

# Credit Card Approval Prediction

Group 9:

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# Intro

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- Analyze credit card approval data to identify key factors influencing approval decisions
- Kaggle dataset...
- **Objectives:**
  1. Determine demographic trends affecting approval
  2. Improve performance in predicting approvals





# Research Questions

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1. What demographic factors most significantly influence credit card approval rates?
2. How can predictive modeling techniques be optimized to accurately forecast credit approval outcomes?

# Data Description

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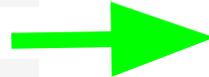
- Application records  ID, gender, age, income, education, occupation, and family status
  - 438,557 entries
- Credit Record  Credit records of applicants
  - 1,036,231 entries

Merged on `ID`  
77,715 records, 20 columns

# Data Preprocessing



	FLAG_MOBIL	DAYS_BIRTH	AMT_INCOME_TOTAL	STATUS	OCCUPATION_TYPE
0	1	-12005	427500.0	C	NaN
1	1	-12005	427500.0	C	NaN
2	1	-12005	427500.0	C	NaN
3	1	-12005	427500.0	C	NaN
4	1	-12005	427500.0	C	NaN
...	...	...	...	...	...
777710	1	-19398	202500.0	C	Drivers
777711	1	-19398	202500.0	C	Drivers
777712	1	-19398	202500.0	C	Drivers
777713	1	-19398	202500.0	C	Drivers
777714	1	-19398	202500.0	C	Drivers



	AGE	AMT_INCOME_TOTAL	STATUS_Approved	OCCUPATION_TYPE
0	32	0.258721	1	Unknown
1	32	0.258721	1	Unknown
2	32	0.258721	1	Unknown
3	32	0.258721	1	Unknown
4	32	0.258721	1	Unknown
...	...	...	...	...
777710	53	0.113372	1	Drivers
777711	53	0.113372	1	Drivers
777712	53	0.113372	1	Drivers
777713	53	0.113372	1	Drivers
777714	53	0.113372	1	Drivers

777715 rows × 5 columns

777715 rows × 4 columns



# Feature Engineering

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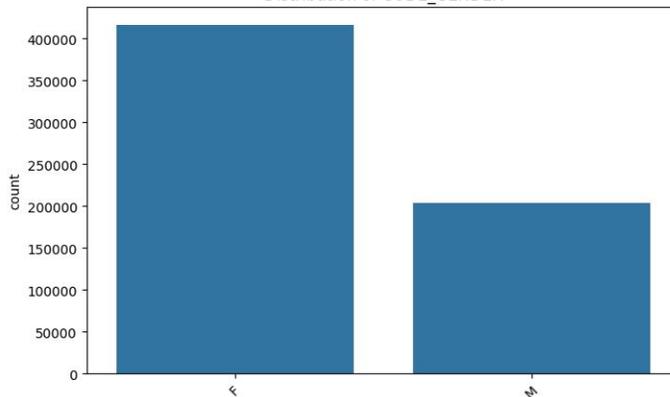
- Calculated age in years then Age Binning
- Categorical Encoding (target / one-hot encoding)
- Mapped the 'STATUS' values to create a binary target variable.
  - '0' to '5': Represent days past due
  - 'C': Indicates the credit is closed.
  - 'X': Indicates no loan for the month.
  - Assign 1 (approved) for 'C' and 'X'.
  - Assign 0 (not approved) for '0' to '5'.



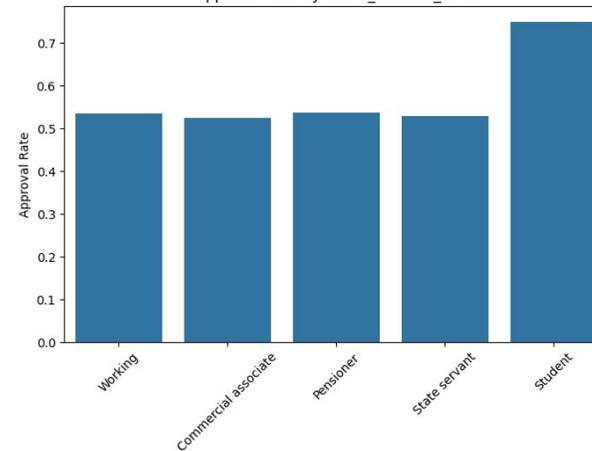
# Exploratory Data Analysis

- Plotted distributions for categorical variables
- Evaluating approval rates by age, education and income type

