

HOME CREDIT DEFAULT RISK

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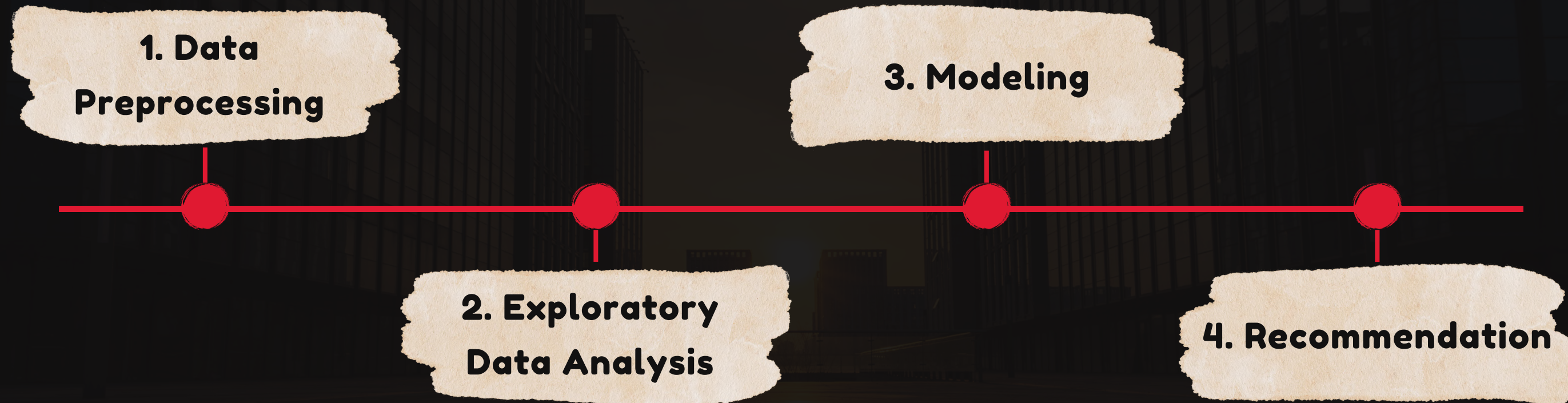
04

