# A quick demonstration of the importance of graphing your data: A polite nod of thanks to F. J. Anscombe. 

As published in Benchmarks RSS Matters, July 2015
http://web3.unt.edu/benchmarks/issues/2015/07/rss-matters

Jon Starkweather, PhD

Jon Starkweather, PhD<br>jonathan.starkweather@unt.edu<br>Consultant<br>Research and Statistical Support

A green light to greatness."
http://www.unt.edu

RSS hosts a number of "Short Courses".
A list of them is available at:
http://www.unt.edu/rss/Instructional.htm

Those interested in learning more about R , or how to use it, can find information here: http://www.unt.edu/rss/class/Jon/R_SC

## A quick demonstration of the importance of graphing your data: A polite nod of thanks to F. J. Anscombe.

This month's article presents a rather interesting reminder of the importance of graphing data. The article also serves as an important reminder that model specification (i.e. a model's form; e.g. linear model, quadratic model, cubic model, etc.) should not be chosen without thought. As an example, consider the linear model; which is so popular it is often the default model form for many researchers. However, a linear model may not always be the most appropriate model (see: Starkweather, 2010).

Many data analysts (me included) often place more emphasis on the precision of textual / numeric output rather than more subjectively interpreted graphical output. This behavior is not recommended because; graphs can often convey rather glaringly the nuances of the data which are not readily conveyed in textual or numeric output. As a reminder to me and others, this article demonstrates a truly ingenious way of illustrating the fact that graphs are equally important with computation when working with data. I have occasionally re-learned this lesson over the years and was truly astonished recently when I came across Anscombe's Quartet (Anscombe, 1973). I still find it hard to believe I had not been made aware of this brilliant quartet of data earlier. However, now that I am aware of it, I felt compelled to pass it along. Anscombe's Quartet consists of four simple data sets, each with 11 cases and each with 2 variables (see Table 1).

Table 1: Anscombe's Quartet

|  | x 1 |  |  |  |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
|  | y 1 | x 2 | y 2 | x 3 | y 3 | x 4 | y 4 |  |
|  | 10.00 | 8.04 | 10.00 | 9.14 | 10.00 | 7.46 | 8.00 | 6.58 |
| 2 | 8.00 | 6.95 | 8.00 | 8.14 | 8.00 | 6.77 | 8.00 | 7.71 |
| 3 | 13.00 | 7.58 | 13.00 | 8.74 | 13.00 | 12.74 | 8.00 | 7.71 |
| 4 | 9.00 | 8.81 | 9.00 | 8.77 | 9.00 | 7.11 | 8.00 | 8.84 |
| 5 | 11.00 | 8.33 | 11.00 | 9.26 | 11.00 | 7.81 | 8.00 | 8.47 |
| 6 | 14.00 | 9.96 | 14.00 | 8.10 | 14.00 | 8.84 | 8.00 | 7.04 |
| 7 | 6.00 | 7.24 | 6.00 | 6.13 | 6.00 | 6.08 | 8.00 | 5.25 |
| 8 | 4.00 | 4.26 | 4.00 | 3.10 | 4.00 | 5.39 | 1.00 | 12.50 |
| 9 | 12.00 | 10.84 | 12.00 | 9.13 | 12.00 | 8.15 | 8.00 | 5.56 |
| 10 | 7.00 | 4.82 | 7.00 | 7.26 | 7.00 | 6.42 | 8.00 | 7.91 |
| 11 | 5.00 | 5.68 | 5.00 | 4.74 | 5.00 | 5.73 | 8.00 | 6.89 |

Note: x1, x2, \& x3 are identical.

## 1 Are these data pairs the same?

First, we can import the data into $R^{1}$ using the function (and file path) listed below.

```
a.df <- read.table("http://www.unt.edu/rss/class/Jon/Benchmarks/Anscombe_df.txt",
    header = TRUE, dec = ".", sep = ",")
```

[^0]Next, we take a look at some descriptive statistics, such as the mean, variance, and standard deviation of each variable.

```
apply(a.df, 2, mean)
\begin{tabular}{llllllll}
\(x 1\) & \(y 1\) & \(x 2\) & \(y^{2}\) & \(x 3\) & \(y 3\) & \(x 4\) & \(y^{4}\)
\end{tabular}
9.0000 7.5009 9.0000 7.5009 9.0000 7.5000 9.0000 7.5009
apply(a.df, 2, var)
\begin{tabular}{rrrrrrrr}
\(x 1\) & \(y 1\) & \(x 2\) & \(y 2\) & \(x 3\) & \(y 3\) & \(x 4\) & \(y 4\) \\
11.0000 & 4.1273 & 11.0000 & 4.1276 & 11.0000 & 4.1226 & 11.0000 & 4.1232
\end{tabular}
apply(a.df, 2, sd)
\begin{tabular}{llllllll}
\(x 1\) & \(y 1\) & \(x 2\) & \(y 2\) & \(x 3\) & \(y^{2}\)
\end{tabular}
```

