Application of Information Theory, Lecture 2
Joint & Conditional Entropy, Mutual Information

Handout Mode

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Part I

Joint and Conditional Entropy

Joint entropy

- Recall that the entropy of rv X over $\mathcal{X}$, is defined by

$$H(X) = -\sum_{x\in\mathcal{X}} \mathrm{P}_X(x)\log \mathrm{P}_X(x)$$

- Shorter notation: for $X \sim p$, let $H(X) = -\sum_x p(x)\log p(x)$ (where the summation is over the domain of X).
- The joint entropy of (jointly distributed) rvs X and Y with $(X,Y) \sim p$, is

$$H(X,Y) = -\sum_{x,y} p(x,y)\log p(x,y)$$

This is simply the entropy of the rv $Z = (X,Y)$.

- Example:

$X \backslash Y$	0	1
0	$\frac{1}{4}$	$\frac{1}{4}$
1	$\frac{1}{2}$	0

$$\begin{aligned} H(X,Y) &= -\frac{1}{2}\log\frac{1}{\frac{1}{2}} - \frac{1}{4}\log\frac{1}{\frac{1}{4}} - \frac{1}{4}\log\frac{1}{\frac{1}{4}} \\ &= \frac{1}{2}\cdot 1 + \frac{1}{2}\cdot 2 = 1\frac{1}{2} \end{aligned}$$

Joint entropy, cont.

- The joint entropy of $(X_1, \ldots, X_n) \sim p$, is

$$H(X_1, \ldots, X_n) = -\sum_{x_1, \ldots, x_n} p(x_1, \ldots, x_n) \log p(x_1, \ldots, x_n)$$

Conditional entropy

- Let $(X, Y) \sim p$.
- For $x \in \text{Supp}(X)$, the random variable $Y|X = x$ is well defined.
- The entropy of Y conditioned on X, is defined by

$$H(Y|X) := \mathop{\mathrm{E}}_{x \leftarrow X} H(Y|X = x) = \mathop{\mathrm{E}}_{X} H(Y|X)$$

- Measures the uncertainty in Y given X.
- Let p_X & $p_{Y|X}$ be the marginal & conational distributions induced by p.

$$\begin{aligned}
H(Y|X) &= \sum_{x \in \mathcal{X}} p_X(x) \cdot H(Y|X = x) \\
&= -\sum_{x \in \mathcal{X}} p_X(x) \sum_{y \in \mathcal{Y}} p_{Y|X}(y|x) \log p_{Y|X}(y|x) \\
&= -\sum_{x \in \mathcal{X}, y \in \mathcal{Y}} p(x, y) \log p_{Y|X}(y|x) \\
&= -\mathop{\mathrm{E}}_{(X,Y)} \log p_{Y|X}(Y|X) \\
&= -\mathop{\mathrm{E}}_{Z = p_{Y|X}(Y|X)} \log Z
\end{aligned}$$

Conditional entropy, cont.

- Example

$X \backslash Y$	0	1
0	$\frac{1}{4}$	$\frac{1}{4}$
1	$\frac{1}{2}$	0

What is $H(Y|X)$ and $H(X|Y)$?

$$\begin{aligned} H(Y|X) &= \mathop{\mathrm{E}}_{x \leftarrow X} H(Y|X=x) \\ &= \frac{1}{2}H(Y|X=0) + \frac{1}{2}H(Y|X=1) \\ &= \frac{1}{2}H(\frac{1}{2},\frac{1}{2}) + \frac{1}{2}H(1,0) = \frac{1}{2}. \end{aligned}$$

$$\begin{aligned} H(X|Y) &= \mathop{\mathrm{E}}_{y \leftarrow Y} H(X|Y=y) \\ &= \frac{3}{4}H(X|Y=0) + \frac{1}{4}H(X|Y=1) \\ &= \frac{3}{4}H(\frac{1}{3},\frac{2}{3}) + \frac{1}{4}H(1,0) = 0.6887 \neq H(Y|X). \end{aligned}$$

Conditional entropy, cont..

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\begin{aligned}
H(X|Y,Z) &= \mathop{\mathrm{E}}_{(y,z)\leftarrow(Y,Z)} H(X|Y=y,Z=z) \\
&= \mathop{\mathrm{E}}_{y\leftarrow Y}\ \mathop{\mathrm{E}}_{z\leftarrow Z|Y=y} H(X|Y=y,Z=z) \\
&= \mathop{\mathrm{E}}_{y\leftarrow Y}\ \mathop{\mathrm{E}}_{z\leftarrow Z|Y=y} H((X|Y=y)|Z=z) \\
&= \mathop{\mathrm{E}}_{y\leftarrow Y} H(X_y|Z_y)
\end{aligned}
$$

for $(X_y, Z_y) = (X,Z)|Y = y$

Relating mutual entropy to conditional entropy

- What is the relation between $H(X)$, $H(Y)$, $H(X, Y)$ and $H(Y|Y)$?
- Intuitively, $0 \leq H(Y|X) \leq H(Y)$