Modeling

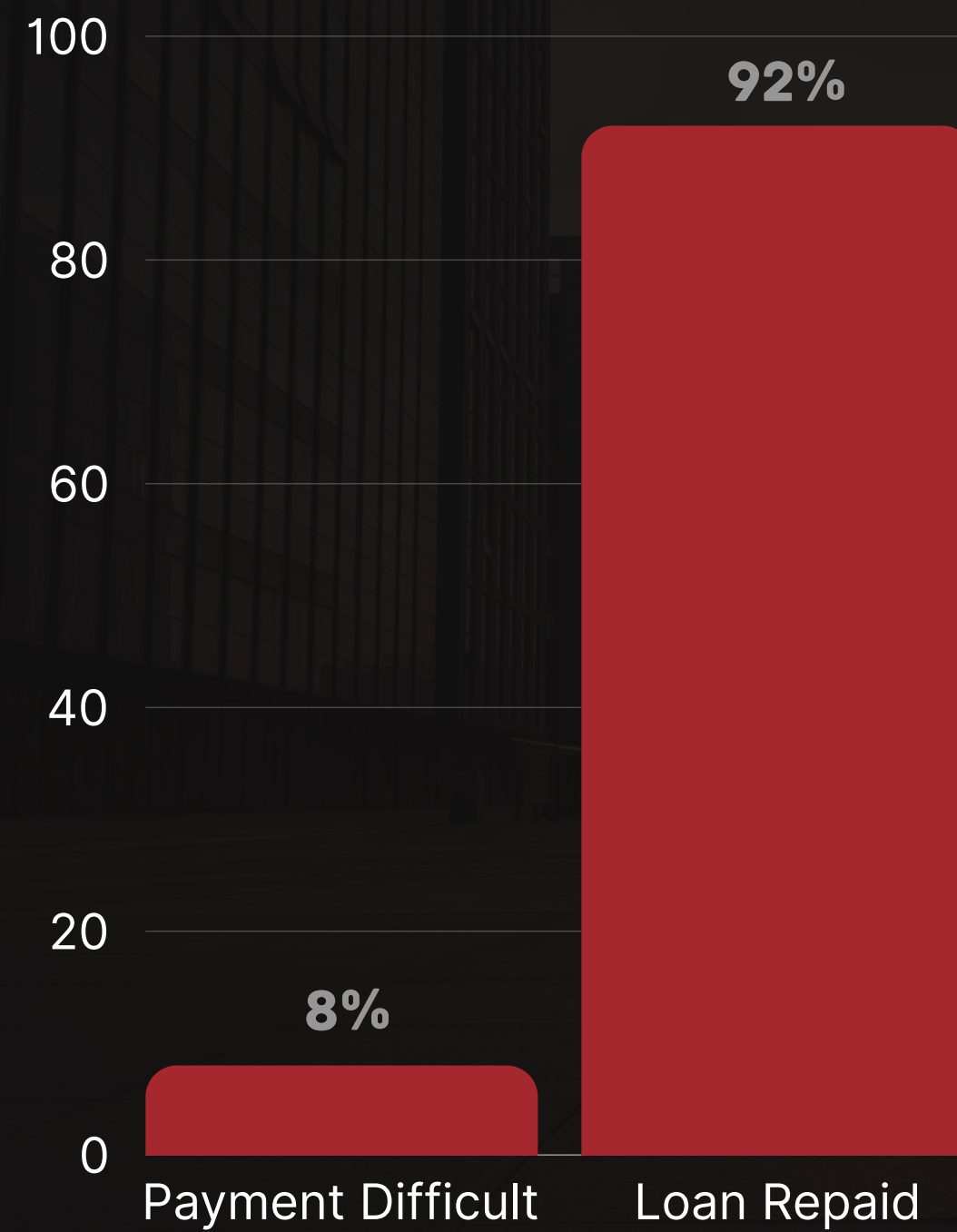
OBJECTIVE

Our main goal is to **create a machine learning model** that can **predict** whether users who will apply for credit can pay on time or will be late / problematic. As a data team, our objective is to **ensure that customers who are able** to make repayments are not rejected when applying for a loan.