Clearly, each pair is virtually identical with respect to the mean ( $M=9.00$ ), variance ( $V=11.00$ ), and standard deviation ( $S D=3.12$ ) of the $x$ variables; and the mean $(M=7.50)$, variance ( $V=4.13$ ), and standard deviation $(S D=2.03)$ of the $y$ variables. Next, we take a look at the correlations of each pair.

```
cor(a.df[,1:2])
    x1 y1
x1 1.0000000 0.8164205
y1 0.8164205 1.0000000
cor(a.df[,3:4])
    x2 y2
x2 1.0000000 0.8162365
y2 0.8162365 1.0000000
cor(a.df[,5:6])
    x3 y3
x3 1.0000000 0.8162867
y3 0.8162867 1.0000000
cor(a.df[,7:8])
    x4 y4
x4 1.0000000 0.8165214
y4 0.8165214 1.0000000
```

Again, we see that each pair of variables displays the same correlation coefficient $(r=0.816)$. Next, as one might expect, we see below the linear regression intercepts and coefficients are the same as well.

```
summary(lm(y1 ~ x1, a.df))$coef
    Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.0000909 1.1247468 2.667348 0.025734051
x1 0.5000909 0.1179055 4.241455 0.002169629
summary(lm(y2 ~ x2, a.df)) $coef
    Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.000909 1.1253024 2.666758 0.025758941
x2 0.500000 0.1179637 4.238590 0.002178816
summary(lm(y3 ~ x3, a.df))$coef
    Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept) 3.0024545 1.1244812 2.670080 0.025619109
x3 0.4997273 0.1178777 4.239372 0.002176305
summary(lm(y4 ~ x4, a.df))$coef
    Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.0017273 1.1239211 2.670763 0.025590425
x4 0.4999091 0.1178189 4.243028 0.002164602
```

So, all four pairs of data result in the same linear regression equation:

$$
\begin{equation*}
y=3.00+0.50 * x \tag{1}
\end{equation*}
$$

## 2 Are these data pairs really the same?

Based on the above textual / numeric computations and output we might think these four pairs of data are the same. However, we quickly see that they are not at all the same once we do a simple scatterplot of each pair.

```
par(mfrow = c(2,2))
plot(a.df[,1], a.df[,2], ylim = c(2,15), xlim = c(2,20), pch = 16)
abline(summary(lm(y1 ~ x1, a.df))$coef[,1], col = "red")
plot(a.df[,3], a.df[,4], ylim = c(2,15), xlim = c(2,20), pch = 16)
abline(summary(lm(y2 ~ x2, a.df))$coef[,1], col = "red")
plot(a.df[,5], a.df[,6], ylim = c(2,15), xlim = c(2,20), pch = 16)
abline(summary(lm(y3 ~ x3, a.df)) $coef[,1], col = "red")
plot(a.df[,7], a.df[,8], ylim = c(2,15), xlim = c(2,20), pch = 16)
abline(summary(lm(y4 ~ x4, a.df))$coef[,1], col = "red")
```



So, let this be a reminder to us all - graphing data really matters. Graphing data is as important as computation when doing initial data inspection. A version of the R script used in this article can be found on the RSS Do-It-Yourself Introduction to R website $\Omega^{2}$ in the Module 12 section.

Until next time; always look on the bright side of life...

[^1]
## 3 References and Resources

Anscombe, F. J. (1973). Graphs in statistical analysis. The American Statistician, 27(1), 17-21. Available at:
http://www.unt.edu/rss/class/Jon/MiscDocs/1973_Anscombe_theQuartet.pdf

Starkweather, J. (2010). Model Specification Error...Are you straight, or do you have curves?
Benchmarks: RSS Matters, April 2010. Available at:
http://www.unt.edu/rss/class/Jon/Benchmarks/Model\ Specification\ Error_

This article was last updated on June 4, 2015.

This document was created using LATEX


[^0]:    1http://cran.r-project.org/

[^1]:    2http://www.unt.edu/rss/class/Jon/R_SC/

