Analyzing Factors Affecting Credit Limit

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Introduction and Motivation

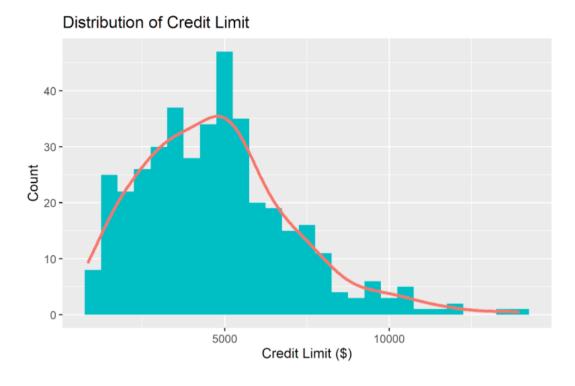
Using the Credit dataset provided by ISLR, we strove to answer:

- What financial and demographic factors contribute to having a higher or lower credit limit?
- Does gender or ethnicity play a role in having a higher credit limit?
- What are the most relevant and statistically significant variables for predicting credit limit?

```
Rows: 400
Columns: 12
$ ID
                                      <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 3~
$ Income
                                      <dbl> 14.891, 106.025, 104.593, 148.924, 55.882, 80.180, 20.996, 71.408, 15.125, 71.061, 63.095, 15.045, 80.616, 43.682, 19.144, 2~
$ Limit
                                      <int> 3606, 6645, 7075, 9504, 4897, 8047, 3388, 7114, 3300, 6819, 8117, 1311, 5308, 6922, 3291, 2525, 3714, 4378, 6384, 6626, 2860~
$ Rating
                                     <int> 283, 483, 514, 681, 357, 569, 259, 512, 266, 491, 589, 138, 394, 511, 269, 200, 286, 339, 448, 479, 235, 458, 213, 398, 156,~
                                      <int> 2, 3, 4, 3, 2, 4, 2, 2, 5, 3, 4, 3, 1, 1, 2, 3, 3, 3, 1, 2, 4, 1, 3, 5, 3, 5, 6, 2, 2, 4, 4, 5, 2, 4, 2, 3, 2, 2, 4, 4, 3, 2~
$ Cards
$ Age
                                      <int> 34, 82, 71, 36, 68, 77, 37, 87, 66, 41, 30, 64, 57, 49, 75, 57, 73, 69, 28, 44, 63, 72, 61, 48, 57, 25, 44, 44, 41, 55, 47, ~
$ Education <int> 11, 15, 11, 11, 16, 10, 12, 9, 13, 19, 14, 16, 7, 9, 13, 15, 17, 15, 9, 9, 16, 17, 10, 8, 15, 16, 12, 16, 14, 16, 5, 16, 13,~
                                      <fct> Male, Female, Male, Female, Male, Male, Female, Male, Female, Female, Male, Female, Male, Female, Female
$ Gender
$ Student
                                     <fct> Yes, Yes, No, No, Yes, No, No, No, No, No, Yes, Yes, No, Yes, Yes, Yes, Yes, Yes, Yes, No, No, Yes, Yes, No, Yes, No, No~
$ Ethnicity <fct> Caucasian, Asian, Asian, Caucasian, Caucasian, African American, Asian, Caucasian, African American, Caucasian, Ca
                                      <int> 333, 903, 580, 964, 331, 1151, 203, 872, 279, 1350, 1407, 0, 204, 1081, 148, 0, 0, 368, 891, 1048, 89, 968, 0, 411, 0, 671, ~
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Credit Limit

A credit limit is the maximum amount of "debt" a person can accumulate on a credit card before their purchases are denied. The credit limit varies from person to person, depending on how confident the company is that they will be paid back.

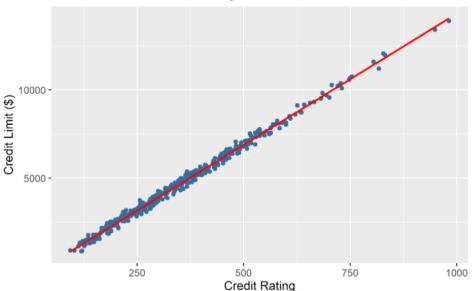


