Automatic Bandwidth Selection for Circular Density Estimation

Charles C. Taylor
Dept. of Statistics, University of Leeds, Leeds LS2 9JT, UK

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Abstract

Given angular data $\theta_1, \ldots, \theta_n \in [0, 2\pi)$ a common objective is to estimate the density. In the case that a kernel estimator is used, bandwidth selection is crucial to the performance. This paper obtains a ‘plug-in rule” for the bandwidth, which is based on the concentration of a reference density, namely, the von Mises distribution. It is seen that this is equivalent to the usual Euclidean plug-in rule in the case that the concentration becomes large. In the case that the concentration parameter is unknown, alternative methods are explored which are intended to be robust to departures from the reference density. Simulations indicate that “wrapped estimators” can perform well in this context.

keywords: Angle data; Kernel density estimators; von Mises distribution; Smoothing parameter selection.
1 Introduction

Given a random sample of angles $\theta_1, \ldots, \theta_n \in [0, 2\pi)$ from some unknown density $f(\theta)$ a natural component of exploratory data analysis is to estimate the function $f(\cdot)$. When a parametric form is assumed, this may be achieved by maximum likelihood, or moment-based estimation. A nonparametric estimator may be naively written as

$$\hat{f}(\theta; h) = \frac{1}{n} \sum_{i=1}^{n} K_h(\theta - \theta_i)$$

(1)

where $K_h(\theta) = K(\theta/h)/h$ is a kernel function, usually a symmetric probability density, and $h$ is a smoothing parameter.

This kernel estimator was first proposed by Fisher (1989) for data lying on the circle, in which he adapted linear data methods of Silverman (1986) and used a quartic kernel function $K(\theta) = 0.9375(1 - \theta^2)^2$. However, when using data on the circle, we cannot use distance in Euclidean space, so all differences $\theta - \theta_i$ should be replaced by considering the angle between two vectors:

$$d_i(\theta) = ||\theta - \theta_i|| = \min(|\theta - \theta_i|, 2\pi - |\theta - \theta_i|).$$

(2)

This may also be written as $d_i = \cos^{-1}(x^T x_i)$ where $x^T = (\cos \theta, \sin \theta)$ is a unit vector. A more natural choice for the kernel function is therefore one of the commonly used circular probability densities, such as the wrapped normal distribution, or the von Mises distribution. This leads to an alternative representation for the kernel density estimate (Jammalamadaka and SenGupta, 2001, page 282):

$$\hat{f}(x; h) = \frac{1}{n} \sum_{i=1}^{n} K_h(1 - x^T x_i).$$

(3)

In studying properties of kernel density estimates in Euclidean space, it is common to take Taylor series approximations to give an asymptotic form for the bias and variance. These can then be combined to give an asymptotically optimal choice for the smoothing parameter; see, for example, Silverman (1986). For data lying on the $q$-dimensional sphere ($q \geq 2$) Hall et al. (1987) described the asymptotic bias and variance of two classes of kernel estimators. This was done by the use of directional derivatives, thus making the results a close analogue of the Taylor series methods used for data in Euclidean space.

One of the difficulties in nonparametric density estimation is to make good choices of the smoothing parameter $h$; see Jones et al. (1996) for an excellent survey of methods. In the Euclidean setting, Silverman (1986) and Jones et al. (1996) give formulae which depend on derivatives of the unknown density $f$. When the data lie in Euclidean space, there are many approaches to this problem, a simple example of which is based on a “Normal-scale rule” or a “rule-of-thumb”. When the kernel function is taken as the gaussian density, this leads to a plug-in selector $h = 1.06\hat{\sigma}n^{-1/5}$ (Silverman, 1986). The goal of this paper is to obtain an equivalent plug-in rule for density estimation on the circle.

