Exploratory Data Analysis

<Marketing Strategy>

<2023.1.20>

Agenda

- Executive Summary
- Problem Statement
- Approach
- EDA
- EDA Summary
- Model Suggestion

Executive Summary

- Clean and preprocess the dataset for analysis
- Analyze features and their associations with customer decision
- Summarize the feature importance and suggest ML models

Problem Statement

- This project aims to fix the problem that there are too many potential clients associate with a Portuguese banking institution. The bank marketing campaigns are primarily based on phone calls. However, there are too many potential clients, and it is impossible to call all of them. Hence, some machine learning techniques are needed to classify the customers and predict if they are going to subscribe the term deposit or not. By implementing ML models, we are able to limit the number of ‘potential clients’ to an acceptable number that make sure the marketing strategies can be carried on.

Approach

- Data Loaded & Cleaning & Preprocessing

Perform basic cleaning & Preprocessing

```
In [5]: my_df.isnull().any()

Out[5]: age               False
        job               False
        marital           False
        education         False
        default           False
        housing           False
        loan              False
        contact           False
        month             False
        day_of_week       False
        duration          False
        campaign          False
        pdays             False
        previous          False
        poutcome          False
        emp.var.rate      False
        cons.price.idx    False
        cons.conf.idx     False
        euribor3m         False
        nr.employed       False
        y                 False
        dtype: bool
```

```
In [7]: my_df.duplicated().any()

Out[7]: True
```

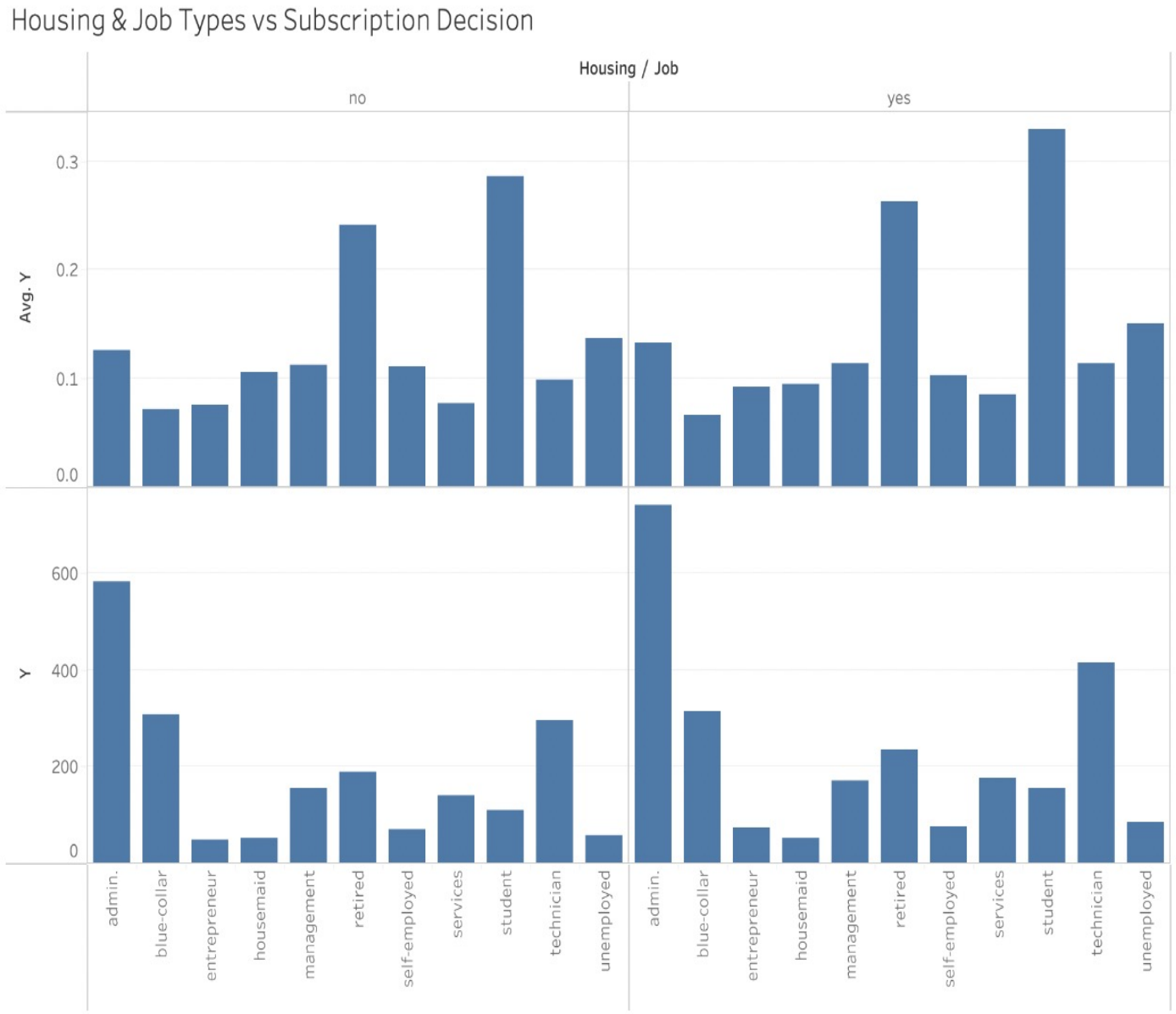
```
In [11]: my_df = my_df.drop_duplicates()
         my_df.shape

Out[11]: (41176, 21)
```

