# Data Scientist Internship Report

Analyzing Afghan Refugees Data

Peyman Kor

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## Contents

# Which countries host the most Afghan refugees and asylum seekers? Create a plot of the Top 10 and a plot of the Top 5 countries with the biggest increase from 2017 to 2018. Where did you find the data and how did you decide to visualize it?

So, first to start our analysis here we import the required library in the R programming language, the line with comments show the *installation* if the package has not been installed in the R.

## Initialization

## Data Loading

For answering the first three questions we use the one data-set, for the last question we will use the another data-set (more complete form of first data-set). So, here the data set was downloaded from the UNHCR in the following link:.

[http://popstats.unhcr.org/en/time_series]

At that link, we select the Years from 2008 until 2018 and as well select the *Afghanistan* as the country of *Origin* and all other countries as the *Host* countries. The following population types were selected depending on the questions was asked:

- Asylum-seekers
- Internally displaced persons
- Refugees (incl. refugee-like situations)

Note that the we skip the first three lines since there are comment for the data and as well set that * in the original data is showed as *NA* after import the data.

```
afghan_data <- read.csv('afghan_data.csv', header = T, skip = 3, na.strings = c('*'))
head(afghan_data)
```

```
##   Year Country...territory.of.asylum.residence      Origin
## 1 2008                             Afghanistan Afghanistan
## 2 2008                               Australia Afghanistan
## 3 2008                               Australia Afghanistan
## 4 2008                                 Austria Afghanistan
## 5 2008                                 Austria Afghanistan
## 6 2008                              Azerbaijan Afghanistan
##                              Population.type  Value
## 1             Internally displaced persons 230670
## 2                           Asylum-seekers     28
## 3 Refugees (incl. refugee-like situations)   4933
## 4                           Asylum-seekers   2016
## 5 Refugees (incl. refugee-like situations)   5387
## 6                           Asylum-seekers     24
```

## Brief Look on Column Names and Type

Here, let's have look on column names and types:

```
sapply(afghan_data, class)
```

```
##                                     Year Country...territory.of.asylum.residence
##                                "integer"                                "factor"
##                                   Origin                         Population.type
##                                 "factor"                                "factor"
##                                    Value
##                                "integer"
```

Data types seems fine, yet some of the column names could be changed to the more convenient names:

```
colnames(afghan_data) <- c('Year','Host','Origin','Type','Value')
```

## The country with most Afghan Refugees and Asylum Seekers

### Year 2017

So we start with the year 2017 and then 2018 which at the end both will be used to show the increase from 2017 to 2018 in question number 3. Here, first we *select* the year 2017 from the the data-set:

```
data_refuge_2017 <- afghan_data %>%
  filter(Year == 2017)
```

Here, we make change that is since question asks about the *Refugees* and *Asylum Seekers*, we rename the those both group one name, since we want the *sum* of them per country of host(residence). (If the question wanted to have separate analysis on Refugees and Asylum Seekers number, then it need a little modified version of this code.)

```
levels(data_refuge_2017$Type)
```

```
## [1] "Asylum-seekers"
## [2] "Internally displaced persons"
## [3] "Refugees (incl. refugee-like situations)"
```

```
data_refuge_2017_agg <- data_refuge_2017
levels(data_refuge_2017_agg$Type) <- c('Asylum_or_refugees', 'IDP','Asylum_or_refugees')
head(data_refuge_2017_agg)
```

```
##   Year                 Host      Origin               Type   Value
## 1 2017          Afghanistan Afghanistan                IDP 1837079
## 2 2017               Angola Afghanistan Asylum_or_refugees       1
## 3 2017              Albania Afghanistan Asylum_or_refugees       1
## 4 2017 United Arab Emirates Afghanistan Asylum_or_refugees      14
## 5 2017 United Arab Emirates Afghanistan Asylum_or_refugees       5
## 6 2017            Argentina Afghanistan Asylum_or_refugees       9
```

