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## GLM I: Introduction to Generalized Linear Models

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Casualty Actuarial Society  
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## Overview

Overview of GLMs

Personal Injury Claims

Intercept Only Models

One Continuous Predictor

One Discrete Predictor

Many Predictors

Key Concepts

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## Standard Linear Model Specification

$$y = \beta_0 + x_1\beta_1 + \dots + x_k\beta_k + \epsilon \quad \text{with } \epsilon \in N(0, \sigma^2)$$

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## Standard Linear Model Specification

$$y = \beta_0 + x_1\beta_1 + \dots + x_k\beta_k + \epsilon \quad \text{with } \epsilon \in N(0, \sigma^2)$$

A better way to think about this would be

$$\mathbb{E}[y] = \beta_0 + x_1\beta_1 + \dots + x_k\beta_k$$

where  $y \in N(\mu, \sigma^2)$  and  $\mu = \beta_0 + x_1\beta_1 + \dots + x_k\beta_k$  is the linear predictor.

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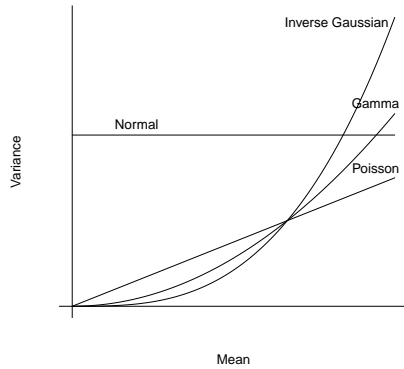
## Generalized Linear Model Specification

$$g(\mathbb{E}[y]) = \beta_0 + x_1\beta_1 + \dots + x_k\beta_k + \text{offset}$$

1. The link function is  $g$
2. The distribution of  $y$  is a member of the exponential family
3. The explanatory variables  $x_i$  may be continuous or discrete
4. Offset terms have a known coefficient of 1 in the linear predictor

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## Mean-Variance Relationship



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## Personal Injury Dataset

The dataset contains 22,036 settled personal injury claims. These claims arose from accidents occurring from July 1989 through January 1999. This is the `persinj.xls` dataset featured in the book by de Jong & Heller [2].

I have taken a random sample of 200 claims.

The variables are:

1. Settled Amount
2. Injury codes
3. Legal representation
4. Accident month
5. Report month
6. Finalization month
7. Operational time

Derived variables:

1. Injured count
2. Accident injury code
3. Report delay
4. Settlement delay

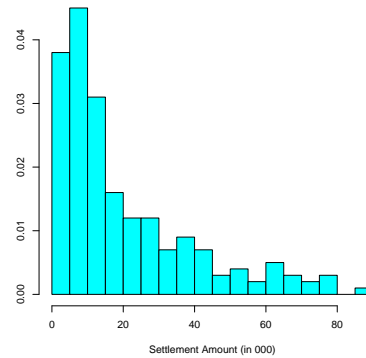
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## Variable Descriptions

Variable	Type	Comments
Settled Amount	Cont	range: \$40 to \$85,000
Injury Codes	Cat	Injury level: 1, 2, ..., 6 = death, 9 = missing
Legal Rep.	Bin	Attorney involved? 1 = Yes, 0 = No
Accident Month	Coded	1 = July 1989, 120 = June 1999
Report Month	Coded	same as accident month
Fin. Month	Coded	same as accident month
Injured Count	Count	Number of persons injured: 1, 2, ..., 5
Acc. Injury	Cat	Highest injury code among those injured
Report Delay	Cont	# months between accident and report
Settle. Delay	Cont	# months between report and settlement

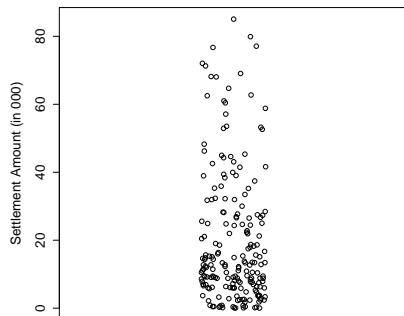
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## Histogram of Settlement Amount



