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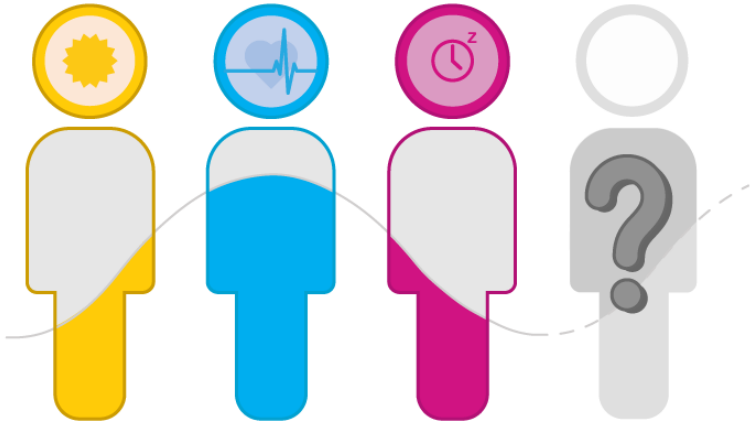
InFoMM
Industrially Focused
Mathematical Modelling

User Cancellation Modelling:

on Clustering of Customer Behaviours



Victor Wang

Supervisors: Andrew Mellor, Junaid Mubeen

Agenda

- Motivation and Goal
- Background – Business Settings at Whizz
- Model
  - Customer Journey
  - Methodology
- Result
  - Clusters
  - Feature Analysis
- Conclusion

Motivation and Goal

Motivation

Motivation and Goal

Motivation

Goal – ***Churn*** (Cancellation) modelling

Who?

- ✓ Identify customers most prone to cancel subscription
- ✓ Assess likelihood

Why?

- ✓ Analyse critical reason triggering cancellation
- ✓ Make bespoke retention policy

Business Settings at Whizz

Cancellation Mechanism

Contractual

- Pupils subscribe to access Whizz products on a 1-month or 1-year contract

Voluntary

- Subscribers make the choice to leave the service at the end of the subscription; otherwise auto-rolled

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Data Records

Time period: 2014-Jan-01 – 2018-Apr-20

Pupil	Subscription	Lesson History
• Pupil ID • Date of birth	• Pupil ID • Start date • End date	• Lesson ID • Pupil ID • Time • Mark • …
✓ 5685 pupils	✓ 28025 subscriptions	✓ ~1.6 million lesson activities

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Features

$$X = \begin{bmatrix} 1.2 & 20 & \cdots & 80\% \\ 52.2 & 34 & & 31\% \\ \vdots & & \ddots & \vdots \\ 25.1 & 99 & \cdots & 43\% \end{bmatrix}$$

Usage time (hours)

Number of visits

Pass rate

Churn outcome (renew / cancel)

$$\begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

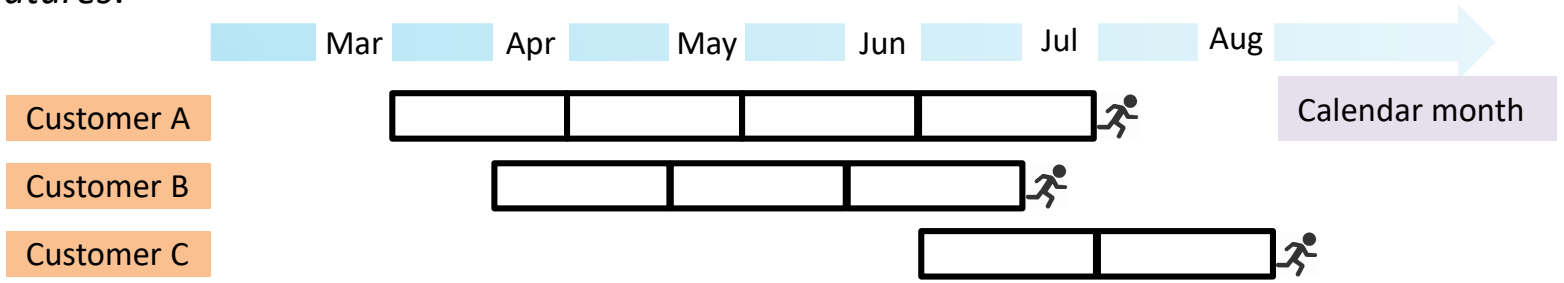
Renew

Cancel

EPSRC Centre for Doctoral Training in Industrially Focused Mathematical Modelling

Customer Journey

Pupils' activities are split into monthly time periods with each **customer-month** represented by *features*.



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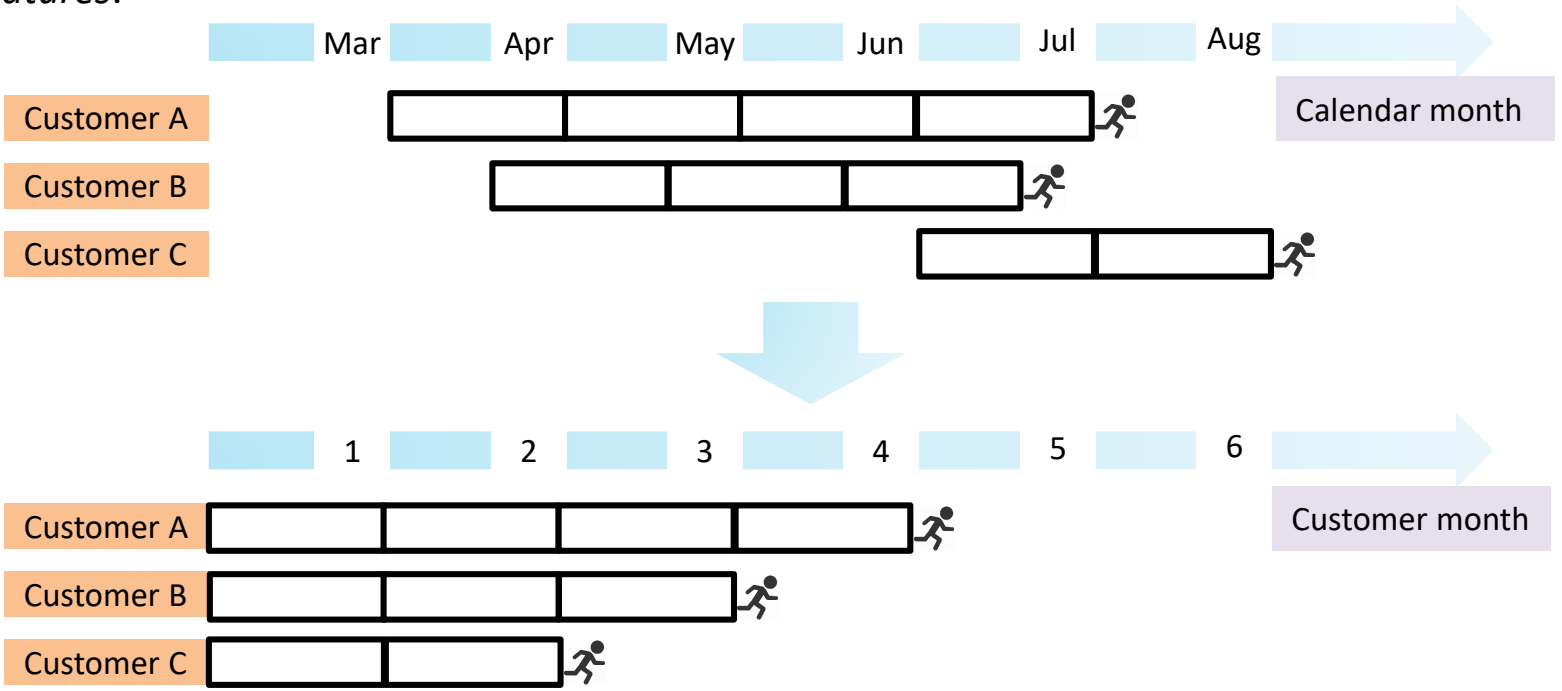

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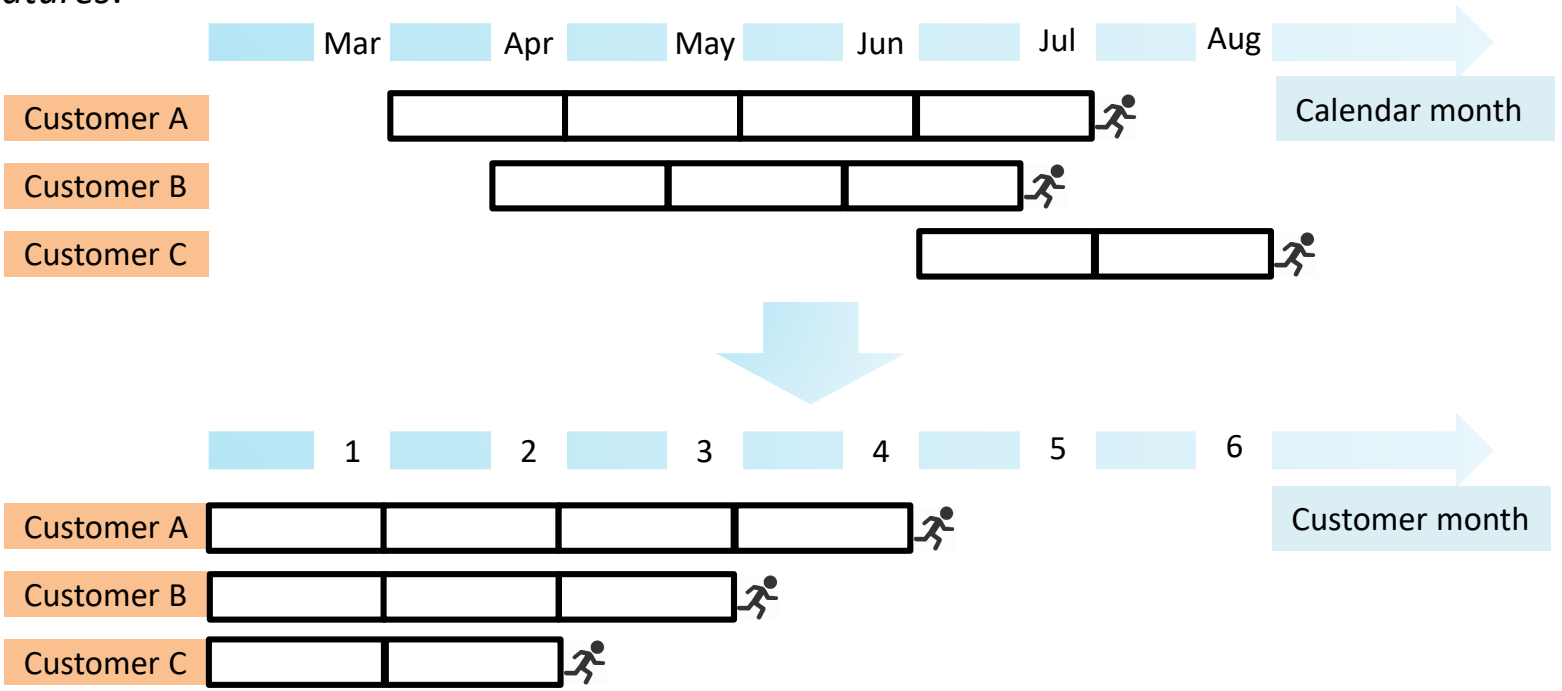

We assume the cancellation to be **ONLY** dependent on the current month.

