

Exercise resolution

- ▶ A researcher conducted a clinical trial of 50 patients with epilepsy, 25 of whom were randomized to receive the new anticonvulsant drug (experimental group) and 25 to receive the old one (control group). The group (experimental or control group), age and outcome were recorded. The outcome variable was seizure counts that occurred during the eight-week follow-up period.

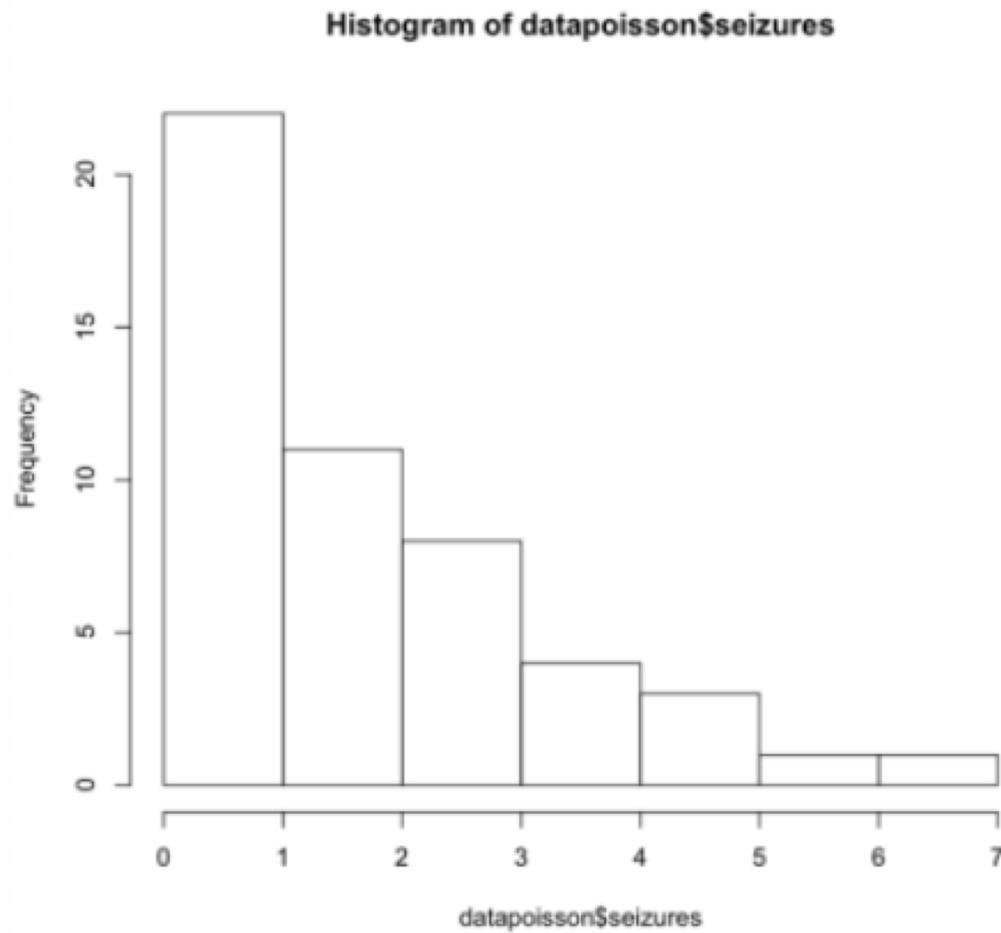


We want to know whether the new drug increases or decreases the number of seizures when adjusted for age.



- ▶ Let's see the distribution of the number of seizures with a histogram

```
hist(datapoisson$seizures)
```



► Outcome: count ➔ Poisson Regression

```
poisson <- glm(datapoison$seizures ~ datapoison$age + datapoison$group, data = datapoison, family = "poisson")
summary(poisson)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.3308	-0.4922	-0.4563	0.3505	2.2198

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.347514	0.678376	0.512	0.60846
datapoison\$age	0.003112	0.021099	0.148	0.88273
datapoison\$groupnew drug	0.561495	0.204292	2.748	0.00599 **

Signif. codes: 0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 61.808 on 49 degrees of freedom
Residual deviance: 53.827 on 47 degrees of freedom
AIC: 177.48

Number of Fisher Scoring iterations: 5

$$\ln(\mu_y) = 0.347514 + 0.003112 \text{ age} + 0.561495 \text{ new group}$$

► Outcome: count ➔ Poisson Regression

