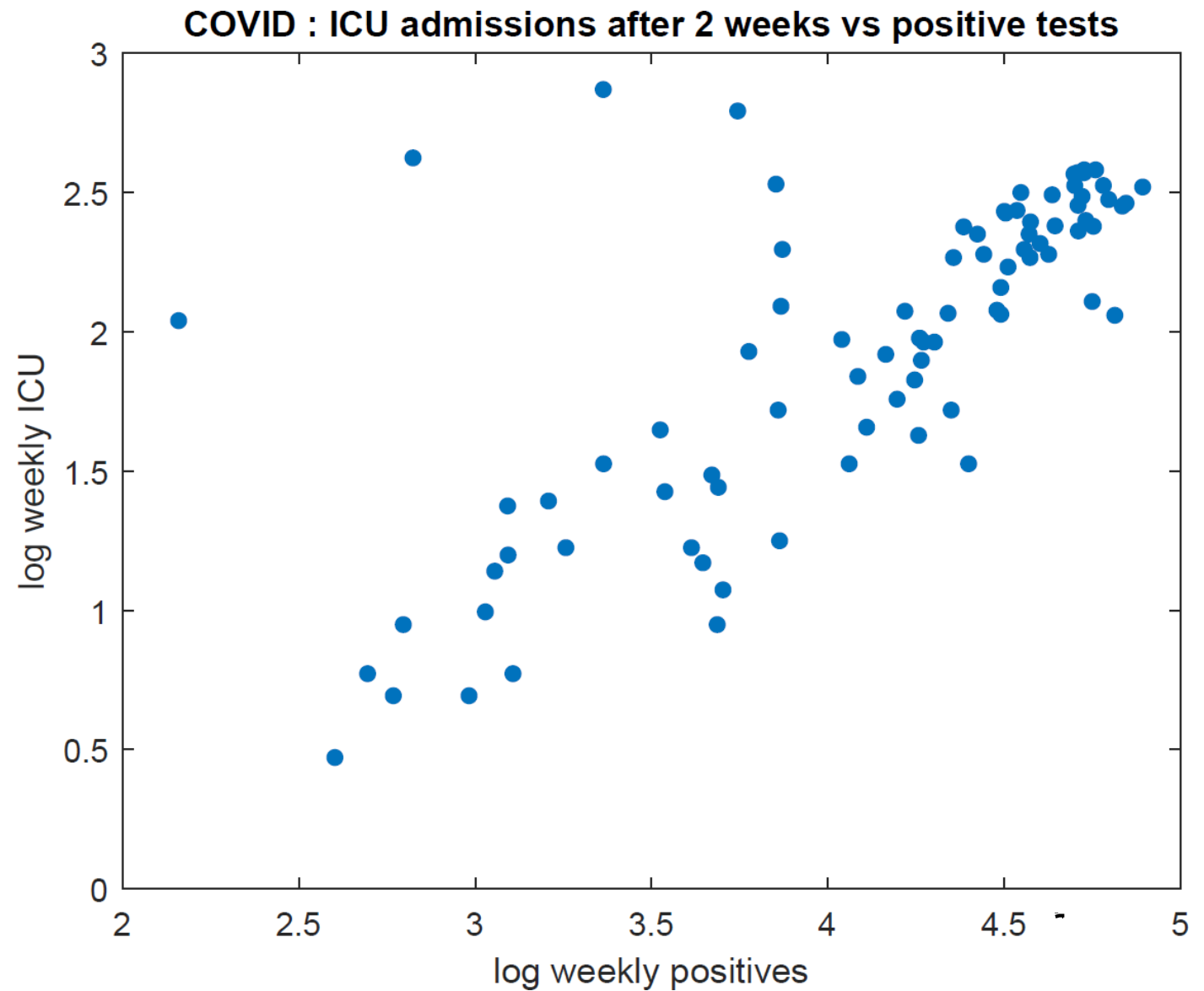


› Predict ICU admissions two weeks ahead based on positives



# Linear Regression

› Marco Loog

# Past, Present, Future

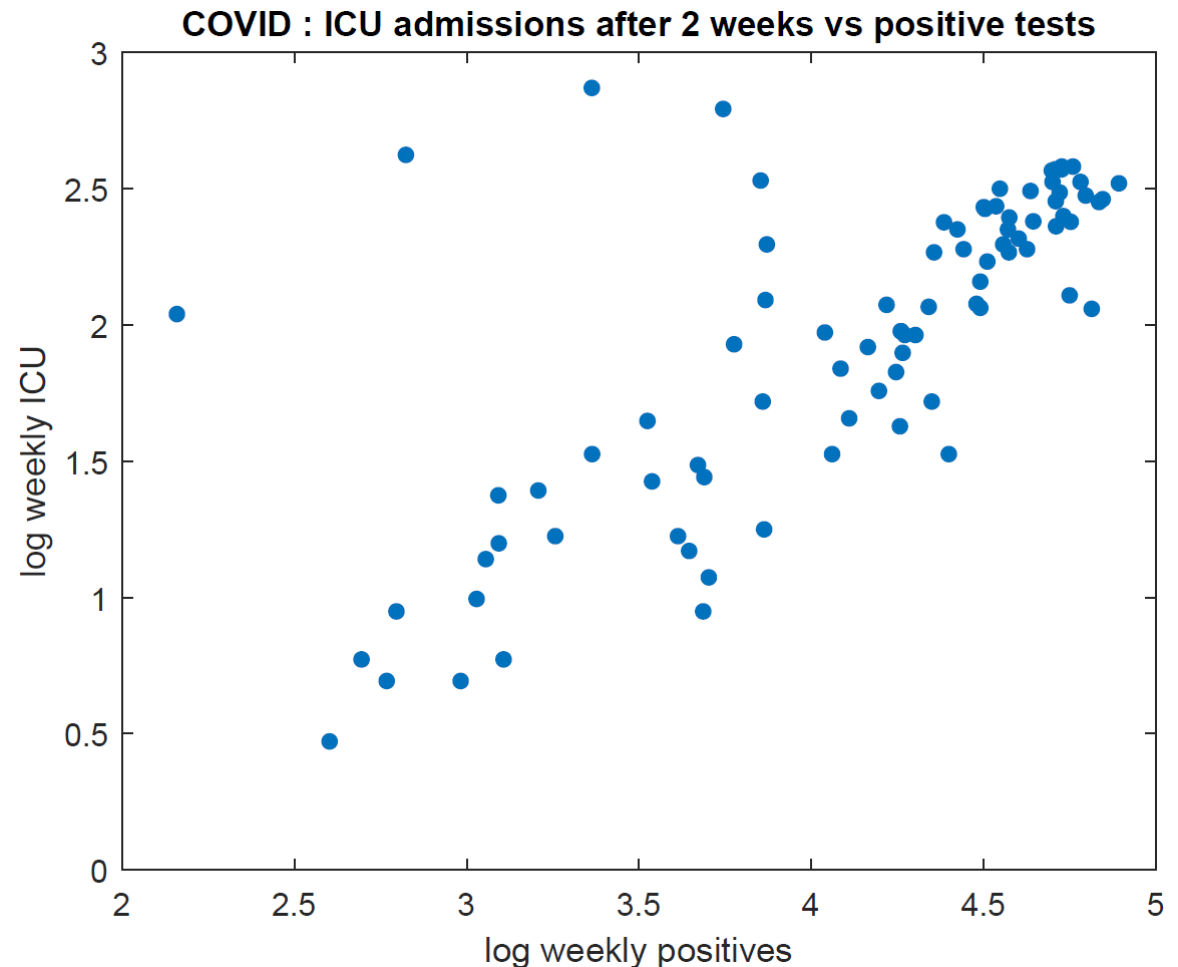
- › Previous focus largely on classification
- › Today linear regression
- › Tomorrow mainly classification again  
With a focus on linear classifiers

