

Project_1

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R Markdown

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When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

Question Restated:

How can our company attract and retain top data science talent while battling the recession despite a highly competitive job market? What salary range should we offer for a full-time data scientist in the U.S. compared to offshore options?

Alternative Questions:

What is a competitive salary range for data scientists at various experience levels?

How do salaries for data scientists vary based on a company's size, location, and remote work ratio?

What are the cost differences between hiring a U.S.-based data scientist versus an offshore data scientist with the same experience level?

How might remote work impact data scientist salaries across offshore options?

```
#file.choose() # find location of file
```

```
library(tidyverse) # Load library
```

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

```
data <- read.csv("C:\\Users\\zdurs\\Downloads\\r project data.csv") # Load/read dataset
```

```
data <- data %>% #create dataset
  mutate(
    experience_level = factor(experience_level, levels = c("EN", "MI", "SE", "EX")), #change variable to factor
    employment_type = factor(employment_type, levels = c("PT", "FT", "CT", "FL")), #change variable to factor
    remote_ratio = factor(remote_ratio, levels = c(0, 50, 100), labels = c("No Remote", "Partially Remote", "Fully Remote")), #change variable to factor
    company_size = factor(company_size, levels = c("S", "M", "L")) #change variable to factor
  )
```

```
colSums(is.na(data)) # check for NAs within each variable in the dataset
```

```
##           X           work_year  experience_level  employment_type
##           0             0             0             0
##   job_title           salary  salary_currency  salary_in_usd
##           0             0             0             0
## employee_residence  remote_ratio  company_location  company_size
##           0             0             0             0
```

```
# Summary for the entire dataset
summary(data)
```

```
##           X           work_year  experience_level  employment_type
##  Min.   : 0.0   Min.   :2020   EN: 88           PT: 10
##  1st Qu.:151.5  1st Qu.:2021   MI:213         FT:588
##  Median :303.0  Median :2022   SE:280         CT: 5
##  Mean   :303.0  Mean   :2021   EX: 26         FL: 4
##  3rd Qu.:454.5  3rd Qu.:2022
##  Max.   :606.0  Max.   :2022
##  job_title           salary           salary_currency  salary_in_usd
##  Length:607           Min.   : 4000   Length:607           Min.   : 2859
##  Class :character     1st Qu.: 70000   Class :character     1st Qu.: 62726
##  Mode  :character     Median : 115000   Mode  :character     Median :101570
##                               Mean   : 324000           Mean   :112298
##                               3rd Qu.: 165000           3rd Qu.:150000
##                               Max.   :30400000           Max.   :600000
## employee_residence  remote_ratio  company_location  company_size
##  Length:607         No Remote    :127   Length:607         S: 83
##  Class :character   Partially Remote: 99   Class :character   M:326
##  Mode  :character   Fully Remote   :381   Mode  :character   L:198
##
##
##
```

```
# To examine each variable individually we can summarize like this
summary(data$work_year)           # Years in the dataset; Years range from 2020-2022
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      2020   2021   2022   2021   2022   2022
```

```
summary(data$experience_level) # Counts for each experience level in the dataset; 4 types of ex
perience level, SE has the highest count
```

```
##  EN  MI  SE  EX
##  88 213 280  26
```

```
summary(data$employment_type) # Counts for employment types; 4 types of employment type, FT ha
s the highest count
```

```
##  PT  FT  CT  FL
##  10 588   5   4
```

```
summary(data$salary)           # Range/distribution of salary; ranges from 4,000 to 30,400,000
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      4000   70000   115000   324000   165000 30400000
```

```
summary(data$salaryinusd)      # Range/distribution of salaries in USD; ranges from 2,859 to 60
0,000
```

```
## Length Class  Mode
##      0  NULL  NULL
```

```
summary(data$employee_residence) # Distribution of employee residence
```

```
##      Length      Class      Mode
##      607 character character
```

```
summary(data$remote_ratio)     # Counts for remote work; 3 types of remote work, fully remote h
as the highest count
```

```
##      No Remote Partially Remote    Fully Remote
##      127          99          381
```

```
summary(data$company_location) # Distribution of company location
```

```
##      Length      Class      Mode
##      607 character character
```

```
summary(data$company_size)      # Company size; 3 types of company size; M has the highest count
```

```
##      S      M      L
##      83 326 198
```

```
# Count unique values for each variable (which type and how many of them for each variable)
sapply(data, function(x) {
  list(Variable_Type = class(x), Unique_Values = length(unique(x)))
})
```

```
##      X      work_year experience_level employment_type job_title
## Variable_Type "integer" "integer" "factor"          "factor"          "character"
## Unique_Values 607       3          4          4          50
##      salary      salary_currency salary_in_usd employee_residence
## Variable_Type "integer" "character"      "integer"      "character"
## Unique_Values 272       17          369          57
##      remote_ratio company_location company_size
## Variable_Type "factor"      "character"      "factor"
## Unique_Values 3          50          3
```

```
# Example tables: Frequency distribution for each variable
table(data$company_size)
```

```
##
##      S      M      L
##      83 326 198
```

```
table(data$remote_ratio)
```

```
##
##      No Remote Partially Remote      Fully Remote
##      127          99          381
```

```
table(data$experience_level)
```

```
##
##      EN      MI      SE      EX
##      88 213 280  26
```

```
table(data$work_year)
```

```
##  
## 2020 2021 2022  
##    72  217  318
```

```
table(data$employment_type)
```

```
##  
##  PT  FT  CT  FL  
##  10 588   5   4
```

```
table(data$job_title)
```

##		
##	3D Computer Vision Researcher	
##		1
##	AI Scientist	
##		7
##	Analytics Engineer	
##		4
##	Applied Data Scientist	
##		5
##	Applied Machine Learning Scientist	
##		4
##	BI Data Analyst	
##		6
##	Big Data Architect	
##		1
##	Big Data Engineer	
##		8
##	Business Data Analyst	
##		5
##	Cloud Data Engineer	
##		2
##	Computer Vision Engineer	
##		6
##	Computer Vision Software Engineer	
##		3
##	Data Analyst	
##		97
##	Data Analytics Engineer	
##		4
##	Data Analytics Lead	
##		1
##	Data Analytics Manager	
##		7
##	Data Architect	
##		11
##	Data Engineer	
##		132
##	Data Engineering Manager	
##		5
##	Data Science Consultant	
##		7
##	Data Science Engineer	
##		3
##	Data Science Manager	
##		12
##	Data Scientist	
##		143
##	Data Specialist	
##		1
##	Director of Data Engineering	
##		2
##	Director of Data Science	

##		7
##	ETL Developer	
##		2
##	Finance Data Analyst	
##		1
##	Financial Data Analyst	
##		2
##	Head of Data	
##		5
##	Head of Data Science	
##		4
##	Head of Machine Learning	
##		1
##	Lead Data Analyst	
##		3
##	Lead Data Engineer	
##		6
##	Lead Data Scientist	
##		3
##	Lead Machine Learning Engineer	
##		1
##	Machine Learning Developer	
##		3
##	Machine Learning Engineer	
##		41
##	Machine Learning Infrastructure Engineer	
##		3
##	Machine Learning Manager	
##		1
##	Machine Learning Scientist	
##		8
##	Marketing Data Analyst	
##		1
##	ML Engineer	
##		6
##	NLP Engineer	
##		1
##	Principal Data Analyst	
##		2
##	Principal Data Engineer	
##		3
##	Principal Data Scientist	
##		7
##	Product Data Analyst	
##		2
##	Research Scientist	
##		16
##	Staff Data Scientist	
##		1

```
table(data$salary)
```

