CS70: Jean Walrand: Lecture 17.

Bayes' Rule, Mutual Independence, Collisions and Collecting

1. Conditional Probability
2. Independence
3. Bayes' Rule
4. Balls and Bins
5. Coupons

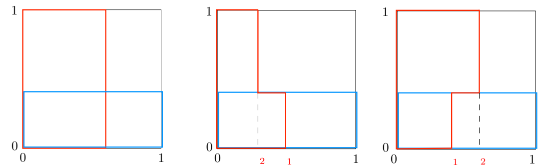
Conditional Probability: Review

Recall:

- $Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]}$.
- Hence, $Pr[A \cap B] = Pr[B]Pr[A|B] = Pr[A]Pr[B|A]$.
- A and B are *positively correlated* if $Pr[A|B] > Pr[A]$,
  i.e., if $Pr[A \cap B] > Pr[A]Pr[B]$.
- A and B are *negatively correlated* if $Pr[A|B] < Pr[A]$,
  i.e., if $Pr[A \cap B] < Pr[A]Pr[B]$.
- A and B are *independent* if $Pr[A|B] = Pr[A]$,
  i.e., if $Pr[A \cap B] = Pr[A]Pr[B]$.
- Note: $B \subset A \Rightarrow A$ and B are positively correlated. ($Pr[A|B] = 1 > Pr[A]$)
- Note: $A \cap B = \emptyset \Rightarrow A$ and B are negatively correlated. ($Pr[A|B] = 0 < Pr[A]$)

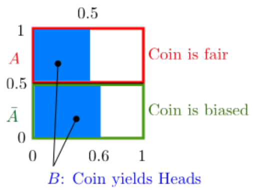
Conditional Probability: Pictures

Illustrations: Pick a point uniformly in the unit square



- Left: A and B are independent. $Pr[B] = b; Pr[B|A] = b$.
- Middle: A and B are positively correlated. $Pr[B|A] = b_1 > Pr[B|\bar{A}] = b_2$. Note: $Pr[B] \in (b_2, b_1)$.
- Right: A and B are negatively correlated. $Pr[B|A] = b_1 < Pr[B|\bar{A}] = b_2$. Note: $Pr[B] \in (b_1, b_2)$.

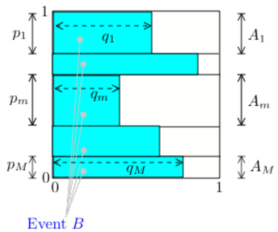
Bayes and Biased Coin



Pick a point uniformly at random in the unit square. Then

$$Pr[A] = 0.5; Pr[\bar{A}] = 0.5$$
$$Pr[B|A] = 0.5; Pr[B|\bar{A}] = 0.6; Pr[A \cap B] = 0.5 \times 0.5$$
$$Pr[B] = 0.5 \times 0.5 + 0.5 \times 0.6 = Pr[A]Pr[B|A] + Pr[\bar{A}]Pr[B|\bar{A}]$$
$$Pr[A|B] = \frac{0.5 \times 0.5}{0.5 \times 0.5 + 0.5 \times 0.6} = \frac{Pr[A]Pr[B|A]}{Pr[A]Pr[B|A] + Pr[\bar{A}]Pr[B|\bar{A}]}$$
$$\approx 0.46 = \text{fraction of } B \text{ that is inside } A$$

Bayes: General Case

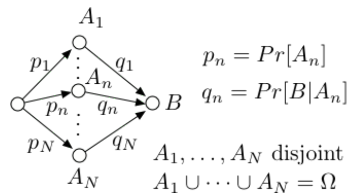


Pick a point uniformly at random in the unit square. Then

$$Pr[A_m] = p_m, m = 1, \ldots, M$$
$$Pr[B|A_m] = q_m, m = 1, \ldots, M; Pr[A_m \cap B] = p_m q_m$$
$$Pr[B] = p_1 q_1 + \cdots p_M q_M$$
$$Pr[A_m|B] = \frac{p_m q_m}{p_1 q_1 + \cdots p_M q_M} = \text{fraction of } B \text{ inside } A_m.$$

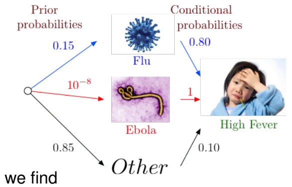
Bayes Rule

Another picture:



$$Pr[A_n|B] = \frac{p_n q_n}{\sum_m p_m q_m}.$$

Why do you have a fever?



