

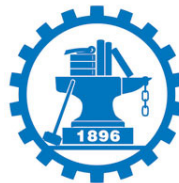
Elements of Information Theory

Lecture 3

Asymptotic Equipartition Property

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Outlines



- **Convergence and Law of Large Number**
- **Asymptotic Equipartition Property**
- **Typical Sequence and Typical Set**
- **High-Probability Sets and Typical Set**

Convergence and LLN

Convergence of a sequence of numbers

A sequence $\{a_n, n = 1, 2, 3, \dots\}$ converges to the constant A if for every ε , there must exist an integer m such that $\forall n > m$, the following inequality holds:

$$|a_n - A| < \varepsilon$$

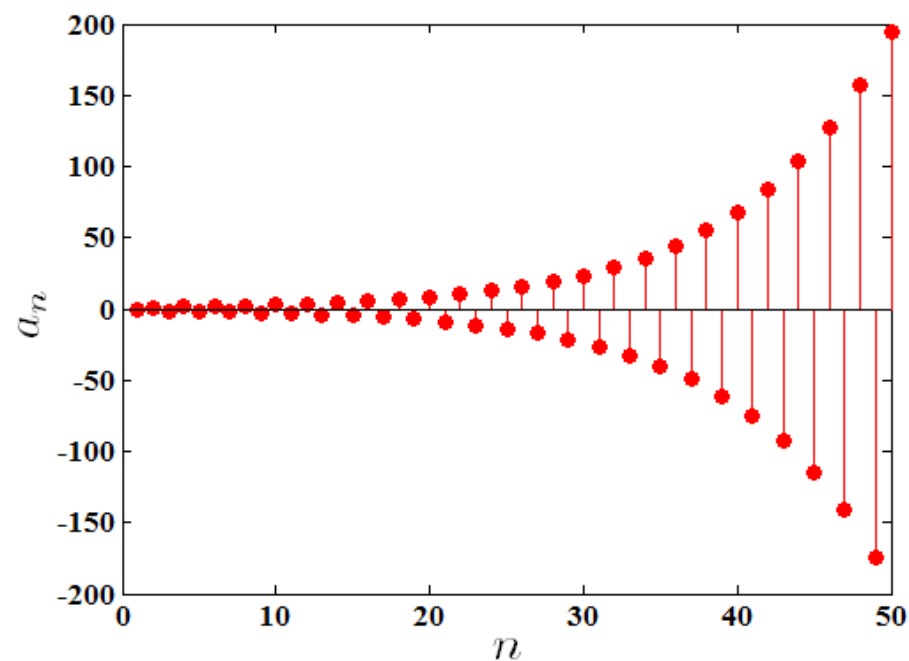
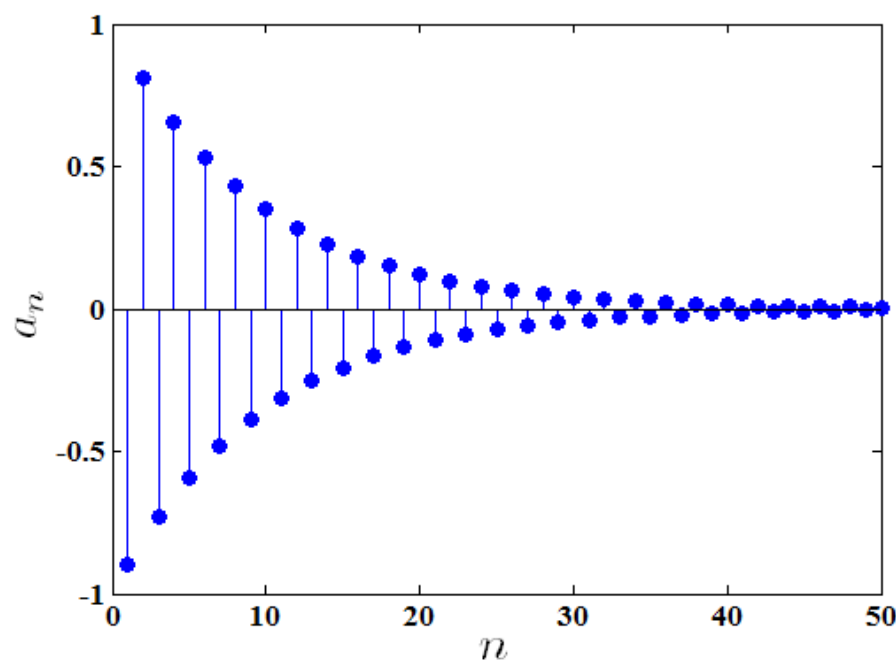
Question:

If the sequence $\{a_n, n = 1, 2, 3, \dots\}$ converges to the constant A , what does it imply?

