

# Fast Fourier transforms for efficient computation of kernel estimators

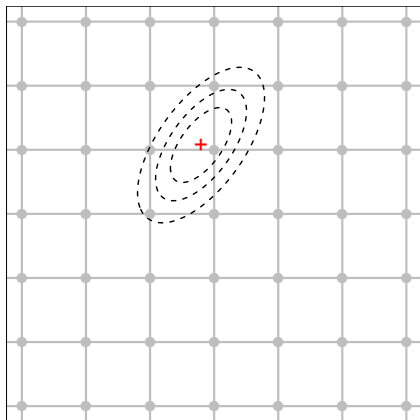
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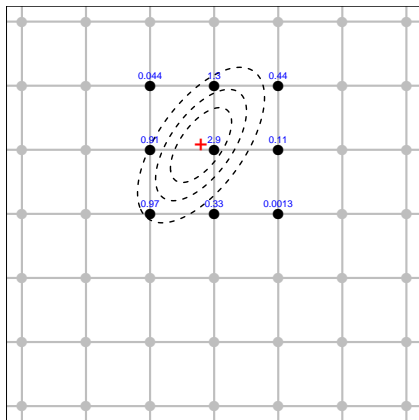
## Exact kernel estimation

- Data point  $X_1 = (0.266, 0.479)$  (red cross)
- Estimation grid  $7 \times 7$  on  $[0, 1] \times [0, 1]$  (grey circles/lines)
- Gaussian kernel  $K$  centred on  $X_1$  with variance  $\mathbf{H} = [0.01; 0.075; 0.0075, 0.015]$   
 $K_{\mathbf{H}}(\mathbf{x} - X_1)$



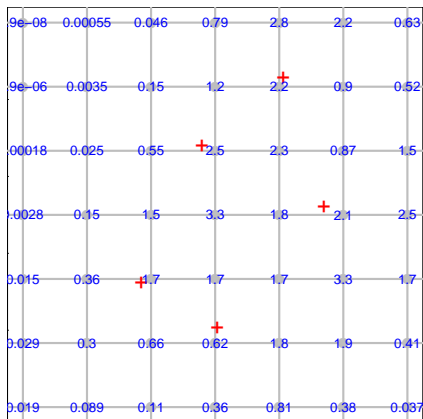
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- Evaluate  $K$  (red values) at all grid points that fall in (effective) support (black circles) of  $K_{\mathbf{H}}(\mathbf{x} - X_1)$



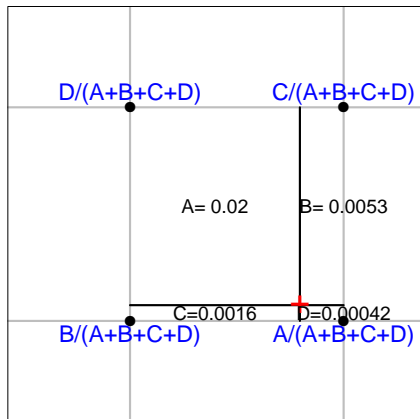
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- Repeat for all  $n$  data points and sum kernel values  $\hat{f}(\mathbf{x}; \mathbf{H}) = \frac{1}{n} \sum_{i=1}^n K_{\mathbf{H}}(\mathbf{x} - X_i)$



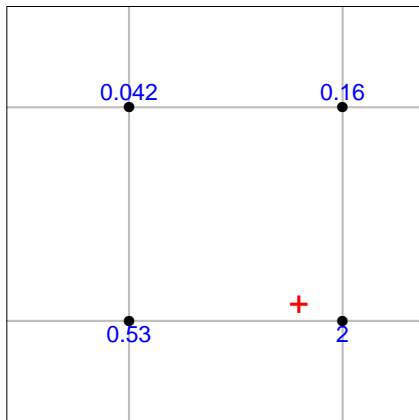
## Linear binning

- Data point  $X_1 = (0.266, 0.479)$  (red cross)
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- Zoom in on bin containing  $X_1$



