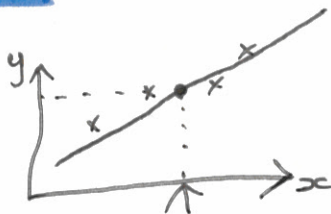


# Bayesian Regression

Previously:

fit functions



$f(x)$  is a single guess of what the output will be.

For classification we fitted

$P(y | \underline{x})$  by max likelihood.

For regression we can also write down a probabilistic model

$$P(y | \underline{x}) = N(y; f(\underline{x}; \underline{w}), \sigma^2)$$

eg  $\underline{w}^T \underline{x}$

For now  
assume the  
same for each  
example.

↑  
noise  
variance  
or  $\sigma_n^2$   
"noise"

## Maximum Likelihood

Minimize negative log-likelihood

$$-\log p(\underset{\uparrow}{\mathbf{y}} | \mathbf{X}, \underline{w}) = -\sum_n \log p(y^{(n)} | \underline{x}^{(n)}, \underline{w})$$

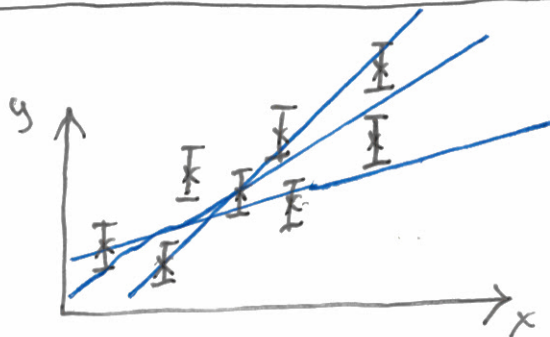
$\{y^{(n)}\}$

$$= \frac{1}{2\sigma^2} \sum_n \left[ (y^{(n)} - f(\underline{x}^{(n)}; \underline{w}))^2 \right] + \sum_n \left[ \frac{1}{2} \log(2\pi\sigma^2) \right]$$

$$= \frac{1}{2\sigma^2} \underbrace{\sum_n \left[ (y^{(n)} - f(\underline{x}^{(n)}; \underline{w}))^2 \right]} + \frac{N}{2} \log(2\pi\sigma^2)$$

That is Minimize sum of squares.

We are uncertain about the model given data



$\downarrow \sigma$   
standard  
deviation  
of noise

We use probability distributions to express beliefs about parameters

For example:


The "posterior distribution"

$$p(\underline{w} | \underbrace{\text{Data}}_{\{y, X\}}) = \frac{P(\text{Data} | \underline{w}) P(\underline{w})}{P(\text{Data})}$$

$$\propto P(\text{Data} | \underline{w}) \underbrace{P(\underline{w})}_{\text{"Prior beliefs"}}$$

