Usecase Delaware: Retail

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About this project

- Customer data for fashion retail
- Customers are leaving, why?
- Can we identify which customers are leaving?

Who are the customers?

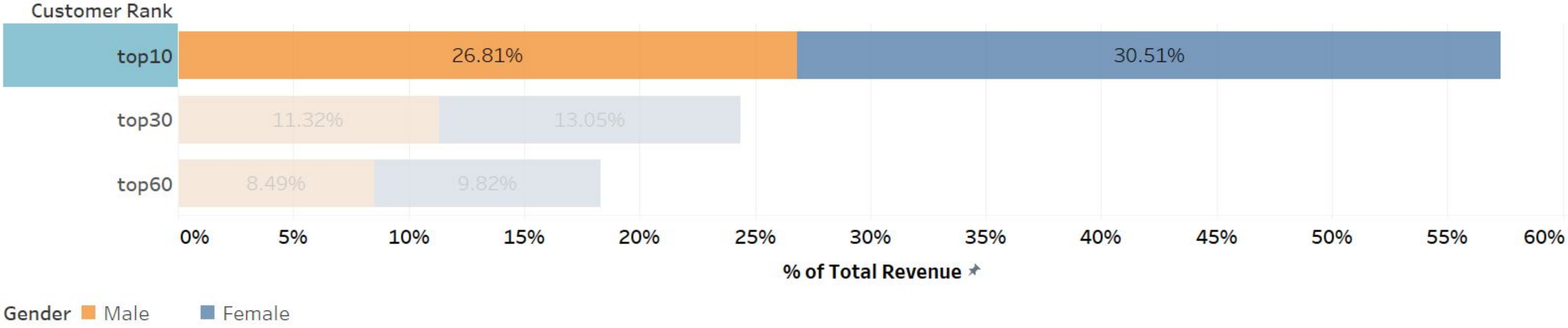
Who are the customers?

- We split the customers in 3 ranks by total revenue
    - 10% highest paying customers
    - 30% middle segment
    - 60% lowest paying

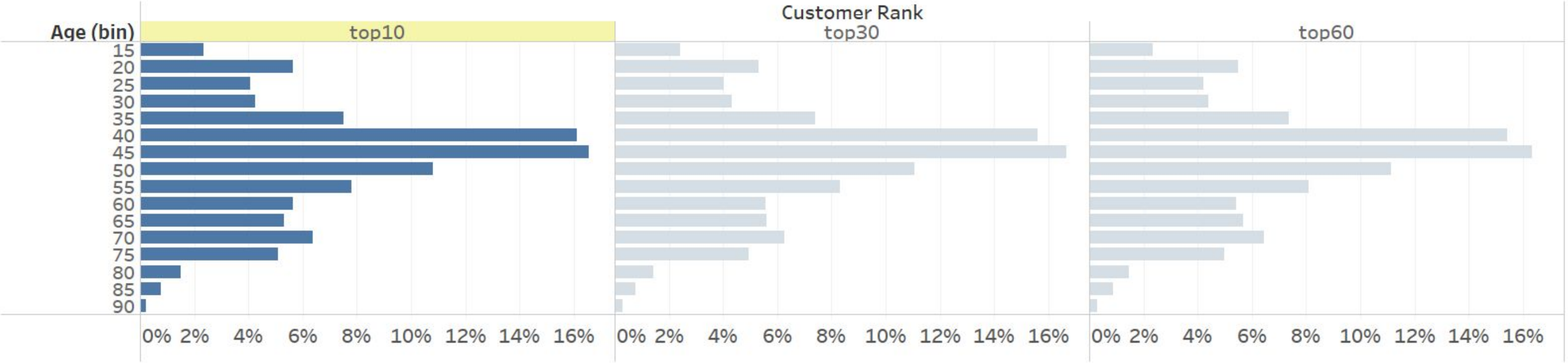
- We only consider registered customers
- 212530 unique customers *(after cleaning)*
- Mostly from Belgium

Some insights about the ranks

The **Top 10** is responsible for **more than 50%** of the total revenue



All **3 Ranks** show a similar **Age Distribution.**



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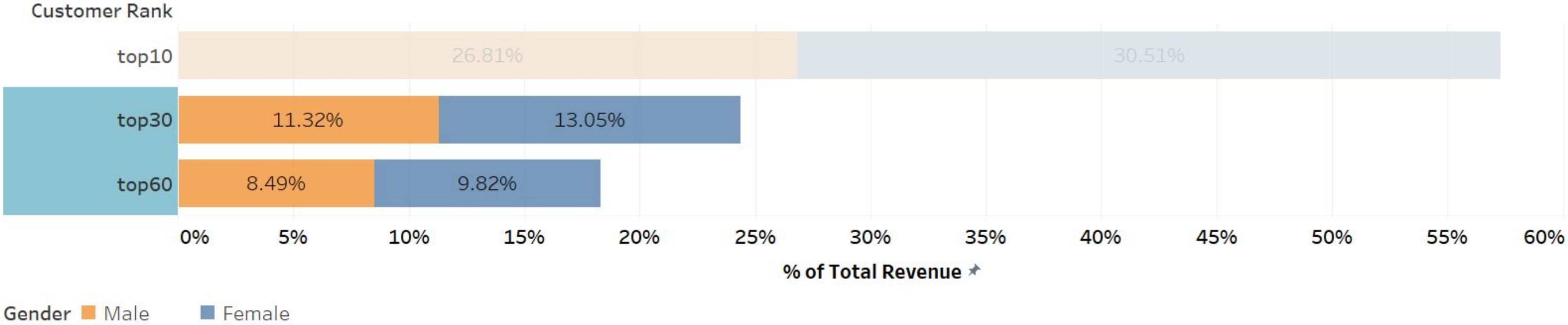

