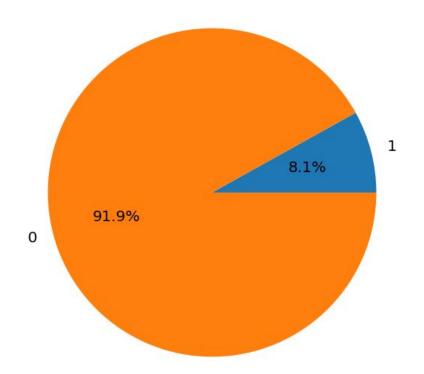
# **Credit Risk Profiling**

**June 2020** 

#### Introduction

- A consumer finance company that specialises in lending various types of loans is trying to identify the applicants that are capable of repaying the loan
- Two types of risks are associated with the lender's decision to approve/reject an applicant:
  - If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company
  - If the applicant is not likely to repay the loan, i.e. they are likely to default, then approving the loan may lead to a financial loss for the company
- The company wants to understand the driving factors behind loan default, i.e. the variables which are strong indicators of default
- They plan to utilise this knowledge for their portfolio and risk assessment
- This analysis identifies a few such factors and provides recommendations on how to identify applicants likely to default on their loans

### **Target Variable**



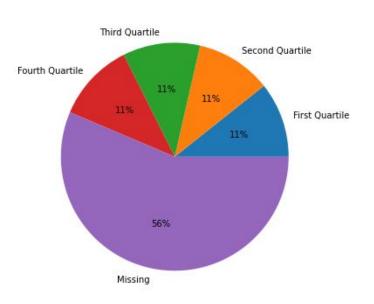
The pie chart on the left shows the imbalance between the values of the Target variable. The data comprises of 8.1% "risky" applicants.

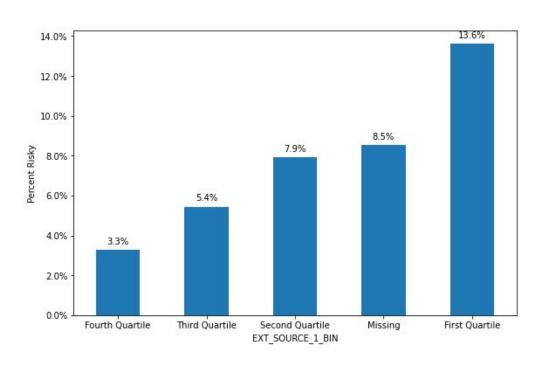
**1** - Clients with payment difficulties: they had late payments more than "X" days on at least one of the first "Y" installments of the loan in our sample

#### **0** - All other cases

In the next few slides, we will discuss the influence of a variety of features on this target. We will also provide recommendations on how to identifying risky applicants.

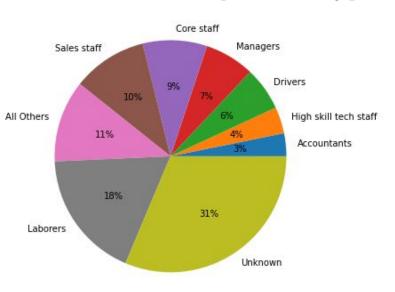
#### **External Data Source 1 Score**

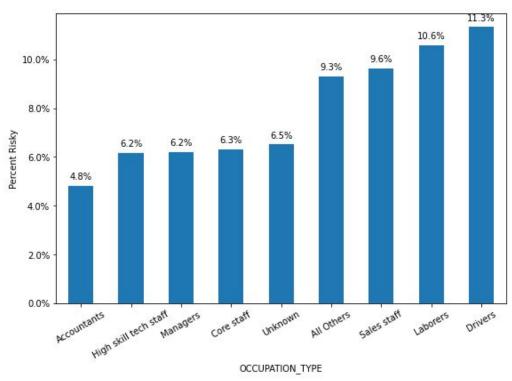




The riskiest segment under "EXT\_SOURCE\_1\_BIN" is "First Quartile" whereas the least risky is "Fourth Quartile". This is a binned variable (into four equal quartiles and one bin for "missings") from "EXT\_SOURCE\_1" variable.

