5. Problem Statement

1. Perform the below given activities:

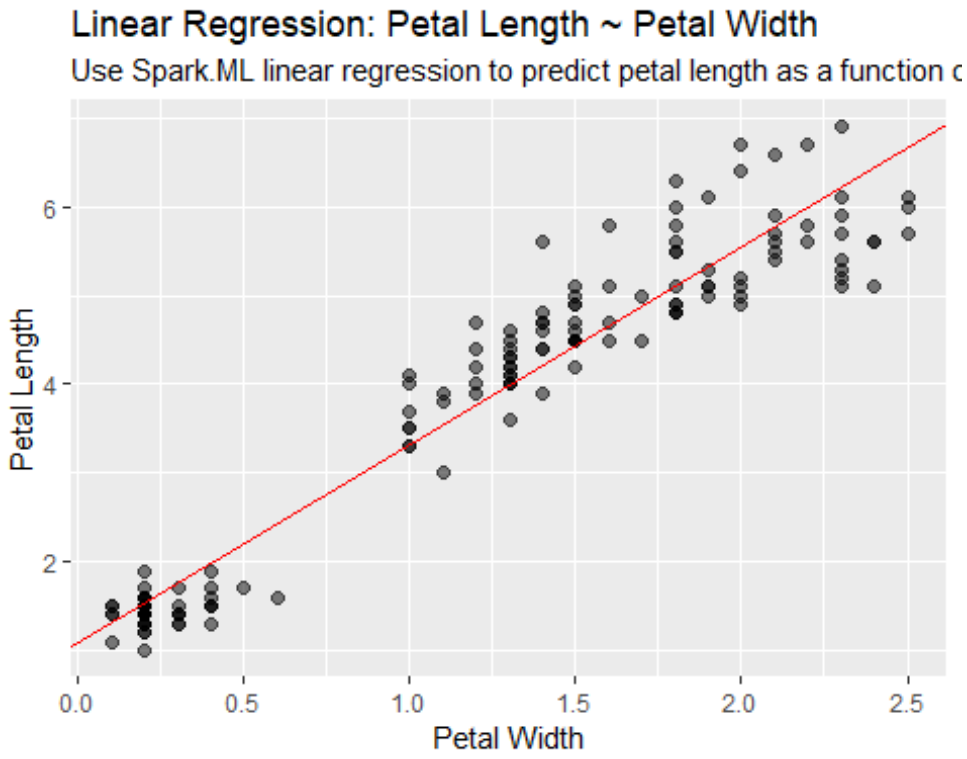
a. Take a sample data set of your choice

b. Apply random forest, logistic regression using Spark R

c. Predict for new dataset

```
library(sparklyr)
library(ggplot2)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

sc <- spark_connect(master = "local")
iris_tbl <- copy_to(sc, iris, "iris", overwrite = TRUE)
iris_tbl

## # Source:   table<iris> [?? x 5]
## # Database: spark_shell_connection
##    Sepal_Length Sepal_Width Petal_Length Petal_Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <chr>
##  1          5.1         3.5          1.4         0.2 setosa
##  2          4.9         3            1.4         0.2 setosa
##  3          4.7         3.2          1.3         0.2 setosa
##  4          4.6         3.1          1.5         0.2 setosa
##  5          5           3.6          1.4         0.2 setosa
##  6          5.4         3.9          1.7         0.4 setosa
##  7          4.6         3.4          1.4         0.3 setosa
##  8          5           3.4          1.5         0.2 setosa
##  9          4.4         2.9          1.4         0.2 setosa
```

```
## 10          4.9         3.1          1.5         0.1 setosa
## # ... with more rows

lm_model <- iris_tbl %>%
  select(Petal_Width, Petal_Length) %>%
  ml_linear_regression(Petal_Length ~ Petal_Width)

iris_tbl %>%
  select(Petal_Width, Petal_Length) %>%
  collect %>%
  ggplot(aes(Petal_Length, Petal_Width)) +
  geom_point(aes(Petal_Width, Petal_Length), size = 2, alpha = 0.5) +
  geom_abline(aes(slope = coef(lm_model)[["Petal_Width"]],
                  intercept = coef(lm_model)[["(Intercept)"]]),
              color = "red") +
  labs(
    x = "Petal Width",
    y = "Petal Length",
    title = "Linear Regression: Petal Length ~ Petal Width",
    subtitle = "Use Spark.ML linear regression to predict petal length as a f
unction of petal width."
  )
```




```
pca_model <- tbl(sc, "iris") %>%
  select(-Species) %>%
  ml_pca()
print(pca_model)
```

```
## Explained variance:
##
##         PC1         PC2         PC3         PC4
## 0.924618723 0.053066483 0.017102610 0.005212184
##
## Rotation:
##                       PC1         PC2         PC3        PC4
## Sepal_Length -0.36138659 -0.65658877  0.58202985  0.3154872
## Sepal_Width   0.08452251 -0.73016143 -0.59791083 -0.3197231
## Petal_Length -0.85667061  0.17337266 -0.07623608 -0.4798390
## Petal_Width  -0.35828920  0.07548102 -0.54583143  0.7536574
```

