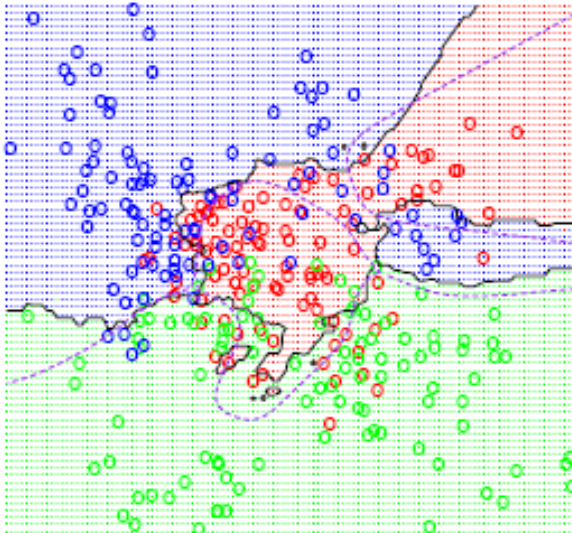


# Machine Learning

## Lecture 7: K-nearest neighbor regression; classification; KNN classifier; logistic regression

*The lectures are mainly offered on white board accompanied by some slides.*



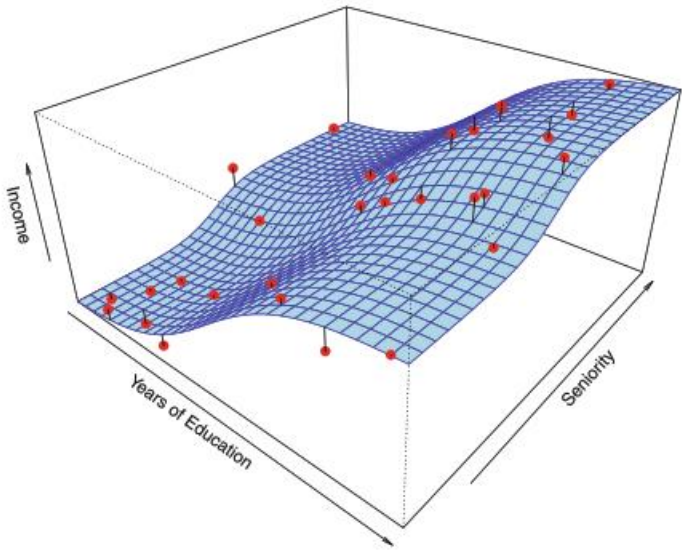
Hesam Montazeri

Department of Bioinformatics, IBB, University of Tehran

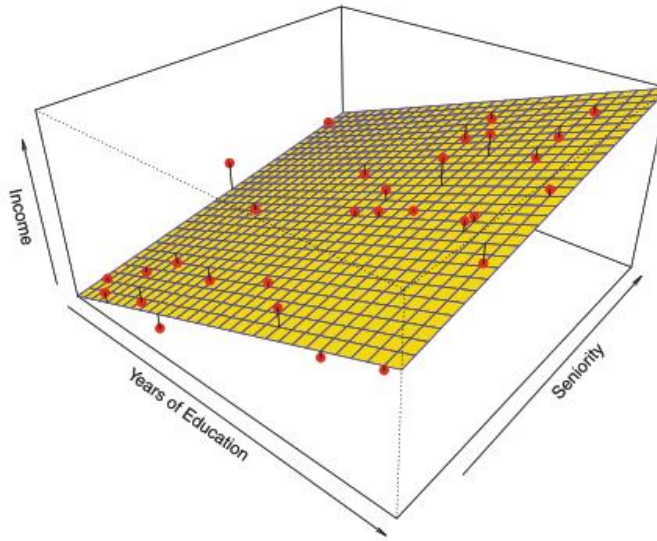
Mehr 21, 1398

# Nonparametric methods

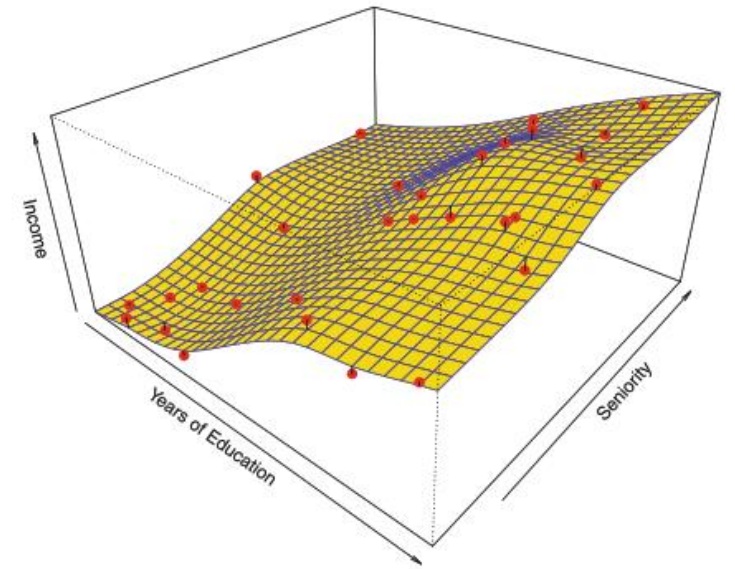
- No assumption about the function form (advantage)
- Try to get as close to data points without being too rough or wiggly
- Disadvantage: need to keep a large number of observations for a good estimate



True underlying relationship



A linear model fit by least squares



A relatively advanced non-parametric method

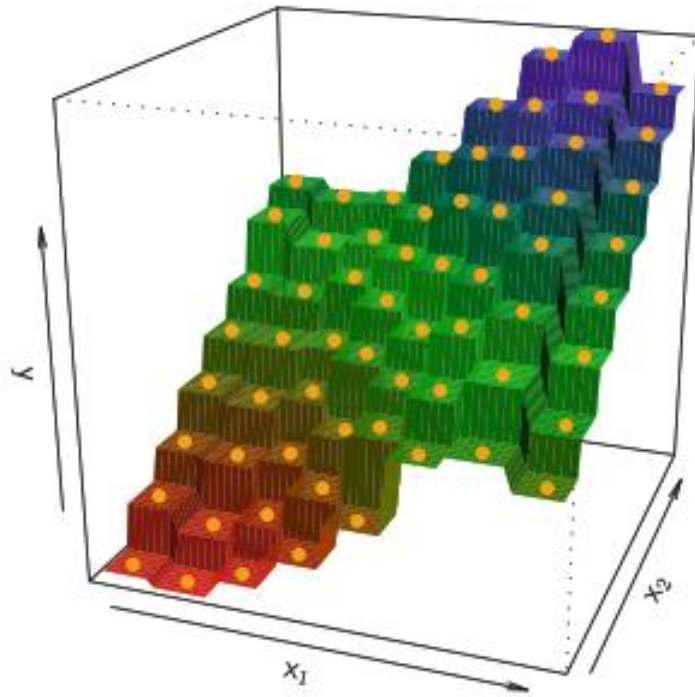
# K-nearest neighbors regression (KNN regression)

