

Mathematical Biostatistics Boot Camp 2: Lecture 12

Brian Caffo

Department of Biostatistics
Johns Hopkins Bloomberg School of Public Health
Johns Hopkins University

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Nonparametric tests

- “Distribution free” methods require fewer assumptions than parametric methods
- Focus on testing rather than estimation
- Not sensitive to outlying observations
- Especially useful for cruder data (like ranks)
- “Throws away” some of the information in the data
- May be less powerful than parametric counterparts, when the parametric assumptions are true
- For large samples, are equally efficient to parametric counterparts

Fish	SR	P	Diff	Sgn rank	Fish	SR	P	Diff	Sng rank
1	.32	.39	.07	+15.5	13	.20	.22	.02	+6.5
2	.40	.47	.07	+15.5	14	.31	.30	-.01	-2.5
3	.11	.11	.00		15	.62	.60	-.02	-6.5
4	.47	.43	-.04	-11.0	16	.52	.53	.01	+2.5
5	.32	.42	.10	+20.0	17	.77	.85	.08	+17.5
6	.35	.30	-.05	-13.5	18	.23	.21	-.02	-6.5
7	.32	.43	.11	+20.0	19	.30	.33	.03	+9.0
8	.63	.98	.35	+23.0	20	.70	.57	-.13	-21.0
9	.50	.86	.36	+24.0	21	.41	.43	.02	+6.5
10	.60	.79	.19	+22.0	22	.53	.49	-.04	-11.0
11	.38	.33	-.05	-13.5	23	.19	.20	.01	+2.5
12	.46	.45	-.01	-2.5	24	.31	.35	.04	+11.0
					25	.48	.40	-.08	-17.5

Measurements are mercury levels in fish (ppm)

Data from Rice Mathematical Statistics and Data Analysis; second edition

Alternatives to the paired t-test

- Let $D_i = \text{difference (P - SR)}$
- Let θ be the population median of the D_i
- $H_0 : \theta = 0$ versus $H_a : \theta \neq 0$ (or $>$ or $<$)
- Notice that $\theta = 0$ iff $p = P(D > 0) = .5$
- Let X be the number of times $D > 0$
 - X is then binomial(n, p)
- The sign test tests whether $H_0 : p = .5$ using X

Example

- $\theta = \text{median difference } p - sr$
- $H_0 : \theta = 0$ versus $H_a : \theta \neq 0$
- Number of instances where the difference is bigger than 0 is 15 out of 25 trials
- `binom.test(15, 25)`
p-value = 0.4244
- Or we could have used large sample tests for a binomial proportion
`prop.test(15, 25, p = .5)`
X-squared = 0.64, df = 1, p-value = 0.4237

Discussion

- Magnitude of the differences is discarded
 - Perhaps too much information lost
- Could easily have tested $H_0 : \theta = \theta_0$ by calculating the number of times $D > \theta_0$ and performing a binomial test
 - We can invert these tests to get a distribution free confidence interval for the median

Signed rank test

- Wilcoxon's statistic uses the information in the **signed ranks** of the differences
- Saves some of the information regarding the magnitude of the differences
- Still tests $H_0 : \theta = 0$ versus the three alternatives
- Appropriately normalized, the test statistic follows a normal distribution
- Also the exact small sample distribution of the signed rank statistic is known (if there are no ties)

Signed rank procedure

- 1 Take the paired differences
- 2 Take the absolute values of the differences
- 3 Rank these absolute values, throwing out the 0s
- 4 Multiply the ranks by the sign of the difference (+1 for a positive difference and -1 for a negative difference)
- 5 Calculate the rank sum W_+ of the positive ranks

Signed rank procedure

- If $\theta > 0$ then W_+ should be large
- If $\theta < 0$ then W_+ should be small
- Properly normalized, W_+ follows a large sample normal distribution
- For small sample sizes, W_+ has an exact distribution under the null hypothesis
- Can get critical values from tables in the textbook

Monte Carlo

- Assume no ties
- Simulate n observations from any distribution that has $\theta = 0$ as its median
- Rank the absolute value of the data, retain the signs, calculate the signed rank statistic
- Apply this procedure over and over, the proportion of time that the observed test statistic is larger or smaller (depending on the hypothesis) is a Monte Carlo approximation to the P-value

Monte Carlo

- Here's a slightly more elegant way to simulate from the null distribution
- Consider the ranks $1, \dots, n$
- Randomly assign the signs as binary with probability .5 of being positive and .5 of being negative
- Calculate the signed rank statistic
- Apply this procedure over and over, the proportion of time that the observed test statistic is larger or smaller (depending on the hypothesis) is a Monte Carlo approximation to the P-value

