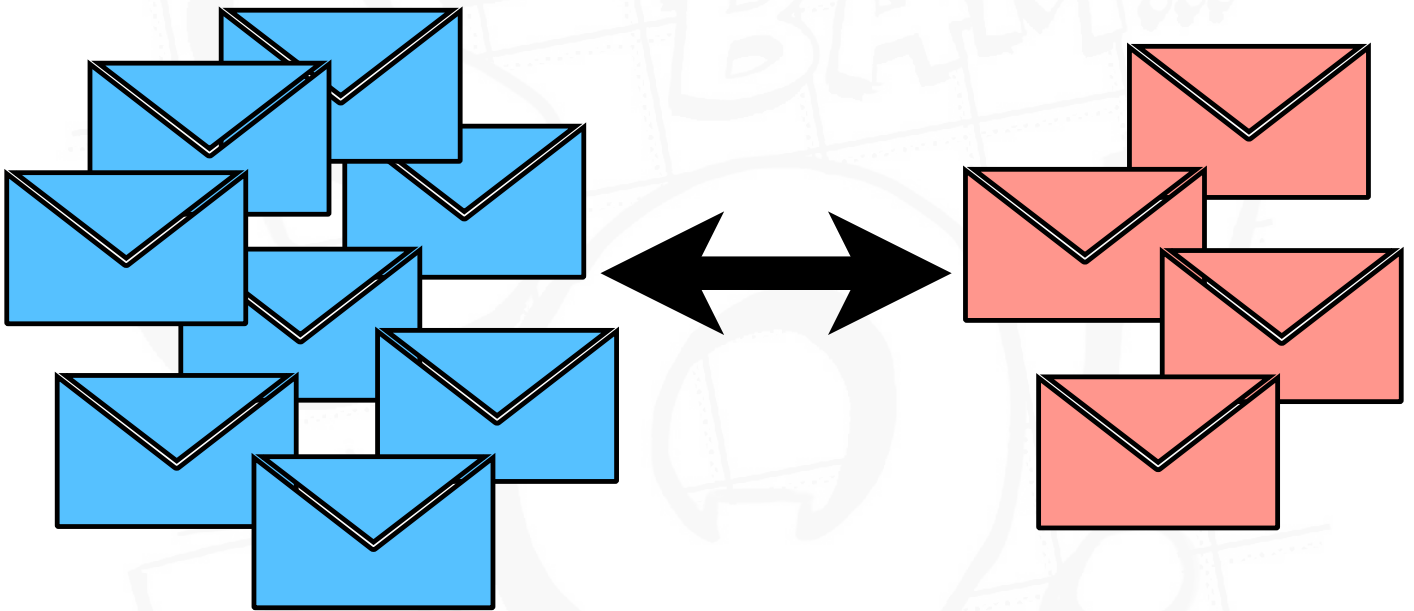




StatQuest!!!

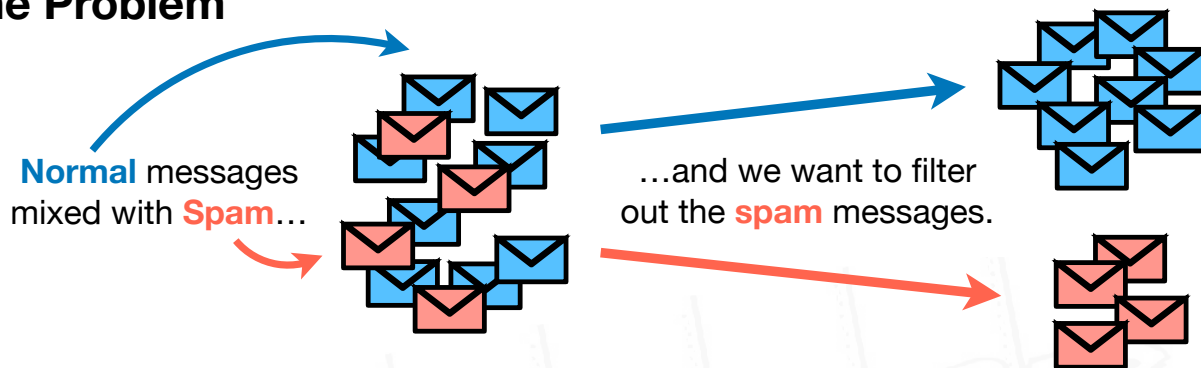
(Multinomial)

Naive Bayes



Study Guide!!!

