# CSE419 – Artificial Intelligence and Machine Learning 2021

PhD Furkan Gözükara, Toros University

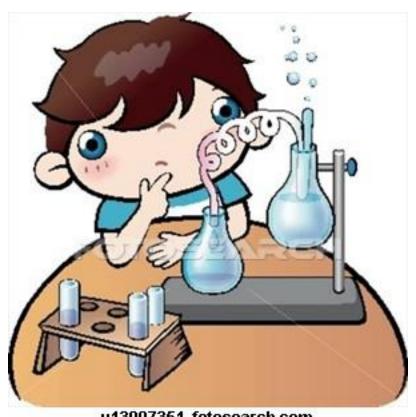
https://github.com/FurkanGozukara/CSE419-Artificial-Intelligence-and-Machine-Learning-2020

# Lecture 4 Geometric View of Data

Based on Asst. Prof. Dr. David Kauchak (Pomona College) Lecture Slides

Source: https://cs.pomona.edu/~dkauchak/classes/f13/cs451-f13/lectures/

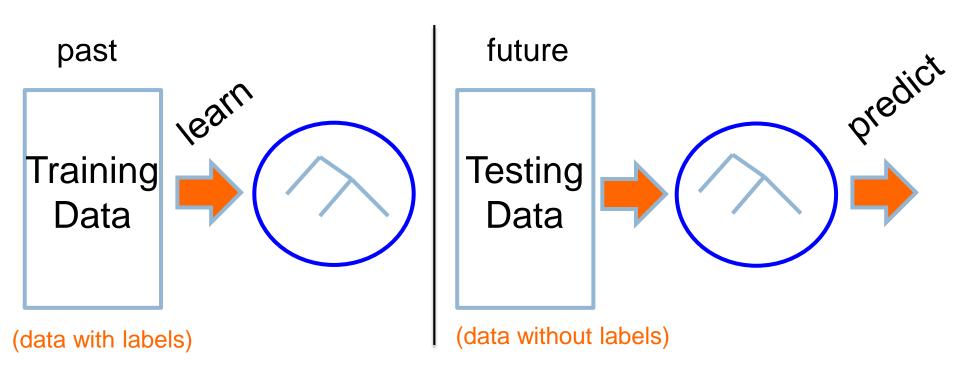
# Proper Experimentation



u13007351 fotosearch.com

### Experimental setup

#### **REAL WORLD USE OF ML ALGORITHMS**



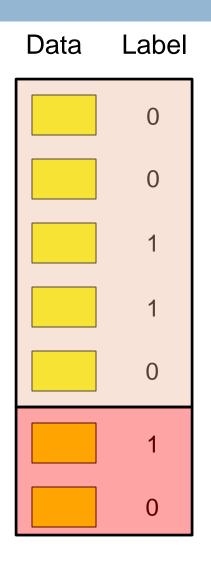
How do we tell how well we're doing?

### Real-world classification

Google has labeled training data, for example from people clicking the "spam" button, but when new messages come in, they're not labeled

7:18 am 6:51 am
6:51 am
2:56 am
Sep 15
Sep 14
Sep 14
Sep 14
Sep 13
Sep 12

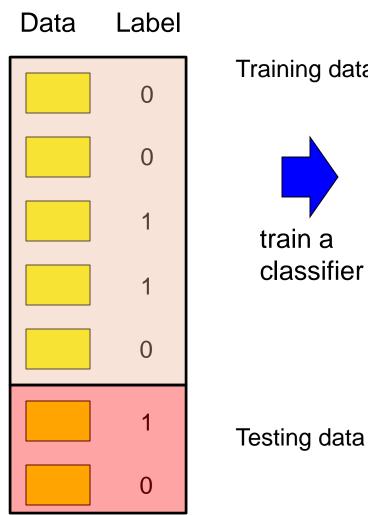
Data Label 0 Use the labeled data we have -abeled data already to create a test set with 0known labels! Why can we do this? 1 Remember, we assume there's 0 an underlying distribution that generates both the training and 1 test examples



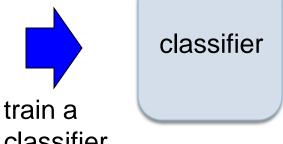
Training data

Testing data

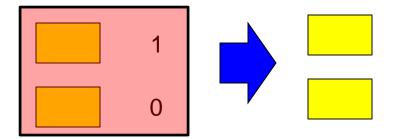
Labeled data



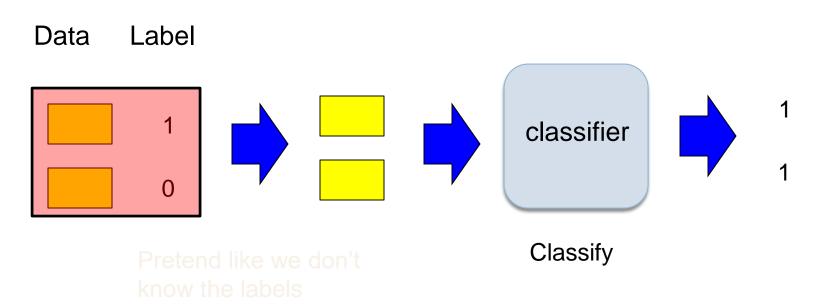
Training data

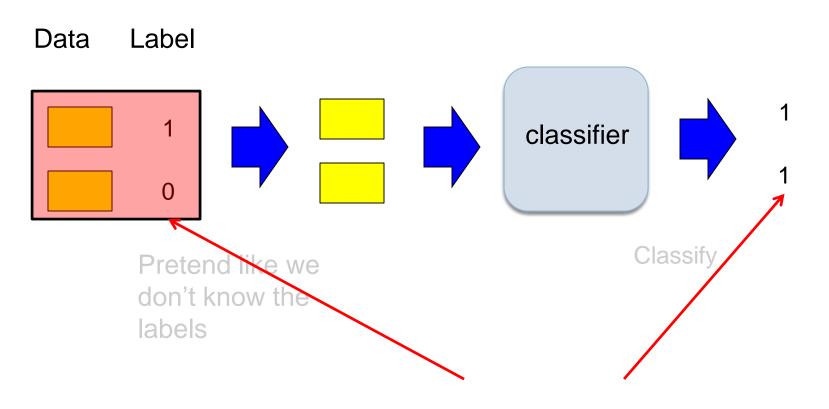


Data Label



Pretend like we don't know the labels





How could we score these for classification?

