THE R ZONE

\# Input data set Churn into Data Frame "Churn"

```
churn <- read.csv(file = "C:/. . . /churn.txt",
   stringsAsFactors=TRUE)
# Show the first ten records
churn[1:10,]
```

```
> churn[1:10,]
   State Account.Length Area.Code    Phone Int.l.Plan
1     KS            128       415 382-4657         no
2     OH            107       415 371-7191         no
3     NJ            137       415 358-1921         no
4     OH             84       408 375-9999        yes
5     OK             75       415 330-6626        yes
6     AL            118       510 391-8027        yes
7     MA            121       510 355-9993         no
8     MO            147       415 329-9001        yes
9     LA            117       408 335-4719         no
10    WV            141       415 330-8173        yes
```

\# Summarize the Churn variable

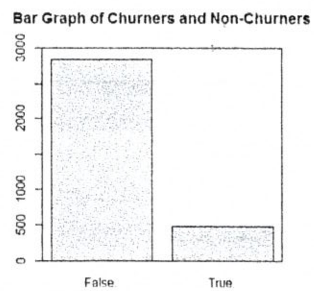
```
sum.churn <- summary(churn$Churn)
sum.churn
```

\# Calculate proportion of churners

```
prop.churn <- sum(churn$Churn == "True") /
   length(churn$Churn)
prop.churn
```

\# Bar chart of variable Churn

```
barplot(sum.churn,
   ylim = c(0, 3000),
   main = "Bar Graph of Churners and Non-Churners",
   col = "lightblue")
box(which = "plot",
   lty = "solid",
   col="black")
```



\# Make a table for counts of Churn and International Plan

```
counts <- table(churn$Churn, churn$Int.l.Plan,
    dnn=c("Churn", "International Plan"))
counts
```

```
> counts
       International Plan
Churn     no  yes
  False. 2664  186
  True.   346  137
```

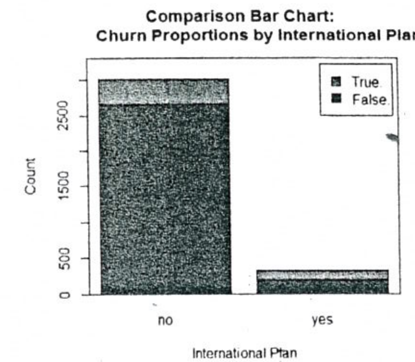
\# Create a table with sums for both variables

```
sumtable <- addmargins(counts, FUN = sum)
sumtable
```

```
> sumtable
       International Plan
Churn     no  yes  sum
  False. 2664  186 2850
  True.   346  137  483
  sum    3010  323 3333
```

\# Overlayed bar chart

```
barplot(counts,
   legend = rownames(counts),
   col = c("blue", "red"),
   ylim = c(0, 3300),
   ylab = "Count",
   xlab = "International Plan",
   main = "Comparison Bar Chart:
   Churn Proportions by International Plan")
box(which = "plot",
   lty = "solid",
   col="black")
```



\# Create a table of proportions over rows

```
row.margin <- round(prop.table(counts,
      margin = 1),
   4)*100
row.margin
```

```
> row.margin
       International Plan
Churn      no   yes
  False. 93.47  6.53
  True.  71.64 28.36
```

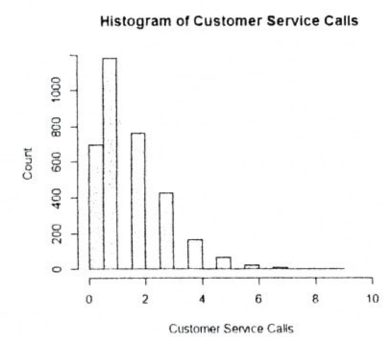
\# Create a table of proportions over columns

```
col.margin <- round(prop.table(counts,
      margin = 2),
   4)*100
col.margin
```

```
> col.margin
       International Plan
Churn      no   yes
  False. 88.50 57.59
  True.  11.50 42.41
```

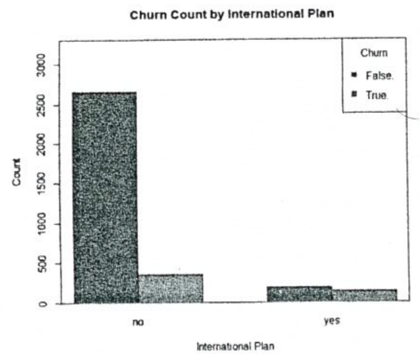
\# Histogram of non-overlayed Customer Service Calls

```
hist(churn$CustServ.Calls,
   xlim = c(0,10),
   col = "lightblue",
   ylab = "Count",
   xlab = "Customer Service Calls",
   main = "Histogram of Customer Service Calls")
```



