Territory Distributions

Keith Hickman

October 26, 2017

R Markdown

Intro:

This analysis presents several options for geographic distribution of territories using Revenue, Number of Accounts, and Types of Account by Industry. The data is loaded via three csv files.[1]

See Domo cards for Geographic Distribution.

Begin with loading required packages:

```
library(ggplot2)
library(DMwR2)
library(data.table)
library(readr)
territorydist <- read_csv("C:/Users/khickman/Desktop/Personal/IUMSDS/AppliedDataMining/territorydist.csv
```

```
## Parsed with column specification:
## cols(
##   territorycode = col_character(),
##   netivcamt = col_double(),
##   standardized = col_double()
## )
```

Summary of our first dataset:

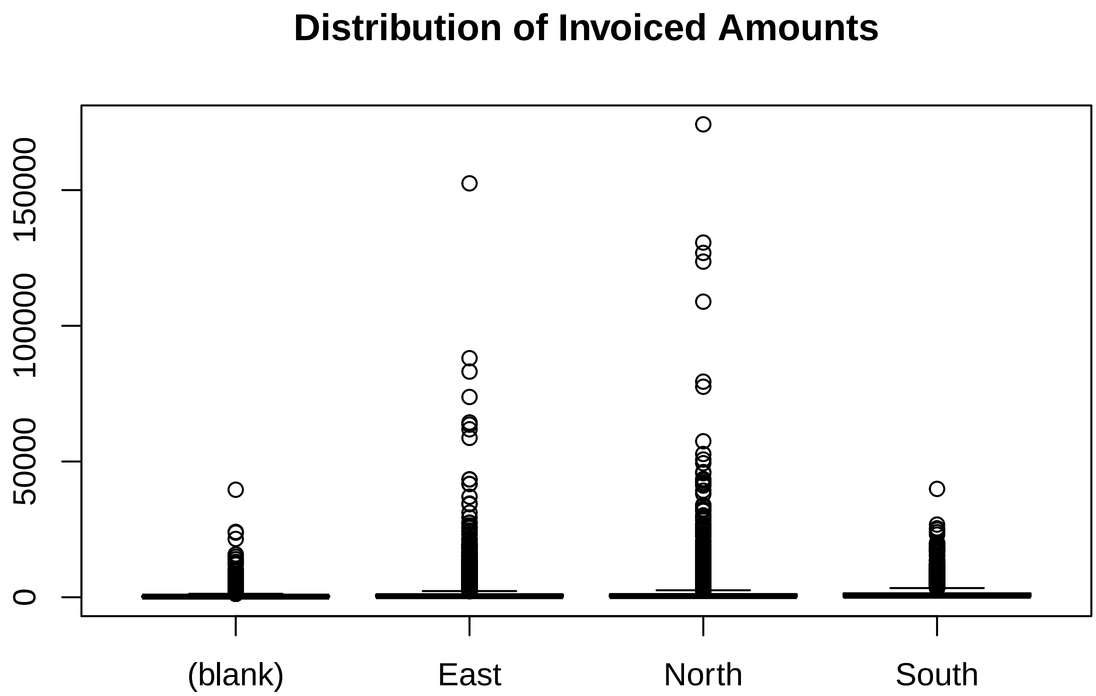
```
summary(territorydist)
```

```
##  territorycode        netivcamt         standardized
##  Length:24587       Min.   :     0.0   Min.   :-0.31817
##  Class :character   1st Qu.:   137.7   1st Qu.:-0.27949
##  Mode  :character   Median :   391.1   Median :-0.20833
##                     Mean   :  1132.9   Mean   : 0.00000
##                     3rd Qu.:  1028.2   3rd Qu.:-0.02938
##                     Max.   :174225.4   Max.   :48.61492
##                     NA's   :1          NA's   :3
```

Revenue Analysis:

We have 24584 observations of three variables as mentioned above. There are some obvious outliers as evidence by the Max values of the netivcamt. Additionally, we can tell that the $q3$ (3rd quartile) is represented lower than the mean, which will not be suitable as a statistic of centrality, as it's sensitive to outliers. We will use median instead going forward.

```
territorydist <- na.omit(territorydist)
boxplot(netivcamt ~ territorycode, territorydist, main="Distribution of Invoiced Amounts")
```



This box plot looks more like a bar chart, but there's some very interesting information here. The distribution of outliers (any values greater than 1.5x the Interquartile Range above $q3$ or below $q1$) clearly shows a much greater concentration of large invoiced amounts in the North and East Territories. The South territory is more aligned with out-of-territory sales.

