

Decision Trees

CS 5703: Machine Learning Practice

Regression / Classification So Far...

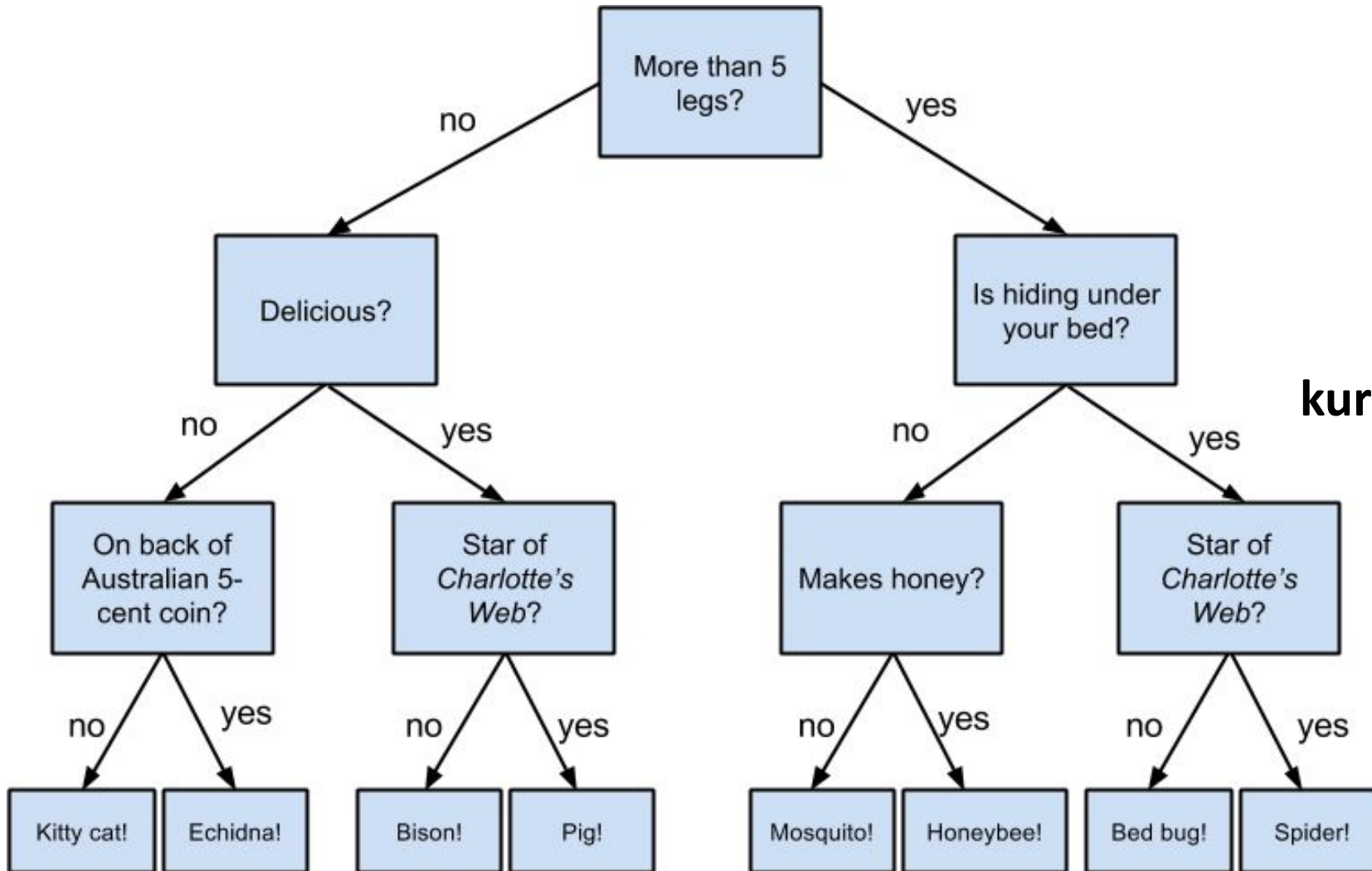
- Input features must be numeric
 - Categorical variables required us to first transform them into numeral variables (via one-hot-encoding)
- Models have been based on continuous functions
- When we have many input features, it is hard to understand how the model works by just looking at the model parameters

Decision Trees

A different way of looking at model representation:

- Ask a recursive set of binary (or N-ary) questions
- Questions refer to specific input features
 - Input features can be numerical or categorical (enumerated data type)
- After the questions: produce a prediction

Decision Tree Example



kurokawa.com

Decision Trees

Tree structure:

- A query starts at the root of the tree (the root node)
- A question node asks something specific about a feature in the query vector
- Depending on the answer, the query “falls down” one of the branches from the question
 - Often binary trees: we have “Yes” or “No” branches
- Each branch can contain additional questions (and branches)
- All paths end in leaf nodes, where the predictions are made

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Decision Trees

- Each question cuts the a feature subspace into two pieces
 - These cuts are axis-aligned
- Sequences of questions along a path to a leaf node are Boolean AND operators
- Branches are OR operators
- A tree sorts a set of queries into different leaf nodes

Types of Leaf Node Predictions

Different types of trees make different types of predictions:

- Standard tree: predict a single class
- Probability tree: predict a probability distribution over possible classes
- Regression tree: predict a continuous value

Tree Learning

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Tree Learning

Incremental, greedy algorithm

- Start with an empty tree
- Grow tree by adding ones new question + leaves
- Recompute the predictions
- Repeat

Generic Tree Learning Algorithm

- Training set: feature vectors + correct answer
- Initialize tree with root node and a leaf
 - All training samples are sorted into this leaf
 - Make a prediction that yields the “best” performance

Generic Tree Learning Algorithm

Until an adequate tree is learned:

- Pick best leaf node to replace with
 - A question
 - A pair of leaves (or more)
- Pick the best question to ask
 - Which feature?
 - Which value (or threshold value?)
- Pick the best prediction for each of the new leaves

Generic Tree Learning Algorithm

Choosing the best next question

- With a small, finite set of discrete features, each with a small number of possible values, it is possible to consider all possible questions when evaluating the “best”
- More generally, we will sample from the possible question set
 - Training process becomes a stochastic one!

Probability Tree Learning

- Desired output: class
- Leaf nodes: probability distribution over the possible classes
- General idea: want each of the leaf nodes to contain a “pure” set of training examples

Probability Tree Learning (Intuition)

- Want leaf nodes to be as pure as possible
- Greedy algorithm:
 - Pick the leaf node with the highest impurity to expand
 - Pick the feature and dividing line that best distinguishes the classes
- The greedy algorithm can keep going to an extreme
 - This is the overfitting problem again!

Formalizing Probability Tree Learning

Measuring purity of leaf nodes:

- Information content
- Gini Impurity

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Information vs Gini

Very similar metrics

- Really is an empirical question as to which one to use
- Gini:
 - Less computation
 - Tries to place most frequent class into one of the main branches
- Information:
 - Better balance of trees

Combating Overfitting

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Model Parameters

- In our modeling work so far, each model had a fixed number of parameters
- We have also discussed the fact that as the complexity of a model increases, we often need more training data to effectively “tie down” the parameters
 - Otherwise, we run the risk of overfitting

Decision Tree Learning

- With trees, we need a distinct set of parameters for:
 - Each question (which feature & which threshold)
 - Each leaf node (e.g., the probability function)
- This means that, as the tree grows, the number of parameters increases
- In fact, a tree can grow beyond the structure that a training set can provide...

Tree Learning

We can allow our tree learning algorithm to execute until all leaves have zero entropy

- Most extreme case: one leaf per training set sample
- Effectively have a custom rule for every training sample

- Very brittle: the regions defined by the tree do not necessarily generalize to independent queries

Combating Overfitting in Trees

Fundamental idea: constrain the complexity of the tree

- But: what is the most effective way to do this?

Regularization in Trees

Different tree learning algorithms make different choices.

Key ideas:

- Limit the maximum depth of the tree
 - At the limit, forces balanced trees
- Limit the number of leaf nodes
 - Allows more unbalanced trees

Regularization in Trees II

Sample-driven decisions for splitting a leaf node:

- Require a minimum number of samples in a leaf node before allowing it to be expanded
- Proposed split must result in a measurable improvement in performance. Possibilities:
 - Entropy change; Gini Score
 - Likelihood Ratio test
 - Crisp classification: Chi-squared test

Example: Probability Tree Learning

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Example: Probability Tree Learning

- 2D classification problem (from SVM data)
- Baby action recognition
 - Adjust the positive examples:
 - Samples leading up to event are now considered positive
 - Dropping samples immediately after events

Example: Probability Tree Learning

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Regression Trees

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Regression Trees

Leaf nodes output a continuous value:

- Simple (most common) form: samples that fall into a particular leaf node are assigned the same value (i.e., constant function)
 - Yields a piecewise-constant function
- More general case: output is some function of the full feature vector
 - Each leaf node has its own function
 - So, more expressive than using the function over the entire training set

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Example: Regression Trees

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Regression Trees

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