Introduction on to Generalized Linear Models (GLM)

STK3100/STK4100 - August 18th 2015

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Program

Plan for first lecture:

1. Introduction, Literature, Program
2. Examples
3. Informal definition of GLM
4. Some extensions of GLM
5. Plan for for the course

Introduction

- The topic of generalized linear models (with extensions) is central classes of more complicated , but standard models beyond multiple regression / anova.
- In particular we will see how binary data, data on counts , categorical (multinomial) data and longetudinal/panel data can be analyzed in a regression (like) setting.
- The purpose of the course is twofold: first to see how these models can be in real applications but also to understand the mathematical background for the models.

Textbook (literature)

Textbook for GLM : "Generalized Linear Models for Insurance Data"

by Piet de Jong og Gillian Z. Heller.

Can be purchased in Akademika.

Web page : `http://www.actuary.mq.edu.au/research/books/GLMsforInsuranceData`

Many data sets we will use can be found here.

As earlier we will use data set from many settings: medicine / biology, social science/ economics/ engineering . But a large part will come from insurance.

Textbook (literature), cont.

Textbook for for the Generalized Linear Mixed Models ,GLMM:

Zuur et al: Mixed Effects Models and Extensions in Ecology with R, 2009. Springer. Available as electronic book.

Textbook (literature), cont.

Additional, optional, literature: Julian J. Faraway: Extending the linear model with R. Generalized linear, mixed effect and nonparametric regression models. Chapman & Hall/CRC 2006"
The book is available in the science library.

Statistical software

In the course the `R` package downloadable from

`http://mirrors.sunsite.dk/cran/` will be used. It runs under the most common operative systems.

Most of the time procedures and functions available in `R` will be used.

Not much own programming will be necessary.

For a short introduction to `R` , see the web page of STK1110 last or this year.

A fine overview of `R` is the book written by Peter Dahlgaard:

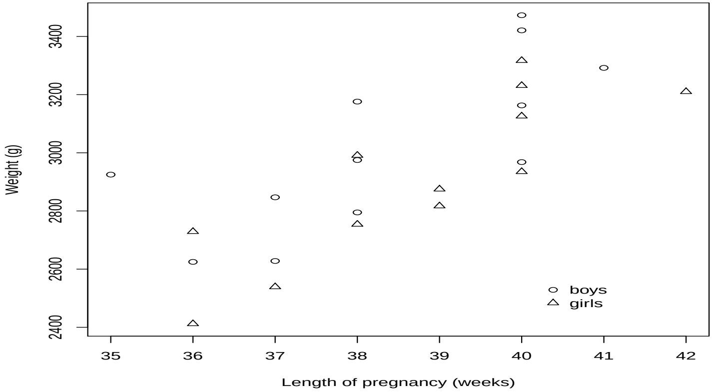
Introductory Statistics with R,2nd ed., 2008, Springer

Example 1: Birth weight and length of pregnancy

	Boys		Girls	
	Length (weeks)	Birth weight (gram)	Length (weeks)	Birth weight (gram)
	40	2968	40	3317
	38	2795	36	2729
	40	3163	40	2935
	35	2925	38	2754
	36	2625	42	3210
	37	2847	39	2817
	41	3292	40	3126
	40	3473	37	2539
	37	2628	36	2412
	38	3176	38	2991
	40	3421	39	2875
	38	2975	40	3231
Average	38.33	3024.00	38.75	2911.33

Of interest is the growth per week at the end of the pregnancy and if the is any difference between boys and girls

Scatter plot for Ex 1.



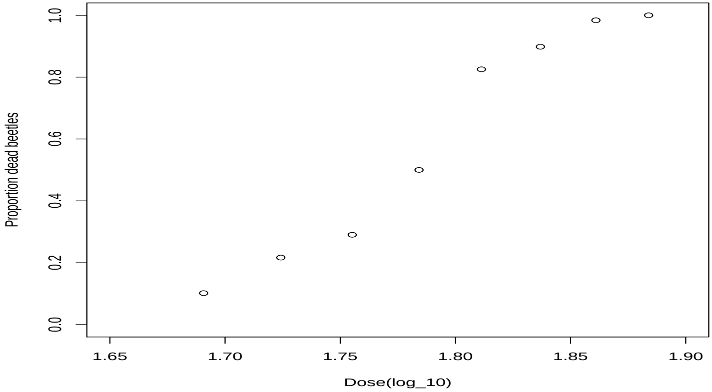
Example 2: Lethal dose for beetles

Around 480 beetles were exposed for eight different concentrations of CS_2. The number of deaths for the various concentrations were recorded.

