

# Supervised Machine Learning

## Module 3



# Let me introduce myself...



 [juan-benavente](#)



## JUAN BENAVENTE



- Industrial engineer
- Computer engineer

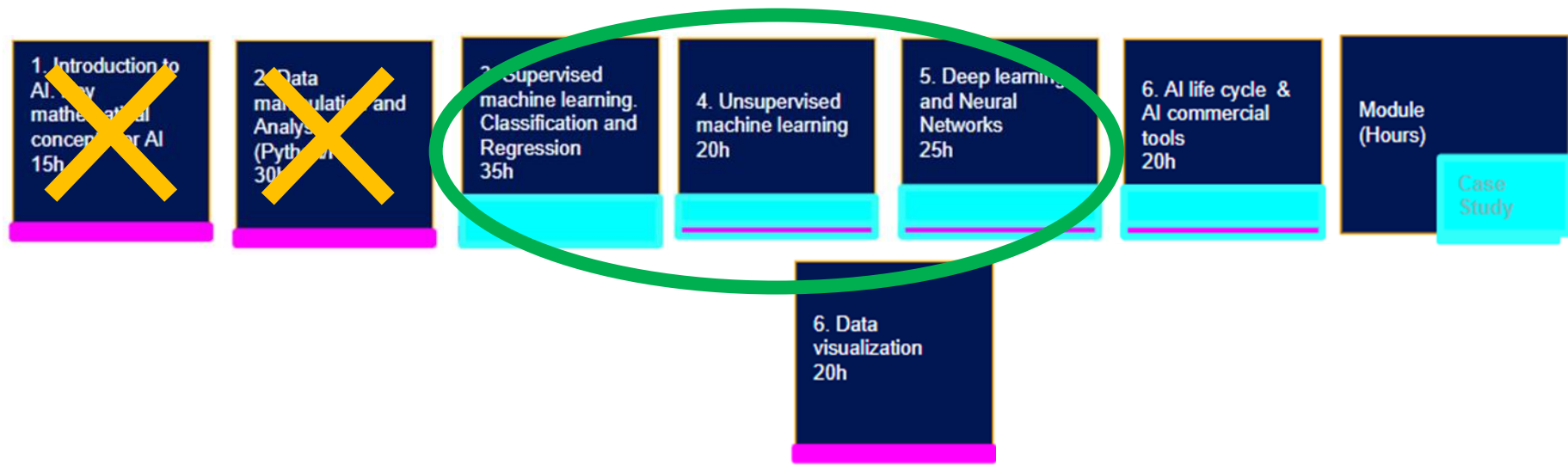


- Smarter Cities Technical Presales (IBM)
- Internet of Things Consultant and Team Lead (IBM)
- Industry 4.0 & Blockchain Solutions Architect (CEPSA)
- Sectors: Energy, Industrial, Public



- 1<sup>st</sup> Runner Up Non-supervisory IT Employee of the year – Mubadala's IT Award
- WPC O&G Spanish Youth Award - Impact of Blockchain in O&G
- Outstanding Technical Achievement Award: Treasure Wild Ducks

# Where are we?



# Why are we here?



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## Tell us about your car

Get an instant valuation – for free

We couldn't identify your car from its registration. Please choose the details here.

\* Make:

Please select

\* Model:

Please select

\* Variant:

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\* Derivative:

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\* Reg Date:

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\* Mileage:

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## Your car valuation

Image unavailable

**Mercedes-Benz C Class 1.6 C180 AMG Sport Edition 7G-Tronic Plus 2dr (13 - 15)**

[OR19ASM](#) | [Petrol](#) | [1595 cc](#) | [Coupe](#) | [Automatic](#)

Mileage: 100,000

Change car

Private guide price

**£7,330**

Price for: 18 April 2020

Part-exchange guide price

**£6,210**

Price for: 18 April 2020



## How do we value cars?

### What determines a car's condition?

The condition your car is in will affect its value.  
There are generally 3 types of condition:

#### Fair:

Bodywork needs minor repairs

Minor or cosmetic damage

Minor or cosmetic damage

Interior has wear and tear

Some interior equipment damaged

Tyres are safe and legal, but worn

Documentation and keys present

Large gaps in service history

Current MOT

No outstanding finance

The car has never been written off

#### Good:

Minor or cosmetic damage

Minor or cosmetic damage to lights, glass and mirrors

All tyres are safe and legal

Documentation and keys present

Partial, documented service history

Current MOT

No outstanding finance

It is not a write-off (category C or D)

#### Excellent:

No damage to bodywork, wheels or glass

No damage to lights, glass or mirrors

All tyres are safe and legal

Documentation and keys present

Full, documented service history

Current MOT with at least six months to go

No outstanding finance

It is not a write-off (category C or D)

### What affects a car's value?

The guide prices we provide give you a starting point for valuing your car when buying or selling it. However, many factors can affect a car's value.

#### Overall condition

Cars of similar ages can have vastly different levels of wear and damage.

#### Number of owners

Typically, cars with more previous owners are worth less, especially if they lack documentation too.

#### Optional extras

Features like sat navs, leather seats and panoramic sunroofs can bump up the value.

#### Colour

Certain colours can be more desirable, depending on current trends and fashions.

#### Service history

Cars are worth more with a fully-documented service history.

#### MOT

Buyers often pay more for a long MOT.

#### Modifications

Additions like body kits, spoilers and so on can increase or decrease the value.

#### Rarity of model

Some cars are desirable because there aren't so many of them around.

#### Extras included in the deal

Such as extended warranties



# Why ML?

- **Problem type:** inference or prediction/estimation
- **Resolution process:** complex or unknown formulas and/or rules -> solution based on previous experience (data)
- **Other characteristics:**
  - Complexity -> many variables
  - Large amounts of data
  - Repetitive problem

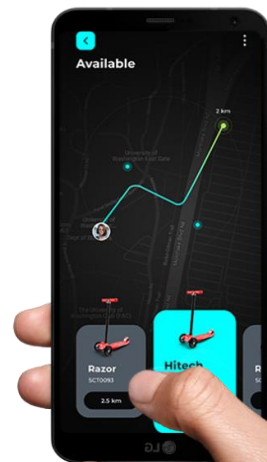
# Is this useful?





# WHEELZ

If you don't dress every day the same, why don't you move around differently?



# Wheelz Design Thinking

- You have just joined Wheelz startup as the **DS Team Leader**
- As a Young company, **ML has not been implemented so far**, but will be the focus during the next 3-5 years
- You organize a **Design Thinking** with your teammates in order to better understand which **data is available** at the company and **identify possible initiatives** to overcome with your team



# Wheelz Design Thinking

- You will be working in **teams**:

- **TEAM 1 (Juan):**

- Daniel Rey
- Laura Martín
- Samuel Carballo
- **Mauricio Asperti**
- **Marcelo Araujo**
- Isabel Hita

- **TEAM 2 (Mónica):**

- Marcos García
- Ignacio Cifuentes
- **María Dolores Carmena**
- Fernando Rodríguez
- **Ayose Sosa Guerra**

- **TEAM 3 (Miguel):**

- Vittoria Reale
- **Rubén Farias**
- José Pascual
- Ángel Moya
- Kay Kozaronek
- **Miguel García**

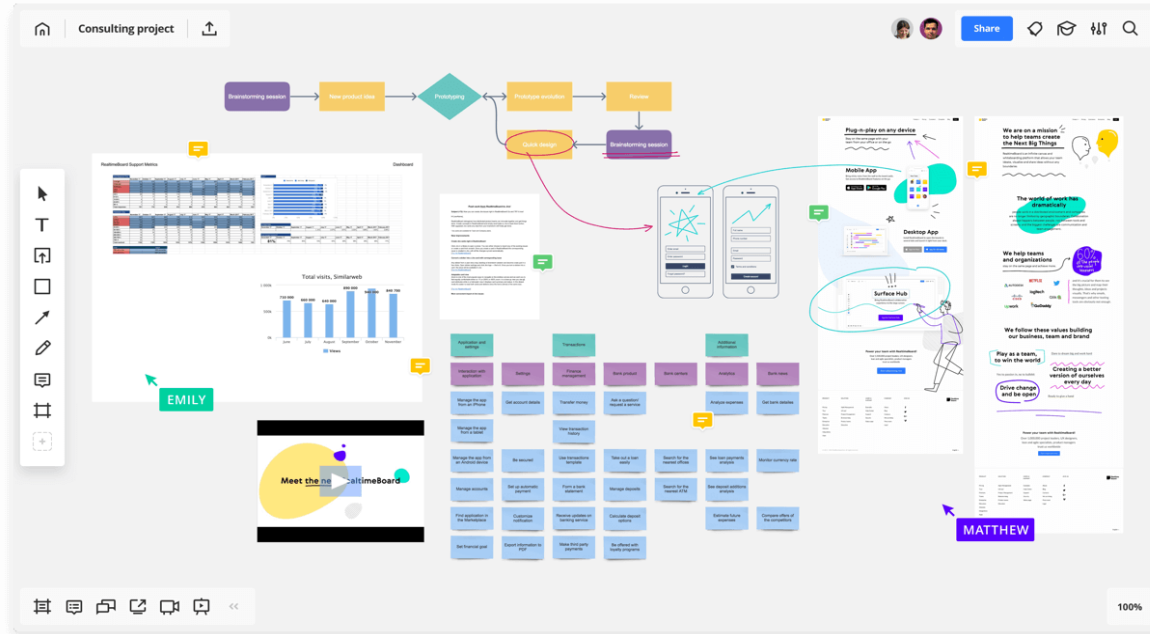
**facilitator** -> timing, everybody speaks,  
go,go,go!