Convergence and LLN

$$a_n = \left(-\frac{9}{10}\right)^n, \quad n = 1, 2, 3, \dots$$

$$a_n = \left(-\frac{10}{9}\right)^n, \quad n = 1, 2, 3, \dots$$



Can we extend the definition of the convergence for the sequence of number to the random variable case?

Convergence and LLN

Convergence of a sequence of random variables

- *It can also be called as “Stochastic Convergence”.*
- *It is an critically important concept in probabilities as well as other applications.*
- *Formalizing the idea that a sequence of essentially random or unpredictable events can sometimes be expected to settle into a pattern.*
- *There are several approaches to characterize the convergence of the sequence of random variables (stochastic convergence).*

Convergence and LLN

A sequence of random variable $\{X_n, n = 1, 2, 3, \dots\}$ can be viewed as converging to the random variable X

1) Convergence in distribution

$$\lim_{n \rightarrow \infty} F_n(x) = F(x), \text{ where } F_n \text{ and } F \text{ are CDFs of } X_n \text{ and } X$$

2) Convergence in probability

$$\lim_{n \rightarrow \infty} \Pr\{|X_n - X| \geq \varepsilon\} = 0$$

3) Almost sure convergence (with probability 1)

$$\Pr\left\{\lim_{n \rightarrow \infty} X_n = X\right\} = 1$$

4) Convergence in mean

$$\lim_{n \rightarrow \infty} \mathbb{E}\{|X_n - X|^r\} = 0, \text{ where } r \text{ is the real number and } r \geq 1$$

when $r = 2 \implies$ Convergence in mean square

Convergence and LLN

Law of Large Numbers (LLN)

- *It describes the result of performing the same experiment a large number of times.*
- *It was first stated by Italian mathematician Gerolamo Cardano.*
- *A special form of LLN (binary random variable) was proved by Jacob Bernoulli ----- “Bernoulli’s Theorem”*
- *It was further described by S. D. Poisson and named as LLN.*
- *Weak LLN and Strong LLN*

Convergence and LLN

Law of Large Numbers (LLN)

Let X_1, X_2, \dots, X_n be a sequence of independent and identically distributed (i.i.d.) random variables with expected (mean) value:

$$\mathbb{E}\{X_1\} = \mathbb{E}\{X_2\} = \dots = \mathbb{E}\{X_n\} = \mu$$

Then, the LLN tells us that the sample average

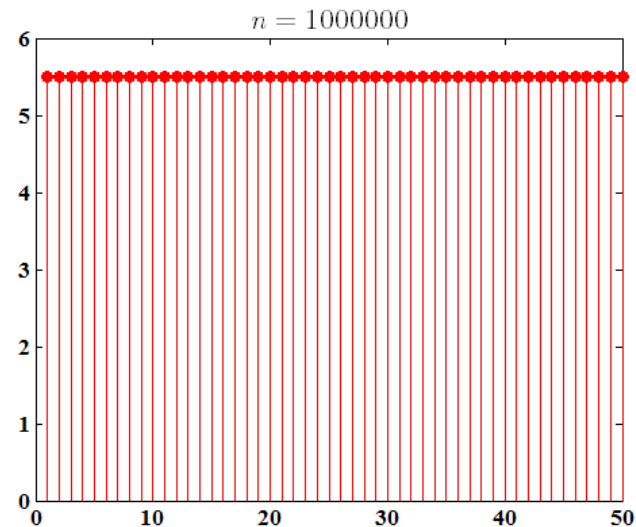
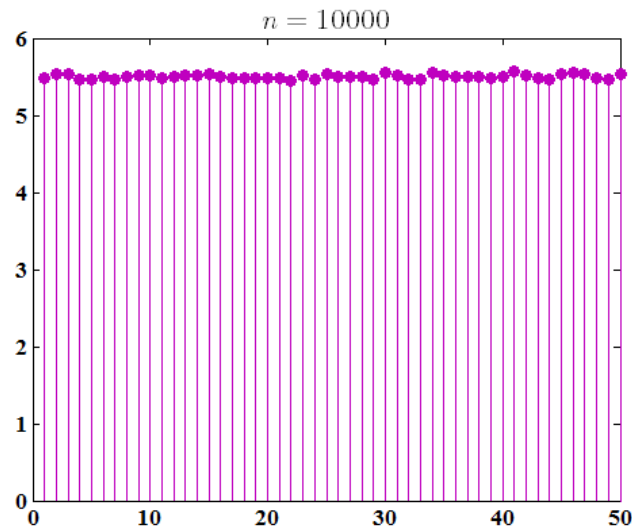
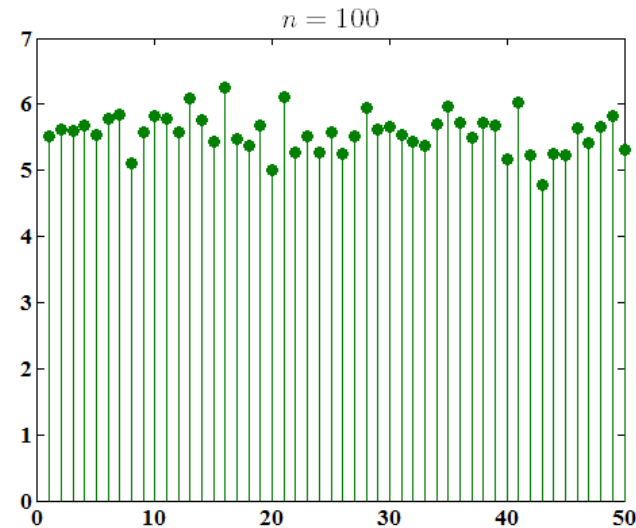
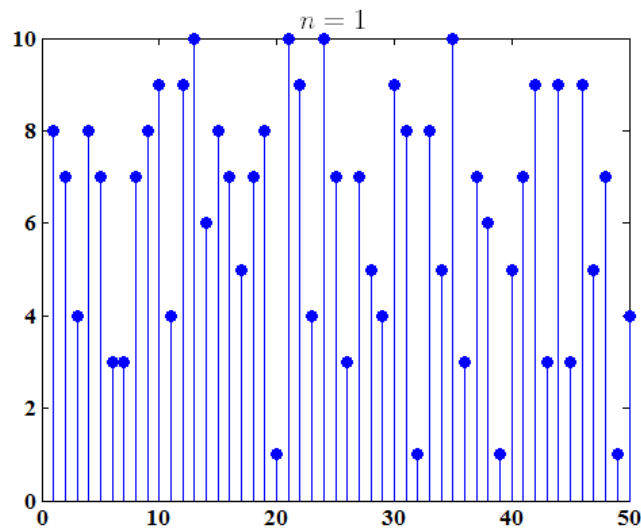
$$\bar{X}_n = \frac{1}{n} (X_1 + X_2 + \dots + X_n)$$

converges to the expected value, i.e.,

$$\bar{X}_n \longrightarrow \mu \quad \text{for } n \rightarrow \infty$$

Convergence and LLN

X_n is uniformly distributed on $\{1, 2, \dots, 10\}$. $\bar{X}_n = \frac{X_1 + \dots + X_n}{n}$



Convergence and LLN

➤ Weak Law

The sample value of the sequence of i.i.d. random variables X_1, X_2, \dots, X_n converges in probability towards the expected value. That is to say for any positive number ε , we have

$$\lim_{n \rightarrow \infty} \Pr \left\{ |\bar{X}_n - \mu| > \varepsilon \right\} = 0$$

➤ Strong Law

The sample value of the sequence of i.i.d. random variables X_1, X_2, \dots, X_n converges almost surely to the expected value, i.e.,

$$\Pr \left\{ \lim_{n \rightarrow \infty} \bar{X}_n = \mu \right\} = 1$$

Outlines



- **Convergence and Law of Large Number**
- **Asymptotic Equipartition Property**
- **Typical Sequence and Typical Set**
- **High-Probability Sets and Typical Set**

Asymptotic Equipartition Property

Example

We consider a sequence

$$\mathbf{u}_L = (u_1, u_2, \dots, u_L), \quad u_l \in \{s_1, \dots, s_K\}$$

Then, the self-information of this sequence is

$$I(\mathbf{u}_L) = \sum_{l=1}^L I(u_l) = L_1 I(s_1) + L_2 I(s_2) + \dots + L_K I(s_K),$$

where L_k denotes the number of symbol s_k in the sequence.

