

# Research Methods and Statistics

## Lecture 24: More Bayes...

Johnny van Doorn



Pictures source: pixabay

# Today

- **Recap of last week**
- Bayesian Inference
  - Correlation
  - T-test
- Bayes & Frequentism
- Statistics in the Wild
- Recap
  - Example exam question

# Bayesian Inference

$$\underbrace{p(\theta \mid \text{data})}_{\text{Posterior beliefs about the world}} = \underbrace{p(\theta)}_{\text{Prior beliefs about the world}} \times \underbrace{\frac{p(\text{data} \mid \theta)}{p(\text{data})}}_{\text{Predictive updating factor}}$$

This is on the level of the *parameter*,  
*within a single model*

We compare how well each specific value of  $\theta$  in the model predicted the data, compared to the other values of  $\theta$

# Bayesian Hypothesis Testing

$$\underbrace{\frac{p(\mathcal{H}_1 \mid \text{data})}{p(\mathcal{H}_0 \mid \text{data})}}_{\text{Posterior beliefs about hypotheses}} = \underbrace{\frac{p(\mathcal{H}_1)}{p(\mathcal{H}_0)}}_{\text{Prior beliefs about hypotheses}} \times \underbrace{\frac{p(\text{data} \mid \mathcal{H}_1)}{p(\text{data} \mid \mathcal{H}_0)}}_{\text{Predictive updating factor}}$$

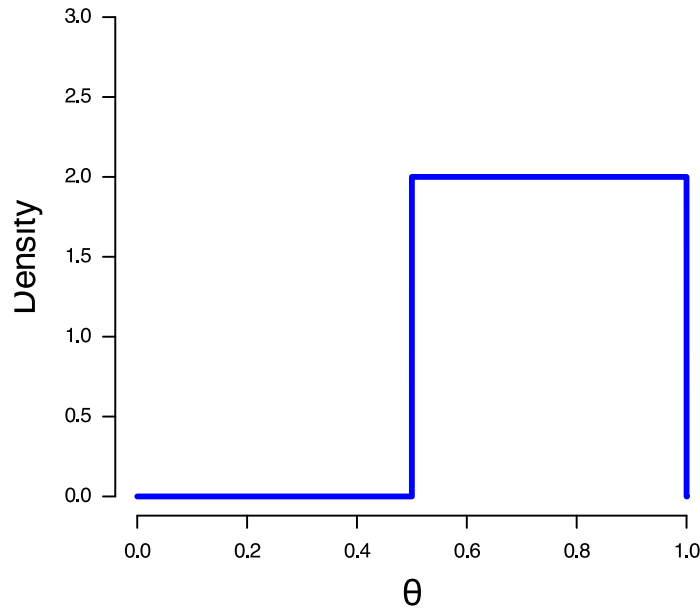
This is on the level of the *hypothesis*

We compare how well the hypotheses predicted the data: we look at how well all values postulated by each hypothesis predicted the data

# What Does the Alternative Hypothesis Predict?

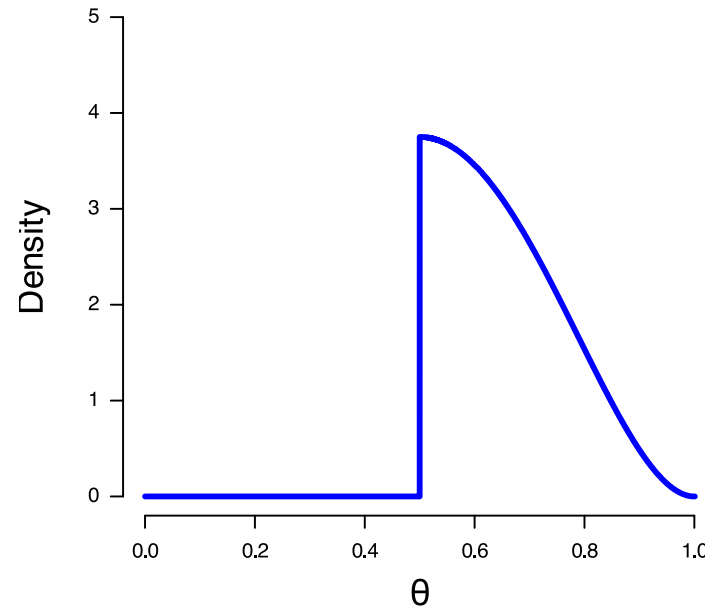
*“If you had 100€ to bet on likely values of  $\theta$ , how would you divide it?”*

Truncated Beta Distribution ( $a = 1, b = 1$ )



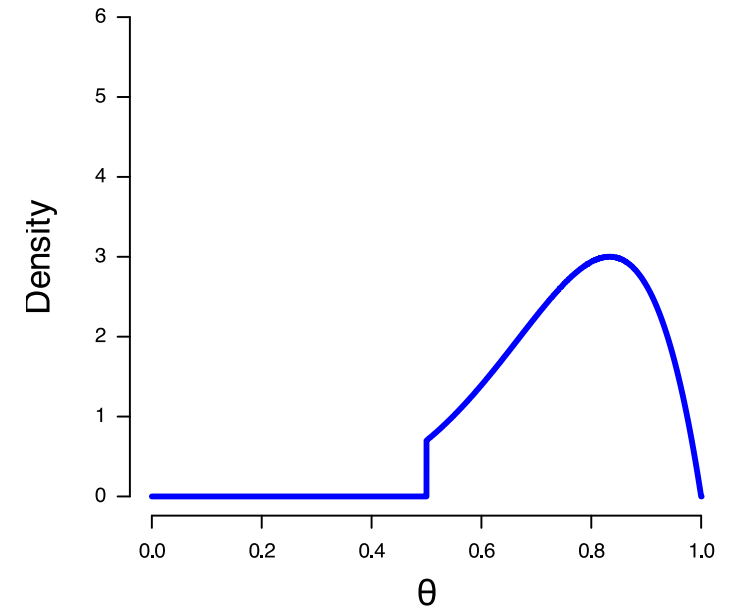
Here, it predicts that only values of  $\theta$  between 0.5 and 1 are possible, and that all values of  $\theta$  between 0.5 and 1 are equally likely.

Truncated Beta Distribution ( $a = 3, b = 3$ )



Here, it predicts that only values of  $\theta$  between 0.5 and 1 are possible, and that values of  $\theta$  closer to 0.5 are more likely than values close to 1.

Truncated Beta Distribution ( $a = 6, b = 2$ )

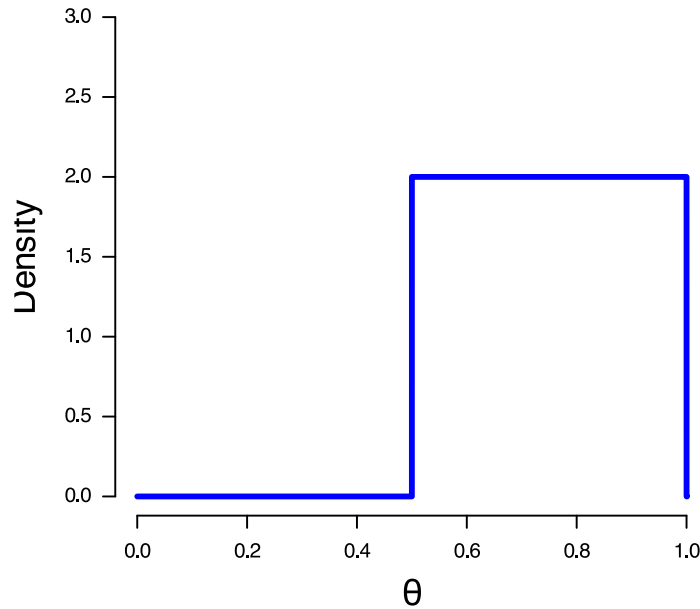


Here, it predicts that all values of  $\theta$  between 0.5 and 1 are possible, and that values of  $\theta$  closer to 0.5 are more likely than values close to 1.

# What Does the Alternative Hypothesis Predict?

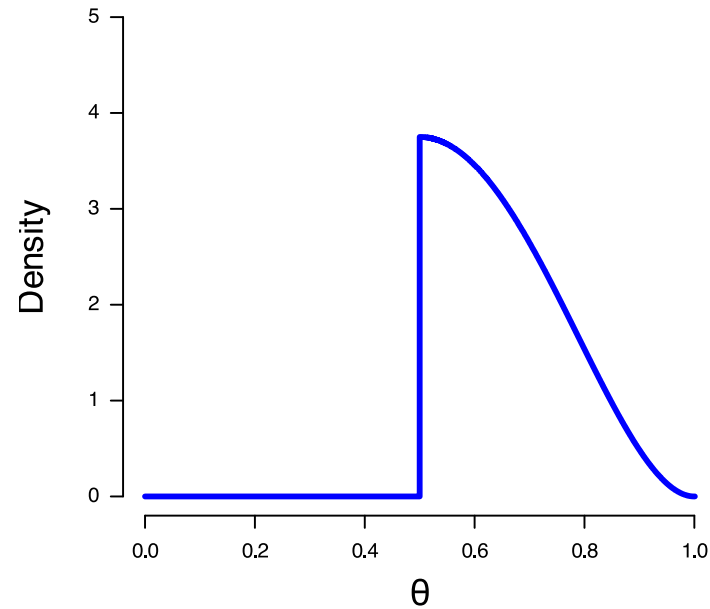
*“If you had 100€ to bet on likely values of  $\theta$ , how would you divide it?”*

Truncated Beta Distribution ( $a = 1, b = 1$ )



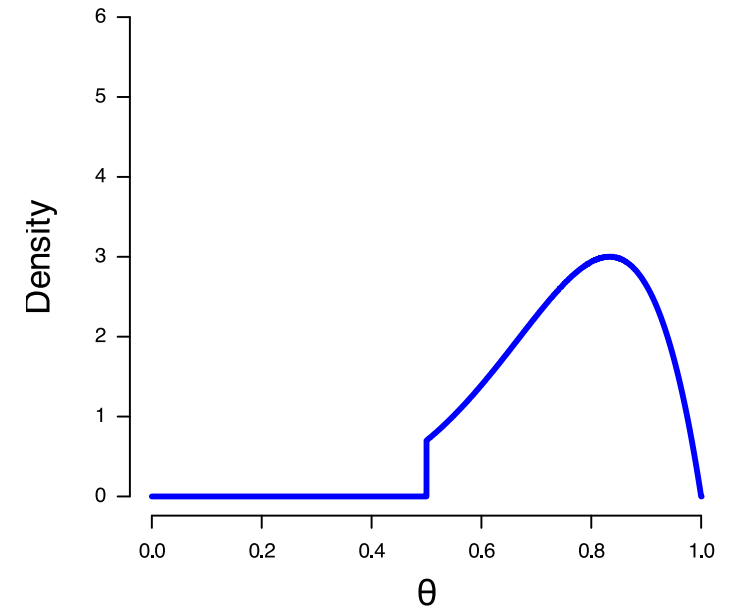
If the observed proportion (i.e., the data) equals 0.55, it will win **as much** money as if the observed proportion equals 0.8

Truncated Beta Distribution ( $a = 3, b = 3$ )



If the observed proportion (i.e., the data) equals 0.55, it will win **more** money than if the observed proportion equals 0.8

Truncated Beta Distribution ( $a = 6, b = 2$ )



If the observed proportion (i.e., the data) equals 0.55, it will win **less** money than if the observed proportion equals 0.8

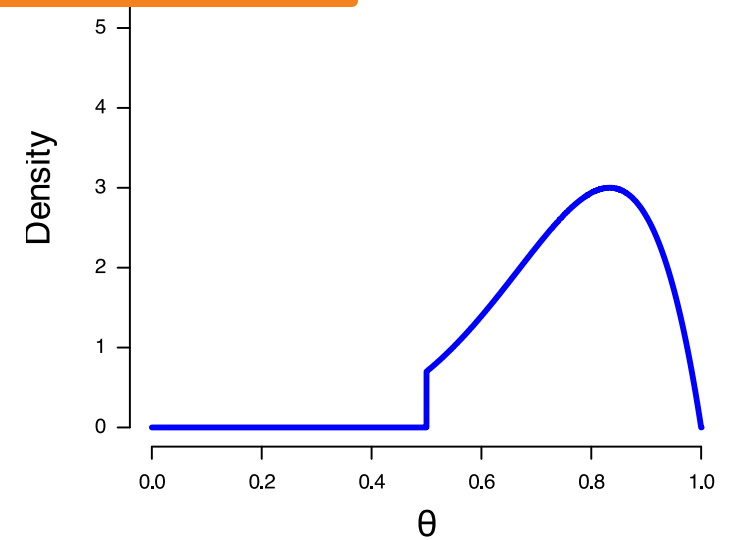
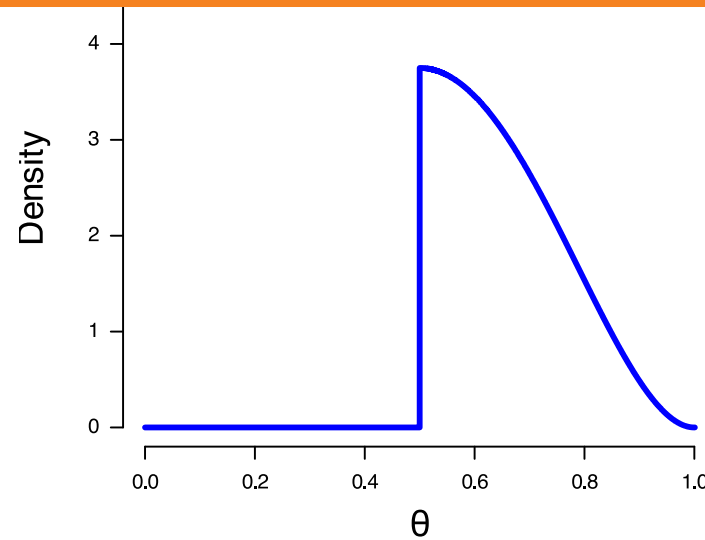
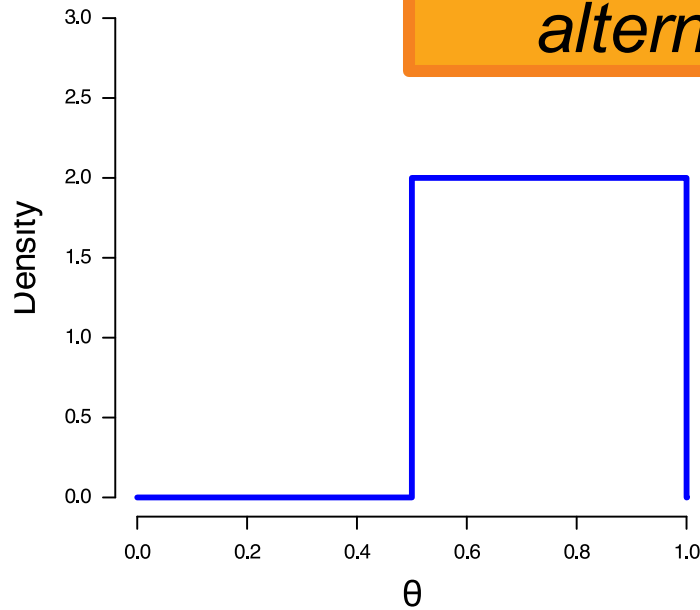
# What Does the Alternative Hypothesis Predict?

*“If you had 100€ to bet on likely values of  $\theta$ , how would you divide it?”*

*Amount of money won = how well did the alternative hypothesis predict the data*

Truncated Beta Dist

Distribution (a = 6, b = 2)



If the observed proportion (i.e., the data) equals 0.55, it will win as much money as if the observed proportion equals 0.8

If the observed proportion (i.e., the data) equals 0.55, it will win more money than if the observed proportion equals 0.8

If the observed proportion (i.e., the data) equals 0.55, it will win less money than if the observed proportion equals 0.8

# Bayesian Hypothesis Testing: Bayes Factor

The average likelihood across all values predicted by  $H_1$  (i.e., the marginal likelihood)

$$\frac{p(\text{data} \mid \mathcal{H}_1)}{\underbrace{p(\text{data} \mid \mathcal{H}_0)}_{\text{Predictive updating factor}}}$$

The average likelihood across all values predicted by  $H_0$  (i.e., the likelihood of the data, given the test value (in this case,  $\theta = 0.5$ ))

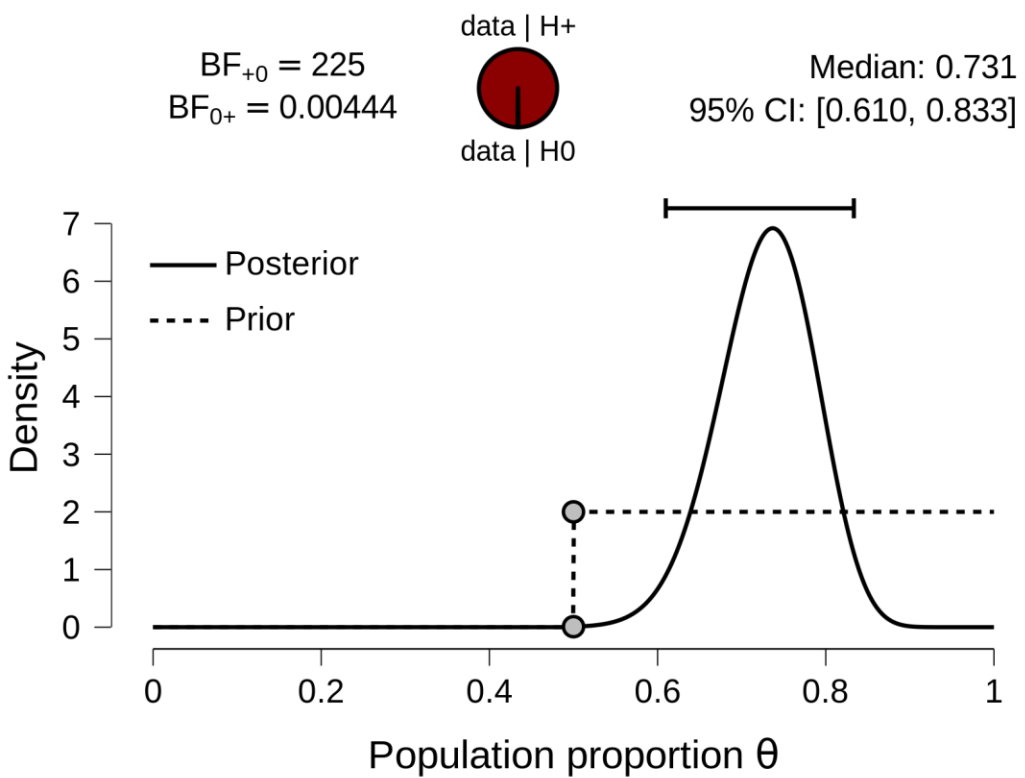
A computational shortcut for calculating this factor is the Savage-Dickey density ratio:

- Take the prior density at the point of testing ( $\theta = 0.5$ )
- Take the posterior density at the point of testing ( $\theta = 0.5$ )

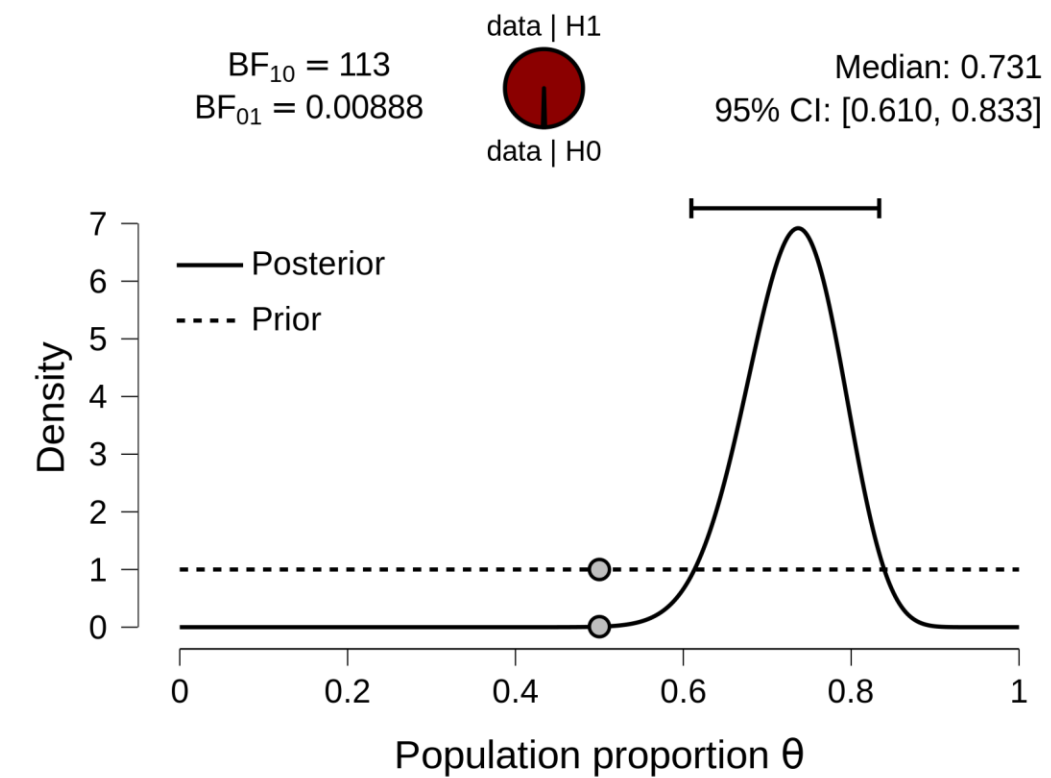
The Bayes factor equals the ratio of those numbers!

# Two-Sided Testing Vs. One-Sided Testing

**Parsimony:** More specific predictions, when still accurate, get rewarded!



$$\mathcal{H}_1 : \theta > 0.5$$



$$\mathcal{H}_1 : \theta \neq 0.5$$

Posterior distribution is beta distribution with

$a$  = prior  $a$  + successes

$b$  = prior  $b$  + failures

The only calculations you need to know  
Bayes factor is ratio of marginal likelihoods

$$BF_{10} = P(\text{data} \mid H_1) / P(\text{data} \mid H_0)$$

$$BF_{01} = P(\text{data} \mid H_0) / P(\text{data} \mid H_1)$$

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  - Correlation
  - T-test
- Bayes & Frequentism
- Statistics in the Wild
- Recap
  - Example exam question

# Choosing the Prior Distribution

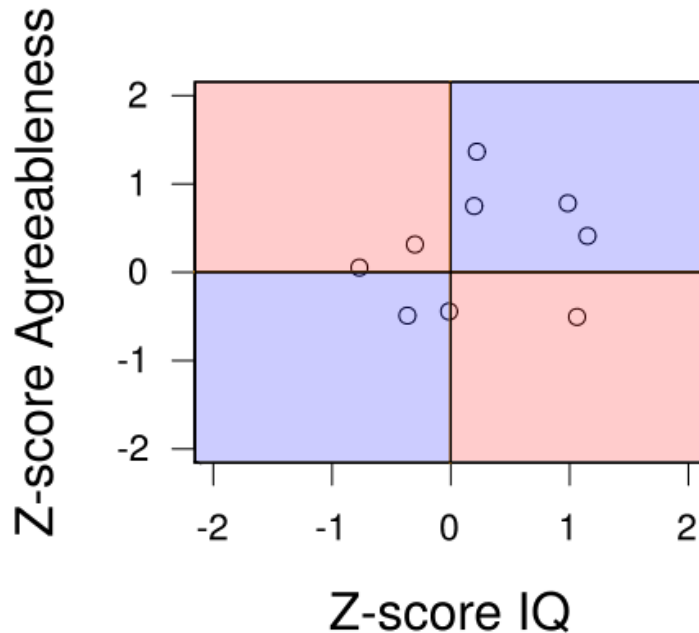
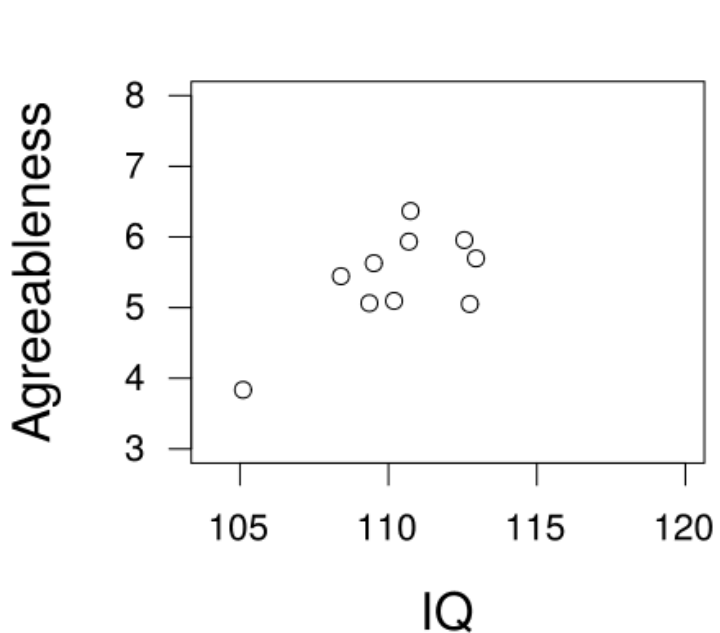
- Before the experiment / looking at the data (so there are no calculations)
- Informed by previous experiments/knowledge or kept uninformative (e.g., uniform prior on the population proportion)
- One-sided / two-sided determined by what you want to test (e.g., do you want to know if there is a difference, or a positive difference?)

# Choosing the Prior Distribution

- The prior distribution is on the same *domain* as the parameter of interest:
  - For a proportion:  $[0, 1]$
  - For a correlation:  $[-1, 1]$
  - For a difference in means:  $[-\infty, \infty]$

# Bayesian Correlation

Instead of inference on the population proportion  $\theta$ , we can estimate/test the **population correlation  $\rho$  (“rho”)**



Values in the blue quadrant:  $Z_x Z_y > 0$   
Contribute to *positive* correlation

Values in the red quadrant:  $Z_x Z_y < 0$   
Contribute to *negative* correlation

# Bayesian Correlation

$$P(\rho \mid \text{data}) = P(\rho) \frac{P(\text{data} \mid \rho)}{P(\text{data})}$$

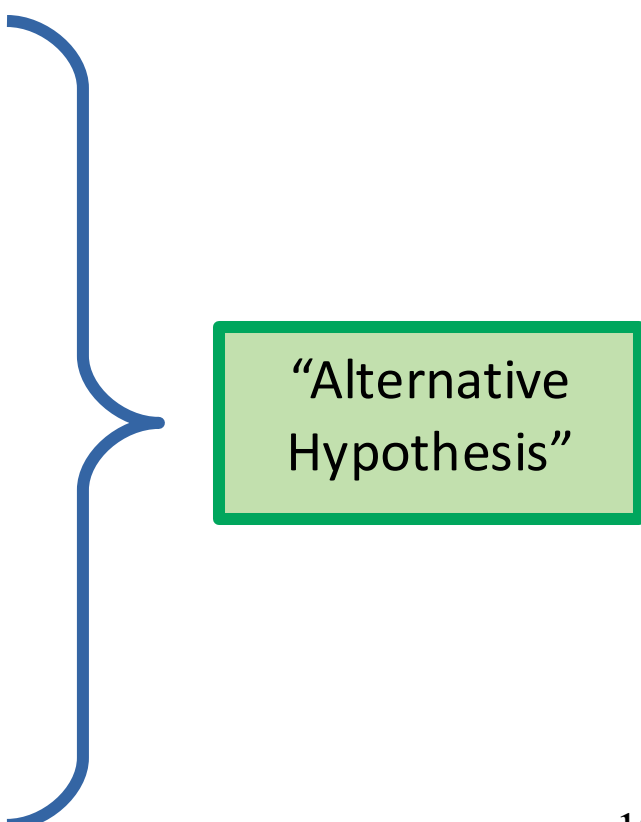
# Bayesian Correlation: Hypothesis

$$\mathcal{H}_0 : \rho = 0$$

$$\mathcal{H}_1 : \rho \neq 0$$

$$\mathcal{H}_+ : \rho > 0$$

$$\mathcal{H}_- : \rho < 0$$

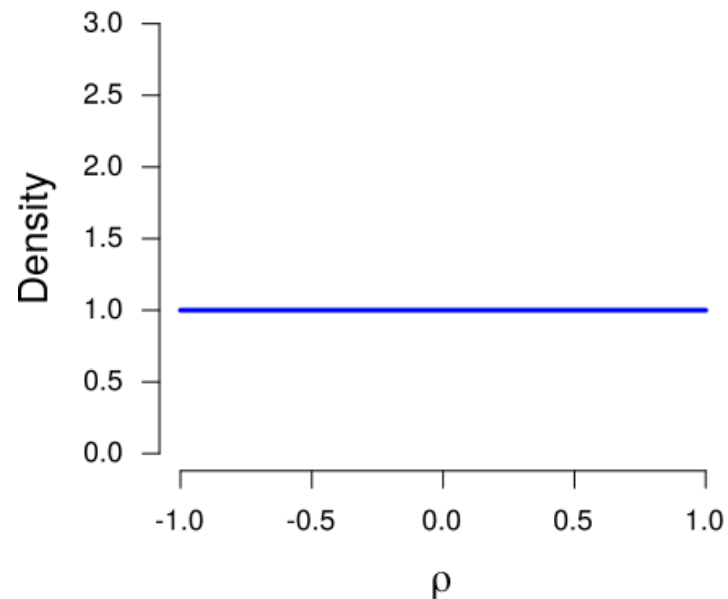


“Alternative Hypothesis”

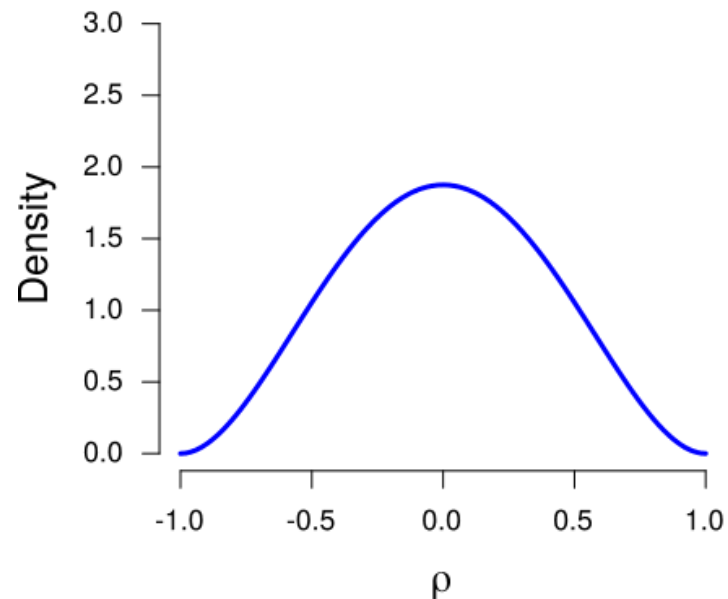
# Bayesian Correlation: Prior Distribution

The prior distribution is on the same domain as the parameter of interest: we can take the **stretched Beta distribution!**  
It is the same as Beta, but then stretched to the domain  $[-1, 1]$

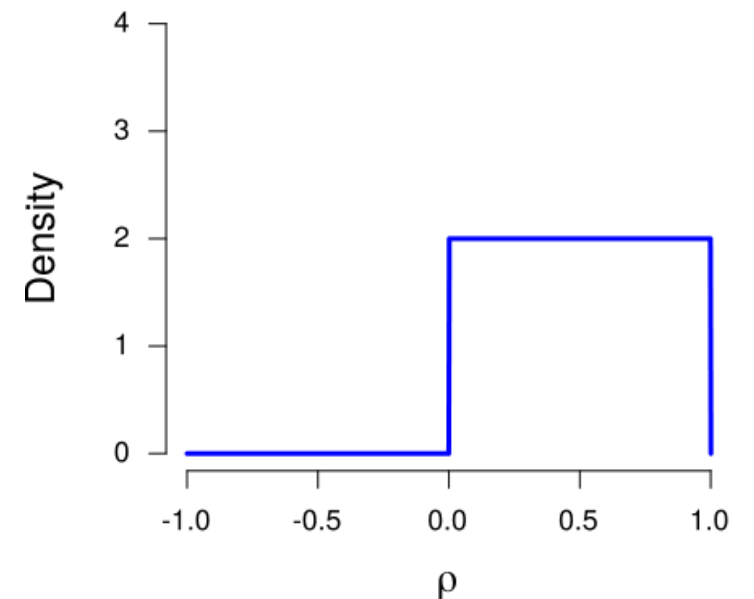
Stretched Beta Distribution ( $a = 1, b = 1$ )



Stretched Beta Distribution ( $a = 3, b = 3$ )



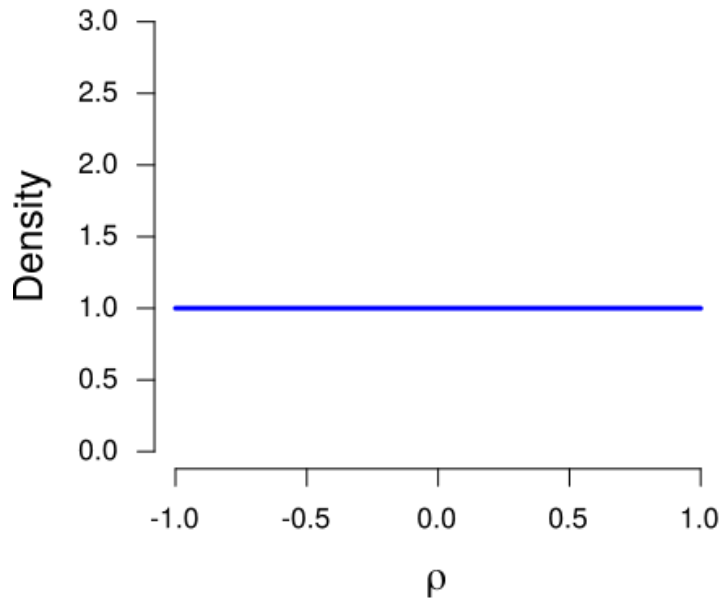
Truncated Stretched Beta Distribution  
( $a = 1, b = 1$ )



# Bayesian Correlation: Prior Distribution

A prior distribution that reflects the belief that all values of  $\rho$  are equally plausible, **a priori**, we call this an *uninformative prior*

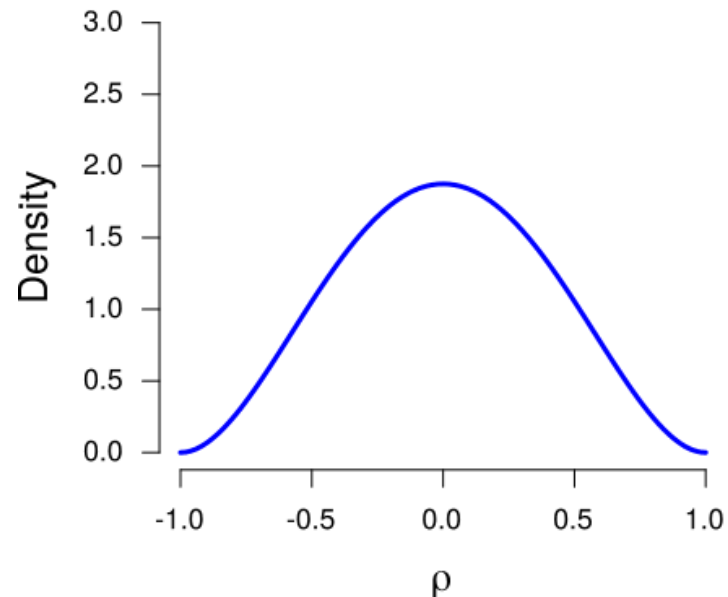
Stretched Beta Distribution ( $a = 1, b = 1$ )



$$\mathcal{H}_1 : \rho \neq 0$$

A prior distribution that reflects the belief that values of  $\rho$  close to 0 are more plausible (i.e., the correlation will be around 0 or not be very strong), **a priori**