The Problem



The Solution - A Naive Bayes Classifier

If we get this message:

Dear Friend

We multiply the **Prior** probability the message is **Normal**...

...by the probabilities of seeing the words **Dear** and **Friend**, given that it's a **Normal Message**...

$$p(\mathbf{N}) \times p(\mathbf{Dear} \mid \mathbf{N}) \times p(\mathbf{Friend} \mid \mathbf{N})$$

...and compare that to the **Prior** probability the message is **Spam**...

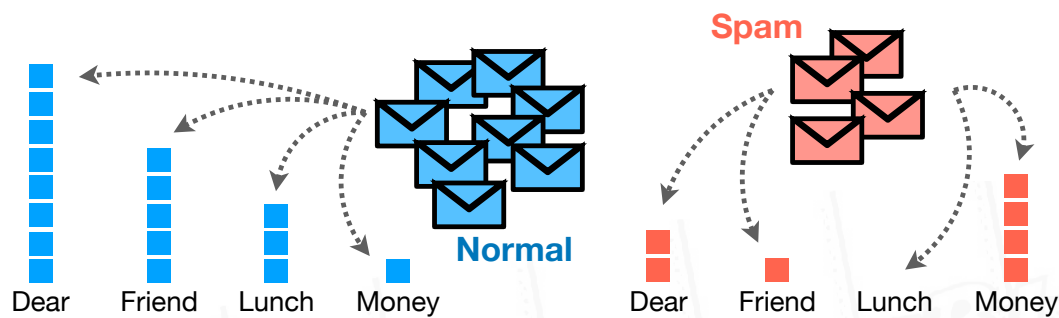
...multiplied by the probabilities of seeing the words **Dear** and **Friend**, given that it's **Spam**.

$$p(\mathbf{S}) \times p(\mathbf{Dear} \mid \mathbf{S}) \times p(\mathbf{Friend} \mid \mathbf{S})$$

Whichever classification has the highest probability is the final classification.

NOTES:

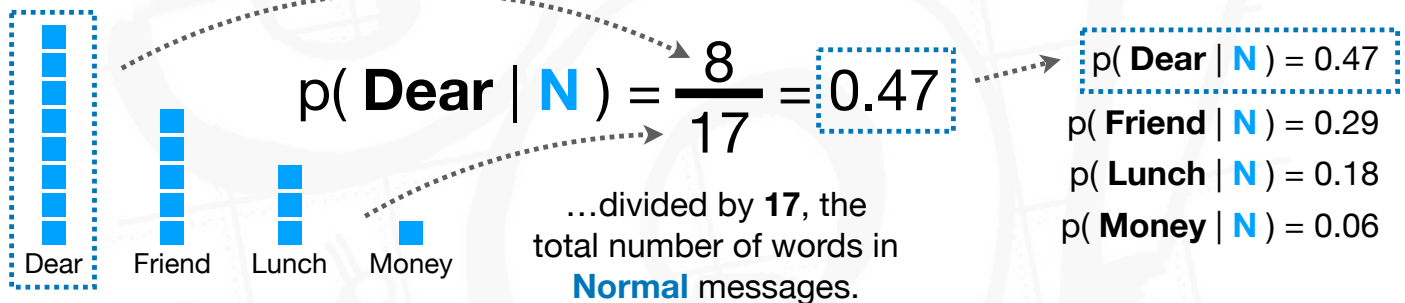
Step 1) Make histograms for all words



NOTE: The word **Lunch** did not appear in the **Spam**. This will cause problems that we will see and fix later.