- ✓ The assumption holds since we observe statistically constant churn rate over customer month.
- ✓ The assumption enables us to treat activities in different customer months indifferently.

Methodology

Key Assumptions

- ✓ Churners and non-churners exhibit different behaviours generated by some **states**

States

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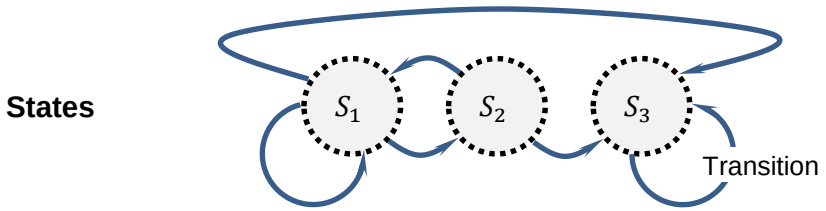

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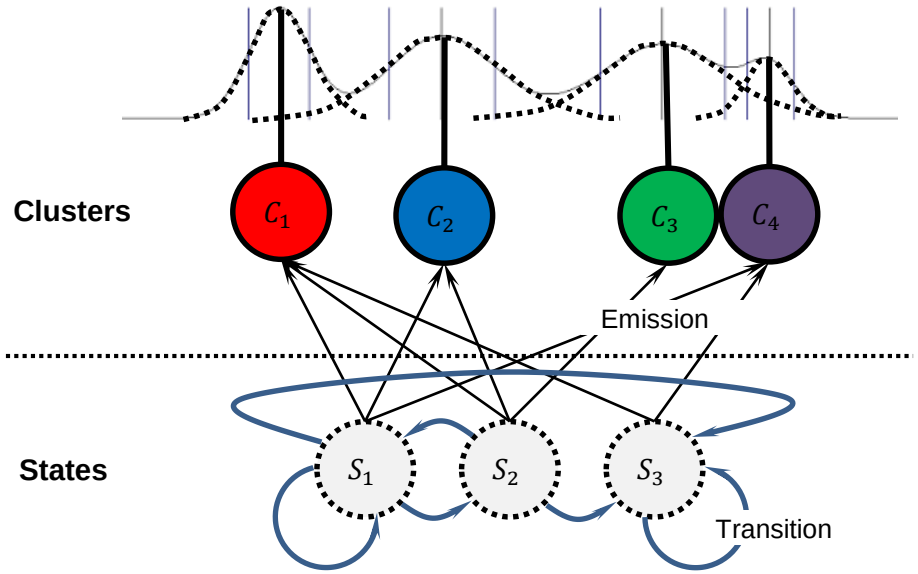

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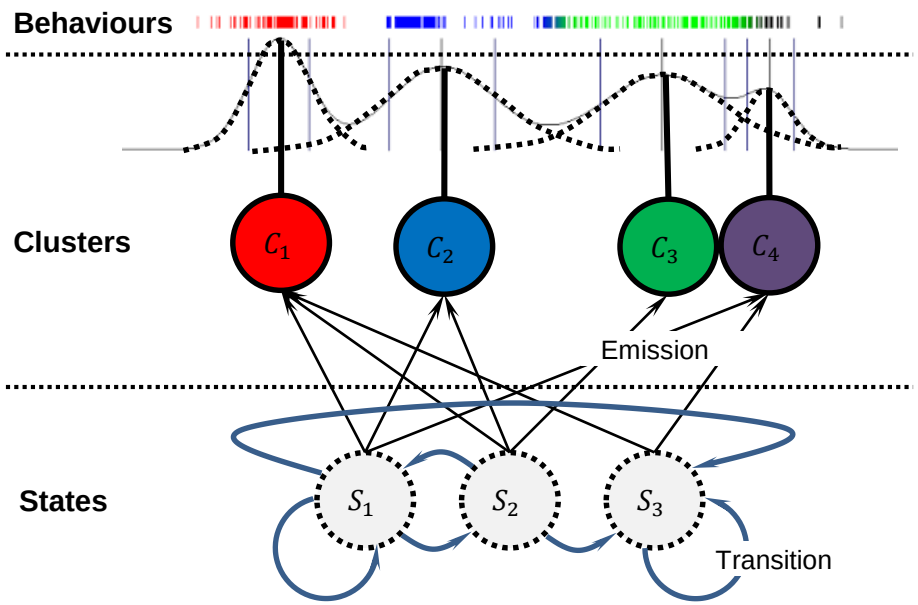

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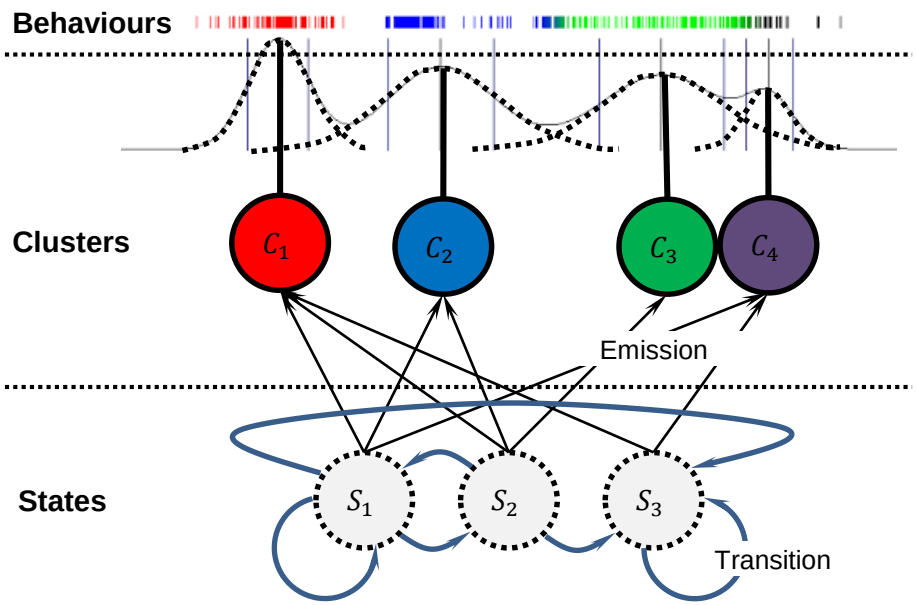

Mixture Model

$$f(\boldsymbol{X}) = \sum_{k=1}^{K} \pi_k \, f_k(\boldsymbol{X} \mid \boldsymbol{\theta_k})$$

Markov State Transition probability

$$A = (a_{ij})$$

$$a_{ij} = P(s_{t+1} = S_i \mid s_t = S_j)$$

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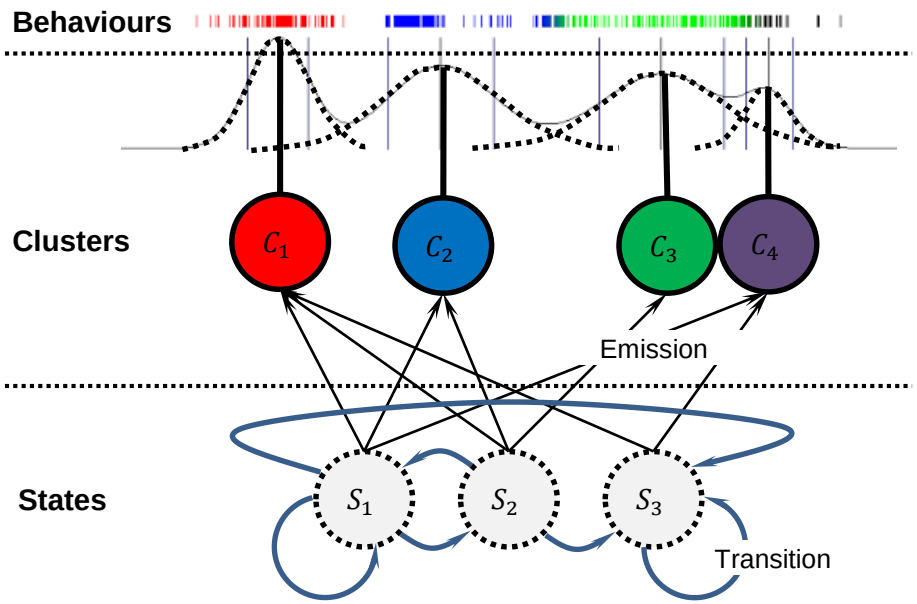

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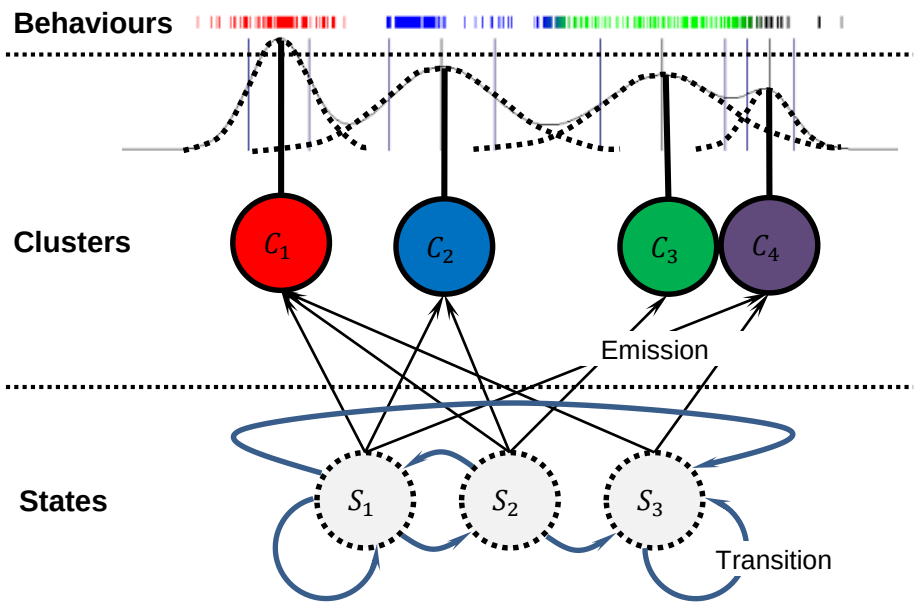

Make inference!

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Extract features to represent customers within a specific customer month.

Feature Distributional Modelling

Assess distributions, correlations, etc.

