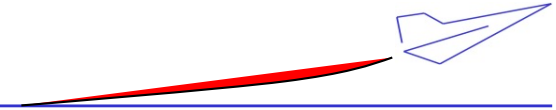


Probability and Statistics

Course Description



□ Probability

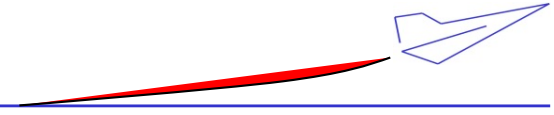
- Probability
- Joint probability, Marginal probability, Conditional probability
- Independence
- Bayes theorem

□ Random Variables

- Random variables
- Distribution functions
- Probability density functions
- Gaussian random variables

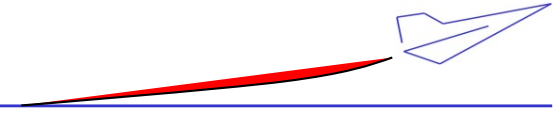
□ Statistics

- Expectation
- Estimation



Probability

Definition of Probability



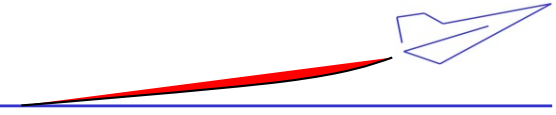
□ Probability models

- Systems work in a chaotic environment
- Probability models
 - ✓ Enable the designer to make sense out of the chaos
 - ✓ Build efficient, reliable, and cost-effective systems

□ Deterministic models

- The **conditions** under which an experiment is carried out determine the exact outcome of the experiment

Definition of Probability



□ Terms of Probability

- Experiment(실험) 및 Trial(시행)

동일한 조건하에서 반복할 수 있고, 또 그 결과가 우연에 의해서 지배되지 만, 가능한 모든 결과의 집합을 알 수 있는 관찰, 조사, 실험

Ex) 주사위를 1회 던질 때 나오는 결과를 다음과 같이 정의하자.

- 1의 눈이 나오는 것을 1
- 2의 눈이 나오는 것을 2
- ...
- 6의 눈이 나오는 것을 6

- Sample space(표본공간)

어떤 시행에서 일어날 수 있는 모든 가능한 결과의 집합

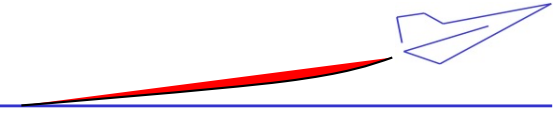
Ex) $S = \{1, 2, 3, 4, 5, 6\}$

- Event(사건)

표본공간 S의 부분집합

Ex) $A = \phi, \{1\}, \{2\}, \dots, \{6\}, \{1, 2\}, \dots, \{1, 2, 3, 4, 5, 6\}$

Definition of Probability



□ Terms of Probability

- Discrete sample space(이산표본공간)

Ex) **Two coins tossed**: When two coins are tossed, there are four possible outcomes. Let H_1 and T_1 denote the head and tail on the first coin and H_2 and T_2 denote the head and tail on the second coin respectively.

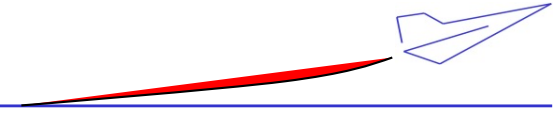
The sample space can be written in the form as

$$S = \{(H_1, H_2), (H_1, T_2), (T_1, H_2), (T_1, T_2)\}$$

Ex) **Two dice tossed**:

$$S = \begin{bmatrix} (1,1) & (1,2) & (1,3) & (1,4) & (1,5) & (1,6) \\ (2,1) & (2,2) & (2,3) & (2,4) & (2,5) & (2,6) \\ (3,1) & (3,2) & (3,3) & (3,4) & (3,5) & (3,6) \\ (4,1) & (4,2) & (4,3) & (4,4) & (4,5) & (4,6) \\ (5,1) & (5,2) & (5,3) & (5,4) & (5,5) & (5,6) \\ (6,1) & (6,2) & (6,3) & (6,4) & (6,5) & (6,6) \end{bmatrix}$$

Definition of Probability



□ Terms of Probability

- Continuous sample space(연속표본공간)

Ex) **Arrival time**: The experimental setting is a metro (underground) station where trains pass (ideally) with equal intervals. A person enters the station. The experiment is to note the time of arrival past the departure time of the last train. If T is the interval between two consecutive trains, then the sample space for the experiment is the interval $[0, T]$, or

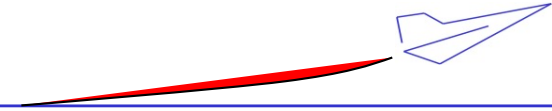
$$S = [0, T] = \{t : 0 \leq t \leq T\}$$

Ex) **Chord length**: Given a circle of radius R , the experiment is to randomly select a chord in that circle. There are many ways to accomplish such a selection. However, the sample space is always the same:

$\{AB: A \text{ and } B \text{ are points on a given circle}\}$.

