PCG: Search Revisited, Evolution, and More

2019-10-30

Satisficing is a decision-making strategy or cognitive heuristic that entails **searching through the available alternatives until an acceptability threshold is met.**[1] The term *satisficing*, a combination of *satisfy* and *suffice*,[2] was introduced by Herbert A. Simon in 1956,[3] although the concept was first posited in his 1947 book *Administrative Behavior*.[4][5] Simon used satisficing to explain the behavior of **decision makers under circumstances in which an optimal solution cannot be determined**. He maintained that many natural problems are characterized by computational intractability or a lack of information, both of which preclude the use of mathematical optimization procedures. He observed in his Nobel Prize in Economics speech that "decision makers can satisfice either by **finding optimum solutions for a simplified world, or by finding satisfactory solutions for a more realistic world**. Neither approach, in general, dominates the other, and both have continued to co-exist in the world of management science".

https://en.wikipedia.org/wiki/Satisficing

N-1: PCG intro

1. PCG can be used to p_____ or a_____ game aspects
2. What are some reasons to use PCG?
3. What are some risks / concerns of PCG?
4. Design-time vs run-time PCG?
5. How does the use of a random seed in PCG effect development and gameplay?
6. What is flow theory? How does it relate to dynamic difficulty adjustment & drama management?
7. How do you know you are generating something interesting?

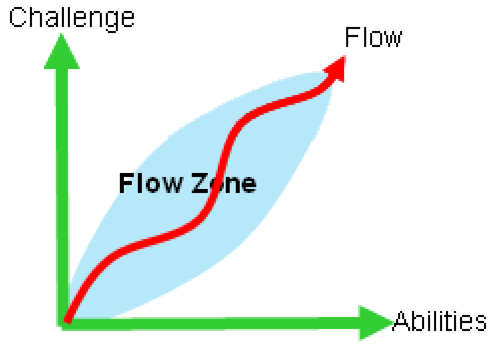


Figure 2 Player in-game Flow experience

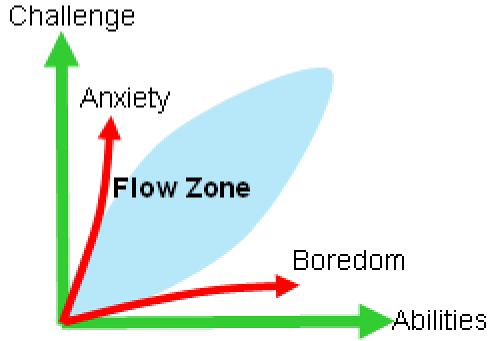


Figure 3 Player encounters psychic entropies

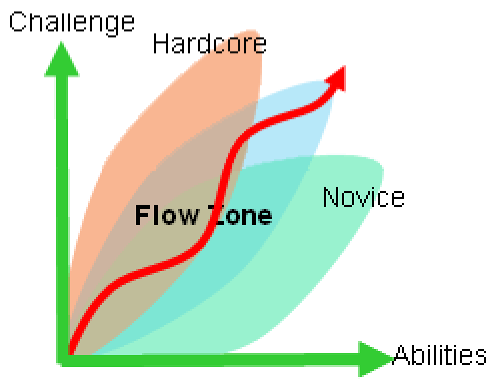


Figure 4 Different players and Flow Zones

http://jenovachen.com/flowingames/designfig.htm

Quick Review: PCG

- Three categories of content to be generated
  - Game bits
  - Game spaces
  - Game scenarios
- Three categories of methods
  - Rule systems
  - Generative grammars
  - Search
  - Constraint solving

Two Major Ways to use PCG

- Runtime PCG: customization, dynamic adjustment, replayability
  - Generate content live in game (No Man’s Sky, Spelunky, Minecraft, Horizon Zero Dawn, etc)

- Offline/Design-time/Developer PCG: Speed up design of static content
  - generate, pick best, and save content
  - generate then edit
  - generate and incorporate (Speedtree)

Create types of game experiences impossible without PCG

Why use PCG?

- Reducing cost of creating content?
  - Yes, when clever (SpeedTree), but can add complications (Mass Effect Andromeda)
  - Exponentially increasing costs (levels, maps, missions, etc.)
- CONTENT IS KING
  - If its interesting/personal/exciting to the player (Borderlands 2 guns), not if its bland oatmeal (No Man's Sky)
  - Computed content saves:
    - development costs
    - Storage and/or main memory
- Keep player playing/replaying
  - Adapting to player (Left4Dead AI director), new every time (Spelunky), or subarea (Bloodborne Chalice Dungeons)

PCG Concerns

Efficiency and Reliability tend to be a core concern.

- Speed (real-time/design time)
- Reliability (catastrophic failures/crashes)
- Controllability (wrt constraints and goals)
- Diversity (variations on a theme)
- Creativity (looks “computer-generated”)

How do you know you are generating something interesting?