For example, we consider the following sequence

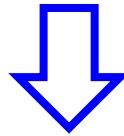
$$\mathbf{u}_L = (1, 2, 0, 3, 5, 2, 1, 2, 3)$$

Then, we have

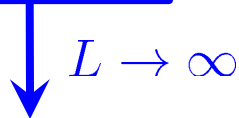
$$I(\mathbf{u}_L) = 1 \cdot I(0) + 2 \cdot I(1) + 3 \cdot I(2) + 2 \cdot I(3) + 1 \cdot I(5)$$

Asymptotic Equipartition Property

$$I(\mathbf{u}_L) = \sum_{l=1}^L I(u_l) = L_1 I(s_1) + L_2 I(s_2) + \cdots + L_K I(s_K)$$



$$\frac{1}{L} I(\mathbf{u}_L) = \boxed{\frac{1}{L} \sum_{l=1}^L I(u_l)} = \frac{L_1}{L} I(s_1) + \frac{L_2}{L} I(s_2) + \cdots + \frac{L_K}{L} I(s_K)$$



Converging to the expected value of $I(u_l)$

Questions

- 1. What is the expected value of the self-information?**
- 2. What can we obtain from this example?**

Asymptotic Equipartition Property

Theorem (Asymptotic Equipartition Property, AEP)

Let X_1, X_2, \dots, X_n be the sequence of i.i.d. random variables with distribution $p(x)$, then we have

$$-\frac{1}{n} \log p(X_1, X_2, \dots, X_n) \rightarrow H(X) \quad \text{in probability,}$$

i.e.,

$$\lim_{n \rightarrow \infty} \Pr \left\{ \left| -\frac{1}{n} \log p(X_1, X_2, \dots, X_n) - H(X) \right| > \varepsilon \right\} = 0, \quad \forall \varepsilon > 0.$$

It is derived by weak LLN. \longrightarrow Weak AEP

Asymptotic Equipartition Property

Strong LLN \longrightarrow Strong AEP

Strong AEP

Let X_1, X_2, \dots, X_n be the sequence of i.i.d. random variables with distribution $p(x)$, then we have

$$-\frac{1}{n} \log p(X_1, X_2, \dots, X_n) \rightarrow H(X) \quad \text{with probability 1,}$$

i.e.,

$$\Pr \left\{ \lim_{n \rightarrow \infty} -\frac{1}{n} \log p(X_1, X_2, \dots, X_n) = H(X) \right\} = 1.$$

Questions:

- 1. What is the relationship between LLN and AEP?**
- 2. Why is it named as AEP?**

Outlines



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- **Typical Sequence and Typical Set**
- **High-Probability Sets and Typical Set**

Typical Sequence and Typical Set

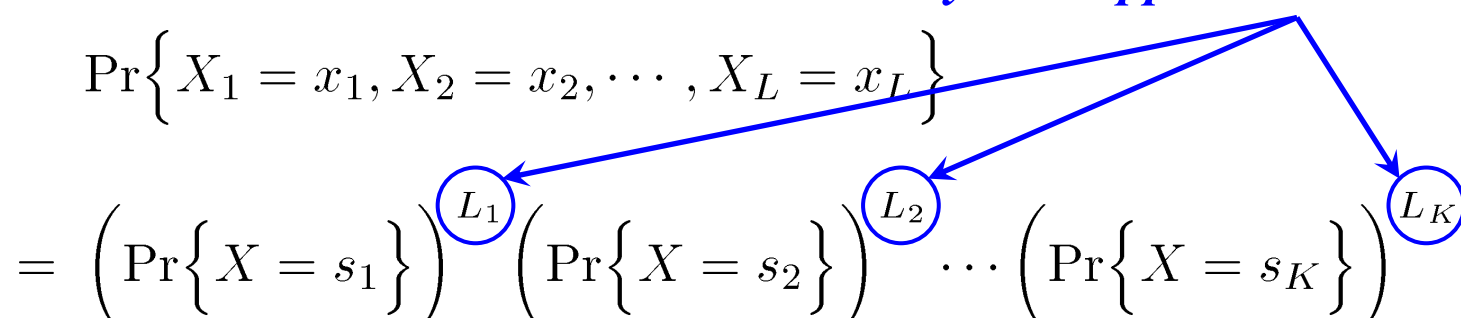
We consider a sequence of i.i.d. random variables

$$\mathbf{X}_L = (X_1, X_2, \dots, X_L), \quad X_i \in \{s_1, \dots, s_K\}$$

with distribution $p(x)$.

