Machine Learning: More ANNs, Genetic and Evolutionary Computation (GEC) Discussion: Genetic Programming

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KSOL course page: http://snipurl.com/v9v3

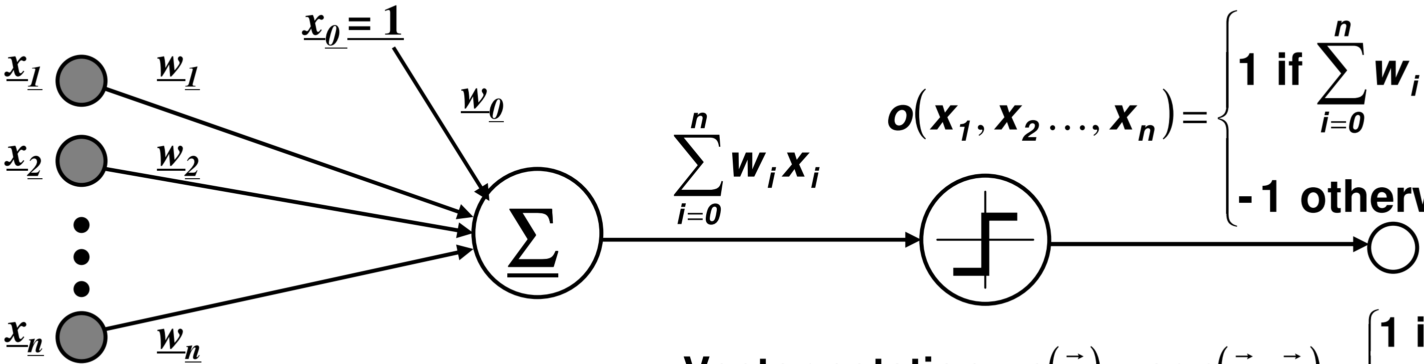
Course web site: http://www.kddresearch.org/Courses/CIS730

Instructor home page: http://www.cis.ksu.edu/~bhsu

Reading for Next Class:

Chapter 20, Russell and Norvig

The Perceptron

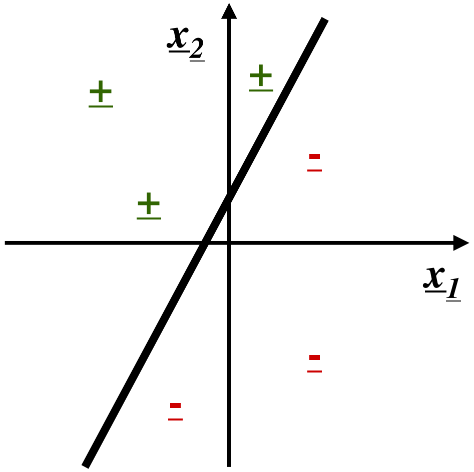


$$o(x_1, x_2 \ldots, x_n) = \begin{cases} 1 \text{ if } \sum_{i=0}^{n} w_i x_i > 0 \\ -1 \text{ otherwise} \end{cases}$$

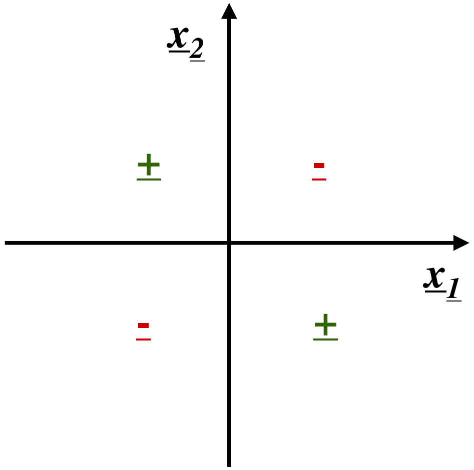
$$\textbf{Vector notation: } o(\vec{x}) = sgn(\vec{x}, \vec{w}) = \begin{cases} 1 \text{ if } \vec{w} \cdot \vec{x} > 0 \\ -1 \text{ otherwise} \end{cases}$$

- **Perceptron: Single Neuron Model**
  - *aka* Linear Threshold Unit (LTU) or Linear Threshold Gate (LTG)
  - Net input to unit: defined as linear combination $net = \sum_{i=0}^{n} w_i x_i$
  - Output of unit: threshold (activation) function on net input (threshold $\theta = w_0$)
- **Perceptron Networks**
  - Neuron is modeled using a unit connected by weighted links w_i to other units
  - Multi-Layer Perceptron (MLP): next lecture

Decision Surface of a Perceptron



Example A



Example B

- **Perceptron: Can Represent *Some* Useful Functions**
  - LTU emulation of logic gates (McCulloch and Pitts, 1943)
  - e.g., What weights represent $g(x_1, x_2) = AND(x_1, x_2)$? $OR(x_1, x_2)$? $NOT(x)$?
- **Some Functions *Not* Representable**
  - e.g., not linearly separable
  - Solution: use networks of perceptrons (LTUs)

