

Symmetric Matrix PDFs (Multivariate Gamma and Inverse Gamma)

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Outline

The Wishart PDF (multivariate gamma)

The Inverse Wishart PDF (multivariate inverse gamma)

Discussion

Homework

The Wishart PDF

In our first Statistics course we learned that if $x_1, x_2, \dots, x_n$ are iid $N(\mu, \sigma^2)$ and we calculate

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2, \text{ then } y = \frac{(n-1)s^2}{\sigma^2} \sim \chi^2(n-1).$$

That is, the PDF of y is

$$f(y | \nu) = \frac{y^{\frac{\nu}{2}-1} e^{-\frac{y}{2}}}{2^{\nu/2} \Gamma(\nu/2)} \quad \text{where } \nu=n-1 \text{ and } y>0.$$

The Wishart PDF

$$y = \frac{(n-1)s^2}{\sigma^2}$$

If we perform the transformation of variable

$$s^2 = \frac{\sigma^2}{(n-1)} y \quad (s^2 \text{ is treated as one symbol})$$

Then $s^2 \sim \Gamma\left(\frac{\nu}{2}, \frac{2\sigma^2}{\nu}\right)$ where $\nu=n-1$

with $f(s^2 | \nu, \sigma^2) = \frac{(s^2)^{\frac{\nu}{2}-1} e^{-\frac{\nu}{2\sigma^2}s^2}}{\Gamma(\nu/2)(2\sigma^2/\nu)^{\nu/2}}$ and $s^2, \sigma^2 > 0$.

$$f(s^2 | \alpha, \beta) = \frac{(s^2)^{\alpha-1} e^{-\frac{s^2}{\beta}}}{\Gamma(\alpha)\beta^\alpha}$$

$$E(s^2 | \alpha, \beta) = \alpha\beta$$

$$\text{var}(s^2 | \alpha, \beta) = \alpha\beta^2$$

$$\alpha = \frac{\nu}{2} \quad \beta = \frac{2\sigma^2}{\nu}$$

$$E(s^2 | \nu, \sigma^2) = \sigma^2 \quad \text{var}(s^2 | \nu, \sigma^2) = \frac{2\sigma^4}{\nu}$$

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i.e. $n=10, m=10^6$

If we were to simulate a large number of samples m each of size n from $N(\mu, \sigma^2)$ then calculate $\bar{x}$ and s^2 for each

<u>sample</u>				
$x_1^{(1)}$	$x_1^{(2)}$	$x_1^{(3)}$		$x_1^{(m)}$
$x_2^{(1)}$	$x_2^{(2)}$	$x_2^{(3)}$	...	$x_2^{(m)}$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$x_n^{(1)}$	$x_n^{(2)}$	$x_n^{(3)}$		$x_n^{(m)}$
$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$
$\bar{x}_{(1)}$	$\bar{x}_{(2)}$	$\bar{x}_{(3)}$	...	$\bar{x}_{(m)}$
$s_{(1)}^2$	$s_{(2)}^2$	$s_{(3)}^2$	...	$s_{(m)}^2$

If we made a histogram of $\bar{x}$'s we would see that they are $N(\mu, \sigma^2/n)$ and ...

If we made a histogram of s^2 's, then we would see that they are $\Gamma(\frac{\nu}{2}, \frac{2\sigma^2}{\nu})$.

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

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We can write the gamma PDF

$$f(s^2 | \nu, \sigma^2) = \frac{(s^2)^{\frac{\nu}{2}-1} e^{-\frac{\nu}{2\sigma^2}s^2}}{\Gamma(\nu/2)(2\sigma^2/\nu)^{\nu/2}}$$

$$\nu = n - 1$$

$$s^2, \sigma^2 > 0$$

as

$$f(s^2 | \nu, \sigma^2) = k \left| \frac{\sigma^2}{\nu} \right|^{-\frac{\nu}{2}} |s^2|^{\frac{\nu-1-1}{2}} e^{-\frac{1}{2} \left(\frac{\sigma^2}{\nu} \right)^{-1} s^2}$$

← Note the eccentric way I wrote this.

$$k = \frac{1}{\Gamma(\nu/2) 2^{\nu/2}}$$

The Wishart PDF

In bivariate (multivariate) statistics if

$$f(s^2 | \nu, \sigma^2) = \frac{(s^2)^{\frac{\nu}{2}-1} e^{-\frac{\nu}{2\sigma^2}s^2}}{\Gamma(\nu/2)(2\sigma^2/\nu)^{\nu/2}}$$

$x_1, x_2, \dots, x_n$ are iid $N(\mu, \Sigma)$ and we calculate the covariance matrix

$$S = \frac{1}{n-1} \sum_{i=1}^n \underbrace{(x_i - \bar{x})}_{2 \times 1} \underbrace{(x_i - \bar{x})'}_{1 \times 2}, \text{ then the PDF of the covariance matrix}$$

S has the (multivariate) generalization of the gamma distribution

$$f(S | \Sigma, \nu) = k_W \left| \Sigma / \nu \right|^{-\frac{\nu}{2}} \left| S \right|^{\frac{\nu-2-1}{2}} e^{-\frac{1}{2} tr(\Sigma/\nu)^{-1} S} \cdot$$

$S, \Sigma > 0$
 $\nu = n - 1$
 $tr() = \text{trace}$

normalizing constant

Remember the eccentric way I wrote this.

$$f(s^2 | \nu, \sigma^2) = k \left| \frac{\sigma^2}{\nu} \right|^{-\frac{\nu}{2}} \left| s^2 \right|^{\frac{\nu-1-1}{2}} e^{-\frac{1}{2} \left(\frac{\sigma^2}{\nu} \right)^{-1} s^2}$$

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i.e. $n=10, m=10^6$

If we were to simulate a large number of samples m each of size n from $N(\mu, \Sigma)$ then calculate $\bar{x}$ and S for each.

sample				
$x_1^{(1)}$	$x_1^{(2)}$	$x_1^{(3)}$		$x_1^{(m)}$
$x_2^{(1)}$	$x_2^{(2)}$	$x_2^{(3)}$	...	$x_2^{(m)}$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$x_n^{(1)}$	$x_n^{(2)}$	$x_n^{(3)}$		$x_n^{(m)}$
$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$
$\bar{x}_{(1)}$	$\bar{x}_{(2)}$	$\bar{x}_{(3)}$	...	$\bar{x}_{(m)}$
$S_{(1)}$	$S_{(2)}$	$S_{(3)}$	...	$S_{(m)}$

If we made histograms of $\bar{x}$'s we would see that they are $N(\mu, \Sigma/n)$ and ...

If we made histograms of S 's, then we would see that they are $W(\Sigma/v, v)$.

$$S_{p \times p} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})'$$

The Wishart PDF

Multivariate version of gamma distribution.

$$S = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})'$$

A random $p \times p$ matrix variate S follows the Wishart

distribution with scale matrix Σ/ν and ν df denoted $S \sim W(\Sigma/\nu, \nu)$

$$\text{iff } f(S | \Sigma, \nu) = k_W \left| \Sigma / \nu \right|^{-\frac{\nu}{2}} \left| S \right|^{\frac{\nu-p-1}{2}} e^{-\frac{1}{2} \text{tr}(\Sigma/\nu)^{-1} S}$$

$$\text{where } k_W^{-1} = 2^{\frac{\nu p}{2}} \pi^{\frac{p(p-1)}{4}} \prod_{j=1}^p \Gamma\left(\frac{\nu+1-j}{2}\right)$$

$$\text{If } p=1, \quad f(s^2 | \nu, \sigma^2) = \frac{(s^2)^{\frac{\nu}{2}-1} e^{-\frac{\nu}{2\sigma^2} s^2}}{\Gamma(\nu/2) (2\sigma^2/\nu)^{\nu/2}} \text{ is}$$

Gamma distribution by $\alpha=\nu/2$ and $\beta=2\sigma^2/\nu$.

