Non-parametric Statistics: Notes 2 Two-sample methods

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Outline

Permutation Tests

Wicoxon Rank Sum and Mann-Whitney U Test

Tests for equality of scale parameters

- ▶ Let's say we want to test formally if there is a difference between two groups.
- ► For instance, we could compare a new procedure to an old procedure.

Two sample tests

- How would you do this parametrically?
- ▶ We use a t-test with the assumption of normality
- Or you can use asymptotic theory and the Central Limit Theorem (CLT)

```
dat<-data.frame(score=c(37,49,55,57,23,31,46),method=c(rep("N",4),rep("0",3)))
dat
    score method
##
## 1
        37
## 2
        49
                N
       55
## 3
                N
## 4
      57
## 5
       23
## 6
       31
                Π
## 7
      46
                Ω
#Computer the observed means
scoreMeans <-tapply (dat $score, dat $method, mean)
scoreMeans
## 49.50000 33.33333
obsDiffMeans <-diff(scoreMeans)
#Compute the observed medians
scoreMedians <- tapply (dat $score, dat $method, median)
scoreMedians
## N O
## 52 31
obsDiffMedians<-diff(scoreMedians)
```

```
library(gtools)
perms<-combinations(7,4)
dim(perms)

## [1] 35 4

permDiffs<-rep(NA,dim(perms)[1])
for (i in 1:dim(perms)[1]) {
    scoresTemp<-c(dat$score[perms[i,]],dat$score[setdiff(c(1:7),perms[i,])] )
    datPermuted<-data.frame(score=scoresTemp,method=dat$method)
    permDiffs[i]<-diff(tapply(datPermuted$score,datPermuted$method,mean))
}</pre>
```

```
## [1] -21.4166667 -16.1666667 -14.4166667 -12.6666667 -10.9166667

## [6] -10.9166667 -9.7500000 -8.0000000 -7.41666667 -6.2500000

## [11] -6.25000000 -5.66666667 -2.7500000 -2.1666667 -1.5833333

## [16] -1.0000000 -1.0000000 -0.4166667 0.7500000 2.5000000

## [21] 2.5000000 3.6666667 4.2500000 4.2500000 5.4166667

## [26] 6.0000000 7.1666667 7.7500000 8.9166667 8.9166667

## [31] 12.4166667 13.000000 14.1666667 17.6666667 19.4166667

## ## [31] 12.4166667 13.000000 14.166667 19.4166667
```

- ▶ How can we use these simulated values to construct a p-value?
- ▶ Well, what is a p-value?
- ▶ It's the probability of observing something as or more extreme than what was actually observed.
- ► How many of the observations were AS or MORE extreme than what we actually observed?

```
#One-Sided p-value
sum(permDiffs<=obsDiffMeans)/length(permDiffs)</pre>
## [1] 0.05714286
#Two-Sided p-value
(sum(permDiffs<=obsDiffMeans)+sum(permDiffs>=abs(obsDiffMeans)
## [1] 0.1142857
#http://spark.rstudio.com/ahmed/permutation/
```

- ► The test we just did was exact in the sense that we looked at all possible permutations.
- ► However, sometimes the number of permutations is very large and so we simply take a sample of all possibilities.
- Let's look at that.

```
dat<-data.frame(score=c(37,49,55,57,23,31,46),
               method=c(rep("N",4),rep("0",3)))
dat
    score method
## 1
       37
## 2
       49
               N
## 3
     55
               N
## 4 57
               N
## 5 23
               0
## 6
     31
## 7 46
scoreMeans <-tapply (dat $score, dat $method, mean)
scoreMeans
## 49.50000 33.33333
diff(scoreMeans)
##
## -16.16667
scoreMedians <-tapply(dat$score, dat$method, median)
```

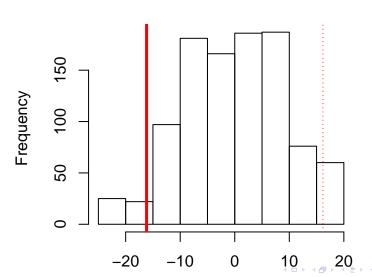
44 L1 4

```
set.seed(1234)
```

```
nsim<-1000
permDiffs<-rep(NA,nsim)
for (i in 1:nsim){print(i)
datPermuted <- data.frame (score=
  sample(dat$score,replace=FALSE),method=dat$method)
permDiffs[i] <-diff(tapply(datPermuted$score,
  datPermuted$method,mean))
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
```

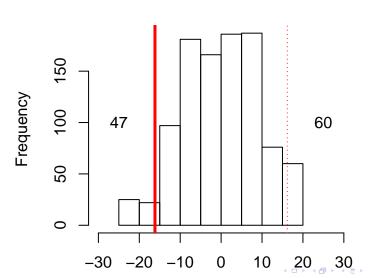
つくに

Histogram of permDiffs



```
lower<-sum(permDiffs<=diff(scoreMeans))</pre>
higher <- sum (permDiffs>=abs(diff(scoreMeans)))
#How do we constuct a p-value now?
#Two sided p-value
(lower+higher)/nsim
## [1] 0.107
#One sided lower p-value
lower/nsim
## [1] 0.047
#Note: the two-sided p-value is not the
#one-sided p-value times 2 here.
#Why not?
```

Histogram of permDiffs



```
## package for these permutation tests
library(perm)
permTS(dat$score^dat$method, alternative="two.sided", exact=TRUE)

##

## Exact Permutation Test (network algorithm)
##

## data: dat$score by dat$method
## p-value = 0.1143
## alternative hypothesis: true mean dat$method=N - mean dat$method=O is not equal to 0
## sample estimates:
## mean dat$method=N - mean dat$method=O
##

16 16667
```

► SAS procedure is "npar1way".

