**kdensity — Univariate kernel density estimation**

**Description**

kdensity produces kernel density estimates and graphs the result.

**Quick start**

Graph of the kernel density estimate for v1
kdensity v1

Add a normal curve
kdensity v1, normal

With a kernel bandwidth of 2
kdensity v1, bwidth(2)

Gaussian kernel function for v1
kdensity v1, kernel(gaussian)

Kernel density estimate for v1 and v2 in the same graph area
twoway kdensity v1 || kdensity v2

Separate graphs of kernel density estimate of v1 for each level of catvar
twoway kdensity v1, by(catvar)

Kernel density estimates of v1 for catvar = 0 and 1 in the same graph area
twoway kdensity v1 if catvar==0 || kdensity v1 if catvar==1

**Menu**

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Syntax

```
kdensity varname [if] [in] [weight] [, options]
```

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<td>store the estimation points in <code>newvar_x</code> and the density estimate in <code>newvar_d</code></td>
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<td><code>n(#)</code></td>
<td>estimate density using # points; default is min(N, 50)</td>
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<td>any options other than by() documented in [G-3] <code>twoway_options</code></td>
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**Kernel**

<table>
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<tr>
<td><code>epanechnikov</code></td>
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<td>biweight kernel function</td>
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<td>cosine trace kernel function</td>
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<td><code>gaussian</code></td>
<td>Gaussian kernel function</td>
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<tr>
<td><code>parzen</code></td>
<td>Parzen kernel function</td>
</tr>
<tr>
<td><code>rectangle</code></td>
<td>rectangle kernel function</td>
</tr>
<tr>
<td><code>triangle</code></td>
<td>triangle kernel function</td>
</tr>
</tbody>
</table>

`fweights`, `aweights`, and `iweights` are allowed; see [U] 11.1.6 `weight`.

**Options**

- `kernel(kernel)` specifies the kernel function for use in calculating the kernel density estimate. The default kernel is the Epanechnikov kernel (`epanechnikov`).
Kernel density estimators approximate the density $f(x)$ from observations on $x$. Histograms do this, too, and the histogram itself is a kind of kernel density estimate. The data are divided into nonoverlapping intervals, and counts are made of the number of data points within each interval. Histograms are bar graphs that depict these frequency counts—the bar is centered at the midpoint of each interval—and its height reflects the average number of data points in the interval.

In more general kernel density estimates, the range is still divided into intervals, and estimates of the density at the center of intervals are produced. One difference is that the intervals are allowed to overlap. We can think of sliding the interval—called a window—along the range of the data and collecting the center-point density estimates. The second difference is that, rather than merely counting the number of observations in a window, a kernel density estimator assigns a weight between
Kernel density estimates have the advantages of being smooth and of being independent of the choice of origin (corresponding to the location of the bins in a histogram).

See Salgado-Ugarte, Shimizu, and Taniuchi (1993) and Fox (1990) for discussions of kernel density estimators that stress their use as exploratory data-analysis tools.

Cox (2007) gives a lucid introductory tutorial on kernel density estimation with several Stata produced examples. He provides tips and tricks for working with skewed or bounded distributions and applying the same techniques to estimate the intensity function of a point process.

Example 1: Histogram and kernel density estimate

Goeden (1978) reports data consisting of 316 length observations of coral trout. We wish to investigate the underlying density of the lengths. To begin on familiar ground, we might draw a histogram. In [R] histogram, we suggest setting the bins to \( \min \left( \sqrt{n}, 10 \cdot \log_{10} n \right) \), which for \( n = 316 \) is roughly 18:

```
. use https://www.stata-press.com/data/r16/trocolen
. histogram length, bin(18)
(bin=18, start=226, width=19.777778)
```

![Histogram of length of coral trout with kernel density estimate](image-url)
The kernel density estimate, on the other hand, is smooth.

```
. kdensity length
```

Kernel density estimators are, however, sensitive to an assumption, just as are histograms. In histograms, we specify a number of bins. For kernel density estimators, we specify a width. In the graph above, we used the default width. `kdensity` is smarter than `twoway histogram` in that its default width is not a fixed constant. Even so, the default width is not necessarily best.

`kdensity` stores the width in the returned scalar `bwidth`, so typing `display r(bwidth)` reveals it. Doing this, we discover that the width is approximately 20.

Widths are similar to the inverse of the number of bins in a histogram in that smaller widths provide more detail. The units of the width are the units of $x$, the variable being analyzed. The width is specified as a half-width, meaning that the kernel density estimator with half-width 20 corresponds to sliding a window of size 40 across the data.

We can specify half-widths for ourselves by using the `bwidth()` option. Smaller widths do not smooth the density as much:

```
. kdensity length, bwidth(10)
```
Example 2: Different kernels can produce different results

When widths are held constant, different kernels can produce surprisingly different results. This is really an attribute of the kernel and width combination; for a given width, some kernels are more sensitive than others at identifying peaks in the density estimate.

We can see this when using a dataset with lots of peaks. In the automobile dataset, we characterize the density of weight, the weight of the vehicles. Below we compare the Epanechnikov and Parzen kernels.

```
use https://www.stata-press.com/data/r16/auto
(1978 Automobile Data)
kdensity weight, kernel(epanechnikov) nograph generate(x epan)
kdensity weight, kernel(parzen) nograph generate(x2 parzen)
label var epan "Epanechnikov density estimate"
label var parzen "Parzen density estimate"
line epan parzen x, sort ytitle(Density) legend(cols(1))
```
We did not specify a width, so we obtained the default width. That width is not a function of the selected kernel, but of the data. See *Methods and formulas* for the calculation of the optimal width.

