



Design and Analysis of Algorithms (XI)

Linear Programming: Introduction

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An Introduction to Linear Programming

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A **linear programming problem** gives a set of **variables**, and assigns **real values** to them so as to

- 1 satisfy a set of **linear equations** and/or **linear inequalities** involving these variables, and
- 2 maximize or minimize a given **linear objective function**.

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Q: How much of each should it produce to **maximize** profits?

- Every box of **Pyramide** has a profit of **\$1**.
- Every box of **Nuit** has a profit of **\$6**.
- The daily demand is limited to at most **200** boxes of **Pyramide** and **300** boxes of **Nuit**.
- The current workforce can produce a total of at most **400** boxes of chocolate per day.

LP Formulation

$$\begin{array}{ll} \text{Objective function} & \max x_1 + 6x_2 \\ \text{Constraints} & x_1 \leq 200 \\ & x_2 \leq 300 \\ & x_1 + x_2 \leq 400 \\ & x_1, x_2 \geq 0 \end{array}$$

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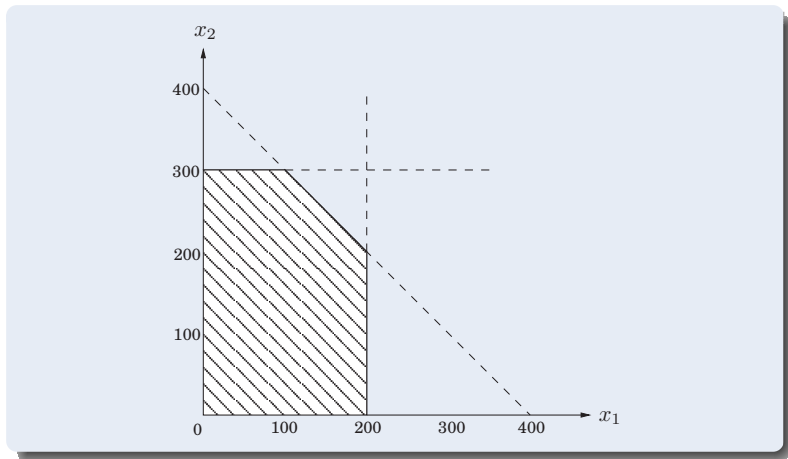
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It is a convex polygon.

The Convex Polygon



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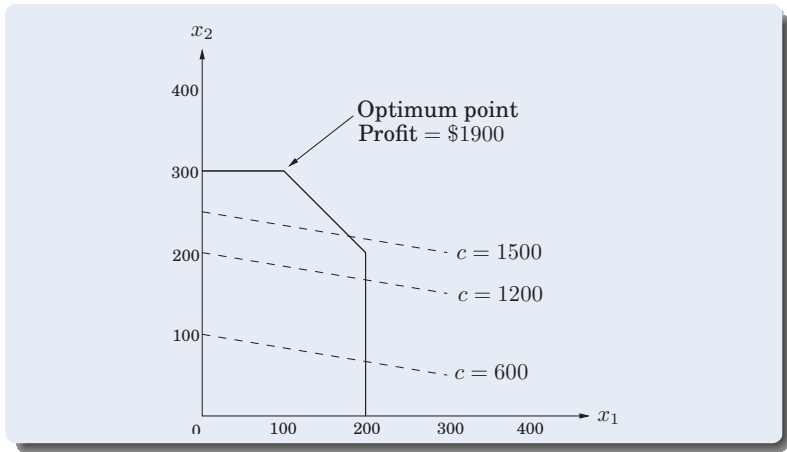
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The optimum solution will be the very last feasible point that the profit line sees and must therefore be a **vertex of the polygon**.

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Upon reaching a vertex that has no better neighbor, simplex declares it to be optimal and halts.

