Stat402- Presentation 1- EDA boxplots

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```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(ggplot2)
library(car)
```

```
## Loading required package: carData
##
## Attaching package: 'car'
##
## The following object is masked from 'package:dplyr':
##
##     recode
##
## The following object is masked from 'package:purrr':
##
##     some
```

```
df <- read.csv("~/Downloads/DataScience_salaries_2024.csv")
head(df)
```

```
##   work_year experience_level employment_type                    job_title
## 1      2021               MI              FT                Data Scientist
## 2      2021               MI              FT               BI Data Analyst
## 3      2020               MI              FT                Data Scientist
## 4      2021               MI              FT                   ML Engineer
## 5      2022               SE              FT Lead Machine Learning Engineer
## 6      2021               MI              FT                   ML Engineer
##     salary salary_currency salary_in_usd employee_residence remote_ratio
## 1 30400000             CLP         40038                 CL          100
```

```
## 2 11000000             HUF         36259                 HU           50
## 3 11000000             HUF         35735                 HU           50
## 4  8500000             JPY         77364                 JP           50
## 5  7500000             INR         95386                 IN           50
## 6  7000000             JPY         63711                 JP           50
##   company_location company_size
## 1               CL            L
## 2               US            L
## 3               HU            L
## 4               JP            S
## 5               IN            L
## 6               JP            S
```

```
sum(complete.cases(df)) == nrow(df) #Check for NA Values TRUE means there is none
```

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

```
df <- unique(df) #Get rid of duplicate observations
```

```
library(tidyverse)
table(df$employment_type)
```

```
##
##   CT   FL   FT   PT
##   26   13 9061   27
```

```
df <- filter(df,employment_type == 'FT') # We will focus on full time salaries
```

```
table(df$work_year) #Too few observations in 2020-2022 so we'll combine them into "Pandemic Era"
```

```
##
## 2020 2021 2022 2023 2024
##   69  206 1099 4616 3071
```

```
df$work_year <- ifelse(df$work_year == 2024, "2024",
                ifelse(df$work_year == 2023, "2023", "Pandemic"))
df$work_year <- factor(df$work_year,levels = c("Pandemic","2023","2024"), ordered = TRUE)
#Relevel
```

```
table(df$experience_level)
```

```
##
##   EN   EX   MI   SE
##  862  353 2445 5401
```

```
df$experience_level <- factor(df$experience_level, levels = c("EN","MI","SE","EX"), ordered = T) #Relev
```

```r
df <- select(df,-c("employment_type","salary","salary_currency","employee_residence"))
#Get rid of employment type as every observation is full time
#Get rid of salary and currency as we have the salary in USD
#Get rid of employee residene as we already have the company location and the company location
#matters more for predicting the salary
```

```r
table(df$remote_ratio)
```

```
##
##    0   50  100
## 5670  233 3158
```

```r
table(df$company_size)
```

```
##
##    L    M    S
##  608 8293  160
```

```r
df$company_size <- factor(df$company_size,levels = c("S","M","L"), ordered = TRUE)
```

```r
df$remote_ratio <- car::recode(df$remote_ratio,"0='In-Person';50='Hybrid';100='Remote'")
df$remote_ratio <- factor(df$remote_ratio, levels = c("In-Person","Hybrid","Remote"))
```

```r
install.packages("countrycode")
```

```
##
## The downloaded binary packages are in
##  /var/folders/6f/s_p8wq6d6x3b87zm12pfwsnm0000gn/T//RtmparSeQB/downloaded_packages
```

```r
library(countrycode)
df$company_location <- countrycode(df$company_location, origin = "iso2c", destination = "country.name")
table(df$company_location)
```

```
##
##           American Samoa                  Andorra                Argentina
##                        3                        1                        7
##                  Armenia                Australia                  Austria
##                        1                       48                       10
##                  Belgium     Bosnia & Herzegovina                   Brazil
##                        4                        2                       21
##                   Canada Central African Republic                    Chile
##                      348                        2                        1
##                    China                 Colombia                  Croatia
##                        1                       14                        3
##                  Czechia                  Denmark                  Ecuador
##                        2                        3                        1
##                    Egypt                  Estonia                  Finland
##                       11                       10                        4
##                   France                  Germany                    Ghana
```

```
##                     59                     93                      2
##             Gibraltar                 Greece               Honduras
##                      1                     11                      1
##   Hong Kong SAR China                Hungary                  India
##                      1                      3                     57
##              Indonesia                   Iraq                Ireland
##                      2                      1                     12
##                 Israel                  Italy                  Japan
##                      3                     13                      8
##                  Kenya                 Latvia                Lebanon
##                      2                     14                      2
##              Lithuania             Luxembourg               Malaysia
##                     16                      2                      1
##                  Malta              Mauritius                 Mexico
##                      3                      1                     15
##               Moldova             Netherlands            New Zealand
##                      1                     26                      5
##               Nigeria                 Norway                   Oman
##                      7                      2                      1
##              Pakistan             Philippines                 Poland
##                      2                      6                     14
##              Portugal             Puerto Rico                  Qatar
##                     28                      4                      1
##               Romania                 Russia           Saudi Arabia
##                      4                      7                      3
##             Singapore               Slovenia           South Africa
##                      5                      6                     13
##           South Korea                  Spain                 Sweden
##                      2                     70                      3
##           Switzerland               Thailand                 Turkey
##                      9                      3                      6
##               Ukraine  United Arab Emirates         United Kingdom
##                      9                      4                    514
##         United States                Vietnam
##                  7483                      3
```

```
developed_countries <- c("Andorra","Australia","Austria","Belgium","Canada","Croatia","Czechia","Denmar

df$company_location <- ifelse(df$company_location == "United States", "US",
                       ifelse(df$company_location %in% developed_countries,"First World","Developing"))
#Combine all first world countries into developed label leaving the rest as the developing countries
df$company_location <- factor(df$company_location, levels = c("US","First World","Developing"))
```

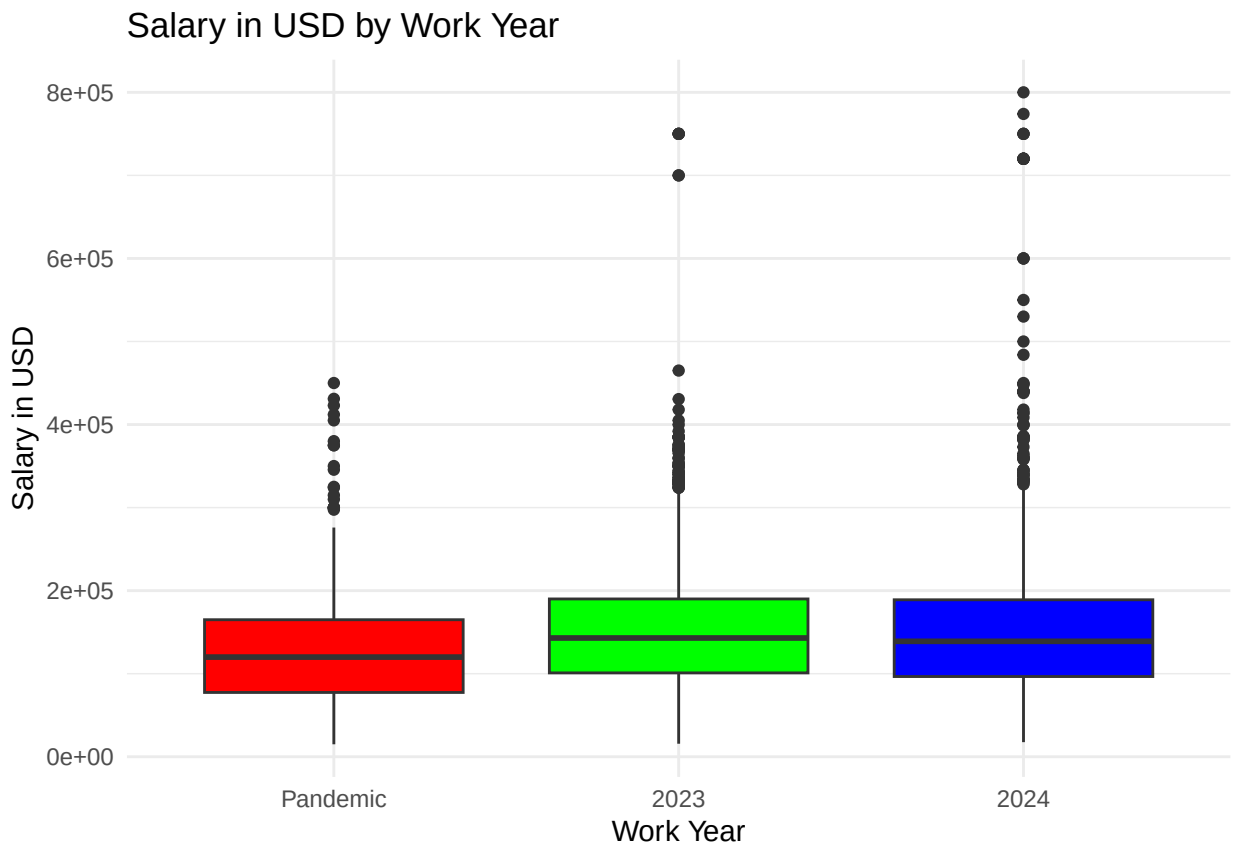
```
titles <- names(table(df$job_title))
analyst <- c(titles[c(1,40,44:51,67,75,78,93,103:104,109,126,134,139,148)])
scientist <- c(titles[c(13,79:89,99,106,111,125,128,137,149)])
mle <- c(titles[c(14:15,107,112:123,129:131,138)])
engineer <- c(titles[c(20,27,38:39,54:56,58,69,72,76,94,110,127,136,147,150)])
BI <- c(titles[c(21:24,28:36,133)])
df$job_title <- ifelse(df$job_title %in% analyst, "DA",
                ifelse(df$job_title %in% scientist,"DS",
                ifelse(df$job_title %in% engineer, "DE",
                ifelse(df$job_title %in% mle,"ML",
                ifelse(df$job_title %in% BI,"BI","Other")))))
```

