Transferring 2013 Analysis to R

Sean Davern

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Objective of this Work

The objective of the work captured in this notebook is to translate part of an analysis done in 2013 (See Davern (2013)) into R to learn and demonstrate multiple R capabilities and workflows.

Import of Data

The original data was provided by John Earling in a work book entitled 'Weekly PayPay & Tithes .xls' workbook. The layout/format of that workbook was not conducive to easily loading into R [nor JMP originally] and so was transcribed into the workbook 'Giving Data.xlsx' and then read into R.

```
source("../code/0-Extract data from Excel.R")
df  # This is the data frame resulting from the import.
```

```
## # A tibble: 469 x 7
##    week.ending         month   year paypal offering  total monthly.giving.~
##    <dttm>              <chr>  <dbl>  <dbl>    <dbl>  <dbl>            <dbl>
##  1 2010-01-03 00:00:00 Janua~  2010     75    1560   1635                NA
##  2 2010-01-10 00:00:00 Janua~  2010    575    3129   3704                NA
##  3 2010-01-17 00:00:00 Janua~  2010    475    2025   2500                NA
##  4 2010-01-24 00:00:00 Janua~  2010     75    1180.  1255.               NA
##  5 2010-01-31 00:00:00 Janua~  2010   2180    2967.  5147.               45
##  6 2010-02-07 00:00:00 Febru~  2010     75    4722.  4798.               NA
##  7 2010-02-14 00:00:00 Febru~  2010    585    2925   3510                NA
##  8 2010-02-21 00:00:00 Febru~  2010    200    3299   3499                NA
##  9 2010-02-28 00:00:00 Febru~  2010   6350    4281  10631                41
## 10 2010-03-07 00:00:00 March   2010    770    1170   1940                NA
## # ... with 459 more rows
```

Some Minor Data Validation

As a first validation I'll check that the weekly PayPal and offering amounts sum to the weekly totals ($paypal_i + offering_i \stackrel{?}{=} total_i$), reporting only those that aren't equal:

```
source("../code/1-Validate totals.R")
```

```
## ***** WARNING *****

## Some 'total' observations don't equal the sum of 'paypal' and 'offering'!

## # A tibble: 3 x 8
##   week.ending         month    year paypal offering total calcd.total  diff
##   <dttm>              <chr>   <dbl>  <dbl>    <dbl> <dbl>       <dbl> <dbl>
## 1 2015-12-27 00:00:00 Decemb~  2015   1902     9306 16958       11208  5750
## 2 2016-12-25 00:00:00 Decemb~  2016   4635    10089 22849       14724  8125
## 3 2017-04-23 00:00:00 April     2017    635     4480  4615        5115  -500
```

Ok, so December 2015 and 2016 seem to have totals greater than accounted for by the PayPal and offering amounts. That's perhaps explainable by other end-of-year giving coming in another way. However, the April 2017 discrepancy seems to be missing $500. I'll need to look into that.

Data Transformation

Aggregating the monthly totals and preparing to model month values…

```
# Data transformation: Calculate monthly giving totals.
# Make Month a categorical variable with levels in the order that
# months occur in the year otherwise months are sorted alphabetically.
df$month <- factor(df$month, month.name)
# Aggregate the monthly Totals from giving.data in sums for each month.
MonthTotals <-
  aggregate(df$total, by = list(df$month, df$year), FUN = sum)
# Exclude the months that don't have totals yet.
MonthTotals <- MonthTotals[complete.cases(MonthTotals), ]
# Extract only rows containing 'monthly.giving.families' data.
df <- df[!is.na(df$monthly.giving.families),]
# Now replace Totals (which were weekly totals) with calculated aggregates
df$total <- MonthTotals$x
# paypal & offering columns are now misleading (only week's value) so remove them.
df <- select(df, -paypal, -offering)
```

Adding the number of giving Sundays in the month and the average giving each week per month…

```
library("magrittr")
source("../code/NumOfGivenDayOfWeekInMonth.R")
# Calculate and add the columns SundaysInMonth with calculated values
# and MonthsGivingPerWeek
df <-  df %>%
  mutate(SundaysInMonth =
           NumOfGivenDayOfWeekInMonth(df$week.ending, "Sunday")) %>%
  mutate(MonthsGivingPerWeek = total / SundaysInMonth)
```