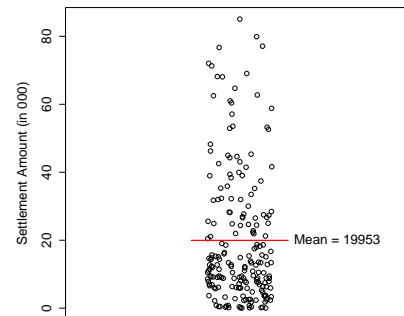
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## Distribution of Settlement Amount



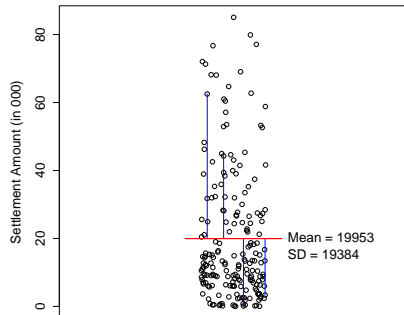
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## Settlement Amount: mean



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### Settlement Amount: mean & standard deviation



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### Linear Model—Intercept only

```
Call:
lm(formula = total ~ 1, data = spinj)

Residuals:
    Min       1Q   Median       3Q      Max
-19913 -13570  -7199   7591  65110

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  19953      1371    14.56 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 19380 on 199 degrees of freedom
```

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### Generalized Linear Model—Normal Id—Intercept only

```
Call: glm(formula = total ~ 1,
          family = gaussian(link = identity), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-19913 -13570  -7199   7591  65110
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  19953      1371    14.56 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 375744867)

Null deviance: 7.4773e+10 on 199 degrees of freedom
Residual deviance: 7.4773e+10 on 199 degrees of freedom
AIC: 4519.5

Number of Fisher Scoring iterations: 2
```

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### Generalized Linear Model—Gamma Id—Intercept only

```
Call: glm(formula = total ~ 1,
          family = Gamma(link = identity), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2293 -0.9588 -0.4165  0.3407  1.9043
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  19953      1371    14.56 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.9438079)

Null deviance: 252.05 on 199 degrees of freedom
Residual deviance: 252.05 on 199 degrees of freedom
AIC: 4366.6

Number of Fisher Scoring iterations: 3
```

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### Generalized Linear Model—Gamma Log—Intercept only

```
Call: glm(formula = total ~ 1,
          family = Gamma(link = "log"), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2293 -0.9588 -0.4165  0.3407  1.9043
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.9011      0.0687   144.1 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

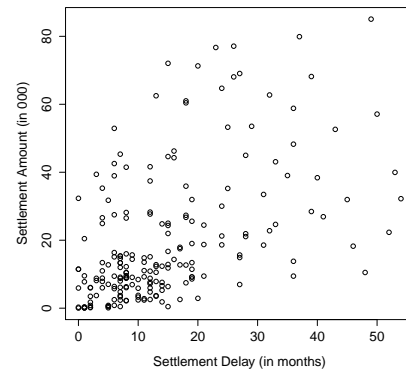
(Dispersion parameter for Gamma family taken to be 0.9438079)

Null deviance: 252.05 on 199 degrees of freedom
Residual deviance: 252.05 on 199 degrees of freedom
AIC: 4366.6

Number of Fisher Scoring iterations: 6
```

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### Settlement Amount vs. Settlement Delay