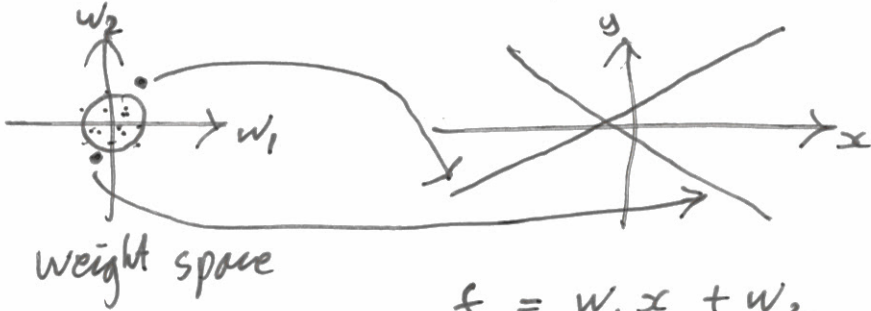
## Bayes' Rule

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

$$P(A|B) \underbrace{P(B)} = P(B|A) P(A)$$


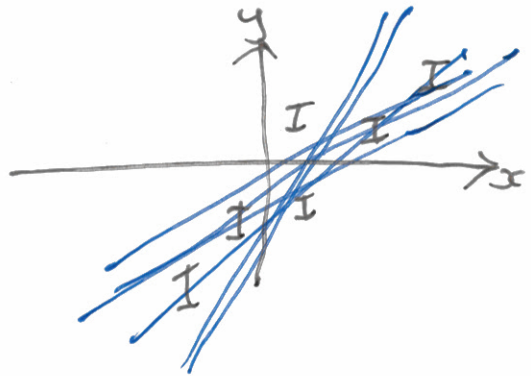
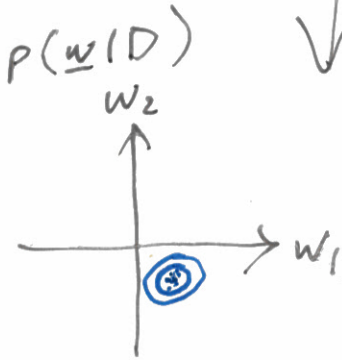
# Prior distribution

$$P(\underline{w}) = N(\underline{w}; 0, \sigma_{\text{prior}}^2)$$



$$f = w_1 x + w_2$$

Bayes Rule  
updates using  
the data



## Computing the Posterior

For linear regression

$\{y, X\}$

$$p(\underline{w} | D) \propto p(\underline{w}) p(D | \underline{w})$$

$$\propto N(\underline{w}; 0, \sigma_{\text{prior}}^2) N(\underline{y}; \underbrace{\Phi \underline{w}}_{\underline{w}}, \sigma^2 \mathbf{I})$$

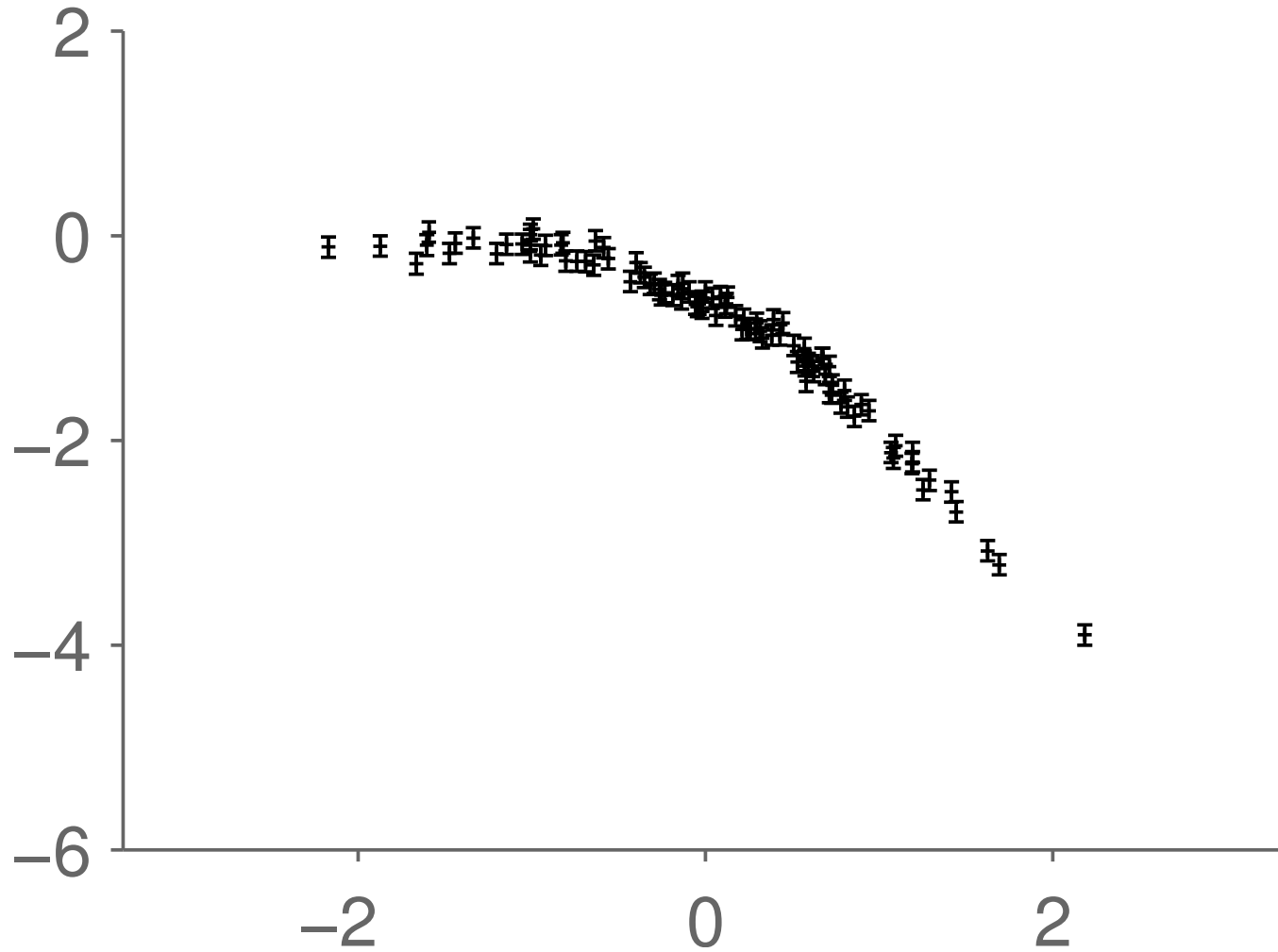
$f(\underline{x}, \underline{w})$   
at each  
input.

