

The background is a dark blue gradient with a pattern of light blue and green line-art icons. These icons include gears, circuit boards, a robot, a laptop, a brain, a speech bubble, a globe, and a book. The words "MACHINE LEARNING" are written in large, light blue, outlined capital letters across the center. Overlaid on this is a white rectangular frame containing the text "k-Nearest Neighbour" in white. 

# k-Nearest Neighbour

**Proverb:**  
birds of a feather flock together

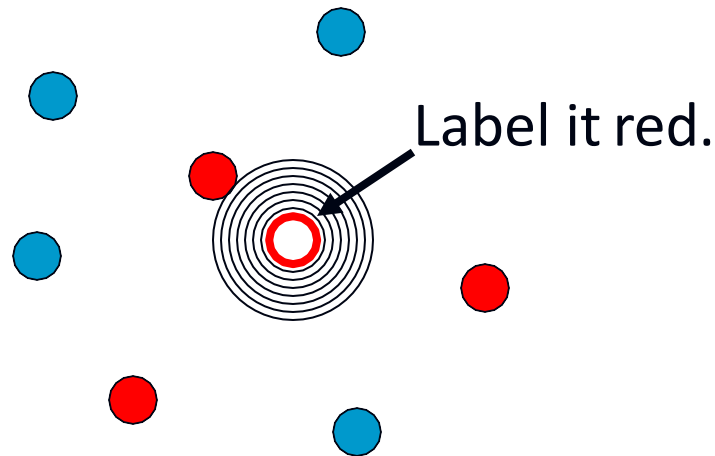