Enable modeling year as factor rather than a number…

```
# Make year a categorical variable so coefficients are easier to interpret.
df$year <- as.factor(df$year)
```

Save the resulting R tibble:

```
# Code chunk eval=false so files don't get overwritten willy nilly.
# Write it as a csv:
write.csv(x = df,
          file = "../data/Cleaned and Transformed Giving Data.csv",
          row.names = FALSE)
# Save it also as an R object that can be loaded into a new R object.
saveRDS(df, file = "../data/Cleaned and Transformed Giving Data.rds")
```

Replicating Previous Modeling

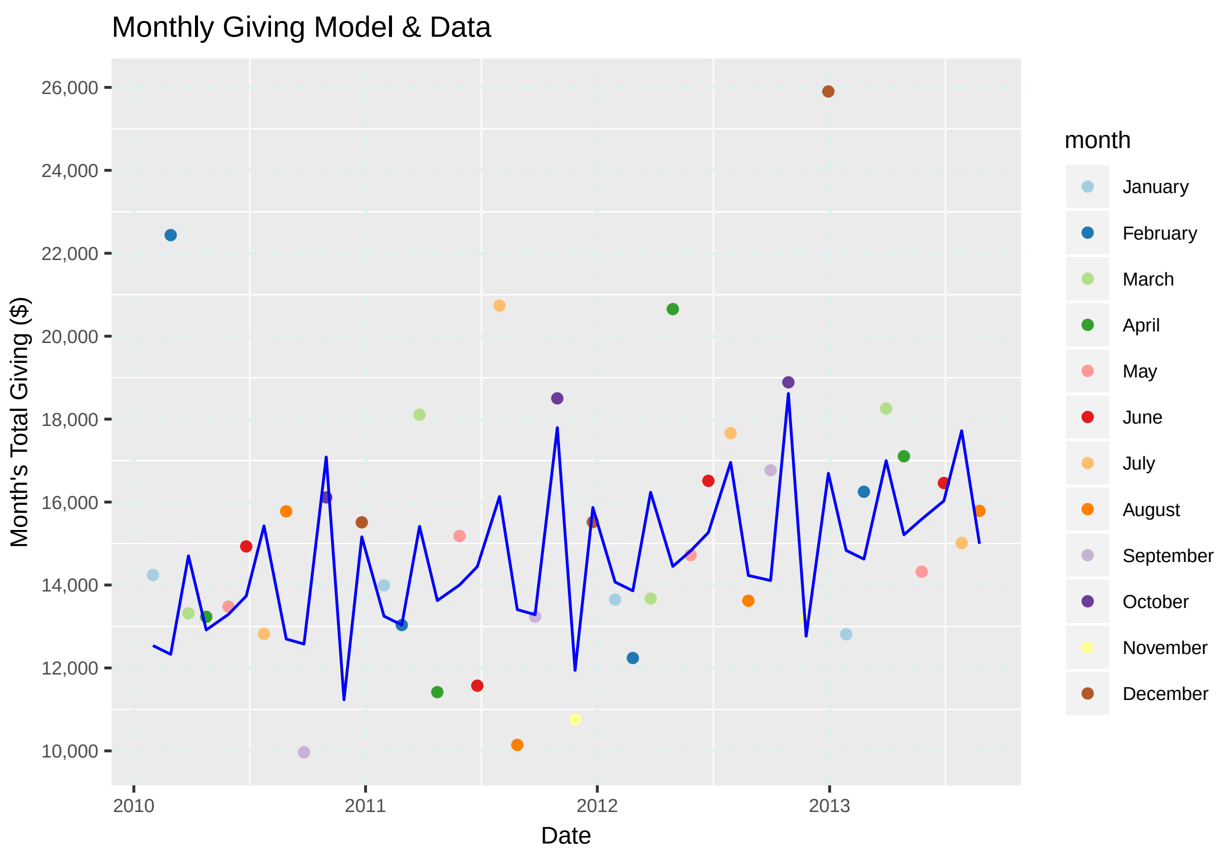
The relatively simple model derived in 2013 (see Davern 2013, pg. 11) and used again in 2018 used this model:

$$Monthly\ Giving = a + b_{year} + c_{month}$$

where a is an overall grand average of the monthly giving amount, b_{year} is an adjustment for the given year and c_{month} is an adjustment for the month. The model was originally regressed on giving data from Jan 2010 through August 2013 excluding 3 high-fliers with known exceptional donations.
The R function lm uses a similar model except where a is the predicted Jan 2011 giving amount, so $b_{2011} = 0$ and $c_{January} = 0$. Regressing this model:

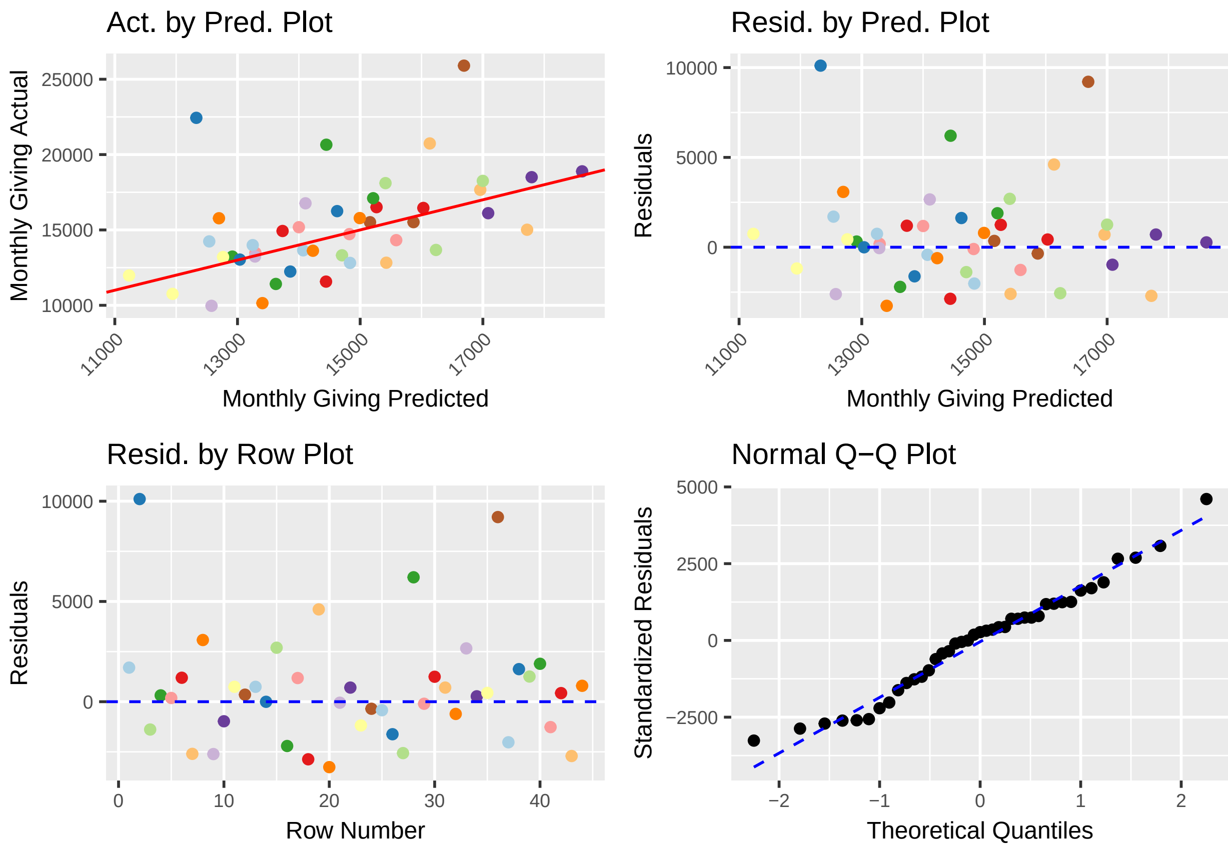
```
library("magrittr")
# Pair the data down to that used in the original analysis
df2 <- df[as.Date(df$week.ending) > "2010-01-01" &
            as.Date(df$week.ending) < "2013-08-31",] %>%
  mutate(excluded = FALSE)
df2$excluded[as.Date(df2$week.ending) == "2010-02-28"] <- TRUE
df2$excluded[as.Date(df2$week.ending) == "2012-04-29"] <- TRUE
df2$excluded[as.Date(df2$week.ending) == "2012-12-30"] <- TRUE
# Regress the model cluding the indicated values:
mod <- lm(
  formula = total ~
    year + month,
  data = df2[df2$excluded!=TRUE,]
)
```