- Give  $K$  and  $x_0$
- $N_0$ :  $K$  closest observation to  $x_0$

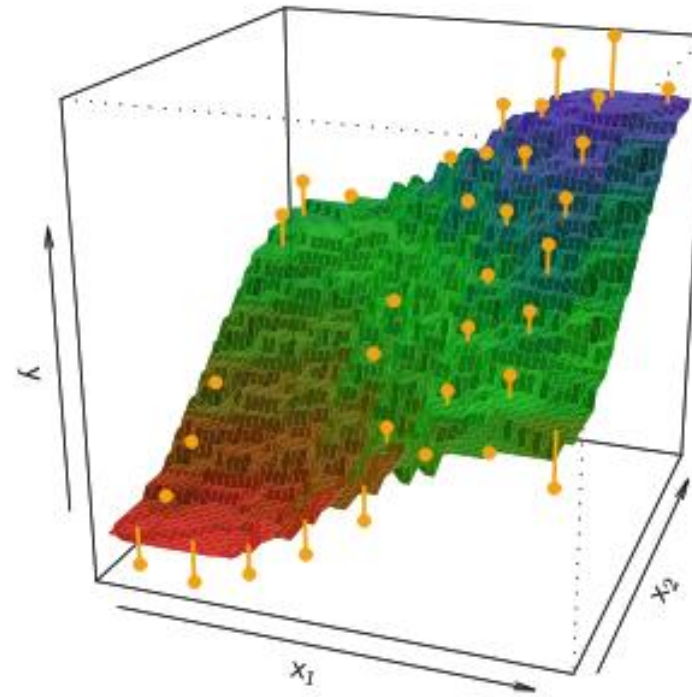
$$\hat{f}(x_0) = \frac{1}{K} \sum_{i \in N_0} y[i]$$

- |           |        |            |
|-----------|--------|------------|
| • $K = 1$ | bias=? | Variance=? |
| • $K=10$  | bias=? | Variance=? |