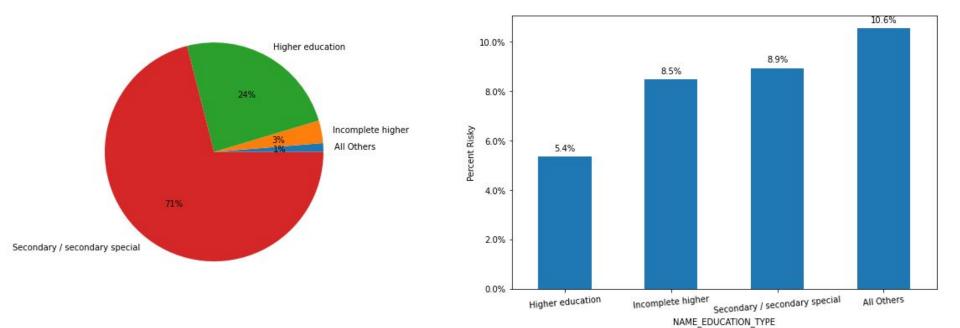
### **Client's Occupation Type**





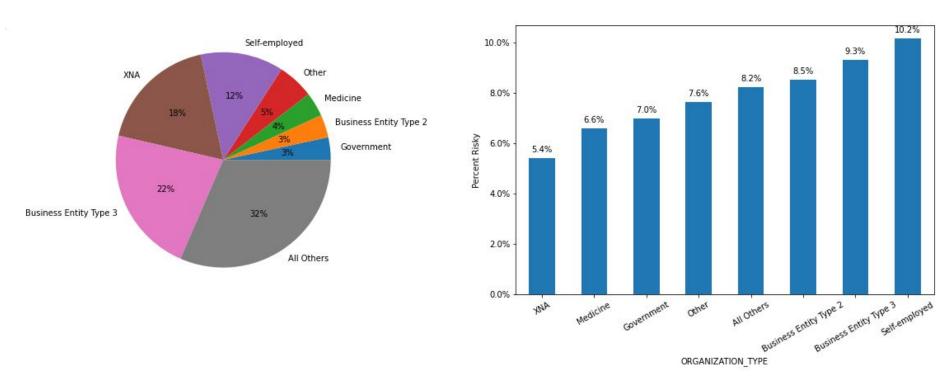
The riskiest segment under "OCCUPATION\_TYPE" (client's occupation type) is "Drivers" whereas the least risky is "Accountants"

# **Client's Education Type**



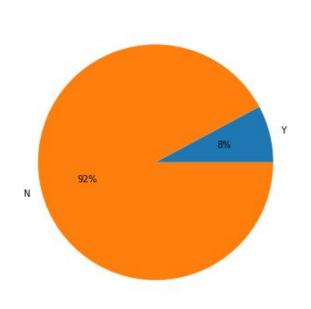
Clients with a higher education are less risky than the ones without

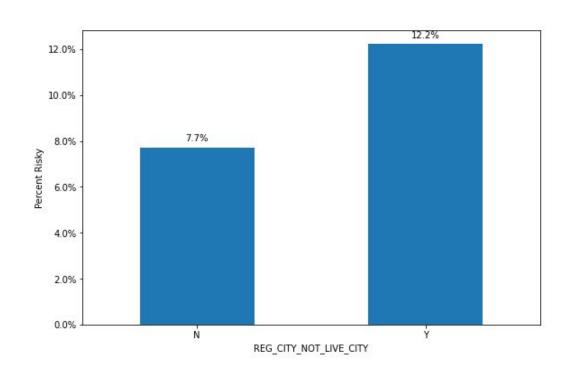
### **Client's Work Organization Type**



The riskiest segment under "ORGANIZATION\_TYPE" (client's work organization type) is "Self-employed" whereas the least risky is when the "ORGANIZATION\_TYPE" is unavailable