```r
df$job_title <- relevel(factor(df$job_title), ref = "DA")
#Condense all titles with data science in the name to data scientist and repeat for analysts, MLE and e
```

```r
head(df)
```

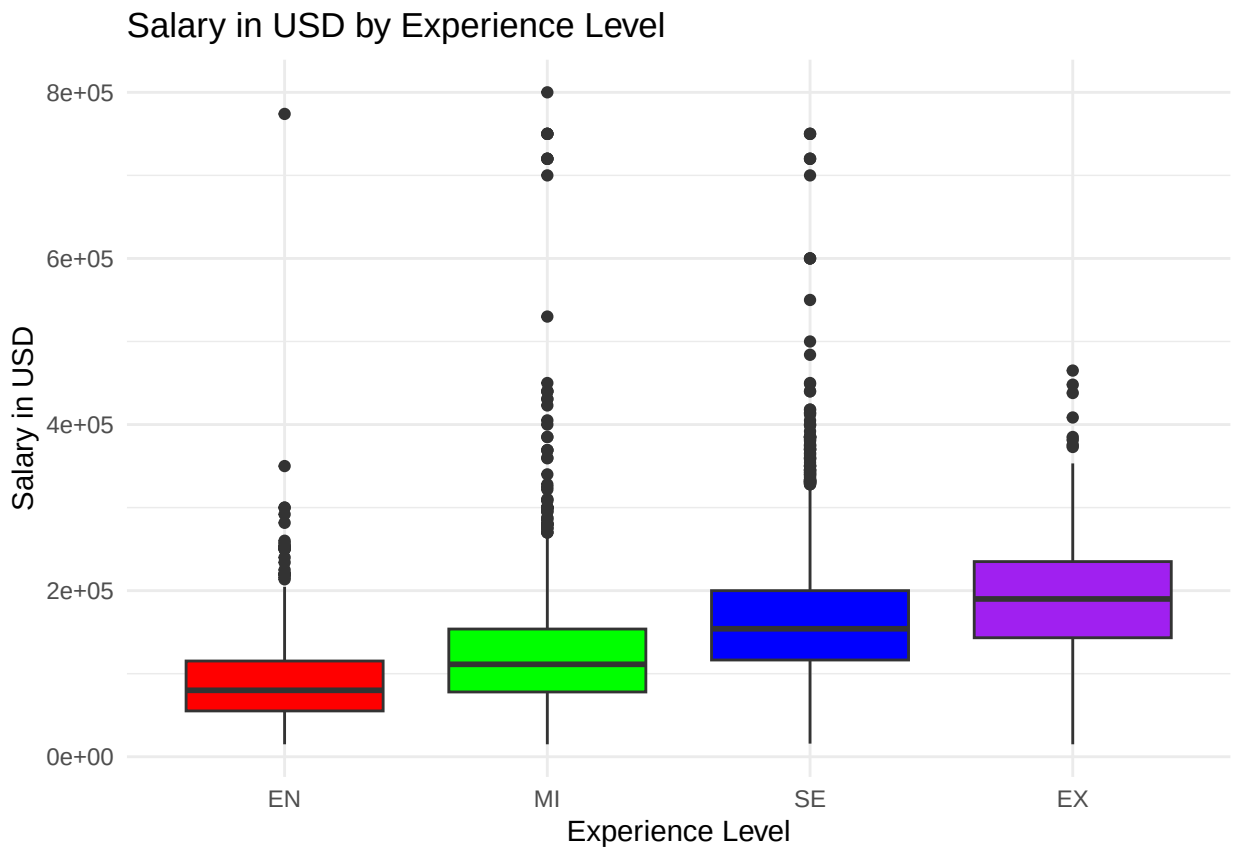
```
##   work_year experience_level job_title salary_in_usd remote_ratio
## 1  Pandemic               MI        DS         40038       Remote
## 2  Pandemic               MI        BI         36259       Hybrid
## 3  Pandemic               MI        DS         35735       Hybrid
## 4  Pandemic               MI        ML         77364       Hybrid
## 5  Pandemic               SE        ML         95386       Hybrid
## 6  Pandemic               MI        ML         63711       Hybrid
##   company_location company_size
## 1       Developing            L
## 2               US            L
## 3       Developing            L
## 4      First World            S
## 5       Developing            L
## 6      First World            S
```