One natural random variable defined on this space is the length of the chord. The variable takes on random length on the interval $[0, T]$, where T is the diameter of the circle at hand. The length of a chord AB is zero if the two points happen to coincide.

Definition of Probability



□ Definition of Probability

- 표본공간 S 에서 정의된 각 사건에 확률(Probability)라고 불리는 음이 아닌 수를 할당

- 확률은 하나의 함수 $P: A \rightarrow \mathbb{R}_+ (\geq 0)$

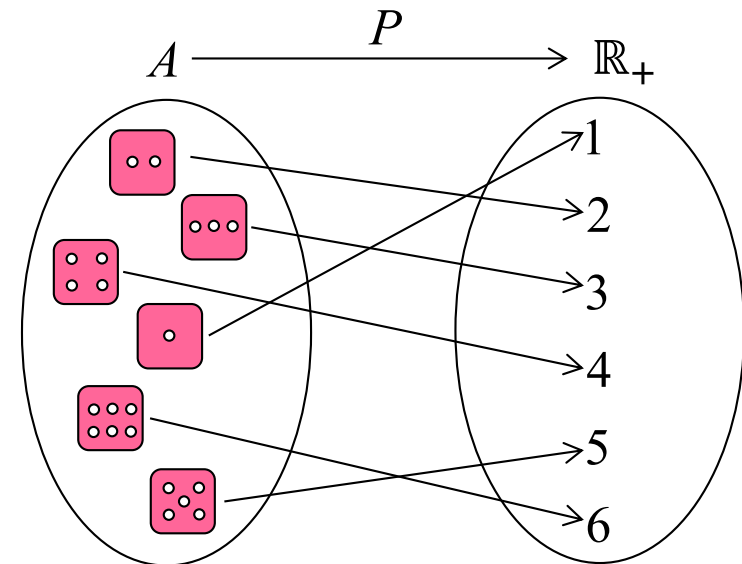
- 사건 A 의 확률 $P[A]$

- 확률의 공리

$$\text{Axiom 1) } P[A] \geq 0$$

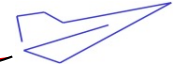
$$\text{Axiom 2) } P[S] = 1$$

$$\text{Axiom 3) } P\left[\bigcup_{n=1}^N A_n\right] = \sum_{n=1}^N P[A_n] \text{ if } A_m \cap A_n = \emptyset \text{ for } m \neq n \text{ and } A_n, A_m \subset S$$



Note) 공리(axiom): 증명을 필요로 하지 않거나 증명할 수 없지만 직관적으로 자명한 진리의 명제인 동시에 다른 명제들의 전제가 되는 명제

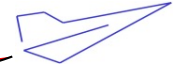
Definition of Probability



□ Ex) 1.3-1

- 0부터 100까지의 점들이 표시된 Fair한 회전판을 돌려서 어떤 수 x 를 구하는 실험
- 표본공간 $S = \{0 < x \leq 100\}$
- $A = \{x_1 < x \leq x_2\} \rightarrow P[A] = \frac{x_2 - x_1}{100} \geq 0$: Axiom 1 is satisfied.
- If $x_2 = 100$ and $x_1 = 0$, then $P[A] = 1$: Axiom 2 is satisfied.
- $A_n = \{x_{n-1} < x \leq x_n\}$, $x_n = \frac{100n}{N}$, $n = 1, 2, \dots, N$, $x_0 = 0 \Rightarrow P(A_n) = \frac{1}{N}$
 $\Rightarrow P\left[\bigcup_{n=1}^N A_n\right] = \sum_{n=1}^N P[A_n] = \sum_{n=1}^N \frac{1}{N} = 1$: Axiom 3 is satisfied.

Definition of Probability



□ Mathematical probability

- $P[A] = \frac{n(A)}{n(S)} = \frac{\text{Number of elementary events belong to } A}{\text{Number of entire elementary events}}$

- Ex) 1.3-2, 두 주사위를 던져서 나오는 수의 합을 관찰하는 시험

$$A = \{x_1 + x_2 = 7\}$$

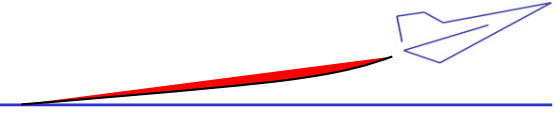
$$B = \{8 < x_1 + x_2 \leq 11\}$$

$$C = \{10 < x_1 + x_2\}$$

$$S = \begin{bmatrix} (1,1) & (1,2) & (1,3) & (1,4) & (1,5) & (1,6) \\ (2,1) & (2,2) & (2,3) & (2,4) & (2,5) & (2,6) \\ (3,1) & (3,2) & (3,3) & (3,4) & (3,5) & (3,6) \\ (4,1) & (4,2) & (4,3) & (4,4) & (4,5) & (4,6) \\ (5,1) & (5,2) & (5,3) & (5,4) & (5,5) & (5,6) \\ (6,1) & (6,2) & (6,3) & (6,4) & (6,5) & (6,6) \end{bmatrix}$$

$$\Rightarrow P[A] = \frac{6}{36} = \frac{1}{6}, P[B] = \frac{9}{36} = \frac{1}{4}, P[C] = \frac{3}{36} = \frac{1}{12}$$

