

# A Brief Introduction to Bandwidth Selection Methods for Univariate Kernel Density Estimation

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## Abstract

Univariate kernel density estimation allows an analyst to get a quick glimpse of some of the distributional properties for some data vector they have in hand. Of utmost importance in kernel density estimation is selecting the bandwidth, which controls the smoothness of the estimate. Insufficient smoothing leads to an estimate which may detect spurious modality, and over-smoothing may obscure important patterns within the data. In this report, we discuss various methods for selecting an optimal bandwidth for univariate kernel density estimation. We discuss Silverman's rule of thumb (1986), a cross-validation technique, Sheather and Jones' plug-in estimator (1991), and Terrell's maximal smoothing principle (1990). We visualize results from univariate density estimation using the different bandwidths for various data vectors, referencing a function written in the R computing environment. We also developed and deployed a Shiny-based web application which provides an interactive summary of some of the important aspects of this report.

## Introduction

Kernel density estimation allows a data analyst to get a view of an estimate of the density from which their data may have come. The univariate kernel density estimate can be used in a visualization setting or in a simulation setting. Furthermore, the KDE can present an analyst with a more refined view of the potential modality within their data than a histogram can.

We can use a kernel density estimate for exploratory analysis, or for more thorough simulation studies. The focus of this report is on the bandwidth of a kernel density estimate. The bandwidth controls how smooth our estimate of the underlying density is. If we select a large bandwidth, we will smooth out some of the interesting features of the distribution of the data. If we select a small bandwidth, our density estimate may be too "wiggly", and over-exaggerate random perturbations in the data as multi-modality. While many methods exist for selecting a bandwidth, it should be noted that no universally best method has been found (Givens and Hoeting 2013, 332).

Suppose we have a sample  $x_1, x_2, \dots, x_n$  which are i.i.d. observations from some density  $f$ . We wish to estimate  $f$  using  $\hat{f}$  for an analysis. We can use the kernel density estimator  $\hat{f}$  to approximate the density.

The kernel density estimate of  $f$  is

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right)$$

where  $h$  is the smoothing parameter known as the bandwidth, and  $K$  is a kernel function which satisfies  $\int K(x)dx = 1$ . In general,  $K$  should also satisfy the conditions (Sheather 2004)

$$\begin{aligned} \int yK(y)dy &= 0 \\ \int y^2K(y)dy &= \mu_2(K) > 0. \end{aligned}$$

The kernel function is generally chosen to be a unimodal probability density function that is symmetric around zero. Popular choices include the Gaussian kernel ( $K(x) = \phi(x)$ ), the Epanechnikov kernel ( $K(x) = \frac{3}{4}(1 - x^2) * \mathbb{I}(|x| < 1)$ ), and the triangular kernel ( $K(x) = (1 - |x|) * \mathbb{I}(|x| < 1)$ ). Provided the kernel function

$K(x)$  satisfies the aforementioned conditions, the choice of kernel will not be as important the selection of a bandwidth.

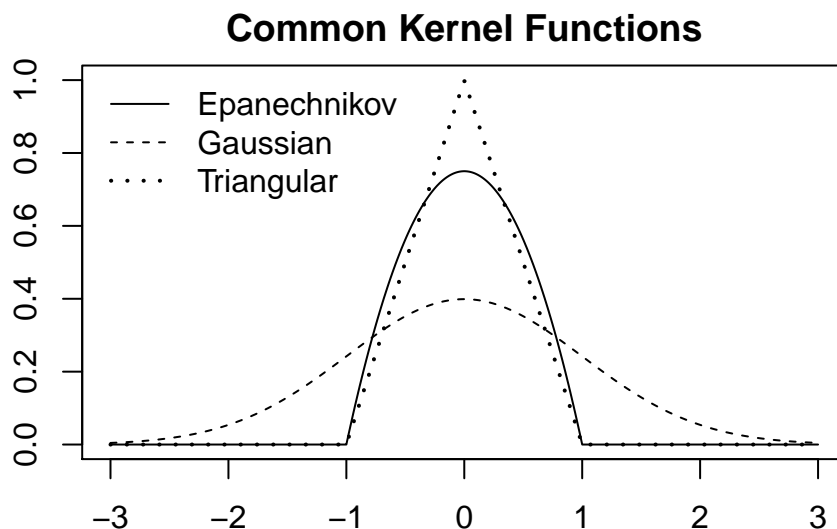


Figure 1: Three Common Kernel Functions: the solid line is the Epanechnikov kernel, the dashed line is the standard Gaussian kernel, and the dotted line is the Triangular kernel

We use the bandwidth to control how much weight we apply to observations around the  $x$  for which we are evaluating  $\widehat{f}_h(x)$ . If  $h$  is too small, we assign density too locally, resulting in wiggly estimates; however, if we select  $h$  to be too large, we spread density too diffusely, smoothing out interesting features of the data (Givens and Hoeting 2013). We have illustrated the effect of bandwidth in Figure 2, where we have evaluated  $\widehat{f}_h(x)$  for 200 points from the  $N(2, 3)$  density.

We have provided three density estimates in Figure 2, each using a Gaussian kernel, but different bandwidths. The lighter solid line is too small of a bandwidth ( $h = 0.2$ ), it is too sensitive to local perturbations. The dashed line is too large of a bandwidth ( $h = 2$ ), so it over-smooths the interesting components of the distribution. The heavy line ( $h = 0.6$ ) seems to be a fairly respectable bandwidth, it does not over-smooth the data, and it also highlights some of the interesting features of the data.

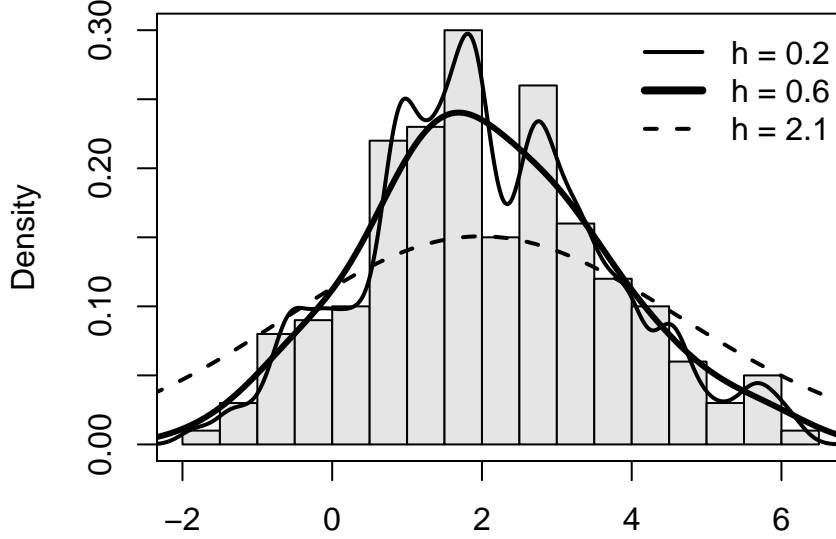


Figure 2: Kernel density estimates using 3 bandwidths for 500 points from  $N(2, 3)$

## Methods for evaluating KDE

To calculate  $\hat{f}_h(x)$ , we need to compute an estimate for every observation  $x_i$ , based on the  $n - 1$  remaining observations in the data. This computation requires  $n(n - 1)$  computations to calculate the final estimate. To get around such a computationally intensive calculation, possible techniques such as linear binning and Fast Fourier Transforms are used (both are implemented in R's `density` function).

