

# MA304 coursework

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### Dataset Description

The dataset provided by Dallas Police department involves the details related to Subject in incidents. The injuries may happen during this course which is also reported. The other details given are Officer and subject race, gender, Officer force type etc. The basic aim of the given data is to analyse the research question if there is any Race effect on the arrests and other crime related incidents involving both parties. We will analyse this question with the help of steps below.

First of all we load the csv file and clean the column alongwith removing columns without any value.

```
df <- read.csv("~/Documents/R_data_Visualizations/37-00049_UOF-P_2016_prepped.csv", na.string
```

### Overview of data

We can get an overview of the our dataset with the help of `head` function. It gives us important information about the data types of variables in the dataset which can help to determine what variables we should keep. The information from this very initial step can help for EDA analysis.

ref:

```
head(df)
```

##	incident_date	incident_time	uof_number	officer_id	officer_gender
## 1	OCCURRED_D	OCCURRED_T	UOFNum	CURRENT_BA	OffSex
## 2	9/3/16	4:14:00 AM	37702	10810	Male
## 3	3/22/16	11:00:00 PM	33413	7706	Male
## 4	5/22/16	1:29:00 PM	34567	11014	Male

## 5	1/10/16	8:55:00 PM	31460	6692	Male
## 6	11/8/16	2:30:00 AM	37879, 37898	9844	Male
##	officer_race	officer_hire_date	officer_years_on_force	officer_injury	
## 1	OffRace	HIRE_DT	INCIDENT_DATE_LESS_	OFF_INJURE	
## 2	Black	5/7/14	2	No	
## 3	White	1/8/99	17	Yes	
## 4	Black	5/20/15	1	No	
## 5	Black	7/29/91	24	No	
## 6	White	10/4/09	7	No	
##	officer_injury_type	officer_hospitalization	subject_id	subject_race	
## 1	OFF_INJURE_DESC	OFF_HOSPIT	CitNum	CitRace	
## 2	No injuries noted or visible	No	46424	Black	
## 3	Sprain/Strain	Yes	44324	Hispanic	
## 4	No injuries noted or visible	No	45126	Hispanic	
## 5	No injuries noted or visible	No	43150	Hispanic	
## 6	No injuries noted or visible	No	47307	Black	
##	subject_gender	subject_injury	subject_injury_type		
## 1	CitSex	CIT_INJURE	SUBJ_INJURE_DESC		
## 2	Female	Yes	Non-Visible Injury/Pain		
## 3	Male	No	No injuries noted or visible		
## 4	Male	No	No injuries noted or visible		
## 5	Male	Yes	Laceration/Cut		
## 6	Male	No	No injuries noted or visible		
##	subject_was_arrested	subject_description	subject_offense		
## 1	CIT_ARREST	CIT_INFL_A	CitChargeT		
## 2	Yes	Mentally unstable	APOWW		
## 3	Yes	Mentally unstable	APOWW		
## 4	Yes	Unknown	APOWW		
## 5	Yes	FD-Unknown if Armed	Evading Arrest		
## 6	Yes	Unknown Other Misdemeanor	Arrest		
##	reporting_area	beat	sector	division	location_district
## 1	RA	BEAT	SECTOR	DIVISION	DIST_NAME
## 2	2062	134	130	CENTRAL	D14
## 3	1197	237	230	NORTHEAST	D9
## 4	4153	432	430	SOUTHWEST	D6
## 5	4523	641	640	NORTH CENTRAL	D11
## 6	2167	346	340	SOUTHEAST	D7
##	street_name	street_direction	street_type		
## 1	STREET	street_g	street_t		
## 2	Ervay	N	St.		
## 3	Ferguson	NULL	Rd.		
## 4	bimebella dr	NULL	Ln.		
## 5	LBJ	NULL	Frwy.		
## 6	Malcolm X	S	Blvd.		
##	location_full_street_address_or_intersection	location_city	location_state		
## 1	Street Address	City	State		

```

## 2          211 N ERVAY ST          Dallas          TX
## 3          7647 FERGUSON RD        Dallas          TX
## 4          716 BIMEBELLA LN        Dallas          TX
## 5          5600 L B J FWY          Dallas          TX
## 6          4600 S MALCOLM X BLVD    Dallas          TX
##   location_latitude location_longitude incident_reason reason_for_force
## 1          Latitude          Longitude          SERVICE_TY          UOF_REASON
## 2          32.782205          -96.797461          Arrest          Arrest
## 3          32.798978          -96.717493          Arrest          Arrest
## 4          32.73971          -96.92519          Arrest          Arrest
## 5          <NA>          <NA>          Arrest          Arrest
## 6          <NA>          <NA>          Arrest          Arrest
##   type_of_force_used1 type_of_force_used2 type_of_force_used3
## 1          ForceType1          ForceType2          ForceType3
## 2 Hand/Arm/Elbow Strike          <NA>          <NA>
## 3          Joint Locks          <NA>          <NA>
## 4          Take Down - Group          <NA>          <NA>
## 5          K-9 Deployment          <NA>          <NA>
## 6          Verbal Command          Take Down - Arm          <NA>
##   type_of_force_used4 type_of_force_used5 type_of_force_used6
## 1          ForceType4          ForceType5          ForceType6
## 2          <NA>          <NA>          <NA>
## 3          <NA>          <NA>          <NA>
## 4          <NA>          <NA>          <NA>
## 5          <NA>          <NA>          <NA>
## 6          <NA>          <NA>          <NA>
##   type_of_force_used7 type_of_force_used8 type_of_force_used9
## 1          ForceType7          ForceType8          ForceType9
## 2          <NA>          <NA>          <NA>
## 3          <NA>          <NA>          <NA>
## 4          <NA>          <NA>          <NA>
## 5          <NA>          <NA>          <NA>
## 6          <NA>          <NA>          <NA>
##   type_of_force_used10 number_ec_cycles force_effective
## 1          ForceType10          Cycles_Num          ForceEffec
## 2          <NA>          NULL          Yes
## 3          <NA>          NULL          Yes
## 4          <NA>          NULL          Yes
## 5          <NA>          NULL          Yes
## 6          <NA>          NULL          No, Yes

