Administration:

Homework Grading signup.
Complexity note

- model assumes source of random bits
- we will assume primitives: biased coins, uniform sampling
- in homework, saw equivalent

Review Game Tree

- Changed presentation from book.
- We used “game tree” with win/loss
- So if win denoted by 0, loss by 1, then function at each node is NOR
- MR uses “MIN/MAX tree” with d “rounds” (1 move per player)
- corresponds to Win/Loss tree of height $2d$ (role of 0/1 in MIN/MAX gets alternately flipped on W/L

Yao’s Minimax Principle

How do we know our randomized algorithm is best possible?
Review tree evaluation.
Lower Bound
Game Theory

- Zero sum games. Scissors Paper Stone. Roberta, Charles.
- Payoff Matrix M. Entries are (large) strategies. chess.

Optimal strategies

- row wants to maximize, column to minimze
- suppose Roberta picks i. Guarantees $\min_j M_{ij}$.
- (Pessimistic) R-optimal strategy: choose i to $\max_i \min_j M_{ij}$.
- (Pessimistic) C-optimal strategy: choose j to $\min_j \max_i M_{ij}$.

When C-optimal and R optimal strategies match, gives **solution** of game.

- if solution exists, knowing opponents strategy useless.
- Sometimes, no solution using these **pure** strategies

Randomization:

- **mixed** strategy: distribution over pure ones

- R uses dist p, C uses dist q, expected payoff $p^T M q$
- Von Neumann:
$$\max_p \min_q p^T M q = \min_q \max_p p^T M q$$
that is, always exists solution in mixed strategies.
- Once p fixed, exists optimal pure q, and vice versa
- Why? Because Mq is a vector with a maximum in one coordinate.

Yao's minimax method:

- Column strategies algorithms, row strategies inputs
- payoff is running time
- randomized algorithm is mixed strategy
- optimum algorithm is optimum randomized strategy
- worst case input is corresponding optimum pure strategy
- Thus:
  - worst case expected runtime of optimum rand. algorithm
  - is payoff of game
  - instead, consider randomized inputs
  - payoff of game via optimum pure strategy
  - which is detemrinistic algorithm!
- Worst case expected runtime of randomized algorithm for any input equals best case running time of a deterministic algorithm for worst distribution of inputs.
- Thus, for lower bound on runtime, show an input distribution with no good deterministic algorithm

Game tree evaluation lower bound.

- Recall Yao's minimax principle.
- lemma: any deterministic alg should finish evaluating one child of a node before doing other: *depth first pruning algorithm.* proof by induction.
- input distribution: each leaf 1 with probability $p = \frac{1}{2}(3 - \sqrt{5})$.
- every node is 1 with probability p
- let $T(h)$ be expected number of leaves evaluated from height h.
- with probablity p, eval one child. else eval 2.
- So
$$T(h) = pT(h-1) + 2(1-p)T(h-1) = (2-p)^h = n^{0.694}$$

Adelman's Theorem.

Consider RP (one sided error)

- Does randomness help?
  - In practice YES
  - in one theory model, no
  - in another, yes!
  - in another, maybe

  - Size n problems (2^n of them)
  - matrix of advice rows by input columns
  - some advice row **witnesses** half the problems.
  - delete row and all its problems
  - remaining matrix still RP (all remaining rows didn't have witness)
  - halves number of inputs. repeat n times.

  Result: on RP of size n, exists n witnesses that cover all problems.

  - polytime algorithm: try n witnesses.
  - Nonuniformity: witnesses not known.
  - $RP \subseteq P/poly$

oblivious versus nonoblivious adversary and algorithms.