The distribution is **strongly skewed to the right**. As a result, when comparing two populations, a difference in medians test would be more applicable than a difference in means. However, many of the null distributions did not approach a normal curve with this test, so instead we use a non-parametric test called the Mann-Whitney U Test to test the hypotheses:

- H_0 : The distributions of credit limit from which the two samples are drawn are the same (don't differ by a shift)
- H_A: The distributions of credit limit from which the two samples are drawn are different (do differ by a shift)

Impact of Credit Rating

Credit Limit vs. Credit Rating



Coefficients:

Multiple R-squared: 0.9938,

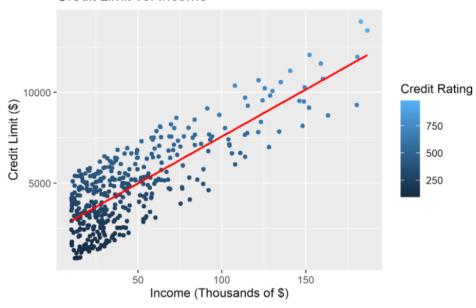
```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -542.92823 22.85026 -23.76 <2e-16 ***
Rating 14.87161 0.05903 251.95 <2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 182.4 on 398 degrees of freedom
```

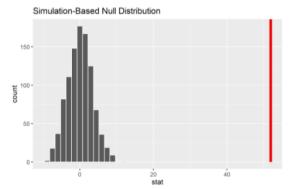
F-statistic: 6.348e+04 on 1 and 398 DF, p-value: < 2.2e-16

Adjusted R-squared: 0.9938

Impact of Income

Credit Limit vs. Income





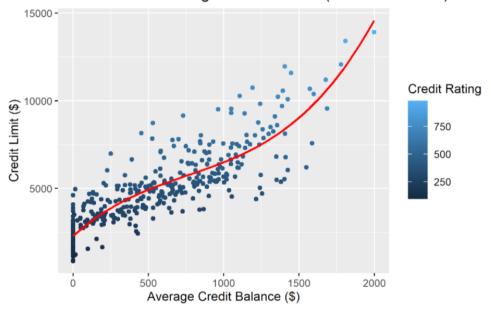
Coefficients:

Estimate Std. Error (Intercept) 2389.869 114.829 Income 51.875 2.004

p value: 0

Impact of Credit Balance

Credit Limit vs. Average Credit Balance (with Cubic Model)

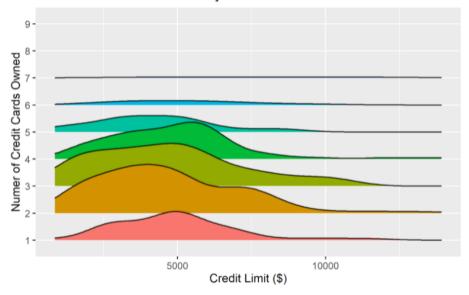


Coefficients:

Residual standard error: 1130 on 396 degrees of freedom Multiple R-squared: 0.762, Adjusted R-squared: 0.7602 F-statistic: 422.7 on 3 and 396 DF, p-value: < 2.2e-16

Impact of Number of Cards

Distributions of Credit Limit by Number of Credit Cards Owned



Estimate Std. Error t value Pr(>|t|) (Intercept) 4684.67 274.98 17.037 <2e-16 *** Cards 17.22 84.37 0.204 0.838

Coefficients:

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

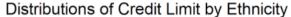
Residual standard error: 2311 on 398 degrees of freedom
Multiple R-squared: 0.0001047, Adjusted R-squared: -0.002408
F-statistic: 0.04167 on 1 and 398 DF, p-value: 0.8384

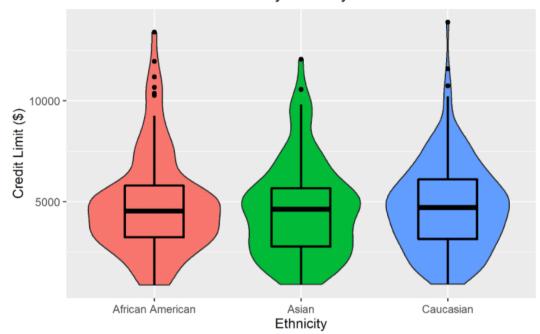
Impact of Gender

Distributions of Credit Limits by Gender Credit Limit (\$) Gender Female Male 5000

Count

Impact of Ethnicity





Wilcoxon rank sum test with continuity correction

10

20

data: Limit by Gender W = 20532, p-value = 0.6304

20

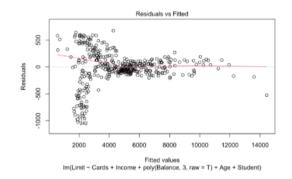
10

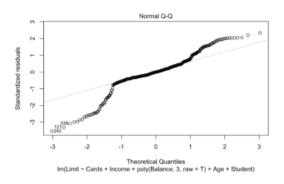
alternative hypothesis: true location shift is not equal to 0

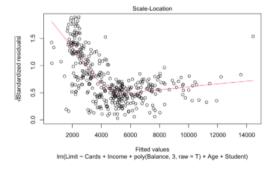
Caucasian.v.Asian Caucasian.v.African American 0.9954448 Asian.v.African American

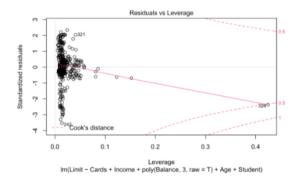
p value 0.4698917 0.5274932

Full Fitted Model (Without Credit Rating)









