

PSTAT 131 Final Project: Model comparison for predicting the salary of a data science job

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Dataset used: <https://www.kaggle.com/datasets/arnabchaki/data-science-salaries-2023>

In this project, we will be fitting several different machine learning algorithms to find out which method of prediction is the most accurate in getting the predicted salary(in usd).

About the data set's variables (excerpt from the kaggle site)

- work_year: The year the salary was paid.
- experience_level: The experience level in the job during the year
- employment_type: The type of employment for the role
- job_title: The role worked in during the year.
- salary: The total gross salary amount paid.
- salary_currency: The currency of the salary paid as an ISO 4217 currency code.
- salary_in_usd: The salary in USD
- employee_residence: Employee's primary country of residence in during the work + year as an ISO 3166 country code.
- remote_ratio: The overall amount of work done remotely
- company_location: The country of the employer's main office or contracting branch
- company_size: The median number of people that worked for the company during the year

```
library(dplyr)
library(randomForest)
library(gbm)
library(ISLR)
library(tree)
library(tidyverse)
library(ggplot2)
library(gridExtra)
library(class)
library(FNN)
library(tibble)
library(recipes)
```

Part 1: Exploratory Data Analysis

Loading the dataset

```
salaries <- read.csv("ds_salaries.csv")
head(salaries)
```

Checking the structure of the dataset

```
str(salaries)
```

Already we can see an issue that needs to be worked on. Several variables seem to supposedly be read in as factors. We will finish conducting checks on the dataset before converting said columns.

Checking the summary of the dataset

```
summary(salaries)
```

Checking for null values

```
colSums(is.na(salaries))
```

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

Fortunately, we have no null values so imputing is not required

Checking potential factor columns for their unique values

```
factor_cols <- salaries[, c(1, 2, 3, 4, 6, 8, 10, 11)]
```

```
# finding unique values, referenced code from https://www.kaggle.com/code/abdulfaheem11/data-science-sa
```

```
# output omitted to prevent too much space being taken up
```

```
sapply(factor_cols, function(col) unique(col))
```

Changing said variables to become factors

```
salaries[, c(1, 2, 3, 4, 6, 8, 10, 11)] <- lapply(factor_cols, factor)
str(salaries)
```

Visualization to search for patterns with regards to the salary_in_usd

Prioritizing focus on work_year, experience_level, employment_type, job_title, employee_residence, remote_ratio, company_location, company_size

```
yearplot <- ggplot(salaries, aes(x = work_year, y = salary_in_usd)) +
  geom_point(color = "red", size = 3) +
  labs(x = "Work Year", y = "Salary in USD", title = "Salary vs Work Year")
expplot <- ggplot(salaries, aes(x = experience_level, y = salary_in_usd)) +
  geom_boxplot(fill = "skyblue") +
  labs(x = "Experience Level", y = "Salary in USD", title = "Salary vs Experience Level")
grid.arrange(yearplot, expplot, ncol = 2)
```



- We can see that the average salary in usd increases as the years go by, as the line congests further upwards towards the end.
- Experience level does not really show much of a trend as it goes towards seniority, We can tell though that EX has the highest average and MI has the highest peak

```
employplot <- ggplot(salaries, aes(x = employment_type, y = salary_in_usd)) +
  geom_boxplot(fill = "skyblue") +
  labs(x = "Employment Type", y = "Salary in USD", title = "Salary vs Employment Type")
remotepplot <- ggplot(salaries, aes(x = remote_ratio, y = salary_in_usd)) +
  geom_point(color = "red", size = 3, shape = 19) +
  labs(x = "Remote Ratio", y = "Salary in USD", title = "Salary vs Remote Ratio")
grid.arrange(employplot, remotepplot, ncol = 2)
```

