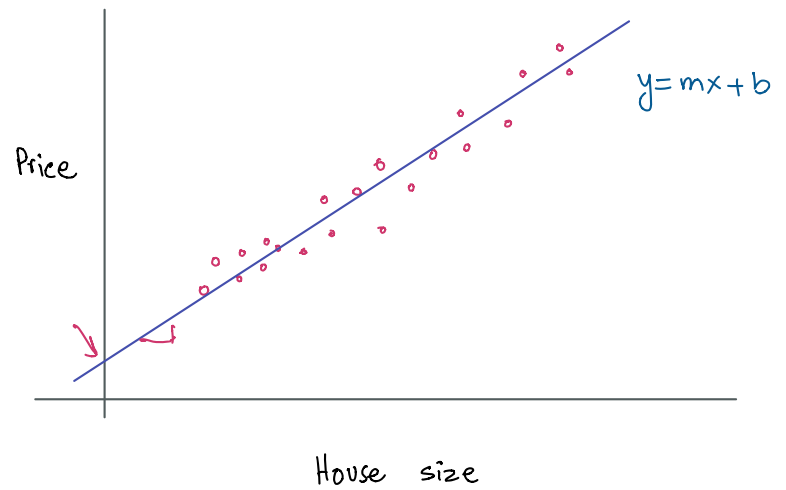


Predicting house prices

To find the relation between
 X and Y , we need
 m and b



Formulae:

$$b = \frac{\sum y \sum x^2 - \sum x \sum xy}{n \sum x^2 - (\sum x)^2}$$

$$m = \frac{n \sum xy - \sum x \sum y}{n \sum x^2 - (\sum x)^2}$$

Regression

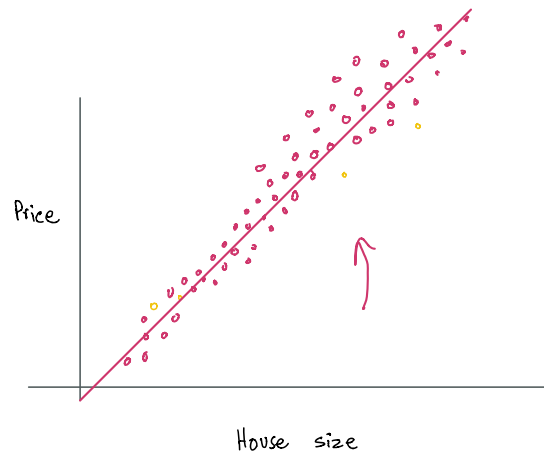
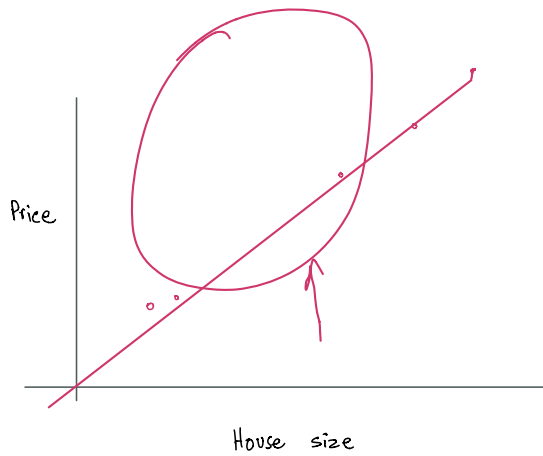
	x	y	xy	x^2	y^2
$\Sigma =$	<u>...</u>	<u>...</u>	<u>...</u>	<u>...</u>	<u>...</u>

We do something very similar in machine learning!

But!

m and b are both "point estimates".

They say nothing about the uncertainty!



↗
The problem is $\{m_1, b_1\}$ here and $\{m_2, b_2\}$ here
are equally "confident".

This is a major problem in classical statistics!

Model parameters are learned through observations alone
and they are point estimates!

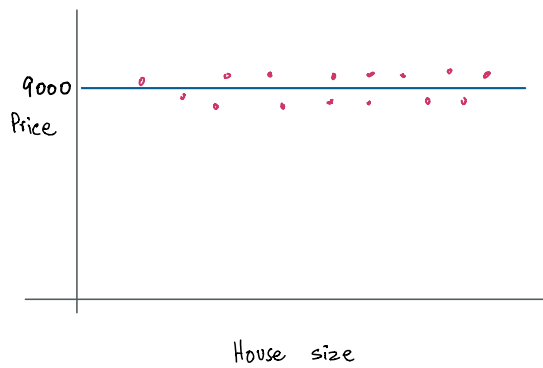
(multiverse shenanigans)
p-value

So, what's the solution?

