

TMA4315 Generalized linear models H2018

Module 4: Count and continuous positive response data (Poisson and gamma regression)

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27.09.2018 and 04.10.2018 [PL], 28.09.2018 and 05.10.2018
[IL] (Version 23.09.2018)

(Latest changes:)

REMARK: module pages for the second week will not be in the final form before October 1, 2018.

Overview

Learning material

- ▶ Textbook: Fahrmeir et al (2013): Chapter 5.2, 5.3.
- ▶ Classnotes 27.09.2018
- ▶ Classnotes 04.10.2018

Topics

First week

- ▶ examples of count data
- ▶ the Poisson distribution
- ▶ regression with count data
- ▶ Poisson regression with log-link
- ▶ parameter estimation (ML): log-likelihood, score vector, information matrix to give iterative calculations
- ▶ asymptotic MLE properties
- ▶ confidence intervals and hypothesis tests (Wald, score and LRT)
- ▶ deviance, model fit and model choice
- ▶ overdispersion

Jump to interactive (week 1)

Second week

- ▶ Count data with Poisson regression: rate models and offset
- ▶ Modelling continuous response data: lognormal and gamma
- ▶ the gamma distribution
- ▶ the gamma GLM model
- ▶ gamma likelihood and derivations thereof
- ▶ dispersion parameter: scaled and unscaled deviance
- ▶ summing up - element in common for normal, binomial, Poisson and gamma

Jump to interactive (week 2)

FIRST WEEK

Examples of count data

- ▶ the number of automobile thefts pr city worldwide
- ▶ the number of UFO sightings around the world
- ▶ the number of visits at web pages
- ▶ the number of male crabs (satellites) residing nearby a female crab
- ▶ the number of goals by the home team and the number of goals for the away team in soccer
- ▶ the number of newspapers sold at newsagents

Sales of newspapers

This is a short description of a project run at the Norwegian Computing Centre a few years ago.

The aim of the project was to provide a statistical model to predict the number of newspapers to be sold at each of 11 thousand outlets all over Norway for a given day (“tomorrow” - maybe scaled to match front page issues). And then based on the prediction to decide on how many newspapers to be delivered to each outlet in order to optimize the overall profit (lost sales if outlet are sold out, return costs if unsold papers).

Response data: number of newspapers (delivered) sold at each outlet. Covariate data: type of outlet, but mainly calendar information= weekday, month, season, public holidays, winter/autumn/easter/xmas, ...

Female crabs with satellites

The example is taken from Agresti (1996): “An Introduction to Categorical Data Analysis”, and the data is from a study of nesting horseshoe crabs (J. Brockmann, Ethology 1996)

First, the study objects were female crabs (horseshoe crabs). Each female crab had a male crab attached to her in her nest. The objective of the study was to investigate factors that affect whether the female crab had any other males, called satellites, residing near her. The following covariates were collected for 173 female crabs:

- ▶ C: the color of the female crab (1=light medium, 2=medium, 3=dark medium, 4=dark)
- ▶ S: spine condition (1=both good, 2=one worn or broken, 3=both worn or broken)
- ▶ W: width of carapace (cm)
- ▶ Wt: weight (kg)

The response was the number of satellites, S_a = male crabs residing nearby.

Modelling counts with the Poisson distribution

The Poisson process

We observe events that may occur within a time interval or a region.

1. The number of events occurring within a time interval or a region, is independent of the number of events that occurs in any other disjoint (non-overlapping) time interval or region.
2. The probability that a single event occurs within a small time interval or region, is proportional to the length of the interval or the size of the region.
3. The probability that more than one event may occur within a small time interval or region is negligible.

When all of these three properties are fulfilled we have a *Poisson process*. This leads to three distributions

- ▶ The number of events in a Poisson process follows a Poisson distribution.
- ▶ Time between two events in a Poisson process follows an exponential distribution.
- ▶ Time between many events in a Poisson process follows a gamma distribution.

We will first study the Poisson distribution - and link it to a regression setting.

The Poisson distribution

We study a Poisson process within a time interval or a region of specified size. Then, the number of events, Y , will follow a *Poisson distribution* with parameter λ

$$f(y) = \frac{\lambda^y}{y!} e^{-\lambda} \text{ for } y = 0, 1, 2,$$

Here the parameter λ is the proportionality factor in the requirement 2 (above) for the Poisson process. Another popular parameterization is μ , or given some interval λt , but we will stick with λ . In R we calculate the Poisson point probabilities using `dpois`.

If you want to see how this distribution function is derived from the binomial distribution you may watch this video: Poisson process and distribution

Cumulative distribution (cdf): The cumulative distribution is calculated by summing $F(y) = \sum_{t \leq y} f(t)$, and we might calculate the Poisson cdf in R with `ppois`.

Expected value and variance: Let Y follow a Poisson distribution with parameter λ . Then

$$E(Y) = \lambda \text{ and } \text{Var}(Y) = \lambda$$

Proof:

$$E(y) = \sum_{y=0}^{\infty} y \frac{\lambda^y}{y!} e^{-\lambda} = \sum_{y=1}^{\infty} y \frac{\lambda^y}{y!} e^{-\lambda} = \sum_{y=1}^{\infty} \frac{\lambda \lambda^{y-1}}{(y-1)!} e^{-\lambda} = \lambda \sum_{z=0}^{\infty} \frac{\lambda^z}{z!} e^{-\lambda} = \lambda$$

In the first transition we use that the term $y = 0$ gives no contribution to the sum. Then we cancel out y in the numerator with the first term of $y!$ in the denominator. Then we let $z = y - 1$, and finally we use that the sum of the Poisson distribution for all possible outcomes equal 1.

To calculate the variance we first use that

$$\text{Var}(Y) = E(Y^2) - (E(Y))^2$$

and then that

Properties of the Poisson distribution

- ▶ A sum of n independent Poisson distributed random variables, Y_i with means λ_i are Poisson distributed with mean $\sum_{i=1}^n \lambda_i$.
- ▶ When the mean increases the Poisson distribution becomes more and more symmetric and for large λ the Poisson distribution can be approximated by a normal distribution.

Exponential family

In Module 1 we introduced distributions of the Y_i , that could be written in the form of a *univariate exponential family*

$$f(y_i | \theta_i) = \exp \left(\frac{y_i \theta_i - b(\theta_i)}{\phi} \cdot w_i + c(y_i, \phi, w_i) \right)$$

where we said that

- ▶ θ_i is called the canonical parameter and is a parameter of interest
- ▶ ϕ is called a nuisance parameter (and is not of interest to us=therefore a nuisance (plage))
- ▶ w_i is a weight function, in most cases $w_i = 1$
- ▶ b and c are known functions.

It can be shown that $E(Y_i) = b'(\theta_i)$ and $\text{Var}(Y_i) = b''(\theta_i) \cdot \frac{\phi_i}{w_i}$, see derivation from Module 1.

