An R Tutorial: Visual Representation of Complex Multivariate Relationships Using the R *qgraph* Package, Part Two

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Abstract

This article is part of my series of articles exploring the use of R packages that allow for visualization of complex relationships among variables. Other articles have examined visual representations produced by the*qgraph* package in both large and small samples with more than three variables.

In this article I look specifically at the R *qgraph* package with a small dataset of N=10, but a large number (14) of variables. Specifically, the R *qgraph.pca* function is examined.

1 The Problem

In two previous blog posts I discussed some techniques for visualizing relationships involving two or three variables and a large number of cases. In this tutorial I will extend that discussion to show some techniques that can be used on datasets with complex multivariate relationships involving three or more variables.

In this post I will use a dataset called ‘Detroit.’ This data set was originally used in the book ‘Subset selection in regression’ by Alan J. Miller published in the Chapman and Hall series of monographs on Statistics and Applied Probability, no. 40. It was also used in other research and appeared in appendix A of ‘Regression analysis and its application: A data-oriented approach’ by Gunst and Mason, *Statistics textbooks and monographs no. 24*, Marcel Dekker. Editor.

The Detroit dataset contains 14 variables and 10 cases. Each case represents a year during the time period 1961-1973. The variables on which data was collected are seen as possible predictors of homicide rate in Detroit during each of the years studied.

These data are shown below:

FTP	UEMP	MAN	LIC	GR	CLEAR	WM	NMAN	GOV	HE	WE	HOM	ACC	ASR
260.35	11.0	455.5	178.15	215.98	93.4	558724.	538.1	133.9	2.98	117.18	8.60	9.17	306.18
269.80	7.0	480.2	156.41	180.48	88.5	538584.	547.6	137.6	3.09	134.02	8.90	40.27	315.16
272.04	5.2	506.1	198.02	209.57	94.4	519171.	562.8	143.6	3.23	141.68	8.52	45.31	277.53
272.96	4.3	535.8	222.10	231.67	92.0	500457.	591.0	150.3	3.33	147.98	8.89	49.51	234.07
272.51	3.5	576.0	301.92	297.65	91.0	482418.	626.1	164.3	3.46	159.85	13.0	55.05	30.84
261.34	3.2	601.7	391.22	367.62	87.4	465029.	659.8	179.5	3.60	157.19	14.57	53.90	17.99
268.89	4.1	577.3	665.56	616.54	88.3	448267.	686.2	187.5	3.73	155.29	21.36	50.62	86.11
295.99	3.9	596.9	1131.21	1029.75	86.1	432109.	699.6	195.4	2.91	131.75	28.03	51.47	91.59
319.87	3.6	613.5	837.60	786.23	79.0	416533.	729.9	210.3	4.25	178.74	31.49	49.16	20.39
341.43	7.1	569.3	794.90	713.77	73.9	401518.	757.8	223.8	4.47	178.30	37.39	45.80	23.03

The variables are as follows:

```
FTP    - Full-time police per 100,000 population
UEMP   - % unemployed in the population
MAN    - number of manufacturing workers in thousands
LIC    - Number of handgun licenses per 100,000 population
GR     - Number of handgun registrations per 100,000 population
CLEAR  - % homicides cleared by arrests
WM     - Number of white males in the population
NMAN   - Number of non-manufacturing workers in thousands
GOV    - Number of government workers in thousands
HE     - Average hourly earnings
WE     - Average weekly earnings
HOM    - Number of homicides per 100,000 of population
ACC    - Death rate in accidents per 100,000 population
ASR    - Number of assaults per 100,000 population
```

[J.C. Fisher "Homicide in Detroit: The Role of Firearms", *Criminology*, vol.14, 387-400 (1976)]

2 Analysis

As I have noted in previous tutorials, social science research projects often start out with many potential independent predictor variables for a given dependent variable. If these are all measured at the interval or ratio level, a correlation matrix often serves as a starting point to begin analyzing relationships among variables. In this particular case a researcher might be interested in looking at factors that are related to total homicides. There are many R techniques to enter data for analysis. In this case I entered the data into an Excel spreadsheet and then loaded the file into the R environment. Install and load the following packages:

```
Hmisc
stats
qgraph
readxl (only needed if importing data from Excel)
```

A correlation matrix can be generated using the *cor* function which is contained in the *stats* package. To produce a matrix using all 14 variables use the following code:

```
#the data file has been loaded as 'detroit'
#the file has 14 columns
#run a pearson correlation and put into the object 'detcor'
detcor=cor(as.matrix(detroit[c(1:14)]), method="pearson")
#
#round the correlation matrix to 2 decimal places for better viewing
round(detcor, 2)
#
#The resulting matrix will be displayed on the screen
```

