Web Traffic Time Series Forecasting

Xin Kang

2019-02-26

Introduction

This project focuses on solving the problem of predicting the future web traffic for approximately 145,000 Wikipedia articles. Detailed data description is covered in the following section. Making future prediction on sequential or temporal observations has emerged in many key real-world problems. By forecasting the future values of multiple web traffic time series, we can answer some questions like how many severs you need in reality and what your total cost for next month is when you need to use external severs. If the performance is satisfactory, similar methods can be applied to other websites to predict their web traffic, and it can help people make smart advertisement decisions and make profit.

Data Description

Available training dataset consists of approximately 145k time series. Each of these time series represents a number of daily views of a different Wikipedia article, starting from July, 1st, 2015 up until June 30th, 2017. And the test dataset consists of times series ranging from July 1st, 2017 to September 10th, 2017. There are different types of traffic. For each time series, we are provided the name of the article as well as the type of traffic that this time series represent (all, mobile, desktop, spider). Unfortunately, the data source for this dataset does not distinguish between traffic values of zero and missing values. A missing value may mean the traffic was zero or that the data is not available for that day.

data.csv - contains traffic data. This is a csv file where each row corresponds to a particular article and each column correspond to a particular date. Some entries are missing data. The page names contain the Wikipedia project (e.g. en.wikipedia.org), type of access (e.g. desktop) and type of agent (e.g. spider). In other words, each article name has the following format: 'name_project_access_agent' (e.g. 'AKB48_zh.wikipedia.org_all-access_spider'). This data file contains times serises starting from July 1st, 2015 to September 10th, 2017, we need to divide it into training set and test set as indicated above.

key.csv - gives the mapping between the page names and the shortened Id column used for prediction.

Exploratory Data Analysis

```
library(readr)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 3.4.4
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
```

```
##     intersect, setdiff, setequal, union
```

```
library(tidyr)
library(data.table)
```

```
## Warning: package 'data.table' was built under R version 3.4.4
```

```
##
## Attaching package: 'data.table'
```

```
## The following objects are masked from 'package:dplyr':
##
##     between, first, last
```

```
library(tibble)
```

```
## Warning: package 'tibble' was built under R version 3.4.4
```

```
library(stringr)
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.4.4
```

```
library(lubridate)
```

```
## Warning: package 'lubridate' was built under R version 3.4.4
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:data.table':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday,
##     week, yday, year
```

```
## The following object is masked from 'package:base':
##
##     date
```

```
library(reshape2)
```

```
## Warning: package 'reshape2' was built under R version 3.4.3
```

```
##
## Attaching package: 'reshape2'
```

```
## The following objects are masked from 'package:data.table':
##
##     dcast, melt
```

```
## The following object is masked from 'package:tidyr':
##
##     smiths
```

```
# key = read_csv("web-traffic-time-series-forecasting/key.csv", n_max = 100)
data = read_csv("web-traffic-time-series-forecasting/data.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_integer(),
##   Page = col_character()
## )
```

```
## See spec(...) for full column specifications.
```

```
## Warning in rbind(names(probs), probs_f): number of columns of result is not
## a multiple of vector length (arg 2)
```

```
## Warning: 1 parsing failure.
## row # A tibble: 1 x 5 col     row col       expected          actual file
```

```
glimpse(key)
```

```
## function (x)
```

```
head(key)
```

```
##
## 1 function (x)
## 2 attr(x, "sorted", exact = TRUE)
```

```
dim(data)
```

```
## [1] 145063    804
```

```
select(head(data,10), 1:5, 800:804)
```

```
## # A tibble: 10 x 10
##    Page  `2015-07-01` `2015-07-02` `2015-07-03` `2015-07-04` `2017-09-06`
##    <chr>        <int>        <int>        <int>        <int>        <int>
##  1 2NE1~           18           11            5           13           27
##  2 2PM_~           11           14           15           18           25
##  3 3C_z~            1            0            1            1            7
##  4 4min~           35           13           10           94           16
##  5 52_H~           NA           NA           NA           NA           23
##  6 5566~           12            7            4            5           20
##  7 91Da~           NA           NA           NA           NA           10
##  8 A'N'~          118           26           30           24           44
##  9 AKB4~            5           23           14           12           44
## 10 ASCI~            6            3            5           12           32
## # ... with 4 more variables: `2017-09-07` <int>, `2017-09-08` <int>,
## #   `2017-09-09` <int>, `2017-09-10` <int>
```

```
select(tail(data,10), 1:5, 800:804)
```

```
## # A tibble: 10 x 10
##    Page  `2015-07-01` `2015-07-02` `2015-07-03` `2015-07-04` `2017-09-06`
##    <chr>        <int>        <int>        <int>        <int>        <int>
##  1 "Dra~           NA           NA           NA           NA            2
##  2 "Ska~           NA           NA           NA           NA            4
##  3 "Leg~           NA           NA           NA           NA            5
##  4 "Dob~           NA           NA           NA           NA           19
##  5 "Mi_~           NA           NA           NA           NA            8
##  6 "Und~           NA           NA           NA           NA            2
##  7 "Res~           NA           NA           NA           NA            5
##  8 "Ena~           NA           NA           NA           NA           13
##  9 "Has~           NA           NA           NA           NA            8
## 10 "Fra~           NA           NA           NA           NA            2
## # ... with 4 more variables: `2017-09-07` <int>, `2017-09-08` <int>,
## #   `2017-09-09` <int>, `2017-09-10` <int>
```

```
sum(is.na(data)) / (nrow(data) * ncol(data))
```

```
## [1] 0.06025302
```

```
head(data$Page, 10)
```

```
##  [1] "2NE1_zh.wikipedia.org_all-access_spider"
##  [2] "2PM_zh.wikipedia.org_all-access_spider"
##  [3] "3C_zh.wikipedia.org_all-access_spider"
##  [4] "4minute_zh.wikipedia.org_all-access_spider"
##  [5] "52_Hz_I_Love_You_zh.wikipedia.org_all-access_spider"
##  [6] "5566_zh.wikipedia.org_all-access_spider"
##  [7] "91Days_zh.wikipedia.org_all-access_spider"
##  [8] "A'N'D_zh.wikipedia.org_all-access_spider"
##  [9] "AKB48_zh.wikipedia.org_all-access_spider"
## [10] "ASCII_zh.wikipedia.org_all-access_spider"
```

