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

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

PSTAT 131 helper for Cross Validation

```r
do.chunk <- function(chunkid, folddef, Xdat, Ydat, ...){
# Get training index
train = (folddef!=chunkid)
# Get training set by the above index
```

```r
Xtr = Xdat[train,]
# Get responses in training set
Ytr = Ydat[train]
# Get validation set
Xvl = Xdat[!train,]
# Get responses in validation set
Yvl = Ydat[!train]
# Predict training labels
predYtr = knn(train=Xtr, test=Xtr, cl=Ytr, ...)
# Predict validation labels
predYvl = knn(train=Xtr, test=Xvl, cl=Ytr, ...)
data.frame(fold = chunkid,
train.error = mean(predYtr != Ytr), # Training error for each fold
val.error = mean(predYvl != Yvl)) # Validation error for each fold
}
```

Part 1: Exploratory Data Analysis

Loading the dataset

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

Checking the structure of the dataset

```r
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

```r
summary(salaries)
```

Checking for null values

```r
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

```r
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 ommitted to prevent too much space being taken up
uniques <- sapply(factor_cols, function(col) unique(col))
```

Changing said variables to become factors

```r
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

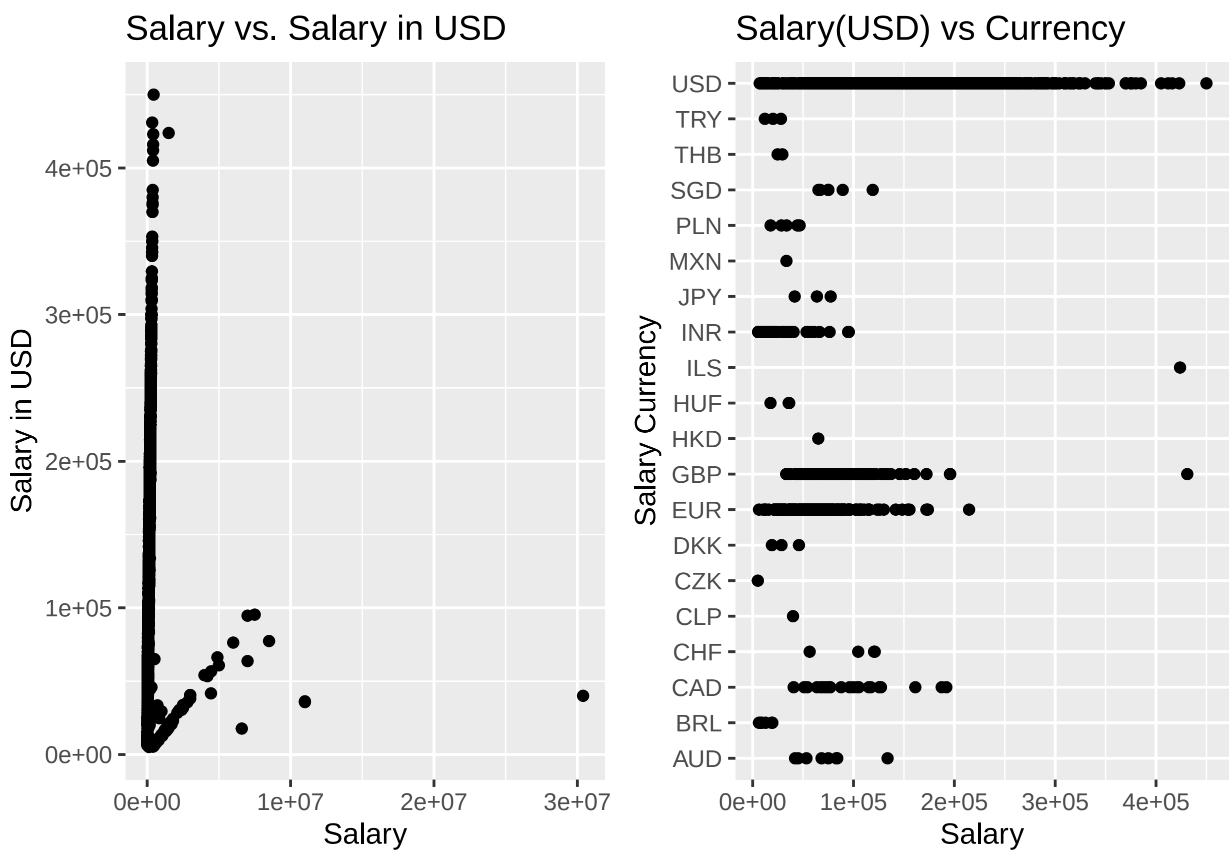
```r
yearplot <- ggplot(salaries, aes(x = work_year, y = salary_in_usd)) +
  geom_point(color = "red", size = 3) +
  labs(x = "Work Year", y = "Salary in USD", title = "Salary vs Work Year")
expplot <- ggplot(salaries, aes(x = experience_level, y = salary_in_usd)) +
  geom_boxplot(fill = "skyblue") +
  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")
remoteplot <- 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, remoteplot, 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]
```

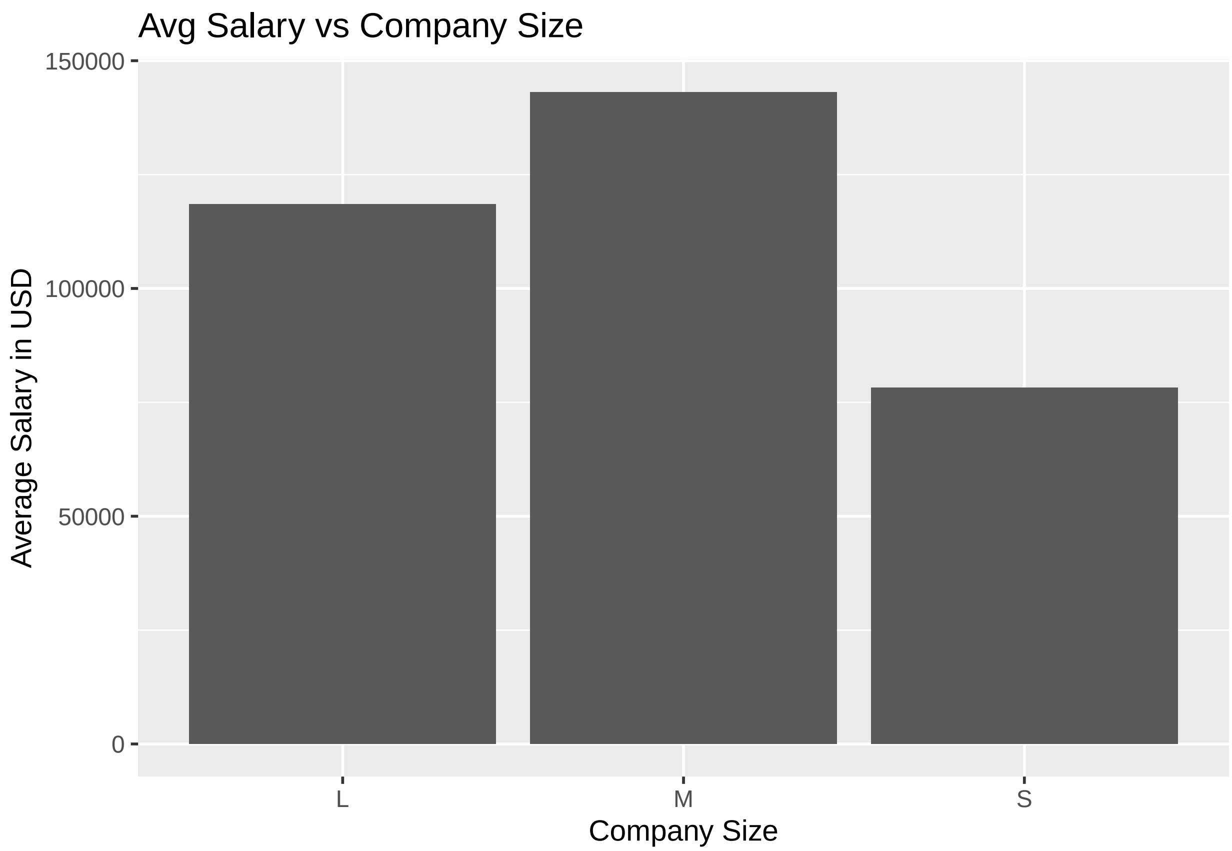
```
## [1] CLP
## 20 Levels: AUD BRL CAD CHF CLP CZK DKK EUR GBP HKD HUF ILS INR JPY MXN ... USD
```

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

