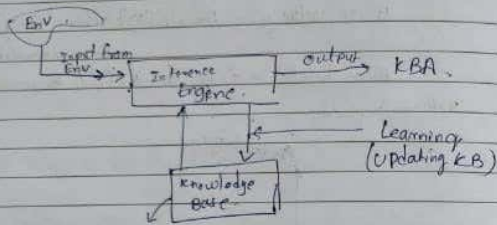


## Introduction to Logic

Knowledge -- decision



Inference Engines:

Deriving new sentences  
previously executed

Designing a knowledge-based Agent

Procedural

Declarative

KB + Inference = Expert system

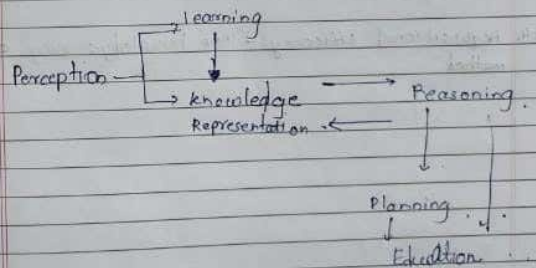
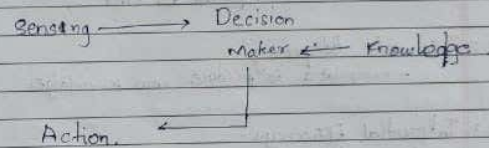
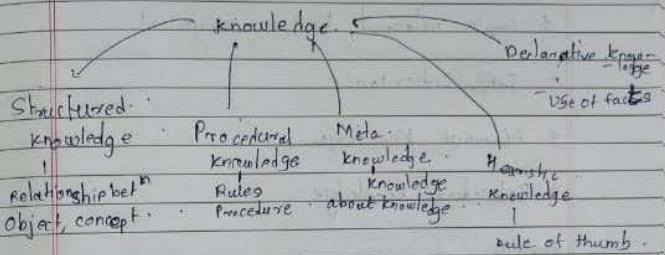
Representing Knowledge

logic (propositional logic, first order logic)

Production Rules

Semantic network

Frames  
name instances

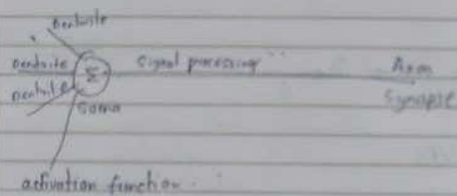


## Neural Network

ANN :-

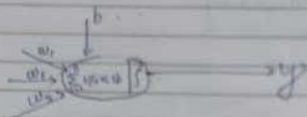
Neural Network :-

Synaptic connection strengths among neurons are used to store the acquired knowledge.



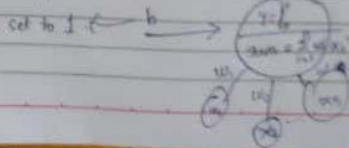
$$y = wx + b$$

$w, b$  are parameters



weight refinement

perception



AND and OR are linear

we can separate by line

Not XOR



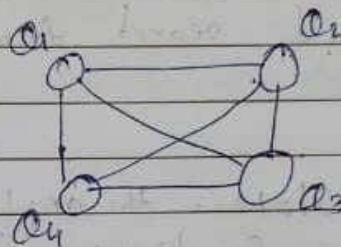
# Constraint Satisfaction

## 1. Forward Checking

Example:- N-Queens.

"Intelligent Backtracking"

for 4 Queens



## Cryptarithmic Problem

$$\begin{array}{r} \text{TWO} \\ + \text{TWO} \\ \hline \text{FOUR} \end{array}$$

Variables:- FTUWRO  $x_1, x_2, x_3$

Domain:-  $\{0, 1, 2, \dots, 9\}$

Constraint:- all diff (F, T, U, W, R, O)  $\rightarrow$  just make sure which Var

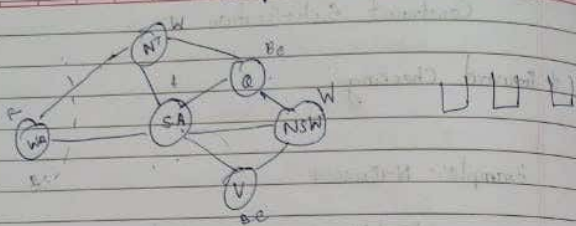
$$0 + 0 = R + 10x_1$$

Non-pairwise





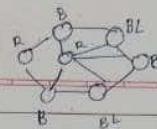
### Constraint Graph



### Standard Search Formulation

- Standard search formulation
- Initial State: the empty assignment,  $\emptyset$
- Successor function: assign a value to an unassigned variable
- Goal Test: The current assignment is complete and satisfies all constraints.

Depth-First search with the one var at a time and check constraints as you go. This is called backtracking search.



### Look-Ahead:-

Applying propagation at each node.

### Forward Checking



Consider WA is assigned red

∴ NT and SA can't have option forward.

