

# THE CAPSTONE PROJECT

## SPRINGBOARD

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# My project starts with this

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I had no idea what I was getting myself into

# OUTLINE



1. Introduction
2. Data Exploration
3. Recommendation Systems
4. Data Analysis
5. Conclusion

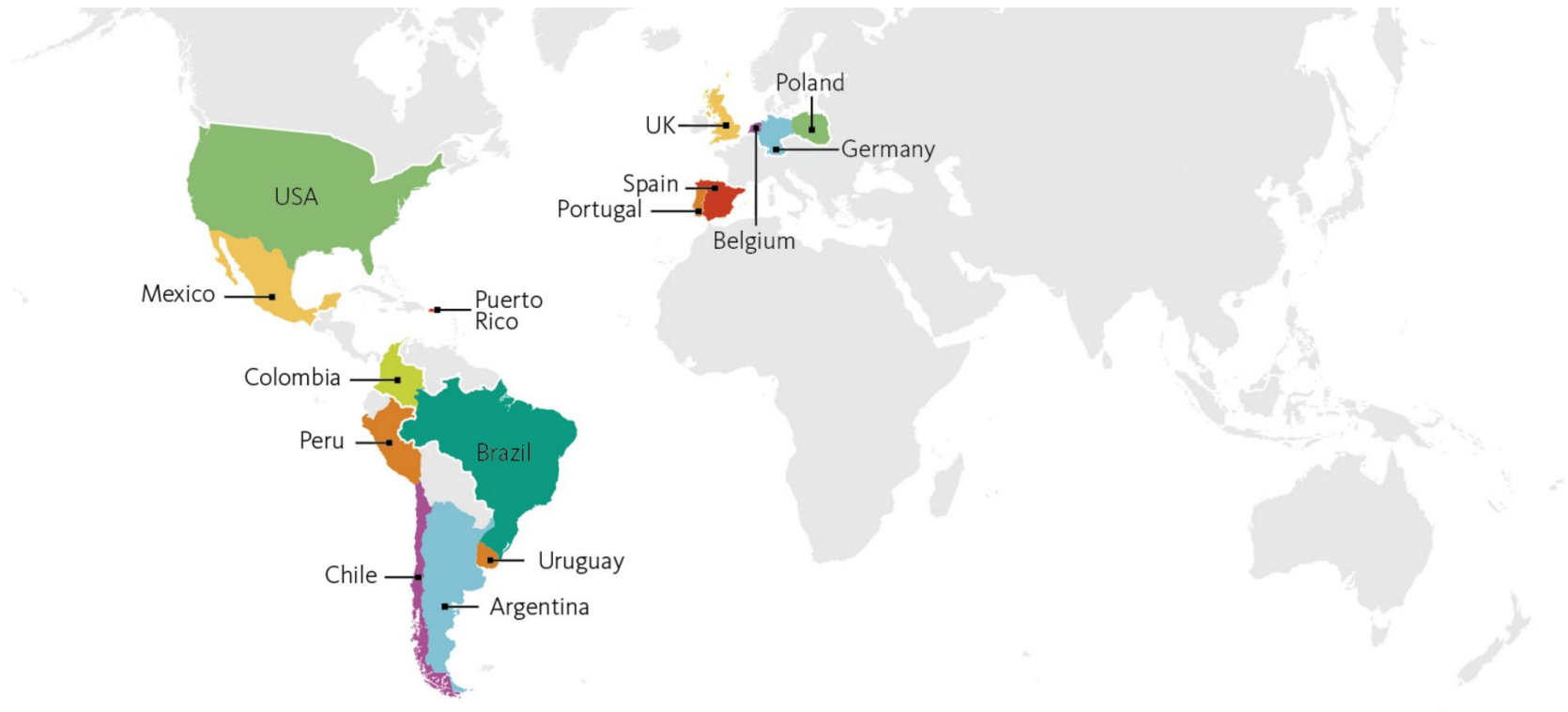
1.

# Introduction

# Background

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- Santander bank is originated from Spain, but has headquarters in many countries



# Problem

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- Currently, their system doesn't recognize the right products to their customers, so that some customers get too many offers while others don't have any.
- Their wish for the solution is to have a recommendation system to predict which products their existing customers will use in the next month based on their past behavior and that of similar customers.

