Machine Learning for Official Statistics and SDGs

First Live Lecture (Webinar):

Starts in **15** minutes

Christophe Bontemps, UN SIAP

UNITED NATIONS
SIAP
Statistical Institute for
Asia and the Pacific

Machine Learning for Official Statistics and SDGs

First Live Lecture (Webinar):

Starts in **10** minutes

Christophe Bontemps, UN SIAP

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First Live Lecture (Webinar):

Starts in **5** minutes

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Statistical learning: *vs* Machine Learning

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[- Reminder -]

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- Ask questions in the chat

[- AGENDA -]

- Introduction

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- Statistical learning *vs* Machine Learning

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- Introduction
- Statistical learning *vs* Machine Learning
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- Next week

What Is Statistical Learning?

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“ Statistical learning refers to a vast set of tools for understanding data”

Gareth James, Daniela Witten, Trevor Hastie , Robert Tibshirani (2021)

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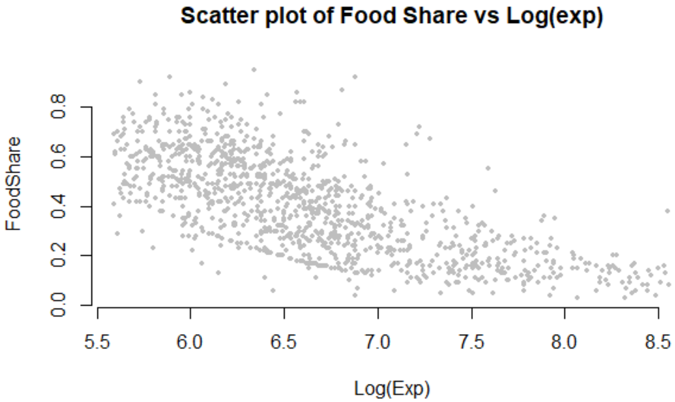
More complex models we'll see at the end of the course

Statistical learning on an example



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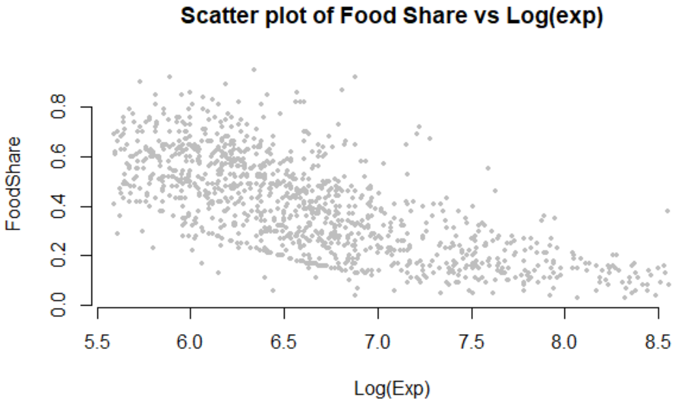
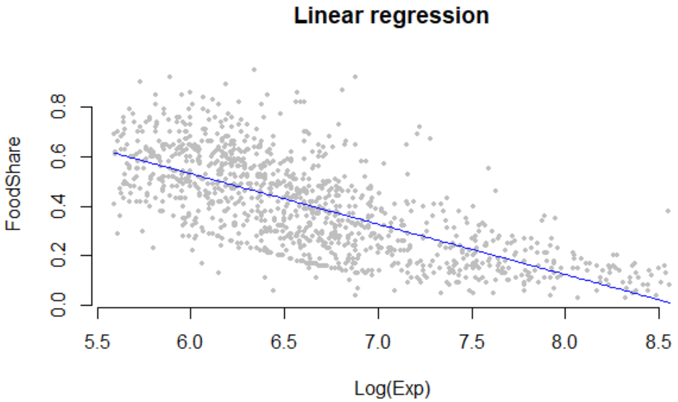