Compare predicted labels to actual labels

### Test accuracy

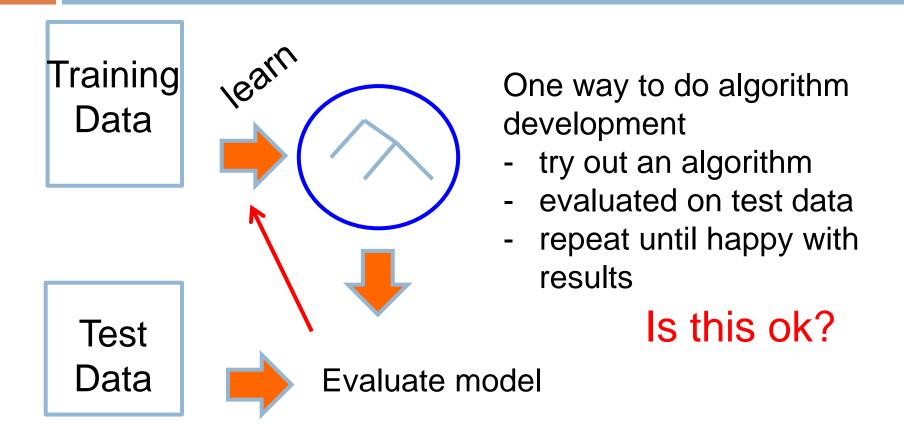
To evaluate the model, compare the predicted labels to the actual labels

prediction

Label

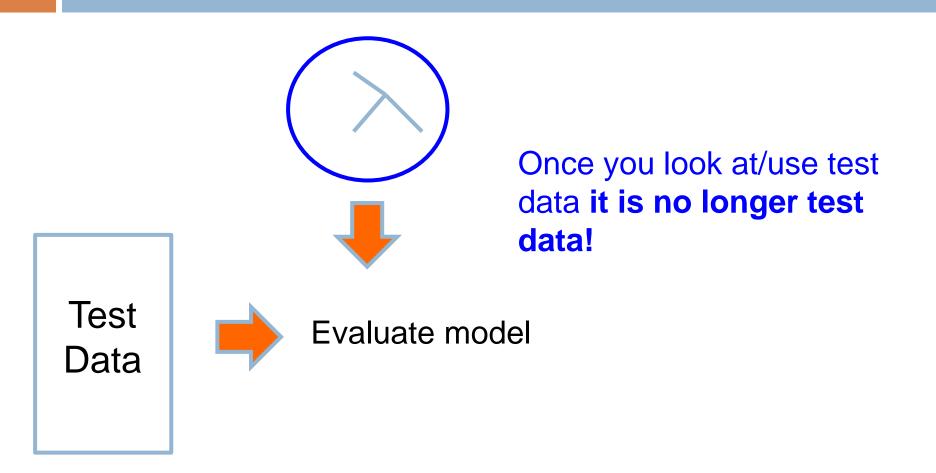
Accuracy: the proportion of examples where we correctly predicted the label

# Proper testing



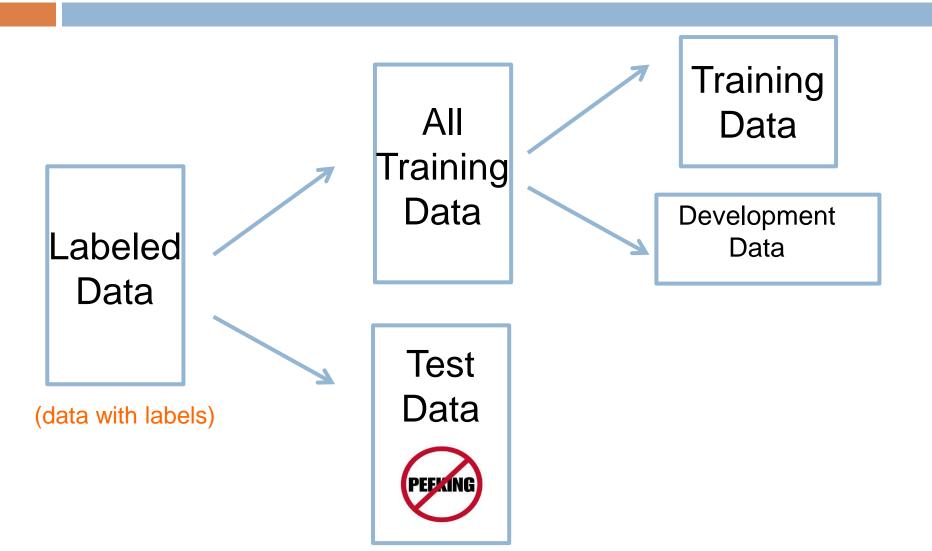
No. Although we're not explicitly looking at the examples, we're still "cheating" by biasing our algorithm to the test data

# Proper testing



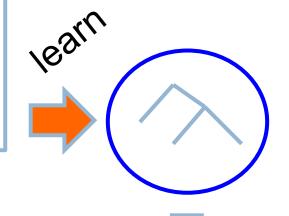
So, how can we evaluate our algorithm during development?

### Development set



### Proper testing

Training Data



Using the development data:

- try out an algorithm
- evaluated on development data
- repeat until happy with results

Development Data

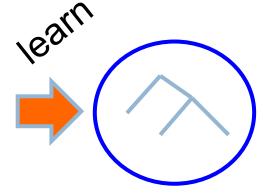


**Evaluate model** 

When satisfied, evaluate on test data

# Proper testing

Training Data



1

Using the development data:

- try out an algorithm
- evaluated on development data
- repeat until happy with results

Development Data

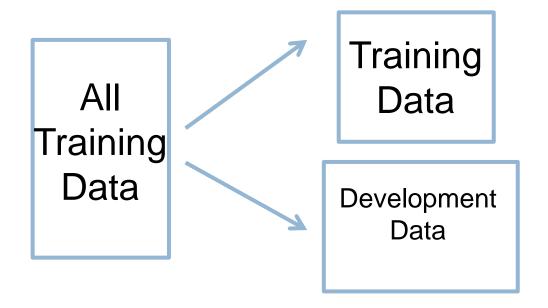


**Evaluate model** 

Any problems with this?