Definition of Probability



□ Probability in a relative frequency

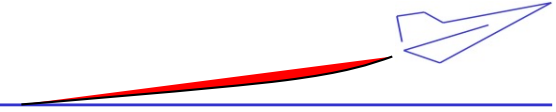
- 동일한 시행을 n 번 반복하여, 사건 A 가 일어난 횟수를 r 이라 할 때, n 을 충분히 크게 하면 상대도수 r/n 은 일정한 값 p 에 가까워진다. 이 p 를 사건 A 의 통계적 확률 또는 경험적 확률이라 한다.

$$P[A] = \lim_{n \rightarrow \infty} \frac{r}{n}$$

- Ex) 어느 고등학교 학생 2,000명의 혈액형을 조사한 결과 A형인 학생이 820명이었다고 한다. 이학교의 학생 1명을 임의로 뽑을 때, 그 학생의 혈액형이 A형일 확률은?

$$P[A] = \frac{820}{2,000} = 0.41$$

Joint Probability



□ Definition of joint probability

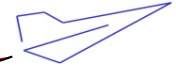
- Joint probability is the probability that two events will occur simultaneously.

$$P[A \cap B] = P[A] + P[B] - P[A \cup B]$$

$$\text{or } P[A \cup B] = P[A] + P[B] - P[A \cap B] \leq P[A] + P[B]$$

$$\text{If } A \text{ and } B \text{ are disjoint, } P[A \cap B] = 0. \Rightarrow P[A \cup B] = P[A] + P[B]$$

Joint Probability

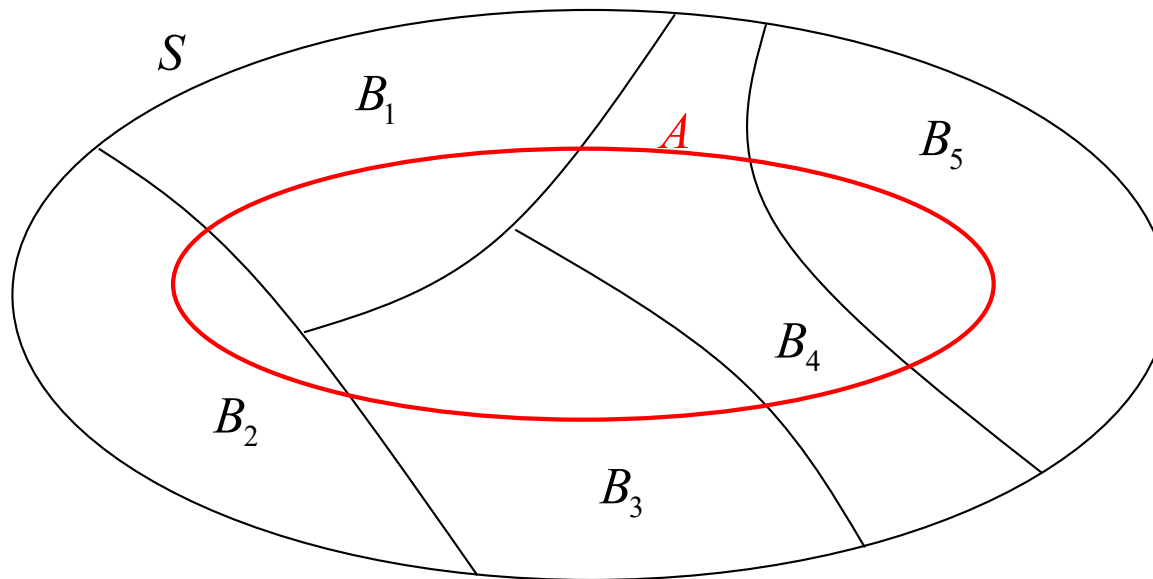


□ Definition of marginal probability

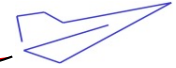
Suppose that a sample space S is partitioned by the events

$$\{B_1, B_2, \dots, B_n\}$$

where $S = \bigcup_{i=1}^n B_i$ and $B_i \cap B_j = \phi$, $i \neq j$.



