

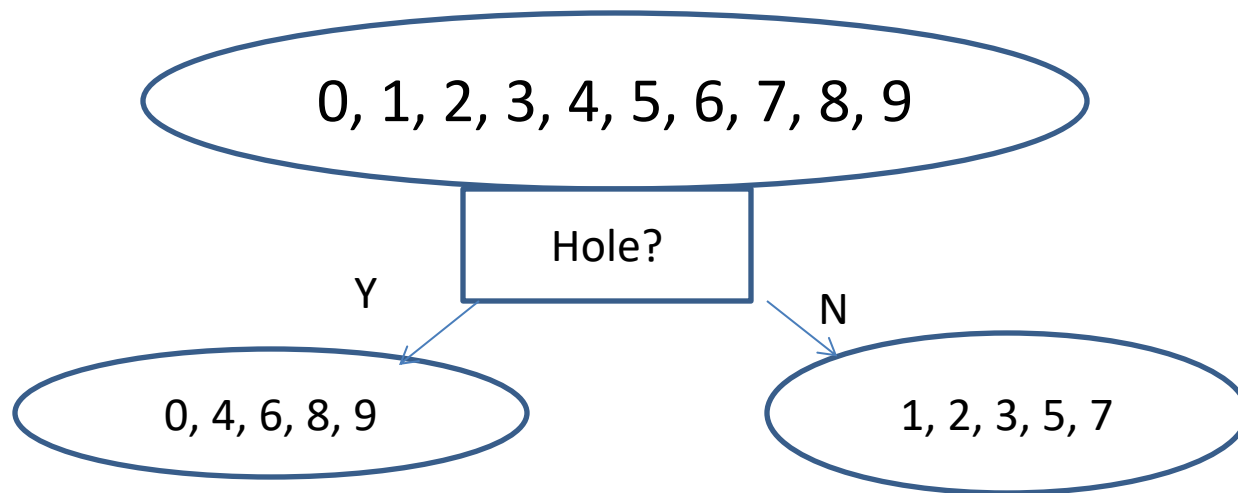
# Decision tree

