

# 1.1 EACH VARIABLES STATISTICS AND SPECIFICATION

## Structure of the dataset:

```
> str(data)
'data.frame': 1543 obs. of 17 variables:
 $ EmployeeID
                         : int 9 59 61 74 79 88 94 105 111 155 ...
                         : Factor w/ 13 levels "", "Atlanta", "Boston", ...: 10 8 2 9 7 5 7 6 6 3 ...
 $ Branch
 $ Tenure
                         : num 10 5 8 4 7 2 10 5 6 6 ...
 $ Salary
                         : num 73500 63500 59000 72000 83000 62500 73500 57000 65500 56000 ...
                         : Factor w/ 15 levels "Accounting", "Administration", ...: 4 3 3 5 8 7 3 3 7 14 ...
 $ Department
 $ JobSatisfaction
                         : num 4 4 3 4 3 3 3 3 3 3 ...
 $ WorkLifeBalance
                         : num 4 3 3.5 3.5 3.5 4.5 4.5 2.5 4 4 ...
                         : Factor w/ 3 levels "Long", "Medium", ...: 3 2 2 1 2 2 1 3 3 3 ...
 $ CommuteDistance
                         : Factor w/ 3 levels "Divorced", "Married", ...: 3 3 3 3 2 3 1 3 3 2 ...
 $ MaritalStatus
                         : Factor w/ 3 levels "Bachelor", "High School", ...: 1 1 3 1 3 1 1 1 1 1 ...
 $ Education
 $ PerformanceRating
                         : num 3.33 2.67 3.33 2.67 3 ...
 $ TrainingHours
                         : num 18 12 24 24 36 12 24 12 6 30 ...
 $ OverTime
                         : int 1111111111...
 $ NumProjects
                   : num 2 3.62 3 2 4 2 2 2 3 3 ...
 $ YearsSincePromotion
                       : num 2000104000...
 $ EnvironmentSatisfaction: num 1 1 1 1 1 1 1 1 1 1 ...
                         : Factor w/ 2 levels "Highly Likely to Churn",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ ChurnLikelihood
```

- 1543 observations (i.e., rows) and 17 variables (i.e. attributes or columns)
- There are 11 variables are numeric and 6 variables are categoric variables

No.	Each Variables Statistics and Specification	Mean	Std.	Min.	Max.
1)	Employee ID: A unique identifier for each employee.	772.0	445.6	1.0	1543.0
2)	Tenure: The number of years the employee has been with the company.	7.6	4.1	0.0	27.0
3)	Salary: The employee's annual salary.	66653.6	8448.9	40000	98000
4)	Job Satisfaction: The employee's self-reported job satisfaction level	3.4	1.1	1.0	5.0
5)	WorkLife Balance: Employee's work-life balance rating	3.8	0.5	2.0	5.0
6)	Years Since Promotion: Number of years since the employee's last promotion.	1.2	2.1	0.0	16.0
7)	Training Hours: The number of hours of training the employee has received.	34.1	21.6	5.2	96.0
8)	Over Time: Whether the employee works overtime or not.	0.9	0.2	0.0	1.0
9)	Num Projects: Number of projects the employee is currently working on.	3.5	0.7	1.5	6.4
10)	Performance Rating: The employee's performance rating	3.5	0.4	1.6	5.0
11)	Environment Satisfaction: Employee's environment satisfaction	NA	NA	NA	NA
12)	Churn Likelihood: Employee's likelihood to leave the company	NA	NA	NA	NA
13)	Department: The department in which the employee works	NA	NA	NA	NA
14)	Commute Distance: The distance the employee commutes to work	NA	NA	NA	NA
15)	Marital Status: The marital status of the employee	NA	NA	NA	NA
16)	Education: The highest level of education attained by the employee	NA	NA	NA	NA

NA

NA

NA

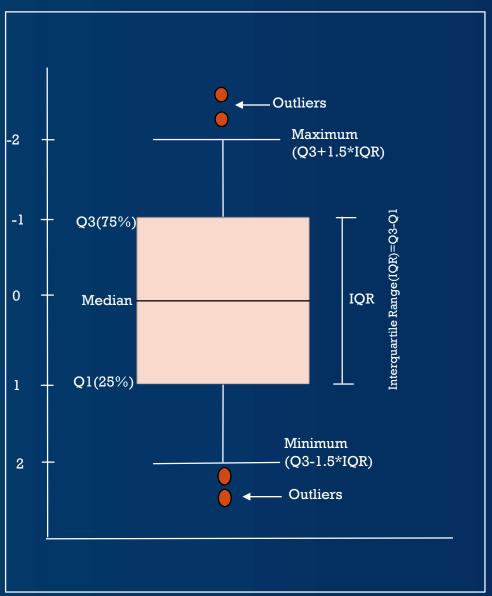
NA

17) Branch: The "Branch" feature represents the geographic location of each employee

