ReDI School of
Digital Integration

Predicting Churn for Bank Customers

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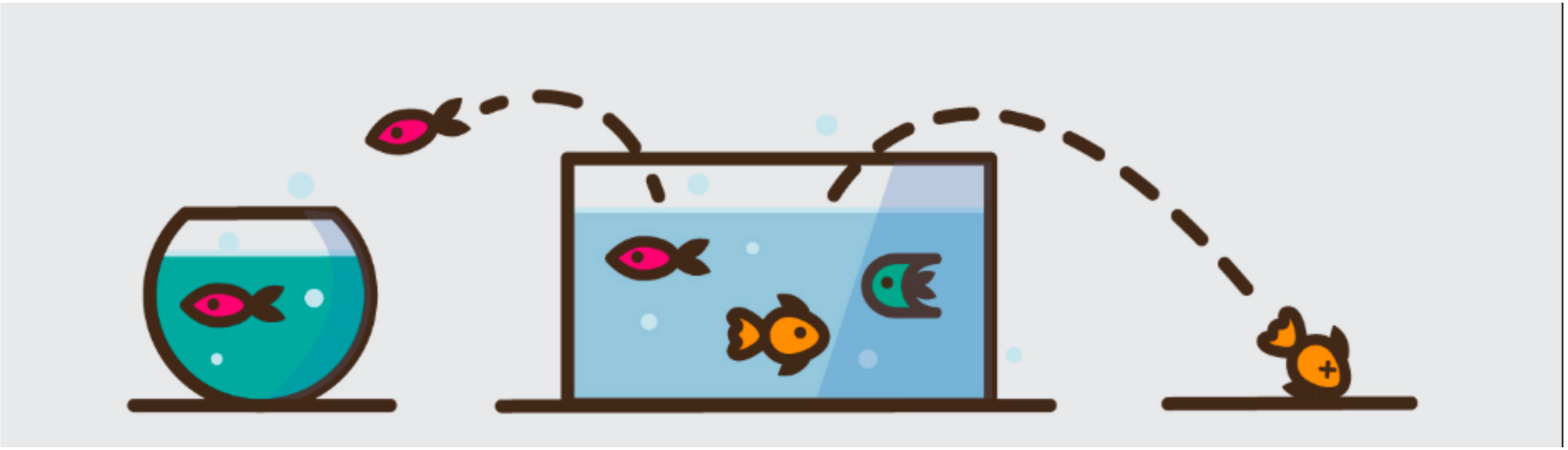
Introduction

Who's going to leave?



Customer churn

Let's try to predict!

Profit

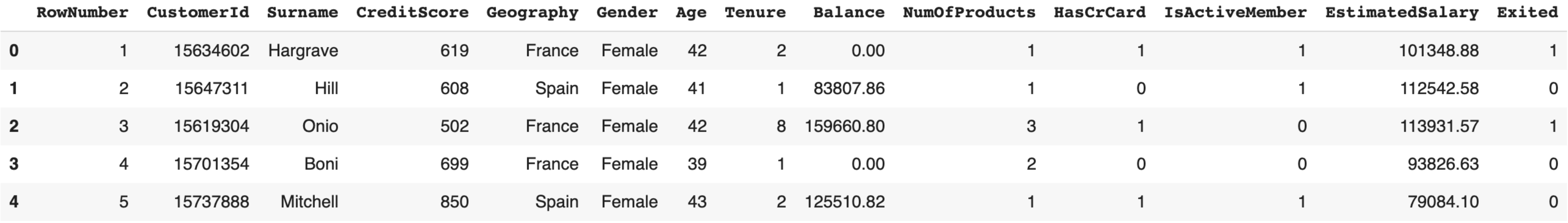
- predict future revenue;
- to identify, address, and get back customers that are likely to churn;
- identify and improve upon areas where customer service is lacking.

Problem

Bank customer churn dataset - [Kaggle](https://www.kaggle.com).

14 features, 10.000 customers.