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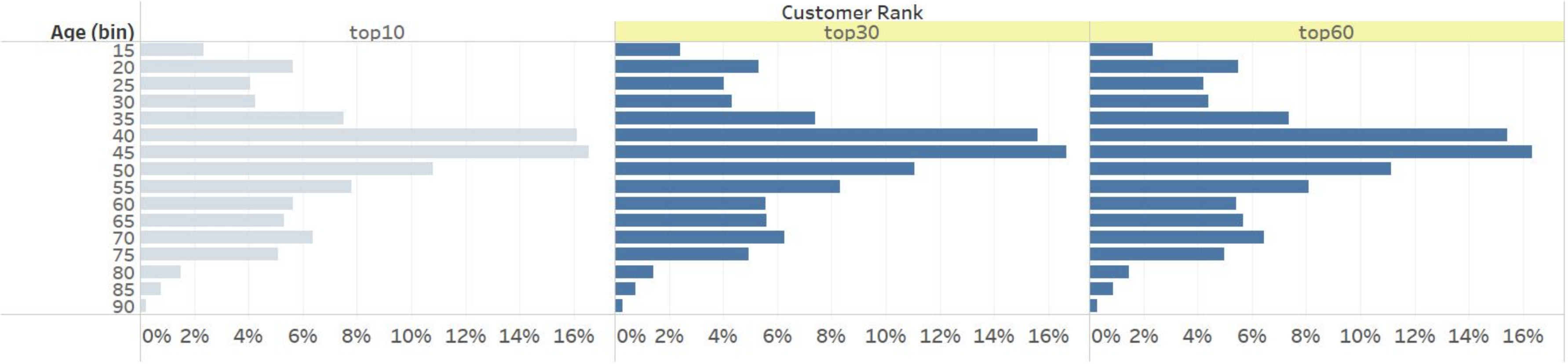


Machine learning

Identifying customer clusters

- **Goal**: Identify similar customers based on the data

- Which clusters are likely to churn?
- Target marketing solutions for these customers

Predicting customer churn

- **Goal**: predict whether a customer will **churn** soon, based on easily obtainable features

- **Train** on early data
- **Predict** churn for most recent new customers *(last 6 months)*

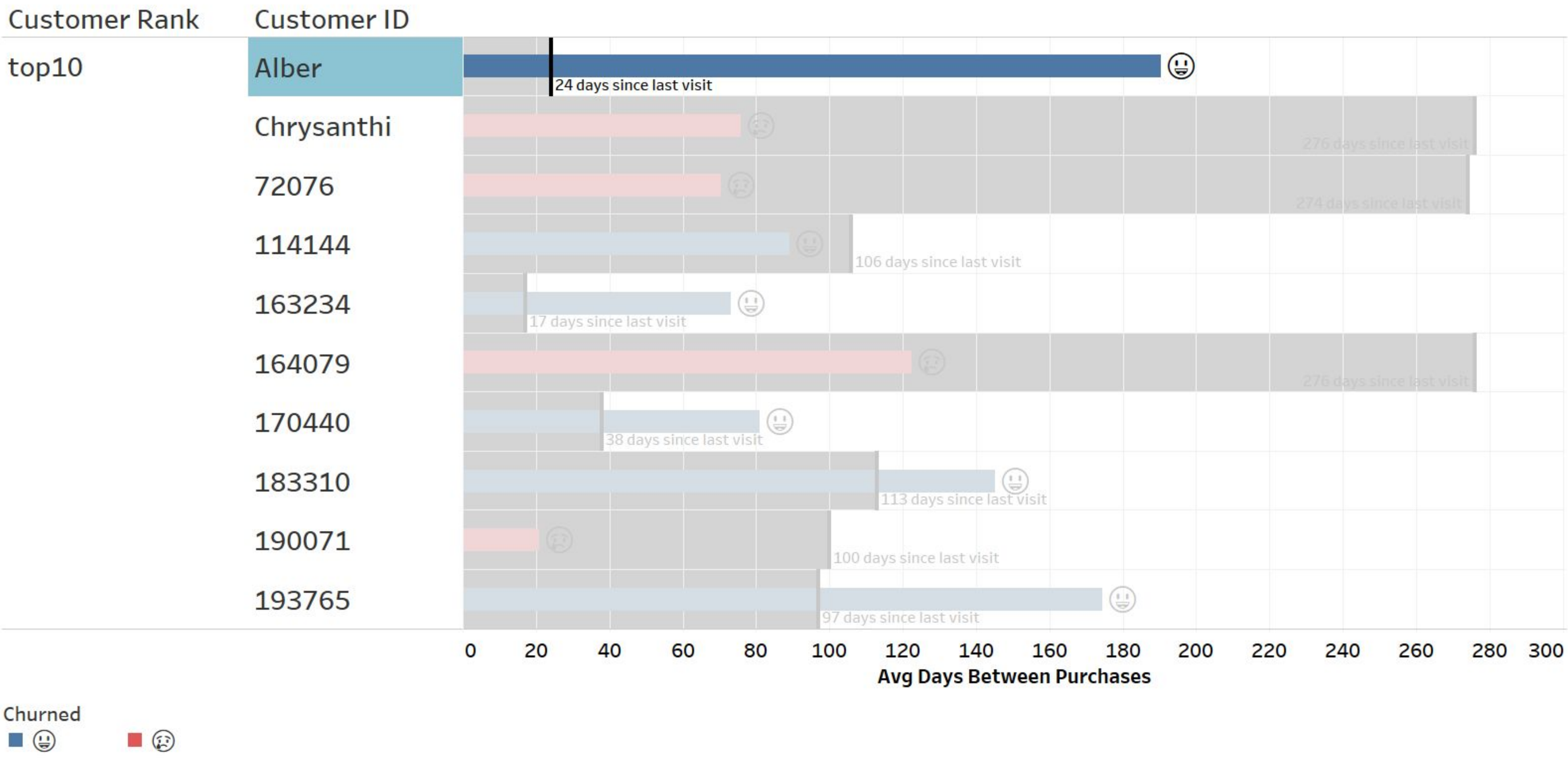
How to label churned?

