CPSC 340: Machine Learning and Data Mining

Supervised Learning and Decision Tree Learning

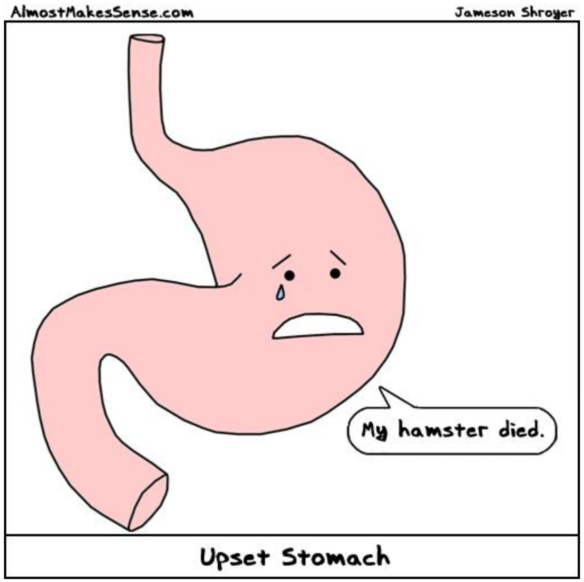
September 14, 2015

Admin

- Tutorials have started today:
  - 11am, 2pm, and 4pm in DMP 201.
  - 5pm in DMP 101.
- Office hours tomorrow:
  - 10am in ICICS X836
  - 4pm in ICICS 146
- Assignment 1 due Friday
  - Get further help on Piazza.
  - Q1 might be input as a UBC survey.
  - Setting up Handin for submission.

Motivating Example: Food Allergies

- You frequently start getting an upset stomach



- You suspect an adult-onset food allergy.

http://www.cliparthut.com/upset-stomach-clipart-cn48e5.html

Motivating Example: Food Allergies

- To solve the mystery, you start a food journal:

Egg	Milk	Fish	Wheat	Shellfish	Peanuts	…	Sick?
0	0.7	0	0.3	0	0		1
0.3	0.7	0	0.6	0	0.01		1
0	0	0	0.8	0	0		0
0.3	0.7	1.2	0	0.10	0.01		1
0.3	0	1.2	0.3	0.10	0.01		1

- But it’s hard to find the pattern:
  - You can’t isolate and only eat one food at a time.
  - You may be allergic to more than one food.
  - The quantity matters: a small amount may be ok.
  - You may be allergic to specific interactions.

Supervised Learning

- We can formulate this as supervised learning:

Egg	Milk	Fish	Wheat	Shellfish	Peanuts	…	Sick?
0	0.7	0	0.3	0	0		1
0.3	0.7	0	0.6	0	0.01		1
0	0	0	0.8	0	0		0
0.3	0.7	1.2	0	0.10	0.01		1
0.3	0	1.2	0.3	0.10	0.01		1

- Input is a set of continuous features.
  - the quantities of food eaten.
- Output is a desired target label:
  - Whether or not we got sick.
- Supervised learning: learn map from features to labels.
  - Given foods, map predicts whether you will get sick.