Then, the probability of event (x_1, x_2, \dots, x_L) can be written as

The number of the corresponding symbol appeared in the sequence

$$\Pr\{X_1 = x_1, X_2 = x_2, \dots, X_L = x_L\}$$

$$= \left(\Pr\{X = s_1\}\right)^{L_1} \left(\Pr\{X = s_2\}\right)^{L_2} \cdots \left(\Pr\{X = s_K\}\right)^{L_K}$$

Different sequences usually have distinct probabilities.

Typical Sequence and Typical Set

Different sequences usually have distinct probabilities.

$$\begin{aligned} & \Pr\{X_1 = x_1, X_2 = x_2, \dots, X_L = x_L\} \\ &= \left(\Pr\{X = s_1\}\right)^{L_1} \left(\Pr\{X = s_2\}\right)^{L_2} \cdots \left(\Pr\{X = s_K\}\right)^{L_K} \end{aligned}$$

For example, we consider the random variable $X \in \{0,1\}$ with $P(0) = 0.3$ and $P(1) = 0.7$. Then, for the following two sequences, we have

$$\Pr\{x_9^1 = (1, 1, 1, 1, 1, 1, 0, 0, 0)\} = 0.0032$$

$$\Pr\{x_9^2 = (0, 0, 0, 0, 0, 0, 1, 1, 1)\} = 0.00025$$

What will happen if L goes to infinite?

Typical Sequence and Typical Set

Weak Asymptotic Equipartition Property

$$\lim_{L \rightarrow \infty} \Pr \left\{ \left| -\frac{1}{L} \log P(X_1, X_2, \dots, X_L) - H(X) \right| \leq \varepsilon \right\} = 1, \quad \forall \varepsilon > 0$$

$$2^{-L(H(X)+\varepsilon)} \leq P(X_1, X_2, \dots, X_L) \leq 2^{-L(H(X)-\varepsilon)}, \quad \forall \varepsilon > 0 \text{ and } L \rightarrow \infty$$

When $L \rightarrow \infty$, different sequences have approximately the same probabilities.

Approximately equal partition on probability

Typical Sequence and Typical Set

We consider a sequence of i.i.d. random variables

$$\mathbf{X}_L = (X_1, X_2, \dots, X_L), \quad X_i \in \{s_1, \dots, s_K\}$$

with distribution $p(x)$.

For different realizations, the numbers of symbols s_1, \dots, s_K are different.

For example, we consider the following two sequences

$$\mathbf{x}_9^1 = (1, 1, 1, 1, 1, 1, 0, 0, 0)$$

$$\mathbf{x}_9^2 = (0, 0, 0, 0, 0, 0, 1, 1, 1)$$

What will happen if L goes to infinite?

Typical Sequence and Typical Set

Strong Asymptotic Equipartition Property



Strong Law of Large Numbers



$$\Pr\left\{\lim_{L \rightarrow \infty} \frac{1}{L} \sum_{i=1}^L X_i = \mathbb{E}\{X\}\right\} = 1$$



$$\forall \mathbf{x}_L = (x_1, \dots, x_L) \Rightarrow \frac{1}{L} \sum_{i=1}^L x_i = \mathbb{E}\{X\}, \text{ if } L \rightarrow \infty$$

$$\sum_{k=1}^K \left[\frac{L_k}{L} - P(s_k) \right] s_k = 0, \text{ if } L \rightarrow \infty$$

The empirical distribution in sequence \mathbf{x}_L should be “close” to the prior probability distribution.

Typical Sequence and Typical Set

We consider a sequence of i.i.d. random variables

$$\mathbf{X}_L = (X_1, X_2, \dots, X_L), \quad X_i \in \{s_1, \dots, s_K\}$$

with distribution $p(x)$.

