Rq2 reproduction

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In this walk-through we'll perform the plot generation and significance testing for rq2. We assume you have read the `rq1_rq3` and `sigTest` walk-throughs, in that order.

Preliminaries

First, libraries, note that I have silenced the shadowing warnings from R:

```
library(ggplot2)   #plotting
library(dplyr)     #dataframe manipulation
library(tidyr)     #dataframe manipulation
library(broom)     #for the tidy function
library(scales)    #for scientific function
library(latex2exp) #for TeX in Labels
library(ggpubr)    #for stat_cor
```

Load the data, and perform some simple munging to select relevant columns

```
finResultsFile <- "../../data/fin_comp_data.csv"
autoResultsFile <- "../../data/auto_comp_data.csv"

finData <- read.csv(file=finResultsFile) %>%
  mutate(Algorithm = as.factor(Algorithm), Config = as.factor(Config))

autoData <- read.csv(file=autoResultsFile) %>%
  mutate(Algorithm = as.factor(Algorithm), Config = as.factor(Config))

finDF <- finData %>% mutate(data = "Fin") %>%
  select(Mean, Algorithm, CompressionRatio, data, ChcCount, PlainCount, Config)

autoDF <- autoData %>% mutate(data = "Auto") %>%
  select(Mean, Algorithm, CompressionRatio, data, ChcCount, PlainCount, Config)
```

Visualization

Now the sharing ratio must be calculated, this is performed via a `spread` and `mutate` operation. `spread` transforms long data into wide data, note that it has been recently deprecated and replaced with `pivot_wider`, see the `tidyverse` documentation for details here. We use `spread` just for convienience and familiarity. Now we find the sharing ratio for each Algorithm, and construct a data frame for each dataset:

```
## finding the sharing ratios for auto
autoPtoP <- autoDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "p-->p") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `p-->p`)) %>%
  select(-"v-->p", -"p-->p")  %>% mutate(Algorithm = "p\U27f6p")
```

```r
autoVtoV <- autoDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "v-->v") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `v-->v`)) %>%
  select(-"v-->v", -"v-->p") %>% mutate(Algorithm = "v\U27f6v")

autoPtoV <- autoDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "p-->v") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `p-->v`)) %>%
  select(-"v-->p", -"p-->v") %>% mutate(Algorithm = "p\U27f6v")

## construct auto data frame
autoSharedDF <- rbind(autoPtoP, autoVtoV, autoPtoV)
```

