

# Decision Trees

# Announcements

- No class on Wednesday Jan 29th - I'm out of town.
- Assignment still due on that Wed afternoon. - you have all information you need.
- Office hours: Wednesdays, 3-5PM (I'll be there today, but not next week.)

# Decision Trees

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**Algorithm 1** DECISIONTREETRAIN(*data*, *remaining features*)

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```
1: guess ← most frequent answer in data // default answer for this data
2: if the labels in data are unambiguous then
3:   return LEAF(guess) // base case: no need to split further
4: else if remaining features is empty then
5:   return LEAF(guess) // base case: cannot split further
6: else // we need to query more features
7:   for all  $f \in$  remaining features do
8:     NO ← the subset of data on which  $f=no$ 
9:     YES ← the subset of data on which  $f=yes$ 
10:    score[ $f$ ] ← # of majority vote answers in NO
11:                + # of majority vote answers in YES
12:                // the accuracy we would get if we only queried on  $f$ 
13:   end for
14:    $f \leftarrow$  the feature with maximal score( $f$ )
15:   NO ← the subset of data on which  $f=no$ 
16:   YES ← the subset of data on which  $f=yes$ 
17:   left ← DECISIONTREETRAIN(NO, remaining features \ { $f$ })
18:   right ← DECISIONTREETRAIN(YES, remaining features \ { $f$ })
19:   return NODE( $f$ , left, right)
20: end if
```

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# Decision Trees

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**Algorithm 2** *DECISIONTREETEST*(*tree*, *test point*)

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```
1: if tree is of the form LEAF(guess) then  
2:   return guess  
3: else if tree is of the form NODE(f, left, right) then  
4:   if f = no in test point then  
5:     return DECISIONTREETEST(left, test point)  
6:   else  
7:     return DECISIONTREETEST(right, test point)  
8:   end if  
9: end if
```

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# Questions

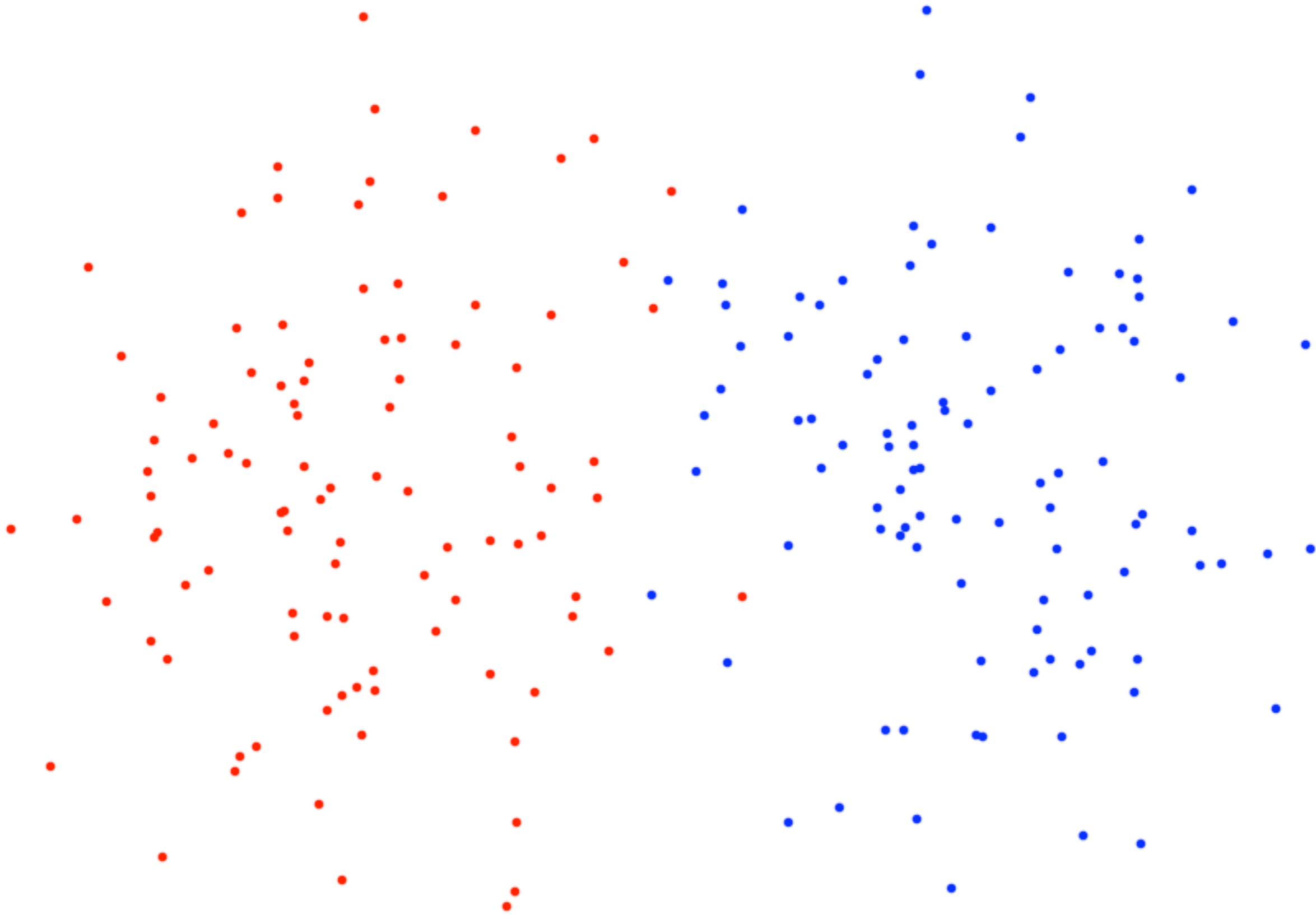
- Is this greedy strategy good?