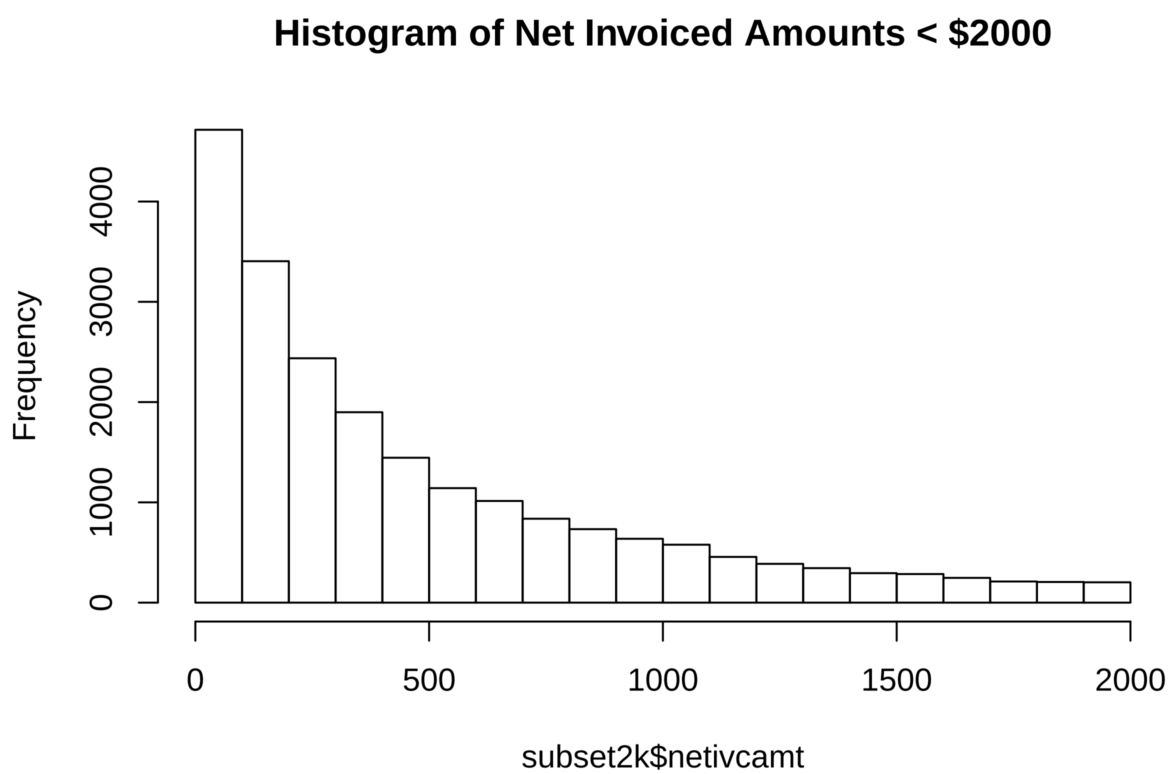
Dealing with outliers: Since this is such a skewed distribution, filtering rows (invoices) above a certain threshold in order to analyze more data is preferable. Typically, we would define outliers as given above. In this case, where even normalizing numbers does not provide a suitable distribution, we can create two classes and analyze those separately. Consider that most of our values (transactions) fall between 0 and 2000 dollars, which will represent the breakpoint for our classes. This still leaves us with 21,476 out of ~24,000 observations in the class under 2k.

```
subset2k <- subset(territorydist, netivcamt<2000)
subset2k
```

