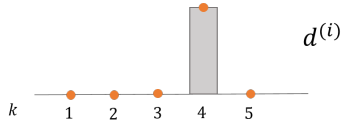
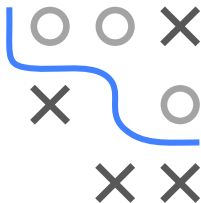


Introduction to Machine Learning

Information Theory

Information Theory for Machine Learning



Learning goals

- Minimizing KL = maximizing log-likelihood
- Minimizing KL = minimizing cross-entropy
- Minimizing CE between modeled and observed probabilities = log-loss minimization

KL VS MAXIMUM LIKELIHOOD

Minimizing KL between the true distribution $p(x)$ and approximating model $q(x|\theta)$ is equivalent to maximizing the log-likelihood.

$$\begin{aligned} D_{KL}(p||q_{\theta}) &= \mathbb{E}_{x \sim p} \left[\log \frac{p(x)}{q(x|\theta)} \right] \\ &= \mathbb{E}_{x \sim p} \log p(x) - \mathbb{E}_{x \sim p} \log q(x|\theta) \end{aligned}$$

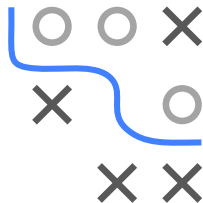
as first term above does not depend on θ . Therefore,

$$\begin{aligned} \arg \min_{\theta} D_{KL}(p||q_{\theta}) &= \arg \min_{\theta} -\mathbb{E}_{x \sim p} \log q(x|\theta) \\ &= \arg \max_{\theta} \mathbb{E}_{x \sim p} \log q(x|\theta) \end{aligned}$$

For a finite dataset of n samples from p , this is approximated as

$$\arg \max_{\theta} \mathbb{E}_{x \sim p} \log q(x|\theta) \approx \arg \max_{\theta} \frac{1}{n} \sum_{i=1}^n \log q(\mathbf{x}^{(i)}|\theta).$$

This also directly implies an equivalence to risk minimization!

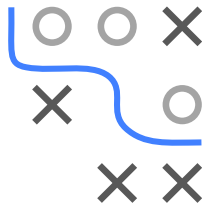


KL VS CROSS-ENTROPY

From this here we can see much more:

$$\arg \min_{\theta} D_{KL}(p||q_{\theta}) = \arg \min_{\theta} -\mathbb{E}_{x \sim p} \log q(x|\theta) = \arg \min_{\theta} H(p||q_{\theta})$$

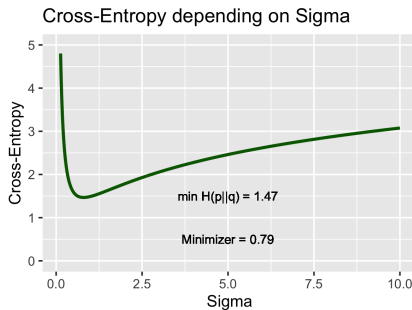
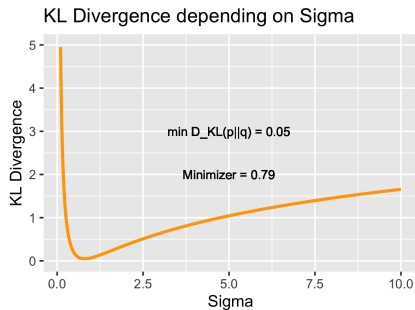
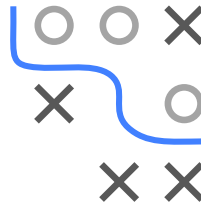
- So minimizing KL is the same as minimizing CE, is the same as maximum likelihood!
- We could now motivate CE as the "relevant" term that you have to minimize when you minimize KL - after you drop $\mathbb{E}_p \log p(x)$, which is simply the neg. entropy $H(p)$!
- Or we could say: CE between p and q is simply the expected negative log-likelihood of q , when our data comes from p !



KL VS CROSS-ENTROPY EXAMPLE

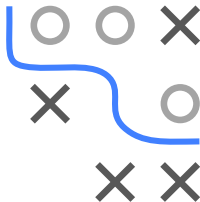
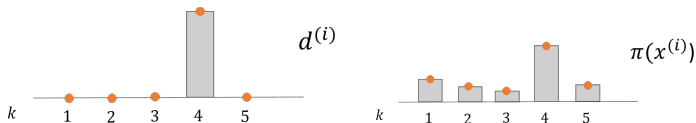
Let $p(x) = N(0, 1)$ and $q(x) = LP(0, \sigma)$ and consider again

$$\arg \min_{\theta} D_{KL}(p||q_{\theta}) = \arg \min_{\theta} -\mathbb{E}_{x \sim p} \log q(x|\theta) = \arg \min_{\theta} H(p||q_{\theta})$$



CROSS-ENTROPY VS. LOG-LOSS

- Consider a multi-class classification task with dataset $\mathcal{D} = ((\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(n)}, y^{(n)}))$.
- For g classes, each $y^{(i)}$ can be one-hot-encoded as a vector $d^{(i)}$ of length g . $d^{(i)}$ can be interpreted as a categorical distribution which puts all its probability mass on the true label $y^{(i)}$ of $\mathbf{x}^{(i)}$.
- $\pi(\mathbf{x}^{(i)}|\theta)$ is the probability output vector of the model, and also a categorical distribution over the classes.



CROSS-ENTROPY VS. BERNOULLI LOSS

For completeness sake:

Let us use the Bernoulli loss for binary classification:

$$L(y, \pi(\mathbf{x})) = -y \log(\pi(\mathbf{x})) - (1 - y) \log(1 - \pi(\mathbf{x}))$$

If p represents a $\text{Ber}(y)$ distribution (so deterministic, where the true label receives probability mass 1) and we also interpret $\pi(\mathbf{x})$ as a Bernoulli distribution $\text{Ber}(\pi(\mathbf{x}))$, the Bernoulli loss $L(y, \pi(\mathbf{x}))$ is the cross-entropy $H(p \parallel \pi(\mathbf{x}))$.



ENTROPY AS PREDICTION LOSS

$$\pi_k = \frac{n_k}{n} = \frac{\sum_{i=1}^n [y^{(i)} = k]}{n}$$

$$\begin{aligned}\mathcal{R} &= \frac{1}{n} \sum_{i=1}^n \left(- \sum_{k=1}^g [y^{(i)} = k] \log \pi_k \right) = - \frac{1}{n} \sum_{k=1}^g \sum_{i=1}^n [y^{(i)} = k] \log \pi_k \\ &= - \sum_{k=1}^g \frac{n_k}{n} \log \pi_k = - \sum_{k=1}^g \pi_k \log \pi_k = H(\pi)\end{aligned}$$

