

Computing Model Variance Without Computing the Complete Generalized Inverse
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1. For uncorrelated data with uniform variance σ_d^2 , the covariance of the estimated model parameters is:

$$\text{cov } \mathbf{m}^{\text{est}} = \sigma_d^2 \mathbf{G}^{-g} \mathbf{G}^{-gT}$$

2. Note that the variance of the k -th model parameter is

$$\text{var } m_k = \sigma_d^2 \sum_i G_{ki}^{-g} G_{ik}^{-gT} = \sigma_d^2 \sum_i G_{ki}^{-g} G_{ki}^{-g}$$

Thus, the variance equals σ_d^2 multiplied by the k -th row of the generalized inverse, dotted into itself.

3. In the case of the Backus-Gilbert generalized inverse, each row of \mathbf{G}^{-g} is computed separately. So after we compute its k -th row, we can calculate $\text{var } m_k$ trivially.

4. The damped least squares generalized inverse has the form

$$\mathbf{G}^{-g} = [\mathbf{G}^T \mathbf{G} + \varepsilon^2 \mathbf{H}^T \mathbf{H}]^{-1} \mathbf{G}^T = \mathbf{A}^{-1} \mathbf{G}^T \quad \text{with} \quad \mathbf{A} = \mathbf{G}^T \mathbf{G} + \varepsilon^2 \mathbf{H}^T \mathbf{H}$$

Note that since \mathbf{A} is symmetric, its inverse will also be symmetric. The relevant issue is how to calculate the k -th row of the generalized inverse \mathbf{G}^{-g} without having to compute the others.

5. Note that the equation

$$\mathbf{A} \mathbf{A}^{-1} = \mathbf{I} \quad \text{or} \quad \sum_k A_{ik} A_{kj}^{-1} = \delta_{ij}$$

can be read as a sequence of vector equations

$$\mathbf{A} \mathbf{v}^{(j)} = \mathbf{s}^{(j)} \quad \text{with} \quad [\mathbf{v}^{(j)}]_i = [\mathbf{A}^{-1}]_{ij} \quad \text{and} \quad [\mathbf{s}^{(j)}]_i = \delta_{ij}$$

That is, $\mathbf{v}^{(j)}$ is the j -th column of \mathbf{A}^{-1} and $\mathbf{s}^{(j)}$ is the corresponding column of the identity matrix. Hence we can solve for the j -th column of \mathbf{A}^{-1} by solving the system $\mathbf{A} \mathbf{v}^{(j)} = \mathbf{s}^{(j)}$. Furthermore, since \mathbf{A}^{-1} is symmetric, we $\mathbf{v}^{(j)T}$ its j -th row.

6. Now notice that

$$\mathbf{G}^{-g} = \mathbf{A}^{-1} \mathbf{G}^T \quad \text{or} \quad [\mathbf{G}^{-g}]_{kj} = \sum_i A_{ki}^{-1} G_{ij}^T$$

Hence, the k -th row of the generalized inverse \mathbf{G}^{-g} is the k -th row of \mathbf{A}^{-1} dotted into \mathbf{G}^T .

Example (with MATLAB code appended below)

Error in inverse AI: 0.000000

Error in generalize inverse GMG: 0.000000

Error in variance vm: 0.000000

```
% tests procedure for calculating the variance of a single
% estimated model parameter.

clear all;

% under-determined problem
N=10;
M=2*N;

% hypothetical data kernel
s=0.1;
G=random('Normal',0, s, N, M ) + eye(N,M);

% stddev of data
sigmad = 1;

% use damped least squares generalized inverse
% GMG = (G'*G + epsi*eye(M,M)) \ G'
epsi = 0.1;
A = (G'*G + epsi*eye(M,M));

% calculate the full version of various matrices,
% which are only needed to check the results of the calculation
% AI: inverse of A
% GMG: generalized inverse
% vm: var m
AI = inv(A);
GMG = A \ (G');
Cm = (sigmad^2) * GMG*GMG';
vm = diag(Cm);

% the target model parameter whose varoiance we wish
% to calculate separately

k=M/2;

% use k-th column of identity matrix to solve for
% k-th column of AI (or row, since its symmetric)
s = zeros(M,1);
s(k) = 1.0;
aik = A \ s;

% check that the calculation was correct
eai = aik-AI(:,k);
Eai = eai'*eai;
fprintf('Error in inverse AI: %f\n', Eai );

% calculate the k-th row of the generalised inverse
gmgk = (aik') * (G');

% check that the calculation was correct
egmg = (gmgk - GMG(k,:))';
Egmg = egmg'*egmg;
fprintf('Error in generalize inverse GMG: %f\n', Egmg );
```

```
% calculate the k-th variance
vmk = (sigmad^2) * gmgk*gmgk';

% check that the calculation was correct
evm = vmk-vm(k);
Evm = evm^2;
fprintf('Error in variance vm: %f\n', Evm );
```