

# Optimization and Complexity

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# Aim

- Give you an intuition of what is meant by
  - Optimization
  - P and NP problems
  - NP-completeness
  - NP-hardness
- Enable you to recognize formalisms of complexity theory, and its usefulness

# Overview

- Motivating example
- Formal definition of a problem
- Algorithm and problem complexity
- Problem reductions
  - NP-completeness
  - NP-hardness
- Glimpse of approximation algorithms and their design

# What is optimization?

- Requires a *measure* of optimality
  - Usually modeled using a mathematical function
- Finding the solution that yields the globally best value of our measure

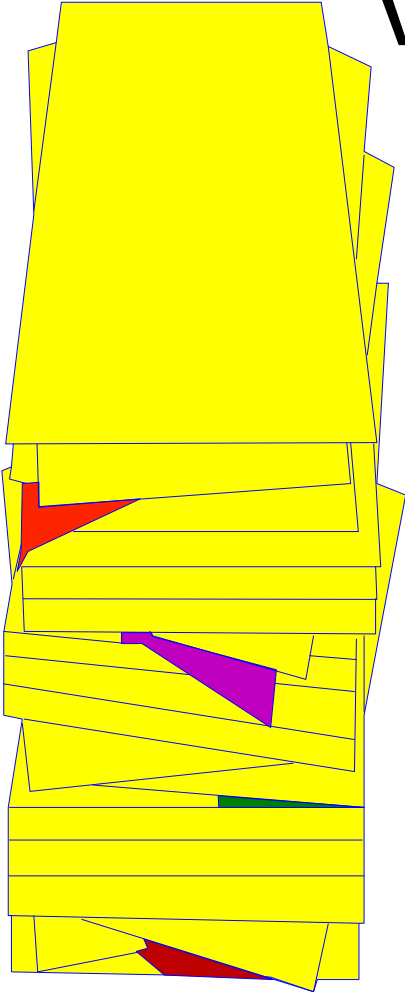
# What is the problem?

- Nike: Just do it
- Not so simple:
  - Even problems that are simple to formally describe can be intractable
  - Approximation is necessary
  - Complexity theory is a tool we use to describe and recognize (intractable) problems

# Example: Variable Selection

- Data tables  $T$  and  $V$  have  $n$  predictor columns and one outcome column. We use machine learning method  $L$  to produce predictive model  $L(T)$  from data table  $T$ . We can evaluate  $L(T)$  on  $V$ , producing a measure  $E(L(T), V)$ .
- We want to find a maximal number of predictor columns in  $T$  to delete, producing  $T'$ , such that
$$E(L(T'), V) = E(L(T), V)$$
- There is no known method of solving this problem optimally (e.g, NP-hardness of determining a minimal set of variables that maintains discernibility in training data, aka the rough set reduct finding problem).

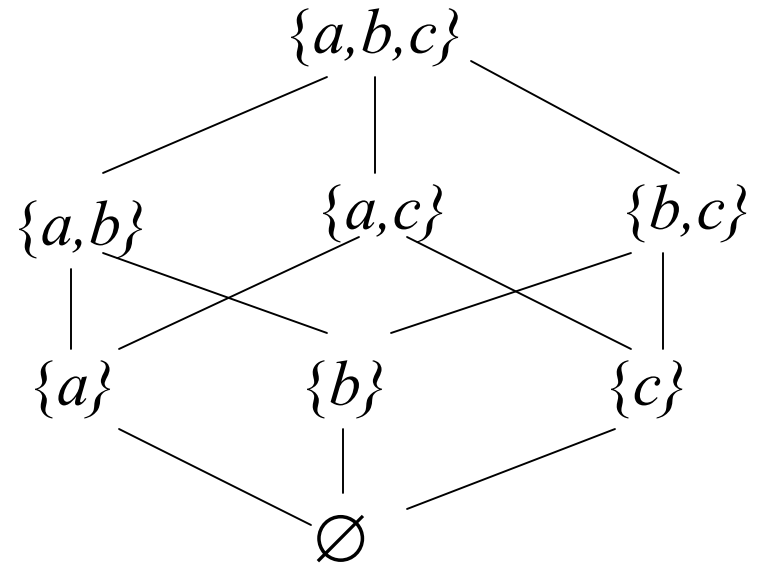
# Search for Optimal Variable Selection



- The space of all possible selections is huge
- 43 variables,  $2^{43} - 1$  possibilities of selecting a non-empty subset, each being a potential solution
- one potential solution pr. post-it gives a stack of post-its reaching more than half way to the moon

