# Individual Assignment by Ian Zhang 54505696

## 1.Research Question & Intro

# 1.1 Research Question

In this individual assignment, I did a Russian state image research from different medium sources including RT(Russia Today) and Western medium including(CNN,BBC,NY times,WashingtonPost)

The research question is "how do RT and Western Medium differ in their reports about Russia".

# 1.2 Purposes & Reasons

By comparing the textual differences between different medium sources, this research aims to find how Russian official media and mainstream Western Medium did in reporting topic choices.

The reason I chose this question is recently, many medium researchers criticized RT. Though RT treated "Question More" as their slogan, Western media doubted it is a "Kremlin-funded English-language television channel". If that is true, It's pretty similar with Chinese medium, so I hope to use textual analysis to reason this.

More info: https://en.wikipedia.org/wiki/RT\_(TV\_network)

#### 2.1.1 Get all searching urls and put them into a vector

```
library(rvest)
library(httr)
library(stringr)
cookies = readRDS("cookies.rds")
user_agent = "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_1) AppleWebKit/537.36 (KHTML, like Gecko) Ch
url_list = c()
title_list = c()
for(i in seq(10))
url = paste0("https://www.rt.com/search?q=Russia&type=&df=&dt=&page=",i)
r = GET(url,set_cookies(cookies),
        user_agent(user_agent))
text = iconv(list(r$content))
text_tree = read_html(text)
text_raw = text_tree%>% html_nodes(css = ".card-list__item") %>% html_text(" ")
text_clean = gsub("[\r\n]", "", text_raw)
text_url = str_extract(text_clean, "https:.+.\\/")
title = text_tree %>% html_nodes(css = ".card_header") %>% html_text("")
title_clean = gsub("[\r\n]", "", title)
title_clean = trimws(title_clean)
url_list = c(url_list,text_url)
title_list = c(title_list,title_clean)
}
```

#### 2.1.2 Pageniations & Get contents

```
for(url in seq(length(url_list)))
{
    print(url)
    url_u = url_list[url]
    r2 = GET(url = url_u)
    text_2 = iconv(list(r2$content))
    text_2_tree = read_html(text_2)

text_raw_2 = text_2_tree %>% html_nodes(css = ".article__text") %>% html_text(" ")
    text_clean_2 = gsub("[\r\n]", "", text_raw_2)
    if(identical(text_clean_2, character(0)))
    {
        text_clean_2 = "none"
    }
    text_list = c(text_list,text_clean_2)
}

head(text_list)
saveRDS(text_list,"RT_text_list.rds")
```

# 2.2 Scraping Western Medium

As I mentioned above. It's pretty hard to scrape Western medium pages as they use JSP to generate pages and have well-built anti-crwaler machinism. So I have to use Facebook API to scrape their posts in their official Facebook pages. By applying Regex, I extracted those posts which contain the word "Russia".

```
library(Rfacebook)
app id = "848961181910429"
app_secret = "36ea66c85eea3f1b14b53111ffde4d86"
token = Rfacebook::fbOAuth(app_id,app_secret)
token = readRDS("token.rds")
posts = getPage("cnninternational", token = token, n = 1000)
posts2 = getPage("bbcnews",token,n = 1000)
posts3 = getPage("nytimes",token,n = 1000)
posts4 = getPage("washingtonpost", token, n = 1000)
posts_a = subset(posts, !is.na(posts$message[(str_extract(posts$message, "Russia"))) == "Russia"]))
posts_b = subset(posts2, !is.na(posts2$message[(str_extract(posts2$message, "Russia"))) == "Russia"]))
posts_c = subset(posts3, !is.na(posts3$message[(str_extract(posts3$message, "Russia"))) == "Russia"]))
posts_d = subset(posts4, !is.na(posts4$message[(str_extract(posts4$message,"Russia"))) == "Russia"]))
posts a["source"] = "cnninternationa"
posts_b["source"] = "bbcnews"
posts_c["source"] = "nytimes"
posts_d["source"] = "washingtonpost"
post_russia_total = rbind(posts_a,posts_b,posts_c,posts_d)
saveRDS(post_russia_total, "Western_Russia.rds")
post_russia_total = readRDS("Western_Russia.rds")
```