In Module 1 we found that the Poisson distribution $Y_i \sim \text{Poisson}(\lambda_i)$ is an exponential family derivation from Module 1,

and that

- ▶ $\theta_i = \ln(\lambda_i)$ is the canonical parameter
- ▶ $\phi = 1$, no nuisance
- ▶ $w_i = 1$
- ▶ $b(\theta_i) = \exp(\theta)$
- ▶ $\mu_i = E(Y_i) = \lambda_i$

For a GLM with linear predictor η_i - to have a canonical link we need

$$\theta_i = \eta_i$$

Since $\eta_i = g(\mu_i) = g(\lambda_i)$ this means to us that we need

$$g(\mu_i) = g(\lambda_i) = \theta_i$$

saying that with the Poisson the canonical link is $\ln(\lambda_i)$.

Q: Why may we want to choose a canonical link?

Regression with count data

Aim

1. Construct a model to help understand the relationship between a count variable and one or many possible explanatory variables. The response measurements are counts.
2. Use the model for understanding what can explain count, and for prediction of counts.

What is we instead want to use the multiple linear regression model?

When modelling the counts some times the normal approximation might be used, especially when the counts are high. It is also possible to use a transformation of the response to get a constant variance. The transformation $\sqrt{Y_i}$ give an approximate constant variance, but then it is not clear if there then is a linear relationship between $E(\sqrt{Y_i})$ and the covariates.

In general, with count data, we instead use a Poisson GLM regression.

The linear Poisson model

It is possible to construct a *linear Poisson model* where we have the direct relationship

$$\lambda_i = \eta_i$$

between the mean of the Poisson distribution and the linear predictor.

This means that the covariates have an additive effect on the rate λ_i .

However, since the rate λ_i can not be negative, then to use this model restrictions on the parameter space of the β is needed.

We will not use the linear Poisson model, but instead the *log-linear Poisson model*.

The log-linear Poisson model

Assumptions:

1. $Y_i \sim \text{Poisson}(\lambda_i)$, with $E(Y_i) = \lambda_i$, and $\text{Var}(Y_i) = \lambda_i$.
2. Linear predictor: $\eta_i = \mathbf{x}_i^T \beta$.
3. Log link

$$\eta_i = \ln(\lambda_i) = g(\lambda_i)$$

and (inverse thereof) response function

$$\lambda_i = \exp(\eta_i)$$

Assumptions 1 and 3 above can be written as

$$Y_i \sim \text{Poisson}(\exp(\eta_i)), \quad i = 1, \dots, n$$

Interpreting parameters in the log-linear Poisson model

In the log-linear model the mean, $E(Y_i) = \lambda_i$ satisfy an exponential relationship to covariates

$$\lambda_i = \exp(\eta_i) = \exp(\mathbf{x}_i^T \beta) = \exp(\beta_0) \cdot \exp(\beta_1)^{x_{i1}} \cdots \exp(\beta_k)^{x_{ik}}.$$

Let us look in detail at β_1 with covariate x_{i1} for observation i .

1. If x_{i1} increases by one unit to $x_{i1} + 1$ then the mean $E(Y_i)$ will in our model change by a factor $\exp(\beta_1)$.
2. If $\beta_1 = 0$ then $\exp(\beta_1) = 1$, so that a change in x_{i1} does not change $E(Y_i)$.
3. If $\beta_1 < 0$ then $\exp(\beta_1) < 1$ so if x_{i1} increase then $E(Y_i)$ decrease.
4. If $\beta_1 > 0$ then $\exp(\beta_1) > 1$ so if x_{i1} increase then $E(Y_i)$ increase.

Thus, the covariates have a multiplicative effect on the rate λ_i .

Example: interpreting parameters for the female crabs with satellites

We fit a log-linear model to S_a , assuming the number of satellites follows a Poisson distribution with log-link.

Q:

1. First the model is fitted with intercept only. What do we assume then? Interpret the fit.
2. Then width W is added as a covariate in the log-linear model. What happens if the width increase by one unit (cm)?
3. What is the predicted number of satellites for the average width?

```
model1 = glm(Sa ~ 1, family = poisson(link = log), data = d)
cat("Intercept only\n")
```

```
## Intercept only
```

```
print(model1$coefficients)
```

```
## (Intercept)
```

```
##      1.071267
```

```
cat("Intercept only, exp\n")
```

```
## Intercept only, exp
```

```
exp(model1$coefficients)
```

```
## (Intercept)
```

```
##      2.919075
```

```
model2 = glm(Sa ~ W, family = poisson(link = log), data = d)
```

Parameter estimation with maximum likelihood

Our parameter of interest is the vector β of regression coefficients, and we have no nuisance parameters. We would like to estimate β from maximizing the likelihood - the presentation here is essentially the same as for Module 3: Binary regression - with “Poisson and log” instead of “Bernoulli and logit”. And, also here we will not have a closed form solution for $\hat{\beta}$ (except for a few special cases).

Likelihood $L(\beta)$

We assume that pairs of covariates and response are measured independently of each other: (\mathbf{x}_i, Y_i) , and Y_i follows the distribution specified above, and \mathbf{x}_i is fixed.

$$L(\beta) = \prod_{i=1}^n L_i(\beta) = \prod_{i=1}^n f(y_i; \beta) = \prod_{i=1}^n \frac{\lambda_i^{y_i}}{y_i!} \exp(-\lambda_i)$$

Note: still a slight misuse of notation - where is β ?

A: $\eta_i = \ln(\lambda_i) = \mathbf{x}_i^T \beta$, so replace λ_i with $\exp(\mathbf{x}_i^T \beta)$.

Loglikelihood $l(\beta)$

The log-likelihood is just the natural log of the likelihood, and we work with the log-likelihood because this makes the mathematics simpler - since we work with exponential families. The main aim with the likelihood is to maximize it to find the maximum likelihood estimate, and since the log is a monotone function the maximum of the log-likelihood will be in the same place as the maximum of the likelihood.

$$l(\beta) = \ln L(\beta) = \sum_{i=1}^n \ln L_i(\beta) = \sum_{i=1}^n l_i(\beta) = \sum_{i=1}^n [y_i \ln(\lambda_i) - \lambda_i - \ln(y!)]$$

Observe that the log-likelihood is a sum of individual contributions for each observation pair i . We often omit the last term since it is not a function of model parameters, only data.

