A/B Testing - Loan Policies

Alexander Bade

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```
# load in data
data <- read_csv('early_2012_2013_loan_sample_with_outcome.csv')
```

```
## Rows: 50000 Columns: 57
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr (20): grade, sub_grade, emp_title, home_ownership, verification_status, ...
## dbl (36): id, member_id, loan_amnt, funded_amnt, funded_amnt_inv, term, int_...
## lgl  (1): loan_is_bad
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Data cleaning was undertaken before doing the A/B test to ensure the data is valid and the results from the test are accurate. The data cleaning steps were excluded from this file.

Loan Policy Definition

We decided to test a conservative loan policy (policy A) against a growth-oriented loan policy (policy B).

We chose the following variables to define our policies for the following reasons:

Grade - gives us LendingClub’s internal credit risk assessment.

Debt-to-income (dti) - gives us an idea of how long it would take an individual to pay back their loan (monthly debt payment amount to their monthly income). Essentially showing us the affordability of the loan

Annual Income - Tells us how much a person is earning in a year, allowing us to decide whether the loan is reasonable compared to their yearly income.

```
# 3 variables chosen to define policies with thresholds
data_policies <- data %>%
  mutate(
    approved_A = if_else(
      grade %in% c('A', 'B') &
      dti <= 30 &
      annual_inc >= 45000,
      1, 0
    ),
    approved_B = if_else(
      grade %in% c('A', 'B', 'C', 'D') &
      dti <= 36 &
      annual_inc >= 30000,
      1, 0
    ),
    loan_is_bad = as.integer(loan_is_bad)
  )
```

Evaluation Metric and Hypotheses

The Overall Evaluation Criterion (OEC) for the simulated A/B test is the default rate among approved loans, defined as P(loan_is_bad = 1 | approved = 1). This metric captures the proportion of loans that would have defaulted among those approved under each policy.

The null hypothesis states that there is no difference in default rate among approved loans between policy A and policy B. The alternative hypothesis states that policy B exhibits a higher default rate among approved loans than policy A.

A/B Test

To compare the two loan review policies, we evaluate the default rate among approved loans. Differences in default rates are assessed using a two-proportion z-test. A t-test is not suitable as the primary test in this simulation, as the overall evaluation criterion is a binary proportion rather than a continuous outcome.

```
# count defaults among approved loans
bad_A <- sum(data_policies$loan_is_bad[data_policies$approved_A == 1])
bad_B <- sum(data_policies$loan_is_bad[data_policies$approved_B == 1])

n_A <- sum(data_policies$approved_A == 1)
n_B <- sum(data_policies$approved_B == 1)
```

```
# run the two-proportion z-test
test <- prop.test(
  x = c(bad_A, bad_B), # number of successes (how many defaults occurred under each policy)
  n = c(n_A, n_B), # number of trials (number of approved loans under each policy)
  alternative = "less",  # testing A < B
  correct = FALSE        # turn off Yates correction for z-test
)

test
```

```
##
##  2-sample test for equality of proportions without continuity correction
##
## data:  c(bad_A, bad_B) out of c(n_A, n_B)
## X-squared = 311.42, df = 1, p-value < 2.2e-16
## alternative hypothesis: less
## 95 percent confidence interval:
##  -1.00000000 -0.04656715
## sample estimates:
##    prop 1    prop 2
## 0.0896209 0.1405837
```

```
# extract the z-statistic for reporting purposes
z <- sqrt(test$statistic)
z
```

```
## X-squared
##   17.6472
```

```
# default rates of approved loans under policies
rates <- data_policies %>%
  summarise(
    rate_A = mean(loan_is_bad[approved_A == 1], na.rm = TRUE),
    rate_B = mean(loan_is_bad[approved_B == 1], na.rm = TRUE)
  )

# effect size
effect_size <- (rates$rate_B - rates$rate_A) * 100

effect_size
```

```
## [1] 5.096278
```

Result:

We reject the null hypothesis and conclude that policy B approves a significantly higher proportion of loans that subsequently default compared to policy A ($z = 17.65$, $p < 0.001$).

Policy B increases the default rate among approved loans by 5.10% compared to policy A. Therefore, policy A is the better choice for the consumer lending business, since more loans that are subject to defaulting are more likely to be rejected. This means that the business loses less money by implementing policy A instead of policy B.

Limitations

Logistic Regression

OPTIONAL! – Not explicitly needed – Just offers more evidence

```
# transform data

data_long <- data_policies %>%
  select(loan_is_bad, approved_A, approved_B) %>%
  pivot_longer(
    cols = c(approved_A, approved_B),
    names_to = 'Policy',
    values_to = 'Approved')
```

```
data_log <- data_long %>%
  mutate(Policy = if_else(Policy == 'approved_A', 'A', 'B'),
         Policy = factor(Policy, levels = c('B', 'A'))) %>%
  filter(Approved == 1)
```

```
log_model <- glm(
  loan_is_bad ~ Policy,
  data = data_log,
  family = binomial
)

summary(log_model)
```

```
##
## Call:
## glm(formula = loan_is_bad ~ Policy, family = binomial, data = data_log)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.81045    0.01392  -130.1   <2e-16 ***
## PolicyA     -0.50782    0.02901   -17.5   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 46437  on 61641  degrees of freedom
## Residual deviance: 46108  on 61640  degrees of freedom
## AIC: 46112
##
## Number of Fisher Scoring iterations: 5
```

```
odds <- exp(-0.34294)
odds
```

```
## [1] 0.7096808
```

```
# Policy B is the baseline. The estimated odds ratio of a loan defaulting after being approve
d, switching from policy B to policy A is 0.71. This means that the odds of a loan defaulting
under policy A is approximately 71% of the odds under policy B.

# Switching from Policy B to Policy A reduces the odds of default among approved loans by app
roximately 29%.
```