# Linear programming COMS20010 (Algorithms II)

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Linear programming is the single most fundamental technique for solving optimisation problems. It's used in:

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These two videos are a very basic overview of a deep and rich theory.

As an example problem: which Warhammer models should Games Workshop produce in order to make as much money as possible?

## Example application: Warhammer

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- Games Workshop cannot produce a negative amount of miniatures, so...they require  $N, D \ge 0$ .

More succinctly, the problem is:

$$4N+10D 
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  $5N+100D \leq 5000;$   $60N+10D \leq 4000;$   $N \leq 100;$   $D \leq 50;$   $N, D \geq 0.$ 

More succinctly, the problem is:

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, subject to  $5N+100D \leq 5000$ ;  $60N+10D \leq 4000$ ;  $N \leq 100$ ;  $D \leq 50$ ;  $N, D \geq 0$ .

We can write this in matrix form:

$$4N+10D \rightarrow \mathsf{max}, \text{ subject to}$$
 
$$\begin{pmatrix} 5 & 100 \\ 60 & 10 \\ 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} N \\ D \end{pmatrix} \leq \begin{pmatrix} 5000 \\ 4000 \\ 100 \\ 50 \end{pmatrix};$$
 
$$N,\ D \geq 0.$$

**Notation:** We say  $\vec{x} \leq \vec{y}$  iff  $\vec{x_i} \leq \vec{y_i}$  for **all** i, and similarly for  $\vec{x} \geq \vec{y}$ .

For example,  $(2,0,1) \ge (0,0,0)$ , but  $(2,0,1) \ge (0,1,0)$ .

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**Problem statement:** We are given a linear objective function  $f: \mathbb{R}^n \to \mathbb{R}$ , an  $m \times n$  matrix A, and an m-dimensional vector  $\vec{b} \in \mathbb{R}^m$ . The desired output is a vector  $\vec{x} \in \mathbb{R}^n$  maximising  $f(\vec{x})$  subject to  $A\vec{x} \leq \vec{b}$  and  $\vec{x} \geq \vec{0}$ .

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We say a  $\vec{x} \in \mathbb{R}^n$  is a **feasible** solution to a linear program if  $\vec{x} \ge \vec{0}$  and  $A\vec{x} \le \vec{b}$ , and an **optimal** solution if  $f(\vec{y}) \le f(\vec{x})$  for all feasible  $y \in \mathbb{R}^n$ .

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Sometimes there is **no** optimal solution, for two reasons:

• Sometimes the constraints are so tight they rule out any feasible solutions at all, e.g.  $x \to \max$  subject to  $x \le -1$  and  $x \ge 0$ .

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But these are the only two things that can go wrong — any bounded linear program with at least one feasible solution has an optimal solution.

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This statement seems quite restrictive. What about:

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All of these can be implemented in the above framework, which is known as **standard form**.

As an example, let's turn the following LP into standard form:

$$4x - 5y + z \rightarrow \min$$
 subject to  $x + y + z = 5$ ;  $x + 2y \ge 2$ ;  $x, z \ge 0$ .

As an example, let's turn the following LP into standard form:

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$$x + y + z = 5;$$

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**Minimisation problems:**  $f(\vec{x})$  is as small as possible if and only if  $-f(\vec{x})$  is as large as possible.

So  $4x - 5y + z \rightarrow \min$  is equivalent to  $-4x + 5y - z \rightarrow \max$ .

As an example, let's turn the following LP into standard form:

$$-4x + 5y - z \rightarrow \text{max} \text{ subject to}$$

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 $\geq$  constraints:  $\sum_{j} a_{ij} x_{j} \geq b_{i}$  if and only if  $-\sum_{j} a_{ij} x_{j} \leq -b_{i}$ .

So  $x+2y \ge 2$  is equivalent to  $-x-2y \le -2$ , and  $x+y+z \ge 5$  is equivalent to  $-x-y-z \le -5$ .

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**Removing non-negativity:** If y doesn't have to be non-negative, we can replace it by  $y_1 - y_2$  where  $y_1, y_2 \ge 0$ . We think of  $y_1$  as the positive part and  $y_2$  as the negative part.

There will be feasible solutions with both  $y_1 > 0$  and  $y_2 > 0$ , but this doesn't matter — any optimal solution of the old problem will be an optimal solution of the new one and vice versa.

As an example, let's turn the following LP into standard form:

$$-4x + 5(y_1 - y_2) - z \rightarrow \text{max subject to}$$

$$x + (y_1 - y_2) + z \le 5;$$

$$-x - (y_1 - y_2) - z \le -5;$$

$$-x - 2(y_1 - y_2) \le -2;$$

$$x, y_1, y_2, z \ge 0.$$

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 subject to

$$\begin{pmatrix} 1 & 1 & -1 & 1 \\ -1 & -1 & 1 & -1 \\ -1 & -2 & 2 & 0 \end{pmatrix} \begin{pmatrix} x \\ y_1 \\ y_2 \\ z \end{pmatrix} \le \begin{pmatrix} 5 \\ -5 \\ -2 \end{pmatrix};$$

$$x, y_1, y_2, x \ge 0.$$

The problem is now in standard form! And these techniques are fully general.

So we have **reduced** the problem of solving a general linear program, which might have a minimisation goal, = or  $\le$  constraints, and/or negative variables, to that of solving a linear program in standard form.

That makes it easier to find an algorithm!