Welcome to Week #13!

K-Nearest Neighbors

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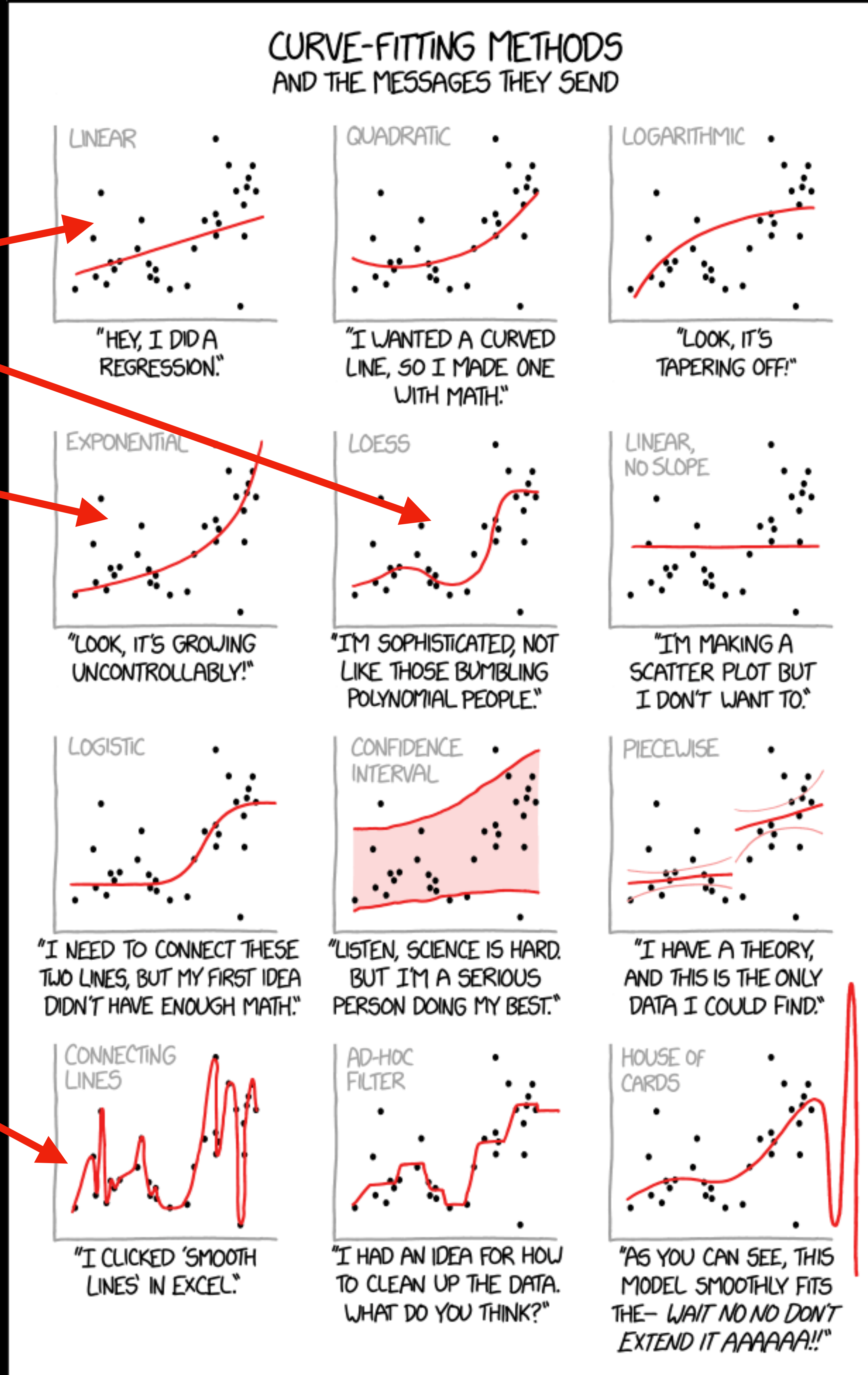
First: an intro to overfitting

Overfit?

Overfit?

Underfit?



Overfit

Is overfitting or underfitting worse?

Bias-Variance Trade-Off (First Glance)

$$E\left(y_0 - \hat{f}(x_0)\right)^2 = \mathrm{Var}(\hat{f}(x_0)) + [\mathrm{Bias}(\hat{f}(x_0))]^2 + \mathrm{Var}(\epsilon)$$

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mean square error if we kept estimating response variable y by our fitted function of our explanatory variables, f(x) with different sample datasets at point x_0

Inherent error in our measurements

Inherent error (bias) in the fact that any model is only an approximation to reality

how much our function, f, changes if we use a different random sample (variance)

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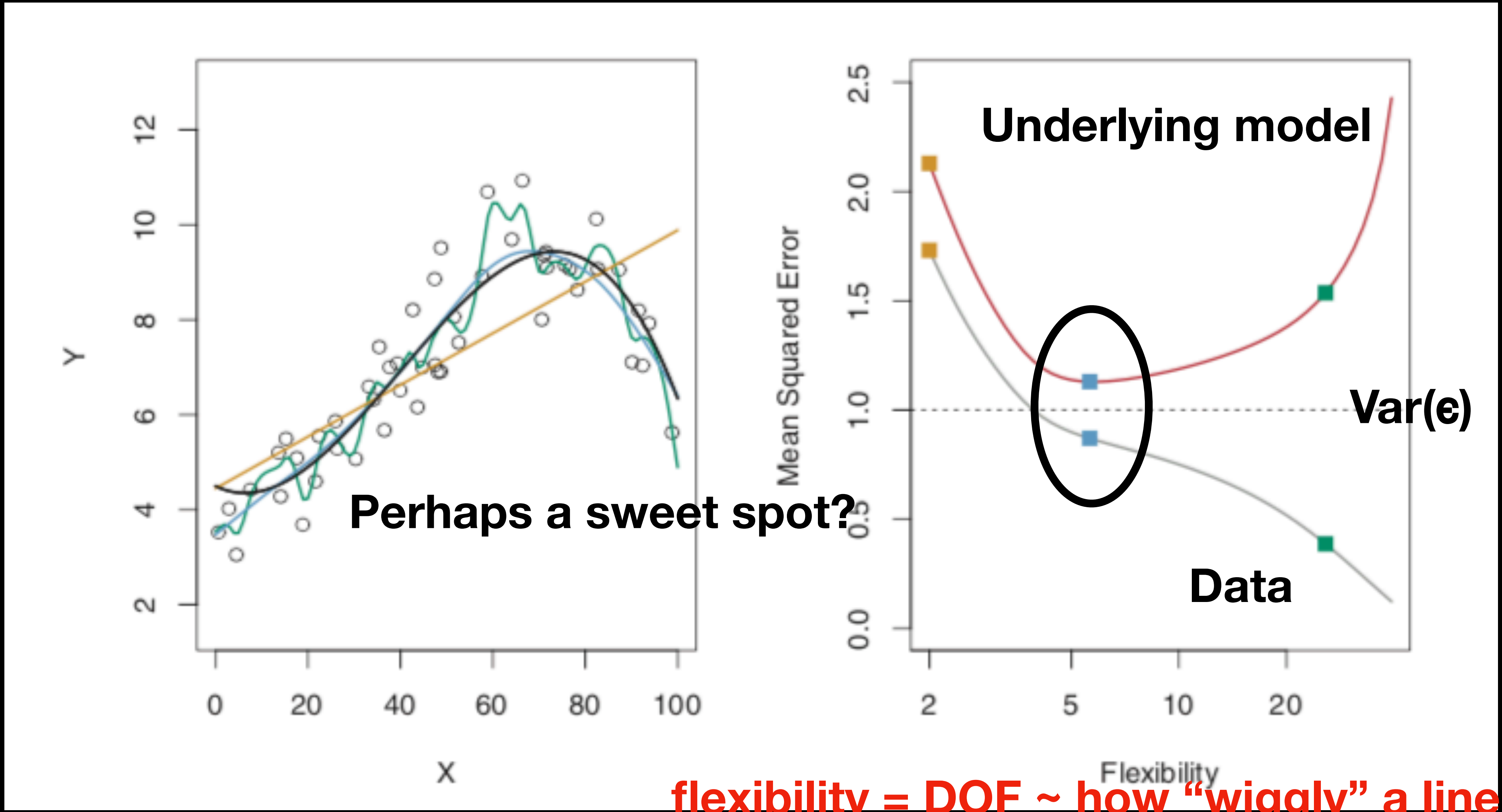
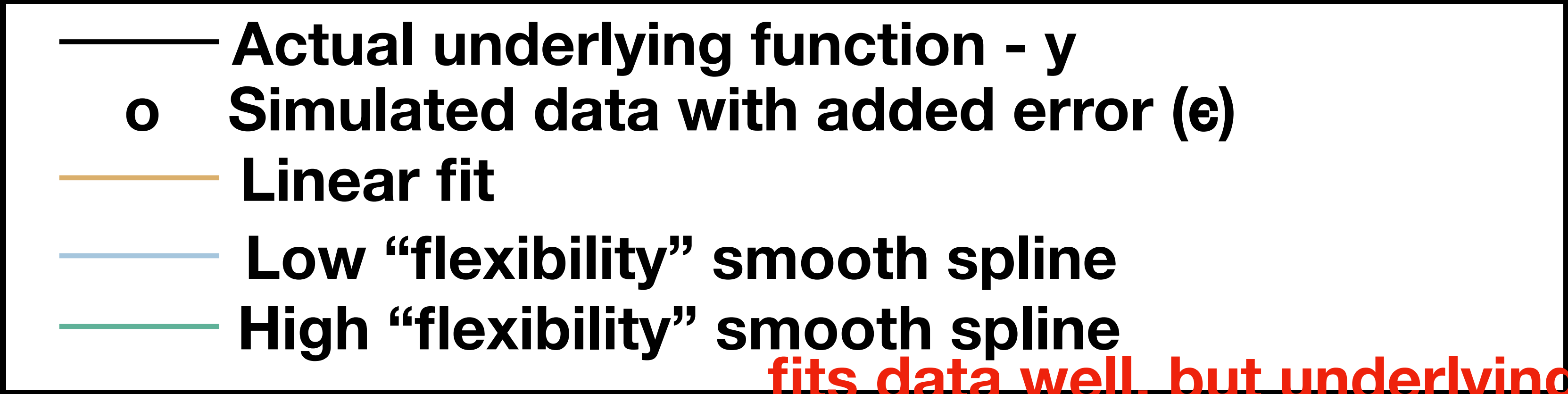


