1. The vitamin C contents of two types of cabbage were surveyed in 10 samples per type:
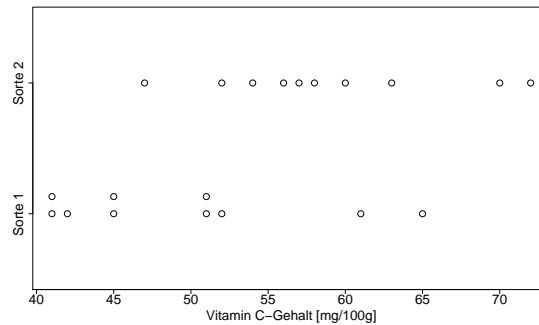
For the samples of type 1 a mean content of $\mu_1 = 49.4$ mg per 100g with standard deviation $s_1 = 8.33$ was found, for type 2 the values were $\mu_2 = 58.9$ and $s_2 = 7.74$. Test the hypothesis that the mean vitamin C contents is the same for both types with a t-test. You may assume that the true variances are equal.

2. Gene expression levels of 100 genes were measured in tissue samples from 20 different fly lines after cold shock and were tested for association with cold resistance, proxied by chill coma recovery time of flies from the same lines. The second column in the file `gene_p_values.csv` contains the p-values from these 100 tests. We aim to obtain a list of genes that are presumably associated with cold resistance.

(a) Compile a list that contains as many genes as possible, but in a way such that genes that are **not** associated with cold resistance must have 95% probability to be **not** on the list.

(b) Compile a list that contains as many genes as possible, but in a way such that the probability that the list contains only genes that are in fact associated to cold resistance is $\approx 95\%$.

(c) Compile a list that contains as many genes as possible, but in a way such that $\approx 95\%$ of the genes on your list are indeed associated with cold resistance.

3. Three groups of chicks were fed with different diets and weighed after three weeks. The results in gram were as follows.

Diet A	215	205	157	175	
Diet B	331	175	167	192	233
Diet C	322	237	238	264	

(a) Visualize the data in an appropriate way.

(b) Perform an ANOVA to test whether there is a difference in the three diets. Do not use the special R commands for anova, and use the quantile table to assess significance. In addition, use the R command `pf` to calculate the p value.

(c) Perform the ANOVA with the special R commands.

(d) Perform pairwise comparisons to check which diets do actually differ from each other in their effects. Don't forget to correct your p-values for multiple testing!

4. (Optional; for those who watched the videos on Wilcoxon tests) To test whether a pharmaceutical increases the reaction time, the latter was tested with nine test persons. Five of them were randomly selected and took the drug. Their reaction times in seconds were 0.78, 0.66, 0.86, 0.90, 0.83. The other four persions had the reaction times 0.82, 0.62, 0.63, 0.69. Apply the Wilcoxon rank sum test and an appropriate t-test by hand (that is, without using the R commands `wilcox.test` and `t.test`) to test whether the drug increases the reaction time.

5. (Optional; for those who watched the videos on Wilcoxon tests) Test the power (that is the ability to reject the null hypothesis if it is wrong) and robustness (against violations of the requirements on the distribution) of the two-sample t-test and the Wilcoxon rank sum test:

(a) Generate two normally distributed samples of size n, one of them with true mean 0 and one with true mean μ (with R: `rnorm(n,mean=`μ`)`). How does the probability that the two-sample t-test or the Wilcoxon rank sum test rejects the null hypothesis "the population means are equal" with significance level $\alpha = 0.05$ on the values of n and μ? Explore this for $\mu \in \{0, 0.5, 2\}$ and $n \in \{5, 10, 20\}$ by repeated simulations.

(b) Repeat (a) with a slight modification. Generate one sample with `rnorm(n,mean=0)` again, but the other one with `rnorm(n,mean=`μ`,sd=`σ`)`, where σ takes a value between 2 and 10.

(c) In another series of simulations generate one sample with `rexp(n,rate=1)` and the other one with `rexp(n,rate=r)`. For r try the values 1, 0.5, and 0.1.