Learning Rules for Perceptrons

- **Learning Rule ≡ Training Rule**
  - Not specific to supervised learning
  - Context: updating a model
- **Hebbian Learning Rule (Hebb, 1949)**
  - Idea: if two units are both active ("firing"), weights between them should increase
  - $w_{ij} = w_{ij} + r\, o_i\, o_j$ where r is a learning rate constant
  - Supported by neuropsychological evidence
- **Perceptron Learning Rule (Rosenblatt, 1959)**
  - Idea: when a target output value is provided for a single neuron with fixed input, it can incrementally update weights to learn to produce the output
  - Assume binary (boolean-valued) input/output units; single LTU
  - $$w_i \leftarrow w_i + \Delta w_i$$
    $$\Delta w_i = r(t - o)x_i$$
    where $t = c(x)$ is target output value, o is perceptron output, r is small learning rate constant (e.g., 0.1)
  - Can prove convergence if D linearly separable and r small enough

Perceptron Learning Algorithm

- **Simple Gradient Descent Algorithm**
  - Applicable to concept learning, symbolic learning (with proper representation)
- **Algorithm *Train-Perceptron* ($D \equiv \{<x, t(x) \equiv c(x)>\}$)**
  - Initialize all weights w_i to random values
  - WHILE not all examples correctly predicted DO

    FOR each training example $x \in D$

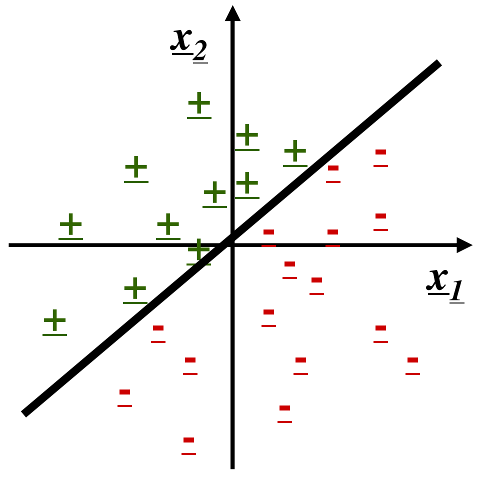
    Compute current output $o(x)$

    FOR i = 1 to n

    $w_i \leftarrow w_i + r(t - o)x_i$ // perceptron learning rule
- **Perceptron Learnability**
  - Recall: can only learn $h \in H$ - i.e., linearly separable (LS) functions
  - Minsky and Papert, 1969: demonstrated representational limitations
    - e.g., parity (n-attribute XOR: $x_1 \oplus x_2 \oplus \ldots \oplus x_n$)
    - e.g., symmetry, connectedness in visual pattern recognition
    - Influential book *Perceptrons* discouraged ANN research for ~10 years
  - NB: *\$64K question* - "Can we transform learning problems into LS ones?"

Linear Separators

- **Functional Definition**
  - $f(x) = 1$ if $w_1 x_1 + w_2 x_2 + \ldots + w_n x_n \geq \theta$, 0 otherwise
  - θ: threshold value
- **Linearly Separable Functions**
  - NB: D is LS does not necessarily imply $c(x) = f(x)$ is LS!
  - Disjunctions: $c(x) = x_1' \vee x_2' \vee \ldots \vee x_m'$
  - m of n: $c(x)$ = at least 3 of $(x_1', x_2', \ldots, x_m')$
  - Exclusive OR (XOR): $c(x) = x_1 \oplus x_2$
  - General DNF: $c(x) = T_1 \vee T_2 \vee \ldots \vee T_m$; $T_i = l_1 \wedge l_1 \wedge \ldots \wedge l_k$
- **Change of Representation Problem**
  - Can we transform non-LS problems into LS ones?
  - Is this meaningful? Practical?
  - Does it represent a significant fraction of real-world problems?



Linearly Separable (LS) Data Set

Perceptron Convergence

- **Perceptron Convergence Theorem**
  - Claim: If there exist a set of weights that are consistent with the data (i.e., the data is linearly separable), the perceptron learning algorithm will converge
  - Proof: well-founded ordering on search region ("wedge width" is strictly decreasing) - see Minsky and Papert, 11.2-11.3
  - Caveat 1: How long will this take?
  - Caveat 2: What happens if the data is *not* LS?
- **Perceptron Cycling Theorem**
  - Claim: If the training data is not LS the perceptron learning algorithm will eventually repeat the same set of weights and thereby enter an infinite loop
  - Proof: bound on number of weight changes until repetition; induction on *n*, the dimension of the training example vector - MP, 11.10
- **How to Provide More Robustness, Expressivity?**
  - Objective 1: develop algorithm that will find closest approximation (today)
  - Objective 2: develop architecture to overcome representational limitation (next lecture)

Gradient Descent: Principle

- **Understanding Gradient Descent for Linear Units**
  - **Consider simpler, unthresholded linear unit:**

$$o(\vec{x}) = net(\vec{x}) = \sum_{i=0}^{n} w_i x_i$$

  - **Objective: find "best fit" to *D***
- **Approximation Algorithm**
  - **Quantitative objective: minimize error over training data set *D***
  - **Error function: sum squared error (SSE)**