Joint Probability



□ Definition of marginal probability

Given $P[A \cap B_i]$, $i = 1, \dots, m$, the event A can be written as

$$A = \bigcup_{i=1}^m (A \cap B_i)$$

where $(A \cap B_i)$, $i = 1, \dots, m$ are disjoint each other, i.e.,

$$(A \cap B_i) \cap (A \cap B_j) = \phi, i \neq j.$$

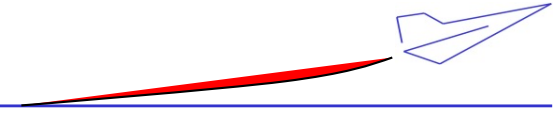
Then,

$$(1) \quad P[A] = P\left[\bigcup_{i=1}^m (A \cap B_i)\right] = \sum_{i=1}^m P[A \cap B_i].$$

Here, $P[A \cap B_i]$ is called the joint probability of the events A and B_i .

$P[A]$, the sum of joint probabilities, is called the marginal probability.

Conditional Probability



□ Definition of conditional probability

The conditional probability is the probability if an occurrence of one event is subject to the hypothesis of the occurrence of another event.

For $P[A | B]$, we consider the event $A \cap B$ in the sample space S .

Construct the conditional probability by the frequency method

$$P[B] = \frac{n(B)}{n(S)}$$

$$\begin{aligned} \text{Then, } P[A | B] &= \frac{n(A \cap B)}{n(B)} = \frac{n(A \cap B) / n(S)}{n(B) / n(S)} \\ &= \frac{P[A \cap B]}{P[B]} \end{aligned}$$

Therefore,

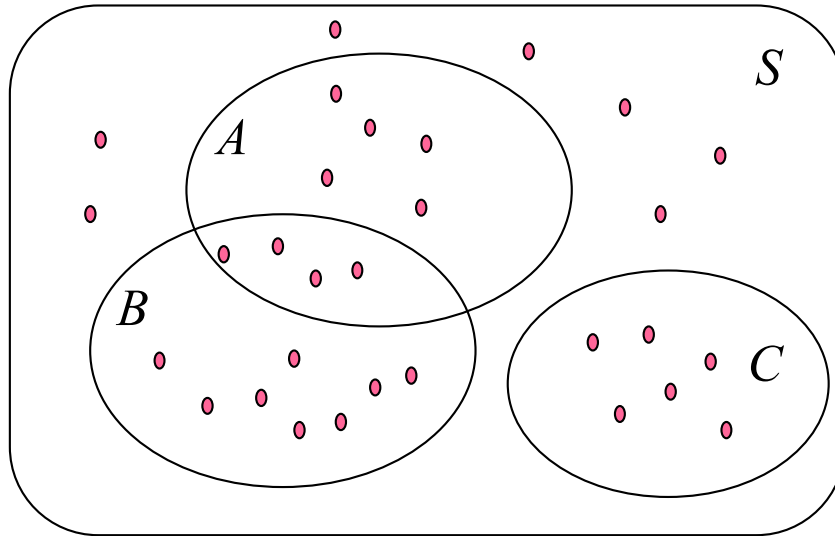
$$(2) \quad P[A \cap B] = P[A | B]P[B].$$

Also, from (1) and (2), we see that

$$P[A] = \sum_{i=1}^m P[A \cap B_i] = \sum_{i=1}^m P[A | B_i]P[B_i]: \text{ Theorem on total probability}$$

Conditional Probability

□ Ex)



$$n(S) = 30$$

$$n(A) = 9$$

$$n(B) = 12$$

$$n(A \cap B) = 4$$

$$n(C) = 6$$

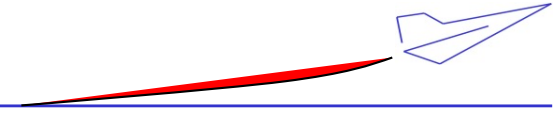
$$P[A] = \frac{n(A)}{n(S)} = \frac{3}{10}, P[B] = \frac{n(B)}{n(S)} = \frac{2}{5}, P[C] = \frac{n(C)}{n(S)} = \frac{1}{5}, P[A \cap B] = \frac{n(A \cap B)}{n(S)} = \frac{2}{15}$$

$$\Rightarrow P[B | A] = \frac{P[A \cap B]}{P[A]} = \frac{2/15}{3/10} = \frac{4}{9} \left(\Rightarrow P[A \cap B] = P[B | A]P[A] = \frac{4}{9} \times \frac{3}{10} = \frac{2}{15} \right)$$

$P[A \cap C] = 0$: A and C are disjoint.

$P[A \cap C] \neq P[A]P[C]$: A and C are not independent.

