29/9/23

Machine Learning & Data Science

→ Basics of ML, different from traditional programming, types, of challenges

→ Visualis^{n}, plotting — Numpy
— Pandas
— Matplotlib
— sklearn

→ Statistics/statistical — train, test
— Validation
— K-cross valid^{n}
— Performance evalu^{n} for classific^{n}

→ Classific^{n} — KNN
— Naive Bayes
— Decision Tree → Ensemble learning.

→ Regression → Mathematics → Linear
→ Logistic
— Confidence & Interval
— ANOVA

→ Regularization & Kernal method.

→ Clustering — EM
— Mixture models
— K Means
— DBSCAN
— Hierarchical Clustering
— Optics

29/1/25 → DR — tSNE
PCA

→ Deep learning — NN
Back propagation
Training methods

Book: ① Principles of DS
② Hands on ML with scikit-Learn, Keras, Tensor flow
③ Data mining - Concepts & Techniques

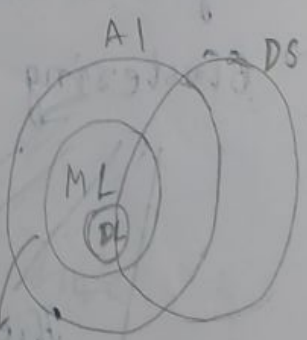
Evaluation:

→ Mid Term 25 M
→ End Term 40 M
→ Assignment 2 — 15 M
10 M
→ 1 or 2 surprise tests . 10 M

80% attendance is compulsory.

AI ML DS

AI - A mechanism that can do everything that a human does.



Less data - ML

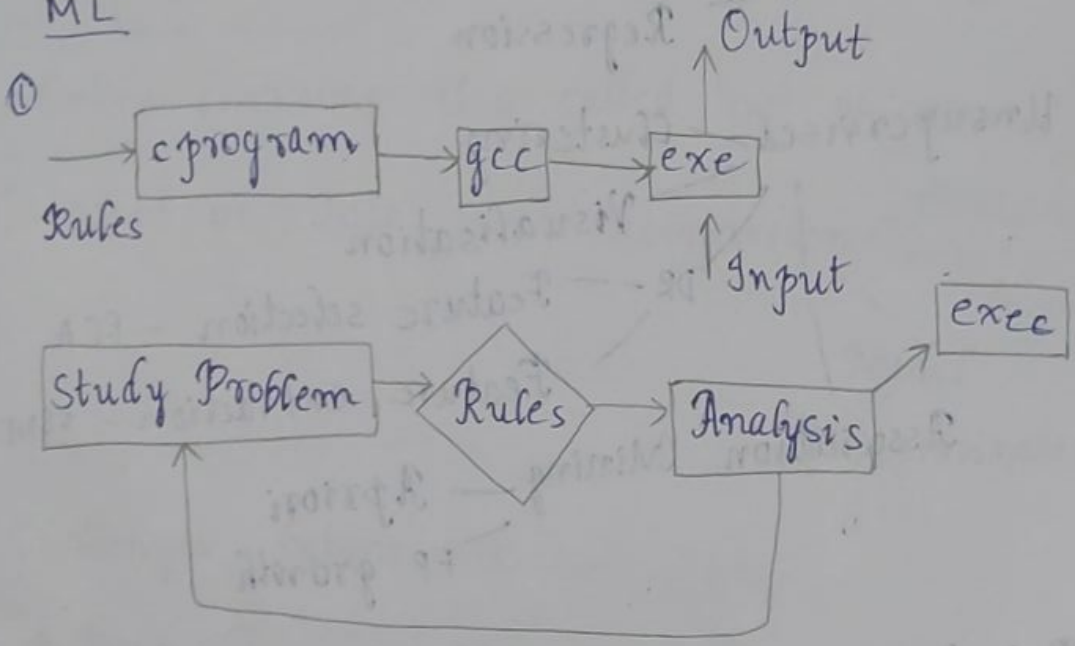
Huge data, hidden characteristics - DL

used for generating end product. (IOT sensors, etc)

29/1/25

DS — Visualisation
DS — Missing
DS — ML

ML



Does this involve any learning? No

→ Here, in C we will set our rules
→ In ML, machine sets its own rules.

ML — Human Supervision — Supervised
Unsupervised
Semi-supervised
RL
ML — Learning Style — Batch
Online Learning
ML — Data Points comparison — Model Based Learning
Instance Based Learning

Online Learning - Model keeps updated on real-time data

Batch Learning - We need to give the data in 1 go

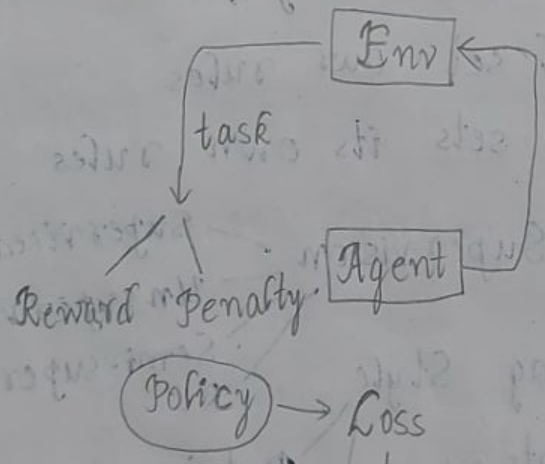
30/7/25

Once the training is completed, we cannot give any data again.

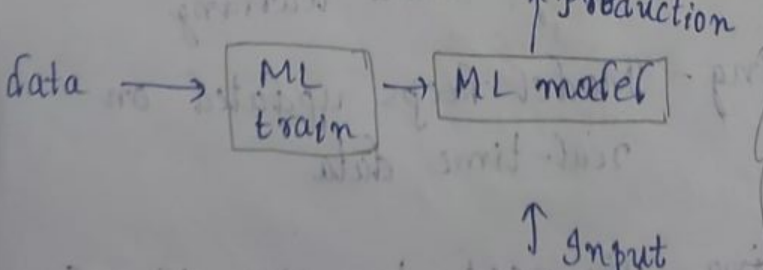
Supervised — Classific^{n}
— Regression

Unsupervised — Clustering
— Visualisation
DR — Feature selection — PCA
— Feature extraction — tSNE
Association Mining — Apriori
— FP growth

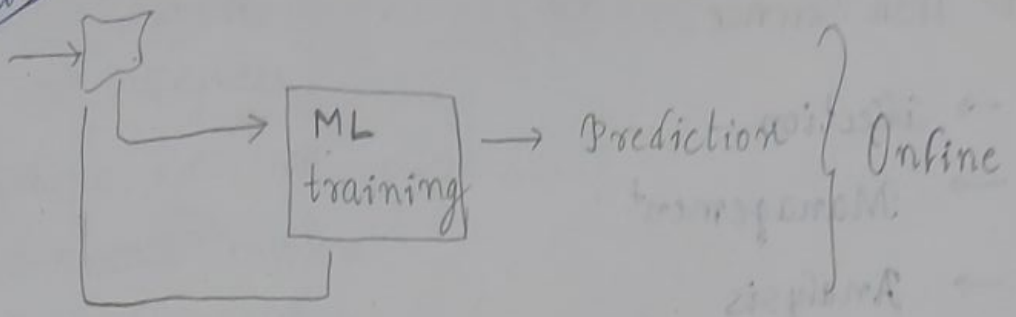
Reinforcement (No Human)



② Based on Learning style — Batch
— Online learning



30/12/25



Online Learning also called "out of core L"

③ Based on Data points comparison — Instance (small dataset)
— Model (Discriminative)

Challenges behind ML

→ Data biased → Not represent

→ Complex data → Low training accuracy

Underfitting → low (training + testing) accuracy

→ Overfitting

↳ Reduce model complexity

↳ Set threshold value

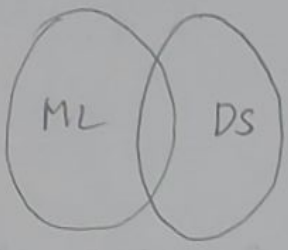
↳ Work on data set

↳ Give important data/feature

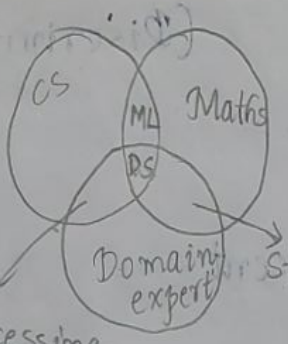
* Revise Pandas, Matplotlib

11/8/25 Data Science

→ Collection
→ Management
→ Analysis



Domain experts collect the data
Management - Store the data - cs experts
Analysis - Maths & statistics

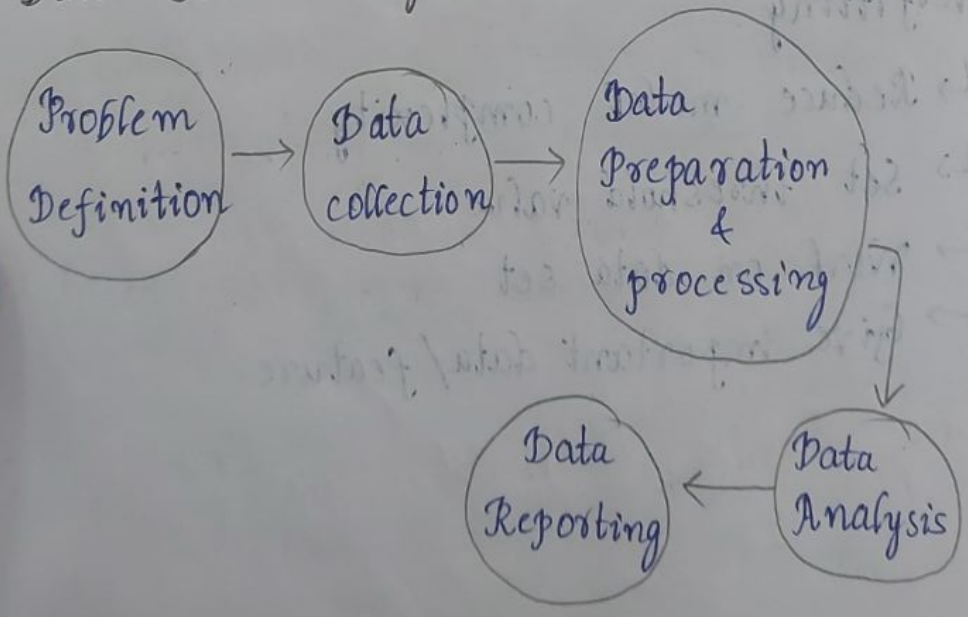


Preprocessing & Visualisation

Descriptive Method — Mean, Median, Mode

Probabilistic method — Gaussian distribⁿ

Data Science Cycle



① We should have clear-cut objective } ①

1/8/25 → Experts
→ Colleagues } ①

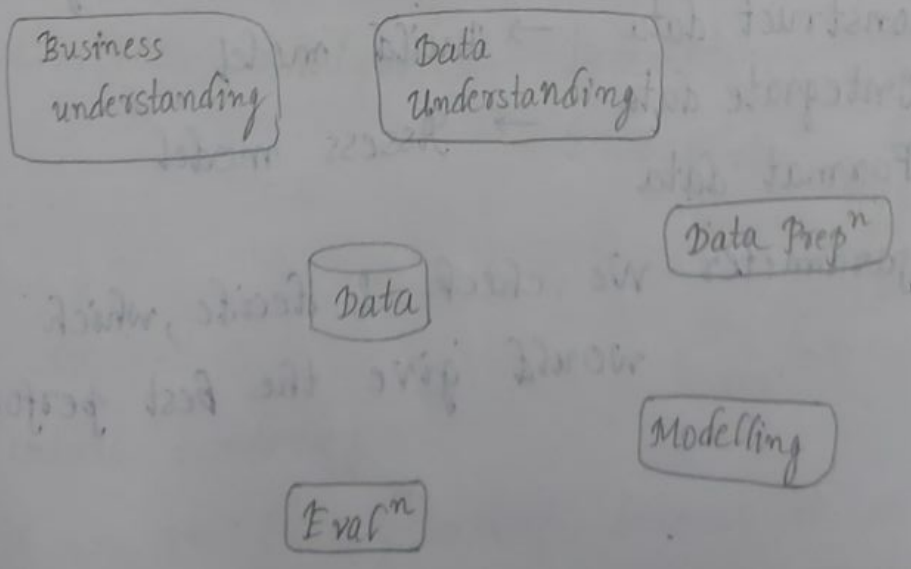
Where we can collect data?
→ Search engine
→ Web scraping
→ Surveys
→ Open ended interviews } ②

