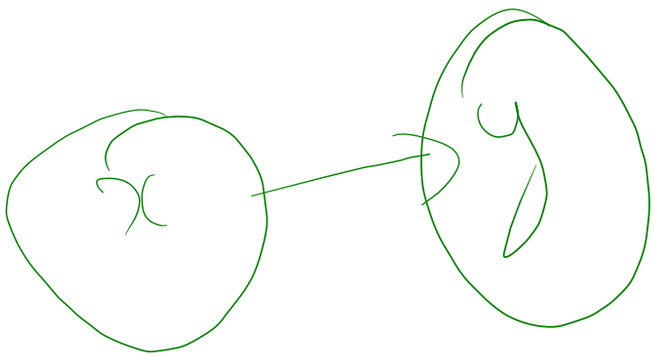
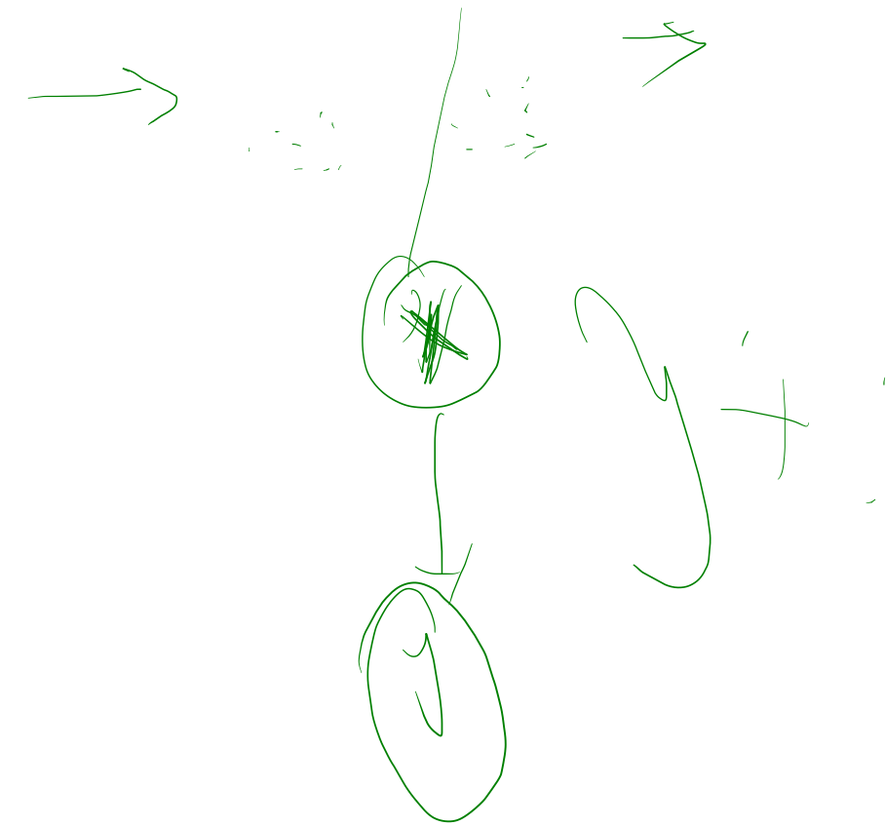
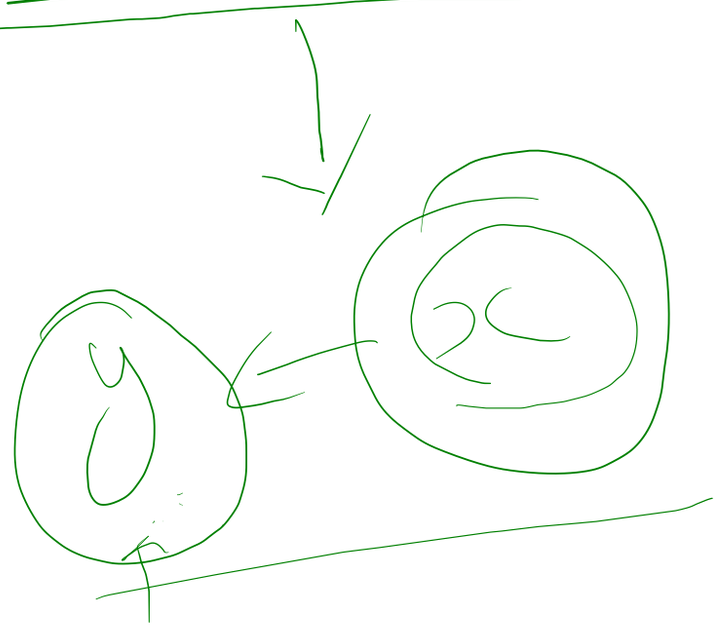
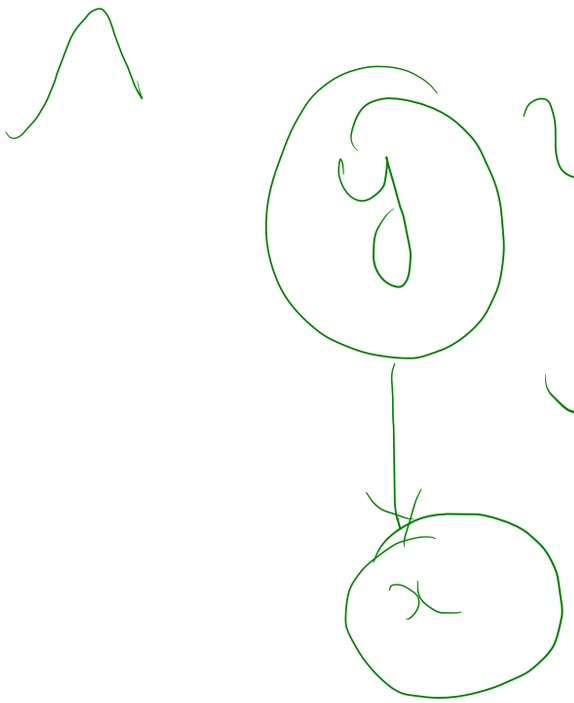
discriminative model (vs) generative model









