

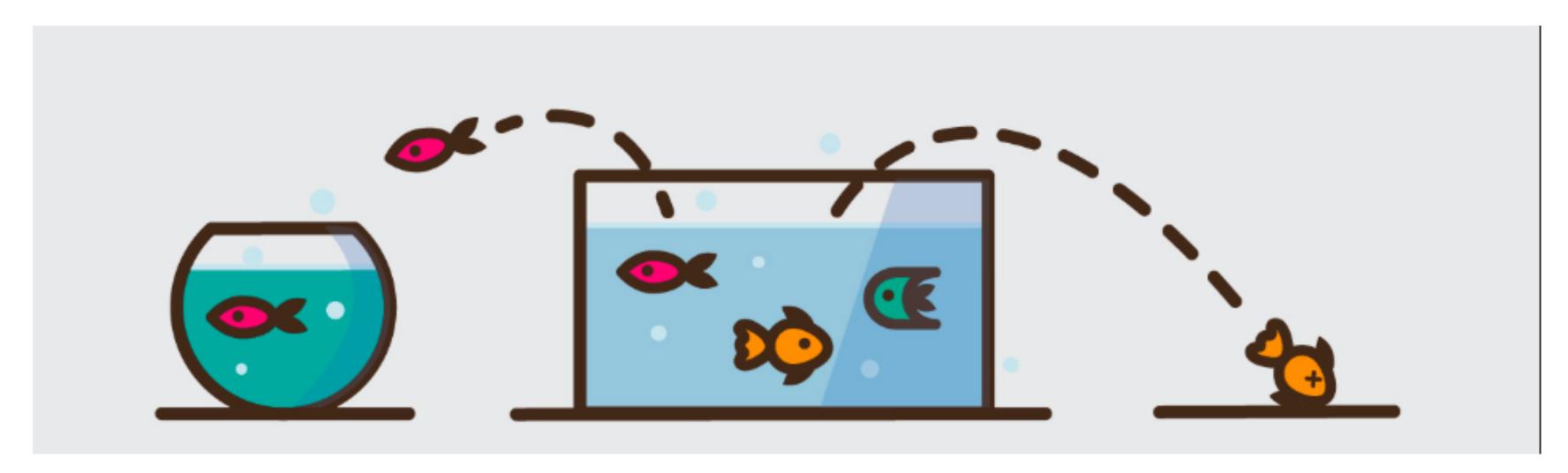
## Predicting Churn for Bank Customers

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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: 14 features, 10.000 customers.