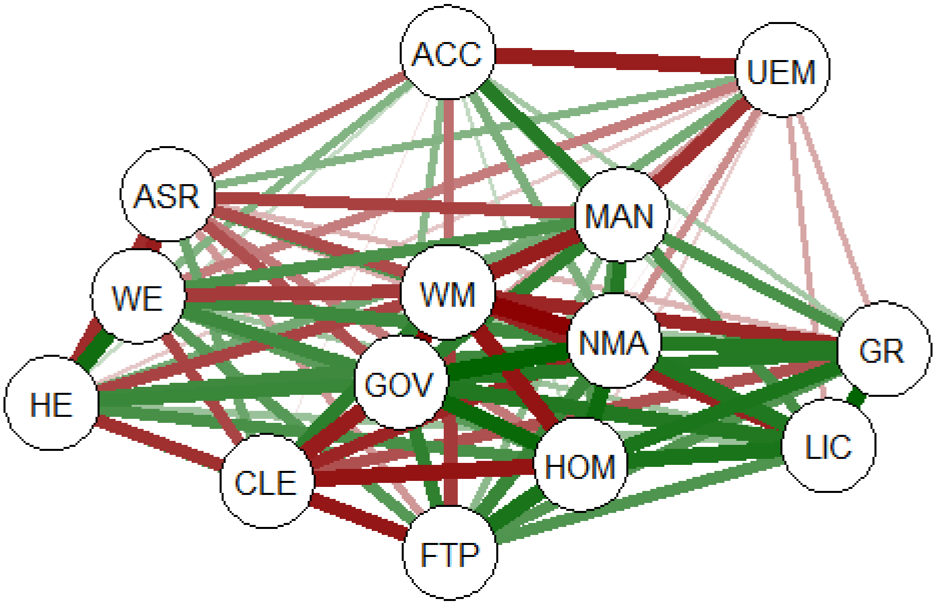
```
The output is as shown below:
```

```
        FTP  UEMP   MAN   LIC    GR  CLEAR  WM   NMAN   GOV    HE    WE   HOM   ACC   ASR
FTP    1.00 -0.06  0.45  0.69  0.68 -0.91 -0.77  0.78  0.82  0.73  0.66  0.90  0.03 -0.41
UEMP  -0.06  1.00 -0.81 -0.35 -0.34  0.11  0.54 -0.45 -0.40 -0.22 -0.51 -0.21 -0.88  0.49
MAN    0.45 -0.81  1.00  0.73  0.71 -0.55 -0.88  0.86  0.82  0.55  0.71  0.67  0.85 -0.74
LIC    0.69 -0.35  0.73  1.00  1.00 -0.69 -0.87  0.87  0.87  0.40  0.39  0.90  0.38 -0.32
GR     0.68 -0.34  0.71  1.00  1.00 -0.68 -0.85  0.86  0.86  0.38  0.37  0.89  0.36 -0.30
CLEAR -0.91  0.11 -0.55 -0.69 -0.68  1.00  0.83 -0.86 -0.89 -0.82 -0.73 -0.92 -0.10  0.58
WM    -0.77  0.54 -0.88 -0.87 -0.85  0.83  1.00 -0.99 -0.98 -0.74 -0.77 -0.92 -0.57  0.69
NMAN   0.78 -0.45  0.86  0.87  0.86 -0.86 -0.99  1.00  1.00  0.76  0.76  0.95  0.51 -0.71
GOV    0.82 -0.40  0.82  0.87  0.86 -0.89 -0.98  1.00  1.00  0.78  0.76  0.96  0.45 -0.69
HE     0.73 -0.22  0.55  0.40  0.38 -0.82 -0.74  0.76  0.78  1.00  0.94  0.72  0.23 -0.83
WE     0.66 -0.51  0.71  0.39  0.37 -0.73 -0.77  0.76  0.76  0.94  1.00  0.65  0.49 -0.89
HOM    0.90 -0.21  0.67  0.90  0.89 -0.92 -0.92  0.95  0.96  0.72  0.65  1.00  0.24 -0.53
ACC    0.03 -0.88  0.85  0.38  0.36 -0.10 -0.57  0.51  0.45  0.23  0.49  0.24  1.00 -0.63
ASR   -0.41  0.49 -0.74 -0.32 -0.30  0.58  0.69 -0.71 -0.69 -0.83 -0.89 -0.53 -0.63  1.00
>
```

