

Univariate Data Analysis Case I: Amazon Host Case

We will try and answer the following questions:

1. What are the major hosts contributing towards the count?
2. How valuable are these hosts?
3. Which one deserves the highest pay per click and which one the lowest?
4. How can you quantify the importance?
5. How much is the size of the effect?

```
> names(amazon)
[1] "Host"      "Count"      "Proportion"
> str(amazon)
'data.frame':    22 obs. of  3 variables:
 $ Host         : Factor w/ 22 levels "24hour-mall.com",...: 21 14 22 11 20 2 13 4
 5 7 ...
 $ Count        : int  89919 7258 6078 4381 4283 1639 1573 1289 1285 1166 ...
 $ Proportion: num  0.4758 0.0384 0.0322 0.0232 0.0227 ...
> tail(amazon)
      Host Count Proportion
17  netscape.com   544 0.00287837
18  dealtime.com   543 0.00287308
19    att.net     533 0.00282017
20 postcards.org   532 0.00281487
21 24hour-mall.com  503 0.00266143
22      Other 63229 0.33455205
```

The function `factor` is used to encode a vector as a factor. If the argument `ordered = TRUE`, the factor levels are assumed to be ordered. We can combine the last 11 sources also into other hosts as they are not varied much. We need to first choose the required rows to remain and then concatenate them into other hosts. Then we need to fix the count variable, by aggregating the remaining and then the same for proportion. Finally let us order the data set by count.

```
> sorted
      Host Count Proportion
11      imdb.com   886 0.004687930
10 daily-blessings.com 1166 0.006169443
9      bmezzine.com 1285 0.006799086
8      atwola.com 1289 0.006820250
7      iwona.com 1573 0.008322927
6      aol.com 1639 0.008672141
5  recipesource.com 4283 0.022661855
4      google.com 4381 0.023180385
3      yahoo.com 6078 0.032159411
2      msn.com 7258 0.038402929
12    other hosts 69239 0.366351669
1 Typed amazon.com 89919 0.475771974
```

1. What are the major hosts contributing towards the count?

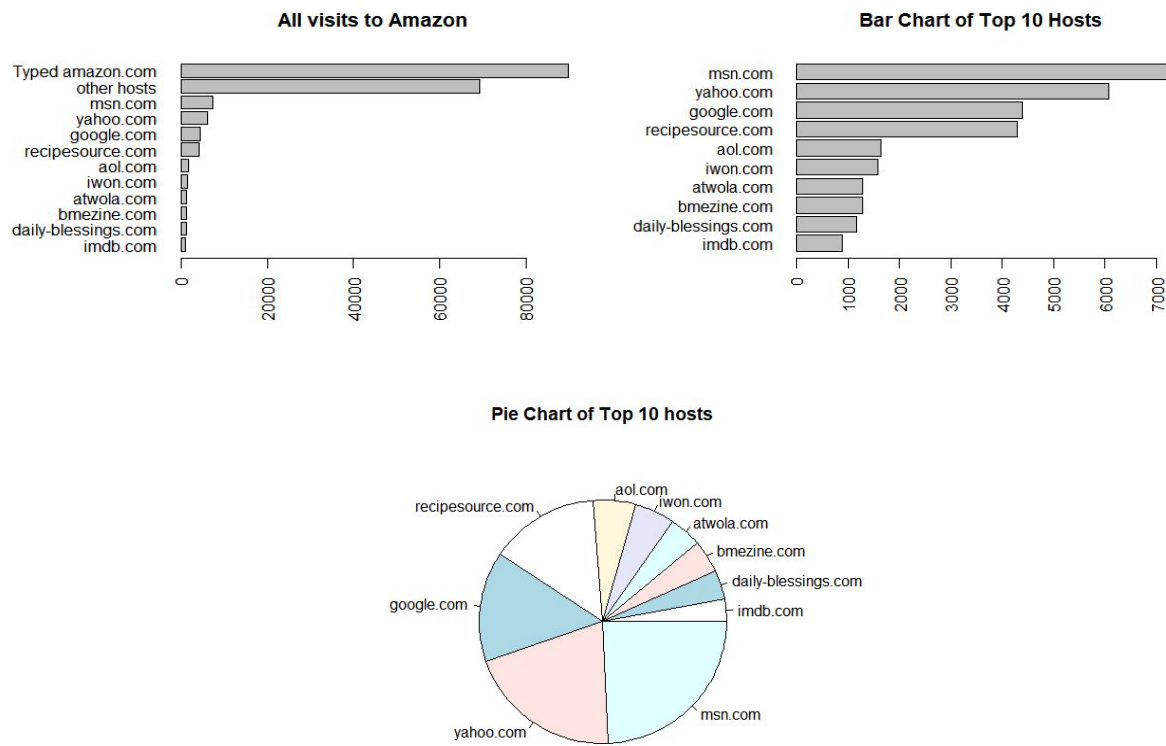
Now let us plot a bar graph to see where we stand:

```
> barplot(sorted$Count, names.arg = sorted$Host, horiz = TRUE, las = 2, main = "All visits to Amazon")
```

From this plot you can't really tell much as other plots are dominant. Hence we try and ignore 'other hosts'.

```
> barplot(sorted$Count[1:10], names.arg = sorted$Host[1:10], horiz = TRUE, las=2, main='Bar Chart of Top 10 Hosts')
```

```
> pie(sorted$Count[1:10], sorted$Host[1:10], main='Pie Chart of Top 10 hosts')
```



The above charts explain the major hosts. Since the dataset consists of categorical variables let us look into mosaic plot. We will be using the **library(gmodels)** library for the same. For this we will use a different dataset specific to understanding how host purchases differ.

```
> names(host_purchase)
```

```
[1] "host"      "purchase"
```

```
> str(host_purchase)
```

```
'data.frame':    17619 obs. of  2 variables:
```

```
 $ host      : Factor w/ 3 levels "msn.com","recipesource.com",...: 1 1 1 3 3...
```

```
 $ purchase: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
> summary(host_purchase)
```

```
      host      purchase
msn.com      :7258      Yes:  516
recipesource.com:4283     No :17103
yahoo.com      :6078
```

Now let us create a contingency table to feed into the mosaic plot.

