

# PREDICTING BANK CREDIT RATING

SATURN'S RINGMASTERS Consulting (Team 2)  
19 May 2023



# OUTLINE

- Introduction
- Data
- Methods
- Variable selection
- Results
- Limitations & suggestions
- Conclusion
- Questions

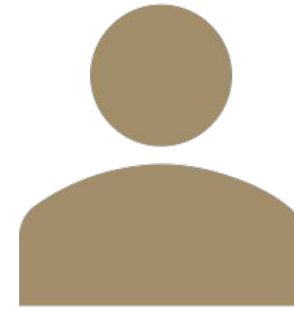




# OBJECTIVES



Effectiveness of the credit  
rating detection



Predict an individual's credit  
rating



# VARIABLES

- **AGE:** age in years

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- **INCOME:** annual income (in dollars)

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- **GENDER:** gender ('female' or 'male')

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- **MARITAL:** marital status ('single', 'married' or 'divsepwid')

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- **NUMKIDS:** number of kids

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- **NUMCARDS:** number of cards

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- **HOWPAID:** how paid ('monthly' or 'quarterly')

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- **MORTGAGE:** mortgage ('yes' or 'no')

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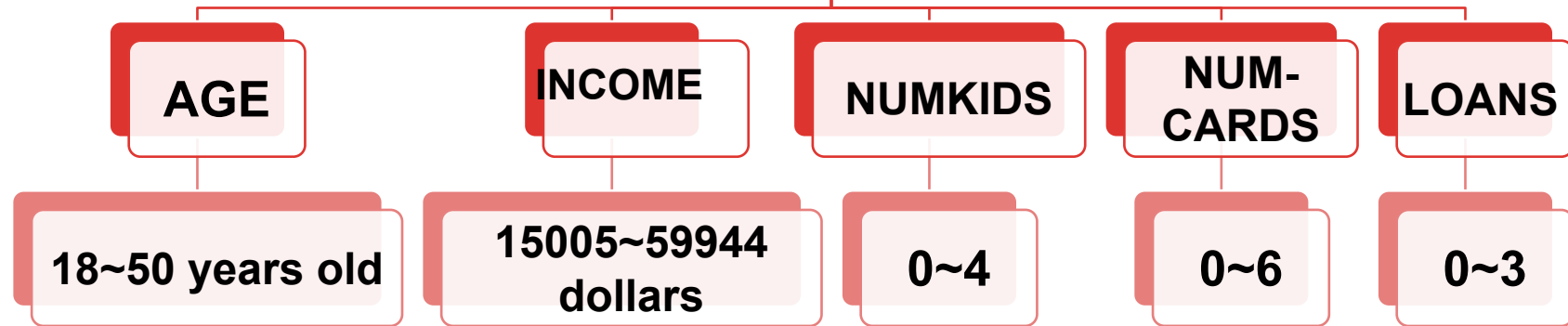
- **LOANS:** number of existing loans



