fFDR Package Vignette (Version 0.1)

David G. Robinson

July 15, 2013

1 Introduction

This is a vignette for the fFDR package, which performs functional false discovery rate control.

2 Example Usage

Simulated data can be found in the simtests dataset.

```
library(fFDR)
data(simtests)
head(simtests)
        pvalue sample.size
                              mean oracle
## 1 6.748e-02
                         25 0.3639
                                      TRUE
## 2 2.729e-01
                         10 0.5518
                                      TRUE
## 3 1.482e-01
                          2 0.3301
                                      TRUE
## 4 2.406e-01
                          3 0.3093
                                      TRUE
## 5 1.088e-01
                         25 0.3923
                                      TRUE
## 6 1.527e-10
                         89 0.5138
                                      TRUE
```

This dataset contains 4000 one-sample t-tests of different means and sample sizes. The means (while provided in the table) can be assumed to be unknown, while the sample sizes are known. Thus, we need to adjust the p-values from the t-tests based on the information we have about the sample sizes.

To do this, we use the fqvalue function, which takes at least two arguments: the p-values and the values it should be controlling for, which in this case is the sample size.

```
fq = fqvalue(simtests$pvalue, simtests$sample.size)
```

This produces a data.table with 6 columns, and the same number of rows as the number of pvalues given:

```
fq
##
          pvalue
                   X
                          qΧ
                                piO cumulative.density fqvalue
##
      1: 0.06748
                  25 0.71525 0.5680
                                                0.3448 0.11116
                                                0.4438 0.43417
##
      2: 0.27285
                  10 0.52400 0.7062
      3: 0.14820
                  2 0.04688 0.8235
                                                0.1631 0.74829
                  3 0.16112 0.8222
                                                0.3074 0.64343
##
      4: 0.24056
##
      5: 0.10882
                  25 0.71525 0.5680
                                                0.4226 0.14625
##
## 3996: 0.20611
                   7 0.43188 0.8017
                                                0.3028 0.54567
## 3997: 0.64535 263 0.96500 0.4936
                                                0.8021 0.39712
## 3998: 0.04598 84 0.89300 0.5031
                                                0.4629 0.04996
## 3999: 0.34497 12 0.56588 0.6369
                                                0.5408 0.40628
## 4000: 0.22800
                  4 0.26700 0.8431
                                                0.3257 0.59011
```

The first two, pvalue and X, are the original inputs, and qX is the quantile of X that was used in the functional FDR computations. pi0 is the estimate of π_0 for each hypothesis, which varies depending on X.

The fqvalue is the functional q-value. This is designed so that rejecting the null hypothesis for all tests with q-value less than q should lead to a false discovery rate of q. The cumulative density is a value used in the computation of the functional q-value: it represents the estimated probability that a p-value at the given X_i would be less than p_i .

2.1 Analysis

The fq\$fqvalue column shows us the computed q-values:

```
sum(fq$fqvalue < 0.05)
## [1] 519
sum(fq$fqvalue < 0.01)
## [1] 359</pre>
```

We can also perform a comparison to a traditional q-value, in this case using the qvalue package, and see how many we find:

```
library(qvalue)

q = qvalue(fq$pvalue)
sum(q$qvalues < 0.05)

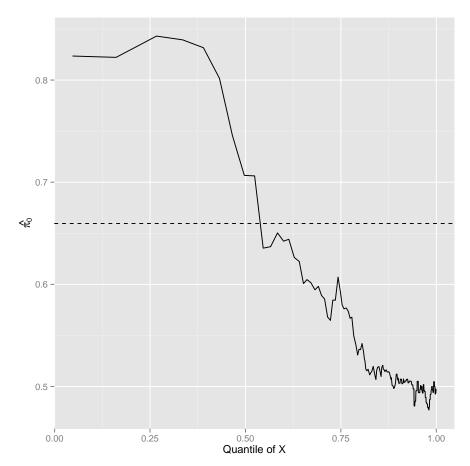
## [1] 478
sum(q$qvalues < 0.01)
## [1] 333</pre>
```

3 Plotting

The fFDR package provides functions for plotting various useful graphs based on the output offqvalue.