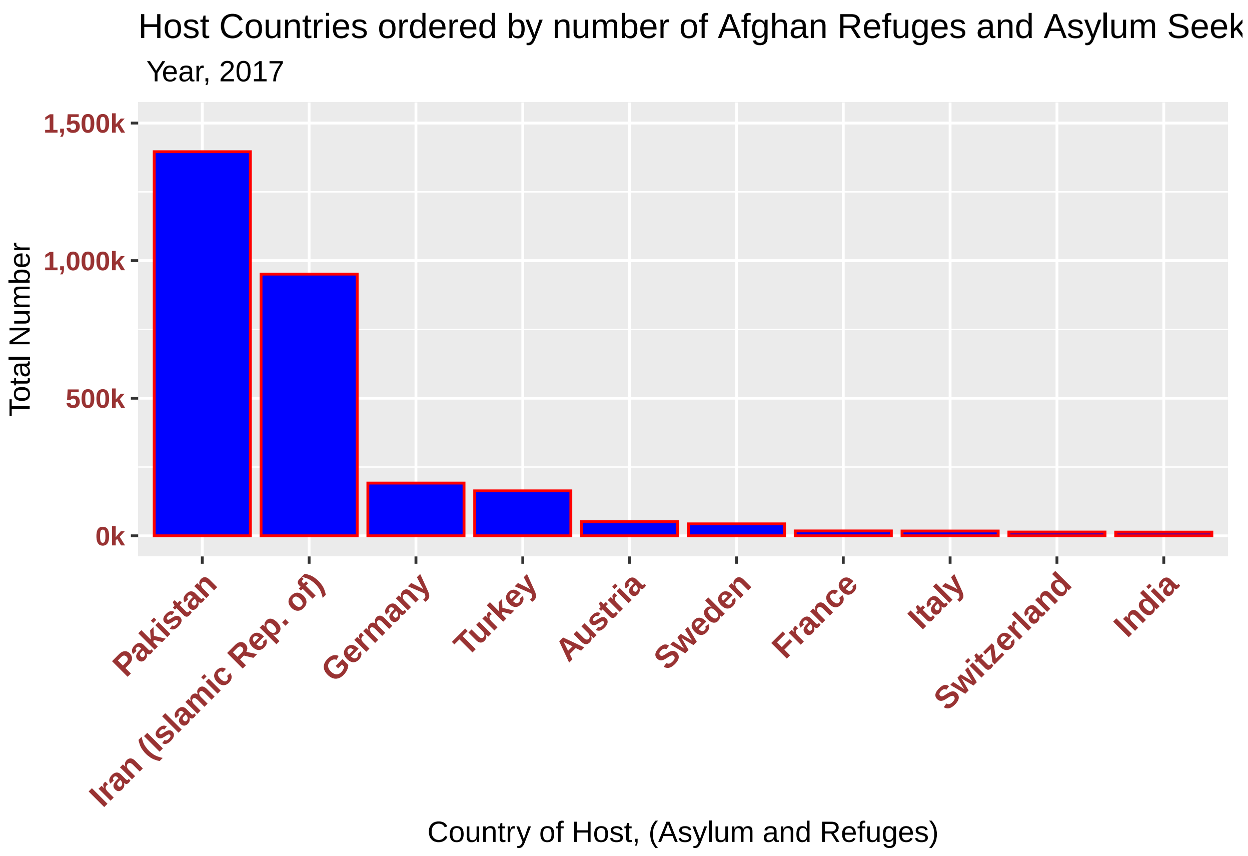
As we can see from the above, those two different group now are showed in one single category *Asylum_or_refugees* . Also, we can see that for this specific question, the first row indicating the *Internally Displacement Persons* is not needed for the below analysis. Then, we simply group the data based on *Host* and *Type* of population and sum on them, order them finally, select the top 10.

```
data_refuge_2017_agg_cor <- data_refuge_2017_agg[-1,]
data_refugee_2017_agg_cor_order <- data_refuge_2017_agg_cor %>%
  group_by(Host,Type) %>%
  summarise(Frequency = sum(Value)) %>%
  arrange(desc(Frequency)) %>%
  head(10)
```

Now, the data named *data_refugee_2017_agg_cor_order* contains the information for top countries in hosting afghan refugees and are ready for visualize:

```
ks <- function (x) { number_format(accuracy = 1,
                                   scale = 1/1000,
                                   suffix = "k",
                                   big.mark = ",")(x) }

ggplot(data_refugee_2017_agg_cor_order, aes(reorder(Host, -Frequency), Frequency)) +
  geom_bar(stat = 'identity', fill='blue', color='red') +
  scale_y_continuous(labels = ks, limits = c(0, 1500000)) +
  labs(x= 'Country of Host, (Asylum and Refuges)') +
  labs(y = 'Total Number') +
  labs(title = 'Host Countries ordered by number of Afghan Refuges and Asylum Seekers') +
  labs(subtitle =' Year, 2017') +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                           size = 12, angle = 45, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                           size = 10, hjust = 1))
```