Clustering

Fit mixture model;

Define states

Analytics and Prediction

Interpret clusters

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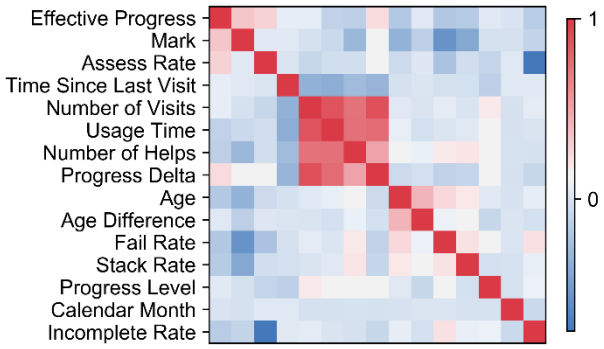

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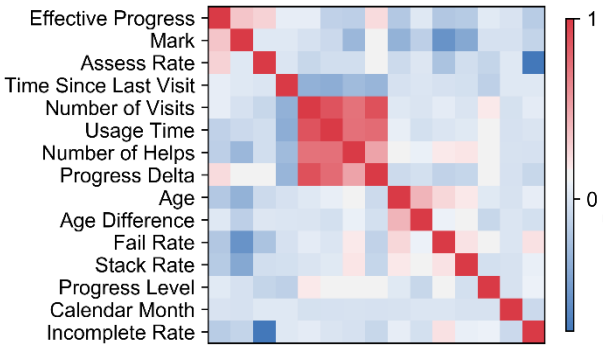

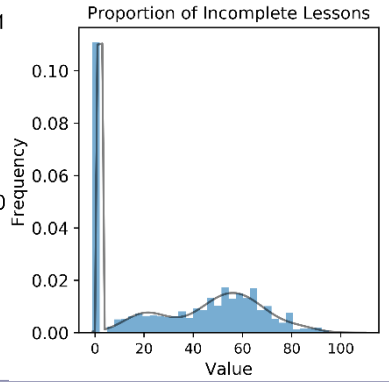

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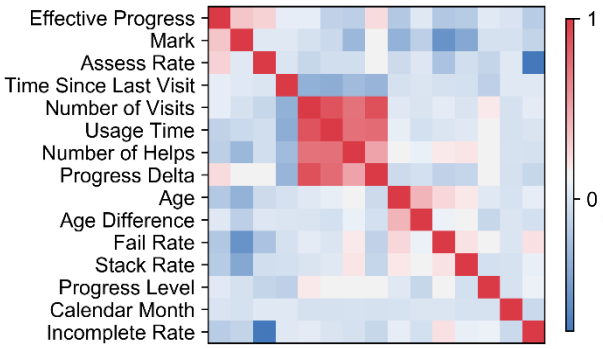

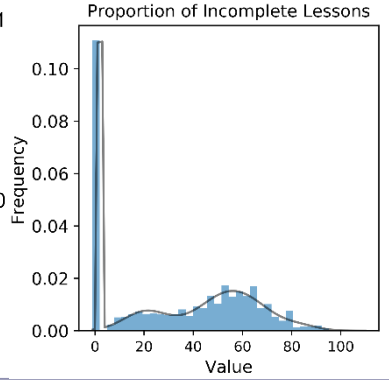

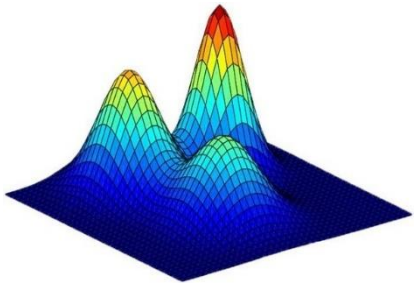

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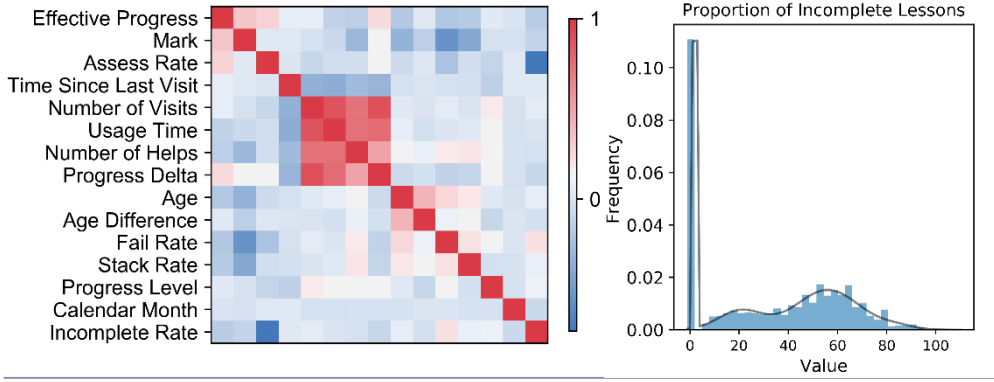

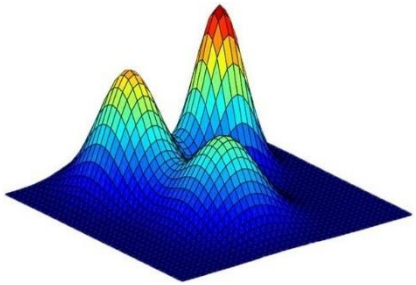

A Closer Look at Clustering…

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Rather than interpolating missing information, we divide customers by activity level.

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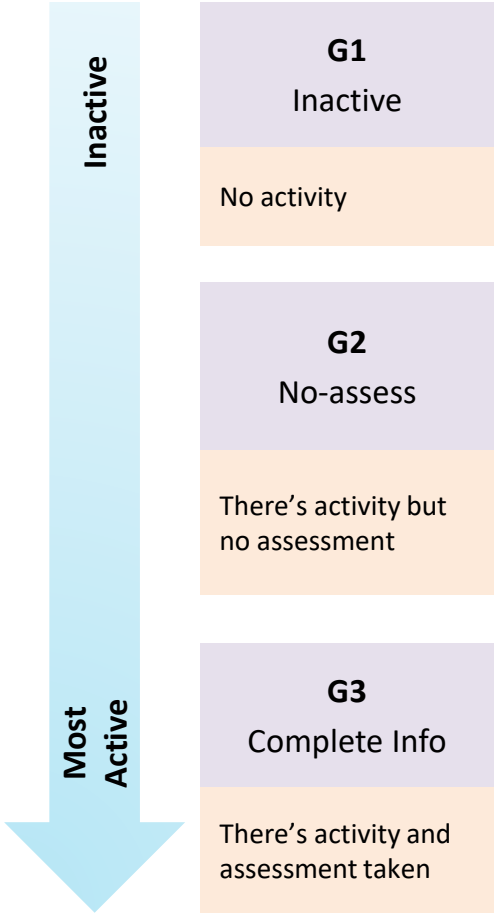

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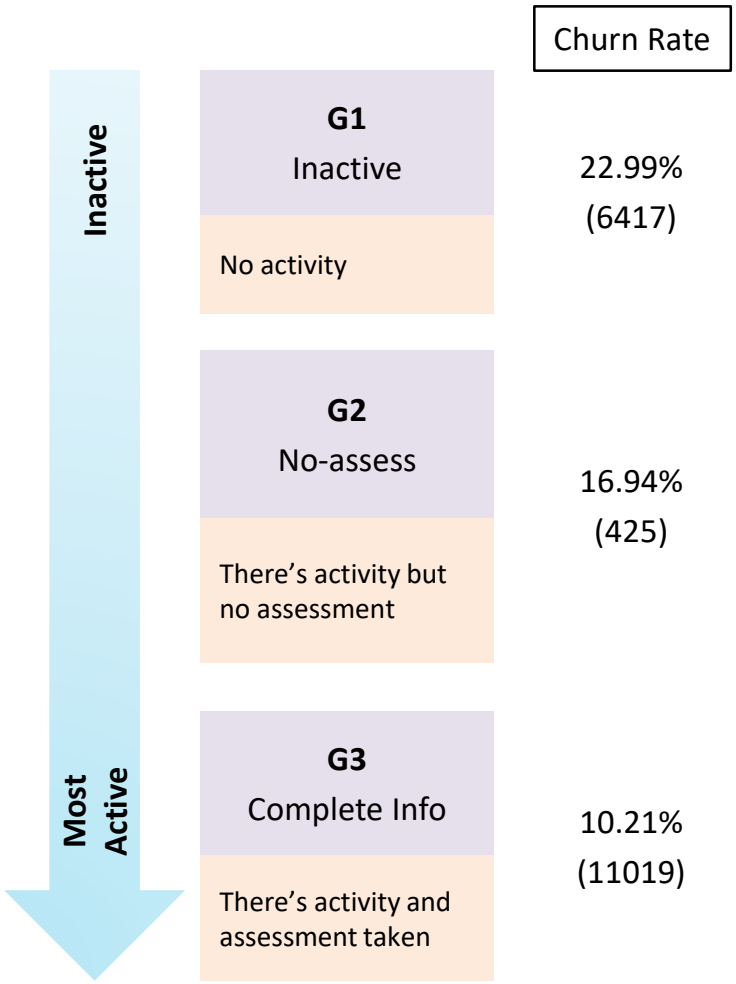

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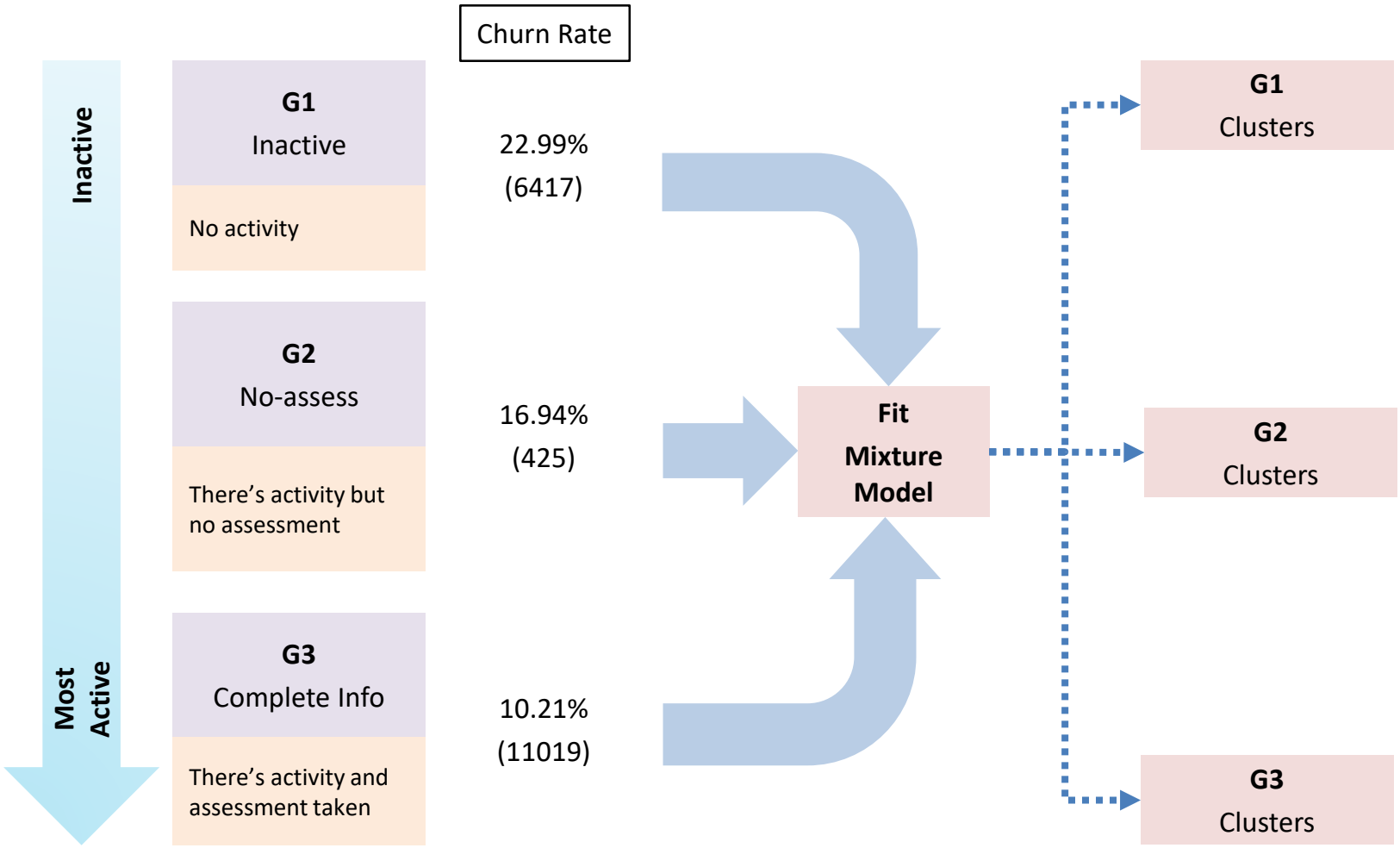
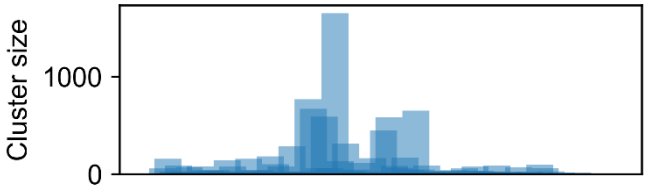