Computing the kernel density estimator amounts to piling up mass around each  $x$ , then summing the mass up over  $x_1, x_2, \dots, x_n$ . Figure 3 demonstrates this computation. We start with 10 i.i.d. observations from  $N(0, 1)$ , which are the red triangles in the plot. Using a Gaussian kernel, we compute the densities (scaled by  $1/nh$ ) for each  $x$ , which are the blue curves in the plot. We then sum across these pointwise densities and are left with our final KDE, which is the black curve. We have provided plots for a large bandwidth and a small bandwidth, demonstrating the micro and macro effects of bandwidth selection.

### Evaluating the Fit of $\hat{f}_h(x)$

Along with the computation of  $\hat{f}_h(x)$ , it is also important to assess the quality of  $\hat{f}$  as an estimator of  $f$ . One choice would be the Integrated Squared Error (ISE):

$$ISE(h) = \int_{-\infty}^{\infty} \left( \hat{f}(x) - f(x) \right)^2 dx.$$

ISE calculates the squared error for *this* sample. It might be reasonable to average ISE over *all* samples, resulting in Mean Integrated Squared Error (MISE):  $MISE(h) = E(ISE(h))$ .

We can rewrite  $MISE(h)$  as:

$$MISE(h) = \int_{-\infty}^{\infty} MSE_h(\hat{f}(x)) dx,$$

and decompose  $MSE$  as  $MSE = bias^2 + var$ :

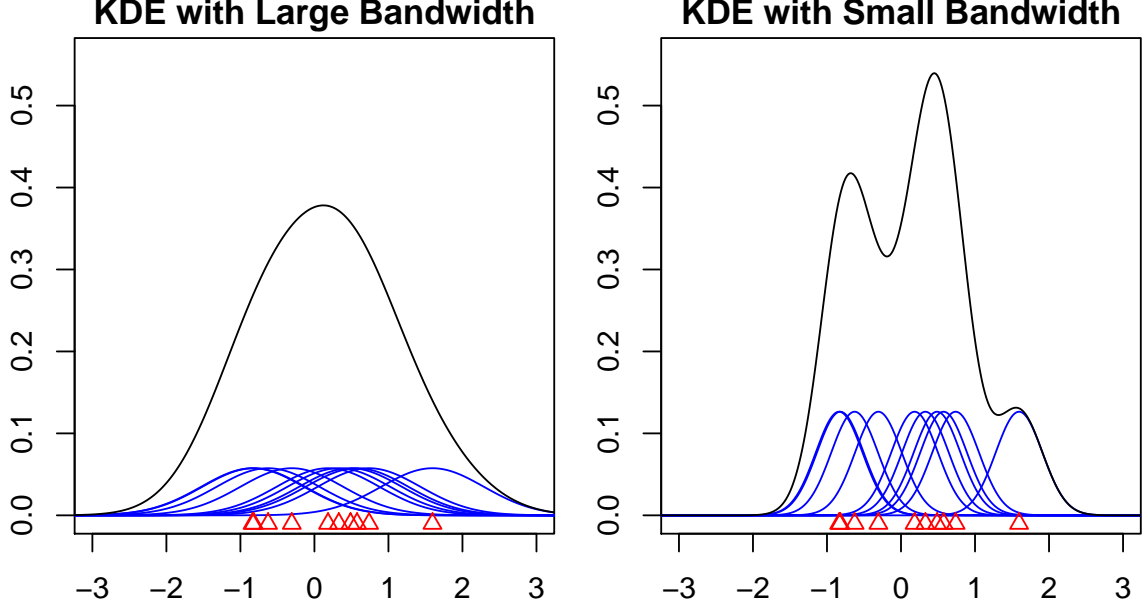


Figure 3: Demonstration of KDE computation. Red triangles are 10 i.i.d. data points from  $N(0,1)$ . Blue lines are scaled densities at each data point. Black line is final KDE. Left panel uses a large bandwidth (more smoothing), right panel uses a small bandwidth (less smoothing).

$$MISE(h) = \int_{-\infty}^{\infty} var\left(\widehat{f}_h(x)\right) + bias\left(\widehat{f}_h(x)\right)^2 dx.$$

Givens and Hoeting (2013, 327) say of the distinction between *ISE* and *MISE*<sup>1</sup>:

The distinction is essentially one between the statistical concepts of loss and risk. Using *ISE*(h) is conceptually appealing because it assesses the estimator's performance with the observed data. However, focusing on *MISE*(h) is an effective way to approximate *ISE*-based evaluation while reflecting the sensible goal of seeking optimal performance on average over many data sets.

Givens and Hoeting (2013, 331) derived  $E[\widehat{f}_h(x)]$  as:

$$E[\widehat{f}_h(x)] = f(x) + \frac{1}{2}\sigma_K^2 f''(x) + o(h^2),$$

where  $\sigma_K^2$  is the variance of  $K$  ( $\int z^2 K(z) dz$ ). So that  $\left(bias(\widehat{f}_h(x))\right)^2 = \frac{1}{4}\sigma_K^4 (f'')^2 + o(h^4)$ , and integrating  $bias^2$  results in:

$$\int bias\left(\widehat{f}_h(x)\right)^2 dx = \frac{1}{4}h^4\sigma_K^4 R(f'') + o(h^4),$$

where  $R$  is a measure of the roughness of a function  $g$ :

$$R(g) = \int_{-\infty}^{\infty} g^2(z) dz.$$

<sup>1</sup>The reader may be interested in our focus on squared error, instead of opting for the  $L_1$  norm. While the  $L_1$  norm is theoretically appealing, due to its invariance under one-to-one smooth transformations, it can be somewhat difficult to analyze mathematically. For this reason it is neglected here.

It can also be shown that  $\text{var}(\hat{f}(x)) = \frac{1}{nh}f(x)R(K) + o(\frac{1}{nh})$ , and integrating  $\text{var}$  results in:

$$\int \text{var}(\hat{f}(x)) dx = \frac{R(K)}{nh} + o\left(\frac{1}{nh}\right).$$

Adding  $\text{bias}^2$  and  $\text{var}$  together results in:

$$\begin{aligned} MISE(h) &= \frac{R(K)}{nh} + o\left(\frac{1}{nh}\right) + \frac{1}{4}h^4\sigma_K^4 R(f'') + o(h^4) \\ &= AMISE(h) + o\left(\frac{1}{nh} + h^4\right), \end{aligned}$$

where  $AMISE$  is the Asymptotic Mean Integrated Squared Error. If  $nh \rightarrow \infty$  and  $h \rightarrow 0$  as  $n \rightarrow \infty$ , then  $MISE(h) \rightarrow 0$ .

Inspection of the  $\text{bias}^2$  and  $\text{var}$  components of  $MISE(h)$  with respect to the bandwidth  $h$  provides an example of the bias-variance tradeoff. Selecting a small value of  $h$  increases variance by producing a wiggly estimate, but reduces bias. Selecting a large value of  $h$  reduces the variance of the estimator, but increases the bias due to over-smoothing. To find an optimal value, we must balance the bias and variance components of  $MISE$ , a typical theme in statistical inference.