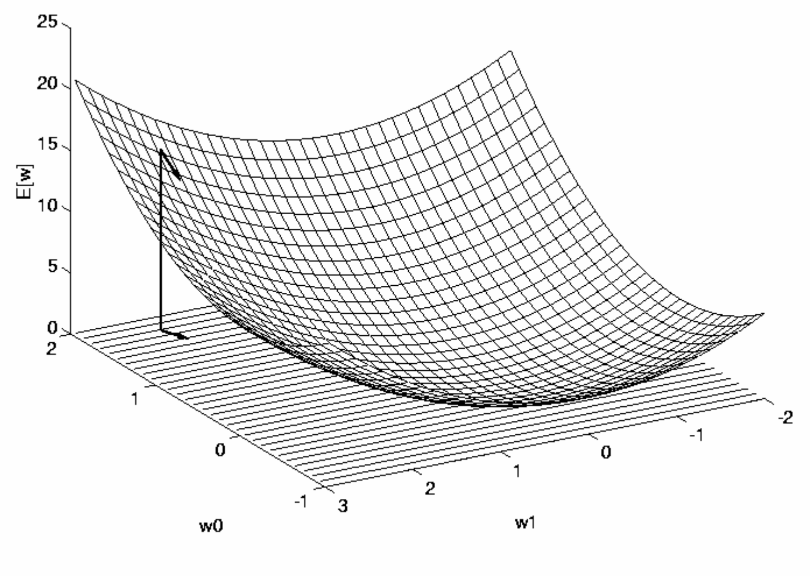
$$E[\vec{w}] = error_D[\vec{w}] = \frac{1}{2} \sum_{x \in D} (t(x) - o(x))^2$$

- **How to Minimize?**
  - **Simple optimization**
  - **Move in direction of steepest gradient in weight-error space**
    - **Computed by finding tangent**
    - **i.e. partial derivatives (of *E*) with respect to weights (w_i)**

Gradient Descent: Derivation of Delta/LMS (Widrow-Hoff) Rule

- **Definition: Gradient**

$$\nabla E[\vec{w}] \equiv \left[\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \ldots, \frac{\partial E}{\partial w_n} \right]$$



- **Modified Gradient Descent Training Rule**

$$\Delta \vec{w} = -r \nabla E[\vec{w}]$$

$$\Delta w_i = -r \frac{\partial E}{\partial w_i}$$

$$\frac{\partial E}{\partial w_i} = \frac{\partial}{\partial w_i} \left[\frac{1}{2} \sum_{x \in D} (t(x) - o(x))^2 \right] = \frac{1}{2} \sum_{x \in D} \left[\frac{\partial}{\partial w_i} (t(x) - o(x))^2 \right]$$

$$= \frac{1}{2} \sum_{x \in D} \left[2(t(x) - o(x)) \frac{\partial}{\partial w_i} (t(x) - o(x)) \right] = \sum_{x \in D} \left[(t(x) - o(x)) \frac{\partial}{\partial w_i} (t(x) - \vec{w} \cdot \vec{x}) \right]$$

$$\frac{\partial E}{\partial w_i} = \sum_{x \in D} [(t(x) - o(x))(-x_i)]$$

Gradient Descent: Algorithm using Delta/LMS Rule

- **Algorithm *Gradient-Descent* (*D*, *r*)**
  - Each training example is a pair of the form <x, $t(x)$>, where x is the vector of input values and $t(x)$ is the output value. r is the learning rate (e.g., 0.05)
  - Initialize all weights w_i to (small) random values
  - UNTIL the termination condition is met, DO

    Initialize each Δw_i to zero

    FOR each <x, $t(x)$> in D, DO

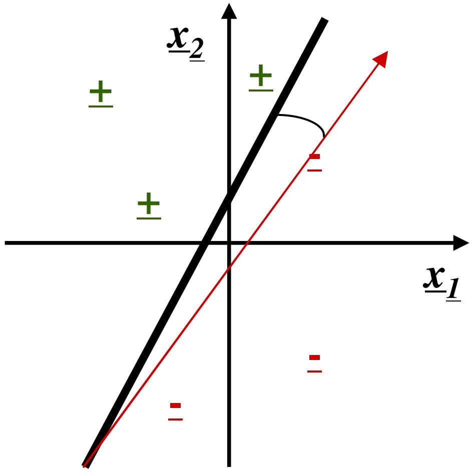
    Input the instance x to the unit and compute the output o

    FOR each linear unit weight w_i, DO

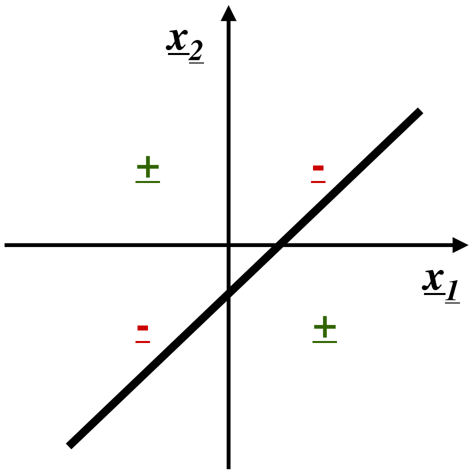
    $\Delta w_i \leftarrow \Delta w_i + r(t - o)x_i$

    $w_i \leftarrow w_i + \Delta w_i$
  - RETURN final w
- **Mechanics of Delta Rule**
  - Gradient is based on a derivative
  - Significance: later, will use nonlinear activation functions (*aka* transfer functions, squashing functions)