Examination of the matrix shows a number of the predictors correlate with the dependent variable 'HOM.' There are also a large number of inter-correlations among the predictor variables. This fact makes it difficult to make any generalizations based on the correlation matrix only. As demonstrated in previous tutorials, the *qgraph* function can be used to produce a visual representation of the correlation matrix. Use the following code:

```
#basic graph with 14 vars zero order correlations
qgraph(detcor, shape="circle", posCol="darkgreen", negCol="darkred", layout="spring", vsize=
```

This will produce graph as seen below:



The graph displays positive correlations among variable as a green line, and negative as a red line. The color intensity indicates the relative strength of the correlation. While this approach provides an improvement over the raw matrix it still rather difficult to interpret. There are many options other than those used in the above example that allow *qgraph* to have a great deal of flexibility in creating visual representation of complex relationships among variables. In the next section I will examine one of these options that uses principal component analysis of the dataset.

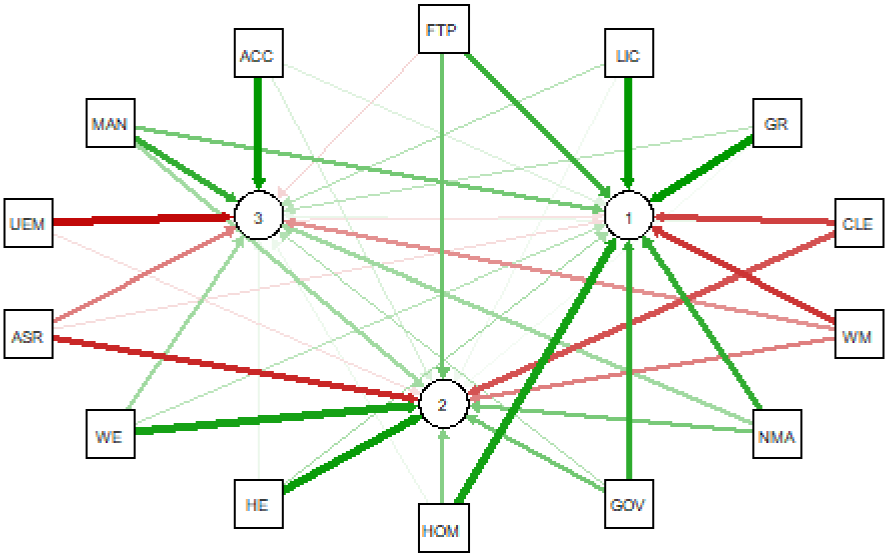
2.1 Using *qgraph* Principal Component Analysis

A discussion of the theory behind principal component exploratory analysis is beyond the scope of this discussion. Suffice it to say that it allows for simplification of a large number of inter-correlations by identifying factors or dimensions that individual correlations relate to. This grouping of variables on specific factors allows *qgraph* to create a visual representation of these relationships. An excellent discussion of the theory of PCA along with R scripts can be found in *Principal Componets Analysis (PCA)*, Steven M. Holland Department of Geology, University of Georgia, Athens, GA, 2008. There are, of course, numerous articles and books dealing with the subject for those wishing to go in-depth.

To produce a graph using the 'detcor' correlation matrix used above use the following code:

```
#correlation matrix used is 'detcor'
#qgraph with loadings from principal components
#basic options used; many other options available
qgraph.pca(detcor, factor=3, rotation="varimax")
#this will yield 3 factors
```

This code produces the output shown below:



As noted above the red and green arrows indicate negative and positive loadings on the factors, and the color intensity indicates the strength. The *qgraph.pca* function produces a useful visual interpretation of the clustering of variables relative to the three factors extracted. This would be very difficult if not impossible with only the correlation matrix or the basic *qgraph* visual representation.

In a future tutorial I will explore more *qgraph* options that can be used to explore the Detroit dataset as well as options for a larger datasets. In future articles I will also explore other R packages that are also useful for analyzing large numbers of complex variable interrelationships in very large, medium, and small samples.

** When developing R code I strongly recommend using an IDE such as RStudio. This is a powerful coding environment and is free for personal use as well as being open source software. RStudio will run on a variety of platforms. If you are developing code for future publication or sharing I would also recommend TeXstudio, a LaTex based document development environment which is also free for personal use. This document was produced using TeXstudio 2.12.6 and RStudio 1.0.136.