### Overfitting to development data

Be careful not to overfit to the development data!



Often we'll split off development data this multiple times (in fact, on the fly), but you can still overfit, but this helps avoid it

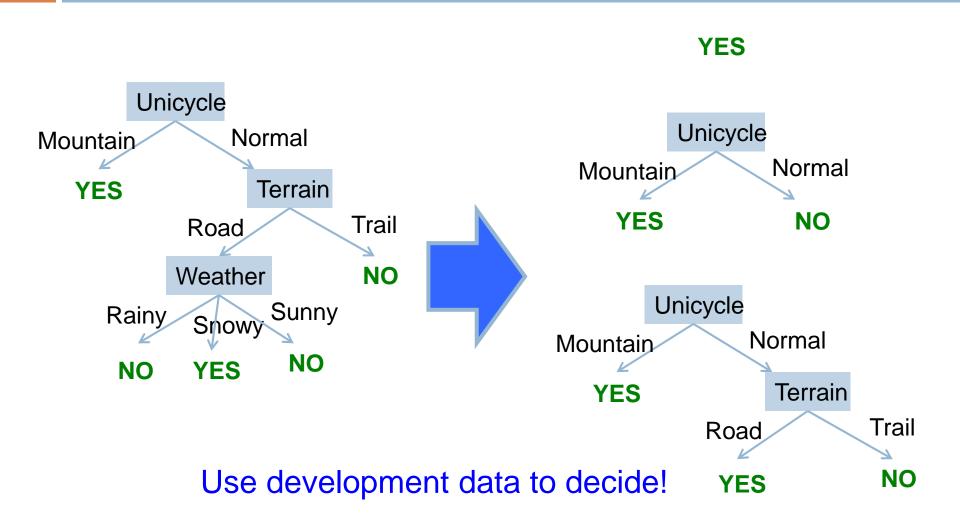
# ML grade here is overfitting because it perfectly fits the model for training set but not for future predictions

Terrain	Unicycle-type	Weather	Jacket	ML grade	Go-For-Ride?
Trail	Mountain	Rainy	Heavy	D	YES
Trail	Mountain	Sunny	Light	C-	YES
Road	Mountain	Snowy	Light	В	YES
Road	Mountain	Sunny	Heavy	Α	YES
	Mountain				YES
Trail	Normal	Snowy	Light	D+	NO
Trail	Normal	Rainy	Heavy	B-	NO
Road	Normal	Snowy	Heavy	C+	YES
Road	Normal	Sunny	Light	A-	NO
Trail	Normal	Sunny	Heavy	B+	NO
Trail	Normal	Snowy	Light	F	NO
	Normal				NO
Trail	Normal	Rainy	Light	С	YES

# Pruning revisited



# Pruning revisited



# Machine Learning: A Geometric View



### Apples vs. Bananas

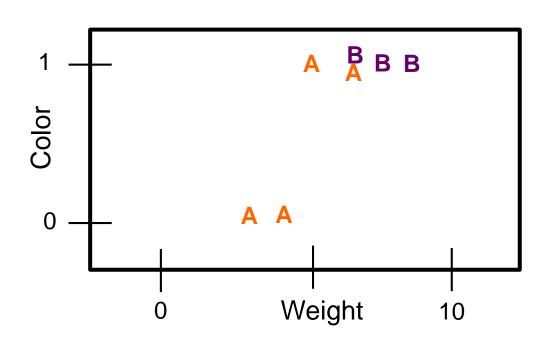
Weight	Color	Label
4	Red	Apple
5	Yellow	Apple
6	Yellow	Banana
3	Red	Apple
7	Yellow	Banana
8	Yellow	Banana
6	Yellow	Apple

Can we visualize this data?

### Apples vs. Bananas

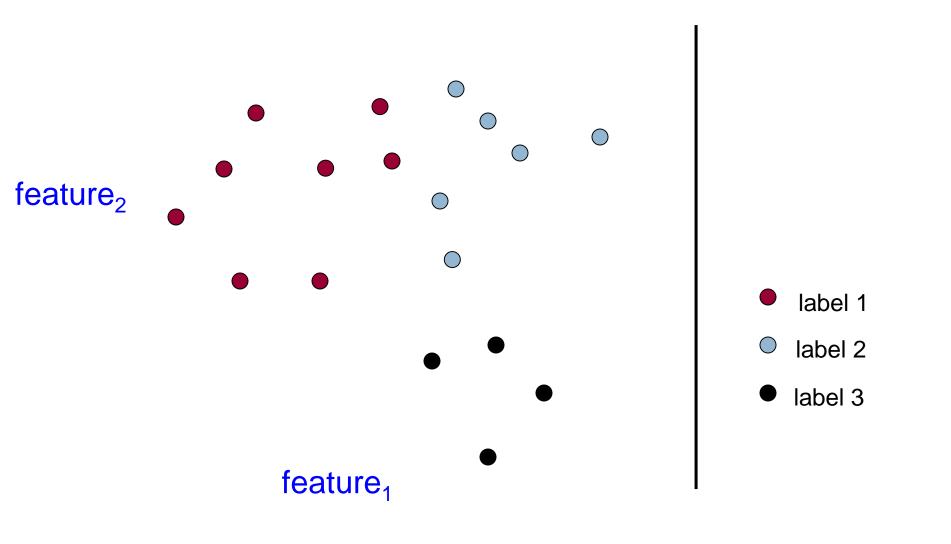
#### Turn features into numerical values