# Purpose for the Project

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- Find a recommendation system for predicting next bank products
- Try different methods of recommendation system

2.

# Data Exploration

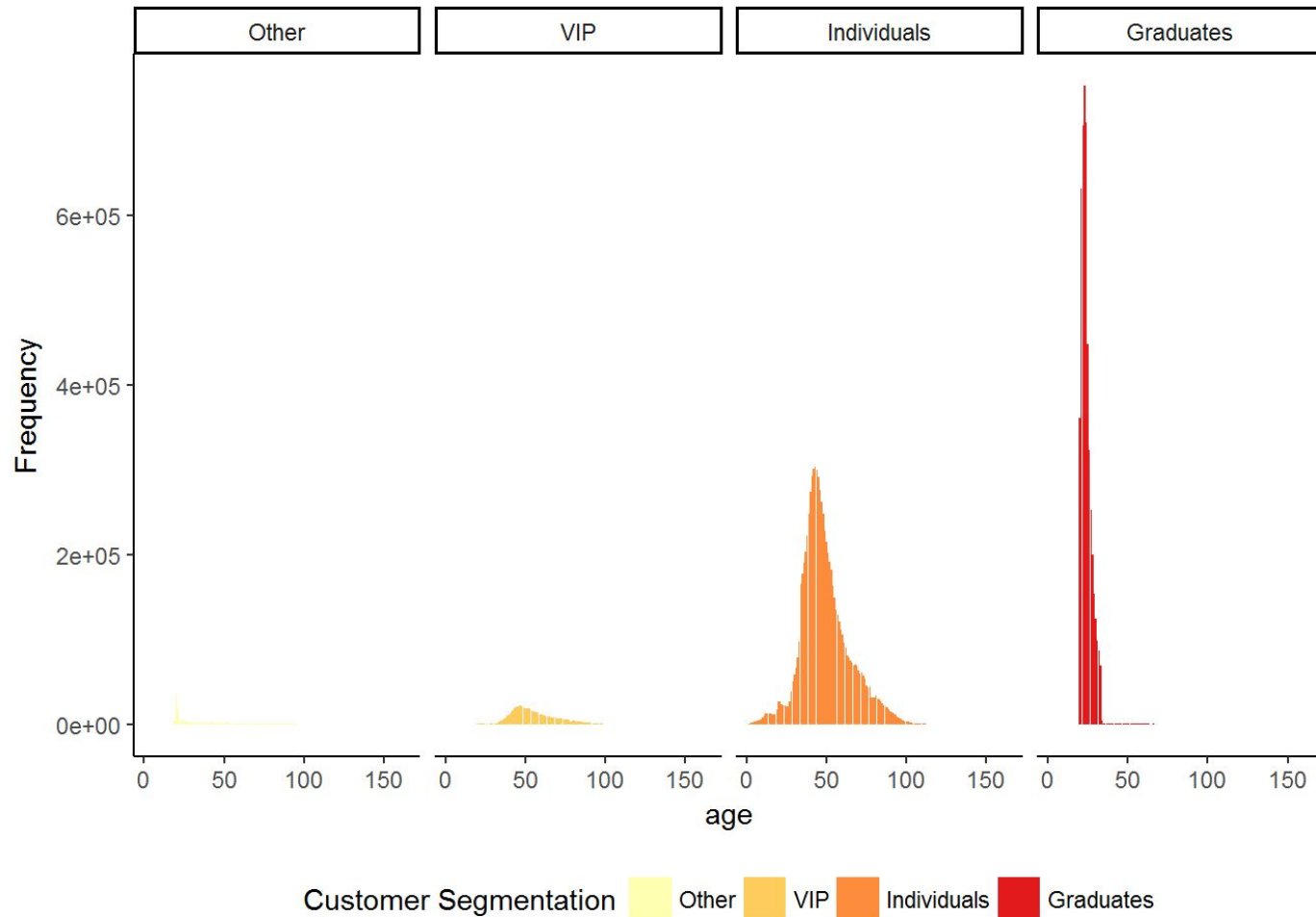


# Main dataset insights

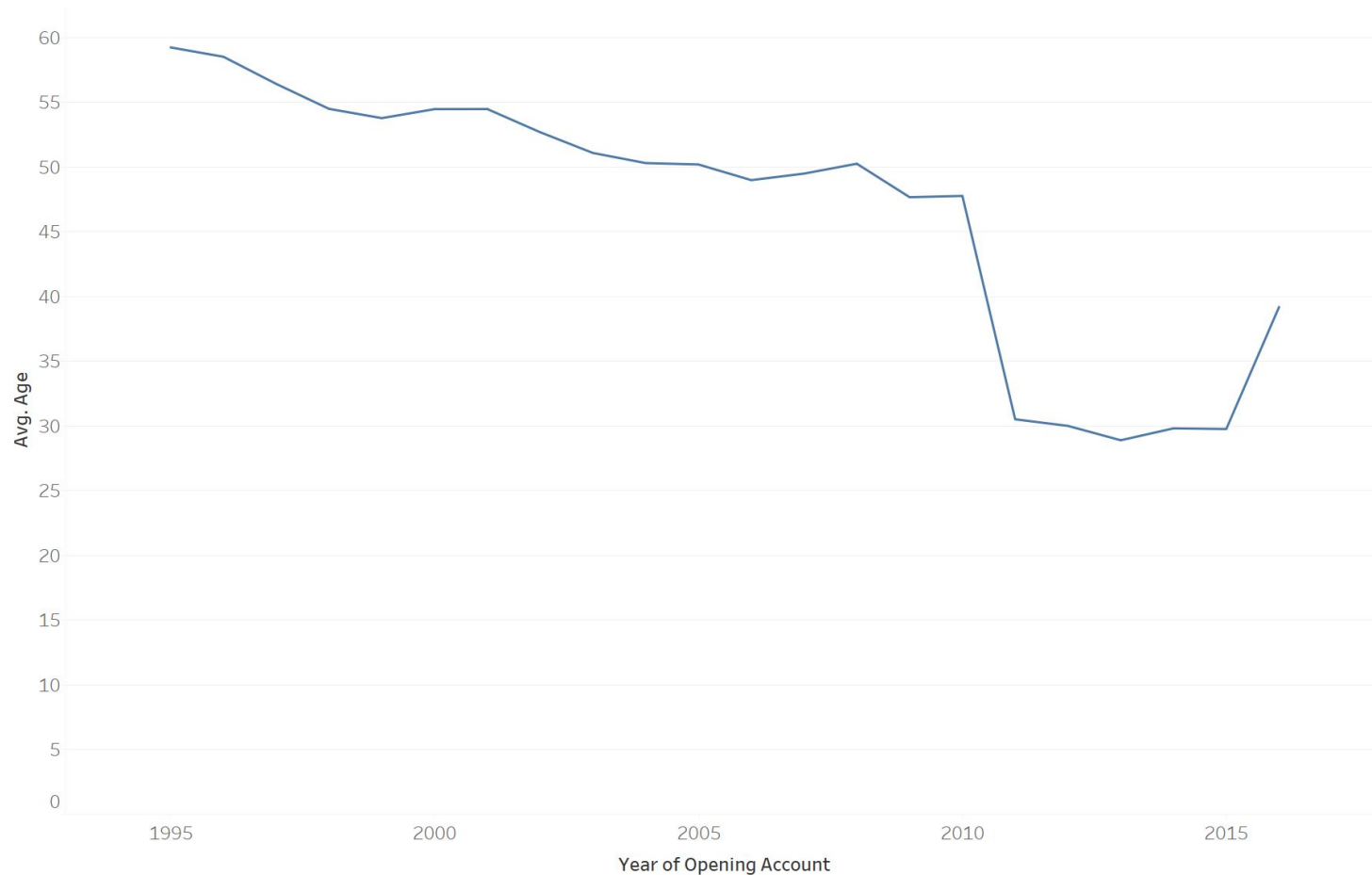
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- There are more than 13 million user database and 48 different variables
- First 24 of them user demographic variables, and last 24 of them bank products
- User demographic info includes age, gender, income, location and etc.
- Bank products are all 0-1 data, 1 being user consumes that product