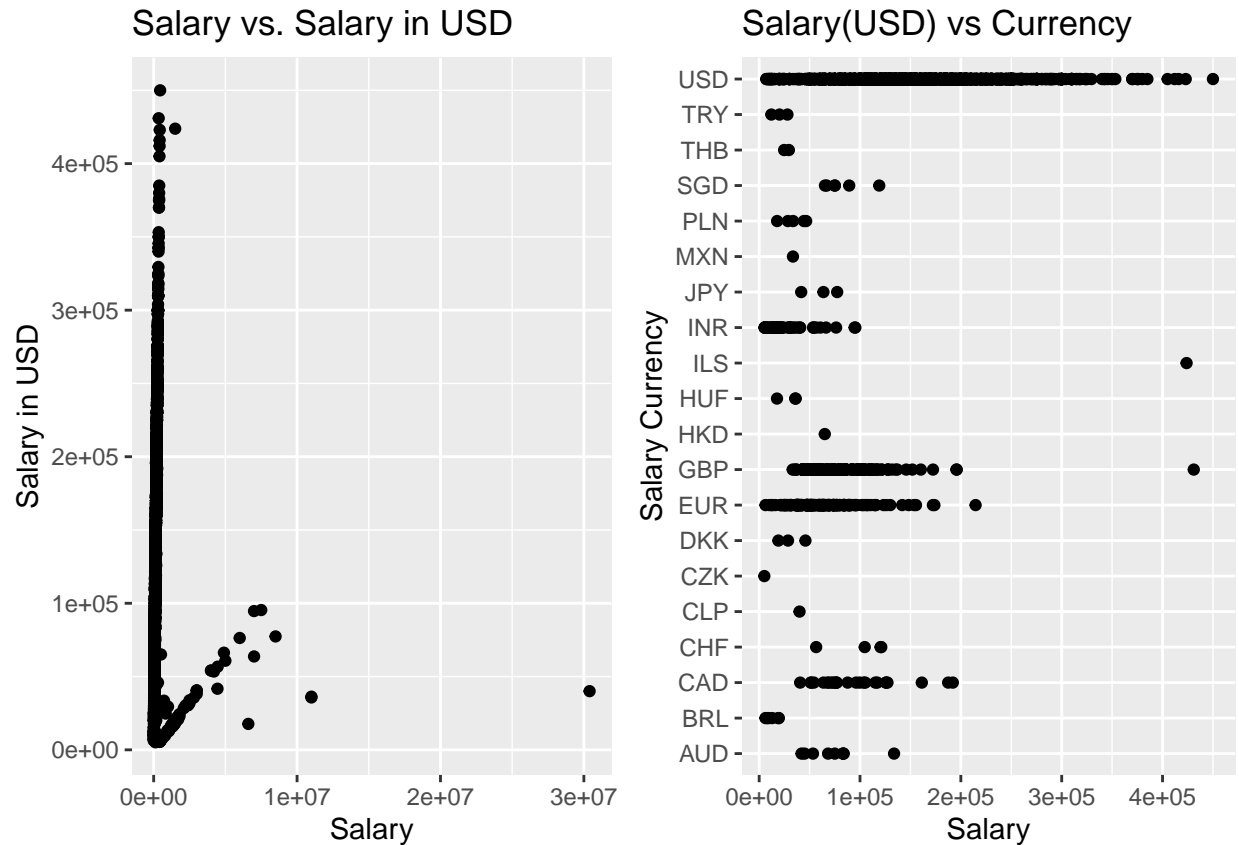


+ In employment type, FT has the highest average as well as higher peaks + Remote ratio consists of 0, 50 and 100. The highest points as well as average are in the order 0>100>50

```
salaryplot <- ggplot(salaries, aes(x = salary, y = salary_in_usd)) +
  geom_point() +
  labs(title = "Salary vs. Salary in USD", x = "Salary", y = "Salary in USD")

# Salary vs. Salary Currency plot
currencyplot <- ggplot(salaries, aes(x = salary_in_usd, y = salary_currency)) +
  geom_point() +
  labs(title = "Salary(USD) vs Currency", x = "Salary", y = "Salary Currency")

# Combine plots into a grid using facet_grid
grid.arrange(salaryplot, currencyplot, ncol = 2)
```