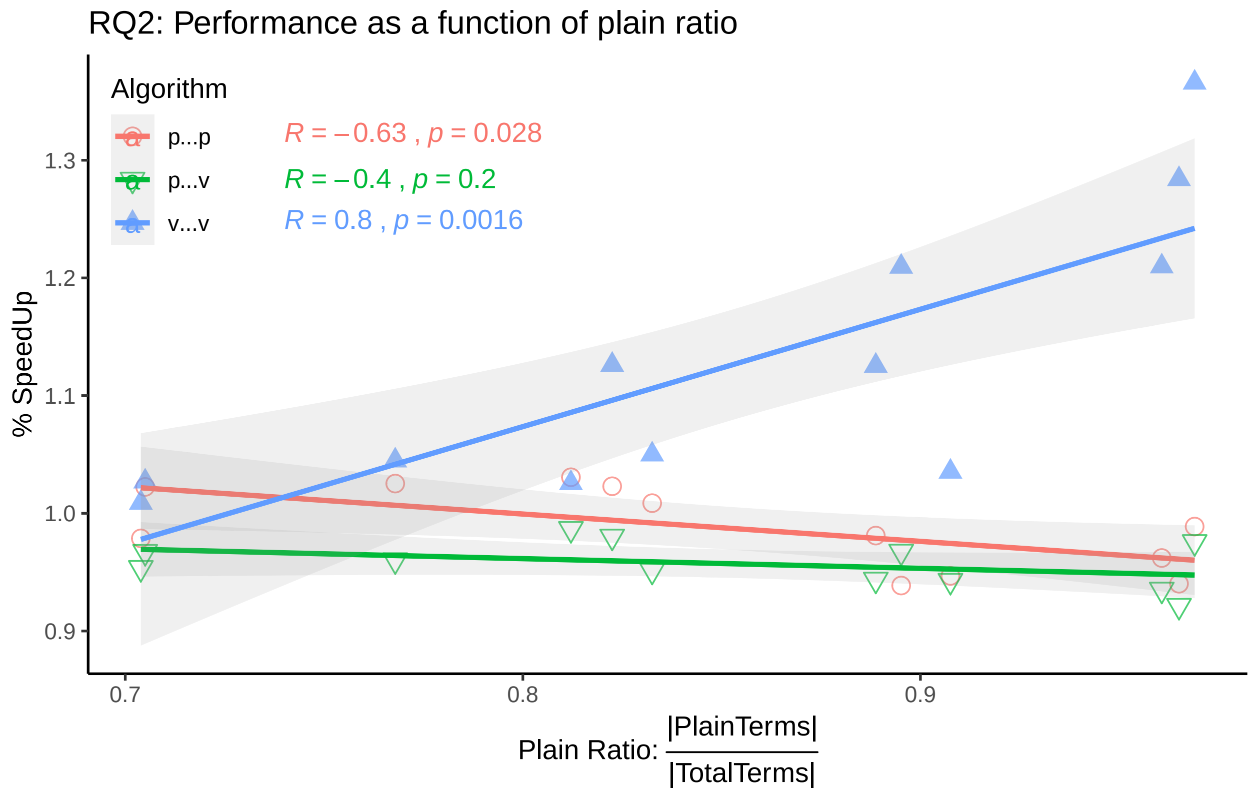
and for `financial`:

```r
## finding the sharing ratios for fin
finPtoP <- finDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "p-->p") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `p-->p`)) %>%
  select(-"v-->p", -"p-->p") %>% mutate(Algorithm = "p\U27f6p")

finVtoV <- finDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "v-->v") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `v-->v`)) %>%
  select(-"v-->v", -"v-->p") %>% mutate(Algorithm = "v\U27f6v")

finPtoV <- finDF %>% group_by(Algorithm, Config) %>%
  filter(Algorithm == "v-->p" || Algorithm == "p-->v") %>%
  spread(Algorithm, Mean) %>% mutate(MeanRatio = (`v-->p` / `p-->v`)) %>%
  select(-"v-->p", -"p-->v") %>% mutate(Algorithm = "p\U27f6v")

## construct fin data frame
finSharedDF <- rbind(finPtoP, finVtoV, finPtoV)
```

Now the data frames are combined and the plot can be generated:

```r
## make the data frame
df <- rbind(autoSharedDF, finSharedDF) %>%
         ## calculate the ratio of plain terms to total terms, i.e., the sharing ratio
  mutate(PlainRatio = PlainCount / (ChcCount + PlainCount),
         ## get the converse ratio at the same time
         ChcRatio = ChcCount / (ChcCount + PlainCount))

## make the plot as a function of plain ratio to mean ratio
ggplot(df, mapping = aes(x=PlainRatio, y=MeanRatio, colour = Algorithm, shape = Algorithm)) +
  ## it is a scatter plot
  geom_point(size=3, alpha=0.7) +
  ylab("% SpeedUp") +
  ## insert LaTeX into the x-axis labels
  xlab(TeX("Plain Ratio:  $\\frac{|Plain Terms|}{|Total Terms|}}")) +
  ## manually scale shapes so the algorithms have the same shape over different plots
  scale_shape_manual(values = c(1,6,17)) +
  ## add the confidence intervals, using a linear regression, alpha makes these more
  ## transparent, se adds the shadings for the 95% confidence intervals
  geom_smooth(method=lm, formula = y ~ x, se=TRUE, alpha=0.15) +
```

```r
  ggtitle("RQ2: Performance as a function of plain ratio") +
  theme_classic() +
  ## stat_cor calculates the R^2 values, that are placed next to the legend
  stat_cor(aes(color=Algorithm),
           label.x=0.74, label.y.npc=c(0.91, 0.89, 0.88)) +
  theme(legend.position = c(0.07, 0.83))
```