**presenter** -> summarizes results

# Wheelz Design Thinking



- You will be using Miro app



# Wheelz Design Thinking

6 min

Discuss which sources of data are present in the company

- 2': individual creation
- 4': put together, discuss, enrich, and cluster



| ENTERPRISE DATA         |  |  |  |  |  |  |  |  |  |
|-------------------------|--|--|--|--|--|--|--|--|--|
| Inventario de patinetes |  |  |  |  |  |  |  |  |  |
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| ML INITIATIVES             |  |  |  |  |  |  |  |  |  |
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| Tiempo de batería restante |  |  |  |  |  |  |  |  |  |
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6 min

Discuss which initiatives we could work at

- 2': individual creation
- 4': put together, discuss, enrich, and cluster



# Wheelz Design Thinking



## ENTERPRISE DATA



## ML INITIATIVES





# Some basic definitions

ML is the science and art of programming computers so that they can **learn from data**.

– Aurélien Géron

ML is the field of study that gives computers the ability to **learn without being explicitly programmed**.

– Arthur Samuel, 1959

A computer program is said to learn from experience  $E$  with respect to some task  $T$  and some **performance measure  $P$** , if its performance on  $T$ , as measured by  $P$ , improves with experience  $E$ .

– Tom Mitchell, 1997

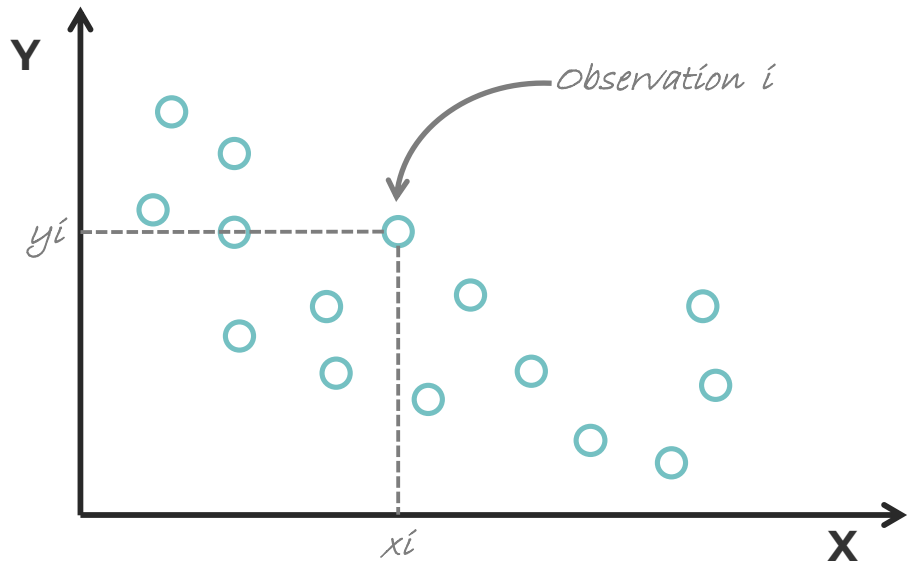
# Module 3 Summary

| SESSION | TITLE                                    | TEACHER |
|---------|--|---------|
| 1       | ML Foundations                           | Juan    |
| 2       | Regression Introduction and Practice     | Juan    |
| 3       | Classification Introduction and Practice | Carlos  |
| 4       | Feature Engineering and Selection for ML | Carlos  |
| 5       | Advanced Supervised Models 1             | Carlos  |
| 6       | Advanced Supervised Models 2             | Carlos  |
| 7       | Hands-on Practice                        | Carlos  |

# **Supervised ML**

## **Module 3.1**

# What is ML?

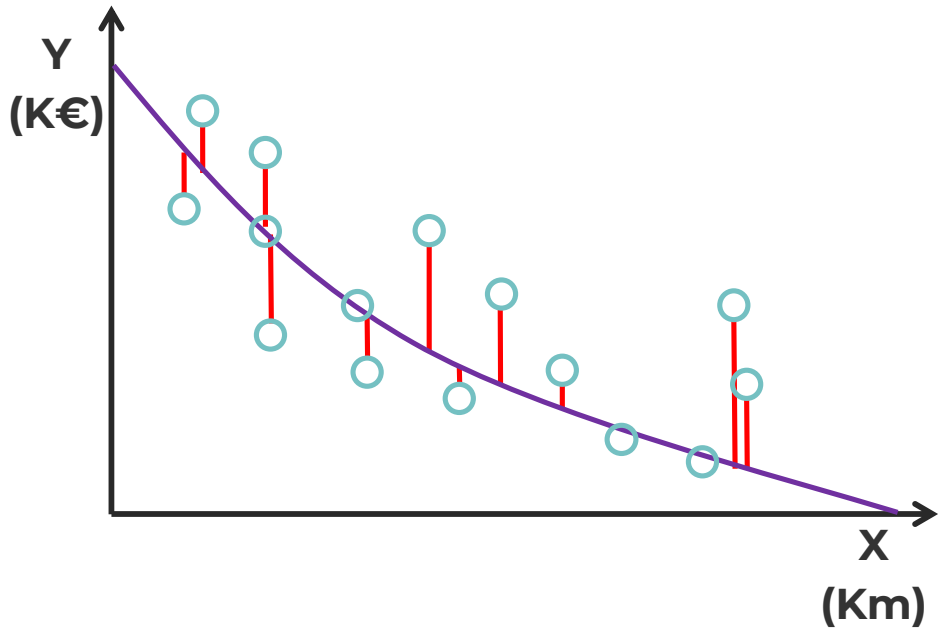


**$X$**  > input variables – predictors,  
independent variables, features  
 $X = (X_1, X_2, \dots, X_p)$

**$Y$**  > output variable – response,  
dependent variable

**Observations** >  $\{(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)\}$

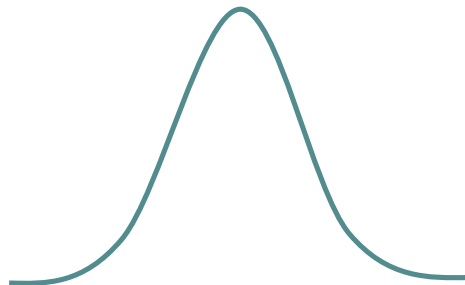
# What is ML?



