DECISION TREES

David Kauchak
CS 158 – Spring 2022

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Admin

Assignment 1 due tomorrow (Friday)

Assignment 2 out soon: start ASAP! (due next Sunday)
- Can (and are encouraged to) work in pairs

Slack

Office hours M-Th, 2:30-3:30pm, starting today (zoom link in sakai)

2

Admin

Lecture notes posted (webpage)

Lecture recordings uploaded (box – see sakai for link)

Keep up with the reading

Videos before class

Class ends at 2:30 ☺

3

Representing examples

examples

What is an example?
How is it represented?

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Features

examples

features

$f_1, f_2, f_3, \ldots, f_n$

$f_1, f_2, f_3, \ldots, f_n$

$f_1, f_2, f_3, \ldots, f_n$

$f_1, f_2, f_3, \ldots, f_n$

How our algorithms actually "view" the data

Features are the questions we can ask about the examples

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Features

examples

features

red, round, leaf, 3oz, …

green, round, no leaf, 4oz, …

yellow, curved, no leaf, 8oz, …

green, curved, no leaf, 7oz, …

How our algorithms actually "view" the data

Features are the questions we can ask about the examples

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Classification revisited

examples	label
red, round, leaf, 3oz, …	apple
green, round, no leaf, 4oz, …	apple
yellow, curved, no leaf, 8oz, …	banana
green, curved, no leaf, 7oz, …	banana

learn

model/ classifier

During learning/training/induction, learn a model of what distinguishes apples and bananas *based on the features*

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Classification revisited

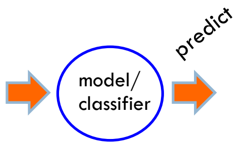
red, round, no leaf, 4oz, … → model/ classifier → predict → Apple or banana?

The model can then classify a new example *based on the features*

8

Classification revisited

red, round, no leaf, 4oz, …



Apple

Why?

The model can then classify a new example *based on the features*

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Classification revisited

Training data

examples	label
red, round, leaf, 3oz, …	apple
green, round, no leaf, 4oz, …	apple
yellow, curved, no leaf, 4oz, …	banana
green, curved, no leaf, 5oz, …	banana

Test set

red, round, no leaf, 4oz, … ?

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Classification revisited

Training data

examples	label
red, round, leaf, 3oz, …	apple
green, round, no leaf, 4oz, …	apple
yellow, curved, no leaf, 4oz, …	banana
green, curved, no leaf, 5oz, …	banana

Test set

red, round, no leaf, 4oz, … ?

Learning is about ***generalizing*** from the training data

What does this assume about the training and test set?

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A sample data set

Features				**Label**
Hour	Weather	Accident	Stall	Commute
8 AM	Sunny	No	No	Long
8 AM	Cloudy	No	Yes	Long
10 AM	Sunny	No	No	Short
9 AM	Rainy	Yes	No	Long
9 AM	Sunny	Yes	Yes	Long
10 AM	Sunny	No	No	Short
10 AM	Cloudy	No	No	Short
9 AM	Sunny	Yes	No	Long
10 AM	Cloudy	Yes	Yes	Long
10 AM	Rainy	No	No	Short
8 AM	Cloudy	Yes	No	Long
9 AM	Rainy	No	No	Short

8 AM, Rainy, Yes, No?
10 AM, Rainy, No, No?

Can you describe a "model" that could be used to make decisions in general?

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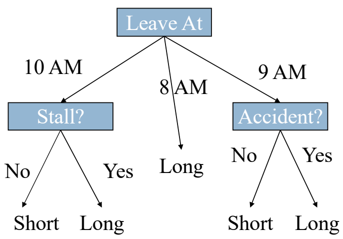
Decision trees



- Tree with internal nodes labeled by features
- Branches are labeled by tests on that feature
- Leaves labeled with classes

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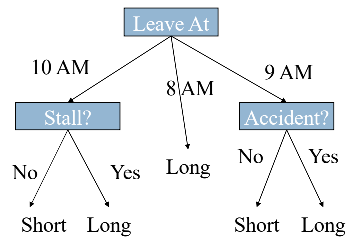
Decision trees



Leave = 8 AM
Weather = Rainy

Accident = Yes
Stall = No

- Tree with internal nodes labeled by features
- Branches are labeled by tests on that feature
- Leaves labeled with classes

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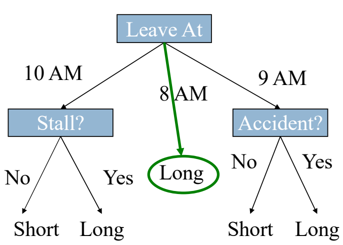
Decision trees