Since key.csv is about 770 MB, I only load the first 100 rows to see its structure. The dimension of training set is 145063 * 804, which means it contains 145063 articles and 804 days. Let's show the first ten rows, the first five columns, and the last five columns. We can see there are many missing values in early dates, and the total is 6% missing values in the data, so we need to deal with these missing values before fitting models.

Since the page names contain the Wikipedia project (e.g. en.wikipedia.org), type of access (e.g. desktop) and type of agent (e.g. spider), which may influence the web traffic of articles, it is better to divide names into four separate parts. During this process, I discover there are three types of project including wikipedia, wikimedia and mediawiki, so I need to deal with these three types separately.

```
data = rownames_to_column(data)
wikipedia = filter(data, str_detect(data$Page, "wikipedia.org")) %>% select(rowname, Page)
nrow(wikipedia)
```

```
## [1] 127208
```

```
wikipedia = wikipedia %>% separate(Page, into = c("first","second"), sep=".wikipedia.org_") %>%
  separate(first, c("name", "project"), sep=-3) %>% separate(second, c("access", "agent"), sep = "_") %
  mutate(project = str_sub(project, 2, 3))
wikipedia[1,]
```

```
## # A tibble: 1 x 5
##   rowname name  project access     agent
##   <chr>   <chr> <chr>   <chr>      <chr>
## 1 1       2NE1  zh      all-access spider
```

```
wikimedia = filter(data, str_detect(data$Page, "wikimedia.org")) %>% select(rowname, Page)
nrow(wikimedia)
```

```
## [1] 10555
```

```
wikimedia = wikimedia %>% separate(Page, into = c("name", "second"), sep=".commons.wikimedia.org_") %>%
  separate(second, c("access", "agent"), sep = "_") %>% mutate(project = "wikimedia")
wikimedia[1,]
```

```
## # A tibble: 1 x 5
##   rowname name    access     agent  project
##   <chr>   <chr>   <chr>      <chr>  <chr>
## 1 13333   Accueil all-access spider wikimedia
```

```
mediawiki = filter(data, str_detect(data$Page, "mediawiki.org")) %>% select(rowname, Page)
nrow(mediawiki)
```

```
## [1] 7300
```

```
mediawiki = mediawiki %>% separate(Page, into = c("name", "second"), sep=".www.mediawiki.org_") %>%
  separate(second, c("access", "agent"), sep = "_") %>% mutate(project = "mediawiki")
mediawiki[1,]
```

```
## # A tibble: 1 x 5
##   rowname name                                access     agent    project
##   <chr>   <chr>                               <chr>      <chr>    <chr>
## 1 19612   "\"Keep_me_logged_in\"_extended_to_~ all-access all-age~ mediawi~
```

```
nrow(mediawiki) + nrow(wikipedia) + nrow(wikimedia) == nrow(data)
```

```
## [1] TRUE
```

```
Pages = full_join(wikipedia, wikimedia,  by = c("rowname", "name", "project", "access", "agent")) %>%
  full_join(mediawiki,  by = c("rowname", "name", "project", "access", "agent"))
head(Pages)
```

```
## # A tibble: 6 x 5
##   rowname name             project access     agent
##   <chr>   <chr>            <chr>   <chr>      <chr>
## 1 1       2NE1             zh      all-access spider
## 2 2       2PM              zh      all-access spider
## 3 3       3C               zh      all-access spider
## 4 4       4minute          zh      all-access spider
## 5 5       52_Hz_I_Love_You zh      all-access spider
## 6 6       5566             zh      all-access spider
```