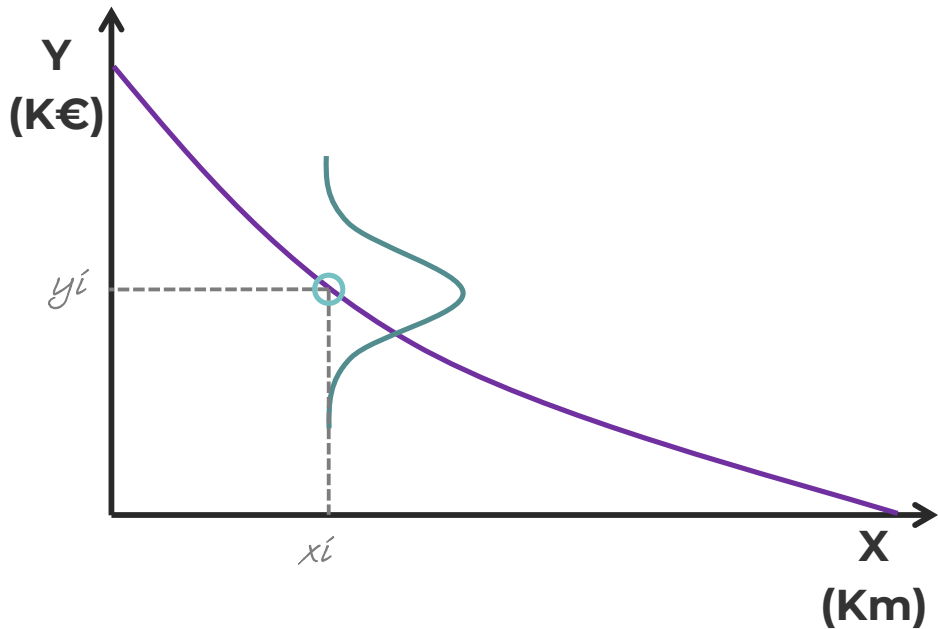
$$Y = f(X) + \epsilon$$

**f(X)** > fixed but unknown function that relates X and Y.

**E** > error term, noise, independent of X and mean 0 (a priori)



# What is ML?



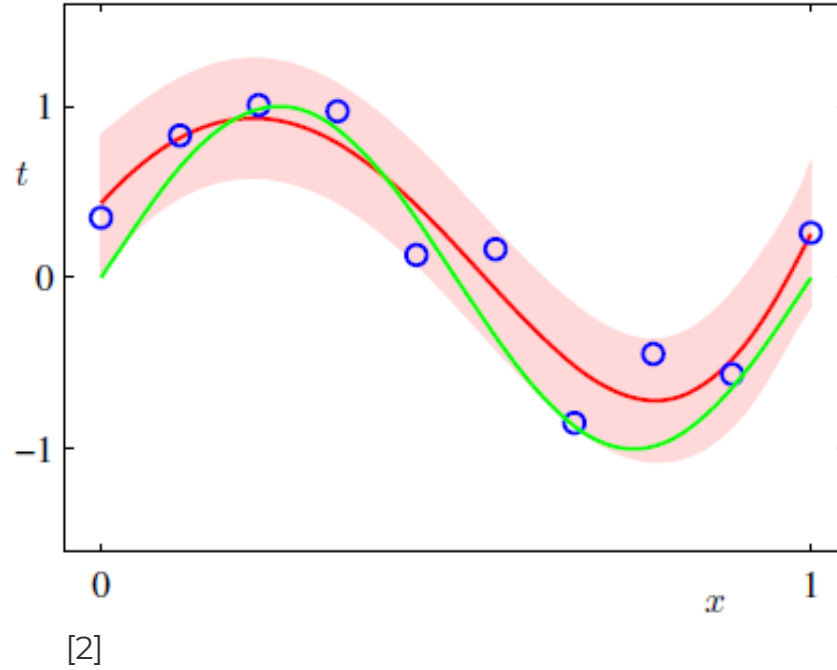
$$Y = f(X) + \epsilon$$

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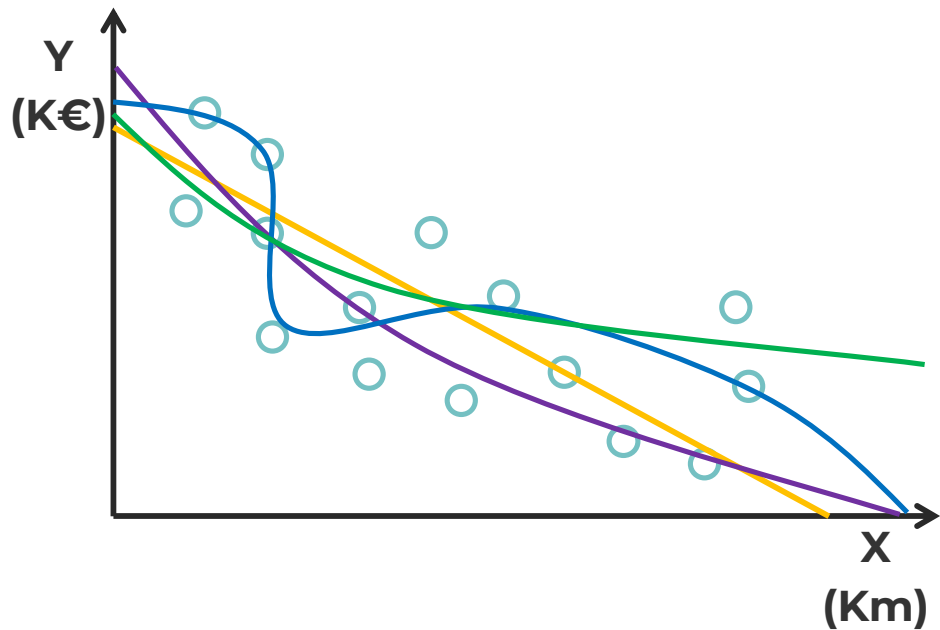
**E** > error term, noise independent of X and mean 0 (a priori)



# What is ML?



# What is ML?



$$\hat{Y} = \hat{f}(X)$$

$\hat{f}(X)$  > estimate for  $f$

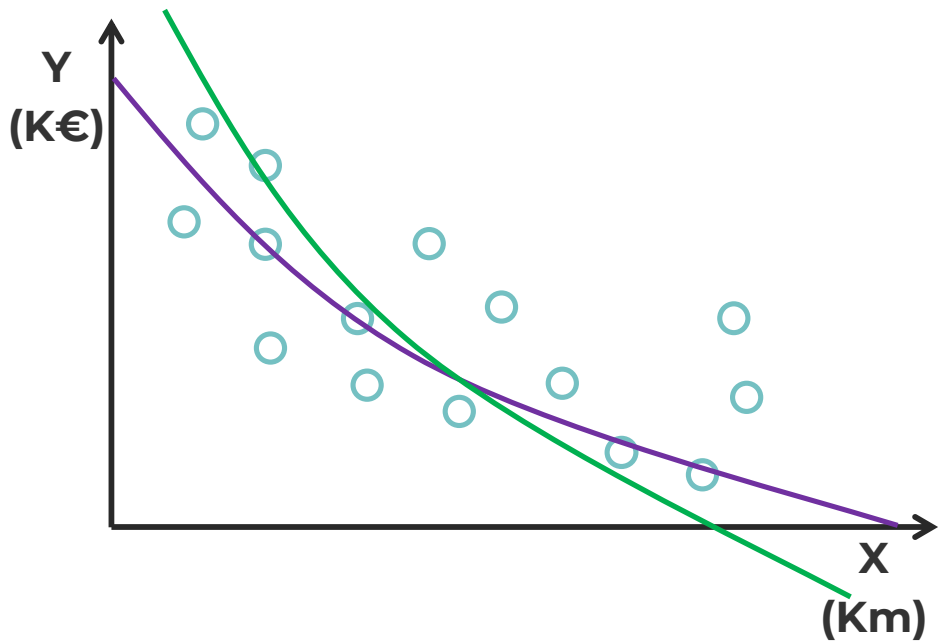
$\hat{Y}$  > resulting prediction for  $Y$

# What is ML?

“Essentially, all models are wrong, but some are useful.”

- George Box, 1987.

$$\hat{Y} = \hat{f}(X)$$



$\hat{f}(X)$  > estimate for  $f$

$\hat{Y}$  > resulting prediction for  $Y$

**reducible error** > prediction function does not suit perfectly to real function

**irreducible error** > unmeasured variables and unmeasurable variation

# Let's model vertical movement



<https://giphy.com/gifs/deadpool-dad-peter-1APafwnHNjbwU5A48H>

# Let's model vertical movement



# What is ML?



$$E \left[ (Y - \hat{Y})^2 \right] = E \left[ \left( f(X) + \epsilon - \hat{f}(X) \right)^2 \right] = \underbrace{\left( f(X) - \hat{f}(X) \right)^2}_{\text{Reducible}} + \underbrace{\text{Var}(\epsilon)}_{\text{Irreducible}}$$

## Reducible:

- dependent on input variables
- higher while higher is the difference between the real function and our estimation
- we can improve our model to reduce this term

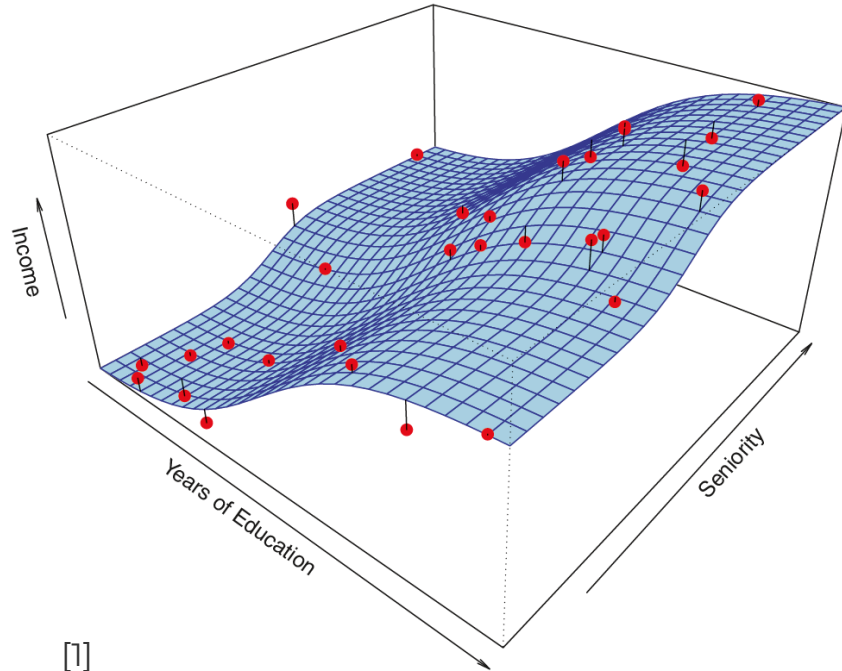
## Irreducible:

- not dependent in input variables
- upper bound for our model's accuracy

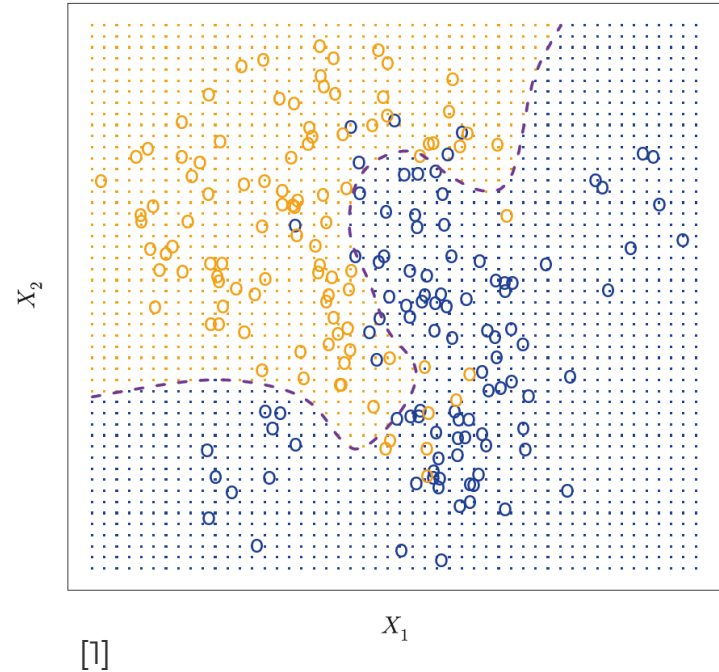


# What is ML?

Different dimensionality....