##								
##	4000	8000	8760	9272	10000	12000	13400	14000
##	2	1	1	1	2	3	1	1
##	18000	19000	20000	21000	21600	21844	22000	24000
##	1	1	6	2	1	1	1	2
##	25000	28500	29000	30000	31000	32000	34000	35000
##	1	1	1	5	1	1	2	4
##	37000	37456	38400	39600	40000	40900	41000	42000
##	1	1	2	1	8	1	1	3
##	43200	44000	45000	45760	48000	50000	51400	51999
##	2	1	6	1	4	13	1	1
##	52000	52500	52800	53000	54000	55000	56000	57000
##	2	1	1	2	3	6	1	1
##	58000	59000	60000	61300	61500	62000	63900	65000
##	4	3	15	2	1	2	1	7
##	65720	66500	67000	68000	69000	69600	69999	70000
##	1	1	2	1	1	1	1	10
##	70500	72000	72500	73000	74000	75000	76760	78000
##	1	1	1	1	1	11	2	1
##	80000	81000	81666	82500	82900	84900	85000	87000
##	18	2	2	2	1	1	7	2
##	88000	90000	90320	90700	91000	93000	93150	93700
##	2	10	5	1	1	1	1	2
##	95000	95550	98000	99000	99050	99100	99360	100000
##	2	1	1	2	1	1	1	18
##	100800	101570	102000	102100	103000	104890	105000	105400
##	1	1	1	2	1	1	5	1
##	106000	106260	108000	108800	109000	109280	110000	110500
##	1	2	1	1	1	2	8	1
##	110925	111775	112000	112300	112900	113000	115000	115500
##	1	1	1	1	4	1	6	1
##	115934	116000	116150	118000	120000	120160	120500	120600
##	2	1	1	1	15	1	1	1
##	121000	123000	124190	125000	126000	126500	128875	129000
##	1	3	1	4	1	2	2	1
##	130000	130800	132000	132320	135000	136000	136600	136620
##	11	1	1	3	9	1	1	1
##	136994	137141	138000	138350	138600	140000	140250	140400
##	1	1	1	1	1	9	1	3
##	141300	144000	144854	145000	146000	147000	147800	148000
##	1	3	1	2	1	2	1	1
##	150000	150075	150260	151000	152000	152500	153000	154000
##	14	1	1	1	1	1	2	1
##	154600	155000	156600	157000	158200	159000	159500	160000
##	2	3	1	2	1	1	1	9
##	160080	161342	164000	164996	165000	165220	165400	167000
##	2	1	1	2	4	1	2	2
##	167875	168000	170000	174000	175000	175100	176000	177000
##	1	1	8	2	2	1	1	1
##	180000	181940	183600	184700	185000	185100	188000	189650
##	8	1	1	1	2	1	1	2
##	190000	190200	192400	192564	192600	195000	200000	200100

##	1	1	1	1	1	1	10	1
##	205300	206699	208775	209100	210000	211500	213120	214000
##	3	1	1	2	5	1	1	1
##	215300	216000	220000	220110	224000	225000	230000	235000
##	2	1	3	2	1	2	3	3
##	240000	241000	242000	243900	250000	256000	260000	266400
##	2	1	1	1	4	1	2	1
##	270000	276000	299000	300000	324000	325000	380000	400000
##	1	1	1	1	1	1	1	1
##	405000	412000	416000	420000	423000	435000	450000	600000
##	1	1	1	1	2	1	4	1
##	700000	720000	1200000	1250000	1335000	1400000	1450000	1600000
##	1	1	1	1	1	2	1	1
##	1672000	1799997	2100000	2200000	2250000	2400000	2500000	3000000
##	1	1	1	1	1	1	1	2
##	4000000	4450000	4900000	6000000	7000000	8500000	11000000	30400000
##	1	1	1	1	2	1	2	1

```
table(data$salary_in_usd)
```

##											
##	2859	4000	5409	5679	5707	5882	6072	8000	9272	9466	10000
##	1	2	1	1	1	1	2	1	1	1	2
##	10354	12000	12103	12901	13400	15966	16228	16904	18000	18053	18442
##	1	3	1	1	1	1	1	1	1	1	2
##	18907	19609	20000	20171	21637	21669	21844	21983	22611	24000	24342
##	1	1	5	1	1	1	1	1	1	1	1
##	24823	25000	25532	26005	28016	28369	28399	28476	28609	29751	30428
##	2	1	1	1	1	1	1	1	1	1	1
##	31615	31875	32974	33511	33808	35590	35735	36259	36643	37236	37300
##	1	1	3	1	1	1	1	1	1	1	1
##	37825	38400	38776	39263	39916	40000	40038	40189	40481	40570	41689
##	1	1	1	2	1	1	1	1	1	1	1
##	42000	42197	43331	43966	45391	45618	45760	45807	45896	46597	46759
##	1	1	1	2	1	1	1	3	1	1	1
##	46809	47282	47899	48000	49268	49461	49646	50000	50180	51064	51321
##	1	1	1	1	1	2	1	5	1	1	1
##	51519	52000	52351	52396	53192	54000	54094	54238	54742	54957	55000
##	1	1	3	1	1	1	1	1	1	3	2
##	56000	56256	56738	58000	58035	58255	58894	59102	59303	60000	60757
##	1	1	1	3	1	1	1	2	1	5	1
##	61300	61467	61896	62000	62649	62651	62726	63711	63810	63831	63900
##	2	1	1	1	1	1	2	1	1	2	1
##	64849	65000	65013	65438	65949	66022	66265	67000	68147	68428	69000
##	1	2	1	3	2	1	1	1	1	1	1
##	69336	69741	69999	70000	70139	70500	70912	71444	71786	71982	72000
##	1	2	1	2	1	1	1	1	1	1	1
##	72212	72500	73000	74000	74130	75000	75774	76833	76940	76958	77364
##	1	1	1	1	1	4	1	3	2	1	1
##	77684	78000	78526	78791	79039	79197	79833	80000	81000	81666	82500
##	1	1	4	2	1	1	2	8	1	2	1
##	82528	82744	82900	84900	85000	86703	87000	87425	87738	87932	88654
##	2	1	1	1	4	1	1	1	1	4	3
##	89294	90000	90320	90700	90734	91000	91237	91614	93000	93150	93427
##	1	6	5	1	2	1	1	2	1	1	1
##	93700	94564	94665	95550	95746	96113	96282	98000	98158	99000	99050
##	2	1	1	1	1	1	1	1	3	2	1
##	99100	99360	99703	100000	100800	101570	102100	102839	103000	103160	103691
##	1	1	1	15	1	1	2	1	1	1	1
##	104702	104890	105000	105400	106000	106260	108800	109000	109024	109280	110000
##	2	1	5	1	1	2	1	1	1	2	5
##	110037	110500	110925	111775	112000	112300	112872	112900	113000	113476	114047
##	1	1	1	1	1	1	1	4	1	1	1
##	115000	115500	115934	116000	116150	116914	117104	117789	118000	118187	119059
##	5	1	2	1	1	1	1	2	1	1	1
##	120000	120160	120600	122346	123000	124190	124333	125000	126000	126500	127221
##	12	1	1	1	3	1	1	3	1	2	1
##	128875	129000	130000	130026	130800	132000	132320	135000	136000	136600	136620
##	2	1	8	1	1	1	3	9	1	1	1
##	136994	137141	138000	138350	138600	140000	140250	140400	141300	141846	144000
##	1	1	1	1	1	8	1	3	1	1	3
##	144854	145000	146000	147000	147800	148261	150000	150075	150260	151000	152000

```
##      1      2      1      1      1      1      12      1      1      1      1
## 152500 153000 153667 154000 154600 155000 156600 157000 158200 159000 160000
##      1      2      1      1      2      3      1      1      1      1      8
## 160080 161342 162674 164000 164996 165000 165220 165400 167000 167875 168000
##      2      1      1      1      2      4      1      2      2      1      1
## 170000 173762 174000 175000 175100 176000 177000 180000 181940 183228 183600
##      8      1      2      2      1      1      1      5      1      1      1
## 184700 185000 185100 187442 188000 189650 190000 190200 192400 192564 192600
##      1      2      1      1      1      2      1      1      1      1      1
## 195000 196979 200000 200100 205300 206699 208775 209100 210000 211500 213120
##      1      1     10      1      3      1      1      2      5      1      1
## 214000 215300 216000 220000 220110 224000 225000 230000 235000 240000 241000
##      1      2      1      3      2      1      2      3      2      1      1
## 242000 243900 250000 256000 260000 266400 270000 276000 324000 325000 380000
##      1      1      2      1      2      1      1      1      1      1      1
## 405000 412000 416000 423000 450000 600000
##      1      1      1      1      2      1
```

```
table(data$salary_currency)
```

```
##
## AUD BRL CAD CHF CLP CNY DKK EUR GBP HUF INR JPY MXN PLN SGD TRY USD
##  2   2  18   1   1   2   2  95  44   2  27   3   2   3   2   3 398
```