```

Table. 1 # EDA Analysis

EDA analysis is an important step for this assignment. We have many data types in our dataframe from characters to double. We will convert the data types to factors and numeric. It will help in data visualization.

At first we get the shape of the data set by `dim` function.

```
dim(df)
```

```
## [1] 2384 47
```

The first row is an extra with same names as the dataframe. We removed by using in code chunk below.

We also use `attach` function of base R which will help to call dataset variables without using the basic `$` sign each time.

With the help of `Exp Data` function we can have a closer look into variables types and other important details of the dataset.

```
library("SmartEDA")
```

```
ExpData(data=df,type=1)
```

##		Descriptions	Value
## 1		Sample size (nrow)	2383
## 2		No. of variables (ncol)	47
## 3		No. of numeric/interger variables	0
## 4		No. of factor variables	0
## 5		No. of text variables	47
## 6		No. of logical variables	0
## 7		No. of identifier variables	0
## 8		No. of date variables	0
## 9		No. of zero variance variables (uniform)	4
## 10		%. of variables having complete cases	76.6% (36)
## 11	%. of variables having >0% and <50% missing cases		4.26% (2)
## 12	%. of variables having >=50% and <90% missing cases		2.13% (1)
## 13	%. of variables having >=90% missing cases		17.02% (8)

The above overview is also given below with data types in each column.

```
library(skimr)
```

```
datatable(skim(df))
```

Variable data types

There are some values in the dataset which will removed periodically in data visualization instead of removing them row by row here.

