MONASH University

MONASH BUSINESS SCHOOL

ETC3580: Advanced Statistical Modelling

Week 6: Generalized Linear Models

Outline

Exponential family distributions

$$f(y|\theta,\phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right]$$

- θ is canonical parameter for location
- ϕ is dispersion parameter for scale
- a, b and c are functions.

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- a, b and c are functions.

Example: Normal

$$f(y|\theta,\phi) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(y-\mu)^2}{2\sigma^2}\right]$$

$\theta = \mu \quad \phi = \sigma^2 \quad a(\phi) = \phi \quad b(\theta) = \theta^2/2$

$c(y,\phi) = -(y^2/\phi + \log(2\pi\phi))/2$

Exponential family distributions

$$f(y|\theta, \phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi)\right]$$

- θ is canonical parameter for location
- ϕ is dispersion parameter for scale
- a, b and c are functions.

Example: Poisson

$$f(y|\theta, \phi) = e^{-\mu}\mu^y/y!$$

What are θ, ϕ, a, b and c?

Exponential family distributions

$$f(y|\theta, \phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi)\right]$$

- θ is canonical parameter for location
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- a, b and c are functions.

Example: Binomial

$$f(y|\theta, \phi) = \binom{m}{y} p^y (1 - p)^{m-y}$$

What are θ, ϕ, a, b and c?

Exponential family distributions

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- θ is canonical parameter for location
- ϕ is dispersion parameter for scale
- a, b and c are functions.

Examples: Normal, Poisson, Binomial, gamma, inverse Gaussian

Moments

1. Mean: $b'(\theta)$
2. Variance: $b''(\theta)a(\phi)$

Some likelihood theory

Let Y have a distribution with parameter θ and let $\ell(\theta)$ denote the likelihood of Y.

$$\mathrm{E}[\ell'(\theta)] = 0$$

$$\mathrm{E}[\ell''(\theta)] = -\mathrm{E}[(\ell'(\theta))^2]$$

Exponential family distributions

$$f(y|\theta,\phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right]$$

Let $\ell(\theta)$ = log-likelihood of single y.

$$\begin{aligned}
\ell(\theta) &= [y\theta - b(\theta)]/a(\phi) + c(y,\phi) \\
\ell'(\theta) &= [y - b'(\theta)]/a(\phi) \\
\mathrm{E}[\ell'(\theta)] &= [\mathrm{E}(y) - b'(\theta)]/a(\phi) \\
\mathrm{E}[\ell'(\theta)] &= 0 \\
\text{So} \qquad \mathrm{E}(y) &= b'(\theta)
\end{aligned}$$

Exponential family distributions

$$\begin{aligned}
\ell'(\theta) &= [y - b'(\theta)]/a(\phi) \\
\ell''(\theta) &= -b''(\theta)/a(\phi) \\
\mathrm{E}[\ell''(\theta)] &= -b''(\theta)/a(\phi) \\
\mathrm{E}[(\ell'(\theta))^2] &= \mathrm{E}[(y - b'(\theta))^2]/a^2(\phi) \\
\text{So} \qquad - b''(\theta)/a(\phi) &- \mathrm{E}[(y - b'(\theta))^2]/a^2(\phi) \\
\text{and} \qquad \mathrm{Var}(y) &= b''(\theta)a(\phi)
\end{aligned}$$

Outline

Generalized Linear Models

A GLM consists of three components:

1. Distribution (from the exponential family of distributions)
2. Linear predictors
3. Link function

Link functions

- The predictors are assumed to affect the response through a linear relationship.
- The link function g “links” the mean to the linear predictors.

$$g(\mu) = \beta_0 + \beta_1 x_1 + \cdots + \beta_q x_q$$

Link functions

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- The link function g "links" the mean to the linear predictors.

$$g(\mu) = \beta_0 + \beta_1 x_1 + \cdots + \beta_q x_q$$

- g must be monotone, continuous and differentiable.
- g must map the space of μ to $\mathbb{R}$.
- Canonical link has $g(\mu) = \theta$, so that $g(b'(\theta)) = \theta$.