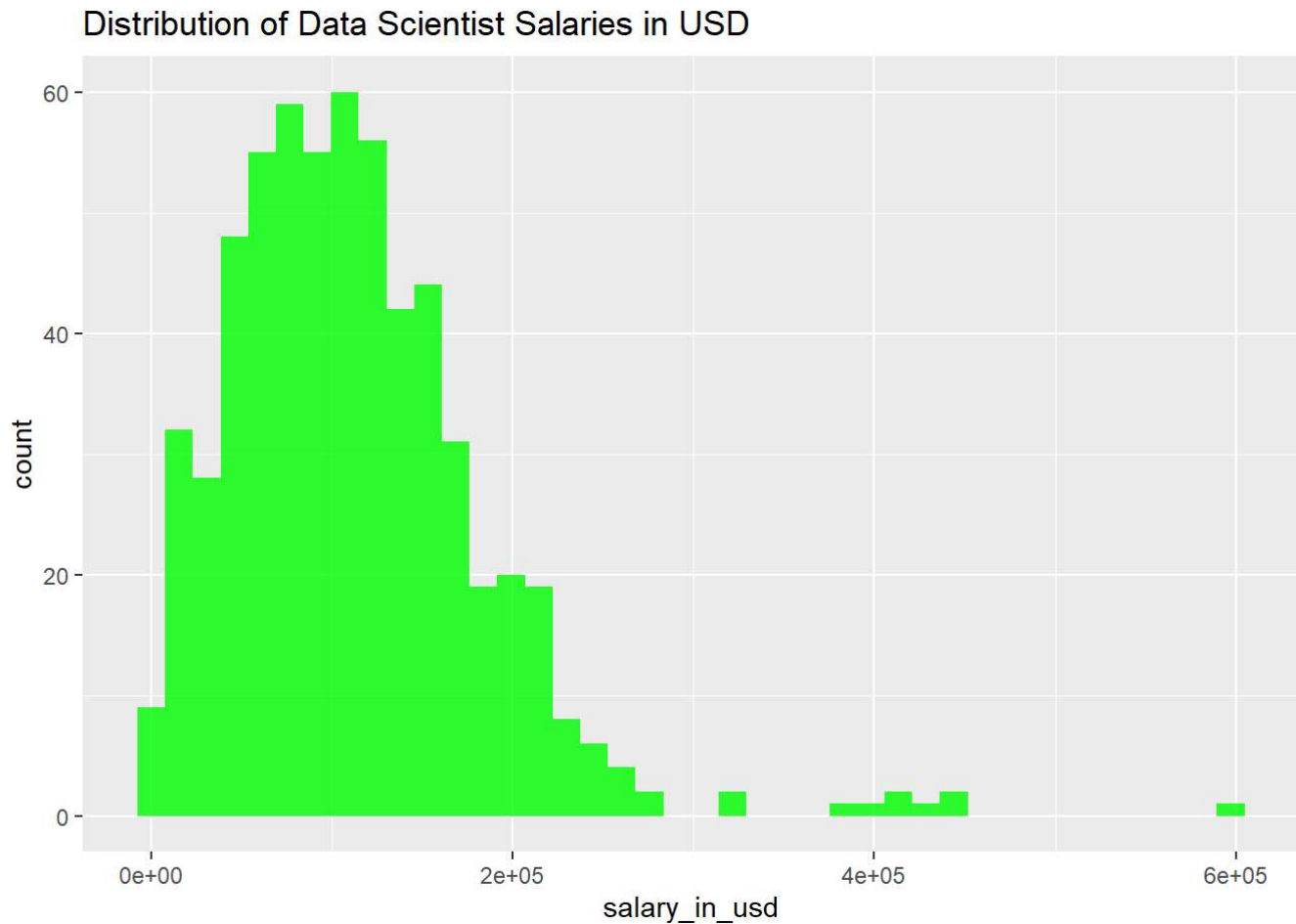
```
table(data$employee_residence)
```

```
##
## AE  AR  AT  AU  BE  BG  BO  BR  CA  CH  CL  CN  CO  CZ  DE  DK  DZ  EE  ES  FR
##  3   1   3   3   2   1   1   6  29   1   1   1   1   1  25   2   1   1  15  18
## GB  GR  HK  HN  HR  HU  IE  IN  IQ  IR  IT  JE  JP  KE  LU  MD  MT  MX  MY  NG
## 44  13   1   1   1   2   1  30   1   1   4   1   7   1   1   1   1   2   1   2
## NL  NZ  PH  PK  PL  PR  PT  RO  RS  RU  SG  SI  TN  TR  UA  US  VN
##  5   1   1   6   4   1   6   2   1   4   2   2   1   3   1 332   3
```

```
table(data$company_location)
```

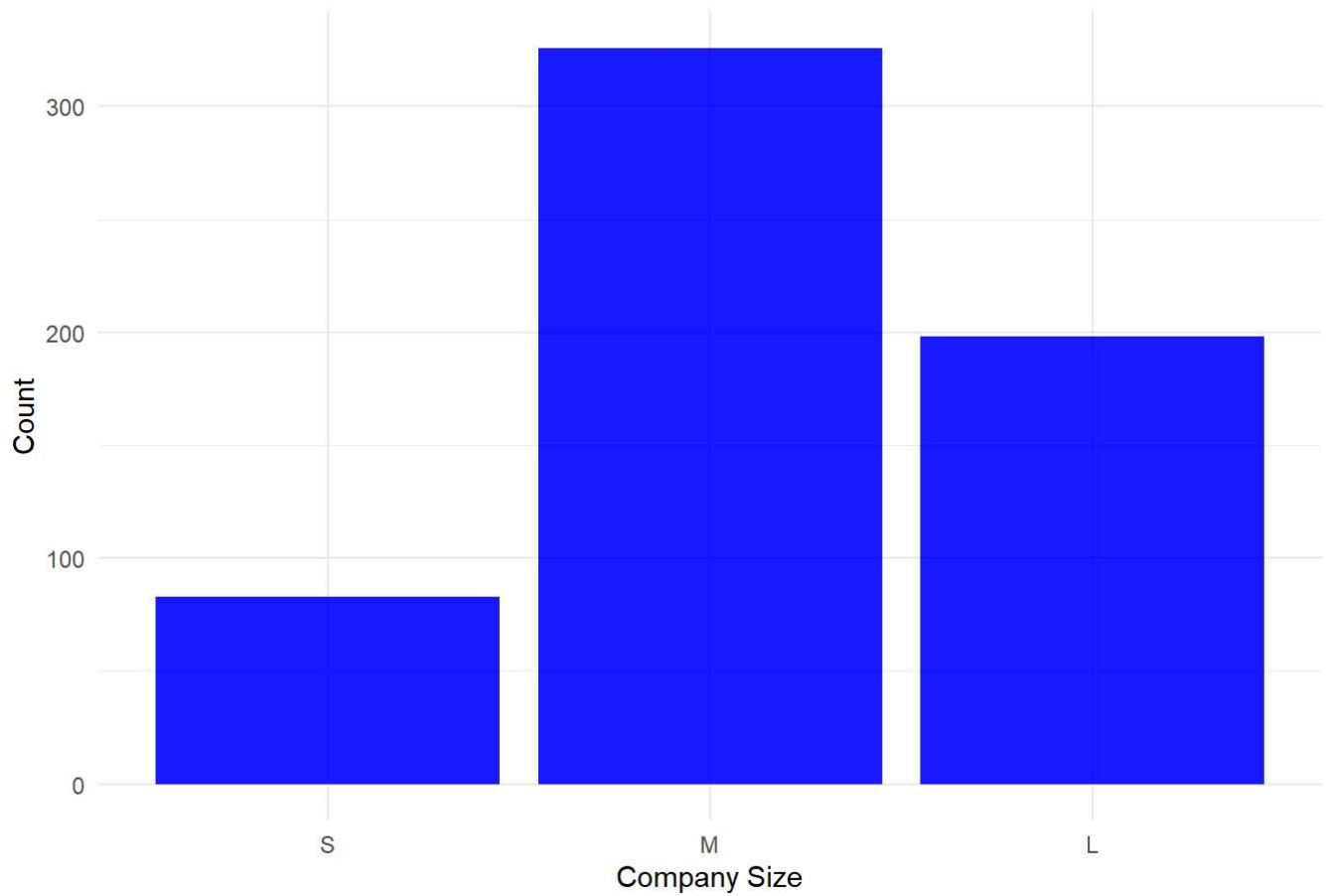
```
##
## AE  AS  AT  AU  BE  BR  CA  CH  CL  CN  CO  CZ  DE  DK  DZ  EE  ES  FR  GB  GR
##  3   1   4   3   2   3  30   2   1   2   1   2  28   3   1   1  14  15  47  11
## HN  HR  HU  IE  IL  IN  IQ  IR  IT  JP  KE  LU  MD  MT  MX  MY  NG  NL  NZ  PK
##  1   1   1   1   1  24   1   1   2   6   1   3   1   1   3   1   2   4   1   3
## PL  PT  RO  RU  SG  SI  TR  UA  US  VN
##  4   4   1   2   1   2   3   1 355   1
```

```
# Example plot
library(ggplot2) #load libraries
library(dplyr)
ggplot(data, aes(x = salary_in_usd)) + #plot salary in USD
  geom_histogram(bins = 40, fill = "green", alpha = 0.8) + #create a histogram
  labs(title = "Distribution of Data Scientist Salaries in USD") #label the title
```