Supervised Learning

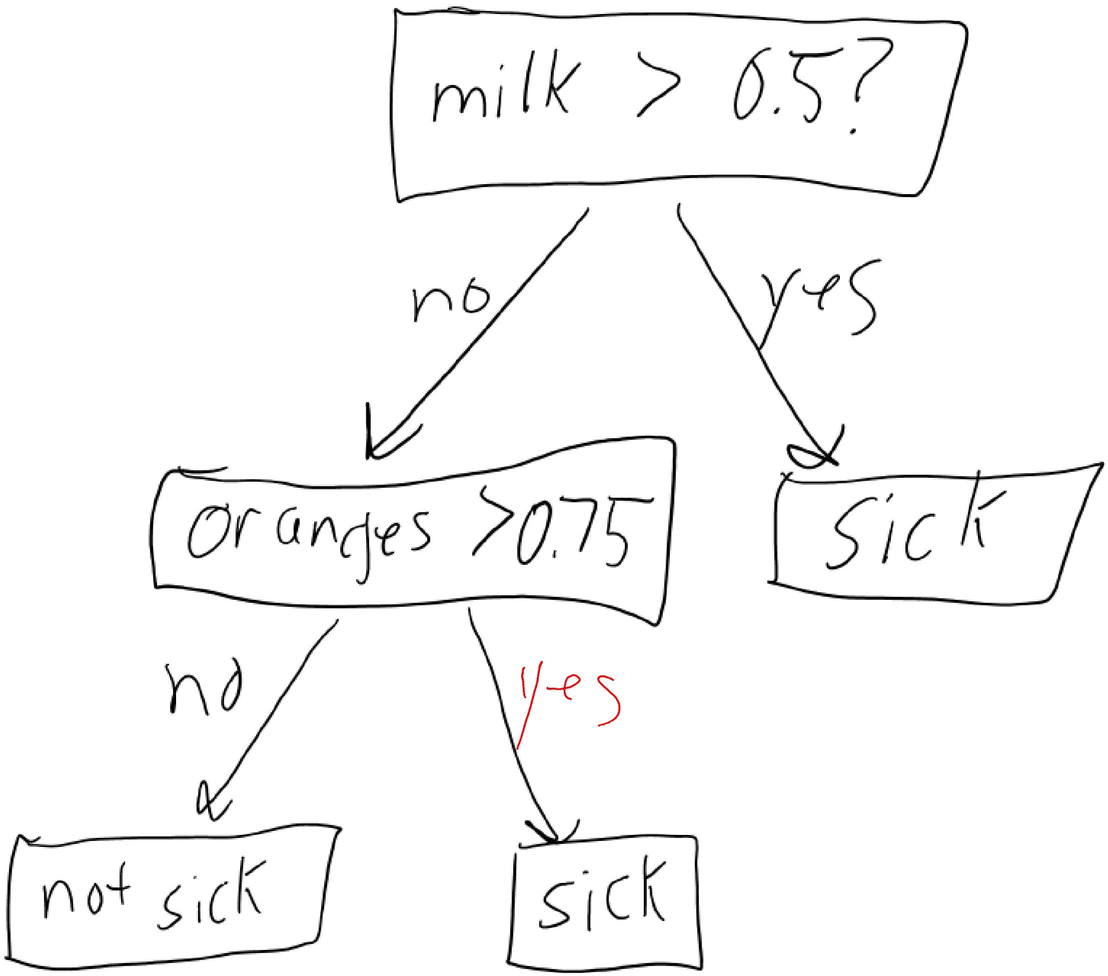
- Supervised learning general case:
  - Input: features and corresponding labels for objects.
  - Output: program that maps from features to labels.
- Most useful when:
  - You don't know how to write a program to do task.
  - But have input/output examples.
- The most successful machine learning technique:
  - Spam filtering, Microsoft Kinect, speech recognition.
- Today we will learn about one approach:
  - Decision trees.

But first....

- Is this data IID? No!
  - ignore it,
  - add "features" from previous day (more data)
- What cleaning/preprocessing steps?

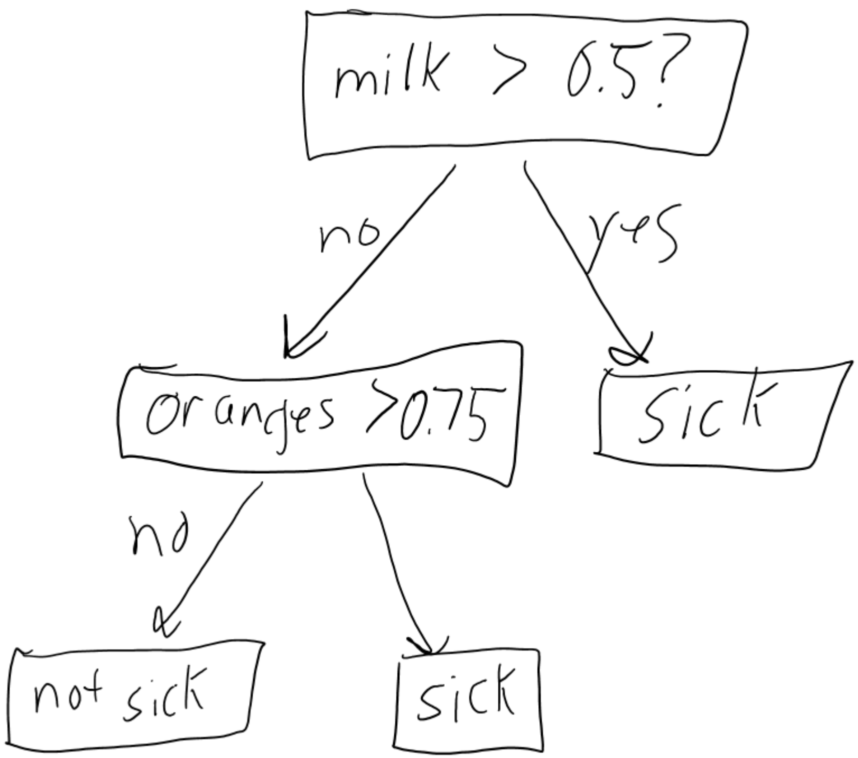
- scaling (convert to grams)
- little data: common allergic ingredients (lactose, gluten, ...)
- lots data: "types" of food (baker bread vs. MacDonald's)

