

Symmetric Matrix PDFs (Multivariate Gamma and Inverse Gamma)

Dr. Daniel B. Rowe
Professor of Computational Statistics
Department of Mathematical and Statistical Sciences
Marquette University



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

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

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

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

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

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

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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

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
$\bar{x}_{(1)}$	$\bar{x}_{(2)}$	$\bar{x}_{(3)}$...	$\bar{x}_{(m)}$
$s_{(1)}^2$	$s_{(2)}^2$	$s_{(3)}^2$...	$s_{(m)}^2$

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 $\Gamma\left(\frac{\nu}{2}, \frac{2\sigma^2}{\nu}\right)$.

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

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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.

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

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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

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

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

normalizing constant

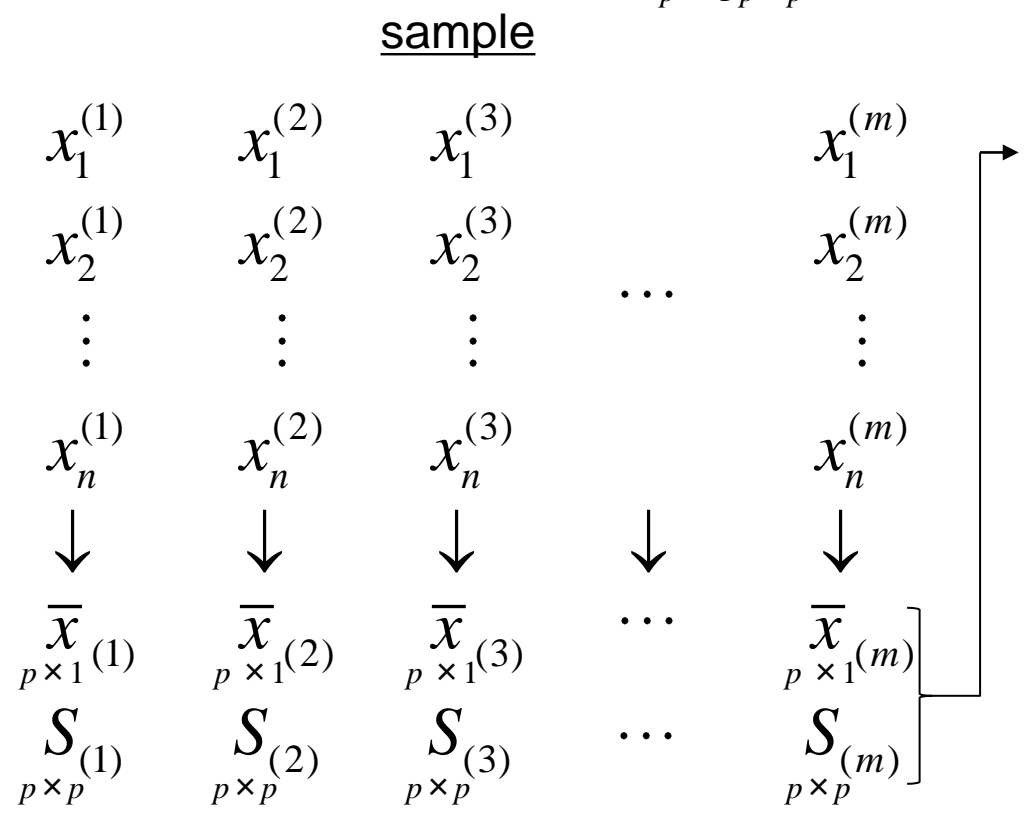
Remember the eccentric way I wrote this.

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

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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.



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 $S \sim W(\Sigma/\nu, \nu)$

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

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

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

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

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The Wishart matrix PDF is

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

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

The mean, variance, and covariance of its elements are

$$E(S | \Sigma, \nu) = \Sigma$$

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

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

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

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

$\begin{matrix} p \times p & p \times p & p \times p & p \times p \end{matrix}$

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

$\begin{matrix} r \times r & r \times p & p \times p & p \times r \end{matrix}$

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

$\begin{matrix} r \times r & r \times r \end{matrix}$

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

$\begin{matrix} r \times r & r \times r \end{matrix}$

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

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

The Wishart PDF

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

$$v = 9$$

Took 10^6 sets of $n=10$ variates x , subtracted mean \bar{x}

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 $W(\Sigma/v, v=n-1)$.

