

Statistics

Introduction to R for Public Health Researchers

Statistics

Now we are going to cover how to perform a variety of basic statistical tests in R.

- Correlation
- T-tests/Rank-sum tests
- Linear Regression
- Logistic Regression
- Proportion tests
- Chi-squared
- Fisher's Exact Test

Note: We will be glossing over the statistical theory and “formulas” for these tests. There are plenty of resources online for learning more about these tests, as well as dedicated Biostatistics series at the School of Public Health

Correlation

`cor()` performs correlation in R

```
cor(x, y = NULL, use = "everything",  
    method = c("pearson", "kendall", "spearman"))
```

Like other functions, if there are NAs, you get NA as the result. But if you specify use only the complete observations, then it will give you correlation on the non-missing data.

```
library(readr)  
circ = read_csv("http://johnmuschelli.com/intro_to_r/data/Charm_City_Circulator")  
cor(circ$orangeAverage, circ$purpleAverage, use="complete.obs")
```

```
[1] 0.9195356
```

Correlation with **corrr**

The `corrr` package allows you to do correlations easily:

```
library(corrr); library(dplyr)
circ %>%
  select(orangeAverage, purpleAverage) %>%
  correlate()
```

Correlation method: 'pearson'

Missing treated using: 'pairwise.complete.obs'

```
# A tibble: 2 x 3
  term                orangeAverage purpleAverage
<chr>                <dbl>          <dbl>
1 orangeAverage      NA              0.920
2 purpleAverage      0.920            NA
```

Correlation

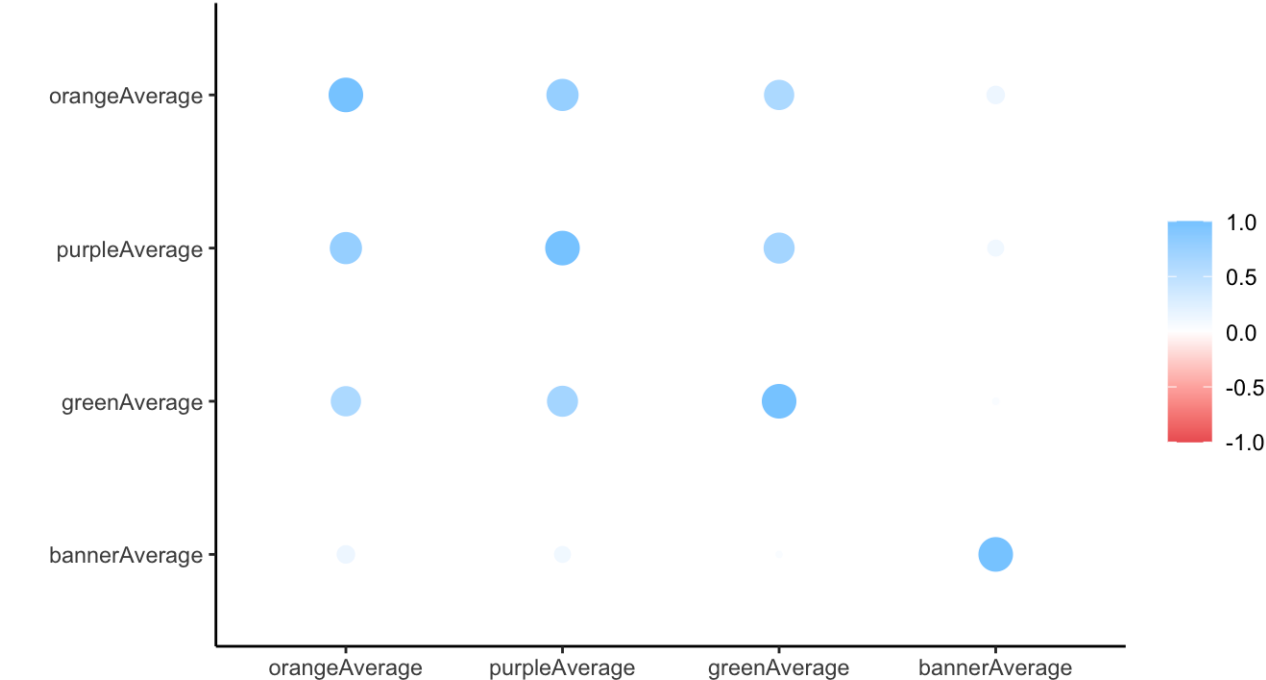
`correlate` is usually better with more than 2 columns:

```
avgs = circ %>% select(ends_with("Average"))
cobj = avgs %>% correlate(use = "complete.obs", diagonal = 1)
cobj %>% fashion(decimals = 3)
```