flexibility = DOF ~ how “wiggly” a line is



fits data well, but underlying model badly

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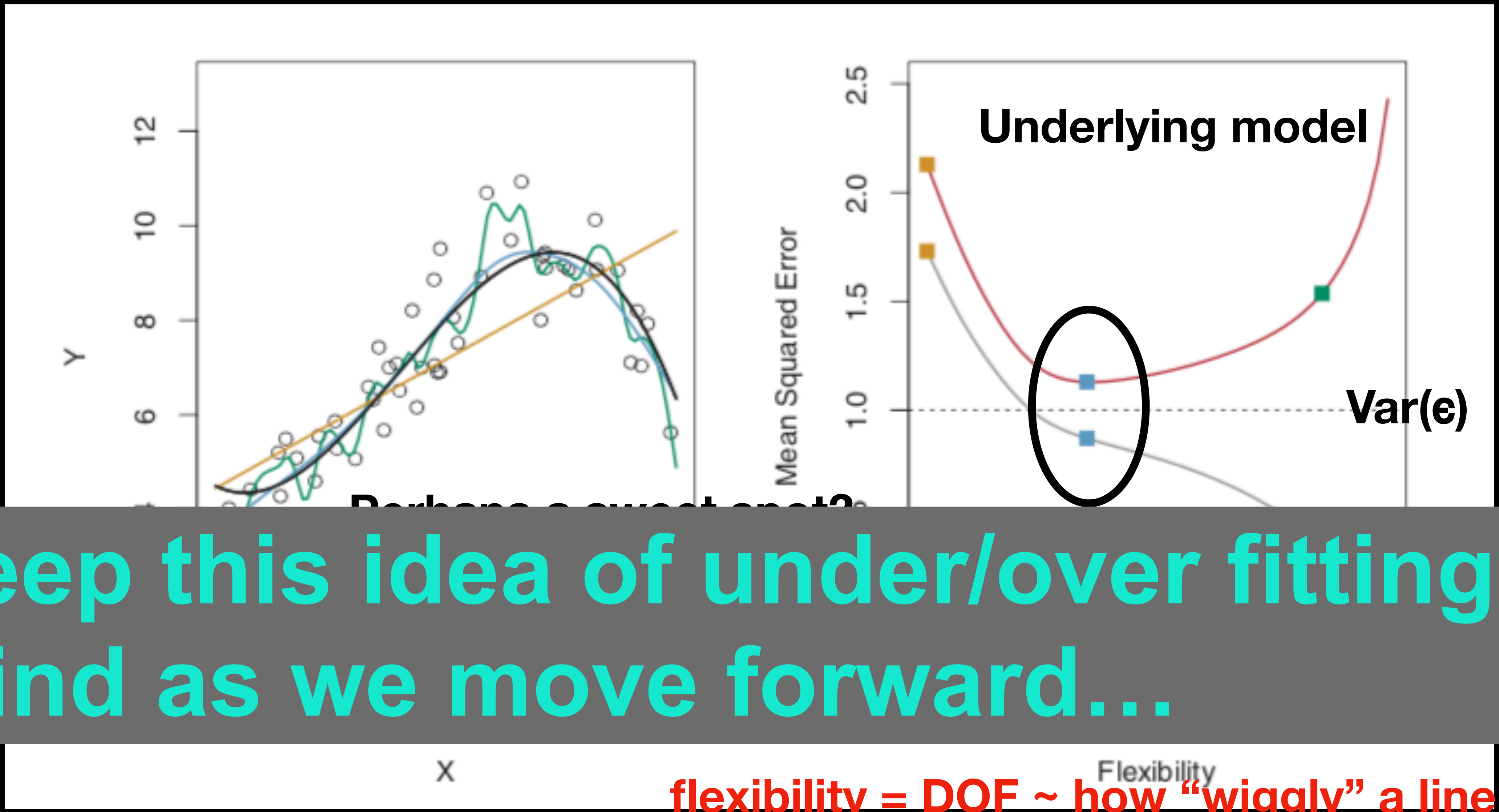

Keep this idea of under/over fitting in mind as we move forward…

flexibility = DOF ~ how “wiggly” a line is

Actual underlying function - y

o Simulated data with added error (ϵ)

Linear fit

Low “flexibility” smooth spline

High “flexibility” smooth spline

fits data well, but underlying model badly

K-Nearest Neighbors

~~First: an intro to overfitting~~

So far…

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n$$

predicted y

intercept

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"I have a basic idea of what the functional form of y looks like (a line or a logit) - computer go find the parameters of that functional form.

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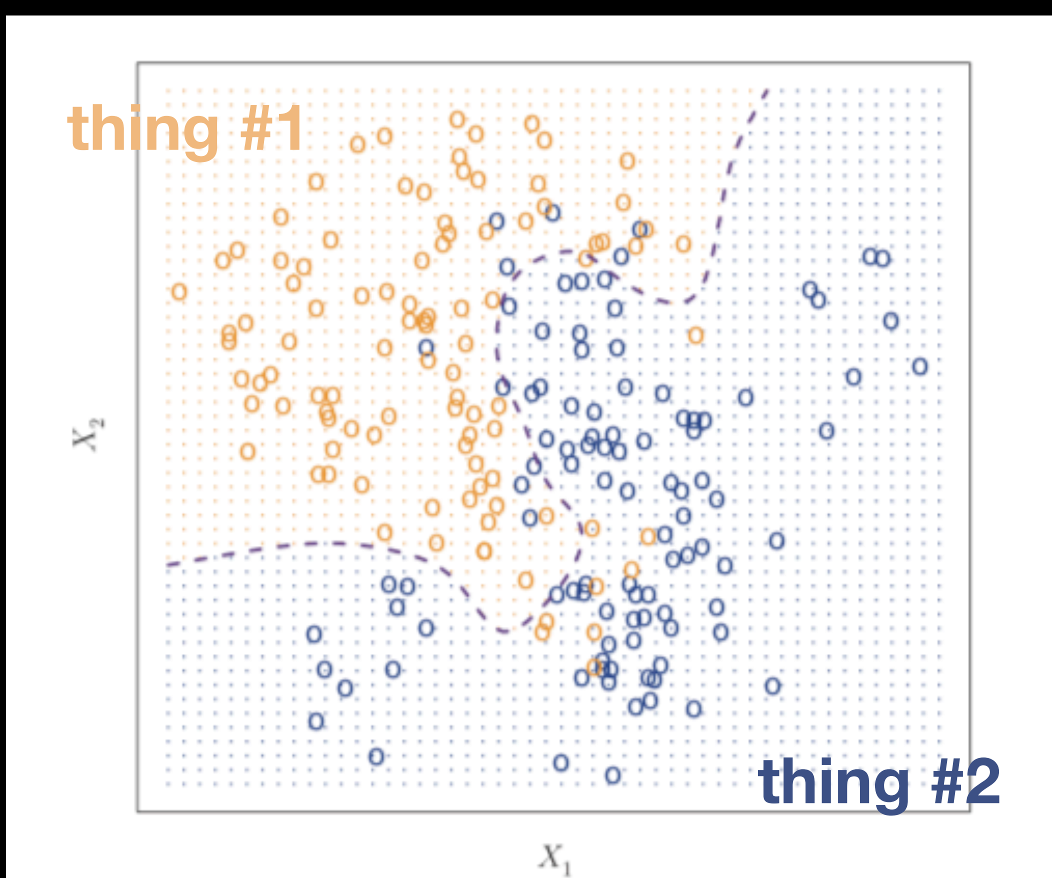

"I want to know where thing #1 and thing #2 live in some 2D space - computer, go figure out the boundary between these two things and let me know"