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The Wishart matrix PDF is

$$f(S | \Sigma, \nu) = k_W \left| \Sigma / \nu \right|_{p \times p}^{-\frac{\nu}{2}} \left| S \right|_{p \times p}^{\frac{\nu-p-1}{2}} e^{-\frac{1}{2} \text{tr}(\Sigma/\nu)^{-1} S_{p \times p}}$$

$$k_W^{-1} = 2^{\frac{\nu p}{2}} \pi^{\frac{p(p-1)}{4}} \prod_{j=1}^p \Gamma\left(\frac{\nu+1-j}{2}\right)$$

The mean, variance, and covariance of its elements are

$$E(S_{ij} | \Sigma, \nu) = \Sigma_{ij}$$

$$\text{var}(S_{ij} | \Sigma, \nu) = (\Sigma_{ij}^2 + \Sigma_{ii} \Sigma_{jj}) / \nu$$

$$\text{cov}(S_{ij} S_{kl} | \Sigma, \nu) = (\Sigma_{ik} \Sigma_{jl} + \Sigma_{il} \Sigma_{jk}) / \nu$$

If $p=1$

$$E(s | \sigma^2, \nu) = \sigma^2$$

$$\text{var}(s^2 | \sigma^2, \nu) = \sigma^4 / \nu$$

The Wishart PDF

Theorem:

If S is a $p \times p$ random matrix variable from $f(S|\Sigma, \nu)$, with

$$f(S | \Sigma, \nu) = k_W \left| \Sigma / \nu \right|_{p \times p}^{-\frac{\nu}{2}} \left| S \right|_{p \times p}^{\frac{\nu-p-1}{2}} e^{-\frac{1}{2} \text{tr}(\Sigma/\nu)^{-1} S}$$

then if we form $Q = A S A'$ where dimensions match

and A full row rank ($A: r \times p, r \leq p$), then $Q \sim W(\Delta = A \Sigma A' / \nu, \nu)$

$$E(Q | \Delta, \nu) = \Delta$$

$$\text{var}(Q_{ij} | \Delta, \nu) = (\Delta_{ij}^2 + \Delta_{ii} \Delta_{jj}) / \nu$$

$$\text{cov}(Q_{ij} Q_{kl} | \Delta, \nu) = (\Delta_{ik} \Delta_{jl} + \Delta_{il} \Delta_{jk}) / \nu$$

The Wishart PDF

$$\mu = \begin{pmatrix} 67 \\ 150 \end{pmatrix}_{2 \times 1} \quad \Sigma = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix}_{2 \times 2} \quad \nu = 9$$

Took 10^6 sets of $n=10$ variates $x_{2 \times 1}$, subtracted mean $\bar{x}_{2 \times 1}$

from each set, transpose multiplied each value, added the 10 values

in set and divided by 9 to form each S . The S 's are now $W(\Sigma/\nu, \nu=n-1)$.

$$E(S_{p \times p} | \Sigma, \nu) = \Sigma_{p \times p}$$

$$\text{var}(S_{ij} | \Sigma, \nu) = (\Sigma_{ij}^2 + \Sigma_{ii} \Sigma_{jj}) / \nu$$

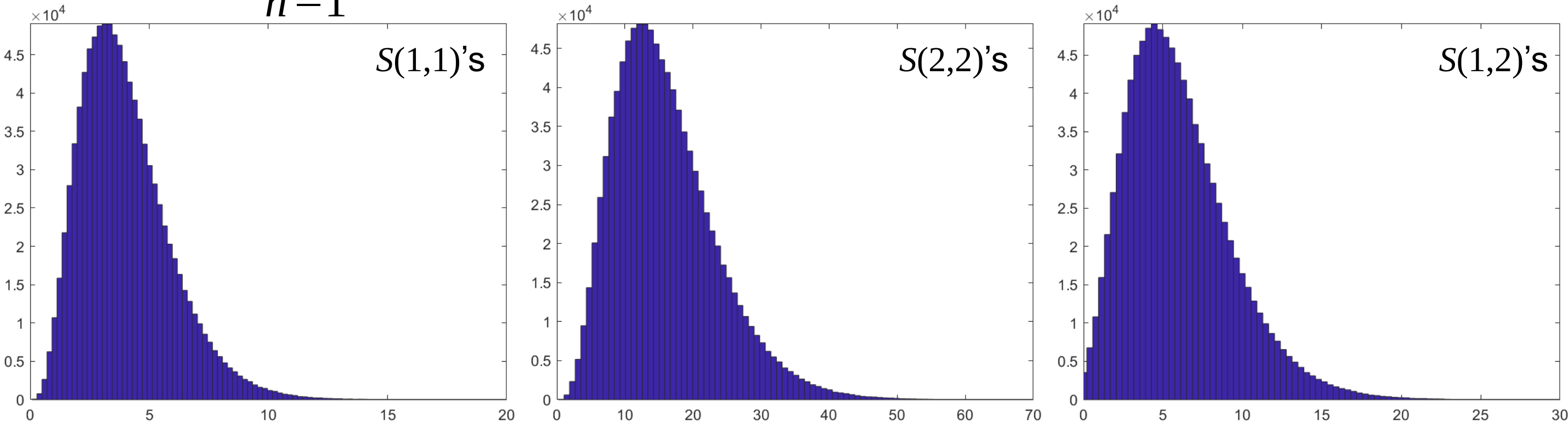
$$\text{cov}(S_{ij} S_{kl} | \Sigma, \nu) = (\Sigma_{ik} \Sigma_{jl} + \Sigma_{il} \Sigma_{jk}) / \nu$$

$$S_{p \times p} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \mu)' (x_i - \mu)$$

The Wishart PDF

The S 's, $S = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})'(x_i - \bar{x})$ are now $W(\Sigma/\nu, \nu=n-1)$.

$$\begin{matrix} \mu = \begin{pmatrix} 67 \\ 150 \end{pmatrix} \\ 2 \times 1 \end{matrix} \quad \begin{matrix} \Sigma = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix} \\ 2 \times 2 \end{matrix} \quad \nu = 9$$



$$E(S \mid \Sigma, \nu) = \Sigma = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix} \quad \text{var}(S_{ij} \mid \Sigma, \nu) = (\Sigma_{ij}^2 + \Sigma_{ii} \Sigma_{jj}) / \nu = \begin{pmatrix} 3.56 & 11.11 \\ 11.11 & 56.89 \end{pmatrix}$$

$$\text{cov}(S_{ij} S_{kl} \mid \Sigma, \nu) = (\Sigma_{ik} \Sigma_{jl} + \Sigma_{il} \Sigma_{jk}) / \nu = 5.33, 8.00, 21.33$$

11,22 11,12 22,12 ← ij,kl

$$\Sigma = AA'$$

$$A = \begin{pmatrix} 2 & 0 \\ 3 & \sqrt{7} \end{pmatrix}$$

The Wishart PDF

```
rng('default')
% define dimensions
p=2;      % dimension of vectors
n=10;     % sample size
m=10^6;  % repeated samples
nu=n-1;

% specify the mean vector
mu=[67;150]

% specify the covariance matrix
Sigma=[2^2, 2*4*.75; 2*4*.75, 4^2]

% Cholesky factorize
A=chol(Sigma)';
A=[2,0;3,sqrt(7)]
```

```
% Wishart Distribution %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Generate via Cholesky
% generate the simulated observations
XX=A*randn(p,n*m)+repmat(mu,[1,n*m]);

X=zeros(p,n,m);
for j=1:m
    X(:, :, j)=XX(:, (j-1)*n+1:n*j);
end
clear j

figure;
hist(squeeze(S(1,1,:)),100)
xlabel('var(height)'), axis tight, xlim([0,20])
figure;
hist(squeeze(S(2,2,:)),100)
xlabel('var(weight)'), axis tight, xlim([0,70])
figure;
hist(squeeze(S(1,2,:)),100)
xlabel('cov(height,weight)'), axis tight,
xlim([0,30])
```

The Wishart PDF

```
% compute the mean in each sample
meanX=squeeze(mean(X,2));
mean(meanX,2)

figure;
hist(meanX(1,:),100)
xlabel('mean(height)'), axis tight
figure;
hist(meanX(2,:),100)
xlabel('mean(weight)'), axis tight

% covariance matrix for each sample
S=zeros(p,p,m);
for j=1:m
    S(:, :, j)=cov(squeeze(X(:, :, j) '), 0);
end
clear j
```

```
% covariance
[Sigma,mean(S,3)]
% true variances
i=1; j=1;
vS11=(Sigma(i,j)^2+Sigma(i,i)*Sigma(j,j))/nu;
i=1; j=2;
vS12=(Sigma(i,j)^2+Sigma(i,i)*Sigma(j,j))/nu;
i=2; j=2;
vS22=(Sigma(i,j)^2+Sigma(i,i)*Sigma(j,j))/nu;
V=[vS11,vS12;vS12,vS22];
[V,var(S,1,3)]
```