Which gives the resulting model fit:



Note: excluded points [high fliers] are shown (above and below) though they weren't included in the regression. Here are the fit diagnostics:

```
## Analysis of Variance Table
##
## Response: total
##           Df    Sum Sq Mean Sq F value Pr(>F)
## year       3  21431854 7143951  1.4506  0.251
## month     11  93473089 8497554  1.7254  0.123
## Residuals 26 128049780 4924992
```




```
##
## Call:
## lm(formula = total ~ year + month, data = df2[df2$excluded !=
##     TRUE, ])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3262.7 -1266.4   269.4  1181.2  4604.5
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     12539.40    1264.30   9.918 2.52e-10 ***
## year2011          708.72     933.26   0.759   0.4544
## year2012         1531.73     997.47   1.536   0.1367
## year2013         2295.36    1082.20   2.121   0.0436 *
## monthFebruary    -210.59    1706.96  -0.123   0.9028
## monthMarch       2164.52    1569.23   1.379   0.1795
```

```
## monthApril       376.99    1707.70   0.221   0.8270
## monthMay         752.68    1569.23   0.480   0.6355
## monthJune       1195.27    1569.23   0.762   0.4531
## monthJuly       2886.33    1569.23   1.839   0.0773 .
## monthAugust      158.54    1569.23   0.101   0.9203
## monthSeptember    37.28    1710.48   0.022   0.9828
## monthOctober    4547.45    1710.48   2.659   0.0132 *
## monthNovember  -1306.57    1710.48  -0.764   0.4518
## monthDecember   2621.14    1956.39   1.340   0.1919
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2219 on 26 degrees of freedom
## Multiple R-squared:  0.4729, Adjusted R-squared:  0.1892
## F-statistic: 1.666 on 14 and 26 DF,  p-value: 0.1261
```

The results obtained are different in a number of ways from what was obtained in 2013. The general fit (residuals) and shape of the predicted values are similar to that obtained in 2013 though the June predictions seem further away than the other months. The regressed coefficients are obviously very different (See Model Generalization below), but this is largely due to the method JMP uses for regressing factor coefficients. However, the difference in the June predictions and slightly different factor p-values tells me that something in the underlying data is probably different. I'm not going to spend the time to diagnose the precise details of the difference since the objective is to translate the analysis to R rather than reproduce JMP.

Model Generalization

Due to R's conventions, the model coefficients, as regressed by R:

$$Monthly\ Giving = a + b_{year} + c_{month}$$

are regressed relative to $month_1$=January ($c_{January} = 0$) and $year_1$=2010 ($b_{2010} = 0$). This is why there is no year2010 nor monthJanuary coeffiencients. A more useful set of references for forecasting would be "an average month" and "an average year". Thus we can modify the model as such:

$$\begin{aligned} Monthly\ Giving &= a + (\overline{b_{year}} + b_{year} - \overline{b_{year}}) + (\overline{c_{month}} + c_{month} - \overline{c_{month}}) \\ &= \left[a + \overline{b_{year}} + \overline{c_{month}}\right] + \left(b_{year} - \overline{b_{year}}\right) + \left(c_{month} - \overline{c_{month}}\right) \end{aligned}$$

where $\overline{b_{year}}$ is the mean of b_{year} coefficients, including $b_{2010} = 0$, and $\overline{c_{month}}$ is the mean of the c_{year} coefficients, including $c_{January} = 0$. The term $\left[a + \overline{b_{year}} + \overline{c_{month}}\right]$ is then the regressed *Monthly Giving* for an average month in an average year over the period covered by the data. Of course no actual month or year is the average, and to reproduce a given month and year prediction the shifted coefficients $(b_{year} - \overline{b_{year}})$ and $(c_{month} - \overline{c_{month}})$ must be employed. However, this facilitates using the model for monthly variance predictions in the upcoming year since:

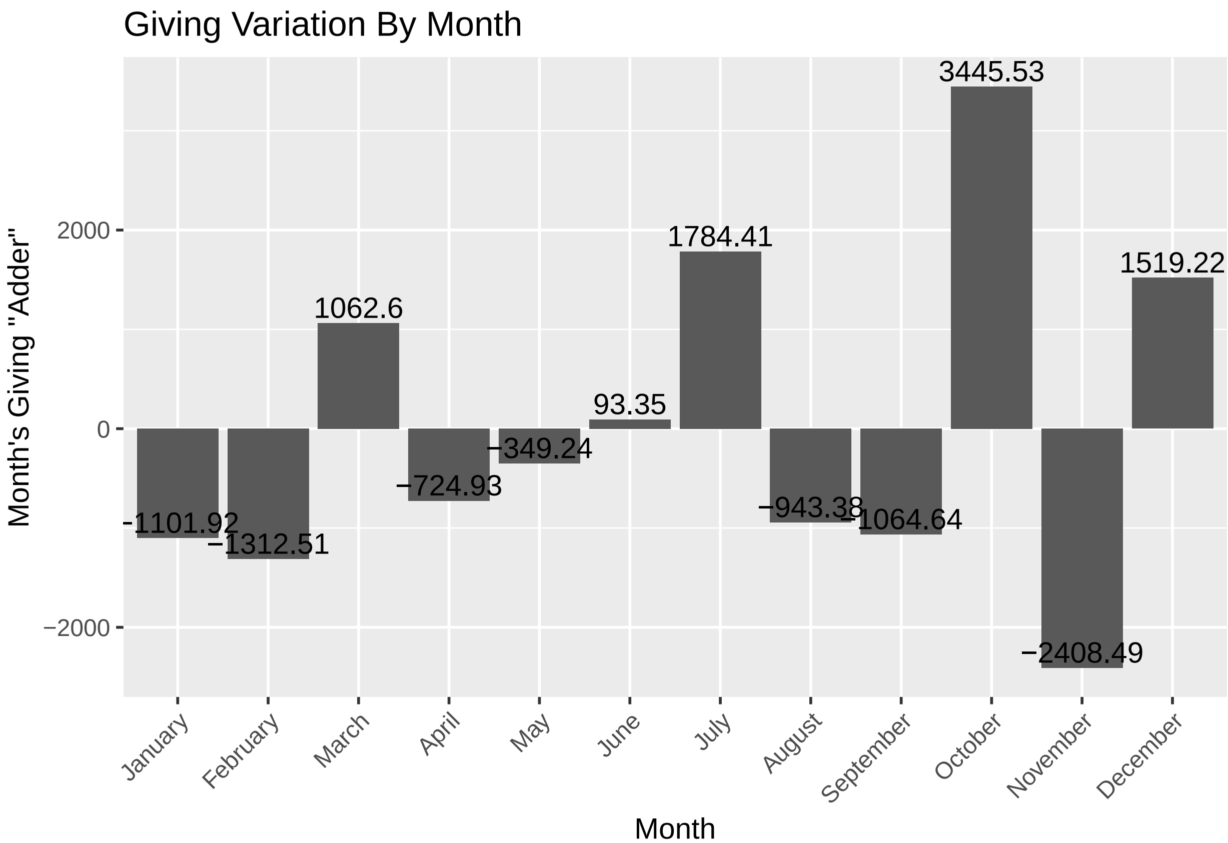
$$\begin{aligned} Average\ Monthly\ Giving_{next\ year} &= \left[a + \overline{b_{year}} + \overline{c_{month}}\right] + \left(b_{next\ year} - \overline{b_{year}}\right) \\ &= \frac{Projected\ Income_{next\ year}}{12} \end{aligned}$$

So even though we don't know $b_{next\ year}$ we can make an estimation for next year's total *Projected Income* and get monthly estimates based on the annual estimate:

$$Monthly\ Giving_{next\ year} = \frac{Projected\ Income_{next\ year}}{12} + \left(c_{month} - \overline{c_{month}}\right)$$

Monthly Variation

This plot shows the resulting *month* regression coeffiecients shifted by $\overline{c_{month}}$ capturing month-to-month variation. $((c_{month} - \overline{c_{month}}))$ The shape of the yearly repeated pattern in the prediction are the result of these terms.



These values are much closer to those regressed in 2013 by JMP.

References

Davern, Sean. 2013. "An Assessment of Requested Seed Core Support for Expansion Based on Analysis of Giving." *Internal Report*, August. file://../Reports/August%202013%20Analysis%20of%20Giving.pdf.