## Lecture 4

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## 1. Today's outline

a. Asymptotic Equipartition Property (A.E.P.)
b. Typical sets
c. Application to data compression

## 2. Review of last lecture

## Notions:

- $\quad H(x), H(x / y), I(x ; y), I(x ; y / z)$
- $D(p / / q)=\sum_{x} p(x) \log \frac{p(x)}{q(x)} \quad$ which is measure of the inefficiency of assuming that the distribution of x is $\mathrm{q}(\mathrm{x})$ when the true distribution is $\mathrm{p}(\mathrm{x})$.
- Markov chain: $X \rightarrow Y \rightarrow Z$ or equivalently $p_{x, y / z}=p_{x / y} p_{z / y}$

Results:

- $\quad D(p / / q) \geq 0$ with equality when $p(x)=q(x)$
- $\quad I(x ; y)=D\left(p_{x, y} / / p_{x} p_{y}\right) \geq 0$
- $H(x / y)=H(x)-I(x ; y) \leq H(x)$
- chain rule: $H\left(x_{1}, \ldots, x_{n}\right) \leq \sum_{i=1}^{n} H\left(x_{i}\right)$
- If $X \rightarrow Y \rightarrow Z$ then $I(x ; z) \leq I(x ; y)$
- If $X \rightarrow Y \rightarrow \hat{X}$ then Fano's inequality: $\operatorname{Pr}(X \neq \hat{X})=P_{e} \geq \frac{H(x / y)-1}{\log \left|\Omega_{x}\right|}$


### 2.1. Review of Fano's inequality

We give two examples which show that Fano's inequality can be either weak or tight.

### 2.1.1. Example 1

$x$ is uniformly distributed over the set of binary n-tuples and $y$ takes values from the set of binary $n / 2$-tuples. I claim no matter distribution I pick for $y, H(x / y) \geq n / 2$.

We have:

$$
\begin{aligned}
& H(x)=\log \left|\Omega_{x}\right|=\log _{2} 2^{n}=n \\
& H(y) \leq \log \left|\Omega_{y}\right|=\log _{2} 2^{n / 2}=n / 2 \\
& H(x / y)=H(x)-I(x ; y)=n-I(x ; y) \\
& I(x ; y)=H(y)-H(y / x) \leq H(y) \leq n / 2
\end{aligned}
$$

Thus, $H(x / y) \geq n / 2$.
Fano's inequality yields (assuming big n):

$$
P_{e} \geq \frac{H(x / y)-1}{\log \left|\Omega_{x}\right|} \approx \frac{n / 2}{n}=0.5
$$

A better bound on $P_{e}$ in this case is:

$$
P(\text { correct decoding }) \leq \frac{2^{n / 2}}{2^{n}} \Rightarrow P(\text { error }) \geq 1-\frac{2^{n / 2}}{2^{n}}
$$

In this example Fano's inequality is very weak!

### 2.1.2. Example 2

$x, y$ are distributed as follows: with probability $p, x=y$, and $x, y$ are uniformly distributed over the set of binary m-tuples and with probability 1-p, $x$ is uniformly distributed over the set of binary n-tuples and $y$ is a constant.

This is the picture of an erasure channel. The best strategy would decode as follows: observe y and assume that this is what it was sent. Obviously $P_{e}=p$ in this case. Fano's inequality yields:
$H(x / y)=p \cdot H(x / y=$ const $)+(1-p) \cdot H(x / y=x)=p \cdot n+0=p \cdot n$ $P_{e} \geq \frac{p \cdot n-1}{n} \approx p$

## 3. Typical sets

We want to answer the following question: if $x_{1}, \ldots, x_{n}$ are iid and $x_{i} \sim p(x), i=1 \ldots n$, what is the probability of the sequence $\left(x_{1}, \ldots, x_{n}\right)$ to occur an $n$ goes large? This will lead us to divide
the set of the sequences into two sets, the typical set, which contains the "highly likely to occur" sequences and the non-typical set which contains all the other sequences.


Actual universe of typical sequences

We will use the law of large numbers to answer the above question.

### 3.1. A.E.P. Lemma

If $x_{1}, \ldots, x_{n}$ are i.i.d. according to $p(x)$ then $-\frac{\log p\left(x_{1} \ldots x_{n}\right)}{n} \rightarrow H(x)$ in probability. In other words: for every $\varepsilon>0, \delta>0$ there exists $n_{o}(\delta, \varepsilon)$ such that for every $n>n_{o}(\delta, \varepsilon)$ the $\operatorname{Pr}\left\{H(x)-\varepsilon \leq-\frac{\log p\left(x_{1} \ldots x_{n}\right)}{n} \leq H(x)+\varepsilon\right\} \geq 1-\delta$. (Actually $\delta$ goes to 0 as $\left.\exp \left(-n \varepsilon^{2}\right)\right)$.

