Identifying customers at risk of churn



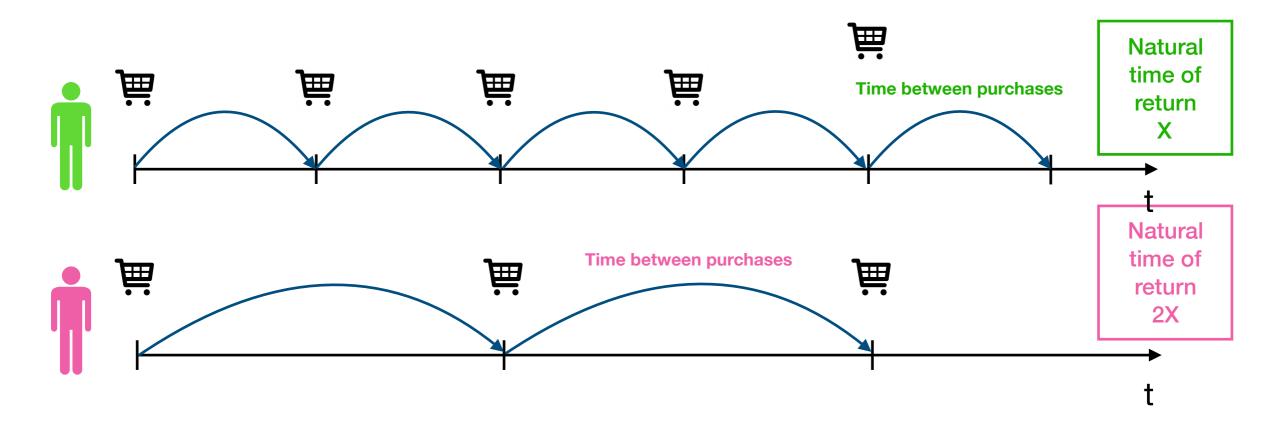
University of Essex - Profusion partnership

Agenda

- Motivation: Customer targeting
- Methodology: How it was done?
 - Segmentation: Customer behaviour
 - Identification: Customer Targeting
- Results: Backtesting

Motivation

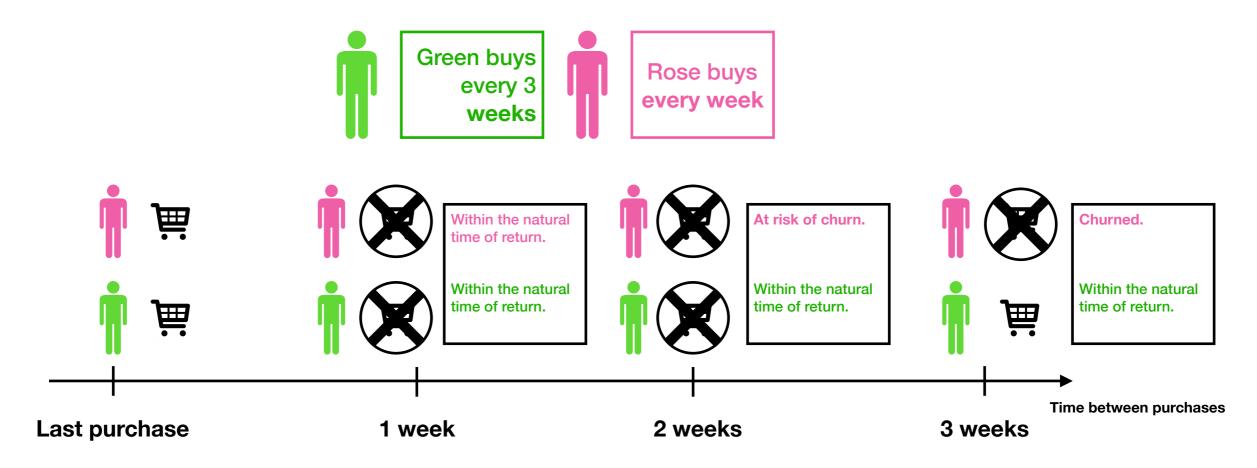
Each **customer** tends to follow a **distinct behaviour**; then, it can be represented as a **natural time** (rate) of return.



Based on the **time between purchases** we can find the **natural time of return**. It will tell us when one of our customers is at **risk of churning** to take a timely action (target those customers).

