

Naive Bayes

(1) Probability

$$P(A) = \frac{\text{The number of ways event can occur}}{\text{The total number of Possible Outcomes}}$$

$$P(\text{apple}) = \frac{2}{3}$$

$$P(\text{banana}) = \frac{1}{3}$$



(2) Conditional Probability

the probability of an event (A), given that another (B) has already occurred

1) calculating the intersection (when two events are independent)

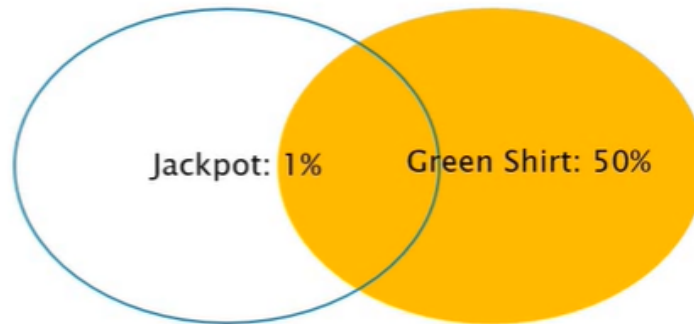
$$P(A \cap B) = P(A) * P(B)$$

$$P(A|B) = P(A)$$

B has no effect on A

$$P(B|A) = P(B)$$

A has no effect on B



If there is a 1% chance that you get jackpot from casino,
and a 50% chance that your t-shirts is green color,
then what is the probability that

You wear green t-shirt and you get jackpot from casino(assuming that t-shirt has no influence on jackpot)?

Since t-shirt has no effect on casino result,
we take these events as independent, and so the probability that both events will occur is

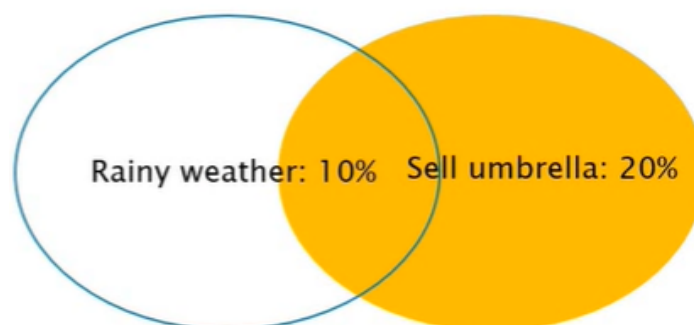
$$P(\text{Jackpot} \cap \text{Green_shirt}) = P(\text{Jackpot}) * P(\text{Green_shirt})$$

$$= (0.01) * (0.5) = 0.005$$

2) calculating the intersection (when two events are dependent)

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

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



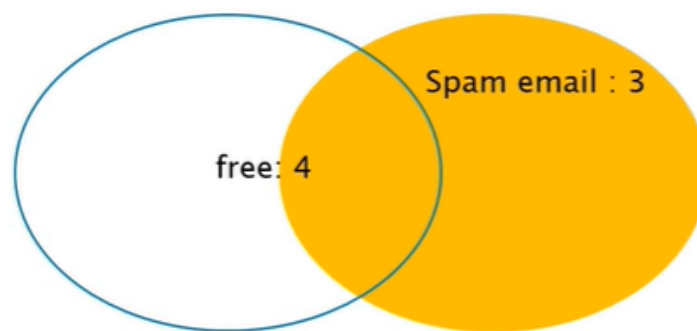
(3) Bayes' Theorem

"You don't have a girl friend. I know it because you watch youtube all weekend, and fat, no sense of fashion!"

$P(\text{no girl friend} \mid \text{fat, youtube, no fashion}) =$

$$\frac{P(\text{fat} \mid \text{no girl friend}) * P(\text{youtube} \mid \text{no girl friend}) * P(\text{no fashion} \mid \text{no girl friend}) * P(\text{no girl friend})}{P(\text{fat}) * P(\text{youtube}) * P(\text{no fashion})}$$

1) Bayes' Theorem proof



"Spam" and "free" are clearly dependent,

Since we assume when we have spam email, there might be "free" in the text, and also when we have "free" in the email, we suspect it is "spam"

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

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

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

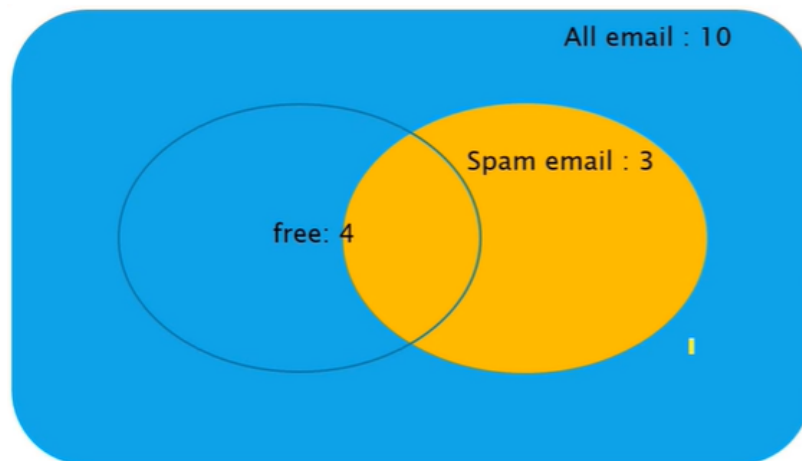
$$P(B \cap A) = P(A \cap B)$$

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

$$P(B \mid A) * P(A) = P(A \mid B) * P(B)$$

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

2) Bayes' Theorem



index	Email
1	I got free two movie ticket from your boy friend
2	free coupon from xx.com
3	watch free new movie from freemovie.com
4	Best deal, promo code here
5	There will be free pizza today 2pm meeting – your boss
6	Scheduled meeting tomorrow
7	Can we have lunch today?
8	I miss you
9	thanks my friend
10	It was good to see you today