Leave = 8 AM
Weather = Rainy

Accident = Yes
Stall = No

- Tree with internal nodes labeled by features
- Branches are labeled by tests on that feature
- Leaves labeled with classes

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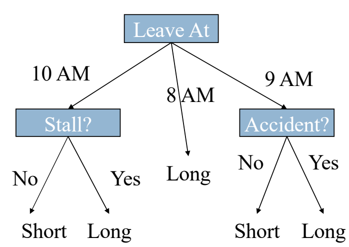
Decision trees



Leave = 10 AM
Weather = Rainy

Accident = No
Stall = No

- Tree with internal nodes labeled by features
- Branches are labeled by tests on that feature
- Leaves labeled with classes

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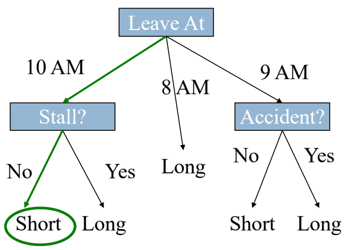
Decision trees



Leave = 10 AM
Weather = Rainy

Accident = No
Stall = No

Tree with internal nodes labeled by features

Branches are labeled by tests on that feature

Leaves labeled with classes

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To ride or not to ride, that is the question…

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES

Build a decision tree

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Recursive approach

Base case: If all data belong to the same class, create a leaf node with that label

Otherwise:

- calculate the "score" for each feature if we used it to split the data
- pick the feature with the highest score, partition the data based on that data value and call recursively

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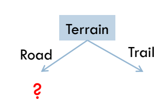
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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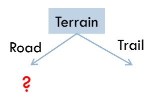
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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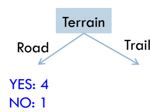
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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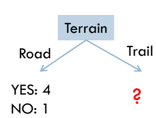
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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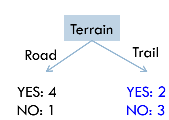
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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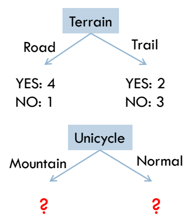
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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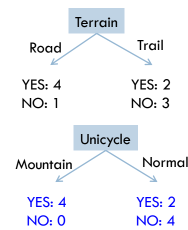
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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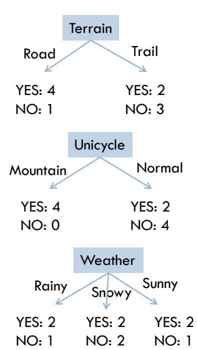
Partitioning the data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES



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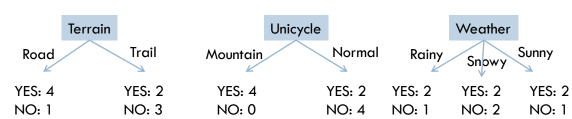
Partitioning the data



calculate the "score" for each feature
if we used it to split the data

What score should we use?

If we just stopped here, which tree would be best?

How could we make these into decision trees?

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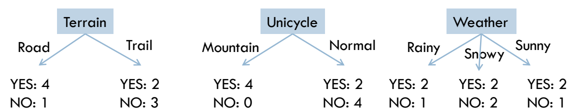
Decision trees



How could we make these into decision trees?

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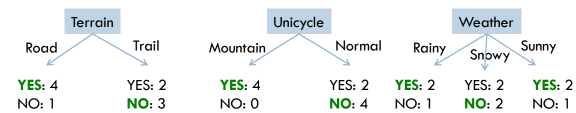
Decision trees



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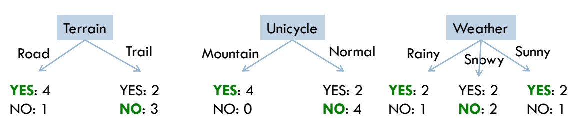
Decision trees



Training error: the average error over the training set

For classification, the most common "error" is the number of mistakes

Training error for each of these?

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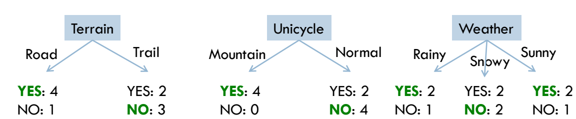
Decision trees



3/10 2/10 4/10

Training error: the average error over the training set

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Training error vs. accuracy

Terrain
Road → YES: 4, NO: 1
Trail → YES: 2, NO: 3

Unicycle
Mountain → YES: 4, NO: 0
Normal → YES: 2, NO: 4

Weather
Rainy → YES: 2, NO: 1
Snowy → YES: 2, NO: 2
Sunny → YES: 2, NO: 1

	Terrain	Unicycle	Weather
Training error:	3/10	2/10	4/10
Training accuracy:	7/10	8/10	6/10

training error = 1-accuracy (and vice versa)

Training error: the average error over the training set

Training accuracy: the average proportion correct over the training set

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Recurse

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES

Unicycle
Mountain → YES: 4, NO: 0
Normal → YES: 2, NO: 4

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Recurse

Unicycle
Mountain → YES: 4, NO: 0
Normal → YES: 2, NO: 4

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Mountain	Snowy	YES

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO

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Recurse

Unicycle
Mountain → YES: 4, NO: 0
Normal

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Mountain	Snowy	YES

What should we do?