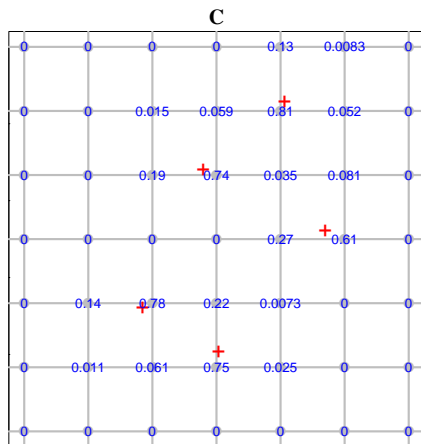
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- Repeat for all data points to create  $C$  by summing any overlapping weights



## Fast Fourier transform (FFT)

- Kernel estimation = smooth convolution with Gaussian kernel
- Replace smooth convolution with faster discrete convolution (FFT)
- Recall that original grid is indexed by  $\ell_1 = 1, \dots, M_1$  and  $\ell_2 = 1, \dots, M_2$
- Let  $\delta$  = dimensions of each bin and  $\kappa_{\ell} = \frac{1}{n} K_{\mathbf{H}}(\delta_1 \ell_1, \delta_2 \ell_2)$ ,  $\ell_1, \ell_2 \in \mathbb{Z}$  is the value of Gaussian kernel on 'extended' grid

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- Create zero-padded  $P_1 \times P_2$  matrices, e.g.  $P_1$  is smallest power of 2 greater than  $M_1$  etc.

$$\mathbf{K}_0 = \begin{bmatrix} \kappa_{-M_1, -M_2} & \dots & \kappa_{-M_1, 0} & \dots & \kappa_{-M_1, M_2} & \dots & \mathbf{0}_{P_1 - 2M_1 + 1}^T \\ \vdots & & \vdots & & \vdots & & \vdots \\ \kappa_{0, -M_2} & \dots & \kappa_{0, 0} & \dots & \kappa_{0, M_2} & \dots & \mathbf{0}_{P_1 - 2M_1 + 1}^T \\ \vdots & & \vdots & & \vdots & & \vdots \\ \kappa_{M_1, -M_2} & \dots & \kappa_{M_1, 0} & \dots & \kappa_{M_1, M_2} & \dots & \mathbf{0}_{P_1 - 2M_1 + 1}^T \\ \mathbf{0}_{P_2 - 2M_2 + 1} & \dots & \mathbf{0}_{P_2 - 2M_2 + 1} & \dots & \mathbf{0}_{P_2 - 2M_2 + 1} & \dots & \mathbf{0}_{P_2 - 2M_2 + 1, P_2 - 2M_1 + 1} \end{bmatrix}$$

$$\mathbf{C}_0 = \begin{bmatrix} \mathbf{0}_{M_1, M_2} & \mathbf{0}_{M_1, M_2} & \mathbf{0}_{M_1, P_2 - 2M_2} \\ \mathbf{0}_{M_1, M_2} & \mathbf{C} & \mathbf{0}_{M_1, P_2 - 2M_2} \\ \mathbf{0}_{P_1 - 2M_1, M_2} & \mathbf{0}_{P_1 - 2M_1, M_2} & \mathbf{0}_{P_1 - 2M_1, P_2 - 2M_2} \end{bmatrix}$$

## Binned kernel density estimation

- $\mathbf{S} = FFT^{-1}(FFT(\mathbf{C}_0)FFT(\mathbf{K}_0))$  is  $P_1 \times P_2$  matrix
- Binned kernel estimator on  $M_1 \times M_2$  grid is central  $M_1 \times M_2$  elements of  $\mathbf{S}$ :

$$\frac{1}{P_1 P_2} \mathbf{S}_{(2M_1-1):(3M_1-2), (2M_2-1):(3M_2-2)}$$

- (Gramacki & Gramacki, 2016) [arxiv.org/abs/1508.02766](https://arxiv.org/abs/1508.02766)



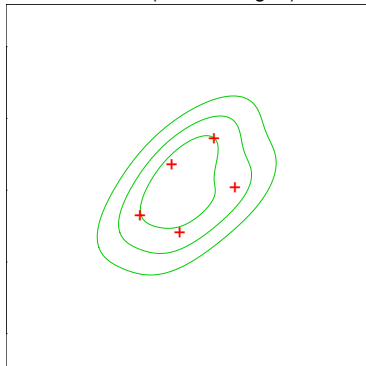
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Binned (151 × 151 grid)



Exact (151 × 151 grid)

