### Customer Analytics HW 4

Qiutong Shi

Fri 8:30 – 11:30

## 1. is the treatment associated with a typically larger or lower number of shares?

```
> #simple linear regression of shares and treatment
> slr = lm(shares~if_videos, data=ds)
> summary(slr)
Call:
lm(formula = shares ~ if_videos, data = ds)
Residuals:
  Min
          10 Median
                       30
                             Max
 -4309 -2310 -1691 -491 838990
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 2891.47
                        73.58 39.30 <2e-16 ***
                       123.76 11.46 <2e-16 ***
if_videos
            1418.71
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1
Residual standard error: 11640 on 38710 degrees of freedom
Multiple R-squared: 0.003383, Adjusted R-squared: 0.003358
F-statistic: 131.4 on 1 and 38710 DF, p-value: < 2.2e-16
```

The treatment is associated with a larger number of shares. According to the output of the linear regression, when treatment is present, number of shares will increase by 1419.

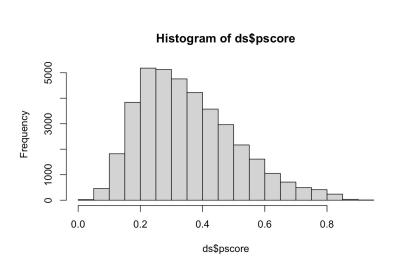
2.1 Evaluate the propensity score overlap between treated and non-treated subsamples.

From my knowledge, I think URL and timedelta have very little causational relationship with the outcome of number of shares. Therefore, it is not a confounding variable. Although I suspect that the number of videos can still affect the number of shares, I need to exclude it in my PS model to avoid it seperating the treatment indicator perfectly.

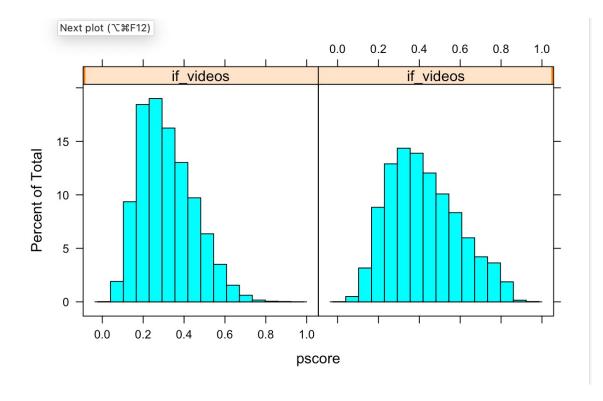
The link refers to my logic in PS model selecton:

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1513192/

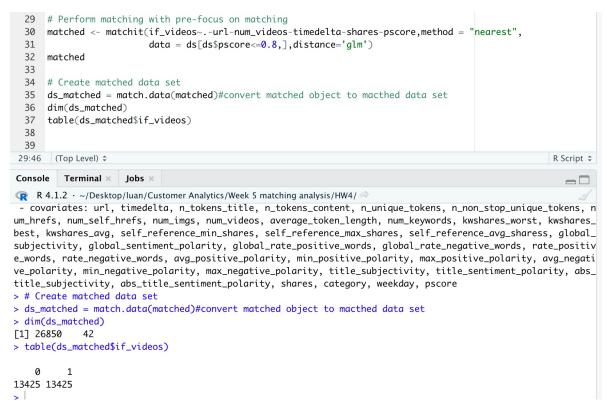
## 2.1 Evaluate the propensity score overlap between treated and non-treated subsamples.



We can observe that there is almos no observation beyond threshold = 0.8



# 2.2 Create a matched sample based on logistic propensity scores and in a way that accounts for overlap considerations



I want to relate the treatment to the covariates on all variables except for url, num\_videos, timedelta, shares, and pscores on ds, used in estimating the propensity score and for which balance is to be assessed. The method I choose is 1:1 near neighbor matching. I use glm in estimating the propensity score (basically asking matchit to replicate what I did for the previous question).

For an even number of control and test being matched, I have prefiltered to focus on pscore<0.8 for enough masses.

#### 2.3 has the matching procedure been successful?

The matching is successful. Before matching, the p-values of the means of the vairables of control and test group are small, indicating that they are statistically significant. This could damage the study of treatment.

After matching, most p-values of the means of the vairables of control and test group are large, indicating that they are not statistically significant.

The following slide would show the p-values side by side. Left-hand-side is before matching, right-hand-side is after matching.

