

# PSY9511: Seminar 4

## The basics of regression and classification

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# K-Nearest Neighbours

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# K-Nearest Neighbours

Linear regression:

$$\hat{f}(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$$

K-Nearest Neighbours:

$$\hat{f}(X) = \frac{1}{K} \sum_{x_i \in \mathcal{N}} y_i$$



# K-Nearest Neighbours

Linear regression:

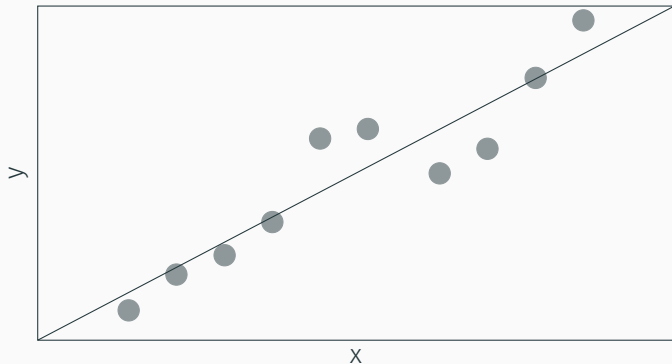
$$\hat{f}(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$$

K-Nearest Neighbours:

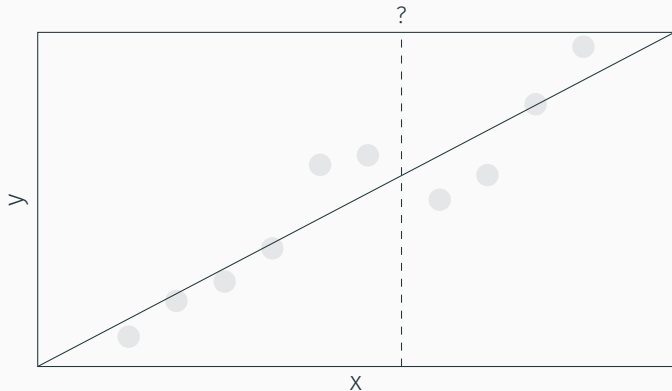
$$\hat{f}(X) = \frac{1}{K} \sum_{x_i \in \mathcal{N}} y_i$$

Blackboard!

