Assignment 1 : Assessing the Effectiveness of Display Advertising

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Understanding Experimental Design

Star Digital wants to measure the causal effect of display advertising (banner ads) on sales conversion. Although online advertising data is easy to capture, measuring the impact of advertisements is difficult. Using click-through conversion might underestimate the effectiveness of advertising, while view-through conversion might overestimate it. So they designed a controlled experiment assigning customers to test and control groups to find the incremental impact of advertisement. The customers in the test group saw the Star Digital banner ad, while the customers in the control group saw a banner ad for a charity organization. Thus, by comparing the sales of test and control groups, the experiment aims to measure the incremental impact of Star Digital advertisement on sales.

As with all randomized controlled experiments, Star Digital also had to estimate the sample size needed to achieve statistically significant results. The challenge with having a large control group is the cost for charity advertisement from which they do not stand to gain any revenue. They decided on 10% of customers in the control group after considering factors like baseline conversion rate, campaign reach, minimum lift they want to detect, and power of the experiment. With this thought-out experimental design, we can reliably detect the causal effects of the advertisement from the data collected.

Checking the experimental data

Missing value check

```
colSums(is.na(ad))
```

```
##       id purchase     test    imp_1    imp_2    imp_3    imp_4    imp_5
##        0        0        0        0        0        0        0        0
##    imp_6
##        0
```

There are no missing values in the data.

Proportion of population between test & control

```
table(ad$test)
```

```
##
##     0     1
##  2656 22647
```

In order to reduce the overhead cost of running charity costs which have no revenue benefit, the proportion between test & control groups is 9:1

Proportion of purchasers

```
table(ad$purchase)
```

```
##
##     0     1
## 12579 12724
```

Interpretation: The total sample size is 25,303.The case states that since the conversion rate was very small(0.153%). To avoid that we only get a few data points for purchased case, the sample was drawn as choice-based sample.In order to detect smaller effects and a reasonable power level, we need large data size.

Randomization check

Intuition: Randomized Experiments require the researcher intervenes to manipulate x at random such that it is nearly guaranteed not to correlate with outcome. We sum impression at website 1-5, as the case states that the advertiser cannot control which of site 1 through 5 it can advertise on.

```
ad <- ad %>% mutate(Timp_1_5 = imp_1+imp_2+imp_3+imp_4+imp_5)
t.test(ad$Timp_1_5 ~ ad$test)
```

```
##
##  Welch Two Sample t-test
##
## data:  ad$Timp_1_5 by ad$test
## t = -0.071371, df = 3268.6, p-value = 0.9431
## alternative hypothesis: true difference in means between group 0 and group 1 is not e
## 95 percent confidence interval:
##  -0.8402427  0.7812196
## sample estimates:
## mean in group 0 mean in group 1
##        6.065512        6.095024
```

```
t.test(ad$imp_6 ~ ad$test)
```

```
##
##  Welch Two Sample t-test
##
## data:  ad$imp_6 by ad$test
## t = 0.43156, df = 2898.4, p-value = 0.6661
## alternative hypothesis: true difference in means between group 0 and group 1 is not e
## 95 percent confidence interval:
```

```
##  -0.3176712  0.4969729
## sample estimates:
## mean in group 0 mean in group 1
##        1.863705        1.774054
```

Interpretation: P-value for above tests are large enough to not reject the null hypothesis that mean purchase between group 0 and group 1 is equal to 0, which means the intervention was randomized.

Question 1: Is online advertising effective for Star Digital?

Intuition: A simple t test can be used to check effect of binary treatment.

```
t.test(ad$purchase ~ ad$test)
```

```
##
##  Welch Two Sample t-test
##
## data:  ad$purchase by ad$test
## t = -1.8713, df = 3309.2, p-value = 0.06139
## alternative hypothesis: true difference in means between group 0 and group 1 is not e
## 95 percent confidence interval:
##  -0.039289257  0.000916332
## sample estimates:
## mean in group 0 mean in group 1
##       0.4856928       0.5048792
```

Interpretation: The p-value of the test is 0.0614, which is marginally significant (<10%). Mean purchase in group 1 is significantly higher than mean purchase in group 2, so online advertising is effective for Star Digital.

Question 2: Whether increasing the frequency of advertising increases the probability of purchase?

Intuition: Use function [purchase = c1 * Timp + c2 * test + c3 * Timp * test (c1, c2, c3 are coefficient)] to test the effect. (Timp is total impressions from all the 6 sites)

```
ad <- ad %>% mutate(Timp = imp_1+imp_2+imp_3+imp_4+imp_5+imp_6)
effect_logit <- glm(formula = purchase ~ Timp + test + Timp*test, family = "binomial", d
summary(effect_logit)
```

```
##
## Call:
## glm(formula = purchase ~ Timp + test + Timp * test, family = "binomial",
##     data = ad)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.9145  -1.1266   0.1299   1.2156   1.2433
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.169577   0.042895  -3.953 7.71e-05 ***
## Timp         0.015889   0.002876   5.524 3.32e-08 ***
## test        -0.013903   0.045613  -0.305    0.761
## Timp:test    0.015466   0.003207   4.823 1.42e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
##     Null deviance: 35077  on 25302  degrees of freedom
## Residual deviance: 34190  on 25299  degrees of freedom
## AIC: 34198
##
## Number of Fisher Scoring iterations: 5
```

```
exp(coef(effect_logit))
```

```
## (Intercept)        Timp        test   Timp:test
##   0.8440214   1.0160156   0.9861932   1.0155865
```

Interpretation:

c1 -> when a customer is shown one more ad (real ad or charity ad), the likelihood of purchasing will increase 1.02%

c2 -> compared with customers shown charity ads, the likelihood of purchasing will increase 0.986% for customers shown real ads

c3 -> for customers who saw real ads, seeing one more ad will increase the likelihood of purchasing by 1.02% c3 is the effect of advertising on purchase we want to test. Since the p-value of c3 is extremely small, the effect is significant. Therefore, increasing the frequency of advertising can increase the probability of purchase.