Clustered Bar Chart, with legend

```
barplot(counts,
  col = c("blue", "red"),
  ylim = c(0, 3300),
  ylab = "Count",
  xlab = "International Plan",
  main = "Churn Count by International Plan",
  beside = TRUE)
legend("topright",
  c(rownames(counts)),
  col = c("blue", "red"),
  pch = 15,
  title = "Churn")
box(which = "plot",
  lty = "solid",
  col="black")
```



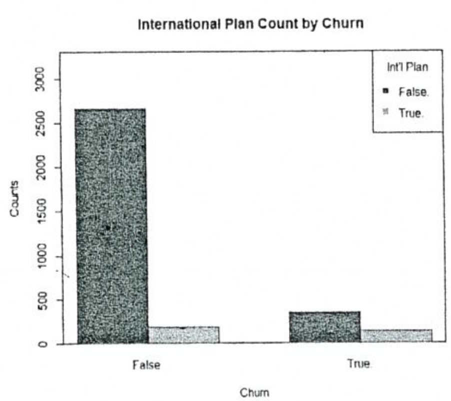
Download and install the R Package *ggplot2*

```
install.packages("ggplot2")
# Pick any CRAN mirror
# (see example image)
# Open the new package
library(ggplot2)
```

```
70: Turkey              71: UK (Bristol)    72: UK (London)
73: UK (St Andrews)     74: USA (CA 1)      75: USA (CA 2)
76: USA (IA)            77: USA (IN)        78: USA (KS)
79: USA (MD)            80: USA (MI)        81: USA (MO)
82: USA (OH)            83: USA (OR)        84: USA (PA 1)
85: USA (PA 2)          86: USA (TN)        87: USA (TX 1)
88: USA (WA 1)          89: USA (WA 2)      90: Venezuela
91: Vietnam

Selection: 74
```

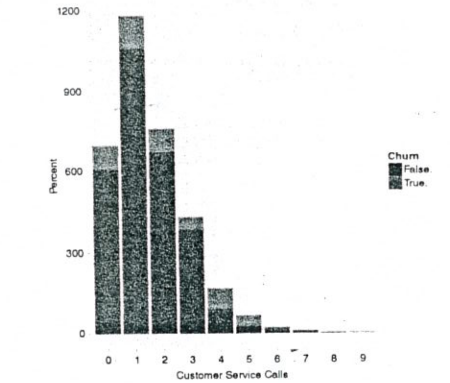
Clustered Bar Chart of Churn and Int'l Plan with legend

```
barplot(t(counts),
  col = c("blue", "green"),
  ylim = c(0, 3300),
  ylab = "Counts",
  xlab = "Churn",
  main = "International Plan Count by Churn",
  beside = TRUE)
legend("topright",
  c(rownames(counts)),
  col = c("blue", "green"),
  pch = 15,
  title = "Int'l Plan")
box(which = "plot",
  lty = "solid",
  col="black")
```

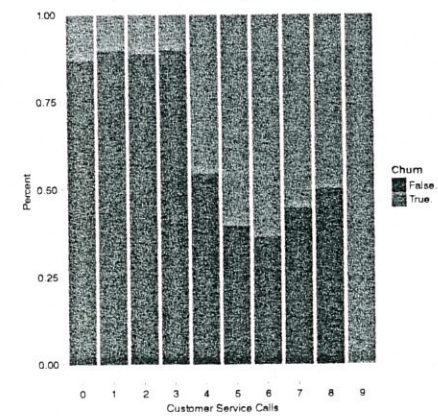


Overlayed bar charts

```
ggplot() +
  geom_bar(data = churn,
  aes(x = factor(churn$CustServ.Calls),
  fill = factor(churn$Churn.)),
  position = "stack") +
  scale_x_discrete("Customer Service Calls") +
  scale_y_continuous("Percent") +
  guides(fill=guide_legend(title="Churn")) +
  scale_fill_manual(values=c("blue", "red"))
```




```
ggplot() +
  geom_bar(data=churn,
  aes(x = factor(churn$CustServ.Calls),
  fill = factor(churn$Churn.)),
  position = "fill") +
  scale_x_discrete("Customer Service Calls") +
  scale_y_continuous("Percent") +
  guides(fill=guide_legend(title="Churn")) +
  scale_fill_manual(values=c("blue", "red"))
```



