

# ENSF 611 – Machine Learning for Software Engineers

**Week 2 – Statistical Learning**



# Lecture Goals

- Introduce the mathematical perspective for machine learning
- Chapters 1 and 2 of *An Introduction to Statistical Learning with Applications in Python*

# ML Workflow

Data Input

Data Processing

ML Model

Validation

Visualization of Results

Data Input

Data Processing

ML Model

Validation

Visualization of Results

# What is Statistical Learning?



# What is a synonym of statistical learning?

# What is statistical (machine) learning?

- Statistical learning refers to a vast set of tools for **understanding data**
- These tools can be classified as **supervised** or **unsupervised**
- Supervised statistical learning involves building a statistical model for **predicting**, or **estimating**, an **output** based on one or more **inputs**



# Output-input relationship

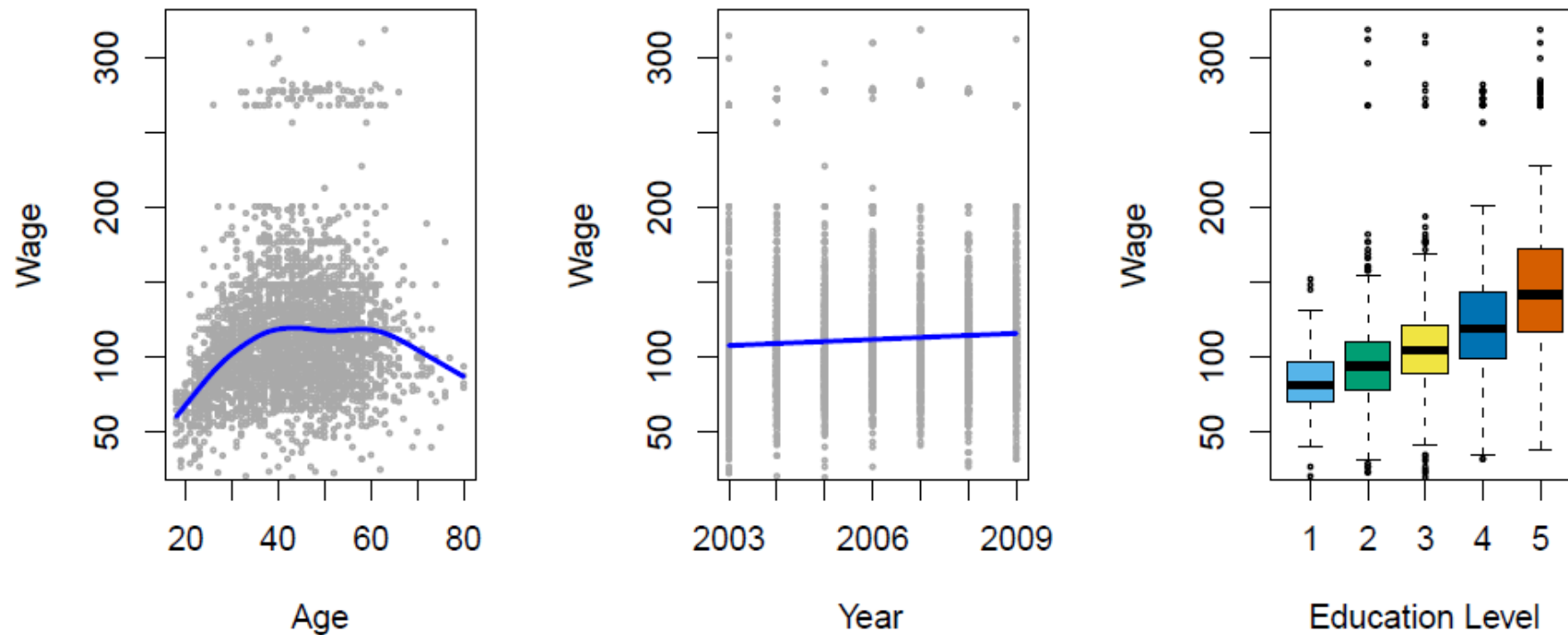
- In mathematics, we represent the relationship between a set of inputs and an output as:

$$y = f(x)$$

- Where  $y$  represents the output,  $x$  represents the input and  $f(\dots)$  represents the relationship between the two

# Wage Example

- Imagine that you have been given income survey data, which includes the wage, education level, age and year
- You would like to use this data to predict what the wages will be for other samples
- To do this, you need to figure out what is the relationship between wage and the other measured factors



**FIGURE 1.1.** Wage data, which contains income survey information for men from the central Atlantic region of the United States. Left: wage as a function of age. On average, wage increases with age until about 60 years of age, at which point it begins to decline. Center: wage as a function of year. There is a slow but steady increase of approximately \$10,000 in the average wage between 2003 and 2009. Right: Boxplots displaying wage as a function of education, with 1 indicating the lowest level (no high school diploma) and 5 the highest level (an advanced graduate degree). On average, wage increases with the level of education.

# Wage Example

- Since the wage seems to be impacted by all three factors (age, year and education), the most accurate prediction would be given by combining all three into one model
- Assuming that:

$$wage = f(age, year, education)$$

- How do we find the best function to give us the most accurate prediction?
- Knowing that we need to account for the non-linear relationship between wage and age



# What are potential sources of model inaccuracy ?

# Model Accuracy

- Can we be 100% accurate with our prediction?
- A more general form of the input-output expression:

$$y = f(x) + \epsilon$$

Where  $\epsilon$  is a random error term, which is independent of  $X$  and has a mean of zero

# Model Accuracy

- We can predict the  $y$  values using the given data:

$$\hat{y} = \hat{f}(x)$$

Where  $\hat{y}$  are the predicted values based on the estimated relationship, represented by  $\hat{f}$ , and the given data,  $x$

# Model Accuracy

- Considering a given estimated function and a given input, assume that both are fixed, and that the only variability comes from the error term:

$$E(y - \hat{y})^2 = E(f(x) + \epsilon - \hat{f}(x))^2$$

$$E(y - \hat{y})^2 = \underbrace{(f(x) - \hat{f}(x))^2}_{\text{Reducible}} + \underbrace{Var(\epsilon)}_{\text{Irreducible}}$$

Where  $E(y - \hat{y})^2$  represents the average (**expected value**) of the squared expected difference between the predicted and actual values, and  $Var(\epsilon)$  represents the variance associated with the error term



# Model Accuracy

- Since the random error term (irreducible error) is independent of the input, there will always be some error in our prediction
  - This error is usually caused by missing information
  - You can't account for every factor that influences the output
- The goal of machine learning is to minimize the **reducible error** by selecting the best fitting model, based on the available data

# What does this mean?

- The training data is used to estimate the relationship ( $\hat{f}$ ) between the given input and output
- The testing data is used to:
  - Estimate the predicted values ( $\hat{y}$ ) using ( $\hat{f}$ )
  - Compare the predicted values ( $\hat{y}$ ) to the given values ( $y$ ) to calculate the accuracy (classification) or error (regression)

# What's next?

- Discuss what metrics to use to compare model performance
- How do we decide if a model works well or not?
- What is the relationship between model performance and model complexity?