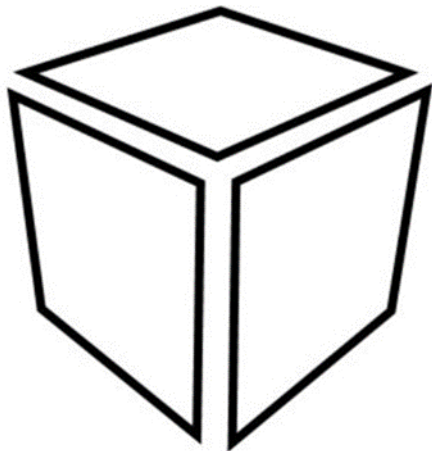
Different nature....



# To explain or to predict?



White-box modelling



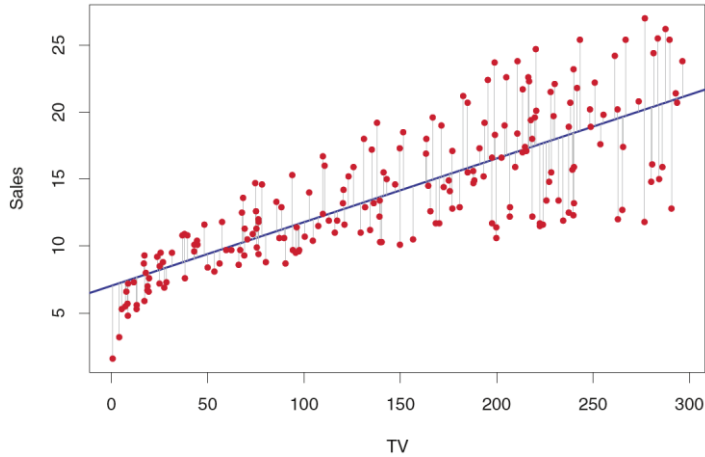
Black-box modelling



or

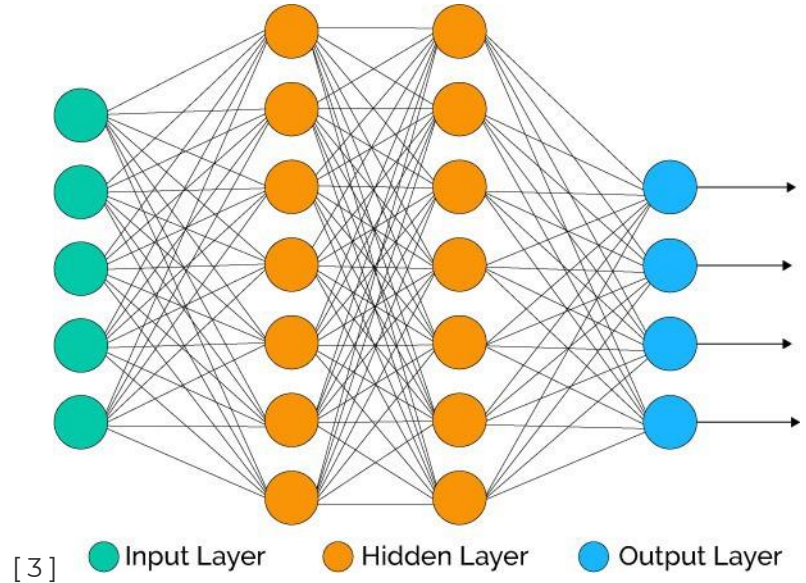
<https://www.linkedin.com/pulse/white-box-black-choosing-machine-learning-model-your-vidyadhar-ranade>

# To explain or to predict?



$$Y = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$$

[1]



# Is interpretability important? Why?



# Interpretability

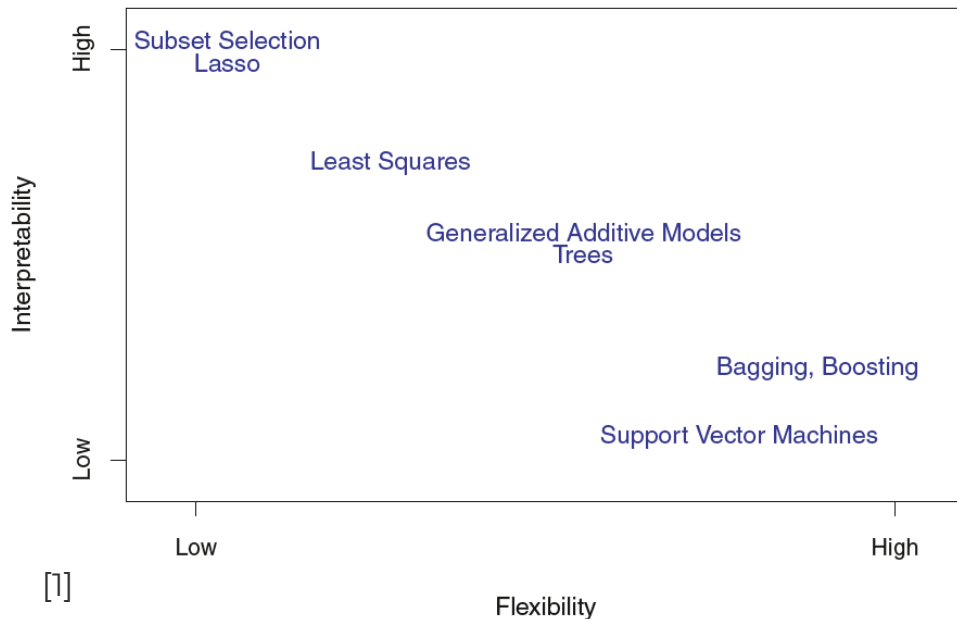


## IMPORTANCE

- Debugging
- Informing feature engineering
- Directing future data collection
- Informing human decision-making
- **Building Trust**

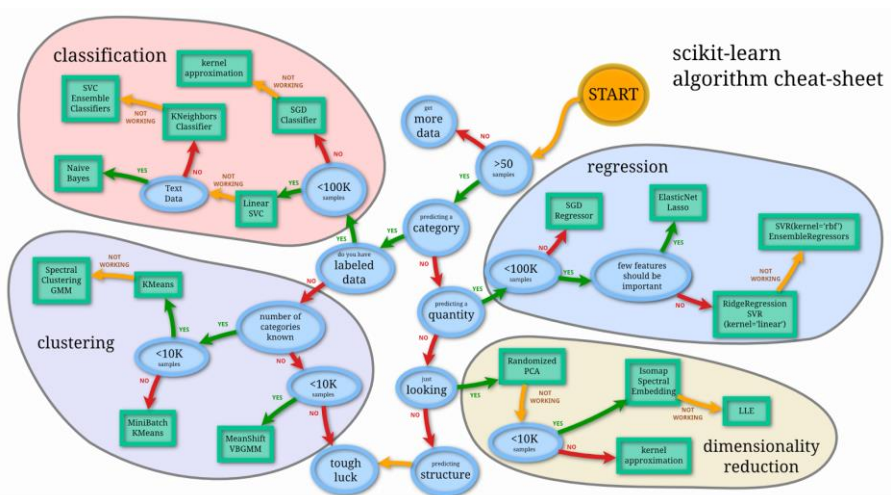
“The problem is that a single metric, such as classification accuracy, is an incomplete description of most real-world tasks.”

- Doshi-Velez and Kim, 2017



# Assessing Model Accuracy

One model to rule them all...



[https://scikit-learn.org/stable/tutorial/machine\\_learning\\_map/index.html](https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html)