Link functions

Family	Canonical link	Variance
Normal	μ	1
Poisson	$\log\mu$	μ
Binomial	$\log(\mu/(1-\mu))$	$\mu(1-\mu)$
Gamma	$1/\mu$	μ^2
Inverse Gaussian	$1/\mu^2$	μ^3

- Canonicial link means $\boldsymbol{X}'\boldsymbol{y}$ is *sufficient*.
- Also makes estimation easier.

Log Likelihood

$$f(y|\theta, \phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi)\right]$$

Log Likelihood

$$f(y|\theta,\phi) = \exp\left[\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right]$$

$$\begin{aligned}\ell(\beta;\mathbf{y}) = \log L(\beta;\mathbf{y}) &= \sum_{i=1}^{n}\left[\frac{y_i\theta_i - b(\theta_i)}{a(\phi)} + c(y_i,\phi)\right] \\ &= \frac{1}{a(\phi)}\sum_{i=1}^{n}[y_i\theta_i - b(\theta_i) + c(y_i,\phi)a(\phi)]\end{aligned}$$

Log Likelihood

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&= \frac{1}{a(\phi)}\sum_{i=1}^{n}\left[y_i\theta_i - b(\theta_i) + c(y_i, \phi)a(\phi)\right]
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \ell(\beta; \mathbf{y})}{\partial \beta_j} &= \frac{1}{a(\phi)}\sum_{i=1}^{n}\frac{\partial}{\partial \beta_j}\left[y_i\theta_i - b(\theta_i)\right] \\
&= \frac{1}{a(\phi)}\sum_{i=1}^{n}\left[y_i\frac{\partial \theta_i}{\partial \beta_j} - \frac{\partial b(\theta_i)}{\partial \beta_j}\right]
\end{aligned}$$

Log Likelihood

Now

$$\frac{\partial b(\theta)}{\partial \beta_j} = b'(\theta)\frac{\partial \theta}{\partial \beta_j} \qquad \text{and} \qquad \frac{\partial \theta}{\partial \beta_j} = \frac{\partial \theta}{\partial \mu}\frac{\partial \mu}{\partial \beta_j} = \frac{1}{b''(\theta)}\frac{\partial \mu}{\partial \beta_j}$$

Therefore

$$\begin{aligned}
\frac{\partial \ell(\boldsymbol{\beta}; \mathbf{y})}{\partial \beta_j} &= \frac{1}{a(\phi)}\sum_{i=1}^{n}\left[y_i \frac{1}{b''(\theta_i)}\frac{\partial \mu_i}{\partial \beta_j} - \frac{b'(\theta_i)}{b''(\theta_i)}\frac{\partial \mu_i}{\partial \beta_j}\right] \\
&= \frac{1}{a(\phi)}\sum_{i=1}^{n}\left[\frac{y_i - b'(\theta_i)}{b''(\theta_i)}\right]\frac{\partial \mu_i}{\partial \beta_j} \\
&= \sum_{i=1}^{n}\left[\frac{y_i - \mu_i}{V(\mu_i)}\right]\frac{\partial \mu_i}{\partial \beta_j}
\end{aligned}$$

Maximum likelihood estimation

Maximum likelihood estimates:

$$\sum_{i=1}^{n} \left[\frac{y_i - b'(\theta_i)}{V(\mu_i)} \right] \frac{\partial \mu_i}{\partial \beta_j} = 0 \qquad \text{for all } j$$

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Same equations as for weighted least squares with known $V(\mu)$:

$$\text{Minimize} \qquad \sum_{i=1}^{n} \left[\frac{(y_i - \mu_i)^2}{V(\mu_i)} \right]$$

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Same equations as for weighted least squares with known $V(\mu)$:

$$\text{Minimize} \qquad \sum_{i=1}^{n} \left[\frac{(y_i - \mu_i)^2}{V(\mu_i)} \right]$$

- When $V(\mu)$ is constant, OLS = MLE
- We can guess μ, and use iterated WLS to solve.
- Distribution not used, only $g(\mu)$ and $V(\mu)$.
- So same equations work for quasi-likelihood

Implementation in R

```r
fit <- glm(y ~ x1 + x2, family, data)
```

family options

```r
binomial(link = "logit")
gaussian(link = "identity")
Gamma(link = "inverse")
inverse.gaussian(link = "1/mu^2")
poisson(link = "log")
quasi(link = "identity", variance = "constant")
quasibinomial(link = "logit")
quasipoisson(link = "log")
```