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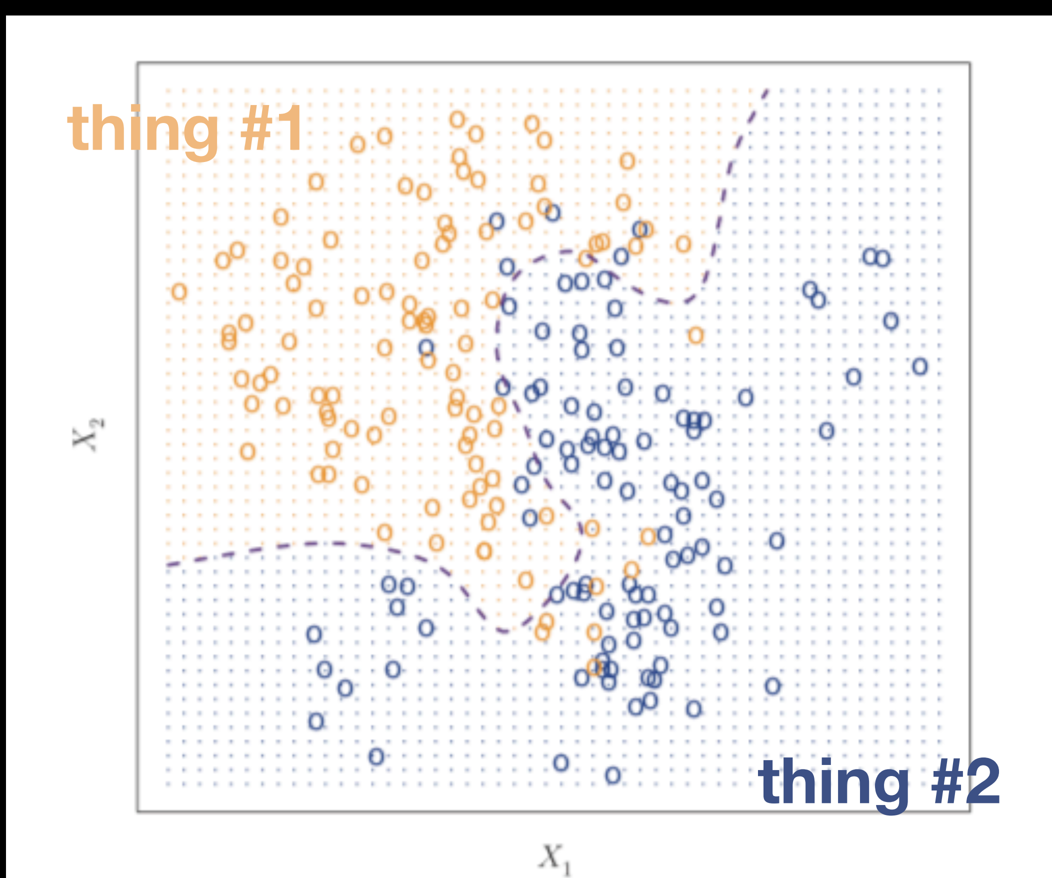
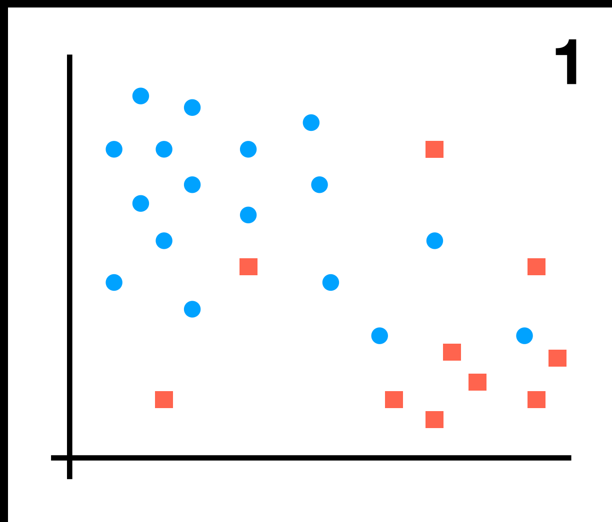


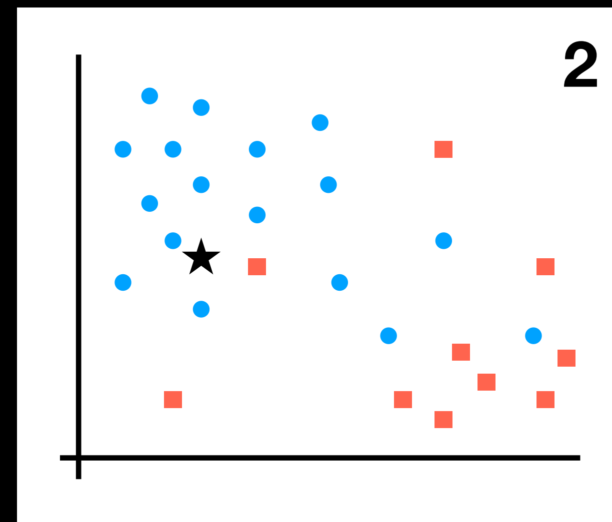
"I want to know where thing #1 and thing #2 live in some 2D space - computer, go figure out the boundary between these two things and let me know"

This is nice because we don't have to assume some model beforehand.

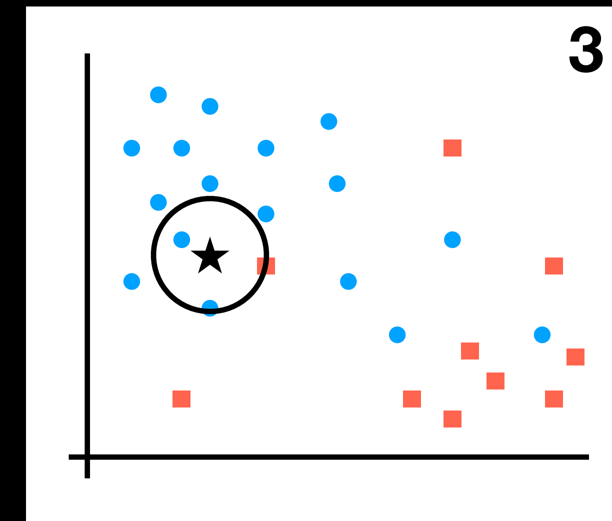
K Nearest Neighbors, in pictures



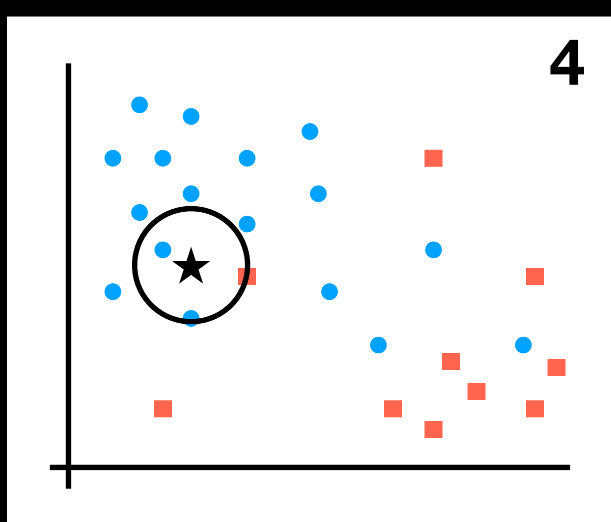
Sample (training) data representing underlying population



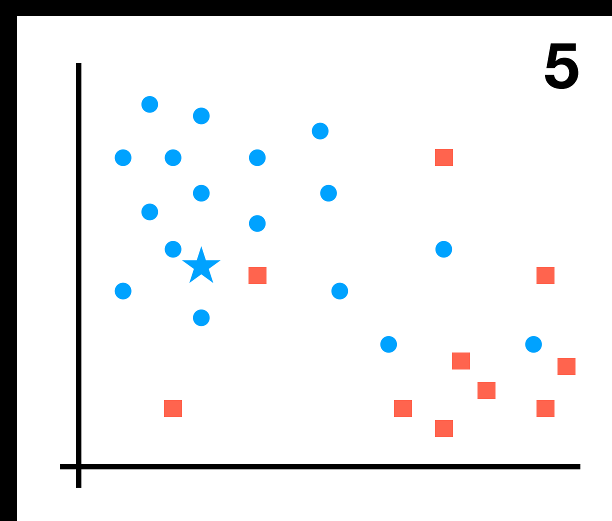
New point of interest



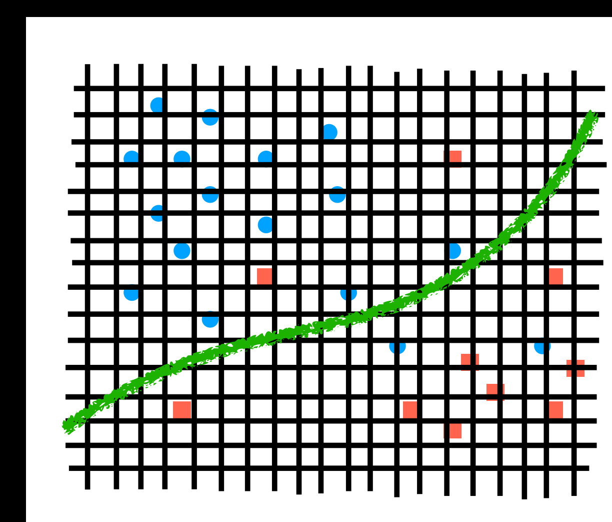
Find k nearest neighbors (here k = 3)