Run time PCG

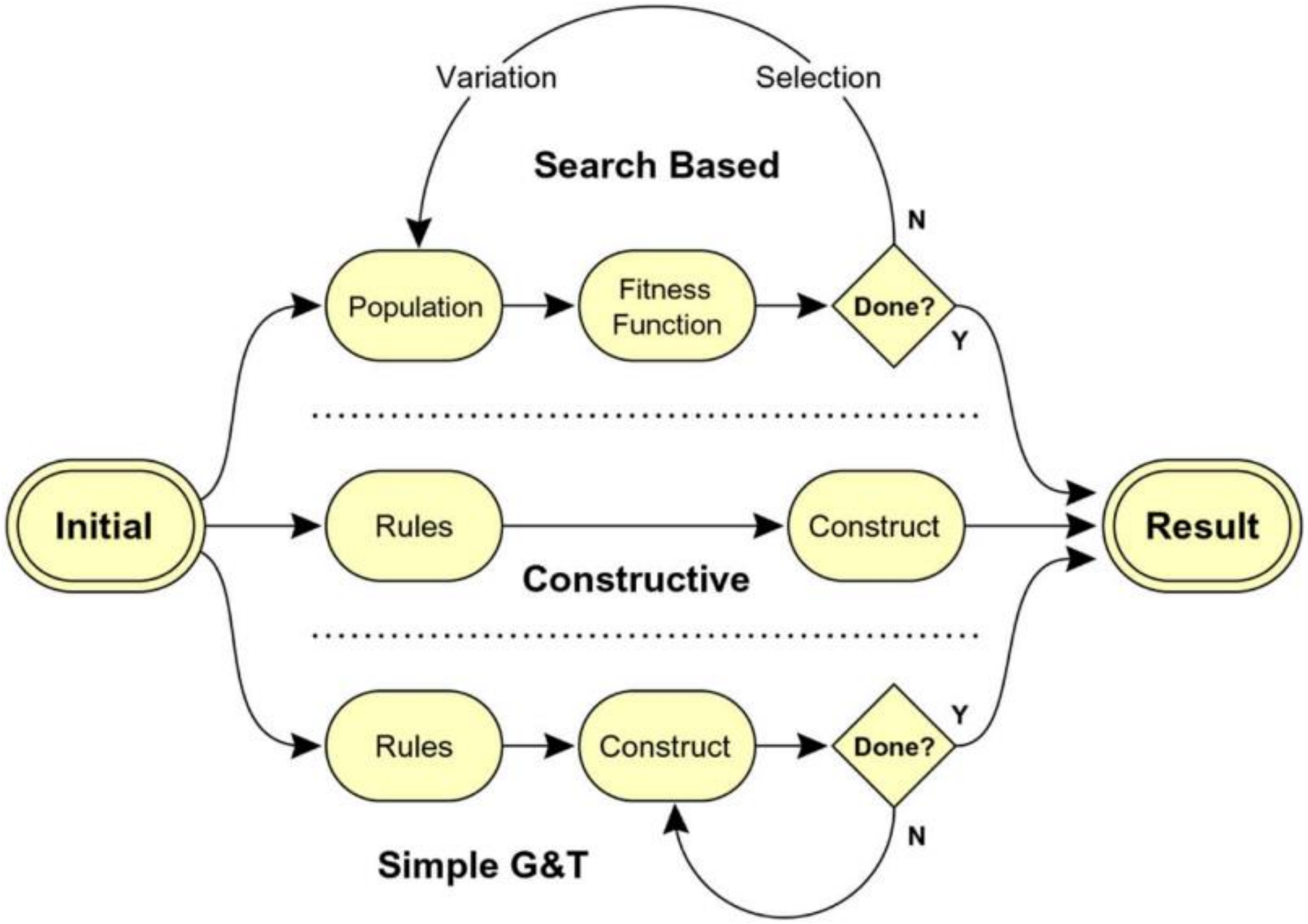
- Players are different: Preferences for pace and playstyle
  - Moderate challenge levels
  - Help avoid getting stuck
  - Adapt to player’s tastes
  - Detecting player exploits
- When to use run-time PCG
  - When decisions can only be made at run-time
  - When you just can’t pre-compute due to storage/memory limits
- Optimization problem
  - What is the set of content that delivers the optimal experience to the player given individual differences?
  - Example: rubber banding

Risks

- PCG can be NP-hard for anything non-trivial
  - But you can’t always make players wait
- Thorough testing of run-time PCG is impossible
  - Best you can do is statistical sampling
- Offensive material
- Bad content
- Algorithm crash
- Meaningless activities
  - Easy to create quests, but if they don’t connect to the larger game, no one cares