- How to know if a customer won’t come back?
- We look at their history:
  - Median time between purchases
  - How far behind are they at the end of the dataset?
  - Set some tolerance with an arbitrary factor

`1.5 × median days between purchases < days since last`
`⇒ churned`

- Exception for recent (new) customers

the **Top 10** of the **Top 10**



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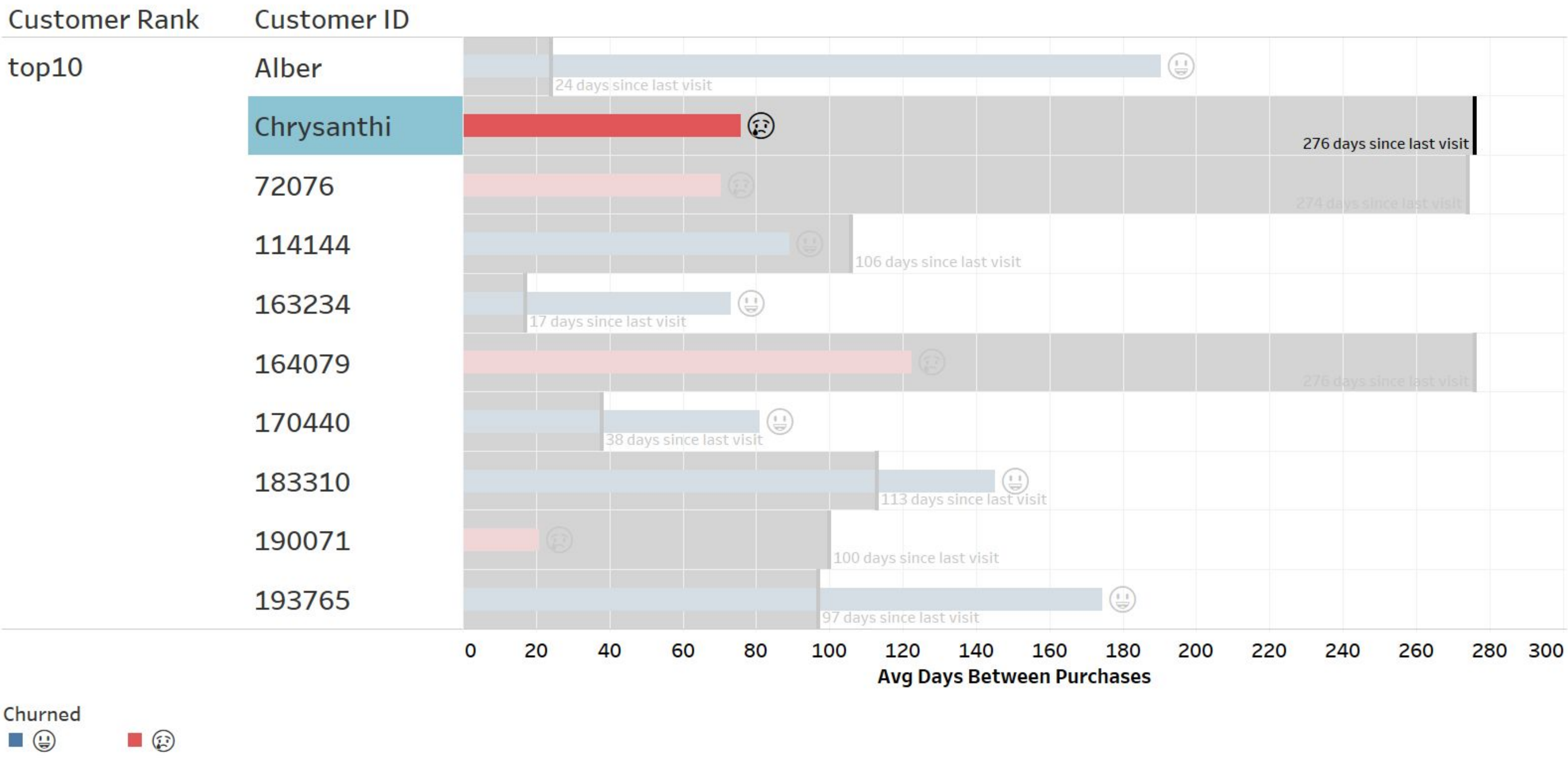

