Locally Linear Regression:

There is another local method, locally linear regression, that is thought to be superior to kernel regression. It is based on locally fitting a line rather than a constant. Unlike kernel regression, locally linear estimation would have no bias if the true model were linear. In general, locally linear estimation removes a bias term from the kernel estimator, that makes it have better behavior near the boundary of the x's and smaller MSE everywhere.

To describe this estimator, let $K_h(u) = h^{-r}K(u/h)$ as before. Consider the estimator $\hat{g}(x)$ given by the solution to

$$\min_{g,\beta} \sum_{i=1}^{n} (Y_i - g - (x - x_i)'\beta)^2 K_h(x - x_i).$$

That is $\hat{g}(x)$ is the constant term in a weighted least squares regression of Y_i on $(1, x - x_i)$, with weights $K_h(x - x_i)$. For

$$Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}, \; X = \begin{pmatrix} 1 & (x - x_1)' \\ \vdots & \vdots \\ 1 & (x - x_n)' \end{pmatrix}$$

$$W = diag(K_h(x - x_1), \ldots, K_h(x - x_n))$$

and e_1 a $(r + 1) \times 1$ vector with 1 in first position and zeros elsewhere, we have

$$\hat{g}(x) = e_1'(X'WX)^{-1}X'WY.$$

This estimator depends on x both through the weights $K_h(x - x_i)$ and through the regressors $x - x_i$.

This estimator is a locally linear fit of the data. It runs a regression with weights that are smaller for observations that are farther from x. In constrast, the kernel regression estimator solves this same minimization problem but with β constrained to be zero, i.e., kernel regression minimizes

$$\sum_{i=1}^{n} (Y_i - g)^2 K_h(x - x_i)$$

Removing the constriant $\beta = 0$ leads to lower bias without increasing variance when $g_0(x)$ is twice differentiable. It is also of interest to note that $\hat{\beta}$ from the above minimization problem estimates the gradient $\partial g_0(x)/\partial x$.

Like kernel regression, this estimator can be interpreted as a weighted average of the Y_i observations, though the weights are a bit more complicated. Let

$$S_0 = \sum_{i=1}^{n} K_h(x - x_i), \; S_1 = \sum_{i=1}^{n} K_h(x - x_i)(x - x_i), \; S_2 = \sum_{i=1}^{n} K_h(x - x_i)(x - x_i)(x - x_i)'$$

$$\hat{m}_0 = \sum_{i=1}^{n} K_h(x - x_i)Y_i,\ \hat{m}_1 = \sum_{i=1}^{n} K_h(x - x_i)(x - x_i)Y_i.$$

Then, by the usual partitioned inverse formula

$$\begin{aligned}
\hat{g}(x) &= e_1' \begin{bmatrix} S_0 & S_1' \\ S_1 & S_2 \end{bmatrix}^{-1} \begin{pmatrix} \hat{m}_0 \\ \hat{m}_1 \end{pmatrix} = (S_0 - S_1' S_2^{-1} S_1)^{-1}(\hat{m}_0 - S_1' S_2^{-1} \hat{m}_1) \\
&= \frac{\sum_{i=1}^{n} a_i Y_i}{\sum_{i=1}^{n} a_i},\ a_i = K_h(x - x_i)[1 - S_1' S_2^{-1}(x - x_i)]
\end{aligned}$$

It is straightforward though a little involved to find asymptotic approximations to the MSE. For simplicity we do this for scalar x case. Note that for $g_0 = (g_0(x_1), \ldots, g_0(x_n))'$,

$$\hat{g}(x) - g_0(x) = e_1'(X'WX)^{-1}X'W(Y - g_0) + e_1'(X'WX)^{-1}X'Wg_0 - g_0(x).$$

Then for $\Sigma = diag(\sigma^2(x_1), \ldots, \sigma^2(x_n))$,

$$\begin{aligned}
E\left[(\hat{g}(x) - g_0(x))^2 | x_1, \ldots, x_n\right] &= e_1'(X'WX)^{-1}X'W\Sigma WX(X'WX)^{-1}e_1 \\
&\quad + \left[e_1'(X'WX)^{-1}X'Wg_0 - g_0(x)\right]^2
\end{aligned}$$

