Bayesian data analysis using JASP

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compcogscisydney.com/jasp-tute.html

Part 1: Theory

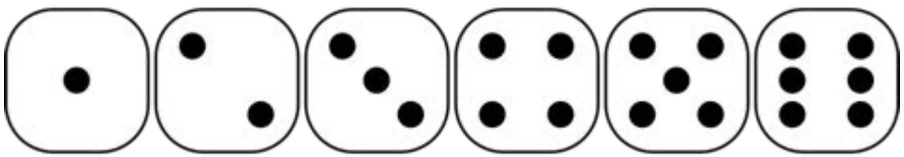
- Philosophy of probability
- Introducing Bayes rule
- Bayesian reasoning
- A simple example
- Bayesian hypothesis testing

Part 2: Practice

- Introducing JASP
- Bayesian ANOVA
- Bayesian t-test
- Bayesian regression
- Bayesian contingency tables
- Bayesian binomial test

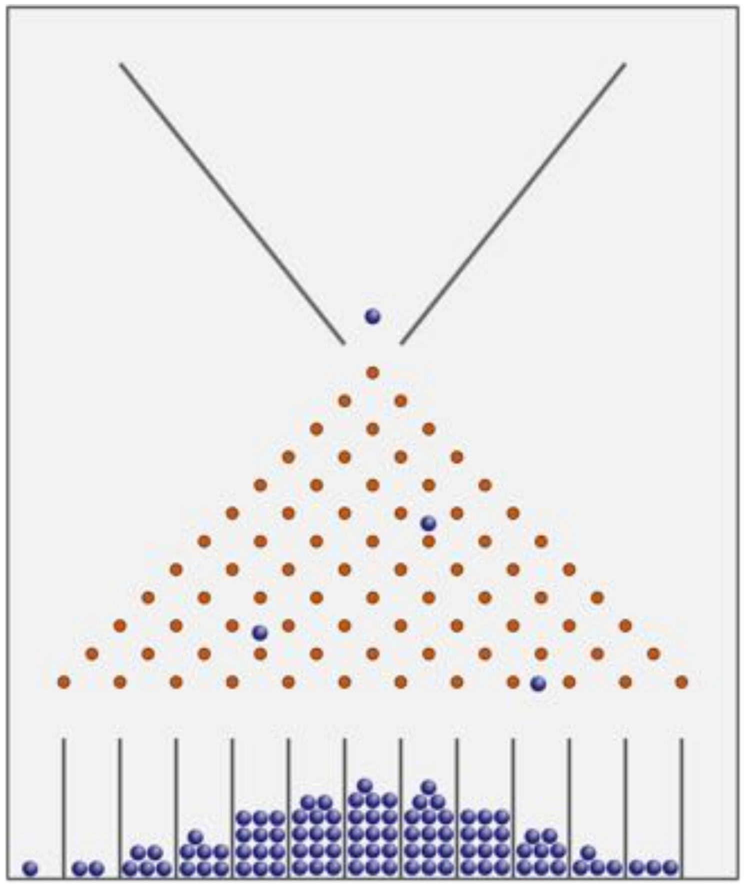
1.1 Philosophy of probability

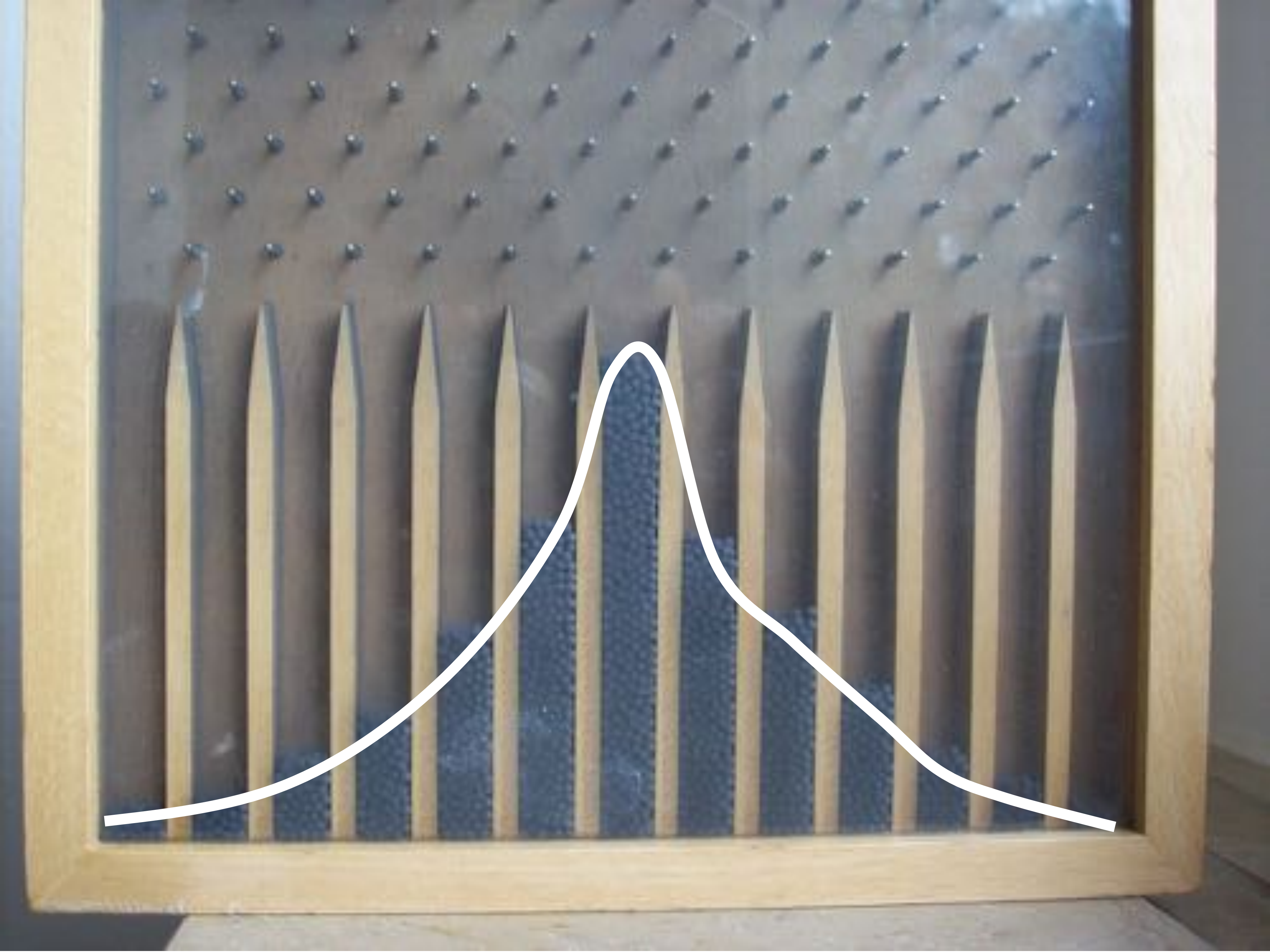
Idea #1: "Aleatory" processes

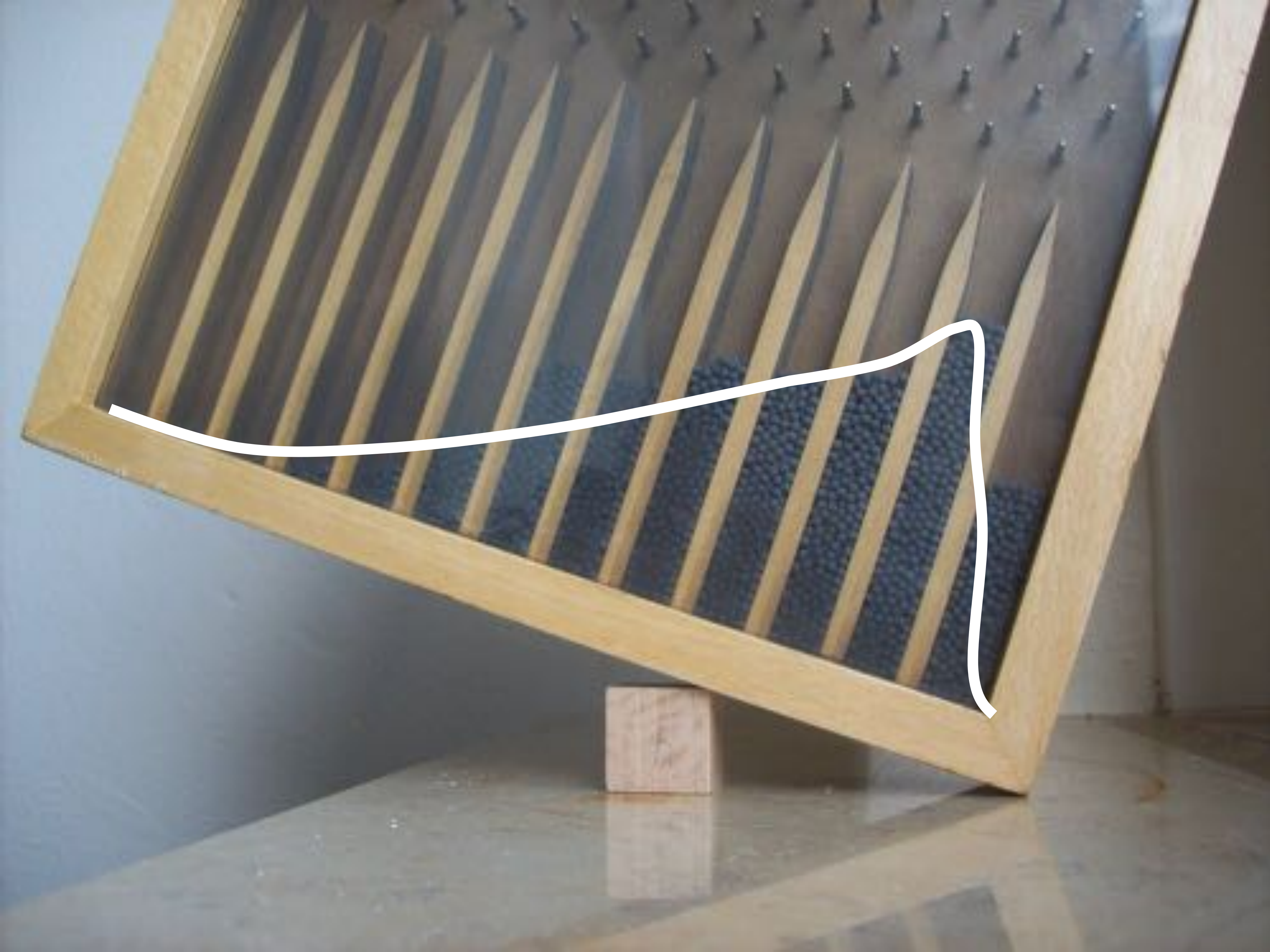


Probability is an objective characteristic associated with physical processes, defined by counting the relative frequencies of different kinds of events when that process is invoked

“Aleatory” processes

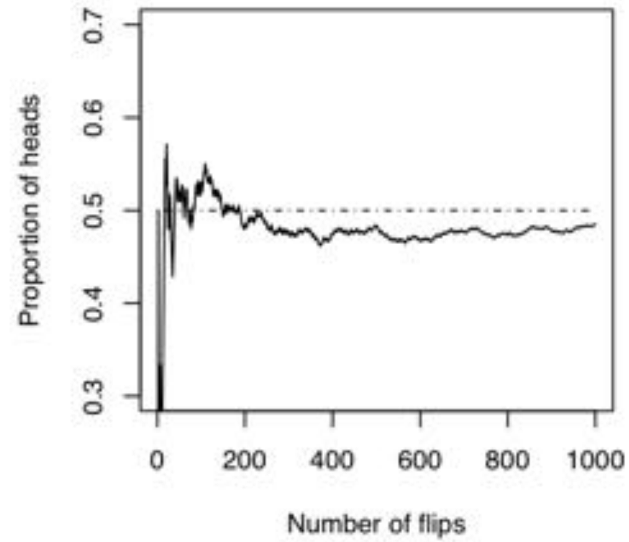






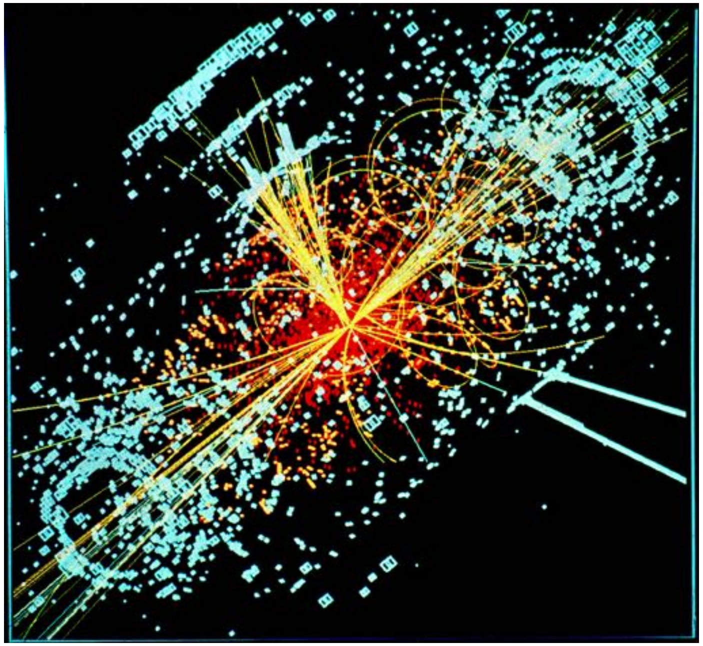
Frequentist statistics

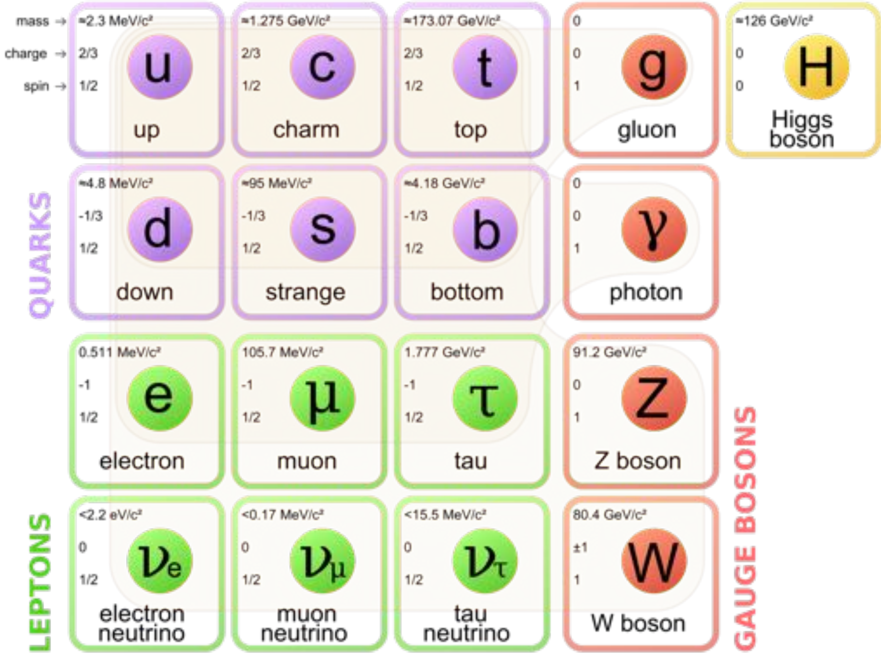
Coin flipping is an aleatory process, and can be repeated as many times as you like



The probability of a head is defined as the long-run frequency

Frequentist statistics



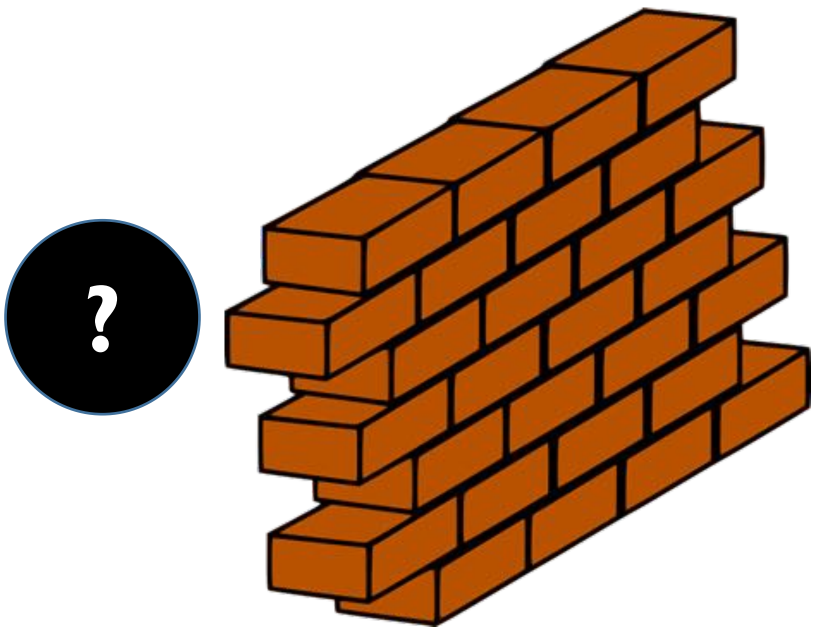


A particle physics experiment is a repeatable procedure, and thus a frequentist probability can be constructed to describe its outcomes

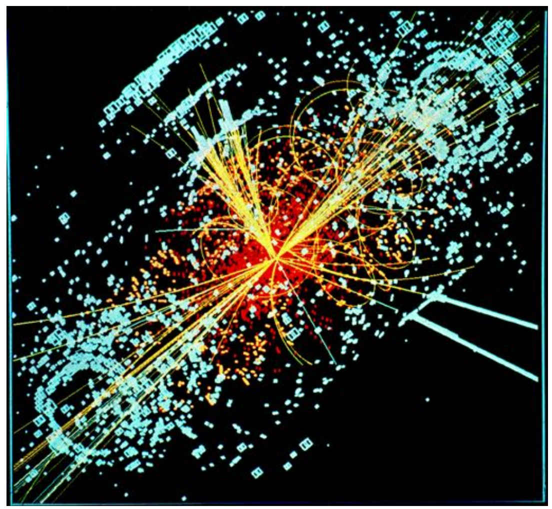
A scientific theory is not a repeatable procedure, and cannot be assigned a probability: there is no such thing as "the probability that my theory is true"

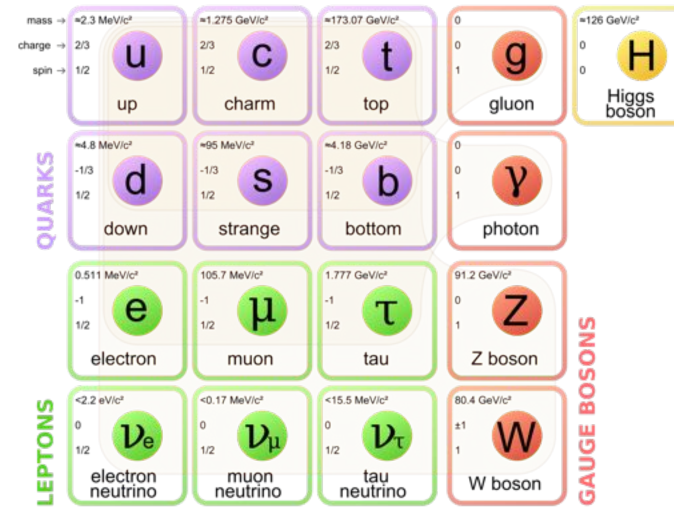
<u>Idea #2:</u>"Epistemic" uncertainty

Probability is an subjective characteristic associated with rational agents, defined by assessing the strength of belief that the agent holds in different propositions



"Bayesian" statistics



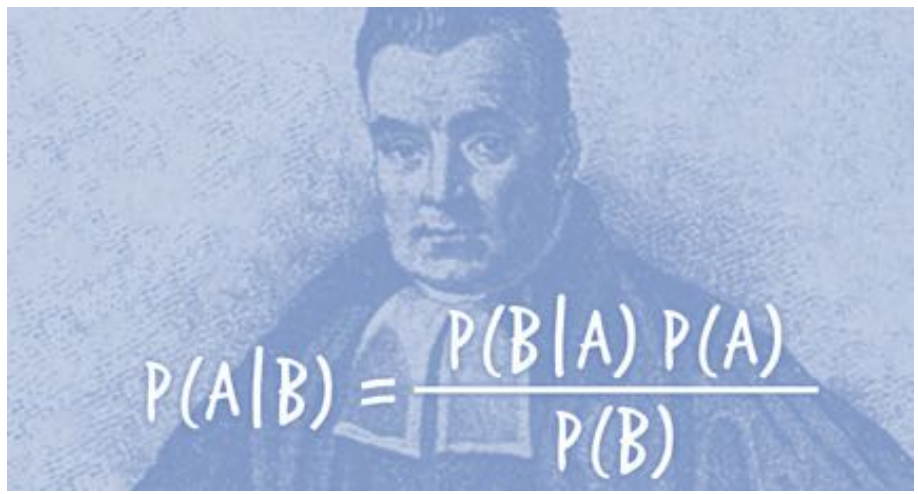


Probabilities can be attached to any proposition that an agent can believe

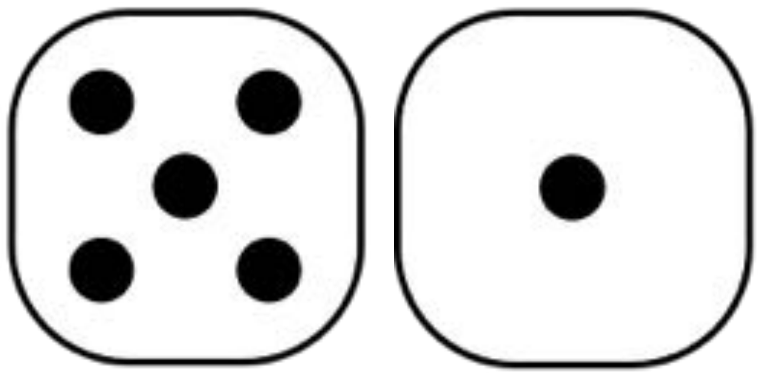
A particle physics experiment generates observable events about which a rational agent might hold beliefs

A scientific theory contains a set of propositions about which a rational agent might hold beliefs

