

Matched pairs Some data:

```
subject druga drugb
           2.0
           3.6
                 5.7
           2.6
                 2.9
           2.6
                 2.4
           7.3
                 3.3
           3.4
          14.9
               16.7
           6.6
                  6.0
                  3.8
           2.3
           2.0
                  4.0
           6.8
```

Matched pairs 1/2

- ▶ Data are comparison of 2 drugs for effectiveness at reducing pain.
 - ▶ 12 subjects (cases) were arthritis sufferers
 - Response is #hours of pain relief from each drug.
- In reading example, each child tried only one reading method.
- But here, each subject tried out both drugs, giving us two measurements.
- Possible because, if you wait long enough, one drug has no influence over effect of other.

Matched pairs 2/2

- Advantage: focused comparison of drugs. Compare one drug with another on same person, removes a lot of variability due to differences between people.
- Matched pairs, requires different analysis.
- Design: randomly choose 6 of 12 subjects to get drug A first, other 6 get drug B first.

Packages

```
library(tidyverse)
library(smmr) # for a sign test later
```

Reading the data

Values aligned in columns:

```
my_url <-
   "http://ritsokiguess.site/datafiles/analgesic.txt"
pain <- read_table(my_url)
pain
# A tibble: 12 x 3</pre>
```

```
subject druga drugb
   <dbl> <dbl> <dbl>
       1 2 3.5
       2 3.6 5.7
3
       3 2.6 2.9
4
      4 2.6 2.4
5
      5 7.3 9.9
6
       6 3.4 3.3
7
         14.9 16.7
8
       8 6.6 6
       9
          2.3
               3.8
```

Paired *t*-test

```
with(pain, t.test(druga, drugb, paired = TRUE))
    Paired t-test
data: druga and drugb
t = -2.1677, df = 11, p-value = 0.05299
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
-4.29941513 0.03274847
sample estimates:
mean difference
      -2.133333
```

- P-value is 0.053.
- Not quite evidence of difference between drugs.

t-testing the differences

Likewise, you can calculate the differences yourself and then do a 1-sample t-test on them.

```
pain %>% mutate(diff = druga - drugb) -> pain
pain
```

```
# A tibble: 12 \times 4
   subject druga drugb diff
    <dbl> <dbl> <dbl> <dbl> <dbl>
            2 3.5 -1.5
 1
 2
        2 \quad 3.6 \quad 5.7 \quad -2.1
3
        3 2.6 2.9 -0.300
        4 2.6 2.4 0.200
4
 5
        5 7.3 9.9 -2.6
 6
        6 3.4 3.3 0.100
        7
           14.9 16.7 -1.80
8
        8 6.6 6 0.600
9
        9 2.3 3.8 -1.5
       10
10
                       -2
```

t-test on the differences

then throw them into t.test, testing that the mean is zero, with same result as before:

```
with(pain, t.test(diff, mu = 0))
```

One Sample t-test

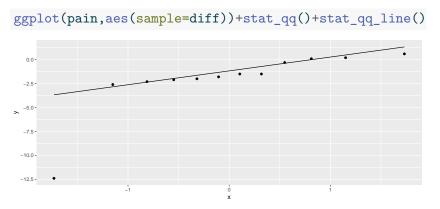
```
data: diff
t = -2.1677, df = 11, p-value = 0.05299
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
   -4.29941513   0.03274847
sample estimates:
mean of x
-2.133333
```

Same P-value (0.053) and conclusion.

Assessing normality

- ▶ 1-sample and 2-sample t-tests assume (each) group normally distributed.
- Matched pairs analyses assume (theoretically) that differences normally distributed.
- How to assess normality? A normal quantile plot.

The normal quantile plot (of differences)



Points should follow the straight line. Bottom left one way off, so normality questionable here: outlier.

What to do instead?

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- ▶ Matched pairs *t*-test based on one sample of differences
- the differences not normal (enough)
- > so do *sign test* on differences, null median 0:

```
$above_below
below above
    9    3

$p_values
    alternative    p_value
1    lower 0.07299805
2    upper 0.98071289
```

two-sided 0.14599609

sign_test(pain, diff, 0)

Comments

- ▶ no evidence of any difference between drugs (P-value 0.1460)
- in t-test, the low outlier difference pulled mean difference downward and made it look more negative than it should have been
- therefore, there really isn't any difference between the drugs.