PCG high-level Methods

- Search
- Rule systems
- Generative Grammars
- Constraint Solving



https://course.ccs.neu.edu/cs5150f13/readings/togelius_sbpcg.pdf

PCG as Parameter Search

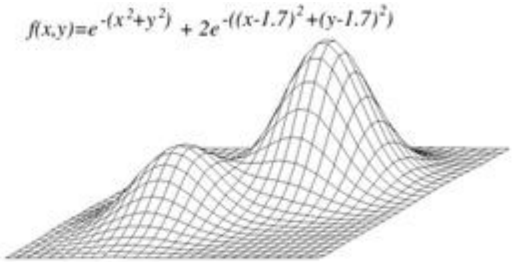
SEARCH-BASED OPTIMIZATION

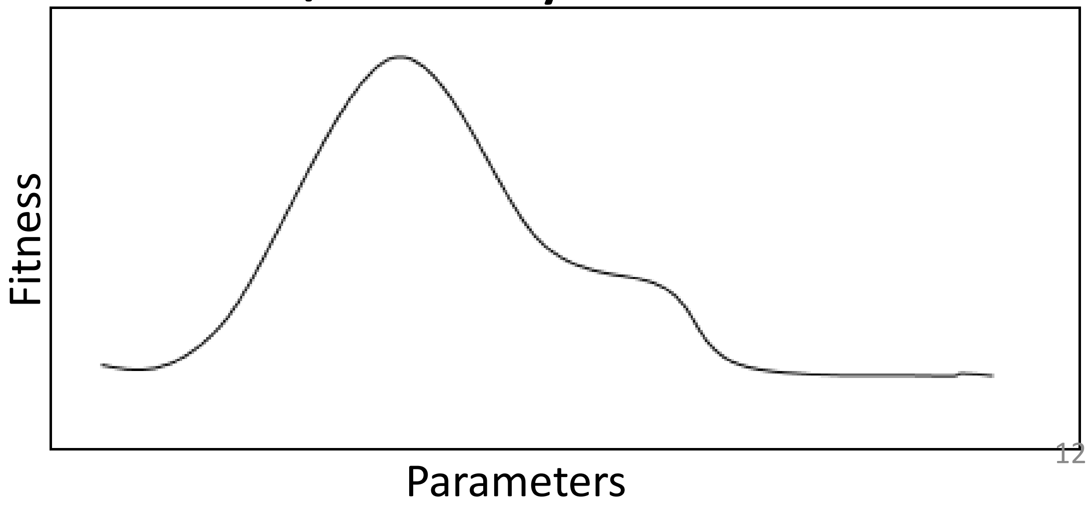
Search-based PCG

- What if we could just give the system a general idea of what we wanted and have it “find” us the answer?
  - From some generated element we can get to “neighbors”, which allows us to define a space
  - The quality of any element can be derived by a heuristic to get some value
- Search! But what is our heuristic?
  - Hill Climbing
  - Simulated Annealing
  - Genetic Algorithms

Start Simple

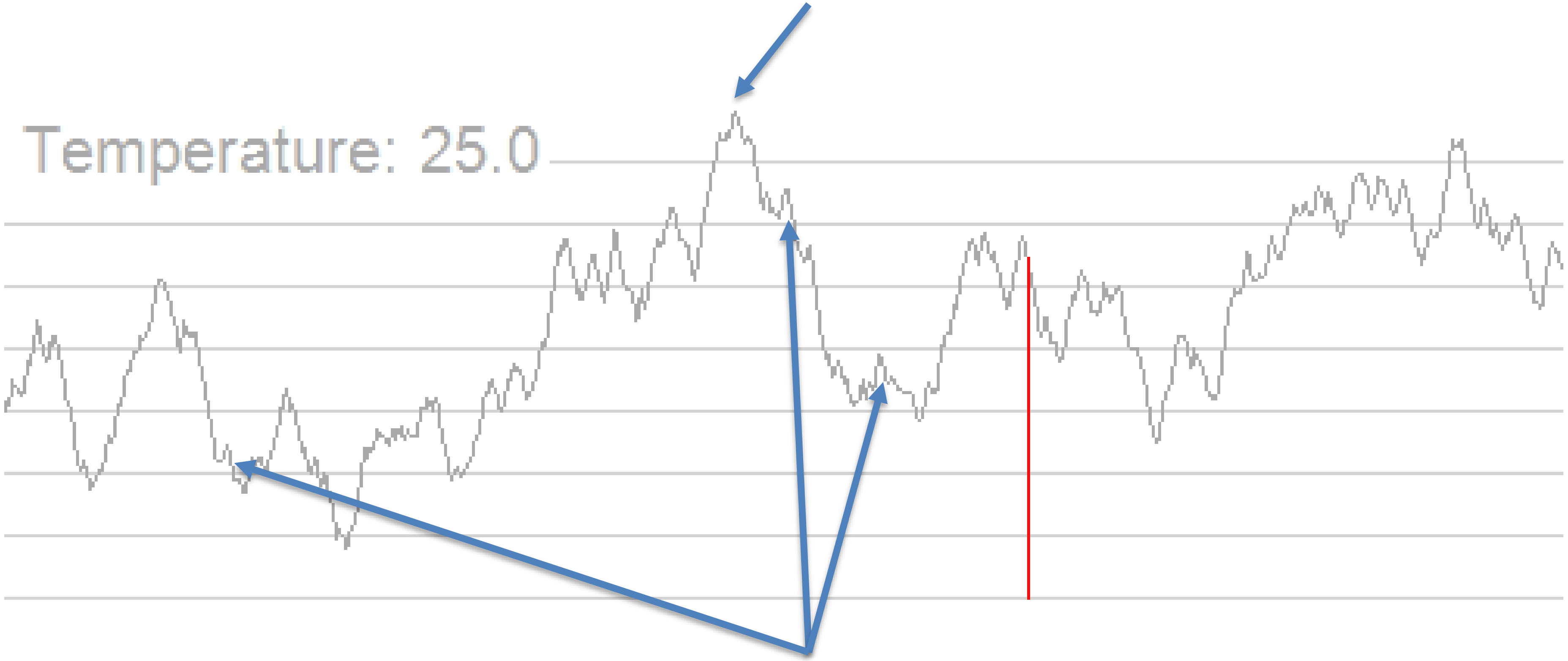
- Magic numbers are everywhere
  - Steering behavior parameters, tactical weights, decision making probabilities, …
- Search over the parameter/configuration space
  - Find/calculate value of 1+ parameters
  - Aim: find best values of parameter/configuration
- Graph: Parameters/Configuration vs Fitness/Quality
  - “landscape”
  - Energy vs fitness
- Assume f(params) → fitness





