**Customer Analytics Assignment 4** 

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Light-colored text boxes contain code, and dark-colored text boxes contain output results.

Completely independent assignment.



#### **Task 1 (a)**

- Import and process data, converting some nonnumeric variables into factors and constructing a treatment indicator(treat\_ind).
- Build a linear regression model using the treatment indicator and shares.

```
1 # Preparation of operating environment
 2 library(tableone)
 3 library(MatchIt)
 4 library(lattice)
 5 options(width = 120)
 6 setwd(paste0(
       "/Users/velen/Documents/",
       "文稿-iCloud/Learning/JHU/Spring I/Customer Analytics/Class 5"
 9))
10 rm(list = ls())
11 ds ← read.csv("D5.2 Mashable.csv")
12
13 # Data cleaning
14 summary(ds)
15 table(ds$disclosed)
16 ds$category ← as.factor(ds$category)
17 ds$weekday ← as.factor(ds$weekday)
18
19 # Creat the treatment indicator
20 ds$treat_ind ← ifelse(ds$num_videos > 0, 1, 0)
21
22 # Task 1a
23 # Build the linear regression
24 model_t1 ← lm(shares ~ treat_ind, data = ds)
25 summary(model_t1)
```

#### **Task 1 (a)**

- In the linear regression results, the coefficient corresponding to the treatment indicator is significantly greater than 0, and the p-value is well below 0.01.
- Therefore, we can conclude that there is a
  positive correlation between the treatment
  indicator and shares, indicating that the
  treatment is associated with a typically larger
  number of shares.

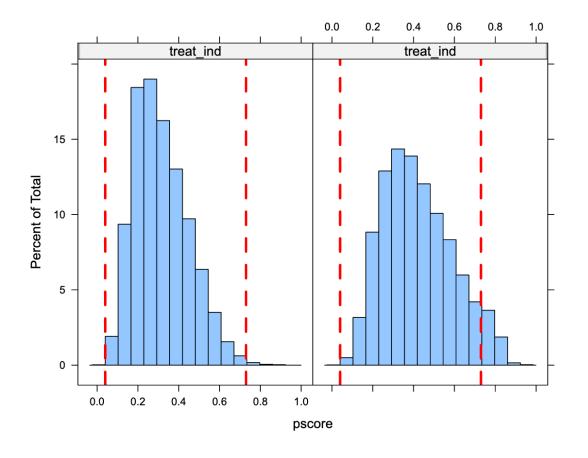
### **Task 2 (a)**

- Remove irrelevant variables, retaining only appropriate covariates. Here, the "url", "timedelta" and variables related to the independent and dependent variables were deleted.
- Generating a summary table that describes the baseline characteristics of the origin dataset and providing a statistical measure of how different the groups are from each other based on those variables.
- Calculate the propensity score using logistic regression and use a histogram to determine the overlap of the propensity score.

```
1 # Task 2a
 2 # Remove irrelevant covariates
 3 drop_list ← c("url", "timedelta", "shares", "treat_ind", "num_videos")
 4 xvars ← setdiff(names(ds), drop_list)
 6 # Pre-match assessment of balance
 7 table_unmatched ← CreateTableOne(
       vars = xvars, data = ds,
       strata = "treat ind"
10)
11 print(table_unmatched, smd = TRUE)
12
13 # Calculate the pscore
14 y_x ← as.formula(paste("treat_ind ~", paste(xvars, collapse = " + ")))
15 model_t2 \leftarrow glm(y_x, family = binomial, data = ds)
16
17 # Assess pscore overlap
18 ds$pscore ← predict(model_t2, type = "response")
19 histogram(~ pscore | treat_ind, data = ds)
21 # Draw reference lines
22 histogram(~ pscore | treat_ind,
       data = ds,
24
       panel = function(x, ...) {
           panel.histogram(x, ...)
25
           panel.abline(v = c(.04, .73), col = "red", lty = 2, lwd = 3)
26
27
28)
```

