

coin: A Computational Framework for Conditional Inference

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1 Introduction

2 Permutation Tests

$(\mathbf{Y}_i, \mathbf{X}_i, w_i, b_i), i = 1, \dots, n.$

$$H_0 : D(\mathbf{Y}|\mathbf{X}) = D(\mathbf{Y})$$

$$\mathbf{T} = \text{vec} \left(\sum_{i=1}^n w_i g(\mathbf{X}_i) h(\mathbf{Y}_i, (\mathbf{Y}_1, \dots, \mathbf{Y}_n))^{\top} \right) \in \mathbb{R}^{pq} \quad (1)$$

The conditional expectation $\mu \in \mathbb{R}^{pq}$ and covariance $\Sigma \in \mathbb{R}^{pq \times pq}$ of \mathbf{T} under

H_0 given all permutations $\sigma \in S$ of the responses are derived by ?:

$$\begin{aligned}
\mu &= \mathbb{E}(\mathbf{T}|S) = \text{vec} \left(\left(\sum_{i=1}^n w_i g(\mathbf{X}_i) \right) \mathbb{E}(h|S)^\top \right), \\
\Sigma &= \mathbb{V}(\mathbf{T}|S) \\
&= \frac{\mathbf{w}_\cdot}{\mathbf{w}_\cdot - 1} \mathbb{V}(h|S) \otimes \left(\sum_i w_i g(\mathbf{X}_i) \otimes w_i g(\mathbf{X}_i)^\top \right) \\
&\quad - \frac{1}{\mathbf{w}_\cdot - 1} \mathbb{V}(h|S) \otimes \left(\sum_i w_i g(\mathbf{X}_i) \right) \otimes \left(\sum_i w_i g(\mathbf{X}_i) \right)^\top
\end{aligned} \tag{2}$$

where $\mathbf{w}_\cdot = \sum_{i=1}^n w_i$ denotes the sum of the case weights, and \otimes is the Kronecker product. The conditional expectation of the influence function is

$$\mathbb{E}(h|S) = \mathbf{w}_\cdot^{-1} \sum_i w_i h(\mathbf{Y}_i, (\mathbf{Y}_1, \dots, \mathbf{Y}_n)) \in \mathbb{R}^q$$

with corresponding $q \times q$ covariance matrix

$$\begin{aligned}
\mathbb{V}(h|S) &= \mathbf{w}_\cdot^{-1} \sum_i w_i (h(\mathbf{Y}_i, (\mathbf{Y}_1, \dots, \mathbf{Y}_n)) - \mathbb{E}(h|S)) \\
&\quad (h(\mathbf{Y}_i, (\mathbf{Y}_1, \dots, \mathbf{Y}_n)) - \mathbb{E}(h|S))^\top.
\end{aligned}$$

Having the conditional expectation and covariance at hand we are able to standardize a linear statistic $\mathbf{T} \in \mathbb{R}^{pq}$ of the form (1). Univariate test statistics c mapping an observed linear statistic $\mathbf{t} \in \mathbb{R}^{pq}$ into the real line can be of arbitrary form. An obvious choice is the maximum of the absolute values of the standardized linear statistic

$$c_{\max}(\mathbf{t}, \mu, \Sigma) = \max \left| \frac{\mathbf{t} - \mu}{\text{diag}(\Sigma)^{1/2}} \right|$$

utilizing the conditional expectation μ and covariance matrix Σ . The application of a quadratic form $c_{\text{quad}}(\mathbf{t}, \mu, \Sigma) = (\mathbf{t} - \mu) \Sigma^+ (\mathbf{t} - \mu)^\top$ is one alternative, although computationally more expensive because the Moore-Penrose inverse Σ^+ of Σ is involved.

The conditional distribution and thus the P -value of the statistics $c(\mathbf{t}, \mu, \Sigma)$ can be computed in several different ways. For some special forms of the linear statistic, the exact distribution of the test statistic is trackable. Conditional Monte-Carlo procedures can be used to approximate the exact distribution. ? proved (Theorem 2.3) that the conditional distribution of linear statistics \mathbf{T} with conditional expectation μ and covariance Σ tends to a multivariate normal distribution with parameters μ and Σ as $n, s \rightarrow \infty$. Thus, the asymptotic conditional distribution of test statistics of the form c_{\max} is normal and can be computed directly in the univariate case ($pq = 1$) or approximated by means of quasi-randomized Monte-Carlo procedures in the multivariate setting (?). For quadratic forms c_{quad} which follow a χ^2 distribution with degrees of freedom given by the rank of Σ (Theorem 6.20, ?), exact probabilities can be computed efficiently.