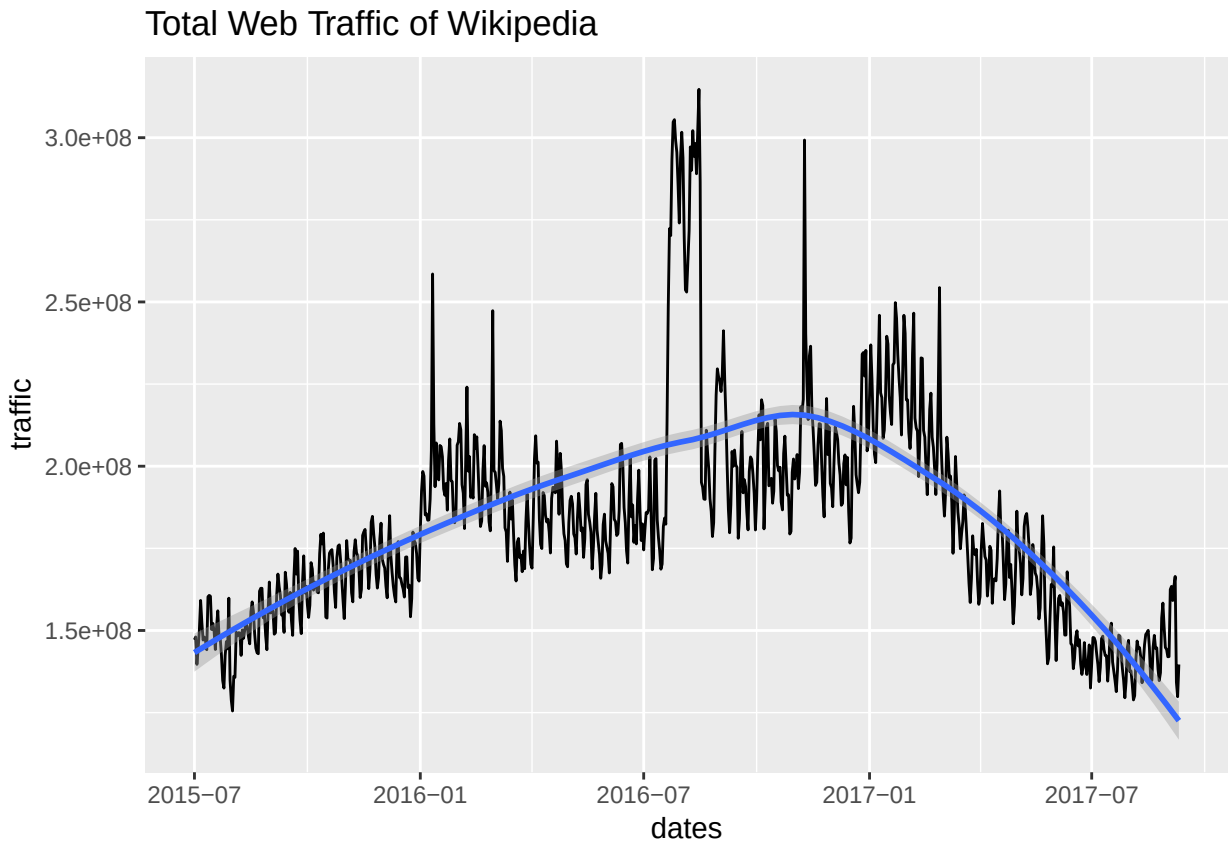
```
temp = data %>% filter(str_detect(Page, "wikipedia")) %>% select(-c(rowname, Page))
wikipediaTotal = as.data.frame(t(sapply(temp, margin = 2, sum, na.rm = TRUE)))
temp = data %>% filter(str_detect(Page, "wikimedia")) %>% select(-c(rowname, Page))
wikimediaTotal = as.data.frame(t(sapply(temp, margin = 2, sum, na.rm = TRUE)))
temp = data %>% filter(str_detect(Page, "mediawiki")) %>% select(-c(rowname, Page))
mediawikiTotal = as.data.frame(t(sapply(temp, margin = 2, sum, na.rm = TRUE)))
```

Now we have respective total web traffic of wikipedia, wikimedia and mediawiki on every day, and want to detect their trends and compare them.

