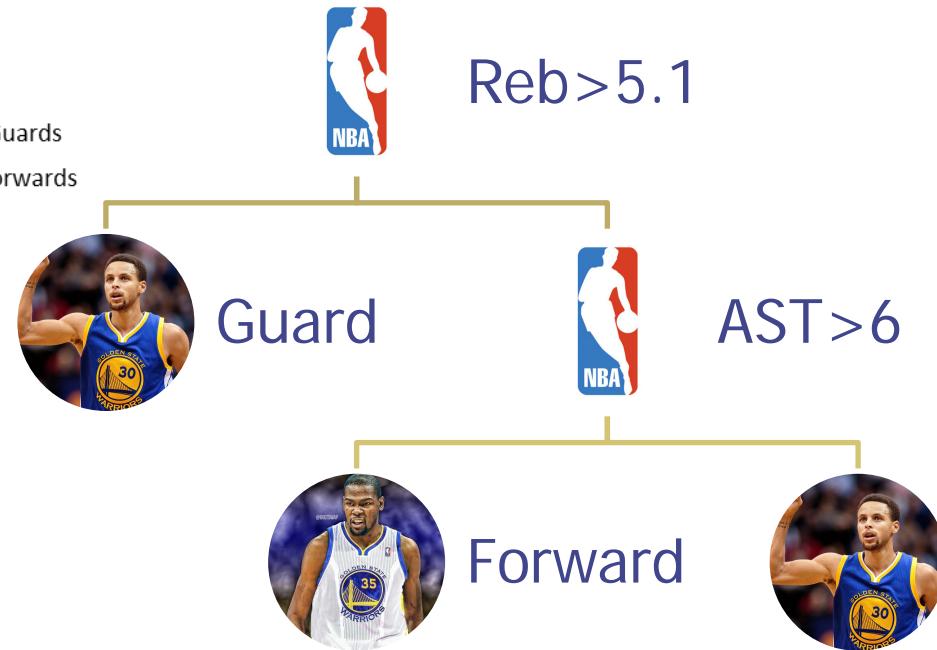
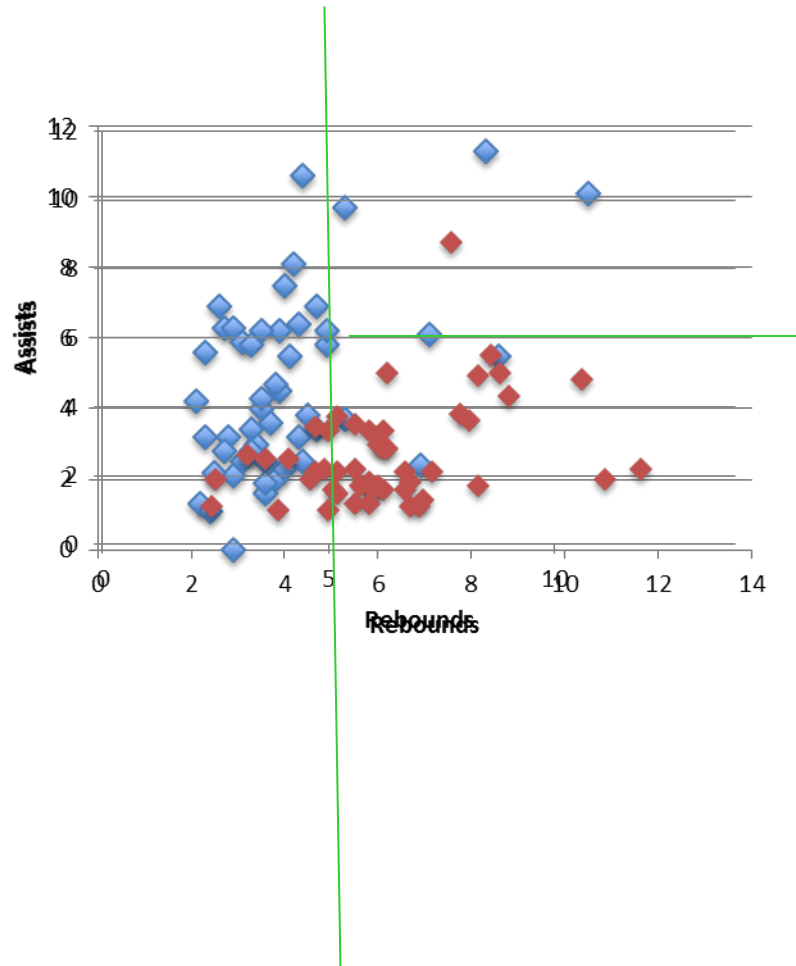


