

343 OPERATIONS RESEARCH

Common Types of LPs

Last Lecture

- ▶ Standard form of an LP
 - ▶ Minimisation problem
 - ▶ No inequalities
 - ▶ All equalities have non-negative right hand sides
 - ▶ All variables non-negative

This Lecture

- ▶ Common types of LP models
 - ▶ Resource allocation & blending models
 - ▶ Operations planning models
 - ▶ Shift scheduling models
 - ▶ Time-phased models
- ▶ Tutorial: Introduction to GLPK

Taxonomy of LP models

- ▶ Linear programs have a fairly simple structure:
 - ▶ Linear objective
 - ▶ Linear constraints
 - ▶ Continuous variables
- ▶ They all look similar... but the **semantics** of variables and constraints changes widely!
 - ▶ How can we translate textual specifications into LP models?
- ▶ Certain formulations arise systematically in specific applications, thus it is useful to **classify LPs**.

Resource Allocation Models

- ▶ The goal of resource allocation models is to **split a resource**.
- ▶ The main issue is how to divide a valuable resource among competing needs.
 - ▶ Resource may be capital, land, CPU time,...
- ▶ Decision variables specify how much of the limited resource is allocated to each use, for example:
 - ▶ $x_j :=$ hours spent on the j th course
 - ▶ $x_j :=$ area to be used for growing the j th cereal type
 - ▶ ...
- ▶ Constraints are often of the type:

$$\sum_j (\text{resource allocation } j) \leq (\text{limit on resource})$$

Example: VM Capacity Allocation

x_j := percentage of CPU time allocated to virtual machine (VM) j
 c_j := analyses completed every minute by VM j for each percentage point of CPU time assigned to it
 s_j := minimum CPU percentage that can be assigned to VM j

Find a CPU assignment that maximizes the completion rate of analyses.

$$\text{maximise } z = c_1x_1 + \dots + c_nx_n$$

$$\text{subject to } x_1 + \dots + x_n \leq 1 \text{ (limit on resource)}$$

$$x_1 \geq s_1, \dots, x_n \geq s_n$$

Blending Models

- ▶ Blending models are similar to resource models, but they **combine resources**.
- ▶ Decide what mix of ingredients best fulfills output requirements.
- ▶ Decision variables specify how much of each ingredient to include in the mix, for example:
 - ▶ $x_j :=$ fraction of ingredient j used in the diet
 - ▶ $x_j :=$ kilograms of chemical j used in solution
- ▶ Blending models often feature **composition constraints**, e.g.
$$\sum_j (\% \text{ of property } k \text{ in ingredient } j) \times (\text{amounts of } j \text{ used}) \leq (\text{allowed amount of property } k \text{ in blend})$$

Example: Diet Problem

Determine **most economical diet**, with **basic nutritional requirements** for good health.

- ▶ n **different foods**: i th sells at price c_i /unit,
- ▶ m basic **nutritional ingredients**: j th ingredient's daily intake for individual is at least b_j units (healthy diet),
- ▶ one unit of food i contains a_{ji} units of the j th ingredient,
- ▶ x_i : units of food i in diet (we allow fractional amounts).



Nutrition Facts	
Serving Size 1 package (456g)	
Amount Per Serving	
Calories 1,030	Calories from Fat 570
% Daily Values*	
Total Fat 64g	98%
Saturated Fat 21g	104%
Cholesterol 680mg	231%
Sodium 2,090mg	87%
Total Carbohydrate 78g	26%
Dietary Fiber 4g	17%
Sugars 22g	
Protein 36g	
Vitamin A 25%	Vitamin C 2%
Calcium 20%	Iron 25%
* Percent Daily Values are based on a diet of other people's misdeeds.	
Calories: 2,000 2,500	
Total Fat	Less than 65g 85g
Sat Fat	Less than 25g 25g
Cholesterol	Less than 300mg 300mg
Sodium	Less than 2,400mg 2,400mg
Total Carbohydrate	300g 375g
Dietary Fiber	25g 30g

(We have a GLPK case study about this.)

