

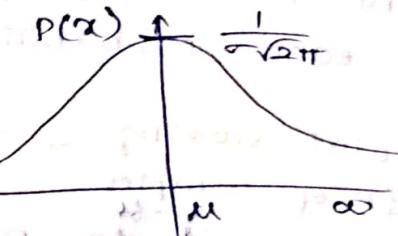
## MOT

Gaussian Distribution (Normal Distribution):

$$\rightarrow P(x|\mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

Univariate

$$\int_{-\infty}^{\infty} P(x) dx = 1 \quad 0 \leq P(x) \leq 1 \quad (\text{continuous})$$



for any fn. to be prob. density

fn., these two must satisfy

Multivariate Gaussian:

Variance tells the spread of the data around  $\mu$

Here variance ~~should~~ also tells about the spread of data over all dimensions (all random variables)

$(x_1, x_2, x_3)$  Here,  $\Sigma$ -covariance matrix does this

It tells how one dimension varies w.r.t other dimension

Consider  $x$  to be a vector (matrix - column)

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \text{ then } \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}$$

$$P(x|\mu, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|} e^{-\frac{1}{2} (x-\mu)^T \Sigma^{-1} (x-\mu)}$$

Mahalanobis distance

When all dimension are independent, i.e, do not effect each other then,  $\Sigma$  is a unit vector.

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \text{ then } \Sigma^{-1} \Rightarrow \text{Unit Vector}$$

Then  $(x-\mu)^T \cdot (x-\mu) \rightarrow$  dot product of two vectors

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix}$$

then mahalanobis dist.  $d_1^2 + d_2^2 + d_3^2$

is large if the r.v is far from  $\mu$   
is small if r.v is nearer to  $\mu$

Consider  $n$  values,

$x_1, x_2, \dots, x_N \rightarrow$  iid identically distributed independent

Joint probability of two independent events is the product of each probability of an event.

Joint scoring =  $\prod_{i=1}^N P(x_i)$  likelihood fn.  
fn of samples (variable)

To we need to maximise the likelihood fn, to find  $\mu, \sigma$   
then we get,  $\mu = \frac{1}{N} \sum x_i$  (Joint scoring fn)

$$\sigma^2 = \frac{1}{N} \sum (x_i - \mu)^2$$

$$\begin{aligned}\log(\text{Joint scoring fn}) &= \log\left(\prod_{i=1}^N P(x_i)\right) \\ &= \sum_{i=1}^N \log\left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x_i-\mu}{\sigma})^2}\right) \\ &= \sum_{i=1}^N \left[ \log\frac{1}{\sqrt{2\pi}\sigma} - \frac{1}{2} \left( \frac{x_i-\mu}{\sigma} \right)^2 \right]\end{aligned}$$

To maximise, diff w.r.t  $\mu$  (1st take derivative w.r.t  $\mu$ )

$$-\frac{1}{2} \times 2 \sum_{i=1}^N \left( \frac{x_i-\mu}{\sigma} \right) \times \frac{-1}{\sigma} = 0 \quad \text{bcz } \sigma \text{ depends on } \mu$$

$$\sum_{i=1}^N \left( \frac{x_i-\mu}{\sigma} \right) = 0$$

$$\text{putting value, } \sum_{i=1}^N x_i - N\mu = 0 \Rightarrow \boxed{\mu = \frac{1}{N} \sum_{i=1}^N x_i}$$

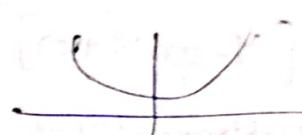
diff w.r.t  $\sigma$ ,

$$+\frac{N}{\sigma} + \frac{-2}{\sigma} \left[ \frac{x_i-\mu}{\sigma} \right] \times \left[ \frac{x_i-\mu}{\sigma^2} \right] = 0$$

$$\sum_{i=1}^N \frac{(x_i-\mu)^2}{\sigma^2} = N$$
$$\boxed{\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i-\mu)^2}$$

Convex function: for any line segment lying on a line that is formed by joining any two points on the curve, must be inside the curve. Then, that curve ( $f_n$ ) is said to be convex fn.