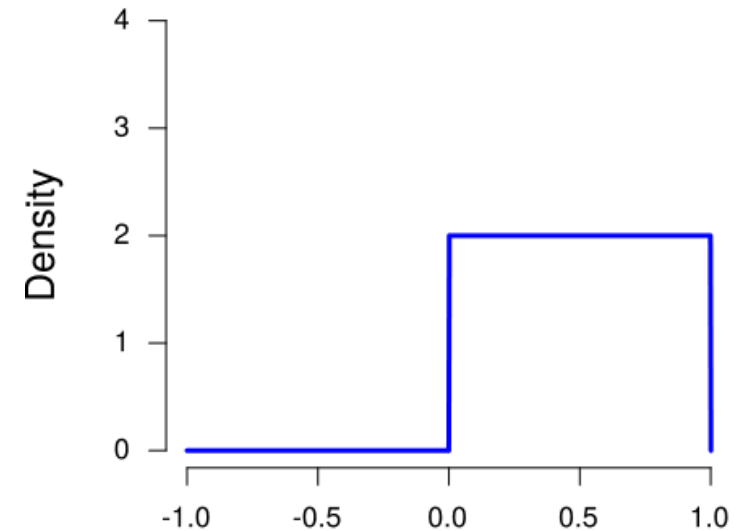
Stretched Beta Distribution ( $a = 3, b = 3$ )



$$\mathcal{H}_1 : \rho \neq 0$$

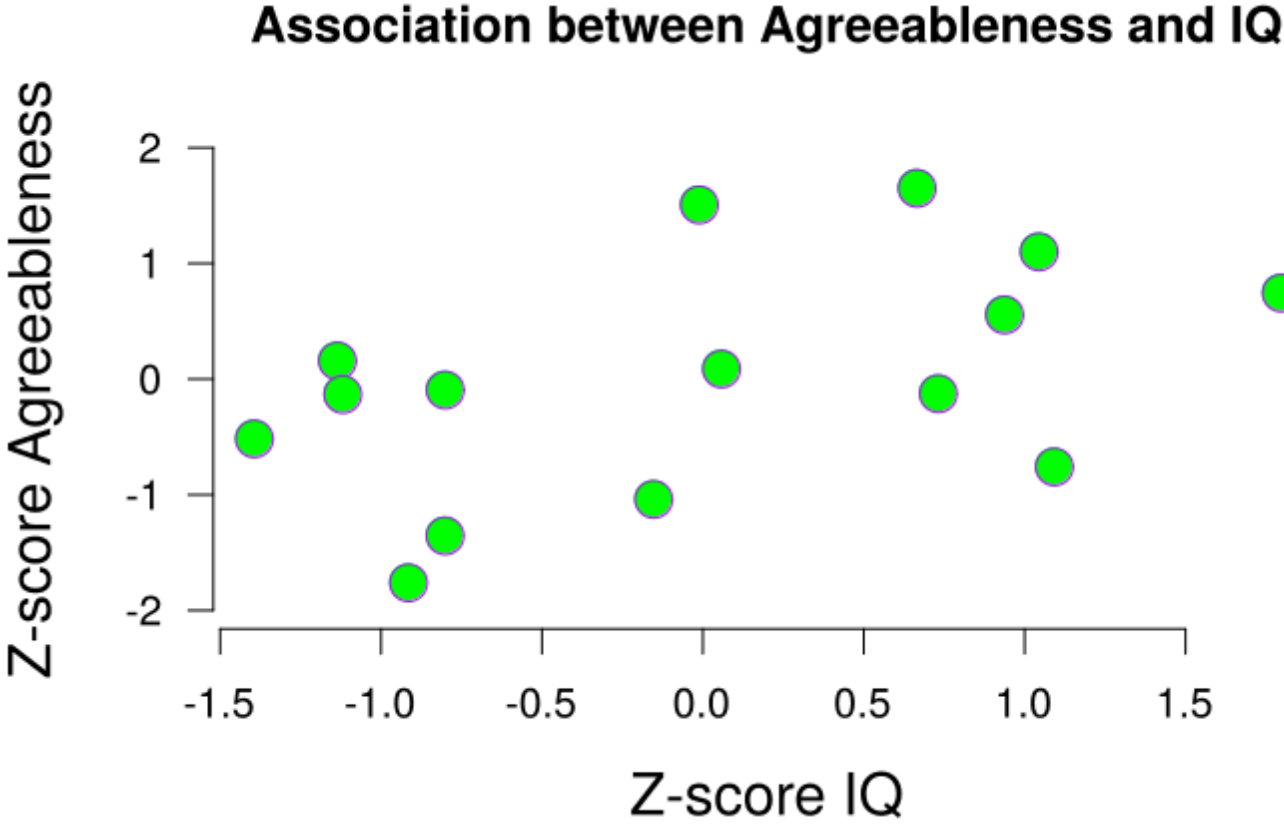
A prior distribution that reflects the belief that only positive values of  $\rho$  are possible and that those values of  $\rho$  are equally plausible (i.e., there will be a positive correlation), **a priori**

Truncated Stretched Beta Distribution ( $a = 1, b = 1$ )

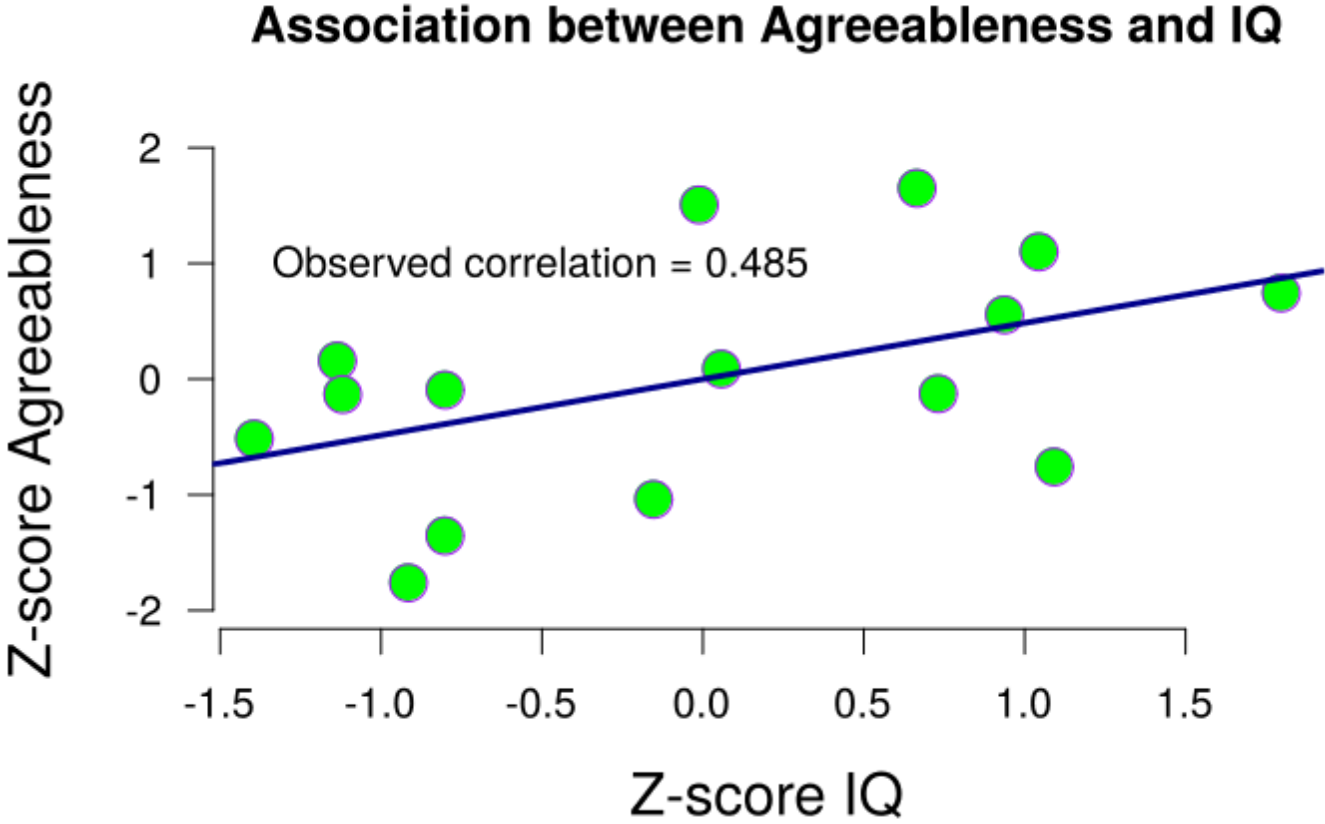


$$\mathcal{H}_+ : \rho > 0$$

# Bayesian Correlation: Data



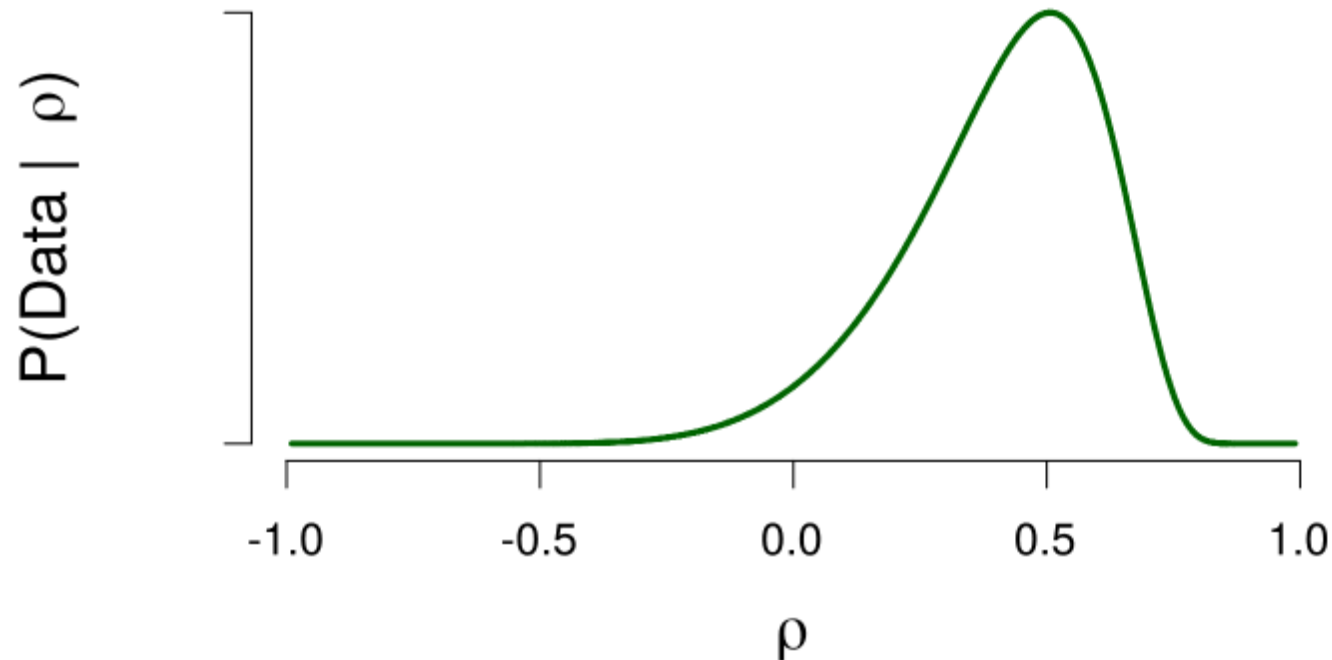
# Bayesian Correlation: Data



# Bayesian Correlation: Likelihood

$$P(\text{data} \mid \rho)$$

Likelihood of the observed data, for each value of  $\rho$

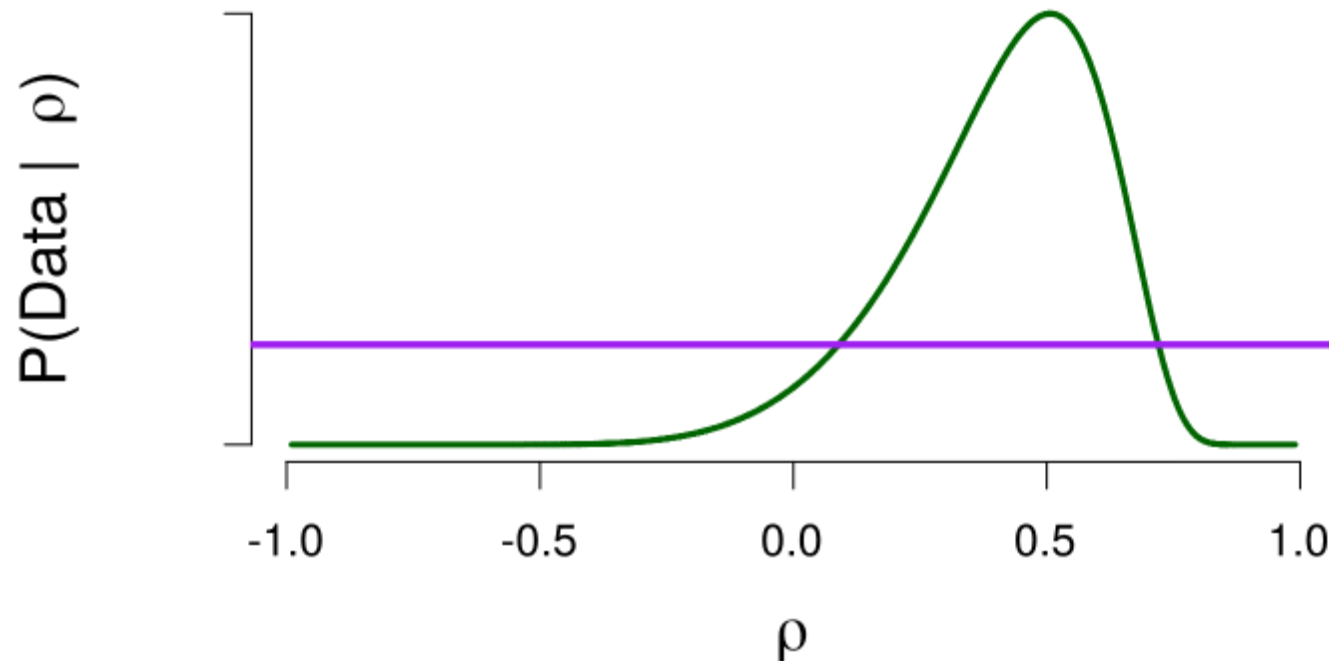


We see that the data are likely for values of  $\rho$  close to 0.5.  
This makes sense, because the observed correlation (i.e., the data) is equal to 0.485!

# Bayesian Correlation: Likelihood

$$P(\text{data} \mid \rho)$$

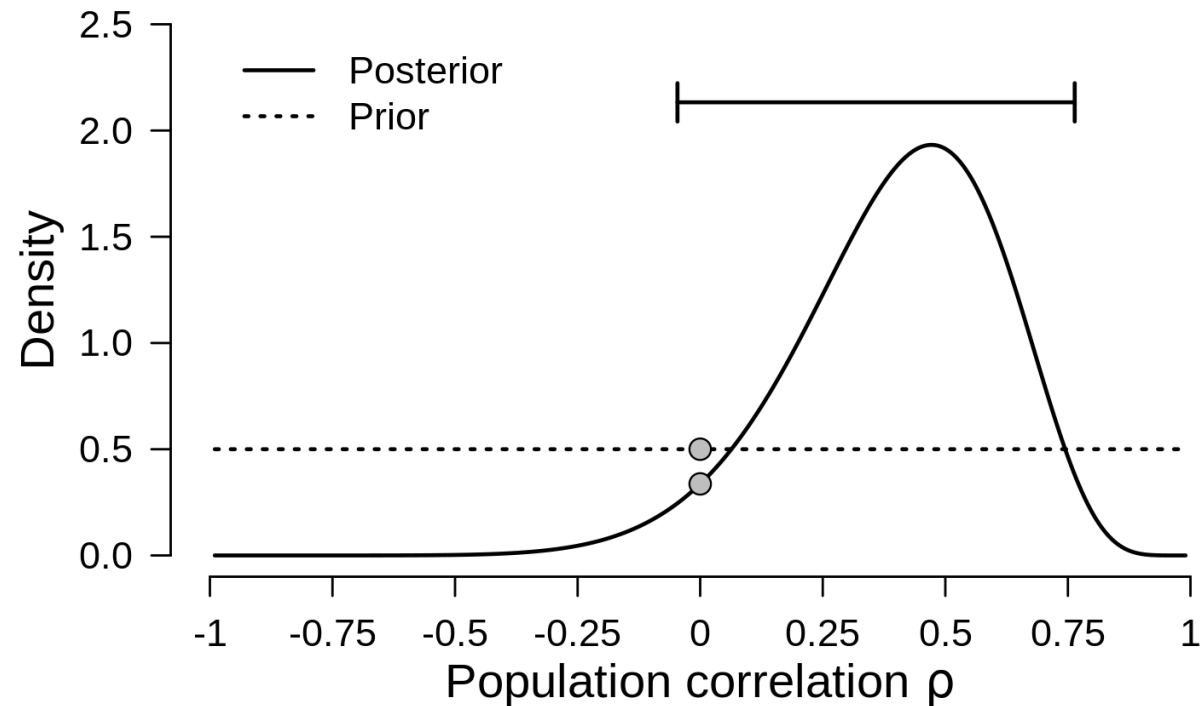
Likelihood of the observed data, for each value of  $\rho$



The **marginal likelihood**, across all values of  $\rho$  in the model

# Bayesian Correlation: Posterior Distribution

$$P(\rho \mid \text{data})$$



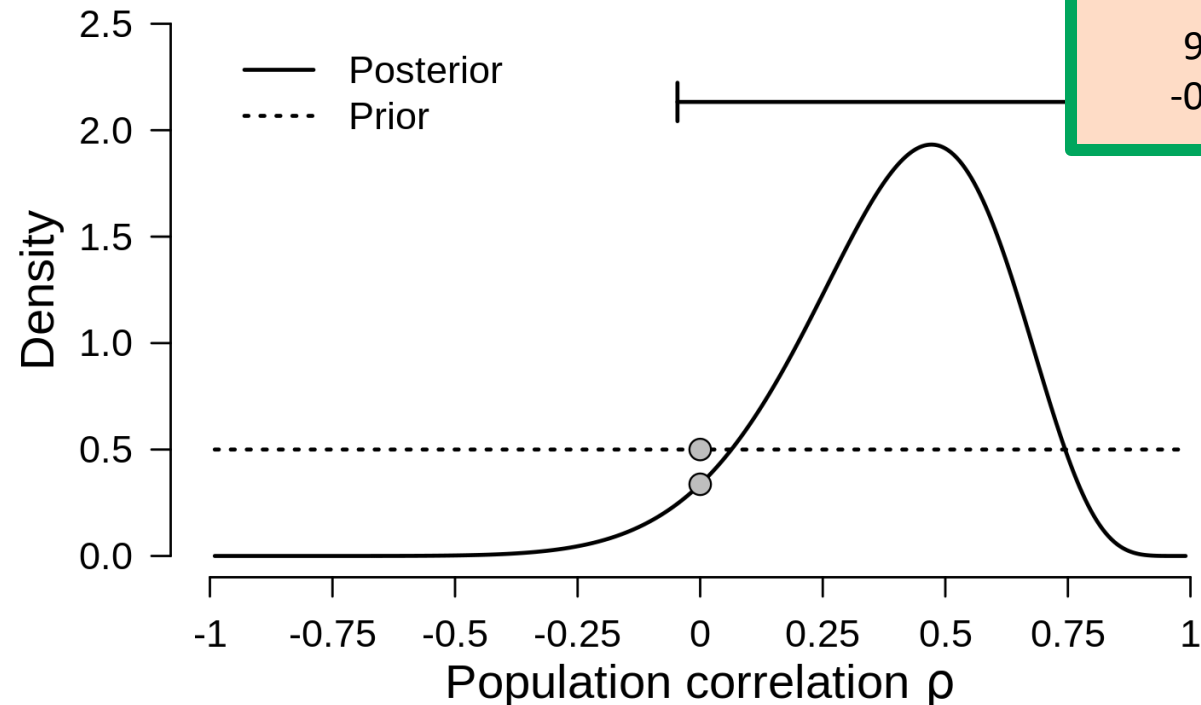
# Bayesian Correlation: Posterior Distribution