```r
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

```r
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

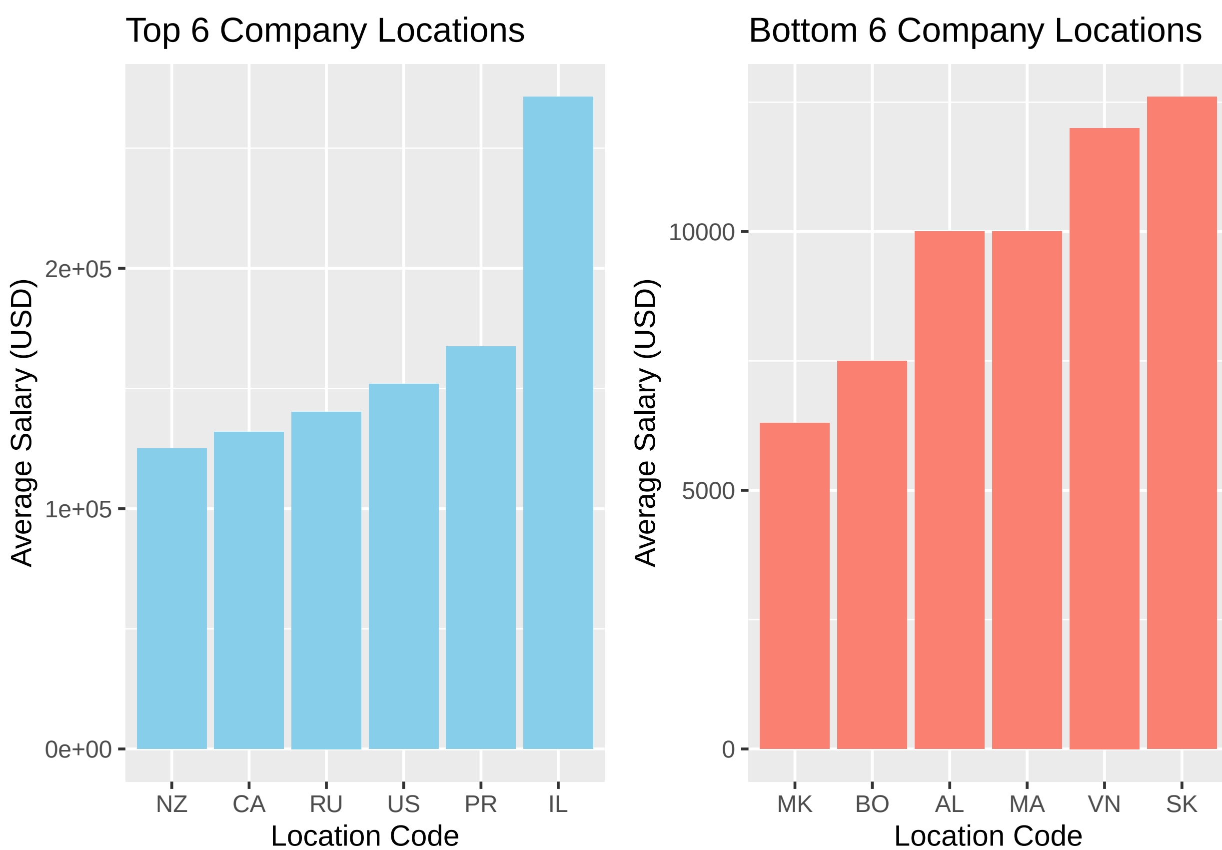
Tabling the 6 highest and lowest paying company locations

```
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

- Linear Regression
- 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

```r
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

```r
library(caret)

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))
colnames(encoded_salaries) <- gsub(" ", "_", colnames(encoded_salaries))
head(encoded_salaries)
```

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

