrict the total number of emails from one category sent in any two-week period

Exact constraint values malleable for different strategies.

### Test Set Optimization Scenario Results



^ Fig 6: Test Outcomes from Different Mix Strategy Sets

## Business Impact



Q: What differentiates clients and their actions during Promo Roll?

A: Through our segmentation of the Promo Roll client base we isolated important subsets of clients and modelled the importance of various factors on churn



Q: What role does Email Campaigns play in Promo Roll?

A: Based on the results of our modelling Emails from a subset of controllable campaigns were found to correlate with reduced churn, and a further **randomized test** was proposed to continue analyzing the impact of emails on churn



Q: Which Emails should be sent to each client undergoing Promo Roll?

A: An optimization formulation based on modelling of churn rates enabled us to generate email mix strategies both universally and by cluster. This resulted in a conservative reduction in churn rate of over **3 percentage points** in offline testing