

Hypothesis testing - a review

Statistical Learning - Modern Inference

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Darwin data

- Charles Darwin collected data on *Zea mays* plants
- The plants were descended from the same parents and planted at the same time.
- Half of the plants were *self-fertilized*, and half were *cross-fertilized*
- Planted *in pairs* in different pots
- Purpose of the experiment: compare *heights*

	Pot	Cross	Self
1	I	23.500	17.375
2	I	12.000	20.375
3	I	21.000	20.000
4	II	22.000	20.000
5	II	19.125	18.375
6	II	21.500	18.625
7	III	22.125	18.625
8	III	20.375	15.250
9	III	18.250	16.500
10	III	21.625	18.000
11	III	23.250	16.250
12	IV	21.000	18.000
13	IV	22.125	12.750
14	IV	23.000	15.500
15	IV	12.000	18.000

Questions

	type	average height
1	Cross	20.19
2	Self	17.57

- ❶ Is the difference in heights too large to have occurred by chance?
- ❷ Can we estimate the height increase, and assess the uncertainty of our estimate?

Hypothesis testing

H_0 : There is no difference in height between cross-fertilized and self-fertilized plants

Hypothesis testing is a type of *stochastic proof by contradiction*

Deterministic proof by contradiction

- ➊ Assume a proposition, the opposite of what you think about, i.e. the opposite conclusion of your theorem
- ➋ Write down a sequence of logical steps/math
- ➌ Derive a contradiction
- ➍ Conclude that the proposition is false (which implies that the theorem is true)

Stochastic proof by contradiction

- ➊ Set H_0 (the proposition)
- ➋ Collect data (which is noisy)
- ➌ Derive an apparent contradiction (i.e. if H_0 is true, then this data is very weird)
- ➍ Hence we reject H_0 ; this is called a “discovery”

Hypothesis testing is stochastic because we might make errors:

Type I (false discoveries) and *Type II* (missed discoveries)

Galton model

Galton considered a model where the height of a self-fertilized plant is

$$Y = \mu + \sigma\varepsilon$$

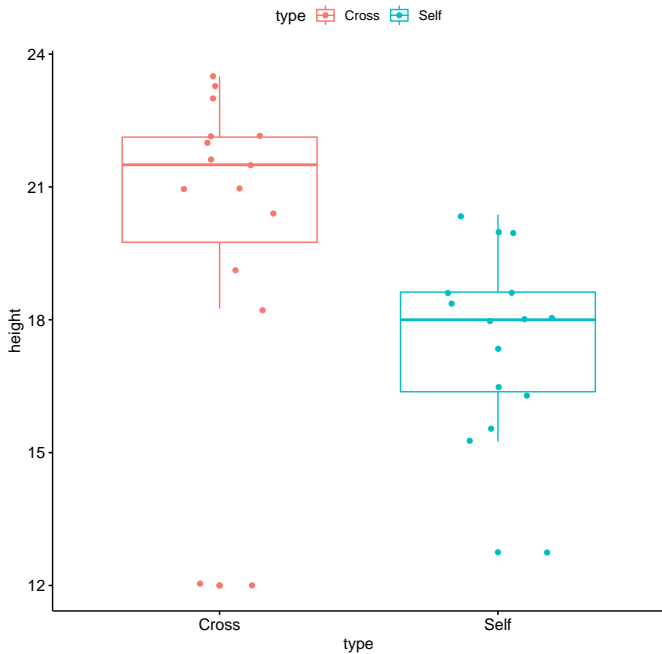
and of a cross-fertilized plant is

$$X = \mu + \theta + \sigma\epsilon$$

where μ , θ and σ are unknown parameters, and ε and ϵ are independent random variables with mean 0 and variance 1

Self-fertilized plants: Y_1, \dots, Y_{15} i.i.d. as Y

Cross-fertilized plants: X_1, \dots, X_{15} i.i.d. as X .



Two-sample t-test

- ❶ Is the average height increase $\theta \neq 0$?
- ❷ Can we estimate θ , and assess the uncertainty of our estimate?