An asymptotic approximation to MSE is obtained by taking the limit as n grows. Note that we have

$$n^{-1}h^{-j}S_j = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i)[(x - x_i)/h]^j$$

Then, by the change of variables $u = (x - x_i)/h$,

$$E\left[n^{-1}h^{-j}S_j\right] = E\left[K_h(x - x_i)\left((x - x_i)/h\right)^j\right] = \int K(u)u^j f_0(x - hu)du = \mu_j f_0(x) + o(1).$$

for $\mu_j = \int K(u)u^j du$ and $h \longrightarrow 0$. Also,

$$\begin{aligned}
var(n^{-1}h^{-j}S_j) &\leq n^{-1}E\left[K_h(x - x_i)^2\left((x - x_i)/h\right)^{2j}\right] \leq n^{-1}h^{-1}\int K(u)^2 u^{2j} f_0(x - hu)du \\
&\leq Cn^{-1}h^{-1} \longrightarrow 0
\end{aligned}$$

for $nh \longrightarrow \infty$. Therefore, for $h \to 0$ and $nh \to \infty$

$$n^{-1}h^{-j}S_j = \mu_j f_0(x) + o_p(1).$$

Now let $H = diag(1, h)$. Then by $\mu_0 = 1$ and $\mu_1 = 0$ we have

$$n^{-1}H^{-1}X'WXH^{-1} = n^{-1}\begin{bmatrix} S_0 & h^{-1}S_1 \\ h^{-1}S_1 & h^{-2}S_2 \end{bmatrix} = f_0(x)\begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix} + o_p(1).$$

Next let $\nu_j = \int K(u)^2 u^j du$. Then by a similar argument we have

$$h \cdot \frac{1}{n}\sum_{i=1}^{n} K_h(x-x_i)^2[(x-x_i)/h]^j \sigma^2(x_i) = \nu_j f_0(x)\sigma^2(x) + o_p(1).$$

It follows by $\nu_1 = 0$ that

$$n^{-1}hH^{-1}X'W\Sigma WXH^{-1} = f_0(x)\sigma^2(x)\begin{bmatrix} \nu_0 & 0 \\ 0 & \nu_2 \end{bmatrix} + o_p(1).$$

Then we have, for the variance term, by $H^{-1}e_1 = e_1$,

$$\begin{aligned}
& e_1'(X'WX)^{-1}X'W\Sigma WX(X'WX)^{-1}e_1 \\
= \; & n^{-1}h^{-1}e_1'H^{-1}\left(\frac{H^{-1}X'WXH^{-1}}{n}\right)^{-1}\frac{hH^{-1}X'W\Sigma WXH^{-1}}{n}\left(\frac{H^{-1}X'WXH^{-1}}{n}\right)^{-1}H^{-1}e_1 \\
= \; & n^{-1}h^{-1}\left[\left(e_1'\begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix}^{-1}\begin{bmatrix} \nu_0 & \nu_1 \\ \nu_1 & \nu_2 \end{bmatrix}\begin{bmatrix} 1 & 0 \\ 0 & \mu_2 \end{bmatrix}^{-1}e_1\right)\frac{\sigma^2(x)}{f(x)} + o_p(1)\right].
\end{aligned}$$

Assuming that $\mu_1 = 0$ as usual for a symmetric kernel we obtain

$$e_1'(X'WX)^{-1}X'W\Sigma WX(X'WX)^{-1}e_1 = n^{-1}h^{-1}\left(\nu_0\frac{\sigma^2(x)}{f(x)} + o_p(1)\right).$$

For the bias consider an expansion

$$g(x_i) = g_0(x) + g_0'(x)(x_i - x) + \frac{1}{2}g_0''(x)(x_i-x)^2 + \frac{1}{6}g_0'''(\bar{x}_i)(x_i-x)^3.$$