If we want a function of $\eta_i = \ln(\lambda_i)$ or β :

$$l(\beta) = \sum_{i=1}^n [y_i \eta_i - \exp(\eta_i) + C_i] = \sum_{i=1}^n y_i \mathbf{x}_i^T \beta - \sum_{i=1}^n \exp(\mathbf{x}_i^T \beta) + C$$

Score function $s(\beta)$

The score function is a $p \times 1$ vector, $s(\beta)$, with the partial derivatives of the log-likelihood with respect to the p elements of the β vector. Remember, the score function is linear in the individual contributions:

$$s(\beta) = \frac{\partial l(\beta)}{\partial \beta} = \sum_{i=1}^n \frac{\partial l_i(\beta)}{\partial \beta} = \sum_{i=1}^n s_i(\beta)$$

We work with $l_i(\beta) = l_i(\pi_i(\eta_i(\beta)))$ and use the chain rule to find $s_i(\beta)$.

$$\begin{aligned} s_i(\beta) &= \frac{\partial l_i(\beta)}{\partial \beta} = \frac{\partial l_i(\beta)}{\partial \eta_i} \cdot \frac{\partial \eta_i}{\partial \beta} = \frac{\partial [y_i \eta_i - \exp(\eta_i) + C_i]}{\partial \eta_i} \cdot \frac{\partial [\mathbf{x}_i^T \beta]}{\partial \beta} \\ &= [y_i - \exp(\eta_i)] \cdot \mathbf{x}_i = (y_i - \lambda_i) \mathbf{x}_i \end{aligned}$$

See Module 3 for rules for partial derivatives of scalar wrt vector.

The score function is given as:

$$s(\beta) = \sum_{i=1}^n s_i(\beta) = \sum_{i=1}^n (y_i - \lambda_i) \mathbf{x}_i$$

Again, observe that $E(s_i(\beta)) = E((Y_i - \lambda_i)\mathbf{x}_i) = 0$ because $E(Y_i) = \lambda_i$, and thus also $E(s(\beta)) = 0$.

To find the maximum likelihood estimate $\hat{\beta}$ we solve the set of p non-linear equations:

$$s(\hat{\beta}) = 0$$

And, as before we do that using the Newton-Raphson or Fisher Scoring iterative methods, so we need the derivative of the score vector (our Fisher information).

The expected Fisher information matrix $F(\beta)$

We saw in Module 3 that the expected Fisher information matrix, $F(\beta)$ is equal the covariance matrix of the score function.

$$F(\beta) = \text{Cov}(s(\beta)) = \sum_{i=1}^n \text{Cov}(s_i(\beta)) \quad (1)$$

$$= \sum_{i=1}^n E \left[\left(s_i(\beta) - E(s_i(\beta)) \right) \left(s_i(\beta) - E(s_i(\beta)) \right)^T \right] \quad (2)$$

$$= \sum_{i=1}^n E(s_i(\beta) s_i(\beta)^T) = \sum_{i=1}^n F_i(\beta) \quad (3)$$

where it is used that the responses Y_i and Y_j are independent, and that $E(s_i(\beta)) = 0 \forall i$.

Remember that $s_i(\beta) = (Y_i - \lambda_i)\mathbf{x}_i$, then:

Observed Fisher information matrix $H(\beta)$

We do not really need the observed version of the Fisher information matrix, and since we use canonical link $H(\beta) = F(\beta)$ - so we already have it.

But, for completeness, we add the direct derivation of $H(\beta)$.

$$\begin{aligned} H(\beta) &= -\frac{\partial^2 l(\beta)}{\partial \beta \partial \beta^T} = -\frac{\partial s(\beta)}{\partial \beta^T} = \frac{\partial}{\partial \beta^T} \left[\sum_{i=1}^n (\lambda_i - y_i) \mathbf{x}_i \right] \\ &= \frac{\partial}{\partial \beta^T} \left[\sum_{i=1}^n (\exp(\eta_i) - y_i) \mathbf{x}_i \right] \end{aligned}$$

because $s(\beta) = \sum_{i=1}^n (y_i - \lambda_i) \mathbf{x}_i$ and hence $-s(\beta) = \sum_{i=1}^n (\lambda_i - y_i) \mathbf{x}_i$. Note that $\lambda_i = \exp(\eta_i)$.

$$H(\beta) = \sum_{i=1}^n \frac{\partial}{\partial \beta^T} [\mathbf{x}_i \lambda_i - \mathbf{x}_i y_i] = \sum_{i=1}^n \frac{\partial}{\partial \beta^T} \mathbf{x}_i \lambda_i = \sum_{i=1}^n \mathbf{x}_i \frac{\partial \lambda_i}{\partial \eta_i} \frac{\partial \eta_i}{\partial \beta^T}$$

Use that

$$\frac{\partial \eta_i}{\partial \beta^T} = \frac{\partial \mathbf{x}_i^T \beta}{\partial \beta^T} = \left(\frac{\partial \mathbf{x}_i^T \beta}{\partial \beta} \right)^T = \mathbf{x}_i^T$$

and

$$\frac{\partial \lambda_i}{\partial \eta_i} = \frac{\partial \exp(\eta_i)}{\partial \eta_i} = \exp(\eta_i) = \lambda_i$$

And thus

$$H(\beta) = \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T \lambda_i.$$

Note that the observed and the expected Fisher information matrix are equal (see below [canonical link](#) that this is a general

Parameter estimation - in practice

To find the ML estimate $\hat{\beta}$ we need to solve

$$s(\hat{\beta}) = 0$$

We have that the score function for the log-linear model is:

$$s(\beta) = \sum_{i=1}^n \mathbf{x}_i(y_i - \lambda_i) = \sum_{i=1}^n \mathbf{x}_i(y_i - \exp(\mathbf{x}_i^T \beta)).$$

Observe that this is a non-linear function in β , and has no closed form solution (except for a few special cases).

Fisher scoring

To solve this we use the Fisher scoring algorithm, were we at iteration $t + 1$ have

$$\beta^{(t+1)} = \beta^{(t)} + F(\beta^{(t)})^{-1}s(\beta^{(t)})$$

Remark: what do we need to do to use the Newton-Raphson method instead? Well, replace F with H , but for canonical link (which is the log-link for the Poisson) $F = H$.

Requirements for convergence

For the Fisher scoring algorithm the expected Fisher information matrix F needs to be invertible, and analogous to what we saw in Module 3 this is possible if $\lambda_i > 0$ for all i and that the design matrix has full rank (p). Since we have the log-link we have that $\lambda_i = \exp(\mathbf{x}_i^T \beta)$ which is always positive, so all good. Note, with the linear link $\lambda_i = \eta_i$ this might be a challenge, and restrictions on β must be set.

Again, it is possible that the algorithm does not converge. This may happen for “unfavorable” data configurations (especially for small samples). According to our text book, Fahrmeir et al (2013), page 284, the conditions for uniqueness and existence of ML estimators are very complex, and the authors suggest that the GLM user instead checks for convergence in practice by performing the iterations - also for the Poisson log-linear model.

Statistical inference

Asymptotic properties of ML estimates

We repeat what we found for Module 3: Under some (weak) regularity conditions:

Let $\hat{\beta}$ be the maximum likelihood (ML) estimate in the GLM model. As the total sample size increases, $n \rightarrow \infty$:

1. $\hat{\beta}$ exists
2. $\hat{\beta}$ is consistent (convergence in probability, yielding asymptotically unbiased estimator, variances goes towards 0)
3. $\hat{\beta} \approx N_p(\beta, F^{-1}(\hat{\beta}))$

Observe that this means that asymptotically $\text{Cov}(\hat{\beta}) = F^{-1}(\hat{\beta})$: the inverse of the expected Fisher information matrix evaluated at the ML estimate.