### Ordering:- Minimum Remaining Values

### Ordering :- Least Constraint Values

### Arc-Consistency

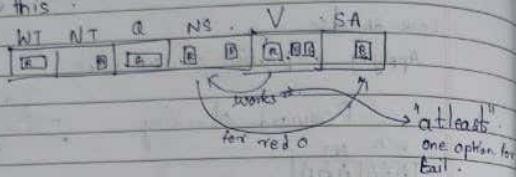
#### Consistency of A Single Arc

an arc  $x \rightarrow y$  is consistent iff for every  $x$  in the tail there is some  $y$  in the head which could be assigned without violating a constraint.

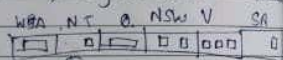


Consider Binary CSP problem  
So remove red from tail

Consider this



- A simple form of propagation makes sure all arcs are consistent.
- Important: if  $x$  loses a value, neighbours of  $x$  need to be rechecked.



It detects failure earlier than forward chaining

Can be run before assignment

function AC-3(csp) returns the CSP possible with reduced inputs: csp, a binary CSP with variables  $\{x_1, x_2, \dots, x_n\}$  and local variables: queue of arcs initially arcs in csp.

while Queue is not empty do

$(x_i, x_j) \leftarrow \text{Remove-First}(\text{Queue})$

If Remove-Inconsistent-Value( $x_i, x_j$ ) then

for each  $x_k$  in Neighbors( $x_i$ ) do

add  $(x_k, x_i)$  to queue

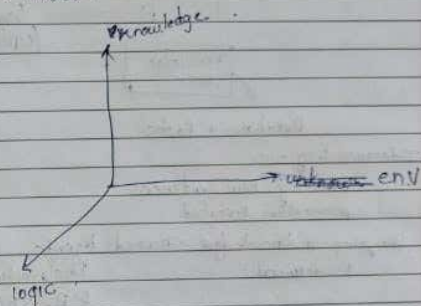
removed false

for each  $x$  in Domain( $x_i$ ) do

if no value  $y$  in Domain( $x_j$ ) allows  $(x, y)$  to satisfy the constraint  $x_i \neq x_j$

then delete  $x$  from domain( $x_i$ ) removed = true

return removed



## Approaches to knowledge representation

1. simple relational Database Management

2. ~~Infer~~ Inheritance

3. Inferential Knowledge

4. Procedural knowledge

Properties

1.1 Representation Accuracy :-  
represent all kind

2.2 Inferential Adequacy :-  
- manipulate to produce new knowledge

3.3 Inferential Efficiency :-  
- guide

4.4 Acquisitional Efficiency :- new knowledge using automatic method

## Learning

Enable the system to perform next exec. more betterly

on some task  $T$  and performance measure  $P$ ...

Given:- task  $T$ ...

## Learning Agent

Learning Agent = Learning element + ~~task~~ performance element...

learning perf = prediction of acc. on test.

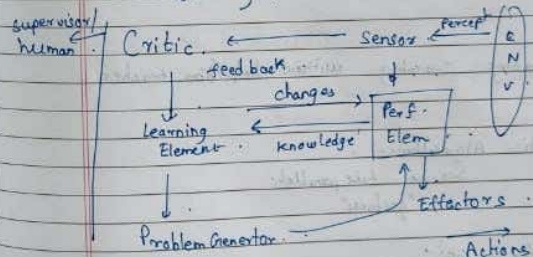
4 main Components

A learning element

A performance element

A Critic and

Problem generator





## Approaches to knowledge representation

1. simple relational Database Management

2. ~~Infer~~ Inheritance

3. Inferential Knowledge

4. Background Knowledge

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representable kind

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4 main Components:-

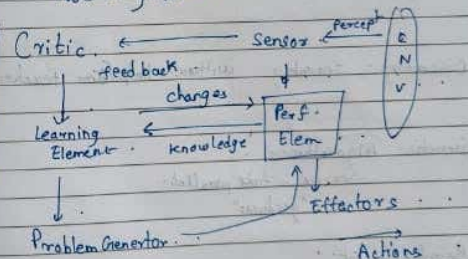
Δ Learning element

Δ Performance element

Δ Critic and

Problem generator

supervisor/  
human



Supervised Learning:- learning from examples.

Unsupervised learning:-  
no one to guide..

Reinforce:- Type of supervised learning with  
sudden feedback.

Paradigms of Machine learning:-

- Rule learning:- Memorizing
- Induction:- learning from example. learn from  
to general conclusion
- Clustering:- Classification.
- Analogy:- Map two
- Discovery:- learning without help from teacher.
- Genetic Algorithm:-  
Searches take parallel.  
"goodness"
- Reinforcement:-  
Reward and penalty

## Machine Learning

Area of Influence:-

Statistics

Brain Models.

Adaptive Control Theory.

Psychology.

