

# National City Bank Case

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*Group Project*

## Introduction

- Data Set: The training data contain 4,000 customers of National City Bank whose marketing department had previously contacted to sell a credit product (used vehicle line of credit).
  - Supplemental third-party data on current and prospective customers were also available.
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# Goal

- Identify the 100 most propense users to accept a used car credit line
- Share some insights about our current customer base

We ran multiple models over the data to come up with the most accurate outcome.



# Cleaning & Analysis

# Obtain the dataset ...

```
> read.csv('CurrentCustomerMktg  
Results.csv', na.strings=c(""))  
  
> joinData <- left_join (currentData, ... )
```

- Data obtained from 4,000 National City bank customers included 30 variables

joinData	4000 obs. of 30 variables
dataID	int 1 2 3 4 5 6 7 8 9 10 ...
HHuniqueID	chr "HHd4d0af8c72" "HH8d3e87c164" "HHdd53ef1db6" "HH6fa0de6516" ...
Communication	chr "telephone" NA "cellular" "cellular" ...
LastContactDay	int 28 26 3 11 3 22 17 12 18 12 ...
LastContactMonth	chr "jan" "may" "jun" "may" ...
NoOfContacts	int 2 5 1 2 1 1 1 4 1 2 ...
DaysPassed	int -1 -1 119 -1 -1 109 -1 -1 -1 -1 ...
PrevAttempts	int 0 0 1 0 0 1 0 0 0 0 ...
past_Outcome	chr NA NA "failure" NA ...
CallStart	chr "13:45:20" "14:49:03" "16:30:24" "12:06:43" ...
CallEnd	chr "13:46:30" "14:52:08" "16:36:04" "12:20:22" ...
Y_AcceptedOffer	chr "DidNotAccept" "DidNotAccept" "Accepted" "Accepted" ...
X	chr "Accepted" "Accepted" "Accepted" "Accepted" ...
carMake	chr "Mitsubishi" "Hyundai" "Ford" "Buick" ...
carModel	chr "Eclipse" "Elantra" "Explorer Sport" "Regal" ...
carYr	int 2014 2009 2011 2008 2008 2013 2019 2017 1985 2018 ...
DefaultOnRecord	int 0 0 0 0 0 0 0 0 0 0 ...
RecentBalance	int 1218 1156 637 373 2694 1625 1000 538 187 3 ...
HHInsurance	int 1 1 1 1 0 0 1 1 1 1 ...
CarLoan	int 0 0 0 0 0 0 0 0 1 ...
headOfhouseholdGender	chr "F" "M" "F" "F" ...
annualDonations	chr NA NA NA NA ...
EstRace	chr "Fijian" NA NA NA ...
PetsPurchases	logi TRUE TRUE FALSE TRUE TRUE TRUE ...
DigitalHabits_E_AlwaysOn	int 1 2 1 1 2 2 1 2 1 1 ...

# ... and capture missing values

What about missing values?

```
> joinData[joinData=="NA"] = NA  
  
> joinData[joinData==""] = NA  
  
> joinData[joinData=="<NA>"] = NA
```

Remove X attribute, adds no quantitative or qualitative value to our data

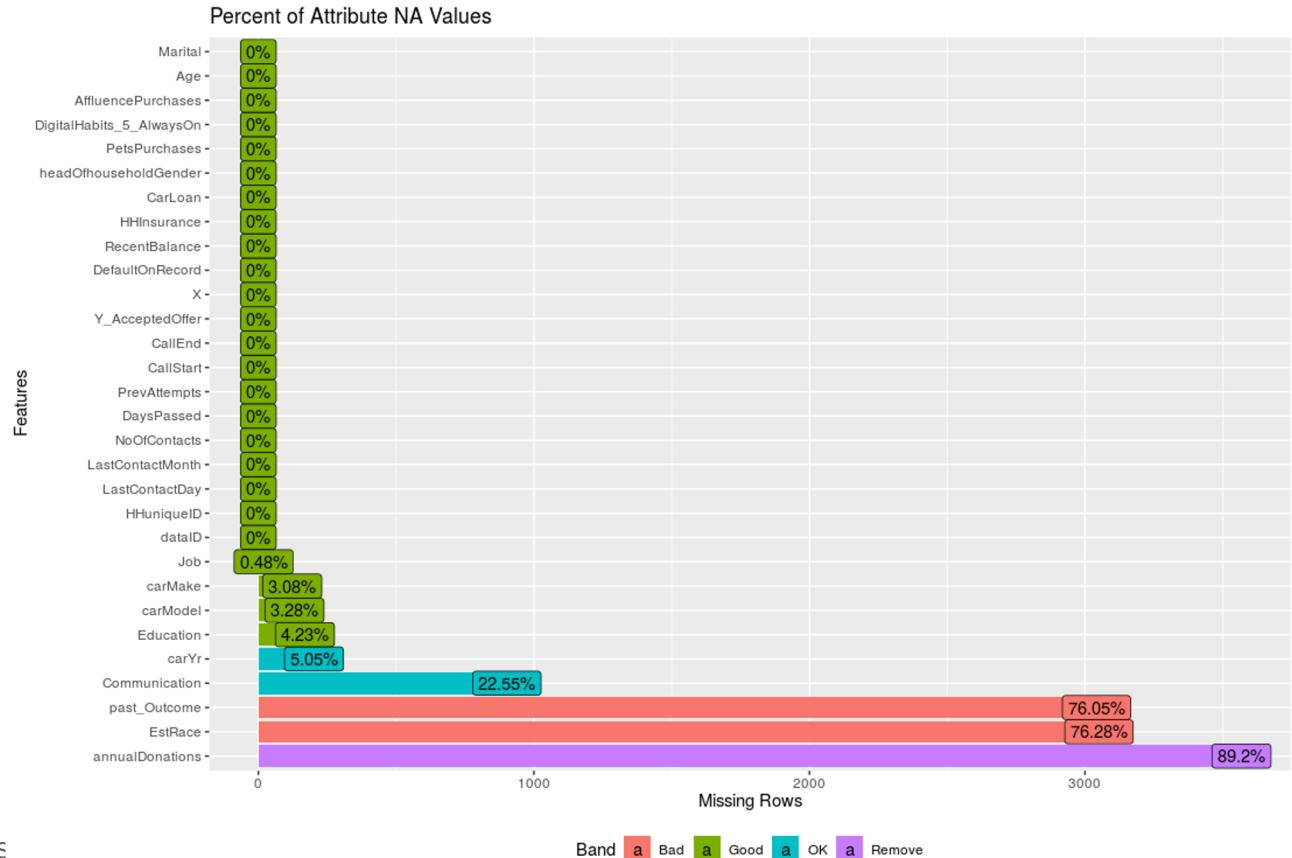
Deal with NA, "" and <NA>

joinData	4000 obs. of 30 variables
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PrevAttempts	int 0 0 1 0 0 1 0 0 0 0 ...
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CallStart	chr "13:45:20" "14:49:03" "16:30:24" "12:06:43" ...
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carYr	int 2014 2009 2011 2008 2008 2013 2019 2017 1985 2018 ...
DefaultOnRecord	int 0 0 0 0 0 0 0 0 0 0 ...
RecentBalance	int 1218 1156 637 373 2694 1625 1000 538 187 3 ...
HHInsurance	int 1 1 1 1 0 0 1 1 1 1 ...
CarLoan	int 0 0 0 0 0 0 0 0 1 ...
headOfhouseholdGender	chr "F" "M" "F" "F" ...
annualDonations	chr NA NA NA NA ...
EstRace	chr "Fijian" NA NA NA ...
PetsPurchases	logi TRUE TRUE FALSE TRUE TRUE TRUE ...
DigitalHabits_E_AlwaysOn	int 1 2 1 1 2 2 1 2 1 1 ...