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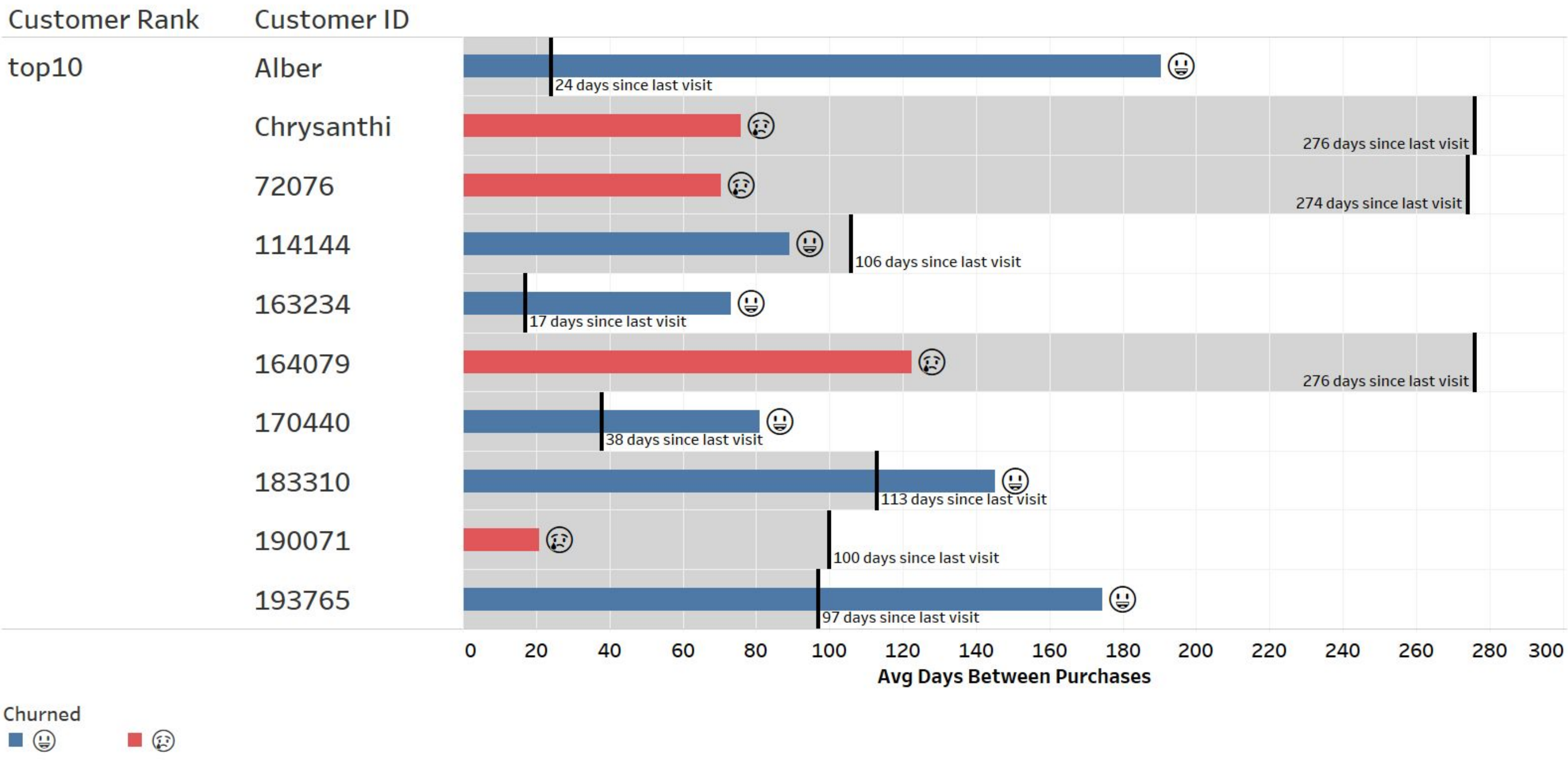
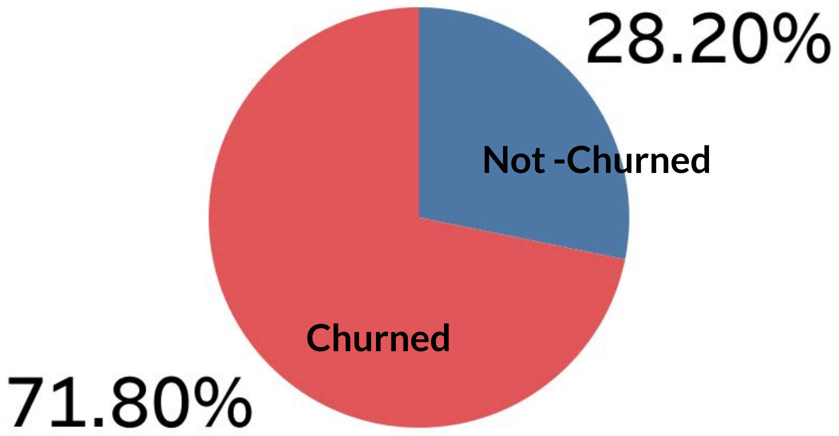



28.20%
Not -Churned
Churned
71.80%

Technical details

- Train with customers that are at least 6 months
- Rebalance the data with SMOTE upsampling
- Random Forest Classification
- 12 features used like gender, age,…
  but also total expense, number of days, amount of discounted purchases…

