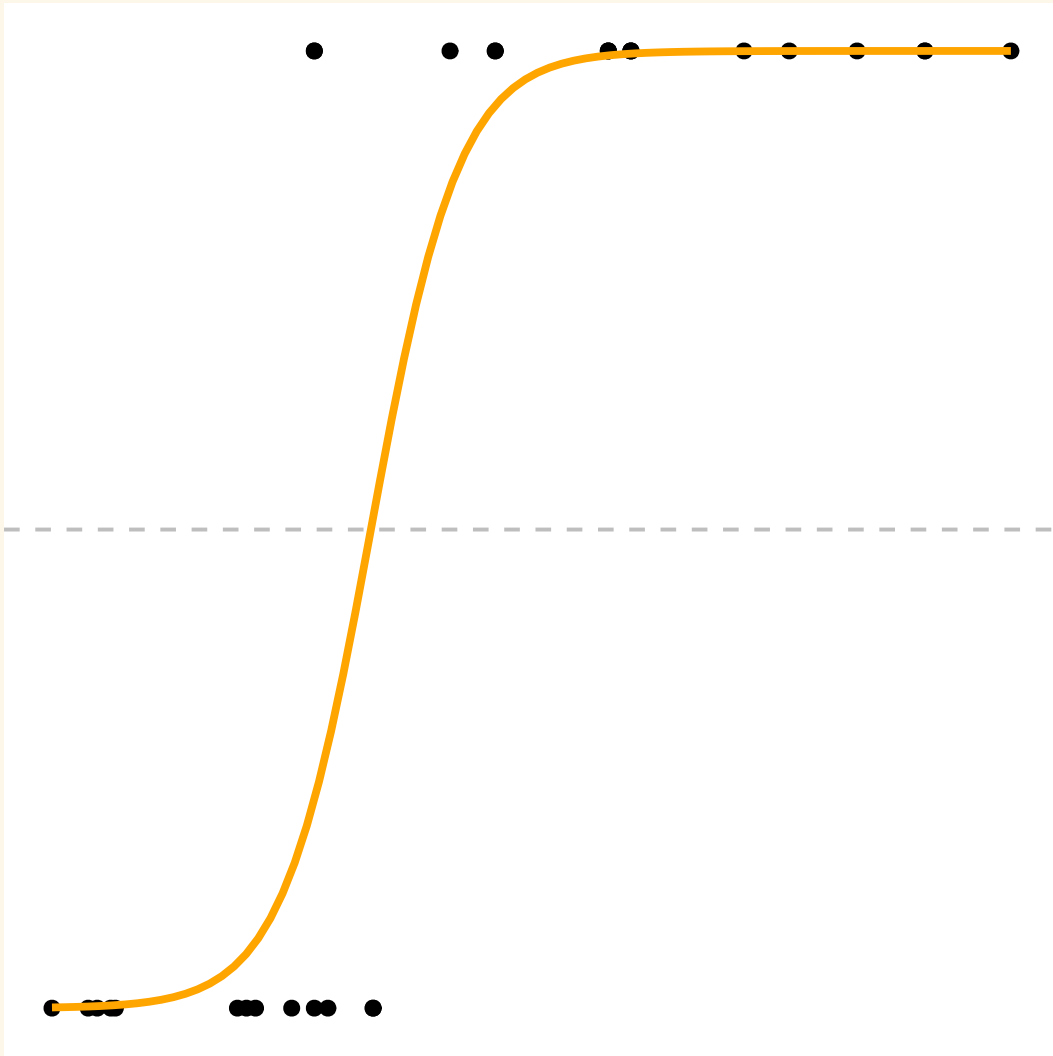


Quasi-binomial model

Stat 230

May 27 2022

Overview



Today:

Quasi models

Fitting in R

GLM model

- GLM assumes $Y \mid x \sim$ some probability distribution where

$$E(Y \mid x) = f(x; \beta_0, \dots, \beta_p) \quad (\text{kernel mean})$$

$$V(Y \mid x) = \sigma^2(x) \quad (\text{some function that may depend on } x)$$

Over (or under) dispersion

But what if our model's mean function is well modeled, but our variance is off

$Y \mid x \sim$ some probability distribution where

$E(Y \mid x) = f(x; \beta_0, \dots, \beta_p)$ (kernel mean)

$V(Y \mid x) \neq \sigma^2(x)$ (some function that could involve x)

E.g. in a binomial logistic model, this means the variance of our response doesn't equal that of a binomial probability model:

$$Y \mid x \sim \text{Binom}(m_i, \pi(x_i))$$

$$E(Y \mid x) = m_i \pi(x_i)$$

$$V(Y_i \mid x_i) \neq m_i \pi(x_i) (1 - \pi(x_i))$$

Estimating the dispersion parameter ψ

- For a GLM, the dispersion parameter ψ ("psi") is estimated from the deviance G^2 from the regular GLM:

$$\hat{\psi} = \frac{G^2}{n - (p + 1)}$$

- $\hat{\psi} > 1$: overdispersion (responses are more variable than expected)
- $\hat{\psi} < 1$: underdispersion (responses are less variable than expected)
- e.g. for a quasi-binomial model, G^2 is the (residual) deviance from a regular binomial logistic model.