From the table above we conclude that almost all variables are of data type **character** which is not helpful for the data analysis via visualization such as boxplot so we will convert the character to factors and dbl to numeric in chunk below.

```
df <- lapply(df, as.factor) %>% data.frame()

df$officer_years_on_force <- as.numeric(as.character(df$officer_years_on_force))

df$street_number <- as.numeric(as.character(df$street_number ))
df$sector <- as.numeric(as.character(df$sector))
```

After getting overall view of the data let's check the measure of central tendency. It will help to determine and introduce the data statistically.

```
diagnose_numeric(df)
```

```
## # A tibble: 3 × 10
```

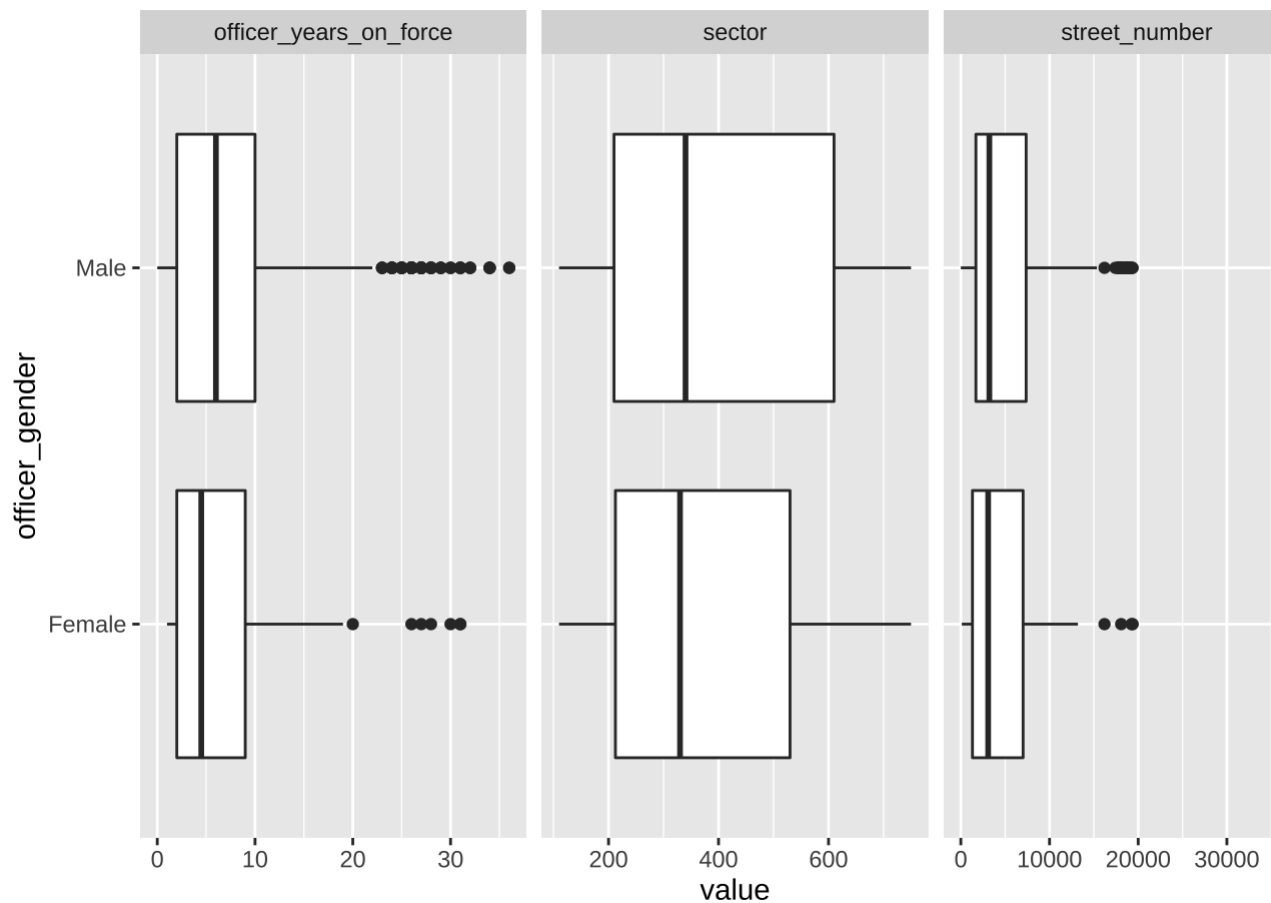
	variables	min	Q1	mean	median	Q3	max	zero	minus	outlier
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<int>	<int>
## 1	officer_years_on_fo...	0	3	8.05e0	6	10	36	3	0	240
## 2	sector	110	210	3.89e2	350	610	750	0	0	0
## 3	street_number	0	1700	4.90e3	3415	7532	54023	1	0	58