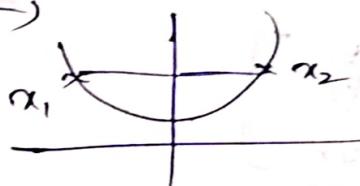
$$y = ax^2 + bx + c$$



### Convex optimisation

(i) Linear Programming

(ii) Quadratic



$$\begin{aligned} & \min f(x) \\ \text{s.t. } & f(x) \leq 0 \end{aligned}$$

$$0 \leq \theta \leq 1$$

$$\text{if } f(\theta x_1 + (1-\theta)x_2)$$

$$\leq \theta f(x_1) + (1-\theta)f(x_2)$$

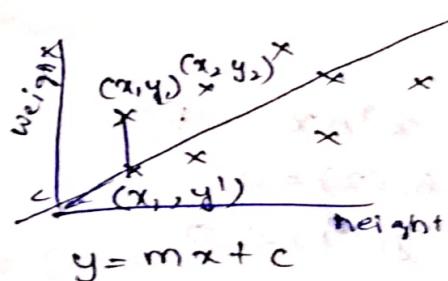
then  $f(x)$  is said to be a convex fn.

### Optimisation

minimise  $f_0(x) \rightarrow x \in \mathbb{R}^n$  { Linear Programming  
such that  $f_i(x) \leq 0$

(1) Least squares problem:

(2) Linear programming



$K=2 \rightarrow$  attributes

two-dimensional

$y = mx + c$  should be chosen such that sum of squares of distances (vertical) from line to each point should be minimum.

Vertical distance  $\rightarrow y_i - f(x_i) \rightarrow$  Point on the line ( $y - mx_i - c$ )

$$(y_1 - (mx_1 + c))^2 + (y_2 - (mx_2 + c))^2 + \dots + (y_n - (mx_n + c))^2 \rightarrow$$

should be minimised

This can be written in vector form as,

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \text{ and } X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$[y - (mx + c)]^T [y - (mx + c)] \Rightarrow (y - (mx + c))^2$$

x - data matrix

Multidimensional  $\rightarrow$  Refer TRB

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{N1} & x_{N2} & \dots & x_{Nk} \end{bmatrix}_{N \times k} \quad k - \text{attributes}$$

$$(y_i - (m_1 x_{i1} + m_2 x_{i2} + m_3 x_{i3}))^2$$

$$\Theta = [y - Xm]^T [y - Xm] \quad Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$[d_1 \dots d_N] \quad \left[ \begin{array}{c} d_1 \\ \vdots \\ d_N \end{array} \right] = \sum_{i=1}^N d_i^2$$

let  $y_i - x_i m$  be  $d_i$

Linear programming:

$$\min c^T x \quad x \in \mathbb{R}^k$$

$$a_i^T x \leq 0 \quad i \in I \subseteq N$$

linear constraint  $Ax \leq 0$

$a_i^T \rightarrow$  vector matrix

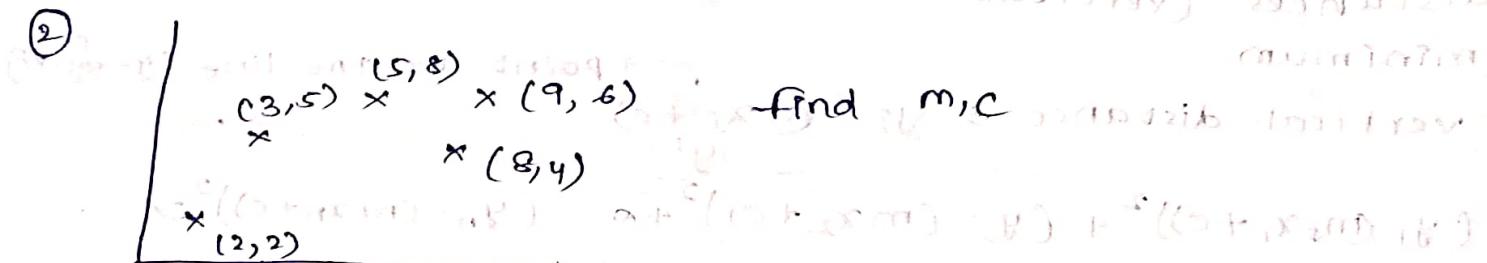
Quadratic Programming:

$$\min x^T Ax$$

$$h_i(x) = 0$$

$$g_i(x) \leq 0$$

① find if (i)  $x \log x$  (ii)  $e^{ax}$  (iii)  $x^\alpha$  where  $\alpha \geq 1$  and  $\alpha < 1$  and  $\alpha > 0$  are convex.