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Recurse

Unicycle

Mountain Normal

YES: 4
NO: 0

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Mountain	Snowy	YES

No need to examine other features since all examples have the same label.

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Recurse

Unicycle

Mountain Normal

YES: 4
NO: 0

YES: 2
NO: 4

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO

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Recurse

Unicycle

Mountain Normal

YES: 4
NO: 0

YES: 2
NO: 4

Still two features left we can split on

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO

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Recurse

Unicycle

Mountain Normal

YES: 4
NO: 0

YES: 2
NO: 4

Terrain

Road Trail

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO

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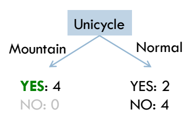
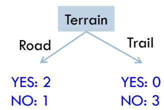
Recurse





Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO

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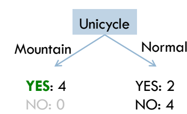
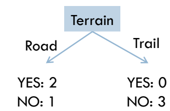
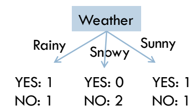
Recurse





Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO



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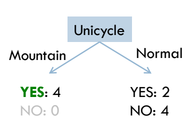
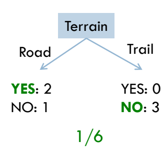
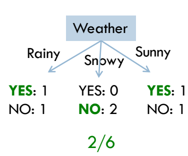
Recurse





Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO



Which should we pick?

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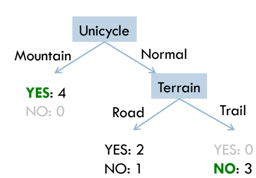
Recurse



Terrain	Unicycle-type	Weather	Go-For-Ride?
Road	Normal	Sunny	YES
Road	Normal	Rainy	YES
Road	Normal	Snowy	NO

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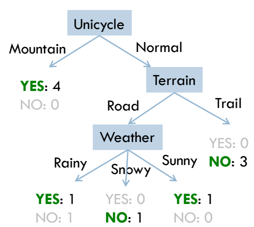
Recurse



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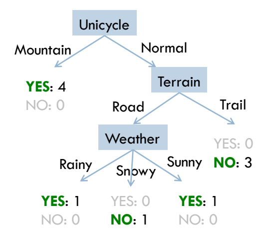
Recurse



Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Rainy	YES
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES

Are we always guaranteed to get a training error of 0?

Training error?

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Problematic data

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Normal	Rainy	NO
Road	Normal	Sunny	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	NO
Trail	Normal	Snowy	NO
Road	Normal	Rainy	YES
Road	Mountain	Snowy	YES
Trail	Normal	Sunny	NO
Road	Normal	Snowy	NO
Trail	Mountain	Snowy	YES

When can this happen?

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Recursive approach

Base case: If all data belong to the same class, create a leaf node with that label ***OR*** all the data has the same feature values

Do we always want to go all the way to the bottom?

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What would the tree look like for…

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO

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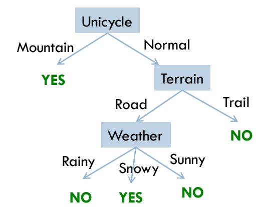
What would the tree look like for…

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO



Is that what you would do?

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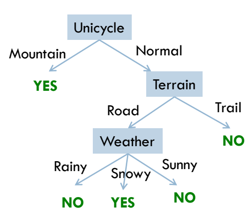
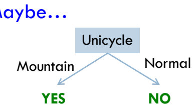
What would the tree look like for…

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO



Maybe…



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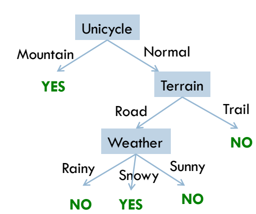
What would the tree look like for…

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO



An aside: how did we decide to pick the label for normal→road→rainy?