# Why Regression?

- › Other examples of prediction problems where you may not be interested in a class label?

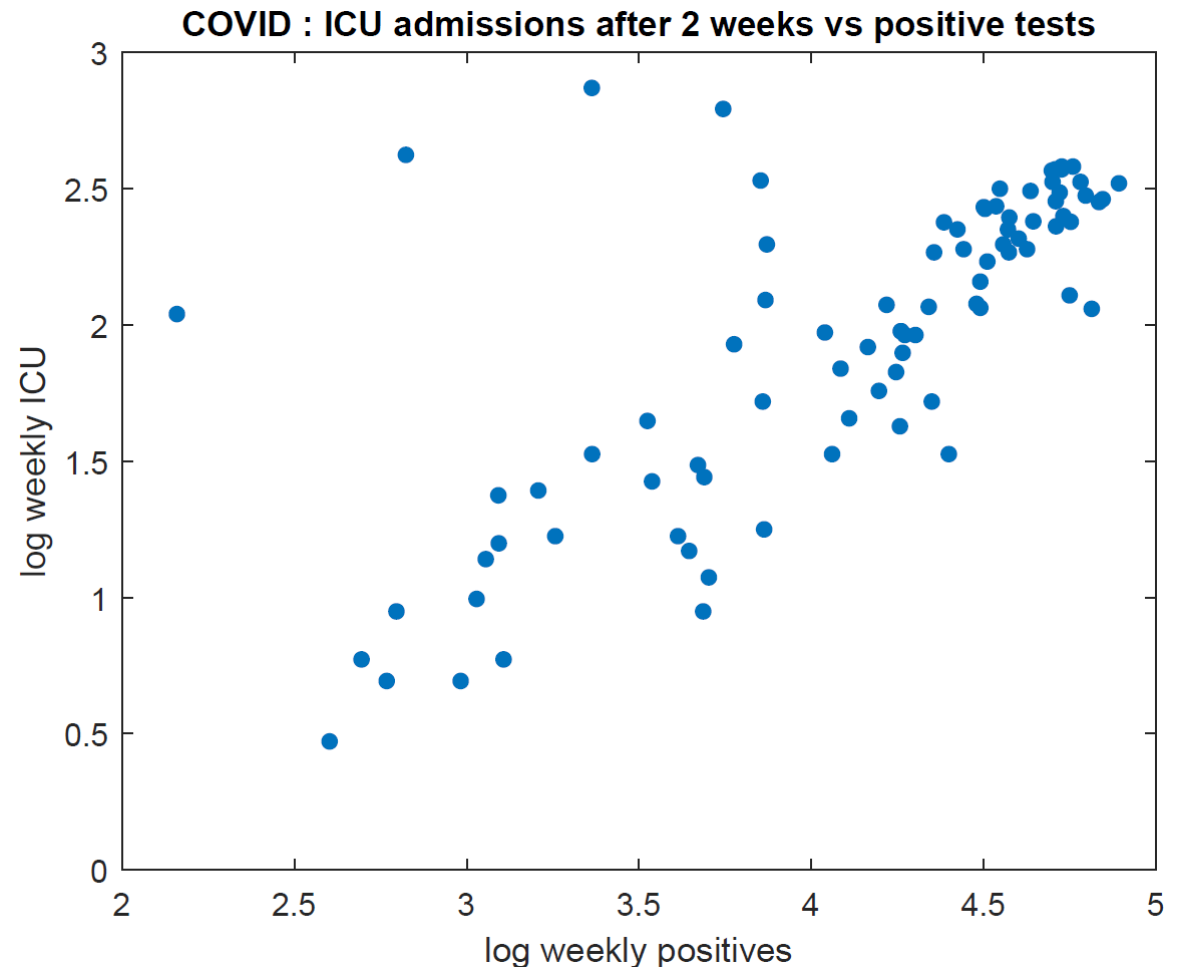
# Input-Output and Error Measure

- › Given input-output data
- › Function  $f(x)$
- › How to measure goodness of fit?



# Input-Output and Error Measure

- › Given  $p(x, y)$   
Distribution over  
input-output
- › Function  $f(x)$
- › How to calculate  
goodness of fit?