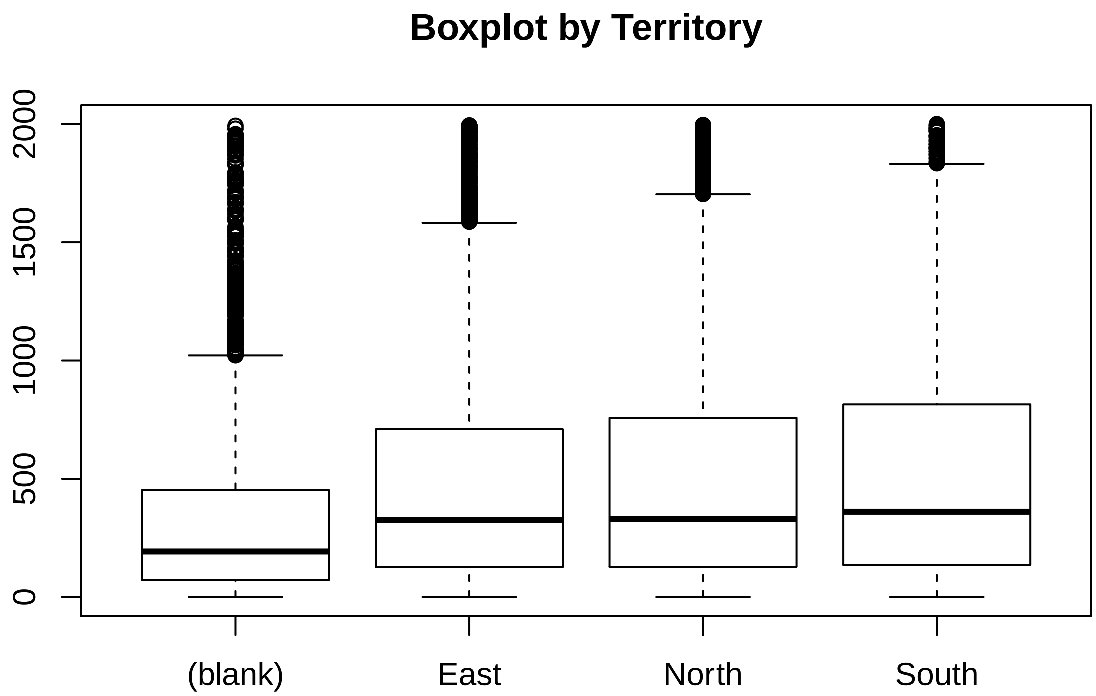
```
## # A tibble: 21,476 x 3
##    territorycode netivcamt standardized
##            <chr>     <dbl>        <dbl>
##  1          East      0.00   -0.3181689
##  2          East      1.00   -0.3178880
##  3          East      1.64   -0.3177083
##  4          East      1.77   -0.3176718
##  5          East      2.04   -0.3175959
##  6          East      2.10   -0.3175791
##  7          East      2.16   -0.3175622
##  8          East      2.40   -0.3174948
##  9          East      2.61   -0.3174359
## 10          East      2.67   -0.3174190
```

```
## # ... with 21,466 more rows
```

```r
hist(subset2k$netivcamt, main="Histogram of Net Invoiced Amounts < $2000")
```




```r
boxplot(subset2k$netivcamt ~ territorycode,subset2k, main="Boxplot by Territory")
```



The in-territory divisions look to be similarly distributed with respect to the $q1$, median, and $q3$ values. The overall number of transactions will likely explain the difference in the totals. The out-of-territory orders tend to be significantly smaller, with a $q3$ under 500 USD. Here, the median of all in-territory values tends to be the same, which would indicate that most of the transactions that happen across all three territories is the same, around $250.

