

23rd International Workshop on Matrices and Statistics
Faculty of Mathematics and Physics
Ljubljana, Slovenia
June 8–12, 2014

**Using the Gram-Schmidt Construction to Develop
Linear Models**

Lynn R. LaMotte
Louisiana State University Health Sciences Center
New Orleans

GS-plus

$$A = (\mathbf{a}_1, \dots, \mathbf{a}_m)$$

GS, with one little addition, constructs Q, T , such that $Q'Q = I$, $\text{sp}(Q) = \text{sp}(A)$, and $Q = AT$.

i -th step: $\text{sp}(Q_i) = \text{sp}(\mathbf{a}_1, \dots, \mathbf{a}_i)$, $Q_i'Q_i = \mathbf{I}$, $Q_i = AT_i$

$\mathbf{a}_{i+1} \in \text{sp}(Q_i)$: $Q_{i+1} = Q_i$, $T_{i+1} = T_i$, $i \longrightarrow i + 1$

$\mathbf{a}_{i+1} \notin \text{sp}(Q_i)$:

$$\begin{aligned}\mathbf{q}_{i+1} &= c_{i+1}(\mathbf{a}_{i+1} - Q_i Q_i' \mathbf{a}_{i+1}) \\ &= c_{i+1} \mathbf{A} \mathbf{e}_{i+1} - c_{i+1} AT_i Q_i' \mathbf{a}_{i+1} \\ &= \underbrace{\mathbf{A} c_{i+1} (\mathbf{e}_{i+1} - T_i Q_i' \mathbf{a}_{i+1})}_{\mathbf{t}_{i+1}} \\ &= \mathbf{A} \mathbf{t}_{i+1}\end{aligned}$$

$Q_{i+1} = (Q_i, \mathbf{q}_{i+1})$, $T_{i+1} = (T_i, \mathbf{t}_{i+1})$

A sequence of easily-proven propositions leading to:

\mathcal{S} is a linear subspace of $\mathfrak{R}^n \implies \exists Q$ such that $Q'Q = I$
and $\text{sp}(Q) = \mathcal{S}$.

Proposition 1

GS establishes that, for any non-zero $n \times m$ matrix A , there exists an $n \times \nu$ matrix Q such that $\text{sp}(Q) = \text{sp}(A)$ and $Q'Q = I_\nu$.

Proposition 2

If $Q'Q = I_\nu$ then

(1) $\mathbf{z} \in \text{sp}(Q) \iff QQ'\mathbf{z} = \mathbf{z}$;

and

(2) $\text{sp}(Q) = \text{sp}(QQ')$.

Proposition 3

If Q and R are $n \times \nu$ and $n \times \eta$ matrices, respectively, such that $Q'Q = I_\nu$ and $R'R = I_\eta$, then

$$\text{sp}(Q) \subset \text{sp}(R)$$



$$RR' - QQ' = (RR' - QQ')(RR' - QQ');$$

and

$$\text{sp}(Q) = \text{sp}(R) \iff RR' = QQ'.$$

Proof uses Prop. 2.

Proposition 4

If $\text{sp}(Q) \subset \text{sp}(R)$ then $\eta \geq \nu$. If $\text{sp}(Q) = \text{sp}(R)$ then $\eta = \nu$.

Proof. $\text{sp}(Q) \subset \text{sp}(R) \implies$, by Prop. 3,

$$(RR' - QQ') = (RR' - QQ')(RR' - QQ')$$

$$\implies \text{tr}(RR' - QQ') = \eta - \nu \geq 0.$$

$\text{sp}(Q) = \text{sp}(R) \implies RR' = QQ'$, by Prop. 3, \implies
 $\text{tr}(RR') = \eta = \text{tr}(QQ') = \nu.$ □

Proposition 5

If $\text{sp}(Q) \subset \text{sp}(R)$ and $\nu = \eta$ then $\text{sp}(Q) = \text{sp}(R)$.

Proof. $\text{sp}(Q) \subset \text{sp}(R) \implies$, by Prop. 3,

$$\text{tr}[(RR' - QQ')(RR' - QQ')] = \text{tr}(RR' - QQ') = \eta - \nu = 0$$

$\implies RR' = QQ'$, \implies , by Prop. 2(2), $\text{sp}(Q) = \text{sp}(R)$. \square

Proposition 6

If S is a linear subspace of \mathbb{R}^n and $S \neq \{\mathbf{0}\}$, then there exists an $n \times \nu$ matrix Q such that $Q'Q = I_\nu$ and $\text{sp}(Q) = S$.

Proof is sequential construction of Q_i with ν_i columns, similar to GS. It ends in at most n steps with $\text{sp}(Q_i) = S$ because $\text{sp}(Q_i) \subset \text{sp}(I_n)$.

Proposition 7

Let S be a non-trivial linear subspace of \mathbb{R}^n , and let \mathbf{y} be an n -vector. There exists exactly one vector $\hat{\mathbf{y}}$ in S such that $\mathbf{y} - \hat{\mathbf{y}}$ is in S^\perp .