Specifically, we consider the estimator in which the kernel function is the von Mises density, which gives

$$\hat{f}(\theta; \nu) = \frac{1}{n(2\pi)I_0(\nu)} \sum_{i=1}^{n} \exp\{\nu \cos(\theta - \theta_i)\}.$$

(4)

where $I_r(\nu)$ is the modified Bessel function of order $r$, and the concentration parameter $\nu$ has now taken the role of the (inverse of the) smoothing parameter $h$. Rather than following the more standard approach of obtaining the smoothing parameter by considering derivatives of the unknown density and then substituting a “reference” density in order to obtain a plug-in rule, we instead follow the approach of Marron and Wand (1992) who obtained the form of the exact mean integrated squared error for densities which can be expressed as a mixture of normal densities.
In Section 2 we write the exact expectation and variance of the estimator (4) under the assumption that the data follow a von Mises distribution. This then leads to an expression for the asymptotic bias and variance, which can be integrated to give AMISE as a function of the concentration parameter of the data ($\kappa$), the smoothing parameter ($\nu$) and the sample size ($n$). Finally, this can be solved to give a simple plug-in rule for $\nu$ dependent only on $\kappa$ and $n$. Section 3 discusses robust estimation of $\kappa$, suited for the plug-in rule, which may be used in case that the underlying density is not von Mises, and Section 4 gives some simulation results. We conclude with a discussion.

2 Asymptotic Integrated Mean Squared Error

We suppose $f(\cdot)$ is von Mises, with concentration parameter $\kappa$ and – without loss of generality – mean $\mu = 0$. Then the first two moments of (4) are given by

$$E\{ \hat{f}(\theta; \nu) \} = \frac{1}{(2\pi)^2 I_0(\kappa) I_0(\nu)} \int_0^{2\pi} \exp\{ \nu \cos(\theta - \phi) + \kappa \cos(\phi) \} d\phi$$

$$= \frac{I_0\{ (\kappa^2 + \nu^2 + 2\nu \kappa \cos \theta)^{1/2} \}}{(2\pi) I_0(\kappa) I_0(\nu)},$$

(Agostinelli, 2007) and

$$\text{var}\{ \hat{f}(\theta; \nu) \} = \frac{1}{n(2\pi)^2 I_0(\nu)^2} \text{var}[\exp\{ \nu \cos(\theta - \Phi) \}]$$

$$= \frac{1}{n(2\pi)^2 I_0(\nu)^2 I_0(\kappa)} \left[ I_0\{ (4\nu^2 + \kappa^2 + 4\nu \kappa \cos \theta)^{1/2} \} - \frac{I_0\{ (\nu^2 + \kappa^2 + 2\nu \kappa \cos \theta)^{1/2} \}^2}{I_0(\kappa)} \right].$$

Note that, when $\nu = 0$ we have $E\{ \hat{f}(\theta; 0) \} = 1/\{(2\pi)I_0(\kappa)\}$ which does not depend on $\theta$ and, as $\nu \to \infty$, the estimator is unbiased. These equations may be used to write down an expression for the exact mean squared error. However, integrating this expression to obtain the exact IMSE seems hard to do analytically, so we now derive asymptotic expressions for the above.

As the smoothing parameter $\nu \to \infty$ the asymptotic bias is

$$\{2\pi I_0(\kappa)\}^{-1} \left( \exp \left[ \nu \left\{ 1 + \frac{\kappa^2}{\nu^2} + \frac{2\kappa}{\nu} \cos \theta \right\}^{1/2} - 1 \right] \right) - \exp\{ \kappa \cos \theta \} + O\left( \nu^{-1/2} \right).$$

Expanding the square root in a Taylor series, then expanding the exponential function in a Taylor series gives a simpler form of the asymptotic bias as

$$(4\pi I_0(\kappa)\nu)^{-1} \kappa^2 \sin^2 \theta \exp(\kappa \cos \theta) + O\left( \nu^{-1/2} \right)$$

(5)

Similarly, for large $n$, and as $\nu \to \infty$ the variance has asymptotic form

$$\{4n\pi^{3/2} I_0(\kappa)\nu^{-1/2} \exp \left[ 2\nu \left\{ 1 + \frac{\kappa^2}{4\nu^2} + \frac{\kappa}{\nu} \cos \theta \right\}^{1/2} - 1 \right] \} + o\left( \frac{\nu^{1/2}}{n} \right)$$

which is valid provided $n/\nu^{1/2} \to \infty$. Again, by expanding the square root, and then the exponential function, as Taylor series, we obtain the simpler form of the asymptotic variance

$$\{4n\pi^{3/2} I_0(\kappa)\}^{-1} \nu^{1/2} \exp(\kappa \cos \theta) + o\left( \frac{\nu^{1/2}}{n} \right).$$

