Lecture 08 of 42

Decision Tree Induction and Overfitting

Thursday, 01 February 2007

William H. Hsu
Department of Computing and Information Sciences, KSU
http://www.cis.ksu.edu/~bhsu

Readings:
Chapter 3.6-3.8, Mitchell

Lecture Outline

- Read Sections 3.6-3.8, Mitchell
- Occam's Razor and Decision Trees
  - Preference biases versus language biases
  - Two issues regarding Occam algorithms
    - Is Occam's Razor well defined?
    - Why prefer smaller trees?
- Overfitting (*aka* Overtraining)
  - Problem: fitting training data too closely
    - Small-sample statistics
    - General definition of overfitting
  - Overfitting prevention, avoidance, and recovery techniques
    - Prevention: attribute subset selection
    - Avoidance: cross-validation
    - Detection and recovery: post-pruning
- Other Ways to Make Decision Tree Induction More Robust

Entropy: Information Theoretic Definition

- **Components**
  - D: a set of examples $\{<x_1, c(x_1)>, <x_2, c(x_2)>, \ldots, <x_m, c(x_m)>\}$
  - $p_+ = Pr(c(x) = +)$, $p_- = Pr(c(x) = -)$
- **Definition**
  - H is defined over a probability density function p
  - D contains examples whose frequency of + and - labels indicates p_+ and p_- *for the observed data*
  - The entropy of D relative to c is:

$$H(D) \equiv -p_+ \log_b (p_+) - p_- \log_b (p_-)$$

- **What Units is H Measured In?**
  - Depends on the base b of the log (bits for $b = 2$, nats for $b = e$, etc.)
  - A single bit is required to encode each example in the worst case ($p_+ = 0.5$)
  - If there is less uncertainty (e.g., $p_+ = 0.8$), we can use less than 1 bit each

Information Gain: Information Theoretic Definition

- **Partitioning on Attribute Values**
  - Recall: a partition of D is a collection of disjoint subsets whose union is D
  - Goal: *measure the uncertainty removed* by splitting on the value of attribute A
- **Definition**
  - The information gain of D relative to attribute A is the expected reduction in entropy due to splitting ("sorting") on A:

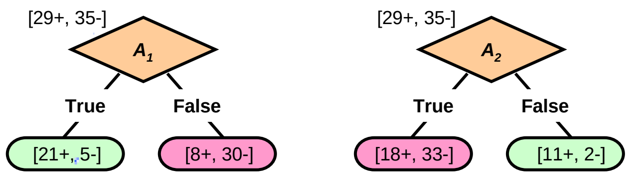
$\sum_{x \in val(A)} H(D|A=v)$

$I(D,A) = \Delta H = H(D) - H(D|A)$ $P(A) \log P(X=x)$

$$Gain(D, A) \equiv -H(D) - \sum_{v \in values(A)} \left[\frac{|D_v|}{|D|} \bullet H(D_v) \right]$$

where D_v is $\{x \in D: x.A = v\}$, the set of examples in D where attribute A has value v

  - Idea: partition on A; scale entropy to the size of each subset D_v
- **Which Attribute Is Best?**



An Illustrative Example

- Training Examples for Concept *PlayTennis*

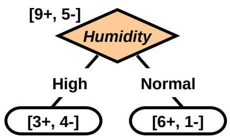
Day	Outlook	Temperature	Humidity	Wind	*PlayTennis*?
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No

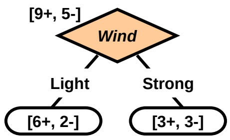
- *ID3* ≡ *Build-DT* using *Gain*(•)
- How Will *ID3* Construct A Decision Tree?

Constructing A Decision Tree for *PlayTennis* using *ID3* [1]

- Selecting The Root Attribute

Day	Outlook	Temperature	Humidity	Wind	*PlayTennis*?
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No





- Prior (unconditioned) distribution: 9+, 5-
  - *H*(*D*) = -(9/14) lg (9/14) - (5/14) lg (5/14) *bits* = 0.94 bits
  - *H*(*D*, *Humidity* = High) = -(3/7) lg (3/7) - (4/7) lg (4/7) = 0.985 bits
  - *H*(*D*, *Humidity* = Normal) = -(6/7) lg (6/7) - (1/7) lg (1/7) = 0.592 bits
  - *Gain*(*D*, *Humidity*) = 0.94 - (7/14) * 0.985 + (7/14) * 0.592 = 0.151 bits
  - Similarly, *Gain* (*D*, *Wind*) = 0.94 - (8/14) * 0.811 + (6/14) * 1.0 = 0.048 bits

$$Gain(D, A) \equiv -H(D) - \sum_{v \in values(A)} \left[\frac{|D_v|}{|D|} \bullet H(D_v) \right]$$