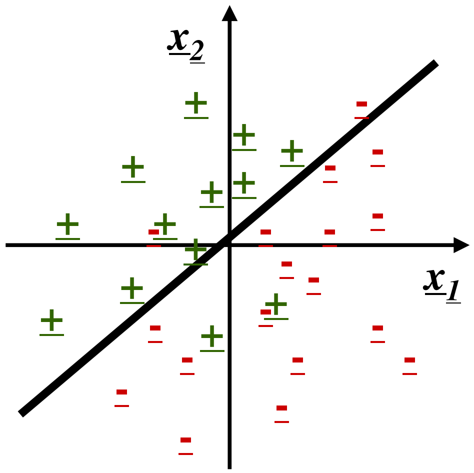
Gradient Descent:
Perceptron Rule versus Delta/LMS Rule



Example A



Example B



Example C

- **LS Concepts: Can Achieve Perfect Classification**
  - **Example A: perceptron training rule converges**
- **Non-LS Concepts: Can Only Approximate**
  - **Example B: not LS; delta rule converges, but can't do better than 3 correct**
  - **Example C: not LS; better results from delta rule**
- **Weight Vector *w* = Sum of Misclassified *x* ∈ *D***
  - **Perceptron: minimize *w***
  - **Delta Rule: minimize *error* ≡ distance from separator (I.e., maximize $\frac{\partial E}{\partial \vec{w}}$)**

Review: Backprop, Feedforward

- **Intuitive Idea: Distribute *Blame* for Error to Previous Layers**
- **Algorithm *Train-by-Backprop* (*D*, *r*)**
  - **Each training example is a pair of the form <*x*, *t*(*x*)>, where x is the vector of input values and *t*(*x*) is the output value. *r* is the learning rate (e.g., 0.05)**
  - **Initialize all weights w_i to (small) random values**
  - **UNTIL the termination condition is met, DO**

    FOR each <*x*, *t*(*x*)> in *D*, DO

    Input the instance *x* to the unit and compute the output $o(x) = \sigma(net(x))$

    FOR each output unit *k*, DO

    $$\delta_k = o_k(x)(1 - o_k(x))(t_k(x) - o_k(x))$$

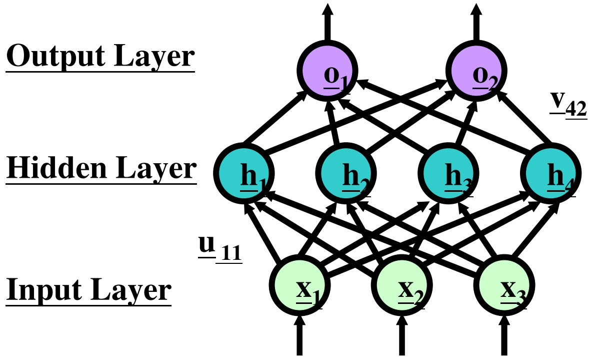
    FOR each hidden unit *j*, DO

    $$\delta_j = h_j(x)(1 - h_j(x)) \sum_{k \in outputs} v_{j,k}\delta_j$$

    Update each $w = u_{i,j}$ ($a = h_j$) or $w = v_{j,k}$ ($a = o_k$)

    $$w_{start\text{-}layer,\ end\text{-}layer} \leftarrow w_{start\text{-}layer,\ end\text{-}layer} + \Delta w_{start\text{-}layer,\ end\text{-}layer}$$

    $$\Delta w_{start\text{-}layer,\ end\text{-}layer} \leftarrow r\, \delta_{end\text{-}layer}\, a_{end\text{-}layer}$$
  - **RETURN final *u*, *v***



Review: Derivation of Backprop

- **Recall: Gradient of Error Function**

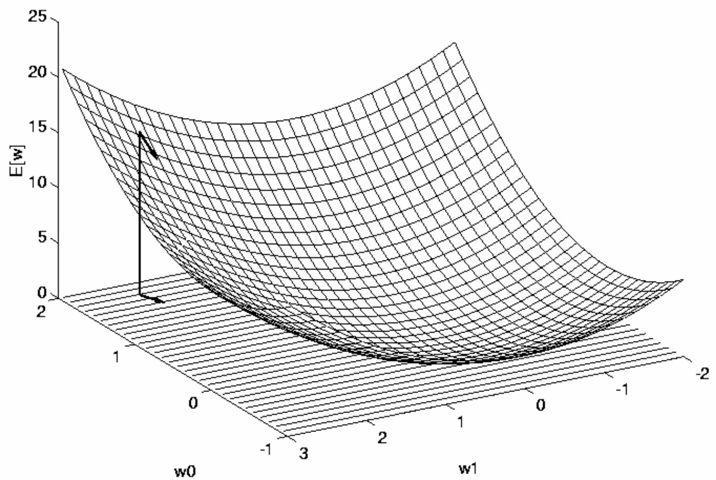
$$\nabla E[\vec{w}] \equiv \left[\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \ldots, \frac{\partial E}{\partial w_n}\right]$$