<https://www.looper.com/189208/saurons-entire-backstory-explained/>

...no

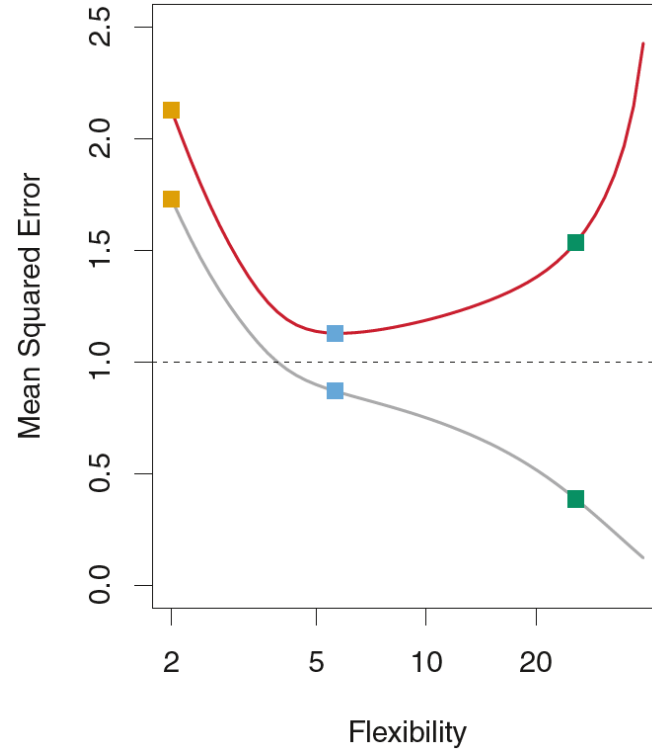
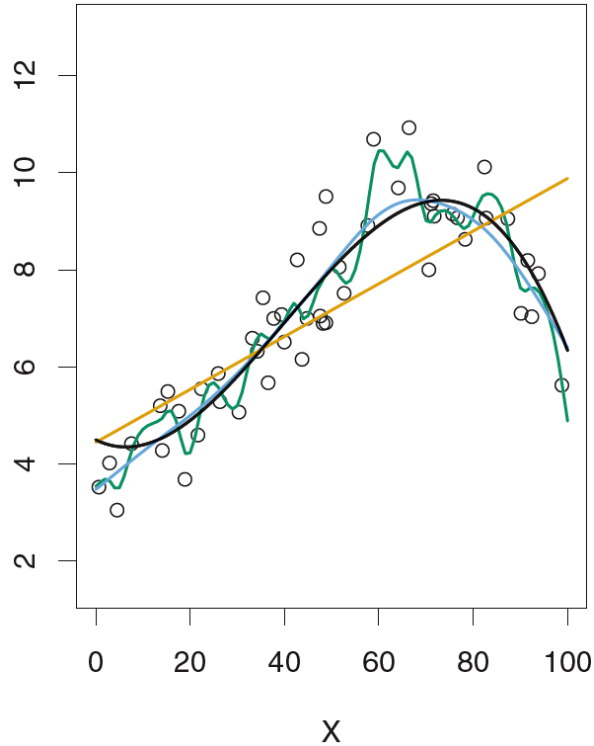


# Mean Squared Error

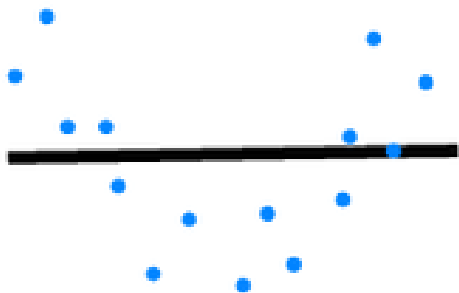
$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2$$

- Evaluate the quality of fit, model performance, model skill
- Small for well fitted model
- Training MSE vs Test MSE

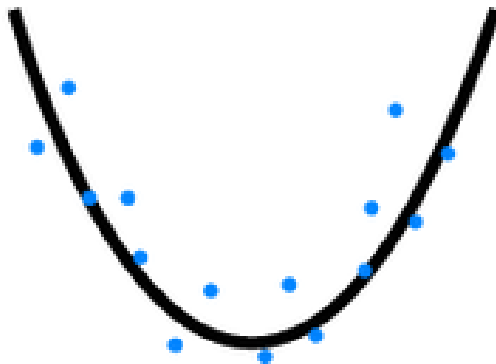
# Mean Squared Error



# Overfitting



Underfitting



Desired

*Memorizing is not learning!*



Overfitting

# Overfitting



# Overfitting

|                           |                           |  |
|---------------------------|---------------------------|--|
|                           | Low <i>Training</i> Error | High <i>Training</i> Error   |
| Low <i>Testing</i> Error  | The model is learning!    | Probably some error in your code. Or you've created a <i>psychic</i> AI. |
| High <i>Testing</i> Error | OVERFITTING               | The model is not learning.   |

# Kahoot!

# Bias-Variance Trade-off



$$E \left[ (Y - \hat{Y})^2 \right] = E \left[ \left( f(X) + \epsilon - \hat{f}(X) \right)^2 \right] = \underbrace{\left( f(X) - \hat{f}(X) \right)^2}_{\text{Bias}} + \underbrace{\text{Var}(\epsilon)}_{\text{Variance}}$$

---

$$\begin{aligned} E \left[ (Y - \hat{Y})^2 \right] &= (E[\hat{f}(X)] - f(X))^2 + E \left[ (\hat{f}(X) - E[\hat{f}(X)])^2 \right] + \text{Var}(\epsilon) \\ &= \underbrace{\left( \text{Bias}(\hat{f}(X)) \right)^2}_{\text{Bias}} + \underbrace{\text{Var}(\hat{f}(X))}_{\text{Variance}} + \underbrace{\text{Var}(\epsilon)}_{\text{Variance}} \end{aligned}$$

# Bias-Variance Trade-off



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

## VARIANCE:

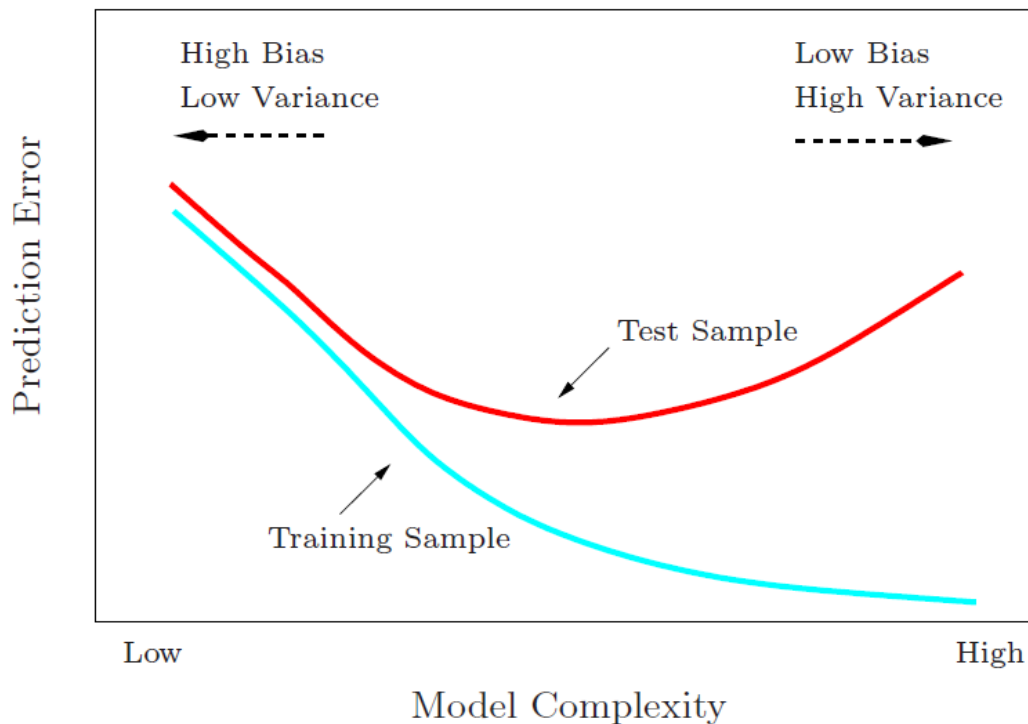
- Overcomplex model assumptions
- Amount by which  $\hat{f}$  would change if we estimated it using a different training data set

## BIAS:

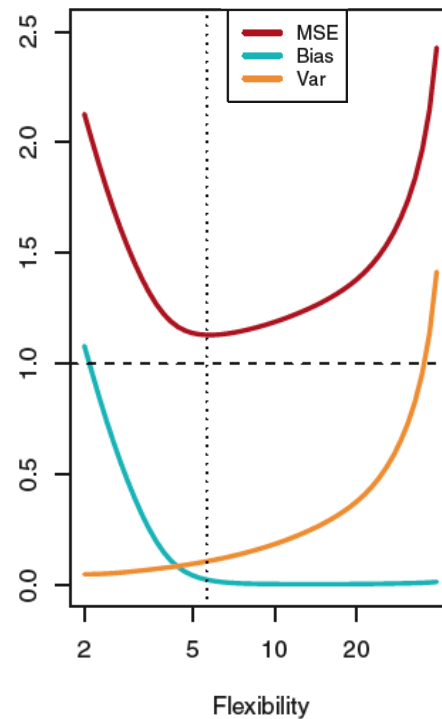
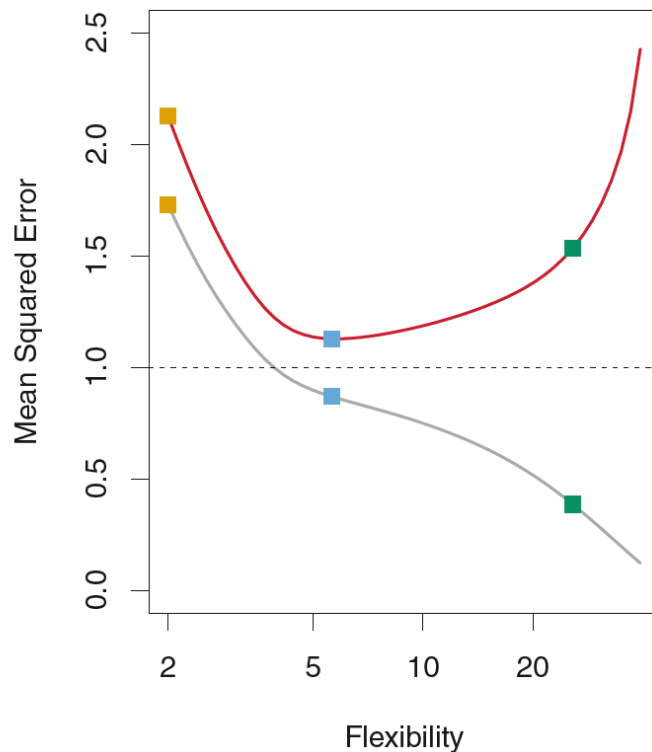
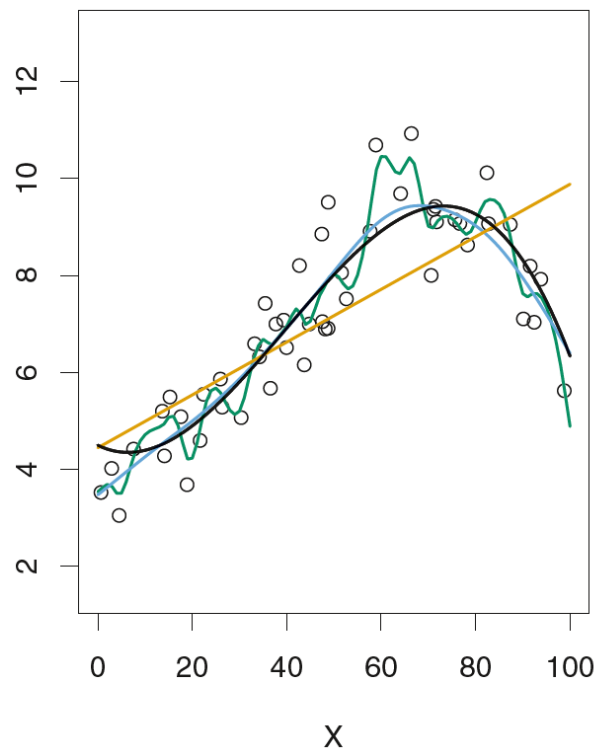
- Oversimplifying model assumptions
- Difference between the average prediction of our model and the correct value which we are trying to predict



