## An Introduction to Linear Models

## Models

- Concept of a Model Equation
- Other aspects of the model
- Expected values, location parameters or first moments
- Second moments or variance-covariance
- Distributional assumptions


## Simple Models

- Performance = Breeding + Feeding
- Phenotype = Genotype + Environment
- Animal Model - model equation

$$
\begin{aligned}
& y=\text { herd }- \text { year }- \text { season }+B V+e \\
& y=X b+Z u+e
\end{aligned}
$$

The "usual" Animal Model

$\left.\operatorname{var}[u]=G=A \sigma_{g}^{2} \operatorname{var}[e]=R=I \sigma_{e}^{2} \operatorname{cov}\left[u, e^{\prime}\right]=0\right]$ $\operatorname{var}[y]=V=Z G Z^{\prime}+R$
3. Dispersion Parameters $]$
$y \sim M V N[X b, V]\}$

Fixed Effects - Linear Regression

$$
\begin{aligned}
& y=X b+e \\
& E[e]=0
\end{aligned}
$$

$$
\operatorname{var}[e]=R=I \sigma_{e}^{2}
$$

Perhaps assume $\quad e \sim N\left[0, I \sigma_{e}^{2}\right]$

$$
e_{i} \stackrel{i i d}{\sim} N\left[0, \sigma_{e}^{2}\right]
$$

## Simple Linear Regression

$$
\begin{aligned}
& y=X b+e \\
& b=\left[\begin{array}{l}
\alpha \\
\beta
\end{array}\right]=\left[\begin{array}{c}
\text { intercept } \\
\text { slope }
\end{array}\right] \\
& X=\left[\begin{array}{cc}
1 & x_{1} \\
1 & x_{2} \\
\vdots & \vdots \\
1 & x_{n}
\end{array}\right]
\end{aligned}
$$

## Multiple Linear Regression

$$
\begin{gathered}
y=X b+e \\
b=\left[\begin{array}{c}
\alpha \\
\beta_{1} \\
\vdots \\
\beta_{k}
\end{array}\right]=\left[\begin{array}{c}
\text { intercept } \\
\text { slope }_{1} \\
\vdots \\
\text { slope }_{k}
\end{array}\right] \\
X=\left[\begin{array}{ccccc}
1 & x_{11} & x_{12} & \cdots & x_{1 k} \\
1 & x_{21} & x_{22} & \cdots & x_{2 k} \\
\vdots & \vdots & \vdots & & \vdots \\
1 & x_{n 1} & x_{n 2} & \cdots & x_{n k}
\end{array}\right]
\end{gathered}
$$

$$
\begin{aligned}
& \text { Estimation } \\
& \text { If } \\
& y=X b+e \\
& \text { then } \\
& K^{\prime} y=K^{\prime} X b+K^{\prime} e \\
& \text { for example, choosing } K^{\prime}=X^{\prime} \\
& X^{\prime} y=X^{\prime} X b+X^{\prime} e \\
& \text { and if } X^{\prime} y=X^{\prime} X b \text { then } X^{\prime} e=0 \\
& \text { so } b \text { is solution to } X^{\prime} X b=X^{\prime} y
\end{aligned}
$$

## Linear Regression

- Linear Regression

$$
y=X b+e
$$

- Residual

$$
e=y-X b \text {, with } E[e]=0, \text { and } \operatorname{var}[e]=I \sigma_{e}^{2}
$$

- Residual Sum of Squares

$$
\begin{aligned}
e^{\prime} e & =(y-X b)^{\prime}(y-X b) \\
& =y^{\prime} y-y^{\prime} X b-b^{\prime} X^{\prime} y+b^{\prime} X^{\prime} X b
\end{aligned}
$$

## Least Squares

- Residual Sum of Squares

$$
e^{\prime} e=y^{\prime} y-y^{\prime} X b-b^{\prime} X^{\prime} y+b^{\prime} X^{\prime} X b
$$

- Take derivatives with respect to vector $b$ $d e^{\prime} e / d b=-X^{\prime} y-X^{\prime} y+\left(X^{\prime} X+\left(X^{\prime} X\right)^{\prime}\right) b$ set $=0$ and solve to find minima/maxima gives $X^{\prime} X b=X^{\prime} y$
known as the Least Squares Equations or the Normal Equations