We may be interested in the **relationship** between the two variables

UNDERSTANDING = ESTIMATE $f(\cdot)$



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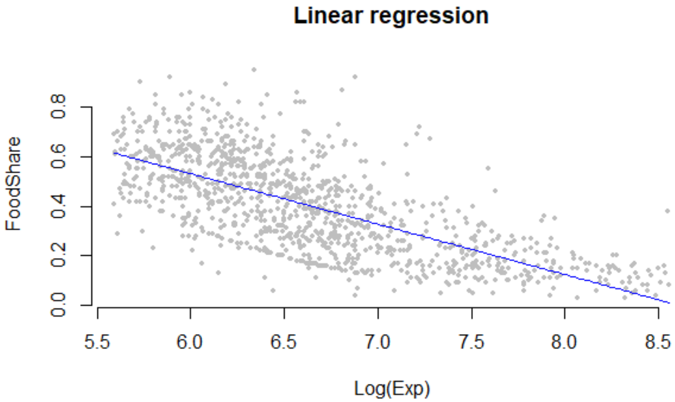

$f(\cdot)$ is the regression line

WHY ESTIMATING $f(\cdot)$?

- Inference

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We denote by $\widehat{f(\cdot)}$ the estimate of $f(\cdot)$

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- The goal is to find the line that is **minimizing** the distance to the observed points (x_i, y_i). The distance is computed as the Mean Square Error (MSE):

$$MSE(\beta_0, \beta_1) = \frac{1}{n} \sum_{i=1}^{n} \big(y_i - (\beta_0 + \beta_1 x_i)\big)^2$$

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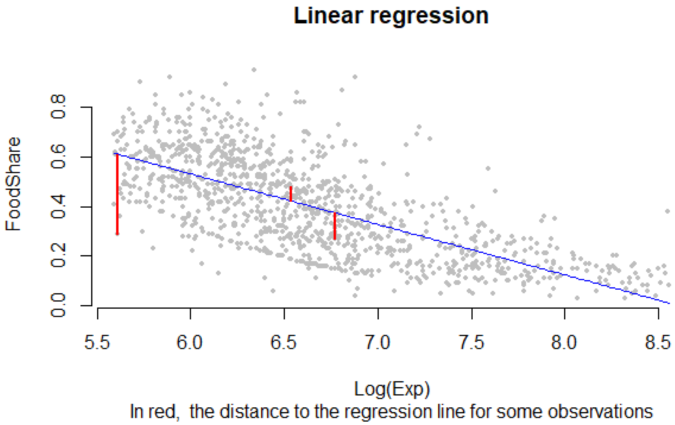
The MSE it is the *cost function* minimized to determine $(\widehat{\beta}_0, \widehat{\beta}_1)$

How to estimate $f(\cdot)$: In practice



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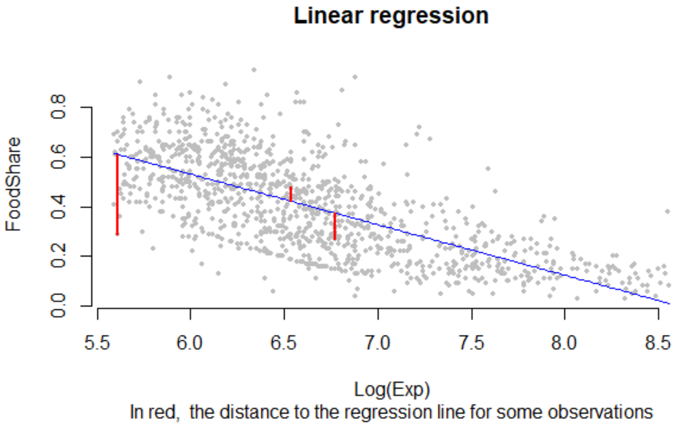


The regression line is found by minimizing the sum of all distances or **MSE**

RESULTS: $\widehat{f(\cdot)}$

From the result and the estimated parameters $(\widehat{\beta}_0, \widehat{\beta}_1)$, we see that there is a relation, and that it is decreasing.