# Machine Learning

## 4771

Instructor: Itsik Pe'er

# Reminder: Decision Trees



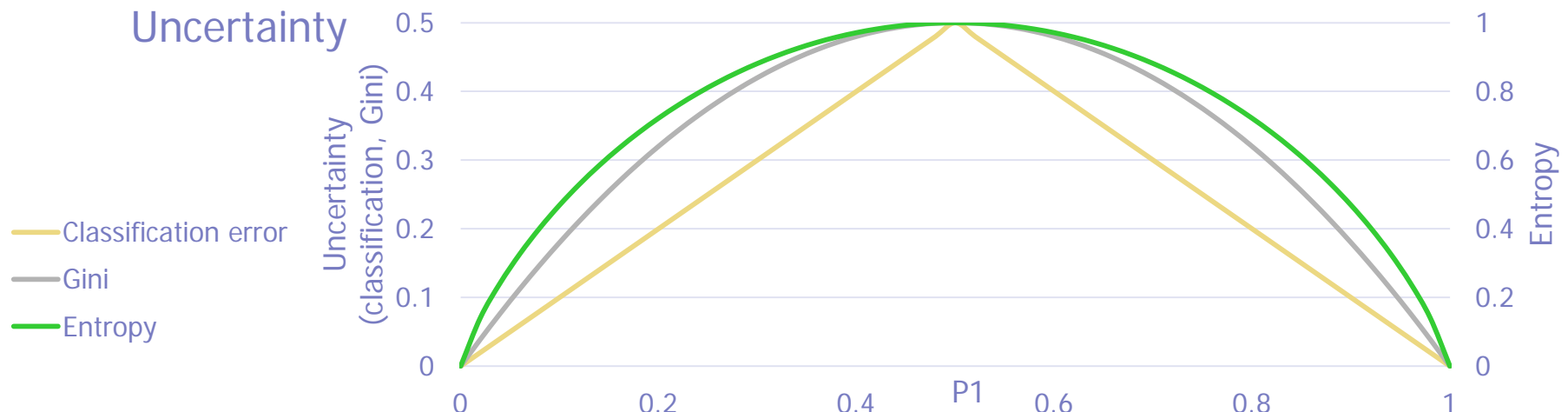
# Objective: Certainty

Choose leaf and split to minimize  
a measure of uncertainty  $X, \Pr(X = i) = p_i$

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- ◆ Classification error:  $1 - \max p_i$
- ◆ Gini index:  $\Pr(x_1 \neq x_2) = 1 - \sum p_i^2$
- ◆ Entropy:  $E[I(X)] = \sum p_i \log_2 \frac{1}{p_i}$



# Objective: Certainty

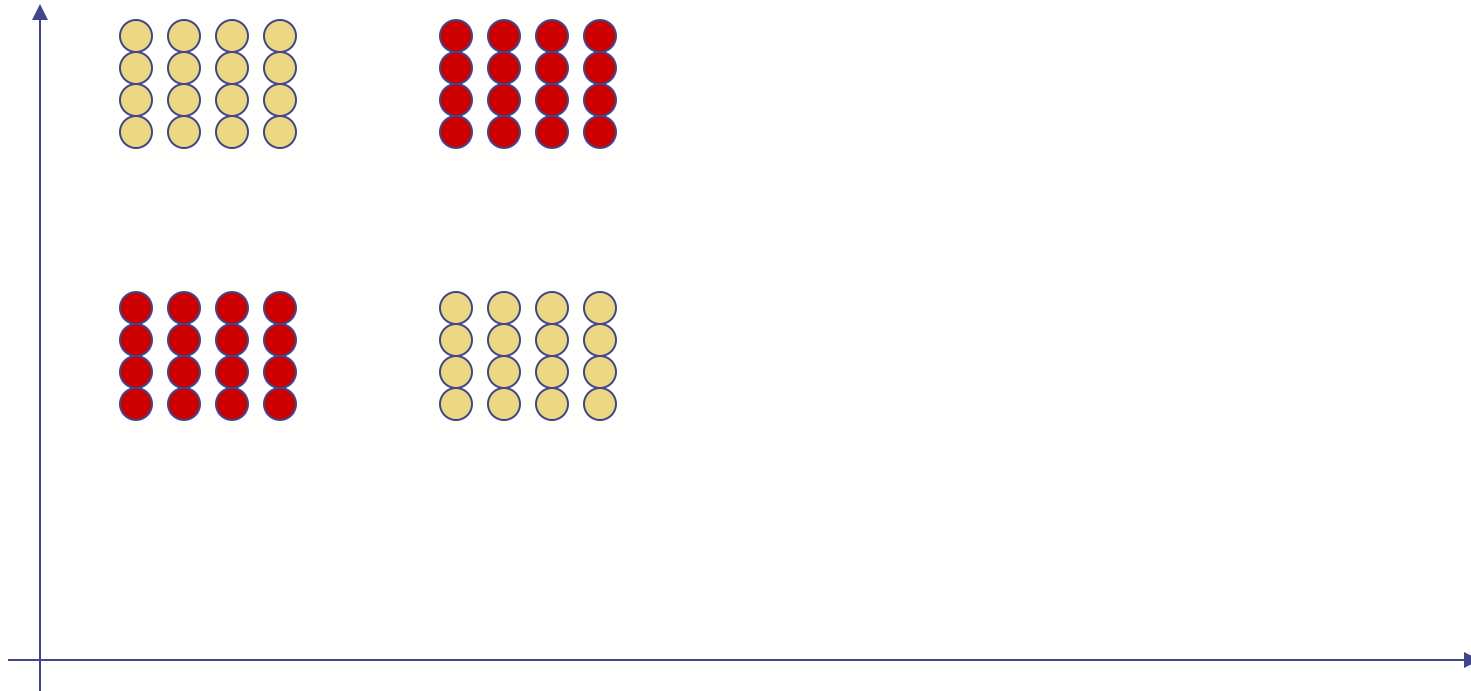
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# Stopping Criteria

