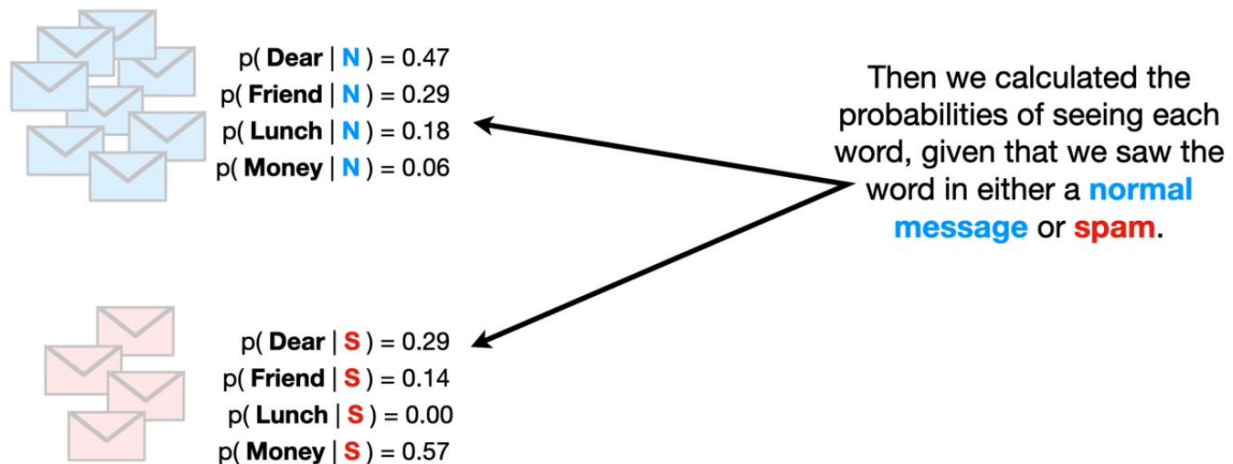
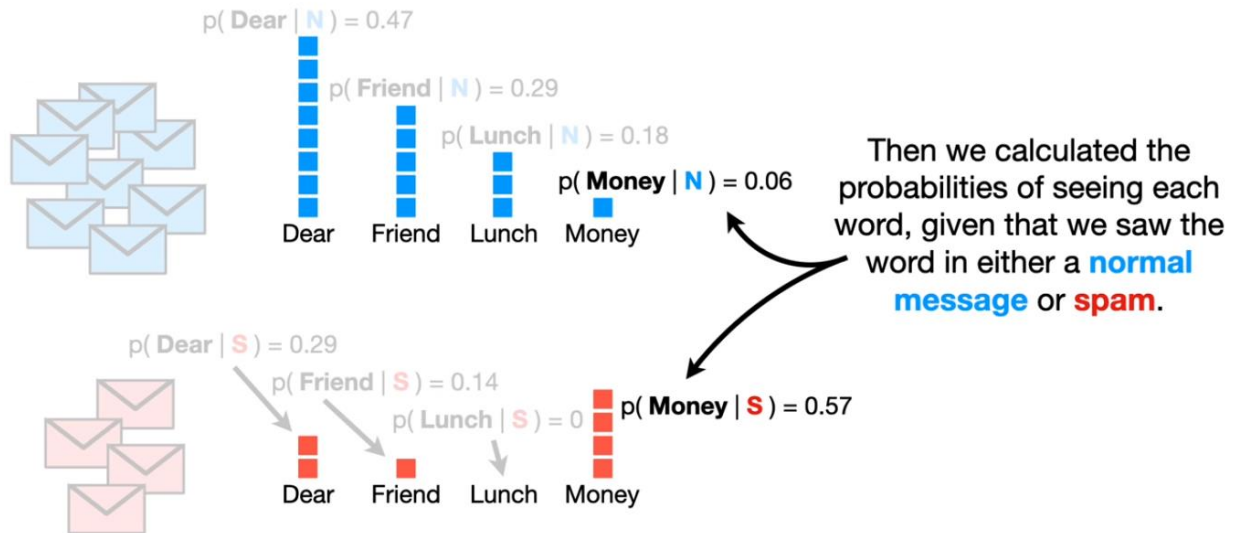
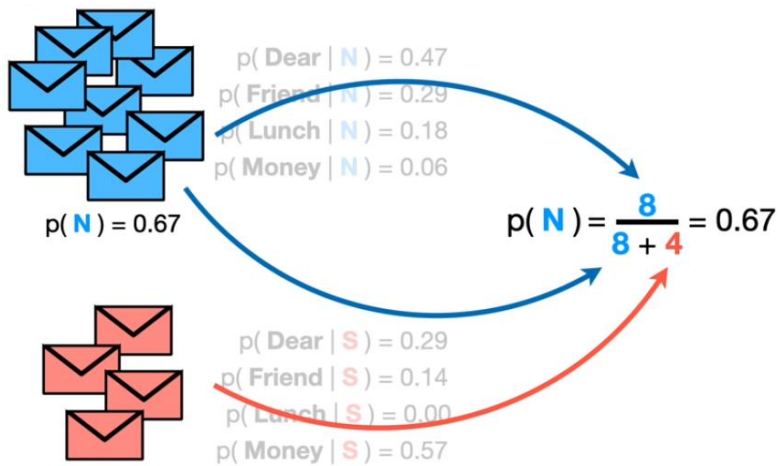