```r
set.seed(123)
encoded_train = sample(1:nrow(encoded_salaries), 3003)
encoded_salaries_train = encoded_salaries[encoded_train, ]
encoded_salaries_test = encoded_salaries[-encoded_train, ]

encoded_YTrain = encoded_salaries_train$salary_in_usd
encoded_XTrain = encoded_salaries_train %>% select(-salary_in_usd)

encoded_YTest = encoded_salaries_test$salary_in_usd
encoded_XTest = encoded_salaries_test %>% select(-salary_in_usd)
```

Part 3: Model Fitting

K-NN Regression

We need to encode all of the categorical variables for this. To do so, create a new dataset just for the KNN's use

```r
cat_cols_2 <- c("job_title", "company_location", "experience_level", "employment_type", "company_size",
formula <- as.formula(paste("~ ."))
encoded_data2 <- dummyVars(formula, data = salaries[, cat_cols])
encoded_salaries2 <- predict(encoded_data2, newdata = salaries)
encoded_salaries2 <- cbind(salaries, encoded_salaries2)
encoded_salaries2 <- subset(encoded_salaries2, select = -c(job_title, company_location, experience_leve

set.seed(123)
nrow(encoded_salaries2)
encoded_train2 = sample(1:nrow(encoded_salaries2), 3003)
knn_salaries_train = encoded_salaries2[encoded_train2, ]
knn_salaries_test = encoded_salaries2[-encoded_train2, ]

knn_YTrain = knn_salaries_train$salary_in_usd
knn_XTrain = knn_salaries_train %>% select(-salary_in_usd)

knn_YTest = knn_salaries_test$salary_in_usd
knn_XTest = knn_salaries_test %>% select(-salary_in_usd)

head(knn_YTrain)
```

Training the reggresor using the encoded training set, for now we will use k=10, decide afterwards if it is worth spending time on cross-validation with this method.

```r
options(max.print = 1000)
set.seed(123)
pred_YTrain = knn.reg(train=knn_XTrain, test=knn_XTrain, y=knn_YTrain, k=10)
```

Calculating the Training MSE

```r
mean((pred_YTrain$pred - knn_YTrain)^2) #3065374515
```

Calculating test MSE

```r
pred.YTest = knn.reg(train=knn_XTrain, test=knn_XTest, y=knn_YTrain, k=10)
mean((pred.YTest$pred - knn_YTest)^2) #3544608428
```

Our MSE is very high due to the curse of dimensionality. When we use OHE, we make the predictor count very high due to the amount of added variables that K-NN will take into consideration, thus affecting the overall prediction negatively.

After some thought and considerations, I believe that the KNN regression method is not worth for this sort of data set. Firstly, the original data set is full of categorical variables, we were only able to fit it into the model after encoding basically everything. Due to this, our training and test MSE seems to be very high. (train mse stays, test mse lowers as k goes from 1 to 10 which is an interesting connection) Visualization is inaccurate too due to KNN regression visualizations only being able to be graphed with 1 response, and in this case the only variable I can graph on would be the work_year, which wouldn't really show anything. Due to the above reasons, I will not be spending time in tuning the lambda for said method.

Linear Regression

Before going into the code below, I need to state that due to the large amount of factor levels, we had to use the encoded dataset as when I tried running the test data from a model uding the training data, it was shown that some factor levels were found in the testing data that arent in the training data, thus leading to error messages and inability to function.

Using log transformation on the response variable to follow a normal