# Missing Data

A number of attributes from the amalgamated data were missing substantial values or altogether irrelevant. To improve the predictive ability of our model, we decided to remove those attributes from the data set. These include:

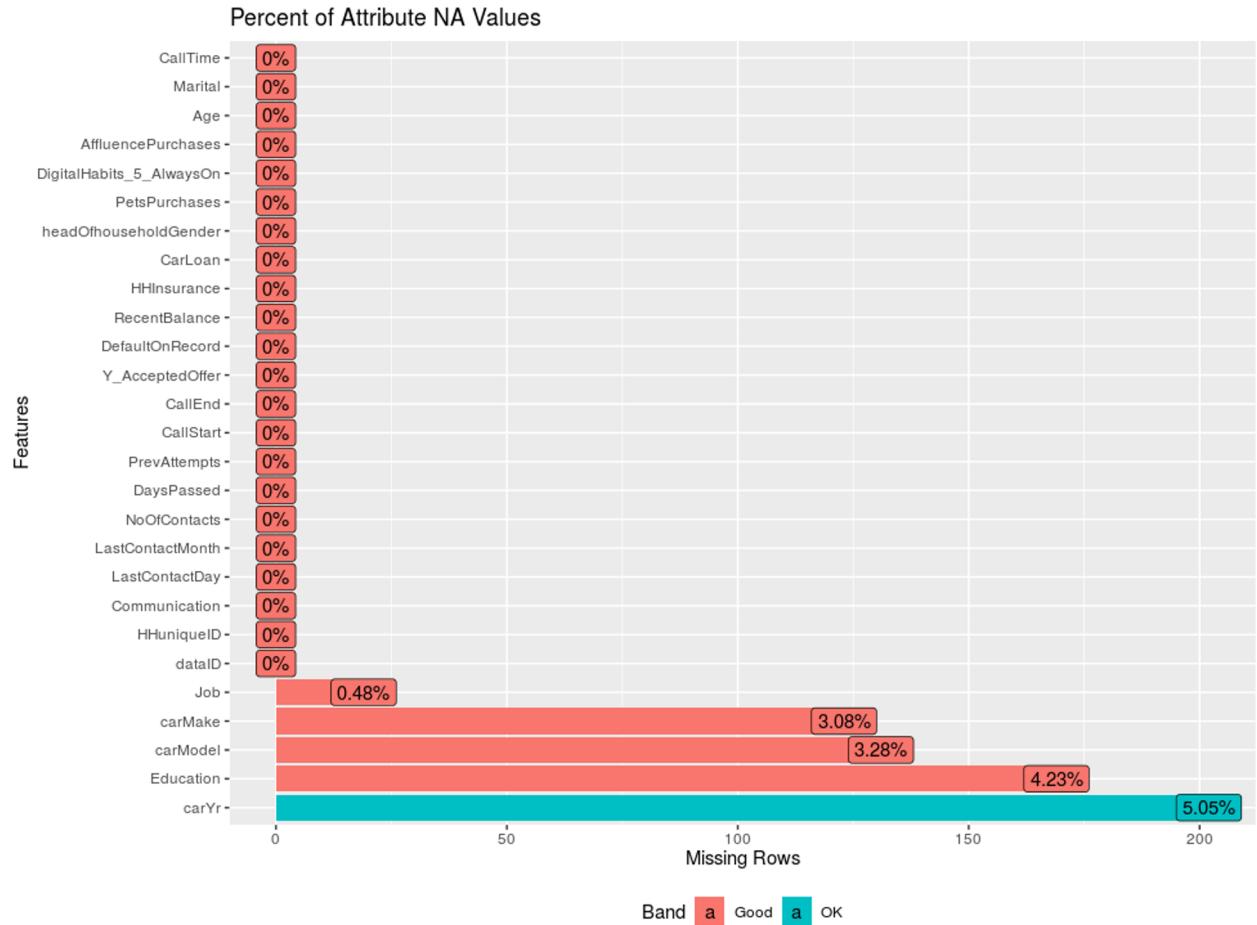
- X
- past\_Outcome
- EstRace
- annualDonations



For Communication, we imputed “cellular” for missing values, which was more than 99% of existing responses.

# Missing Data

After cleaning data, the percent of attributes NA values dropped dramatically.



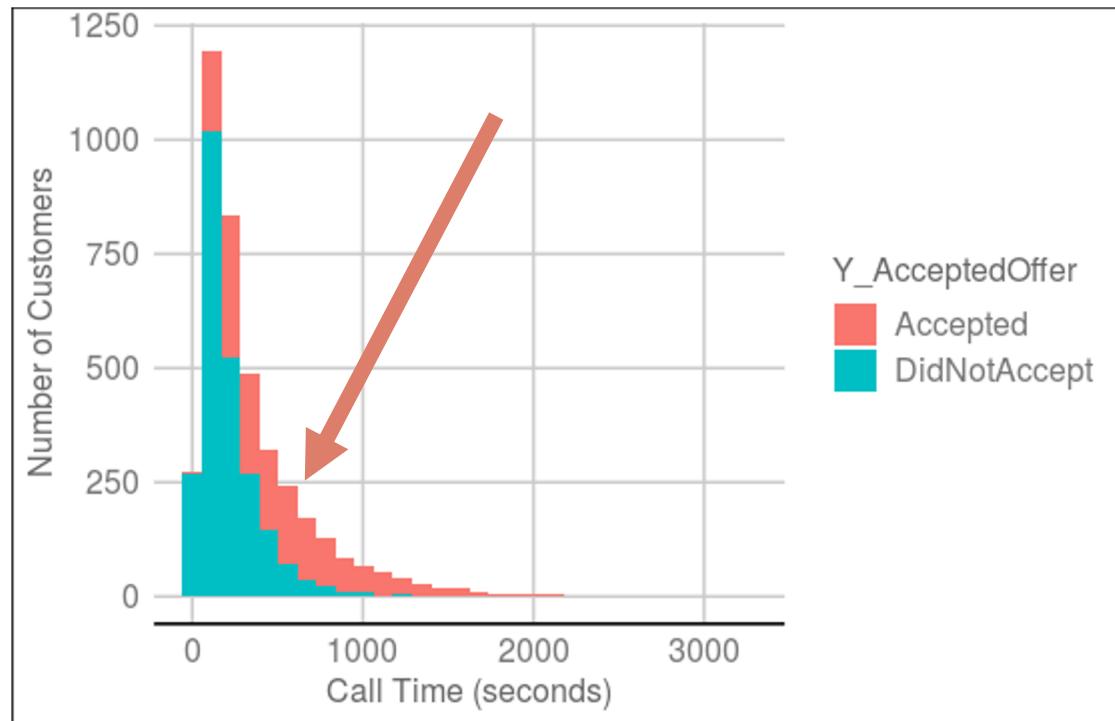
## New Data

What value-added insights can we glean from our existing data?

```
CallTime <- callend - callstart
```

```
joinData$CallTime <- CallTime
```

*Longer calls are correlated with a greater likelihood of accepting offer*



# Customer Marketing Insights

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## Females v Males

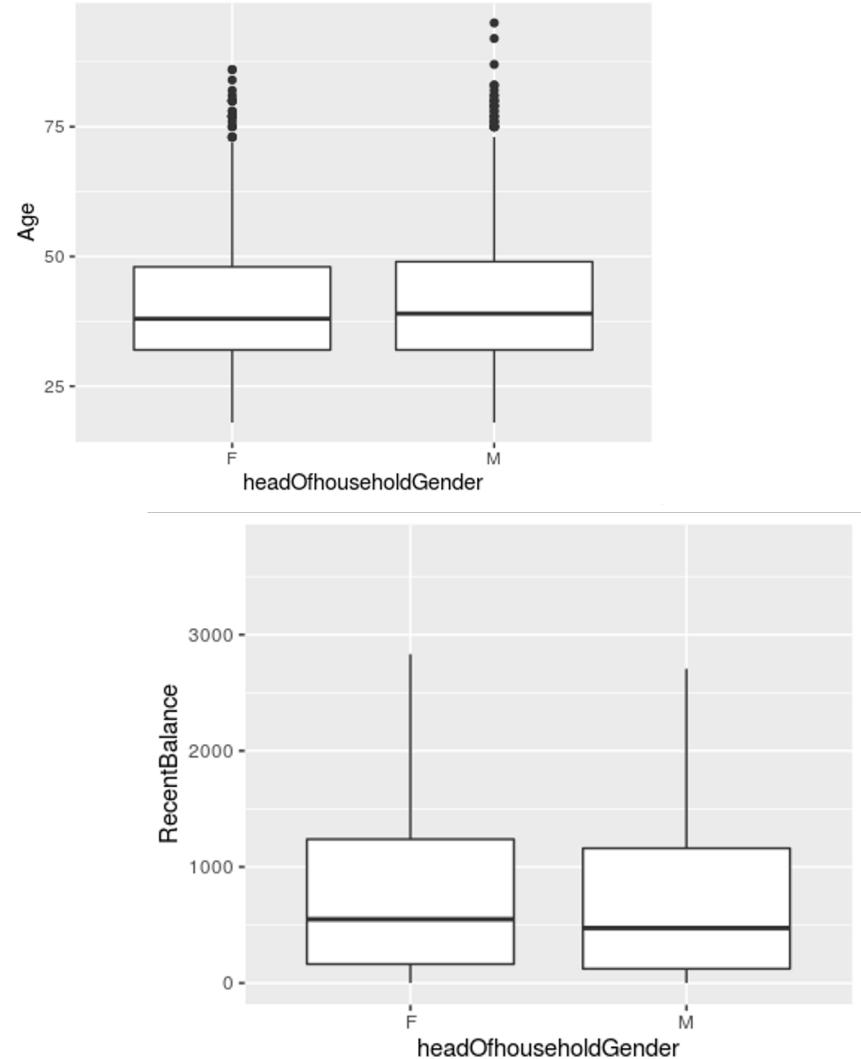
Median age for both males and females are about the same, with a few older outliers for men.

