Entropy	
$ \begin{array}{cccc} O & & & & & & & & & & & & & & & & & & &$	
a) H(x) 70	
b) H(x)=0 <>> random vouriable X is not 'random',	
C) Interpretation: X is more random, H(X) is bigger (entropy)	
achieve mosòmum when X is uniformly distributed	
2) Jointly Entropy $H(X,Y) = -\sum_{x,y} p(x,y) \log p(x,y)$	
a) H(×,y) > 0	
b) $H(x,y)=0 \Leftrightarrow (x,y)$ is not random"	
C) (X,Y) is more random than X , in the sense that	
X is the marginal of (X,Y)	
Therefore, in principle, $H(XY) \geqslant H(X)$ generally holds!	
$H(X Y) = \sum_{Y} P(Y) \cdot H(X Y=Y) = -\sum_{Y} P(Y) \sum_{X} P_{X Y}(X Y) \cdot \log_{Y} P_{X Y}(X Y)$	y.
3) conditional Entropy $H(X Y) = H(X,Y) - H(Y) > 0 = -\sum_{xy} P_{x,y}(x,y) \log P_{X Y}(x Y)$	
$= -\sum_{xy} P_{x,y} (x,y) \log \frac{P_{xy} (x,y)}{P_{y} (y)}$	
= E(H(XIX)]	
$= - \sum_{x,y} P_{x,y}(x,y) \log P_{x y}(x y)$	
a) H(XIY) 70	
b) measure the uncertainty of X given Y	
(f) Mutual info $I(X;Y) = I(Y;X)$	
= H(X)- H(X Y) = H(Y)- H(Y X)	
= H(x) + H(y) - H(x,y)	
= * E Pxy(x,y) log Pxy(xy)	

Px(x) Py(y) in dependent X, Y = D (Px,y (·,·) || Px,y (·,·)) $P_{x,y}(x,y) = P_{x}(x) P_{y}(y)$ where a) $I(X;Y) = I(Y;X) \geqslant 0$ $H(X|Y) \in H(x) \leftarrow H(x,y)$ 6) mutual info conditional entupy H(X(Y) KL-divergence D(Px() | Qx()) $= \sum_{x} \beta_{x}(x) \log \frac{\beta_{x}(x)}{Q_{x}(x)} = 0$ I(x,y):= D(Px,y(.,.)) (x,y(.,.)) Qxx is the independently joint distribution of X&Y Summary $H(x,y)-H(x)=H(y|x) \longrightarrow H(y)$ $H(y) - H(y|x) \rightarrow I(x_1y) = I(y_1x)$ = H(x) + H(y) - H(xy)Interpretation: $0 \text{ H(X)} \longrightarrow \text{ the measure of randomness of } X$ = $-\sum p(x) \log_2 p(x) \in [0, \log_1 K]$ $H(X,Y) \rightarrow Similar to H(X)$ δ(γ)= H(x̄y) = H(x,y)-H(y) L) give a Y=y, we can construct a r.v. $\widehat{X}_{y} = X | Y = y \rightarrow H(\widehat{X}_{y})$ measure the randomness of