- **Gradient of Sigmoid Activation Function**

$$\frac{\partial E}{\partial w_i} = \frac{\partial}{\partial w_i}\left[\frac{1}{2}\sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left(t(\vec{x}) - o(\vec{x})\right)^2\right] = \frac{1}{2}\sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left[\frac{\partial}{\partial w_i}\left(t(\vec{x}) - o(\vec{x})\right)^2\right]$$

$$= \frac{1}{2}\sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left[2\left(t(\vec{x}) - o(\vec{x})\right)\frac{\partial}{\partial w_i}\left(t(\vec{x}) - o(\vec{x})\right)\right] = \sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left[\left(t(\vec{x}) - o(\vec{x})\right)\left(-\frac{\partial o(\vec{x})}{\partial w_i}\right)\right]$$

$$= -\sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left[\left(t(\vec{x}) - o(\vec{x})\right)\frac{\partial o(\vec{x})}{\partial net(\vec{x})}\frac{\partial net(\vec{x})}{\partial w_i}\right]$$



- **But We Know:**

$$\frac{\partial o(\vec{x})}{\partial net(\vec{x})} = \frac{\partial \sigma(net(\vec{x}))}{\partial net(\vec{x})} = o(\vec{x})\left(1 - o(\vec{x})\right)$$

$$\frac{\partial net(\vec{x})}{\partial w_i} = \frac{\partial(\vec{w} \cdot \vec{x})}{\partial w_i} = x_i$$

- **So:**

$$\frac{\partial E}{\partial w_i} = -\sum_{\langle \vec{x}, t(\vec{x})\rangle \in D}\left[\left(t(\vec{x}) - o(\vec{x})\right) \cdot \left(o(\vec{x})\left(1 - o(\vec{x})\right)\right) \cdot x_i\right]$$

Simple Genetic Algorithm (SGA)

- **Algorithm *Simple-Genetic-Algorithm* (*Fitness*, *Fitness-Threshold*, *p*, *r*, *m*)**

  // *p*: population size; *r*: replacement rate (*aka* generation gap width), *m*: string size

  - $P \leftarrow p$ random hypotheses // initialize population
  - FOR each *h* in *P* DO $f[h] \leftarrow Fitness(h)$ // evaluate *Fitness*: *hypothesis* $\rightarrow \mathbb{R}$
  - WHILE (*Max*(*f*) < *Fitness-Threshold*) DO
    - 1. Select: Probabilistically select $(1 - r)p$ members of *P* to add to P_S

$$P(h_i) = \frac{f[h_i]}{\sum_{j=1}^{p} f[h_j]}$$

    - 2. Crossover:
      - Probabilistically select $(r \cdot p)/2$ pairs of hypotheses from *P*
      - FOR each pair $<h_1, h_2>$ DO

        P_S += *Crossover* $(<h_1, h_2>)$ // $P_S[t+1] = P_S[t] + <offspring_1, offspring_2>$
    - 3. Mutate: Invert a randomly selected bit in $m \cdot p$ random members of P_S
    - 4. Update: $P \leftarrow P_S$
    - 5. Evaluate: FOR each *h* in *P* DO $f[h] \leftarrow Fitness(h)$
  - RETURN the hypothesis *h* in *P* that has maximum fitness $f[h]$

GA-Based Inductive Learning (*GABIL*)

- GABIL System [Dejong *et al*, 1993]
  - Given: concept learning problem and examples
  - Learn: disjunctive set of propositional rules
  - Goal: results competitive with those for current decision tree learning algorithms (e.g., C4.5)
- Fitness Function: $Fitness(h) = (Correct(h))^2$
- Representation
  - Rules: IF $a_1 = T \wedge a_2 = F$ THEN $c = T$; IF $a_2 = T$ THEN $c = F$
  - Bit string encoding: a_1 [10] . a_2 [01] . c [1] . a_1 [11] . a_2 [10] . c [0] = 10011 11100
- Genetic Operators
  - Want variable-length rule sets
  - Want only well-formed bit string hypotheses

CROSSOVER: VARIABLE-LENGTH BIT STRINGS

- Basic Representation
  - Start with

	a_1	a_2	c	a_1	a_2	c
h_1	1[0	01	1	11	1]0	0
h_2	0[1	1]1	0	10	01	0

  - Idea: allow crossover to produce variable-length offspring
- Procedure
  - 1. Choose crossover points for h_1, e.g., after bits 1, 8
  - 2. Now restrict crossover points in h_2 to those that produce bitstrings with well-defined semantics, e.g., <1, 3>, <1, 8>, <6, 8>
- Example
  - Suppose we choose <1, 3>
  - Result

h_3	11	10	0						
h_4	00	01	1	11	11	0	10	01	0

GABIL Extensions

- New Genetic Operators
  - Applied probabilistically
  - 1. *<u>A</u>dd<u>A</u>lternative*: generalize constraint on a_i by changing a 0 to a 1
  - 2. *<u>D</u>rop<u>C</u>ondition*: generalize constraint on a_i by changing <u>every</u> 0 to a 1
- New Field
  - Add fields to bit string to decide whether to allow the above operators

a_1	a_2	c
01	11	0

a_1	a_2	c	<u>*AA*</u>	<u>*DC*</u>
10	01	0	1	0

  - So now the learning strategy also evolves!
  - *aka* <u>genetic wrapper</u>

GABIL Results

- Classification Accuracy
  - Compared to symbolic rule/tree learning methods
    - *C4.5* [Quinlan, 1993]
    - *ID5R*
    - *AQ14* [Michalski, 1986]
  - Performance of *GABIL* comparable
    - Average performance on a set of 12 synthetic problems: 92.1% test accuracy
    - Symbolic learning methods ranged from 91.2% to 96.6%
- Effect of Generalization Operators
  - Result above is for *GABIL* without *AA* and *DC*
  - Average test set accuracy on 12 synthetic problems with *AA* and *DC*: 95.2%