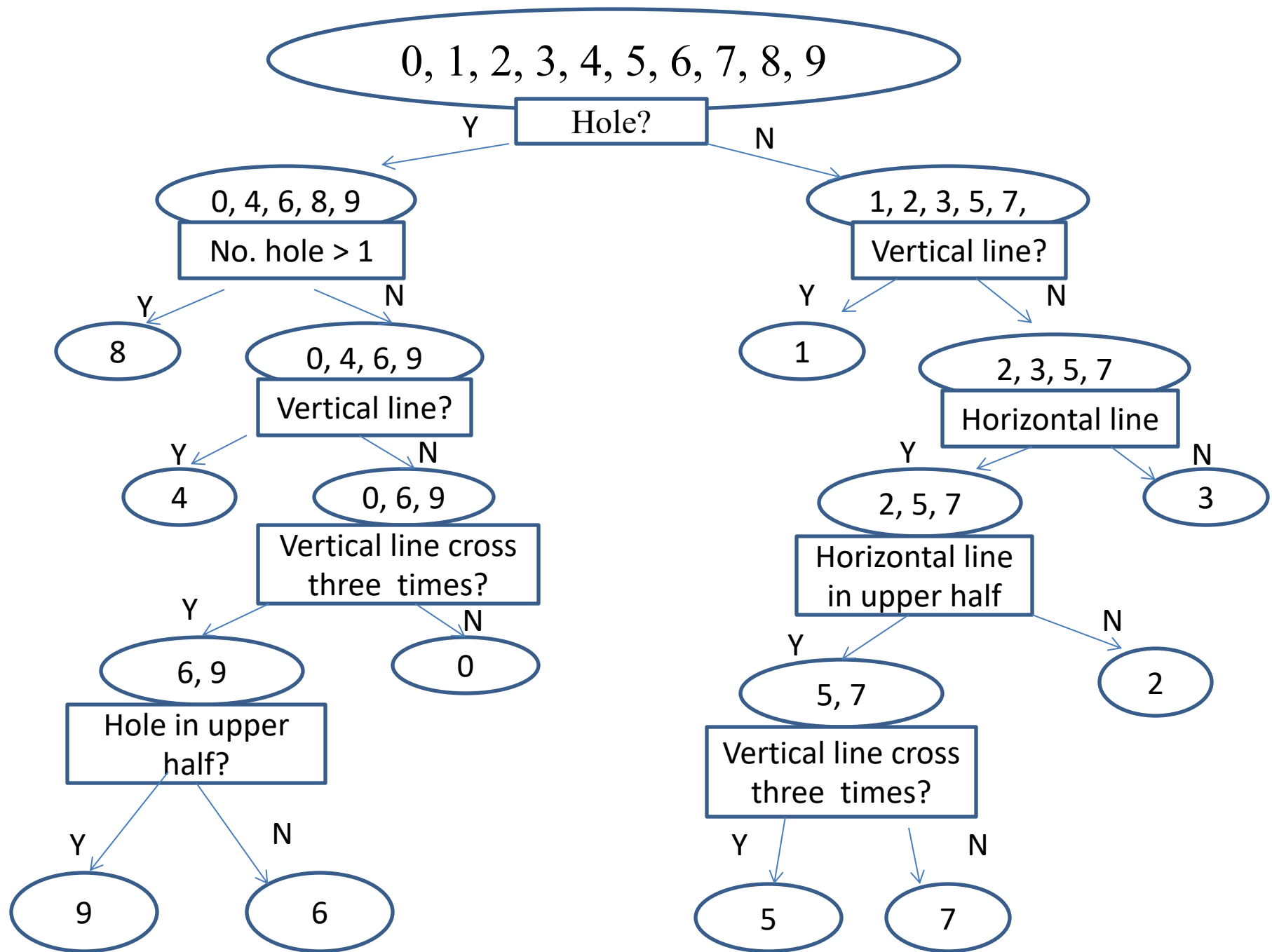
# Motivating example: postal letter sorting