Operations Planning Models

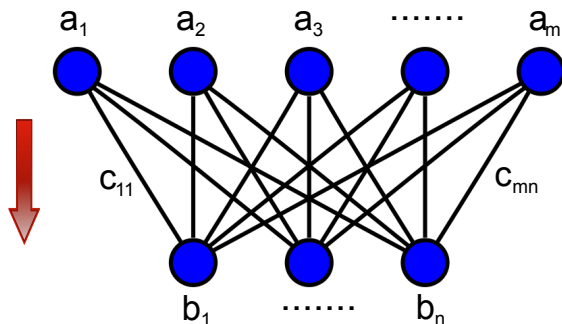
- ▶ Organizations must decide what to do, when and where.
 - ▶ Manufacturing, distribution, government, ...
- ▶ Multiple indexes can be assigned to variables to identify products, types of activities, processing facilities, etc.
 - ▶ $x_{m,f} :=$ amount of material m shipped to factory f
 - ▶ $x_{d,f} :=$ amount of drink d produced with flavour f
 - ▶ $x_{q,v,t} :=$ amount of logs of quality q bought from vendor v and peeled with tickness t
- ▶ Operations planning models often feature **balance constraints**:
(in-flows at stage i) = \sum_j (out-flows from i to stage j).
- ▶ For efficiency, decision variables of relatively large magnitude are often approximately modelled as **continuous**.

Example: Transportation Problem

- ▶ Quantities a_1, a_2, \dots, a_m of a product to be shipped from m locations
- ▶ Products demanded in amounts b_1, b_2, \dots, b_n at n destinations
- ▶ c_{ij} : unit cost of transporting product from i to j ,
- ▶ x_{ij} : amounts to be shipped from i to j ($i = 1, \dots, m$; $j = 1, \dots, n$). Assume to allow fractional amounts.

Determine x_{ij} to satisfy shipping requirements and minimise total cost.

Example: Transportation Problem (cont)



Generalised by the transshipment problem (see Tutorial 1).

Shift Scheduling Models

- ▶ Contrary to operations planning, in shift scheduling the **work is fixed** and we must plan **how to accomplish it**.
 - ▶ How many and what type of workers and shifts best cover all work requirements?
- ▶ The decision variables often indicate a number of workers
 - ▶ $x_h :=$ number of employees beginning shift at hour h
 - ▶ $x_d :=$ number of part-time employees on shift on day d
- ▶ Shift scheduling models often include **covering constraints**:
$$\sum_{s \in \text{shifts}} (\text{output/worker}) (\text{workers in } s) \geq (\text{output requirement})$$

Shift Scheduling Models (Example)

Assume that shifts are 3 hours:

- ▶ x_h := employees beginning shift at hour h
- ▶ y_h := trainees beginning shift at hour h
- ▶ b_h := maximum number of operators on shift at hour h
- ▶ c := shift pay rate (halved for trainees)

$$\min z = c(x_{11} + x_{12} + x_{13} + x_{14}) + (c/2)(y_{11} + y_{12} + y_{13} + y_{14})$$

subject to:

$$x_{11} + y_{11} \leq b_{11} \quad (11:00 \text{ shift})$$

$$x_{11} + y_{11} + x_{12} + y_{12} \leq b_{12} \quad (12:00 \text{ shift})$$

$$x_{11} + y_{11} + x_{12} + y_{12} + x_{13} + y_{13} \leq b_{13} \quad (13:00 \text{ shift})$$

$$x_{12} + y_{12} + x_{13} + y_{13} + x_{14} + y_{14} \leq b_{14} \quad (14:00 \text{ shift})$$