# 3 Analysing the Data

# 3.1 Cleaning up and combine the two data sets

Combining those data to a dataframe.

```
Western_russia = readRDS("Western_Russia.rds")
RT_russia = readRDS("RT_text_list.rds")

RT_russia_data = data.frame(RT_russia)
RT_russia_data["source"] = "RT"

Western_russia_data = Western_russia[c("message", "source")]
colnames(RT_russia_data) = c("message", "source")
combined = rbind(RT_russia_data, Western_russia_data)

text_from_RT = combined$message[combined$source == "RT"]
text_from_Western = combined$message[combined$source != "RT"]
as.character(text_from_RT[1]) # Example from RT
```

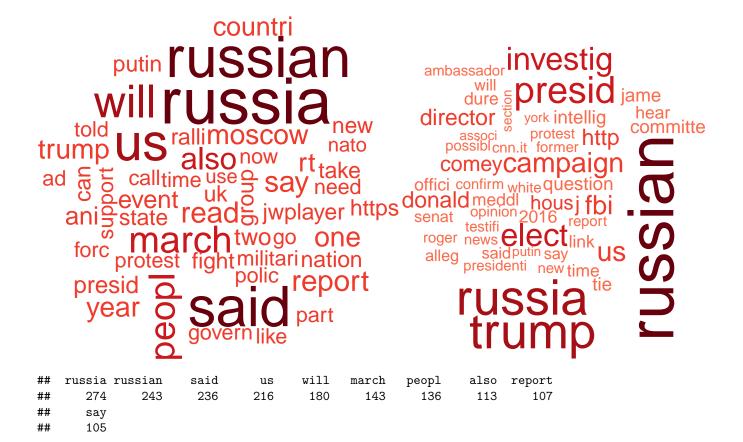
## [1] "'Thanks for separating Crimea and Ukraine'The forum's moderator Geoff Cutmore of CNBC couldn't refra IN THE NOW (@IntheNow\_tweet) March 30, 2017"Once Reagan, discussing taxes, addressed Americans, saying 'Read No'!" the Russian leader said. 'Hot Finnish guys'Finland's leader, Sauli Niinisto, addressed the issue of hea Ruptly (@Ruptly) March 30, 2017"Need help?" the Russian leader asked, jokingly offering military assistance RT (@RT\_com) March 30, 2017"

```
as.character(text_from_Western[1]) # Example from Western Medium
```

## [1] "Neither of Jared Kushner's meetings - with the Russian ambassador and with a Russian banker - were about sanctions, a source says."

## 3.2 Conduct a textual analysis of at least one of the data sets

Getting the topic words and wordclouds



From two Wordclouds and Topfeatures words we could know, first one the reports from RT also mentioned the "US", "march", "protest" (happened in Russia recently) and so on. But from Western medium we could see it emphasized the "Trump", "President", "Investigate", which means that maybe most reports are involved around the US-Russia relationship or Trump's business with Russia.

23

presid investig

29

elect

23

us campaign

19

20

Based on the above hypothesis, I conduct a the exploratory analysis and topic model analysis which will prove this point.

# 3.3 Simple Exploratory Analysis

russia

donald

40

15

trump

40

##

##

##

##

russian

55

18

fbi

Using corpora.compare we could get what are overrepresented in both data frame, then using dictionary analysis to prove what has been emphasized in both corpus (number of items per source or per target).

```
cmp = corpustools::corpora.compare(dtm_text_RT,dtm_text_Western)
cmp = cmp[order(cmp$over, decreasing = F), ]

h = rescale(log(cmp$over), c(1, .6666))
s = rescale(sqrt(cmp$chi), c(.25,1))
cmp$col = hsv(h, s, .33 + .67*s)

cmp = arrange(cmp, -termfreq)
with(head(cmp, 50), plotWords(x=log(over), words=term, wordfreq=termfreq, random.y = T, col=col, scale=
```

```
text(-2, 0, "WM", srt=90, col="red", cex=2)
text(2, 0, "RT", srt=90, col="blue", cex=2)
title(xlab="Overrepresentation")
                                        govern
                                                       fight
         trump
                                         go
                               say
                                       alsogrouprt
                                                      cañ
                        timenew
                                                    militari
                                         support uk
         elect
                                                      forc
                                         year
                                  ani polic
                                                    jwplayer
                                             like
                                                      call ralli
                                nowmoscow
                                                    march
                                                   ad takehttps
                                   report state
                                                     eventone
                                                    peopl
                                            nation
                           protest
                                               countri
                                     need
            -2
                                                                2
-3
                                      0
                                                   1
                         -1
                          Overrepresentation
d = dictionary(list(trump=c("investig*", "trump"), protest=c("protest*", "putin")))
dfm_2 = dfm(corpus(as.character(text_from_RT)),dictionary = d)
dfm_3 = dfm(corpus(as.character(text_from_Western)),dictionary = d)
k1 = data.frame(dfm_2)
k2 = data.frame(dfm_3)
sum(k1$trump)
## [1] 128
sum(k1$protest)
## [1] 135
sum(k2$trump)
## [1] 53
sum(k2$protest)
## [1] 11
rt_trump_protest_ratio = sum(k1$trump)/sum(k1$protest)
western_trump_protest_ratio = sum(k2$trump)/sum(k2$protest)
print(rt_trump_protest_ratio)
## [1] 0.9481481
print(western_trump_protest_ratio)
```