Dose ($\log_{10} \mathrm{CS}_2 \mathrm{mg\,l}^{-1}$)	No	Dead
1.6907	59	6
1.7242	60	13
1.7552	62	18
1.7842	56	28
1.8113	63	52
1.8369	59	53
1.8610	62	61
1.8839	60	60

What is the relation of size of dose and mortality?

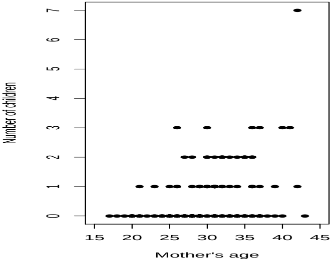
Proportion dead beetles in Ex 2.

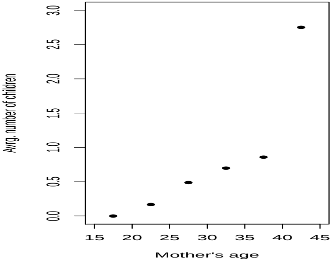


Example 3: number of children among pregnant.

de Jong & Heller, page 15-16: Data for number of children among 141 pregnant women of different ages.

The number increases with age, see figure 1.11 i deJ&H





Example 3b: number of third party claims

de Jong & Heller, side 17: Data over number of claims in 176 geographical regions in New South Wales in a en 12-months period.

Explanative variables, covariates:

- Statistical category, 13 categories
- Number of accidents in the region
- Number of killed and injured
- Size of population

In both examples: the response may be Poisson distributed.

Typical model for Ex 1: Linear regression

For $k = 1, ..., 12$ and $j = 1, 2$ (where $j = 1$ denotes boy and $j = 2$ denotes girl)

$$y_{jk} = \text{birth weight for baby nr. } k \text{ gender nr. } j$$
$$x_{jk} = \text{length of pregnace for baby nr. } k \text{ gender nr. } j$$

assume

$$y_{jk} = \alpha_j + \beta x_{jk} + \varepsilon_{jk}$$

where $\varepsilon_{jk} \sim \text{N}(0, \sigma^2)$, i.e. normally distributed with expectation 0 and same variance σ^2 and also independent.

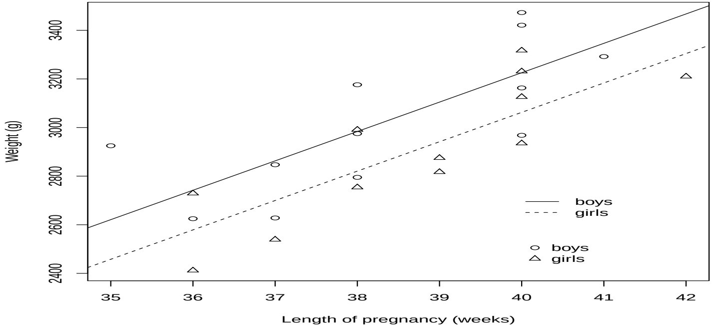
Typical model for Ex 1, cont.

Parameters :

$$\beta = \quad \text{slope}$$

$$\alpha_j = \quad \text{intercept for gender } j$$

Least squares fit for Example 1.



Estimates: $\hat{\alpha}_1 = -1447, \hat{\alpha}_2 = -1610, \hat{\beta} = 121$

Alternative formulation Ex. 1

- Linearity: $\mathrm{E}[y_{jk}] = \mu_{jk} = \alpha_j + \beta x_{jk}$
- Constant variance: $\mathrm{Var}[y_{jk}] = \sigma^2$
- Normality assumption: $y_{jk} \sim N(\mu_{jk}, \sigma^2)$
- Independent responses: y_{jk}'s independent

Alternative formulation Ex. 1, cont

I GLM (and STK3100) three first features are modified to

- Linearity after transformation via "link-function" $g()$:

  $g(\mu_{jk}) = \alpha_j + \beta x_{jk}$
- Variance may depend on the expectation of the responses.
- Other distributions for the responses: Binomial, Poisson, Gamma, ...