**Median:**  
50% probability that  $\rho$  is equal to or lower than 0.416, under this model

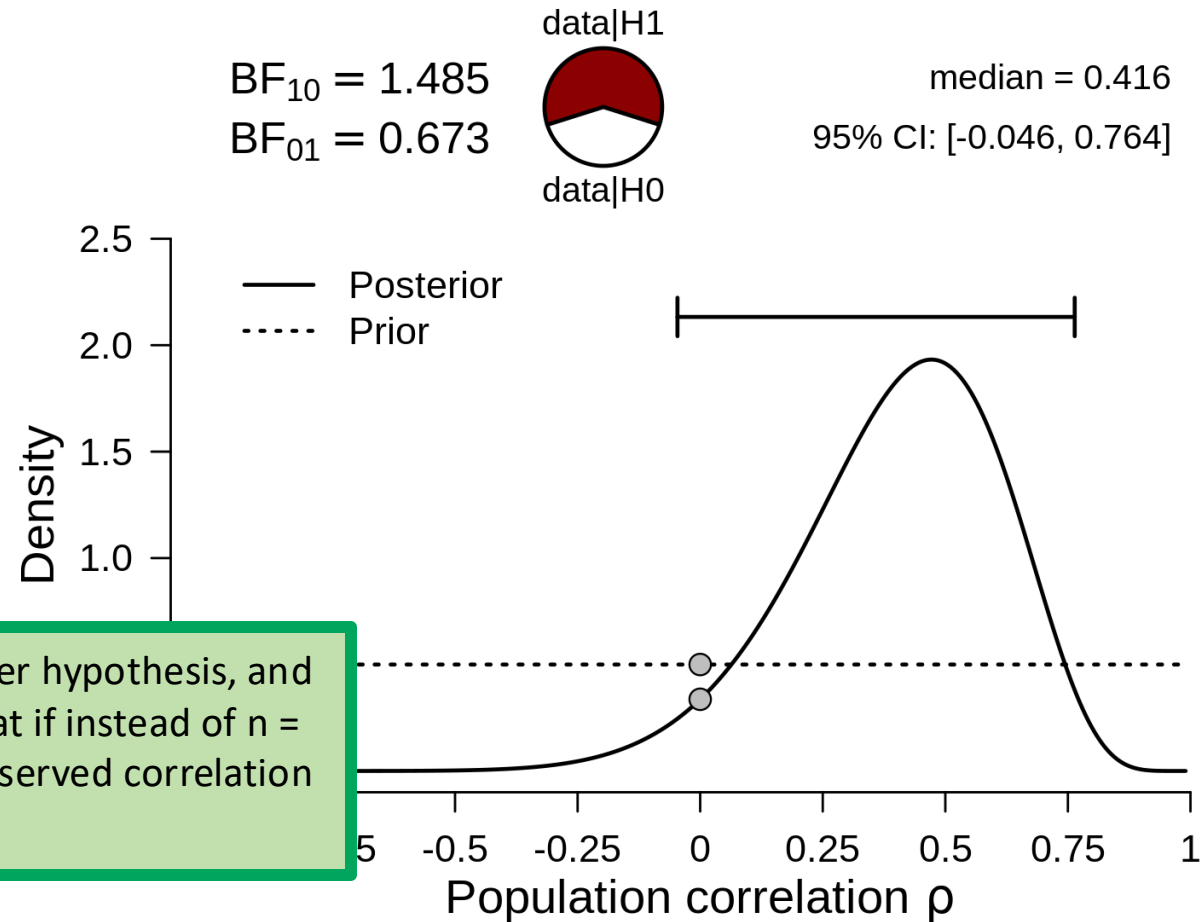
median = 0.416

95% CI: [-0.046, 0.764]

**95% Credible interval:**  
95% probability that  $\rho$  is between -0.046 and 0.764, under this model

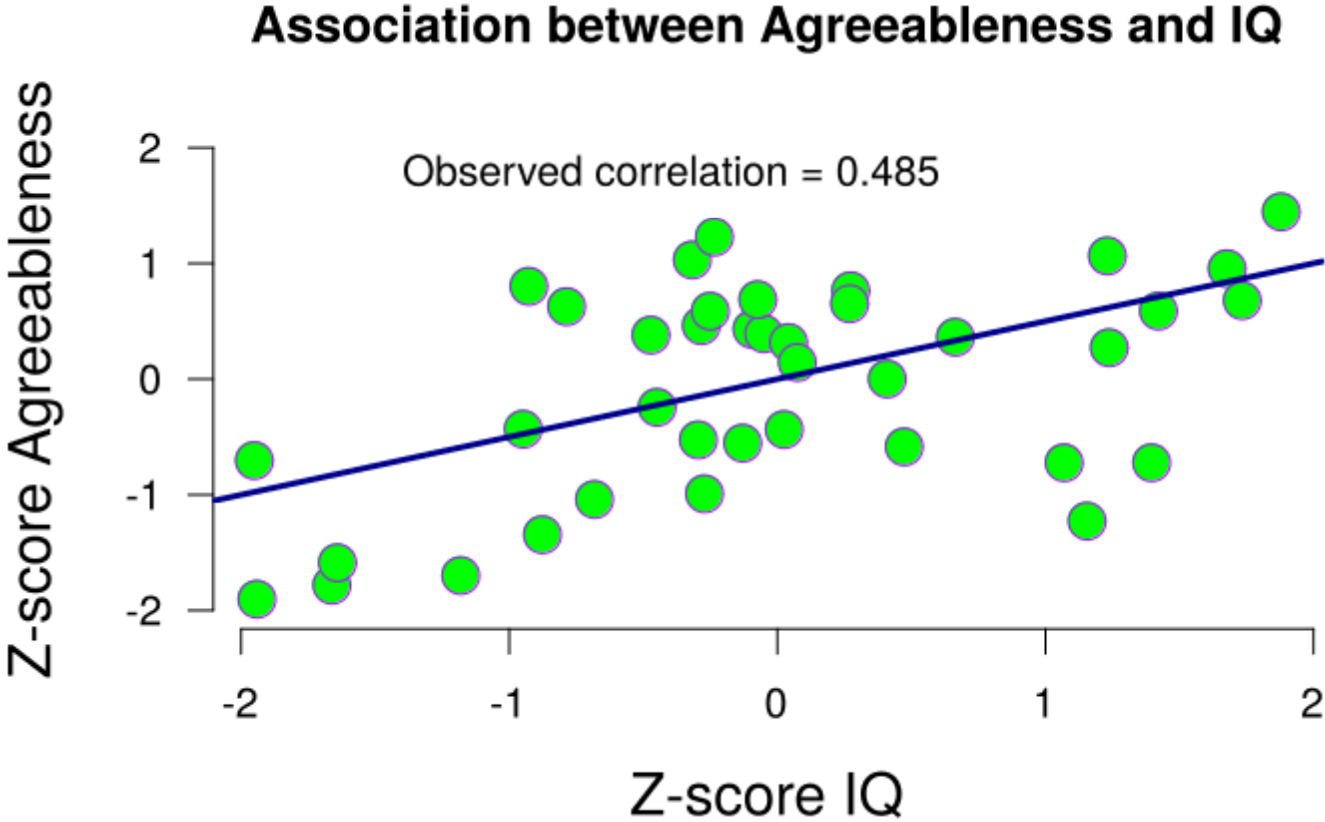


# Bayesian Correlation: Bayes Factor



Very weak evidence in favor of either hypothesis, and a very wide credible interval... What if instead of  $n = 15$ , we had  $n = 40$ , but the same observed correlation (0.485)?

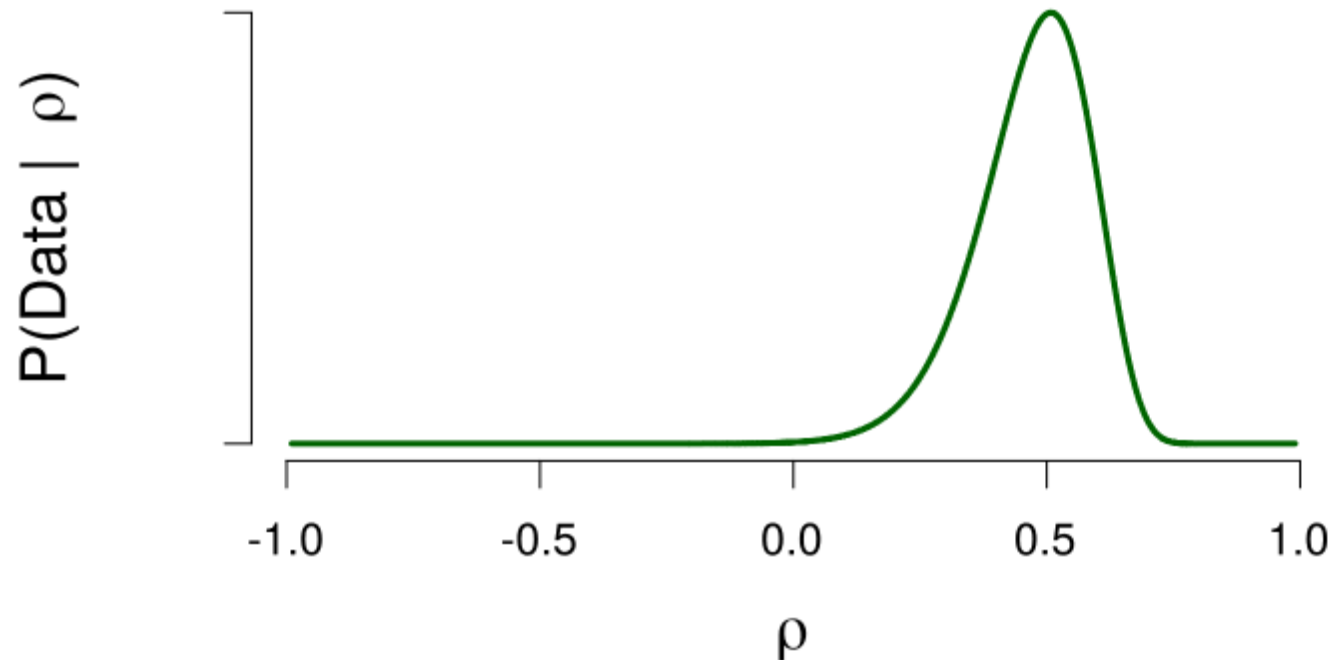
# Bayesian Correlation: Data



# Bayesian Correlation: Likelihood

$$P(\text{data} \mid \rho)$$

Likelihood of the observed data, for each value of  $\rho$



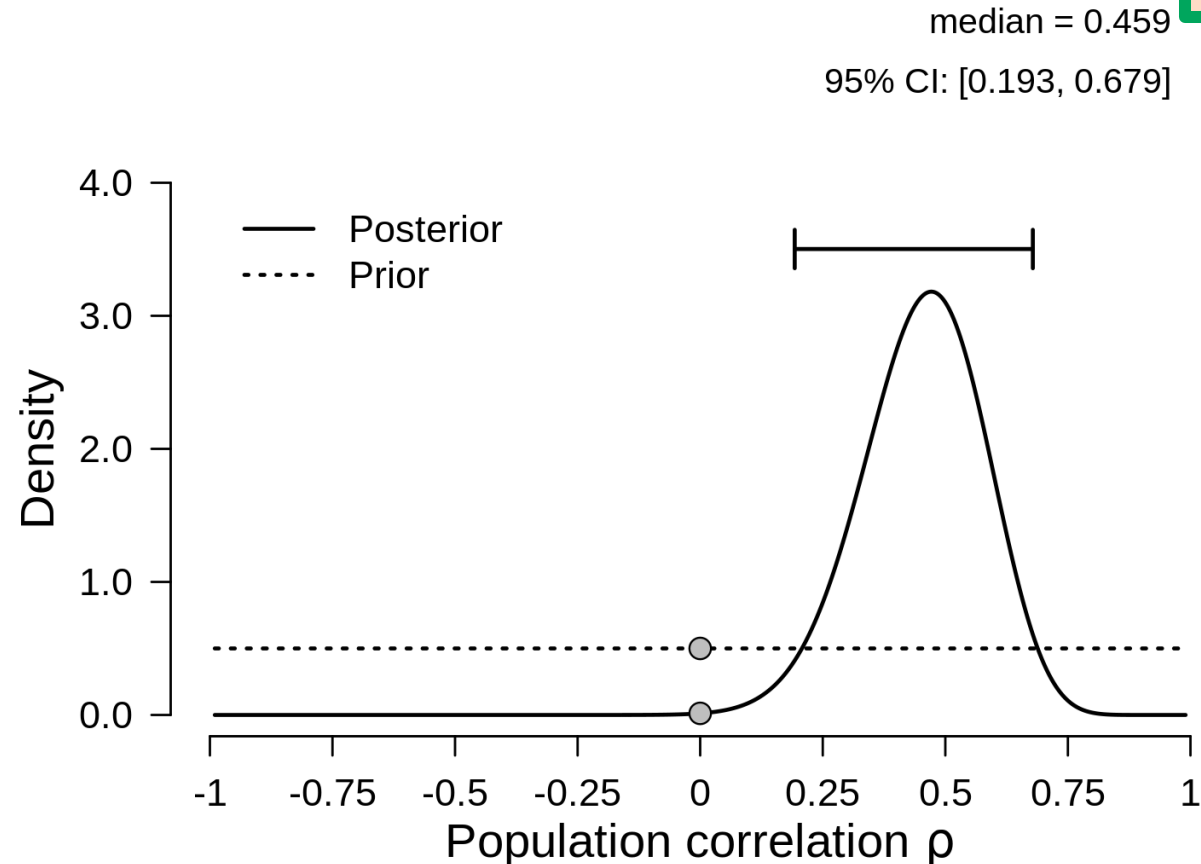
The likelihood grew more narrow, compared to when we had a lower sample size!

# Bayesian Correlation: Posterior Distribution

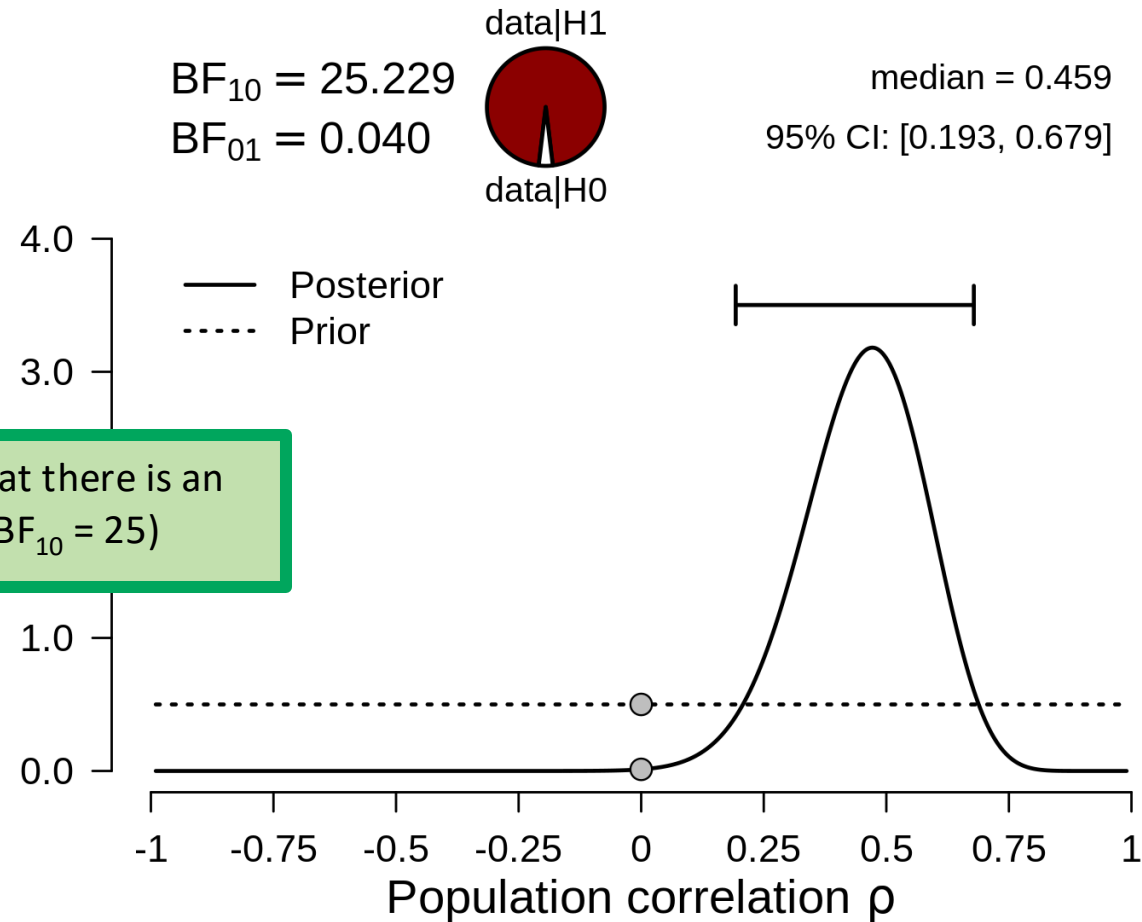
**95% Credible interval:**  
“95% probability that  $\rho$  is between 0.193 and 0.679”