  Non-negativity is immediate. We prove upperbound later.
- $H(Y|X) = H(Y)$ iff X and Y are independent.
- In our example, $H(Y) = H(\frac{3}{4}, \frac{1}{4}) > \frac{1}{2} = H(Y|X)$
- Note that $H(Y|X = x)$ might be larger than $H(Y)$ for some $x \in \text{Supp}(X)$.
- Chain rule (proved next). $H(X, Y) = H(X) + H(Y|X)$
- Intuitively, uncertainty in (X, Y) is the uncertainty in X plus the uncertainty in Y given X.
- $H(Y|X) = H(X, Y) - H(X)$ is as an alternative definition for $H(Y|X)$.

Chain rule (for the entropy function)

Claim 1

For rvs X, Y, it holds that $H(X, Y) = H(X) + H(Y|X)$.

- Proof immediately follow by the grouping axiom:

$X \backslash Y$			
	$P_{1,1}$	$\dots$	$P_{1,n}$
	$\vdots$	$\vdots$	$\vdots$
	$P_{n,1}$	$\dots$	$P_{n,n}$

Let $q_i = \sum_{j=1}^{n} p_{i,j}$

$$\begin{aligned} & H(P_{1,1}, \dots, P_{n,n}) \\ &= H(q_1, \dots, q_n) + \sum q_i H(\frac{P_{i,1}}{q_i}, \dots, \frac{P_{i,n}}{q_i}) \\ &= H(X) + H(Y|X). \end{aligned}$$

- Another proof. Let $(X, Y) \sim p$.
- $p(x, y) = p_X(x) \cdot p_{Y|X}(x|y)$.

$\implies \log p(x, y) = \log p_X(x) + \log p_{Y|X}(x|y)$

$\implies \mathrm{E} \log p(X, Y) = \mathrm{E} \log p_X(X) + \mathrm{E} \log p_{Y|X}(Y|X)$

$\implies H(X, Y) = H(X) + H(Y|X)$.

$H(Y|X) \leq H(Y)$

Jensen inequality: for any concave function f, values $t_1, \ldots, t_k$ and $\lambda_1, \ldots, \lambda_k \in [0, 1]$ with $\sum_i \lambda_i = 1$, it holds that $\sum_i \lambda_i f(t_i) \leq f(\sum_i \lambda_i t_i)$.

Let $(X, Y) \sim p$.

$$\begin{aligned}
H(Y|X) &= -\sum_{x,y} p(x,y) \log p_{Y|X}(y|x) \\
&= \sum_{x,y} p(x,y) \log \frac{p_X(x)}{p(x,y)} \\
&= \sum_{x,y} p_Y(y) \cdot \frac{p(x,y)}{p_Y(y)} \log \frac{p_X(x)}{p(x,y)} \\
&= \sum_{y} p_Y(y) \sum_{x} \frac{p(x,y)}{p_Y(y)} \log \frac{p_X(x)}{p(x,y)} \\
&\leq \sum_{y} p_Y(y) \log \sum_{x} \frac{p(x,y)}{p_Y(y)} \frac{p_X(x)}{p(x,y)} \\
&= \sum_{y} p_Y(y) \log \frac{1}{p_Y(y)} = H(Y).
\end{aligned}$$

$H(Y|X) \leq H(Y)$ cont.

- Assume X and Y are independent (i.e., $p(x,y) = p_X(x) \cdot p_Y(y)$ for any x, y)

$\implies \quad p_{Y|X} = p_Y$

$\implies \quad H(Y|X) = H(Y)$

Other inequalities

- $H(X), H(Y) \le H(X,Y) \le H(X) + H(Y)$.
  Follows from $H(X,Y) = H(X) + H(Y|X)$.
  - Left inequality since $H(Y|X)$ is non negative.
  - Right inequality since $H(Y|X) \le H(Y)$.
- $\mathrm{H}(X,Y|Z) = H(X|Z) + H(Y|X,Z)$ (by chain rule)
- $H(X|Y,Z) \le \mathrm{H}(X|Y)$

Proof:

$$\begin{aligned} H(X|Y,Z) &= \mathop{\mathrm{E}}_{Z,Y} H(X \mid Y,Z) \\ &= \mathop{\mathrm{E}}_{Y} \mathop{\mathrm{E}}_{Z|Y} H(X \mid Y,Z) \\ &= \mathop{\mathrm{E}}_{Y} \mathop{\mathrm{E}}_{Z|Y} H((X \mid Y) \mid Z) \\ &\le \mathop{\mathrm{E}}_{Y} \mathop{\mathrm{E}}_{Z|Y} H(X \mid Y) \\ &= \mathop{\mathrm{E}}_{Y} H(X \mid Y) \\ &= H(X|Y). \end{aligned}$$

Chain rule (for the entropy function), general case

Claim 2

For rvs $X_1, \ldots, X_k$, it holds that
$H(X_1, \ldots, X_k) = H(X_i) + H(X_2|X_1) + \ldots + H(X_k|X_1, \ldots, X_{k-1})$.

