STAT 401A - Statistical Methods for Research Workers

Modeling assumptions

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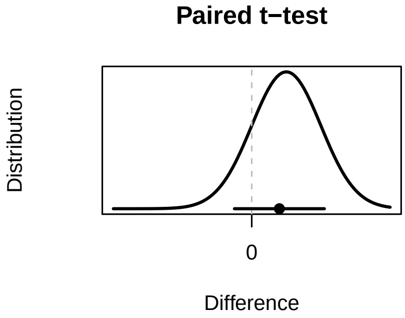
Normality assumptions

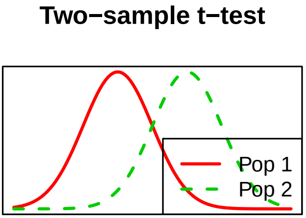
In the paired t-test, we assume

$$D_i \stackrel{iid}{\sim} N(\mu, \sigma^2).$$

In the two-sample t-test, we assume

$$Y_{ij} \stackrel{ind}{\sim} N(\mu_j, \sigma^2).$$





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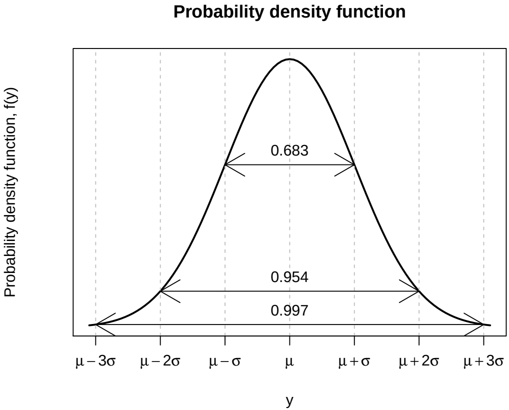
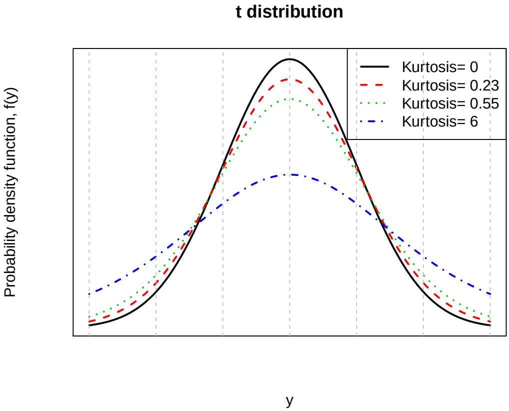
Key features of the normal distribution assumption:

- Centered at the mean (expectation) μ
- Standard deviation describes the spread
- Symmetric around μ (no skewness)
- Non-heavy tails, i.e. outliers are rare (no kurtosis)

Normality assumptions



Kurtosis (heavy-tailedness)



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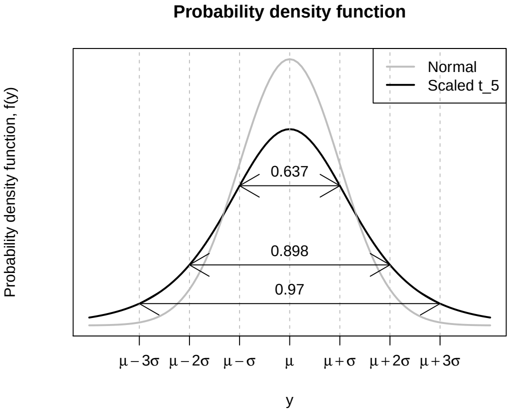

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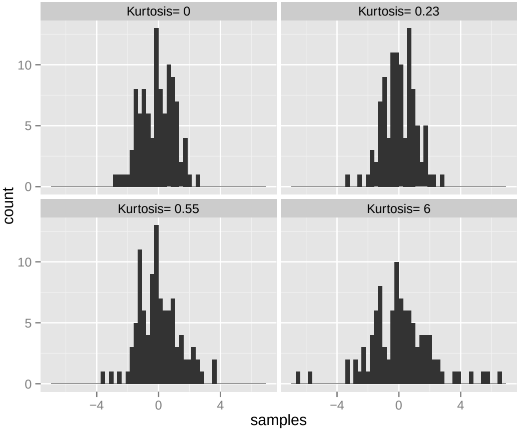