Decision Tree



Decision Tree

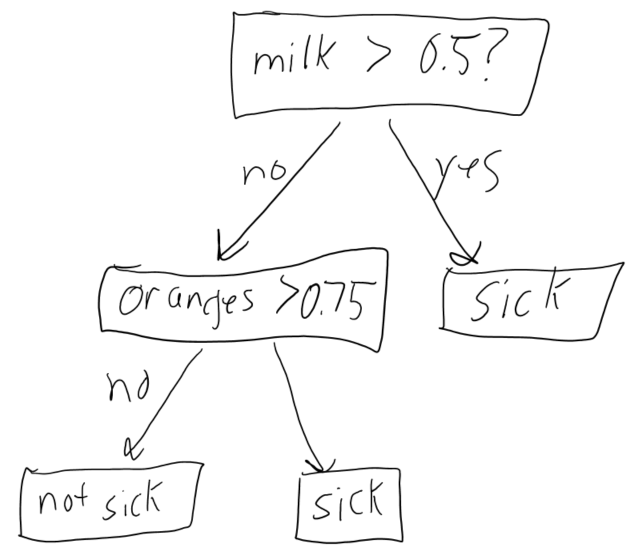
1. Start at root note.
2. Branch using splitting rule.
3. Leaf nodes are labeled.
   a) If leaf, return label.
   b) Otherwise, go to 2.



Decision Tree as a Program

- Think of this as a simple program:

```
If (milk > 0.5)
        Return 'sick'
Else {
        If (oranges > 0.75)
                Return 'sick'
        Else
                Return 'not sick'
}
```

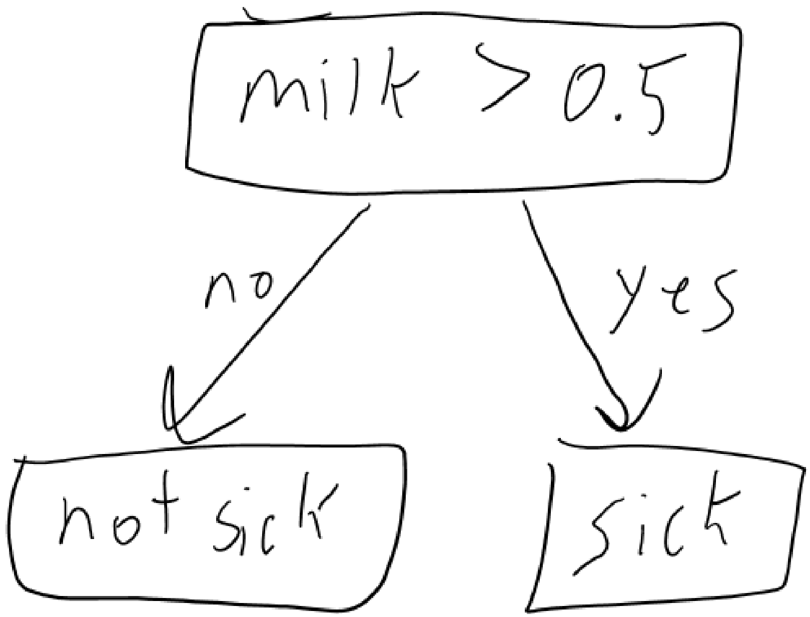


Decision Tree Learning

- We could write decision program by hand.
- But might be hard:
  - Huge number of variables.
  - Sequences of rules might be hard to find.
- Decision tree learning:
  - Use data to automatically write the program.
- Usual ‘greedy’ procedure:
  - Start with all data and learn one simple rule.
  - Split data based on rule, recurse on subsets.

Learning A Decision Stump

- Decision stump: decision tree with one rule.



- How do we find the variable and threshold?
  1. Define a 'score' for the rule.
  2. Search for the rule with the best score.

Decision Stump: Accuracy Score

- Most intuitive score: classification accuracy.
  - "If we use this rule, how many objects do we label correctly?"
- Computing classification accuracy:
  - Input is a rule like (eggs > 2).
  - Go through all objects, and find out which class is more likely given rule.
    - E.g., (eggs > 2) implies 'sick' more often than 'not sick', and (eggs <= 2) implies 'not sick' more often than 'sick'.
  - Go through all objects again, counting how many times the rule predicts the correct object label.
    - E.g., how many times did (eggs > 2) actually gave 'sick', plus how many times did (eggs <=2) actually gave 'not sick'.
  - Output: sum of these counts divided by number of objects.
- Accuracy score of '1': rule gives perfect prediction.
- Accuracy score of '0.50': rule tells you nothing.
  (if you only have two classes)

Decision Stump: Rule Search

- Accuracy score evaluates how ‘good’ a rule is.
- To find the ‘best’ stump, find the ‘best’ rule.
- Attempt 1 (exhaustive search):

Compute score of (eggs > 0)	Compute score of (milk > 0)	…
Compute score of (eggs > 0.01)	Compute score of (milk > 0.01)	…
Compute score of (eggs > 0.02)	Compute score of (milk > 0.02)	…
Compute score of (eggs > 0.03)	Compute score of (milk > 0.03)	…
…	…	…
Compute score of (eggs > 99.99)	Compute score of (milk > 0.99)	…

- As you go, keep track of the highest score.
- Return rule with highest score.