Missing values
Outleirs } ③

→ Statistical techniques
→ Probability
→ ANOVA
→ t-
p-test
→ Sample } ④

Data Science Market

① CRISP DM process (CRISP-DM Guide)



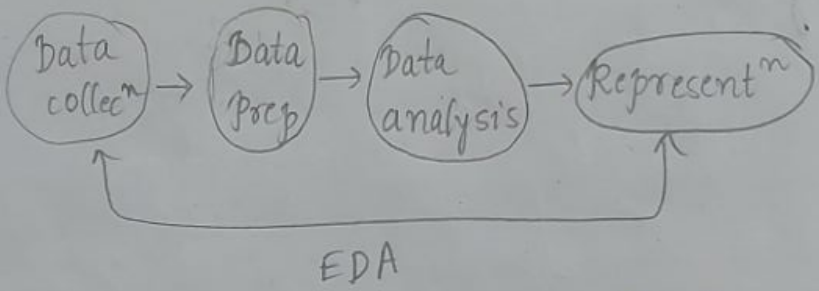
1/9/25

① Business Understanding

→ Determine business objectives
→ Assess situation
→ Determine data mining goals
→ Produce project plan

② Data Understanding

→ Collect initial data
→ Describe data
→ Explore data
→ Verify data quality



③ Data Prepⁿ

→ Select data
→ Clean data
→ Construct data
→ Integrate data
→ Format data

④ Modeling

→ Select modeling technique
→ Generate test design
→ Build model
→ Assess model

Hyperparameter - We check & decide, which would give the best perform

Helps

⑤ Deployment

→ Plan deployment
→ Plan monitoring & maintainance
→ Produce Final Report
→ Review project

Types of Data

① Quantitative
- Numerical
  - Discrete
  - Continuous
- Categories
  - Nominal – No dependency
  - Ordinal – Order
  - Ratio – based on %
  - Interval – Range

② Qualitative

↳ subjective nature
→ Surveys
→ Interviews

Datasets
- structured
- Unstructured

CSV
JSON
XML

Statistical Analysis
- Descriptive
  - Central tendency
  - Variations
  - Positions
- Probability
  - Hypothesis testing
  - Z-score
  - confidence level

Descriptive

① Central tendency

If we are taking whole dataset, it is

5/8/25

represented by N. If we take a small sample, n.

N → population size — Mean μ — $\mu = \frac{\Sigma x}{N}$

n → sample size — $\bar{x}$ — $\bar{x} = \frac{\Sigma x}{n}$

① Central Tendency — Mean → Trimmed Mean

0.001 0.003 10 20 30 40 1000 2000

Trim 20% ⇒ 10 20 30 40

(Will be removed from lower value & higher value)

→ Median → n is odd $\frac{n+1}{2}$

→ n is even $\frac{n}{2}$ & $\frac{n}{2}+1$

→ Mode — frequency

mean = $\frac{x \cdot f}{n}$ (in this case)

Variation (spread) — Range → Max - Min (If outliers are present, it will get affected & we are not counting each every value)

Variance → spread on mean

Std deviaⁿ

coefficent of variation

Sample variance

$s^2 = \frac{\Sigma (x - \bar{x})^2}{n-1}$ → HW

population variance $\sigma^2 = \frac{\Sigma (x-\mu)^2}{N}$

6/8/20

$$SD = s = \sqrt{\frac{\Sigma (x-\bar{x})^2}{n-1}}$$

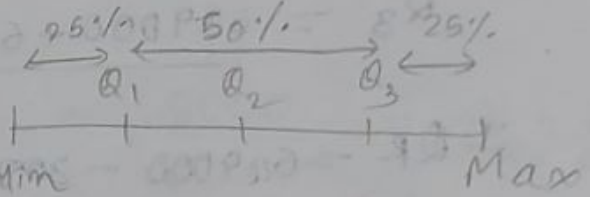
$$\sigma = \sqrt{\frac{\Sigma (x-\mu)^2}{N}}$$

If mean are different: (when we take from 2 datasets)

CV: $\text{sample} = \frac{s}{\bar{x}} \times 100\%$

$\text{pop}^n = \frac{\sigma}{\mu} \times 100\%$

Positions < Percentile, Quartile → , Z-score



Find Q_1, Q_2, Q_3.

5.4, 6.0, 6.3, 6.8, 7.1, 7.2, 7.4, 7.5, 7.9, 8.2, 8.7

→ We need to have ordered dataset

$25 = \frac{x}{11} \xrightarrow{\times 100} x = \frac{25 \times 11}{100} = \frac{11}{4}$

→ Take middle value → Q_2

Take mean → Q_1 & Q_3

$Q_1 = 6.3$

$Q_3 = 7.9$

IQR - Inter Quartile Range

Where my 50% of data is there?

$IQR = Q_3 - Q_1$

Lower bound $= Q_1 - (1.5 \cdot IQR)$

Upper bound $= Q_3 + (1.5 \cdot IQR)$

Stats

389950, 230500, 158000, 479000, 639000,
114950, 5500000, 387000, 659000, 529000,
575000, 488800, 1095000

114950, 158000, 230500, 387000, 389950, 479000,
488800, 529000, 575000, 639000, 659000, 1095000,
5500000

$Q_2 = 488800$

$Q_1 = \frac{230500 + 387000}{2} = 308750$

$Q_3 = \frac{639000 + 659000}{2} = 649000$

$IQR = 649000 - 308750 = 340250$

$(1.5)(IQR) = (1.5)(340250) = 510375$

Lower bound $= Q_1 - (1.5)(IQR) =$ ____

(Written by me)

Why $n-1$? (in sample variance)

In the case of skewed data, experiment^n have shown that, having $n-1$ gives better results. That is approximately equal to popul^n variance σ^2.

With the help of sample variance, we should estimate the popul^n variance

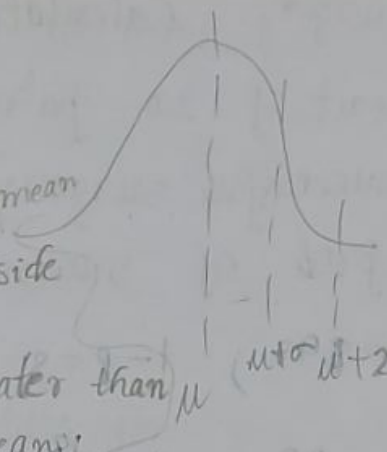
$S^2 \approx \sigma^2$

Mam: Degree of freedom concept

6/8/25

Z-score

$$\text{Z-score} = \frac{x - \mu}{\sigma}$$



Z can be
- −ve → below mean, left side
- 0 → eq
- +ve → greater than mean

Suppose the x value of house price is 270000, Mean is 350000, std is 40000, then calculate the z-score

$$Z = \frac{270000 - 350000}{40000} = -\frac{8000}{40000} = -\frac{1}{5}$$

Probability Distribution

Binomial Distribution
↳ two success, failure
→ Independent trails, prob should not be changed
→ x → Discrete value

Discrete — Binomial, Poisson
Continuous — Normal, Gaussian

$$P(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

A sample of 20 patients is selected for

6/8/25 surgery, Calculate the prob that 18 out of 20 patients will be having the successful surgery. From the past data, prob of success is 92%.

Sol):- $p = .92$, $1-p = .8$

$$P(x) = {}^{20}C_{18} \left(\frac{92}{100}\right)^{18} \left(\frac{8}{100}\right)^{2}$$

$$= \frac{20 \times 19}{1 \times 2} \left(\frac{92}{100}\right)^{18} \left(\frac{8}{100}\right)^{2}$$

$$= 190 \left(\frac{92}{100}\right)^{18} \left(\frac{8}{100}\right)^{2}$$

$$= 0.271$$

Poisson Distribution

Each n every thing will be dependent on whole dataset

μ, σ

$$P(x) = \frac{\mu^{x} e^{-\mu}}{x!}$$

(2) From the past data, a traffic engineer demands the avg. no of vehicles entering a biking garrage, a 7 per 10 min period Calculate the prob that the no of the vehicles entering in a parking is 9 in certain 10 min period

6/8/25

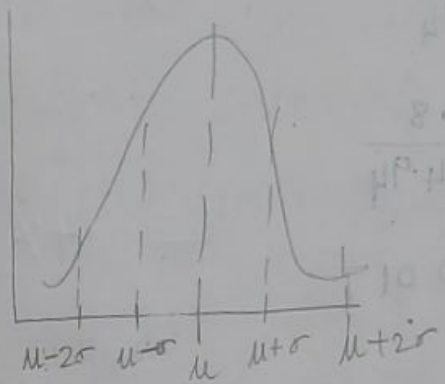
Ans $e = 2.718$ Ans 0.101

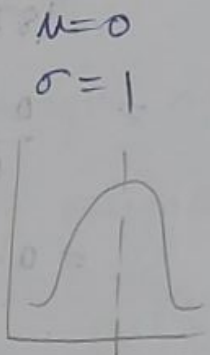
$$P(x) = \frac{(1)^9 (2.718)^{-1}}{9!}$$

$=$

PMF – Probability Mass fn

Normal Distribution





Mean
Median
Mode
} overlap

$x \sim N(x, y)$

Mean, Std

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

Each n every normal distribution will be standardized by z-score.

6) At a software company, the mean of employe's salary is 60000 with a std dev 7500, Calculate the prob that a random employee earns more than 68000.