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

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

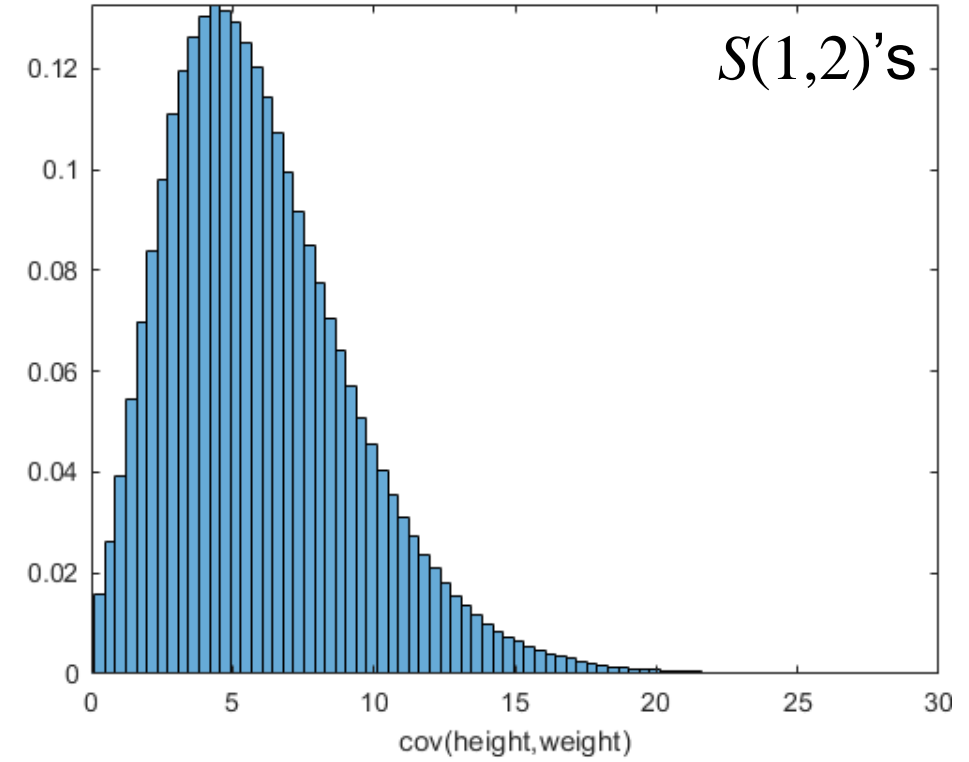
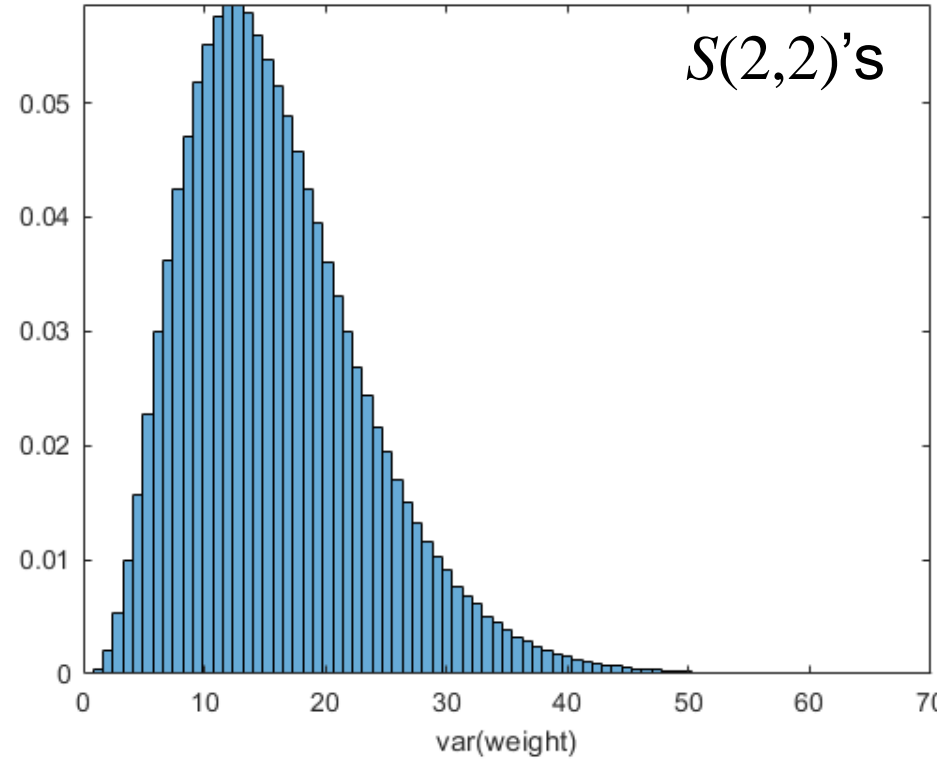
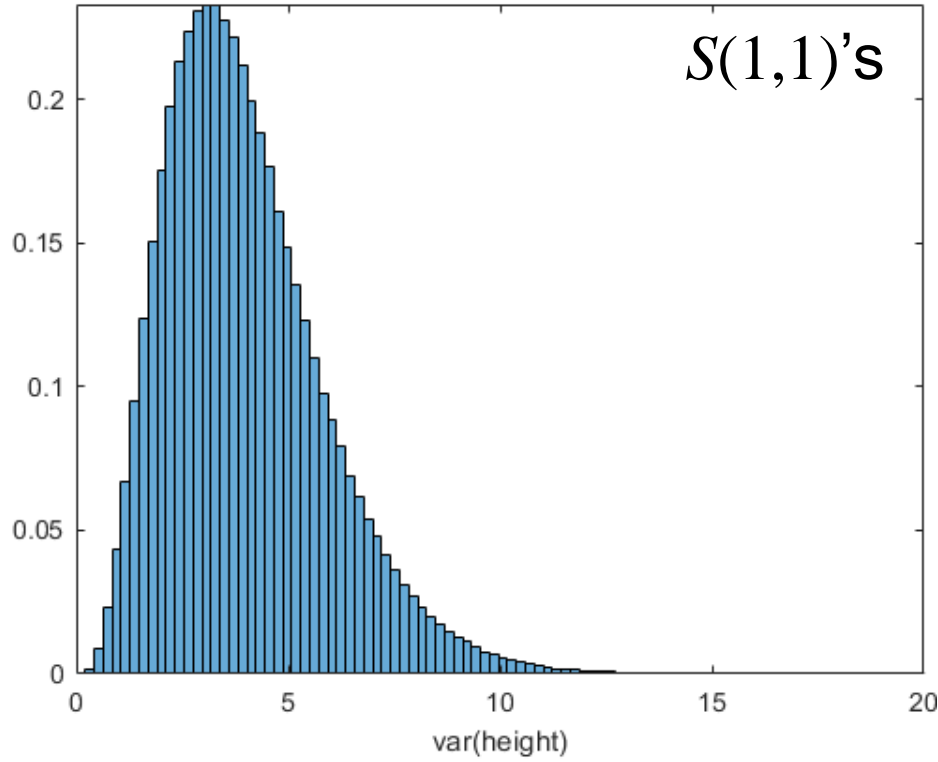
$$\text{cov}(S_{ij}S_{kl} | \Sigma, v) = (\Sigma_{ik}\Sigma_{jl} + \Sigma_{il}\Sigma_{jk}) / v$$

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

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 $W(\Sigma/\nu, \nu=n-1)$.