Cost of Decision Stumps (Attempt 1)

- How much does this cost?
- Assume we have:
  - 'n' objects (days that we measured).
  - 'd' features (foods that we measured).
  - 't' thresholds (>0, >0.01, >0.02,…)
- Computing the score costs O(n):
  - We need to go through all 'n' examples.
- Total cost is O(ndt):
  - Need to compute score for a total of d*t rules.
- Can we do better?

(if you are not familiar with "O(n)" see notes on webpage)

Cost of Decision Stumps (Attempt 1)

- We can ignore rules outside feature ranges:
  - E.g., we never have (eggs > 50) in our data.
  - These rules can never improve accuracy.
  - Restrict the thresholds to the range of each feature.
- Most of the thresholds give the same score.
  - E.g., if never have (eggs == 0.05) in the data, then (eggs > .04) and (eggs > 0.05) have the same score.'
  - Restrict thresholds to values of the features in data.

Decision Stump: Rule Search

- Accuracy score evaluates how ‘good’ a rule is.
- To learn ‘best’ stump, find the ‘best’ rule.
- Attempt 2 (search over features in data):

Compute score of (eggs > 0)	Compute score of (milk > 0.5)	…
Compute score of (eggs > 1)	Compute score of (milk > 1)	…
Compute score of (eggs > 2)	Compute score of (milk > 1.5)	…
Compute score of (eggs > 3)	Compute score of (milk > 2)	…
Compute score of (eggs > 4)		…
Compute score of (eggs > 5)		…

- Now at most ‘n’ thresholds for each feature.
- So we now consider only O(nd) rules.
- Total cost changes from O(ndt) to O(n^2d).