Finding an optimal bandwidth  $h_{AMISE}$ , is straightforward:

$$\begin{aligned} AMISE &= \frac{R(K)}{nh} + \frac{h^4\sigma_K^4 R(f'')}{4} \\ \frac{dAMISE}{dh} &= \frac{-R(K)}{nh^2} + h^3\sigma_K^4 R(f'') \\ 0 &= \frac{-R(K)}{n} + h^5\sigma_K^4 R(f'') \\ h^5 &= \frac{R(K)}{n\sigma_K^4 R(f'')} \\ h_{AMISE} &= \left(\frac{R(K)}{n\sigma_K^4 R(f'')}\right)^{\frac{1}{5}}. \end{aligned}$$

All of the components of  $h_{AMISE}$  are known to us, except for  $R(f'')$ .  $R(f'')$  possesses a key to determining an appropriate bandwidth, of  $R(f'')$ , Sheather (2004, 589) states:

Thus, the functional  $R(f'')$  is a measure of the underlying roughness or curvature. In particular, the larger the value of  $R(f'')$  is, the larger is the value of  $AMISE$  (i.e., the more difficult it is to estimate  $f$ ) and the smaller is the value of  $h_{AMISE}$  (i.e., the smaller the bandwidth needed to capture the curvature in  $f$ ).

## Bandwidth Selection

The possible choices for bandwidth depend on navigating around the fact that  $R(f'')$  is unknown. We investigate four bandwidth selection strategies which employ different methods to circumvent not knowing  $R(f'')$ .

- Cross validation: choose a different objective function based on  $ISE$ , and use a leave one out (LOO) cross validation estimator to find  $\int \hat{f}_h f$
- Silverman's ROT: replace  $f$  with the  $N(0, \sigma^2)$  density

- Sheather-Jones: empirically estimate  $f''(x)$  to find  $h$  in a two-step method
- Terrell's Maximal Smoothing: minimize  $R(f'')$  for a given  $\sigma$

## Unbiased Cross Validation

We can represent integrated squared error as:

$$ISE(h) = \int (\hat{f}_h - f)^2 = \int \hat{f}_h^2 - 2 \int \hat{f}_h f + \int f^2.$$

In  $ISE(h)$ , only the first two terms rely on  $h$ , and the first term is entirely known. We can estimate the second term ( $2 \int \hat{f}_h f = 2E(\hat{f}_h f)$ ) using  $2/n \sum_{i=1}^n \hat{f}_{-i}(x_i)$ . Where

$$\hat{f}_{-i}(x_i) = \frac{1}{h(n-1)} \sum_{j \neq i} K\left(\frac{x_i - x_j}{h}\right)$$

is the leave-one-out kernel density estimator at  $x_i$  using all of the data except  $x_i$ .

We then attempt to minimize

$$UCV(h) = R(\hat{f}) - \frac{2}{n} \sum_{i=1}^n \hat{f}_{-i}(x_i)$$

with respect to  $h$ .

$UCV(h)$  is called the “unbiased cross-validation” criterion because  $E[UCV(h) + R(f)] = MISE(h)$  (Givens and Hoeting 2013, 333). To estimate the unbiased cross validation bandwidth for a data vector  $\mathbf{x}$  in  $\mathbf{R}$ , a user can write `bw.ucv(x)`. Along with “unbiased cross-validation”, it is sometimes referred to as “least-squares cross validation” as it minimizes the integrated squared error. When we refer to the cross-validated bandwidth selector, we denote the bandwidth as  $h_{LSCV}$ .

For this report, we have focused on the Gaussian kernel.  $UCV(h)$  has a straightforward expression (equation 10.23, Givens and Hoeting (2013, 333)) when a Gaussian kernel is used, which makes the computation of  $h_{LSCV}$  rather tidy.

The unbiasedness of the objective function is a nice feature, but it comes at the cost of imbuing  $h_{LSCV}$  with excessive variance (Jones, Marron, and Sheather 1992, 6). The objective function  $UCV$  tends to depend too heavily on the sample in hand, since it is still random (unlike  $MISE$ , which is averaged over *all* samples). The heavy dependence on the data in hand often leads to high variation in  $\hat{f}_h$ . This excessive variation is displayed in the *Examples* section of this report.

## Silverman's Rule of Thumb

A simpler method relies on selecting an appropriate density to approximate  $R(f'')$  in

$$h_{AMISE} = \left( \frac{R(K)}{n\sigma_K^4 R(f'')} \right)^{\frac{1}{5}}.$$

If we choose  $f$  to be the normal density with mean 0 and variance  $\sigma^2$ , and use the Gaussian kernel for  $K$ , we can express  $h_{AMISE}$  as:

$$\begin{aligned}
h_{AMISE} &= \left( \frac{(2\sqrt{\pi})^{-1}}{\frac{3}{8}\pi^{-\frac{1}{2}}\sigma^{-5}} \right)^{1/5} n^{-1/5} \\
&= 1.06\sigma n^{-\frac{1}{5}}.
\end{aligned}$$

A natural estimate of  $\sigma$  is  $\hat{\sigma}$ , the sample standard deviation. If the true  $f$  deviates from the features of a normal distribution (for instance, it is multimodal), this approximation may do a poor job (i.e. it will oversmooth). A possibility is to use the interquartile range, which is a more robust measure of spread. We then replace  $\hat{\sigma}$  with  $\tilde{\sigma} = \min \left[ \hat{\sigma}, \frac{IQR(x)}{1.34} \right]$ . This leads to Silverman's rule of thumb:

$$h_{SROT_1} = 1.06\tilde{\sigma}n^{-\frac{1}{5}}.$$

In our report, we replace 1.06 in the previous equation with 0.9, so that  $h_{SROT} = \frac{0.9}{1.06}h_{SROT_1}$ . This replacement dampens some of the over-smoothing that takes place when this method is used, and attempts to avoid missing bimodality in the distribution (Silverman 1986, 48). In R, a user can obtain  $h_{SROT_1}$  for a data vector  $\mathbf{x}$  by using `bw.nrd(x)`, and can obtain  $h_{SROT}$  by using `bw.nrd0(x)`.

The computation of  $h_{SROT}$  is fairly simple, and requires no optimization or cross-validation scheme. The simplicity comes at a cost; however, since this bandwidth tends to oversmooth the estimate, even after the IQR correction is made. The over-smoothing gets worse as  $f$  deviates from normality.

## Sheather-Jones Bandwidth

Silverman's rule of thumb relies on selecting a candidate density to estimate  $R(f'')$ . Sheather and Jones (1991) opt for a different approach: empirically estimate  $R(f'')$ . An empirical estimate of  $f''$  is formulated as:

$$\begin{aligned}
\hat{f}''(x) &= \frac{d^2}{dx^2} \left\{ \frac{1}{nh_0} \sum_{i=1}^n L\left(\frac{x-x_i}{h_0}\right) \right\} \\
&= \frac{1}{nh_0^3} \sum_{i=1}^n L''\left(\frac{x-x_i}{h_0}\right).
\end{aligned}$$

Where  $h_0$  is another bandwidth, different from  $h_{opt}$  (and typically  $h_0 > h_{opt}$  Givens and Hoeting (2013, 336)), and  $L$  is a kernel function.

To compute the optimal bandwidth  $h_{SJ}$ , Sheather and Jones use a two-step process. First, a simple rule of thumb is used to calculate  $h_0$ . Then  $h_0$  is used to estimate  $R(f'')$ , which is the only unknown quantity in the expression for  $h_{AMISE}$ . After plugging in the estimator for  $R(f'')$  in the expression for  $h_{AMISE}$ , we arrive at the Sheather-Jones bandwidth. An expression for the optimal bandwidth when  $L = \phi$  is in the Appendix. This expression requires a root-finding scheme such as Newton's method.