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



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

$$\Sigma = AA'$$

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

11,22 11,12 22,12 ← ij,kl

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

The Wishart PDF

```

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

% compute the mean in each sample
meanX=squeeze(mean(X,2));
mean(meanX,2)
% compute the covariance in each sample
S=zeros(p,p,m);
for j=1:m
    S(:,:,j)=cov(squeeze(X(:,:,j)'));
end

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

```

The Wishart PDF

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

% 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

```
% 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)]
```


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
```

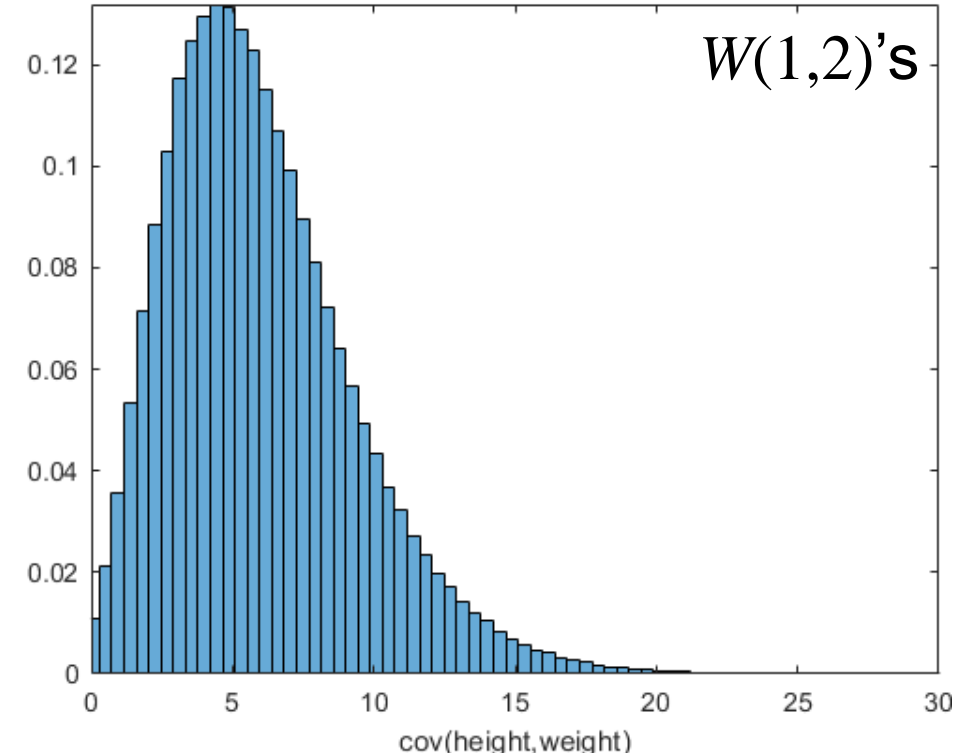
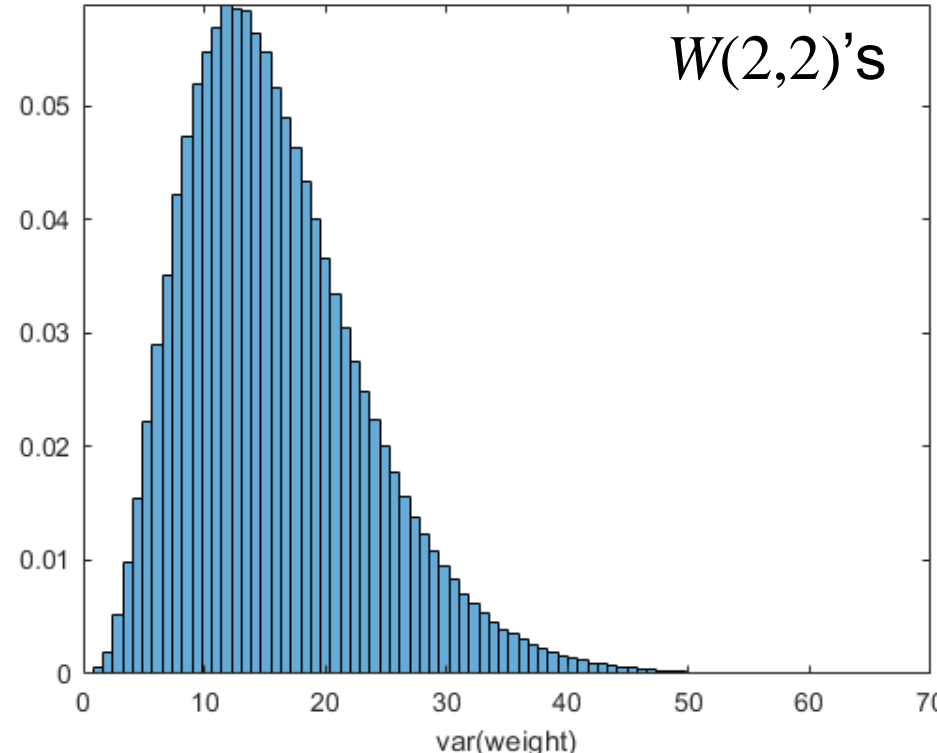
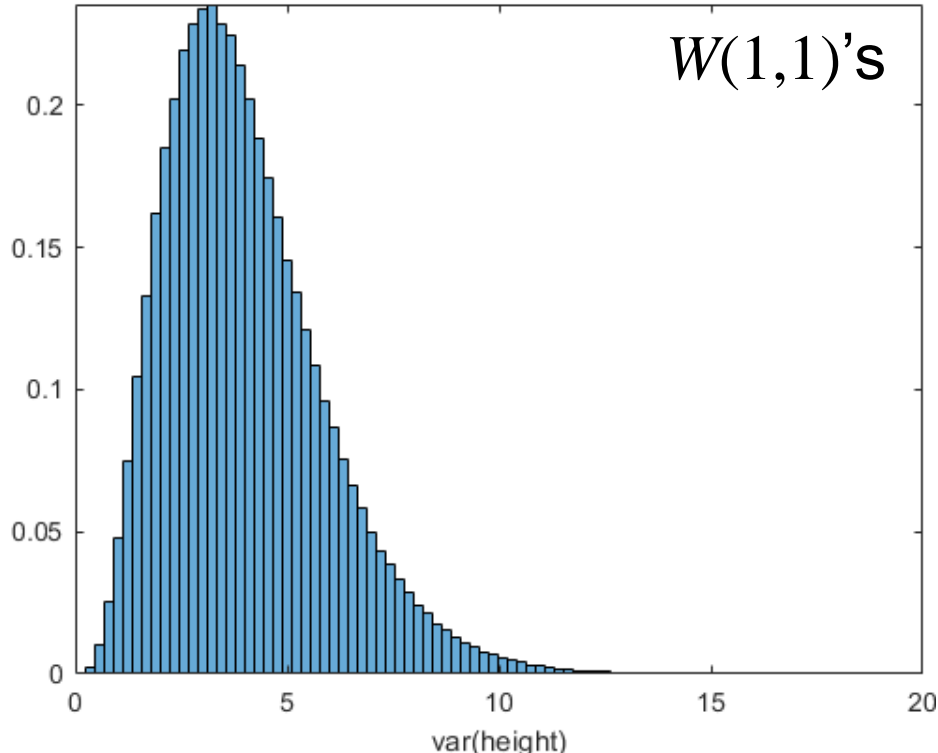
```
i=1; j=1; k=1; l=2;
cG1112=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
i=1; j=1; k=2; l=2;
cG1122=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
i=1; j=2; k=2; l=2;
cG1222=(Sigma(i,k)*Sigma(j,l)+Sigma(i,l)*Sigma(j,k))/nu;
[cG1112,cG1122,cG1222]
covG1112=cov(squeeze(Wmat(1,1,:)),squeeze(Wmat(1,2,:)));
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)`