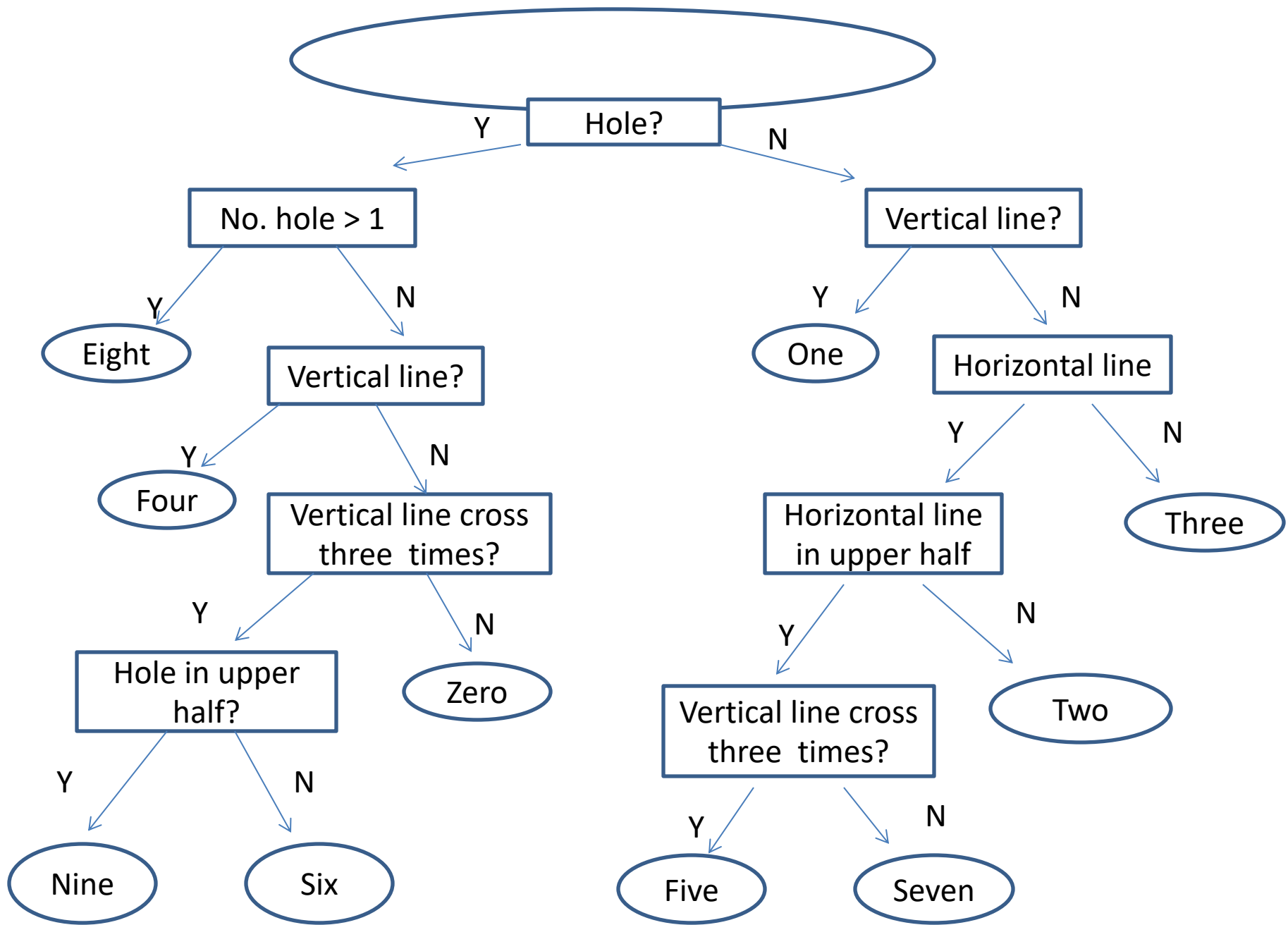
- Sorting postal letter according to pin number.
- To do that you have to recognize each numerical digits( 0, 1, 2, ... , 9).