In our case we have

$$F(\beta) = \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T \lambda_i = \mathbf{X}^T \mathbf{W} \mathbf{X},$$

where $\mathbf{W} = \text{diag}(\lambda_i)$. This means $\text{Cov}(\hat{\beta}) = (\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1}$ (remember that $\hat{\beta}$ comes in with $\hat{\lambda}_i$ in \mathbf{W}).

Let $\mathbf{A}(\beta) = F^{-1}(\beta)$, and $a_{jj}(\beta)$ is diagonal element number j .

For one element of the parameter vector:

$$Z_j = \frac{\hat{\beta}_j - \beta_j}{\sqrt{a_{jj}(\hat{\beta})}}$$

is standard normal, which can be used to make confidence intervals
- and test hypotheses.

Confidence intervals

In addition to providing a parameter estimate for each element of our parameter vector β we should also report a $(1 - \alpha)100\%$ confidence interval (CI) for each element.

Let $z_{\alpha/2}$ be such that $P(Z_j > z_{\alpha/2}) = \alpha/2$. We then use

$$P(-z_{\alpha/2} \leq Z_j \leq z_{\alpha/2}) = 1 - \alpha$$

insert Z_j and solve for β_j to get

$$P(\hat{\beta}_j - z_{\alpha/2}\sqrt{a_{jj}(\hat{\beta})} \leq \beta_j \leq \hat{\beta}_j + z_{\alpha/2}\sqrt{a_{jj}(\hat{\beta})}) = 1 - \alpha$$

A $(1 - \alpha)\%$ CI for β_j is when we insert numerical values for the upper and lower limits.

Example: Female crabs with satellites

Q:

1. Explain what is done in the R-print-out.
2. What if we instead want a CI for $\beta_0 + \beta_1 x_{i1}$?
3. What if we instead want a CI for $\lambda_i = \exp(\beta_0 + \beta_1 x_{i1})$?

```
model2 = glm(Sa ~ W, family = poisson(link = log), data = d)
summary(model2)
```

```
##
```

```
## Call:
```

```
## glm(formula = Sa ~ W, family = poisson(link = log), data = d)
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -2.8526  -1.9884  -0.4933   1.0970   4.9221
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.30476    0.54224  -6.095  1.1e-09 ***
## W            0.16405    0.01997   8.216  < 2e-16 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
```

```
##
```

```
## (Dispersion parameter for poisson family taken to be 1)
```

```
##
```


Hypothesis testing

There are three methods that are mainly used for testing hypotheses in GLMs - these are called Wald test, likelihood ratio test and score test. In Module 3 we looked at the Wald and likelihood ratio test - and what we found there still applies for the Poisson GLM. We only repeat the previous findings, and then add an example with the crab data.

We will look at null hypotheses and alternative hypotheses that can be written

$$H_0 : \mathbf{C}\beta = \mathbf{d} \text{ vs. } \mathbf{C}\beta \neq \mathbf{d}$$

by specifying \mathbf{C} to be a $r \times p$ matrix and \mathbf{d} to be a column vector of length r ,

and/or where we define

- ▶ A: the larger model and
- ▶ B: the smaller model (under H_0), and the smaller model is nested within the larger model (that is, B is a submodel of A).

The Wald test

The Wald test statistic is given as:

$$w = (\mathbf{C}\hat{\beta} - \mathbf{d})^T [\mathbf{C}F^{-1}(\hat{\beta})\mathbf{C}^T]^{-1} (\mathbf{C}\hat{\beta} - \mathbf{d})$$

and measures the distance between the estimate $\mathbf{C}\hat{\beta}$ and the value under the null hypothesis \mathbf{d} , weighted by the asymptotic covariance matrix of $\mathbf{C}\hat{\beta}$, and under the null follows a χ^2 distribution with r degrees of freedom (where r is the number of hypotheses tested).

P -values are calculated in the upper tail of the χ^2 -distribution.

The likelihood ratio test

Notation:

- ▶ A: the larger model and
- ▶ B: the smaller model (under H_0), and the smaller model is nested within the larger model (that is, B is a submodel of A).

The likelihood ratio statistic is defined as

$$-2 \ln \lambda = -2(\ln L(\hat{\beta}_B) - \ln L(\hat{\beta}_A))$$

which under the null is asymptotically χ^2 -distributed with degrees of freedom equal the difference in the number of parameters in the large and the small model.

Again, p -values are calculated in the upper tail of the χ^2 -distribution.

The score test

We continue to use the notation that A: the larger model (under H_1) and B: the smaller model (under H_0), and still assume that the smaller model is nested within the larger model (that is, B is a submodel of A).

The *score statistics* is based on the *score function*, and measures the distance to the score test at the maximum likelihood for model A (which is 0) and scales with the covariance to form the test statistic.

- ▶ Under the null hypothesis investigated let $\tilde{\beta}$ be the ML estimate (that is, model B, the smaller model) - that means that this is a restricted ML estimate, and
- ▶ under H_1 we have the larger model (A) with maximum likelihood $\hat{\beta}$.

The score statistics is:

$$U = (s(\tilde{\beta}) - \mathbf{0})^T \mathbf{F}^{-1}(\tilde{\beta})(s(\tilde{\beta}) - \mathbf{0})$$

Here $s(\tilde{\beta})$ represents a subvector of the score function where only the elements that is in H_1 and not in H_0 are present, but the score function is evaluated based on parameter estimates under H_0 .

To calculate $\mathbf{F}^{-1}(\tilde{\beta})$ this is a submatrix of the full inverted matrix (not invert just the submatrix).

When the null hypothesis is true U as an asymptotic χ^2 -distribution with r degrees of freedom (difference in number of estimated parameters between the large and small model).

Remark: In R the function `glm.scoretest` in the package `statmod` calculates the score test for a GLM when the difference between H_0 and H_1 is one parameter. The output from the `glm.scoretest` is the square root of U and must be squared and related to a χ_1^2 distribution (see example below).

The score test is very useful for special situations when the smaller model is to be tested towards many larger models, because only the smaller model has to be fitted.

The score test is perhaps the the most complex and least studied of the three tests, and in this course the main focus will be on the Wald and LRT tests. But, it is important for you to have heard of the score test, because in special situation it may be the preferred test.

Example: Female crabs with satellites - the different tests.

We fit a model with two covariates, one is categorical and we use effect coding. We want to test if we need to add these covariates.