# Search for Optimal Variable Selection

- Search space
  - discrete
  - structure that lends itself to *stepwise search* (add a new or take away one old)
  - optimal point is not known, nor is optimal evaluation value





# Popular Stepwise Search Strategies

- Hill climbing:
  - select starting point and always step in the direction of most positive change in value

# Popular Stepwise Search Strategies

- Simulated annealing:
  - select starting point and select next stepping direction stochastically with increasing bias towards more positive change

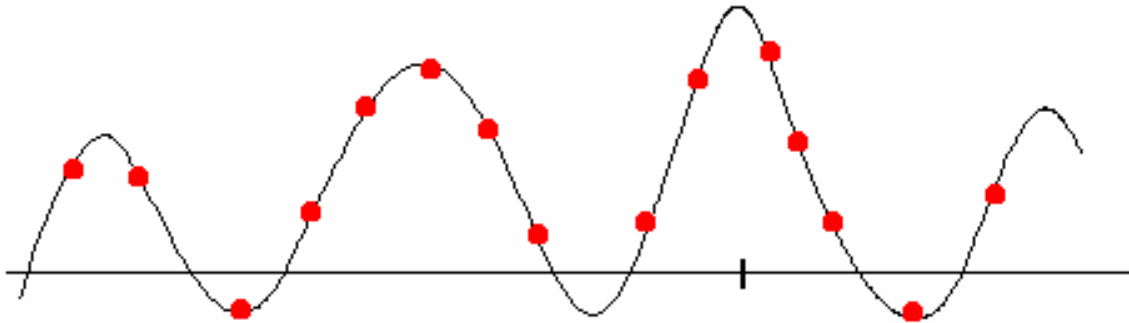
# Problems

- Exhaustive search: generally intractable because of the size of the search space (exponential in the size of variables)
- Stepwise: no consideration of synergy effects
  - Variables  $a$  and  $b$  considered in isolation from each other are excluded, but their combination would not be

# Genetic Algorithm Search

- population of solutions
- Stochastic selection of parents with bias towards “fitter” individuals
- “mating” and “mutation” operations on parents
- Merging of old population with offspring
- Repeat above until no improvement in population