Statistical Significance

We perform the same two way ANOVA to ensure fair comparisons:

```r
### Perform the anova
res.aov <- aov(MeanRatio ~ PlainRatio * Algorithm, data = df)
res.aov
```

```
## Call:
##    aov(formula = MeanRatio ~ PlainRatio * Algorithm, data = df)
##
## Terms:
##                 PlainRatio  Algorithm PlainRatio:Algorithm  Residuals
## Sum of Squares  0.01522695 0.19480856           0.08822280 0.06465027
## Deg. of Freedom          1          2                    2         30
##
## Residual standard error: 0.04642207
## Estimated effects may be unbalanced
```

```r
### Check the summary to see what is significant, all of it is as expected
summary(res.aov)
```

```
##                      Df  Sum Sq Mean Sq F value   Pr(>F)
```

```
## PlainRatio             1 0.01523 0.01523   7.066   0.0125 *
## Algorithm              2 0.19481 0.09740  45.199 8.86e-10 ***
## PlainRatio:Algorithm   2 0.08822 0.04411  20.469 2.48e-06 ***
## Residuals             30 0.06465 0.00216
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

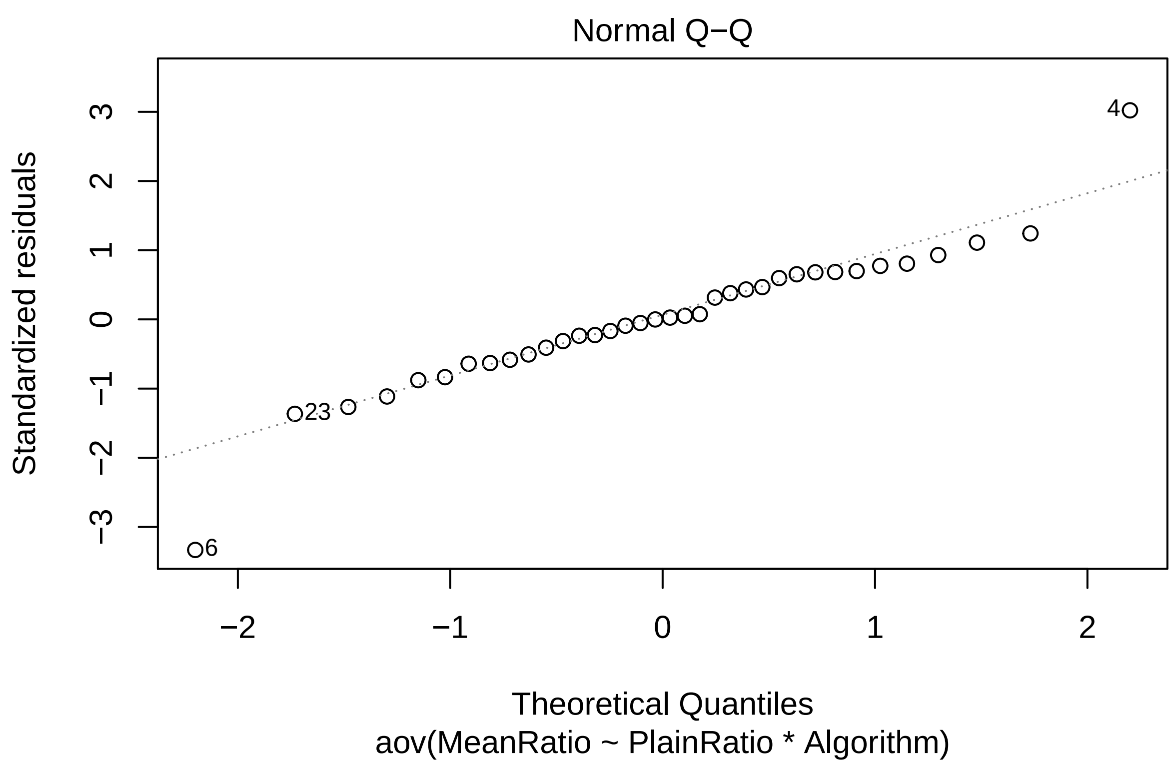
We see that `Algorithm`, `PlainRatio`, and their interaction are significant. This makes sense given then nature of the tool and analysis. We perform a `Tukey pair-wise` comparison to check the significantly different comparisons in the dataset.