Q: Comment on what you see in the print-out. Which hypotheses are we testing? Compare the test statistics.

```
library(statmod)
model3 = glm(Sa ~ W + C, family = poisson(link = log), data = data)
summary(model3)
```

```
##
## Call:
## glm(formula = Sa ~ W + C, family = poisson(link = log),
##      contrasts = list(C = "contr.sum"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.0415  -1.9581  -0.5575   0.9830   4.7523
```

Optional: We also include the results for the score test, but to test an hypothesis for a factor (more than one column in our design matrix) the `glm.scoretest` can not be used and then some manual programming is done below. There exists other packages to perform score tests for GLMs, but is not considered here.

```
# for score test we need ML under H0, and we need to fit the  
# models here when H0 is model with intercept and W:  
model2a = glm(Sa ~ W, family = poisson(link = log), data = crab)  
# when H0 is model with intercept and C:  
model2b = glm(Sa ~ C, family = poisson(link = log), data = crab)  
  
# First H0 is intercept and C and H1 is to add W (only one  
testobs3b = glm.scoretest(model2b, x2 = crab$W)^2  
testobs3b  
  
## [1] 51.51423  
  
1 - pchisq(testobs3b, 1)
```


Residuals

Two types of residuals are popular: *deviance* and *Pearson*.

Deviance residuals

Recall that the deviance was defined by relating a *candidate* model to a *saturated model* and calculating the likelihood ratio statistic with these two models.

Saturated model: If we were to provide a perfect fit to our data then we would estimate the mean λ_i by the observed count for observation i . That is, $\tilde{\lambda}_i = y_i$. Then $\tilde{\lambda}$ is an n dimensional column vector with the elements $\tilde{\lambda}_i$.

Candidate model: The model that we are investigated can be thought of as a *candidate* model. Then we maximize the likelihood and get $\hat{\beta}$ which through our linear predictor and link function we turn into $\hat{\lambda}_i$, also called \hat{y}_i . Then $\hat{\lambda}$ is an n -dimensional column vector with the elements $\hat{\lambda}_i$, also called \hat{y} .

$$D = -2(\ln L(\text{candidate model}) - \ln L(\text{saturated model})) = -2(l(\hat{\lambda}) - l(\tilde{\lambda}))$$

Inserting the Poisson likelihood and λ_i estimates this gives:

$$D = 2 \sum_{i=1}^n [y_i \ln(\frac{y_i}{\hat{y}_i}) - (y_i - \hat{y}_i)]$$

Where $\hat{y}_i = \exp(\mathbf{x}_i^T \hat{\beta})$. Verify this by yourself.

The deviance residuals are given by a signed version of each element in the sum for the deviance, that is

$$d_i = \text{sign}(y_i - \hat{y}_i) \cdot \left\{ 2[y_i \ln(\frac{y_i}{\hat{y}_i}) - (y_i - \hat{y}_i)] \right\}^{1/2}$$

where the term $\text{sign}(y_i - \hat{y}_i)$ makes negative residuals possible - and we get the same sign as the *Pearson residuals*

Pearson residuals

The Pearson residuals are given as

$$r_i = \frac{o_i - e_i}{\sqrt{e_i}}$$

where o_i is the observed count for observation i and e_i is the estimated expected count for observation i . We have that $o_i = y_i$ and $e_i = \hat{y}_i = \hat{\lambda}_i = \exp(\mathbf{x}_i^T \hat{\beta})$.

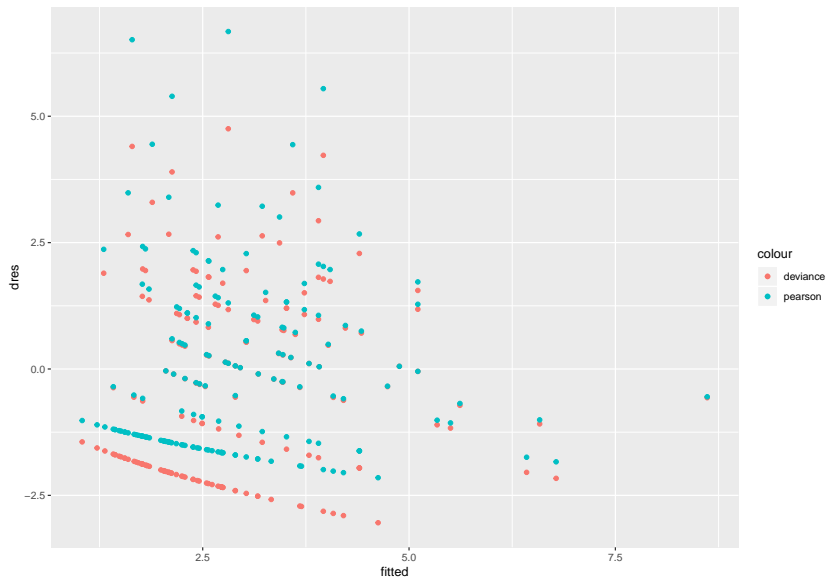
Remark: A standardized version scales the Pearson residuals with $\sqrt{1 - h_{ii}}$ similar to the standardized residuals for the normal model. Here h_{ii} is the diagonal element number i in the hat matrix $\mathbf{H} = \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$.

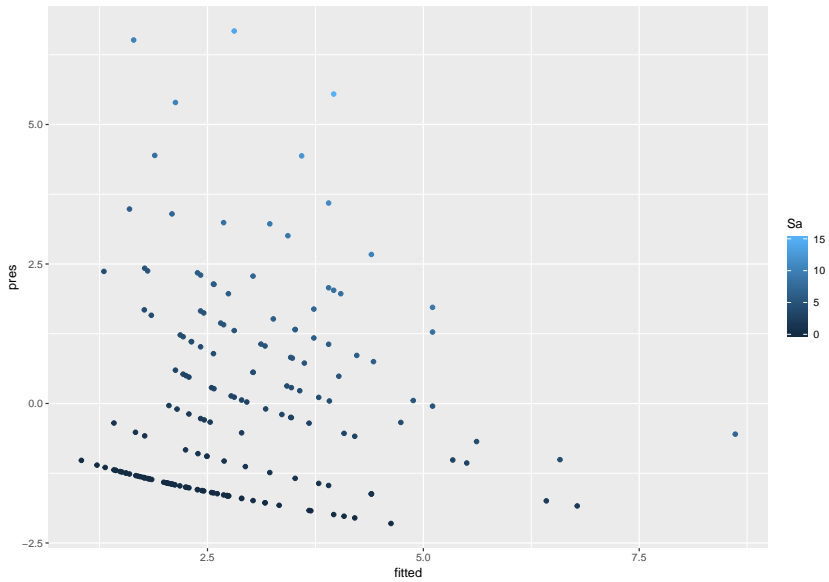
Plotting residuals

Deviance and Pearson residuals can be used for checking the fit of the model, by plotting the residuals against fitted values and covariates. Normality of residuals are also assumed, and can be checked using qq-plots as for the MLR in Module 2.

Below - notice the trend in the residuals, this is due to the discrete nature of the response. The plot with different shades of blue shows that the structures are for equal values of y .