```
exp(cbind(RR = coef(poisson), confint(poisson)))
```

	RR	2.5 %	97.5 %
(Intercept)	1.415545	0.3667683	5.258693
datapoisson\$age	1.003117	0.9626480	1.045765
datapoisson\$groupnew drug	1.753292	1.1809467	2.637163

The new drug increases the number of seizures by 1.8 times even adjusted for age.

But we can even predict the average number of seizures over an eight-year period weeks in a patient, for example, **30 years old** with epilepsy treated with the new drug:

$$\ln(\mu_y) = 0.347514 + 0.003112 \text{ age} + 0.561495 \text{ new group}$$

$$e^{\ln(\mu_y)} = \mu_y = e^{0.347514 + 0.003112 \times \text{age} + 0.561495 \times \text{new drug group}}$$

$$\mu_y = e^{0.347514 + 0.003112 \times 30 + 0.561495 \times 1}$$

$$\mu_y = e^{0.561495} = 2,7$$

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$$e^{\ln(\mu_y)} = \mu_y = e^{0.347514 + 0.003112 \times \text{age} + 0.561495 \times \text{new drug group}}$$

$$\mu_y = e^{0.347514 + 0.003112 \times 30 + 0.561495 \times 0}$$

$$\mu_y = e^{0.440874} = 1,5$$

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- ▶ The observations are independent
- ▶ The rate is constant
- ▶ Mean=variance (right skewed)

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- ▶ Mean=variance (right skewed)

A common problem with Poisson regression is the problem of overdispersion i.e. variance > mean.

The problem of oversdispersion

- ▶ A common problem with Poisson regression is the problem of oversdispersion i.e. variance > mean.
- ▶ If there is more variability than expected, the estimated standard errors will be very low (exaggerated levels of accuracy) but the coefficients estimates are OK. The problema is only with the inference (confidence intervals and p values)

The problem of oversdispersion

- ▶ We can compute the dispersion

```
DISPERSION <- (sum(residuals(poisson,type="pearson")^2))/poisson$df.residual
```

```
DISPERSION
```

```
[1] 1.095602
```

- ▶ Dispersion above one is **overdispersion**.
- ▶ **Underdispersion** (below one) is less common, but it can exist.
- ▶ We want a dispersion close to one.

As rule we can say that a dispersion above 2 is when this problem of overdispersion becomes a real problem.

The problem of oversdispersion

- ▶ In this exercise overdispersion was not a problem but when it exists, a possible solution is to try to include more relevant independent variables in the model as this problem may be related to the fact that we failed to include many of the important independent variables for the model.
- ▶ If the problema was not the lack of important independent variables and overdispersion is still a problem, we can try to adjust a model using the quasi-likelihood function. In this way, the estimates will be the same but the standard errors will be adjusted (will be larger).

The problem of oversdispersion

```
quasipoisson <- glm(datapoison$seizures ~ datapoison$age + datapoison$group, data = datapoison, family = "quasipoisson")
```

poisson model	quasi-poisson model
Deviance Residuals:	Deviance Residuals:
Min 1Q Median 3Q Max	Min 1Q Median 3Q Max
-2.3308 -0.4922 -0.4563 0.3505 2.2198	-2.3308 -0.4922 -0.4563 0.3505 2.2198
Coefficients:	Coefficients:
Estimate Std. Error z value Pr(> z)	Estimate Std. Error t value Pr(> t)
(Intercept) 0.347514 0.678376 0.512 0.60846	(Intercept) 0.347514 0.710063 0.489 0.6268
datapoison\$age 0.003112 0.021099 0.148 0.88273	datapoison\$age 0.003112 0.022084 0.141 0.8885
datapoison\$groupnew drug 0.561495 0.204292 2.748 0.00599 **	datapoison\$groupnew drug 0.561495 0.213835 2.626 0.0116 *
---	---
Signif. codes: 0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	Signif. codes: 0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for poisson family taken to be 1)	(Dispersion parameter for quasipoisson family taken to be 1.095602)
Null deviance: 61.808 on 49 degrees of freedom	Null deviance: 61.808 on 49 degrees of freedom
Residual deviance: 53.827 on 47 degrees of freedom	Residual deviance: 53.827 on 47 degrees of freedom
AIC: 177.48	AIC: NA
Number of Fisher Scoring iterations: 5	Number of Fisher Scoring iterations: 5