everything you wanted to know about computers*

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*but were too afraid to ask

Overview

- Functions as representation
- Function optimization methods, issues
  - Steepest Descent
  - Simulated Annealing
  - Genetic Algorithms
- Analysis of shape grammars
- Possibilities

Ode to Functions

- Math is based on them
- Computers are based on them
- Very general representation: a mapping
- Helpful as intermediate object too
  - aid to formalization, rigor

- Limited
  - only maps numbers to numbers
  - is mapping *it*?

Functions

- $y = f(x)$
- x,y: vector of parameters (‘parametric’?)

- “Form function”
  – Vertices = f(dimensions, key pts, etc)
- “Fitness function”
  – Quality = f(vertices)

Functions

- $y = f(x)$
- x,y are each a vector of parameters

- Each parameter can be either
  - discrete (combinatorial): 0, 1, 2, 3, 4
  - continuous: 0-4

Functions

- $y = f(x)$
- such that $c(x) = 0$

- Constraints: valid parameter combinations

Trouble with Functions in Design

- Pre-Optimization questions:
  - how to define a useful form function?
    - Vertices = f(dimensions, key pts, etc)
  - how to define a useful fitness function?
    - fitness = f(geometry only)?

  - generality vs. specificity
  - myth: computer functions can be random
  - myth: designers' functions are random

Trouble with Functions in Design

- Optimization question:
  - how to find the most fit form?
- Pre, mid, post-optimization question:
  - how to handle emergence?
    - changing form, fitness functions during design
    - changing question in middle of trying to answer it

Architectural Function Optimization

- Vertices = f(model parameters)
- Quality = f(vertices)
- Quality = f(model parameters)

- Optimization = vary model parameters to maximize goodness

Function Optimization

$$\mathbf{max\ q(p_0, p_1, \ldots, p_n)}$$

Keeping $c_0(p_0, p_1, \ldots, p_n) = 0$

and $c_1(p_0, p_1, \ldots, p_n) = 0$ and…

$$\mathbf{max\ q\ (p)}$$

keeping $c(p) = 0$

given some initial state p_0

Function Optimization

max q (p)

keeping c(p) = 0

p_0: initial state

- Goodness must be a single number
  - "multi-objective optimization"
- The problem: given start, where to go next?
  - in which direction?
  - how far?

Functions – Moving Around

- Move in a *direction* for a certain *distance*
- Start: (0,0)
- Move to (2,2): moving in (1,1) direction for a distance of 2.

- ‘Direction’ = a change in each parameter
- ‘Distance’ = multiplier of a direction

Functions – Continuity

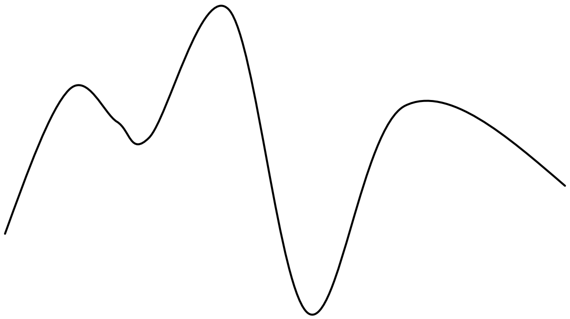
- Changing continuous parameters: nicer
  - correlation: direction (1,1) roughly equals combination of effects from directions (1,0) and (0,1)
  - correlation: moving further along (.5, 4.2) tends to produce more of what that direction does
  - derivatives: can determine effect of parameter change without trying all possible changes
- Combinatorial: no correlation between directions, between distance and outcome
  - (usually)
  - shape grammars are combinatorial

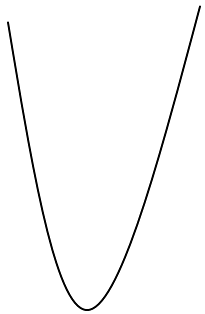
Optimization Techniques

- Steepest Descent
- Simulated Annealing
- Genetic Algorithms

Hill-Climbing/Steepest Descent

- Go downhill
  - best downhill direction: downhill for each parameter
  - distance: select best along direction
  - can't go downhill? Stop.