In simulation studies (summarized in Jones, Marron, and Sheather (1996)), it was seen that  $h_{SJ}$  tended to be superior to both  $h_{LSCV}$  and  $h_{SROT}$ . In general,  $h_{SJ}$  demonstrates less variation than  $h_{LSCV}$  and is centered near  $h_{AMISE}$  for easy-to-estimate densities. For more difficult densities,  $h_{SJ}$  will overshoot  $h_{AMISE}$ , but is still much smaller than  $h_{SROT}$ .  $h_{SJ}$ , then, seems to be a suitable compromise between the low-variance high-bias  $h_{SROT}$  and the high-variance low-bias  $h_{LSCV}$ .

## Terrell's Maximal Smoothing Principle

Terrell (1990) opted for a different approach in determining an optimal bandwidth. Rather than focusing on finding a good estimator of  $f''$  or  $R(f'')$  in the expression for  $h_{AMISE}$ , Terrell chose to find some density function  $g$  that would minimize  $R(g'') = \int (g''(x))^2 dx$  for a given variance  $\sigma^2$ . By minimizing  $\int (g'')^2$ , we

could determine an upper bound for  $h_{opt}$ , by using  $g$  in place of  $f$ . Terrell (1990, 472) justifies using the maximally smoothed bandwidth, because it avoids the tendency of the under-smoothed density estimate to “display features such as asymmetries and multiple modes that could have come about by chance”.

Terrell’s estimate is built on the result that the  $beta(k + 2, k + 2)$  family minimizes  $\int (f^{(k)})^2$  for a given standard deviation (Terrell 1990, 471). For a kernel with variance 1 (e.g. the Gaussian kernel), the maximal smoothing bandwidth is:

$$h_{MS} = 3\hat{\sigma} \left( \frac{R(K)}{35n} \right)^{\frac{1}{5}}.$$

The maximal smoothing principle has an intuitive justification, and its ideas permeate through wider areas of statistical inference. It would be desirable for an inferential scheme to prevent an analyst from claiming features of a data set exist that may have arisen by pure chance alone (Terrell 1990, 472). The maximal smoothing principle applies this idea to the display of kernel density estimates.

In terms of kernel density estimation; however, the maximal smoothing principle provides only an upper bound on the optimal bandwidth. Silverman’s rule of thumb is an over-smoother, and Terrell’s maximal smoothing bandwidth smooths out even more features of the data than  $h_{SROT}$  does (Jones, Marron, and Sheather 1992, 9).

## Examples Using the kde Function

To examine the four different bandwidth selections we have investigated, we use four different data vectors to investigate the changes in density estimation as the data deviates from the normal distribution. Two vectors are simulated, and two vectors are from real data sets.<sup>2</sup> Our main interest is on if the bandwidth options lead to under-smoothing or over-smoothing of the data.

We plot histograms and density estimates for each of the data vectors using the `kde` function. The `kde` function takes in a data vector, and calculates  $h_{SROT}$ ,  $h_{SJ}$ ,  $h_{LSCV}$ , and  $h_{MS}$ . It then calculates  $\hat{f}_h(x)$ . For small data vectors ( $n \leq 1,000$ ), `kde` will calculate the densities “by hand”, using a grid of size 512. For larger data vectors, the function will use the `density` function in base R. In addition to creating plots, the `kde` function will print the four bandwidths, and can also return  $\hat{f}_h(x)$  for an evenly spaced grid of length 512 for each  $h$ .

In each example, we choose a data vector and display the output from `kde`. We then attempt to interpret the results, taking special care to analyze the effect of each bandwidth choice on  $\hat{f}_h$ . Inspecting a kernel density estimate is not an objective task, as one analyst may perceive different features than another. It is important to present multiple density estimates, and iterate through different bandwidths to arrive at a more common conclusion.

We include each  $\hat{f}_h$  on the same graph rather than allowing each  $\hat{f}_h$  to have its own panel. This strategy allows for the other three  $\hat{f}_h$ ’s to act as “reality checks” for the  $\hat{f}_h$  of the  $h$  we are focusing on. Keeping the estimates on the same graph allows for effective comparisons between the  $\hat{f}_h$ ’s.

## Shiny Web Application

In addition to the `kde` function, a Shiny-based web application was developed and deployed to <https://bgstieber.shinyapps.io/kdeshinyapp/>. The application creates density plots for a variety of data choices, and allows the user to investigate different bandwidths for simulated and real-world data sets. The application also allows a user to visualize pointwise confidence intervals for kernel density estimates using the approximate

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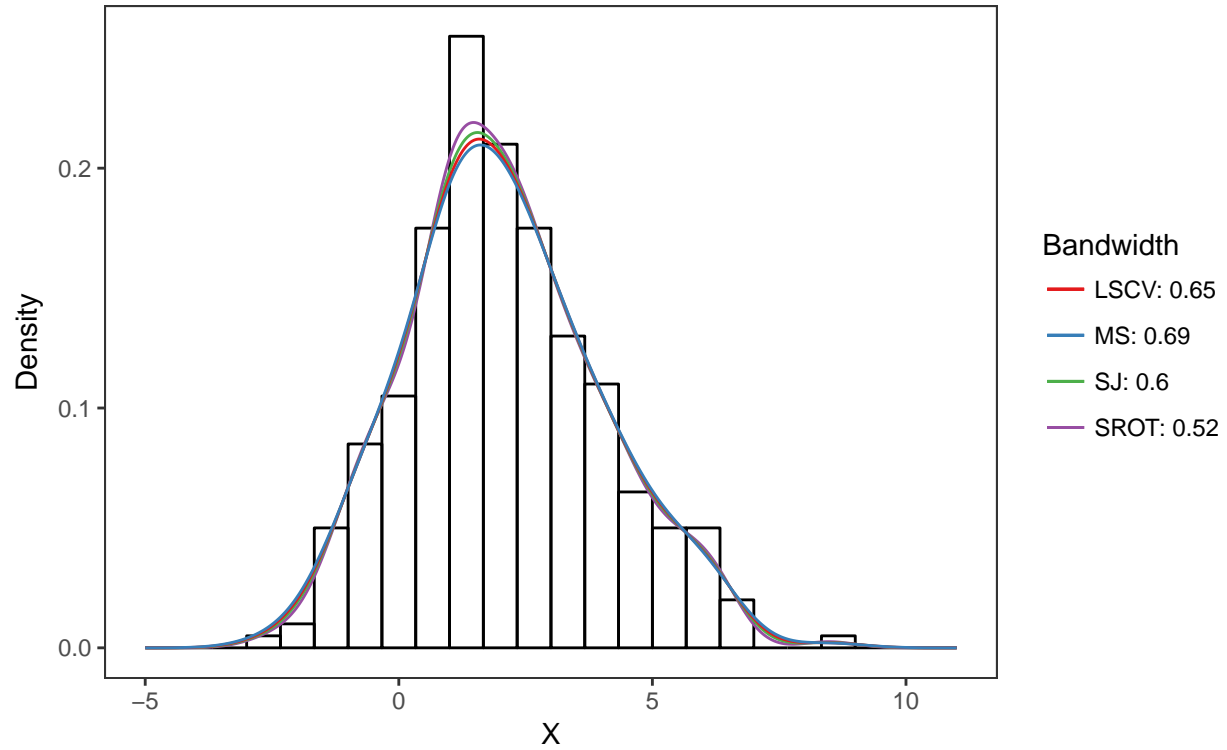
<sup>2</sup>The R code used to generate the data can be found on the author’s Github: <https://github.com/bgstieber/Project771/blob/master/Project%20Files/DataGeneration.R>



variance (Jann (2007)), and a nonparametric bootstrap percentile method. Additionally, the app allows a user to upload a one column `.csv` file and investigate the kernel density estimate as well. Screenshots of the application are in the *Appendix*.