Building Blocks (Schemas)

- Problem
  - How to characterize evolution of population in GA?
  - Goal
    - ⇨ Identify basic building block of GAs
    - ⇨ Describe *family of individuals*
- Definition: <u>Schema</u>
  - String containing 0, 1, * ("don't care")
  - Typical schema: 10**0*
  - Instances of above schema: 101101, 100000, …
- Solution Approach
  - Characterize population by number of instances representing each possible schema
  - $m(s, t) \equiv$ number of instances of schema s in population at time t

Selection and Building Blocks

- Restricted Case: Selection Only
  - $\bar{f}(t)$ ≡ average fitness of population at time *t*
  - $m(s, t)$ ≡ number of instances of schema *s* in population at time *t*
  - $\hat{u}(s, t)$ ≡ average fitness of instances of schema *s* at time *t*
- Quantities of Interest
  - Probability of selecting *h* in one selection step
    $$P(h) = \frac{f(h)}{\sum_{i=1}^{n} f(h_i)}$$
  - Probability of selecting an instance of *s* in one selection step
    $$P(h \in s) = \sum_{h \in (s \cap p_t)} \frac{f(h)}{n \cdot \bar{f}(t)} = \frac{\hat{u}(s, t)}{n \cdot \bar{f}(t)} m(s, t)$$
  - Expected number of instances of *s* after *n* selections
    $$E[m(s, t+1)] = \frac{\hat{u}(s, t)}{\bar{f}(t)} \cdot m(s, t)$$

Schema Theorem

- Theorem

$$E[m(s,t+1)] \geq \frac{\hat{u}(s,t)}{\bar{f}(t)} \cdot m(s,t) \cdot \left(1 - p_c \frac{d_s}{l-1}\right) \cdot (1 - p_m)^{o(s)}$$

  - $m(s, t)$ ≡ number of instances of schema *s* in population at time *t*
  - $\bar{f}(t)$ ≡ average fitness of population at time *t*
  - $\hat{u}(s, t)$ ≡ average fitness of instances of schema *s* at time *t*
  - p_c ≡ probability of single point crossover operator
  - p_m ≡ probability of mutation operator
  - l ≡ length of individual bit strings
  - $o(s)$ ≡ number of defined (non "*") bits in *s*
  - $d(s)$ ≡ distance between rightmost, leftmost defined bits in *s*
- Intuitive Meaning
  - "The expected number of instances of a schema in the population tends toward its relative fitness"
  - A fundamental theorem of GA analysis and design

Terminology

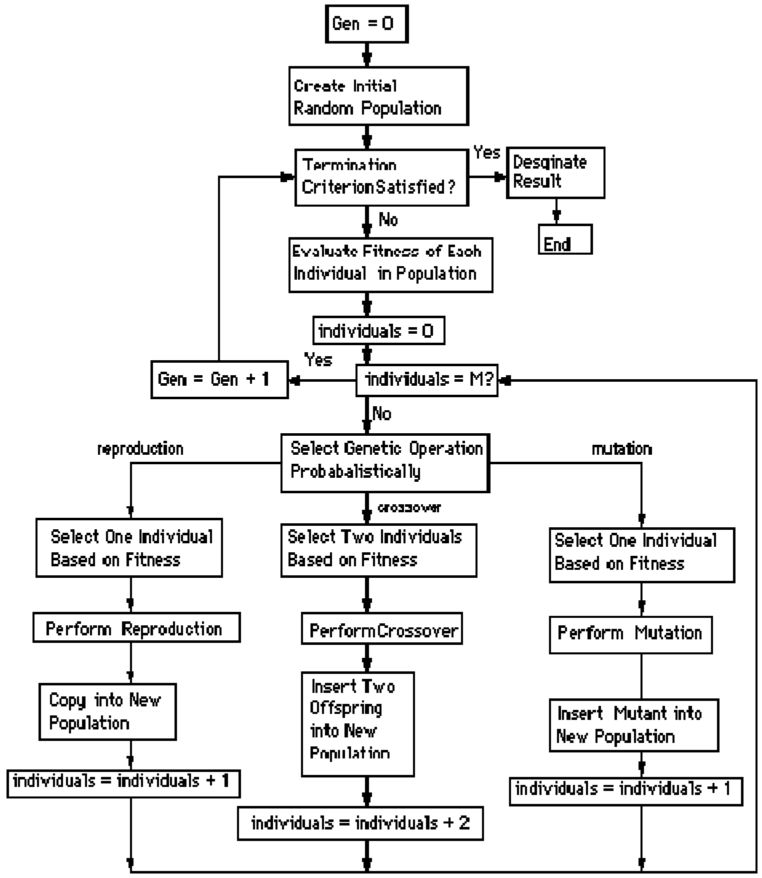
- Evolutionary Computation (EC): Models Based on Natural Selection
- Genetic Algorithm (GA) Concepts
  - Individual: single entity of model (corresponds to hypothesis)
  - Population: collection of entities in competition for survival
  - Generation: single application of selection and crossover operations
  - Schema *aka* building block: descriptor of GA population (e.g., 10**0*)
  - Schema theorem: *representation of schema proportional to its relative fitness*
- Simple Genetic Algorithm (SGA) Steps
  - Selection
    - Proportionate reproduction (*aka* roulette wheel): $P(individual) \propto f(individual)$
    - Tournament: let individuals compete in pairs or tuples; eliminate unfit ones
  - Crossover
    - Single-point: 11101001000 × 00001010101 → { 11101010101, 00001001000 }
    - Two-point: 11101001000 × 00001010101 → { 11001011000, 00101000101 }
    - Uniform: 11101001000 × 00001010101 → { 10001000100, 01101011001 }
  - Mutation: single-point ("bit flip"), multi-point