**Meaning:**  
People with the same tastes and interests will  
be found together

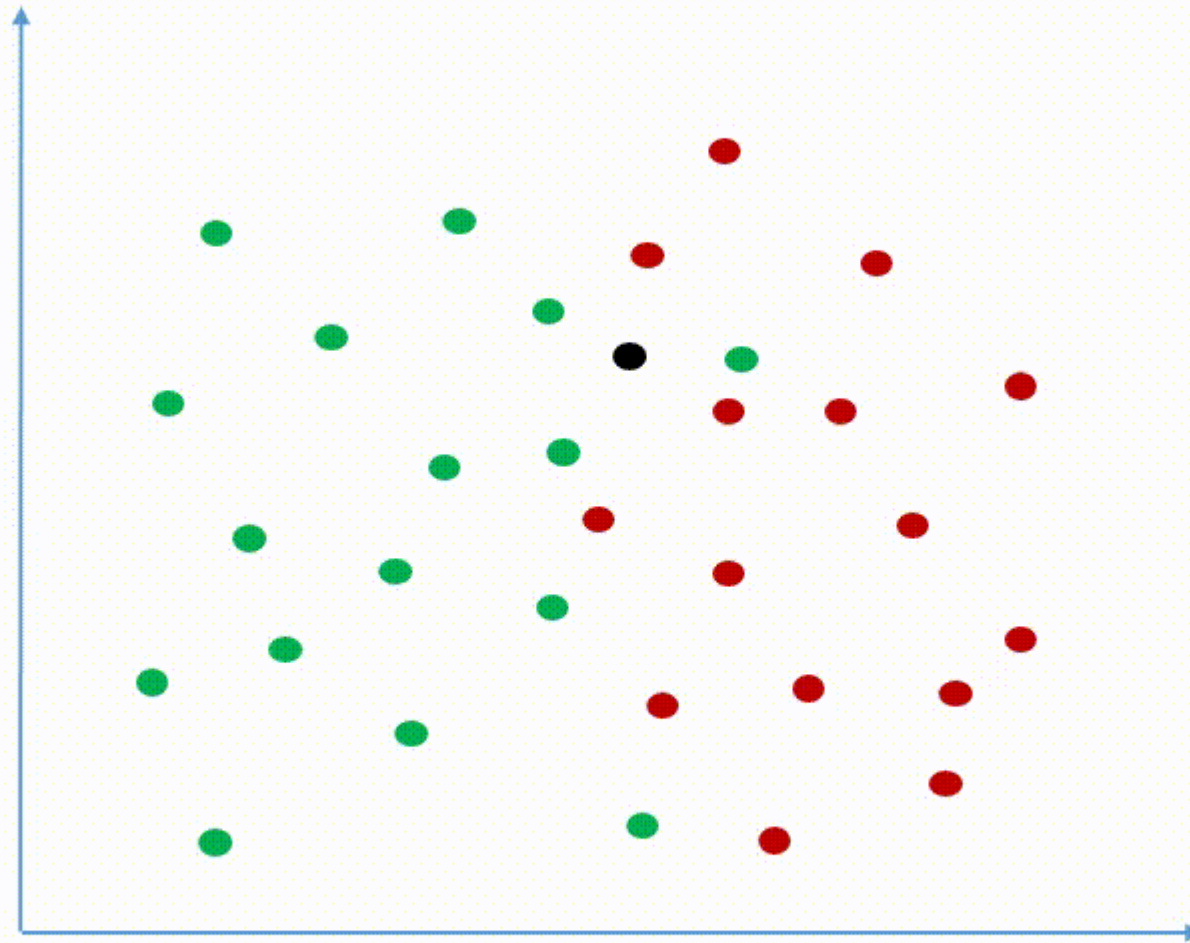


# 1-Nearest Neighbor

- One of the simplest of all machine learning classifiers
- Simple idea: label a new point the same as the closest known point



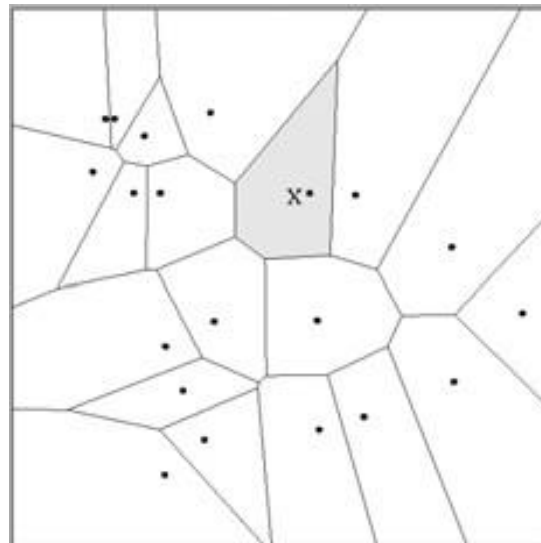
# K-Nearest Neighbors Classification





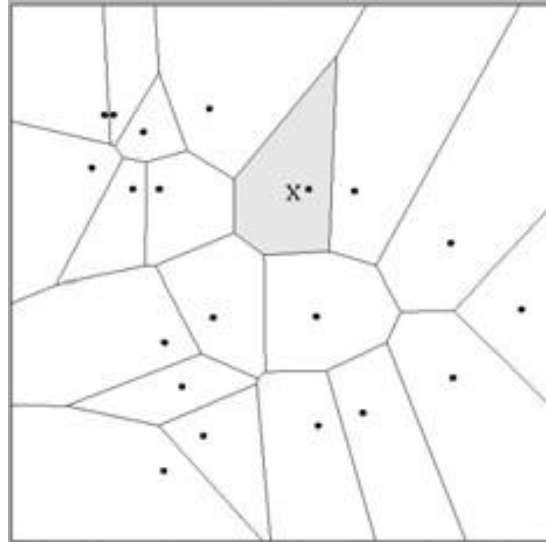
# 1-Nearest Neighbor

- A type of instance-based learning
  - Also known as “memory-based” learning
- Forms a Voronoi tessellation of the instance space