## The country with most Afghan Refugees and Asylum Seekers

### Year 2018

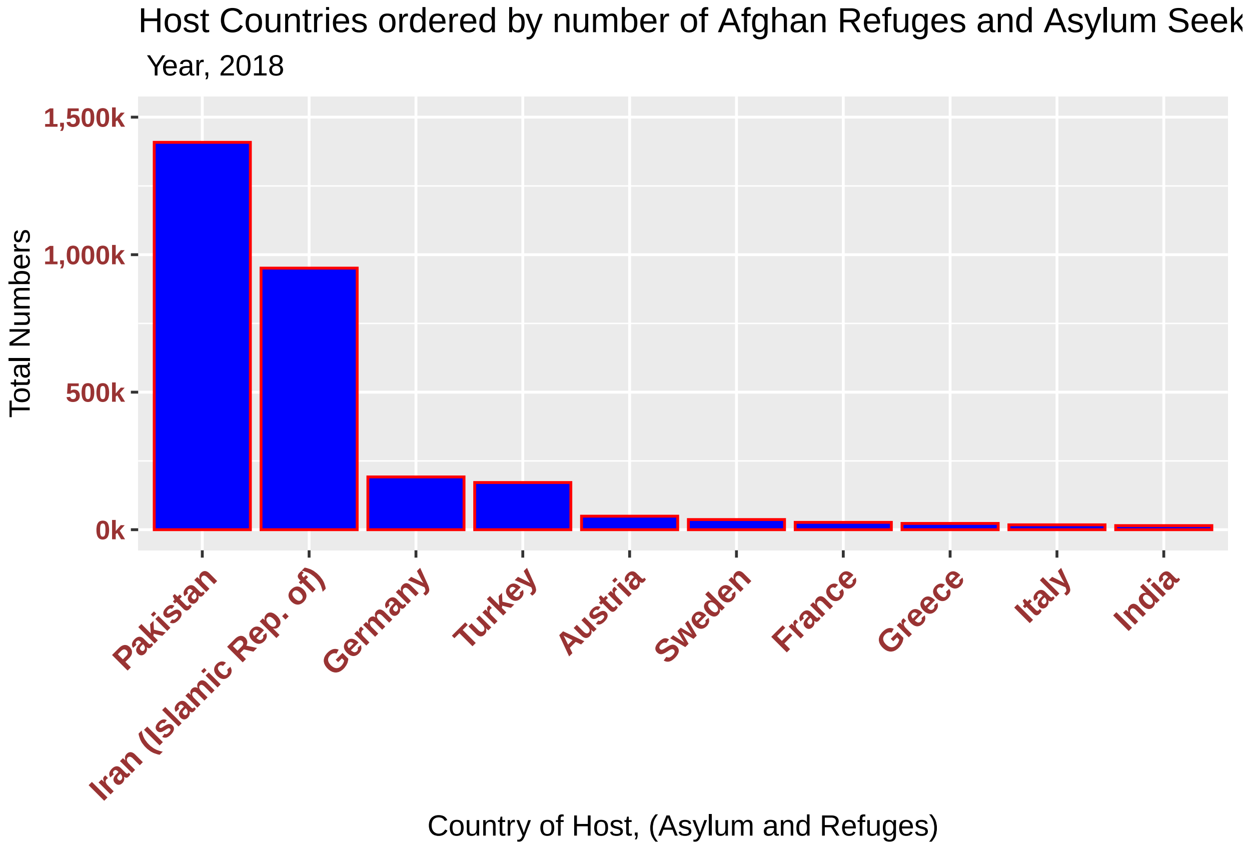
Now, let's repeat the above analysis for for the year 2018. It follows exactly like the previous case with only difference here we select the *Year* for 2018:

```
data_refuge_2018 <- afghan_data %>%
  filter(Year == 2018)
data_refuge_2018_agg <- data_refuge_2018
levels(data_refuge_2018_agg$Type) <- c('Asylum_or_refugees', 'IDP','Asylum_or_refugees')
data_refuge_2018_agg_cor <- data_refuge_2018_agg[-1,]

data_refugee_2018_agg_cor_order <- data_refuge_2018_agg_cor %>%
  group_by(Host,Type) %>%
  summarise(Frequency = sum(Value)) %>%
  arrange(desc(Frequency)) %>%
  head(10)


ggplot(data_refugee_2018_agg_cor_order, aes(reorder(Host, -Frequency), Frequency)) +
  geom_bar(stat = 'identity', fill='blue', color='red') +
  scale_y_continuous(labels = ks, limits = c(0, 1500000)) +
  labs(x= 'Country of Host, (Asylum and Refuges)') +
  labs(y = 'Total Numbers') +
```

```r
  labs(title = 'Host Countries ordered by number of Afghan Refuges and Asylum Seekers') +
  labs(subtitle =' Year, 2018') +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                                   size = 12, angle = 45, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                                   size = 10, hjust = 1))
```