Proof: ?

- Extremely useful property!
- Analogously to the two variables case, it also holds that:
- $H(X_i) \leq H(X_1, \ldots, X_k) \leq \sum_i H(X_i)$
- $H(X_1, \ldots, X_K|Y) \leq \sum_i H(X_i|Y)$

Examples

- (from last class) Let $X_1, \ldots, X_n$ be Boolean iid with $X_i \sim (\frac{1}{3}, \frac{2}{3})$. Compute $H(X_1, \ldots, X_n)$
- As above, but under the condition that $\bigoplus_i X_i = 0$?
  - Via chain rule?
  - Via mapping?

Applications

- Let $X_1, \ldots, X_n$ be Boolean iids with $X_i \sim (p, 1-p)$ and let $X = X_1, \ldots, X_n$. Let f be such that $\Pr[f(X) = z] = \Pr[f(X) = z']$, for every $k \in \mathbb{N}$ and $z, z' \in \{0,1\}^k$. Let $K = |f(X)|$.

  Prove that $\mathrm{E}\, K \leq n \cdot h(p)$.

- $$\begin{aligned} n \cdot h(p) &= H(X_1, \ldots, X_n) \\ &\geq H(f(X), K) \\ &= H(K) + H(f(X) \mid K) \\ &= H(K) + \mathrm{E}\, K \\ &\geq \mathrm{E}\, K \end{aligned}$$

- Interpretation

- Positive results

Applications cont.

- How many comparisons it takes to sort n elements?

  Let A be a sorter for n elements algorithm making t comparisons.

  What can we say about t?

- Let X be a uniform random permutation of $[n]$ and let $Y_1, \ldots, Y_t$ be the answers A gets when sorting X.

- X is determined by $Y_1, \ldots, Y_t$.

  Namely, $X = f(Y_1, \ldots, Y_t)$ for some function f.

- $H(X) = \log n!$

- $$\begin{aligned} H(X) &= H(f(Y_1, \ldots, Y_n)) \\ &\leq H(Y_1, \ldots, Y_n) \\ &\leq \sum_i H(Y_i) \\ &= t \end{aligned}$$

$\Longrightarrow \quad t \geq \log n! = \Theta(n \log n)$

Concavity of entropy function

Let $p = (p_1, \ldots, p_n)$ and $q = (q_1, \ldots, q_n)$ be two distributions, and for $\lambda \in [0, 1]$ consider the distribution $\tau_\lambda = \lambda p + (1 - \lambda)q$.
(i.e., $\tau_\lambda = (\lambda p_1 + (1 - \lambda)q_1, \ldots, \lambda p_n + (1 - \lambda)q_n)$).

Claim 3

$H(\tau_\lambda) \geq \lambda H(p) + (1 - \lambda)H(q)$

Proof:

- Let Y over $\{0, 1\}$ be 1 wp λ
- Let X be distributed according to p if $Y = 0$ and according to q otherwise.
- $H(\tau_\lambda) = H(X) \geq H(X \mid Y) = \lambda H(p) + (1 - \lambda)H(q)$

We are now certain that we drew the graph of the (two-dimensional) entropy function right...

Part II

Mutual Information

Mutual information

- $I(X;Y)$ — the “information" that X gives on Y
- $$\begin{aligned} I(X;Y) &:= H(Y) - H(Y|X) \\ &= H(Y) - (H(X,Y) - H(X)) \\ &= H(X) + H(Y) - H(X,y) \\ &= I(Y;X). \end{aligned}$$
- The mutual information that X gives about Y equals the mutual information that Y gives about X.
- $I(X;X) = H(X)$
- $I(X;f(X)) = H(f(X))$ (and smaller then $H(X)$ is f is non-injective)
- $I(X;Y,Z) \geq I(X;Y), I(X;Z)$ (since $H(X \mid Y,Z) \leq H(X \mid Y), H(X \mid Z)$)
- $I(X;Y|Z) := H(Y|Z) - H(Y|X,Z)$
- $I(X;Y|Z) = I(Y;X|Z)$ (since $I(X';Y') = I(Y';X')$)

Numerical example

- Example

$X \backslash Y$	0	1
0	$\frac{1}{4}$	$\frac{1}{4}$
1	$\frac{1}{2}$	0

$$
\begin{aligned}
I(X;Y) &= H(X) - H(X|Y) \\
&= 1 - \frac{3}{4} \cdot h(\frac{1}{3}) \\
&= I(Y;X) \\
&= H(Y) - H(Y|X) \\
&= h(\frac{1}{4}) - \frac{1}{2} h(\frac{1}{2})
\end{aligned}
$$

Chain rule for mutual information

Claim 4 (Chain rule for mutual information)

For rvs $X_1, \ldots, X_k, Y$, it holds that
$I(X_1, \ldots, X_k; Y) = I(X; Y) + I(X_2; Y|X_1) + \ldots + I(X_k; Y|X_1, \ldots, X_{k-1})$.