The posterior is also more narrow!  
This also leads to a more narrow credible interval (still 95%, but the two numbers are closer together (e.g., 0 is no longer in the interval))

We can make a more specific prediction, with the same certainty (95%)

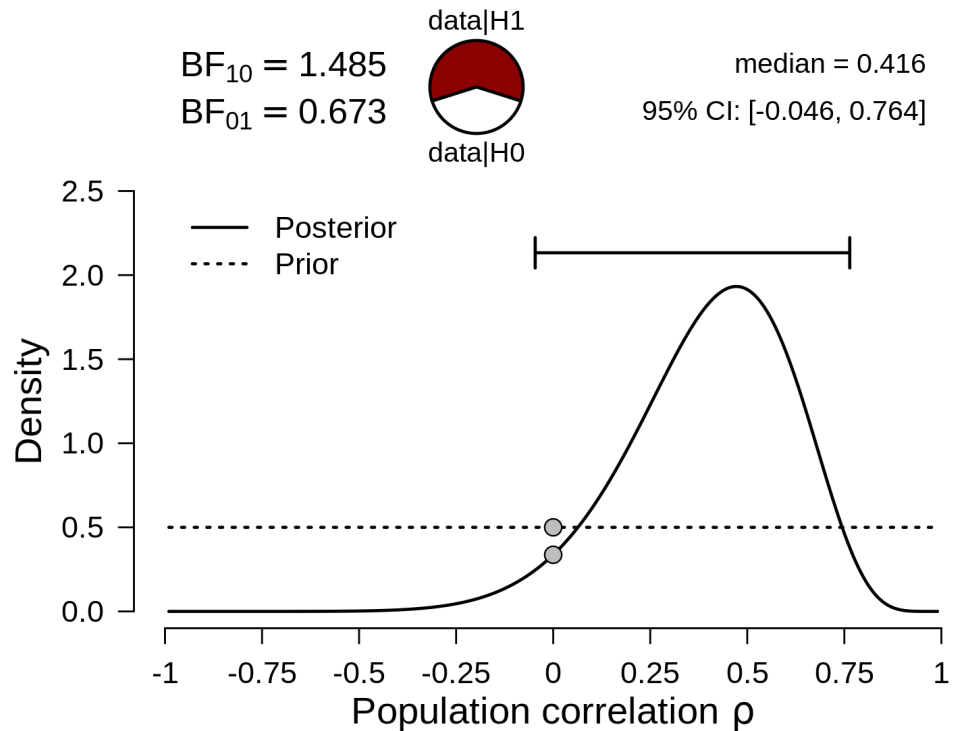


# Bayesian Correlation: Bayes Factor

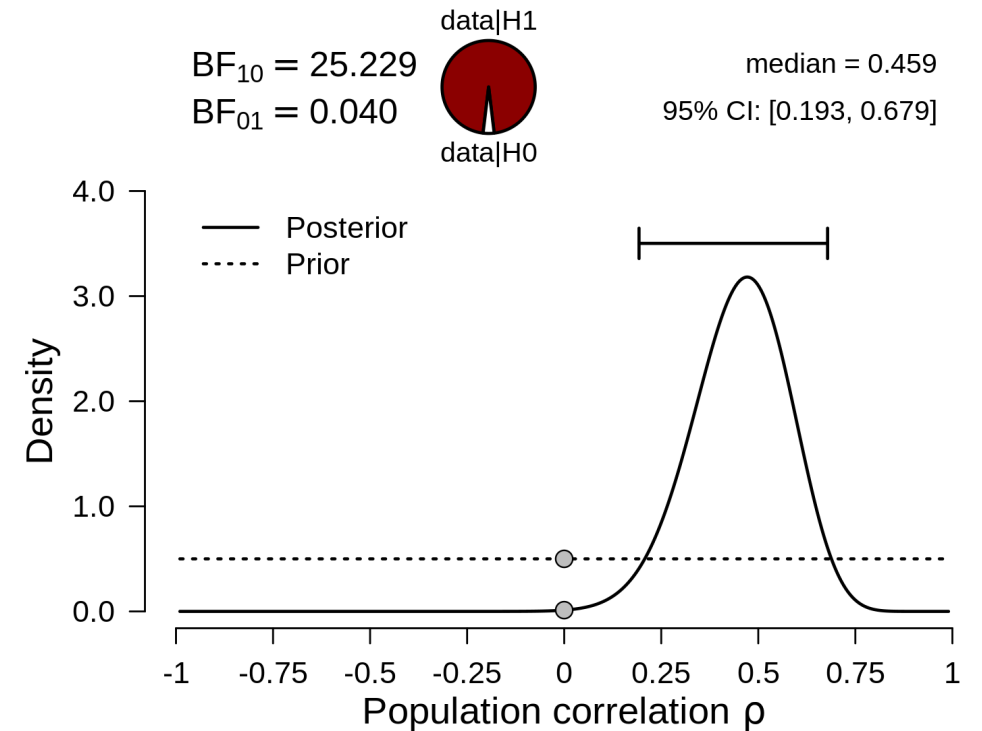


Now we have pretty strong evidence that there is an association between the variables ( $BF_{10} = 25$ )

# Bayesian Correlation: Bayes Factor



N = 15, observed correlation = 0.485



N = 40, observed correlation = 0.485

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  - **T-test**
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# Bayesian T-Test

- What about differences between means?
- In psychology, differences between groups are characterized by  $\delta$  (“delta”, also known as Cohen’s *d*): a *standardized* difference between groups

<i>Effect size</i>	<i>d</i>	<b>Reference</b>
Very small	0.01	Sawilowsky, 2009
Small	0.20	Cohen, 1988
Medium	0.50	Cohen, 1988
Large	0.80	Cohen, 1988

As with the Bayes factor, this is a table to provide some intuition for the magnitude of an effect – there are no hard cut-off values here!  
(don’t need to study this table for exam)

For further reading and formulas (not exam material):

[https://en.wikipedia.org/wiki/Effect\\_size#Difference\\_family:\\_Effect\\_sizes\\_based\\_on\\_differences\\_between\\_means](https://en.wikipedia.org/wiki/Effect_size#Difference_family:_Effect_sizes_based_on_differences_between_means)

# Bayesian T-Test

$$P(\delta \mid \text{data}) = P(\delta) \frac{P(\text{data} \mid \delta)}{P(\text{data})}$$

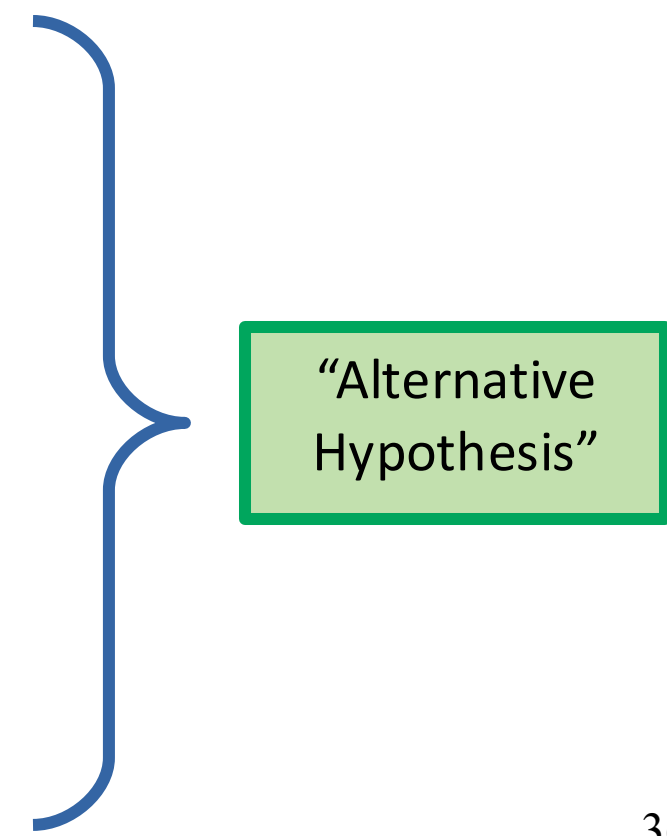
# Bayesian T-Test: Hypothesis

$$\mathcal{H}_0 : \delta = 0$$

$$\mathcal{H}_1 : \delta \neq 0$$

$$\mathcal{H}_+ : \delta > 0$$

$$\mathcal{H}_- : \delta < 0$$



“Alternative Hypothesis”

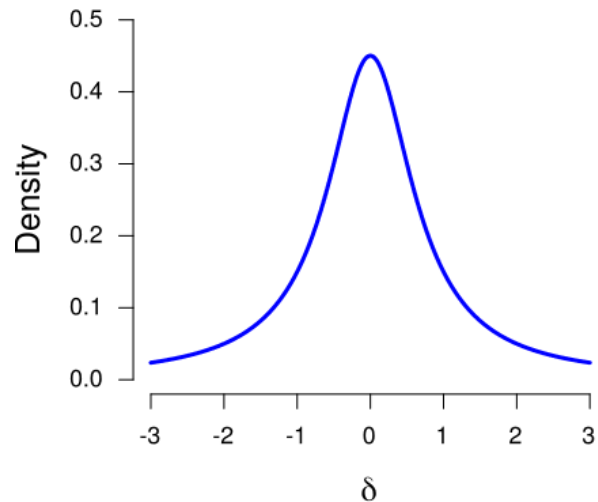
# Bayesian T-Test: Prior Distribution

The prior distribution is on the same domain as the parameter of interest: so we need a distribution that is between  $[-\infty, \infty]$ .  
A normal distribution could work, but the convention is to use a t-distribution with  $df = 1$ . This is known as the **Cauchy** distribution

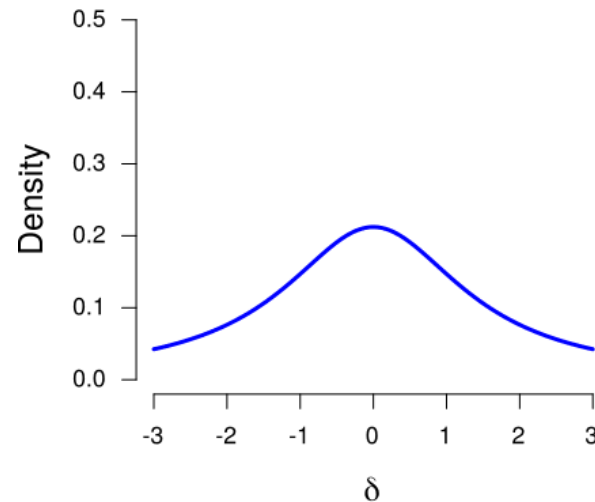
A uniform distribution would not work here, because delta has an infinite domain

The Cauchy distribution is governed by a single shape parameter that determines how wide it is

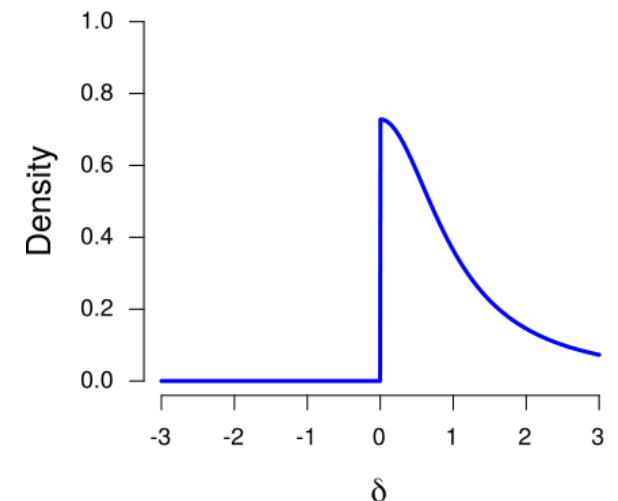
Cauchy Distribution (width = 0.707)



Cauchy Distribution (width = 1.5)



Truncated Cauchy Distribution (width = 0.707)



# Bayesian T-Test: Prior Distribution

A prior distribution that reflects the belief that 50% of the values of  $\delta$  are located between -0.707 and 0.707, a **priori**

A prior distribution that reflects the belief that 50% of the values of  $\delta$  are located between -1.5 and 1.5, a **priori**

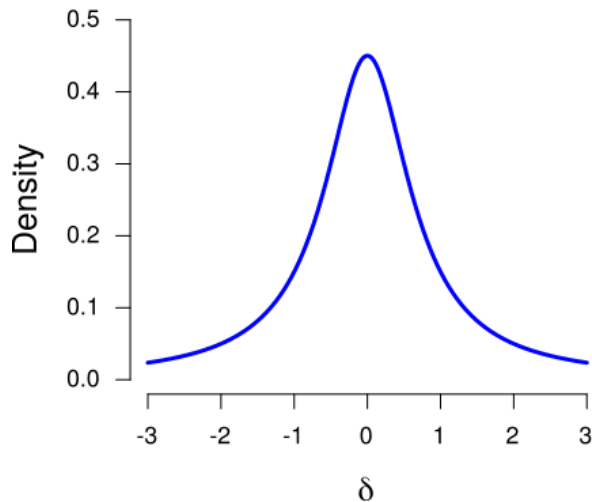
A prior distribution that reflects the belief that only positive values of  $\delta$  are possible and that 50% of the values of  $\delta$  are between 0 and 0.707, a **priori**

This is often selected as the “uninformative” option. Why? Unfortunately that is a long and technical story, not suited for this course :(

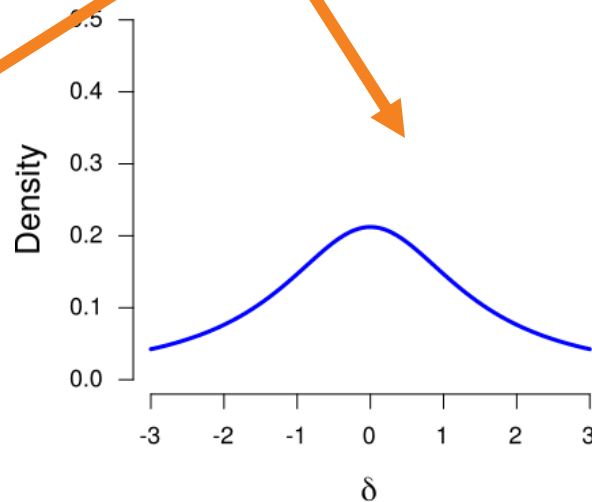
$$\mathcal{H}_1 : \delta \neq 0$$

$$\mathcal{H}_+ : \delta > 0$$

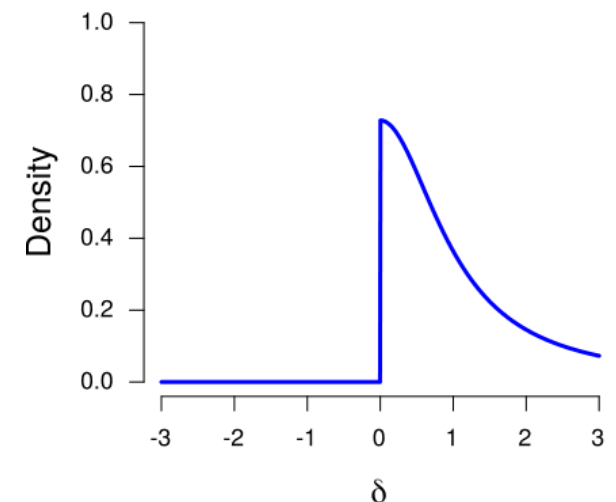
Cauchy Distribution (width = 0.707)



Cauchy Distribution (width = 1.5)



Truncated Cauchy Distribution (width = 0.707)

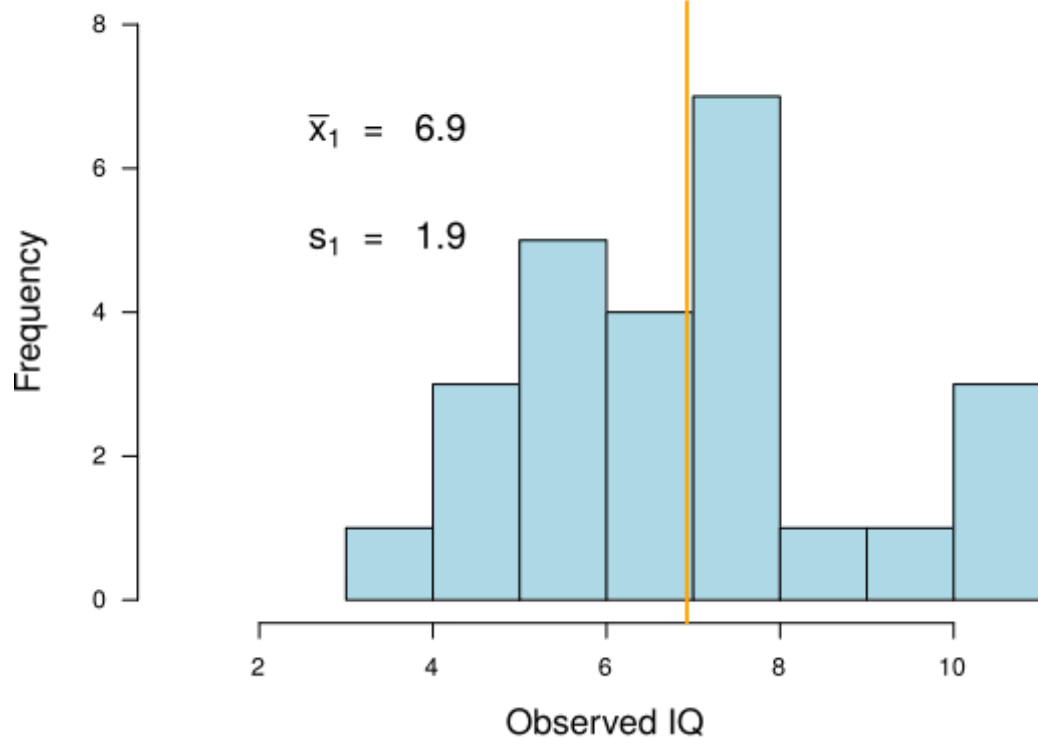


# Bayesian T-Test: Data

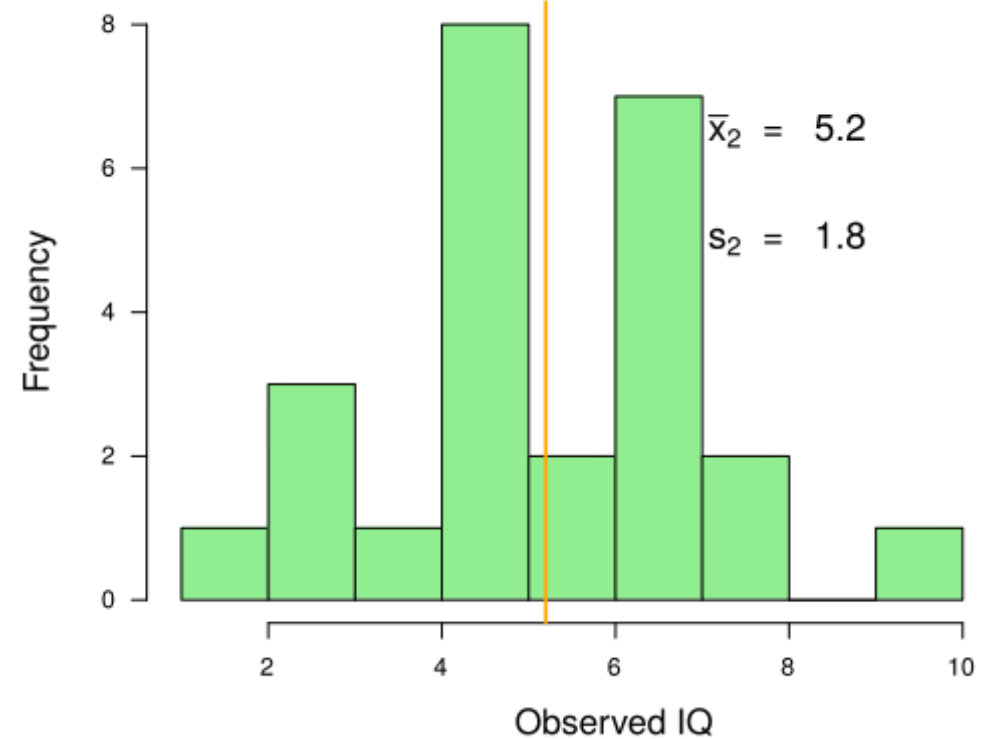
Observed  $\delta = 0.95$   
( $t = 3.27$ )