①  $f(x) = x \log x$

$$f(\theta x_1 + (1-\theta)x_2) \leq \theta f(x_1) + (1-\theta)f(x_2)$$

$$\begin{aligned}
 (\theta x_1 + (1-\theta)x_2) \log (\theta x_1 + (1-\theta)x_2) &\leq \theta x_1 \log x_1 + (1-\theta)(x_2 \log x_2) \\
 \log (\theta(x_1 - x_2) + x_2) &\leq \theta x_1 \log x_1 + x_2 \log x_2 \\
 &\quad - \theta x_2 \log x_2 \\
 &\leq \theta \left( \log \frac{x_1}{x_2} \right) + x_2 \log x_2
 \end{aligned}$$

(2)  $f(x) = e^{ax}$

~~fx & e^ax~~

$$\begin{aligned}
 (2) \quad \mathbf{e} \cdot \mathbf{x} &= \begin{bmatrix} 2 \\ 3 \\ m \\ 5 \\ 8 \\ 9 \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} 2 \\ 5 \\ 8 \\ 4 \\ 6 \end{bmatrix} \\
 [\mathbf{y} - (m\mathbf{x} + c)] &\Rightarrow \begin{bmatrix} 2 - (2m+c) \\ 5 - (3m+c) \\ 8 - (5m+c) \\ 4 - (8m+c) \\ 6 - (9m+c) \end{bmatrix} \\
 [\mathbf{y} - (m\mathbf{x} + c)]^T [\mathbf{y} - (m\mathbf{x} + c)] &= \begin{cases} (2 - (2m+c))^2 + (5 - (3m+c))^2 \\ + (8 - (5m+c))^2 + (4 - (8m+c))^2 \\ + (6 - (9m+c))^2 \end{cases} \\
 2(2 - (2m+c))(5 - (3m+c)) + 2(5 - (3m+c))(8 - (5m+c)) &+ 10(8 - (5m+c)) \\
 + 16(4 - (8m+c)) + 18(6 - (9m+c)) &= 0 \\
 2(2 - (2m+c)) + 2(5 - (3m+c)) + 2(8 - (5m+c)) &+ 2(4 - (8m+c)) = 0
 \end{aligned}$$

$$\begin{aligned}
 (2) \quad \sum (y_i - (mx_i + c))^2 &\leq (y_i^2 + m^2 x_i^2 + c^2 + 2mx_i c \\
 &\quad - 2mx_i y_i - 2y_i c)
 \end{aligned}$$

$\therefore r = \sum y_i^2 + m^2 \leq x_i^2 + nc^2 + 2mc \leq x_i - 2m \leq x_i y_i - 2c \leq y_i$

$\frac{d}{dm} \Rightarrow 2m \leq x_i^2 + 2c \leq x_i - 2 \leq x_i y_i = 0$

$\frac{d}{dc} \Rightarrow 2nc + 2m \leq x_i - 2 \leq y_i = 0$

$\sum x_i = 27 \quad \sum y_i = 25 \quad \sum x_i^2 = 183 \quad \sum y_i^2 = 145 \quad \sum x_i y_i = 145$

$366m + 54c - 290 = 0 \quad 10c + 54m - 50 = 0 \quad m = 0.26, c = 3.54$

$$O(2^{n+1}) \quad O(n^2) \leq O(2^n n^2)$$

$10^{21} e^{2^{10}}$

$$\textcircled{1} \quad f(x) = e^x$$

$$f'(x) = e^x$$

$$f''(x) = e^x$$

$$f'''(x) = e^x$$

$$\dots$$

$$f^{(k)}(x) = e^x$$

$$\textcircled{2} \quad k \cdot x = \begin{bmatrix} 2 \\ 5 \\ 8 \\ \vdots \\ 2 \\ 5 \\ 8 \\ \vdots \\ 2 \\ 5 \\ 8 \end{bmatrix}$$