| | term | orangeAverage | purpleAverage | greenAverage | bannerAverage |
|---|---------------|---------------|---------------|--------------|---------------|
| 1 | orangeAverage | 1.000 | .908 | .840 | .545 |
| 2 | purpleAverage | .908 | 1.000 | .867 | .521 |
| 3 | greenAverage | .840 | .867 | 1.000 | .453 |
| 4 | bannerAverage | .545 | .521 | .453 | 1.000 |

Correlation

```
cobj %>% rplot()
```



Correlation

You can also use `cor.test()` to test for whether correlation is significant (ie non-zero). Note that linear regression may be better, especially if you want to regress out other confounders.

```
ct = cor.test(circ$orangeAverage, circ$purpleAverage,  
              use = "complete.obs")  
ct
```

Pearson's product-moment correlation

```
data:  circ$orangeAverage and circ$purpleAverage  
t = 73.656, df = 991, p-value < 2.2e-16  
alternative hypothesis: true correlation is not equal to 0  
95 percent confidence interval:  
 0.9093438 0.9286245  
sample estimates:  
      cor  
0.9195356
```

Correlation

For many of these testing result objects, you can extract specific slots/results as numbers, as the `ct` object is just a list.

```
# str(ct)
names(ct)
```

```
[1] "statistic"  "parameter"  "p.value"    "estimate"   "null.value"
[6] "alternative" "method"     "data.name"  "conf.int"
```

```
ct$statistic
```

```
      t
73.65553
```

```
ct$p.value
```

```
[1] 0
```


Broom package

The `broom` package has a `tidy` function that puts most objects into `data.frames` so that they are easily manipulated:

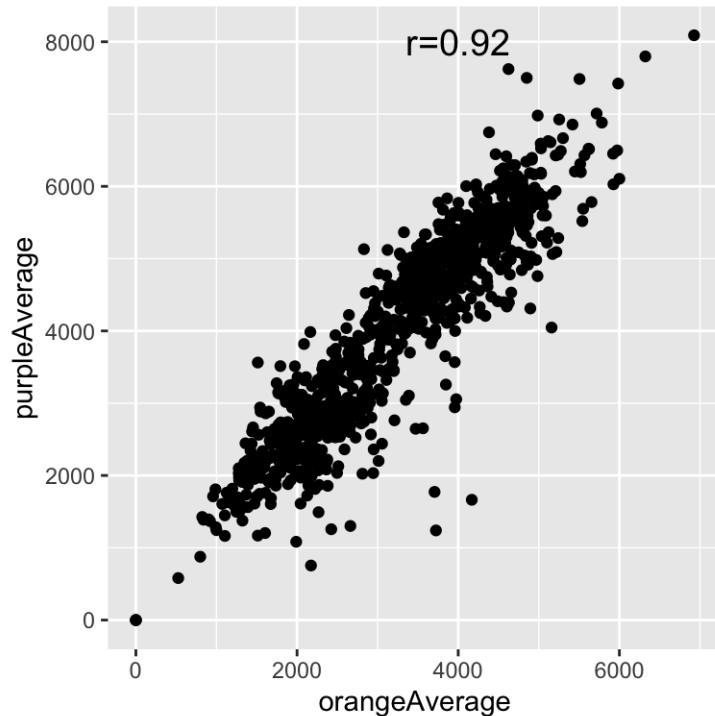
```
library(broom)
tidy_ct = tidy(ct)
tidy_ct
```

```
# A tibble: 1 x 8
  estimate statistic p.value parameter conf.low conf.high method      alternati
  <dbl>      <dbl>   <dbl>      <int>    <dbl>    <dbl> <chr>      <chr>
1   0.920       73.7     0         991    0.909    0.929 Pearson's... two.sided
```

Correlation

Note that you can add the correlation to a plot, via the `annotate`

```
library(ggplot2)
txt = paste0("r=", signif(ct$estimate, 3))
q = ggplot(data = circ, x = orangeAverage, y = purpleAverage)
q + annotate("text", x = 4000, y = 8000, label = txt, size = 5)
```



T-tests

The T-test is performed using the `t.test()` function, which essentially tests for the difference in means of a variable between two groups.