#### 2.3 has the matching procedure been successful?

<pre>&gt; print(CreateTableOne(vars = xvars, data = ds, strata = "if_videos", smd = TRUE))</pre>					> print(CreateTableOne(vars = xvars, data = ds_matched, strata = "if_videos", smd = TRUE))				
	Stratified by if_video:	S	Stratified by if_videos						
	0	1	р .	test		0	1	р	test
n	25026	13686			n	13425	13425		
n_tokens_title (mean (SD))	10.21 (2.10)	10.69 (2.10)	<0.001		n_tokens_title (mean (SD))	10.58 (2.12)	10.66 (2.10)	0.006	
n_tokens_content (mean (SD))	554.98 (449.36)	526.87 (501.64)	<0.001		n_tokens_content (mean (SD))	551.96 (456.51)	535.38 (501.68)	0.005	
n_unique_tokens (mean (SD))	0.56 (4.43)	0.53 (0.17)	0.429		n_unique_tokens (mean (SD))	0.53 (0.13)	0.54 (0.16)	<0.001	
n_non_stop_unique_tokens (mean (SD))	0.70 (4.11)	0.67 (0.19)	0.286		n_non_stop_unique_tokens (mean (SD))	0.67 (0.14)	0.68 (0.18)	<0.001	
num_hrefs (mean (SD))	11.04 (11.31)	10.61 (11.34)	<0.001		num_hrefs (mean (SD))	10.98 (11.40)	10.75 (11.21)	0.093	
num_self_hrefs (mean (SD))	3.25 (4.06)	3.34 (3.52)	0.028		<pre>num_self_hrefs (mean (SD))</pre>	3.38 (4.30)	3.38 (3.42)	0.931	
num_imgs (mean (SD))	4.68 (8.12)	4.20 (8.42)	<0.001		num_imgs (mean (SD))	4.59 (7.30)	4.28 (8.48)	0.001	
<pre>average_token_length (mean (SD))</pre>	4.64 (0.63)	4.39 (1.11)	<0.001		<pre>average_token_length (mean (SD))</pre>	4.55 (0.79)	4.45 (0.98)	<0.001	
num_keywords (mean (SD))	7.19 (1.94)	7.30 (1.84)	<0.001		num_keywords (mean (SD))	7.28 (1.96)	7.30 (1.85)	0.400	
kwshares_worst (mean (SD))	318.09 (510.46)	302.34 (768.52)	0.016		kwshares_worst (mean (SD))	295.85 (473.33)	302.48 (760.17)	0.391	
kwshares_best (mean (SD))	236112.80 (121726.01)	271367.86 (133997.25)	<0.001		kwshares_best (mean (SD))	254034.08 (118100.07)	266952.60 (130669.11)	<0.001	
kwshares_ava (mean (SD))	2969.13 (1164.23)	3259.51 (1453.11)	<0.001		kwshares_avg (mean (SD))	3101.51 (1225.33)	3215.61 (1352.63)	<0.001	
self_reference_min_shares (mean (SD))	4027.48 (21038.58)	4022.10 (17739.38)	0.980		<pre>self_reference_min_shares (mean (SD))</pre>	3938.91 (17278.48)	4054.65 (17842.94)	0.589	
self_reference_max_shares (mean (SD))	8906.44 (35549.18)	12945.53 (49804.74)	<0.001		<pre>self_reference_max_shares (mean (SD))</pre>	9705.26 (37050.48)	11739.15 (39941.20)	<0.001	
<pre>self_reference_avq_sharess (mean (SD))</pre>	5873.04 (23925.79)	7433.21 (25319.44)	<0.001		<pre>self_reference_avg_sharess (mean (SD))</pre>	6097.96 (20873.86)	6961.62 (21740.94)	0.001	
<pre>global_subjectivity (mean (SD))</pre>	0.44 (0.10)	0.44 (0.14)	0.018		<pre>global_subjectivity (mean (SD))</pre>	0.45 (0.11)	0.45 (0.13)	0.243	
<pre>global_sentiment_polarity (mean (SD))</pre>	0.12 (0.09)	0.11 (0.10)	<0.001		<pre>global_sentiment_polarity (mean (SD))</pre>	0.12 (0.10)	0.11 (0.10)	0.082	
<pre>global_rate_positive_words (mean (SD))</pre>	0.04 (0.02)	0.04 (0.02)	<0.001		<pre>global_rate_positive_words (mean (SD))</pre>	0.04 (0.02)	0.04 (0.02)	0.563	
global_rate_negative_words (mean (SD))	0.02 (0.01)	0.02 (0.01)	<0.001		<pre>global_rate_negative_words (mean (SD))</pre>	0.02 (0.01)	0.02 (0.01)	0.082	
rate_positive_words (mean (SD))	0.70 (0.17)	0.65 (0.22)	<0.001		rate_positive_words (mean (SD))	0.68 (0.18)	0.66 (0.21)	<0.001	
rate_negative_words (mean (SD))	0.29 (0.15)	0.29 (0.17)	0.097		rate_negative_words (mean (SD))	0.30 (0.15)	0.29 (0.16)	0.060	
avg_positive_polarity (mean (SD))	0.36 (0.09)	0.35 (0.12)	<0.001		<pre>avg_positive_polarity (mean (SD))</pre>	0.36 (0.10)	0.36 (0.11)	0.183	
min_positive_polarity (mean (SD))	0.09 (0.07)	0.10 (0.08)	<0.001		min_positive_polarity (mean (SD))	0.10 (0.07)	0.10 (0.08)	0.429	
max_positive_polarity (mean (SD))	0.76 (0.23)	0.74 (0.28)	<0.001		<pre>max_positive_polarity (mean (SD))</pre>	0.76 (0.24)	0.76 (0.26)	0.075	
avg_negative_polarity (mean (SD))	-0.25 (0.12)	-0.27 (0.14)	<0.001		<pre>avg_negative_polarity (mean (SD))</pre>	-0.27 (0.13)	-0.27 (0.14)	0.164	
min_negative_polarity (mean (SD))	-0.51 (0.28)	-0.53 (0.30)	<0.001		<pre>min_negative_polarity (mean (SD))</pre>	-0.54 (0.29)	-0.54 (0.30)	0.849	
max_negative_polarity (mean (SD))	-0.11 (0.09)	-0.11 (0.11)	0.003		<pre>max_negative_polarity (mean (SD))</pre>	-0.11 (0.10)	-0.11 (0.10)	0.252	
title_subjectivity (mean (SD))	0.27 (0.32)	0.31 (0.34)	<0.003		title_subjectivity (mean (SD))	0.30 (0.33)	0.30 (0.34)	0.031	
title_sentiment_polarity (mean (SD))	0.07 (0.26)	0.07 (0.28)	0.760		title_sentiment_polarity (mean (SD))	0.07 (0.27)	0.07 (0.28)	0.331	
abs_title_subjectivity (mean (SD))	0.34 (0.19)	0.34 (0.19)	0.068		abs_title_subjectivity (mean (SD))	0.34 (0.19)	0.34 (0.19)	0.580	
abs_title_sentiment_polarity (mean (SD))		0.17 (0.24)	<0.003		abs_title_sentiment_polarity (mean (SD))	, ,	0.17 (0.23)	0.025	

