To simplify this problem lets begin in the case of simple linear regression where there is only one response y and one predictor x. Then the standard definitions of y and X state that $y^{T} = (y_{1}, ..., y_{n}), \text{ and } X^{T} = \begin{bmatrix} 1 & \cdots & 1 \\ x_{1} & \cdots & x_{n} \end{bmatrix}.$ Part (a): Let's first consider linear regression. We use (2.2) and (2.6), but we avoid just copying the formulas blindly. We have $\hat{\beta} = (X^T X)^{-1} X^T y$, and then set

 $\hat{f}(x_0) = [x_0 \ 1]\hat{\beta} = [x_0 \ 1](X^TX)^{-1}X^Ty.$ In terms of the notation of the question,

Ex. 2.7 (forms for linear regression and k-nearest neighbor regression)

 $\ell_i(x_0; \mathcal{X}) = [x_0 \ 1] (X^T X)^{-1} \begin{bmatrix} 1 \\ x_i \end{bmatrix}$

for each i with $1 \le i \le n$. More explicitly, $X^TX = \begin{bmatrix} n & \sum_{i \le j} x_i \\ \sum_{i \le j} x_i^2 \end{bmatrix}$ which has determinant $(n-1)\sum_i x_i^2 - 2n\sum_{i < j} x_i x_j$.

This allows us to calculate $(X^TX)^{-1}$ and $\ell_i(x_0; \mathcal{X})$ even more explicitly if we really want to. In the case of k-nearest neighbor regression $\ell_i(x_0; \mathcal{X})$ is equal to 1/k if x_i is one of the nearest

k points and 0 otherwise.