Some columns will be removed which has large number of NaN

```
df <- df %>% select(-c("uof_number",matches("used")))
```

The outliers can also be detected with boxplots.

```
df %>% filter(subject_gender==c("Male","Female"))%>%
plot_boxplot(., by ="officer_gender")
```



We observe that most outliers related to male officers with several years of service. Moreover the average service of officers from both genders is less than 10 years.

With regards to the factor variables such as 'officer\_injury\_type' we can have detailed description of each incident separately. At first we start with the duplicates detection.

```
p <- df %>% get_dupes(officer_injury_type)%>% ggboxplot(x="officer_injury_type",y="dupe_count",
ylim(0, 100))
ggplotly(p)
```

We observe that most of duplicates are the No injury for both officer genders. Similar observation can be checked for subjects which shows the similar trend although the duplicates for abrasive injuries for subjects are higher.

```
p <- df %>% get_dupes(subject_injury_type)%>% filter(subject_gender!=c(NULL,"Unknown")) %>%
ggplotly(p)
```

Duplicates in the dataset for injury type

We can find the number of incidents for time period of each race separately by using `tabyl` function.

```
datatable(tabyl(df,incident_time,subject_race) %>% select(-NULL))
```

We observe that most incidents are occurring late night and in the morning around 9AM.

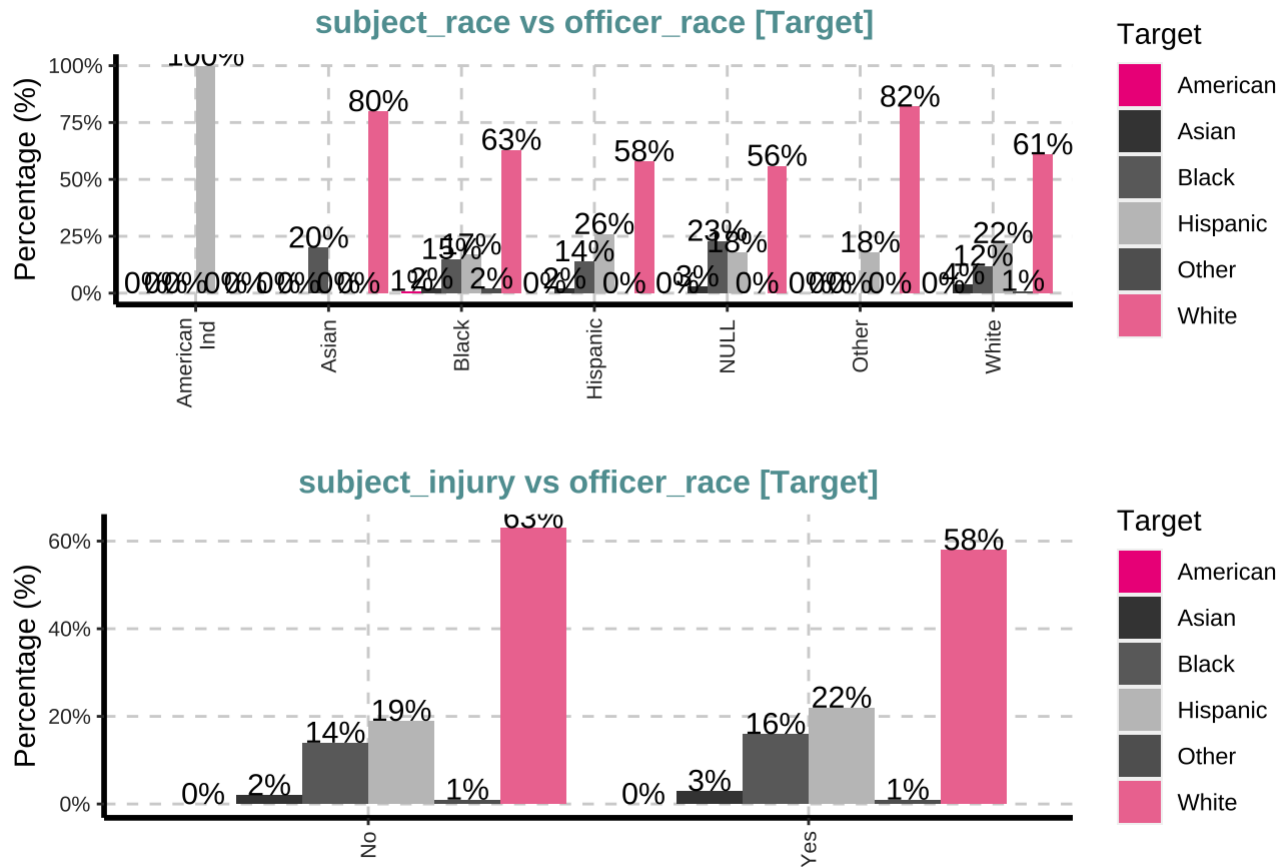
Furthermore we can find a summary statistics of categorical variables. We can run several test on the input categorical variables such as **chi-square** test. The p-value which is basically a statistical check to analyse if there exist significant difference between variables at commonly chosen 5% significance level.