	Estimate	Std. Error	t value	$Pr(>\|t\|)$
(Intercept)	1.75	0.04	41.09	0
ltexp	-0.20^{***}	0.01	-31.84	0

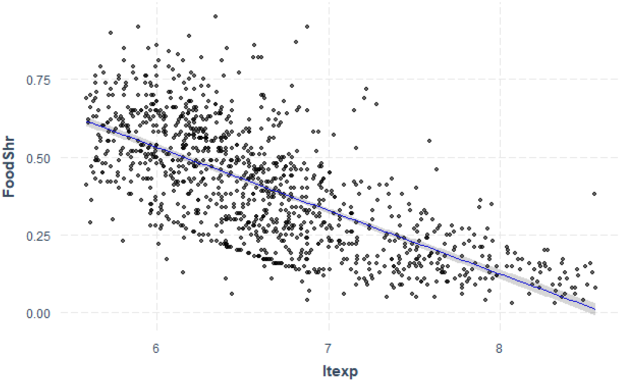
The quality of the adjustment may be measured by the $R^2 = 0.478$

Beyond linearity

Beyond linearity

- A linear model may be unadapted or too simple

$$y = \beta_0 + \beta_1 x + \varepsilon$$



The fit (measured by R^2) is: $R^2 = 0.478$

Beyond linearity

- A Polynomial model may be better adapted: **Quadratic** model

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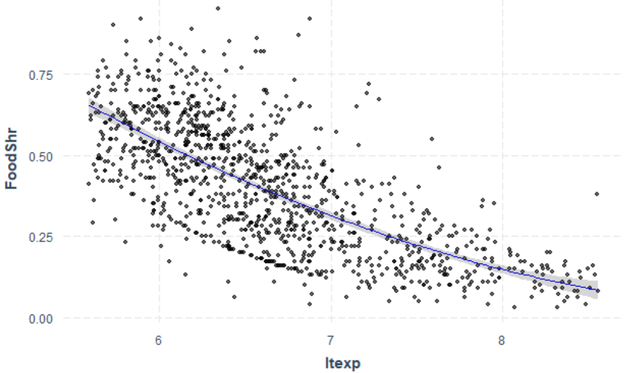

Do we have a better fit? $R^2 = 0.484$

BEYOND LINEARITY

- Polynomial may be better adapted: **Cubic** model

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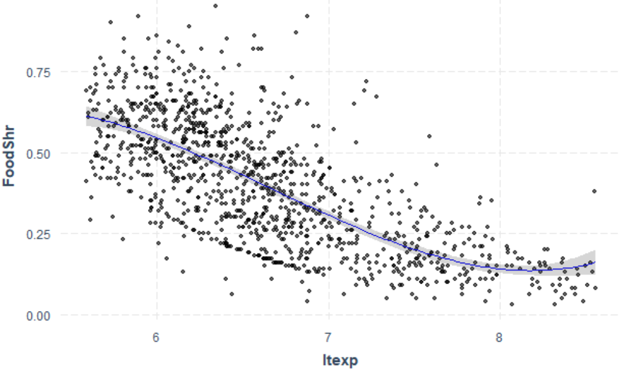

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$\hookrightarrow$ *How does that relates to the learning exercise?*

Nearest neighbors (k-NN)

- Other methods more flexible

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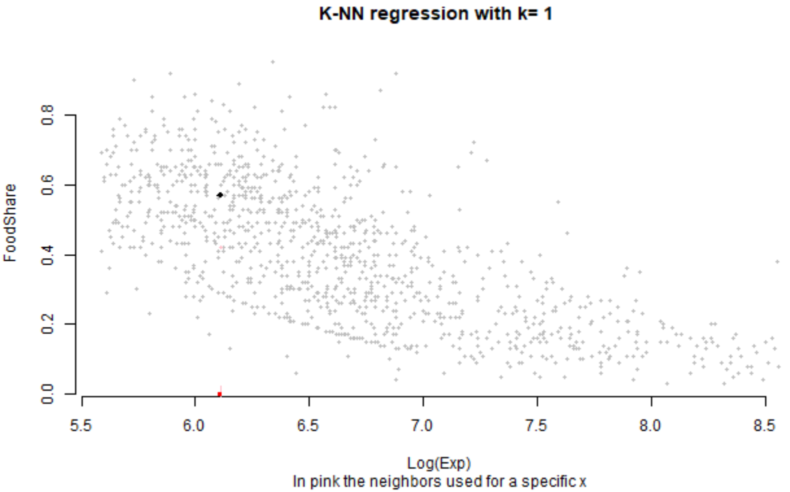
"*Observations close in the x dimension should be close in the y dimension*"