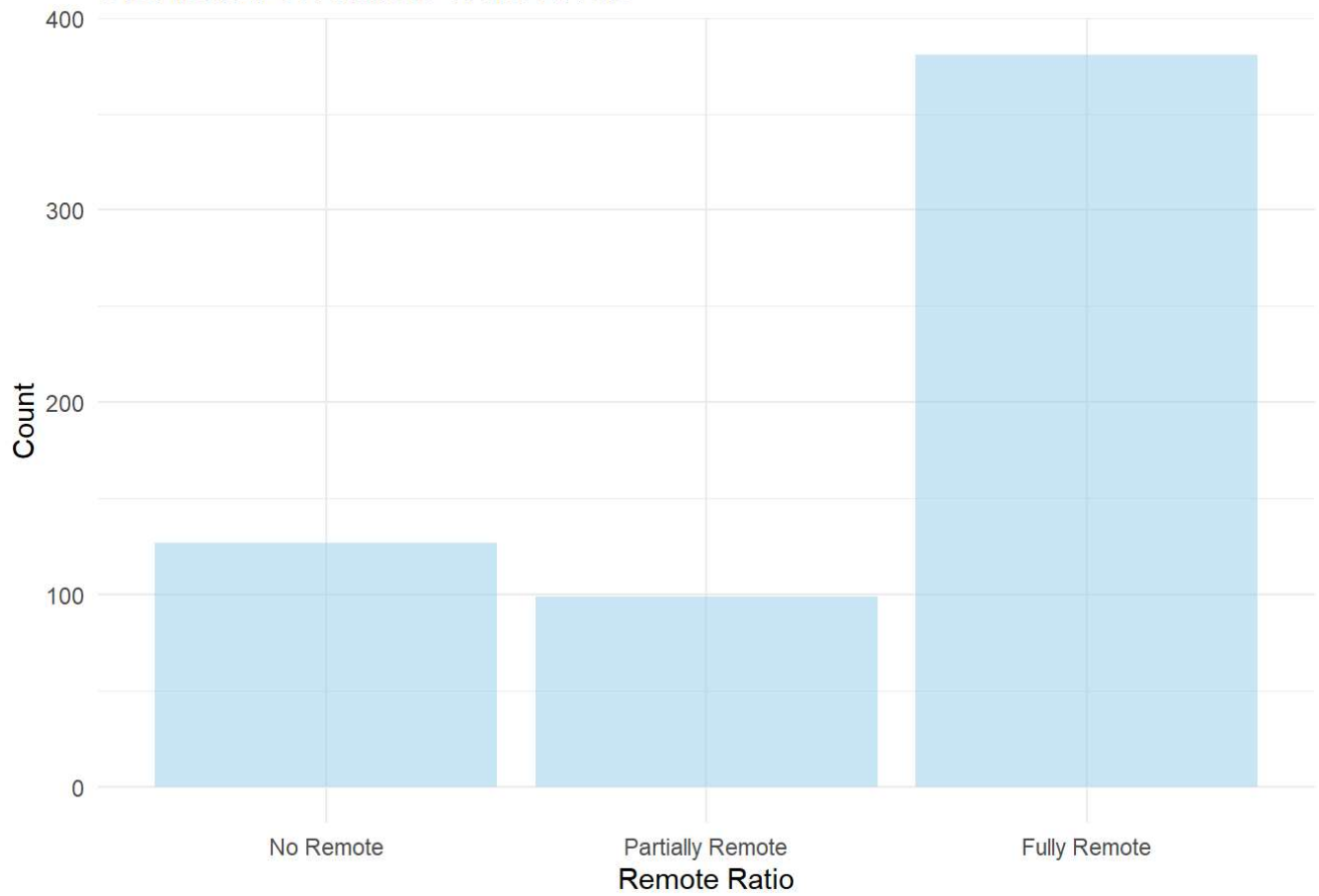
```
ggplot(data, aes(x = company_size)) +
  geom_bar(fill = "blue", alpha = 0.9) +
  labs(title = "Distribution of Company Sizes", x = "Company Size", y = "Count") +
  theme_minimal()
```

Distribution of Company Sizes

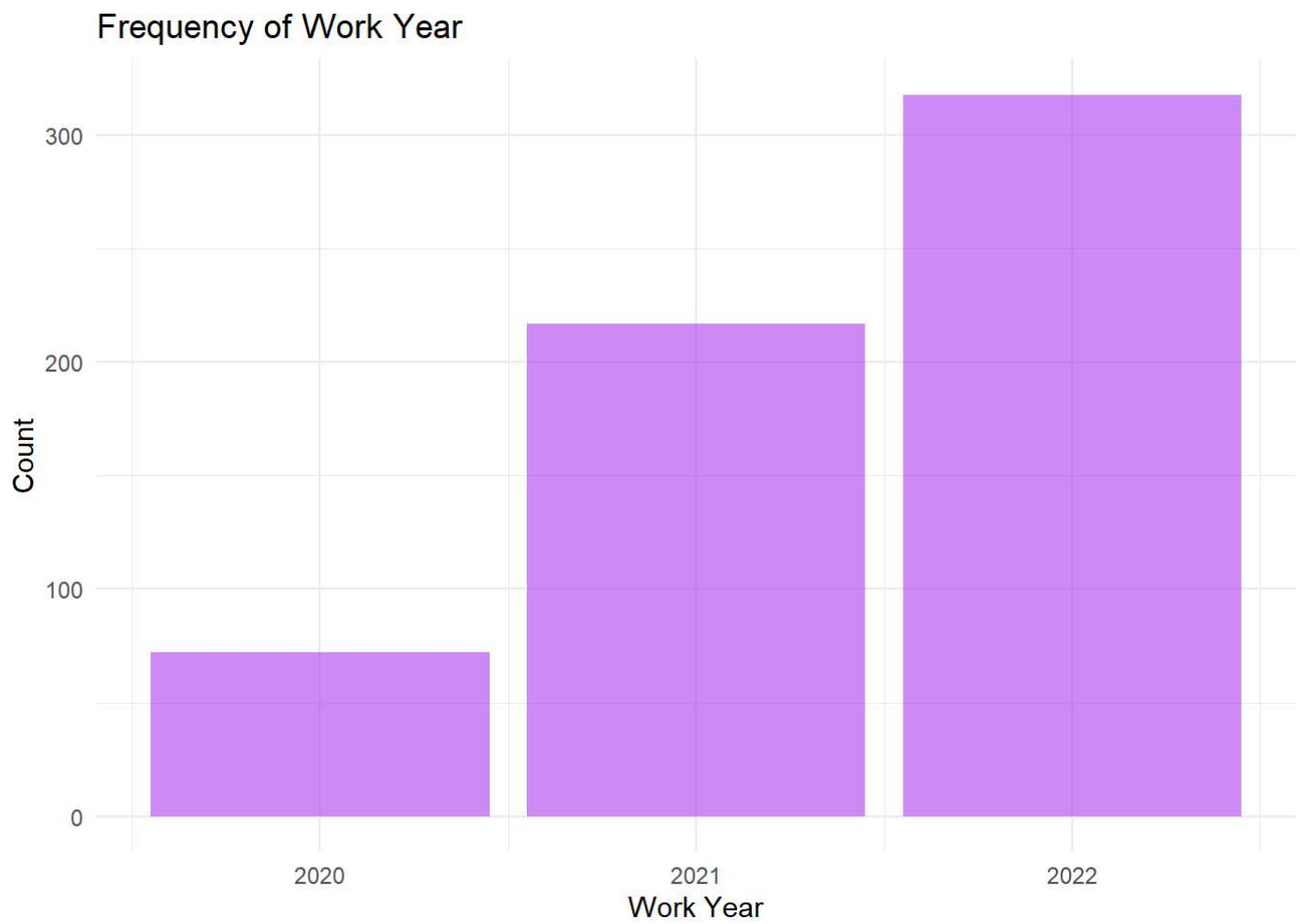


```
ggplot(data, aes(x = factor(remote_ratio))) +  
  geom_bar(fill = "skyblue", alpha = 0.45) +  
  labs(title = "Distribution of Remote Work Levels", x = "Remote Ratio", y = "Count") +  
  theme_minimal()
```