Large sample distribution of W_+

- Under H_0 and if there are no ties
 - $E(W_+) = n(n+1)/4$
 - $Var(W_+) = n(n+1)(2n+1)/24$
 - $TS = \{W_+ - E(W_+)\}/Sd(W_+) \rightarrow \text{Normal}(0, 1)$
- There is a correction term necessary for ties
- Without ties, it's possible to do an exact (small sample) test

Example

```
diff <- c(.07, .07, .00, -.04, ...)  
wilcox.test(diff, exact = FALSE)
```

- $H_0 : \text{Med diff} = 0$ versus $H_a : \text{Med diff} \neq 0$
- $W_+ = 194.5$
- $E(W_+) = 24 \times 25/4 = 150$
- $\text{Var}(W_+) = 24 \times 25 \times 49/24 = 1,225$
- $TS = (194.5 - 150)/\sqrt{1,224} = 1.27$
- P-value = .20
- R's P-value (uses correction for ties) = 0.21

Methods for unpaired samples

Comparing two measuring techniques A and B

Units are in deg C per gram

Method A		Method B
79.98	80.05	80.02
80.04	80.03	79.94
80.02	80.02	79.98
80.04	80.00	79.97
80.03	80.02	79.97
80.03		80.03
80.04		79.95
79.97		79.97

Data from Rice Mathematical Statistics and Data Analysis; second edition

The Mann/Whitney test

- Tests whether or not the two treatments have the same location
- Assumes independent identically distributed errors, not necessarily normal
- Null hypothesis can also be written more generally as a stochastic shift for two arbitrary distributions
- Test uses the sum of the ranks obtained by discarding the treatment labels
- Also called the Wilcoxon rank sum test

The Mann-Whitney test

- Procedure
 - ① Discard the treatment labels
 - ② Rank the observations
 - ③ Calculate the sum of the ranks in the first treatment
 - ④ Either
 - calculate the asymptotic normal distribution of this statistic
 - compare with the exact distribution under the null hypothesis

Method A		Method B
7.5	21.0	11.5
19.0	15.5	1.0
11.5	11.5	7.5
19.0	9.0	4.5
15.5	11.5	4.5
15.5		15.5
19.0		2.0
4.5		4.5
180		51

Sum has to add up to $21 \times 22/2 = 231$

Gauss supposedly came up with this in grade school

$$\begin{array}{rcccccccc} x & = & 1 & + & 2 & + & 3 & + & 4 & + & \dots & + & n \\ x & = & n & + & n-1 & + & n-2 & + & n-3 & + & \dots & + & 1 \end{array}$$

Therefore

$$2x = n+1 + n+1 + n+1 + n+1 + \dots + n+1$$

$$\text{So } 2x = n(n+1) / 2$$

$$\text{So } x = n(n+1) / 2$$

Results

- Let W be the sum of the ranks for the first treatment (A)
- Let n_A and n_B be the sample sizes
- Then
 - $E(W) = n_A(n_A + n_B + 1)/2$
 - $\text{Var}(W) = n_A n_B (n_A + n_B + 1)/12$
 - $TS = \{W - E(W)\} / \text{Sd}(W) \rightarrow N(0, 1)$
- Also the exact distribution of W can be calculated

Example

- $W = 51$
- $E(W) = 8(8 + 13 + 1)/2 = 88$
- $Sd(W) = \sqrt{8 \times 13(8 + 13 + 1)/12} = 13.8$
- $TS = (51 - 88)/13.8 = -2.68$
- Two-sided P-value = .007
- R function `wilcox.test` will perform the test

Monte Carlo

- Note that under H_0 , the two groups are **exchangeable**
- Therefore, any allocation of the ranks between the two groups is equally likely
- Procedure: Take the ranks $1, \dots, N_A + N_B$ and permute them
- Take the first N_A ranks and allocate them to Group A; allocate the remainder to Group B
- Calculate the test statistic
- Repeat this process over and over; the proportion of times the test statistic is larger or smaller (depending on the alternative) than the observed value is an exact P-value

Notes about nonpar tests

- Tend to be more robust to outliers than parametric counterparts
- Do not require normality assumptions
- Usually have exact small-sample versions
- Are often based on ranks rather than the raw data
- Loss in power over parametric counterparts is often not bad
- Nonpar tests are not assumption free

Permutation tests

- Permutation tests are similar to the rank-sum tests, though they use the actual data rather than the ranks
- That is, consider the null hypothesis that the distribution of the observations from each group is the same
- Then, the group labels are irrelevant
- We then discard the group levels and permute the combined data
- Split the permuted data into two groups with n_A and n_B observations (say by always treating the first n_A observations as the first group)
- Evaluate the probability of getting a statistic as large or large than the one observed
- An example statistic would be the difference in the averages between the two groups; one could also use a t-statistic

- This is an easy way to produce a null distribution for a test of equal distributions
- Similar in flavor to the bootstrap
- This procedure produces an exact test
- Less robust, but more powerful than the rank sum tests
- Very popular in genomic applications

Histogram of simTheta