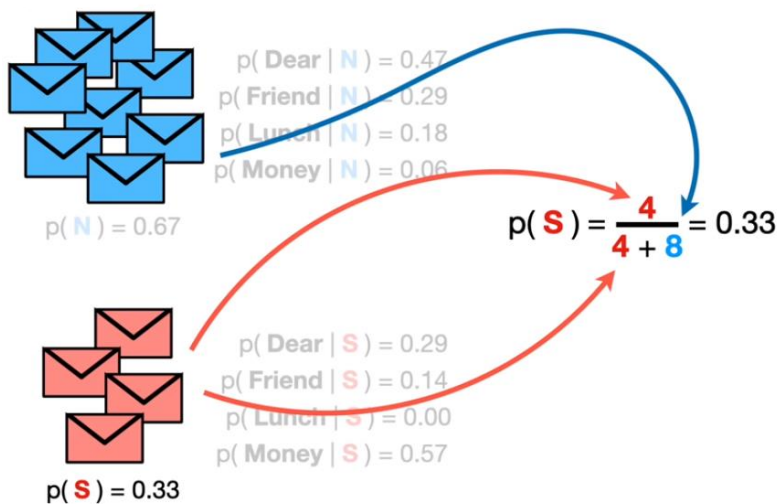
# Naïve Bayes and its explanation

ASAD ASHRAF KAREL

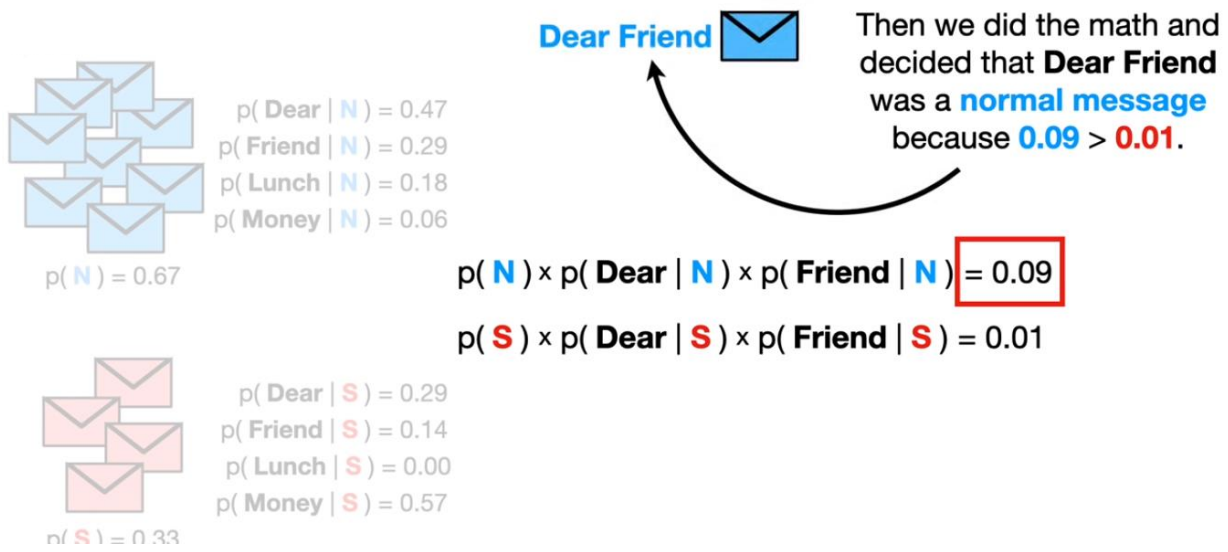




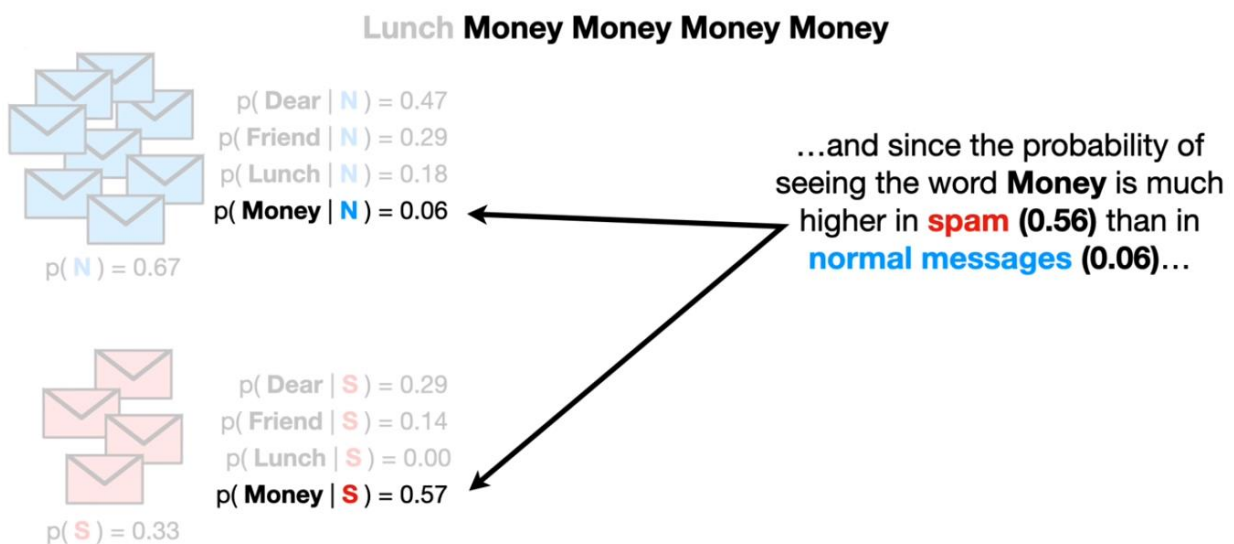
This guess can be anything between 0 and 1, but we based ours on the classifications in the **Training Dataset**.



Then made the same sort of guess about the probability of seeing **spam**.




Let's see a complicated example:



Hence  $p(\text{Money} | S) > p(\text{Money} | N)$ , hence we can conclude that, the message is from spam.

