Sampling Distributions

Merlise Clyde

STA721 Linear Models

Duke University

September 8, 2016

Outline

Topics

- Normal Theory
- Chi-squared Distributions
- Student t Distributions

Readings: Christensen Apendix C, Chapter 1-2

Prostate Example

```
> library(lasso2); data(Prostate)    # n = 97, 9 variables
> summary(lm(lpsa ~ ., data=Prostate))
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.669399   1.296381   0.516  0.60690
lcavol       0.587023   0.087920   6.677 2.11e-09 ***
lweight      0.454461   0.170012   2.673  0.00896 **
age         -0.019637   0.011173  -1.758  0.08229 .
lbph         0.107054   0.058449   1.832  0.07040 .
svi          0.766156   0.244309   3.136  0.00233 **
lcp         -0.105474   0.091013  -1.159  0.24964
gleason      0.045136   0.157464   0.287  0.77506
pgg45        0.004525   0.004421   1.024  0.30885
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7084 on 88 degrees of freedom
Multiple R-squared:  0.6548,Adjusted R-squared:  0.6234
```

Summary of Distributions

Models: Full $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$
Assume $\mathbf{X}$ is full rank with the first column of ones $\mathbf{1}_n$ and p additional predictors $r(\mathbf{X}) = p + 1$

$$\hat{\boldsymbol{\beta}} \mid \sigma^2 \sim \mathrm{N}(\boldsymbol{\beta}, \sigma^2(\mathbf{X}^T\mathbf{X})^{-1})$$

$$\frac{\mathrm{SSE}}{\sigma^2} \sim \chi^2_{n-r(\mathbf{X})}$$

$$\frac{\hat{\beta}_j - \beta_j}{\mathrm{SE}(\hat{\beta}_j)} \sim t_{n-r(\mathbf{X})}$$

where $\mathrm{SE}(\hat{\beta})$ is the square root of the jth diagonal element of $\hat{\sigma}^2(\mathbf{X}^T\mathbf{X})^{-1}$ and $\hat{\sigma}^2$ is the unbiased estimate of σ^2

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{AZ}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

- $\mathsf{E}[\mathbf{W}] = \mu$

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{AZ}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

- $\textsf{E}[\mathbf{W}] = \mu$
- $\textsf{Cov}(\mathbf{W}) = \mathbf{AA}^T \geq 0$

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

- $\mathsf{E}[\mathbf{W}] = \mu$
- $\mathsf{Cov}(\mathbf{W}) = \mathbf{A}\mathbf{A}^T \geq 0$
- $\mathbf{W} \sim \mathsf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma} = \mathbf{A}\mathbf{A}^T$

If $\boldsymbol{\Sigma}$ is singular then there is no density (on $\mathbb{R}^n$), but claim that $\mathbf{W}$ still has a multivariate normal distribution!

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

- $\mathsf{E}[\mathbf{W}] = \mu$
- $\mathsf{Cov}(\mathbf{W}) = \mathbf{A}\mathbf{A}^T \geq 0$
- $\mathbf{W} \sim \mathsf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma} = \mathbf{A}\mathbf{A}^T$

If $\boldsymbol{\Sigma}$ is singular then there is no density (on $\mathbb{R}^n$), but claim that $\mathbf{W}$ still has a multivariate normal distribution!

Definition

$\mathbf{W} \in \mathbb{R}^n$ has a multivariate normal distribution $\mathsf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ if for any $\mathbf{v} \in \mathbb{R}^n$ $\mathbf{v}^T\mathbf{Y}$ has a normal distribution with mean $\mathbf{v}^T\boldsymbol{\mu}$ and variance $\mathbf{v}^T\boldsymbol{\Sigma}\mathbf{v}$

General Case

$\mathbf{W} = \boldsymbol{\mu} + \mathbf{AZ}$ with $\mathbf{Z} \in \mathbb{R}^d$ and $\mathbf{A}$ is $n \times d$

- $\textsf{E}[\mathbf{W}] = \mu$
- $\textsf{Cov}(\mathbf{W}) = \mathbf{AA}^T \geq 0$
- $\mathbf{W} \sim \textsf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma} = \mathbf{AA}^T$

If $\boldsymbol{\Sigma}$ is singular then there is no density (on $\mathbb{R}^n$), but claim that $\mathbf{W}$ still has a multivariate normal distribution!