Types of Maxima

Global Maximum: A point better than all other points



Local Maxima: A point better than all its neighbors

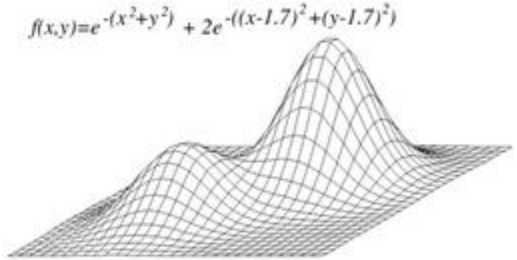
PCG AS PARAMETER SEARCH: HILL CLIMBING

Hill Climbing

- Hill climbing attempts to maximize (or minimize) a target function f(x), where x is a vector of continuous and/or discrete values (parameters)
  - Does not require target function to be differentiable
  - Assume fixed step size
- General approach:
  - From random start point
  - Generate 1 or more neighbors/successors
    - Simple (first) vs Steepest Ascent (best) vs Stochastic (random)
  - Pick the best neighbor (equivalent to greedy/best-first search)

Hill Climbing

- Amounts to guess, check, modify parameter value, check…
  - Stop when improvement stops
  - Achieves optimal solutions in convex problems
  - Simple, fast, can give good results
- Problems?
  - Locality: equivalent to greedy/best-first search
  - In non-convex problems finds local maximum
  - Plateaus and (non-axis-aligned) Ridges