K-NN in practice



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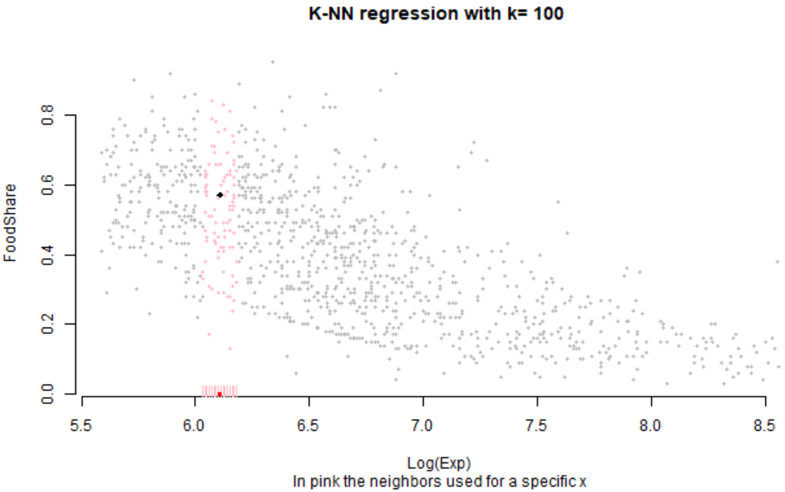

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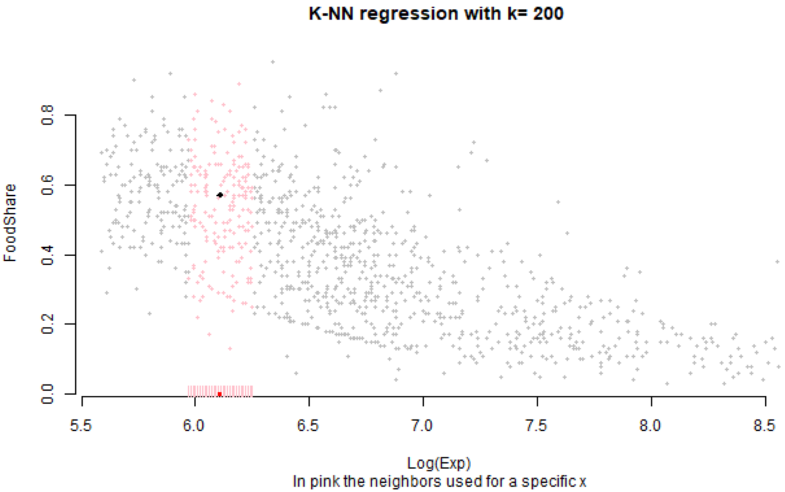

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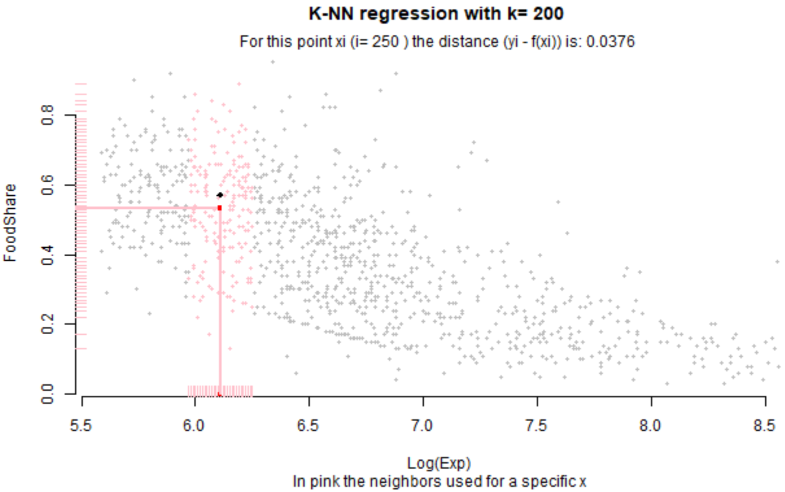

