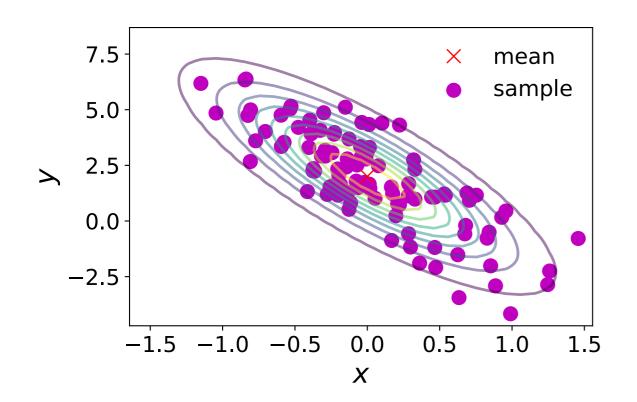
ENM 5310: Data-driven Modeling and Probabilistic Scientific Computing

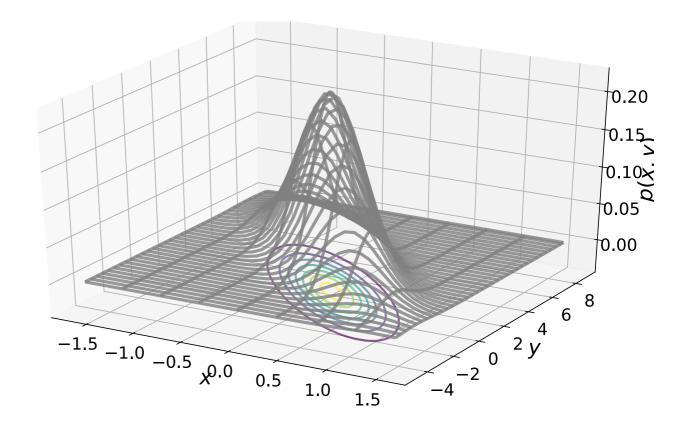
Lecture #3

Statistical Estimation



The multivariate Gaussian





$$p(\boldsymbol{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = (2\pi)^{-\frac{D}{2}} |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^{\top} \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})\right)$$