AI:-

Evolutionary Model:-

Mathematical Modelling:-



Q. let  $x$  denote the number of scores in a test.  
If  $x$  is normally distributed with mean 100 and std 15  
find the probability that  $x$  doesn't exceed 130.

$$\rightarrow P(X \leq 130) = ?$$

$$Z = \frac{130 - 100}{15}$$

$$Z = 2$$

$$\therefore P(X \leq 130) = P(Z \leq 2) \\ = 0.9772.$$

Q. The random variable with mean 9 and std 3. find the probability when

$$i) X \geq 15 \quad ii) X \leq 15 \quad iii) 0 < X < 9 \quad iv) X < 15$$

$$\rightarrow P(Z = \frac{15 - 9}{3} = 2)$$

$$i) \Rightarrow P(Z \geq 2) = 1 - 0.9772 = 0.0228$$

$$ii) P(Z \leq 2) = 0.9772$$

$$Z = \frac{0 - 9}{3} = -3$$

$$iii) P(-3 < Z < 0) = P(0) - P(-3) = 0.5 - 0.0044 \\ = 0.4956$$

$$iv) P(Z < 15) = 0.9772$$

Q. A research scientist reports that a mice will live an average of 40 months when there their diets are sharply restricted and enriched with proteins and fats. Assuming that the lifetime of such mice are normally distributed with a std. of 6.3 month. Find the probability that the given mice will live

- 1) more than 32 months
- less than 28 months
- more than 37 months & ..
- less than 49 months.

Q. The mean height of 500 student is 151 cm and std is 15 cm. assuming that the heights are normally distributed. Find how many students height lies between 120 and 155 cm.

Q. If  $X$  is normal with mean 100 and std 5 then find

- i)  $P(95 < X < 110)$
- ii)  $P(X < 50)$
- iii) If  $P(X > k) = 0.3192$
- iv)  $X = ?$  if  $P(X)$

## Normal distribution

① pdf:-

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{x-\mu}{\sigma} \right)^2}$$

for standard normal distribution

②

$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

$-\sigma < x < \sigma \Rightarrow$  inflection point

$$P(X \leq x) = P(X < x)$$

$$= \text{pnorm}(x, \mu, \sigma)$$

③

Properties:

④

$$\Phi(-a) = 1 - \Phi(a)$$



⑤

$$P(-a < Z < a) = 2\Phi(a) - 1$$

$$= P(Z < a) - P(Z \leq -a)$$

$$= \Phi(a) - \Phi(-a)$$

$$= \Phi(a) - (1 - \Phi(a))$$

$$P(-a < Z < a) = 2\Phi(a) - 1$$



### ⇒ Exponential Distribution

It is used when we assume that the future lifetime is independent of the lifetime that has already taken place.

Then the waiting time can be considered to be exponentially distributed.

A random variable  $X$  is said to follow an exponential distribution with parameter  $\lambda$  if its pdf is given by

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases}$$

Also  $X \sim \text{Exp}(\lambda)$

$$E(X) = \frac{1}{\lambda} \text{ and } \text{Var}(X) = \frac{1}{\lambda^2}$$

CDF is

$$F(x) = P(X \leq x) = P(X \leq x) = \begin{cases} 1 - e^{-\lambda x} & x \geq 0 \\ 0 & \text{else} \end{cases}$$

The number of events  $N$  occurring within a continuum amount of time is poisson distribution with parameters

$$X \sim \text{Poisson}(\lambda) \quad P(X \leq x) = \text{poexp}(x, \lambda)$$

### Memorylessness Property

If time ' $t$ ' has already been reached then the probability of reaching a time  $t + \Delta$  doesn't depend on  $t$ .

$$P(X > t + \Delta | X > t) = P(X > \Delta); \quad t, \Delta > 0$$

$$\therefore \text{EPR} = \frac{P(X > t + \Delta \cap X > t)}{P(X > t)}$$

$$\begin{aligned} &= \frac{P(X > t + \Delta)}{P(X > t)} \\ &= \frac{1 - P(X \leq t + \Delta)}{1 - P(X \leq t)} \\ &= \frac{1 - [1 - e^{-(t+\Delta)\lambda}]}{1 - [1 - e^{-t\lambda}]} \\ &= \frac{e^{-(t+\Delta)\lambda}}{e^{-t\lambda}} \\ &= e^{-\Delta\lambda} \\ &= 1 - 1 + e^{-\Delta\lambda} \\ &= 1 - (1 - e^{-\Delta\lambda}) \\ &= 1 - P(X \leq \Delta) \\ &= P(X > \Delta) \end{aligned}$$

length

Q. The ~~XXX~~ of telephone conversation with exp dis. with mean 3. Find probability.

- call ends in less than 3 min.
- takes bet<sup>n</sup> 3 to 5 min

$$\therefore E(X) = \frac{1}{\lambda} = 3$$

$$\therefore \lambda = 1/3$$

$$1) \quad F(x) = 1 - e^{-x/3} = 1 - e^{-1} = \frac{e-1}{e} = \frac{1.7}{2.7}$$

$$2) \quad F(x) = (1 - e^{-5/3}) - (1 - e^{-3/3}) = e^{-1} - e^{-5/3}$$



## Distribution of Arithmetic Mean in Case of Normal Distribution.

Assume that  $X \sim N(\mu, \sigma^2)$

Consider a random sample

$X_i (X_1, X_2, \dots, X_n)$  of  $n$  i.i.d Random Variable with  $X_i \sim N(\mu, \sigma^2)$

Then  $\bar{X}$  Arithmetic Mean

$$\text{and } E(\bar{X}) = \mu$$

$$\text{Var}(\bar{X}) = \sigma^2/n$$

Note:- If  $X_1, X_2, \dots, X_n$  are  $n$  independent normal random variables with mean  $\mu_1, \mu_2, \dots, \mu_n$  and variance  $\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2$

then for any real number  $a_1, a_2, \dots, a_n$

$$a_1 X_1 + a_2 X_2 + \dots + a_n X_n$$

$\sim N(a_1 \mu_1 + a_2 \mu_2 + \dots + a_n \mu_n, a_1^2 \sigma_1^2 + a_2^2 \sigma_2^2 + \dots + a_n^2 \sigma_n^2)$  hold.