Motivation

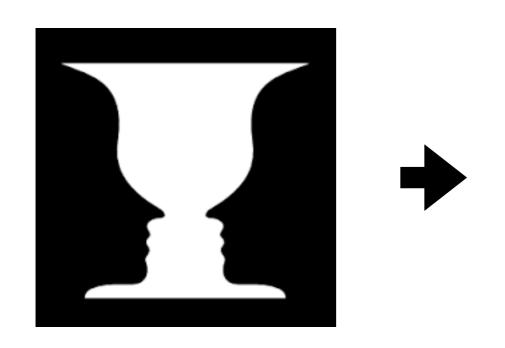
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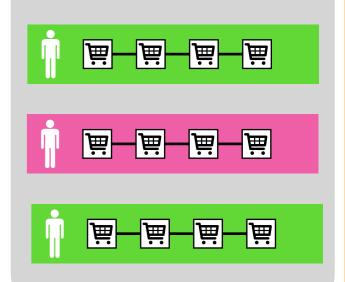
We can **see** the **data** in many **different ways**; There are several **approaches** to use the same data



One vase or two faces?

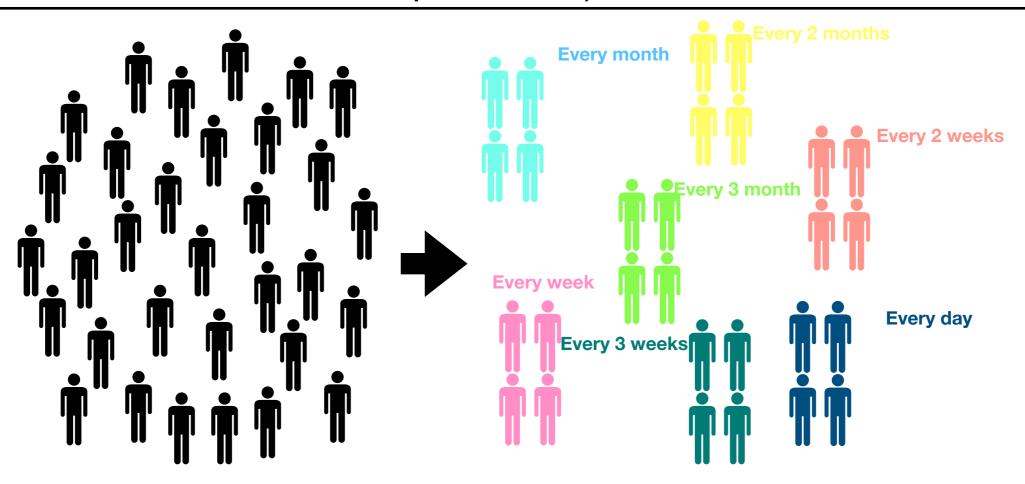
Each customer can be seen as a collection of individual transactions.

Each customer can be seen as a function made of transactions.



Methodology: Segmentation

Cluster the customers based on their behaviour (time between purchases)



Each resulting cluster will contain customers with similar behaviour, and the natural time of return can identify it.

Methodology: Segmentation

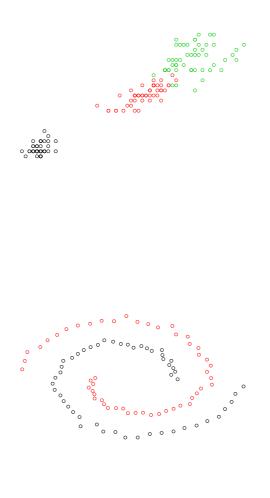
Two different approaches to **cluster** the customers:

K-Means clustering



Treats each customer can be seen as a collection of individual transactions.