But independent responses are still assumed.

EX. 2: Mortality of beetles

It is reasonable to assume y_i = number dead beetles for dose x_i is binomially distributed.

$$y_i \sim \text{bin}(n_i, \pi_i)$$

where π_i = probability for beetle dying with dose x_i and n_i = number of beetles receiving dose x_i.

Linear model for π_i fitted with least squares problematic because

- $0 \leq \pi_i \leq 1$ in contrast to expression $\alpha + \beta x_i$
- $\text{Var}(y_i) = n_i \pi_i (1 - \pi_i)$, i.e. non-constant (heteroskedastisc) structure of variance

Usual model for Ex. 2: Logistic regression

Logistic model of regression:

$$\pi_i = \frac{\exp(\alpha + \beta x_i)}{1 + \exp(\alpha + \beta x_i)}$$

Then $0 \leq \pi_i \leq 1$

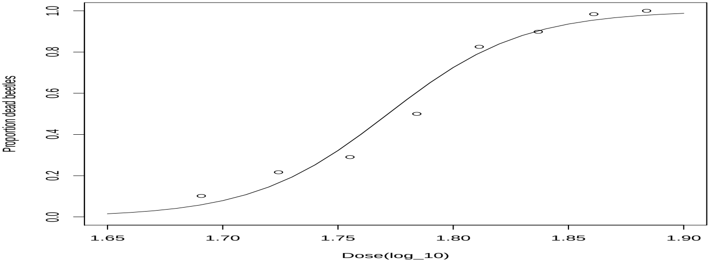
Fit the logistic model of regression with Maximum Likelihood (ML).

- Takes into account binomially distributed responses (and non-constant variance)
- Efficient estimators (approximately for large data)

Logistisc regression for Ex. 2: Number of dead beetles

MLE: $\hat{\alpha} = -60.72, \hat{\beta} = 34.27$

Predicted probabilities: $\hat{\pi} = \frac{\exp(\hat{\alpha}+\hat{\beta}x)}{1+\exp(\hat{\alpha}+\hat{\beta}x)}$



Estimating logistic regression

Storvik: "Numerical optimization of likelihoods: Additional literature for STK2120" describes a Newton-Rahpson routine in R for fitting logistisc regression to such observations. This is already

implemented in R. Use commando

```
glm(cbind(Dead,No-Dead)~Dose,family=binomial)
```

Example of GLM

- `glm` = Generalized Linear Model
- `family=binomial` because data binary or binomial.
- For binomial data `cbind(Dead,No-Dead)` needs "no. successes" (dead) and "no. failures" (No-Dead).

Ex. 3: number of previous children for mothers

y_i = number of previous children for mother i.

Reasonable to assume y_i Poisson distributed with expectation μ_i where μ_i depends on x_i = mothers age.

As in Ex. 2:

- Expectations $\mu_i > 0$
- Variance of y_i equals μ_i, i.e. non-constant variance

Ex. 3: number of previous children for mothers, cont.

Usual solution: Poisson-regression

$y_i \sim \text{Po}(\mu_i)$ where $\mu_i = \exp(\alpha + \beta x_i)$

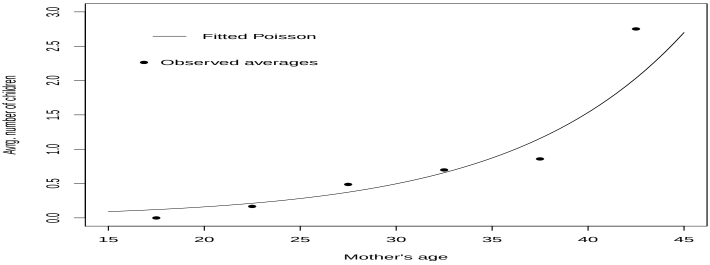
This is also a GLM and can be fitted with the `glm`-routine.