One of fFDR's functionalities is to calculate how π_0 varies based on X. Plotting this π_0 based on the quantile of X can show how the

plot.pi0(fq, horizontal.line = TRUE)



Another question is to what extent the functional q-value differs from the traditional q-value, which does not take X into account.

Another way of comparing traditional q-values to functional q-values is to scatter the p-values against the quantiles of the X distribution.

compare.qvalue(fq)

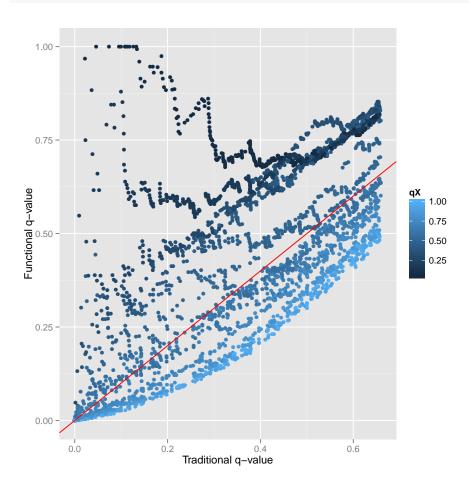


Figure 1: Comparison between the traditional q-value and the functional q-value, colored based on the quantile of the X distribution. Notably, values with high X have functional q-values that are lower than their traditional q-values, while values with low X have higher functional q-values.

```
plot.pvalue.qX(fq)
## Loading required package: plyr
##
## Attaching package: 'reshape'
## The following object(s) are masked from 'package:plyr':
##
##
      rename, round_any
##
    qvalue
               pvalue
     0.005 0.0005095
## 1
## 2
       0.01 0.0012332
## 3
       0.05 0.0089293
## 4
     0.1 0.0238818
```

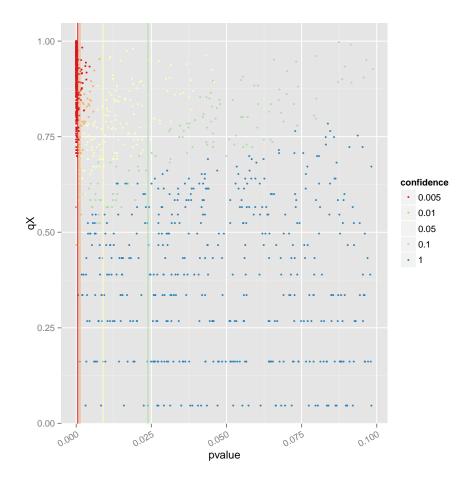


Figure 2: The vertical lines represent the q-value significance thresholds using traditional methods, in which the q-value depends only on the p-value and not X. The colors of the points represent the significance thresholds of the functional q-value.

```
plot.pvalue.qX(fq, doublelog = TRUE)

## qvalue pvalue
## 1 0.005 0.0005095
## 2 0.01 0.0012332
## 3 0.05 0.0089293
## 4 0.1 0.0238818
```

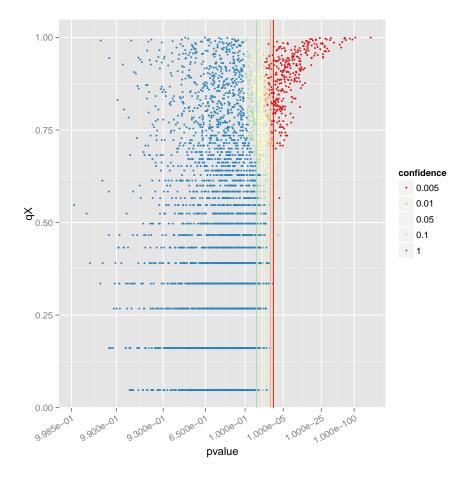


Figure 3: Equivalent to Figure 2, but places the p-value on a $\log(-\log(p))$ scale, which more clearly shows the effects on very low p-values.