### Top 5 countries with biggest increase from 2017 to 2018:

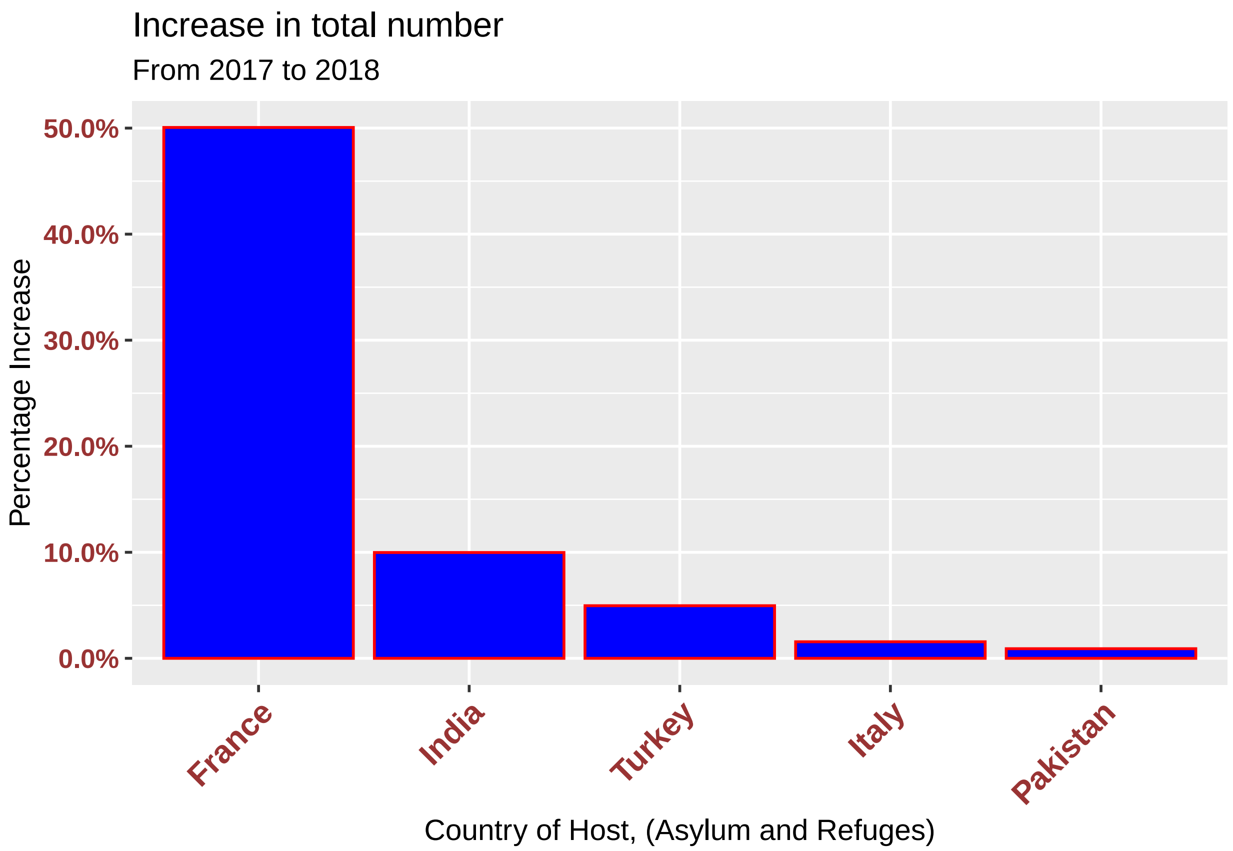
Here, we do the *inner_join* between the clean data of the year 2017 and 2018. Then, we add the new column named *Growth* which give the the ratio of increase of the total Refuges and Asylum seekers from 2017 to 2018. At the end, we visualize the top 5 countries based on the growth.

Note: It must be mentioned here we calculate the *Percentage* increase from the year 2017.

```r
data_refugee_2017_2018 <- left_join(data_refugee_2017_agg_cor_order,
                                    data_refugee_2018_agg_cor_order, by='Host')

data_refugee_2017_2018_growth <- data_refugee_2017_2018 %>%
  `colnames<-`(c("Host", "Typex", "Number_2017",'Typey', 'Number_2018')) %>%
  select(Host, Number_2017, Number_2018) %>%
  mutate(Growth = (Number_2018-Number_2017)/Number_2017) %>%
  arrange(desc(Growth)) %>%
  head(5)
```

```r
ggplot(data_refugee_2017_2018_growth, aes(reorder(Host, -Growth), Growth)) +
  geom_bar(stat = 'identity', fill='blue', color='red') +
  labs(x= 'Country of Host, (Asylum and Refuges)') +
  labs(y = 'Percentage Increase') +
  labs(title = 'Increase in total number') +
  labs(subtitle ='From 2017 to 2018') +
  scale_y_continuous(labels = scales::percent) +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                                   size = 12, angle = 45, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                                   size = 10, hjust = 1))
```



## Is there a relationship between the number of Afghan refugees and asylum seekers in a country and the distance between that country and Afghanistan?