Independent Variables

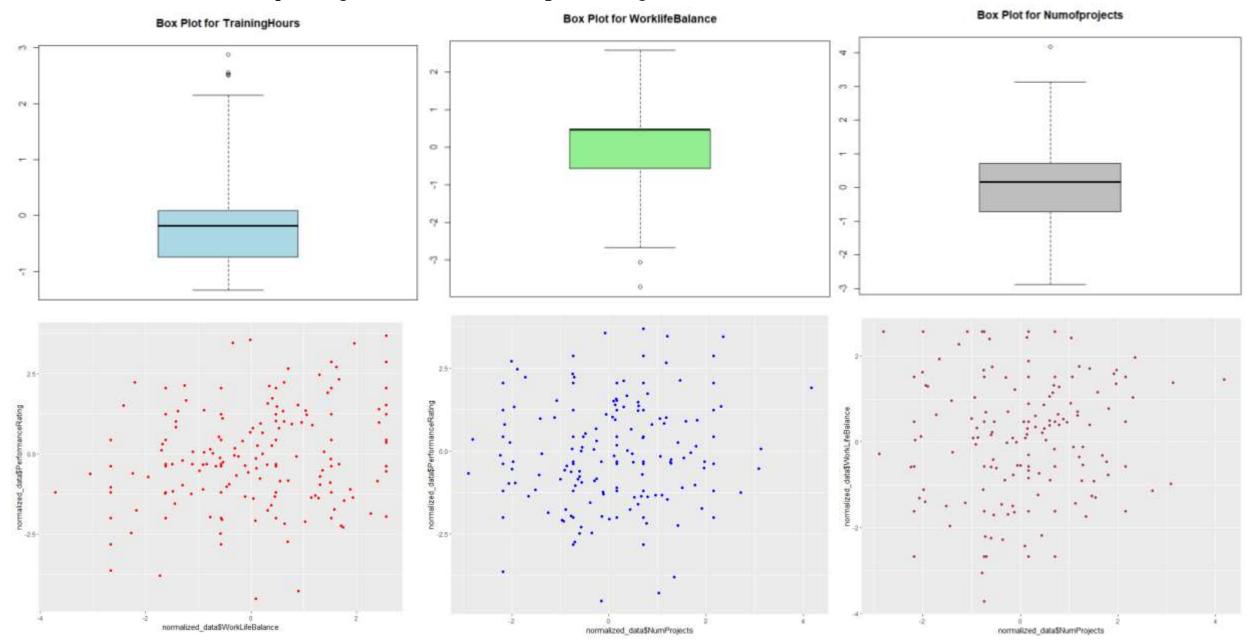
> Dependent Variable

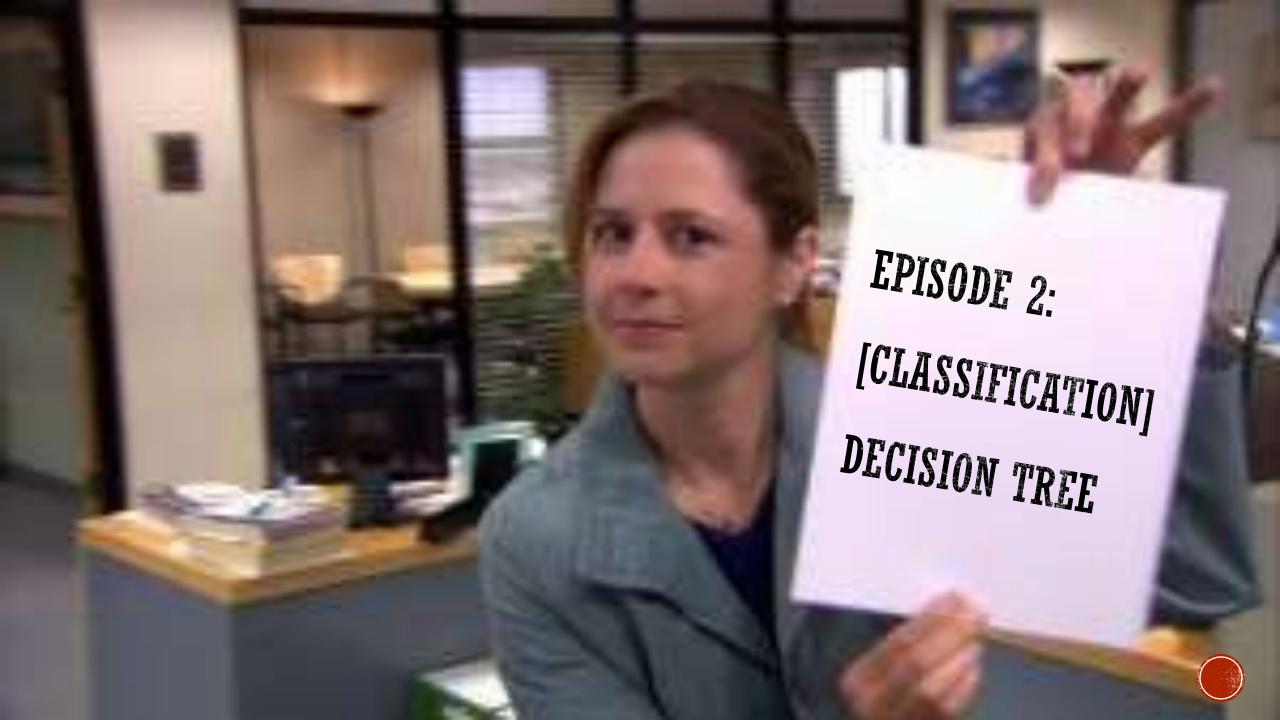
# 1.2 Outlier Detection by using Box Plot and Pre-processing



```
# Load data from the CSV file into a data frame named 'data'
data <- read.csv("output file (2).csv", header=TRUE, stringsAsFactors=TRUE)
# Display the structure of the data frame
str(data)
# Identify numeric columns in the data frame using sapply and is.numeric
numeric cols <- sapply(data, is.numeric)</pre>
# Subset the data frame to include only numeric columns
numeric data <- data[, numeric cols]
# Subset the data frame to include only non-numeric columns
non numeric data <- data[, !numeric cols]
# Normalize the numeric data using z-score normalization
normalized data <- as.data.frame(scale(numeric data))
# Create a box plot for the 'TrainingHours' column
boxplot.default(normalized data$TrainingHours,range= 2.5,col = "lightblue",main="Box Plot for TrainingHours")
# Create a box plot for the 'WorklifeBalance' column
boxplot.default(normalized data$WorkLifeBalance,range= 2.0,col = "lightgreen",main="Box Plot for
WorklifeBalance")
# Create a box plot for the 'Numofprojects' column
boxplot.default(normalized data$NumProjects,range= 2.0 ,col = "grey",main="Box Plot for Numofprojects")
