Adaboost, GDBoosting,
XGBoost, Bagging, RF, DT, LogisticReg, KNN → Classification Problem

Linear Regression
- Simple LR
- multiple LR ✓
- Polynomial Reg
  - KNN ×
  - DT ✓ ×
  - RF ✓ ✓
  - All ensemble model — (XGBoost)
  - Gradient
  - → Regularization
    - Lasso
    - Ridge
    - ElasticNet

Automation — Pycaret ✓

→ SVM - kernel (approach)
- Polynomial
- linear
- Sigmoid
- RBF - radial Basis func ✓

  - Classifi? ✓
  - Regresⁿ? ×

Bayes thm → Naive Bayes theorem ✓

→ Ensemble model
- voting ensemble model
- stacking/blending model

> combine all model including ensm

cluster — K Means
— Hierarchical
— DBSCAN

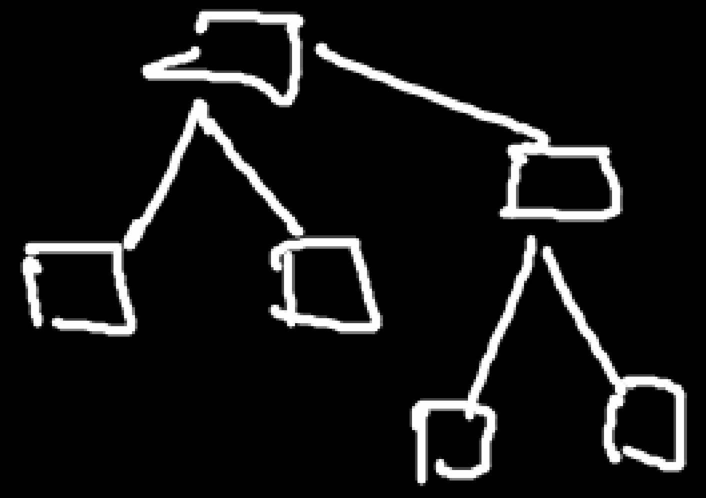
→ unsupervise ML

Association rule mining / market Basket Analytics

Recommendation System — project — 2 lecture

Web Scrapping → 〃

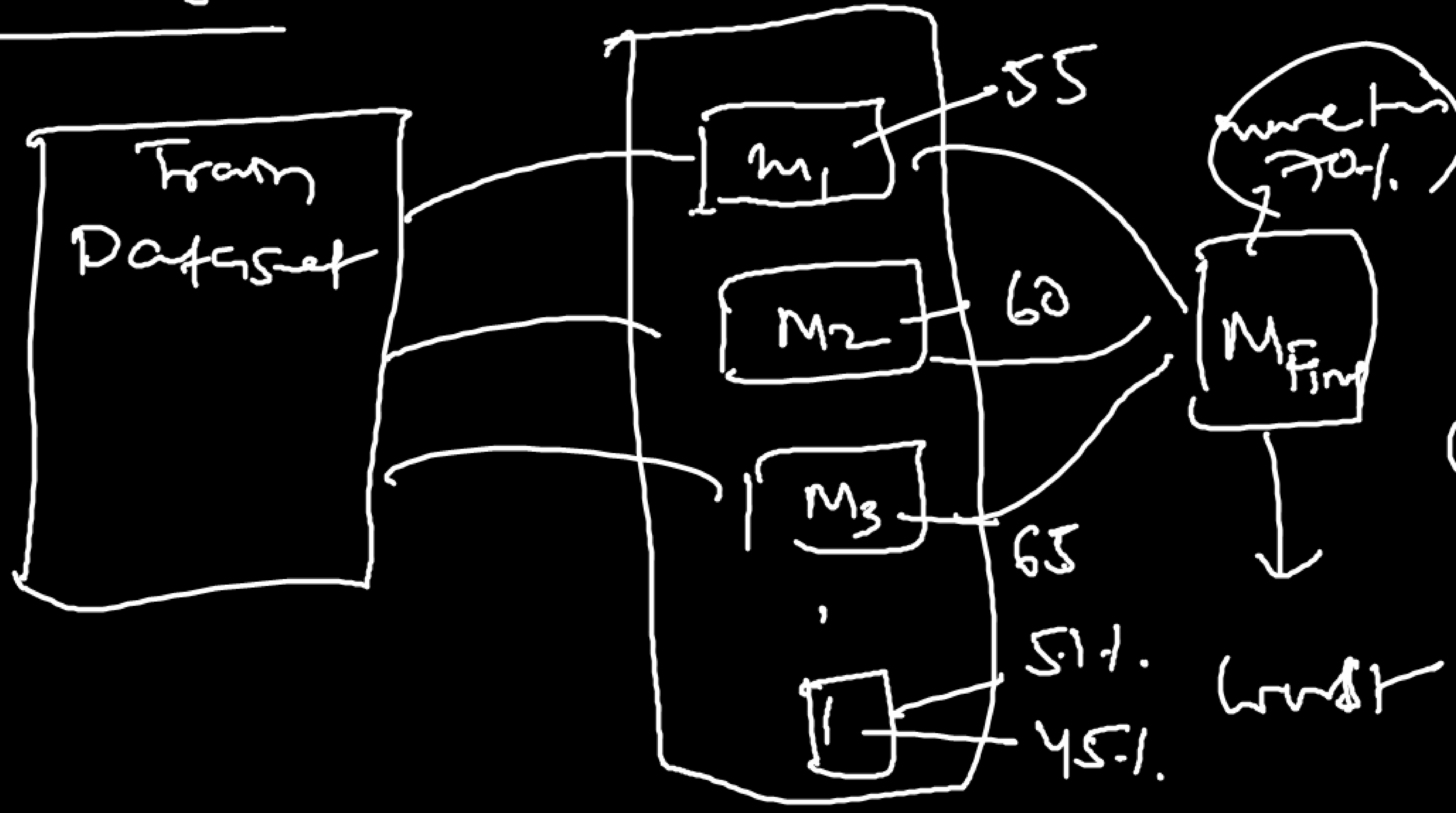
✓ PCA | t-SNE | LDA — Eigen value | vector