$$y = \begin{bmatrix} 2 \\ 5 \\ 8 \\ \vdots \\ 0 \end{bmatrix}$$

$$[y - (mx + c)] = \begin{bmatrix} 2 - (2m + c) \\ 5 - (5m + c) \\ 8 - (8m + c) \\ \vdots \\ 2 - (9m + c) \end{bmatrix}$$

$$[y - (mx + c)]^T [y - (mx + c)] = \left\{ \begin{array}{l} (2 - (2m + c))^2 + (5 - (5m + c))^2 \\ + (8 - (8m + c))^2 + (4 - (4m + c))^2 \\ + (6 - (6m + c))^2 \end{array} \right.$$

$$4(2 - (2m + c))(-2) + 6(5 - (5m + c))(-5) + 10(8 - (8m + c))(-8)$$

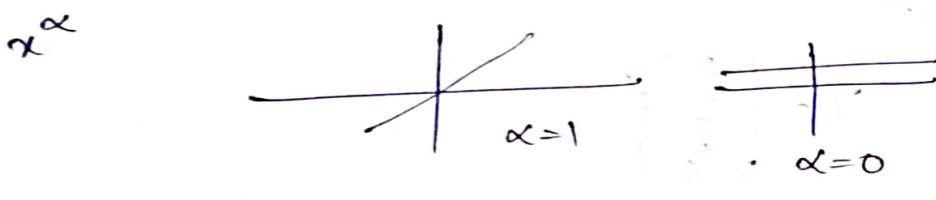
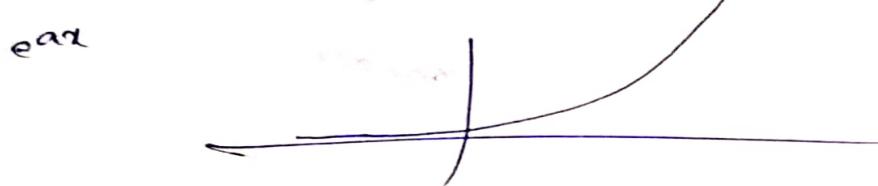
$$2(2 - (2m + c)) + 18(6 - (6m + c)) = 0$$

$$\textcircled{2} \quad \frac{\partial}{\partial m} [(y - (mx + c))^T (y - (mx + c))] + 2(2 - (2m + c))$$

$$\frac{\partial}{\partial m} \sum_{i=1}^n (y_i - (m x_i + c))^2 = \sum_{i=1}^n (2x_i^2 + 2m x_i^2 + 2c x_i^2 + 2x_i + 2m x_i + 2c x_i)$$

$$\frac{\partial}{\partial c} \sum_{i=1}^n (y_i - (m x_i + c))^2 = \sum_{i=1}^n (2y_i - 2m x_i - 2c x_i)$$

$$\sum_{i=1}^n 4 = 22 \quad \sum_{i=1}^n (-2m x_i - 2c x_i) = 200 \times 4 = 800 - 200 = 600$$



Optimising multi dimensional variate:

$$(Y - Xm)^T (Y - Xm)$$

$$\Rightarrow Y^T Y - Y^T Xm - Y^T Xm + m^T x^T Y$$

$$- Y^T Xm - Y^T Xm + m^T x^T X m + m^T x^T X m$$

$$\Rightarrow Y^T Y - 2 Y^T Xm + X^T m^T X$$

$$\frac{\partial}{\partial m} \Rightarrow -2 Y^T X$$

$$\Rightarrow Y^T Y - 2 Y^T Xm + m^T X^T X m$$

$m = a$  notation

$$\frac{\partial}{\partial a} \Rightarrow -2 Y^T X + X^T X a = 0$$

$$(a = (X^T X)^{-1}(Y^T X))$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$$

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} \\ 1 & x_{21} & x_{22} \end{bmatrix}_{n \times k}$$

$$m = \begin{bmatrix} m_1 \\ m_2 \\ \vdots \\ m_k \end{bmatrix}_{k \times 1}$$

$X^T X \rightarrow$  positive definite matrix

↳ whose eigen values are +ve.