In this syntax, `x` and `y` are the column of data for each group.

```
tt = t.test(circ$orangeAverage, circ$purpleAverage)
tt
```

Welch Two Sample t-test

```
data:  circ$orangeAverage and circ$purpleAverage
t = -17.076, df = 1984, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1096.7602  -870.7867
sample estimates:
mean of x mean of y
 3033.161  4016.935
```

T-tests

Using `t.test` treats the data as independent. Realistically, this data should be treated as a paired t-test. The `paired = TRUE` argument to do a paired test

```
t.test(circ$orangeAverage, circ$purpleAverage, paired = TRUE)
```

Paired t-test

```
data:  circ$orangeAverage and circ$purpleAverage
t = -42.075, df = 992, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -799.783 -728.505
sample estimates:
mean of the differences
      -764.144
```

T-tests

`t.test` saves a lot of information: the difference in means `estimate`, confidence interval for the difference `conf.int`, the p-value `p.value`, etc.

```
names(tt)
```

```
[1] "statistic"    "parameter"    "p.value"      "conf.int"     "estimate"
[6] "null.value"   "stderr"       "alternative"   "method"       "data.name"
```

T-tests

```
tidy(tt)
```

```
# A tibble: 1 x 10
  estimate estimate1 estimate2 statistic  p.value parameter conf.low conf.high
  <dbl>      <dbl>      <dbl>      <dbl>    <dbl>      <dbl>      <dbl>      <dbl>
1   -984.      3033.      4017.     -17.1 4.20e-61     1984.    -1097.    -871.
# ... with 2 more variables: method <chr>, alternative <chr>
```

T-tests

You can also use the 'formula' notation. In this syntax, it is $y \sim x$, where x is a factor with 2 levels or a binary variable and y is a vector of the same length.

```
library(tidyr)
long = circ %>%
  select(date, orangeAverage, purpleAverage) %>%
  pivot_longer(!date, names_to = "line", values_to = "avg")
tt = t.test(avg ~ line, data = long)
tidy(tt)
```

```
# A tibble: 1 x 10
  estimate estimate1 estimate2 statistic  p.value parameter conf.low conf.high
  <dbl>      <dbl>      <dbl>      <dbl>    <dbl>      <dbl>      <dbl>      <dbl>
1   -984.      3033.      4017.     -17.1 4.20e-61    1984.     -1097.     -871.
# ... with 2 more variables: method <chr>, alternative <chr>
```

Wilcoxon Rank-Sum Tests

Nonparametric analog to t-test (testing medians):

```
tidy(wilcox.test(avg ~ line, data = long))
```

```
# A tibble: 1 x 4  
  statistic p.value method alternative  
    <dbl>    <dbl> <chr>      <chr>  
1 336714. 4.56e-58 Wilcoxon rank sum test with continuity correct... two.sided
```


Lab Part 1

[Website](#)

Analysis of Variance

The `aov` function exists for ANOVA, but we'd recommend `lm` (Linear models):

```
long3 = circ %>%  
  select(date, orangeAverage, purpleAverage, bannerAverage) %>%  
  pivot_longer(!date, names_to = "line", values_to = "avg")  
anova_res = aov(avg ~ line, data = long3)  
anova_res
```

Call:

```
aov(formula = avg ~ line, data = long3)
```

Terms:

| | line | Residuals |
|-----------------|------------|------------|
| Sum of Squares | 2214242251 | 3724379811 |
| Deg. of Freedom | 2 | 2396 |

Residual standard error: 1246.762

Estimated effects may be unbalanced

1039 observations deleted due to missingness

Linear Regression

Now we will briefly cover linear regression. I will use a little notation here so some of the commands are easier to put in the proper context.