```r
# Create the side-by-side boxplots for work_year
ggplot(df, aes(x = work_year, y = salary_in_usd, fill = work_year)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Work Year",
       x = "Work Year",
       y = "Salary in USD") +
  scale_fill_manual(values = c("Pandemic" = "red", "2023" = "green", "2024" = "blue")) +
  theme_minimal() +
  theme(legend.position = "none") # Hide the legend as fill corresponds to x-axis categories
```



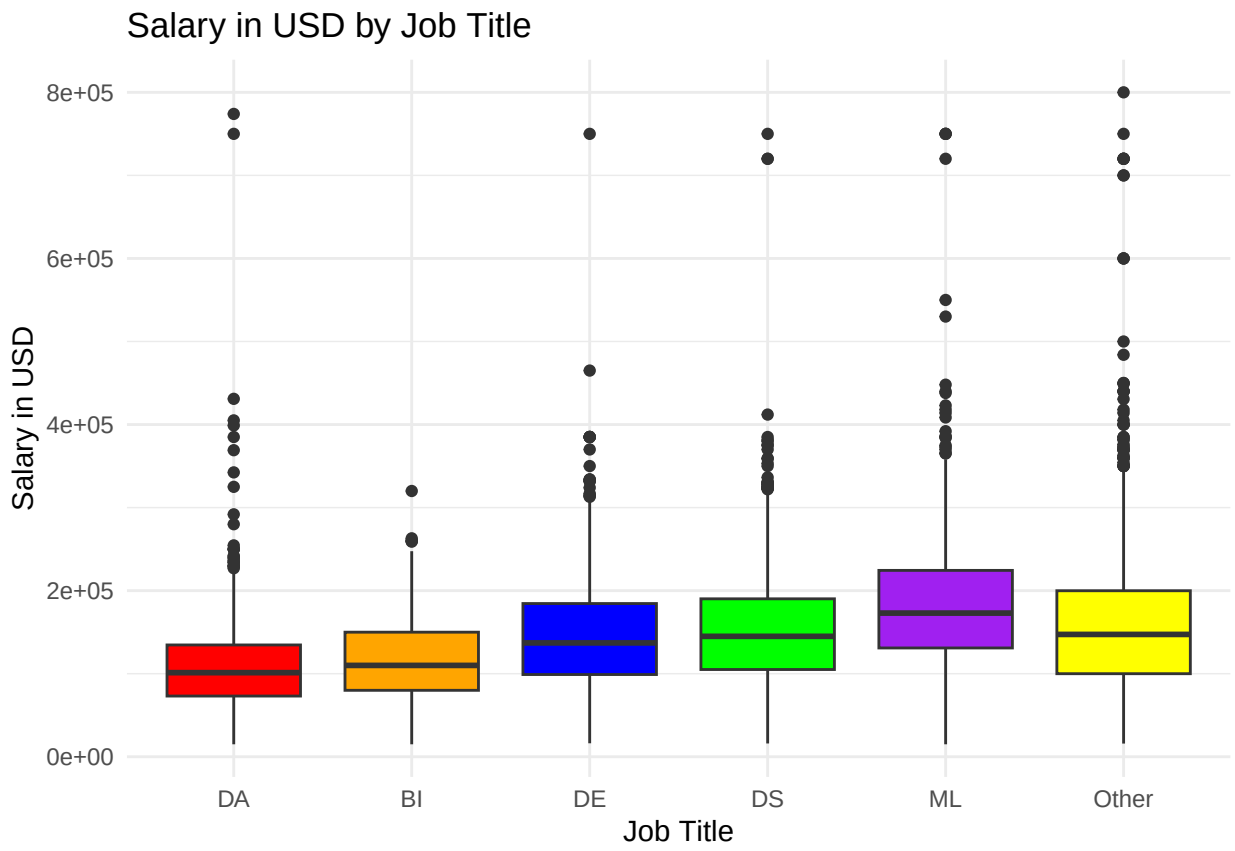
In the side-by-side boxplots of Salary by Work Year, we can see that all three factors have high outliers and are skewed right, with 2024 having the most outliers and strongest skew. Might consider tranforming (logarithmic?). There is variability (IQR) for all three factors is similar.

```
# Create the boxplot side-by-side boxplots for experience_level
ggplot(df, aes(x = experience_level, y = salary_in_usd, fill = experience_level)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Experience Level",
       x = "Experience Level",
       y = "Salary in USD") +
  scale_fill_manual(values = c("EN" = "red", "MI" = "green", "SE" = "blue", "EX" = "purple")) +
  theme_minimal() +
  theme(legend.position = "none") # Hide legend as fill is mapped to x-axis categories
```

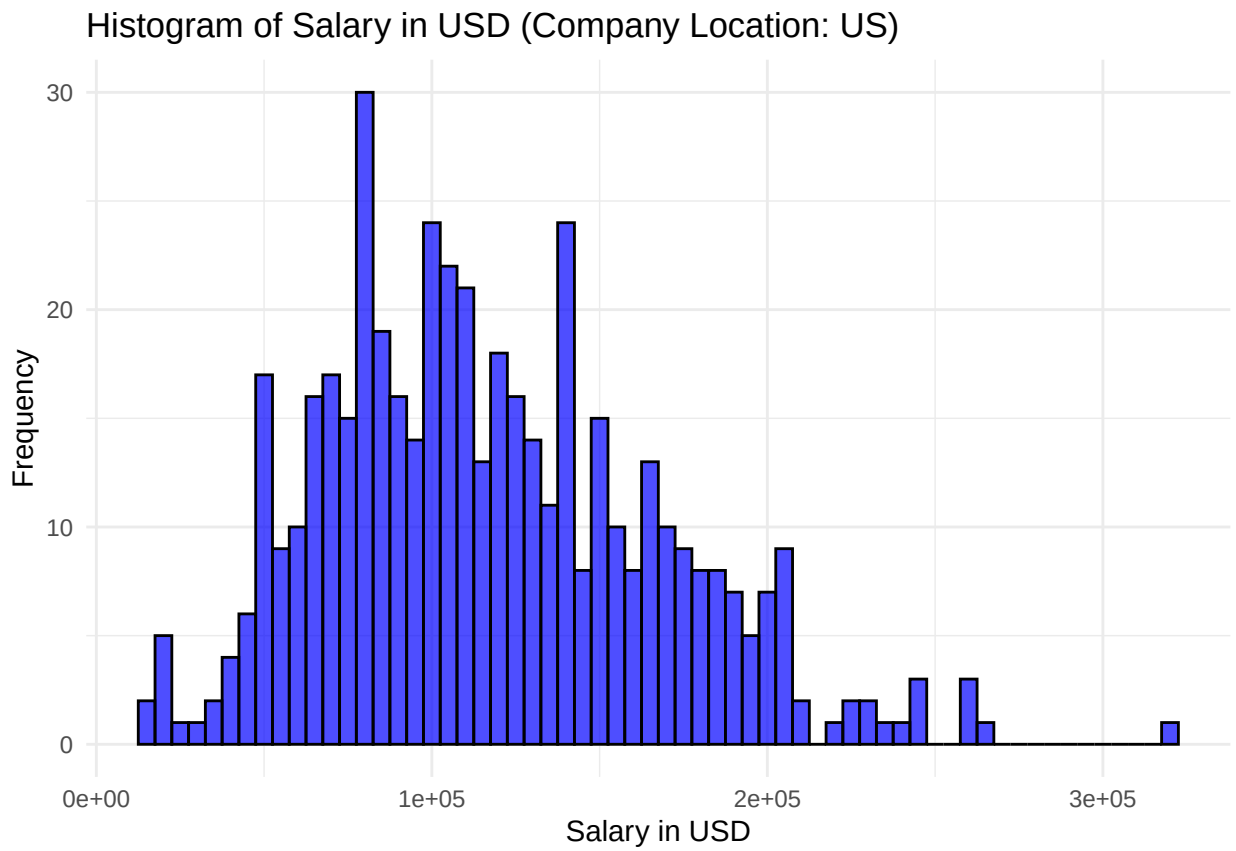


In the side-by-side boxplots of Salary by Experience Level, we can see that all factors have high outliers and are skewed right, with Mid and Senior levels having the most outliers and strongest skew. Might consider tranforming (or looking at subset of data, under 3-400K?). The pattern is predictable that as experience level increase so do the median/ majority of salaries.