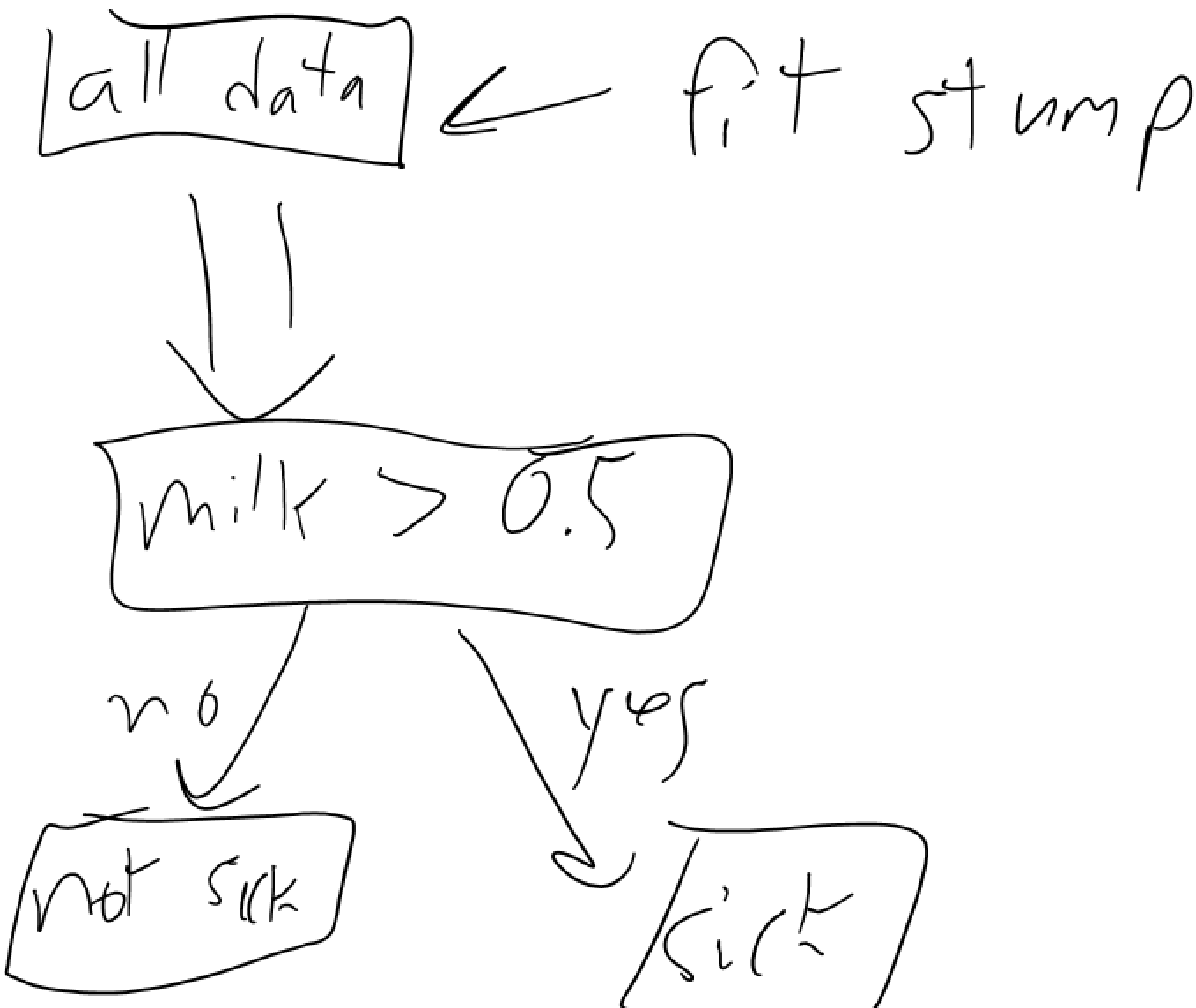
Decision Stump: Rule Search

- Do we have to compute score from scratch?
  - Rule (eggs > 1) and (eggs >2) have same score, except when (eggs == 2).
  - Sort the examples based on ‘eggs’.
  - Go through the rules in order, updating score.
- Sorting costs O(n log n) per feature.
- You do at most O(n) score updates per feature.
- Total is down from $O(n^2d)$ to O(nd log n).
- This is a good runtime:
  - O(nd) is size of data, this is only slightly bigger.

