

### **Selecting bandwidth for kernel estimator:**

see Chap 20 of Wasserman's "All of Statistics, A Concise Course in Statistical Inference" for various risk estimators and bandwidth selectors.

- \* caveat: it's missing details like data splitting that are part of the equations, but, that he has in his lecture notes:

<https://www.stat.cmu.edu/~larry/=sml/densityestimation.pdf>

36-708 Statistical Methods for Machine Learning by Larry Wasserman, CMU

- \* regarding loss functions in context of estimating kernel densities:

Kullback-Leibler is not a good loss function to use for nonparametric density estimation because it is completely dominated by the tails of the densities. The use of an assumed gaussian for the unknown distribution can also be problematic for non-symmetric distributions, including multi-modal.

- \* end of chapter 20 footnote: For large data sets the kernel density estimator, and (20.25) can be computed quickly using the fast Fourier transform.

see Chap 6 of Bishop's "Pattern Recognition and Machine Language"

see Section 5 of "A Reliable Data-Based Bandwidth Selection Method for Kernel Density Estimation"

S. J. Sheather, M. C. Jones, 1991, J.R. Statistic Society B, Volume 53, Issue 3, 1991, Pages 683-690

A fast implementation using FFT

<https://kdepy.readthedocs.io/en/latest/introduction.html#Selecting-a-suitable-bandwidth>

see wikipedia for a single mode data, gaussian estimate:

[https://en.m.wikipedia.org/wiki/Kernel\\_density\\_estimation#A\\_rule-of-thumb\\_bandwidth\\_estimator](https://en.m.wikipedia.org/wiki/Kernel_density_estimation#A_rule-of-thumb_bandwidth_estimator)