$n = 25$

Placebo Pills IQ (group 1)



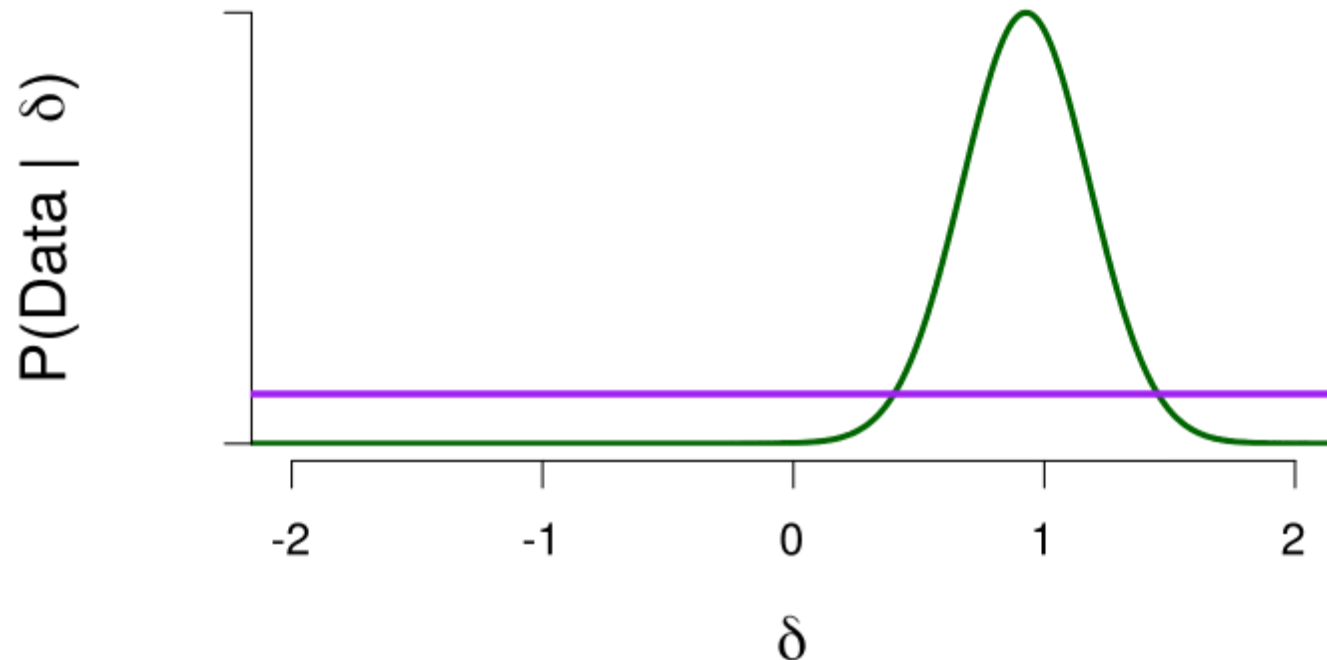
Smart Pills IQ (group 2)



# Bayesian T-Test: Likelihood

$$P(\text{data} \mid \delta)$$

Likelihood of the observed data, for each value of  $\delta$

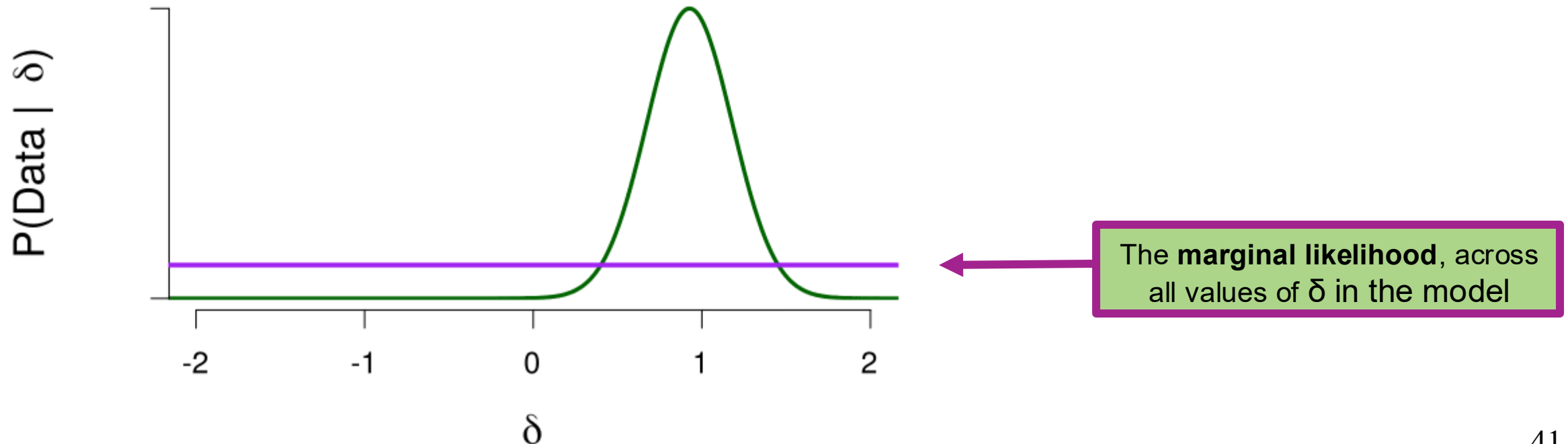


We see that the data are likely for values of  $\delta$  close to 1.  
This makes sense, because the observed delta (i.e., the data) is equal to 0.95!

# Bayesian T-Test: Likelihood

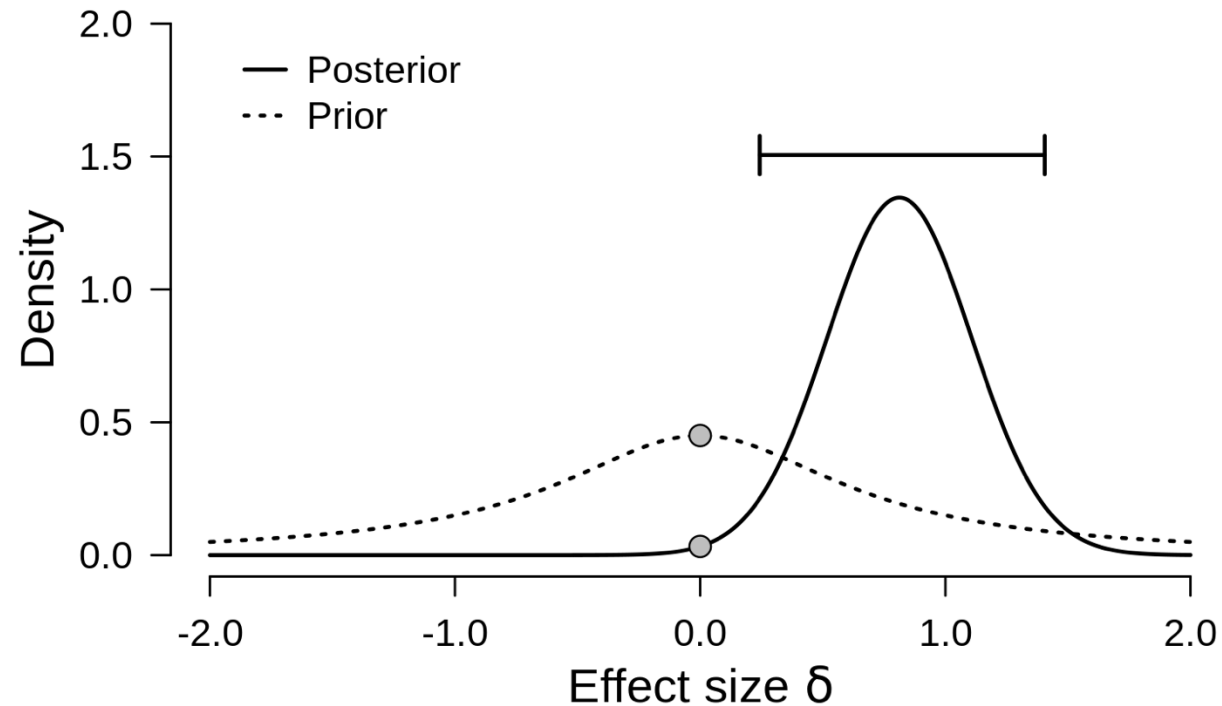
$$P(\text{data} \mid \delta)$$

Likelihood of the observed data, for each value of  $\delta$

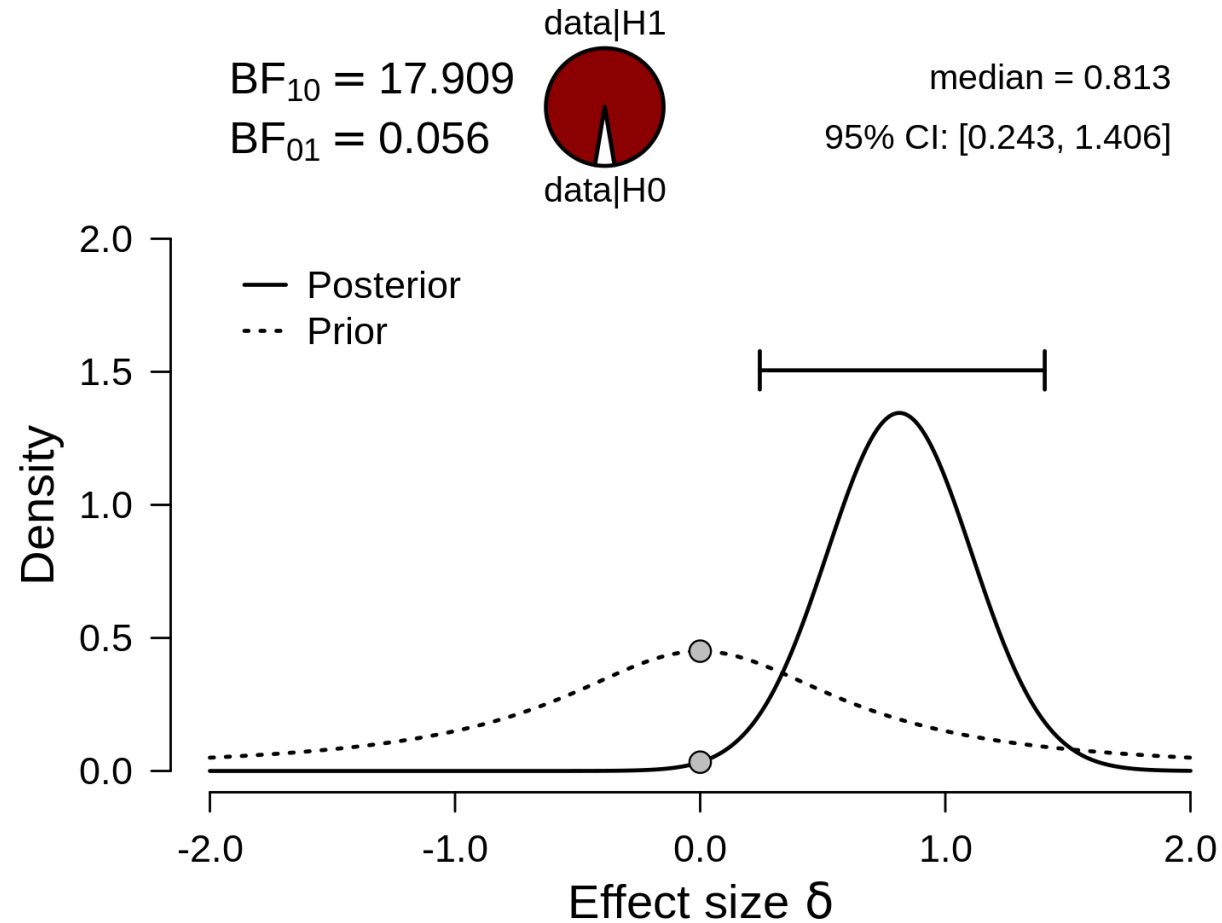


# Bayesian T-Test: Posterior Distribution

$$P(\delta \mid \text{data})$$



# Bayesian T-Test: Bayes Factor

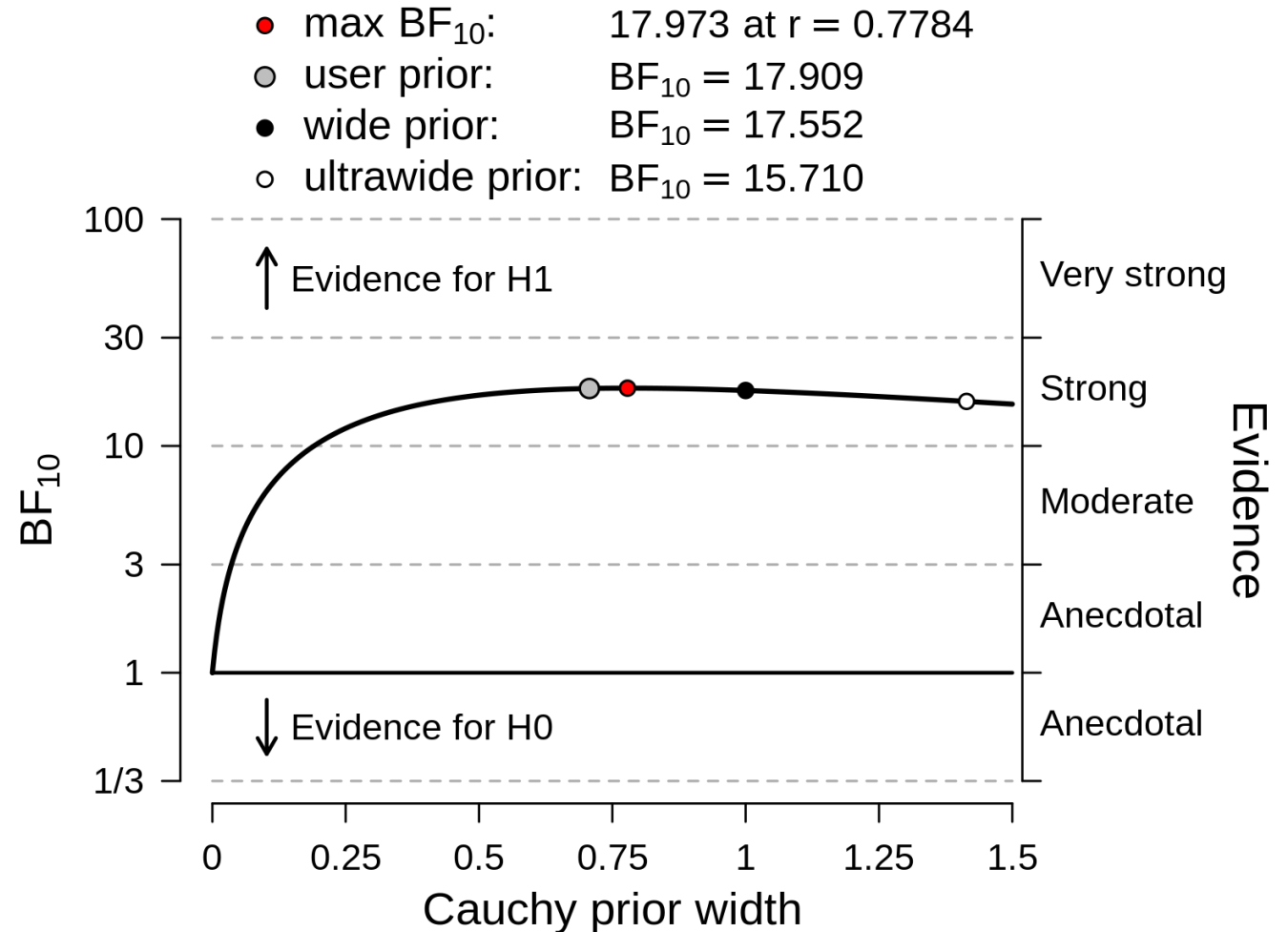


# Bayesian T-Test: Robustness Check

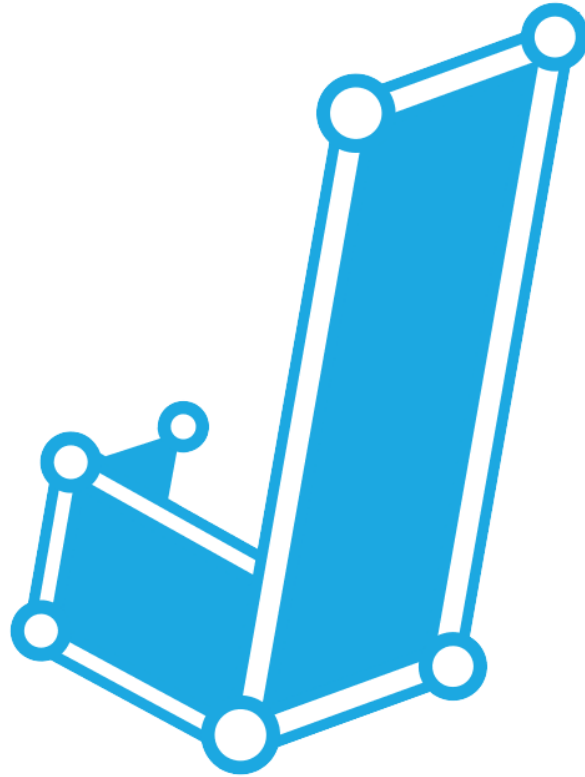
Because choosing the prior setting is fairly subjective, we can explore what would have happened if we had chosen a different value for the prior width. This is known as a **Bayes factor robustness check, or sensitivity analysis**