I	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

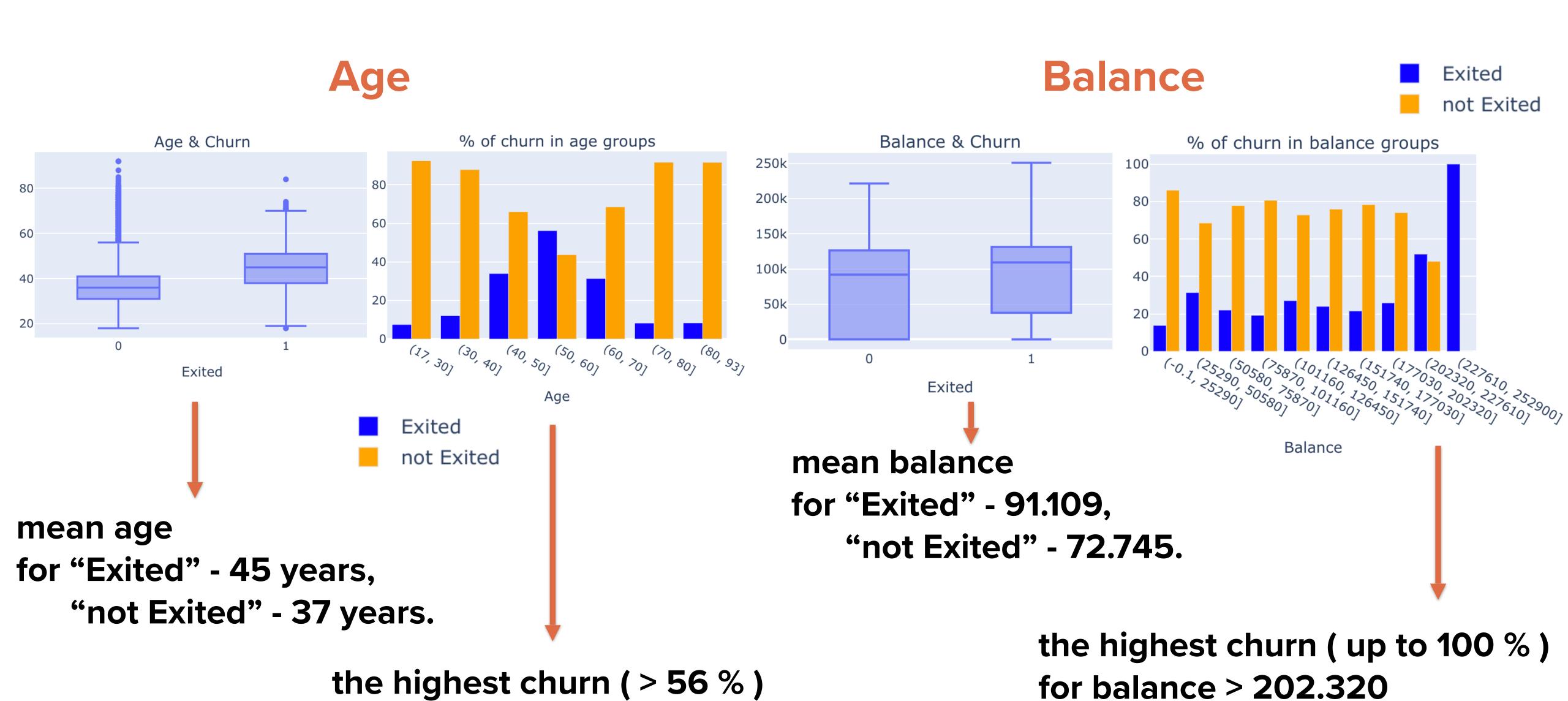
## Objectives

- 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



only 29 customers

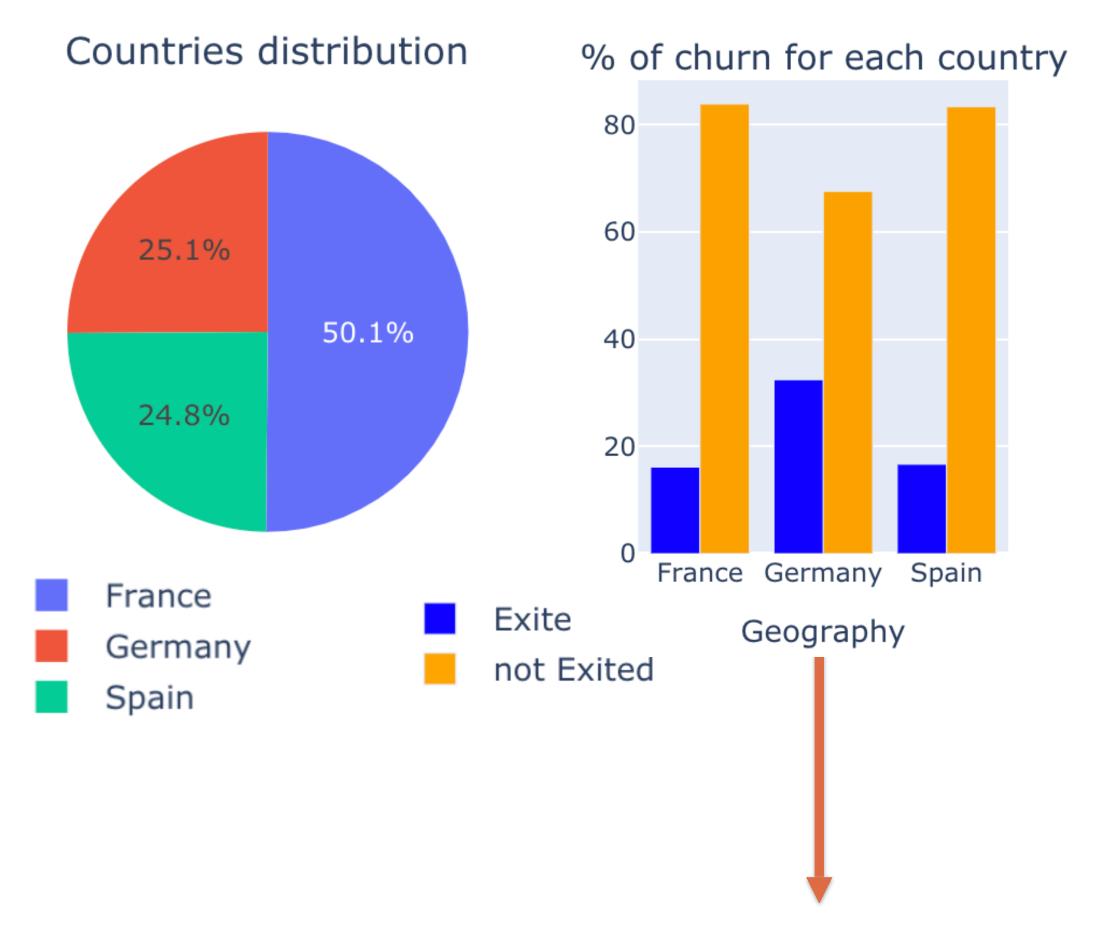


for age range (50,60]