b. Apply random forest, logistic regression using Spark R

c. Predict for new dataset

```
#Random Forest
#Use Spark's Random Forest to perform regression or multicla
ss classification.

rf_model <- iris_tbl %>%
  ml_random_forest(Species ~ Petal_Length + Petal_Width, type = "classificati
on")

rf_predict <- sdf_predict(rf_model, iris_tbl) %>%
  ft_string_indexer("Species", "Species_idx") %>%
  collect

## Warning in sdf_predict.ml_model(rf_model, iris_tbl): The signature
## sdf_predict(model, dataset) is deprecated and will be removed in a future
## version. Use sdf_predict(dataset, model) or ml_predict(model, dataset)
## instead.

table

## function (..., exclude = if (useNA == "no") c(NA, NaN), useNA = c("no",
##     "ifany", "always"), dnn = list.names(...), deparse.level = 1)
## {
##     list.names <- function(...) {
##         l <- as.list(substitute(list(...)))[-1L]
##         nm <- names(l)
##         fixup <- if (is.null(nm))
##             seq_along(l)
##         else nm == ""
##         dep <- vapply(l[fixup], function(x) switch(deparse.level +
##             1, "", if (is.symbol(x)) as.character(x) else "",
##             deparse(x, nlines = 1)[1L]), "")
##         if (is.null(nm))
```

```
##             dep
##         else {
##             nm[fixup] <- dep
##             nm
##         }
##     }
##     miss.use <- missing(useNA)
##     miss.exc <- missing(exclude)
##     useNA <- if (miss.use && !miss.exc && !match(NA, exclude,
##         nomatch = 0L))
##         "ifany"
##     else match.arg(useNA)
##     doNA <- useNA != "no"
##     if (!miss.use && !miss.exc && doNA && match(NA, exclude,
##         nomatch = 0L))
##         warning("'exclude' containing NA and 'useNA' != \"no\"' are a bit
contradicting")
##     args <- list(...)
##     if (!length(args))
##         stop("nothing to tabulate")
##     if (length(args) == 1L && is.list(args[[1L]])) {
##         args <- args[[1L]]
##         if (length(dnn) != length(args))
##             dnn <- if (!is.null(argn <- names(args)))
##                 argn
##             else paste(dnn[1L], seq_along(args), sep = ".")
##     }
##     bin <- 0L
##     lens <- NULL
##     dims <- integer()
##     pd <- 1L
##     dn <- NULL
##     for (a in args) {
##         if (is.null(lens))
##             lens <- length(a)
##         else if (length(a) != lens)
##             stop("all arguments must have the same length")
##         fact.a <- is.factor(a)
##         if (doNA)
##             aNA <- anyNA(a)
##         if (!fact.a) {
##             a0 <- a
##             a <- factor(a, exclude = exclude)
##         }
##         add.na <- doNA
##         if (add.na) {
##             ifany <- (useNA == "ifany")
##             anNAc <- anyNA(a)
##             add.na <- if (!ifany || anNAc) {
##                 ll <- levels(a)
```

```
##                 if (add.ll <- !anyNA(ll)) {
##                   ll <- c(ll, NA)
##                   TRUE
##                 }
##                 else if (!ifany && !anNAc)
##                   FALSE
##                 else TRUE
##             }
##             else FALSE
##         }
##         if (add.na)
##             a <- factor(a, levels = ll, exclude = NULL)
##         else ll <- levels(a)
##         a <- as.integer(a)
##         if (fact.a && !miss.exc) {
##             ll <- ll[keep <- which(match(ll, exclude, nomatch = 0L) ==
##                 0L)]
##             a <- match(a, keep)
##         }
##         else if (!fact.a && add.na) {
##             if (ifany && !aNA && add.ll) {
##                 ll <- ll[!is.na(ll)]
##                 is.na(a) <- match(a0, c(exclude, NA), nomatch = 0L) >
##                   0L
##             }
##             else {
##                 is.na(a) <- match(a0, exclude, nomatch = 0L) >
##                   0L
##             }
##         }
##         nl <- length(ll)
##         dims <- c(dims, nl)
##         if (prod(dims) > .Machine$integer.max)
##             stop("attempt to make a table with >= 2^31 elements")
##         dn <- c(dn, list(ll))
##         bin <- bin + pd * (a - 1L)
##         pd <- pd * nl
##     }
##     names(dn) <- dnn
##     bin <- bin[!is.na(bin)]
##     if (length(bin))
##         bin <- bin + 1L
##     y <- array(tabulate(bin, pd), dims, dimnames = dn)
##     class(y) <- "table"
##     y
## }
## <bytecode: 0x0000000019782370>
## <environment: namespace:base>
```