Results for predicting churn

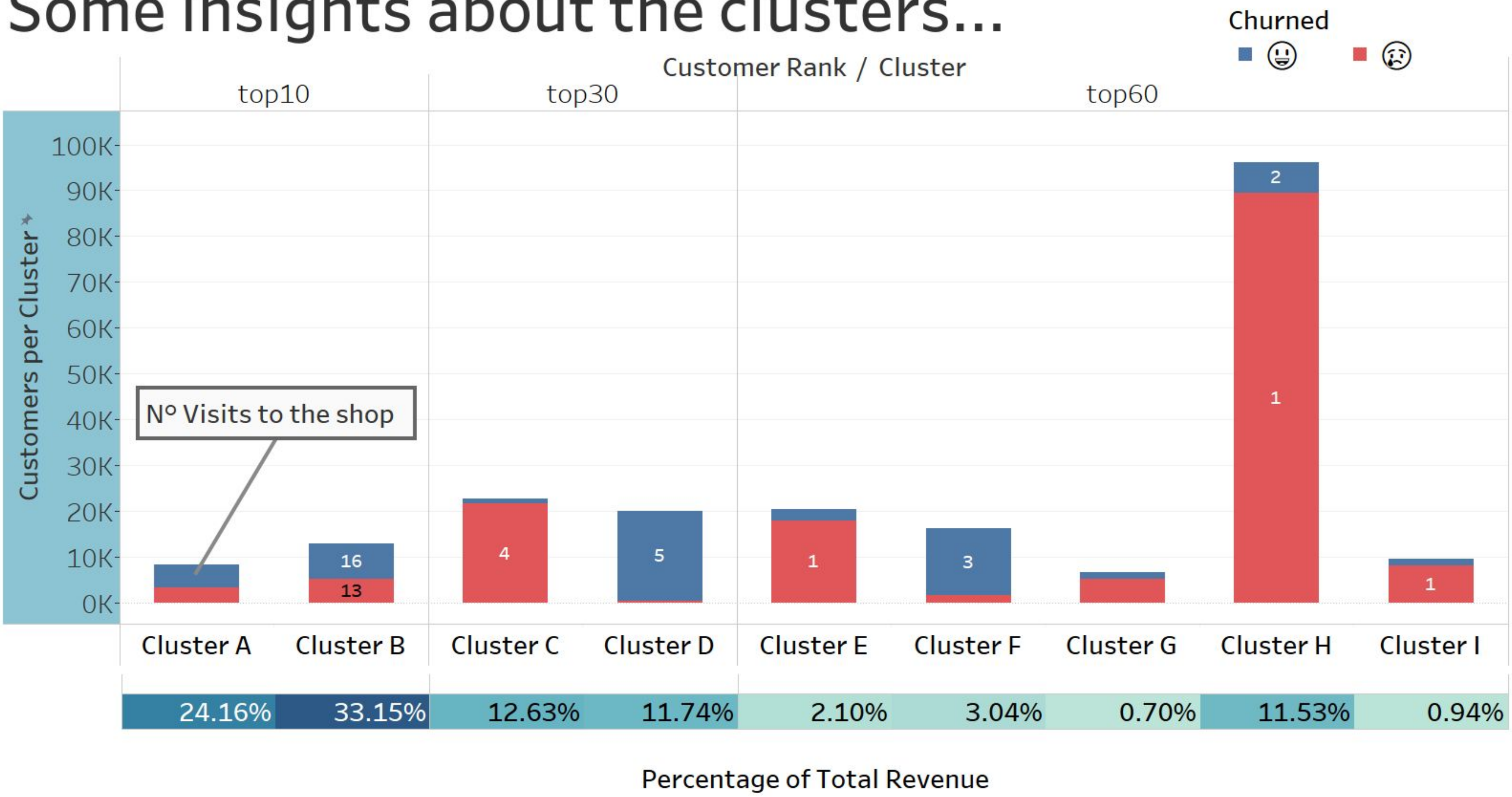
	precision	recall
loyal	86%	96%
churned	96%	85%

- If model predicts churn:
  - 4% chance that it will not churn
  - 15% of churns are missed

How to “clustering”?

- Which data to use?:
  - Grouped by “Customer ID”
- Explore the right number of cluster and the features.
- Clusters per customer ranks (Top 10/30/60)
- We found 2 - 2 - 5 clusters
- Cluster → K-means algorithm

Some insights about the clusters...



