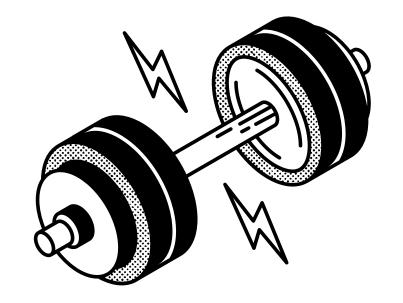
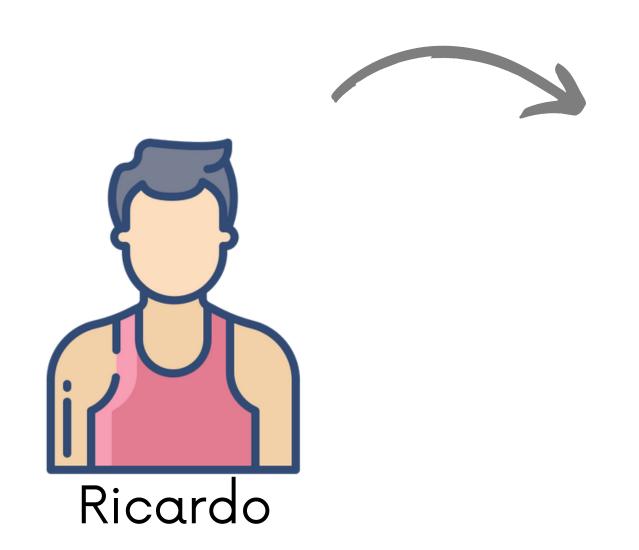
Gympass: churn prediction

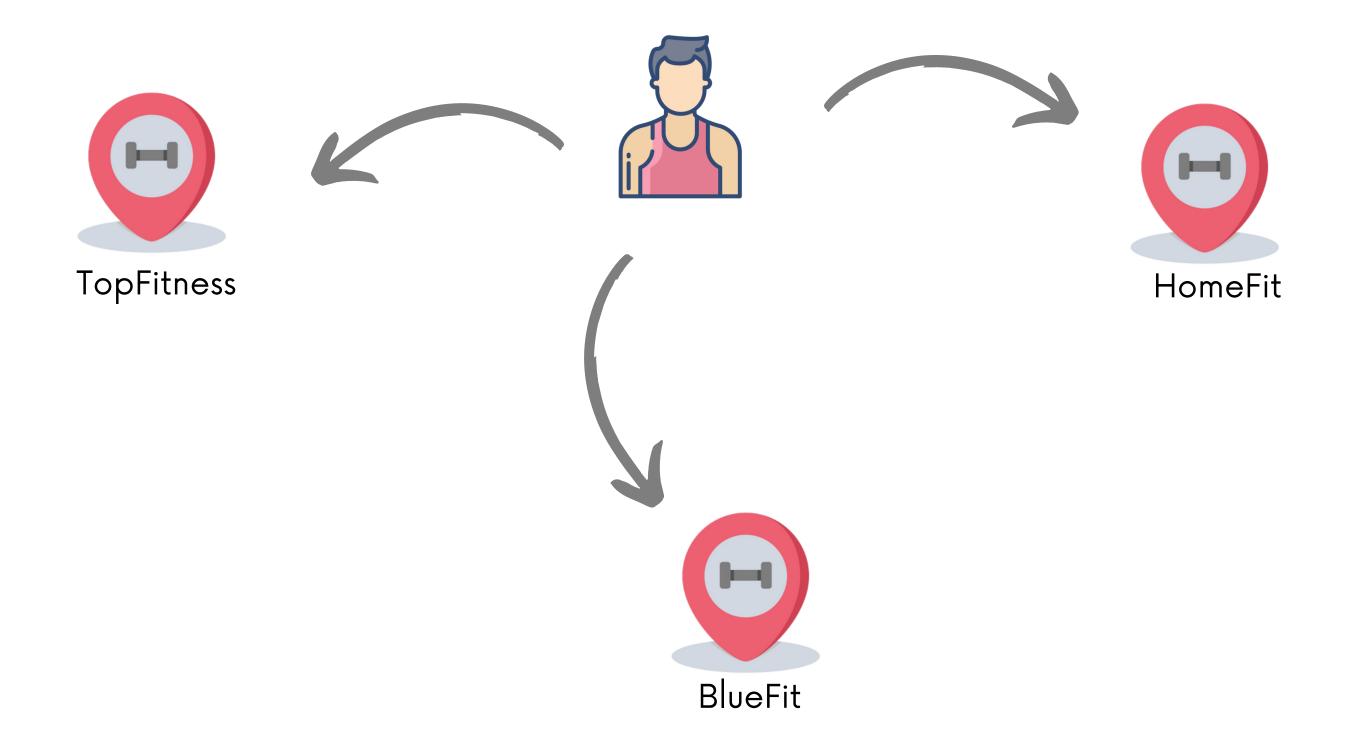


Introducing Ricardo

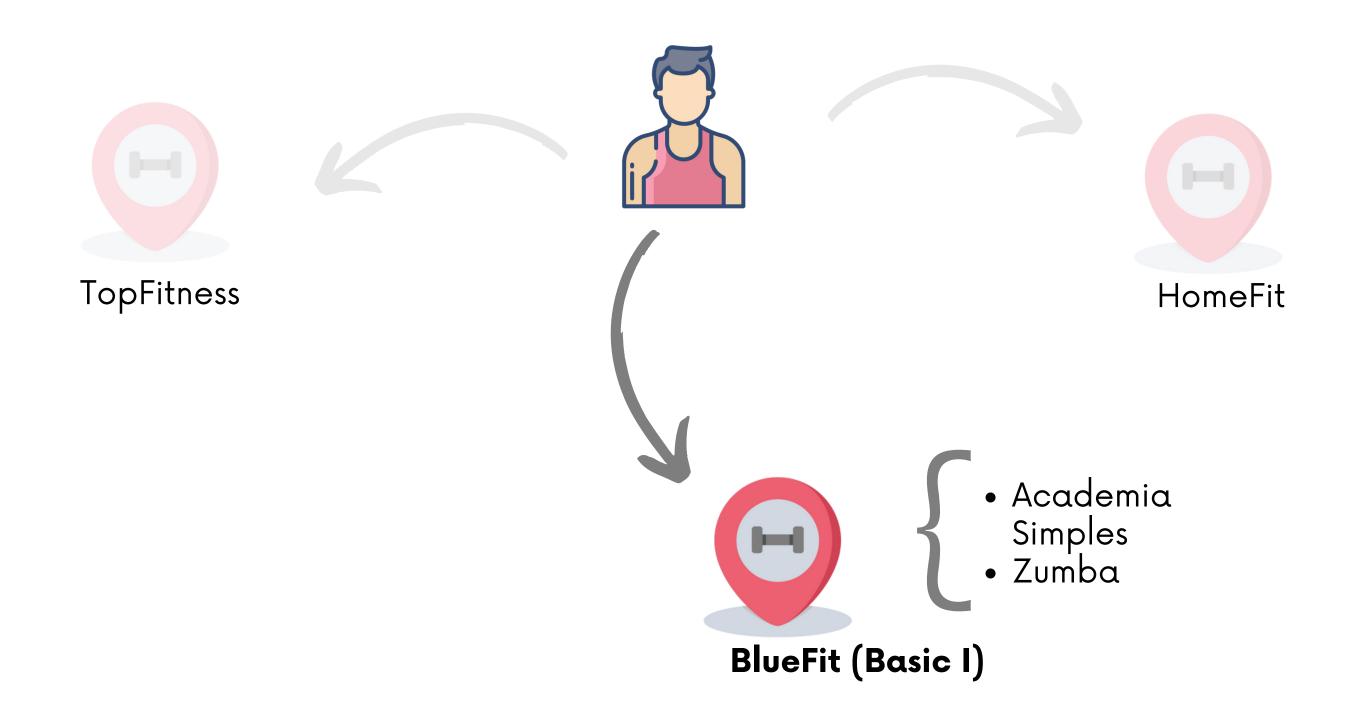


- He wants to start a fitness lifestyle.
- Your company has a contract with
 Gympass.

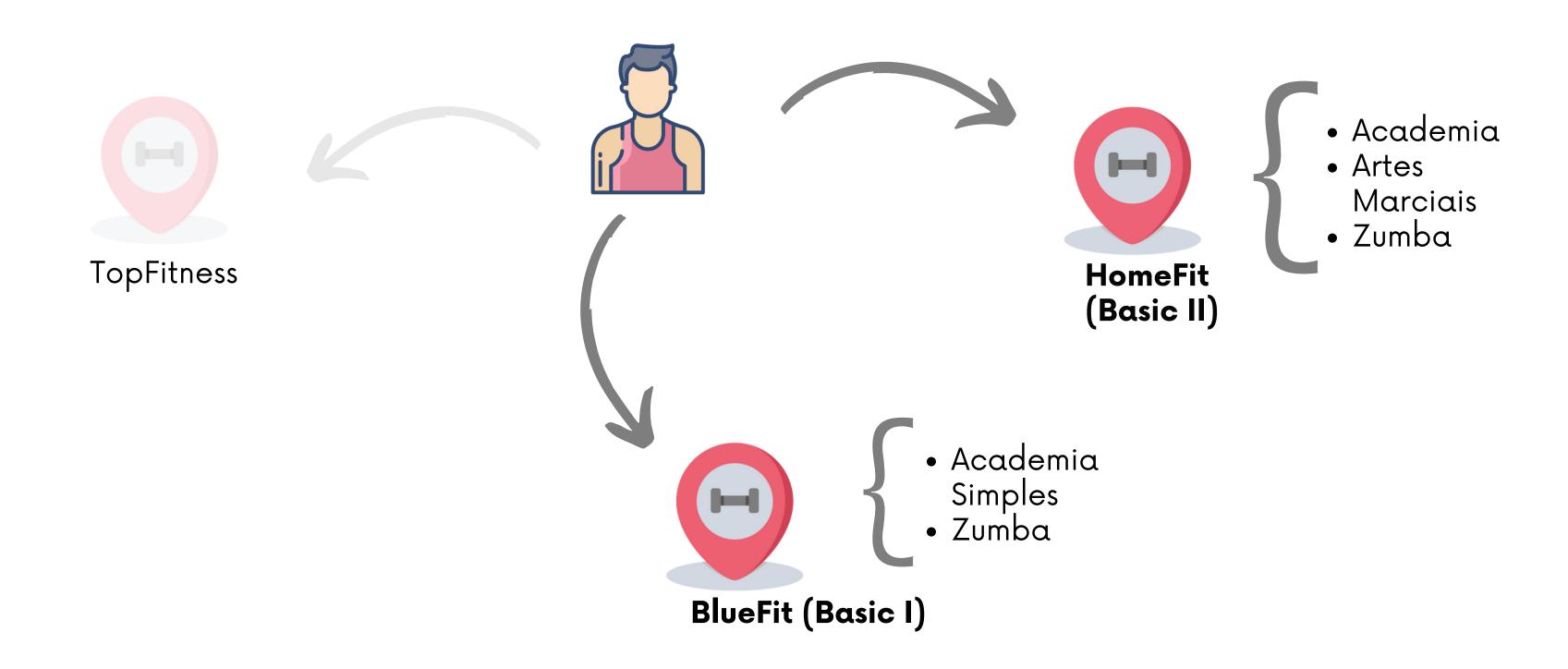
What is gympass?



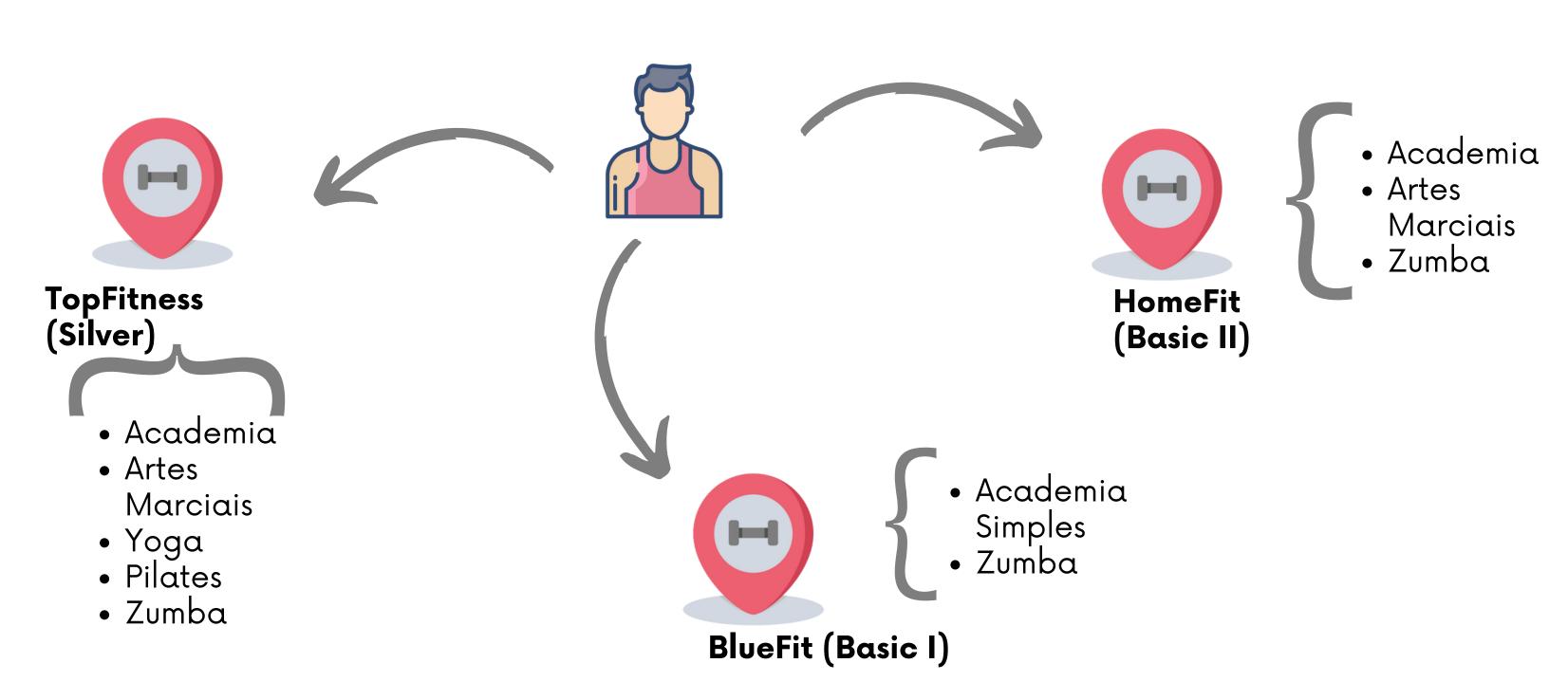
Gympass Plans Basic I



Gympass Plans Basic II



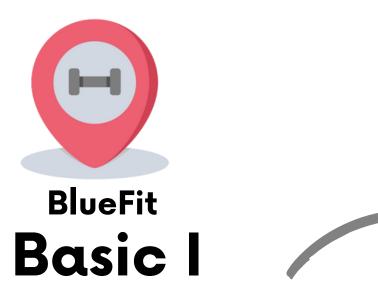
Gympass Plans Silver



Gympass Plans

- Basic I: 39.90
- Basic II: 59.90
- Silver: 99.90
- Silver+: 149.90

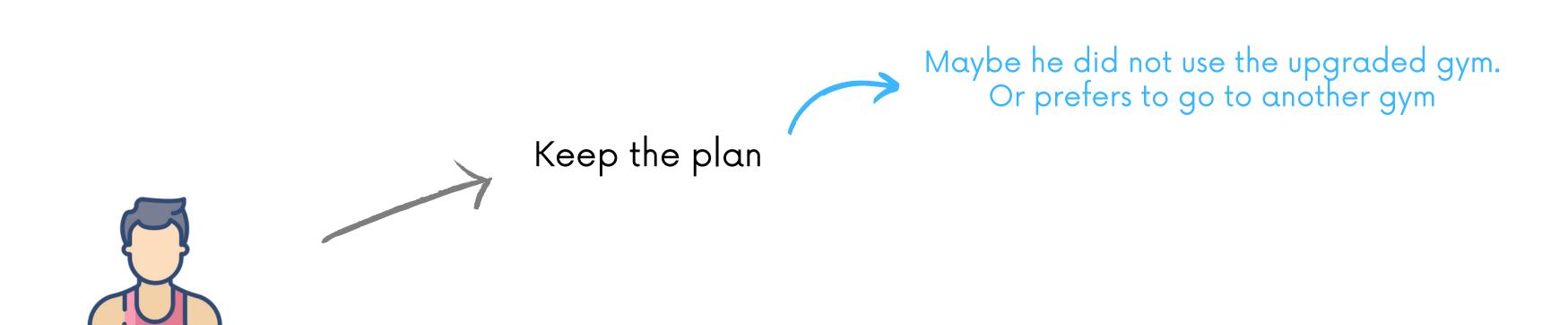
Business problem: Sometimes a Gym wants to **upgrade** an plan