Approach

- EDA analysis & Visualization using Tableau
- Machine Learning Algorithms

EDA

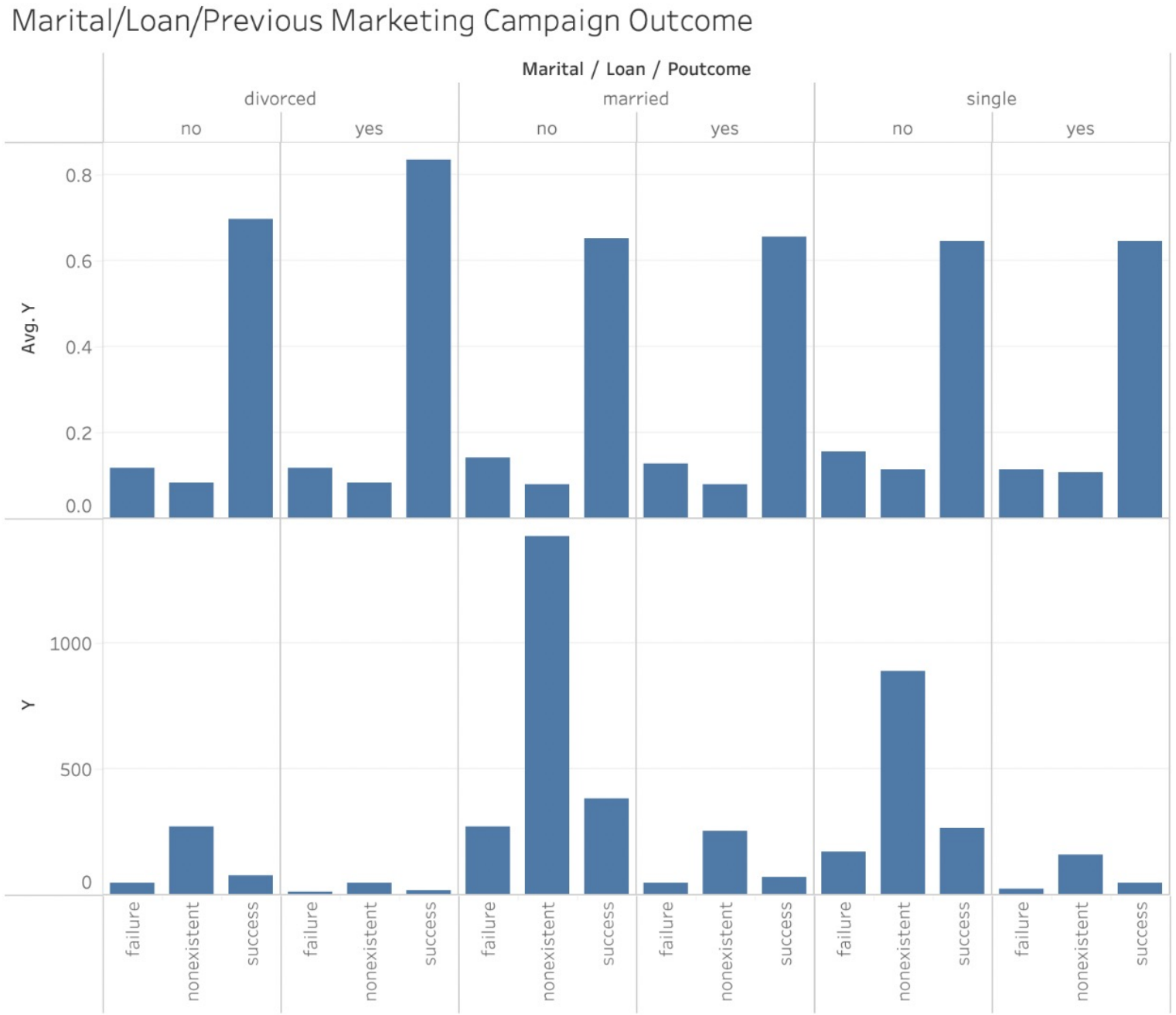
Housing & Job Types



Average of Y and sum of Y for each Job broken down by Housing. The view is filtered on Housing and Job. The Housing filter keeps no and yes. The Job filter excludes unknown.