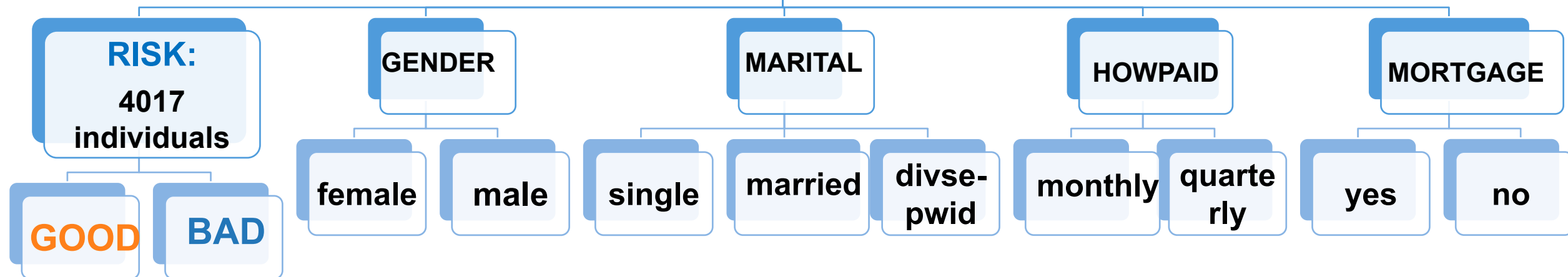
# DATA SETS

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## Numerical



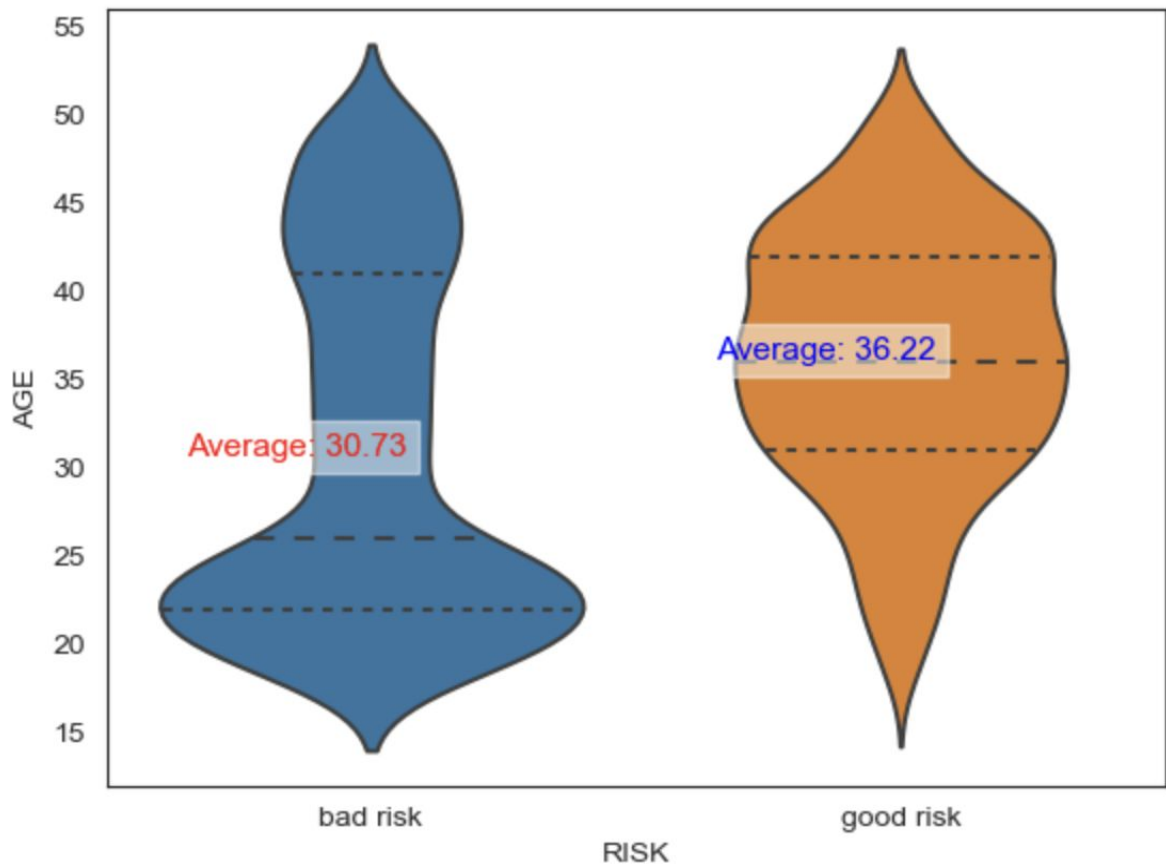
## Categorical



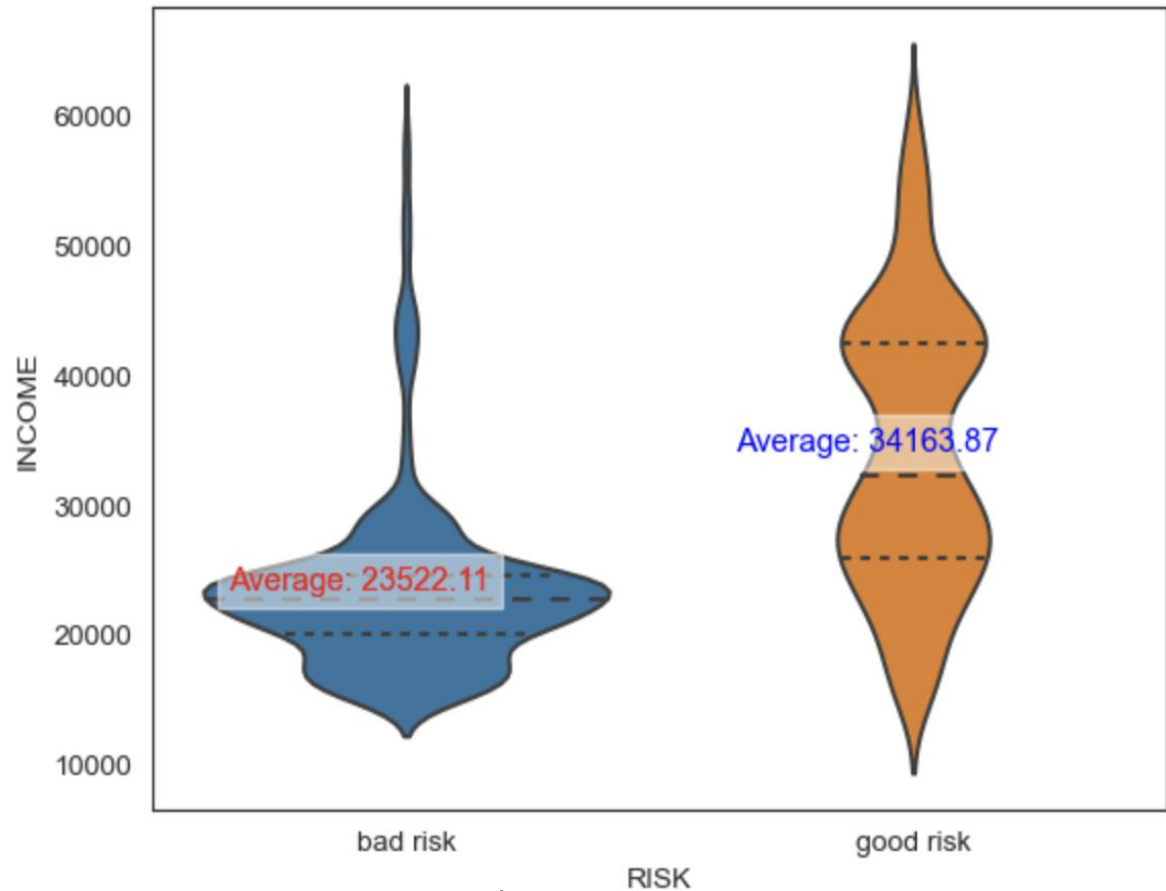
# AGE AND INCOME

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AGE V.S RISK



INCOME V.S RISK



**AGE** in years

**Bad risk:** 20~30

**Good risk:** 35~40

**INCOME** in \$

**Bad risk:**  
20000 to 25000

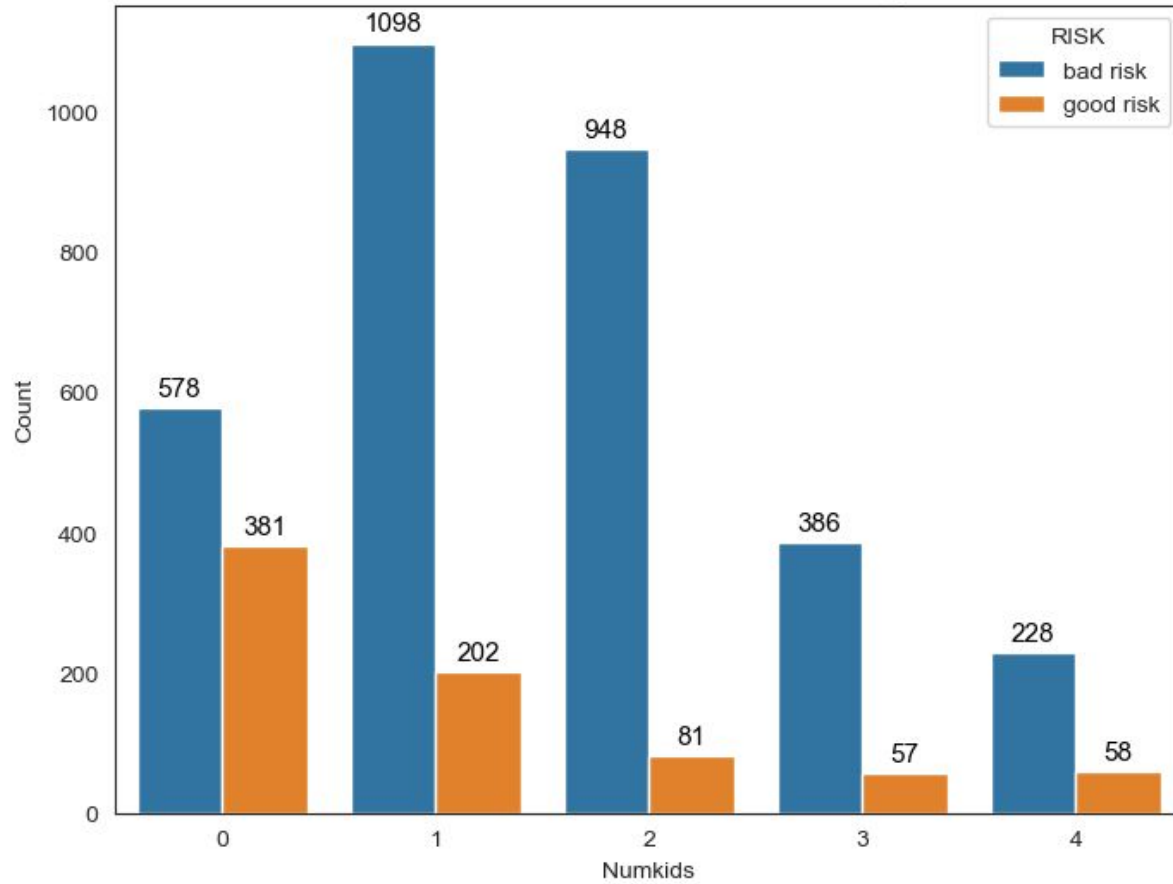
**Good risk:**  
25000~30000  
or 40000~45000



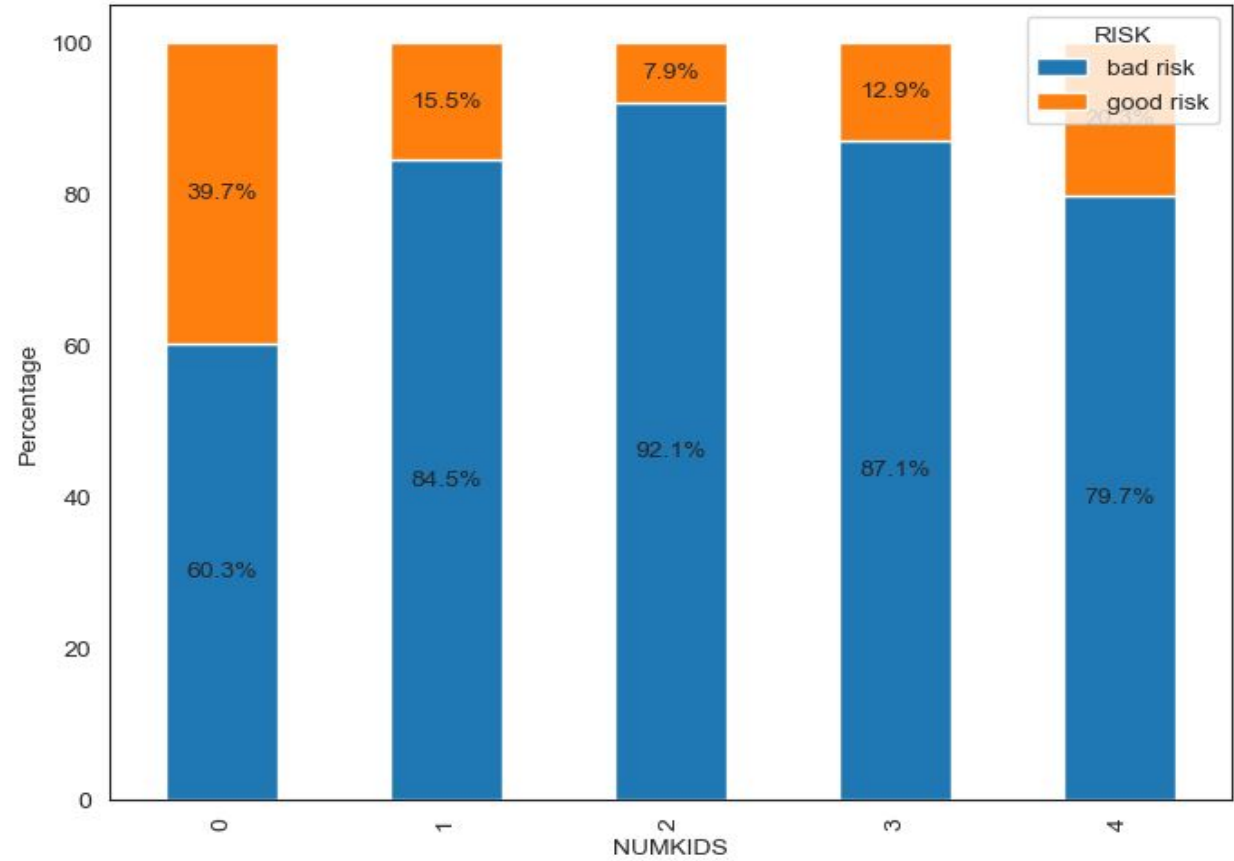
# NUMBER OF KIDS

7

Distribution of Numkids within Risk Groups

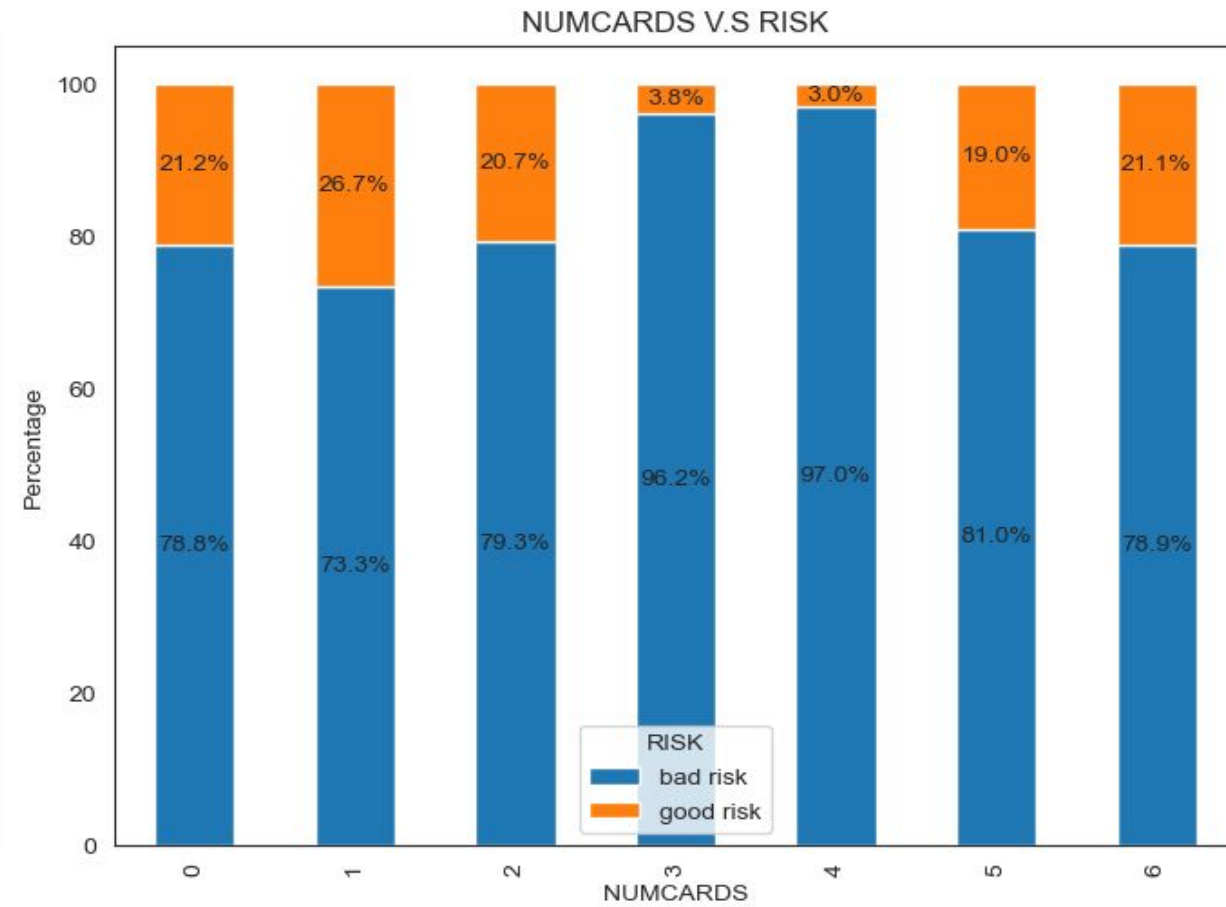
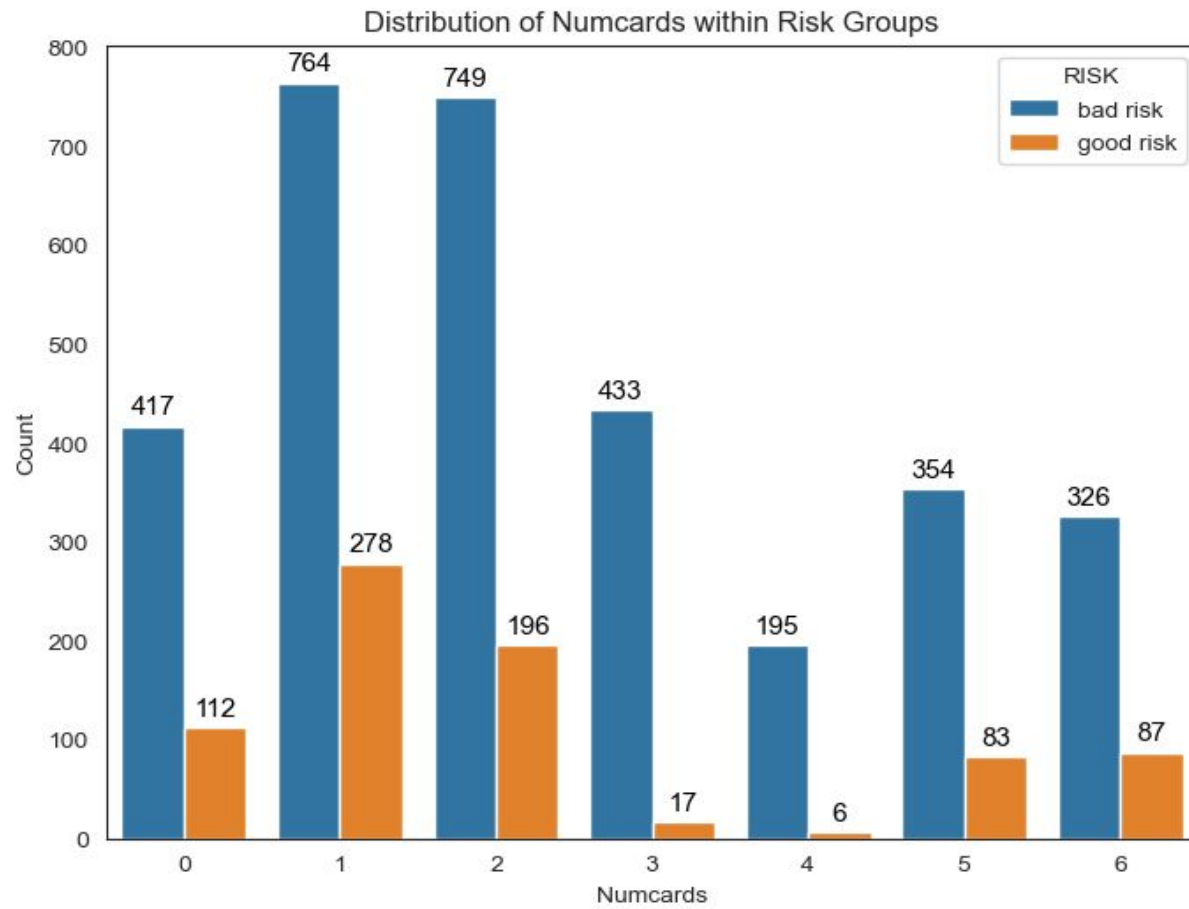