METHODOLOGY



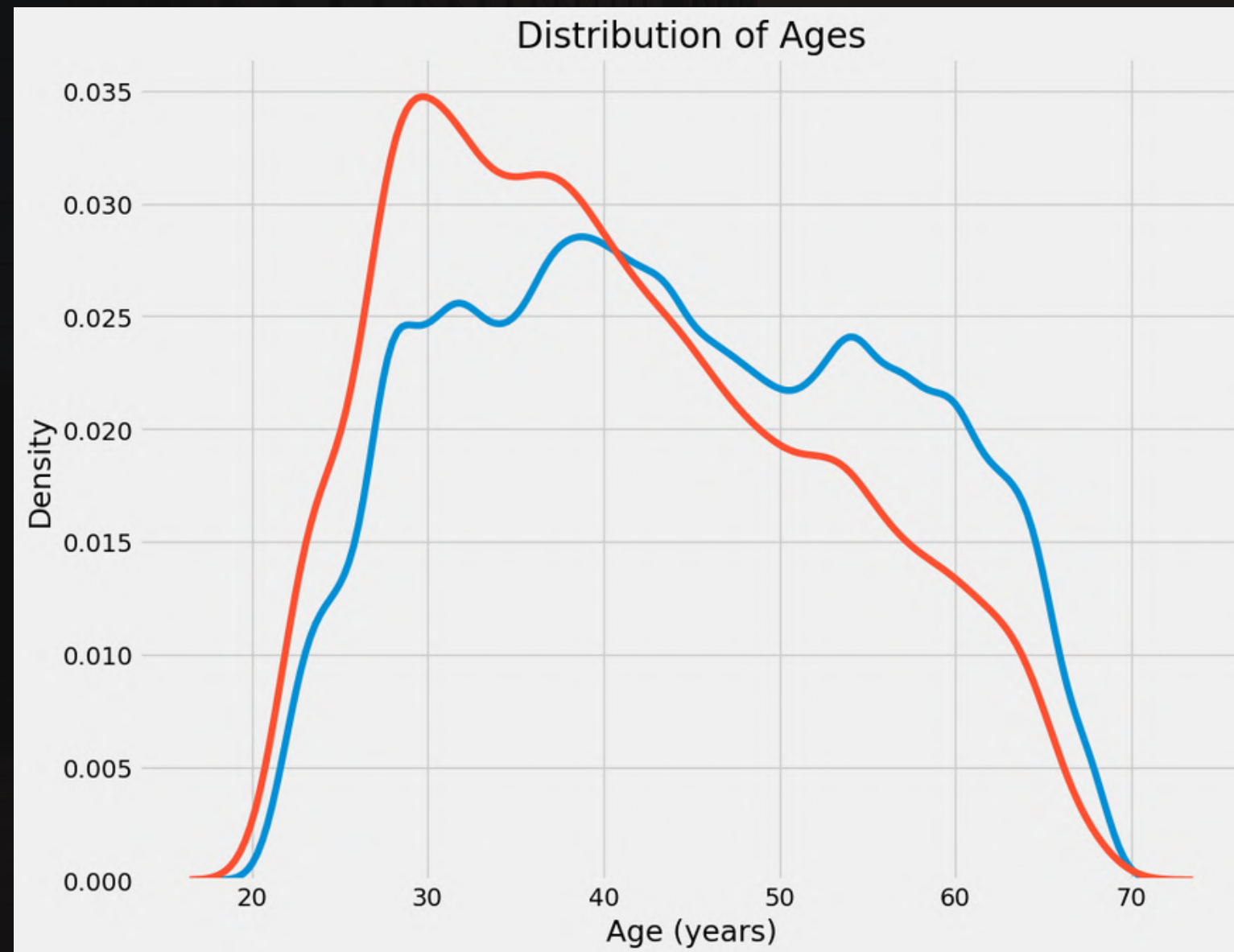
TARGET COLUMN DISTRIBUTION



92%

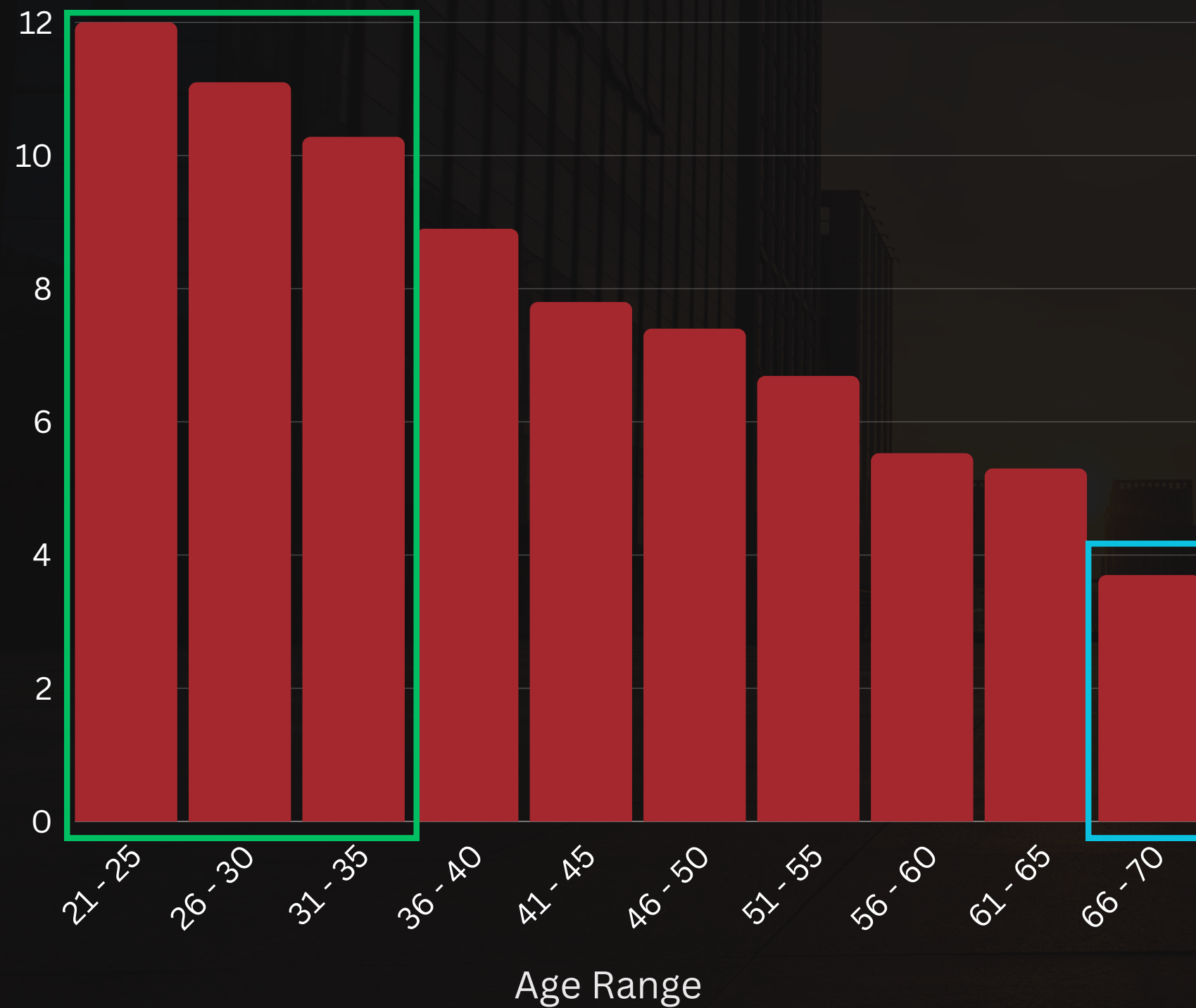
loans are **repaid on time** far more often than defaults.