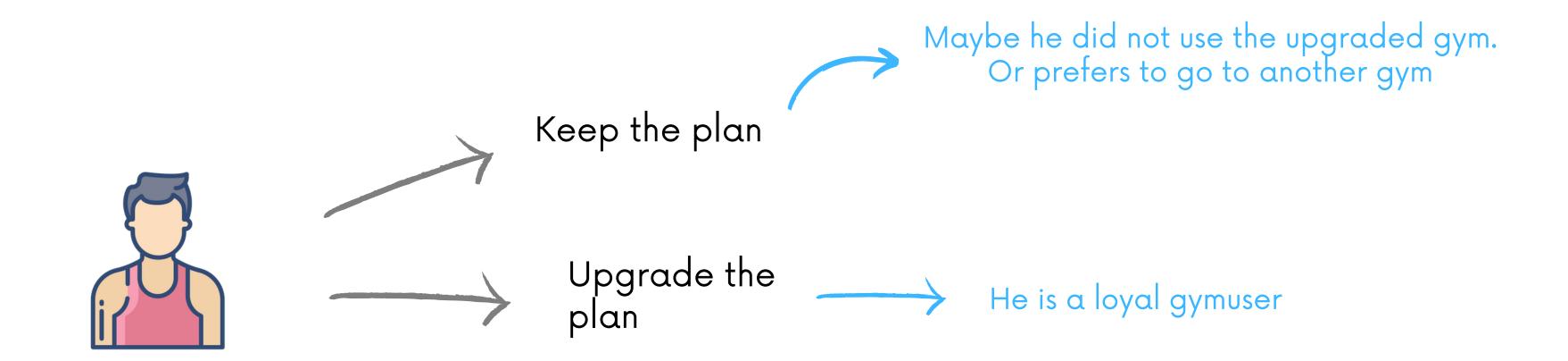


However, it's not so easy

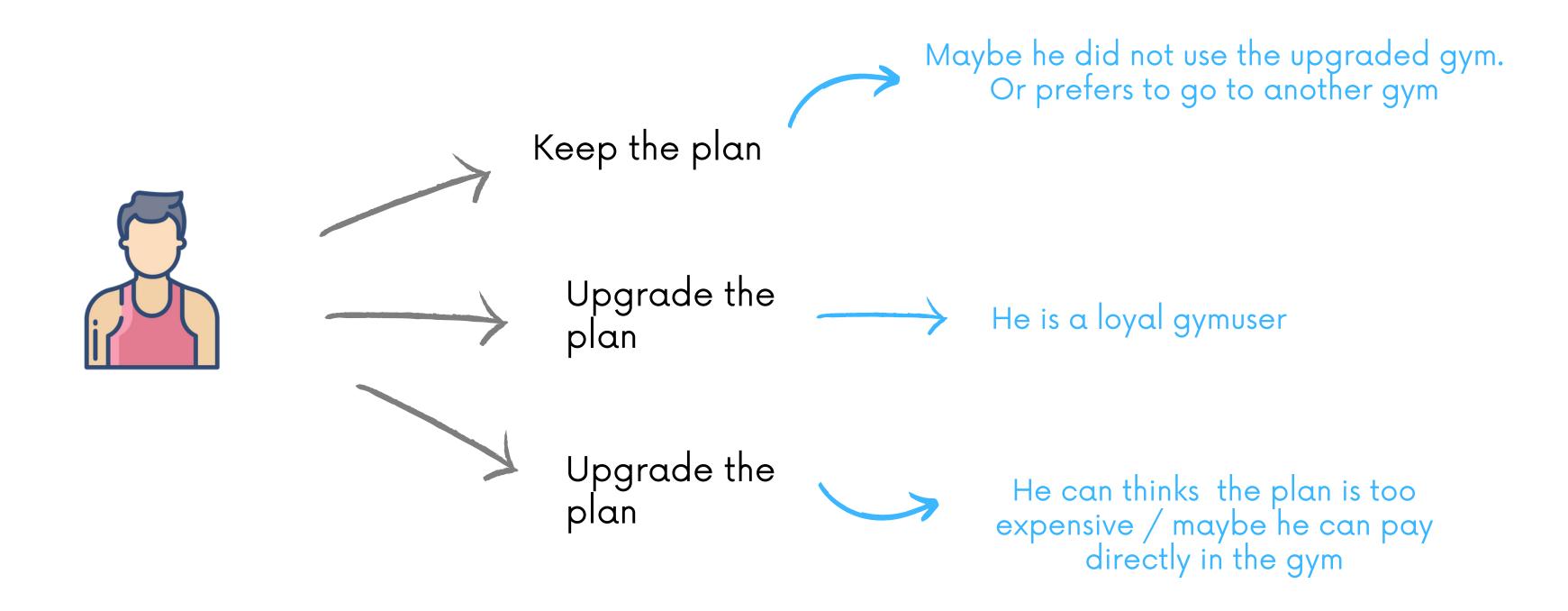
After an gym uptier:



After an gym uptier:



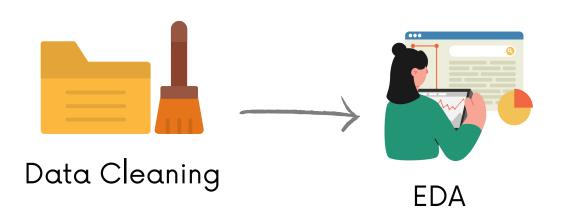
After an gym uptier:

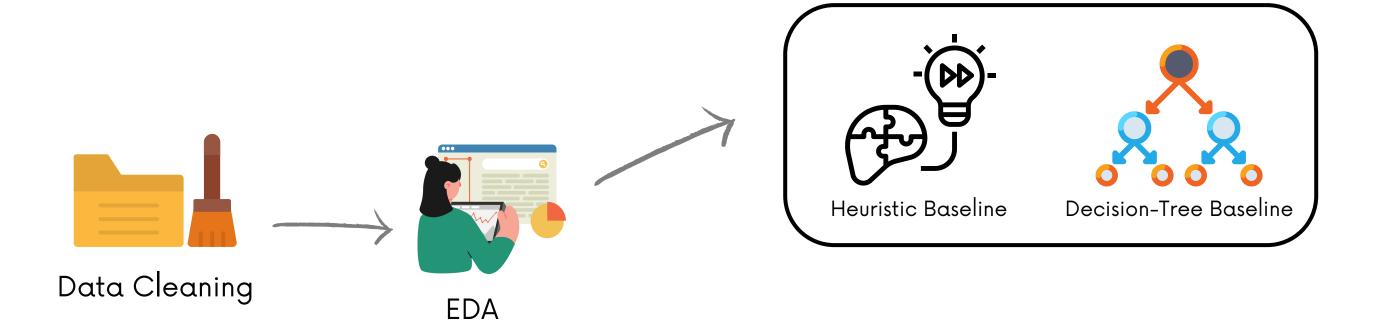


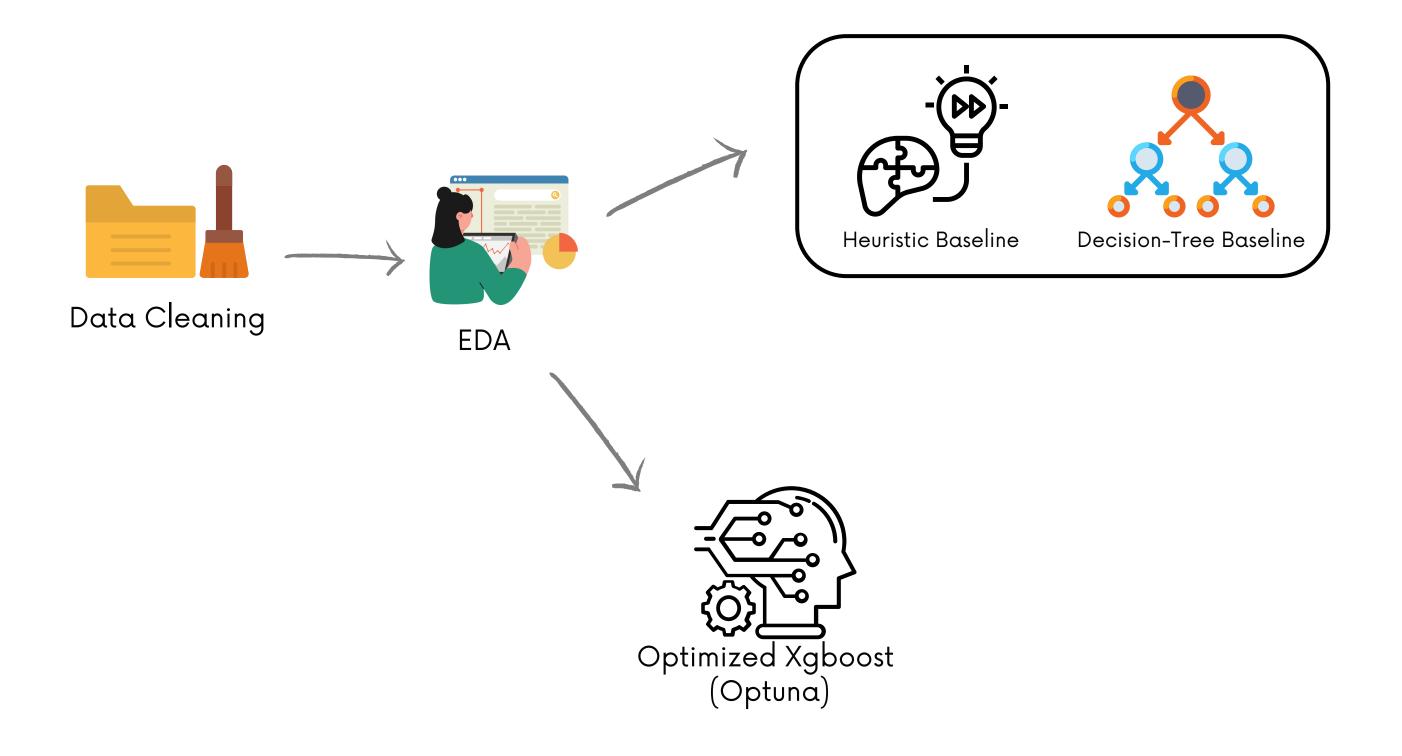
In this task, our goal is to predict which gyms are suitable for an upgrade • We need to predict user churn.

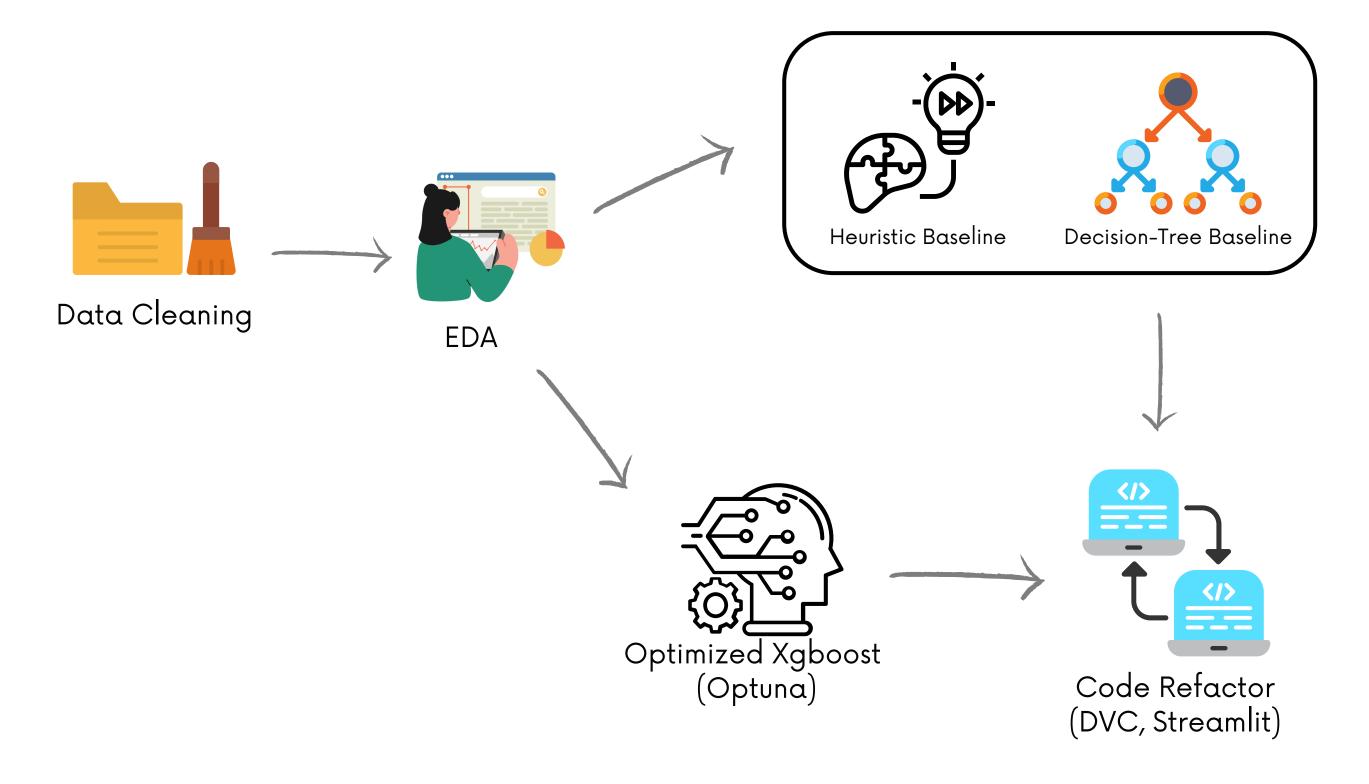
Strategy

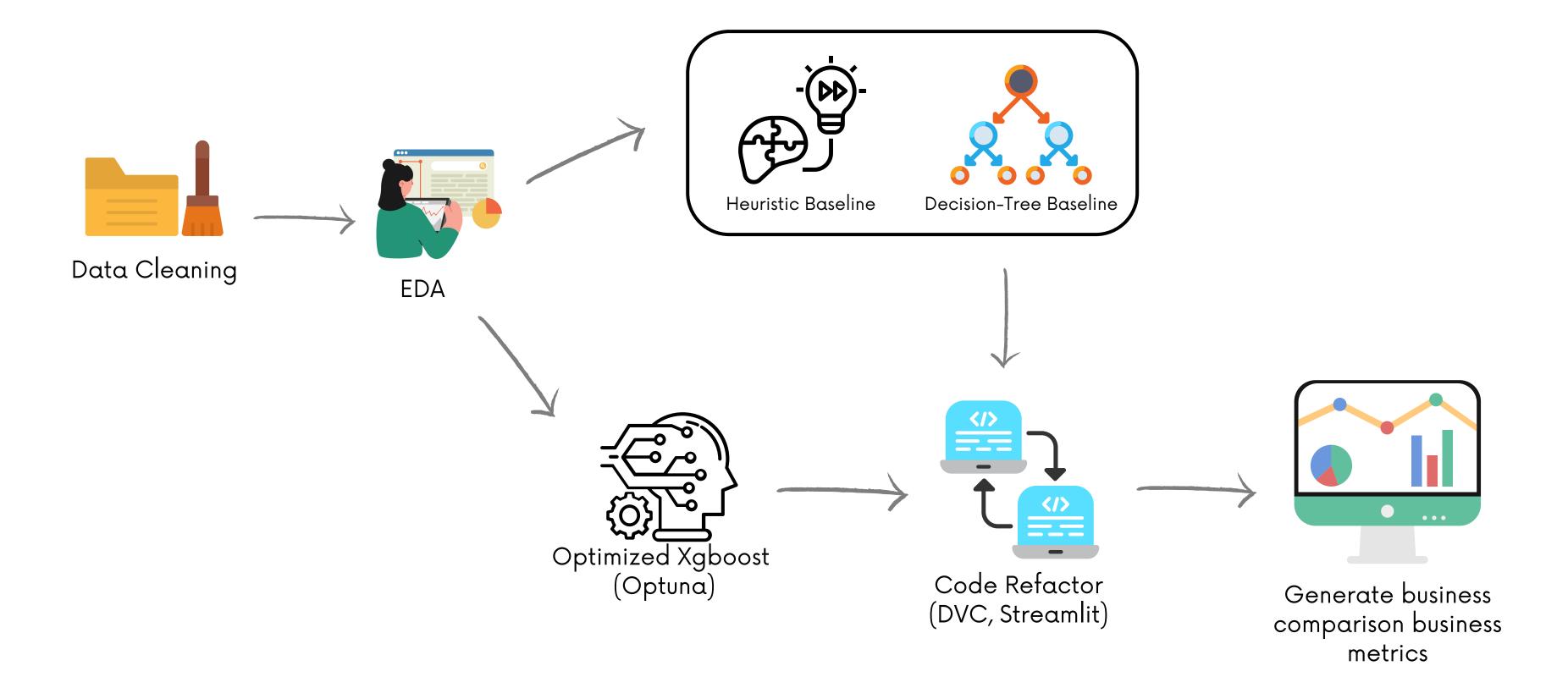
The main ideia was to classify each user as churn or non-churn user, and after calculate the total churn users by gim