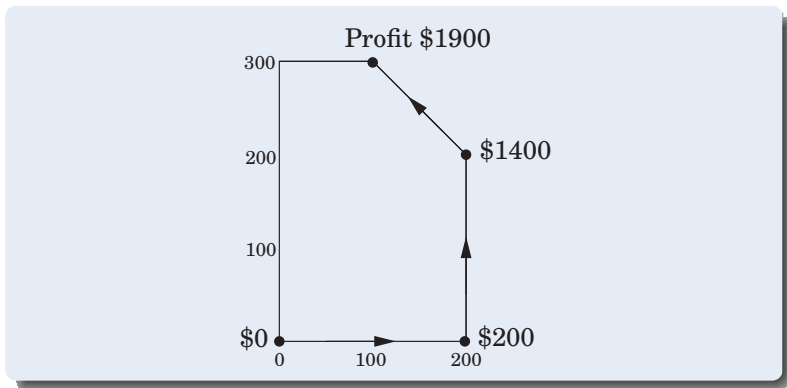
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Q: Why does this local test imply **global optimality**?

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By simple **geometry**. Since all the vertex's neighbors lie below the line, the rest of the **feasible polygon** must also lie below this line.

The Example



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Nuit and **Luxe** require the same packaging machinery. Luxe uses it **three times** as much, which imposes another constraint $x_2 + 3x_3 \leq 600$.



$$\max x_1 + 6x_2 + 13x_3$$

$$x_1 \leq 200$$

$$x_2 \leq 300$$

$$x_1 + x_2 + x_3 \leq 400$$

$$x_2 + 3x_3 \leq 600$$

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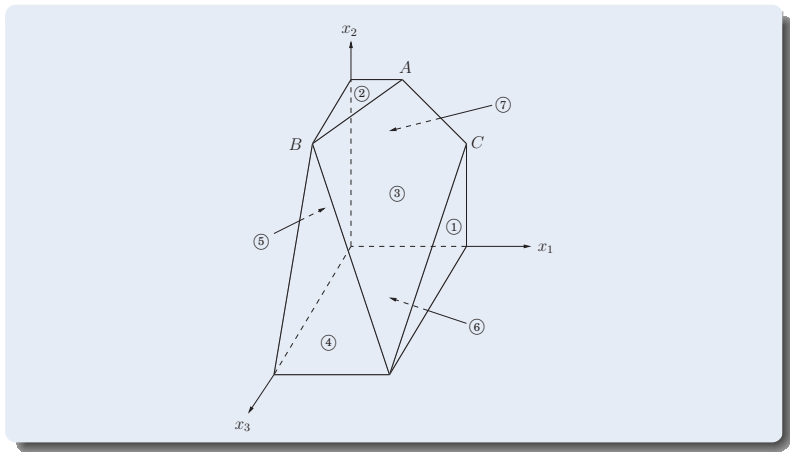
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A profit of c corresponds to the plane $x_1 + 6x_2 + 13x_3 = c$.

As c increases, this profit-plane moves parallel to itself, further into the positive **orthant** until it no longer touches the feasible region.

The Example



The point of final contact is the **optimal vertex**: $(0, 300, 100)$, with total **profit** \$3100.

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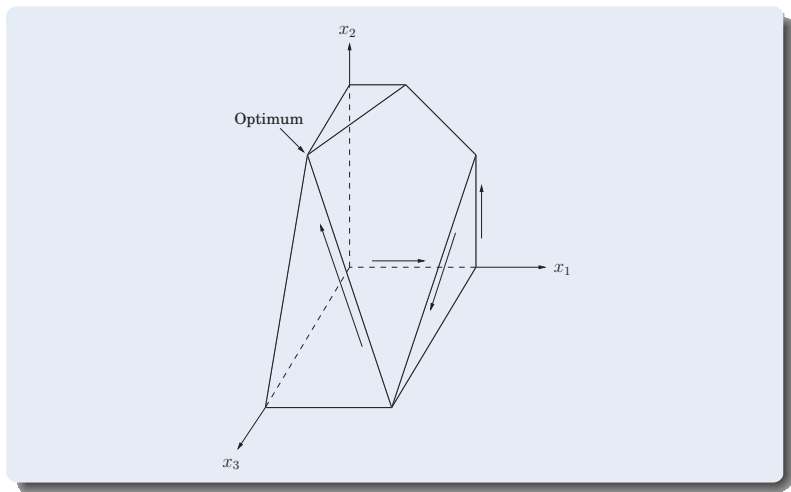
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A possible **trajectory**