```
Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)
Cards
Income
poly(Balance, 3, raw = T)1 5.905e+00
poly(Balance, 3, raw = T)2 -3.336e-03
poly(Balance, 3, raw = T)3
                                                   2.458
                                       8.659e-01
StudentYes
                                       5.124e+01 -27.688
               0 \***' 0.001 \**' 0.01 \*' 0.05 \.' 0.1 \' 1
Residual standard error: 291.7 on 392 degrees of freedom
Multiple R-squared: 0.9843,
                                  Adjusted R-squared: 0.984
F-statistic: 3513 on 7 and 392 DF, p-value: < 2.2e-16
```

- The Normal Q-Q plot does not fall along a straight line. Since the tails twist counterclockwise, this suggests that the distribution has "heavy tails" (leptokurtosis)
- The leverage plot displays several points with high leverage, one of which has a Cook's Distance less than -0.5 (and is thus is strongly influencing the model)
- The scale-location plot has significantly higher standardized residuals at lower fitted values of credit limit

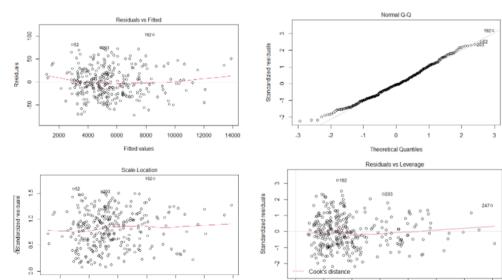
Model for Balance > 0

Coefficients:

Fitted values

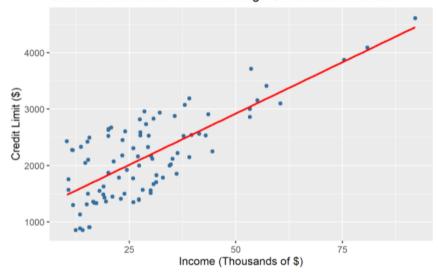
```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.151e+03 7.721e+00 278.60 <2e-16 ***
Cards -7.593e+01 1.302e+00 -58.34 <2e-16 ***
Income 3.063e+01 5.573e-02 549.57 <2e-16 ***
Balance 3.061e+00 5.091e-03 601.17 <2e-16 ***
Age 3.067e+00 1.097e-01 27.97 <2e-16 ***
StudentYes -1.533e+03 5.720e+00 -267.97 <2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 32.38 on 304 degrees of freedom Multiple R-squared: 0.9998, Adjusted R-squared: 0.9998 F-statistic: 2.483e+05 on 5 and 304 DF, p-value: < 2.2e-16



Model for Balance == 0

Model for Individuals Where Average Credit Balance is Zero



Only one variable (Income) was found significant for this model.

Conclusions

- Credit rating is an extremely strong predictor of credit balance.
- The credit limits for those with zero average credit balance are fundamentally different than those with a positive average credit balance.
- For those with a positive average credit balance (on average, all else held constant):
 - Expected decrease in credit limit by \$76 per addition credit card
 - Expected increase in credit limit by \$31 per additional \$1000 in income
 - Expected increase in credit limit by \$3 per additional dollar of average credit balance
 - Expected increase in credit limit by \$3 per additional year in age
 - Expected decrease in credit limit by \$1533 for students compared to non-students
- For those with no credit balance, income is the only significant predictor.
 - Expected increase in credit limit by \$36 per additional \$1000 in income
- No significant difference between credit limits was found based on gender and ethnicity -- age was the only demographic predictor which was significant.
 - The coefficient is still quite small, so it isn't particularly significant in practice

References

- Climbs_lika_Spyder. (2016, October 21). *Emulate GGPLOT2 Default Color Palette*. Stack Overflow. Retrieved December 5, 2021, from https://stackoverflow.com/a/40181166.
- gung Reinstate Monica. (2013, March 14). QQ Plot Does Not Match Histogram. Cross Validated. Retrieved December 5, 2021, from https://stats.stackexchange.com/a/52221.
- Kim, B. (2015, September 21). *Understanding Diagnostic Plots for Linear Regression Analysis*. Research Data Services + Sciences. Retrieved December 5, 2021, from https://data.library.virginia.edu/diagnostic-plots/.
- strictlystat. (2014, June 10). *Making Back-to-Back Histograms*. A HopStat and Jump Away. Retrieved December 5, 2021, from https://hopstat.wordpress.com/2014/06/10/making-back-to-back-histograms/.