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

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



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

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

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

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

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

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

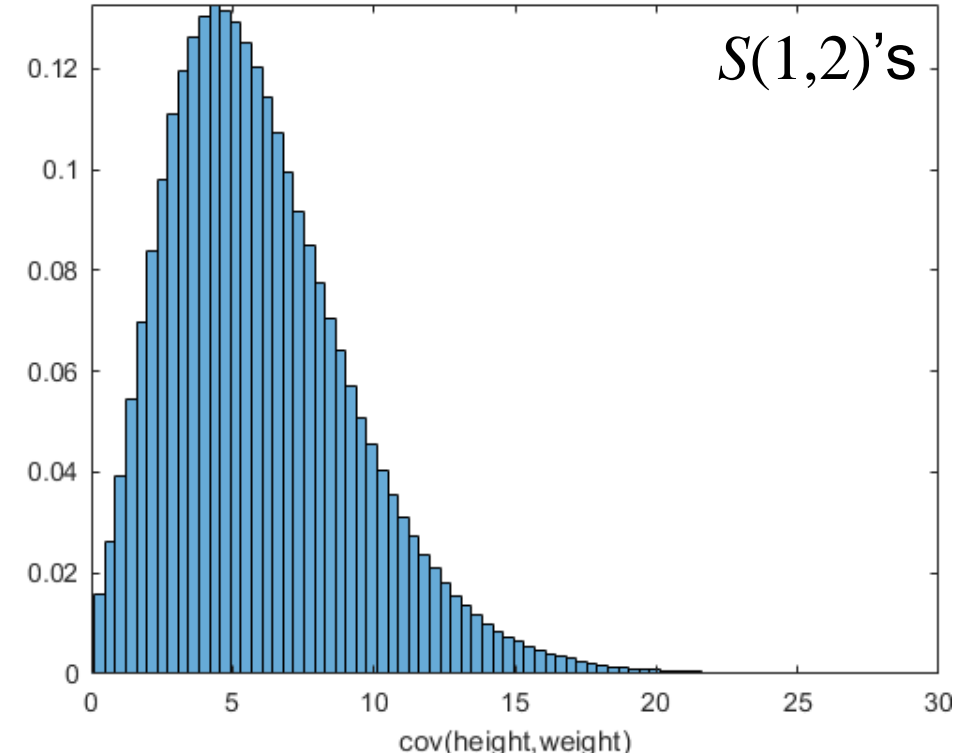
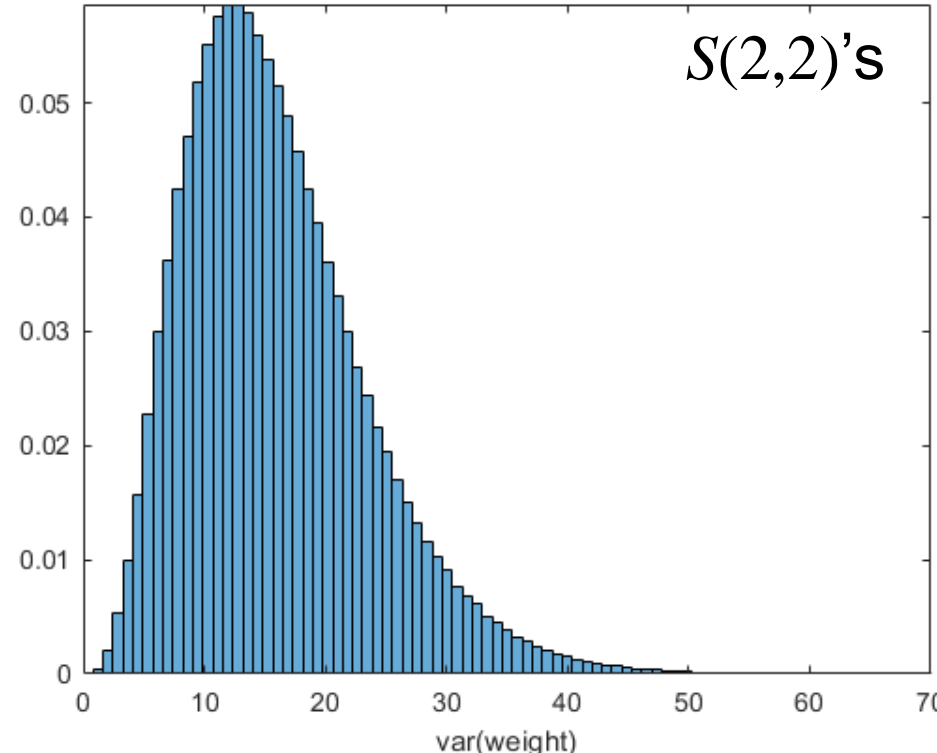
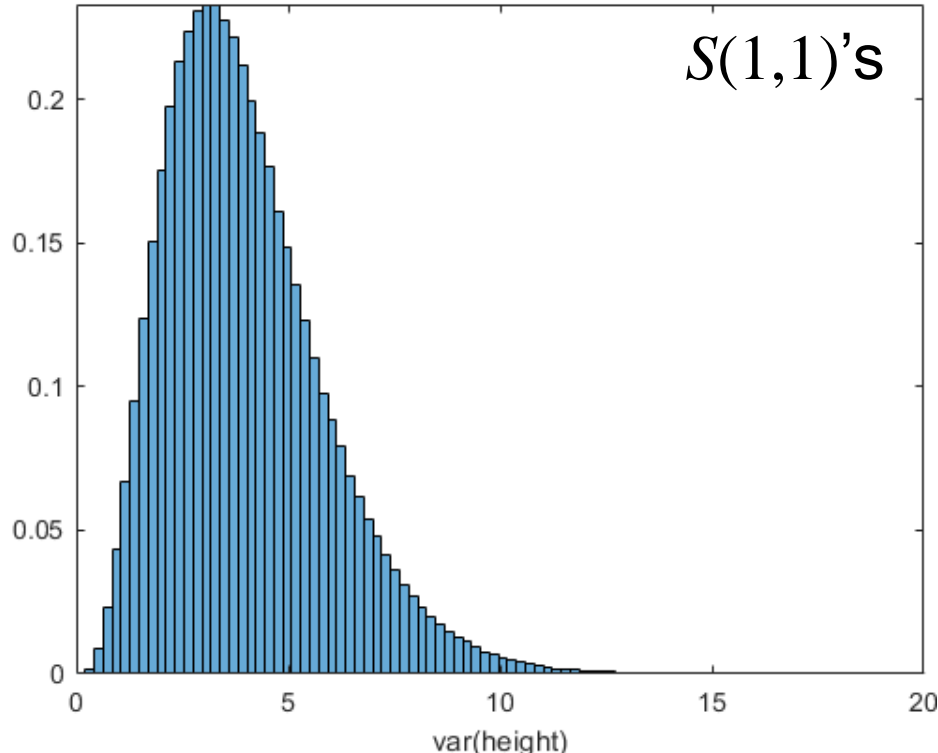
toggle forward