```
# Create the boxplot side-by-side boxplots for job_title
ggplot(df, aes(x = job_title, y = salary_in_usd, fill = job_title)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Job Title",
       x = "Job Title",
       y = "Salary in USD") +
  scale_fill_manual(values = c("DA" = "red", "DS" = "green", "DE" = "blue", "ML" = "purple", "BI" = "ora
  theme_minimal() +
  theme(legend.position = "none") # Hide legend as fill is mapped to x-axis categories
```

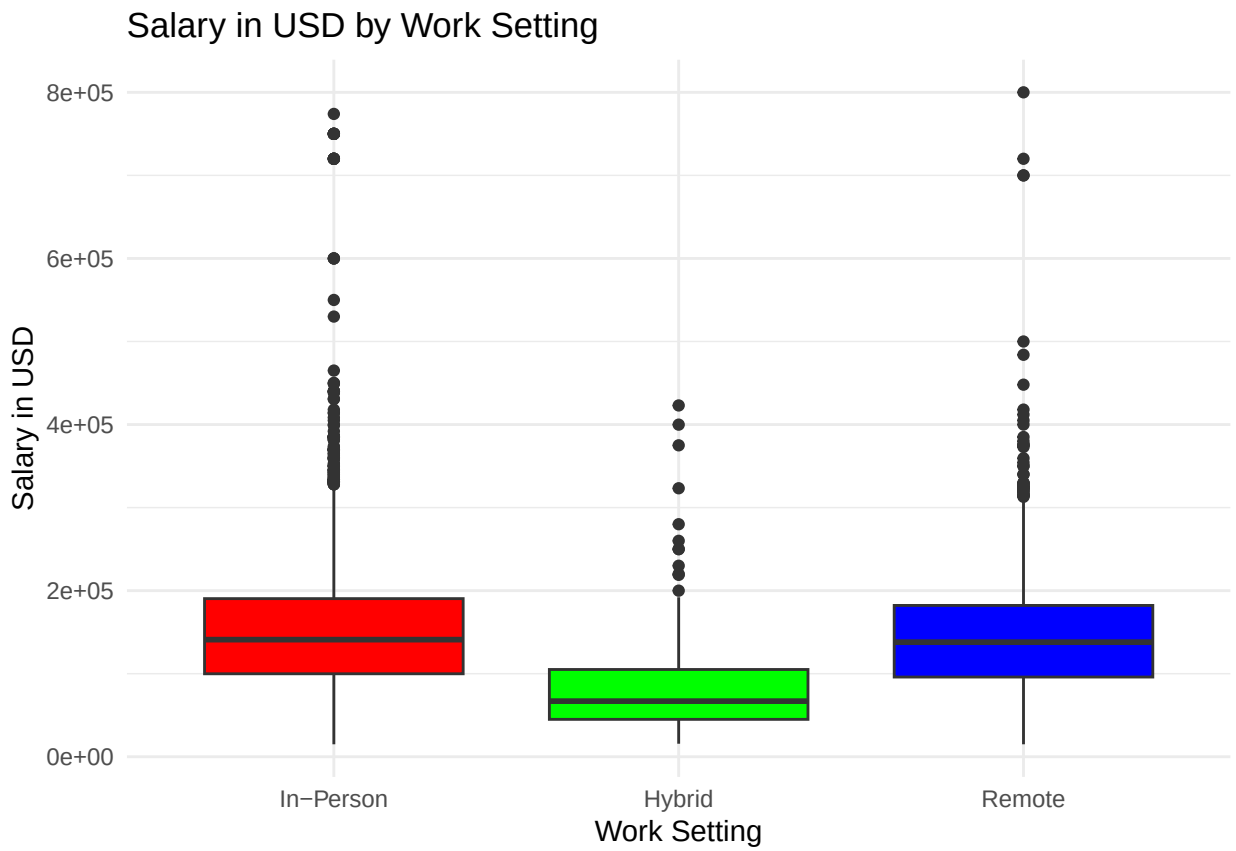



```
# Create histogram of salary_in_usd for job_title "BI"
ggplot(df %>% filter(job_title == "BI"), aes(x = salary_in_usd)) +
  geom_histogram(binwidth = 5000, fill = "blue", color = "black", alpha = 0.7) +
  labs(title = "Histogram of Salary in USD (Company Location: US)",
       x = "Salary in USD",
       y = "Frequency") +
  theme_minimal()
```



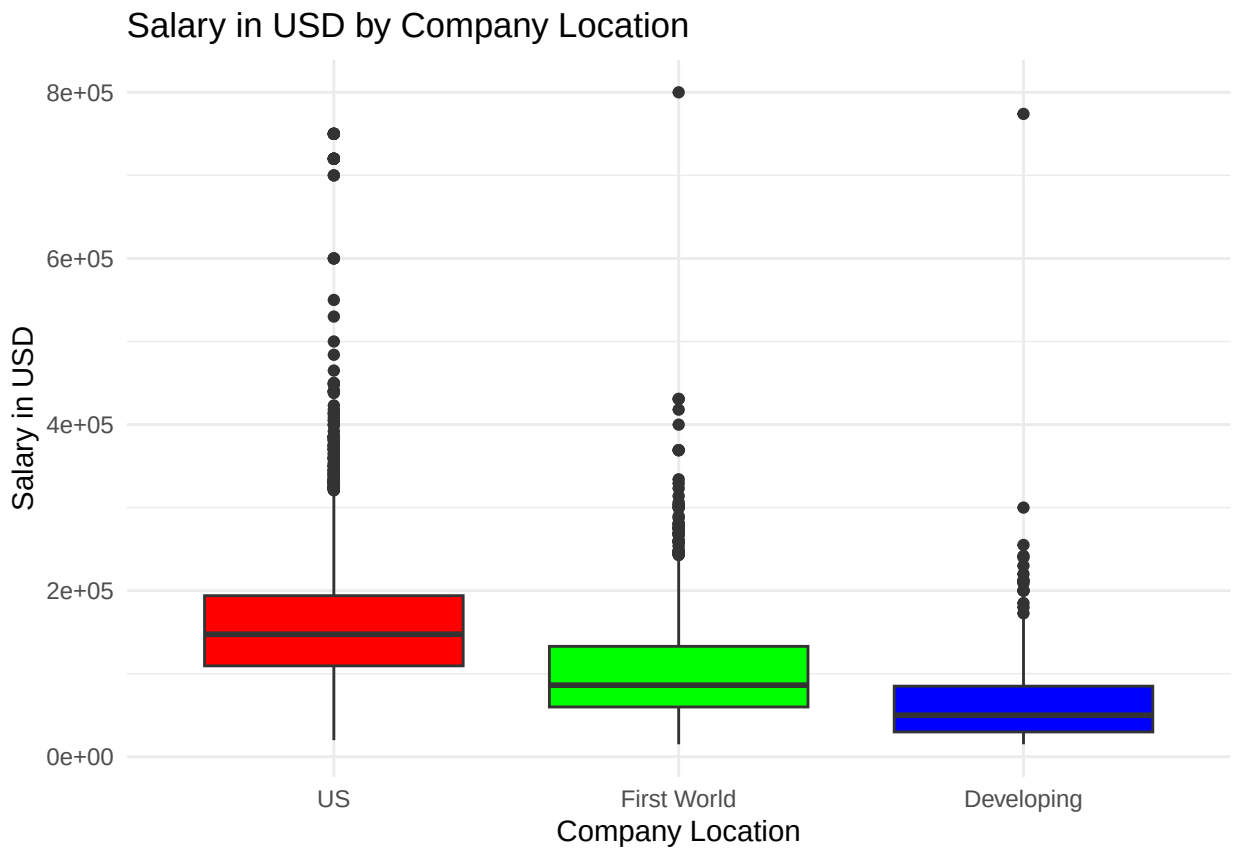
In the side-by-side boxplots of Salary by Job Title, we can see that all factors have high outliers and are skewed right, except BI which has the least amount of outliers and slightly symmetric. Might consider tranforming (or looking at subset of data, under 3-400K?).