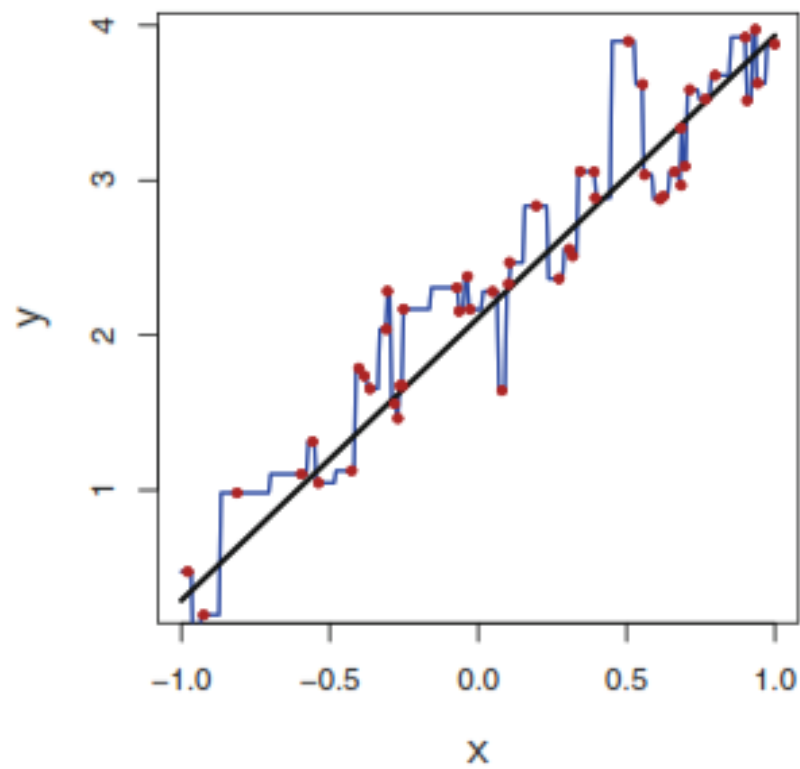
# KNN regression



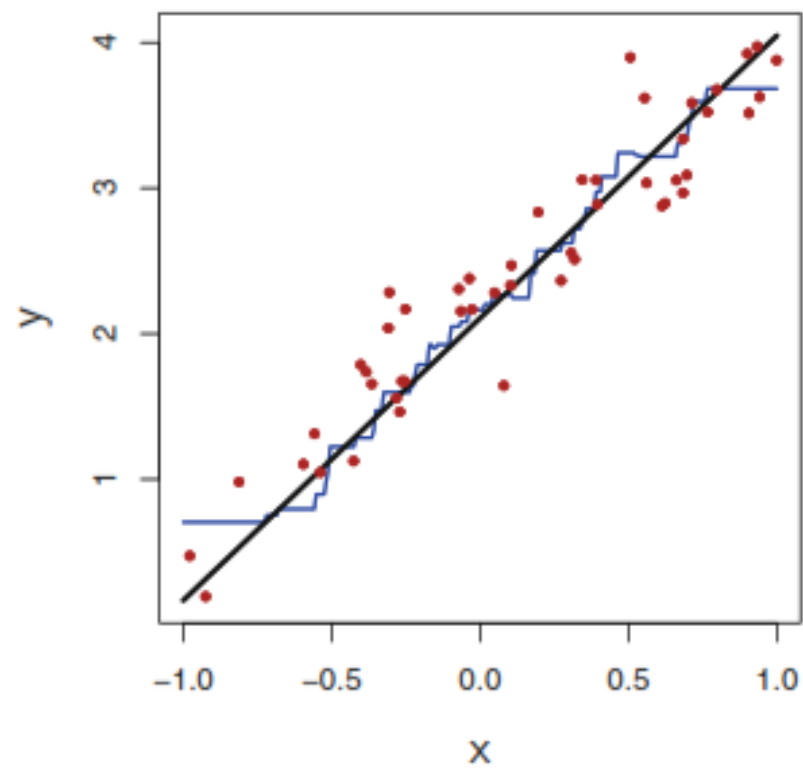
K=1



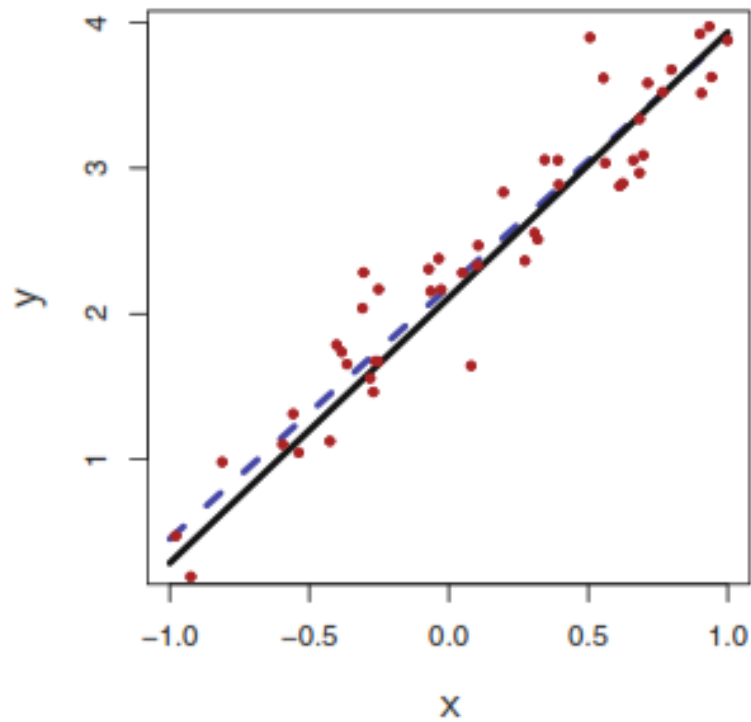
K=9



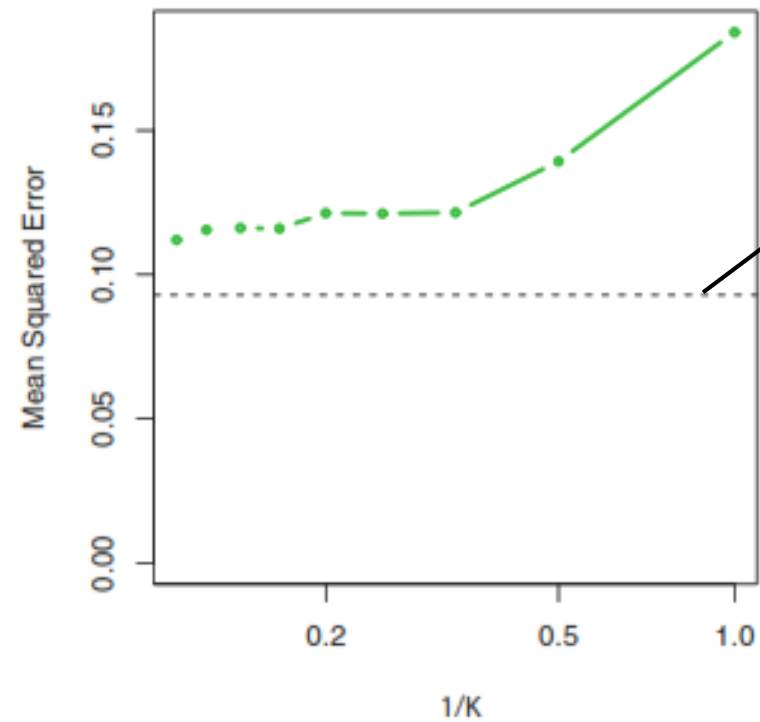
K=1



K=9



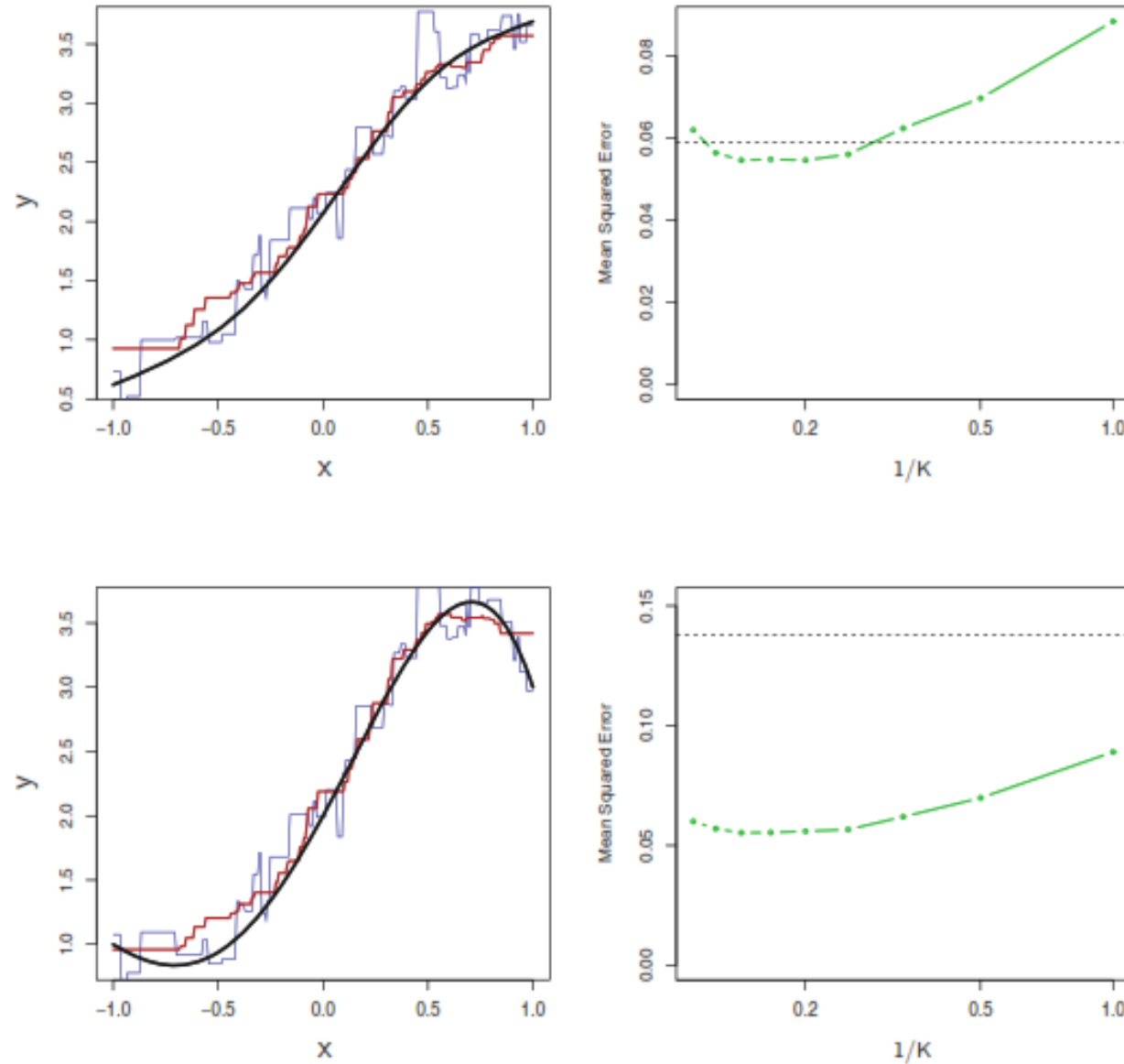
Least squares fit



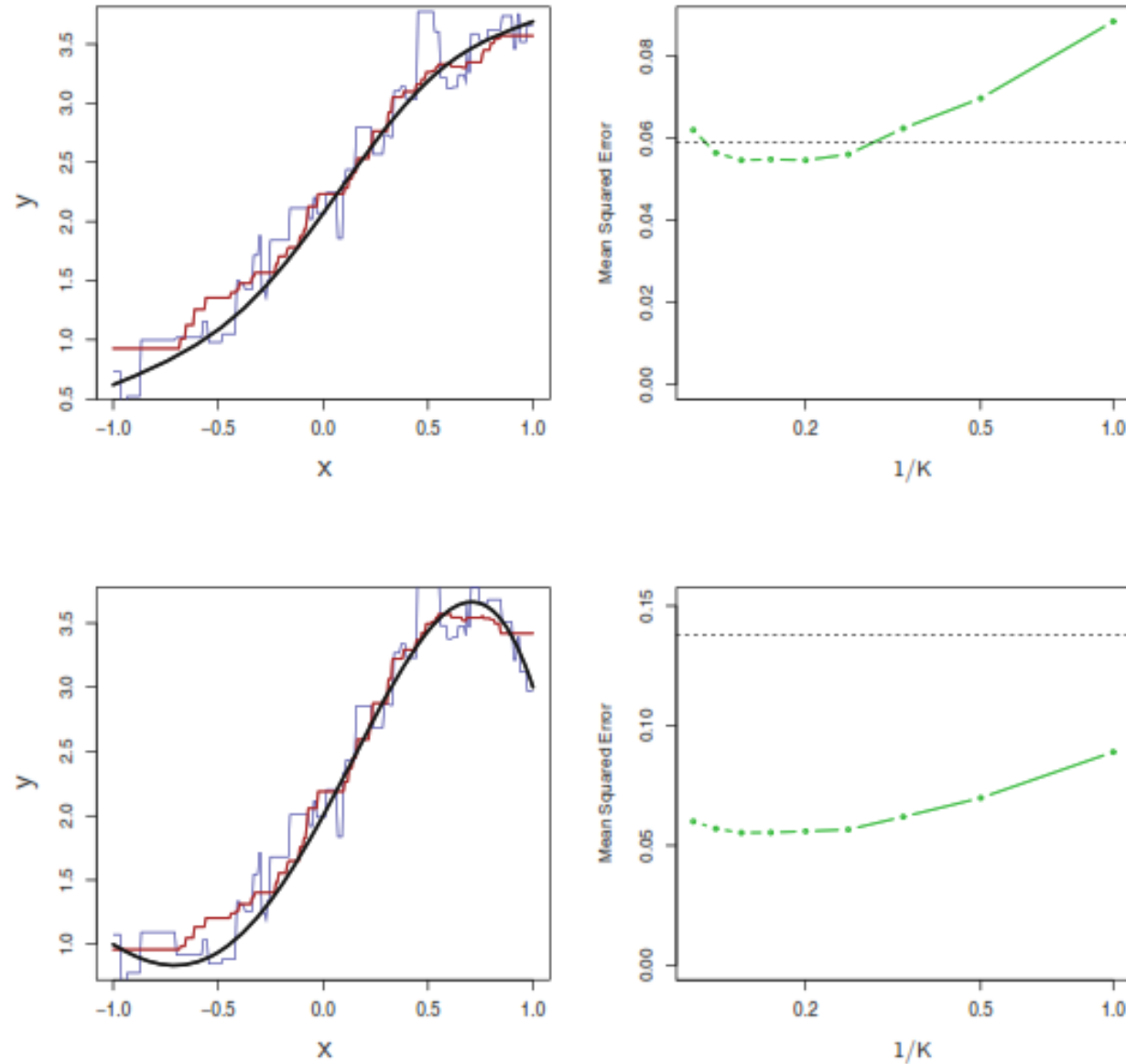
MSE for Least  
squares fit

The MSE

# Non-linear relationship between X and Y



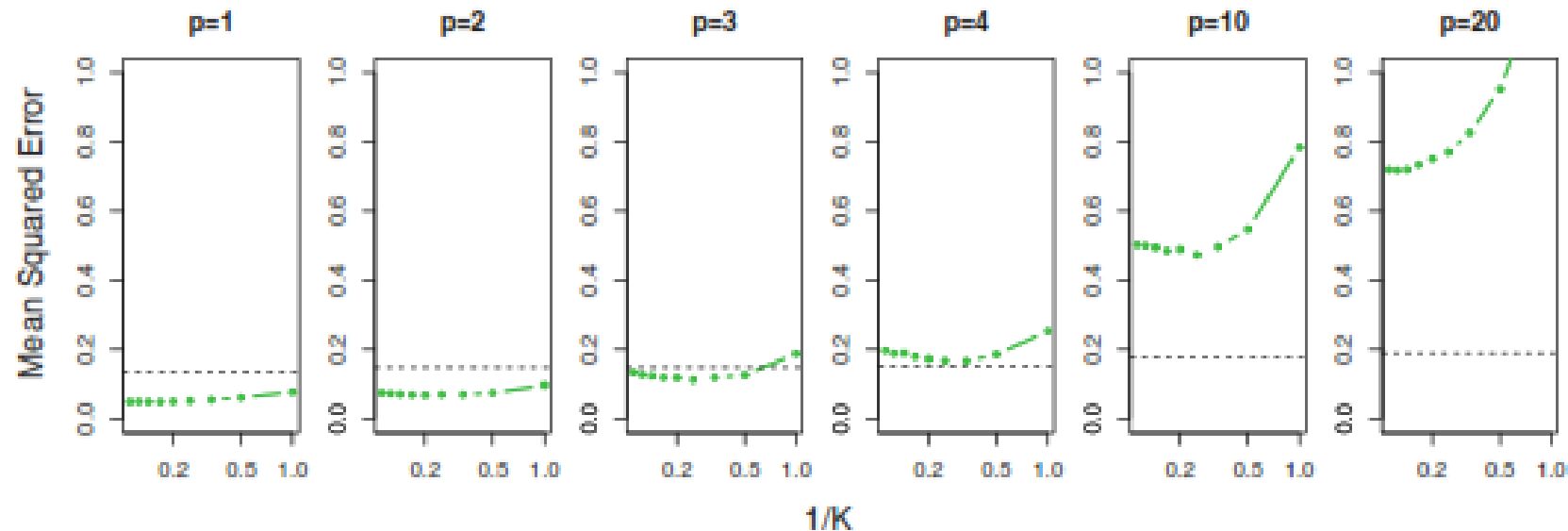
# Non-linear relationship between X and Y





# Curse of dimensionality

- $K$  observations that are close to  $x_0$  may be very far away in  $p$ -dimensional space when  $p$  is large.