Distribution of Remote Work Levels

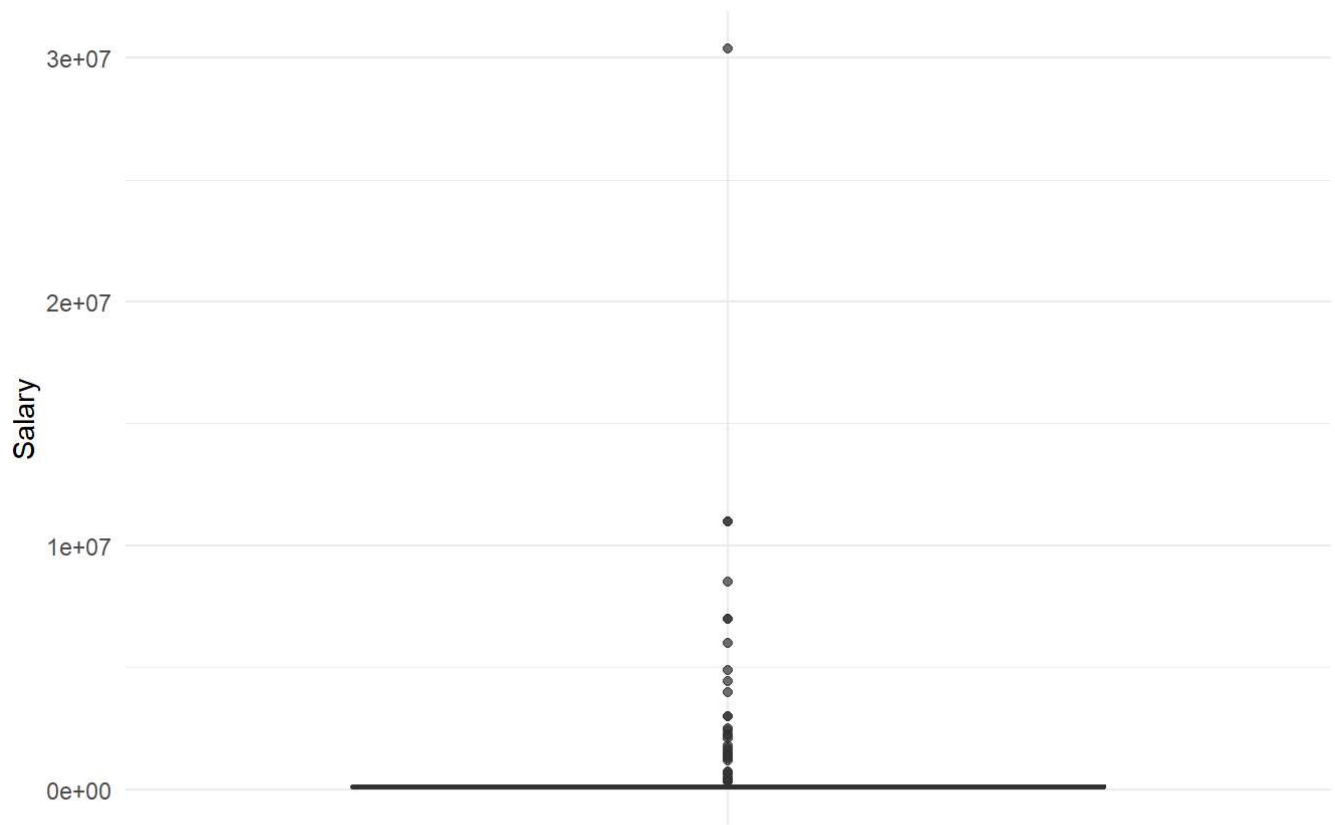


```
ggplot(data, aes(x = work_year)) +  
  geom_bar(fill = "purple", alpha = 0.5) +  
  labs(title = "Frequency of Work Year", x = "Work Year", y = "Count") +  
  theme_minimal()
```



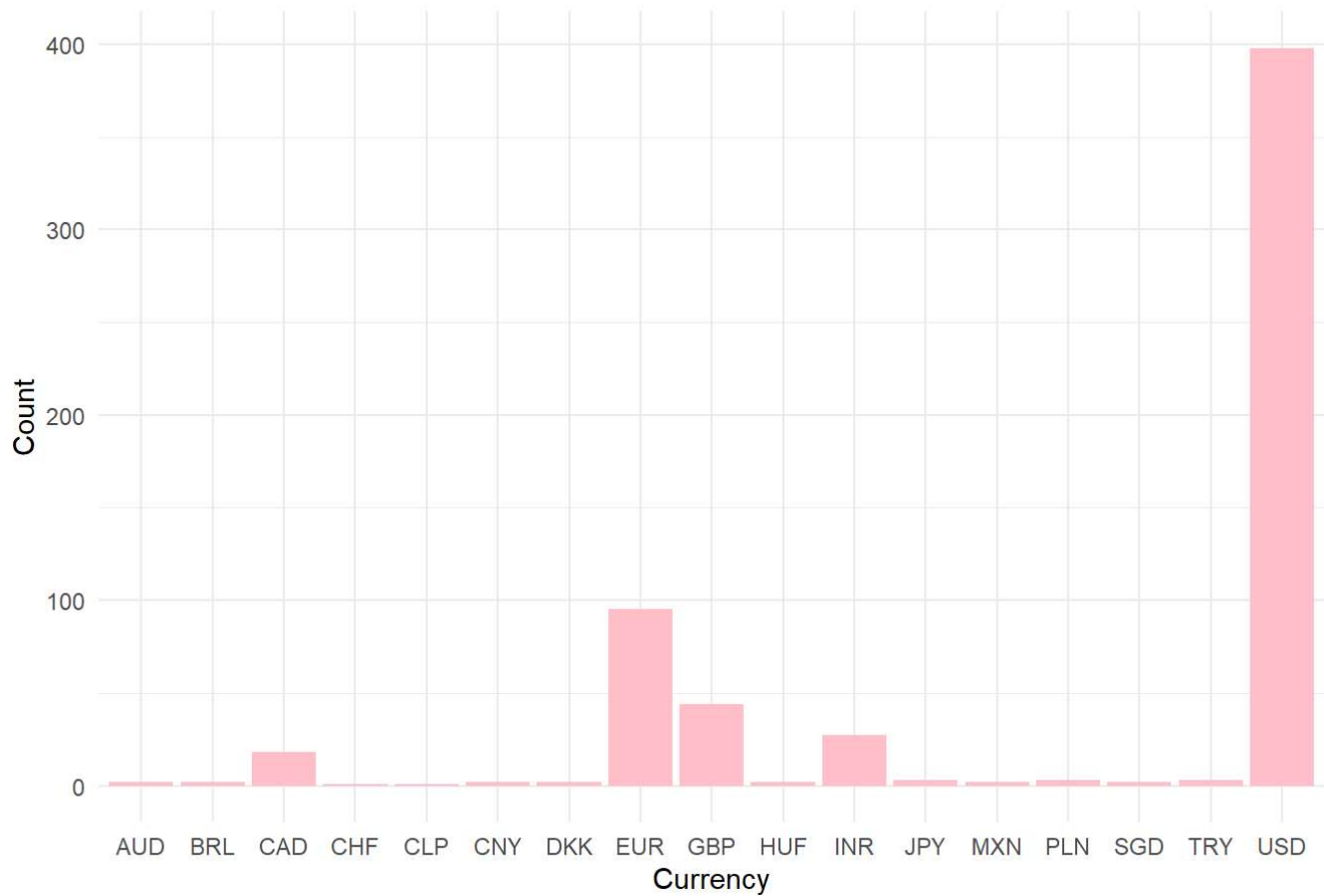
```
ggplot(data, aes(x = "", y = salary)) +  
  geom_boxplot(fill = "orange", alpha = 0.7) +  
  labs(title = "Salary Distribution", x = "", y = "Salary") +  
  theme_minimal()
```

Salary Distribution



```
ggplot(data, aes(x = salary_currency)) +  
  geom_bar(fill = "pink", alpha = 1.2) +  
  labs(title = "Distribution of Salary Currencies", x = "Currency", y = "Count") +  
  theme_minimal()
```