Proof. $\hat{\mathbf{y}} = QQ'\mathbf{y} \in \text{sp}(Q) = S$ and $Q'(\mathbf{y} - \hat{\mathbf{y}}) = \mathbf{0}$.

$\tilde{\mathbf{y}} \in S$ and $Q'(\mathbf{y} - \tilde{\mathbf{y}}) = \mathbf{0} \implies QQ'\tilde{\mathbf{y}} = \tilde{\mathbf{y}}$, by Prop. 2(1),

$\implies \mathbf{0} = QQ'(\mathbf{y} - \tilde{\mathbf{y}}) = \hat{\mathbf{y}} - \tilde{\mathbf{y}}$. □

Proposition 8

Let Q be an $n \times \nu$ matrix such that $Q'Q = I_\nu$, $\nu \geq 1$.

If P is an $n \times n$ matrix such that, for each $\mathbf{y} \in \mathbb{R}^n$, $P\mathbf{y} \in \text{sp}(Q)$ and $\mathbf{y} - P\mathbf{y} \in \text{sp}(Q)^\perp$, then $P = QQ'$.

Definition 1

The orthogonal projection of $\mathbf{y} \in \mathbb{R}^n$ on a linear subspace S of \mathbb{R}^n is the vector $\hat{\mathbf{y}} \in S$ such that $\mathbf{y} - \hat{\mathbf{y}} \in S^\perp$.

Let \mathbf{P}_S denote the matrix such that $\mathbf{P}_S\mathbf{y} \in S$ and $\mathbf{y} - \mathbf{P}_S\mathbf{y} \in S^\perp \forall \mathbf{y} \in \mathbb{R}^n$.

Linear equations $A\mathbf{x} = \mathbf{b}$

GS on $A \longrightarrow Q, T$ such that $\text{sp}(Q) = \text{sp}(A)$, $Q'Q = I$,
 $Q = AT$.

Check consistency with $\mathbf{P}_A \mathbf{b} - \mathbf{b}$.

If $\mathbf{b} \in \text{sp}(A)$, then $\mathbf{x}_* = TQ'\mathbf{b}$ is a solution.

$$\{\mathbf{x} : A\mathbf{x} = \mathbf{b}\} = \{\mathbf{x}_*\} + \text{sp}(I - TQ'A)$$

GS on $A = (A_1, A_2) \longrightarrow Q = (Q_1, Q_2)$

$$\text{sp}(Q_1) = \text{sp}(A_1)$$

and $\text{sp}(Q_2) = \text{sp}(A) \cap \text{sp}(A_1)^\perp$.

$$Q_2 Q_2' = \mathbf{P}_A - \mathbf{P}_{A_1}.$$

Least Squares

Let \mathcal{S} be a linear subspace of \mathbb{R}^n and let \mathbf{m}_0 be a given n -vector.

Let $\mathcal{M} = \{\mathbf{m}_0\} + \mathcal{S}$.

Proposition 9

Let $\mathbf{y} \in \mathbb{R}^n$.

$$\operatorname{argmin}_{\mathbf{m} \in \mathcal{M}} (\mathbf{y} - \mathbf{m})'(\mathbf{y} - \mathbf{m}) = \mathbf{m}_0 + \mathbf{P}_{\mathcal{S}}(\mathbf{y} - \mathbf{m}_0)$$

and

$$\min_{\mathbf{m} \in \mathcal{M}} (\mathbf{y} - \mathbf{m})'(\mathbf{y} - \mathbf{m}) = (\mathbf{y} - \mathbf{m}_0)'(\mathbf{I} - \mathbf{P}_{\mathcal{S}})(\mathbf{y} - \mathbf{m}_0).$$

The Canonical Form of the Regression Model

$$E(\mathbf{Y}) = X\boldsymbol{\beta}, \quad \text{Var}(\mathbf{Y}) = \sigma^2\mathbf{I},$$

with X a given $n \times (k + 1)$ matrix and unknown parameters

$$\boldsymbol{\beta} \in \mathfrak{R}^{k+1}, \quad \sigma^2 > 0.$$

The model for $\boldsymbol{\mu} = E(\mathbf{Y})$ is $\boldsymbol{\mu} \in \mathcal{M} = \text{sp}(X)$.

Given a realization \mathbf{y} of \mathbf{Y} , the objective is inference about the mean vector $\boldsymbol{\mu}$.

Basic LS Statistics

Given \mathbf{y} , the least-squares (LS) estimate of $\boldsymbol{\mu} = X\boldsymbol{\beta}$ is $\hat{\mathbf{y}} = \mathbf{P}_X \mathbf{y}$.