Definition

$\mathbf{W} \in \mathbb{R}^n$ has a multivariate normal distribution $\textsf{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ if for any $\mathbf{v} \in \mathbb{R}^n$ $\mathbf{v}^T\mathbf{Y}$ has a normal distribution with mean $\mathbf{v}^T\boldsymbol{\mu}$ and variance $\mathbf{v}^T\boldsymbol{\Sigma}\mathbf{v}$

see Lessons in Normal Theory in Sakai for videos using Characteristic functions

Linear Transformations are Normal

If $\mathbf{Y} \sim \mathrm{N}_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ then for $\mathbf{A}$ $m \times n$

$$\mathbf{AY} \sim \mathrm{N}_m(\mathbf{A}\boldsymbol{\mu}, \mathbf{A\Sigma A}^T)$$

$\mathbf{A\Sigma A}^T$ does not have to be positive definite!

Equal in Distribution

Multiple ways to define the same normal:

Equal in Distribution

Multiple ways to define the same normal:

- $\mathbf{Z}_1 \sim \mathsf{N}(\mathbf{0}, \mathbf{I}_n)$, $\mathbf{Z}_1 \in \mathbb{R}^n$ and take $\mathbf{A}$ $d \times n$

Equal in Distribution

Multiple ways to define the same normal:

- $\mathbf{Z}_1 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_n)$, $\mathbf{Z}_1 \in \mathbb{R}^n$ and take $\mathbf{A}$ $d \times n$
- $\mathbf{Z}_2 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_p)$, $\mathbf{Z}_2 \in \mathbb{R}^p$ and take $\mathbf{B}$ $d \times p$

Equal in Distribution

Multiple ways to define the same normal:

- $\mathbf{Z}_1 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_n)$, $\mathbf{Z}_1 \in \mathbb{R}^n$ and take $\mathbf{A}$ $d \times n$
- $\mathbf{Z}_2 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_p)$, $\mathbf{Z}_2 \in \mathbb{R}^p$ and take $\mathbf{B}$ $d \times p$
- Define $\mathbf{Y} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}_1$

Equal in Distribution

Multiple ways to define the same normal:

- $\mathbf{Z}_1 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_n)$, $\mathbf{Z}_1 \in \mathbb{R}^n$ and take $\mathbf{A}$ $d \times n$
- $\mathbf{Z}_2 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_p)$, $\mathbf{Z}_2 \in \mathbb{R}^p$ and take $\mathbf{B}$ $d \times p$
- Define $\mathbf{Y} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}_1$
- Define $\mathbf{W} = \boldsymbol{\mu} + \mathbf{B}\mathbf{Z}_2$

Equal in Distribution

Multiple ways to define the same normal:

- $\mathbf{Z}_1 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_n)$, $\mathbf{Z}_1 \in \mathbb{R}^n$ and take $\mathbf{A}$ $d \times n$
- $\mathbf{Z}_2 \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_p)$, $\mathbf{Z}_2 \in \mathbb{R}^p$ and take $\mathbf{B}$ $d \times p$
- Define $\mathbf{Y} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}_1$
- Define $\mathbf{W} = \boldsymbol{\mu} + \mathbf{B}\mathbf{Z}_2$

Theorem

If $\mathbf{Y} = \boldsymbol{\mu} + \mathbf{A}\mathbf{Z}_1$ *and* $\mathbf{W} = \boldsymbol{\mu} + \mathbf{B}\mathbf{Z}_2$ *then* $\mathbf{Y} \stackrel{\mathrm{D}}{=} \mathbf{W}$ *if and only if* $\mathbf{A}\mathbf{A}^T = \mathbf{B}\mathbf{B}^T = \boldsymbol{\Sigma}$