# GA Optimization Animation



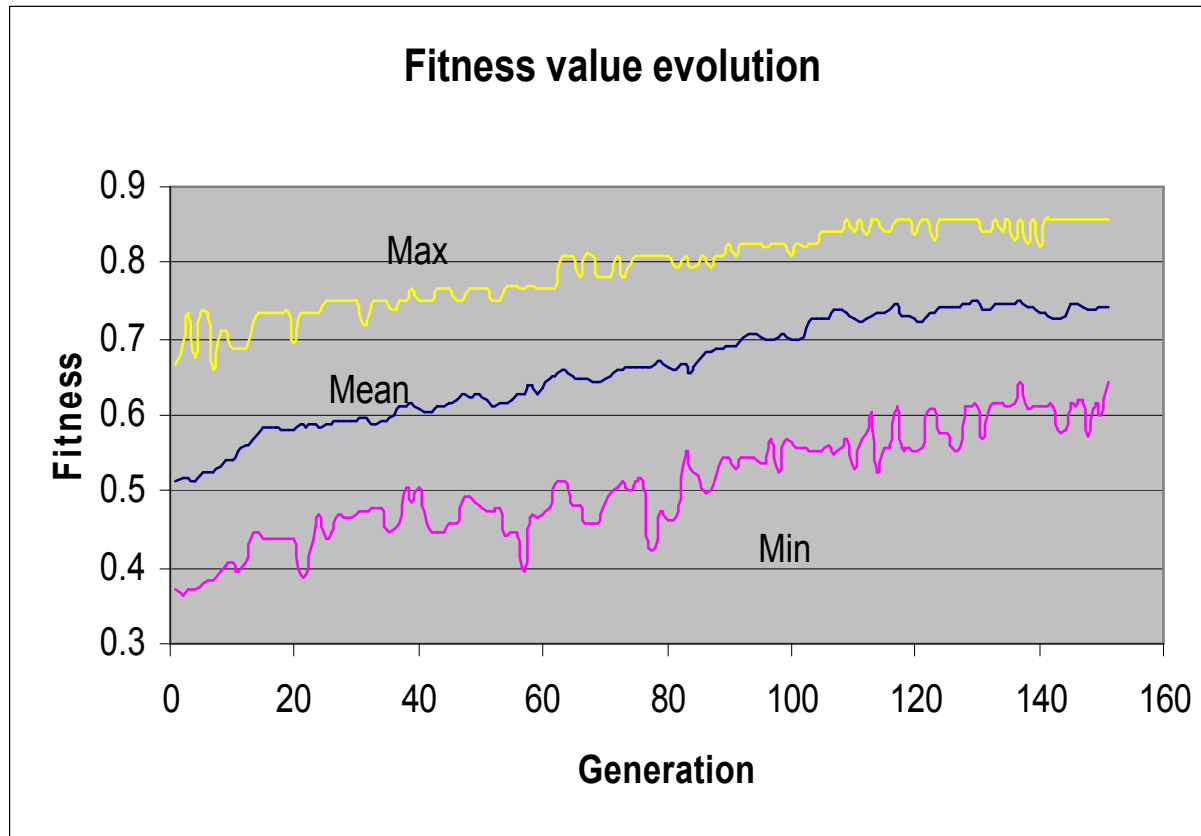
# Addressing the Synergy Problem of Stepwise Search

- Genetic algorithm search
  - Non-stepwise, non-exhaustive
  - Pros:
    - Potentially finds synergy effects
    - Does not a priori exclude any parts of the search space
  - Cons:
    - Computationally expensive
    - Difficult to analyze, no comprehensive theory for parameter specification

# Variable Selection for Logistic Regression using GA

- Data:
  - 43 predictor variables
  - Outcome: MI or not MI (1 or 0)
  - Training ( $T$ , 335 cases) and Holdout ( $H$ , 165 cases) from Sheffield, England
  - External validation ( $V$ , 1253 cases) from Edinburgh, Scotland

# GA Variable Selection for LR: Generational Progress





# GA Variable Selection for LR: Results

- Table presenting results on validation set E, including SAS built-in variable selection methods (removal/entry level 0.05)

Selection	Size	ROC AUC
Genetic	6	0.95
none	43	0.92
Backward	11	0.92
Forward	13	0.91
Stepwise	12	0.91

$P < 0.05$

# Problem Example

- Boolean formula  $f$  (with variables)
  - Is there a truth assignment such that  $f$  is true?
  - Does this given truth assignment make  $f$  true?
  - Find a satisfying truth assignment for  $f$
  - Find a satisfying truth assignment for  $f$  with the minimum number of variables set to true

# Problem Formally Defined

- A problem  $P$  is a relation from a set  $I$  of instances to a set  $S$  of solutions:  $P \subseteq I \times S$ 
  - Recognition: is  $(x,y) \in P$  ?
  - Construction: for  $x$  find  $y$  such that  $(x,y) \in P$
  - Optimization: for  $x$  find the *best*  $y$  such that  $(x,y) \in P$

# Solving Problems

- Problems are solved by an algorithm, a finite description of steps, that compute a result given an instance of the problem.

# Algorithm Cost

- Algorithm cost is measured by
  - How many operations (steps) it takes to solve the problem (time complexity)
  - How much storage space the algorithm requires (space complexity)

on a particular machine type as a function of input length (e.g., the number of bits needed to store the problem instance).

