

Plug-in Bandwidth Selectors for Bivariate Kernel Density Estimation

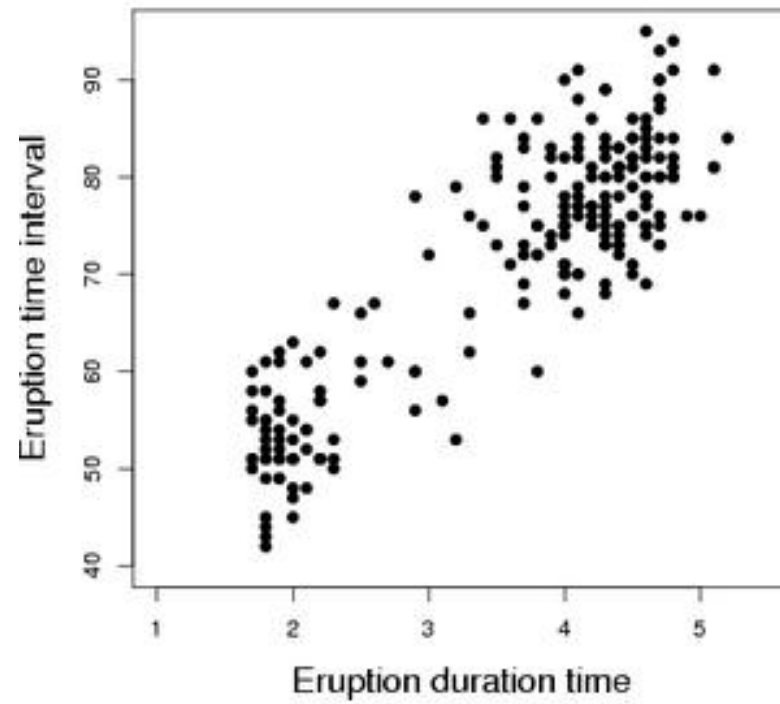
Tarn Duong
Supervisor: Dr Martin Hazelton

May 2002

Outline

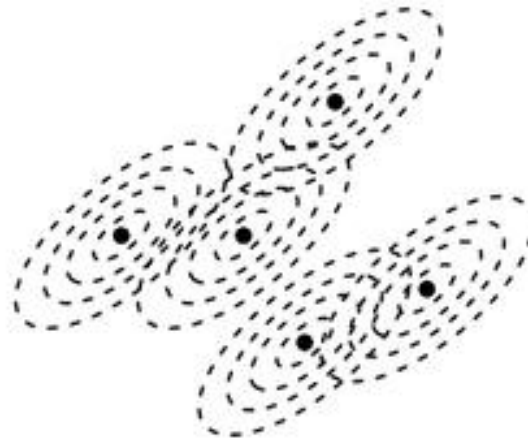
1. Motivation
2. Basics of KDE
3. Plug-in bandwidth selectors
 - Existing and proposed methods
4. Simulation and real data results
5. Summary

Motivation

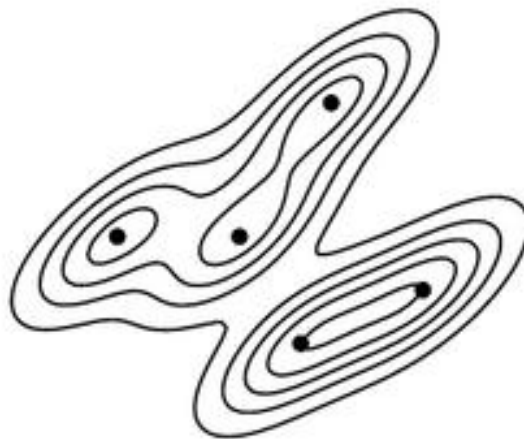


Forming KDE (1)

Full bandwidths



Forming KDE (2)



Equation for KDE

Kernel density estimate is

$$\hat{f}(\mathbf{x}; \mathbf{H}) = n^{-1} \sum_{i=1}^n K_{\mathbf{H}}(\mathbf{x} - \mathbf{X}_i)$$

where

- $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$ is sample of n data points
- \mathbf{H} is **bandwidth** matrix
- $K_{\mathbf{H}}(\mathbf{x} - \mathbf{X}_i)$ is normal pdf with mean \mathbf{X}_i and variance \mathbf{H}