The Wishart PDF

```
figure;
hist(squeeze(S(1,1,:)),100)
xlabel('var(height)'), axis tight, xlim([0,20])
figure;
hist(squeeze(S(2,2,:)),100)
xlabel('var(weight)'), axis tight, xlim([0,70])
figure;
hist(squeeze(S(1,2,:)),100)
xlabel('cov(height,weight)'), axis tight, xlim([0,30])

% true covariances
i=1; j=1; k=1; l=2;
cS1112=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
i=1; j=1; k=2; l=2;
cS1122=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
i=1; j=2; k=2; l=2;
cS1222=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
[cS1112,cS1122,cS1222]
% sample covariances
covS1112=cov(squeeze(S(1,1,:)),squeeze(S(1,2,:)));
covS1122=cov(squeeze(S(1,1,:)),squeeze(S(2,2,:)));
covS1222=cov(squeeze(S(1,2,:)),squeeze(S(2,2,:)));
[covS1112(1,2),covS1122(1,2),covS1222(1,2)]
```

```
% make histograms of the SS elements
figure;
hist(squeeze(S(1,1,:)),100)
xlabel('var(height)'), axis tight
figure;
hist(squeeze(S(2,2,:)),100)
xlabel('var(weight)'), axis tight
figure;
hist(squeeze(S(1,2,:)),100)
xlabel('cov(height,weight)'), axis tight
```

The Wishart PDF

We can generate random matrix variate observations directly from the Wishart PDF via the Matlab function `wishrnd(Sigma/nu,nu)`

```
% define dimensions
p=2;      % dimension of vectors
n=10;     % sample size
m=10^6;   % repeated samples
nu=n-1;   % degrees of freedom
% specify the covariance matrix
Sigma=[2^2, 2*4*.75; 2*4*.75, 4^2]

% use matlab function %%%%%%%%%%%
Wmat=zeros(p,p,m); D=chol(Sigma/nu); Hmat=zeros(p,p,m);
for count=1:m
    Wmat(:, :, count) = wishrnd(Sigma, nu, D);
    Hmat(:, :, count) = inv(squeeze(Wmat(:, :, count))); % use later
end
```

and compare sample to theoretical values!

The Wishart PDF

% mean and variances

```
[Sigma,mean(Wmat,3)]
[(Sigma(1,1)^2+Sigma(1,1)*Sigma(1,1)),
(Sigma(1,2)^2+Sigma(1,1)*Sigma(2,2)),...
(Sigma(2,2)^2+Sigma(2,2)*Sigma(2,2))]/nu
```

```
varWmat=var(Wmat,[],3);
```

```
[varWmat(1,1),varWmat(1,2),varWmat(2,2)]
```

% covariances

```
i=1; j=1; k=1; l=2;
```

```
cG1112=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
```

```
i=1; j=1; k=2; l=2;
```

```
cG1122=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
```

```
i=1; j=2; k=2; l=2;
```

```
cG1222=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
```

```
[cG1112,cG1122,cG1222]
```

```
covG1112=cov(squeeze(Wmat(1,1,:)),squeeze(Wmat(1,2,:)));
```

```
covG1122=cov(squeeze(Wmat(1,1,:)),squeeze(Wmat(2,2,:)));
```

```
covG1222=cov(squeeze(Wmat(1,2,:)),squeeze(Wmat(2,2,:)));
```

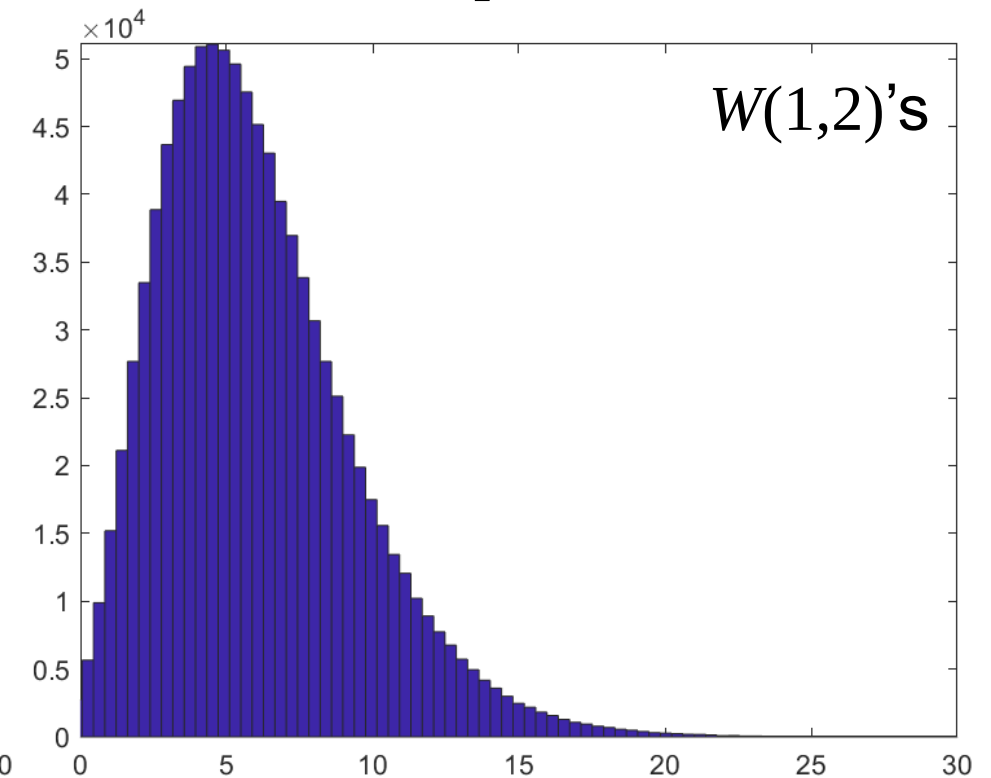
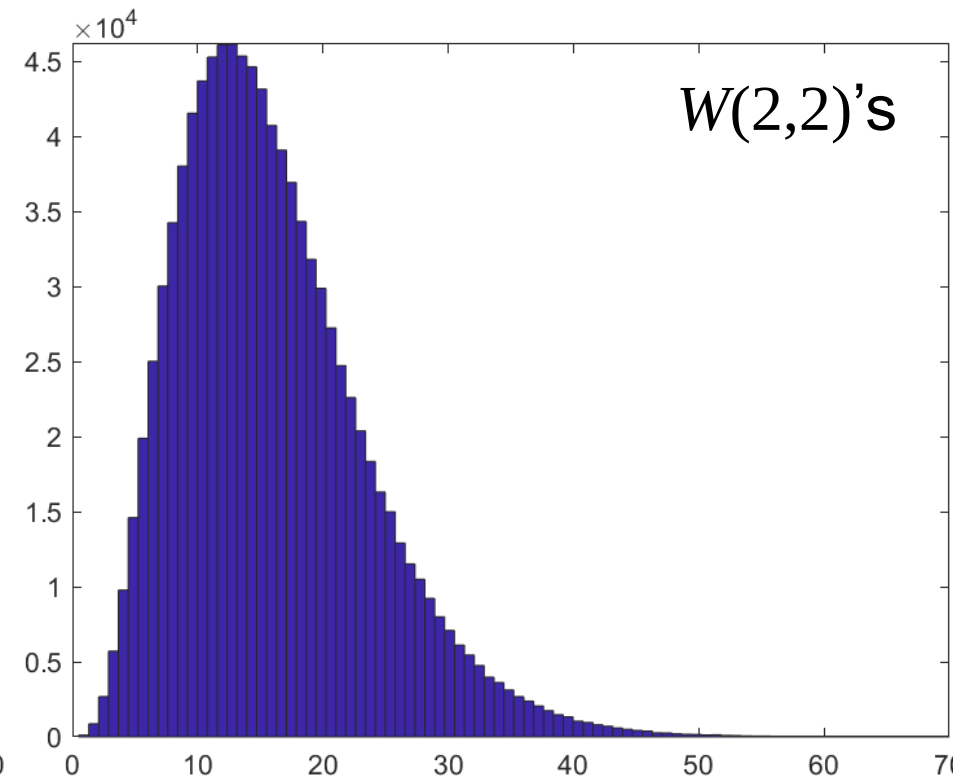
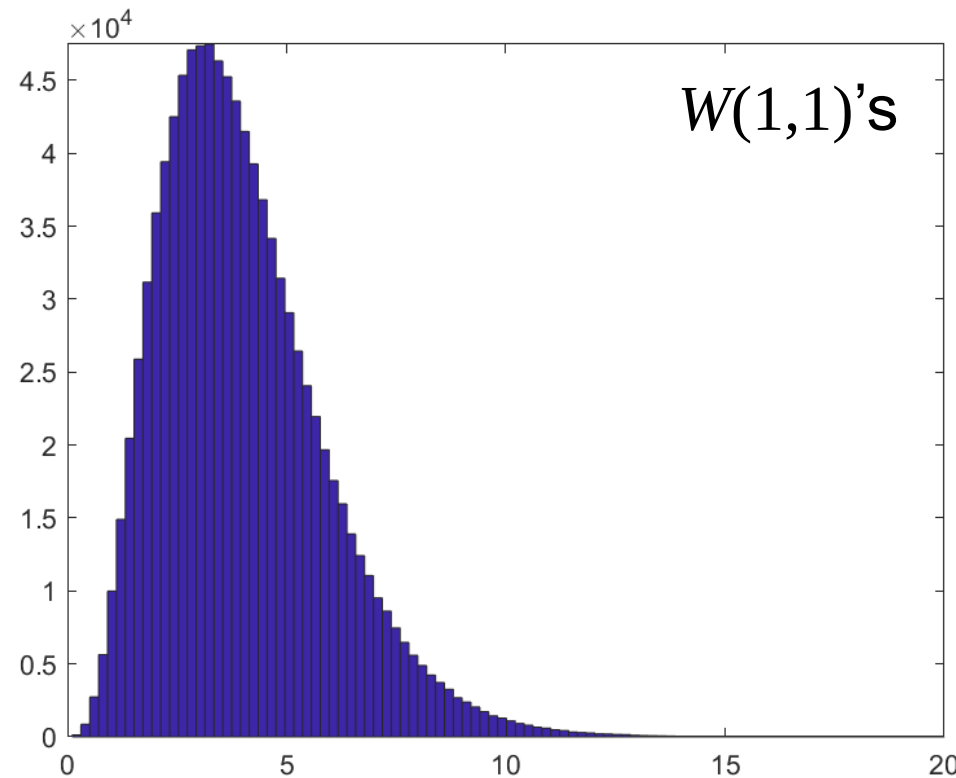
```
[covG1112(1,2),covG1122(1,2),covG1222(1,2)]
```

