LINEAR PROGRAMMING

[V. CH4]: EFFICIENCY OF THE SIMPLEX METHOD

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PERFORMANCE MEASURES

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WORST-CASE ANALYSIS OF THE SIMPLEX METHOD

EMPIRICAL AVERAGE PERFORMANCE

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We saw that the simplex method (equipped with anti-cycling rules) will solve any linear programming problem for which an optimal solution exists. The question, now, is *how fast* it will solve such a problem.

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Performance measures are:

• worst case

looks at all problems of a given "size" and asks how much effort is needed to solve the hardest.

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looks at all problems of *a given "size"* and asks how much effort is needed to solve the *hardest*.

• average case

looks at the average amount of effort needed to solve all.

→ Worst-case analyses are generally easier.

It needs to provide an upper bound on how much effort required + a specific example attaing this bound.

 \sim On an average case analysis, one needs a stochastic model of random problems and evaluate the amount of effort required to solve every problem in the sample space.

worst-case is more tractable, but less relevant while dealing with real problems

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Even with the last one, "size" of data might still be ambiguous. (why?) we shall simply focus on *m* and *n* to characterize the size of a problem.

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First factor is platform-independent and so a *resasonable suragate* for the acctual time (not when different algorithm are compared!)

We simply count the number of iterations (pivots).

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Since the simplex method operates by moving from one dictionary to another (without cycling), an upper bound on the number of iterations is simply the number of possible dictionaries:

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\binom{n+m}{m}
```

For a fixed value of the sum n + m, this expression is maximized when m = n.

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For a fixed value of the sum n + m, this expression is maximized when m = n.

How big is it? Not hard to show:

$$\frac{1}{2n}2^{2n} \le \binom{2n}{n} \le 2^{2n}$$

For
$$n = 25$$
:
 $2^{50} = 1.1259 \times 10^{15}$

Our best chance for finding a bad example is to look at the case where m = n.

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lets look at the generic example:

Given constants $1 = \beta_1 \ll \beta_2 \ll \cdots \ll \beta_n$

$$\max_{x} \quad \sum_{j=1}^{n} 2^{n-j} x_{j} - \frac{1}{2} \sum_{j=1}^{n} 2^{n-j} \beta_{j}$$
s.t.
$$2 \sum_{j=1}^{i-1} 2^{i-j} x_{j} + x_{i} \le \sum_{j=1}^{i-1} 2^{i-j} \beta_{j} + \beta_{i} \quad i = 1, 2, \dots, n$$

$$x_{j} \ge 0 \qquad i = 1, 2, \dots, n$$

For n = 3

$$\max_{x} \quad 4x_{1} + \quad 2x_{2} + \quad 1x_{3} - \quad 2\beta_{1} - \beta_{2} - \frac{1}{2}\beta_{3} \\ \text{s.t.} \quad 1x_{1} + \quad + \quad \leq \beta_{1} \\ 4x_{1} + \quad 1x_{2} + \quad \leq 2\beta_{1} + \beta_{2} \\ 8x_{1} + \quad 4x_{2} + \quad 1x_{3} \leq 4\beta_{1} + 2\beta_{2} + \beta_{3} \\ x_{1}, \qquad x_{2}, \qquad x_{3} \geq 0 \\ \end{array}$$

For n = 3

$$\max_{x} \quad 4x_{1} + \quad 2x_{2} + \quad 1x_{3} - \quad 2\beta_{1} - \beta_{2} - \frac{1}{2}\beta_{3}$$
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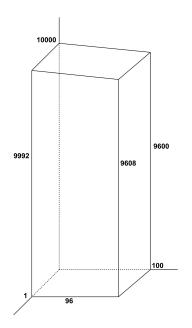
$$4x_{1} + \quad 1x_{2} + \quad \leq 2\beta_{1} + \beta_{2}$$

$$8x_{1} + \quad 4x_{2} + \quad 1x_{3} \leq 4\beta_{1} + 2\beta_{2} + \beta_{3}$$

$$x_{1}, \qquad x_{2}, \qquad x_{3} > 0$$

Assuming $\beta_2 = 98, \beta_3 = 9800$, the feasible region looks like :

WORST-CASE ANALYSIS OF THE SIMPLEX METHOD



Constraints represent a "minor" distortion to an 3-dimensional hypercube:

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This region has $2^{n=3}$ vertices and the idea is to trick the pivot rule so as to visit all of them.

Back to the generic Klee-Minty example (n = 3), the first dictionary is

$\zeta = -$	$2\beta_1$ –	$1\beta_2$ –	$0.5\beta_{3} +$	$4 x_1 +$	$2 x_2 +$	$1 x_3$
$w_1 = +$	$1\beta_1$		_	$1x_1$		
$w_2 = +$	$2\beta_1 +$	$1\beta_2$	_	$4x_1 - $	$1x_{2}$	
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which is feasible.

Using the largest-coefficient rule: (x_1, w_1) are the entering, leaving pair.

Corresponding vertex on the Klee-Minty cube is: (0, 0, 0)

After the first pivot

$\zeta = +$	$2\beta_1$ –	$1\beta_2$ –	$0.5\beta_3$ $-$	$4w_1 + $	$2 x_2 +$	$1 x_3$
$x_1 = +$	$1\beta_1$		_	$1w_1$		
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for the next pivot: (x_2, w_2)

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Corresponding vertex on the Klee-Minty cube is: $(\beta_1, 0, 0)$

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for the next pivot: (x_1, w_1)

Corresponding vertex on the Klee-Minty cube is: $(0, 2\beta_1 + 1\beta_2, -4\beta_1 - 2\beta_2 + 1\beta_3)$

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for the next pivot: (w_1, x_1)

Corresponding vertex on the Klee-Minty cube is: $(1\beta_1, 0, -4\beta_1 + 2\beta_2 + 1\beta_3)$

And finally after the seventh pivot

$\zeta = +$	$2\beta_1 +$	$1\beta_2 +$	$0.5\beta_3$ –	$4x_1 - $	$2x_2 -$	$1w_3$	
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The optimal dictionary.

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The optimal dictionary.

Corresponding vertex on the Klee-Minty cube is: $(0, 0, +4\beta_1 + 2\beta_2 + 1\beta_3)$

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On a machin with 1000 ips. It will take 40 billion years to solve! (The age of the universe is estimated to be 13.7 billion years)

Yet, problems with 10,000 to 100,000 variables/constraints are solved routinely every day. (Worst case analysis!)

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Does there exist a varient of the Simplex method with polynomial worst case performance?

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- Indeed this is an open question :

Does there exist a varient of the Simplex method with polynomial worst case performance?

• However, For linear programs, we have other algorithm (called *interior point* methods) with *polynomial worstcase performance*. In contrast to the simplex algorithm, which finds an optimal solution by traversing the edges between vertices on a polyhedral set, interior-point methods move through the interior of the feasible region.

• Note that every pivot is the *swap* of an x_j with the corresponding w_j .

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These are the necessary steps needed to take toward a proof of worst case exaponantial time of the generic Klee-Minty example. (Left as part of to the second HW)

PERFORMANCE MEASURES

WORST-CASE ANALYSIS OF THE SIMPLEX METHOD

EMPIRICAL AVERAGE PERFORMANCE

P. KELDENICH, A. MORADI (IBR ALGORITHMIK)

LINEAR PROGRAMMING

Lets again consider the simple simplex implementation discussed previous week.