```
# Create the boxplot side-by-side boxplots for remote_ratio
ggplot(df, aes(x = remote_ratio, y = salary_in_usd, fill = remote_ratio)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Work Setting",
       x = "Work Setting",
       y = "Salary in USD") +
  scale_fill_manual(values = c("In-Person" = "red", "Hybrid" = "green", "Remote" = "blue")) +
  theme_minimal() +
  theme(legend.position = "none") # Hide legend as fill is mapped to x-axis categories
```

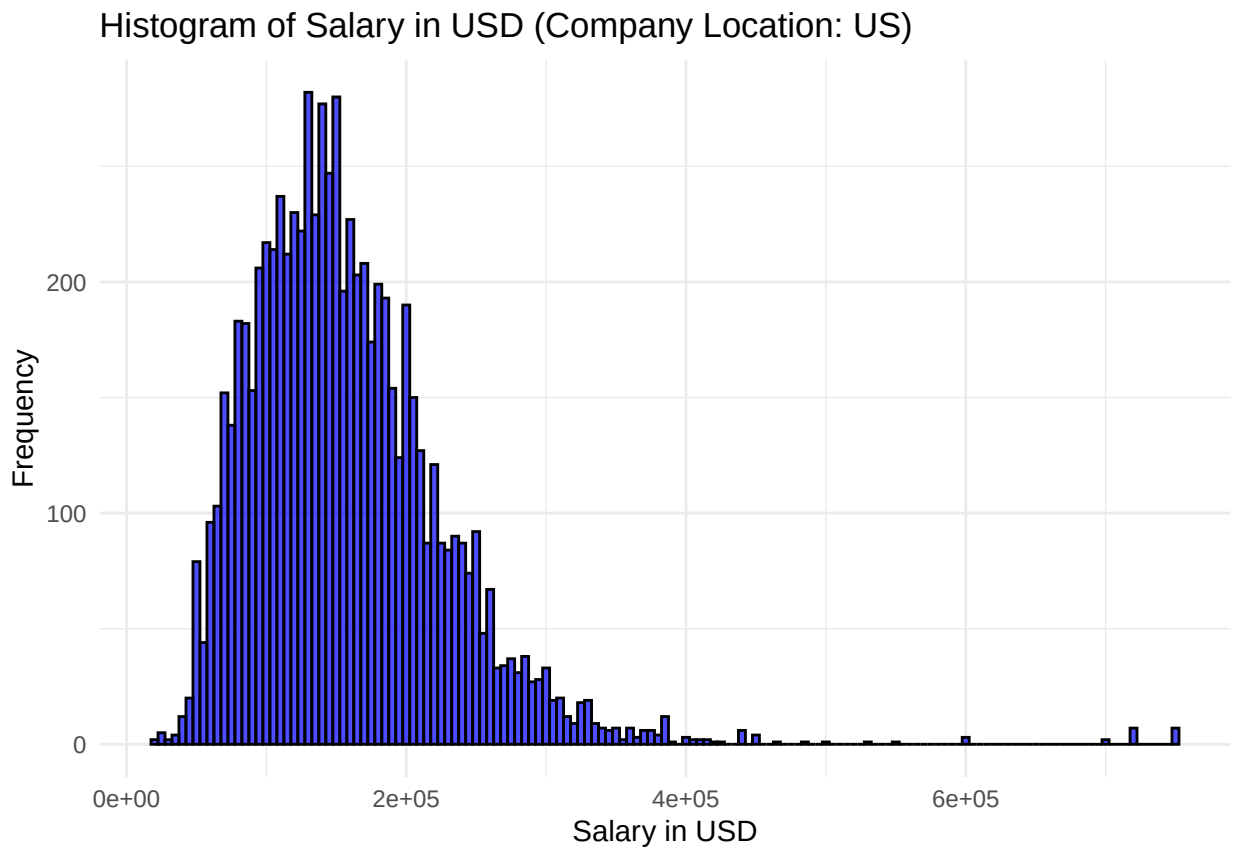


In the side-by-side boxplots of Salary by Work Setting, we can see that all factors have high outliers and are skewed right, with In-Person and Remote making significantly more than the "Hybrid"setting.

```
# Create the boxplot side-by-side boxplots for company_location
ggplot(df, aes(x = company_location, y = salary_in_usd, fill = company_location)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Company Location",
       x = "Company Location",
       y = "Salary in USD") +
  scale_fill_manual(values = c("US" = "red", "First World" = "green", "Developing" = "blue")) +
  theme_minimal() +
  theme(legend.position = "none") # Hide legend as fill is mapped to x-axis categories
```

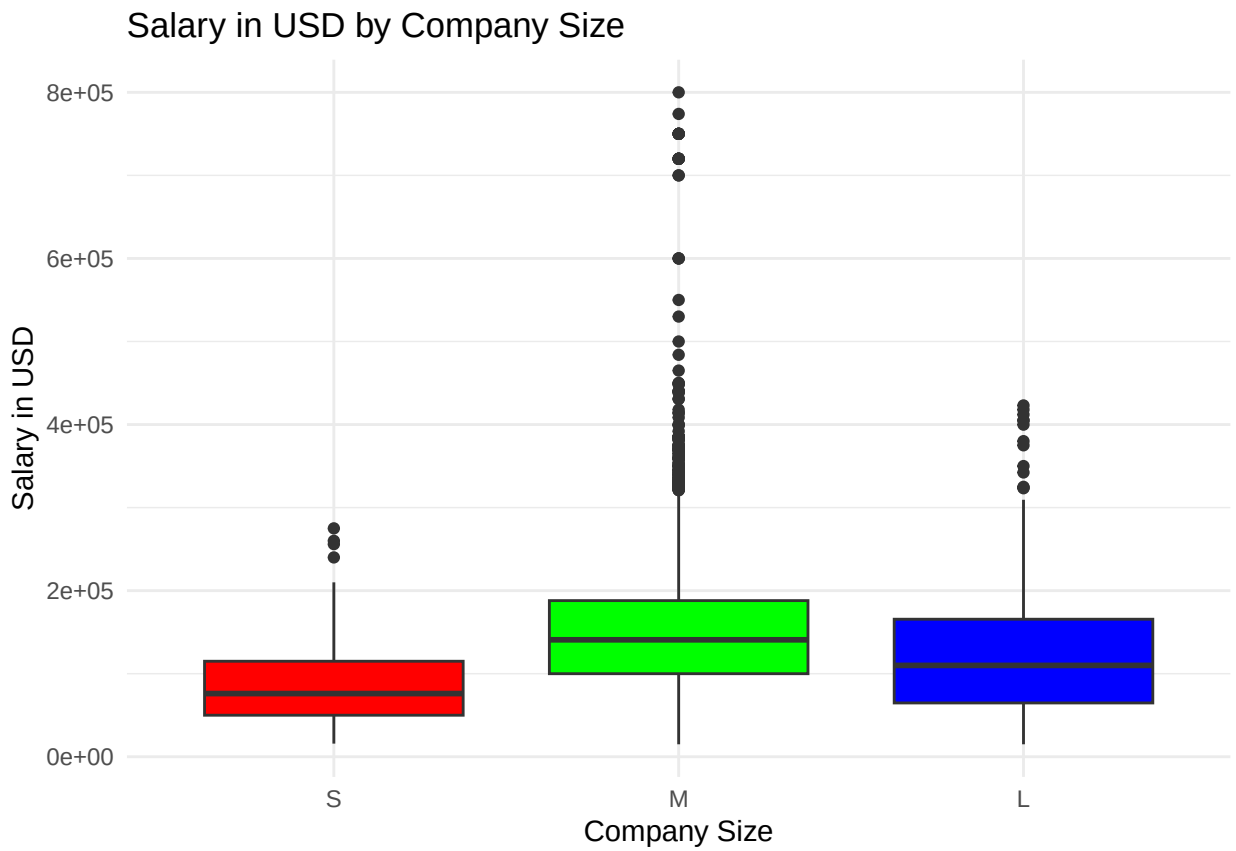



```r
# Create histogram of salary_in_usd for company_location "US"
ggplot(df %>% filter(company_location == "US"), aes(x = salary_in_usd)) +
  geom_histogram(binwidth = 5000, fill = "blue", color = "black", alpha = 0.7) +
  labs(title = "Histogram of Salary in USD (Company Location: US)",
       x = "Salary in USD",
       y = "Frequency") +
  theme_minimal()
```



In the side-by-side boxplots of Salary by Company Location, we can see that all factors have high outliers and are skewed right. With the US making the most on average, followed by First world, then developing countries. Might consider tranforming (or looking at subset of data, under 3-400K?). Or should we look at just US data?