- By our definition,  $Y$  ONLY depends on the first predictor. The additional predictors are noise.

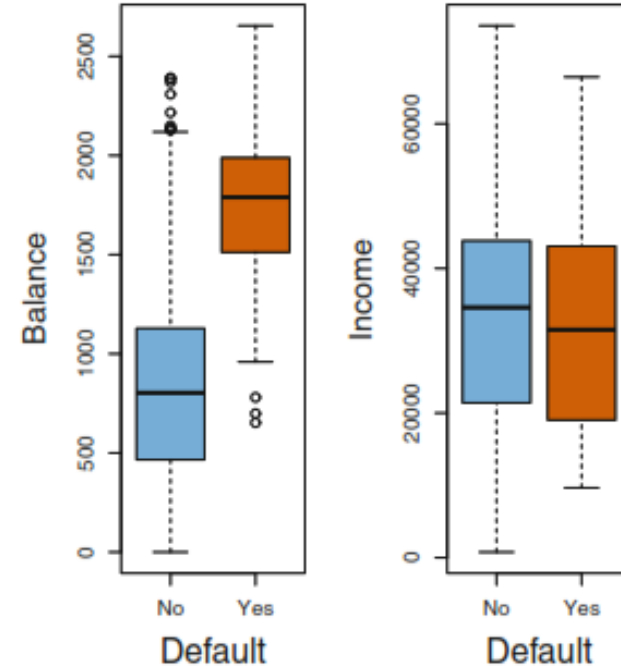
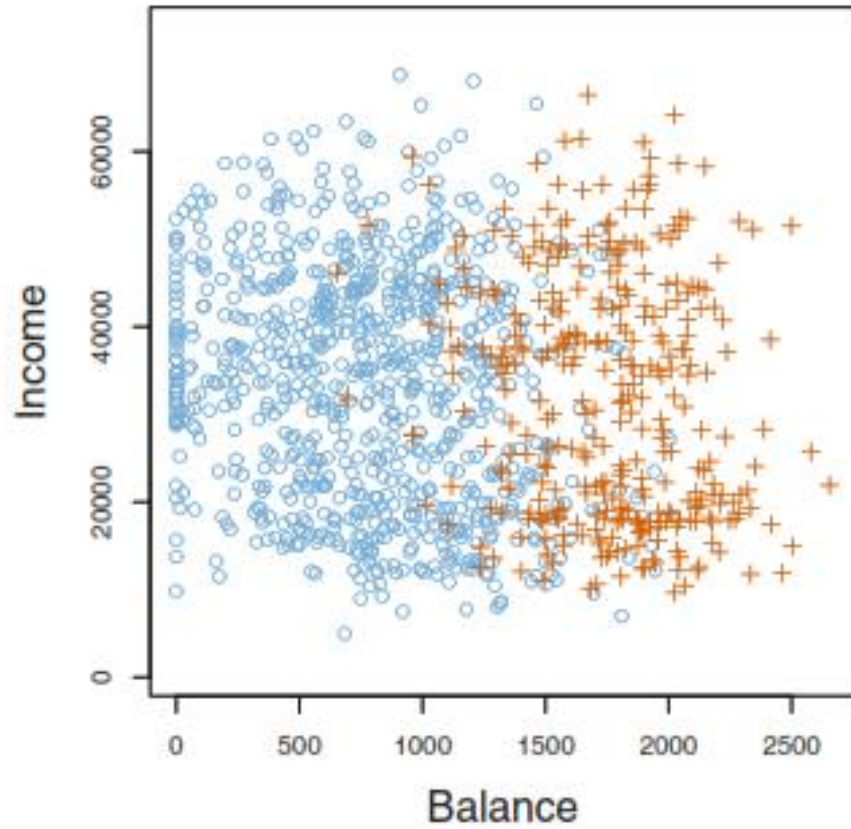


# Classification

# Classification

- The response variable is qualitative/categorical.
- $D = \{(x[1], y[1]), \dots, (x[n], y[n])\}$
- Examples:
  - Ex1: Input: gene expression data, response variable: origin of cancer (breast, lung, kidney, ...)
  - Ex2: to classify an email to spam/non-spam
- We define a new loss function:
  - Zero-one loss function:  $I(y \neq \hat{y})$  where  $\hat{y}$  is an estimate for  $x$
- Training error rate:  $\frac{1}{n} \sum_{i=1}^n I(y[i] \neq \hat{y}[i])$
- Test error rate:  $E(I(y \neq \hat{y}))$

# Example



Response variable:

$$Y = \begin{cases} 0 & \text{if No} \\ 1 & \text{if Yes.} \end{cases}$$

# The Bayes classifier

- Assign each data point to the most likely class, given its predictor values

- Formally, the Bayes classifier is defined

$$\hat{y} = \arg \max_c P(Y = c | x)$$

- Often not possible in practice! Why?