Target



	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

Independent variables

Churn - 20%

Objectives

- **identify and visualize which factors contribute to the customer churn;**
- **build a prediction model that will classify if a customer is going to churn or not.**

Features that contribute the most

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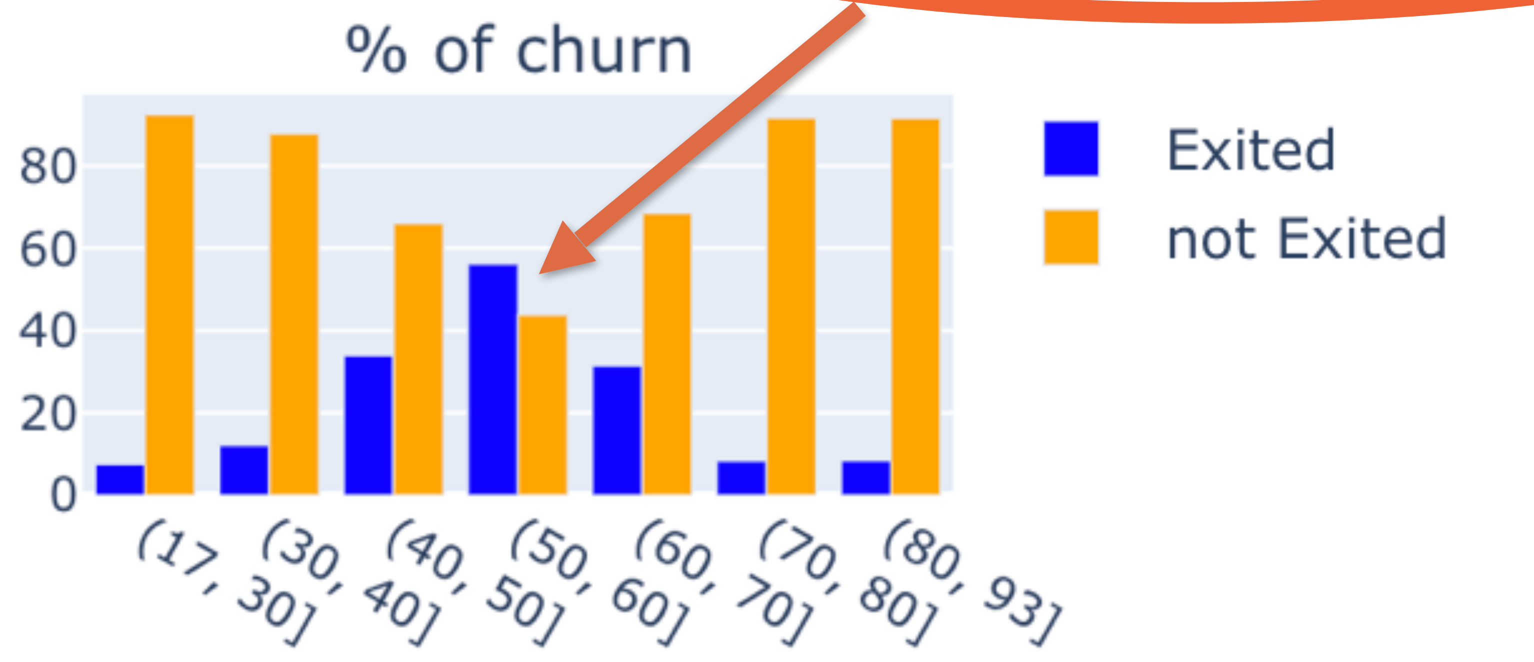
THE HIGHEST RISK ZONE

