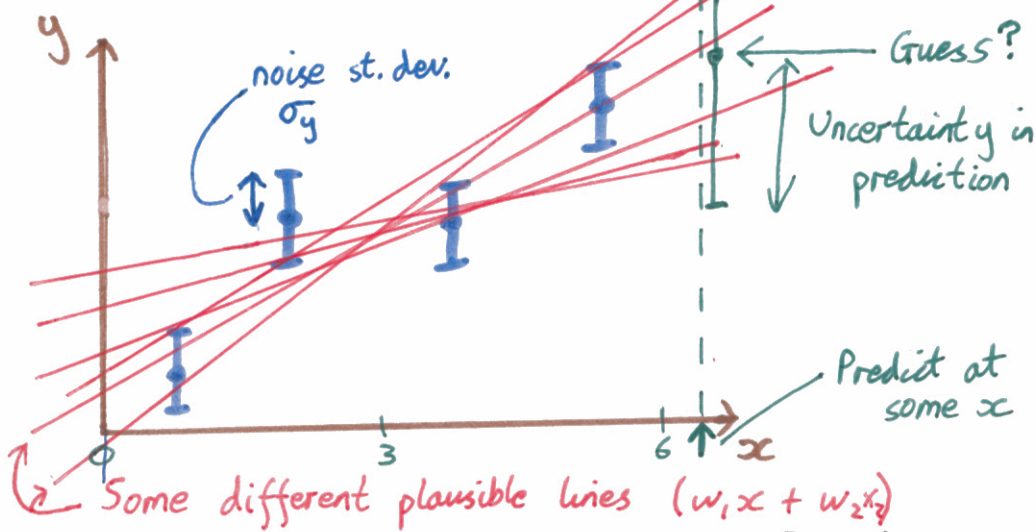


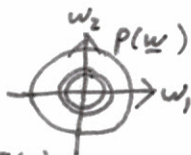
# Bayesian Linear Regression



$$\underline{w}^T \underline{x}, \text{ with } x_2 = 1$$

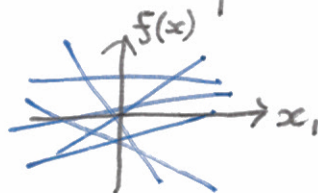
Prior (Example)  $p(\underline{w}) = N(\underline{w}; \underline{0}, \sigma_w^2 \mathbf{I})$

$\Rightarrow$  Broad range functions plausible before see data

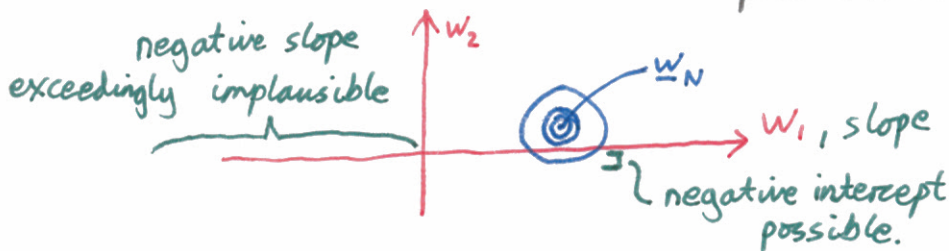


Posterior  $\sim$  "data"  $\times$  likelihood

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

$$= N(\underline{w}; \underline{w}_N, V_N)$$


(For Gaussian prior and noise)



# Mid-Semester Survey

Thanks for the useful responses!

tinyurl.com/

mlpr 2018 mss

(I will reply next week.)

---

Assignment 2

Due 20 Nov  
(3 days before MLP)

Shouldn't take that long.

→ Do it next week?

## Compute posterior

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

↑  
Data,  $y$

Assume  $X$  known.

$p(y | \underline{w}, X)$

for regression

$$\propto N(\underline{w}; \underline{0}, \sigma_w^2 \mathbf{I}).$$

$$N(y; \underline{f}, \sigma_y^2 \mathbf{I})$$

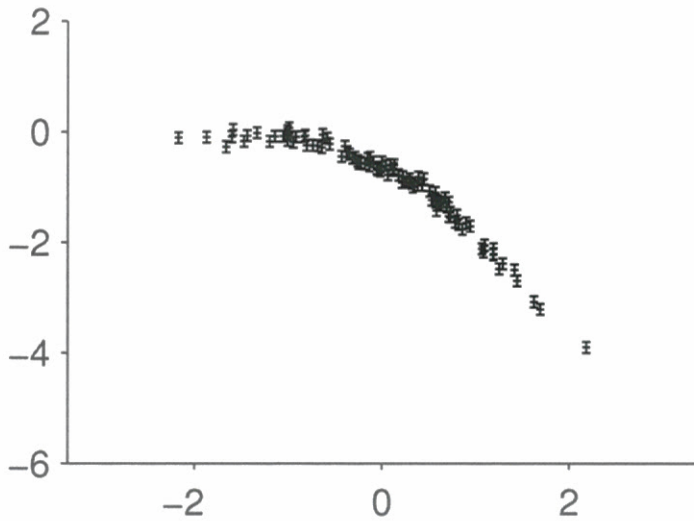
↑  
 $\Phi \underline{w}$

$$\propto e^{-\frac{1}{2}(\text{some quadratic } \underline{w})}$$

$$\propto N(\underline{w}; \underline{\quad}, \underline{\quad})$$

Linear Algebra Exercise  
(Cf Tut 2 Q2)