Weight	Color	Label
4	0	Apple
5	1	Apple
6	1	Banana
3	0	Apple
7	1	Banana
8	1	Banana
6	1	Apple

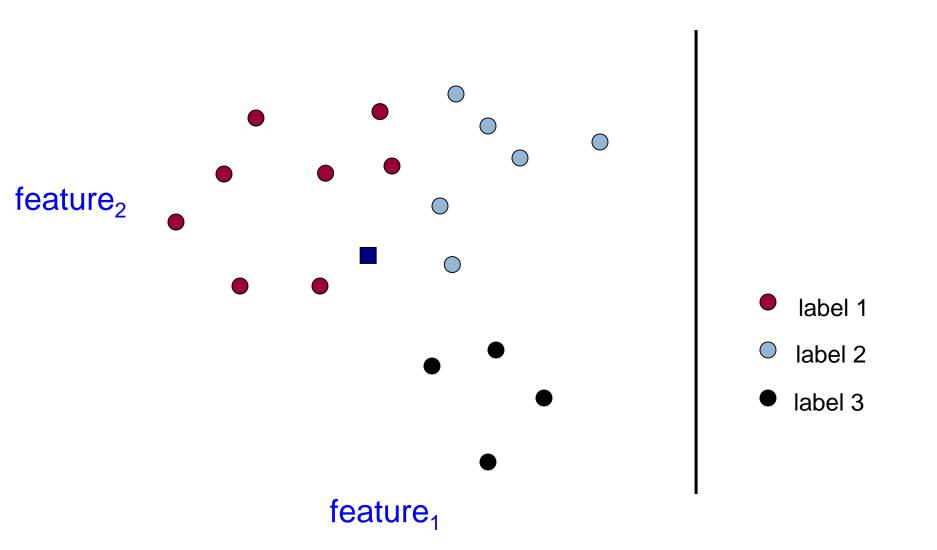


We can view examples as points in an *n*-dimensional space where *n* is the number of features

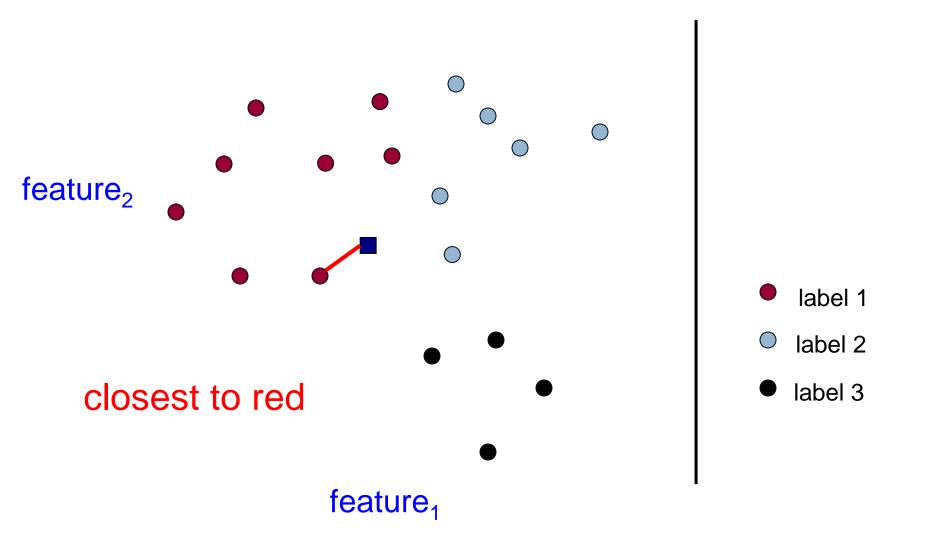
### Examples in a feature space



### Test example: what class?



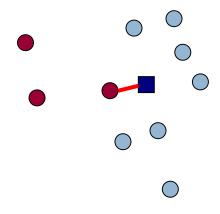
### Test example: what class?



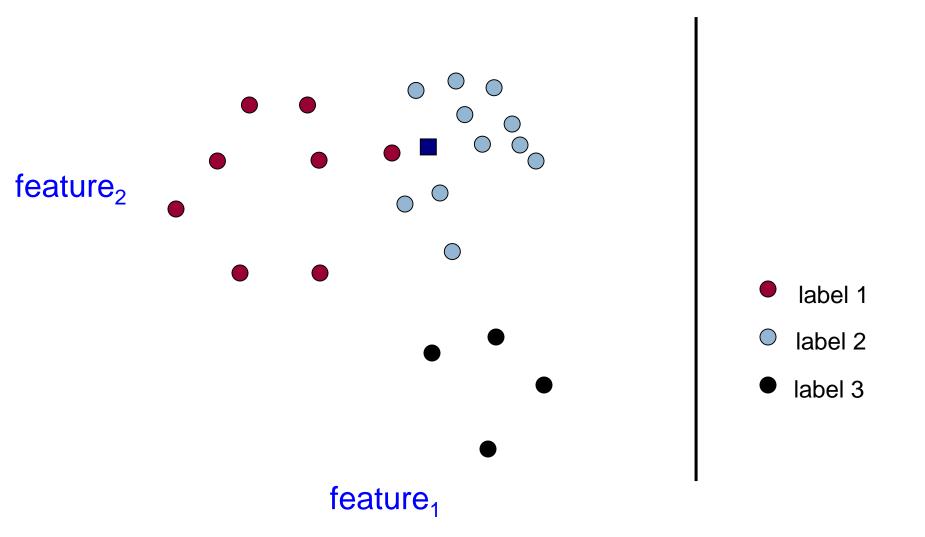
### Another classification algorithm?