## Calculations:

**Lunch Money Money Money Money**




$p(\text{Dear} | \text{N}) = 0.47$   
 $p(\text{Friend} | \text{N}) = 0.29$   
 $p(\text{Lunch} | \text{N}) = 0.18$   
 $p(\text{Money} | \text{N}) = 0.06$   
 $p(\text{N}) = 0.67$

When we do the math, we get this tiny number.

$$p(\text{N}) \times p(\text{Lunch} | \text{N}) \times p(\text{Money} | \text{N})^4 = 0.000002$$



$p(\text{Dear} | \text{S}) = 0.29$   
 $p(\text{Friend} | \text{S}) = 0.14$   
 $p(\text{Lunch} | \text{S}) = 0.00$   
 $p(\text{Money} | \text{S}) = 0.57$   
 $p(\text{S}) = 0.33$

**Lunch Money Money Money Money**



$p(\text{Dear} | \text{N}) = 0.47$   
 $p(\text{Friend} | \text{N}) = 0.29$   
 $p(\text{Lunch} | \text{N}) = 0.18$   
 $p(\text{Money} | \text{N}) = 0.06$   
 $p(\text{N}) = 0.67$

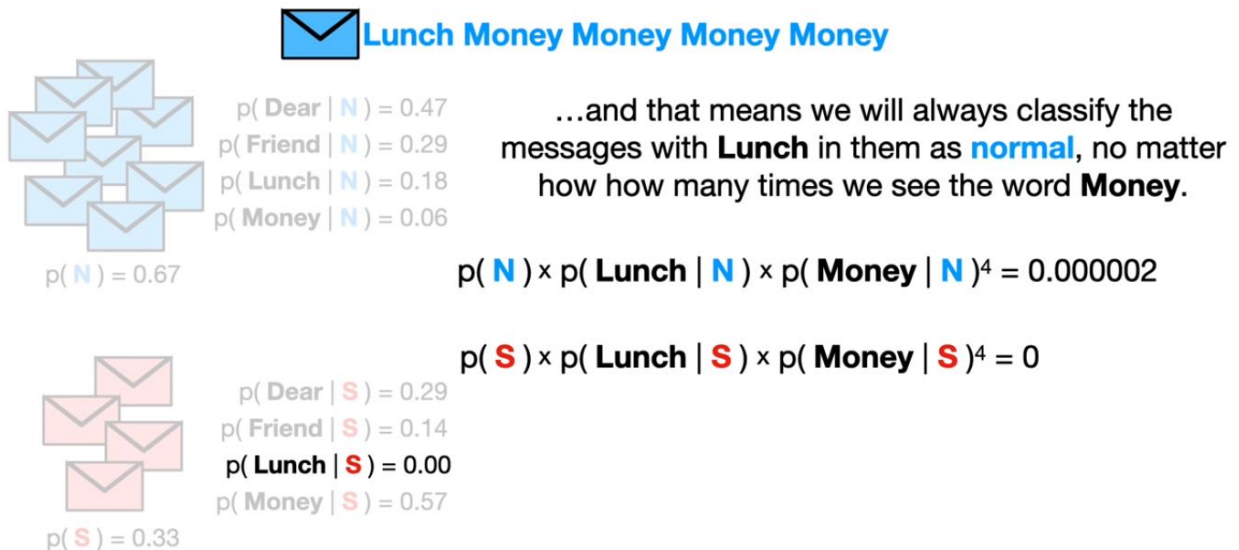
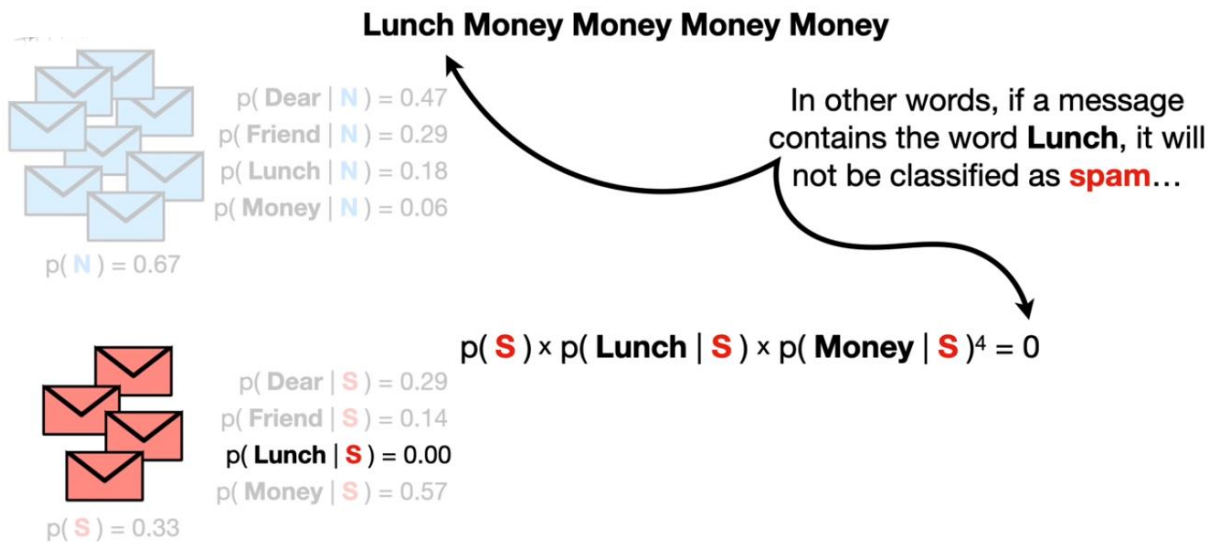
This is because the probability we see **Lunch** in **spam** is **0**, since it was not in the **Training Data**.