NUMKIDS V.S RISK



# NUMBER OF CARDS

8

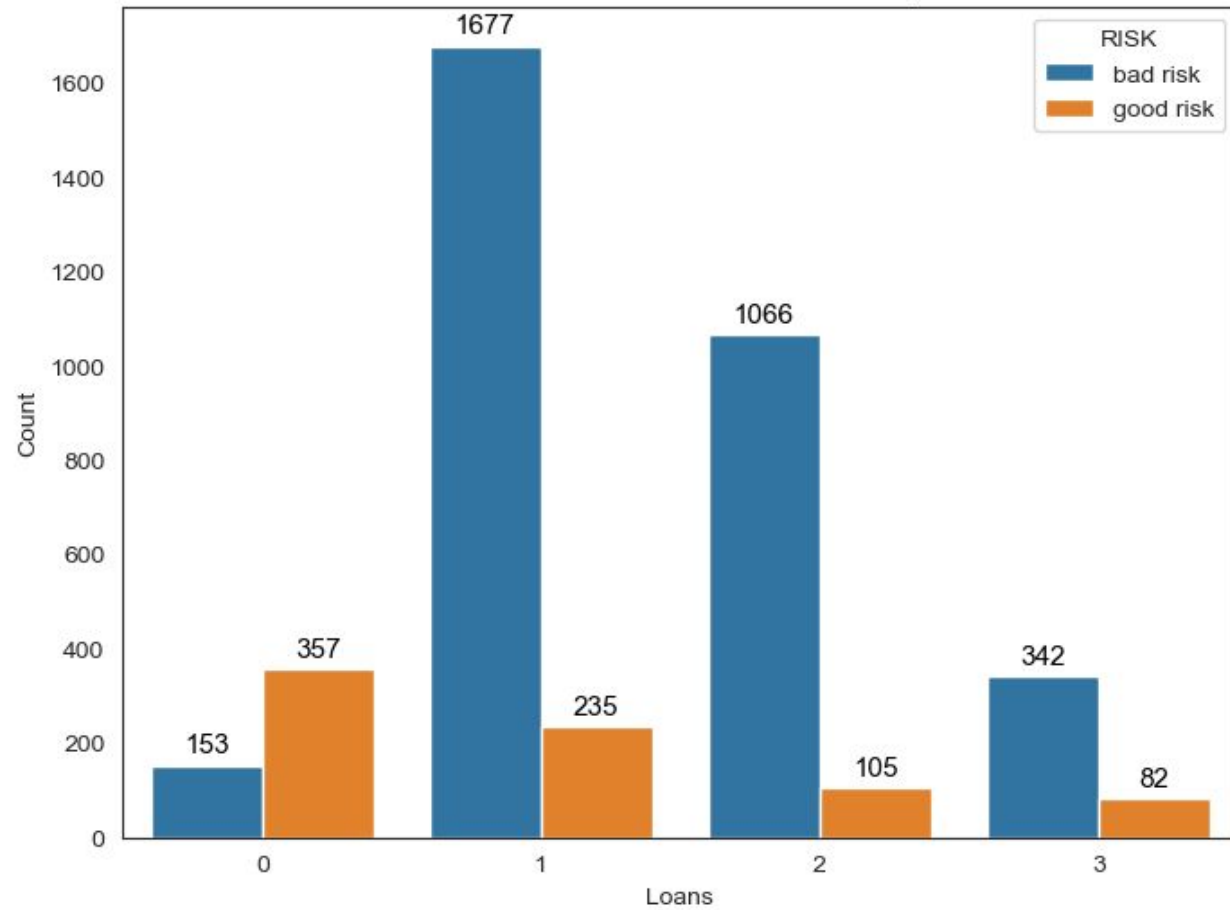




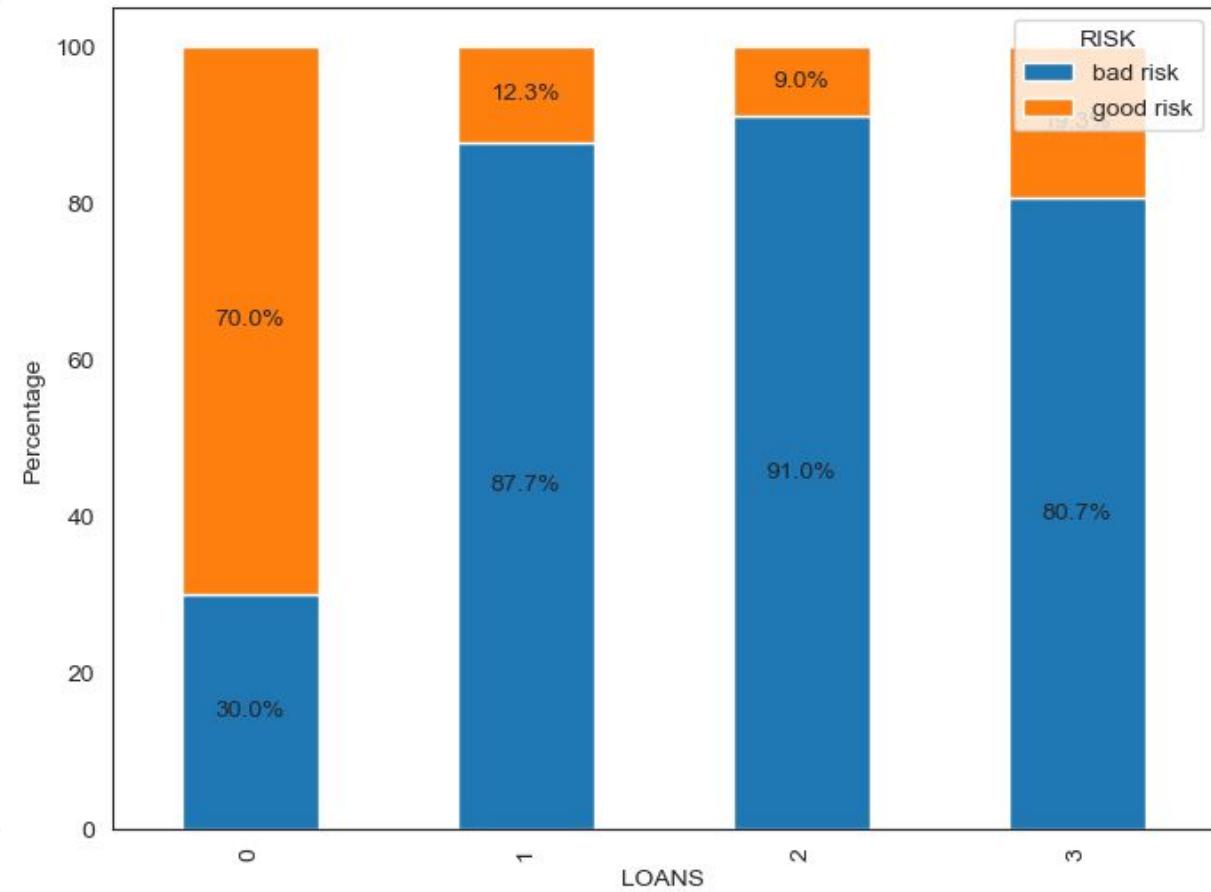
# NUMBER OF EXISTING LOANS

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Distribution of Loans within Risk Groups