(6)
We now integrate the square of the asymptotic bias (5) and the asymptotic variance (6), to obtain

$$3\kappa \{\kappa I_0(2\kappa) - I_1(2\kappa)\} / \{32\pi^2 I_0(\kappa)^2\}$$

and

$$\nu^{1/2} / \left(2n\pi^{1/2}\right)$$

respectively. Thus the asymptotic integrated mean squared error is of the form $a\nu^{-2} + b\nu^{1/2}$ which can be minimized by differentiating with respect to $\nu$ and equating to zero. This leads to a “von Mises-scale plug-in rule” for the smoothing parameter $\nu$ based on the estimated $\kappa$:

$$\nu = \left[3n\hat{\kappa} \{4\pi^{1/2} I_0(\hat{\kappa})^2\}^{-1} \{\kappa I_0(2\hat{\kappa}) - I_1(2\hat{\kappa})\}\right]^{2/5}$$

(7)

Note that this is of a similar asymptotic form as the normal-scale plug-in rule when we recall that $\nu$ is the concentration parameter, and so takes the role of $1/h^2$ in $h = 1.06\hat{\sigma}n^{-1/5}$. Moreover, if we consider the limit as $\kappa \to \infty$ then the von Mises distribution tends to a Normal distribution, with $\sigma = \kappa^{1/2}$. Hence, in the limit we have $h = \nu^{-1/2} = 1.06\kappa^{-1/2}n^{-1/5}$ which is exactly the same as the usual rule of thumb used for the Normal distribution. A simple method could be to estimate $\kappa$ from the data, and use equation (7) to select the smoothing parameter for use in (4).

Two obvious questions arise at this point: what happens if the data do not come from this reference density (von Mises); how good are all these Taylor series approximations in practice? The next two sections address these questions in turn.

3 Robust Estimation of Spread

When the data are unimodal, the above selection rule (7) is likely to work reasonably well. However, for bimodal data, the usual estimate of $\kappa$ – either by maximum likelihood, or the method of moments – may be almost useless. In the most extreme case, an equal mixture of data tightly clustered around $\phi$ combined with a similar distribution of data clustered around $\phi + \pi$ will lead to an estimate of $\kappa$ close to zero. When $\hat{\kappa} = 0$ then equation (7) gives $\nu = 0$ which will result in $\hat{f}(\theta) \equiv 1/(2\pi)$, and so such automatic methods may lead to very misleading density estimates.

In the case of Euclidean data, an alternative rule-of-thumb proposed by Silverman (1986, p. 47) was to take $\hat{\sigma} = \min\{s, \text{iqr}/1.349\}$, where $s$ is the sample standard deviation, and iqr is the inter-quartile range. This will work better for bimodal data, and give similar results when the data are normal. This proposal was obtained by comparing the population inter-quartile range to the standard deviation. For circular data, if $m$ is the (estimated) median then, for $0 < p < 0.5$ define $q_i(p) \in [0, \pi)$ such that

$$p = \int_{m-q_i(p)}^{m} f(\theta)d\theta = \int_{m}^{m+q_2(p)} f(\theta)d\theta$$

which can be solved for known $f(\cdot)$ and given $p$. In particular, for the reference (von Mises) distribution, without loss of generality we can set $m = 0$. The inter $p$-quantile range for the reference distribution is then given by $q_2(p) + q_1(p) = 2q_1(p)$. The sample circular median is defined (Mardia & Jupp, 1999, p. 17) as the value $\hat{m}$ such that half the data lies in $[\hat{m}, \hat{m} + \pi)$ and more data lies closer to $\hat{m}$ than to $\hat{m} + \pi$. Sample values of $q_i(p)$ can then be easily found from the data. The procedure is then as follows:
1. Select \( p \in (0, 1/2) \)

2. Form a look-up table which defines \( q_1(p) \) as a function of \( \kappa \) for the reference distribution \( vM(0, \kappa) \)