Implementation in R

```
fit <- glm(y ~ x1 + x2, family, data)
```

link options

```
identity
log
inverse
logit
probit
cauchit
cloglog
sqrt
1/mu^2
power
```

Question

What is the difference between these?

```
lm(y ~ x)
```

and

```
glm(y ~ x)
```

Question

What is the difference between these?

```r
lm(log(y) ~ x)
```

and

```r
glm(y ~ x, family=gaussian(link='log'))
```

Deviances

GLM	**Deviance:** $D = -2\log L$
Gaussian	$\sum (y_i - \hat{\mu}_i)^2$
Poisson	$2\sum \left[y_i \log\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i - \hat{\mu}_i)\right]$
Binomial	$2\sum \left[y_i \log\left(\frac{y_i}{\hat{\mu}_i}\right) + (m - y_i)\log\left(\frac{m - y_i}{m - \hat{\mu}_i}\right)\right]$
Gamma	$2\sum \left[-\log\left(\frac{y_i}{\hat{\mu}_i}\right) + \frac{y_i - \hat{\mu}_i}{\hat{\mu}_i}\right]$
Inverse Gaussian	$\sum \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i^2 y_i}$

Hypothesis tests

Goodness-of-fit test

- Does data fit assumed distribution?
- Deviance has χ^2 distribution with df = $n -$ # estimated parameters
- Only works for large *n* and for distributions with no dispersion parameter.
- Does not work for binary GLM, Gaussian LM, or any quasi family
- Binary does not need checking
- For Gaussian, look at residuals
- For quasi family, it depends …

Hypothesis tests

Comparing nested models

Large model Ω; small model ω

- Change in Deviance ($D_\omega - D_\Omega$) equivalent to log-ratio test and has χ^2 distribution with df = $\mathrm{df}_\omega - \mathrm{dw}_\Omega$ = difference in number of parameters
- For quasi-likelihood, use an F approximation instead (exact for Gaussian).

$$F = \frac{D_\omega - D_\Omega}{\hat{\phi}(\mathrm{df}_\omega - \mathrm{df}_\Omega)} \quad \text{where} \quad \hat{\phi} = \frac{1}{n-p}\sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{V(\mu_i)}$$

Outline

Offsets

How to deal with fixed constants?

For Gaussian regression, we adjust the response:

$$y_i - c_i \sim N(\beta' \mathbf{x}_i, \sigma^2)$$
$$y_i / c_i \sim N(\beta' \mathbf{x}_i, \sigma^2)$$

But this won't work for other sample spaces.

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But this won't work for other sample spaces.

Solution: Define an offset:

$$g(\mu_i) = c_i + \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_q x_{q,i}$$

where c is fixed and specified (not estimated).

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where c is fixed and specified (not estimated).

You can also use an offset when you know the coefficient of a predictor.

Offsets

Example: Modelling per-capita counts

$$y_i \sim \text{Poisson}(\exp(\log(z_i) + \beta'\mathbf{x}_i))$$

- y_i is # prisoners in region i
- z_i is population of region i.
- $\log(z_i)$ is the “offset”.
- $\text{E}(y_i/z_i) = \exp(\beta'\mathbf{x}_i)$

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Most common for Poisson regression, but possible in any GLM.

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- $\text{E}(y_i/z_i) = \exp(\beta'\mathbf{x}_i)$

Most common for Poisson regression, but possible in any GLM.

```
glm(y ~ offset(z) + x1 + x2, family, data)
```

Outline

GLM Residuals

Response residuals: Observation – estimate

$$e_i = y_i - \hat{\mu}_i$$

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Pearson residuals: Standardized

$$r_i = \frac{y_i - \hat{\mu}_i}{\sqrt{V(\hat{\mu}_i)}}$$

GLM Residuals

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$$e_i = y_i - \hat{\mu}_i$$

Pearson residuals: Standardized

$$r_i = \frac{y_i - \hat{\mu}_i}{\sqrt{V(\hat{\mu}_i)}}$$

Deviance residuals: Signed root contribution to $-2 \log L$.