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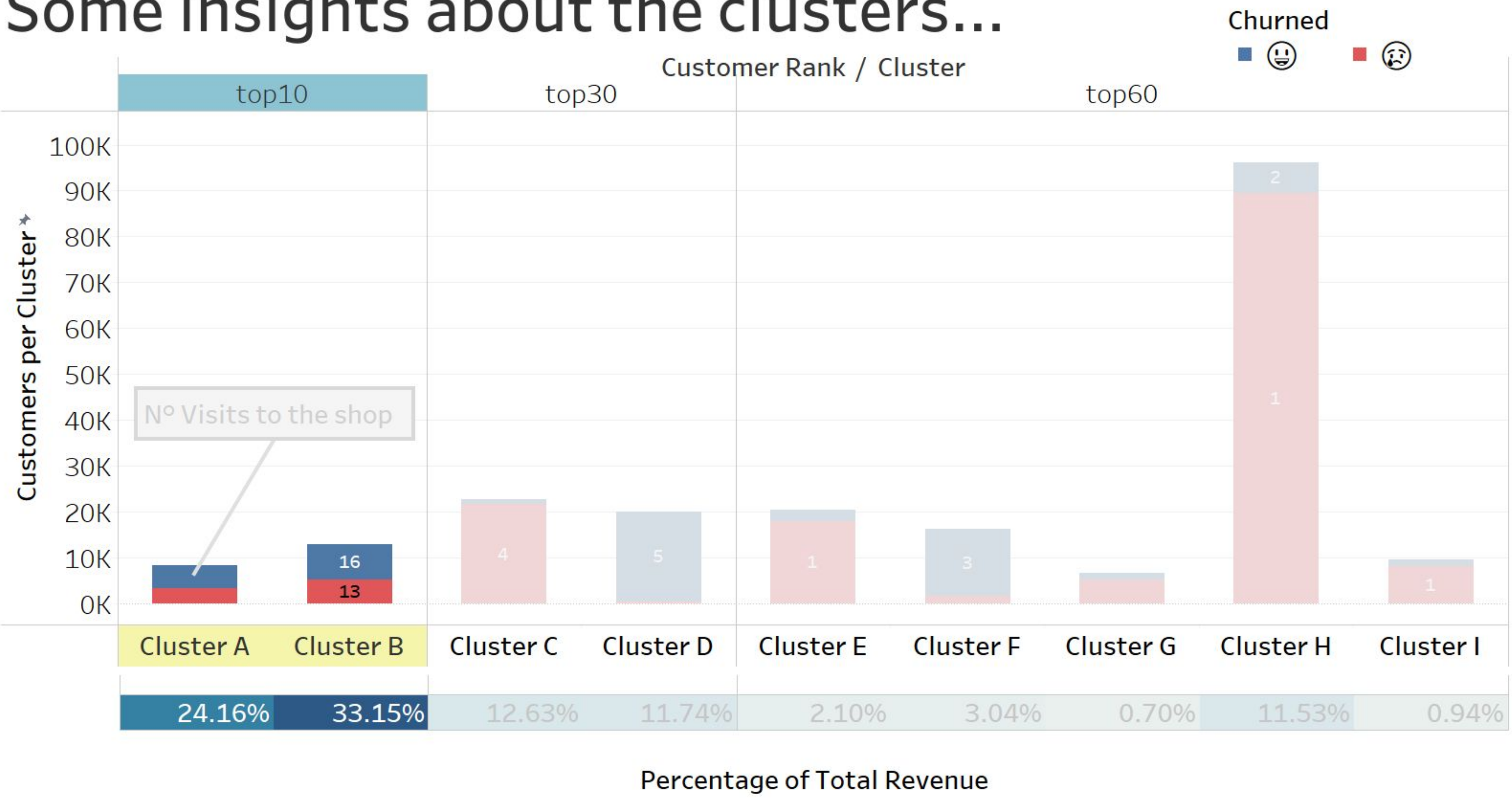

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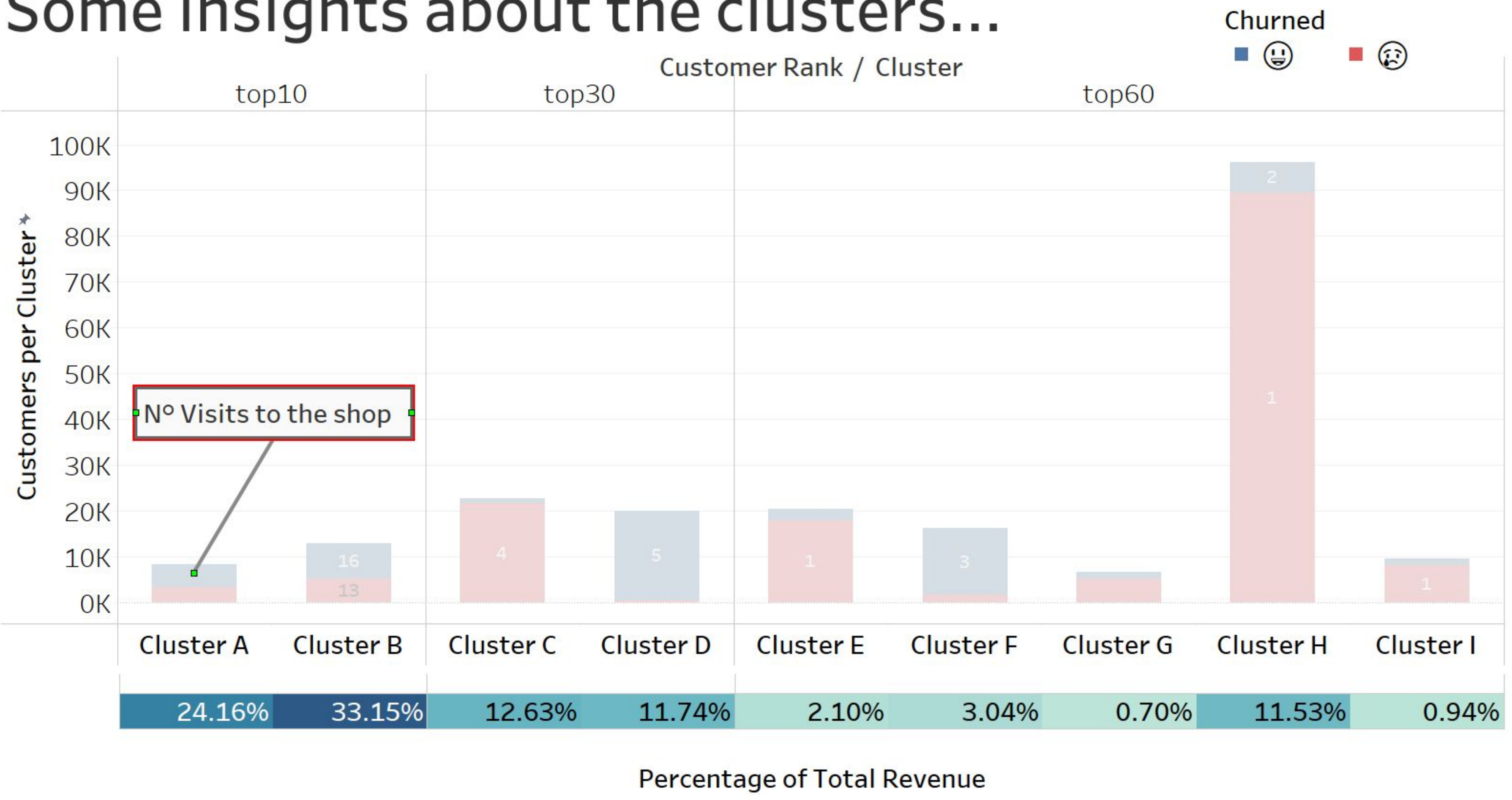