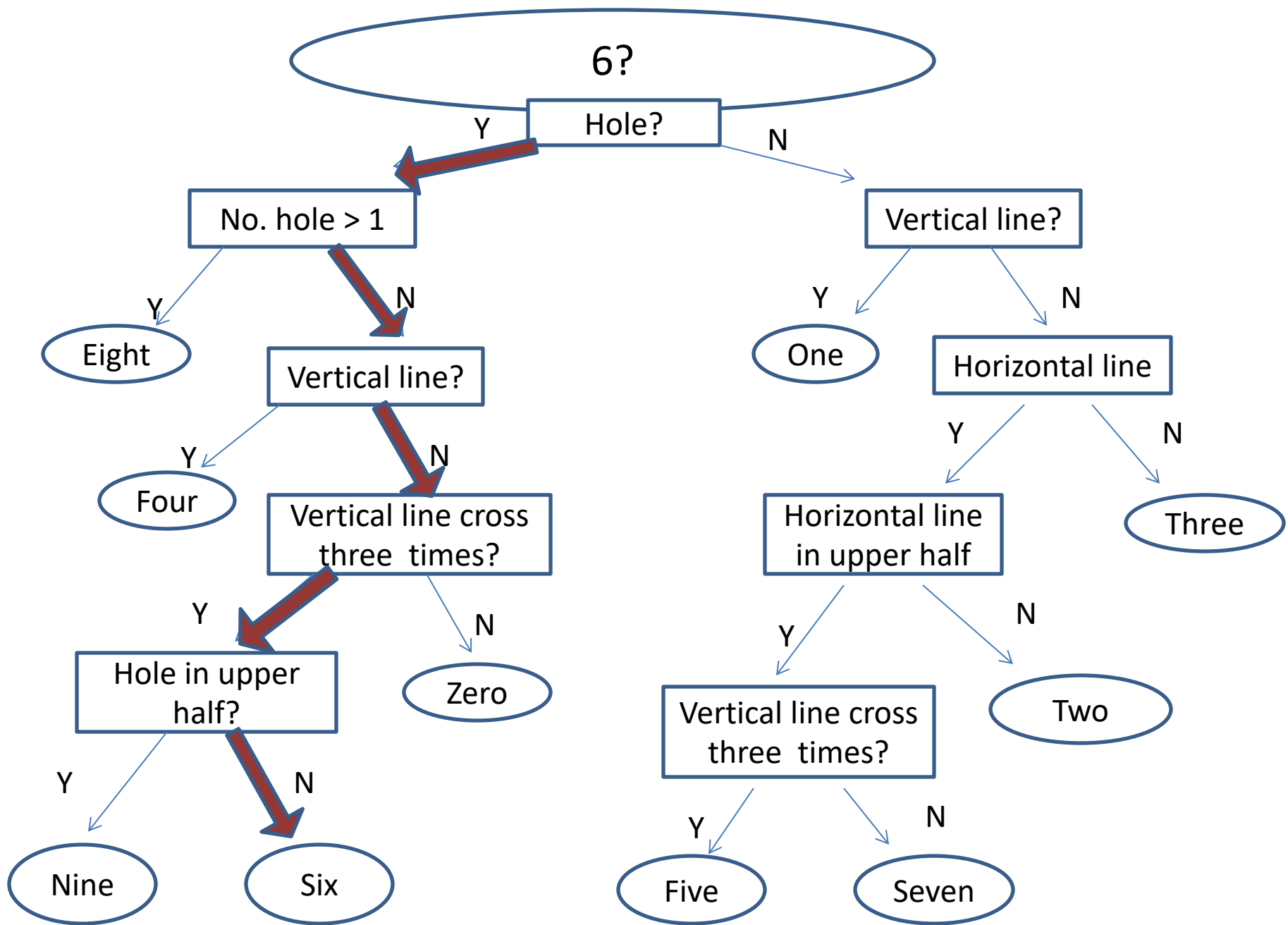
# Numerical digit recognition

- Numerical digits: 0 1 2 3 4 5 6 7 8 9









- This is called **Tree classifier** or **Decision tree** classifier.
- At each node you have to take a decision.
- Through some sequence of decisions we can build a classifier.
- Leaf node gives the label.

# Why tree

- Simplicity of design
- Interpretability
- Ease of implementation
- Good performance in practice



# There are several questions?

- How many decision outcomes or splits will be at node?
- Which feature should be tested at a node?
- When should a node be declare a leaf node?
- If the tree becomes too large, how can it be made smaller and simpler?
- If a leaf node is impure, how should the category label be assigned?
- How should missing data be handled?