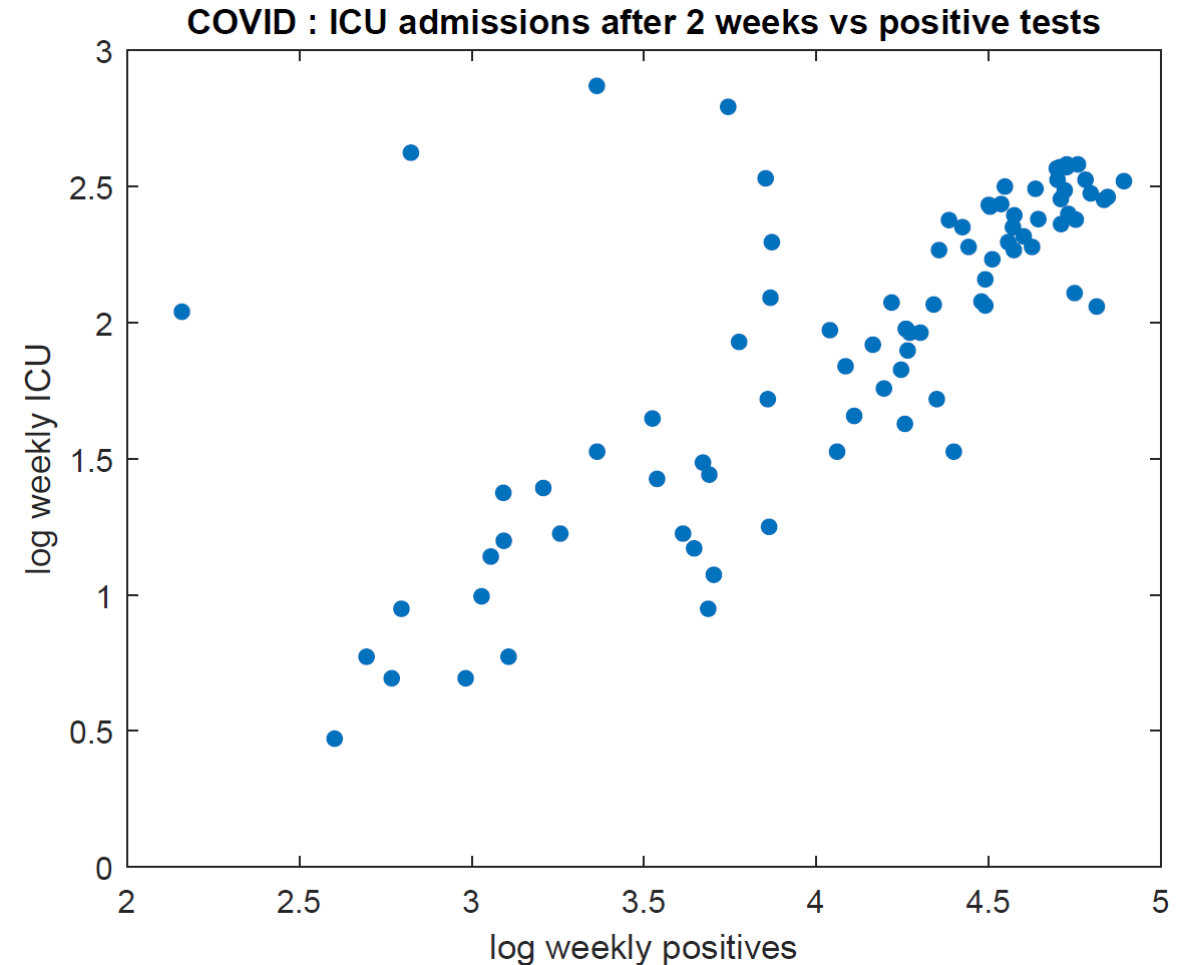


# Taking Squared Loss...

- › Risk of interest and “Bayes regression function”?  
I.e., what is the optimal solution given  $p(x, y)$ ?  
Consider a fixed  $x$  for this...

# Model Assumption

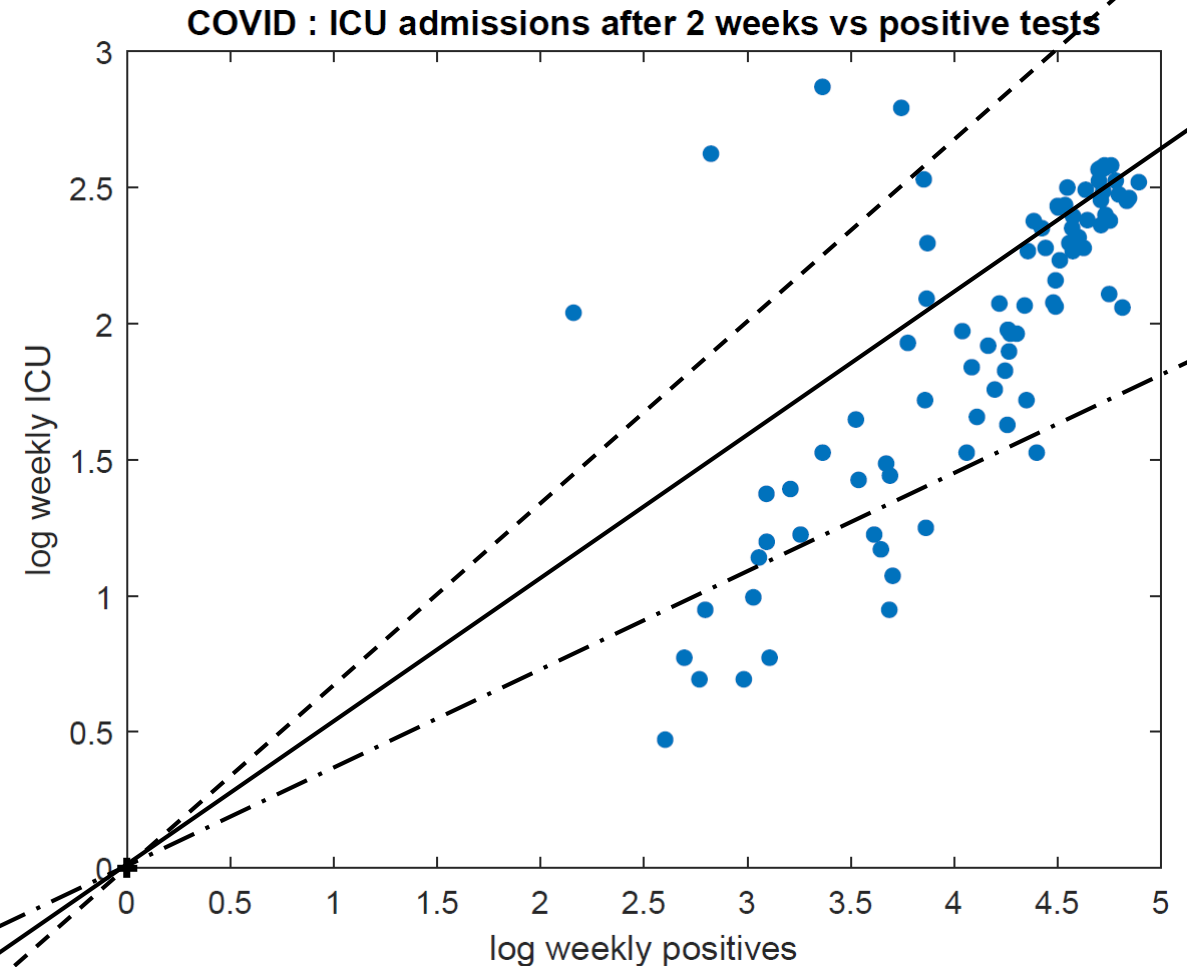
- › Given examples of (positives, admissions)  
input = positives  
output = admissions
- › What functions to consider?