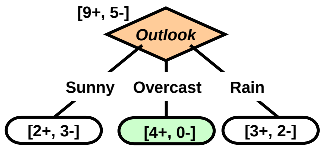
CIS 732: Machine Learning and Pattern Recognition
Kansas State University
Department of Computing and Information Sciences

Constructing A Decision Tree for *PlayTennis* using *ID3* [2]

- **Selecting The Root Attribute**

Day	Outlook	Temperature	Humidity	Wind	*PlayTennis?*
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No

  - *Gain*(*D*, *Humidity*) = 0.151 bits
  - *Gain*(*D*, *Wind*) = 0.048 bits
  - *Gain*(*D*, *Temperature*) = 0.029 bits
  - *Gain*(*D*, *Outlook*) = <u>0.246 bits</u>



- **Selecting The Next Attribute (Root of Subtree)**
  - Continue until every example is included in path or purity = 100%
  - What does purity = 100% mean?
  - Can *Gain*(*D*, *A*) < 0?

H(D | Outlook = Overcast) = 0

Constructing A Decision Tree for *PlayTennis* using *ID3* [3]

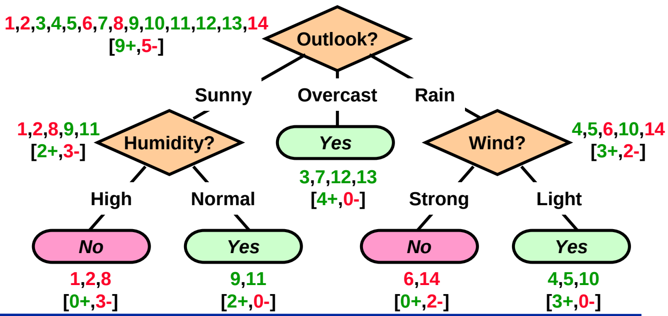
- **Selecting The Next Attribute (Root of Subtree)**

Day	Outlook	Temperature	Humidity	Wind	*PlayTennis?*
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No

  - Convention: lg (0/a) = 0
  - $Gain(D_{Sunny}, Humidity)$ = 0.97 - (3/5) * 0 - (2/5) * 0 = <u>0.97 bits</u>
  - $Gain(D_{Sunny}, Wind)$ = 0.97 - (2/5) * 1 - (3/5) * 0.92 = 0.02 bits
  - $Gain(D_{Sunny}, Temperature)$ = 0.57 bits
- **Top-Down Induction**
  - For discrete-valued attributes, terminates in $O(n)$ splits
  - Makes at most one pass through data set at each level (why?)

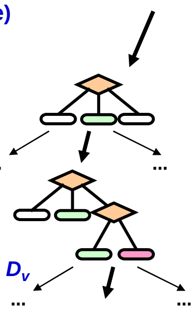
Constructing A Decision Tree for *PlayTennis* using *ID3* [4]

Day	Outlook	Temperature	Humidity	Wind	*PlayTennis?*
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No



Hypothesis Space Search by *ID3*

- **Search Problem**
  - Conduct a search of the *space of decision trees*, which can represent all possible discrete functions
    - Pros: expressiveness; flexibility
    - Cons: computational complexity; large, incomprehensible trees (next time)
  - Objective: to find the best decision tree (minimal consistent tree)
  - Obstacle: finding this tree is NP-hard
  - Tradeoff
    - Use heuristic (figure of merit that guides search)
    - Use greedy algorithm
    - *Aka* hill-climbing (gradient "descent") without backtracking
- **Statistical Learning**
  - Decisions based on statistical descriptors p_+, p_- for subsamples D_v
  - In ID3, *all data used*
  - Robust to noisy data



Inductive Bias in *ID3*

- Heuristic : Search :: Inductive Bias : Inductive Generalization
  - *H* is the power set of instances in *X*
  - ⇒ Unbiased? Not really…
    - Preference for short trees (termination condition)
    - Preference for trees with high information gain attributes near the root
    - *Gain*(•): a heuristic function that *captures the inductive bias of ID3*
  - Bias in *ID3*
    - Preference for some hypotheses is encoded in heuristic function
    - Compare: a restriction of hypothesis space *H* (previous discussion of propositional normal forms: *k*-CNF, etc.)
- Preference for Shortest Tree
  - Prefer shortest tree that fits the data
  - An Occam's Razor bias: shortest hypothesis that explains the observations