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

where:

- y_i is the outcome for person i
- α is the intercept
- β is the slope
- x_i is the predictor for person i
- ε_i is the residual variation for person i

Linear Regression

The R version of the regression model is:

$y \sim x$

where:

- y is your outcome
- x is/are your predictor(s)

Linear Regression

For a linear regression, when the predictor is binary this is the same as a t-test:

```
fit = lm(avg ~ line, data = long)
fit
```

Call:

```
lm(formula = avg ~ line, data = long)
```

Coefficients:

| | |
|-------------|-------------------|
| (Intercept) | linepurpleAverage |
| 3033.2 | 983.8 |

'(Intercept)' is α

'linepurpleAverage' is β

Linear Regression

```
fit = lm(avg ~ line, data = long3)
fit
```

Call:

```
lm(formula = avg ~ line, data = long3)
```

Coefficients:

| | | |
|-------------|-------------------|-------------------|
| (Intercept) | lineorangeAverage | linepurpleAverage |
| 827.3 | 2205.9 | 3189.7 |

Linear Regression

The `summary` command gets all the additional information (p-values, t-statistics, r-square) that you usually want from a regression.

```
sfit = summary(fit)
print(sfit)
```

Call:

```
lm(formula = avg ~ line, data = long3)
```

Residuals:

| Min | 1Q | Median | 3Q | Max |
|---------|---------|--------|-------|--------|
| -4016.9 | -1008.4 | 5.6 | 973.1 | 4072.6 |

Coefficients:

| | Estimate | Std. Error | t value | Pr(> t) | |
|-------------------|----------|------------|---------|----------|-----|
| (Intercept) | 827.27 | 75.88 | 10.90 | <2e-16 | *** |
| lineorangeAverage | 2205.89 | 84.41 | 26.13 | <2e-16 | *** |
| linepurpleAverage | 3189.67 | 85.57 | 37.27 | <2e-16 | *** |

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

Residual standard error: 1247 on 2396 degrees of freedom
(1039 observations deleted due to missingness)

Multiple R-squared: 0.3729, Adjusted R-squared: 0.3723

F-statistic: 712.2 on 2 and 2396 DF, p-value: < 2.2e-16

Linear Regression

We can `tidy` linear models as well and it gives us all of this in a tibble:

```
tidy(fit)
```

```
# A tibble: 3 x 5
  term                estimate std.error statistic    p.value
  <chr>              <dbl>    <dbl>    <dbl>    <dbl>
1 (Intercept)         827.      75.9      10.9 4.76e- 27
2 lineorangeAverage  2206.      84.4      26.1 1.16e-132
3 linepurpleAverage  3190.      85.6      37.3 2.98e-240
```


Linear Regression

The `confint` argument allows for confidence intervals

```
tidy(fit, conf.int = TRUE)
```

```
# A tibble: 3 x 7
  term                estimate std.error statistic    p.value conf.low conf.high
  <chr>              <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
1 (Intercept)        827.      75.9     10.9 4.76e- 27     678.     976.
2 lineorangeAverage  2206.      84.4     26.1 1.16e-132    2040.    2371.
3 linepurpleAverage  3190.      85.6     37.3 2.98e-240    3022.    3357.
```