Cluster Churn Rates (Who)

Identified Clusters: Size



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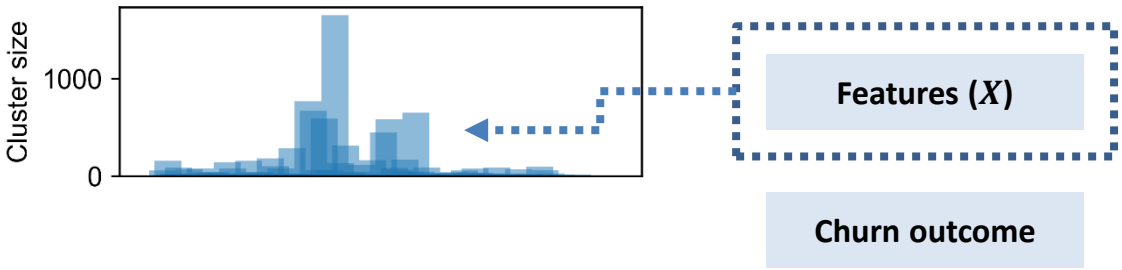
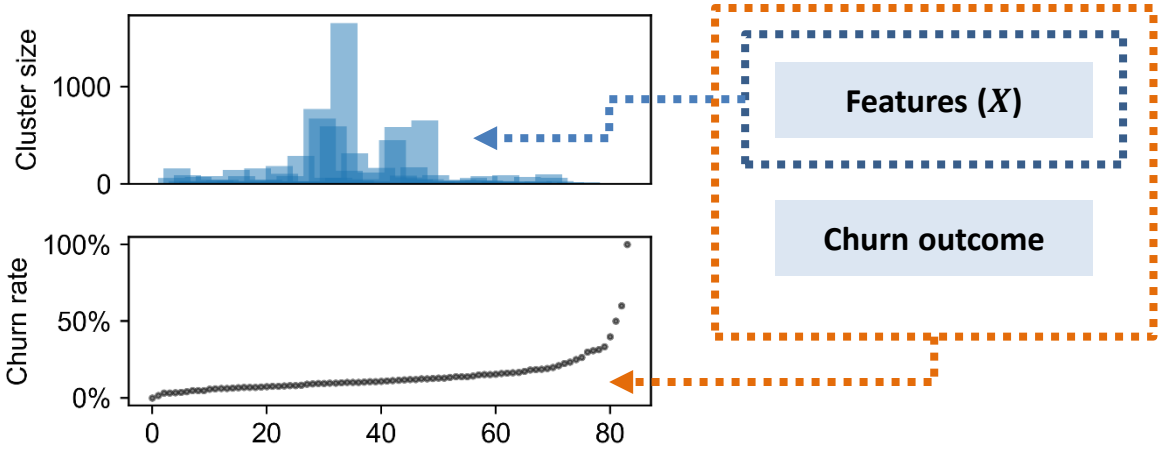


Cluster Churn Rates (Who)

Identified Clusters: Size and Churn Rate



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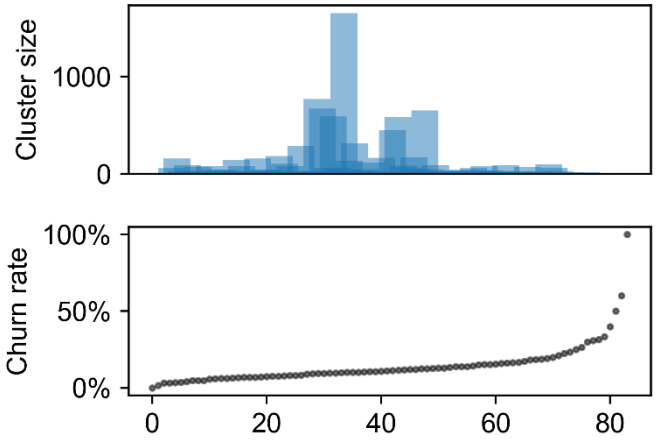

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- ✓ The purely behaviour based model infer many clusters:
  - ❑ the corresponding churn rate ranges from 0% to 100%.
- ✓ It is more challenging to identify users of extreme high/low churn probability:
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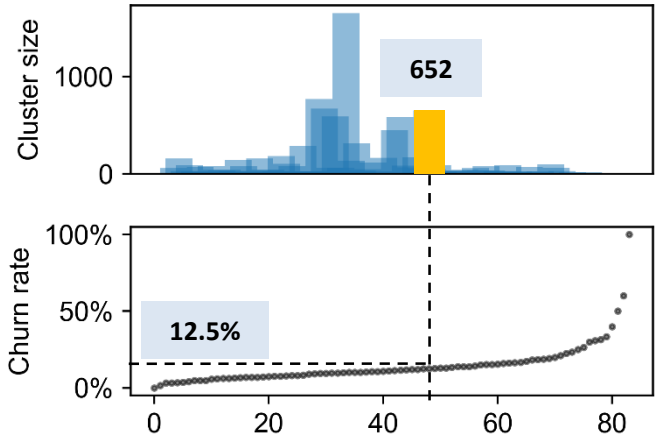

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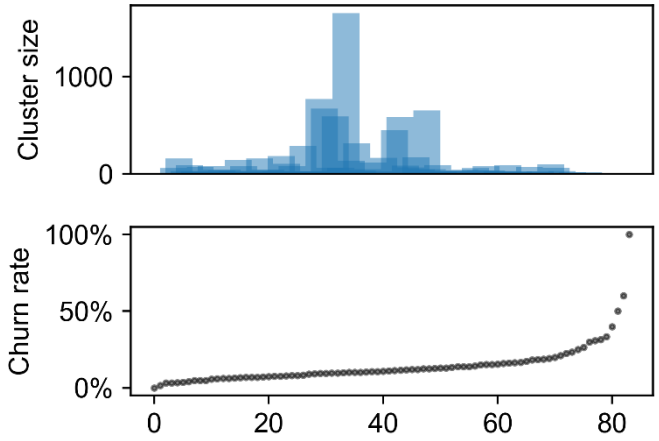

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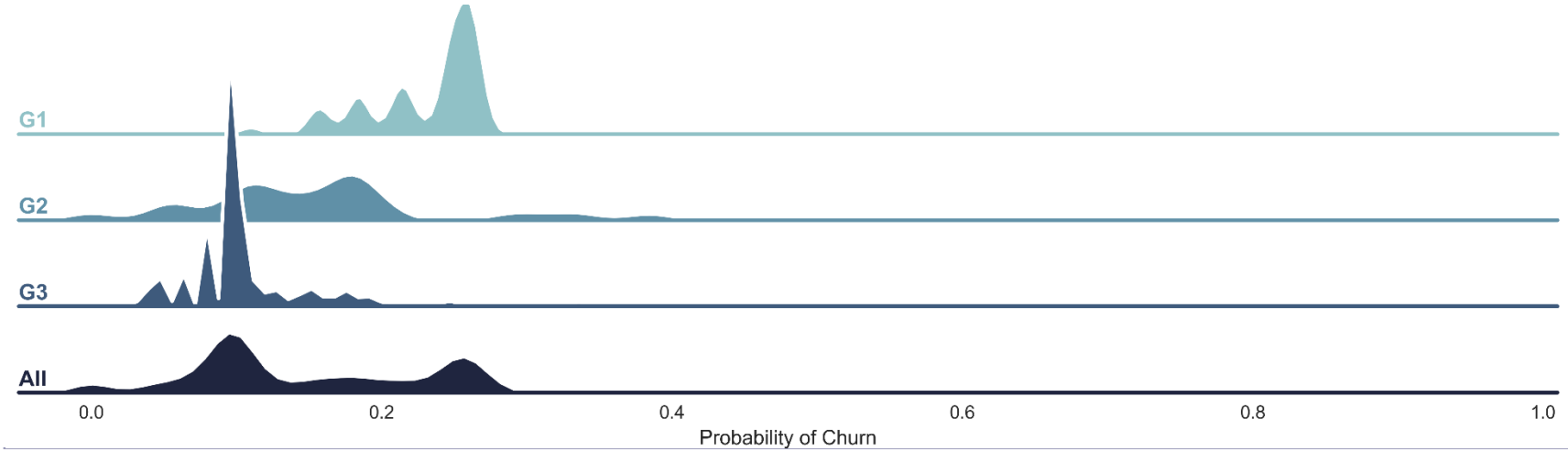

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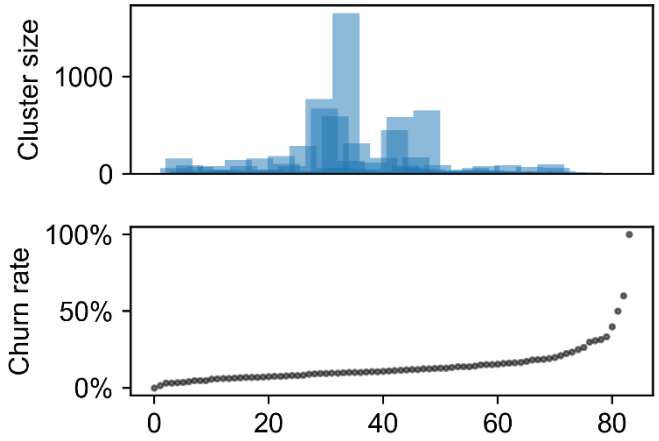

