Case Study

DMResources Limited - personalized micro credits

Default risk model

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THE PROBLEM:

PROFIT AFFECTED BY UNEXPECTED DEFAULT RATE

50.3% CLIENTS IN DEFUALT

Higher-than-expected credit risk demands higher reserves which in turn reduces capital availability and profit

Poor lending procedures open the door to liability with regulators

When it comes to digital automation some of the best tools for growth and profit in banking have been on credit underwriting automated models

THE RESULTS:

NEW DATA COLLECTION REQUIRED!

KEY FINDINGS

Proposed allocation procedures lead to **decreases of 15% in defaults**

Low predictive power on variables led to poor results in any model tested. But still, some applicable results

Creating **new data collection efforts** is a must for increasing accuracy and insights

Surprising!
(Using those predictions with high certainty can lead to real improvements, even with low predictive power)

Unexpected!
(Typical variables like Gender, Partner, and Dependents were not significant enough, unlike the general population)

MODEL REVIEW

LASSO LOGISTIC REGRESSION

Dataset

80% Training

20% Testing

Other models tested

1. Random Forests
2. SVM

TOTAL

65% Accuracy

75% Sensibility

55% Specificity

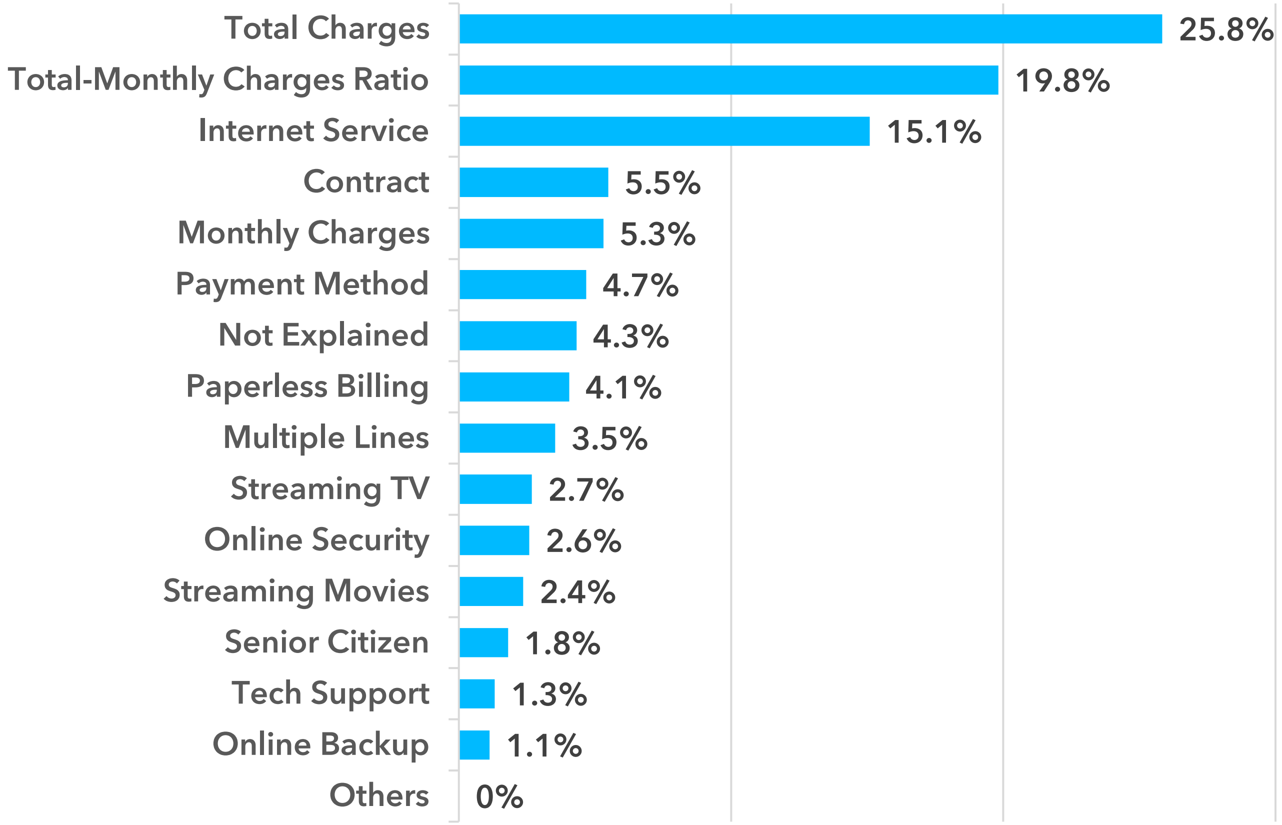
HIGH CONFIDENCE PREDICTIONS*

75% Accuracy

80% Sensibility

71% Specificity

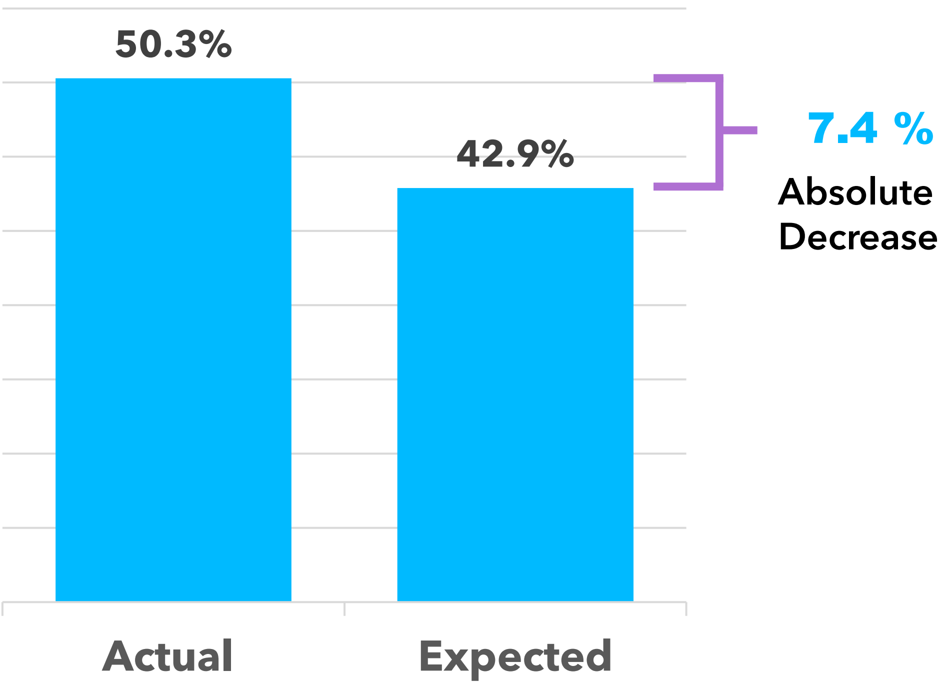
Feature Importance



*Probabilities predictions under 35% or over 65%

RESULTS REVIEW

EXPECTED DEFAULT RATE DECREASE



Using the highest confidence positive predictions to not allocate credit*

↓ **1160** Less Defaults

↓ **14.7%** Decrease in Default Rate

*Probabilities predictions over 65%

POTENTIAL NEW DATA POINTS

Industry wide used metrics

ADDRESS

INCOME

EDUCATION

JOB INDUSTRY

DEBT

CREDIT SCORE

AGE

DEBT RATIO

Appendix 1

Rank	New data points	Dificulty	Description
1	Monthly Income	Medium	Monthly Income
2	Debt ratio	Medium	Monthly debt payments, alimony, living costs divided by income
3	Number of open credit lines	Medium	Number of Open loans and Lines of credit
4	Job industry	Low	Job industry e.g. Finance, Education, Retail, etc.
5	Age	Low	Date of birth
6	Education	Low	Highest level of formal education finished
7	Address	Low	Complete address with ZIP code
8	Local Credit Score	Low	Local Credit Score

For more information, visit https://github.com/diegoandregarciam/Accenture_Case