The table generated from the code chunks gives us many insights into the dataset. None of the variables is predictive enough to give us major result about dataset as shown in last column. Although the p-values are less than 0.05 yet the degree of association is very weak between categorical variables in our dataset as shown by result of chi-square test.

```
p <- datatable(ExpCatStat(df,Target="subject_race",result = "Stat",clim=10,nlim=5,Pclass="Y
p
```

Graphical representation for categorical variables in given below.

```
ExpCatViz(df,target="officer_race",fname=NULL,clim=10,col=NULL,margin=2,Page = c(2,1),sample
## $'0'
```

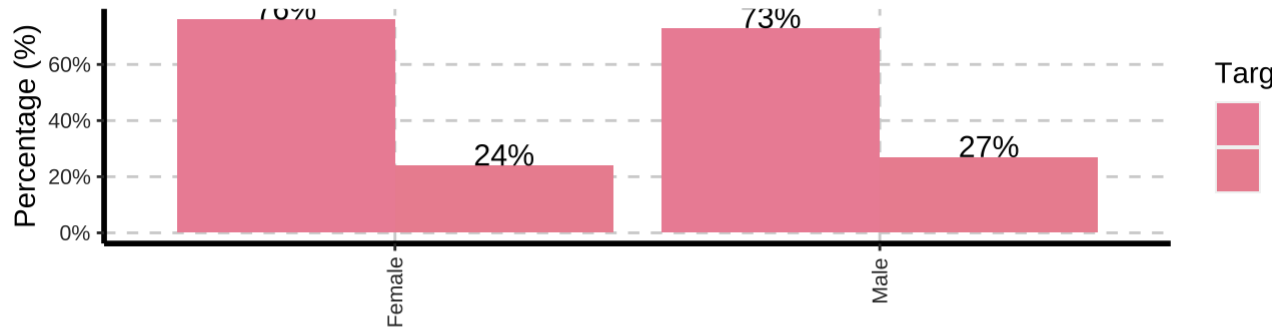


```
ExpCatViz(df,target="subject_injury",fname=NULL,clim=10,col=NULL,margin=2,Page = c(2,1),samp
```