Zero Correlation and Independence

Theorem

For a random vector $\mathbf{Y} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ *partitioned as*

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix} \right)$$

Zero Correlation and Independence

Theorem

For a random vector $\mathbf{Y} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ *partitioned as*

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix} \right)$$

then $Cov(\mathbf{Y}_1, \mathbf{Y}_2) = \boldsymbol{\Sigma}_{12} = \boldsymbol{\Sigma}_{21}^T = \mathbf{0}$ *if and only if* $\mathbf{Y}_1$ *and* $\mathbf{Y}_2$ *are independent.*

Independence Implies Zero Covariance

Proof.

$$\text{Cov}(\mathbf{Y}_1, \mathbf{Y}_2) = \text{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T]$$

Independence Implies Zero Covariance

Proof.

$$\mathrm{Cov}(\mathbf{Y}_1, \mathbf{Y}_2) = \mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T]$$

If $\mathbf{Y}_1$ and $\mathbf{Y}_2$ are independent

Independence Implies Zero Covariance

Proof.

$$\mathrm{Cov}(\mathbf{Y}_1, \mathbf{Y}_2) = \mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T]$$

If $\mathbf{Y}_1$ and $\mathbf{Y}_2$ are independent

$$\mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T] = \mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)\mathrm{E}(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T] = \mathbf{0}\mathbf{0}^T = \mathbf{0}$$

Independence Implies Zero Covariance

Proof.

$$\mathrm{Cov}(\mathbf{Y}_1, \mathbf{Y}_2) = \mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T]$$

If $\mathbf{Y}_1$ and $\mathbf{Y}_2$ are independent

$$\mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T] = \mathrm{E}[(\mathbf{Y}_1 - \boldsymbol{\mu}_1)\mathrm{E}(\mathbf{Y}_2 - \boldsymbol{\mu}_2)^T] = \mathbf{0}\mathbf{0}^T = \mathbf{0}$$

therefore $\boldsymbol{\Sigma}_{12} = \mathbf{0}$

$\square$

Zero Covariance Implies Independence

Assume $\mathbf{\Sigma}_{12} = \mathbf{0}$

Proof

- Choose an

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_2 \end{bmatrix}$$

such that $\mathbf{A}_1\mathbf{A}_1^T = \mathbf{\Sigma}_{11}$, $\mathbf{A}_2\mathbf{A}_2^T = \mathbf{\Sigma}_{22}$

Zero Covariance Implies Independence

Assume $\mathbf{\Sigma}_{12} = \mathbf{0}$

Proof

- Choose an
$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_2 \end{bmatrix}$$
such that $\mathbf{A}_1\mathbf{A}_1^T = \mathbf{\Sigma}_{11}$, $\mathbf{A}_2\mathbf{A}_2^T = \mathbf{\Sigma}_{22}$
- Partition
$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_1 \\ \mathbf{Z}_2 \end{bmatrix} \sim \mathrm{N}\left(\begin{bmatrix} \mathbf{0}_1 \\ \mathbf{0}_2 \end{bmatrix}, \begin{bmatrix} \mathbf{I}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_2 \end{bmatrix} \right) \text{ and } \boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}$$

Zero Covariance Implies Independence

Assume $\mathbf{\Sigma}_{12} = \mathbf{0}$

Proof

- Choose an
$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_2 \end{bmatrix}$$
such that $\mathbf{A}_1\mathbf{A}_1^T = \mathbf{\Sigma}_{11}$, $\mathbf{A}_2\mathbf{A}_2^T = \mathbf{\Sigma}_{22}$
- Partition
$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_1 \\ \mathbf{Z}_2 \end{bmatrix} \sim \mathsf{N}\left(\begin{bmatrix} \mathbf{0}_1 \\ \mathbf{0}_2 \end{bmatrix}, \begin{bmatrix} \mathbf{I}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_2 \end{bmatrix} \right) \text{ and } \boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}$$
- then $\mathbf{Y} \stackrel{\mathrm{D}}{=} \mathbf{A}\mathbf{Z} + \boldsymbol{\mu} \sim \mathsf{N}(\boldsymbol{\mu}, \mathbf{\Sigma})$

Continued

Proof.