Using Bayes' rule, we find

$$Pr[\text{Flu}|\text{High Fever}] = \frac{0.15 \times 0.80}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 0.58$$

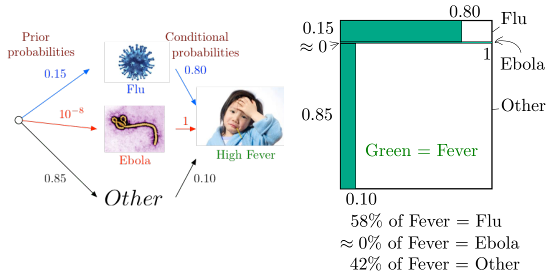
$$Pr[\text{Ebola}|\text{High Fever}] = \frac{10^{-8} \times 1}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 5 \times 10^{-8}$$

$$Pr[\text{Other}|\text{High Fever}] = \frac{0.85 \times 0.1}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 0.42$$

The values $0.58, 5 \times 10^{-8}, 0.42$ are the posterior probabilities.

Why do you have a fever?

Our "Bayes' Square" picture:



Note that even though $Pr[\text{Fever}|\text{Ebola}] = 1$, one has

$$Pr[\text{Ebola}|\text{Fever}] \approx 0.$$

This example shows the importance of the prior probabilities.

Why do you have a fever?

We found

$$Pr[\text{Flu}|\text{High Fever}] \approx 0.58,$$
$$Pr[\text{Ebola}|\text{High Fever}] \approx 5 \times 10^{-8},$$
$$Pr[\text{Other}|\text{High Fever}] \approx 0.42$$

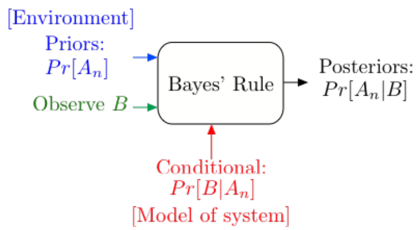
One says that 'Flu' is the Most Likely a Posteriori (MAP) cause of the high fever.
'Ebola' is the Maximum Likelihood Estimate (MLE) of the cause: it causes the fever with the largest probability.
Recall that

$$p_m = Pr[A_m], q_m = Pr[B|A_m], Pr[A_m|B] = \frac{p_m q_m}{p_1 q_1 + \cdots + p_M q_M}.$$

Thus,

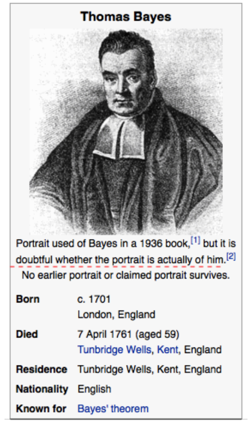
- MAP = value of m that maximizes $p_m q_m$.
- MLE = value of m that maximizes q_m.

Bayes' Rule Operations



Bayes' Rule is the canonical example of how information changes our opinions.

Thomas Bayes



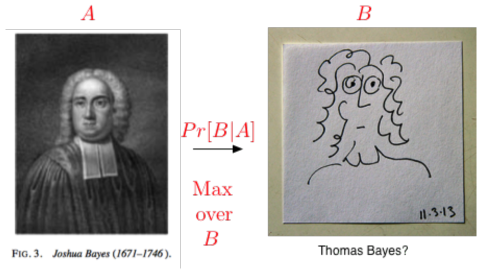
Thomas Bayes

Portrait used of Bayes in a 1936 book,[1] but it is doubtful whether the portrait is actually of him.[2] No earlier portrait or claimed portrait survives.

