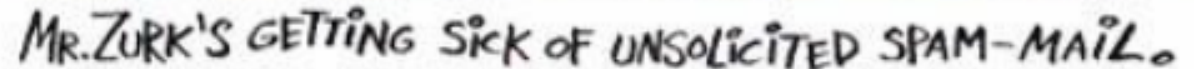


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Applications of Bayes' Theorem

Let E and F be events from sample space S such that $p(E) \neq 0$ and $p(F) \neq 0$. Then we have:

$$p(F|E) = \frac{p(E|F)p(F)}{p(E)} = \frac{p(E|F)p(F)}{p(E|F)p(F) + p(E|\bar{F})p(\bar{F})}$$

Bayesian Reasoning – updating our prior belief about an event ($p(F)$) based on an observation or new knowledge of another event E .

One possible application is an email SPAM filter.

- The SPAM filter updates our belief of the probability that an email is SPAM or not based on the event that particular words show up in the email.

Applications of Bayes' Theorem – SPAM filters

Bayesian spam filters (BSF) use information about previously seen emails to predict whether or not an incoming email is SPAM.

Simple BSFs might look for occurrences of particular words in the message that would indicate the message is spam.

Commerce

| | | |
|------------------|-------------------|------------|
| As seen on | Buy | Buy direct |
| Buying judgments | Clearance | Order |
| Order status | Orders shipped by | shopper |

Medical

| | | |
|----------------------|------------------|----------------------|
| Cures baldness | Diagnostics | Fast Viagra delivery |
| Human growth hormone | Life Insurance | Lose weight |
| Lose weight spam | Medicine | No medical exams |
| Online pharmacy | Removes wrinkles | Reverses aging |
| Stop snoring | Valium | Viagra |
| Vicodin | Weight loss | Xanax |

Applications of Bayes' Theorem – SPAM filters

Financial - Personal

| | | |
|-----------------------------|-------------------------|-----------------------|
| Avoid bankruptcy | Calling creditors | Collect child support |
| Consolidate debt and credit | Consolidate your debt | Eliminate bad credit |
| Eliminate debt | Financially independent | Get out of debt |
| Get paid | Lower interest rate | Lower monthly payment |
| Lower your mortgage rate | Lowest insurance rates | Pre-approved |
| Refinance home | Social security number | Your income |

General

| | | |
|--------------|-------------|---------|
| Acceptance | Accordingly | Avoid |
| Chance | Dormant | Freedom |
| Here | Hidden | Home |
| Leave | Lifetime | Lose |
| Maintained | Medium | Miracle |
| Never | Passwords | Problem |
| Remove | Reverses | Sample |
| Satisfaction | Solution | Stop |
| Success | Teen | Wife |

Applications of Bayes' Theorem – SPAM filters

Financial - Personal

Free

| | | |
|-------------------|--------------------|-------------------|
| Free | Free access | Free cell phone |
| Free consultation | Free DVD | Free gift |
| Free grant money | Free hosting | Free installation |
| Free Instant | Free investment | Free leads |
| Free membership | Free money | Free offer |
| Free preview | Free priority mail | Free quote |
| Free sample | Free trial | Free website |

| | | |
|-----------------------------|-------------------------|-----------------------|
| Avoid bankruptcy | Calling creditors | Collect child support |
| Consolidate debt and credit | Consolidate your debt | Eliminate bad credit |
| Eliminate debt | Financially independent | Get out of debt |
| Get paid | Lower interest rate | Lower monthly payment |
| Lower your mortgage rate | Lowest insurance rates | Pre-approved |
| Refinance home | Social security number | Your income |

Applications of Bayes' Theorem – SPAM filters

Suppose you've catalogued a bunch of emails. Some of them as SPAM, and some as actual emails that you'd want to read.

Could you estimate the probability that the email is SPAM, given that the word w appears in an email?

Want $p(\text{SPAM} \mid w)$



"It's not the most sophisticated Spam blocker I've tried, but it's the only one that works!"