Female heads of household have slightly higher bank balances than males.

***The median female has \$58 more dollars in the bank than the median male.***

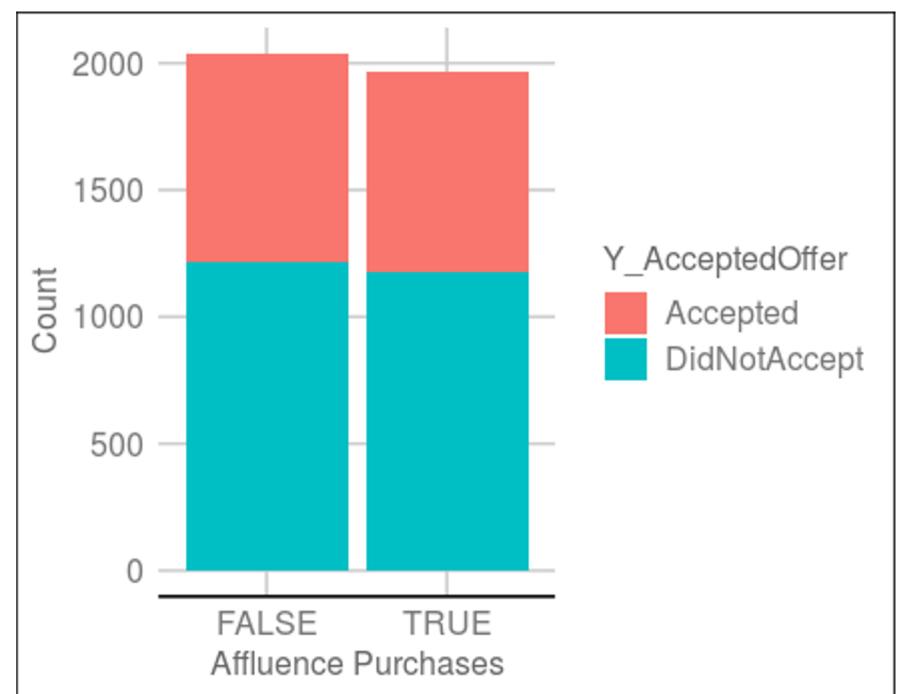
```
headOfhouseholdGender medianbalance
```

1	F
2	M



## Females v Males

Affluence purchases are no more likely than other customers to accept the offer.



# Divorcees

Divorcees have lower bank balances

Divorcees have *\$138 less in the bank* than Married individuals.

***That's a 23% lower bank balance.***

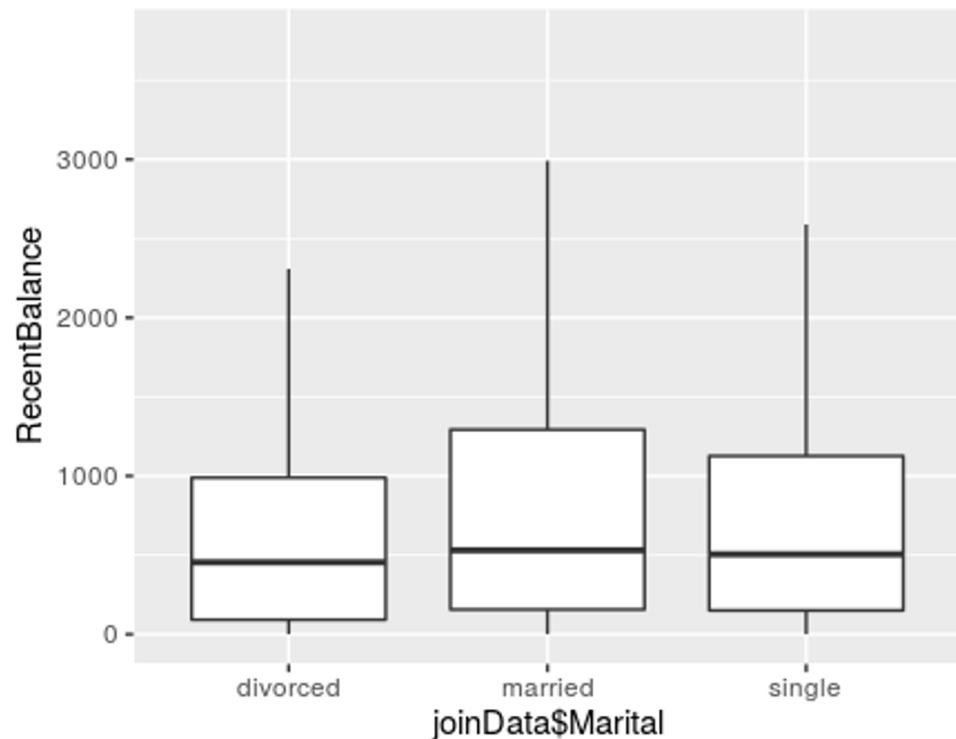
Marital medianbalance

<chr> <dbl>

1 divorced 458

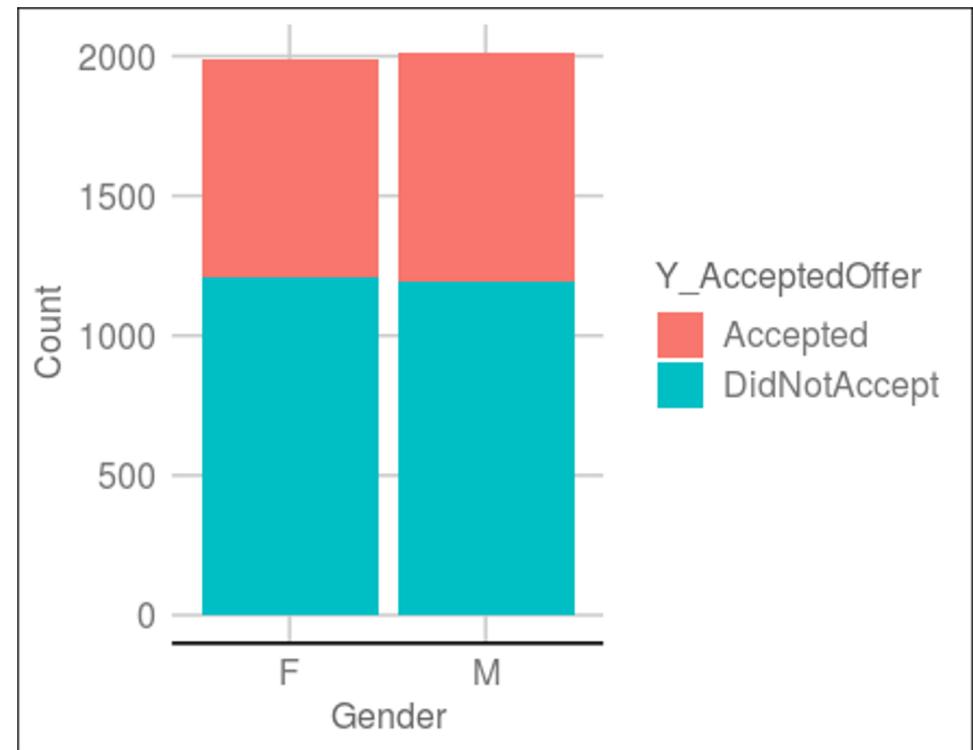
2 married 596.