# Ingredients

- › Model
  - Will look at linear models
- › Fitting function
  - Squared loss
  - Probabilistic



# So...

- › Regression aims to minimize expected squared loss

$$\int (f(x) - y)^2 p(x, y) dx dy$$

Other losses possible of course

- › We do not know  $p$
- › We need to assume a model for  $f$

# Least Squares Linear Regression

› Assuming linearity...

Given  $N$  iid input-output pairs  $(x_i, y_i)$

Find the  $w$  that minimizes

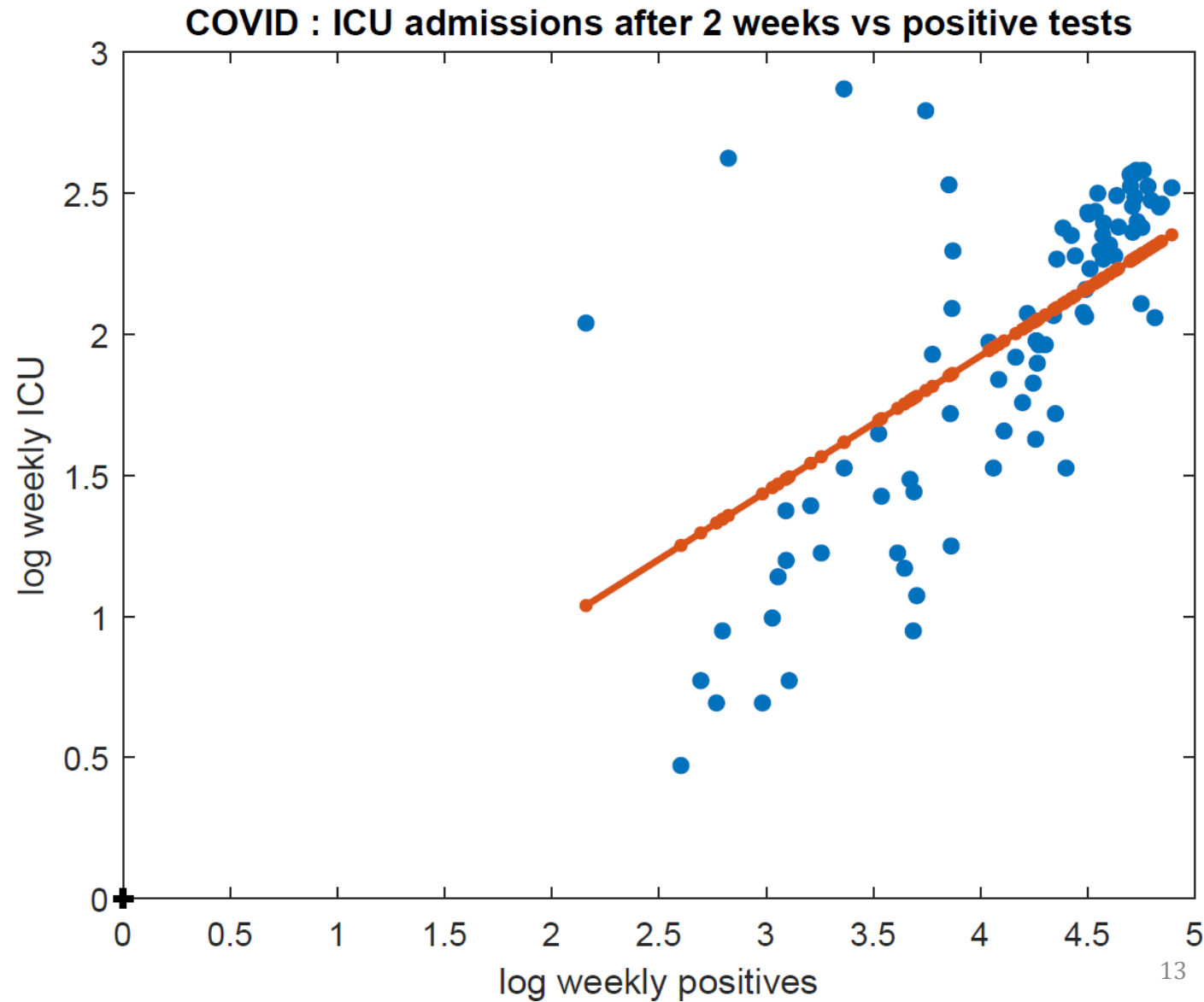
Note : input typically is multidimensional!