A *least-squares solution* for $\boldsymbol{\beta}$ is $\tilde{\mathbf{b}}$ such that $X\tilde{\mathbf{b}} = \mathbf{P}_X \mathbf{y}$.
From GS on X , $\hat{\mathbf{b}} = TQ' \mathbf{y}$ is a LS solution.

$$SST = \mathbf{y}'(\mathbf{I} - \mathbf{P}_1)\mathbf{y}$$

$$SSR = \mathbf{y}'(\mathbf{P}_X - \mathbf{P}_1)\mathbf{y}$$

$$SSE = \mathbf{y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{y}$$

Degrees of freedom

$$\nu_R = \text{tr}(\mathbf{P}_X - \mathbf{P}_1), \nu_E = \text{tr}(\mathbf{I} - \mathbf{P}_X)$$

Sampling distributions

If $\mathbf{Y} \sim \mathbf{N}(\boldsymbol{\mu}, \sigma^2 \mathbf{I})$ and $\mathbf{Q}'\mathbf{Q} = \mathbf{I}_\nu$

then $\mathbf{Z} = (1/\sigma)\mathbf{Q}'\mathbf{Y} \sim \mathbf{N}((1/\sigma)\mathbf{Q}'\boldsymbol{\mu}, \mathbf{I}_\nu)$,

and $(1/\sigma^2)\mathbf{Y}'(\mathbf{Q}\mathbf{Q}')\mathbf{Y} \sim \chi^2$

with ν degrees of freedom and $\text{ncp } \delta^2 = \boldsymbol{\mu}'\mathbf{Q}\mathbf{Q}'\boldsymbol{\mu}/\sigma^2$.

A major teaching objective: develop and justify the test statistic for the general linear hypothesis

$$H_0 : G'\beta = \mathbf{c}_0$$

for given G and \mathbf{c}_0 .

Restricted model

$$\begin{aligned} \mathcal{M}_0 &= \{X\beta \in \mathcal{M} : \beta \in \mathbb{R}^{k+1} \text{ and } G'\beta = \mathbf{c}_0\} \\ &= \{X\mathbf{b}_0\} + \text{sp}(XN), \end{aligned}$$

$$\mathbf{b}_0 : G'\mathbf{b}_0 = \mathbf{c}_0 \text{ and } \text{sp}(N) = \text{sp}(G)^\perp.$$

$$\begin{aligned}
SSE_{Full} &= \min_{X\beta \in \mathcal{M}} (\mathbf{y} - X\beta)'(\mathbf{y} - X\beta) \\
&= \mathbf{y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{y} \\
df_{Full} &= \text{tr}(\mathbf{I} - \mathbf{P}_X) \\
SSE_{Rest} &= \min_{X\beta \in \mathcal{M}_0} (\mathbf{y} - X\beta)'(\mathbf{y} - X\beta) \\
&= (\mathbf{y} - X\mathbf{b}_0)'(\mathbf{I} - \mathbf{P}_{XN})(\mathbf{y} - X\mathbf{b}_0), \\
&\quad G'\mathbf{b}_0 = \mathbf{c}_0 \text{ and } \text{sp}(N) = \text{sp}(G)^\perp \\
df_{Rest} &= \text{sp}(\mathbf{I} - \mathbf{P}_{XN}) \\
\Delta SSE &= SSE_{Rest} - SSE_{Full} \\
&= (\mathbf{y} - X\mathbf{b}_0)'(\mathbf{P}_X - \mathbf{P}_{XN})(\mathbf{y} - X\mathbf{b}_0), \\
\Delta df &= \text{tr}(\mathbf{P}_X - \mathbf{P}_{XN})
\end{aligned}$$

The test statistic:

$$F = \frac{\Delta SSE / \Delta df}{\hat{\sigma}^2}$$

with $\hat{\sigma}^2 = SSE_{Full} / df_{Full}$.

Note that $\mathbf{P}_X - \mathbf{P}_{XN}$ can be had as $\mathbf{Q}_2 \mathbf{Q}_2' = \mathbf{P}_H$ from GS on (XN, X) . Then

$$F = \frac{(\mathbf{y} - X\mathbf{b}_0)' \mathbf{P}_H (\mathbf{y} - X\mathbf{b}_0) / \text{tr}(\mathbf{P}_H)}{\hat{\sigma}^2}.$$

Bridges

With $\text{sp}(Q) = \text{sp}(A)$ and $Q'Q = I_\nu$,
column rank(A) = $\dim(\text{sp}(A)) = \nu = \text{tr}(QQ')$.

From GS on A , $A(TQ')A = A$ and $(TQ')A(TQ') = TQ'$:

TQ' is a reflexive generalized inverse of A .

TT' is a reflexive generalized inverse of $A'A$.

Show that the column rank of A equals the row rank of A :

GS on $A \rightarrow Q, T; Q'Q = I_\nu, \text{sp}(Q) = \text{sp}(A), Q = AT$.
The column rank of A is ν .

By Prop. 2(1), $QQ'A = A \implies A' = A'QQ' \implies$
 $\text{sp}(A') \subset \text{sp}(A'Q)$. That also $\text{sp}(A'Q) \subset \text{sp}(A') \implies$
 $\text{sp}(A') = \text{sp}(A'Q)$.

The ν columns of $A'Q$ are linearly independent:
 $A'Qz = \mathbf{0} \implies T'A'Qz = Q'Qz = z = \mathbf{0}$.

Therefore the column rank of A' is ν .