➤ Example 3: Density with overlaid normal density

In examining the density estimates, we may wish to overlay a normal density or a Student’s *t* density for comparison. Using automobile weights, we can get an idea of the distance from normality by using the `normal` option.

```
. kdensity weight, kernel(epanechnikov) normal
```

![Kernel density estimate with overlaid normal density](image)

➤ Example 4: Compare two densities

We also may want to compare two or more densities. In this example, we will compare the density estimates of the weights for the foreign and domestic cars.

```
. use https://www.stata-press.com/data/r16/auto, clear
   (1978 Automobile Data)
. kdensity weight, nograph generate(x fx)
. kdensity weight if foreign==0, nograph generate(fx0) at(x)
. kdensity weight if foreign==1, nograph generate(fx1) at(x)
. label var fx0 "Domestic cars"
. label var fx1 "Foreign cars"
```
Technical note

Although all the examples we included had densities of less than 1, the density may exceed 1.

The probability density \( f(x) \) of a continuous variable, \( x \), has the units and dimensions of the reciprocal of \( x \). If \( x \) is measured in meters, \( f(x) \) has units \( 1/meter \). Thus the density is not measured on a probability scale, so it is possible for \( f(x) \) to exceed 1.

To see this, think of a uniform density on the interval 0 to 1. The area under the density curve is 1: this is the product of the density, which is constant at 1, and the range, which is 1. If the variable is then transformed by doubling, the area under the curve remains 1 and is the product of the density, constant at 0.5, and the range, which is 2. Conversely, if the variable is transformed by halving, the area under the curve also remains at 1 and is the product of the density, constant at 2, and the range, which is 0.5. (Strictly, the range is measured in certain units, and the density is measured in the reciprocal of those units, so the units cancel on multiplication.)

Stored results

kdensity stores the following in r():

 Scalars
   r(bwidth)    kernel bandwidth
   r(n)         number of points at which the estimate was evaluated
   r(scale)     density bin width

 Macros
   r(kernel)    name of kernel
Methods and formulas

A kernel density estimate is formed by summing the weighted values calculated with the kernel function $K$, as in

$$\hat{f}_K = \frac{1}{qh} \sum_{i=1}^{n} w_i K \left( \frac{x - X_i}{h} \right)$$

where $q = \sum_i w_i$ if weights are frequency weights (fweight) or analytic weights (aweight), and $q = 1$ if weights are importance weights (iweights). Analytic weights are rescaled so that $\sum_i w_i = n$ (see [U] 11 Language syntax). If weights are not used, then $w_i = 1$, for $i = 1, \ldots, n$. kdensity includes seven different kernel functions. The Epanechnikov is the default function if no other kernel is specified and is the most efficient in minimizing the mean integrated squared error.

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Biweight</td>
<td>$K[z] = \begin{cases} 15 \left(1 - z^2\right)^2 &amp; \text{if }</td>
</tr>
<tr>
<td>Cosine</td>
<td>$K[z] = \begin{cases} 1 + \cos(2\pi z) &amp; \text{if }</td>
</tr>
<tr>
<td>Epanechnikov</td>
<td>$K[z] = \begin{cases} \frac{3}{4}(1 - \frac{1}{5}z^2)/\sqrt{5} &amp; \text{if }</td>
</tr>
<tr>
<td>Epan2</td>
<td>$K[z] = \begin{cases} \frac{3}{4}(1 - z^2) &amp; \text{if }</td>
</tr>
<tr>
<td>Gaussian</td>
<td>$K[z] = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$</td>
</tr>
<tr>
<td>Parzen</td>
<td>$K[z] = \begin{cases} \frac{4}{3} - 8z^2 + 8</td>
</tr>
<tr>
<td>Rectangular</td>
<td>$K[z] = \begin{cases} 1/2 &amp; \text{if }</td>
</tr>
<tr>
<td>Triangular</td>
<td>$K[z] = \begin{cases} 1 -</td>
</tr>
</tbody>
</table>

From the definitions given in the table, we can see that the choice of $h$ will drive how many values are included in estimating the density at each point. This value is called the window width or bandwidth. If the window width is not specified, it is determined as

$$m = \min \left( \sqrt{\text{variance}_x}, \frac{\text{interquartile range}_x}{1.349} \right)$$

$$h = \frac{0.9m}{n^{1/5}}$$

where $x$ is the variable for which we wish to estimate the kernel and $n$ is the number of observations.

Most researchers agree that the choice of kernel is not as important as the choice of bandwidth. There is a great deal of literature on choosing bandwidths under various conditions; see, for example, Parzen (1962) or Tapia and Thompson (1978). Also see Newton (1988) for a comparison with sample spectral density estimation in time-series applications.
 Acknowledgments

We gratefully acknowledge the previous work by Isaías H. Salgado-Ugarte of Universidad Nacional Autónoma de México, and Makoto Shimizu and Toru Taniuchi of the University of Tokyo; see Salgado-Ugarte, Shimizu, and Taniuchi (1993). Their article provides a good overview of the subject of univariate kernel density estimation and presents arguments for its use in exploratory data analysis.

References


Also see

[R] histogram — Histograms for continuous and categorical variables

[R] npregress kernel — Nonparametric kernel regression

[R] npregress series — Nonparametric series regression