$$a^T \quad X \quad a$$

$$\begin{bmatrix} a_1 & a_2 \end{bmatrix} \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}$$

$$(a_1 a_1 + a_2 a_2, a_1 a_2 + a_2 a_1)$$

$$a_1^2 x_{11} + a_1 a_2 x_{12} + a_2^2 x_{22} + a_1 a_2 x_{21}$$

$$\frac{\partial(a^T x a)}{\partial a} = \begin{bmatrix} 2a_1 x_{11} + 2a_2 x_{21} \\ 2a_2 x_{22} + 2a_1 x_{21} \end{bmatrix} = 2x a$$

Considering  $a \propto x$  to symmetric matrix

Affine set: Affine hull

Affine combination: Linear sum of all data points

$$\theta_1 x_1 + \theta_2 x_2 + \dots + \theta_k x_k \quad \text{where } \theta_1 + \theta_2 + \dots + \theta_k = 1$$

Convex set:

Convex combination  $\rightarrow$  similar to affine comb. except that

Convex hull

$$(\theta_1 x_1 + \theta_2 x_2 + \dots + \theta_k x_k) \quad 0 \leq \theta_i \leq 1$$

$$\theta_1 + \theta_2 + \dots + \theta_k = 1$$

Affine function:

$$f(x) = Ax + b$$

$\hookrightarrow$  helps  $x$  in transformation

$$A \in \mathbb{R}^{m \times n} \quad x \in \mathbb{R}^{n \times 1} \quad b \in \mathbb{R}^m$$

$Ax \in \mathbb{R}^m \rightarrow x$  is undergoing transformation.

And  $b$  is allowing the vector to move (changes the distance)

fn that allows transformation of a vector with some displacement

Convex fn: Consider two points from convex set. Let them be  $x_1, y$

$$f(\theta x_1 + (1-\theta)y) \leq \theta f(x_1) + (1-\theta)f(y) \quad (x_1, f(x_1)) \quad (y, f(y))$$

Convex:

affine:  $ax+b$  on  $\mathbb{R}$ , for any  $a, b \in \mathbb{R}$

exponential:  $e^{ax}$ , for any  $a \in \mathbb{R}$

powers:  $x^\alpha$  on  $\mathbb{R}_{++}$  for  $\alpha \geq 1$  or  $\alpha \leq 0$

powers of absolute value:  $|x|^p$  on  $\mathbb{R}$ , for  $p \geq 1$

negative entropy:  $x \log x$  on  $\mathbb{R}_{++}$

concave:

powers:  $x^\alpha$  on  $\mathbb{R}_{++}$ , for  $0 \leq \alpha \leq 1$

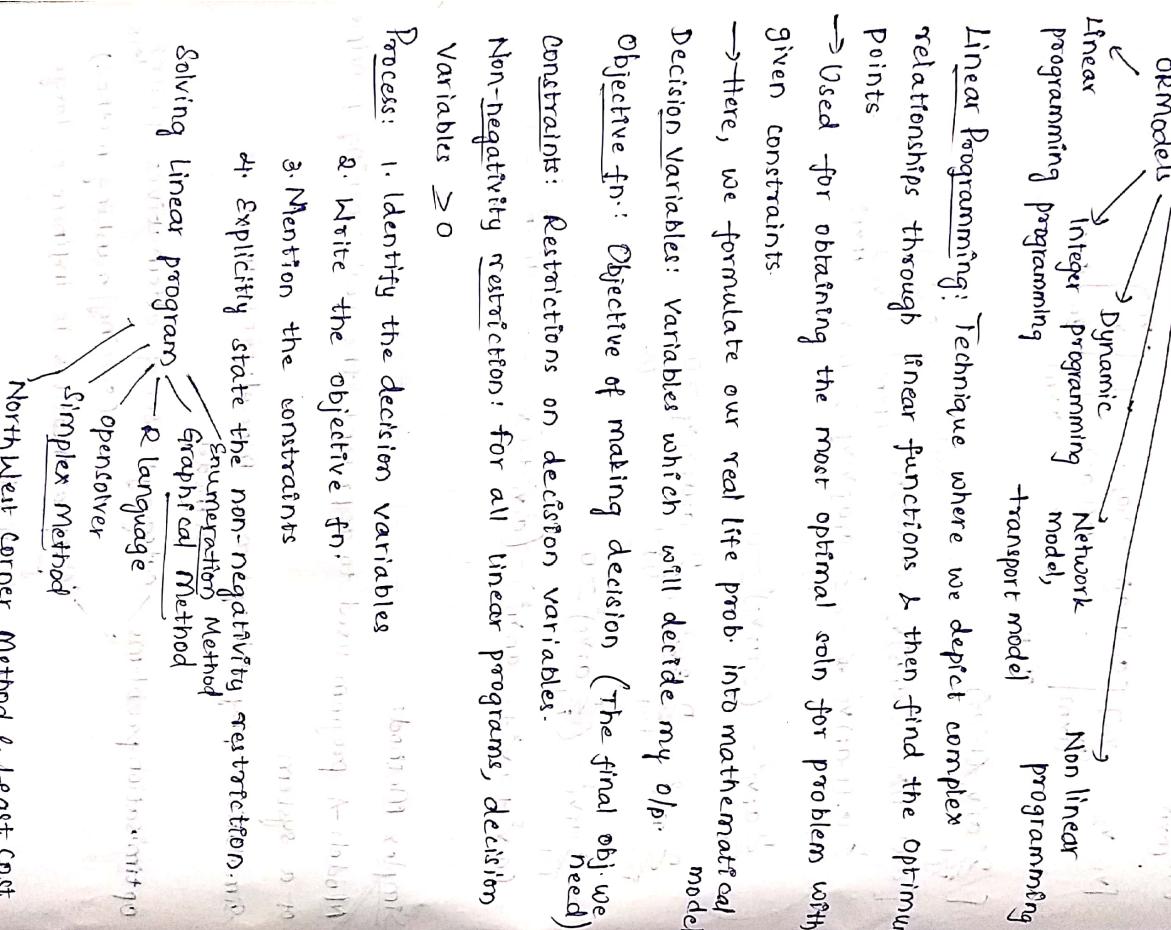
logarithm:  $\log x$  on  $\mathbb{R}_{++}$

affine:  $ax+b$  on  $\mathbb{R}$ , for any  $a, b \in \mathbb{R}$





**Operation research**: It is an <sup>(cor)</sup> **decision approach** to decision-making, which involves a set of methods to operate a system.



→ Iterative procedure for getting the most feasible soln.  
→ Here, we keep transforming the value of basic variables to get maximum value for the objective fn.

\* A linear programming fn. is in its standard form if it seeks to maximize the obj-fn.

$Z = c_1x_1 + c_2x_2 + \dots + c_nx_n$

subject to constraints,

→ uses resources

→ some resources are unused.

Linear Programming: Technique where we depict complex relationships through linear functions & then find the optimum points  
→ Used for obtaining the most optimal soln for problem with

given constraints.

Decision Variables: Variables which will decide my objective function.

Objective fn.: Objective of making decision (The final obj. we need)

Non-negativity restriction: for all linear programs, decision variables must be non-negative.

**Process:** 1: Identify the decision variables

- Q. Write the objective fn. & constraints

4. Explicitly state the non-negativity restriction.

Statistical software R language  
Statistical program SPSS

Simplex Method

**Graphical Method**

L-Principle: The optimal feasible soln is achieved at the point of int. where of linear inequalities subjected to the constraints.

feasible region explains the values our model can take.

## Simplex Method:



Start from feasible  $\rightarrow$  Optimality

Computational technique of simplex method:

Conditions: Optimality condition  $\rightarrow$  used for finding entering variable  
Feasibility condition  $\rightarrow$  used for finding leaving variable

Entering variable: Some var. from non-basic var. set to basic var. set

Leaving variable: Some var. leaving the basic var. set

Used for finding leaving variable.

var.

	$x_1$	$x_2$	$s_1$	$s_2$	$s_3$	$s_4$	soln	Ratio
$s_1$	6	24	0	4	0	0	0	20
$s_2$	1	6	6	6	0	0	0	1
$s_3$	-1	1	-1	-1	0	0	0	
$s_4$	0	2	0	0	0	0	0	

Variable having min. tie ratio is called taken as leaving variable.