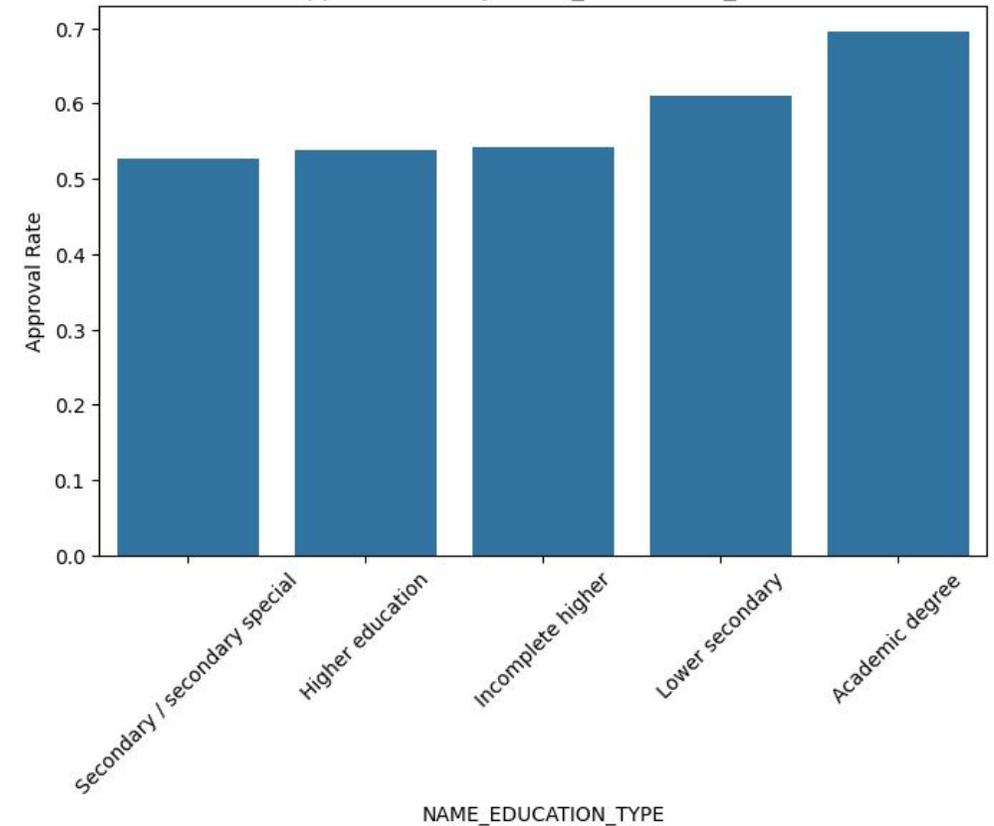
Distribution of CODE\_GENDER



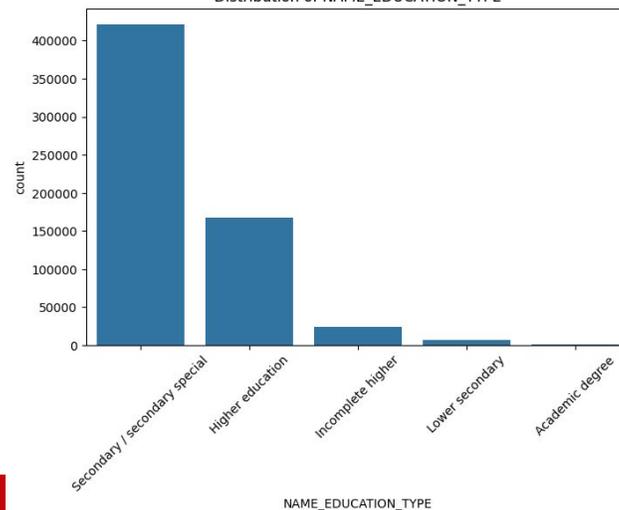
Approval Rate by NAME\_INCOME\_TYPE



Approval Rate by NAME\_EDUCATION\_TYPE

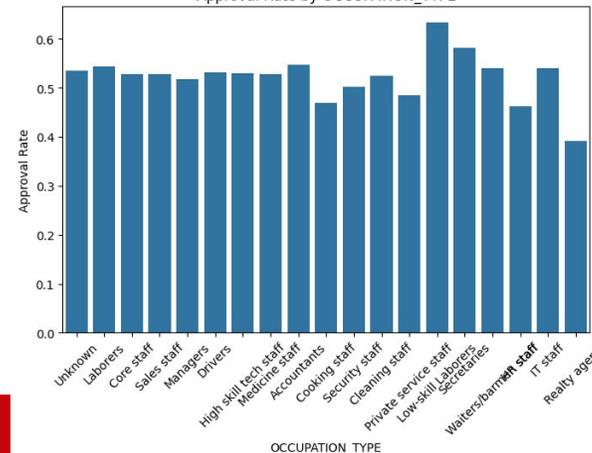


Distribution of NAME\_EDUCATION\_TYPE



NAME\_INCOME\_TYPE

Approval Rate by OCCUPATION\_TYPE

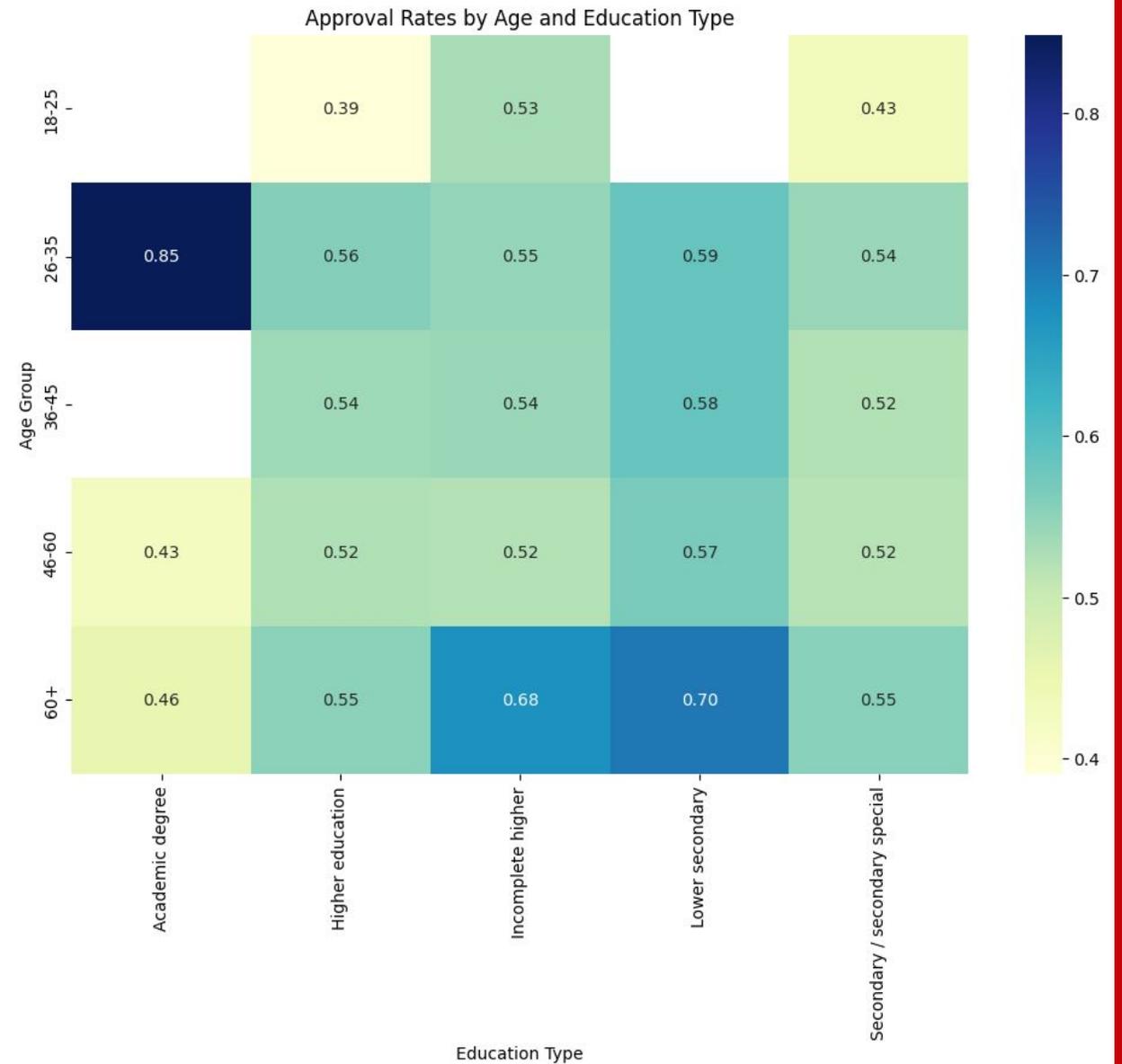