MLC++: A Machine Learning Library

- *MLC++*
  - http://www.sgi.com/Technology/mlc
  - An object-oriented machine learning library
  - Contains a suite of inductive learning algorithms (including *ID3*)
  - Supports incorporation, reuse of other DT algorithms (*C4.5*, etc.)
  - Automation of statistical evaluation, cross-validation
- Wrappers
  - Optimization loops that iterate over inductive learning functions (inducers)
  - Used for performance tuning (finding subset of *relevant* attributes, etc.)
- Combiners
  - Optimization loops that iterate over or interleave inductive learning functions
  - Used for performance tuning (finding subset of *relevant* attributes, etc.)
  - Examples: bagging, boosting (later in this course) of *ID3*, *C4.5*
- Graphical Display of Structures
  - Visualization of DTs (AT&T *dotty*, SGI *MineSet TreeViz*)
  - General logic diagrams (projection visualization)

Occam's Razor and Decision Trees: A Preference Bias

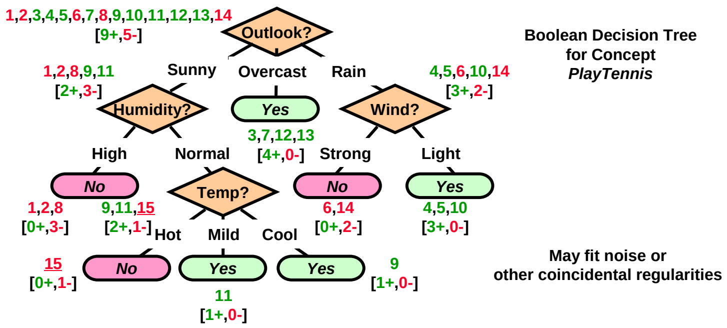
- **Preference Biases versus Language Biases**
  - Preference bias
    - Captured ("encoded") in *learning algorithm*
    - Compare: *search heuristic*
  - Language bias
    - Captured ("encoded") in *knowledge (hypothesis) representation*
    - Compare: *restriction of search space*
    - *aka* restriction bias
- **Occam's Razor: Argument in Favor**
  - Fewer short hypotheses than long hypotheses
    - e.g., half as many bit strings of length n as of length $n + 1$, $n \geq 0$
    - Short hypothesis that fits data less likely to be coincidence
    - Long hypothesis (e.g., tree with 200 nodes, $|D| = 100$) could be coincidence
  - Resulting justification / tradeoff
    - All other things being equal, complex models tend not to generalize as well
    - Assume more model flexibility (specificity) won't be needed later

Occam's Razor and Decision Trees: Two Issues

- **Occam's Razor: Arguments Opposed**
  - *size*(h) based on H - circular definition?
  - Objections to the preference bias: "fewer" not a justification
- **Is Occam's Razor Well Defined?**
  - Internal knowledge representation (KR) defines which h are "short" - arbitrary?
  - e.g., single "(*Sunny* $\wedge$ *Normal-Humidity*) $\vee$ *Overcast* $\vee$ (*Rain* $\wedge$ *Light-Wind*)" test
  - Answer: L fixed; imagine that *biases tend to evolve quickly, algorithms slowly*
- **Why Short Hypotheses Rather Than Any Other Small H?**
  - There are many ways to define small sets of hypotheses
  - For any size limit expressed by preference bias, some specification S restricts *size*(h) to that limit (i.e., "accept trees that meet criterion S")
    - e.g., trees with a prime number of nodes that use attributes starting with "Z"
    - Why small trees and not trees that (for example) test A_1, A_1, …, A_{11} in order?
    - What's so special about small H based on *size*(h)?
  - Answer: *stay tuned*, more on this in Chapter 6, Mitchell