```
log.train <- encoded_salaries_train
log.train$salary_in_usd <- log1p(encoded_salaries_train$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 = encoded_salaries_train$salary_in_usd, Predicted = exp(predicted_va
comparison_df
```

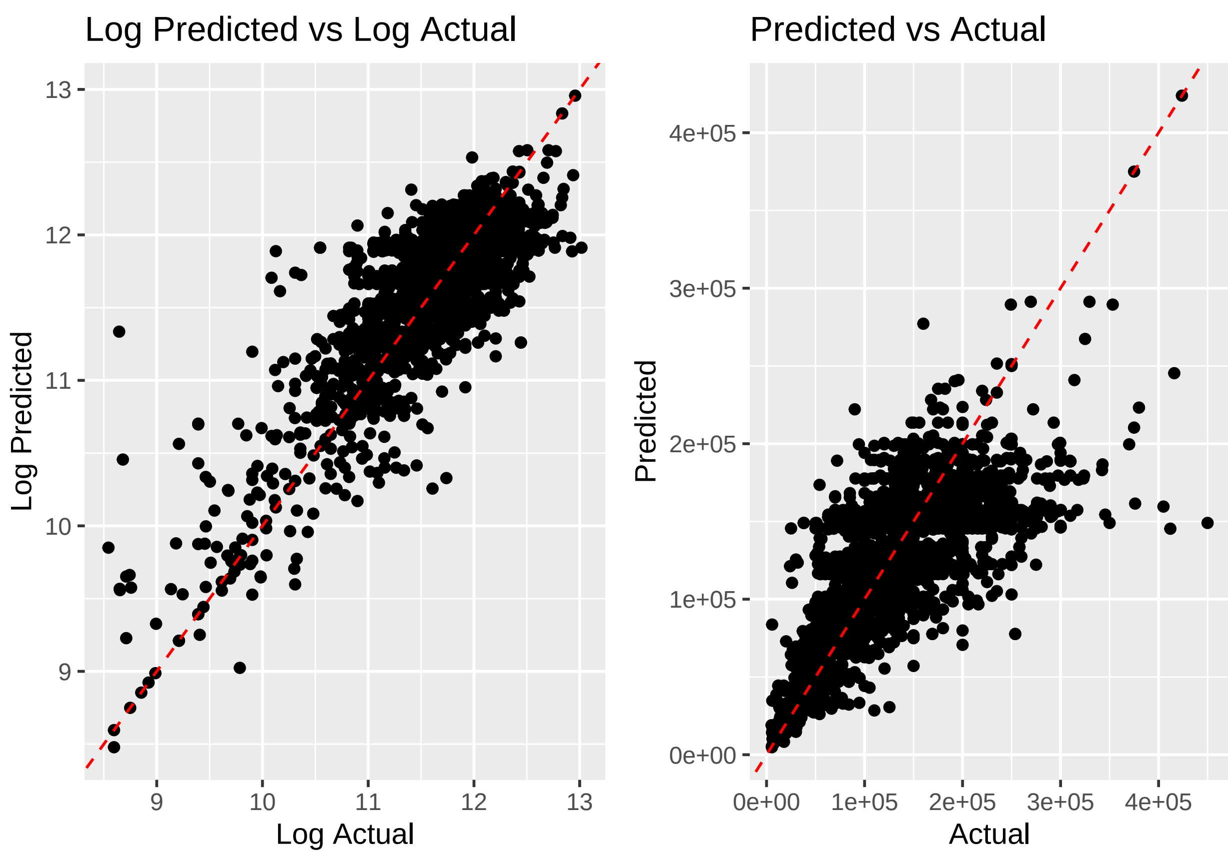
```
##      Actual Predicted
## 2463 240000  146227.7
## 2511 170000  146227.7
## 2227 180000  124124.8
##  [ reached 'max' / getOption("max.print") -- omitted 3000 rows ]
```

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

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



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

```r
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

```r
predicted_values_nonlog <- exp(predict(lmod))
residuals_nonlog <- encoded_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

```r
lmod_test_predicted <- predict(lmod, newdata = encoded_XTest)
```

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

```r
mse_test <- mean((lmod_test_predicted - encoded_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. Multicolinearity could also affect this since we had to use encoding, thus creating a lot more variables that could be collinear to each other.

