



## Poisson Regression Model

Data:  $\{(x_{11},...,x_{1p}),Y_1\},....,\{(x_{n1},...,x_{np}),Y_n\}$  where  $Y_1,...,Y_n$  are event count data per observation unit with a Poisson distribution

### **Assumptions:**

- Linearity Assumption:  $log(E(Y|x_1, ..., x_p)) = \beta_0 + \beta_1 x_1 + ... + \beta_p x_p$
- Independence Assumption: Y<sub>1</sub>,.., Y<sub>n</sub> are independent random variables
- Variance Assumption:  $E(Y|x_1, ..., x_p) = V(Y|x_1, ..., x_p)$

There is no error term! How to check the assumptions?

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# Residuals in Poisson Regression

### **Poisson Regression:**

 $Y_i|(x_{i1},...,x_{ip}) \sim Poisson(l(x_{i1},...,x_{ip}))$ 

- Estimated rates are:  $\hat{\lambda}_i = \hat{\lambda}(\mathbf{x}_{i1,...}\mathbf{x}_{ip}) = e^{\hat{\beta}_0 + \hat{\beta}_1 \mathbf{x}_{i1} + ... + \hat{\beta}_p \mathbf{x}_{ip}}$
- · Pearson Residuals:

$$r_i = \frac{Y_i - \hat{\lambda}_i}{\sqrt{\hat{\lambda}_i}}$$

Deviance Residuals:

$$d_i = 2\sum_{i=1}^n \left\{ Y_i \log \left( \frac{Y_i}{\hat{\lambda}_i} \right) - (Y_i - \hat{\lambda}_i) \right\}$$

- Pearson's residuals follow directly a normal approximation to a binomial. Hence approximately N(0,1)
- The deviance residuals are the signed square root of the log-likelihood evaluated at the saturated model vs. the fitted model. Thus approximately N(0,1) if the model is a good fit.
- Deviances play the role of sum of squares in a linear model.

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### Goodness of Fit

#### **GOF Visual Analytics:**

- Normal Probability plot & Histogram of the Residuals
- Log of the event rate vs predictors

#### **Hypothesis Testing Procedure:**

 $H_0$ : the Poisson model fits the data

H<sub>A</sub>: the Poisson model does not fit the data

Deviance test statistic:  $D = \sum_{i=1}^{n} d_i^2$ 

Under null hypothesis,  $D \sim \chi_{df}^2$  with df = n-p-1

Reject the <u>null that the model is correct</u> if p-value =  $P(\chi_{df}^2 > D)$  small.

Note that for this test, we want large p-values!!!!

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### What if No Goodness of Fit?

- Add predicting variables, consider interaction terms, or/and transform predicting variables to improve linearity;
- Identify unusual observations (outliers, leverage points);
- The Poisson distribution isn't appropriate:
  - Overdispersion: the variability of the estimated rates is larger than would be implied by a Poisson model
    - Correlation in the observed responses
    - Heterogeneity in the rates that hasn't been modeled



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### Overdispersion

Overdispersion: the variability of the response variable is larger than would be implied by the model

### Binomial regression model:

- $V(Y_i|\mathbf{x}_1,...,\mathbf{x}_p) = n_i p(\mathbf{x}_{i1},...,\mathbf{x}_{ip}) (1-p(\mathbf{x}_{i1},...,\mathbf{x}_{ip}))$  Overdispersed Binomial:  $V(Y_i|\mathbf{x}_1,...,\mathbf{x}_p) = \phi n_i p(\mathbf{x}_{i1},...,\mathbf{x}_{ip}) (1-p(\mathbf{x}_{i1},...,\mathbf{x}_{ip}))$

### Poisson regression model:

- $$\begin{split} & \text{V}(Y_i | \mathbf{x}_1, \dots, \mathbf{x}_p) = \lambda(\mathbf{x}_{i1}, \dots, \mathbf{x}_{ip}) \\ & \text{Overdispersed Poisson: } & \text{V}(Y_i | \mathbf{x}_1, \dots, \mathbf{x}_p) = \phi \lambda(\mathbf{x}_{i1}, \dots, \mathbf{x}_{ip}) \end{split}$$

### Overdispertion Parameter: $\phi$

- Estimate:  $\hat{\phi} = \frac{D}{n-p-1}$  where D is the sum of the squared deviances
- If  $\hat{\phi} > 2$  then overdispersed model

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## Summary