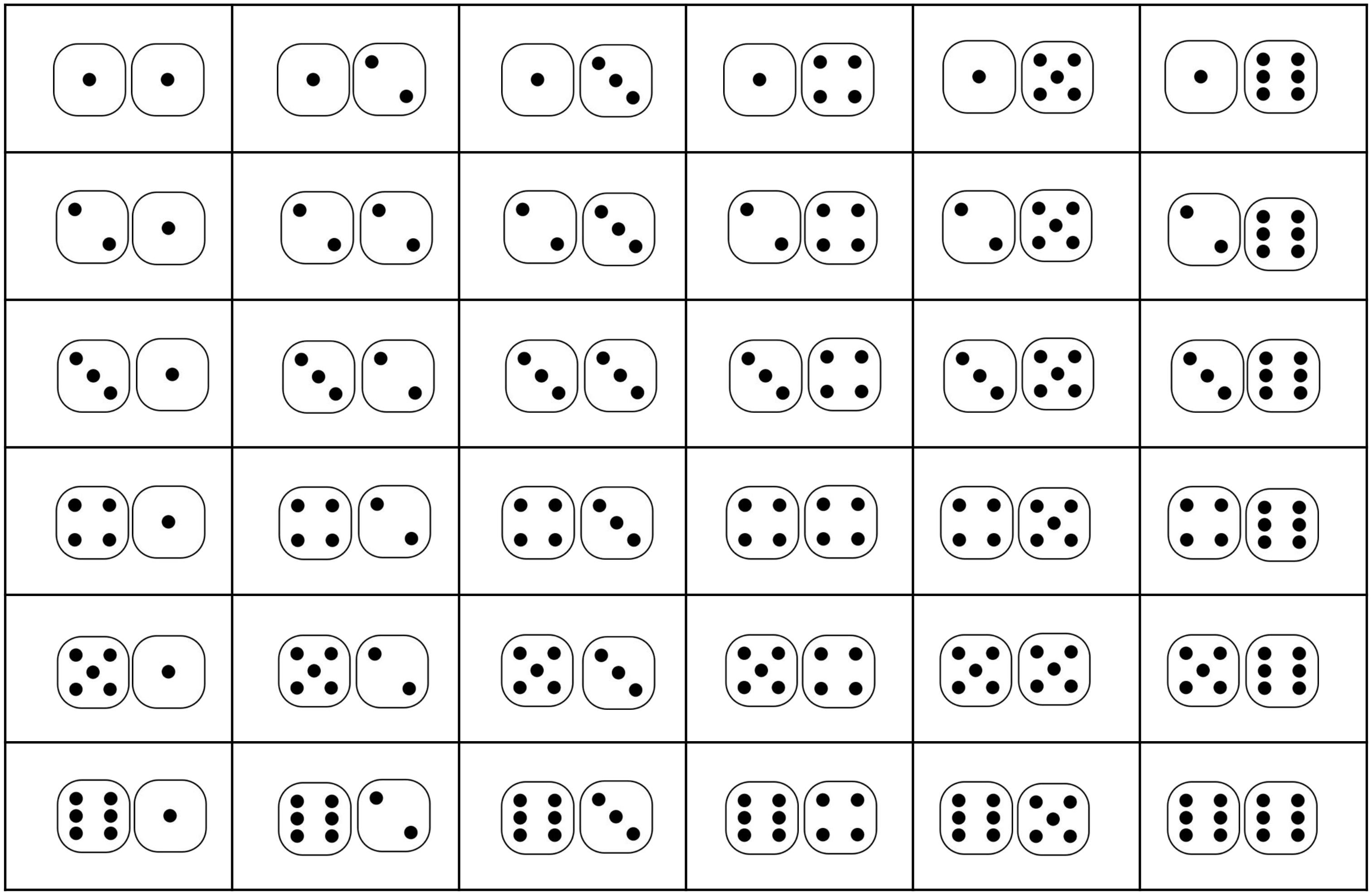
1.2 Introducing Bayes rule



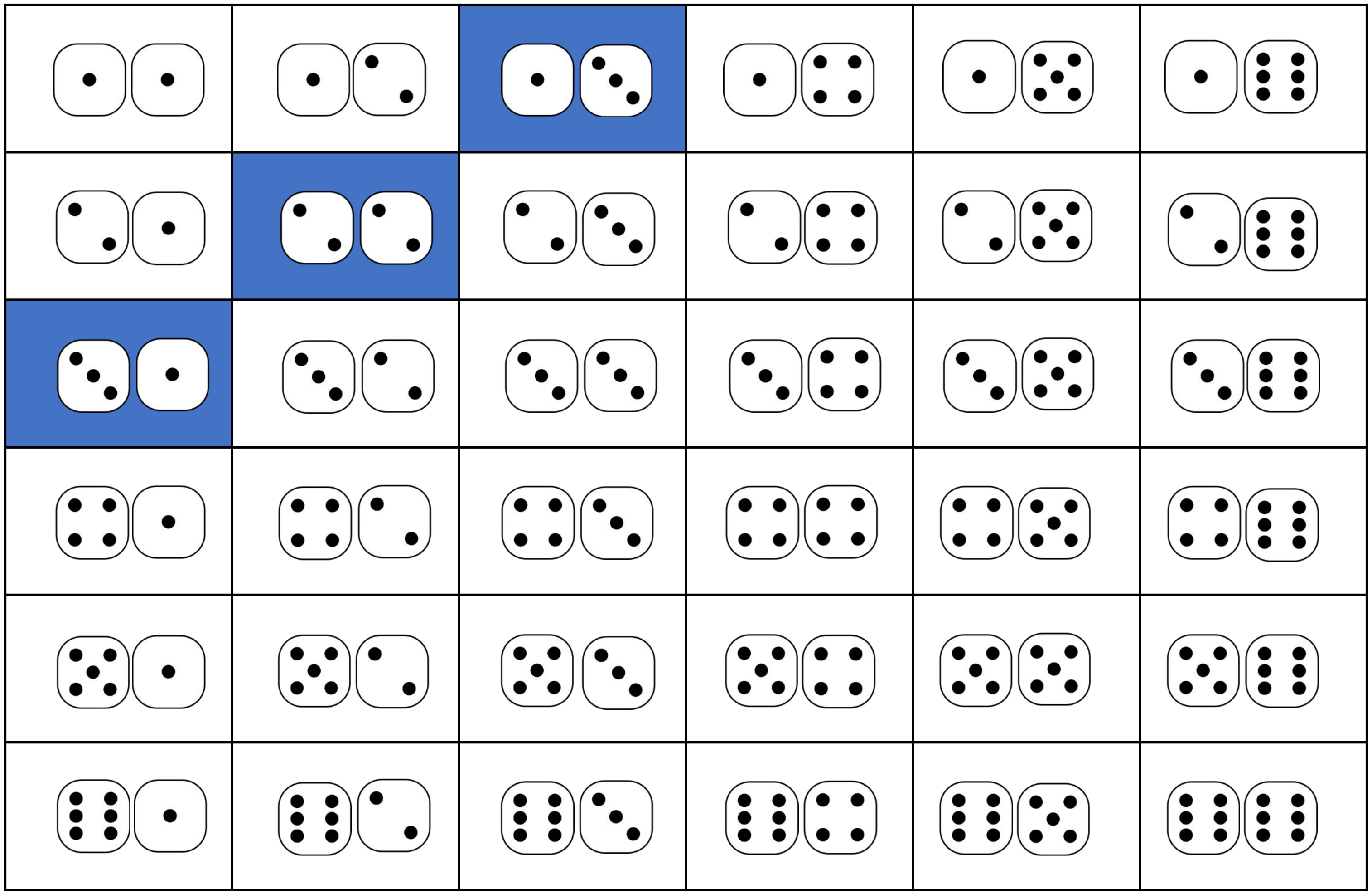
Roll two dice…



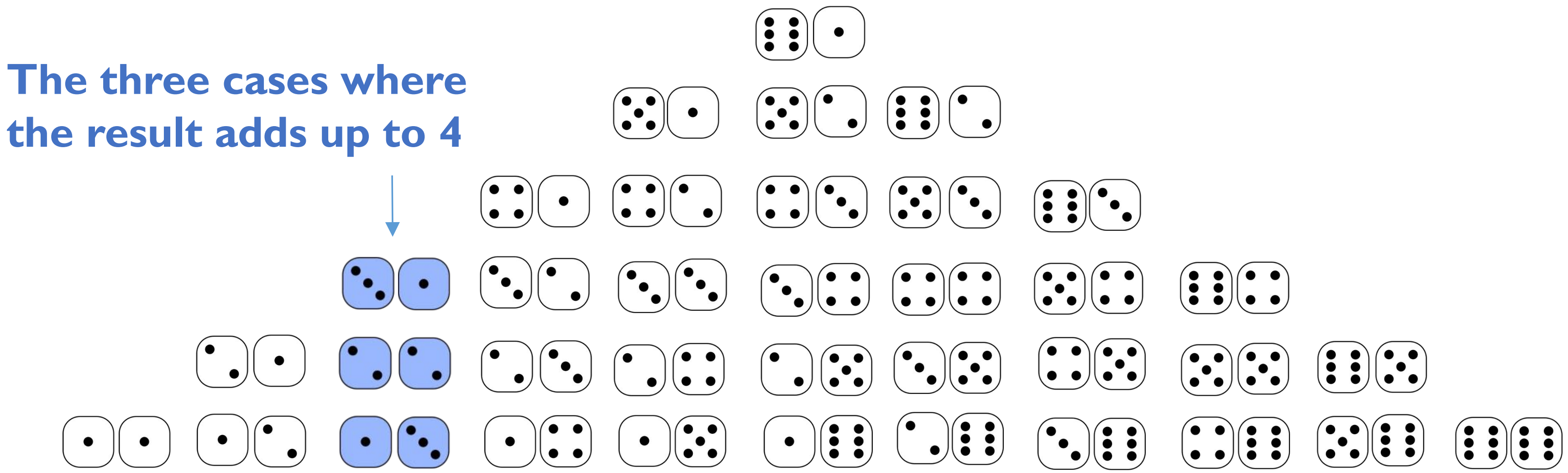
Thirty six possible cases

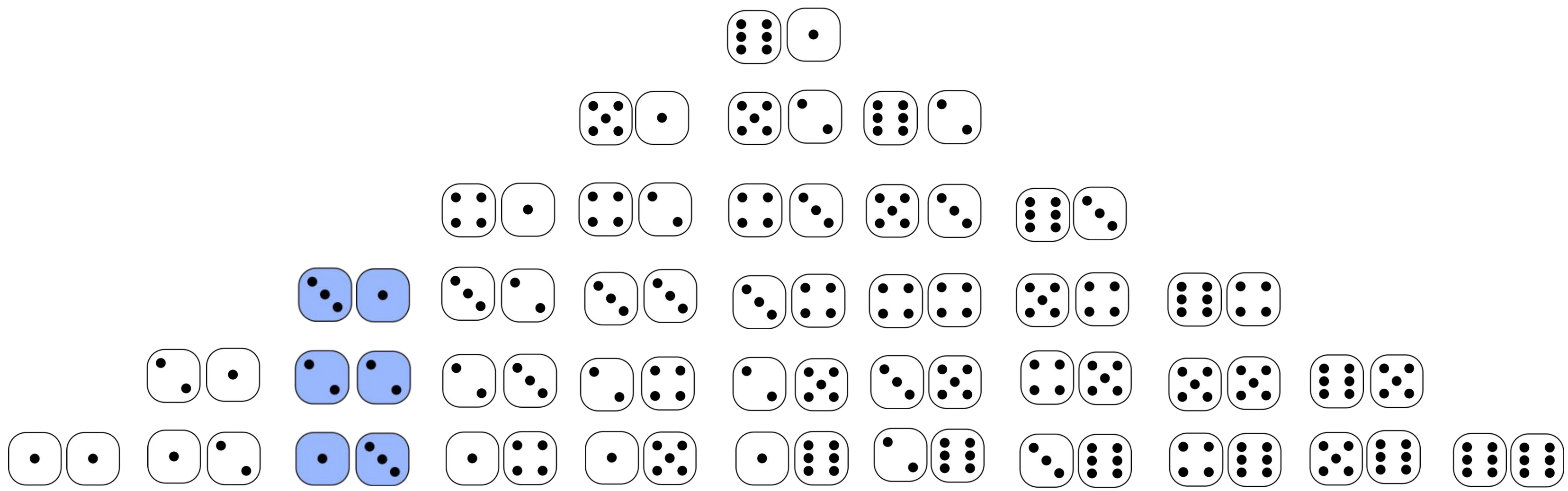


Three cases where the dice add up to 4

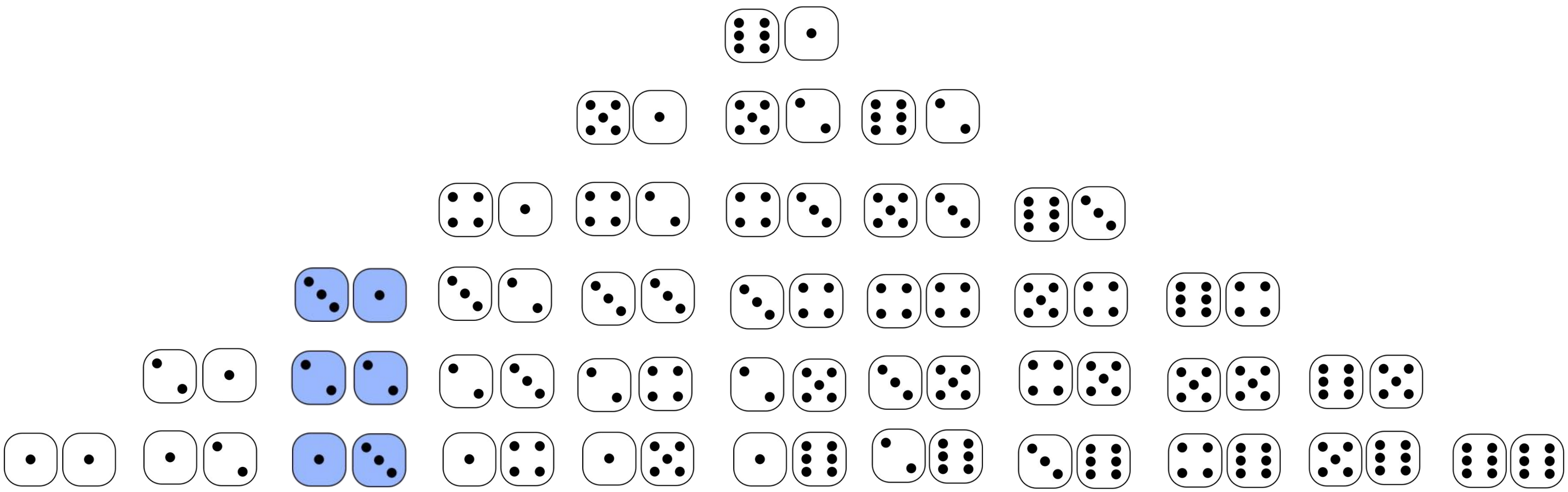


All 36 cases organised by outcome





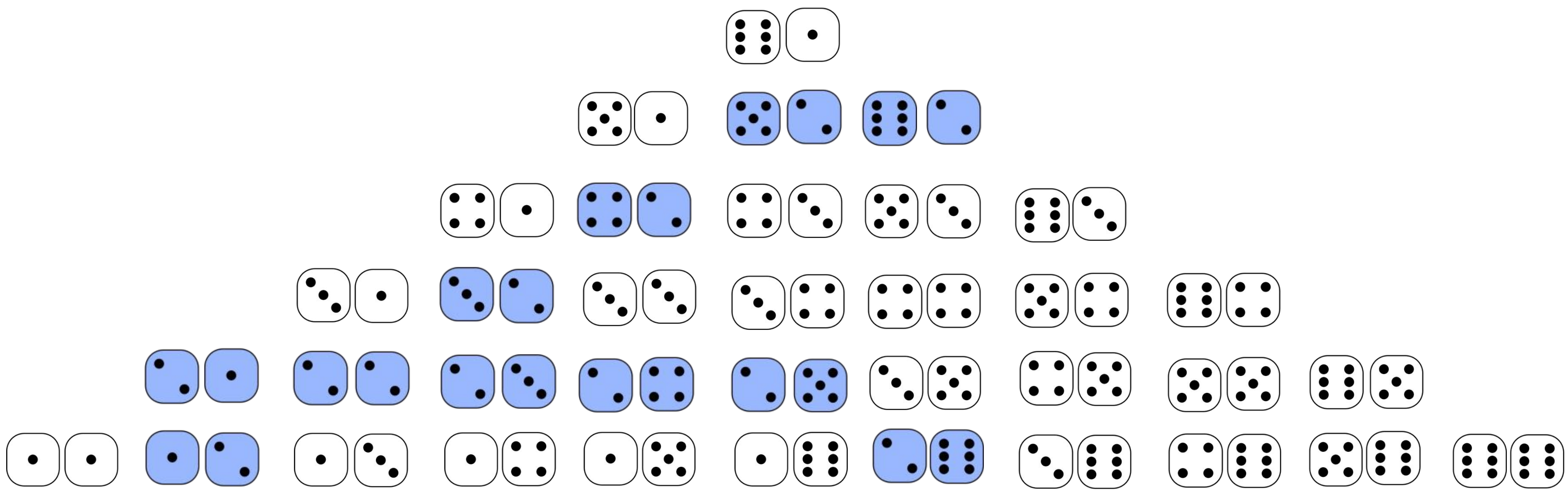
Roll	2	3	4	5	6	7	8	9	10	11	12
N	1	2	3	4	5	6	5	4	3	2	1



Roll	2	3	4	5	6	7	8	9	10	11	12
N	1	2	3	4	5	6	5	4	3	2	1
Prob	.028	.056	.083	.111	.139	.167	.139	.111	.083	.056	.028

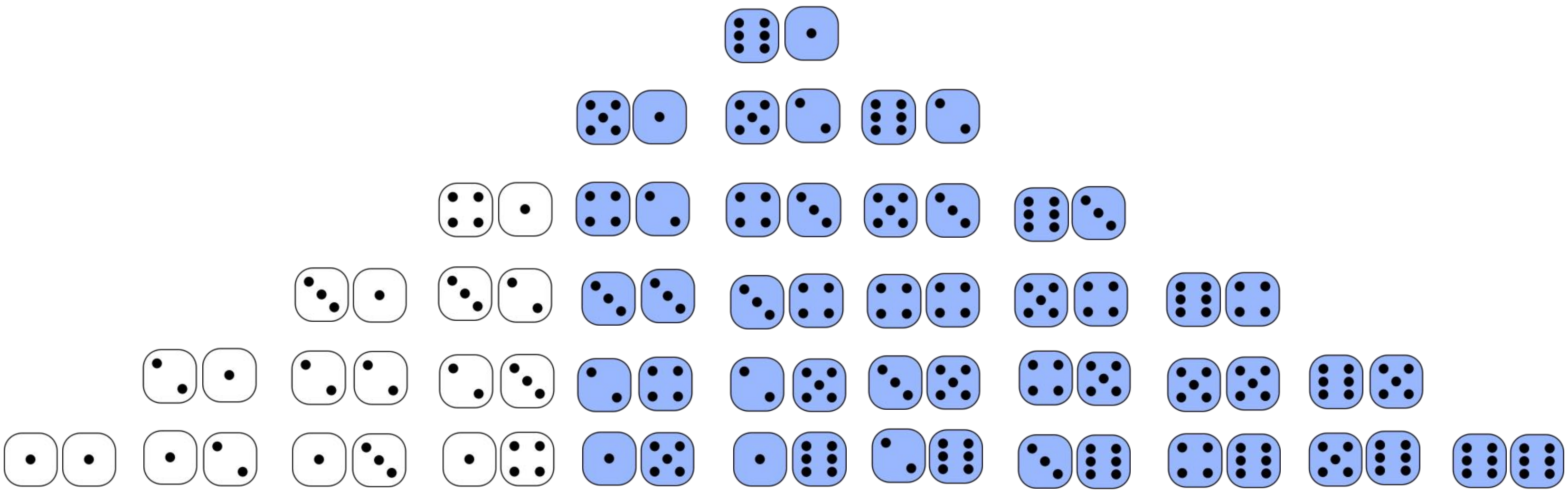
Probability = 3/36 = .083

A: "at least one die has a value of 2"



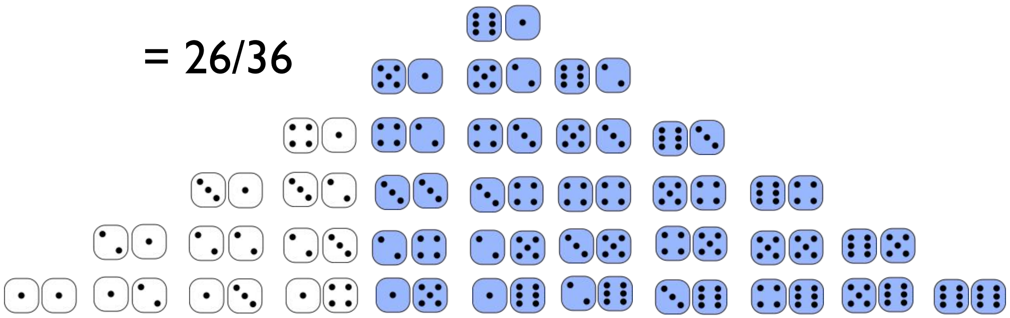
$$P(A) = \frac{11}{36} = .31$$

B: "the total is at least six"



$$P(B) = \frac{26}{36} = .72$$

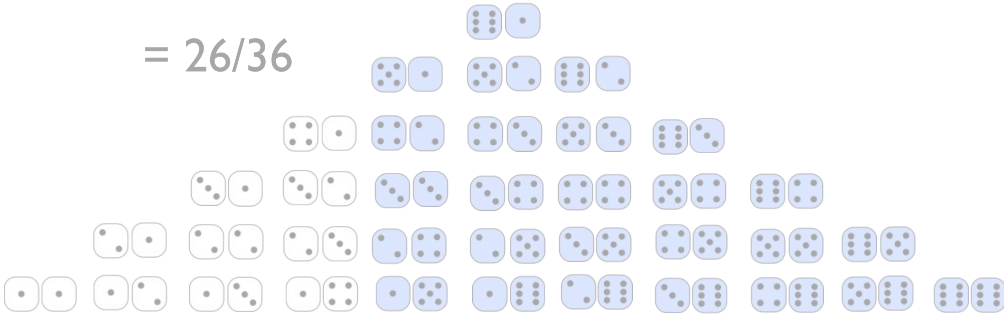
= 26/36



Probability that the total is at least 6

$$P(B)$$

= 26/36

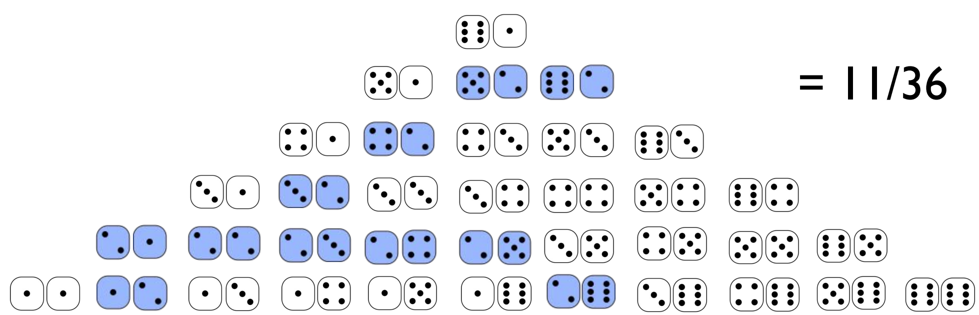


Probability that the total is at least 6

$$P(B)$$

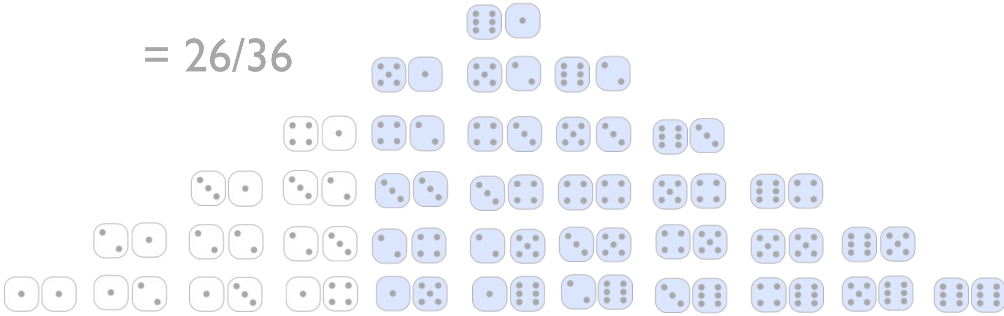
$$P(A)$$

Probability that at least one die has a 2



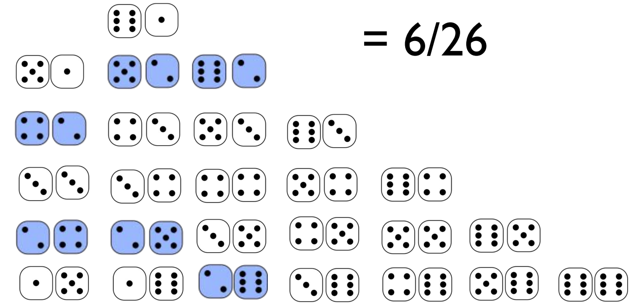
= 11/36

= 26/36



Probability that the total is at least 6

= 6/26

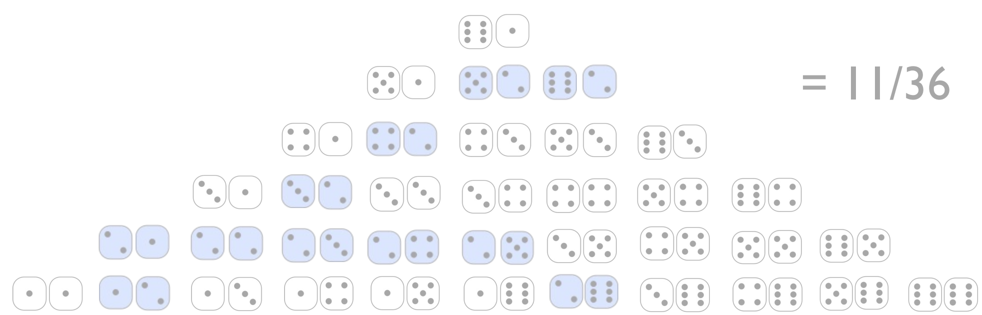


Probability that at least one die has a 2 **given** that the total is at least 6

$$P(B) \qquad P(A|B)$$

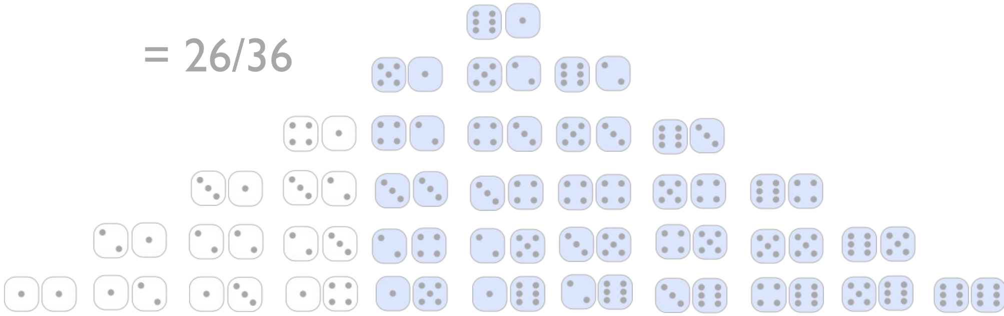
$$P(A)$$

Probability that at least one die has a 2

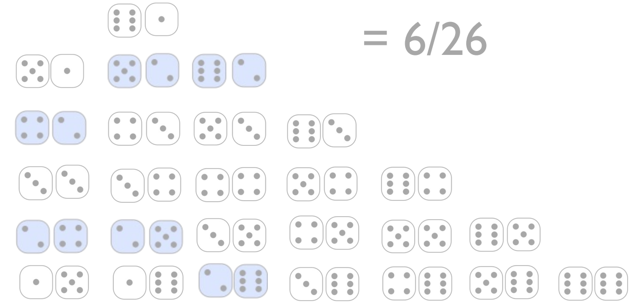


= 11/36

= 26/36



Probability that the total is at least 6



= 6/26

Probability that at least one die has a 2 given that the total is at least 6

$$P(B) \qquad P(A|B)$$

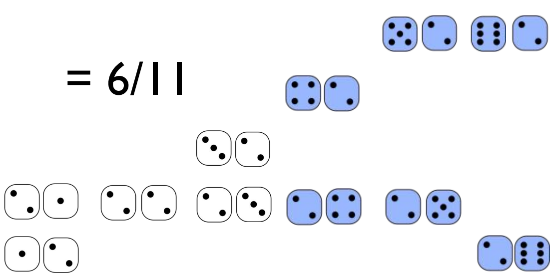
$$P(B|A)$$

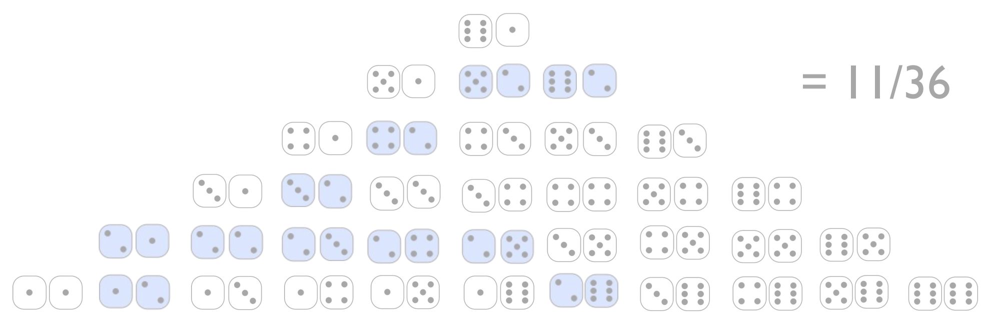
$$P(A)$$

Probability that the total is at least 6 **given** that at least one die has a 2

Probability that at least one die has a 2

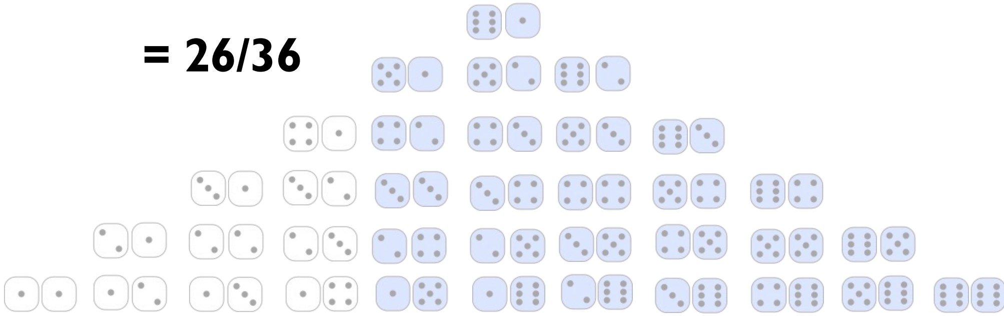
= 6/11



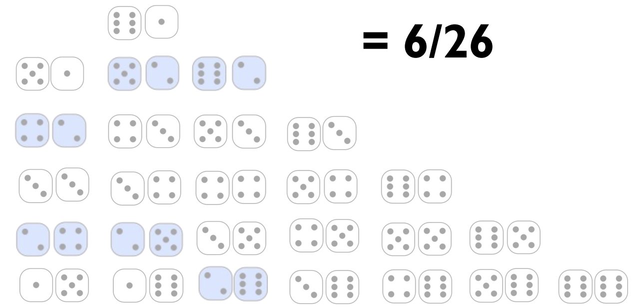


= 11/36

= 26/36



Probability that the total is at least 6



= 6/26

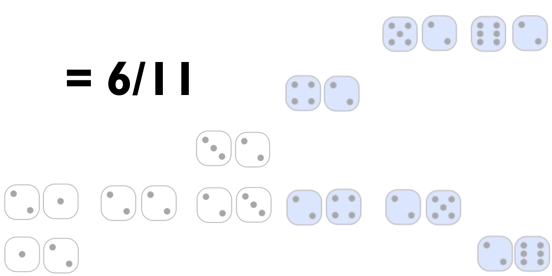
Probability that at least one die has a 2 given that the total is at least 6

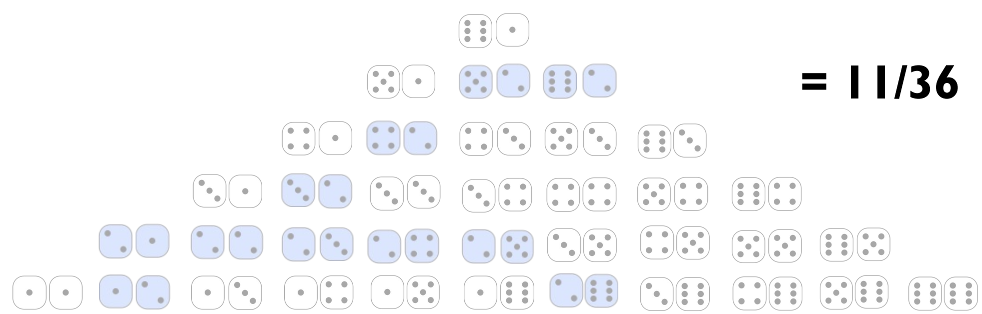
$$P(B|A) = \frac{P(B) \times P(A|B)}{P(A)}$$