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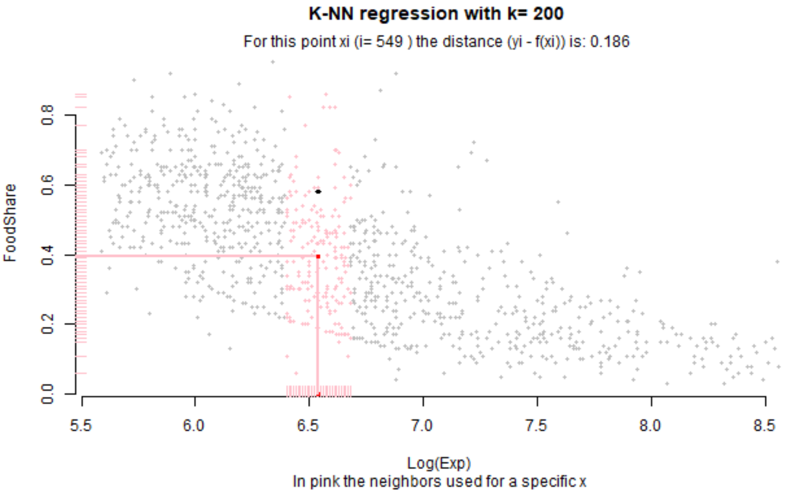

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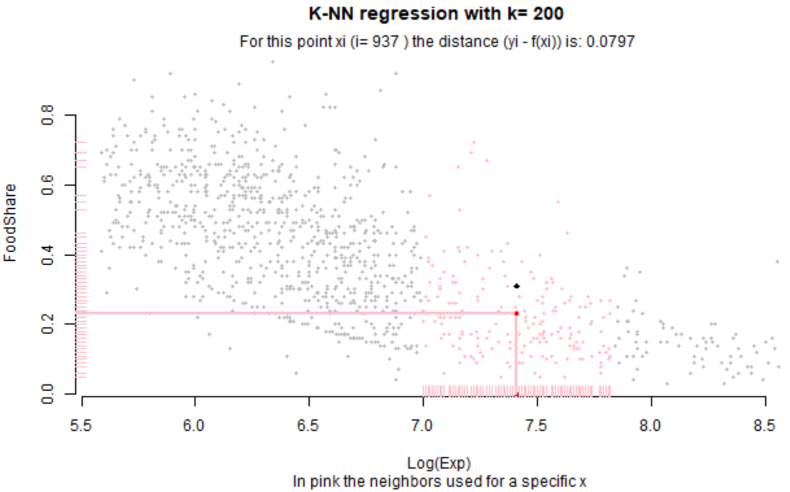

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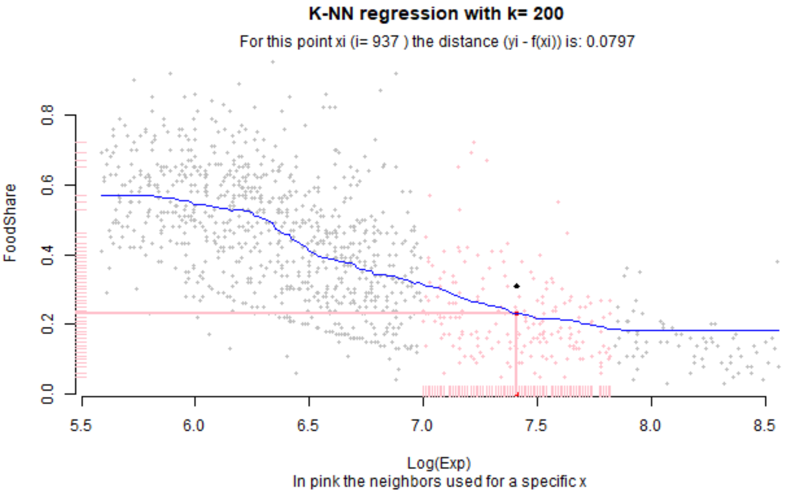