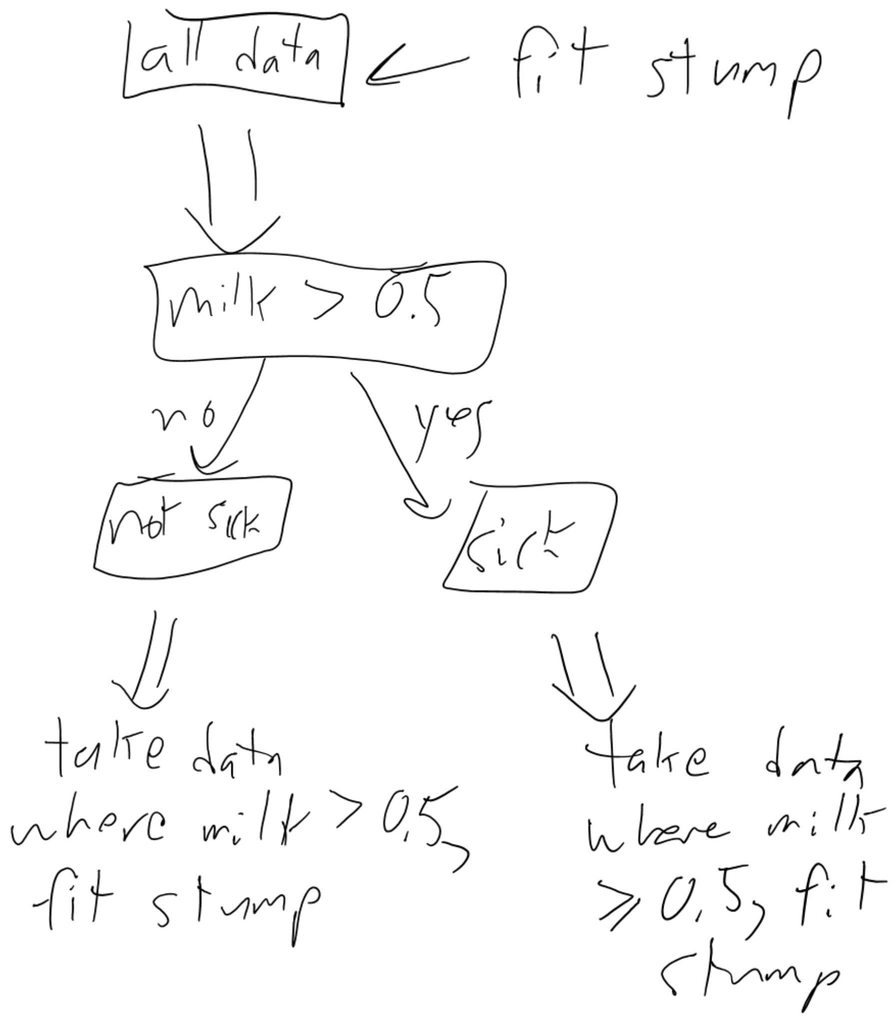
Greedily Making Trees From Stumps

$\boxed{\text{all data}}$ ← fit stump

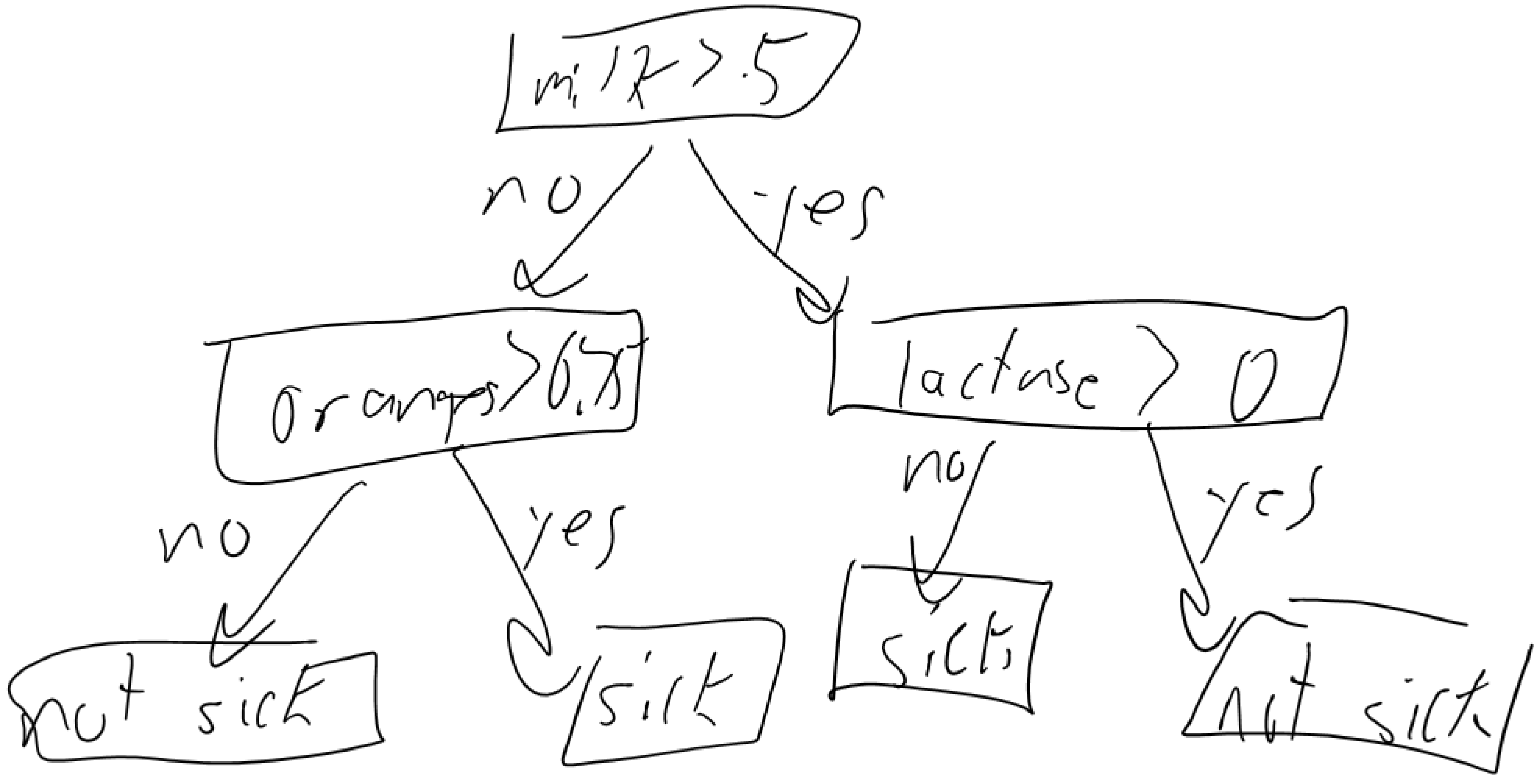
Greedily Making Trees From Stumps



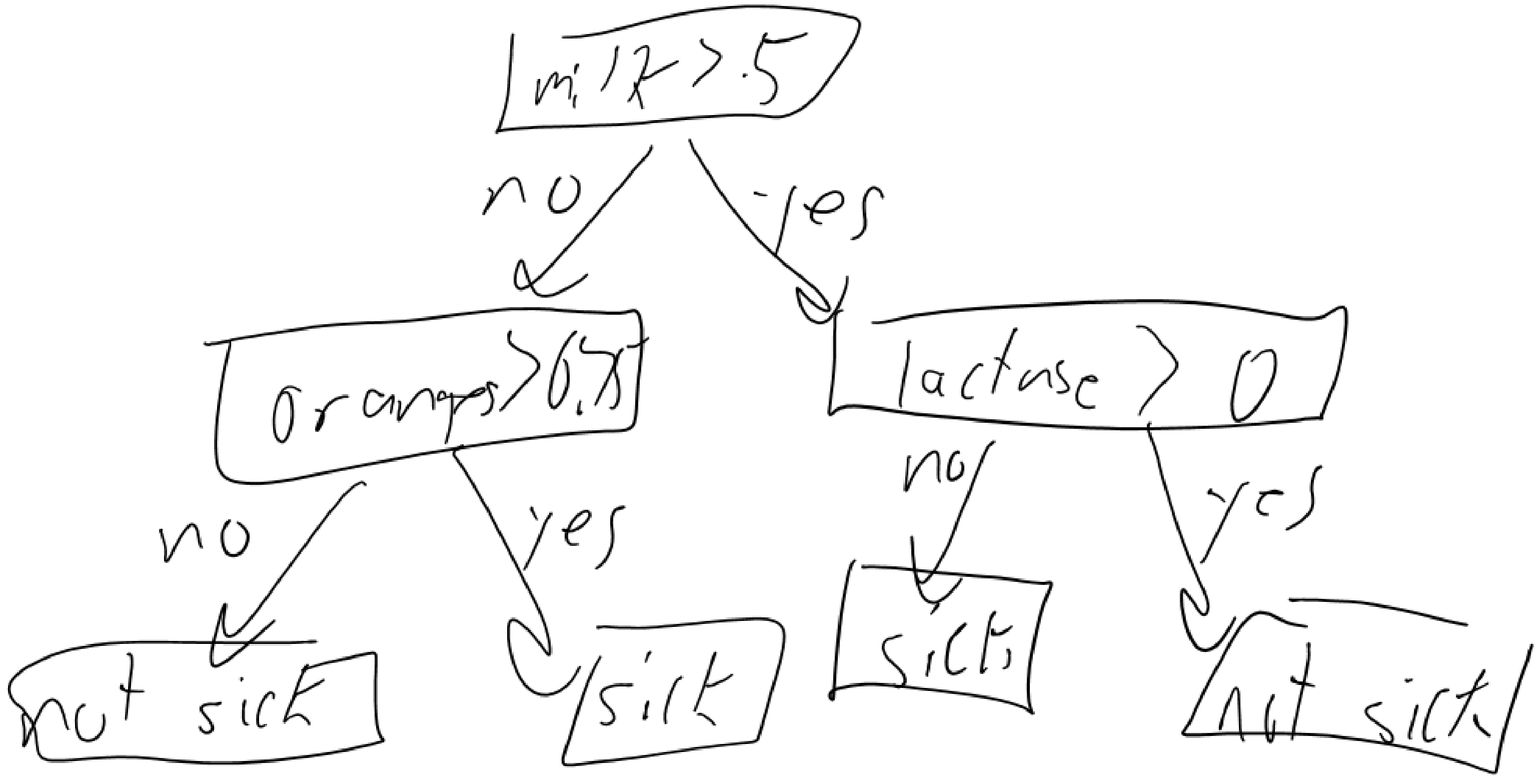