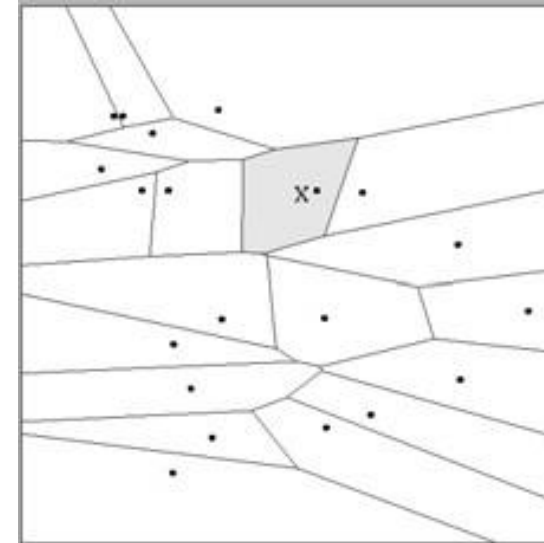


# Distance Metrics

- Different metrics can change the decision surface



$$\text{Dist}(\mathbf{a}, \mathbf{b}) = (a_1 - b_1)^2 + (a_2 - b_2)^2$$



$$\text{Dist}(\mathbf{a}, \mathbf{b}) = (a_1 - b_1)^2 + (3a_2 - 3b_2)^2$$

- Standard Euclidean distance metric:
  - Two-dimensional:  $\text{Dist}(\mathbf{a}, \mathbf{b}) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2}$
  - Multivariate:  $\text{Dist}(\mathbf{a}, \mathbf{b}) = \sqrt{\sum (a_i - b_i)^2}$

# Four Aspects of an Instance-Based Learner:

1. A distance metric
2. How many nearby neighbors to look at?
3. A weighting function (optional)
4. How to fit with the local points?

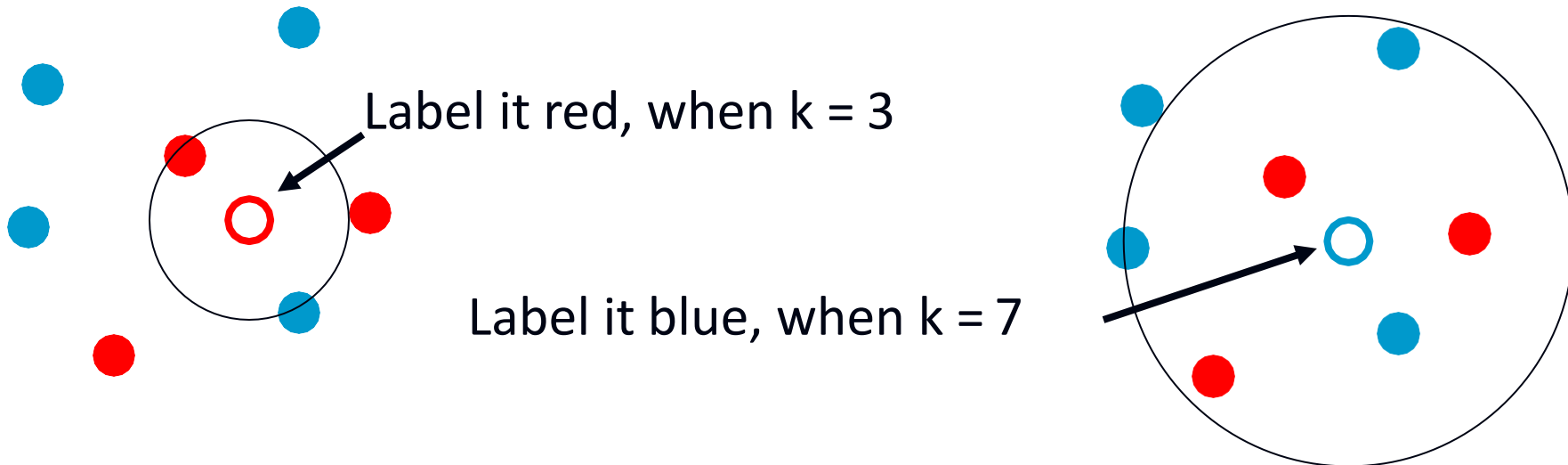
# 1-NN's Four Aspects as an Instance-Based Learner:

1. A distance metric
  - *Euclidian*
2. How many nearby neighbors to look at?
  - *One*
3. A weighting function (optional)
  - *Unused*
4. How to fit with the local points?
  - *Just predict the same output as the nearest neighbor.*