$$\sum_{i=1}^N (w^T x_i - y_i)^2 = \|Xw - Y\|^2$$

$$\sum_{i=1}^N (w^T x_i - y_i)^2 = \|Xw - Y\|^2$$

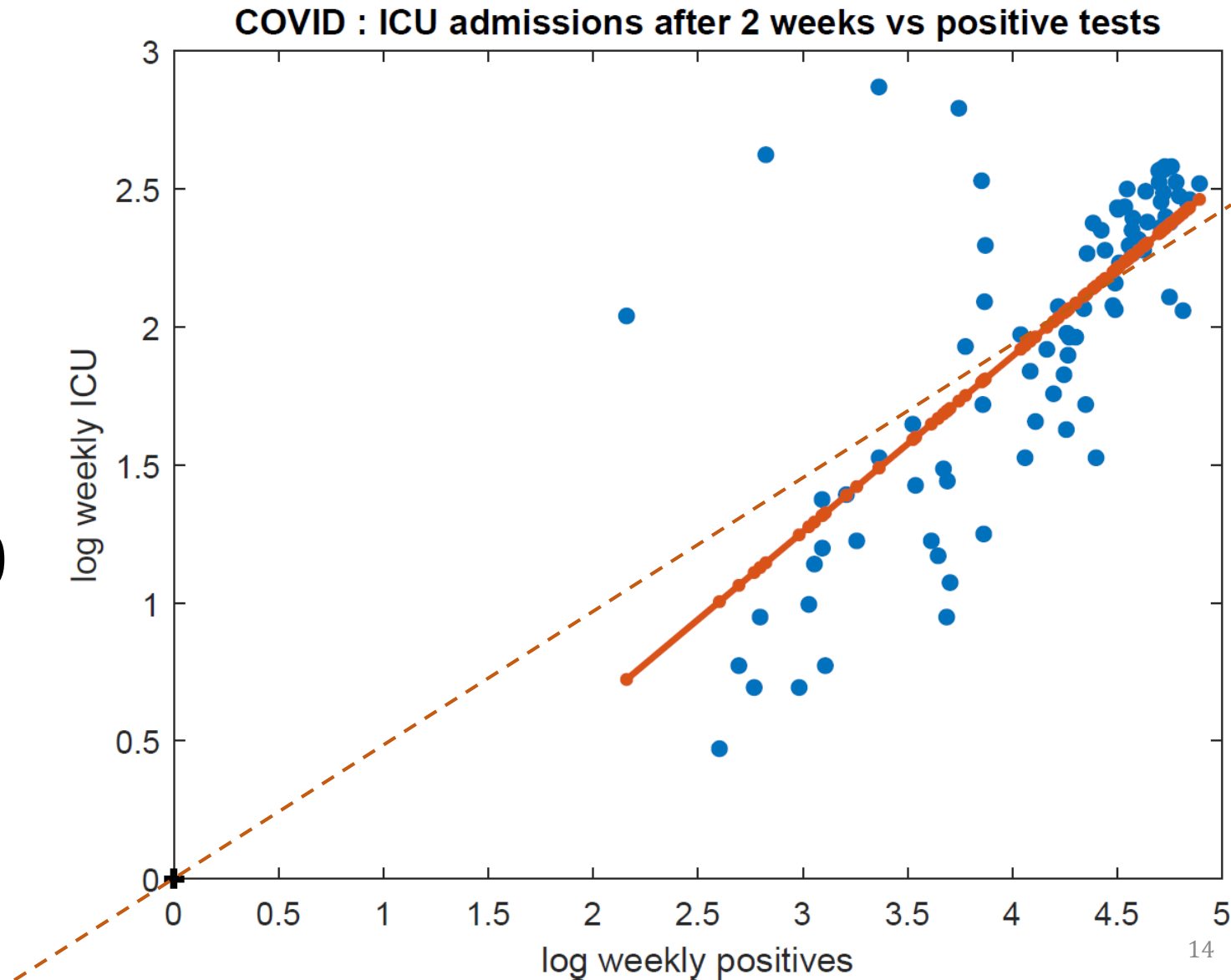
› Let's solve this for 1D inputs...

# On Our Running Example



# Note : Intercept / Bias

›  $w^T x$  always goes through 0 for input 0  
How do we fix this?