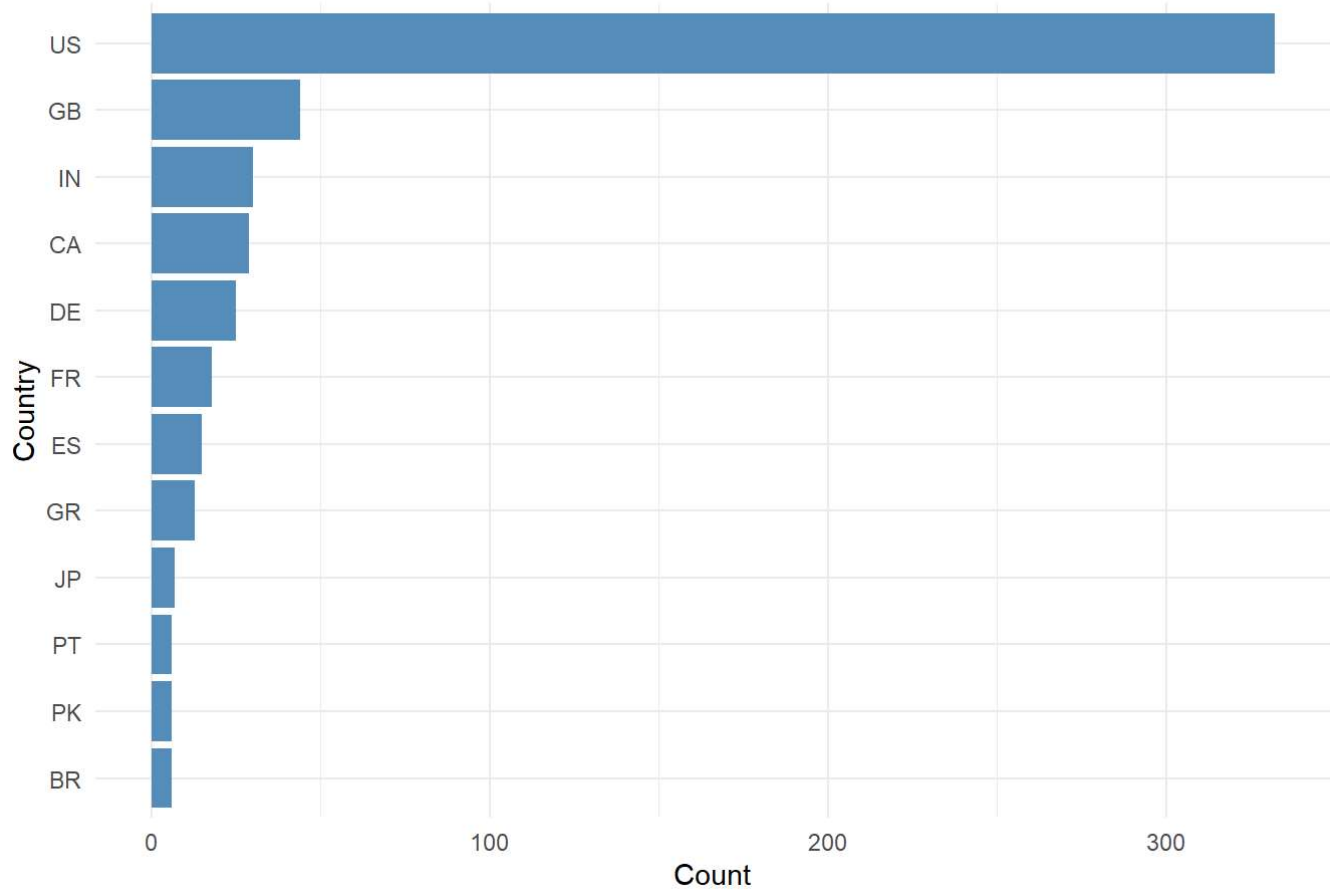

Distribution of Salary Currencies



```
data %>%  
  count(employee_residence, sort = TRUE) %>%  
  top_n(10) %>%  
  ggplot(aes(x = reorder(employee_residence, n), y = n)) +  
  geom_bar(stat = "identity", fill = "steelblue", alpha = 0.9) +  
  coord_flip() + #flip axis  
  labs(title = "Top 10 Employee Residences", x = "Country", y = "Count") +  
  theme_minimal()
```

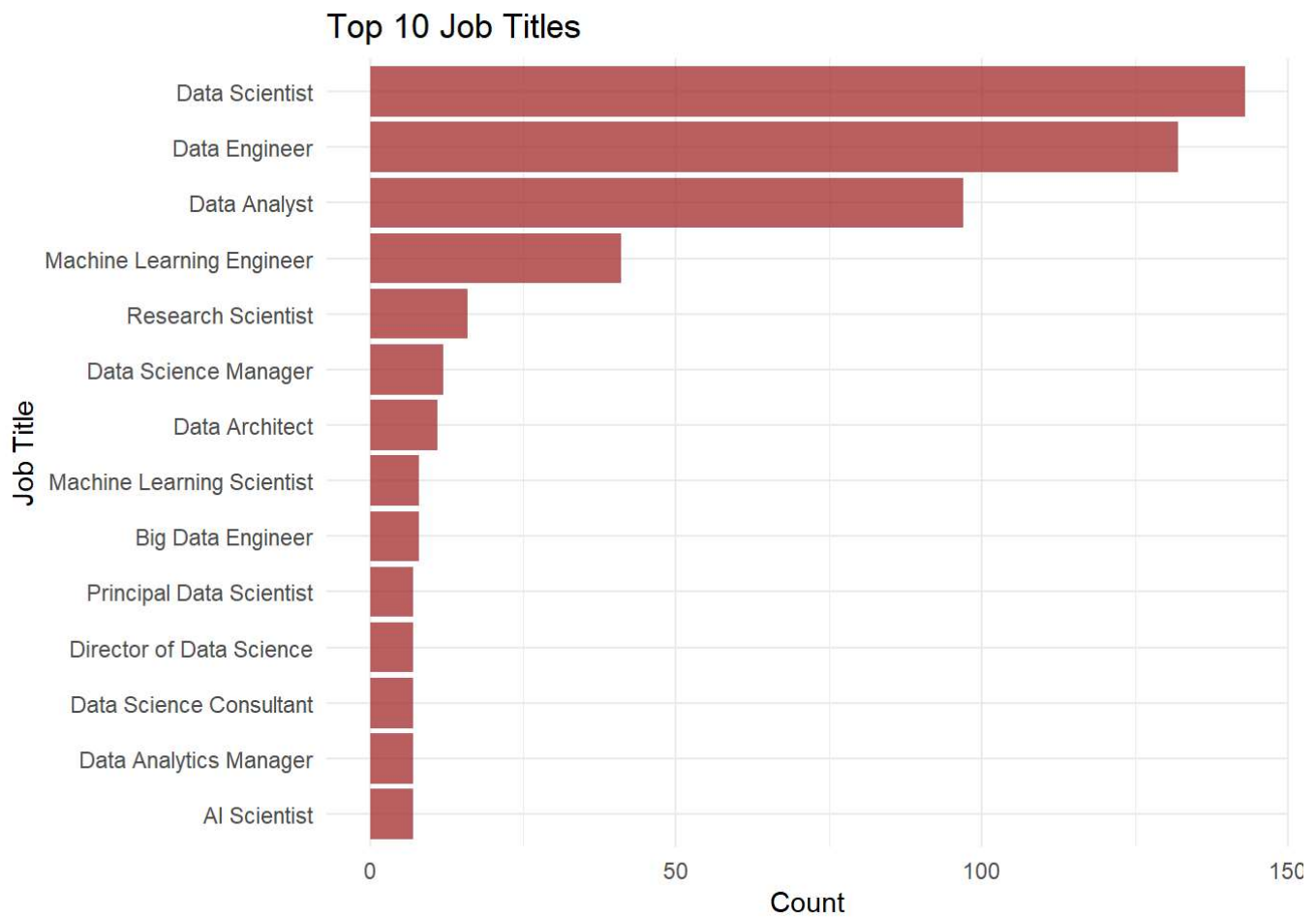
```
## Selecting by n
```

Top 10 Employee Residences



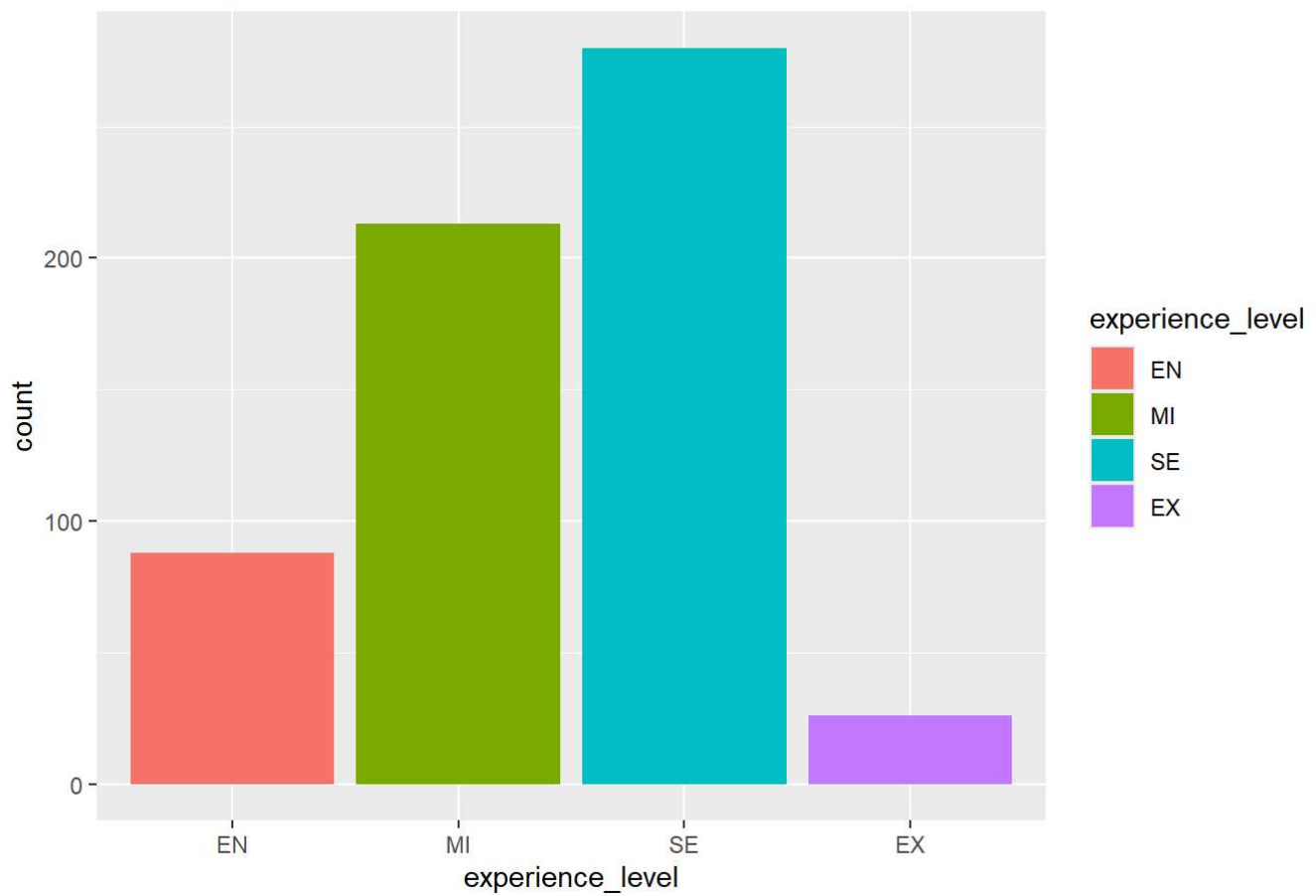
```
data %>%  
  count(job_title, sort = TRUE) %>%  
  top_n(10) %>%  
  ggplot(aes(x = reorder(job_title, n), y = n)) +  
  geom_bar(stat = "identity", fill = "brown", alpha = 0.75) +  
  coord_flip() +  
  labs(title = "Top 10 Job Titles", x = "Job Title", y = "Count") +  
  theme_minimal()
```

```
## Selecting by n
```

