

# Estimating the conditional variance by local linear regression

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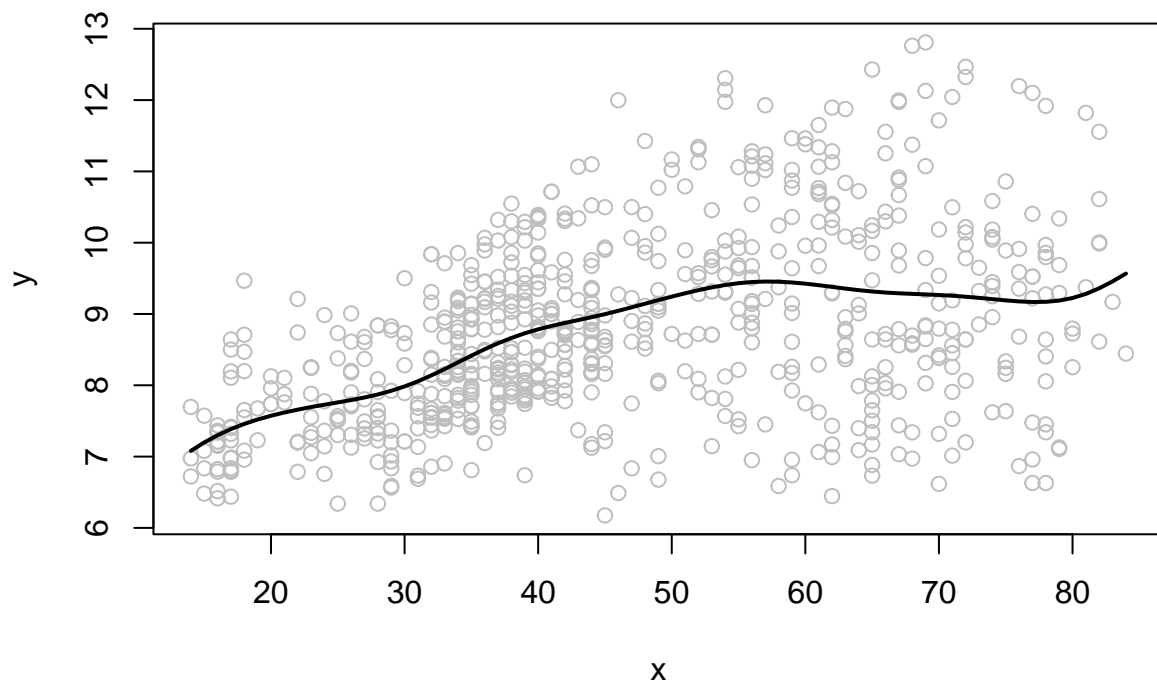
2023-11-12

```
x <- Yr  
y <- lg_weight  
n <- length(x)
```

## Estimating the conditional variance (Using loc.pol.reg)

1. Fit a nonparametric regression to data  $(x_i, y_i)$  and save the estimated values  $\hat{m}(x_i)$ .

```
fit.lpr <- fit.loc_pol_reg(x, y)
```



```
fit_y <- fit.lpr$lpr
mtgr <- fit_y$mtgr # \hat{m}(x_i)
```