Born	c. 1701 London, England
Died	7 April 1761 (aged 59) Tunbridge Wells, Kent, England
Residence	Tunbridge Wells, Kent, England
Nationality	English
Known for	Bayes' theorem

Source: Wikipedia.

Thomas Bayes



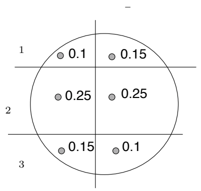
A Bayesian picture of Thomas Bayes.

Independence

Recall :

A and B are independent
$\Leftrightarrow Pr[A \cap B] = Pr[A]Pr[B]$
$\Leftrightarrow Pr[A|B] = Pr[A]$.

Consider the example below:

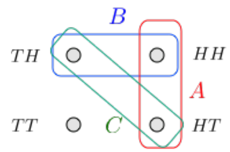


(A_2, B) are independent: $Pr[A_2|B] = 0.5 = Pr[A_2]$.
$(A_2, \bar{B})$ are independent: $Pr[A_2|\bar{B}] = 0.5 = Pr[A_2]$.
(A_1, B) are not independent: $Pr[A_1|B] = \frac{0.1}{0.5} = 0.2 \neq Pr[A_1] = 0.25$.

Pairwise Independence

Flip two fair coins. Let

- $A =$ 'first coin is H' $= \{HT, HH\}$;
- $B =$ 'second coin is H' $= \{TH, HH\}$;
- $C =$ 'the two coins are different' $= \{TH, HT\}$.



A, C are independent; B, C are independent;
$A \cap B, C$ are not independent. ($Pr[A \cap B \cap C] = 0 \neq Pr[A \cap B]Pr[C]$.)

If A did not say anything about C and B did not say anything about C, then $A \cap B$ would not say anything about C.

Example 2

Flip a fair coin 5 times. Let A_n = 'coin n is H', for $n = 1, \ldots, 5$.

Then,

A_m, A_n are independent for all $m \neq n$.

Also,

A_1 and $A_3 \cap A_5$ are independent.

Indeed,

$$Pr[A_1 \cap (A_3 \cap A_5)] = \frac{1}{8} = Pr[A_1]Pr[A_3 \cap A_5]$$

. Similarly,

$A_1 \cap A_2$ and $A_3 \cap A_4 \cap A_5$ are independent.

This leads to a definition ....

Mutual Independence

Definition Mutual Independence

(a) The events $A_1, \ldots, A_5$ are mutually independent if

$$Pr[\cap_{k \in K} A_k] = \Pi_{k \in K} Pr[A_k], \text{ for all } K \subseteq \{1, \ldots, 5\}.$$

(b) More generally, the events $\{A_j, j \in J\}$ are mutually independent if

$$Pr[\cap_{k \in K} A_k] = \Pi_{k \in K} Pr[A_k], \text{ for all finite} K \subseteq J.$$

Example: Flip a fair coin forever. Let A_n = 'coin n is H.' Then the events A_n are mutually independent.

Mutual Independence

Theorem

(a) If the events $\{A_j, j \in J\}$ are mutually independent and if K_1 and K_2 are disjoint finite subsets of J, then

$$\cap_{k \in K_1} A_k \text{ and } \cap_{k \in K_2} A_k \text{ are independent.}$$

(b) More generally, if the K_n are pairwise disjoint finite subsets of J, then the events

$$\cap_{k \in K_n} A_k \text{ are mutually independent.}$$

(c) Also, the same is true if we replace some of the A_k by $\bar{A}_k$.

Proof:
See Notes 25, 2.7. □

Balls in bins

One throws m balls into $n > m$ bins.