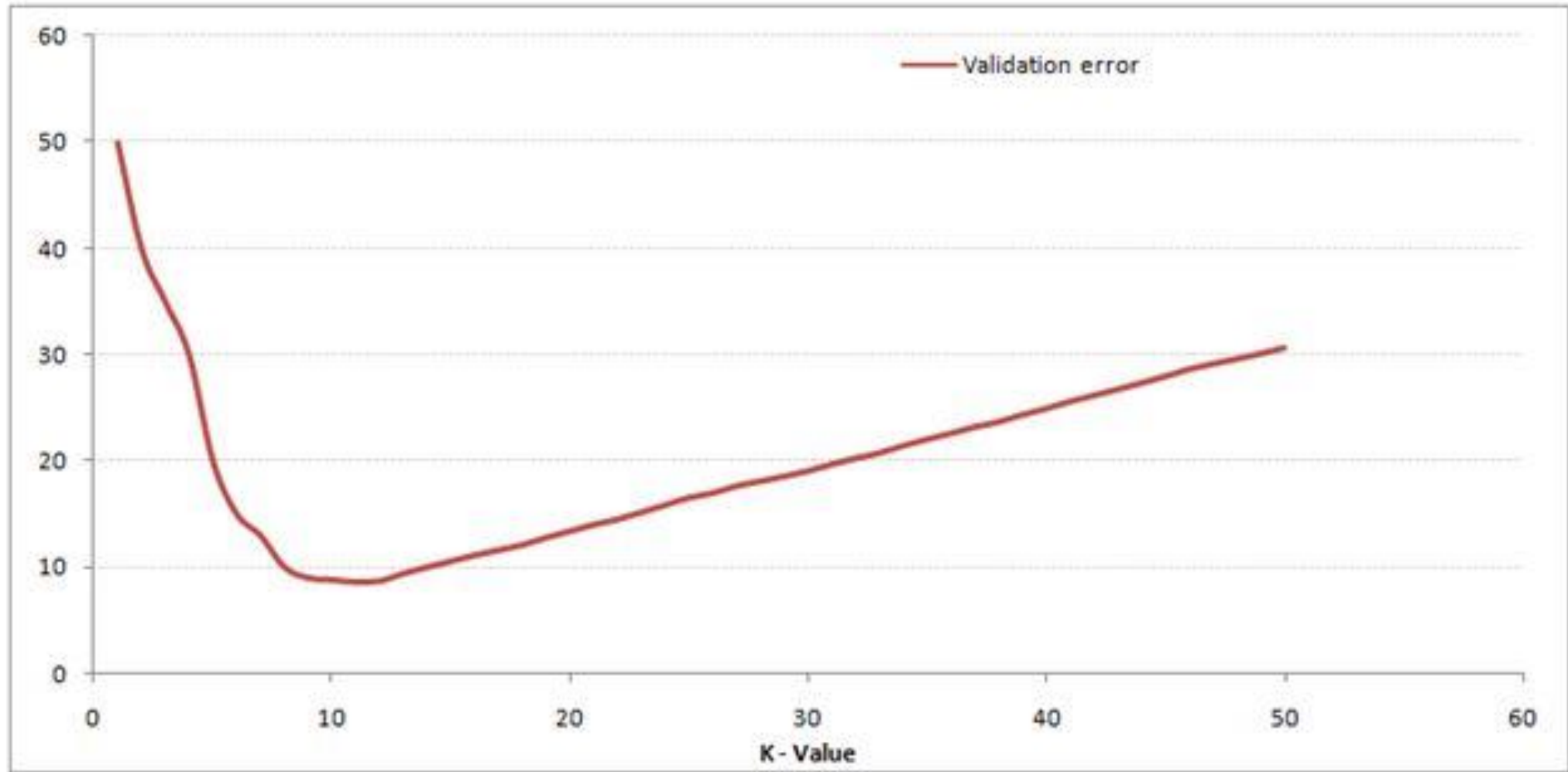


# k – Nearest Neighbor

- Generalizes 1-NN to smooth away noise in the labels
- A new point is now assigned the most frequent label of its  $k$  nearest neighbors