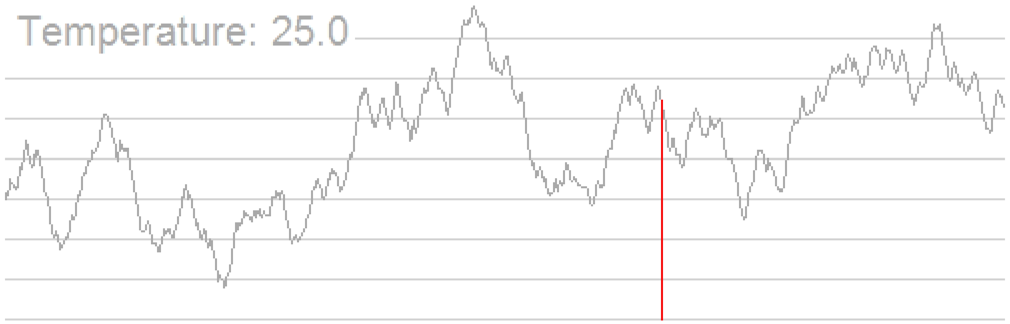


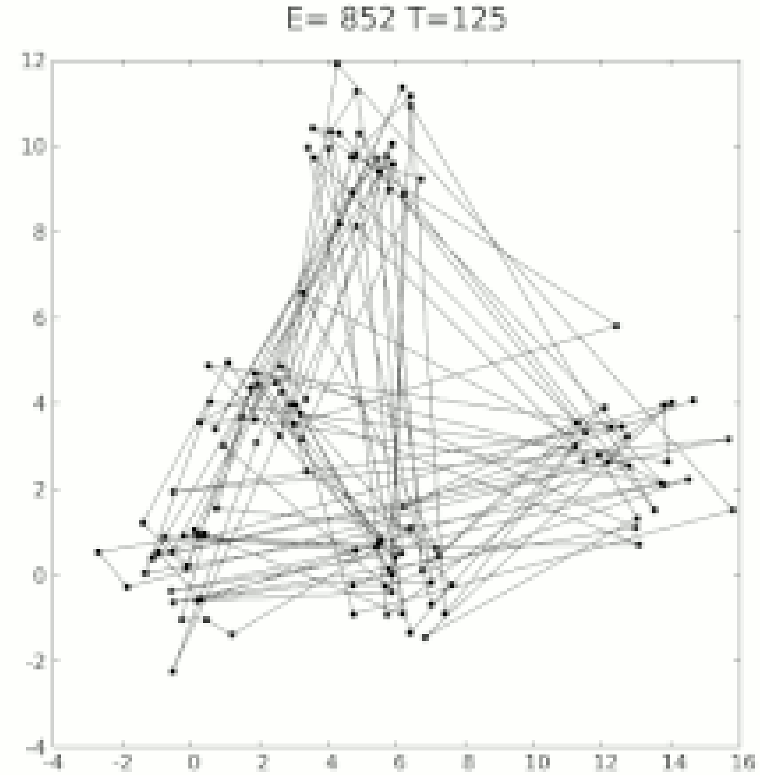
Extensions to Hill Climbing

- Local (sub)optimality, search gets “stuck”
  - The more local maxima, more difficult to solve
  - At worst, fitness is random/not correlated to nearby values
  - Step back. Is goal to find “optimal”? “Satisficing”
- Fixes
  - Momentum (record prev score improvements)
  - Adaptive resolution (think granularity)
  - Multiple trials (initial guesses)
  - Annealing (add term to rep temperature)

Simulated Annealing

- Find approximate to the global optimum
- Inspired by annealing in metallurgy
  - slow cooling interpreted as slow decrease in probability of accepting worse solutions
  - Exploration vs Exploitation
- Pick a neighbor based on the some probability *T* (based on how long the algorithm has been running) and the quality of that neighbor





Simulated Annealing

```
state= randomly choose a state

for k = 0 through maxTimeSteps:
        T = calculateTemperature(1- k/maxTimeSteps)
        newState = randomSelect(neighbors(state))
        if P(E(state), E(newState), T)>=random(0,1):
                state = newState
return state
```

* Also keep track of best sample seen so far in case final state is not as good

Acceptance Probability Function: probability of transitioning from state to newstate based on their energies and current temperature

Simulated Annealing

- Can give good results!
- Highly dependent on the temperature function, which is domain (and even problem) dependent
- Restarts can be useful: sometimes better to move back rather than always moving from the current state
- At worst it is basically random search, with all those associated fallbacks

PCG AS PARAMETER SEARCH:
GENETIC & EVOLUTIONARY ALGORITHMS

Video Examples

- Evolving Virtual Creatures (Karl Sims)
- Evolving muscle-based bipedal locomotion
- Evolving Faces
- Evolving Artificial Creatures
- Killer Fish

Genetic Algorithms

- Loosely inspired by Darwin's Theory of Evolution
- Sometimes called "Evolutionary search"
- Consistently pretty popular (if only for the tagline "evolving artificial intelligence to solve…")

GA Applications

- Applications anywhere with a large search domain
  - Especially where traditional search or optimization would be slow
- Useful when:
  - Domain knowledge is scarce
  - Hard to encode expert knowledge
  - No mathematical analysis available
- Best used offline
- See also list of applications: https://en.wikipedia.org/wiki/List_of_genetic_algorithm_applications

Genetic Algorithm Pseudocode (variants)

population = set of random points of size *X*

time = 0

while E(population)<*threshold* and time<max:

    time ++

    Mutate(population)

    population = **Crossover**(population)

    population = **Reduce**(population)

return bestE(population)

GA Pseudocode cont

- **Mutate**: Given some probability, randomly replace a member of the population with a neighbor
  - Make a random change
- **Crossover/recombination**: Take pairs of the initial population (chosen based on fitness), and combine their features randomly till population grows up to size *Y* (where *X*<*Y*)
- **Reduce**: Reduce the size of the population back down to *X*

Genetic Algorithms

- Mutate amounts to Exploration (global neighborhood)
  - Only mutation will mean the program is randomly guessing and could run indefinitely
  - Breadth-first
- Crossover amounts to Exploitation (local neighborhood)
  - Only crossover will mean that the program is more likely to get stuck at a local optimum
  - Depth-first
- Source and example: https://www.youtube.com/watch?v=9bht7Vq0DqY