## # Central Limit Theorem:-

If  $\bar{X}$  is the mean of random sample of size  $N$  taken from a population with a mean  $\mu$  and finite variance  $\sigma^2$  then the limiting form of distribution is

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \text{ as } n \rightarrow \infty \rightarrow \text{Standard}$$

1. The sample size  $n=30$  is a guideline to use for central limit th<sup>n</sup>
2. The normal approx. for  $\bar{X}$  will be good if  $n \geq 30$  provided the population distribution is not skewed.
3. If the population is not too different from a normal dis. then approx. is good the  $n < 30$  as well.

## Sampling Distribution.

There are three types of sampling distribution.

1. Chi-square distribution
2. t-distribution
3. F-distribution

$\chi^2$ -distribution

i) Def<sup>n</sup>:-

let  $Z_1, Z_2, \dots, Z_n$  be i.i.d Normal Random Variable that the sum of their squares is

$$Z_1^2 + Z_2^2 + \dots + Z_n^2 = \sum_{i=1}^n Z_i^2 \text{ is}$$

$\chi^2$ -distribution

with degree of freedom  $n$  (If = degree of freedom)

ii) pdf is

$$f(x) = \begin{cases} \frac{1}{2^{n/2} \Gamma(n/2)} e^{-x/2} x^{n/2-1} & x \geq 0 \\ 0 & \text{else} \end{cases}$$

where  $\Gamma$  is gamma function.

$$\text{i.e. } \Gamma = \begin{cases} (x-1)! & \text{for five integer} \\ \int_0^\infty t^{x-1} e^{-t} dt & \text{else} \end{cases}$$

iii)  $\chi^2$  distribution is not symmetric

iv)  $\chi^2$  lies b/w 0 to  $\infty$

v) Mean =  $E(X) = df$

Var(X) = 2df

vi) Small value of df gives high value of tail



Vii) Theorem:-  
Consider two independent Variables which are chi-squared-  
 $\chi_m^2$  and  $\chi_n^2$  then the Sum of this two r.v. is  $\chi_{m+n}$   
distributed

Q Using statistical tables And  
i)  $\chi_{0.05}^2$  when df = 15  
ii)  $\chi_{0.05}^2$  when df = 25  
→  $\chi_{0.05}^2$  with df = 15 =  
→ 27.488  
ii) 37.652

Q Find the probability that a random sample of  
25 observation from a normal population with var = 6  
will have var  $s^2 > 9.1$  b.  $s^2$  lies between 3.462  
and 10.745

→  $P(s^2 > 9.1) \cdot n = 25, \text{Var} = 6$   
 $P\left(\frac{(n-1)s^2}{\sigma^2} > \frac{(n-1)9.1}{\sigma^2}\right) = P\left(\chi_{24}^2 > 36.4\right)$   
 $= 0.05$

b)  $P(3.462 < s^2 < 10.745) \quad P(X)$

$P\left(42.98 < \chi_{24}^2 < 13.848\right) = 1 - P(42.98 < \chi_{24}^2)$   
 $\quad \quad \quad P(\chi_{24}^2 > 13.848)$   
 $= 0.99 - 0.95$   
 $= 0.04$

Th<sup>m</sup>  
A Chi-squared distributed random variable having sample  
Variance  $s^2$  in and iid sample of size  $n$  from normal  
distributed population

$$\frac{(n-1)s^2}{\sigma^2} \sim \chi_{n-1}^2$$

$$s^2 = \frac{\sum (X_i - \bar{X})^2}{n-1} \quad \left| \quad \frac{\sigma^2}{\sigma^2} = \frac{\sum (X_i - \mu)^2}{n} \right.$$

$$\sum_{i=1}^n Z_i^2 = \sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2$$

$$= \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \mu)^2$$

$$= \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X} + \bar{X} - \mu)^2$$

$$= \frac{1}{\sigma^2} \left[ \sum_{i=1}^n (X_i - \bar{X})^2 + (\bar{X} - \mu)^2 + 2(\bar{X} - \mu) \sum_{i=1}^n (X_i - \bar{X}) \right]$$

$$= \frac{1}{\sigma^2} \left[ \sum_{i=1}^n (X_i - \bar{X})^2 + n(\bar{X} - \mu)^2 + 2 \sum_{i=1}^n (\bar{X} - \mu)(X_i - \bar{X}) \right]$$