# Create a scatter plot for 'TrainingHours', 'WorklifeBalance', 'NumProjects'.
ggplot(normalized data)+geom point(mapping
=aes(normalized data$WorkLifeBalance,normalized data$PerformanceRating),col="red")
ggplot(normalized data)+geom point(mapping =
aes(normalized data$NumProjects,normalized data$PerformanceRating),col="blue")
gaplet/permelized data), geem point/manning -
```

# 1.2 Outlier Detection by using Box Plot and Pre-processing





# 2.1 Splitting the data into training and test data

```
getwd()
install.packages("rpart.plot")
install.packages("rpart")
library("rpart","rpart.plot")
# split the data into training and testing data sets
# Randomly select 2/3 of the rows
#set.seed(400) # for reproducible results
#set.seed(300) # for reproducible results
set.seed(345) # for reproducible results
train = sample(1:nrow(B_Project), nrow(B_Project)*(2/3))
train
# Using the train index set to split the dataset
# The split is 2/3 and 1/3 each for train and test set
B_Project.train = B_Project[train,]
B_Project.test = B_Project[-train,]
```

# 2.2 Growing a tree and display basic results

**INPUT:** 

**OUTPUT**:

# 2.3 Plotting a tree and make an interpretation

R code: rpart.plot(fit, type = 1, extra = 1,main = "Decision Tree For Employee Churn Prediction")