Proof: ? HW

Examples

- Let $X_1, \ldots, X_n$ be iid with $X_i \sim (p, 1-p)$, under the condition that $\bigoplus_i x_i = 0$. Compute $I(X_1, \ldots, X_{n-1}; X_n)$.

  By chain rule

$$\begin{aligned}
&I(X_1, \ldots, X_{n-1}; X_n) \\
&\quad = \quad H(X_1; X_n) + H(X_2; X_n|X_1) + \ldots + H(X_{n-1}; X_n|X_1, \ldots, X_{n-2}) \\
&\quad = \quad 0 + 0 + \ldots + 1 = 1.
\end{aligned}$$

- Let T and F be the top and front side, respectively, of a 6-sided fair dice. Compute $I(T; F)$.

$$\begin{aligned}
I(T; F) &= H(T) - H(T|F) \\
&= \log 6 - \log 4 \\
&= \log 3 - 1.
\end{aligned}$$

Part III

Data processing

Data processing Inequality

Definition 5 (Markov Chain)

Rvs $(X, Y, Z) \sim p$ form a Markov chain, denoted $X \to Y \to Z$, if $p(x, y, z) = p_X(x) \cdot p_{Y|X}(y|x) \cdot p_{Z|Y}(z|y)$, for all x, y, z.

Example: random walk on graph.

Claim 6

If $X \to Y \to Z$, then $I(X; Y) \geq I(X; Z)$.

- By Chain rule, $I(X; Y, Z) = I(X; Z) + I(X; Y|Z) = I(X; Y) + I(X; Z|Y)$.
- $I(X; Z|Y) = 0$
  - $p_{Z|Y=y} = p_{Z|Y=y,X=x}$ for any x, y
  - $$\begin{aligned} I(X; Z|Y) &= H(Z|Y) - H(Z|Y, X) \\ &= \mathop{\mathrm{E}}_{Y} H(p_{Z|Y=y}) - \mathop{\mathrm{E}}_{Y,X} H(p_{Z|Y=y,X=x}) \\ &= \mathop{\mathrm{E}}_{Y} H(p_{Z|Y=y}) - \mathop{\mathrm{E}}_{Y} H(p_{Z|Y=y}) = 0. \end{aligned}$$
- Since $I(X; Y|Z) \geq 0$, we conclude $I(X; Y) \geq I(X; Z)$.□

Fano's Inequality

- How well can we guess X from Y?
- Could with no error if $H(X|Y) = 0$. What if $H(X|Y)$ is small?

Theorem 7 (Fano's inequality)

For any rvs X and Y, and any (even random) g, it holds that

$$h(P_e) + P_e \log|\mathcal{X}| \geq H(X|\hat{X}) \geq H(X|Y)$$

for $\hat{X} = g(Y)$ and $P_e = \Pr\left[\hat{X} \neq X\right]$.

- Note that $P_e = 0$ implies that $H(X|Y) = 0$
- The inequality can be weekend to $1 + P_e \log|\mathcal{X}| \geq H(X|Y)$,
- Alternatively, to $P_e \geq \frac{H(X|Y)-1}{\log|\mathcal{X}|}$
- Intuition for $\propto \frac{1}{\log|\mathcal{X}|}$
- We call $\hat{X}$ an estimator for X (from Y).

Proving Fano's inequality

Let X and Y be rvs, let $\hat{X} = g(Y)$ and $P_e = \Pr\left[\hat{X} \neq X\right]$.

- Let $E = \begin{cases} 1, & \hat{X} \neq X \\ 0, & \hat{X} = X. \end{cases}$

$$\begin{aligned} H(E, X|\hat{X}) &= H(X|\hat{X}) + \underbrace{H(E|X, \hat{X})}_{=0} \\ &= \underbrace{H(E|\hat{X})}_{\leq H(E) = h(P_e)} + \underbrace{H(X|E, \hat{X})}_{\leq P_e \log|\mathcal{X}| (?)} \end{aligned}$$

- It follows that $h(P_e) + P_e \log|\mathcal{X}| \geq H(X|\hat{X})$
- Since $X \to Y \to \hat{X}$, it holds that $I(X;Y) \geq I(X;\hat{X})$
  $\Longrightarrow H(X|\hat{X}) \geq H(X|Y)$