```
# Create the boxplot side-by-side boxplots for company_size
ggplot(df, aes(x = company_size, y = salary_in_usd, fill = company_size)) +
  geom_boxplot() +
  labs(title = "Salary in USD by Company Size",
       x = "Company Size",
       y = "Salary in USD") +
  scale_fill_manual(values = c("S" = "red", "M" = "green", "L" = "blue")) +
  theme_minimal() +
  theme(legend.position = "none") # Hide legend as fill is mapped to x-axis categories
```



In the side-by-side boxplots of Salary by Company size, we can see that all factors have high outliers and Medium size companies have the strongest right skew and most outliers, followed by Large then small size companies. Might consider tranforming (or looking at subset of data, under 3-400K?).

```
# Create a two-way table
two_way_table <- table(df$job_title, df$company_location)

# Convert to proportions
proportional_table <- prop.table(two_way_table)

# Print the proportional table
print(proportional_table)
```

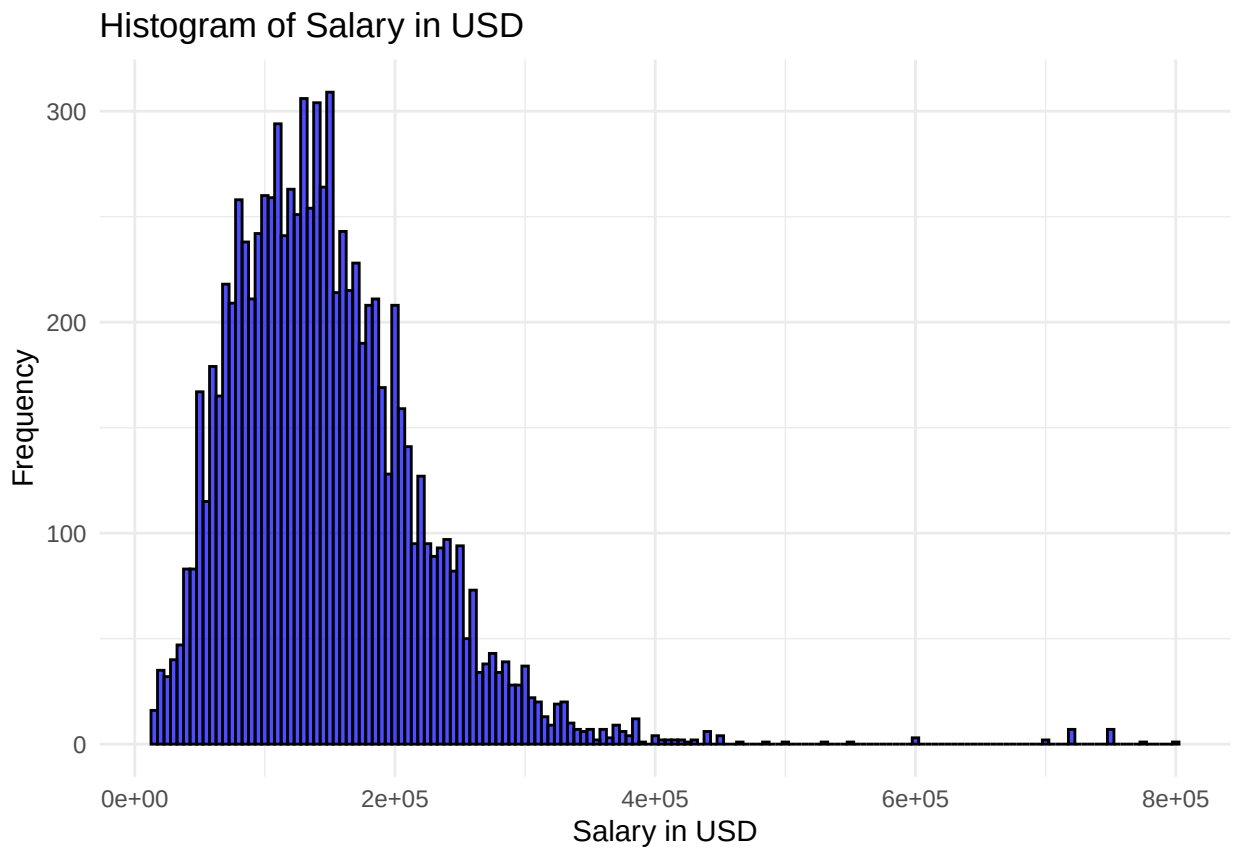
```
##
##                  US First World  Developing
##   DA    0.126696833 0.022514071 0.003973071
##   BI    0.043483059 0.007835780 0.001765810
##   DE    0.163116654 0.030901666 0.004855976
##   DS    0.192693963 0.036309458 0.006069970
##   ML    0.112239267 0.021410440 0.004304161
##   Other 0.187617261 0.028804768 0.005407792
```

```
total <- colSums(proportional_table)
total
```

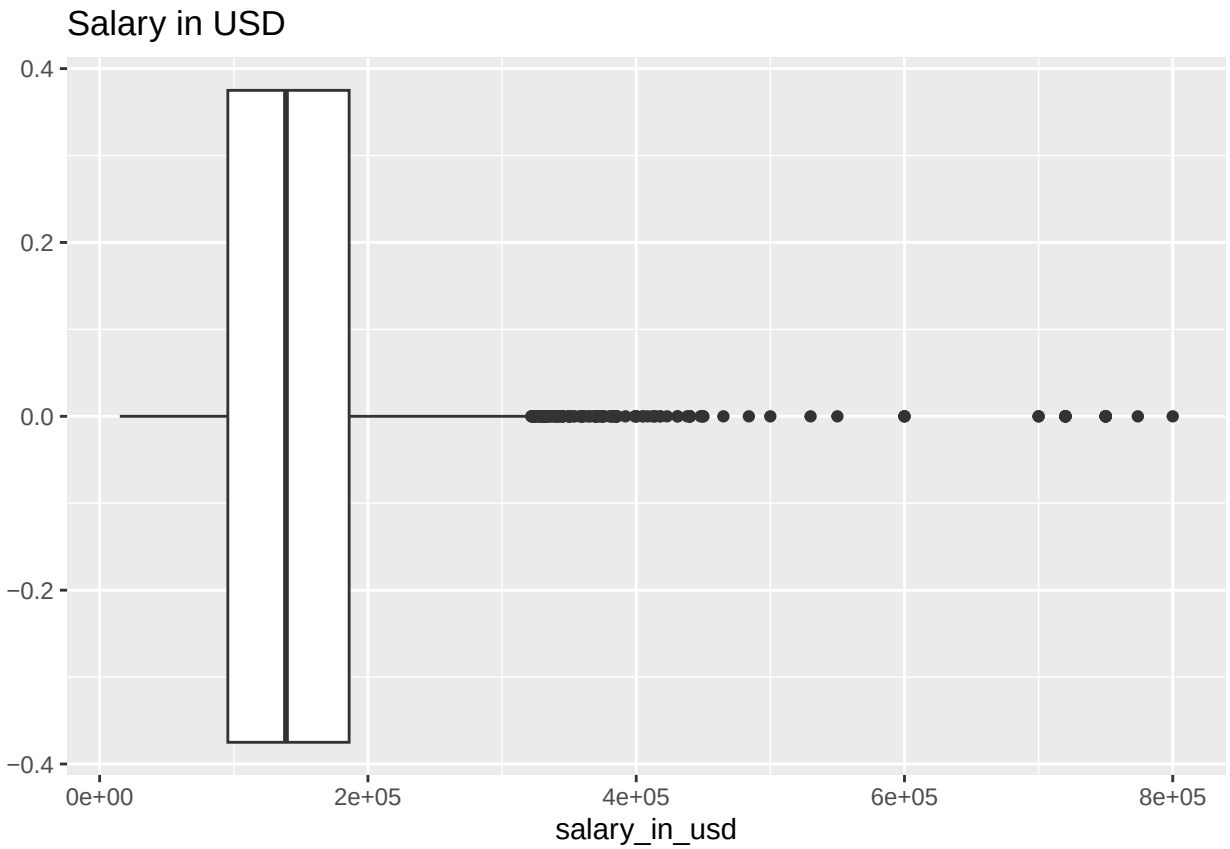
```
##          US First World  Developing
##  0.82584704  0.14777618  0.02637678
```

We can see a majority of the data comes from the US. I am wondering how much the context changes outside of the US, would it be worth it to make predictions based on data only from the US?