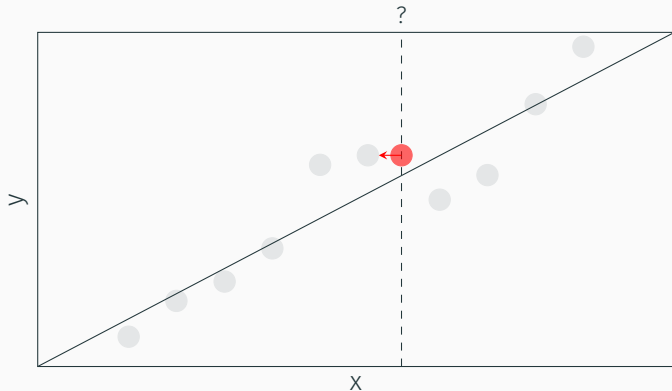
# K-Nearest Neighbours



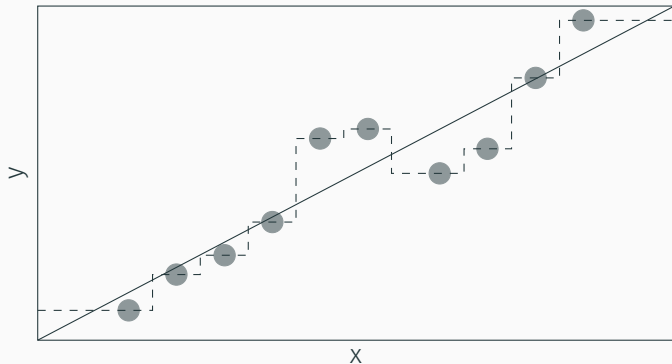
# K-Nearest Neighbours



# K-Nearest Neighbours

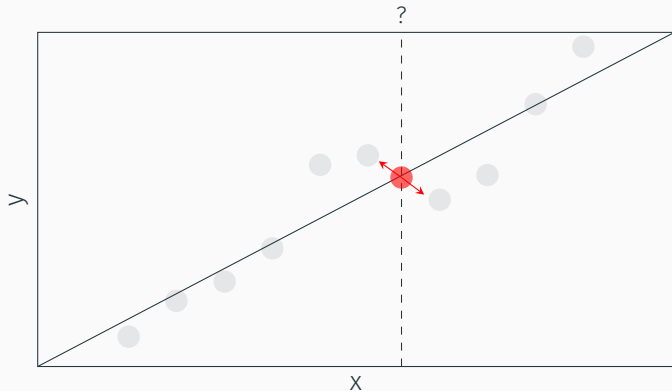


# K-Nearest Neighbours

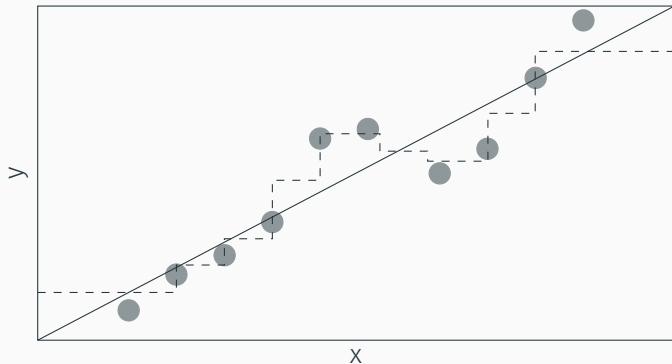




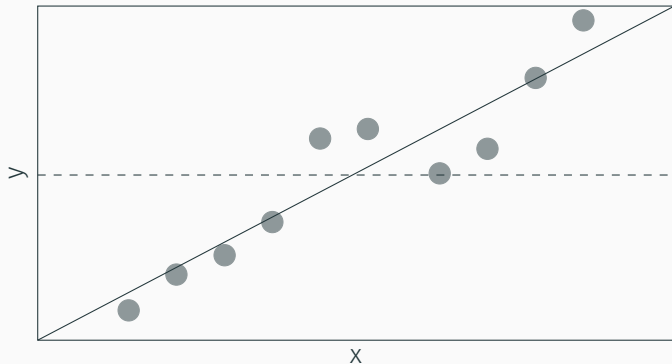
# K-Nearest Neighbours



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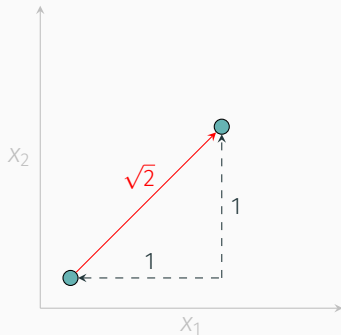
Blackboard exercise:

How does the bias-variance trade-off relate to the choice of  $K$ ?

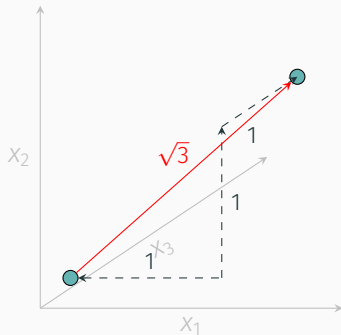
# K-Nearest Neighbours



# K-Nearest Neighbours



# K-Nearest Neighbours



# K-Nearest Neighbours

K-Nearest Neighbours: An intuitive model relying on similar datapoints to make a prediction

- No assumptions about the functional relationship between inputs and outputs
- Directly trades off bias and variance through the choice of  $K$
- Does not work well in high dimensions as the neighbourhoods get sparse





# Logistic regression

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| mpg | manufacturer | chevrolet |
|-----|--------------|-----------|
| 36  | Chevrolet    | 1         |
| 15  | Ford         | 0         |
| 25  | Chevrolet    | 1         |
| 26  | Chevrolet    | 1         |
| 17  | Ford         | 0         |
| 15  | Ford         | 0         |
| 32  | Chevrolet    | 1         |
| 14  | Ford         | 0         |
| 14  | Ford         | 0         |
| 28  | Chevrolet    | 1         |