Functional Clustering

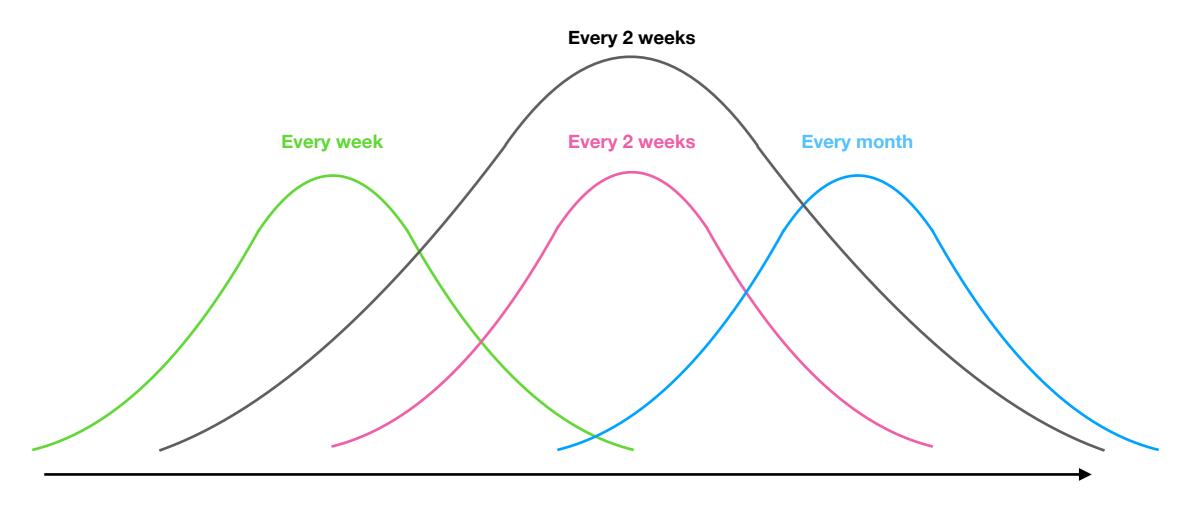


Treats each customer can be seen as a function made of transactions.



Methodology: Segmentation

The resulting clusters will represent each behaviour.



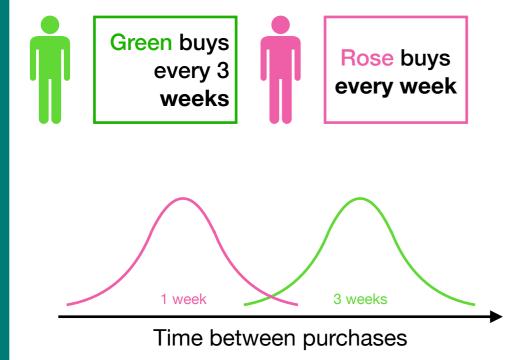
Time between purchases

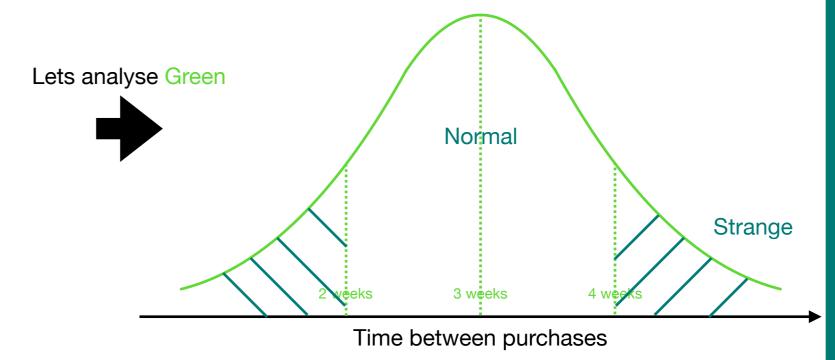
Methodology: Identification

Each resulting **cluster** will contain customers with **similar behaviour**. Then, a customer will be **at risk** of churned when it **behaviour** is **"strange"**.

However, what is "strange"? standard deviation approach

Given Green's **behaviour**, we know that he comes often **every 3 weeks**. Sometimes **1 week before**, sometimes **1 week after**.





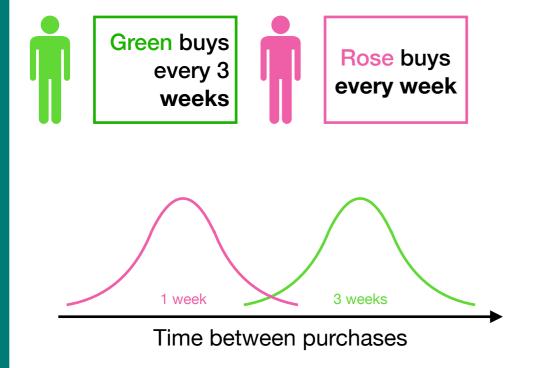
Then, it will be "strange" if Green is out of the range.

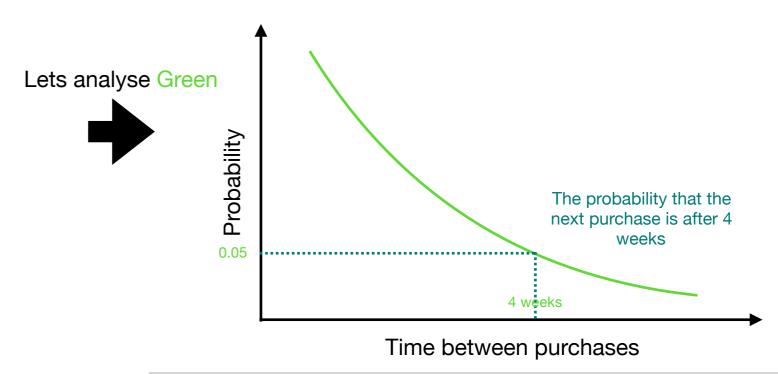
Methodology: Identification

Each resulting **cluster** will contain customers with **similar behaviour**. Then, a customer will be **at risk** of churned when it **behaviour** is **"strange"**.