#### 2.3 has the matching procedure been successful?

category (%)			<0.001	category (%)			0.001
business	4893 (19.6)	1365 (10.0)		business	1459 (10.9)	1357 (10.1)	
entertainment	3152 (12.6)	2973 (21.7)		entertainment	2726 (20.3)	2915 (21.7)	
lifestyle	1631 ( 6.5)	468 ( 3.4)		lifestyle	473 ( 3.5)	468 (3.5)	
socialmedia	1642 ( 6.6)	681 (5.0)		socialmedia	727 ( 5.4)	679 (5.1)	
tech	5275 (21.1)	2071 (15.1)		tech	2240 (16.7)	2068 (15.4)	
world	8433 (33.7)	6128 (44.8)		world	5800 (43.2)	5938 (44.2)	
weekday (%)			<0.001	weekday (%)			0.772
friday	3561 (14.2)	2008 (14.7)		friday	1967 (14.7)	1964 (14.6)	
monday	4164 (16.6)	2313 (16.9)		monday	2248 (16.7)	2272 (16.9)	
saturday	1677 ( 6.7)	724 ( 5.3)		saturday	756 ( 5.6)	722 ( 5.4)	
sunday	1791 ( 7.2)	853 ( 6.2)		sunday	907 ( 6.8)	850 (6.3)	
thursday	4619 (18.5)	2505 (18.3)		thursday	2454 (18.3)	2465 (18.4)	
tuesday	4541 (18.1)	2683 (19.6)		tuesday	2555 (19.0)	2605 (19.4)	
wednesday	4673 (18.7)	2600 (19.0)		wednesday	2538 (18.9)	2547 (19.0)	
if_videos (mean (SD))	0.00 (0.00)	1.00 (0.00)	<0.001	if_videos (mean (SD))	0.00 (0.00)	1.00 (0.00)	<0.001

## 3.1 Based on your analysis above, provide a matching ATE estimate. Do videos increase the number of shares? By how much?

```
> # Estimate ATE
> summary(lm(shares ~ if_videos, data = ds_matched))
Call:
lm(formula = shares ~ if_videos, data = ds_matched)
Residuals:
   Min
          10 Median
 -4272 -2773 -1973 -673 839027
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
                        115.2 26.330 < 2e-16 ***
(Intercept) 3034.2
if_videos 1238.8 163.0 7.601 3.03e-14 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 13350 on 26848 degrees of freedom
Multiple R-squared: 0.002148, Adjusted R-squared: 0.00211
F-statistic: 57.78 on 1 and 26848 DF, p-value: 3.027e-14
```

The average treatment effect is 1238.8. Videos increase the number of shares by 1239.

### 3.2 Provide a rationale that explains the disparity between the estimate of 3.a and 1.a

The estimate of 3a is smaller than 1a. The regression on a matched dataset shows that the impact of the treatment on number of shares might be smaller when other covariates are matched. Matching analysis helps alleviate potential model dependency by aligning the covariates.

## 3.3 what could then be the "fudge factor" (discussed in class) in this case?

#### A few fudge factors I could think of:

- 1. Time in a month the article is posted. It might be the case that people have no LTE or fast-speed data near the end of the month that affects whether they actually see an article with many videos and therefore share or not.
- 2. Pattern in sharing articles. People might feel uncomfortable sharing too many articles in a certain period of time to avoid flooding friends' inbox. For example, they could read 3 articles themselves and decide to share one.