This homework set will focus on the linear least squares problem

$$
\operatorname{LLS} \quad \min _{x \in \mathbb{R}^{n}} \frac{1}{2}\|A x-b\|_{2}^{2}
$$

where $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^{m}$.
(1) Listed below are two functions. In each case write the problem $\min _{x} f(x)$ as a linear least squares problem by specifying the matrix $A$ and the vector $b$, and then solve the associated problem.
(a) $f(x)=\left(2 x_{1}-x_{2}+1\right)^{2}+\left(x_{2}-x_{3}\right)^{2}+\left(x_{3}-1\right)^{2}$
(b) $f(x)=\left(1-x_{1}\right)^{2}+\sum_{j=1}^{5-1}\left(x_{j}-x_{j+1}\right)^{2}$
(2) Consider the data points $(x, y) \in \mathbb{R},(1,1),(2,0),(-1,2)$, and $(0,-1)$. We wish to determine a real polynomial of degree 2 that best fits this data. A general real polynomial of degree 2 has the form $p(\lambda)=x_{0}+x_{1} \lambda+x_{2} \lambda^{2}$, where $x=\left(x_{0}, x_{1}, x_{2}\right)^{T} \in \mathbb{R}^{3}$. Note that there are more data points that there are unknown coefficients $x_{0}, x_{1}$, and $x_{2}$ and so it is unlikely that there exists a second degree polynomial that fits this data precisely.
(a) Write the problem of determining the quadratic polynomial that "best" fits this data as a linear least squares problem by specifying the matrix $A$ and the vector $b$.
(b) Solve this linear least squares problem.
(3) Find the quadratic polynomial $p(t)=x_{0}+x_{1} t+x_{2} t^{2}$ that best fits the following data in the least-squares sense:

$$
\begin{array}{c|ccccc}
t & -2 & -1 & 0 & 1 & 2 \\
\hline y & 2 & -10 & 0 & 2 & 1
\end{array} .
$$

(4) Consider the problem LLS with

$$
A=\left[\begin{array}{ccc}
1 & -1 & 0 \\
1 & 1 & 2 \\
1 & -1 & 0 \\
1 & 1 & 2
\end{array}\right] \quad \text { and } \quad b=\left[\begin{array}{l}
1 \\
1 \\
1 \\
0
\end{array}\right]
$$

(a) What are the normal equations for this $A$ and $b$.
(b) Solve the normal equations to obtain a solution to the problem LLS for this $A$ and $b$.
(c) What is the general reduced QR factorization for this matrix $A$ ?
(d) Compute the orthogonal projection onto the range of $A$.
(e) Use the recipe

$$
\begin{aligned}
A P & =Q\left[\begin{array}{ll}
R_{1} & R_{2}
\end{array}\right] & & \text { the general reduced } \mathrm{QR} \text { factorization } \\
\hat{b} & =Q^{T} b & & \text { a matrix-vector product } \\
\bar{w}_{1} & =R_{1}^{-1} \hat{b} & & \text { a back solve } \\
\bar{x} & =P\left[\begin{array}{c}
R_{1}^{-1} \hat{b} \\
0
\end{array}\right] & & \text { a matrix-vector product. }
\end{aligned}
$$

to solve LLS for this $A$ and $b$.
(f) If $\bar{x}$ solves LLS for this $A$ and $b$, what is $A \bar{x}-b$ ?
(5) Consider the matrix

$$
A=\left[\begin{array}{lll}
1 & 1 & 1 \\
1 & 1 & 0 \\
1 & 0 & 0 \\
1 & 0 & 1
\end{array}\right]
$$

(a) Compute the orthogonal projection onto $\operatorname{Ran}(A)$.
(b) Compute the orthogonal projection onto $\operatorname{Null}\left(A^{T}\right)$.
(6) Let $A \in \mathbb{R}^{m \times n}$. Show that $\operatorname{Null}(A)=\operatorname{Null}\left(A^{T} A\right)$.
(7) Let $A \in \mathbb{R}^{m \times n}$ be such that $\operatorname{Null}(A)=\{0\}$.
(a) Show that $A^{T} A$ is invertible.
(b) Show that the orthogonal projection onto $\operatorname{Ran}(A)$ is the matrix $P:=A\left(A^{T} A\right)^{-1} A^{T}$.