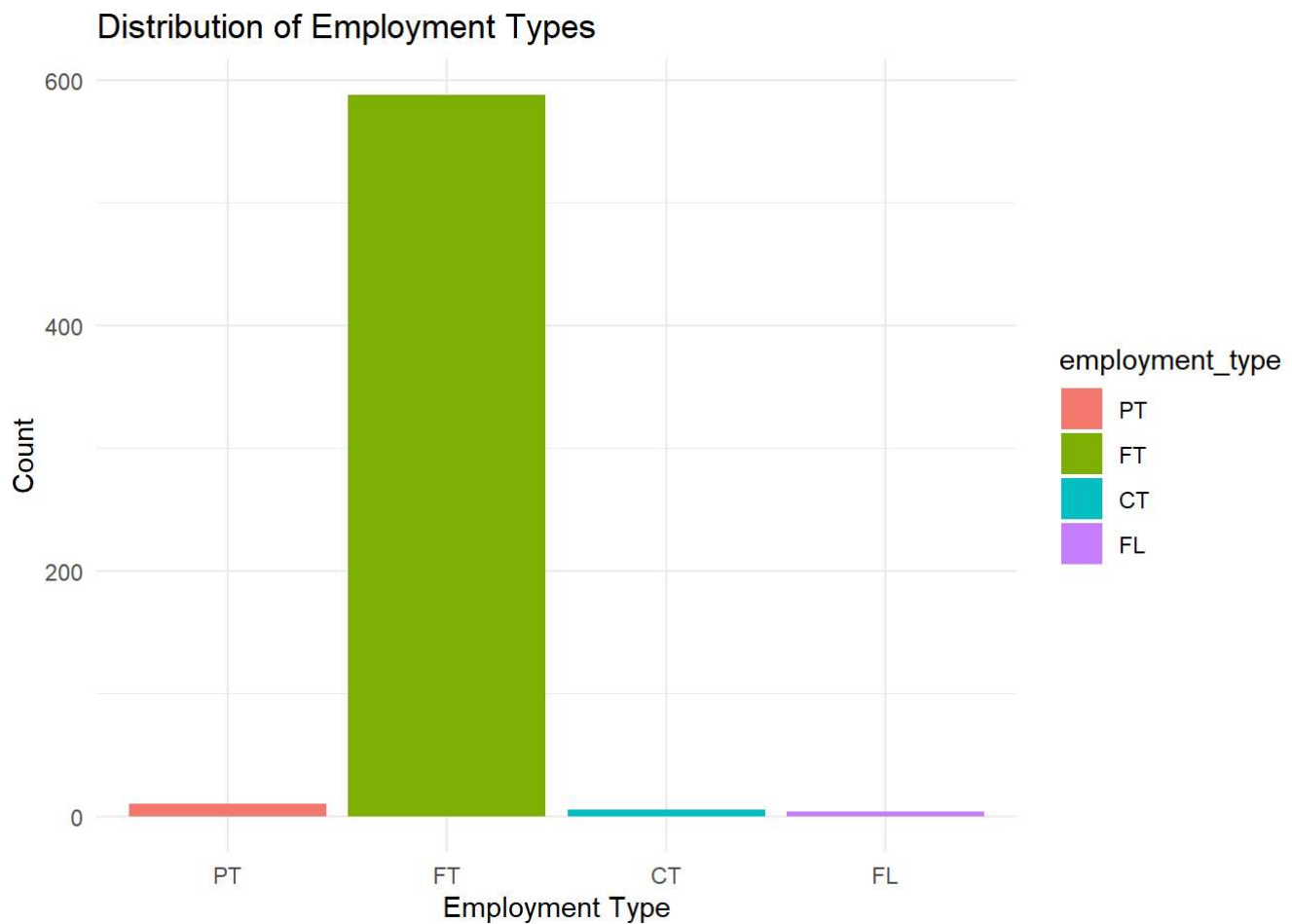


```
ggplot(data, aes(x = experience_level, fill = experience_level)) +  
  geom_bar() +  
  labs(title = "Frequency of Experience Levels")
```

Frequency of Experience Levels



```
data %>%  
  count(employment_type) %>%  
  ggplot(aes(x = employment_type, y = n, fill = employment_type)) +  
  geom_col(alpha = 0.97) +  
  labs(  
    title = "Distribution of Employment Types",  
    x = "Employment Type",  
    y = "Count"  
  ) +  
  theme_minimal()
```



```
# Salary for Data related positions based on Experience Level and Employee Residence
summary_table <- data %>%
  group_by(experience_level, employee_residence) %>%
  summarise(
    mean_salary = mean(salary_in_usd, na.rm = TRUE),
    median_salary = median(salary_in_usd, na.rm = TRUE),
    count = n()
  )
```

```
## `summarise()` has grouped output by 'experience_level'. You can override using
## the `.groups` argument.
```

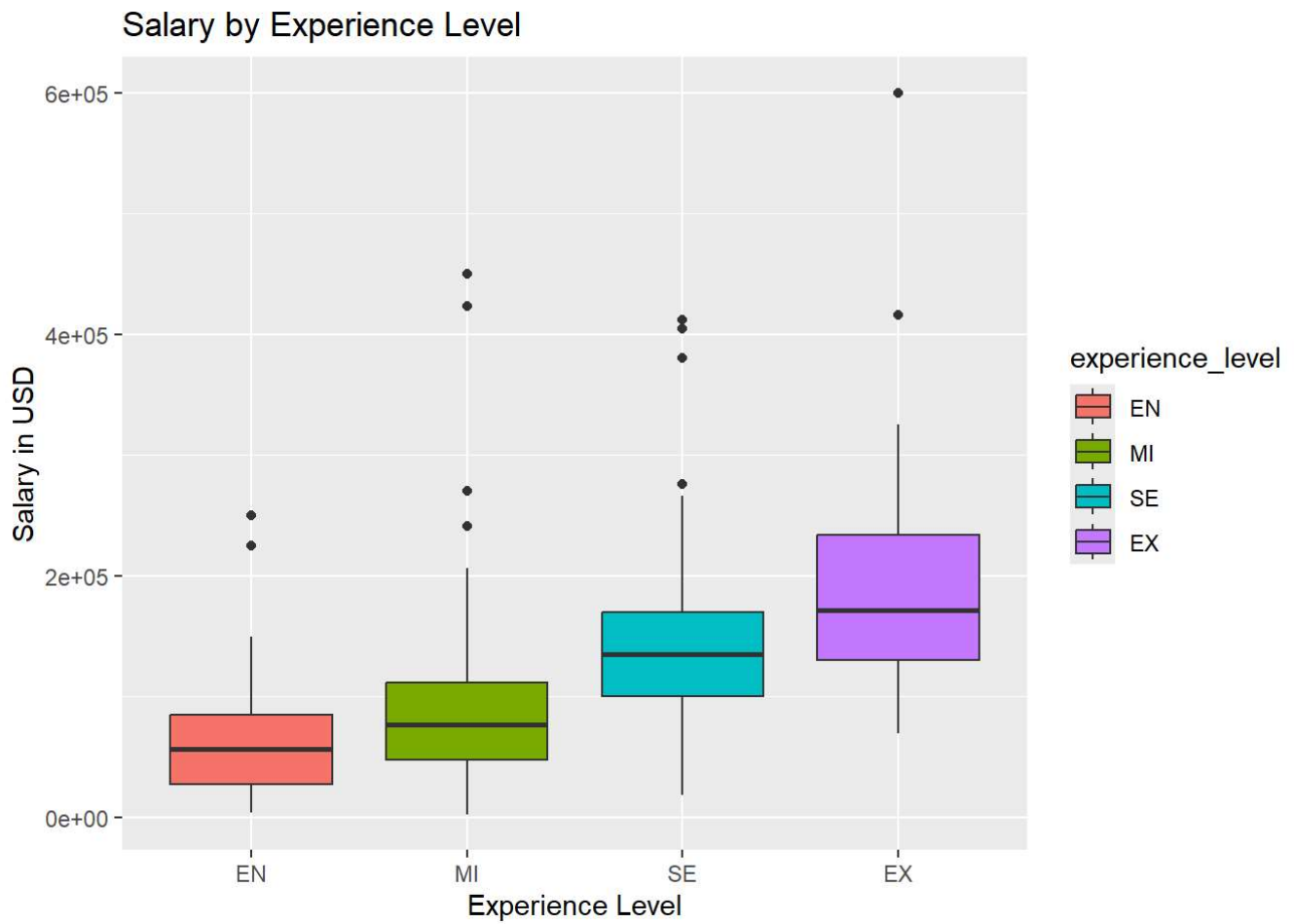
```
print(summary_table)
```

```
## # A tibble: 103 × 5
## # Groups:   experience_level [4]
##   experience_level employee_residence mean_salary median_salary count
##   <fct>           <chr>           <dbl>         <dbl> <int>
## 1 EN             AU             118352.       118352.     2
## 2 EN             BR              12000         12000      1
## 3 EN             CA             57132         52396      3
## 4 EN             CO             21844         21844      1
## 5 EN             DE             54412.        63278.     8
## 6 EN             DK             37252.        37252.     2
## 7 EN             DZ            100000        100000      1
## 8 EN             ES             10354         10354      1
## 9 EN             FR             47326.        49646      5
## 10 EN            GB             65605.        52351      5
## # i 93 more rows
```