Estimating with a quasi-GLM

- Parameter estimates for β are from the regular GLM model.
- e.g. $\hat{\beta}$ from a regular binomial logistic model
- Quasi model Standard errors for $\hat{\beta}'$ s are adjusted versions of the regular GLM SE:

$$SE_{quasi}(\hat{\beta}_i) = \sqrt{\hat{\psi}} SE_{GLM}(\hat{\beta}_i)$$

- e.g. for a quasi-binomial model, $SE_{\text{binom}}(\hat{\beta}_i)$ are the usual SE from a regular binomial logistic model.

Inference with a quasi-GLM

- Conduct "z"-inference (Wald tests/CI) using SEs equal to $SE_{quasi}(\hat{\beta}_i)$
- Compare quasi-binomial models using a F-test stat equal to

$$F = \frac{(G^2_{\text{reduced}} - G^2_{\text{full}}) / (\# \text{ terms tested})}{\hat{\psi}}$$

using an F-distribution with degrees of freedom equal to the number of terms tested and $n - (p + 1)$. G^2 is the model deviance from fitting the usual binomial model for two competing models.

R: Quasi-binomial model

- A quasi-binomial model is fit with

```
glm(y/m ~ x1 + x2, family = quasibinomial, weights = m, data = mydata)
```

- Model comparisons with a quasi-binomial model are done with anova:

```
anova(red_quasi, full_quasi, test = "F")
```


Example: Rake data

The USGS monitors submersed aquatic vegetation (SAV) in the Mississippi by using a long-handled rake (from a boat) to pull SAV from the river bottom.

```
RakeData <- read.csv("https://raw.githubusercontent.com/deepbas/statdatasets/main/RakeData.csv")
glimpse(RakeData)
```

```
Rows: 27
Columns: 6
$ X      <int> 1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 17, 18, 20, ...
$ SiteRake <int> 6, 6, 2, 6, 5, 6, 6, 2, 2, 4, 6, 6, 1, 6, 6, 2, 6, 6, 6, 0, ...
$ SiteM    <int> 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, ...
$ SiteBiom <dbl> 287.5731, 118.0538, 118.0381, 1064.3720, 254.8879, 225.2125, ...
$ SiteDepth <dbl> 0.1000000, 0.4000000, 0.6000000, 0.8000000, 1.0833333, 0.500...
$ SiteSub  <chr> "sand", "silt", "silt", "sand", "silt", "sand", "silt", "san..."
```

Data description

- Cases = 27 sites that contain SAV
- $m = \text{SiteM} = 6$ locations (quadrats) raked per site
- $Y = \text{SiteRake} = \#$ locations with SAV detected per site
- X = total site biomass, average water depth, substrate (soil type: silt or sand)
- $\pi(X)$ = Probability the rake detects SAV at a site with predictors X

Binomial logistic regression

```
rake_glm <- glm(SiteRake/SiteM ~ log(SiteBiom+1) + SiteDepth + SiteSub,  
               family = binomial,  
               weights = SiteM,  
               data = RakeData)
```

Binomial logistic regression

```
summary(rake_glm)
```

```
Call:
glm(formula = SiteRake/SiteM ~ log(SiteBiom + 1) + SiteDepth +
    SiteSub, family = binomial, data = RakeData, weights = SiteM)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2516  -0.3863   0.8381   1.0709   1.7355

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -1.8528     0.8319  -2.227   0.0259 *
log(SiteBiom + 1)  0.7475     0.1157   6.461 1.04e-10 ***
SiteDepth      -1.2472     0.8175  -1.526   0.1271
SiteSubsilt      0.4691     0.4545   1.032   0.3020
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 118.36  on 26  degrees of freedom
Residual deviance:  50.44  on 23  degrees of freedom
AIC: 82.189

Number of Fisher Scoring iterations: 4
```