- $$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \stackrel{\mathrm{D}}{=} \begin{bmatrix} \mathbf{A}_1 \mathbf{Z}_1 + \boldsymbol{\mu}_1 \\ \mathbf{A}_2 \mathbf{Z}_2 + \boldsymbol{\mu}_2 \end{bmatrix}$$

Continued

Proof.

- $$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \stackrel{\mathrm{D}}{=} \begin{bmatrix} \mathbf{A}_1\mathbf{Z}_1 + \boldsymbol{\mu}_1 \\ \mathbf{A}_2\mathbf{Z}_2 + \boldsymbol{\mu}_2 \end{bmatrix}$$
- But $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent

Continued

Proof.

- $$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \stackrel{\mathrm{D}}{=} \begin{bmatrix} \mathbf{A}_1\mathbf{Z}_1 + \boldsymbol{\mu}_1 \\ \mathbf{A}_2\mathbf{Z}_2 + \boldsymbol{\mu}_2 \end{bmatrix}$$
- But $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent
- Functions of $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent

Continued

Proof.

- $$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \stackrel{\mathrm{D}}{=} \begin{bmatrix} \mathbf{A}_1\mathbf{Z}_1 + \boldsymbol{\mu}_1 \\ \mathbf{A}_2\mathbf{Z}_2 + \boldsymbol{\mu}_2 \end{bmatrix}$$
- But $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent
- Functions of $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent
- Therefore $\mathbf{Y}_1$ and $\mathbf{Y}_2$ are independent

Continued

Proof.

- $$\begin{bmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{bmatrix} \stackrel{D}{=} \begin{bmatrix} \mathbf{A}_1\mathbf{Z}_1 + \boldsymbol{\mu}_1 \\ \mathbf{A}_2\mathbf{Z}_2 + \boldsymbol{\mu}_2 \end{bmatrix}$$
- But $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent
- Functions of $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are independent
- Therefore $\mathbf{Y}_1$ and $\mathbf{Y}_2$ are independent

□

For Multivariate Normal Zero Covariance implies independence

Another Useful Result

Corollary

If $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *and* $\mathbf{A}\mathbf{B}^T = \mathbf{0}$ *then* $\mathbf{AY}$ *and* $\mathbf{BY}$ *are independent.*

Another Useful Result

Corollary

If $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ and $\mathbf{A}\mathbf{B}^T = \mathbf{0}$ then $\mathbf{AY}$ and $\mathbf{BY}$ are independent.

Proof.

- $$\begin{bmatrix} \mathbf{W}_1 \\ \mathbf{W}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{A} \\ \mathbf{B} \end{bmatrix} \mathbf{Y} = \begin{bmatrix} \mathbf{AY} \\ \mathbf{BY} \end{bmatrix}$$

Another Useful Result

Corollary

If $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *and* $\mathbf{A}\mathbf{B}^T = \mathbf{0}$ *then* $\mathbf{AY}$ *and* $\mathbf{BY}$ *are independent.*

Proof.

- $$\begin{bmatrix} \mathbf{W}_1 \\ \mathbf{W}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{A} \\ \mathbf{B} \end{bmatrix} \mathbf{Y} = \begin{bmatrix} \mathbf{AY} \\ \mathbf{BY} \end{bmatrix}$$
- $\textsf{Cov}(\mathbf{W}_1, \mathbf{W}_2) = \textsf{Cov}(\mathbf{AY}, \mathbf{BY}) = \sigma^2 \mathbf{A}\mathbf{B}^T$

Another Useful Result

Corollary

If $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ and $\mathbf{A}\mathbf{B}^T = \mathbf{0}$ then $\mathbf{AY}$ and $\mathbf{BY}$ are independent.

Proof.