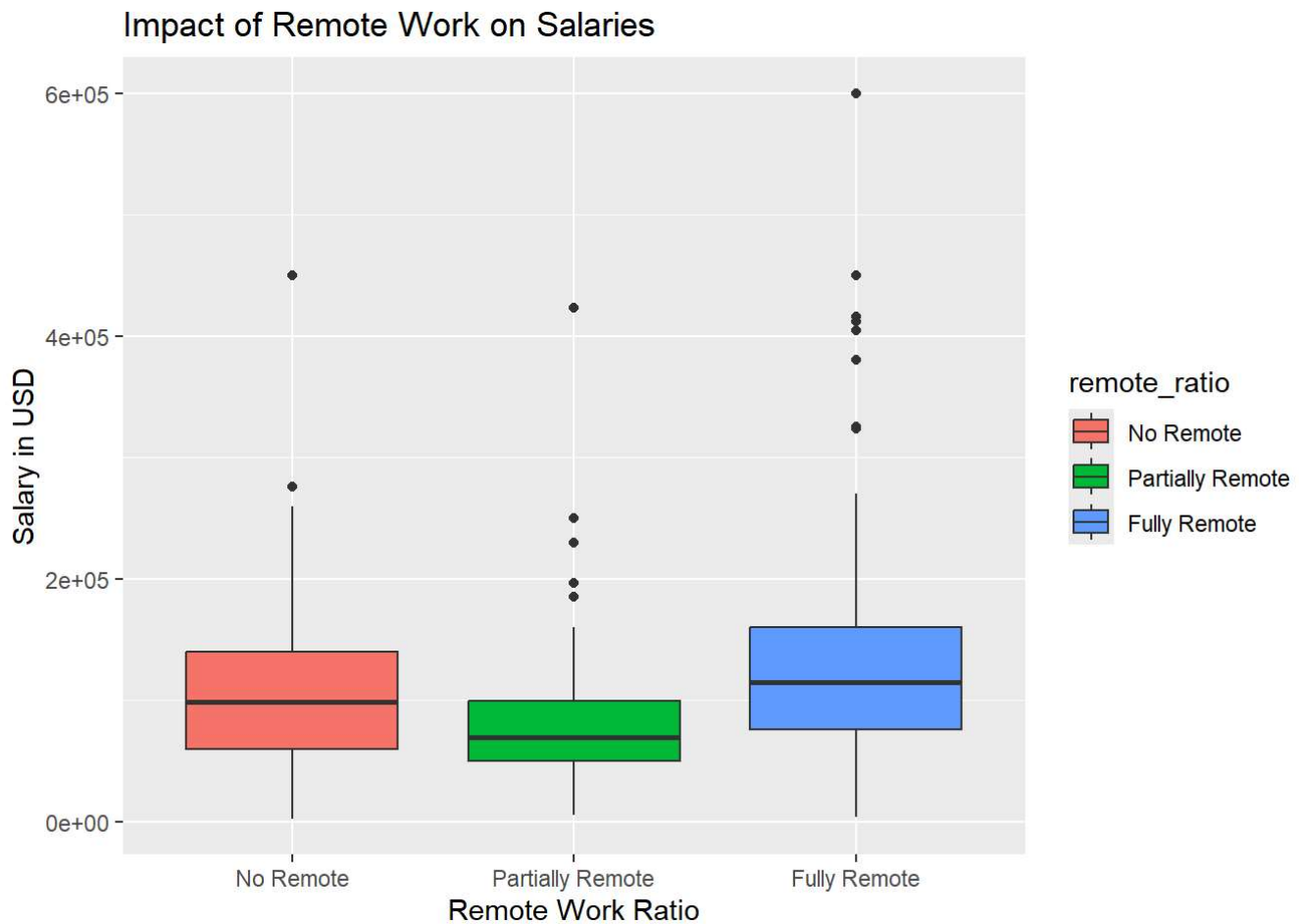
```
# U.S. versus Offshore Salary
comparison_table <- data %>%
  mutate(location_type = ifelse(employee_residence == "US", "US", "Offshore")) %>%
  group_by(location_type) %>%
  summarise(
    mean_salary = mean(salary_in_usd, na.rm = TRUE),
    median_salary = median(salary_in_usd, na.rm = TRUE),
    count = n()
  )
print(comparison_table)
```

```
## # A tibble: 2 × 4
##   location_type mean_salary median_salary count
##   <chr>         <dbl>         <dbl> <int>
## 1 Offshore     67754.        62649    275
## 2 US          149194.       138475    332
```

```
# Salary by Experience Level
ggplot(data, aes(x = experience_level, y = salary_in_usd, fill = experience_level)) +
  geom_boxplot() +
  labs(title = "Salary by Experience Level",
    y = "Salary in USD",
    x = "Experience Level")
```



```
# The impact of Remote Work on Salary
ggplot(data, aes(x = remote_ratio, y = salary_in_usd, fill = remote_ratio)) +
  geom_boxplot() +
  labs(title = "Impact of Remote Work on Salaries", y = "Salary in USD", x = "Remote Work Ratio")
```



Conclusion:

We can see that the salary for data related positions is rather high in the US when compared to outsourcing data professionals from offshore countries. For example, the mean annual salary of a data related position in the US is 149,194 dollars compared to the offshore mean annual salary of 67,754 dollars. This equals a savings of roughly 81,000 dollars per employee if an offshore employee is hired instead. Therefore to limit costs spent on hiring data scientists, hiring highly experienced data professionals from offshore locations should be utilized. This is important because our company can hire well-equipped data professionals for the job and we can pay them less than we would if they were from the US, as their expectations for pay are lower. Another important thing to note is that the salaries of entry-level employees are generally lower than those of mid-level and senior employees based on the data. You may want to cut costs, however, sacrificing experience level may impact the company's overall efficiency. In this case, I believe that the best course of action would be to focus on hiring mid-level data professionals from offshore locations. This would allow the company to cut down on some costs while not overpaying a US employee with a significant amount of experience, and not sacrificing work quality by hiring only entry-level employees with minimal experience. The increase in salary on average from entry-level jobs to mid-level positions is much smaller than the jump from mid-level jobs to senior positions. Despite having slightly higher average annual salaries, senior level candidates are slightly less expensive as expert professionals. Finally, we must consider the impact of remote work on salaries. The average and the range of salaries for partially remote positions are the smallest, compared to the no remote work option salary which is slightly higher on average with a wider range, but the fully remote jobs have the highest average salary and generally have a higher range of salaries than partially remote and non-remote jobs. It makes most sense to hire a candidate that has mid-level to senior-level experience, works offshore, and as a result of working offshore that candidate works fully remote (relocation might require a higher salary).