Open-Source Machine Learning for an Embedded System

Decision Trees with Processing and Arduino Lucas Spicer B.S.EE spicerrobots.com



Machine Learning (ML)

A branch of Artificial Intelligence which deals with algorithms which allow computers to generalize example data probability distributions in order to improve their behaviors

ML traditionally attempts to improve complex relationship recognition from limited data and to provide human intelligible insight into those relationships

Examples: Netflix Suggestions, Google Instant Search, Credit Card Fraud Detection, etc.

The Challenge

Because Machine Learning is traditionally performed on expensive proprietary software systems (like Matlab) the goal for this project is:

To use open-source free software to generate decision trees from arbitrary numbers of examples with arbitrary numbers of attributes and arbitrary numbers of levels of those attributes, as well as arbitrary numbers of output classes

To provide source-code output to implement the generated decision trees on an open-source low cost embedded development system, as well as human readable or graphical output to explain and educate how the generation process works

Processing

Processing is a free open-source programming language, development environment, and online community that promotes software literacy within the visual arts

Processing was initially created to serve as a software sketchbook and to teach fundamentals of computer programming within a visual context

http://processing.org



Processing Sketchbook IDE running the Decision Tree Generator



Arduino is an open-source electronics prototyping platform based on flexible, easyto-use hardware and software. It's intended for artists, designers, hobbyists, and anyone interested in creating interactive objects or environments.

http://arduino.cc

Decision Trees



function ID3

Input: (R: a set of non-target attributes, C: the target attribute, S: a training set) returns a desired

S: a training set) returns a decision tree;

begin If S is empty, return a single node with
 value Failure;

If S consists of records all with the same
 value for the target attribute,
 return a single leaf node with that value;

If R is empty, then return a single node
 with the value of the most frequent of the
 values of the target attribute that are
 found in records of S; [in that case
 there may be be errors, examples
 that will be improperly classified];
Let A be the attribute with largest

Gain(A,S) among attributes in R; Let {aj| j=1,2, .., m} be the values of attribute A;

Let {Sj| j=1,2, .., m} be the subsets of S consisting respectively of records with value aj for A;

Return a tree with root labeled A and arcs
labeled a1, a2, ..., am going respectively
to the trees (ID3(R-{A}, C, S1), ID3(R-{A}, C, S2),
....,ID3(R-{A}, C, Sm);

```
Recursively apply ID3 to subsets {Sj| j=1,2, .., m}
```

until they are empty

J. Ross Quinlan's classic Decision Tree Algorithm ID3

Assumes Discrete Data Classes

Recursive Splitting is based on Entropy and Information Gain Entropy is a Measure of Uncertainty in Data S is a data set p_i is the proportion of the set from the ith class of S

Zero Entropy occurs when the entire set is from one class

$$Entropy(S) = \sum_{i=1}^{c} -p_i \log_2 p_i$$

The concept was introduced by Claude E. Shannon in his 1948 paper "A Mathematical Theory of Communication"

Information Gain is a Reduction in Entropy S is a data set A is a subset of S with a given attribute

$$Gain(S,A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

Goal is to test attributes which provide the maximum information gain for a given data set

Example Data Set

Day	Outlook	Temperature	Humidity	Wind	PlayTennis?
1	sunny	hot	high	weak	No
2	sunny	hot	high	strong	No
3	overcast	hot	high	weak	Yes
4	rain	mild	high	weak	Yes
5	rain	cool	normal	weak	Yes
6	rain	cool	normal	strong	No
7	overcast	cool	normal	strong	Yes
8	sunny	mild	high	weak	No
9	sunny	cool	normal	weak	Yes
10	rain	mild	normal	weak	Yes
11	sunny	mild	normal	strong	Yes
12	overcast	mild	high	strong	Yes
13	overcast	hot	normal	weak	Yes
14	rain	mild	high	strong	No
15	sunny	hot	normal	strong	No
16	sunny	hot	normal	strong	Yes

L decision_trees_code_gen_05

- 0 X



Node = [1 1] Collection Entropy = 0.9402859, Max Attribute Gain = 0.24674976, Maximum Gain Attribute = Outlook Attribute Branch = Overcast Node = [2 1] Collection Entropy = 0, Leaf = Yes 1 Attribute Branch = Rain Node = [2 2] Collection Entropy = 0.9709506, Max Attribute Gain = 0.9709506, Maximum Gain Attribute = Wind Attribute Branch = Weak Node = [3 1] Collection Entropy = 0, Leaf = Yes 1 Attribute Branch = Strong Node = [3 2] Collection Entropy = 0, Leaf = No 0 Attribute Branch = Sunny Node = [2 3] Collection Entropy = 0.9709506, Max Attribute Gain = 0.9709506, Maximum Gain Attribute = Humidity Attribute Branch = Normal Node = [3 1] Collection Entropy = 0, Leaf = Yes 1 Attribute Branch = Normal Node = [3 2] Collection Entropy = 0, Leaf = Yes 1

Example Decision Tree Output

Calculations and Graphical Representation of Tree Example Auto-Generated Arduino Function output from Processing

Allows Arduino to implement the tree "grown" (trained) on a computer running Processing

```
/* play tennis decision Tree file for Arduino
                                                       */
1
     /* Date: 28 Feb 2012
                                                       */
 2
                                                      */
 3
     /* Time: 22:0:46
    ⊟#ifndef play_tennis_H
     #define play tennis H
 6
 7
 8
    =#if defined(ARDUINO) && ARDUINO >= 100
9
     #include "Arduino.h"
10
     #else
11
     #include "WProgram.h"
12
     #endif
13
14
     // Output (Decision):
15
     // play tennis levels: 0 = No 1 = Yes
16
     // Input (Attributes):
17
     // Outlook levels: 0 = Overcast 1 = Rain 2 = Sunny
18
     // Temp levels: 0 = Cool 1 = Mild 2 = Hot
19
     // Humidity levels: 0 = Normal 1 = High
20
     // Wind levels: 0 = Weak 1 = Strong
21
22
23
   int play tennis(int Outlook, int Temp, int Humidity, int Wind){
24
         if(Outlook == 0) { // Outlook == Overcast?
25
             return 1; // play_tennis = Yes
26
27
         else if(Outlook == 1) { // Outlook == Rain?
28
             if (Wind == 0) { // Wind == Weak?
29
                 return 1; // play tennis = Yes
30
31
             else if (Wind == 1) { // Wind == Strong?
32
                 return 0; // play tennis = No
33
34
35
         else if (Outlook == 2) { // Outlook == Sunny?
36
             if(Humidity == 0) { // Humidity == Normal?
37
                 return 1; // play_tennis = Yes
38
             1
39
             else if (Humidity == 1) { // Humidity == High?
40
                 return 0; // play tennis = No
41
42
43
     ł
44
45
     #endif
```

Validation

- Key task for ML systems is to validate their ability to generalize from examples
- > Data Set is partitioned into a training set and a validation set.
- Training set is used to build the decision tree and validation set is used to test its ability to generalize



Validation on Fisher's Iris Data

Applications

- Freely and easily available educational tool to instruct about machine learning
- Software library to give small robot hobbyists ability to make smarter, learning robots (or other embedded devices)
- Examples: smart watering can, obstacle avoiding robots, automatic failure diagnosis for small embedded devices, etc.

