Least Squares Problems

- First posed and formulated by Gauss.
- Surveyors tried to identified boundaries lie between plots and land by measuring certain angles and distances from known landmarks.
- To update the location of landmarks, new measurements of angles and distances between landmarks.
- Given a set of old locations $\{(x_i, y_i)\}$, find corrections $\{(\delta x_i, \delta y_i)\}$ such that $\{(x_i+\delta x_i, y_i+\delta y_i)\}$ better match new measurements.
- In general,

constraints
$$\left\{ \begin{array}{c} a_{1,1}x_1 + a_{1,2}x_2 + \dots + a_{1,n}x_n = b_1 \\ \vdots \\ a_{m,1}x_1 + a_{m,2}x_2 + \dots + a_{m,n}x_n = b_m \end{array} \right\} \text{ observations}$$

i.e.
$$A x = b$$
 $A \begin{vmatrix} x \\ x \end{vmatrix} = b$

In general, $r = b - A x \neq 0$.

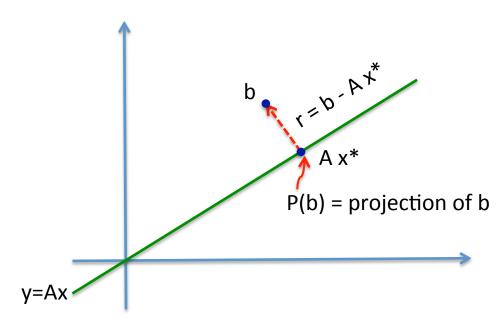
Idea: min the residual vector r

$$\min_{x \in R^n} \|b - Ax\|_2^2 \qquad A \in R^{m \times n}, \ b \in R^m, \ m \ge n$$

• Least squares (LS) problems.

Solving LS problems

Geometric interpretation:



<u>Theorem</u>: Let $A \subseteq R^{mxn}$, $b \subseteq R^m$, $m \ge n$ and A has full rank. A vector $x \subseteq R^n$ minimizes

$$||r||^2 = ||b - Ax||^2$$

if and only if $r \perp range(A)$.

Hence
$$r^T A = 0 \iff A^T r = 0 \iff A^T (b - A x) = 0$$

 $\iff A^T A x = A^T b$

<u>Def</u>: $A^+ = (A^T A)^{-1} A^T$ is called the pseudoinverse of A.

The least squares solution is given by:

$$x = (A^T A)^{-1} A^T b = A^+ b$$

Why is x the minimizer of $||b-Ax||^2$?

Let x' = x + e be another point.

$$||b - A x'||^{2} = (b - A x')^{T} (b - A x')$$

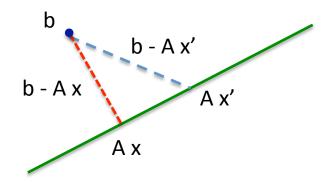
$$= (b - A x - A e)^{T} (b - A x - A e)$$

$$= (b - A x)^{T} (b - A x) + 2 (A e)^{T} (b - A x) + (Ae)^{T} (Ae)$$

$$= ||b - A x||^{2} + ||Ae||^{2} + 2e^{T} (A^{T}b A^{T}A x)$$

$$= ||b - A x||^{2} + ||Ae||^{2}$$

Hence $||b - Ax'||^2 > ||b - Ax||^2$ if $e \ne 0$



Method 1: Normal equations

Solve
$$A^TA x = A^T b$$

- Compute Cholesky factorization $A^TA = GG^T$, $G = lower \Delta$
- Compute x by forward and backward solves

Complexity

flops(A^TA) ~ mn², flops(GG^T) ~ 1/3 n³
Total flops ~ mn² + 1/3 n³ (m
$$\geq$$
 n)

Method 2: QR factorization

<u>Def</u>: Q is orthogonal if $Q^{-1} = Q^{T}$

i.e. $Q^T Q = Q Q^T = I$

<u>Theorem</u>: $||Qx||_2 = ||x||_2$

Pf:
$$||Qx||^2 = (Qx)^T (Qx) = x^T Q^T Qx = x^T x = ||x||^2$$

Note:

multiplication by
$$Q = \begin{cases} \text{rotation} & \text{if } det(Q) = 1 \\ \text{reflection} & \text{if } det(Q) = -1 \end{cases}$$