The Wishart PDF

Matlab: `Wmat=wishrnd(Sigma/nu,nu)`

$$\mu = \begin{pmatrix} 67 \\ 150 \end{pmatrix} \quad \Sigma = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix}$$

$$p = 2 \quad \nu = 9$$



$$E(W) = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix}$$

$$\bar{W} = \begin{pmatrix} 3.9978 & 5.9952 \\ 5.9952 & 15.9916 \end{pmatrix}$$

$$\text{var}(W) = \begin{pmatrix} 3.5556 & 11.1111 \\ 11.1111 & 56.8889 \end{pmatrix}$$

$$s_W^2 = \begin{pmatrix} 3.5426 & 11.0882 \\ 11.0882 & 56.7960 \end{pmatrix}$$

$$\text{cov}(W_{ij}) = (5.3333, 8.0000, 21.3333)$$

$$s_{W_{ij}} = (5.3152, 7.9784, 21.2961)$$

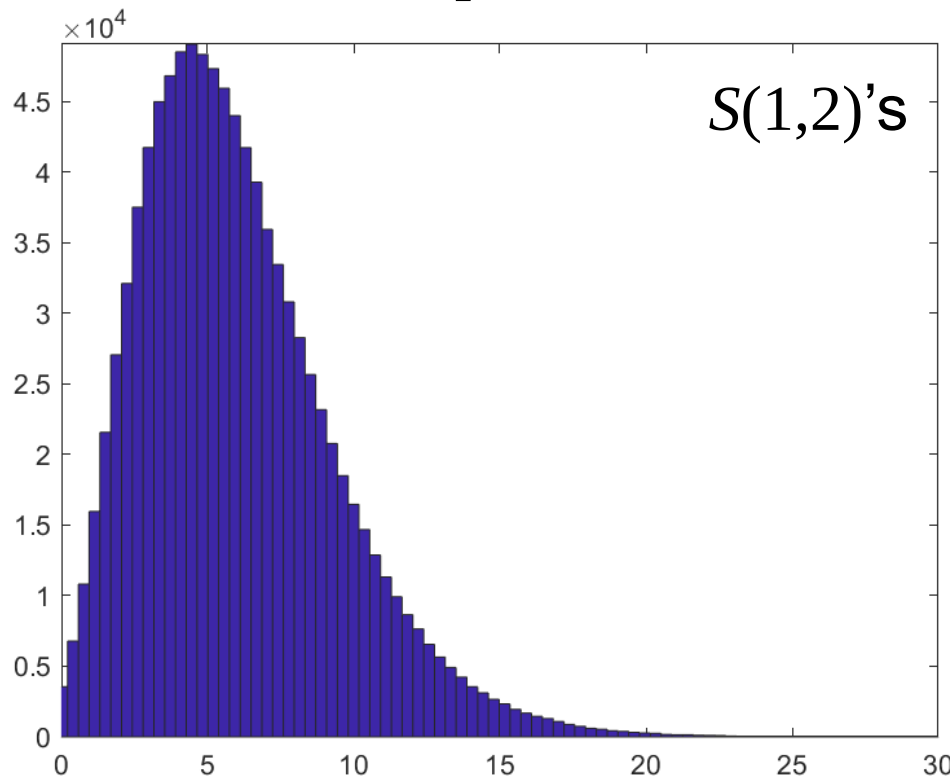
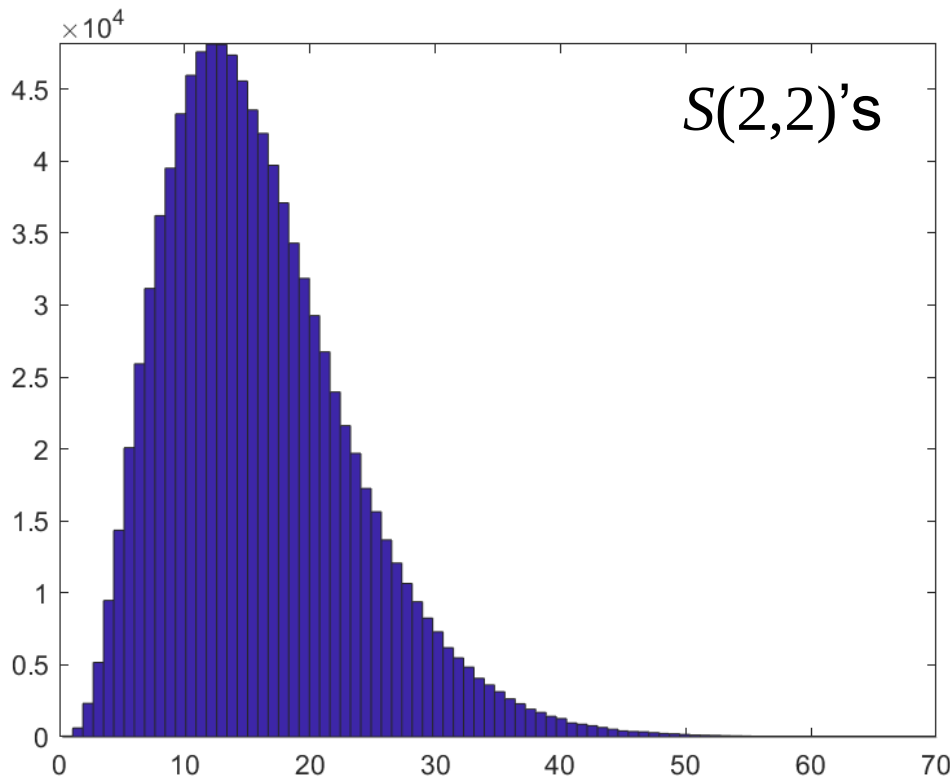
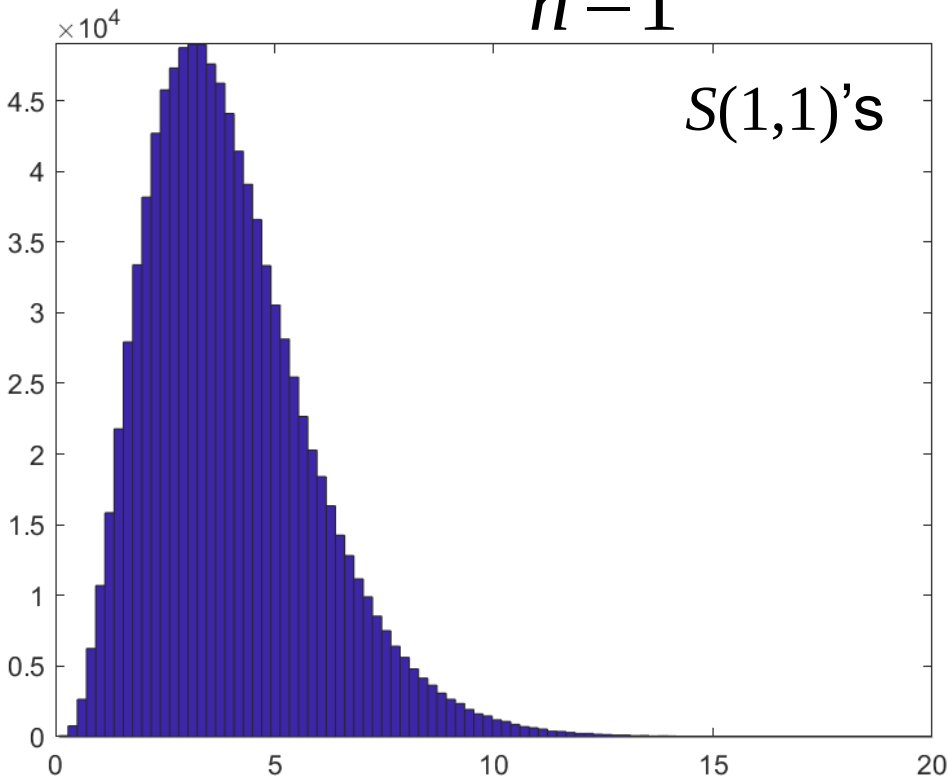
toggle forward

