# Discrete Response Model Lecture 5

Models for Count Response, Discrete Response Model Evaluation, and Model Selection

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# Poisson Probability Model

## Count Response Data

Count responses can also arise from other mechanisms that have nothing to do with Bernoulli trials. Examples include:

- The number of credit cards an individual owns
- The number of arrests for a city per year
- The number of people arriving at an airport on a given day
- The number of cars stopped at the 33rd and Holdrege streets intersection
- The number of people standing in line at a specific Starbucks between 6 AM and 7 PM

For these settings, a Poisson distribution can be used to model the count responses.

#### Poisson PMF

Poisson PMF:

$$P(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}$$

for y = 0, 1, 2, ..., where

Y is a random variable y denotes the possible outcomes of Y  $\boldsymbol{\mu}$  is a parameter that is greater than 0

We often write Y  $\sim$  Po( $\mu$ ) as shorthand notation to mean that Y has a Poisson distribution with parameter  $\mu$  .

Y will denote the number of occurrences of an event.

### Properties

Below are characteristics of a Poisson distribution and associated items of interest:

One can show the mean and variance of Y to be:

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

Having the mean and variance BOTH equal to  $\mu$  is nice, but this is also limiting. Often, the actual variability observed in a sample is GREATER than  $\mu$ .

This is referred to as overdispersion.

If  $Y_1$ , ...,  $Y_n$  are independent with distribution Po( $\mu$ ), then  $\sum_{k=1}^{n} Y_k \sim Po(\sum_{k=1}^{n} \mu = n\mu)$ .

If each  $Y_k$  had a different mean, we would have  $\sum_{k=1}^n Y_k \sim Po(\sum_{k=1}^n \mu_k)$ 

$$\sum_{k=1}^{n} Y_k \sim Po(\sum_{k=1}^{n} \mu_k)$$

## Properties

Likelihood function:

$$L(\mu; y_1, ..., y_n) = \prod_{k=1}^n \frac{e^{-\mu} \mu^{y_k}}{y_k!}$$

MLE for 
$$\mu$$
 is  $\boldsymbol{\hat{\mu}} = \boldsymbol{n}^{-1} \sum_{k=1}^n \boldsymbol{y}_k$  , i.e., the sample mean

The estimated variance for  $\hat{\mu}$  is

$$Var(\hat{\mu}) = -\left[E\left(\frac{\partial^2 \log[L(\mu \mid Y_1, ..., Y_n)]}{\partial \mu^2}\right)\right]^{-1}\bigg|_{\mu=\hat{\mu}} = \frac{\hat{\mu}}{n}$$

## Hypothesis Testing and Score CI for $\mu$

$$H_0$$
:  $\mu = \mu_0$  vs.  $H_a$ :  $\mu \neq \mu_0$ 

Wald test statistic: 
$$Z_0 = \frac{\hat{\mu} - \mu_0}{\sqrt{\hat{\mu} / n}}$$

Score test statistic: 
$$Z_0 = \frac{\hat{\mu} - \mu_0}{\sqrt{\mu_0 / n}}$$

Score CI for  $\mu$ 

$$\left(\hat{\mu} + \frac{Z_{1-\alpha/2}^2}{2n}\right) \pm Z_{1-\alpha/2} \sqrt{\frac{\hat{\mu} + Z_{1-\alpha/2}^2 / 4n}{n}}$$

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