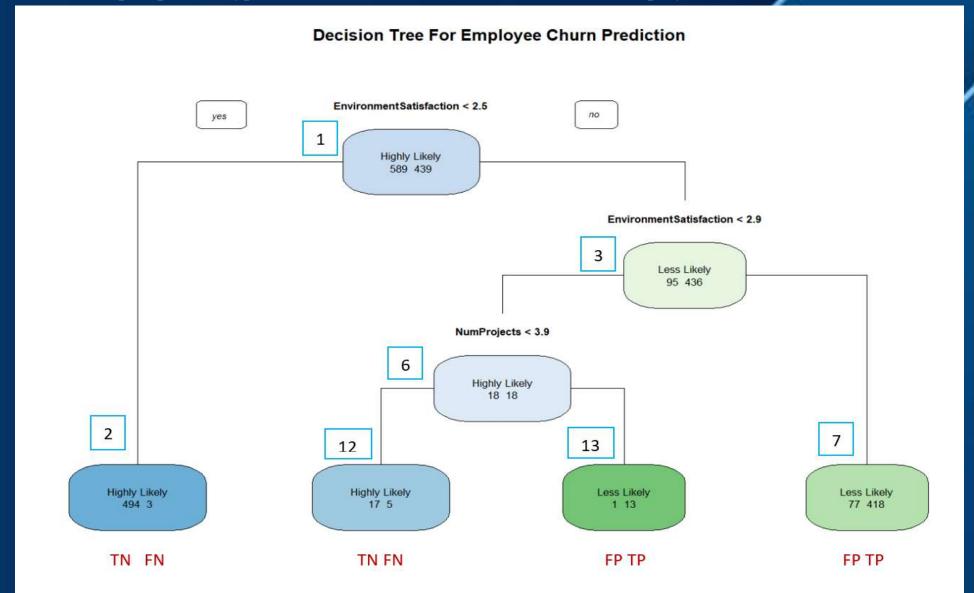
Tree Interpretation
Definitions

True Positive (TP): Pred Pos & Actual Pos TP = 418+13 = 431

False Positive (FP): Pred Pos & Actual Neg FP = 1+77 = 78

True Negative (TN): Pred Neg & Actual Neg TN = 494 +17 = 511

False Negative (FN): Pred Neg & Actual Pos FN = 3+5 = 8



## 2.4 ACCURACY ON THE TRAINING & TEST DATA

```
NPITT
```

```
# extract the vector of predicted class for each observation in B_Project.train
B_Project.pred <- predict(fit, B_Project.train, type="class")
# extract the actual class of each observation in B_Project.train
B_Project.actual <- B_Project.train$ChurnLikelihood
# now building the confusion matrix
confusion.matrix <- table(B_Project.pred, B_Project.actual)
confusion.matrix</pre>
```

```
# Accuracy on the Training Data
B_Project.pred<-predict(fit, B_Project.train, type="class")
B_Project.actual<-B_Project.train$ChurnLikelihood
confusion.matrix<-table(B_Project.pred, B_Project.actual)
pt<-prop.table(confusion.matrix)
#accuracy
pt[1,1] + pt[2,2]

# Accuracy on the Testing data
B_Project.pred <- predict(fit, B_Project.test, type="class")
B_Project.actual <- B_Project.test$ChurnLikelihood
confusion.matrix <- table(B_Project.pred, B_Project.actual)
addmargins(confusion.matrix)
pt <- prop.table@confusion.matrix)
#accuracy
pt[1,1] + pt[2,2]</pre>
```

# )UTPUT:

```
> confusion.matrix
                B_Project.actual
B_Project.pred Highly Likely Less Likely
 Highly Likely
 Less Likely
                                         431
> B_Project.pred<-predict(fit, B_Project.train, type="class")</p>
> B_Project.actual <- B_Project.train$ChurnLikelihood
confusion.matrix<-table(B_Project.pred, B_Project.actual)</p>
pt<-prop.table(confusion.matrix)</pre>
> #Accuracy on Training
> pt[1,1] + pt[2,2]
[1] 0.9163424
 # Accuracy on the Testing data
B_Project.pred <- predict(fit, B_Project.test, type="class")</p>
> B_Project.actual <- B_Project.test$ChurnLikelihood</p>
> confusion.matrix <- table(B_Project.pred, B_Project.actual)</p>
> addmargins(confusion.matrix)
B_Project.pred Highly Likely Less Likely Sum
  Highly Likely
                           253
  Less Likely
                            42
                                        215 257
                                        220 515
                           295
> pt <- prop.table(confusion.matrix)
> #Accuracy on Test
> pt[1,1] + pt[2,2]
[1] 0.9087379
```

