

Lecture 4 - Bayesian correlation

Let's recall the definition of the (Pearson) correlation coefficient.

Consider two sets of scores - to what degree are they associated?

↳ i.e., how do they co-vary?

X	Y	$X - \bar{X}$	$Y - \bar{Y}$	$(X - \bar{X})(Y - \bar{Y})$
6	6	2	2	4
2	2	-2	-2	4
5	6	1	2	2
3	4	-1	0	0
4	2	0	-2	0
$\bar{X} = 4$ $\sigma_x = 1.41$		$\bar{Y} = 4$ $\sigma_y = 1.79$		$\sum = 10$

Define: covariance

$$\sigma_{xy} = \frac{1}{N} \sum (x_i - \bar{x})(y_i - \bar{y})$$

$$\sum = 10 \rightarrow \sigma_{xy} = \frac{1}{5} \times 10 = 2$$

From covariance, we can define the Pearson correlation:

$$\rho = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y}$$

So for our example,

$$\rho = \frac{2}{(1.41)(1.79)} = 0.79$$

Facts:

* $-1 \leq \rho \leq 1$

* as $\rho \rightarrow \pm 1$, degree of association increases

Suppose we are interested in the relationship between math anxiety and performance on a standardized assessment.

Define hypotheses about (population) correlation ρ
 $H_0: \rho = 0$, $H_1: \rho \neq 0$

Collect data

$N = 65$
 $r = 0.37$

Compute:
 $p(\text{data} | H_0)$
"p-value"

Interpretation:
If p is small, data is rare under H_0 , so we reject H_0 in favor of H_1 .

Compute:
 $BF_{01} = \frac{p(\text{data} | H_0)}{p(\text{data} | H_1)}$
"Bayes factor"

Interpretation:
if $BF_{01} > 1$, data more likely under H_0 .
if $BF_{01} < 1$, data more likely under H_1 .

$$p\text{-value} = p(\text{data} | H_0)$$

1) only considers fit of H_0 as a potential model for data

2) ignores fit of H_1 ,

Thus, "support" for H_1 is only indirect

$$\text{Bayes factor} = \frac{p(\text{data} | H_0)}{p(\text{data} | H_1)}$$

1) considers relative adequacy of both models as predictors of data.

2) can directly index support for either H_0 or H_1 .

Ex: $BF_{01} = 8 \rightarrow$ "The observed data are 8 times more likely under H_0 than H_1 ."

Jeffreys (1961):

BF	Evidence*
1-3	anecdotal
3-10	moderate
10-30	strong
30-100	very strong
> 100	extreme

* these are only guidelines!

$$BF_{10} = \frac{1}{8}$$

How does Bayes work?

for single model \mathcal{H} :

$$p(\mathcal{H} \mid \text{data}) = p(\mathcal{H}) \times \frac{p(\text{data} \mid \mathcal{H})}{p(\text{data})}$$

↪ posterior belief in \mathcal{H} = prior belief in \mathcal{H} × updating factor

for two models:

$$\frac{p(\mathcal{H}_0 \mid \text{data})}{p(\mathcal{H}_1 \mid \text{data})} = \frac{p(\mathcal{H}_0)}{p(\mathcal{H}_1)} \times \frac{p(\text{data} \mid \mathcal{H}_0)}{p(\text{data} \mid \mathcal{H}_1)}$$

↪ posterior odds = prior odds × Bayes factor

What do we mean by prior?

Two types of "priors":

1) priors on models

2) priors on parameters within a given model

① Priors on models — before observing data, what is relative likelihood of competing models?

