$$f_X(x): \mathcal{X} \to [0, \infty), f_X(x) = \lim_{\epsilon \to 0} \frac{1}{\epsilon} \cdot \Pr[x \le X \le x + \epsilon]$$

• Continuous cdf:

$$F_x(x) := \Pr[X \le x] \text{ where } \Pr[a \le X \le b] = \int_a^b f_x(x) dx$$

$$f_X(x) = 1/(v-u)$$
 for $x \in \mathcal{X}$

• Uniform distribution on $\mathcal{X} = [u, v]$:

• Normal distribution:

$$f_X(x) = (2\pi)^{-1/2} \exp(-x^2/2)$$

• Dirac delta property:

$$\int_{-\infty}^{\infty} dx \, b(x) \delta(x - a) = b(a)$$

• Expectation value of g(X) where $X \in \mathcal{X}$:

$$\mathbb{E}[g(X)] = \sum_{x \in \mathcal{X}} \Pr[X = x] g(x)$$
 , k'th moment of $X = \mathbb{E}[X^k]$

• Statistical distance of $X, Y \in \mathcal{X}$:

$$\Delta(X,Y) = \frac{1}{2} \sum_{x \in \mathcal{X}} |\mathbb{P}(x) - \mathbb{Q}(x)|$$

• Covariance matrix *K*:

$$K_{i,j} = \mathbb{E}[X_i X_j] - \mathbb{E}[X_i] \cdot \mathbb{E}[X_j]$$

Zero covariance ($K_{1,2} = K_{2,1} = 0$) does not imply X_1 and X_2 are independent.

• Marginal distribution for X when $(X,Y) \sim \mathbb{P}$:

$$\Pr[X = x] = \sum_{y} \mathbb{P}(x, y)$$

• Conditional probability for
$$(X,Y) \sim \mathbb{P}$$
:
$$\Pr[X = x | Y = y] = \frac{\Pr[X = x, Y = y]}{\Pr[Y = y]} = \frac{\mathbb{P}(x,y)}{\mathbb{P}_2(y)}$$

• (Shannon) Entropy rules:

1. Additivity: inf of a set of indep. RVs must be the sum of indiv. inf. contents

4. **Normalization**: The distrib
$$(1/2, 1/2)$$
 has inf. of 1 bit.

5. The distrib
$$(p, 1-p)$$
 for $p \to 0$ has zero inf.

Shannon entropy:

$$H(X) = \sum_{x \in \mathcal{X}} p_x \log_2 \frac{1}{p_x}$$

• Binary entropy function: 2 outcomes with prob. p and 1 - p:

$$h(p) = p \log \frac{1}{p} + (1-p) \log \frac{1}{1-p}$$

• Differential entropy for continuous RV
$$X \sim \rho$$
:

$$h_{\text{diff}}(X) = -\int dx \, \rho(x) \log \rho(x) = \mathbb{E}_x \log \frac{1}{\rho(x)}$$

• Relative entropy (Kullback-Leibler distance):

$$D(\mathbb{P}||\mathbb{Q}) = \sum_{x \in \mathcal{X}} \mathbb{P}(x) \log \frac{\mathbb{P}(x)}{\mathbb{Q}(x)}$$

• Entropy of jointly distrib. RVs: H(X,Y) or H(XY):

$$H(X,Y) = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p_{xy} \log \frac{1}{p_{xy}}$$

• Conditional entropy:

$$\begin{array}{l} H(X|Y) = \mathbb{E}_y[H(X|Y=y)] = -\sum_{x \in \mathcal{X}} p_x \sum_{y \in \mathcal{Y}} p_{x|y} \log p_{x|y} \\ H(X|Y) = H(X,Y) - H(Y) \end{array}$$

Mutual information:

$$\mathbf{I} = H(X) - H(X|Y)$$

$$\mathbf{I} = H(Y) - H(Y|X)$$

$$\mathbf{I} = H(X,Y) - H(X|Y) - H(Y|X)$$

$$\mathbf{I} = H(X) + H(Y) - H(X, Y)$$