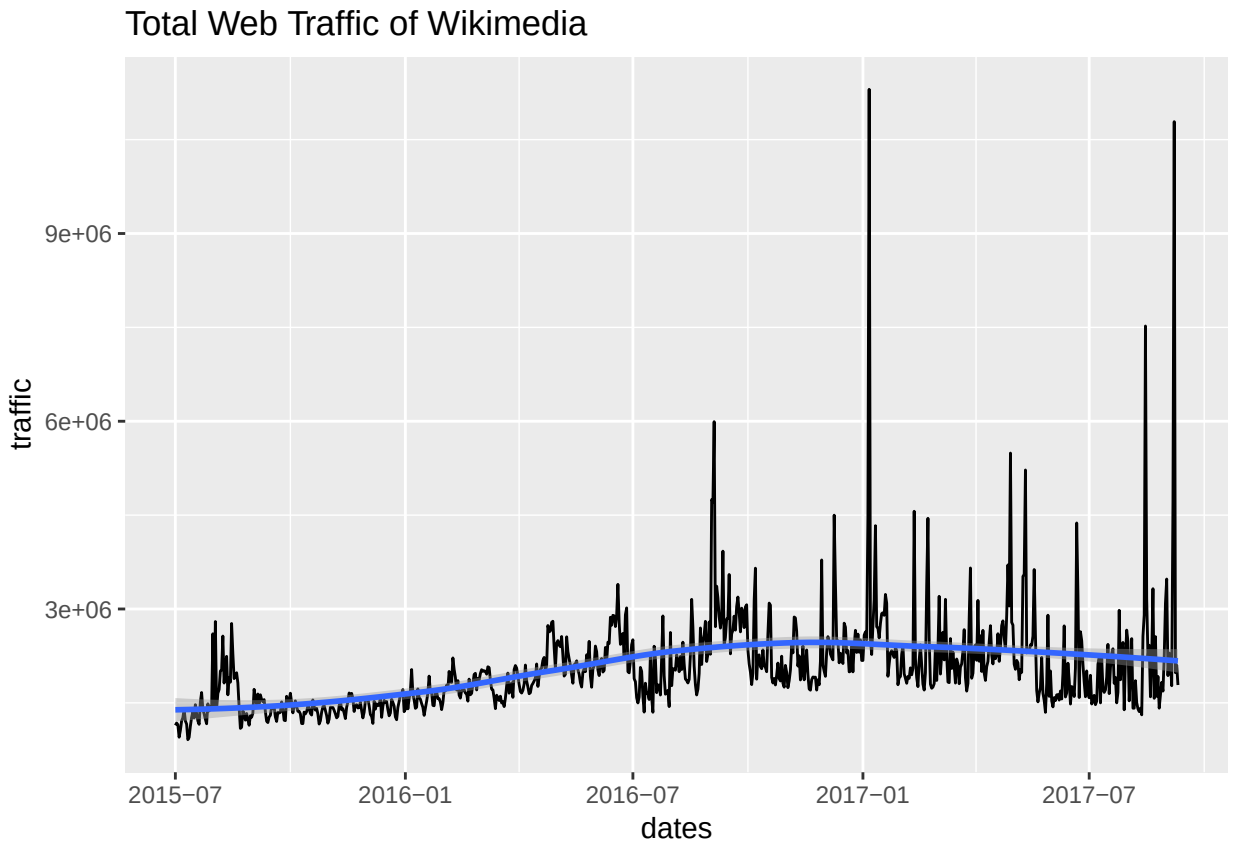
```
wikipediaTotal = wikipediaTotal %>% t() %>% as.data.frame %>% rownames_to_column %>%
  rename(dates = rowname, traffic = V1) %>% mutate(dates = as.Date(dates))
```

```
## Warning in strptime(xx, f <- "%Y-%m-%d", tz = "GMT"): unknown timezone
## 'zone/tz/2018i.1.0/zoneinfo/Asia/Shanghai'
```

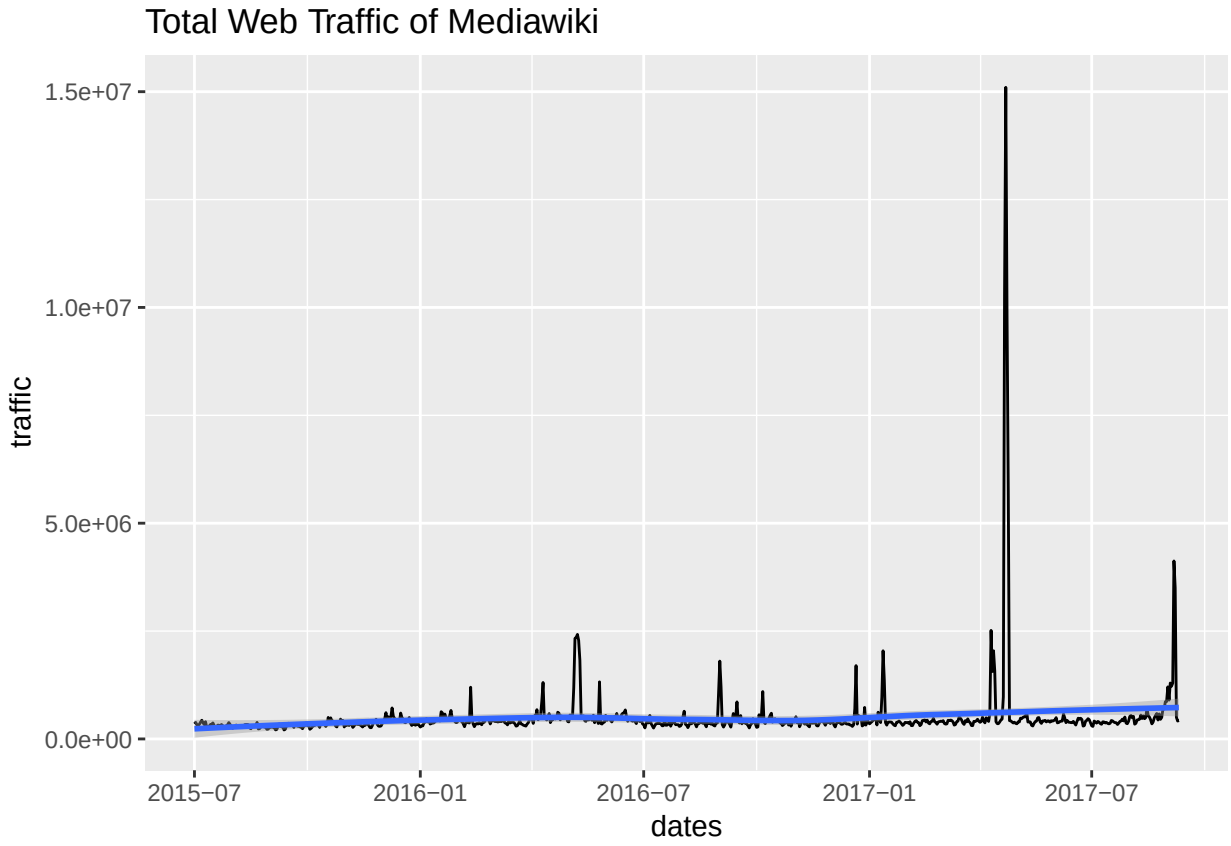
```
wikimediaTotal = wikimediaTotal %>% t() %>% as.data.frame %>% rownames_to_column %>%
  rename(dates = rowname, traffic = V1) %>% mutate(dates = as.Date(dates))
mediawikiTotal = mediawikiTotal %>% t() %>% as.data.frame %>% rownames_to_column %>%
  rename(dates = rowname, traffic = V1) %>% mutate(dates = as.Date(dates))
ggplot(wikipediaTotal, aes(dates, traffic)) + geom_line() + geom_smooth(method = 'loess') +
  labs(title = "Total Web Traffic of Wikipedia")
```




```
ggplot(wikimediaTotal, aes(dates, traffic)) + geom_line() + geom_smooth(method = 'loess') +
  labs(title = "Total Web Traffic of Wikimedia")
```




```
ggplot(mediawikiTotal, aes(dates, traffic)) + geom_line() + geom_smooth(method = 'loess') +
  labs(title = "Total Web Traffic of Mediawiki")
```