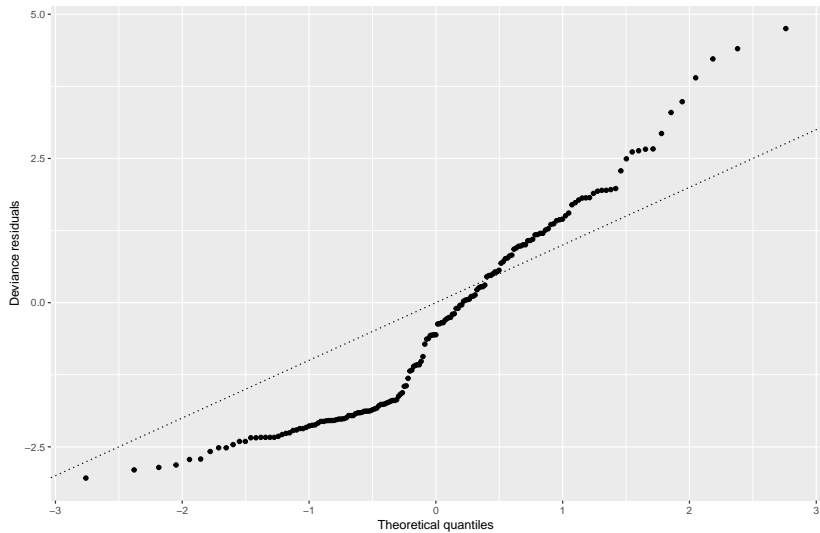
```
model3 = glm(Sa ~ W + C, family = poisson(link = log), data = data,
             S = "contr.sum"))
df = data.frame(Sa = crab$Sa, fitted = model3$fitted.values,
               type = "deviance"), pres = residuals(model3, type = "pe
```





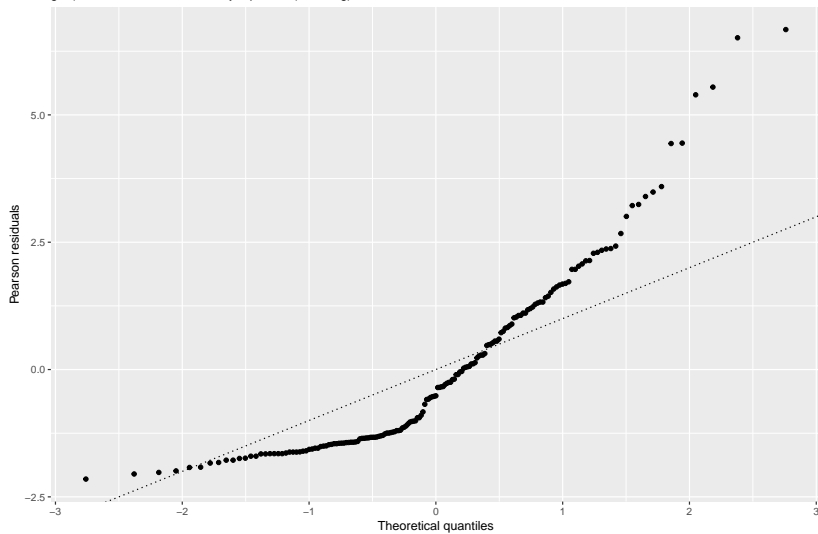
Normal Q-Q

`glm(formula = Sa ~ W + C, family = poisson(link = log), data = crab,`



Normal Q-Q

`glm(formula = Sa ~ W + C, family = poisson(link = log), data = crab,`



Model Assessment and model choice

The fit of the model can be assessed based on goodness of fit statistics (and related tests) and by residual plots. Model choice can be made from analysis of deviance, or by comparing the AIC for different models.

Deviance test

We may use the deviance test presented in Module 3 to test if the model under study is preferred compared to the saturated model.

We may write the deviance test as a sum of the squared deviance residuals.

$$D = 2 \sum_{i=1}^n [y_i \ln(\frac{y_i}{\hat{y}_i}) - (y_i - \hat{y}_i)]$$

Remark: if $\sum_{i=1}^n y_i = \sum_{i=1}^n \hat{y}_i$ then deviance residuals will be equal to

$$D = 2 \sum_{i=1}^n y_i \ln(\frac{y_i}{\hat{y}_i})$$

Q: is this the case for the log-linear model?

A: yes, but only if an intercept is included in the model?

The deviance statistic might be approximately χ^2_{n-p} , at least when the counts are high.

Pearson test

The Pearson χ^2 -goodness of fit statistic is given as the sum of the squared Pearson residuals

$$\chi_P^2 = \sum_{i=1}^n r_i^2 = \sum_{i=1}^n \frac{(y_i - \hat{y}_i)^2}{\hat{y}_i}$$

where $\hat{y}_i = \hat{\lambda}_i = \exp(\mathbf{x}_i^T \hat{\beta})$. The Pearson χ^2 statistic is asymptotically equivalent to the deviance statistic and thus is asymptotically χ_{n-p}^2 .

Remark: the asymptotic distribution of both statistics (deviance and Pearson) are questionable when there are many low counts. Agresti (1996, page 990) suggest analysing grouped data, for example by grouping by width in the crab example.

Remark: The Pearson statistic is also used for testing independence in contingency tables - we will do that in Compulsory Exercise 2.

Example: goodness of fit with female crabs

Q: Comment on the print-out. Is this a good fit? What might a bad fit be due to?

```
model3 = glm(Sa ~ W + C, family = poisson(link = log), data = data)
summary(model3)
```

```
##
## Call:
## glm(formula = Sa ~ W + C, family = poisson(link = log),
##      contrasts = list(C = "contr.sum"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.0415  -1.9581  -0.5575   0.9830   4.7523
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.02080     0.56010   3.6095 0.00034 ***
## W             0.00000     0.00000   0.0000 1.00000
## C             0.00000     0.00000   0.0000 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

AIC

Identical to Module 3 - we may use the Akaike informations criterion. Let p be the number of regression parameters in our model.

$$AIC = -2 \cdot l(\hat{\beta}) + 2p$$

A scaled version of AIC, standardizing for sample size, is sometimes preferred. And, we may also use the BIC, where $2p$ is replaced by $\log(n) \cdot p$.

Analysis of deviance

Identical to Module 3 we may also sequentially compare models, and use analysis of deviance for this.

Overdispersion

Count data might show greater variability in the response counts than we would expect if the response followed a Poisson distribution. This is called *overdispersion*.

Our model states that the variance $\text{Var}(Y_i) = \lambda_i$. If we change the model to $\text{Var}(Y_i) = \phi\lambda_i$ we may allow for an increased variance due to heterogeneity among subjects.

Agresti (1996, page 92) explains: For our crab data set, what if width, weight, colour and spine affect the number of satellites for a female crab, and we only fitted a model with width as covariate. Then the crabs with a certain width are a mixture of crabs of various weights, colours and spine condition - that is, a mixture of several Poisson populations, each with its own mean for the response. This heterogeneity may give an overall response distribution where the variance is greater than the standard Poisson variance.

The overdispersion parameter can be estimated as the average Pearson statistic or average deviance

$$\hat{\phi}_D = \frac{1}{n - p} D$$

where D is the deviance. Note that similarity to $\hat{\sigma}^2 = 1/(n - p) \cdot \text{SSE}$ in the MLR. The $\text{Cov}(\hat{\beta})$ can then be changed to $\hat{\phi} F^{-1}(\hat{\beta})$, so we multiply the standard error by the square root of $\hat{\phi}_D$.

Remark: We are now moving from likelihood to quasi-likelihood theory, where only $E(Y_j)$ and $\text{Var}(Y_j)$ - and not the distribution of Y_j - are used in the estimation.