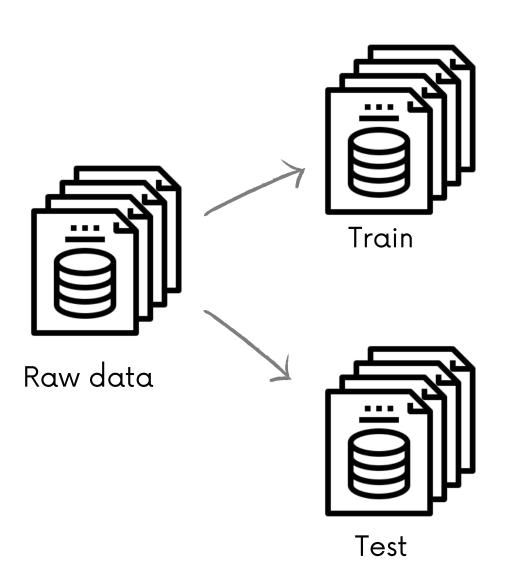


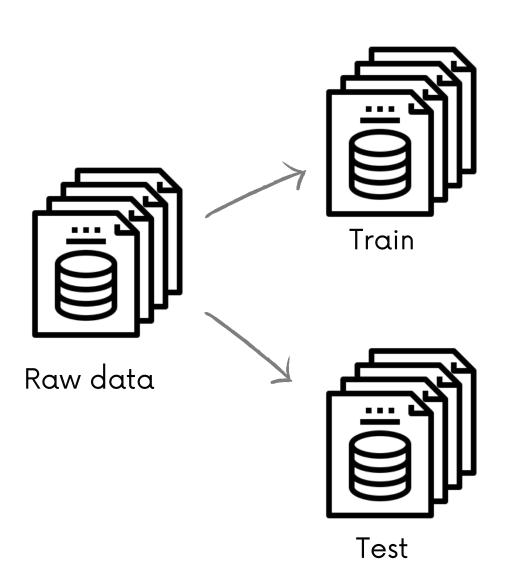




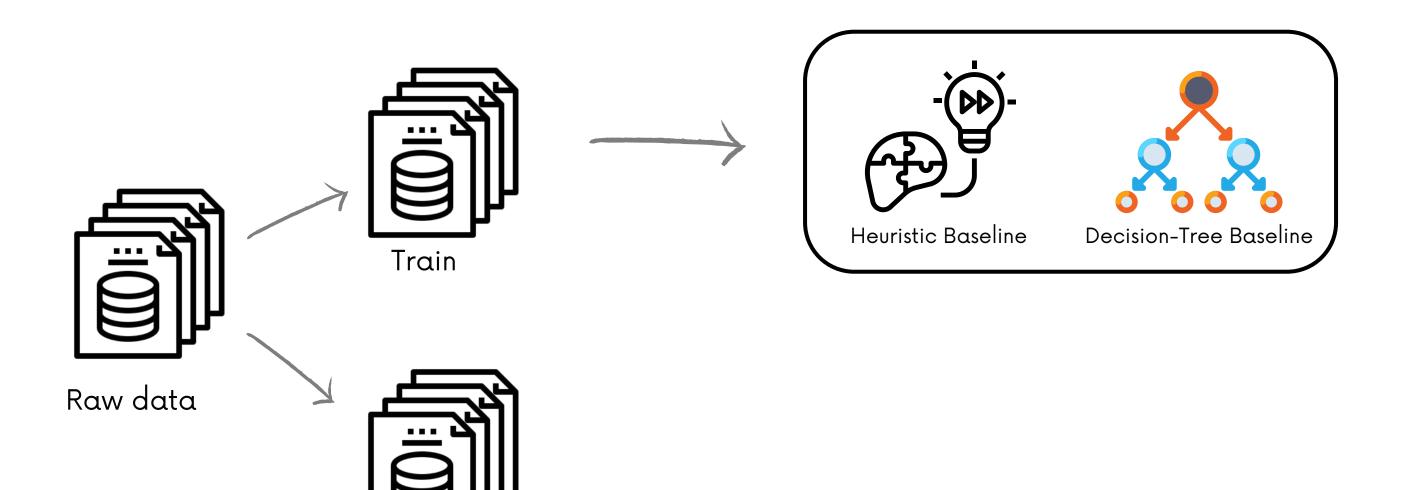






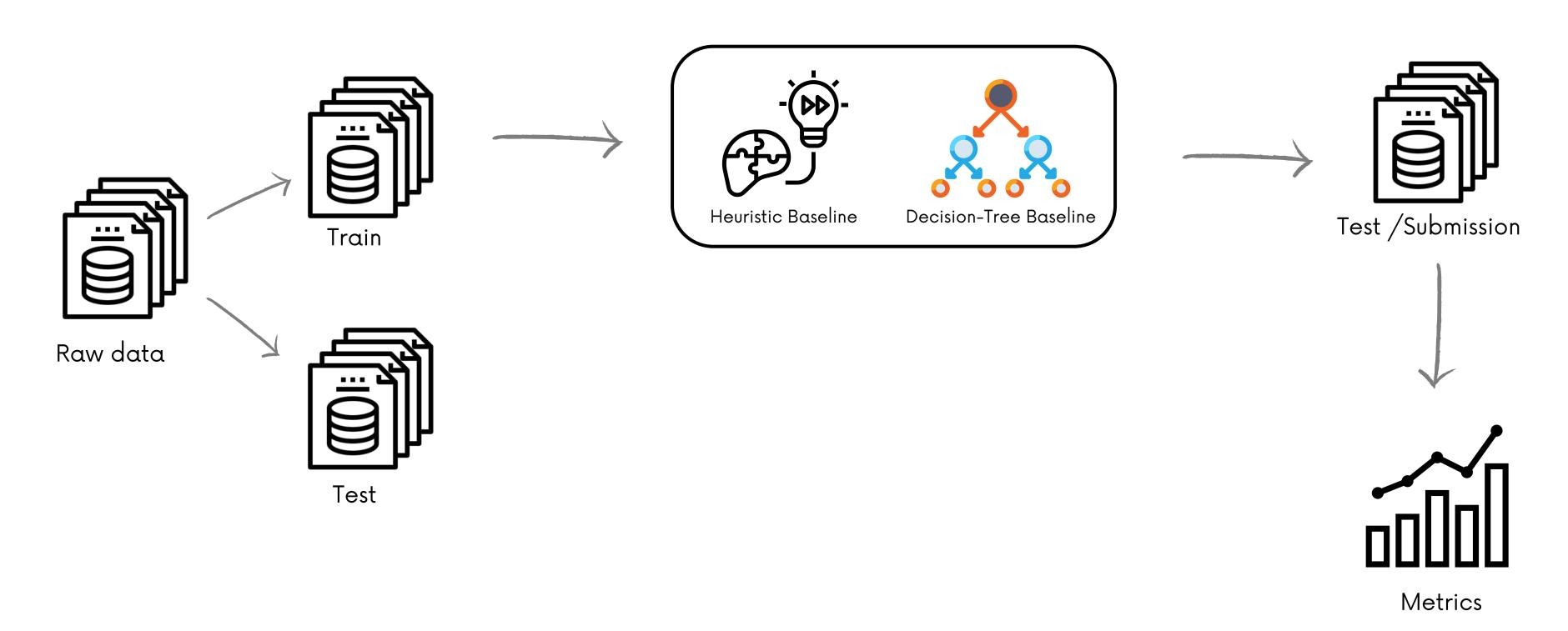


^{*} I splitted considering gym indexes, not users

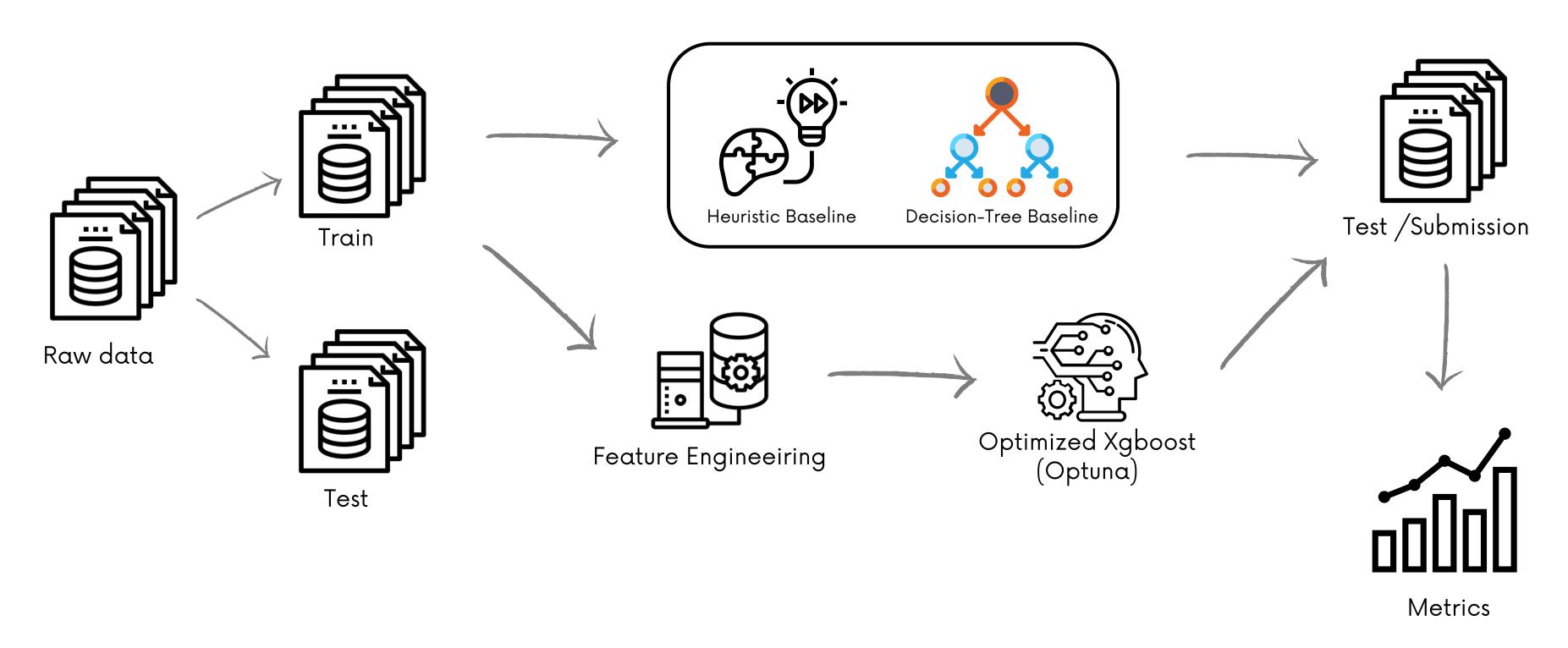


Test

^{*} I splitted considering gym indexes, not users



^{*} I splitted considering gym indexes, not users

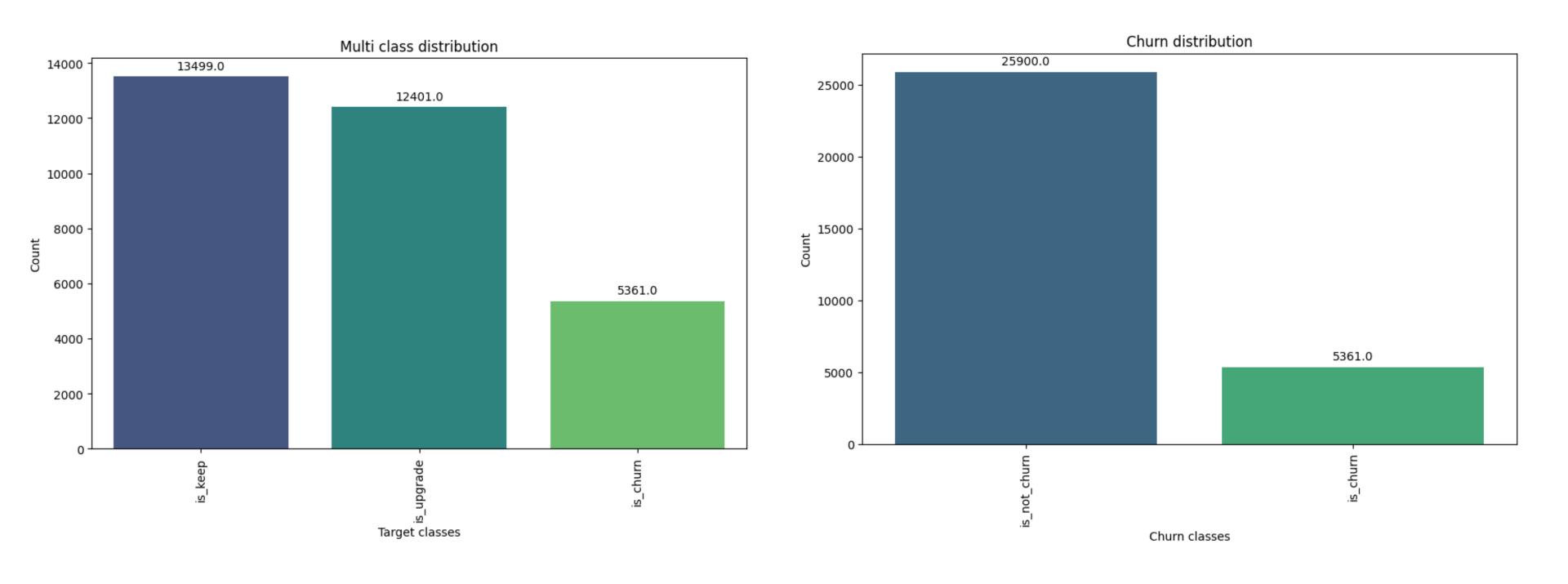


^{*} I splitted considering gym indexes, not users

Exploratory Data Analysis

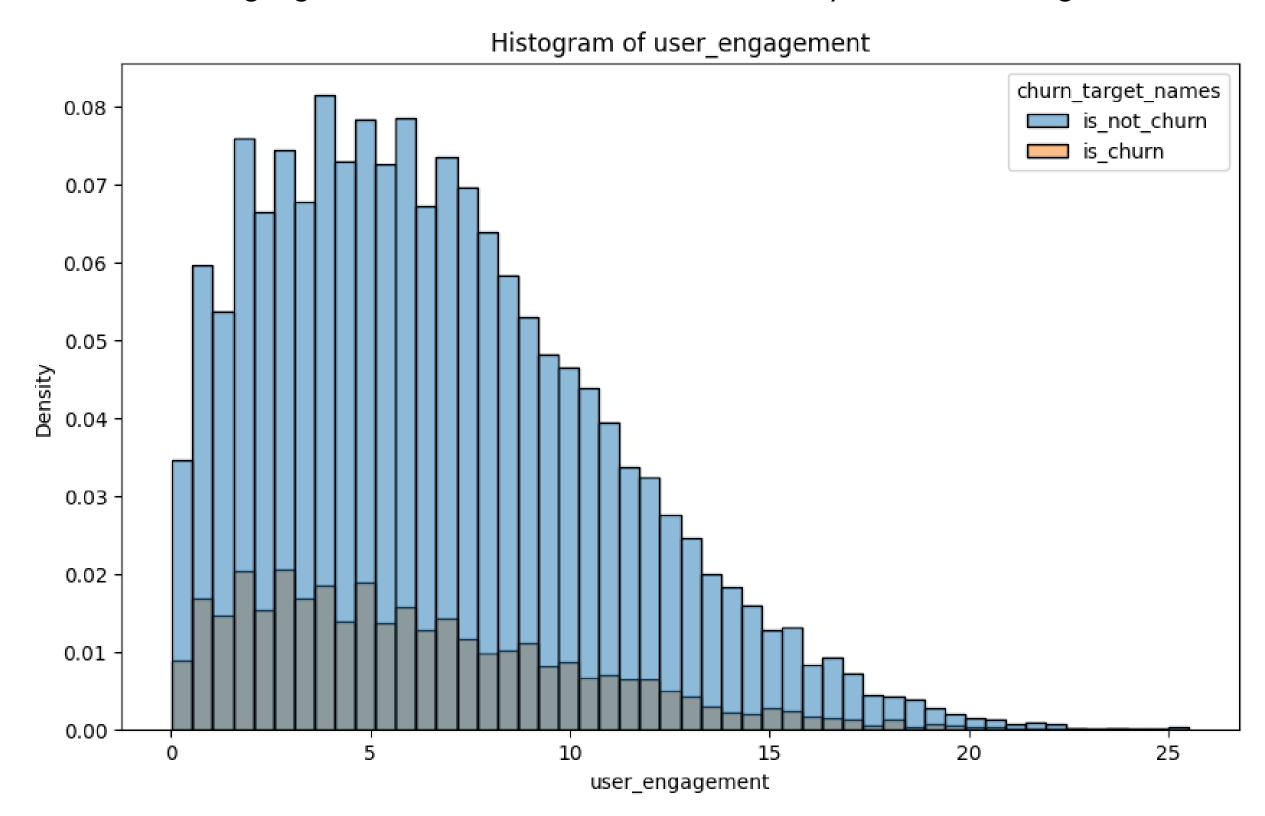
The most found important patterns

Target Distribution

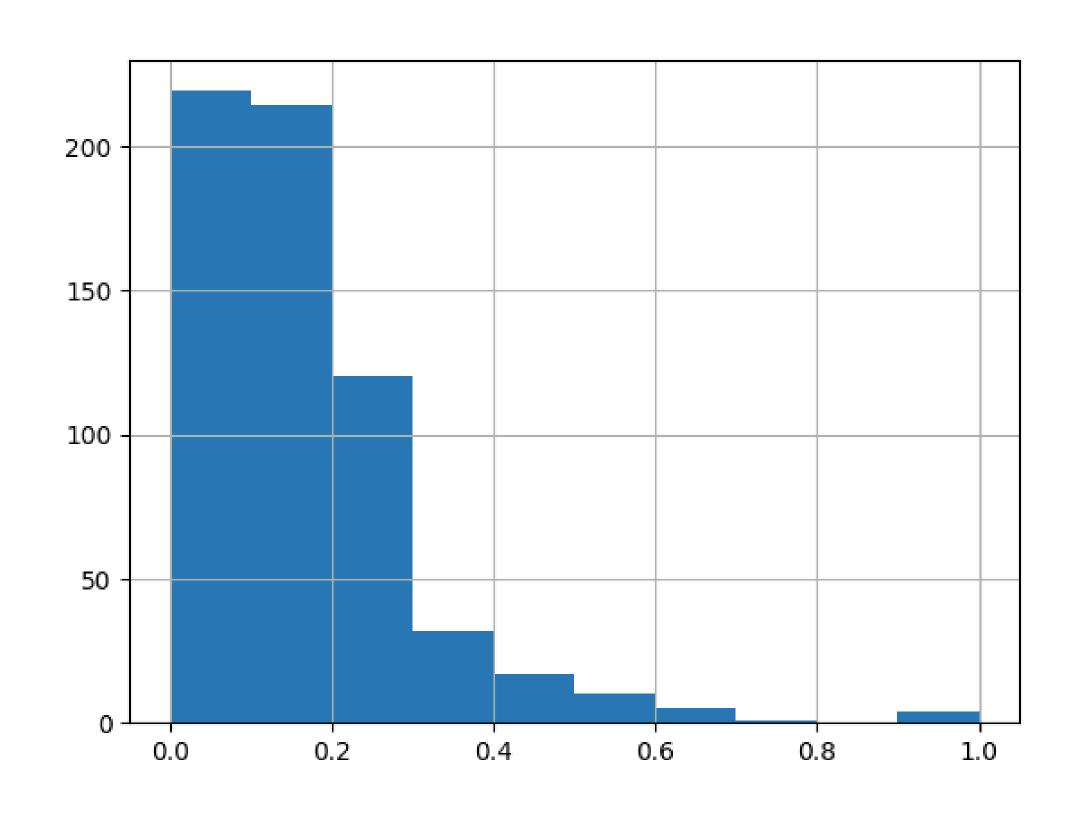