We see here that the Bayes factor is pretty stable (i.e., flat line) across many values for the prior width. Except for very strong prior settings (0.15 and lower) does the evidence for  $H_1$  decrease

*“Here, the Bayes factor does not qualitatively differ for a wide range of prior specifications (0.25 – 1.5)”*



# Bayesian T-Test - Demonstration



[www.jasp-stats.org](http://www.jasp-stats.org)

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  - Correlation
  - T-test
- **Bayes & Frequentism**
- Statistics in the Wild
- Recap
  - Example exam question

# Bayes & Frequentism

## Frequentist Hypothesis testing

- 1) **Specify alpha**
- 2) Assumptions
- 3) Hypothesis
- 4) **Test statistic + sampling distribution**
- 5) **P-value**
- 6) Conclusion

## Bayesian Hypothesis testing

- 1) Assumptions
- 2) Hypothesis
- 3) **Set prior distribution**
- 4) **Compute likelihood**
- 5) **Bayes factor**
- 6) Conclusion

# Bayes & Frequentism

Bayes	Frequentism
Compare the predictive quality of two hypotheses	Minimize type 1 error (incorrectly reject $H_0$ )

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Check assumptions	Check assumptions
Still incomplete (but steadily expanding)	Has wide range of types of analyses
Sampling plan: can monitor the results and stop when satisfied	Have to specify sampling plan before, based on hypothesized effect size

# Dichotomous reasoning of p-values is arbitrary

“It’s funny how significance  
make a difference”  
- MF DOOM

- Compare:
  - Group A has a higher on verbal IQ than group B
    - ( $p = 0.049$ )
  - There is no difference between the groups in verbal IQ
    - ( $p = 0.051$ )
- Fisher (1935):
  - Founder of p-value
  - In a footnote: *“You may think of the idea of rejecting the null-hypothesis at some value, **for instance** at 0.05”*



# Not intuitive

- Common mistakes when working with p-values

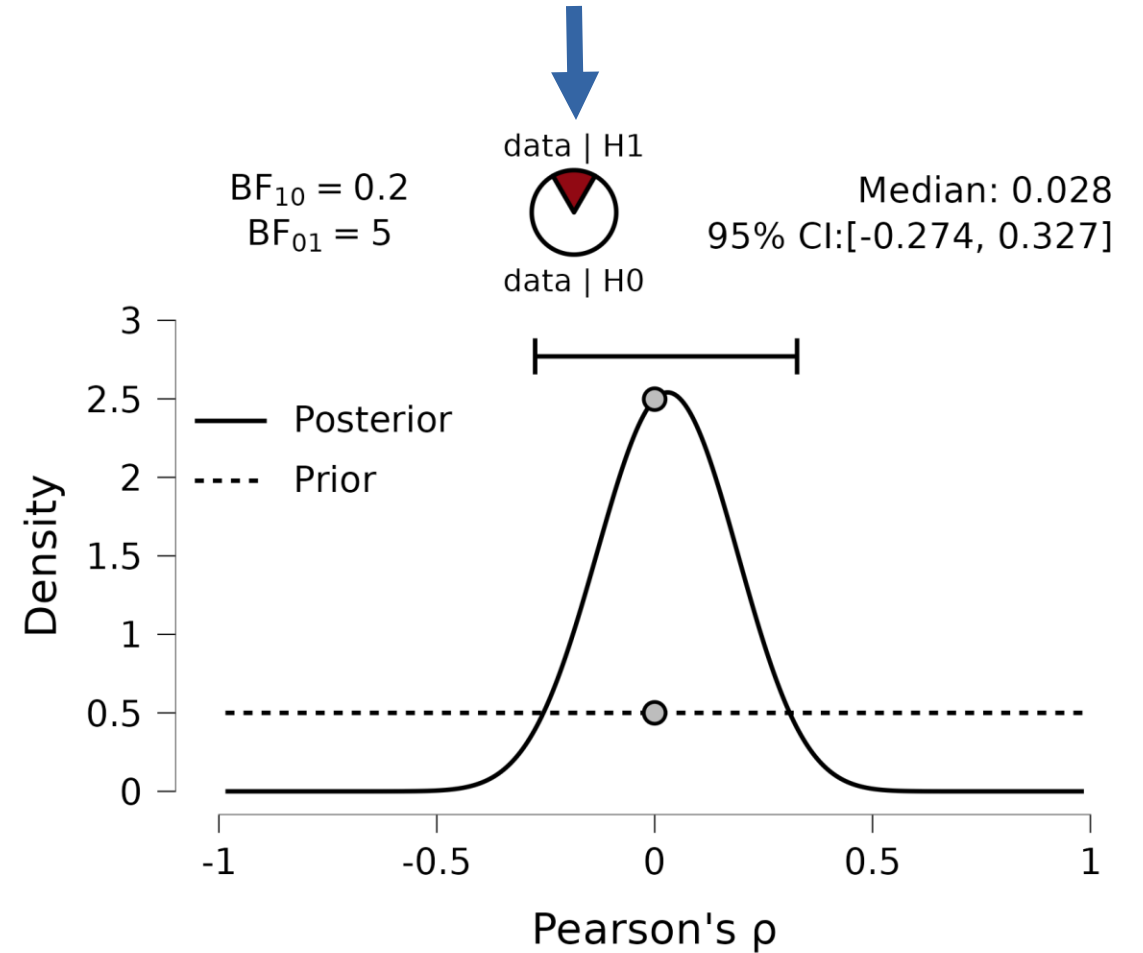
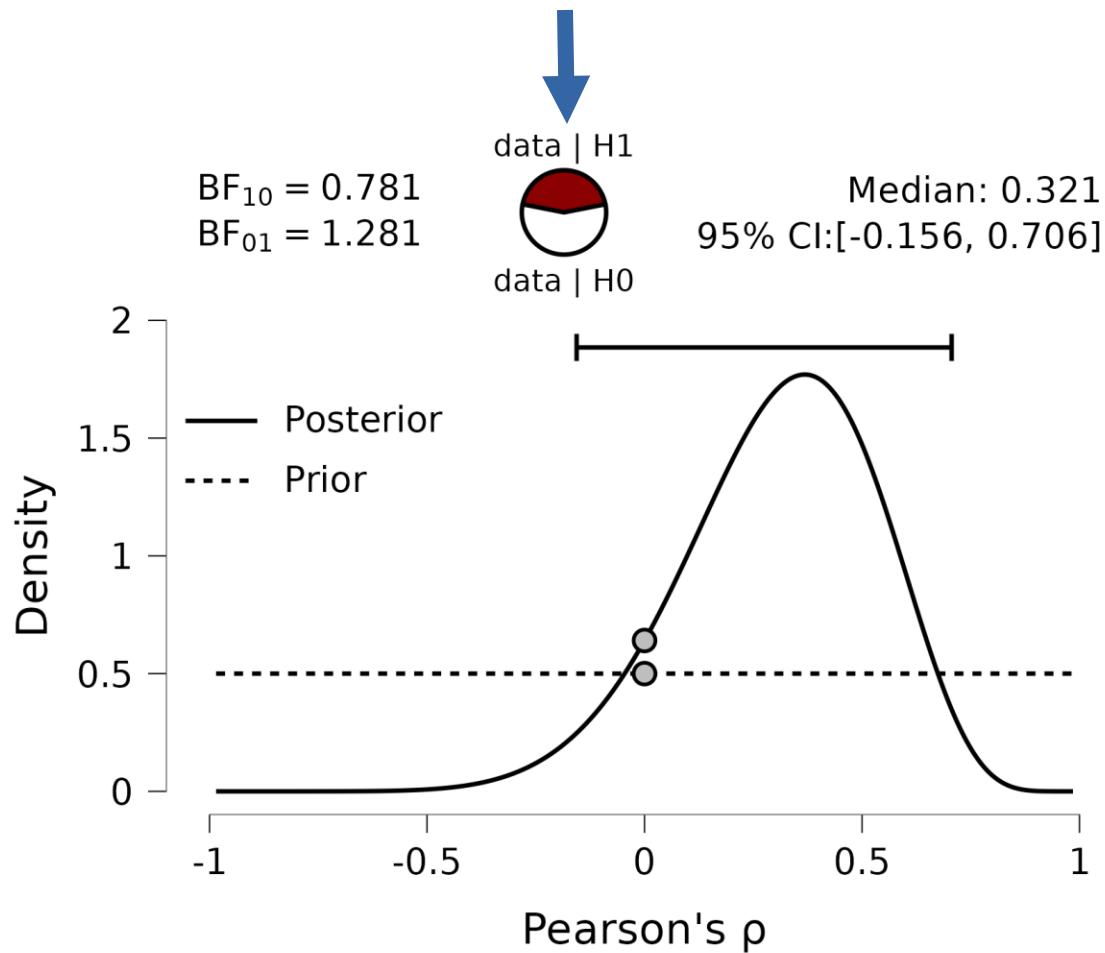
- ‘evidence for  $H_A$ ’
- ‘probability that  $H_0$  is true’



These are **incorrect** interpretations!

- Understandable because this is what we actually want to know
- What is the p-value again?
  - ‘The probability of these *data* or more extreme if  $H_0$  is true’

# “Absence of evidence” vs “evidence of absence”



Both analyses would yield a non-significant p-value – but what does that actually mean?

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# Statistics in the Wild

Just test some extra subjects (and not do Bayes)

Often, there is great pressure to publish articles, and to publish, “non-null effects” are needed...

My data is not really normal, but who cares about assumptions?

So what if you spent a year of research collecting a data set, but your result is not significant? Or your Bayes factor is inconclusive (i.e., close to 1)?

I will just test another hypothesis...

If I only report this alternative prior distribution, my Bayes factor is way higher!

If I conduct a t-test instead of a Wilcoxon test, I can reject  $H_0$ !

Deleting this one “outlier” makes my effect significant!



Hey, my computer can simulate data!



# Statistics in the Wild

- There has been an increase in statistical rigor since the Reproducibility crisis:
  - Center for Open Science tried to replicate 100 published psychological studies
  - Only 35 studies replicated

- <https://science.sciencemag.org/content/349/6251/aac4716.full?ijkey=1xgFoCnpLswpk&keytype=ref&siteid=sci>
- [https://en.wikipedia.org/wiki/Reproducibility\\_Project](https://en.wikipedia.org/wiki/Reproducibility_Project)

# Statistics in the Wild



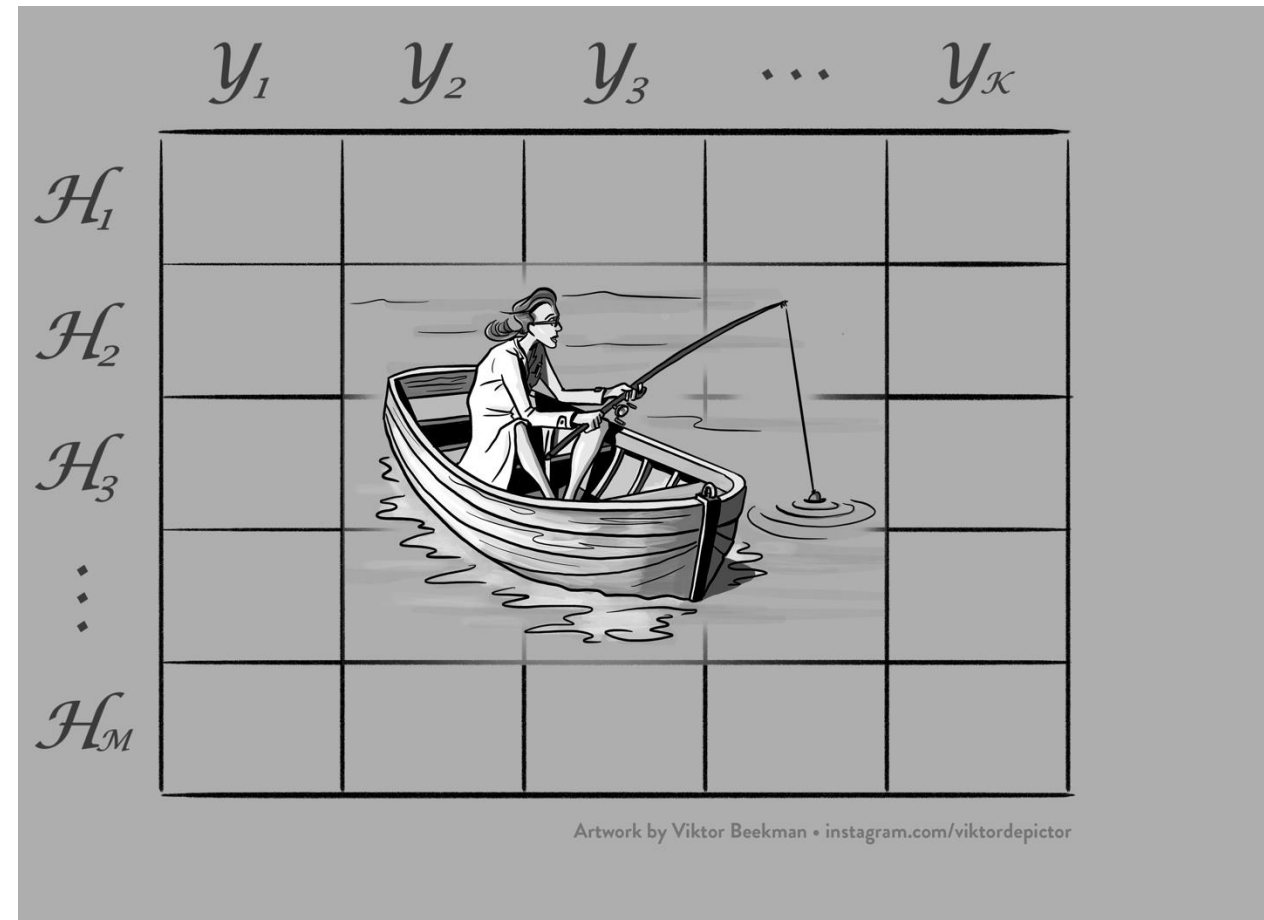
- A powerful initiative to reduce bias in reporting is preregistration
  - Before you conduct your study, you preregister several pieces of information:
    - Description of study and sampling plan
    - Hypotheses (+ one-sided/two-sided)
    - Analysis plan: what statistical tests, and what settings: prior and Bayes factor / alpha-level for accepting or rejecting hypothesis

• [Munafò, M., Nosek, B., Bishop, D. et al. A manifesto for reproducible science. Nat Hum Behav 1, 0021 \(2017\) doi:10.1038/s41562-016-0021](#)

# Statistics in the Wild: Preregistration

Preregistration prevents **Data Dredging/Fishing/Hacking**: trying all sorts of different analyses/settings in order to get a significant result

“Oh, this two-sided t-test was not significant, let’s try a one-sided t-test instead! Hey, now it’s significant 😬”



# Statistics in the Wild: Preregistration

Preregistration prevents **presenting exploratory research as confirmatory research**: *exploratory* research is used to generate theories and hypotheses; *confirmatory* research is used to test those