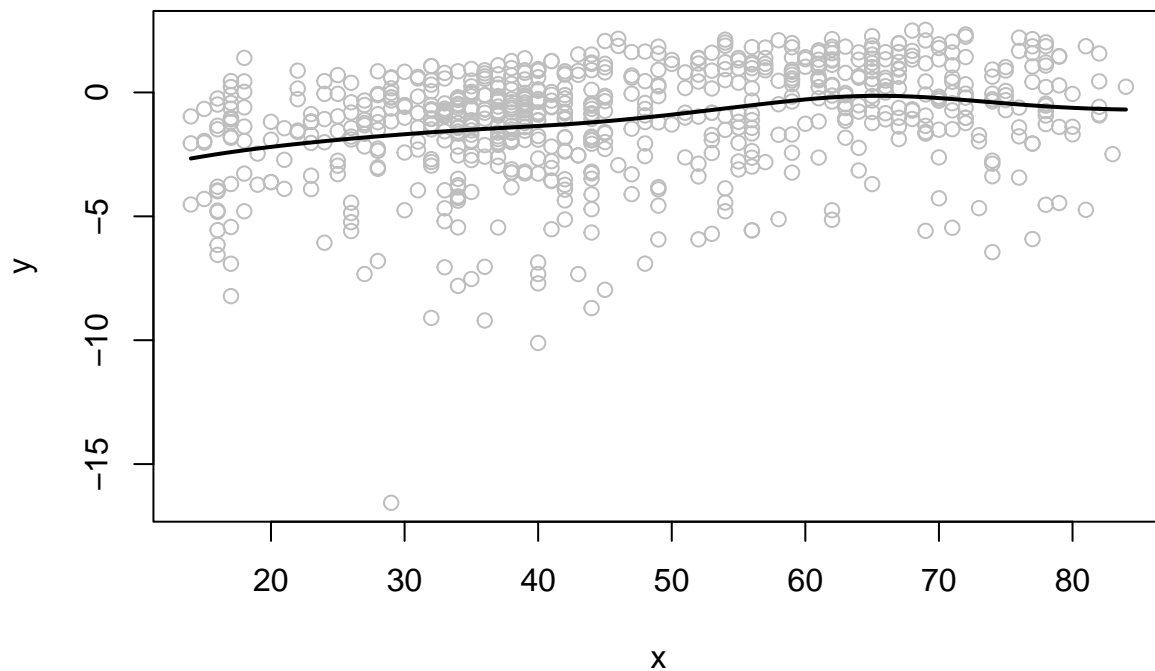
2. Transform the estimated residuals  $\hat{\epsilon} = y_i - \hat{m}(x_i)$

$$z_i = \log \epsilon_i^2 = \log((y_i - \hat{x}_i)^2)$$

```
hat_e <- y - mtgr
z <- log((hat_e)^2)
```

3. Fit a nonparametric regression to data  $(x_i, z_i)$  and call the estimated function  $\hat{q}(x)$ . Observe that  $\hat{q}(x)$  is an estimate of  $\log \sigma^2(x)$ .

```
fit_z <- fit.loc_pol_reg(x, z)$lpr
```



```
qtgr <- fit_z$mtgr
```