#### Features that contribute the most

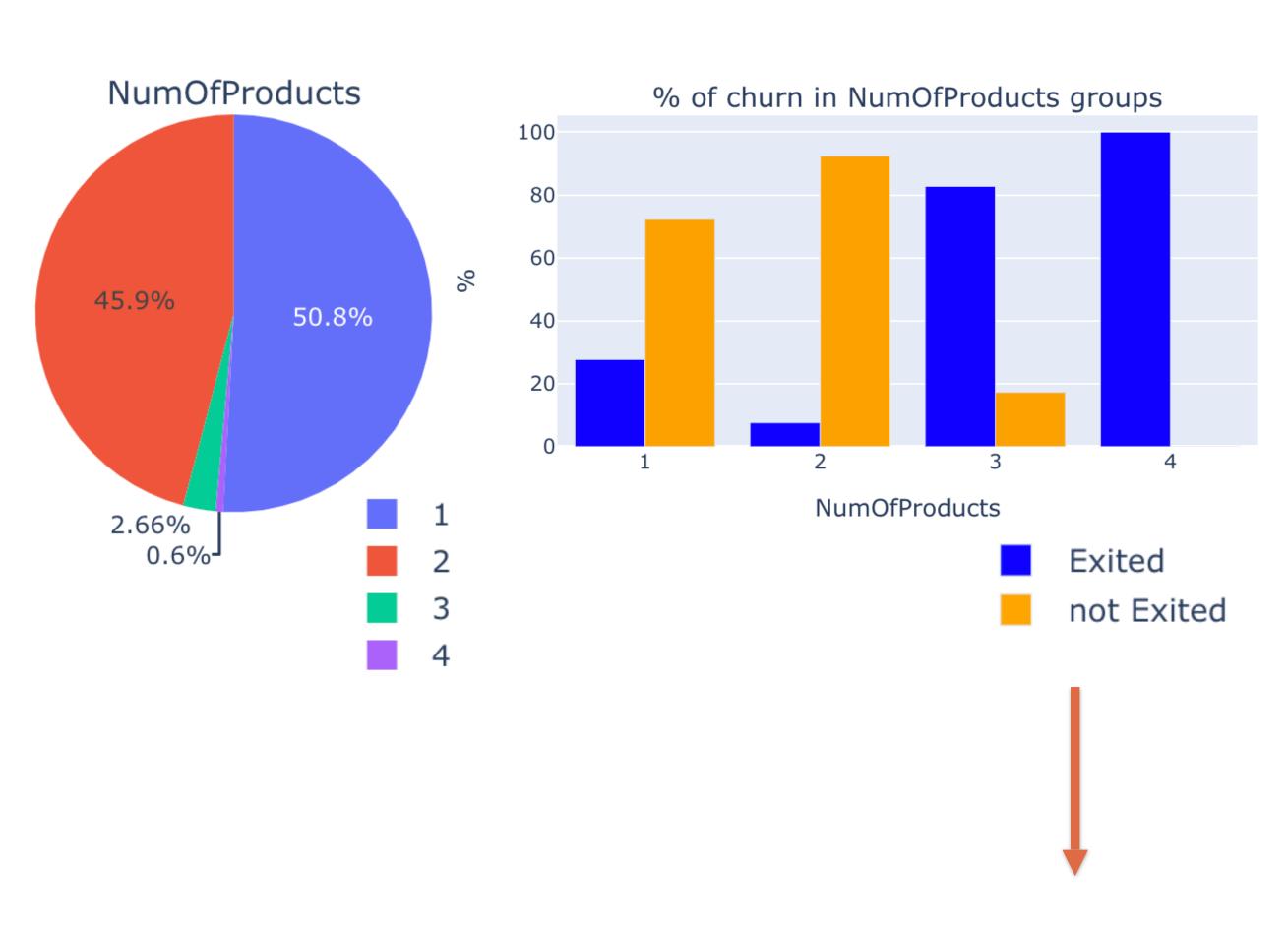


### Geography



the highest churn (>32 %) for Germany

#### NumOfProducts



the highest churn: 83% - 3 products, 100% - 4 products

## 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



## Applications

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



# THANKYOU!