Here, since we are looking for overall relationship between total number of Refugees and Asylum Seekers, we first select the top 50 countries hosting the the Afghans:

```
data_refugee_2018_agg_cor_order_top50 <- data_refuge_2018_agg_cor %>%
  group_by(Host,Type) %>%
  summarise(Frequency = sum(Value)) %>%
  arrange(desc(Frequency)) %>%
  head(50)
```

Then, for distance from Afghanistan to other countries, we do the web scraping. We use the web [https://www.geodatos.net/en/distances/country/afghanistan] to find the distance between Afghanistan to at least 100 countries.

### Web Scarping for Distance Between Countries

```
web <- read_html('https://www.geodatos.net/en/distances/country/afghanistan')
Table <- web %>%
  html_node('table') %>%
  html_table(fill = T)

head(Table)
```

```
##          Distance between countries Kilometers    Miles
## 1         From Afghanistan to China   3,310 km 2,057 mi
## 2         From Afghanistan to India   1,849 km 1,149 mi
## 3 From Afghanistan to United States  11,916 km 7,404 mi
## 4     From Afghanistan to Indonesia   6,163 km 3,830 mi
## 5        From Afghanistan to Brazil  13,585 km 8,441 mi
## 6      From Afghanistan to Pakistan     425 km   264 mi
```

However, we can see a few issues regarding this table. So, we clean this table as the below: * The first column must be just name of host country * The *mi* sign should be removed from the integer column * The country name *Iran* must be changed to as the name in the above data (*Iran (Islamic Rep. of)*)

Then, after doing the above we can simply change the column names and select the desired columns:

```
Table$`Distance between countries` <-  gsub("From Afghanistan to "
                                            , "",
                                            as.character(Table$`Distance between countries`))
Table$Miles <-  gsub( " mi", "", as.character(Table$Miles))
Table$Miles <-  gsub( ",", "", as.character(Table$Miles))
Table$Miles <- as.integer(Table$Miles)
Table[18,1] <- 'Iran (Islamic Rep. of)'
colnames(Table) <- c("Host", "XX", "Miles")
Distance_host_miles <- Table %>%
  select(Host, Miles)

head(Distance_host_miles)
```

```
##             Host Miles
## 1          China  2057
## 2          India  1149
## 3 United States  7404
## 4      Indonesia  3830
## 5         Brazil  8441
## 6       Pakistan   264
```

### Inner_join the Number of Refugees and Asylum with the Distance Table

Here, we do the inner join the two tables with the common column name *Host* and could have look on the data:

Note: Here because of the limitation in the data bank of the website we used, it was only to find the distance for 33 countries, which could be sufficiently enough to make initial argument about the correlation:

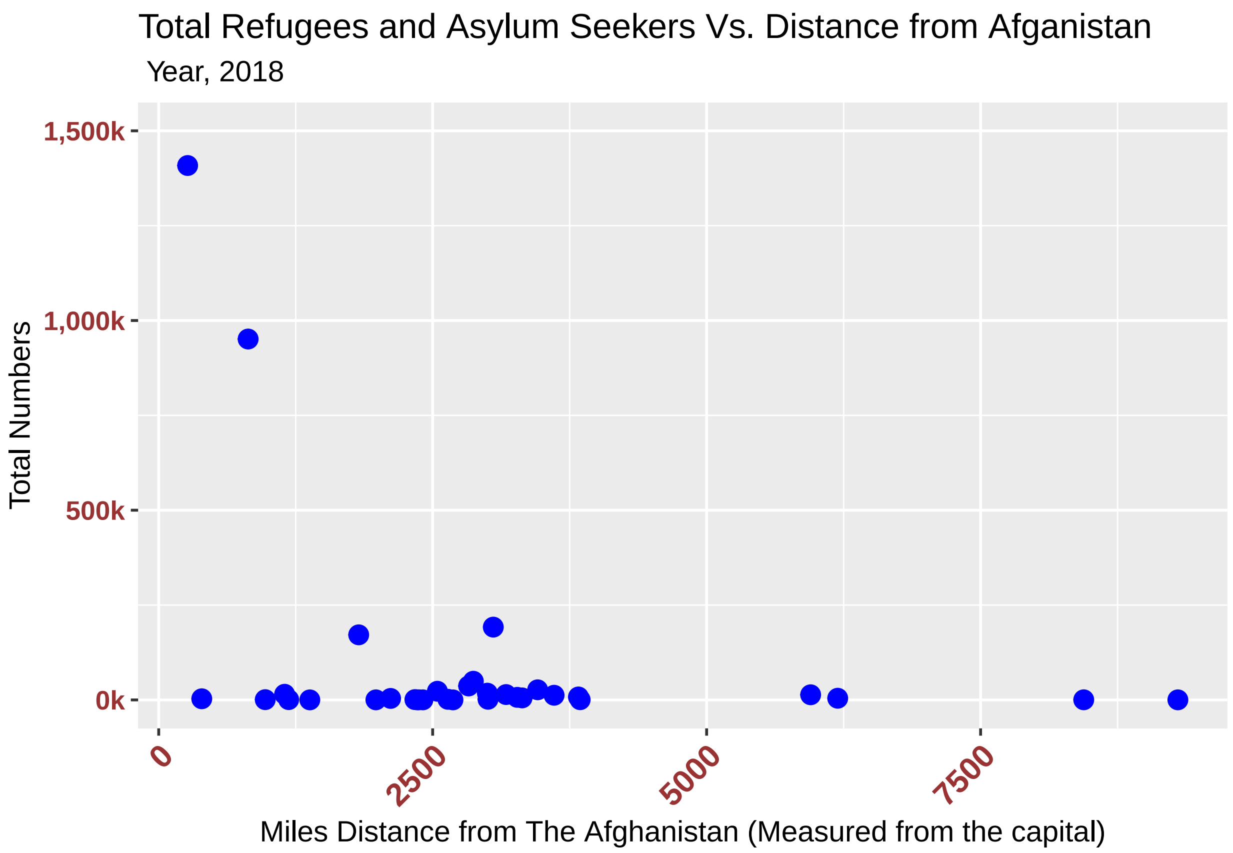
```
refugee_dis_2018 <- inner_join(data_refugee_2018_agg_cor_order_top50,Distance_host_miles
                              , by= 'Host')
```

```
## Warning: Column `Host` joining factor and character vector, coercing into
## character vector
```

```
head(refugee_dis_2018)
```

```
## # A tibble: 6 x 4
## # Groups:   Host [6]
##   Host                     Type                Frequency Miles
##   <chr>                    <fct>                   <int> <int>
## 1 Pakistan                 Asylum_or_refugees    1408533   264
## 2 Iran (Islamic Rep. of) Asylum_or_refugees     951142   816
## 3 Germany                  Asylum_or_refugees     191856  3053
## 4 Turkey                   Asylum_or_refugees     171519  1825
## 5 Austria                  Asylum_or_refugees      49196  2871
## 6 Sweden                   Asylum_or_refugees      36818  2828
```

```
ggplot(refugee_dis_2018, aes(Miles, Frequency)) +
  geom_point(size=3, color='blue') +
  scale_y_continuous(labels = ks, limits = c(0, 1500000)) +
  labs(x= 'Miles Distance from The Afghanistan (Measured from the capital)') +
  labs(y = 'Total Numbers') +
  labs(title = 'Total Refugees and Asylum Seekers Vs. Distance from Afganistan') +
  labs(subtitle =' Year, 2018') +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                          size = 12, angle = 45, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                          size = 10, hjust = 1))
```



Looking on the above plot, we can argue that there is no meaningful correlation between distance from Afghanistan and total number of the refugees and asylum seekers from Afghanistan. Especially, looking on the close distance from Afghanistan, the neighborhood countries of the Afghanistan have different number of Afghans while having similar distance from the Afghanistan.

## Visualize for the last 10 years: total number of refugees and asylum seekers from Afghanistan together with the number of internally displaced from Afghanistan.

Here, referring to the first data set, we can compute the total numbers as well we have the number of internally displaced persons in Afghanistan on every years. Then, we plot both two trends in one column.