Applications of Bayes' Theorem – SPAM filters

$$\underbrace{p(\text{spam} | w)} = \frac{p(w | \text{spam}) p(\text{spam})}{p(w)} = \frac{p(w | \text{spam}) p(\text{spam})}{p(w | \text{spam}) p(\text{spam}) + p(w | \text{ham}) p(\text{ham})}$$

↓ ↓

↖ ↘

↓

Note: We're letting $\overline{\text{spam}} = \text{ham}$



Applications of Bayes' Theorem – SPAM filters

$$p(w \mid spam) = \frac{|W|}{|S|} = \frac{\text{\# spam messages containing } w}{\text{total \# of spam messages}}$$

$$p(w \mid ham) = \frac{|W|}{|H|} = \frac{\text{\# ham messages containing } w}{\text{total \# of ham messages}}$$

What about $p(spam)$ and $p(ham)$?

Applications of Bayes' Theorem – SPAM filters

$$p(spam) = \frac{\# \text{ spam messages}}{\text{total \# messages}}$$

$$p(ham) = \frac{\# \text{ ham messages}}{\text{total \# messages}}$$

Applications of Bayes' Theorem – SPAM filters

Example: Given the following set of messages, estimate $p(\text{spam} | \text{fly})$ and $p(\text{ham} | \text{fly})$

| spam | spam | spam | ham | ham |
|---------|---------|-------|-------|---------|
| nigeria | fly | money | money | mom |
| fly | buy | buy | buy | fly |
| money | nigeria | pills | work | nigeria |

Bayes' Theorem

$$p(\text{spam} | \text{fly}) = \frac{p(\text{fly} | \text{spam}) p(\text{spam})}{p(\text{fly})} = \frac{p(\text{fly} | \text{spam}) p(\text{spam})}{p(\text{fly} | \text{spam}) p(\text{spam}) + p(\text{fly} | \text{ham}) p(\text{ham})}$$

$$p(\text{ham} | \text{fly}) = \frac{p(\text{fly} | \text{ham}) p(\text{ham})}{p(\text{fly})} = \frac{p(\text{fly} | \text{ham}) p(\text{ham})}{p(\text{fly} | \text{spam}) p(\text{spam}) + p(\text{fly} | \text{ham}) p(\text{ham})}$$

Law of Total Prob.

Applications of Bayes' Theorem – SPAM filters

Example: Given the following set of messages, estimate $p(\text{spam} | \text{fly})$ and $p(\text{ham} | \text{fly})$

| spam | spam | spam | ham | ham |
|---------|---------|-------|-------|---------|
| nigeria | fly | money | money | mom |
| fly | buy | buy | buy | fly |
| money | nigeria | pills | work | nigeria |

$$p(\text{spam} | \text{fly}) = \frac{p(\text{fly} | \text{spam}) p(\text{spam})}{p(\text{fly} | \text{spam}) p(\text{spam}) + p(\text{fly} | \text{ham}) p(\text{ham})} = \frac{\frac{2}{3} \cdot \frac{3}{5}}{\frac{2}{3} \cdot \frac{3}{5} + \frac{1}{2} \cdot \frac{2}{5}} = \frac{\frac{2}{5}}{\frac{2}{5} + \frac{1}{5}} = \frac{2}{3}$$

$$p(\text{ham} | \text{fly}) = \frac{p(\text{fly} | \text{ham}) p(\text{ham})}{p(\text{fly} | \text{spam}) p(\text{spam}) + p(\text{fly} | \text{ham}) p(\text{ham})} = \frac{\frac{1}{2} \cdot \frac{2}{5}}{\frac{2}{3} \cdot \frac{3}{5} + \frac{1}{2} \cdot \frac{2}{5}} = \frac{\frac{1}{5}}{\frac{3}{5}} = \frac{1}{3}$$

Applications of Bayes' Theorem – SPAM filters

How should we classify an email that we receive, based only on the word fly?

Since $p(\text{spam} | \text{fly}) > 0.5$, it's reasonable to classify the email as spam, but we can also set a threshold different from 0.5 based on how bad it would be to make a classification mistake.