6/8/18

$$P(68000) = \frac{1}{\sqrt{2\pi}\cdot 7500} e^{-\frac{(68000-60000)^2}{2(7500)^2}}$$

$$= \frac{1}{18794.94} (2.718)^{-\frac{64\times10^6}{5625\times10^4}}$$

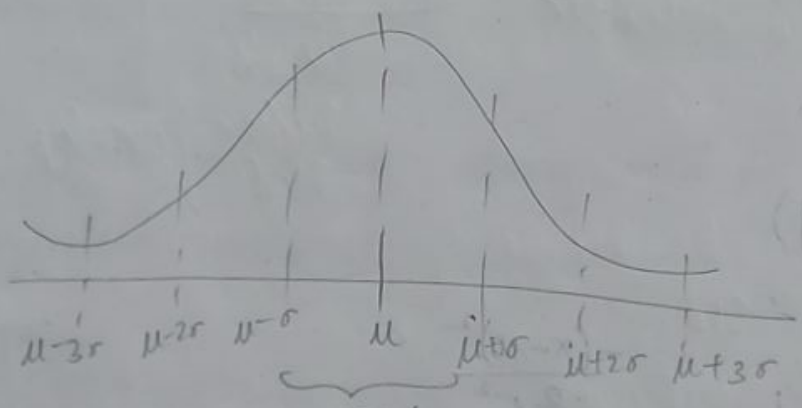
$$= \frac{1}{18794.94} (2.718)^{-\frac{6400}{5625}}$$

$$= \frac{1}{18794.94} (2.718)^{-1.137}$$

$$= \frac{0.3208}{18794.94}$$

$$= 0.000017$$

Ans: 14%



Q) Suppose an automated designer is interested in designing automatic seats to accomodate different heights of 95%. The heights of customers follow normal distribution with the mean value 68 f

6/8/18 Std 3. For wt range of heights, should the designer model the car seats

NEXT CLASS: CONFIDENCE LEVEL, ANOVA, HYPOTHESIS TESTING

Inferential statistics

We take some observ^n from sample & use it for popul^n

→ We find out error also

Confidence interval → Margin of error

Any statistic → Point of estimate poe ± e

Confidence Interval ↓ confidence level

Lower bound of CI = poe − ME

Upper bound of CI = Poe + ME

A sample of 100 patients is taken. Determined sample mean is at 64 years old. Assume that the corresponding MOE for a 95% CI is calculated to be 4 yrs.

= 64 − 4 → 60 to 68

= 64 + 4

Mean is going to lie btw CI 60-68

Mean → Assumption, μ → popul^n mean

Proportion

μ_x → sample mean

$\mu_x = \mu$

$s_x = \frac{\sigma}{\sqrt{n}}$ n → sample size

Central Limit Theorem → When we are

Instead going to aggregate the samples, it will form normal distribution
We might get skewed graph.

2 cond^ns: ① We don't know dataset distrib^n
We know mean, std
If sample size > 30 ! for a m sh gu

② Std is not known

CL → Mean — σ known → z-test (→ z-score)
— σ Not known → t-test

σ is known

Confidence level for mean = $z_c \frac{\sigma}{\sqrt{n}}$

Lower B of CI → Mean − E_c

Upper B of CI → Mean + E_c

Q) Sample size = 50, POE = Popul^n mean = 85000
Std = 9000. Distrib^n isn't known Calculate the mean & std for sample & comment the shape of distrib^n for sample.

Sol)
So
85000
90000
} Popul^n

Sample

Sample std dev $S_{\bar{x}} = \frac{\sigma}{\sqrt{x}}$

$= \frac{9000}{\sqrt{50}}$

$= \frac{9000}{5\sqrt{2}}$

13/8hrs * According to CLT, if sample size > 30, then it follows normal distribution.

Find CI for 95% confidence, $z = 1.96$

error of margin $= 1.96 \times \frac{9000}{\sqrt{50}} = \frac{196}{100} \times \frac{9000}{5\sqrt{2}} = 98\sqrt{2} \times 18$

$= 1764\sqrt{2}$

~~$= 1730.52$~~

$= 2494.66$

Q) Suppose sample of 50 students is taken, in that 50 students, the mean of time spent on HW is 12.5 hrs. The popⁿ std devⁿ is 6.3 hrs. Create a forecasted CI using CL 90% & 95% and provide a conclusion regarding these confidence level that which interval is wider.

z-score for 90% = 1.645, 95% = 1.960

Sol):- $SS = 50 \Rightarrow$ Normal distribⁿ

Mean = 12.5, $\sigma = 6.3$

CI Mean (90%) $= (1.645) \times \frac{6.3}{\sqrt{50}} = 1.4656$

CI Mean (95%) $= (1.960) \times \frac{6.3}{\sqrt{50}} = 1.7462$

(90%) Lower B = 12.5 ± 1.465

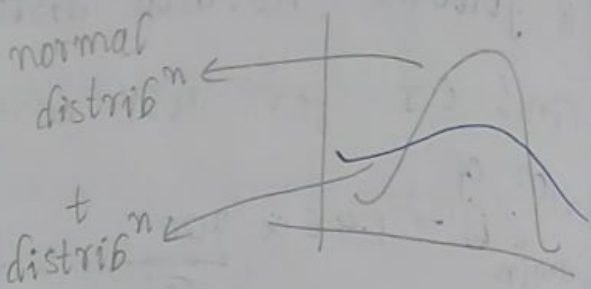
(95%) Upper B = $12.5 \pm 1.746 \rightarrow$ Wider

→ Random Sample
→ 30 or ND
→ σ

→ If σ is not known, find out S_x

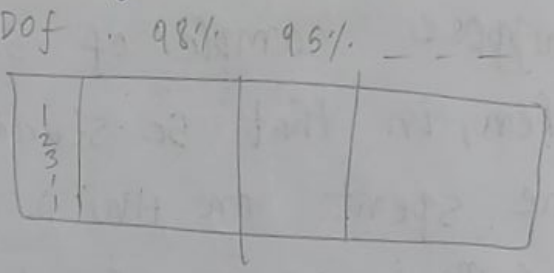
13/8/25

$$E_c = t_c \frac{S_x}{\sqrt{n}}$$



degree of freedom $= n-1$

→ Check from table



Q) Suppose in a company 5000 employees r there. Administr^n decided to take sample of 16 employee to find mean salary. The sample data indicate, sample mean of salary is 15.8 lakhs & the std is 3.2 lakh. Calculate the 99% CL, CI for salary.
$t_c = 2.947$

Sol):-

$$E_c = (2.947)\frac{(3.2)}{\sqrt{16}} = 2.3576$$

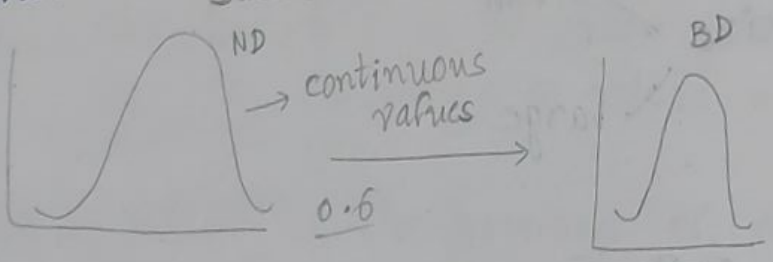
$CI = 15.8 \pm 2.357$

$= [$~~13.14~~$, 13.44, 18.16]$

13/8/25 Confidence Interval for Proportions

$$\hat{p} = \frac{x}{n}$$

Normal distrib^n is applicable for continuous values



$\begin{bmatrix} np \\ n(1-p) \end{bmatrix}$ → at least 5

If it is greater than 5, Normal distrib^n can represent binomial distrib^n also.

$$E_c = z_c \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

Q) A medical researcher wants to see the change in the propor^n of smokers from 5 yrs ago & the " of adult " was 28%. A random sample of 1500 adults is taken & 360 were found smokers. Calculate the 95% confidence interval for the true pop^n portion of adults who smoke. $z_c = 1.960$

Sol) $\hat{p} = \frac{360}{1500}$

$E_c = (1.960)\sqrt{\frac{0.24(1-0.24)}{1500}}$

$= 0.0005$

$\hat{p} \pm E_c$

$n\hat{p}$. $n(1-\hat{p})$ should be atleast 5

13/8/25

Q) How can we determine the sample size if we take small sample?

Sample size → small – wide
→ large –

Mean $E_c = z_c \frac{\sigma}{\sqrt{n}}$

$n = \left(\frac{z_c \sigma}{E_c}\right)^2$

~~$n = \left(\frac{z_c}{E_c}\right)^2 \cdot (1-\hat{p})$~~

~~$n = 2$~~

Proportion $E_c = z_c \sqrt{\frac{(1-\hat{p})\cdot\hat{p}}{n}}$

$n = \left(\frac{z_c}{E_c}\right)^2 (1-\hat{p})\hat{p}$

Q) A Benefits analyst ~~is~~ ~~need~~ interested in 95% CL for _____ for mean salary of employee. What should be the ~~MOE~~ Sample ~~size~~ / ~~is dired~~ / ~~Popu~~ size if margin of error 1000 is desired. σ(popu^n) = 8000

– (z_c = /– 645)

$\Rightarrow n = \left(\frac{1.645 \times 8000}{1000}\right)^2 = \left(\frac{13160}{1000}\right)^2 = (13.16)^2$

$= 173.18$

$\simeq 174$ / whole number will be take

13/8/25

2Q) One ~~candidate~~ candidate is ~~smith~~ ~~for~~ smith is

Q) 1 candidate is smith is planning a survey to determine 95% C.I for the proportion of voters who planned to vote for smith. How many should be survived. $E_c = 3\%$, $z = 1.96$?

Case-1: Assume there is no prior estimate for the 0.5 (default) proportion of voters who vote for smith

Case-2: Based on the previous elections, 42% ppl voted for smith

(I) $E_c = 3\%$, $z = 1.96$

95% CI

$$n = \left(\frac{1.96}{0.03}\right)^2 (1-0.95)(0.95)$$

$$= 1043$$

Bootstrap sampling

Mean → 30, ND

Proportion → np $n(1-p) \rightarrow 5$

Bootstrap → sample with replacement

Wt is the advantage of bootstrap sampling?

(i) To increase popuⁿ size
(ii) Help us use validⁿ
(iii) Helps remove bias in sample

$^6C_1 \times ^4C_1$ → Sample without replacement

19/8/25

Stratified sampling:

If dataset contains 60% class A & 40% class B,

then sample should also contain ||

① Population → repeatedly generate sample

② $\bar{x}$, $\bar{s}_x$

③ Sort

④ 95%, $P_{2.5}$ $P_{92.5}$

⑤ 90%, P_5, P_{95}

Hypothesis Testing

We were defining statistical parameter & we were mapping it with popⁿ ||
(Previously)

Null H_0 — Alternate H_a

↓ — ↓

=, ≤, ≥ — ≠, >, <

H_0 $\mu = 25\%$

H_a $\mu \neq 25\%$

After claiming, we need to apply some statiscal approach.

$\sigma \rightarrow$ z-test

$\rightarrow$ t-test

Then, we'll set some level of significance

$Z < p$ (or) ... $Z > p$

19/8/25

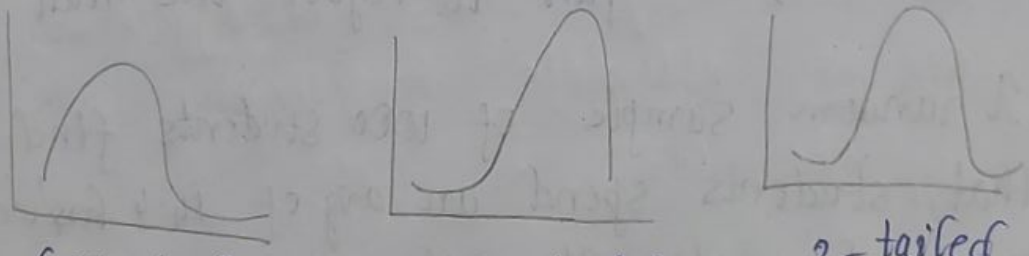
ACTUAL \ Predicⁿ	Yes	No
Yes	TP	FN → Type 2 error
No	FP	TN

↓ Type 1 error

If my null hypothesis is true & I'm failing to reject that one – Type 1

bcoz actually it is true but we r failing.

