

3. Projection matrices

P is square
 $P^2 = P$

- (a) Assume $I - P$ is a projection matrix. Then $(I - P)^2 = I - P$.

$$\begin{aligned}(I - P)^2 &= (I - P) \cdot (I - P) \\ &= I^2 - 2IP + P^2 = I - 2P + P^2 \\ &= I - 2P + P = I - P\end{aligned}$$

Therefore $I - P$ is a projection matrix.

- (b) $(A(A^T A)^{-1} A^T)^2 = (A(A^T A)^{-1} A^T) \cdot (A(A^T A)^{-1} A^T)$
 $= A \cdot (A^T A)^{-1} (A^T A) (A^T A)^{-1} A^T$
 $= A (A^T A)^{-1} A^T$

A has linearly independent columns, so it is full rank, so it is a square matrix.

Therefore, $(A(A^T A)^{-1} A^T)^2$ is a projection matrix.

- (c) Let $U = [\underline{u}_1 \quad \underline{u}_2 \quad \dots \quad \underline{u}_K]$. Since $\underline{u}_i \forall i$ are orthonormal vectors, U is an orthogonal matrix.

Then:

$$U \cdot U^T = \begin{bmatrix} \underline{u}_1 & \underline{u}_2 & \dots & \underline{u}_K \end{bmatrix} \cdot \begin{bmatrix} \underline{u}_1^T \\ \underline{u}_2^T \\ \vdots \\ \underline{u}_K^T \end{bmatrix} = \underline{u}_1 \underline{u}_1^T + \underline{u}_2 \underline{u}_2^T + \dots + \underline{u}_K \underline{u}_K^T$$

$$\begin{aligned}\text{and } (U U^T)^2 &= \overset{=I}{(U U^T)} (U U^T) \\ &= U U^T \therefore \text{projection matrix}\end{aligned}$$

4. (a) Using the Vandermonde matrix:

$$\underbrace{\begin{bmatrix} x_1^2 & x_1 & 1 \\ x_2^2 & x_2 & 1 \\ \vdots & \vdots & \vdots \\ x_n^2 & x_n & 1 \end{bmatrix}}_X \cdot \underbrace{\begin{bmatrix} p \\ q \\ r \end{bmatrix}}_{\underline{w}} \approx \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}}_{\underline{y}} \Rightarrow \underline{x} \underline{w} \approx \underline{y}$$

So we want to minimize the difference between $\underline{x} \underline{w}$ and \underline{y} : $\min_{\underline{w}} \|\underline{y} - \underline{x} \underline{w}\|_2^2$.
 Since the Vandermonde matrix is always invertible: $\hat{\underline{w}} = (X^T X)^{-1} X^T \underline{y}$.

(b) If our vertical offset is 1, that specifies our choice of $r: r=1$.

$$\begin{bmatrix} x_1^2 & x_1 & 1 \\ x_2^2 & x_2 & 1 \\ \vdots & \vdots & \vdots \\ x_n^2 & x_n & 1 \end{bmatrix} \cdot \begin{bmatrix} p \\ q \\ 1 \end{bmatrix} \approx \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \Rightarrow \underbrace{\begin{bmatrix} x_1^2 & x_1 \\ x_2^2 & x_2 \\ \vdots & \vdots \\ x_n^2 & x_n \end{bmatrix}}_X \cdot \underbrace{\begin{bmatrix} p \\ q \end{bmatrix}}_w \approx \underbrace{\begin{bmatrix} y_1 - 1 \\ y_2 - 1 \\ \vdots \\ y_n - 1 \end{bmatrix}}_y \Rightarrow \hat{w} = \min_w \|Xw - y\|_2^2 = (X^T X)^{-1} X^T y$$