Wilcoxon Rank Sum

- Let's say we have two groups as before.
- ► Take all of the data in both groups, combine them, and then rank them.
- Add up the ranks from group 1 (or group 2, either will work).
- Call this sum W₁.
- ▶ Do a permutation test based on the ranks to find a p-value.

Mann-Whitney U Test

Value	Brand Rank		
3.6	Brand 1 1		
3.8	Brand 2 2		
3.9	Brand 1 3		
4.0	Brand 1 4		
4.1	Brand 2	nd 2 5	
4.3	Brand 1 6		
4.5	Brand 2	7	
4.8	Brand 2	8	
		$W_2 = 22$	

Mann-Whitney U Test

	Brand 1	Brand 2	
0	3.6	3.8	1
1	3.9	4.1	3
1	4.0	4.5	4
2	4.3	4.8	4
Sum=4			Sum=12

$$U=max(4,12)=12$$

Linearly related tests

$$W_2=\frac{1}{2}n(n+1)+U$$

Check it:

$$22 = \frac{1}{2}4(5) + 12$$

[1] 22

set.seed(1234)

```
nsims<-10000
rankSumPerms<-rep(NA,nsims)
for (i in 1:nsims){
   rankSumPerms[i]<- sum(sample(1:8,4,replace=FALSE))
   }
#pvalue
sum(rankSumPerms>=W2)/nsims
## [1] 0.1739
```

Tests for equality of scale parameters

- Siegel-Tukey
- Ansari-Bradley

Siegel-Tukey

- Arrange observations from smallest to largest.
- Assign 1 to the smallest observation, 2 to the largest observation, 3 to the next largest, 4 to the next smallest observation, etc.
- Perform the Wilcoxon rank-sum test. Smaller ranks are associated with the group with larger variability.
- Problem is why start the ranking with the smallest? Could just as easily start with the largest. (Ansari-Bradley!)

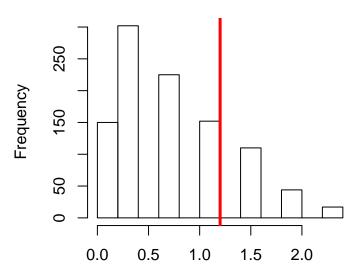
Ansari-Bradley

- Arrange observations from smallest to largest.
- ► Assign 1 to the smallest and largest observations, 2 to the next smallest and next largest, etc.
- ► Compute the Wilcoxon rank-sum and compute a p-value. (Can't use a traditional Wilcoxon rank-sum table. But we shouldn't be using tables anyway! It's 2016!)

```
dat[c(1,2,6,7),]
##
        scores trt
## 1 6.378803
## 2 10.832288 1
## 6 12.530279 2
## 7 7.126300 2
#Some code for Ansari Bradley
dat<-dat[order(dat$scores).]
dat \frac{c(1:(dim(dat)[1]/2),(dim(dat)[1]/2):1)}{dat}
abs(diff(tapply(dat$ranks,dat$trt,mean)))
##
## 1.2
```

```
#Now simulate a null distribution.
#Some code for Ansari Bradley
nsim<-1000
ok<-rep(NA, nsim)
for (i in 1:nsim){print(i)
dat<-dat[sample(1:10,10,replace=FALSE),]</pre>
dat \frac{c(1:(dim(dat)[1]/2),(dim(dat)[1]/2):1)}{dat}
ok[i] <- abs (diff((tapply(dat$ranks,dat$trt,mean))))
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
```

Histogram of ok

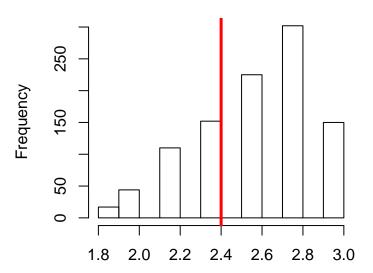


```
#P-value for this test:
sum(ok>=1.2)/nsim
## [1] 0.323
```

```
#let's try it again, but with a small change
#Some code for Ansari Bradley
dat<-dat[order(dat$scores),]
dat$ranks<-c(1:(dim(dat)[1]/2),(dim(dat)[1]/2):1)
min(tapply(dat$ranks,dat$trt,mean))
## [1] 2.4</pre>
```

```
#Now simulate a null distribution.
#Some code for Ansari Bradley
nsim<-1000
ok<-rep(NA, nsim)
for (i in 1:nsim){print(i)
dat<-dat[sample(1:10,10,replace=FALSE),]</pre>
dat \frac{c(1:(dim(dat)[1]/2),(dim(dat)[1]/2):1)}{dat}
ok[i] <-min((tapply(dat$ranks,dat$trt,mean)))
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
```

Histogram of ok



```
#P-value for this test:
sum(ok<=2.4)/nsim
## [1] 0.323</pre>
```