EDA

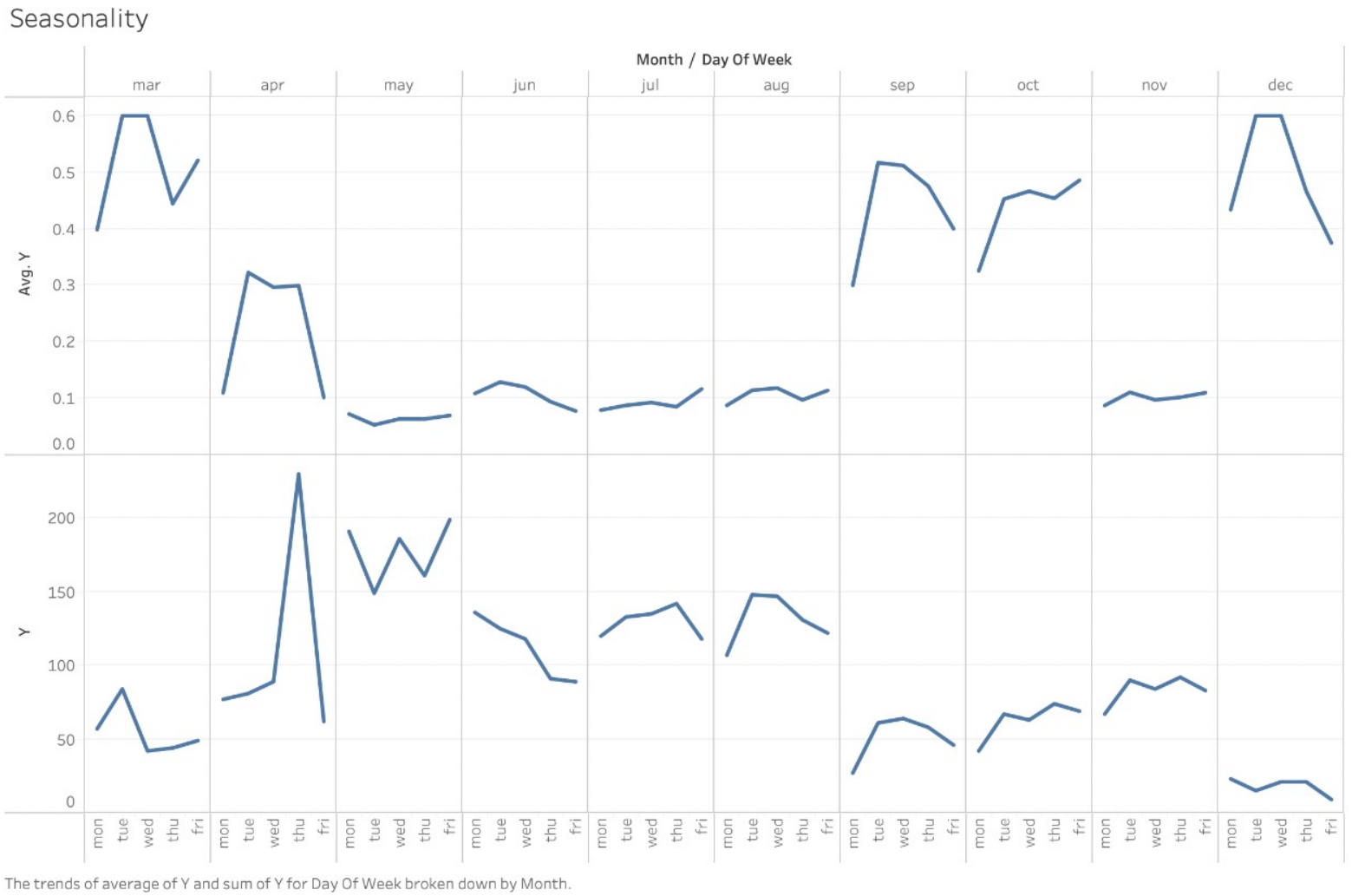
- **Marital & Loan &Previous Marketing Campaign**
- **Marital does not have much effects**
- **Clients have records of Previous Marketing Campaign have significantly higher outcome.**



Average of Y and sum of Y for each Poutcome broken down by Marital and Loan. The data is filtered on Housing and Job. The Housing filter keeps no and yes. The Job filter excludes unknown. The view is filtered on Marital, which keeps divorced, married and single.