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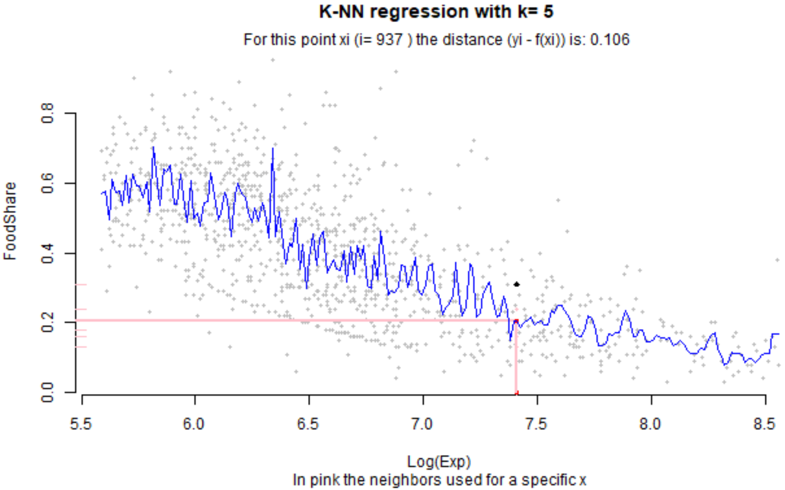

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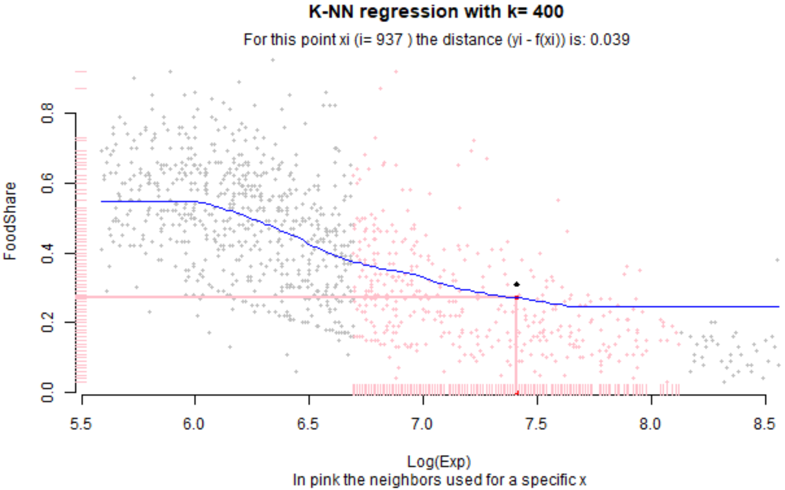

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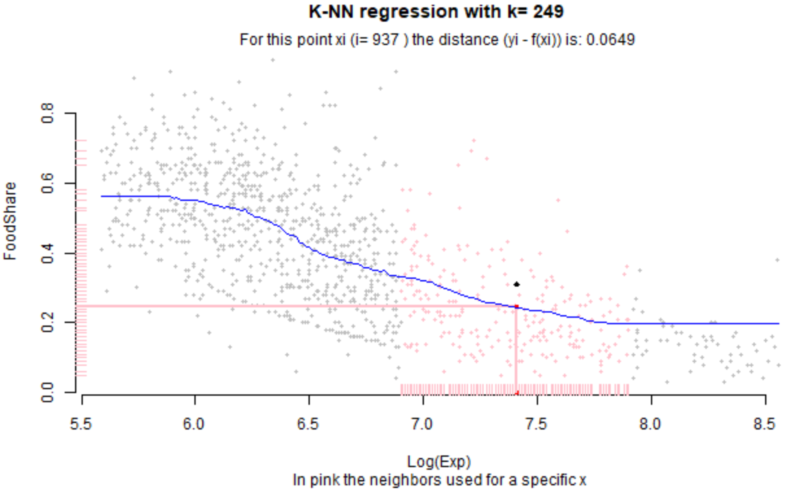