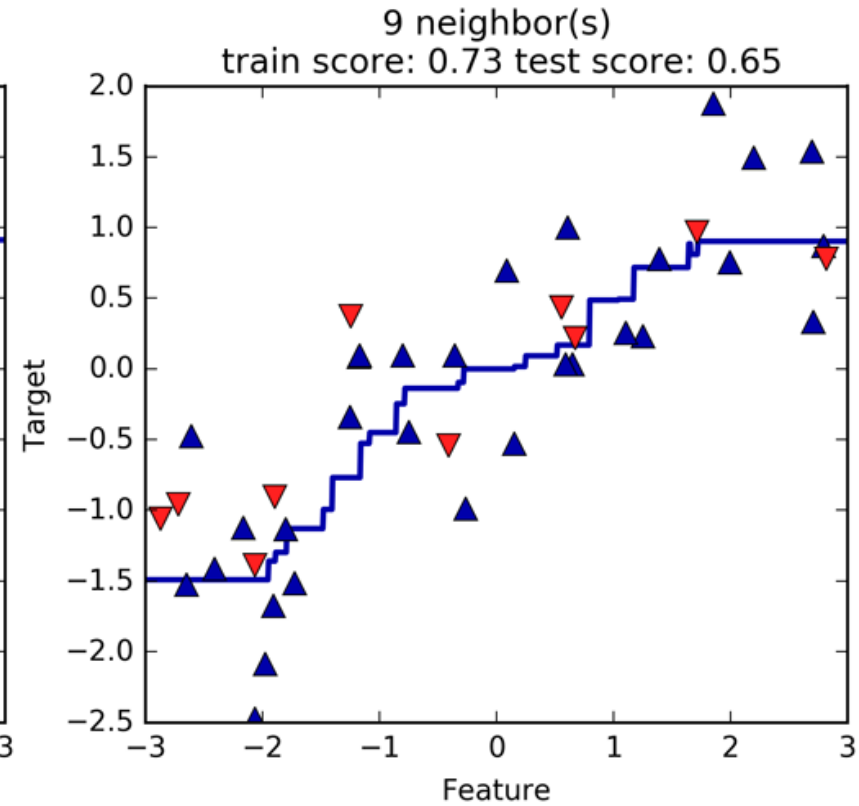
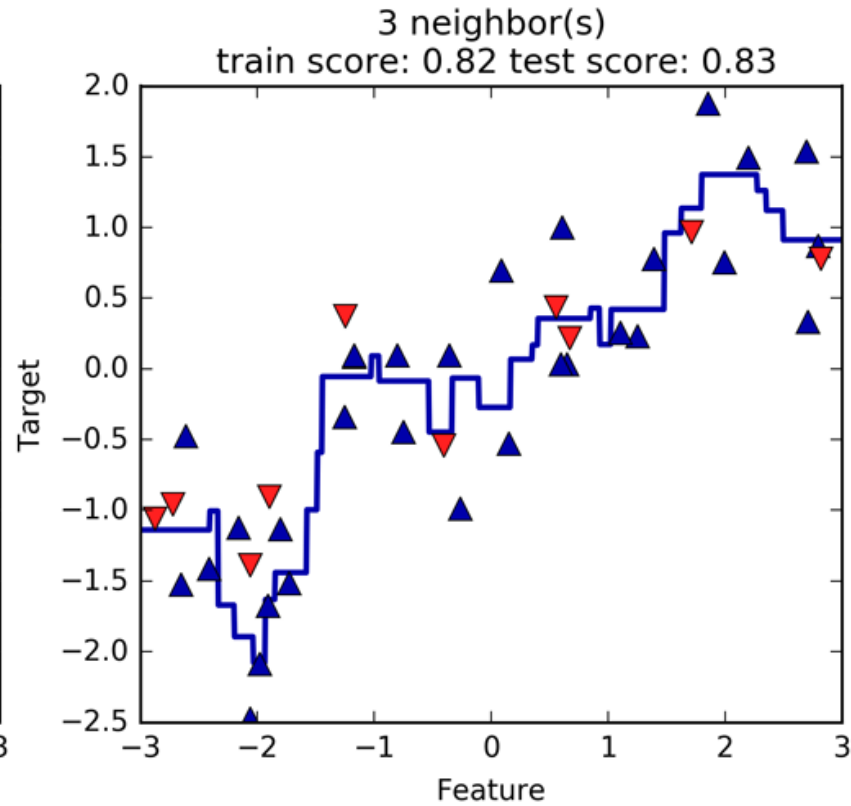
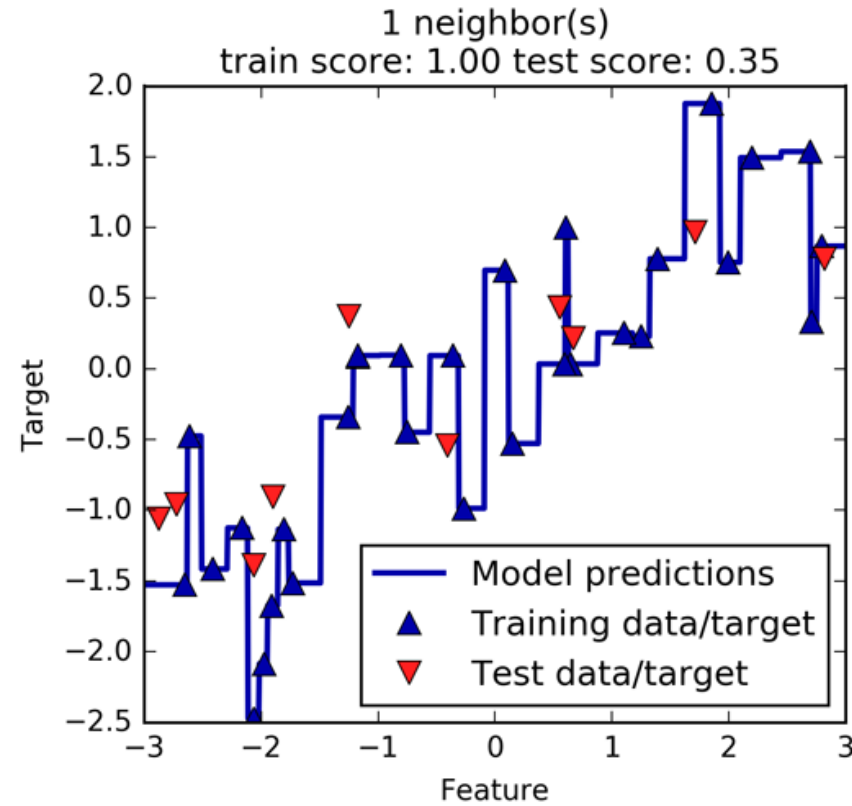
# Choosing K