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## Linear Model—Intercept and Slope

```
Call:
lm(formula = total ~ settle.delay, data = spinj)

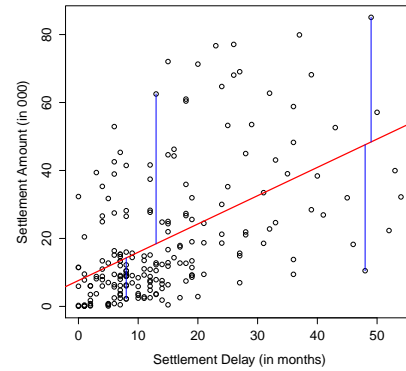
Residuals:
    Min       1Q   Median       3Q      Max
-37059 -10395 -5085   4366  51957

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7614.05   1861.85   4.089 6.28e-05 ***
settle.delay  832.30    97.44   8.542 3.50e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16610 on 198 degrees of freedom
Multiple R-squared:  0.2693, Adjusted R-squared:  0.2656
F-statistic: 72.96 on 1 and 198 DF, p-value: 3.504e-15
```

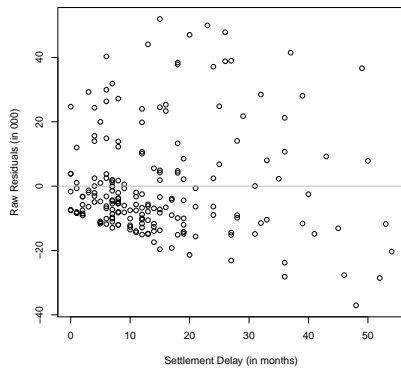
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## Settlement Amount vs. Delay: Least Squares Line



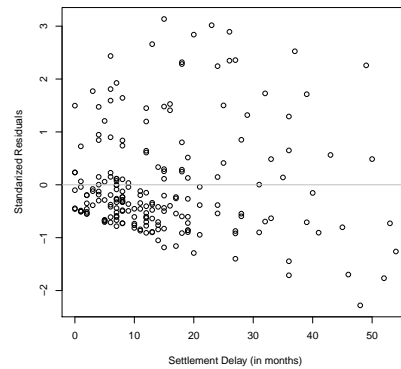
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## Raw Residuals vs. Settlement Delay



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## Standardized Residuals vs. Settlement Delay



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## Many Flavors of Residuals

Raw  $y - \hat{y}$  or  $y - \mu$  or  $y - \mathbb{E}[y]$   
 Pearson  $(y - \mu) / \sqrt{V}$   
 Deviance  $\text{sgn}(y - \mu) \sqrt{\text{deviance}}$

Standardized Divide residual by  $\sqrt{1 - h}$ , which aims to make its variance constant; where  $h$  are the diagonal elements of the projection ('hat') matrix,  $H = X(X^T X)^{-1} X^T$ , which maps  $y$  into  $\hat{y}$

Studentized Divide residual by  $\sqrt{\phi}$ ; where  $\phi$  is the scale parameter

Stan & Stud Divide residual by both standardized and studentized adjustments

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## Deviance

Distribution	Contribution to Squared Deviance
Normal	$(y_i - \mu_i)^2$
Poisson	$2\{y_i \log(y_i / \mu_i) - y_i + \mu_i\}$
Gamma	$2\{-\log(y_i / \mu_i) + (y_i - \mu_i) / \mu_i\}$
Inverse Gaussian	$(y_i - \mu_i)^2 / (\mu_i^2 y_i)$

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### Gamma Log GLM—Intercept and Slope

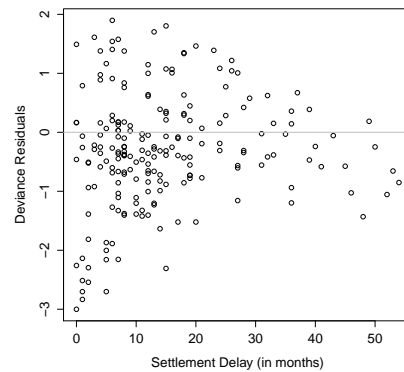
```
Call: glm(formula = total ~ settle.delay,
          family = Gamma(link = "log"), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.0008 -0.8017 -0.3145  0.1991  1.8982
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.187173   0.102174  89.917 < 2e-16 ***
settle.delay  0.040473   0.005347   7.569 1.39e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.8310652)

Null deviance: 252.05  on 199  degrees of freedom
Residual deviance: 206.47  on 198  degrees of freedom
AIC: 4321.8

Number of Fisher Scoring iterations: 7
```