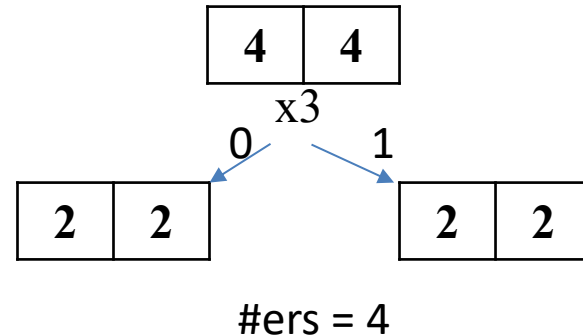
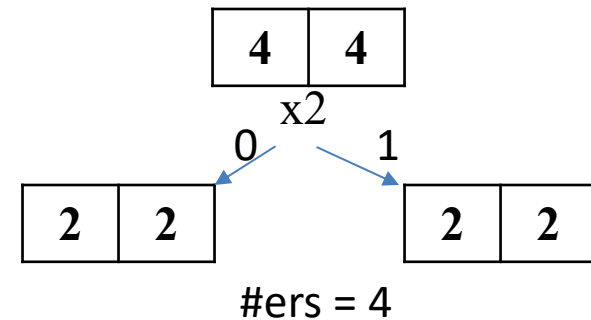
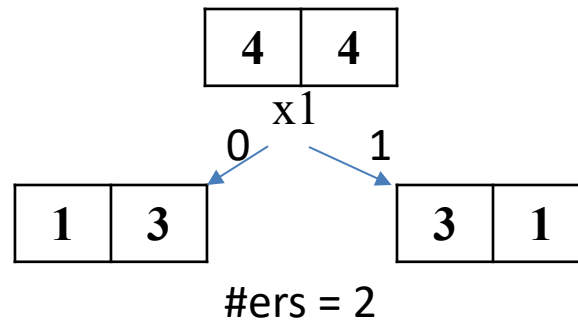
# How many decision outcomes or splits?

- 1, 2, 3, ....., C
- Every decision can be represented using just binary decision.
- Binary tree (widely used)
  - easy to handle
  - theoretical development

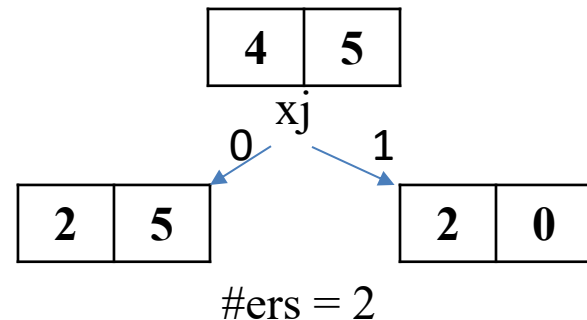
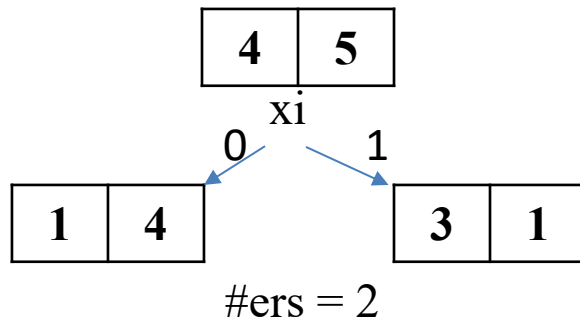
# Which feature should be tested at a node?

- Much of the work on decision tree to answer this question

x1	x2	x3	y
0	0	0	1
0	0	1	0
0	1	0	1
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	0
1	1	1	0



# Which feature should be tested at a node?



- Which one ( $x_i$  or  $x_j$ ) should be tested?
- Why?

# Better Heuristics

- Let  $X$  be a random variable with the following probability distribution:

$P(X=0)$	$P(X=1)$
0.1	0.9

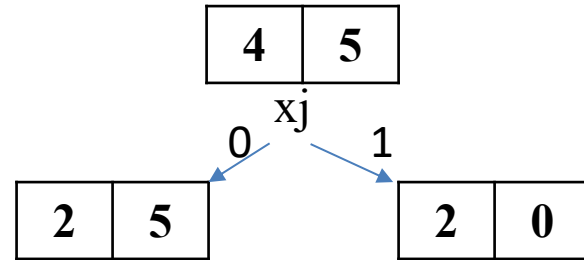
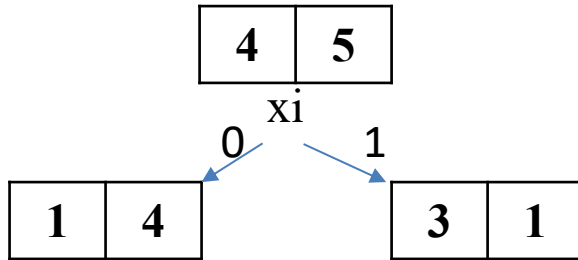
- Define *surprise* of each values of  $X$  as:

$$S(X = x) = -\log(P(X = x))$$

- Entropy** (*average surprise*):

$$H(X) = - \sum_{x=0}^1 P(X = x) \log(P(X = x))$$

$$H(X) = -(4/9)\log(4/9) - (5/9)\log(5/9) = 0.9911$$



$$H(L_{xi}) = -(1/5)\log(1/5) - (4/5)\log(4/5) = 0.7219$$

$$H(R_{xi}) = -(3/4)\log(3/4) - (1/4)\log(1/4) = 0.8113$$

$$H(X|xi) = (5/9)H(L_{xi}) + (4/9)H(R_{xi}) = 0.7847$$

$$IG(xi) = H(X) - H(X|xi) = 0.9911 - 0.7847 = 0.2064$$

$$H(L_{xj}) = -(2/7)\log(2/7) - (5/7)\log(5/7) = 0.8631$$

$$H(R_{xj}) = -(2/2)\log(2/2) - (0/2)\log(0/2) = 0$$

$$H(X|xj) = (7/9)H(L_{xj}) + (2/9)H(R_{xj}) = 0.6713$$

$$IG(xj) = H(X) - H(X|xj) = 0.9911 - 0.6713 = 0.3198$$

# Entropy impurity

- If a node has a proportion of  $p_j$  of each of the classes then the information or entropy is:

$$i(N) = -\sum_j p_j \log p_j$$

where  $0\log 0 = 0$

# Gini impurity

- This is the most widely used measure of impurity
- Gini index is:

$$i(N) = \sum_{i \neq j} p_i p_j = 1 - \sum_j p_j^2$$



# Feature selection at a node

- Best query value  $s$  is the choice for feature that maximize  $\Delta i(N)$

$$\Delta i(N) = i(N) - \sum_{k=1}^B P_k i(N_k)$$

Where  $P_k$  's are the fraction of patterns at node  $N$  that will go to  $N_k$