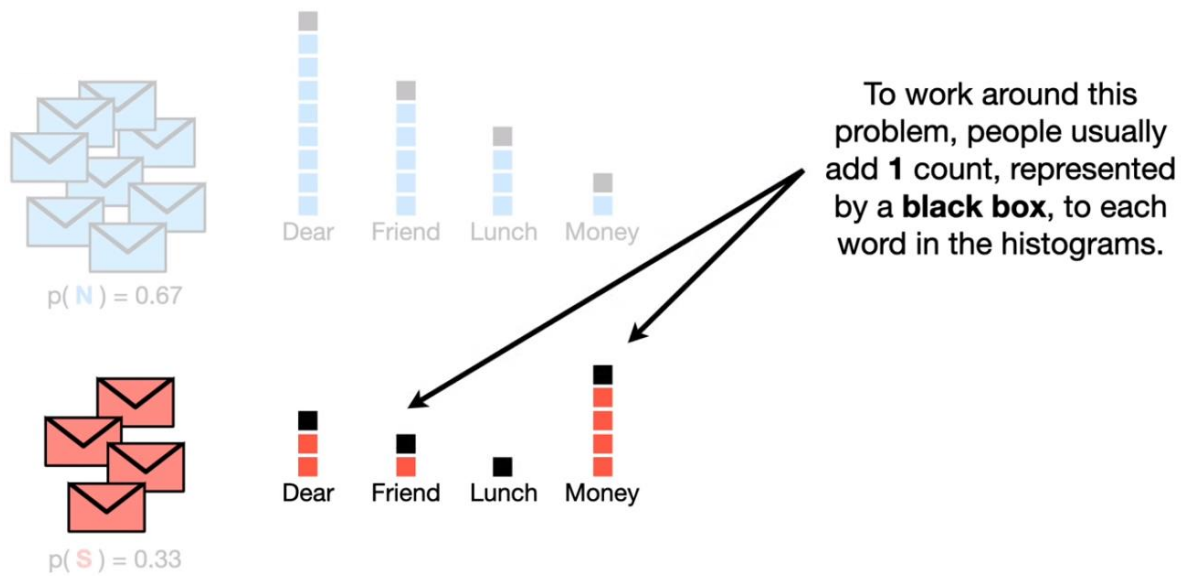
$p(\text{Dear} | \text{S}) = 0.29$   
 $p(\text{Friend} | \text{S}) = 0.14$   
 $p(\text{Lunch} | \text{S}) = 0.00$   
 $p(\text{Money} | \text{S}) = 0.57$   
 $p(\text{S}) = 0.33$

$$p(\text{S}) \times p(\text{Lunch} | \text{S}) \times p(\text{Money} | \text{S})^4 = 0$$

