

1 Overview

The previous lecture included discussion about probability spaces and geometric probability.

This lecture includes basic concept of independence of random variables and conditional probability.

Fact: Suppose that $\Omega = \bigcup_{k=0}^n A_k$ is such that: $(\forall i, j)(i \neq j \longrightarrow A_i \cap A_j = \emptyset)$ and $\forall_i (A_i \in \mathcal{S})$. Let $B \in \mathcal{S}$. Then:

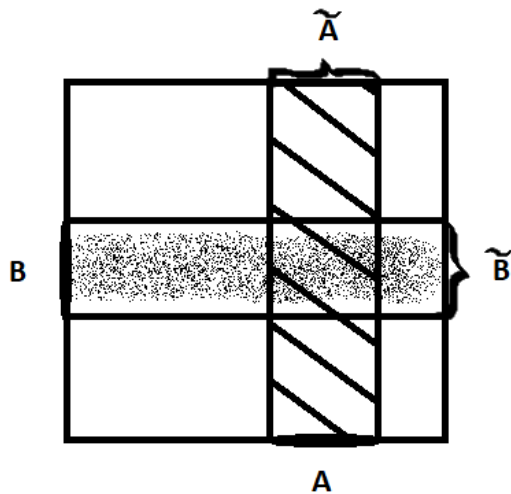
$$P(B) = \sum_{k=0}^n P(B \cap A_k) \quad \leftarrow \text{total probability formula}$$

Proof:

$$B = \bigcup_{k=0}^n (B \cap A_k) : i \neq j \longrightarrow (B \cap A_i) \cap (B \cap A_j) = \emptyset$$

2 Independence

Definition 1 (independence of random variables). *Random variables $A, B \in \mathcal{S}$ are independent if $P(A \cap B) = P(A)P(B)$.*



Example: Let $\Omega = [0, 1]^2$, $A, B \subseteq [0, 1]$, $\tilde{A} = A \times [0, 1]$ and $\tilde{B} = [0, 1] \times B$.

Then we have:

$$\lambda^{(2)}(\tilde{A}) = \lambda^{(1)}(A) \cdot 1 = \lambda^{(1)}(A);$$

$$\lambda^{(2)}(\tilde{B}) = 1 \cdot \lambda^{(1)}(B) = \lambda^{(1)}(B);$$

$$\lambda^{(2)}(\tilde{A} \cap \tilde{B}) = \lambda^{(1)}(A) \cdot \lambda^{(1)}(B) = \lambda^{(2)}\tilde{A} \cap \lambda^{(2)}\tilde{B}$$

so $\{\tilde{A}, \tilde{B}\}$ are independent.

Example: Let $\Omega_1 = \{1, \dots, n\}$, $P(i) = p_i$, $p_1 + \dots + p_n = 1$, $p_i \geq 0$,
 $\Omega_2 = \{1, \dots, m\}$, $P(i) = q_i$, $q_1 + \dots + q_m = 1$, $q_i \geq 0$ and $\Omega = \Omega_1 \times \Omega_2$, $A \subseteq \Omega : P(A) = \sum_{i,j \in A} (p_i \cdot q_j)$.

- $A \subset \Omega_1$, $B \subseteq \Omega_2$, $\tilde{A} = A \times \Omega_2$, $\Omega_1 \times \tilde{B}$;
- $P(\tilde{A}) = P(A)$

$$P(\tilde{A}) = \sum_{i,j \in \tilde{A}} p_i q_j = \sum_{\substack{i \in A \\ j \in \Omega_2}} p_i q_j = \sum_{i \in A} \sum_{j \in \Omega_2} p_i q_j = \sum_{i \in A} p_i \left(\sum_{j \in \Omega_2} q_j \right) = \sum_{i \in A} p_i = P(A);$$

- $P(\tilde{B}) = P(B)$ (analogously to the previous one);
- $P(\tilde{A} \cap \tilde{B}) = P(\tilde{A}) \cdot P(\tilde{B})$

$$\begin{aligned} P(\tilde{A} \cap \tilde{B}) &= \sum_{i,j \in \tilde{A} \times \tilde{B}} p_i q_j = \sum_{\substack{i \in A \\ j \in B}} p_i q_j = \sum_{i \in A} \sum_{j \in B} p_i q_j = \sum_{i \in A} p_i \left(\sum_{j \in B} q_j \right) = \sum_{i \in A} p_i P(B) = \\ &= P(A) \cdot P(B) = P(\tilde{A}) \cdot P(\tilde{B}); \end{aligned}$$

so \tilde{A}, \tilde{B} are independent.

Definition 2. Let $A = \{A_1, \dots, A_n\} \subseteq \mathcal{S}$. We say A is independent if for any $1 \leq i_1 < \dots < i_k \leq n$ ($k \geq 2$) we have:

$$P(A_{i_1} \cap \dots \cap A_{i_k}) = P(A_{i_1}) \cdot \dots \cdot P(A_{i_k}).$$

Example: Let $\mathcal{A} = \{A, B, C\}$.

$$\mathcal{A} \text{ is independent} \equiv \begin{cases} P(A \cap B) = P(A) \cdot P(B); \\ P(A \cap C) = P(A) \cdot P(C); \\ P(B \cap C) = P(B) \cdot P(C); \\ P(A \cap B \cap C) = P(A) \cdot P(B) \cdot P(C). \end{cases}$$

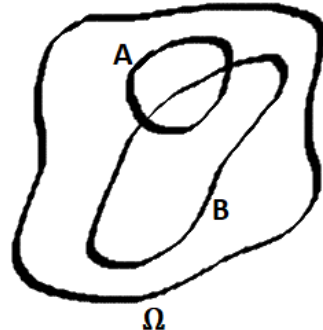
First three conditions are not enough to be certain about independence. Without the last one A, B, C are only pairwise independent.