# Questions

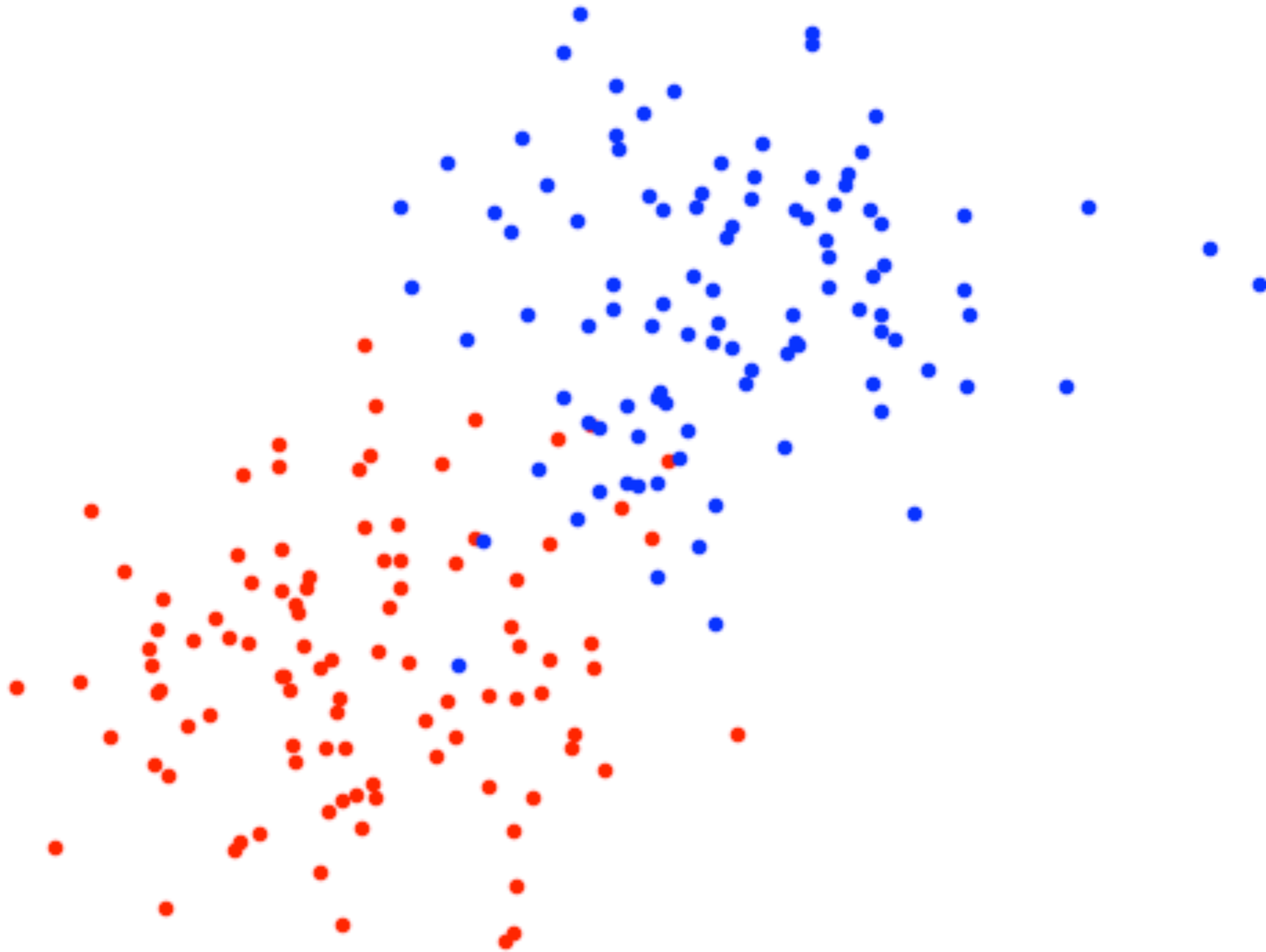
- Is this greedy strategy **always** good?