### Gamma Model: Deviance Residuals vs. Settlement Delay



### Poisson Log GLM—Intercept and Slope

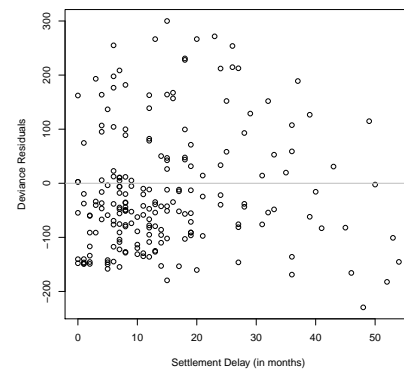
```
Call: glm(formula = tot.amt ~ settle.delay,
          family = poisson(link = "log"), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-229.41 -92.18 -42.51  35.74  299.99
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  9.323e+00  8.583e-04 10862.1 < 2e-16 ***
settle.delay  3.280e-02  3.338e-05  982.7 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

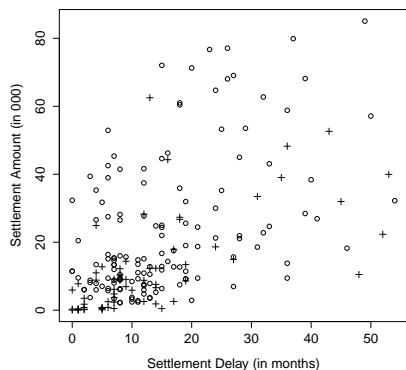
Null deviance: 3366902  on 199  degrees of freedom
Residual deviance: 2515703  on 198  degrees of freedom
AIC: 2517928

Number of Fisher Scoring iterations: 5
```

### Poisson Model: Deviance Residuals vs. Settlement Delay



### Legal Representation?



### Gamma Log GLM—Legal Representation?

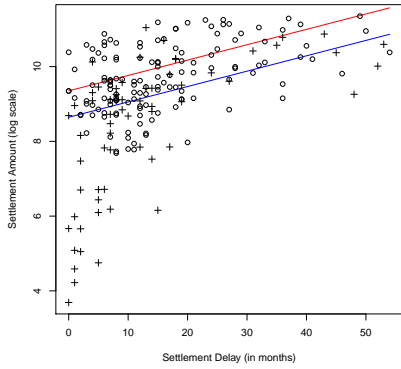
```
Call: glm(formula = total ~ settle.delay + legrep,
          family = Gamma(link = "log"), data = spinj)
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8152 -0.8183 -0.3115  0.2864  2.6778
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.64459   0.13476  64.148 < 2e-16 ***
settle.delay  0.04112   0.00539   7.628 9.96e-13 ***
legrep1      0.70702   0.13989   5.054 9.85e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.8354751)

Null deviance: 252.05  on 199  degrees of freedom
Residual deviance: 186.98  on 197  degrees of freedom
AIC: 4300.9

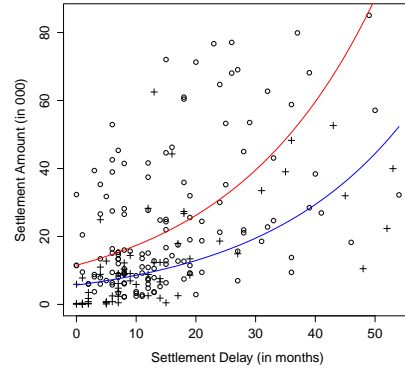
Number of Fisher Scoring iterations: 8
```

### Legal Representation: Linear Predictor



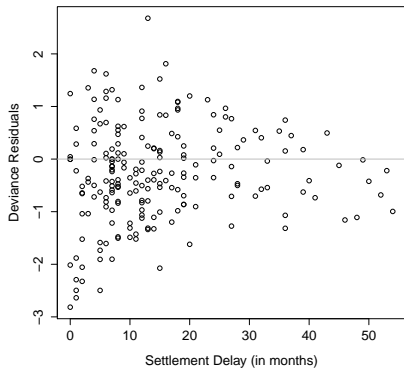
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### Legal Representation: Fitted Values