Goodness-of-fit

H_0 : logistic model

H_A : saturated model

```
1 - pchisq(50.44, df = 23)
```

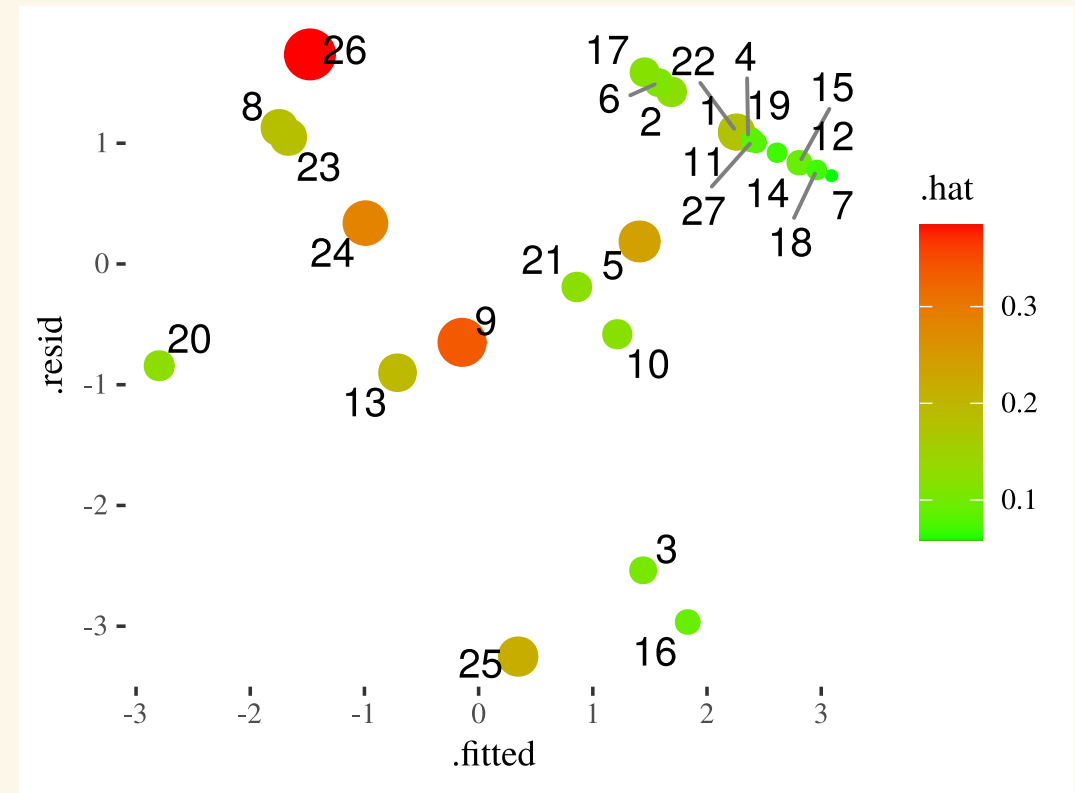
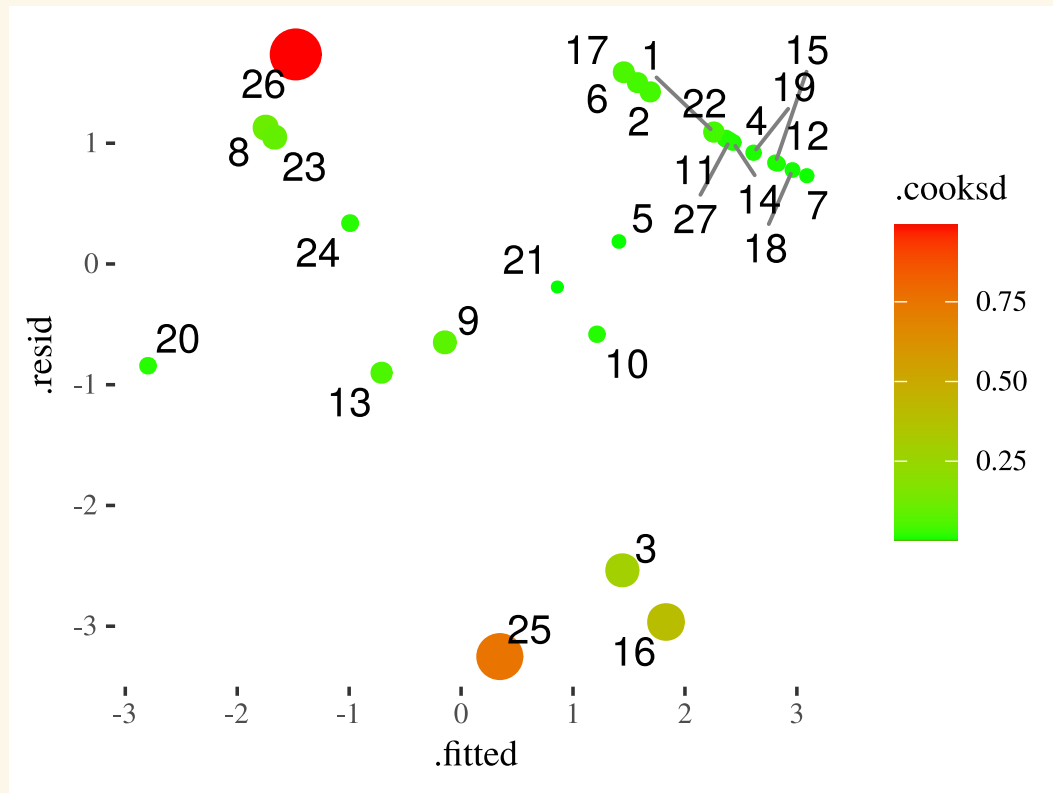
```
[1] 0.0008063917
```

