INFORMATION THEORY & CODING

Week 4: Asymptotic Equipartition Property (AEP)
以新近集分性)

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Stock Market

 Initial investment Y₀, daily return ratio r_i, in t-th day, your money is

$$Y_t = Y_0 r_1 \cdot \ldots \cdot r_t$$
.

• Now if returns ratio r_i are i.i.d., with

$$r_i = \begin{cases} 4, & \text{w.p. } 1/2 \\ 0, & \text{w.p. } 1/2 \end{cases}$$

- So you think the expected return ratio is $E[r_i] = 2$.
- And then

$$E[Y_t] = E[Y_0r_1 \cdot ... \cdot r_t] = Y_0(E[r_i])^t = Y_02^t$$
???



Stock Market

- With $Y_0 = 1$, actual return Y_t goes like
 - 1 4 16 0 0 ...

- Why?
 - The 'typical' sequences will end up with 0 return.
 - Occasionally, we got high return.
 - The expected return is increasing.
 - Expectation does not show the typical feature of this random sequence. We can turn to typical set.



Weak Law of Large Numbers (数)

Theorem (Weak Law of Large Numbers) Suppose that X_1, X_2, \ldots, X_n are n independent, identically distributed (i.i.d.) random variables, then

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$$\frac{1}{n} \sum_{i=1}^{n} X_i \stackrel{\uparrow}{\to} E[X] \qquad \text{in probability},$$

i.e. for every number $\epsilon > 0$,

$$\lim_{n\to\infty} \Pr\left[\left|\frac{1}{n}\sum_{i=1}^n X_i - E[X]\right| \le \epsilon\right] = 1.$$



Definition (Convergence of random variables)

Given a sequence of random variables, X_1, X_2, \ldots , we say that the sequence X_1, X_2, \ldots converges to a random variable X:

- **1** In probability if for every $\epsilon > 0$, $\Pr[|X_n X| \ge \epsilon] \to 0$
- ② In mean square if $E[(X_n X)^2] \rightarrow 0$
- With probability 1 (a.k.a. almost surely) if $\Pr[\lim_{n\to\infty}X_n=X]=1$



Asymptotic Equipartition Property (AEP) $\forall \xi > 0$, $\lim_{N \to \infty} P_r[-\frac{1}{N} \log (X_1 - \dots - X_N)] = 1$.

Theorem 3.1.1 (AEP) joint distribution. If X_1, X_2, \ldots are i.i.d. $\sim p(x)$, then

If
$$X_1, X_2, \ldots$$
 are i.i.d. $\sim p(x)$, then
$$-\frac{1}{n}\log p(X_1, X_2, \ldots, X_n) \to H(X) \qquad \text{in probability}.$$

Proof.

Since X_i are i.i.d., so are $\log p(X_i)$. Hence, by the weak law of large numbers,

$$-\frac{1}{n}\log p\left(X_{1},X_{2},\ldots,X_{n}\right)=-\frac{1}{n}\sum_{i}\log p\left(X_{i}\right)$$

$$\overrightarrow{\text{will}}\overrightarrow{U}.^{-}E[\log p(X)] \qquad \text{in probability}$$

$$=H(X)$$

Typical Set

Definition

A *typical set* $A_{\epsilon}^{(n)}$ contains all sequence realizations $(x_1, x_2, \dots, x_n) \in \mathcal{X}^n$ with

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

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$$-\epsilon \leq -\frac{1}{h} \log p(X_1, X_2, \dots, X_n) - H(X) \leq \epsilon$$

$$H(X) - \epsilon \leq -\frac{1}{h} \log p(X_1, X_2, \dots, X_n) \leq H(X) + \epsilon$$

$$2^{-n[H(X) + \epsilon]} \leq p(X_1, X_2, \dots, X_n) \leq 2^{-n[H(X) - \epsilon]}$$

$$\Rightarrow p(X_1, X_2, \dots, X_n) \approx 2^{-nH(X)} \Rightarrow \text{Region partition.}$$

$$A_{e}^{(n)} = \left\{ (\chi_{1}, \dots, \chi_{n}) \mid + \frac{1}{n} \log p(\chi_{1}, \chi_{2}, \dots, \chi_{n}) - H(\chi) \right\} \leq \epsilon$$