If my null hypothesis is false & we fail, – Type 2



left tailed ($<$) | right-tailed ($>$) | 2-tailed ($=$)

σ known

mean $z = \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}}$

σ not known

mean $t = \frac{\bar{x} - \mu}{s/\sqrt{n}}$

propor^n In any sample, how many ← are there

$\hat{p} = \frac{x}{n} \rightarrow n\hat{p}$ & $n(\hat{p}-1)$ at least 5.

$z = \frac{\hat{p} - p}{\sqrt{p(1-p)/n}}$

p → claim propor^n of hypothesis

14/8/25

Q) An auto repair facility claims the avg time for oil-change is less than 20 mins.

atleast, atmost → null
less than, greater → alternate

Null $\mu \geq 20$
Alt. $\mu < 20$

Q) A medical researcher claims that the proportion of adults in the United States who r smokers is atmost 25%.

Null $\mu \leq 25\%$
Alt $\mu > 25\%$

* If $\hat{p}$ value is less than or equal to significance value, we reject
* If $\hat{p}$ value is greater " value, we fail to reject the null

Q) A random sample of 1000 students find that, students spend an avg of 14.4 hrs/week on social media. Use this sample data to test the claim that Clg student spend atleast 15 hrs/week on social media. Level of Significance = 0.05, Popn of std devn = 3.25

Sol):-

Null $\mu \geq 15$

$\mu < 15$

$$Z = \frac{14.4 - 15}{\frac{3.25}{\sqrt{1000}}}$$

-1.83

0.05

0.0324 < 0.05

19/8/25 We're going to reject the null hypothesis

→ The claim will be on sample, that is going to be reflected in popuⁿ.

Based on t-test

Q) A smart phone manufacturer claims that the mean battery life of the phone is 25 hrs. Consumer & collect the sample of 50 S.P. and determine the mean value 24.1 hr & std dev 4.1 hr. Use this sample data to test the claim made by smart phone manufacturer. Use the level of significance, 0.10.

Null $\mu = 25$

Alt $\mu \neq 25$

$$t = \frac{50 - \cancel{25}\ 24.1}{\frac{4.1}{\sqrt{50}}} = \frac{25.9}{s/\sqrt{n}} = -1.552$$

↳ 0.0635

2 tails ⇒ double value

0.127

→ we r failing to reject the null hypothesis

i.e, we r accepting.

0.127 > 0.1

So, wt the manufacturer is claiming is true

Based on Proporⁿ

Q) A Chg professor claims that the proporⁿ of students using the Chatgpt in their

19/8/25 assignment is less than 45%. Professor selects sample of 200 students & figure it out that 74 out of 200 use gpt. Use LOS = 0.05

Sol):-

Null $\mu \geq 0.45$ $p = 0.45$

Alt $\mu < 0.45$ $\hat{p} = 74$

$$z = \frac{74 - 0.45}{\sqrt{0.45(1-0.45)/200}} =$$

first, $n\hat{p} = 200 \times 74 \geq 5$

$n(\hat{p}-1) = 200(74-1) \geq 5$

$z = -2.274$

$z \hookrightarrow$ p-value $= 0.012 < 0.05$

→ We will reject the null hypothesis, accept alternate hypothesis.

∴ The claim is true.

Hypothesis Testing for two samples

μ_1, μ_2 – mean of sample 1 & sample 2

Null $\mu_1 = \mu_2$ $\mu_1 \geq \mu_2$ $\mu_1 \leq \mu_2$

Alt $\mu_1 \neq \mu_2$ $\mu_1 < \mu_2$ $\mu_1 > \mu_2$

Samples can be dependent or independent

Independent

→ Random & Indept

20/8/25

→ Sample should be of size 30 or follow normal distribu^n

→ sample variance or SD

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Q) Suppose a SE is claiming that the avg salary of women engineer is less than male. Two samples are taken, sample 1 = 45, sample 2 = 50, LOS = 0.05

	WE	ME
~~Sim~~		
Sample mean	72700	76900
SD	9800	10700
Size	45	50

WE ≤ ME ⇒ Null : $\mu_1 \geq \mu_2$

μ_1 μ_2 At $\mu_1 < \mu_2$

If there is no difference, then there is no change in claim. So, there is = always in null hypothesis.

$\therefore \mu_1 = \mu_2 \Rightarrow (\mu_1 - \mu_2) = 0$

$t =$ (

$= -1.997$ → $0.025 < 0.05$

20/8/25

∴ The claim is true

Dependent samples:

difference (d) - before data - after data

$$\bar{d} = \frac{\Sigma d}{n}$$

$$t = \frac{\bar{d} - \mu_d}{s_d/\sqrt{n}}$$

→ when drug is taken, what is the bp & when drug is not taken, what is bp?

μ_d, k constant

Null $\mu_d = 0$ or k , $\mu_d \geq k$

A $\mu_d \neq 0$ or k , $\mu_d < k$

$\mu_d \leq k$

$\mu_d > k$

Q) Cholesterol lowering medicine.

Claim - Medicⁿ helps to lower cholestrol level., LOS = 0.05

Null $\mu_d <= 0$ Claim - cholestrol is lower

∴ Alt $\mu_d > 0$ ∴ before - after > 0

But if claim is cholestrol is higher then before - after < 0

20/8/26

Patient	BM	AM
1	218	210
2	232	241
3	259	223
4	265	244
5	248	227
6	298	273
7	263	252
8	281	276
9	290	281
10	271	259

$\bar{d} = \frac{\Sigma d}{n} = 13.9 \rightarrow$ On avg

$S_d = 12.414$

$$t = \frac{13.9 - 0}{\frac{12.414}{\sqrt{10}}} = 3.541$$

$\hookrightarrow 0.003$

$0.003 < 0.05$

Two proportion

x_1 x_2

n_1 n_2

$$\hat{P}_1 = \frac{x_1}{n_1}, \quad \hat{P}_2 = \frac{x_2}{n_2}$$

$$\bar{P} = \frac{x_1 + x_2}{n_1 + n_2}$$

$n_1\bar{P}$, $n_2\bar{P}$, $n_1(1-\bar{P})$, $n_2(1-\bar{P})$ should be atleast 5

$$Z = \frac{(\hat{P}_1 - \hat{P}_2) - (P_1 - P_2)}{\sqrt{\bar{P}(1-\bar{P})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

→ based on our hypothesis

Q) Investigⁿ to address lung cancer.
People who took drug in 211 was cancer free among 250, 172 among 230
LOS = 0.01

Claim: Proportion of ~~subjects~~ candidates $P_1 > P_2$ taking cancer-free drug are more cancerfree than the candidates who r not taking drug.

Sol: $n_1 \bar{P} =$

$$\hat{P}_1 = \frac{211}{250}, \hat{P}_2 = \frac{172}{230}$$

$$\bar{P} = \frac{211+172}{250+230} = 0.798$$

$$n_1 \bar{P} = 250 \times 0.798 = 199.5 > 5$$

$Z = 2.6$

$0.004 < 0.01$

ANOVA test — random, independent.

Analysis btw the variance

→ Z, t → one sample

→ t → two sample $< P_I$

22/8/25

F → distribution

① $\bar{x}_1, \bar{x}_2, \bar{x}_3$ & s_1^2, s_2^2, s_3^2

② Grand mean $\bar{\bar{x}}$

③ $SSB = n_1(\bar{x}_1 - \bar{\bar{x}})^2 + n_2(\bar{x}_2 - \bar{\bar{x}})^2 + n_3(\bar{x}_3 - \bar{\bar{x}})^2$

④ $SSW = (n_1 - 1)s_1^2 + (n_2 - 1)s_2^2 + (n_3 - 1)s_3^2$

⑤ df_n = no of groups − 1

df_d = total ss − no of group

⑥ $MSB = \frac{SSB}{df_n}$ ⑦ $MSW = \frac{SSW}{df_d}$

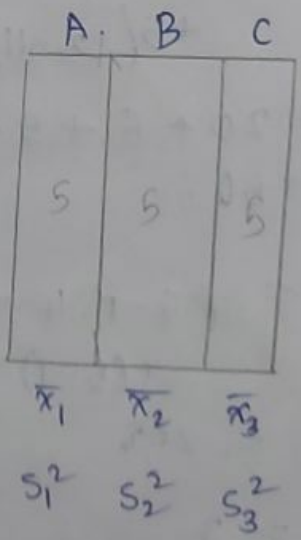
⑧ $F = \frac{MSB}{MSW}$

From Utube:
If F > LOS
Reject H_0
F ≤ LOS
Fail to Reject H_0

two degree

→ no of group

→ total no samples − no of group



F < level of

P-value < level of sig

22/8/25

S.No	A	B	C	D
1	8	12	18	13
2	10	11	12	9
3	12	9	16	12
4	8	14	6	16
5	7	4	8	15

Claim: Height of popⁿ > Mean value of popⁿ ✗

Mean(A) = $\frac{45}{5}$ = 9 Var(A) = $\frac{16}{4}$ = 4 Std(A) = 2

Mean(B) = $\frac{50}{5}$ = 10 Var(B) = $\frac{58}{4}$ = 14.5 Std(B) = 3.8

Mean(C) = $\frac{60}{5}$ = 12 Var(C) = $\frac{104}{4}$ = 26 Std(C) = 5.099

Mean(D) = $\frac{65}{5}$ = 13 Var(D) = $\frac{30}{4}$ = 7.5 Std(D) = 2.73

② Grand mean $\bar{\bar{x}} = \frac{9+10+12+13}{4} = 11$

⑤ $SSB = 5(9-11)^2 + 5(10-11)^2 + 5(12-11)^2 + 5(13-11)^2$

$= 20 + 5 + 5 + 20$

$= 50$

④ $SSW = (5-1)4 + (5-1)14.5 + (5-1)26 + (5-1)7.56$

$= 208$

⑤ $df_n = 3$

$df_d = 20 - 3 = 17$

e2 18/ns

⑥ $MSB = \frac{50}{3}$

$= 16.66$

⑦ $MSW = \frac{208}{17}$

$= 12.23$

Correlation Analysis → Regression

~~Represent~~

Whether the features are going to have impact on output or not.

+ve → ↑ indep ↑ dep

0 → X

-ve → ↑ inde ↓ dep

Pearson correlation $= \frac{n\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{n\Sigma x^2 - (\Sigma x)^2}\sqrt{x\Sigma y^2 - (\Sigma y)^2}}$

r

value → strength

sign → direction

ρ → Popul^n P.C Coefficient

Linear relationship ⇒ $|r| > \frac{2}{\sqrt{n}}$

6) Suppose the chief financial officer is investigating the correl^n between rest of price

In a sample data size, 10 points r taken. Now, based on this analysis can chief financial

22/8/23 officer conclude that the correlation is significant btw the stock price & unemployment rate with the LOS = 0.06.