<u>Theorem</u>: Suppose $A \subseteq R^{mxn}$ has full rank. Then there exist a unique orthogonal matrix $\hat{Q} \subseteq R^{mxn}$ ($Q^TQ = I$) and a unique upper Δ matrix $\hat{R} \subseteq R^{nxn}$ with positive diagonals ($r_{ii} > 0$) such that

$$A = \hat{Q}\hat{R}$$
 i.e.
$$A = \hat{Q}$$

$$\hat{R}$$

Note:

The column of \hat{Q} are orthogonal to each other and their norm = 1.

Consider the LS problem:

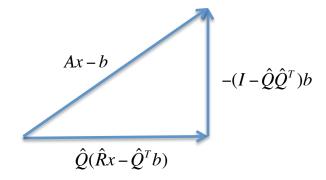
min
$$|| Ax - b ||^2$$

•
$$Ax - b = \hat{Q}\hat{R}x - b$$

$$= \hat{Q}\hat{R}x - (\hat{Q}\hat{Q}^T + I - \hat{Q}\hat{Q}^T)b$$

$$= \hat{Q}(\hat{R}x - \hat{Q}^Tb) - (I - \hat{Q}\hat{Q}^T)b$$

Note:
$$\hat{Q}(\hat{R}x - \hat{Q}^Tb) \perp (I - \hat{Q}\hat{Q}^T)b$$



Pythagoras thm:
$$||Ax - b||^2 = ||\hat{Q}(\hat{R}x - \hat{Q}^Tb)||^2 + ||(I - \hat{Q}\hat{Q}^T)b||^2$$

$$= ||\hat{R}x - \hat{Q}^Tb||^2 + ||(I - \hat{Q}\hat{Q}^T)b||^2$$

The RHS is min if the first term is 0.

i.e.
$$\hat{R}x = \hat{Q}^T b \implies x = \hat{R}^{-1} \hat{Q}^T b$$

Notes

1)
$$A^+ = \hat{R}^{-1} \hat{Q}^T$$

2)
$$A^{T}Ax = A^{T}b \Leftrightarrow (\hat{R}^{T}\hat{Q}^{T})(\hat{Q}\hat{R})x = (\hat{R}^{T}\hat{Q}^{T})b$$

$$\hat{R}^{T}\hat{R}x = \hat{R}^{T}\hat{Q}^{T}b$$

$$\hat{R}x = \hat{Q}^{T}b$$

$$x = \hat{R}^{-1}\hat{Q}^{T}b$$

QR factorization (reduced version)

Let $A = [a_1 \ a_2 \ \dots \ a_n]$. Want to find orthogonal vectors $\{q_i\}$ such that span $\{q_1, \dots, q_j\}$ = span $\{a_1, \dots, a_j\}$ $j = 1, 2, \dots, n$.

This amounts to:

$$\begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} = \begin{bmatrix} q_1 & q_2 & \cdots & q_n \end{bmatrix} \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ & \ddots & \vdots \\ & & r_{nn} \end{bmatrix}$$

i.e.
$$a_1 = r_{11} q_1$$

 $a_2 = r_{12} q_1 + r_{22} q_2$
:

Matrix form: $A = \hat{Q}\hat{R}$

• \hat{Q} has orthonormal columns, \hat{R} upper Δ .

QR factorization (full version)

• Append additional m-n orthonormal columns to

i.e.
$$[q_{n+1} \ q_{n+2} \ \cdots \ q_m] \equiv \hat{Q}_{m-n}$$
 Then
$$[A]_{m\times n} = [\hat{Q} \ \hat{Q}_{m-n}]_{m\times m} [\hat{R}]_{m\times n} \}_{\text{m-n zero rows}}$$

• Usually for theoretical purpose.