User Engagement Distribution

user_engagement = user_lifetime_visits / user_billings

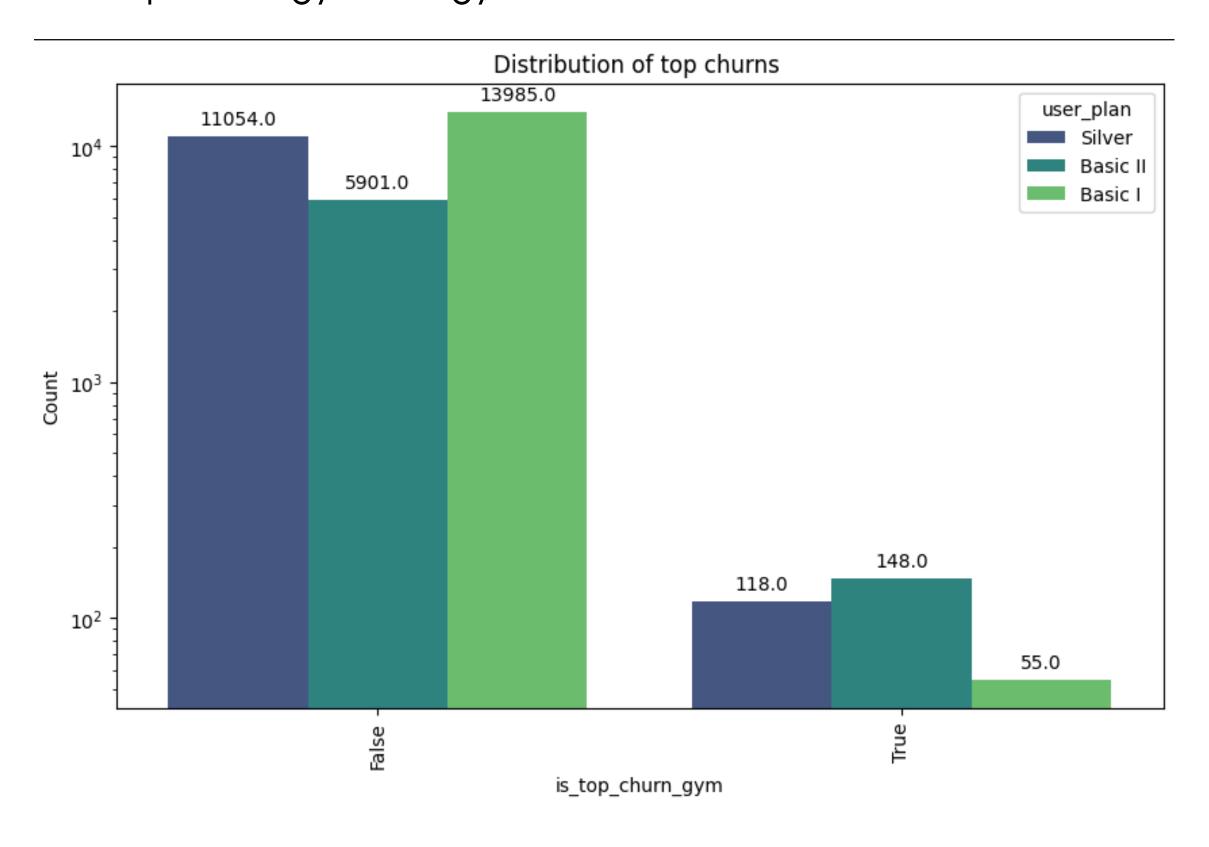


Churn rate gym distribution churn_rate = rate of lost users



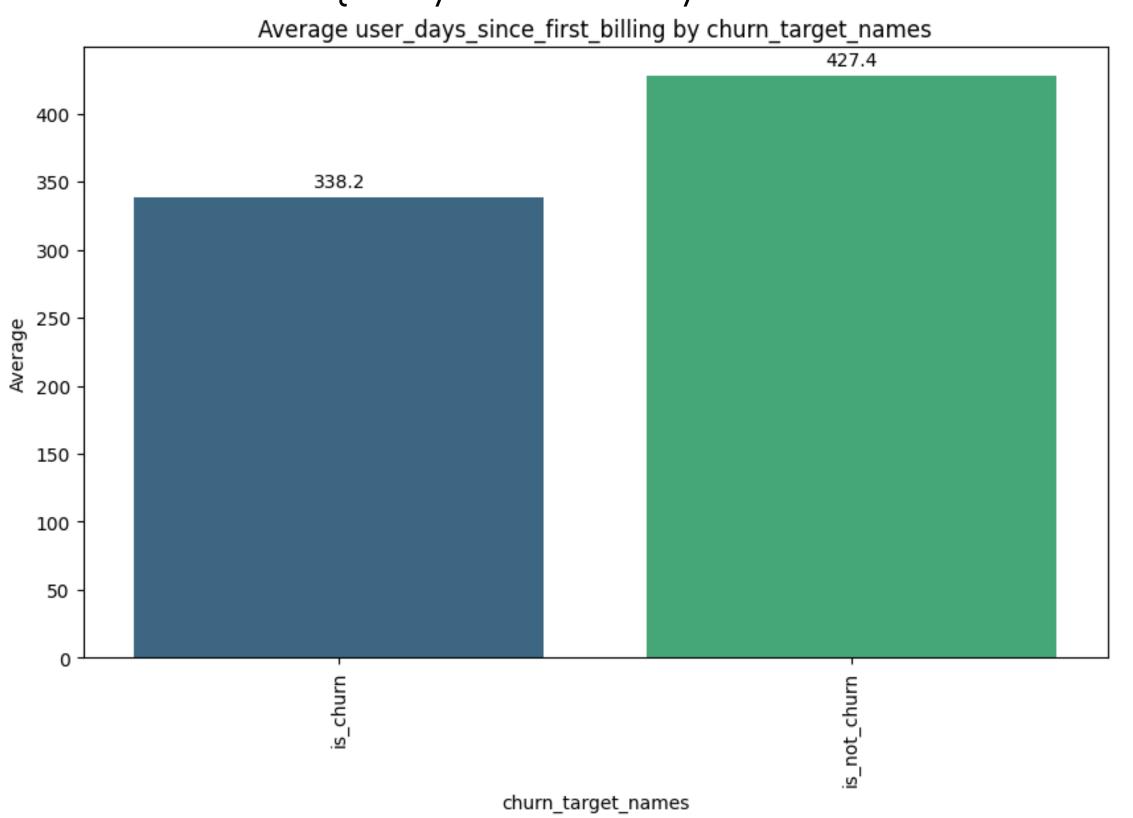
Top churn gym user plan distribution

Top churn gym is a gym that has churn_rate > 0.5

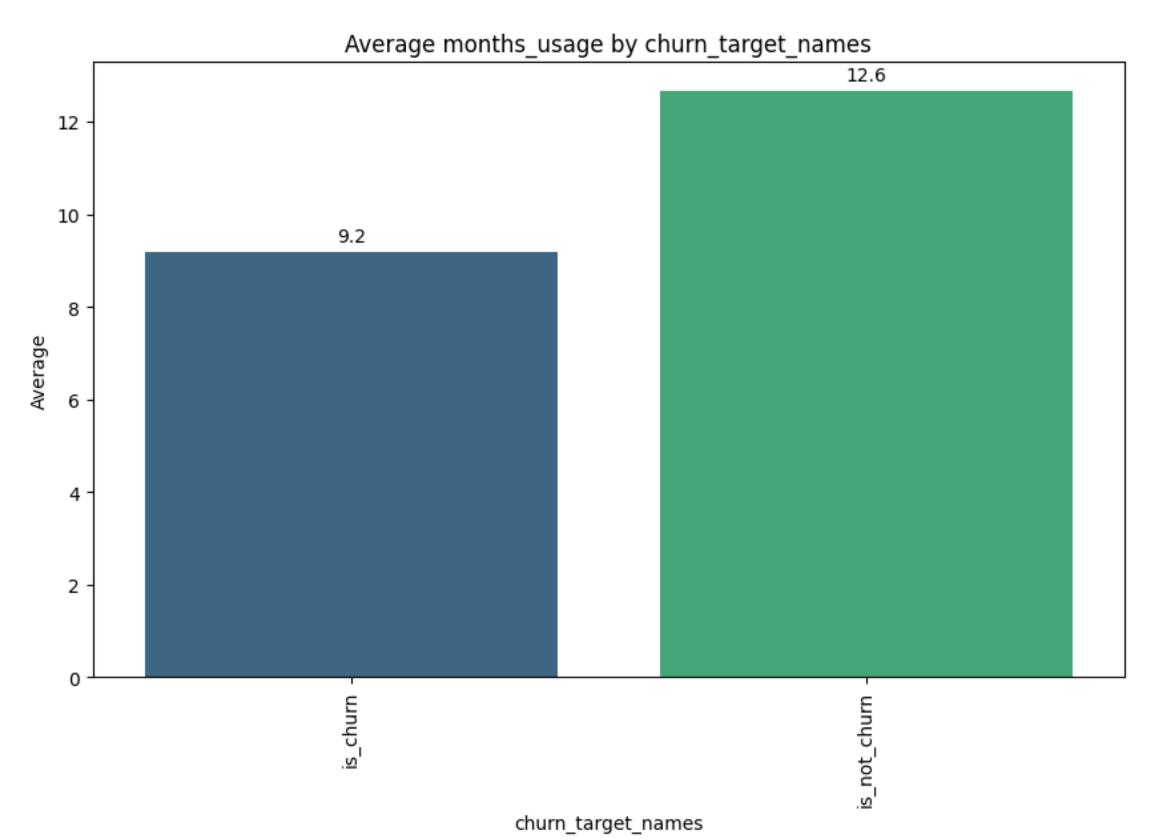


Average user_days_since_first_billing by target

Frequency and Recency affects churn

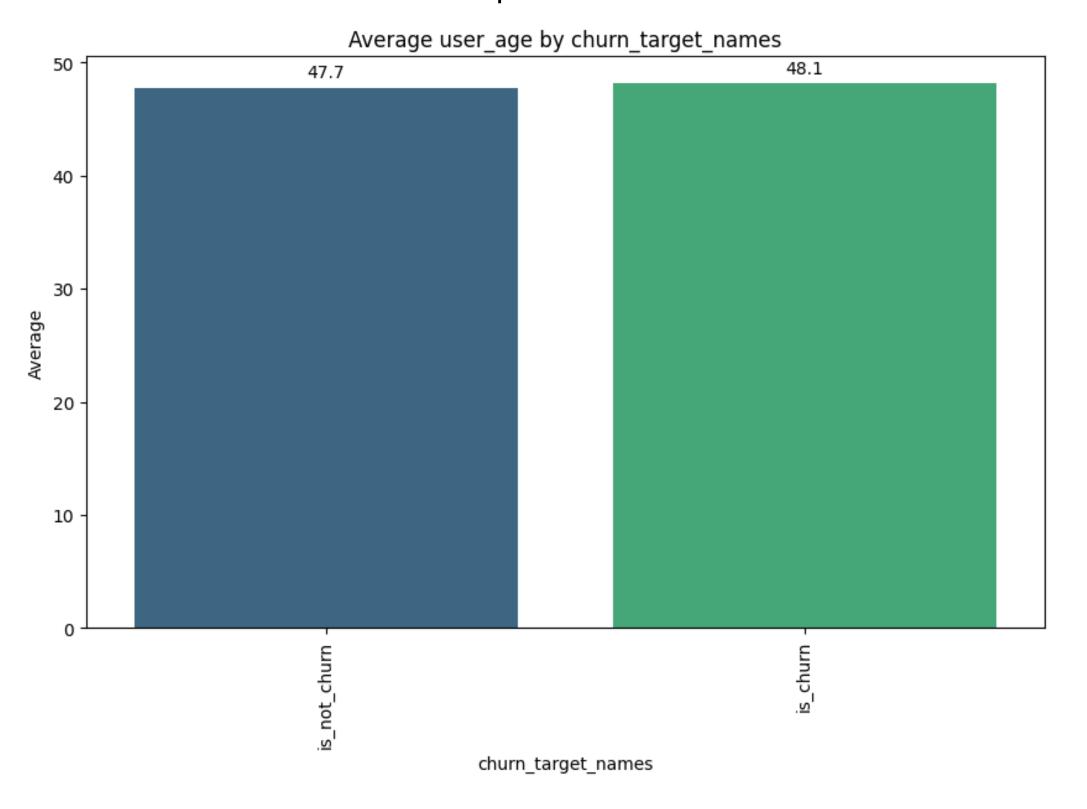


Number of user_billings (months_usage) affects churn

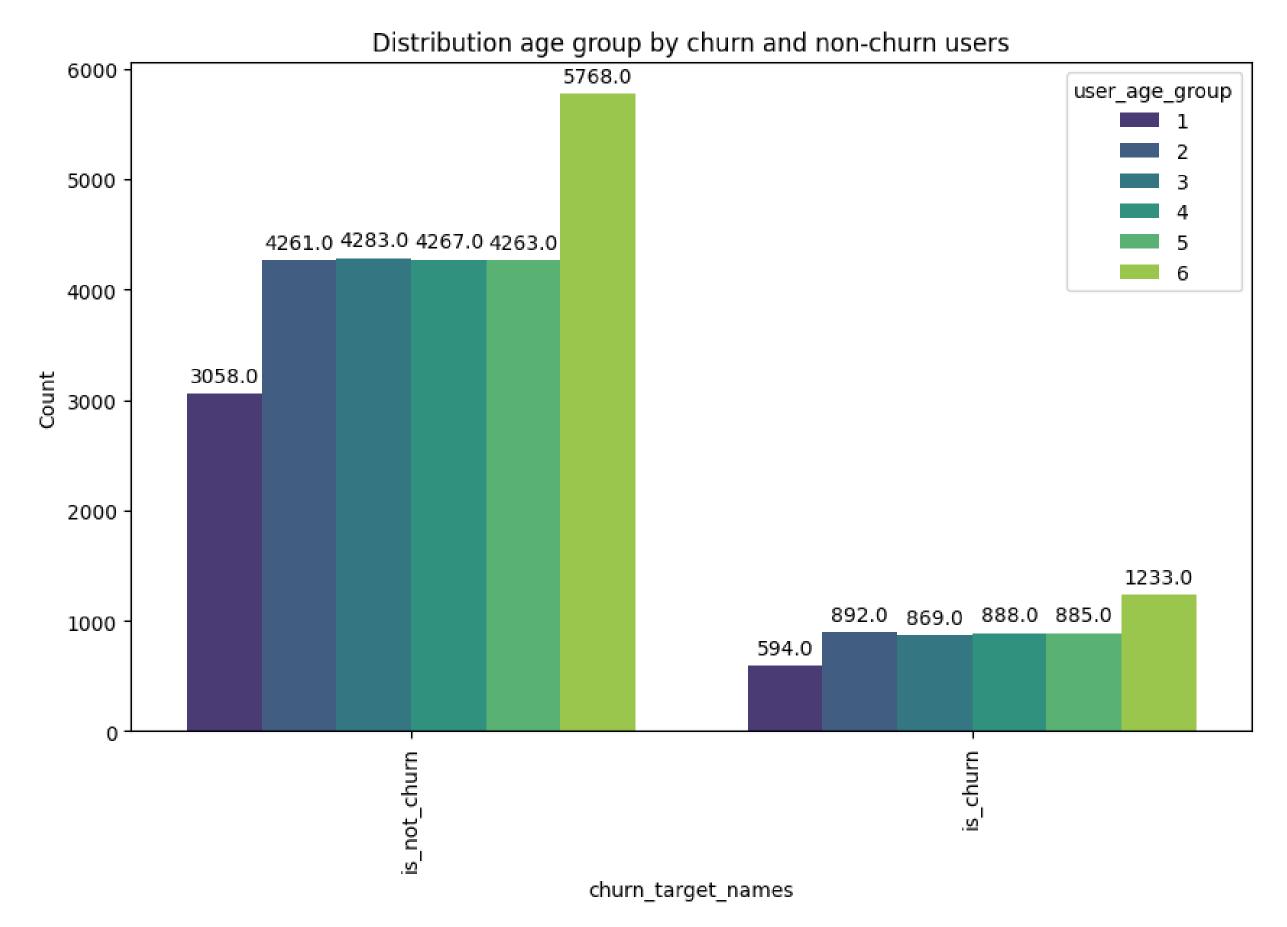


Average user_age by target