$\bar{X} = \bar{X}_1$

arithmetic mean

$$= \frac{1}{\sigma^2} \left[ \sum_{i=1}^n (X_i - \bar{X})^2 + n \sum_{i=1}^n (\bar{X} - \mu)^2 \right]$$

$$\sum_{i=1}^n Z_i^2 = \sum_{i=1}^n \left( \frac{X_i - \bar{X}}{\sigma} \right)^2 + \sum_{i=1}^n \left( \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \right)^2$$

$$\sum_{i=1}^n Z_i^2 \sim \chi_{n-1}^2 + \chi_1^2$$

$$\chi_{n-1}^2 + \chi_1^2 \sim \chi_n^2$$

now consider  $s^2 = \frac{\sum (X_i - \bar{X})^2}{n-1}$

$$\chi_{n-1}^2 \sim \frac{(n-1)s^2}{\sigma^2}$$



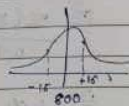
Q. Light bulbs life is approx normally dist. with mean = 800 hr and std as 40hr. find the probability that a random sample of 16 bulbs will have an avg life of less than 775hr.

$$\Rightarrow \bar{X} = \frac{X - \mu}{\sigma/\sqrt{n}}$$

$$= \frac{-25}{40/4}$$

$$Z = \frac{-25}{10} = -2.5$$

$$P(Z < -2.5) = 0.0062$$



T-distribution

i) Let  $x$  and  $y$  be two independent n.v. such that  $X \sim N(0,1)$  and  $y$  is  $\chi^2_n$  distributed. Then, the ratio  $\frac{X}{\sqrt{Y/n}} \sim t_n$ .

ii) pdf is given by:-

$$f(x) = \frac{\Gamma(\frac{n+1}{2})}{\Gamma(\frac{n}{2}) \sqrt{np}} \left(1 + \frac{x^2}{n}\right)^{-\frac{(n+1)}{2}}$$

iii) Student Theorem:-

let  $X = (X_1, X_2, \dots, X_n)$  with  $X_i \stackrel{iid}{\sim} N(\mu, \sigma^2)$ .

then the ratio  $\frac{(\bar{X} - \mu) \sqrt{n}}{\sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2}} \sim t_{n-1}$

is t-distributed with  $n-1$  degree of freedom.

(iv) If sample size  $n \leq 30$ , then use this distribution.

and for  $n > 30$ , we use Normal distribution.

(v)  $t_{-a} = -t_{a,n}$

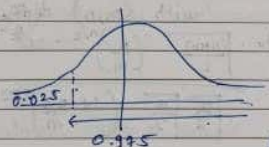
Q. T-value of with df 14 leaving an area of 0.025 to the left.

→

$$t_{\alpha} = -t_{1-\alpha}$$

$$t_{0.975} = -t_{0.025}$$

$$= -2.145$$

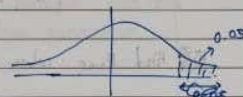


$$P(-t_{0.025} < T < t_{0.025}) =$$

↓

$$t_{0.975}$$

$$\text{E.g. } 0.975 - 0.05 = 0.925$$



Q. Find  $k$  such that  $P(k < T < -1.761) = 0.045$

for a random variable sample of size 15 from a normal population.

→

$$df = n-1 = 14$$

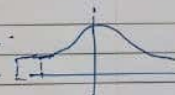
$$-t_{0.05} = t_{0.95}$$

$$P(k < T < -t_{0.05}) = 0.045$$

$$P(k < T) - 0.05 = 0.045$$

$$P(k < T) = 0.095$$

$$P(k < T) = t_{0.05}$$



$$P(k < T < t_{0.95}) = 0.045$$

$$P(k < T) - P(k < T) = 0.95 = 0.045$$

$$P(k < T) = 0.995$$

$$t_{0.995} = -t_{0.005}$$

$$= -2.977$$



### F-distribution

Def<sup>n</sup>:- let  $X$  and  $Y$  be  $\chi^2_m$  and  $\chi^2_n$  distributed random variable then the distribution ratio is

$\frac{X^2/m}{Y^2/n} = F_{m,n}$  distributed

with  $(m,n)$  degrees of freedom

$$f(x) = \frac{\left(\frac{nm}{2}\right)^{\frac{n}{2}} \left(\frac{n}{m}\right)^{\frac{n}{2}} \cdot x^{\frac{n}{2}-1}}{\left(\frac{n}{2}\right)^{\frac{n}{2}} \left(\frac{m}{2}\right)^{\frac{m}{2}} \left(1 + \frac{nx}{m}\right)^{\frac{nm}{2}}}, x > 0$$

Q. Find  $F_{0.05}$  when dof are 6 and 10.

$\gamma_1 \quad \gamma_2$

→ 3.22

R-Command

→ `qchisq(p, df)`

→ `qt(p, df)`

→ `qf(p, df1, df2)`

## Inferences

### 1. Simple Random Sample:-

It's a sample in which each voter has an equal probability of being selected in the sample and is independently chosen from sample population.

### 2. Parameters of population:-

It's a numeric value that gives a characteristic of entire population. It is denoted by  $\theta$ .

### 3. Sample estimates:-

Numerical values calculated from a sample provides estimates or approximation of population parameter.