3 single 533



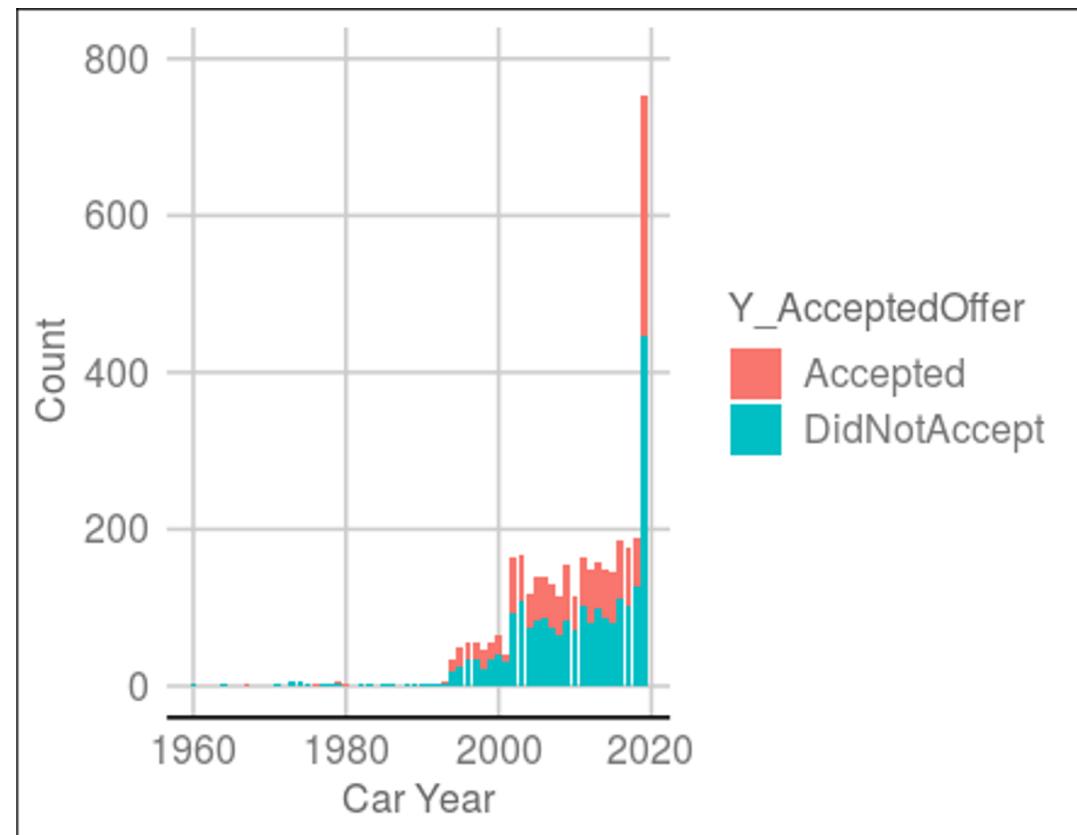
## Accepting the Offer

Gender plays no role in acceptance of credit offer:  
Men and Women accepted the offer in equal proportion



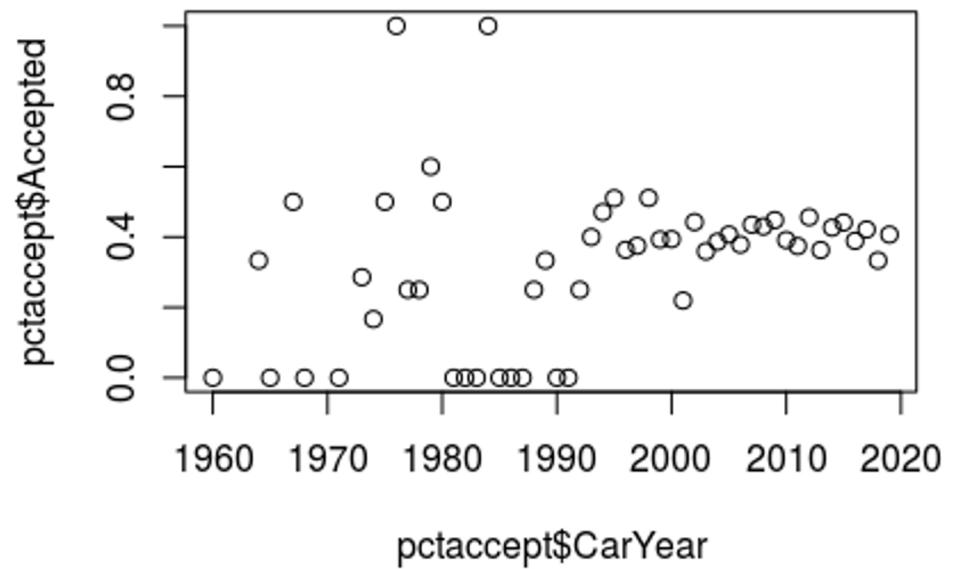
## Accepting the Offer

2019 models more likely to accept offer



## Accepting the Offer

Data show percent acceptances level off at about 40% of offers tendered for vehicle models made between 1995-2019



# Targeting our users

Length of call by gender is equal at 232 seconds

i.e., **Median call length was 3 minutes 52 seconds**

```
joinData %>% group_by(headOfhouseholdGender) %>% summarise(mediancalltime =  
median(CallTime))
```

```
headOfhouseholdGender mediancalltime
```

```
<chr> <drttn>
```

```
1 F 232 secs
```

```
2 M 232 secs
```

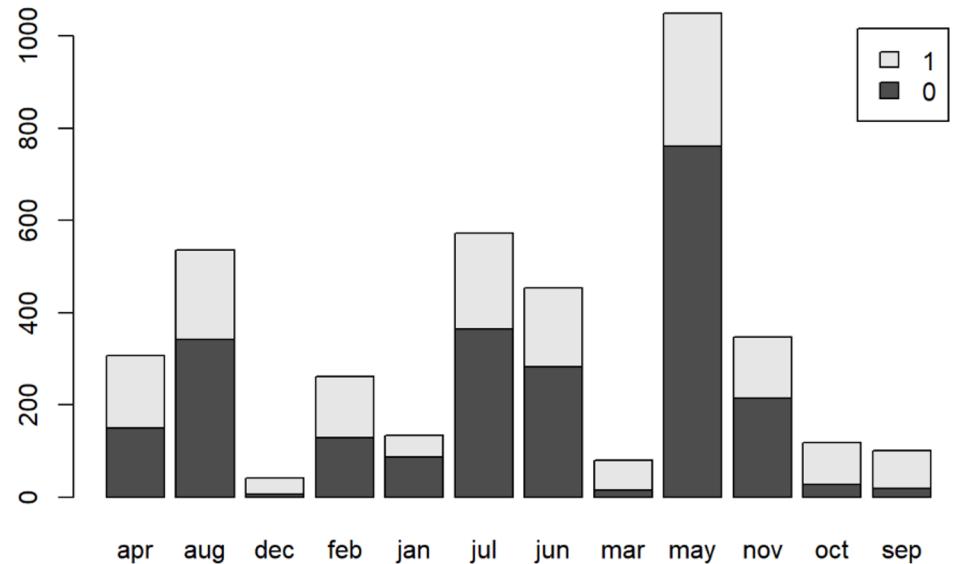
# Targeting our users

Rate conversion by month provides insights on when to contact users and for how long to target the campaign

Length of call by gender is equal at 232 seconds

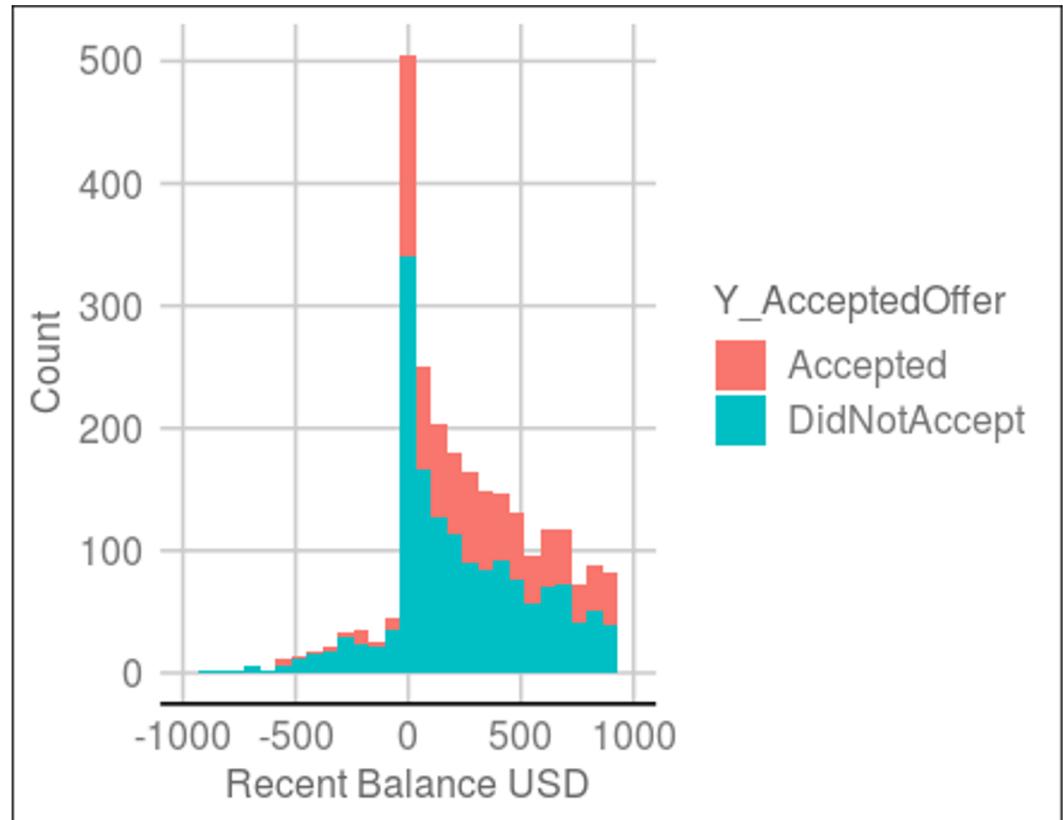
i.e., Median call length was 3 minutes 52 seconds