+ In the first plot, we see that there is a point that is way further to the right than any of the other points. We will have to check that out right after this + On the 2nd plot, aside from seeing that we might have the most observations in USD, we can also see that it has the highest salary just based on numbers

Checking out the “outlier” observation

```
max(salaries$salary)
```

```
## [1] 30400000
```

```
outlierindex <- which(salaries$salary == max(salaries$salary))
salaries$salary_currency[outlierindex]
```

```
## [1] CLP
```

```
## 20 Levels: AUD BRL CAD CHF CLP CZK DKK EUR GBP HKD HUF ILS INR JPY MXN ... USD
```

It seems to be an observation from the CLP currency. and connecting it back to the graph, we can see that it also only has that one observation. I will deem it insignificant for now, to avoid a potential leverage point affecting the models I will be removing said observation.

```
salaries <- salaries[-outlierindex, ]
```

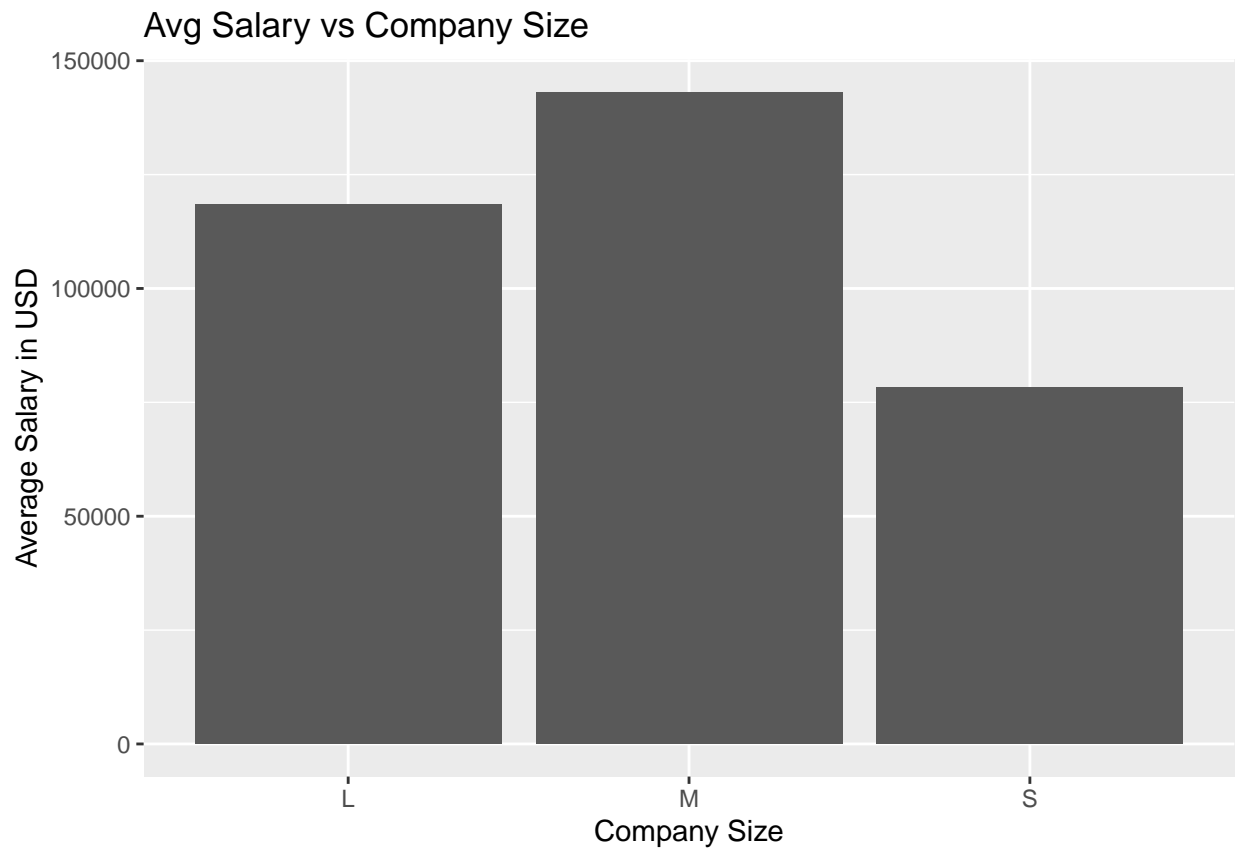
Plot showing salary vs Company Size

```

usd_salary_by_size <- salaries%>%
  group_by(company_size)%>%
  summarise(Avg_sal=mean(salary_in_usd))

sizeplot <- ggplot(usd_salary_by_size, aes(x=company_size, y=Avg_sal)) +
  geom_col() +
  labs(title='Avg Salary vs Company Size', x='Company Size', y='Average Salary in USD')
sizeplot