Using Cars Data

```
http_data_dir = "http://johnmuschelli.com/intro_to_r/data/"
cars = read_csv(
  paste0(http_data_dir, "kaggleCarAuction.csv"),
  col_types = cols(VehBCost = col_double()))
head(cars)
```

```
# A tibble: 6 x 34
  RefId IsBadBuy PurchDate Auction VehYear VehicleAge Make Model Trim SubMod
  <dbl>   <dbl>   <chr>    <chr>    <dbl>    <dbl> <chr> <chr> <chr> <chr>
1     1       0 12/7/2009 ADESA      2006         3 MAZDA MAZD... i 4D SED
2     2       0 12/7/2009 ADESA      2004         5 DODGE 1500... ST QUAD C
3     3       0 12/7/2009 ADESA      2005         4 DODGE STRA... SXT 4D SED
4     4       0 12/7/2009 ADESA      2004         5 DODGE NEON   SXT 4D SED
5     5       0 12/7/2009 ADESA      2005         4 FORD  FOCUS  ZX3 2D COU
6     6       0 12/7/2009 ADESA      2004         5 MITS... GALA... ES 4D SED
# ... with 24 more variables: Color <chr>, Transmission <chr>, WheelTypeID <chr>,
# WheelType <chr>, VehOdo <dbl>, Nationality <chr>, Size <chr>,
# TopThreeAmericanName <chr>, MMRAcquisitionAuctionAveragePrice <chr>,
# MMRAcquisitionAuctionCleanPrice <chr>,
# MMRAcquisitionRetailAveragePrice <chr>,
# MMRAcquisitonRetailCleanPrice <chr>, MMRCurrentAuctionAveragePrice <chr>,
# MMRCurrentAuctionCleanPrice <chr>, MMRCurrentRetailAveragePrice <chr>,
# MMRCurrentRetailCleanPrice <chr>, PRIMEUNIT <chr>, AUCGUART <chr>,
# BYRNO <dbl>, VNZIP1 <dbl>, VNST <chr>, VehBCost <dbl>, IsOnlineSale <dbl>,
# WarrantyCost <dbl>
```

Linear Regression

We'll look at vehicle odometer value by vehicle age:

```
fit = lm(VehOdo~VehicleAge, data = cars)
print(fit)
```

Call:

```
lm(formula = VehOdo ~ VehicleAge, data = cars)
```

Coefficients:

| | |
|-------------|------------|
| (Intercept) | VehicleAge |
| 60127 | 2723 |

Linear Regression

Note that you can have more than 1 predictor in regression models. The interpretation for each slope is change in the predictor corresponding to a one-unit change in the outcome, holding all other predictors constant.

```
fit2 = lm(VehOdo ~ IsBadBuy + VehicleAge, data = cars)
tidy(fit2)
```

```
# A tibble: 3 x 5
  term          estimate std.error statistic  p.value
<chr>         <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)  60142.        135.      446.      0
2 IsBadBuy      1329.        158.       8.42 3.83e-17
3 VehicleAge    2680.         30.3      88.5      0
```

Linear Regression: Interactions

The * does interactions:

```
fit3 = lm(VehOdo ~ IsBadBuy * VehicleAge, data = cars)
tidy(fit3)
```

```
# A tibble: 4 x 5
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> |
|---|---------------------|-------------------|--------------------|--------------------|------------------|
| 1 | (Intercept) | 60140. | 143. | 420. | 0 |
| 2 | IsBadBuy | 1347. | 456. | 2.95 | 0.00315 |
| 3 | VehicleAge | 2681. | 32.5 | 82.4 | 0 |
| 4 | IsBadBuy:VehicleAge | -3.79 | 88.7 | -0.0427 | 0.966 |

Linear Regression: Interactions

You can take out main effects with minus

```
fit4 = lm(VehOdo ~ IsBadBuy * VehicleAge -IsBadBuy , data = cars)
tidy(fit4)
```

```
# A tibble: 3 x 5
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> |
|---|---------------------|-------------------|--------------------|--------------------|------------------|
| 1 | (Intercept) | 60272. | 136. | 443. | 0 |
| 2 | VehicleAge | 2653. | 31.1 | 85.2 | 0 |
| 3 | IsBadBuy:VehicleAge | 242. | 30.7 | 7.89 | 3.19e-15 |

Linear Regression

Factors get special treatment in regression models - lowest level of the factor is the comparison group, and all other factors are relative to its values.

```
fit3 = lm(VehOdo ~ factor(TopThreeAmericanName), data = cars)
tidy(fit3)
```

```
# A tibble: 5 x 5
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> |
|---|------------------------------------|-------------------|--------------------|--------------------|------------------|
| 1 | (Intercept) | 68248. | 93.0 | 734. | 0 |
| 2 | factor(TopThreeAmericanName) FORD | 8523. | 158. | 53.8 | 0 |
| 3 | factor(TopThreeAmericanName) GM | 4952. | 129. | 38.4 | 2.74e-319 |
| 4 | factor(TopThreeAmericanName) NULL | -2005. | 6362. | -0.315 | 7.53e- 1 |
| 5 | factor(TopThreeAmericanName) OTHER | 585. | 160. | 3.66 | 2.55e- 4 |

Logistic Regression and GLMs

Generalized Linear Models (GLMs) allow for fitting regressions for non-continuous/normal outcomes. The `glm` has similar syntax to the `lm` command. Logistic regression is one example. See `?family` for

