part2 - a

$$\begin{split} D &= E(\frac{1}{n} \| f - \hat{f} \|^2) \\ &= E(\frac{1}{n} \| f - E(\hat{f}) - \hat{f} + E(\hat{f}) \|^2) \\ &= E(\frac{1}{n} \| f - E(\hat{f}) - \hat{f} + E(\hat{f}) \|^2) \\ &= E(\frac{1}{n} \| f - E(\hat{f}) - \hat{f} + E(\hat{f}) \|^2) \\ &= \frac{1}{n} [E(\| f - E(\hat{f}) \|^2) + E(\| \hat{f} - E(\hat{f}) \|^2) + 2E(E(\| f - E(\hat{f}) \|)E(\| \hat{f} - E(\hat{f}) \|)] \end{split}$$

Note that $E(E(\|\hat{f} - E(\hat{f})\|)) = 0$, two terms are independent to each other, therefore the cross term $2E(E(\|f - E(\hat{f})\|)E(\|\hat{f} - E(\hat{f})\|) = 0$.

$$D = \frac{1}{n} [E(\|f - E(\hat{f})\|^2) + E(\|\hat{f} - E(\hat{f})\|^2)]$$

Separately write two terms.

Since $\hat{f} = Wy$ and $y = f + \epsilon$, where y, f, ϵ are vectors, $E(\hat{f}) = E(Wy) = WE(f + \epsilon) = Wf$

$$E(\|f - E(\hat{f})\|^2) = E(\|f - Wf\|^2)$$
$$= E(\|(W - I)f\|^2)$$

Since W depends only on bandwidth, and f is parameter, this term can be written as $\|(W-I)f\|^2$

 $E(\|\hat{f} - E(\hat{f})\|^2)$ is the variance of $\|\hat{f}\|$, where $\hat{f} = Wy$.

$$\begin{split} E(\|\hat{f} - E(\hat{f})\|^2) &= Var(\|W\|y) \\ &= \|W^2\|Var(y) \\ &= trace(W^TW)\sigma^2 \end{split}$$

Combine these two term, we proved:

$$D = \frac{1}{n} (\|(W - I)f\|^2 + trace(W^T W)\sigma^2)$$