Proof: Note that $p\left(x_{1}, \ldots, x_{n}\right)$ is the probability of observing the sequence $\left(x_{1}, \ldots, x_{n}\right)$. We have that $\mathrm{x}_{\mathrm{i}}$ are iid so:

$$
\frac{1}{n} \log p\left(x_{1} \ldots x_{n}\right)=\frac{1}{n} \log \coprod_{i=1}^{n} p\left(x_{i}\right)=\frac{1}{n} \sum_{i=1}^{n} \log p\left(x_{i}\right)
$$

Let us call a new r.v. $z_{i}=-\log p\left(x_{i}\right)$. The $\mathrm{z}_{\mathrm{i}}$ 's are also i.i.d. and $E[z]=H(x)$. Applying the law of large numbers we have:

$$
-\frac{1}{n} \sum_{i=1}^{n} \log p\left(x_{i}\right)=\frac{1}{n} \sum_{i=1}^{n} z_{i} \xrightarrow{L L N} E[z]=H(x)
$$

Rewriting the above result we note that the probability to observe a sample sequence $\left(x_{1}, \ldots, x_{n}\right)$ is bounded as: $2^{-n(H(x)+\varepsilon)} \leq p\left(x_{1}, \ldots, x_{n}\right) \leq 2^{-n(H(x)-\varepsilon)}$. This motivates the definition of the typical set.

### 3.2. Definition: Typical set

$$
A_{\varepsilon}^{(n)}=\left\{\left(x_{1}, \ldots, x_{n}\right) \mid 2^{-n(H(x)+\varepsilon)} \leq p\left(x_{1}, \ldots, x_{n}\right) \leq 2^{-n(H(x)-\varepsilon)}\right\}
$$

### 3.3. Typical set theorem

i) $\operatorname{Pr}\left\{A_{\varepsilon}^{(n)}\right\} \geq 1-\delta$
ii) $\left|A_{\varepsilon}^{(n)}\right| \leq 2^{n(H(x)+\varepsilon)}$
iii) $\left|A_{\varepsilon}^{(n)}\right| \geq(1-\delta) 2^{n(H(x)-\varepsilon)}$

## Proof:

i) A.E.P. Lemma
ii) $1 \geq \operatorname{Pr}\left\{A_{\varepsilon}^{(n)}\right\} \geq\left|A_{\varepsilon}^{(n)}\right| \cdot 2^{-n(H(x)+\varepsilon)} \Rightarrow\left|A_{\varepsilon}^{(n)}\right| \leq 2^{n(H(x)+\varepsilon)}$
iii) $\left|A_{\varepsilon}^{(n)}\right| \cdot 2^{-n(H(x)-\varepsilon)} \geq \operatorname{Pr}\left\{A_{\varepsilon}^{(n)}\right\} \geq 1-\delta \Rightarrow\left|A_{\varepsilon}^{(n)}\right| \geq(1-\delta) \cdot 2^{n(H(x)-\varepsilon)}$

### 3.4. Example

Let $z=\left\{\begin{array}{ll}0 & \text { w.p. } 9 / 10 \\ 1 & \text { w.p. } 1 / 20 \\ -1 & \text { w.p. } 1 / 20\end{array}\right\}$
We expect the typical sequences $\left(z_{1}, \ldots, z_{n}\right)$ to contain $\frac{9}{10} n\left(1 \pm \varepsilon^{\prime}\right)$ "zeros", $\frac{1}{20} n\left(1 \pm \varepsilon^{\prime}\right)$ "ones" and $\frac{1}{20} n\left(1 \pm \varepsilon^{\prime}\right)$ "minus ones". Furthermore, $\left|A_{\varepsilon}^{(n)}\right| \approx 2^{n\left(H(z) \pm \varepsilon^{\prime}\right)}$

## 4. Application: Data compression

Compression is a mapping (function) of a higher dimensional space onto a lower one. Suppose we want to map the set $\Omega_{\mathrm{x}}$ of binary n-tuples to the set $\Omega_{\mathrm{y}}$ of the binary mtuples with $\mathrm{m}<\mathrm{n}$. Obviously, the mapping is not " $1-1$ " so errors will occur during decoding. We divide $\Omega_{\mathrm{x}}$ into two sets: the $A_{\varepsilon}^{(n)}$ and its complement. We are computing the following quantity:
$\operatorname{Pr}\{$ decoding correctly $\}=\underbrace{\operatorname{Pr}\left\{\text { decoding correctly } / \Omega_{\mathrm{x}} \backslash A_{\varepsilon}^{(n)}\right\}}+\operatorname{Pr}\left\{\right.$ decoding correctly $\left./ A_{\varepsilon}^{(n)}\right\}$
$=\delta+\operatorname{Pr}\left\{\left(x_{1}, \ldots, x_{n}\right) \in A_{\varepsilon}^{(n)}\right.$ and $\left(x_{1}, \ldots, x_{n}\right) \in$ image of decoder $\}$
$\leq \delta+\left|\Omega_{y}\right| \max \left(\operatorname{Pr}\left\{\left(x_{1}, \ldots, x_{n}\right) \in A_{\varepsilon}^{(n)}\right\}\right)=\delta+2^{m} \cdot 2^{-n(H(x)-\varepsilon)} \leq \delta+2^{m} \frac{2^{2 n \varepsilon}}{\left|A_{\varepsilon}^{(n)}\right|}$