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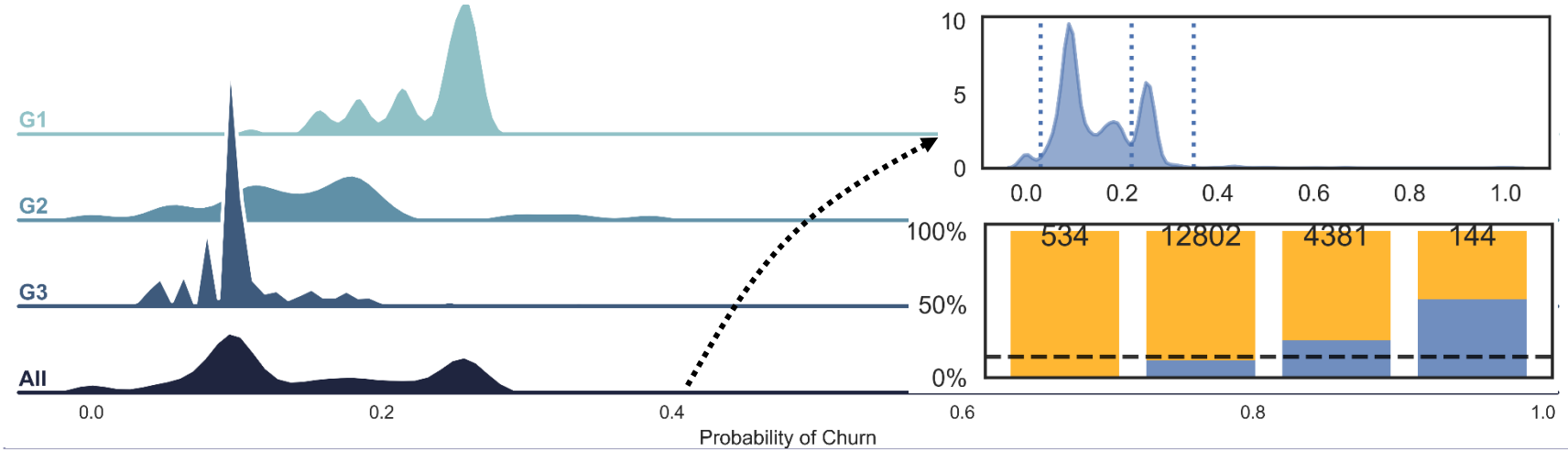
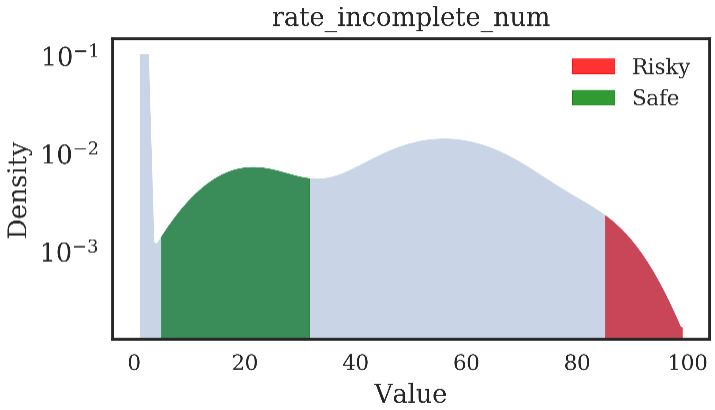
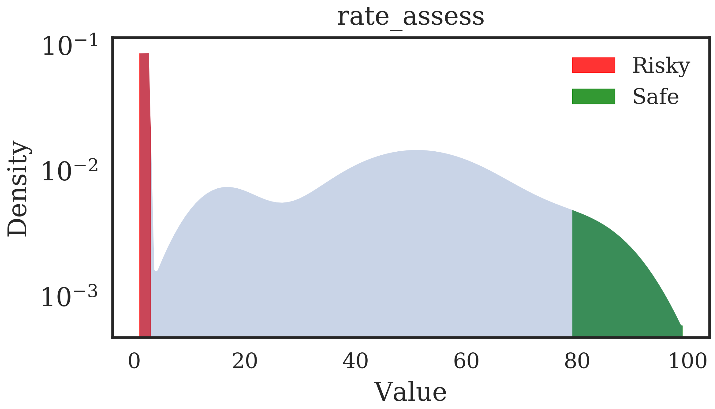


Feature Analysis (Why)

The mixture model methodology, by its nature, is designed for identifying clusters, but not explicitly for analysing feature importance.
However, by counting frequencies of components of **risky** and **safe** clusters, we can see how feature impacts churn outcome.





Risky cluster: churn rate > 50%

Safe cluster: churn rate < 5%

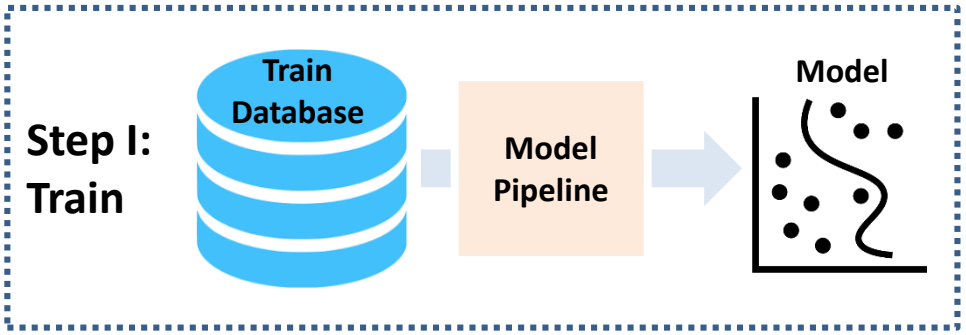
We can look at the component each cluster falls in for features.

Observations:

- ✓ Subscribers having many incomplete lesson records are most likely to churn.
- ✓ Subscribers taking few assessment are most likely to churn

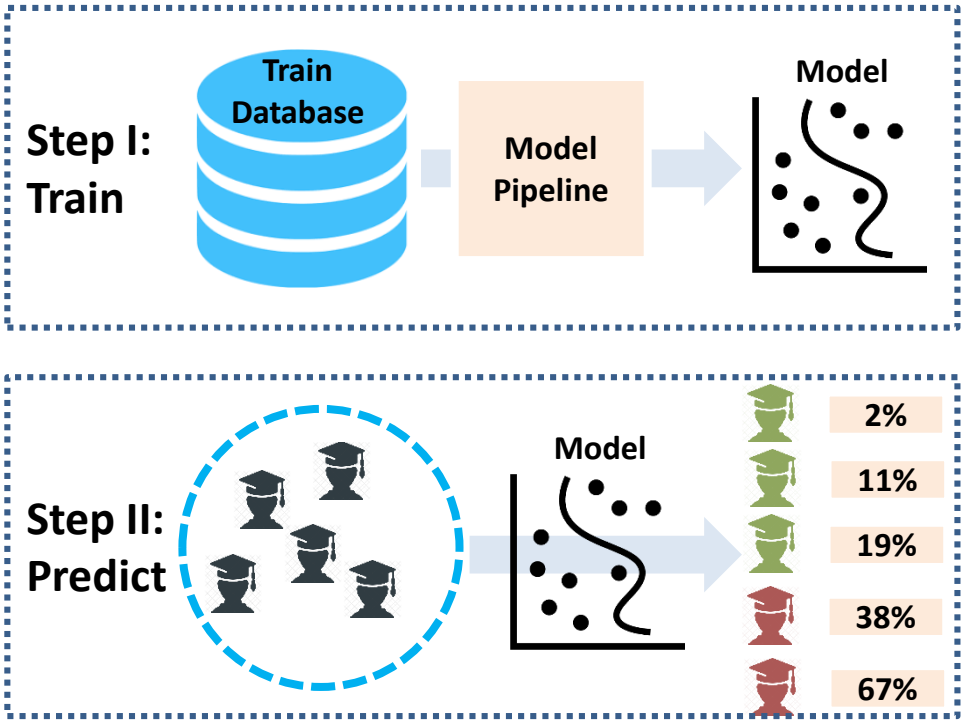
Prediction Workflow

How does Whizz use this model to predict the risk of churn for a set of subscribers?



Prediction Workflow

How does Whizz use this model to predict the risk of churn for a set of subscribers?