Genetic Algorithms

Pros

- Middling authorial burden (more than hill climbing, less than generative grammars/rule system)
- High likelihood of finding global optima-ish

Cons

- Takes skill to pick and balance mutation/crossover
- Over-reliance

Search-based PCG

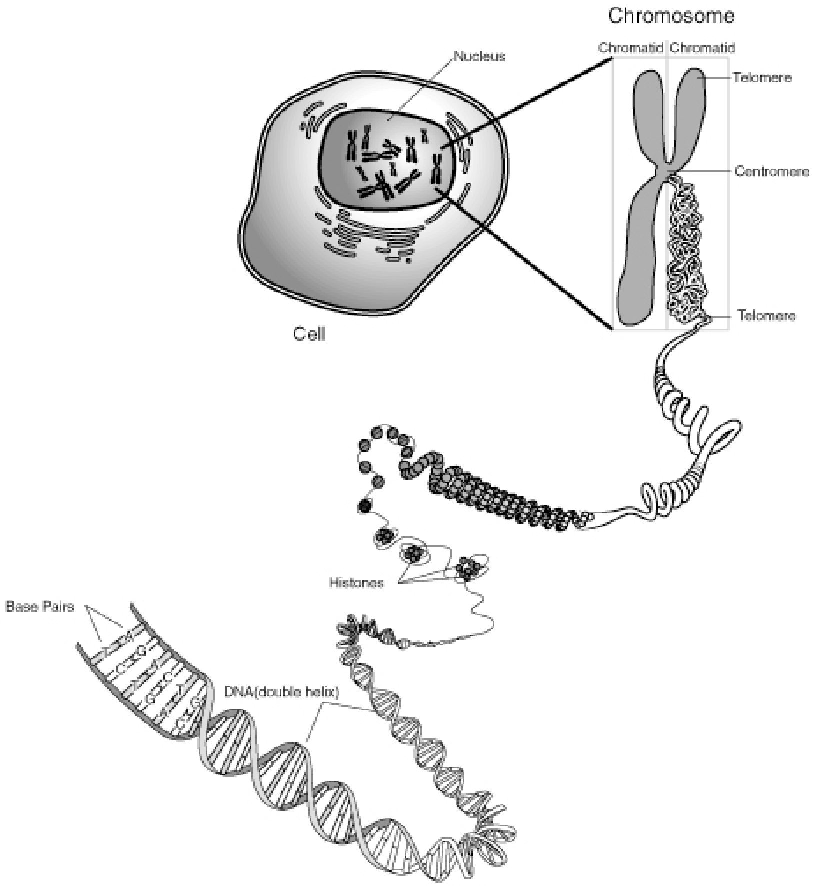
Pros
- Allows for designers to specify high-level desires rather than low level content authoring

Cons
- Coming up with a good heuristic is hard
  - Representation of state
  - Evaluating fitness/quality
  - Perturbing a member
  - Tuning search parameters
- Many devs will prefer to just use generative grammars

DEEPER DIVE ON GENETIC ALGORITHMS

Biology Metaphor

“Variation is a feature of natural populations and every population produces more progeny than its environment can manage**.** The consequences of this overproduction is that **those individuals with the best genetic fitness for the environment will produce offspring that can more successfully compete in that environment.** Thus the subsequent generation will have a higher representation of these offspring and the population will have evolved.**”**
-Darwin



The GA Problem

- 1st Step: Encoding a solution to your problem (i.e. a *chromosome*)
  – e.g. values for coefficients in a function, numeric preferences for selecting rules, type and number of tiles, or weights in your FSM or BT
- May or may not be human readable
  – 10101010000101011101010101011010
  – S8G2P1M4

Steps

1. Create a random set of n chromosomes ["population"]

   Each chromosome represents an individual or a state or a particular agent, and is a combination of genes

Steps

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2. Test each chromosome to see how good it is at solving the problem; Assign a fitness score to each tested chromosome

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5. Reduce: cull population using some strategy
    - e.g. Remove the m% (m < 100) worst chromosomes

Steps

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2. Test each chromosome to see how good it is at solving the problem; Assign a fitness score to each tested chromosome
3. Mutate: Randomly mutate
4. Cross-over: Cycle through selected pairs of chromosomes and cross-over
5. Reduce: cull some chromosomes
6. Repeat steps 2-5 until optimality is reached (local or global?)