✓ Time Series Forecasting — 14 hrs — 1 week
— Mandatory for everyone

V.V. Imp

Voting



Assumption

1. All model work independently
2. All model accuracy min should be 51% otherwise voting will be given worst result.

core intuition

Ada — m_1 — 0.7 | 0.3

GD — m_2 — 0.7 | 0.3

SVM — m_3 — 0.7 | 0.3

$100 - (34.3 + 14.7 + 14.7 + 14.7)$

$100 - (34.3 + 46.1) = 100 - 81.1$

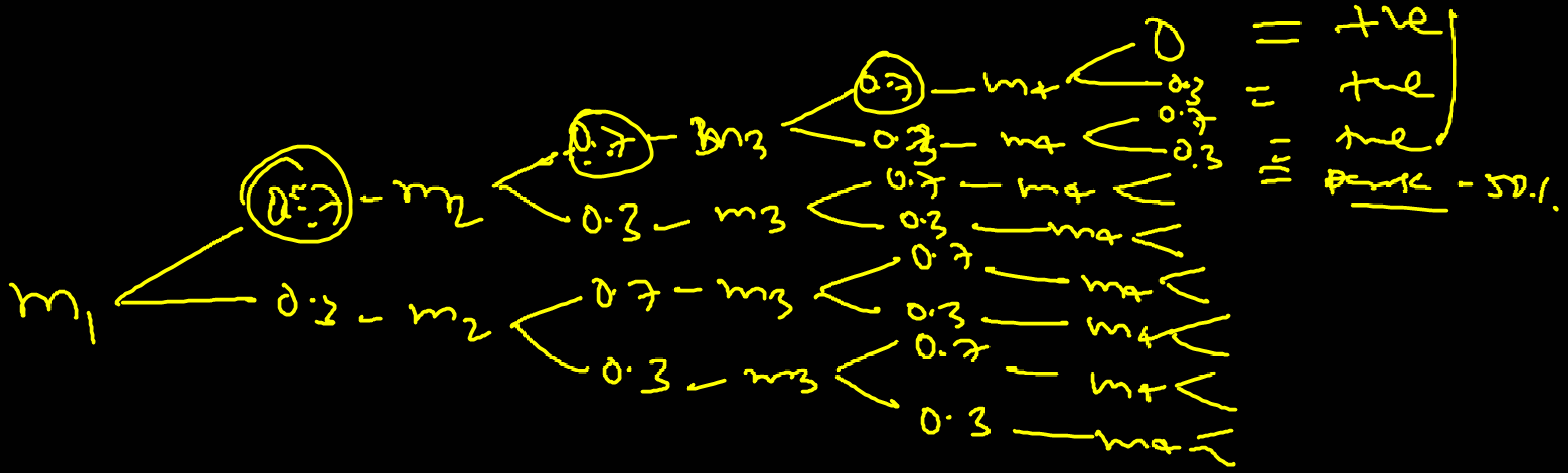
$= 19.1$

m_1
- 0.7 — m_2
  - 0.7 — m_3
    - 0.7 — 0.343 = 34.3 %
    - 0.3 — 0.147 — 14.7 %
  - 0.3 — m_3
    - 0.7 — 0.147 — 14.7
    - 0.3 — 0.063 = 0
- 0.3 — m_2
  - 0.7 — m_3
    - 0.7 — 0.147
    - 0.3 — 0.063
  - 0.3 — m_3
    - 0.7 — 0.063
    - 0.3 — 0.027

0.3 0.3 0.7 = (−)ve

0.7, 0.7, 0.7 = (+)ve = 0.343

0.7 . 0.7 . 0.3 = (+)ve


m1
0.7 – m2
0.3 – m2
0.7 – m3
0.3 – m3
0.7 – m4
0.3 – m4
0.7
0.3
0 = +ve
0.3 = +ve
0.7
0.3 = +ve
= ~~Break~~ – 50%

$(0.7)^4$

100 – .

