

PA 2018 04

Small addendum to density estimation

Converting the unsupervised Density estimation task to a supervised task (from HTF sec 14.2.4)

⇒ Perform a regression on the joint sample space to model the density (relative to the reference density) (14.2.4)

Mean Shift Algorithm

Method for finding the modes of a PDF.

Applications are essentially applications of clustering:

- data exploration
- image segmentation, denoising, ...
- dimensionality/complexity reduction

Let $S = x_1, x_2, \dots, x_N$ denote N d-dimensional observations x_i . The multivariate kernel estimate is

$$p(x) = \frac{1}{N} * \sum_{i=1}^N K_\lambda(x_i, x)$$

The maxima of $p(x)$ are characterized by the locations x where $\nabla p(x)$ vanishes.

$$\nabla p(x) = \nabla \frac{1}{N} * \sum_{i=1}^N K_\lambda(x_i, x) = \frac{1}{N} * \sum_{i=1}^N \nabla K_\lambda(x_i, x)$$

Let us assume that the kernel is radial symmetric

$$K_\lambda(x_i, x) = C_d * k_\lambda(\|x_i - x\|_2^2)$$

Derive the kernel:

$$\frac{\partial k_\lambda(s)}{\partial s} = k'_\lambda(s) \text{ derivative of the kernel}$$

$$\frac{\partial s}{\partial x} = \frac{(x_i - x)^T (x_i - x)}{x} = 2(x_i - x) \text{ application of the chain rule}$$

$$\nabla p(x) = \frac{1}{N} * \sum_{i=1}^N C_d * k'_\lambda(\|x_i - x\|_2^2) * (-2(x_i - x)) = 0 \Leftrightarrow \sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2) * x_i - \sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2) * x = 0$$

$$\Rightarrow \frac{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2) * x_i}{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2)} - x = 0 \text{ Mean shift equation}$$

To perform gradient ascent, we have to compute the gradient and to "walk upwards" along the gradient direction until the gradient vanishes

Algorithm:

1) compute the mean shift vector

$$m(x^{(t)}) = \frac{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2) * x_i}{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2)} - x = 0$$

$$2) \text{ update } x^{(t+1)} = x^{(t)} + m(x^{(t)}) = \frac{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2) * x_i}{\sum_{i=1}^N k'_\lambda(\|x_i - x\|_2^2)}$$

Why "MEAN SHIFT"?

If the kernel is chosen as the Epanechnikov kernel, then the update simplifies to computing the weighted "mean" of all feature vectors a sphere around x

Epanechnikov Kernel: $K_E(x) = c * (1 - x^T x)$ if $x^T x \leq 1$ otherwise 0

Paper: Comaniciu, Meer: "Mean Shift: A robust Approach Toward Feature Space Analysis"