Mean, variance & high-order moments

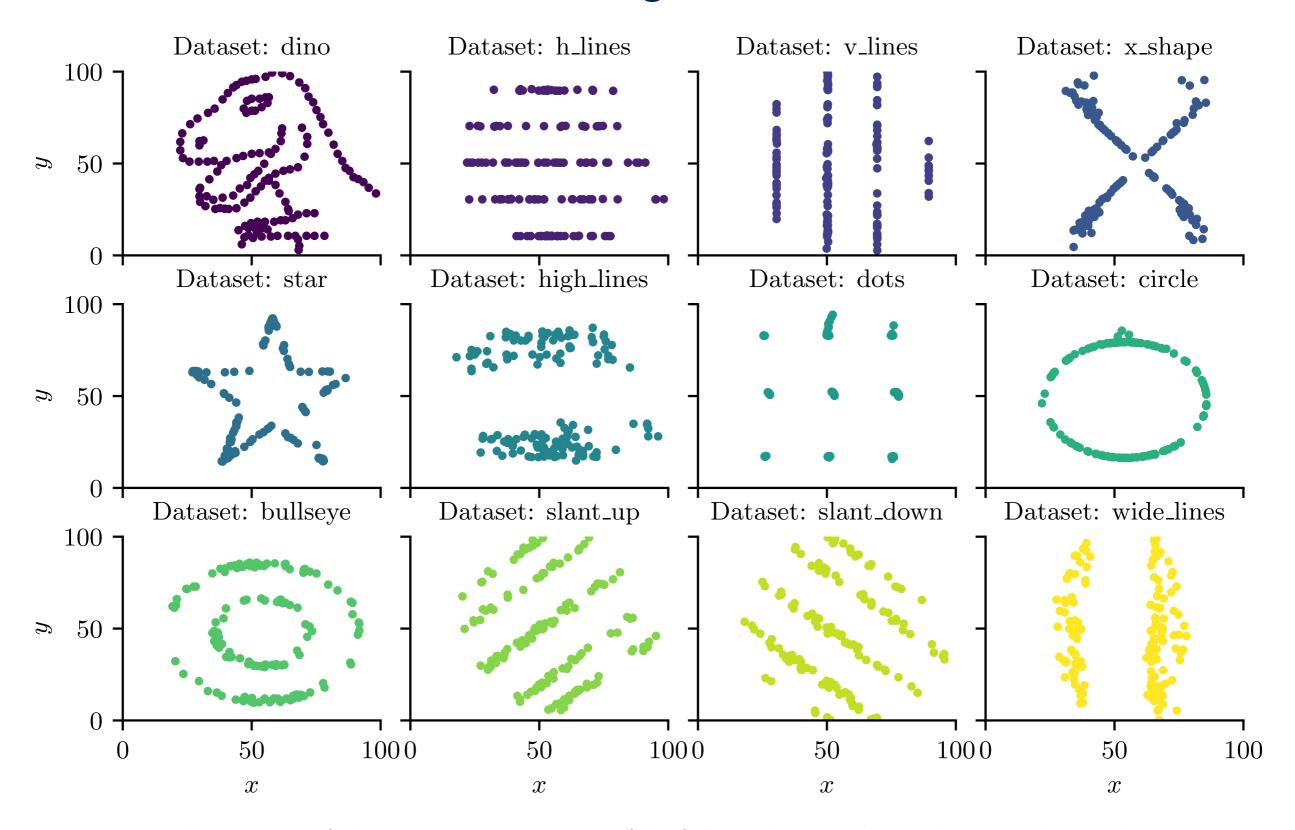
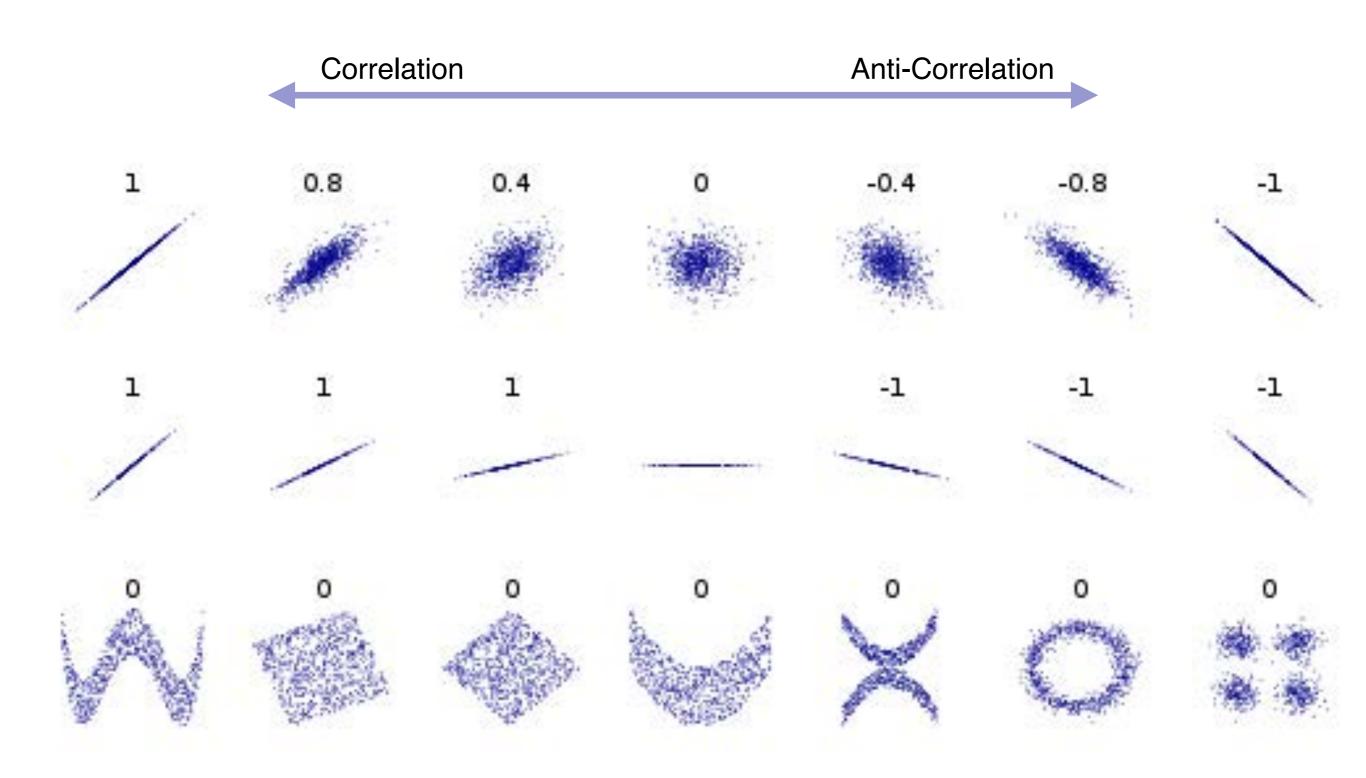


