Today

Routing and Experts. Review: linear programming. Taking Duals.

Congestion minimization and Experts.

Will use gain and $[0, \rho]$ version of experts: $G \ge (1 - \varepsilon)G^* - \frac{\rho \log n}{\varepsilon}$. Let $T = \frac{k \log n}{\varepsilon^2}$ 1. Row player runs multiplicative weights: $w_i = w_i(1 + \varepsilon)^{g_i/k}$. 2. Route all paths along shortest paths. 3. Output the average of all routings: $\frac{1}{T} \sum_t f(t)$. **Claim:** The congestion, c_{max} is at most $C^* + 2k\varepsilon$. Proof: $G \ge G^*(1 - \varepsilon) - \frac{k \log n}{\varepsilon T} \rightarrow G^* - G \le \varepsilon G^* + \frac{k \log n}{\varepsilon T}$ $T = \frac{k \log n}{\varepsilon^2} \rightarrow G^* - G \le 2\varepsilon k$ $G^* = c_{max}$ — Best row payoff against average routing. $G \le C$ — each day, gain is average congestion \le opt max congestion. $\rightarrow c_{max} - C^* \le 2\varepsilon k$

Toll/Congestion

Given: G = (V, E). Given $(s_1, t_1) \dots (s_k, t_k)$. Row: choose routing of all paths. Column: choose edge. Row pays if column chooses edge on any path.

Matrix: row for each routing: *r* column for each edge: *e*

A[r, e] is congestion on edge e by routing r

Offense: (Best Response.) Router: route along shortest paths. Toll: charge most loaded edge.

Defense: Toll: maximize shortest path under tolls. Route: minimize max congestion on any edge.

Better setup.

Runtime: O(km) to route in each step. $O(k \log n(\frac{1}{\epsilon^2}))$ steps $\rightarrow O(k^2 m \log n)$ to get a constant approximation. Homework: $O(km \log n)$ algorithm.

Two person game.

Row for every roting. (A[r, e])An exponential number of rows! Two person game with experts won't be so easy to implement. Version with row and column flipped may work. A[e, r] - congestion of edge *e* on routing *r*. *m* rows. Exponential number of columns. Multiplicative Weights only maintains *m* weights. Adversary only needs to provide best column each day. Runtime only dependent on *m* and *T* (number of days.)

Fractional versus Integer.

Did we solve path routing? Yes? No? No! Average of *T* routings. We approximately solved fractional routing problem. No solution to the path routing problem that is $(1 + \varepsilon)$ optimal! Homework 2. Problem 1. Decent solution to path routing problem?

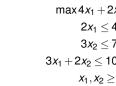
Randomized Rounding

For each s_i , t_i , choose path p_i with probability $f(p_i)$. Congestion c(e) edge rounds to $\tilde{c}(e)$. Edge e. used by paths p_1, \ldots, p_m . Let $X_i = 1$, if path p_i is chosen. otherwise, $X_i = 0$. Rounded congestion, $\tilde{c}(e)$, is $\sum_i X_i$. Expected Congestion: $\sum_{i} E(X_i)$. $E(X_i) = 1Pr[X_i = 1] + 0Pr[X_i = 0] = f(p_i)$ $\rightarrow \sum_{i} E(X_{i}) = \sum_{i} f(p_{i}) = c(e).$ $\rightarrow E(\tilde{c}(e)) = c(e).$ Concentration (law of large numbers) c(e) is relatively large $(\Omega(\log n))$ $\rightarrow \tilde{c}(e) \approx c(e).$ Concentration results? later.

Profit maximization.

Plant Carrots or Peas? 2\$ bushel of carrots. 4\$ for peas. Carrots take 3 unit of water/bushel. Peas take 2 units of water/bushel. 100 units of water. Peas require 2 yards/bushel of sunny land. Carrots require 1 yard/bushel of shadyland. Garden has 60 yards of sunny land and 75 yards of shady land. To pea or not to pea, that is the question!

A linear program.

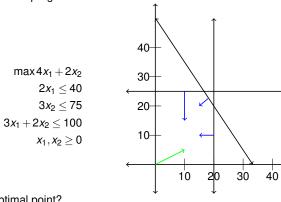


 $\max 4x_1 + 2x_2$ $2x_1 \le 40$ $3x_2 \le 75$ $3x_1 + 2x_2 < 100$ $x_1, x_2 \ge 0$

Try every point if we only had time! How many points? Real numbers?

