Genetic Algorithms

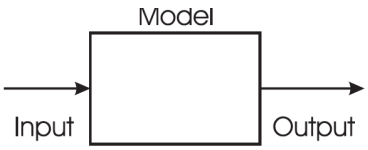
CS 419/519

GAs: What are they used for?

Problems can be classified in different ways:

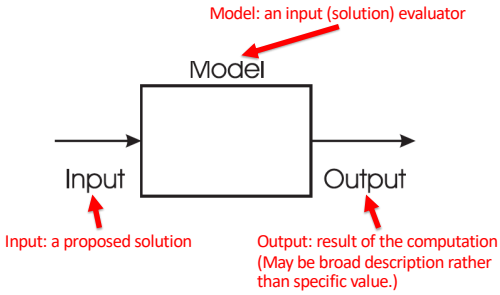
- Black box model
- Search problems
- Optimization vs constraint satisfaction
- NP problems

"Black box" model



- "Black box" model consists of 3 components
- Two components are known, one is unknown
- Each unknown results in a different problem type

"Black box" model



Examples

- Traveling salesperson problem:
  - Input: a sequence of destinations
  - Model: function to sum distances between adjacent destinations
  - Output: total distance traveled
- University classroom scheduler:
  - Input: a schedule assigning classes to classrooms
  - Model: function to determine time conflicts, seat shortages, etc
  - Output: values for number of conflicts, seat delta, etc
- Eight-queens problem:
  - Input: arrangement of eight queens on chessboard
  - Model: checker for conflicts
  - Output: indication of conflict or not

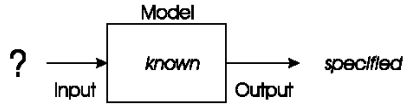
Important distinction: problem instance vs. input

- Problem instance: what we often think of as an "input" to our algorithms.
- Input (for the purposes of this discussion): a candidate solution to the problem.

- Example: TSP
  - Problem instance: a set of destinations
  - Input: a sequence of the destinations
- Example: Classroom scheduling
  - Problem instance: sets of classes and classrooms
  - Input: a schedule that may or may not satisfy all constraints

"Black box" model: Input unknown Optimization

- Model and desired output are known. We seek inputs that maximize or minimize the desired variable(s)

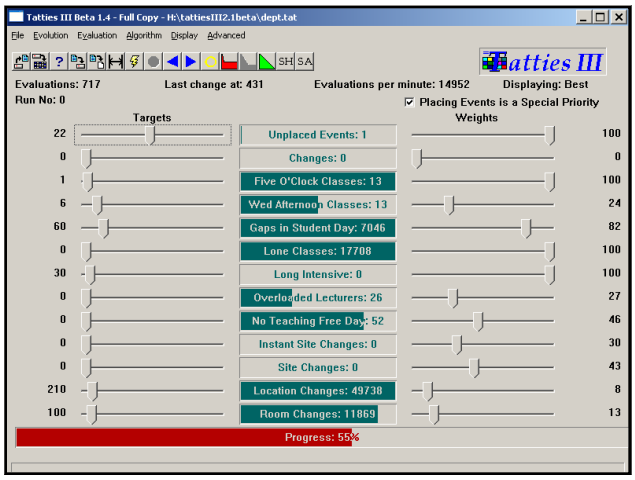


- Examples:
  - Time tables for university, call center, or hospital
  - Design specifications (circuit, probe placement)
  - Traveling salesperson problem (TSP)
  - Eight-queens problem

"Black box" model: Optimisation example 1: university timetabling

Task: find a timetable

- Enormously big search space
- Timetables must be *good*
- "Good" is defined by a number of competing criteria
  - Courses well distributed
  - Not too many late in the day
- Timetables must be feasible
  - Satisfies constraints
    - Enough seats
    - No time conflicts
- Vast majority of search space is infeasible



"Black box" model: Optimization example 2: satellite structure

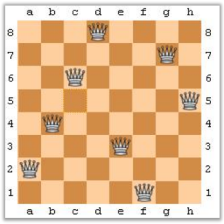
Task: find a design

- Optimized satellite designs for NASA to maximize vibration isolation
- Evolving: design structures
- Fitness: vibration resistance
- Evolutionary "creativity"

"Black box" model: Optimization example 3: 8 queens problem

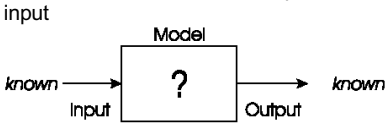
Task: find an arrangement

- Given an 8-by-8 chessboard and 8 queens
- Place the 8 queens on the chessboard without any conflict
- Two queens conflict if they share same row, column or diagonal
- Can be extended to an n queens problem (n>8)



"Black box" model: Model unknown Modelling

- We have corresponding sets of inputs & outputs. We seek a model that delivers correct output for every known input



- Examples:
  - Stock market prediction
  - Loan applicant evaluation
  - Facial recognition
  - Autonomous driving

"Black box" model: Model unknown
Modelling

- Note: modelling problems can be transformed into optimisation problems
  - Error rate (or success rate) of the model is quantity to be minimized (or maximized)
- Examples
  - Evolutionary machine learning
    - Evolve a neural network that maximizes hit rate of identifications
  - Predicting stock exchange
    - Minimize difference between predicted value and actual value
  - Voice control system for smart homes
    - Minimize error in commands performed

"Black box" model:
Modeling example: loan applicant evaluation

- British bank evolved creditability model to predict loan paying behavior of new applicants
- Evolving: prediction models
- Fitness: model accuracy on historical data

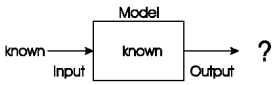
"Black box" model:
Modeling example: stock market prediction

Two methods

- Build a time machine
  - DeLoreans are hard to find
- Evolve a predictive model
  - Fitness: difference between actual value of DJIA and predicted value
  - What are the inputs?