> confusion.matrix <- table(B\_Project.pred, B\_Project.actual)</p>

\*Overall Performance Accuracy (0.916)

```
Total Number of
Obs.

(TP + TN)/

(TP+FP+TN+FN) = (431+511)/

(431+78+511+8) = 0.916
```

Total Correct /

Error Rate =
Total Incorrect /
Total Number of
Obs. = 1 Accuracy = 10.737 = 0.084

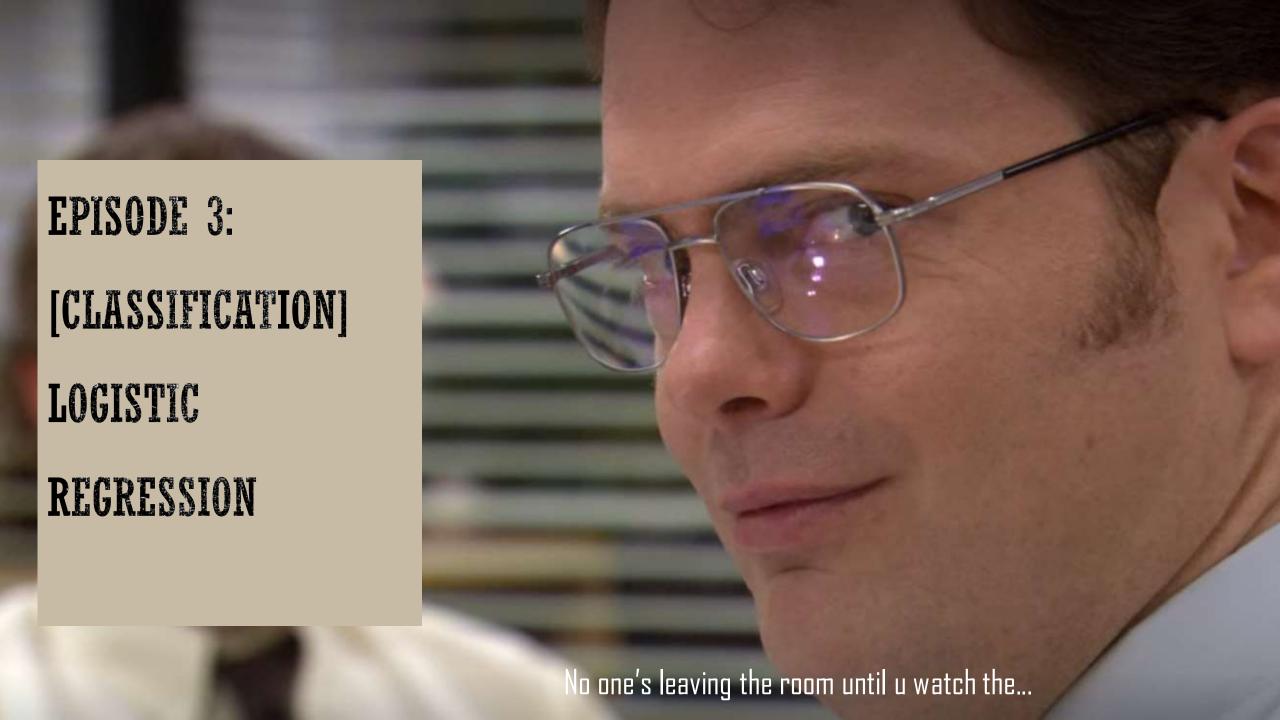
TPR = Recall =
(Sensitivity) =
TP/P =
431/(431+78) =
0.847