Soln: $r = -0.68$

$n = 10$

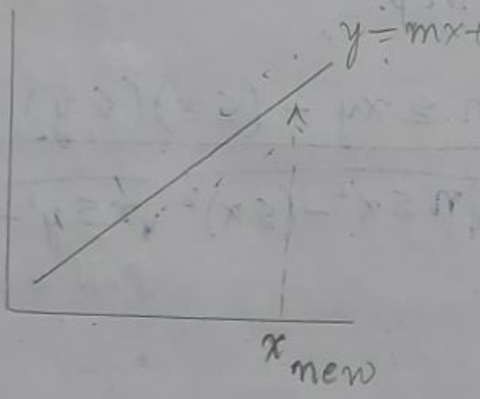
$|-0.68| > \frac{2}{\sqrt{10}}$

$0.68 > 0.63$

Yes, the relⁿ ship is there.

They're going to be -vely correlated

Linear Regression



Supervised ML
- Classificⁿ (Discrete) — CM, P, R, A
- Regression (Continuous) — Loss/cost

$\hat{y} = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 + c$

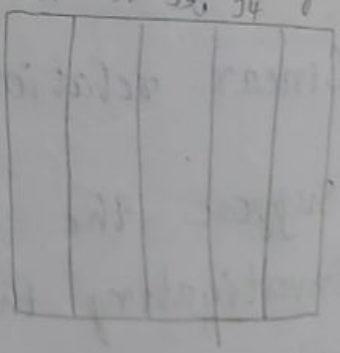
$c = w_0 f_0$

$f_0 = 1$

$\hat{y} = w_0 f_0 + w_1 f_1 + \dots + w_n f_n$

$\hat{y} = WF \quad -\hat{y} = WX$

$\rightarrow y = ax + b$



→ Closed Normal form $\frac{\partial \text{Loss}}{\partial w}$

→ Gradient descent → η

26/8/25

Linear Regression

$y = mx + c$

$\omega_1\ \omega_2\ \omega_3\ \omega_4$

$x_1\ x_2\ x_3\ x_4$ y

$\hat{y} = \omega_1 x_1 + \omega_2 x_2 + \omega_3 x_3 + \omega_4 x_4 + c$

$\downarrow \omega_0 x_0$

where $x_0 = 1$

$\hat{y} = WX$

$W = [\omega_0 \ldots \omega_n]$

$X = [x_0 \ldots x_n]$

where $x_0 = 1$

Loss / Cost / Error / Bias

We will minimize

$y - \hat{y}$

$MAE = \frac{1}{n} |y - \hat{y}|$

$MSE = \frac{1}{n} (y - \hat{y})^2$

$RMSE = \sqrt{\frac{1}{n} (y - \hat{y})^2}$

Cross entropy

↳ $\hat{y}^y (1-\hat{y})(1-y)$

LR — Closed normal form

— Gradient descent

$\hat{y} = WX$

$Loss = \frac{1}{n} (y - \hat{y})^2$

$\frac{\partial Loss}{\partial \omega} = \frac{1}{n} [2(y - \hat{y})] \times \frac{\partial}{\partial \omega} (y - \hat{y})$

$= 2X(y - \hat{y}) * \frac{\partial}{\partial \omega} (y - X\omega)$

→ Equate it to 0.

26/8/22

$$2(y-\hat{y}) * \frac{\partial}{\partial w}(y - Xw) = 0$$

$$2(y - Xw) * (-X) = 0$$

$$2 : X^T(y - Xw) = 0$$

$$X^T(y - Xw) = 0$$

$$X^Ty - X^TXw = 0$$

$$X^TXw = X^Ty$$

$$w = (X^TX)^{-1}X^Ty$$

Code

```
X = 2 * np.random.rand(m, 1)
y = 4 + 3 * X + np.random.randn(m, 1)
```

↓ normal distributed values

```
from sklearn.preprocessing
    import add_dummy_feature
X_b =                                   a.T → a^T
theta_best = np.linalg.inv(X_b.T.dot(X_b)).
theta_best                              dot(X_b.T).dot
X_new = np.array([[0], [2]])
print(X_new)
X_new_b = add_dummy_feature(X_new)
y_predict = X_new_b.dot(theta_best)
y_predict
```

26/8/23

Using SKlearn:

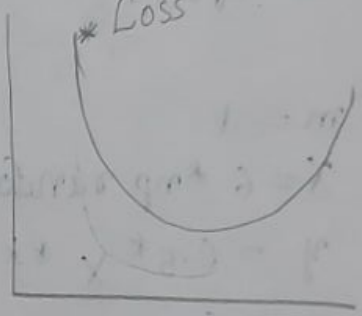
```
from .linear_model import L R
lin_reg = L R ()
lin_reg.fit(X, y)
lin_reg.intercept_, lin_reg.coef_
```

ω_0 ω_1

Gradient descent

$$\omega_{i+1} = \omega_i - \eta \frac{\partial}{\partial \omega} \text{Loss}$$

η ↓ learning rate

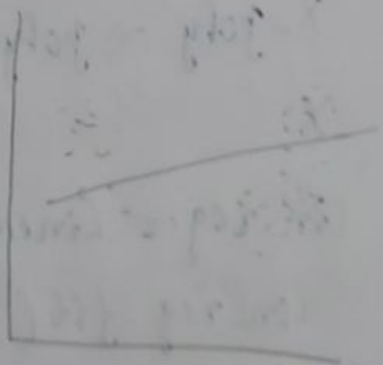


In the starting, take some random values for ω.

Curve should be convex curve

GD — Batch G-D. - Whole dataset is given in 1go
— Stochastic G-D - Any 1 random instance
— Mini-batch

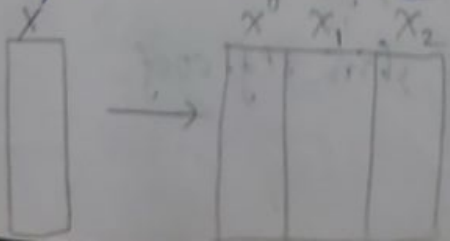
Underfitting ←



Polynomial Regression

x, d = 2

x^0, x^1, x^2 $\omega_0 \omega_1 \omega_2$



x, y, degree - 2

1, x, y, xy, x², y²

$\omega_1, \omega_2, \omega_3$

26/8/25 degree - d, num of features - n

→ How many new features will come?

$$^{n+d}C_d = \frac{(n+d)!}{n! \times d!}$$

$y = WX$

$= w_0 + w_1 x$ ⇒

$w_0 x_0 + w_1 x$

where $x_0 = 1$

Code

```
m = 1
X = 6 * np.random.rand(m,1) - 3
y = 0.5 * X ** 2 + X + 2 + np.random.randn(m,1)
```

for finding polynomial features:

```
from                    import PolynomialFeatures
poly_features = PolynomialFeatures
                (degree=2, include_bias=False)
X_poly = poly_features.fit_transform(X)
X
lin_reg = LinearRegression()
lin_reg.fit(X_poly, y)
lin_reg.intercept_, lin_reg.coef_
```

Regularization

$$\text{Cost} = \frac{1}{n}(y-\hat{y})^2 + \dots$$

↙ Minimize w.

Regularizⁿ — Ridge (L2 Norm)
— Lasso (L1 Norm)
\ Elastic Net

1) Ridge $J(\theta) = \text{MSE} + \alpha \sum_{i=1}^{m} \theta_i^2$

$$\text{Cost} = \frac{1}{n}\cdot(y-\hat{y})^2 + \alpha \sum_{i=1}^{n} \theta_i^2$$

$$= \frac{1}{n}(y-\hat{y})^2 + \alpha \cdot \theta^2$$

$$\frac{\partial \text{Cost}}{\partial \theta} = \frac{1}{n} \times 2 \times (y-\hat{y}) \times \frac{\partial}{\partial \theta}(y-\hat{y}) + \alpha \times 2\theta$$

$$= \frac{2}{n}(y - X\theta) \times \frac{\partial}{\partial \theta}(y - X\theta) + 2\alpha\theta$$

$$= \frac{2}{n}\cdot(y-X\theta) \times (-X) + 2\alpha\theta = 0$$

$$= -Xy + X^T X\theta + \alpha\theta = 0$$

$$= \theta = \frac{Xy}{X^T X + \alpha}$$

$\alpha \to$ large $\Rightarrow$ $\theta \to$ very small $\Rightarrow$ Underfitting

2) Lasso Regularizⁿ

$$J(\theta) = \text{MSE} + \alpha \sum_{i=1}^{n} |\theta_i|$$

29/8/25

$$\text{cost} = \frac{1}{n}[y-\hat{y}]^2 + \alpha\theta$$

$$\frac{\partial}{\partial\theta}\text{cost} = \frac{1}{n} \times 2\,[y-\hat{y}] \times \frac{\partial}{\partial\theta}[y-\hat{y}] + \alpha$$

$$= \frac{2}{n}[y - X\theta] \times \frac{\partial}{\partial\theta}[y - X\theta] + \alpha$$

$$= \frac{2}{n}[y - X\theta] \times (-X) + \alpha = 0$$

$$-\frac{2}{n} X y + \frac{2}{n} X^T X\theta + \alpha = 0$$

$$\theta = \frac{\frac{2}{n} X y - \alpha}{\frac{2}{n} X^T X}$$

3) Elastic Net

$$J(\theta) = MSE + r\alpha \underbrace{\sum_{i=1}^{m} \theta_i}_{L1} + \frac{1-r}{2}\alpha \underbrace{\sum_{i=1}^{n} \theta_i^2}_{L2}$$

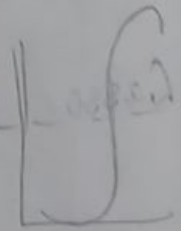
Lass — Ridge

Wer adding something to MSE, so that our model will work in real-time scenario

Logistic Regression

→ Classification

Apply sigmoid fn 0-1 $\Rightarrow \frac{1}{1+e^{-t}}$



0.5 < N Negative Class

> P Positive Class

Softmax — multi-class classific^{n}

$$\frac{e^{z_x}}{\sum_{i=1}^{n} e_i^{z_x}}$$

Classification

→ Binary — Yes — ✓ / x
No — ✓ / x

Actual \ Predicted	Yes	No
Yes	TP	FN → Type II
No	FP ↓ Type I	TN

Precision → $\frac{TP}{TP+FP}$

Recall (Completeness) → $\frac{TP}{TP+FN}$

Accuracy → $\frac{TP+TN}{TP+TN+FP+FN}$

we need a mid-way of Precision & Recall → F1-score → $\frac{2 \times Precis^{n} \times Recall}{Precis^{n} + Recall}$

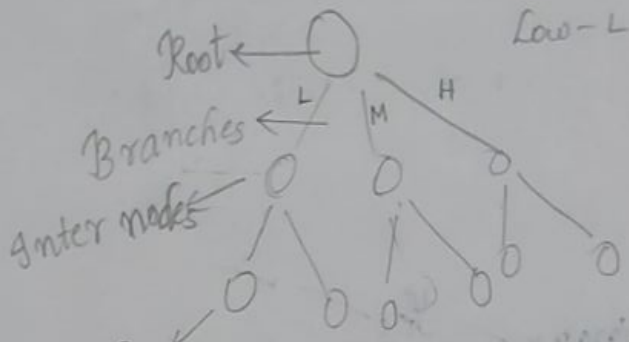
Underfitting → Training x Testing x

Overfitting → Training ✓ Testing x

$Loss/error = Bias^2 + Variance + Irreducible\ Noise$

2/9/25

Decision tree



Low-L Medium-M High-H

2/3/B

* On leaf node, we'll be having final class

→ It can work on n-dimensional dataset
→ Prior info is not required
→ Domain-expert

} Advantages

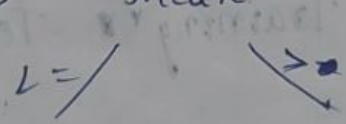
→ Overfitting - Because it's a rule-based algorithm
No learning

} Disadvantage

How are we going to split & Attribute selection?