# Example:

## No split reduces uncertainty



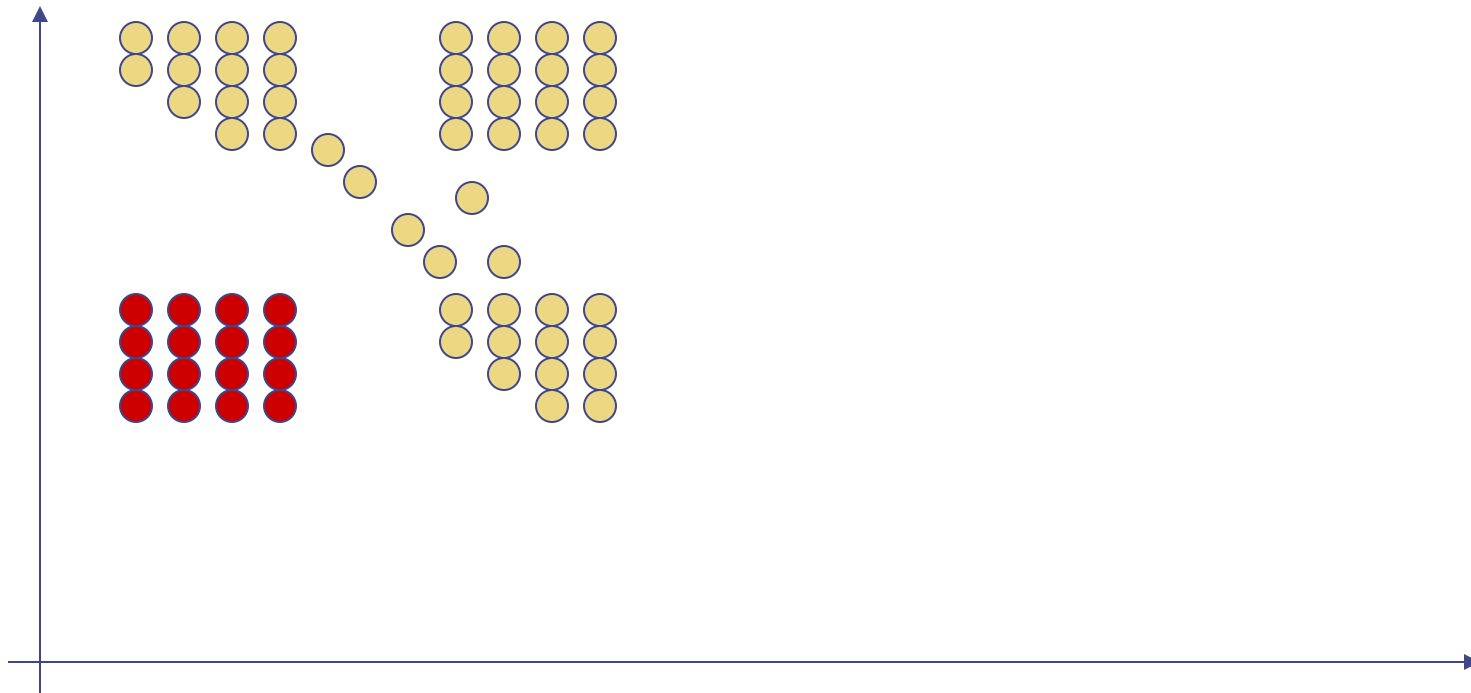
# Stopping Criteria

- ◆ No improvement?
- ◆ Certain tree size
- ◆ When leaves are pure

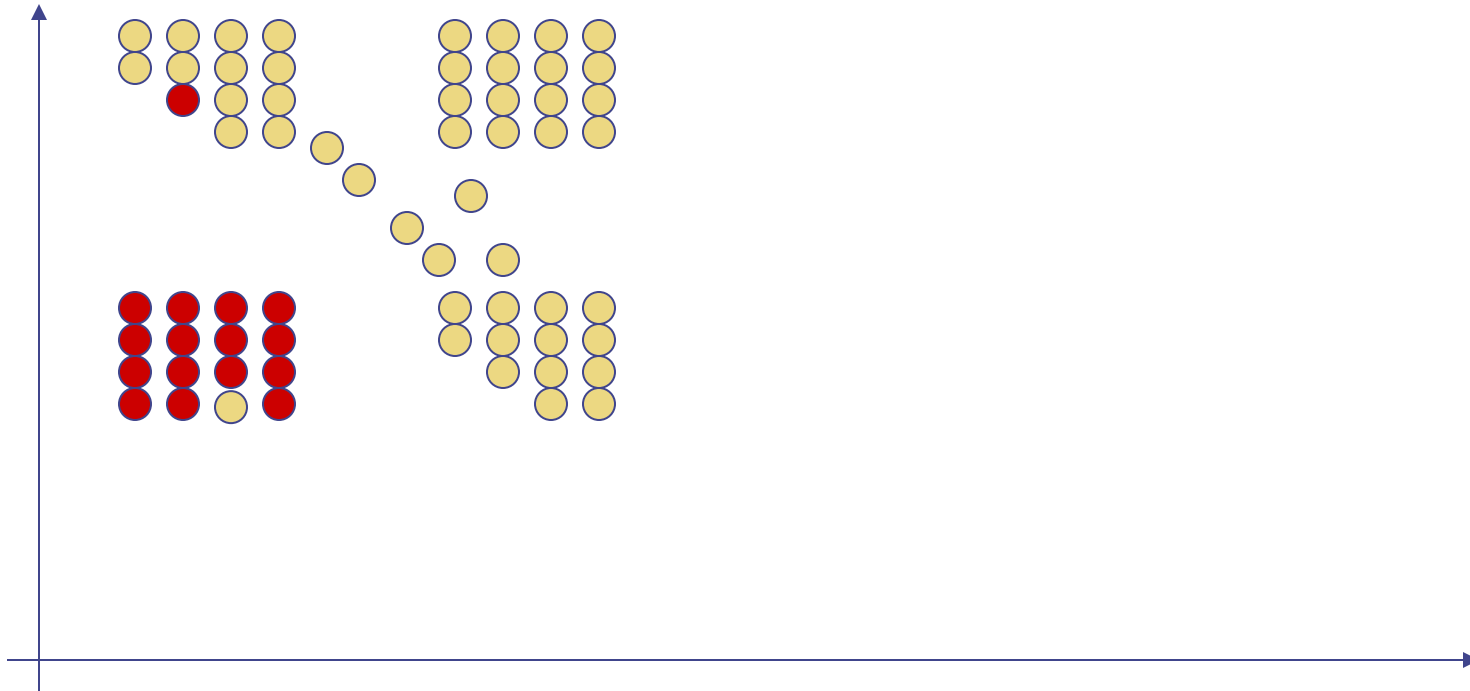


# Example:

## Clear split if clean data



# Example: Overfit if noisy data



# Stopping Criteria

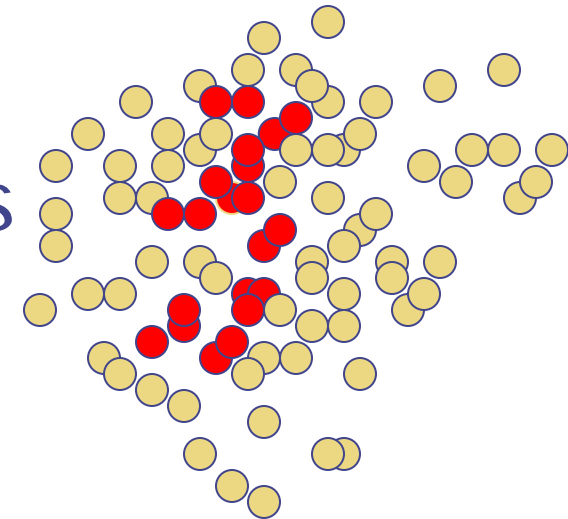
- ◆ No improvement?
- ◆ Certain tree size
- ◆ When leaves are pure
  - Overfitting. Requires pruning
  - Address by validation set.
  - Prune the pure-training tree