### Example 1: 300 samples from $N(2, 2^2)$

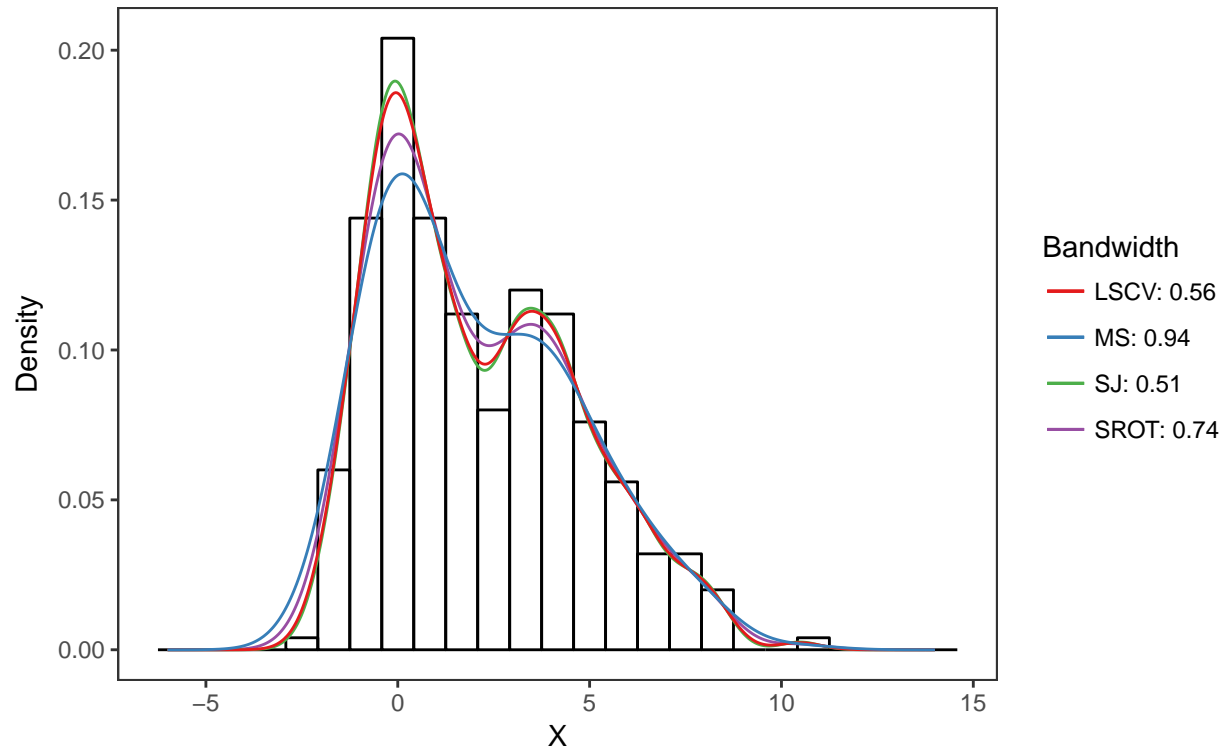
##	LS CV	T MS	SJ BW Silverman's	ROT
##	0.648	0.691	0.598	0.519



We begin by examining  $\hat{f}_h(x)$  for a data vector sampled solely from  $N(2, 2^2)$ . In this case, we see that each bandwidth selection does a fairly good job of estimating the density.  $h_{SROT}$  relies on a normal approximation, so we would expect this bandwidth to perform well on this vector. In fact, it is the most aggressive bandwidth estimator, resulting in the smallest  $h$  value of the four. A *best bandwidth* is not apparent from these results.

## Example 2: 50/50 Mixture of $N(0, 1)$ and $N(4, 2^2)$

##	LS CV	T MS	SJ BW Silverman's R0T
##	0.562	0.944	0.515 0.742

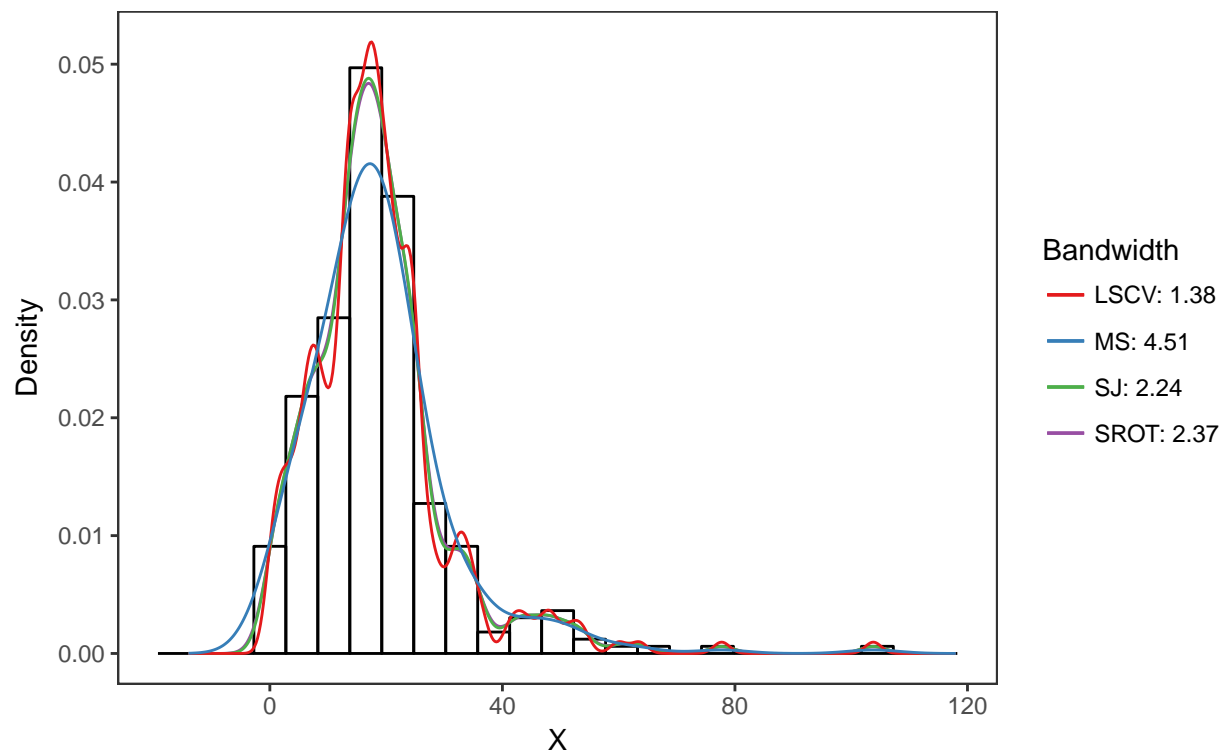


Moving on to a somewhat harder density to estimate, we simulate a 50/50 distribution coming from  $N(0, 1)$  and  $N(2, 2^2)$ .  $h_{SJ}$  and  $h_{LSCV}$  both seem to capture the bimodality of the distribution quite well.  $h_{SROT}$  smooths out some of the interesting features, but the bimodality is still somewhat detectable.  $h_{MS}$  over-smooths disastrously - without knowing the underlying structure of the data, it would not be obvious that the data came from a bimodal distribution.