```



+ From this plot we can also see that medium sized companies pay the largest on average, followed by large then small

Tabling the 6 highest and lowest paying jobs

```

top_6_job_salaries<-salaries%>%
  group_by(job_title)%>%
  summarise(Avg_Sal=mean(salary_in_usd))%>%
  arrange(desc(Avg_Sal))%>%
  head()
top_6_job_salaries
bottom_6_job_salaries<-salaries%>%
  group_by(job_title)%>%
  summarise(Avg_Sal=mean(salary_in_usd))%>%
  arrange(Avg_Sal)%>%
  head()
bottom_6_job_salaries

```

Plotting the 6 highest and lowest paying jobs

```
top6jobplot <- ggplot(top_6_job_salaries, aes(x = reorder(job_title, Avg_Sal), y = Avg_Sal)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Top 6 Job Salaries", x = "Job Title", y = "Average Salary (USD)")
bot6jobplot <- ggplot(bottom_6_job_salaries, aes(x = reorder(job_title, Avg_Sal), y = Avg_Sal)) +
  geom_bar(stat = "identity", fill = "salmon") +
  labs(title = "Bottom 6 Job Salaries", x = "Job Title", y = "Average Salary (USD)")
top6jobplot <- top6jobplot + theme(axis.text.x = element_text(angle = 90, vjust = 0.75, size=7, hjust=1))
bot6jobplot <- bot6jobplot + theme(axis.text.x = element_text(angle = 90, vjust = 0.75, size=7, hjust=1))
grid.arrange(top6jobplot, bot6jobplot, ncol = 2)
```



+ We can tell that the data science tech lead job has the highest average pay by far + we can also tell that the power bi developer has the lowest pay out of all the jobs