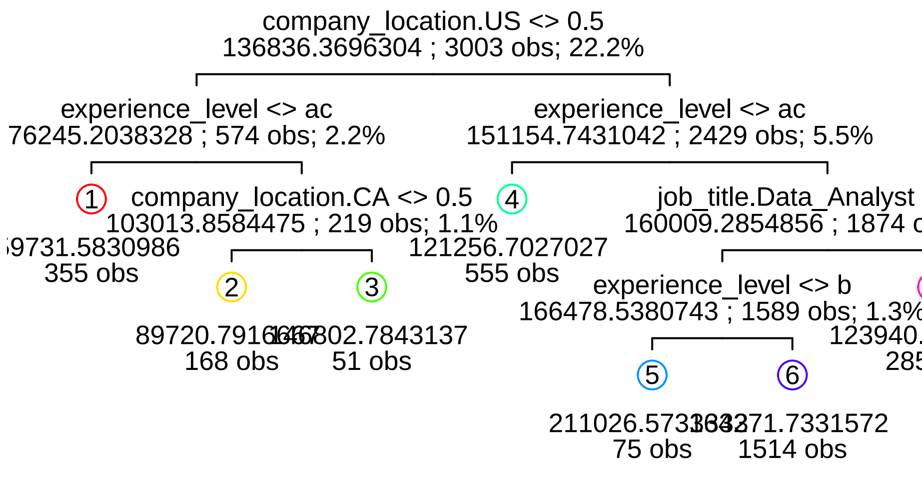
Tree based methods

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

```r
set.seed(123)
salaries_count = sample(1:nrow(salaries), 3003)
salaries_train = salaries[salaries_count, ]
salaries_test = salaries[-salaries_count, ]

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)
```

```r


head(encoded_salaries)
tree_salaries <- tree(salary_in_usd ~ ., data = encoded_salaries_train)
```

```r


draw.tree(tree_salaries, nodeinfo=TRUE, cex = 0.8)
```



Decision Regression Trees

Total deviance explained = 37.7 %. Here, it doesn't seem like we need to prune the tree, due to how less complex it is given the dataset with variables holding a large variable level. R seems to have already decided the important variables on its base iteration.

Tabling real values in salaries_train vs the predicted tree values

```
predicted_values1 <- predict(tree_salaries, newdata = encoded_salaries_train)

comparison_table1 <- data.frame(Real = encoded_salaries_train$salary_in_usd, Predicted = predicted_valu
```

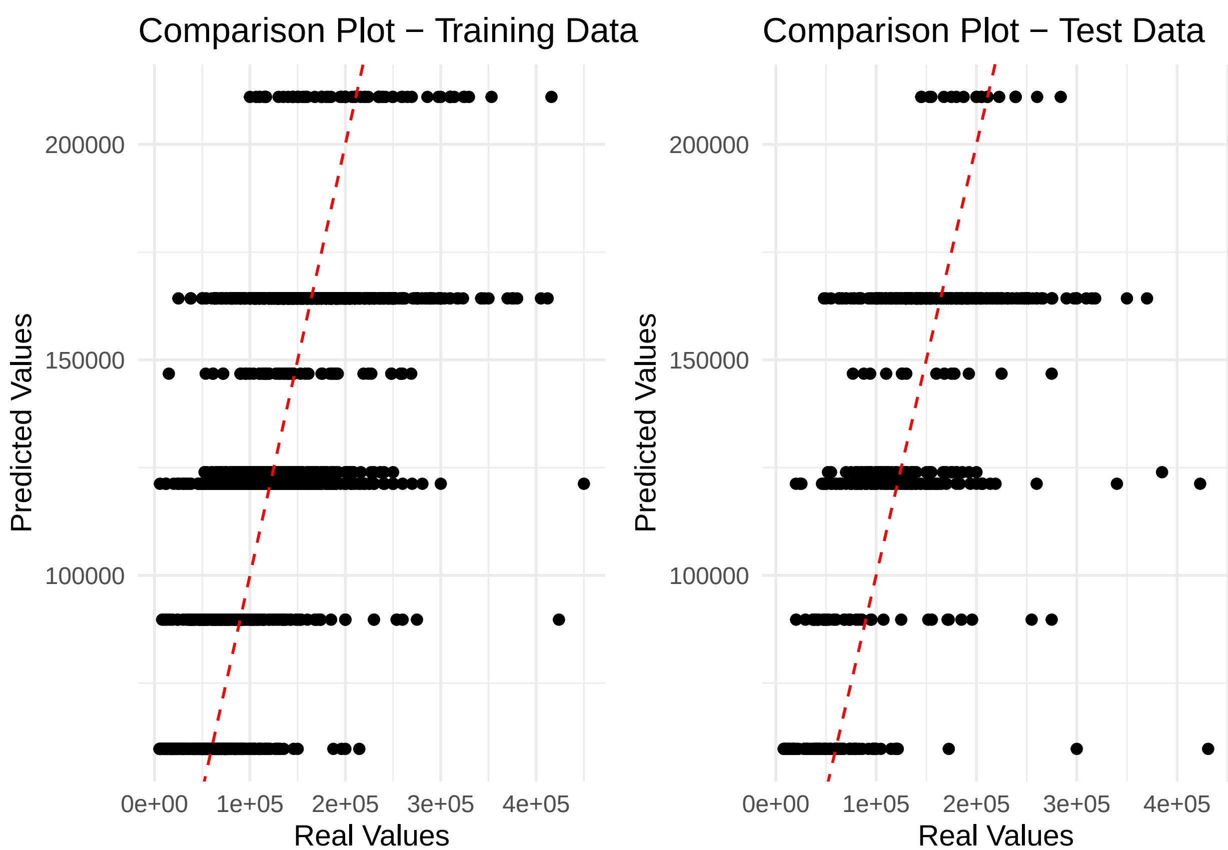
Similarly for the training set

```
predicted_values2 <- predict(tree_salaries, newdata = encoded_salaries_test)

comparison_table2 <- data.frame(Real = encoded_salaries_test$salary_in_usd, Predicted = predicted_value
```