Only have to specify that data is assumed to be Poisson distributed with `family=poisson`

Poisson-regression for Ex. 3

MLE for (α, β): $(\hat{\alpha}, \hat{\beta}) = (-4.0895, 0.1129)$

Fitted probabilities: $\hat{\mu}_i = \exp(\hat{\alpha} + \hat{\beta} x_i)$



Definition of GLM

Independent responses $y_1, y_2, \dots, y_n$

Vectors of covariates $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$

where $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{ip})$ er p-dimensional

A GLM = Generalized Linear Model is defined by the following three components:

Definition of GLM, cont.

- $y_1, y_2, \ldots, y_n$ has a distribution belonging to an exponential family
  (Exponential families will be defined later, suffices to know that normal-, binomial-, Poisson-, gamma-distributions belong to the exponential family)
- Linear components (predictors) $\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$
- Link function $g()$: The expectation $\mu_i = \mathrm{E}[y_i]$ is related to the linear component by $g(\mu_i) = \eta_i$

Linear regression is a GLM

- Responses (y_i-er) from normal distribution
- Linear component $\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$
- $\mathrm{E}[y_i] = \mu_i = \eta_i$, i.e link function $g(\mu_i) = \mu_i$ is the identity function

In particular R-commands `lm` for linear regression and `glm` essentially the same, only a bit different output.

Linear regression is in particular default-specification of `glm`

Ex. 1: Birth weights

```
> lm(vekt~sex+svlengde)

Call:
 lm(formula = vekt ~ sex + svlengde)

Coefficients:
(Intercept)          sex     svlengde
    -1447.2       -163.0        120.9
```

Ex. 1: Birth weights

```
> glm(vekt~sex+svlengde)

Call:  glm(formula = vekt ~ sex + svlengde)

Coefficients:
(Intercept)          sex     svlengde
    -1447.2       -163.0        120.9

Degrees of Freedom: 23 Total (i.e. Null);  21 Residual
Null Deviance:      1830000
Residual Deviance: 658800       AIC: 321.4
```

Logistisc regression is GLM

- Responses (y_i-er) binomially distributed bin(n_i, π_i)
- Linear component $\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$
- $E[y_i]/n_i = \pi_i = \frac{\exp(\eta_i)}{1+\exp(\eta_i)}$, so that link function $g(\pi_i) = \log(\frac{\pi_i}{1-\pi_i})$

Denote $g(\pi) = \log(\frac{\pi}{1-\pi}) = \text{logit}(\pi)$ as logit-function.

Logistisc regression is GLM, cont.

```
> glm(cbind(Dode,Ant-Dode)~Dose,family=binomial)

Call:  glm(formula = cbind(Dode, Ant - Dode) ~ Dose, family = binomial)
Coefficients:
(Intercept)         Dose
     -60.72        34.27

Degrees of Freedom: 7 Total (i.e. Null);  6 Residual
Null Deviance:      284.2
Residual Deviance: 11.23        AIC: 41.43
```

Poisson regression is a GLM

- Response $y_i \sim \text{Po}(\mu_i)$
- Linear component $\eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$
- $\text{E}[y_i] = \mu_i = \exp(\eta_i)$, i. e. link function $g(\mu_i) = \log(\mu_i)$ is the (natural) logarithmic function.

Poisson regression is a GLM, cont.

```
> glm(children~age,family=poisson)

Call:  glm(formula = children ~ age, family = poisson)

Coefficients:
(Intercept)          age
    -4.0895       0.1129

Degrees of Freedom: 140 Total (i.e. Null);  139 Residual
Null Deviance:       194.4
Residual Deviance: 165  AIC: 290
```

Some extensions

Other GLM's:

- Count data with negative binomial distribution: Over dispersion.
- Continuous, non-normal responses: gamma-, inverse gaussian distributions

These will be considered.