Figure 2.6: Illustration of the Datasaurus Dozen. All of these datasets have the same low order summary statistics. Adapted from Figure 1 of [MF17]. Generated by datasaurus_dozen.ipynb.

Correlation and linear dependence



Entropy and Mutual Information

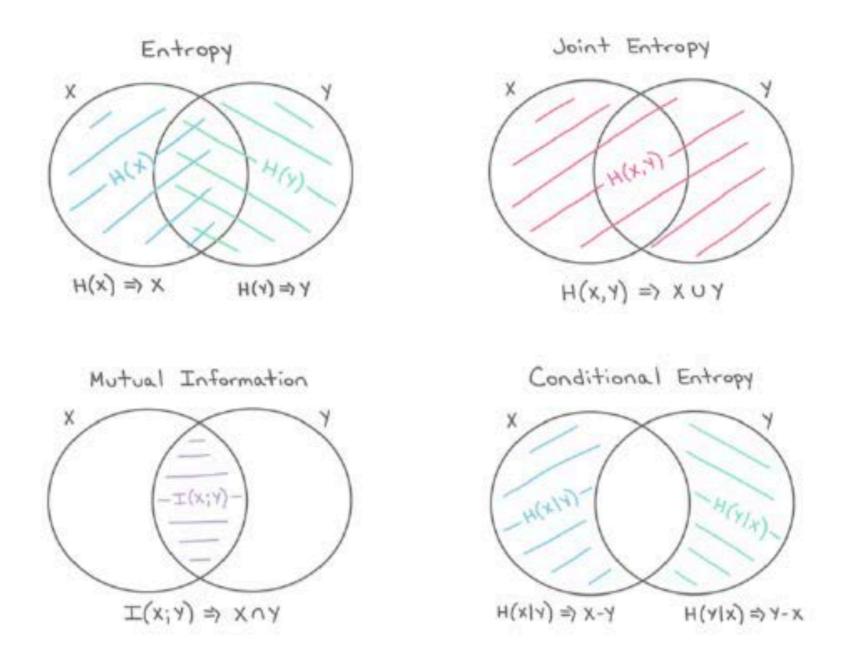