## [1] 4.818182

The overrepresentation analysis shows us that Western media seems to just emphasize the what Trump did

with Russia, but From RT we could find there are lots of topic have been covered, they didn't avoid to report domestic Bad news including mock protest. From dictionary analysis it would be more clear: Western media mentioned Trump 53 times in their report but just report protest 11 times. However, for RT both Trump and Protest just are treated as common topics.

# 3.4 Topic Modeling Analysis

## 3.4.1 Creating topic models

```
library(corpustools)
d = convert(dfm, to="topicmodels")
m = LDA(d, k = 10, method = "Gibbs", control=list(alpha=.1, iter=100))
saveRDS(m,"topic.rds")

d2 = convert(dtm_text_Western, to="topicmodels")
m2 = LDA(d2, k = 10, method = "Gibbs", control=list(alpha=.1, iter=100))
saveRDS(m2,"topic2.rds")
```

## 3.4.2 Combining topics into a data frame and analysis

After finding the topics, I set a threshold (0.1) to check whether those articles are related to this topic or not and I make a dataframe to load them.

```
m = readRDS(file = "topic.rds")
m2 = readRDS(file = "topic2.rds")
tpd = posterior(m)$topics
tpd = as.data.frame(tpd)
colnames(tpd) = c("UK", "Fighter", "Nuclear", "Oil", "Hockey", "Moscow_Protest", "Trump", "Ukrainian", "Putin",
tpd2 = posterior(m2)$topics
tpd2 = as.data.frame(tpd2)
colnames(tpd2) = c("Moscow_Protest", "Meddle_Election", "America_Russia", "America_Russia", "Moscow_Protest
print(head((tpd)))
##
                 UK
                         Fighter
                                                        Oil
                                      Nuclear
                                                                  Hockey
## text1 0.16881720 0.0146953405 0.0326164875 0.0003584229 0.0577060932
## text2 0.02720307 0.0003831418 0.8624521073 0.0003831418 0.0003831418
## text3 0.07854478 0.2016791045 0.0151119403 0.0039179104 0.0001865672
## text4 0.14518072 0.0006024096 0.0006024096 0.0126506024 0.0006024096
## text5 0.14464286 0.0017857143 0.0017857143 0.0196428571 0.0017857143
## text6 0.31033210 0.0003690037 0.0003690037 0.5391143911 0.0003690037
##
        Moscow Protest
                               Trump
                                        Ukrainian
           0.0003584229\ 0.0003584229\ 0.0003584229\ 0.69569892\ 0.0290322581
## text1
           0.0157088123 0.0042145594 0.0118773946 0.06934866 0.0080459770
## text2
## text3  0.0001865672 0.3751865672 0.0244402985 0.30055970 0.0001865672
## text4
           0.0006024096 0.0006024096 0.0006024096 0.25963855 0.5789156627
## text5
           0.2339285714 0.0375000000 0.1267857143 0.43035714 0.0017857143
## text6
           0.0003690037 0.0003690037 0.0003690037 0.14797048 0.0003690037
print(head((tpd2)))
```