Looks like not help in churn information



Average user_age_group by target



Most important assumptions for modelling

1 I assumed the "applications" file contains information of all users of each gym

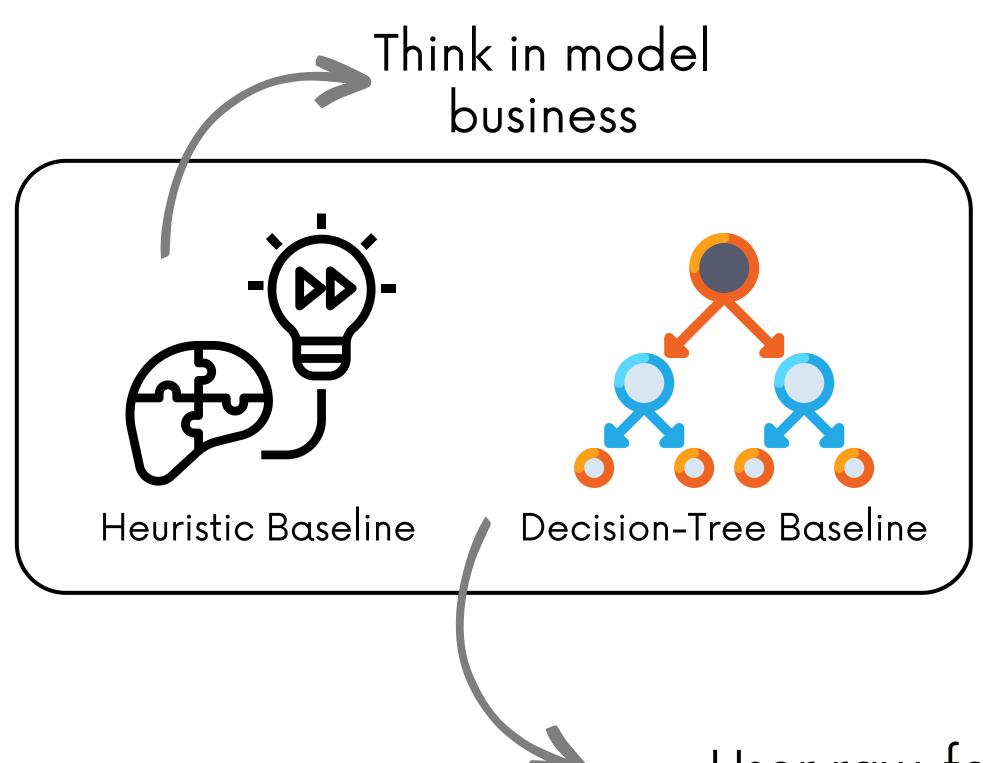
2 Loyalty affects churn

3 Recency and Frequency affects churn

4 User characteristics affects (e.g user age) churns

Baselines

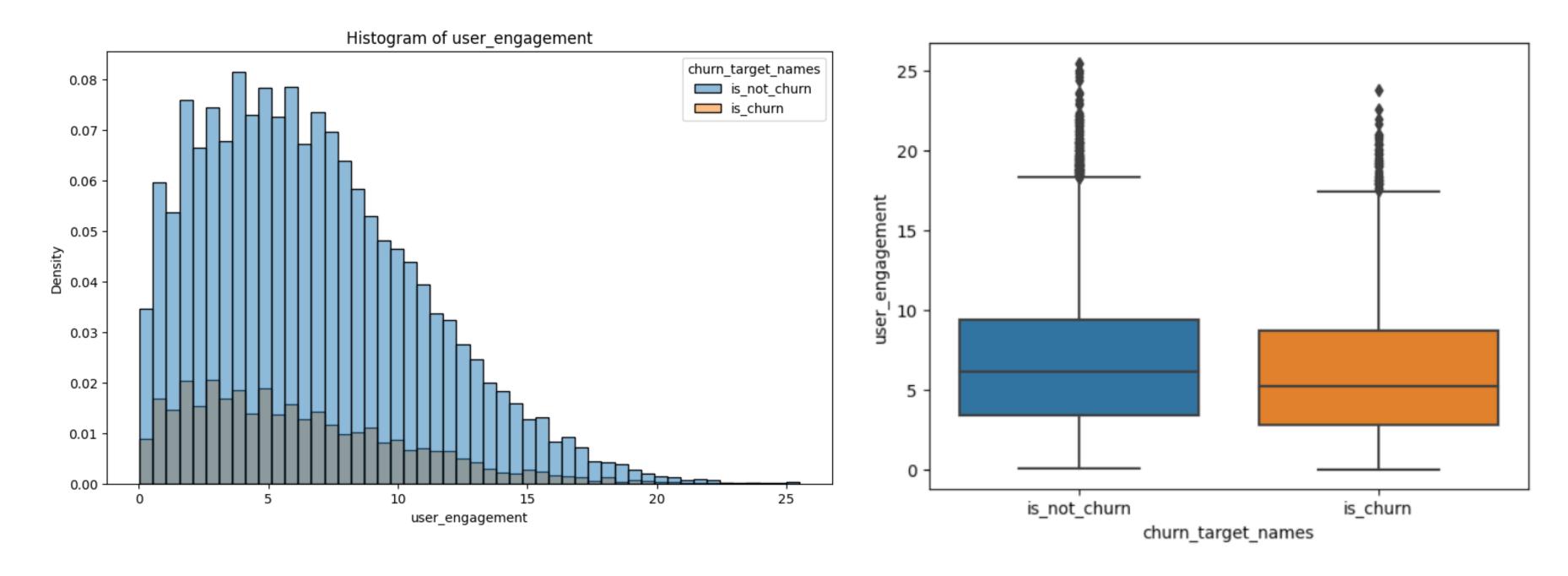
Baselines



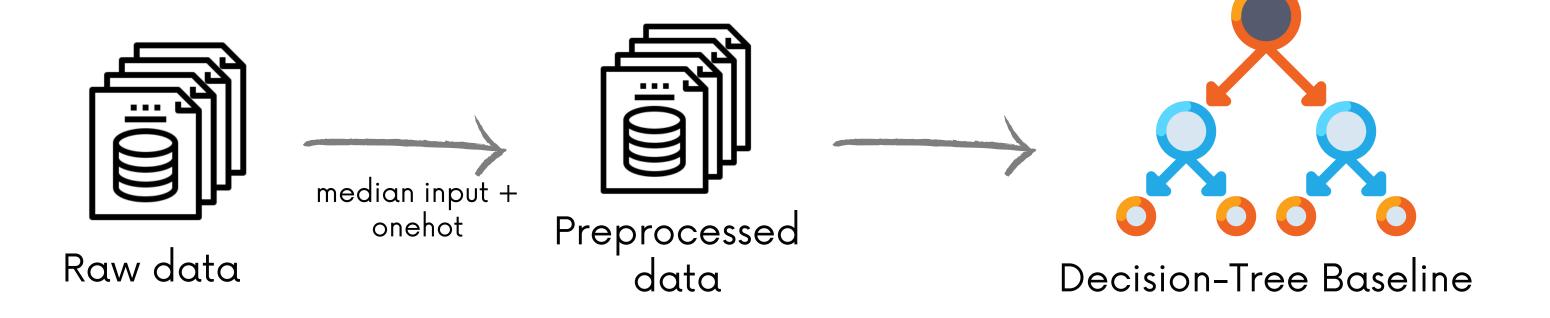
User raw-features

Heuristic Baseline

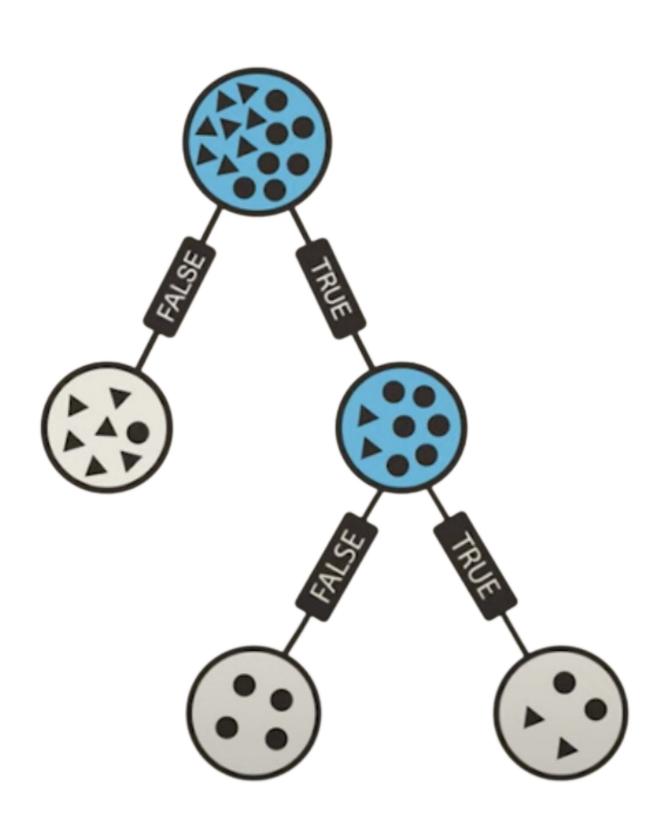
user_engagement.quantile < 20, selected threshold to maintain a similar distribution