Greedily Making Trees From Stumps



Greedily Making Trees From Stumps



Greedily Making Trees From Stumps



Stop when:

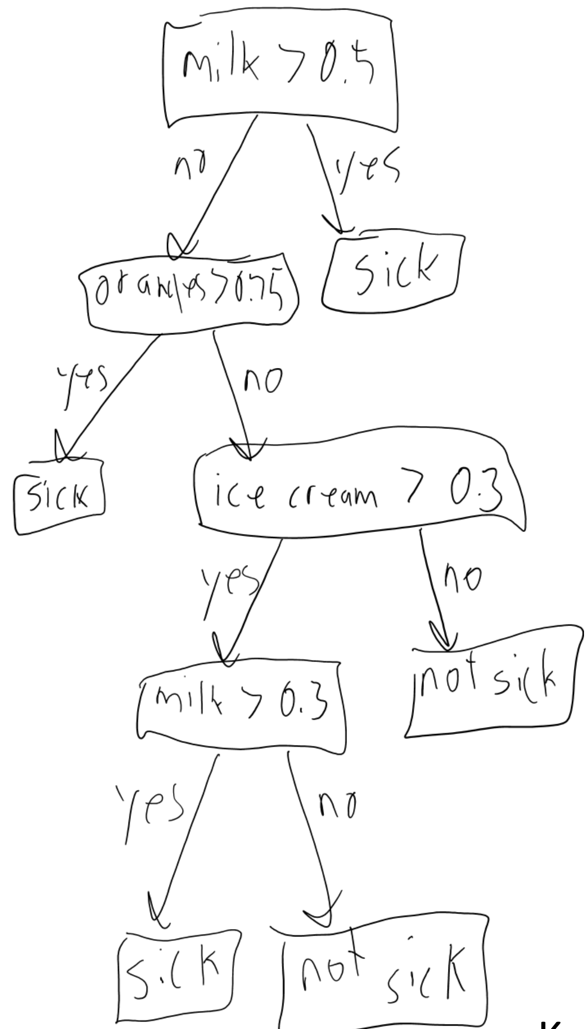
- only have one label left.
- reach user-defined maximum depth.