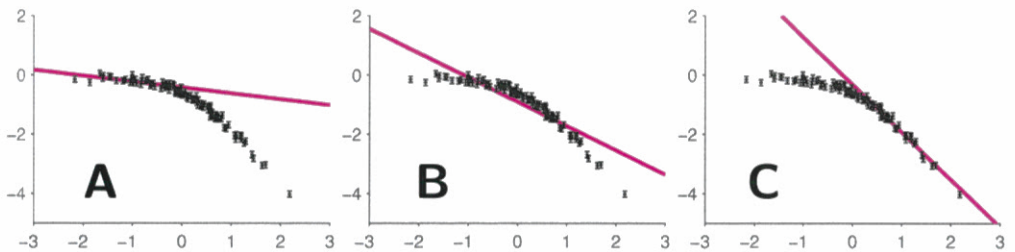
# Model mismatch



What will Bayesian linear regression do?

# Quiz

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

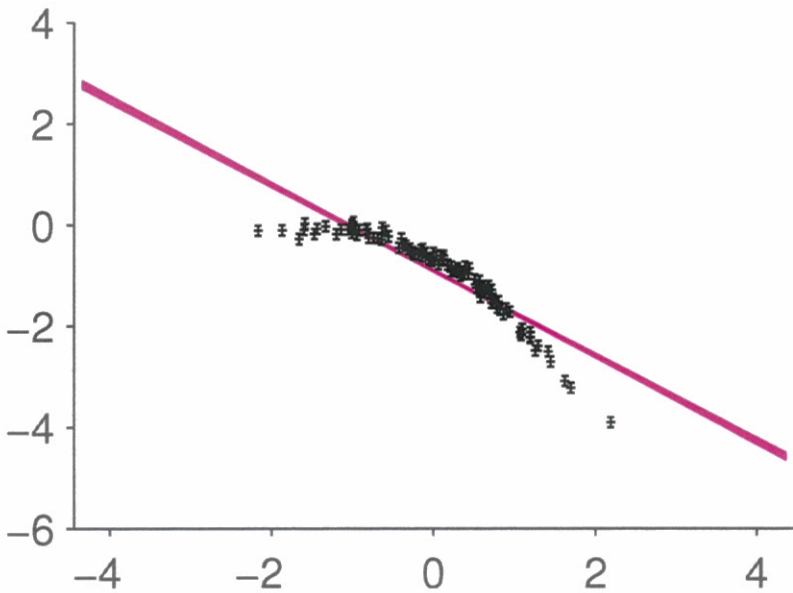


**D** All of the above

**E** None of the above

**Z** Not sure

# 'Underfitting'



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

### 3 cards

w | B

①

B | B

②

w | w

③

Picked 1 at random  
Way up is random

Observation  $x_1 = B$  (Black face)

Q)  $P(x_2 = w \mid x_1 = B)$ ?

↳ other side of same card

A)  $1/3$    B)  $1/2$    C)  $2/3$    D) Other

E) Don't know.

What not to do

$$P(x_2 = w | x_1 = B) = \frac{P(x_1 = B | x_2 = w) P(x_2 = w)}{P(x_1 = B)}$$

Don't know

First Step: write down model

Picked a card,  $c$ :

$$P(c) = \begin{cases} 1/3 & c=1 & w|B \\ 1/3 & c=2 & B|B \\ 1/3 & c=3 & w|w \end{cases}$$

Observed face 1:

$$P(x_1 = B | c) = \begin{cases} 1/2 & c=1 \\ 1 & c=2 \\ 0 & c=3 \end{cases}$$

Inference

$$P(c | x_1 = B) \propto p(x_1 = B | c) P(c)$$
$$\propto \begin{cases} 1/2 & c=1 \\ 1 & c=2 \\ 0 & c=3 \end{cases} = \begin{cases} 1/3 & c=1 \\ 2/3 & c=2 \end{cases}$$



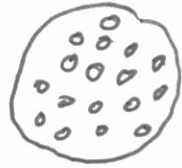
# Another example



6-sided  
Dice



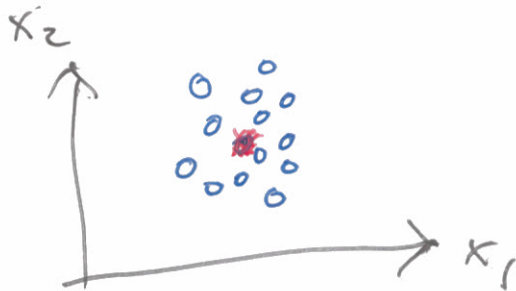
10-sided  
Dice



100-sided  
Dice

Pick random die

Roll it  $\rightarrow$  got an 8



## Making a Prediction

$$P(x_2 = w | x_1 = B) = \sum_{c \in \{1, 2, 3\}} P(x_2 = w, c | x_1 = B)$$

(Sum Rule)

$$= \sum_c P(x_2 = w | c, x_1 = B) P(c | x_1 = B)$$

(Product Rule)

$$= \underline{\underline{1/3}}$$

## Prediction for Linear Regression

$$p(y | \underline{x}, D) = \int p(y, \underline{w} | \underline{x}, D) d\underline{w}$$

(Sum rule)

$$= \int \underbrace{p(y | \underline{w}, \underline{x}, D)}_{N(y | \underline{w}^T \underline{x}, \sigma_y^2)} \underbrace{P(\underline{w} | D, \underline{x})}_{\text{Product Rule}}$$

For standard regression.