Infinite. Uncountably infinite!

Optimal point?



Optimal point?

To pea or not to pea.

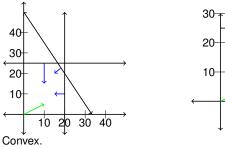
4\$ for peas. 2\$ bushel of carrots. x_1 - to pea! x_2 to carrot? Money $4x_1 + 2x_2$ maximize max $4x_1 + 2x_2$. Carrots take 2 unit of water/bushel. Peas take 3 units of water/bushel. 100 units of water.

$3x_1 + 2x_2 \le 100$

Peas 2 yards/bushel of sunny land. Have 40 sq vards. $2x_1 < 40$ Carrots get 3 yards/bushel of shady land. Have 75 sq. yards. $3x_2 < 75$ Can't make negative! $x_1, x_2 \ge 0$. A linear program.

> $\max 4x_1 + 2x_2$ $2x_1 \le 40$ $3x_2 < 75$ $3x_1 + 2x_2 \le 100$ $x_1, x_2 > 0$

Feasible Region.



Any two points in region connected by a line in region. Algebraically:

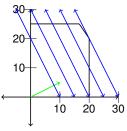
10

20

30

If x and x' satisfy onstraint,

 $\rightarrow x'' = \alpha x + (1 - \alpha)x$



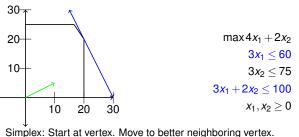
Optimal at pointy part of feasible region! Vertex of region. Intersection of two of the constraints (lines in two dimensions)! Try every vertex! Choose best. $O(m^2)$ if *m* constraints and 2 variables. For *n* variables, *m* constraints, how many? $nm? \binom{m}{n}? n+m?$ $\binom{m}{n}$ Finite!!!!!! Exponential in the number of variables.

Duality.

$\max x_1 + 8x_2$
$x_1 \leq 4$
<i>x</i> ₂ ≤ 3
$x_1 + 2x_2 \le 7$
$x_1, x_2 \ge 0$

Solution value: 25. Add equation 1 and 8 times equation 2 gives.. $x_1 + 8x_2 \le 4 + 24 = 28$. Better way to add equations to get bound on function? Sure: 6 times equation 2 and 1 times equation 3. $x_1 + 8x_2 \le 6(3) + 7 = 25$. Thus, the value is at most 25. The upper bound is same as solution!

Proof of optimality!



Until no better neighbor. This example. (0,0) objective $0. \rightarrow (0,25)$ objective 50. $\rightarrow (16\frac{2}{3},25)$ objective $115\frac{2}{3}$ $\rightarrow (20,20)$ objective 120. Duality: Add blue equations to get objective function? 1/3 times first plus second. Get $4x_1 + 2x_2 \le 120$. Every solution must satisfy this inequality! Objective value: 120. Can we do better? No! Dual problem: add equations to get best upper bound.

Duality:example

Idea: Add up positive linear combination of inequalities to "get" upper bound on optimization function.

Will this always work?

How to find best upper bound?

Duality.

$\max x_1 + 8x_2$
$x_1 \leq 4$
<i>x</i> ₂ ≤ 3
$x_1 + 2x_2 \le 7$
$x_1, x_2 \ge 0$

One Solution: $x_1 = 1, x_2 = 3$. Value is 25. Best possible? For any solution. $x_1 \le 4$ and $x_2 \le 3$so $x_1 + 8x_2 \le 4 + 8(3) = 28$. Added equation 1 and 8 times equation 2 yields bound on objective.. Better solution? Better upper bound?

Duality: computing upper bound.

Best Upper Bound.

Multiplier	Inequality
y 1	$x_1 \leq 4$
y 2	$x_2 \leq 3$
<i>y</i> 3	$x_1 + 2x_2 \le 7$

Adding equations thusly... $(y_1 + y_3)x_1 + (y_2 + 2y_3)x_2 \le 4y_1 + 3y_2 + 7y_3.$ The left hand side should "dominate" optimization function:

If $y_1, y_2, y_3 \ge 0$ and $y_1 + y_3 \ge 1$ and $y_2 + 2y_3 \ge 8$ then.. $x_1 + 8x_2 \le 4y_1 + 3y_2 + 7y_3$ Find best y_i 's to minimize upper bound?