Discrete ⇒ L/M/H or Yes/No

Continuous ⇒ Mean



[value <= Mean]

Attribute selection — Entropy or Info^n. Gain → ID3

Gain Ratio → C4.5

Index Root → CART

Slides

Entropy (or) IG

→ Randomness → Measure that quantifies the avg amount of inform^n or uncertainity.

$IG_E(Class) = $ ~~Σ~~

$$= - \sum P_i \log_2 P_i$$

→ how the class is going to be distributed

0 0 1 1 2 0 3 4

$\frac{3}{8}$ $\frac{2}{8}$ $\frac{1}{8}$

$$IG_A(Class) = \sum_{i=1}^{N} \frac{|D_i|}{|D|} \times IG(D_i)$$

Root

D_1 D_2

$$\Delta Gain_A(Class) = IG(Class) - IG_A(Class)$$

→ When all instances are saying, this is the class

→ If all instances & rows are fully utilized

Basic criteria for stopping DT:

① All instances are agreeing for 1 class

② All attributes are utilized

③ Subset that we are generating does not have any instance.

8/9/25

S.N	Age	Income	Student	Credit Rating	Buy-comp
1.	Y	H	N	F	N
2.	Y	H	N	E	N
3.	M	H	N	F	Y
4.	S	M	N	F	Y
5.	S	L	Y	F	Y
6.	S	L	Y	E	N
7.	M	L	Y	E	Y
8.	Y	M	N	F	N
9.	Y	L	Y	F	Y
10.	S	M	Y	F	Y
11.	Y	M	Y	E	Y
12.	M	M	N	E	Y
13.	M	H	Y	F	Y
14.	S	M	N	E	N

0.029 0.151 0.048

Y-Youth, M-Middle Age, S-Senior Citizen

$$IG(Class) = -\sum_{i=1}^{n} P_i \log_2 P_i$$

$$IG_{Att}(Class) = \sum_{i=1}^{N} \frac{|D_i|}{|D|} * IG(D_i)$$

3/a/as

$$\Delta G_{(A)} = IG(Class) - IG_{Att}(Class)$$

$Y = 9/14$ $\quad IG(Buy-Comp) = -\frac{9}{14}\log_2\frac{9}{14}$

$N = 5/14$ $\quad -\frac{5}{14}\log_2\frac{5}{14}$

$$= -\frac{9}{14}(-0.637) - \frac{5}{14}(-1.485)$$

$$= 0.4095 + 0.5303$$

$$\neq 1.449$$

$$= 0.939$$

$$\approx 0.94$$

$$\log_a b = \frac{\log b}{\log a}$$

$$\log_2\frac{9}{14} = \frac{\log\frac{9}{14}}{\log 2}$$

$$IG.(Class)_{Age} = \frac{5}{14}IG(D_1) + \frac{4}{14}IG(D_2) + \frac{5}{14}IG(D_3)$$

Y 5 < 2 Y, 3 N

M 4 < 4 Y, 0 N

S 5 < 3 Y, 2 N

$$= \frac{5}{14}\left[\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}\right]$$

$$+ \frac{4}{14}\left[\frac{-4}{4}\log_2\frac{4}{4} - 0\right]$$

$$+ \frac{5}{14}\left[\frac{-3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right]$$

$$= \frac{5}{14}\left[\frac{-2}{5}(-1.321) - \frac{3}{5}(-0.736)\right]$$

$$+ \frac{4}{14}\left[-1(0) - 0\right] + \frac{5}{14}\left[\frac{-3}{5}(-0.736) - \frac{2}{5}(-1.321)\right]$$

$$= \frac{5}{14}\left[0.5284 + 0.441\right] + \frac{5}{14}\left[0.4416 + 0.5284\right]$$

$$= \frac{5}{14} \times 0.9694 + \frac{5}{14} \times 0.9694 = 0.692$$

$$\approx 0.694$$

3/9/25

$\Delta G = 0.94 - 0.694$

$= 0.246$

$IG(\text{Student}) = IG_{\text{student}}(\text{Class}) = \frac{7}{14} IG(D_1) + \frac{7}{14} IG(D_2)$

Age

N — 7

Y — 7

Y — 6, 1

N — 3, 4

$= \frac{7}{14}\left[-\frac{6}{7}\log_2\frac{6}{7} - \frac{1}{7}\log_2\frac{1}{7}\right] + \frac{7}{14}\left[-\frac{3}{7}\log_2\frac{3}{7} - \frac{4}{7}\log_2\frac{4}{7}\right]$

$= \frac{7}{14}[0.191 + 0.401] + \frac{7}{14}[0.524 + 0.461]$

$= \frac{7}{14} \times 0.592 + \frac{7}{14} \times 0.985$

$= 0.296 + 0.493 = 0.789$

$\Delta G_{(\text{Student})} = 0.94 - 0.789 = 0.151$

$IG_{\text{Income}}(\text{Class}) = \frac{4}{14} IG(D_1) + \frac{6}{14} IG(D_2) + \frac{4}{14} IG(D_3)$

L — 3, 1

M — 4, 2

H — 2, 2

$= \frac{4}{14}\left[-\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4}\right] + \frac{6}{14}\left[-\frac{4}{6}\log_2\frac{4}{6} - \frac{2}{6}\log_2\frac{2}{6}\right] + \frac{4}{14}\left[-\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4}\right]$

$= \frac{4}{14}[0.311 + 0.5] + \frac{6}{14}[0.390 + 0.528] + \frac{4}{14}[1]$

$= \frac{4}{14}(0.811) + \frac{6}{14}(0.918) + 0.286$

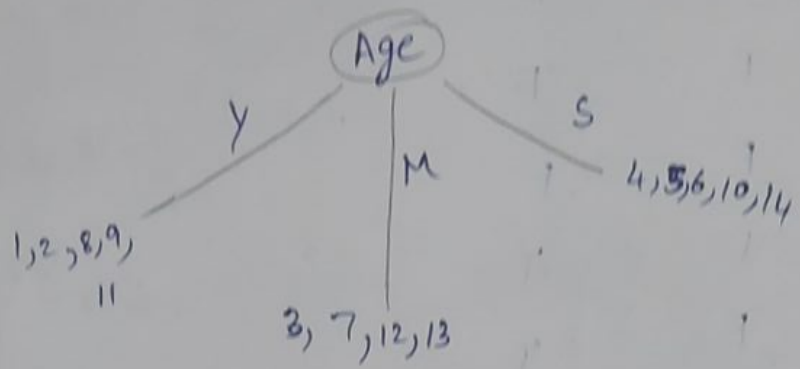
$= 0.232 + 0.393 + 0.286 = 0.911$

$\Delta G_{\text{Income}} = 0.94 - 0.911 = 0.029$

Similarly, $\Delta G_{\text{Credit Rating}} = 0.048$

3/9/26

* Age has highest - 0.246
So, it will be root node



$$IG(D_1) = -\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}$$

$$IG_{income}(D_1) = \frac{2}{5}IG(D_1^{H}) + \frac{2}{5}IG(D_1^{M}) + \frac{1}{5}IG(D_1^{L})$$

$$IG_{student}(D_1) = +\frac{2}{5}\left[-\frac{2}{5}\log_2\frac{2}{5} - \frac{2}{5}\log_2\frac{2}{5}\right.$$

$IG_{CR}(D_1)$

H = 2 (2, 0)

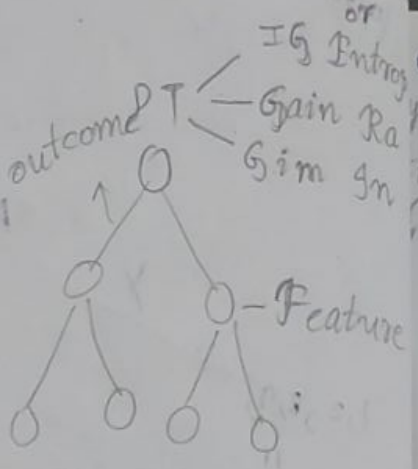
M = 2 (1, 3)

L = 1 (1, 2)

9/9/25

	GPA	Studied	Passed
1	L	F	F
2	L	T	T
3	M	F	F
4	M	T	T
5	H	F	T
6	H	T	T

Added by me, not feature



$$IG(Class) = -\sum_{i=1}^{n} P_i \log_2 P_i$$

$$IG_A(Class) = \sum_{i=1}^{n} \frac{|D_i|}{|D|} IG\left(\frac{D_i}{D}\right)$$

$$\Delta G = IG(Class) - IG_A(Class)$$

Stopping Criteria for DT:→ All instances belong to same class

→ No features are left

→ No instances are left

$$IG(Class) = -\frac{4}{6}\log_2\frac{4}{6} - \frac{2}{6}\log_2\frac{2}{6}$$
$$= 0.390 + 0.528$$
$$= 0.918 \approx 0.92$$

$$IG_{GPA}(Class) = \frac{2}{6}[IG(D_1)] + \frac{2}{6}IG(D_2) + \frac{2}{6}IG(D_3)$$

L ≤ 1
M ≤ 1
H ≤ 2
0

$$= \frac{2}{6}\left[\frac{-1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right] + \frac{2}{6}\left[\frac{-1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right]$$

$$+ \frac{2}{6}\left[\frac{-2}{2}\log_2\frac{2}{2} - 0\right]$$

$$= \frac{2}{6}[1] + \frac{2}{6}[1] + \frac{2}{6}[0] = \frac{4}{6} = 0.667$$

$$IG_{Studied}(Class) = \frac{3}{6} IG(D_1) + \frac{3}{6} IG(D_2)$$

T ← 3, 0
F ← 1, 2

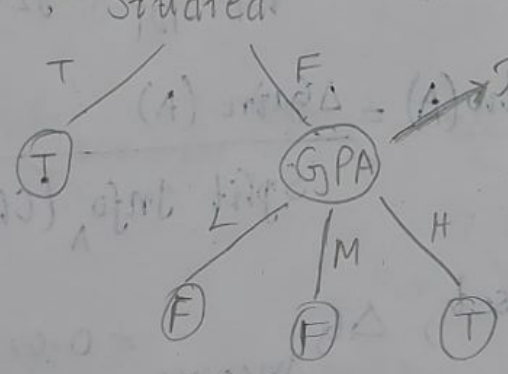
$$= \frac{3}{6}\left[\frac{-3}{3}\log_2\frac{3}{3} - 0\right] + \frac{3}{6}\left[\frac{-1}{3}\log_2\frac{1}{3} - \frac{2}{3}\log_2\frac{2}{3}\right]$$

$$= \frac{3}{6}[0] + \frac{3}{6}[0.528 + 0.390]$$

$$= \frac{3}{6}[0.918] = 0.459$$

$$\Delta G_{GPA} = 0.92 - 0.67 = 0.25$$

$$\Delta G_{Studied} = 0.92 - 0.46 = 0.46 \checkmark$$



All instances doesn't match. So, branching will come here. Then we should calculate IG but since only 1 attribute is left, we take it.