Is Gaussian:

$e^{-}$  some quadratic in  $\underline{w}$

We find linear & quadratic coeff's of  
 $\underline{w} \Rightarrow$  mean & covariance.

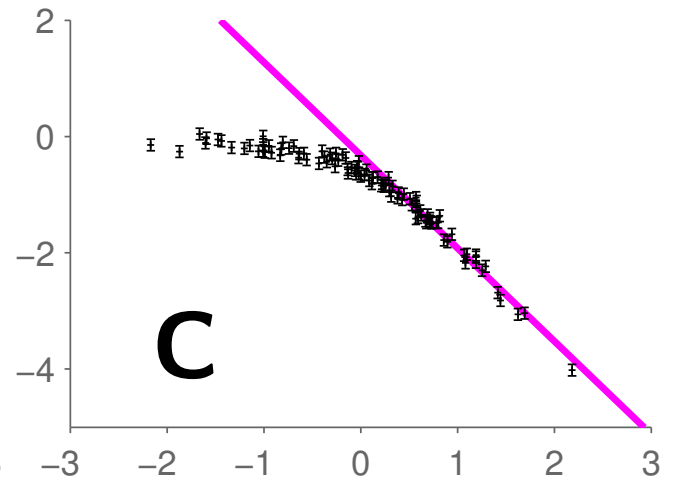
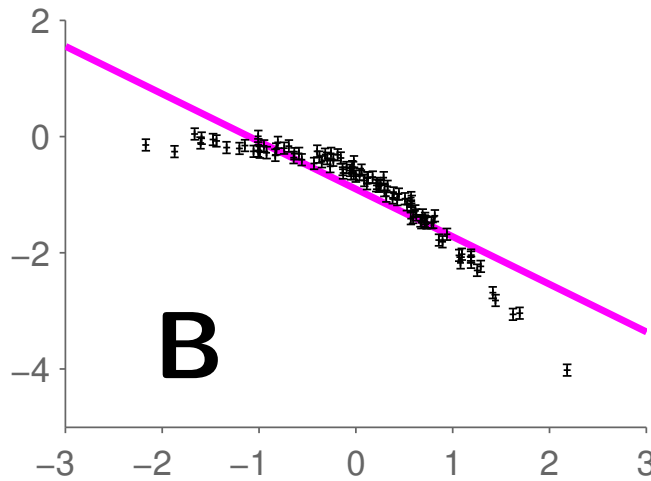
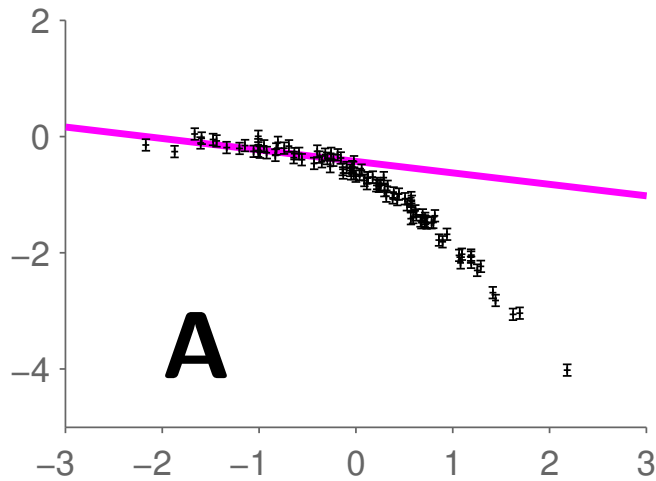
# Model mismatch



What will Bayesian linear regression do?