**Relation between month of Contact and campaign success**



## Accepting the Offer

Customers with negative bank balances are less likely to accept offer



# Pet Purchasers

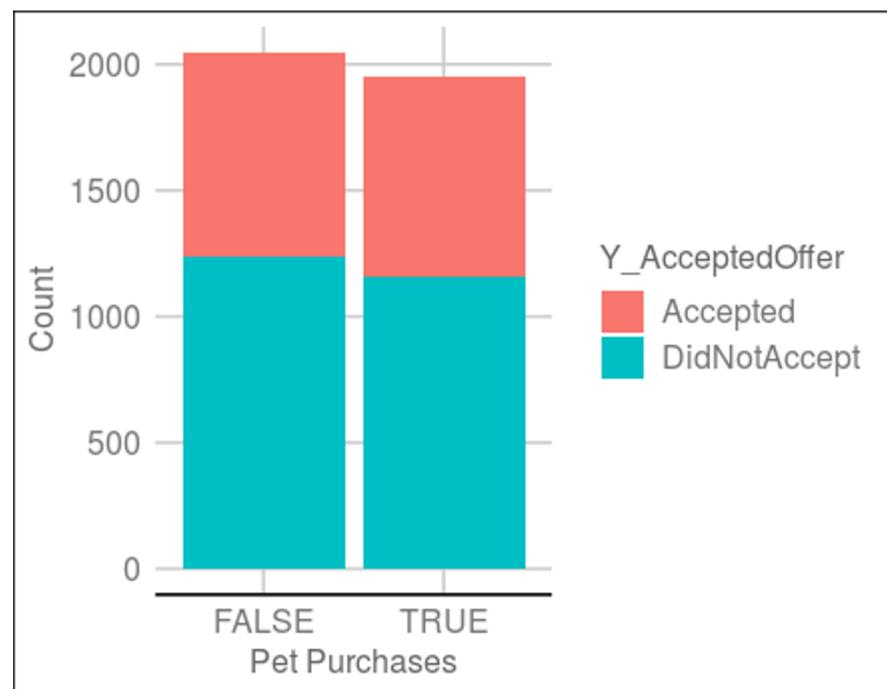
Pet purchasers have more purchasing power.

They hold **\$79 more dollars in the bank** than non-pet purchasers

PetsPurchases medianrecentbalance

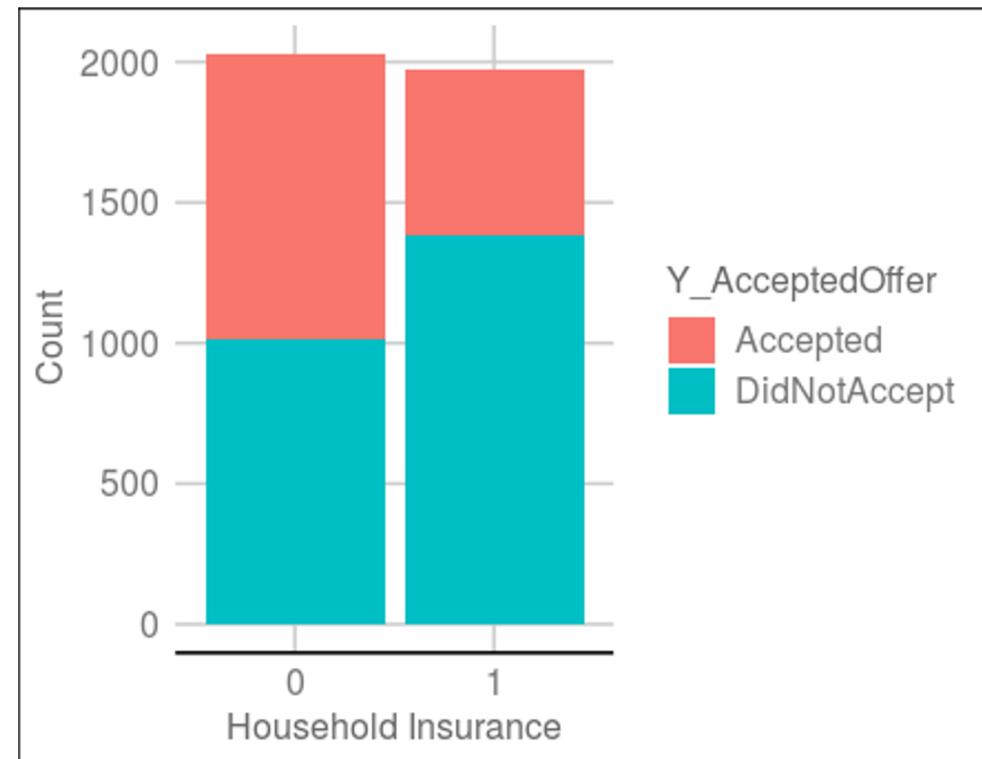
1 FALSE	514
2 TRUE	593

But NOT more likely to accept the credit product.



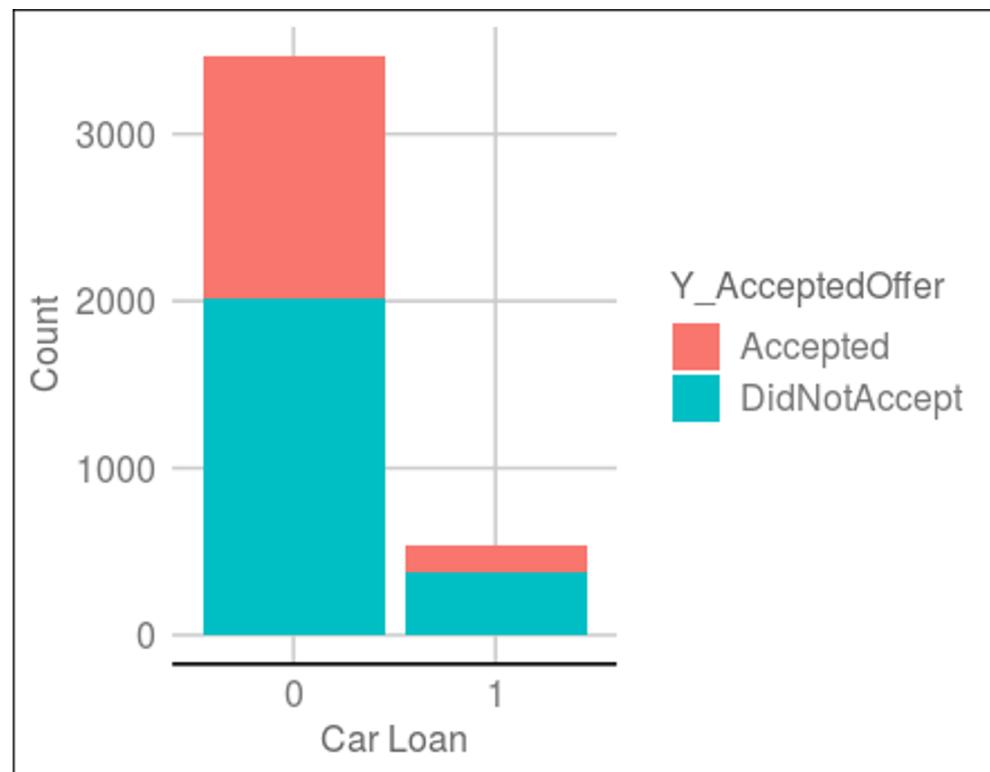
## Household Insurance

Customers **WITHOUT** household insurance with the bank were more likely to accept offer.