```
model.disp = glm(Sa ~ W, family = quasipoisson(link = log))
summary.glm(model.disp)
```

```
##
```

```
## Call:
```

```
## glm(formula = Sa ~ W, family = quasipoisson(link = log))
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -2.8526  -1.9884  -0.4933   1.0970   4.9221
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.30476    0.96729  -3.417 0.000793 ***
## W           0.16405    0.03562   4.606 7.99e-06 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
```

```
##
```

```
## (Dispersion parameter for quasipoisson family taken to be
```

```
##
```


Interactive session - first week

Problem 1: Exam 2005 (Problem 1d-f - slightly modified) - Female crabs and satellites

(Only a subset of 20 crabs in the original data was used in the exam problems, but we will use the full data set of 173 crabs - so results will not be the same. Permitted aids for the exam was “all printed and handwritten material and all calculators” - NB that is not the case for 2018!)

We assume that the number of satellites for each female crab follows a Poisson distribution and want to perform a Poisson regression using a log-link to find if there is a connection between the expected number of satellites S_a and the width W and colour C of the carapace of the female crab.

- ▶ C : the color of the female crab (1=light medium, 2=medium, 3=dark medium, 4=dark)
- ▶ W : width of carapace (cm)

The following model was fitted

Problem 2: Exam 2017 (Problem 1) - Poisson regression

Consider a random variable Y . In our course we have considered the univariate exponential family having distribution (probability density function for continuous variables and probability mass function for discrete variables)

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

where θ is called the *natural parameter* (or parameter of interest) and ϕ the *dispersion parameter*.

The Poisson distribution is a discrete distribution with probability mass function

$$f(y) = \frac{\lambda^y}{y!} \exp(-\lambda), \text{ for } y = 0, 1, \dots$$

where $\lambda > 0$.

a) (10 points)

Poisson regression for count data

What did we do last week?

Rate models and offset

In the Poisson process we might analyse an event that occurs within a time interval or region in space, and therefore it is often of interest to model the *rate* at which events occur.

Agresti (1996, page 86): what if we want to model the number of auto thefts for a year in a sample of cities. We would make a rate for each city by dividing the number of auto thefts by the population size of the city. The model could then describe how this rate depends on unemployment rate, median income, percentage of residents having completed high school.

Now we don't want a model for Y_i but for Y_i/t_i , where t_i denotes the index (population size in the example) associated with observation i . The expected value of Y_i/t_i would then be $E(Y_i)/t_i = \lambda_i/t_i$, and a log-linear model would be

$$\log(\lambda_i/t_i) = \mathbf{x}_i^T \beta$$

We may equivalently write the model as

$$\log(\lambda_i) - \log(t_i) = \mathbf{x}_i^T \beta$$

Modelling continuous positive response data

Examples of continuous positive responses

- ▶ Insurance: Claim sizes
- ▶ Medicine: Time to blood coagulation (main example)
- ▶ Biology: Time in various development stages for fruit fly
- ▶ Meteorology: Amount of precipitation (interactive session - exam question 2012)

Models for continuous positive responses

- ▶ Lognormal distribution on response
- ▶ Gamma distribution on response
- ▶ Inverse Gaussian distribution on response (we will not consider this here)

Time to blood coagulation

This data is described in McCullagh and Nelder (1989, page 300). The data represents clotting time of blood (in seconds) y for normal plasma diluted to nine different percentage concentrations u with so-called prothrombin-free plasma. To induce the clotting a chemical called thromboplasting was used, and in the experiment two different lots of the chemical were used - denoted `lot`. Our aim is to investigate the relationship between the clotting time and the dilution percentage, and look at differences between the lots.

```
clot = read.table("https://www.math.ntnu.no/emner/TMA4315/2019/data/clotting.txt")
clot$lot = as.factor(clot$lot)
summary(clot)
```

##	u	time	lot
##	Min. : 5	Min. : 12.0	1:9
##	1st Qu.: 15	1st Qu.: 18.0	2:9
##	Median : 30	Median : 23.0	
##	Mean : 40	Mean : 22.5	

Lognormal distribution

Let Y_i be the response on the original scale, where $Y_i > 0$.

Transform the response to a logarithmic scale: $Y_i^* = \ln(Y_i)$. Then, assume that transformed responses follow a normal distribution (or follows approximately) and use ordinary MLR. This means we have a GLM with normal response and identity link (on logarithmic scale of response).

1. $Y_i^* \sim N(\mu_i^*, \sigma^{*2})$
2. $\eta_i = \mathbf{x}_i^T \beta$
3. $\mu_i^* = \eta_i$ (identity link)

There are two ways of looking at this,

1. either this is just a transformation to achieve approximate normality, or
2. we assume that the original data follows a lognormal distribution.

In genomics one usually assume the former, and reports back results on the exponential scale - just say that the mean of original

Gamma regression

The gamma distribution

We have seen that a gamma distributed variable may be the result of the time between events in a Poisson process. The well known χ^2_{δ} -distribution is a special case of the gamma distribution ($\frac{\nu}{\mu_i} = 2$, $\nu = \frac{\delta}{2}$).

There are many parameterization for the gamma distribution, but we will stick with the one used in our textbook (page 643):

$Y_i \sim Ga(\mu_i, \nu)$ with density

$$f(y_i) = \frac{1}{\Gamma(\nu)} \left(\frac{\nu}{\mu_i}\right)^{\nu} y_i^{\nu-1} \exp\left(-\frac{\nu}{\mu_i} y_i\right) \text{ for } y_i > 0$$

```
mu = 1
nu = 0.3
library(ggplot2)
xrange = range(rgamma(1000, shape = mu/nu, scale = nu))
ggplot(data.frame(x = xrange), aes(xrange)) + xlab("expressions")
```

We found in Module 1, see exponential family that the gamma distribution is an exponential family, with

- ▶ $\theta_i = -\frac{1}{\mu_i}$ is the canonical parameter
- ▶ $\phi = \frac{1}{\nu}$,
- ▶ $w_i = 1$
- ▶ $b(\theta_i) = -\ln(-\theta_i)$
- ▶ $E(Y_i) = b'(\theta_i) = -\frac{1}{\theta_i} = \mu_i$
- ▶ $\text{Var}(Y_i) = b''(\theta_i) \frac{\psi}{w_i} = \frac{\mu_i^2}{\nu}$

For a GLM model we have canonical link if

$$\theta_i = \eta_i$$

Since $\eta_i = g(\mu_i)$ this means to us that we need

$$\theta_i = g(\mu_i) = -\frac{1}{\mu_i}$$

saying that with the canonical link is $-\frac{1}{\mu_i}$. However, the most commonly used link is $g(\mu_i) = \ln(\mu_i)$, and the identity link is also used.

Q: Discuss the implications on ∞ when using the canonical link

Gamma GLM model

1. $Y_i \sim \text{Ga}(\mu_i, \nu)$
2. $\eta_i = \mathbf{x}_i^T \beta$
3. Popular link functions:
 - ▶ $\eta_i = \mu_i$ (identity link)
 - ▶ $\eta_i = \frac{1}{\mu_i}$ (inverse link)
 - ▶ $\eta_i = \ln(\mu_i)$ (log-link)

Remark: In our model the parameter μ_i varies with i but ν is the same for all observations.

Example: Time to blood coagulation

A simple model to start with is as follows (dosages often analysed on log scale):