# Task 2 (a)

						test SMD
n takana titla (mana (CD))	25026		13686			
n_tokens_title (mean (SD))						
n_tokens_content (mean (SD))						
n_unique_tokens (mean (SD))					0.429	
n_non_stop_unique_tokens (mean (SD))						
num_hrefs (mean (SD))						
<pre>num_self_hrefs (mean (SD))</pre>						
num_imgs (mean (SD))						
average_token_length (mean (SD))						
num_keywords (mean (SD))					<0.001	
kwshares_worst (mean (SD))						
<pre>kwshares_best (mean (SD))</pre>						
<pre>kwshares_avg (mean (SD)) self reference min shares (mean (SD))</pre>		(1164.23)		(1453.11)		
self_reference_min_shares (mean (SD))						
<pre>self_reference_max_shares (mean (SD))</pre>		(35549.18) (23925.79)			<0.001 <0.001	
<pre>self_reference_avg_sharess (mean (SD))</pre>		(23923.79) $(0.10)$		(25319.44) (0.14)	0.018	
<pre>global_subjectivity (mean (SD))</pre>					<0.001	
<pre>global_sentiment_polarity (mean (SD)) global_rate_positive words (mean (SD))</pre>		(0.09)		(0.10)	<0.001	
		(0.02)		(0.02) (0.01)	<0.001	
<pre>global_rate_negative_words (mean (SD))</pre>						
rate_positive_words (mean (SD))		(0.17) (0.15)		(0.22) (0.17)		
<pre>rate_negative_words (mean (SD)) avg_positive_polarity (mean (SD))</pre>		(0.09)		(0.17)	<0.097	
min_positive_polarity (mean (SD))						
max_positive_polarity (mean (SD))						
avg_negative_polarity (mean (SD))		(0.12) (0.28)		(0.14) (0.30)	<0.001 <0.001	
min_negative_polarity (mean (SD))					0.003	
<pre>max_negative_polarity (mean (SD)) title_subjectivity (mean (SD))</pre>		(0.09) (0.32)		(0.11) (0.34)	<0.003	
		(0.26)				
title_sentiment_polarity (mean (SD))						
abs_title_subjectivity (mean (SD))					0.068	
<pre>abs_title_sentiment_polarity (mean (SD))</pre>						
category (%) business				(10.0)		
		(12.6)		(21.7)		
entertainment lifestvle		(12.6)				
socialmedia		(6.6)		(5.0)		
tech		(21.1)		(15.1)		
world		(33.7)				
wortu weekday (%)	0433		0128	(44.0)		
fridav		(14.2)		(14.7)		
monday						
saturdav				(5.3)		
saturday sunday		( 0.7)		(6.2)		
thursday		(18.5)				
tuesday		(18.1)		(18.3)		
tuesday wednesday	4673			(19.6)		



### **Task 2 (a)**

- From the table, we can see that the gap between the covariates of the two sample groups is not large, with the p-values generally being less than 0.001.
- From the overlap diagram, the common overlap between the two is concentrated in the range of 0.04 <= n <= 0.73, indicating a relatively large overlap range.

### **Task 2 (b)**

- Using the nearest neighbor matching method, perform the matching process based on the propensity score, and filter the matched dataset to ensure it only includes samples within the propensity score overlap region(0.04 <= n <= 0.73).
- In the result, there are 13,686 values corresponding to 0 and 13,686 values corresponding to 1, which is balanced.

```
1 # Task 2b
2 # Perform matching by pscore
3 ds_matched ← ds[ds$pscore ≥ .04 & ds$pscore ≤ .73, ]
4 matched ← matchit(y_x, method = "nearest", data = ds)
5 ds_matched ← match.data(matched)
6 table(ds_matched$treat_ind)
```