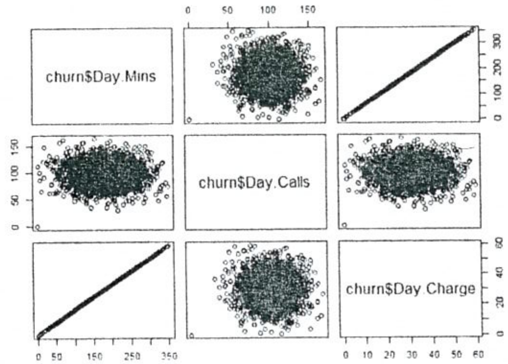
Two-sample T-Test for Int'l Calls

```
# Partition data
churn.false <- subset(churn,
  churn$Churn == "False")
churn.true <- subset(churn,
  churn$Churn == "True")
# Run the test
t.test(churn.false$Intl.Calls,
  churn.true$Intl.Calls)
```

```
> t.test(churn.false$Intl.Calls,
+        churn.true$Intl.Calls)

 Welch Two Sample t-test

data:  churn.false$Intl.Calls and churn.true$Intl.Calls
t = 2.9604, df = 640.643, p-value = 0.003186
alternative hypothesis: true difference in means is not
equal to 0
95 percent confidence interval:
 0.1243807 0.6144620
sample estimates:
mean of x mean of y
 4.532982  4.163561
```

 # Scatterplot matrix

```
pairs(~churn$Day.Mins+
  churn$Day.Calls+
  churn$Day.Charge)
```



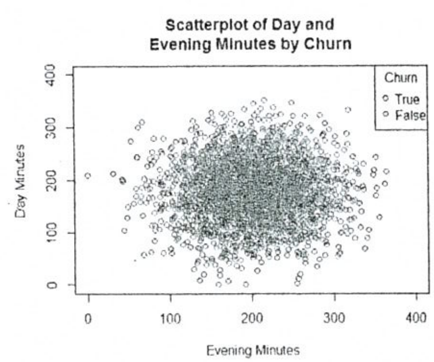
 # Regression of Day Charge vs Day Minutes

```
fit <- lm(churn$Day.Charge ~
  churn$Day.Mins)
summary(fit)
```

```
> summary(fit)

Call:
lm(formula = churn$Day.Charge ~ churn$Day.Mins)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0045935 -0.0025391  0.0004326  0.0024587  0.0045224

Coefficients:
                Estimate Std. Error   t value Pr(>|t|)
(Intercept)    6.134e-04  1.711e-04 3.585e+00 0.000341 ***
churn$Day.Mins 1.700e-01  9.108e-07 1.866e+05  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.002864 on 3331 degrees of freedom
Multiple R-squared:     1,	Adjusted R-squared:     1
F-statistic: 3.484e+10 on 1 and 3331 DF,  p-value: < 2.2e-16
```

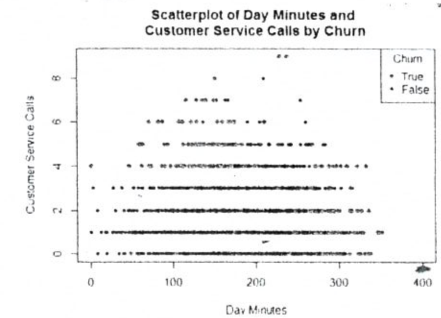
 # Scatterplot of Evening Minutes and Day Minutes, colored by Churn

```
plot(churn$Eve.Mins,
  churn$Day.Mins,
  xlim = c(0, 400),
  ylim = c(0, 400),
  xlab = "Evening Minutes",
  ylab = "Day Minutes",
  main = "Scatterplot of Day and Evening
    Minutes by Churn",
  col = ifelse(churn$Churn=="True",
    "red",
    "blue"))
legend("topright",
    c("True",
    "False"),
  col = c("red",
    "blue"),
  pch = 1,
  title = "Churn")
```



 # Scatterplot of Day Minutes and Customer Service Calls, colored by Churn

```
plot(churn$Day.Mins,
  churn$CustServ.Calls,
  xlim = c(0, 400),
  xlab = "Day Minutes",
  ylab = "Customer Service Calls",
  main = "Scatterplot of Day Minutes and
    Customer Service Calls by Churn",
  col = ifelse(churn$Churn=="True",
    "red",
    "blue"),
  pch = ifelse(churn$Churn=="True",
    16, 20))
legend("topright",
  c("True",
    "False"),
  col = c("red",
    "blue"),
  pch = c(16, 20),
  title = "Churn")
```