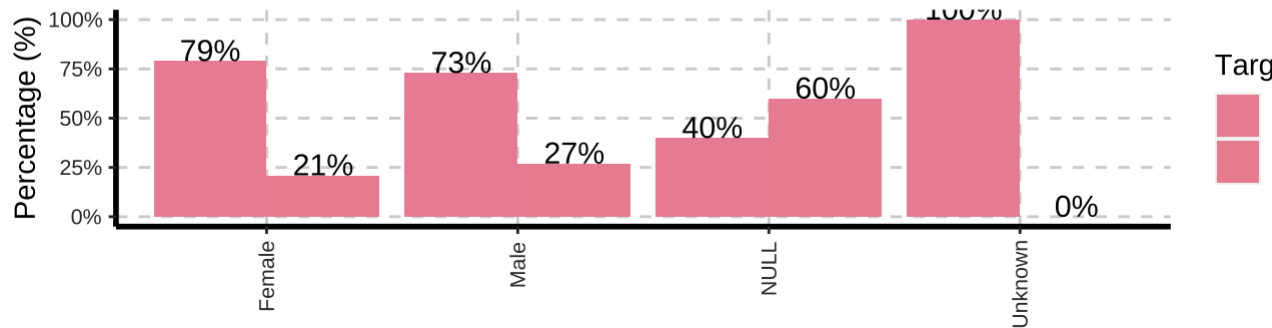
```
## $'0'
```



officer\_gender vs subject\_injury  
[Target]



subject\_gender vs subject\_injury  
[Target]



Above 2 figures show that the percentage of officer getting injury during incidents are high as they are in large percentage in total count of officers. The percentage of injury hispanic officers is almost equal at 19% and 20%. On the other hand there 15% chance of asian officers not able to arrest the subject. Officers are also most likely to be hospitalized alongwith subjects in the incidents involving unfavorable conditions.

We can find the correlation between variables as well which gives results in the form of correlation coefficient. The results show that none of numeric variables are strongly correlated with each other.

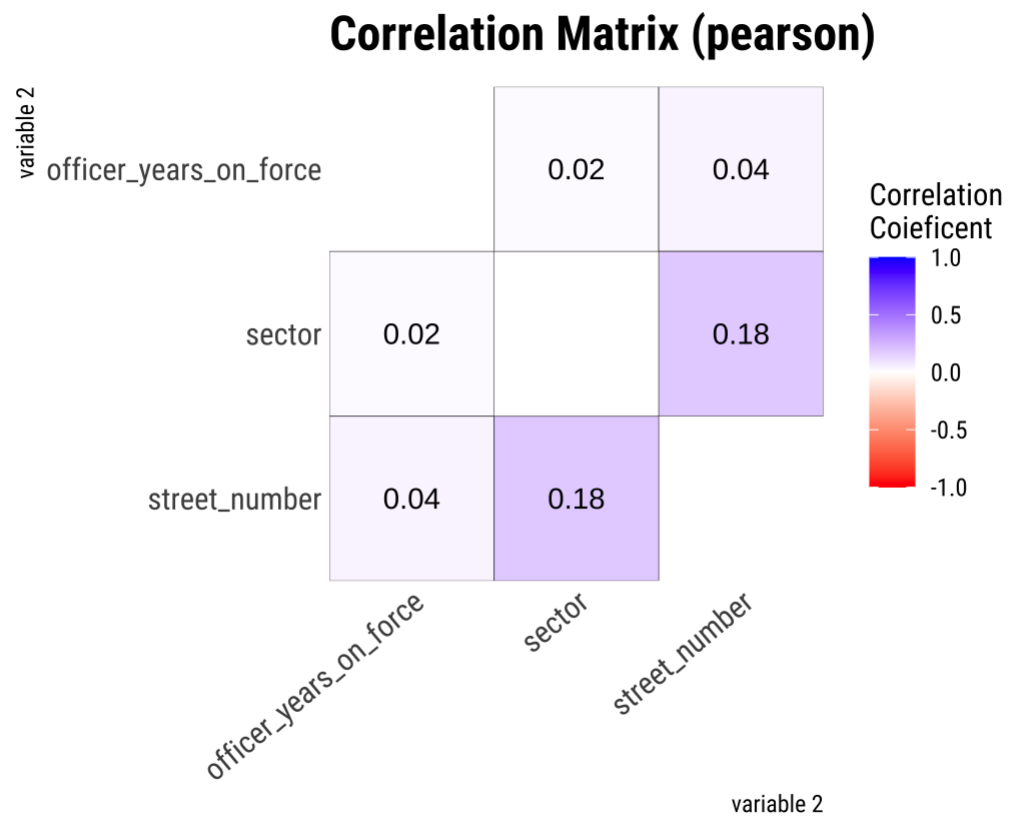
```
correlate(df)
```

```
## # A tibble: 6 × 3
##   var1                var2                coef_corr
##   <fct>              <fct>              <dbl>
```

```
## 1 sector            officer_years_on_force  0.0182
## 2 street_number    officer_years_on_force  0.0410
## 3 officer_years_on_force sector            0.0182
## 4 street_number    sector                  0.183
## 5 officer_years_on_force street_number     0.0410
## 6 sector            street_number          0.183
```