count “types” - here 2/3 points are blue
P(blue) = 2/3
P(red) = 1/3

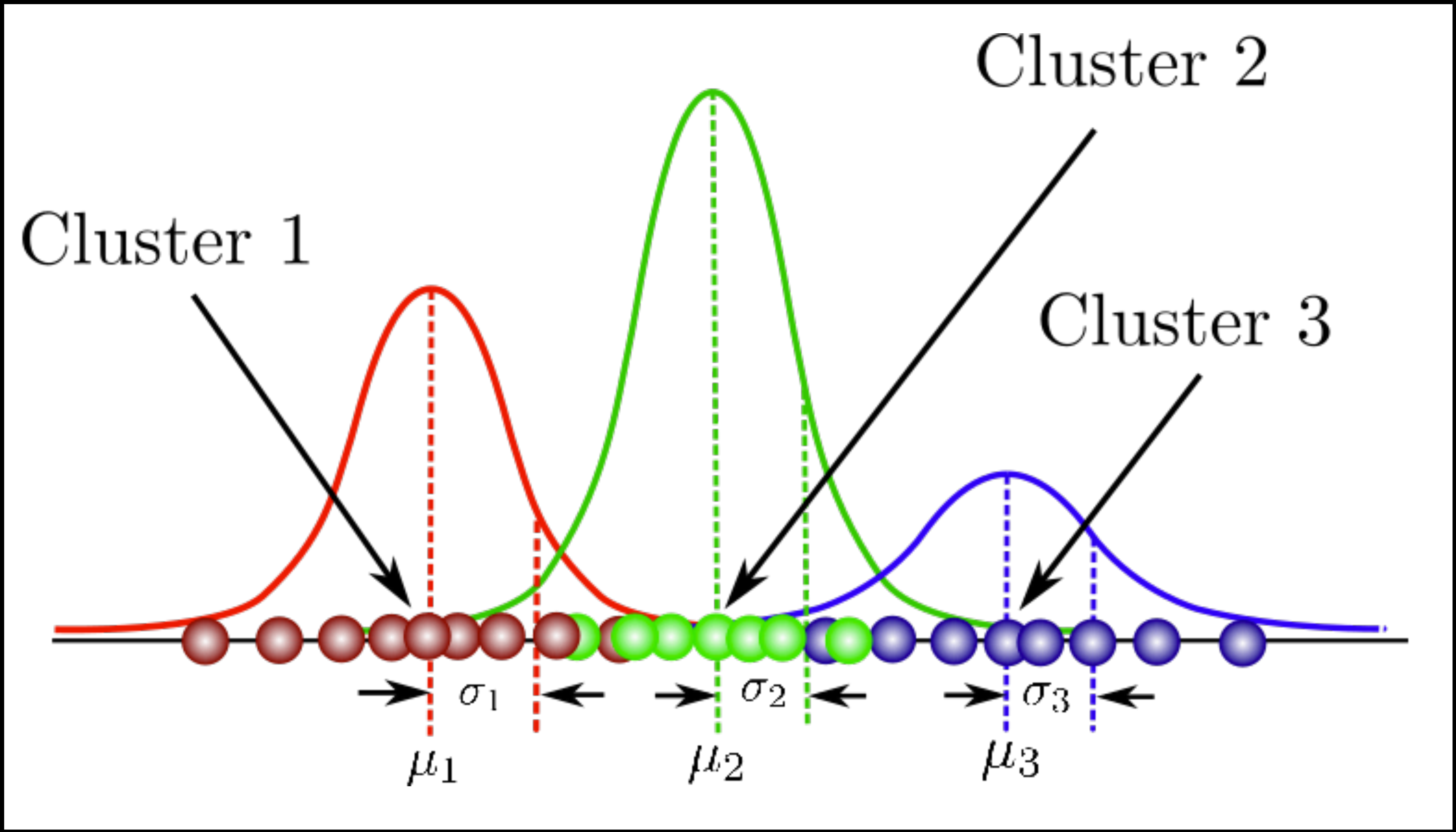


if P > cut off say new point is in that group here: P(blue) > 0.5



Repeat 2-3 on a grid & draw a separating line

K Nearest Neighbors - with Gaussian Mixture Models.



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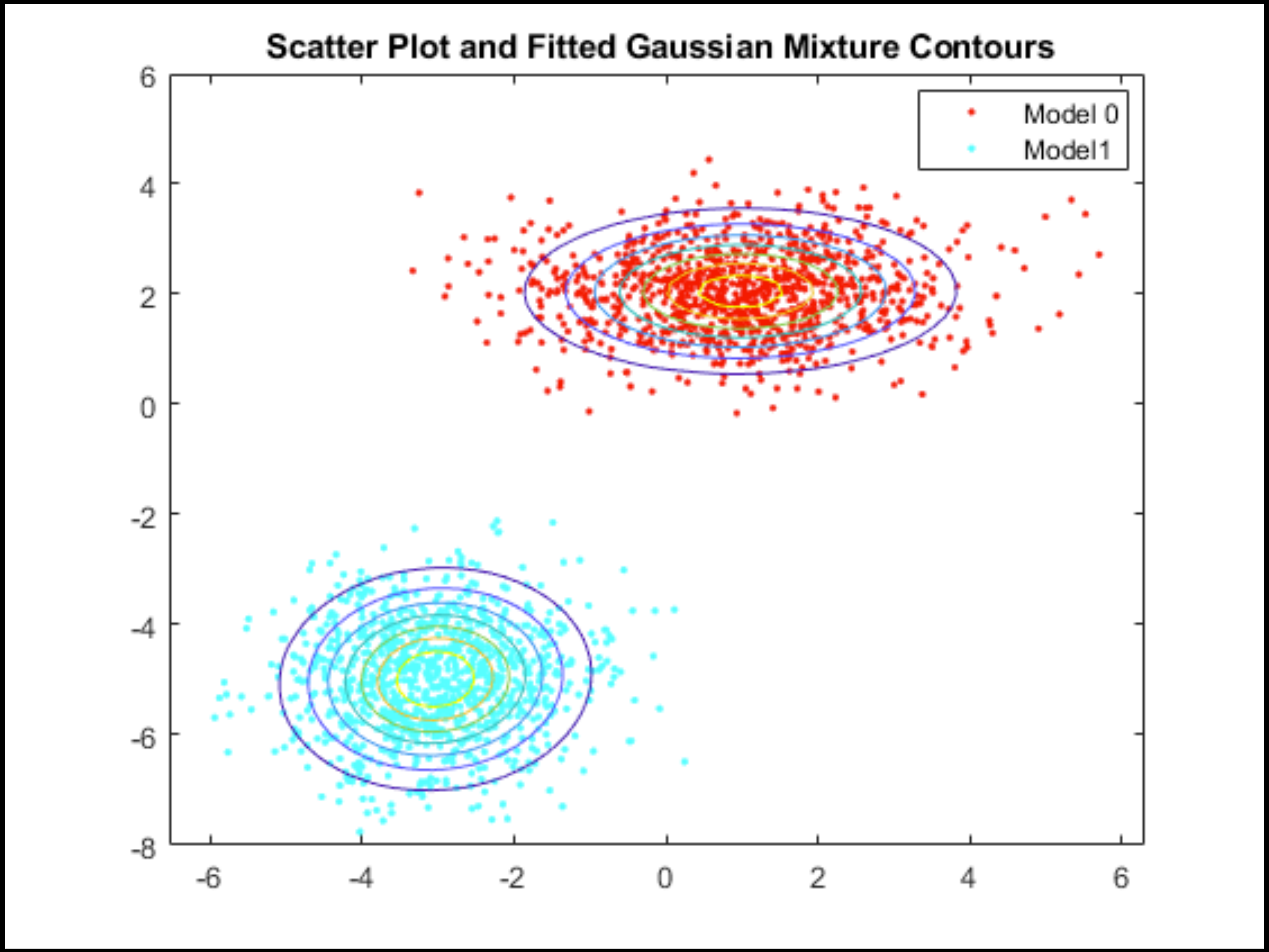