Conditional Probability



□ Ex)

Select a ball from an urn containing balls numbered 1 to 4
(1,2: Black, 3,4: White)

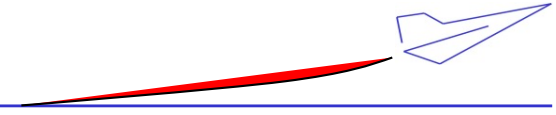
Sample space $S = \{(1,b), (2,b), (3,w), (4,w)\}$: Equally likely outcomes

- $A = \{(1,b), (2,b)\}$: Black ball selected
- $B = \{(2,b), (4,w)\}$: Even-numbered ball selected
- $C = \{(3,w), (4,w)\}$: Number of ball is greater than 2

$$P[A | B] = P[A \cap B] / P[B] = 0.25 / 0.5 = 0.5 = P[A]$$

$$P[A | C] = P[A \cap C] / P[C] = 0.0 / 0.5 = 0$$

Conditional Probability



□ Ex) Theorem on Total Probability

Two black balls and three white balls are in an urn. Two balls are sequentially selected at random without replacement. Find the probability of the event W_2 that the second ball is white. $W_2 = \{(b, w), (w, w)\}$

- $B_1 = \{(b, b), (b, w)\}$: The first ball is black.

- $W_1 = \{(w, b), (w, w)\}$: The first ball is white.

$\Rightarrow B_1, W_1$ form a partition of S .

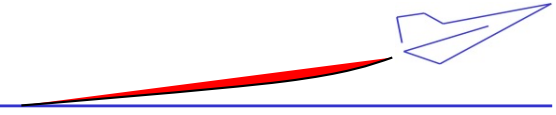
- $n(b, b) = 2, n(b, w) = 6 \Rightarrow n(B_1) = 8, n(W_2 | B_1) = 6 / 8 = 3 / 4$

- $n(w, b) = 6, n(w, w) = 6 \Rightarrow n(W_1) = 12, n(W_2 | W_1) = 6 / 12 = 1 / 2$

- $n(S) = 20$

$$\begin{aligned} \therefore P[W_2] &= P[W_2 | B_1]P[B_1] + P[W_2 | W_1]P[W_1] \\ &= \frac{3}{4} \cdot \frac{8}{20} + \frac{1}{2} \cdot \frac{12}{20} = \frac{3}{4} \cdot \frac{2}{5} + \frac{1}{2} \cdot \frac{3}{5} = \frac{3}{5} \end{aligned}$$

Independence of Events



□ Definition

If $P[A \cap B] = P[A]P[B]$, then A and B are **independent**.

$$\Leftarrow P[A] = P[A | B] = \frac{P[A \cap B]}{P[B]}$$

- implies that $P[A] = P[A | B]$, $P[B] = P[B | A]$

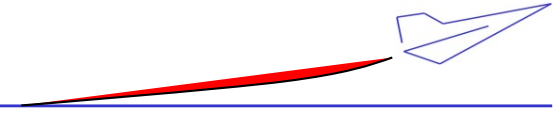
- implies also that $P[A] \neq 0$ and $P[B] \neq 0$

Two events A and B are **mutually exclusive** or disjoint if $P[A] \neq 0$, $P[B] \neq 0$, $P[A \cap B] = 0$.

$\Rightarrow A$ and B cannot be independent.

$\because P[A \cap B] = P[A]P[B] = 0 \Leftarrow$ contradiction

Independence of Events

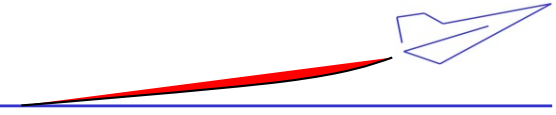


□ Definition

$$P[A] = P[A | B]$$

- When the proportion of outcomes in S that lead to the occurrence of A is equal to the proportion of outcomes in B that lead to A .
- Knowledge of the occurrence of B does not alter the probability of occurrence of A .

Bayes' Rule



□ Definition

Note that $P[A \cap B] = P[A | B]P[B] = P[B | A]P[A]$.

Hence,

$$(3) \quad P[B | A] = \frac{P[A | B]P[B]}{P[A]}$$

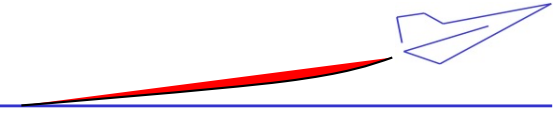
Also, we see that

$$P[B_i | A] = \frac{P[A | B_i]P[B_i]}{P[A]}.$$

If $B_j, j = 1, \dots, m$ are disjoint each other and form $S = \sum_{j=1}^m B_j$, then we have the following from the theorem on total probability

$$(4) \quad P[B_i | A] = \frac{P[A | B_i]P[B_i]}{\sum_{j=1}^m P[A | B_j]P[B_j]}: \text{Bayes' Rule}$$

Bayes' Rule



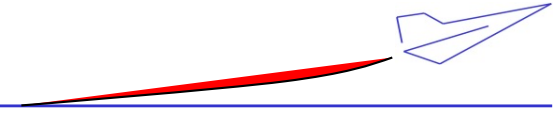
□ Meanings of Bayes Rule

$$P[B_i | A] = \frac{P[A | B_i]P[B_i]}{\sum_{j=1}^m P[A | B_j]P[B_j]}$$

$P[B_i]$: *a priori* knowledge(probabilities) (unconditional probabilities),
the probabilities of the events before the experiment is performed
 $P[B_i | A]$: *a posteriori* knowledge(probabilities) (conditional probabilities),
the probabilities of the events in the partition $P[B_j | A]$ given this
additional information

Bayes' Rule provides a basis of the filtering theory to estimate most probable states under noisy circumstances.