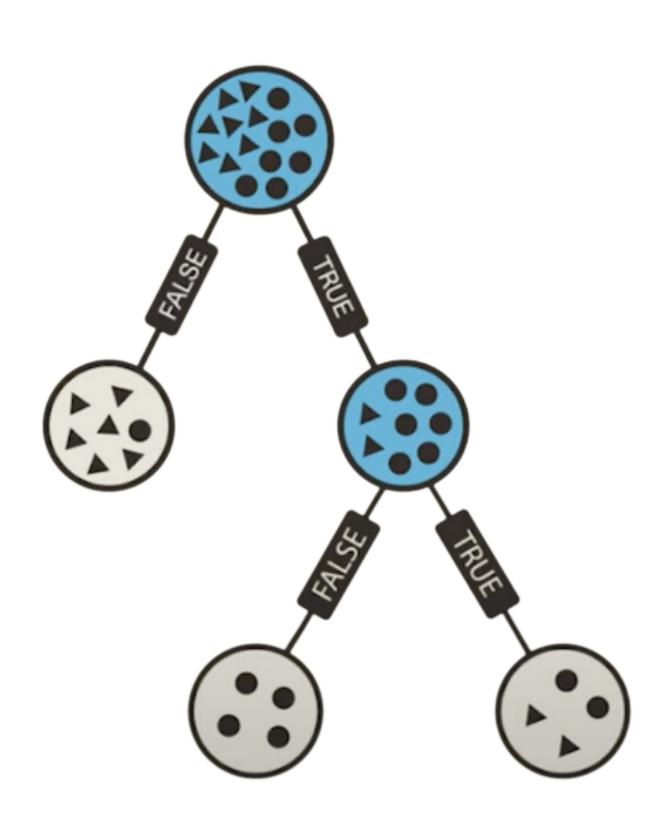
Decision-Tree



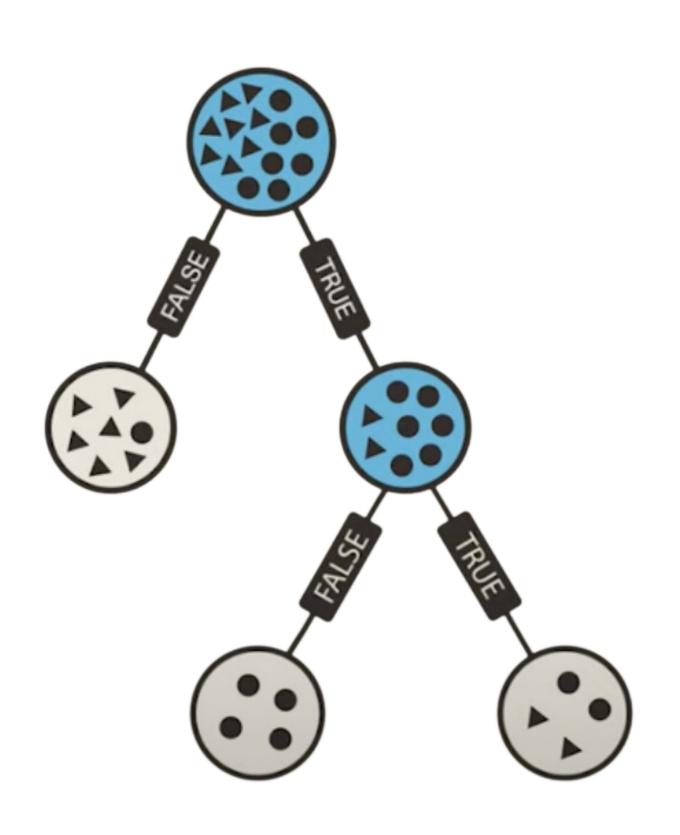
overall concept



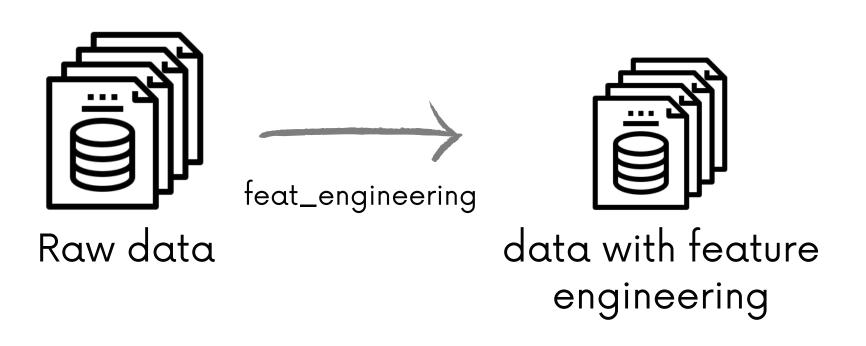
1. Represents decision as the branch of each node.

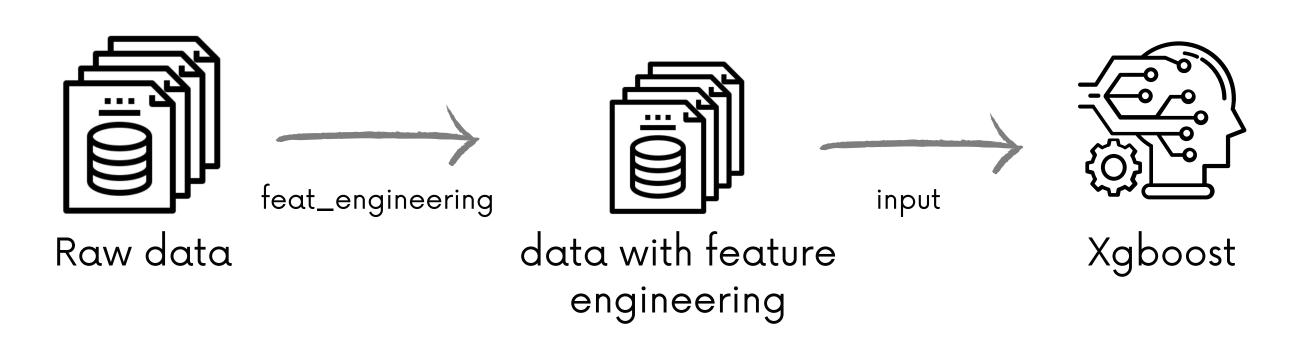


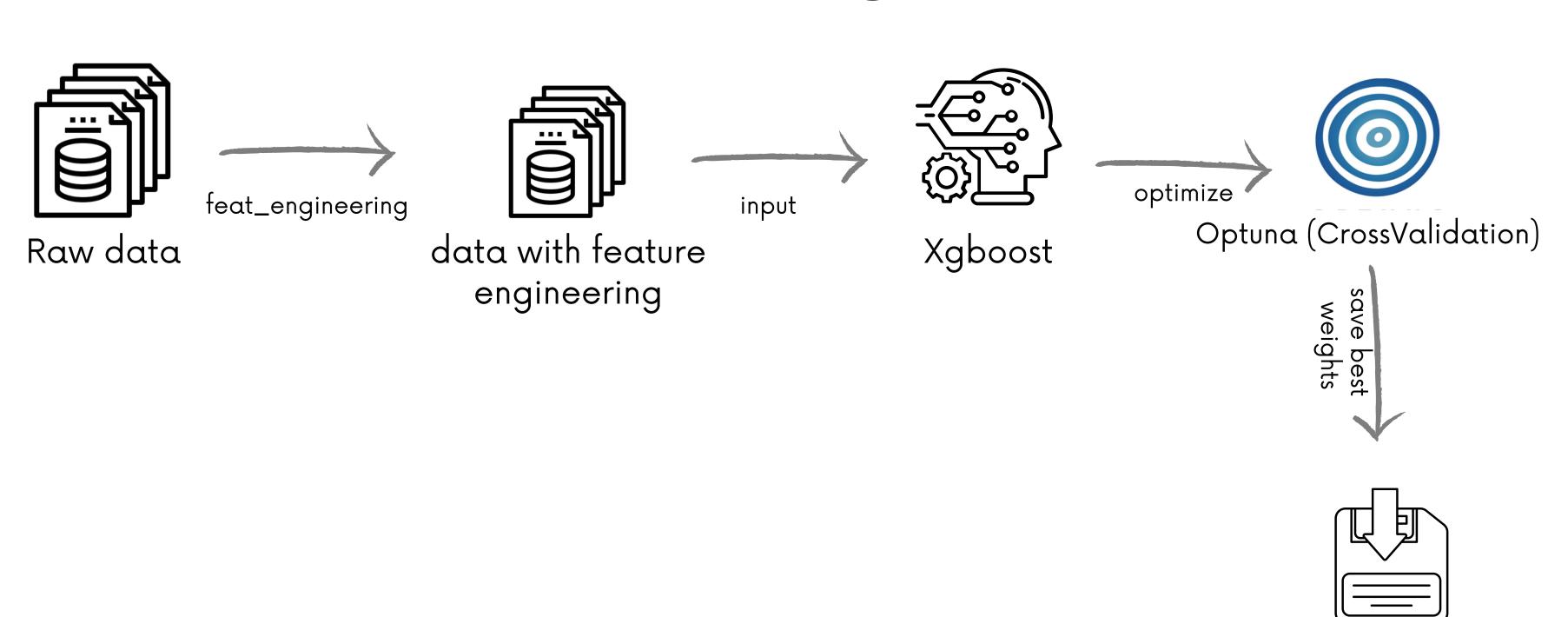
- 1. Represents decision as the branch of each node.
- 2. Each node is calculated thinking in the amount of information gain.



- 1. Represents decision as the branch of each node.
- 2. Each node is calculated thinking in the amount of information gain.
 - a. The info gain is calculated at the impurity level of the child nodes
 - b. We have multiple formulas for info gain: gini, entropy, etc.







xgboost_best_weights.bin

1 Created most of features thinking about how to calculate how loyal the user is.

2 Use TargetEncoder for categorical features

- 3 Tried to create "gym features". I just aggregated features with stats metrics for each gym, example:
 - Average, Standard Deviation, Skew, Kurtosis of user_life_time

4 Use TargetEncoder for categorical features

5 Transformed features using log to solve skewing.

6 Transformed the 1% of gym categories to "Other"

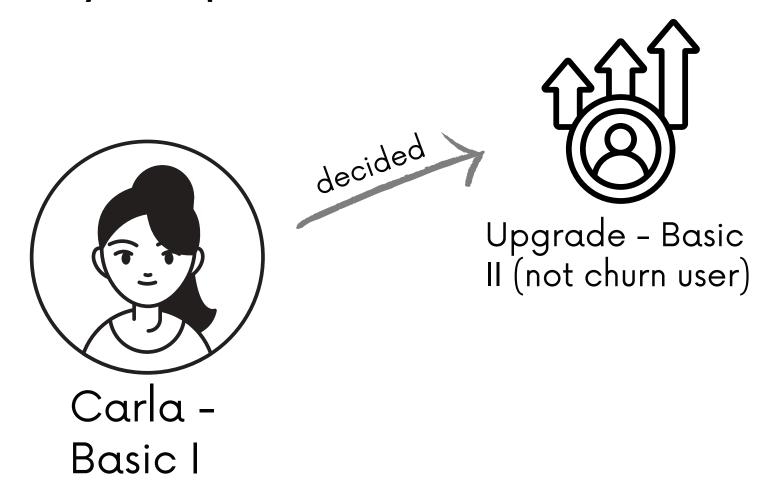
How Xgboost works?

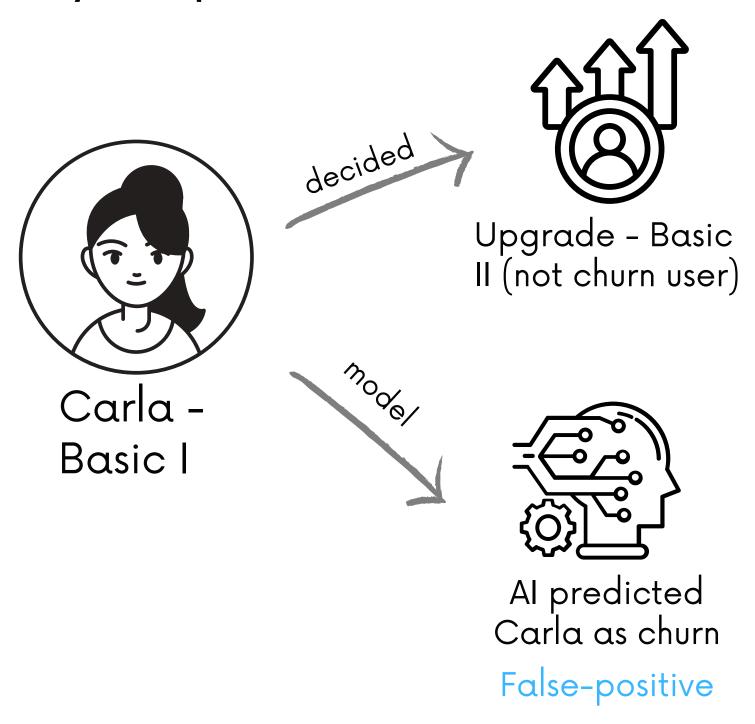
overall concept

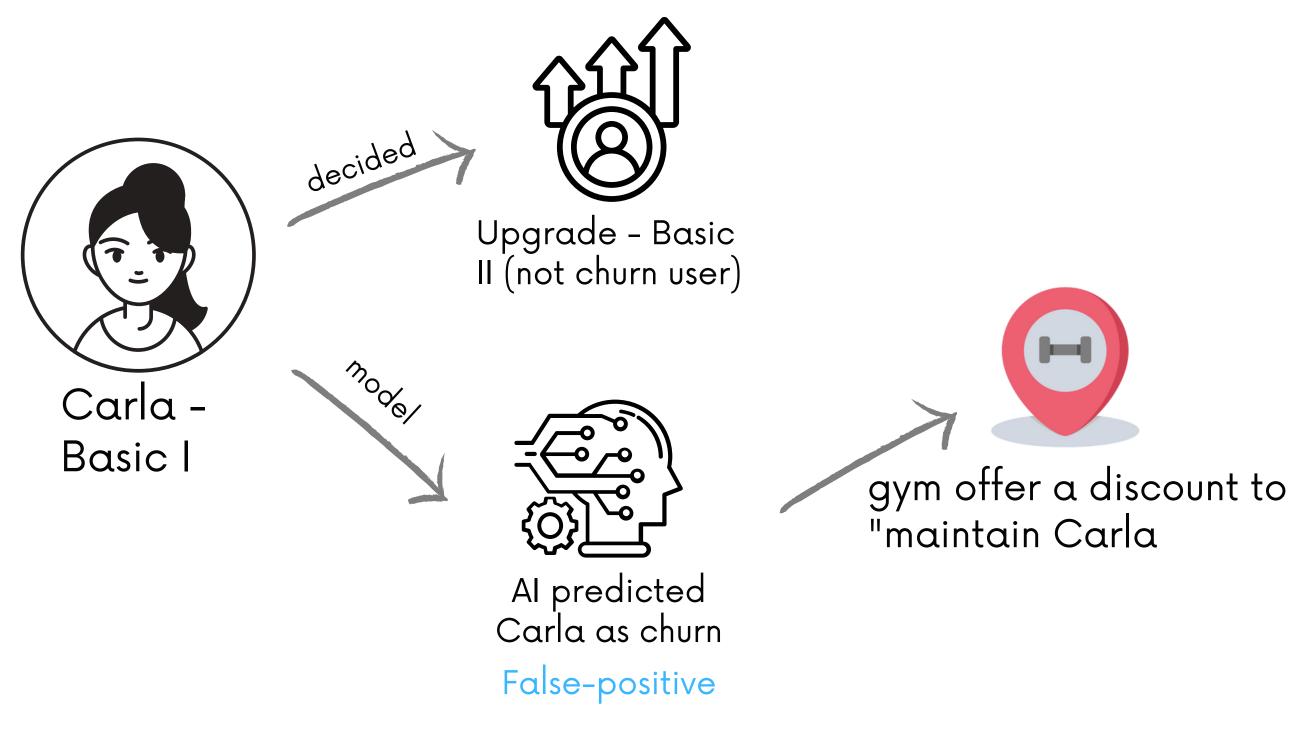
How Xgboost works?