# Quiz

Given a (wrong) linear assumption, which explanations are typical of the posterior distribution?



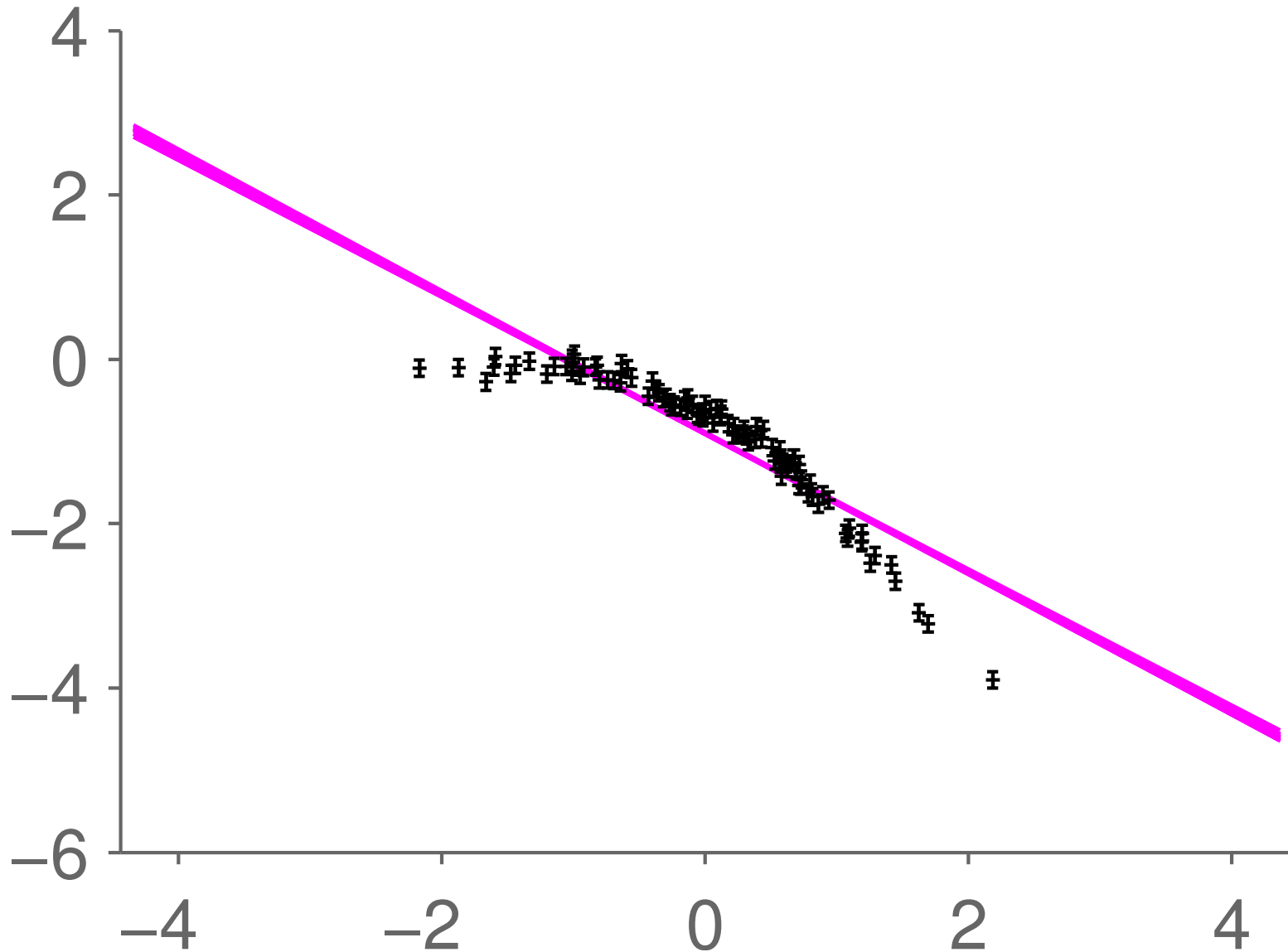
**D** All of the above

**E** None of the above

**Z** Not sure



# 'Underfitting'



Posterior *very* certain despite blatant misfit. Peaked around least bad option.