The Wishart PDF

From x 's:
$$S = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})'(x_i - \bar{x})$$

$$\mu = \begin{pmatrix} 67 \\ 150 \end{pmatrix} \quad \Sigma = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix}$$

$$p = 2 \quad \nu = 9$$



$$E(S) = \begin{pmatrix} 4 & 6 \\ 6 & 16 \end{pmatrix}$$

$$\bar{S} = \begin{pmatrix} 4.0010 & 6.0007 \\ 6.0007 & 15.9936 \end{pmatrix}$$

$$\text{var}(S) = \begin{pmatrix} 3.5556 & 11.1111 \\ 11.1111 & 56.8889 \end{pmatrix}$$

$$s_W^2 = \begin{pmatrix} 3.5647 & 11.1342 \\ 11.1342 & 56.9372 \end{pmatrix}$$

$$\text{cov}(S_{ij}) = (5.3333, 8.0000, 21.3333)$$

$$s_{S_{ij}} = (5.3477, 8.0200, 21.3676)$$

[toggle backward](#)

The Wishart PDF

```
% make histograms of the SS elements
figure;
hist(squeeze(Wmat(1,1,:)),100)
xlabel('var(height)'), axis tight, xlim([0,20])
figure;
hist(squeeze(Wmat(2,2,:)),100)
xlabel('var(weight)'), axis tight, xlim([0,70])
figure;
hist(squeeze(Wmat(1,2,:)),100)
xlabel('cov(height,weight)'), axis tight, xlim([0,30])
```

The Inverse Wishart PDF

A random variable h has a continuous

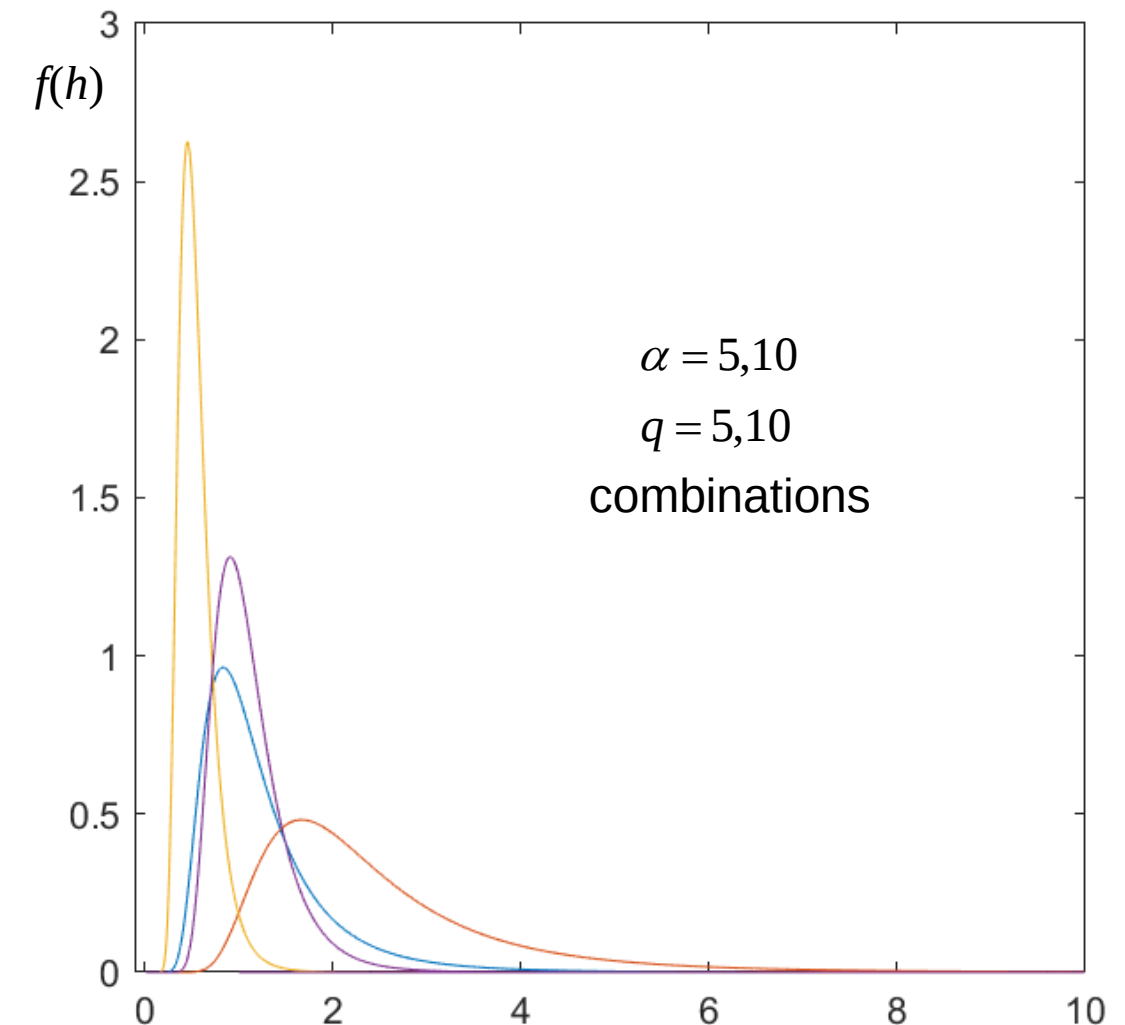
Inverse Gamma distribution, $h \sim \Gamma^{-1}(\alpha, q)$ if

$$f(h | \alpha, q) = \frac{q^\alpha}{\Gamma(\alpha)} h^{-\alpha-1} e^{-q/h},$$

where $\alpha, q > 0$ and $h > 0$.

And can take on many shapes.