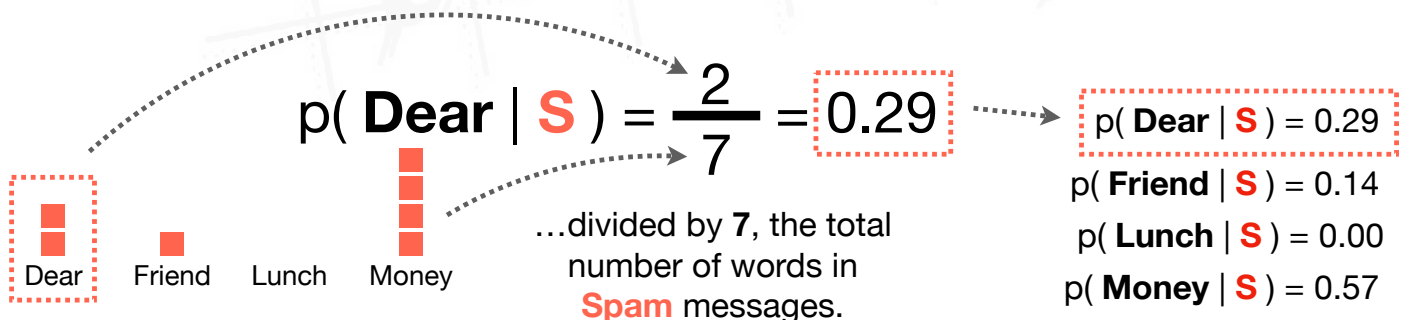
Step 2a) Calculate conditional probabilities for Normal, N

For example, the probability that the word **Dear** occurs given that it is in a **Normal** message is the number of times **Dear** occurred in **Normal** messages, 8...



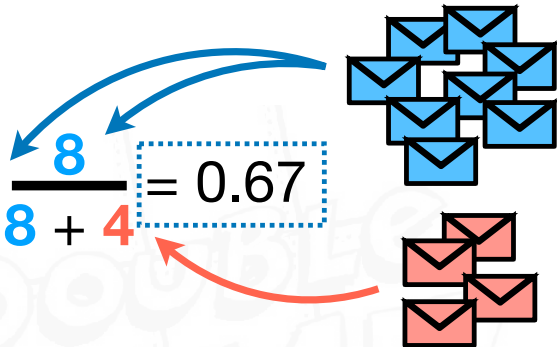
Step 2b) Calculate conditional probabilities for Spam, S

For example, the probability that the word **Dear** occurs given that it is in **Spam** is the number of times **Dear** occurred in **Spam**, 2...

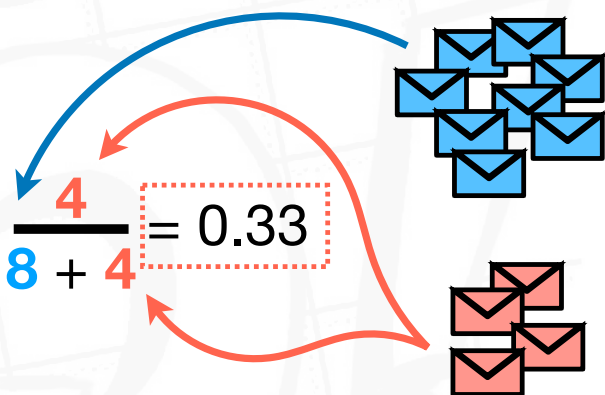


Step 3a) Calculate prior probability for Normal, $p(N)$

NOTE: The **Prior Probabilities** can be set to any probabilities we want, but a common guess is estimated from the training data like so:

$$p(N) = \frac{\text{\# of Normal Messages}}{\text{Total \# of Messages}} = \frac{8}{8 + 4} = 0.67$$


Step 3b) Calculate prior probability for Spam, $p(S)$

$$p(S) = \frac{\text{\# of Spam Messages}}{\text{Total \# of Messages}} = \frac{4}{8 + 4} = 0.33$$


NOTE: The reason **Naive Bayes** is *naive*, is that it does not take word order or phrasing into account.

In other words, **Naive Bayes** would give the exact same probability to the phrase **I like pizza** as it would to the phrase **Pizza like I...**

...even though people frequently say **I like pizza** and almost never say **Pizza like I**.



Because keeping track of every phrase and word ordering would be impossible, **Naive Bayes** doesn't even try.

That said, **Naive Bayes** works well in practice, so keeping track of word order must not be super important.

4a) Calculate probability of seeing the words Dear Friend, given the message is **Normal**

The **Prior** probability the message is **Normal**...

...multiplied by the probabilities of seeing the words **Dear** and **Friend**, given that it's **Normal**.

$$p(\mathbf{N}) \times p(\mathbf{Dear} \mid \mathbf{N}) \times p(\mathbf{Friend} \mid \mathbf{N})$$

$$p(\mathbf{N}) = 0.67$$

$$p(\mathbf{Dear} \mid \mathbf{N}) = 0.47$$

$$p(\mathbf{Friend} \mid \mathbf{N}) = 0.29$$

$$0.67 \times 0.47 \times 0.29 = 0.09$$

NOTE: This probability makes the *naive* assumption that **Dear** and **Friend** are not correlated.