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

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

The Inverse Wishart PDF

A random variable h has a continuous

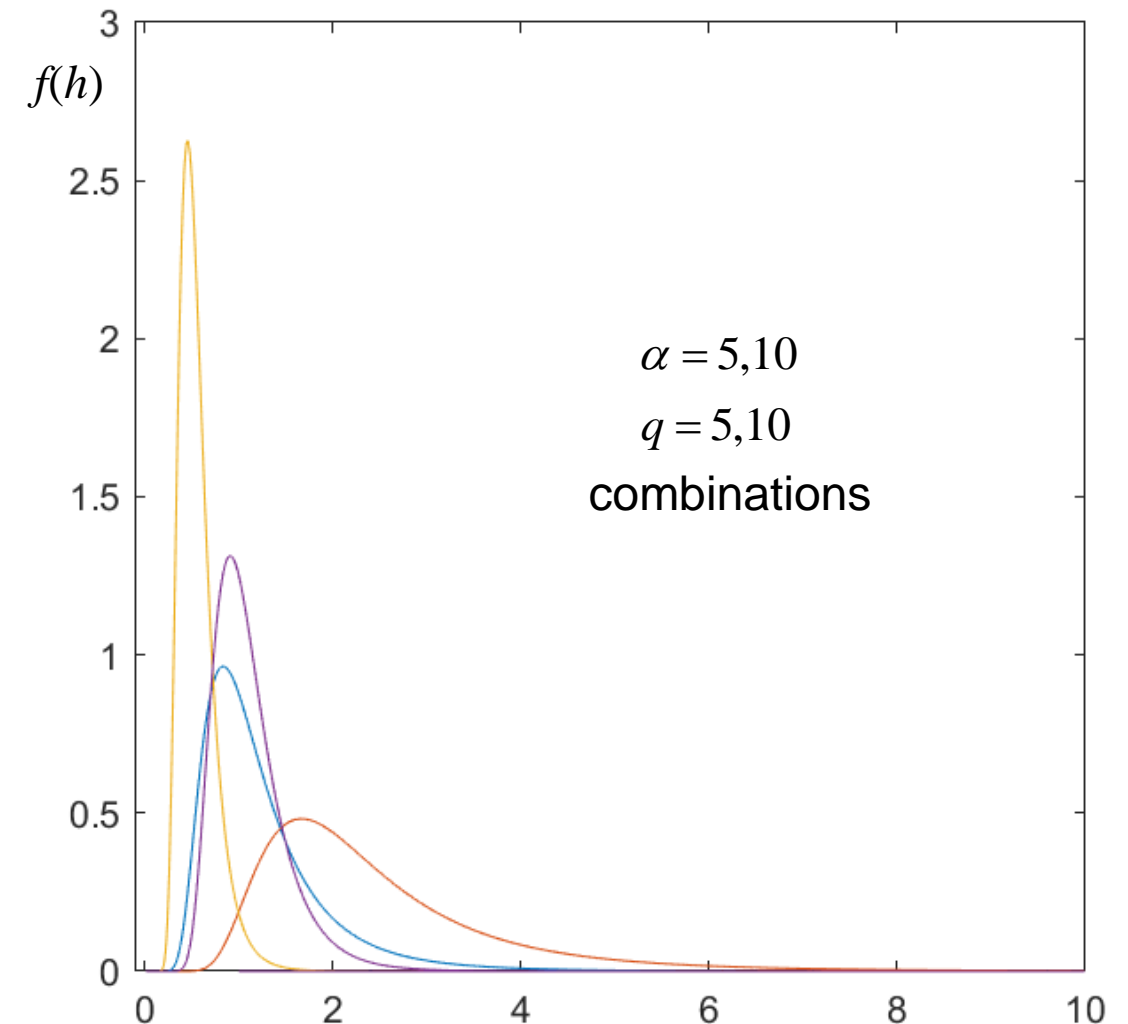
Inverse Gamma distribution, $h \sim \Gamma^{-1}(\alpha, q)$ if