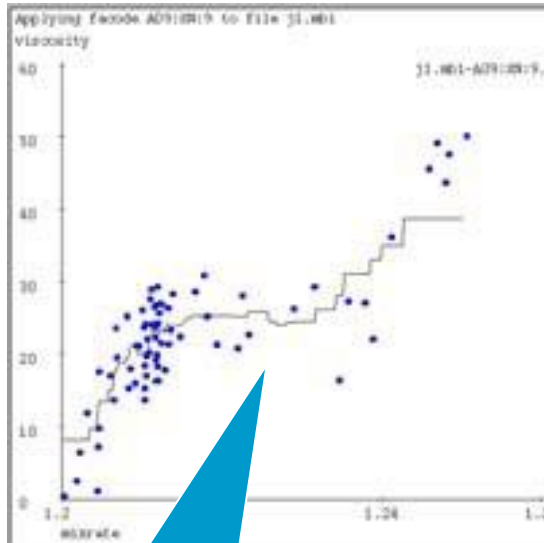
# Elbow Method



# KNN Regression

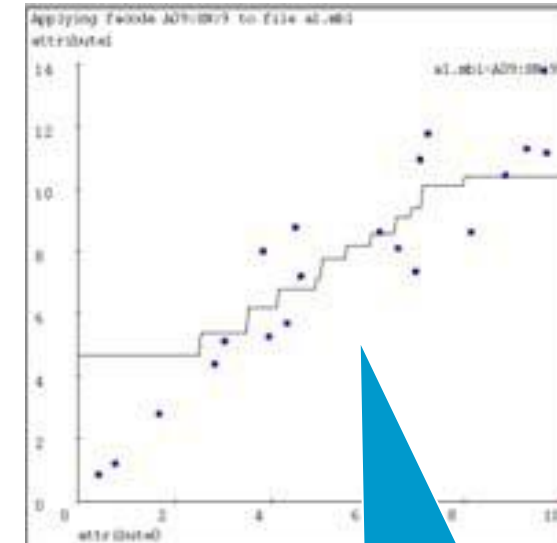
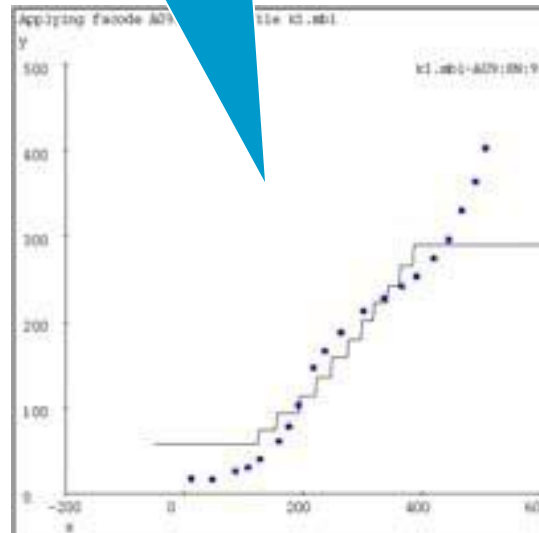