### Example 3: Mixture of $\Gamma(\alpha = 1, \beta = 1/20)$ , $\Gamma(\alpha = 4, \beta = 1/5)$ , $\Gamma(\alpha = 20, \beta = 1)$

A mixture of gamma distributions may seem like a “toy” example, but the gamma distribution can be very helpful in modeling rainfall (e.g. Husak, Michaelsen, and Funk (2007)).

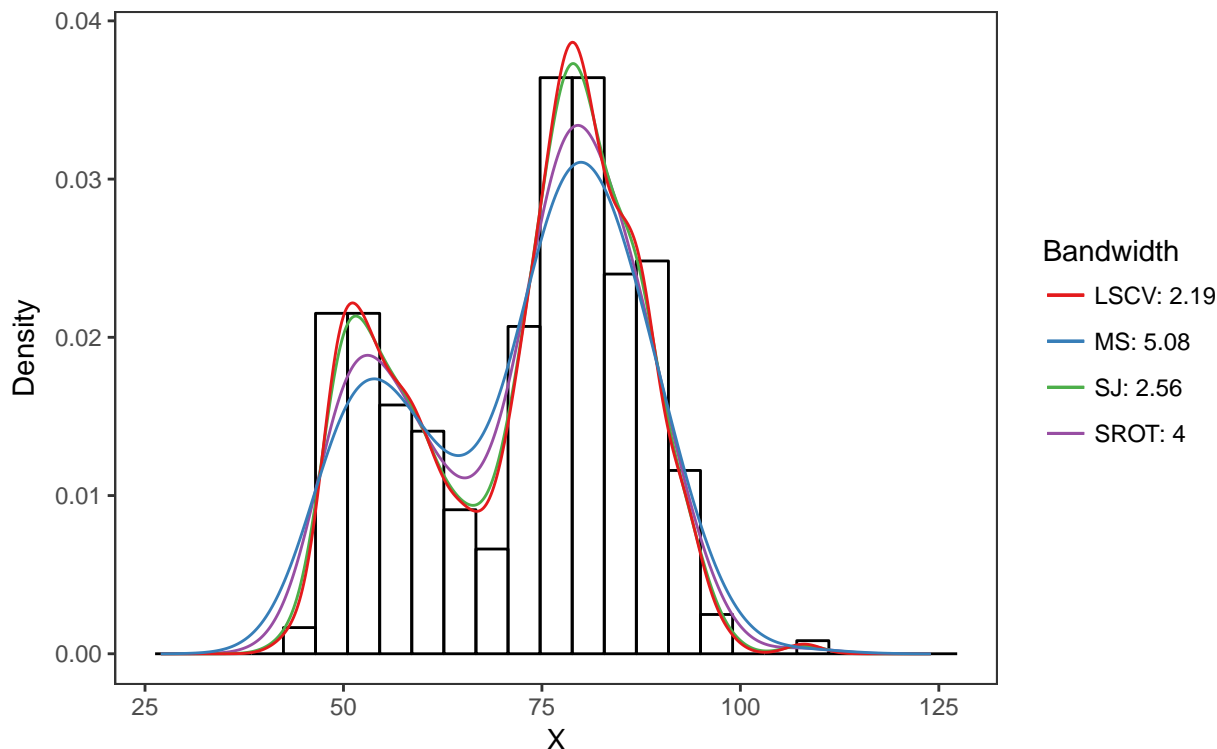
##	LS CV	T MS	SJ BW Silverman's ROT
##	1.382	4.514	2.241 2.374



Here we see the excessive variation caused by using  $h_{LSCV}$ . The density estimate provided by  $h_{LSCV}$  is far too wiggly to be useful for a data analyst. We also see that  $h_{MS}$  provides a much smoother estimate than the those proposed by Silverman and Sheather and Jones, it seems that it is too conservative. The best bandwidth would take a value somewhere in the range between  $h_{SJ}$  and  $h_{MS}$ .

## Example 4: Old Faithful Waiting Time

##	LS CV	T MS	SJ BW Silverman's	ROT
##	2.190	5.081	2.560	3.998



Using data from Azzalini and Bowman (1990), contained in the **MASS** package, we calculate the kernel density estimate for the waiting time for eruptions from August 1 to August 15, 1985 at the Old Faithful geyser in Yellowstone National Park, Wyoming.

Each bandwidth choice seems to capture the bimodality in the distribution of waiting times with varying levels of success.  $h_{LSCV}$  may be too aggressive, while  $h_{MS}$  does not reach far enough up the left-side peak.  $h_{SJ}$  and  $h_{LSCV}$  seem grouped together and  $h_{SROT}$  and  $h_{MS}$  seem grouped together as well. Between  $h_{SJ}$  and  $h_{LSCV}$ , we would want to choose the more conservative bandwidth, which is  $h_{SJ}$ . Conversely, between  $h_{MS}$  and  $h_{SROT}$ , we would want to choose the more aggressive bandwidth, which is  $h_{SROT}$ .

## Conclusion

In this report we have presented four options for selecting a bandwidth for univariate kernel density estimation. We have discussed bandwidths that oversmooth ( $h_{MS}$ ), and bandwidths that under-smooth ( $h_{LSCV}$ ). No universally optimal bandwidth selection has been found, which makes selecting a bandwidth an iterative and subjective process.

A safe option for a novice data analyst is to use at least two bandwidths when analyzing the data. One bandwidth should have the tendency to under-smooth (e.g.  $h_{SROT}$  or  $h_{MS}$ ), and another bandwidth should produce estimates that are more wiggly (e.g.  $h_{SJ}$ , **but not**  $h_{LSCV}$ ). If visualizing is the goal (rather than simulation), then including a histogram will provide even more clarity when making density plots (note that making a histogram also requires selecting a bandwidth, though).

In our *Examples* section, we saw the devastating effects of over-smoothing and under-smoothing. There is a large amount of literature on univariate bandwidth selection, but a universally optimal bandwidth has

yet to be found. Selecting a bandwidth results presents a bias-variance tradeoff to the analyst, with a good bandwidth being dependent on the analytical task. Sheather (2004, 596) suggests to “produce a family of density estimates based on a number of values of the bandwidth”. We agree with this suggestion, and believe it to be sage advice for exploratory analysis.