To classify an example **d**:

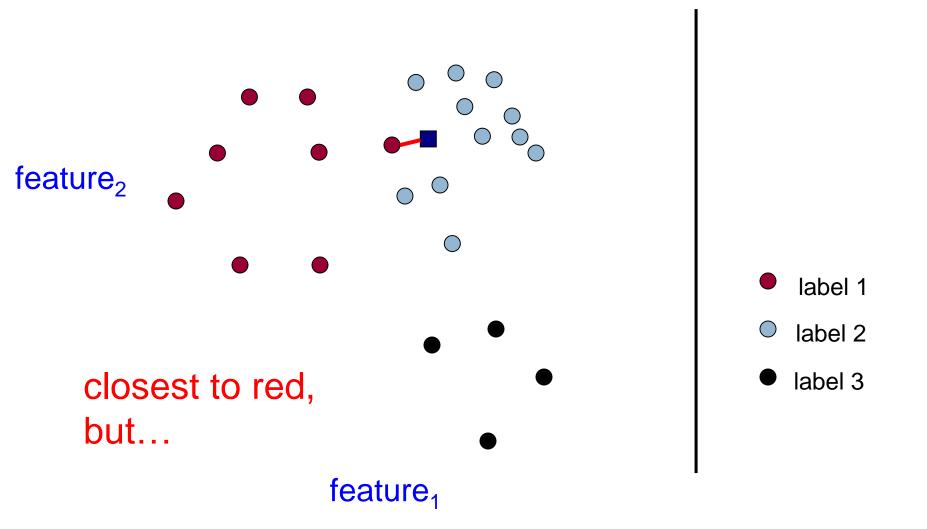
Label **d** with the label of the closest example to **d** in the training set



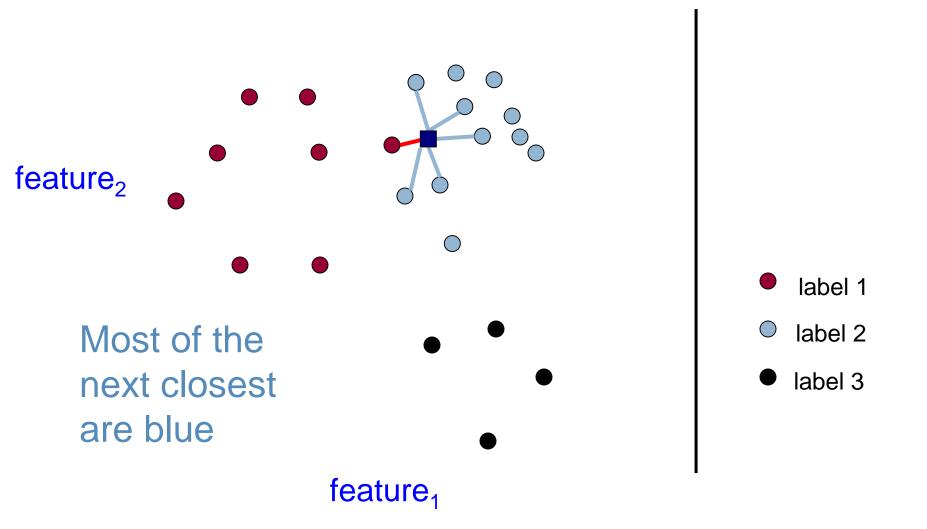
### What about this example?



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### What about this example?



# k-Nearest Neighbor (k-NN)

To classify an example **d**:

- Find k nearest neighbors of d
- Choose as the label the majority label within the k nearest neighbors

# k-Nearest Neighbor (k-NN)

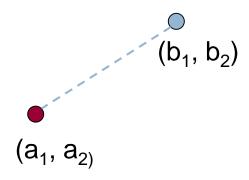
To classify an example **d**:

- Find k nearest neighbors of d
- Choose as the label the majority label within the k nearest neighbors

How do we measure "nearest"?

### Euclidean distance

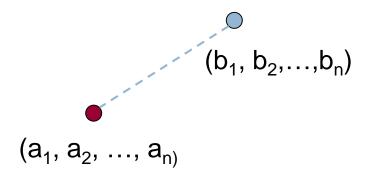
In two dimensions, how do we compute the distance?



$$D(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2}$$

### Euclidean distance

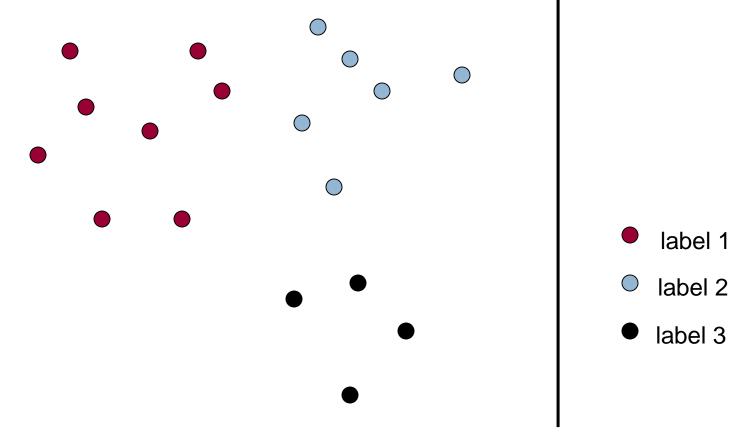
In n-dimensions, how do we compute the distance?



$$D(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots + (a_n - b_n)^2}$$

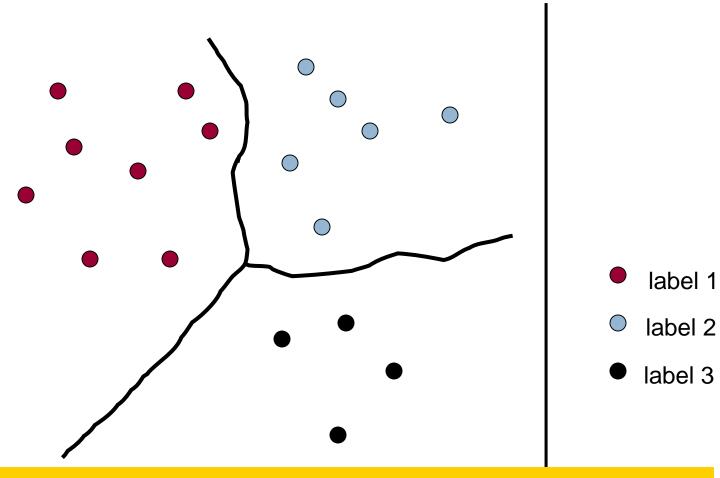
### Decision boundaries

The decision boundaries are places in the features space where the classification of a point/example changes