# Q? / Recap / Remainder

› Regression is for ordered / continuous outputs

$$\sum_{i=1}^N (w^T x_i + w_0 - y_i)^2$$

Probabilistic extension

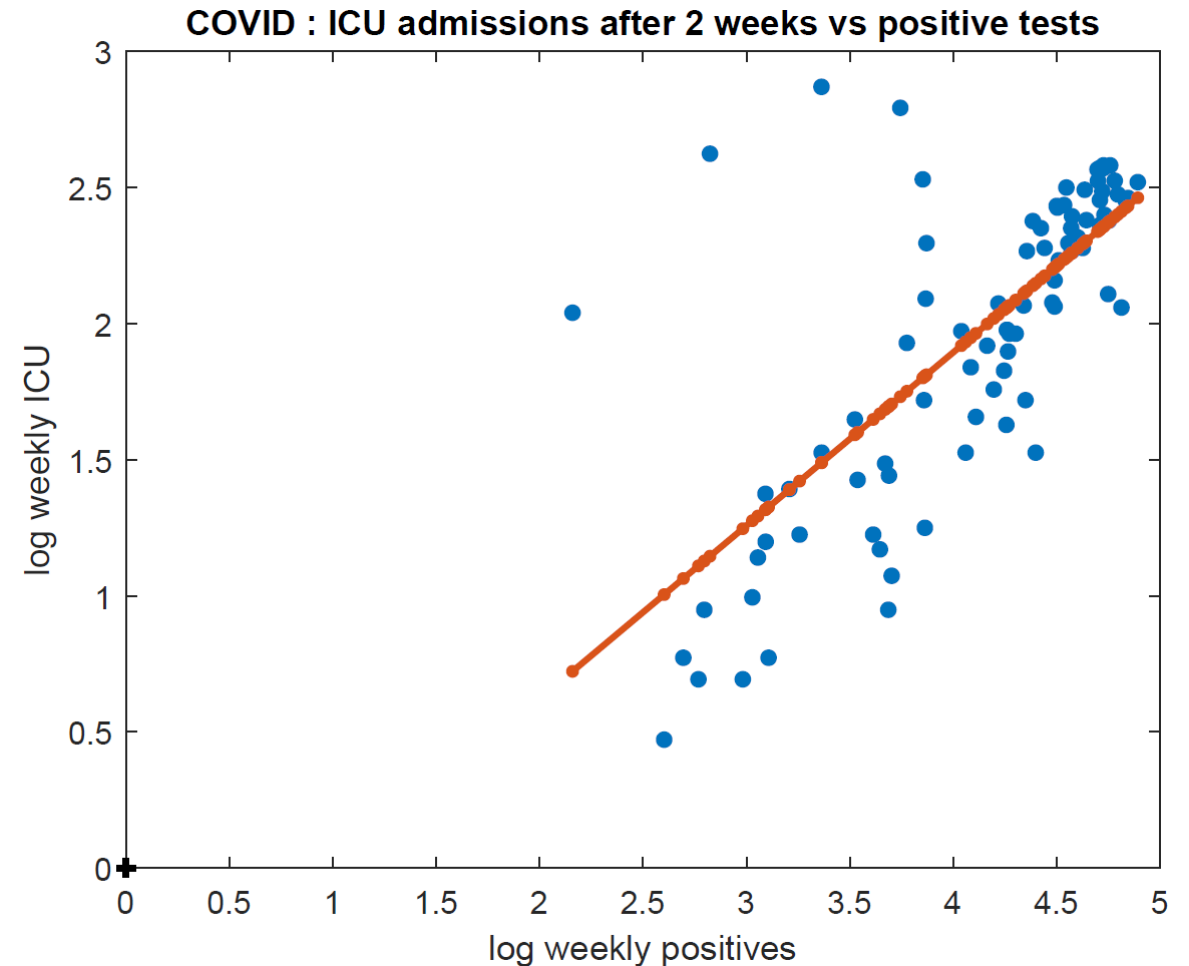
Simple prior knowledge

“Nonlinear” model

# Extension to Probabilistic Model

› But why?

Model spread in prediction  
Express confidence  
Combine with other  
probabilistic models



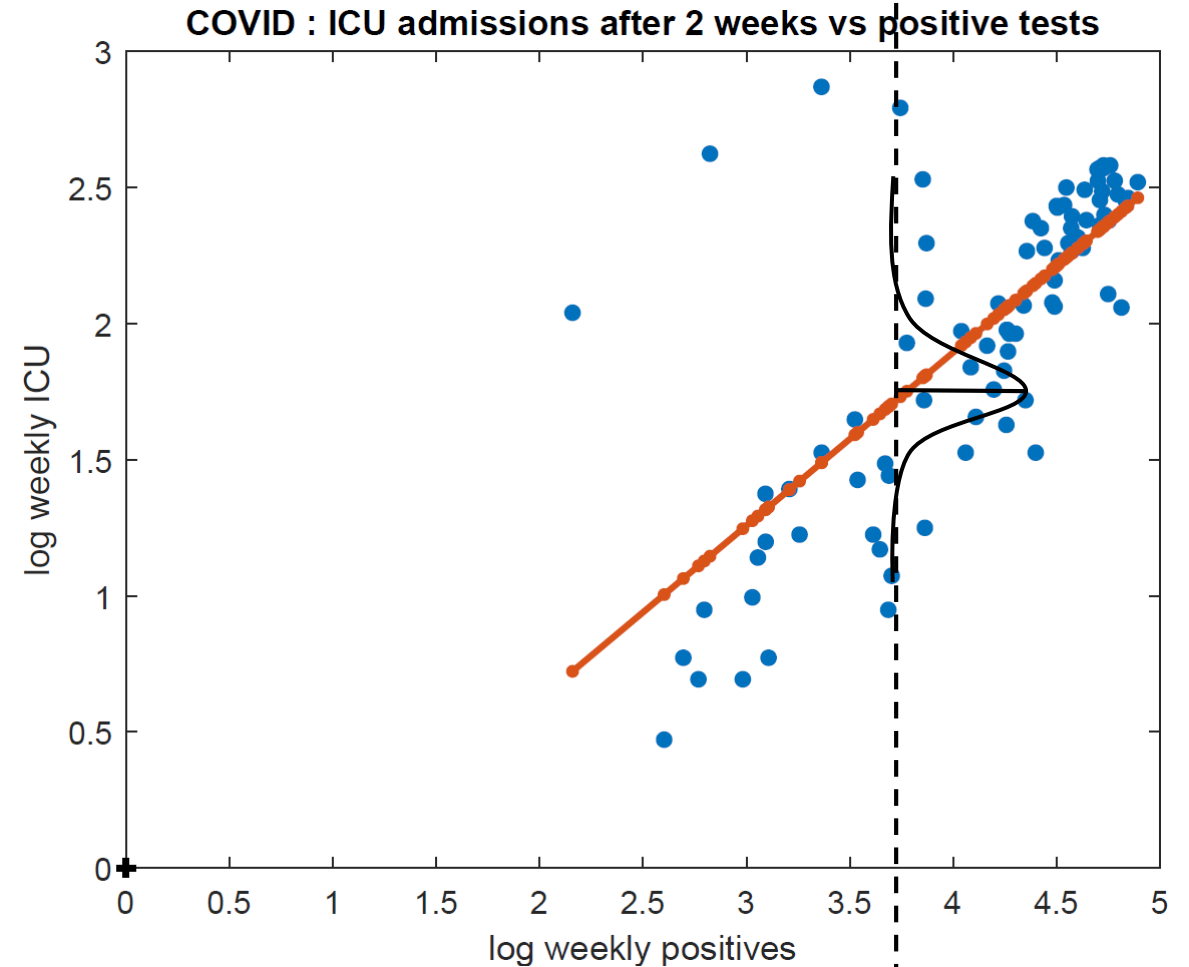


# Extension to Probabilistic Model

› How to?