# O-Notation

- O-notation describes an upper bound on a function

- let  $g, f: \mathbb{N} \rightarrow \mathbb{N}$

$f(n)$  is  $O(g(n))$

if there exists constants  $a, b, m$   
such that for all  $n \geq m$

$$f(n) \leq a * g(n) + b$$

# O-Notation Examples

$$f(n) = 99999999999999999999 \\ \text{is } O(1)$$

$$f(n) = 1000000n + 100000000 \\ \text{is } O(n)$$

$$f(n) = 3n^2 + 2n - 3 \\ \text{is } O(n^2)$$

(Exercise: convince yourselves of this please)

# Worst Case Analysis

- Let  $t(x)$  be the running time of algorithm  $A$  on input  $x$
- Let  $T(n) = \max\{t(x) \mid |x| = n\}$ 
  - I.e.,  $T(n)$  is the worst running time on inputs not longer than  $n$ .
- $A$  is of time complexity  $O(g(n))$  if  $T(n)$  is  $O(g(n))$



# Problem Complexity

- A problem  $P$  has a time complexity  $O(g(n))$  if there exists an algorithm that has time complexity  $O(g(n))$
- Space complexity is defined analogously

# Decision Problems

- A *decision problem* is a problem  $P$  where the set of Instances can be partitioned into  $Y_P$  of positive instances and  $N_P$  of non-positive instances, and the problem is to determine whether a particular instance is a positive instance
- Example: satisfiability of Boolean CNF formulae, does a satisfying truth assignment exist for a given instance?

# Two Complexity Classes for Decision Problems

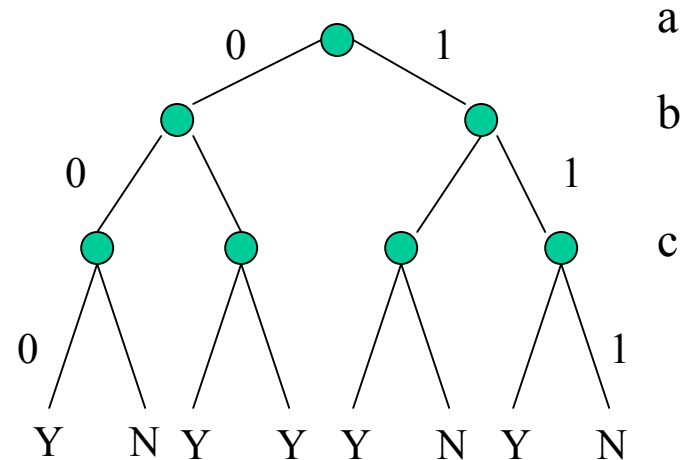
- P – all decision problems of time complexity  $O(n^k)$ ,  $0 = k = \infty$
- NP – all decision problems for which there exists a non-deterministic algorithm with time complexity  $O(n^k)$ ,  $0 = k = \infty$

# What is a non-deterministic algorithm?

- Algorithm: finite description (program) of steps.
- Non-deterministic algorithm: an algorithm with “guess” steps allowed.

# Computation Tree

- Each guess step results in a “branching point” in a computation tree
- Example: satisfying a Boolean formula with 3 variables



$$((\sim a \wedge b) \vee \sim c)$$

# Non-deterministic algorithm time complexity

- A ND algorithm  $A$  solves the decision problem  $P$  in time complexity  $t(n)$  if, for any instance  $x$  with  $|x| = n$ ,  $A$  halts for any possible guess sequence and  $x \in Y_P$  if and only if there exists at least one sequence which results in YES in time at most  $t(n)$

# P and NP

- We have that
  - $P \subseteq NP$
- If there are problems in NP that are not in P is still an open problem, but it is strongly believed that this is the case.

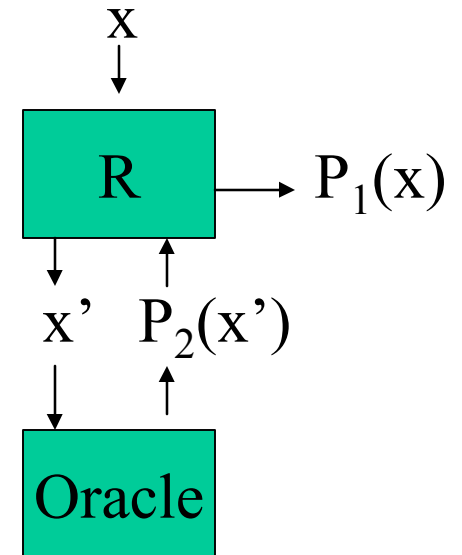
# Problem Reduction

- A reduction from problem  $P_1$  to problem  $P_2$  presents a method for solving  $P_1$  using an algorithm for  $P_2$ .
  - $P_2$  is then intuitively at least as difficult as  $P_1$