- The Bayes error rate:

- The Bayes classifier produces the lowest possible test error rate.
- The overall error rate is given by

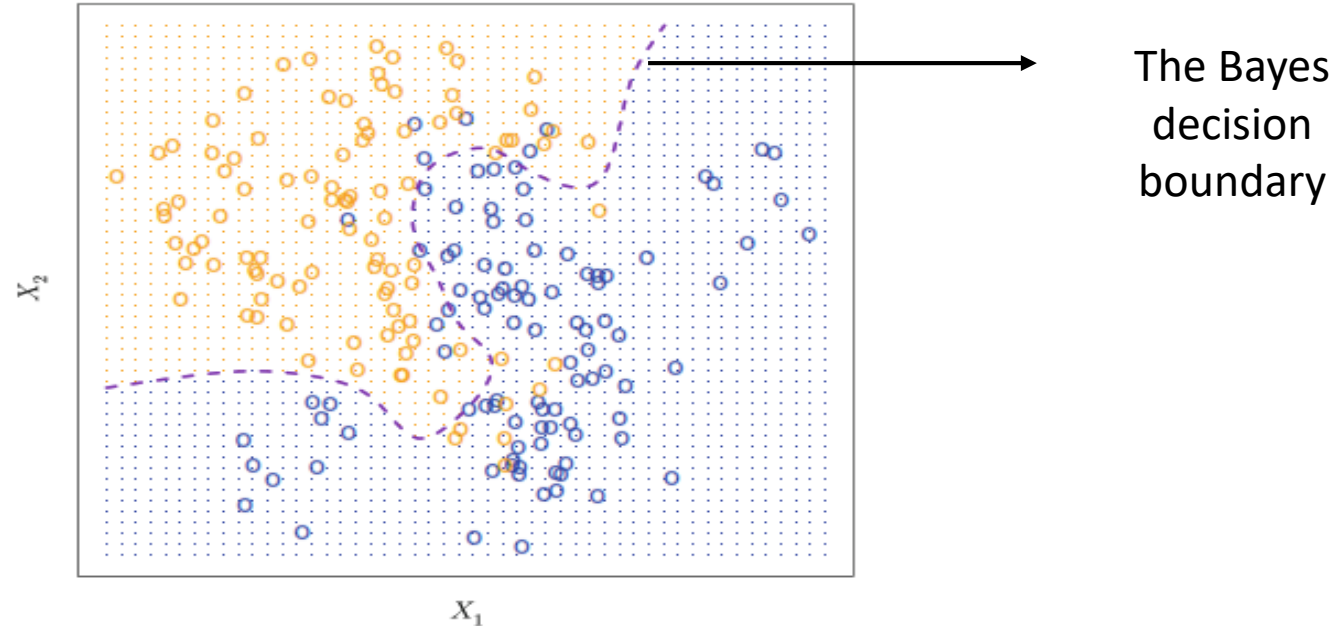
$$1 - E(\max_c P(Y = c | X))$$

Expectation over all possible  
values for  $X$

- Analogous to irreducible error in regression

# The Bayes-optimal decision boundary

- Two-class problem: orange and blue



- Given the generating density for each class, we can calculate the boundary exactly.