# Exploring Customer Age

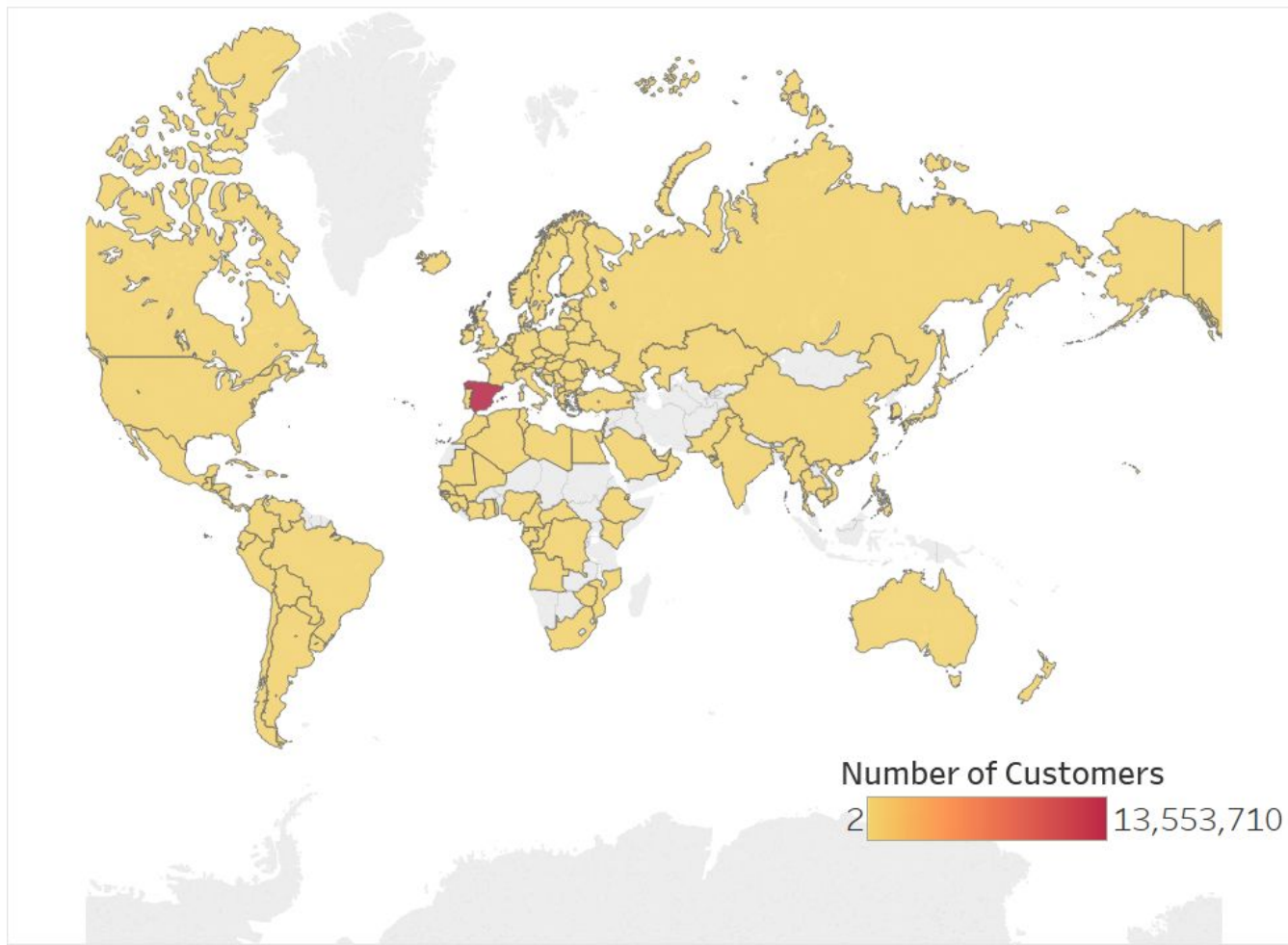


# Changing Age Distributions Over the