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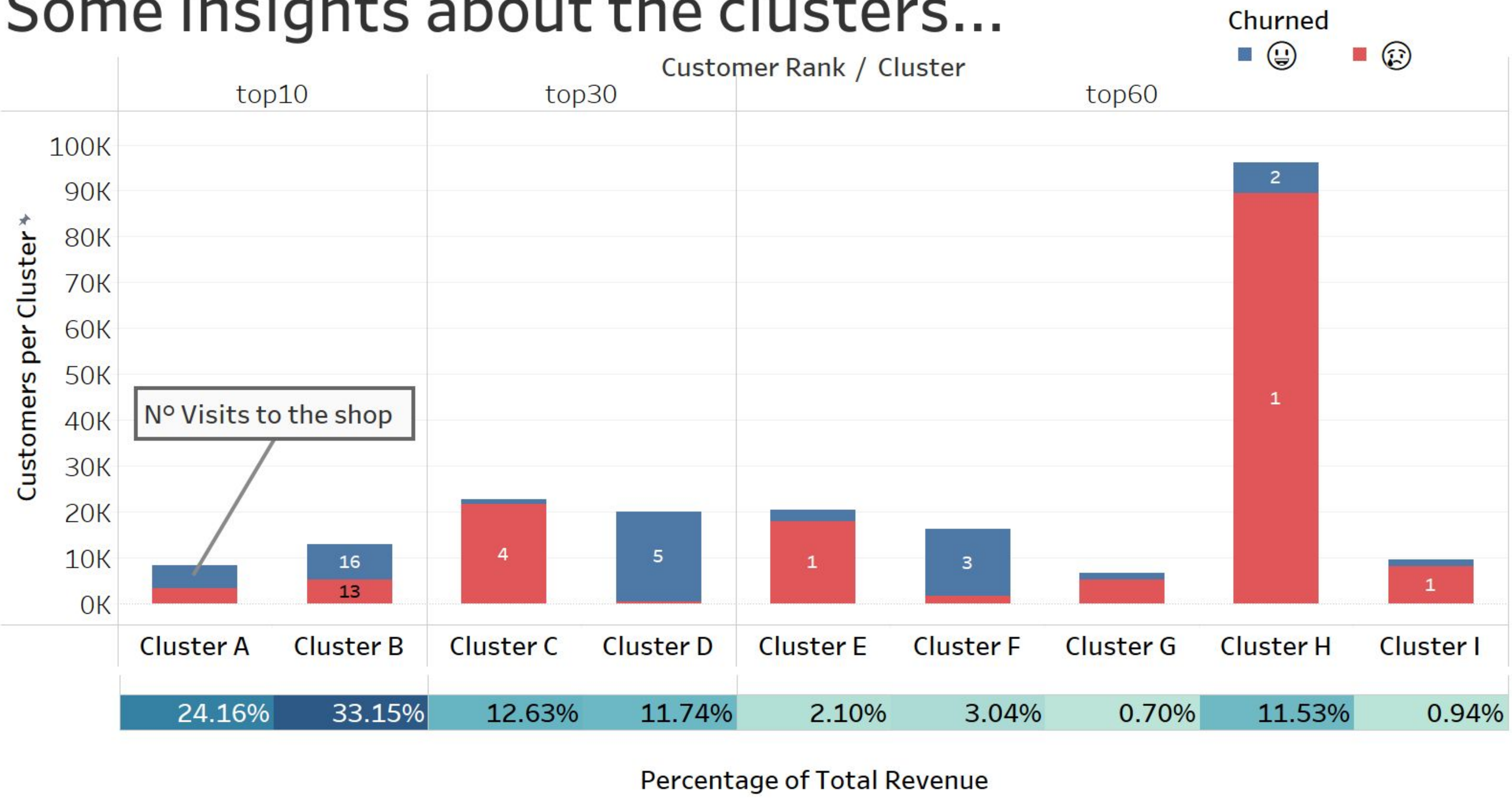