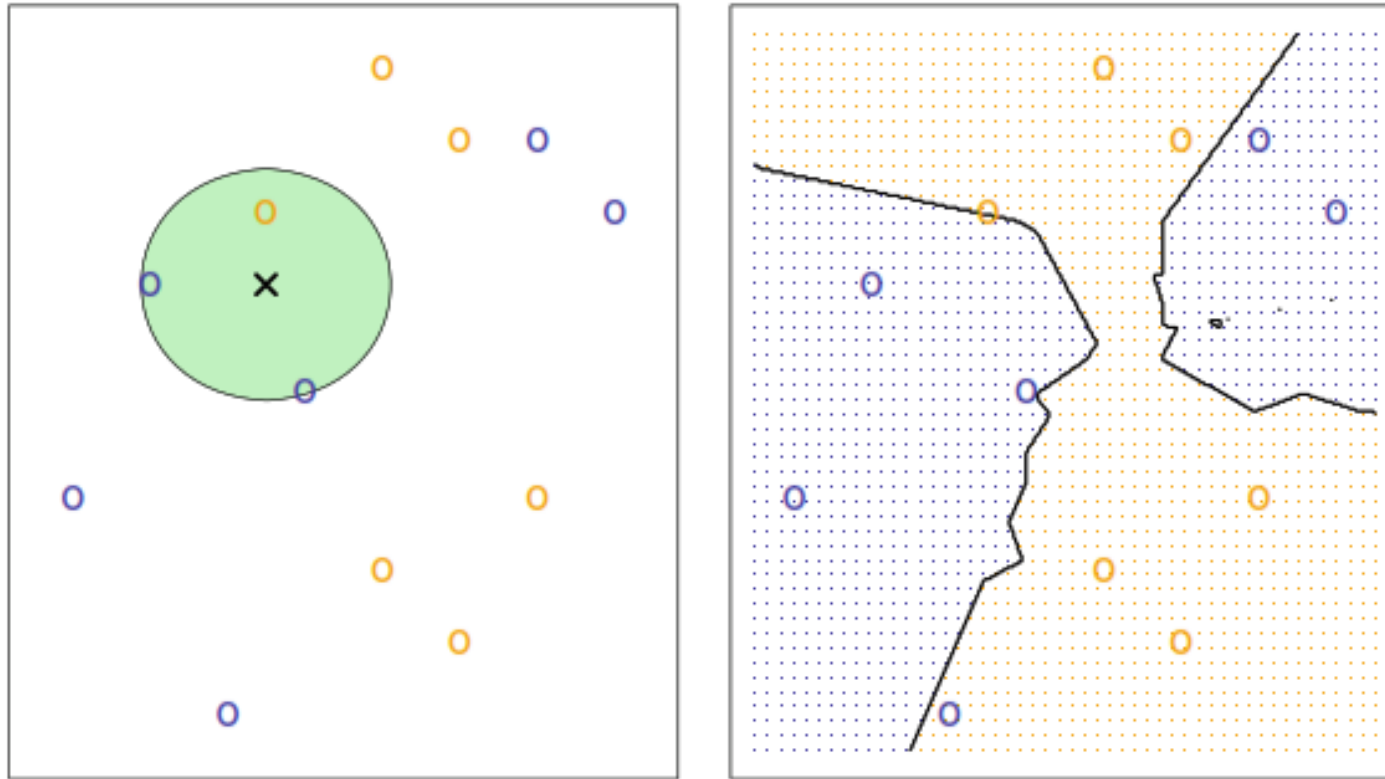
# K-nearest neighbor classifier

- $P(Y | X)$  is not known for real data, so computing the Bayes classifier is impossible!
- Many classifiers attempt to estimate  $P(Y | X)$
- K-nearest neighbor classifier is such a method:

$$P(Y = c | x) = \frac{1}{K} \sum_{i \in N_0} I(y[i] = c)$$

where  $N_0$  is  $K$  closest observation to  $x$

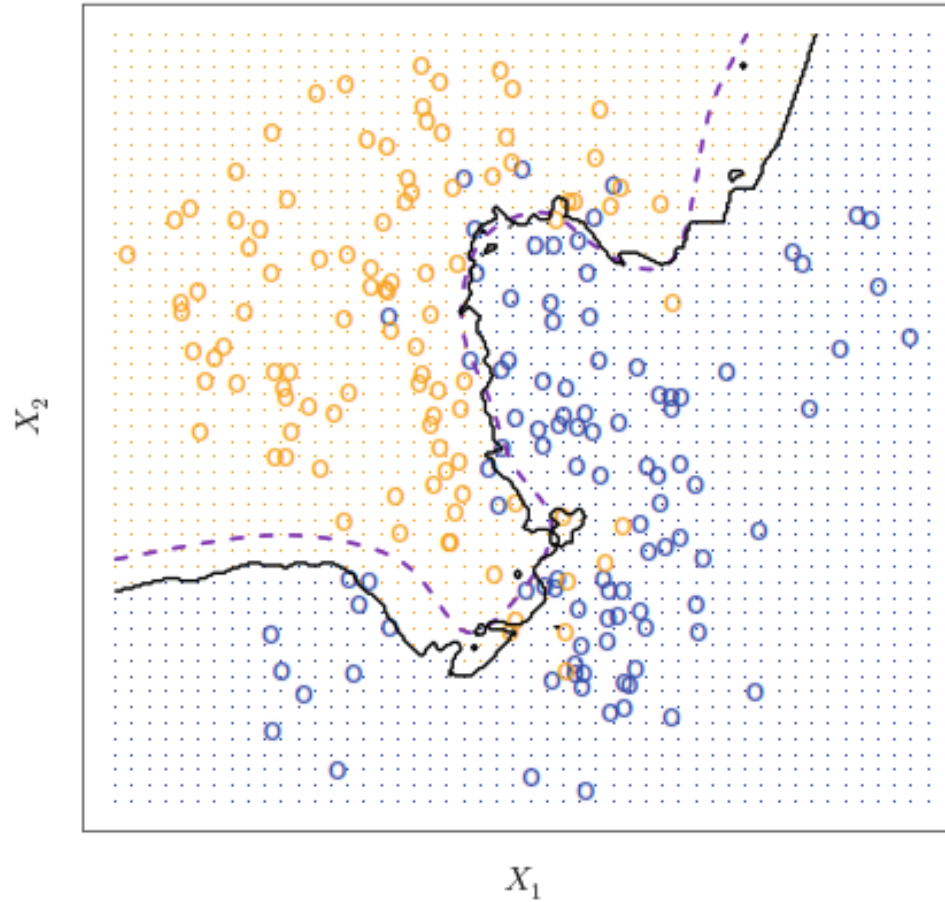
# K-nearest neighbors in two dimensions



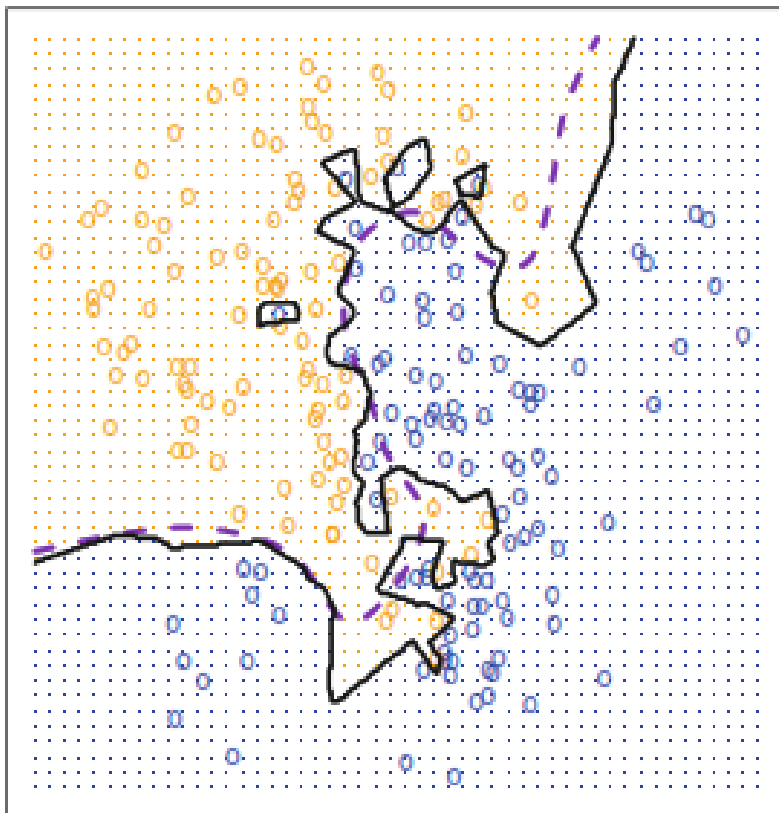
$K = 3$



# K-nearest neighbors: $K=10$

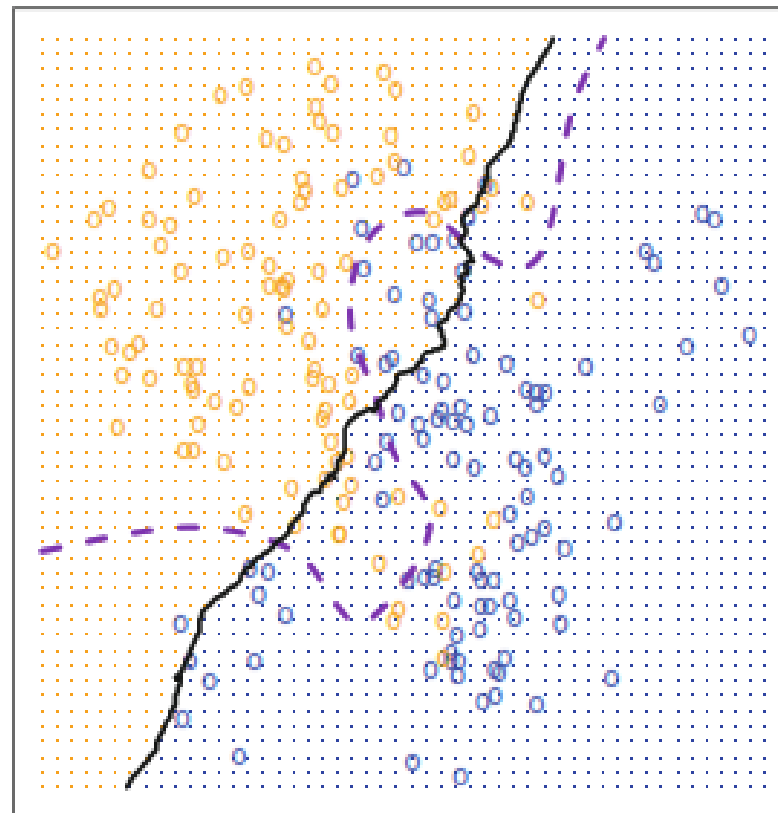


KNN: K=1



Flexible boundary

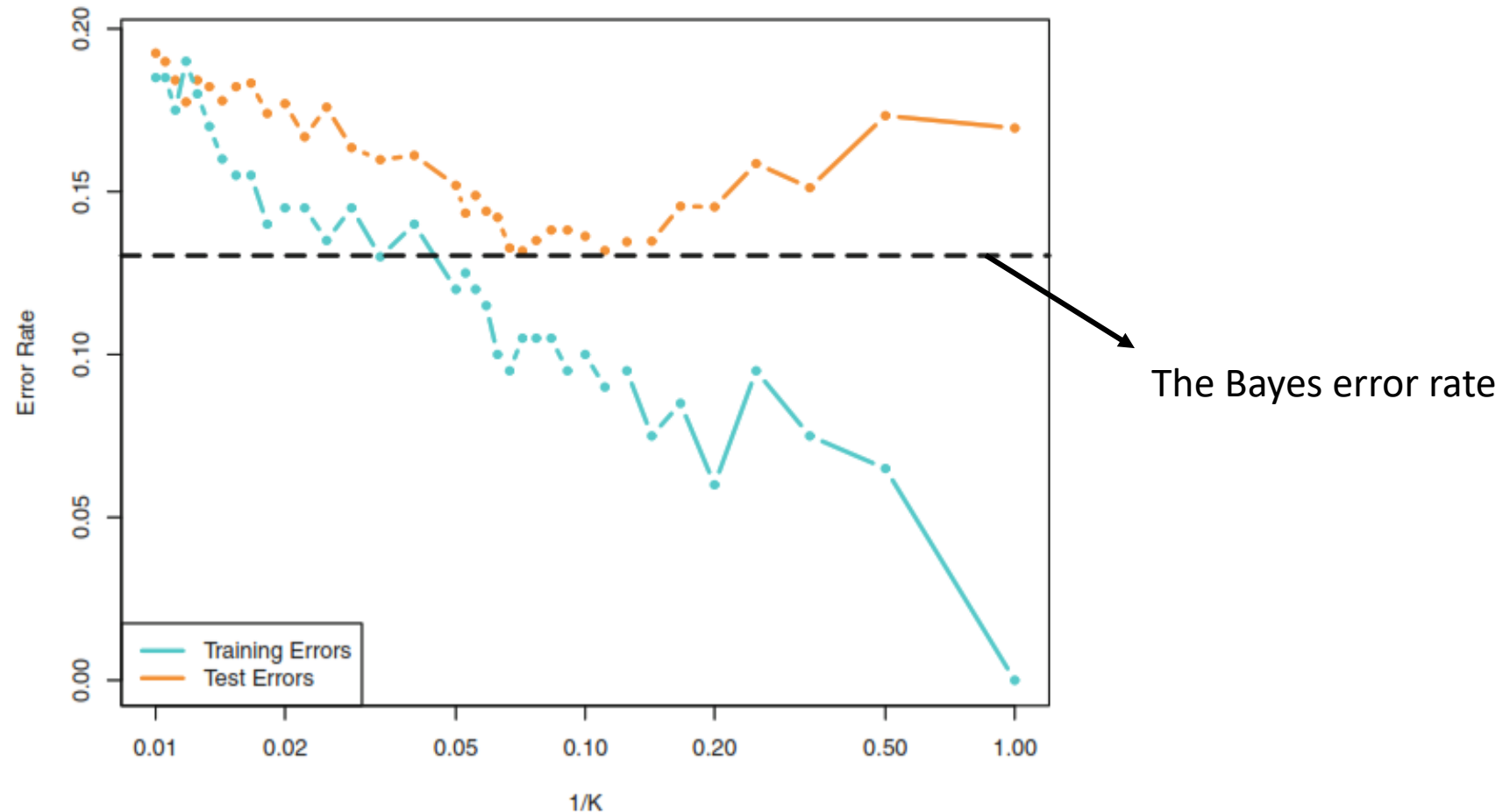
KNN: K=100



In flexible boundary

# Training and test error rates

- 200 training observations, 5000 test observations



# References and Acknowledgement

- References

- An Introduction to Statistical Learning, with applications in R, 2013

- Acknowledgement

- Some of the figures in this presentation are taken from "An Introduction to Statistical Learning, with applications in R" (Springer, 2013) with permission from the authors: G. James, D. Witten, T. Hastie and R. Tibshirani. Few slides are also adjusted from theirs.