

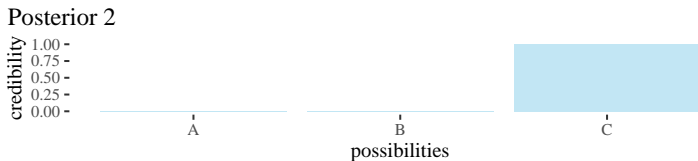
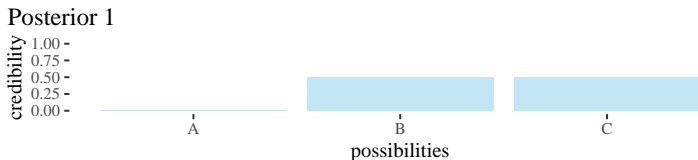
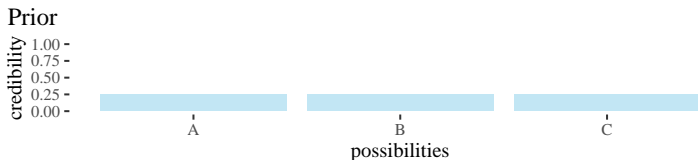
# Intro to Bayesian Thinking

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# Sherlock's naivete

## A rather unhelpful piece of advice

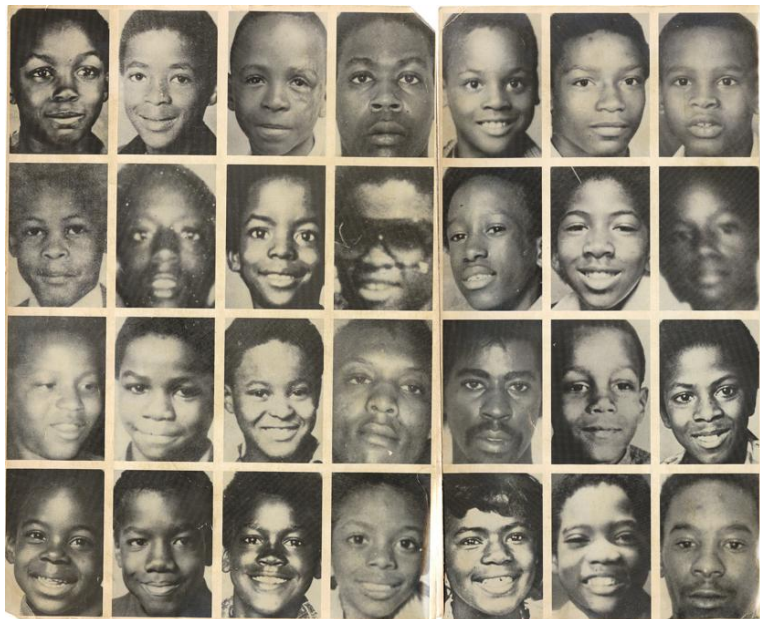
"...when you have eliminated the impossible, whatever remains, however, improbable, must be the truth."



# Trouble in paradise

- Data have only probabilistic relations to hypotheses  
*Many people may have similar footprints*
- Measurements only probabilistically narrow down the range  
*We mathematically can describe the footprints up to some level of precision*
- Association does not directly translate into causation  
*There may be various confounding factors explaining why people who received a given drug have lower blood pressure*
- There often is natural variation  
*The weight of a newborn baby may vary naturally due to genetics and environmental factors, rather than a specific cause*

## Wayne Williams case



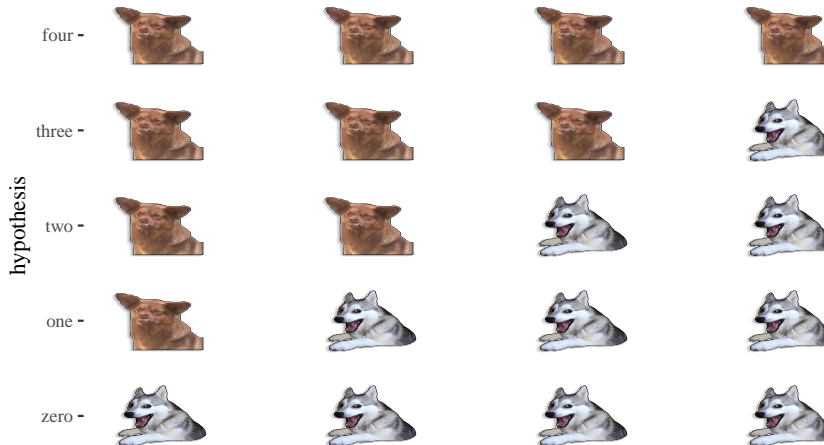
## Two items of evidence

- Dog hair evidence, random match probability (RMP) is about 0.0256.
- Human hair evidence, RMP is about 0.0253

Questions that come to mind?





