Lecture Outline

- Readings / Viewings
  - View GP videos 1-3
    - GP1 – *Genetic Programming: The Video*
    - GP2 – *Genetic Programming: The Next Generation*
    - GP3 – *Genetic Programming: Human-Competitive*
  - Suggested: Chapters 1-5, Koza
- Previously
  - Genetic and evolutionary computation (GEC)
  - Generational vs. steady-state GAs; relation to simulated annealing, MCMC
  - Schema theory and GA engineering overview
- Today: GP Discussions
  - Code bloat and potential mitigants: types, OOP, parsimony, optimization, reuse
  - Genetic programming vs. human programming: similarities, differences
- Thursday: Course Review

GP Flow Graph

Flowchart for Genetic Programming



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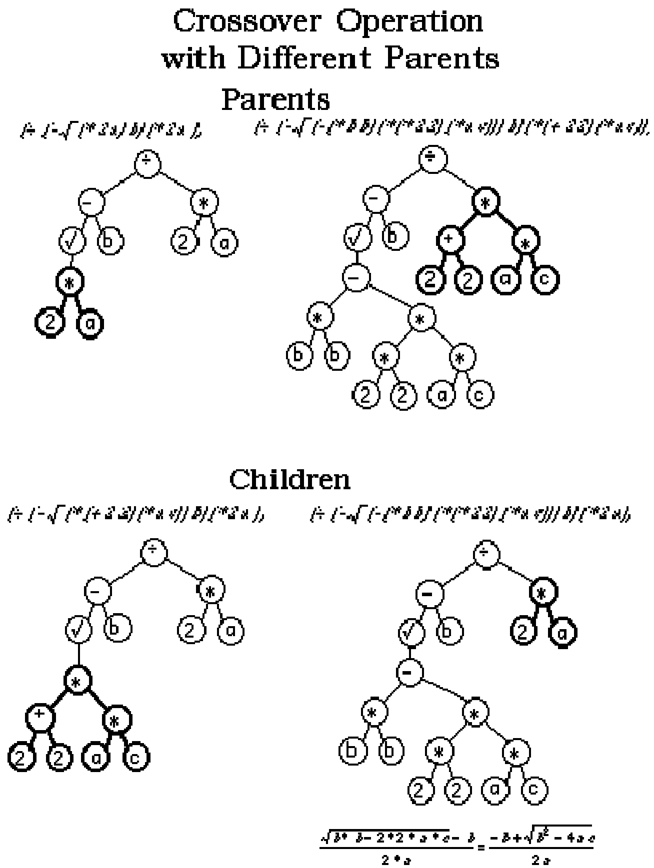
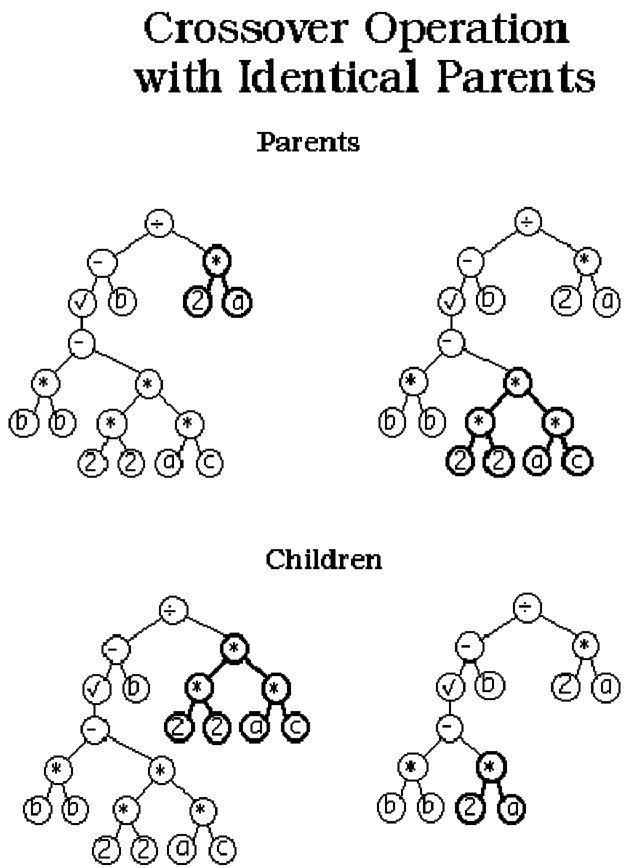
http://www.geneticprogramming.com