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

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

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

defining

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

and performing a transformation of variable resulting in

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

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

for the multivariate case.

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

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)]

```

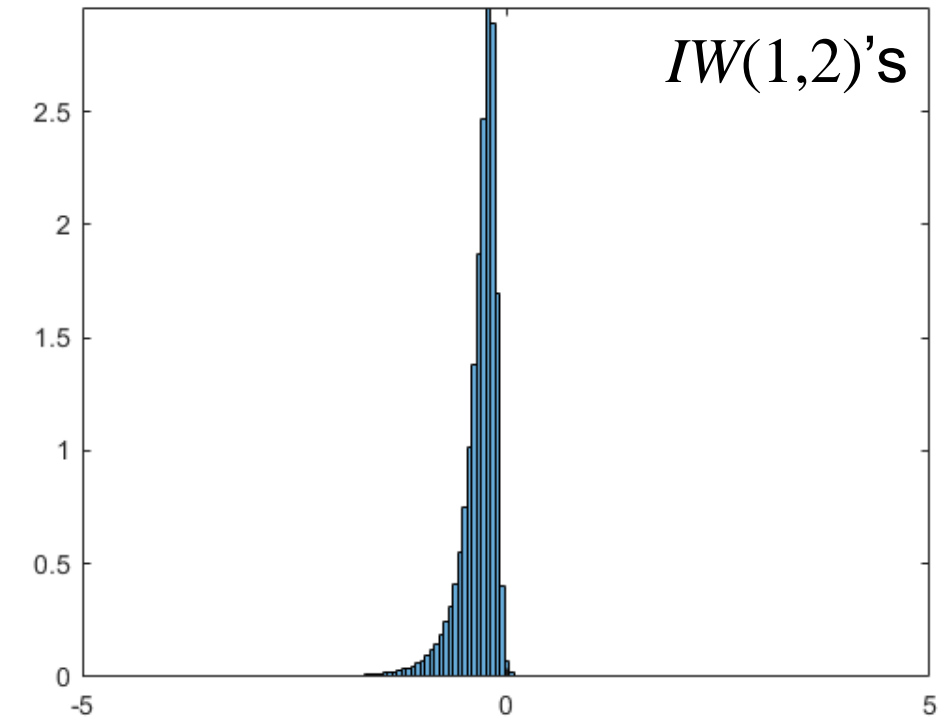
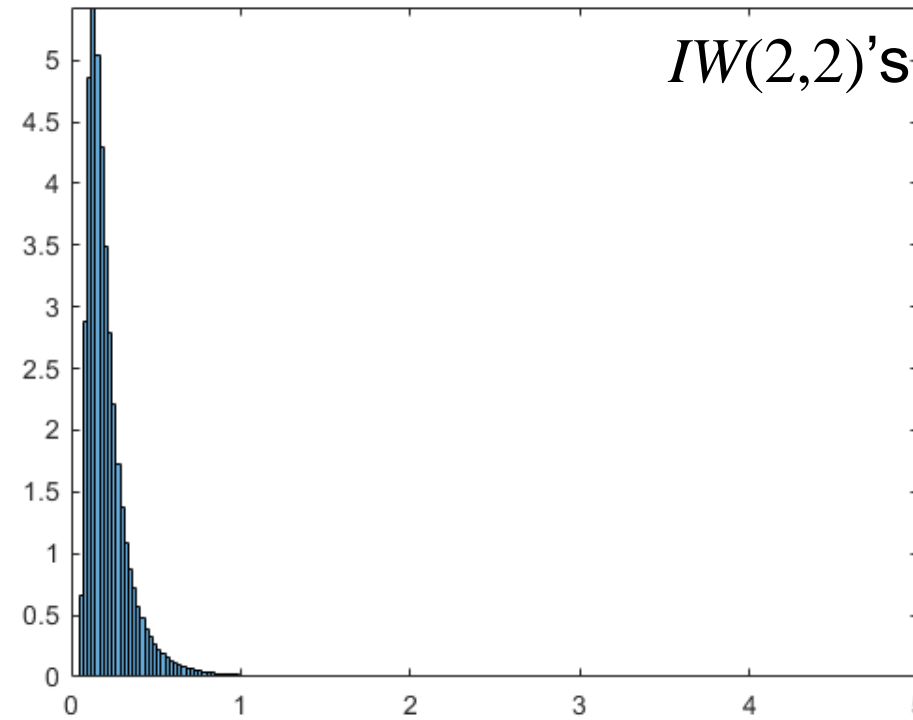
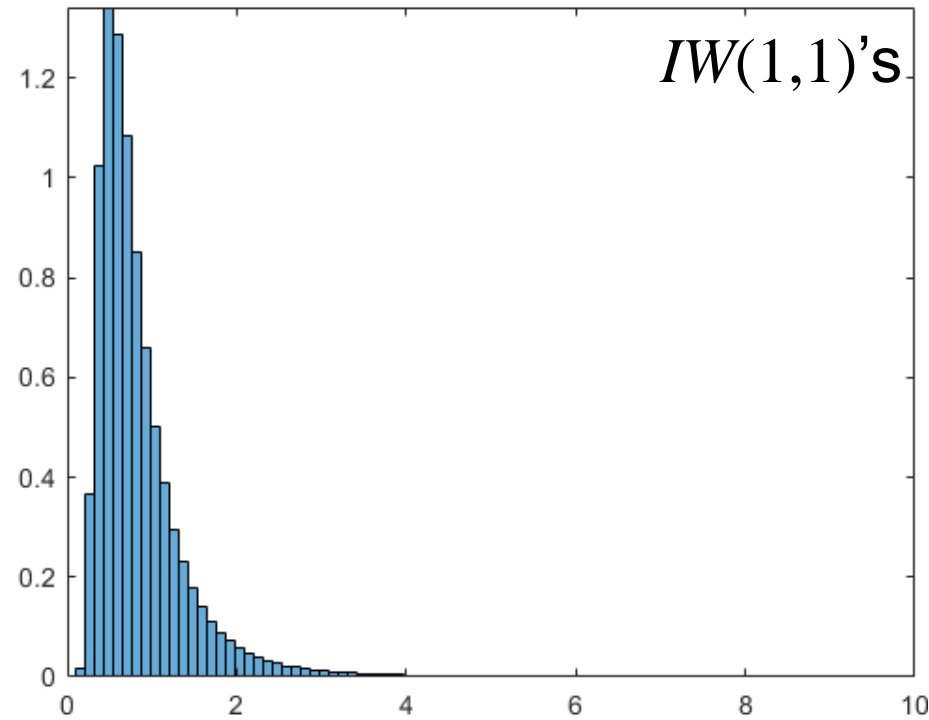
The Wishart PDF

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

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

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

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



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

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