- Classifying spam as not spam, is annoying.
- Classifying an important message as spam could be terrible!

In practice, maybe we'd set the threshold for SPAM classification higher than 0.5.

Applications of Bayes' Theorem – SPAM filters

We just classified an email based on one word. In practice, we may want to classify an email with as many words as possible simultaneously.

We need to make a **key assumption** about the relationship of words in emails: Words are ***conditionally independent***, given their category.

Events A and B are ***conditionally independent*** given Y , if and only if

$$p(A \cap B | Y) = p(A | Y) \cdot p(B | Y)$$

independence : $p(A \cap B) = p(A) \cdot p(B)$

e.g. $p(\text{fly and nigeria} | \text{spam}) = \underbrace{p(\text{fly} | \text{spam})} \cdot \underbrace{p(\text{nigeria} | \text{spam})}$

Applications of Bayes' Theorem – SPAM filters

Example: $p(\text{fly and nigeria} \mid \text{spam}) = p(\text{fly} \mid \text{spam}) \cdot p(\text{nigeria} \mid \text{spam})$

| spam | spam | spam | ham | ham |
|---------|---------|-------|-------|---------|
| nigeria | fly | money | money | mom |
| fly | buy | buy | buy | fly |
| money | nigeria | pills | work | nigeria |

We could estimate $p(\text{spam} \mid \{\text{fly}, \text{nigeria}\})$ and $p(\text{ham} \mid \{\text{fly}, \text{nigeria}\})$ by counting up the instances of both “fly” and “nigeria”, in spam or ham emails.

However:

1. We don't want to have to re-estimate all the specific combinations of words whenever we get a new email.
2. We might not have many emails with both words.

Applications of Bayes' Theorem – SPAM filters

Note: The denominators are the same for $p(\text{ham} | \text{email})$ and $p(\text{spam} | \text{email})$:

$$p(\text{ham} | \text{email}) = \frac{p(\text{email} | \text{ham}) p(\text{ham})}{p(\text{email})}$$

$$p(\text{spam} | \text{email}) = \frac{p(\text{email} | \text{spam}) p(\text{spam})}{p(\text{email})}$$

❖ We can classify an email entirely based on which numerator is larger.

Applications of Bayes' Theorem – SPAM filters

e.g. $\frac{1}{5} < \frac{4}{5}$

Example: Based on this example, predict whether the email containing “fly” and “nigeria” is spam or ham.

| spam | spam | spam | ham | ham |
|---------|---------|-------|-------|---------|
| nigeria | fly | money | money | mom |
| fly | buy | buy | buy | fly |
| money | nigeria | pills | work | nigeria |

use conditional independence

$$p(\text{spam} | \text{fly} \cap \text{nigeria}) = \frac{p(\text{fly} \cap \text{nigeria} | \text{spam}) p(\text{spam})}{(\text{denominator})} = \frac{p(\text{fly} | \text{spam}) \cdot p(\text{nigeria} | \text{spam}) p(\text{spam})}{(\text{denominator})}$$

$$= \frac{2}{3} \cdot \frac{2}{3} \cdot \frac{3}{5} = \frac{4}{15}$$

$$p(\text{ham} | \text{fly} \cap \text{nigeria}) = \frac{p(\text{fly} \cap \text{nigeria} | \text{ham}) p(\text{ham})}{(\text{denominator})} =$$

$$= p(\text{fly} | \text{ham}) \cdot p(\text{nigeria} | \text{ham}) p(\text{ham}) = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{2}{3} = \frac{1}{10}$$

We used Bayesian Reasoning to update our belief about the probability of an email being ham or spam.

- Start with our prior beliefs. $p(spam)$ or $p(ham)$
- Make observations of particular words in an incoming email, and want to update our belief about spam or ham based on these observations.
 $p(spam | 'words in email')$ and $p(ham | 'words in email')$
- Bayes' Theorem allows us to calculate these based on the words in old emails that we know are spam or ham.

Next: Recursion!