TNR =
(Specificity) =
TN/N =
511/(511+8) =
0.985

FPR = FP/N = Type 1 Error Rate  $(\alpha)$ = 78/(519) = 0.151

FNR = FN/P = Type 2 Error Rate  $(\beta)=8/(509)=$ 0.0157





## 3.1 SPLITTING THE DATA INTO TRAINING AND TEST DATA

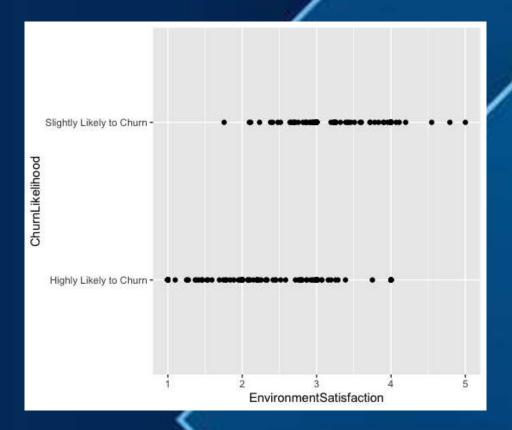
```
1
    #Training and Test Data
    churn.df<-read.csv("Employee Churn Dataset 2.csv"); #Loading the data
    churn.df$ChurnLikelihood<-as.factor(churn.df$ChurnLikelihood); #Converting output as factor
    churn.df$Department<-factor(churn.df$Department); #Treating Department as categorical
 6
    set.seed(2); #Splitting the data into training and test data sets
    train<-sample(1:nrow(churn.df), (0.6)*nrow(churn.df))
    train.df<-churn.df[train,]
    test.df<-churn.df[-train,]
> #Training and Test Data
> churn.df<-read.csv("Employee Churn Dataset 2.csv") ; #Loading the data</pre>
> churn.df$ChurnLikelihood<-as.factor(churn.df$ChurnLikelihood) ; #Converting output as factor</pre>
> churn.df$Department<-factor(churn.df$Department) ; #Treating Department as categorical</pre>
> set.seed(2); #Splitting the data into training and test data sets
> train<-sample(1:nrow(churn.df), (0.6)*nrow(churn.df))</pre>
> train.df<-churn.df[train,]</pre>
> test.df<-churn.df[-train,]</pre>
```

## 3.2 LOGISTIC REGRESSION AND DISPLAY THE RESULTS

## **INPUT:**

#### **OUTPUT**:

```
> #Logistic regression and display the results
> logit.reg <-glm(ChurnLikelihood ~ Salary + JobSatisfaction + WorkLifeBalance
+ CommuteDistance + MaritalStatus + PerformanceRating + TrainingHours
+ OverTime + NumProjects + YearsSincePromotion + EnvironmentSatisfaction,
data = train.df, family = "binomial")</pre>
```



$$y = \frac{e^{(b_0 + b_1 X)}}{1 + e^{(b_0 + b_1 X)}}$$

## 3.3 INTERPRETATION OF SIGNIFICANCY AND COEFFICIENT

### **INPUT:**

```
#Interpretation of Significancy and Coefficient
summary(logit.reg); #Results of logistic regression

#Accuracy on the training & test data
logitPredict<-predict(logit.reg, test.df, type = "response");#Computing predicted probabilities
logitPredictClass<-ifelse(logitPredict> 0.5, 1, 0); #Converting probability to a classification
logitPredictClass
```

## <u>Interpretation:</u>

- $b_1 = 4.99$
- Therefore, Odds Ratio= $e^{b1} = e^{4.99} = 146.94$

#### Which means.

- An increase of 1 unit of Environment Satisfaction multiplies the odds of acceptance of a Likelihood by 146.94
- An increase of 1 unit of Environment Satisfaction with an increase of \_\_\_\_\_ in the odds of acceptance of a Likelihood

#### **OUTPUT**:

- > #Interpretation of Significancy and Coefficient
- > summary(logit.reg); #Results of logistic regression