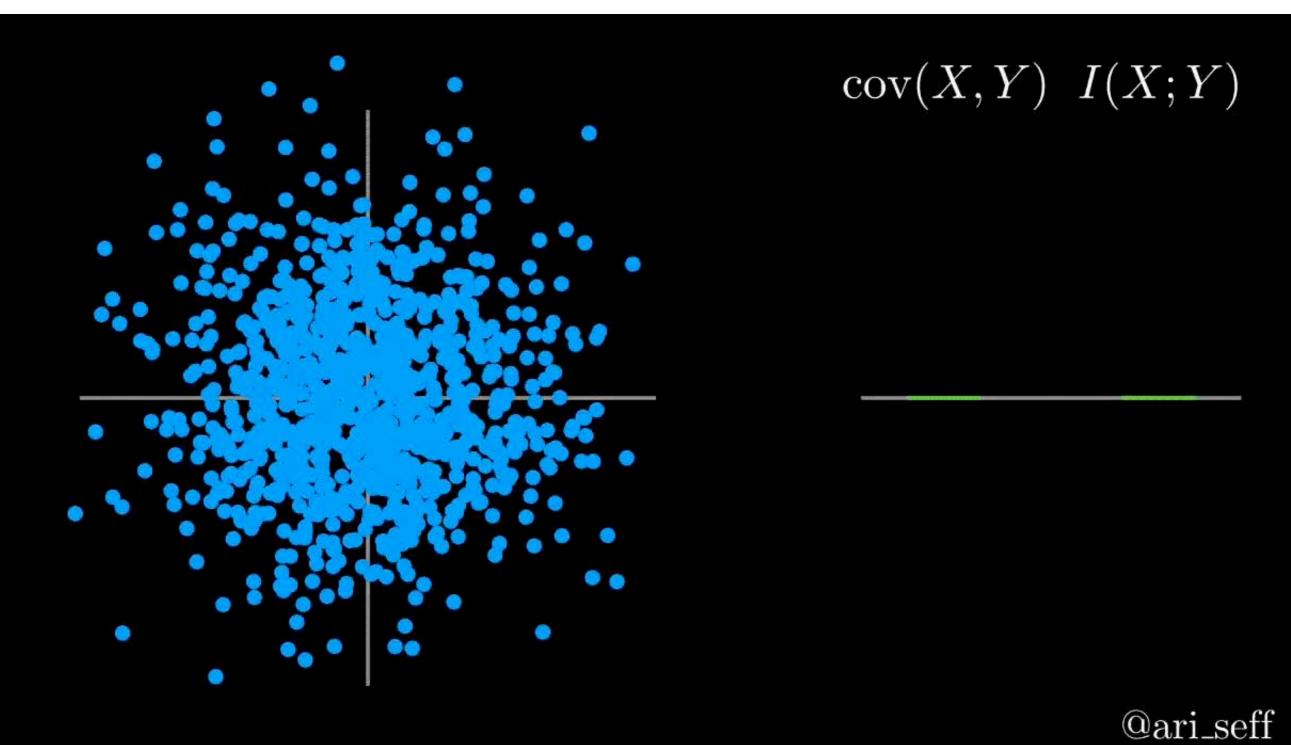
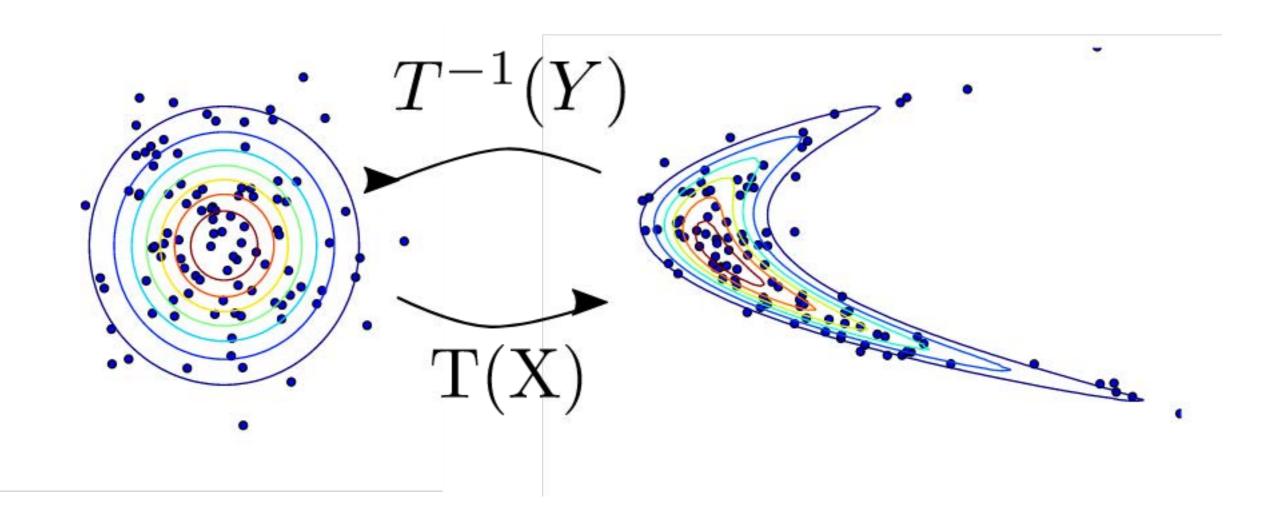


Figure 6.4: The marginal entropy, joint entropy, conditional entropy and mutual information represented as information diagrams. Used with kind permission of Katie Everett.