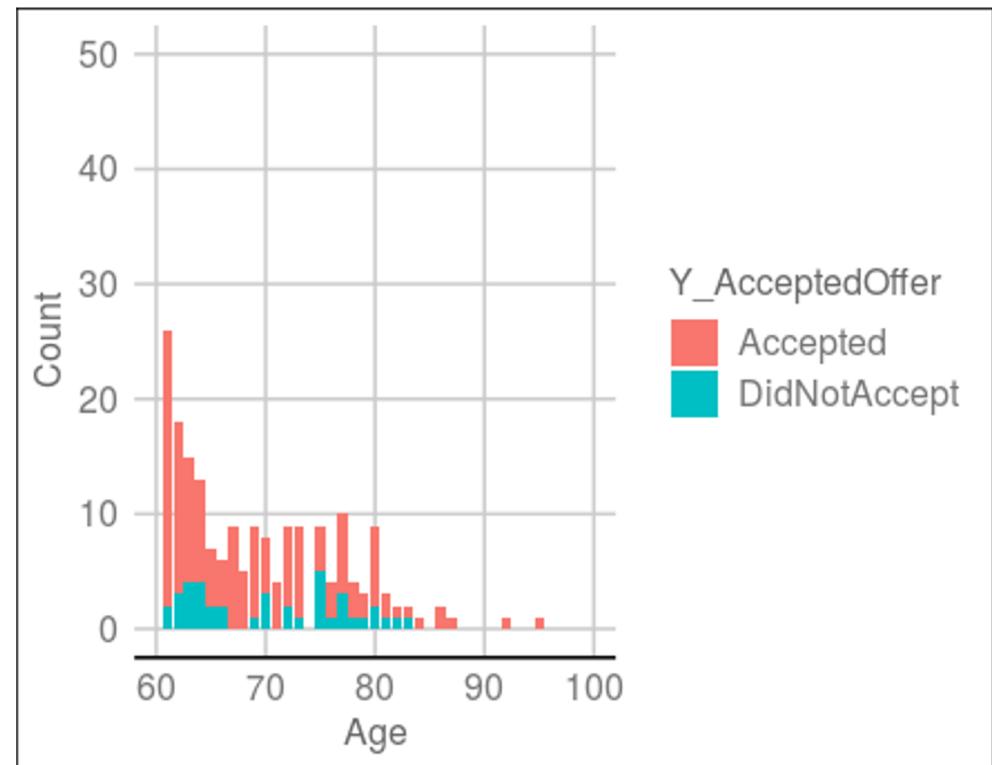
## Car Loan

Customers WITHOUT a car loan were **13% more likely** to accept offer.



## Old age

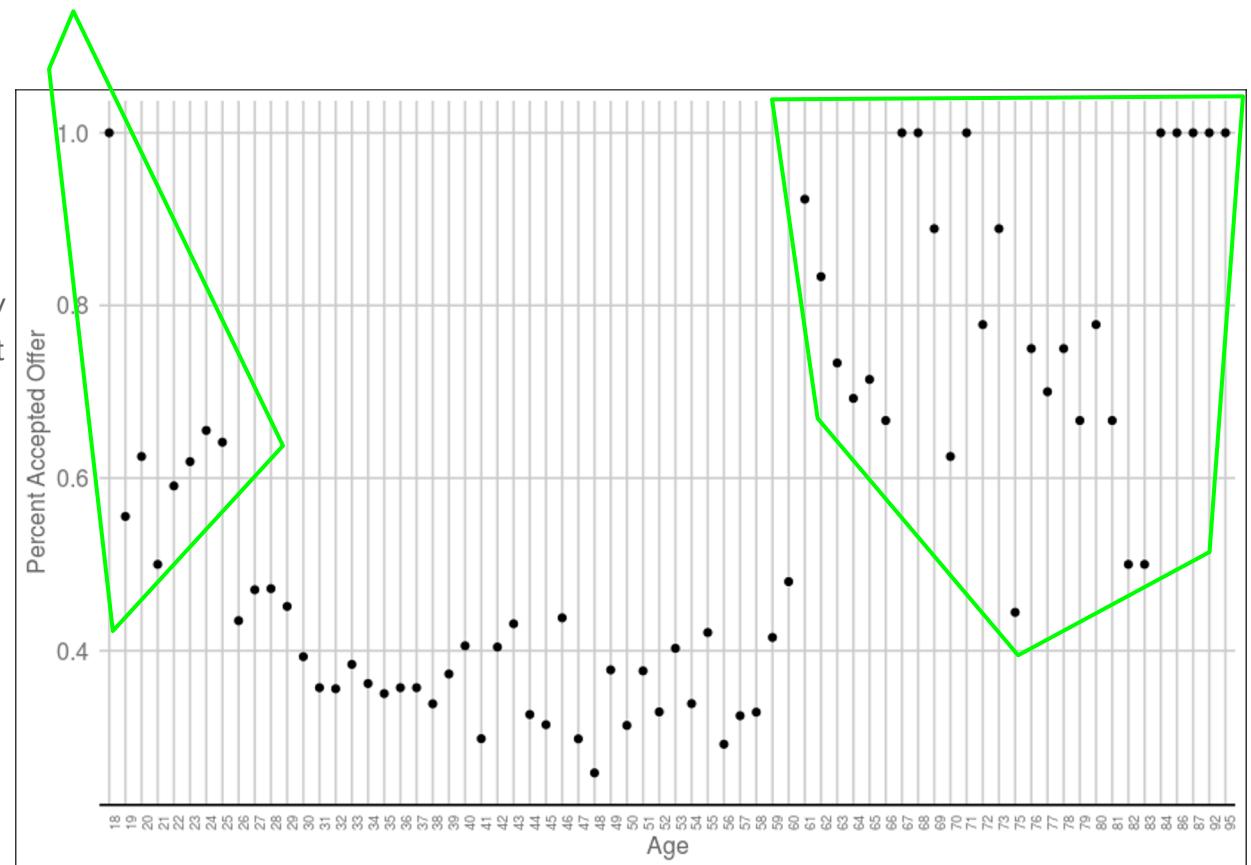
Customers aged 61 and older were more likely than all other age groups to accept offer...



## Old age

But don't count out the youngin's

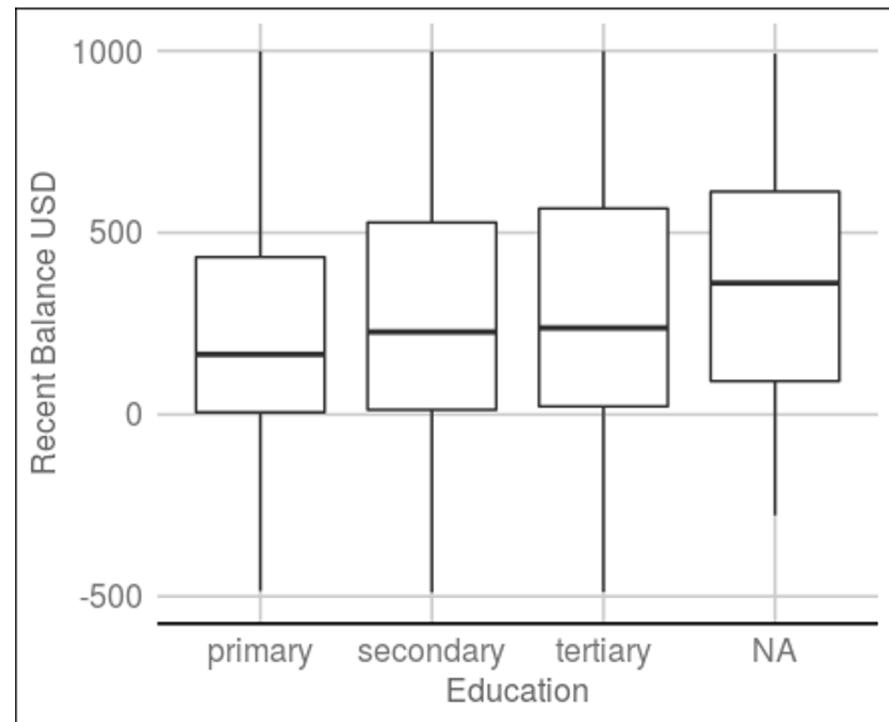
Customers ages 18-26 are also statistically more likely than not, to accept the product offer.



# Education

Customers with higher Educations are more likely to have higher recent balances

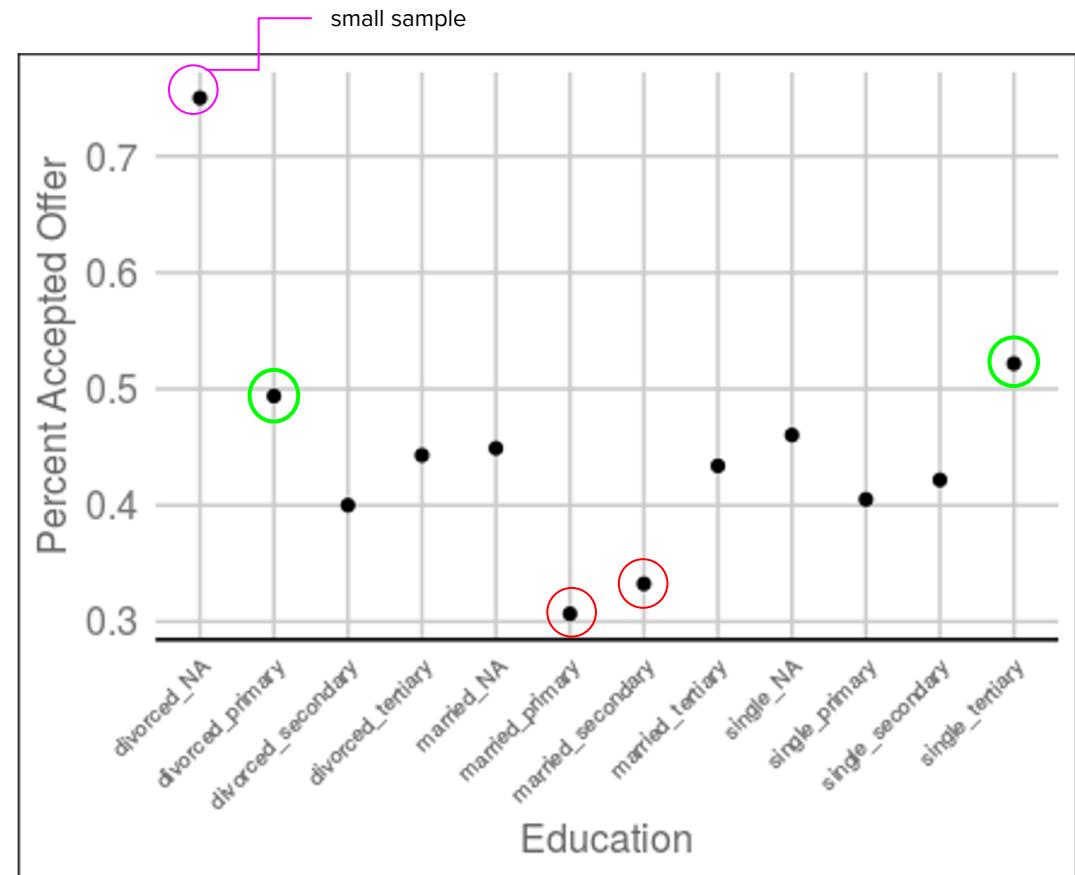
Customers with tertiary educations have median recent balances **\$211 higher** than customers with only a primary education.