Advantages of KDE

- does not require parametric form i.e. is non-parametric
- always guaranteed to be a proper pdf

MISE

Mean Integrated Squared Error (MISE) is

$$\begin{aligned} \text{MISE } \hat{f}(\cdot; \mathbf{H}) &= \int_{\mathbb{R}^2} \text{MSE } \hat{f}(\mathbf{x}; \mathbf{H}) \, d\mathbf{x} \\ &= \int_{\mathbb{R}^2} \mathbb{E}[\hat{f}(\mathbf{x}; \mathbf{H}) - f(\mathbf{x})]^2 \, d\mathbf{x} \end{aligned}$$

where

- $\hat{f}(\mathbf{x}; \mathbf{H})$ is kernel density estimate
- $f(\mathbf{x})$ is target density

AMISE

Asymptotic Mean Integrated Squared Error (AMISE) is

$$\text{AMISE } \hat{f}(\cdot; \mathbf{H}) = n^{-1}(4\pi)^{-1}|\mathbf{H}|^{-1/2} + \frac{1}{4}(\text{vech}^T \mathbf{H})\Psi(\text{vech } \mathbf{H})$$

where

- $\text{vech } \mathbf{H}$ is vector of lower triangular half of \mathbf{H}
i.e. if $\mathbf{H} = \begin{bmatrix} h_1^2 & h_{12} \\ h_{12} & h_2^2 \end{bmatrix}$ then $\text{vech } \mathbf{H} = [h_1^2 \ h_{12} \ h_2^2]$
- Ψ is matrix of functionals that depend on f

Plug-in selector

1. choose diagonal or full bandwidth matrix
2. estimate Ψ
3. PI is AMISE with Ψ replaced with $\hat{\Psi}$

$$\text{PI}(\mathbf{H}) = n^{-1}(4\pi)^{-1}|\mathbf{H}|^{-1/2} + \frac{1}{4}(\text{vech}^T \mathbf{H})\hat{\Psi}(\text{vech } \mathbf{H})$$

4. optimal bandwidth is $\hat{\mathbf{H}}_{\text{PI}} = \underset{\mathbf{H}}{\text{argmin}} \text{PI}(\mathbf{H})$

Existing and proposed methods

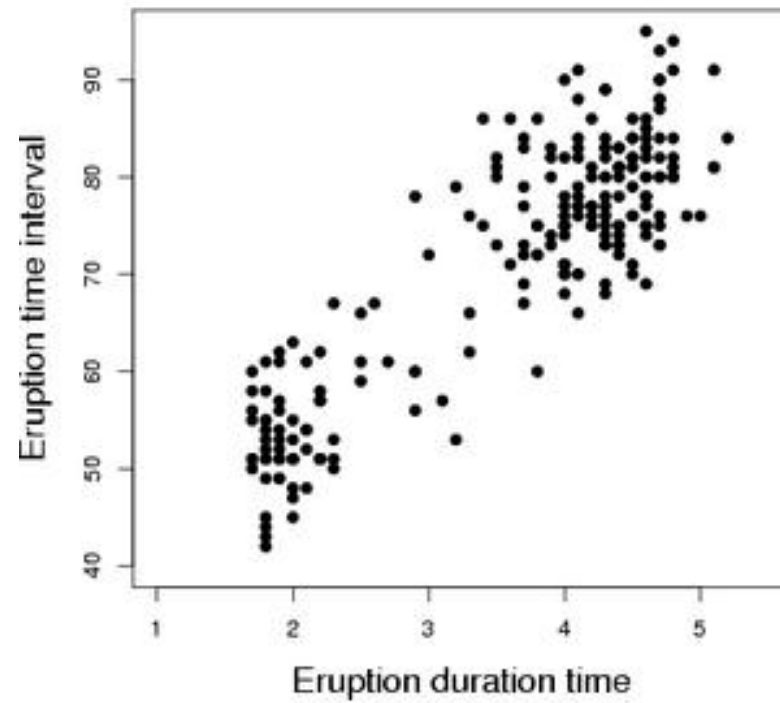
- **Existing**

1. use diagonal bandwidth matrix
2. estimate Ψ element-wise

- **Proposed**

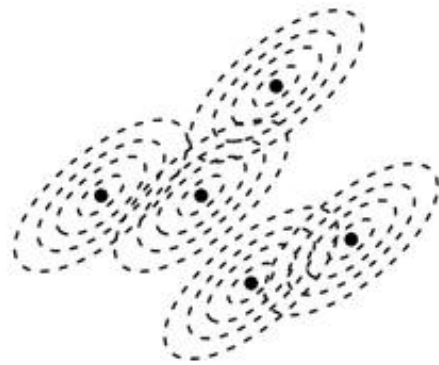
1. use full bandwidth matrix
2. estimate Ψ matrix-wise