OCCUPATION\_TYPE

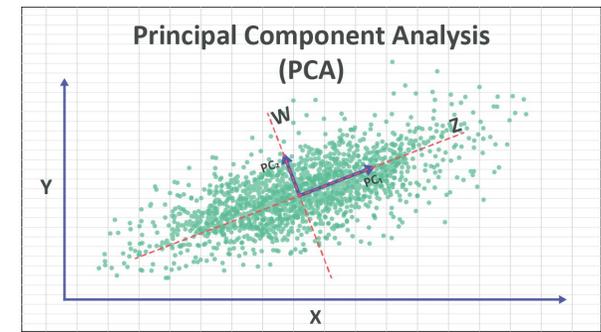


# Exploratory Data Analysis

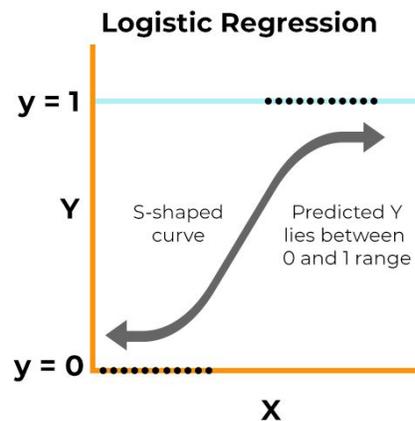
- 26-35 Age Group with an Academic Degree has the highest approval rate



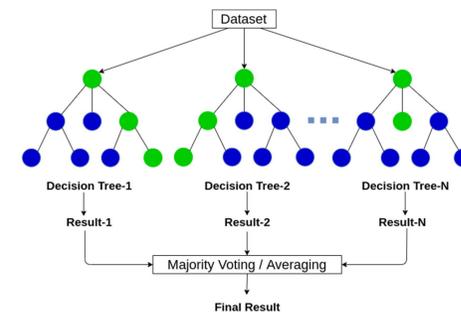
# Machine Learning



1. Used stratified sampling to create a balanced sample of the data.
2. Scaled numerical features
3. PCA, regularization, and feature importance analysis
4. Train and test split
5. Models:
  - Logistic Regression → Area Under ROC Curve (AUC) score: **0.612177**
  - Random Forest Classifier → AUC: **0.712067**
6. Cross-Validation scores:
  - Logistic Regression → Area Under ROC Curve (AUC) score: **0.608112 ± 0.007**
  - Random Forest Classifier → AUC: **0.705041 ± 0.005**