 # Correlation values, with p-values

```
days <- cbind(churn$Day.Mins,
  churn$Day.Calls,
  churn$Day.Charge)
MinsCallsTest <- cor.test(churn$Day.Mins,
  churn$Day.Calls)
MinsChargeTest <- cor.test(churn$Day.Mins,
  churn$Day.Charge)
CallsChargeTest <- cor.test(churn$Day.Calls,
  churn$Day.Charge)
round(cor(days),
  4)
MinsCallsTest$p.value
MinsChargeTest$p.value
CallsChargeTest$p.value
```

```
> round(cor(days), 4)
       [,1]   [,2]   [,3]
[1,] 1.0000 0.0068 1.0000
[2,] 0.0068 1.0000 0.0068
[3,] 1.0000 0.0068 1.0000
> MinsCallsTest$p.value
[1] 0.6968515
> MinsChargeTest$p.value
[1] 0
> CallsChargeTest$p.value
[1] 0.6967428
```

```
# Correlation values and p-values in matrix form

# Collect variables of interest
corrdata <- cbind(churn$Account.Length,
   churn$VMail.Message,
   churn$Day.Mins,
   churn$Day.Calls,
   churn$CustServ.Calls)
# Declare the matrix
corrpvalues <- matrix(rep(0, 25),
   ncol = 5)
# Fill the matrix with correlations
for (i in 1:4) {
  for (j in (i+1):5) {
    corrpvalues[i,j] <- corrpvalues[j,i] <-
      round(cor.test(corrdata[,i],
        corrdata[,j])$p.value,
    4)
  }
}
round(cor(corrdata), 4)
corrpvalues
```

```
> round(cor(corrdata), 4)
        [,1]    [,2]    [,3]    [,4]    [,5]
[1,]  1.0000 -0.0046  0.0062  0.0385 -0.0038
[2,] -0.0046  1.0000  0.0008 -0.0095 -0.0133
[3,]  0.0062  0.0008  1.0000  0.0068 -0.0134
[4,]  0.0385 -0.0095  0.0068  1.0000 -0.0189
[5,] -0.0038 -0.0133 -0.0134 -0.0189  1.0000
> corrpvalues
       [,1]   [,2]   [,3]   [,4]   [,5]
[1,] 0.0000 0.7894 0.7198 0.0264 0.8266
[2,] 0.7894 0.0000 0.9642 0.5816 0.4440
[3,] 0.7198 0.9642 0.0000 0.6969 0.4385
[4,] 0.0264 0.5816 0.6969 0.0000 0.2743
[5,] 0.8266 0.4440 0.4385 0.2743 0.0000
```

REFERENCE

1. Blake, C.L. and Merz, C.J., *Churn Data Set*, UCI Repository of Machine Learning Databases, University of California, Department of Information and Computer Science, Irvine, CA, 1998, kdd.ics.uci.edu/. Accessed March 17, 2014.

EXERCISES

1. Explain the difference between EDA and hypothesis testing, and why analysts may prefer EDA when doing data mining.
2. Why do we need to perform exploratory data analysis? Why should not we simply proceed directly to the modeling phase and start applying our high powered data mining software?
3. Why do we use contingency tables, instead of just presenting the graphical results?
4. How can we find the marginal distribution of each variable in a contingency table?
5. What is the difference between taking row percentages and taking column percentages in a contingency table?
6. What is the graphical counterpart of a contingency table?
7. Describe what it would mean for interaction to take place between two categorical variables, using an example.
8. What type of histogram is useful for examining the relationship between a numerical predictor and the target?
9. Explain one benefit and one drawback of using a normalized histogram. Should we ever present a normalized histogram without showing its nonnormalized counterpart?
10. Explain whether we should omit a predictor from the modeling stage if it does not show any relationship with the target variable in the EDA stage, and why.
11. Describe how scatter plots can uncover patterns in two dimensions that would be invisible from one-dimensional EDA.
12. Make up a fictional data set (attributes with no records is fine) with a pair of anomalous attributes. Describe how EDA would help to uncover the anomaly.
13. Explain the objective and the method of binning based on predictive value.
14. Why is binning based on predictive value considered to be somewhat of an art?
15. What step should precede the deriving of a new numerical variable representing the mean of two other numerical variables?
16. What does it mean to say that two variables are correlated?
17. Describe the possible consequences of allowing correlated variables to remain in the model.
18. A common practice among some analysts when they encounter two correlated predictors is to omit one of them from the analysis. Is this practice recommended?
19. Describe the strategy for handing correlated predictor variables at the EDA stage.
20. For each of the following descriptive methods, state whether it may be applied to categorical data, continuous numerical data, or both.
    - **a.** Bar charts
    - **b.** Histograms
    - **c.** Summary statistics
    - **d.** Crosstabulations
    - **e.** Correlation analysis
    - **f.** Scatter plots
    - **g.** Web graphs
    - **h.** Binning

HANDS-ON ANALYSIS

21. Using the *churn* data set, develop EDA which shows that the remaining numeric variables in the data set (apart from those covered in the text above) indicate no obvious association with the target variable.

Use the *Adult* data set from the book series website for the following exercises. The target variable is *income*, and the goal is to classify income based on the other variables.

22. Which variables are categorical and which are continuous?
23. Using software, construct a table of the first 10 records of the data set, in order to get a feel for the data.