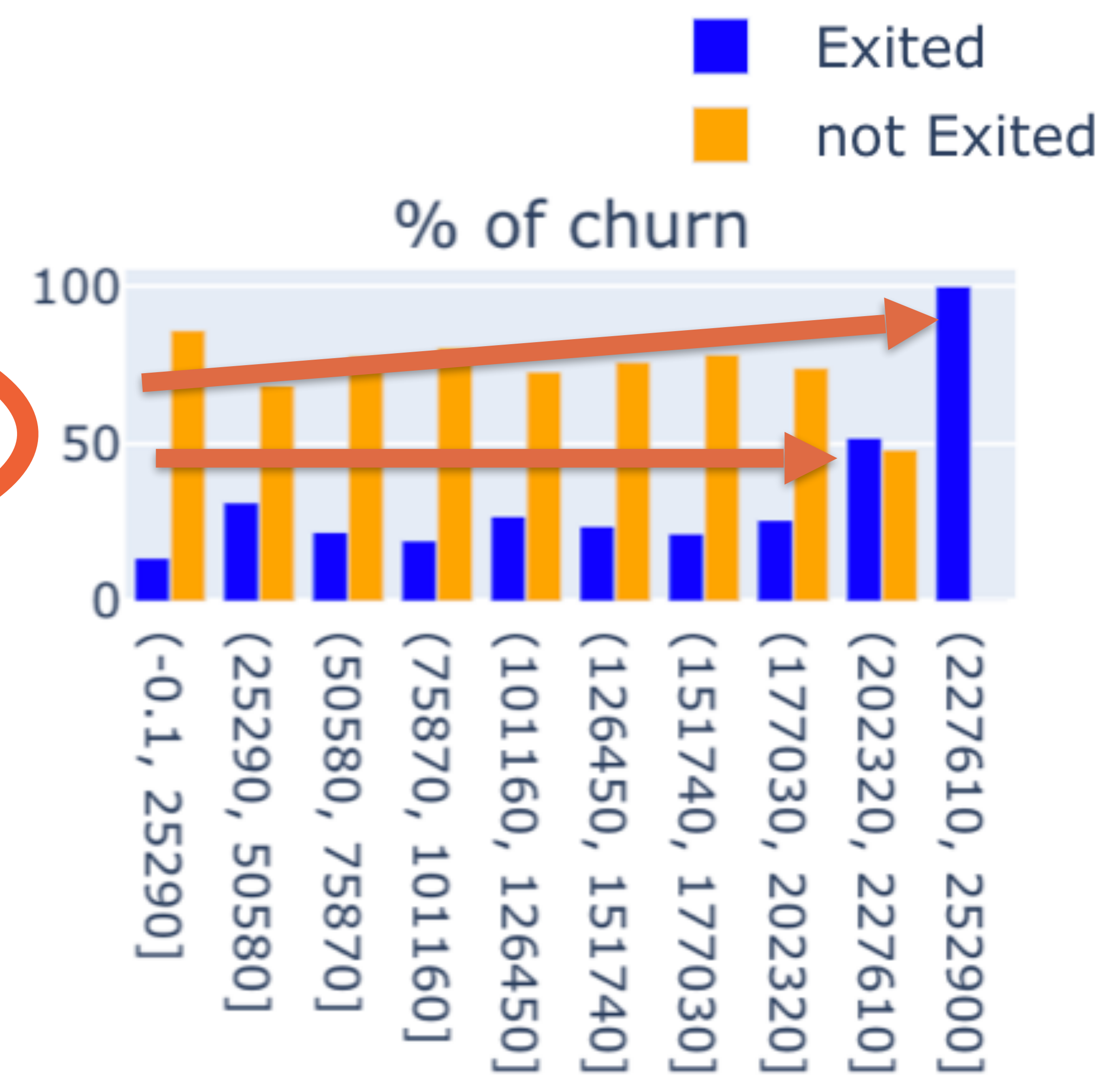
Age

age range - (50, 60]