Bayes' Rule



□ Ex) Communication System Error

Communication from a transmitter to a receiver is done by the binary digit, 0 or 1. There are communication errors in change of 0 and 1. For example, 10010110 \rightarrow 10110010.

Suppose B_1 is the event with the symbol 1 and B_2 is the event with the symbol 0 before communication. And, A_1 and A_2 are the events with the symbol 1 and 0 after communication, respectively.

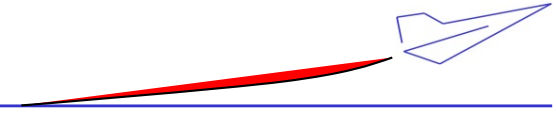
Assume that $P[B_1] = 0.6$ and $P[B_2] = 0.4$.

And, we already know the following information from lots of experiments;

$$P[A_1 | B_1] = 0.9 \text{ and } P[A_2 | B_1] = 0.1$$

$$P[A_1 | B_2] = 0.1 \text{ and } P[A_2 | B_2] = 0.9.$$

Bayes' Rule



□ Ex) Communication System Error

Then, from the theorem on total probability

$$P[A_1] = P[A_1 | B_1]P[B_1] + P[A_1 | B_2]P[B_2] = 0.9 \cdot 0.6 + 0.1 \cdot 0.4 = 0.58$$

$$P[A_2] = P[A_2 | B_1]P[B_1] + P[A_2 | B_2]P[B_2] = 0.1 \cdot 0.6 + 0.9 \cdot 0.4 = 0.42$$

The a posteriori probability for correct communication becomes

$$P[B_1 | A_1] = \frac{P[A_1 | B_1]P[B_1]}{P[A_1]} = \frac{0.9 \cdot 0.6}{0.58} \approx 0.931$$

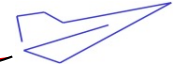
$$P[B_2 | A_2] = \frac{P[A_2 | B_2]P[B_2]}{P[A_2]} = \frac{0.9 \cdot 0.4}{0.42} \approx 0.857$$

and the probabilities of false communication are

$$P[B_1 | A_2] = \frac{P[A_2 | B_1]P[B_1]}{P[A_2]} = \frac{0.1 \cdot 0.6}{0.42} \approx 0.143$$

$$P[B_2 | A_1] = \frac{P[A_1 | B_2]P[B_2]}{P[A_1]} = \frac{0.1 \cdot 0.4}{0.58} \approx 0.069$$

Bayes' Rule



□ Ex) Estimation of an integer variable

(Case 1)

Suppose that x is an unknown integer, which is to be estimated by using some measurements.

Define event B_n as follows;

Event $B_n : x = n$

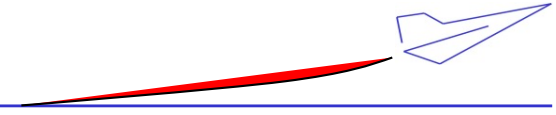
In the beginning, the only information we have is that x is bounded in $[-2, 2]$. (Of course this information may not be true)

So we assign the *a priori* probabilities of each event as

$P[B_{-2}] = 0.2, P[B_{-1}] = 0.2, P[B_0] = 0.2, P[B_1] = 0.2, P[B_2] = 0.2$

and $P[B_n] = 0$ if $x \geq 3$ or $x \leq -3$.

Bayes' Rule



□ Ex) Estimation of an integer variable

The unknown x is measured by using a sensor which has a model given by

$$\text{Measurement: } z = x + v$$

where v is the sensor noise of the following statistical properties.

$$P[v = -1] = 0.2, \quad P[v = 0] = 0.6, \quad P[v = 1] = 0.2, \quad \text{and } P[|v| > 1] = 0.$$