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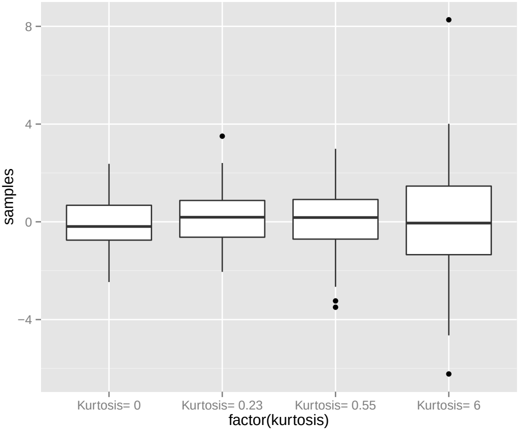
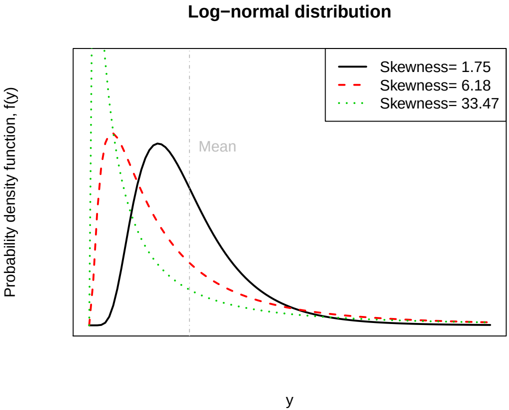
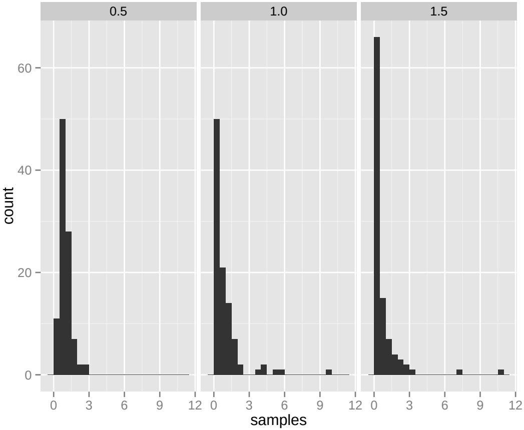


Skewness


Log−normal distribution
Skewness= 1.75
Skewness= 6.18
Skewness= 33.47
Mean
Probability density function, f(y)
y

Samples from skewed distributions



Robustness

Definition

A statistical procedure is robust to departures from a particular assumption if it is valid even when the assumption is not met.

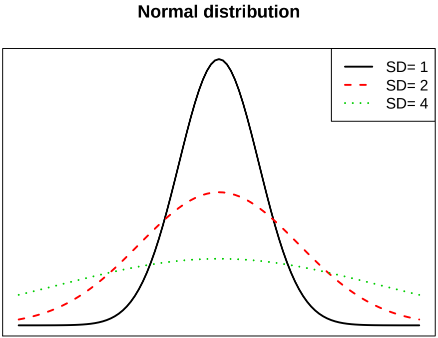
Remark If a 95% confidence interval is robust to departures from a particular assumption, the confidence interval should cover the true value about 95% of the time.

Robustness to skewness and kurtosis

Percentage of 95% confidence intervals that cover the true difference in means in an equal-sample two-sample t-test with non-normal populations (where the distributions are the same other than their means).

sample size	strongly skewed	moderately skewed	mildly skewed	heavy-tailed	short-tailed
5	95.5	95.4	95.2	98.3	94.5
10	95.5	95.4	95.2	98.3	94.6
25	95.3	95.3	95.1	98.2	94.9
50	95.1	95.3	95.1	98.1	95.2
100	94.8	95.3	95.0	98.0	95.6