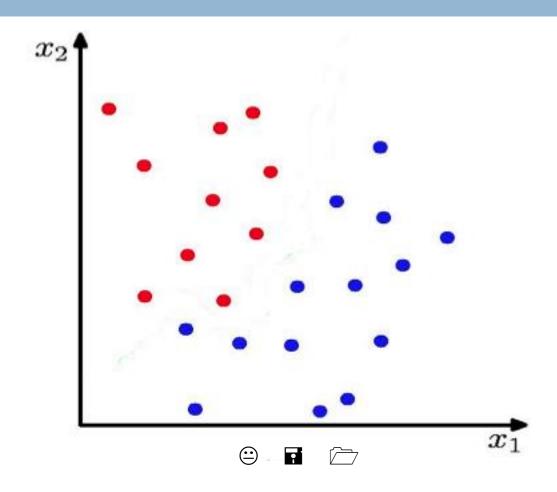
Where are the decision boundaries for k-NN?

### k-NN decision boundaries

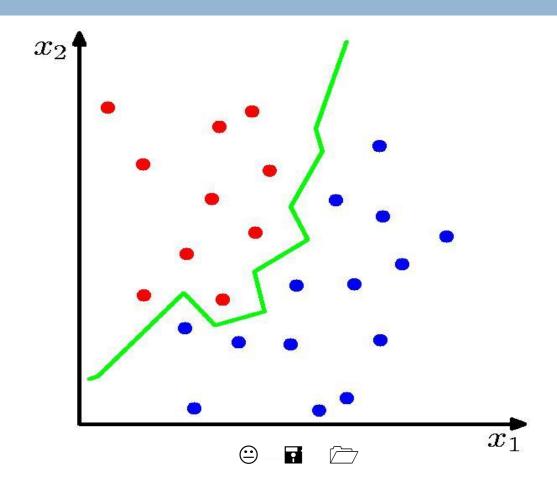


k-NN gives locally defined decision boundaries between classes

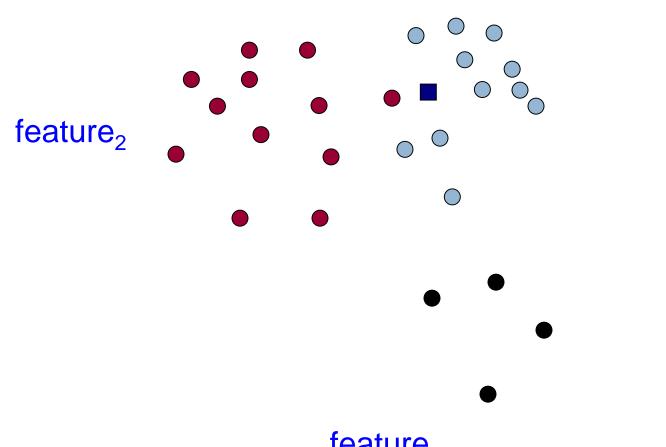
# Nearest Neighbour (kNN)Classifier



# Nearest Neighbour (kNN)Classifier



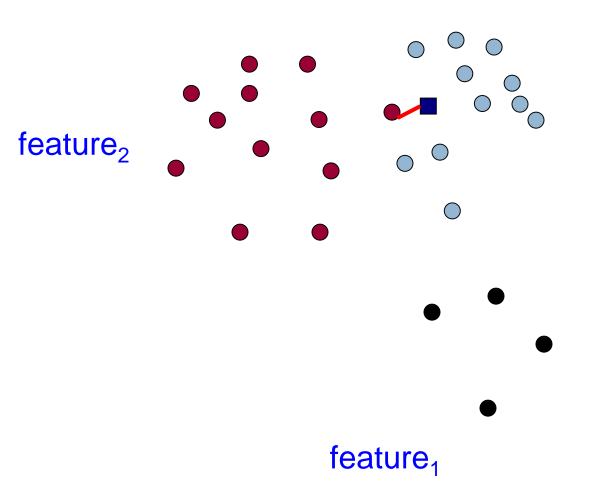
What is the label with k = 1?



- label 1
- label 2
- label 3

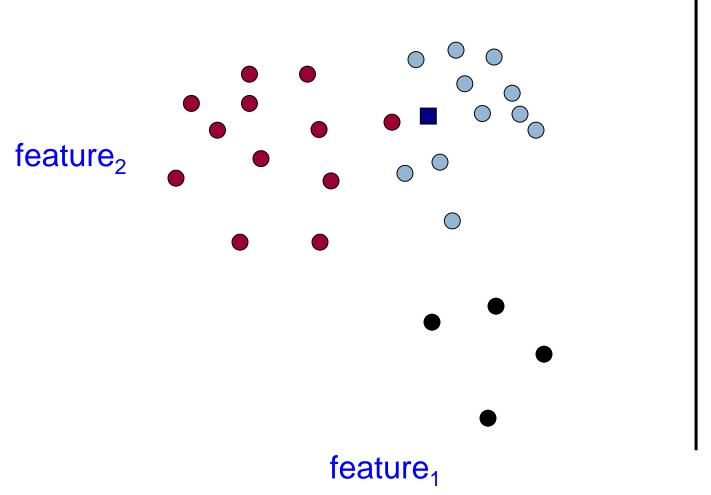
feature<sub>1</sub>

We'd choose red. Do you agree?



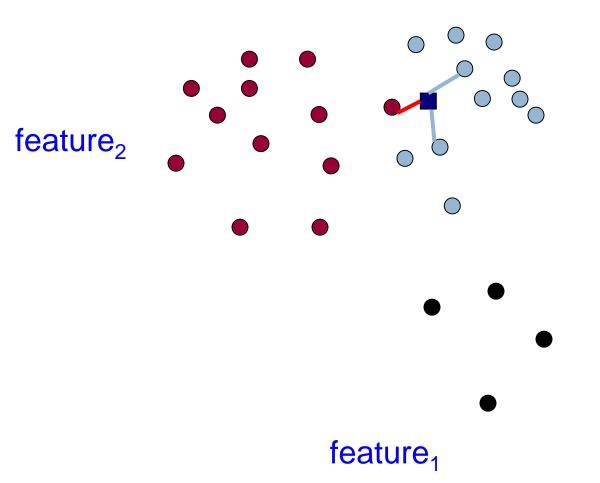
- label 1
- label 2
- label 3

What is the label with k = 3?