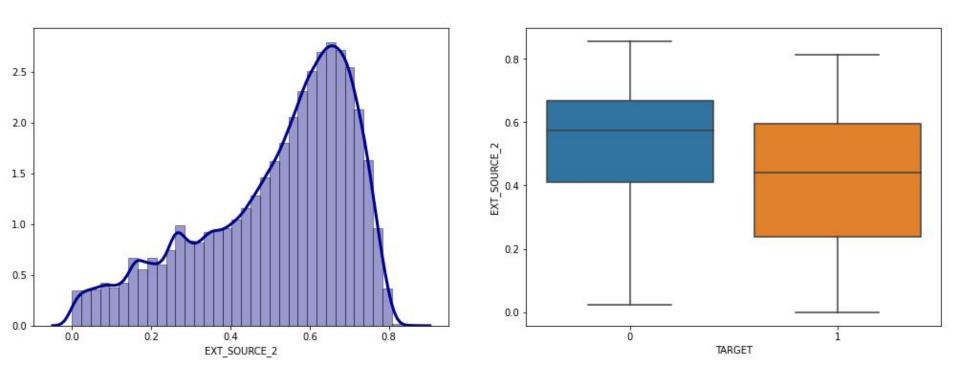
#### Mismatch between client's permanent and contact address





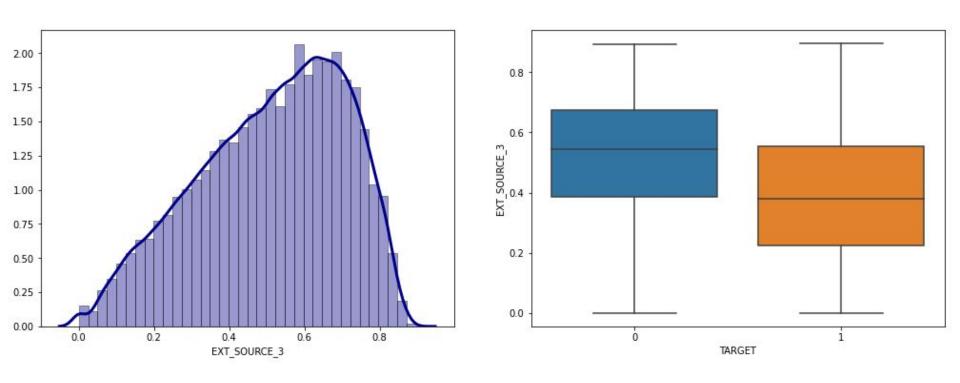
Client's with a mismatch between permanent and contact address are riskier

#### **External Source 2 Score**



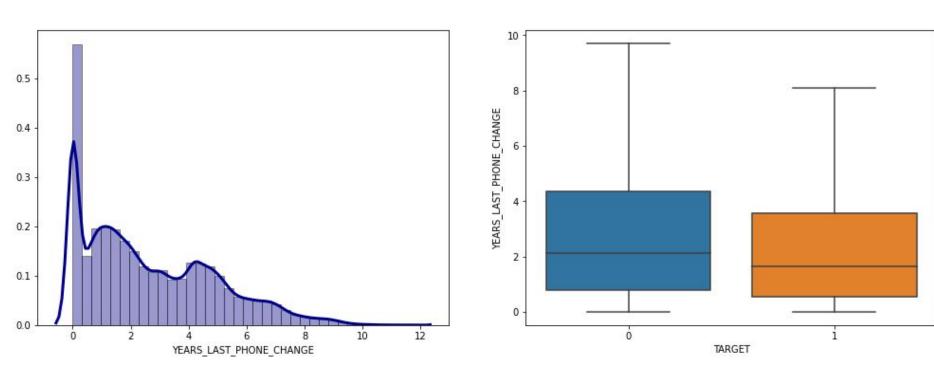
Non risky clients have higher values of "EXT\_SOURCE\_2" compared to risky customers