Naïve bayes

P(y) ① marginal prob

P(x|y) ② conditional prob

P(y|x) ③ joint prob

④ P(A ∪ B)

union prob

⑤ P(A ∩ B)

joint

Bayes Theorem → $\overset{\circ}{\underset{\circ}{X}}{}^{\circ}$

likelihood

prior

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

posterior

total law of m

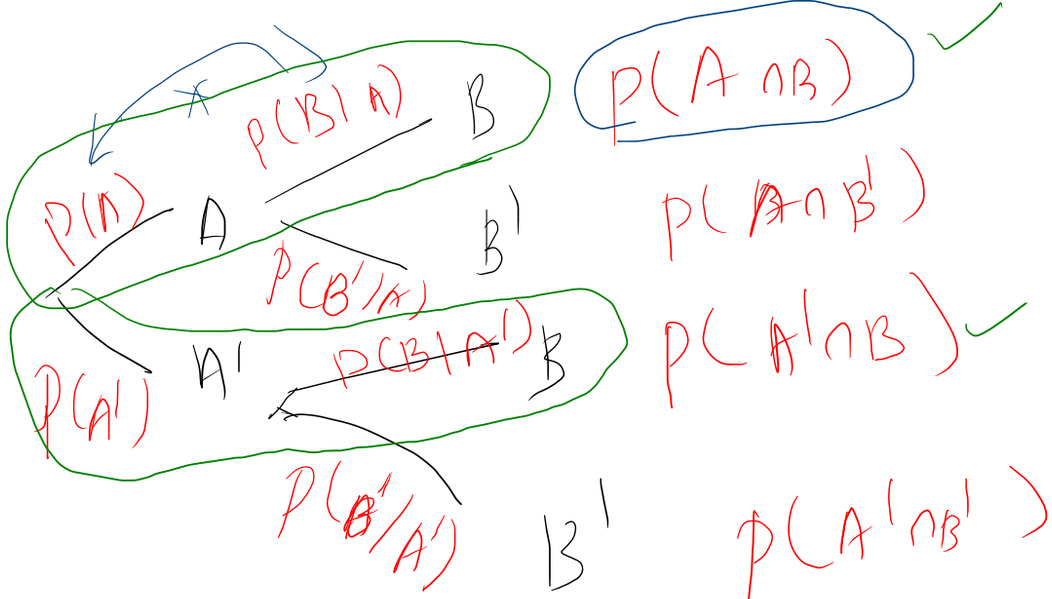
$P(B) \to P(A)P(B|A) + P(A')P(B|A')$

evidence

unknown ← known

P

P



$$P(A \cap B) = P(B \cap A)$$

$$P(A \cap B) = P(A)\, P(B/A)$$

$$P(A|B) = ? = \frac{P(B \cap A)}{P(B)}$$

$$P(B) = P(A \cap B) + P(A' \cap B)$$

$$= P(A)\, P(B/A) + P(A')\, P(B/A')$$

Posterior

$$= \frac{\overset{\text{prior}}{P(A)}\, \overset{\text{Likelihood}}{P(B/A)}}{P(B)}$$

total Law of prob ...

naive Bayes

10 condition

7 ...

