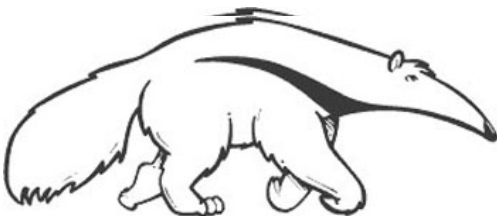


# Maximum Entropy Learning

Learning in Graphical Models

Prof. Alexander Ihler



# Maximum Entropy Learning

$$\max_{q(x)} \mathbb{H}(q) \quad s.t. \quad \forall i \quad \mathbb{E}_q[u_i(x)] = \hat{\mu}_i$$

Shorthand:

$$\mu_i(q) = \mathbb{E}_q[u_i(x)]$$

- Maximum Entropy Learning Principle
  - Identify some features  $u_i(x)$ , and their desired expectations
  - Find the most “agnostic” distribution that matches the data
  - $q(x)$  can be any distribution, of any form

# Maximum Entropy Learning

$$\max_{q(x)} \mathbb{H}(q) \quad s.t. \quad \forall i \quad \mathbb{E}_q[u_i(x)] = \hat{\mu}_i$$

Shorthand:

$$\mu_i(q) = \mathbb{E}_q[u_i(x)]$$

Lagrangian:

$$\max_{q(x)} \min_{\theta} \mathbb{H}(q) + \theta \cdot (\mu(q) - \hat{\mu})$$

$$\text{Dual: } \min_{\theta} \max_{q(x)} \mathbb{H}(q) + \theta \cdot (\mu(q) - \hat{\mu})$$

$$\Leftrightarrow \min_{\theta} \max_{q(x)} -D(q||p) + A(\theta) - \theta \cdot \hat{\mu}$$

$$\Rightarrow q^*(x) = p(x) \Rightarrow \min_{\theta} A(\theta) - \theta \cdot \hat{\mu}$$

Optimal  $q^*$  is exponential family with features  $u(x)$ !

Optimal parameters  $\theta$  are the MLE estimates!

Define:

$$f(x) = \exp(\theta \cdot u(x))$$

$$Z = \sum_x f(x)$$

$$p(x) = Z^{-1} f(x)$$

then,

$$D(q||p)$$

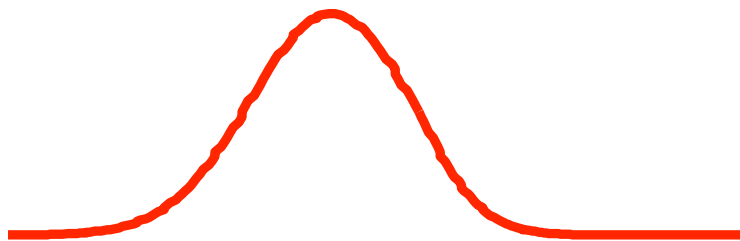
$$= \mathbb{E}_q[\log q - \log p]$$

$$= -\mathbb{H}(q) - \theta \cdot \mu(q) + A(\theta)$$

# Maximum Entropy Learning

- Example: Gaussian distribution
  - Exponential family with features  $x, x^2$
  - Has the highest entropy of any distribution with variance  $v$

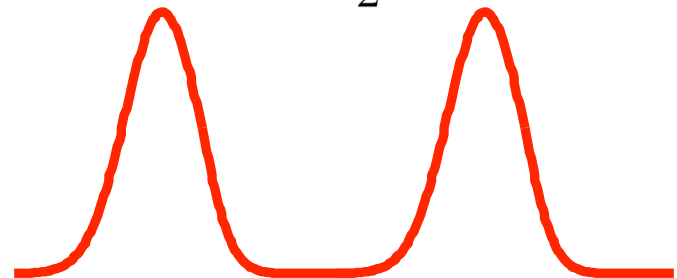
$$\mathcal{N}(x; 0, 1)$$



$$\mathbb{E}[(x - \mu)^2] = 1$$

$$\mathbb{H}[x] \approx 1.41$$

$$\frac{1}{2}\mathcal{N}(x; -1, .25) + \frac{1}{2}\mathcal{N}(x; 1, .25)$$



$$\mathbb{E}[(x - \mu)^2] \approx 1$$

$$\mathbb{H}[x] \approx 0.73$$