```
### perform the pair-wise Tukey comparison to test the difference
### between groups
TukeyHSD(res.aov) %>% tidy %>% mutate(pVal = scientific(adj.p.value, 3))
```

```
## # A tibble: 3 x 7
##   term      comparison estimate conf.low conf.high   adj.p.value pVal
##   <chr>     <chr>         <dbl>    <dbl>     <dbl>         <dbl> <chr>
## 1 Algorithm p v-p p     -0.0300  -0.0768    0.0167 0.268         2.68e-01
## 2 Algorithm v v-p p      0.139    0.0921    0.186  0.000000109   1.09e-07
## 3 Algorithm v v-p v      0.169    0.122     0.216  0.00000000185 1.85e-09
```

We observe that `v-->v` differs from the other algorithms, and the difference is statistically significant. Next, we check the residuals to assess normality.

```
res.ass <- plot(res.aov, 2)
```



Residuals looks good and there three outliers, which agrees with other analyses. To verify, we perform the `Shapiro-Wilks` test, identically to `rq3`.

```
aov.resids <- residuals(object=res.aov)

## Shapiro-Wilk normality test
```

```r
shapiro.test(x = aov.resids)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  aov.resids
## W = 0.92064, p-value = 0.01315
```

Unfortunately, We see that again the dataset violates the assumptions of the ANOVA test, so we perform the Kruskal-Wallis test instead:

```r
## Algorithms are significant
kruskal.test(MeanRatio ~ Algorithm, df)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  MeanRatio by Algorithm
## Kruskal-Wallis chi-squared = 23.73, df = 2, p-value = 7.033e-06
```

Algorithms are found to be statistically different as expected.

```r
## Plain ratio is not significant!!
kruskal.test(MeanRatio ~ PlainRatio, df)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  MeanRatio by PlainRatio
## Kruskal-Wallis chi-squared = 4.2733, df = 11, p-value = 0.9612
```

Plain ratio, interestingly is found not to be statistically different, which agrees with the ANOVA analysis.

```r
## Interaction is not significant surprisingly
rq2.inters <- interaction(df$Algorithm, df$PlainRatio)
kruskal.test(MeanRatio ~ rq2.inters, df)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  MeanRatio by rq2.inters
## Kruskal-Wallis chi-squared = 35, df = 35, p-value = 0.4682
```

However, when accounting for Algorithms, i.e., when analyzing the interaction between the two, we find the interaction is just barely significant. We perform the `Pairwise Wilcox test` to check what exactly is significant:

```r
## Show the pairs which are significant
pairwise.wilcox.test(df$MeanRatio, df$Algorithm,
                              p.adj="bonf" , exact=TRUE, paired=FALSE) %>%
  tidy %>% arrange(p.value)
```

```
## # A tibble: 3 x 3
##   group1 group2    p.value
##   <chr>  <chr>       <dbl>
## 1 v v    p v    0.00000222
## 2 v v    p p    0.0000666
## 3 p v    p p    0.116
```

We find that `v-->v` is statistically different from the other algorithms, confirming the hypothesis for `rq2`