Years



# Exploring Customer Location

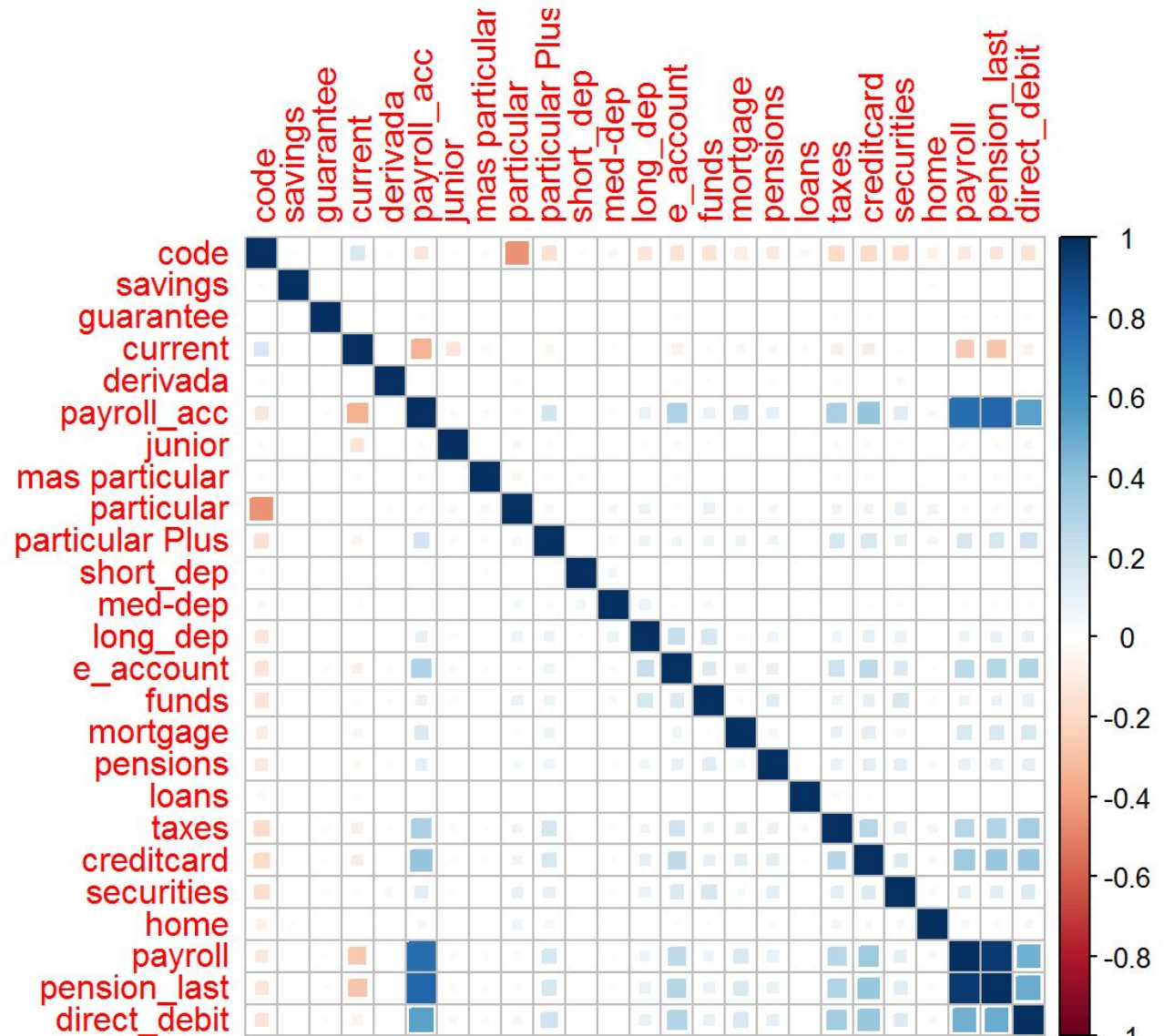
Where Bank Customers Come From?