# k-Nearest Neighbor (k = 9)



A magnificent job of noise smoothing. Three cheers for 9-nearest-neighbor.  
...But the jerkiness isn't good.

Appalling behavior!  
Loses all the detail that 1-nearest neighbor would give. The tails are horrible!



Fits much less of the noise, captures trends. But still, frankly, pathetic compared with linear regression.

Adapted from "Instance-Based Learning"  
lecture slides by Andrew Moore, CMU.

# Weights in kNN

```
class sklearn.neighbors.KNeighborsClassifier(n_neighbors=5, *, weights='uniform',  
algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None,  
n_jobs=None, **kwargs)[source]
```

weights{'uniform', 'distance'} or callable, default='uniform'

weight function used in prediction. Possible values:

'uniform' : uniform weights. All points in each neighborhood are weighted equally.

'distance' : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.



# Learning Algorithm

```
class sklearn.neighbors.KNeighborsClassifier(n_neighbors=5, *, weights='uniform',  
algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None,  
n_jobs=None, **kwargs)[source]
```

algorithm{'auto', 'ball\_tree', 'kd\_tree', 'brute'}, default='auto'

Algorithm used to compute the nearest neighbors:

'ball\_tree' will use BallTree

'kd\_tree' will use KDTree

'brute' will use a brute-force search.

'auto' will attempt to decide the most appropriate algorithm based on the values passed to fit method.

# Neighbors in Sklearn

<code>neighbors.BallTree(X[, leaf_size, metric])</code>	BallTree for fast generalized N-point problems
<code>neighbors.DistanceMetric</code>	DistanceMetric class
<code>neighbors.KDTree(X[, leaf_size, metric])</code>	KDTree for fast generalized N-point problems
<code>neighbors.KernelDensity(*[, bandwidth, ...])</code>	Kernel Density Estimation.
<code>neighbors.KNeighborsClassifier([...])</code>	Classifier implementing the k-nearest neighbors vote.
<code>neighbors.KNeighborsRegressor([n_neighbors, ...])</code>	Regression based on k-nearest neighbors.
<code>neighbors.KNeighborsTransformer(*[, mode, ...])</code>	Transform X into a (weighted) graph of k nearest neighbors
<code>neighbors.LocalOutlierFactor([n_neighbors, ...])</code>	Unsupervised Outlier Detection using Local Outlier Factor (LOF)
<code>neighbors.RadiusNeighborsClassifier([...])</code>	Classifier implementing a vote among neighbors within a given radius
<code>neighbors.RadiusNeighborsRegressor([radius, ...])</code>	Regression based on neighbors within a fixed radius.
<code>neighbors.RadiusNeighborsTransformer(*[, ...])</code>	Transform X into a (weighted) graph of neighbors nearer than a radius
<code>neighbors.NearestCentroid([metric, ...])</code>	Nearest centroid classifier.
<code>neighbors.NearestNeighbors(*[, n_neighbors, ...])</code>	Unsupervised learner for implementing neighbor searches.
<code>neighbors.NeighborhoodComponentsAnalysis([...])</code>	Neighborhood Components Analysis
<hr/>	
<code>neighbors.kneighbors_graph(X, n_neighbors, *)</code>	Computes the (weighted) graph of k-Neighbors for points in X
<code>neighbors.radius_neighbors_graph(X, radius, *)</code>	Computes the (weighted) graph of Neighbors for points in X



**நன்றி வணக்கம்**