Sch → today

Prior

likelihood (50)

2010

evidence (50)

past

posterior

2022

future

2

yes/no)

$P(yes/x) \rightarrow \frac{p(yes)\ p(x/yes)}{p(x)} \rightarrow 0$

$p(no/x) \rightarrow \frac{p(no)\ p(x/no)}{p(x)} \rightarrow 1$

$$\boxed{p(y/x) = p(y)\ p(x/y)}$$

$p(x) \rightarrow$ constant

yes/no)

$P(yes/x) \rightarrow \frac{p(yes)\ p(x/yes)}{p(x)} \rightarrow 0$

$p(no/x) \rightarrow \frac{p(no)\ p(x/no)}{p(x)} \rightarrow 1$

$$\boxed{p(y/x) = p(y)\ p(x/y)}$$

$p(x) \rightarrow$ constant

$P(y \mid x_1, x_2, x_3)$

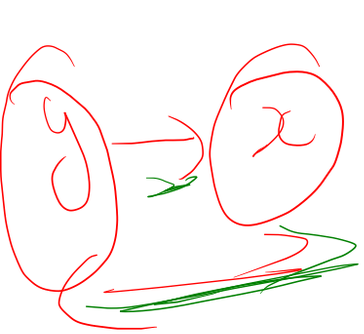
$P(y \mid x_1, x_2, x_3) = P(yes) \times P(x_1/yes) \times P(x_2/yes) \cdots\cdots P(x_n/yes)$

naive Bayes

assumption

↳ no multicollinearity

↳ independent should not be related with each.