Theorem 3.1.2

- If $(x_1, x_2, ..., x_n) \in A_{\epsilon}^{(n)}$, then $H(X) - \epsilon \le -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \le H(X) + \epsilon.$
- $\Pr[(X_1, X_2, ..., X_n) \in A_{\epsilon}^{(n)}] > 1 \epsilon$ for n sufficiently large.
- $|A_{\epsilon}^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where |A| denotes the cardinality of the set A.
- $|A_{\epsilon}^{(n)}| > (1-\epsilon)2^{n(H(X)-\epsilon)}$ for n sufficiently large.

Proof.

. Immediate from the definition of $A_{\epsilon}^{(n)}$.

The number of bits used to describe sequences in typical set is approximately nH(X).

 $\Rightarrow \forall \delta, \exists \Lambda_{0}, \text{ for } n \geq \Lambda_{0}$ $Pr[\left| -\frac{1}{n} \log P(X_{1}, \dots, X_{n}) - H(X) \right| \leq \epsilon \right] \in (F \delta, I]$ $Pr[\left| (X_{1}, \dots, X_{n}) \in A_{\epsilon}^{(N)} \right| \geq 1 - \delta > 1 - \epsilon$ $| \geq \sum_{(X_{1}, X_{2}, \dots, X_{n})} P(X_{1}, X_{2}, \dots, X_{n}) > 1 + \epsilon \text{ for large } n$ $| (X_{1}, X_{2}, \dots, X_{n}) \in A_{\epsilon}^{(N)}$ $| (Y_{1}, X_{2}, \dots, X_{n}) \in A_{\epsilon}^{(N)}$ for largen

→ tE>O, lim Pr[|-tlog P(X, -... Xn)-H(X)|=E]=|

Theorem 3.1.2

- If $(x_1, x_2, \dots, x_n) \in A_{\epsilon}^{(n)}$, then $H(X) \epsilon \le -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \le H(X) + \epsilon.$
- $\Pr[A_{\epsilon}^{(n)}] > 1 \epsilon$ for n sufficiently large.
- $|A_{\epsilon}^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where |A| denotes the cardinality of the set A.
- $|A_{\epsilon}^{(n)}| \ge (1 \epsilon)2^{n(H(X) \epsilon)}$ for n sufficiently large.

Proof.

2. By Theorem 3.1.1, the probability of the event $(X_1, X_2, \ldots, X_n) \in A_{\epsilon}^{(n)}$ tends to 1 as $n \to \infty$. Thus, for any $\delta > 0$, there exists an n_0 such that for all $n \ge n_0$, we have

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

Setting $\delta = \epsilon$, the conclusion follows.

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Theorem 3.1.2

- If $(x_1, x_2, \dots, x_n) \in A_{\epsilon}^{(n)}$, then $H(X) \epsilon \le -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \le H(X) + \epsilon.$
- $\Pr[A_{\epsilon}^{(n)}] > 1 \epsilon$ for n sufficiently large.
- $|A_{\epsilon}^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where |A| denotes the cardinality of the set A.
- $|A_{\epsilon}^{(n)}| \ge (1 \epsilon)2^{n(H(X) \epsilon)}$ for n sufficiently large.

Proof.

3.

$$1 = \sum_{\mathbf{x} \in \mathcal{X}^n} p(\mathbf{x}) \ge \sum_{\mathbf{x} \in A_{\epsilon}^{(n)}} p(\mathbf{x})$$

$$\ge \sum_{\mathbf{x} \in A_{\epsilon}^{(n)}} 2^{-n(H(X) + \epsilon)}$$

$$= 2^{-n(H(X) + \epsilon)} \left| A_{\epsilon}^{(n)} \right|.$$

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Theorem 3.1.2

- If $(x_1, x_2, \dots, x_n) \in A_{\epsilon}^{(n)}$, then $H(X) \epsilon \le -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \le H(X) + \epsilon.$
- $\Pr[A_{\epsilon}^{(n)}] > 1 \epsilon$ for n sufficiently large.
- $|A_{\epsilon}^{(n)}| \leq 2^{n(H(X)+\epsilon)}$, where |A| denotes the cardinality of the set A.
- $|A_{\epsilon}^{(n)}| \ge (1 \epsilon)2^{n(H(X) \epsilon)}$ for n sufficiently large.