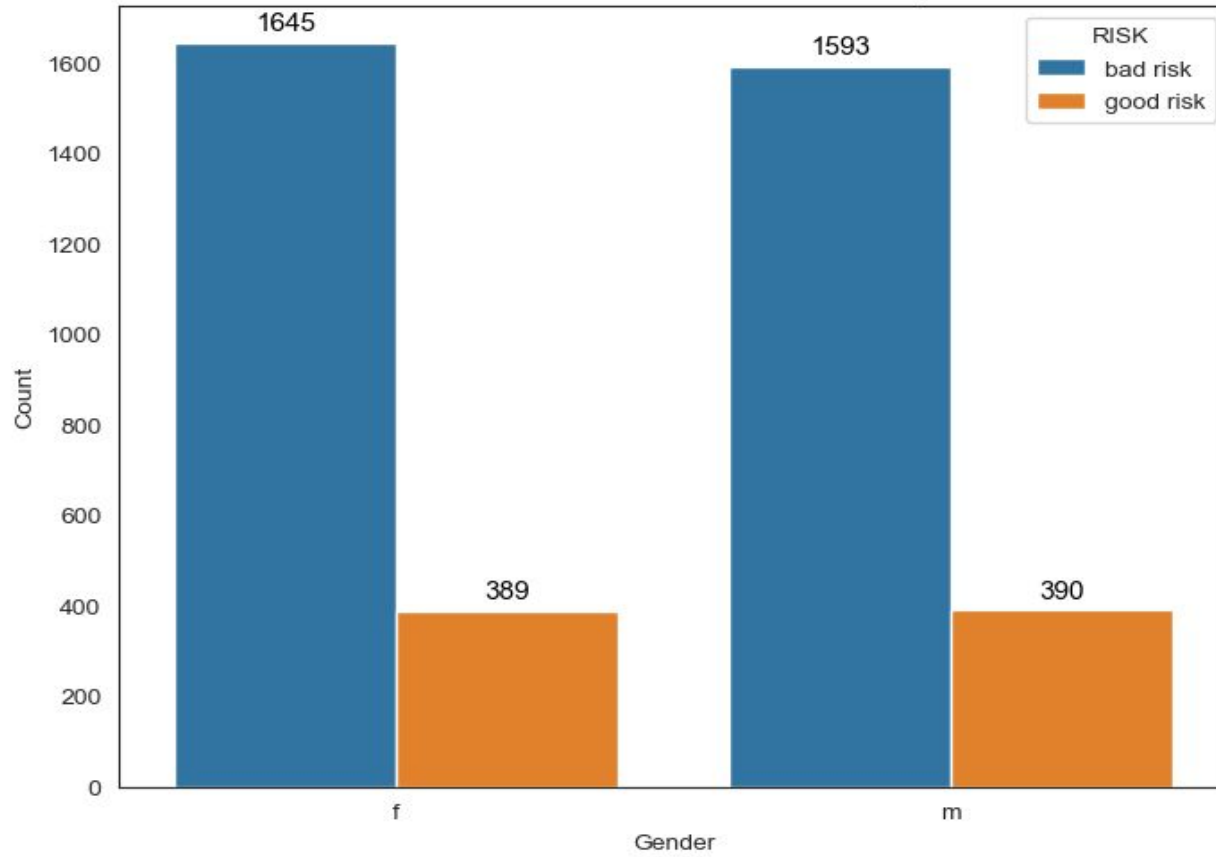
LOANS V.S RISK



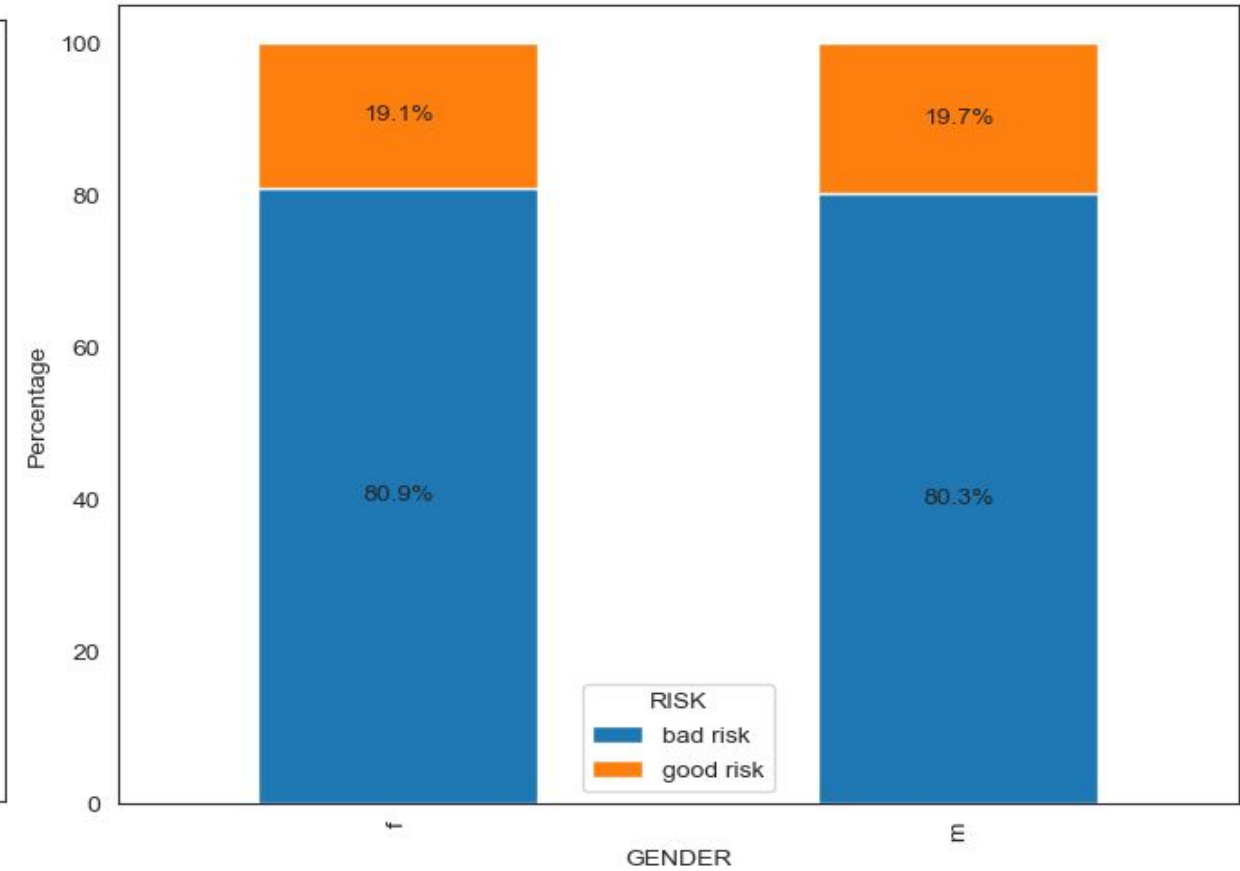
# GENDER

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Distribution of Gender within Risk Groups



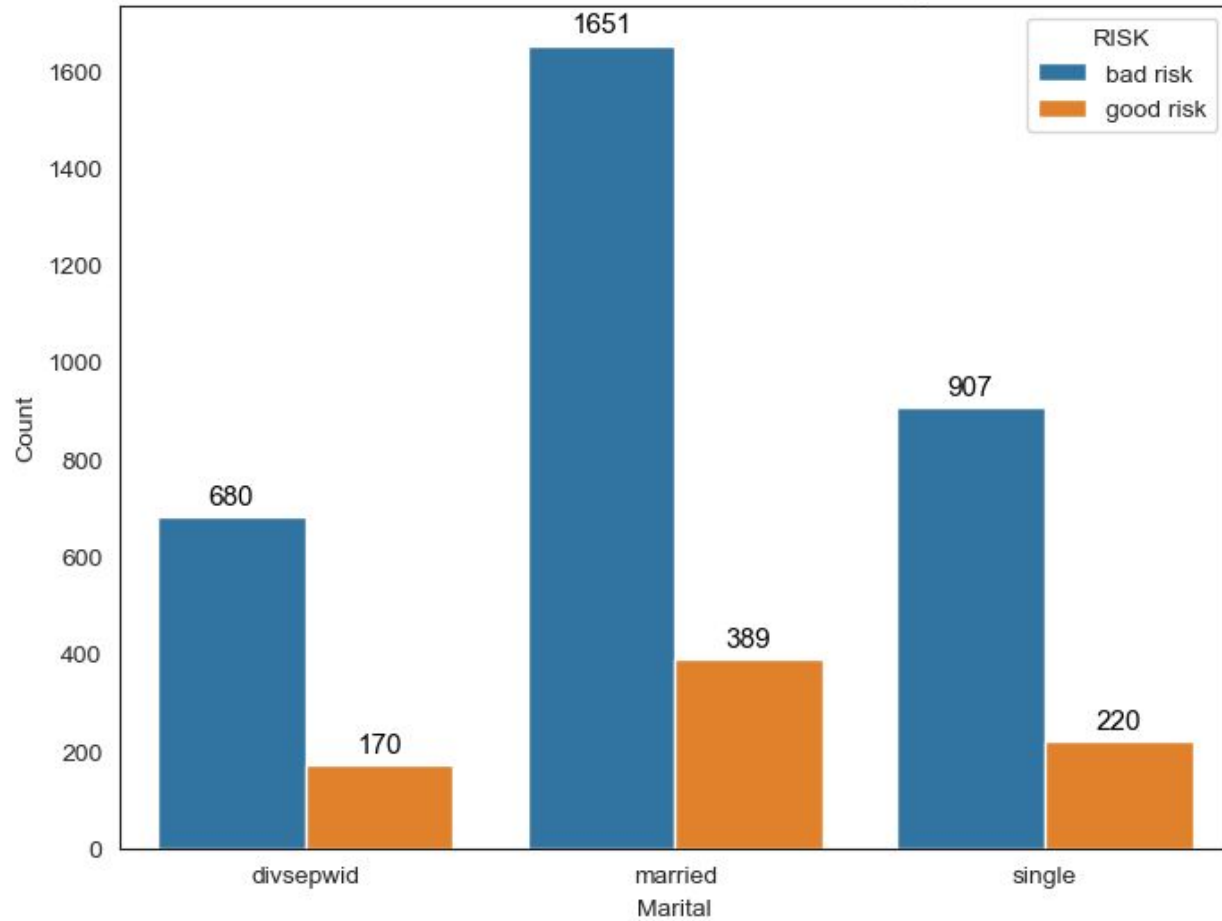
GENDER V.S RISK



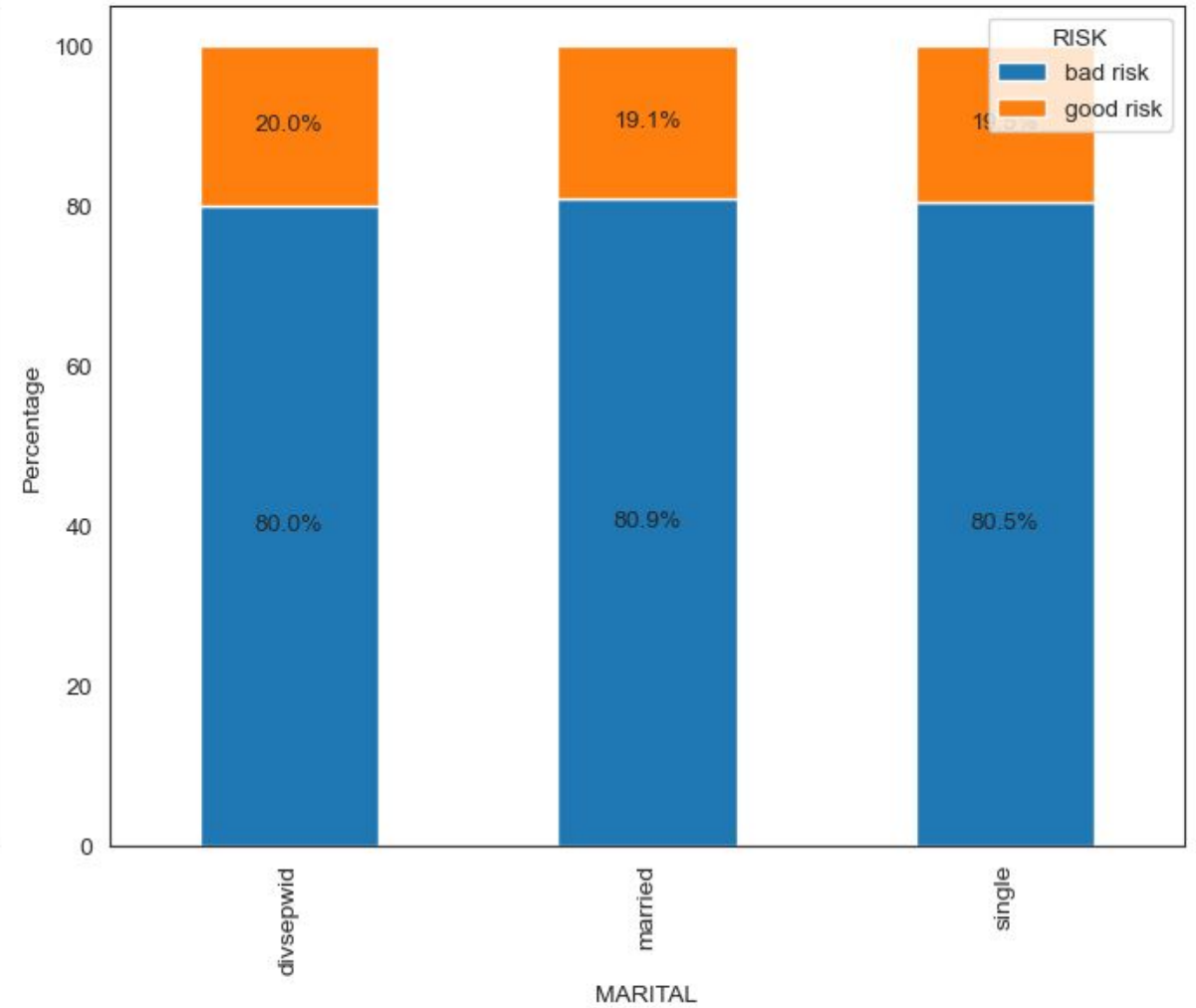
# MARITAL STATUS

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Distribution of Marital within Risk Groups