REDUCE / SELECTION

Population

- How many individuals (or chromosome representations) you have in the gene pool
- How many should you have? How many should you reproduce?
  - Small pop.: Risk replacing individuals before reproduction; Less diversity
  - Large pop.: More diversity; converge fast initially, but little progress later

Kiss: μ + λ

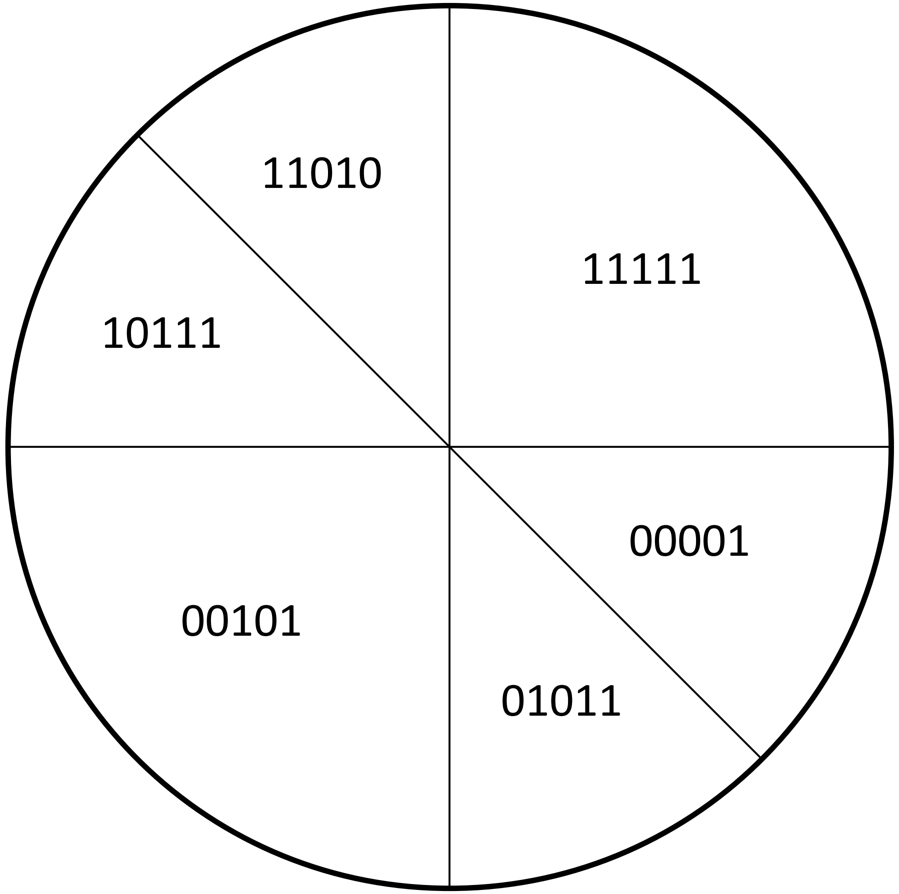
- Create a population of μ + λ individuals
- Each generation
  - Evaluate all individuals in population
  - Sort by fitness
  - Remove the worst λ individuals
  - Replace those removed with mutated copies of the μ best (no crossover)

Elitist Selection

- Select the *n%* best individuals from the population and advance them *unchanged* to the next generation
- Typically, $1 < n < 10$; potentially $n < 20$
- Too much elitism ---> early convergence

Generally, you want some elitism regardless of your other selection techniques.

Roulette Wheel Selection



This is a way of choosing members from the population of chromosomes **in a way that is proportional to their fitness**

Scaling

- Used in combination with Roulette Selection
- Helps prevent premature convergence

- Rank scaling
  - Starting with raw fitness scores, convert to rank listing
  - Use ranks for roulette proportions

  e.g. [235, 123, 54, 45, 32] becomes [5,4,3,2,1]
  - Especially in early generations, to help prevent premature convergence
  - Good because fitness scores early on may be too widespread

Scaling

- Used in combination with Roulette Selection
- Helps prevent premature convergence

- Rank scaling
- Sigma scaling (σ is std dev of fitnesses)

  NewFit[i] = (RawFit[i] – AvgFit) / 2σ

  – Keeps selection pressure (diversity) constant over many generations.

Scaling

- Used in combination with Roulette Selection
- Helps prevent premature convergence

- Rank scaling
- Sigma scaling
- Boltzmann scaling

    NewFit[i] = (RawFit[i]/Temperature) / Avg(RawFit/Temperature)

  Temperature is found through trial and error

    e.g. T = 3*pop_size – 0.05*numGenerations

  - Keeps selection pressure low at beginning and high at the end.
  - As alg converges, fitter individuals are given a preference
    (High selection pressure = low diversity)

Tournament Selection

- Select n% of the population (typically 2<n<10)
  - As n decreases, diversity increases
- The most fit member of the group is used for crossover
  - Alternately, crossover the 2 most fit members of the group
- Faster than roulette selection

CROSSOVER

Crossover

Having a good crossover function that fits the structure of your problem representation is crucial. Crossover happens at the gene level

- Given crossover rate and format, swap bits of the parents

  e.g. 100111 and 101001 would potentially yield:

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  101011 and 100101 (Two-point crossover)

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  100111 and 101001 (Random point selection)