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What would the tree look like for…

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	B	YES
Road	Mountain	Sunny	Heavy	A	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	C	YES

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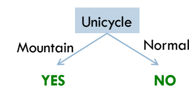
Overfitting

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO



Overfitting occurs when we bias our model too much towards the training data

Our goal is to learn a **general** model that will work on the training data as well as other data (i.e., test data)

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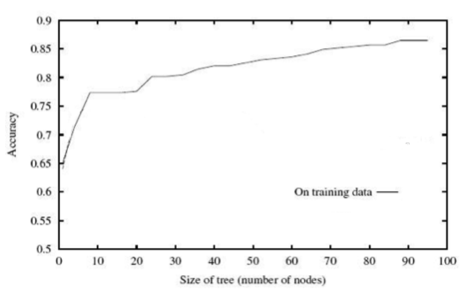
Overfitting



Our decision tree learning procedure always decreases training error

Is that what we want?

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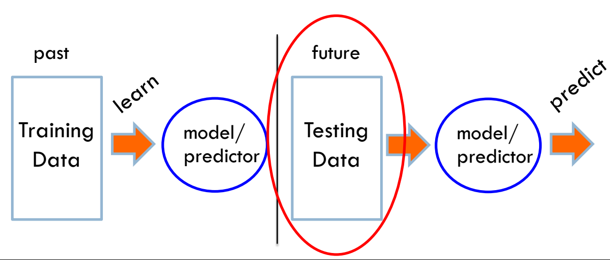
Test set error!

Machine learning is about predicting the future based on the past.
-- Hal Daume III



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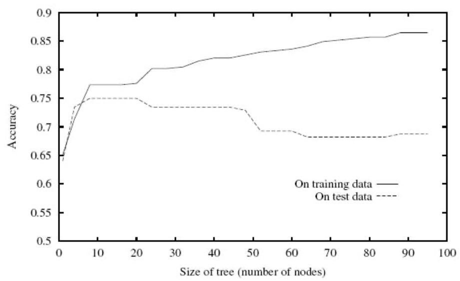
Overfitting



Even though the training error is decreasing, the testing error can go up!

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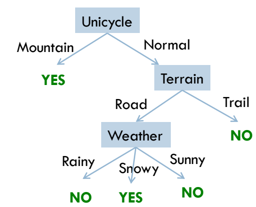
Overfitting

Terrain	Unicycle-type	Weather	Go-For-Ride?
Trail	Mountain	Rainy	YES
Trail	Mountain	Sunny	YES
Road	Mountain	Snowy	YES
Road	Mountain	Sunny	YES
Trail	Normal	Snowy	NO
Trail	Normal	Rainy	NO
Road	Normal	Snowy	YES
Road	Normal	Sunny	NO
Trail	Normal	Sunny	NO



How do we prevent overfitting?

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Preventing overfitting

Base case:

- If all data belong to the same class, create a leaf node with that label
- ***OR*** all the data has the same feature values
- ***OR*** We've reached a particular depth in the tree
- ?

One idea: stop building the tree early

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Preventing overfitting

Base case:

- If all data belong to the same class, create a leaf node with that label
- ***OR*** all the data has the same feature values
- ***OR*** We've reached a particular depth in the tree
- We only have a certain number/fraction of examples remaining
- We've reached a particular training error
- Use development data (more on this later)
- …

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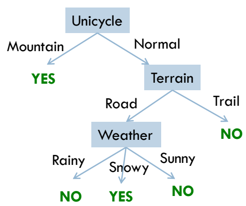
Preventing overfitting: pruning



Pruning: after the tree is built, go back and "prune" the tree, i.e. remove some lower parts of the tree

Similar to stopping early, but done after the entire tree is built

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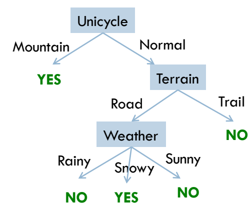
Preventing overfitting: pruning



Build the full tree

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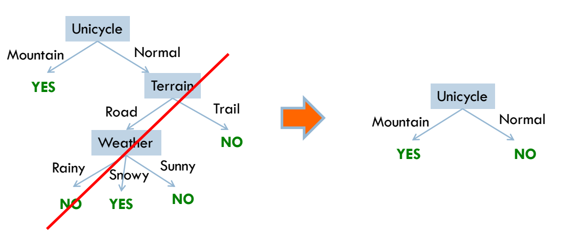
Preventing overfitting: pruning



Build the full tree

Prune back leaves that are too specific

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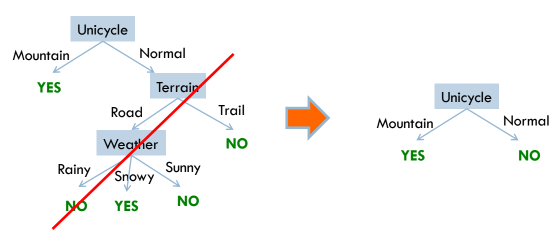
Preventing overfitting: pruning



Pruning criterion?