The dual, the dual, the dual.

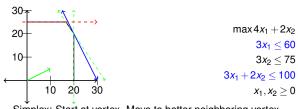
Find best y_i 's to minimize upper bound?

Again: If you find $y_1, y_2, y_3 \ge 0$ and $y_1 + y_3 \ge 1$ and $y_2 + 2y_3 \ge 8$ then.. $x_1 + 8x_2 \le 4y_1 + 3y_2 + 7y_3$ min $4y_1 + 3y_2 + 7y_3$ $y_1 + y_3 \ge 1$ $y_2 + 2y_3 \ge 8$ $y_1, y_2, y_3 \ge 0$

A linear program.

The Dual linear program. Primal: $(x_1, x_2) = (1,3)$; Dual: $(y_1, y_2, y_3) = (0,6,1)$. Value of both is 25! Primal is optimal ... and dual is optimal!

Again: simplex



Simplex: Start at vertex. Move to better neighboring vertex. Until no better neighbor. Duality: Add blue equations to get objective function? 1/3 times first plus second. Get $4x_1 + 2x_2 \le 120$. Every solution must satisfy this inequality! Geometrically and Complementary slackness: Add tight constraints to "dominate objective function."

Don't add this equation! Shifts.

The dual.

In general.

Primal LP	Dual LP
max c · x	min $y^T b$
$Ax \leq b$	$y^T A \ge c$
$x \ge 0$	$y \ge 0$

Theorem: If a linear program has a bounded value, then its dual is bounded and has the same value.

Weak Duality: primal (P) \leq dual (D)

Feasible
$$(x, y)$$

 $P(x) = c \cdot x \le y^T A x \le y^T b \cdot x = D(y).$

Strong Duality: next lecture.

Example: review.

$\max x_1 + 8x_2$	min $4y_1 + 3y_2 + 7y_3$
$x_1 \leq 4$	$y_1 + y_3 \ge 1$
<i>x</i> ₂ ≤ 3	$y_2+2y_3\geq 8$
$x_1 + 2x_2 \le 7$	$x_1, x_2 \ge 0$
$y_1, y_2, y_3 \ge 0$	

"Matrix form"

$$\begin{array}{ll} \max[1,8] \cdot [x_1,x_2] & \min[4,3,7] \cdot [y_1,y_2,y_3] \\ \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 2 \end{pmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 4 \\ 3 \\ 7 \end{bmatrix} & [y_1,y_2,y_3] \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 2 \end{pmatrix} \geq \begin{bmatrix} 1 \\ 8 \end{bmatrix} \\ [x_1,x_2] \geq 0 & [y_1,y_2,y_3] \end{array}$$

Complementary Slackness

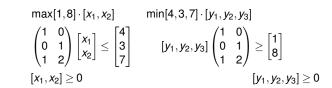
Primal LP	Dual LP
max c · x	min $y^T b$
$Ax \leq b$	$y^T A \ge c$
$x \ge 0$	$y \ge 0$

Given A, b, c, and feasible solutions x and y.

Solutions x and y are both optimal if and only if $x_i(c_i - (y^T A)_i) = 0$, and $y_j(b_j - (Ax)_j)$. $x_i(c_i - (y^T A)_i) = 0 \rightarrow$ $\sum_i (c_i - (y^T A)_i)x_i = cx - y^T Ax \rightarrow cx = y^T Ax$. $y_j(b_j - (Ax)_j) = 0 \rightarrow$ $\sum_i y_j(b_j - (Ax)_j) = yb - y^T Ax \rightarrow by = y^T Ax$. cx = by.

If both are feasible, $cx \le by$, so must be optimal. In words: nonzero dual variables only for tight constraints!

Matrix equations.



We can rewrite the above in matrix form.

$$\begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 2 \end{pmatrix} \qquad \qquad c = [1,8]b = [4,3,7]$$

The primal is $Ax \le b, \max c \cdot x, x \ge 0$. The dual is $y^T A \ge c, \min b \cdot y, y \ge 0$.

A =

 \geq 0

See you on Tuesday.