Then, the probability of event (x_1, x_2, \dots, x_L) can be written as

$$\begin{aligned} & \Pr\{X_1 = x_1, X_2 = x_2, \dots, X_L = x_L\} \\ &= \left(\Pr\{X = s_1\}\right)^{L_1} \left(\Pr\{X = s_2\}\right)^{L_2} \cdots \left(\Pr\{X = s_K\}\right)^{L_K} \end{aligned}$$

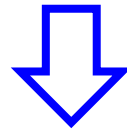
Different sequences usually have distinct probabilities.

Typical Sequence and Typical Set

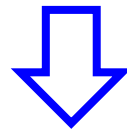
Different sequences usually have distinct probabilities.

$$\begin{aligned} & \Pr\{X_1 = x_1, X_2 = x_2, \dots, X_L = x_L\} \\ &= \left(\Pr\{X = s_1\}\right)^{L_1} \left(\Pr\{X = s_2\}\right)^{L_2} \cdots \left(\Pr\{X = s_K\}\right)^{L_K} \end{aligned}$$

Strong Asymptotic Equipartition Property



Empirical distribution = Prior probability distribution



Constant and equal to $2^{-LH(X)}$ when L goes to infinity.

Typical Sequence and Typical Set

Definition (Weakly Typical Sequence)

Let $X \sim p(x)$. Then, the sequence

$$(x_1, x_2, \dots, x_n) \in \mathcal{X}^n$$

is weakly typical sequence if

$$\left| -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) - H(X) \right| \leq \varepsilon.$$

Definition (Strongly Typical Sequence)

Let $X \sim p(x)$. Then, the sequence

$$(x_1, x_2, \dots, x_n) \in \mathcal{X}^n$$

is strongly typical sequence if the empirical distribution of each symbol is “close” to its prior probability distribution.

Typical Sequence and Typical Set

Definition (Weakly Typical Set)

The weakly typical set $A_\epsilon^{(n)}$ with respect to $p(x)$ is the set of sequences

$$(x_1, x_2, \dots, x_n) \in \mathcal{X}^n$$

with the property

$$\left| -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) - H(X) \right| \leq \epsilon.$$

Definition (Strongly Typical Set)

The strongly typical set $\mathcal{T}_\epsilon^{(n)}$ with respect to $p(x)$ is the set of sequences

$$(x_1, x_2, \dots, x_n) \in \mathcal{X}^n$$

with the property

$$\forall a \in \mathcal{X}, \quad \left| \frac{1}{n} N(a; x^n) - p(a) \right| \leq \epsilon p(a),$$

where $N(a; x^n)$ is the number of occurrences of symbol a in sequence.

Typical Sequence and Typical Set

- *Strong typical set v.s. Weak typical set*
 - *Strong typical set – Strong typical sequence*
 - *Weak typical set – Weak typical sequence*

Example

- ✓ $X = \{a,b,c,d\}$ with probability distribution $\{0.5, 0.25, 0.125, 0.125\}$
- ✓ Sample sequences consisting of 8 i.i.d. samples
- ✓ Strong typical sequence
 - Symbols with correct proportions, e.g., *aaaabbcd*
- ✓ Weak typical sequence
 - Self-information per symbol equals to the entropy, e.g., *aabbbbbbb*

Typical Sequence and Typical Set

Example

- ✓ *Bit-sequences of length n*
- ✓ *The probability distribution is $P(1) = p$ and $P(0) = 1-p$*
- ✓ *Strong typicality?*
- ✓ *Weak typicality?*
- ✓ *What will happen when $p=0.5$?*

Some Discussions

1. *All sequence in the typical set have roughly equal probabilities.*
2. *Most or least likely sequences may NOT be in the typical set.*

Typical Sequence and Typical Set

Properties of (Weakly) Typical Set

1. If $(x_1, x_2, \dots, x_n) \in A_\epsilon^{(n)}$, then we have

$$H(X) - \epsilon \leq -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \leq H(X) + \epsilon$$

2. $\Pr\{A_\epsilon^{(n)}\} > 1 - \epsilon$ for n sufficiently large.

3. $|A_\epsilon^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where $|A|$ denotes the number of elements in the set A .

4. $|A_\epsilon^{(n)}| \geq (1 - \epsilon)2^{n(H(X)-\epsilon)}$ for n sufficiently large.