Crossover

- Given crossover rate and format, swap bits of the parents

  e.g. 100111 and 101001 would potentially yield:

  100001 and 101111 (One-point crossover); or…

  101011 and 100101 (Two-point crossover); or…

  100111 and 101001 (Random point selection)
- Multi-point crossover
  - Select each gene from either parent, possibly ensuring that an equal number come from each parent

MUTATION & FITNESS

Mutation Rate

- Why do we have crossover and mutation?
  - Crossover explores faster. Mutation exploits local region.
  - You ALWAYS need to have mutation
- What is the benefit of mutation?
  - Making random changes to our solutions helps get us out of local maxima

- Small chance of a bit being flipped
- 101111 becomes 101110

Niching

- Method for retaining diversity
- Useful when environment might have multiple peaks
- Also good for protecting a new innovation within a population

- Explicit Fitness Sharing

  NewFit[i] = OldFit[i] / NumNeighbors

Niching

- Method for retaining diversity
- Useful when environment might have multiple peaks

- Explicit Fitness Sharing
- Speciation
  - Requires crossover only occurs within “breeds”
  - Species are killed when pop = 0 or fitness hasn’t increased over several generations
  - Might want to try higher mutation rates

Simple Example

Problem:

Given the digits 0 through 9 and the operators +, -, *, and /, **find a sequence that will represent a given target number**. The operators will be applied sequentially from left to right as you read and any extraneous information will be ignored.

Encoding

0:	0000	7:	0111
1:	0001	8:	1000
2:	0010	9:	1001
3:	0011	+:	1010
4:	0100	-:	1011
5:	0101	*:	1100
6:	0110	/:	1101

Example Solution

23 = 6 + 5 * 4 /2 + 1

--->

0110 1010 0101 1100 0100 1101 0010 1010 0001

6 + 5 * 4 / 2 + 1

Deciding on a Fitness Function

- Hardest part of the process
- e.g., “inverse proportional to the difference between the solution and the chromosome’s value”
- e.g., with a target of 42 and a value of 23
  - Fitness: 1/(42-23) = 1/19
  - 1/0 ---> success

Using Real Values

- In games, we may want our genomes to use real floating-point numbers instead of bit strings
- Allows us to exploit mathematical properties of a landscape

Tuning Parameters

- Population size
- Number of generations
- Fitness function
- Representation
- Mutation rate
- Crossover operations
- Selection procedure
- Number of solutions to keep

Large pop takes too long. Small pop doesn't search a large enough space, and converges to poor soln.

Too much mutation leads to random search. Not enough, then we lose diversity and stagnate.

Criticisms

- Repeated fitness evaluation may be expensive
- Unclear stop criterion
- Challenge to scale with complexity
- Prone to local, rather than global, maxima

GAs and Decision Making

- GAs can be used to tune parameters in rules and FSMs

```
if (enemy.distance <= 5)
    ATTACK-WITH-KNIFE()
else if (enemy.distance > 5 AND enemy.distance <=30)
    ATTACK-WITH-SUBMACHINE-GUN
else ATTACK-WITH-RIFLE
```

GAs and Decision Making

- Counterstrike example
  - Select parameters to tune
  - Allow the GA to evolve the parameters
  - Pit the evolved bots against hand-tuned bots
- Fitness function: $ earned
- GA bots performed as well as hand-tuned bots

Using a Genetic Algorithm to Tune First-Person Shooter Bots. Nicholas Cole, Sushil J. Louis, and Chris Miles. 2004. https://pdfs.semanticscholar.org/24ec/f958b25b791b63271774b3e115ad38185015.pdf

GAs and RTS Games

- Tune AI strategy to target human player weaknesses
  – Tune parameters that define AI personality (e.g. unit preference, scientific advance preference, offense vs. defense, etc.)
- Tune behavior of individuals or groups of units

Ponsen, Marc, and Pieter Spronck. *Improving adaptive game AI with evolutionary learning*. Diss. Masters Thesis, Delft University of Technology, 2004.
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.109.6055&rep=rep1&type=pdf

GAs and Game AI

- GAs seek optimal solutions. Is that what we want from Game AI?

GAs in Review

- Have problems with local maxima
  - Niche penalty can avoid this sometimes
- GAs can rapidly find *good* solutions in general
- Problem domains
  - Scheduling and timetabling
  - Engineering // optimization problems

PCG See also

- IGDA Webinar, 10 December 2014: PCG in games: perspectives from the ivory tower
  - https://www.youtube.com/watch?v=UVRqCK6m7m4
- PCG Book http://pcgbook.com/
  - Grammars: Chapter 5 http://pcgbook.com/wp-content/uploads/chapter05.pdf
- 9.1: Genetic Algorithms and Evolutionary Computing - The Nature of Code
  - https://www.youtube.com/watch?v=6l6b78Y4V7Y