#### **External Source 3 Score**



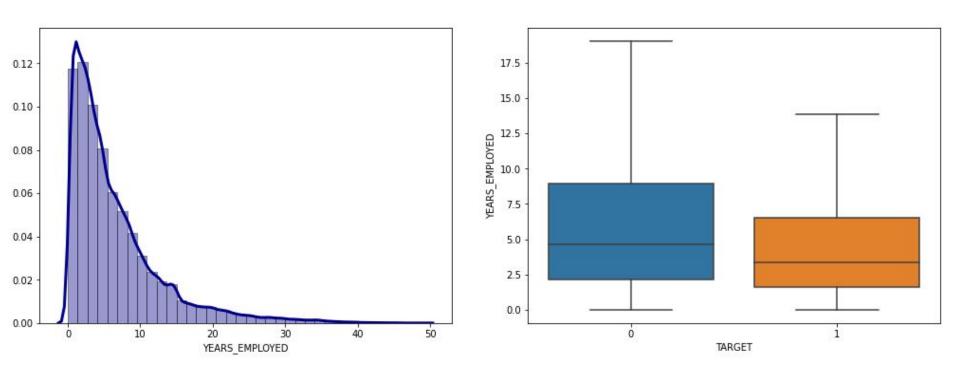
Non risky clients have higher values of "EXT\_SOURCE\_3" compared to risky customers

# **Phone Number Change Recency**



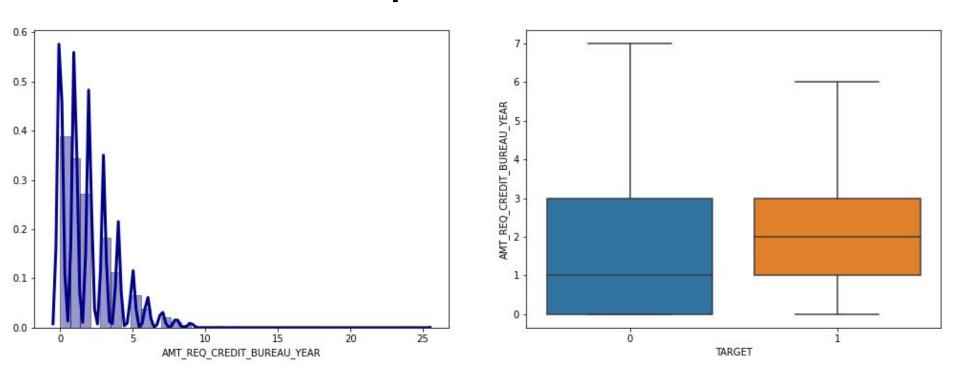
Clients with recent phone number changes seem to be riskier

# **Client's Current Employment Duration**



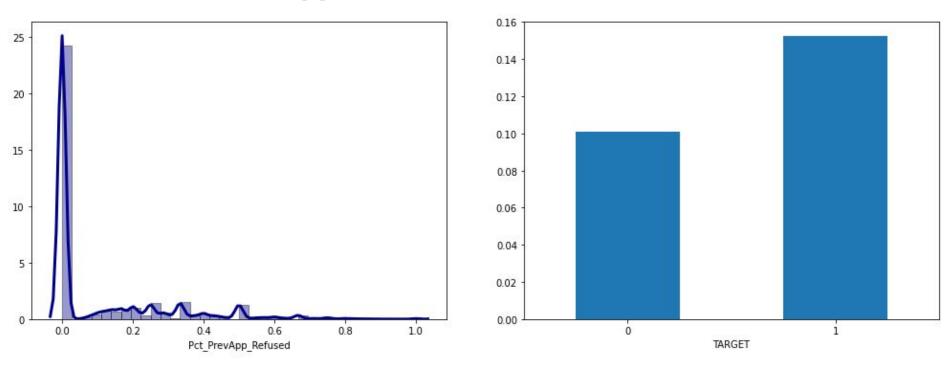
Clients with smaller durations of current employment are riskier

# Client's Credit Bureau Inquiries in a Year



Clients with more number of credit bureau inquiries (in a year) are riskier

# **Client's Previous Application Refusal Rate**



Clients with higher proportion of past refusals are riskier

#### **Recommendations and Conclusion**

We recommend to only approve applicants with the following characteristics:

- Higher Values For: External Source Scores 1/2/3, Client's Current Employment Duration and Phone Number Change Recency
- Lower Values For: Client's Previous Application Refusal Rate and Credit Bureau Inquiries in a Year
- Who are Highly Educated and who provide the correct Contact/Permanent Address
- Occupation Type In: Accountants, Managers and High Skill Tech & Core Staff
- Work Organization Type Not In: Self Employed and Business Entity Types 2/3

Following the above guidelines should help the company in getting the clients least likely to default