3 Examples

Independent K -Sample Problems \mathbf{Y} is univariate numeric (or censored) and \mathbf{X} a factor at K levels. g is the dummy matrix and h by be arbitrary.

```
> library(coin)

Loading required package: survival
Loading required package: splines
Loading required package: mvtnorm

> YOY <- data.frame(length = c(46, 28, 46, 37, 32, 41, 42, 45,
+   38, 44, 42, 60, 32, 42, 45, 58, 27, 51, 42, 52, 38, 33, 26,
+   25, 28, 28, 26, 27, 27, 27, 31, 30, 27, 29, 30, 25, 25, 24,
+   27, 30), site = factor(c(rep("I", 10), rep("II", 10), rep("III",
+   10), rep("IV", 10))))
> kruskal_test(length ~ site, data = YOY)

      Asymptotical Kruskal-Wallis Test

data:  length by groups I, II, III, IV
T = 22.8524, df = 3, p-value = 4.335e-05

> it <- independence_test(length ~ site, data = YOY, ytrafo = function(data) trafo(data,
+   numeric_trafo = rank), teststat = "quadtype")
> statistic(it, "linear")

      [,1]
I      278
II     307
III    119
IV     116

> expectation(it)

      [,1]
I      205
II     205
III    205
IV     205

> covariance(it)

      [,1]      [,2]      [,3]      [,4]
[1,] 1019.0385 -339.6795 -339.6795 -339.6795
[2,] -339.6795 1019.0385 -339.6795 -339.6795
[3,] -339.6795 -339.6795 1019.0385 -339.6795
[4,] -339.6795 -339.6795 -339.6795 1019.0385
```

```
> statistic(it, "standardized")
```

```
      [,1]
I      2.286797
II     3.195250
III   -2.694035
IV    -2.788013
```

```
> statistic(it)
```

```
[1] 22.85242
```

```
> pvalue(it)
```

```
[1] 4.334659e-05
```

Independence in Contingency Tables

```
> data(jobsatisfaction)
```

```
> jobsatisfaction
```

```
, , Gender = Female
```

	Job.Satisfaction		
Income	Very Dissatisfied	A Little Dissatisfied	Moderately Satisfied
<5000	1	3	11
5000-15000	2	3	17
15000-25000	0	1	8
>25000	0	2	4

	Job.Satisfaction	
Income	Very Satisfied	
<5000	2	
5000-15000	3	
15000-25000	5	
>25000	2	

```
, , Gender = Male
```

	Job.Satisfaction		
Income	Very Dissatisfied	A Little Dissatisfied	Moderately Satisfied
<5000	1	1	2
5000-15000	0	3	5
15000-25000	0	0	7
>25000	0	1	9

	Job.Satisfaction	
Income	Very Satisfied	
<5000	1	

```

5000-15000    1
15000-25000   3
>25000        6

```

```

> it <- cmh_test(jobsatisfaction)
> it

```

Asymptotical Generalised Cochran-Mantel-Haenszel Test

data: Job.Satisfaction by groups <5000, 5000-15000, 15000-25000, >25000 stratified by Gender
T = 10.2001, df = 9, p-value = 0.3345

```

> statistic(it, "standardized")

```

	Very Dissatisfied	A Little Dissatisfied	Moderately Satisfied
<5000	1.3112789	0.69201053	-0.2478705
5000-15000	0.6481783	0.83462550	0.5175755
15000-25000	-1.0958361	-1.50130926	0.2361231
>25000	-1.0377629	-0.08983052	-0.5946119

	Very Satisfied
<5000	-0.9293458
5000-15000	-1.6257547
15000-25000	1.4614123
>25000	1.2031648

Ordered Alternatives

```

> lbl_test(jobsatisfaction)

```

Asymptotical Linear-by-Linear Association Test

data: Job.Satisfaction (ordered) by groups <5000 < 5000-15000 < 15000-25000 < >25000 stratified by Gender
T = 6.6235, df = 1, p-value = 0.01006

```

> lbl_test(jobsatisfaction, scores = list(Job.Satisfaction = c(1,
+      3, 4, 5), Income = c(3, 10, 20, 35)))

```

Asymptotical Linear-by-Linear Association Test

data: Job.Satisfaction (ordered) by groups <5000 < 5000-15000 < 15000-25000 < >25000 stratified by Gender
T = 6.1563, df = 1, p-value = 0.01309

Multivariate Problems