Probability that the total is at least 6 given that at least one die has a 2

Probability that at least one die has a 2

= 6/11





= 11/36

Let's check that:

$$P(A|B)$$

$$\frac{26}{36} \times \frac{6}{26} \div \frac{11}{36}$$

$$P(B) \qquad P(A)$$

Let’s check that:

$$\underbrace{\frac{26}{36}}_{P(B)} \times \overbrace{\frac{6}{26}}^{P(A|B)} \div \underbrace{\frac{11}{36}}_{P(A)} = \frac{\cancel{26}}{\cancel{36}} \times \frac{6}{\cancel{26}} \times \frac{\cancel{36}}{11} = \overbrace{\frac{6}{11}}^{P(B|A)}$$

1.3 Bayesian reasoning

Bayes' rule is a mathematical fact that probabilities must obey

26/36

6/26

$$P(B|A) = \frac{P(B) \times P(A|B)}{P(A)}$$

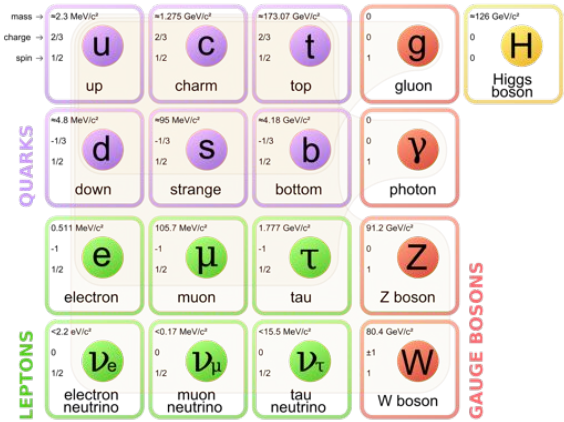
6/11

11/36

Bayesian reasoning happens when we combine this mathematical rule with epistemic probability

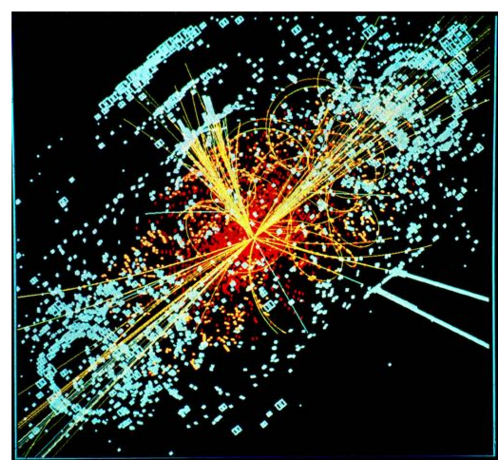
$$P(B|A) = \frac{P(B) \times P(A|B)}{P(A)}$$

For example…



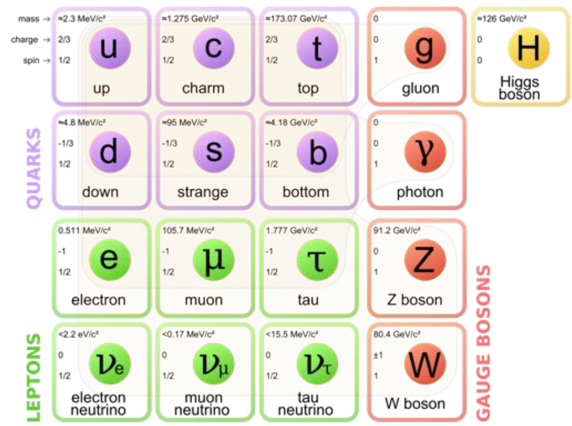
h = A hypothesis about the world

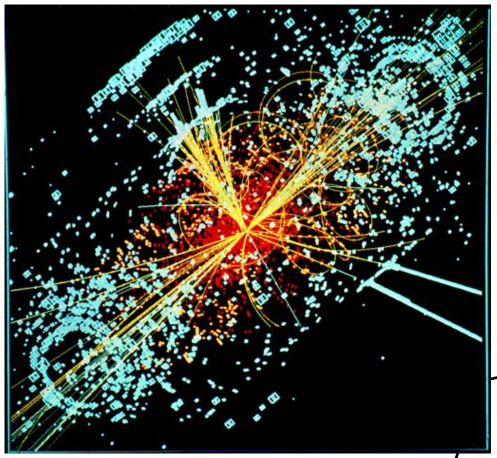
d = Some observable data



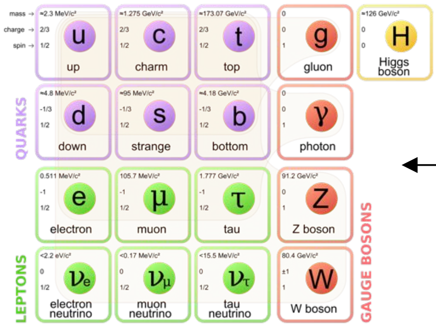
How strongly should I believe in this hypothesis…

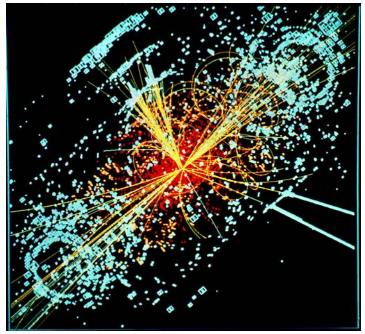
… given that I have observed these data?





h|d

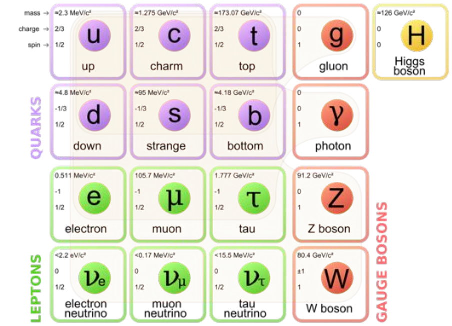




The **posterior probability** that my hypothesis is true given that I have observed these data…

$$P(h|d) = \frac{P(d|h) \times P(h)}{P(d)}$$

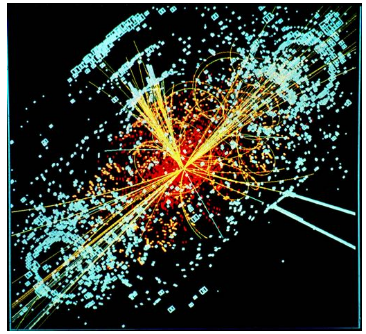
h

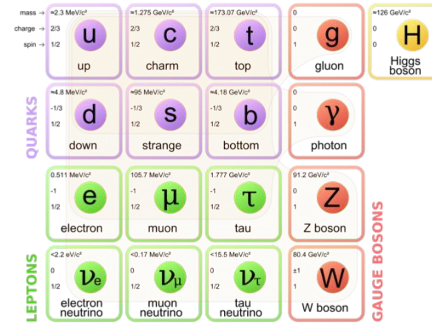


The **prior probability** that I assigned to this hypothesis before observing the data

$$P(h|d) = \frac{P(d|h) \times P(h)}{P(d)}$$

d|h



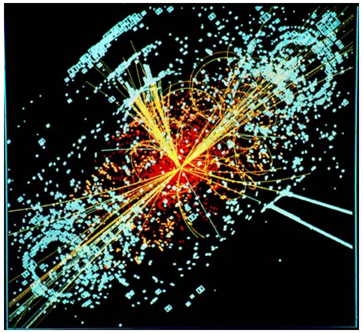


The **likelihood** that I would have observed these data if the hypothesis is true

$$P(h|d) = \frac{P(d|h) \times P(h)}{P(d)}$$

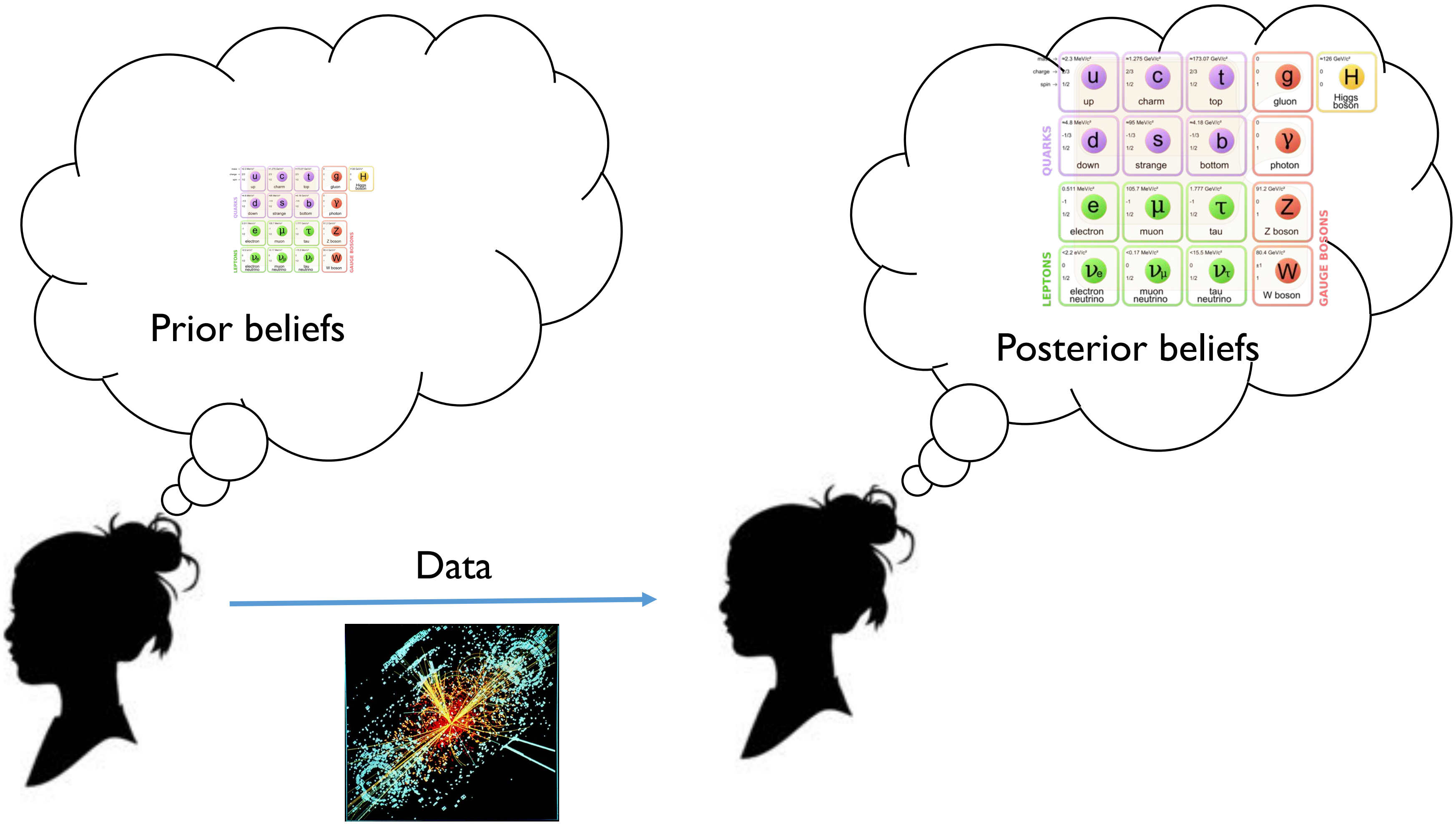
$$P(h|d) = \frac{P(d|h) \times P(h)}{P(d)}$$

d



The "marginal" probability of observing these particular data (more on this shortly)

Belief revision!



P(d|h) : the likelihood of observing d if h is true

P(h) : the prior probability that h is true

P(h|d) : the posterior probability that h is true

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

P(d) : discussed later

1.4 Example of Bayesian reasoning

Many possibilities

dropped a wine glass

broke a window

psychic explosion

earthquake

a wizard did it

etc…

Let’s compare two of them

I dropped a wine glass

Kids broke the window

"Prior odds"

$$\frac{P(h_1)}{P(h_2)} = \frac{\text{broken window}}{\text{wine glass dropping}} = 0.1$$

Before learning anything else I think "wine glass dropping" is 10 times more plausible than "broken window"

Some data

There is a cricket ball
next to the broken glass

Likelihood of the data

When I drop a wine glass…

… It's very unlikely that I just happen to do so right next to a cricket ball

P(d|h) = 0.001

Likelihood of the data

When the kids break a window…

… It’s not at all uncommon for a cricket ball to end up near the glass

$P(d|h) = 0.15$

Bayes factor

(a.k.a. likelihood ratio)

$$\frac{P(d|h_1)}{P(d|h_2)} =$$

$$= \frac{0.15}{0.001} = 150$$

I think it is 150 times more likely that I would find a cricket ball when a window breaks than when a wine glass is broken

Posterior odds

$$\frac{P(h_1|d)}{P(h_2|d)} = \frac{P(d|h_1)}{P(d|h_2)} \times \frac{P(h_1)}{P(h_2)}$$

Posterior odds

= 15

Likelihood ratio

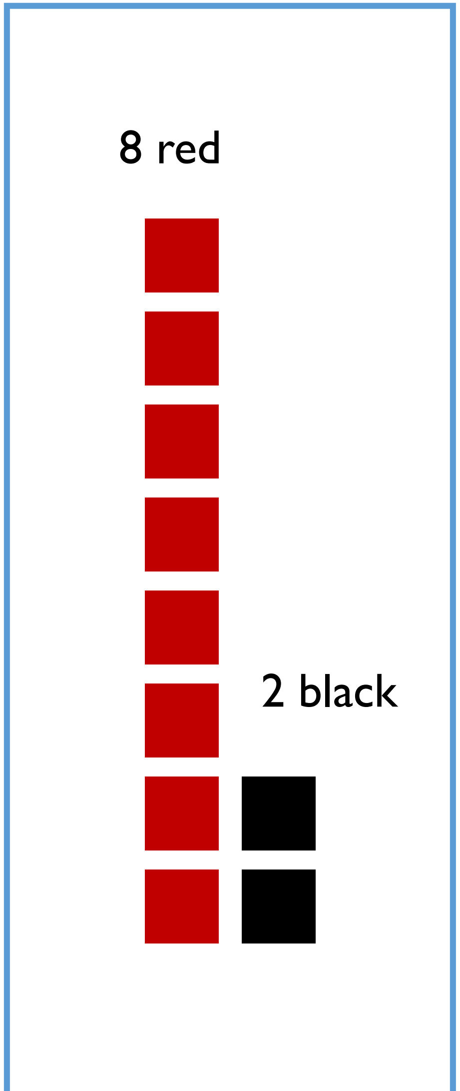
= 150

Prior odds

= .1

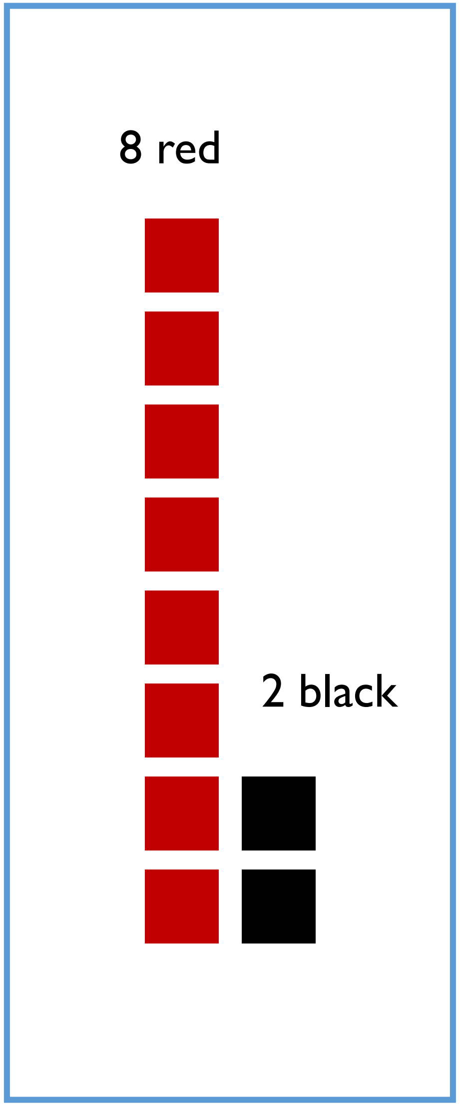
In light of the evidence, I now think the window-breaking hypothesis is 15 times more likely than the wine-glass hypothesis

1.5 Bayesian hypothesis testing



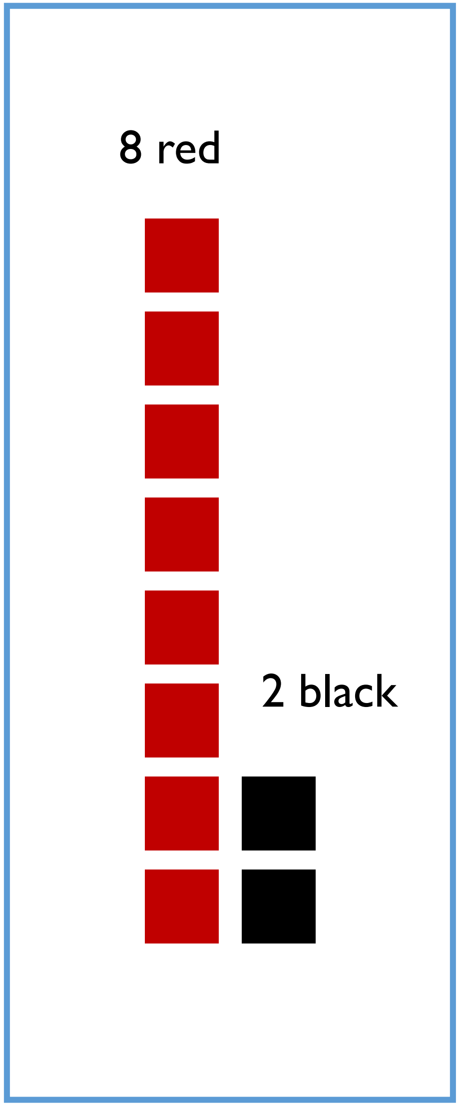
Is this roulette wheel unbalanced?

We're ignoring the zero



Null model, h_0

The roulette wheel has an equal probability of producing red and black



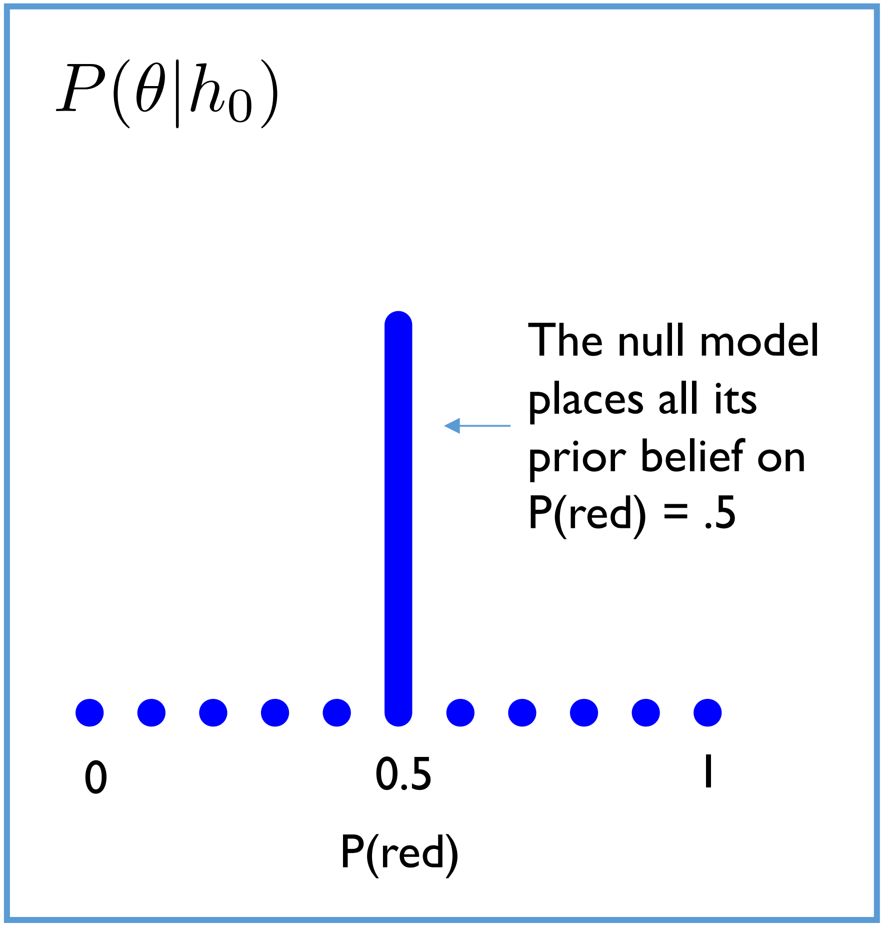
<u>Null model,</u> h_0

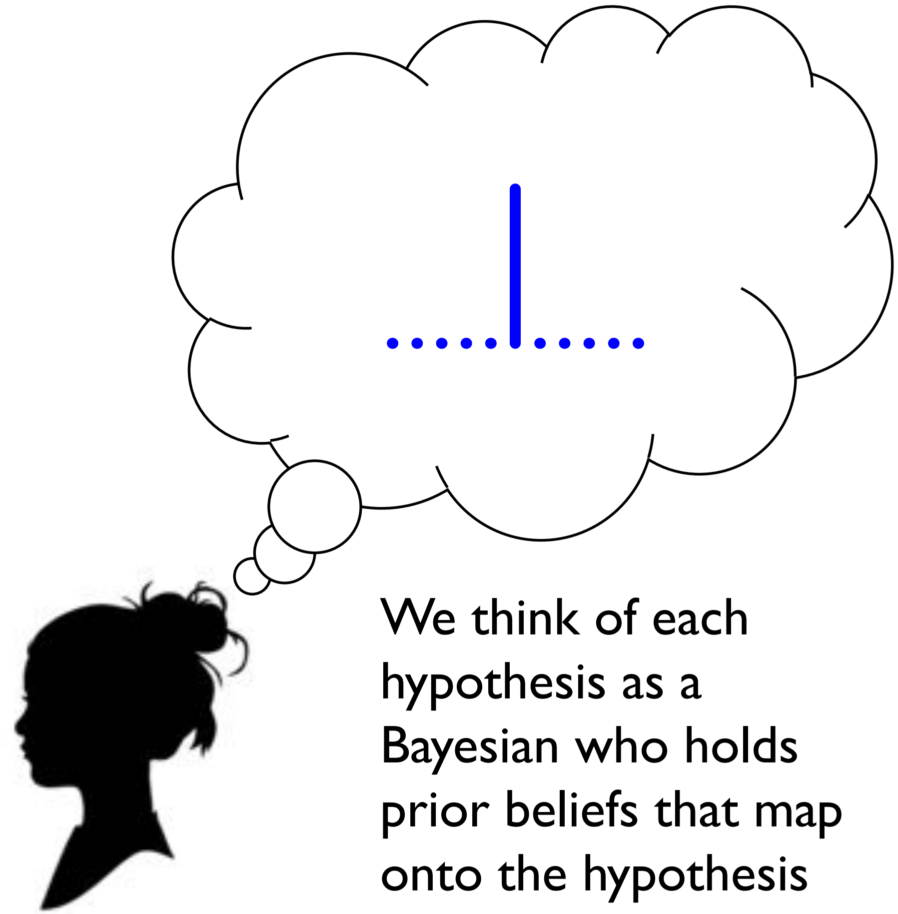
The roulette wheel has an equal probability of producing red and black

<u>Alternative model,</u> h_1

The roulette wheel has a bias, but we don't know what it is

Null hypothesis



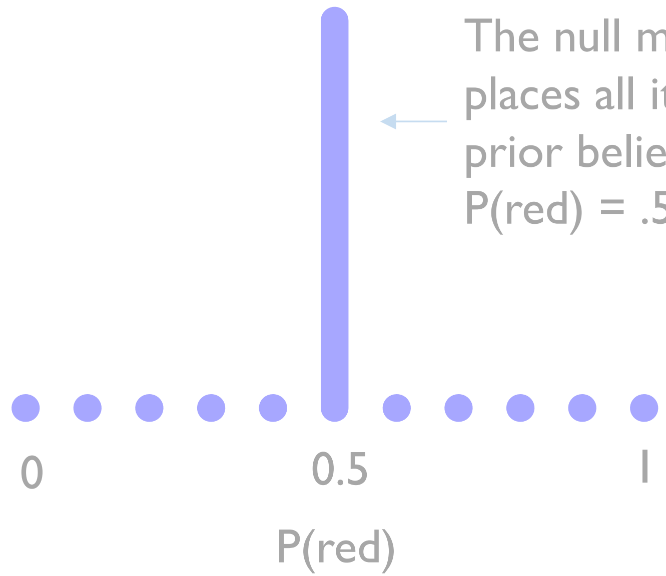


We think of each hypothesis as a Bayesian who holds prior beliefs that map onto the hypothesis

Let's pretend that there's no such thing as "continuous numbers", and act as if the only possible values for P(red) are 0, 0.1, 0.2, …, 1.0 ☺