```
# Create histogram of salary_in_usd
ggplot(df, aes(x = salary_in_usd)) +
  geom_histogram(binwidth = 5000, fill = "blue", color = "black", alpha = 0.7) +
  labs(title = "Histogram of Salary in USD",
       x = "Salary in USD",
       y = "Frequency") +
  theme_minimal()
```




```
# Create the boxplot for salary_in_usd
ggplot(df, aes(salary_in_usd)) +
  geom_boxplot() +
  labs(title = "Salary in USD")
```

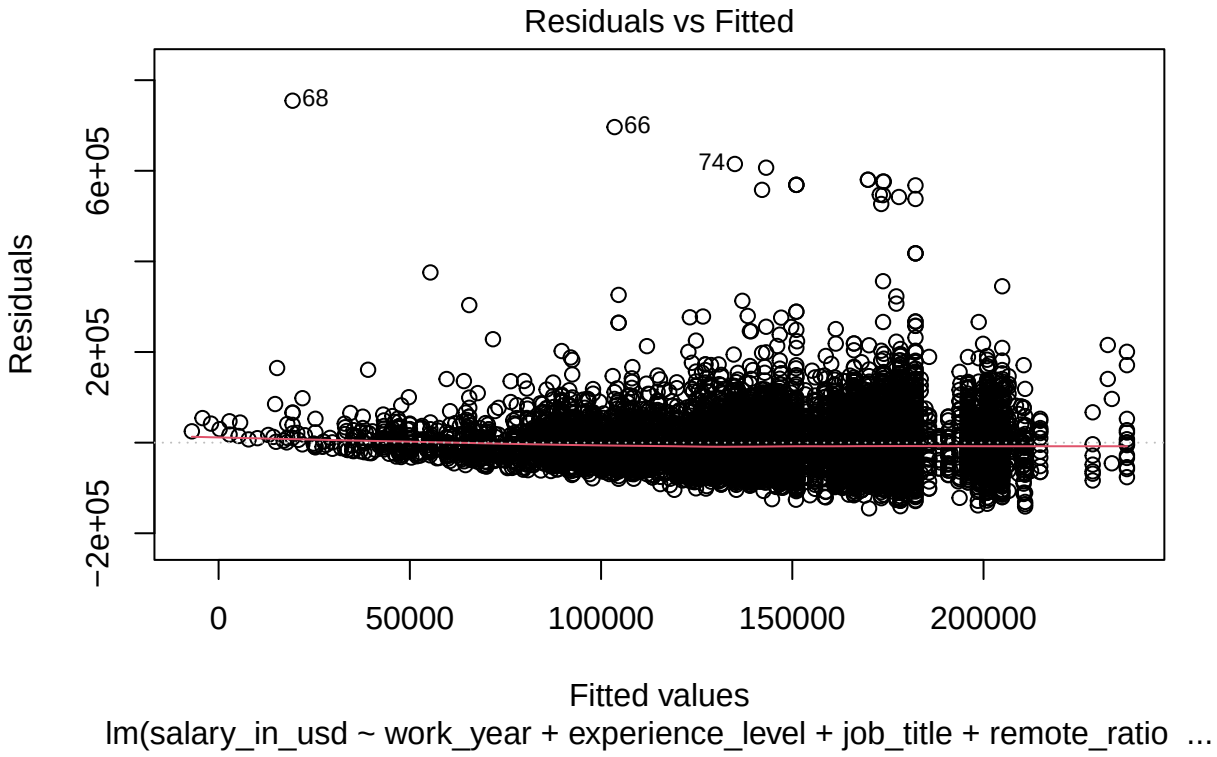


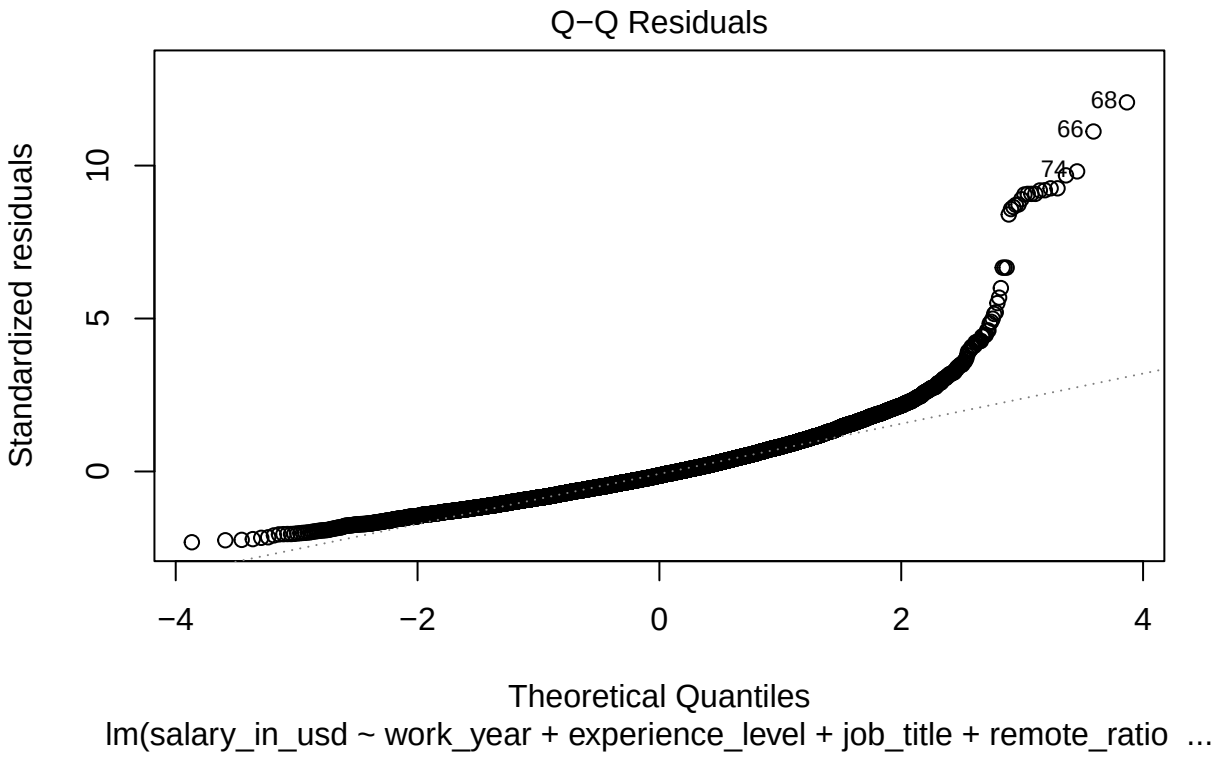