Wikipedia has a much higher number of views than wikimedia and mediawiki. The web traffic of wikipedia increases a lot from 2015-07 to the end of 2016, and then decreases. Wikimedia shows a smoothly increasing trend, and the trend of mediawiki is a flat curve. There are different types of wikipedia project, one thing that might be interesting is that how these different project might affect web traffic.

```
table(Pages$project)
```

```
##
##        de        en        es        fr        ja mediawiki        ru
##     18547     24108     14069     17802     20431      7300     15022
## wikimedia        zh
##     10555     17229
```

We can see that there are seven languages plus wikimedia and mediawiki. The languages used here are: English, Japanese, German, French, Chinese, Russian, and Spanish.

```
rowsnum = Pages %>% filter(project == "en") %>% select(rowname)
english = data %>% filter(rowname %in% as.vector(t(rowsnum))) %>% select(-c(rowname, Page))
german = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "de")])  %>%
  select(-c(rowname, Page))
spanish = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "es")])  %>%
  select(-c(rowname, Page))
french = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "fr")])  %>%
  select(-c(rowname, Page))
japanese = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "ja")])  %>%
  select(-c(rowname, Page))
russian = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "ru")])  %>%
  select(-c(rowname, Page))
chinese = data %>% filter(rowname %in% Pages$rowname[which(Pages$project == "zh")])  %>%
```

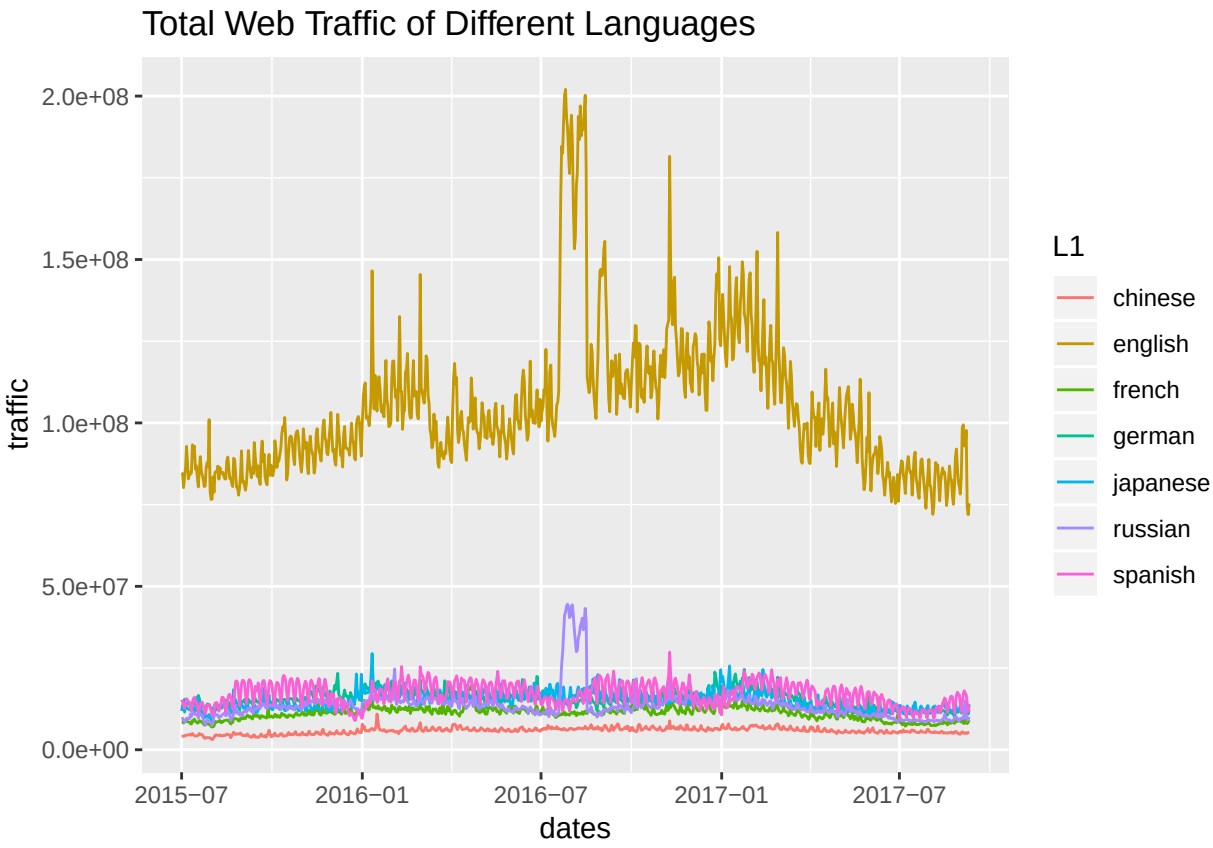
```
  select(-c(rowname, Page))
languages = list(english=english, german=german, spanish=spanish, french=french,
  japanese=japanese, russian=russian, chinese=chinese)
langs = names(languages)
languagesSum = list()
for (l in langs){
    languagesSum[[l]] = as.data.frame(t(sapply(languages[[l]], margin = 2, sum, na.rm = TRUE)))
}
plotLang = melt(languagesSum)
```

```
## No id variables; using all as measure variables
## No id variables; using all as measure variables
## No id variables; using all as measure variables
## No id variables; using all as measure variables
## No id variables; using all as measure variables
## No id variables; using all as measure variables
## No id variables; using all as measure variables
```

```
sample_n(plotLang, 6)
```

```
##     variable    value       L1
## 1 2016-02-25 13301957 japanese
## 2 2017-03-27 10588749   french
## 3 2016-07-02  6106227  chinese
## 4 2017-07-22  5445181  chinese
## 5 2016-09-18 12279339   french
## 6 2017-08-19  5085727  chinese
```

```
ggplot(plotLang, aes(as.Date(variable), value)) + geom_line(aes(color=L1)) +
  labs(x="dates", y="traffic", title = "Total Web Traffic of Different Languages")
```