Null hypothesis

$P(\theta|h_0)$

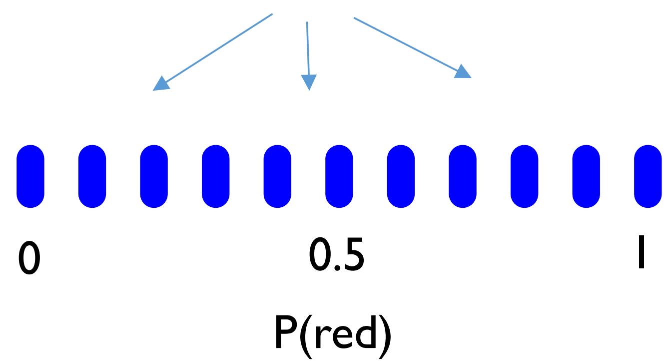


The null model places all its prior belief on P(red) = .5

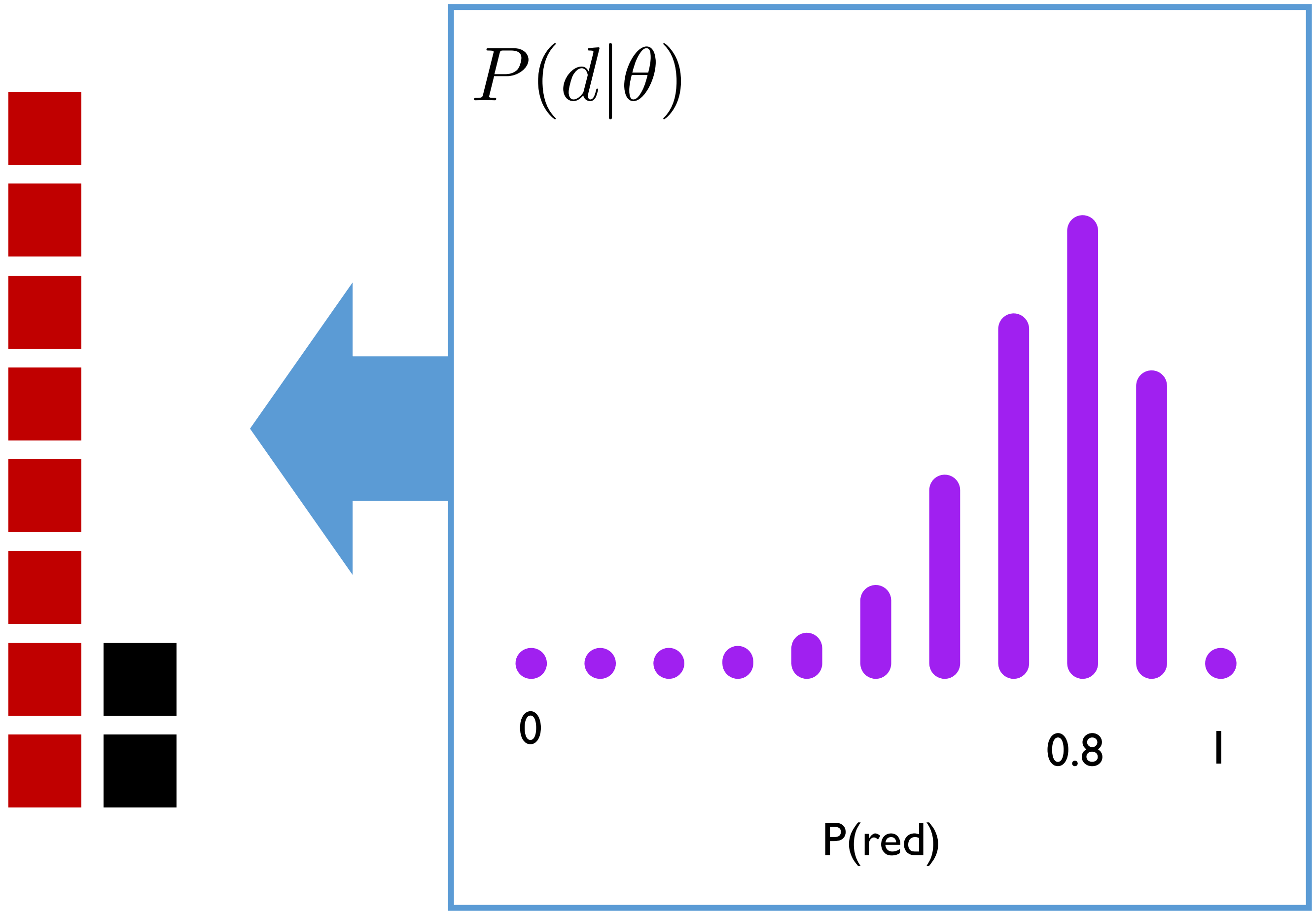
Alternative hypothesis

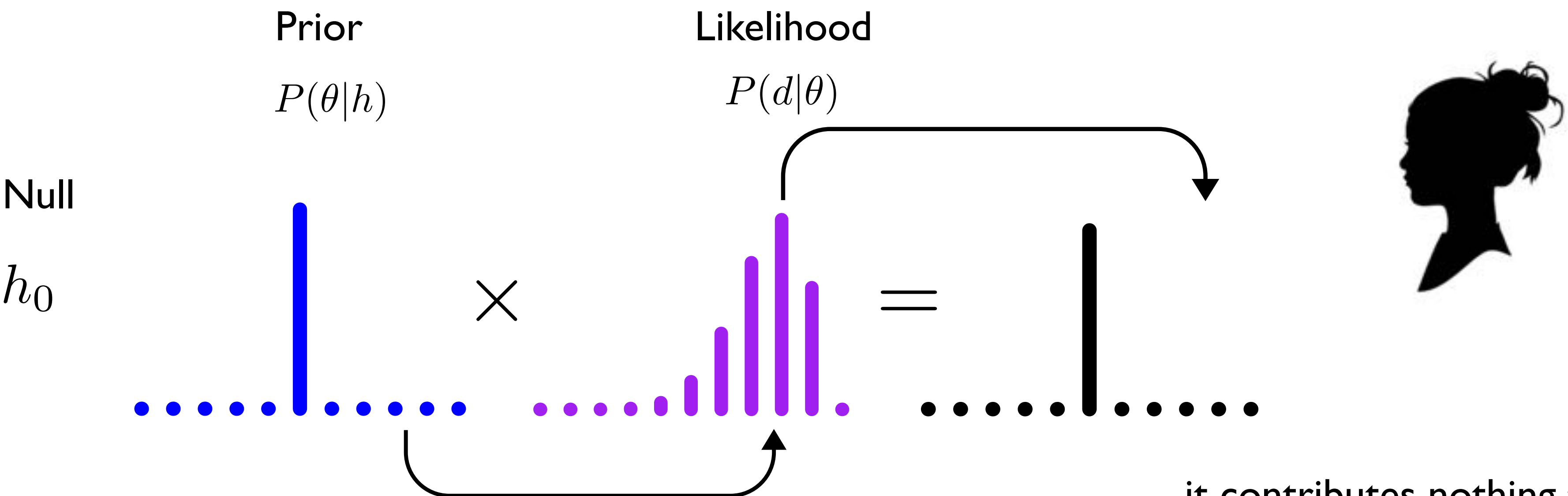
$P(\theta|h_1)$

The alternative model spreads its prior belief equally across all possibilities



Likelihoods … the probability of the data given every possible value of P(red)

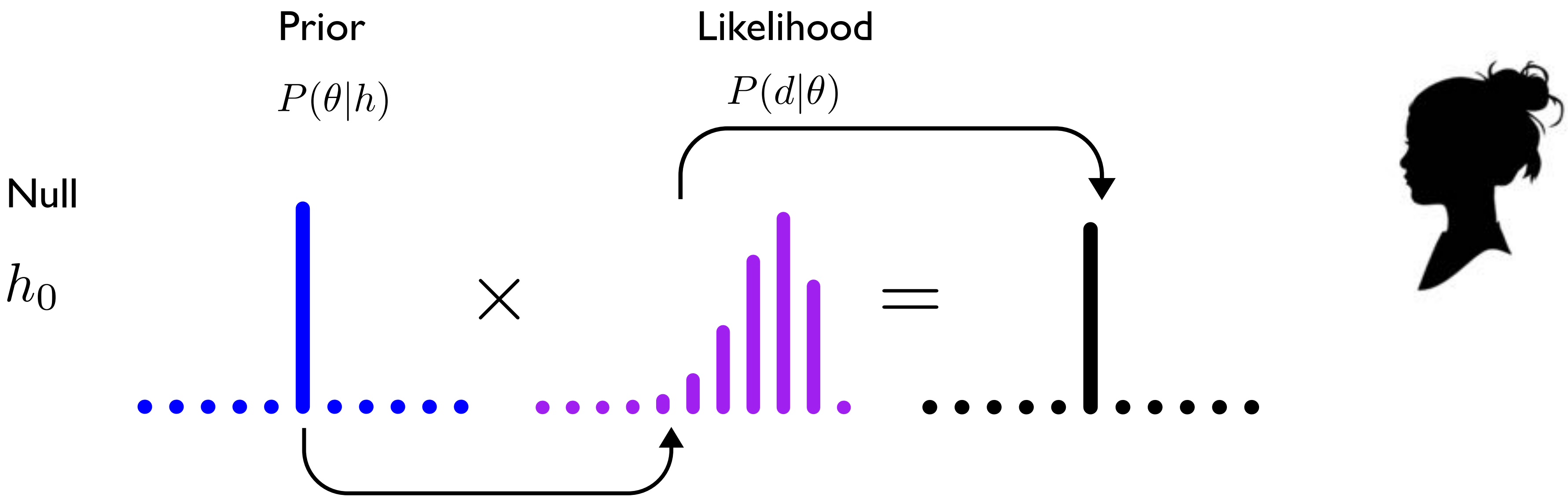




… it contributes nothing to the a priori "prediction" made by the null

The null hypothesis assigns prior probability 0 to the possibility that P(red) = 0.8 …

… so even though it assigns highest likelihood to the observed data ….

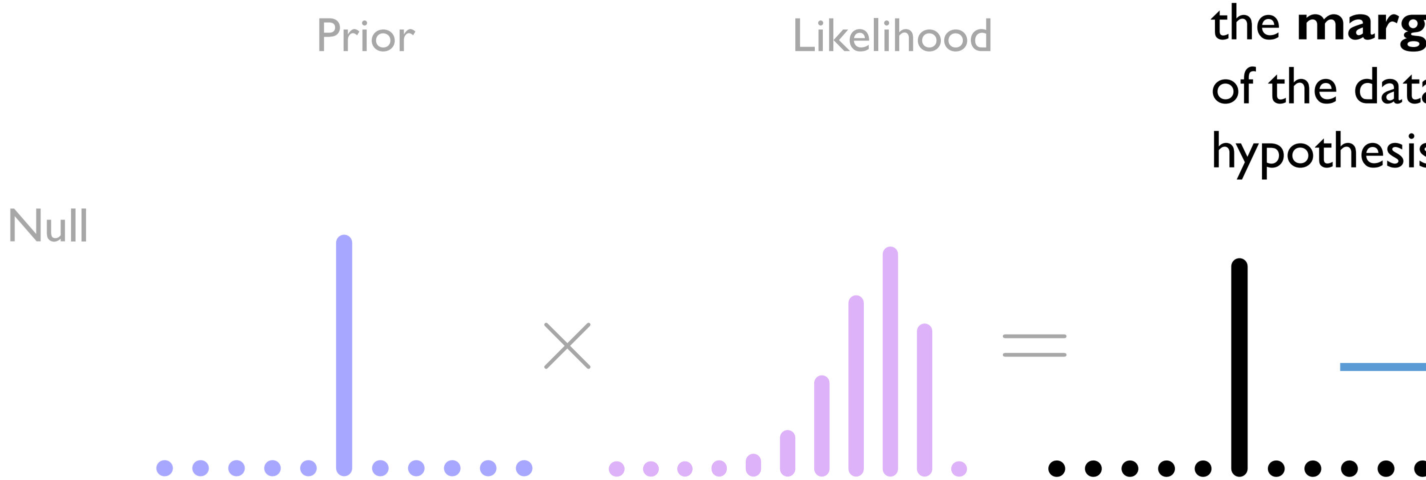


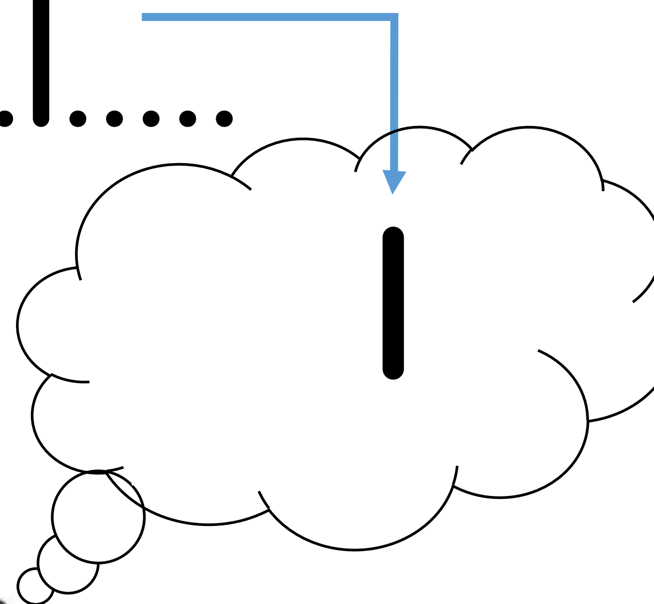
… it is the only contributor to the prediction made by this model

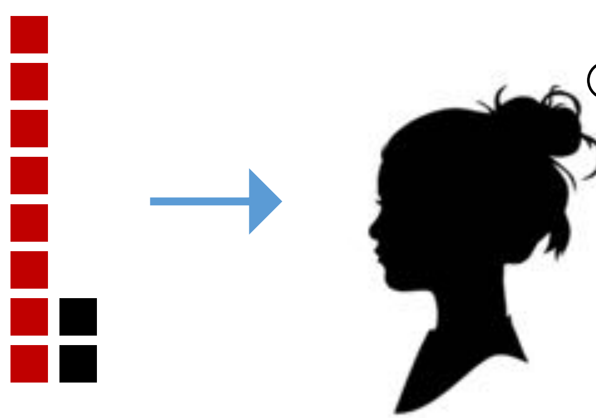
The null hypothesis assigns prior probability 1 to the possibility that P(red) = 0.5 …

… so even though it assigns a pretty small likelihood to the observed data ….

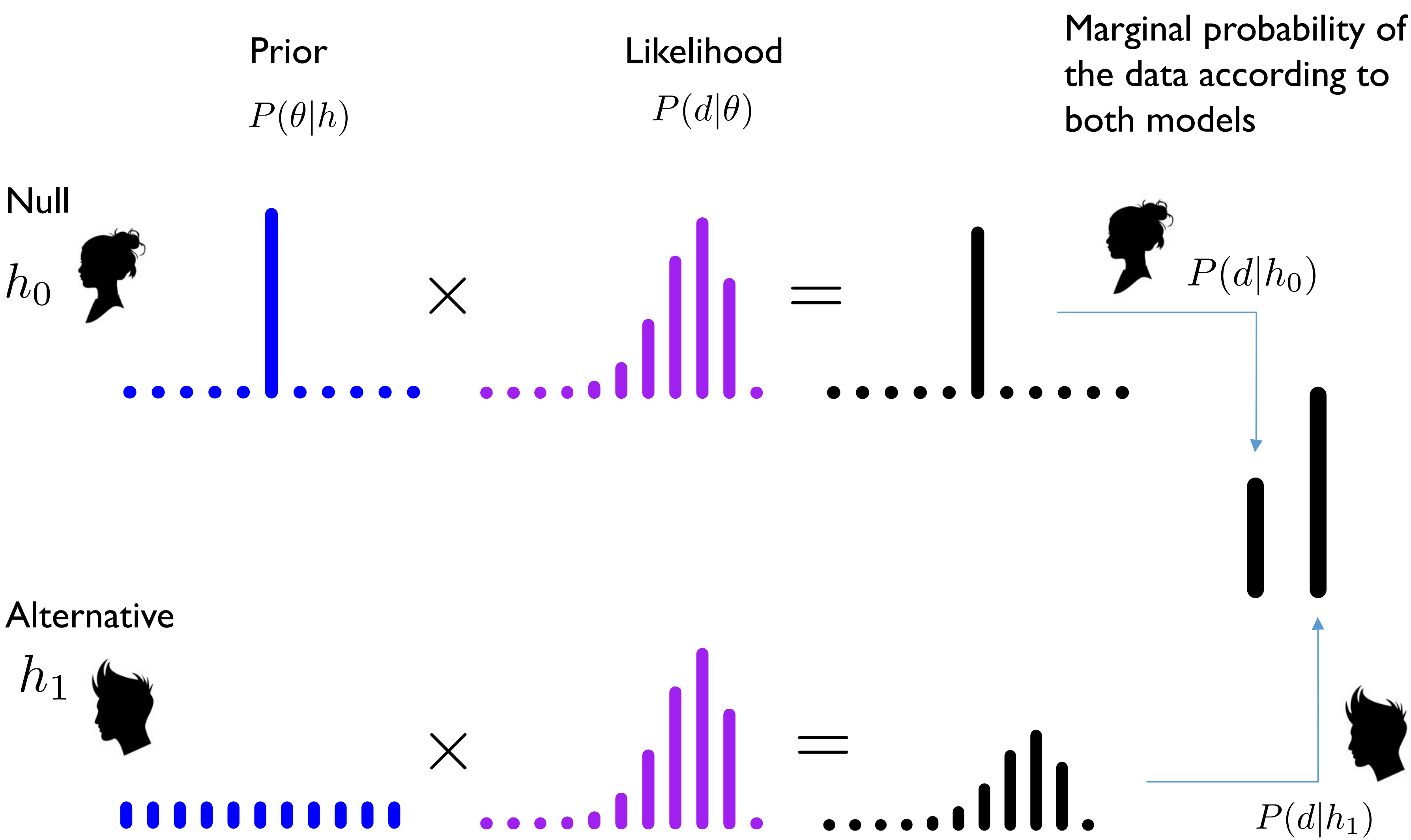
Summing these values gives the **marginal probability** of the data under the null hypothesis...

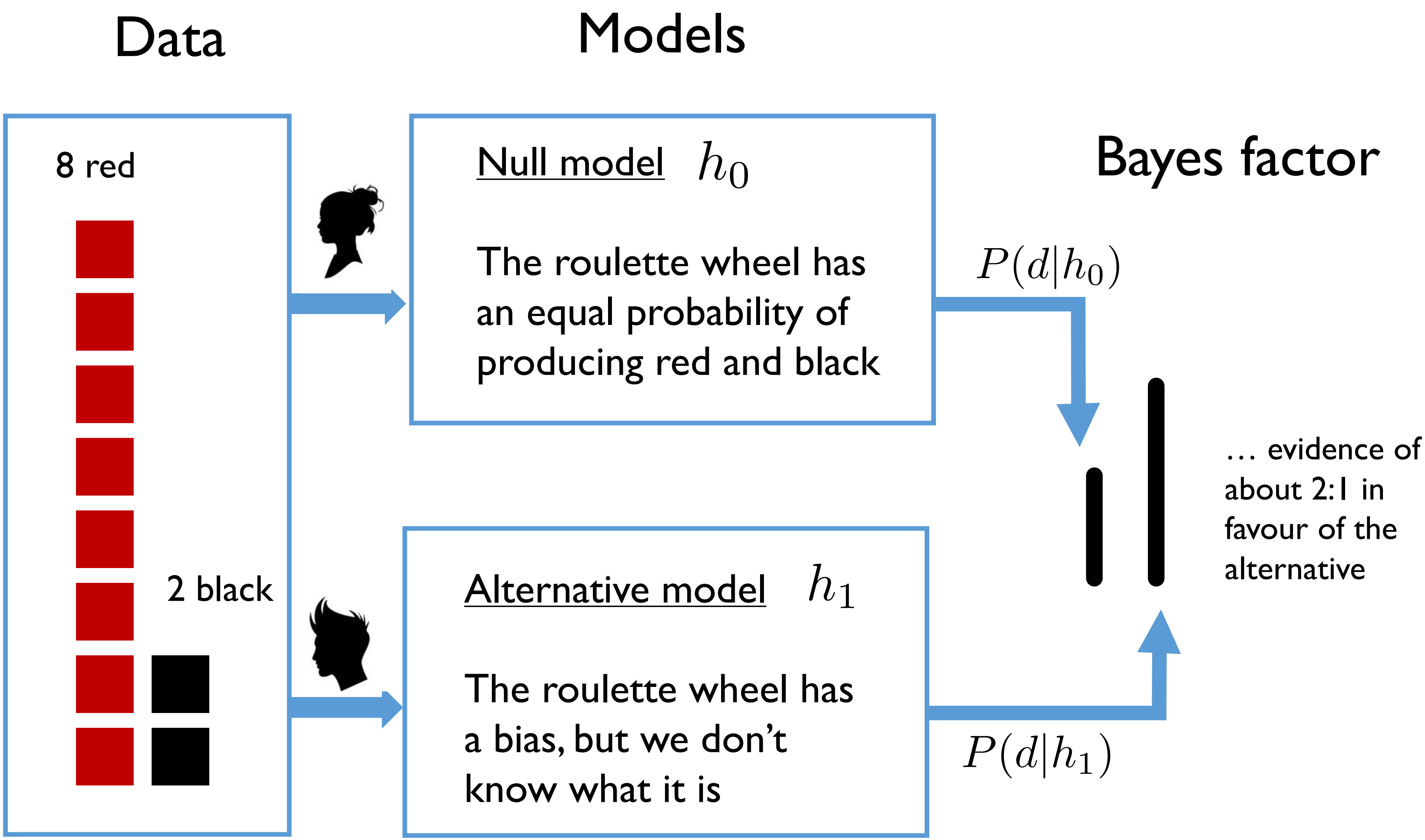






i.e., how likely did the null model "think" we were to observe this specific pattern of data?


Prior
$P(\theta|h)$
Likelihood
$P(d|\theta)$
Marginal probability of the data according to both models
Null
h_0
$P(d|h_0)$
Alternative
h_1
$P(d|h_1)$



$$\mathrm{BF}_{10} = \frac{P(d|h_1)}{P(d|h_0)} = \frac{\sum_\theta P(d|\theta) \times P(\theta|h_0)}{\sum_\theta P(d|\theta) \times P(\theta|h_1)} = 1.87$$

2.1 Just another stats package

https://jasp-stats.org

https://jasp-stats.org
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JASP
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A Fresh Way to Do Statistics
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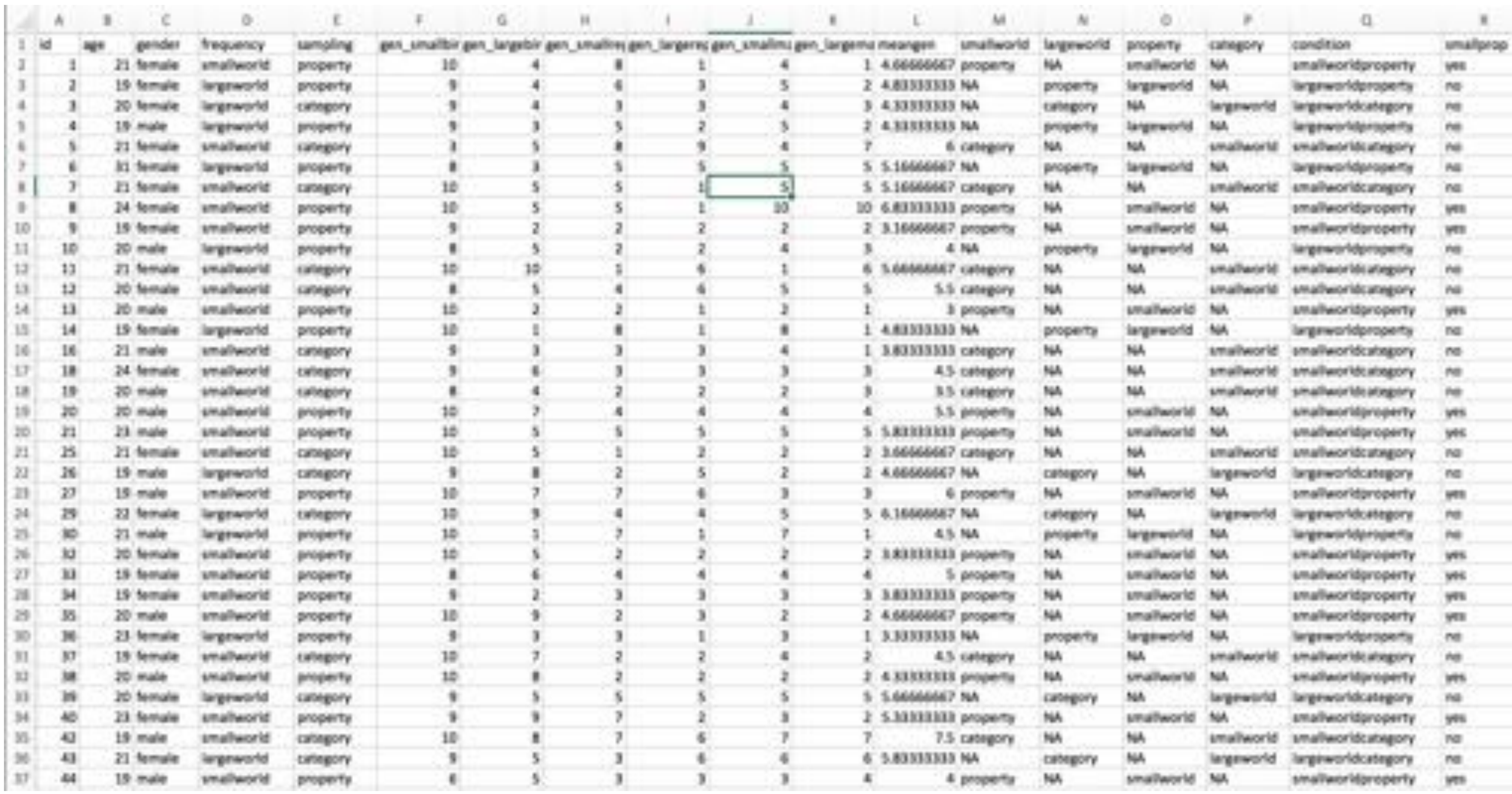
NEW RELEASE
EPS format support

Illustrating the JASP workflow

What?	Where?
open a CSV file	**File > Open**
descriptive statisitics	**Common > Descriptives**
run a frequentist ANOVA	**Common > ANOVA > ANOVA**
save data and results to JASP file	**File > Save As**

Here's a real data set with many variables!



	id	age	gender	frequency	sampling	gen_smallbir	gen_largebir	gen_smallre	gen_largere	gen_smallmi	gen_largemi	meangen	smallworld	largeworld	property	category	condition	smallprop
2	1	21	female	smallworld	property	10	4	8	1	4	1	4.66666667	property	NA	smallworld	NA	smallworldproperty	yes
3	2	19	female	largeworld	property	9	4	6	3	5	2	4.83333333	NA	property	largeworld	NA	largeworldproperty	no
4	3	20	female	largeworld	category	9	4	3	3	4	3	4.33333333	NA	category	NA	largeworld	largeworldcategory	no
5	4	19	male	largeworld	property	9	3	5	2	5	2	4.33333333	NA	property	largeworld	NA	largeworldproperty	no
6	5	21	female	smallworld	category	3	5	8	9	4	7	6	category	NA	NA	smallworld	smallworldcategory	no
7	6	31	female	largeworld	property	8	3	5	5	5	5	5.16666667	NA	property	largeworld	NA	largeworldproperty	no
8	7	21	female	smallworld	category	10	5	5	1	5	5	5.16666667	category	NA	NA	smallworld	smallworldcategory	no
9	8	24	female	smallworld	property	10	5	5	1	10	10	6.83333333	property	NA	smallworld	NA	smallworldproperty	yes
10	9	19	female	smallworld	property	9	2	2	2	2	2	3.16666667	property	NA	smallworld	NA	smallworldproperty	yes
11	10	20	male	largeworld	property	8	5	2	2	4	3	4	NA	property	largeworld	NA	largeworldproperty	no
12	11	21	female	smallworld	category	10	10	1	6	1	6	5.66666667	category	NA	NA	smallworld	smallworldcategory	no
13	12	20	female	smallworld	category	8	5	4	6	5	5	5.5	category	NA	NA	smallworld	smallworldcategory	no
14	13	20	male	smallworld	property	10	2	2	1	2	1	3	property	NA	smallworld	NA	smallworldproperty	yes
15	14	19	female	largeworld	property	10	1	8	1	8	1	4.83333333	NA	property	largeworld	NA	largeworldproperty	no
16	16	21	male	smallworld	category	9	3	3	3	4	1	3.83333333	category	NA	NA	smallworld	smallworldcategory	no
17	18	24	female	smallworld	category	9	6	3	3	3	3	4.5	category	NA	NA	smallworld	smallworldcategory	no
18	19	20	male	smallworld	category	8	4	2	2	2	3	3.5	category	NA	NA	smallworld	smallworldcategory	no
19	20	20	male	smallworld	property	10	7	4	4	4	4	5.5	property	NA	smallworld	NA	smallworldproperty	yes
20	21	23	male	smallworld	property	10	5	5	5	5	5	5.83333333	property	NA	smallworld	NA	smallworldproperty	yes
21	25	21	female	smallworld	category	10	5	1	2	2	2	3.66666667	category	NA	NA	smallworld	smallworldcategory	no
22	26	19	male	largeworld	category	9	8	2	5	2	2	4.66666667	NA	category	NA	largeworld	largeworldcategory	no
23	27	19	male	smallworld	property	10	7	7	6	3	3	6	property	NA	smallworld	NA	smallworldproperty	yes
24	29	22	female	largeworld	category	10	9	4	4	5	5	6.16666667	NA	category	NA	largeworld	largeworldcategory	no
25	30	21	male	largeworld	property	10	1	7	1	7	1	4.5	NA	property	largeworld	NA	largeworldproperty	no
26	32	20	female	smallworld	property	10	5	2	2	2	2	3.83333333	property	NA	smallworld	NA	smallworldproperty	yes
27	33	19	female	smallworld	property	8	6	4	4	4	4	5	property	NA	smallworld	NA	smallworldproperty	yes
28	34	19	female	smallworld	property	9	2	3	3	3	3	3.83333333	property	NA	smallworld	NA	smallworldproperty	yes
29	35	20	male	smallworld	property	10	9	2	3	2	2	4.66666667	property	NA	smallworld	NA	smallworldproperty	yes
30	36	23	female	largeworld	property	9	3	3	1	3	1	3.33333333	NA	property	largeworld	NA	largeworldproperty	no
31	37	19	female	smallworld	category	10	7	2	2	4	2	4.5	category	NA	NA	smallworld	smallworldcategory	no
32	38	20	male	smallworld	property	10	8	2	2	2	2	4.33333333	property	NA	smallworld	NA	smallworldproperty	yes
33	39	20	female	largeworld	category	9	5	5	5	5	5	5.66666667	NA	category	NA	largeworld	largeworldcategory	no
34	40	23	female	smallworld	property	9	9	7	2	3	2	5.33333333	property	NA	smallworld	NA	smallworldproperty	yes
35	42	19	male	smallworld	category	10	8	7	6	7	7	7.5	category	NA	NA	smallworld	smallworldcategory	no
36	43	21	female	largeworld	category	9	5	3	6	6	6	5.83333333	NA	category	NA	largeworld	largeworldcategory	no
37	44	19	male	smallworld	property	6	5	3	3	3	4	4	property	NA	smallworld	NA	smallworldproperty	yes