#### Call:

Coefficients: (1 not defined because of singularities)

```
Estimate Std. Error z value Pr(>|z|)
                                 2.49e+00
(Intercept)
                      -1.68e+01
                                            -6.75 1.5e-11 ***
Salary
                      3.12e-05
                                 1.84e-05
                                             1.69
                                                     0.091 .
JobSatisfaction
                                 1.30e-01
                                                    0.539
                      -8.01e-02
                                            -0.61
                      -2.86e-01
WorkLifeBalance
                                 3.33e-01
                                            -0.86
                                                    0.391
                                                    0.835
CommuteDistanceMedium
                      -7.60e-02 3.64e-01
                                            -0.21
                      -2.86e-01 3.55e-01
                                            -0.81
                                                    0.420
CommuteDistanceShort
MaritalStatusMarried
                      -3.44e-02
                                 3.72e-01
                                            -0.09
                                                     0.926
MaritalStatusSingle
                      -9.97e-02
                                 4.59e-01
                                            -0.22
                                                     0.828
PerformanceRating
                      4.58e-01
                                 3.96e-01
                                                     0.247
                                             1.16
TrainingHours
                       9.40e-03
                                 6.85e-03
                                             1.37
                                                     0.170
OverTimeTRUE
                       2.58e-01
                                                     0.282
NumProjects
                                  2.40e-01
                                             1.08
YearsSincePromotion
                      -7.01e-03
                                  8.51e-02
                                            -0.08
                                                     0.934
EnvironmentSatisfaction 4.99e+00
                                            12.19
                                  4.09e-01
                                                  < 2e-16 ***
```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' '1

## 3.4 ACCURACY ON THE TRAINING & TEST DATA

#Accuracy on the training & test data

logitPredict<-predict(logit.reg, test.df, type = "response") ;#Computing predicted probabilities
logitPredictClass<-ifelse(logitPredict> 0.5, 1, 0) ; #Converting probability to a classification
logitPredictClass

