Math Review Solutions. Information Theory Problem Set 1.

1. Let

$$J(p_1, \dots, p_n, \lambda) = \sum_{k=1}^n p_k \log(p_k) - \lambda\left(\sum_{k=1}^n p_k - 1\right)$$

where λ is a Lagrange multiplier. Differentiating J and setting the derivative to 0 yields

$$\frac{\partial J}{\partial p_m} = p_m \frac{1}{p_m} + \log(p_m) - \lambda = 0$$
$$\implies \lambda - 1 = \log(p_m) \implies 2^{\lambda - 1} = p_m$$

Applying the constraint

$$\sum_{m=1}^{n} 2^{\lambda-1} = \sum_{m=1}^{n} p_m \implies n 2^{\lambda-1} = 1.$$

Finally, it follows from $2^{\lambda-1} = p_m$ that $np_m = 1$ so $p_m = \frac{1}{n}$.

2. Mutual Information is given by $\mathcal{M}(\mathbf{p}, \mathbf{q}) = \sum_{m} \sum_{n} f(p_m, q_n) \log\left(\frac{f(p_m, q_n)}{p_m q_n}\right)$. It can be calculated as follows:

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MI1 = 0;
for m = 1:3;
    pm = p(m);
    for n = 1:3;
       qn = q1(n);
       MI1= MI1+pq1(m,n)*log2(pq1(m,n)/(pm*qn));
    end;
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end;
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which gives the answers $\mathcal{M}(\mathbf{p}, \mathbf{q}_1) = 0.0865$ and $\mathcal{M}(\mathbf{p}, \mathbf{q}_2) = 0$. If one uses the natural logarithm (base *e*) instead of base 2, the answers are $\mathcal{M}(\mathbf{p}, \mathbf{q}_1) = 0.0599$ and $\mathcal{M}(\mathbf{p}, \mathbf{q}_2) = 0$.

- 3. (a) An example of a convex function is shown in C.8
 - (b) To develop intuition, observe the plots of entropy for $\mathbf{p} = (p, (1-p))$ and $\mathbf{p} = (p_1, p_2, 1 (p_1 + p_2))$ as shown in C.9:

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Figure C.8 An example of a convex function.



Figure C.9 Plots of Entropy for 2 and 3 variable pdfs.

The plots suggest that entropy is concave although it is not a proof. One argument is: Consider a single term of entropy, $f(p_m) = -p_m log(p_m)$. The derivative of f is $\frac{df}{dp_m} = -(1 + log(p_m))$. The second derivative is $\frac{d^2}{dp_m^2} = -\frac{1}{p_m} < 0$ assuming $p_m \neq 0$. Hence, $\frac{df}{dp_m}$ is strictly decreasing so f is concave. Suppose f and g are concave functions of a single, real-valued variable with domain $A \subset \mathbb{R}$. Then

$$(f+g) (ax + (1-a) y) =$$

$$f (ax + (1-a) y) + g (ax + (1-a) y) \ge$$

$$af (x) + (1-a) f (y) + ag (x) + (1-a) g (y) =$$

$$a (f+g) (x) + (1-a) (f+g) (y)$$

so f + g is concave. Therefore, entropy is concave. Do you believe this argument? How about the argument in part (c)? We'll discuss in class.

(c) Mutual Information can be written as follows

$$\begin{split} \mathcal{M} &= \sum_{x} \sum_{y} p\left(x, y\right) \log\left(\frac{p\left(x, y\right)}{p\left(x\right) p\left(y\right)}\right) = \sum_{x} \sum_{y} p\left(y|x\right) p\left(x\right) \log\left(\frac{p\left(y|x\right)}{p\left(y\right)}\right) = \\ &= \sum_{x} p\left(x\right) \sum_{y} p\left(y|x\right) \log\left(\frac{p\left(y|x\right)}{p\left(y\right)}\right) = \sum_{x} p\left(x\right) \operatorname{KL}\left(p\left(y|x\right), p\left(y\right)\right) = \\ &= \mathbb{E}_{p(x)} \left[\operatorname{KL}\left(p\left(y|x\right), p\left(y\right)\right)\right]. \end{split}$$

The last expression shows that \mathcal{M} is a linear function of p(x). Therefore it is both convex and concave as a function of p(x). The derivative of \mathcal{M} with respect to p(y|x) for a specific $y = y_d$ and $x = x_d$ is $\frac{d\mathcal{M}}{dp(y_d|x_d)} = p(x_d) [1 + \log (p(y_d|x_d)) - \log (y_d)]$ and the second derivative is $\frac{p(x_d)}{p(y_d|x_d)} \ge 0$. Therefore, \mathcal{M} is convex with respect to p(y|x) for any y and x.

4. (a) Note that $H(Y|X = x) = -\sum_{y} p(y|x) \log (p(y|x))$. Take $p(x) = p_x$ for x = 1, 2, 3 and $p(y) = p_y$ for y = 1, 2, 3. Then $p(y|x) = \frac{p(x,y)}{p(x)} = \frac{p(x,y)}{p_x}$. For **p** and **q**, the latter expression is

$$p(Y|X) = \begin{bmatrix} 0.30 & 0.40 & 0.30\\ 0.02 & 0.68 & 0.30\\ 0.10 & 0.60 & 0.30 \end{bmatrix}$$

where the element in row r and column c represents $\frac{p(r,c)}{p_r}$. Then

$$\begin{split} \mathbf{h} &= (H\left(Y|X=1\right), H\left(Y|X=2\right), H\left(Y|X=3\right))^t = (1.57, 1.01, 1.30)^t \\ \text{and} \\ &H\left(Y|X\right) = \mathbb{E}_{p(x)}\left[H\left(Y|X=x\right)\right] = \mathbf{p}^t \mathbf{h} = 1.21. \end{split}$$

- (b) Applying algebra and using the fact the $\sum_{y} p(y|x) = 1$ yields H(X,Y) = H(Y|X) + H(X). Since entropy is non-negative, it must be true that $H(X,Y) \ge H(Y|X)$.
- 5. it is easy to construct a joint pdf with Mutual Information 0. Take 2 pdfs of one variable, $p_1(x)$ and $q_1(y)$ and compute all possible products, $p(x, y) = p_1(x) q_1(y)$. To create one with Mutual Information non-zero, modify the one with zero by adding and subtracting values while maintaining the stochastic constraints. For example, starting with p(x, y), let d be any number satisfying $0 < d < min(p_1(x) q_1(y))$ and take

$$q(x_1, y_1) = p_1(x_1) q_1(y_1) + d$$

$$q(x_2, y_1) = p_1(x_2) q_1(y_1) - d$$

$$q(x_1, y_2) = p_1(x_1) q_1(y_2) - d$$

$$q(x_2, y_2) = p_1(x_2) q_1(y_2) + d$$

and q(x, y) = p(x, y) otherwise.

6. See the solution to problem 3.