'Old Faithful' geyser data

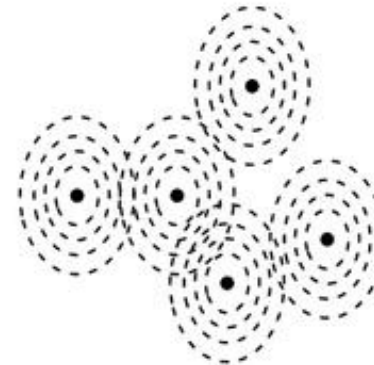


Diagonal and full bandwidth matrices

Full bandwidths



Diagonal bandwidths



Explicit expression for Ψ

- partial derivative: $f^{(r_1, r_2)}(\mathbf{x}) = \frac{\partial^{(r_1+r_2)}}{\partial x_1^{r_1} \partial x_2^{r_2}} f(\mathbf{x})$

- ψ functional: $\psi_{r_1, r_2} = \int_{\mathbb{R}^2} f^{(r_1, r_2)}(\mathbf{x}) f(\mathbf{x}) d\mathbf{x}$

- matrix: $\Psi = \begin{bmatrix} \psi_{40} & 2\psi_{31} & \psi_{22} \\ 2\psi_{31} & 4\psi_{22} & 2\psi_{13} \\ \psi_{22} & 2\psi_{13} & \psi_{04} \end{bmatrix}$

Estimating ψ_{r_1, r_2}

- $\psi_{r_1, r_2} = \mathbb{E} f^{(r_1, r_2)}(\mathbf{X})$
- $\hat{\psi}_{r_1, r_2} = n^{-1} \sum_{i=1}^n \hat{f}^{(r_1, r_2)}(\mathbf{X}_i; g)$
where g is a (scalar) **pilot** bandwidth
- choose g via minimising MSE ψ_{r_1, r_2}

Estimating ψ_{r_1, r_2} - existing method (1)

Asymptotic MSE of $\hat{\psi}_{r_1, r_2}$ is

$$\begin{aligned} \text{AMSE } \hat{\psi}_{r_1, r_2}(g) &= (4\pi)^{-1} n^{-2} g^{-10} \\ &+ \left[n^{-1} g^{-6} K^{(r_1, r_2)}(\mathbf{0}) + \frac{1}{2} g^2 (\psi_{r_1+2, r_2} + \psi_{r_1, r_2+2}) \right]^2 \end{aligned}$$

Estimating ψ_{r_1, r_2} - existing method (2)

If r_1, r_2 are both even then

$$g_{r_1, r_2} = \left[\frac{-2K^{(r_1, r_2)}(\mathbf{0})}{(\psi_{r_1+2, r_2} + \psi_{r_1, r_2+2})n} \right]^{1/8}$$

If r_1, r_2 are both odd then

$$g_{r_1, r_2} = \left[\frac{5\psi_{0,0}}{2\pi(\psi_{r_1+2, r_2} + \psi_{r_1, r_2+2})^2 n^2} \right]^{1/14}$$

Estimating Ψ - existing method

$$\hat{\Psi} = \begin{bmatrix} \hat{\psi}_{40}(g_{40}) & 2\hat{\psi}_{31}(g_{31}) & \hat{\psi}_{22}(g_{22}) \\ 2\hat{\psi}_{31}(g_{31}) & 4\hat{\psi}_{22}(g_{22}) & 2\hat{\psi}_{13}(g_{13}) \\ \hat{\psi}_{22}(g_{22}) & 2\hat{\psi}_{13}(g_{13}) & \hat{\psi}_{04}(g_{04}) \end{bmatrix}$$

$\hat{\Psi}$ can be

- not +ve definite so no finite min for $\text{PI}(\mathbf{H})$
- nearly singular so numerical instability in $\text{PI}(\mathbf{H})$

Estimating ψ_{r_1, r_2} - proposed method (1)

Sum of AMSE is

$$\begin{aligned} \text{SAMSE}(g) &= \sum_{r_1=0}^4 \text{AMSE} \hat{\psi}_{r_1, r_2}(g) \quad \text{where } r_2 = 4 - r_1 \\ &= n^{-2} g^{-12} A_2 + n^{-1} g^{-4} A_3 + \frac{1}{4} g^4 A_4 \end{aligned}$$

where $A_2, A_4 > 0$ and $A_3 < 0$.