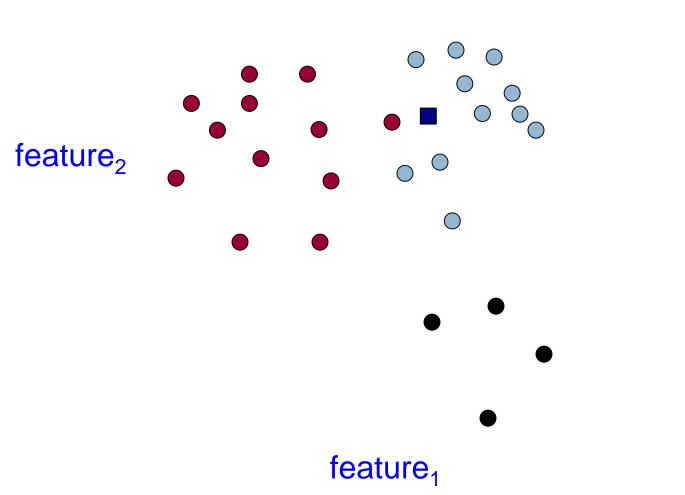
- label 1
- label 2
- label 3

We'd choose blue. Do you agree?



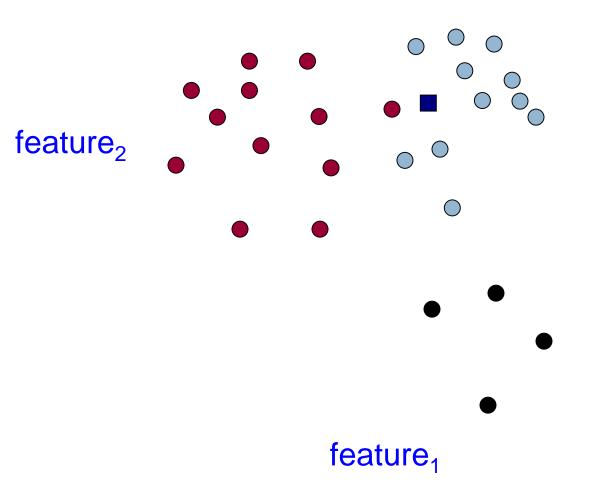
- label 1
- label 2
- label 3

What is the label with k = 100?



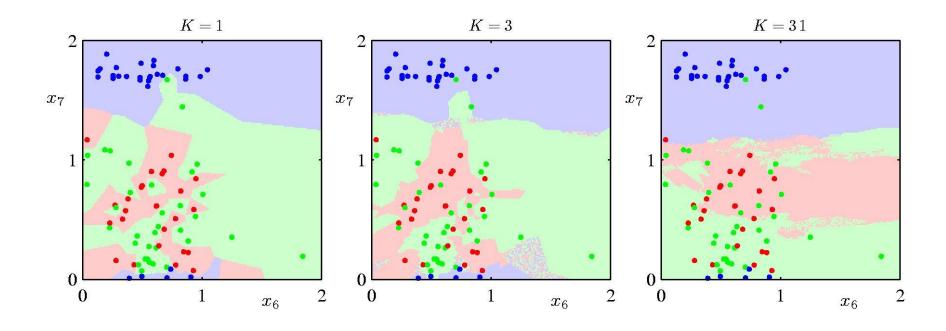
- label 1
- label 2
- label 3

We'd choose blue. Do you agree?



- label 1
- label 2
- label 3

## The impact of k



What is the role of k?
How does it relate to overfitting and underfitting?
How did we control this for decision trees?

## k-Nearest Neighbor (k-NN)

To classify an example **d**:

- Find k nearest neighbors of d
- Choose as the class the majority class within the k nearest neighbors

How do we choose *k*?

## How to pick k

#### Common heuristics:

- often 3, 5, 7
- choose an odd number to avoid ties

Use development data

### k-NN variants

To classify an example **d**:

- Find k nearest neighbors of d
- Choose as the class the majority class within the k nearest neighbors

Any variation ideas?

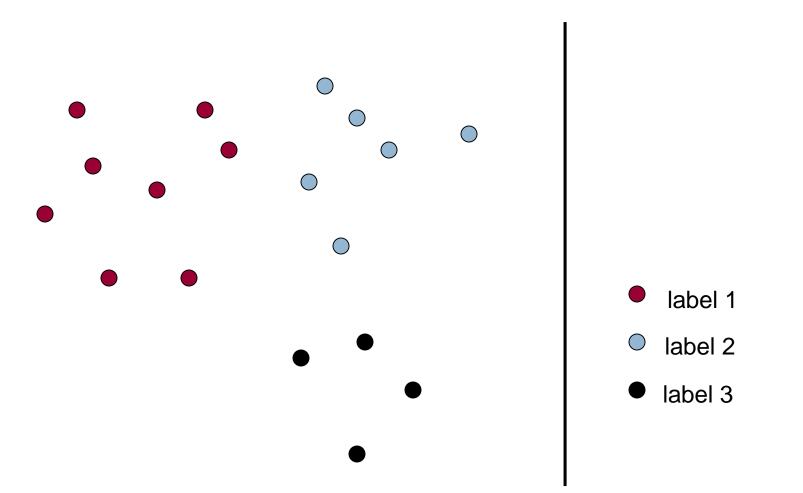
### k-NN variations

Instead of *k* nearest neighbors, count majority from all examples within a fixed distance

