

5. Maximum entropy principle.

Setting:

Given n data points $x^{(1)}, \dots, x^{(n)}$.

A feature function $\phi: \mathcal{X} \to \mathbb{R}^d$.

Define the empirical moments: $\hat{\mu} := \frac{1}{n} \sum_{i=1}^{n} \phi(x^{(i)})$

Define $Q := \{ q \in \Delta_{|\mathcal{X}|} : E_q[\phi(x_7)] = \hat{\mu} \}$, where $E_q[\phi(x_7)] := \sum q(x_7)\phi(x_7)$ Note: $|\mathcal{X}|$ can be large but q only have d constraints.

[Definition 2] maximum entropy principle.

Choose the distribution q with the highest entropy:

9 := argmax H(q)

where H (9) := Eq [-109 9 (x)]

We will show that Maximum Likelihood is equivalent to Maximum Entropy, in the following theorem.

[Theorem 1] maximum entropy duality:

Assume Q is non-empty, then

 $argmax H(q) = argmax = leg P(x^{(i)})$ $q \in Q$

Pf: Straightforward application of Langrangian duality.

max $H(q) = \max_{q \in \Delta_{|x|}} \min_{\theta \in |x|} H(q) - \theta \cdot (\widehat{\mu} - E_q[\phi(x)])$ (i)

Since Q is non-empty (Slater's condition), we can switch the min X max.

 $\min_{\theta \in \mathbb{R}^d} \max_{q \in \Delta_{|\mathcal{X}|}} - \sum_{x \in \mathcal{X}} q(x) \log_q(x) - \theta \cdot (\hat{\mu} - \sum_{x \in \mathcal{X}} q(x) \varphi(x))$ (ii)

Next, differentiate with y und set it to some constant C: $-(1+\log q(x)) + \theta \cdot \varphi(x) = c \quad , \quad \text{for each } x \in \mathcal{X}.$ (Since $\sum q(x) = 1$)

Solving for q (rewrite as q_{θ}), then $q_{\theta}(x) \propto \exp(0.\varphi(x))$. By (ii), we have

min - $(\theta \cdot E_{\theta}[\phi(x)] - A(\theta)) - \theta \cdot (\hat{\mu} - E_{\theta}[\phi(x)])$

 \Leftrightarrow max $\theta \cdot \hat{\mu} - A(\theta)$, which is the maximum likelihood objective.

Using the fact $\Delta A(\theta) = E_{\theta}[\phi(x)]$, we have $0 = \hat{\mu} - \Delta A(\theta) = \hat{\mu} - E_{\theta}[\phi(x)]$.

which means 9 & EQ