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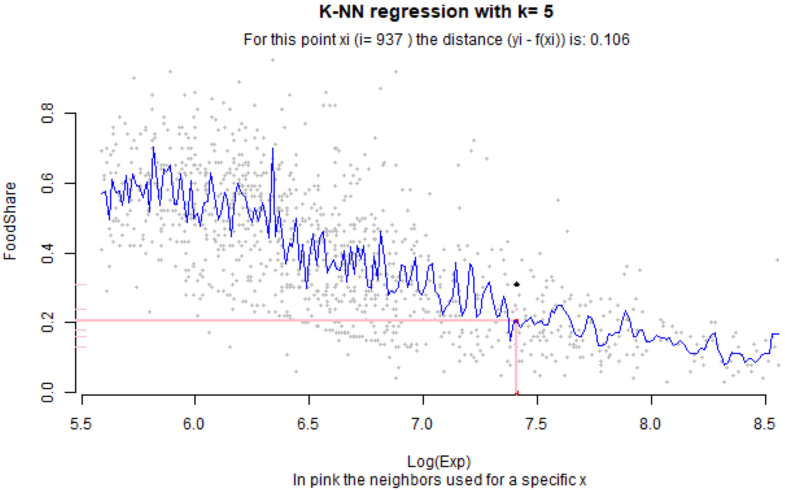

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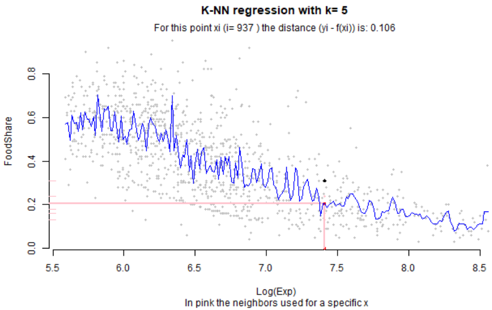

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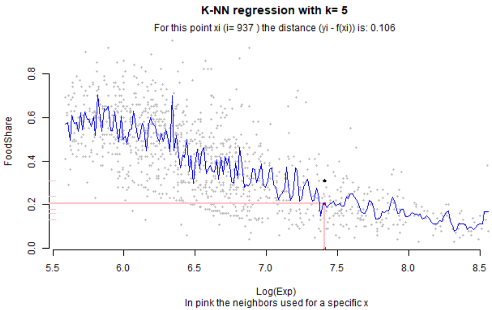

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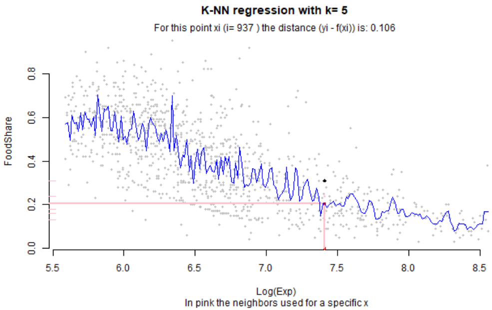

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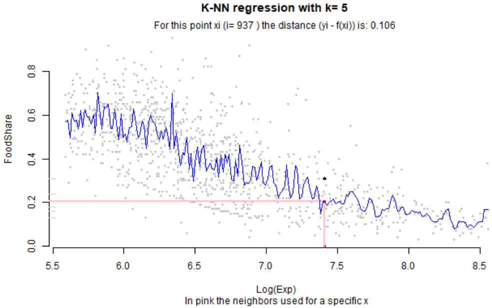

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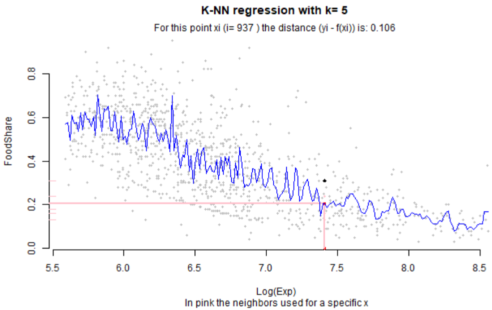

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- The estimated curve follows the **errors** too closely
- The estimated function will not provide good estimates on **new observations**

STATISTICAL *vs* MACHINE LEARNING

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- In practice we'll use both tools to "*understand the data*"

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The classical approach

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- We have estimated $f(\cdot)$ by $\widehat{f}(\cdot)$ and minimized some cost function
- The data serve **both** for estimating $f(\cdot)$ **and** computing the prediction error

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A different approach: *resampling*

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- Compare y_i with the prediction based on the validation set xs

Why different sets?