Visualization plot

```
library(ggplot2)

plot1 <- ggplot(comparison_table1, aes(x = Real, y = Predicted)) +
  geom_point() +
  ggtitle("Comparison Plot - Training Data") +
  xlab("Real Values") +
  ylab("Predicted Values") +
  geom_abline(intercept = 0, slope = 1, color = "red", linetype = "dashed") +
```

```
  theme_minimal()

plot2 <- ggplot(comparison_table2, aes(x = Real, y = Predicted)) +
  geom_point() +
  ggtitle("Comparison Plot - Test Data") +
  xlab("Real Values") +
  ylab("Predicted Values") +
  geom_abline(intercept = 0, slope = 1, color = "red", linetype = "dashed") +
  theme_minimal()

gridExtra::grid.arrange(plot1, plot2, ncol = 2)
```



Train and Test MSE calculation

```
residuals1 <- predicted_values1 - encoded_salaries_train$salary_in_usd
train_mse <- mean(residuals1^2)
residuals2 <- predicted_values2 - encoded_salaries_test$salary_in_usd
test_mse <- mean(residuals2^2)

train_mse #2509462123
test_mse #2818380612
```

We notice that with a regular simple decision tree, that other variables like remote_ratio, company_size and employment type were not fit into the decision. It also seems that through the visualization, factors that have a ton of levels did not split as much as expected. This causes a very small amount of possible responses which although helps with overfitting, makes the response less accurate. Still, the MSEs were way lower than those from the regression methods by 2 digits. To try and make a more complex structure, we will try other methods like random-forest and XGBoosting

```r
rf_salaries <- randomForest(salary_in_usd ~ ., data = encoded_salaries_train, importance=TRUE)
```

```r
rf_salaries
```

Random Forest Regression Trees

```
##
## Call:
##  randomForest(formula = salary_in_usd ~ ., data = encoded_salaries_train,      importance = TRUE)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 56
##
##           Mean of squared residuals: 2272427161
##                     % Var explained: 41.97
```

```r
predicted_values3 <- predict(rf_salaries, newdata = encoded_salaries_train)

comparison_table3 <- data.frame(Real = encoded_salaries_train$salary_in_usd, Predicted = predicted_valu
head(comparison_table1)
```

```
##        Real Predicted
## 2463 240000  164271.7
## 2511 170000  164271.7
## 2227 180000  121256.7
##  [ reached 'max' / getOption("max.print") -- omitted 3 rows ]
```

```r
residuals1 <- predicted_values3 - encoded_salaries_train$salary_in_usd
train_mse <- mean(residuals1^2)
train_mse
```

```
## [1] 1719746025
```