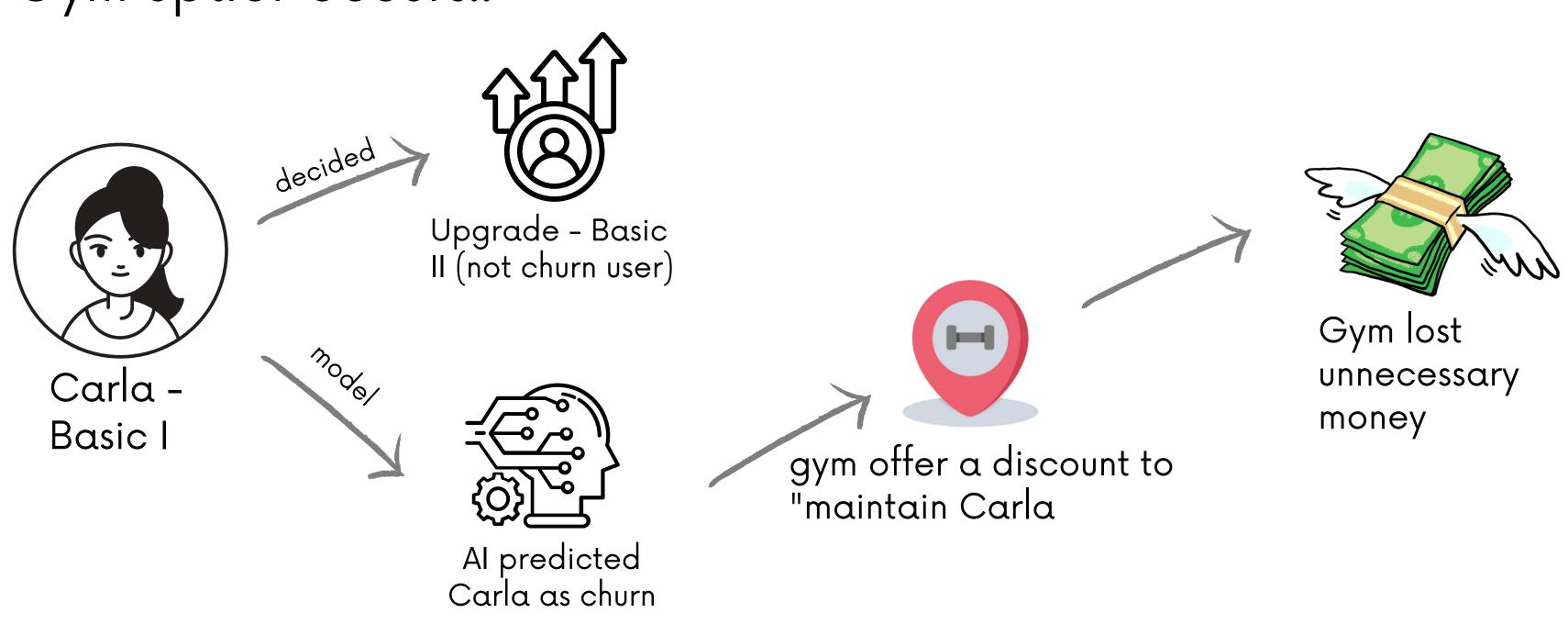
Model Evaluation





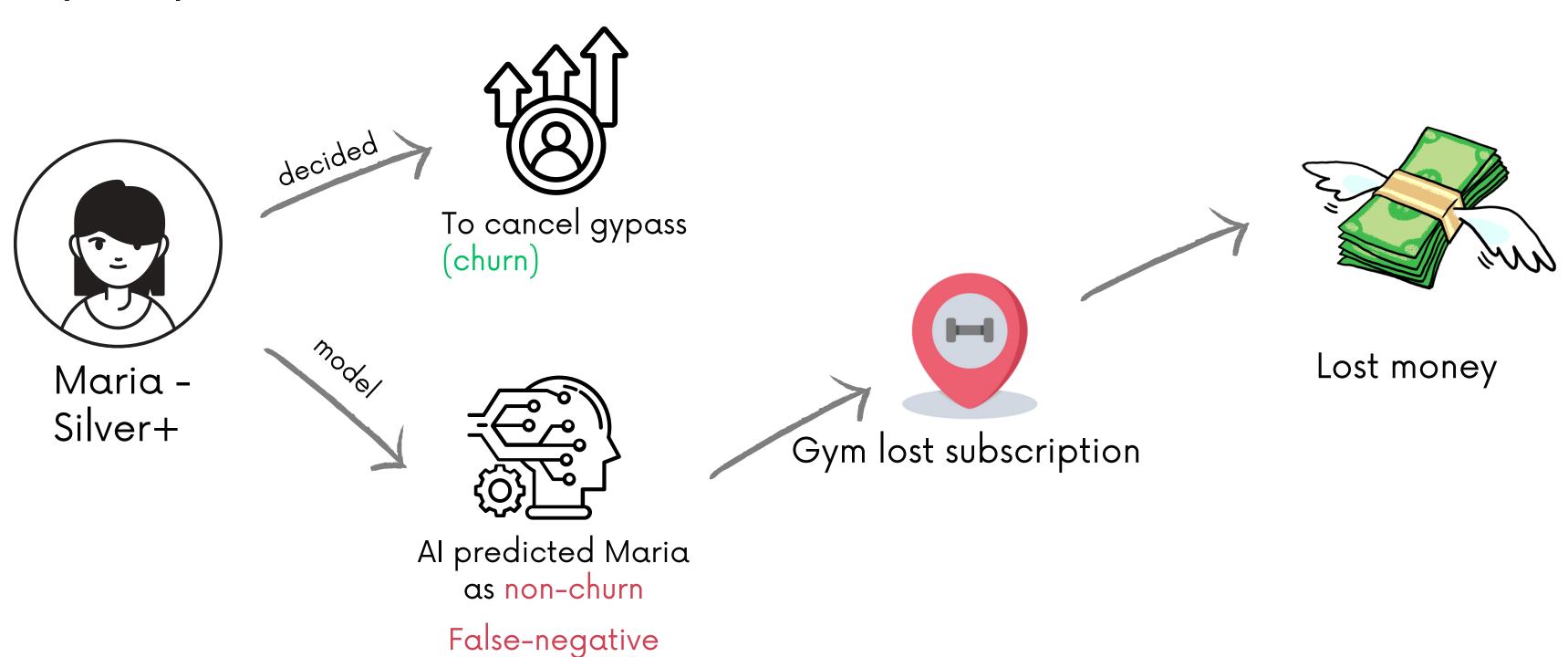


Gym uptier occurs..