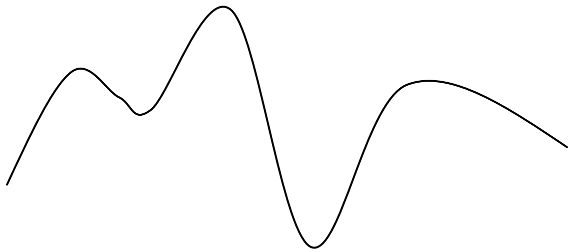
- Local or global extrema?
  - fundamental problem

Simulated Annealing

- Jump around…
- Jump around…
- Jump up, jump up….
- …and get down.

Simulated Annealing

- Jump around/up...
  - provisionally jump around a distance j ('taking' the new position if it's better - or not *much* worse)
- …and get down
  - steadily lower jump distance j and uphill tolerance t
    - lower the energy of the system
    - steel cooling, water flooding
  - t = 0, small j: must get better at each step = hill-falling



Genetic Algorithms

- GA concepts can be thought of functionally:
  - Phenotype = f(genotype)
    - form = f(dimensions)
  - Fitness = f(phenotype)
    - fitness = f(form)

  - Genotype = dimensions
  - Phenotype = form

Genetic Algorithms

- Evolution as functional optimization
  - arbitrary directions
    - generated by:
      - interleaving parameters of parents (crossover)
      - 'random' change of parameter (mutation)
    - ignore direction, distance correlations
    - assume crossover groups are independent of each other
    - generates invalid parameter sets
    - locking down substrings: when? how many? for how long?
  - multiple kids: parallel optimization
    - i.e., multiple directions at once
  - unknown improvement in kids
    - have to evaluate fitness of each kid after generating it
  - possibly no improvement in kids (convergence?)

Shape Grammars - Generation

Generate all shapes s(rules, s_0, n)

s_0: initial shape

rules: shape rules

n: number of iterations

- Fitness function inside human operator
- Human optimizer changes parameters to increase fitness
- Implicit fitness/recognition function

Shape Grammars - Generation

- $(r_0,r_1,r_2,\ldots)$ = recognizer(shape, set of all rules)
  - recognizer compares left sides, allowing for translation, scale, and rotation
  - recognizer as local fitness function: only certain rules are fit for this situation
- $(r_0,r_1,r_2,\ldots)$ are a set of (equally good!) directions
- Go in all directions, distance 1 (apply all valid rules once), producing $shape_0$, $shape_1$, …, $shape_n$
- Recurse on all the kid shapes

Shape Grammars - Optimization

$$\mathbf{max\ q\ (s_0, r_0, r_1, r_2, .., r_n)}$$

keeping $c(s_0, r_0, r_1, r_2, .., r_n) = 0$

s_0: initial shape

n: number of rules to apply

- Combinatorial representation
  - regardless of fitness function, no good way to search the space

The Tough Questions

- Form function: What bogus forms are allowed? What useful forms are *not* allowed? What framework is embodied in the function?
- Fitness function: What does ‘fitness’ mean? (Does it encode architectural knowledge? How?)
- Representation of emergence?
- Optimization: Is it finding the global minimum (by starting near solution or being a bowl-shaped function)? If not, what is it finding?
- Recognition = binning based on sliding qualities
  - ‘x is awfully chair-like’ -> ‘x is a chair’
  - ‘x is somewhat chair-like’ -> ‘x is a chair’??
  - When is x not a chair? Who’s deciding, and how?

Computers in Design: Future

- support quick, narrow optimizations
  - support form changes
    - quick specification of formwork as it changes
  - brainstorming – show all combinations
- more fine-grained study of frameworks and how they change
  - given explicit representation, computer can help

Difficult Things Computers Do

- Simulation
  - light
  - structural strength
  - sound
  - heat
- Visualization
  - realistic: simulation of light
  - non-realistic: arbitrary artistic techniques to convey information
    - false color, overlays, collage, false perspective
    - show temperature, airflow, etc
- Calculation
  - area, cost, number of parts