Proof.

4. For sufficiently large n, $\Pr[A_{\epsilon}^{(n)}] > 1 - \epsilon$, so that

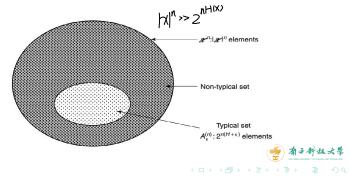
$$\begin{split} 1 - \epsilon &< \Pr\left[A_{\epsilon}^{(n)}\right] \\ &\leq \sum_{\mathbf{x} \in A_{\epsilon}^{(n)}} 2^{-n(H(X) - \epsilon)} \\ &= 2^{-n(H(X) - \epsilon)} \left|A_{\epsilon}^{(n)}\right|. \end{split}$$

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Typical set diagram

This enables us to divide all sequences into two sets

- Typical set: high probability to occur, sample entropy is close to true entropy
 - so we will focus on analyzing sequences in typical set
- Non-typical set: small probability, can ignore in general





Theorem 3.2.1

Let $X_1, X_2, ..., X_n$ be i.i.d. random variables with distribution p(x), and $X^n = X_1 X_2 ... X_n$. For arbitrarily small $\epsilon > 0$, there exists a code that maps every realization $x^n = x_1 x_2 ... x_n$ of X^n into one binary string, such that the mapping is one-to-one (and therefore invertible) and

$$E\left[\frac{1}{n}\ell(X^n)\right] \leq H(X) + \epsilon$$

for a sufficiently large n.



需要的性数. 平均比特数 < (1-E) [h[HKX)te]t2] t @ [nlog_|X)+2]
< n[H(X)te]+2+e[nlog_|X|+2] $A_{\epsilon}^{(n)} :\leq n [H(x)t \epsilon] + 2$ $\overline{A_C^{(n)}} := n \log_2 |\chi| + 2$.

判極情景所需的收拾 E H(x)te+元+G[log_lX]t元]

Theorem 3.2.1

$$E\left[\frac{1}{n}\ell(X^n)\right] \leq H(X) + \epsilon.$$

for n sufficiently large.

Proof.

Description in typical set requires no more than $n(H(X) + \epsilon) + 1$ bits (correction of 1 bit because of integrality).

Description in atypical set $A_{\epsilon}^{(n)^{C}}$ requires no more than $n \log |\mathcal{X}| + 1$ bits.

Add another bit to indicate whether in $A_{\epsilon}^{(n)}$ or not to get whole description.



Theorem 3.2.1

$$E[\frac{1}{n}\ell(X^n)] \le H(X) + \epsilon.$$

for n sufficiently large.

Proof.

Let $\ell(x^n)$ be the length of the binary description of x^n . Then, $\forall \epsilon > 0$, there exists n_0 s.t. $\forall n > n_0$, $E\left(\ell\left(X^{n}\right)\right) = \sum p\left(X^{n}\right)\ell\left(X^{n}\right)$ $= \sum_{x^n \in A_{\epsilon}^{(n)}} p(x^n) \ell(x^n) + \sum_{x^n \in A_{\epsilon}^{(n)^C}} p(x^n) \ell(x^n)$ $\leq \sum p(x^n)(n(H+\epsilon)+2)+\sum p(x^n)(n\log|\mathcal{X}|+2)$ $x^n < A^{(n)}$ $=\Pr[A_{\epsilon}^{(n)}](n(H+\epsilon)+2)+\Pr[A_{\epsilon}^{(n)}](n\log|\mathcal{X}|+2)$ $\leq n(H+\epsilon) + \epsilon n(\log |\mathcal{X}|) + 2$ $=n(H+\epsilon')$

where $\epsilon' = \epsilon + \epsilon \log |\mathcal{X}| + \frac{2}{n}$ can be made arbitrarily small by choosing n properly.

Reading & Homework

Reading: 2.10 and whole Chapter 3

Homework: Problems 2.32, 3.8, 3.10