Typical Sequence and Typical Set

1. *If $(x_1, x_2, \dots, x_n) \in A_{\epsilon}^{(n)}$, then we can obtain from the definition of weak typical set that*

$$\left| -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) - H(X) \right| \leq \epsilon$$

$$H(X) - \epsilon \leq -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \leq H(X) + \epsilon$$

2. *Based on weak AEP, we have*

$$\lim_{n \rightarrow \infty} \Pr \left\{ \left| -\frac{1}{n} \log p(X_1, X_2, \dots, X_n) - H(X) \right| > \epsilon \right\} = 0, \quad \forall \epsilon > 0$$

For any given $\delta > 0$, there must exist n_0 such that when $n > n_0$, we have

$$\Pr \left\{ \left| -\frac{1}{n} \log p(X_1, X_2, \dots, X_n) - H(X) \right| \leq \epsilon \right\} > 1 - \delta$$

— *Let $\delta = \epsilon$, we have $\Pr \left\{ A_{\epsilon}^{(n)} \right\} > 1 - \epsilon$.*

Typical Sequence and Typical Set

3. Proof for property (3)

$$H(X) - \epsilon \leq -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \leq H(X) + \epsilon$$

$$2^{-n[H(X)+\epsilon]} \leq p(x_1, x_2, \dots, x_n) \leq 2^{-n[H(X)-\epsilon]}$$

$$1 = \sum_{\mathbf{x} \in \mathcal{X}^n} p(\mathbf{x}) \geq \sum_{\mathbf{x} \in A_\epsilon^{(n)}} p(\mathbf{x}) \geq \sum_{\mathbf{x} \in A_\epsilon^{(n)}} 2^{-n[H(X)+\epsilon]} = 2^{-n[H(X)+\epsilon]} |A_\epsilon^{(n)}|$$

4. Proof for property (4)

$$\begin{aligned} 1 - \epsilon < \Pr\{A_\epsilon^{(n)}\} &= \sum_{\mathbf{x} \in A_\epsilon^{(n)}} p(\mathbf{x}) \\ &\leq \sum_{\mathbf{x} \in A_\epsilon^{(n)}} 2^{-n[H(X)-\epsilon]} = 2^{-n[H(X)-\epsilon]} |A_\epsilon^{(n)}| \end{aligned}$$

Outlines



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- **High-Probability Sets and Typical Set**

High- Probability Sets and Typical Set

- Typical set is a fairly small set that contains most of the probability.
- It is not clear whether it is the smallest such set.

Definition (Smallest Set)

For each $n=1,2,\dots$, let $B_{\delta}^{(n)} \subset \mathcal{X}^n$ be the smallest set with

$$\Pr\left\{B_{\delta}^{(n)}\right\} \geq 1 - \delta$$

- *The smallest set is different from the typical set.*
- *The smallest set must have significant intersection with the typical set and therefore must have about as many elements.*

High- Probability Sets and Typical Set

Theorem

Let X_1, X_2, \dots, X_n be i.i.d. random variables with probability distribution $p(x)$. For $\delta < 1/2$ and any $\delta' > 0$, if

$$\Pr\left\{B_{\delta}^{(n)}\right\} \geq 1 - \delta$$

is satisfied, that we have

$$\frac{1}{n} \log \left| B_{\delta}^{(n)} \right| > H - \delta'$$

for n sufficiently large.

The theorem tells us $B_{\delta}^{(n)}$ must have at least 2^{nH} elements and is about the same size as the $A_{\epsilon}^{(n)}$.

Summary

➤ AEP

$$-\frac{1}{n}\log p(X_1, X_2, \dots, X_n) \rightarrow H(X) \quad \text{in probability}$$

➤ Typical Set

$$2^{-n(H(X)+\varepsilon)} \leq p(x_1, x_2, \dots, x_n) \leq 2^{-n(H(X)-\varepsilon)}$$

➤ Properties

1. If $(x_1, x_2, \dots, x_n) \in A_\epsilon^{(n)}$, then

$$H(X) - \epsilon \leq -\frac{1}{n}\log p(x_1, x_2, \dots, x_n) \leq H(X) + \epsilon$$

2. $\Pr \{ A_\epsilon^{(n)} \} > 1 - \epsilon$ for n sufficiently large.

3. $|A_\epsilon^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where $|A|$ denotes the number of elements in the set A .