Total number of transactions:

Time series data is also informative. Here, we'll examine monthly sales data from 1/1/2014 through 10/26/2017. Read in the data:

```
territorytime <- read_csv("C:/Users/khickman/Desktop/Personal/IUMSDS/AppliedDataMining/timeseries.csv")
```

```
## Parsed with column specification:
## cols(
##   Year = col_integer(),
##   Month = col_integer(),
##   East = col_double(),
##   North = col_double(),
##   South = col_double(),
##   OOT = col_double()
## )
```

```
summary(territorytime)
```

```
##       Year          Month             East             North
##  Min.   :2014   Min.   : 1.000   Min.   : 464047   Min.   :507030
##  1st Qu.:2014   1st Qu.: 3.250   1st Qu.: 541310   1st Qu.:578918
##  Median :2015   Median : 6.000   Median : 605006   Median :650957
```

```
##  Mean   :2015   Mean   : 6.283   Mean   : 625801   Mean   :661857
##  3rd Qu.:2016   3rd Qu.: 9.000   3rd Qu.: 670575   3rd Qu.:703714
##  Max.   :2017   Max.   :12.000   Max.   :1047061   Max.   :989420
##      South              OOT
##  Min.   : 82705   Min.   : 52975
##  1st Qu.:157676   1st Qu.: 80949
##  Median :195065   Median : 95181
##  Mean   :196677   Mean   :104256
##  3rd Qu.:234719   3rd Qu.:113116
##  Max.   :298438   Max.   :253198
```

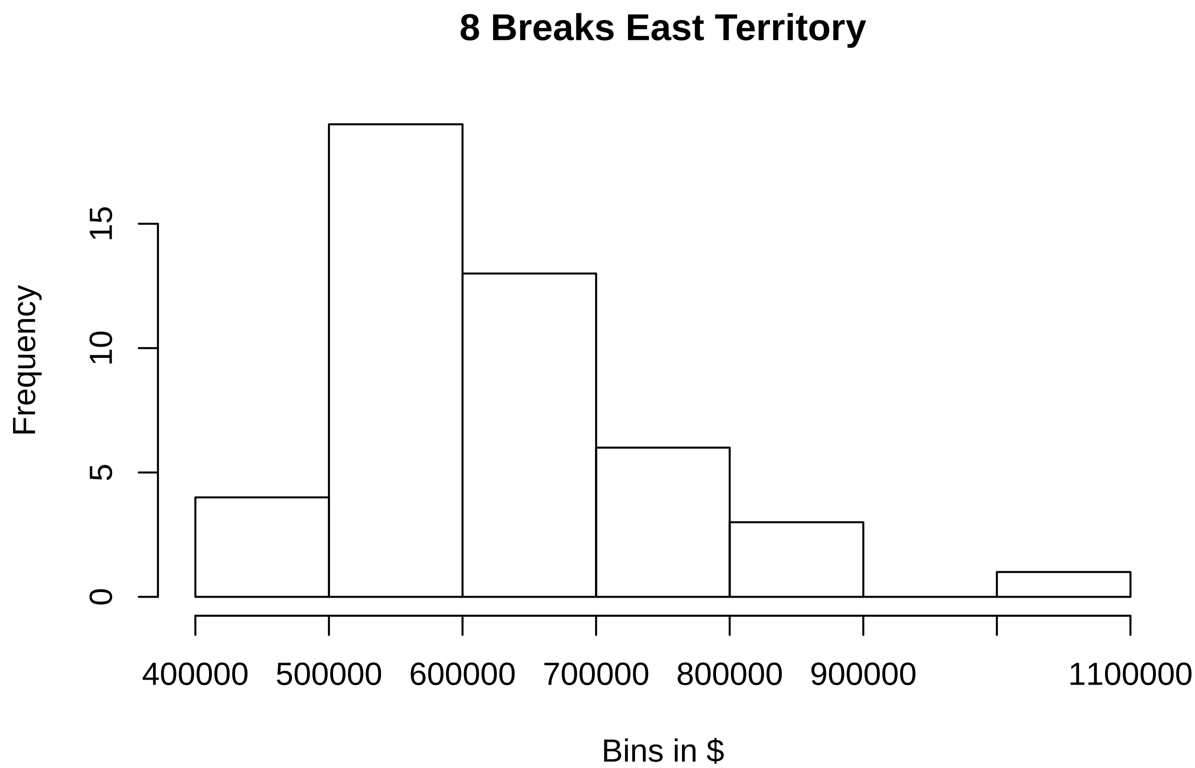
Modify the column data types:

```
territorytime$Year <- as.factor(territorytime$Year)
territorytime$Month <- as.factor(territorytime$Month)
summary(territorytime)
```