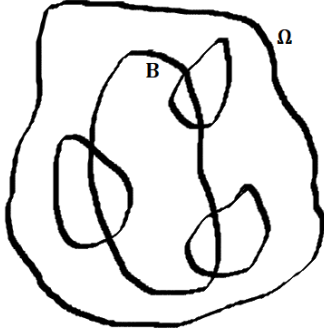
Example: Kolmogorov Cube.

3 Conditional probability

When we want to measure a probability of some particular event, knowing that another one has already occurred we count the conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad \text{where} \quad P(B) > 0.$$





$$P(B^c|B) = \frac{P(B^c \cap B)}{P(B)} = 0$$

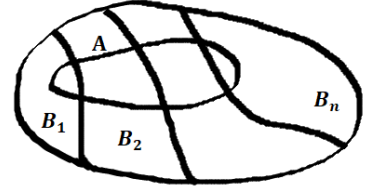
$$\tilde{\mathcal{S}} = \{A \cap B : A \in \mathcal{S}\}$$

Check: $(B, \tilde{\mathcal{S}}, \tilde{P}) \leftarrow \text{probability space}$

$$\tilde{P}(X) = \frac{P(X)}{P(B)}$$

Lets consider such Ω :

$$\Omega = \bigcup_{k=1}^n B_k, B_i \cap B_j = \emptyset, i \neq j \quad \text{where} \quad P(B_i) \neq 0.$$



Now let's count the probability of event A.

$$P(A) = \sum_{k=1}^n P(A \cap B_k) = \sum_{k=1}^n \frac{P(A \cap B_k)}{P(B_k)} P(B_k) = \sum_{k=1}^n P(A|B_k) P(B_k)$$

Fact 3. If A and B are independent, then we have:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A) \cdot P(B)}{P(B)} = P(A).$$

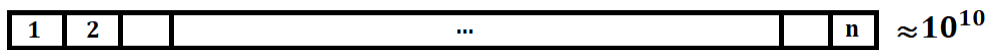
Example: Suppose that we have a dice. We throw it 2 times independently. X_i is the result of i-th throw.

$$P(1) = \dots = P(6) = \frac{1}{6} \quad \left(\equiv \Omega = \{1, \dots, 6\}, P(i) = \frac{1}{6} \right);$$

- $P((X_1 \leq 2) \wedge (X_2 \geq 3)) = P(X_1 \leq 2) \cdot P(X_2 \geq 3) = \frac{2}{6} \cdot \frac{4}{6} = \frac{2}{9};$
- $P(X_1 + X_2 = 4) = \sum_{k=1}^3 P(X_1 + X_2 = 4 | X_1 = k) \cdot P(X_1 = k) = \frac{1}{6} P(X_1 + X_2 = 4 | X_1 = k) = \frac{1}{6} P(X_2 = 4 - k) = \frac{1}{6} \sum_{k=1}^3 \frac{1}{6} = \frac{1}{6} \cdot \frac{3}{6} = \frac{1}{12}.$

4 Streaming

Now let's consider quite large dataset of a size about 10^{10} for which we have a pointer.



$$P(X = i) = \frac{1}{n}; \quad \text{where} \quad i = 1, \dots, n,$$

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X=0
data=NIL
n=0

onGet(A){
  n++;
  if (random() <= 1/n){
    X=n
    data=A
  }
}

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Let us assume that after reading n -th item we have:

$$\forall_{i \in \{1, \dots, n\}} \left(P(X_n = i) = \frac{1}{n} \right).$$

What happens after reading $n + 1$ item?

$$\begin{aligned}
P(X_{n+1} = i) &= P\left(X_{n+1} = i \mid \text{rand}() \leq \frac{1}{n+1}\right) \cdot P\left(\text{rand}() \leq \frac{1}{n+1}\right) \\
&+ \underbrace{P\left(X_{n+1} = i \mid \text{rand}() > \frac{1}{n+1}\right) \cdot P\left(\text{rand}() > \frac{1}{n+1}\right)}_{1 - \frac{1}{n+1}}
\end{aligned}$$

$$P\left(X_{n+1} = i \mid \text{rand}() \leq \frac{1}{n+1}\right) \cdot \frac{1}{n+1} = \begin{cases} i \neq n+1 & \rightsquigarrow 0; \\ i = n+1 & \rightsquigarrow \frac{1}{n+1}; \end{cases}$$

$$P\left(X_{n+1} = i \mid \text{rand}() > \frac{1}{n+1}\right) \cdot \left(1 - \frac{1}{n+1}\right) = \begin{cases} i \neq n+1 & \rightsquigarrow 0; \\ i \leq n & \rightsquigarrow \frac{1}{n} \left(1 - \frac{1}{n+1}\right); \end{cases}$$

$$\frac{1}{n} \left(1 - \frac{1}{n+1}\right) = \frac{1}{n} \cdot \frac{n+1-1}{n+1} = \frac{n}{n(n+1)} = \frac{1}{n+1}$$

Therefore similarly to n -th item we obtain:

$$\forall_{i \in \{1, \dots, n+1\}} \left(P(X_{n+1} = i) = \frac{1}{n+1} \right).$$