## Marital + Education

**Divorced customers with primary educations & single customers with tertiary educations** more likely to accept offer.

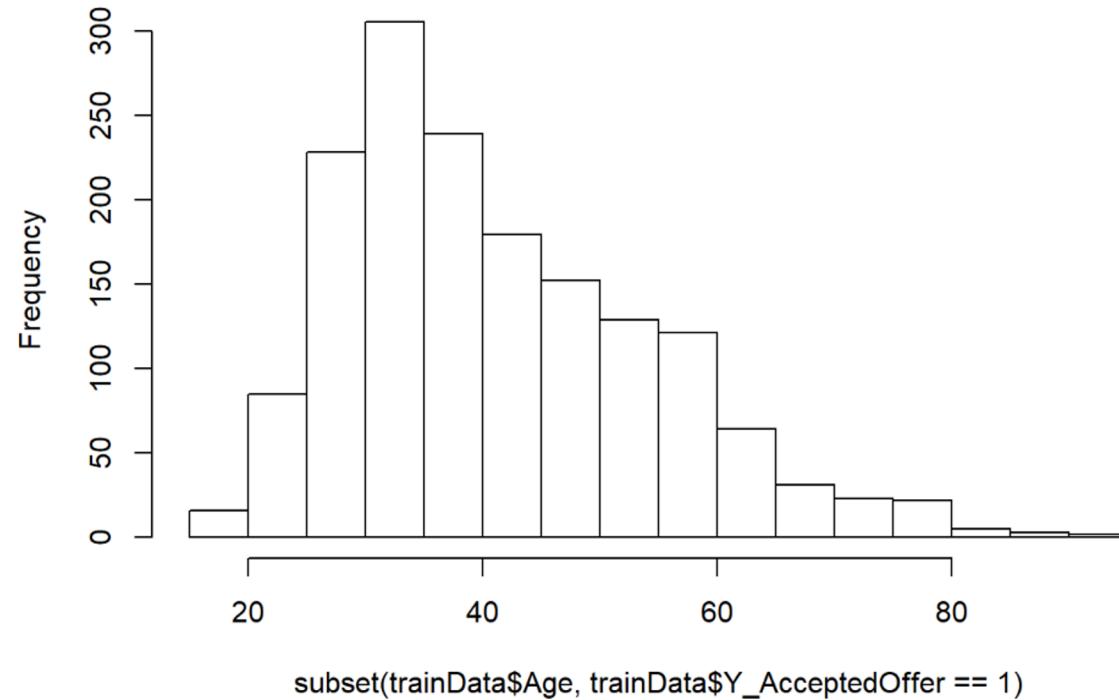
Married customers with primary or secondary educations **least likely to accept**.



# Age

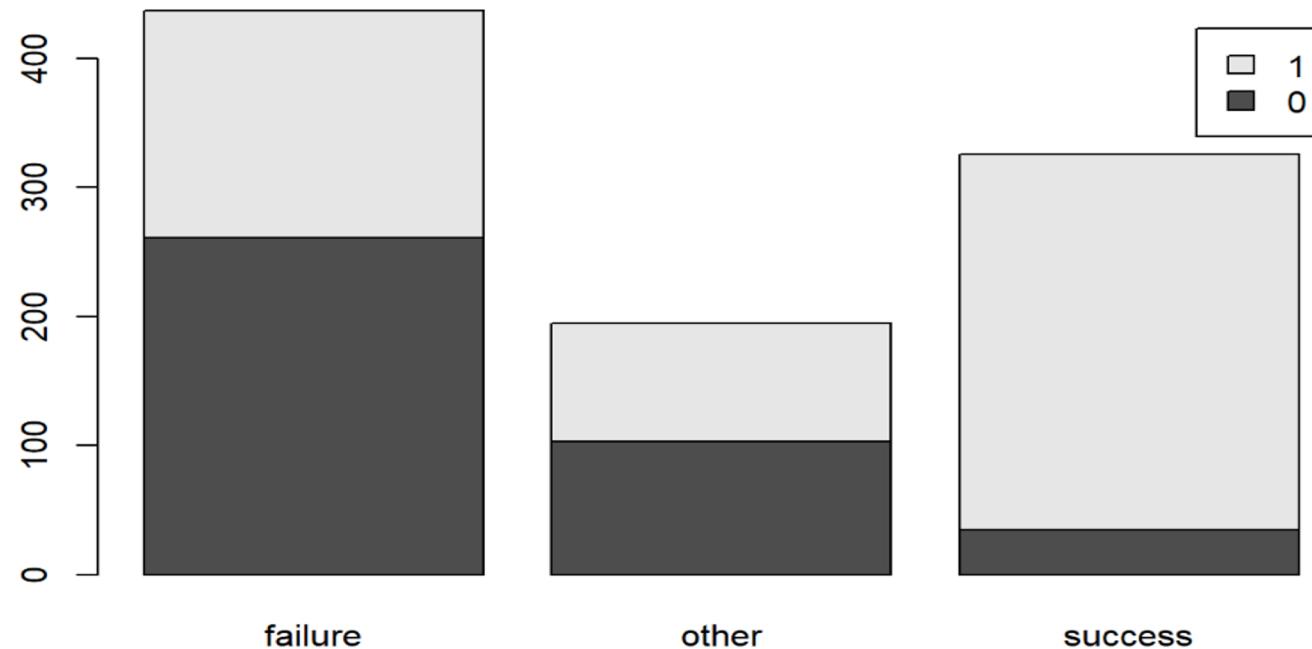
The majority of the users that have accepted a loan range in ages 20 to 40

**Age distribution of current Acceptors**



# Previous Offer Acceptance

**Acceptance rate in relation to a previous campaign success**



## Summary of the current customers

- Age 25-40
- Evenly spread among males and females
- Predominantly managers or technicians  
(retired have as well a good conversion rate ->opportunity)
- Single or married  
(divorced customers having a much lower conversion rate)
- Prefer to be contacted via mobile
- The customers that had already accepted an offer in the past are much more likely to accept an offer in this campaign.

## Other cleaning and enrichment steps

- After EDA, we removed the variables Call End, Call Start and duration of the call from the prospective data to match inquiry vectors used in both the training and scoring data sets.
- We dropped the car model, and the last contacted day. (Not informative enough)

# Model

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# 83%

Our model accurately predicts top 100 customers having an average 83% likelihood of accepting the financial product offer

We ran four models - KNN, Log Reg, Random Forest, and Decision Tree. We compared the accuracies across all the models. We chose and optimized a Random Forest model to predict the most likely prospective respondents.