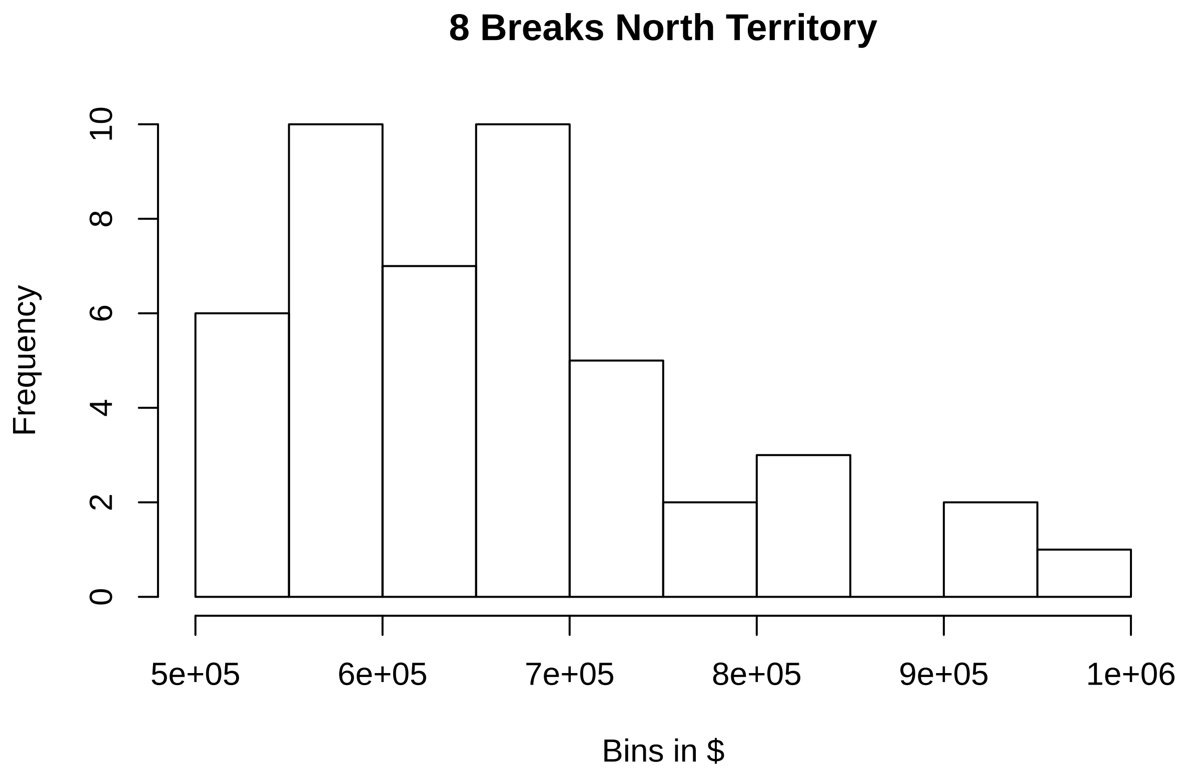
```
##    Year         Month          East              North
##  2014:12   1      : 4   Min.   : 464047   Min.   :507030
##  2015:12   2      : 4   1st Qu.: 541310   1st Qu.:578918
##  2016:12   3      : 4   Median : 605006   Median :650957
##  2017:10   4      : 4   Mean   : 625801   Mean   :661857
##            5      : 4   3rd Qu.: 670575   3rd Qu.:703714
##            6      : 4   Max.   :1047061   Max.   :989420
##            (Other):22
##      South              OOT
##  Min.   : 82705   Min.   : 52975
##  1st Qu.:157676   1st Qu.: 80949
##  Median :195065   Median : 95181
##  Mean   :196677   Mean   :104256
##  3rd Qu.:234719   3rd Qu.:113116
##  Max.   :298438   Max.   :253198
##
```