English shows a much higher number of views. The English and Russian plots show very large spikes around 2016-08, with several more spikes in the English data later in 2016 and earlier in 2017. There are also several spikes in the Engilish data earlier in 2016. There is a clear periodic structure in the Spanish data.

Next analyzing different types of access and different types of agent.

```
table(Pages$project)
```

```
##
##        de        en        es        fr        ja mediawiki        ru
##     18547     24108     14069     17802     20431      7300     15022
## wikimedia        zh
##     10555     17229
```

```
table(Pages$access)
```

```
##
## all-access    desktop mobile-web
##      74315      34809      35939
```

```
table(Pages$agent)
```

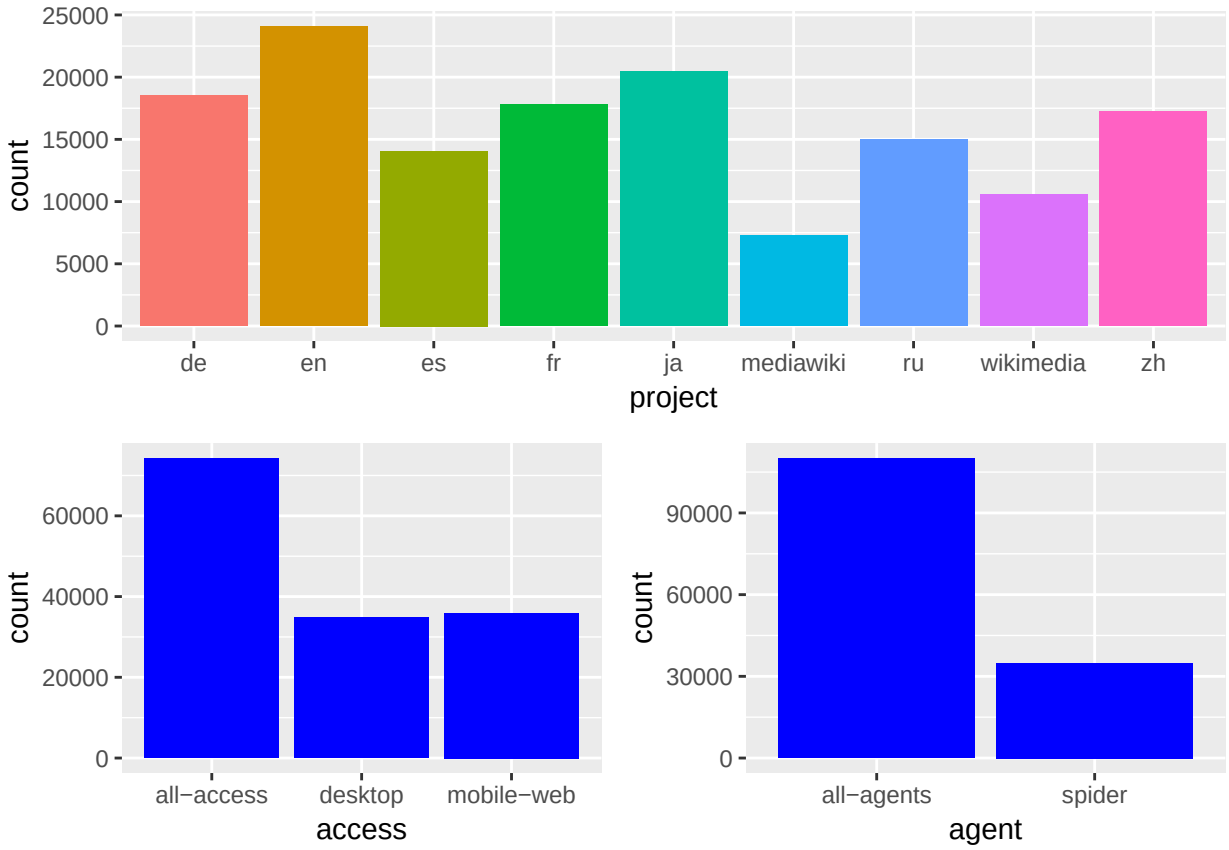
```
##
## all-agents     spider
##     110150      34913
```