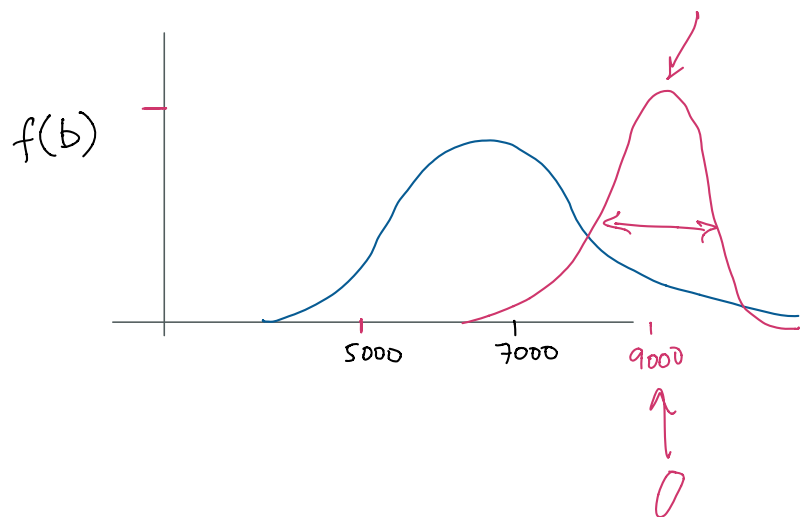
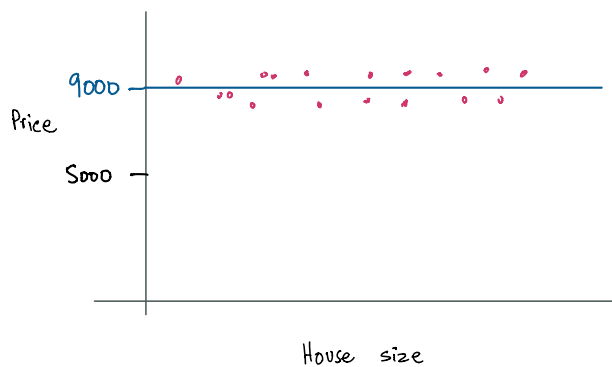
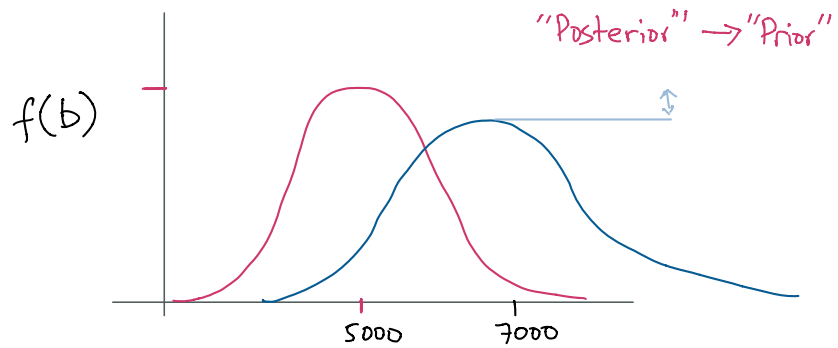
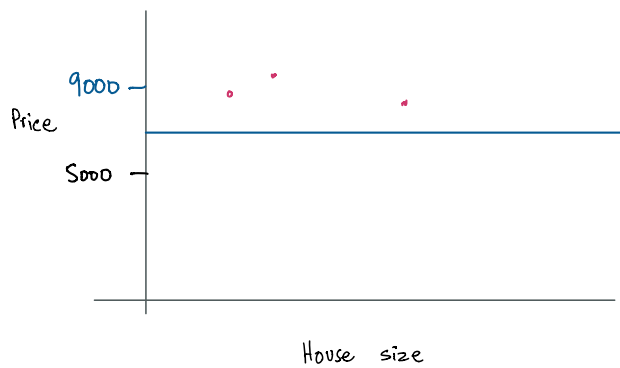
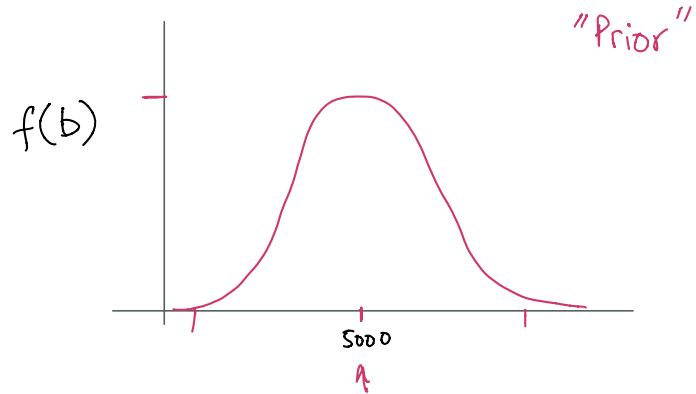
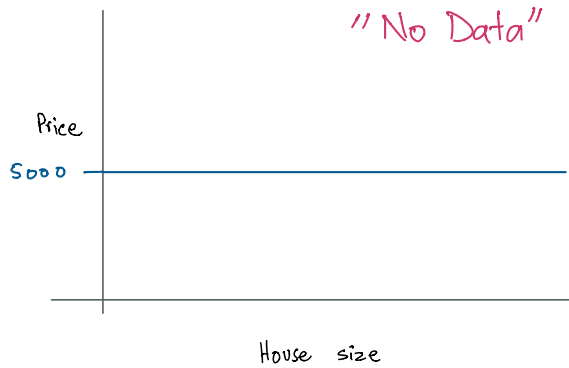
Bayesian inference!