- $$\begin{bmatrix} \mathbf{W}_1 \\ \mathbf{W}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{A} \\ \mathbf{B} \end{bmatrix} \mathbf{Y} = \begin{bmatrix} \mathbf{AY} \\ \mathbf{BY} \end{bmatrix}$$
- $\textsf{Cov}(\mathbf{W}_1, \mathbf{W}_2) = \textsf{Cov}(\mathbf{AY}, \mathbf{BY}) = \sigma^2 \mathbf{A}\mathbf{B}^T$
- $\mathbf{AY}$ and $\mathbf{BY}$ are independent if $\mathbf{A}\mathbf{B}^T = \mathbf{0}$

$\square$

Sampling Distribution of β

If $\mathbf{Y} \sim \mathrm{N}(\mathbf{X}\beta, \sigma^2 \mathbf{I}_n)$
Then $\hat{\beta} \sim \mathrm{N}(\beta, \sigma^2(\mathbf{X}^T\mathbf{X})^{-1})$

Unknown σ^2

$$\hat{\beta}_j \mid \beta_j, \sigma^2 \sim \mathsf{N}(\beta, \sigma^2[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj})$$

Unknown σ^2

$$\hat{\beta}_j \mid \beta_j, \sigma^2 \sim \mathsf{N}(\beta, \sigma^2[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj})$$

What happens if we substitute $\hat{\sigma}^2 = \mathbf{e}^t\mathbf{e}/(n - r(\mathbf{X}))$ in the above?

Unknown σ^2

$$\hat{\beta}_j \mid \beta_j, \sigma^2 \sim \mathsf{N}(\beta, \sigma^2[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj})$$

What happens if we substitute $\hat{\sigma}^2 = \mathbf{e}^t\mathbf{e}/(n - r(\mathbf{X}))$ in the above?

$$\frac{(\hat{\beta}_j - \beta_j)/\sigma\sqrt{[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj}}}{\sqrt{\mathbf{e}^T\mathbf{e}/(\sigma^2(n - r(\mathbf{X}))}} \stackrel{\mathrm{D}}{=} \frac{N(0,1)}{\sqrt{\chi^2_{n-r(\mathbf{X})}/(n - r(\mathbf{X})}} \sim t(n - r(\mathbf{X}), 0, 1)$$

Need to show that $\mathbf{e}^T\mathbf{e}/\sigma^2$ has a χ^2 distribution and is independent of the numerator!

Central Student t Distribution

Definition

Let $Z \sim \mathrm{N}(0, 1)$ and $S \sim \chi^2_p$ with Z and S independent,

Central Student t Distribution

Definition

Let $Z \sim \mathsf{N}(0, 1)$ and $S \sim \chi^2_p$ with Z and S independent, then

$$W = \frac{Z}{\sqrt{S/p}}$$

has a (central) Student t distribution with p degrees of freedom

Central Student t Distribution

Definition

Let $Z \sim \mathrm{N}(0,1)$ and $S \sim \chi^2_p$ with Z and S independent, then

$$W = \frac{Z}{\sqrt{S/p}}$$

has a (central) Student t distribution with p degrees of freedom

See Casella & Berger or DeGroot & Schervish for derivation - nice change of variables and marginalization problem!

Chi-Squared Distribution

Definition

If $Z \sim \mathrm{N}(0, 1)$ then $Z^2 \sim \chi^2_1$ (A Chi-squared distribution with one degree of freedom)

Chi-Squared Distribution

Definition

If $Z \sim \mathrm{N}(0,1)$ then $Z^2 \sim \chi^2_1$ (A Chi-squared distribution with one degree of freedom)

- Density

$$f(x) = \frac{1}{\Gamma(1/2)}(1/2)^{-1/2} x^{1/2-1} e^{-x/2} \qquad x > 0$$

Chi-Squared Distribution

Definition

If $Z \sim \mathrm{N}(0,1)$ then $Z^2 \sim \chi^2_1$ (A Chi-squared distribution with one degree of freedom)