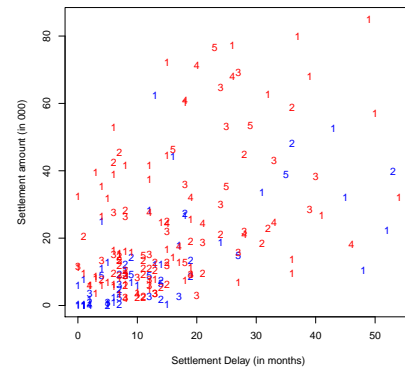
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### Legal Representation: Deviance Residuals



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### Number of Injured Persons



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### Gamma Log GLM—Many Predictors

Call: glm(formula = total ~ settle.delay + legrep + inj.count, family = Gamma(link = "log"), data = spinj)

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	8.722358	0.141721	61.546	< 2e-16 ***
settle.delay	0.042138	0.005222	8.069	7.38e-14 ***
legrep1	0.786161	0.139411	5.639	6.01e-08 ***
inj.count2	-0.300230	0.160788	-1.867	0.0634 .
inj.count3	-0.416338	0.177247	-2.349	0.0198 *
inj.count4	-0.216891	0.244640	-0.887	0.3764
inj.count5	0.005267	0.254395	0.021	0.9835

Null deviance: 252.05 on 199 degrees of freedom  
Residual deviance: 181.44 on 193 degrees of freedom  
AIC: 4302

Number of Fisher Scoring iterations: 9

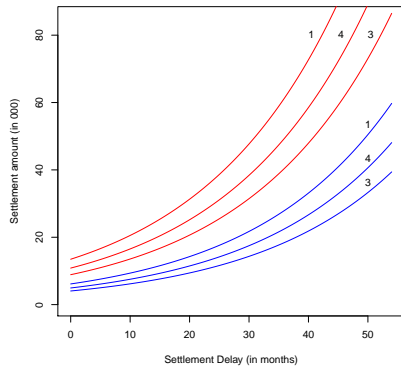
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### Predicted Values

Settle Delay	Legal Rep?	Injured Count	Linear Predictor	Fitted Value
0	No	1	$8.7 + 0 \cdot 0.042 = 8.7$	$e^{8.7} = 6003$
0	Yes	1	$8.7 + 0 \cdot 0.042 + 0.79 = 9.5$	$e^{9.5} = 13360$
10	No	4	$8.7 + 10 \cdot 0.042 - 0.22 = 8.5$	$e^{8.9} = 7332$

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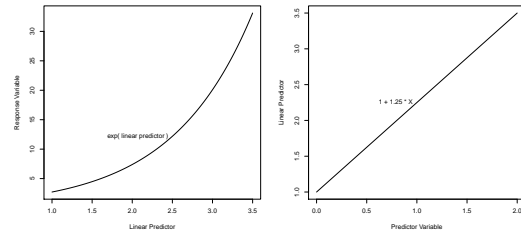
## Many Predictors: Fitted Values



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## Summary Key Concepts: Link Function

The link function is the bridge between the space of the linear predictor and the space of the response.



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## Summary Key Concepts: Deviance

The deviance tells us how to measure the distance between an observation and its fitted value.

Distribution	Contribution to Squared Deviance
Normal	$(y_i - \mu_i)^2$
Poisson	$2\{y_i \log(y_i/\mu_i) - (y_i - \mu_i)\}$
Gamma	$2\{-\log(y_i/\mu_i) + (y_i - \mu_i)/\mu_i\}$
Inverse Gaussian	$(y_i - \mu_i)^2 / (\mu_i^2 y_i)$



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## References

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-  Piet De Jong and Gillian Z. Heller. *Generalized Linear Models for Insurance Data*. Cambridge University Press, 2008.
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