binary

Gaussian

NB

$y \leftarrow x$

nominal

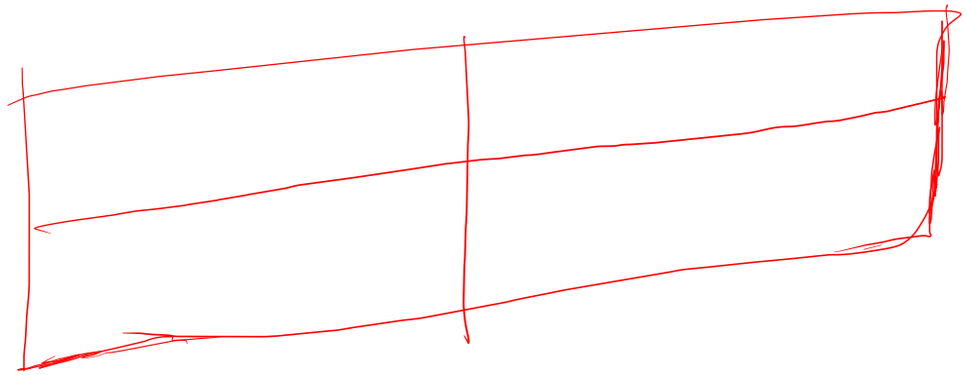
multinomial

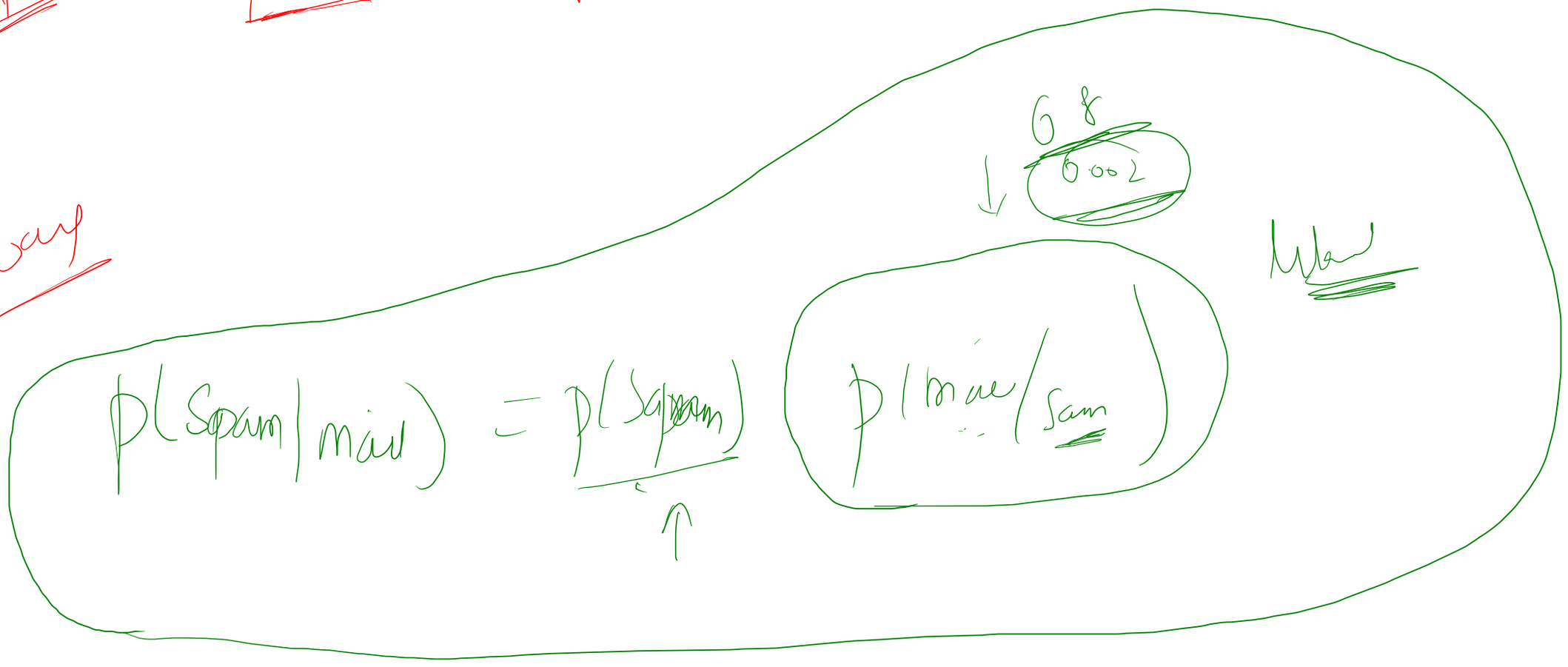
Zero frequency problem

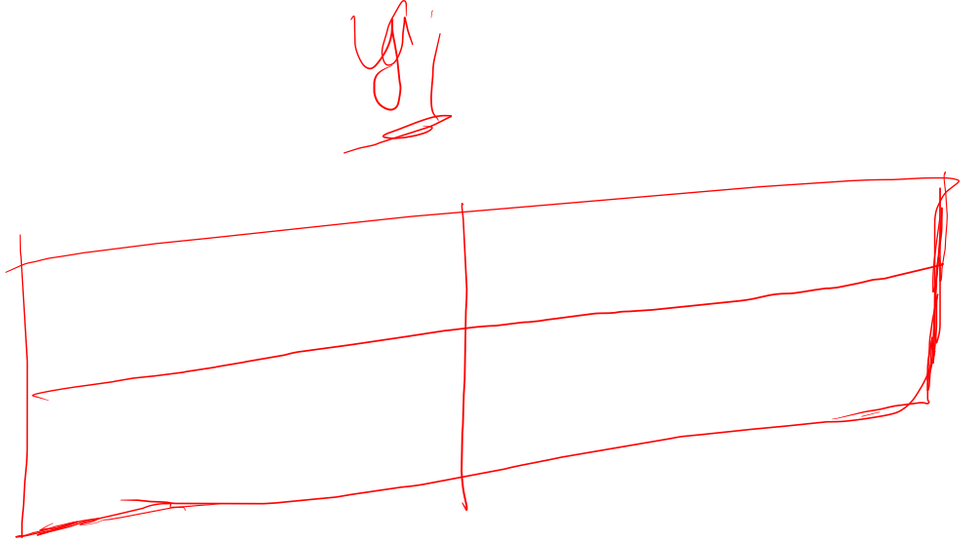
$p(y|x_1, x_2, x_3) = p(y) \; p(x_1|y) \; p(x_2|y) \; p(x_3|y)$

↳ generative model

Smoothing




p(Spam | mail) = p(Spam) p(mail/Spam)



