# CS 445 Introduction to Machine Learning

Features and the KNN Classifier

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# Features

*If it walks like a duck, and quacks like a duck, it probably is a duck.* 

Features describe the observation:



### **Decision Tree Architecture**

**Idea**: Identify the feature and the value of the feature (split point) that divides the data into 2 groups that minimizes the weighted "impurity" of each group. Repeat this process on each leaf until happy.



**Observation:** The model splits the data one feature at a time.

# Distance (dissimilarity) between observations

Define a method to measure the distance between two observations. This

distance incorporates a set of the features into a single number (scalar).

Idea: Small distances between observations imply similar class labels.

### **Euclidean Distance and Nearest Point Classifier**

 Compute distance from new point *p* (the black diamond) and the training set.



# Distance (dissimilarity) between observations

Define a method to measure the distance between two observations. This

distance incorporates **all** the features at once.

Idea: Small distances between observations imply similar class labels.

### **Euclidean Distance and Nearest Point Classifier**

- Compute distance from new point p (the black diamond) and the training set.
- 2. Identify the nearest point and assign its label to point *p*



# **Euclidean Distance and Nearest Point Classifier**

### Voronoi Diagram

(https://en.wikipedia.org/wiki/Voronoi\_diagram) Create regions such that for any point *p* in the same region, their closest data point (the dots) are the same.



# **Euclidean Distance and Nearest Point Classifier**

### Voronoi Diagram

(<u>https://en.wikipedia.org/wiki/Voronoi\_diagram</u>) Create regions such that for any point *p* in the same region, their closest data point (the dots) are the same.

**Outlier –** an object different than most other objects of the same type



# **Euclidean Distance and K-Nearest Point Classifier**

Idea: Increase the number of neighbors (k) and take a majority vote.

### Algorithm

- k = number of nearest neighbors
- D = training examples and labels (x, y)
- z = point (vector of points) to classify



Compute dist( $x_i$ , z) (distance between z and every training data point  $x_i$ )

 $D_z$  = set of k closest examples to z ( $D_z \subseteq D$ )

$$z_{\text{predict}} = \underset{v}{\operatorname{argmin}} \sum_{(x_i, y_i) \in D_z} I(v = y_i)$$

# **Decision Boundaries:**



Boundaries are perpendicular (orthogonal) to the feature being split.

# What do the KNN decision boundaries look like?

# Will I go Outside to play Today?

Let's try and build a model and predict.

Feature	Values
Weather	Sunny, Rainy, Overcast
Temperature	Hot, Mild, Cold



The label/class will be to predict if the child will play outside (Yes/No).

Issues?

# **Computing Distances**

How to compute a distance between Sunny, Rainy, and Overcast?



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How to compute a distance between Sunny, Rainy, and Overcast?



Is Dist(Sunny, Cloudy) == Dist(Sunny, Rainy) ?

# **Computing Distances**

How to compute a distance between Sunny, Rainy, and Overcast?



Difference between **ordinal** and **nominal** datatypes (see IDD section 2.1.2)

# Smallest Distance means Most Similar?



Who is the most similar person to

this in the dataset (right)?

Age = **39** Salary = **75**,**750** 

Age	Salary
23	56K
35	75K
55	76K

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p = (Age = 39, Salary = 75, 750)

### Dataset

Age	Salary
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35	75K
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Age 23 However, the Euclidian 35

Age	Salary	Distance to point <i>p</i>
23	56K	$\sqrt{(39-23)^2 + (75750 - 56000)^2} \approx 19,750$
35	75K	$\sqrt{(39 - 35)^2 + (75750 - 75000)^2} \approx 750$
55	76K	$\sqrt{(39-55)^2 + (75750 - 76000)^2} \approx 251$

distances say otherwise.

# Normalization

**Idea**: Make the range of all features the same. Start with age. Min value: 23, max value: 55

$$x'_{i,j} = \frac{x_{i,j} - \min(X_i)}{\max(X_i) - \min(X_i)}$$
 p = (Age = 39, Salary = 75,750)

Age	Salary
23	56K
35	75K
55	76K

Age	Salary	Dist (orig)	Age normalized	Salary Normalized	Dist (with normalized values)
23	56K	19,750	(23 – 23)/(55-23) = 0	(56k –56k)/(76k – 56k) = 0	
35	75K	750	(35-23)(55-23) = 0.375	(75k – 56k)/(76k-56k) = 0.95	
55	76K	251	(55-23)/(55-23) = 1.0	(76k-56k)/(76k-56k) = 1	

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Age	Salary	Dist (orig)	Age normalized	Salary Normalized	Dist (with normalized values)
23	56K	19,750	(23 – 23)/(55-23) = 0	(56k –56k)/(76k – 56k) = 0	1.1
35	75K	750	(35-23)(55-23) = 0.375	(75k – 56k)/(76k-56k) = 0.95	0.13
55	76K	251	(55-23)/(55-23) = 1.0	(76k-56k)/(76k-56k) = 1	0.50