Bayes' rule

$$
\begin{aligned}
& \operatorname{Pr}(B, D)=1 / 5 \\
& P(B) P(D \mid B)=\left(\frac{8}{5}\right)\left(\frac{1}{3}\right)=\frac{1}{5} \\
& p(D) p(B \mid D)=\left(\frac{1}{5}\right)\left(\frac{E}{5}\right)=\frac{1}{5} \\
& p(D) P(B \mid D)=p(B) p(D \mid B) \\
& P(B \mid D)=\frac{p(B) p(D \mid B)}{P(D)} \\
& \text { Bayes; Rule }
\end{aligned}
$$

$\{$ total $\underset{\substack{\text { marginal } \\ \text { nconlifional }}}{ }$ Probability of "Dotted" (unconditional $\frac{1}{2}=3 / 10+2 / 10$


## Bayes' rule (cont.)

$$
\begin{aligned}
\operatorname{Pr}(B \mid D) & =\frac{\operatorname{Pr}(B) \operatorname{Pr}(D \mid B)}{\operatorname{Pr}(D)} \\
\rho(B \mid D) & =\frac{\operatorname{Pr}(D, B)}{\operatorname{Pr}(D, B)+\operatorname{Pr}(D, W)}
\end{aligned}
$$

$\leftarrow$ sum
over
$\operatorname{Pr}(D)$ is the marginal probability of being dotted To compute it, we marginalize over colors

$$
p(\omega \mid D)=\frac{p(D, \omega)}{p(D, B)+\sigma(D, \omega)}
$$

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$$
p(B \mid D)+p(w \mid D)=\frac{p(D, B)+p(D, w)}{p(D, B)+p(D, w)}=1
$$

## Marginal (total) probabilities

$$
\begin{aligned}
& \text { B W }
\end{aligned}
$$

## Bayes' rule (cont.)

$$
\begin{aligned}
& \operatorname{Pr}(B \mid D)=\frac{\operatorname{Pr}(B) \operatorname{Pr}(D \mid B)}{\operatorname{Pr}(D, B)+\operatorname{Pr}(D, W)} \\
& \quad=\frac{\operatorname{Pr}(B) \operatorname{Pr}(D \mid B)}{\frac{\operatorname{Pr}(B) \operatorname{Pr}(D \mid B)+\operatorname{Pr}(W) \operatorname{Pr}(D \mid W)}{P}} \\
& \quad=\frac{\operatorname{Pr}(B) \operatorname{Pr}(D \mid B)}{\sum_{\uparrow \in\{B, W\}} \operatorname{Pr}(\theta) \operatorname{Pr}(D \mid \theta)} \leftarrow
\end{aligned}
$$

## Bayes' rule in statistics



## Simplest paternity example

 child's genotype:Aa mother's genotype:@ possible fathers| Possibilities | $\left(\theta_{1}\right)$ | $\left(\theta_{2}\right)$ | Row sum |
| :---: | :---: | :---: | :---: |
| Genotypes | (AA) | Aà | -- |
| Prior | $\frac{1}{2}$ | $\frac{1}{2}$ | 1 |
| Likelihood | 1 | $\frac{1}{2}$ | - |
| Likelihood $\times$ <br> Prior | $\frac{1}{2}$ | $\frac{1}{4}$ | $\frac{3}{4}$ |
| Posterior | $\frac{2}{4}$ | $1 / 3$ | 1 |

## Likelihood vs. Probability



## The prior can be your friend

Suppose the test for araredisease has the following
is true and false positive probabilities:


Suppose further I test positive for the disease. How worried should I be?

It is very tempting to (mis)interpret the likelihood as a posterior probability and conclude "There is a $100 \%$ chance that I have the disease."

## The prior can be your friend



Thus, the odds against having the disease are actually 10000 to 1!

## Bayes' rule: continuous case



## If you had to guess...



Not knowing anything about my archery abilities, draw a curve representing your view of the chances of my arrow landing a distance $d$ from the center of the target (if it helps, I'm standing 50 meters away from the target)

## Case 1: assume I have talent



Case 2: assume I have a talent for missing the target!


## Case 3: assume I have no talent




## Probability density

 0.8 curve

A probability density curve is scaled so that the value of this integral (i.e. the total area) equals 1.0



## Usually there are many parameters...

A 2-parameter example
Prior probability
Likelihood density


Posterior probability density

An analysis of 100 sequences under the simplest model (JC69) requires (197) pranch length parameters. The denominator is a 197 -fold integral in this case! Now consider summing over all possible tree topologies!

It would thus be nice to avoid having to calculate the marginal probability of the data...

## Markov chain Monte Carlo (MCMC)



For more complex problems, we might settle for a good approximation
to the posterior distribution

## MCMC robot's rules



## (Actual) MCMC robot rules