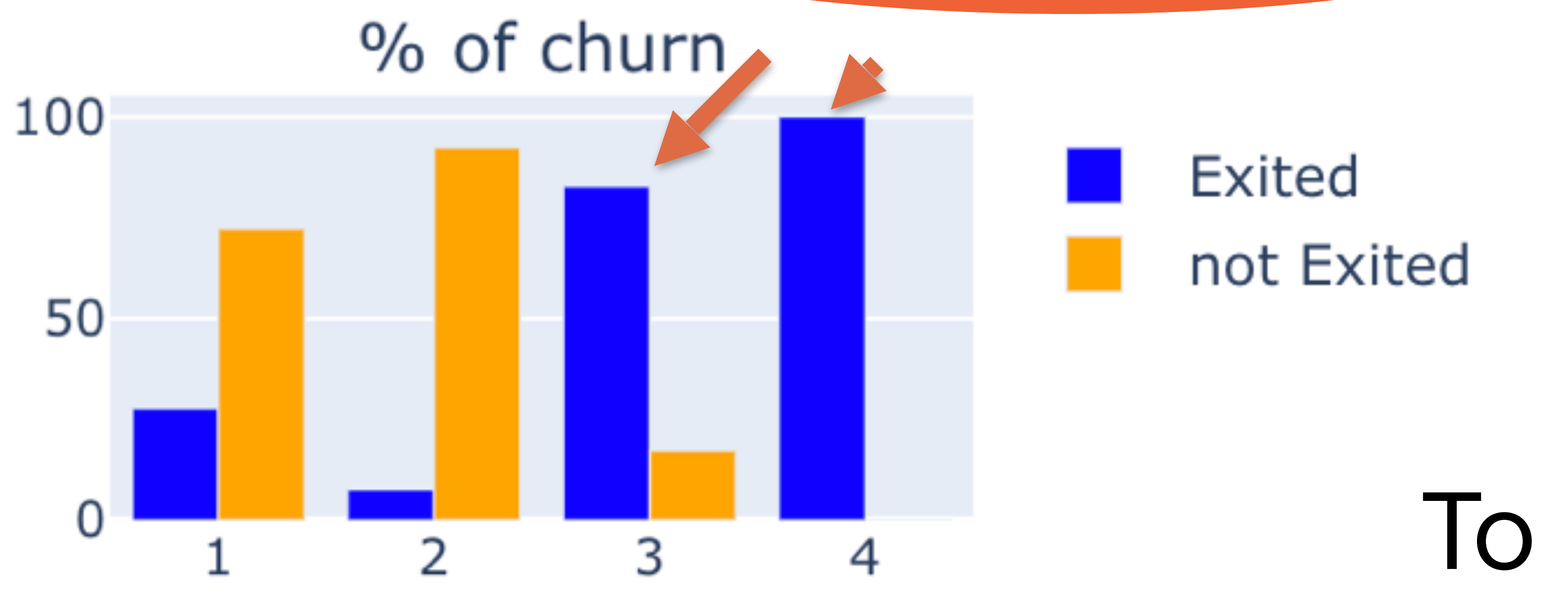
Balance

balance > 200.000



