Sampling Distributions

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STA721 Linear Models

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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 $r(\mathbf{X}) = p + 1$

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

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

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

where $\mathsf{SE}(\hat{\beta})$ 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

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

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

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

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

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, 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!

Fitted Values and Residuals are Independent

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

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

Characteristic Function

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

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

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 $\boldsymbol{\mu} \in C(\mathbf{X})$, $\mathbf{I} - \mathrm{P}_{\mathbf{X}}$ is a projection on $C(\mathbf{X})^{\perp}$

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

Putting it all together

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

- $(\hat{\beta}_j - \beta_j)/\sigma[(\mathbf{X}^T\mathbf{X})^{-1}]_{jj} \sim \mathsf{N}(0, 1)$
- $\mathbf{e}^T\mathbf{e}/\sigma^2 \sim \chi^2_{n-r(\mathbf{X})}$
- $\hat{\beta}$ 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: $\hat{\beta}_j \pm t_{\alpha/2}\text{SE}(\hat{\beta}_j$ use `qt(a, df)` for t quantile
- derive from pivotal quantity $t = (\hat{\beta}_j - \beta_j)/\text{SE}(\hat{\beta}_j)$ where $P(t \in (t_{\alpha/2}, t_{1-\alpha/2})) = \alpha$

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 $\hat{\beta}_j \pm t_{\alpha/2}\text{SE}(\hat{\beta}_j$
- for log transforms

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

- if $\mathbf{X}$ is logged $\mathbf{X}_j = \log(|W_j)$ then look at 2-fold or % increases in $\mathbf{W}$
- 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%

Derivation