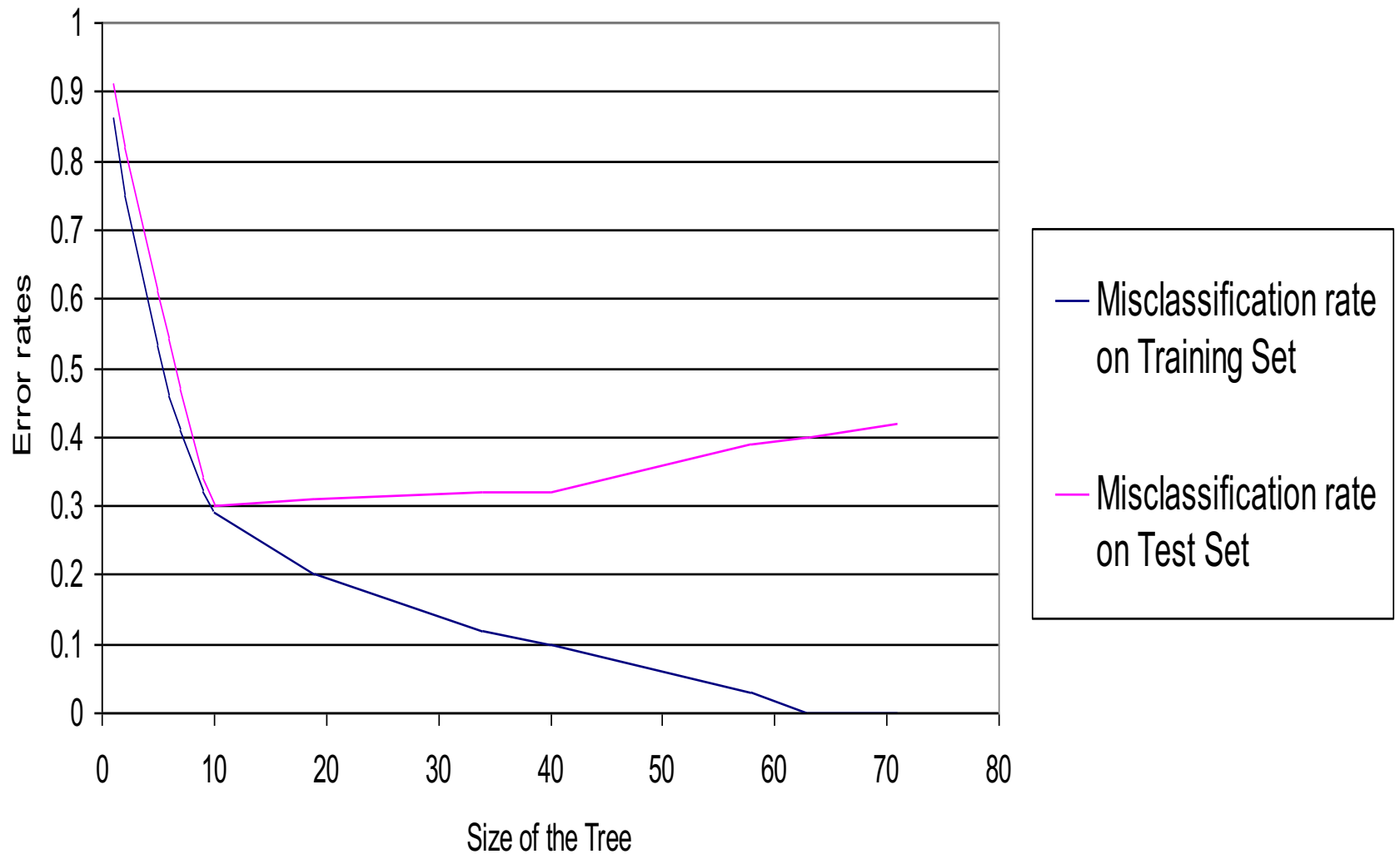
# When should a node be declare a leaf node?

- Impurity is zero
  - over fitting
- Threshold on number of points
  - difficult to choose