## Conclusion:

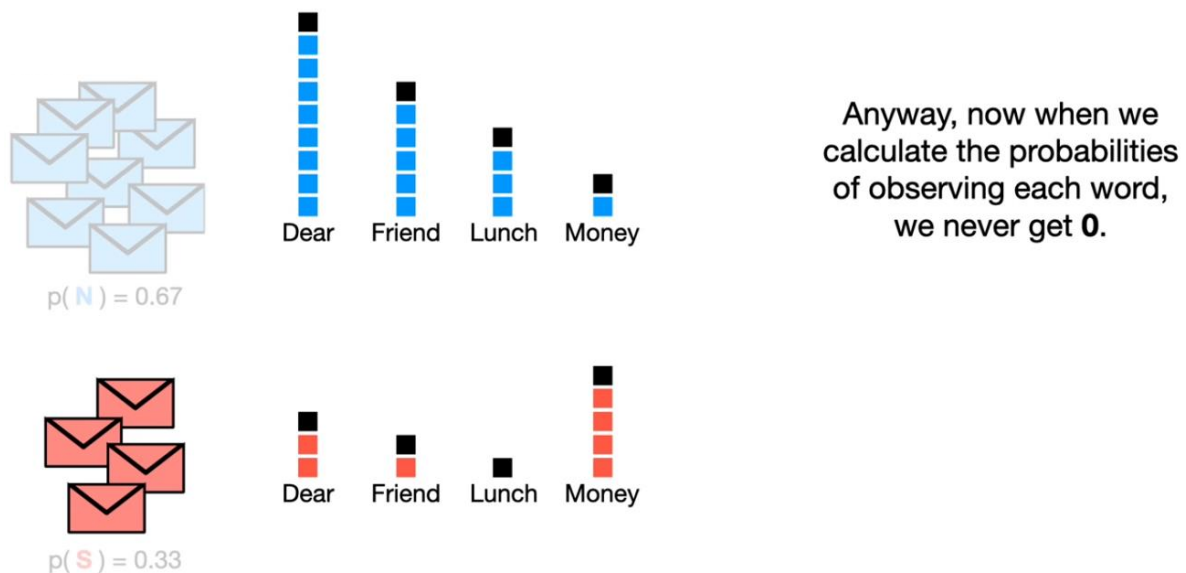


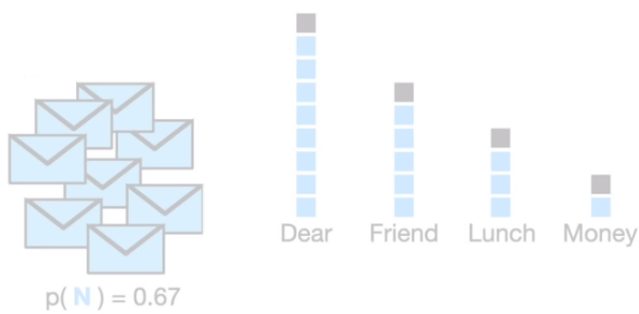
To avoid 'Lunch' is zero; let's add the one more word in each class:



Let suppose the increment is alpha ( $\alpha$ ):

Let's here  $\alpha = 1$



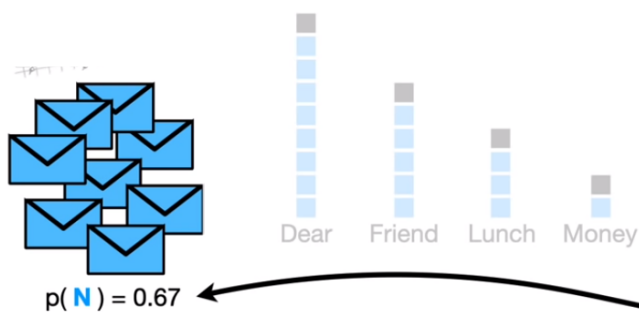


And that gives us **0.09**.