- Density

$$f(x) = \frac{1}{\Gamma(1/2)}(1/2)^{-1/2}x^{1/2-1}e^{-x/2} \qquad x > 0$$

- Characteristic Function

$$\mathrm{E}[e^{itZ^2}] = \varphi(t) = (1-2it)^{-1/2}$$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \overset{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \overset{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Characteristic Function

$$\varphi_X(t) = \mathsf{E}[e^{it\sum_j^p Z_j^2}]$$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \stackrel{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Characteristic Function

$$
\begin{aligned}
\varphi_X(t) &= \mathsf{E}[e^{it\sum_j^p Z_j^2}] \\
&= \prod_{j=1}^{p} \mathsf{E}[e^{itZ_j^2}]
\end{aligned}
$$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \overset{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Characteristic Function

$$
\begin{aligned}
\varphi_X(t) &= \mathsf{E}[e^{it\sum_j^p Z_j^2}] \\
&= \prod_{j=1}^{p} \mathsf{E}[e^{itZ_j^2}] \\
&= \prod_{j=1}^{p} (1-2it)^{-1/2}
\end{aligned}
$$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \stackrel{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Characteristic Function

$$\begin{aligned}
\varphi_X(t) &= \mathsf{E}[e^{it\sum_j^p Z_j^2}] \\
&= \prod_{j=1}^p \mathsf{E}[e^{itZ_j^2}] \\
&= \prod_{j=1}^p (1-2it)^{-1/2} \\
&= (1-2it)^{-p/2}
\end{aligned}$$

Chi-Squared Distribution with p Degrees of Freedom

If $Z_j \overset{\text{iid}}{\sim} \mathsf{N}(0,1)$ $j = 1, \ldots p$ then $X \equiv \mathbf{Z}^T\mathbf{Z} = \sum_j^p Z_j^2 \sim \chi^2_p$

Characteristic Function

$$
\begin{aligned}
\varphi_X(t) &= \mathsf{E}[e^{it\sum_j^p Z_j^2}] \\
&= \prod_{j=1}^p \mathsf{E}[e^{itZ_j^2}] \\
&= \prod_{j=1}^p (1-2it)^{-1/2} \\
&= (1-2it)^{-p/2}
\end{aligned}
$$

A Gamma distribution with shape $p/2$ and rate $1/2$, $G(p/2, 1/2)$

$$
f(x) = \frac{1}{\Gamma(p/2)}(1/2)^{-p/2} x^{p/2-1} e^{-x/2} \qquad x > 0
$$

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *with* $\boldsymbol{\mu} \in C(\mathbf{X})$ *then if* $\mathbf{Q}$ *is a rank* k *orthogonal projection on to* $C(\mathbf{X})^\perp$, $(\mathbf{Y}^T \mathbf{Q} \mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U} \boldsymbol{\Lambda} \mathbf{U}^T = \mathbf{U}_k \mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T \mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *with* $\boldsymbol{\mu} \in C(\mathbf{X})$ *then if* $\mathbf{Q}$ *is a rank* k *orthogonal projection on to* $C(\mathbf{X})^\perp$, $(\mathbf{Y}^T \mathbf{Q} \mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U} \boldsymbol{\Lambda} \mathbf{U}^T = \mathbf{U}_k \mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T \mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

$$\mathbf{Y}^T \mathbf{Q} \mathbf{Y} = \mathbf{Y}^T \mathbf{U}_k \mathbf{U}_k^T \mathbf{Y}$$

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ with $\boldsymbol{\mu} \in C(\mathbf{X})$ then if $\mathbf{Q}$ is a rank k orthogonal projection on to $C(\mathbf{X})^\perp$, $(\mathbf{Y}^T\mathbf{Q}\mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^T = \mathbf{U}_k\mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T\mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

$$\begin{aligned}
\mathbf{Y}^T\mathbf{Q}\mathbf{Y} &= \mathbf{Y}^T\mathbf{U}_k\mathbf{U}_k^T\mathbf{Y} \\
\mathbf{Z} &= \mathbf{U}_k^T\mathbf{Y}/\sigma \sim \mathrm{N}(\mathbf{U}_k^T\boldsymbol{\mu}, \mathbf{U}_k^T\mathbf{U}_k)
\end{aligned}$$