### **Task 2 (c)**

- Construct a table to assess the sample in terms of covariate balance, comparing samples from two different datasets.
- After comparing the two (see next page), I
  believe the propensity score matching process
  was successful because it effectively reduced
  the SMD, improved the balance between the two
  groups, and the corresponding p-value also
  increased. A reduction in SMD means that the
  differences in these covariates between the two
  groups have been effectively minimized,
  enhancing the accuracy of the estimation.

```
1 # Task 2c
2 # Match assessment of balance
3 table_matched 	CreateTableOne(
4    vars = xvars, data = ds_matched,
5    strata = "treat_ind"
6 )
7 print(table_unmatched, smd = TRUE)
8 print(table_matched, smd = TRUE)
```

### **Task 2 (c)**

	unmatched, smd = TRUE)	Stratified	by treat_in				
							SMD
		25026					
	le (mean (SD))						
	tent (mean (SD))						
7 n_unique_tol	ens (mean (SD))					129	
	nique_tokens (mean (SD))						
9 num_hrefs (r	ean (SD))						
LO num_self_hre	fs (mean (SD))					028	
.1 num_imgs (me	an (SD))		(8.12)				
	n_length (mean (SD))		(0.63)				
.3 num_keywords	(mean (SD))						
.4 kwshares_wo	st (mean (SD))		(510.46)				0.024
	t (mean (SD))						
	(mean (SD))						
	ce_min_shares (mean (SD))						
	ce_max_shares (mean (SD))						
	ce_avg_sharess (mean (SD))	5873.04		7433.21		001	
	ctivity (mean (SD))		(0.10)			018	0.024
	ment_polarity (mean (SD))		(0.09)				
	positive_words (mean (SD))		(0.02)		(0.02)	001	0.090
	negative_words (mean (SD))						
	e_words ( <mark>mean</mark> (SD))		(0.17)				
	e_words ( <mark>mean</mark> (SD))		(0.15)				
	_polarity (mean (SD))		(0.09)				
27 min_positive	_polarity (mean (SD))					001	
	_polarity (mean (SD))		(0.23)				
	_polarity (mean (SD))						
	_polarity (mean (SD))						
	_polarity (mean (SD))						
	tivity (mean (SD))		(0.32)				
	ent_polarity (mean (SD))		(0.26)				
	bjectivity (mean (SD))						
	ntiment_polarity (mean (SD))		(0.22)				
86 category (%							
38 entertain							
39 lifestyle							
l1 tech							
l6 saturday							
l8 thursday							
0 wednesday							

```
Stratified by treat_ind
                                                                                           test SMD
kwshares_best (mean (SD))
kwshares avg (mean (SD))
avg positive polarity (mean (SD))
```

# **Task 3 (a)**

 Reconstruct the linear regression model using the matched dataset, where the coefficient of treat\_ind represents the estimated ATE of videos on the number of shares.

#### **Task 3 (a)**

 Based on the regression results, with the coefficient of treat\_ind being positive, we can conclude that videos indeed increase the number of shares, with an estimated increase of about 1320.8 shares.

# **Task 3 (b)**

- The data in 1.a was unprocessed, and after reprocessing with the propensity score, the samples associated with treat\_ind became more balanced, reducing selection bias. This leads to a smoother and more objective overall sample distribution.
- Matching makes the groups more similar in terms of important covariates, thereby reducing the bias these covariates might introduce.
- At the same time, we removed some outliers, which will not be included in the model in 3.a. This also leads to a smaller coefficient in 3.a compared to 1.a.

# **Task 3 (c)**

- The "fudge factor" in this case may include the following:
  - 1. Due to copyright and other reasons, some articles cannot legally cite videos. Some video materials may have strict copyright restrictions; therefore, these articles can only display images or textual descriptions, which results in the treatment indicator being 0.
  - 2. Some articles do not require the use of videos because text and images are sufficient to outline the content for specific readers, which also leads to the absence of videos in the articles.
- All the above are random factors that could affect the treatment indicator but are not included in the dataset. Moreover, they are not directly related to shares.

Thank you

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