# Summary – Decision Trees

- ◆ Decision trees grow greedily
- ◆ Effective when “dominant” dimensions

# Summary – Decision Trees

- ◆ Decision trees grow greedily
- ◆ Effective when “dominant” dimensions
- ◆ Is there an RBF analog?  
Based on proximity, not axis



# Nearest Neighbor

◆ Idea: Small  $\|x - \tilde{x}\|$  implies  $y = \tilde{y}$

◆ Example: OCR

```

0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1
0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0
0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0
0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0
0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0
0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0
0 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0
1 1 1 1 1 0 0 0 1 1 1 0 0 0 0 0 0
0 1 1 1 0 0 0 0 0 0 1 1 0 0 0 0 0
1 1 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0
1 1 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0
1 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0
1 1 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0
0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
    
```

7 2 1 0 4 1 4 9 5 9  
 0 6 9 0 1 5 9 7 8 4  
 9 6 6 5 4 0 7 4 0 1  
 3 1 3 4 7 2 7 1 2 1  
 1 7 4 2 3 5 1 2 4 4

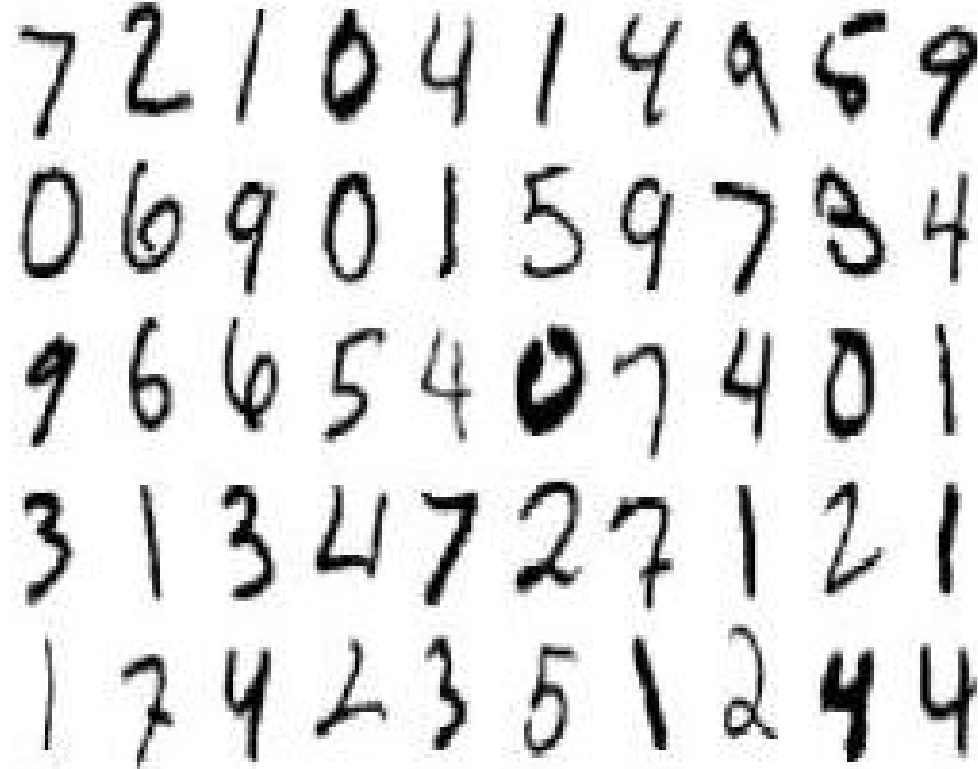
# Nearest Neighbor

◆ Idea: Small  $\|x - \tilde{x}\|$  implies  $y = \tilde{y}$

◆ Example: OCR

◆  $x \in \mathbf{R}^{28 \times 28}$

$y \in \{0, \dots, 9\}$



# Nearest Neighbor

◆ Idea: Small  $\|x - \tilde{x}\|$  implies  $y = \tilde{y}$

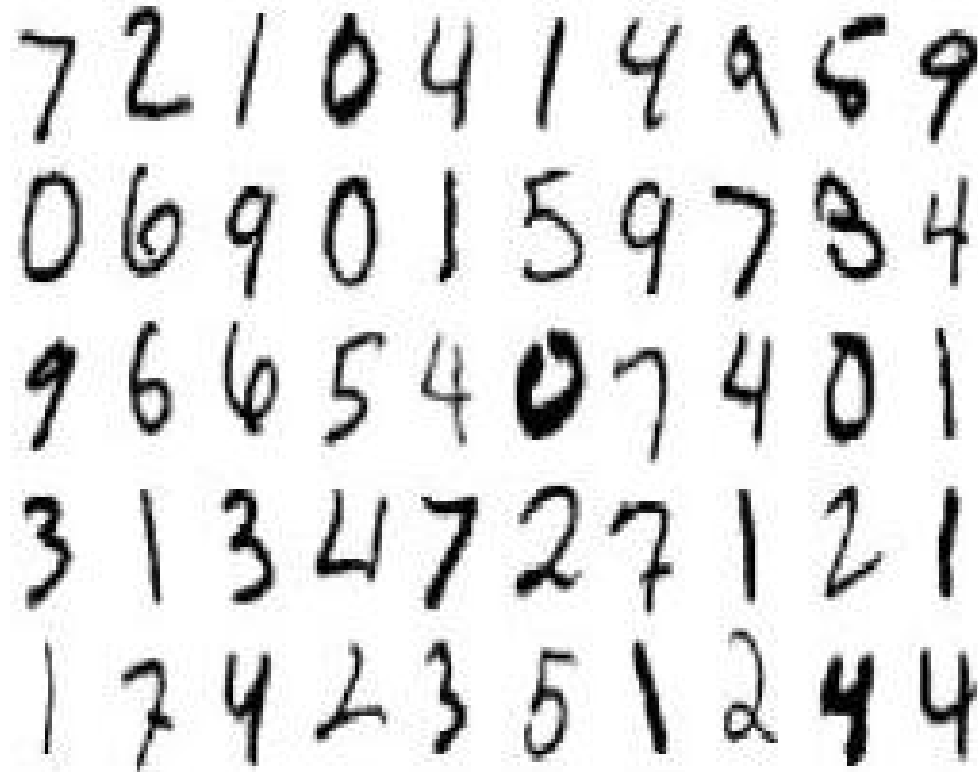
◆ Example: OCR

◆ Training  $\{(x_i, y_i)\}$

◆ Classify( $x$ ):

$j \leftarrow \operatorname{argmin}_i \|x - x_i\|$

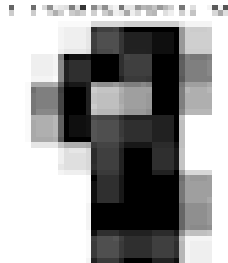