Overfitting in Decision Trees: An Example

- **Recall: Induced Tree**



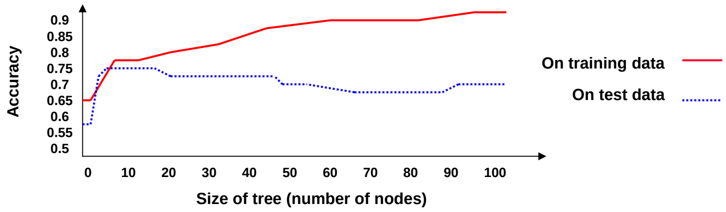
- **Noisy Training Example**
  - Example 15: <*Sunny, Hot, Normal, Strong, -*>
    - Example is noisy because the correct label is +
    - Previously constructed tree misclassifies it
  - How shall the DT be revised (incremental learning)?
  - New hypothesis *h' = T'* is expected to perform *worse* than *h = T*

Overfitting in Inductive Learning

- **Definition**
  - Hypothesis *h* overfits training data set *D* if ∃ an alternative hypothesis *h'* such that $error_D(h) < error_D(h')$ but $error_{test}(h) > error_{test}(h')$
  - Causes: sample too small (decisions based on too little data); noise; coincidence
- **How Can We Combat Overfitting?**
  - Analogy with computer virus infection, process deadlock
  - Prevention
    - Addressing the problem "before it happens"
    - Select attributes that are *relevant* (i.e., will be useful in the model)
    - *Caveat*: chicken-egg problem; requires some predictive measure of relevance
  - Avoidance
    - Sidestepping the problem just when it is about to happen
    - Holding out a test set, stopping when *h* starts to do worse on it
  - Detection and Recovery
    - Letting the problem happen, detecting when it does, recovering afterward
    - Build model, remove (prune) elements that contribute to overfitting

Decision Tree Learning: Overfitting Prevention and Avoidance

- **How Can We Combat Overfitting?**
  - **Prevention (more on this later)**
    - **Select attributes that are *relevant* (i.e., will be useful in the DT)**
    - **Predictive measure of relevance: attribute filter or subset selection wrapper**
  - **Avoidance**
    - **Holding out a validation set, stopping when *h* ≡ *T* starts to do worse on it**

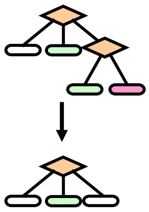


- **How to Select "Best" Model (Tree)**
  - **Measure performance over training data *and* separate validation set**
  - **Minimum Description Length (MDL):**
    minimize *size*(*h* ≡ *T*) + *size* (*misclassifications* (*h* ≡ *T*))

Decision Tree Learning: Overfitting Avoidance and Recovery

- **Today: Two Basic Approaches**
  - **Pre-pruning (avoidance): *stop growing tree at some point during construction* when it is determined that there is not enough data to make reliable choices**
  - **Post-pruning (recovery): *grow the full tree and then remove nodes* that seem not to have sufficient evidence**
- **Methods for Evaluating Subtrees to Prune**
  - **Cross-validation: reserve hold-out set to evaluate utility of *T* (more in Chapter 4)**
  - **Statistical testing: test whether observed regularity can be dismissed as likely to have occurred by chance (more in Chapter 5)**
  - **Minimum Description Length (MDL)**
    - **Additional complexity of hypothesis *T* greater than that of remembering *exceptions*?**
    - **Tradeoff: coding *model* versus coding *residual error***

Reduced-Error Pruning



- **Post-Pruning, Cross-Validation Approach**
- **Split Data into Training and Validation Sets**
- **Function *Prune*(*T, node*)**
  - **Remove the subtree rooted at *node***
  - **Make *node* a leaf (with majority label of associated examples)**
- **Algorithm *Reduced-Error-Pruning* (*D*)**
  - **Partition *D* into D_{train} (training / "growing"), $D_{validation}$ (validation / "pruning")**
  - **Build complete tree *T* using *ID3* on D_{train}**
  - **UNTIL accuracy on $D_{validation}$ decreases DO**

    FOR each non-leaf node *candidate* in *T*

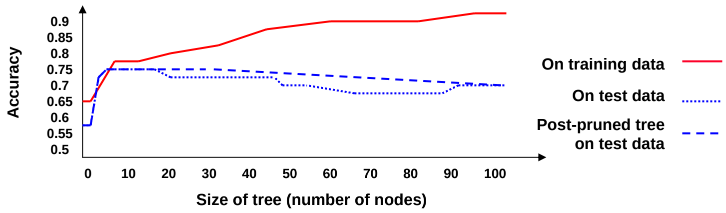
    ***Temp*[*candidate*] ← *Prune* (*T*, *candidate*)**

    ***Accuracy*[*candidate*] ← *Test* (*Temp*[*candidate*], $D_{validation}$)**

    $T \leftarrow T' \in$ *Temp* with best value of *Accuracy* (best increase; *greedy*)
  - **RETURN (pruned) *T***