Question 3 : Which sites should Star Digital advertise on? In particular, should it put its advertising dollars in Site 6 or Sites 1 through 5?

Intuition: Building a logistic regression model that predicts the probability of purchase based on variables

1. Timp_1_5 - total impressions from sites 1 to 5

2. imp_6 - impressions from site 6
3. Timp_1_5_t - read ads impressions from sites 1 to 5
4. imp_6_t - real ads impressions from site 6

```
ad <- ad %>% mutate(Timp_1_5_t = Timp_1_5*test,imp_6_t = imp_6*test)
comparing_sites_logit <- glm(formula = purchase ~ Timp_1_5 + imp_6 + Timp_1_5_t + imp_6_
summary(comparing_sites_logit)
```

```
##
## Call:
## glm(formula = purchase ~ Timp_1_5 + imp_6 + Timp_1_5_t + imp_6_t,
##     family = "binomial", data = ad)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -5.1260  -1.1198   0.1187   1.2215   1.2495
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.171919   0.014669 -11.720  < 2e-16 ***
## Timp_1_5     0.019603   0.003265   6.005 1.92e-09 ***
## imp_6        0.004068   0.004263   0.954   0.3399
## Timp_1_5_t   0.014437   0.003562   4.054 5.04e-05 ***
## imp_6_t      0.013344   0.005321   2.508   0.0121 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
##     Null deviance: 35077  on 25302  degrees of freedom
## Residual deviance: 34166  on 25298  degrees of freedom
## AIC: 34176
##
## Number of Fisher Scoring iterations: 5
```

Interpretation: From the above results, we observe that the p-values for total impressions on sites 1 to 5 is statistically significant.

Lets us evaluate the below scenarios to evaluate the any cost benefits in advertising on sites 1-5 or site 6 specifically.

1. Showing ads on sites 1–5 and not site 6 (real ads are shown to test group on sites 1–5, and the charity ads are shown to control group on site 6)

Calculating the probability of purchase when the real ads are only shown on sites 1-5

```
log_prob = comparing_sites_logit$coefficients[1] + comparing_sites_logit$coefficients[2]
purchase_prob_1_5 = 1/(1+exp(log_prob))
purchase_prob_1_5
```

```
## (Intercept)
##   0.5334028
```

2. Showing ads on site 6 and not sites 1-5 (real ads are shown to test group on site 6, and the charity ads are shown to control group on sites 1-5)

   Calculating the probability of purchase when the real ads are only shown on site 6

```
log_prob = comparing_sites_logit$coefficients[1] + comparing_sites_logit$coefficients[2]
purchase_prob_6 = 1/(1+exp(log_prob))
purchase_prob_6
```

```
## (Intercept)
```

```
## 	0.533675
```

As per the sample data set, the data is over sampled to have a sample purchase rate of 50% but the population purchase rate is 0.153%. So we re-scale the probabilities obtained above as per the population purchase rate, Re-scale Factor = 0.153/50

```
re_scale_factor = 0.153/50
purchase_prob_1_5 = purchase_prob_1_5 * re_scale_factor
purchase_prob_6 = purchase_prob_6 * re_scale_factor
```

Doing an ROI analysis to find if a difference between sites 1-5 and site 6 exists

Metric	Sites 1-5	Site 6
cost per impression	\$0.025	\$0.02
purchase probability	53.34%	53.36%
contribution per purchase	\$1,200	\$1,200
Revenue per impression	\$1.958	\$1.959
ROI	77.34	96.98

Findings and recommendations

1. Based on our analysis on the relationship between number of impressions and purchase behavior, we observe that showing more advertisements to customer helps attract them to buy the product. The company can consider to target customers with a larger volume of ads to nudge them to make a purchase.

2. The ROI from running ads on site 6 is higher compared to running ads sites 1-5. Based on the above evidence, advertising dollars should be directed towards site 6.

Potential areas of concern and threats to inference

In real life, various factors determine whether or not a customer makes a purchase. For instance, it may be the case that people using mobile devices are more likely to look at the advertisement, while those using desktops might rather switch to another tab instead. Randomizing the customers can help minimize the chances that other factors, like mobile versus desktop, affect the results. We checked the randomization of the test and control group for impressions on sites 1 through 5 and site-6 and failed to reject the null hypothesis that both test and control groups are similar.

Discussing threats to causal inference:

1. **Interference:** We assume that the test and control groups are independent and one group does not affect the other. One possible threat to causal inference is interference. The person in the test group might have directly or indirectly (e.g. through social media posts) influenced the person in the control group to buy the product.

2. **Omitted variable bias:** There is no reason to suspect omitted variable bias. By randomly assigning customers to test and control groups, they eliminated any possibility of an unobserved confound.

3. **Simultaneity:** We have no evidence to suggest that the purchase will make the customer visit the sites more and increase the chances of looking at the advertisement. So, we can safely say that there is no simultaneity bias.

4. **Measurement error:** In-store purchases not taken into account. Also, the campaign's objective is not only to encourage people to make a purchase but also to generate interest in the brand. If people see advertisements on the website, they may have brand awareness but make purchases later after experimentation ends.

5. **Selection bias:** The case shows that the conversion rate is small hence the sample is drawn as a choice-based sample