return  $y_j$



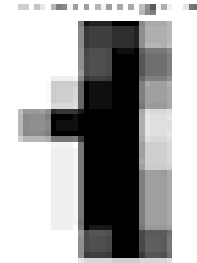


# Nearest Neighbor(s)

- ◆ Problem: sensitivity to class outliers  
this 9



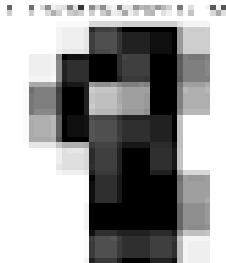
will cause this



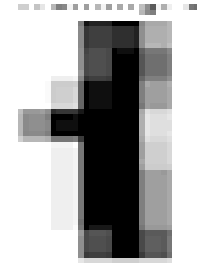
to be labeled 9

# Nearest Neighbor(s)

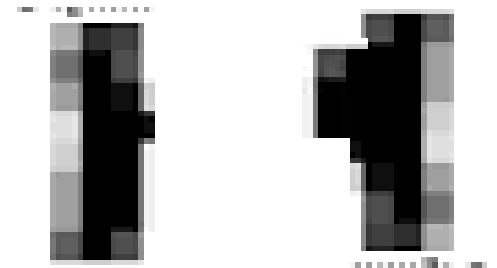
- ◆ Problem: sensitivity to class outliers  
this 9



will cause this

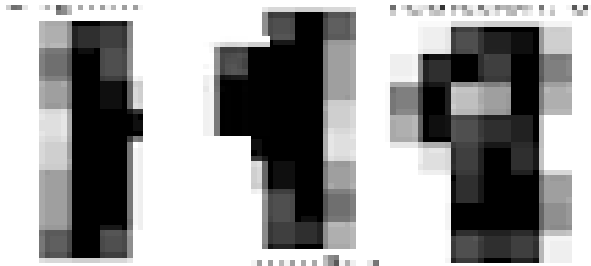


to be labeled 9

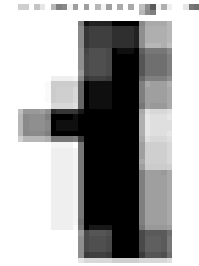


# Nearest Neighbor(s)

- ◆ Problem: sensitivity to class outliers  
this 9



will cause this



to be labeled 9

- ◆ Solution: rely on  $k > 1$  neighbors  
Idea: 1NN of 0.1 error worse than  
Maj(9 NN) each 0.3 error

# k Nearest Neighbors

◆  $\text{Classify}(x)$ :

while  $|J| < k$

$J \leftarrow J \cup \{\operatorname{argmin}_{i \notin J} \|x - x_i\|\}$

return  $\text{Plurality}(\{y_j | j \in J\})$

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◆ What is  $k$  ?

◆ Distance?

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while  $|J| < k$

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return  $\text{Plurality}(\{y_j | j \in J\})$

◆ What is  $k$  ? Determine by validation set

◆ Distance? Domain dependent

# Distance Functions

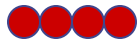
- ◆ Euclidean

- ◆ Images, audio:

How much warping need to turn  $x$  to  $\tilde{x}$  ?

- ◆ Strings: edit distance

# Known issues: Bad Features





# Known issues: Bad Features



Need distance to prioritize “good” features

# Complexity

◆ How complex is  $\text{FindClosest}(X, x)$  ?

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◆ Naively,  $O(N)$  distance evaluations

◆ 1D:

Preprocessing:  $O(\log N)$



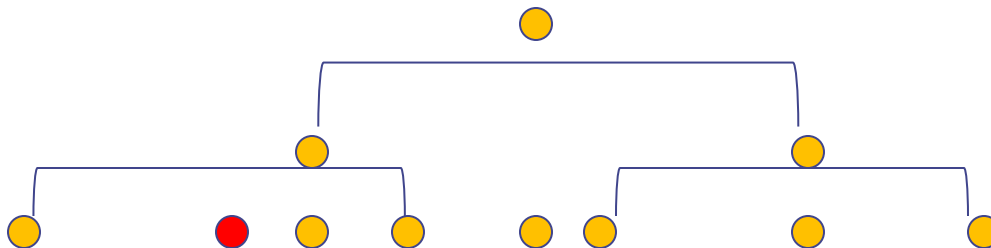
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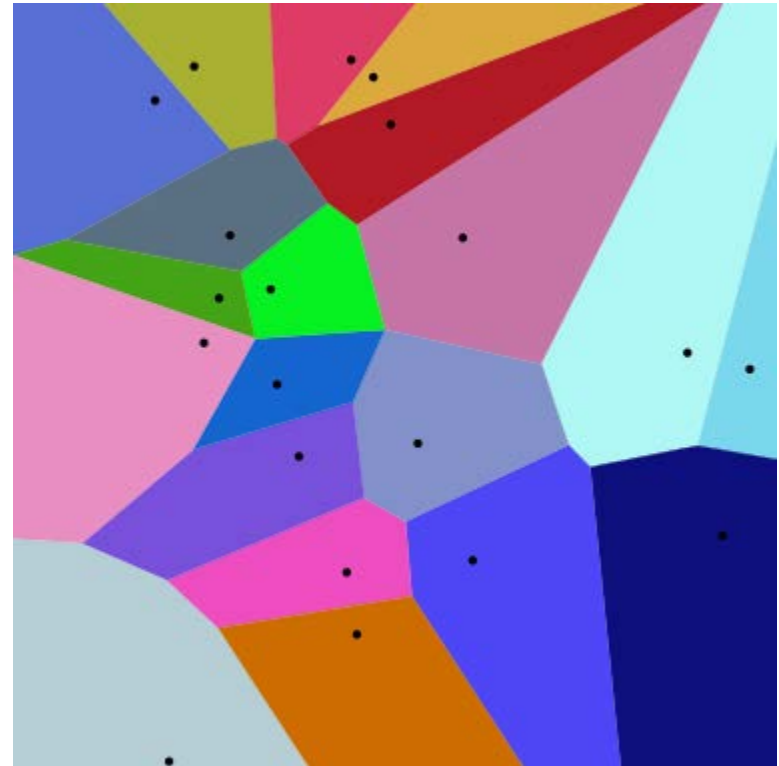
◆ 1D:

Preprocessing:  $O(\log N)$



# Preprocessing Higher D

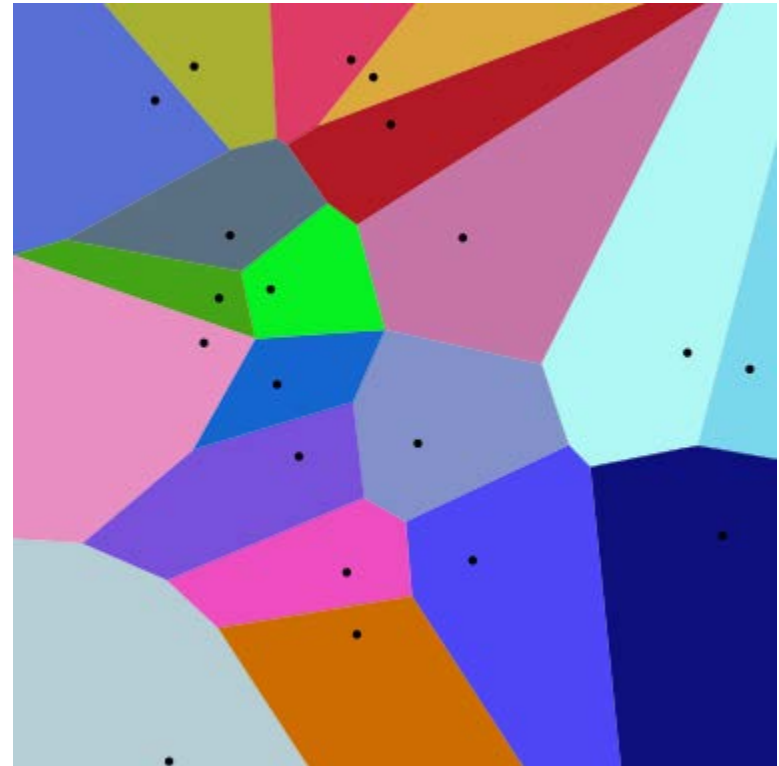
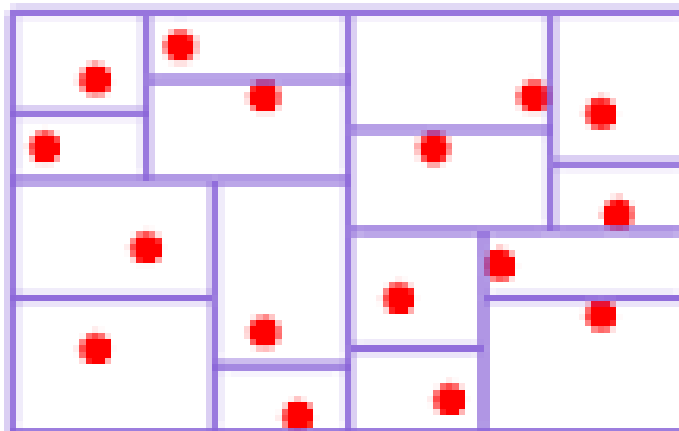
## ◆ Voronoi Diagrams