																										- 40	•						
> #Ac	curac	y on	the t	raini	ng &	test	data										733		738	744	745	746	748	752	755	756	757	1000000	759	760	761	762	763
								df, t	ype =	"res	ponse	") :#	Compu	ting	predi	cted probabilities	0	0	0	0	0	0	NA	1	1	1	NA	NA	0	1	0	1	1
																o a classification	766	767	769	770	771	778	782	785	790	791	793	795	798	800	805	806	808
	itPre								A.C. CARL						-		1	NA	1	1	1	1	1	1	1	1	NA	NA.	1	NA	1	1	1
2	4	5	6	10	12	14	17	18	19	22	30	33	40	41	51	62	812	813	819	820	821	825	831	832	833	835	844	847	852	853	858	863	864
NA	0	0	0	0	0	0	NA	0	0	0	0	Ø	0	0	0	9	1	NA	1	1	1	1	1	1	NA.	1	1	1	NA	1	1	NA	1
63	64	66	67	69	72	73	74	76	78	81	86	87	91	92	94	95	865	867	871	877	879	883	884	885	888	892	895	896	898	900	903	904	905
0	NA	0	0	0	0	NA	0	0	0	0	0	0	NA	a	a	9	1	1	1	1	1	1	NA	1	1	NA	1	1	1	1	NA	1	1
96	97	98	101	102	105	106	107	112	115	117	118	120	122	123	125	126	911	913	914	915	921	924	925	926	930	931	935		948	949	951	952	953
0	a	NA	0	0	0	0	0	0	0	0	0	NA	NA	NA	0	0	1	1	NA	1	1	1	1	1	1	1	NA	NA	1	NA	1	1	NA
127	128	133	135	136	139	150	152	153	154	155	159	163	171	174	175	177	954	955	956	957	958	961	964	973	974	977	983	150.00	985	988	990	991	992
0	0	233	133	230	0	0	0	233	NA	233	233	0	2,1	0	1,3		NA	1	1	1	1	1	1	. 1	NA	1	1	NA	1	1	1	1	NA
178	183	189	195	197	198	202	208	209	210	211	216	217	219	220	224	225	995	999	1001	1004	1009	1012	1014	1015	1017	1019		1026	1027	1029	1031	1035	
0	103	NA	193	157	150	NA	0	NA	210	211	210	211	219	220	0	NA NA	1	1	1	. 1	1	_ 1	1	1	1		1	NA	1	1	1	. 1	NA.
229	230	232	236	237	240	242	244	245	246	249	250	256	257	261	265	271	1040	1043	1047	1048	1050	1052	1053	1054	.7796070	1061	1066		1068	10/0	1071	1075	727000000
1 2221	NA.	NA	NA.	231	0	0	0	0	NA.	249	230	230	237	201	203	0	1	1000	1	1	NA TOOR	NA	1	1	NA	1	1	NA	1	1	1	1	NA *****
NA 274	276	277	279	282	289	290	298		302	307	308	300	212	214	216		177.77			1096		1101	1103	1104	1300000		75.55	- 700000000	1114	1123	1124	1125	1126
274	0	211	2/9	NA.	289	290	298	301	302	307	308	309	312	314	316	319 Ø	1	NA	NA 1126	NA	NA	1		1		1	NA	NA	1 1	1100	1100	1150	1
NA 224	322	274	330		336	-			346	351	-		NA	350	360	200.00	0.00				1139	1140	1141	1142	1144	1145		1148	1149	1155		1158	1129
321	7770	324	2020	332		338	339	345	346	351	354	355	356	359	360	363	11160	1163	1164	1100	1157	1160	1177	1176	1170	1101	NA	1105	1100	1102	NA 1103	1194	1105
0	0	9	9	NA 275	0	9	9	9	70A	200	207	300	NA	304	306	100	115-1-1-1	1102	1104	NA	1107	1169	11/2	11/6	11/0	1191	1102	1105	1190		1192	1134	1132
364	366	367	372	375	378	379	380	382	384	386	387	389	393	394	396	400	1196	1100	1201	1202	1205	1206	1209	1212	1717	1210	1771	1222	1224	1220	1230	1231	1235
0	NA	NA	NA 107	400	0	0	NA.	0	0	430	0	NA	.0	NA	435	136	1196	1155	NA	1202	1205	1200	1209	1213	1	NA.	1	1222	NA	1 223	NA	NA	1233
402	403	406	407	409	411	412	414	417	418	420	421	422	423	424	425	426	1222	1238	1230	1243	1745	1749	1250	1252			L	1250		1261	1265	1270	1274
0	0	0	NA		NA	NA	0	0	0	0	0	0	0	0	NA	NA .	1	NA	1235	1243	NA.	1	12.50	1232	NA	1230	1230	12.35	1200	NA	NA	NA	1274
433	436	438	439	441	448	449	450	451	453	458	459	463	467	470	477	481	1275	1277	1279	1270	1284	1295	1790	1203		1202	1304	1205	1211	1212	1216	1319	1324
NA	0	0	NA	0	0	0	0	0	0	0	0	0	NA	0	Ø	NA	12/3	NA	1270	12/3	1204	1 1	1205	1293	1	1303	1304	1303	1	NA	1310	1319	1324
485	487	489	490	491	494	495	496	497	501	504	506	507	511	513	515	517	1328		1331	1332	1333	1334	1335	1336	1338	1343	1344	1348	1349		1351	1353	1356
0	0	0	0	0	0	0	NA	NA	0	0	0	0	NA	0	0	NA	1	1	NA	NA	1	1	NA	1	1	1	NA	1	1	1	1	NA	1
521	527	530	531	532	535	536	537	540	541	542	544	545	546	548	551	553					1366	1370		1379	W. 050-		17.00000	1388	1390	1393	1394	1397	1398
0	0	0	0	Ø	0	0	NA	Ø	0	0	0	Ø	Ø	0	NA	0	1	1	NA	1	NA	1	NA	1	1	NA	1	1	1	1	1	NA	1
555	557	559	560	561	562	565	566	569	570	572	573	574	575	576	578	579	1401		1409	1411	1417	1414		1420			1000000	1428	1429	1433	1435	1436	1437
NA	0	NA	0	0	NA	0	0	0	0	0	0	0	0	0	0	0	NA	1	1	NA	NA	1	1	1	1	1	1	1	1	1	NA	1	1
580	587	589	593	595	597	598	601	602	605	609	610	611	612	616	617	625	1439		1441	1442	1445	1446	1458	1461	1464	1468	43700-70		1476	1482	1489	1491	3000.000
0	NA	0	0	0	0	NA	0	0	0	NA	0	NA	NA	0	0	Ø	1	1	1	1	1	NA	1	1	NA	1	1	NA	1	NA	NA	1	1
626	631	633	641	642	646	650	651	653	656	657	664	667	669	673	674	682	1494	1496	1498	1504	1507	1510	1512	Announced the		2471349257			District Visit		1532	1533	10 - Yakin - Ca
0	NA	0	0	0	0	0	0	0	0	0	0	0	0	NA	0	0	NA	1	1	1	NA	1		NA			NA						
686	688	692	694	695	702	703	707	712	715	718	721	722	723	724	726	731	1538	1539	1540	1541		2 154				1.00	1.27	1.003					75.7
0	0	0	0	0	0	0	0	0	NA.	NA	0	0	NA	0	0	0	NA	N/	N/	N/	N.	A N	Α .										