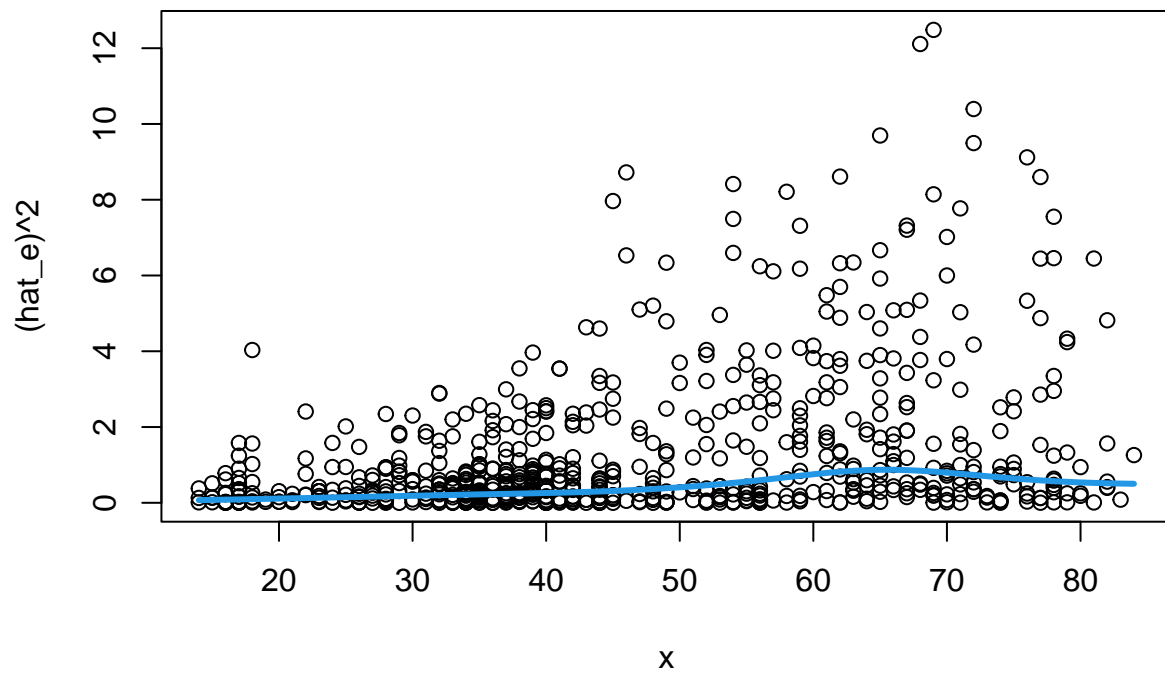
4. Estimate  $\sigma^2(x)$  by

$$\hat{\sigma}^2(x) = e^{\hat{q}(x)}$$

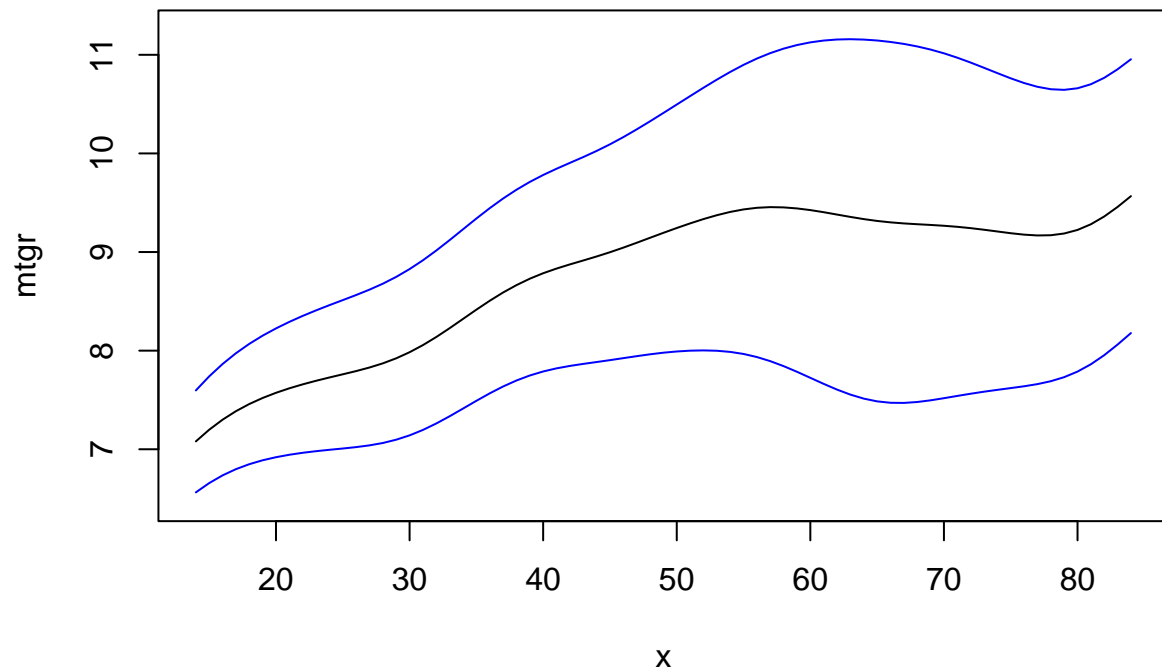
```
sig.sqr <- exp(qtgr)
```

## plots

```
plot(x, (hat_e)^2)  
lines(x, sig.sqr, col=4, lwd=3)
```



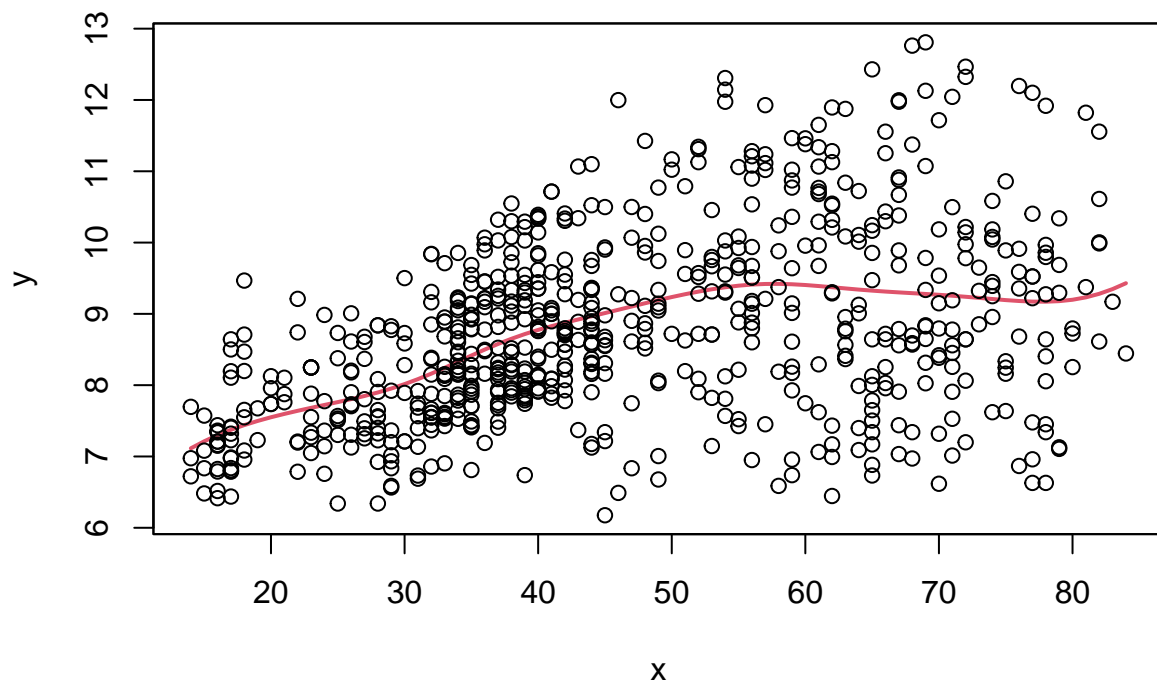
```
y.min <- min(mtgr - 1.96 * sqrt(sig.sqr)) - 0.1  
y.max <- max(mtgr + 1.96 * sqrt(sig.sqr)) + 0.1  
plot(x, mtgr, type = 'l', ylim=c(y.min, y.max))  
lines(x, mtgr + 1.96 * sqrt(sig.sqr), col="blue")  
lines(x, mtgr - 1.96 * sqrt(sig.sqr), col="blue")
```