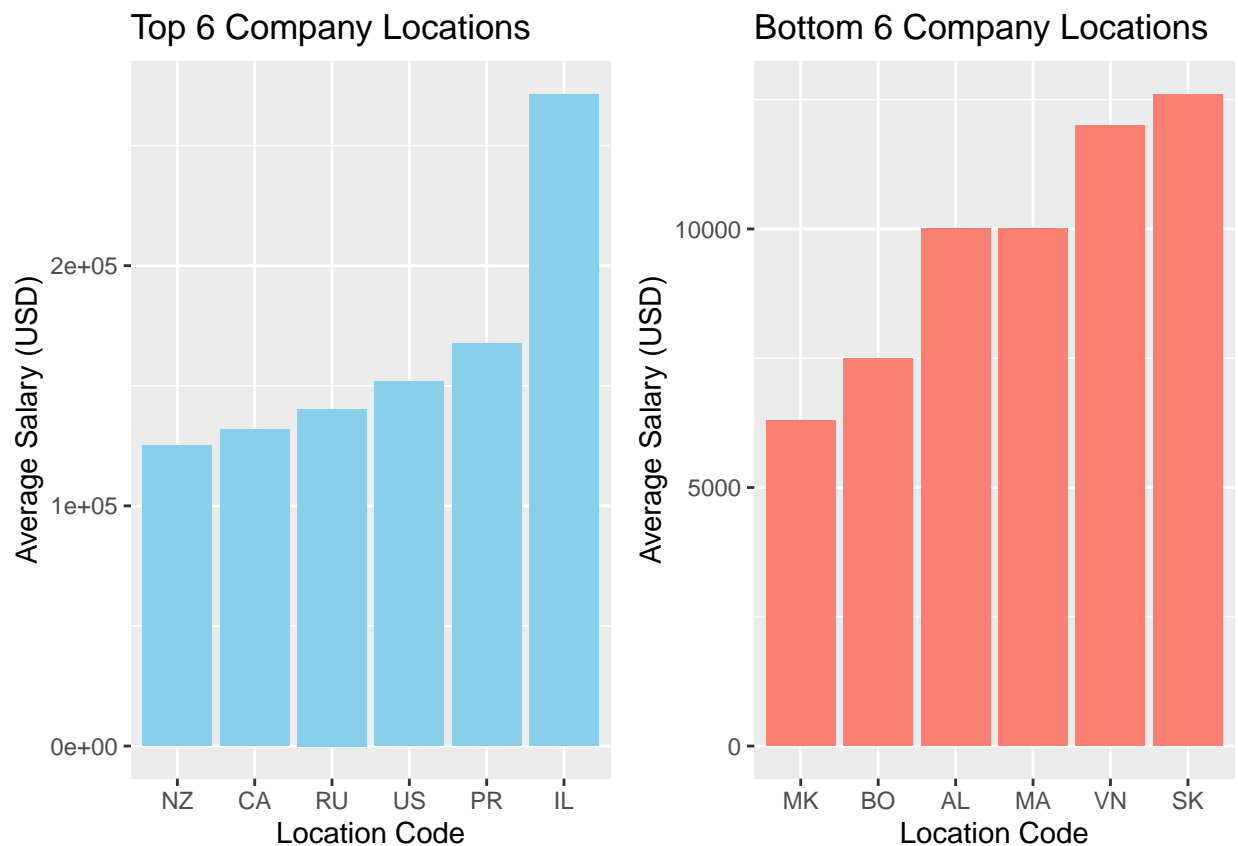
Tabling the 6 highest and lowest paying company locations

```
top_6_loc <- salaries %>%
  group_by(company_location) %>%
  summarise(Avg_Sal = mean(salary_in_usd)) %>%
  arrange(desc(Avg_Sal)) %>%
  head()
top_6_loc
bottom_6_loc <- salaries %>%
  group_by(company_location) %>%
  summarise(Avg_Sal = mean(salary_in_usd)) %>%
  arrange(Avg_Sal) %>%
```

```
head()
bottom_6_loc
```

Plotting the 6 highest and lowest paying company locations

```
top6locplot <- ggplot(top_6_loc, aes(x = reorder(company_location, Avg_Sal), y = Avg_Sal)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Top 6 Company Locations", x = "Location Code", y = "Average Salary (USD)")
bot6locplot <- ggplot(bottom_6_loc, aes(x = reorder(company_location, Avg_Sal), y = Avg_Sal)) +
  geom_bar(stat = "identity", fill = "salmon") +
  labs(title = "Bottom 6 Company Locations", x = "Location Code", y = "Average Salary (USD)")
top6resplot <- top6locplot + theme(axis.text.x = element_text(angle = 90, vjust = 0.75, size=7, hjust=1))
bot6resplot <- bot6locplot + theme(axis.text.x = element_text(angle = 90, vjust = 0.75, size=7, hjust=1))
grid.arrange(top6locplot, bot6locplot, ncol = 2)
```



+ It seems that IL has the highest paying jobs when it comes to company location + MK has the lowest paying job out of all the locations by far

Part 2: Problem formulation and discussion of statistical learning algorithms used

The main goal of this project, as mentioned before is to compare several statistical learning methods in predicting the salary given the parameters. We will be focusing on the following methods:

- K-Nearest Neighbors

- Using K-NN means
 - Scaling the predictors
- Linear Regression
 - Test with adding polynomials, etc
- Ridge and LASSO Regression
 - Using CV methods to find the best lambda
 - Conducting variable selection with LASSO
- Regression Trees
 - Decision Trees
 - Random-Forest
 - Boosting
- Support Vector Machines
 - Testing SVMs with different OSH methods