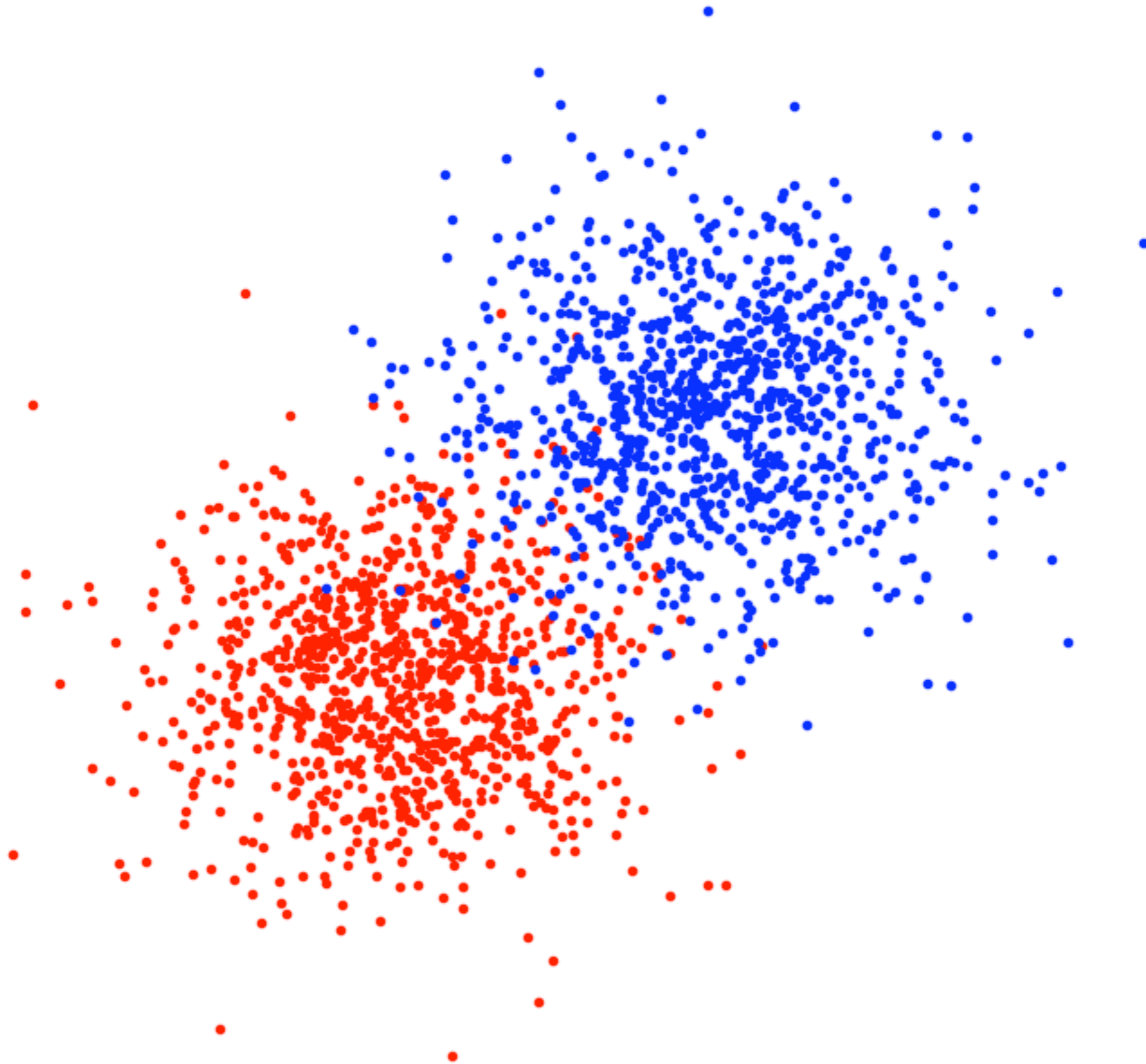
# Extensions to Ponder

- What if labels are categorical but not binary?
- What if features are categorical but not binary?
- What if features are numeric?
- What if labels are numeric?









# Induction Learning

As you've seen, there are several issues that we must take into account when formalizing the notion of learning.

- The performance of the learning algorithm should be measured on unseen "test" data.
- The way in which we measure performance should depend on the problem we are trying to solve.
- There should be a strong relationship between the data that our algorithm sees at training time and the data it sees at test time.

# Setting up the learning problem

- Where does the data come from?
  - Data Generating Distribution
- How do we define that the model is good?
  - The loss function
- How do we combine those?

$$\epsilon \triangleq \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(y, f(x))] = \sum_{(x,y)} \mathcal{D}(x,y) \ell(y, f(x))$$

So, putting it all together, we get a formal definition of induction machine learning: **Given (i) a loss function  $\ell$  and (ii) a sample  $D$  from some unknown distribution  $\mathcal{D}$ , you must compute a function  $f$  that has low expected error  $\epsilon$  over  $\mathcal{D}$  with respect to  $\ell$ .**

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?

Why might it be a bad idea to use zero/one loss to measure performance for a regression problem?



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?

Verify by calculation that we can write our training error as  $\mathbb{E}_{(x,y) \sim D} [\ell(y, f(x))]$ , by thinking of  $D$  as a distribution that places probability  $1/N$  to each example in  $D$  and probability 0 on everything else.