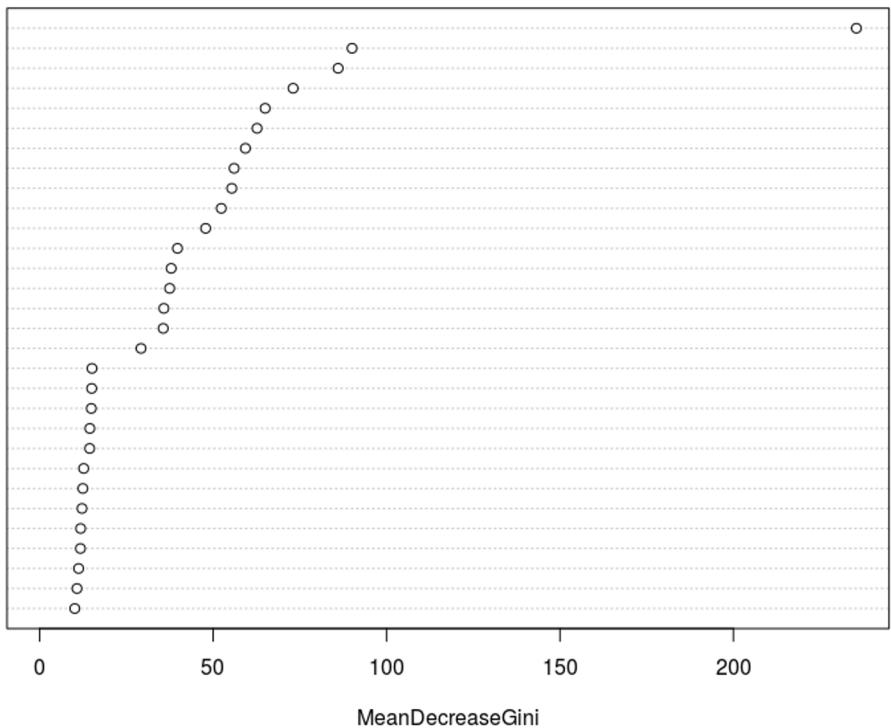
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# Our Model

Found **carModel**, **Age** and **RecentBalance** among the most important predictive variables in accepting the product offer.

carModel\_catB  
Age  
RecentBalance  
LastContactMonth\_catB  
LastContactDay  
carMake\_catB  
LastContactMonth\_catP  
carModel\_catP  
carYr  
carMake\_catP  
DaysPassed  
NoOfContacts  
Job\_catB  
PrevAttempts  
HHInsurance  
DigitalHabits\_5\_AlwaysOn  
Job\_catP  
Education\_catP  
headOfhouseholdGender\_lev\_x\_F  
PetsPurchases  
Education\_catB  
AffluencePurchases  
headOfhouseholdGender\_lev\_x\_M  
LastContactMonth\_lev\_x\_may  
CarLoan  
Marital\_lev\_x\_married  
Marital\_catP  
Marital\_catB  
LastContactMonth\_lev\_x\_apr  
Education\_lev\_x\_secondary

moreTreeFit



# Your Top Prospective Customers

Our model finds these 100 prospects most likely to accept the offer.

```
> top100 <- head(successclasses, 100)
> top100
[1] "HH7f6d4585ad" "HHdb87dc6e7a" "HH43c8759373" "HH1a33226c3d" "HH5ed73b551f" "HHc47c129a68"
[7] "HH27aa9c576a" "HH24950c7841" "HH6edbc8212a" "HH446184e6cf" "HH7e5d9ebe4d" "HH7057883c68"
[13] "HH43154ad8fd" "HH0793198f3e" "HH7f0f16440c" "HH09cdde08cf" "HHf1eed2cadb" "HH723000ae17"
[19] "HH59847f671d" "HHe787f56b64" "HHf0b25e587f" "HH3fb640624" "HHf134d2ac30" "HHa790aa13fe"
[25] "HH07d8cade5d" "HHe8c454dfab" "HH161bc4c4c0" "HHad613bc2eb" "HHccc4bcb00c" "HHc78254e402"
[31] "HHfbaf4748cd" "HHd5915c4d00" "HHe5252221ce" "HHa069b24baa" "HH38b558270f" "HHad9f6632a3"
[37] "HH4f58ca91f4" "HH566a73acc0" "HH6c08f5b786" "HH6a5835f323" "HH2f94c20bf2" "HHccb6c83f3d"
[43] "HH5a97ec205d" "HHf70acd4c5e" "HH7b64e60645" "HHc9b1d48c10" "HHdd7ab8dc96" "HHdde8e2bbbd"
[49] "HH205b964fef" "HH6bc5e432d5" "HH7ada840fcc" "HHc7707daa69" "HH49df785161" "HHd60991b43c"
[55] "HHee3f05a8af" "HH8e3c45eb7e" "HH621e6c0fdb" "HH1e772cc201" "HH7b3f008f2f" "HH69d287d315"
[61] "HHa3aa29b7f2" "HH138070ca75" "HHcd2530dc33" "HHcb19d64c50" "HH5fbe40c17c" "HH84f50a3671"
[67] "HH314fde17b5" "HH840291d606" "HH67cc96e24f" "HH3ec7dbbe37" "HH1d05a7ffb3" "HH59b703c8ce"
[73] "HH9f3f799917" "HH714f3c26a2" "HH32827939bb" "HH6d48cca377" "HH971108bf95" "HH18cd0c68fd"
[79] "HHc5c1770498" "HH495acba15a" "HHad15a796e1" "HHebaa51c47f" "HHc2d068f82f" "HHb395536c6c"
[85] "HHa1727a4bf4" "HH09a83de3b5" "HHaa66459333" "HHc2ebfbbe83" "HH8cacb60619" "HHe742e0f52c"
[91] "HH7beacbd3d2" "HHb2eec2c397" "HHca84cc79a6" "HH3ec1aac9f2" "HH22fd5cb8f6" "HH0e899bce96"
[97] "HH011ae3bd0a" "HH39b55ca312" "HHe6f4eedcd" "HH5d7fa4c802"
```

# Prospective Targets - Insights

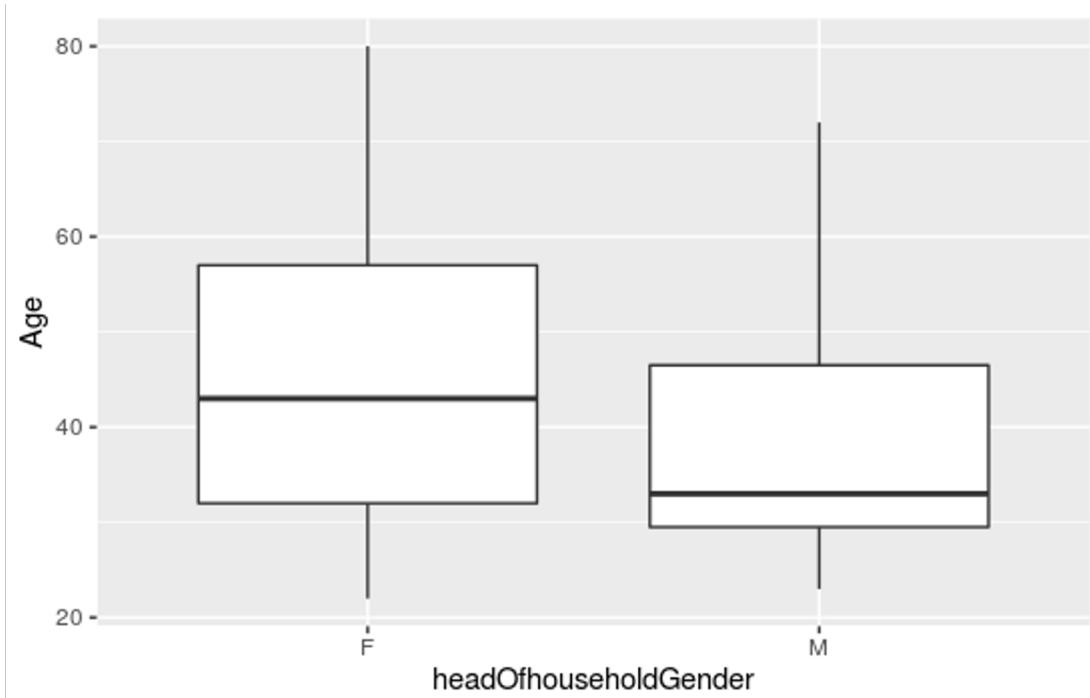
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# Your Top Prospective Customers

Median Age

F: 43

M: 33



# Your Top Prospective Customers

*Top prospective customers have **24% higher recent balances** than current customers who accepted the line of credit.*

```
joinData %>% group_by(Y_AcceptedOffer) %>%  
summarise(medianbalance = median(RecentBalance))
```

```
top100joined %>% group_by(headOfhouseholdGender) %>%  
summarise(medianbalance = median(RecentBalance))
```

Y\_AcceptedOffer medianbalance

<fct>

1 Accepted

<dbl>

700

headOfhouseholdGender medianbalance

<int>

916

2 DidNotAccept

457

1 F

926

2 M

# Conclusion

Your prospective customers can be targeted by many factors. They are:

- Are more likely to be female
  - Potential for campaigns targeting middle-aged females
- Are more likely to be married
  - Potential for marketing campaigns targeting married couples with recent model cars.
- More likely to have higher bank balances
  - Targeting wealthier individuals, who may be more familiar with lines of credit products.