⋮

Time-Phased Models

- ▶ Time-Phased Models are LPs used to address circumstances that vary over time.
 - ▶ Common in cash flow management and scheduling.
- ▶ Examples of time-phased decision variables are
 - ▶ $x_t :=$ projected return on investment by year t
 - ▶ $x_{t,p} :=$ projected revenue in week t from sales of product p
 - ▶ $x_h :=$ throughput of jobs at hour h
- ▶ Time-phase balance constraints are typical in these models:
(starting level in period t) + (impacts of period t activities)
= (starting level in period $t + 1$)

Time-Phased Models (Example)

- ▶ x_q := cars produced in quarter q
- ▶ i_q := cars held in inventory at the end of quarter q
- ▶ d_q := customer demand in quarter q

(initial inventory) + (product) = (demand) + (ending inventory)

minimise ending inventory: $\min z = i_4$

subject to:

$$0 + x_1 = d_1 + i_1 \quad (\text{quarter 1})$$

$$i_1 + x_2 = d_2 + i_2 \quad (\text{quarter 2})$$

$$i_2 + x_3 = d_3 + i_3 \quad (\text{quarter 3})$$

$$i_3 + x_4 = d_4 + i_4 \quad (\text{quarter 4})$$

Other Types of LPs

Several other types of LPs exist:

- ▶ Scenario-based LPs
- ▶ Feasibility problems
- ▶ Computational geometry problems
- ▶ ...

Tutorial: Solving LPs with GLPK

- ▶ GLPK is the official linear programming solver by GNU
 - ▶ Free to use
 - ▶ Open source (GPL license, written in C)
 - ▶ Made available by GNU on Linux, ported by others to Windows
- ▶ GLPK implements solution methods we see in class:
 - ▶ Linear Programming: Simplex algorithm
 - ▶ Integer Linear Programming: Branch-and-Bound, Gomory cuts
- ▶ GLPK is an solver fairly similar to the ones used by OR professionals
 - ▶ Slower than commercial solvers, but language and features are similar to the AMPL+CPLEX commercial suite.
 - ▶ AMPL+CPLEX is a leader in the OR software market
- ▶ Online community and resources:
<https://www.gnu.org/software/glpk/>

Download and Installation

In most cases, GLPK is trivial to install:

- ▶ Ubuntu Linux: `sudo apt-get install glpk`
- ▶ Linux tarball: <http://ftp.gnu.org/gnu/glpk/>
- ▶ Windows:
<http://sourceforge.net/projects/winglpk/files/winglpk/>
- ▶ Windows GUI: <http://gusek.sourceforge.net/gusek.html>

We always refer to the Linux distribution, but you can use the Windows version if you prefer.

Structure of the Kit

- ▶ GLPK available on all DoC machines (let us know if we missed one!)
- ▶ Case studies tested with GLPK v4.45 under Ubuntu 13
- ▶ GLPK v4.45 offers:
 - ▶ A command-line linear programming solver ([glpsol](#))
 - ▶ The GNU MathProg language (GMPL)
 - ▶ Model specification
 - ▶ Display and post-processing of results
 - ▶ A callable C API (Java's JNI compatible)
 - ▶ A lot of nice examples under the installation folder

Example 1: Resource Allocation Problem

Example seen in Lecture 1.

maximise $y = x_1 + x_2$: objective function

subject to $2x_1 + x_2 \leq 11$: constraint on supply of X

$x_1 + 3x_2 \leq 18$: constraint on supply of Y

$x_1 \leq 4$: constraint on demand of A

$x_1, x_2 \geq 0$: non-negativity constraints

Solving Example 1 with GLPK in Two Steps

1. Define a GMPL file specifying the linear program

- ▶ GMPL files are files in plain text with `.mod` extension
- ▶ Every `mod` file must be terminated by the keyword `end`;
- ▶ A `mod` file may include the keyword `solve` to explicitly request the solution of the optimization program.
- ▶ Comments are delimited either by `/*...*/` or `#`
- ▶ GMPL syntax available in manuals¹

```
# example1.mod
var x{i in 1..2}, >=0; /* decision variables */
maximize y : x[1]+x[2];
s.t.
availX : 2*x[1]+x[2] <= 11;
availY : x[1]+3*x[2] <= 18;
demandA : x[1] <= 4;
solve;
end;
```

¹<https://www3.nd.edu/~jeff/mathprog/glpk-4.47/doc/gmpl.pdf>

Solving Example 1 in Two Steps

2. Solve the LP: `glpsol -m example1.mod -o example1.out`

- Solution saved in `example1.out`, it is indeed vertex $Q=(3,5)$ from Lecture 1!

