

Comparing Systems Using Sample Data

CS 700

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Comparing alternatives

- ❑ Today's lecture: comparing two alternatives
 - use confidence intervals
- ❑ Comparing more than two alternatives
 - ANOVA
 - Analysis of Variance
 - Will discuss later this semester

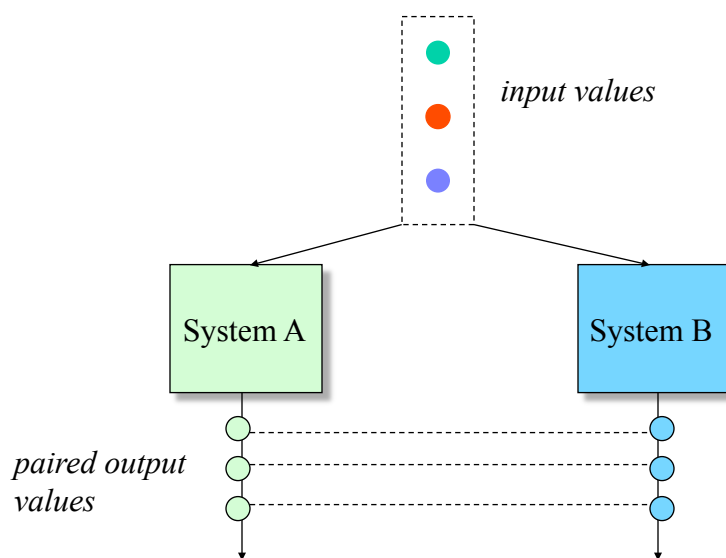
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Comparing Two Alternatives

- ❑ Suppose you want to compare two cache replacement policies under similar workloads.
- ❑ Metric of interest: cache hit ratio.
- ❑ Types of comparisons:
 - Paired observations
 - Unpaired observations.

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Paired Observations



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Example of Paired Observations

- Six similar workloads were used to compare the cache hit ratio obtained under object replacement policies A and B on a Web server. Is A better than B?

Workload	Cache Hit Ratio		A-B
	Policy A	Policy B	
1	0.35	0.28	0.07
2	0.46	0.37	0.09
3	0.29	0.34	-0.05
4	0.54	0.60	-0.06
5	0.32	0.22	0.10
6	0.15	0.18	-0.03
Sample mean			0.02000
Sample variance			0.00552
Sample standard dev.			0.07430

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Example of Paired Observations

Sample mean	0.02000
Sample variance	0.00552
Sample standard dev.	0.07430

In Excel:
TINV(1-0.9,5)

0.95 quantile of t-variable with 5 degrees of freedom

2.015

90% confidence interval

lower bound

-0.0411

upper bound

0.0811

$$\left(\bar{x} - t_{[1-\alpha/2;n-1]} \frac{s}{\sqrt{n}}, \bar{x} + t_{[1-\alpha/2;n-1]} \frac{s}{\sqrt{n}} \right)$$

Annotations for the formula:

- 0.02 points to \bar{x}
- 2.015 points to $t_{[1-\alpha/2;n-1]}$
- 0.0743 points to s
- 6 points to n

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Example of Paired Observations

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Sample standard dev.	0.07430

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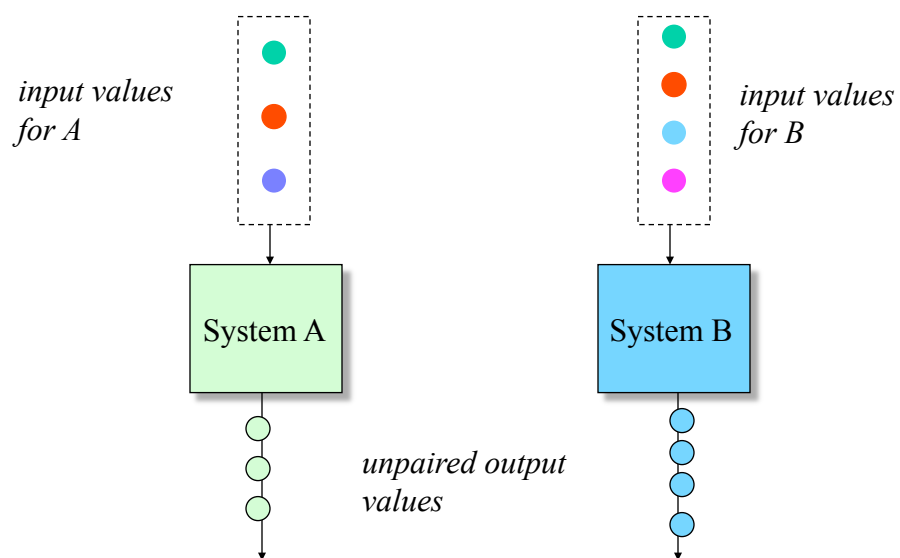
upper bound

0.0811

The interval includes zero, so we cannot say that policy A is better than policy B.