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Handling non-binary attributes

PassengerId	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Survived
804	3	0	0.42	0	1	2625	8.5167	0	1
756	2	0	0.67	1	1	250649	14.5	2	1
470	3	1	0.75	2	1	2666	19.2583	0	1
645	3	1	0.75	2	1	2666	19.2583	0	1
79	2	0	0.83	0	2	248738	29	2	1
832	2	0	0.83	1	1	29106	18.75	2	1
306	1	0	0.92	1	2	113781	151.55	2	1
165	3	0	1	4	1	3101295	39.6875	2	0
173	3	1	1	1	1	347742	11.1333	2	1
184	2	0	1	2	1	230136	39	2	1
382	3	1	1	0	2	2653	15.7417	0	1
387	3	0	1	5	2	2144	46.9	2	0
789	3	0	1	1	2	2315	20.575	2	1
828	2	0	1	0	2	2079	37.0042	0	1
8	3	0	2	3	1	349909	21.075	2	0
17	3	0	2	4	1	382652	29.125	1	0
120	3	1	2	4	2	347082	31.275	2	0
206	3	1	2	0	1	347054	10.4625	2	0
298	1	1	2	1	2	113781	151.55	2	0
341	2	0	2	1	1	230080	26	2	1
480	3	1	2	0	1	3101298	12.2875	2	1

What do we do with features that have multiple values? Real-values?

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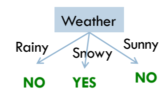
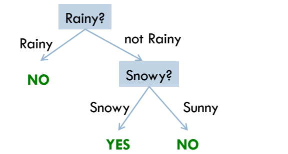
Features with multiple values



Treat as an n-ary split



Treat as multiple binary splits

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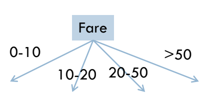
Real-valued features

Use any comparison test (>, <, ≤, ≥) to split the data into two parts

Select a range filter, i.e. min < value < max



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Other splitting criterion

Otherwise:

- calculate the "score" for each feature if we used it to split the data
- pick the feature with the highest score, partition the data based on that data value and call recursively

We used training error for the score. Any other ideas?

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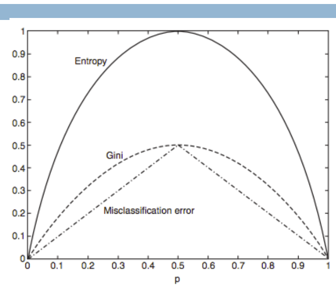
Other splitting criterion



- Entropy: how much uncertainty there is in the distribution over labels after the split
- Gini: sum of the square of the label proportions after split
- Training error = misclassification error

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Decision trees

Good? Bad?

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Decision trees: the good

Very intuitive and easy to interpret

Fast to run and fairly easy to implement (Assignment 2 ☺)

Historically, perform fairly well (especially with a few more tricks we'll see later on)

No prior assumptions about the data

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Decision trees: the bad

Be careful with features with lots of values if you're not doing binary splits

ID	Terrain	Unicycle-type	Weather	Go-For-Ride?
1	Trail	Normal	Rainy	NO
2	Road	Normal	Sunny	YES
3	Trail	Mountain	Sunny	YES
4	Road	Mountain	Rainy	YES
5	Trail	Normal	Snowy	NO
6	Road	Normal	Rainy	YES
7	Road	Mountain	Snowy	YES
8	Trail	Normal	Sunny	NO
9	Road	Normal	Snowy	NO
10	Trail	Mountain	Snowy	YES

Which feature would be at the top here?

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Decision trees: the bad

Can be problematic (slow, bad performance) with large numbers of features

Can't learn some very simple data sets (e.g. some types of linearly separable data)

Pruning/tuning can be tricky to get right

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Final DT algorithm

DT_train(data):

Base cases:

1. If all data belong to the same class, pick that label
2. If all the data have the same feature values, pick majority label
3. If we're out of features to examine, pick majority label
4. If the we don't have any data left, pick majority label of *parent*
5. *If some other stopping criteria* exists to avoid overfitting, pick majority label

Otherwise (i.e. if none of the base cases apply):

- calculate the "score" for each feature if we used it to split the data
- pick the feature with the highest score, partition the data based on that data, e.g. data_left and data_right
- Recurse, i.e. DT_train(data_left) and DT_train(data_right)
- Make tree with feature as the splitting criterion with the decision trees returned from the recursive calls as the children

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