I want to start off by deciding that the salary_currency and salary are not significant to our prediction of the salary_in_usd. Similarly for employee_residence, as the company_location should be sufficient

```
salaries <- subset(salaries, select = -c(salary, salary_currency, employee_residence))
head(salaries)
```

Due to a huge amount of levels in factors, our training dataset may not have the columns present in the testing dataset and vice versa. To prevent this, I will create a new data set where I use one-hot encoding on those categorical variables

```
library(caret)
```

```
## Loading required package: lattice
```

```
##
```

```
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
```

```
##
```

```
## lift
```

```
cat_cols <- c("job_title", "company_location")
formula <- as.formula(paste("~ ."))
encoded_data <- dummyVars(formula, data = salaries[, cat_cols])
encoded_salaries <- predict(encoded_data, newdata = salaries)
encoded_salaries <- cbind(salaries, encoded_salaries)
encoded_salaries <- subset(encoded_salaries, select = -c(job_title, company_location))
head(encoded_salaries)
```

Preparing the training and testing data set with Train/Test/Split

```

set.seed(123)
nrow(encoded_salaries) #data has 3755 observations
# initial split (70-30)
train = sample(1:nrow(encoded_salaries), 3003)
salaries.train = encoded_salaries[train, ]
salaries.test = encoded_salaries[-train, ]

YTrain = salaries.train$salary_in_usd
XTrain = salaries.train %>% select(-salary_in_usd)

YTest = salaries.test$salary_in_usd
XTest = salaries.test %>% select(-salary_in_usd)

```

K-NN Regression

```
set.seed(123)
```

Linear Regression

Using log transformation on the response variable to follow a normal

```

log.train <- salaries.train
log.train$salary_in_usd <- log1p(salaries.train$salary_in_usd)

```

Fitting the model

```

lmod <- lm(salary_in_usd ~ ., log.train)
summary(lmod)

```

Checking Predictions

```

options(max.print = 6)
predicted_values <- predict(lmod)
comparison_log_df <- data.frame(Actual = log.train$salary_in_usd, Predicted = predicted_values)
comparison_log_df

```

```

##           Actual Predicted
## 2463 12.38840  11.89292
## 2511 12.04356  11.89292
## 2227 12.10072  11.72904
## [ reached 'max' / getOption("max.print") -- omitted 3000 rows ]

```

Creating plot of predicted values vs the actual values (displayed with the non log plot below)

```

gg_comparison_log <- ggplot(comparison_log_df, aes(x = log.train$salary_in_usd, y = predicted_values)) +
  geom_point() +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Log Predicted vs Log Actual", x = "Log Actual", y = "Log Predicted")

```

checking non log'd predictions

```
options(max.print = 6)
comparison_df <- data.frame(Actual = salaries.train$salary_in_usd, Predicted = exp(predicted_values))
comparison_df
```