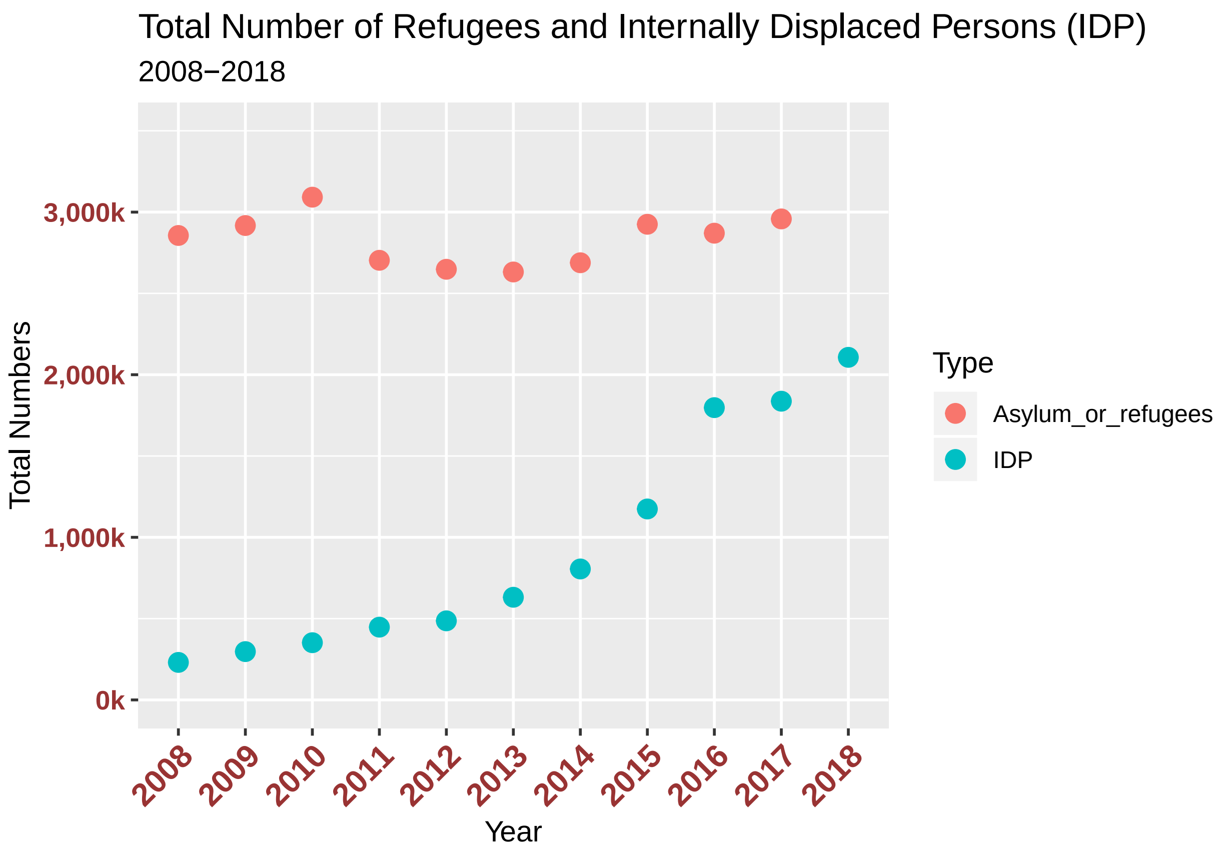
Note: The data of refuges and Asylum seekers for year 2018 is not complete, therefore it is not showed for the year 2018 in the below plot.

```
tot_ref_idp <-afghan_data
levels(tot_ref_idp$Type) <- c('Asylum_or_refugees', 'IDP','Asylum_or_refugees')
tot_ref_idp$Year <- as.factor(tot_ref_idp$Year)
tot_ref_idp$Type <- as.factor(tot_ref_idp$Type)

tot_ref_idp_sum <- tot_ref_idp %>%
  group_by(Year, Type) %>%
  summarise(Total = sum(Value))


ggplot(tot_ref_idp_sum, aes(Year,Total)) +
  geom_point(aes(colour = Type), size = 3) +
  scale_y_continuous(labels = ks, limits = c(0, 3500000)) +
  labs(x= 'Year') +
  labs(y = 'Total Numbers') +
  labs(title = 'Total Number of Refugees and Internally Displaced Persons (IDP)') +
  labs(subtitle ='2008-2018 ') +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                                   size = 12, angle = 45, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                                   size = 10, hjust = 1))
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```


Total Number of Refugees and Internally Displaced Persons (IDP)
2008−2018
Total Numbers
3,000k
2,000k
1,000k
0k
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Year
Type
Asylum_or_refugees
IDP

## If you were to design a model for forecasting next year's refugees and asylum seekers from Afghanistan, what type of model would you want to try and what kind of input do you think is needed for it to work? (NB: You do not need to actually build the model.)

### Look on The Data (Longer Span)

Here, we have look on the total number of refugees and asylum seekers in the longer perspective. To do so, we now look on the data of from earlier possible date available in UNHRC (from 1979) and visualize the data to get the sense of the trend of the:

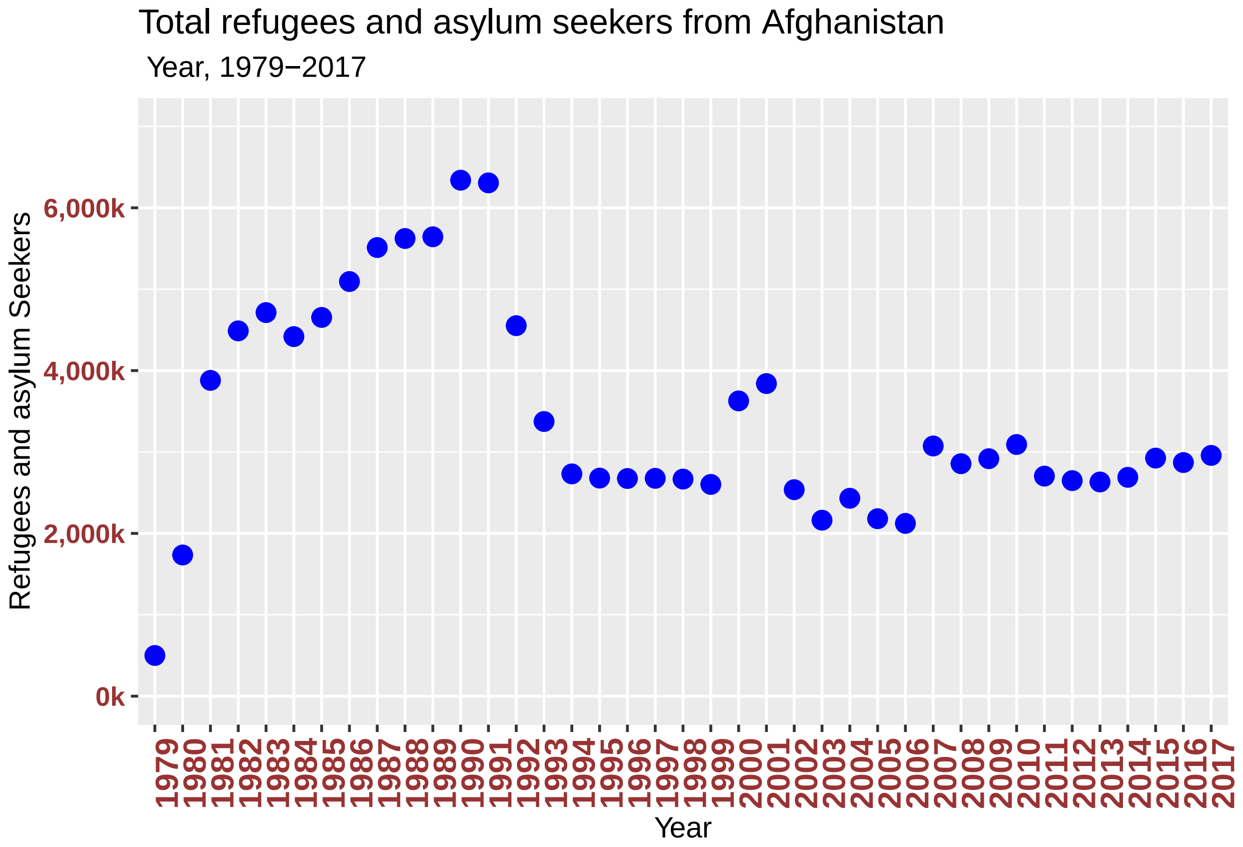
```r
all_years <-read.csv('all_year_data.csv', header = T, skip = 3, na.strings = c('*'))
colnames(all_years) <- c('Year','Host','Origin','Type','Value')