### 4. Statistic:-

A function of r.v. is called statistic. It is denoted by  $T(X)$

A statistic is called a r.v.

Statistic is used to estimate a population parameter that is  $T(X)$  is an estimator of  $\theta$ .

i.e.  $T(X) = \hat{\theta}$

### 5. Unbiased estimator:-

An estimator is unbiased if

$$E_0(T(X)) = \theta$$

The Bias of an estimator is

$$\text{Bias}_0(T(X)) = E_0(T(X)) - \theta$$

An estimator is unbiased if its bias is 0.

$$6. \text{Var}(T(X)) = E\{[T(X) - E(T(X))]^2\}$$

Mean Squared Error (MSE)

$$\text{Also, } \text{MSE}_0(T(X)) = \text{Var}_0(T(X)) + [\text{Bias}_0(T(X))]^2$$

$$\text{MSE}_0(T(X)) = E[T(X) - \theta]^2$$

Th<sup>m</sup>

Let  $X = (X_1, X_2, X_3, \dots, X_n)$  be an i.i.d sample of sample variable as  $X$  with population mean  $\mu$  and population var.  $\sigma^2$ , then the arithmetic mean  $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$  is an unbiased estimator of  $\mu$ .

And sample variance  $s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$  is an unbiased estimator of  $\sigma^2$ .

Proof:

→ Given population mean:  $\mu$   
Sample Mean:  $\bar{X}$   
pop. Var.:  $\sigma^2$

II]  $E(s^2) = \sigma^2$

$$\text{Consider } \frac{\sum_{i=1}^n (X_i - \mu)^2}{n} = \frac{\sum_{i=1}^n (X_i - \bar{X} + \bar{X} - \mu)^2}{n}$$

$$= \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n} + \frac{\sum_{i=1}^n (\bar{X} - \mu)^2}{n} + \frac{\sum_{i=1}^n 2(X_i - \bar{X})(\bar{X} - \mu)}{n}$$

$$= \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n} + n(\bar{X} - \mu)^2 + 0$$

$$\Rightarrow E\left(\frac{\sum_{i=1}^n (X_i - \mu)^2}{n}\right) = E\left(\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n} + n(\bar{X} - \mu)^2\right)$$

$$\frac{1}{n} \sum_{i=1}^n E(X_i - \mu)^2 = \frac{E(s^2)}{n} + n E(\bar{X} - \mu)^2$$

$$\frac{1}{n} \sum_{i=1}^n \text{Var}(X_i) = \frac{E(s^2)}{n} + n \text{Var}(\bar{X})$$

$$\sigma^2 = \frac{\sum_{i=1}^n \sigma_{X_i}^2}{n}; \text{Var}(\bar{X}) = \frac{\sigma^2}{n}$$

$$\frac{n\sigma^2}{n-1} = E(s^2) + \frac{\sigma^2}{n-1}$$

$$E(s^2) = \sigma^2$$

Ex. Let  $x_1, x_2, x_3, \dots, x_n$  be i.i.d sample of size  $n$ , with population mean  $\mu$  and Pop. variance  $\sigma^2$ .

1.  $\tilde{X} = \bar{X} + 1 = \frac{\sum_{i=1}^n (X_i + 1)}{n}$  is biased estimator of  $\mu$ .

→ Consider  $E(\tilde{X}) = E(\bar{X} + 1)$   
Now by th<sup>m</sup> we know that  
 $E(\bar{X} + 1) = E(\bar{X}) + E(1)$   
 $= \mu + 1$

2.  $\tilde{s}^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n}$  is biased estimator of  $\sigma^2$ .

→ By th<sup>m</sup> we know that  
 $E(\tilde{s}^2) \neq E(s^2) = \sigma^2$



$H_0$	$H_1$	Test
$\theta = \theta_0$	$\theta \neq \theta_0$	two-sided test
$\theta > \theta_0$	$\theta \leq \theta_0$	one-sided test
$\theta \leq \theta_0$	$\theta > \theta_0$	one-sided test

Decision	$H_0$ is true	$H_0$ is not true
$H_0$ is not rejected	Correct decision	Type-II error
$H_0$ is rejected	Type-I error	Correct Decision

$P(H_1 | H_0) = \alpha \rightarrow$  level of significance  
rejected  $\leftarrow$   $H_0$  true

$P(H_0 | H_1) = \beta \rightarrow$  level of confidence  
 $= 1 - \alpha$

Test: 9.

Q10. A sample of 100 tires is taken from a lot. The mean life of tires in the sample was found 39350 kms. std is 3260 kms.

Test at 1% level with mean life of 40000 kms.

→ ① (i) Given:  $\bar{x} = 39350$  kms,  $\sigma = 3260$  km,  $n = 100$ ,  $\mu = 40000$   
(ii)  $H_0: \mu = 40000$  km.

$H_1: \mu \neq 40000$  km

(iii)  $\alpha = 1\% = 0.01$ .

②  $T(V) = \frac{\bar{X} - \mu_0}{\sigma_0 / \sqrt{n}}$

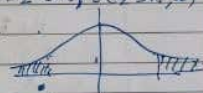
③  $H_0: \mu = 40000$  and  $H_1: \mu \neq 40000$   
we will take.