```
glmfit = glm(IsBadBuy ~ VehOdo + VehicleAge, data=cars, family = binomial())
tidy(glmfit)
```

```
# A tibble: 3 x 5
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> |
|---|---------------|-------------------|--------------------|--------------------|------------------|
| 1 | (Intercept) | -3.78 | 0.0638 | -59.2 | 0 |
| 2 | VehOdo | 0.00000834 | 0.000000853 | 9.78 | 1.33e-22 |
| 3 | VehicleAge | 0.268 | 0.00677 | 39.6 | 0 |

Tidying GLMs

```
tidy(glmfit, conf.int = TRUE)
```

```
# A tibble: 3 x 7
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> | conf.low <dbl> | conf.hic <dbl> |
|---|---------------|-------------------|--------------------|--------------------|------------------|-------------------|-------------------|
| 1 | (Intercept) | -3.78 | 0.0638 | -59.2 | 0 | -3.90 | -3.65 |
| 2 | VehOdo | 0.00000834 | 0.000000853 | 9.78 | 1.33e-22 | 0.00000667 | 0.000010 |
| 3 | VehicleAge | 0.268 | 0.00677 | 39.6 | 0 | 0.255 | 0.281 |

Tidying GLMs

```
tidy(glmfit, conf.int = TRUE, exponentiate = TRUE)
```

```
# A tibble: 3 x 7
```

| | term <chr> | estimate <dbl> | std.error <dbl> | statistic <dbl> | p.value <dbl> | conf.low <dbl> | conf.high <dbl> |
|---|---------------|-------------------|--------------------|--------------------|------------------|-------------------|--------------------|
| 1 | (Intercept) | 0.0229 | 0.0638 | -59.2 | 0 | 0.0202 | 0.0259 |
| 2 | VehOdo | 1.00 | 0.0000000853 | 9.78 | 1.33e-22 | 1.00 | 1.00 |
| 3 | VehicleAge | 1.31 | 0.00677 | 39.6 | 0 | 1.29 | 1.32 |

Logistic Regression

Note the coefficients are on the original scale, we must exponentiate them for odds ratios:

```
exp(coef(glmfit))
```

| (Intercept) | VehOdo | VehicleAge |
|-------------|------------|------------|
| 0.02286316 | 1.00000834 | 1.30748911 |

Chi-squared tests

`chisq.test()` performs chi-squared contingency table tests and goodness-of-fit tests.

```
chisq.test(x, y = NULL, correct = TRUE,  
          p = rep(1/length(x), length(x)), rescale.p = FALSE,  
          simulate.p.value = FALSE, B = 2000)
```

```
tab = table(cars$IsBadBuy, cars$IsOnlineSale)  
tab
```

| | 0 | 1 |
|---|-------|------|
| 0 | 62375 | 1632 |
| 1 | 8763 | 213 |

Chi-squared tests

You can also pass in a table object (such as `tab` here)

```
cq = chisq.test(tab)
cq
```

Pearson's Chi-squared test with Yates' continuity correction

```
data: tab
X-squared = 0.92735, df = 1, p-value = 0.3356
```

```
names(cq)
```

```
[1] "statistic" "parameter" "p.value"    "method"    "data.name" "observed"
[7] "expected"  "residuals" "stdres"
```

```
cq$p.value
```

```
[1] 0.3355516
```

Chi-squared tests

Note that does the same test as `prop.test`, for a 2x2 table (`prop.test` not relevant for greater than 2x2).

```
chisq.test(tab)
```

Pearson's Chi-squared test with Yates' continuity correction

```
data:  tab
X-squared = 0.92735, df = 1, p-value = 0.3356
```

```
prop.test(tab)
```

2-sample test for equality of proportions with continuity correction

```
data:  tab
X-squared = 0.92735, df = 1, p-value = 0.3356
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.005208049  0.001673519
sample estimates:
   prop 1    prop 2 
0.9745028 0.9762701
```

Fisher's Exact test

`fisher.test()` performs contingency table test using the hypogeometric distribution (used for small sample sizes).