```r
partitions <- tbl(sc, "iris") %>%
  sdf_partition(training = 0.75, test = 0.25, seed = 1099)

fit <- partitions$training %>%
  ml_linear_regression(Petal_Length ~ Petal_Width)

estimate_mse <- function(df){
  sdf_predict(fit, df) %>%
    mutate(resid = Petal_Length - prediction) %>%
    summarize(mse = mean(resid ^ 2)) %>%
    collect
}

sapply(partitions, estimate_mse)
```

```
## Warning in sdf_predict.ml_model(fit, df): The signature sdf_predict(model,
## dataset) is deprecated and will be removed in a future version. Use
## sdf_predict(dataset, model) or ml_predict(model, dataset) instead.

## Warning: Missing values are always removed in SQL.
## Use `AVG(x, na.rm = TRUE)` to silence this warning

## Warning in sdf_predict.ml_model(fit, df): The signature sdf_predict(model,
## dataset) is deprecated and will be removed in a future version. Use
## sdf_predict(dataset, model) or ml_predict(model, dataset) instead.

## Warning: Missing values are always removed in SQL.
## Use `AVG(x, na.rm = TRUE)` to silence this warning

## $training.mse
## [1] 0.2374596
##
## $test.mse
## [1] 0.1898848
```

```r
#Use ft_string_indexer and ft_index_to_string to convert a character column i
nto a numeric column and back again.

ft_string2idx <- iris_tbl %>%
  ft_string_indexer("Species", "Species_idx") %>%
  ft_index_to_string("Species_idx", "Species_remap") %>%
  collect

table(ft_string2idx$Species, ft_string2idx$Species_remap)
```

```
##
##              setosa versicolor virginica
##   setosa         50          0         0
##   versicolor      0         50         0
##   virginica       0          0        50
```

```
ft_string2idx <- iris_tbl %>%
  sdf_mutate(Species_idx = ft_string_indexer(Species)) %>%
  sdf_mutate(Species_remap = ft_index_to_string(Species_idx)) %>%
  collect

ft_string2idx %>%
  select(Species, Species_idx, Species_remap) %>%
  distinct
```

```
## # A tibble: 3 x 3
##   Species    Species_idx Species_remap
##   <chr>            <dbl> <chr>
## 1 setosa               2 setosa
## 2 versicolor           0 versicolor
## 3 virginica            1 virginica
```

```
#Use Spark's logistic regression to perform logistic regression, modeling a b
inary outcome as a function of one or more explanatory variables.

# Prepare beaver dataset
beaver <- beaver2
beaver$activ <- factor(beaver$activ, labels = c("Non-Active", "Active"))
copy_to(sc, beaver, "beaver")
```

```
## # Source:   table<beaver> [?? x 4]
## # Database: spark_shell_connection
##      day  time  temp activ
##    <dbl> <dbl> <dbl> <chr>
##  1   307   930  36.6 Non-Active
##  2   307   940  36.7 Non-Active
##  3   307   950  36.9 Non-Active
##  4   307  1000  37.2 Non-Active
##  5   307  1010  37.2 Non-Active
##  6   307  1020  37.2 Non-Active
##  7   307  1030  37.2 Non-Active
##  8   307  1040  36.9 Non-Active
##  9   307  1050  37.0 Non-Active
## 10   307  1100  36.9 Non-Active
## # ... with more rows
```

```
beaver_tbl <- tbl(sc, "beaver")

glm_model <- beaver_tbl %>%
mutate(binary_response = as.numeric(activ == "Active")) %>%
ml_logistic_regression(binary_response ~ temp)

glm_model
```

```
## Formula: binary_response ~ temp
##
## Coefficients:
```

```
## (Intercept)        temp
##   550.52331   -14.69184

#First, we will copy the mtcars dataset into Spark.

mtcars_tbl <- copy_to(sc, mtcars, "mtcars")

# transform our data set, and then partition into 'training', 'test'
partitions <- mtcars_tbl %>%
  filter(hp >= 100) %>%
  sdf_mutate(cyl8 = ft_bucketizer(cyl, c(0,8,12))) %>%
  sdf_partition(training = 0.5, test = 0.5, seed = 888)

# fit a linear mdoel to the training dataset
fit <- partitions$training %>%
  ml_linear_regression(mpg ~ wt + cyl)

# summarize the model
summary(fit)

## Deviance Residuals:
##     Min      1Q  Median      3Q     Max
## -2.0947 -1.2747 -0.1129  1.0876  2.2185
##
## Coefficients:
## (Intercept)          wt         cyl
##   33.795576   -1.596247   -1.580360
##
## R-Squared: 0.8267
## Root Mean Squared Error: 1.437
```