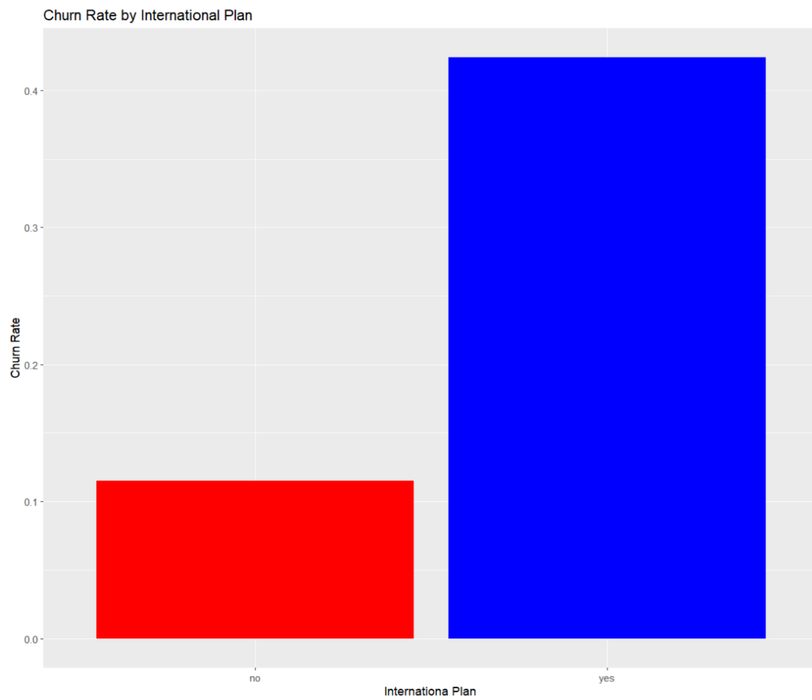
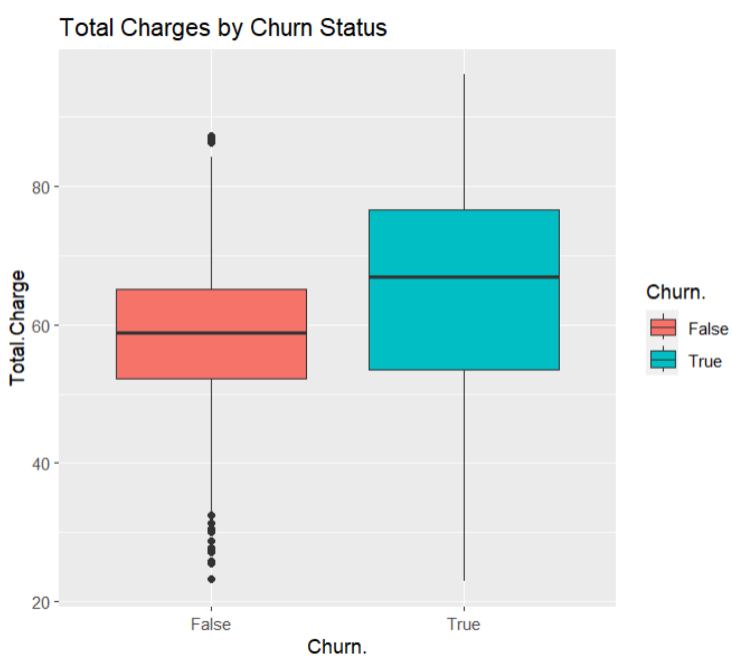
PART 1:



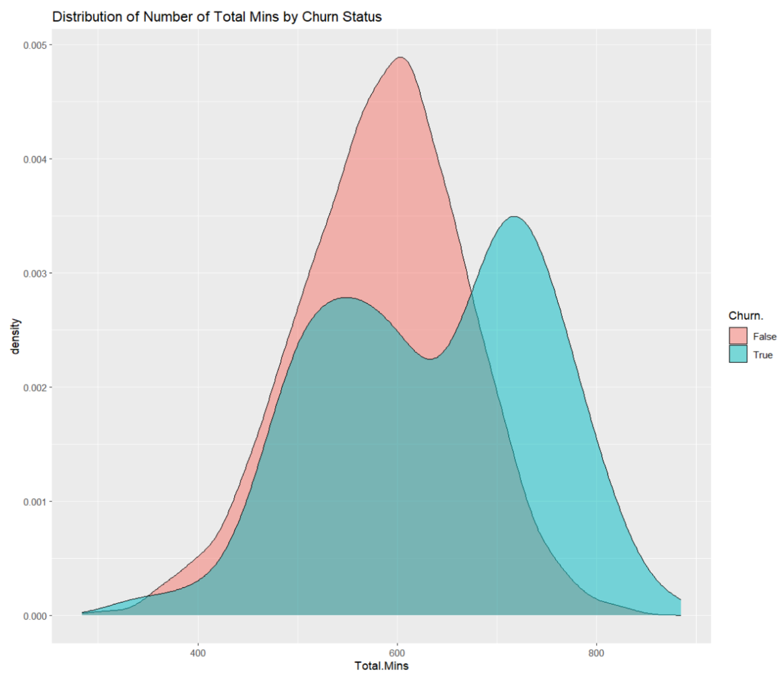

**This chart displays the churn rate by people who have an international plan. We can see that people who typically have the plan have a high rate of churn. From this, we can infer a couple of things. One thing to infer is the charge for international plans could be a bit too high to the point it may not be worth it or maybe a good amount of people had to churn in order to have more international calls.**

PART 2:



**Here is a chart that relates people's charges to Churn status. A repeating trend that we see here with the data is that people whose Churn value is equal to true typically have higher charges. From the repeating signs of high charges, it could be safe to assume that this company may be charging higher prices than others.**

PART 3:




**What we can see here in the density chart is a visualization of people's churn rate in relation to the total amount of minutes they spend on calls. As people tend to spend more minutes on their phones it is more likely that they have a churn value equal to true, by analyzing the data we can see that maybe if you spend on average of 600 minutes, this selection of this cell provider might not be a bad option considering the rate of people's whose churn value is false around 600**.

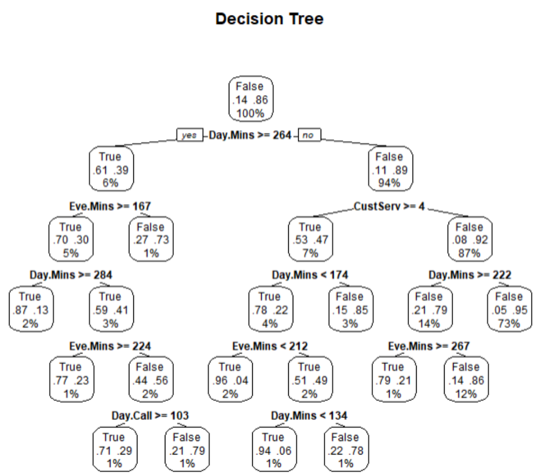
PART 4:

```
> summary(churning$Intl.Mins)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   0.00    8.50   10.30   10.24   12.10   20.00
```

```
sample estimates:
mean in group False  mean in group True
           10.15888            10.70000
```

**It should be important to note that if we take a look at people's minutes and churn values, It's safe to say after looking at our previous data on minutes that International does NOT have a strong effect on whether someone has a churn value of true or not. This could mean that although there isn't alot of time spent on international calls, people may be getting overcharged in their international plans.**

PART 5:




```
> print(accuracy)
[1] 0.898
> print(error_rate)
[1] 0.102
> print(sensitivity)
[1] 0.9762752
> print(specificity)
[1] 0.477707
> print(precision)
[1] 0.9093923
> print(recall)
[1] 0.9762752
> print(f_measure)
[1] 0.9416476
>
```

```
> print(dtree.perf)
        Predicted
Actual   True False
  True     75    82
  False    20   823
>
```

As we can see here, we ran the data through a Decision Tree. First we cleaned up all of the irrelevant data then we were able to separate training and testing data with 70% for training and 30% for testing. We can see that we landed an 89% accuracy rating and visual representation of the tree.