However, what is "strange"? survival analysis approach

We can find the **probability** that the **next purchase** will be after a **particular time**.

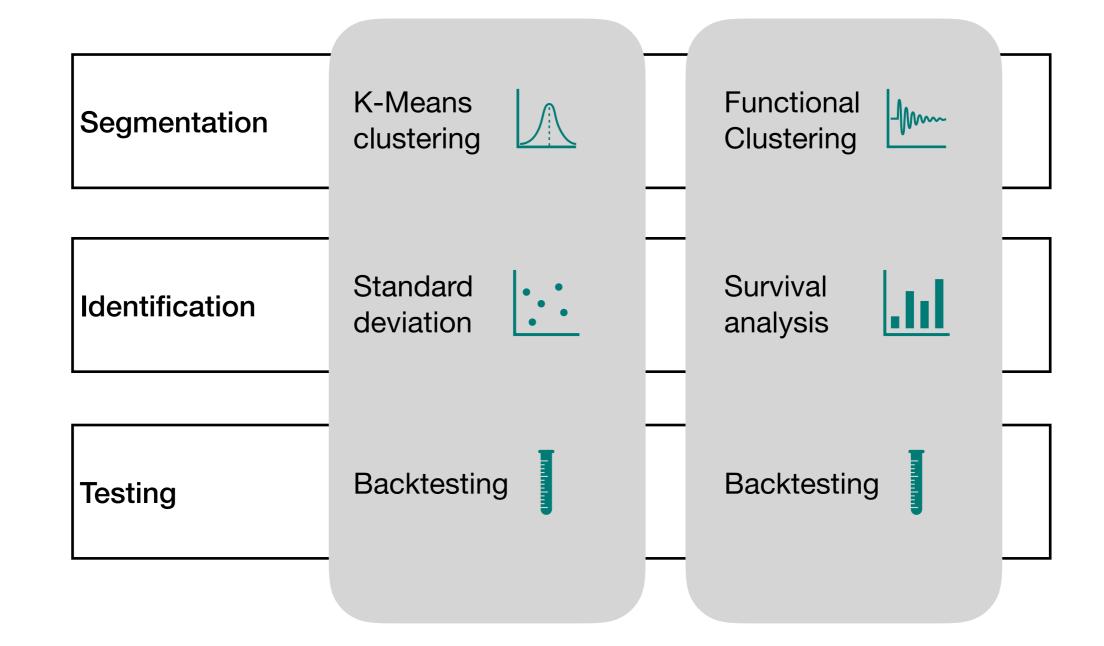




Small probabilities are associated with a "strange" behaviours

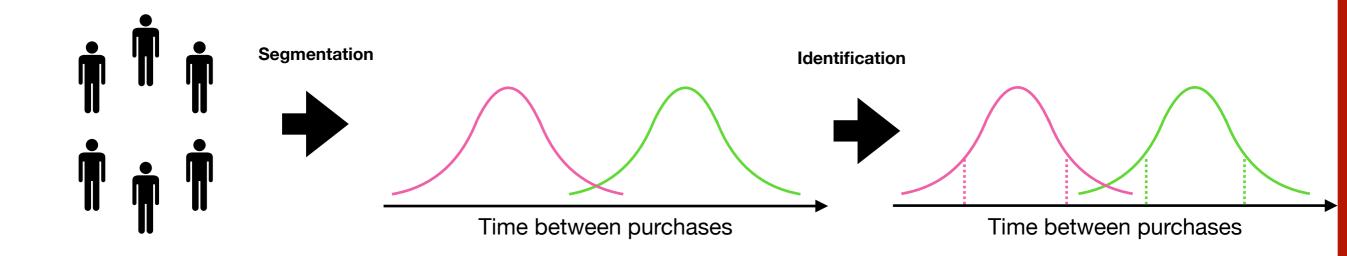
Methodology: Flow

Two different approaches



Results: Backtesting

We used the **transactions** for **10 thousand** customers between **2016** and **2017**.



As a very **conservative** test, the customers that were **marked** as **churned** were **tracked** over 1 year to check if they **came back**.

Results: Backtesting

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21% of the customers that were marked as churned didn't return.

47% of churned customers were correctly identified.

Survival

analysis

Functional

Clustering

Identifying customers at risk of churn



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