There are several ways to examine the data. Let's look at each territory's distribution of sales months. The bins represent

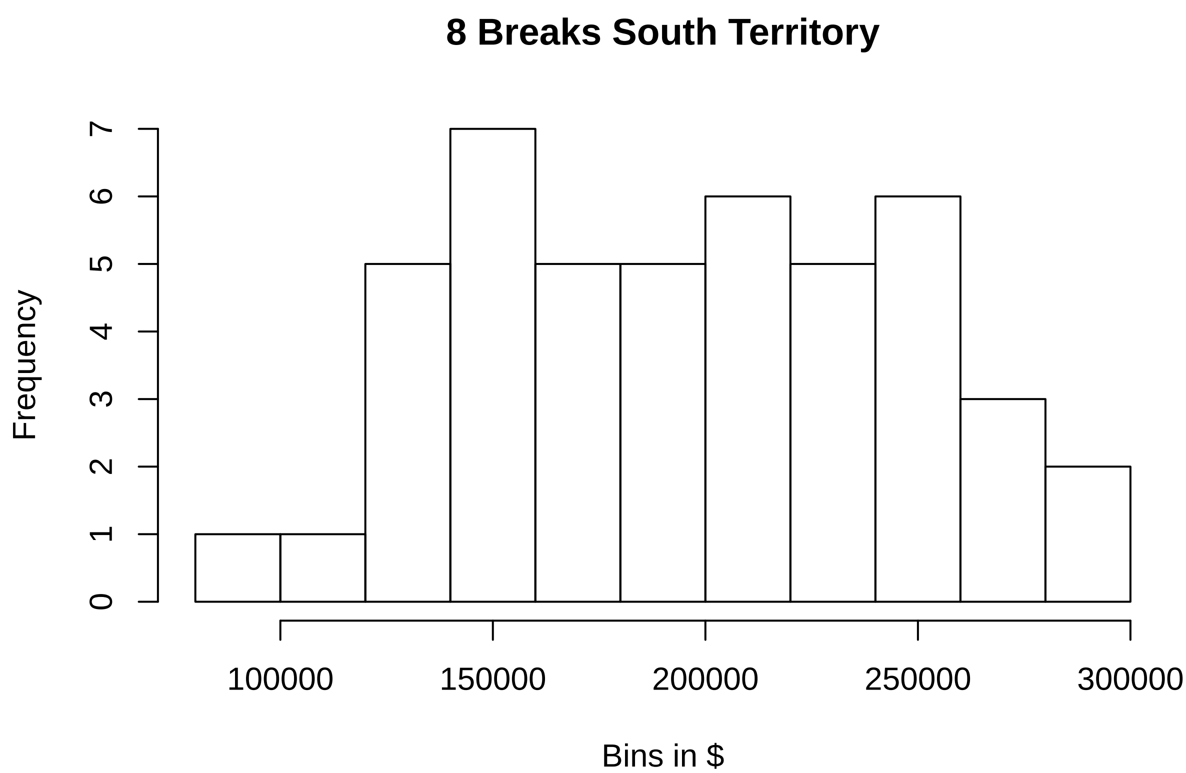
```
tt_east <- territorytime$East
tt_north <- territorytime$North
tt_south <- territorytime$South
tt_oot <- territorytime$OOT

hist(tt_east,breaks=8, main="8 Breaks East Territory",xlab="Bins in $")
```