$$\widehat{\text{mpg}} = \beta_0 + \beta_1 \times \text{chevrolet}$$



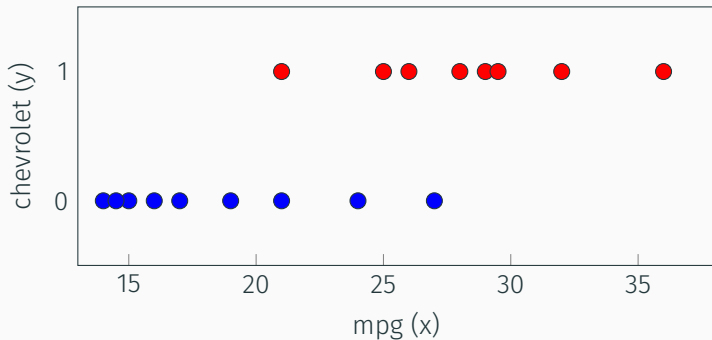


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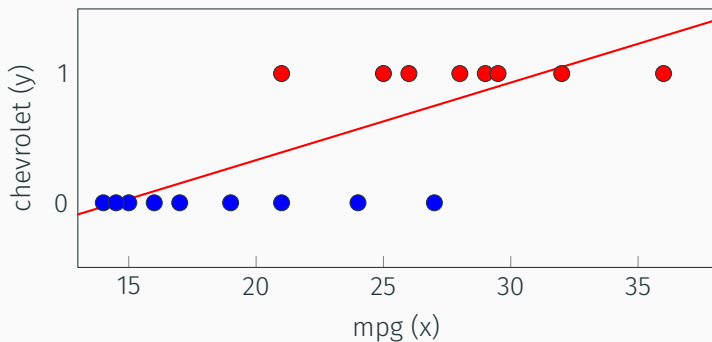
$$\widehat{\text{chevrolet}} = \beta_0 + \beta_1 \times \text{mpg}$$



# Logistic regression

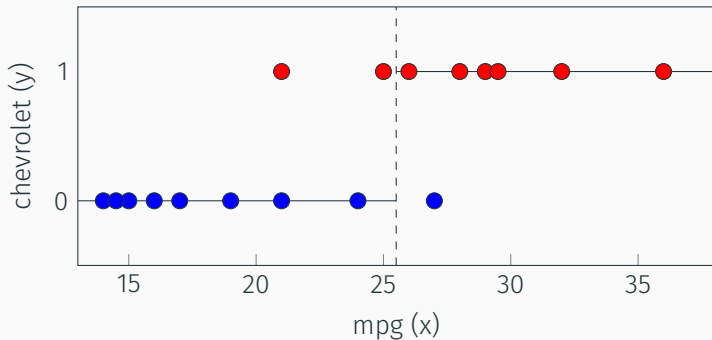


# Logistic regression

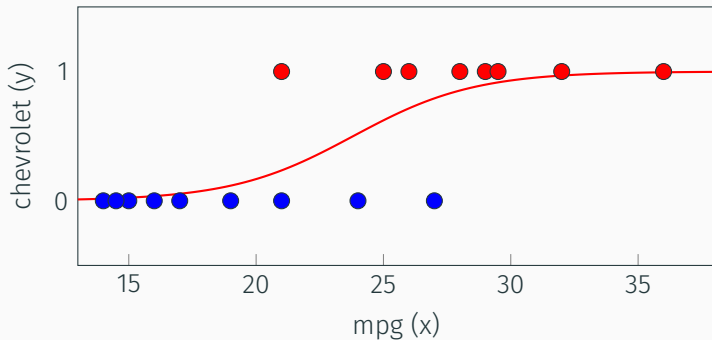


$$\widehat{\text{chevrolet}} = -0.87 + 0.06 \times \text{mpg}$$

# Logistic regression



# Logistic regression



$$\widehat{\text{chevrolet}} = \frac{e^{-10.22+0.42 \times \text{mpg}}}{1 + e^{-10.22+0.42 \times \text{mpg}}}$$



$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$







$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$e^{\beta_0 + \beta_1 x} \rightarrow 0$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$e^{\beta_0 + \beta_1 x} \rightarrow 0 \implies \hat{y} = 0$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\begin{aligned} e^{\beta_0 + \beta_1 x} \rightarrow 0 &\implies \hat{y} = 0 \\ e^{\beta_0 + \beta_1 x} \rightarrow \infty &\end{aligned}$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\begin{aligned} e^{\beta_0 + \beta_1 x} \rightarrow 0 &\implies \hat{y} = 0 \\ e^{\beta_0 + \beta_1 x} \rightarrow \infty &\implies \hat{y} = 1 \end{aligned}$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

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$$0 \leq \hat{y} \leq 1$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\begin{aligned} e^{\beta_0 + \beta_1 x} \rightarrow 0 &\implies \hat{y} = 0 \\ e^{\beta_0 + \beta_1 x} \rightarrow \infty &\implies \hat{y} = 1 \end{aligned}$$

$$0 \leq \hat{y} \leq 1 \implies \hat{y} = \Pr(Y = 1|X)$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\log \left( \frac{p(X)}{1 - p(X)} \right) = \beta_0 + \beta_1 x$$







$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\log \left( \frac{p(X)}{1 - p(X)} \right) = \beta_0 + \beta_1 x$$

*"... counterintuitive and challenging to interpret."* - James Jaccard





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

More than one class?





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

More than one class?

$$Pr(Y = k | X = x) = \frac{e^{\beta_{0k} + \beta_{1k}x}}{\sum_{l=1}^K e^{\beta_{0l} + \beta_{1l}x}}$$





$$\hat{y} = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

More than one class?

$$Pr(Y = k | X = x) = \frac{e^{\beta_{0k} + \beta_{1k}x}}{\sum_{l=1}^K e^{\beta_{0l} + \beta_{1l}x}}$$



# Generative models