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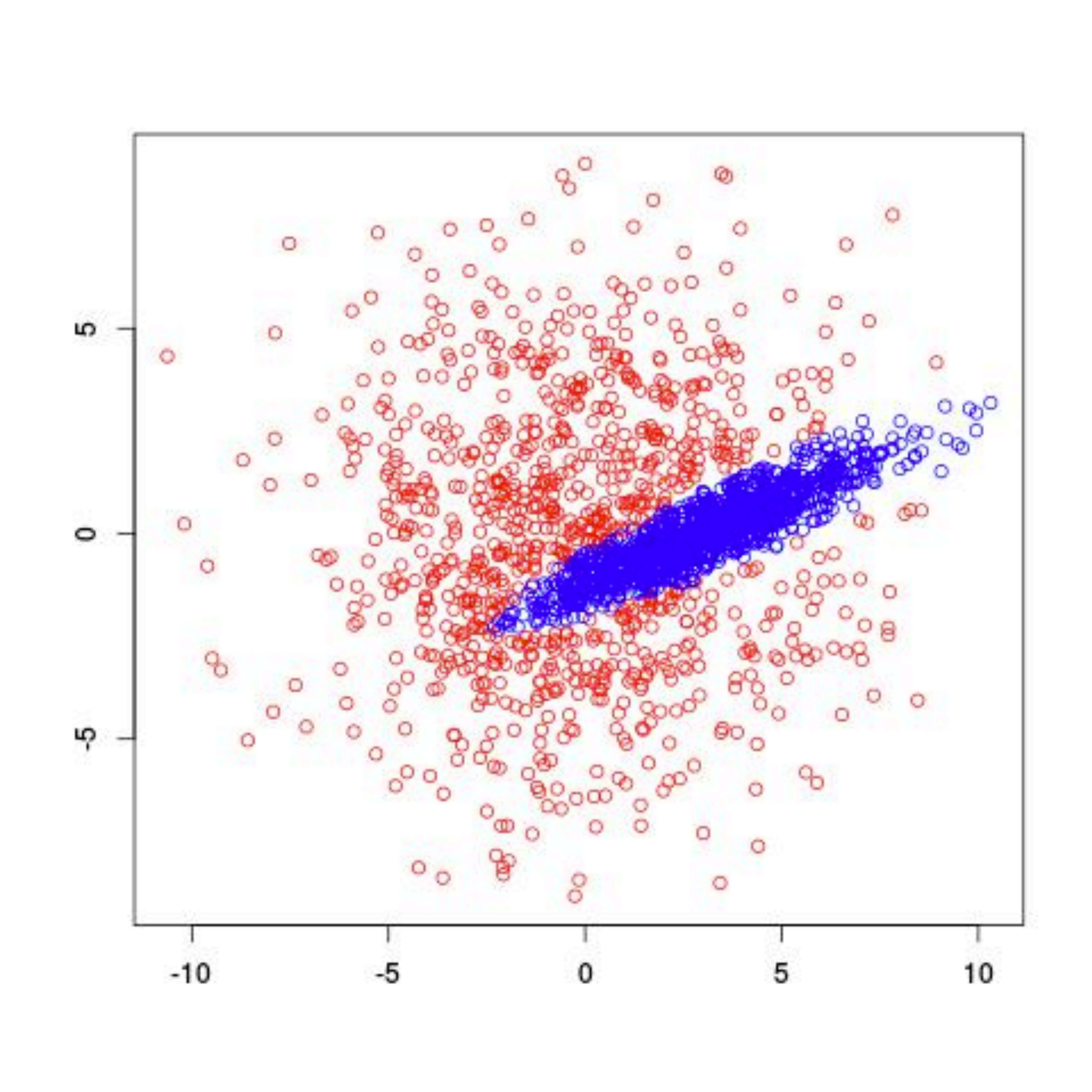
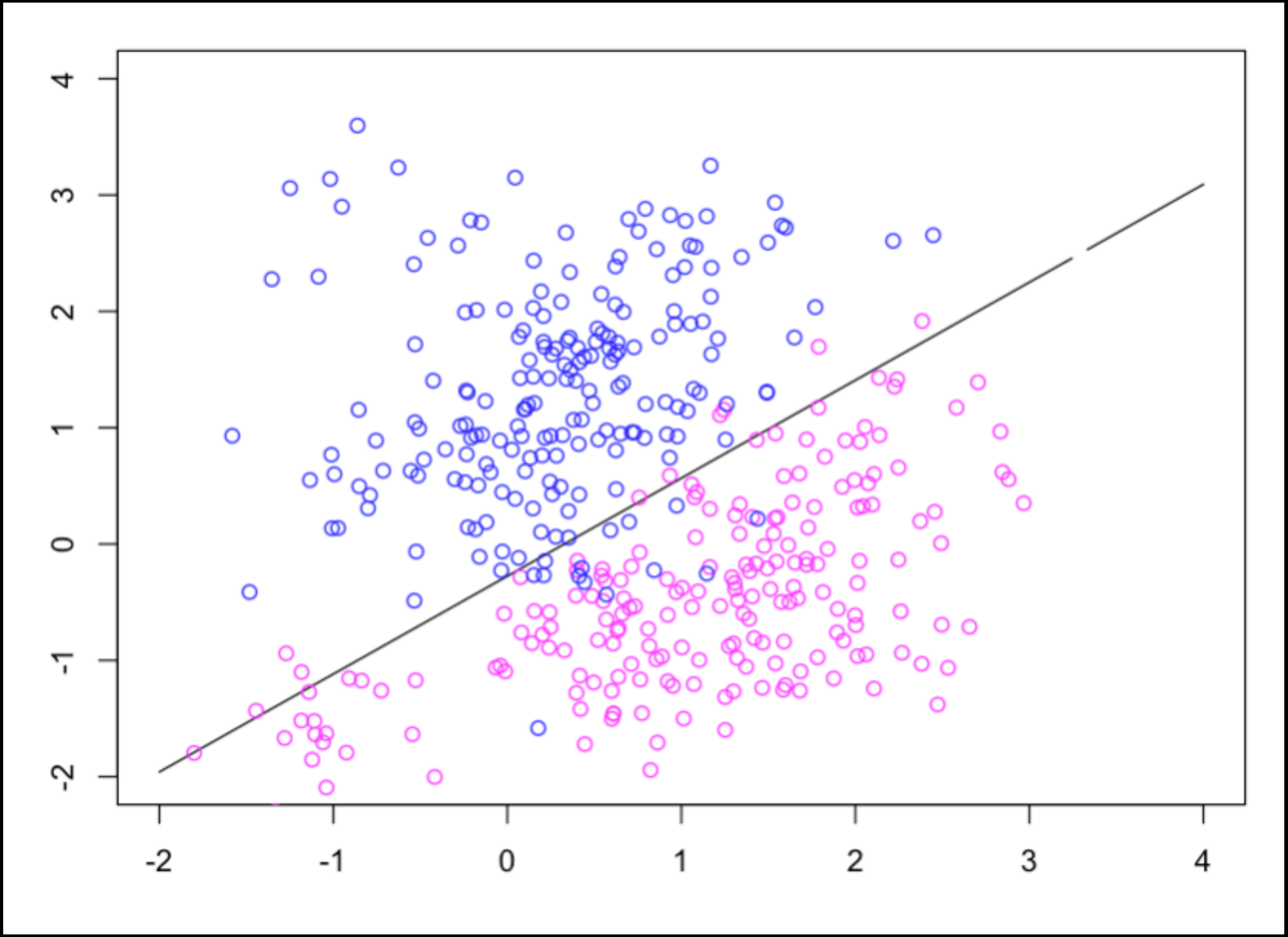
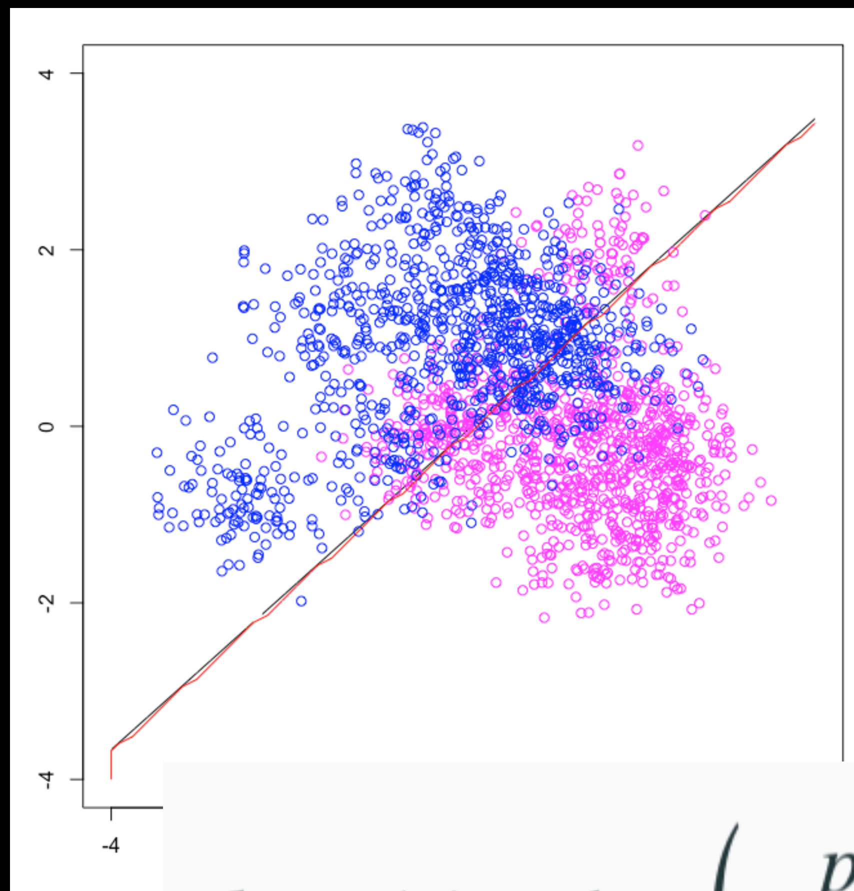


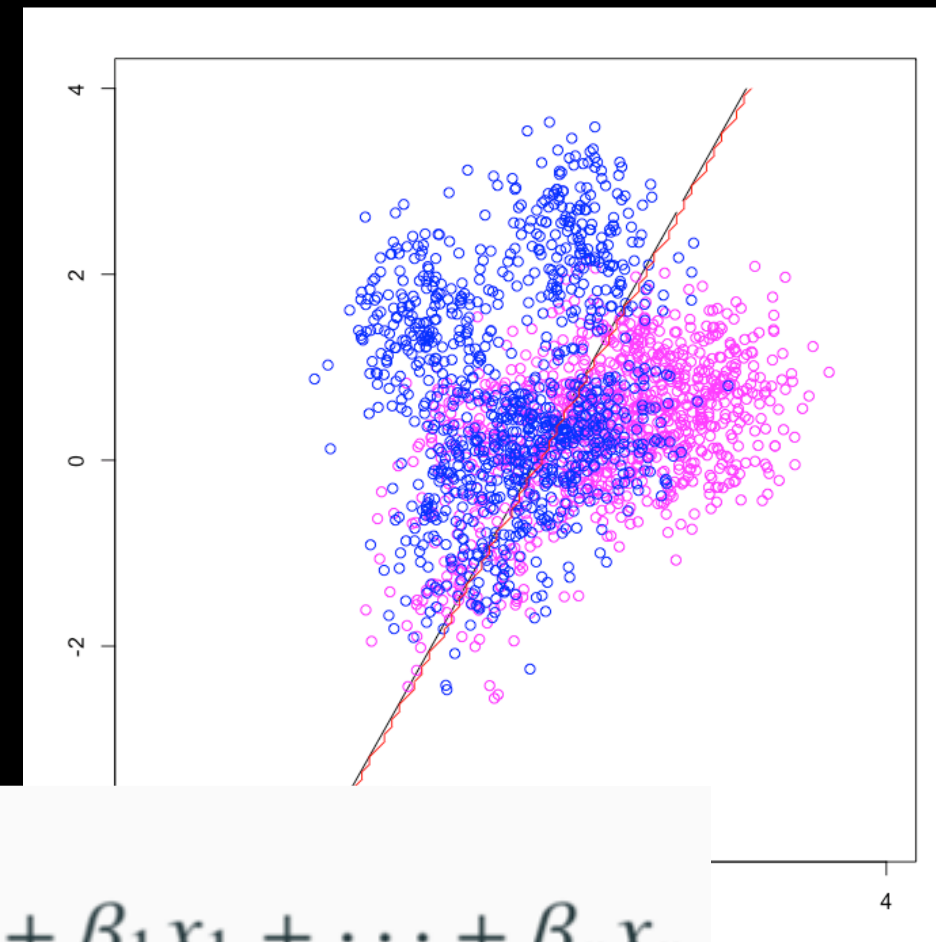
K Nearest Neighbors, in R!