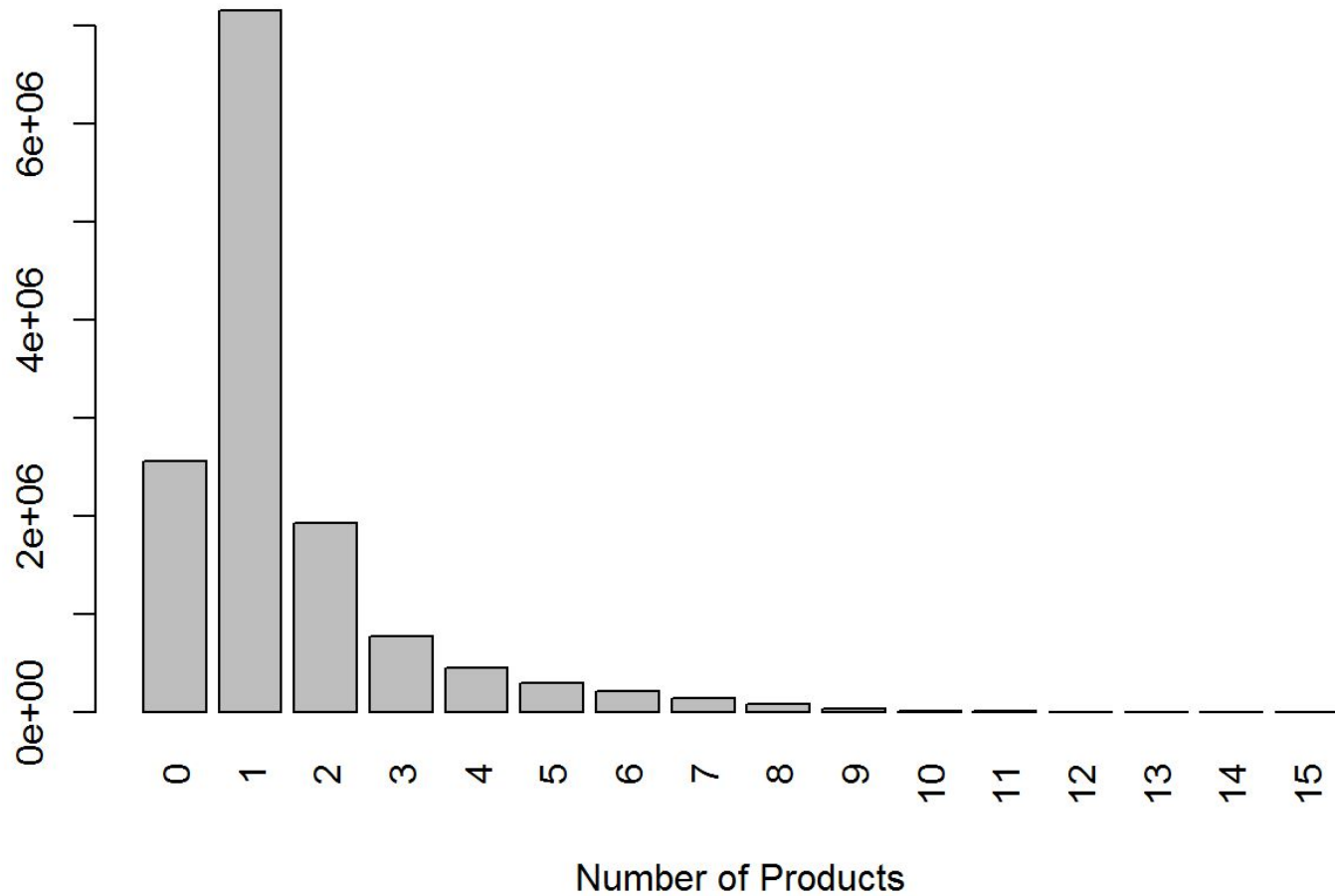
# Exploring Customer Income



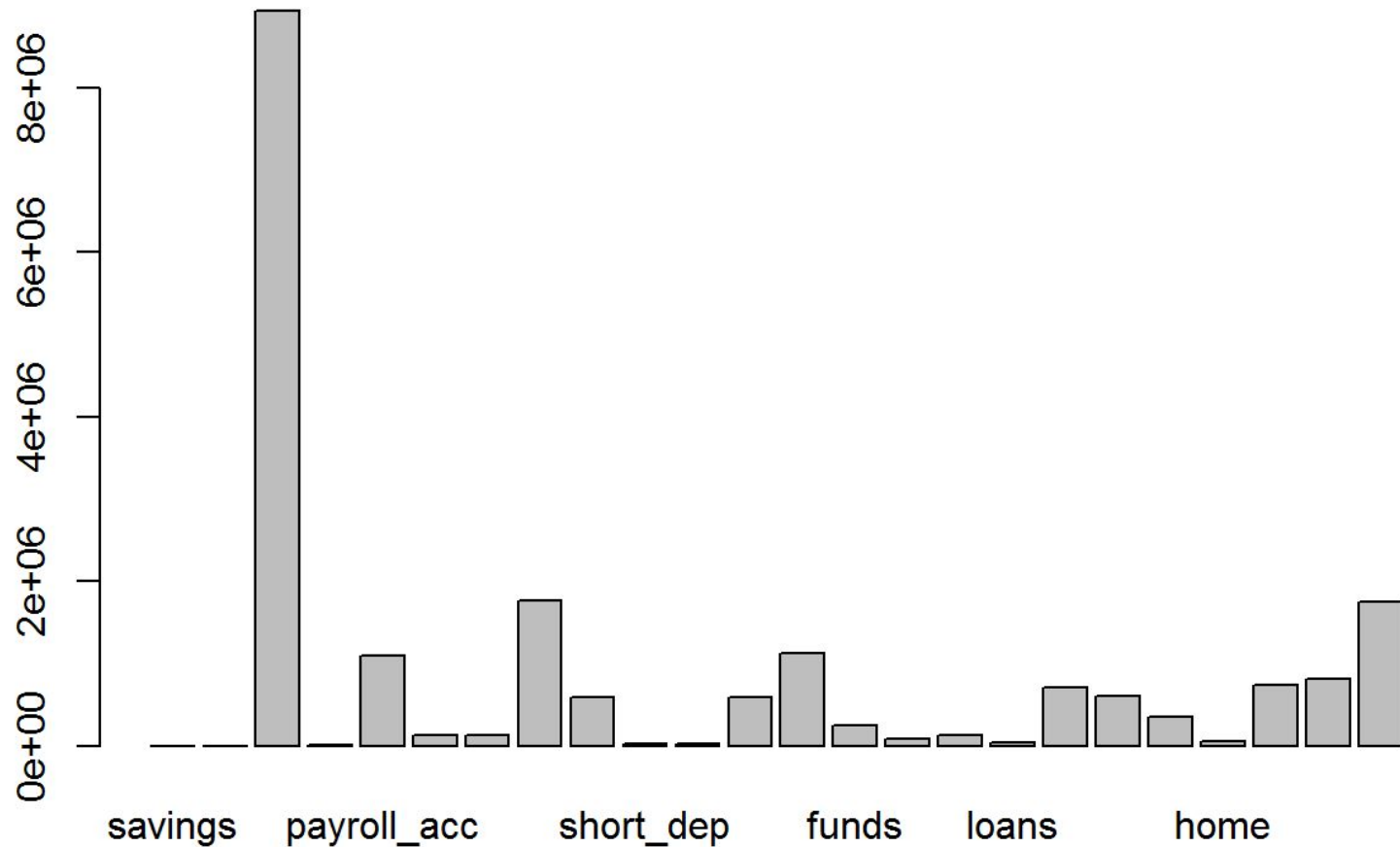
# Exploring Bank Products



# Exploring Bank Products



# Exploring Bank Products





**3.**

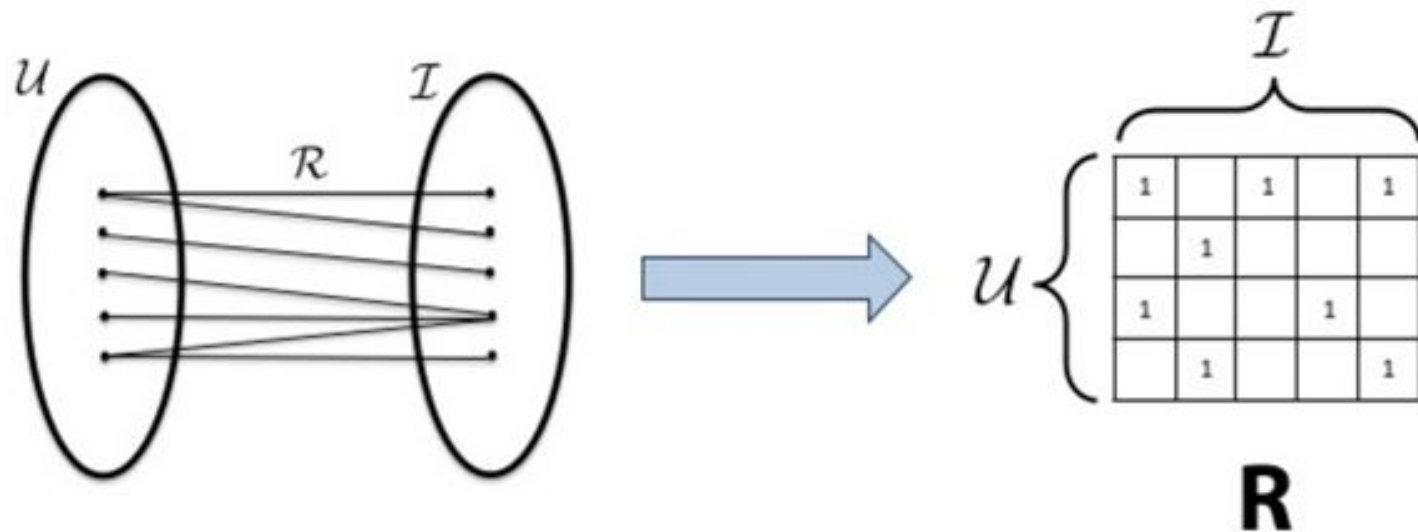
# **Recommendation Systems**

# Binary Recommendation System

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- Binary recommendation system is bit different than traditional recommendation system
- Rating is not based on 1-5 Likert Scale
- 0-1 data, another word Positive-only data, to show user preference
- 0 represents either user has no preference now, or user doesn't know about the product, or does not like the product

# Binary Recommendation System



# Collaborative Filtering



## Item-based

Determine similar products

Give more weights to the most similar products

## User-based

Determine similar users

Give more weights to the opinions of similar users

4.

**Analysis:  
Item-based  
Collaborative  
Filtering**

# Process of Item-based Collaborative Filtering

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```
graph TD; A(Create matrix) --> B(Find similarities using cosine measure); B --> C(Find similar items);
```

Create  
matrix

Find  
similarities  
using  
cosine  
measure

Find  
similar  
items