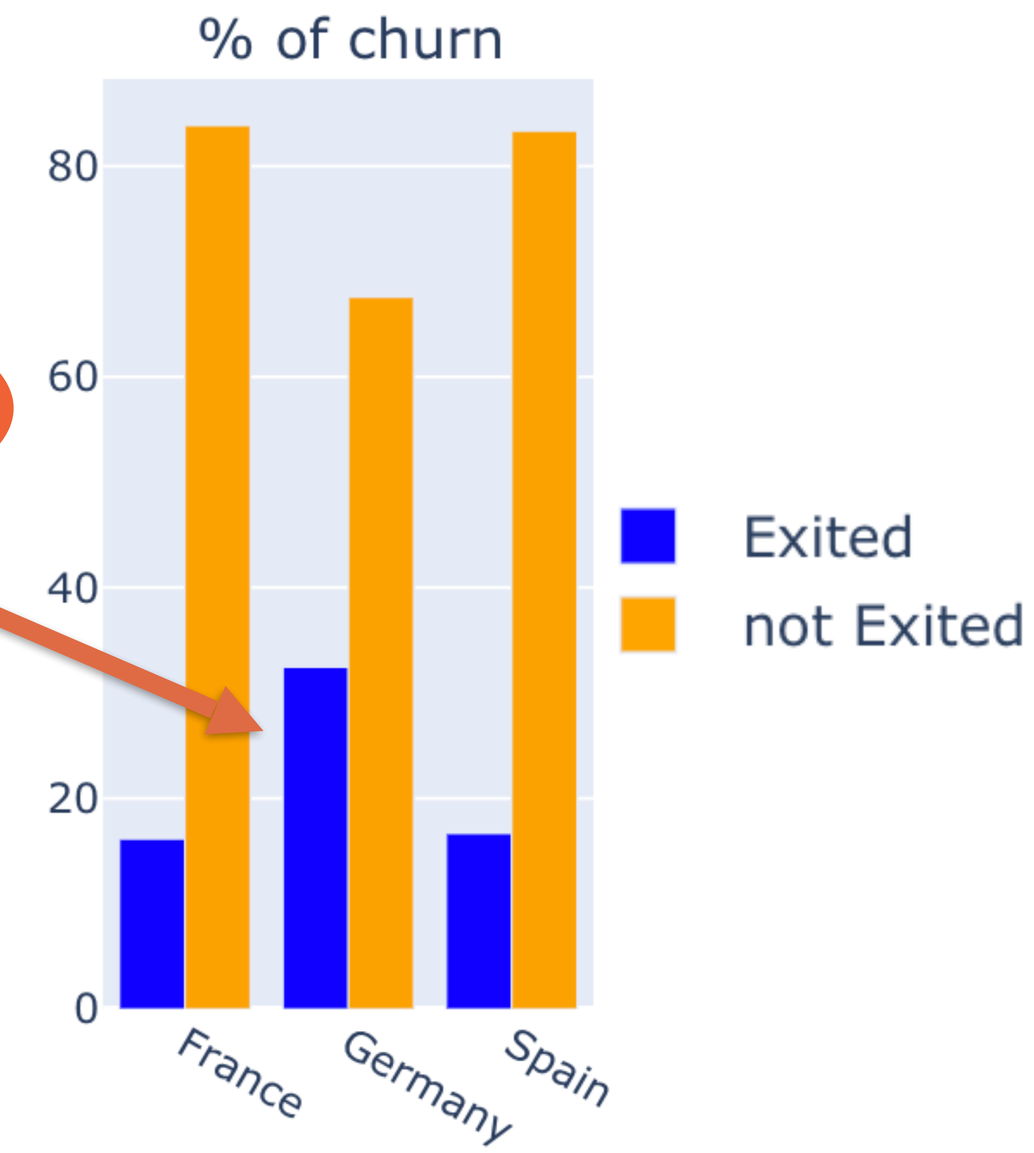
NumOfProducts

3 or 4 products



Geography

location in Germany