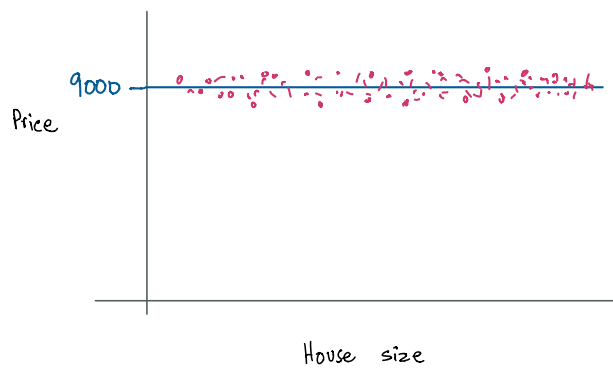
- Start with a prior distribution
- Update prior to posterior distribution based on evidence

Let's ignore the slope for now and focus on "b"

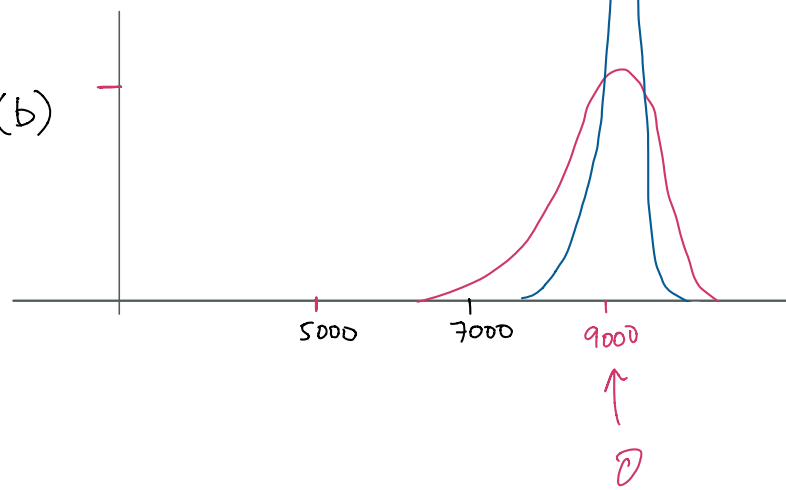


Our data will eventually look like this



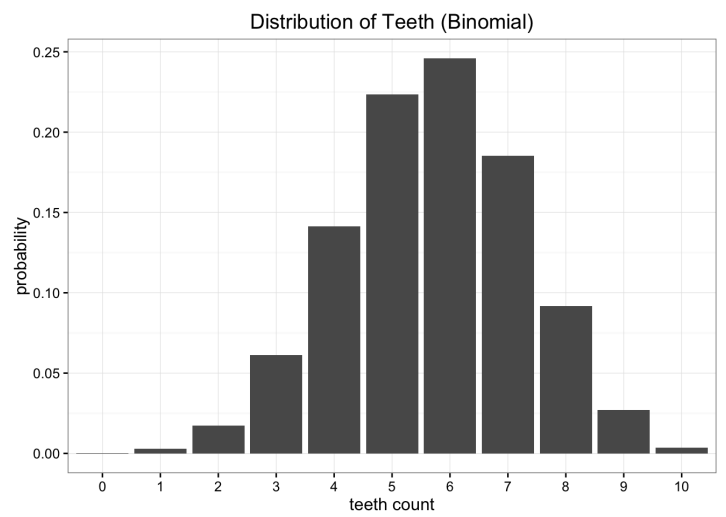
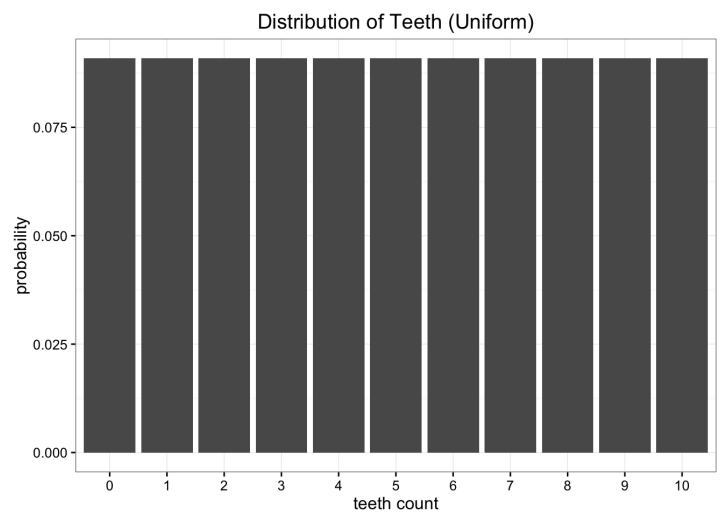
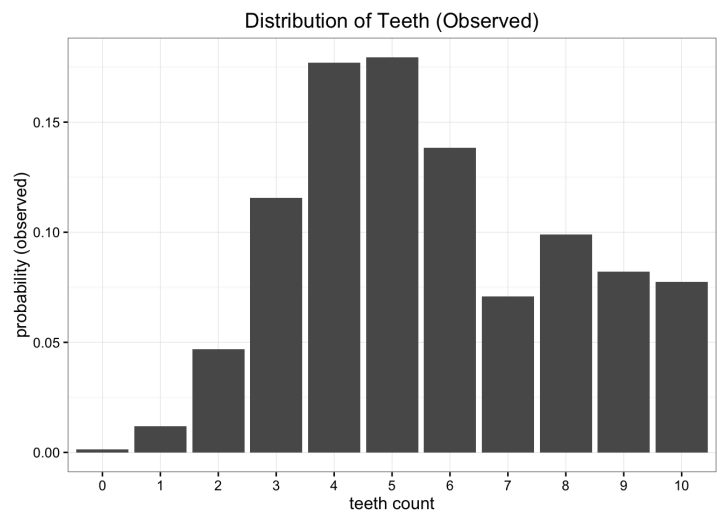


$f(b)$



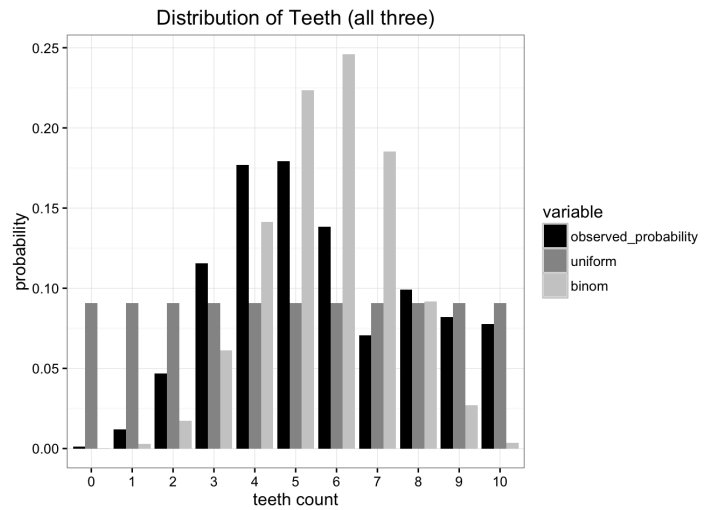
Notice that :

"b" still has a distribution. We have the uncertainty quantified — at all times!



$$H = - \sum_{i=1}^N p(x_i) \cdot \log p(x_i)$$

neg. info



$-\lg p(x) \rightsquigarrow$ info in p
 $-\lg q(x) \rightsquigarrow$ info in q

$$\sum_{i=1}^N p(x_i) \left[-\lg q(x_i) - (-\lg p(x_i)) \right]$$

(Expected)
information difference (loss)

$$= \sum_i p(x_i) \left[\lg p(x_i) - \lg q(x_i) \right]$$

$$D_{KL}(p||q) = \sum_{i=1}^N p(x_i) \cdot \log \frac{p(x_i)}{q(x_i)}$$

"Expected info difference".

$$D_{kl}(\text{Observed} || \text{Uniform}) = 0.338$$

$$D_{kl}(\text{Observed} || \text{Binomial}) = 0.477$$

(closer)