Effect of Reduced-Error Pruning

- **Reduction of Test Error by Reduced-Error Pruning**



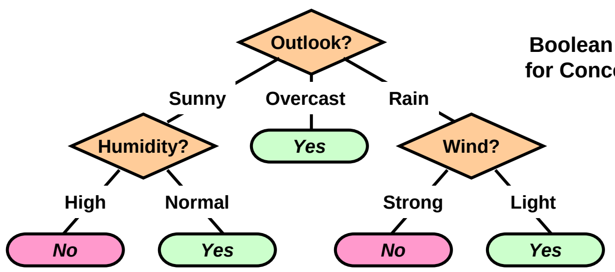
  - **Test error reduction achieved by pruning nodes**
  - ***NB*: here, $D_{validation}$ is different from both D_{train} and D_{test}**
- **Pros and Cons**
  - **Pro: Produces smallest version of most accurate *T'* (subtree of *T*)**
  - **Con: Uses less data to construct *T***
    - **Can afford to hold out $D_{validation}$?**
    - **If not (data is too limited), may make error worse (insufficient D_{train})**

Rule Post-Pruning

- **Frequently Used Method**
  - Popular anti-overfitting method; perhaps most popular pruning method
  - Variant used in *C4.5*, an outgrowth of *ID3*
- **Algorithm *Rule-Post-Pruning* (*D*)**
  - Infer *T* from *D* (using *ID3*) - grow until *D* is fit as well as possible (allow overfitting)
  - Convert *T* into equivalent set of rules (one for each root-to-leaf path)
  - Prune (generalize) each rule *independently* by <u>deleting any preconditions</u> whose deletion improves its estimated accuracy
  - Sort the pruned rules
    - Sort by their estimated accuracy
    - Apply them in sequence on D_{test}

Converting a Decision Tree into Rules

- **Rule Syntax**
  - LHS: precondition (<u>conjunctive formula</u> over attribute equality tests)
  - RHS: class label



Boolean Decision Tree for Concept *PlayTennis*

- **Example**
  - IF (*Outlook* = *Sunny*) $\wedge$ (*Humidity* = *High*) THEN *PlayTennis* = *No*
  - IF (*Outlook* = *Sunny*) $\wedge$ (*Humidity* = *Normal*) THEN *PlayTennis* = *Yes*
  - …

Continuous Valued Attributes

- **Two Methods for Handling Continuous Attributes**
  - Discretization (e.g., histogramming)
    - Break real-valued attributes into ranges *in advance*
    - e.g., {*high* ≡ *Temp* > 35º C, *med* ≡ 10º C < *Temp* ≤ 35º C, *low* ≡ *Temp* ≤ 10º C}
  - Using thresholds for splitting nodes
    - e.g., $A \le a$ produces subsets $A \le a$ and $A > a$
    - *Information gain is calculated the same way* as for discrete splits
- **How to Find the Split with Highest Gain?**
  - FOR each continuous attribute *A*

    Divide examples $\{x \in D\}$ according to $x.A$

    FOR each ordered pair of values (l, u) of *A* with different labels

    Evaluate gain of mid-point as a possible threshold, i.e., $D_{A \le (l+u)/2}$, $D_{A > (l+u)/2}$
  - Example
    - $A \equiv Length$: 10 15 21 28 32 40 50
    - Class: - + + - + + -
    - Check thresholds: $Length \le 12.5$? ≤ 24.5? ≤ 30? ≤ 45?

Attributes with Many Values

- **Problem**
  - If attribute has many values, *Gain*(•) will select it (why?)
  - Imagine using *Date* = 06/03/1996 as an attribute!
- **One Approach: Use *GainRatio* instead of *Gain***

$$Gain(D, A) \equiv -H(D) - \sum_{v \in values(A)} \left[\frac{|D_v|}{|D|} \bullet H(D_v) \right]$$

$$GainRatio(D, A) \equiv \frac{Gain(D, A)}{SplitInformation(D, A)}$$

$$SplitInformation(D, A) \equiv -\sum_{v \in values(A)} \left[\frac{|D_v|}{|D|} \lg \frac{|D_v|}{|D|} \right]$$