$k = (-\infty, -Z_{1-\frac{\alpha}{2}}) \cup (Z_{1-\frac{\alpha}{2}}, \infty)$   
 $0.995$

$k = (0.995) \rightarrow (1.9599)$   
 $k = (-\infty, -2.575) \cup (2.575, \infty)$

④  $t(x) = \frac{\bar{X} - \mu_0}{\sigma_0 / \sqrt{n}} = \frac{39350 - 40000}{3260 / 10}$   
 $t(x) = -1.9938$

⑤  $t(x) \neq k$ .  $H_1$  is rejected.  
 $H_0$  is accepted.





T-test

i)  $H_0, H_1$

ii)

iii)

$$T(X) = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \quad S^2 = \frac{1}{n-1} \left( \sum_{i=1}^n (x_i - \bar{X})^2 \right)$$

$H_0$	$H_1$
$\sigma = \sigma_0$	$(-\infty, -k_1 - \frac{\sigma_0}{\sqrt{n}}) \cup (k_1 - \frac{\sigma_0}{\sqrt{n}}, \infty)$
$\sigma > \sigma_0$	$(-\infty, k_1 - \frac{\sigma_0}{\sqrt{n}})$
$\sigma < \sigma_0$	$(k_1 - \frac{\sigma_0}{\sqrt{n}}, \infty)$

④  $t(x)$

⑤ Dec. Rule

①  $\mu = 0.5, n=8, \sigma^2 = ?$   
0.6, 0.7, 0.2, 0.3, 0.4, 0.5, 0.4 and 0.2

$$\mu = 0.5$$

$$H_1: \mu \neq 0.5$$

$$\bar{X} = \frac{3.8}{8} = 0.475$$

$$T(X) = 0.475 - 0.5$$

$$S^2 = \frac{1}{n-1} \left( \sum (x_i - \bar{X})^2 \right)$$

$$\sigma = 0.9 \text{ yrs}, n=10, s=1.2, \sigma > 0.9 \text{ yrs}$$

$$\alpha = 0.05$$

$$\Rightarrow \textcircled{1} \quad \text{i) } \sigma = 0.9, n=10, \sigma = 1.2 \text{ yrs}$$

$$\text{ii) } H_0: \sigma \leq 0.9$$

$$H_1: \sigma > 0.9$$

$$\textcircled{2} \quad T(X) = \frac{(n-1)s^2}{\sigma_0^2}$$

$$\textcircled{3} \quad (x^2, \infty) \quad \alpha = 0.05$$

$$\textcircled{4} \quad T(X) = \frac{(n-1)s^2}{\sigma_0^2} = \frac{(9)(1.2)^2}{0.9^2} = \frac{12.96}{0.81} = 16$$

⑤ We accept Null hypothesis  
Hence

$$\textcircled{2} \quad f\text{-test} \quad f(x_1, x_2) = \frac{1}{f(1-x_1, x_1)}$$

③ Critical Regions:-

Note:-

Consider two samples X and Y in i.i.d of size m and n from normal population are given by

$$S_x^2 = \frac{1}{m-1} \sum (x_i - \bar{x})^2$$

$$S_y^2 = \frac{1}{n-1} \sum (y_i - \bar{y})^2$$

then  $\frac{S_x^2}{S_y^2} \sim F_{m-1, n-1}$

- ① If men  $\Rightarrow \sigma = 6.4$  Test:  $\sigma_1^2 = \sigma_2^2$   
 14 women  $\Rightarrow \sigma = 5.3$   $\sigma_1^2 > \sigma_2^2$   
 $\rightarrow$  ① i) Given:  $n=11, m=14, \sigma_1=6.4, \sigma_2=5.3$   
 ii)  $H_0: \sigma_1 \leq \sigma_2$   
 $H_1: \sigma_1 > \sigma_2$   
 iii)  $\alpha = 0.05$

②  $T(X) = \frac{S_x^2}{S_y^2}$

③ Critical Region

$$k = (F_{\alpha, m-1, n-1})$$

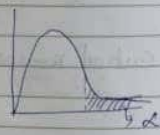
$$= (F_{0.05, 10, 13}, \infty)$$

④  $k = (2.67, \infty)$

⑤  $t(x) = \frac{(6.1)^2}{(5.3)^2} = 1.3246$

⑥  $H_0$  is not

Hence, we fail to reject Null hypothesis



$\chi^2$  goodness of fit test -

①  $\chi^2 = \frac{\sum (N_i - np_i)^2}{np_i}$

RY	PG	EY	ER
245	108	101	82

$$n = 556$$

Preparation  $n = 9.33:1 \Rightarrow \frac{9}{9.33} : \frac{3}{9.33} : \frac{2}{9.33} : \frac{1}{9.33}$

② Given: (i)