2. How valuable are these hosts?
3. Which one deserves the highest pay per click and which one the lowest?

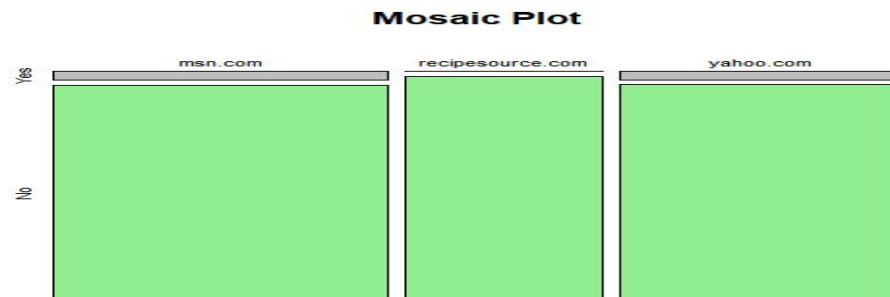
```
> host_table = CrossTable(host_purchase$purchase, host_purchase$host,
prop.chisq = F, prop.c = F, prop.t = F)
```

```
Cell Contents
|-----|
|              N |
| N / Row Total |
|-----|
```

Total Observations in Table: 17619

host_purchase\$purchase	host_purchase\$host			Row Total
	msn.com	recipesource.com	yahoo.com	
Yes	285	1	230	516
	0.552	0.002	0.446	0.029
No	6973	4282	5848	17103
	0.408	0.250	0.342	0.971
Column Total	7258	4283	6078	17619

```
> mosaicplot(host_table$t, color = c("grey","lightgreen"), xlab = "Host", ylab = "Purchase", main = "Mosaic Plot")
```



4. How can you quantify the importance?

We need to quantify this impact to see if it is real or by chance by conducting hypothesis testing:

$$H_0 : \text{Host does not affect Purchase}$$

$$H_0 : \text{Host affects Purchase}$$

```
> chisq.test(host_purchase$host, host_purchase$purchase)
```

Pearson's Chi-squared test

data: host_purchase\$host and host_purchase\$purchase

X-squared = 168.24, df = 2, p-value < 2.2e-16

Since the p-value is lower than 0.5% significance level we need to reject the null hypothesis and conclude that the host does indeed affect the Purchase. Now let us further explore as to which host contributes more.

```
> chisq.test(msnrecipe$host, msnrecipe$purchase)
Pearson's Chi-squared test with Yates'
continuity correction
```

data: msnrecipe\$host and msnrecipe\$purchase
X-squared = 168.2, df = 1, p-value < 2.2e-16

Since the p-value is lower than 0.5% significance level we need to reject the null hypothesis and conclude that the host does indeed affect the Purchase. Now let us look into msn and yahoo.

```
> chisq.test(msnyahoo$host, msnyahoo$purchase)
Pearson's Chi-squared test with Yates'
continuity correction
```

data: msnyahoo\$host and msnyahoo\$purchase
X-squared = 0.14472, df = 1, p-value = 0.7036

In this case, we need to accept the null hypothesis as the p-value is above the significance level of 0.5%.

Hence these tests reveal that:

1. Msn and Recipesource have different impacts on purchase.
2. There is no statistically significant difference between msn and yahoo.

Now let us look into the size of effect by looking at their confidence intervals. Let us look into one sample t-test to test whether a population mean is significantly different from some hypothesized value.

```
> t.test(as.numeric(host_msn$purchase=="Yes"))
One Sample t-test
```

data: as.numeric(host_msn\$purchase == "Yes")
t = 17.222, df = 7257, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
0.03479753 0.04373650
sample estimates:
mean of x
0.03926702

```
> t.test(as.numeric(host_recipesource$purchase=="Yes"))
One Sample t-test
```

data: as.numeric(host_recipesource\$purchase == "Yes")
t = 1, df = 4282, p-value = 0.3174

```

alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.0002242629  0.0006912253
sample estimates:
 mean of x
0.0002334812
> t.test(as.numeric(host_yahoo$purchase=="Yes"))
One Sample t-test

```

```

data: as.numeric(host_yahoo$purchase == "Yes")
t = 15.46, df = 6077, p-value < 2.2e-16
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 0.03304299 0.04263980
sample estimates:
mean of x
0.0378414

```

5. How much is the size of the effect?

We cannot use p-value for size. We need to use Confidence Intervals.

```

> t.test(msnrecipe.purchase ~ msnrecipe$host)
Welch Two Sample t-test

```

```

data: msnrecipe.purchase by msnrecipe$host
t = 17.031, df = 7408.6, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.03454069 0.04352638
sample estimates:
 mean in group msn.com
0.0392670157
mean in group recipesource.com
0.0002334812

```

Hence the 95% CI for Prob(msn) - Prob(recipesource)

```

> t.test(msnyahoo.purchase ~ msnyahoo$host)
Welch Two Sample t-test
data: msnyahoo.purchase by msnyahoo$host
t = 0.42618, df = 13001, p-value = 0.67
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.005131295  0.007982536
sample estimates:
 mean in group msn.com mean in group yahoo.com
0.03926702             0.03784140

```