Moscow\_Protest Meddle\_Election America\_Russia America\_Russia

```
## text1
            0.341666667
                             0.008333333
                                            0.258333333
                                                            0.008333333
## text2
            0.009090909
                             0.009090909
                                            0.009090909
                                                            0.009090909
## text3
            0.003571429
                             0.003571429
                                            0.003571429
                                                            0.003571429
## text4
            0.005000000
                             0.005000000
                                            0.905000000
                                                            0.005000000
## text5
            0.005882353
                             0.005882353
                                            0.947058824
                                                            0.005882353
## text6
            0.052380952
                             0.004761905
                                            0.004761905
                                                            0.004761905
##
         Moscow Protest Meddle Election Moscow Protest Russia Hacker
## text1
            0.008333333
                             0.008333333
                                            0.008333333
                                                           0.008333333
## text2
            0.009090909
                             0.009090909
                                            0.009090909
                                                           0.009090909
## text3
            0.003571429
                             0.003571429
                                            0.003571429
                                                           0.003571429
## text4
            0.005000000
                             0.005000000
                                            0.005000000
                                                           0.055000000
## text5
            0.005882353
                             0.005882353
                                            0.005882353
                                                           0.005882353
## text6
            0.004761905
                             0.004761905
                                            0.290476190
                                                           0.004761905
##
         America_Russia America_Russia
            0.341666667
                            0.008333333
## text1
## text2
            0.009090909
                            0.918181818
## text3
            0.003571429
                            0.967857143
## text4
            0.005000000
                            0.005000000
## text5
            0.005882353
                            0.005882353
## text6
            0.004761905
                            0.623809524
topicmodel = function(tpd)
  list_freq = c()
  for (i in seq(length(colnames(tpd))))
    list_freq = c(list_freq,colnames(tpd)[i])
    list_freq = c(list_freq,(table(tpd[,i]>=0.1)))
    freq = as.matrix(list_freq)
  }
  return(freq)
}
tpd_overrepresentation = topicmodel(tpd)
tpd2_overrepresentation = topicmodel(tpd2)
df = data.frame(tpd_overrepresentation,tpd2_overrepresentation)
print(df)
```

```
##
      tpd_overrepresentation tpd2_overrepresentation
## 1
                            UK
                                         Moscow Protest
## 2
                            65
                                                       78
## 3
                            35
                                                       14
## 4
                       Fighter
                                        Meddle_Election
## 5
                            77
                                                       68
## 6
                            23
                                                       24
## 7
                       Nuclear
                                         America_Russia
## 8
                            77
                                                       72
## 9
                            23
                                                       20
## 10
                           Oil
                                          America_Russia
## 11
                            80
                                                       82
## 12
                            20
                                                       10
## 13
                        Hockey
                                         Moscow_Protest
## 14
                            92
                                                       84
                             8
                                                        8
## 15
## 16
               Moscow_Protest
                                        Meddle_Election
```

17	79	62
18	21	30
19	Trump	Moscow_Protest
20	74	82
21	26	10
22	Ukrainian	Russia_Hacker
23	93	74
24	7	18
25	Putin	America_Russia
26	43	64
27	57	28
28	Syria	America_Russia
29	76	71
30	24	21
	18 19 20 21 22 23 24 25 26 27 28 29	18 21 19 Trump 20 74 21 26 22 Ukrainian 23 93 24 7 25 Putin 26 43 27 57 28 Syria 29 76

From the above table,we could know Putin. UK(Brexit),Syria,Moscow Protest are top topics for RT. But for western medium, they just focus on recent America Russia relationship and whether Russia meddles the election of president.

#### Conclusion

From this individual assignment, By analysing and comparing the text difference between the report of RT and Western Medium, I get the primary answer to the research question "how do RT and Western Medium differ in their reports about Russia".

Generally Speaking, from reports of RT I could see they tend to cover every aspect which has relations with Russia, as their topics and overrepresentation are pretty various, which including domestic issues and other countries issues. They are 2 features I could conclude

- RT likes to report those countries which have **national interest** with its(UK,Syria,US).
- They also like to emphasize their president Putin(in topic analysis 57 articles occured Putin).

So it has the features of a national media agency(like Xinhua Agency in China). However, I have not found any clues from data about "Kremlin-funded English-language television channel", as they also treat their domestic turmoil also as a important topic. However, due to I didn't analyze the sentiment of those articles, so that would be my improvement part to do further analysis.

However, western medium has a bias when reports Russia. From the data, we could know recently they just focus on the relationship between Trump and Russia. It deeply explained how does medium in different countries cater to their domestic readers.