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *with* $\boldsymbol{\mu} \in C(\mathbf{X})$ *then if* $\mathbf{Q}$ *is a rank* k *orthogonal projection on to* $C(\mathbf{X})^\perp$, $(\mathbf{Y}^T \mathbf{Q} \mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U} \boldsymbol{\Lambda} \mathbf{U}^T = \mathbf{U}_k \mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T \mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

$$
\begin{aligned}
\mathbf{Y}^T \mathbf{Q} \mathbf{Y} &= \mathbf{Y}^T \mathbf{U}_k \mathbf{U}_k^T \mathbf{Y} \\
\mathbf{Z} &= \mathbf{U}_k^T \mathbf{Y}/\sigma \sim \mathrm{N}(\mathbf{U}_k^T \boldsymbol{\mu}, \mathbf{U}_k^T \mathbf{U}_k) \\
\mathbf{Z} &\sim \mathrm{N}(\mathbf{0}, \mathbf{I}_k)
\end{aligned}
$$

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ *with* $\boldsymbol{\mu} \in C(\mathbf{X})$ *then if* $\mathbf{Q}$ *is a rank* k *orthogonal projection on to* $C(\mathbf{X})^{\perp}$, $(\mathbf{Y}^T \mathbf{Q} \mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U} \boldsymbol{\Lambda} \mathbf{U}^T = \mathbf{U}_k \mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T \mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

$$
\begin{aligned}
\mathbf{Y}^T \mathbf{Q} \mathbf{Y} &= \mathbf{Y}^T \mathbf{U}_k \mathbf{U}_k^T \mathbf{Y} \\
\mathbf{Z} &= \mathbf{U}_k^T \mathbf{Y}/\sigma \sim \mathrm{N}(\mathbf{U}_k^T \boldsymbol{\mu}, \mathbf{U}_k^T \mathbf{U}_k) \\
\mathbf{Z} &\sim \mathrm{N}(\mathbf{0}, \mathbf{I}_k) \\
\mathbf{Z}^T \mathbf{Z} &\sim \chi^2_k
\end{aligned}
$$

Quadratic Forms

Theorem

Let $\mathbf{Y} \sim N(\boldsymbol{\mu}, \sigma^2\mathbf{I}_n)$ with $\boldsymbol{\mu} \in C(\mathbf{X})$ then if $\mathbf{Q}$ is a rank k orthogonal projection on to $C(\mathbf{X})^\perp$, $(\mathbf{Y}^T\mathbf{Q}\mathbf{Y})/\sigma^2 \sim \chi^2_k$

Proof.

For an orthogonal projection $\mathbf{Q} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^T = \mathbf{U}_k\mathbf{U}_k^T$ where $C(\mathbf{Q}) = C(\mathbf{U}_k)$ and $\mathbf{U}_k^T\mathbf{U}_k = \mathbf{I}_k$ (Spectral Theorem)

$$\begin{aligned}
\mathbf{Y}^T\mathbf{Q}\mathbf{Y} &= \mathbf{Y}^T\mathbf{U}_k\mathbf{U}_k^T\mathbf{Y} \\
\mathbf{Z} &= \mathbf{U}_k^T\mathbf{Y}/\sigma \sim \mathrm{N}(\mathbf{U}_k^T\boldsymbol{\mu}, \mathbf{U}_k^T\mathbf{U}_k) \\
\mathbf{Z} &\sim \mathrm{N}(\mathbf{0}, \mathbf{I}_k) \\
\mathbf{Z}^T\mathbf{Z} &\sim \chi^2_k
\end{aligned}$$

Since $U^T\mathbf{Y}/\sigma \overset{\mathrm{D}}{=} \mathbf{Z}$, $\frac{\mathbf{Y}^T\mathbf{Q}\mathbf{Y}}{\sigma^2} \sim \chi^2_k$ $\square$

Residual Sum of Squares Example

Sum of Squares Error (SSE)