(c) $y = px^2 + qx + 1$
 $y' = 2px + q$

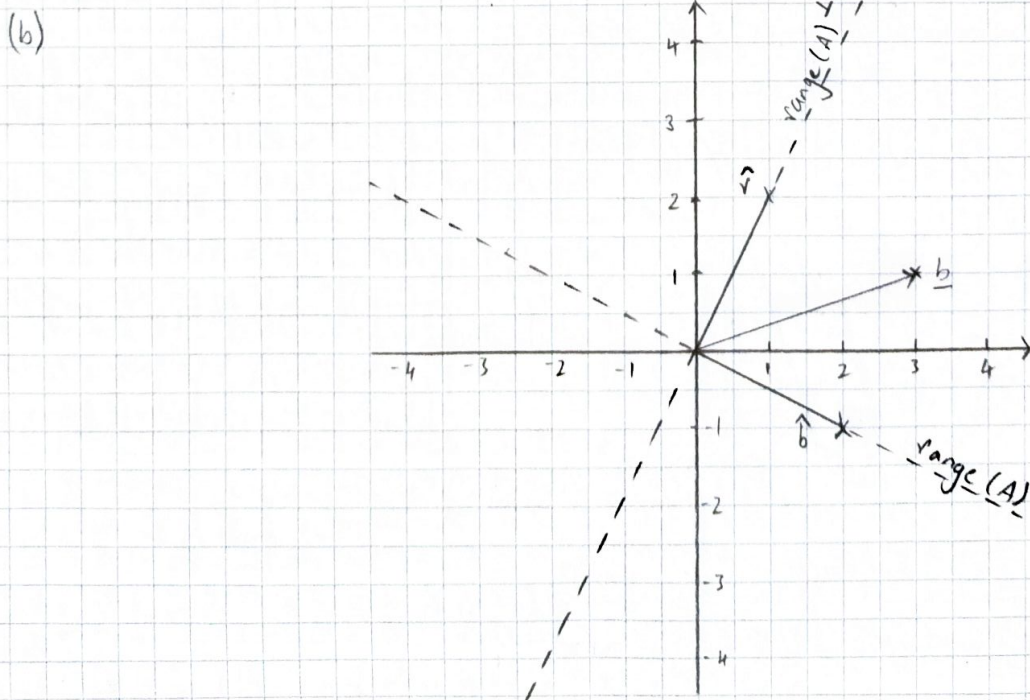
$y'(0) = 2p(0) + q = 1$ (since it's an angle of 45° at launch, $t=0$)
 $\Rightarrow q = 1$

$$\begin{bmatrix} x_1^2 & x_1 \\ x_2^2 & x_2 \\ \vdots & \vdots \\ x_n^2 & x_n \end{bmatrix} \cdot \begin{bmatrix} p \\ q \end{bmatrix} \approx \begin{bmatrix} y_1 - 1 \\ y_2 - 1 \\ \vdots \\ y_n - 1 \end{bmatrix} \Rightarrow \underbrace{\begin{bmatrix} x_1^2 \\ x_2^2 \\ \vdots \\ x_n^2 \end{bmatrix}}_X \cdot \underbrace{\begin{bmatrix} p \\ q \end{bmatrix}}_w \approx \underbrace{\begin{bmatrix} y_1 - x_1 - 1 \\ y_2 - x_2 - 1 \\ \vdots \\ y_n - x_n - 1 \end{bmatrix}}_y \Rightarrow \hat{w} = \min_w \|Xw - y\|_2^2 = (X^T X)^{-1} X^T y$$

5. Visualizing least-squares

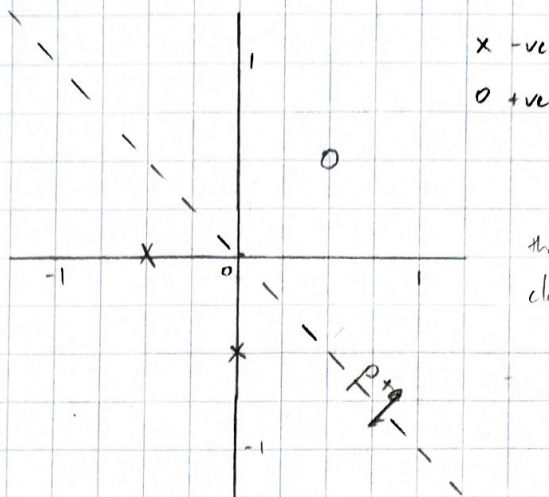
(a) $\hat{x} = (A^T A)^{-1} A^T \cdot \underline{b}$
 $= \left(\begin{bmatrix} 2 & -1 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -1 \end{bmatrix} \right)^{-1} \cdot \begin{bmatrix} 2 & -1 \end{bmatrix} \cdot \begin{bmatrix} 3 \\ 1 \end{bmatrix}$
 $= (5)^{-1} \cdot (5)$
 $= 1$

$\therefore \hat{\underline{b}} = A \cdot \hat{x} = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$
 $\hat{\underline{r}} = \begin{bmatrix} 3 \\ 1 \end{bmatrix} - \begin{bmatrix} 2 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$



6. A Microbiology Experiment

(a)



if we let $w_1 = 1$ and $w_2 = 1$,
the boundary that forms successfully
classifies our data

(b) Our weight vector $\underline{w} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$ has no offset, so all decision boundaries

$w_1 p_1 + w_2 q_2 = 0$ pass through the origin. There's no way to arrange the weights
such that (p_4, q_4) is classified correctly while leaving the other classifications correct.
However, any offset $-0.5 < r < 0.1$ would work:

$$\hat{y} = \text{sign}(1 \cdot p + 1 \cdot q + 0.3).$$

7. Properties of the SVD

- (a)
- Σ is a diagonal matrix
 - Σ is sorted in descending order
 - $V^T V = I$
 - $U^T U = I$