# Preprocessing Higher D

◆ Voronoi Diagrams

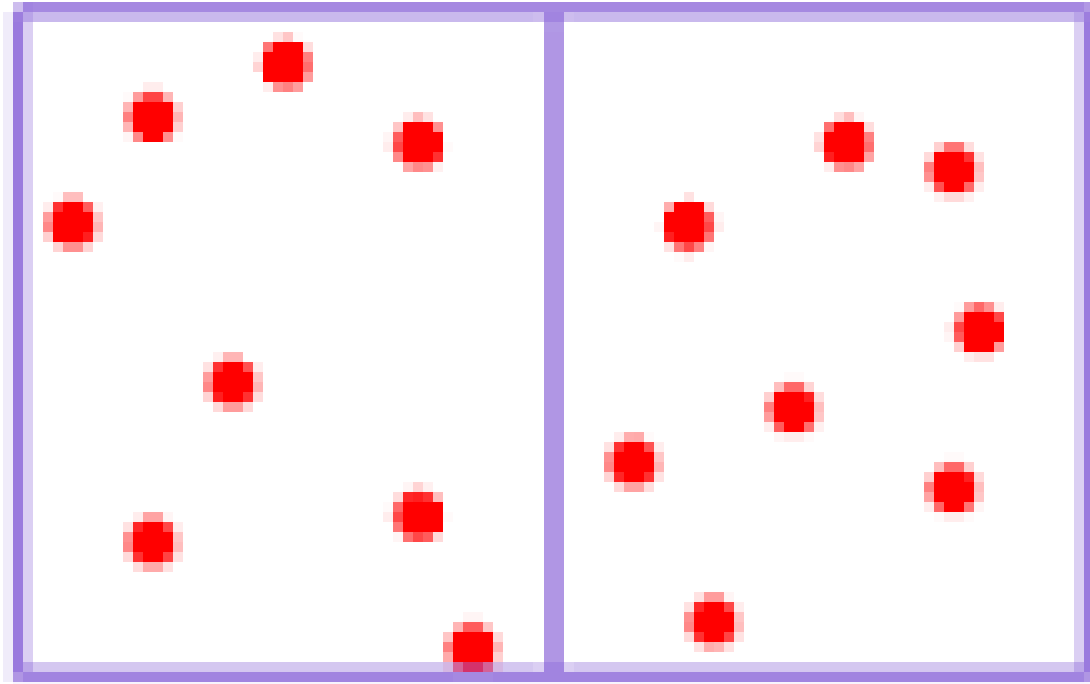
◆ k-d tree



# k-d Tree Construction

## ◆ Repeat

- Pick dimension
- Split by median

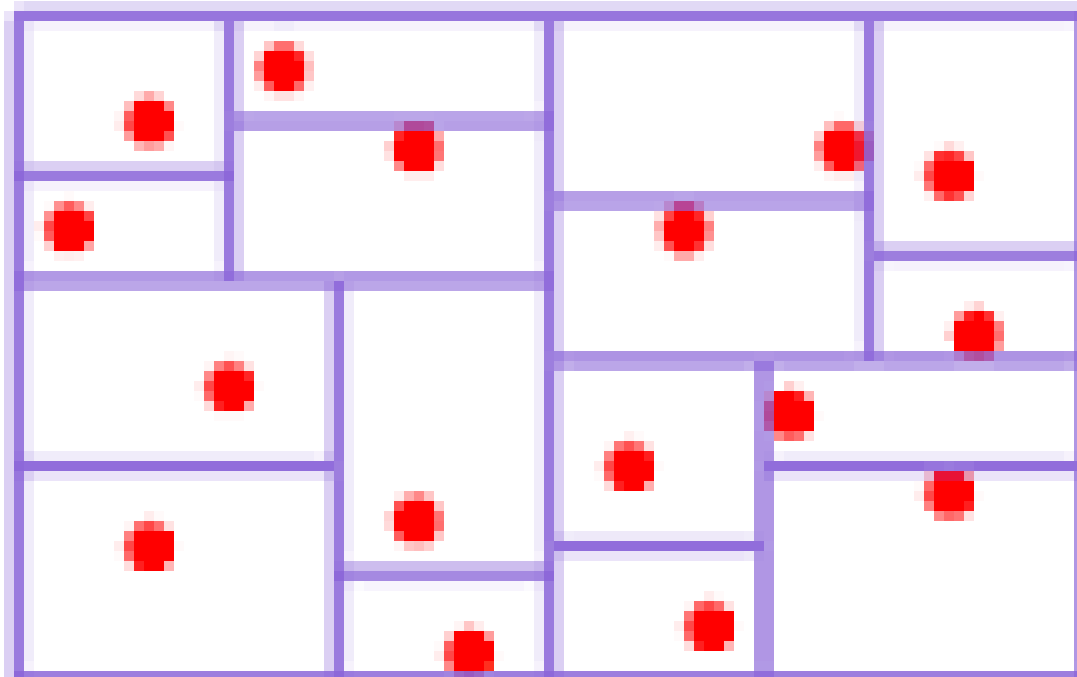


# k-d Tree Search

## ◆ Repeat

- Compare to median
- Choose side
- Recurse

→



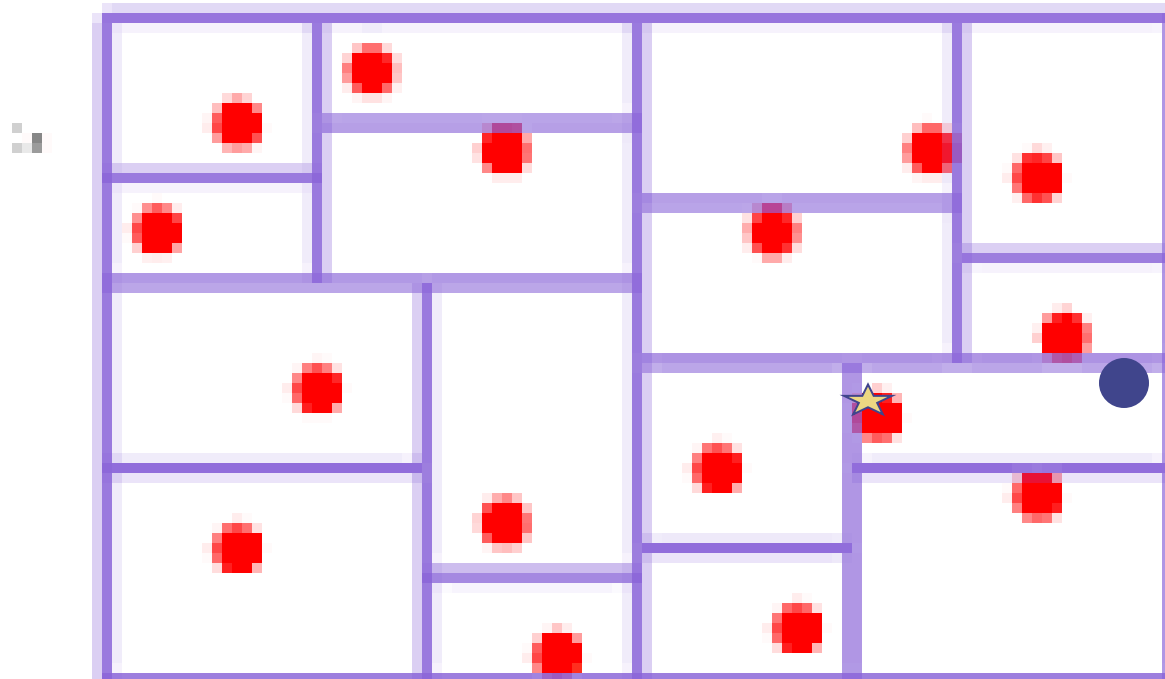


# k-d Tree Search (training x)

## ◆ Repeat

- Compare to median
- Choose side
- Recurse

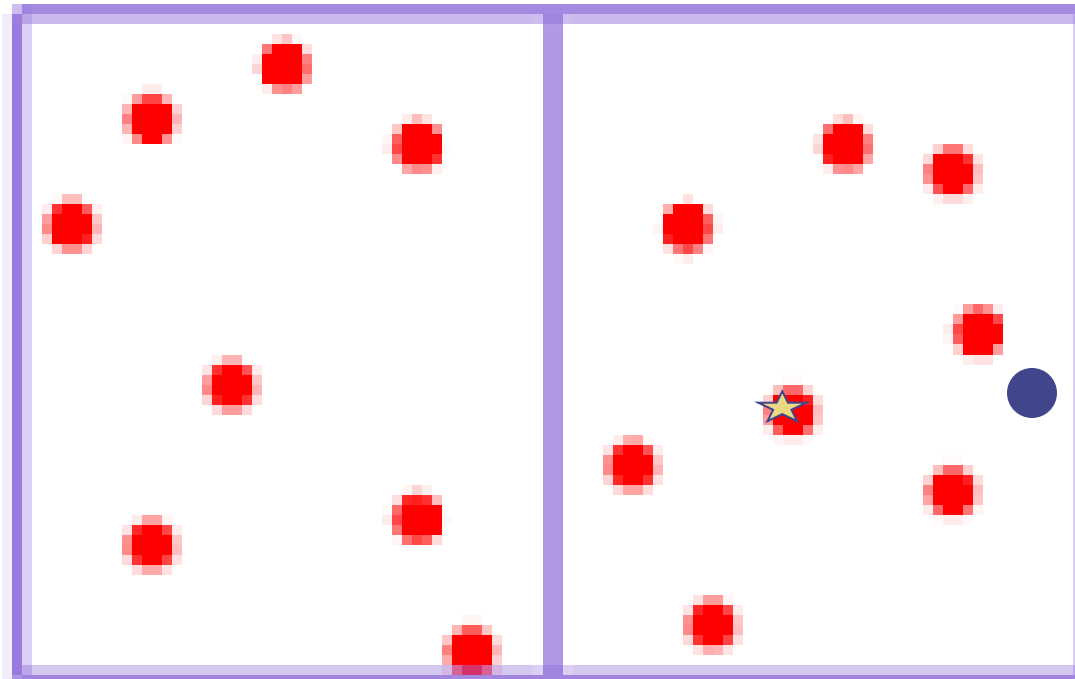