JASP isn't (currently?) good for computing new variables, so it's best to do that in Excel or whatever you prefer

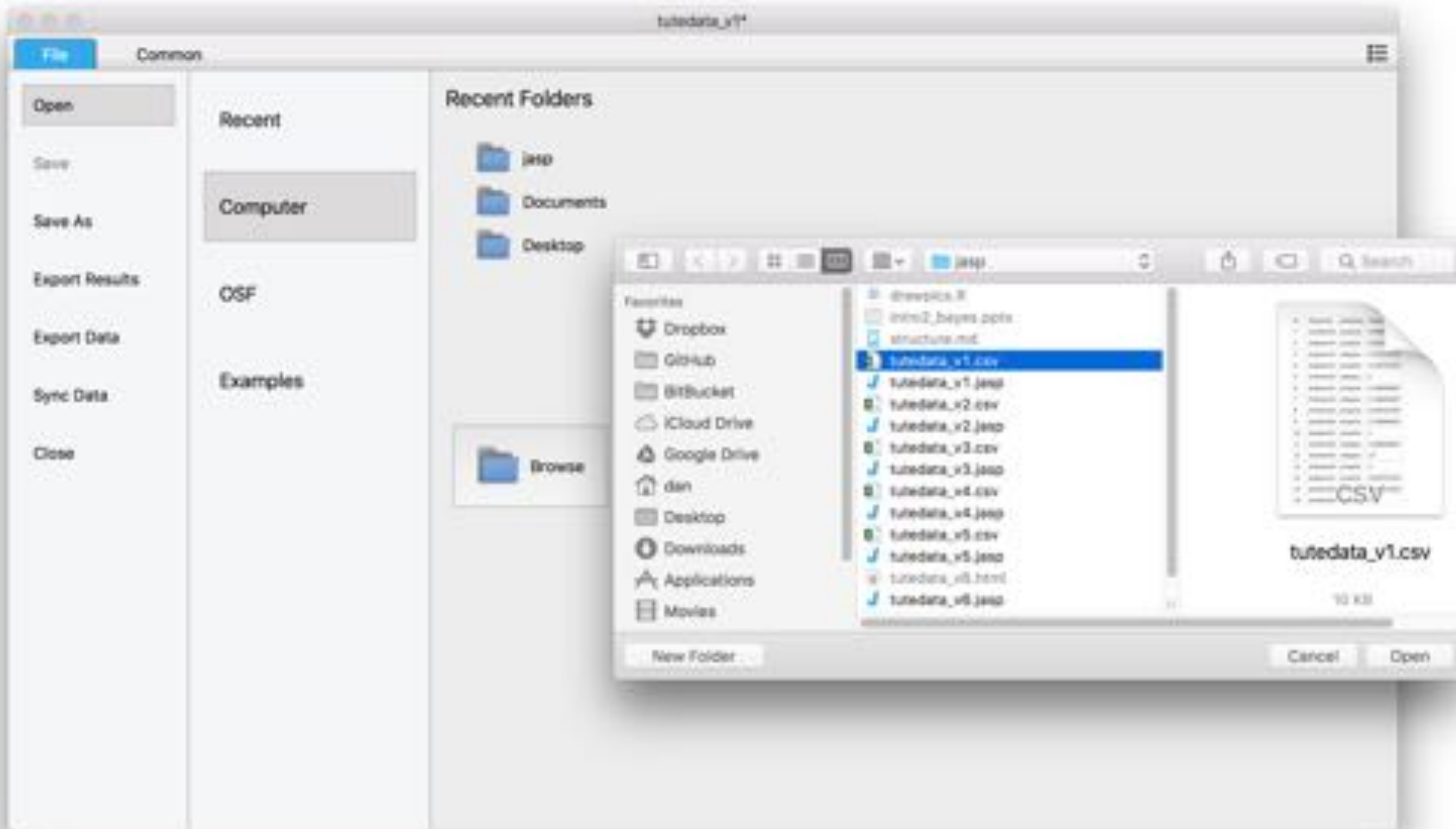
tutedataall.xlsx

A	B	C	D
id	frequency	sampling	meangen
1	smallworld	property	4.67
2	largeworld	property	4.83
3	largeworld	category	4.33
4	largeworld	property	4.33
5	smallworld	category	6.00
6	largeworld	property	5.17
7	smallworld	category	5.17
8	smallworld	property	6.83
9	smallworld	property	3.17
10	largeworld	property	4.00
11	smallworld	category	5.67
12	smallworld	category	5.50
13	smallworld	property	3.00
14	largeworld	property	4.83
16	smallworld	category	3.83
18	smallworld	category	4.50
19	smallworld	category	3.50
20	smallworld	property	5.50

For simplicity I'll use small CSV files with only the relevant variables

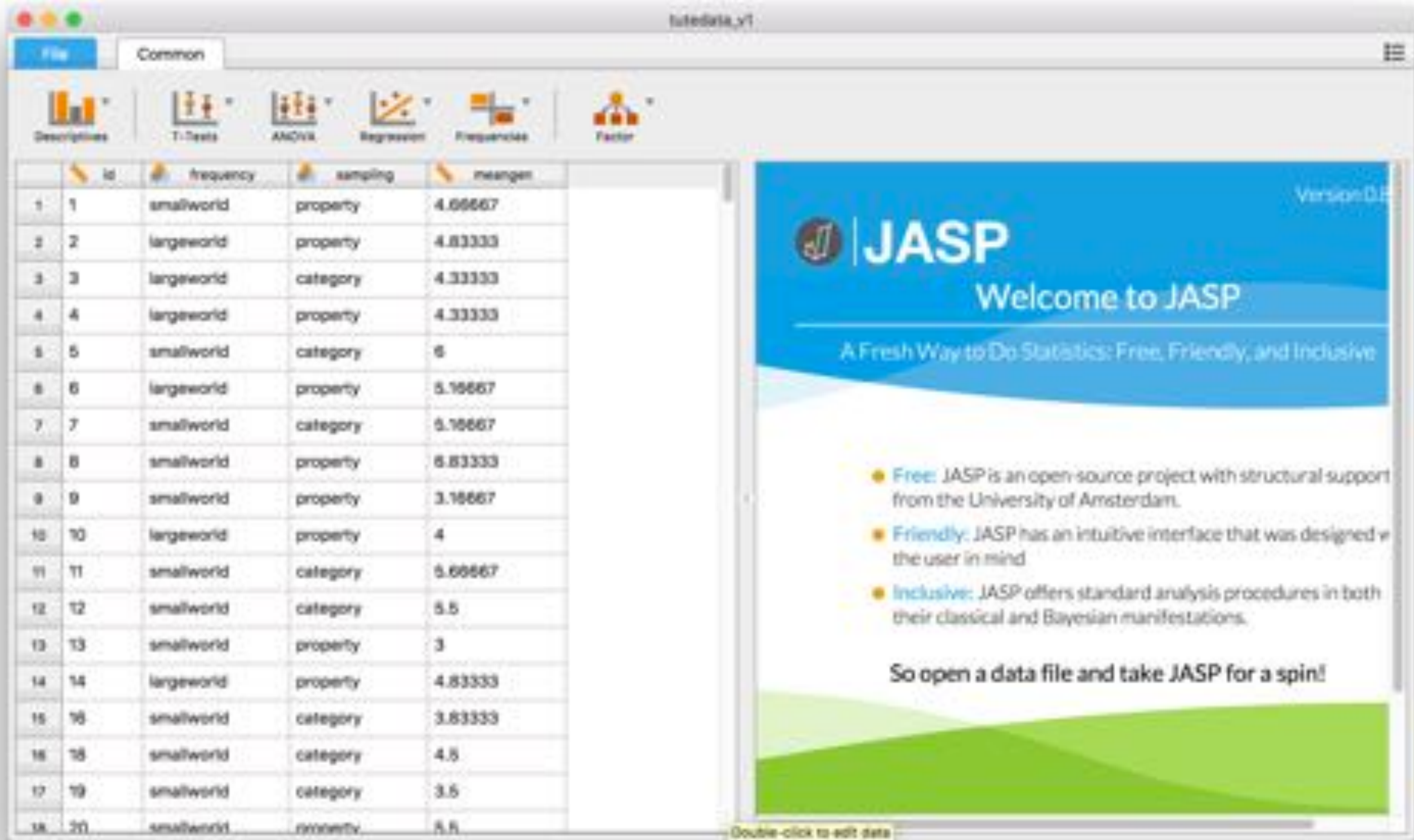
tutedata1.csv

File > Open

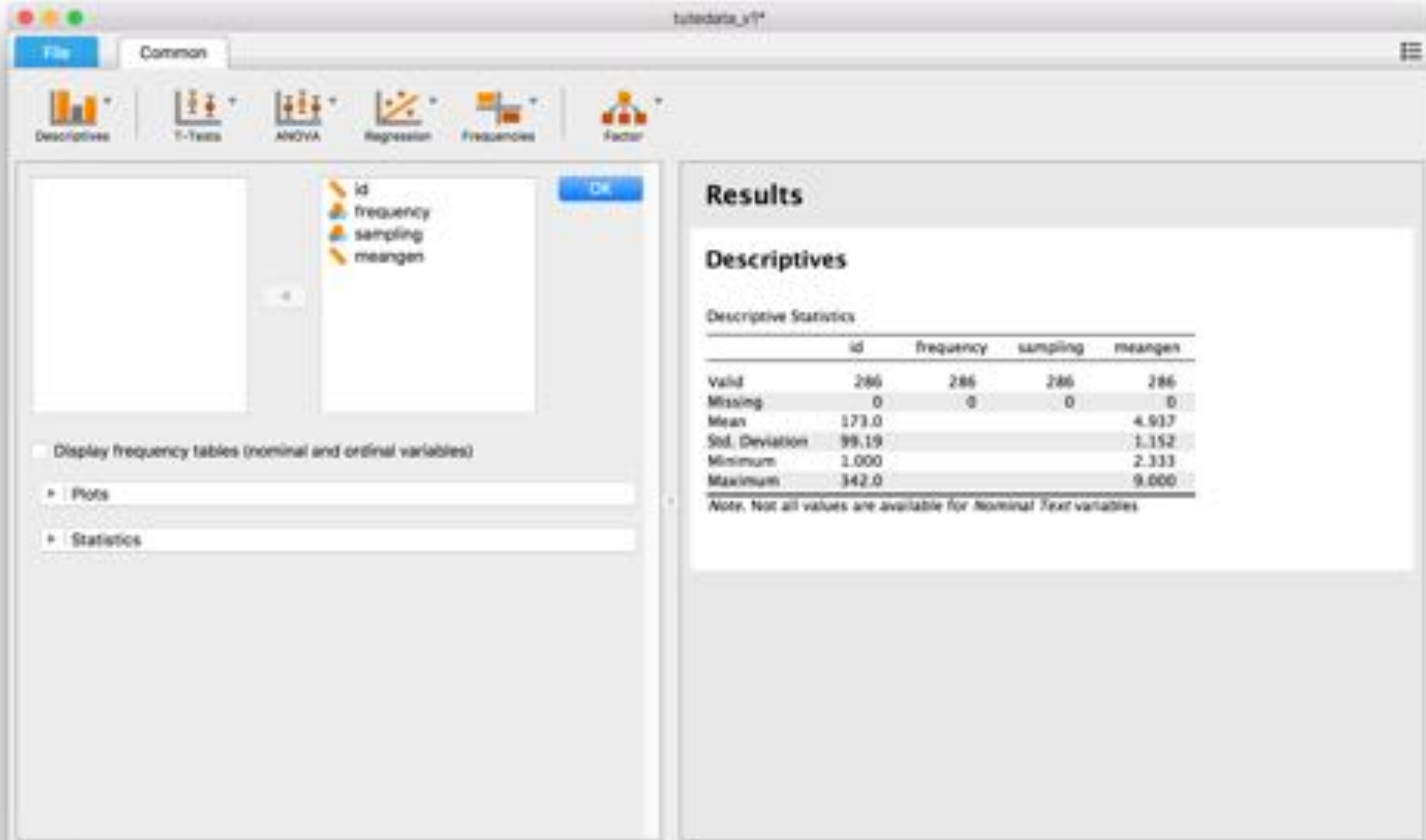


tutedata_v1*
File
Common
Open
Save
Save As
Export Results
Export Data
Sync Data
Close
Recent
Computer
OSF
Examples
Recent Folders
jasp
Documents
Desktop
Browse
jasp
Favorites
Dropbox
GitHub
BitBucket
iCloud Drive
Google Drive
dan
Desktop
Downloads
Applications
Movies
tutedata_v1.csv
tutedata_v1.jasp
tutedata_v2.csv
tutedata_v2.jasp
tutedata_v3.csv
tutedata_v3.jasp
tutedata_v4.csv
tutedata_v4.jasp
tutedata_v5.csv
tutedata_v5.jasp
tutedata_v6.jasp
CSV
tutedata_v1.csv
New Folder
Cancel
Open

Common


tutedata_v1
File
Common
Descriptives
T-Tests
ANOVA
Regression
Frequencies
Factor
id
frequency
sampling
meangen
JASP
Welcome to JASP
A Fresh Way to Do Statistics: Free, Friendly, and Inclusive
Free: JASP is an open-source project with structural support from the University of Amsterdam.
Friendly: JASP has an intuitive interface that was designed w the user in mind
Inclusive: JASP offers standard analysis procedures in both their classical and Bayesian manifestations.
So open a data file and take JASP for a spin!
Double-click to edit data

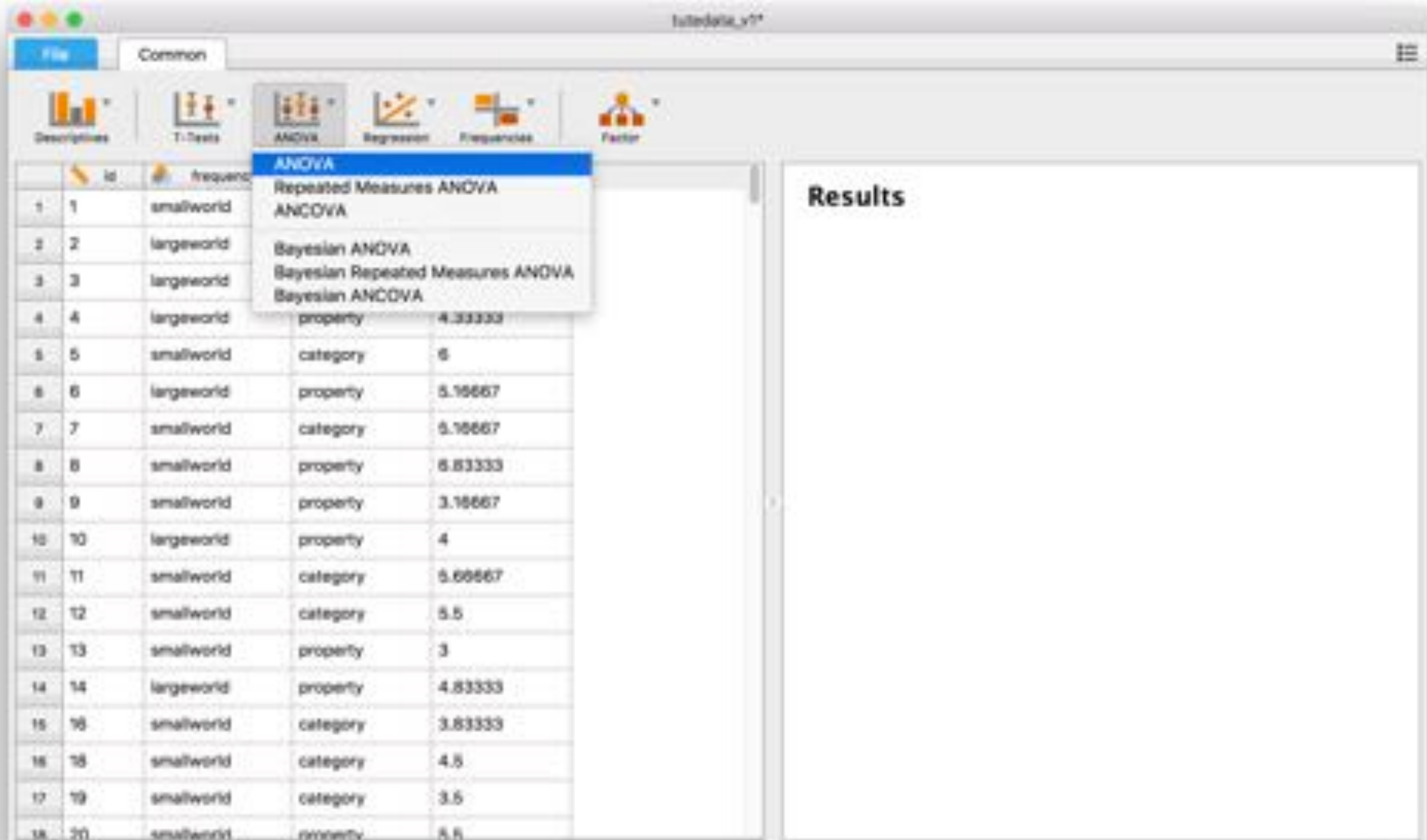
Common > Descriptives



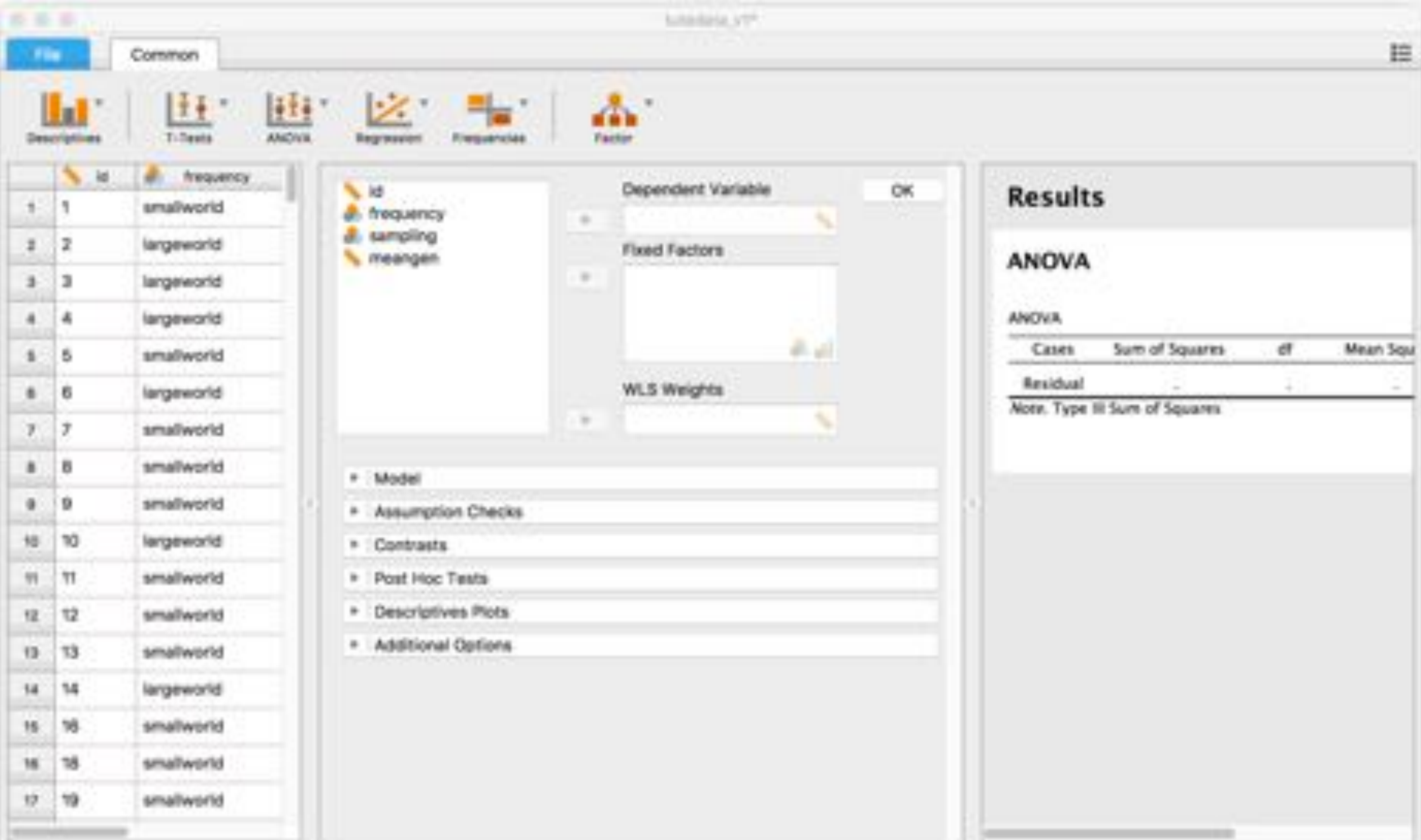
	id	frequency	sampling	meangen
Valid	286	286	286	286
Missing	0	0	0	0
Mean	173.0			4.937
Std. Deviation	99.19			1.152
Minimum	1.000			2.333
Maximum	342.0			9.000