$\Gamma(a) = (a-1)!$ for integer a .



$$E(h | \alpha, q) = \frac{q}{\alpha - 1}$$

$$\text{var}(h | \alpha, q) = \frac{q^2}{(\alpha - 1)^2 (\alpha - 2)}$$

The Inverse Wishart PDF

The inverse gamma PDF can be arrived at by starting with

$$f(s^2 | \alpha, \beta) = \frac{(s^2)^{\alpha-1} e^{-\frac{s^2}{\beta}}}{\Gamma(\alpha) \beta^\alpha} \quad \alpha = \frac{\nu}{2} \quad \beta = \frac{2\sigma^2}{\nu}$$

defining

$$h = s^{-2} \quad J(s^2 \rightarrow h) = h^{-2} \quad q = 1 / \beta$$

and performing a transformation of variable resulting in

$$f(h | \alpha, q) = \frac{q^\alpha}{\Gamma(\alpha)} h^{-\alpha-1} e^{-qh^{-1}} \quad \begin{array}{l} h > 0 \\ q, \nu > 0 \end{array}$$

for the univariate case.

The Inverse Wishart PDF

$$f(h | \nu, q) = \frac{q^{\nu/2}}{\Gamma(\nu / 2)} h^{-\nu/2+1} e^{-qh^{-1}}$$

And upon generalizing to higher dimensions, we obtain the

inverse Wishart PDF.

$$f(H | Q, \nu) = k_{IW} Q^{\nu/2} |H|^{-(\nu+p+1)/2} e^{-\frac{1}{2} \text{tr} Q H^{-1}} \quad \begin{matrix} H, Q > 0 \\ \nu > 0 \end{matrix}$$

$$k_{IW}^{-1} = 2^{\nu p/2} \pi^{p(p-1)/4} \prod_{j=1}^p \Gamma\left(\frac{\nu-1-j}{2}\right)$$

$$E(H | Q, \nu) = \frac{Q}{\nu - p - 1} \quad \text{var}(H_{ii} | Q, \nu) = \frac{2Q_{ii}^2}{(\nu - p - 1)^2 (\nu - p - 3)}$$

$$\text{var}(H_{ij} | Q, \nu) = \frac{(\nu - p + 1)Q_{ij}^2 + (\nu - p - 1)Q_{ii}Q_{jj}}{(\nu - p)(\nu - p - 1)^2 (\nu - p - 3)}$$

$$\text{cov}(H_{ij} | Q, \nu) = \frac{2Q_{ij}Q_{kl} + (\nu - p - 1)(Q_{ik}Q_{jl} + Q_{il}Q_{kj})}{(\nu - p)(\nu - p - 1)^2 (\nu - p - 3)}$$

The Inverse Wishart PDF

The inverse Wishart PDF can be arrived at by starting with

$$f(S | V, \nu) = k_W |V|^{-\frac{\nu}{2}} |S|^{\frac{\nu-p-1}{2}} e^{-\frac{1}{2} \text{tr} V^{-1} S}$$

defining

$$\begin{matrix} H = S^{-1} \\ p \times p & p \times p \end{matrix} \quad \begin{matrix} Q = V^{-1} = \nu \Sigma^{-1} \\ p \times p & p \times p \end{matrix} \quad J(S \rightarrow H) = H^{-(p+1)}$$

and performing a transformation of variable resulting in

$$\begin{matrix} f(H | Q, \nu) = k_{IW} |Q|^{\nu/2} |H|^{-(\nu+p+1)/2} e^{-\frac{1}{2} \text{tr} (Q H^{-1})} \\ p \times p & p \times p & p \times p & p \times p \end{matrix} \quad \begin{matrix} H, Q > 0 \\ \nu > 0 \end{matrix}$$

$$k_{IW}^{-1} = 2^{\nu p/2} \pi^{p(p-1)/4} \prod_{j=1}^p \Gamma\left(\frac{\nu-p-j}{2}\right)$$

for the multivariate case.

$$f(h | \nu, q) = \frac{q^{\nu/2}}{\Gamma(\nu/2)} h^{-\nu/2-1} e^{-\frac{1}{2} q h^{-1}}$$

The Inverse Wishart PDF

We can invert each of the Wishart distributed matrix observations, $H=S^{-1}$, then the H has an inverse Wishart PDF **or** we can generate random matrix variate observations from the inverse Wishart PDF via the Matlab function

`iwishrnd(Sigma/nu,nu)`

```
% Matlab function
```

```
IWmat=zeros(p,p,m); Q=inv(Sigma/nu); DI=chol(inv(Q));
```

```
for count=1:m
```

```
    IWmat(:, :, count) = iwishrnd(Q,nu,DI);
```

```
end
```

and compare sample to theoretical values

The Inverse Wishart PDF

```
% Inverse Wishart Distribution %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Q=inv(Sigma/nu);
% means and variances
[Q/(nu-p-1),mean(Hmat,3)]
[2*Q(1,1)^2/((nu-p-1)^2*(nu-p-3)),...
 ((nu-p+1)*Q(1,2)^2+(nu-p-1)*Q(1,1)*Q(2,2))/((nu-p)*(nu-p-1)^2*(nu-p-3)),...
 2*Q(2,2)^2/((nu-p-1)^2*(nu-p-3))]
varHmat=var(Hmat,[],3);
[varHmat(1,1),varHmat(1,2),varHmat(2,2)]
% covariances
i=1;;j=1;;k=1;;l=2;
cH1112=(2*Q(i,j)*Q(k,l)+(nu-p-1)*(Q(i,k)*Q(j,l)+Q(i,l)*Q(k,j)))/((nu-p)*(nu-p-1)^2*(nu-p-3));
i=1;;j=1;;k=2;;l=2;
cH1122=(2*Q(i,j)*Q(k,l)+(nu-p-1)*(Q(i,k)*Q(j,l)+Q(i,l)*Q(k,j)))/((nu-p)*(nu-p-1)^2*(nu-p-3));
i=1;;j=2;;k=2;;l=2;
cH1222=(2*Q(i,j)*Q(k,l)+(nu-p-1)*(Q(i,k)*Q(j,l)+Q(i,l)*Q(k,j)))/((nu-p)*(nu-p-1)^2*(nu-p-3));
[cH1112,cH1122,cH1222]
covH1112=cov(squeeze(Hmat(1,1,:)),squeeze(Hmat(1,2,:)));
covH1122=cov(squeeze(Hmat(1,1,:)),squeeze(Hmat(2,2,:)));
covH1222=cov(squeeze(Hmat(1,2,:)),squeeze(Hmat(2,2,:)));
[covH1112(1,2),covH1122(1,2),covH1222(1,2)]
```