In addition to seven languages, there are three types of access including all-access, desktop and mobile-web, and two types of agent including all-agents and spider.

```
library(grid)
#library(Rmisc)
```

```
p1 = ggplot(Pages, aes(project, fill=project)) + geom_bar(show.legend = FALSE)
p2 = ggplot(Pages, aes(access)) + geom_bar(fill = 'blue')
p3 = ggplot(Pages, aes(agent)) + geom_bar(fill = 'blue')

grid.newpage()
pushViewport(viewport(layout = grid.layout(2,2)))
vplayout = function(x,y)viewport(layout.pos.row = x,layout.pos.col = y)
print(p1,vp = vplayout(1,1:2))
print(p2,vp = vplayout(2,1))
print(p3,vp = vplayout(2,2))
```




```
dev.off()
```

```
## null device
##           1
```

```
nrow(data)
```

```
## [1] 145063
```

```
Data = merge(data, Pages, by = 'rowname', sort = FALSE)
nrow(Data)
```

```
## [1] 145063
```

```
Data = Data %>% select(-c(rowname, Page)) %>% gather(dates, traffic, -c(name, project, access, agent))
head(Data)
```

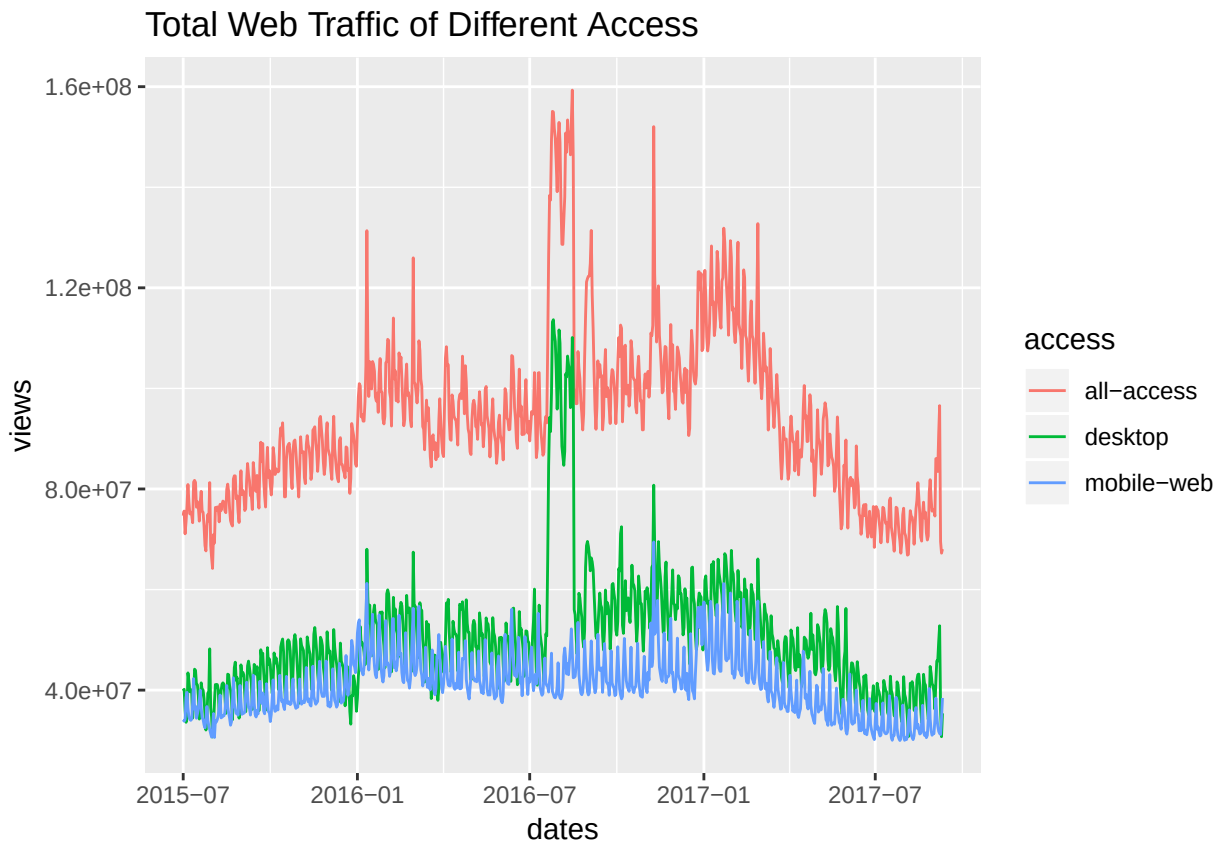
```
##                name project     access  agent      dates traffic
```

```
## 1              2NE1      zh all-access spider 2015-07-01      18
## 2               2PM      zh all-access spider 2015-07-01      11
## 3                3C      zh all-access spider 2015-07-01       1
## 4          4minute      zh all-access spider 2015-07-01      35
## 5 52_Hz_I_Love_You      zh all-access spider 2015-07-01      NA
## 6              5566      zh all-access spider 2015-07-01      12
```