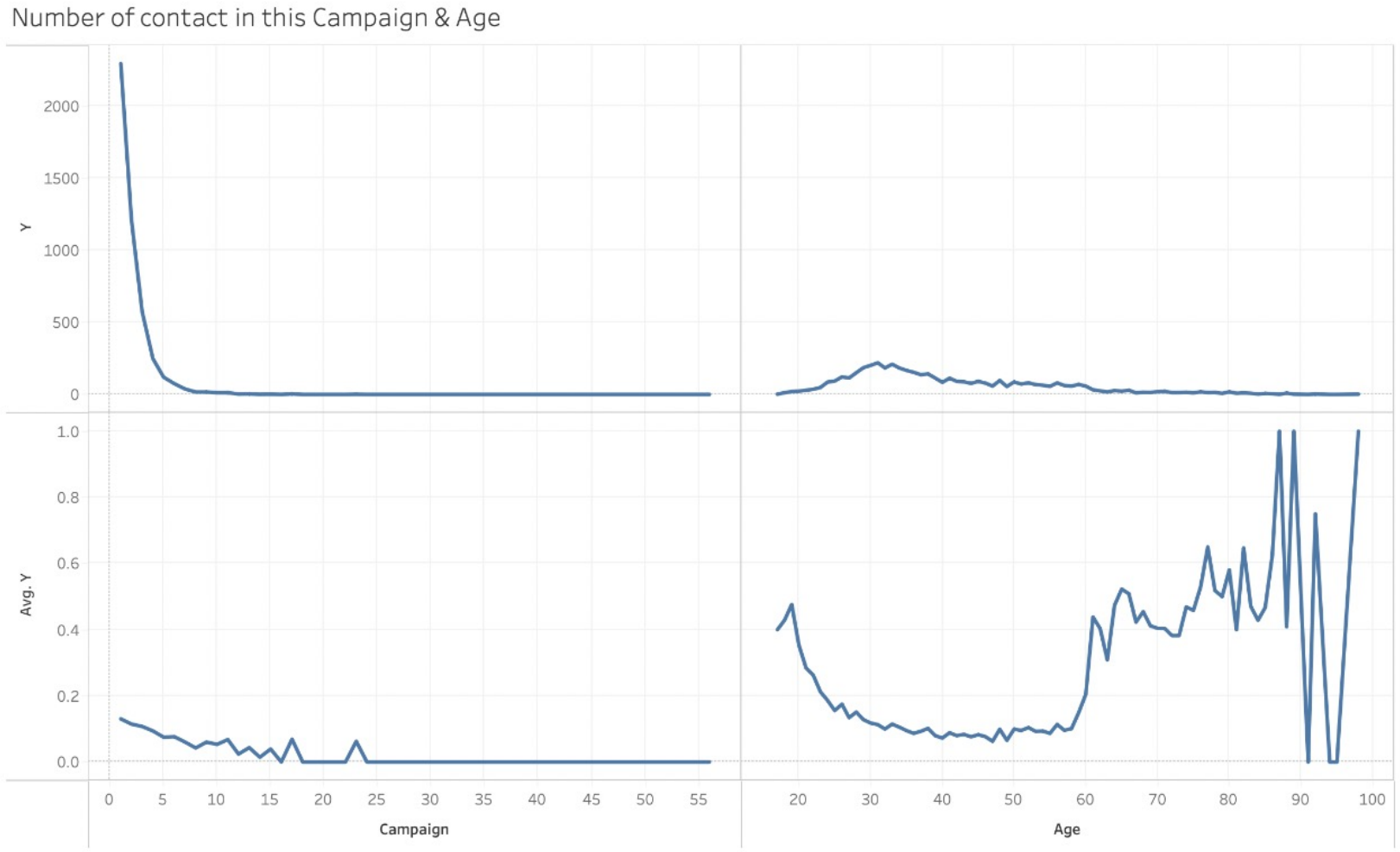
EDA

- **Seasonality**
- **Peak: Dec – Mar**
- **Low: May – Aug**
- **No obvious weekly seasonal trends detected**