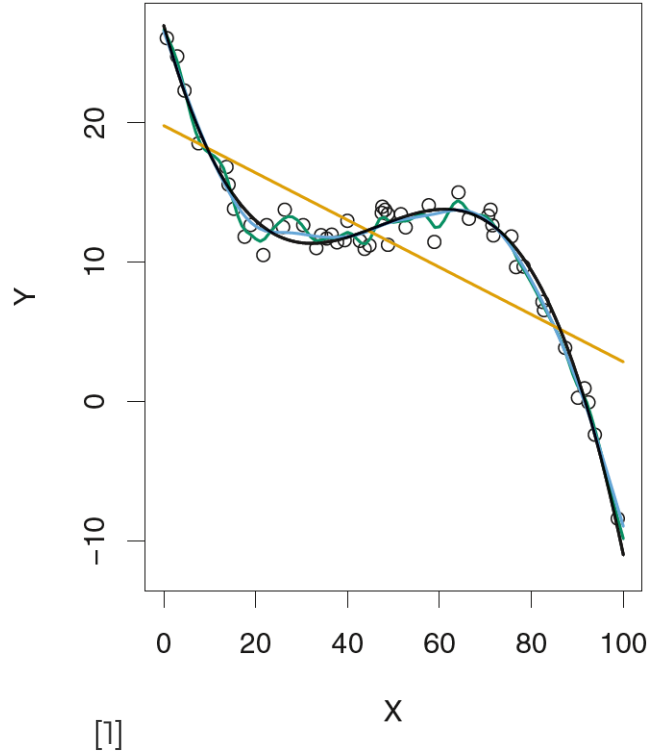
# Bias-Variance Trade-off



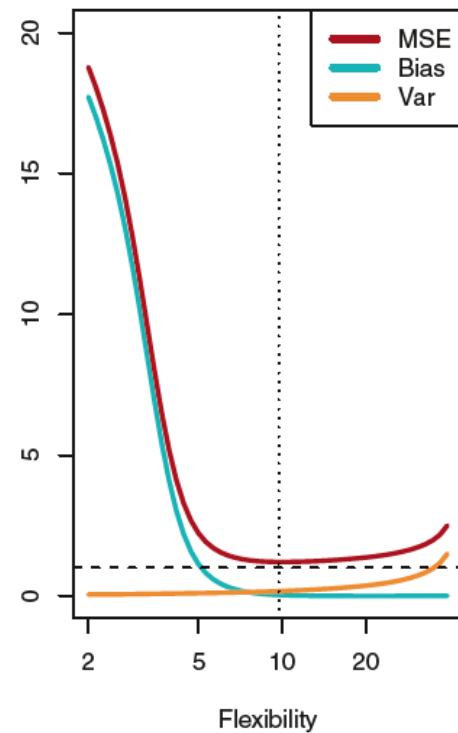
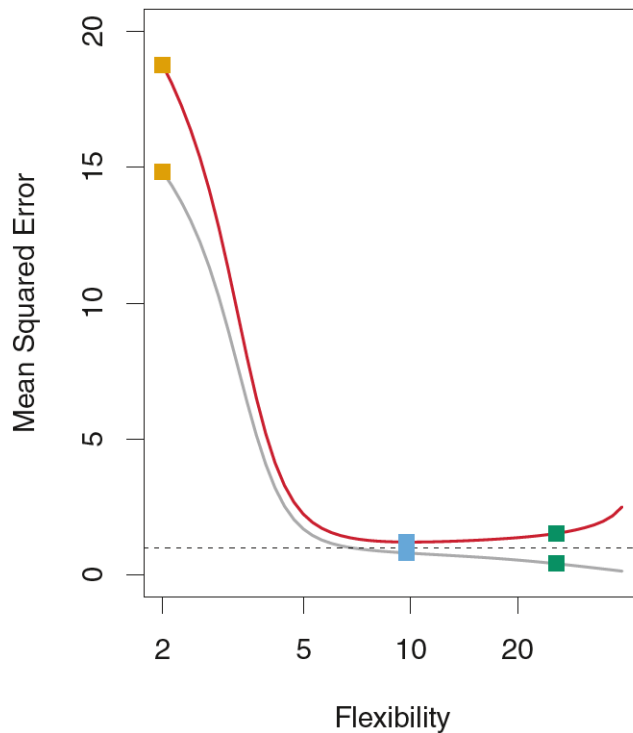
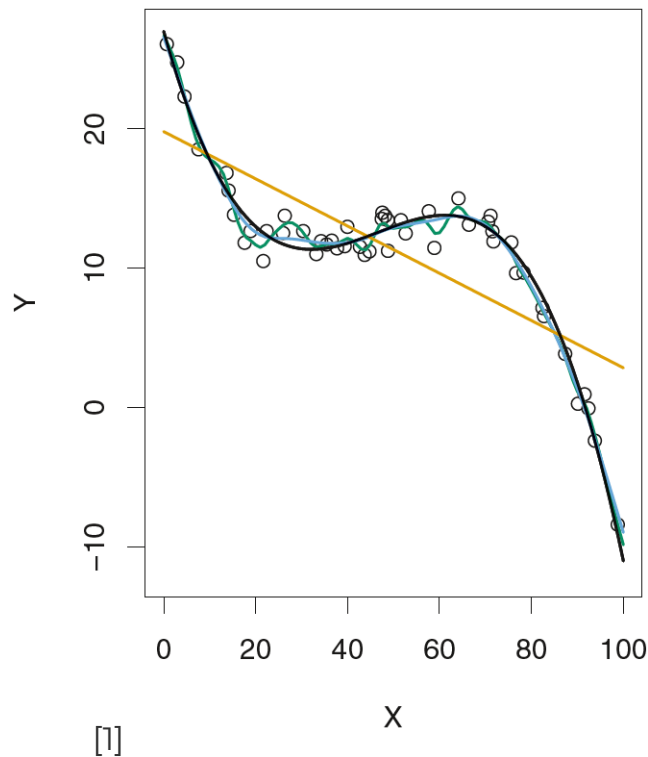
# Bias-Variance Trade-off