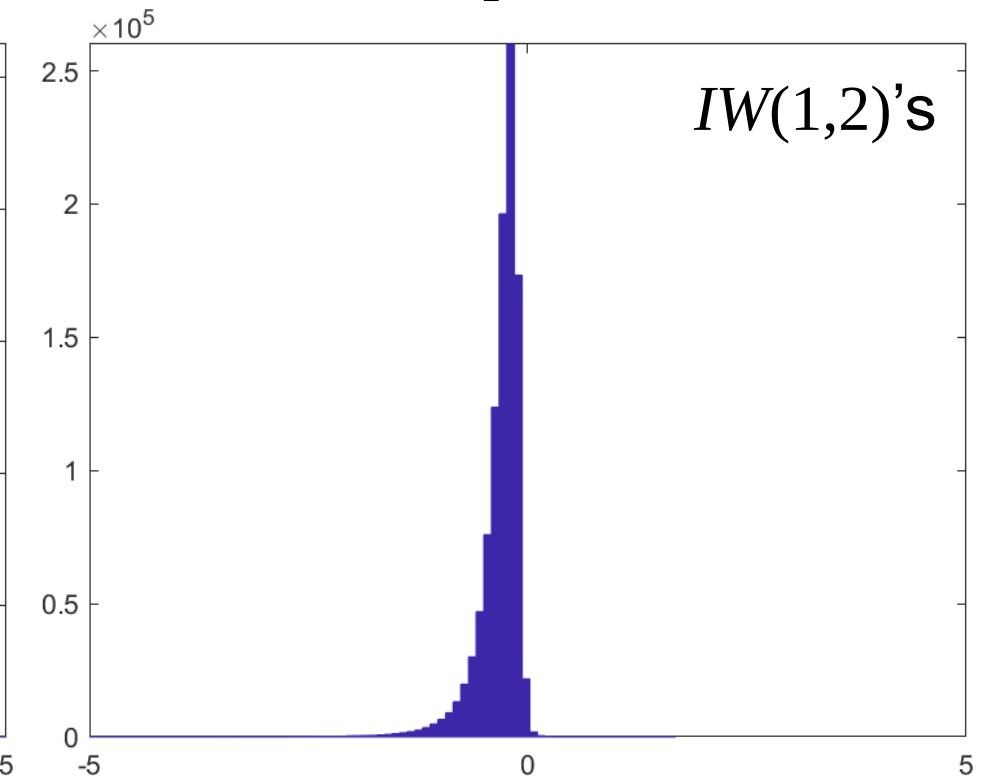
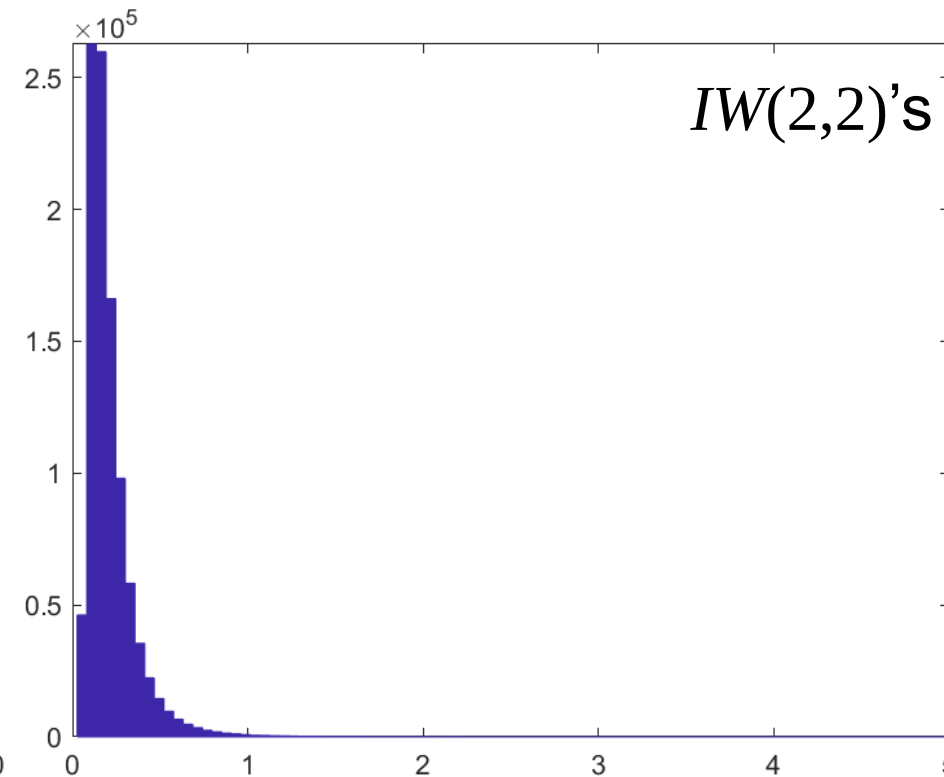
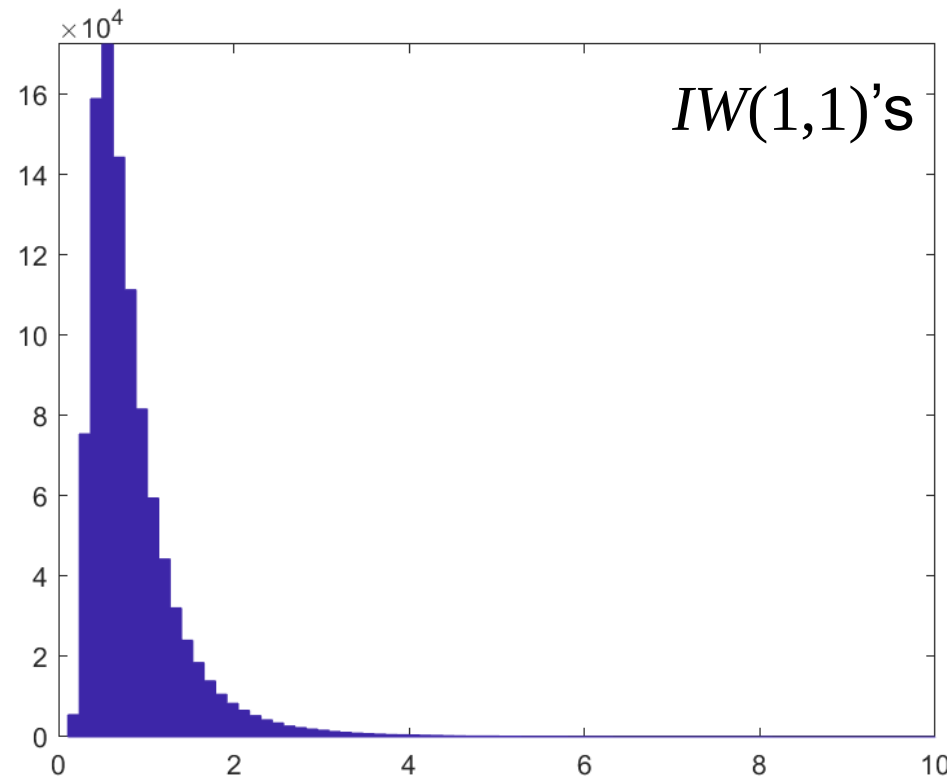
The Wishart PDF

$$E(H | Q, \nu) = \frac{Q}{\nu - p - 1}$$

$$Q = \begin{pmatrix} 5.1429 & -1.9286 \\ -1.9286 & 1.2857 \end{pmatrix}$$

$$p = 2 \quad \nu = 9$$

Matlab: `IWmat = iwishrnd(Q,nu,DI);`



$$E(IW) = \begin{pmatrix} 0.8571 & -0.3214 \\ -0.3214 & 0.2143 \end{pmatrix}$$

$$\overline{IW} = \begin{pmatrix} 0.8568 & -0.3216 \\ -0.3216 & 0.2144 \end{pmatrix}$$

$$\text{var}(IW) = \begin{pmatrix} 0.3673 & 0.0689 \\ 0.0689 & 0.0230 \end{pmatrix}$$