## Random Forest



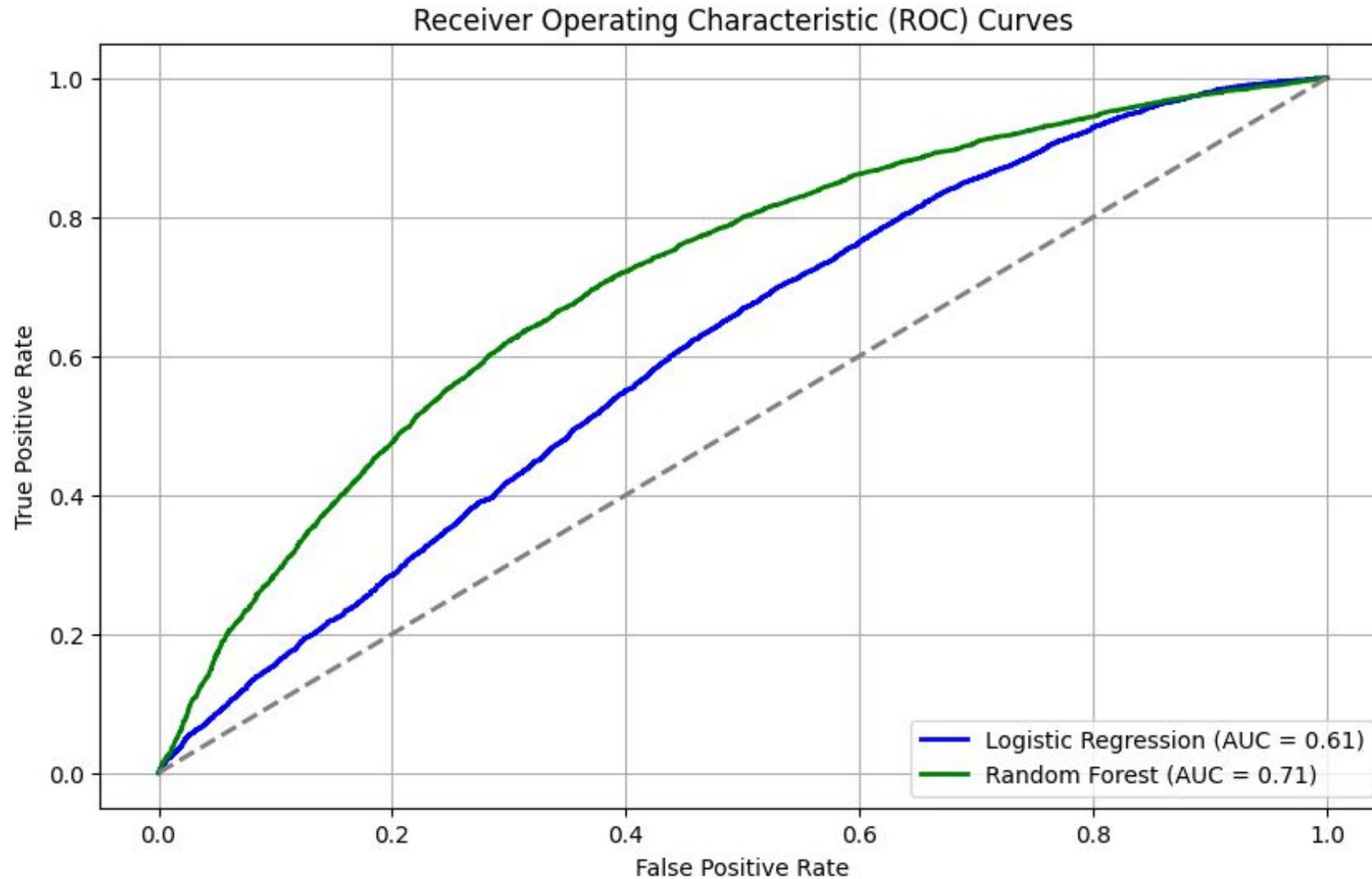


# Selected Features

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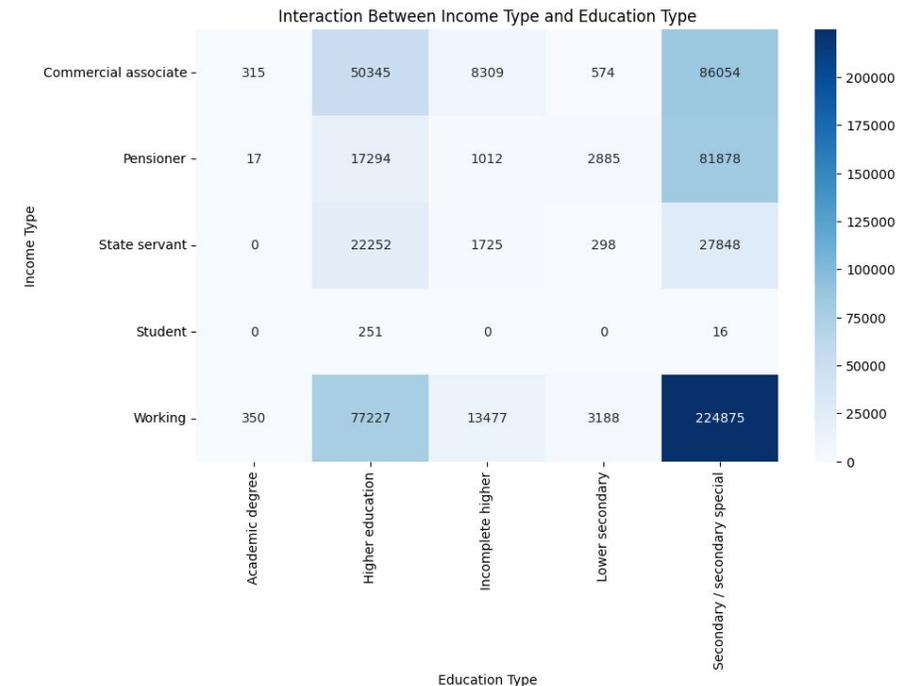
- 'CNT\_FAM\_MEMBERS',
- 'DAYS\_EMPLOYED',
- 'AGE',
- 'MONTHS\_BALANCE' - record month
- 'CNT\_CHILDREN' - number of children
- 'OCCUPATION\_TYPE'
- 'FLAG\_PHONE' - if theres a phone