## ◆ Does not find closest!



# k-d Tree Search (any x)

## ◆ Repeat

- Compare to median
- Choose side
- Recurse(side)
- If needed
  - ◆ Recurse(other)

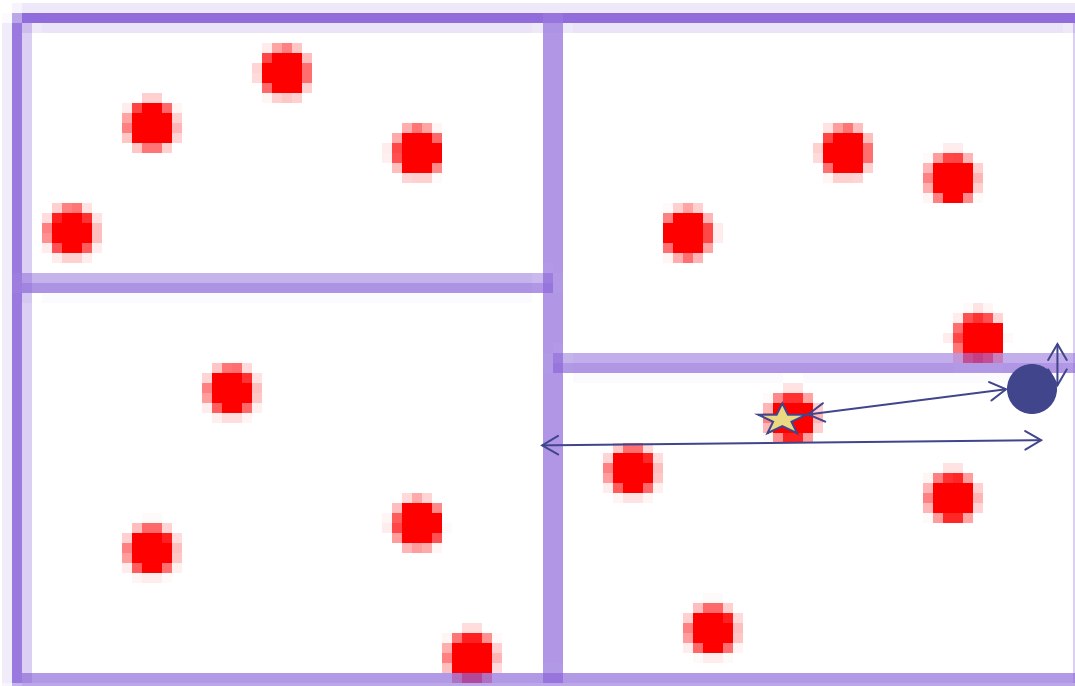


# k-d Tree Search (any x)

## ◆ Repeat

- Compare to median
- Choose side
- Recurse(side)
- If needed
  - ◆ Recurse(other)

## ◆ No $O(\log n)$ guarantee



# Summary+notes

- ◆ kNN : distance-based effective classification
  - Non-parametric
- ◆ Data structures for preprocessing
- ◆ Consistency guarantee