Maximize  $Z = 5x_1 + 4x_2$  s.t.  $6x_1 + 4x_2 \leq 24$   
 $x_1 + 2x_2 \leq 6$   
 $x_1 + x_2 + s_3 = 1$   
 $x_2 + s_4 = 2$

$x_1, x_2 \geq 0$

$$x_1 + x_2 + s_3 = 1$$

$$x_2 + s_4 = 2$$

$$x_1, x_2 \geq 0$$

$$x_1 + x_2 \leq 1$$

$$x_2 \leq 2$$

$$x_1 + x_2 + s_3 = 1$$

$$x_2 + s_4 = 2$$

Basic variables  $= 4$  Non-basic variables  $= 4$

Initial Simplex table:

	$x_1$	$x_2$	$s_1$	$s_2$	$s_3$	$s_4$	soln	
$Z$	1	0	-2/3	5/6	0	0	0	20
$s_1$	0	1	2/3	1/6	0	0	0	4
$s_2$	0	0	4/3	-1/6	1	0	0	2
$s_3$	0	0	5/3	1/6	0	1	0	5
$s_4$	0	0	0	0	0	0	1	2

Gauss Jordan method:

To find out revised entries:

New pivot row = Old pivot row  $\times$  Pivot element

Remaining rows  $\Rightarrow$  Current row (old) - (pivot column coeffs  $\times$  New pivot row)

$$\text{Eq: } Z_{\text{new}} = (1, -5, -4, 0, 0, 0, 0, 0) - [(-5) \times (0, 1, 2/3, 1/6, 0, 0, 0, 0)]$$

$\Rightarrow 4$  basic variables (usually slack variables)

With ref to  $(0, 0)$ ,  $x_1, x_2 = 0 \Rightarrow s_1, s_2, s_3, s_4 \Rightarrow$  basic variables

$$Z = 5x_1 + 4x_2 + 0s_1 + 0s_2 + 0s_3 + 0s_4 = 0$$

Entering variables  $\Rightarrow (x_1, x_2)$  for  $Z$

The most negative value for nonbasic variable in the row is considered as entering variable.

$x_1 \Rightarrow$  entering variable (most -ve : since has higher impact)

The column containing entering variable - pivot column.  
Leaving variable is determined by feasibility condition.

$s_1 \rightarrow$  leaving variable Pivot row  $\rightarrow$  row containing leaving variable.

Pivot element - intersection of pivot row & column.

Next Iteration:

	$x_1$	$x_2$	$s_1$	$s_2$	$s_3$	$s_4$	soln	
$Z$	1	0	-2/3	5/6	0	0	0	20
$s_1$	0	1	2/3	1/6	0	0	0	4
$s_2$	0	0	4/3	-1/6	1	0	0	2
$s_3$	0	0	5/3	1/6	0	1	0	5
$s_4$	0	0	0	0	0	0	1	2

will stop the algorithm.

No. of variables in initial pro. - all should enter the basic row.

Entering variable  $\Rightarrow x_2$  leaving variable  $\Rightarrow s_2$



$$\begin{array}{cccccc} & & x_1 & x_2 & x_3 & x_4 \\ -1 & a_1 & 0 & 0 & 1/22 & 1 \\ 0 & a_1 & 1 & 0 & -3/22 & 0 \\ 0 & a_2 & 0 & 1 & 2/11 & 0 \\ 0 & a_2 & 1 & 1 & 1/11 & -2/11 \\ & & & & \text{Labeled } 8/11 & \\ & & & & & \end{array}$$

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0	$x_1$
0	$x_2$
1	$x_3$
-8/	$x_4$

the *Journal of the Royal Society* of Medicine, 1930, 23, 100-101.

$$\left| \begin{array}{cccccc} 0 & x_3 & 0 & 0 & 1 & -16 \\ -2 & x_4 & 1 & 0 & 0 & -2 \\ -3 & x_2 & 0 & 1 & 0 & 3 \end{array} \right|$$

$$\begin{aligned}x_1 &= 4 \\x_2 &= 1 \\x_3 &= -1\end{aligned}$$

$$\begin{array}{cccccc} -3 & \alpha_2 & & 0 & 1 & 0 \\ \alpha_1 - z_i & & & 0 & 0 & 0 \\ & & & 0 & 0 & 0 \end{array}$$