Note. Not all values are available for *Nominal Text* variables

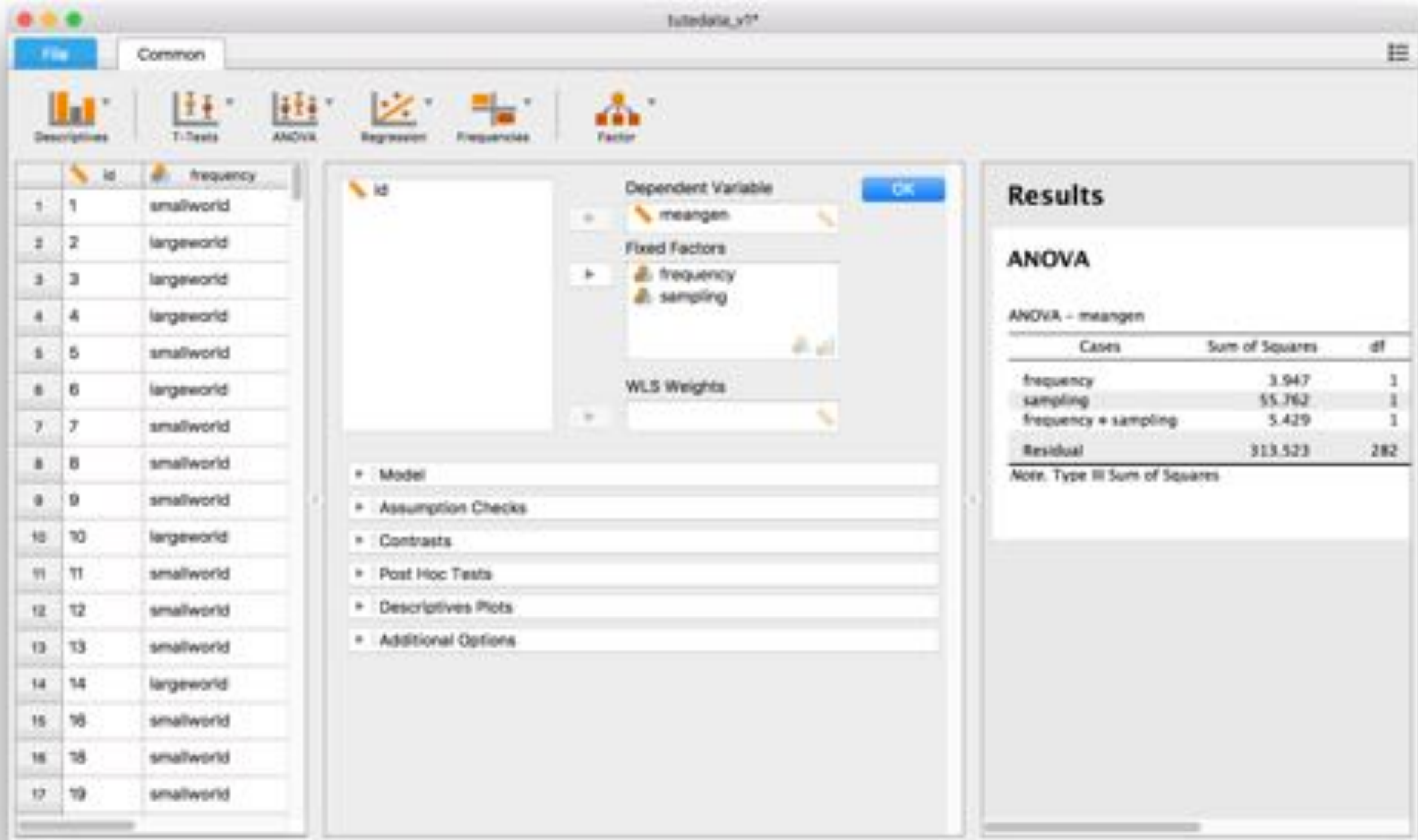
Common > ANOVA



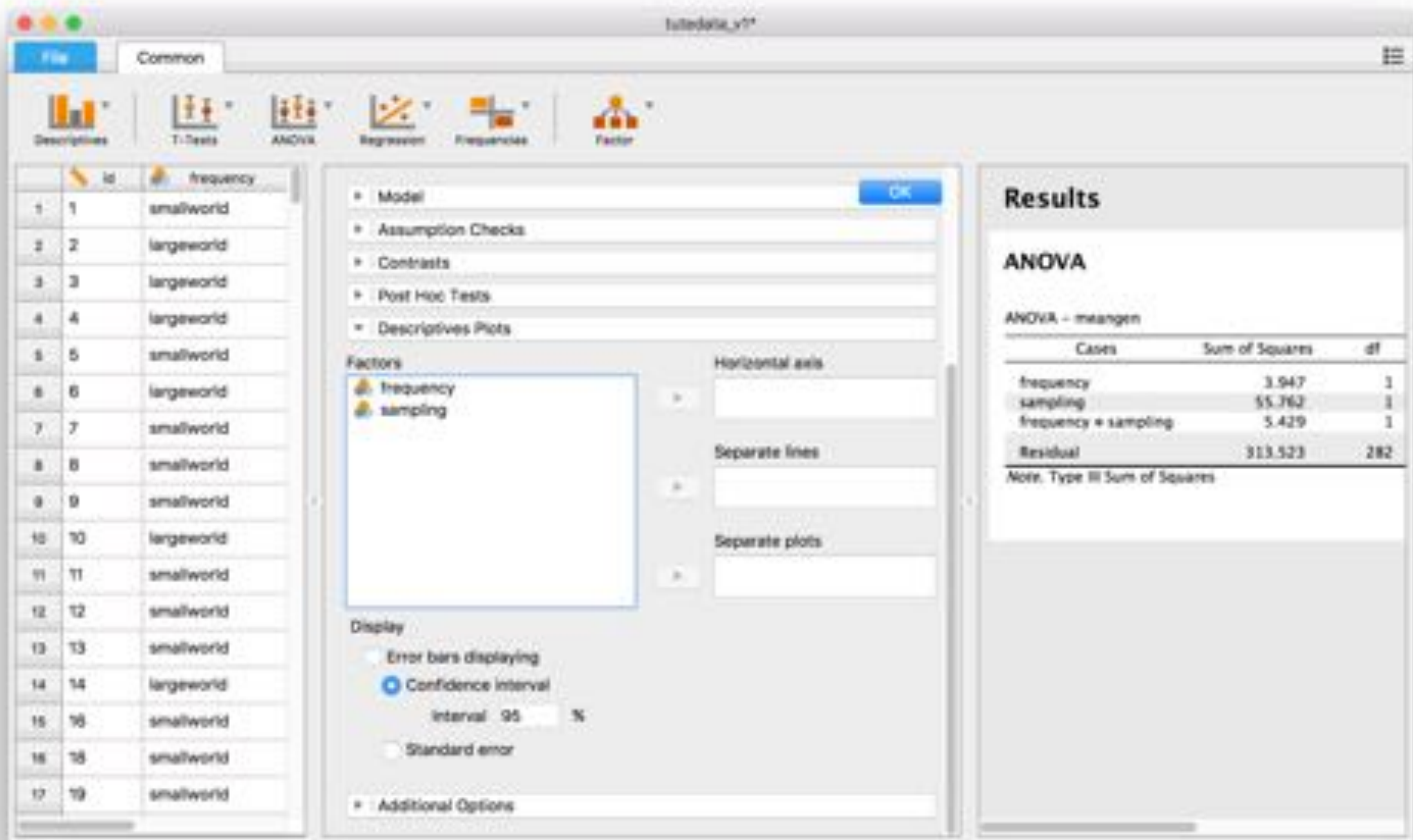
Common > ANOVA > ANOVA



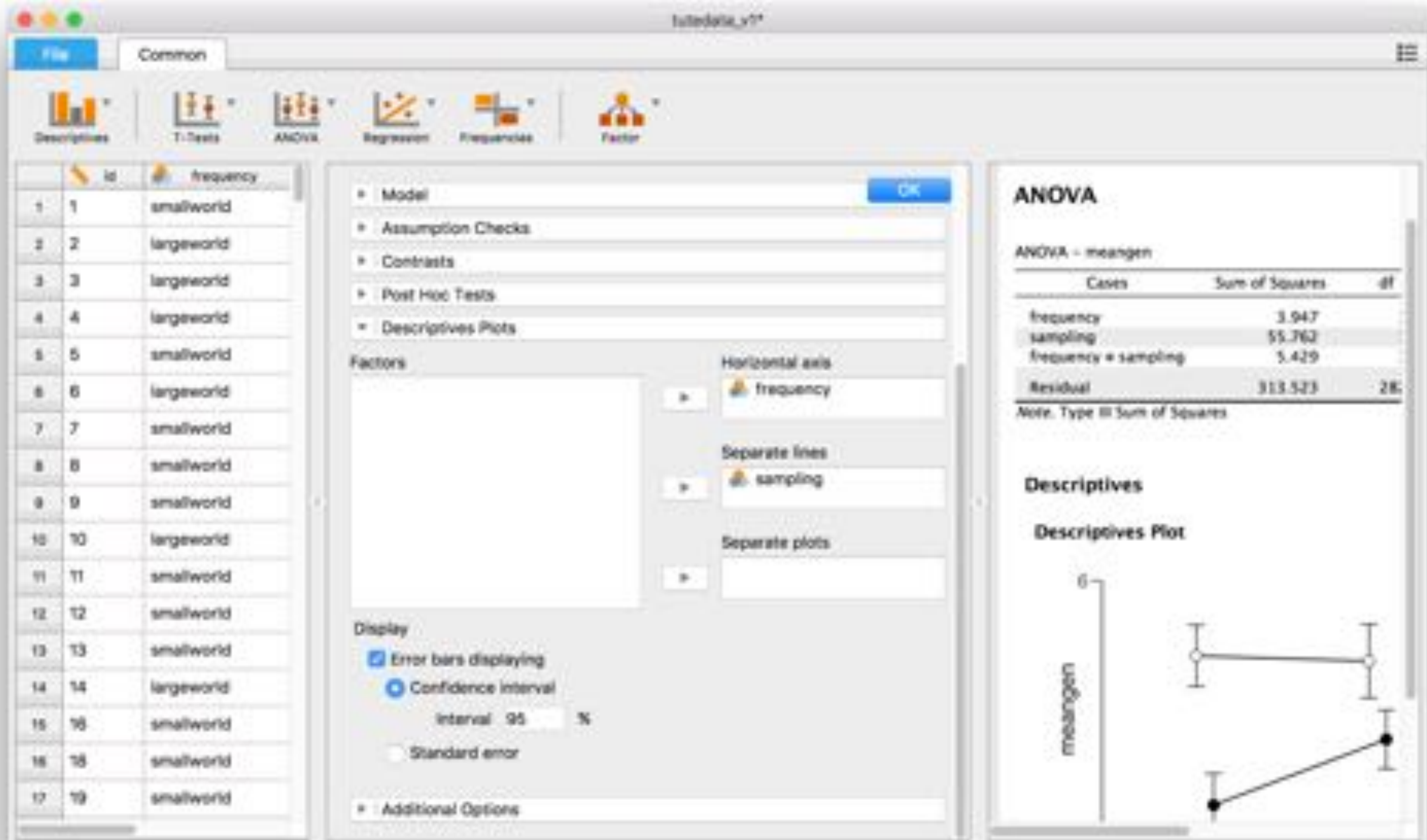
Common > ANOVA > ANOVA



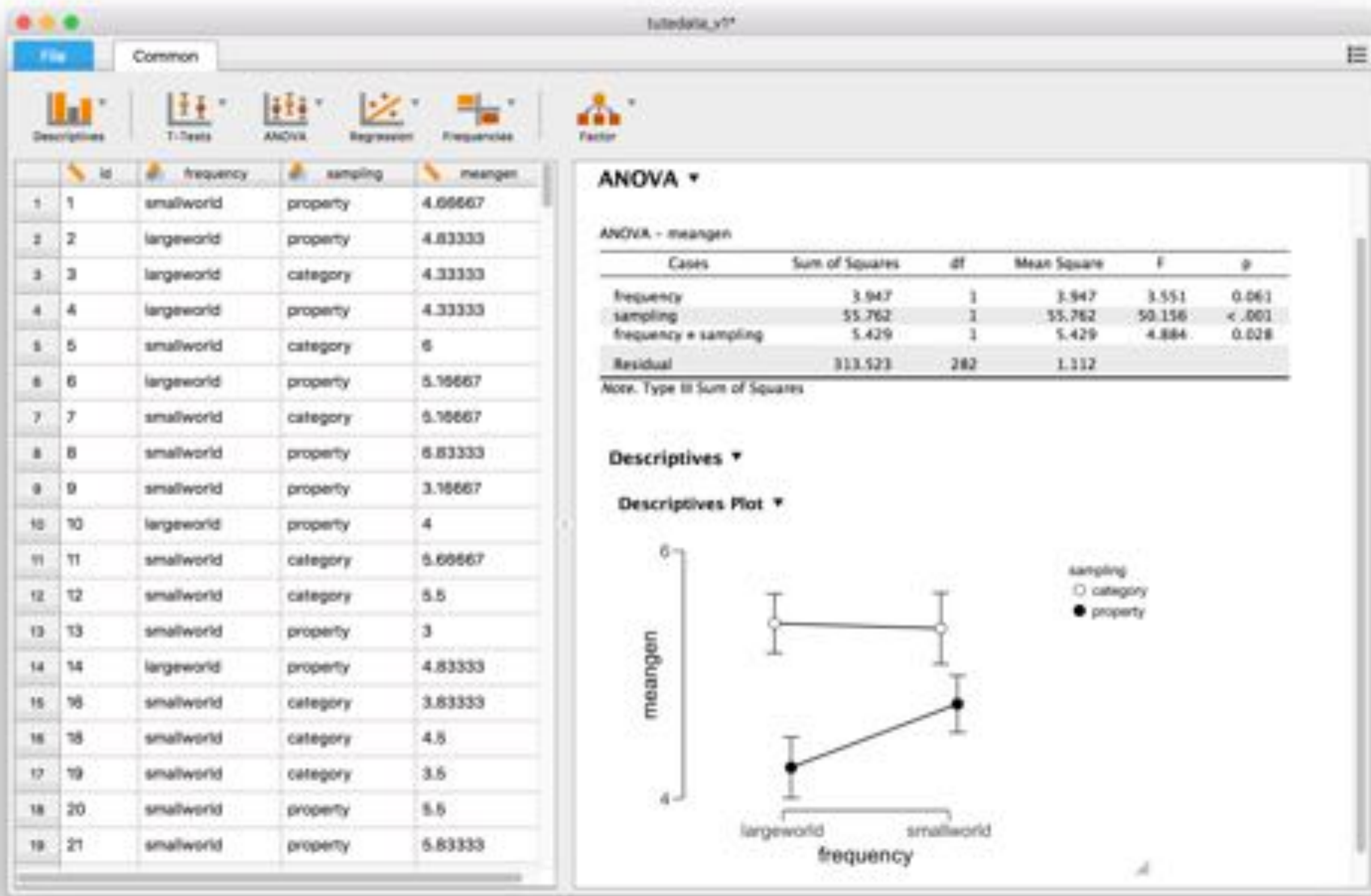
Common > ANOVA > ANOVA > Descriptive Plots



Common > ANOVA > ANOVA > Descriptive Plots

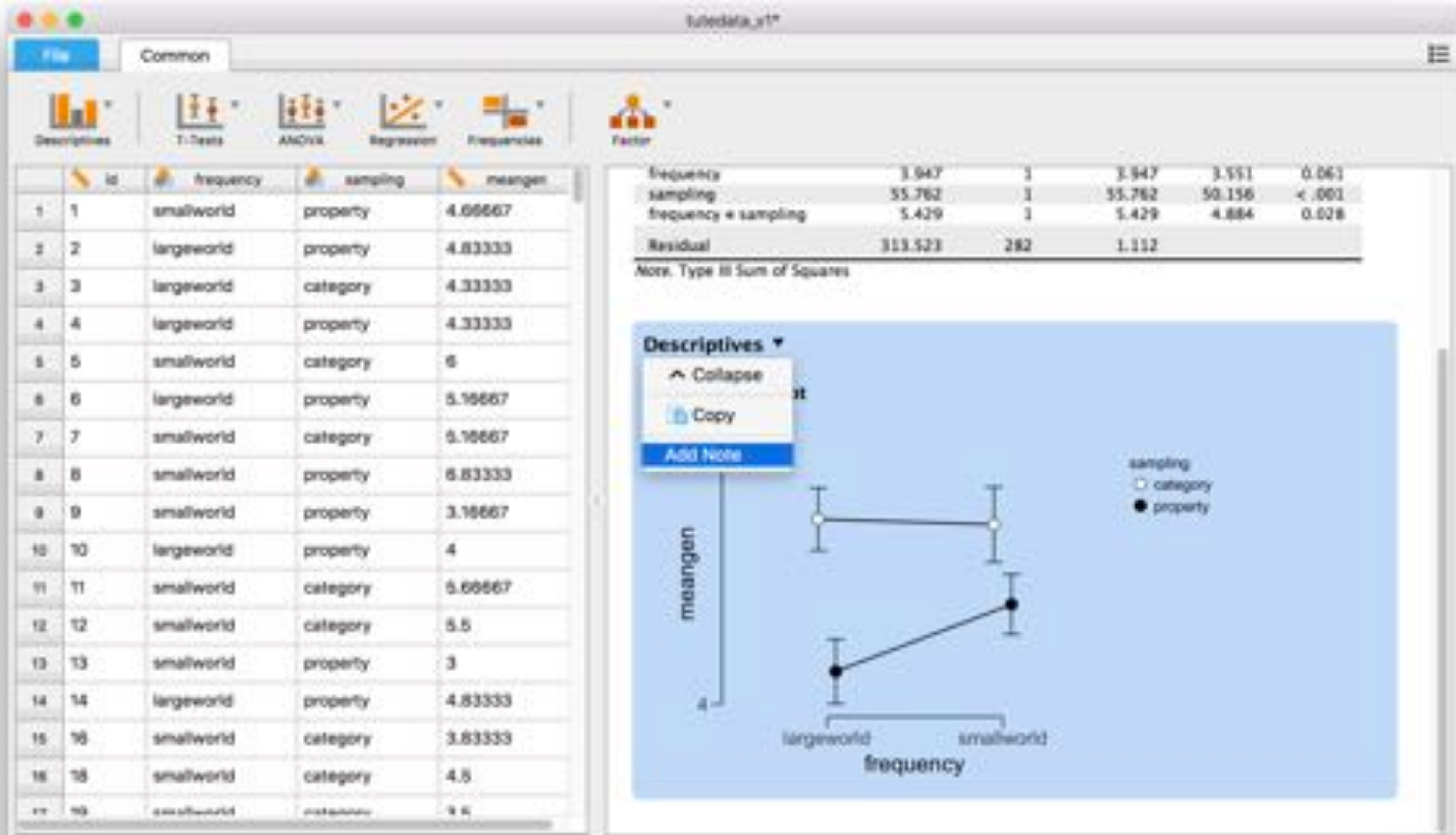


Common



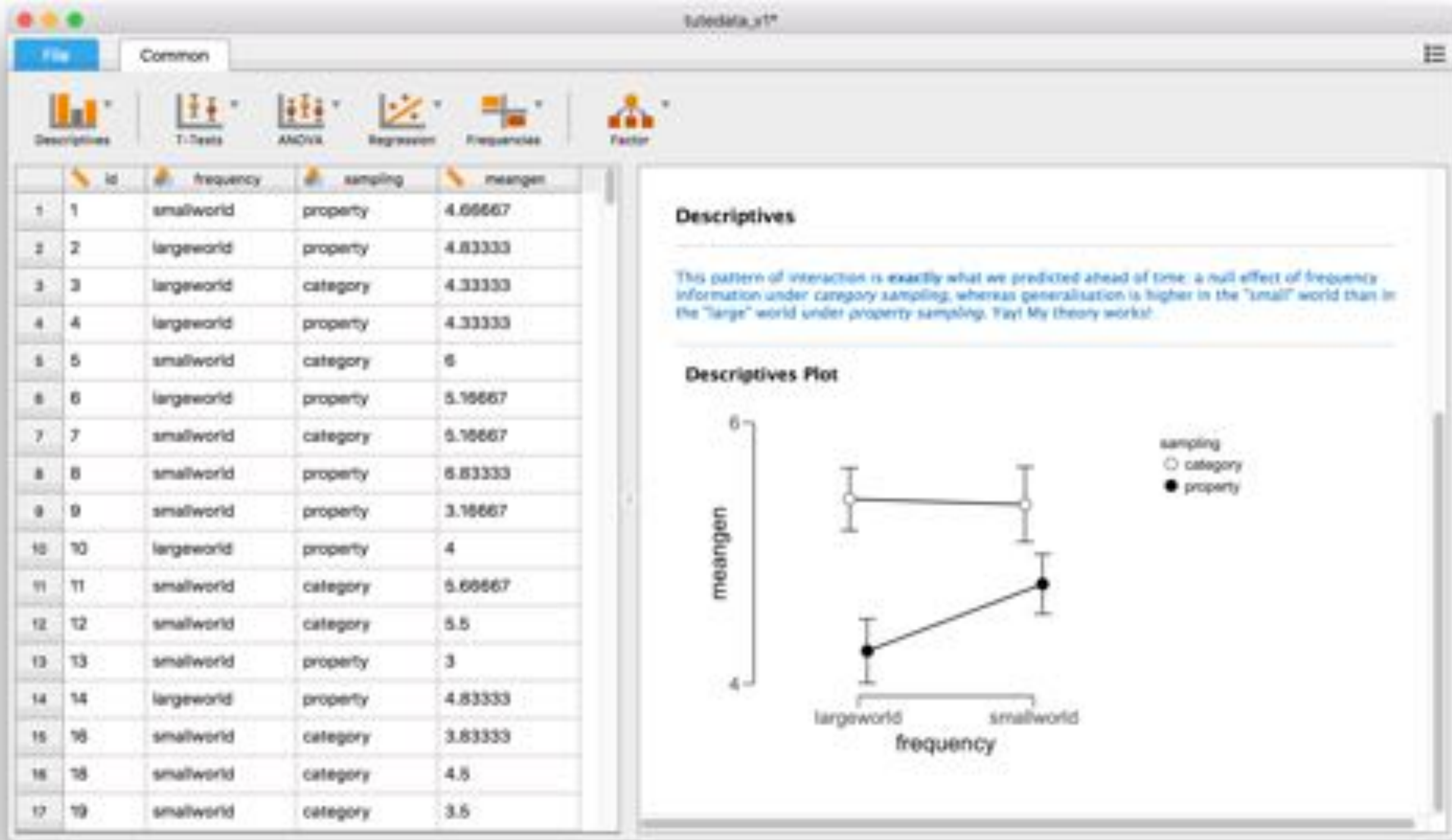
File
Common
Descriptives
T-Tests
ANOVA
Regression
Frequencies
Factor
id
frequency
sampling
meangen
1 1 smallworld property 4.66667
2 2 largeworld property 4.83333
3 3 largeworld category 4.33333
4 4 largeworld property 4.33333
5 5 smallworld category 6
6 6 largeworld property 5.16667
7 7 smallworld category 5.16667
8 8 smallworld property 6.83333
9 9 smallworld property 3.16667
10 10 largeworld property 4
11 11 smallworld category 5.66667
12 12 smallworld category 5.5
13 13 smallworld property 3
14 14 largeworld property 4.83333
15 16 smallworld category 3.83333
16 18 smallworld category 4.5
17 19 smallworld category 3.5
18 20 smallworld property 5.5
19 21 smallworld property 5.83333
ANOVA
ANOVA - meangen
Cases Sum of Squares df Mean Square F p
frequency 3.947 1 3.947 3.551 0.061
sampling 55.762 1 55.762 50.156 < .001
frequency ∗ sampling 5.429 1 5.429 4.884 0.028
Residual 313.523 282 1.112
Note. Type III Sum of Squares
Descriptives
Descriptives Plot
6
4
meangen
sampling
category
property
largeworld
smallworld
frequency

Common

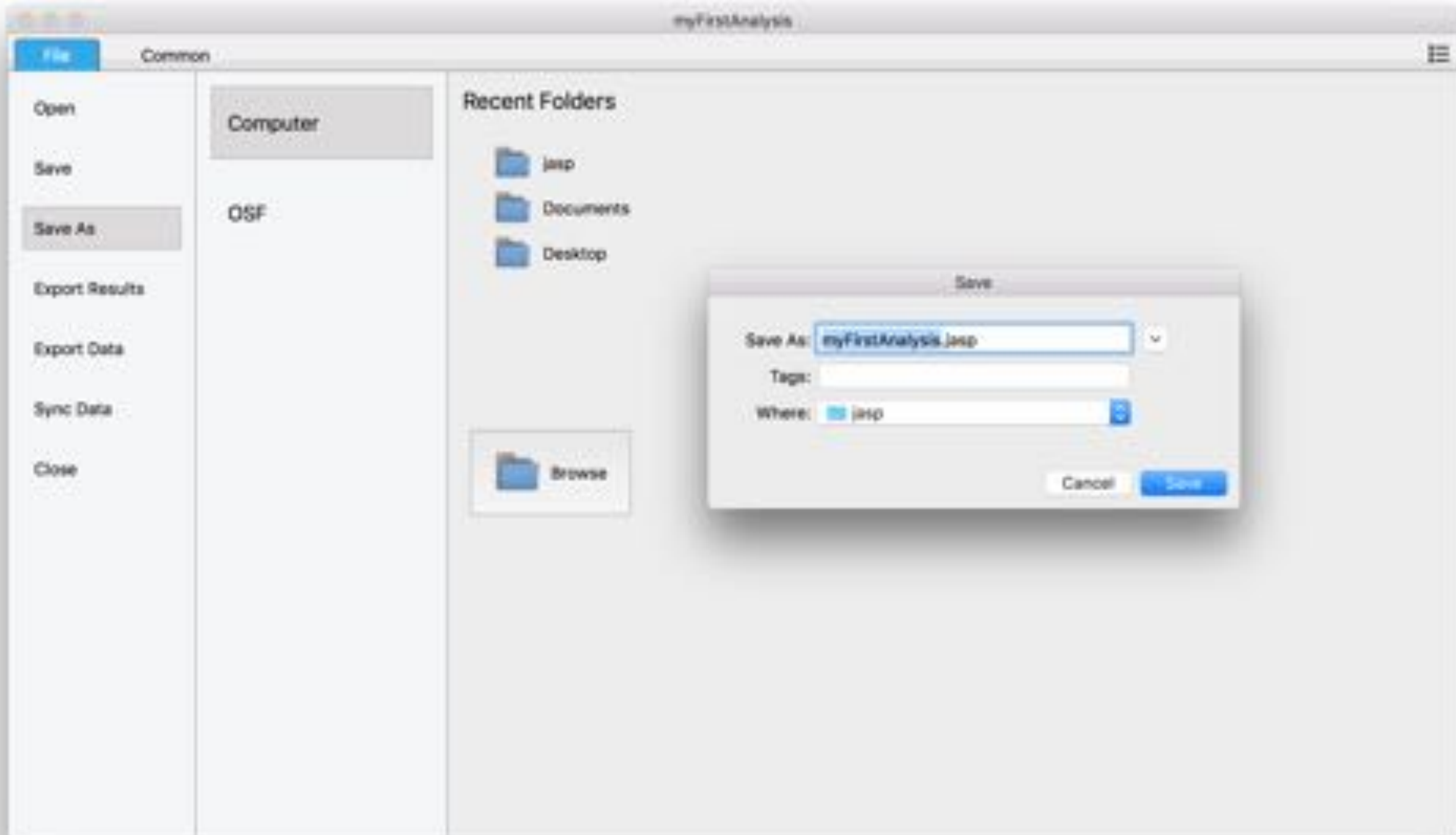


Common
Descriptives
T-Tests
ANOVA
Regression
Frequencies
Factor
id
frequency
sampling
meangen
Descriptives
Collapse
Copy
Add Note
sampling
category
property
meangen
largeworld
smallworld
frequency

Common

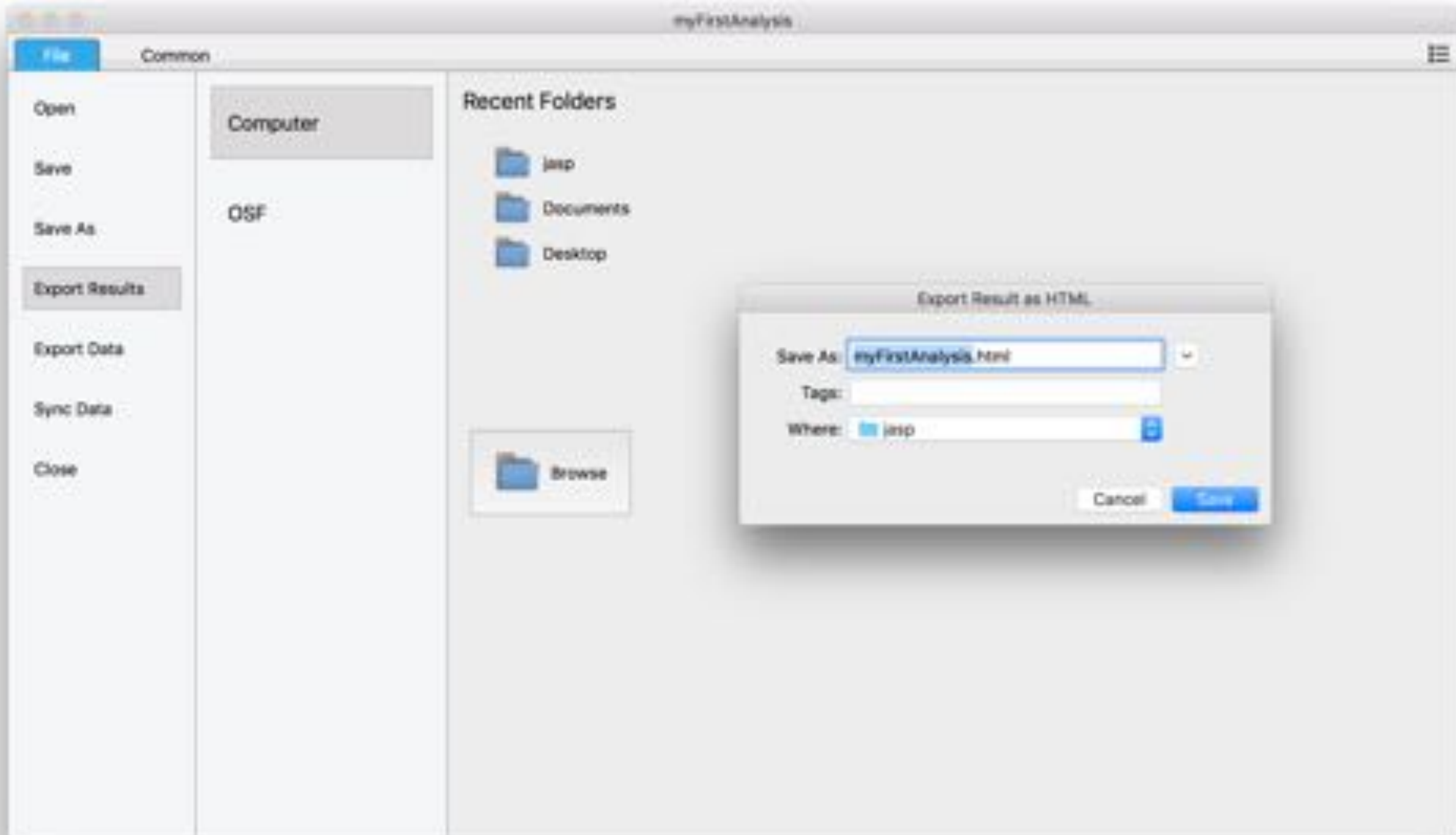

File
Common
Descriptives
T-Tests
ANOVA
Regression
Frequencies
Factor
id
frequency
sampling
meangen
Descriptives
This pattern of interaction is exactly what we predicted ahead of time: a null effect of frequency information under category sampling, whereas generalisation is higher in the "small" world than in the "large" world under property sampling. Yay! My theory works!
Descriptives Plot
sampling
category
property
meangen
frequency
largeworld
smallworld