2 way

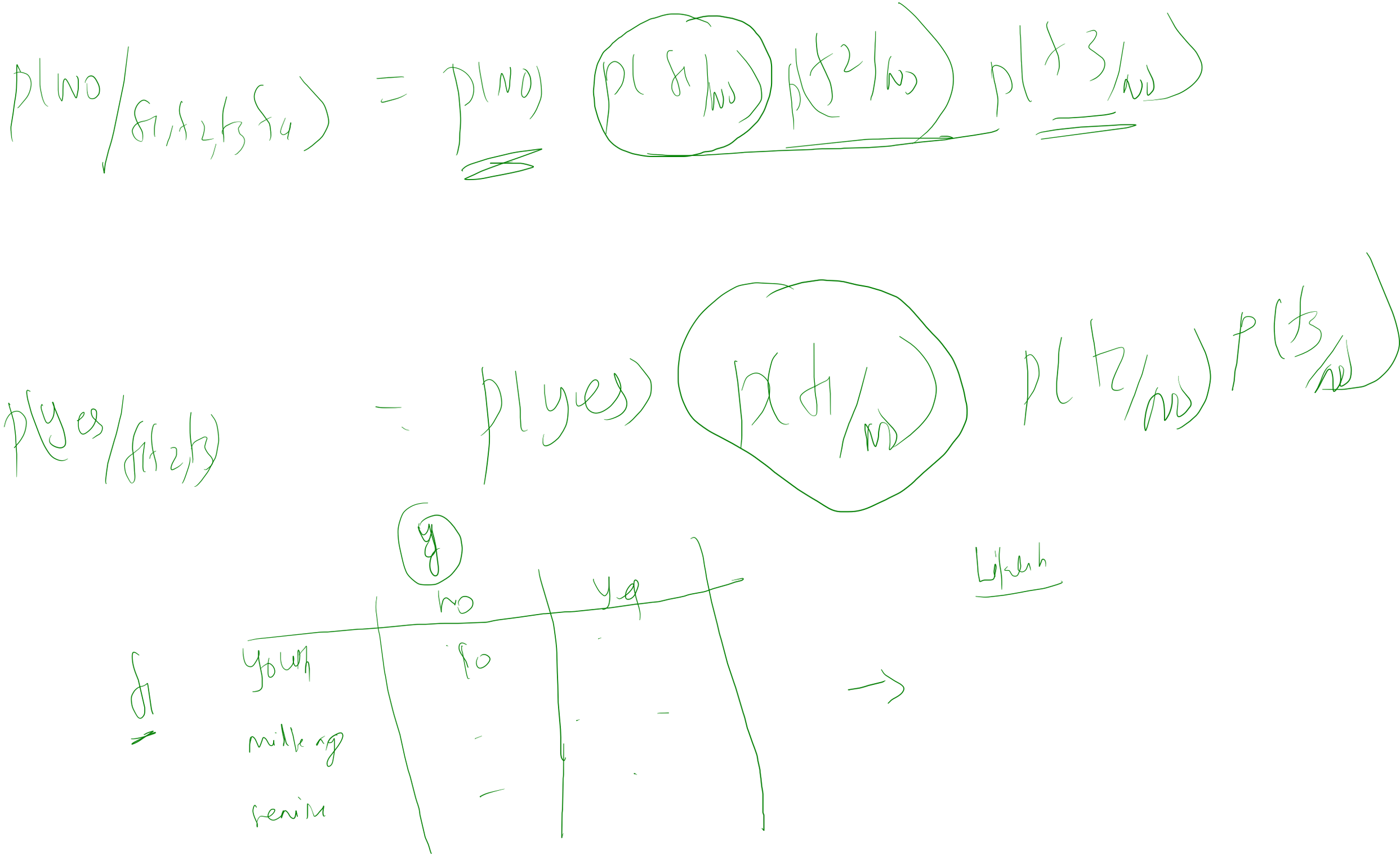
$$p(\text{Spam} \mid \text{mail}) = p(\text{Spam}) \; p(\text{mail} \mid \text{Sam})$$

0.8

0.002

Mail

Mail



$$p(no / f_1, f_2, f_3, f_4) = p(no)\, p(f_1/no)\, p(f_2/no)\, p(f_3/no)$$

$$p(yes / f_1 f_2 f_3) = p(yes)\, p(f_1/no)\, p(f_2/no)\, p(f_3/no)$$

f_1

	y: no	y: yes
youth	f_0	
middle age		
senior		

$\rightarrow$ Likelihood

$$P(yes|sunny) = \frac{P(yes)\ P(sunny|yes)}{P(sunny)} = \frac{0.71 * 0.3 * 0.59}{0.36} =$$

$$P(no|sunny) = \frac{P(no)\ P(sunny|no)}{P(sunny)} = \frac{0.36 \times 0.4}{0.36} = 0.41$$