```
fit1 = glm(time ~ lot + log(u), data = clot, family = Gamma)
summary(fit1)
```

```
##
```

```
## Call:
```

```
## glm(formula = time ~ lot + log(u), family = Gamma(link =
```

```
##      data = clot)
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min        1Q      Median        3Q        Max
```

```
## -0.17470 -0.11596 -0.04281  0.06919  0.27749
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  5.44660      0.12453   40.48  <.0001
```

Gamma regression: likelihood and derivations thereof

Likelihood:

$$L(\beta) = \prod_{i=1}^n \exp\left(-\frac{\nu y_i}{\mu_i} - \nu \ln \mu_i + \nu \ln \nu + (\nu - 1) \ln y_i - \ln(\Gamma(\nu))\right)$$

Log-likelihood:

$$l(\beta) = \sum_{i=1}^n \left[-\frac{\nu y_i}{\mu_i} - \nu \ln \mu_i + \nu \ln \nu + (\nu - 1) \ln y_i - \ln(\Gamma(\nu)) \right]$$

Observe that we now- for the first time - have a nuisance parameter ν here.

To produce numerical estimates for the parameter of interest β we may proceed to the score function, and solve using Newton Raphson or Fisher scoring. If we do not have the canonical link the observed and expected Fisher information matrix may not be equal.

What about ϕ ? Also estimated using maximum likelihood.

Scaled and unscaled deviance

We have defined the deviance as

$$D = -2(\ln L(\text{candidate model}) - \ln L(\text{saturated model}))$$

This is often called the *scaled deviance*.

The *unscaled deviance* is then defined as ϕD , but is sadly sometimes also called the deviance - for example by R.

1. For the normal model the

- ▶ scaled deviance is $D = \frac{1}{\sigma^2} \sum_{i=1}^n (y_i - \mu_i)^2$, while
- ▶ unscaled deviance is $\phi D = \sum_{i=1}^n (y_i - \mu_i)^2$

2. For the binomial and Poisson model $\phi = 1$ so the scaled and unscaled deviance are equal.

3. What about the Gamma model?

⊕ some calculations - see IL week 2, problem 1b.

$$-2 \sum_{i=1}^n \left[\ln\left(\frac{y_i}{\hat{\mu}_i}\right) - \frac{y_i - \hat{\mu}_i}{\hat{\mu}_i} \right]$$

Comparing models

Comparing models based on deviance

```
fit2 = glm(time ~ lot + log(u) + lot:log(u), data = clot, 1  
anova(fit1, fit2)
```

```
## Analysis of Deviance Table
```

```
##
```

```
## Model 1: time ~ lot + log(u)
```

```
## Model 2: time ~ lot + log(u) + lot:log(u)
```

```
##   Resid. Df Resid. Dev Df   Deviance
```

```
## 1         15      0.32110
```

```
## 2         14      0.31576  1 0.0053352
```

The deviance table does not include ϕ , so the unscaled deviance is reported. If significance testing is done, the estimated ϕ from the largest model is used, and p -values are based on the scaled deviance.

Comparing models based on AIC

```
AIC(fit1, fit2)
```

```
##          df          AIC
## fit1    4 104.2763
## fit2    5 105.9738
```

Q: would you prefer fit1 or fit2?

AIC can also be used when we compare models with different link functions (models that are not nested).

The literature suggests to plot y_i vs. each covariate to get a hint about which link function to use.

- ▶ Identity: Plot of y_i vs x_i should be close to linear
- ▶ In : Plot of $\ln(y_i)$ vs x_i should be close to linear
- ▶ Inverse (reciprocal): Plot of $1/y_i$ vs x_i should be close to linear

Interactive session - second week

Problem 1: Exam 2007 (Problem 1, a bit modified) - Smoking and lung cancer

(Permitted aids for the exam was “Tabeller og formler i statistikk”, Matematisk formelsamling (Rottmann), one A5 sheet with your own handwritten notes, and a simple calculator.)

The dataset given in `smoking.txt` consists of four variables:

- ▶ `deaths`: number of lung cancer deaths over a period of six years [remark: incorrectly 1 year in exam question]
- ▶ `population`: the number of people [remark: incorrectly in 100 000 people in exam question]
- ▶ `age`: in five-year age groups (40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+)
- ▶ `ageLevel`: age group as numbers from 1 to 9 (1 corresponds to 40-44, 2 to 45-59, and so on)
- ▶ `smoking status`: doesn't smoke (no), smokes cigars or pipe only (`cigarPipeOnly`), smokes cigarettes and cigar or pipe

Problem 3: Taken from UiO, STK3100, 2015, problem 2

(For reference: here is the original exam).

Do not look at the dataset before the end of the exercise! You should solve the exercise without using R, just as if you were at an exam.

In this problem you shall consider data of survivals from a study of treatment for breast cancer. The response is the number that survived for three years. The covariates were the four factors

- ▶ `app`: appearance of tumor, two levels, 1 = malignant, 2 = benign
- ▶ `infl`: inflammatory reaction, two levels, 1 = minimal, 2 = moderate or severe
- ▶ `age`: age of patients, three levels, 1 = under 50, 2 = 50 to 69, 3 = 70 or older
- ▶ `country`: hospital of treatment, three levels, 1 = Japan, 2 = US, 3 = UK

The dataset we have used differs slightly from the one they used at

Work on your own: Exam questions

December 2013 (Essay exam)

We will consider the following Poisson regression

$$Y_i \sim \text{Poisson}(\exp(\eta_i)), \quad i = 1, \dots, n$$

where the linear predictor is $\eta_i = \mathbf{x}_i^T \beta$. Here \mathbf{x}_i is a vector of the p covariates for the i th observation Y_i and β is unknown p dimensional column vector of unknown regression coefficients.

Write an introduction to Poisson regression and its practical usage, for a student with a good background in statistics, but no knowledge about Generalized Linear Models (GLM). Topics you may want to consider, are

- ▶ When to use it? Underlying assumptions.
- ▶ Parameter estimation, limiting results for the MLE, Fisher information and observed Fisher information, confidence intervals and hypothesis testing.
- ▶ Output analysis, residual plots and interpretation of results

R packages

libraries needed to run this module page

```
install.packages(c("tidyverse", "ggplot2", "statmod", "corrplot",  
                  "GGally", "boot"))
```

Further reading

- ▶ Agresti (1996): “An Introduction to Categorical Data Analysis”,