Again : assume a model

One possibility is to  
assume Gaussian  
conditional for  $p(y|x)$



# How To

- › Conditional at  $x$  :  $p(y|x) = N(y|w^T x, \sigma^2)$
- › Fit to data by maximizing (conditional) likelihood

$$\prod_{i=1}^N N(y_i | w^T x_i, \sigma^2)$$

What are the parameters to optimize?  
Depends on what the model assumes...

$$\prod_{i=1}^N N(y_i | w^T x_i, \sigma^2)$$

› Let's fit it assuming  $\sigma$  known...

$$\prod_{i=1}^N N(y_i | w^T x_i, \sigma^2)$$

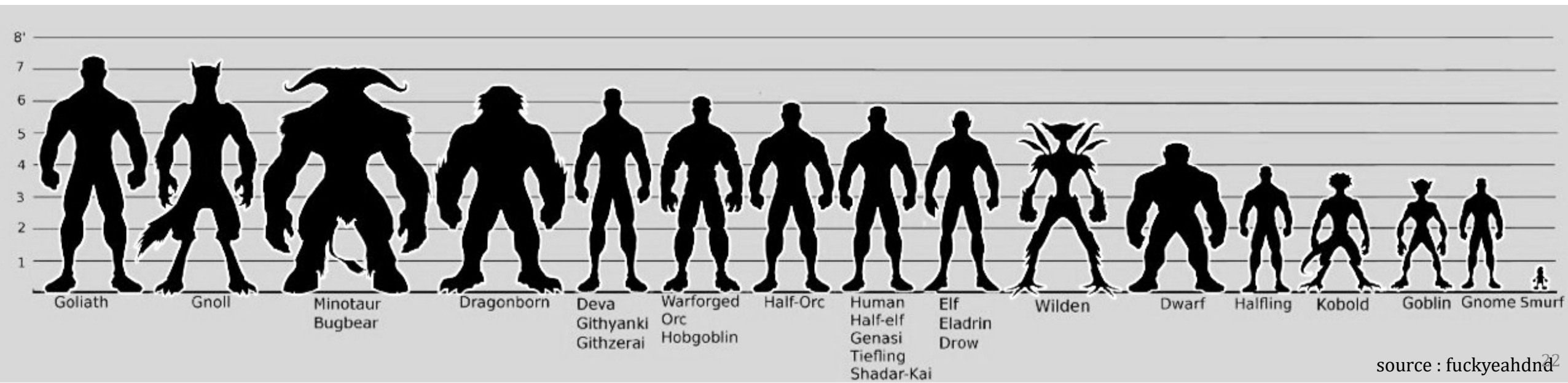
› What if we assume  $w$  known?

# Q? / Recap / Further Topics

- › Can reinterpret standard linear regression in terms of a probabilistic model
- › First : important way of incorporating prior knowledge [more on this in Week 5]
- › Second : nonlinear relations [relates to Week 4]

# Initial Idea

- › Estimate average student height in specific ML class
- › What do you do in case of 0 observations?



# Maximum a Posteriori Estimation

- › One way of combining a prior information with actual data : take likelihood  $\times$  [so-called] prior

$$p(\text{data}|\theta)p(\theta)$$

- › MAP estimate obtained by maximizing for  $\theta$

So, think about how you would approach ML student height estimation...

# Generic Prior in Regression

- › Assume that  $w$  is [relatively] close to 0
- › More specifically take prior  $N(w|0, \alpha I)$  [ $\alpha$  = fixed!]
- › MAP estimate  $\hat{w}_{\text{MAP}}$  maximizes
$$\left( \prod_{i=1}^N N(y_i | w^T x_i, \sigma^2) \right) N(w | 0, \alpha I)$$

You should be able to solve this [at least for 1D case,  $\sigma$  fixed]



# Generic Prior in Regression

› MAP estimate  $\hat{w}_{\text{MAP}}$  maximizes

$$\left( \prod_{i=1}^N N(y_i | w^T x_i, \sigma^2) \right) N(w | 0, \alpha I)$$

› Solution for this specific choice [with  $\sigma$  fixed]

$$\hat{w}_{\text{MAP}} = \left( X^T X + \frac{\sigma^2}{\alpha} I \right)^{-1} X^T Y$$

# Behavior?

› Solution for this specific choice [with  $\sigma$  fixed]

$$\hat{W}_{\text{MAP}} = \left( X^T X + \frac{\sigma^2}{\alpha} I \right)^{-1} X^T Y$$