File > Save As



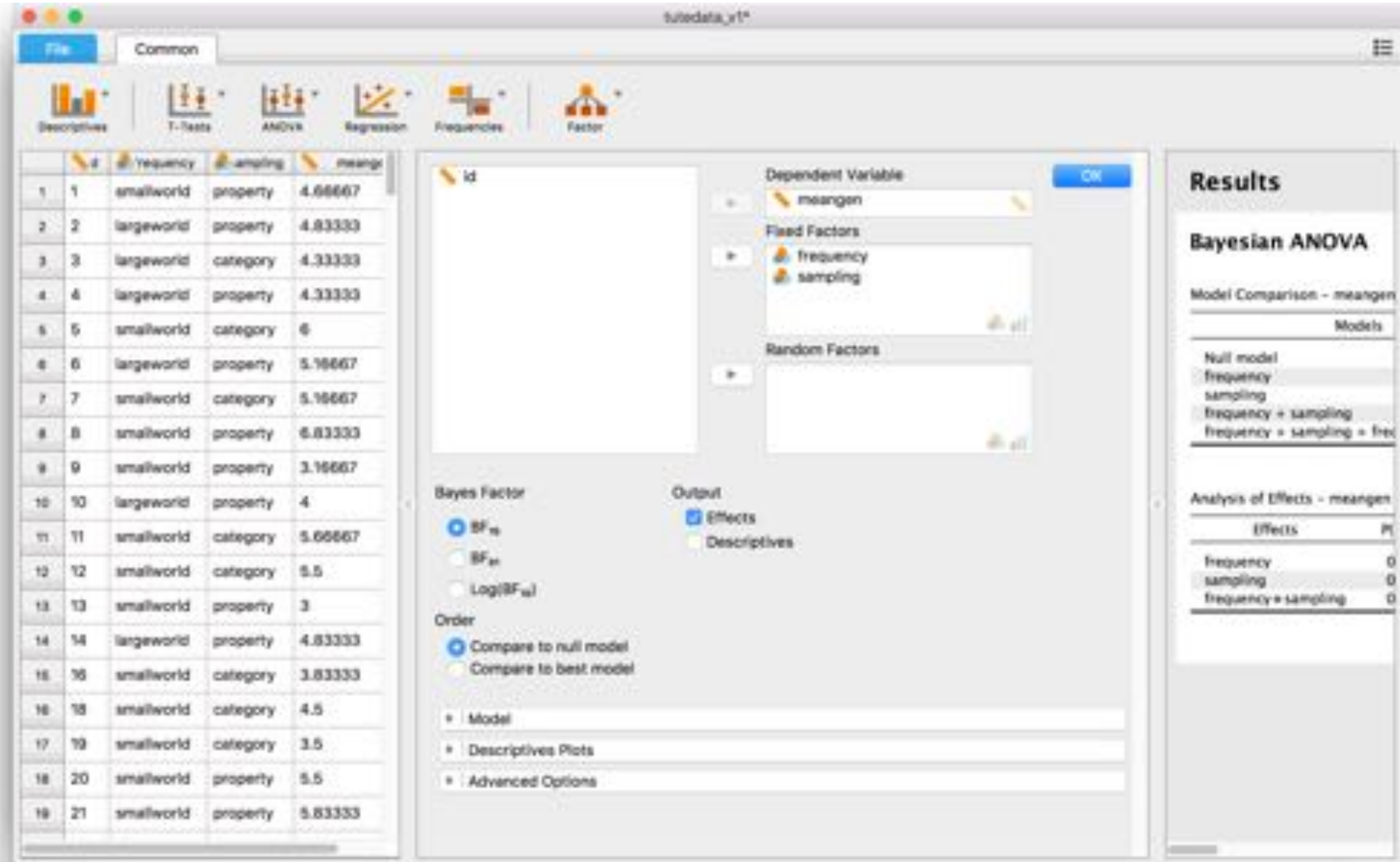
myFirstAnalysis
File
Common
Open
Save
Save As
Export Results
Export Data
Sync Data
Close
Computer
OSF
Recent Folders
jasp
Documents
Desktop
Browse
Save
Save As: myFirstAnalysis.jasp
Tags:
Where: jasp
Cancel
Save

File > Export Results

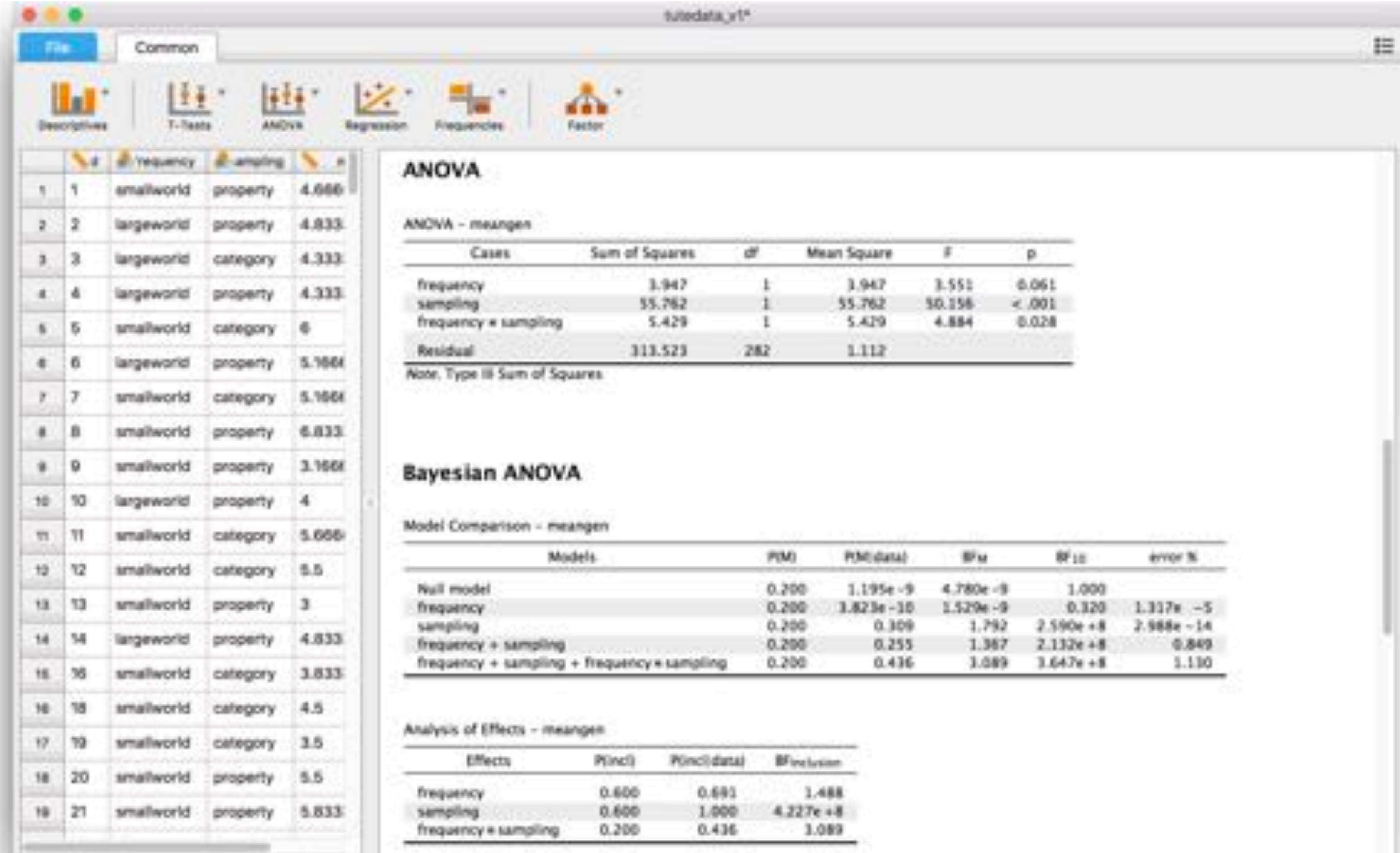


2.2 Bayesian ANOVA

Common > ANOVA > Bayesian ANOVA



Common > ANOVA > Bayesian ANOVA



ANOVA - meangen

Cases	Sum of Squares	df	Mean Square	F	p
frequency	3.947	1	3.947	3.551	0.061
sampling	55.762	1	55.762	50.156	< .001
frequency ∗ sampling	5.429	1	5.429	4.884	0.028
Residual	313.523	282	1.112		

Note. Type III Sum of Squares

Model Comparison - meangen

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Null model	0.200	1.195e -9	4.780e -9	1.000	
frequency	0.200	3.823e -10	1.529e -9	0.320	1.317e -5
sampling	0.200	0.309	1.792	2.590e +8	2.988e -14
frequency + sampling	0.200	0.255	1.367	2.132e +8	0.849
frequency + sampling + frequency ∗ sampling	0.200	0.436	3.089	3.647e +8	1.130

Analysis of Effects - meangen

Effects	P(incl)	P(incl|data)	$BF_{Inclusion}$
frequency	0.600	0.691	1.488
sampling	0.600	1.000	4.227e +8
frequency ∗ sampling	0.200	0.436	3.089

Common > ANOVA > Bayesian ANOVA

Model Comparison – meangen

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
Null model	0.200	1.195e -9	4.780e -9	1.000	
frequency	0.200	3.823e -10	1.529e -9	0.320	1.317e -5
sampling	0.200	0.309	1.792	2.590e +8	2.988e -14
frequency + sampling	0.200	0.255	1.367	2.132e +8	0.849
frequency + sampling + frequency ∗ sampling	0.200	0.436	3.089	3.647e +8	1.130

Analysis of Effects – meangen

Effects	P(incl)	P(incl|data)	$BF_{Inclusion}$
frequency	0.600	0.691	1.488
sampling	0.600	1.000	4.227e +8
frequency ∗ sampling	0.200	0.436	3.089

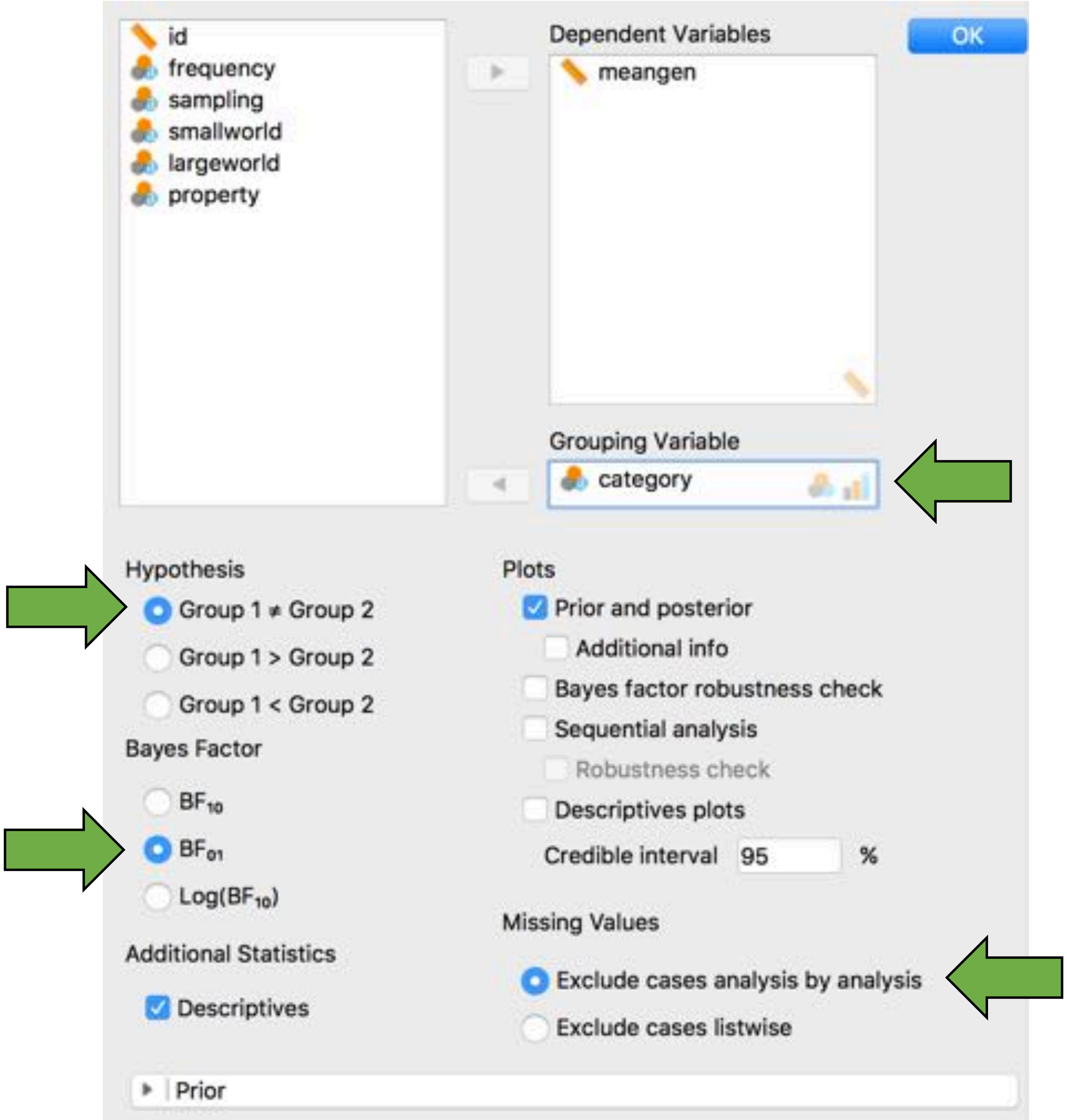
2.3 Bayesian t-test

Planned analysis #1:
Null effect under category sampling?

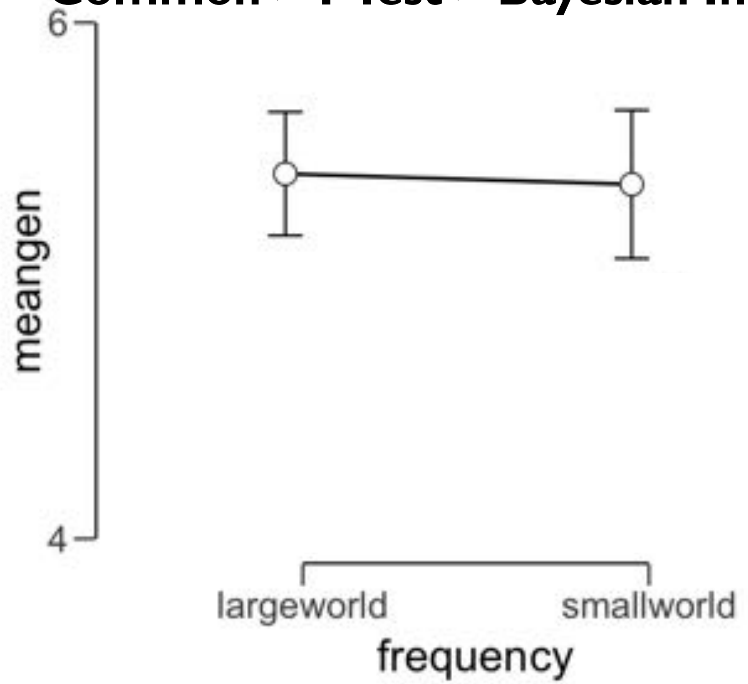
id	frequency	sampling	meangen	smallworld	largeworld	property	category
1	smallworld	property	4.67	property		smallworld	
2	largeworld	property	4.83		property	largeworld	
3	largeworld	category	4.33		category		largeworld
4	largeworld	property	4.33		property	largeworld	
5	smallworld	category	6.00	category			smallworld
6	largeworld	property	5.17		property	largeworld	
7	smallworld	category	5.17	category			smallworld
8	smallworld	property	6.83	property		smallworld	
9	smallworld	property	3.17	property		smallworld	
10	largeworld	property	4.00		property	largeworld	
11	smallworld	category	5.67	category			smallworld
12	smallworld	category	5.50	category			smallworld
13	smallworld	property	3.00	property		smallworld	

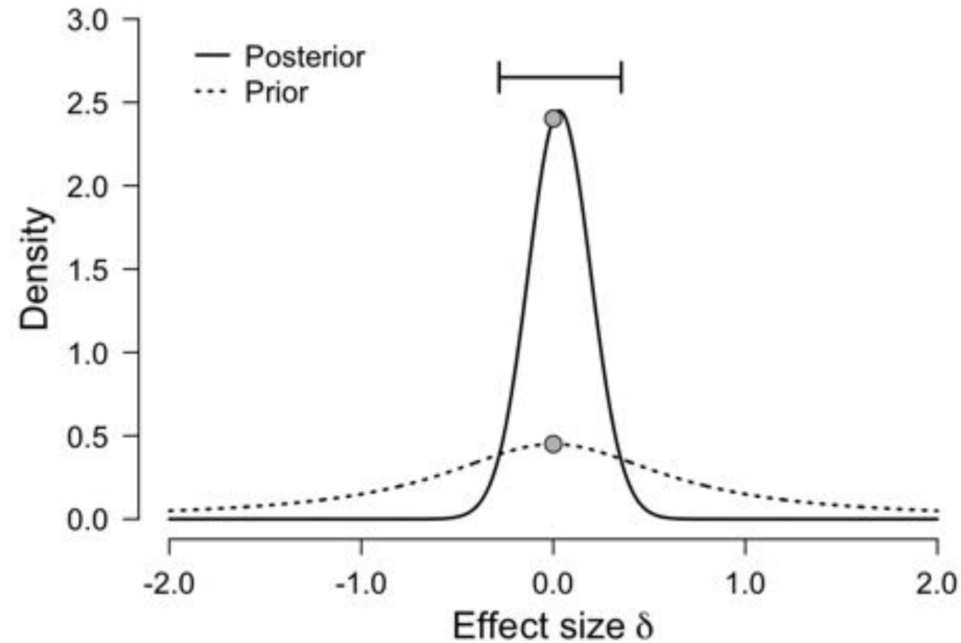
tutedata2.csv

Common > T-Test > Bayesian Independent Samples T-Test



Common > T-Test > Bayesian Independent Samples T-Test





Bayesian Independent Samples T-Test

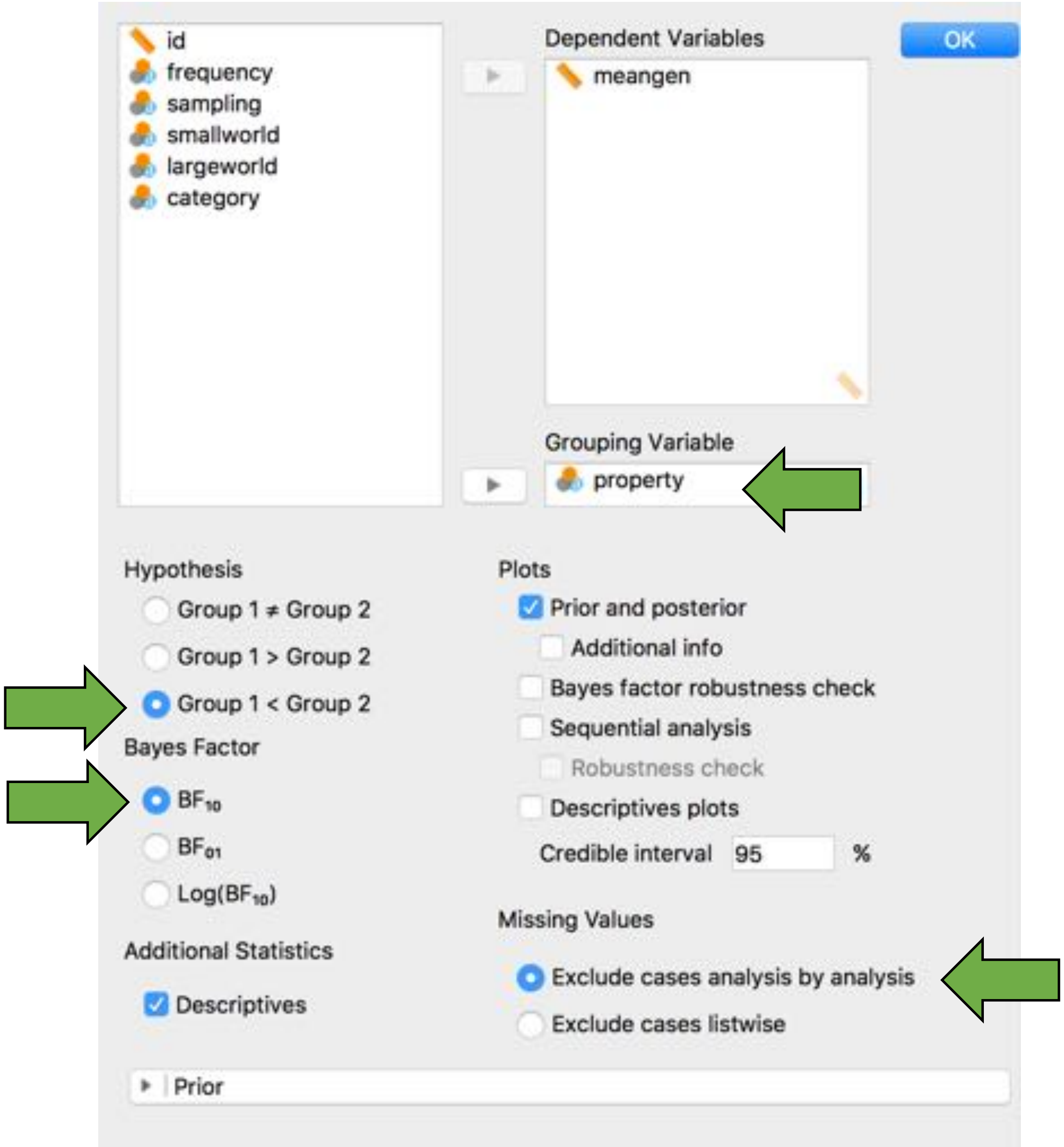
	BF_{01}	error %
meangen	5.305	9.941e −7

Planned analysis #2:
large < small under property sampling

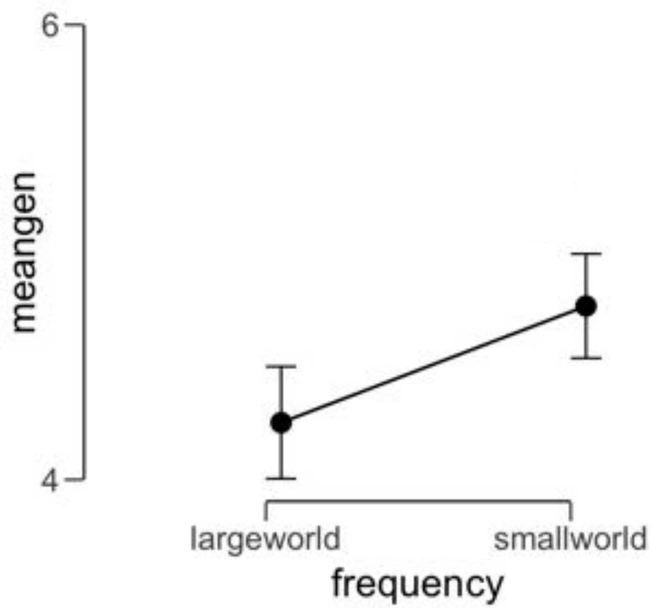
id	frequency	sampling	meangen	smallworld	largeworld	property	category
1	smallworld	property	4.67	property		smallworld	
2	largeworld	property	4.83		property	largeworld	
3	largeworld	category	4.33		category		largeworld
4	largeworld	property	4.33		property	largeworld	
5	smallworld	category	6.00	category			smallworld
6	largeworld	property	5.17		property	largeworld	
7	smallworld	category	5.17	category			smallworld
8	smallworld	property	6.83	property		smallworld	
9	smallworld	property	3.17	property		smallworld	
10	largeworld	property	4.00		property	largeworld	
11	smallworld	category	5.67	category			smallworld
12	smallworld	category	5.50	category			smallworld
13	smallworld	property	3.00	property		smallworld	

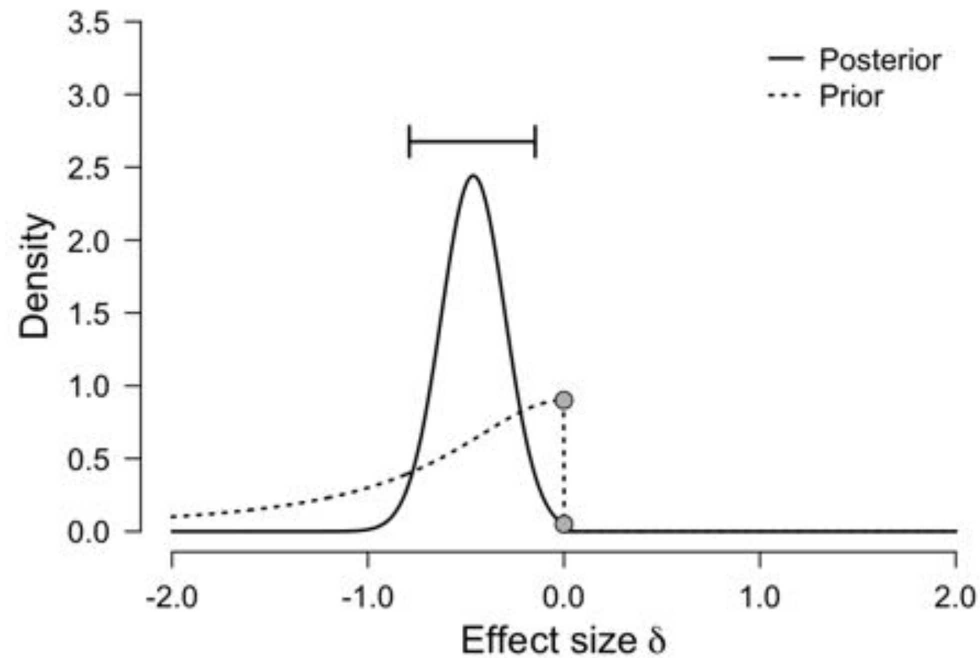
tutedata2.csv

Common > T-Test > Bayesian Independent Samples T-Test



Common > T-Test > Bayesian Independent Samples T-Test





Bayesian Independent Samples T-Test ▼

	BF_{-0}	error %
meangen	22.49	~3.662e −6

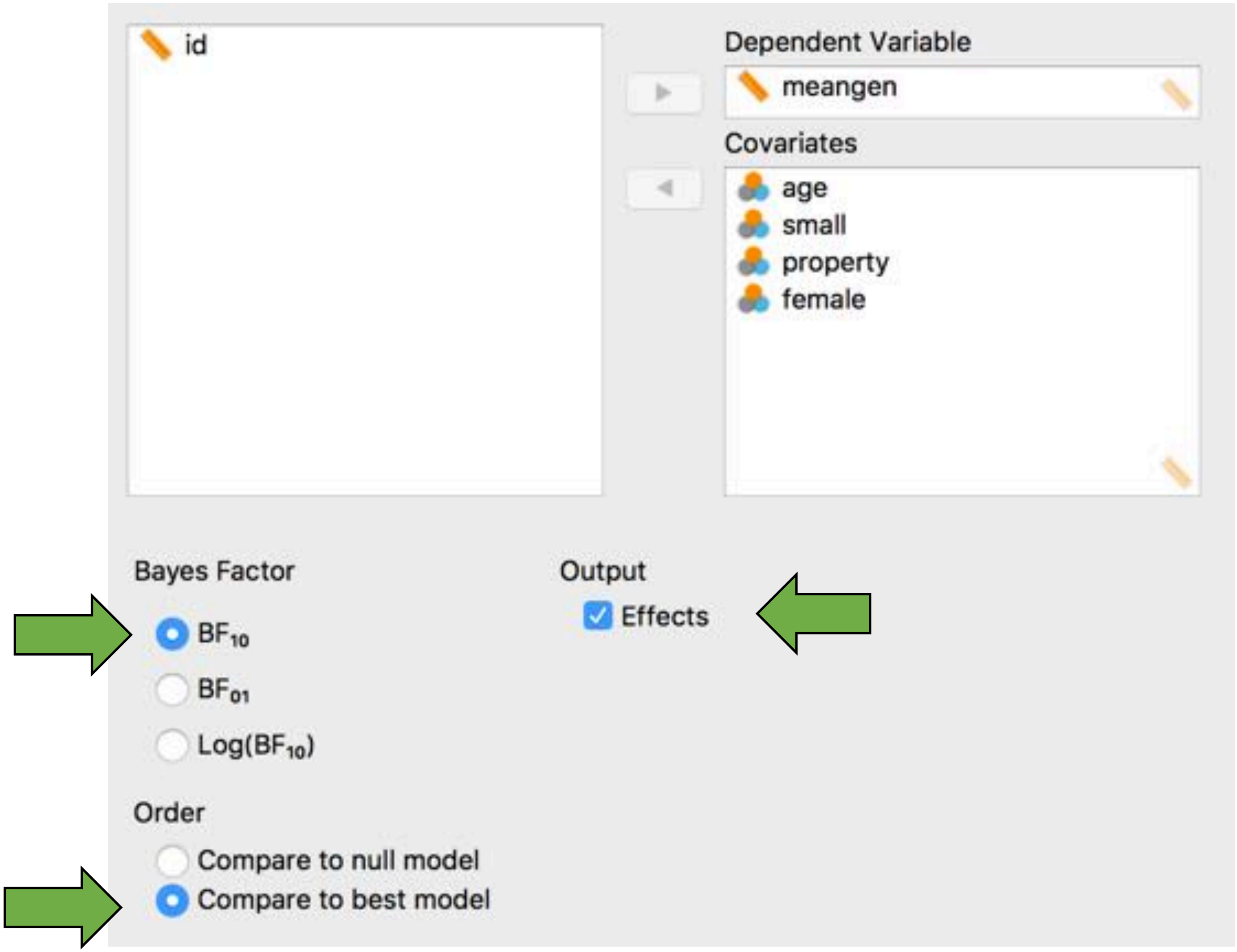
Note. For all tests, the alternative hypothesis specifies that group *largeworld* is less than group *smallworld*.