Covariance vs Mutual Information



Transformations



Change of Variables

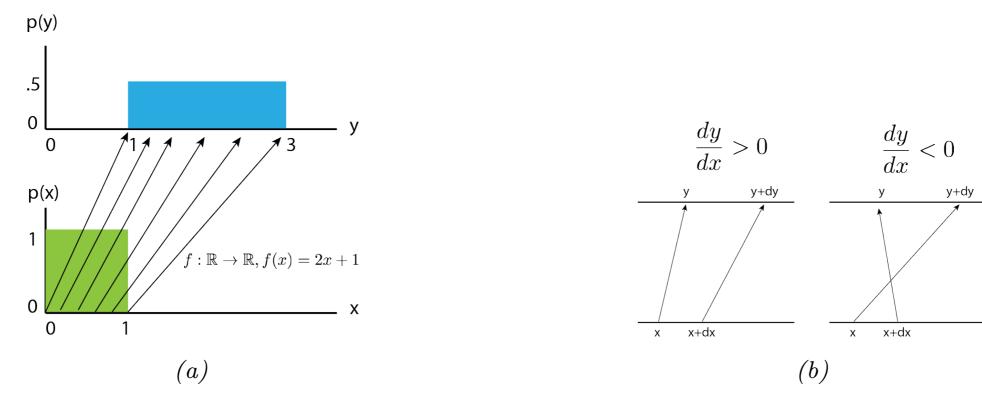
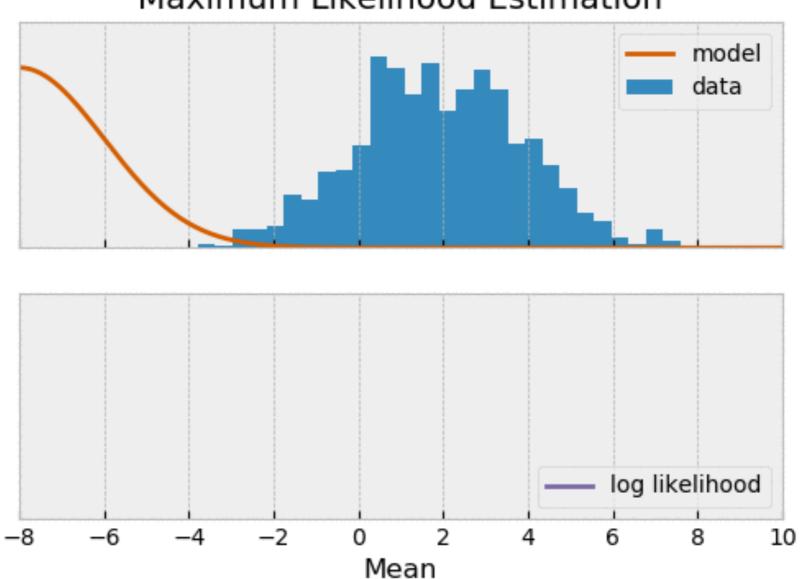


Figure 2.19: (a) Mapping a uniform pdf through the function f(x) = 2x + 1. (b) Illustration of how two nearby points, x and x + dx, get mapped under f. If $\frac{dy}{dx} > 0$, the function is locally increasing, but if $\frac{dy}{dx} < 0$, the function is locally decreasing. From [Jan18]. Used with kind permission of Eric Jang.

Maximum likelihood estimation

$$\theta_{\text{MLE}} = \arg \max_{\theta \in \Theta} p(\mathcal{D}|\theta)$$

Maximum Likelihood Estimation



Bayesian estimation

$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta)p(\theta)}{p(\mathcal{D})}$$