The above tabular correlation data can be shown in graphical form.

```
df %>%
  correlate() %>%
  plot()
```



The skewness check of numeric variables is given below.

```
find_skewness(df)

## [1] 7 24

find_skewness(df, index = FALSE)

## [1] "officer_years_on_force" "street_number"

find_skewness(df, value = TRUE)

## officer_years_on_force      sector      street_number
##                1.484                0.268                2.313
```

So the major numeric variables of on duty years is skewed which need to analysed to remove skewness. Other 2 variables can be reject for skewness removal since they do not weigh much in the analysis.

Following graphs shows that the officers with more service years are used for crowd control in the department. Furthermore there is very high chance of use of force when subject has weapons. Senior officers will go for severe levels of use of force when the subject is black as shown in boxplot with green fill.

```
p <- df %>%
  filter(!(subject_race %in% "NULL")) %>%
  filter(!(reason_for_force %in% "NULL")) %>%
  ggplot() +
  aes(x = officer_years_on_force, y = reason_for_force, fill = subject_race) +
  geom_boxplot() +
  scale_fill_hue(direction = 1) +
  ggthemes::theme_base()+theme(legend.position = "bottom")

ggplotly(p)
```

The chart given below shows that males subjects mostly undergo use of force during arrest as compared to their counterparts. Similar trend is observed for for almost all cases of use of force with more proportion towards males class.

```
df1 <- df %>% select(subject_gender,reason_for_force,officer_gender)

p <- df1 %>%
  filter(subject_gender %in% c("Female", "Male")) %>%
  filter(!(reason_for_force %in% "NULL")) %>%
  ggplot() +
  aes(x = reason_for_force, fill = subject_gender) +
```

```
geom_bar(position = "dodge") +  
scale_fill_hue(direction = 1) +  
coord_flip() +  
theme_minimal()  
  
ggplotly(p)
```

## Summary

Data Analysis is conducted for the Dallas, USA Police equity dataset in view of the racial recognition effects. The analysis shows that major portion of both classes of officer genders can go uninjured during incidents while this is not the case of subjects. Black race subjects are involved in high percentage in the incidents followed by hispanics. Statistical analysis of categorical variables show that there is variable which can serve as predictive variable. Similarly, the male officers, which consist of more 70% of officers in service, can have skewness in their data on the basis of service years. Normality of dataset was checked which gave us a p-value  $< 0.05$  at 95% confidence level. The correlation matrix shows that none of numeric variables is correlated to each other. The statistical tables show that asian officers have less chance of completing arrests in incidents as compared to white police officers.