Prediction Workflow

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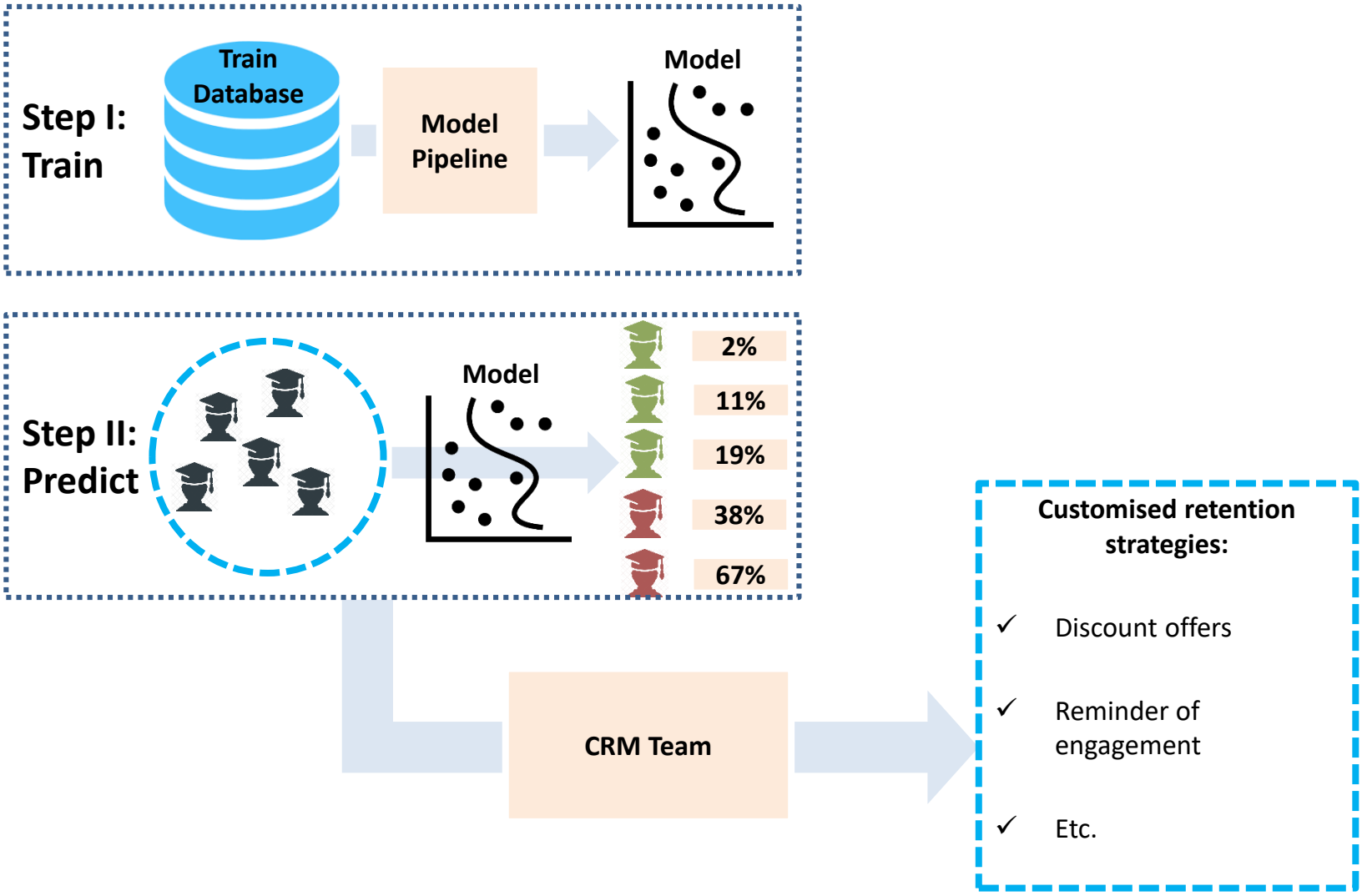
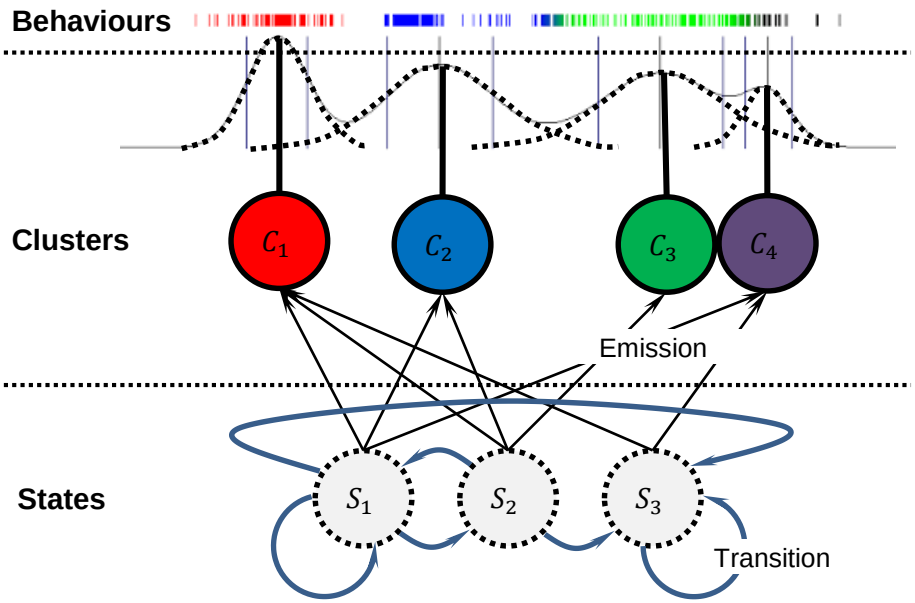
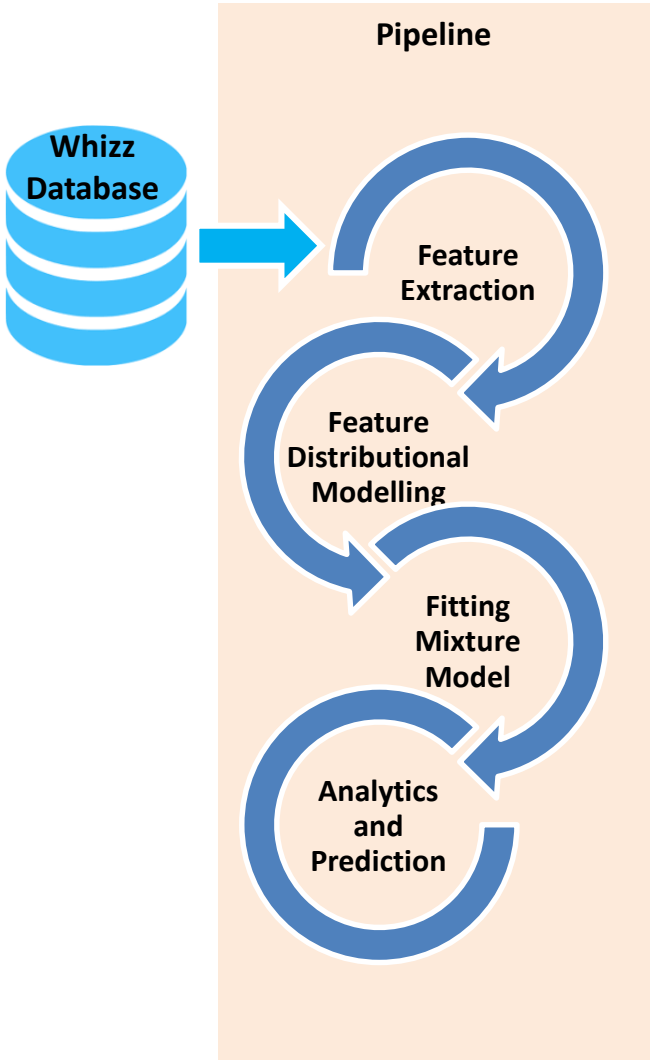
How does Whizz use this model to predict the risk of churn for a set of subscribers?

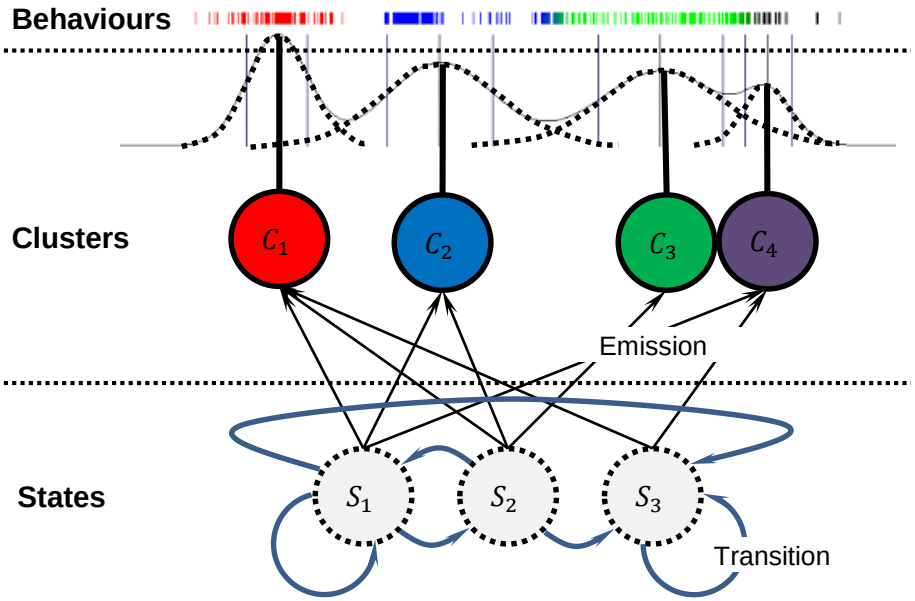


Conclusion


Behaviours
Clusters
C_1
C_2
C_3
C_4
Emission
States
S_1
S_2
S_3
Transition

Conclusion


Pipeline
Whizz Database
Feature Extraction
Feature Distributional Modelling
Fitting Mixture Model
Analytics and Prediction


Behaviours
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Conclusion

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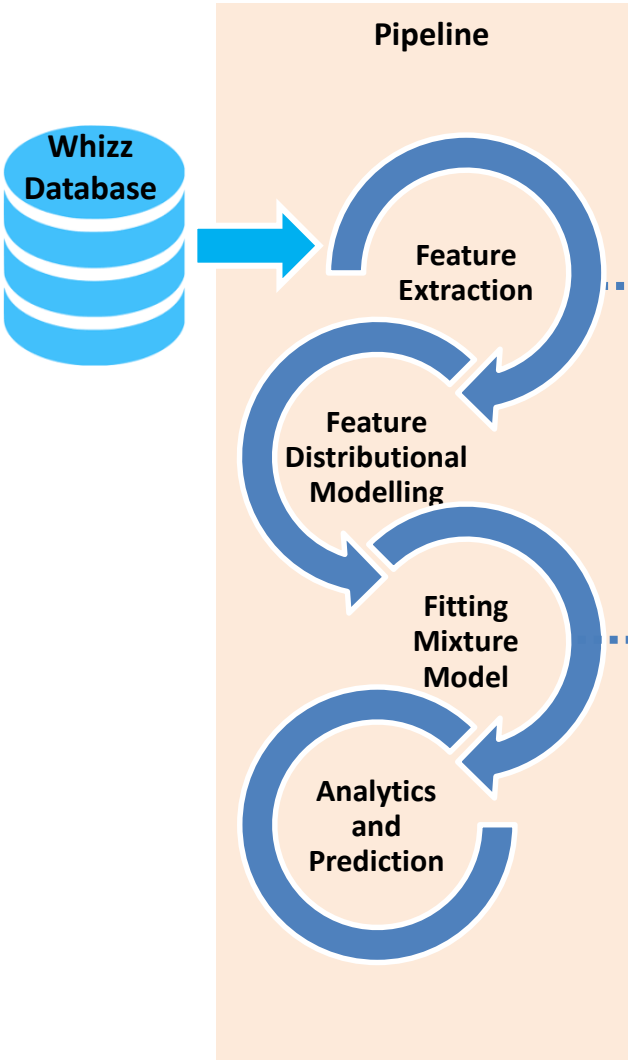
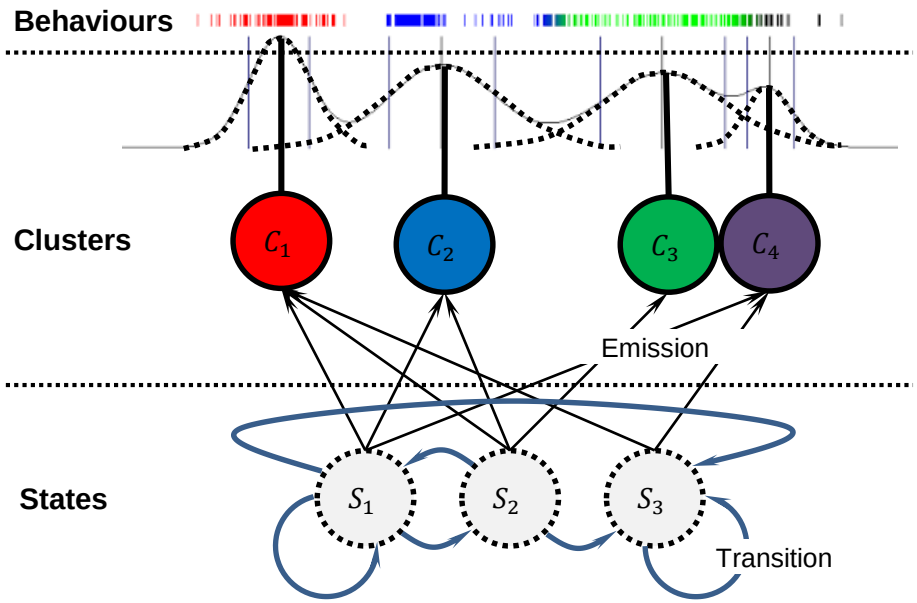


Feature selection:

- ✓ Select features by industrial expertise
- ✓ Add nonlinear transformation / interaction of existing features

Feature importance :