"Black box" model: Output unknown
Simulation

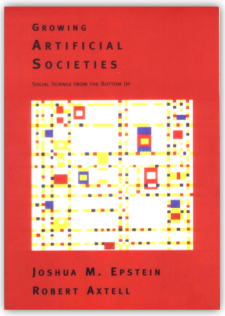
- We have a given model. We seek the outputs that arise under different input conditions



- Often used to answer "what-if" questions in evolving dynamic environments
- Examples
  - Evolutionary economics, Artificial Life
  - Weather forecast system
  - Impact analysis of new tax systems

"Black box" model: Simulation example: evolving artificial societies

- Simulating trade, economic competition, etc. to calibrate models
- Use models to optimize strategies and policies
- Evolutionary economy
- Survival of the fittest is universal (big/small fish)



"Black box" model: Simulation example 2: cosmology

Simulate the physics beginning at some point in time to test our understanding of the universe

Large number of variables and values requires substantial computational resources

Search problems

- Simulation is different from optimization/modelling
- Optimization/modeling problems search through huge space of possibilities
- Search space: collection of all objects of interest including the desired solution(s)
- Question: how large is the search space for different tours through *n* destinations?

Problems vs. problem solvers

Important distinction:

- search problems: define search spaces
- problem-solvers: describe how to move through search spaces

Optimization vs. constraint satisfaction

- Objective function: a way of assigning a value to a possible solution that reflects its quality
  - Number of un-checked queens (maximize)
  - Length of a tour visiting given set of destinations (minimize)
- Constraint: binary evaluation telling whether a given requirement holds or not
  - Find a configuration of eight queens on a chessboard such that no two queens check each other
  - Find a tour with minimal length where city X is visited after city Y

Optimization vs. constraint satisfaction

Goal:

A solution that:

- "performs well" according to the objective function
- satisfies all constraints

Optimization vs. constraint satisfaction

- When combining the two:

	Objective function	
Constraints	Yes	No
Yes	Constrained optimization problem	Constraint satisfaction problem
No	Free optimization problem	No problem

Optimization vs. constraint satisfaction

	Objective function	
Constraints	Yes	No
Yes	Constrained optimization problem	Constraint satisfaction problem
No	Free optimization problem	No problem

Problem: maximize number of unchecked queens on a chess board

Which category?

Free optimization problem (FOP)

Optimization vs. constraint satisfaction

	Objective function	
Constraints	**Yes**	**No**
Yes	Constrained optimization problem	Constraint satisfaction problem
No	Free optimization problem	No problem

Problem: find a configuration of eight queens on a chess board such that no two queens check each other

Which category?
Constraint satisfaction problem (CSP)

Optimization vs. constraint satisfaction

	Objective function	
Constraints	**Yes**	**No**
Yes	Constrained optimization problem	Constraint satisfaction problem
No	Free optimization problem	No problem

Problem: minimize length of tour visiting every destination, in a set of n destinations, exactly once (TSP)

Which category?
Free optimization problem (FOP)

Optimization vs. constraint satisfaction

	Objective function	
Constraints	**Yes**	**No**
Yes	Constrained optimization problem	Constraint satisfaction problem
No	Free optimization problem	No problem

Problem: find a TSP tour with minimal length such that city X is visited after city Y

Which category?
Constrained optimization problem (COP)

Another classification scheme: P and NP

- So far, we have only looked at classifying problems; we have not discussed problem solvers
- For this new classification scheme, we need the properties of the problem solver – we will classify problems by how easy or hard they are to solve
- Applies to combinatorial optimization problems – these are problems for which the variables are discrete rather than continuous

NP problems: Key notions

- Problem size: dimensionality of the problem at hand and number of different values for the problem variables
- Running-time: number of operations the algorithm takes to terminate
  - Worst-case as a function of problem size
  - Polynomial, super-polynomial, exponential
- Problem reduction: transforming current problem into another via mapping

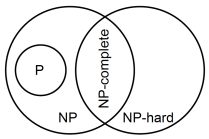
NP problems: Class

- The 'difficultness' of a problem can now be classified:
  - Class P: algorithm can solve the problem in polynomial time (worst-case running-time for problem size n is less than F(n) for some polynomial formula F)
  - Class NP: problem can be solved and any solution can be verified within polynomial time by some other algorithm (P subset of NP)
  - Class NP-complete: problem belongs to class NP and any other problem in NP can be reduced to this problem by an algorithm running in polynomial time
  - Class NP-hard: problem is at least as hard as any other problem in NP-complete but solution cannot necessarily be verified within polynomial time

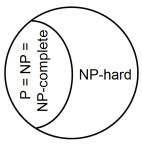
NP problems: Difference between classes

- P is different from NP-hard
- Not known whether P is different from NP

if: $P \neq NP$



$P = NP$



NP problems: Why should you care?

Let's say we have a computer with a clock rate defined by the speed of light: 3×10^{-24} sec (~13 orders of magnitude faster than any modern computer)

What is size of search space for TSP?

How many clock cycles for our computer since the dawn of the universe? $\sim 10^{42}$ or about 2^{120}

If our computer could evaluate one solution per clock cycle, for a TSP instance with 120 destinations it would take more time than the age of the universe to consider all of them.

NP problems:
Yeah, so?

So, this means that it is not possible to guarantee an optimal solution to even moderately sized instances of hard problems.

Where does this leave us?

Approximation Algorithms

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* Genetic algorithms are a form of approximation algorithm *
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