K Nearest Neighbors, in R!
- just kidding logistic regression

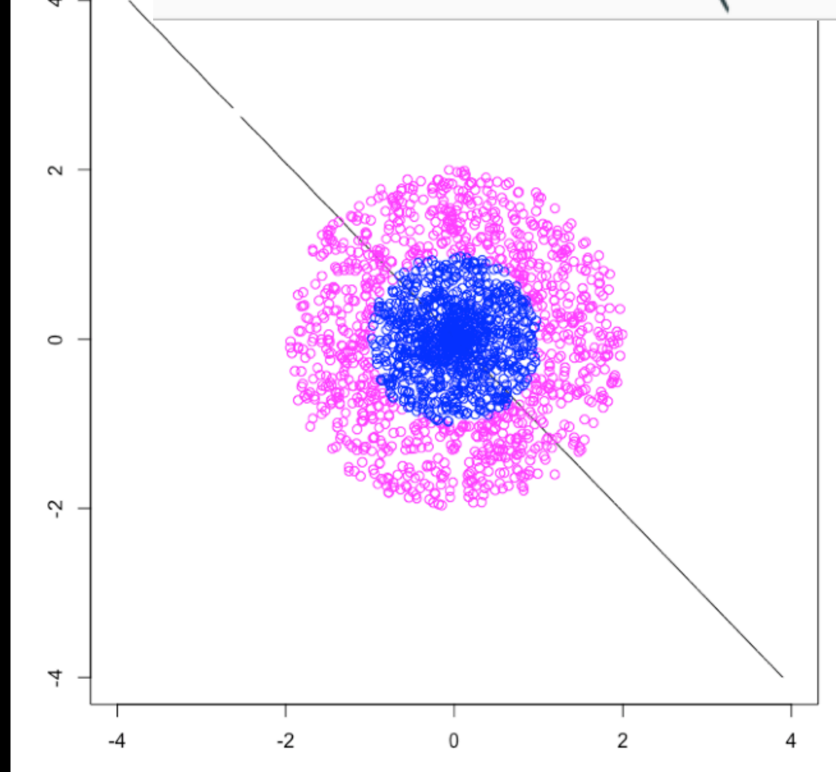


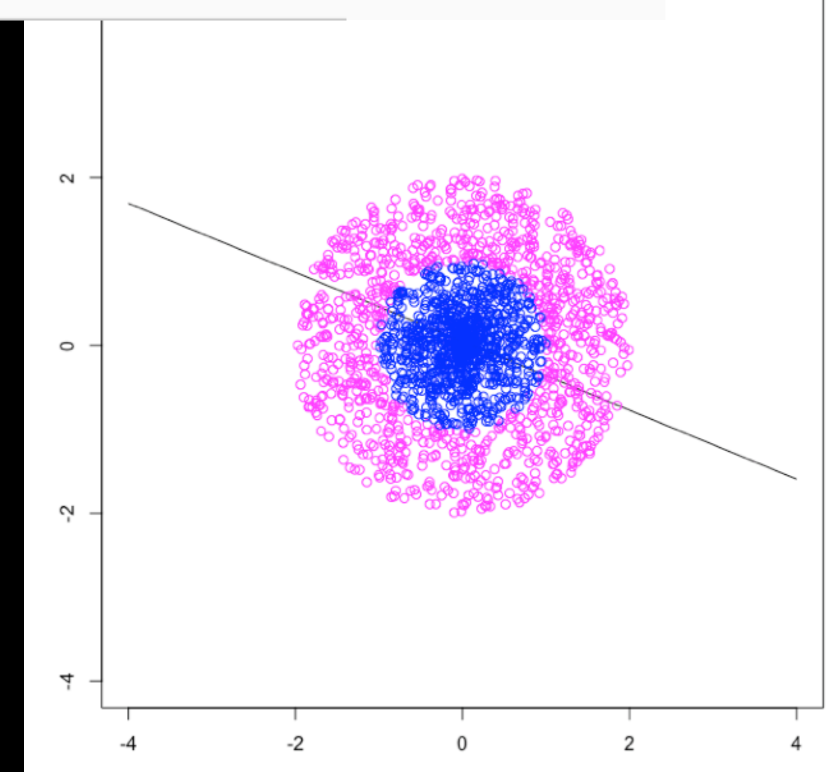
GLM is clearly getting something wrong





$$logit(p) = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$$





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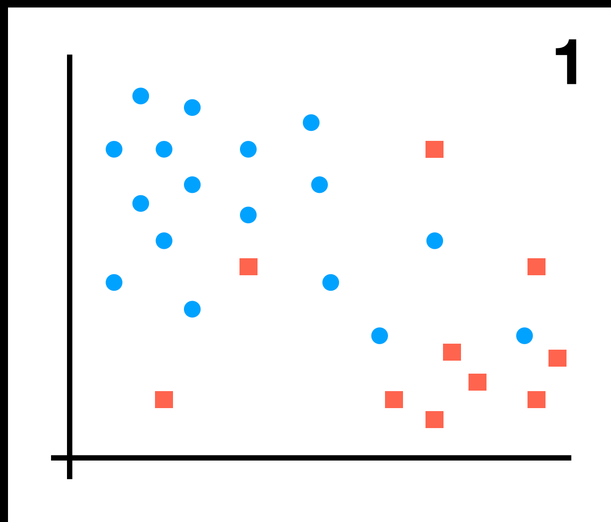

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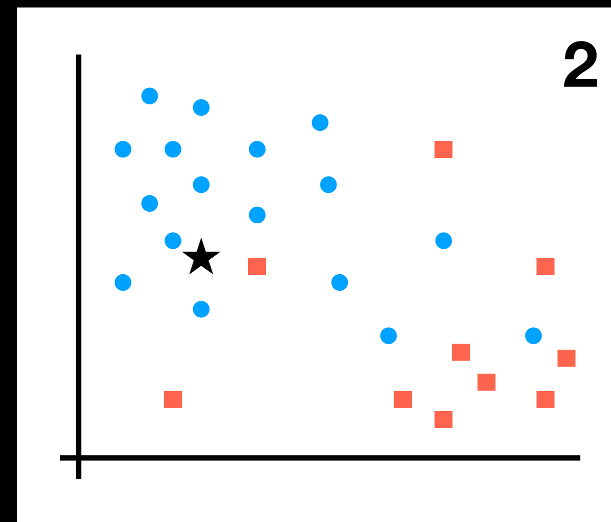

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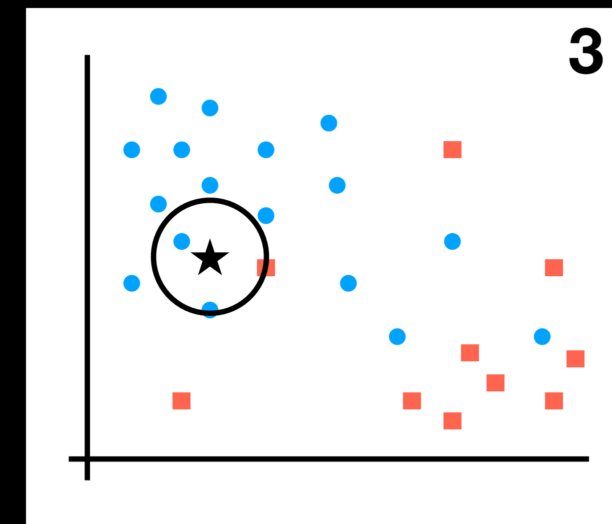

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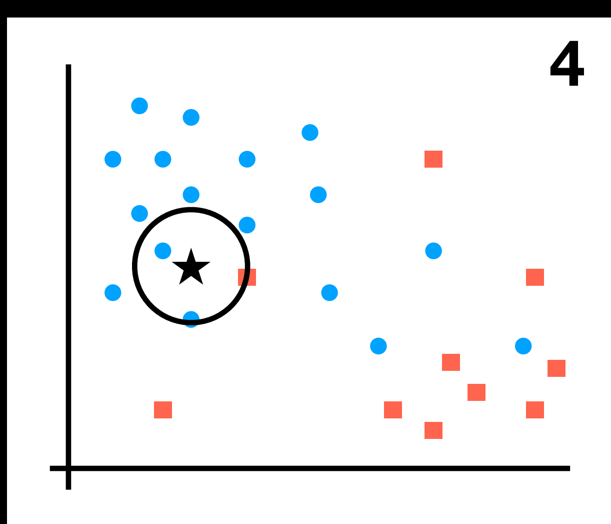