- common default: $p(H_0) = p(H_1) = 1/2$

- ↳ i.e., "1-1 prior odds"

- these prior model probabilities must add to 1

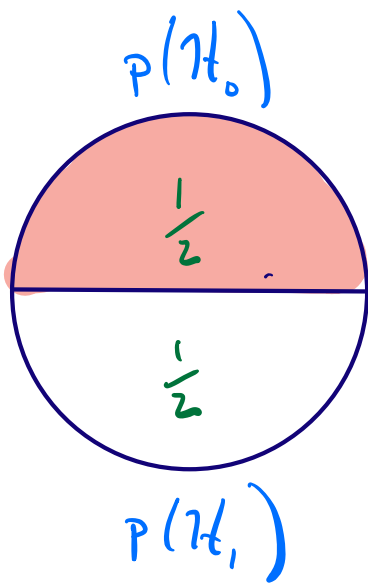
- ↳ $p(H_0) + p(H_1) = \frac{1}{2} + \frac{1}{2} = 1$

- prior model probabilities are updated after observing data:

Posterior odds = prior odds \times BF

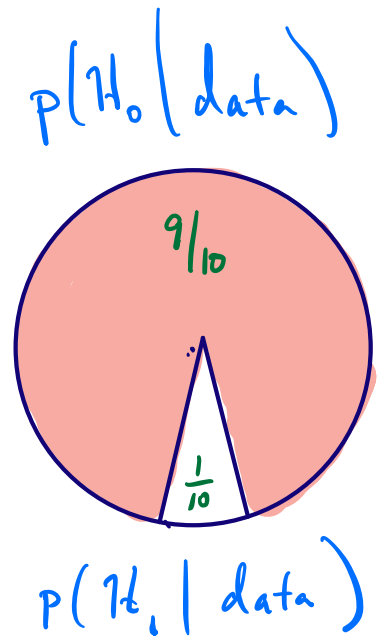
$$p(H_0 | \text{data}) = \frac{\text{posterior odds}}{1 + \text{posterior odds}}$$

Example:



Prior odds = 1:1

observe
data
→
 $BF_{01} = 9$



Posterior odds = 9:1

$$p(H_0 | \text{data}) = \frac{\text{posterior odds}}{1 + \text{posterior odds}}$$

$$= \frac{9}{9+1} = \frac{9}{10} = 0.90$$

② priors on parameters within a given model.

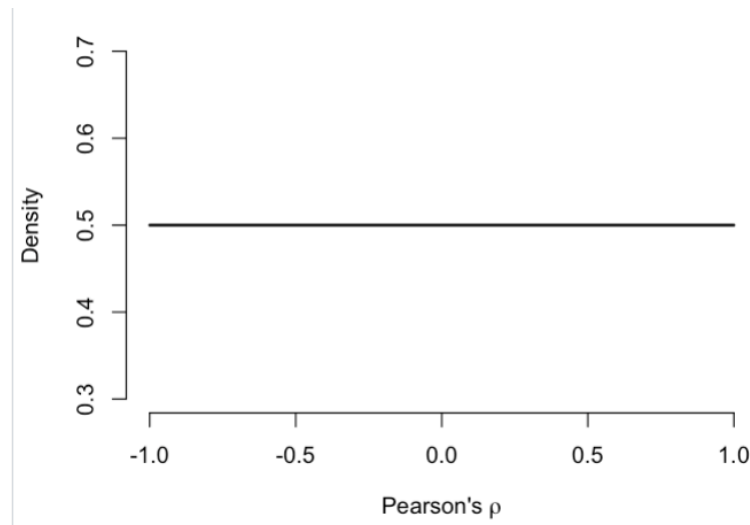
- model definitions: $H_0: \rho = 0$

$H_1: \rho \neq 0$ ← what exactly do we mean here?

- we quantify our uncertainty about the correlation ρ under H_1 by placing a distribution on ρ

- suppose we have no idea what to expect. Here, we might believe any value of ρ is equally likely to occur.