Differences in variances



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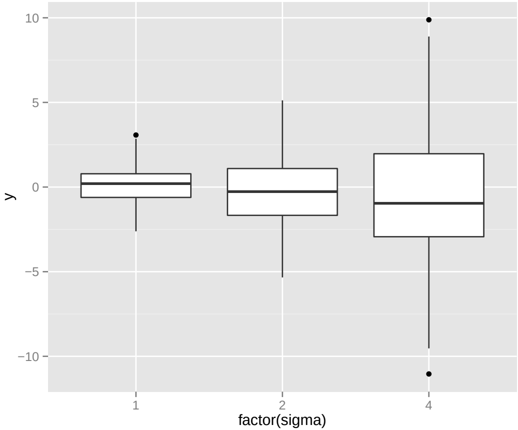


Robustness to differences in variances

Percentage of 95% confidence intervals that cover the true difference in means in an equal-sample two-sample t-test ($r = \sigma_1/\sigma_2$).

n1	n2	r=1/4	r=1/2	r=1	r=2	r=4
10	10	95.2	94.2	94.7	95.2	94.5
10	20	83.0	89.3	94.4	98.7	99.1
10	40	71.0	82.6	95.2	99.5	99.9
100	100	94.8	96.2	95.4	95.3	95.1
100	200	86.5	88.3	94.8	98.8	99.4
100	400	71.6	81.5	95.0	99.5	99.9

Outliers

Definition

A statistical procedure is resistant if it does not change very much when a small part of the data changes, perhaps drastically.

Identify outliers:

1. If recording errors, fix.
2. If outlier comes from a different population, remove and report.
3. If results are the same with and without outliers, report with outliers.
4. If results are different, use resistant analysis or report both analyses.

Common ways for independence to be violated

- Cluster effect
  - e.g. pigs in a pen
- Correlation effect
  - e.g. measurements in time with drifting scale
- Spatial effect
  - e.g. corn yield plots (drainage)

Common transformations for data

From: http://en.wikipedia.org/wiki/Data_transformation_(statistics)

Definition

In statistics, data transformation refers to the application of a deterministic mathematical function to each point in a data set that is, each data point y_i is replaced with the transformed value $z_i = f(y_i)$, where f is a function.

The most common transformations to

- If $y \in (0, 1)$, then $f(y) = sin^{-1}(\sqrt{y})$.
- If y is a count, then $f(y) = \sqrt{y}$.
- If y is positive and right-skewed, then $f(y) = log(y)$, the *natural logarithm* of y.

Remark Since $log(0) = -\infty$, the logarithm cannot be used directly when some y_i are zero. In these cases, use $\log(y + c)$ where c is something small relative to your data, e.g. half of the minimum non-zero value.

Log transformation

If $z_{ij} = log(y_{ij})$ and we run a two-sample t-test on the z's, then we assume

$$Z_{ij} \stackrel{ind}{\sim} N(\mu_j, \sigma^2)$$

and we calculate the quantity $\overline{Z}_2 - \overline{Z}_1$ and $\exp\left(\overline{Z}_2 - \overline{Z}_1\right) = e^{\overline{Z}_2 - \overline{Z}_1}$ estimates

$$\frac{\text{Median of population 2}}{\text{Median of population 1}}$$

on the original scale or, equivalently, it estimates the multiplicative effect of moving from population 1 to population 2.

Log transformation interpretation

If we have a randomized experiment:

Remark It is estimated that the response of an experimental unit to treatment 2 will be $\exp\left(\overline{Z}_2 - \overline{Z}_1\right)$ times as large as its response to treatment 1.

If we have an observational study:

Remark It is estimated that the median for population 2 is $\exp\left(\overline{Z}_2 - \overline{Z}_1\right)$ times as large as the median for population 1.