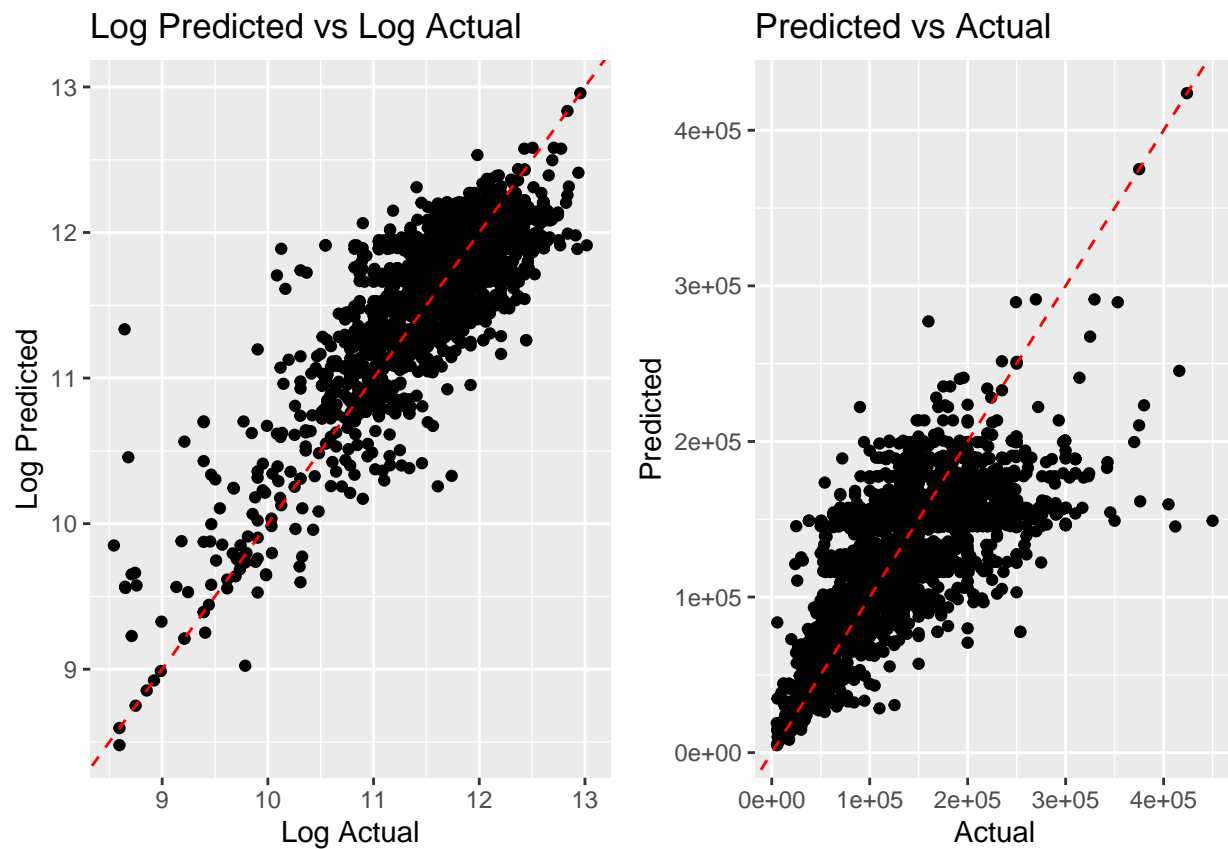
```
##      Actual Predicted
## 2463 240000 146227.7
## 2511 170000 146227.7
## 2227 180000 124124.8
## [ reached 'max' / getOption("max.print") -- omitted 3000 rows ]
```

Creating the non log plot

```
gg_comparison <- ggplot(comparison_df, aes(x = Actual, y = Predicted)) +
  geom_point() +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Predicted vs Actual", x = "Actual", y = "Predicted")
```

Displaying the 2 plots

```
grid.arrange(gg_comparison_log, gg_comparison, ncol = 2)
```



Getting R^2 , Mean absolute error and Mean Squared Error for the log training response

```
rsquared_log <- summary(lmod)$r.squared
residuals_log <- residuals(lmod)
mae_log <- mean(abs(residuals_log))
mse_log <- mean(residuals_log^2)
rsquared_log #0.6678302
mae_log #0.2639758
mse_log #0.1206688
```

MSE of the non log training response

```
predicted_values_nonlog <- exp(predict(lmod))
residuals_nonlog <- salaries.train$salary_in_usd - predicted_values_nonlog
mse_nonlog <- mean(residuals_nonlog^2)
mse_nonlog #2110682376
```

Predicting the test data & its MSE using the model we built

```
lmod_test_predicted <- predict(lmod, newdata = XTest)
```

```
## Warning in predict.lm(lmod, newdata = XTest): prediction from rank-deficient
## fit; attr(*, "non-estim") has doubtful cases
```

```
mse_test <- mean((lmod_test_predicted - YTest)^2)
mse_test #23967797489
```

Overall, although we are able to fit the response variable quite well into a linear model thanks to the logarithmic transformation, the overall prediction is not very good judging from the very high MSE we get. This is probably due to the dataset mostly only having categorical predictor variables (factors with 70+ levels), making it really bad for fitting a linear model.