

Image Denoising - Homework 7

Ex 2.11

$$E_{\theta}^{\text{ToE}}(u, v) = \frac{1}{2\sigma^2} \|u - v\|^2 + \sum_{k \in \mathcal{K}} \sum_{i=1}^N \phi_i(k_i * u(x)) + \ell$$

where $\phi_i(z) = \alpha_i \log\left(1 + \frac{z^2}{2}\right)$

$$\nabla E_{\theta}^{\text{ToE}} = \frac{2}{2\sigma^2} (u - v) + \sum_{i=1}^N \phi_i(k_i * u(x)) * \bar{k}_i$$

where \bar{k}_i is a π -rotation of k_i

since when denoising a convolution the kernels are shifted

Ex 2.2 | Let $L_{\infty}(\theta) = \mathbb{E}\{\log p_{\theta}(u)\} = \int \log(p_{\theta}(u)) p(u) du$
 $= \lim_{m \rightarrow \infty} \frac{1}{m} \sum_{j=1}^m \log p_{\theta}(u_j)$

let $KL(p(u) || p_{\theta}(u)) = \int \log\left(\frac{p(u)}{p_{\theta}(u)}\right) p(u) du$

$$KL(p(u) || p_{\theta}(u)) = \int \log(p(u)) p(u) du - \int \log(p_{\theta}(u)) p(u) du$$

$$= \underbrace{\int \log(p(u)) p(u) du}_{\text{doesn't depend on } \theta} - L_{\infty}(\theta)$$

\Rightarrow maximizing $L_{\infty}(\theta)$ minimizes $KL(p(u) || p_{\theta}(u))$