## Question

Using the `density` function and the beer data (`abv.complete`, which are the alcohol by volume measures for the top 250 beers as rated by BeerAdvocate.com) provided below, estimate a 95% pointwise bootstrapped percentile interval. Additionally, use the approximate variance function  $\tilde{V}$  given by Jann (2007, 2) to estimate a 95% pointwise confidence interval. Create plots using `bw.SJ` and `bw.nrd0`.

$$\tilde{V}\left(\widehat{f_K}(x;h)\right) = \frac{1}{nh}R(K)\widehat{f_K}(x;h) - \frac{1}{n}\widehat{f_K}(x;h)^2$$

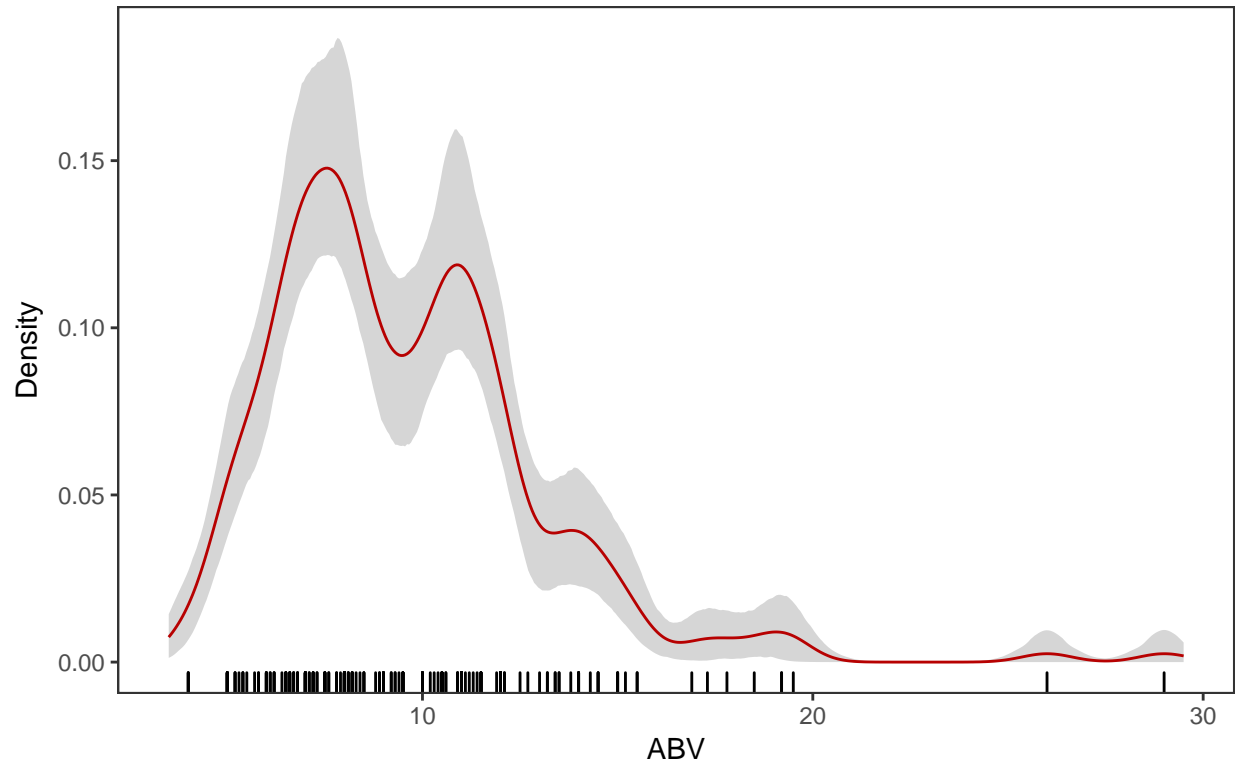
```
# data comes from the ABV of beer advocate's top 250 beers for 2016  
# 2 beers have missing abv data  
# quick R script to read in the .csv  
library(RCurl)  
git_file <-  
getURL("https://raw.githubusercontent.com/bgstieber/Top250Beer/master/Top250Beers.csv")  
beer_data <- read.csv(text = git_file, stringsAsFactors = FALSE)  
abv.complete <- beer_data[!is.na(beer_data$ABV), ]$ABV
```

## Solution

### Bootstrap percentile interval

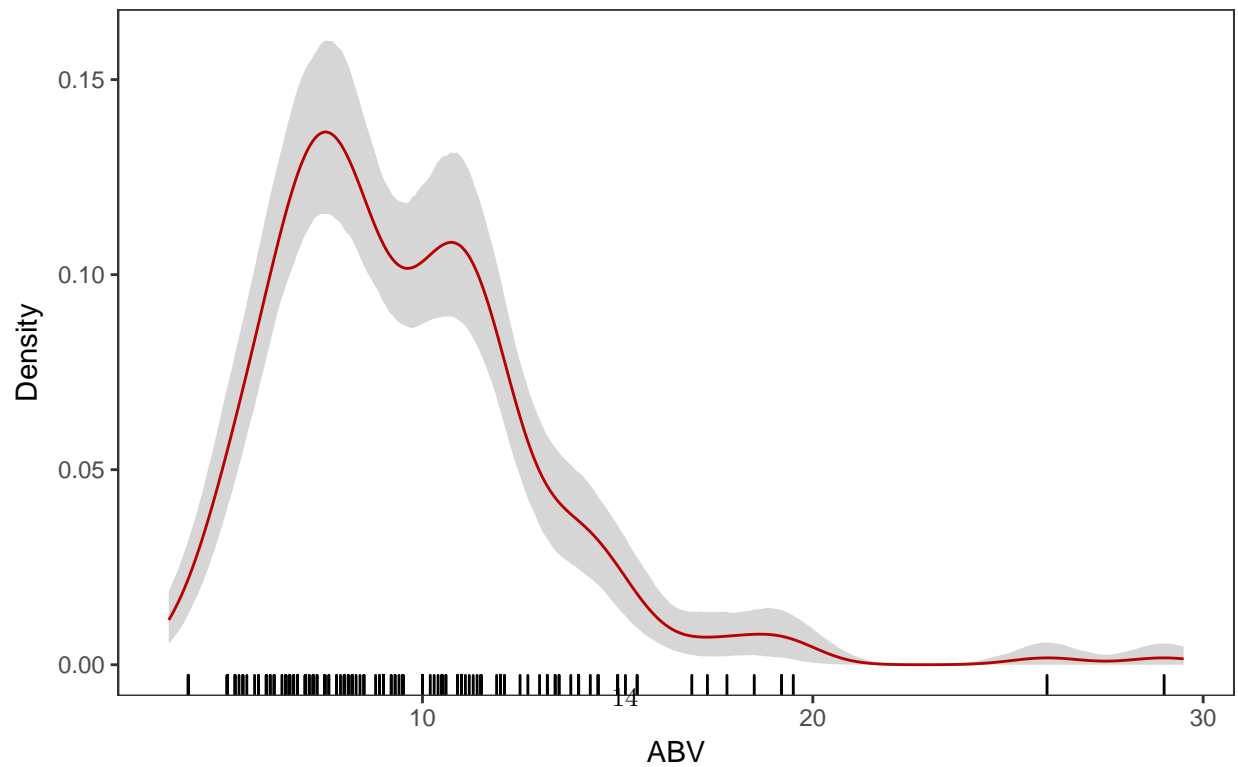
ABV Density and 95% Bootstrapped Percentile Interval

