

Joint-conditional entropy and mutual information

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1 Entropy, joint entropy, conditional entropy, and mutual information

Consider the discrete source (the transmitter) X with $n = 3$ symbols with $p(x_i) = [0.125, 0.25, 0.625]$. Compute the entropy of the source H_X

$$H(X) = - \sum_{i=1}^n p(x_i) \log_2(p(x_i))$$

and the maximal entropy in the case of a uniform distribution.

Entropy of the source H_X = 1.29879 bit

Max. entropy = 1.58496 bit

Consider a receiver Y with $m = 4$ symbols with the following conditional probabilities

$$\begin{aligned} p(y_1|x_1) &= 0.75 \\ p(y_2|x_1) &= 0.25 \\ p(y_2|x_2) &= 0.5 \\ p(y_3|x_2) &= 0.5 \\ p(y_3|x_3) &= 0.25 \\ p(y_4|x_3) &= 0.75 \end{aligned}$$

The other probabilities are equal to zero. Note that for each transmitted symbol x_i , it has been assured that

$$\sum_{j=1}^m p(y_j|x_i) = 1 \quad \forall x_i \text{ with } i \in [1, n]$$

as the sum over all possible probabilities must be equal to one.

P_Y_cond_X:

```
[[0.75 0.25 0.  0.  ]
 [0.    0.5  0.5  0.  ]
 [0.    0.    0.25 0.75]]
```

Check that row of the matrix represents a probability.

```
[1. 1. 1.]
```

Compute the joint probabilities using Bayes' rule

$$p(x_i, y_j) = p(y_j|x_i)p(x_i),$$

the probability of y_j as marginal of $p(x_i, y_j)$

$$p(y_j) = \sum_{i=1}^n p(x_i, y_j)$$

and the conditional probabilities $p(x_i|y_j)$ using Bayes' rule

$$p(x_i|y_j) = \frac{p(x_i, y_j)}{p(y_j)} = \frac{p(y_j|x_i)p(x_i)}{p(y_j)}.$$

P_joint:

$$\begin{bmatrix} [0.09375 & 0.03125 & 0. & 0. &] \\ [0. & 0.125 & 0.125 & 0. &] \\ [0. & 0. & 0.15625 & 0.46875] \end{bmatrix}$$

P_y:

$$[0.09375 \ 0.15625 \ 0.28125 \ 0.46875]$$

P_X_cond_Y:

$$\begin{bmatrix} [1. & 0.2 & 0. & 0. &] \\ [0. & 0.8 & 0.44444444 & 0. &] \\ [0. & 0. & 0.55555556 & 1. &] \end{bmatrix}$$

Compute the entropy $H(X)$

$$H(Y) = - \sum_{j=1}^m p(y_j) \log_2(p(y_j))$$

and the joint entropy

$$H(X, Y) = - \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) \log p(x_i, y_j)$$

and the the conditional entropies

$$H(Y|X) = - \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) \log p(y_j|x_i)$$

and

$$H(X|Y) = - \sum_{i=1}^n \sum_{j=1}^m p(x_i, y_j) \log p(x_i|y_j).$$

Entropy H_Y = 1.76571 bit

Joint entropy: H(X,Y) = 2.15725 bit

Conditional entropy: H(Y|X) = 0.85846 bit

Conditional entropy: H(X|Y) = 0.39154 bit

Compute the mutual information between X and Y

$$I(X; Y) = H(X) - H(X|Y).$$

Mutual information: I(X;Y) = 0.90725 bit

Verify the following theoretical results using the numerical results and the venn-diagrams

$$H(Y|X) = H(X, Y) - H(X)$$

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

$$H(X|Y) = H(X, Y) - H(Y)$$

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

$$0 \leq \max [H(X), H(Y)] \leq H(X, Y) \leq H(X) + H(Y)$$

$$I(X; Y) = H(X) - H(X|Y)$$

$$I(X; Y) = H(X) + H(Y) - H(X, Y)$$

$$I(X; Y) = H(Y) - H(Y|X)$$

$$I(X; Y) = H(X, Y) - H(X|Y) - H(Y|X)$$

$$0 \leq I(X; Y) \leq H(X)$$

`H_X = 1.29879`

`H_Y = 1.76571`

`H(X, Y) = 2.15725`

`H(Y|X) = 0.85846`

`H(X|Y) = 0.39154`

`I(X; Y) = 0.90725`

`[H_Y_cond_X, H_joint-H_X] :`

`[0.8584585930558105, 0.8584585924787329]`

`[H_X_cond_Y, H_joint-H_Y] :`

`[0.3915414064482629, 0.3915414057900335]`

`[I_X_Y, H_X-H_X_cond_Y, H_X+H_Y-H_joint, H_Y-H_Y_cond_X, H_joint-H_X_cond_Y-H_Y_cond_X] :`

`[0.9072535342471355, 0.9072535342471355, 0.9072535349053652, 0.9072535343282874, 0.9072535336700579]`