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Unpaired Observations



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Inferences concerning two means

- For large samples, we can statistically test the equality of the means of two samples by using the statistic

$$Z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

- Z is a random variable having the standard normal distribution.
- We need to check if the confidence interval of Z at a given level includes zero
- We can approximate the population variances above with sample variances when n_1 and n_2 are greater than 30

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Inferences concerning two means (cont'd)

- For small samples, if the population variances are unknown, we can test for equality of the two means using the t-statistic below, provided we can assume that both populations are normal with equal variances

$$t = \frac{\bar{X}_1 - \bar{X}_2}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

- t is a random variable having the t-distribution with $n_1 + n_2 - 2$ degrees of freedom and S_p is the square root of the pooled estimate of the variance of the two samples

$$S_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{(n_1 - 1) + (n_2 - 1)}$$

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Inferences concerning two means (cont'd)

- The pooled-variance t test can be used if we assume that the two population variances are equal
 - In practice, we can use it if one sample variance is less than 4 times the variance of the other sample
- If this is not true, we need another test
 - Smith-Satterthwaite test described on the following slides

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Unpaired Observations (t-test)

1. Size of samples for A and B: n_A and n_B
2. Compute sample means:

$$\bar{x}_A = \frac{1}{n_A} \sum_{i=1}^{n_A} x_{iA}$$

$$\bar{x}_B = \frac{1}{n_B} \sum_{i=1}^{n_B} x_{iB}$$

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Unpaired Observations (t-test)

3. Compute the sample standard deviations:

$$s_A = \sqrt{\frac{\left(\sum_{i=1}^{n_A} x_{iA}^2\right) - n_A (\bar{x}_A)^2}{n_A - 1}}$$

$$s_B = \sqrt{\frac{\left(\sum_{i=1}^{n_B} x_{iB}^2\right) - n_B (\bar{x}_B)^2}{n_B - 1}}$$

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Unpaired Observations (t-test)

4. Compute the mean difference: $\bar{x}_a - \bar{x}_b$
 5. Compute the standard deviation of the mean difference:

$$s = \sqrt{\frac{s_a^2}{n_a} + \frac{s_b^2}{n_b}}$$

6. Compute the effective number of degrees of freedom.

$$v = \frac{\left(s_a^2/n_a + s_b^2/n_b\right)^2}{\frac{1}{n_a - 1} \left(\frac{s_a^2}{n_a}\right)^2 + \frac{1}{n_b - 1} \left(\frac{s_b^2}{n_b}\right)^2}$$

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Unpaired Observations (t-test)

7. Compute the confidence interval for the mean difference:

$$(\bar{x}_a - \bar{x}_b) \pm t_{[1-\alpha/2, v]} \times S$$

8. If the confidence interval includes zero, the difference is not significant at 100(1- α)% confidence level.

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Example of Unpaired Observations

- Two cache replacement policies A and B are compared under similar workloads. Is A better than B?

Workload	Cache Hit Ratio	
	Policy A	Policy B
1	0.35	0.49
2	0.23	0.33
3	0.29	0.33
4	0.21	0.55
5	0.21	0.65
6	0.15	0.18
7	0.42	0.29
8		0.35
9		0.44
Mean	0.2657	0.4011
St. Dev	0.0934	0.1447

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Example of Unpaired Observations

na	7
nb	9
mean diff	-0.135
st.dev diff.	0.059776
Eff. Deg. Freed.	13
alpha	0.1
1-alpha/2	0.95
t[1-alpha/2,v]	1.782287

for 90% confidence interval

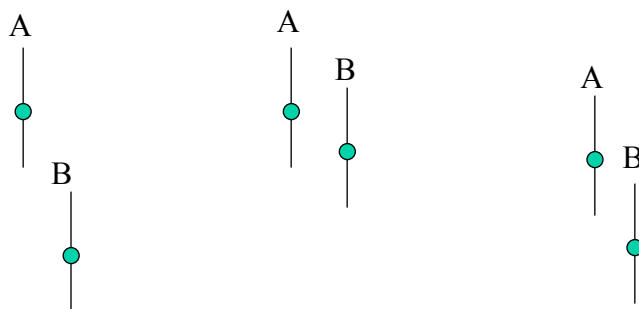
In Excel: $TINV(1-0.9,13-1)$

90% Confidence Interval	
lower bound	-0.24193
upper bound	-0.02886

At a 90% confidence level the two policies are not identical since zero is not in the interval. With 90% confidence, the cache hit ratio for policy A is smaller than that for policy B. So, policy B is better at that confidence level.