The GOF p-value for this model is 0.0008, which suggests that there is enough evidence to say the model is not adequate

Residual analysis



Leverage and Cook's distance



Estimate the dispersion parameter

Null deviance: 118.36 on 26 degrees of freedom
Residual deviance: 50.44 on 23 degrees of freedom

$$\hat{\psi} = \frac{50.44}{23} \approx 2.1$$

The dispersion parameter is estimated as 2.14

Fit the quasi-binomial model

```
rake_quasi_glm <- glm(SiteRake/SiteM ~ log(SiteBiom+1) + SiteDepth + SiteSub,  
                      family = quasibinomial,  
                      weights = SiteM,  
                      data = RakeData)
```

Quasi-binomial logistic regression

```
summary(rake_quasi_glm)
```

Call:

```
glm(formula = SiteRake/SiteM ~ log(SiteBiom + 1) + SiteDepth +  
    SiteSub, family = quasibinomial, data = RakeData, weights = SiteM)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.2516	-0.3863	0.8381	1.0709	1.7355

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.8528	1.2168	-1.523	0.141474
log(SiteBiom + 1)	0.7475	0.1692	4.417	0.000199 ***
SiteDepth	-1.2472	1.1958	-1.043	0.307814
SiteSubsilt	0.4691	0.6648	0.706	0.487527

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

(Dispersion parameter for quasibinomial family taken to be 2.139552)

Null deviance: 118.36 on 26 degrees of freedom
Residual deviance: 50.44 on 23 degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 4

Standard errors

Binomial Model

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-1.8528	0.8319	-2.227	0.0259	*
log(SiteBiom + 1)	0.7475	0.1157	6.461	1.04e-10	***
SiteDepth	-1.2472	0.8175	-1.526	0.1271	
SiteSubsilt	0.4691	0.4545	1.032	0.3020	

Quasi-binomial Model

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-1.8528	1.2168	-1.523	0.141474	
log(SiteBiom + 1)	0.7475	0.1692	4.417	0.000199	***
SiteDepth	-1.2472	1.1958	-1.043	0.307814	
SiteSubsilt	0.4691	0.6648	0.706	0.487527	

$$SE\left(\hat{\beta}_i^{quasi}\right) = \sqrt{2.139552} \times SE(\hat{\beta}_i)$$

Quasi-binomial F-test

```
anova(rake_glm)
```

Analysis of Deviance Table

Model: binomial, link: logit

Response: SiteRake/SiteM

Terms added sequentially (first to last)

	Df	Deviance	Resid.	Df	Resid. Dev
NULL				26	118.357
log(SiteBiom + 1)	1	64.263		25	54.094
SiteDepth	1	2.571		24	51.522
SiteSub	1	1.083		23	50.440

Your Turn 1

05:00



Complete (1a-c):

Test the hypotheses (1d):

$$H_0 : \beta_2 = \beta_3 = 0$$

$$H_A : \text{at least one } \beta_2, \beta_3 \neq 0$$

Compare models using `anova` with the F test in R

```
rake_quasi_glm_red <- update(rake_quasi_glm, ~ . - SiteDepth - SiteSub)
anova(rake_quasi_glm_red, rake_quasi_glm, test = "F")
Analysis of Deviance Table
```

```
Model 1: SiteRake/SiteM ~ log(SiteBiom + 1)
```

```
Model 2: SiteRake/SiteM ~ log(SiteBiom + 1) + SiteDepth + SiteSub
```

	Resid. Df	Resid. Dev	Df	Deviance	F	Pr(>F)
1	25	54.094				
2	23	50.440	2	3.6542	0.854	0.4388

The p-value is from an F-distribution with 2 and 25 degrees of freedom. The test results suggest that neither depth nor substrate are statistically significant ($F = 0.854$, $p\text{-value}=0.439$).