Let $\mathbf{Y} \sim \mathrm{N}(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ with $\boldsymbol{\mu} \in C(\mathbf{X})$.
Because $\boldsymbol{\mu} \in C(\mathbf{X})$, $\mathbf{I} - \mathbf{P}_{\mathbf{X}}$ is a projection on $C(\mathbf{X})^{\perp}$

Residual Sum of Squares Example

Sum of Squares Error (SSE)

Let $\mathbf{Y} \sim \mathrm{N}(\boldsymbol{\mu}, \sigma^2 \mathbf{I}_n)$ with $\boldsymbol{\mu} \in C(\mathbf{X})$.
Because $\boldsymbol{\mu} \in C(\mathbf{X})$, $\mathbf{I} - \mathbf{P_X}$ is a projection on $C(\mathbf{X})^{\perp}$

$$\frac{\mathbf{e}^T \mathbf{e}}{\sigma^2} = \mathbf{Y}^T \frac{(\mathbf{I}_n - \mathbf{P_X})}{\sigma}^2 \mathbf{Y} \sim \chi^2_{n-r(\mathbf{X})}$$

Estimated Coefficients and Residuals are Independent

If $\mathbf{Y} \sim \mathrm{N}(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I}_n)$
Then $\mathrm{Cov}(\hat{\boldsymbol{\beta}}, \mathbf{e}) = \mathbf{0}$ which implies independence

Functions of independent random variables are independent (show characteristic functions or densities factor)

Putting it all together

$\hat{\boldsymbol{\beta}} \sim \mathrm{N}(\boldsymbol{\beta}, \sigma^2(\mathbf{X}^T\mathbf{X})^{-1})$

- $(\hat{\beta}_j - \beta_j)/\sigma[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj} \sim \mathrm{N}(0, 1)$
- $\mathbf{e}^T\mathbf{e}/\sigma^2 \sim \chi^2_{n-r(\mathbf{X})}$
- $\hat{\beta}$ and $\mathbf{e}$ are independent

$$\frac{(\hat{\beta}_j - \beta_j)/\sigma[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj}}{\sqrt{\mathbf{e}^T\mathbf{e}/(\sigma^2(n - r(\mathbf{X}))}} \sim t(n - r(\mathbf{X}), 0, 1)$$

Inference

- 95% Confidence interval: $\hat{\beta}_j \pm t_{\alpha/2} \mathrm{SE}(\hat{\beta}_j)$

Inference

- 95% Confidence interval: $\hat{\beta}_j \pm t_{\alpha/2}\text{SE}(\hat{\beta}_j)$ use `qt(a, df)` for t_a quantile
- derive from pivotal quantity $t = (\hat{\beta}_j - \beta_j)/\text{SE}(\hat{\beta}_j)$ where $P(t \in (t_{\alpha/2}, t_{1-\alpha/2})) = 1 - \alpha$

Prostate Example

`xtable(confint(prostate.lm))` from library(MASS) and library(xtable)

	2.5 %	97.5 %
(Intercept)	-1.91	3.25
lcavol	0.41	0.76
lweight	0.12	0.79
age	-0.04	0.00
lbph	-0.01	0.22
svi	0.28	1.25
lcp	-0.29	0.08
gleason	-0.27	0.36
pgg45	-0.00	0.01

interpretation

- For a "1" unit increase in $\mathbf{X}_j$, expect $\mathbf{Y}$ to increase by $\hat{\beta}_j \pm t_{\alpha/2}\mathrm{SE}(\hat{\beta}_j)$
- for log transforms

$$\mathbf{Y} = \exp(\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}) = \prod \exp(\mathbf{X}_j \beta_j) \exp(\boldsymbol{\epsilon})$$

- if $\mathbf{X} = \log(\mathbf{W}_j)$ then look at 2-fold or % increases in $\mathbf{W}$ to look at multiplicative increase in median of $\mathbf{Y}$
- if `cavol` increases by 10% then we expect `PSA` to increase by $1.10^{(CI)} = (1.0398\%, 1.0751\%)$ or by 3.98 to 7.51 percent

For a 10% increase in cancer volume, we are 95% confident that the PSA levels will increase by approximately 4 to 7.5 percent.

Derivation