#### Weighted *k*-NN:

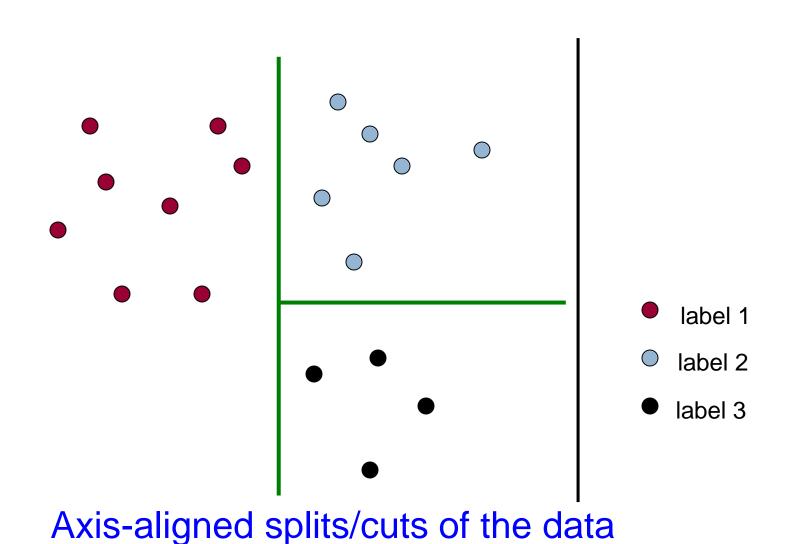
- Right now, all examples within examples are treated equally
- weight the "vote" of the examples, so that closer examples have more vote/weight
- often use some sort of exponential decay

# Decision boundaries for decision trees

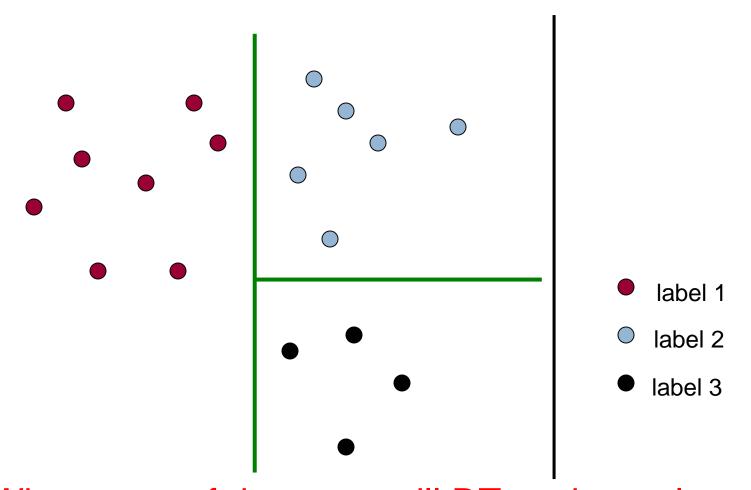


What are the decision boundaries for decision trees like?

# Decision boundaries for decision trees

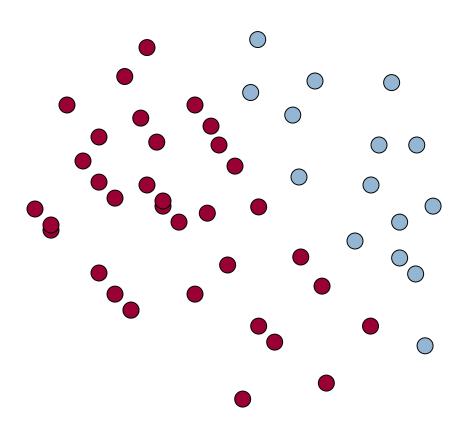


# Decision boundaries for decision trees



What types of data sets will DT work poorly on?

### Problems for DT



### Decision trees vs. k-NN

Which is faster to train?

Which is faster to classify?

Do they use the features in the same way to label the examples?

### Decision trees vs. k-NN

Which is faster to train?

k-NN doesn't require any training!

Which is faster to classify?

For most data sets, decision trees

Do they use the features in the same way to label the examples?

k-NN treats all features equally! Decision trees "select" important features

## A thought experiment

What is a 100,000-dimensional space like?

You're a 1-D creature, and you decide to buy a 2-unit apartment





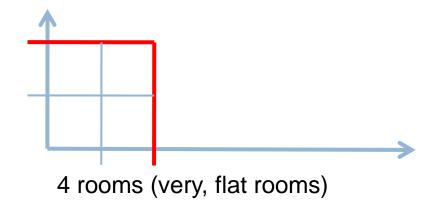
2 rooms (very, skinny rooms)

## Another thought experiment

What is a 100,000-dimensional space like?

Your job's going well and you're making good money. You upgrade to a 2-D apartment with 2-units per dimension

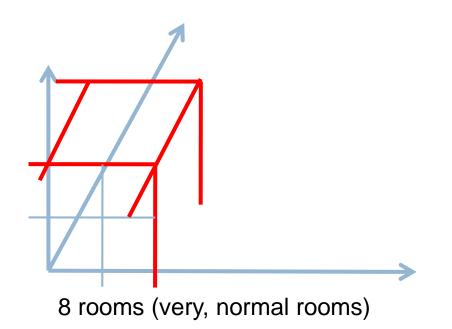




## Another thought experiment

What is a 100,000-dimensional space like?

You get promoted again and start having kids and decide to upgrade to another dimension.





Each time you add a dimension, the amount of space you have to work with goes up exponentially

## Another thought experiment

What is a 100,000-dimensional space like?

Larry Page steps down as CEO of google and they ask you if you'd like the job. You decide to upgrade to a 100,000 dimensional apartment.

How much room do you have? Can you have a big party?



 $2^{100,000}$  rooms (it's very quiet and lonely...) = ~10<sup>30</sup> rooms per person if you invited everyone on the planet

## The challenge

Our intuitions about space/distance don't scale with dimensions!



## Important to Watch Videos

- A.I. Experiments: Visualizing High-Dimensional Space
- https://www.youtube.com/watch?v=wvsE8jm1GzE

- Neural Network 3D Simulation
- https://www.youtube.com/watch?v=3JQ3hYko51Y