Issues with Decision Trees

- Advantages:
  - Interpretable.
  - Fast to learn.
  - Very fast to classify
- Disadvantages:
  - Hard to find optimal set of rules.
  - Rules are very simple.
  - Not the most accurate.
- Issues:
  - Can you revisit a feature?
  - More complicated rules?
  - Is accuracy the best score?
  - What depth?

Can you re-visit a feature?

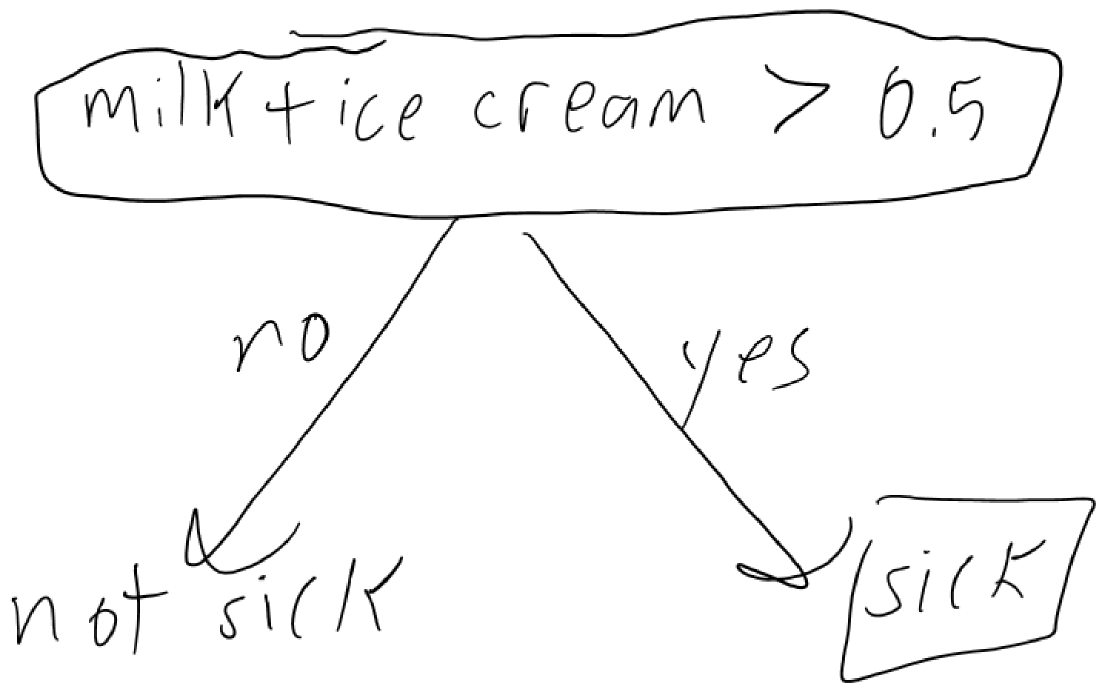
- Yes.



Knowing you had ice cream makes small milk quantities more relevant.

Can you have more complicated rules?

- Yes:



- But searching for best rule is more expensive.

Which Score Function?

- Shouldn't we just use accuracy score?
  - For leafs: yes, just maximize accuracy.
  - For internal nodes: maybe not.
    - There may be no simple rule like (eggs > 0.5) that improves accuracy.

- Most common score in practice: information gain.
  - How much does entropy ("randomness") of labels decrease if I use this rule to split the data?
  - Hope is that later rules on 'less random' data will be able to improve accuracy.

Summary

- Supervised learning: using data to build program that outputs labels from input features.
- Decision trees: making a decision via a sequence of simple rules.
- Decision stumps: very simple decision trees that we can very efficiently fit.
- We can greedily construct decision trees from a sequence of decision stumps.
  - Fast/interpretable, but may not be very accurate.