$$-2 \log L = \sum \delta_i$$

$$d_i = sign(y_i - \hat{\mu}_i)\sqrt{\delta_i}$$

GLM Residuals

Response residuals

```
augment(fit, type.residuals='response')
```

Pearson residuals

```
augment(fit, type.residuals='pearson')
```

Deviance residuals

```
augment(fit, type.residuals='deviance')
augment(fit)
```

GLM Leverage and Influence

IRWLS algorithm used for estimation means that we can easily define the hat matrix:

$$\boldsymbol{H} = \boldsymbol{W}^{1/2}\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{W}^{1/2}$$

where $\boldsymbol{W}$ is diagonal with values $\frac{1}{V(\mu_i)}\left(\frac{\partial\mu_i}{\partial\eta_i}\right)^2$.

- Leverage values are diagonals of $\boldsymbol{H}$.
- `augment(fit) %>% select(.hat)`

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where $\boldsymbol{W}$ is diagonal with values $\frac{1}{V(\mu_i)}\left(\frac{\partial\mu_i}{\partial\eta_i}\right)^2$.

- Leverage values are diagonals of $\boldsymbol{H}$.
- `augment(fit) %>% select(.hat)`

Cooks Distance

$$D_i = \frac{(\hat{\beta}_{(i)} - \hat{\beta})'(\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X})(\hat{\beta}_{(i)} - \hat{\beta})}{p\hat{\phi}}$$

- `augment(fit) %>% select(.cooksd)`

Diagnostics

Case checking

- Outliers (large residuals)
- High leverage points (large effect on estimates)

Model checking

- Heteroskedasticity
- Linearity
- Distribution

Diagnostics

Case checking

- Why do we have outliers? Perhaps omit them?
- Reduce leverage through transforming predictors

Model checking

- Heteroskedasticity: perhaps use weights?
- Linearity:
  - transform predictors
  - add quadratic or other transformed variable
  - use nonparametric regressor (later)
- Distribution:
  - allow for overdispersion using quasilikelihood
  - zero-inflated
  - often fixing hetero and linearity will fix distribution

Outline

Gamma GLM

Defined on $\mathbb{R}^+$

Gamma distribution

$$f(y) = \frac{1}{\Gamma(\nu)}\lambda^{\nu}y^{\nu-1}e^{-\lambda y}$$

- ν describes shape; λ describes scale
- χ^2 is special case ($\lambda = 0.5$, df $= 2\nu$)

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Reparameterize with $\lambda = \nu/\mu$:

$$f(y) = \frac{1}{\Gamma(\nu)}\left(\frac{\nu}{\mu}\right)^\nu y^{\nu-1}e^{-y\nu/\mu}$$

- ν describes shape
- μ is mean; $\mathrm{Var}(Y) = \mu^2/\nu$

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- ν describes shape
- μ is mean; $\mathrm{Var}(Y) = \mu^2/\nu$

```
glm(y ~ x1+x2, family=Gamma(link='log'))
```

Gamma GLM

- Canonical link is inverse. Better to use log.
- When variance small, it is very similar to Gaussian model with logged response.
- Inference sensitive to distributional mis-specification

Inverse Gaussian GLM

Defined on $\mathbb{R}^+$

Inverse Gaussian distribution

$$f(y) = \sqrt{\frac{\lambda}{2\pi y^3}} \exp\left[-\lambda(y-\mu)^2/2\mu^2 y\right]$$

- μ = mean; Var = μ^3/λ
- μ = 1 is special case (Wald distribution)

Inverse Gaussian GLM

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Inverse Gaussian distribution

$$f(y) = \sqrt{\frac{\lambda}{2\pi y^3}} \exp\left[-\lambda(y-\mu)^2/2\mu^2 y\right]$$

- μ = mean; Var = μ^3/λ
- μ = 1 is special case (Wald distribution)

- Canonical link is $1/\mu^2$
- Variance increases with μ more rapidly than Gamma.
- As $\lambda \to \infty$, distribution converges to Gaussian.
- First derived by Schrödinger

Tweedie GLM

Tweedie distribution

Exponential family distribution where $\mathrm{Var}(Y) = a\mu^p$, $a > 0$, $p > 0$.