- ✓ Measure importance of dimension in a multivariate setting



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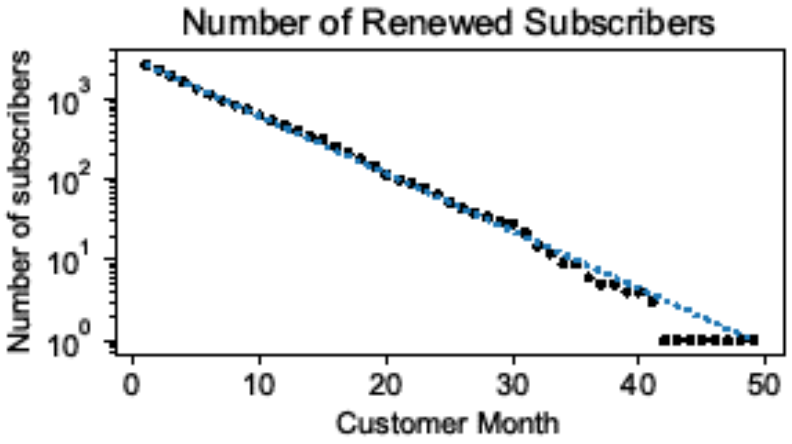
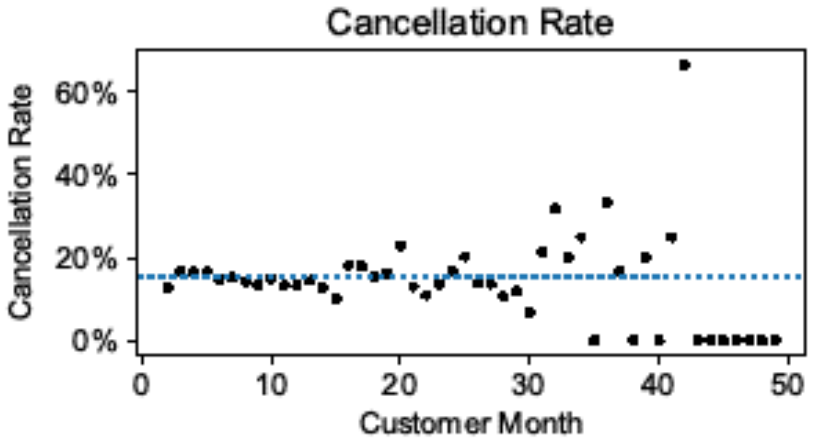
Appendix

Customer Month Independence

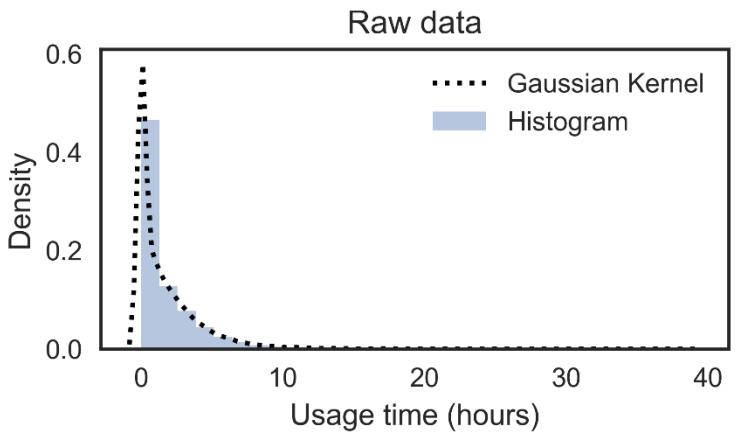
We assume the cancellation to be **ONLY** dependent on the current month.

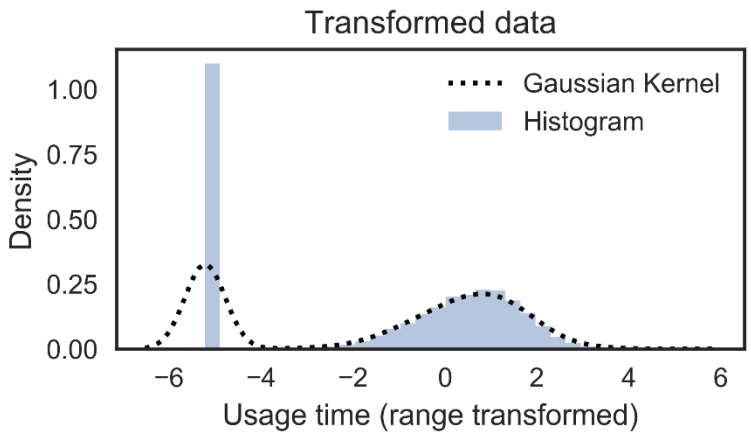
- ✓ The assumption holds since we observe statistically constant churn rate over customer month.
- ✓ The assumption enables us to treat activities in different customer months indifferently.

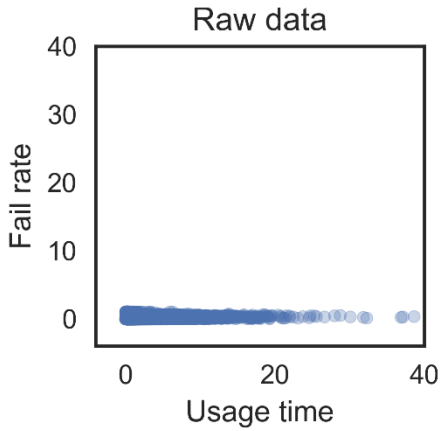


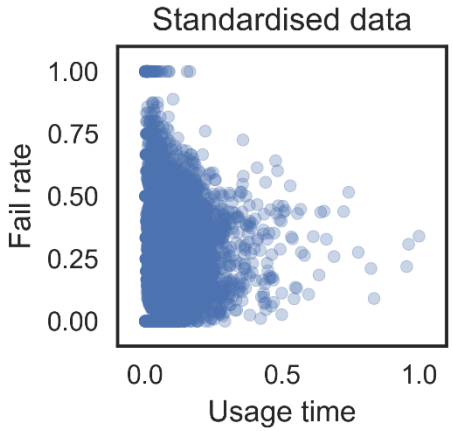


Data Transformation

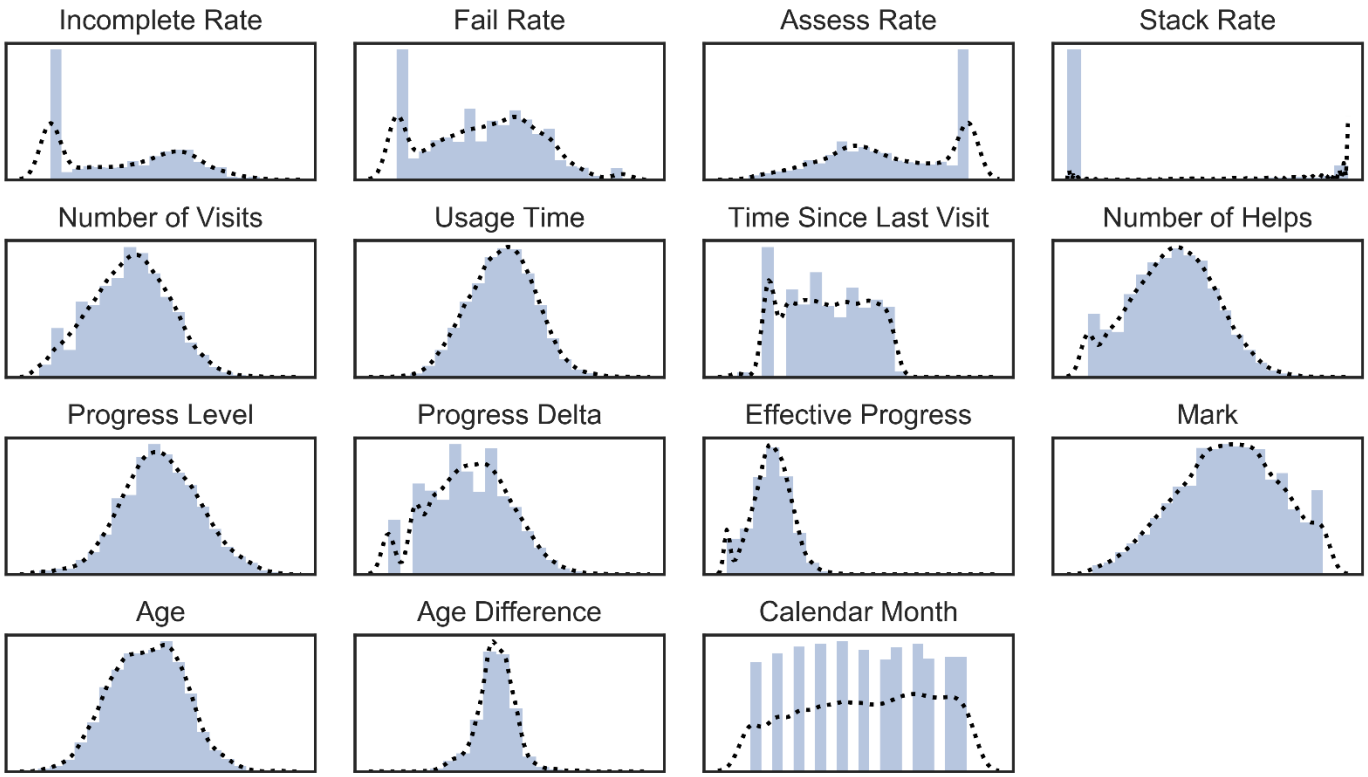




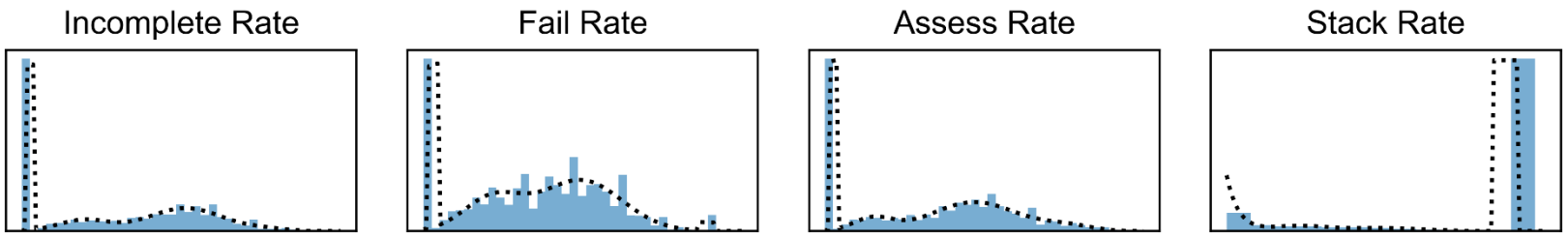


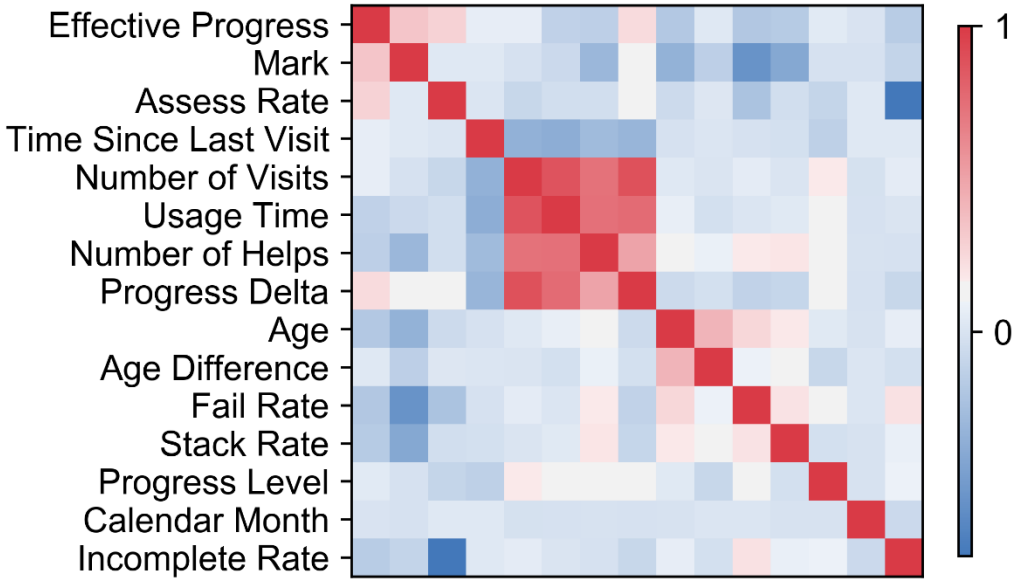


Distributional Modelling – I



Distributional Modelling – II





Dirichlet Process Mixture – I

DP mixture model

$$\boldsymbol{x}|\theta \sim f(\cdot\,|\theta), \qquad \theta|G \sim G(\cdot), \qquad G \sim DP(\cdot\,|G_0, \alpha)$$