  - *SplitInformation*: directly proportional to $c = |\ values(A)\ |$
  - i.e., penalizes attributes with more values
    - e.g., suppose $c_1 = c_{Date} = n$ and $c_2 = 2$
    - *SplitInformation* $(A_1) = \lg(n)$, *SplitInformation* $(A_2) = 1$
    - If $Gain(D, A_1) = Gain(D, A_2)$, $GainRatio(D, A_1) \ll GainRatio(D, A_2)$
  - Thus, *preference bias* (for lower branch factor) expressed via *GainRatio*(•)

Attributes with Costs

- **Application Domains**
  - Medical: *Temperature* has cost \$10; *BloodTestResult*, \$150; *Biopsy*, \$300
    - Also need to take into account *invasiveness* of the procedure (<u>patient utility</u>)
    - Risk to patient (e.g., amniocentesis)
  - Other units of cost
    - <u>Sampling time</u>: e.g., robot sonar (range finding, etc.)
    - Risk to artifacts, organisms (about which information is being gathered)
    - Related domains (e.g., tomography): *nondestructive evaluation*
- **How to Learn A Consistent Tree with Low Expected Cost?**
  - One approach: replace gain by ***<u>Cost-Normalized-Gain</u>***
  - Examples of normalization functions
    - [Nunez, 1988]:

$$Cost\text{-}Normalized\text{-}Gain(D, A) \equiv \frac{Gain^2(D, A)}{Cost(D, A)}$$

    - [Tan and Schlimmer, 1990]:

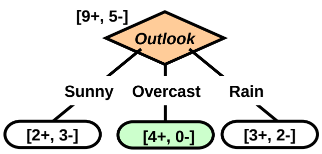
$$Cost\text{-}Normalized\text{-}Gain(D, A) \equiv \frac{2^{Gain(D, A)} - 1}{(Cost(D, A) + 1)^w} \quad w \in [0, 1]$$

where w determines importance of cost

Missing Data: Unknown Attribute Values

- **Problem: What If Some Examples Missing Values of *A*?**
  - Often, values not available for all attributes during training or testing
  - Example: medical diagnosis
    - *<Fever = true*, *Blood-Pressure = normal*, …, *Blood-Test = ?*, …>
    - Sometimes values truly unknown, sometimes low priority (or cost too high)
  - Missing values in learning versus classification
    - <u>Training</u>: evaluate *Gain* (*D*, *A*) where for some $x \in D$, a value for *A* is not given
    - <u>Testing</u>: classify a new example *x* without knowing the value of *A*
- **Solutions: Incorporating a *Guess* into Calculation of *Gain*(*D*, *A*)**

Day	Outlook	Temperature	Humidity	Wind	*PlayTennis?*
1	Sunny	Hot	High	Light	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Light	Yes
4	Rain	Mild	High	Light	Yes
5	Rain	Cool	Normal	Light	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	???	Light	No
9	Sunny	Cool	Normal	Light	Yes
10	Rain	Mild	Normal	Light	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Light	Yes
14	Rain	Mild	High	Strong	No



Terminology

- Occam's Razor and Decision Trees
  - Preference biases: captured by hypothesis space *search algorithm*
  - Language biases : captured by *hypothesis language* (search space definition)
- Overfitting
  - Overfitting: *h* does better than *h'* on training data and worse on test data
  - Prevention, avoidance, and recovery techniques
    - Prevention: attribute subset selection
    - Avoidance: stopping (termination) criteria, cross-validation, pre-pruning
    - Detection and recovery: post-pruning (reduced-error, rule)
- Other Ways to Make Decision Tree Induction More Robust
  - Inequality DTs (decision surfaces): a way to deal with continuous attributes
  - Information gain ratio: a way to normalize against many-valued attributes
  - Cost-normalized gain: a way to account for attribute costs (utilities)
  - Missing data: unknown attribute values or values not yet collected
  - Feature construction: form of constructive induction; produces new attributes
  - Replication: repeated attributes in DTs

Summary Points

- Occam's Razor and Decision Trees
  - Preference biases versus language biases
  - Two issues regarding Occam algorithms
    - Why prefer smaller trees? (less chance of "coincidence")
    - Is Occam's Razor well defined? (*yes*, under certain assumptions)
  - MDL principle and Occam's Razor: more to come
- Overfitting
  - Problem: fitting training data too closely
    - General definition of overfitting
    - Why it happens
  - Overfitting prevention, avoidance, and recovery techniques
- Other Ways to Make Decision Tree Induction More Robust
- Next Week: Perceptrons, Neural Nets (Multi-Layer Perceptrons), Winnow