- normal distribution, $p = 0$
- Poisson distribution, $p = 1$
- compound Poisson–gamma distribution, $1 < p < 2$
- gamma distribution, $p = 2$
- positive stable distributions, $2 < p < 3$
- inverse Gaussian distribution, $p = 3$
- positive stable distributions, $p > 3$
- extreme stable distributions, $p = \infty$

For $0 < p < 1$ no Tweedie model exists.

Compound Poisson-gamma distribution

$$Y = \sum_{i=1}^{N} X_i, \qquad N \sim \text{Poisson}, \qquad X_i \sim \text{Gamma}$$

- Continuous on $[0, \infty]$ with a spike at 0. (e.g., rainfall, insurance payouts.)
- Tweedie distribution with $1 < p < 2$.
- Poisson mean: $\mu^{2-p}/[(2-p)\phi]$.
- Gamma parameters: $\nu = (2-p)/(p-1)$, $\lambda = 1/[\phi(p-1)\mu^{p-1}]$

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- Tweedie distribution with $1 < p < 2$.
- Poisson mean: $\mu^{2-p}/[(2-p)\phi]$.
- Gamma parameters: $\nu = (2-p)/(p-1)$, $\lambda = 1/[\phi(p-1)\mu^{p-1}]$

Show mean = μ.
Show var = $\phi\mu^p$

Compound Poisson-gamma distribution

$$
\begin{aligned}
\mathrm{E}(N) &= \mathrm{Var}(N) = \frac{\mu^{2-p}}{(2-p)\phi} \\
\mathrm{E}(X) &= \frac{(2-p)}{(p-1)} \left(\phi(p-1)\mu^{p-1}\right) = \phi(2-p)\mu^{p-1} \\
\mathrm{Var}(X) &= \frac{(2-p)}{(p-1)} \left(\phi^2(p-1)^2\mu^{2(p-1)}\right) \\
&= \phi^2(2-p)(p-1)\mu^{2(p-1)}
\end{aligned}
$$

Compound Poisson-gamma distribution

$$
\begin{aligned}
\mathrm{E}(Y) &= \mathrm{E}_N[Y \mid N] \\
&= \mathrm{E}_N[N\mathrm{E}(X)] \\
&= \mathrm{E}(N)\mathrm{E}(X) \\
&= \frac{\mu^{2-p}}{(2-p)\phi}\left[\phi(2-p)\mu^{p-1}\right] \\
&= \mu
\end{aligned}
$$

Compound Poisson-gamma distribution

$$
\begin{aligned}
\mathrm{Var}(Y) &= \mathrm{Var}_N[\mathrm{E}_X(Y \mid N)] + \mathrm{E}_N[\mathrm{Var}_X(Y \mid N)] \\
&= \mathrm{Var}_N[N\mathrm{E}(X)] + \mathrm{E}_N[N\mathrm{Var}(X)] \\
&= \mathrm{Var}(N)[\mathrm{E}(X)]^2 + \mathrm{E}(N)\mathrm{Var}(X) \\
&= \mathrm{E}(N)\left([\mathrm{E}(X)]^2 + \mathrm{Var}(X)\right) \\
&= \frac{\mu^{2-p}}{(2-p)\phi}\Big(\phi^2(2-p)^2\mu^{2(p-1)} \\
&\qquad\qquad + \phi^2(2-p)(p-1)\mu^{2(p-1)}\Big) \\
&= \frac{\mu^{2-p+2p-2}\phi^2(2-p)}{(2-p)\phi}\Big((2-p)+(p-1)\Big) \\
&= \phi\mu^p
\end{aligned}
$$

Compound Poisson-gamma GLM

```r
mgcv::gam(y ~ x1 + x2,
              family=tw(link="log"))
```

- Estimates p assuming it is in $(1, 2)$.

Tweedie GLMs

- No R function for general Tweedie GLM.
- When using R, user needs to choose
  - $p = 0$ (Gaussian)

    `lm` or `glm`
  - $p = 1$ (Poisson)

    `glm(family=poisson)`
  - $1 < p < 2$ (Compound Poisson gamma)

    `mgcv::gam(family=tw)`
  - $p = 2$ (Gamma)

    `glm(family=Gamma)`
  - $p = 3$ (Inverse Gaussian)

    `glm(family=inverse.gaussian`