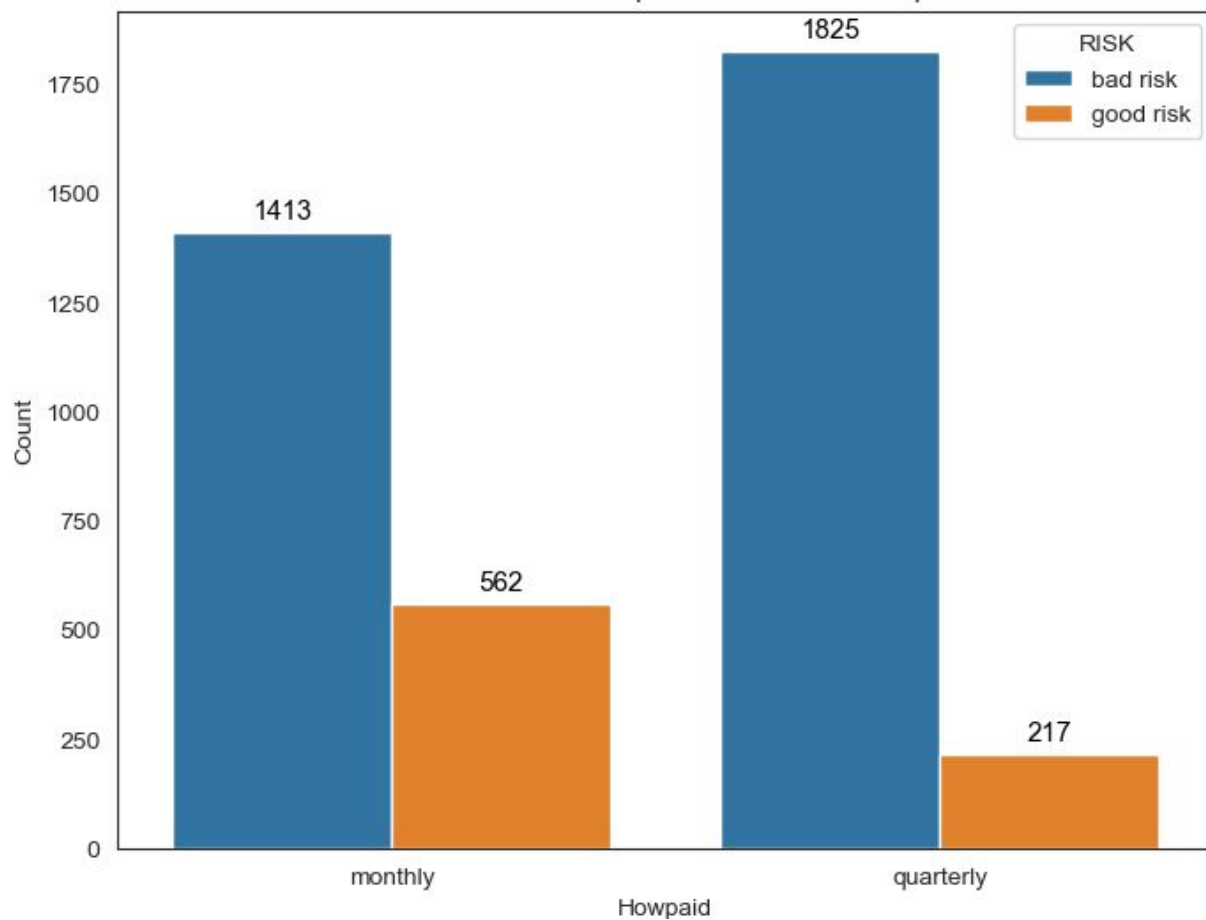
MARITAL V.S RISK



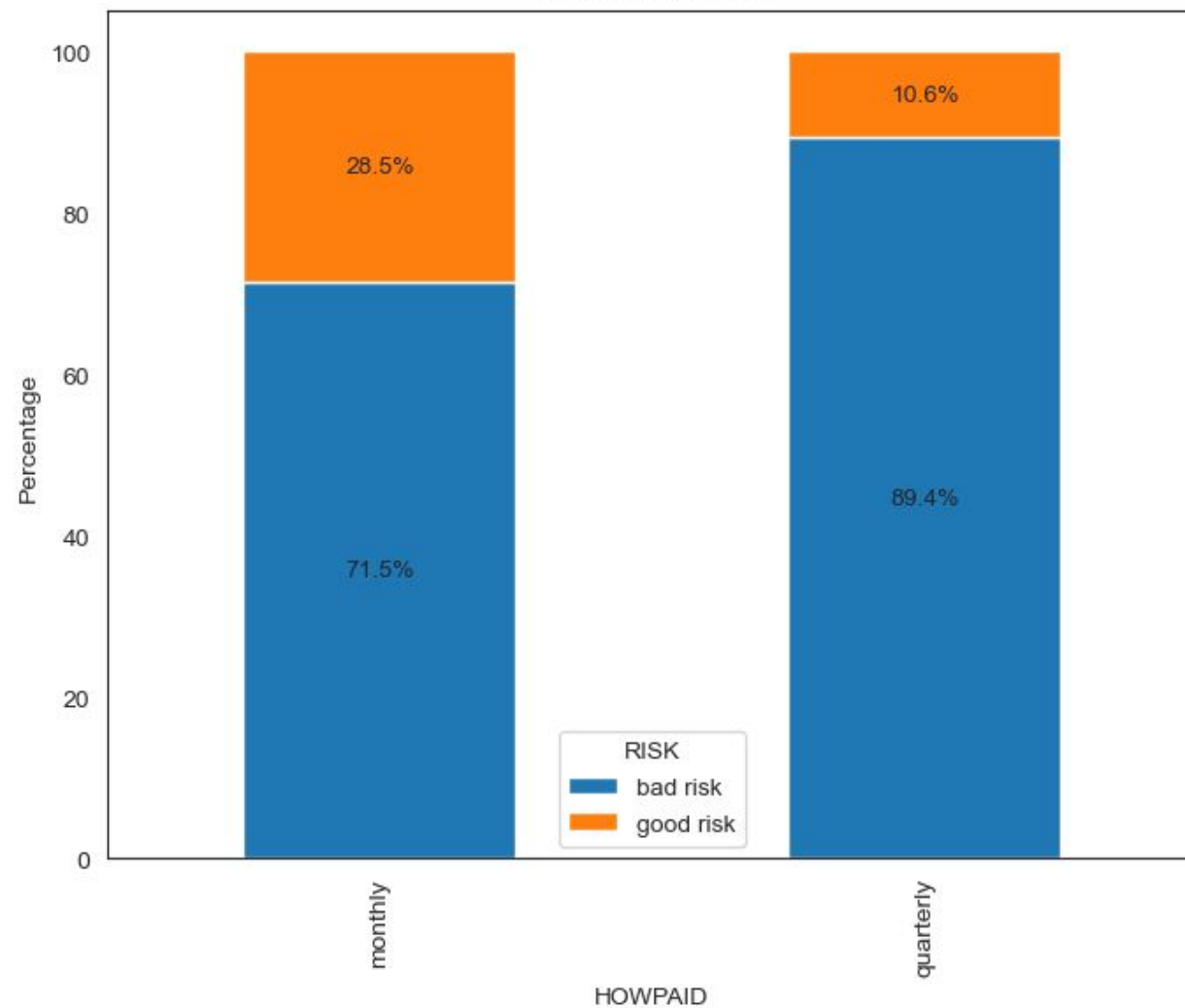
# HOW PAID

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Distribution of Howpaid within Risk Groups



HOWPAID V.S RISK

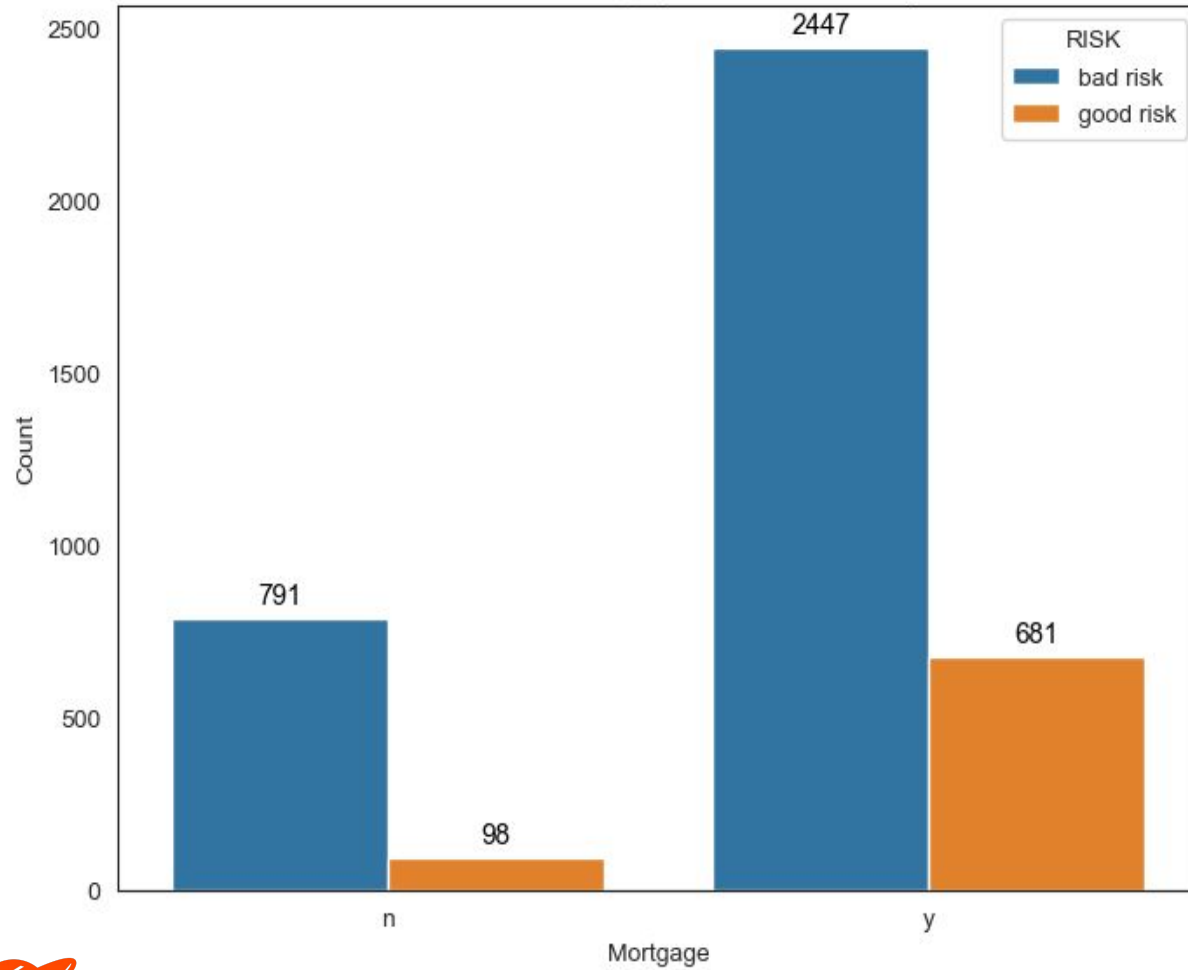




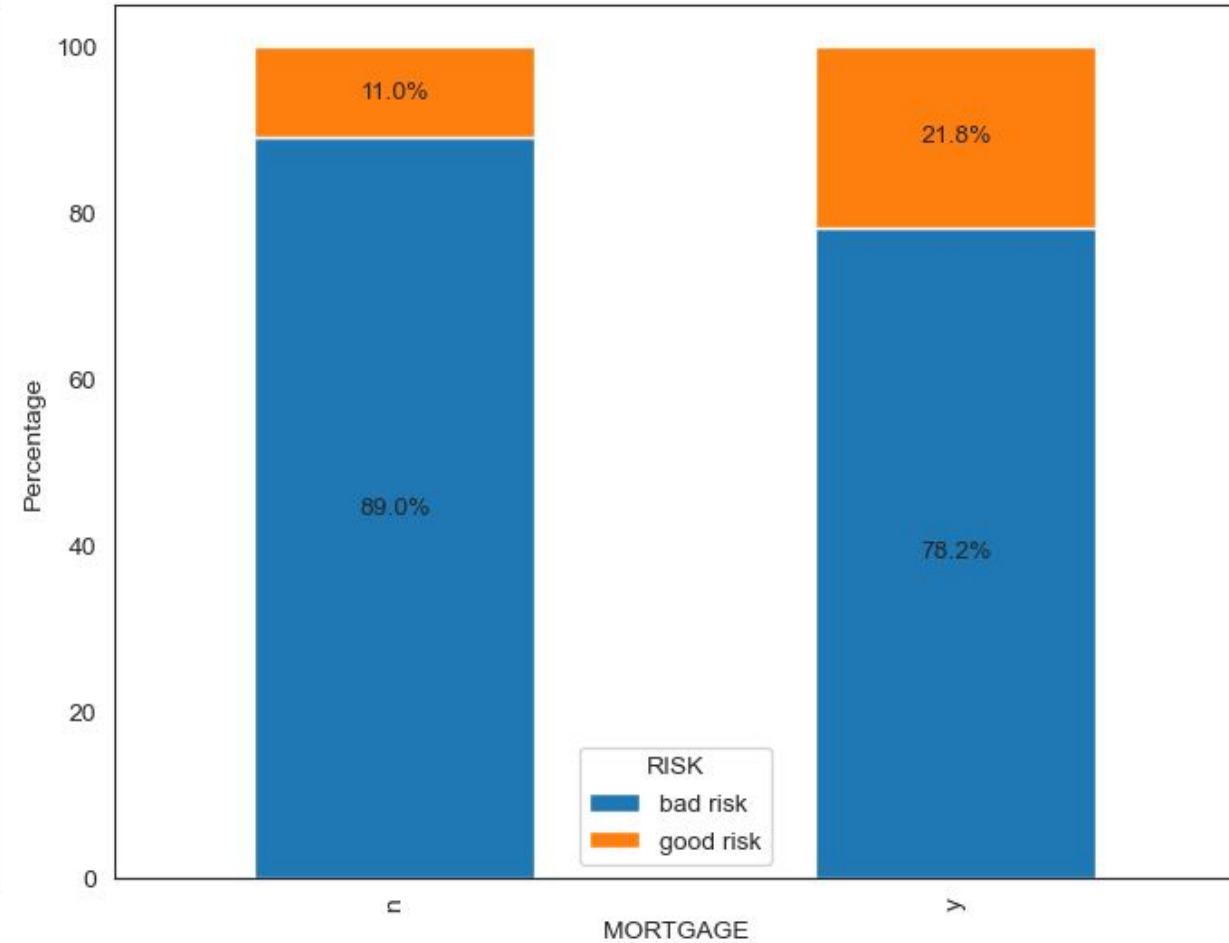
# MORTGAGE

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Distribution of Mortgage within Risk Groups