We also define event A_m as

$$\text{Event } A_m : \quad z = m$$

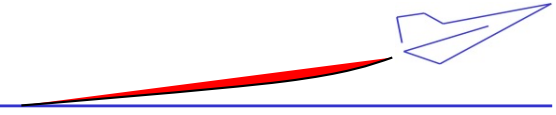
Conditional probability $P[A_m | B_n]$ can be calculated from the statistical properties of v ; for example

$$P[A_0 | B_{-1}] = P[z = 0 | x = -1] = P[v = 1] = 0.2$$

$$P[A_2 | B_0] = P[z = 2 | x = 0] = P[v = 2] = 0$$

$$P[A_1 | B_1] = P[z = 1 | x = 1] = P[v = 0] = 0.6$$

Bayes' Rule



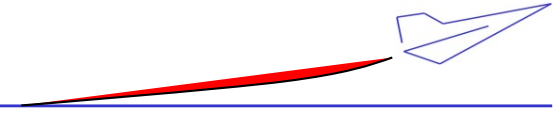
□ Ex) Estimation of an integer variable

Suppose that the first measurement is A_1 . Then, the conditional probability $P[B_n | A_1]$ is calculated by applying the Bayes' Rule of Eq.(4):

$$P[B_n | A_1] = \frac{P[A_1 | B_n]P[B_n]}{\sum_{j=1}^m P[A_1 | B_j]P[B_j]}$$

$$\begin{aligned} \text{Denominator} = P[A_1] &= \sum_{j=-2}^2 P[A_1 | B_j]P[B_j] \\ &= P[A_1 | B_{-2}]P[B_{-2}] + P[A_1 | B_{-1}]P[B_{-1}] + \dots + P[A_1 | B_2]P[B_2] \\ &= P[v = 3]P[B_{-2}] + P[v = 2]P[B_{-1}] + P[v = 1]P[B_0] \\ &\quad + P[v = 0]P[B_1] + P[v = -1]P[B_2] \\ &= 0 \cdot 0.2 + 0 \cdot 0.2 + 0.2 \cdot 0.2 + 0.6 \cdot 0.2 + 0.2 \cdot 0.2 \\ &= 0.2 \end{aligned}$$

Bayes' Rule



□ Ex) Estimation of an integer variable

$$\text{Hence, } P[B_{-2} | A_1] = \frac{P[A_1 | B_{-2}]P[B_{-2}]}{\sum_{j=-2}^2 P[A_1 | B_j]P[B_j]} = \frac{0 \cdot 0.2}{0.2} = 0$$

$$P[B_{-1} | A_1] = \frac{P[A_1 | B_{-1}]P[B_{-1}]}{\sum_{j=-2}^2 P[A_1 | B_j]P[B_j]} = \frac{0 \cdot 0.2}{0.2} = 0$$

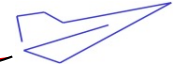
$$P[B_0 | A_1] = \frac{P[A_1 | B_0]P[B_0]}{\sum_{j=-2}^2 P[A_1 | B_j]P[B_j]} = \frac{0.2 \cdot 0.2}{0.2} = 0.2$$

$$P[B_1 | A_1] = \frac{P[A_1 | B_1]P[B_1]}{\sum_{j=-2}^2 P[A_1 | B_j]P[B_j]} = \frac{0.6 \cdot 0.2}{0.2} = 0.6$$

$$P[B_2 | A_1] = \frac{P[A_1 | B_2]P[B_2]}{\sum_{j=-2}^2 P[A_1 | B_j]P[B_j]} = \frac{0.2 \cdot 0.2}{0.2} = 0.2$$

These conditional probabilities are *a posteriori* probabilities of the events B_i when the outcome of the measurement is A_1 .

Bayes' Rule



□ Ex) Estimation of an integer variable

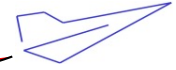
Suppose that the first measurement is not A_1 but A_2 . The conditional probability $P[B_n | A_2]$ can be calculated in a similar way. However, note that

$$P[A_2 | B_3] = P[z = 2 | x = 3] = P[v = -1] = 0.2 \neq 0$$

Hence, we need to include B_3 in this case:

$$\begin{aligned} \text{Denominator} &= \sum_{j=-2}^3 P[A_2 | B_j] P[B_j] \\ &= P[A_2 | B_{-2}] P[B_{-2}] + P[A_2 | B_{-1}] P[B_{-1}] + P[A_2 | B_0] P[B_0] \\ &\quad + P[A_2 | B_1] P[B_1] + P[A_2 | B_2] P[B_2] + P[A_2 | B_3] P[B_3] \\ &= P[v = 4] P[B_{-2}] + P[v = 3] P[B_{-1}] + P[v = 2] P[B_0] \\ &\quad + P[v = 1] P[B_1] + P[v = 0] P[B_2] + P[v = -1] P[B_3] \\ &= 0 \cdot 0.2 + 0 \cdot 0.2 + 0 \cdot 0.2 + 0.2 \cdot 0.2 + 0.6 \cdot 0.2 + 0.2 \cdot 0 \\ &= 0.16 \end{aligned}$$

Bayes' Rule



□ Ex) Estimation of an integer variable

$$\text{Hence, } P[B_{-2} | A_2] = \frac{P[A_2 | B_{-2}]P[B_{-2}]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0 \cdot 0.2}{0.16} = 0$$

$$P[B_{-1} | A_2] = \frac{P[A_2 | B_{-1}]P[B_{-1}]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0 \cdot 0.2}{0.16} = 0$$