# If the tree becomes too large, how can it be made smaller and simpler?

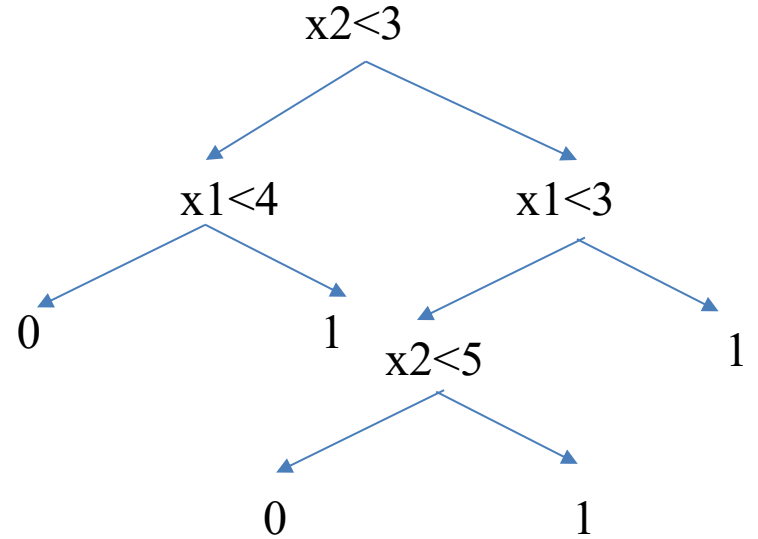
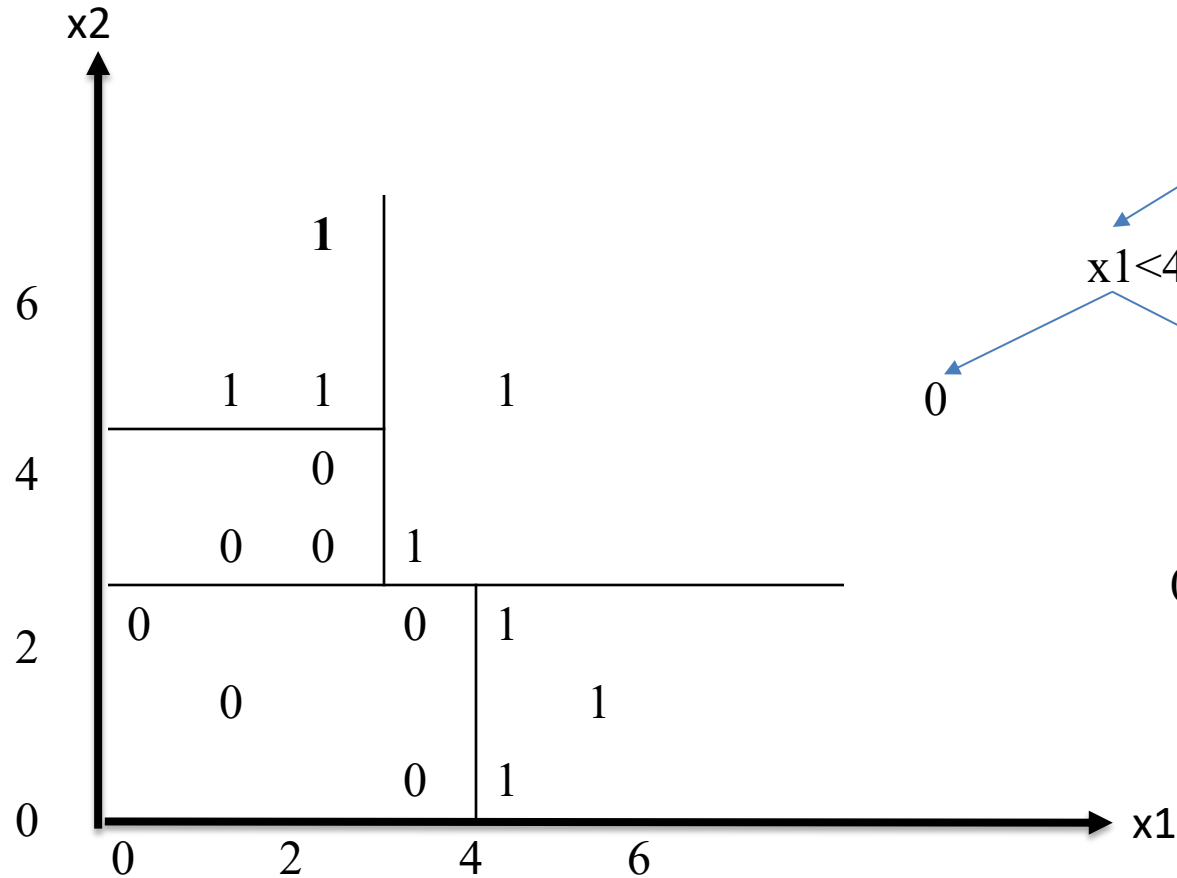
- Pruning
- The pruning is based on the misclassification rate. However the error rate will always drop (or at least not increase) with every split. This does not mean that the error rate on test data will improve.
- The solution to this problem is **cross-validation**.

# Misclassification Rates



- If a leaf node is impure, how should the category label be assigned?
  - majority voting
- How should missing data be handled?
  - delete that feature
  - interpolation

# Decision Tree Boundaries



# References

- Please follow the suggested reading material