If we assume that ε and ϵ have a $N(0, 1)$ distribution, we can use

Two Sample t-test

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data: height by type
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```
t = 2.4371, df = 28, p-value = 0.02141
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alternative hypothesis: true difference in means is not equal to 0
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95 percent confidence interval:
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0.4173433 4.8159900
```

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sample estimates:
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mean in group Cross	mean in group Self
20.19167	17.57500

Fisher model

Comparison of different pairs would involve differences in humidity, growing conditions, and lighting, which are not of interest, whereas *comparison within pairs* would depend only on the type of fertilization. Fisher considered the model

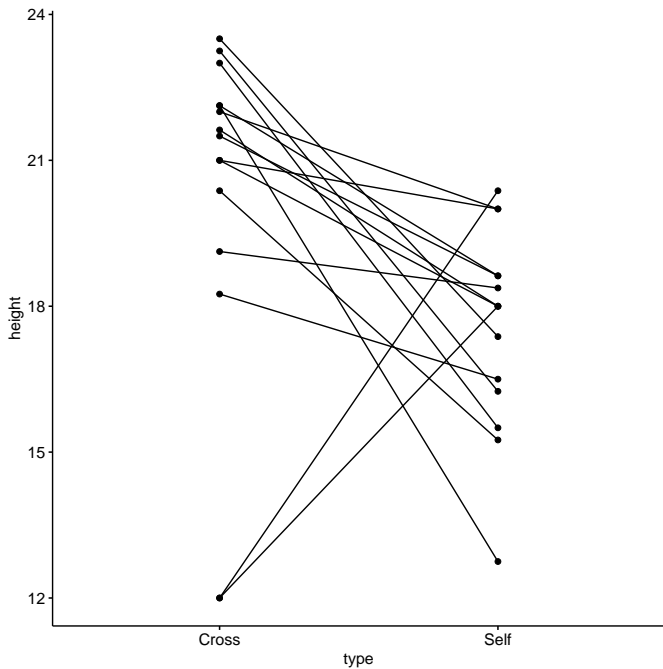
$$Y_i = \mu_i + \sigma\varepsilon_i, \quad X_i = \mu_i + \theta + \sigma\epsilon_i, \quad i = 1, \dots, n$$

The parameter μ_i represents the effects of the planting conditions for the i th pair, and ε_i and ϵ_i are independent random variables with mean 0 and variance 1.

The μ_i could be eliminated by using the differences

$$D_i = X_i - Y_i$$

which have mean θ and variance $2\sigma^2$.



Paired t-test

If we assume that ε and ϵ have a $N(0, 1)$ distribution, we can use

One Sample t-test

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data: differences
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t = 2.148, df = 14, p-value = 0.0497
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alternative hypothesis: true mean is not equal to 0
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95 percent confidence interval:
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0.003899165 5.229434169
```

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sample estimates:
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mean of x
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2.616667
```

P-values

- Choose a test statistic $T = t(Y)$, large values of which cast doubts on H_0
- Observe the data y_{obs} , realization of Y
-

$$p_{obs} = P_0(T \geq t_{obs})$$

where $t_{obs} = t(y_{obs})$ and P_0 is the probability under H_0

P-value null distribution

- $p_{\text{obs}} = 1 - F_0(t_{\text{obs}})$, where F_0 is the null distribution function of T , supposed to be continuous and invertible.
- One interpretation of p_{obs} stems from the corresponding random variable $P = 1 - F_0(T)$
- The null distribution of P is *Uniform*(0,1): for any $u \in (0, 1)$,

$$P_0(P \leq u) = P_0(F_0^{-1}(1 - u) \leq T) = 1 - F_0(F_0^{-1}(1 - u)) = u$$

Valid p-values

We have a *valid test* if its p -value is uniformly distributed under H_0 , i.e.

$$P_0(P \leq u) = u \quad \forall u \in (0, 1) \quad (1)$$

or more generally if the p -value is *stochastically dominated* by the uniform distribution under H_0 , i.e.

$$P_0(P \leq u) \leq u \quad \forall u \in (0, 1) \quad (2)$$

One- and two-sided tests

- Suppose that we have a test statistic T (with continuous distribution), small and large values of which indicate a departure from H_0
- Calculate

$$p_{\text{obs}}^- = P_0(T \leq t_{\text{obs}}), \quad p_{\text{obs}}^+ = P_0(T \geq t_{\text{obs}})$$

- The p -value is

$$p_{\text{obs}} = 2 \min(p_{\text{obs}}^-, p_{\text{obs}}^+)$$

This follows because the null distribution of $Q = \min(P^-, P^+)$ is

$$Q = \min(1 - U(0, 1), U(0, 1)) = U(0, 1/2)$$

thus the null distribution of $2Q$ is $U(0, 1)$

Nonparametric tests

Consider a more general matched pair model for the Darwin data:

$$Y_i = \mu_i + \sigma_i \varepsilon_i, \quad X_i = \mu_i + \theta + \tau_i \epsilon_i, \quad i = 1, \dots, n$$

The height differences may be written as

$$D_i = \theta + (\tau_i \epsilon_i - \sigma_i \varepsilon_i)$$

If we assume that ε_i and ϵ_i are independent and symmetrically distributed around 0, then D_i is symmetrically distributed around θ , i.e.

$$D_i - \theta \stackrel{d}{=} \theta - D_i \quad i = 1, \dots, n$$

Sign test

- If $H_0 : \theta = 0$ is true, then the probability that D_i falls on either side of 0 is $1/2$ (because D_i is symmetric around 0)

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$$T = \sum_{i=1}^n \mathbb{1}\{D_i > 0\}$$

- Under H_0 , $T \sim \text{Binomial}(n, 1/2)$

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$$p_{\text{obs}}^+ = P_0(T \geq t_{\text{obs}}) = \sum_{k=t_{\text{obs}}}^n \binom{n}{k} \frac{1}{2^n}$$

$$p_{\text{obs}}^- = P_0(T \leq t_{\text{obs}}) = \sum_{k=0}^{t_{\text{obs}}} \binom{n}{k} \frac{1}{2^n}$$

In a discrete problem p_{obs} is $q_{\text{obs}} = \min(p_{\text{obs}}^-, p_{\text{obs}}^+)$ plus the achievable p -value from the other tail of the distribution nearest to but not exceeding q_{obs} .

Exact binomial test

data: 13 and 15

number of successes = 13, number of trials = 15,

p-value = 0.007385

alternative hypothesis:

true probability of success is not equal to 0.5

95 percent confidence interval:

0.5953973 0.9834241

sample estimates:

probability of success

0.8666667