# Let's focus on dog fur

## Five chilaquil hypotheses























# Ways dogs could be (likelihoods)

Ways to observe (h,c,h)

				h	c	h	(h,c,h)		
hypothesis	four -					0	4	0	0
	three -					1	3	1	3
	two -					2	2	2	8
	one -					3	1	3	9
	zero -					4	0	4	0

# Updating with new observations

Ways to observe (h,c,h)

				h	c	h	(h,c,h)	h	(h,c,h,h)	
four -					0	4	0	0	0	0
three -					1	3	1	3	1	3
two -					2	2	2	8	2	16
one -					3	1	3	9	3	27
zero -					4	0	4	0	4	0



## Now with probabilities

p	ways0	ways0pr	ways1	ways1pr
0.00	0	0.00	0	0.0000000
0.25	3	0.15	3	0.0652174
0.50	8	0.40	16	0.3478261
0.75	9	0.45	27	0.5869565
1.00	0	0.00	0	0.0000000

## More dogs, Bayesian style!

$$P(C = c, H = h|\theta) = \frac{(c + h)!}{c!h!} \theta^c (1 - \theta)^h$$

$$P(A, B) = P(A|B)P(B)$$

$$H \sim \text{Binomial}(N, \theta)$$

$$\theta \sim \text{Uniform}(0, 1)$$

$$P(c, h, \theta) = P(c, h|\theta)P(\theta)$$

$$P(c, h, \theta) = P(\theta|c, h)P(c, h)$$

$$P(\theta|c, h)P(c, h) = P(c, h|\theta)P(\theta)$$

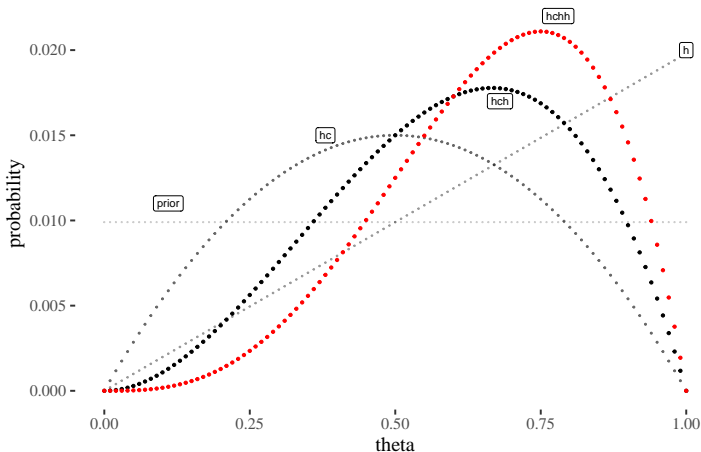
$$\underbrace{P(\theta|c, h)}_{\text{posterior}} = \frac{\overbrace{P(c, h|\theta)}^{\text{likelihood}} \overbrace{P(\theta)}^{\text{prior}}}{\underbrace{P(c, h)}_{\text{(average) data}}}$$

# The underlying mechanism

plausibility(hypothesis  $n$  | data)  $\propto$

ways hypothesis  $n$  can produce data  $\times$  prior plausibility of hypothesis  $n$