3 emails out of total of 10 are spam messages : $P(\text{spam}) = 3 / 10$

4 emails out of those 10 contain the word “free” : $P(\text{free}) = 4 / 10$

2 emails containing the word “free” have been marked as spam :

$P(\text{free} | \text{spam}) = 2 / 3$

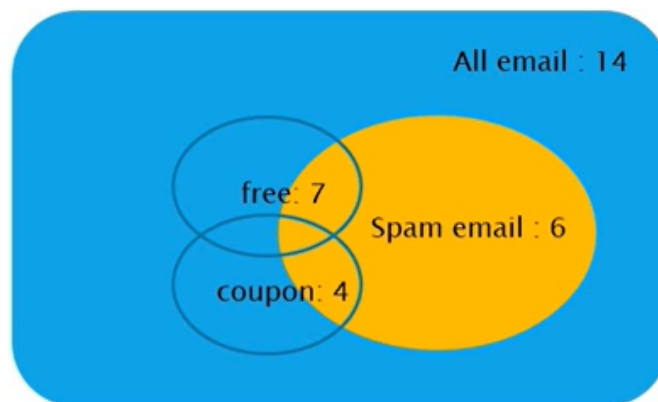
$$\begin{aligned}
 P(\text{spam} | \text{free}) &= \frac{P(\text{free} | \text{spam}) * P(\text{spam})}{P(\text{free})} = \frac{P(\text{free} | \text{spam}) * P(\text{spam})}{P(\text{free})} \\
 &= \frac{\frac{2}{3} * \frac{3}{10}}{\frac{4}{10}}
 \end{aligned}$$

So easy, I think I don't need machine's help for spam filtering...

Well, the real world, is much more complicated We filter spam with complicated combination of words(free, coupon, \$, fuXX, sexy, ...)

Don't you need machine's help for all the combination?

Spam classifier, contains 'free', 'coupon'



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4	Best deal, promo code here
5	There will be free pizza
6	Scheduled meeting tomorrow
7	Can we have lunch today?
8	I miss you
9	thanks my friend
10	It was good to see you today
11	Free coupon, last deal
12	Free massage coupon
13	I sent the coupon you asked, it is not free
14	Coupon, promo code here!

To make this tutorial as eash as possible,

I will assume “free” and “coupon” are independent

6 emails out of a total of 14 are spam messages : $P(\text{spam}) = 6/14$

7 emails out of those 14 contain the word “free” : $P(\text{free}) = 4/14$

4 emails containing the word “free” have been marked as spam :

$P(\text{free} | \text{spam}) = 2/6$

4 emails out of a those 14 containe the word “coupon” : $P(\text{coupon}) = 4/14$

3 emails containing the word “coupon” have been marked as spam :

$P(\text{coupon} | \text{spam}) = 3/6$

$$P(\text{spam} | \text{free, coupon}) = \frac{P(\text{free} | \text{spam} \cap \text{coupon}) * P(\text{coupon} | \text{spam}) * P(\text{spam})}{P(\text{free} | \text{coupon}) * P(\text{coupon})}$$

$$= \frac{\frac{3}{4} * \frac{4}{6} * \frac{6}{14}}{\frac{4}{5} * \frac{5}{14}}$$

So what? Shouldn't we talk about machine learning?

If $P(\text{spam} | \text{free, coupon}) > P(\text{not a spam} | \text{free, coupon})$, the email is spam.

I will filter emails has "free" and "coupon" because it has higher probability of spam.

3) practice

$$P(\text{spam} | \text{word}) = \frac{P(\text{word} | \text{spam}) * P(\text{spam})}{P(\text{word})}$$

$$P(\text{spam} | \text{free, coupon}) = \frac{P(\text{free, coupon} | \text{spam}) * P(\text{spam})}{P(\text{free, coupon})}$$

$$P(\text{spam} | w_0, w_1, w_2 \dots w_n) = \frac{P(w_0, w_1, w_2 \dots w_n | \text{spam}) * P(\text{spam})}{P(w_0, w_1, w_2 \dots w_n)}$$

$$P(\text{spam} | w_0, w_1, w_2 \dots w_n) = \frac{P(w_0 | \text{spam}) * \dots * P(w_n | \text{spam}) * P(\text{spam})}{P(w_0) * P(w_1) * P(w_2) * \dots * P(w_n)}$$

※참고

<https://www.manning.com/books/machine-learning-in-action>

author : Peter Harrington