$$s_{IW}^2 = \begin{pmatrix} 0.3723 & 0.0721 \\ 0.0721 & 0.0245 \end{pmatrix}$$

$$\text{cov}(IW_{ij}) = (-0.1378, 0.0574, -0.0344)$$

$$s_{IW_{ij}} = (-0.1400, 0.0583, -0.0348)$$

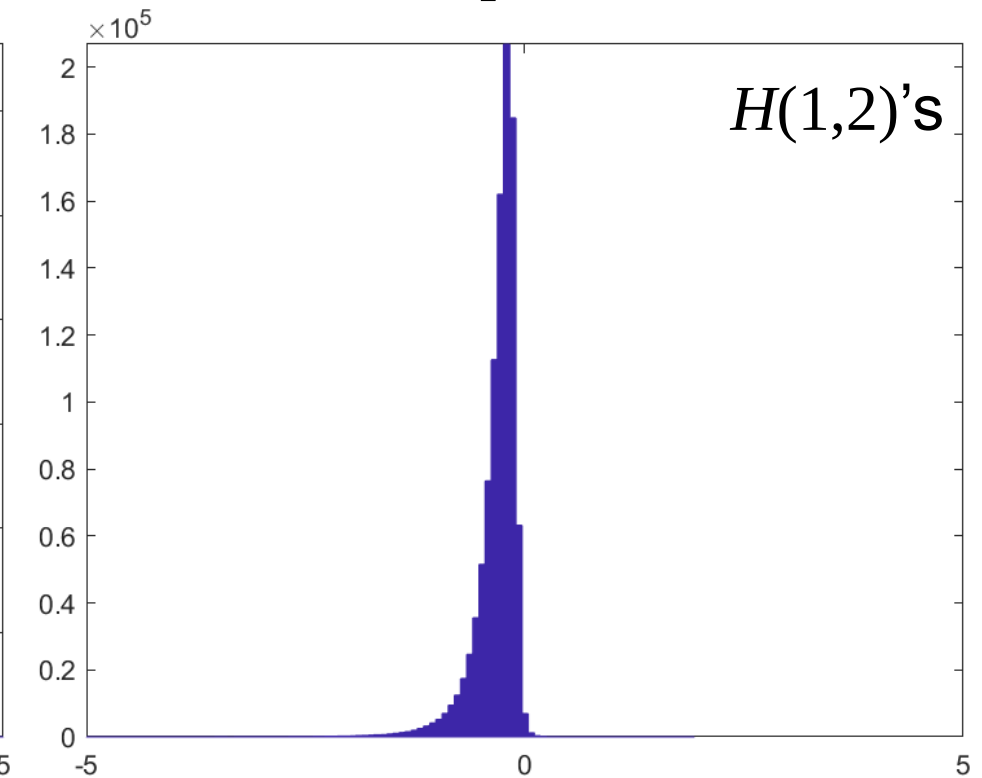
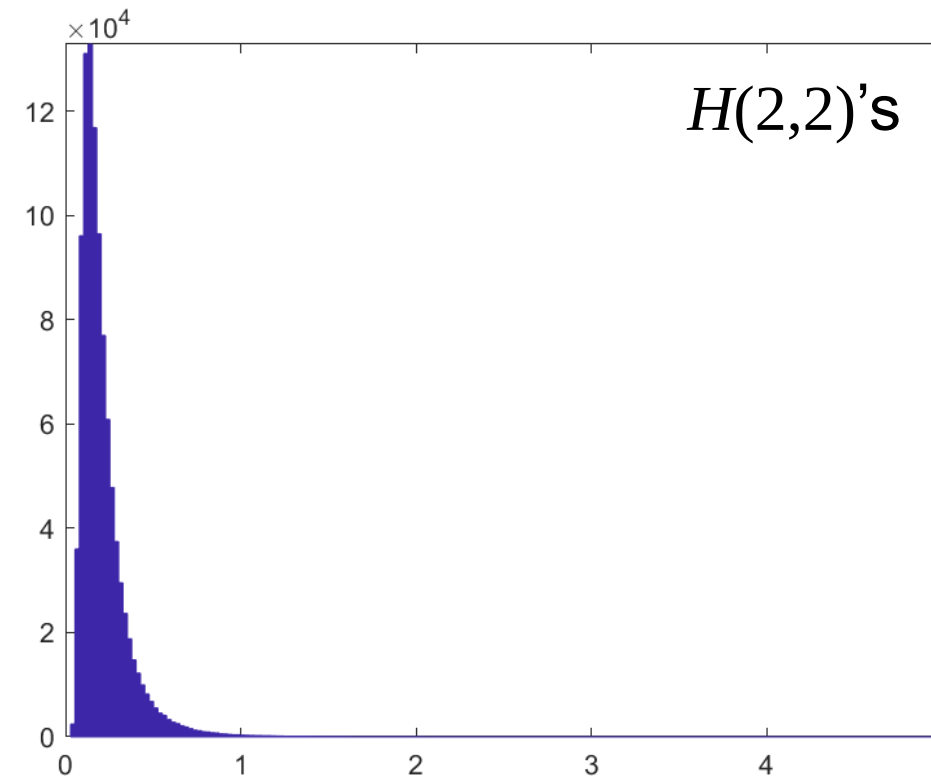
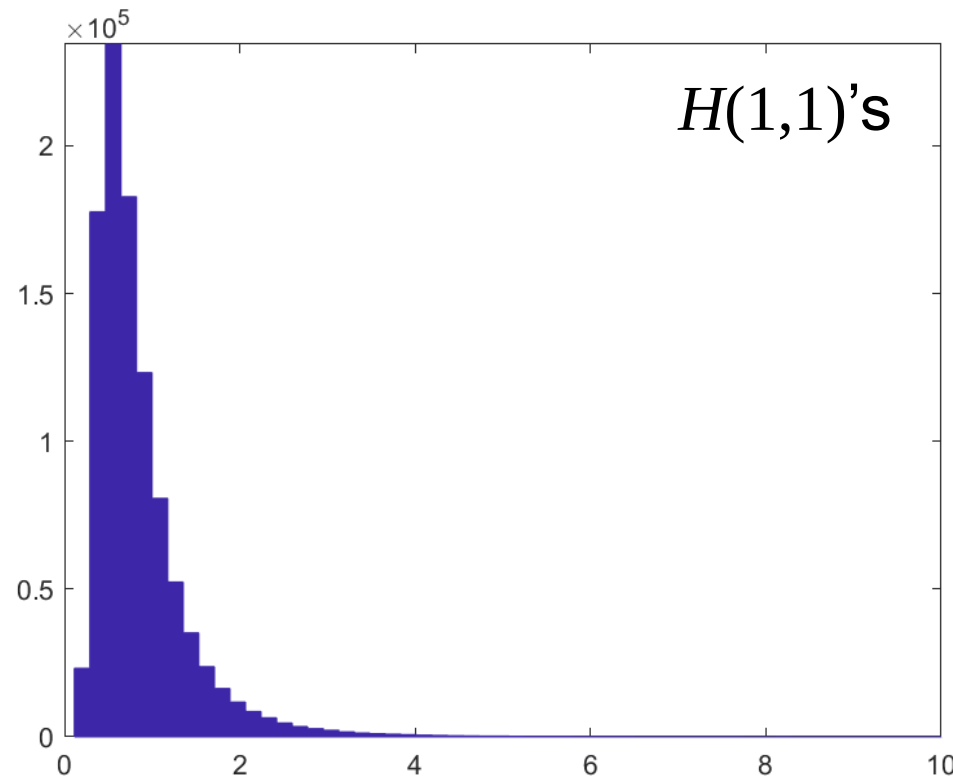
The Wishart PDF

From x 's: $H = S^{-1}$

$$E(H | Q, \nu) = \frac{Q}{\nu - p - 1}$$

$$Q = \begin{pmatrix} 5.1429 & -1.9286 \\ -1.9286 & 1.2857 \end{pmatrix}$$

$$p = 2 \quad \nu = 9$$



$$E(H) = \begin{pmatrix} 0.8571 & -0.3214 \\ -0.3214 & 0.2143 \end{pmatrix}$$

$$\bar{H} = \begin{pmatrix} 0.8568 & -0.3216 \\ -0.3216 & 0.2144 \end{pmatrix}$$

$$\text{var}(H) = \begin{pmatrix} 0.3673 & 0.0689 \\ 0.0689 & 0.0230 \end{pmatrix}$$

$$s_H^2 = \begin{pmatrix} 0.3723 & 0.0721 \\ 0.0721 & 0.0245 \end{pmatrix}$$

$$\text{cov}(H_{ij}) = (-0.1378, 0.0574, -0.0344)$$

$$s_{H_{ij}} = (-0.1400, 0.0583, -0.0348)$$

The Inverse Wishart PDF

```
% make histograms of the SS elements
figure;
hist(squeeze(IWmat(1,1,:)),500),axis tight,xlim([0,10])
figure;
hist(squeeze(IWmat(2,2,:)),500),axis tight,xlim([0,5])
figure;
hist(squeeze(IWmat(1,2,:)),500),axis tight,xlim([-5,5])
```

Questions?

Homework 6

1. Assume Marquette Undergrads heights have $\mu_h=70$ in and $\sigma_h=3$ in while their weights have $\mu_w=160$ lbs and $\sigma_w=4$ lbs with $\rho=.75$.
 - a) Generate 10^7 h/w 2×1 vectors using the Cholesky, $\Sigma=AA'$.
 - b) Divide the 10^7 random vectors into samples (sets) of 10.
 - c) Calculate means, variances, and covariance from each 10.
 - d) Calculate the mean of: means, variances, and covariance.
 - e) Calculate the variance of: means, variances, and covariance.
 - f) Calculate the covariance between: means, variances & covariances.
 - g) Make histograms of everything. Do your results match theory?

Homework 6

2*. With pencil and paper sketch out the transformation from the Wishart RV S to the inverse Wishart RV H where $H=S^{-1}$, use $J(S \rightarrow H) = |H|^{-(p+1)}$.

This is a similar transformation as $h = (s^2)^{-1}$ using $J(s^2 \rightarrow h) = h^{-2}$ for gamma to inverse gamma. (Do this one first.)

* For students in MSSC 5790.

Homework 6

3**.Compute the inverse of each of your S matrices from 1 to form H matrices.

Make histograms of 11, 22, and 12 elements of H .

Calculate means, variances, and covariances of the elements of H . Compare to the theoretical values.

** For students that have had 6010 and 6020.