DISTRIBUTION OF AGES



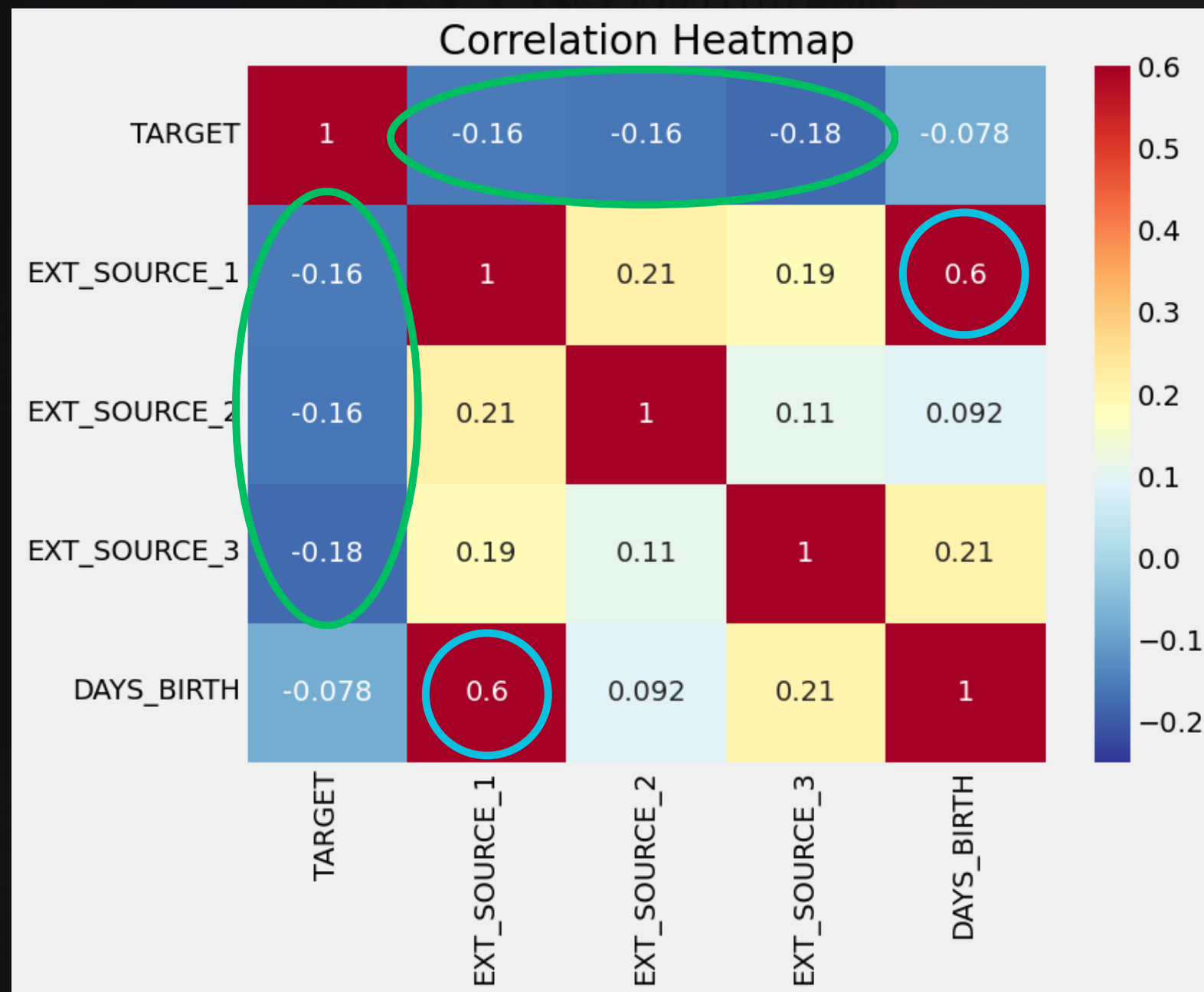
There is a negative linear relationship with the target which means that as **customers age**, **they tend to repay their loans on time more often.**

EFFECT OF AGE ON REPAYMENT



Younger applicants are **less likely to repay** their loans!
Default rates are **above 10%** for the three youngest age groups and **below 5%** for the oldest age group.