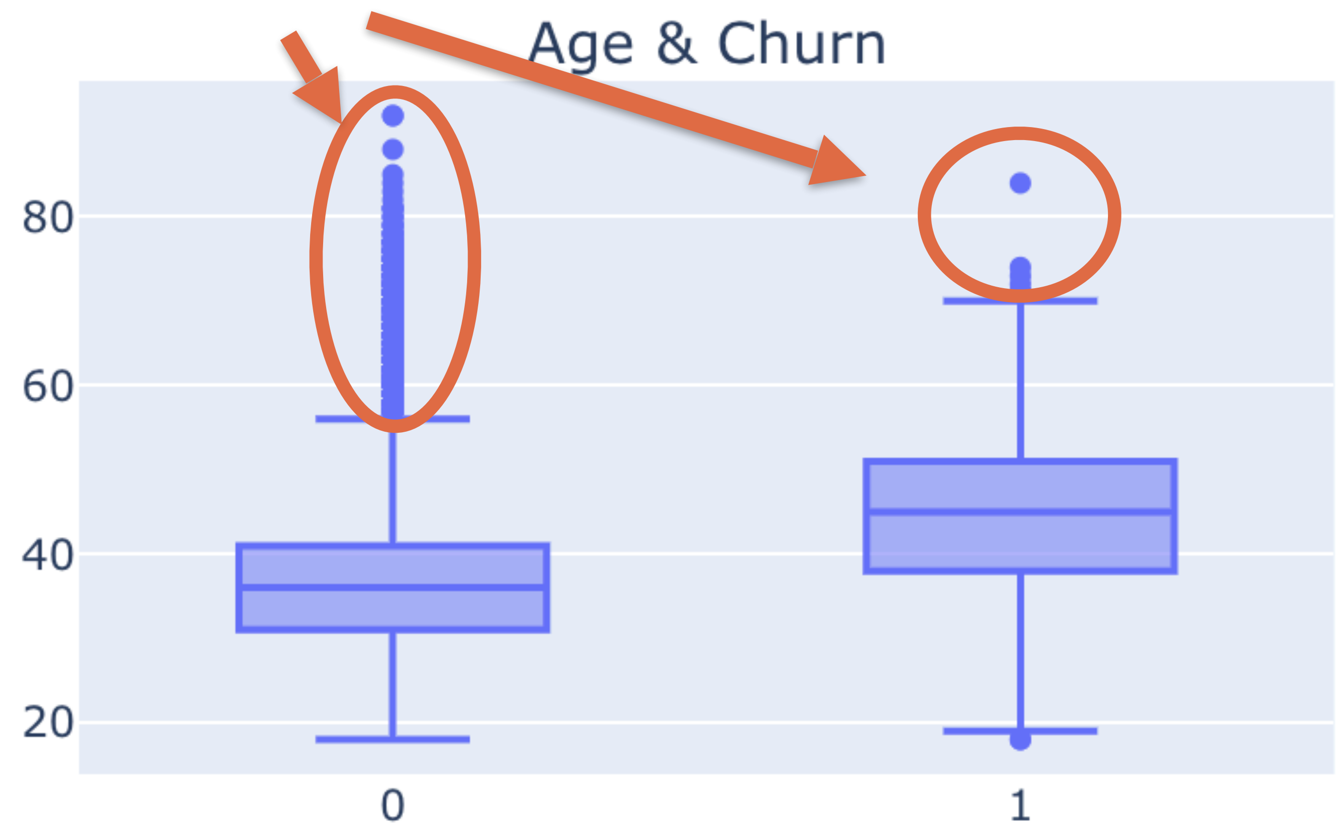
Tools: correlation analysis, pandas, numpy, plotly.