False-positive

False-positives affects precision

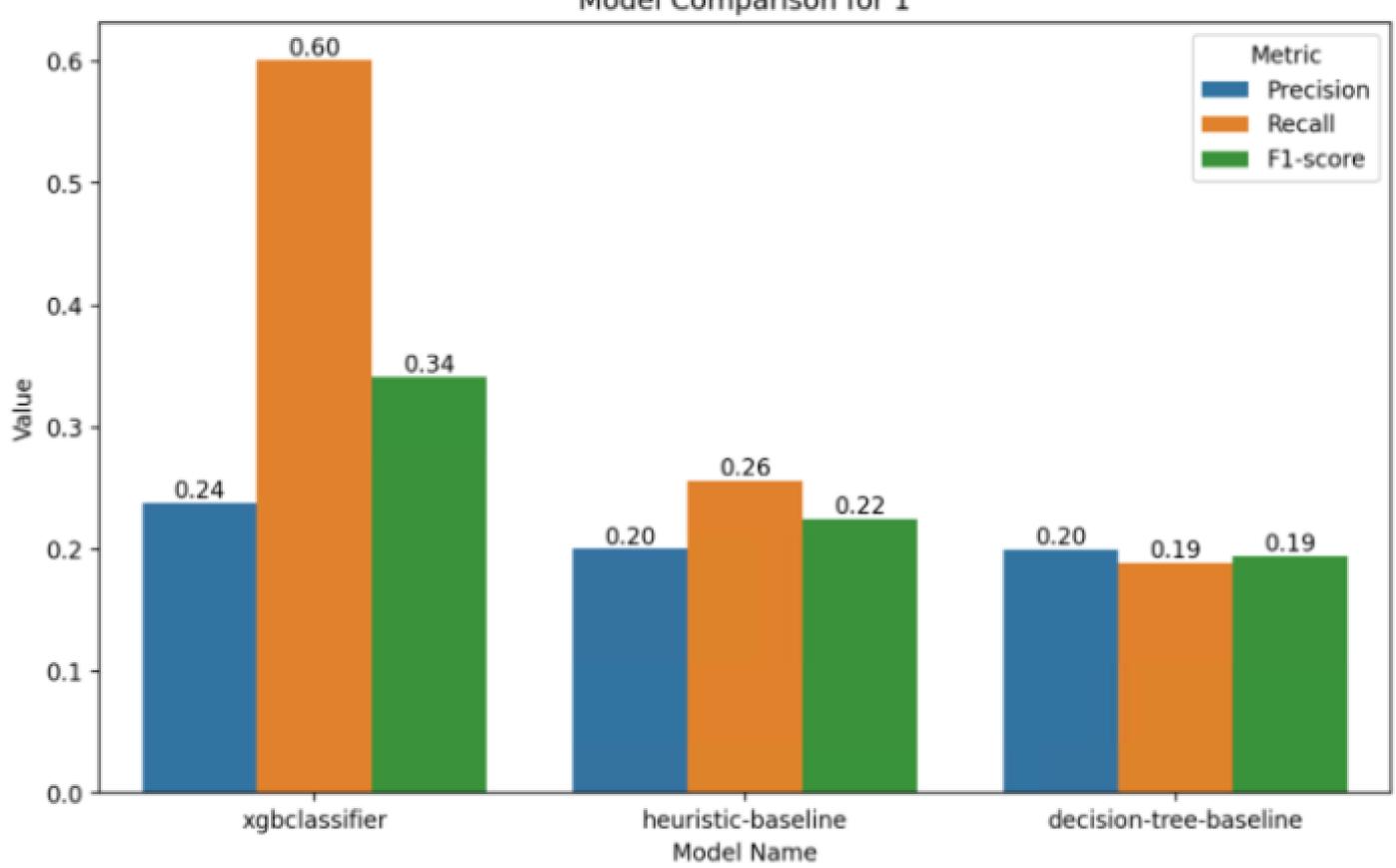


False-negatives affects recall

Model Results

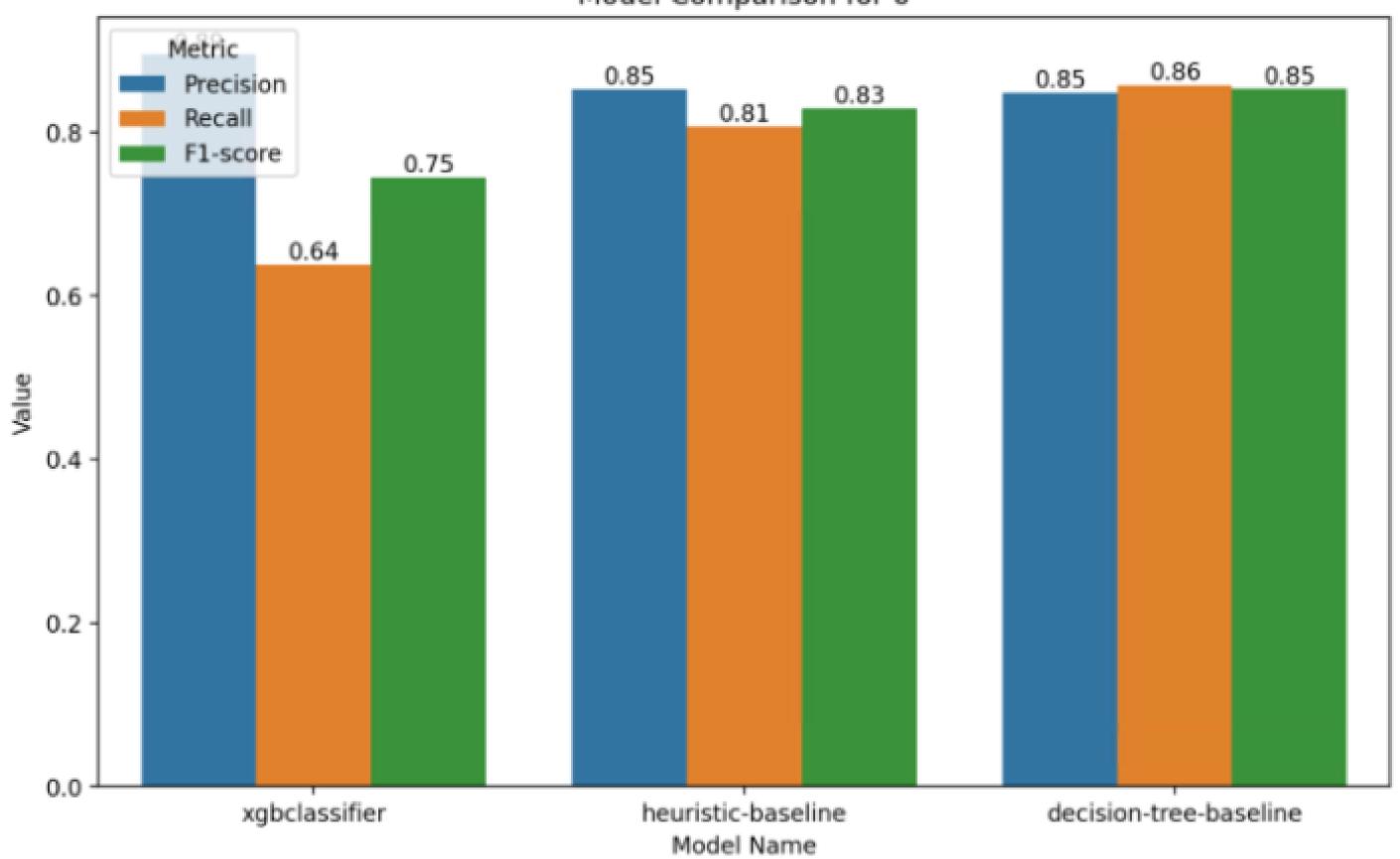
Churn class

Model Comparison for 1



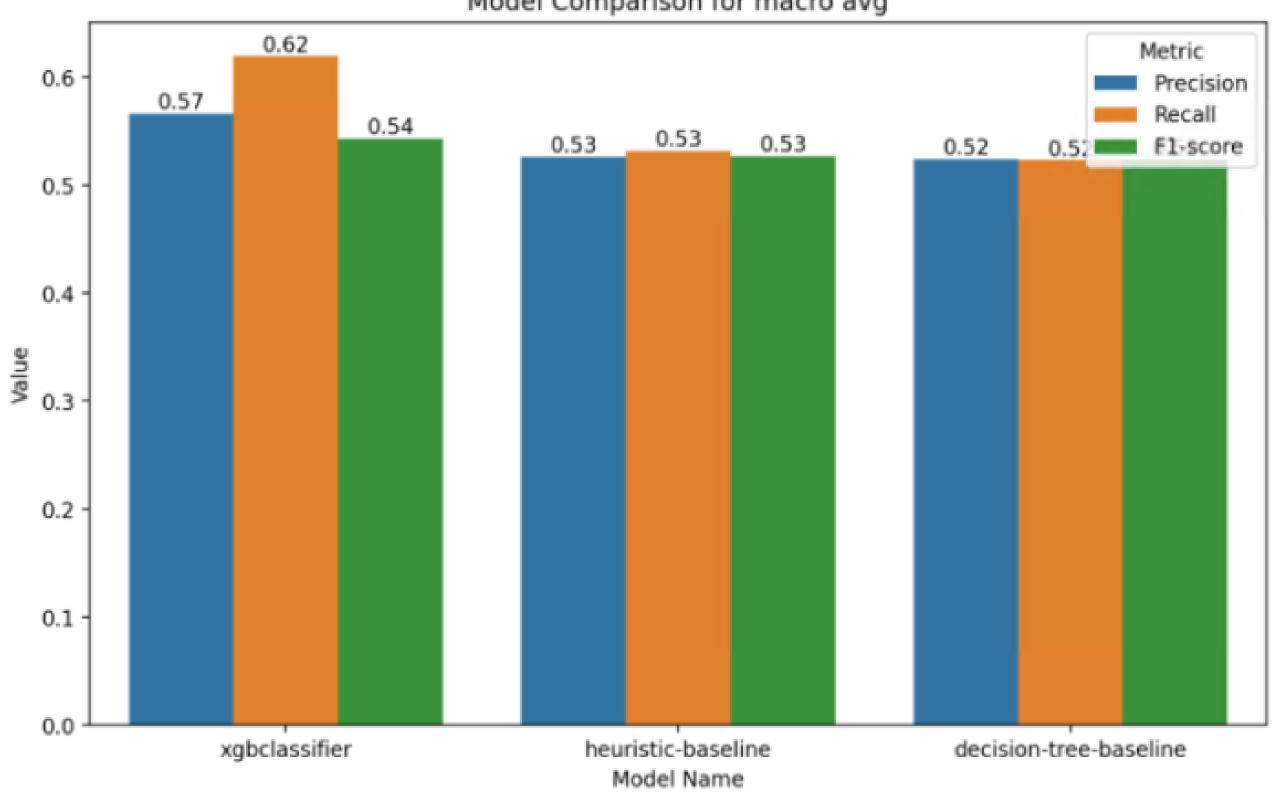
Non-churn class

Model Comparison for 0

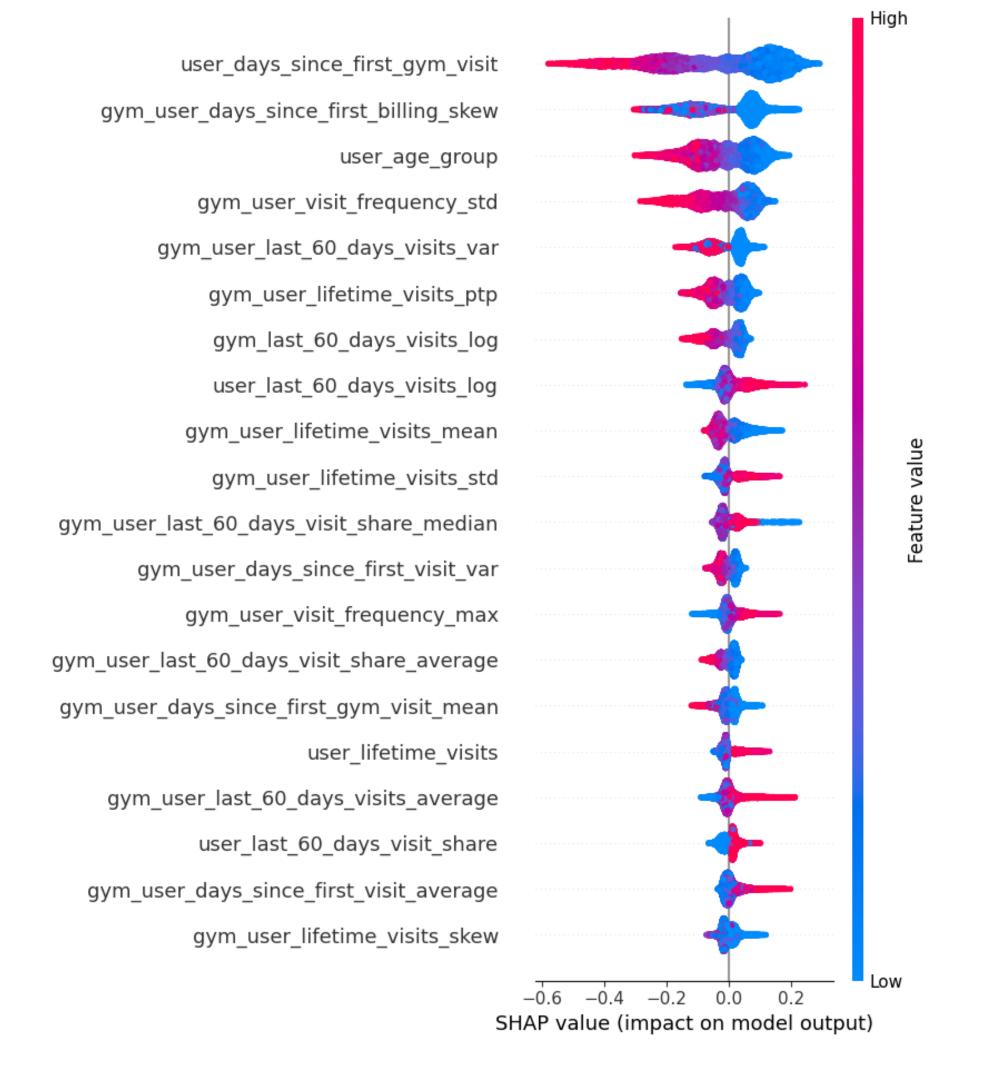


Both class





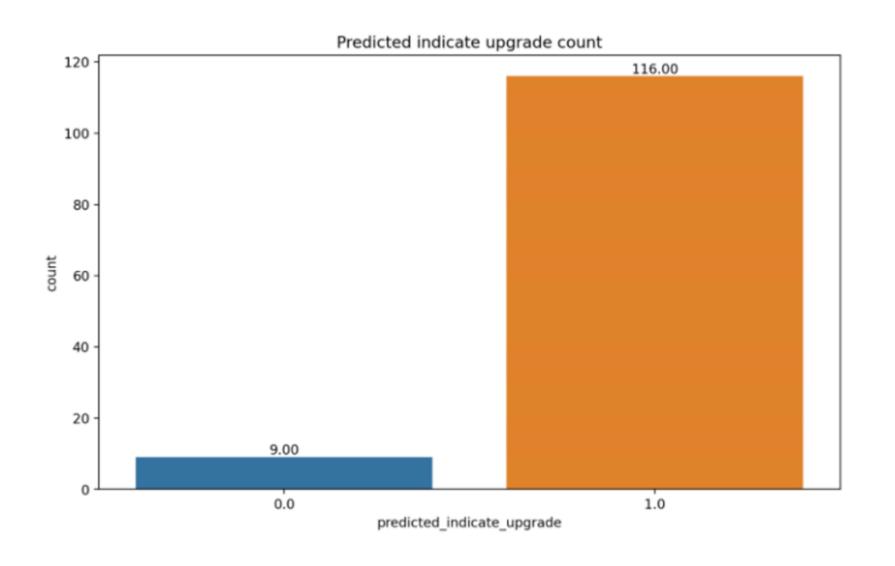
Model Interpretation (SHAP)

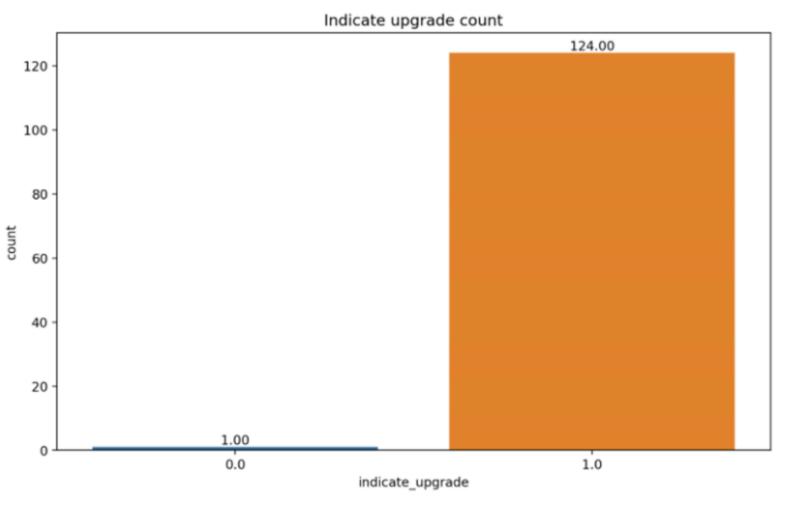


Gyms to indicate upgrade

In test dataset

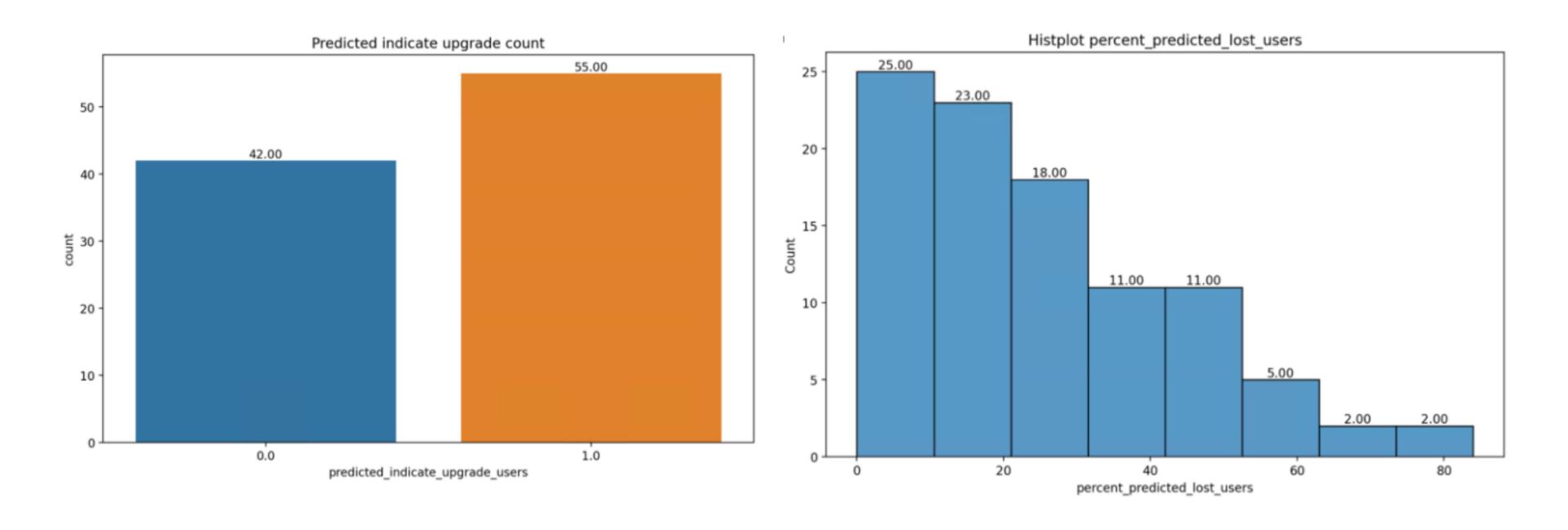
• show streamlit (to show the decision threshold vs profit)





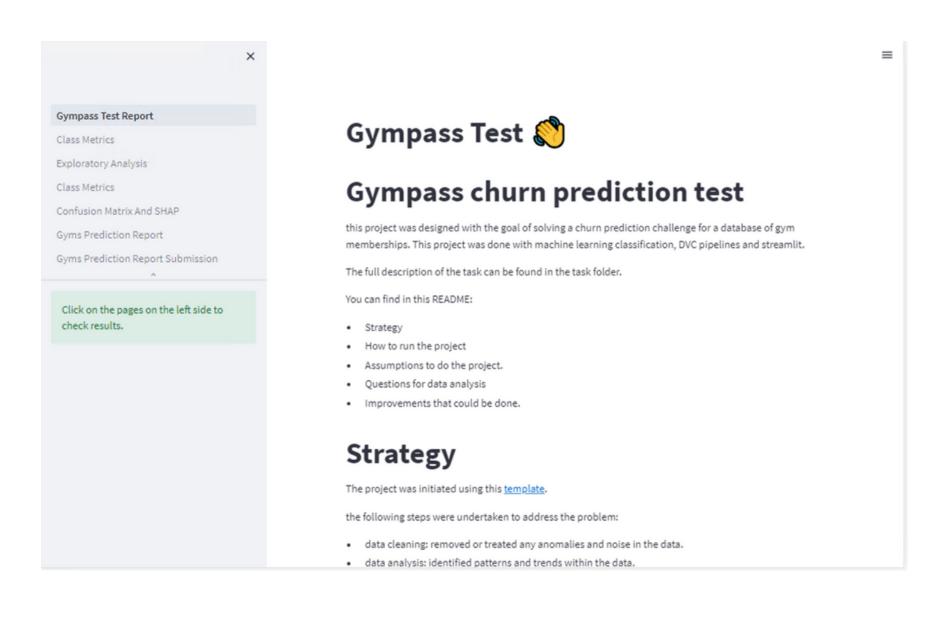
In submission dataset

• show streamlit (to show the decision threshold)



Code Refactor

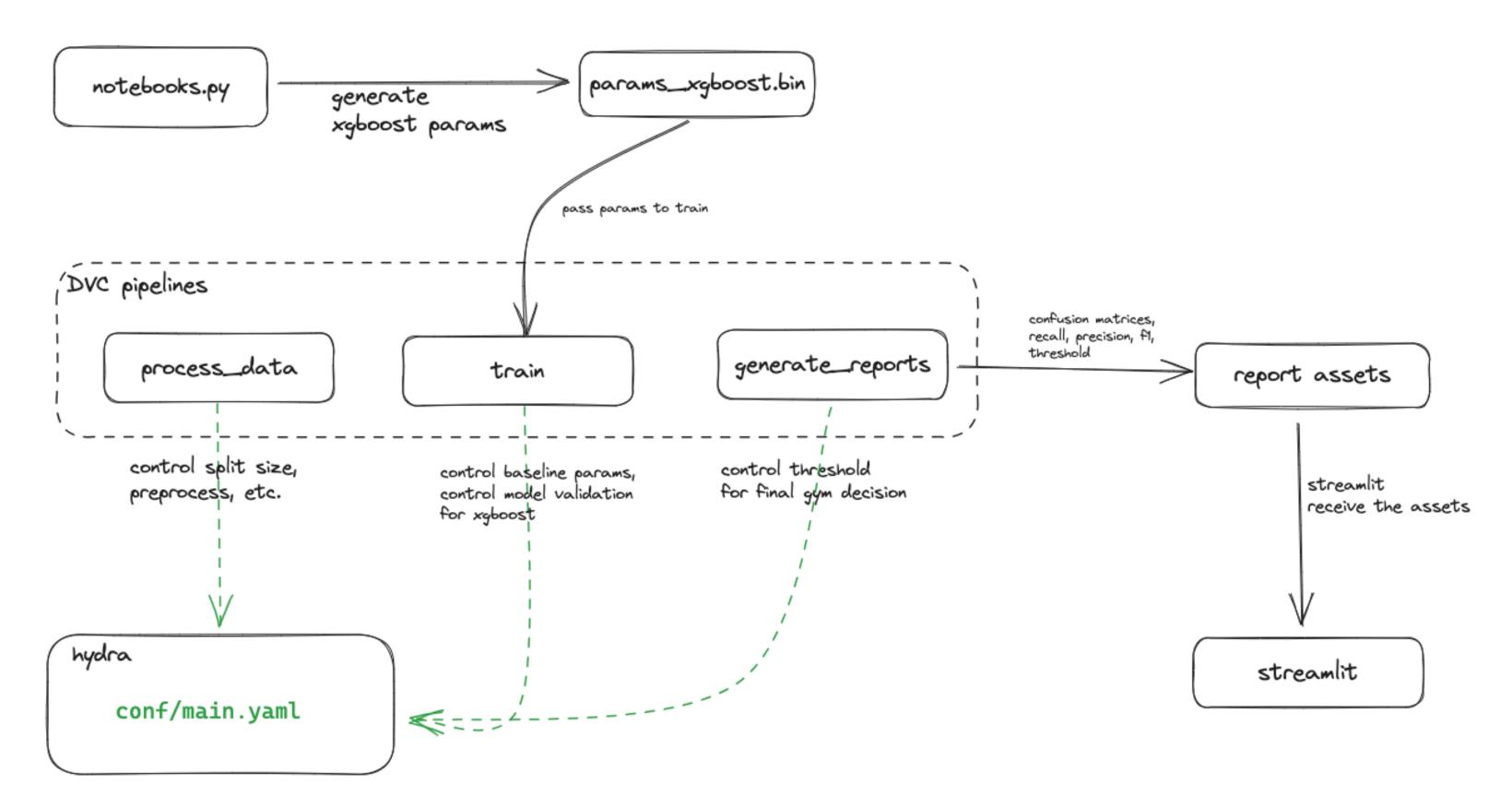
Code Refactor



For code refactoring we used:

- Hydra to use static params in yaml
- DVC to create pipelines
- Streamlit for report

Code Refator



Try **aggregated** data by gyms instead of focusing in users → Transform in regression problem

Use the features by **different windows** instead of just 60. To do this I would need the timestamp of each visit (or other interaction) to the gym

Fix the confusion matrix (maybe the level is reversed)

Use user **app interactions**: user search tokens, time using the app, time using other gym pass partnership apps (zenklub, etc)

Use **gym location**, address, state, city, region. Maybe try to join **with public data** (ex: the financial health of the location, if its local is dangerous, number of stars in google maps)

Get RFM and other loyalty metrics (CLV, Customer Score, etc) for each customer

Use the distance of how far the visited gym is from user's home

Use TVAE to synthesize churn data or other techniques (imbalance problem)

Use number of upgrades/cancel/downgrades of each user in past.

Model SHAP interpretation by sample cases

Retrain in all database before predict to submission data

Ensembles