# #1 Step

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- Create matrix that holds NA from the current dataframe

```
holder <- matrix(NA, nrow=ncol(bank.recom),ncol=ncol(bank.recom),dimnames=list(colnames(bank.recom),colnames(bank.recom)))

bank.recom.similarity <- as.data.frame(holder)

for(i in 1:ncol(bank.recom)) {
  for(j in 1:ncol(bank.recom)) {
    bank.recom.similarity[i,j]= getCosine(bank.recom[i],bank.recom[j])
  }
}
```

## #2 Step

- Calculate similarity matrix between all items based on available users' ratings.
- Cosine Similarity

$$\cos(A, B) = \frac{A \times B}{\|A\| \|B\|}$$

- Final similarity matrix:

```
##          current payroll_acc particular e_account    taxes
## current    1.00000000  0.04887032  0.3687681 0.2747616 0.1902221
## payroll_acc 0.04887032  1.00000000  0.1391024 0.3674849 0.3687115
## particular 0.36876805  0.13910241  1.0000000 0.1153420 0.1672927
## e_account   0.27476158  0.36748492  0.1153420 1.0000000 0.2688076
## taxes       0.19022212  0.36871153  0.1672927 0.2688076 1.0000000
## payroll     0.05957614  0.76568900  0.1245008 0.3153189 0.3153222
##          payroll pension_last direct_debit
## current    0.05957614  0.06127241  0.3545048
## payroll_acc 0.76568900  0.79755111  0.5742283
## particular 0.12450081  0.13023025  0.1897989
## e_account   0.31531889  0.33744902  0.3753149
## taxes       0.31532222  0.33478083  0.4053543
## payroll     1.00000000  0.95606375  0.5062049
```



## #3 Step

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- Store only n closest items to each item;

```
bank.neighbours <- matrix(NA,  
nrow=ncol(bank.recom.similarity),ncol=2,dimnames=list(colnames(bank.recom.similarity)))
```

- Calculate predicted rating for each item based on available ratings of user u by weighting available ratings of users on similarities.

```
For (i in 1:ncol(bank.recom))  
{  
  bank.neighbours[i,] <-  
  (t(head(n=2,rownames(bank.recom.similarity[order(bank.recom.similarity[,i],decreasing=TRUE),][i]))))  
}
```

# Results: Recommended Products for First 5 Users



	Users	Additional Products
1	"657788"	particular
2	"657795"	pension_last
3	"657790"	current
4	"657794"	direct_debit
5	"657789"	direct_debit

# Conclusion

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- **Limitations:**
  - Limited Time
  - Little experience to deal with large dataset
  - User-based approach
- **Recommendation:**
  - Model Evaluation
  - Model expansion
  - Other models

# Thanks!

## Any questions?



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# Credits



Special thanks to all the people who made and released these awesome resources for free:

- Presentation template by [SlidesCarnival](#)
- Photographs by [Unsplash](#)