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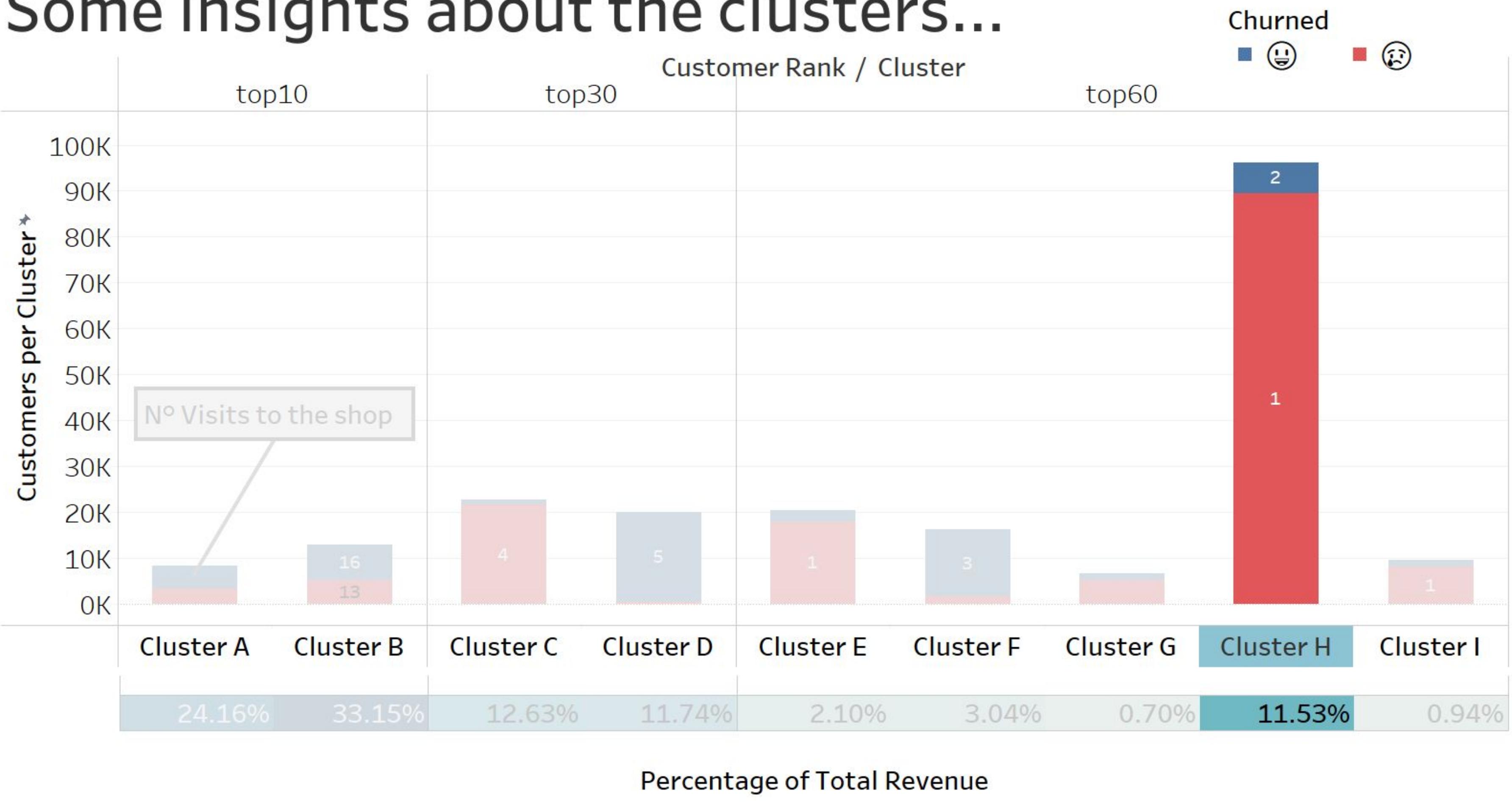

What did we learn from the data?

About Churn prediction

- Quite reliable churn prediction if enough data available
  - Important to have more than 1 transaction for the customer
  - Trust more in “churned” result
- Real validation needed?

About Clustering

If we focus on the **“cool”** customer, who brings the highest amount of revenue **(TOP10):**

Cluster A:

- Main product type:
  - 1° -> KIDS
  - 2° -> WOMENS (winter)
- Avg. Price per Product ≈ 50€

Cluster B:

- Main product type:
  - 1° -> ONLY KIDS
- Avg. Price per Product ≈ 35€

About Clustering

If we focus on the “**regular”** customer” **(TOP30):**

Cluster D:

- Main product type:
  - 1° -> KIDS
  - 2° -> WOMENS (winter)
- Avg. Price per Product ≈ 35€

About Clustering

If we focus on the **“passing by”** customer” **(TOP60):**

Cluster H:

- Main product type:
    - 1° -> KIDS
    - 2° -> WOMENS (summer & winter)
- Avg. Price per Product ≈ 40€

Improvements

How useful can ML be?

- **Classification**
  Depends on the quality of the data
  Time-dependant properties, so need full customer history to make good predictions

- **Clustering**
  Found cluster-dependant results, clear patterns are debatable.

To do better

- Model deployment
- Explore alternative classification and cluster algorithms
- It would be interesting to compare the *churn rate* with other companies of the same sector.
- Try more varied conditions for the *churn rate*
- Customers profiles can be improved with more data
    - Increase the level of trust in the data collected (add zip code, product categories ....)

Conclusions

Conclusions & our advice

- Churn rate is very high
  - Biggest spending customers are relatively loyal
- A lot of one time customers
  - Not necessarily bad (10% of revenue)

Questions?