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Approximate Visual Test



CIs do not overlap:
A is higher than B

CIs overlap and mean
of A is in B's CI:
A and B are similar

CIs overlap and mean
of A is not in B's CI:
need to do t-test

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Example of Visual Test

Workload	Cache Hit Ratio	
	Policy A	Policy B
1	0.35	0.49
2	0.23	0.33
3	0.29	0.33
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6	0.15	0.18
7	0.42	0.29
8		0.35
9		0.44
Mean	0.2657	0.4011
St. Dev	0.0934	0.1447

na	7		
nb	9		
alpha	0.1	for	90% confidence interval
1-alpha/2	0.95		
	Policy A	Policy B	
t[1-alpha/2,v]	1.9432	1.8595	
90% Confidence Interval			
lower bound	0.197	0.311	
upper bound	0.334	0.491	

CIs overlap but mean of A is not in CI of B and vice-versa.
Need to do a t-test.

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Non-parametric tests

- The unpaired t-tests can be used if we assume that the data in the two samples being compared are taken from normally distributed populations
- What if we cannot make this assumption?
 - We can make some normalizing transformations on the two samples and then apply the t-test
 - Some non-parametric procedure such as the Wilcoxon rank sum test that does not depend upon the assumption of normality of the two populations can be used

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Rank-sum (Wilcoxon test)

- Non-parameteric test, i.e., does not depend upon distribution of population, for comparing two samples
- Example:
 - Suppose the time between two successive crashes are recorded for two competing computer systems as follows (time in weeks):
 System I: 0.63 0.17 0.35 0.49 0.18 0.43 0.12 0.20 0.47
 1.36 0.51 0.45 0.84 0.32 0.40
 System II: 1.13 0.54 0.96 0.26 0.39 0.88 0.92 0.53 1.01
 0.48 0.89 1.07 1.11 0.58
 - The problem is to determine if the two populations are the same or if one is likely to produce larger observations than the other

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Rank-sum test (cont'd)

- U-test is a non-parameteric alternative to the paired and unpaired t-tests
- First step in the U-test is to rank the data jointly, in increasing order of magnitude

0.12	0.17	0.18	0.20	0.26	0.32	0.35	0.39	0.40	0.43
I	I	I	I	II	I	I	II	I	I
0.45	0.47	0.48	0.49	0.51	0.53	0.54	0.58	0.63	0.84
I	I	II	I	I	II	II	II	I	I
0.88	0.89	0.92	0.96	1.01	1.07	1.11	1.13	1.36	
II	II	II	II	II	II	II	II	I	
- Assign each data item a rank in this order
 - If there are ties among values, the rank assigned to each observation is the mean of the ranks which they jointly occupy

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Rank-sum test (cont'd)

- The values in the first sample occupy ranks 1, 2, 3, 4, 6, 7, 9, 10, 11, 12, 14, 15, 19, 20 and 29
- The sum of the ranks for the two samples, $W_1 = 162$ and $W_2 = 273$
- The U-test is based on the statistics

$$U_1 = W_1 - \frac{n_1(n_1 + 1)}{2}$$

or

$$U_2 = W_2 - \frac{n_2(n_2 + 1)}{2}$$

or on the statistic U which is the smaller of the two

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Rank-sum test (cont'd)

- Under the null hypothesis that the two samples come from identical populations, it can be shown that the mean and variance of the sampling distribution of U_1 are

$$\mu_{U_1} = \frac{n_1 n_2}{2}$$

and

$$\sigma_{U_1}^2 = \frac{n_1 n_2 (n_1 + n_2 + 1)}{12}$$

- Numerical studies have shown that the sampling distribution of U_1 can be approximated closely by the normal distribution when n_1 and n_2 are both greater than 8

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Rank-sum test (cont'd)

- Thus, the test of the null hypothesis that both samples come from identical populations can be based on

$$Z = \frac{U_1 - \mu_{U_1}}{\sigma_{U_1}}$$

which is a random variable having approximately the standard normal distribution

- The alternative hypothesis is either:
 - Two-sided test (Populations are not identical)
 - We reject the null hypothesis if $Z < -z_{\alpha/2}$ or $Z > z_{\alpha/2}$
 - One-sided test
 - Population 2 is stochastically larger than Population 1
 - We reject the null hypothesis if $Z < -z_{\alpha}$
 - Or, Population 1 is stochastically larger than Population 2
 - We reject the null hypothesis if $Z > z_{\alpha}$

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Example cont'd

- At the 0.01 level of significance, test the null hypothesis that the two samples in our example come from the same population
 - Alternative hypothesis, populations are not identical
 - For $\alpha = 0.01$, we can reject the null hypothesis if $Z < -2.575$ or $Z > 2.575$
 - Calculations: $n_1 = 15$, $n_2 = 14$, $W_1 = 162$
 $U_1 = 162 - 15 \times 16 / 2 = 42$
 $Z = (42 - 15 \times 14 / 2) / \sqrt{((15 \times 14 \times 30) / 12)} = -2.75$
 - Since Z is less than -2.575 , we reject the null hypothesis; we conclude there is a difference between the two systems

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