# Estimating the conditional variance (Using sm.regression)

**1. Fit a nonparametric regression to data  $(x_i, y_i)$  and save the estimated values  $\hat{m}(x_i)$ .**

```
h.dpi <- dpill(x=x, y=y, range.x=range(x))
sm_regression <- sm.regression(x=x, y=y, eval.points=x, h=h.dpi, pch=1, cex=1, col=2, lwd=2)
```



```
mtgr_sm <- sm_regression$estimate
```

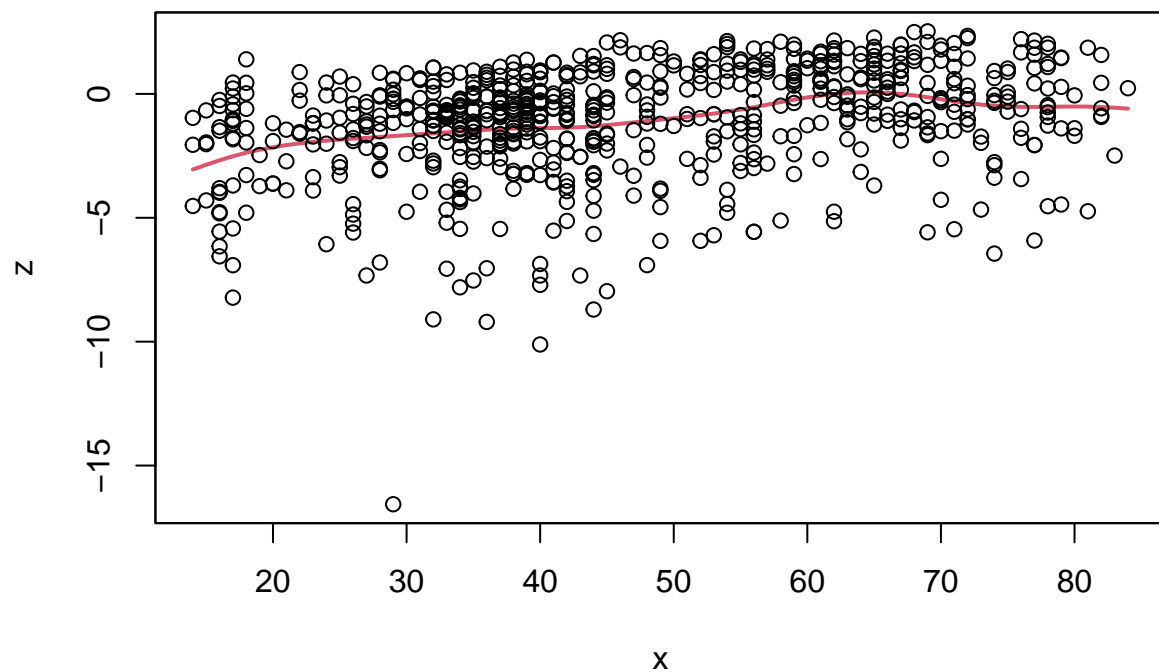
2. Transform the estimated residuals  $\hat{\epsilon} = y_i - \hat{m}(x_i)$

$$z_i = \log \epsilon_i^2 = \log((y_i - \hat{x}_i)^2)$$

```
hat_e_sm <- y - mtgr_sm
z_sm <- log((hat_e_sm)^2)
```