→ Then all belongs to same class.

High Variance → Overfitting
(Training accuracy is high & testing accuracy is less)

Why?

9/9/25 Problems of Information Gain or Entropy method

$$IG_{S.No}(Class) = \frac{1}{6}\left[\frac{1}{1}\log_2\frac{1}{1}\right] + \frac{1}{6}\left[\frac{1}{1}\log_2 1\right]$$
$$= 0$$

$$\Delta G_{S.No} = 0.92 - 0$$
$$= 0.92$$

→ Uncertainity very low for these columns then ΔG high.

Gain Ratio

$$\text{Split Info}_A(Class) = -\sum_{i=1} \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|}$$

$$\text{Gain Ratio}(A) = \frac{\Delta \text{Gain}(A)}{\text{Split Info}_A(Class)}$$

From 1st dataset, $\Delta G_{\text{Income}} = 0.029$

$$\text{Split Info}_{\text{Income}}(Class) = -\frac{4}{14}\log_2\frac{4}{14} - \frac{6}{14}\log_2\frac{6}{14}$$
$$= -\frac{4}{14}\log_2\frac{4}{14}$$
$$= 0.516 + 0.524 + 0.516$$
$$= 1.556$$

$$\text{Gain Ratio}_{(\text{Income})} = \frac{0.029}{1.556} = 0.019$$

a/9/25

2nd dataset:

$\Delta G_{GPA} = 0.26$

Split $Info_{GPA}(Class) = -\frac{2}{6}\log_2\frac{2}{6} - \frac{2}{6}\log_2\frac{2}{6} - \frac{2}{6}\log_2\frac{2}{6}$

$= 0.528 \times 3 = 1.584$

Gain ratio $(GPA) = \frac{0.26}{1.584} = 0.164$

$\Delta G_{studied} = 0.46$

Split $Info_{studied}(Class) = \frac{-3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6}$

$= 0.5 + 0.5 = 1$

Gain ratio $(Studied) = \frac{0.46}{1} = 0.46$

$\Delta G_{S.No} = 0.92$

Split $Info_{S.No}(Class) = \frac{-1}{6}\log_2\frac{1}{6} \times 6$

$= 0.431 \times 6$

$= 2.586$

Gain ratio $_{S.No} = \frac{0.92}{2.586} = 0.358$

Name of DT based on Gain Ratio = C45 (wrong)

Name of DT based on Inform^n Gain = ID3

Data mining & Techniques - Chapter 8.

Decision Tree

10/9/25

Gini Index → CART

⇒ This will be used for classific^{n} & regression.

$$Gini\ (Class) = 1 - \sum_{i=1}^{n} P_i^2$$

$$Gini_A\ (Class) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2)$$

$$\Delta Gini_A\ (Class) = Gini\ (Class) - Gini_A\ (Class)$$

→ Gini index is working on the binary split

→ We're going to form the sets.

3 attributes:

{∅} {L} {M} {H} {L M}

{L H} {M H} {L M H}

→ Whichever split has higher Δ value, that split will be considered.

* In the question, if it is mentioned 'multiway' split, then no need to do that process.

10/9/26

S.No	Body Temp	Birth	4 legged	Hibernates	Class (Mammal)
1	Warm	Y	Y	Y	Y
2	Warm	Y	Y	N	Y
3	Warm	Y	N	Y	N
4	Warm	Y	N	N	N
5	Cold	N	Y	Y	N
6	Cold	N	Y	N	N
7	Cold	N	N	Y	N
8	Cold	N	N	N	N
9	Warm	N	N	N	N
10	Cold	Y	N	N	N

$$\text{Gini Index (Class)} = 1 - \sum_{i=1}^{n} P_i^2$$

$$= 1 - \left(\frac{2}{10}\right)^2 - \left(\frac{8}{10}\right)^2$$

$$= 0.32$$

$$\text{Gini}_{\text{Body Temp}}(\text{Class}) = \frac{5}{10}\,\text{Gini (Warm)} + \frac{5}{10}\,\text{Gini (Cold)}$$

W – 2, 3 C – 0, 5

$$= \frac{5}{10}\left[1 - \left(\frac{2}{5}\right)^2 - \left(\frac{3}{5}\right)^2\right] + \frac{5}{10}\left[1 - 0 - \left(\frac{5}{5}\right)^2\right]$$

$$= \frac{5}{10}\left[0.48\right] + \frac{5}{10}(0) = 0.24$$

$$\Delta\text{Gini}_{\text{Body temp}}(\text{Class}) = 0.32 - 0.24 = 0.08$$

$$\text{Gini}_{\text{Birth}}(\text{Class}) = \frac{5}{10}\,\text{Gini}(Y) + \frac{5}{10}\,\text{Gini}(N)$$

Y – 2, 3 N – 0, 5

$$= 0.24$$

$$\therefore \Delta\text{Gini}_{\text{Birth}} = 0.08$$

10/9/25

$$\text{Gini}_{\text{4 legged}} = \frac{4}{10}\left[1-\left(\frac{2}{4}\right)^2-\left(\frac{2}{4}\right)^2\right]+\frac{6}{10}\left[1-\left(\frac{6}{6}\right)^2\right]$$

Y < 2, 2

N < 0, 6

$$= \frac{4}{10} \times 0.5 + 0$$

$$= 0.2$$

$$\Delta\text{Gini}_{\text{4 legged}} = 0.12$$

$$\text{Gini}_{\text{Hibernate}} = \frac{4}{10}\left[1-\left(\frac{1}{4}\right)^2-\left(\frac{3}{4}\right)^2\right]+\frac{6}{10}\left[1-\left(\frac{1}{6}\right)^2-\left(\frac{5}{6}\right)^2\right]$$

Y < 1, 3

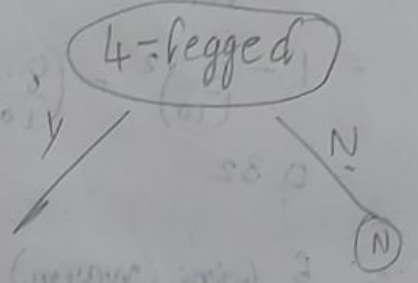
N < 1, 5

$$= \frac{4}{10} \times 0.375 + \frac{6}{10}[0.278]$$

$$= 0.15 + 0.167$$

$$= 0.317$$

$$\Delta G_{\text{Hibernate}} = 0.32 - 0.317 = 0.003$$



$$\text{Gini}(\text{Class } D_1) = 1-\left(\frac{2}{4}\right)^2-\left(\frac{2}{4}\right)^2 = 0.5$$

$$\text{Gini}_{BT}(D_1) = \frac{2}{4}\left[1-\left(\frac{2}{2}\right)^2-0\right]+\frac{2}{4}\left[1-\left(\frac{2}{2}\right)^2-0\right]$$

W < 2, 2

C < 0, 2

$$= 0$$

$$\Delta\text{Gini}_{BT} = 0.5 - 0 = 0.5$$

10/9/25

Gini Birth $(D_1) = \frac{2}{4}\left[1-\left(\frac{2}{2}\right)^2-0\right] + \frac{2}{4}\left[1-\left(\frac{2}{2}\right)^2-0\right]$

$= 0$

Y — 2, 0

N — 0, 2

Δ Gini Birth $= 0.5 - 0 = 0.5$

Gini Hibernate $(D_1) = \frac{2}{4}\left[1-\left(\frac{1}{2}\right)^2-\left(\frac{1}{2}\right)^2\right] + \frac{2}{4}\left[1-\left(\frac{1}{2}\right)^2-\left(\frac{1}{2}\right)^2\right]$

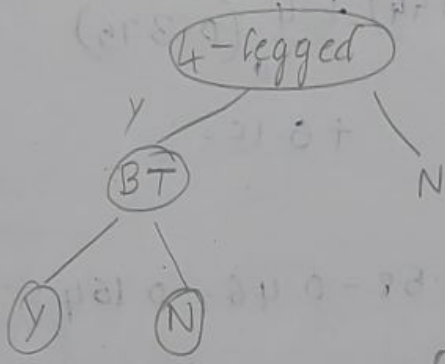
Y — 1, 1

N — 1, 1

$= \frac{2}{4}(0.5) + \frac{2}{4}(0.5)$

$= 0.5$

Δ Gini Hibernate $= 0.5 - 0.5 = 0$



Multiway Split :

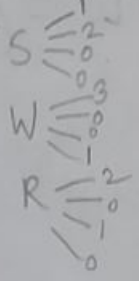
SNO	Weather (Sunny, Winter, Rainy)	Parents	Money (Rich, Poor)	Decision (Cinema, Tennis, stay in, shopping)
1	S	Y	R	C
2	S	N	R	T
3	W	Y	R	C
4	R	Y	P	C
5	R	N	R	S
6	R	Y	P	C
7	W	N	P	C
8	W	N	R	Sh
9	W	Y	R	C
10	S	N	R	T

10/9/25

$$Gini(Class) = 1 - \left[\left(\frac{6}{10}\right)^2 + \left(\frac{2}{10}\right)^2 + \left(\frac{1}{10}\right)^2 + \left(\frac{1}{10}\right)^2\right]$$

$$= 0.58$$

$$Gini_{Weather}(Class) = \frac{3}{10}\left[1 - \left(\frac{1}{3}\right)^2 - \left(\frac{2}{3}\right)^2\right]$$



$$+ \frac{4}{10}\left[1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2\right]$$

$$+ \frac{3}{10}\left[1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2\right]$$

$$= \frac{6}{10}(0.444) + \frac{4}{10}(0.375)$$

$$= 0.266 + 0.15$$

$$= 0.416$$

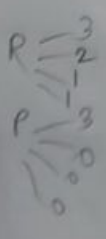
$$\Delta Gini_{Weather} = 0.58 - 0.46 = 0.164$$

$$Gini_{Parents}(Class) = \frac{5}{10}\left[1 - \left(\frac{5}{5}\right)^2\right] + \frac{5}{10}\left[1 - \left(\frac{1}{5}\right)^2 - \left(\frac{2}{5}\right)^2 - \left(\frac{1}{5}\right)^2 - \left(\frac{1}{5}\right)^2\right]$$

$$= 0 + \frac{5}{10}\left[0.72\right] = 0.36$$

$$\Delta Gini_{Parents} = 0.58 - 0.36 = 0.22$$

$$Gini_{Money}(Class) = \frac{7}{10}\left[1 - \left(\frac{3}{7}\right)^2 - \left(\frac{2}{7}\right)^2 - \left(\frac{1}{7}\right)^2 - \left(\frac{1}{7}\right)^2\right]$$