Let $r_i = g_0(x_i) - g_0(x) - [dg_0(x)/dx](x_i - x)$. Then by the form of X we have

$$g = (g_0(x_1), \ldots, g_0(x_n))' = g_0(x)We_1 - g_0'(x)We_2 + r$$

It follows by $e_1'e_2 = 0$ that the bias term is

$$e_1'(X'WX)^{-1}X'Wg - g_0(x) = e_1'(X'WX)^{-1}X'WXe_1g_0(x) - g_0(x)$$

$$+e_1'(X'WX)^{-1}X'WXe_2g_0'(x) + e_1'(X'WX)^{-1}X'Wr = e_1'(X'WX)^{-1}X'Wr.$$

Recall that

$$n^{-1}h^{-j}S_j = \mu_j f_0(x) + o_p(1).$$

Therefore

$$
\begin{aligned}
& n^{-1}h^{-2}H^{-1}X'W((x-X_1)^2,\ldots,(x-X_n)^2)'\frac{1}{2} \\
= & \left(\begin{array}{ccc} n^{-1} & h^{-2} & S_2 \\ n^{-1} & h^{-3} & S_3 \end{array}\right)\frac{1}{2}g_0''(x) = f_0(x)\left(\begin{array}{c} \mu_2 \\ \mu_3 \end{array}\right)\frac{1}{2}g_0''(x) + o_p(1).
\end{aligned}
$$

Also, by $g_0'''(\bar{x}_i)$ bounded

$$
\begin{aligned}
& \left\| n^{-1}h^{-2}H^{-1}X'W\left((x-x_1)^3 g_0'''(\bar{x}_1),\ldots,(x-x_n)^3 g_0'''(\bar{x}_n)\right)' \right\| \\
\leq & \; C\max\left\{ n^{-1}h^{-2}\sum_i K_h(x-x_i)|x-x_i|^3, n^{-1}h^{-2}S_4 \right\} \longrightarrow 0.
\end{aligned}
$$

Therefore, we have

$$
\begin{aligned}
e_1'(X'WX)^{-1}X'Wr &= h^2 e_1' H^{-1}\frac{(H^{-1}X'WXH^{-1})^{-1}}{n}\cdot\frac{h^{-2}H^{-1}X'Wr}{n} \\
&= \frac{h^2}{2}g_0''(x)e_1'\left(\begin{array}{cc} 1 & 0 \\ 0 & \mu_2 \end{array}\right)^{-1}\left(\begin{array}{c} \mu_2 \\ \mu_3 \end{array}\right) = \frac{h^2}{2}g_0''(x)\mu_2.
\end{aligned}
$$

Exercise: Apply analogous calculation to show kernel regression bias is

$$
\mu_2 h^2\left(\frac{1}{2}g_0''(x) + g_0'(x)\frac{f_0'(x)}{f_0(x)}\right)
$$

Notice bias is *zero* if function is linear.

Combining the bias and variance expression, we have the following form for asymptotic MSE:

$$
\frac{1}{nh}\nu_0\frac{\sigma^2(x)}{f_0(x)} + \frac{h^4}{4}g_0''(x)^2\mu_2^2.
$$

In constrast, the kernel MSE is

$$
\frac{1}{nh}\nu_0\frac{\sigma^2(x)}{f_0(x)} + \frac{h^4}{4}\left[g_0''(x) + 2g_0'(x)\frac{f_0'(x)}{f_0(x)}\right]^2\mu_2^2.
$$

Bias will be much bigger near boundary of the support where $f_0'(x)/f_0(x)$ is large. For example, if $f_0(x)$ is approximately x^α for $x > 0$ near zero, then $f_0'(x)/f_0(x)$ grows like $1/x$ as x gets close to zero. Thus, locally linear has smaller boundary bias. Also, locally linear has no bias if $g_0(x)$ is linear but kernel obviously does.

Simple method is to take expected value of MSE.