Estimating ψ_{r_1, r_2} - proposed method (2)

$$g = \left[\frac{6A_2}{(-A_3 + \sqrt{A_3^2 + 3A_1A_2})n} \right]^{1/8}$$

Estimating Ψ - proposed method

$$\hat{\Psi} = \begin{bmatrix} \hat{\psi}_{40}(g) & 2\hat{\psi}_{31}(g) & \hat{\psi}_{22}(g) \\ 2\hat{\psi}_{31}(g) & 4\hat{\psi}_{22}(g) & 2\hat{\psi}_{13}(g) \\ \hat{\psi}_{22}(g) & 2\hat{\psi}_{13}(g) & \hat{\psi}_{04}(g) \end{bmatrix}$$

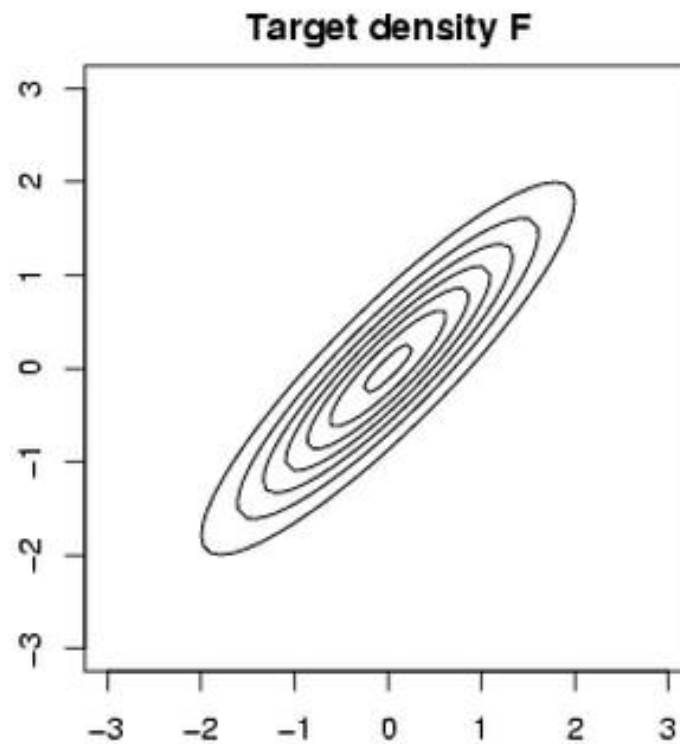
- $\hat{\Psi}$ is +ve definite.
- lose a little efficiency compared to existing method

Simulation results (1)

- normal mixture densities
 - wide range of features
 - closed form for $\text{ISE} \hat{f}(\cdot; \mathbf{H}) = \int_{\mathbb{R}^2} [\hat{f}(\mathbf{x}; \mathbf{H}) - f(\mathbf{x})]^2 d\mathbf{x}$
- use $\log(\text{ISE})$ to compare performance between
 - diagonal selector with different pilots
 - full selector with different pilots
 - full selector with single pilot
- 400 simulations, each of size $n = 1000$