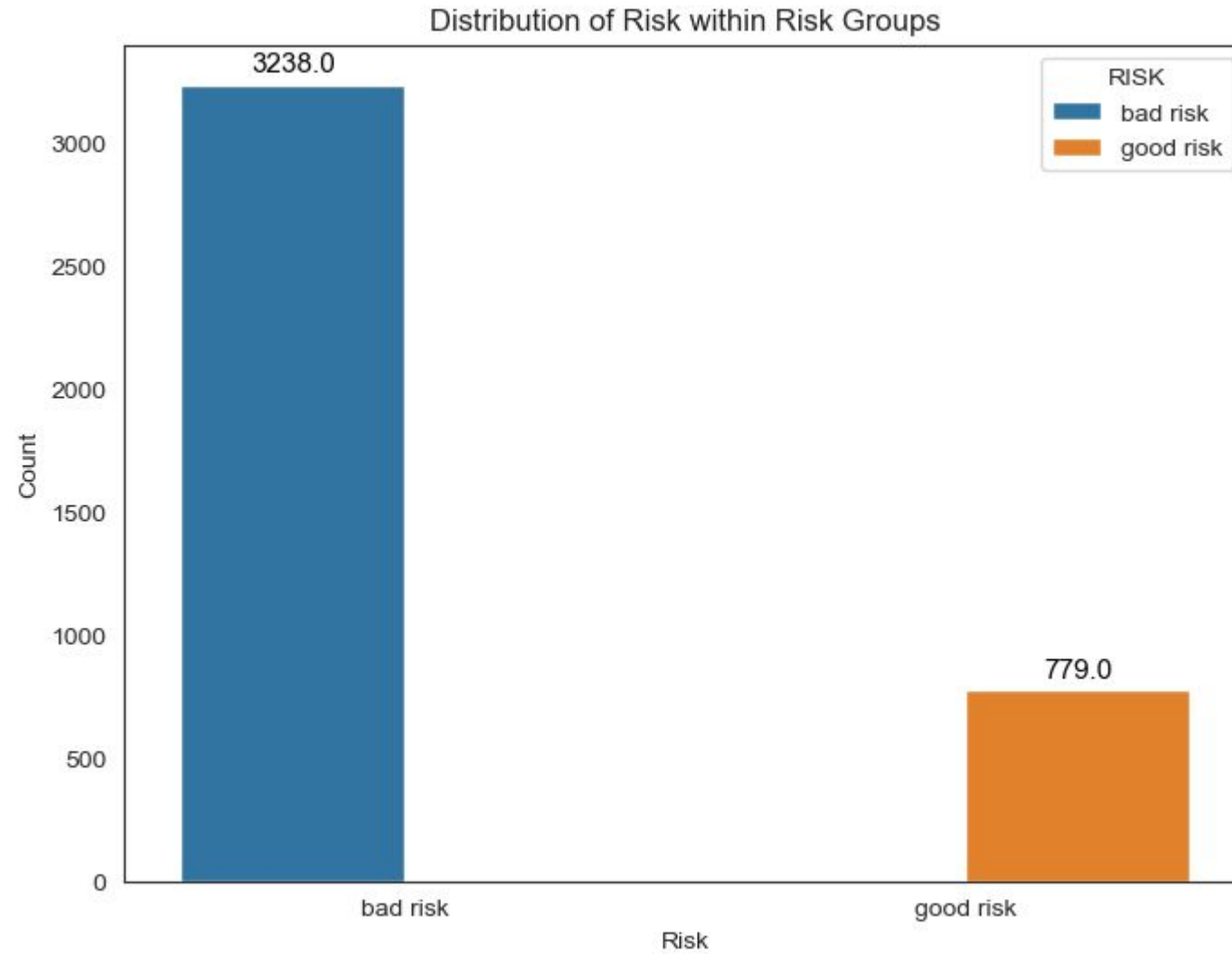


MORTGAGE V.S RISK



# OUTCOME VARIABLE

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# FIRST METHOD



# METHOD 1: DECISION TREE



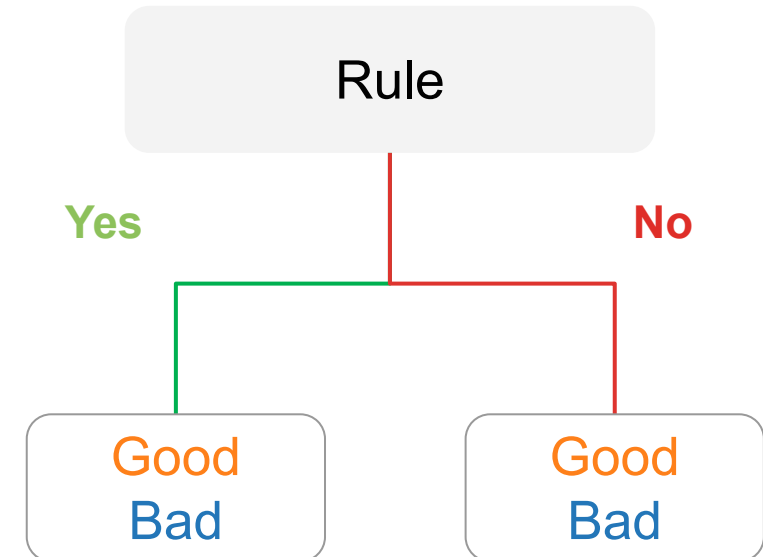
***Make predictions based on how a previous set of questions were answered.***

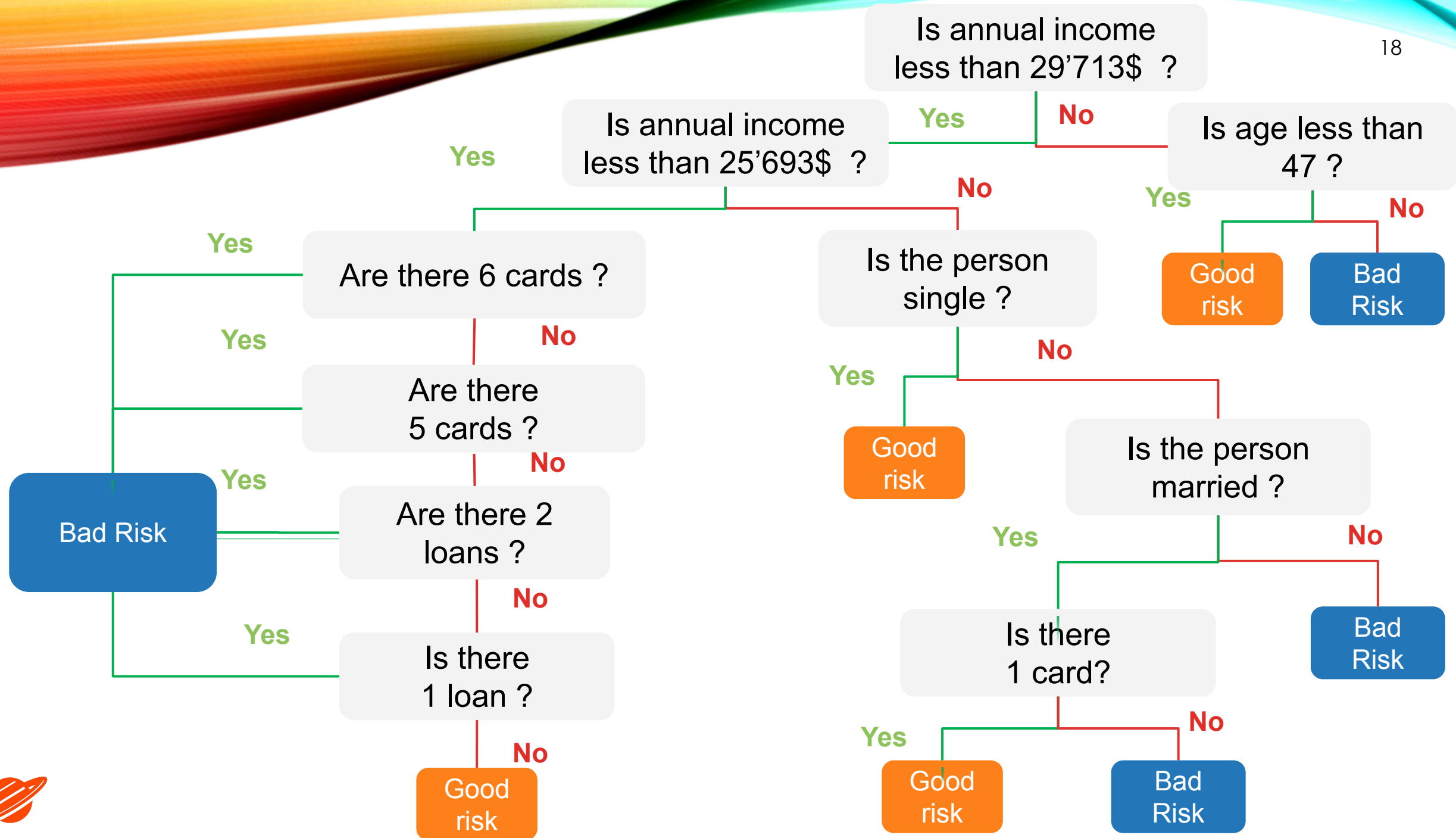


# METHOD 1: DECISION TREE



Example:





# METHOD 1: DECISION TREE

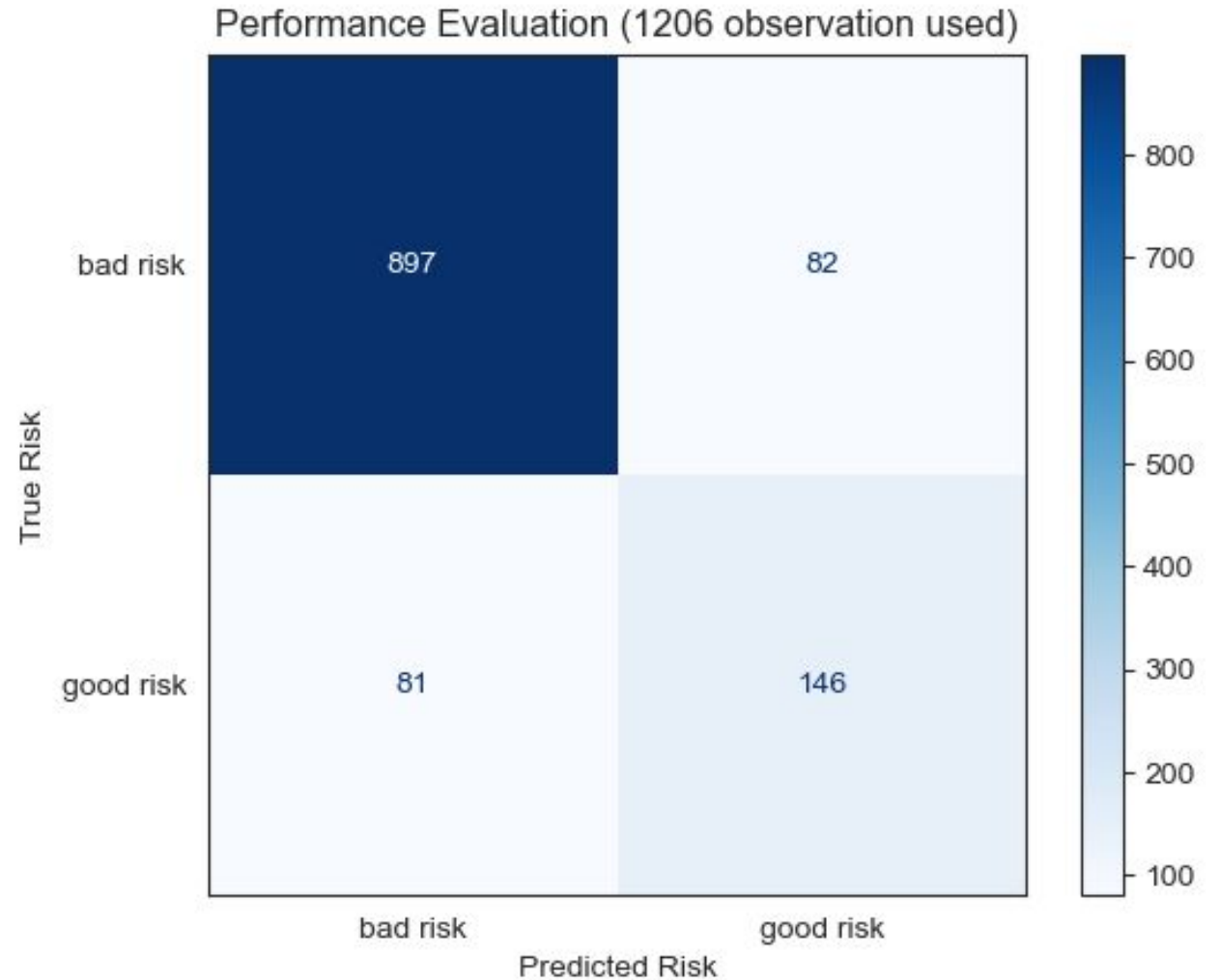
## Performance evaluation

For ***bad risk*** category:

- high accuracy
- low misjudgement

For ***good risk*** category:

- high accuracy
- some misclassification





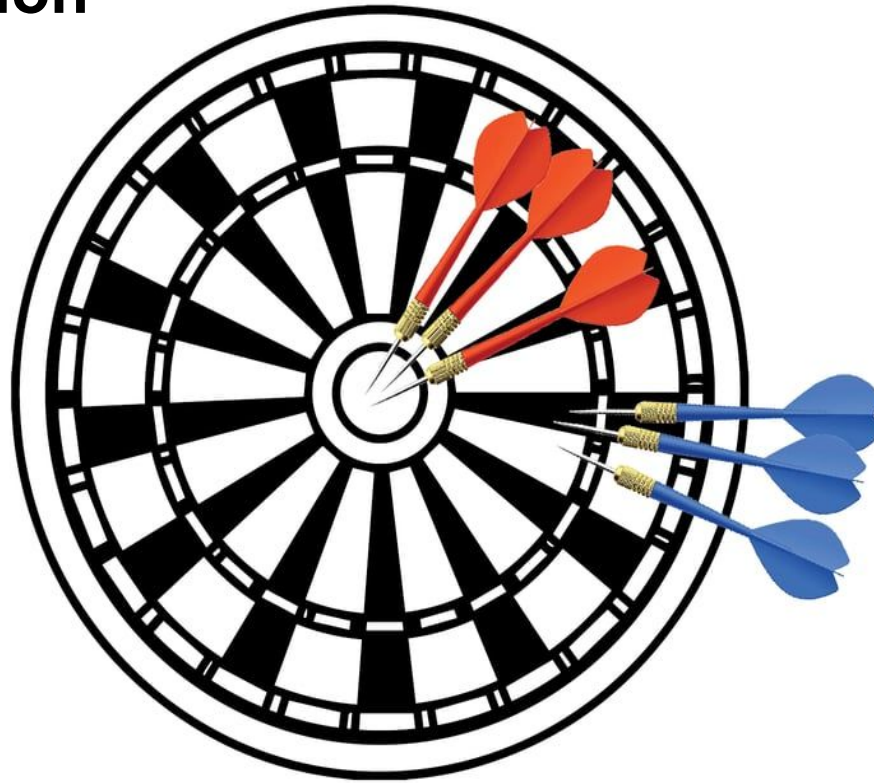
# METHOD 1: DECISION TREE

## Accuracy vs. Precision

Assume the objective is to hit the bullseye.

The **blue** dart is **precise**, but not **accurate**.

The **red** dart is both **precise** and **accurate**



**Overall Accuracy: 86%**

**Precision:**

Bad risk: 92%

Good risk: 64%





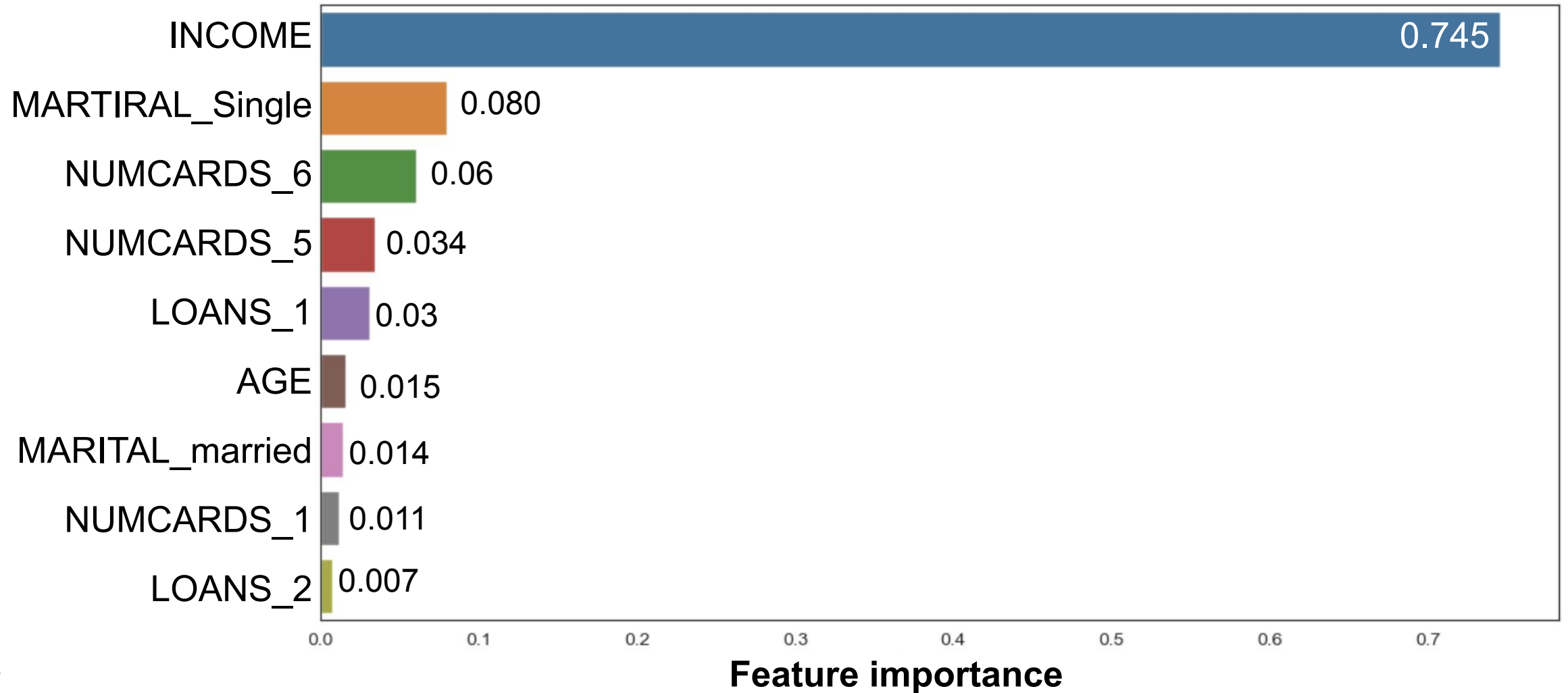
# METHOD 1: DECISION TREE

WHY?

Due to a class imbalance in the data  
there are more *bad risk* 3238 than *good risk* 779



# METHOD 1: DECISION TREE





Is there room for improvement ?



# MODEL IMPROVEMENT





# METHOD 2: BOOSTED DECISION TREE

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***Creating series of trees,  
where each tree is built to  
improve the mistakes of the  
previous tree.***

# METHOD 2: BOOSTED DECISION TREE

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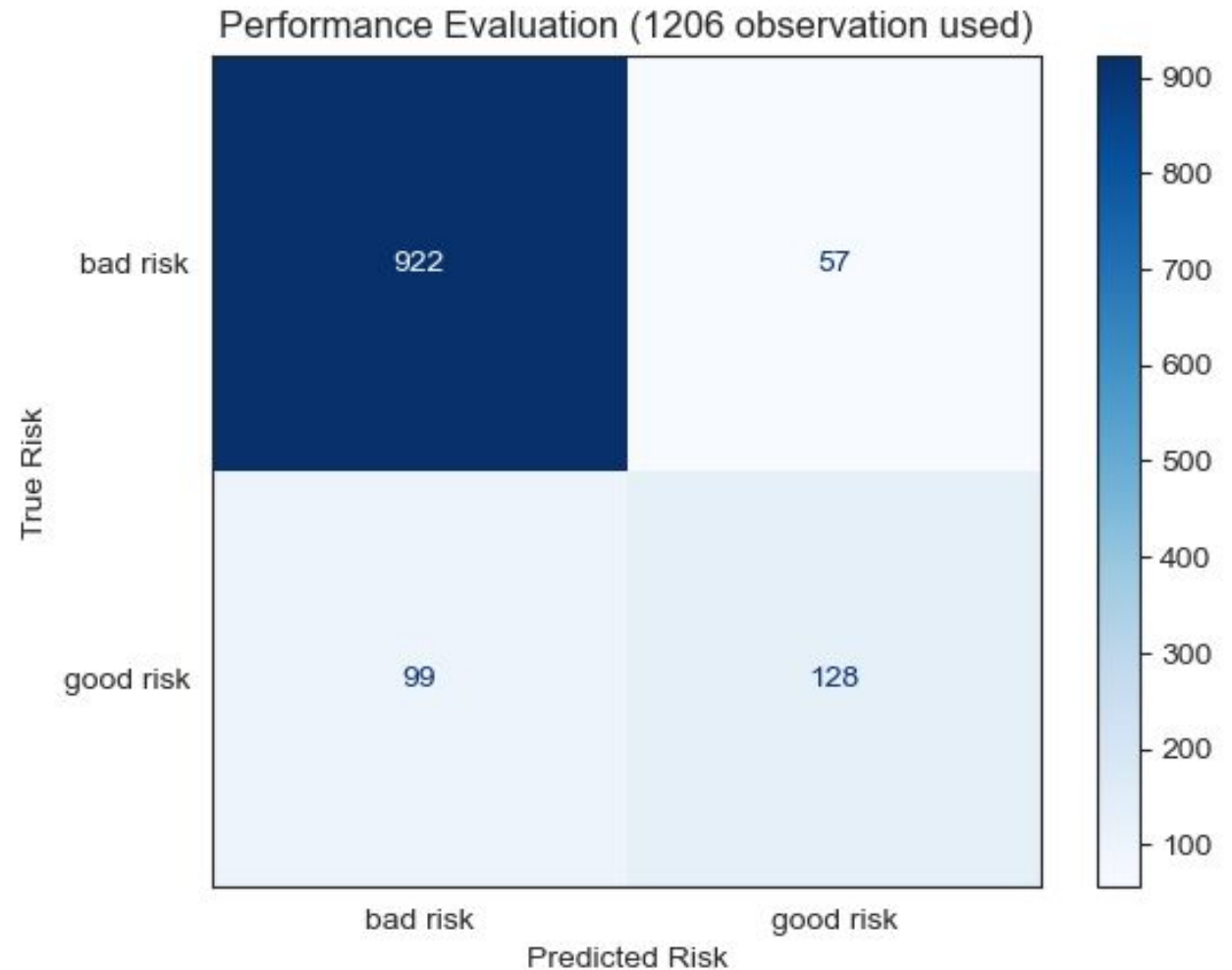
## Performance evaluation

For **bad risk** category:

- Small decrease in precision
- Still very good performances

For **good risk** category:

- Improved performances



# METHOD 2: BOOSTED DECISION TREE

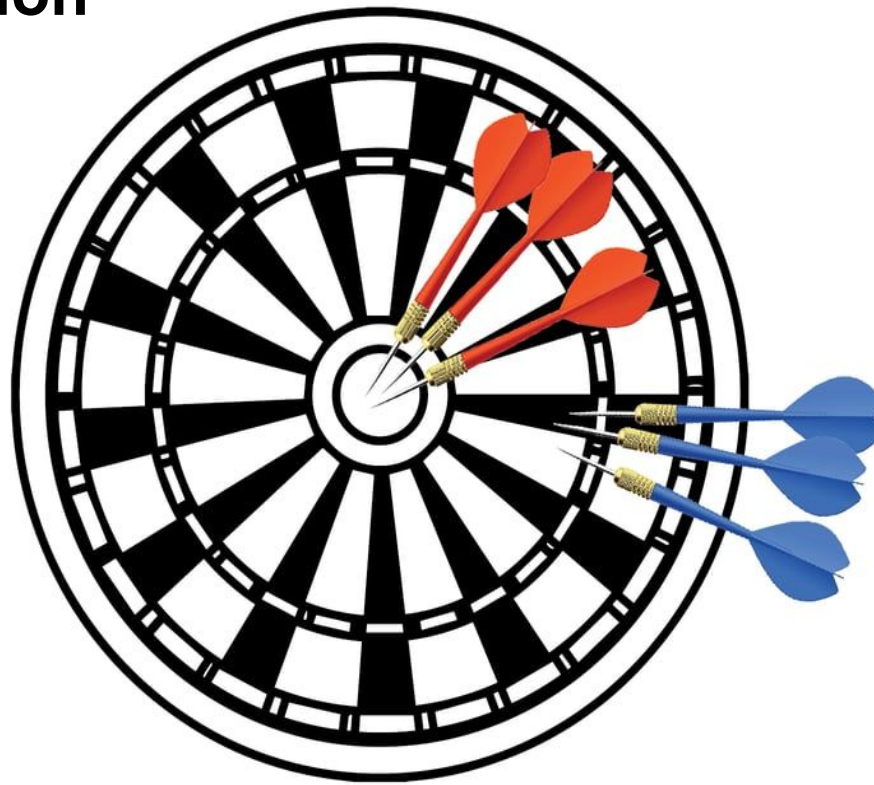
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## Accuracy vs. Precision

Assume the objective is to hit the bullseye.