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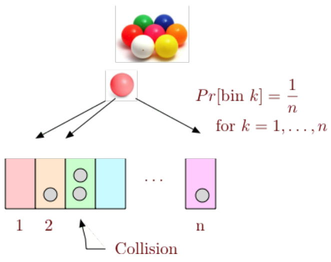

Theorem:
$Pr[\text{no collision}] \approx \exp\{-\frac{m^2}{2n}\}$, for large enough n.

Balls in bins

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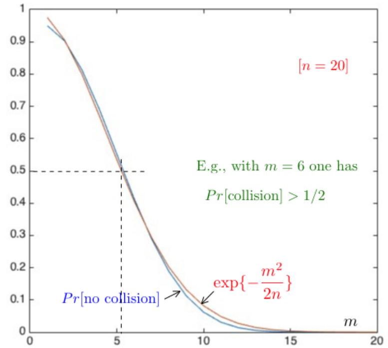


Balls in bins

Theorem:
$Pr[\text{no collision}] \approx \exp\{-\frac{m^2}{2n}\}$, for large enough n.

In particular, $Pr[\text{no collision}] \approx 1/2$ for $m^2/(2n) \approx \ln(2)$, i.e.,

$$m \approx \sqrt{2\ln(2)n} \approx 1.2\sqrt{n}.$$

E.g., $1.2\sqrt{20} \approx 5.4$.

Roughly, $Pr[\text{collision}] \approx 1/2$ for $m = \sqrt{n}$. ($e^{-0.5} \approx 0.6$.)

The Calculation.

A_i = no collision when ith ball is placed in a bin.

$Pr[A_i | A_{i-1} \cap \cdots \cap A_1] = (1 - \frac{i-1}{n})$.

no collision = $A_1 \cap \cdots \cap A_m$.

Product rule:
$Pr[A_1 \cap \cdots \cap A_m] = Pr[A_1]Pr[A_2|A_1] \cdots Pr[A_m|A_1 \cap \cdots \cap A_{m-1}]$

$$\Rightarrow Pr[\text{no collision}] = \left(1 - \frac{1}{n}\right) \cdots \left(1 - \frac{m-1}{n}\right).$$

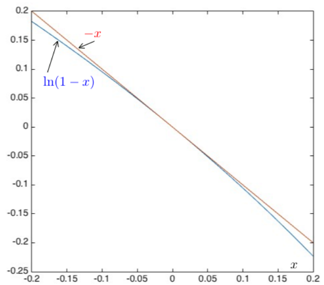
Hence,

$$\ln(Pr[\text{no collision}]) = \sum_{k=1}^{m-1} \ln(1 - \frac{k}{n}) \approx \sum_{k=1}^{m-1} (-\frac{k}{n}) \; (*)$$
$$= -\frac{1}{n}\frac{m(m-1)}{2}^{(\dagger)} \approx -\frac{m^2}{2n}$$

(*) We used $\ln(1-\varepsilon) \approx -\varepsilon$ for $|\varepsilon| \ll 1$.

(†) $1 + 2 + \cdots + m - 1 = (m-1)m/2$.

Approximation



$$\exp\{-x\} = 1 - x + \frac{1}{2!}x^2 + \cdots \approx 1 - x, \text{ for } |x| \ll 1.$$

Hence, $-x \approx \ln(1-x)$ for $|x| \ll 1$.

Today's your birthday, it's my birthday too..

Probability that m people all have different birthdays?
With $n = 365$, one finds

$Pr[\text{collision}] \approx 1/2$ if $m \approx 1.2\sqrt{365} \approx 23$.

If $m = 60$, we find that

$$Pr[\text{no collision}] \approx \exp\{-\frac{m^2}{2n}\} = \exp\{-\frac{60^2}{2 \times 365}\} \approx 0.007.$$

If $m = 366$, then $Pr[\text{no collision}] = 0$. (No approximation here!)

Checksums!

Consider a set of m files.
Each file has a checksum of b bits.
How large should b be for $Pr[\text{share a checksum}] \leq 10^{-3}$?

Claim: $b \geq 2.9\ln(m) + 9$.