2.4 Bayesian regression

id	age	small	property	female	meangen
1	21	1	1	1	4.67
2	19	0	1	1	4.83
3	20	0	0	1	4.33
4	19	0	1	0	4.33
5	21	1	0	1	6.00
6	31	0	1	1	5.17
7	21	1	0	1	5.17
8	24	1	1	1	6.83
9	19	1	1	1	3.17
10	20	0	1	0	4.00
11	21	1	0	1	5.67
12	20	1	0	1	5.50
13	20	1	1	0	3.00
14	19	0	1	1	4.83
16	21	1	0	0	3.83
18	24	1	0	1	4.50
19	20	1	0	0	3.50
20	20	1	1	0	5.50

tutedata5.csv

Common > Regression > Bayesian Linear Regression



Common > Regression > Bayesian Linear Regression

Model Comparison – meangen ▼

Models	P(M)	P(M|data)	BF_M	BF_{10}	error %
property	0.063	0.326	7.243	1.000	
small + property	0.063	0.234	4.572	0.717	0.012
age + small + property	0.063	0.151	2.663	0.463	0.012
age + property	0.063	0.141	2.457	0.432	0.012
property + female	0.063	0.050	0.791	0.154	0.013
small + property + female	0.063	0.043	0.678	0.133	0.012
age + small + property + female	0.063	0.030	0.471	0.093	0.013
age + property + female	0.063	0.025	0.392	0.078	0.012
Null model	0.063	6.055e -10	9.083e -9	1.860e -9	0.012
age	0.063	3.438e -10	5.157e -9	1.056e -9	0.012
small	0.063	1.745e -10	2.617e -9	5.358e -10	0.012
age + small	0.063	1.697e -10	2.546e -9	5.211e -10	0.013
female	0.063	1.023e -10	1.535e -9	3.142e -10	0.012
age + female	0.063	7.768e -11	1.165e -9	2.385e -10	0.014
age + small + female	0.063	4.557e -11	6.835e -10	1.399e -10	0.012
small + female	0.063	4.301e -11	6.451e -10	1.321e -10	0.015

Common > Regression > Bayesian Linear Regression

Analysis of Effects – meangen ▼

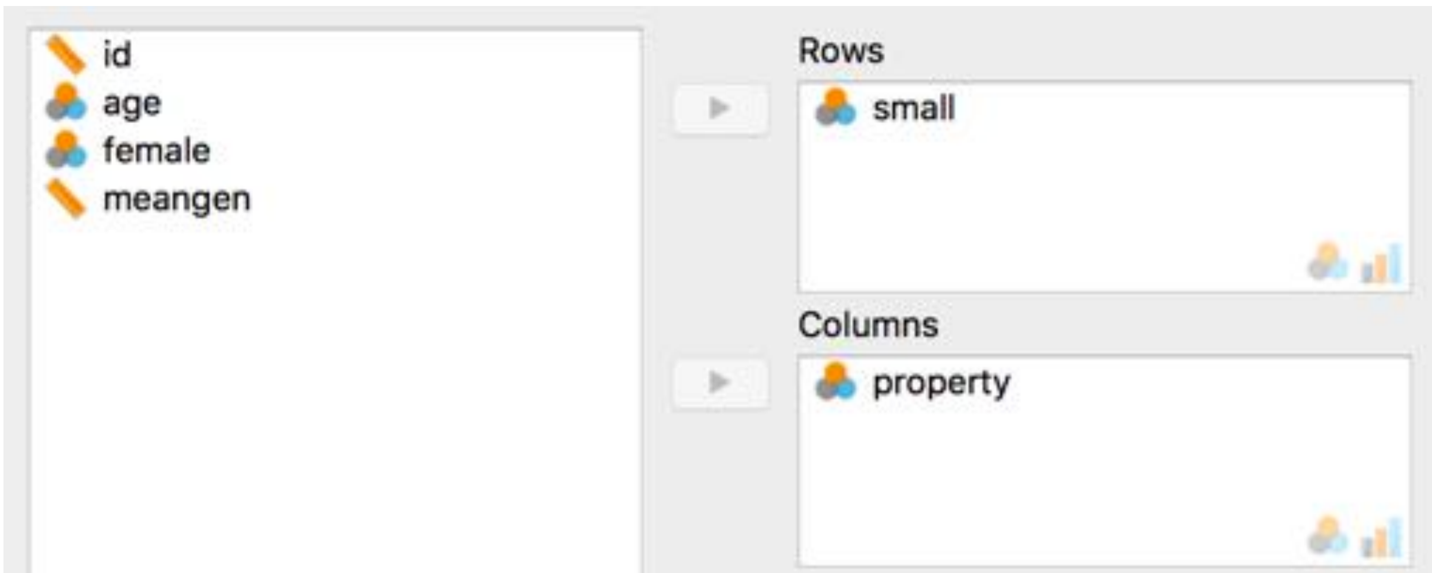
Effects	P(incl)	P(incl|data)	$BF_{Inclusion}$
age	0.500	0.347	0.532
small	0.500	0.458	0.845
property	0.500	1.000	6.402e +8
female	0.500	0.149	0.175

2.5 Bayesian contingency tables

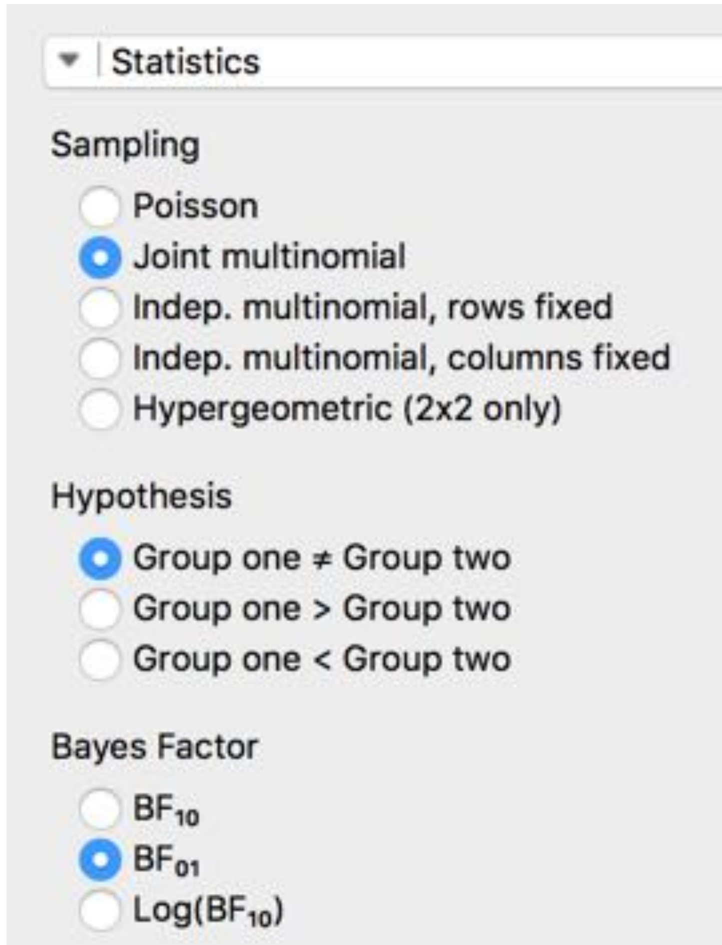
id	age	small	property	female	meangen
1	21	1	1	1	4.67
2	19	0	1	1	4.83
3	20	0	0	1	4.33
4	19	0	1	0	4.33
5	21	1	0	1	6.00
6	31	0	1	1	5.17
7	21	1	0	1	5.17
8	24	1	1	1	6.83
9	19	1	1	1	3.17
10	20	0	1	0	4.00
11	21	1	0	1	5.67
12	20	1	0	1	5.50
13	20	1	1	0	3.00
14	19	0	1	1	4.83
16	21	1	0	0	3.83
18	24	1	0	1	4.50
19	20	1	0	0	3.50
20	20	1	1	0	5.50

tutedata5.csv

Common > Frequencies > Bayesian Contingency Tables



Common > Frequencies > Bayesian Contingency Tables



Common > Frequencies > Bayesian Contingency Tables

Bayesian Contingency Tables ▼

	property		
small	0	1	Total
0	73	71	144
1	62	78	140
Total	135	149	284

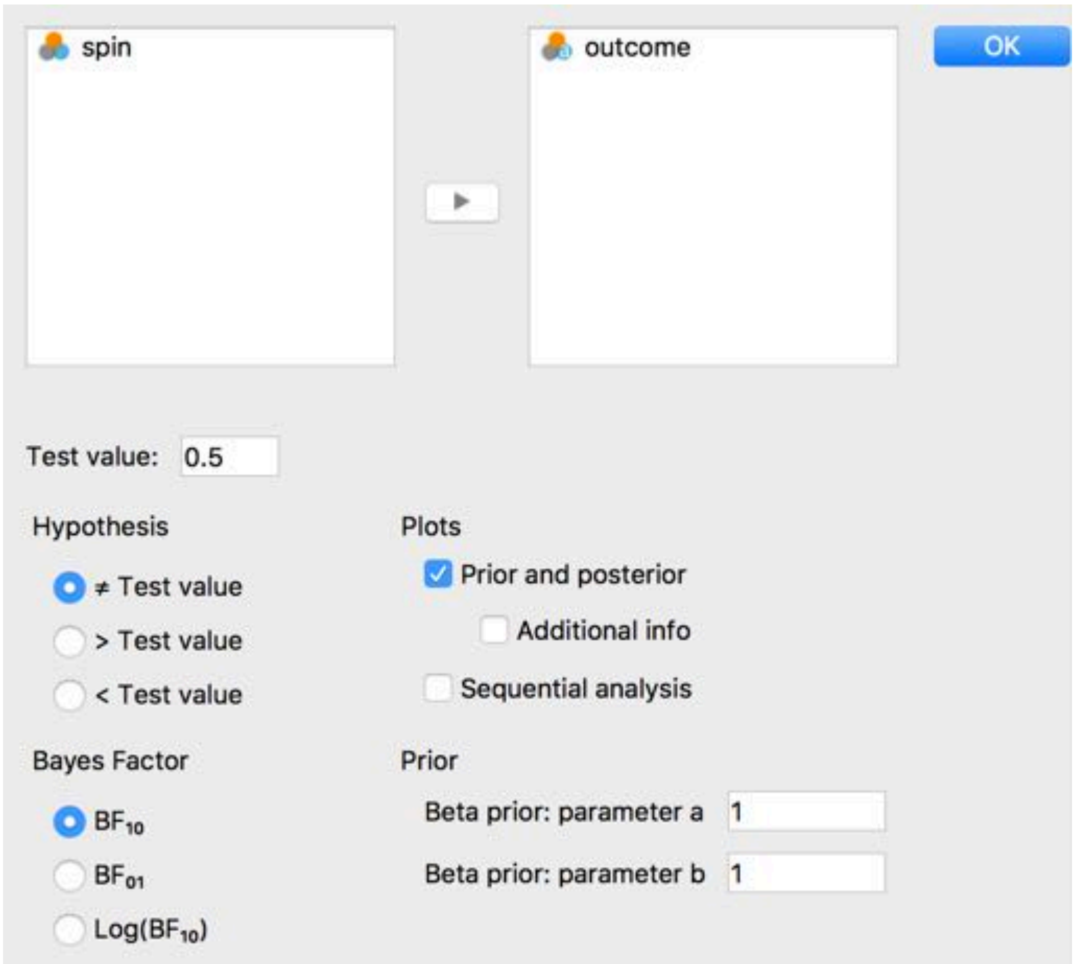
Bayesian Contingency Tables Tests

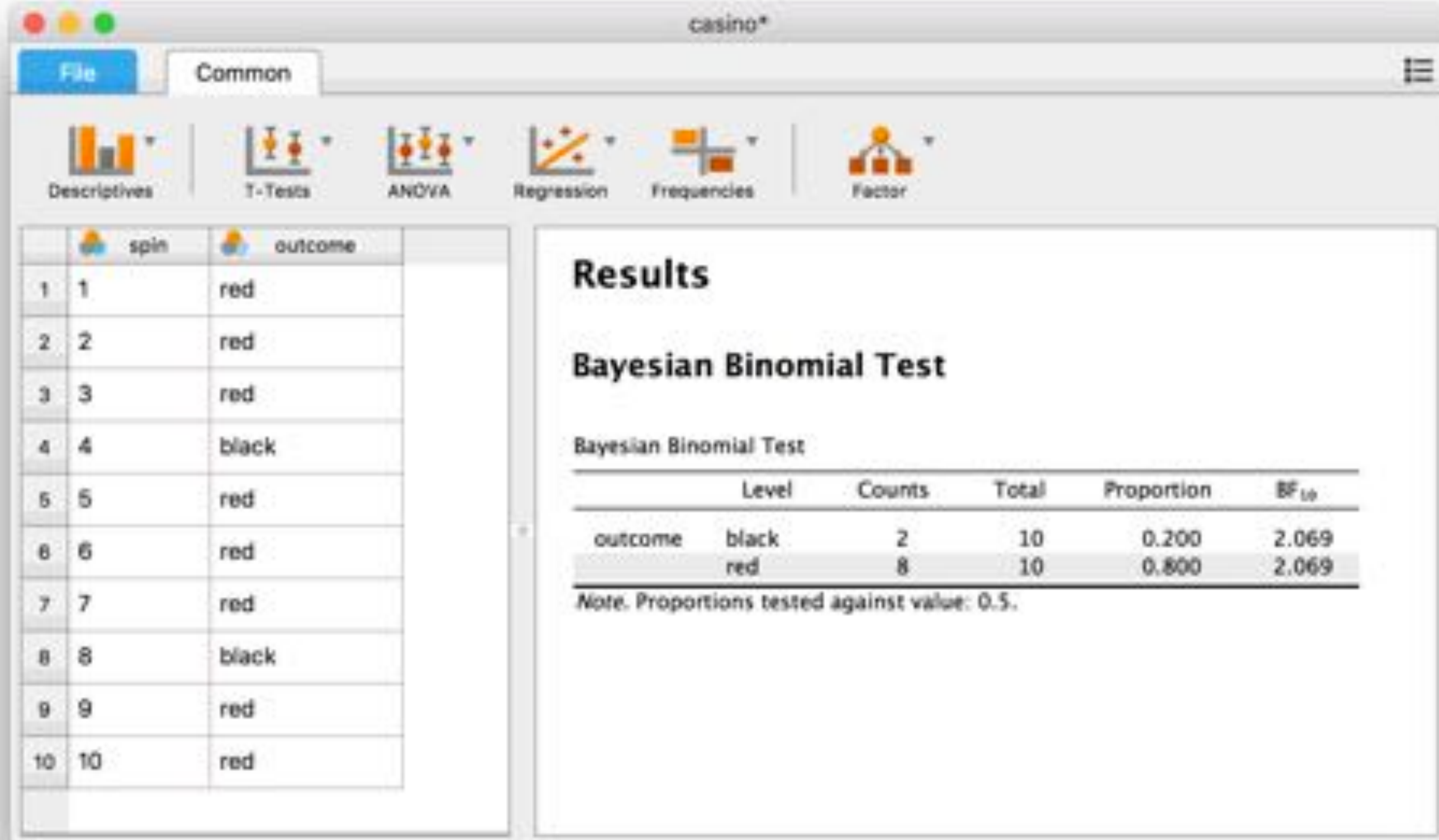
	Value
BF_{01} joint multinomial	2.540
N	284

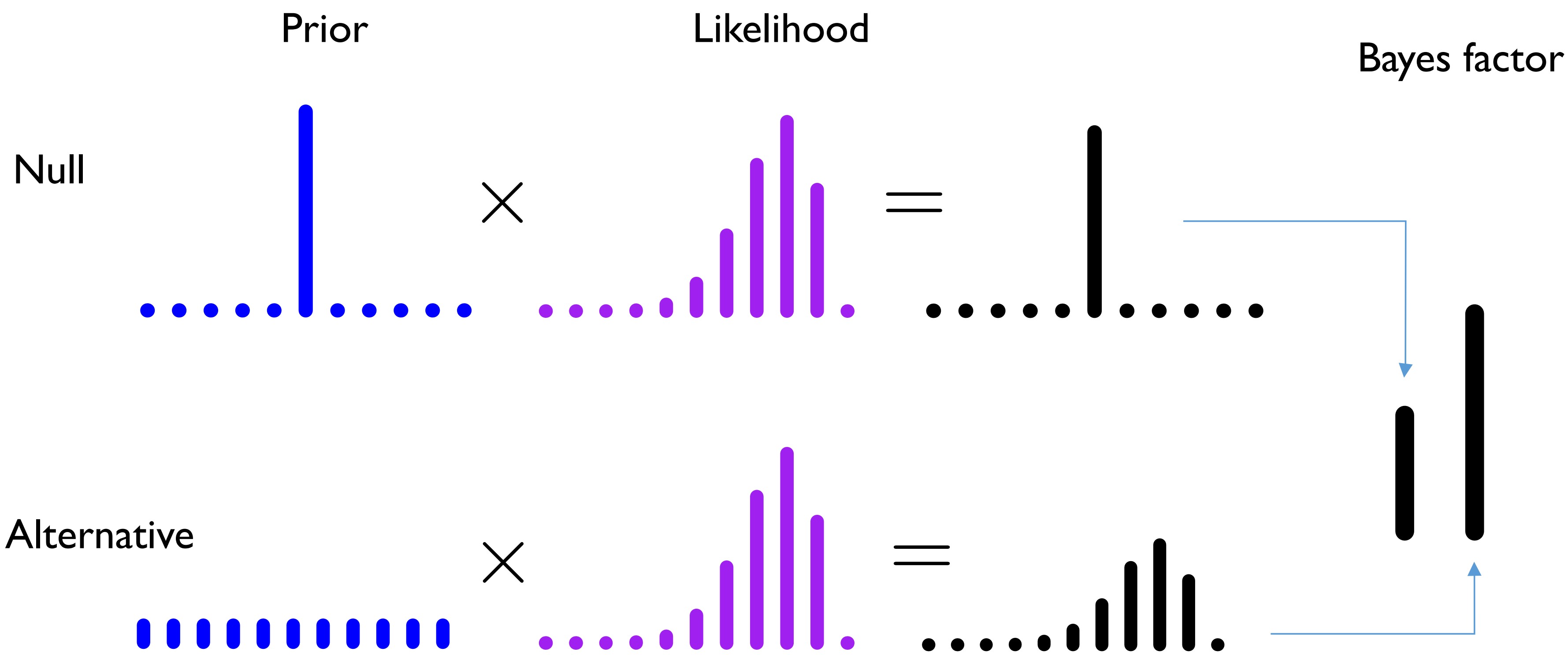
2.6 Bayesian binomial test

spin	outcome
1	red
2	red
3	red
4	black
5	red
6	red
7	red
8	black
9	red
10	red

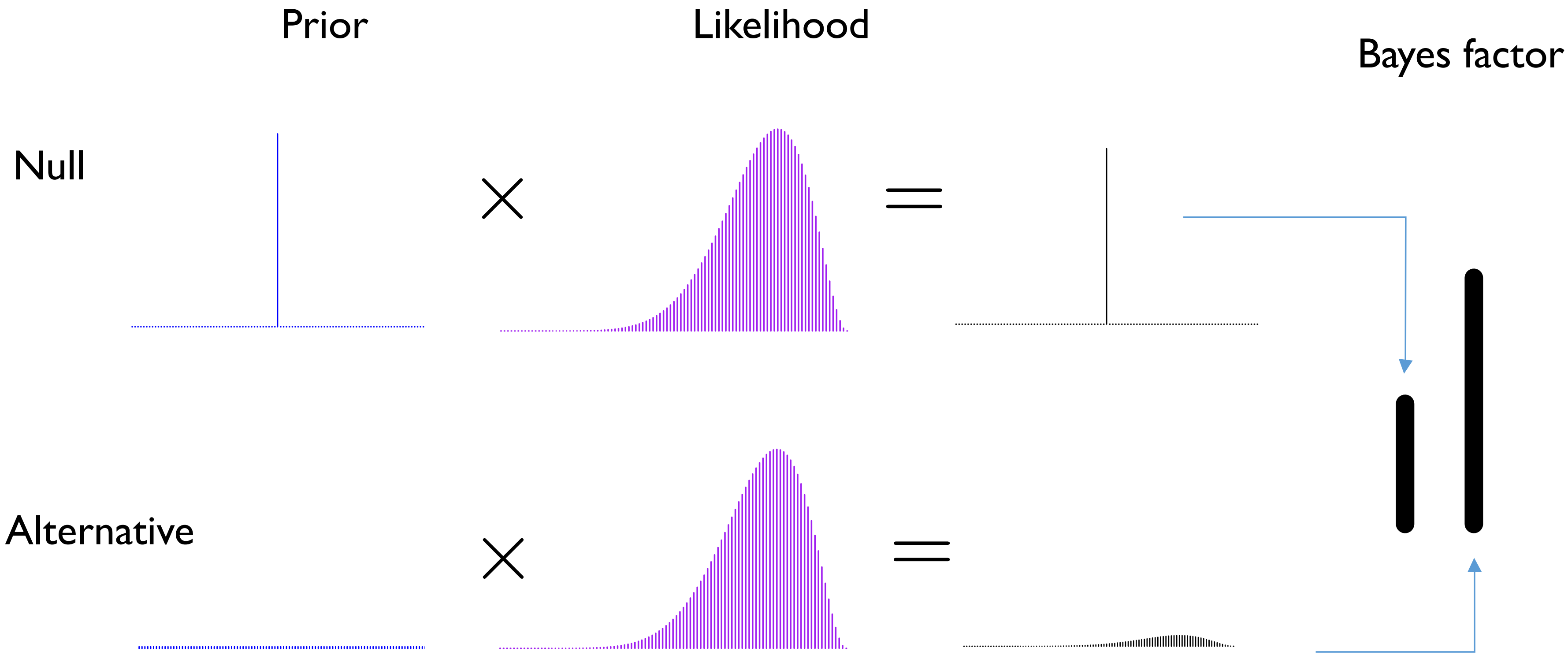
Common > Frequencies > Bayesian Binomial Test




casino*
File
Common
Descriptives
T-Tests
ANOVA
Regression
Frequencies
Factor
spin
outcome
1 1 red
2 2 red
3 3 red
4 4 black
5 5 red
6 6 red
7 7 red
8 8 black
9 9 red
10 10 red
Results
Bayesian Binomial Test
Bayesian Binomial Test
Level Counts Total Proportion BF10
outcome black 2 10 0.200 2.069
red 8 10 0.800 2.069
Note. Proportions tested against value: 0.5.



Wait… we got 1.87 for this
Bayes factor and JASP says 2.07



It's just an approximation error… if we use finer-grained approximation to "continuous numbers" we get 2.05

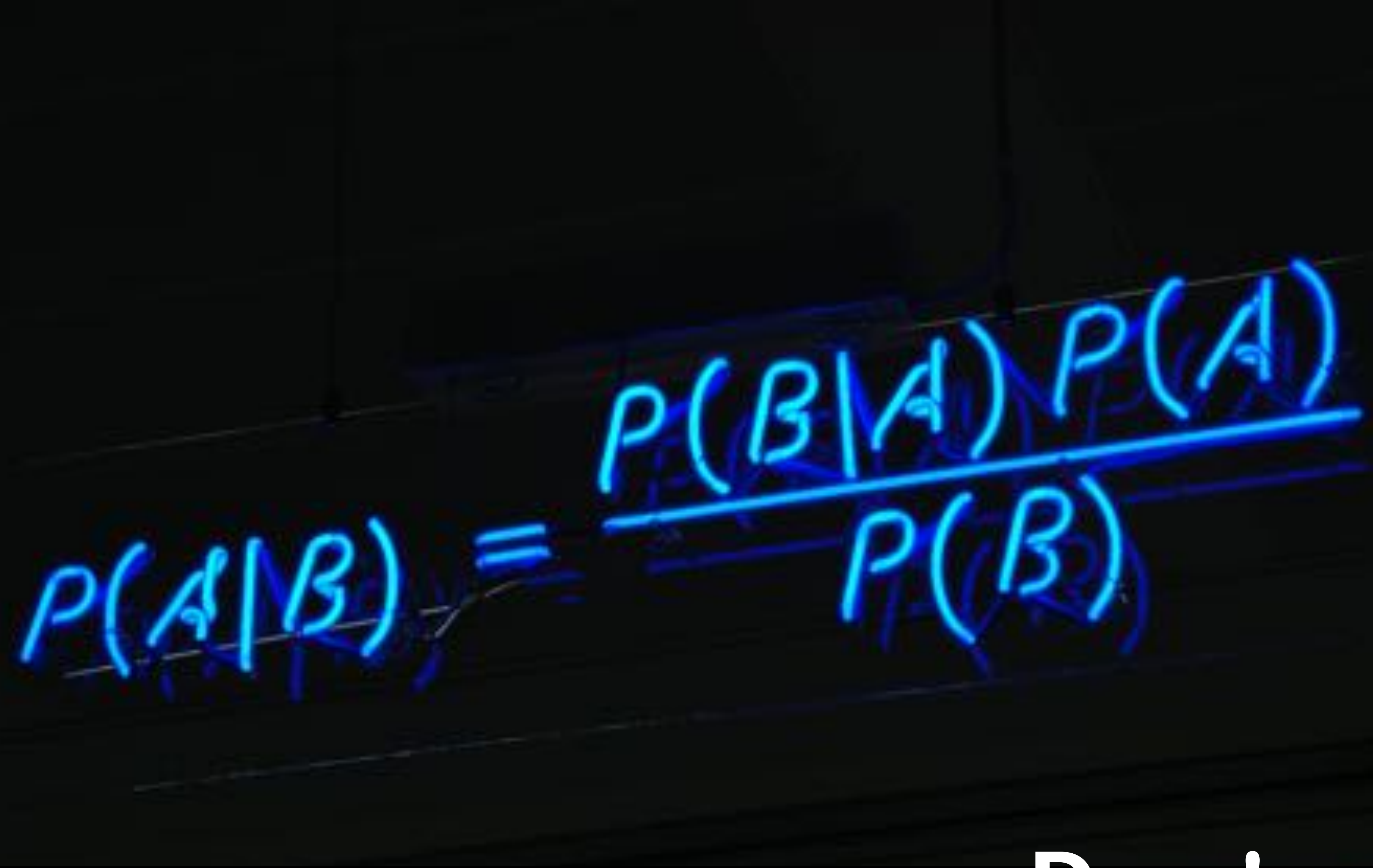
2.7 Beyond basics

JASP

Stan

… R

… to be added at a later stage!



Done!