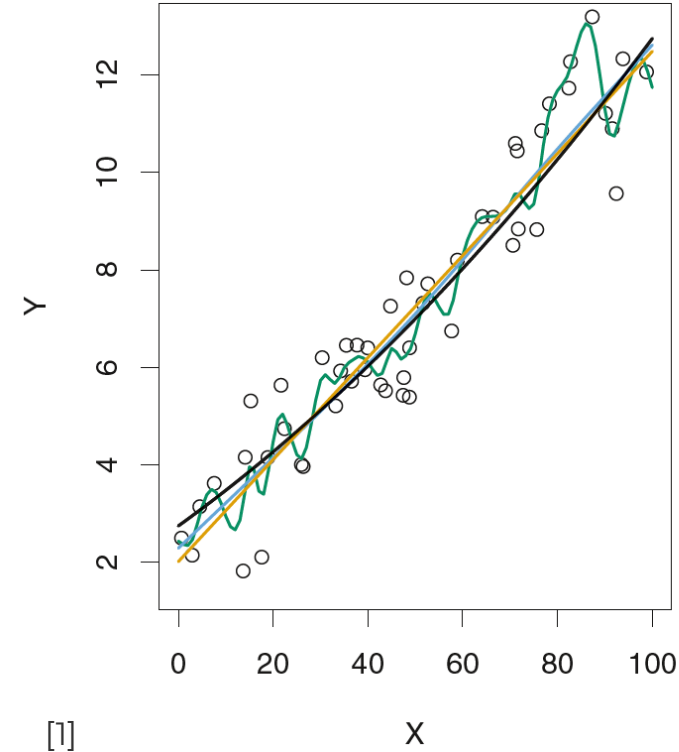
# Bias-Variance Trade-off



# Bias-Variance Trade-off

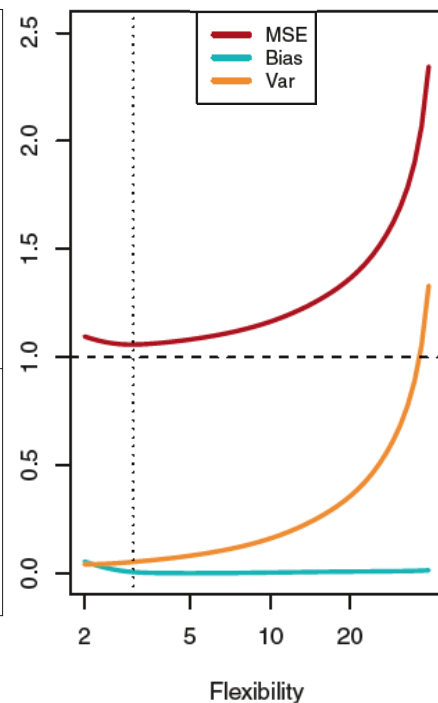
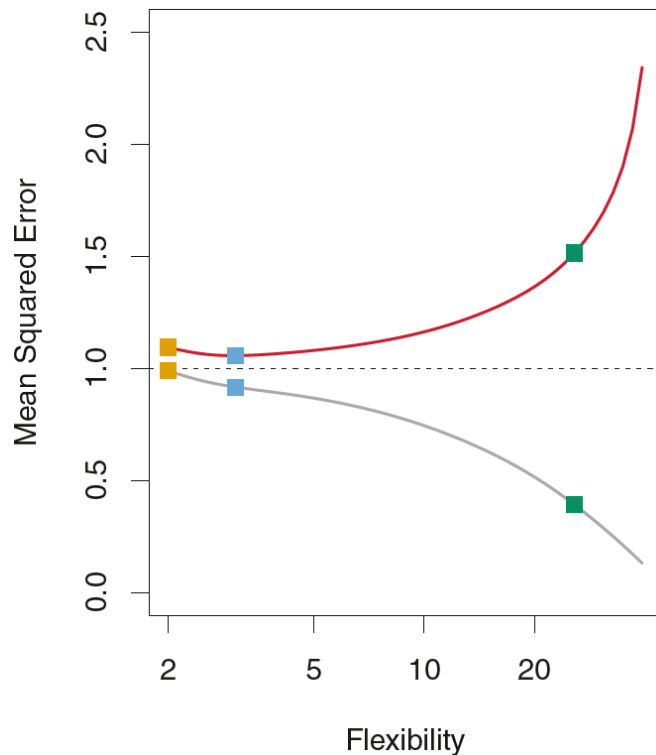
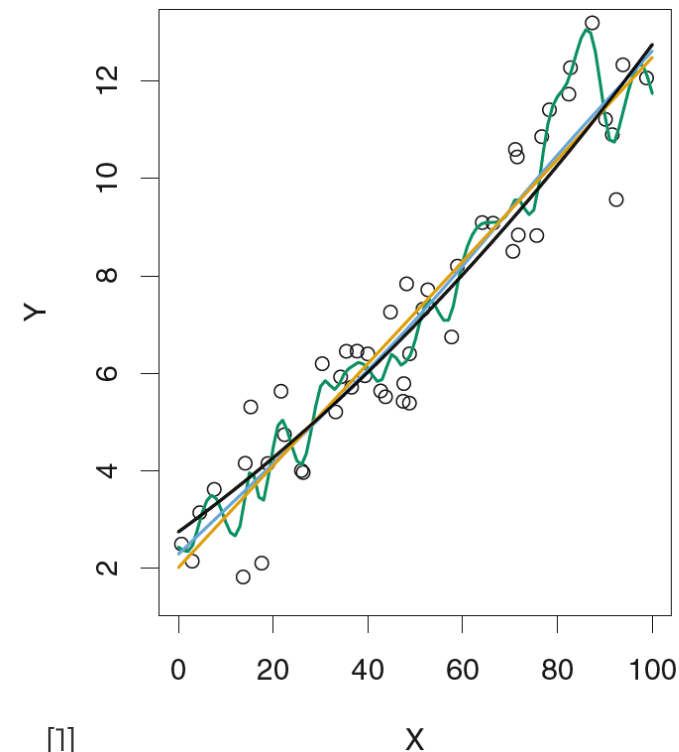


# Bias-Variance Trade-off



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# Bias-Variance Trade-off



# What is sampling?



# Sampling

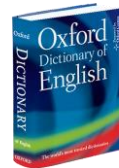
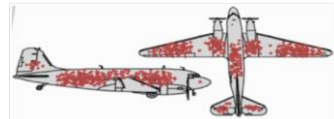
- **WHAT:** Process of selecting subsets of examples from a population with the objective of estimating properties of the population



- **WHY:** manageability, time, computational cost

- **HOW:**

- Information redundancy has no business value
- Removing Data vs. Removing Information
- Consider:
  - Population
  - Sample goal and size
  - Selection criteria





# Sampling techniques

- **SIMPLE RANDOM SAMPLING:** select a subset of a population in which each member of the subset has an **equal probability of being chosen**. With or without replacement
- **STRATIFIED SAMPLING:** **objects are drawn from each group** even though the groups are of different sizes. Either same amount from each group or proportional amounts



# Resampling methods

## WHAT:

- Repeatedly drawing samples from a training set and refitting a model of interest on each sample
- Might be computationally expensive

## WHY:

- Extract as much information as possible from a finite size dataset, information that could not be available from fitting the model only once
- Estimate the skill of a machine learning model on unseen data
- Model selection vs. model assessment

## HOW:

- Cross-validation
- Bootstrap



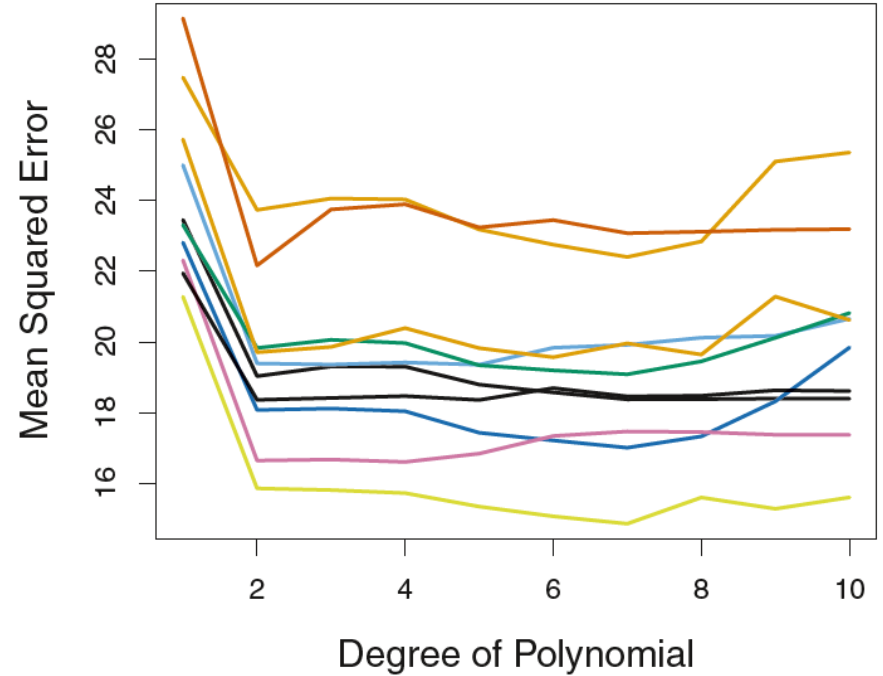
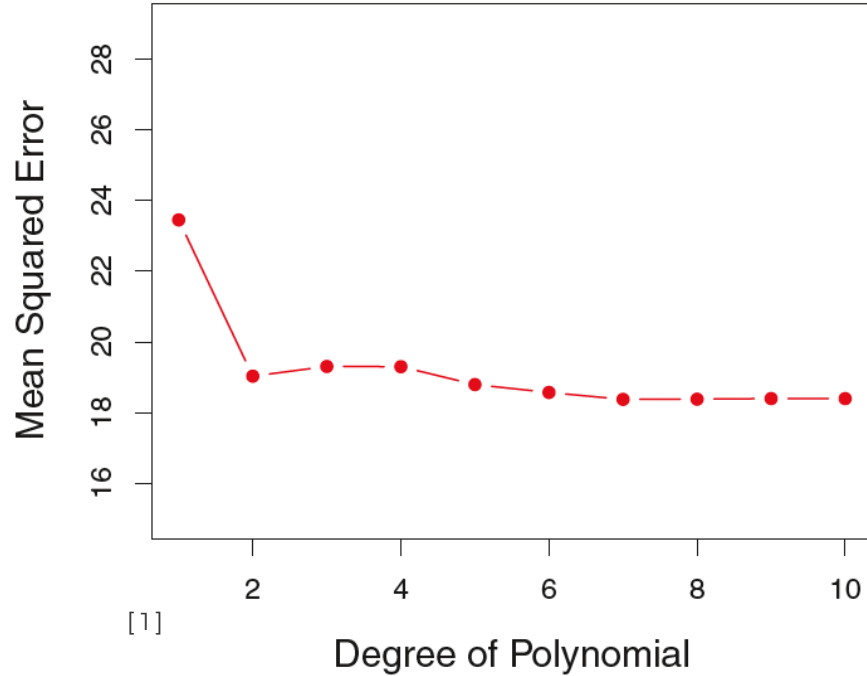
# Validation set