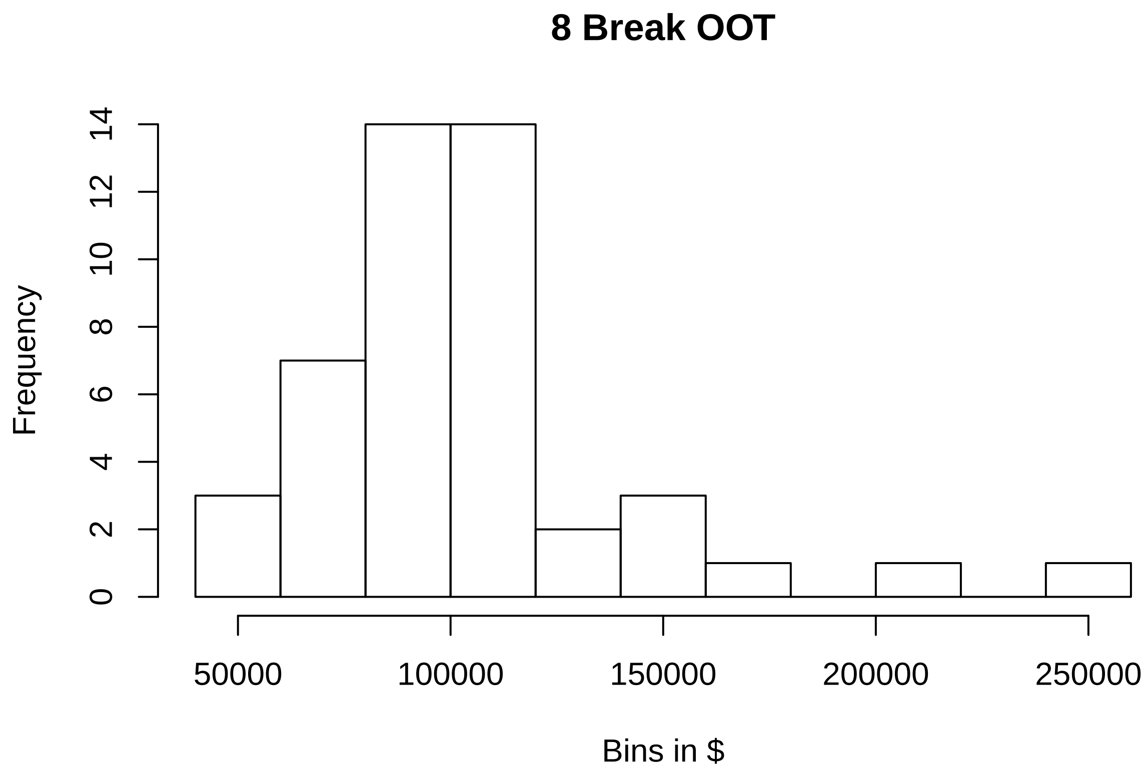

```
hist(tt_north, breaks=8, main = "8 Breaks North Territory",xlab="Bins in $")
```




```
hist(tt_south, breaks=8,main="8 Breaks South Territory",xlab="Bins in $")
```




```r
hist(tt_oot,breaks=8, main="8 Break OOT",xlab="Bins in $")
```



A history of monthly sales by territory. *Insert excel chart here* There has been a steady decline in the South territory, as well as a recent dip in sales for the East territory. No territory has had monthly sales of over $800,000 since late 2016. Beginning in mid-2016, the South and East have declined markedly, while North has remained steady.

```r
mean(tt_east)
```

```
## [1] 625800.5
```

```r
mean(tt_north)
```

```
## [1] 661856.8
```

```r
mean(tt_south)
```

```
## [1] 196676.9
```

```r
mean(tt_oot)
```

```
## [1] 104256.3
```

[1] The data files are territorydist, which contains a list of invoices and the respective territory codes; timeseries, which contains month and year invoiced amounts, and industry, which contains invoiced amounts by industry. Columns in this dataset include `'territorycode'`, `netivcamt`, and `standardized`. territorycode represents the current tagged geo location based on county. netivcamt is the amount of each transaction, with a row or observation representing one transaction (invoice). `standardized` is the normalized value of the netivcamt column.
Additionally, this data was extracted from Domo using the Account Master Zips and Fips dataset, with a filter applied to aggregate by transaction, and a date filter of > 1/1/2016 applied.