Problem: `example1`

Rows: `4`

Columns: `2`

Non-zeros: `7`

Status: `OPTIMAL`

Objective: `y = 8 (MAXimum)`

No.	Column name	St	Activity	Lower bound
1	<code>x[2]</code>	B	5	0
2	<code>x[1]</code>	B	3	0

GMPL Basics: Parameters

- ▶ **Parameters**: used to inform glpsol about known values
- ▶ Parameters may be indexed by variables defined over **sets**
 - ▶ A parameter can be indexed over multiple sets
- ▶ **Set**: either a range or a finite collection of numbers or strings

```
param m := 3 ;  
param n := 2 ;  
set M := 1..m ;  
set N := 1..n ;  
param A {i in M, j in N} ;  
param b {j in M} ;  
set S := Apple Orange ;
```

GMPL Basics: Data

- Parameters and sets can be specified anywhere, but it is often convenient to group them in the **data section**
 - The data section is typically at the end of **mod** file or in a separate data file (**.dat**)

```
# example1.dat
```

```
data;
```

```
param A :
```

```
1 2 :=
```

```
1 2.0 1.0
```

```
2 1.0 3.0
```

```
3 1.0 0.0 ;
```

```
param b :=
```

```
1 11.0
```

```
2 18.0
```

```
3 4.0 ;
```

```
end;
```


GMPL Basics: Variables & Constraints

- ▶ **Variables:** decision variables, the unknowns!

- ▶ Variables can be indexed over sets
- ▶ Bounds can also be specified

```
var x {j in N}, >= 0 ;  
var u {j in N}, >= 0, <= 3 ;  
var w {j in M}, >= 0, <= max {k in M} b[k];
```

- ▶ **Constraints:** set of linear equalities or inequalities
 - ▶ Not necessarily in standard form
 - ▶ Each constraint **must** have a label (e.g., “c1” for constraint 1)
 - ▶ A set of constraints can be specified by indexing the label

```
s.t.  
c1{i in M}: sum{j in N} A[i,j]*x[j] <= b[i];  
c2: u[1]+w[1] = 0;
```

GMPL Basics: Objective

- ▶ **Objective**: a linear objective function
 - ▶ Either **maximize** or **minimize**
 - ▶ The objective **must** have a label

```
maximize z: sum {j in N} x[j];
```

Further Remarks on GMPL

- ▶ GLPK allows to index variables using text strings

```
set S := Apple Orange;  
var x {i in S}, >=1, <=5; /* units to buy */  
  
:  
  
s.t. c1: x[" Apple"] >= 2*x[" Orange"];
```

- ▶ Parameters can be assigned a **default** value

- ▶ Every time glpsol does not have information about a value, it will use the default.
- ▶ Useful for sparse matrices and vectors, you list the non-zero elements and set **default 0.0** for the others

```
param cost {i in S} default 1.00;  
param matrix default 0.0 :  
      1      2      3      :=  
Apple      .      .      .  
Orange     1.0    .      2.0
```

Further Remarks on GMP

- Results can be displayed with `printf`

```
/* LP */  
set S;  
param cost {i in S} default 1.00;  
var x {i in S}, >=1, <=5; /* units to buy */  
minimize z: sum {i in S} cost[i]*x[i];  
s.t. c1: x["Apple"] >= 2*x["Orange"];  
solve;  
  
/* post-processing */  
printf {i in S} "\tx*[%s] = %3.2f\n", i, x[i];  
  
/* data section */  
data;  
set S := Apple Orange;  
end;
```