EDA

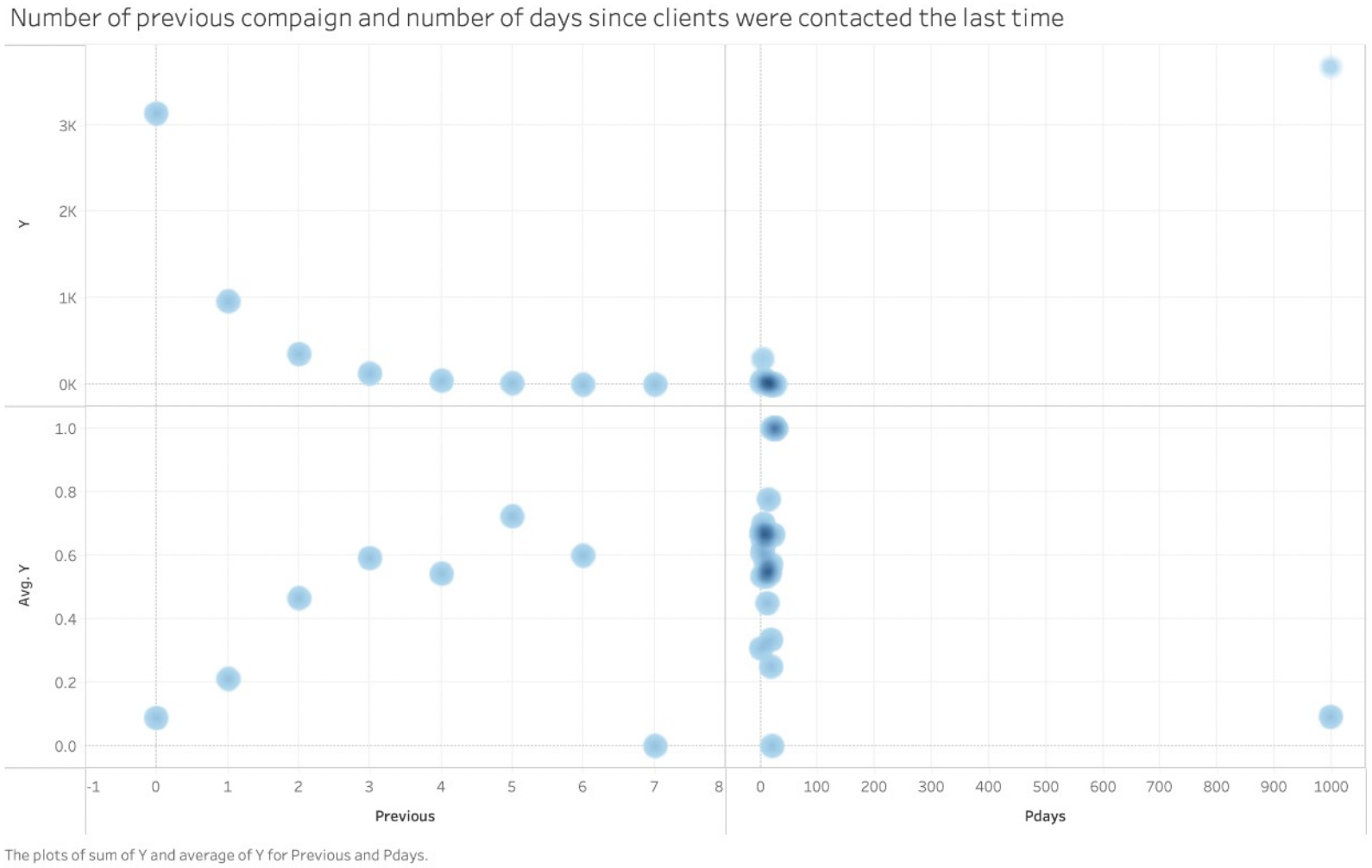
- **Number of Contact**
- **The number of contacts are centered mostly at the range below 10**
- **Age is uncertainty. The fluctuation is very big as age goes up.**



The trends of sum of Y and average of Y for Campaign and Age.

EDA

- **Number of days since last contact & previous contact**
- **Number of previous contacts is most effective when p-days equal to 5.**



EDA Summary

- As above, we analyzed the features and their potential influence to the outcome subscription decision. We found that Number of contact in the current campaign, number of previous contact, job type, education have relatively stronger influence on the outcome decision, while some other feature could help us categorize customers and help us make strategies with respect to different group of customer.¶

ML Model Suggestion

- **Linear Model (LDA, Logistic Regression)**
- **Bayesian Model (Naïve Bayes, Gaussian NB)**
- **SVM (Linear SVM, SVM with different kernels)**
- **KNN**
- **Tree Based models (XGBoost, Random Forest, Extra Trees)**
- **Neural Networks (Multi-Layer Perceptron)**

Thank You