Proportion learning from flat prior



## Back to the fur testimony (grid approximation)

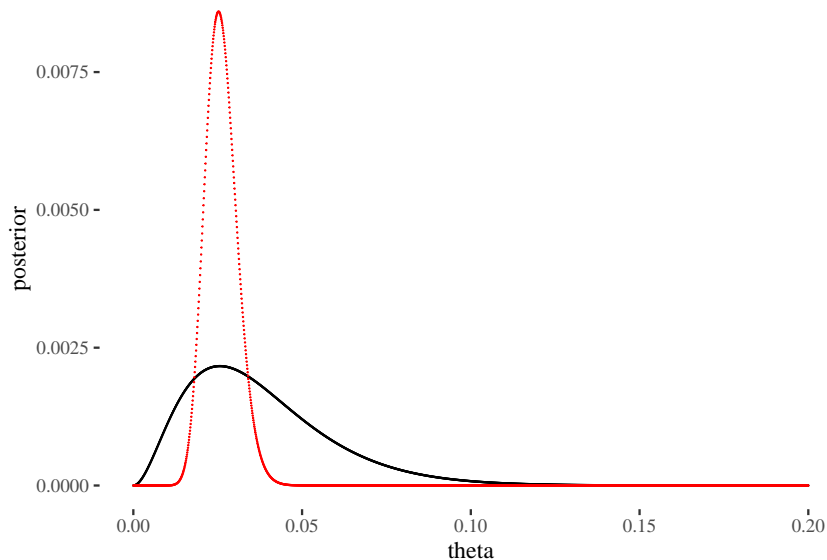
```
theta <- seq(0,1, length.out = 10001)
prior <- rep(1/10001,10001)

likelihoodDog <- dbinom(2,78, theta)
likelihoodHuman <- dbinom(29,1148, theta)

posteriorDogUnst <- likelihoodDog * prior
posteriorHumanUnst <- likelihoodHuman * prior

posteriorDog <- posteriorDogUnst/sum(posteriorDogUnst)
posteriorHuman <- posteriorHumanUnst/sum(posteriorHumanUnst)
```

## Back to the fur testimony (grid approximation)



# Steps of Bayesian data analysis

1. Identify the data, variables, predictors
2. Define a descriptive and appropriate model
3. Specify a prior distribution (over parameters)
4. Use Bayesian inference to reallocate credibility in light of the training data
5. Test whether the posterior predictions are reasonable as compared to validation data

## Build your first model!

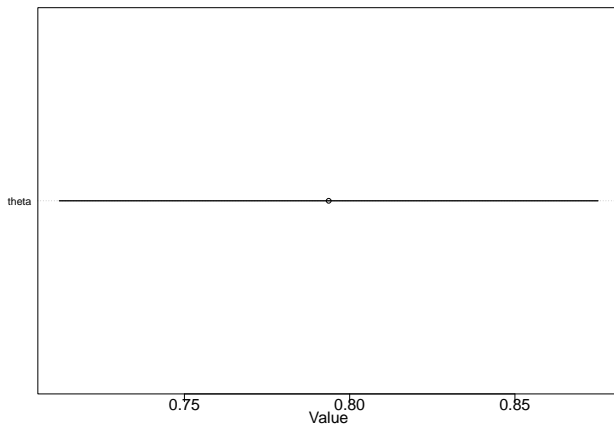
```
dogsModel <- quap(  
  alist(  
    h ~ dbinom( h + c , theta),  
    theta ~ dunif(0,1)  
  ) ,  
  data=list(h=50,c=13) )
```

# Build your first model!

```
precis(dogsModel)
```

```
##           mean          sd    5.5%    94.5%  
## theta 0.7936496 0.05098465 0.7121663 0.8751329
```

```
par(cex.axis=1.5, cex.lab=1.5)  
plot(precis(dogsModel))
```





# Liar detectors

## The task

Out of 100 suspects, 10 are innocent

Polygraph sensitivity ( $P(+|T)$ ) and specificity ( $P(-|F)$ ) are 70%

A suspect is polygraph-positive

So what?

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So what?

## Population considerations

- Out of 10 000 suspects, 1000 will be guilty, 9 000 will not
- Out of 1000 guilty, 700 will be positive, out of 9 000 innocent, 2700
- So out of 2700+700 positive, 700 will be guilty. That's around 20.5%.

## Liar detectors

```
pos_if_g = .7
pos_if_ng = .3
g = .1

pos = ( pos_if_g * g + pos_if_ng * (1-g) )

g_if_pos = ( pos_if_g * g ) / pos

g_if_pos

## [1] 0.2058824
```

# Signal detection and why data can't save us

## Simplified structure of the goal of science

- some binary state is hidden
- we observe imperfect hints
- we use Bayes to learn

## Simplified assumptions

- sensitivity is .95
- false positive rate is .05
- base rate: most hypotheses are false, with  $pr = .01$

## A simplified observation

The posterior is only .16.