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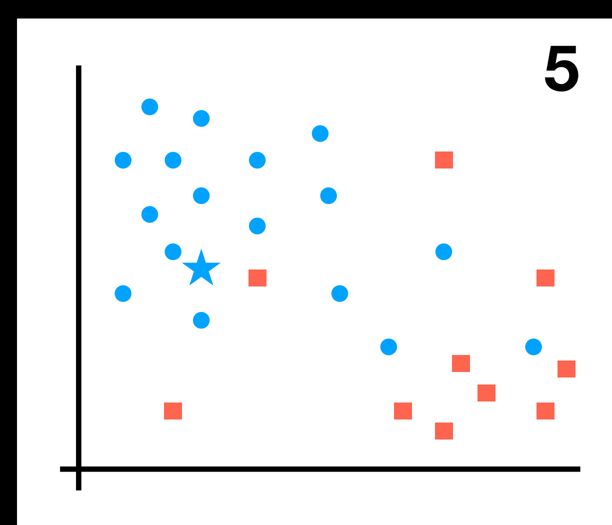

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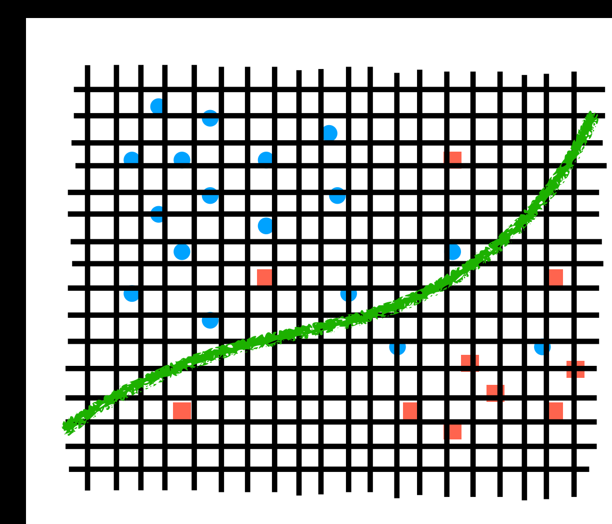

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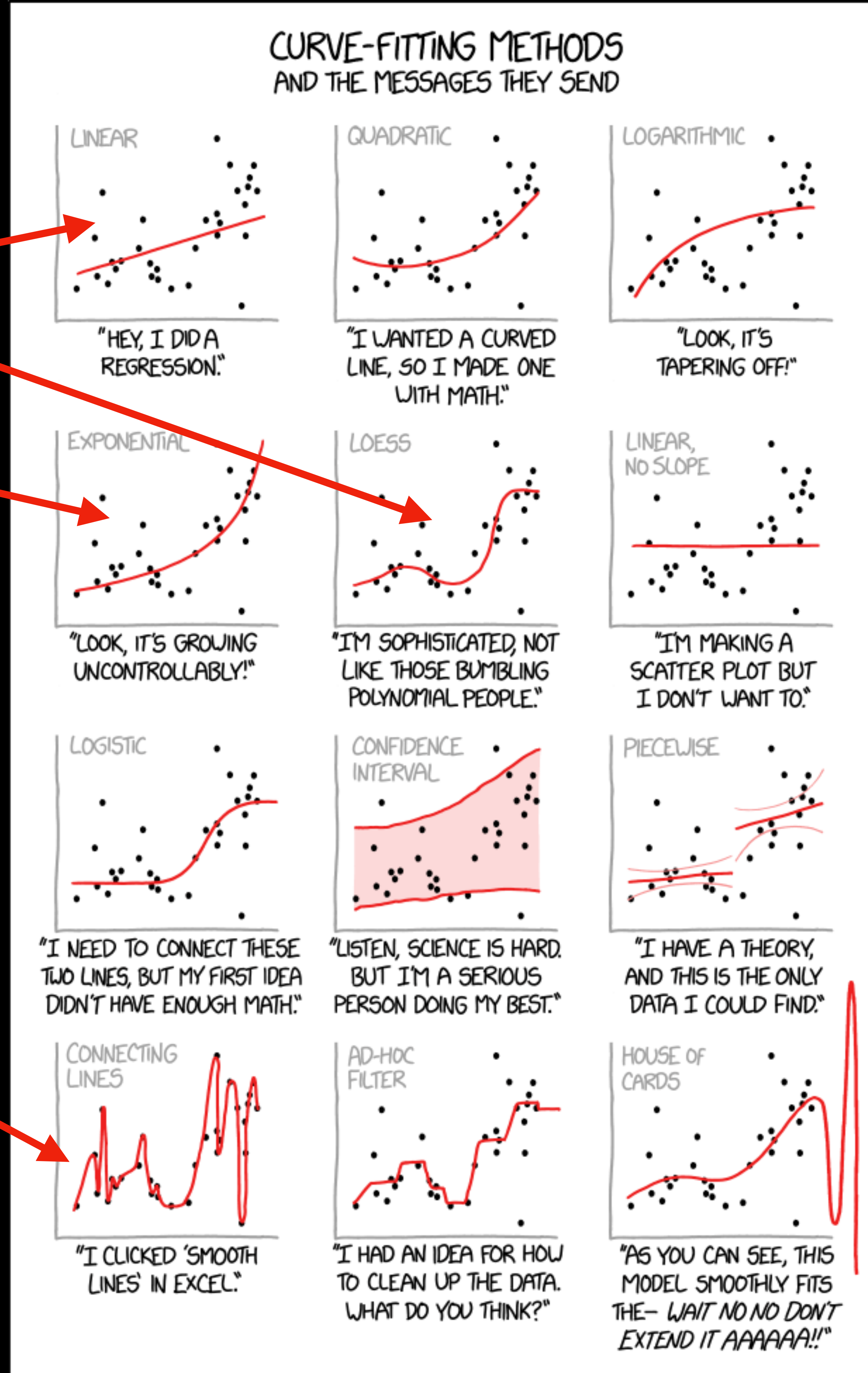
K Nearest Neighbors, in R!
For real this time!

Over/Under fitting - Quantifying how good your model is

Overfit?

Overfit?

Underfit?



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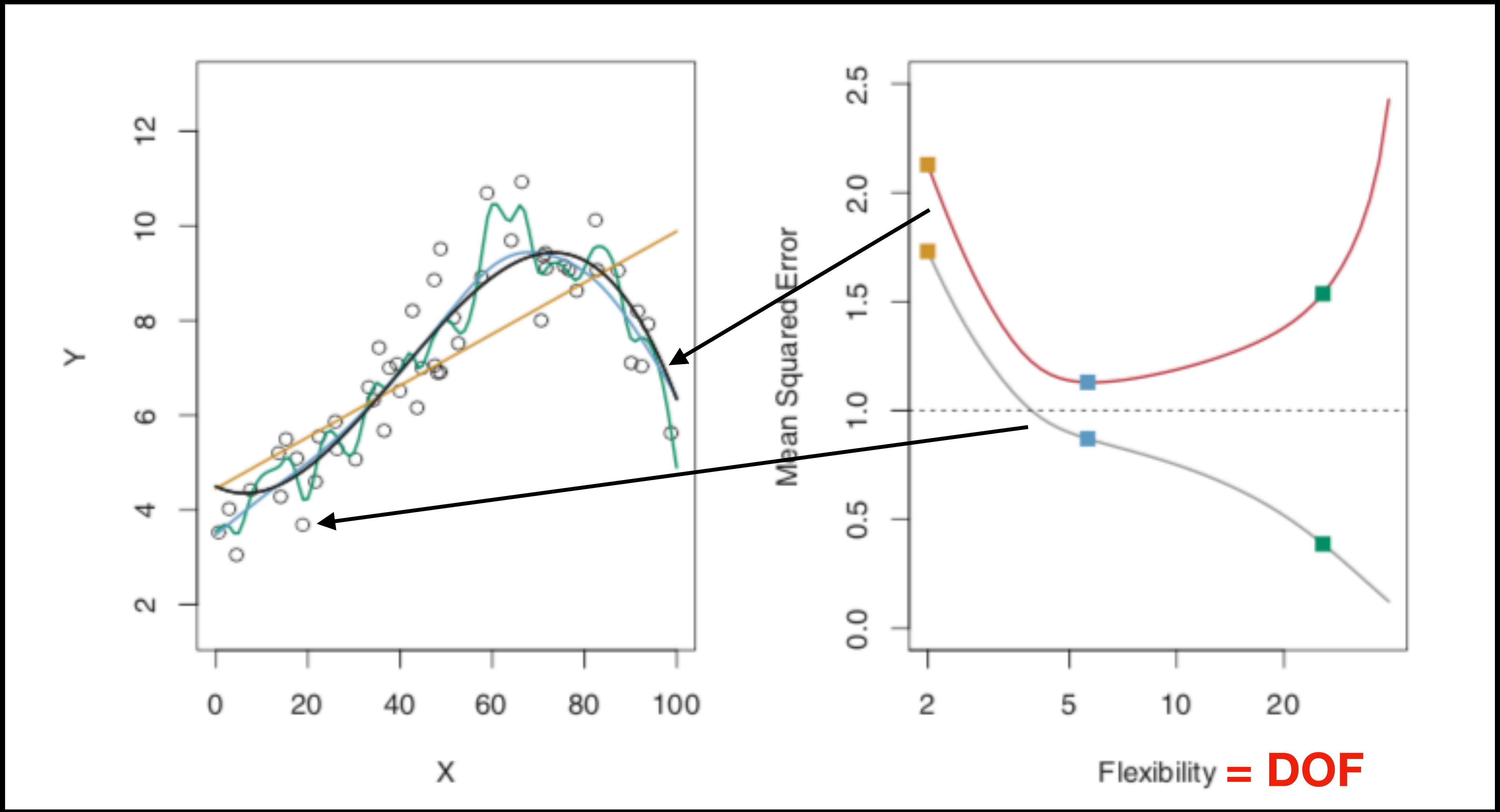