(b) Since the last row of Σ is zeros, one possible change could be

$$\tilde{U} = \frac{1}{3} \begin{bmatrix} 2 & 1 & 2 \\ 1 & 2 & -2 \\ 2 & -1 & -1 \end{bmatrix}$$

and we still get that $A = \tilde{U} \Sigma V^T$

(c) Since the smallest element of Σ is 15 (i.e. the smallest amplification factor), the
matrix x should correspond to the last column of V : $x = \begin{bmatrix} -4 \\ 3 \end{bmatrix}$

(d) Since the largest element of Σ is 30, the best rank-1 approximation of A is
 $X = \left(\frac{1}{3} \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix} \right) \cdot \overset{2 \times 10}{(30)} \cdot \left(\frac{1}{5} \begin{bmatrix} 3 & 4 \end{bmatrix} \right) = \begin{bmatrix} 12 & 16 \\ 6 & 8 \\ 12 & 16 \end{bmatrix}$

(e) For the least squares solution \hat{x} to result in a zero residual, b must lie in the range of A , which is spanned by the first 2 columns of u .

(f) b must then lie in the nullspace of A , so it must lie in the span of the last column of u :

$$b \in \text{span}\left(\begin{bmatrix} -2 \\ 2 \\ 1 \end{bmatrix}\right)$$

8. $f(x) = (x-1)^2 + \lambda x^2$

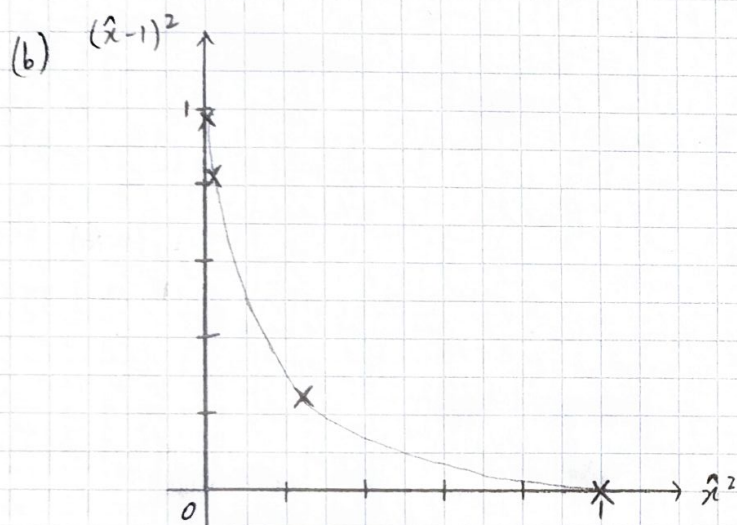
(a) $f'(x) = 2(x-1) \cdot 1 + 2\lambda x$

at min point, $f'(x) = 0$

$$0 = 2x - 2 + 2\lambda x$$

$$x = \frac{2x(1+\lambda)}{2(1+\lambda)}$$

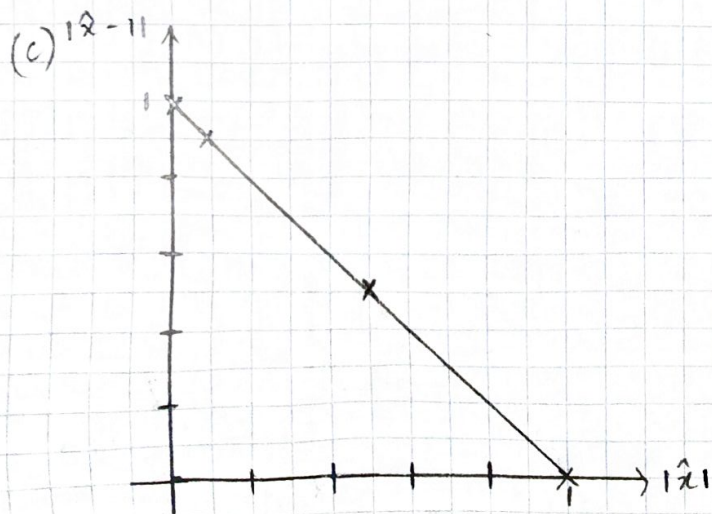
$$\Rightarrow \hat{x} = \frac{1}{1+\lambda}$$



$$\hat{x}^2 = \frac{1}{(\hat{x}+1)^2}$$

$$\begin{aligned} (\hat{x}-1)^2 &= \hat{x}^2 - 2\hat{x} + 1 \\ &= \frac{1}{(1+\lambda)^2} - \frac{2}{1+\lambda} + 1 \\ &= \frac{1 - 2(1+\lambda) + (1+\lambda)^2}{(1+\lambda)^2} \end{aligned}$$

λ	\hat{x}^2	$(\hat{x}-1)^2$	$ \hat{x} $	$ \hat{x}-1 $
0	1	0	1	0
1	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{2}$
10	0.0083	0.8264	0.0909	0.9090
100	0.0001	0.9803	0.0099	0.9900



We are looking for a value of \hat{x} that is close to 1, and in $0 \leq \hat{x} \leq 1$, $x^2 \leq x$. So while this is a straight line, the above curve is quadratic.