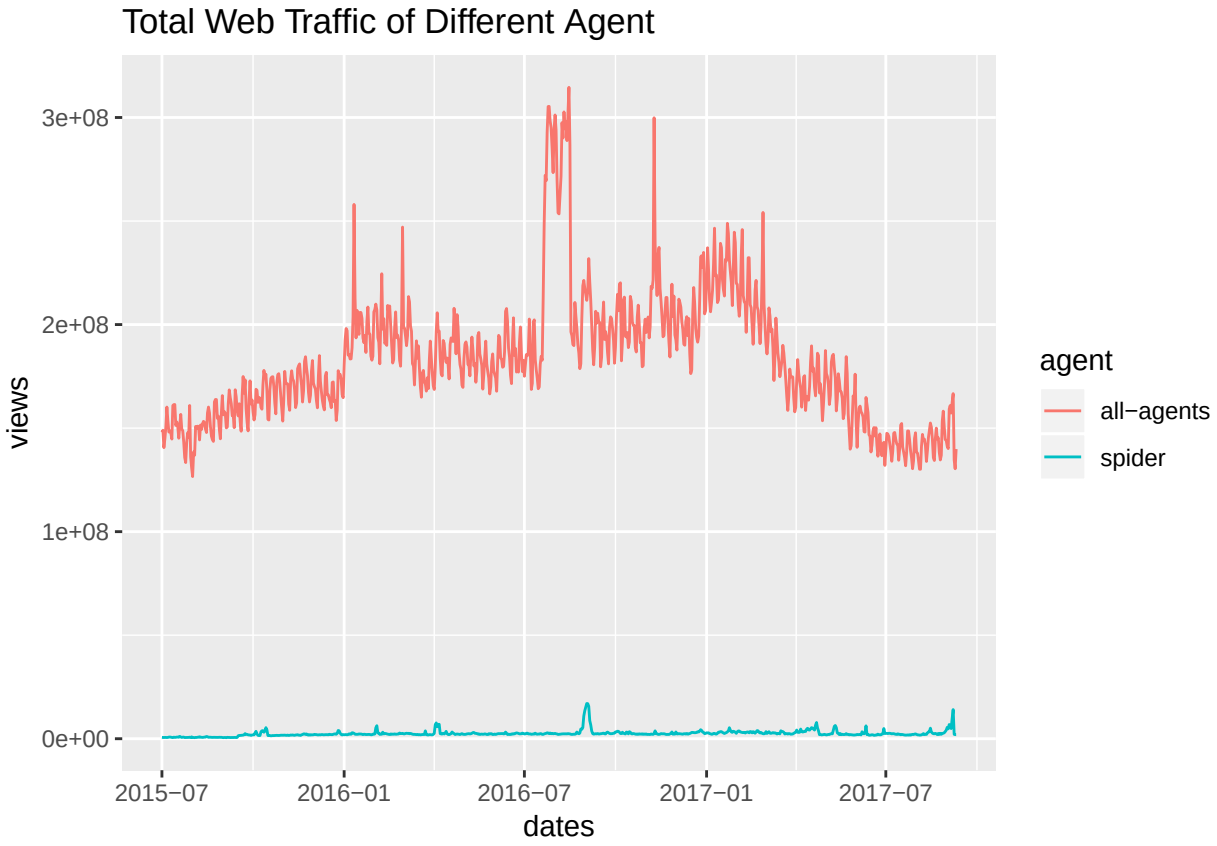
```
nrow(Data)
```

```
## [1] 116485589
```

```
temp = Data %>% select(dates, access, traffic) %>% group_by(dates, access) %>%
  summarize(views = sum(traffic, na.rm = TRUE))
temp %>% ggplot(aes(ymd(dates), views, color = access)) + geom_line() +
  labs(x = "dates", y = "views", title = "Total Web Traffic of Different Access")
```




```
temp = Data %>% select(dates, agent, traffic) %>% group_by(dates, agent) %>%
  summarize(views = sum(traffic, na.rm = TRUE))
temp %>% ggplot(aes(ymd(dates), views, color = agent)) + geom_line() +
  labs(x = "dates", y = "views", title = "Total Web Traffic of Different Agent")
```



#Next Step After some exploratory data analyses, I need to deal with missing data, data standization, feature engineering and model fitting. I plan to try ARIMA and LSTM to predict future views for wikipedia articles, and I will also do some data interpretation like explaining the feature importance and some patterns in the data.