Data Preprocessing for Machine Learning

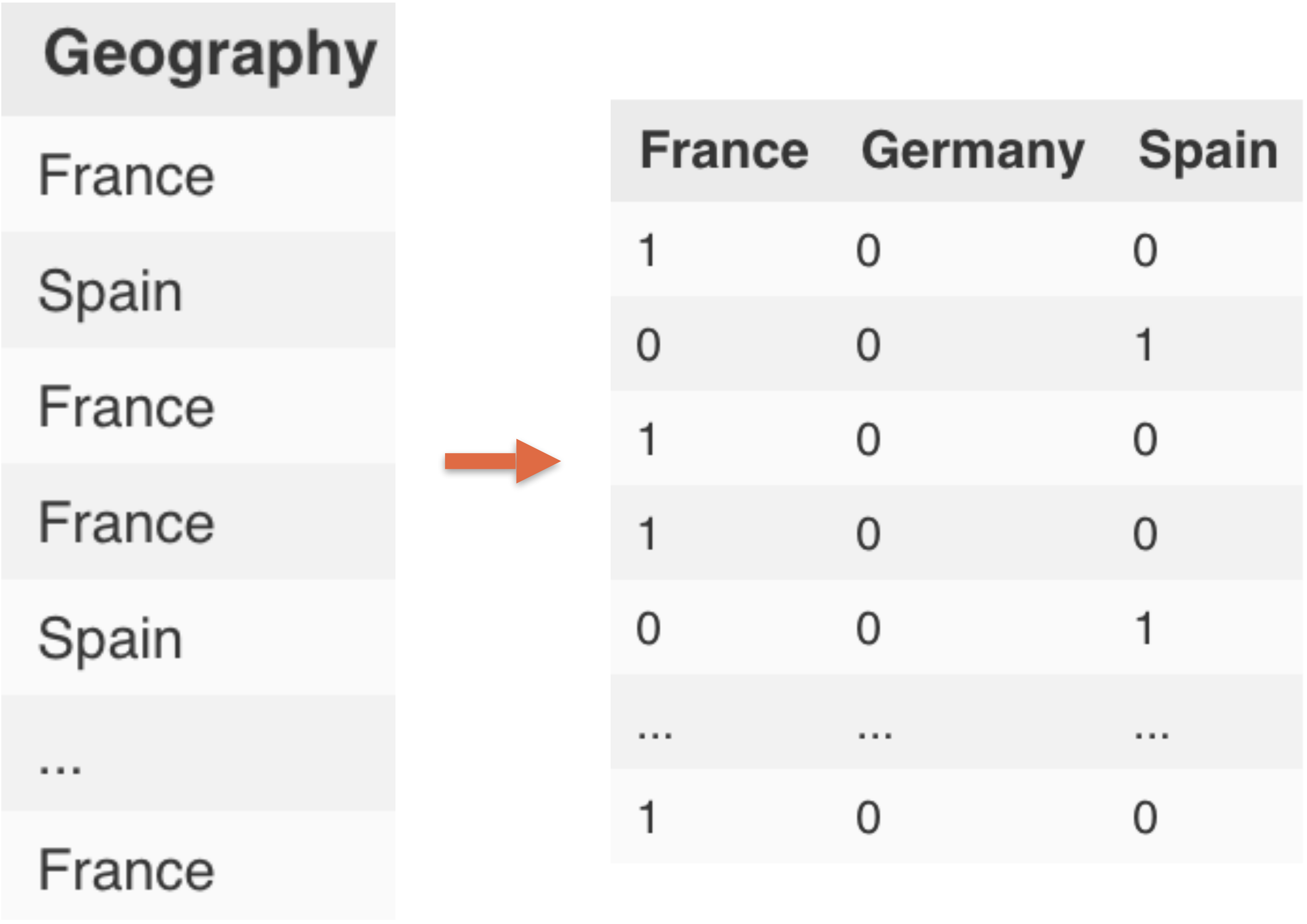
1. Feature selection

removing irrelevant features (including correlation analysis)

2. Removing outliers



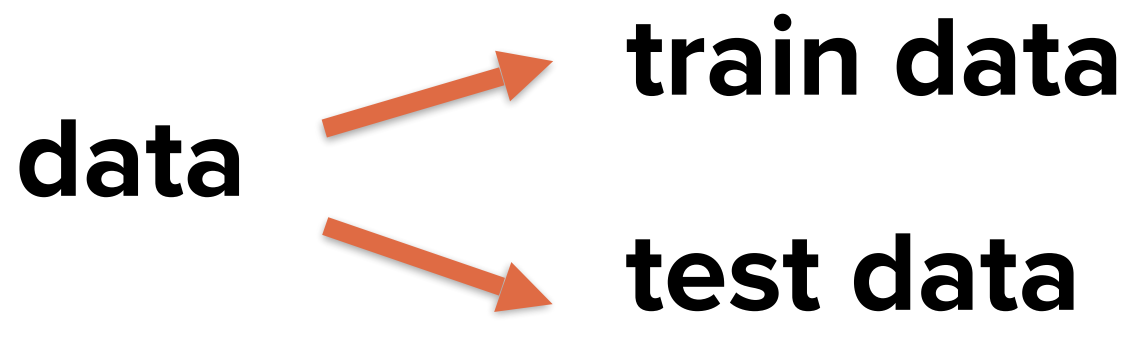
3. Encoding categorical variables



Geography
France
Spain
France
France
Spain
...
France

France	Germany	Spain
1	0	0
0	0	1
1	0	0
1	0	0
0	0	1
...	...	...
1	0	0

4. Splitting the dataset



data

train data

test data

5. Scaling

$$\frac{x - \bar{x}}{s}$$

Machine learning models

	Accuracy	Precision	Recall	F1
Logistic regression	0.85	0.74	0.50	0.60
K nearest neighbours	0.85	0.78	0.39	0.52
Support Vector Machine	0.86	0.84	0.43	0.57
Random Forest	0.87	0.78	0.52	0.63

52% of actual "Exited" customers are predicted correctly.

78% of predicted to be "Exited" customers are actual “Exited”.

Conclusions

How to use?

- developing retention programs for high-risk groups of customers;
- **further research to identify reasons for high churn (for example, for Germany).**

THANK YOU!