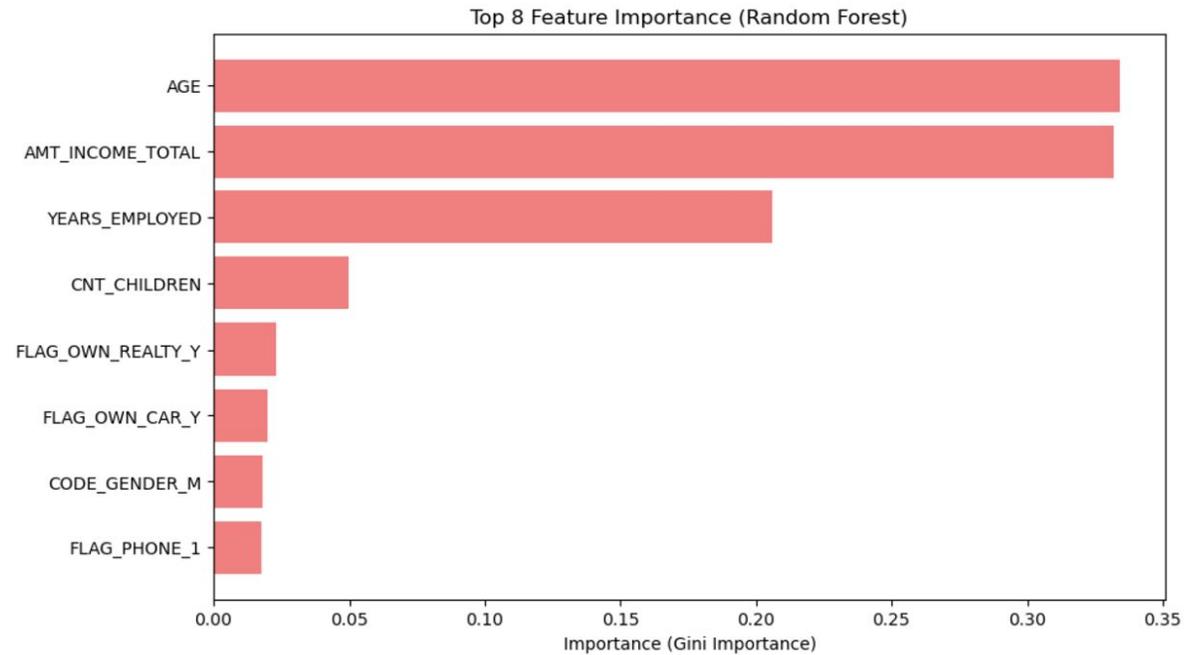
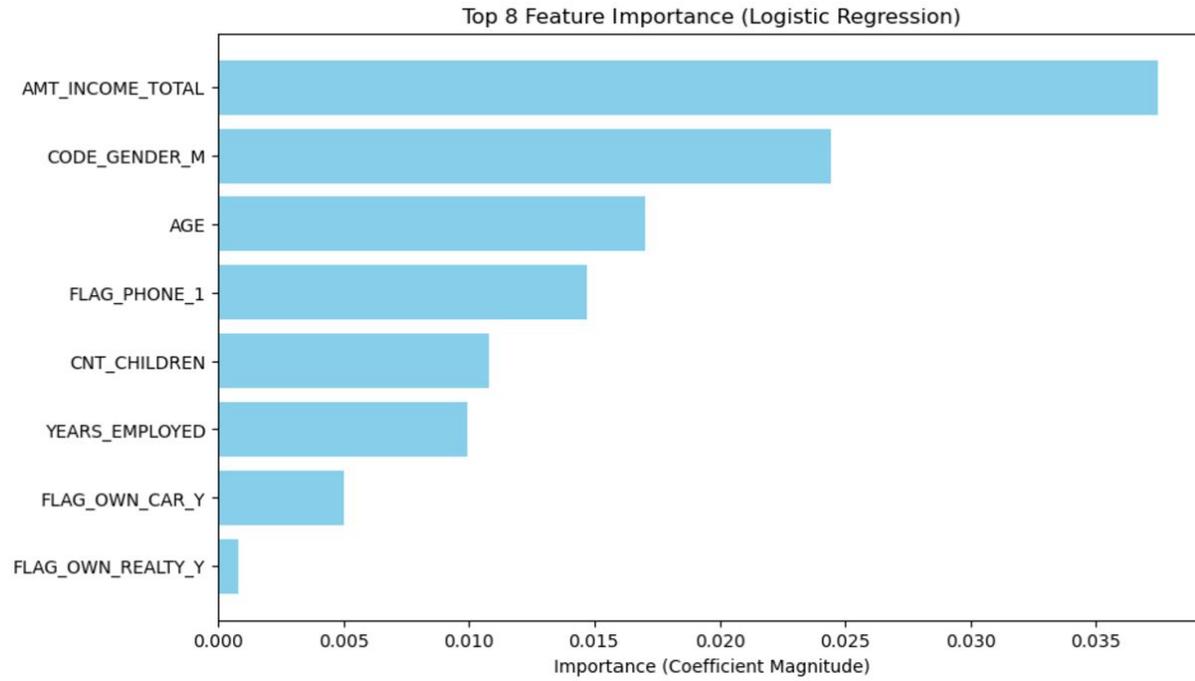
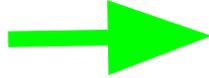
# ROC Curves



# Challenges

- Handled missing data in occupation type
- Class imbalance (approved vs not approved)
  - stratified sampling
- Moderate predictive power
- Feature selection/engineering (interaction between variables)





# Conclusion

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- Data Quality and Preprocessing
- Demographic Insights
- Approval Rate Analysis
- Modeling
- Bias and Fairness
- Considering more advanced methods