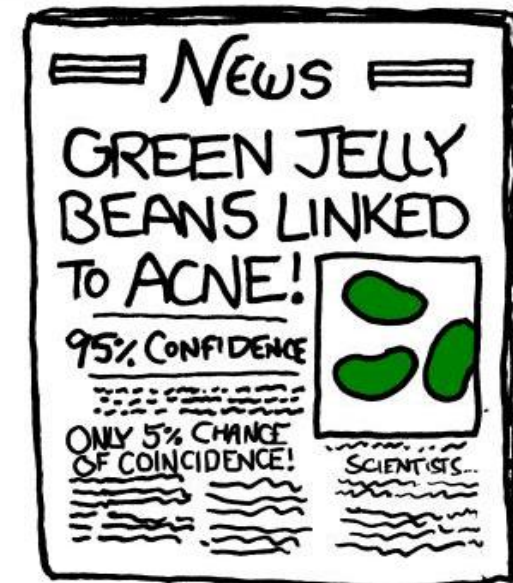
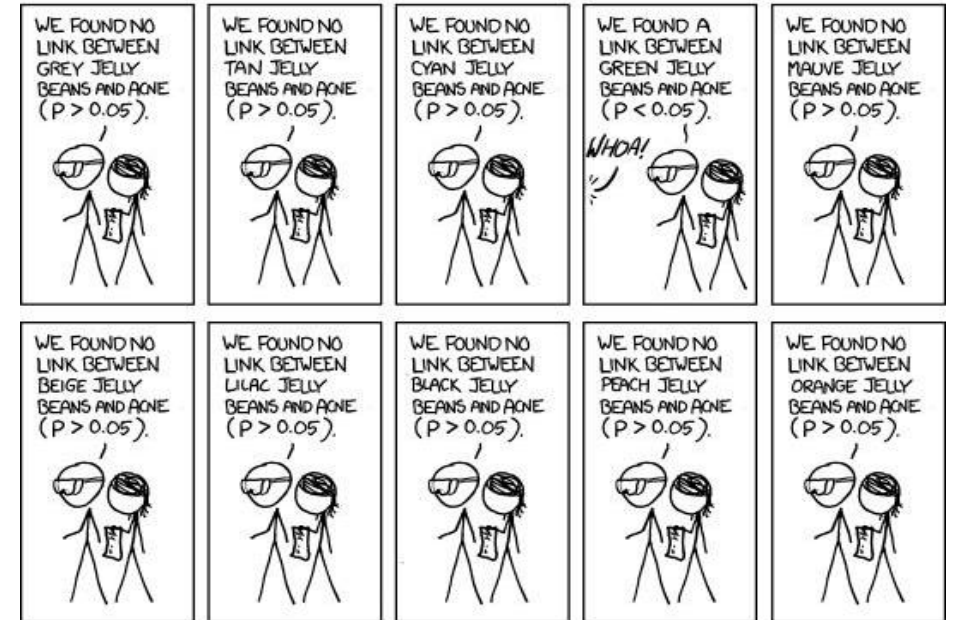
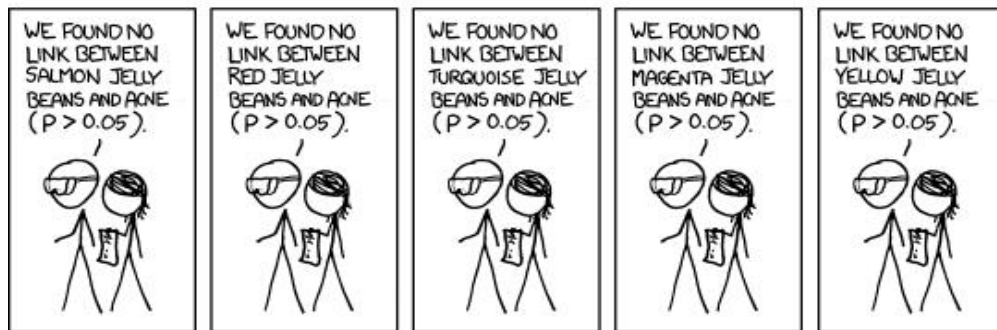
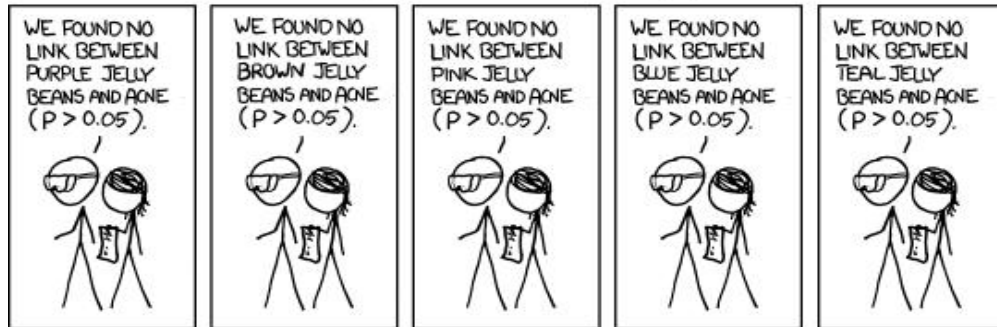
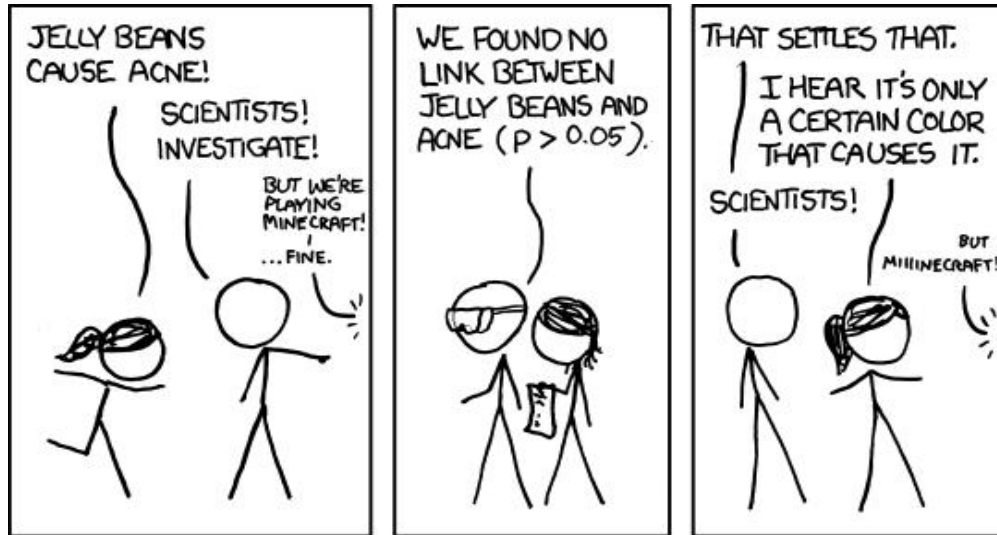
**Exploratory**: Let's measure all big 5 personality traits and look at all possible correlations to see which ones correlate

**Confirmatory**: Let's measure all big 5 personality traits, because my theory postulates that C & N, O & E, and E & A traits are positively

**Presenting exploratory as confirmatory**: "Oh I found a positive correlation between E & A – that was my theory all along so my theory is now confirmed!"



# Statistics in the Wild: Preregistration



# Statistics in the Wild

- Luckily, journals are also cooperating
  - Registered reports:
    - Write most of your paper+preregistration, without conclusions, when it gets accepted by the journal you conduct the experiment fill in the results and conclusion section of your paper based on the results
  - Increased support for null findings
- Transparency is key: sharing analysis files/code, making data available

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# Recap

- The same flow of inference we saw for the proportion can also be extended to other tests: for instance correlation and t-test
- We can investigate the effect of the prior on the Bayes factor: robustness check or sensitivity analysis
- We have seen cases where  $p < 0.05$ , yet the Bayes factor is close to 1

# Recap

- The Bayes factor is a relative metric! Pay attention to what is being compared to what
- Bayes does not fix all your problems: equally vulnerable to assumption violations and statistical malpractice!
- Preregistration and Open Science can help with this

# Big Recap

We have applied this to multiple methodological designs: 1/2/3+ groups, quantitative/categorical/ordinal variables

Descriptive statistics: sample mean/correlation → test statistic

Inferential statistics: Use data and statistics to quantify our uncertainty when making statements based on data

What would happen if we repeat the experiment over and over?  
→ Sampling distribution

How well do all values of the parameters predict the data?  
→ Prior & likelihood = posterior

estimation

testing

estimation

testing

## Confidence interval

If repeated this over and over, x% of the intervals contain true value

## P-value:

If the null is true, the probability of the data or more extreme data

## Credible interval

x% probability that this contains true value

## Bayes factor

Data are x times more likely under this H than under this other H

Conclusion!!  
Create/update theory  
Publish/party

# More Cool Stuff to Read

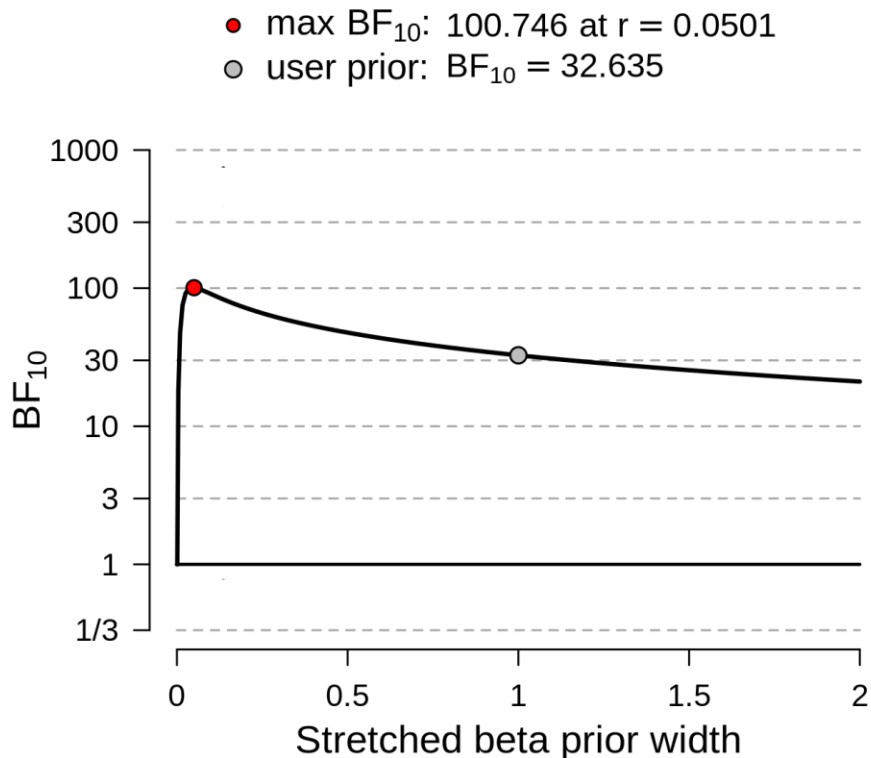
- [One statistical analysis must not rule them all](#)
  - Any single analysis hides an iceberg of uncertainty. Multi-team analysis can reveal it.
- [The rise and fall of peer review](#)
  - Why the greatest scientific experiment in history failed, and why that's a great thing
- [Good Research Practices \(PhD dissertation from our department\)](#)
  - Research practices and reform ideas aiming to combat the crisis of confidence in psychology
- [Strong public claims may not reflect researchers' private convictions](#)
  - Small questionnaire we sent around to empirical researchers to gauge how confident they are in their papers' claims

# Today

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# Example Exam Question

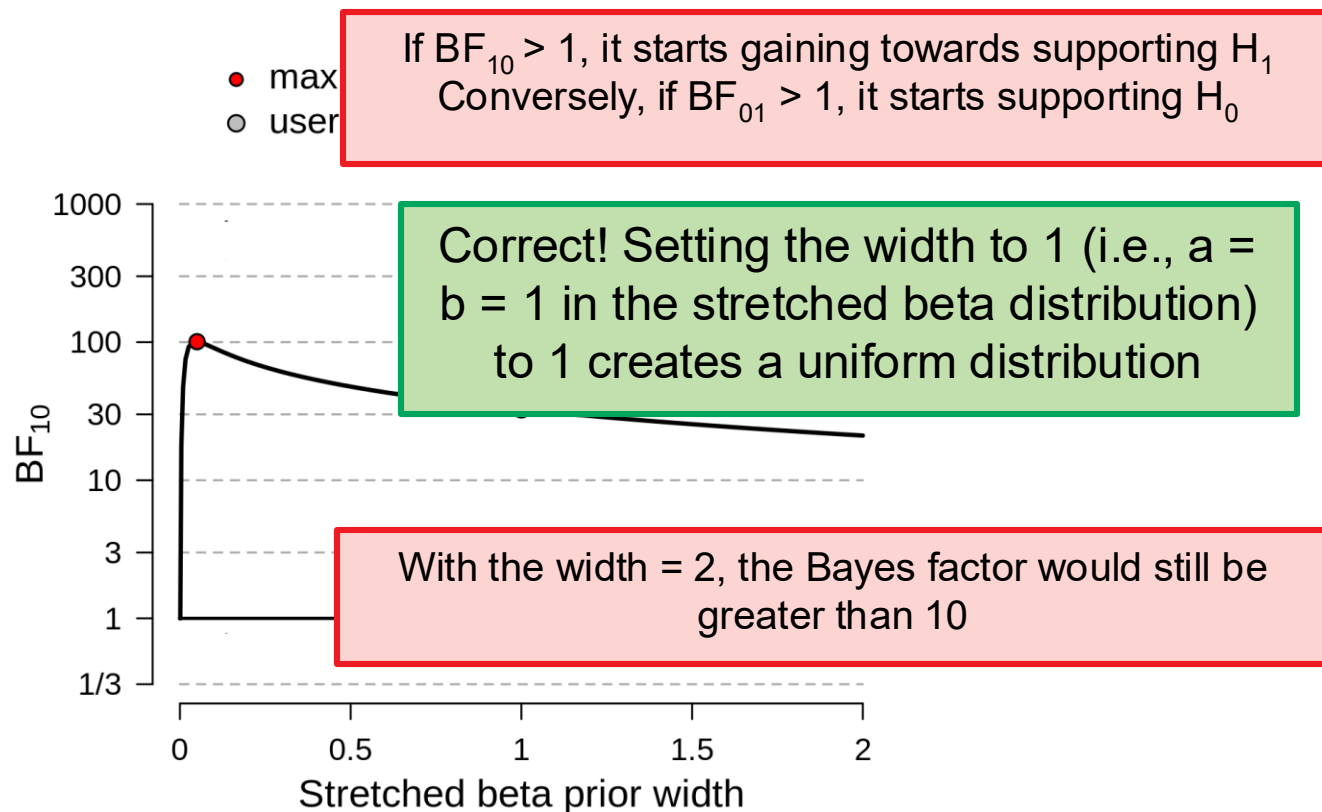
We measure two variables: Openness and Extraversion. After a Bayesian correlation analysis we look at the effect of the prior we chose. What statement is true?



- a) We gained evidence in favor of the null hypothesis
- b) We used a uniform prior for the correlation
- c) If we had specified the prior width equal to 2, the Bayes factor would be inconclusive (i.e.,  $< 3$ )

# Example Exam Question

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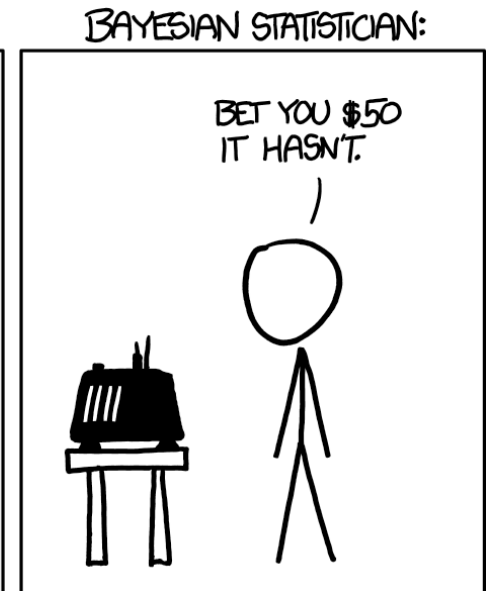
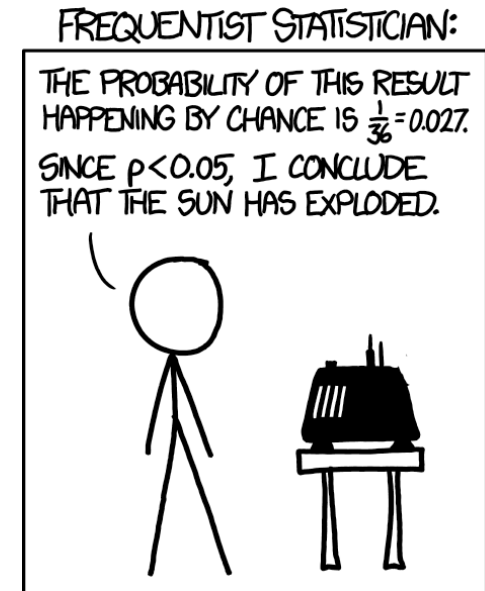
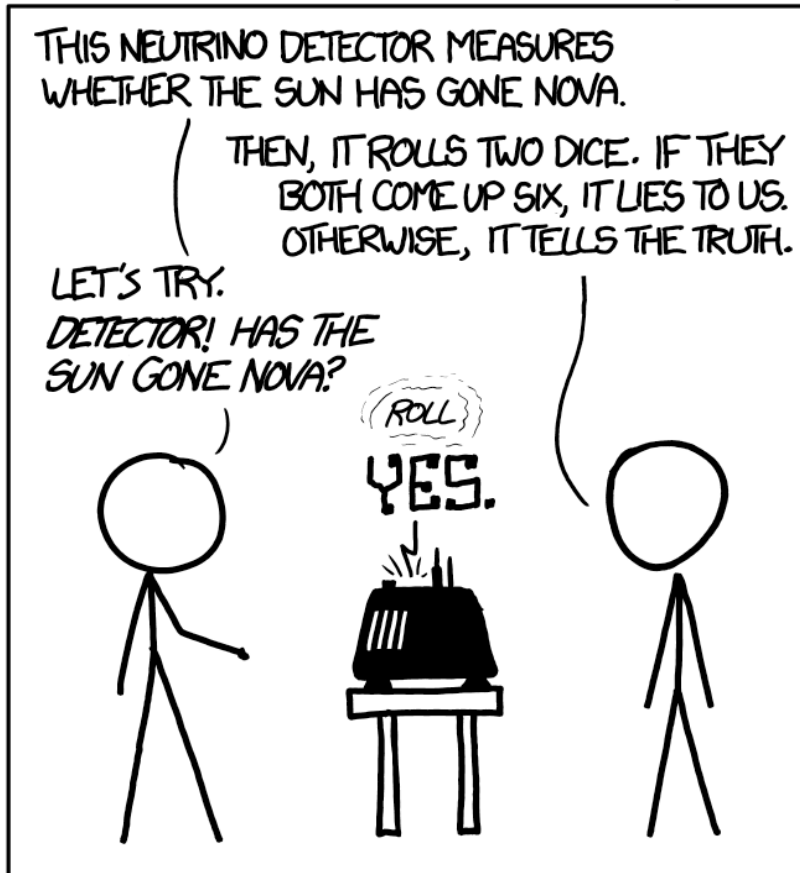
b) We used a uniform prior for the correlation

c) If we had specified the prior width equal to 2, the Bayes factor would be inconclusive (i.e.,  $< 3$ )

# Questions?

Thank you for your attention

DID THE SUN JUST EXPLODE?  
(IT'S NIGHT, SO WE'RE NOT SURE.)



# Bonus Article

There is a lot more cool stuff happening in Psychological Methods than just Bayesians criticizing Frequentists. Here at the UvA, Denny Borsboom and his lab have developed network models for dealing with complex psychological phenomena, such as psychiatric disorders. Based on correlations between many variables, they can visualize how such complex systems function.

Here is a cool interactive network plot of how psychiatric symptoms in the DSM V are connected:

Symptoms are represented as nodes and connected by an edge whenever they figure in the same disorder. The color of nodes represents the DSM-IV chapter in which they occur most often. The link above links to the article itself.

[https://www.annualreviews.org/doi/suppl/10.1146/annurev-clinpsy-050212-185608/suppl\\_file/cp9\\_borsboom\\_fig3.svg](https://www.annualreviews.org/doi/suppl/10.1146/annurev-clinpsy-050212-185608/suppl_file/cp9_borsboom_fig3.svg)