Estimating parameters using predictions accuracy

- When estimating $f(\cdot)$ on the whole data set, over-fitting may occur

Why different sets?

Estimating parameters using predictions accuracy

- When estimating $f(\cdot)$ on the whole data set, over-fitting may occur
- The validation set provides a good way to evaluate the prediction capabilities of a model and the prediction error on a new data set

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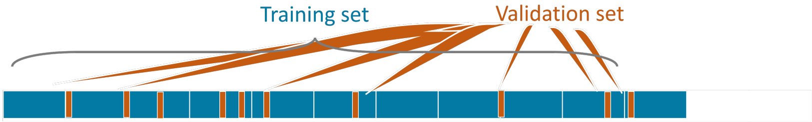

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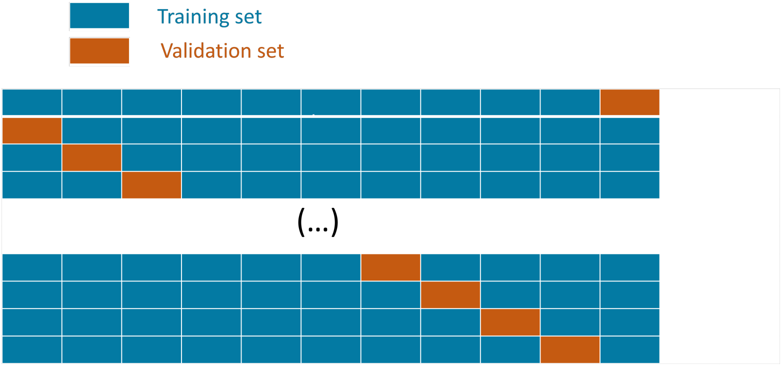

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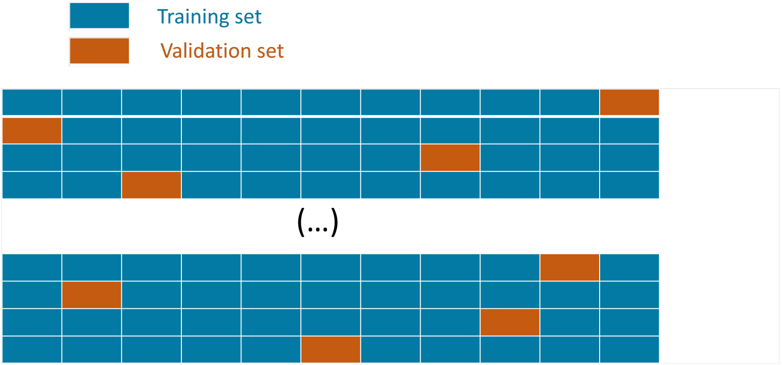

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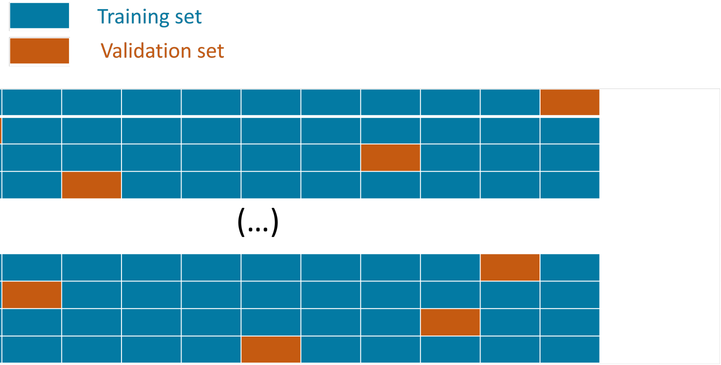

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↪ Example: select k in k-NN regression

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$\hookrightarrow$ In a machine learning framework, the efficiency of the prediction will guide the choices, not the statistical properties!

[Q&A]

Write your questions in the chat

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Have a nice week!