levels(all_years$Type) <- c('Asylum_or_refugees', 'IDP','Asylum_or_refugees')

all_year_sum <- all_years %>%
  group_by(Year, Type) %>%
  summarise(Total = sum(Value)) %>%
  filter(Type=='Asylum_or_refugees')

all_year_sum$Year <- as.factor(all_year_sum$Year)


all_year_sum <- all_year_sum[-40,]
ggplot(all_year_sum, aes(Year,Total)) +
  geom_point(size = 3, fill='red', color='blue') +
  scale_y_continuous(labels = ks, limits = c(0, 7000000)) +
  labs(x= 'Year') +
  labs(y = 'Refugees and asylum Seekers') +
  labs(title = 'Total refugees and asylum seekers from Afghanistan') +
  labs(subtitle =' Year, 1979-2017') +
  theme(axis.text.x = element_text(face = "bold", color = "#993333",
                           size = 12, angle = 90, hjust = 1)) +
  theme(axis.text.y = element_text(face = "bold", color = "#993333",
                           size = 10, hjust = 1))
```



## Comments for Model Building

To do the forecasting, for the period after the 1990 we could try the time sery model. Looking on the data possibly the ARMA model are the good choice for the forecasting. On the other hand, deep learning model like the Recurrent Neural Network as well could be tested. On the other hand, we can figure out that there are some spikes in the around 1990 and 2002 in total number of the refugees and asylum seekers. These two spikes could b attributed to the some internal changes, for example in this case wars inside the Afghanistan. Therefore, information like the is there conflict zone insides the country or economy level as well could help to make a better model for this data set.