6

$$\begin{array}{ccccccc} & x_1 & x_2 & x_3 & x_4 & a_1 & q_2 \\ \rightarrow & a_1 & 3 & 2 & 0 & 0 & 0 & 0 \\ & & & & & & & 14 \\ & & & & & & & 4 \end{array}$$

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8 24 3 0 0 0 0 0 0

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卷之三

$$-1 \quad a_1 \\ -1 \quad a_2 \\ -1 \quad a_3 \\ -1 \quad a_4 \\ -1 \quad a_5 \\ -1 \quad a_6$$

11/11 15 28 0 0 0 0 0

$$\begin{array}{cccccc} & & & & 0 \\ & & & & \overline{8} \\ & & & & 3/2 & 0 & 0 \\ & & & & -3/2 & -1 & 1 \end{array}$$

11

$$\text{Maximize } z = -5x_1 - 3x_2 + 7x_3$$

$$3x_1 - 5x_2 + 3x_3 \leq 5$$

$$-4x_1 - 9x_2 + 4x_3 \leq -4$$

$$x_1 \geq -x_2 \quad 0 \leq x_2 \leq 1$$

$$\alpha_2 + \beta_1 = y \quad \rightarrow \quad \alpha_2 \leq y \text{ and } \alpha_2 < y$$

$$2(2_1+2) + 42_2 + 62_3 = 7+4$$

$$3(x_1+2) - 3x_2 - 3x_3 \leq 3 + 6 \\ + 4(x_1+2) + 9x_2 - 4x_3 \geq 4 + 8$$

$$2x_1 + 4x_2 + 6x_3 - 6x_4 = 11$$

$$3x_1 - 5x_2 + 3x_3 - 3x_4 + \frac{x_5}{5} = 11$$

$$\alpha_2 + \alpha_6 = 4$$





$$\min c^T x \quad \text{st} \quad Ax = b \quad (n-m) \times m \text{ variables}$$

(n-m)  $\geq$  m  $\Rightarrow$  n  $>$  m  $\Rightarrow$  n variables

$$A \text{ (m} \times n\text{)} \xrightarrow{\text{rank}} B_{m \times m} \quad \text{rank } B = Nm \times (n-m)$$

$$A = B|N \xrightarrow{\text{rank}} \begin{matrix} \text{Basic} \\ \downarrow \\ \text{Non Basic} \end{matrix} \quad \begin{matrix} \text{rank } B + N = n \\ \downarrow \\ \text{rank } B + N < n \end{matrix} \quad \text{rank } A < n$$

$$0 \geq x_B = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}_{m \times 1} \quad (B^T B = I_m \text{ rank } B = m) \in \mathbb{R}^m$$

$$0 \leq x_N = \begin{bmatrix} x_{m+1} \\ \vdots \\ x_{m+(n-m)} \end{bmatrix}_{m \times 1} \quad (B^T B + N = I_n \text{ rank } B + N = n) \in \mathbb{R}^{n-m}$$

$Ax = b$  can be written as  $Bx_B + Nx_N = b$

Standard form:

$$x_B = B^{-1}(b - Nx_N)$$

$$\min c_B^T x_B + c_N^T x_N$$

$$\Rightarrow c_B^T (B^{-1}b - B^{-1}Nx_N) + c_N^T x_N$$

$$\Rightarrow c_B^T B^{-1}b + (c_N^T - c_B^T B^{-1}N)x_N$$

constant.

$$c_i - z_j$$

$$0 \geq c_B^T B^{-1}b + (c_N^T - c_B^T B^{-1}N)x_N$$

$$0 \geq c_B^T B^{-1}b + c_N^T x_N - c_B^T B^{-1}N x_N$$

$$b \geq c_B^T B$$

$$\text{also } c_N^T \geq 0 \quad \text{and } x_N \geq 0$$

$$c_B^T B \geq b \quad \text{and } c_N^T x_N \geq 0$$