Lending Insights

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Executive Summary

- ▶ Dataset contains all approved customers with mostly Good to Excellent credit rating (>=0.7), but still 17% people defaulted and we saw net Loss of \$8,370
- ► Mean Loss/customer (-\$14.5) is 5-6x of mean Profit/customer (\$2.8)
- I fit a Logistic Regression model on available data, which predicted whether a new user will default or not
- Assuming new users behave similarly to past ones, I identified key drivers behind loan defaults & decided on individual outcomes
- Resulted into Losses turning to Profits, with 40-50% loss of New customers
- Individual models were fitted for \$10, \$20 & \$30 loan amounts to determine key factors in each case

Data Quality

- ▶ 66,786 newly approved customers
- Repayment Amount and Repayment Date columns had missing values, which indicate Loan Defaulters
- Some Defaulters repaid partial amount
- ► Loan Use Category had negligible missing values but was useful
- Some Daily Income ranges conflicted with respective Annual Income values
- Phone Ownership and New Phone fields had 1.5% missing values

Outcome 1 - Factors influencing Defaults

- Default influencers
- Across all loans, Business & Personal loans were highly risky
- Emergency loans are 2x as likely to default than other loans
- Self-employed persons are 40% more likely to default
- Default suppressors
- ▶ In contrast, higher the Credit Score lower the Default risk
- Customers with a PhD have 40% lower risk than other candidates
- Being Employed decreases risk by 40%
- Owning phone over 3 yrs., having Other loans reduce risk by 20-30%

Outcome 1 - Other Factors for \$10 Loan

- Default influencers
- Self-employed persons are 50% riskier
- ▶ Persons without formal Education are 50% more likely to default
- Default suppressors
- Employed persons are 40% less risky
- Candidates with Referrals are 30% less risky

Outcome 1 - Other Factors for \$20 Loan

- Default influencers
- Persons without formal Education are 2.4x more risky
- Students/Unemployed persons are 2x more likely to default
- Default suppressors
- Persons with other Outstanding loans are 40% less risky
- Phone Owners are 35% less risky

Outcome 1 - Other Factors for \$30 Loan

- Default influencers
- Students/Unemployed persons are 10x riskier
- Persons with 3-6 month old National IDs are 2x riskier
- Default suppressors
- Persons with 1-3 month old National IDs are 40% less risky
- Persons with other Outstanding loans are 30% less risky

Outcome 2 - Net Profit Vs New Customers

	Initial Profit (\$)	Predicted Profit (\$)	Change (\$)	New Customer Loss (%)
All Loans	-1,767	8,976	10,743	42
\$10	-2,943	1,274	4,217	44
\$20	-2,610	1,822	4,432	38
\$30	-1,830	705	2,535	48
\$40	Data Insufficient, results unstable			

Other Useful Data

- Currently only loan amounts \$10-\$40 can be predicted using Linear Regression
- ▶ To predict loan amounts over \$40, we need respective historical data
- Information on Cellular phone usage (call type, duration & frequency, SMS, data usage) would further assist the analysis

Thank you!

Appendix - Odds Ratio Table (All Loans)

- Business & Personal loans are 60-80x riskier
- ▶ PhDs are 0.6x or 40% less riskier candidates

83.46 81.73
72.83
70.70
66.11
1.84
1.41
1.39
0.80
0.75
0.74
0.71
0.66
0.57
0.01

Appendix - Profit Summary (~20k rows)

Initial profit: -1766.76 Final profit: 8975.9 Change: 10742.66

New Customer Loss (%): 42.59

Defaulter	Profit	Prediction	Predicted Profit
1	-10.0	0	-10.0
1	-10.0	1	-0.0
1	-14.0	0	-14.0
1	-10.0	1	-0.0
1	-10.0	1	-0.0
1	-10.0	1	-0.0
1	-10.0	0	-10.0
1	-10.0	1	-0.0
1	-10.0	1	-0.0
1	-10.0	1	-0.0
Defaulter	Profit	Prediction	Predicted Profit
Defaulter 0	Profit 4.50	Prediction 0	Predicted Profit 4.5
0	4.50	0	4.5
0 0	4.50 1.50	0 0	4.5 1.5
0 0 0	4.50 1.50 4.50	0 0 0	4.5 1.5 4.5
0 0 0	4.50 1.50 4.50 3.00	0 0 0	4.5 1.5 4.5 3.0
0 0 0 0	4.50 1.50 4.50 3.00 1.50	0 0 0 0 1	4.5 1.5 4.5 3.0 0.0
0 0 0 0 0	4.50 1.50 4.50 3.00 1.50 3.00	0 0 0 0 1 1	4.5 1.5 4.5 3.0 0.0 0.0
0 0 0 0 0	4.50 1.50 4.50 3.00 1.50 3.00 6.00	0 0 0 0 1 1	4.5 1.5 4.5 3.0 0.0 0.0 6.0