Use DP as prior for $\boldsymbol{\theta}$

Definitions A Dirichlet Process (DP) is a distribution of a random measure. Let G_0 be a base distribution (measure) for our cluster density parameter $\theta \in \Theta$, a measurable space, and let α be a positive, real-valued scalar. A random measure G is then distributed according to *Dirichlet Process* with scaling parameter α and base measure G_0:

$$G \sim \mathrm{DP}(\cdot|G_0, \alpha), \tag{16a}$$

if for all $K \in \mathbb{N}$, and all $\{\Theta_1, \ldots, \Theta_K\}$ finite partitions of Θ:

$$(G(\theta_1), \ldots, G(\theta_K)) \sim \mathrm{Dir}\left(\alpha G_0(\theta_1), \ldots, \alpha G_0(\theta_K)\right), \tag{16b}$$

where $\mathrm{Dir}(\cdot)$ denotes the *Dirichlet distribution*. The Dirichlet distribution is a distribution of the standard $K-1$ simplex. Let $\boldsymbol{\pi} = \{\pi_k\}_{k=1}^K$ with $\sum_{k=1}^K \pi_k = 1$ and $\forall k : \pi_k \geq 0$, and let $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_K)$ with $\alpha_1, \ldots, \alpha_K \geq 0$. Then

$$\mathbb{P}(\boldsymbol{\pi}|\boldsymbol{\alpha}) = \mathrm{Dir}(\alpha_1, \ldots, \alpha_K) = \frac{1}{\mathrm{Beta}(\boldsymbol{\alpha})} \prod_{k=1}^K \pi_k^{\alpha_k - 1} = \frac{\Gamma\left(\sum_k \alpha_k\right)}{\prod_k \Gamma(\alpha_k)} \prod_{k=1}^K \pi_k^{\alpha_k - 1}, \tag{16c}$$

where $\mathrm{Beta}(\cdot)$ is the beta function, $\Gamma(\cdot)$ is the gamma function.

Dirichlet Process Mixture – II

Clustering Effect We use DP as a prior to distribution of cluster parameter θ:

$$\theta|G \sim G(\cdot) \quad \text{and} \quad G \sim \mathrm{DP}(\cdot|G_0, \alpha). \tag{17}$$

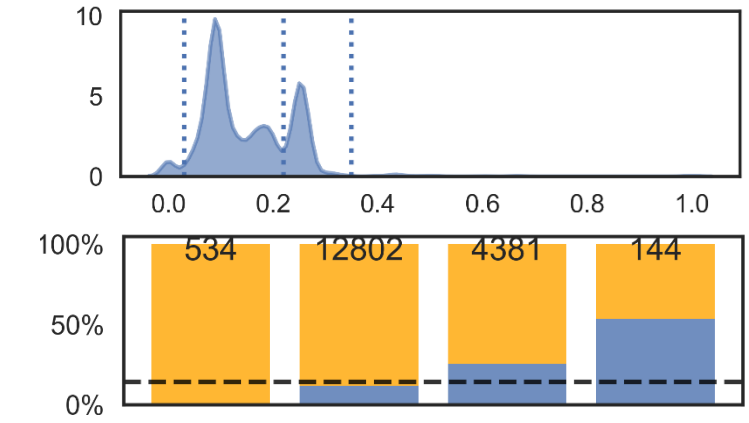
This model exhibits a "clustering effect" which enables us to infer number of clusters from data rather than pre-defining it. Suppose we independently draw n random values $\theta^{(j)}$ from G under the model (17), then Blackwell and MacQueen's urn representation theorem [1] states that, marginalising out the random measure G, the joint distribution of the collection of variables $\{\theta^{(1)}, \ldots, \theta^{(n)}\}$ exhibits a clustering effect:

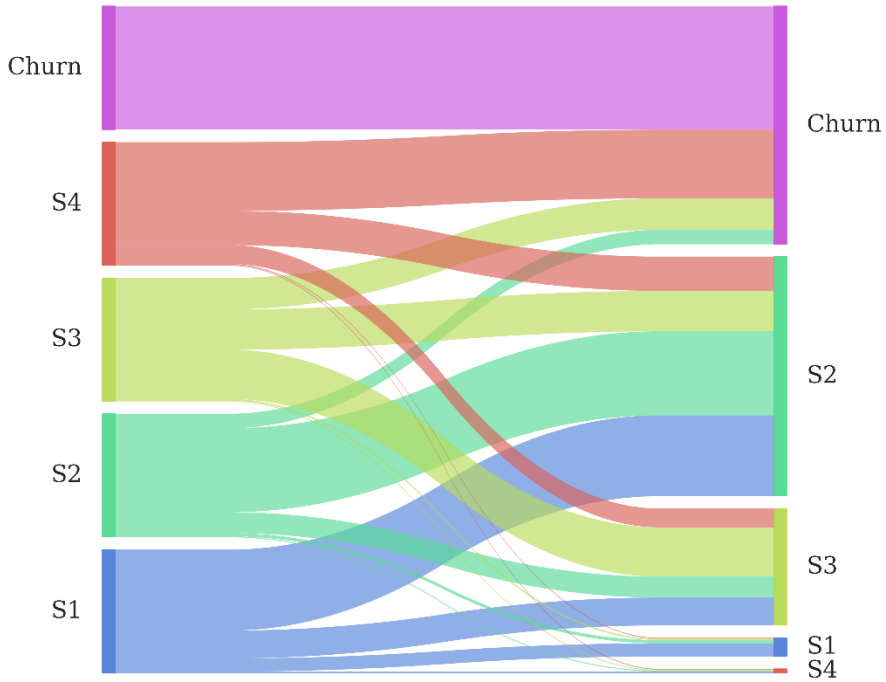
$$\mathbb{P}\left(\theta^{(j)}|\theta^{(1)}, \ldots, \theta^{(j-1)}\right) \propto \alpha G_0(\theta^{(j)}) + \sum_{l=1}^{j-1} \delta_{\theta^{(l)}}(\theta^{(j)}), \tag{18}$$

where $\delta_{\theta^{(l)}}(\cdot)$ is a Dirac delta at $\theta^{(l)}$. Thus the variables $\{\theta^{(1)}, \ldots, \theta^{(n)}\}$ are randomly partitioned according to which variables are equal to the same value. Moreover, let $\{\theta_1, \ldots, \theta_K\}$ denote the distinct values of the drawn samples $\{\theta^{(1)}, \ldots, \theta^{(j-1)}\}$, let $\{\kappa_1, \ldots, \kappa_{j-1}\}$ be the assignment variables such that $\theta^{(l)} = \theta_{\kappa_l}$. Then,

$$\mathbb{P}\left(\theta^{(j)}|\theta^{(1)}, \ldots, \theta^{(j-1)}\right) \propto \frac{\alpha}{j-1+\alpha} G_0(\theta^{(j)}) + \sum_{k=1}^{K} \frac{|\{l : \kappa_l = k\}|}{j-1+\alpha} \delta_{\theta^{(l)}}(\theta^{(j)}). \tag{19}$$

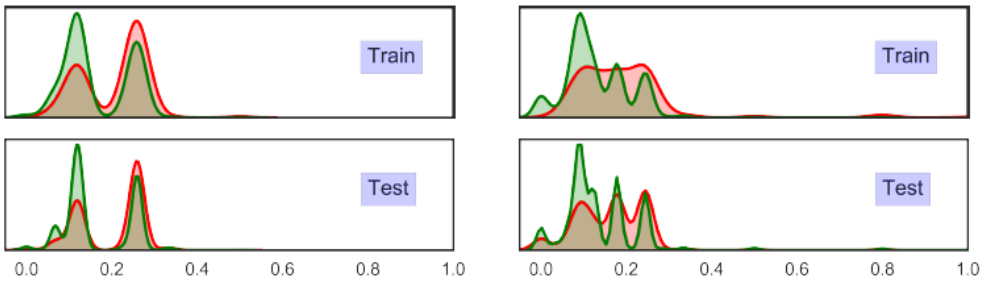
Temporal Transition of States





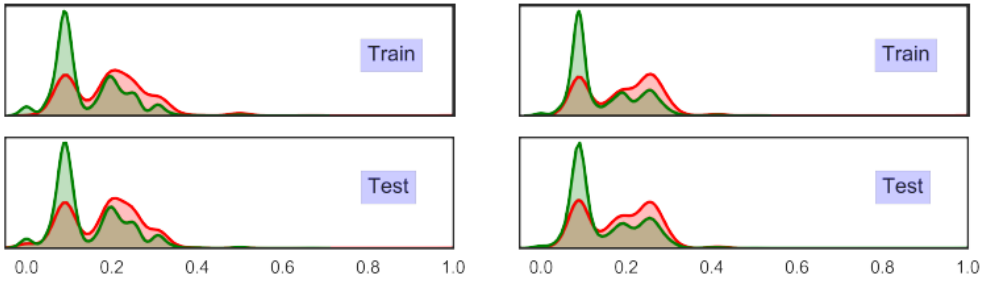
- ✓ S2 is the largest destination state, which makes sense as S2 represents a “normal” state in which the churn probability is approximately the same as population average.
- ✓ Barely pupils transit from other states to S4 (the riskiest state). This seems imply that the reason for strong intention of churn might be purely external and irrelevant to customer experience at Whizz, since there is little chance of transiting to S4.

Overfitting



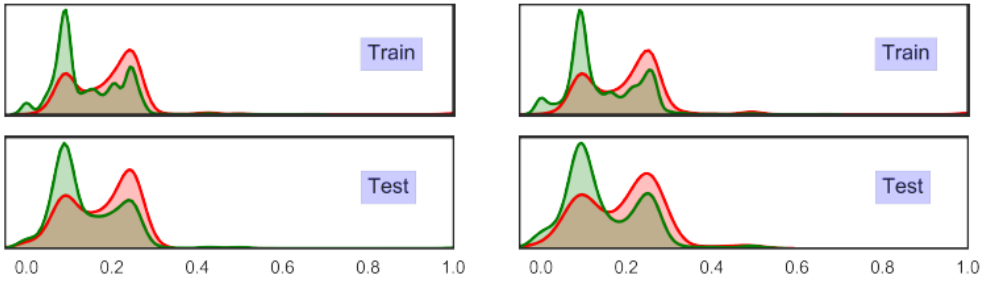
(a) Train Pct = 5%

(b) Train Pct = 10%



(c) Train Pct = 50%

(d) Train Pct = 70%



(e) Train Pct = 90%

(f) Train Pct = 95%