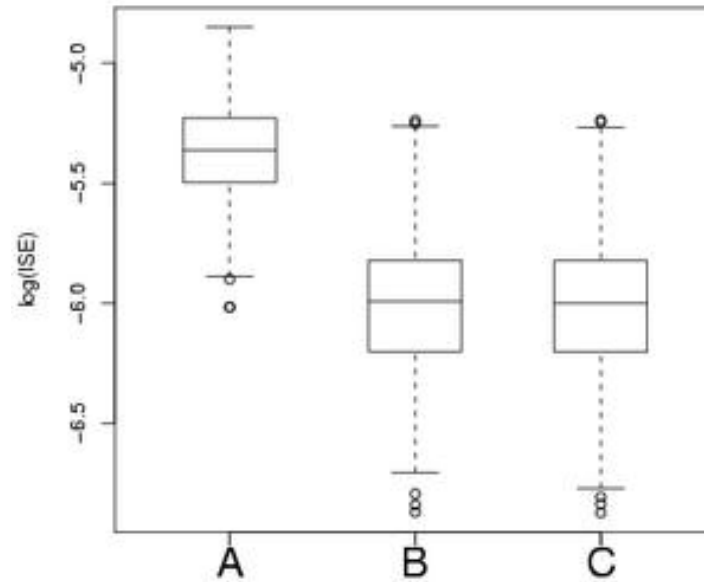
Simulation results (2)

Highly correlated normal density - contour plot



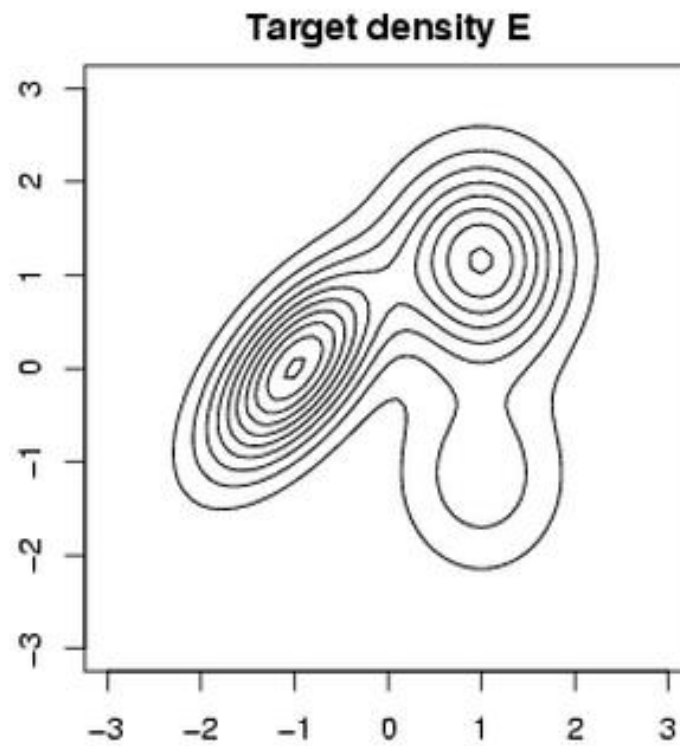
Simulation results (3)

Highly correlated normal density - boxplot



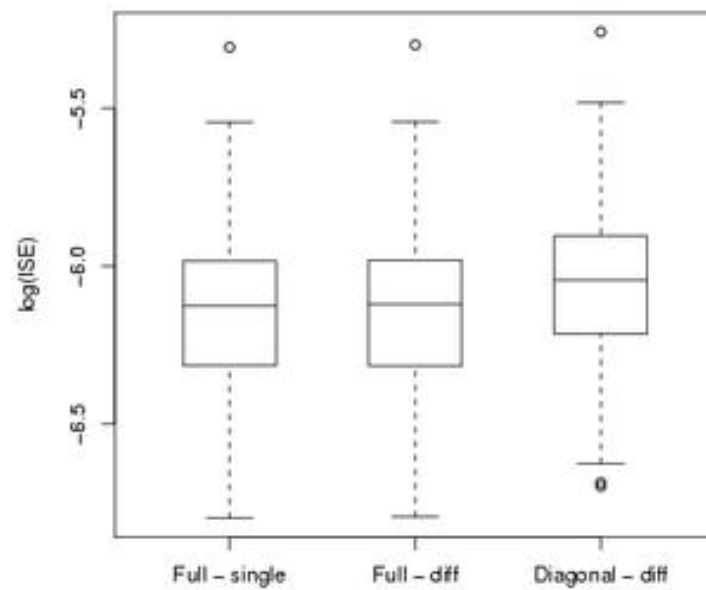
Simulation results (4)