```
fisher.test(x, y = NULL, workspace = 200000, hybrid = FALSE,  
            control = list(), or = 1, alternative = "two.sided",  
            conf.int = TRUE, conf.level = 0.95,  
            simulate.p.value = FALSE, B = 2000)
```

```
fisher.test(tab)
```

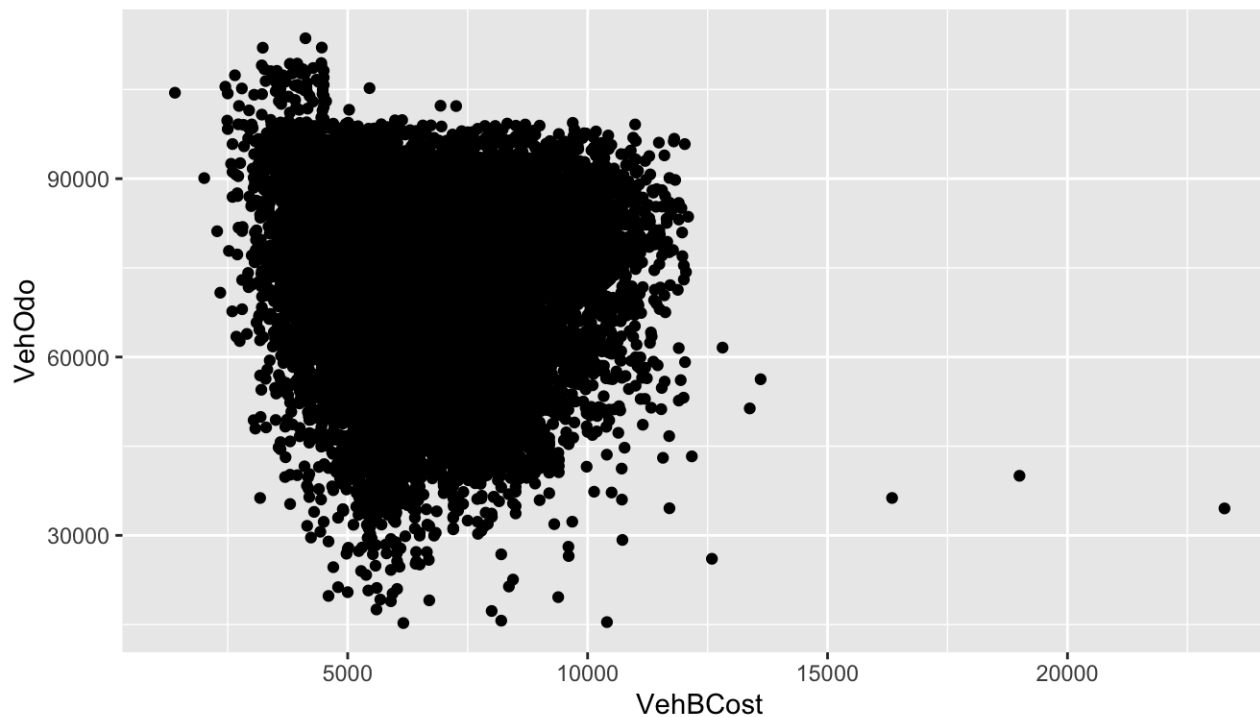
Fisher's Exact Test for Count Data

```
data:  tab  
p-value = 0.3324  
alternative hypothesis: true odds ratio is not equal to 1  
95 percent confidence interval:  
 0.8001727 1.0742114  
sample estimates:  
odds ratio  
 0.9289923
```

Sampling

Also, if you want to only plot a subset of the data (for speed/time or overplotting)

```
samp.cars = sample_n(cars, size = 10000)
samp.cars = sample_frac(cars, size = 0.2)
ggplot(aes(x = VehBCost, y = VehOdo),
       data = samp.cars) + geom_point()
```



Lab Part 2

[Website](#)