= (-)ve

Naive Bayes Theorem → classification algorithm

↳ Probability based theorem

↳ Ad-hoc request ~~or~~ Text Analytics

conditional probability

$$\boxed{P(A/B) = \frac{P(A \cap B)}{P(B)}}$$

— conditional probability

if $P(B) \neq 0$

Dice - Roll

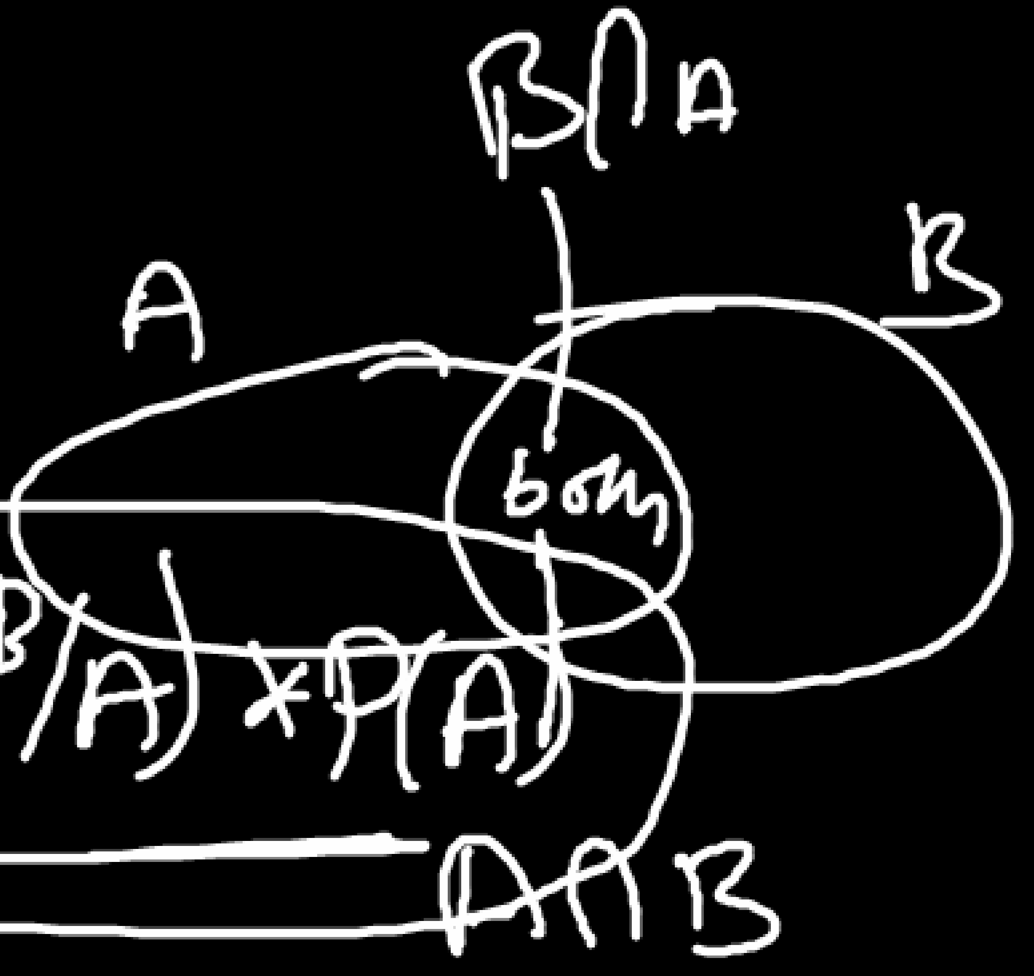
$$P(B/A) = \frac{P(B \cap A)}{P(A)}, \text{ if } P(A) \neq 0$$

$$P(A/B) = \frac{P(A\cap B)}{P(B)} \quad — (1)$$

conditn

$$\Rightarrow P(B/A) = \frac{P(B\cap A)}{P(A)} \quad — (2)$$

$$\boxed{P(B\cap A) = P(B/A) * P(A)}$$



Set theory concept,

$$\boxed{P(A\cap B) = P(B\cap A)}$$

From eqn. (1), sub $P(B\cap A)$

$$\boxed{P(A/B) = \frac{P(B/A) * P(A)}{P(B)}}$$

Bayes Theorem

simple, elegant, useful, Powerful, Beautiful model

Likelihood

$$P(A/B) = \frac{P(B/A) * P(A)}{P(B)}$$

Prior

Posterior

Evidence
or
marginal