

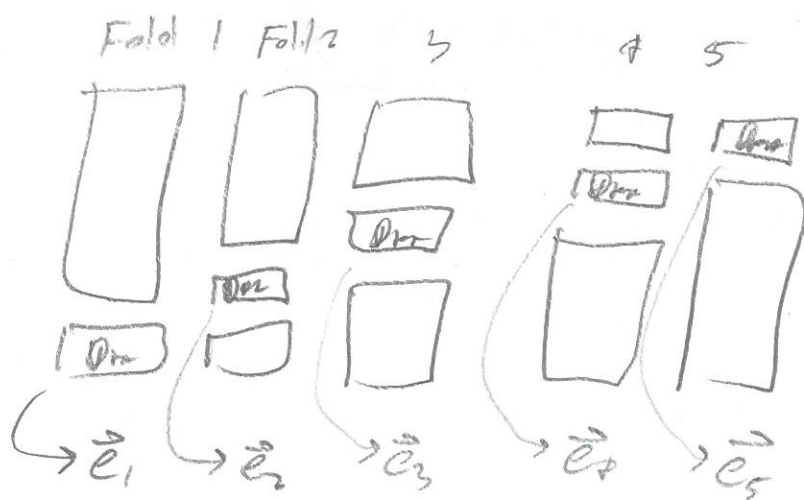
Validation



$$K=5 \Rightarrow \frac{N_{test}}{N} = \frac{1}{K} = 20\%$$

If you compare \hat{y}_c on D_{test} ,

$P(\hat{y}_c | D_{train}, D_{test})$ means if you get lucky or unlucky is your choice of training and/or test split, your results are not accurate. Single experiment: (called K "folds") cross-validation. ^(CV) For this procedure K times, moving D_{test} through all N



See $\vec{e}_{cv} = \begin{bmatrix} \vec{e}_1 \\ \vec{e}_2 \\ \vdots \\ \vec{e}_K \end{bmatrix}$

and then compare error measures on \vec{e}_{cv}

R^2, \hat{y}_c , etc... This is a good est of gen. error of model

Also, ϵ_e will be variable. Use the $K=5$ estimate of ϵ_e
 from $\epsilon_{e_1} = en(\vec{e}_1), \epsilon_{e_2} = en(\vec{e}_2), \dots, \epsilon_{e_K} = en(\vec{e}_K)$

to obtain a std error of the estimate to see
 how variable it is.

$$s_{\epsilon_e} = \sqrt{\frac{1}{K-1} \sum_{i=1}^K (\epsilon_{e_i} - \bar{\epsilon_e})^2}$$

Not independence of
 $\epsilon_{e_1}, \dots, \epsilon_{e_K}$.

They are "somewhat" \perp .

How to pick K ? If K small then the error will be
 biased upwards since you are not using all data to estimate ϵ_e .

If K large, the estimates $\epsilon_{e_1}, \dots, \epsilon_{e_K}$ will be very variable
 as they are not estimated with lots of y_{test} . Also $\epsilon_{e_1}, \dots, \epsilon_{e_K}$
 will lose independence.

\Rightarrow Nobody knows the optimal K . 5 or 10 is default.