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

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

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

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

toggle forward

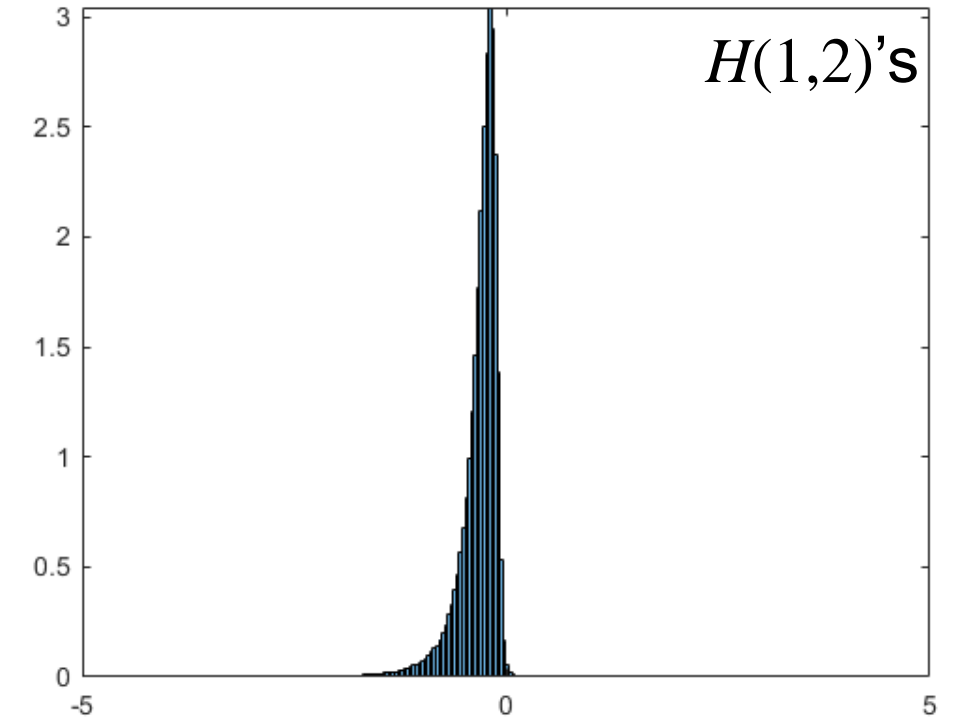
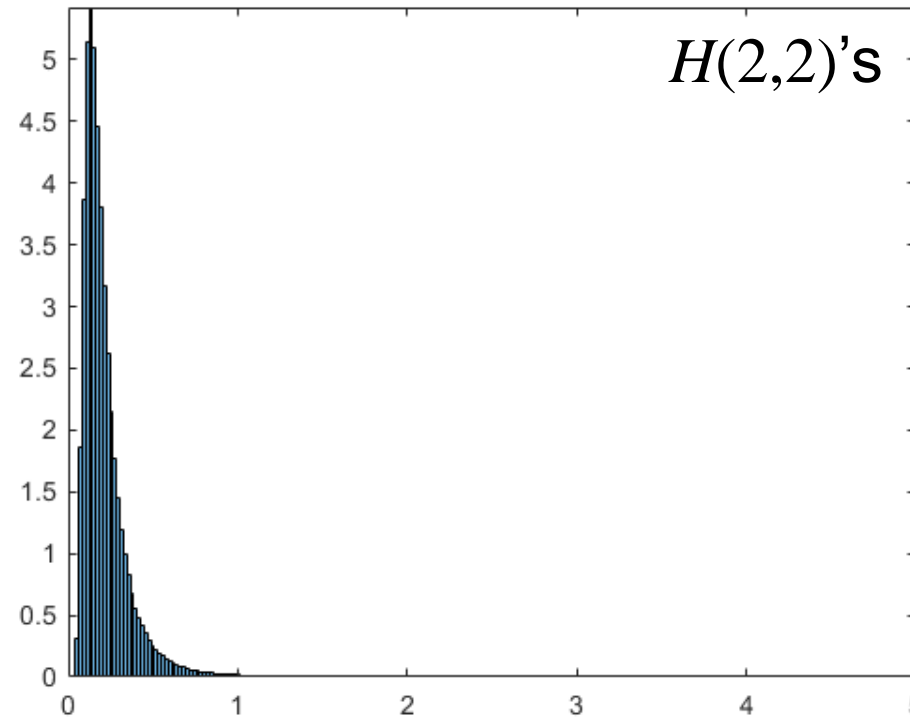
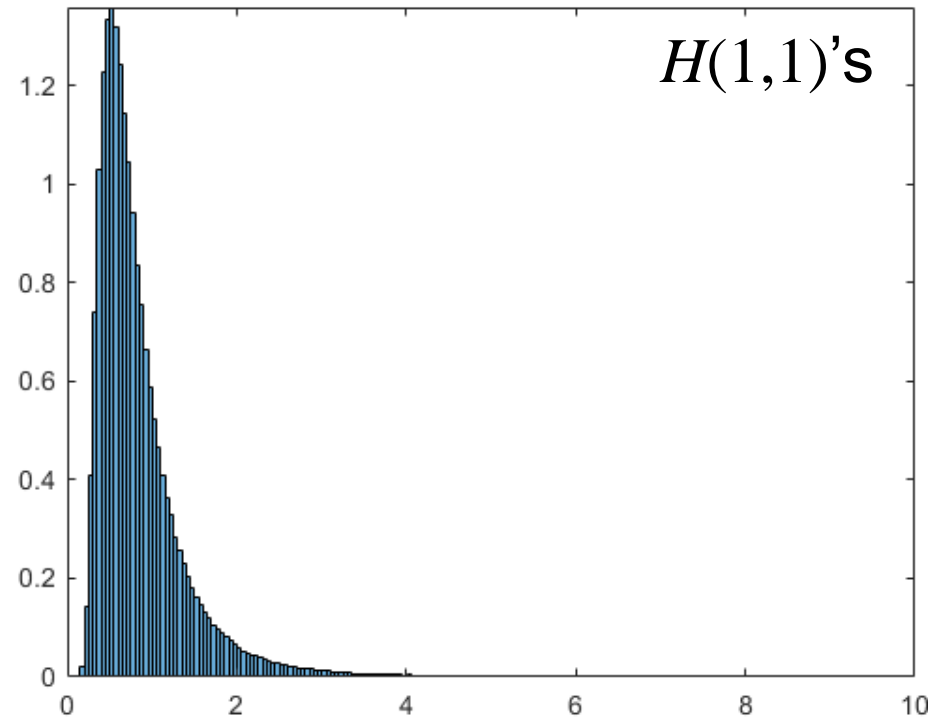
The Wishart PDF

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

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

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

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



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

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

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

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

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

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

toggle backward

The Inverse Wishart PDF