Sheather – Jones Bandwidth



ABV Density and 95% Bootstrapped Percentile Interval

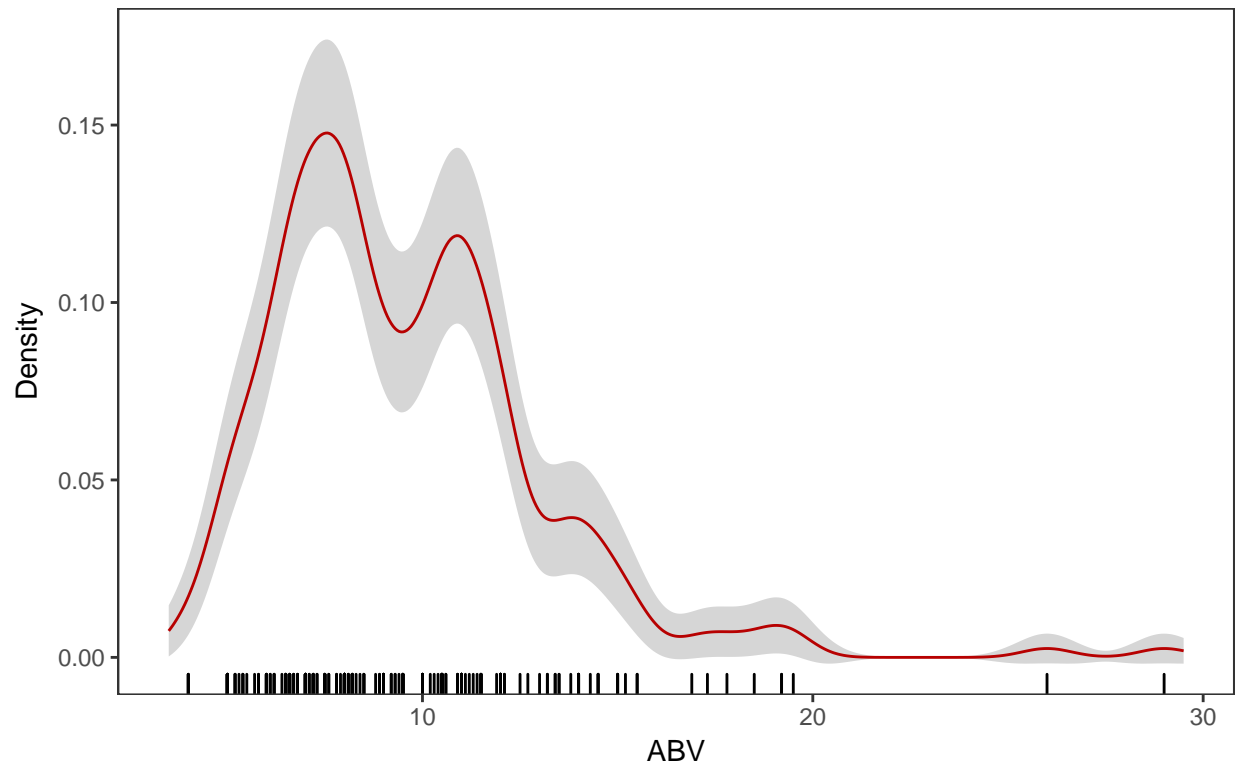
Silverman's ROT Bandwidth



## Approximate Confidence Interval

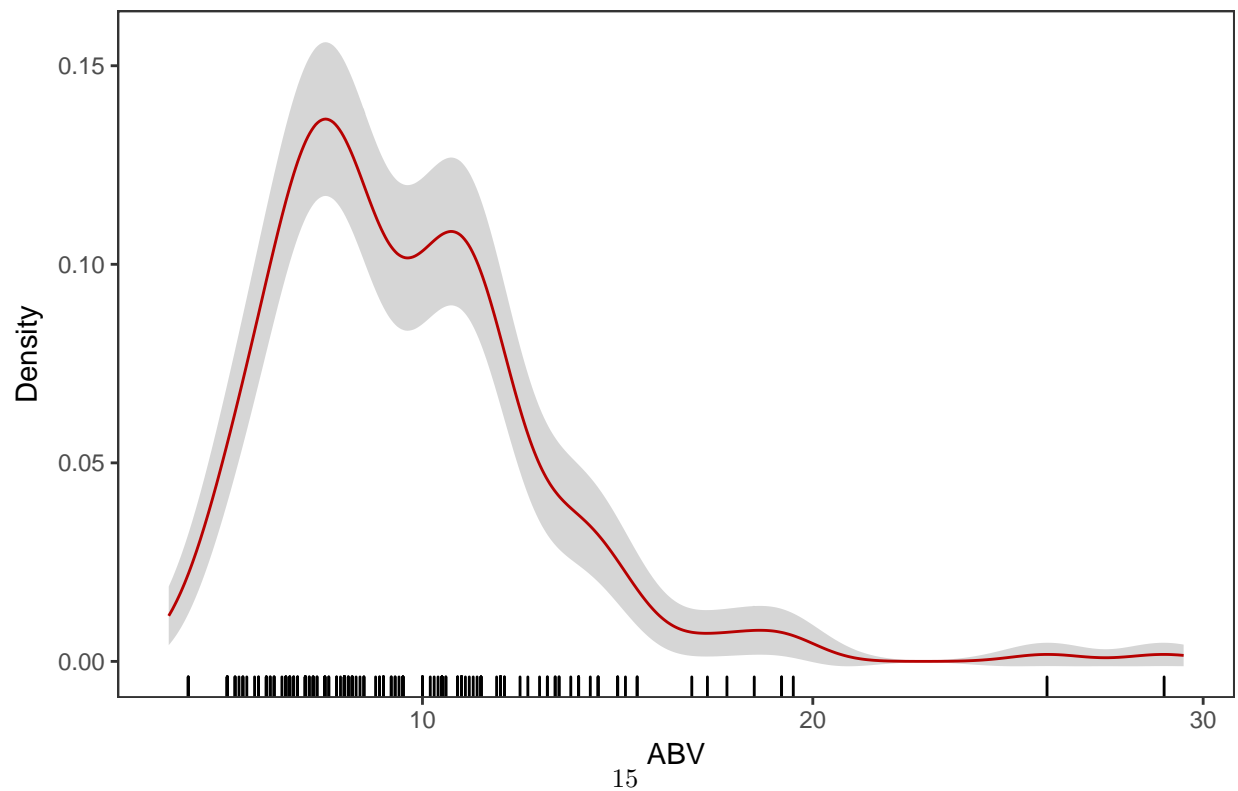
### ABV Density and 95% Pointwise CI

Sheather – Jones Bandwidth



### ABV Density and 95% Pointwise CI

Silverman's ROT Bandwidth



# Appendix

## Expression for Sheather-Jones Bandwidth

As found in Givens and Hoeting (2013, 337), Sheather-Jones bandwidth can be found by solving the equation (using  $L = \phi$ ):

$$\left( \frac{R(K)}{n\sigma_K^4 \hat{R}_{\hat{\alpha}(h)}(f'')} \right)^{1/5} - h = 0,$$

where:

$$\begin{aligned} \hat{R}_{\hat{\alpha}(h)}(f'') &= \frac{1}{n(n-1)\alpha^5} \sum_{i=1}^n \sum_{j=1}^n \phi^{(4)}\left(\frac{x_i - x_j}{\alpha}\right), \\ \hat{\alpha}(h) &= \left( \frac{6\sqrt{2}h^5 \hat{R}_a(f'')}{\hat{R}_b(f''')} \right)^{1/7}, \\ \hat{R}_a(f'') &= \frac{1}{n(n-1)a^5} \sum_{i=1}^n \sum_{j=1}^n \phi^{(4)}\left(\frac{x_i - x_j}{a}\right), \\ \hat{R}_b(f''') &= \frac{1}{n(n-1)b^7} \sum_{i=1}^n \sum_{j=1}^n \phi^{(6)}\left(\frac{x_i - x_j}{b}\right), \\ a &= \frac{0.920IQR}{n^{1/7}}, \\ b &= \frac{0.912IQR}{n^{1/9}}, \end{aligned}$$

where  $IQR$  is the interquartile range of the data, and  $\phi^{(i)}$  is the  $i$ th derivative of the standard normal density function. To determine the Sheather-Jones bandwidth in **R**, a user can write `bw.SJ(x)`, which uses the `uniroot` function to perform the root-finding.

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