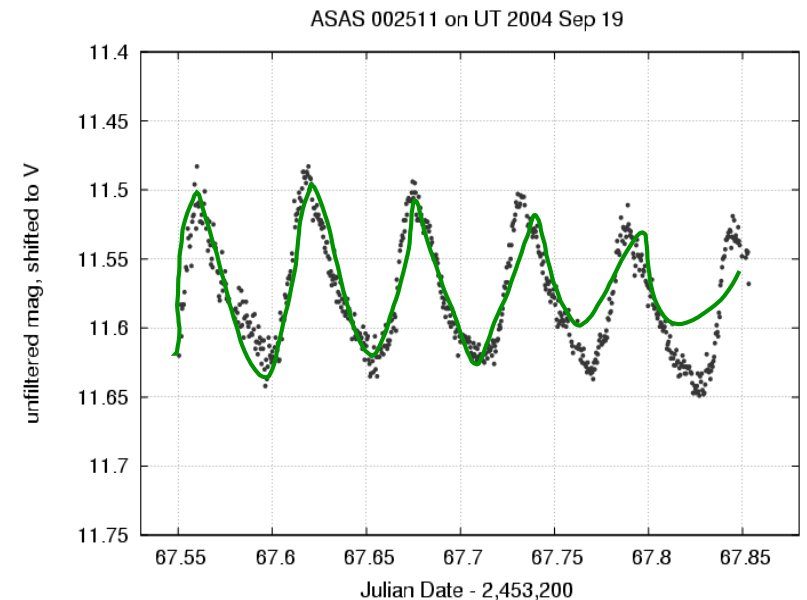
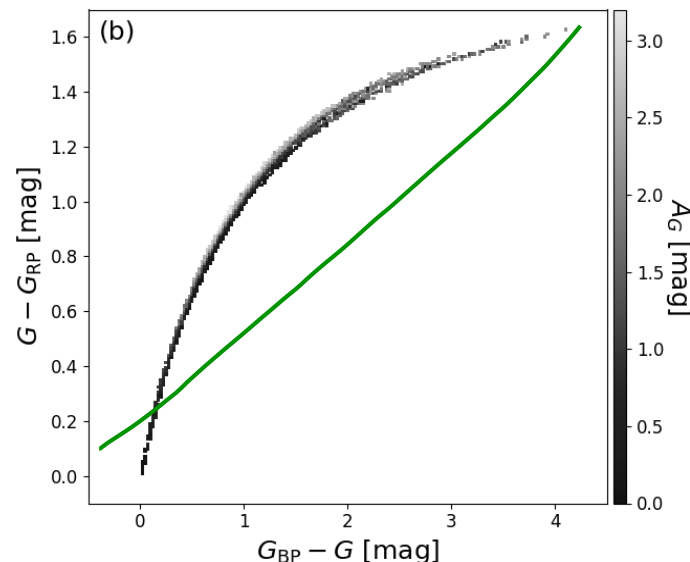
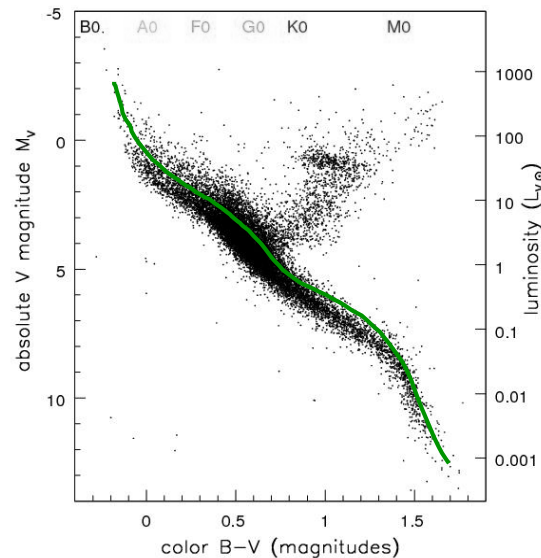
What if  $\alpha \rightarrow \infty$ ?

What if  $\alpha \downarrow 0$ ?

Makes sense?

# Next : Nonlinear Relations...

- › Often variables relate in a nonlinear way
- ›  $E = mc^2$ ,  $G = \frac{m_1 m_2}{r^2}$ , etc.
- › What can we do?



# Feature Transformations

- › Nothing prevents inventing own combinations
- › Already added constant for intercept / bias / offset
- › Why stop there?
  - With  $x \in \mathbb{R}^3$  a feature vector, we could add...  
 $x_1^2, \sin x_3, x_1 x_2$ , etc.
  - [Note potential confusion with indexed samples]
- › Generally, invent mapping  $\phi: \mathbb{R}^d \rightarrow \mathbb{R}^D$  from  $d$ -dimensional space to new  $D$ -dimensional one

# Feature Transformations

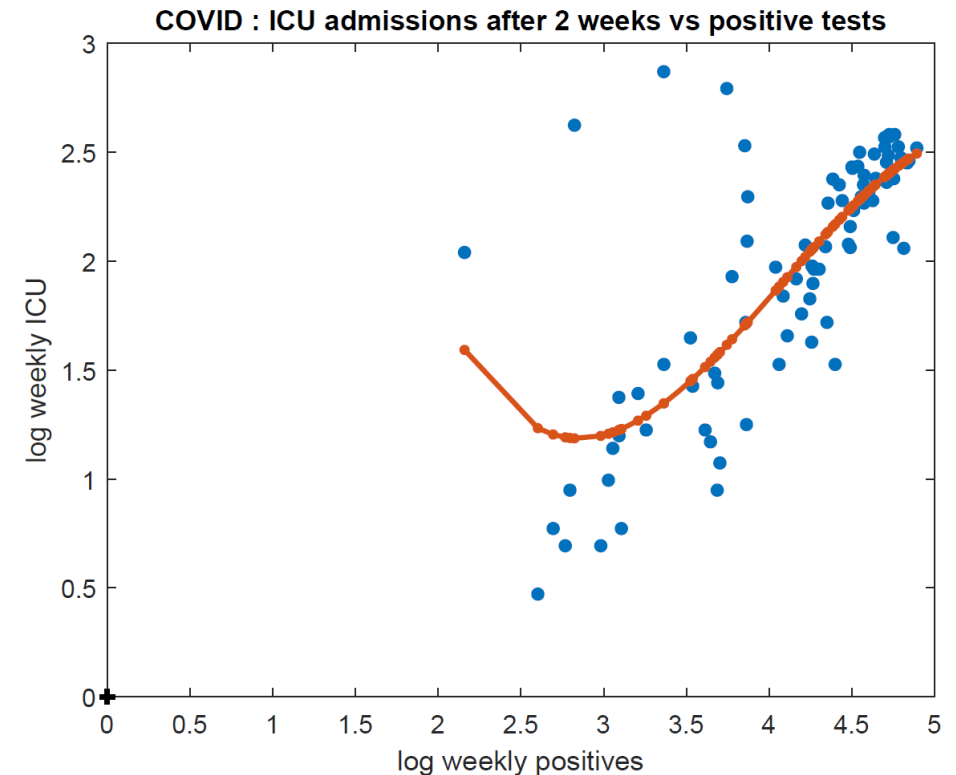
› With your choice of  $\phi$ , new objective becomes

$$\sum_{i=1}^N (w^T \phi(x_i) - y_i)^2$$

Typically, model is still called linear

- › Special case : polynomial regression of some order
- › Relation to the kernel trick [Week 4]

# Feature Transformations



- › Special case : polynomial regression of some order
- › Relation to the kernel trick [Week 4]

# Wrap-up

- › Discussed regression, linear in particular
- › Both squared loss formulation and probabilistic
- › Extensions using prior and feature transformations
- › Tomorrow we look at linear classifiers
- › Think about the following :
  - Which linear ones did you see already?
  - How to use linear regression to build a linear classifier?