Confidence intervals with log transformation

If $z_{ij} = log(y_{ij})$ and we assume

$$Z_{ij} \stackrel{ind}{\sim} N(\mu_j, \sigma^2),$$

then a $100(1-\alpha)\%$ two-sided confidence interval for $\mu_2 - \mu_1$ is

$$(L, U) = \overline{Z}_2 - \overline{Z}_1 \pm t_{n_1+n_2-2}(1-\alpha/2) SE\left(\overline{Z}_2 - \overline{Z}_1\right).$$

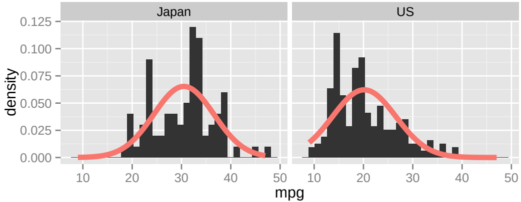
A $100(1-\alpha)\%$ confidence interval for

$$\frac{\text{Median of population 2}}{\text{Median of population 1}}$$

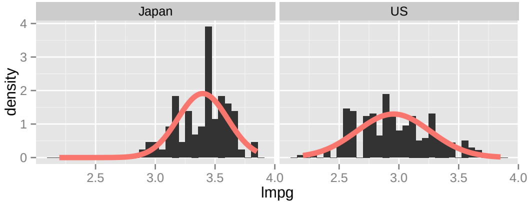
is (e^L, e^U).

Miles per gallon data

Untransformed:



Logged:



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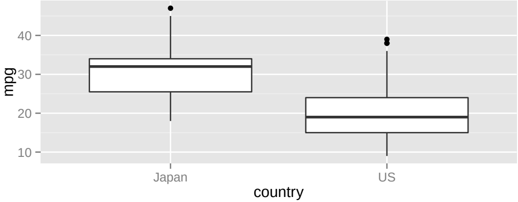

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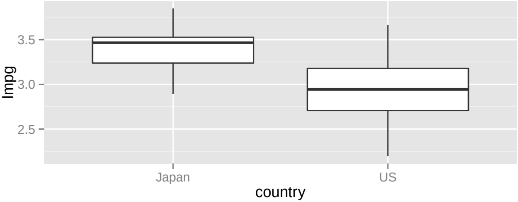

Equal variances?

We might also be concerned about the assumption of equal variances.

Untransformed:

	country	n	mean	sd
1	Japan	79	30.48	30.48
2	US	249	20.14	20.14

the ratio of the standard deviations is around 1.5 and there are 3 times as many observations in the US.

Logged:

	country	n	mean	sd
1	Japan	79	3.40	3.40
2	US	249	2.96	2.96

Now the ratio of standard deviations is only 1.15.

Using R for t-test using logarithms

```
t = t.test(log(mpg)~country, d, var.equal=TRUE)
exp(t$estimate)
```

```
mean in group Japan    mean in group US
              29.85               19.21
```

```
exp(-diff(t$estimate)) # I had to put in the negative sign
```

```
mean in group US
           1.554
```

```
exp(t$conf.int)
```

```
[1] 1.445 1.672
attr(,"conf.level")
[1] 0.95
```

SAS code for t-test using logarithms

```
DATA mpg;
  INFILE 'mpg.csv' DELIMITER=',' FIRSTOBS=2;
INPUT mpg country $;

PROC TTEST DATA=mpg TEST=ratio;
CLASS country;
VAR mpg;
run;
```

SAS output for t-test using logarithms

The TTEST Procedure

Variable: mpg

country	N	Geometric Mean	Coefficient of Variation	Minimum	Maximum
Japan	79	29.8525	0.2111	18.0000	47.0000
US	249	19.2051	0.3147	9.0000	39.0000
Ratio (1/2)		1.5544	0.2928		

country	Method	Geometric Mean	95% CL Mean		Coefficient of Variation	95% CL CV	
Japan		29.8525	28.4887	31.2817	0.2111	0.1820	0.2514
US		19.2051	18.4825	19.9560	0.3147	0.2882	0.3467
Ratio (1/2)	Pooled	1.5544	1.4452	1.6719	0.2928	0.2712	0.3183
Ratio (1/2)	Satterthwaite	1.5544	1.4636	1.6508			

Method	Coefficients of Variation	DF	t Value	Pr > |t|
Pooled	Equal	326	11.91	<.0001
Satterthwaite	Unequal	193.33	14.46	<.0001

Equality of Variances

Method	Num DF	Den DF	F Value	Pr > F
Folded F	248	78	2.17	0.0001

Conclusion

Japanese median miles per gallon is 1.55 [95% CI (1.46,1.65)] times as large as US median miles per gallon.