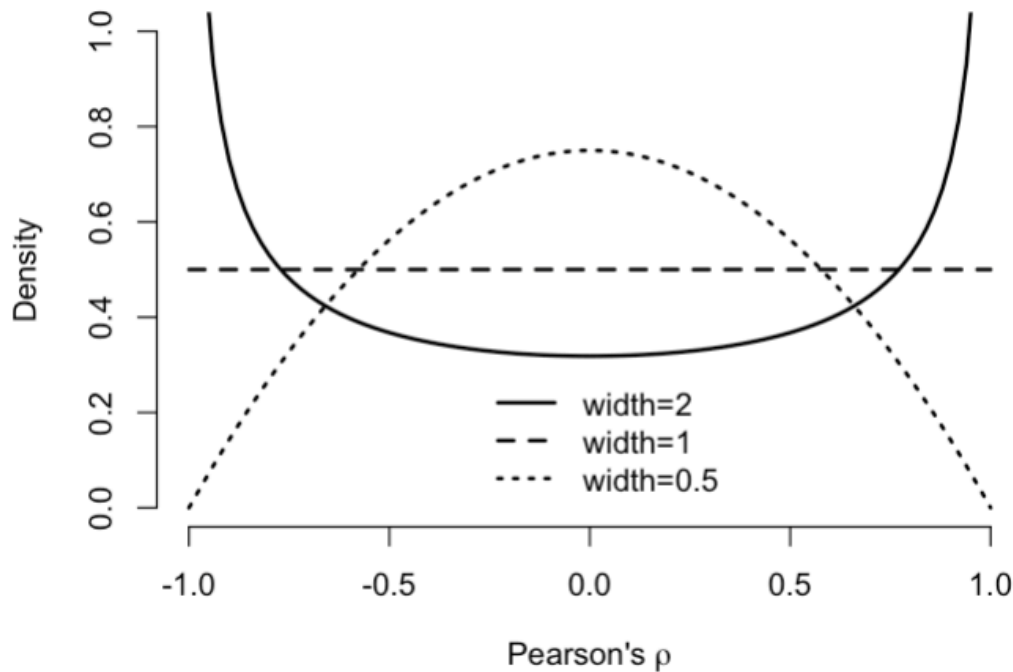
↳ we say ρ is uniformly distributed on $(-1, 1)$



* Note - this is the "default" used in JASP.

Other priors:

↳ the uniform prior is a special case of a useful class of priors called a "stretched Beta prior"



Shape of the prior is controlled by the width parameter

* width 1 → uniform prior (JASP default)

* width 0.5 → more prior mass at 0

↳ useful if you believe the correlation is small

* width 2 → more prior mass at ± 1

↳ useful if you believe correlation is strong (ex: testing reliability)

Let's continue our working example. Suppose we tested $N = 65$ participants and observed a correlation of $r = 0.37$.

- use JASP "Summary Statistics" module

Elements to report:

1. report results of hypothesis test

- define H_0 , H_1 , and specify prior under H_1 .

"Under the null hypothesis we expect a correlation of 0 between maths anxiety and performance.

Thus, we define $H_0: \rho = 0$. The alternative hypothesis is two-sided, $H_1: \rho \neq 0$, and we assigned a uniform prior probability to all values of ρ between -1 and +1."

- report and interpret Bayes factor

"We found a Bayes factor of $BF_{10} = 13.93$, which means that the observed data are approximately 14 times more likely under H_1 than H_0 . This result indicates strong evidence in favor of H_1 ."

- calculate and report posterior model probability for preferred model.

- from earlier,

$$p(H_1 | \text{data}) = \frac{\text{posterior odds}}{1 + \text{posterior odds}}$$

$$= \frac{13.93}{1 + 13.93} = 0.93.$$

- "Assuming prior odds of 1-1 for H_1 and H_0 , our observed data updated these odds to 13.93-to-1 in favor of H_1 . This is equivalent to a posterior model probability of $p(H_1 | \text{data}) = 0.93$."

2. report results of parameter estimation

- only if H_1 is the preferred model!
- specify parameter of interest and remind reader of prior under H_1
 - "of interest is the posterior distribution for ρ , the population-level correlation between maths anxiety and performance. Under H_1 , ρ was assigned a uniform prior over the interval from -1 to +1."

- report the 95% credible interval.

- "The posterior distribution for p had a median of 0.356, with a central 95% credible interval that ranges from 0.134 to 0.554."