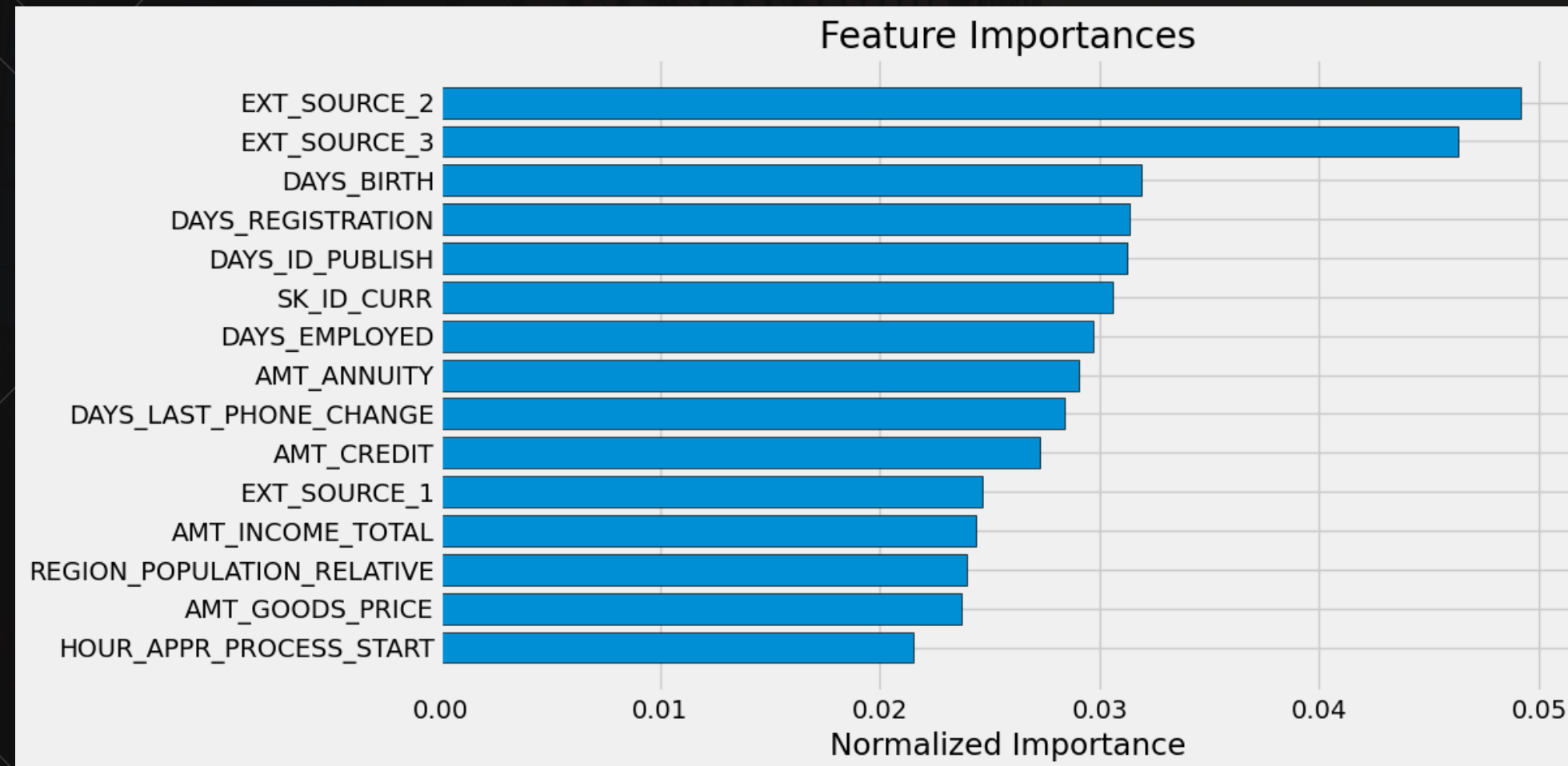
STRONG CORRELATION



All three EXT_SOURCE features have a **negative correlation** with the target, which suggests that as the EXT_SOURCE score increases, it is more likely that the client will repay the loan.

We can also see that DAYS_BIRTH is **positively correlated** with EXT_SOURCE_1 which suggests that perhaps one of the factors in this score is the client's age.

MODELLING AND FEATURE IMPORTANCE



Model	ROC_AUC
Logistic Regression	68
Random Forest	70

As expected, the most important features are those dealing with EXT_SOURCE and DAYS_BIRTH.

We see that all four of our hand-engineered features made it into the top 15 most important! This should give us confidence that our domain knowledge was at least partially on track.

Thank You

[Link Project on Github](#)