# Problem Reduction

- Problem  $P_1$  is *reducible* to  $P_2$  if there exists an algorithm  $R$  which solves  $P_1$  by querying an *oracle* for  $P_2$ . In this case,  $R$  is said to be a *reduction* from  $P_1$  to  $P_2$ , and we write  $P_1 = P_2$
- If  $R$  is of polynomial time complexity we write  $P_1 =^p P_2$



# NP-completeness

- A decision problem  $P$  is NP-complete if
  - It is in NP, and
  - For any other problem  $P'$  in NP we have that  $P' \leq^p P$ ,
- This means that any NP problem can be solved in polynomial time if one finds a polynomial time algorithm for NP-complete  $P$
- There are problems in NP for which the best known algorithms are exponential in time usage, meaning that NP-completeness is a sign of problem intractability

# Optimization Problems

- Problem  $P$  is a quadruple  $(I_P, S_P, m_P, g_P)$ 
  - $I_P$  is the set of instances
  - $S_P$  is a function that for an instance  $x$  returns the set of feasible solutions  $S_P(x)$
  - $m_P(x, y)$  is the positive integer measure of solution quality of a feasible solution  $y$  of a given instance  $x$
  - $g_P$  is either min or max, specifying whether  $P$  is a maximization or minimization problem
- The optimal value for  $m_P$  for  $x$  over all solutions is denoted  $m_P(x)$ . A solution  $y$  for which  $m_P(x, y) = m_P(x)$  is called optimal and is denoted  $y^*(x)$ .

# Optimization Problem Example

- Minimum hitting set problem
  - $I = \{ C \mid C \subseteq 2^U \}$
  - $S = \{ H \mid H \cap c \neq \emptyset, c \in C \}$
  - $m(C, H) = |H|$
  - $g = \min$

# Complexity Class NPO

An optimization problem  $(I, S, m, g)$  is in NPO if

1. An element of  $I$  is recognizable as such in polynomial time
2. Solutions of  $x$  are bounded in size by a polynomial  $q(|x|)$ , and are recognizable as such in  $q(|x|)$  time
3.  $m$  is computable in polynomial time

Theorem: For an NPO problem, the decision problem whether  $m(x) = K$  ( $g=\min$ ) or  $m(x) = K$  ( $g=\max$ ) is in NP

# Complexity Class PO

- An optimization problem  $P$  is said to be in PO if it is in NPO and there exists an algorithm that for each  $x$  in  $I$  computes an element  $y^*(x)$  and its value  $m(x)$  in polynomial time

# NP-hardness

- NP-completeness is defined for decision problems
- An optimization problem  $P$  is NP-hard if for every NP decision problem  $P'$  we have that  $P' \leq^p P$
- Again, NP-hardness is a sign of intractability

# Approximation Algorithms

- An algorithm that for an NPO problem  $P$  always returns a feasible solution is called an *approximation algorithm* for  $P$
- Even if an NPO problem is intractable it might not be difficult to design a polynomial time approximation algorithm



# Approximate Solution Quality

- Any feasible solution is an approximate solution, and is characterized by the distance from its value to the optimal one.
- An approximation algorithm is characterized by its complexity, and by the ratio of the distance above to the optimum, and the growth of this performance ratio with input size
- An algorithm is a  $p$ -approximate algorithm if the performance ratio is bounded by the function  $p$  in input size

# Some Design Techniques for Approximation Algorithms

- Local search
  - Given solution, search for better “neighbor” solution
- Linear programming
  - Formulate problem as a linear program
- Dynamic Programming
  - Construct solution from optimal solutions to sub-problems
- Randomized algorithms
  - Algorithms that include random choices
- Heuristics
  - Exploratory, possibly learning strategies that offer no guarantees

Thank you

That's all folks