$$\frac{(0, 0, 0)}{\$0} \rightarrow \frac{(200, 0, 0)}{\$200} \rightarrow \frac{(200, 200, 0)}{\$1400} \rightarrow \frac{(200, 0, 200)}{\$2800} \rightarrow \frac{(0, 300, 100)}{\$3100}$$

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With no initial surplus of carpets.

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- 3 **Storing surplus production**, costing **\$8** per carpet per month. Currently without stored carpets on hand, and without any carpets stored at the end of year.

- w_i = number of workers during i -th month; $w_0 = 30$.
- x_i = number of carpets made during i -th month.
- o_i = number of carpets made by overtime in month i .
- h_i, f_i = number of workers hired and fired, respectively, at beginning of month i .
- s_i = number of carpets stored at end of month i ; $s_0 = 0$.

LP Formulation

All variables must be **nonnegative**:

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The **number of workers** can potentially change at the start of each month:

$$w_i = w_{i-1} + h_i - f_i$$

LP Formulation

The number of carpets stored at the end of each month is what we started with, plus the number we made, minus the demand for the month:

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And overtime is limited:

$$o_i \leq 6w_i$$

The **objective function** is to minimize the total cost:

$$\min 2000 \sum_i w_i + 320 \sum_i h_i + 400 \sum_i f_i + 8 \sum_i s_i + 180 \sum_i o_i$$

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In the example, most of the variables take on fairly large values, and thus **rounding** is unlikely to affect things too much.

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In NP problems, finding the optimum integer solution of an LP is an important but very hard problem, called integer linear programming.

Duality

Product Planning Revisit

Recall:

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We take the first inequality and add it to six times the second inequality:

$$x_1 + 6x_2 \leq 2000$$

Multiplying the three inequalities by 0, 5, and 1, respectively, and adding them up yields

$$x_1 + 6x_2 \leq 1900$$

Multipliers

Let's investigate the issue by describing what we expect of these three multipliers, call them y_1 , y_2 , y_3 .

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We want the left-hand side to look like the **objective function** $x_1 + 6x_2$ so that the right-hand side is an upper bound on the **optimum solution**.

$$x_1 + 6x_2 \leq 200y_1 + 300y_2 + 400y_3$$

if

$$y_1, y_2, y_3 \geq 0$$

$$y_1 + y_3 \geq 1$$

$$y_2 + y_3 \geq 6$$

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What we want is a bound as tight as possible, so we **minimize**

$$200y_1 + 300y_2 + 400y_3$$

subject to the preceding inequalities. This is a **new linear program!**

The Dual Program

$$\min 200y_1 + 300y_2 + 400y_3$$

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Here is just such a pair:

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They both have value **1900** and certify each other's optimality.

Matrix-Vector Form and Its Dual

Primal LP

$$\begin{aligned} \max \quad & c^T \mathbf{x} \\ \text{Ax} \leq & b \\ \mathbf{x} \geq & 0 \end{aligned}$$

Dual LP

$$\begin{aligned} \min \quad & \mathbf{y}^T b \\ \mathbf{y}^T A \geq & c^T \\ \mathbf{y} \geq & 0 \end{aligned}$$

Primal LP:

$$\begin{aligned} \max \quad & c_1 x_1 + \cdots + c_n x_n \\ & a_{i1} x_1 + \cdots + a_{in} x_n \leq b_i \quad \text{for } i \in I \\ & a_{i1} x_1 + \cdots + a_{in} x_n = b_i \quad \text{for } i \in E \\ & x_j \geq 0 \quad \text{for } j \in N \end{aligned}$$