- Split observations randomly into two sets:
  - Training set
  - Test/Validation/hold-out set



- Repeat the process several times (if necessary)
- Drawbacks:
  - Validation estimate of the test error can be **highly variable** depending on which observations are included
  - Only a subset of observations used to fit model -> **overestimate error**

# Validation set



# Leave-one-out cross validation (LOOCV)

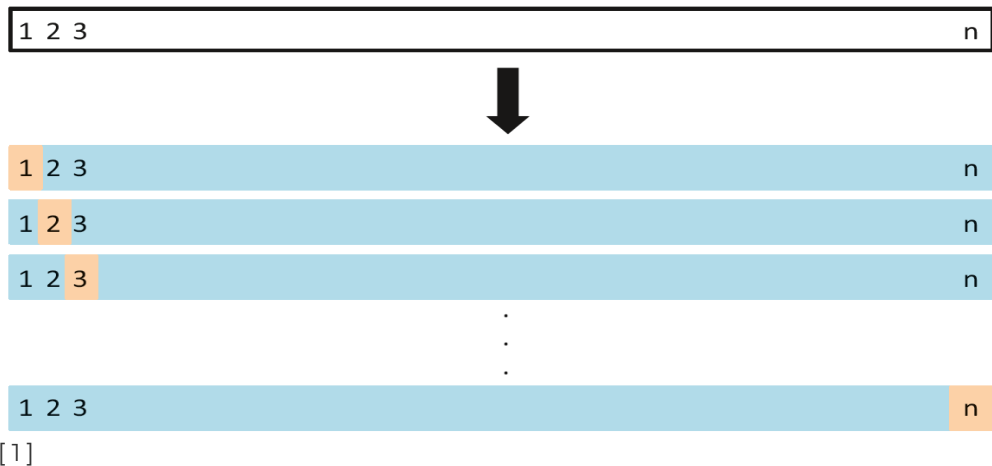
Split observations into two sets:

- Training set:  $n-1$  observations  $\triangleright \{(x_2, y_2), \dots, (x_n, y_n)\}$
- Test/Validation/hold-out set: 1 observation  $\triangleright (x_1, y_1)$

$$MSE_1 = (y_1 - \hat{y}_1)^2$$

Repeat the process  $n$  times:

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^n MSE_i$$



[1]

# Leave-one-out cross validation (LOOCV)

## ADVANTAGES:

- **Less bias** >
  - we use almost every data we have in every fit
  - test error less overestimated
- **No randomness** > executing it multiple times, leads to same results
- **General method** > can be used with any kind of predictive modeling

## DRAWBACKS:

**Expensive to implement**, since the model has to be fit  $n$  times. This can be very time consuming if  $n$  is large, and if each individual model is slow to fit

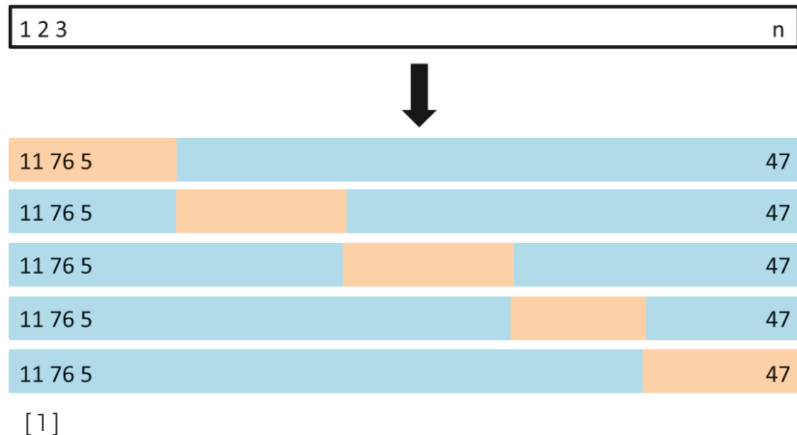
# K-Fold Cross Validation

Split observations into k sets (*folds*):

- Observations are randomly allocated to each fold
- Each fold is of the same size (or similar)
- First fold is used for validation and the rest for training

Repeat the process n times using different folds for validation:

$$CV_{(n)} = \frac{1}{k} \sum_{i=1}^k MSE_i$$



# K-Fold Cross Validation

k=5 or k=10

## ADVANTAGES:

- Computationally cheaper than LOOCV
- Some variability  $\triangleright$  much lower than validation set approach
- Often gives better results than LOOCV due to bias-variance trade-off

## BIAS-VARIANCE TRADE-OFF ( $k < n$ )

- **BIAS:**

- LOOCV is almost unbiased as it takes into account  $n-1$  observations
- K-Fold CV has intermediate level of bias as it considers less observations

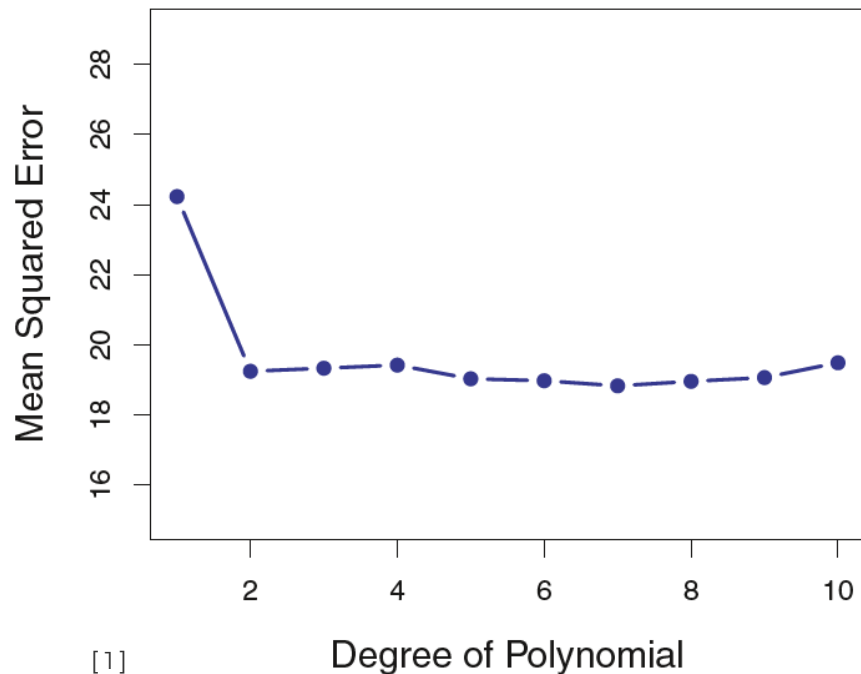
- **VARIANCE:**

- LOOCV has the highest variance as model is fitted on almost identical sets of observations highly correlated with each other  $\triangleright$  higher variance
- K-Fold CV models are less correlated  $\triangleright$  lower variance

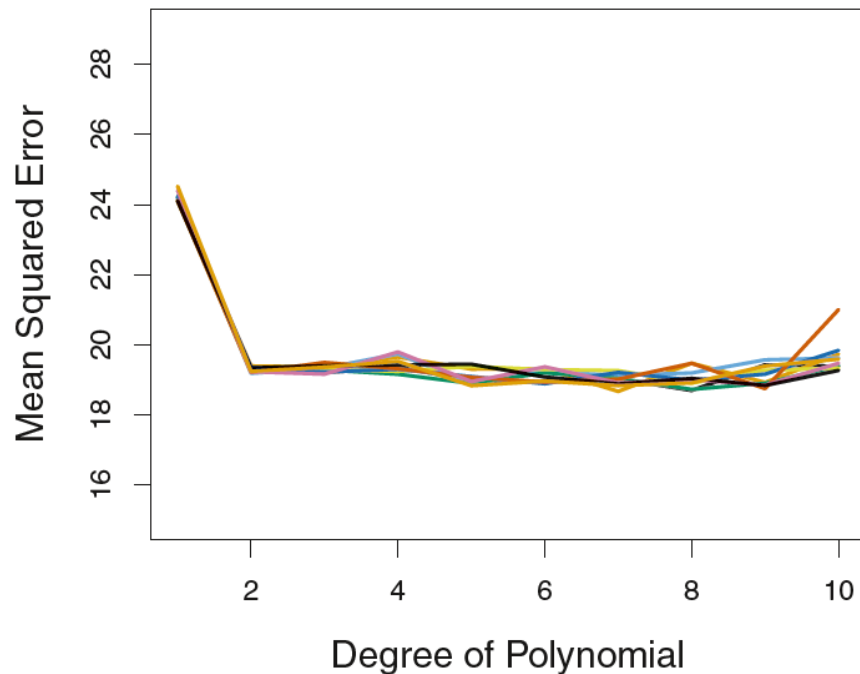


# K-Fold Cross Validation

LOOCV



10-fold CV



# Let's try it ourselves...



# References

- [1] G. James, D. Witten, T. Hastie, R. Tibshirani. An Introduction to Statistical Learning with Applications in R. Springer, 2017.
- [2] T. Hastie, R. Tibshirani, J. Friedman. The Elements of Statistical: Data Mining, Inference and Prediction. Springer, 2009.
- [3] <https://towardsdatascience.com/>



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