Actual underlying function - y

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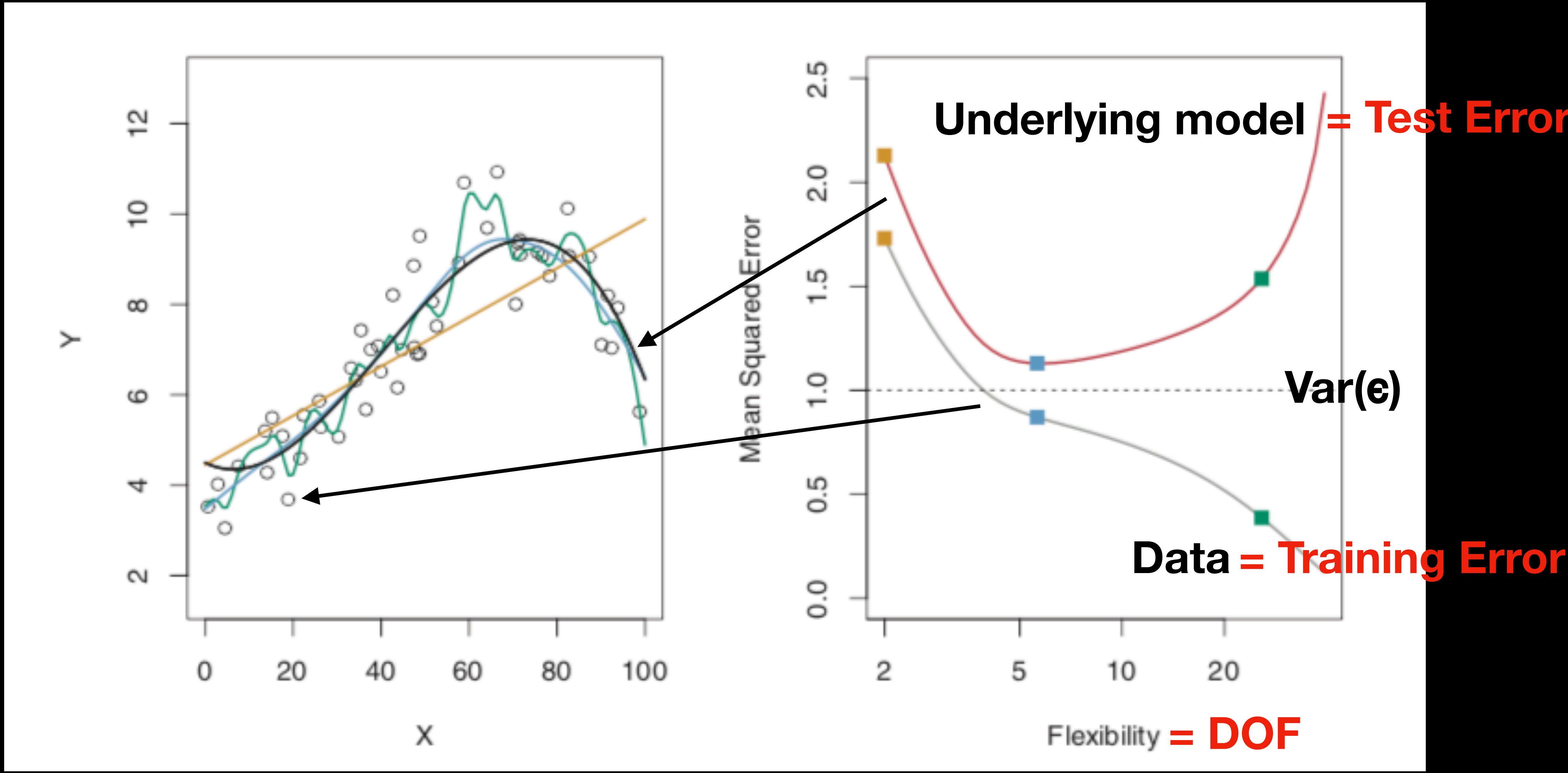

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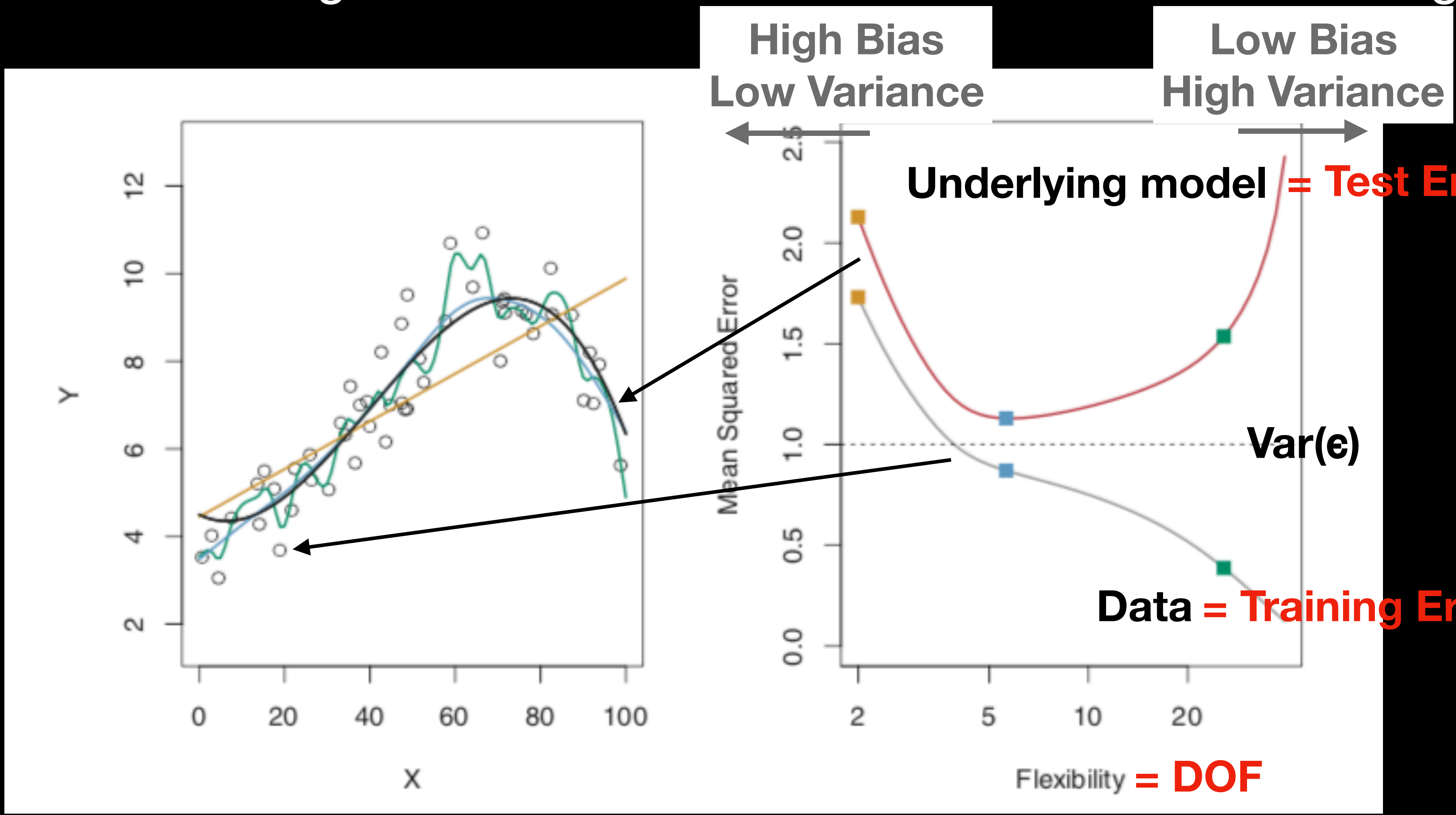
- In contrast, the training error can be easily calculated by applying the statistical learning method to the observations used in its training.



Test & Training Error in KNN: With Math!

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$$\text{Ave}\left(I(y_0 \neq \hat{y}_0)\right)$$

new observation, requires we know what that would be from an underlying model (or more observations)

What our calculated fit/ model would predict

- In contrast, the training error can be easily calculated by applying the statistical learning method to the observations used in its training.

$$\frac{1}{n}\sum_{i=1}^{n} I(y_i \neq \hat{y}_i)$$

an observation in our current dataset

What our fit/model would predict

Here I = 1 if y_i != $\hat{y}_i$ and I = 0 if y_i = $\hat{y}_i$, so larger I means worse model

K Nearest Neighbors (and MLR) → Cross-Validation & Bootstrap

p-values quantify the fit of individual parameters

quantify how good the *model* is

But first: some definitions!

Using our KNN example in R with an underlying model!