

# Credit Approval Analysis

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# Background

## **Objective:**

To demonstrate the analytical techniques taught during the Special Topics in Audit Analytics course at Rutgers University

## **Data:**

- Dataset- Credit Screening on Credit Card Applications
- Source- UCI Machine Learning Repository

## **Assumptions:**

Field names and values changed to meaningless values. Made assumptions about what attributes the data represents.

# Research Question - 1

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**A:** Relationships exists between Prior default, Years employed, Credit score, and Income level. These variables are reasonable management strategies.

## Research Question - 2

**Q:** Ethnicity is a protected status and the decision to approve or deny an application cannot be based on the applicant's ethnicity. Is there a statistically significant difference in how credit is granted between ethnicities that could indicate bias or discrimination?

*H0: Ethnicity and approval are independent.*

*H1: Approval status is associated with the ethnicity and credit card company has a compliance risk.*

## Research Question - 2

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*H0: Ethnicity and approval are independent.*

*H1: Approval status is dependent on the ethnicity and credit card company has a compliance risk.*

**A:** A chi-squared test did not give evidence that ethnicity and approval status are dependent. We cannot reject the null hypothesis.

# Analytic Methods Used

Methods used:

- ▶ Linear regression
- ▶ Descriptive Statistics and Normalization
- ▶ Association Rules
- ▶ Logistic regression
- ▶ Classification and Regression Tree
- ▶ Ensembling

# Linear Regression

Used to fill in missing values in Age

	Age	Debt	YearsEmployed	CreditScore	Income
Age	1.000	0.202	0.396	0.186	0.019
Debt	0.202	1.000	0.301	0.271	0.122
YearsEmployed	0.396	0.301	1.000	0.327	0.053
CreditScore	0.186	0.271	0.327	1.000	0.063
Income	0.019	0.122	0.053	0.063	1.000

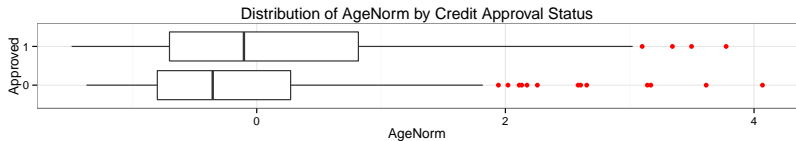
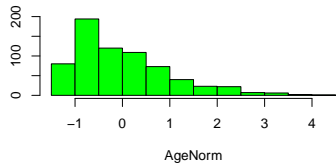
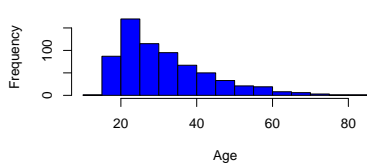
(Intercept)	YearsEmployed
28.446953	1.412399



# Descriptive Stats and Normalization

## Convert values to Z-Scores

Distribution of Values Before and After Normalization



# Association Rules

1. Support: Support is how often the left hand side of the rule occurs in the dataset. In our example above, we would count how many times  $\{u,g,c\}$  occurs and divide by the total number of transactions.
2. Confidence: Confidence measures how often a rule is true. First, we find the subset of all transactions that contain  $\{u,g,c\}$ . Of this subset, we then count the number of transactions that match the right hand side of rule, or  $\{1\}$ . The confidence ratio is calculated by taking the number of times the rule is true and dividing it by the number of times the left hand side occurs.

	lhs	rhs	support	confidence	
1	{EducationLevel=c}	=> {Male=0}	0.1545319	0.7647059	1.099

# Baseline Model

- ▶ Simple mean of results.
- ▶ Establish benchmark to measure model accuracy
- ▶

	Total	Success	Percent
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1	517	230	44.49
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# Logistic Regression

Call:

```
glm(formula = Approved ~ AgeNorm + DebtLog + YearsEmployedLog +  
CreditScoreLog + IncomeLog, family = binomial, data = T)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.4339	-0.7848	-0.4970	0.7164	2.1596

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.10596	0.11283	-0.939	0.347648	
AgeNorm	0.01541	0.11674	0.132	0.894965	
DebtLog	0.08430	0.11635	0.725	0.468744	
YearsEmployedLog	0.70937	0.13021	5.448	5.10e-08	***
CreditScoreLog	1.01687	0.13944	7.293	3.04e-13	***
IncomeLog	0.46610	0.12089	3.855	0.000116	***

# CART Model

n= 517

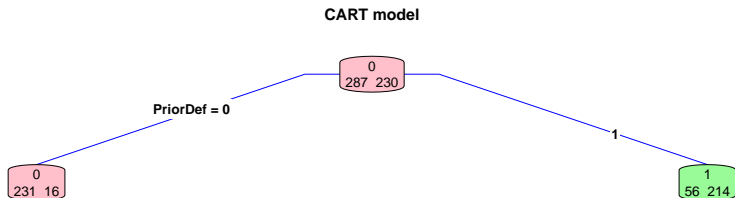
node), split, n, loss, yval, (yprob)

\* denotes terminal node

1) root 517 230 0 (0.55512573 0.44487427)

2) PriorDefault=0 247 16 0 (0.93522267 0.06477733) \*

3) PriorDefault=1 270 56 1 (0.20740741 0.79259259) \*



# References

Data:

[http://archive.ics.uci.edu/ml/  
machine-learning-databases/credit-screening](http://archive.ics.uci.edu/ml/machine-learning-databases/credit-screening)

Analytic Report:

<http://www.rpubs.com/kuhnrl30/CreditScreen>