Trimodal density - contour plot

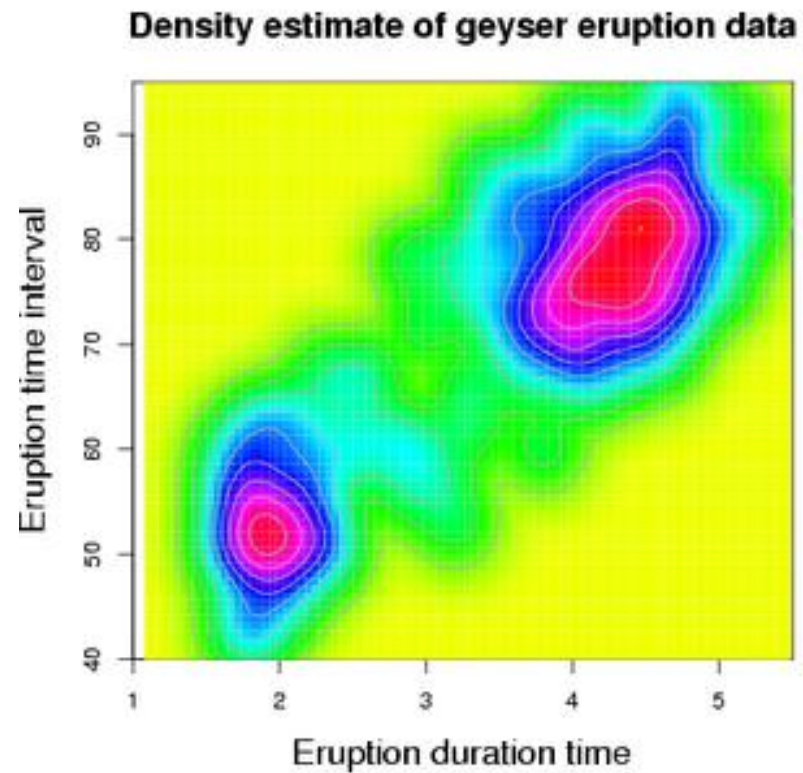


Simulation results (5)

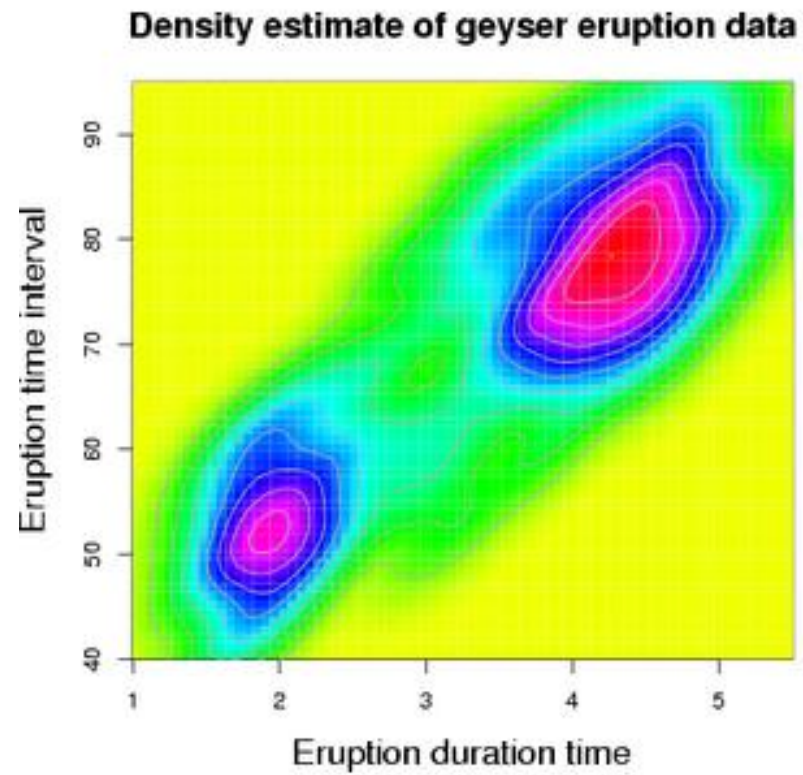
Trimodal density - boxplot



Real data KDE - existing method



Real data KDE - proposed method



Summary

Existing method	Proposed method
Diagonal \mathbf{H}	Full \mathbf{H}
Different pilots	Single pilot
$\hat{\Psi} \neq 0$	$\hat{\Psi} > 0$
Poor estimation of data not aligned to axes	Good estimation of data not aligned to axes