Structural Crossover





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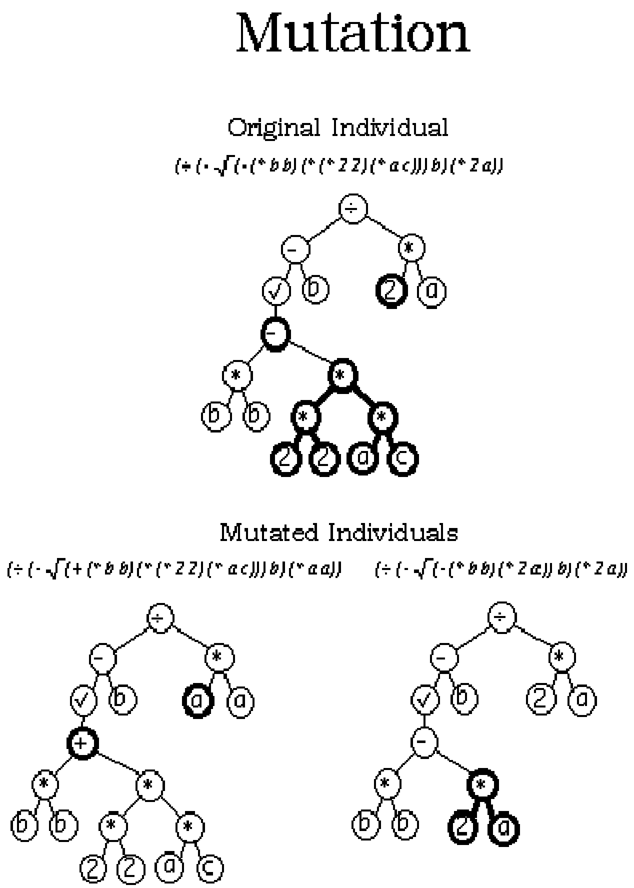
Structural Mutation



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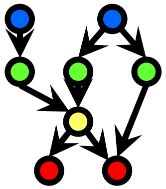

Genetic Programming: The Next Generation (Synopsis and Discussion)

- Automatically-Defined Functions (ADFs)
  - *aka* macros, anonymous inline functions, subroutines
  - Basic method of software reuse
- Questions for Discussion
  - *What are advantages, disadvantages of learning anonymous functions?*
  - *How are GP ADFs similar to and different from human-produced functions?*
- Exploiting Advantages
  - Reuse
  - Innovation
- Mitigating Disadvantages
  - Potential lack of meaning – semantic clarity issue (and topic of debate)
  - Redundancy
  - Accelerated bloat – scalability issue

Code Bloat [1]: Problem Definition

- Definition
  - Increase in program size not commensurate with increase in functionality (possibly as function of problem size)
  - Compare: structural criteria for overfitting, overtraining
- Scalability Issue
  - Large GPs will have this problem
  - Discussion: *When do we expect large GPs?*
  - Machine learning: large, complex data sets
  - Optimization, control, decision making / DSS: complex problem
- What Does It Look Like?
- What Can We Do About It?
  - ADFs
  - Advanced reuse techniques from software engineering: e.g., design patterns
  - Functional, object-oriented design; theory of types
  - Controlling size: parsimony (MDL-like), optimization (cf. compiler)

Code Bloat [2]: Mitigants

- Automatically Defined Functions
- Types
  - Ensure
    - Compatibility of functions created
    - Soundness of functions themselves
  - Define: abstract data types (ADTs) – object-oriented programming
  - Behavioral subtyping – still “future work” in GP
  - Generics (cf. C++ templates)
  - Polymorphism
- Advanced Reuse Techniques
  - Design patterns
  - Workflow models
  - Inheritance, reusable classes

Code Bloat [3]: More Mitigants

- Parsimony (cf. Minimum Description Length)
  - Penalize code bloat
  - Inverse fitness = loss + cost of code (evaluation)
  - May include terminals
- Target Language Optimization
  - Rewriting of constants
  - Memoization
  - Loop unrolling
  - Loop-invariant code motion

GENETIC PROGRAMMING 3 (SYNOPSIS AND DISCUSSION [1])

- **16 Criteria for Automatic Program Synthesis by Computational Intelligence**
  - **1. Specification: starts with *what needs to be done***
  - **2. Procedural representation: tells us how to do it**
  - **3. Algorithm implementation: produces a computer program**
  - **4. Automatic determination of program size**
  - **5. Code reuse**
  - **6. Parametric reuse**
  - **7. Internal storage**
  - **8. Iteration (while / for), recursion**
  - **9. Self-organization of hierarchies**
  - **10. Automatic determination of architecture**
  - **11. Wide range of programming constructs**
  - **12. Well-defined**
  - **13. Problem independent**

Genetic Programming 3 (Synopsis and Discussion [2])

- 16 Criteria for Automatic Program Synthesis …
  - 14. Generalization: wide applicability
  - 15. Scalability
  - 16. Human-competitiveness
- Current Bugbears: Generalization, *Scalability*
- Discussion: Human Competitiveness?

More Food for Thought and Research Resources

- Discussion: Future of GP
- Current Applications
- Conferences
  - *GECCO: ICGA + ICEC + GP*
  - *GEC*
  - *EuroGP*
- Journals
  - *Evolutionary Computation Journal (ECJ)*
  - *Genetic Programming and Evolvable Machines (GPEM)*