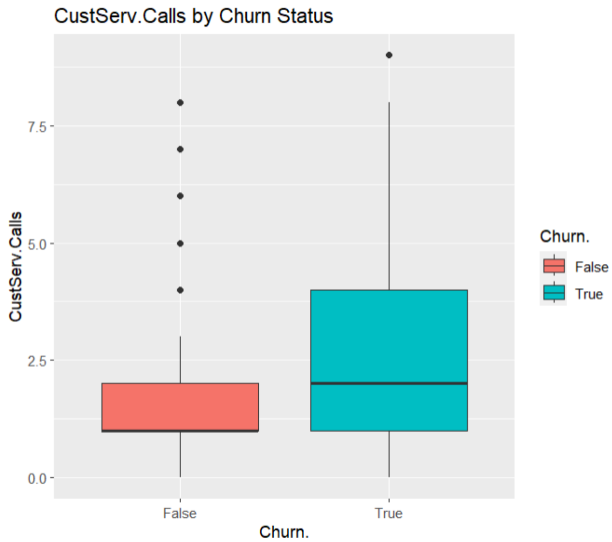
PART 6:

```
> print(accuracy)
[1] 0.853
> print(error_rate)
[1] 0.147
> print(sensitivity)
[1] 0.9442467
> print(specificity)
[1] 0.3630573
> print(precision)
[1] 0.8883929
> print(recall)
[1] 0.9442467
> print(f_measure)
[1] 0.9154687
>
```

```
> print(nb.perf)
        Predicted
Actual   True False
  True     57   100
  False    47   796
>
```

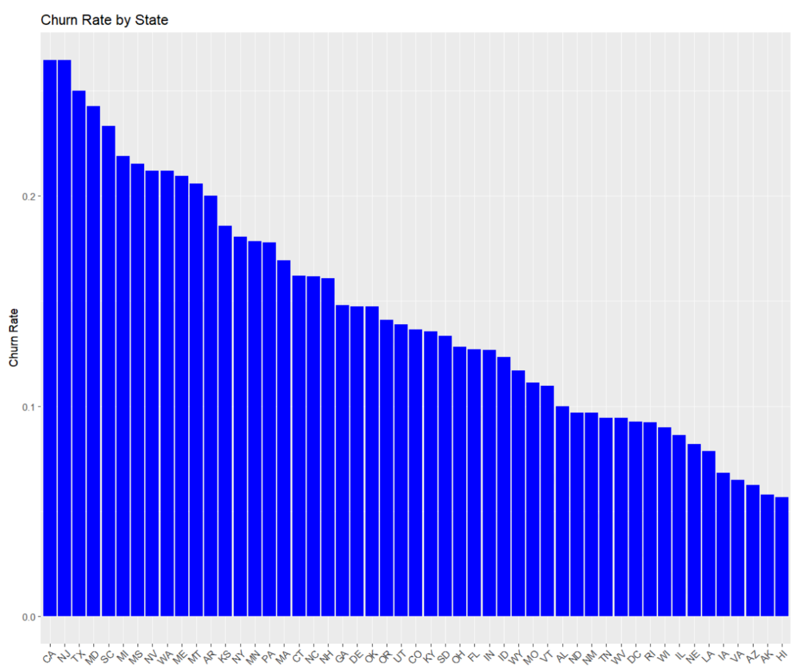
In this part we ran the code through a Naïve Bayesian model, to compare the accuracy of which the classification method would perform better. It appears that the Decison Tree model is better for this situation.

PART 7:



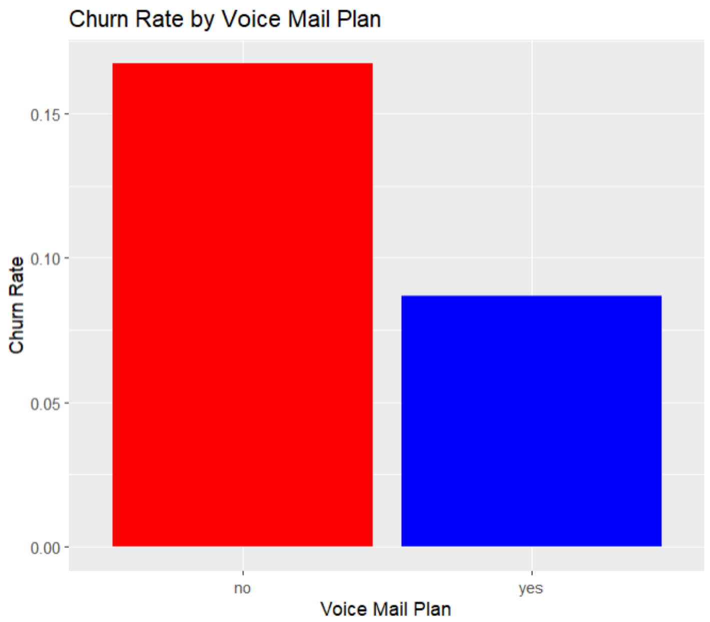

**As expected, we can see that the higher amount of calls that customers typically made resulted in more of a likeness that a customer's Churn value is set to True. This is makes sense as customers typically tend to call customer service whenever they come across a problem, also leading to callers who call to churn.**

PART 8:



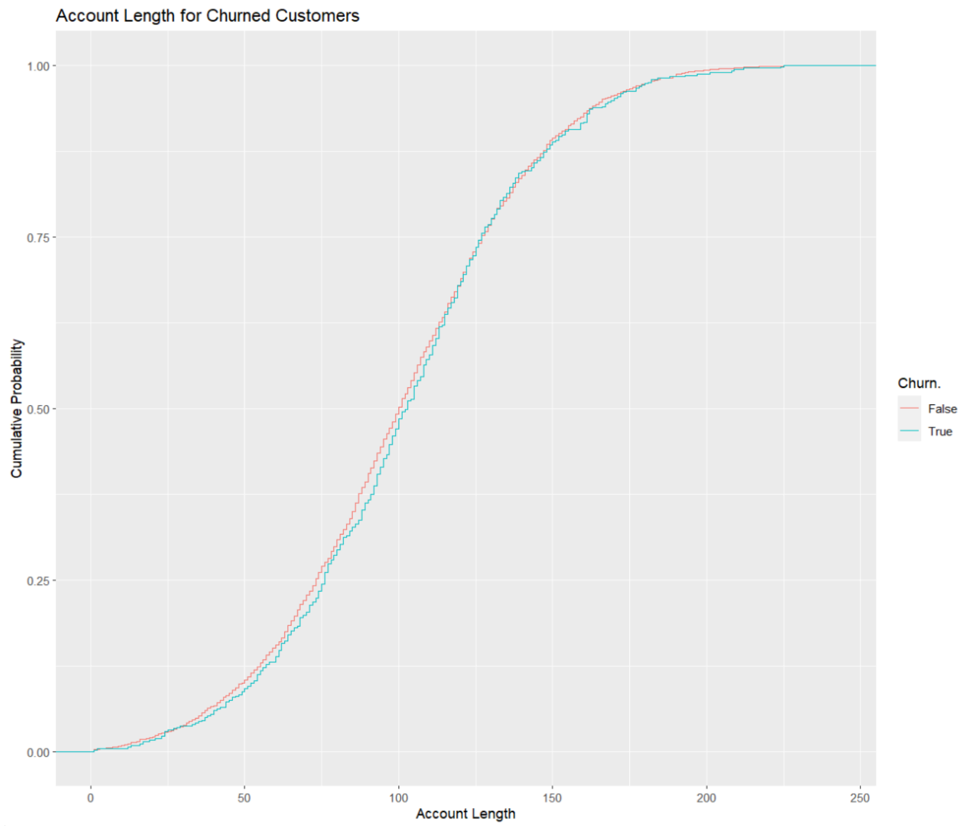

**This chart displays the rate of churn in which the value is equal to true by state, it can be noted that the highest states with churn are the most populated/densely populated states, more people equals the respective rate of churn for each state**

PART 9:




**We can see in this chart that a good amount of people who have the Voice mail plan tend to stick with the company causing a majority of these users to have a churn value of false. This is reason enough to believe that customers are generally satisfied with the plan.**

PART 10:




**From this chart, we were able to visualize the rate of churn in relation to the length of days the customer has their account for. We can see that the length of days rate for Churn value of true and false are really similar indicating that the amount of time it takes for someone to have churn value to be true doesn't have much of an effect.**