#### Generalized Linear Models

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# A generalized linear model

- 1.  $y = (y_1, \ldots, y_n)$
- 2. X and coefficients  $\beta$
- 3. a link function g so that  $\hat{y} = g^{-1}(X\beta)$
- 4. a data distribution
- 5. other parameters, for example?

#### Link function

What is the link function g(u) for the linear regression?

- a the identity:  $u^{-1}$
- b the logarithm:  $log^{-1}(u)$
- c the square:  $u^{-2}$

# Poisson regression model

- $ightharpoonup i 
  ightarrow ext{setting (location, time interval, index street)}$
- $\triangleright$   $y_i$  the number of events (n. of traffic accident)
- $y_i \sim Poisson(\theta_i)$
- $\bullet \ \theta_i = \exp(X_i\beta)$

## Interpreting the coefficient

$$y_i \sim Poisson(exp(2.8 + 0.012 X_{i1} - 0.20 X_{i2})$$

 $X_{i1} \rightarrow$  average speed (in miles per hour, mph) on the nearby street

 $X_{i2} = 1$  if the intersection has a traffic signal, or 0 otherwise

# Interpreting the coefficient

$$y_i \sim Poisson(exp(2.8 + 0.012 X_{i1} - 0.20 X_{i2})$$

 $X_{i1} o$  average speed (in miles per hour, mph) on the nearby street  $X_{i2} = 1$  if the intersection has a traffic signal, or 0 otherwise

- the intercept not interpretable
- $lackbox{e}^{0.012}=1.012
  ightarrow 1.2\%$  in the rate of traffic accidents per mph
- $e^{-0.20} = 0.82 \rightarrow \text{reduction of } 18\% \text{ with traffic signal}$

### Data set: Police Stop

stop and frisk data (with noise added to protect confidentiality)

ID code for the identification of the sample

stops NYC police stops

arrests number of arrests in the previous year

precincts numbered 1-75

ethnicity 1=black, 2=hispanic, 3=white

 $\texttt{crime type} \quad 1 \texttt{=} \texttt{violent}, \, 2 \texttt{=} \texttt{weapons}, \, 3 \texttt{=} \texttt{property}, \, 4 \texttt{=} \texttt{drug} \\$ 

Question 2 and question 3 in prismia!

## The Poisson model: Police Stop

```
\label{eq:Routput} R \ \mbox{output} \qquad \mbox{glm(formula = stops $\tilde{$}$ factor(eth), family=poisson,} \\ \mbox{offset=log(arrests))}
```

Coef.	coef est	coef sd	p val
Intercept	-0.58	0.0038	< 2e - 16
factor(eth)2	0.07	0.006	< 2e - 16
factor(eth)3	-0.16	0.008	< 2e - 16

Model	Deviance
Null	183981
Eth. covariate	183297

## The ethnicity coefficient in the Poisson model

Compared to the baseline category 1 (blacks) how many stops category 2 (hispanics) has (coef: 0.07)?

- 1. 7% more
- 2. 70 % more
- 3. 7% less

## The ethnicity coefficient in the Poisson model

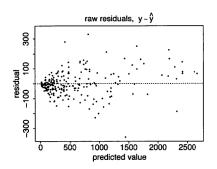
Compared to the baseline category 1 (blacks) how many stops category 3 (whites) has (coef: -0.16)?

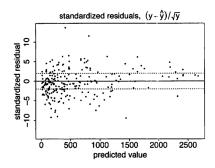
- 1. 16 % less
- 2. 14% less
- 3. 85% more

### Model with precincts

```
glm(formula = stops ~ factor(eth) + factor(precinct), family=poisson,
   offset=log(arrests))
                 coef.est coef.se
(Intercept)
                    -4.03
                            0.05
factor(eth)2
                    0.00 0.01
factor(eth)3
                -0.42 0.01
factor(precinct)2 -0.06 0.07
factor(precinct)3 0.54 0.06
factor(precinct)75
                     1.41
                            0.08
 n = 225, k = 77
 residual deviance = 2828.6, null deviance = 44877 (difference = 42048.4)
 overdispersion parameter = 18.2
```

# Testing for overdispersion in a Poisson regression model





#### The test

Estimated overdispersion = 
$$\frac{1}{n-k} \sum_{i=1}^{n} z_i^2$$

This is a  $\chi^2_{n-k}$ 

```
 yhat <- predict (glm.police, type="response") \\ z <- (stops-yhat)/sqrt(yhat) \\ cat ("overdispersion ratio is ", sum(z^2)/(n-k), "\n") \\ cat ("p-value of overdispersion test is ", pchisq (sum(z^2), n-k), "\n") \\
```

The estimated overdispersion factor is 2700/148=18.2, and the p-value is 1.

# Adjusting Inference for overdispersion

- multiply the standard errors by  $\sqrt{18.2}$
- example whites

before: 
$$-0.42 \pm 0.01$$
 now:  $-0.42 \pm 0.04$ 

confidence intervals

$$e^{-0.42\pm1.96\times0.04} = [0.61, 0.71]$$



# Binary Data as a special case of count-data model

Logit or Probit?

$$Pr(y_i = 1) = \Phi(X_i\beta)$$

$$y_i = \begin{cases} 1 & \text{if } z_i > 0 \\ 0 & \text{if } z_i < 0 \end{cases}$$

$$z_i = X_i\beta + \epsilon_i$$

$$\epsilon_i \sim N(0, 1),$$

#### Probit or logit?

```
fit.probit <- glm (switch ~ dist100, family=binomial(link="probit"))
> summary(fit.probit)
Call:
glm(formula = switch ~ dist100, family = binomial(link = "probit"))
Deviance Residuals:
             10 Median 30
                                     Max
   Min
-1.4409 -1.3055 0.9669 1.0312
                                   1.6674
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.37781 0.03730 10.13 < 2e-16 ***
dist100 -0.38741 0.06034 -6.42 1.36e-10 ***
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '. '0.1 ' '1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 4118.1 on 3019 degrees of freedom
Residual deviance: 4076.3 on 3018 degrees of freedom
AIC: 4080.3
Number of Fisher Scoring iterations: 4
```

#### Probit or logit?

```
fit.logit <- alm (switch ~ dist100, family=binomial(link="logit"))
> summary(fit.logit)
Call:
glm(formula = switch ~ dist100, family = binomial(link = "logit"))
Deviance Residuals:
   Min
             10 Median 30
                                      Max
-1.4406 -1.3058 0.9669 1.0308 1.6603
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.60596 0.06031 10.047 < 2e-16 ***
dist100 -0.62188 0.09743 -6.383 1.74e-10 ***
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 4118.1 on 3019 degrees of freedom
Residual deviance: 4076.2 on 3018 degrees of freedom
AIC: 4080.2
Number of Fisher Scoring iterations: 4
```

# Logit Distribution

Normal (0, 1.6<sup>2</sup>) probability density distribution