```
#MLR model
model1 <- lm(salary_in_usd ~ work_year + experience_level + job_title + remote_ratio + company_location
summary(model1)
```

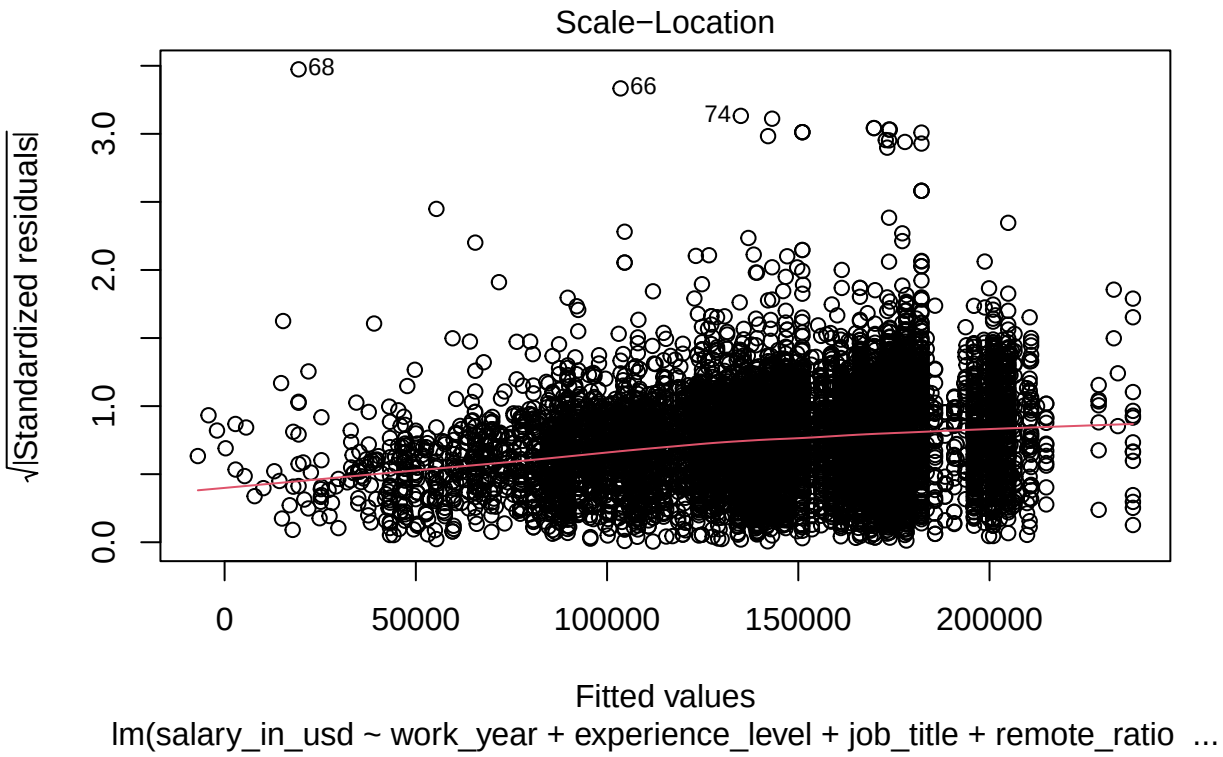
```
##
## Call:
## lm(formula = salary_in_usd ~ work_year + experience_level + job_title +
##     remote_ratio + company_location + company_size, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -145076  -39646   -8260   29673  754653
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   119213       2840  41.977  < 2e-16 ***
## work_year.L                     9976       1587   6.287 3.39e-10 ***
## work_year.Q                    -2536       1154  -2.198 0.027972 *
## experience_level.L             64702       2735  23.657  < 2e-16 ***
## experience_level.Q              5161       2140   2.411 0.015917 *
## experience_level.C             -1653       1368  -1.208 0.226892
## job_titleBI                     2791       3345   0.834 0.404048
## job_titleDE                    26921       2284  11.788  < 2e-16 ***
## job_titleDS                    34723       2207  15.735  < 2e-16 ***
## job_titleML                    61726       2495  24.738  < 2e-16 ***
## job_titleOther                 39054       2221  17.580  < 2e-16 ***
```

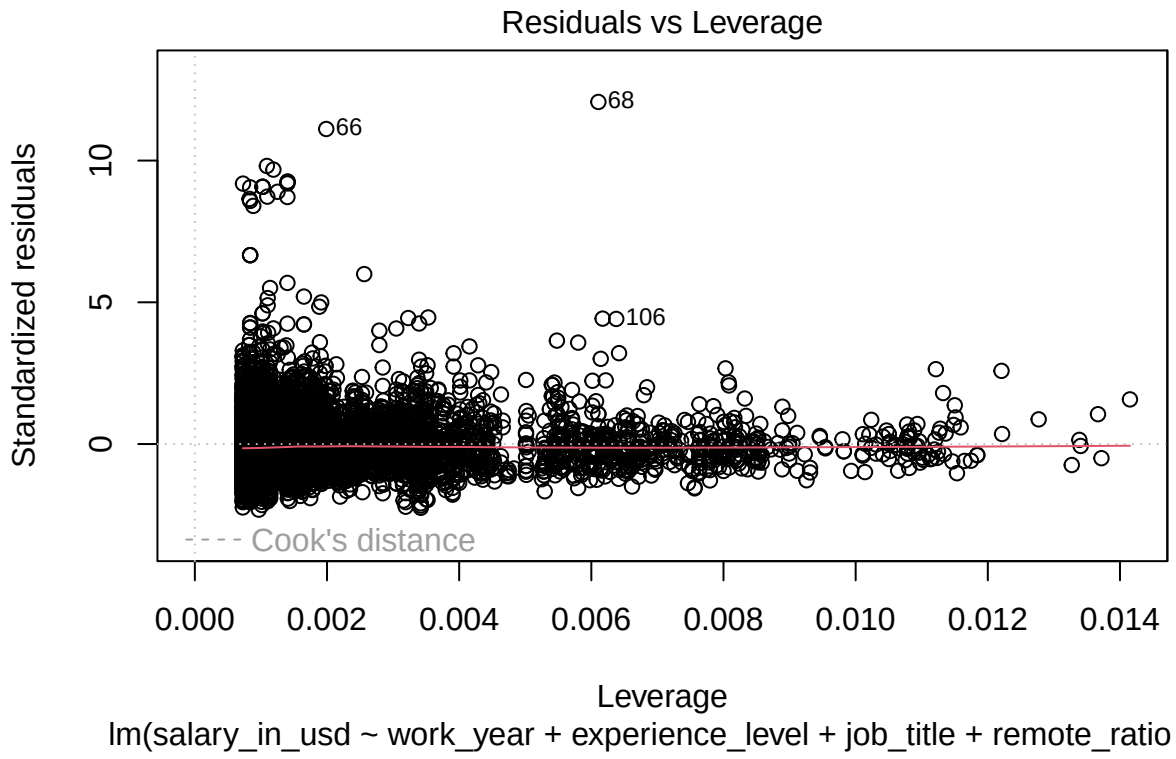
```
## remote_ratioHybrid            -15131       4743  -3.190 0.001427 **
## remote_ratioRemote             -5010       1441  -3.477 0.000510 ***
## company_locationFirst World   -42517       1941 -21.904  < 2e-16 ***
## company_locationDeveloping    -70359       4273 -16.468  < 2e-16 ***
## company_size.L                 14136       3971   3.560 0.000373 ***
## company_size.Q                 -6034       2640  -2.286 0.022285 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 62730 on 9044 degrees of freedom
## Multiple R-squared:  0.2673, Adjusted R-squared:  0.266
## F-statistic: 206.2 on 16 and 9044 DF,  p-value: < 2.2e-16
```

```
plot(model1)
```




Q−Q Residuals
Standardized residuals
0
5
10
68
66
74
−4
−2
0
2
4
Theoretical Quantiles
lm(salary_in_usd ~ work_year + experience_level + job_title + remote_ratio ...


Scale−Location
68
66
74
√|Standardized residuals|
0.0
1.0
2.0
3.0
0
50000
100000
150000
200000
Fitted values
lm(salary_in_usd ~ work_year + experience_level + job_title + remote_ratio ...




```
#see funnel pattern in residual, and qqplot does not follow the normal line

library(car)  # for VIF function
vif(model1)
```

```
##                     GVIF Df GVIF^(1/(2*Df))
## work_year       1.244481  2        1.056202
## experience_level 1.130474  3        1.020650
## job_title       1.093594  5        1.008987
## remote_ratio    1.346636  2        1.077240
## company_location 1.154817  2        1.036641
## company_size    1.380094  2        1.083870
```

We can see see funnel pattern in residual, and qqplot does not follow the normal line. From the Q-Q residual plot that the data is mostly linear until it gets about 2 standard deviations above the mean. (Consider subsetting this data?). All VIF values are pretty low, suggesting low multicollinearity.