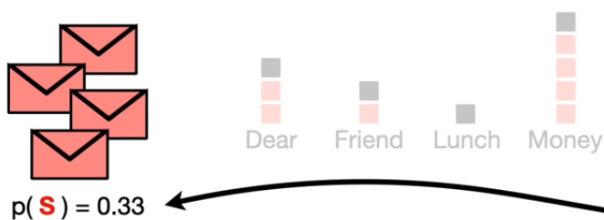
$$p(\text{Lunch} | \text{Spam}) = \frac{1}{7 + 4} = 0.09$$



Hence



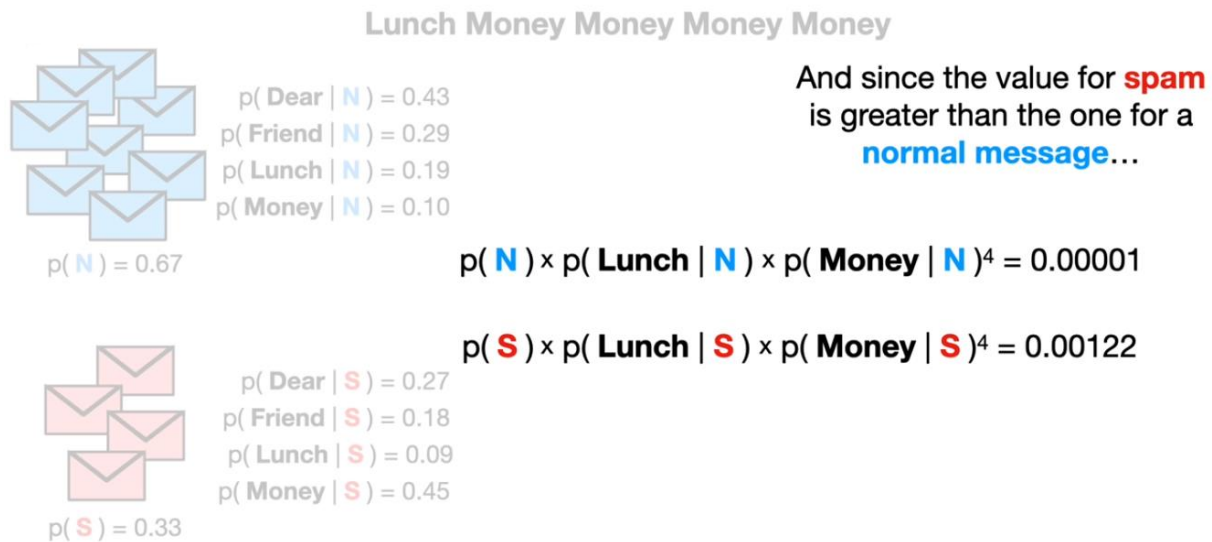
**NOTE:** Adding counts (black boxes) to each word does not change our initial guess that a message is **normal**,  $p(N)$ ...



...or the initial guess that a message is **spam**,  $p(S)$ ...

Moreover the actual count has not changed hence still  $p(N)$  and  $p(S)$  has not even changed.

After the calculation:



**0.00122 > 0.00001, hence we classify the message as spam.**

**It is said Naïve Bayes, because it separates the classes very well by scoring each class. It fixes the score for every class by likelihood into the training data, it recognizes by the score only as shown above.**

**It has high bias (due to high values) and low variance (in practice).**