```
% make histograms of the inv S elements
figure;
histogram(squeeze(IWmat(1,1,:)),500,'normalization','pdf'), axis tight,xlim([0,10])
figure;
histogram(squeeze(IWmat(2,2,:)),500,'normalization','pdf'), axis tight,xlim([0,5])
figure;
histogram(squeeze(IWmat(1,2,:)),500,'normalization','pdf'), axis tight,xlim([-5,5])

% make histograms of the inv S elements
figure;
histogram(squeeze(Hmat(1,1,:)),500,'normalization','pdf'), axis tight,xlim([0,10])
figure;
histogram(squeeze(Hmat(2,2,:)),500,'normalization','pdf'), axis tight,xlim([0,5])
figure;
histogram(squeeze(Hmat(1,2,:)),500,'normalization','pdf'), axis tight,xlim([-5,5])
```

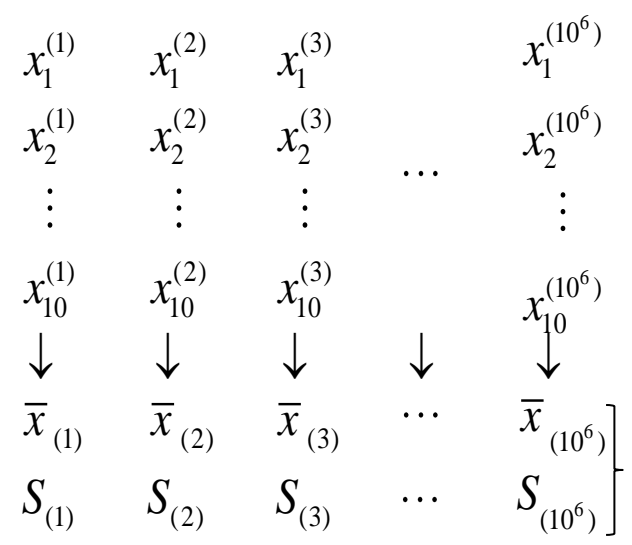
Discussion

Questions?



Homework 5

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 5

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 $h=s^{-2}$ using $J(s^2 \rightarrow h) = h^{-2}$ for gamma to inverse gamma. (Do this one first.)

Homework 5

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.

Homework 5

4*. Develop a method to generate matrix observation from the 2×2 inverse Wishart PDF using rejection sampling.

$$f(S_{11}, S_{22}, S_{12} | V, \nu) = k_W \begin{vmatrix} V_{11} & V_{12} \\ V_{12} & V_{22} \end{vmatrix}^{-\frac{\nu}{2}} \begin{vmatrix} S_{11} & S_{12} \\ S_{12} & S_{22} \end{vmatrix}^{\frac{\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \text{tr} \left[\begin{pmatrix} V_{11} & V_{12} \\ V_{12} & V_{22} \end{pmatrix}^{-1} \begin{pmatrix} S_{11} & S_{12} \\ S_{12} & S_{22} \end{pmatrix} \right] \right\}$$

* Only for students that have had MSSC 5790 Bayesian Statistics.
Excused from 1, 2, and 3.