Dual LP:

$$\begin{aligned} \min \quad & b_1 y_1 + \cdots + b_m y_m \\ & a_{1j} y_1 + \cdots + a_{mj} y_m \geq c_j \quad \text{for } j \in N \\ & a_{1j} y_1 + \cdots + a_{mj} y_m = c_j \quad \text{for } j \notin N \\ & y_i \geq 0 \quad \text{for } i \in I \end{aligned}$$

Matrix-Vector Form and Its Dual

$$\begin{aligned} \max \quad & x_1 + 6x_2 \\ & x_1 \leq 200 \\ & x_2 \leq 300 \\ & x_1 + x_2 \leq 400 \\ & x_1, x_2 \geq 0 \end{aligned}$$

$$\begin{aligned} \min \quad & 200y_1 + 300y_2 + 400y_3 \\ & y_1 + y_3 \geq 1 \\ & y_2 + y_3 \geq 6 \\ & y_1, y_2, y_3 \geq 0 \end{aligned}$$

Theorem (Duality)

If a linear program has a *bounded optimum*, then so does its *dual*, and the two optimum values *coincide*.

Complementary Slackness

The number of variables in the dual is equal to that of constraints in the primal and the number of constraints in the dual is equal to that of variables in the primal.

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The **complementary slackness** refers to a relationship between the slackness in a primal constraint and the associated dual variable.

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$$x_1 = 100, x_2 = 300$$

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$$y_1 = 0, y_2 = 5, y_3 = 1$$

Theorem

Assume LP problem (P) has a solution x^* and its dual problem (D) has a solution y^* .

- 1 If $x_j^* > 0$, then the j -th constraint in (D) is binding.
- 2 If the j -th constraint in (D) is not binding, then $x_j^* = 0$.
- 3 If $y_i^* > 0$, then the i -th constraint in (P) is binding.
- 4 If the i -th constraint in (P) is not binding, then $y_i^* = 0$.

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Proof.

Assignment !

A Concrete Example for Duality

Brewery Problem

Small brewery produces ale and beer.

- Production limited by scarce resources: corn, hops, barley malt.
- Recipes for ale and beer require different proportions of resources.

Beverage	Corn(pounds)	Hops(ounces)	Malt(pounds)	Profit(\$)
Ale (barrel)	5	4	35	13
Beer (barrel)	15	4	20	23
constraint	480	160	1190	

LP and its Dual

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$$\begin{aligned} \max & 13x_1 + 23x_2 \\ & 5x_1 + 15x_2 \leq 480 \\ & 4x_1 + 4x_2 \leq 160 \\ & 35x_1 + 20x_2 \leq 1190 \\ & x_1, x_2 \geq 0 \end{aligned}$$

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$$\begin{aligned} \min & 480y_1 + 160y_2 + 1190y_3 \\ & 5y_1 + 4y_2 + 35y_3 \geq 13 \\ & 15y_1 + 4y_2 + 20y_3 \geq 23 \\ & y_1, y_2, y_3 \geq 0 \end{aligned}$$

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$$x_1^* = 12, x_2^* = 28$$

Brewer: find optimal mix of beer
and ale to maximize profits.

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$$y_1^* = 1, y_2^* = 2, y_3^* = 0$$

Entrepreneur: buy individual resources from brewer at min cost.

LP Duality: Sensitivity Analysis

Q. How much should brewer be willing to pay (marginal price) for additional supplies of scarce resources?

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A. At least $2 (\$1) + 5 (\$2) + 24 (\$0) = \12 / barrel.

Referred Materials

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Content of this lecture comes from Section 7.1 and 7.4 in [DPV07], Section 29.2 in [CLRS09], and Section 7.3 in [WS11].