3. Find the sample median \( \hat{m} \) and \( \hat{q}_i(p), i = 1, 2 \) from the data

4. Obtain the estimated \( \kappa \) from the look-up table, using \( ||\hat{m} + \hat{q}_2(p) - (\hat{m} - \hat{q}_1(p))|| \) where the distance used is as in Equation (2)

An alternative approach is to note that, for the von Mises distribution, the maximum likelihood estimate of \( \kappa \) is obtained from the solution to

\[
A_1(\kappa) = \frac{1}{n} \sum_{i=1}^{n} \cos(\theta_i - \hat{\mu})
\]

where \( A_k(\kappa) = I_k(\kappa)/I_0(\kappa) \) and \( \hat{\mu} = \tan^{-1}(\sum\sin \theta_i, \sum \cos \theta_i) \). This follows from a more general identity using trigonometric moments which states that \( E \cos\{k(\theta - \mu)\} = I_k(\kappa)/I_0(\kappa) \). Thus, alternative estimates of \( \kappa \) (for a von Mises distribution) are given by solutions to

\[
A_k(\kappa) = \frac{1}{n} \sum_{i=1}^{n} \cos\{k(\theta_i - \hat{\mu}_k)\}
\]

where \( \hat{\mu}_k = \tan^{-1}(\sum k\theta_i, \sum \cos k\theta_i) \), for \( k = 1, 2, \ldots \). In the case that the data are von Mises, different values of \( k \) will lead to similar estimates of \( \kappa \) (though not equally efficient). However, in the case of multimodal data, then rather different estimates will ensue. Hence, a possible procedure is to estimate \( \kappa \) using \( k = 1, \ldots, K \) in Equation (8) giving, say, \( \hat{\kappa} \), and then taking \( \hat{\kappa} = \max\{\hat{\kappa}_k, k = 1, \ldots, K\} \) for use in Equation (7).

4 Simulations

For the standard von Mises distribution, we can compare the average integrated squared error \( \text{ISE} \) with the approximate MISE given in Section 2, when \( \kappa \) is known. The results, for 500 simulations, and \( n = 50 \) and \( n = 500 \) are shown in Figure 1.

The approximation looks quite good, improving with \( n \). We now explore the effectiveness of the plug-in rule, when the data are taken from a mixture of \( M(\geq 1) \) von Mises distributions. Specifically, we simulate \( \theta_1, \ldots, \theta_n \sim f(\theta) \) where the distribution is given by

\[
f(\theta) = \frac{1}{2\pi} \sum_{j=1}^{M} p_j \exp\{\kappa_j \cos(\theta - \mu_j)\} / I_0(\kappa_j), \quad i = 1, \ldots, n \quad \text{with} \quad \sum_{j=1}^{M} p_j = 1 \quad (9)
\]

and we evaluate \( \text{ISE}(\nu) = \int (\hat{f}(\theta; \nu) - f(\theta))^2 d\theta \) over \( N = 500 \) datasets (using a grid of 500 points to evaluate the integrals numerically). For each distribution, we note the value of \( \nu \) which minimizes \( \text{ISE}(\nu) \), say \( \nu_0 \), as well as \( \text{ISE}(\nu_0) \). We also give \( \text{ISE}(\nu) \) when \( \nu \) is obtained for each dataset from the plug-in rule (7) and \( \hat{\kappa} \) is estimated by one of the methods described in Section 3. Finally, we give results when cross-validation is used to select the bandwidth. Here, we select \( \nu \) to maximize the likelihood cross-validation function \( \text{LCV}(\nu) = \prod_i \hat{f}_{-i}(\theta_i; \nu) \), where