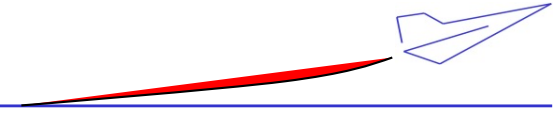
$$P[B_0 | A_2] = \frac{P[A_2 | B_0]P[B_0]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0 \cdot 0.2}{0.16} = 0$$

$$P[B_1 | A_2] = \frac{P[A_2 | B_1]P[B_1]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0.2 \cdot 0.2}{0.16} = 0.25$$

$$P[B_2 | A_2] = \frac{P[A_2 | B_2]P[B_2]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0.6 \cdot 0.2}{0.16} = 0.75$$

$$P[B_3 | A_2] = \frac{P[A_2 | B_3]P[B_3]}{\sum_{j=-2}^3 P[A_2 | B_j]P[B_j]} = \frac{0.2 \cdot 0}{0.16} = 0$$

Bayes' Rule

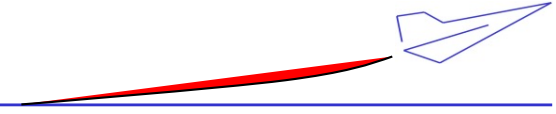


□ Ex) Estimation of an integer variable

Observe that $P[B_3 | A_2] = 0$ is against our intuition. The measurement A_2 is quite probable when $x = 3$. Then what is wrong?

The problem comes from that our *a priori* probability assignment is not adequate. If x has any chance of taking the value of 3, $P[B_3]$ should have some non-zero value. Otherwise, x can not be properly estimated.

Bayes' Rule



□ Ex) Successive measurements

Let $A(i)$ denote the i -th measurement. Suppose that we have $A(1)$ and the associated *a posteriori* probabilities are calculated. In processing of $A(2)$, these *a posteriori* probabilities are then treated as *a priori* probabilities.

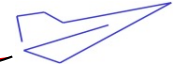
For simplicity, we use the following notation:

$$P[X, Y, Z] \triangleq P[X \cap Y \cap Z]$$

Then, note that

$$\begin{aligned} P[B_i | A(1), A(2)] &= \frac{P[B_i, A(1), A(2)]}{P[A(1), A(2)]} \\ &= \frac{P[B_i, A(1), A(2)]}{\sum_{j=1}^m P[B_j, A(1), A(2)]} \end{aligned}$$

Bayes' Rule



□ Ex) Successive measurements

but

$$\begin{aligned} P[B_j, A(1), A(2)] &= \frac{n(B_j, A(1), A(2))}{n(B_j, A(1))} \frac{n(B_j, A(1))}{n(S)} \\ &= P[A(2) | B_j, A(1)] \cdot P[B_j, A(1)] \end{aligned}$$

Assume that each measurement is independent, then we observe

$$P[A(2) | B_j, A(1)] = P[A(2) | B_j]$$

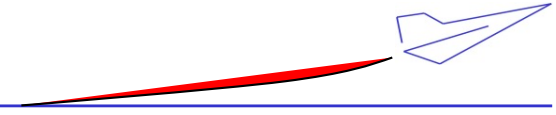
$$\text{Also, } P[B_j, A(1)] = P[B_j | A(1)]P[A(1)]$$

$$\text{Hence, } P[B_j, A(1), A(2)] = P[A(2) | B_j] \cdot P[B_j | A(1)] \cdot P[A(1)]$$

and

$$\begin{aligned} P[B_i | A(1), A(2)] &= \frac{P[B_i, A(1), A(2)]}{\sum_{j=1}^m P[B_j, A(1), A(2)]} \\ &= \frac{P[A(2) | B_i] \cdot P[B_i | A(1)] \cdot \cancel{P[A(1)]}}{\sum_{j=1}^m P[A(2) | B_j] \cdot P[B_j | A(1)] \cdot \cancel{P[A(1)]}} \end{aligned}$$

Bayes' Rule



□ Ex) Successive measurements

This expression provides a recursive algorithm for sequential processing of the measurements;

$$P[B_j | A(1), A(2), A(3)] = \frac{P[A(3) | B_j] \cdot P[B_j | A(1), A(2)]}{\sum_{j=1}^m P[A(3) | B_j] \cdot P[B_j | A(1), A(2)]}$$

⋮

$$P[B_j | A(1), A(2), \dots, A(k+1)] = \frac{P[A(k+1) | B_j] \cdot P[B_j | A(1), A(2), \dots, A(k)]}{\sum_{j=1}^m P[A(k+1) | B_j] \cdot P[B_j | A(1), A(2), \dots, A(k)]}$$