③ (ii)  $H_0: P(X=i) = p_i$

or  $H_1: P(X=i) \neq p_i$

(iii)  $\alpha = 0.05$

④  $T(X) = \sum_{i=1}^k \frac{(N_i - np_i)^2}{np_i}$

$$k=4$$

classification of samples

⑤  $K = \chi^2_{\alpha}$  for  $\gamma = k-1 = 3$   
 $K = 7.815$

⑥  $t(X) = \frac{(315 - 556 \times \frac{9}{9.33})^2}{556 \times \frac{9}{9.33}} = 0.016$   
 $+ \frac{(108 - 2 \times 556 \times \frac{3}{9.33})^2}{556 \times \frac{3}{9.33}} = 0.035$   
 $+ \frac{(101 - 2 \times 556 \times \frac{2}{9.33})^2}{556 \times \frac{2}{9.33}} = 0.101$   
 $+ \frac{(82 - 556 \times \frac{1}{9.33})^2}{556 \times \frac{1}{9.33}} = \dots$

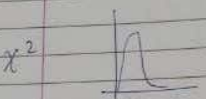




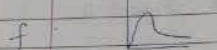
$n > 30$   $\sigma$  known



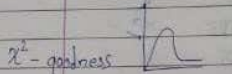
$n < 30$   $\sigma$  unknown



Normally dist.  $\sigma^2$  known



Comparing Variance



$\chi^2$  - goodness

$\sigma^2$  or  $\sigma^2$

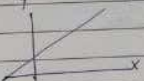
## Linear Regression

① Variable (X, Y)

② Regression Parameter ( $\alpha, \beta$  or  $a, b$ )

dependent  $\leftarrow y = \alpha + \beta x \rightarrow$  independent  
Intercept slope

① if  $\beta$  is +ve



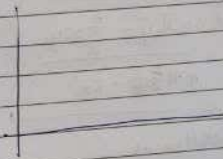
② if  $\beta$  is -ve



③ if  $\beta$  is +ve and  $\alpha = 0$



④ if  $\beta$  is -ve and  $\alpha = 0$





Consider  $n$  sets of observation given  $P = (X_i, Y_i)$ ,  $i=1,2,3$  obtained on time variable  $P = (X, Y)$ . The method of least squares says that a line can be fitted to the given dataset such that errors are minimized. denoted by  $\hat{\beta}$ . We need to determine estimate of  $\alpha$  and  $\beta$ , such that sum of all squared distance between data points and the line  $Y = \alpha + \beta X$  is minimized.

$$y_i = \alpha + \beta x_i + e_i$$

$$y_{i+1} = \alpha + \beta x_{i+1} + e_{i+1}$$

$$y_n = \alpha + \beta x_n + e_n$$

$$\sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \alpha - \beta x_i)^2$$

By minimize this, use the principle of Maximal Min.

$$\frac{\partial}{\partial \alpha} \left( \sum_{i=1}^n e_i^2 \right) = 0 \quad \frac{\partial}{\partial \beta} \left( \sum_{i=1}^n e_i^2 \right) = 0$$

$$-2 \sum_{i=1}^n (y_i - \alpha - \beta x_i) = 0 \quad + 2 \sum_{i=1}^n (y_i - \alpha - \beta x_i) x_i = 0$$

$$\sum_{i=1}^n y_i - \sum_{i=1}^n \alpha - \beta \sum_{i=1}^n x_i = 0$$

$$\sum_{i=1}^n y_i - \alpha n - \beta \sum_{i=1}^n x_i = 0$$

$$\alpha = \bar{y} - \beta \bar{x}$$

$$\sum_{i=1}^n x_i y_i - \sum_{i=1}^n \alpha x_i - \beta \sum_{i=1}^n x_i^2 = 0$$

$$\sum_{i=1}^n x_i y_i - \sum_{i=1}^n \bar{y} x_i + \beta \sum_{i=1}^n \bar{x} x_i - \beta \sum_{i=1}^n x_i^2 = 0$$

$$\hat{\beta} = \frac{\sum_{i=1}^n x_i y_i - \bar{y} \sum_{i=1}^n x_i}{\sum_{i=1}^n x_i^2 - n \bar{x}^2}$$

$$\sum_{i=1}^n x_i^2 - n \bar{x}^2$$

$$\hat{\beta} = \frac{n \bar{x} \bar{y} - \sum_{i=1}^n x_i y_i}{n \bar{x}^2 - \sum_{i=1}^n x_i^2}$$

Also can be written as

$$\hat{\beta} \sum_{i=1}^n (x_i^2 - n \bar{x}^2) = \sum_{i=1}^n (x_i y_i - n \bar{x} \bar{y})$$

$$= \sum_{i=1}^n (x_i y_i) + \sum_{i=1}^n \bar{x} \bar{y} - n \bar{x} \bar{y} - \sum_{i=1}^n \bar{x} \bar{y}$$

$$= \sum_{i=1}^n (x_i y_i) + n \bar{x} \bar{y} - n \bar{x} \bar{y} - \sum_{i=1}^n \bar{x} \bar{y}$$

$$= \sum_{i=1}^n (x_i y_i) - \sum_{i=1}^n \bar{x} \bar{y}$$

$$= \sum_{i=1}^n (x_i y_i) - n \bar{x} \bar{y}$$

$$\hat{\beta} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i^2 - n \bar{x}^2)}$$