Some other extensions

Extensions of GLM:

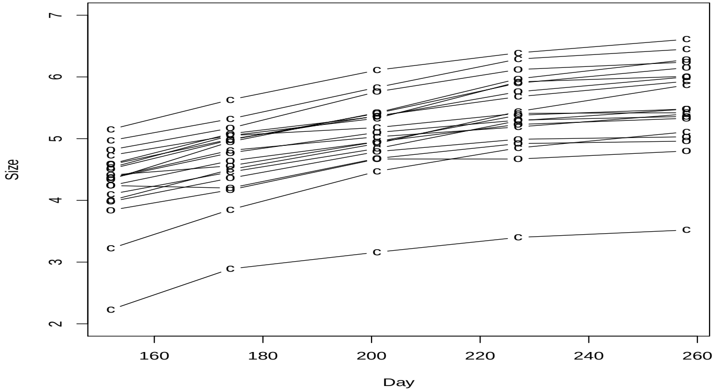
- Multinomial responses (ordinal and nominal)
- Life time data
- Analysis of dependent data,GLMM
- Generalized additive models (GAM)

We will consider multinomial responses and GLMM.

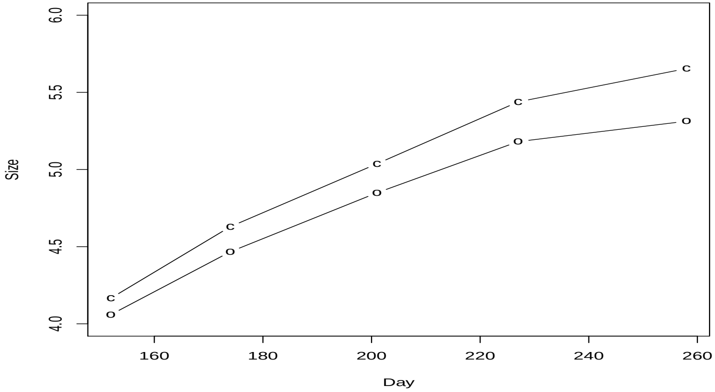
Example 4: Growth of trees and ozone exposure

Growth for two groups of trees is recorded at five different points of time. Of the trees 54 are located in an environment with heavy traffic and 25 trees are a control group. In total there are 395 measurements $y_{i,j},\ i = 1, \cdots, 79,\ j = 1, \cdots, 5$.

Plot of 10 profiles in each group



Plot of average profiles



Exposure of ozone

```
Linear mixed-effects model fit by maximum likelihood

Random effects:
 Formula: ~1 + Time | tree
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.790968468 (Intr)
Time        0.002487428 -0.649
Residual    0.162608831

Fixed effects: size ~ Time + factor(treat) * Time
                             Value  Std.Error  DF   t-value p-value
(Intercept)              2.1217179 0.17806707 314 11.915274  0.0000
Time                     0.0141472 0.00063379 314 22.321782  0.0000
factor(treat)ozone       0.2216775 0.21537748  77  1.029251  0.3066
Time:factor(treat)ozone -0.0021385 0.00076658 314 -2.789663  0.0056
```

Survey of textbook by de Jong & Heller

- Chapter 1: Introduction, Data examples: will not be treated in detail
- Chapter 2: Diverse distributions: with some exceptions known before
- Chapter 3: Exponential classes, ML-estimation
- Chapter 4: Linear modeling (mainly known from STK1110/STK2120)
- Chapter 5: Generalized linear models

Survey of textbook by de Jong & Heller, cont.

- Chapter6: Count data (Poisson regression, over dispersion)
- Chapter 7: Categorical responses (binomial data, multinomial data)
- Chapter 8: Continuous responses
- Chapter 9: Correlated data
- Chapter 10: Extensions

Plan for course, STK3100/STK4100

Will follow the textbook of de Jong & Heller, but not in all details, and not in sequence. Also some parts must be supplemented.
In the last part of the course we will treat GLMM and the relevant material in Zuur et al.

Approximate plan for first lectures:

Plan for course, STK3100/STK4100, cont.

- Introduction, today!
- Chapter 4. Linear models, mainly repetition of STK1110/STK2120, Thursday August 20th and Tuesday August 25th
- Chapter 3: Exponential classes, September 1st.
- Chapter 5: GLM and ML-theory September 8th.
- Chapter 7: Binomial and binary data
- Chapter 6: Count data

Plan for course, STK3100/STK4100, cont.

- Chapter 7: Multinomial data
- Chapter 8: A little of continuous responses
- Extensions: Correlated data and GAM, material from Zuur et al. chapters 6, 7 and 13.