The **blue** dart is **precise**, but not **accurate**.

The **red** dart is both **precise** and **accurate**



**Overall Accuracy: 87%**

**Precision:**

Bad risk: 90%

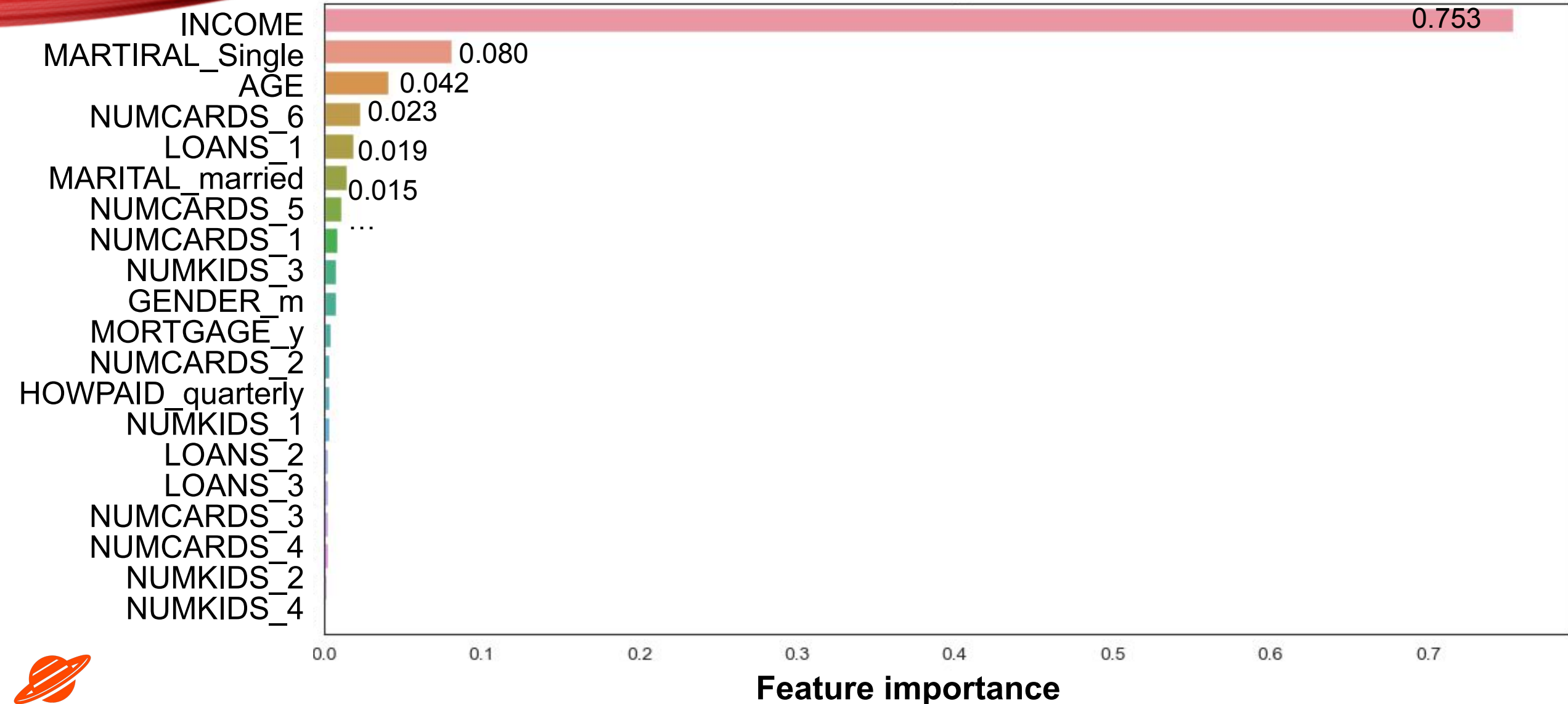
Good risk: 69%





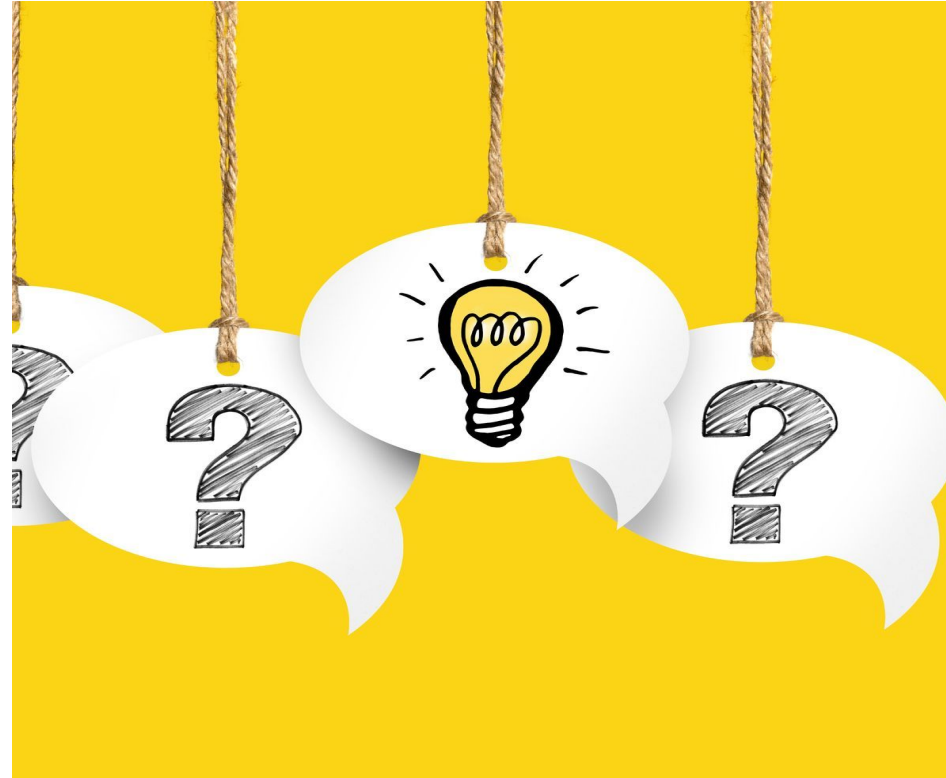
# METHOD 2: BOOSTED DECISION TREE

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# RESULTS



Which model should we use ?



# RESULTS

- Decision Tree Model if we are interested in predicting the bad risks.
- Boosting Model if we interested in predicting the good risks  
(**with reservations** )



# RESULTS

## Effectiveness of the credit rating detection:

- Performed **well** in the **bad risk** category, with **high precision**.
- Performed **poorly** in the **good risk** category, with relatively **low precision**.

## Decision rules:

- It should include variables related to: *Income; Age; Marital status; Loans; Cards*



# LIMITATIONS

- The sample of customers in the *good risk* category was small which lead to bias the model towards predicting the majority class (*bad risk*).
- Sample collection method
- Is the sample representative of the true population (the bank)?
- The feature selections
- Economic conditions





# SUGGESTIONS

- Increase the sample data
- Introduce more features
- Consult our team for your next data collection

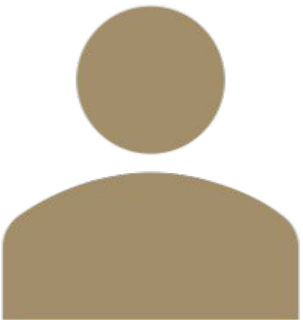


# CONCLUSION



## **Effectiveness of the credit rating detection:**

We focused on bad risk customers and we are able to detect credit rating: precision 92%

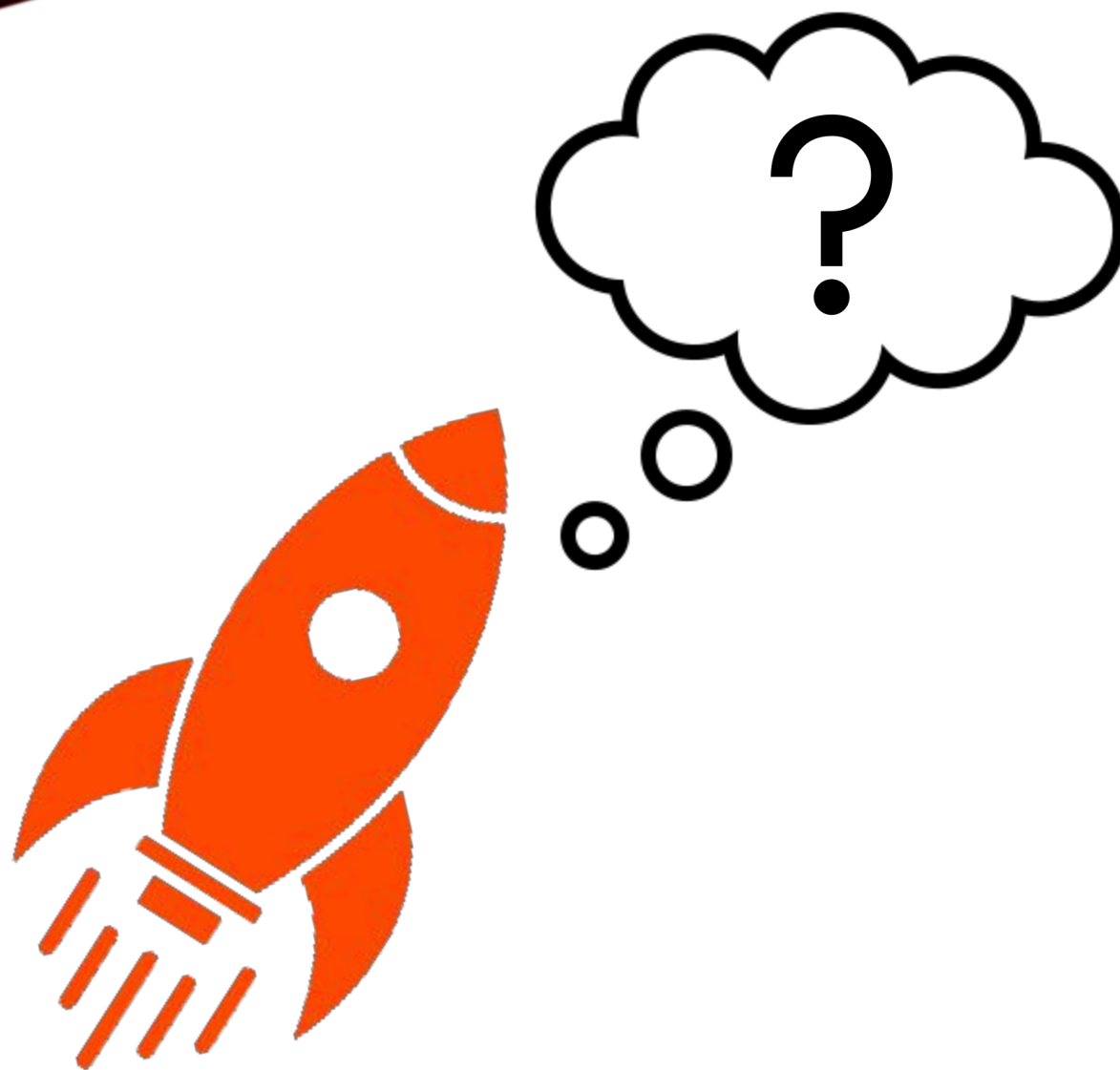


## **Predicting credit rating:**

We rely essentially on:

- I. Income
- II. Number of cards
- III. Marital status
- IV. Loan
- V. Age







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