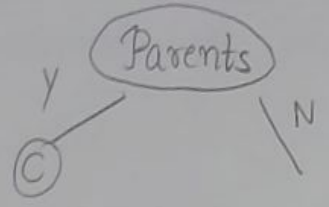


$$+ \frac{3}{10}\left[1 - \left(\frac{3}{3}\right)^2\right]$$

$$= \frac{7}{10}\left[0.694\right] + 0 = 0.486$$

$$\Delta Gini_{Money} = 0.58 - 0.486 = 0.094$$

10/4/25



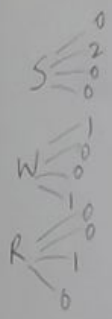
$$Gini\ (Class_P) = 1 - \left[\left(\frac{1}{5}\right)^2 + \left(\frac{2}{5}\right)^2 + \left(\frac{1}{5}\right)^2 + \left(\frac{1}{5}\right)^2\right]$$

$$= 1 - 0.28 = 0.72$$

$$Gini_{Weather}\ (Class_P) = \frac{2}{5}\left[1 - \left(\frac{2}{2}\right)^2\right] + \frac{2}{5}\left[1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2\right]$$

$$+ \frac{1}{5}\left[1 - \left(\frac{1}{1}\right)^2\right]$$

$$= \frac{2}{5}(0.5) = 0.2$$

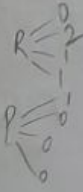


$$\Delta Gini_{Weather} = 0.72 - 0.2 = 0.52$$

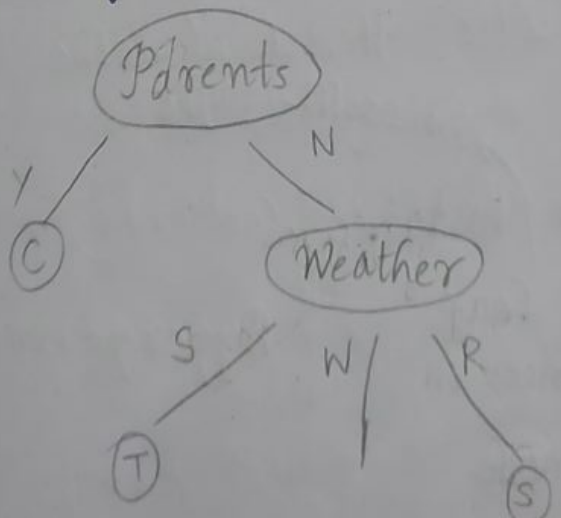
$$Gini_{Money}\ (Class_P) = \frac{4}{5}\left[1 - \left(\frac{2}{4}\right)^2 - \left(\frac{1}{4}\right)^2 - \left(\frac{1}{4}\right)^2\right]$$

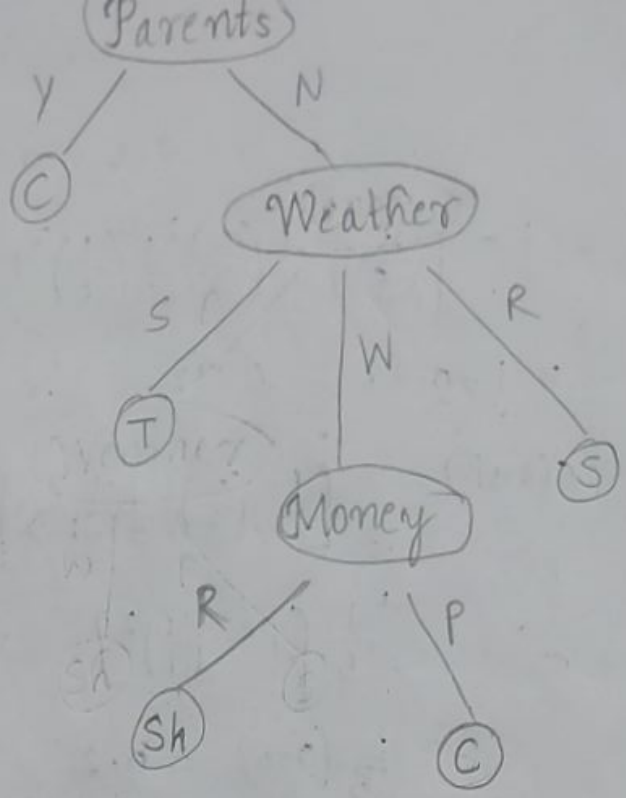
$$+ \frac{1}{5}\left[1 - \left(\frac{1}{1}\right)^2\right]$$

$$= \frac{4}{5}(0.625) = 0.5$$

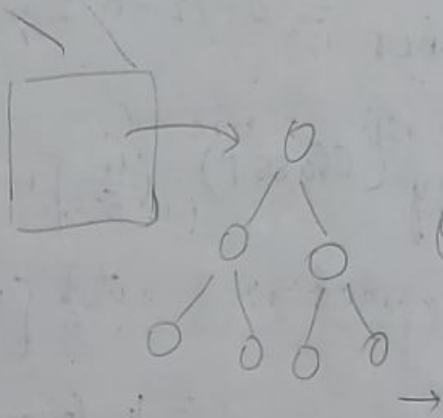


$$\Delta Gini_{Money} = 0.72 - 0.5 = 0.22$$





Tree Pruning



Tree Pruning — Pre-Pruning
Post-Pruning

→ We will set some threshold value

→ Max-depth

→ Min-sample instance → (50 or 60)

→ Min no of leaf instances in

→ Max_leaf node

→ Max_features

Min_split_sample

hyperparameters

12/2/26

Assignmt: Take any dataset, set hyperparameter, if value low-impact? } based on this what's the analysis?
" " high-impact? }

Take the features 1 by 1.

→ We need to check if X_1 & X_2 are required for Y_2 or not. Test is there:- chi-square test

Pre-Pruning → Thresholds
→ Dependency
→ Improvement for each split ← (difference in delta values)

Post → Whole decision tree should be constructed

→ Removal of a branch impacts the DT accuracy or not. For this, we can apply cross validation approach.

KNN

Predicⁿ based on Majority Voting : Class

Brightness	Saturation	Class
40	20	Red
60	50	Blue
60	90	Blue
10	25	Red
70	70	Blue
60	10	Red..
25	80	Blue

k=5
Brightness = 20
Saturⁿ = 35
Class = ?

Dist(new, X_i)	
② 25	$\sqrt{(20-40)^2+(35-20)^2}$
③ 33.54	$\sqrt{(20-50)^2+(35-50)^2}$ 3 Red, 2 Blue → R
68.01	$\sqrt{(20-60)^2+(35-90)^2}$
① 14.1	$\sqrt{(20-10)^2+(35-25)^2}$
61.03	$\sqrt{(20-70)^2+(35-70)^2}$
⑤ 47.17	$\sqrt{(20-60)^2+(35-10)^2}$
④ 45.27	$\sqrt{(20-25)^2+(35-80)^2}$

KNN - Instance based

Limitation of KNN:

① Applicable only for small dataset.
RAM capacity cannot be that much to calculate many distances.

② $x_1 \rightarrow 0.1$, $x_2 \rightarrow 100000$ → Varying ranges btw features
Apply normaliz^n first

③ It is applicable only for numeric data
Issue of missing values, even if we fill it, it will effect the performance

KNN Limitat^{ns} — Small
— Numeric
— Normaliz^n is required

Training time is 0, testing time is high.

likelihood

$$P(C/X) = \frac{P(X/C) \cdot P(C)}{P(X)} \approx P(X/C) * P(C)$$

Prior

$P(C)$

$$P\left(\frac{A}{B}\right) = \frac{P(B/A) \cdot P(A)}{P(B)}$$

$$P\left(\frac{A}{B}\right) = \frac{P(A \cap B)}{P(B)}$$

$$P\left(\frac{B}{A}\right) = \frac{P(A \cap B)}{P(A)}$$

If 2 classes: $P\left(\frac{C_1}{X_{new}}\right)$ $P\left(\frac{C_2}{X_{new}}\right)$

Model-based learning.

It will tell the class properties.

$$P(X/C) = \prod_{i=1}^{k} P(X_i/C)$$

↳ $X_1 \dots X_n$

$$P\left(\frac{C_1}{X_{new}}\right) = \frac{P(X_{new}/C_1) \times P(C_1)}{P(X)}$$

$$P\left(\frac{C_2}{X_{new}}\right) = \frac{P(X_{new}/C_2) \times P(C_2)}{P(X)}$$

2 more terms:

① Generative classifier

② Discriminative classifier

→ Naive-Bayes is Generative classifier

Code

Initial

```
X_iris = iris.data[["petal length (cm)",
                    "petal width (cm)"]].values
y_iris = iris.target
print(iris)
tree_clf = Dec..Tr..Cl..
           (max_depth=, )
```

Assignment

② Apply DT on regression

16/9/25

Plotting the tree:

```
matplotlib import pyplot as plt
from sklearn import tree
```

* By default, it gives binary split & uses Gini Index

~~Ensemble learning~~

Naive Bayes

$$P(C/x) = P(x/c) \times P(c)$$

* Buy Computer Dataset

Q) age = y
Income = Medium
Student = Yes
CR = fair,
Class = ?

$P(Yes) = \frac{9}{14}$

$P(No) = \frac{5}{14}$

$P(Age-Y/Yes) = \frac{2}{9}$

$P(Income\_M/Yes) = \frac{4}{9}$

$P(St-Yes/Yes) = \frac{6}{9}$

$P(CR-F/Yes) = \frac{6}{9}$

$P\left(\frac{X}{C}\right) = \frac{2}{9} \times \frac{4}{9} \times \frac{6}{9} \times \frac{6}{9}$ (C → Class)

Syllabus for Mid

→ Basic ML ≡ Challenges
→ PE, A, P, R, Confusion, k-cross, variance, bias
→ Life cycle of DS
→ Statistical → Descriptive, Probability
→ Inferential Statistics
→ Linear Regression
→ Classification → K-NN, Naive Bayes
→ Decision tree

Time: 1 & half hr
Marks: 25 M

16/9/29 $P(Yes/X) = P(X/Yes) \times P(Yes)$ $[\because P(c/x) = P(x/c) \cdot P(c)]$

$= \frac{2}{9} \times \frac{4}{9} \times \frac{6}{9} \times \frac{6}{9} \times \frac{9}{14} = \boxed{0.028}$

0.019

$P(Age-Y/No) = \frac{3}{5}$

$P(Income-M/No) = \frac{2}{5}$

$P(St-Yes/No) = \frac{1}{5}$

$P(CR-F/No) = \frac{2}{5}$

$P\left(\frac{X}{No}\right) = \frac{3}{5} \times \frac{2}{5} \times \frac{1}{5} \times \frac{2}{5}$

$P\left(\frac{No}{X}\right) = P(X/No) \times P(No)$

$= \frac{3}{2} \times \frac{2}{5} \times \frac{1}{5} \times \frac{2}{5} \times \frac{5}{14}$

$= \boxed{0.007}$

Generative Classifier: It respects each & every class.

Ex: 2 Classes - Cat & dog → 4 features

tail, legs, face shape, strap

It will find the probability for each n every feature of cat & dog. They will be considered as indep^t

Discriminative Classifier: For new instance, it will check face & strap on neck. They are going to set some margin (or) decision boundary.