3. Fit a nonparametric regression to data  $(x_i, z_i)$  and call the estimated function  $\hat{q}(x)$ . Observe that  $\hat{q}(x)$  is an estimate of  $\log \sigma^2(x)$ .

```
sm_regression_z <- sm.regression(x=x, y=z, pch=1, cex=1, col=2, lwd=2,
                                eval.points=x,
                                h=dpill(x=x, y=z, range.x=range(x)))
```



```
qtgr_sm <- sm_regression_z$estimate
```

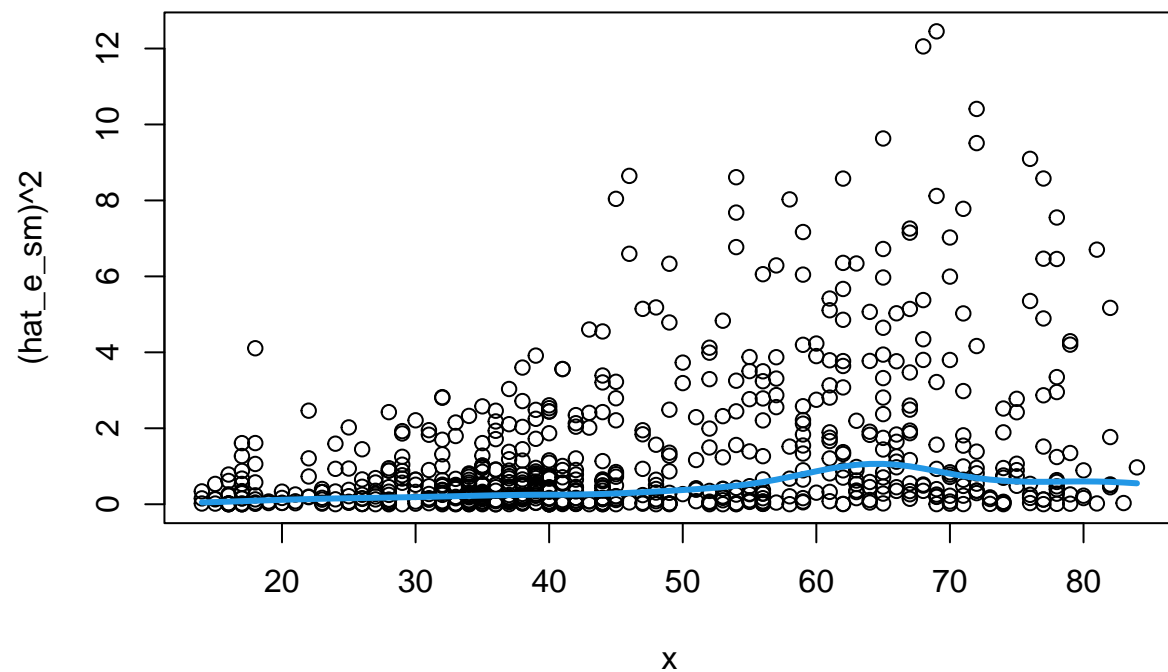
4. Estimate  $\sigma^2(x)$  by

$$\hat{\sigma}^2(x) = e^{\hat{q}(x)}$$

```
sig.sqr_sm <- exp(qtgr_sm)
```

plots

```
plot(x, (hat_e_sm)^2)
lines(x, sig.sqr_sm, col=4, lwd=3)
```



```

y.min_sm <- min(mtgr_sm - 1.96 * sqrt(sig.sqr_sm)) - 0.1
y.max_sm <- max(mtgr_sm + 1.96 * sqrt(sig.sqr_sm)) + 0.1
plot(x,mtgr_sm, type = 'l', ylim=c(y.min_sm, y.max_sm))
lines(x,mtgr_sm + 1.96 * sqrt(sig.sqr_sm), col="blue")
lines(x,mtgr_sm - 1.96 * sqrt(sig.sqr_sm), col="blue")

```