In other words, this is not a realistic model (high bias), but it works in practice (low variance).

4b) Calculate probability of seeing the words Dear Friend, given the message is **Spam**

The **Prior** probability the message is **Spam**...

...multiplied by the probabilities of seeing the words **Dear** and **Friend**, given that it's **Spam**.

$$p(\mathbf{S}) \times p(\mathbf{Dear} \mid \mathbf{S}) \times p(\mathbf{Friend} \mid \mathbf{S})$$

$$p(\mathbf{S}) = 0.33$$

$$p(\mathbf{Dear} \mid \mathbf{S}) = 0.29$$

$$p(\mathbf{Friend} \mid \mathbf{S}) = 0.14$$

$$0.33 \times 0.29 \times 0.14 = 0.01$$

NOTE: In practice, these probabilities can get very small, so we calculate the **log()** of the probabilities to avoid underflow errors on the computer.

5) Classification

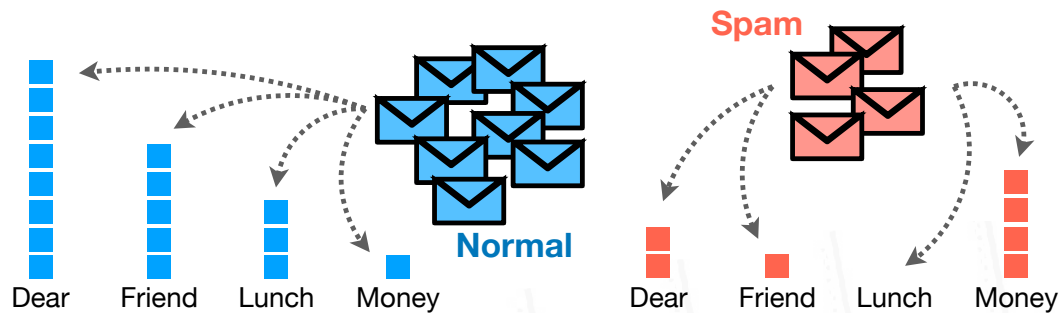
Because **Dear Friend** has a higher probability of being **Normal** (0.09) than **Spam** (0.01), we classify it as **Normal**.

Dear Friend



BAM!!!

Dealing With Missing Data



Remember, the word **Lunch** did not occur in any of the **Spam**...

...and that means the probability of seeing **Lunch** in **Spam** = 0.

$$p(\text{Dear} | S) = 0.29$$

$$p(\text{Friend} | S) = 0.14$$

$$p(\text{Lunch} | S) = 0.00$$

$$p(\text{Money} | S) = 0.57$$

This means that any message with the word **Lunch** in it will be classified as **Normal**, because the probability of being **Spam** = 0.

For example, the probability that this message is **Spam**:

Lunch Money Money Money Money

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

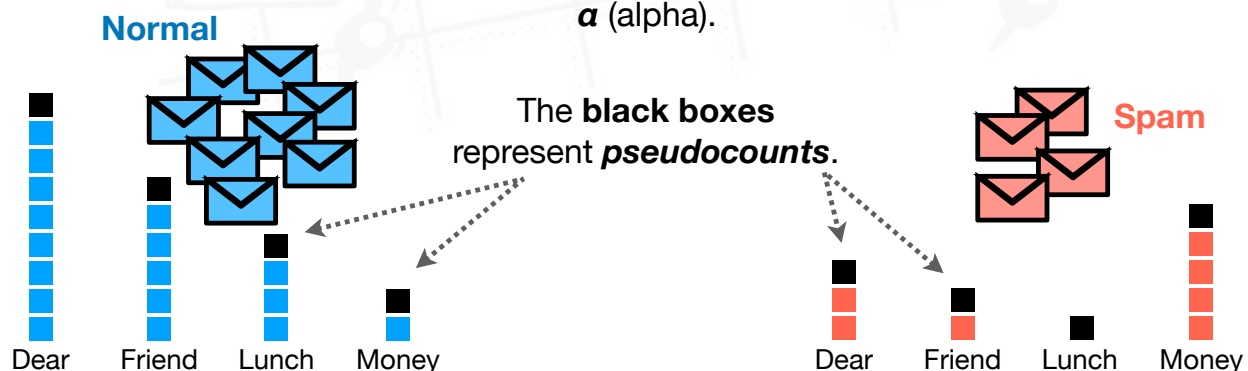
$$p(S) = 0.33$$

$$p(\text{Lunch} | S) = 0.00$$

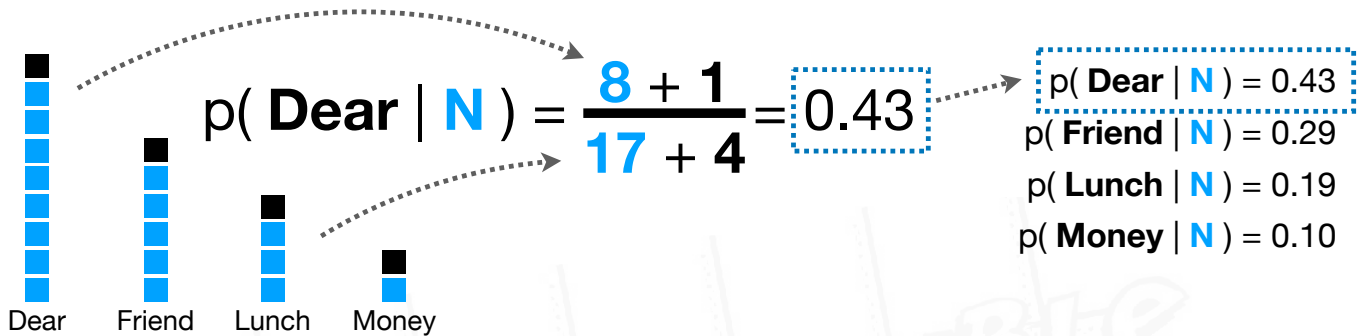
$$p(\text{Money} | S) = 0.57$$

$$0.33 \times 0.00 \times 0.57^4 = 0$$

To solve this problem a **pseudocount** is added to each word. Usually that means adding 1 count to each word, but you can add any number by changing α (alpha).



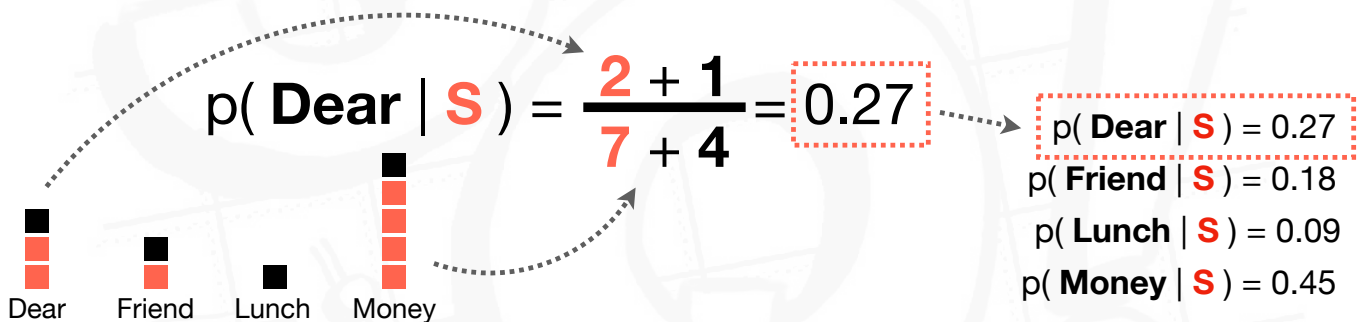
Using Pseudocounts...



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

$p(\text{N}) = 0.67$ $p(\text{Lunch} | \text{N}) = 0.19$ $p(\text{Money} | \text{N}) = 0.10$

$$0.67 \times 0.19 \times 0.10^4 = 0.00001$$



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

$p(\text{S}) = 0.33$ $p(\text{Lunch} | \text{S}) = 0.09$ $p(\text{Money} | \text{S}) = 0.45$

$$0.33 \times 0.09 \times 0.45^4 = 0.00122$$

Because **Lunch Money Money Money Money** has a higher probability of being **Spam** (0.00122) than **Normal** (0.00001), we classify it as **Spam**.

Lunch Money Money Money Money





SPAM!!!