## Estimation

$$
\begin{aligned}
& \widehat{b} \text { is solution to } X^{\prime} X b=X^{\prime} y \\
& \text { which for full rank } X \text { is } \widehat{b}=\left[X^{\prime} X\right]^{-1} X^{\prime} y \\
& E[\widehat{b}]=E\left[\left[X^{\prime} X\right]^{-1} X^{\prime} y\right] \\
&=\left[X^{\prime} X\right]^{-1} X^{\prime} E[y] \\
&=\left[X^{\prime} X\right]^{-1} X^{\prime} X b=b \\
& \operatorname{var}[\widehat{b}]=\operatorname{var}\left[\left[X^{\prime} X\right]^{-1} X^{\prime} y\right] \\
&=\left[X^{\prime} X\right]^{-1} X^{\prime} \operatorname{var}[y] X\left[X^{\prime} X\right]^{-1} \\
&=\left[X^{\prime} X\right]^{-1} X^{\prime} I \sigma_{e}^{2} X\left[X^{\prime} X\right]^{-1} \\
&=\left[X^{\prime} X\right]^{-1} X^{\prime} X\left[X^{\prime} X\right]^{-1} \sigma_{e}^{2} \\
&=\left[X^{\prime} X\right]^{-1} \sigma_{e}^{2}
\end{aligned}
$$

## Linear functions of $b$

$k^{\prime} b$ is estimated from $k^{\prime} \hat{b}$ with var $\left[k^{\prime} \widehat{b}\right]=k^{\prime}\left[X^{\prime} X\right]^{-1} k \sigma_{e}^{2}$

## X not full rank

$k^{\prime} b$ is estimated from $k^{\prime} \widehat{b}$ with $\operatorname{var}\left[k^{\prime} \widehat{b}\right]=k^{\prime}\left[X^{\prime} X\right]^{-} k \sigma_{e}^{2}$ provided $k^{\prime}=k^{\prime}\left[X^{\prime} X\right]^{-} X^{\prime} X$
rows of $k^{\prime}$ can be stacked in a matrix $K$ vector $K b$ is estimated from $K \widehat{b}$ with var $-\operatorname{cov}[K \widehat{b}]=K\left[X^{\prime} X\right]^{-} K^{\prime} \sigma_{e}^{2}$ provided $K=K\left[X^{\prime} X\right]^{-} X^{\prime} X$

## Residual Standard Error

$$
\begin{aligned}
& \widehat{\sigma_{e}^{2}}=M S_{\text {ERROR }}=S S_{\text {ERROR }} / d f \\
& \quad=(y-X \widehat{b})^{\prime}(y-X \widehat{b}) /(N-\operatorname{rank}(X)) \\
& S S_{\text {ERROR }}=S S_{\text {TOOAL }}-S S_{\text {MODEL }} \\
& =y^{\prime} y-\widehat{b^{\prime}} X^{\prime} y \\
& R^{2}=S S_{\text {MODEL/MEAN }} / S S_{\text {TOTAL/MEAN }} \\
& S S_{\text {MODEL/MEAN }}=S S_{\text {MODEL }}-S S_{\text {MEAN }} \\
& S S_{\text {MEAN }}=N \bar{y}^{2} \\
& S S_{\text {TOTAL/MEAN }}=S S_{\text {TOTAL }}-S S_{\text {MEAN }} \\
& =y^{\prime} y-N \bar{y}^{2}
\end{aligned}
$$

## Generalized LeastSquares

$$
\begin{aligned}
& y=X b+(Z u+e) \\
& \quad=X b+\varepsilon \\
& \text { var }[y]=V=Z G Z '+R \\
& \widehat{b} \text { is solution to } X^{\prime} V^{-1} X b=X^{\prime} V^{-1} y
\end{aligned}
$$

## Weighted Least Squares

$y=X b+e$
$\operatorname{var}[e]=R=D=\operatorname{diag}\left(\sigma_{e_{e}}^{2}\right)$
$\widehat{b}$ is solution to $X^{\prime} D^{-1} X b=X^{\prime} D^{-1} y$

## Hypothesis Testing

- To test hypotheses we need to know the distribution of the test statistic
- Which is derived from the distribution of the residuals
- Commonly assumed to be normally (iid) distributed


## Linear Regression

1. Least Squares simple linear regression (unknown $\beta_{0}$ and $\beta_{1}$ )
2. Gibbs Sampler with known $\sigma_{\mathrm{e}}{ }^{2}$
3. Bayesian Gibbs sampler with unknown $\sigma_{\mathrm{e}}{ }^{2}$
4. As above but with random not fixed $\beta_{1}$
5. Bayesian (multiple) linear regression (many random $\beta^{\prime}$ 's)
6. Various models (BLUP, BayesA, B, C, C $\pi$ etc)