Proof:

Let $n = 2^b$ be the number of checksums.
We know $Pr[\text{no collision}] \approx \exp\{-m^2/(2n)\} \approx 1 - m^2/(2n)$.
Hence,

$$Pr[\text{no collision}] \approx 1 - 10^{-3} \Leftrightarrow m^2/(2n) \approx 10^{-3}$$
$$\Leftrightarrow 2n \approx m^2 10^3 \Leftrightarrow 2^{b+1} \approx m^2 2^{10}$$
$$\Leftrightarrow b + 1 \approx 10 + 2\log_2(m) \approx 10 + 2.9\ln(m).$$

Note: $\log_2(x) = \log_2(e)\ln(x) \approx 1.44\ln(x)$.

Coupon Collector Problem.

There are n different baseball cards.
(Brian Wilson, Jackie Robinson, Roger Hornsby, ...)

One random baseball card in each cereal box.

Theorem: If you buy m boxes,

(a) $Pr[\text{miss one specific item}] \approx e^{-\frac{m}{n}}$

(b) $Pr[\text{miss any one of the items}] \leq ne^{-\frac{m}{n}}$.

Coupon Collector Problem: Analysis.

Event A_m = 'fail to get Brian Wilson in m cereal boxes'
Fail the first time: $(1 - \frac{1}{n})$
Fail the second time: $(1 - \frac{1}{n})$
And so on ... for m times. Hence,

$$Pr[A_m] = (1 - \frac{1}{n}) \times \cdots \times (1 - \frac{1}{n})$$
$$= (1 - \frac{1}{n})^m$$
$$ln(Pr[A_m]) = m\ln(1 - \frac{1}{n}) \approx m \times (-\frac{1}{n})$$
$$Pr[A_m] \approx \exp\{-\frac{m}{n}\}.$$

For $p_m = \frac{1}{2}$, we need around $n\ln 2 \approx 0.69n$ boxes.

Collect all cards?

Experiment: Choose m cards at random with replacement.

Events: E_k = 'fail to get player k' , for k = 1, . . . , n

Probability of failing to get at least one of these n players:

$$p := Pr[E_1 \cup E_2 \cdots \cup E_n]$$

How does one estimate p? Union Bound:

$$p = Pr[E_1 \cup E_2 \cdots \cup E_n] \leq Pr[E_1] + Pr[E_2] \cdots Pr[E_n].$$

$$Pr[E_k] \approx e^{-\frac{m}{n}}, k = 1, \ldots, n.$$

Plug in and get

$$p \leq ne^{-\frac{m}{n}}.$$

Collect all cards?

Thus,

$$Pr[\text{missing at least one card}] \leq ne^{-\frac{m}{n}}.$$

Hence,

$$Pr[\text{missing at least one card}] \leq p \text{ when } m \geq n\ln(\frac{n}{p}).$$

To get $p = 1/2$, set $m = n\ln(2n)$.

E.g., $n = 10^2 \Rightarrow m = 530; n = 10^3 \Rightarrow m = 7600$.

Summary.

Bayes' Rule, Mutual Independence, Collisions and Collecting

Main results:

- Bayes' Rule: $Pr[A_m|B] = p_m q_m/(p_1 q_1 + \cdots + p_M q_M)$.
- Product Rule:
  $Pr[A_1 \cap \cdots \cap A_n] = Pr[A_1]Pr[A_2|A_1] \cdots Pr[A_n|A_1 \cap \cdots \cap A_{n-1}]$.
- Balls in bins: m balls into $n > m$ bins.
  $$Pr[\text{no collisions}] \approx \exp\{-\frac{m^2}{2n}\}$$
- Coupon Collection: n items. Buy m cereal boxes.
  $Pr[\text{miss one specific item}] \approx e^{-\frac{m}{n}}$; $Pr[\text{miss any one of the items}] \leq ne^{-\frac{m}{n}}$.

Key Mathematical Fact: $\ln(1 - \varepsilon) \approx -\varepsilon$.