\[
\hat{f}_{-i}(\theta_i; \nu) = \frac{1}{(n-1)(2\pi)I_0(\nu)} \sum_{j \neq i}^{n} \exp\{\nu \cos(\theta_i - \theta_j)\}
\]
Figure 1: Average integrated squared error – $\overline{\text{ISE}}$ – (points) and MISE (lines) for 500 simulations of size $n = 50$ (top panel) and $n = 500$ (bottom panel) from a von Mises distribution with $\kappa = 1$. 
is the leave-one-out estimator. Let \( \nu_{CV} \) denote the value of \( \nu \) which maximizes LCV(\( \nu \)). Denote by \( \nu_K \) when \( \nu \) is estimated with \( \hat{\kappa} = \max\{\hat{\kappa}_k, k = 1, \ldots, K\} \) and \( \hat{\kappa}_k \) is the solution to (8). Denote by \( \nu_p \) the value of \( \nu \) when \( \kappa \) is estimated using the inter \( p \)-quantile range. The results are given in Table 1. Note that, for the standard von Mises distribution, if the known \( \kappa = 1 \) is used in (8), then the smoothing parameter is \( \nu = 3.51 \) for \( n = 50 \) and \( \nu = 8.82 \) for \( n = 500 \), which shows the accuracy of the asymptotic results for finite samples. Further, note that using the maximum likelihood estimator for \( \kappa \) leads to \( \nu_1 \) in this table.

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<th>( \nu_0 )</th>
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<th>( \nu_{CV} )</th>
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<th>( \nu_2 )</th>
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Table 1: Average integrated squared error (IMSE) results for various plug-in rules. The parameters of the distribution, given by (9), are \( (\mu_1, \kappa_1, p_2, \mu_2, \kappa_2, \ldots, p_M, \mu_M, \kappa_M) \). Numerical integration used on 500 grid values; averages taken over 500 datasets of size \( n \). \( \nu_0 \) is the smoothing parameter to minimize IMSE, and ISE(\( \nu_0 \)) the corresponding minimum. For each method, we list the ratio ISE(\( \nu^* \))/ISE(\( \nu_0 \)) with \( \nu^* \) selected by cross-validation (\( \nu_{CV} \)), by \( \nu_K, K = 1, 2, 3 \) in the case that the wrapped estimator is used, or \( \nu_p \) in the case that the \( p \)-quantile range estimator is used.

In Table 1 we see that the cross-validation estimate \( \nu_{CV} \) is never terrible, and that the \( p \)-quantile range estimators often fare badly with none standing out. Amongst the wrapped estimators, the “standard” plug-in rule \( \nu_1 \) can do very poorly, with both \( \nu_2 \) and \( \nu_3 \) performing similarly, overall, the the cross-validation estimate, but at a cheaper computational cost.

5 Concluding Remarks

The above results can be extended in a number of ways. Obtaining plug-in smoothing parameters for multivariate data is straightforward if a multiplicative kernel, with equal bandwidths in each dimension, is used. For example, in two dimensions, if \( f \) is assumed to be a multivariate von Mises, with independent components, and common concentration \( \kappa \), then we can approximate the asymptotic integrated variance of the kernel density estimate as \( \nu/(4n\pi) \) with asymptotic integrated bias-squared as

\[
\kappa \left[ 3\kappa I_0(2\kappa)^2 - 3I_0(2\kappa)I_1(2\kappa) + \kappa I_1(2\kappa)^2 \right] / (32\pi^2 I_0(\kappa)^4 \nu^2)
\]

Hence in this case, the rule of thumb is

\[
\nu = \left[ n\hat{\kappa} \left[ 3\hat{\kappa} I_0(2\hat{\kappa})^2 - 3I_0(2\hat{\kappa})I_1(2\hat{\kappa}) + \hat{\kappa} I_1(2\hat{\kappa})^2 \right] / (4\pi I_0(\hat{\kappa})^4) \right]^{1/3}.
\]
Extending some of the above results to a mixture of von Mises distributions would also be straightforward, and would proceed along the lines of Marron & Wand (1992). However, although we could obtain expressions for the approximate MISE, it would depend on the mixing proportions (as well as the means and concentrations of each component), and no plug-in rule would be readily available.

Agostinelli (2007) has considered alternative approaches to the robust estimation of $\kappa$ which could also be used in Equation (7) in place of those considered here.

Finally, we note the survey paper of Jones et al., (1996) which addresses the issue of bandwidth selection for real-valued data. In addition to the ideas of the current paper, there are several alternatives which will have a counterpart for directional data.

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References


