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## Generalized Linear Models

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Logistic Regression

Goal

Logistic regression models a Bernoulli distributed response variable in terms of linear combinations of explanatory variables.

This extends least squares regression to the case where the response variable captures a dichotomous outcome (e.g., “success” vs “failure”).

Bernoulli as EFD

If $Y \sim \text{Bernoulli}(p)$, then its pmf is:
\[ f(y;p) = p^y (1-p)^{1-y} \]
\[ = \exp \left\{ \log \left( \frac{p}{1-p} \right) y + \log(1-p) \right\} \]

In exponential family distribution (EFD) notation,
\[ \eta(p) = \log \left( \frac{p}{1-p} \right) \equiv \logit(p), \]
\[ A(\eta(p)) = \log(1 + \exp(\eta)) \equiv \logit\left( \frac{y}{1-y} \right), \]

\[ \text{y is the sufficient statistic.} \]

Model
\( (X_1,Y_1),(X_2,Y_2),\ldots,(X_n,Y_n) \) are distributed so that \( Y_i | X_i \sim \text{Bernoulli}(p_i) \), where \( \{Y_i | X_i\}_{i=1}^n \) are jointly independent and
\[ \logit(\mathbb{E}[Y_i | X_i]) = \log \left( \frac{\Pr(Y_i = 1 | X_i)}{\Pr(Y_i = 0 | X_i)} \right) = X_i \beta. \]

From this it follows that
\[ p_i = \frac{\exp(X_i \beta)}{1 + \exp(X_i \beta)}. \]

**Maximum Likelihood Estimation**

The \( \beta \) are estimated from the MLE calculated from:
\[ \ell(\beta; y, X) = \sum_{i=1}^n \left\{ \log \left( \frac{p_i}{1-p_i} \right) y_i + \log(1-p_i) \right\} = \sum_{i=1}^n (x_i \beta) y_i - \log(1 + \exp(x_i \beta)) \]

**Iteratively Reweighted Least Squares**

1. Initialize \( \hat{\beta}^{(1)} \).
2. For each iteration \( t = 1, 2, \ldots \), set
   \[ p_i^{(t)} = \logit^{-1}\left( x_i \hat{\beta}^{(t)} \right), \quad z_i^{(t)} = \logit\left( p_i^{(t)} \right) + \frac{y_i - p_i^{(t)}}{p_i^{(t)} (1 - p_i^{(t)})} \]
   and let \( z^{(t)} = \left\{ z_i^{(t)} \right\}_{i=1}^n \).
3. Form \( n \times n \) diagonal matrix \( W^{(t)} \) with \((i,i)\) entry equal to \( p_i^{(t)} (1 - p_i^{(t)}) \).
4. Obtain \( \hat{\beta}^{(t+1)} \) by performing the weighted least squares regression (see GLS from earlier)
   \[ \hat{\beta}^{(t+1)} = \left( X^T W^{(t)} X \right)^{-1} X^T W^{(t)} z^{(t)}. \]
5. Iterate Steps 2-4 over \( t = 1, 2, 3, \ldots \) until convergence, setting \( \hat{\beta} = \hat{\beta}^{(\infty)} \).
GLMs

For exponential family distribution response variables, the generalized linear model is

\[ \eta(\mathbb{E}[Y|X]) = X\beta \]

where \( \eta(\theta) \) is function of the expected value \( \theta \) into the natural parameter. This is called the canonical link function in the GLM setting.

The iteratively reweighted least squares algorithm presented above for calculating (local) maximum likelihood estimates of \( \beta \) has a generalization to a large class of exponential family distribution response variables.

glm() Function in R

Example: Grad School Admissions

```r
> mydata <-
+   read.csv("https://stats.idre.ucla.edu/stat/data/binary.csv")
> dim(mydata)
[1] 400  4
> head(mydata)
  admit  gre  gpa  rank
1      0  380 3.61  3
2      1  660 3.67  3
3      1  800 4.00  1
4      1  640 3.19  4
5      0  520 2.93  4
6      1  760 3.00  2
```

Data and analysis courtesy of https://stats.idre.ucla.edu/r/dae/logit-regression/.

Explore the Data

```r
> apply(mydata, 2, mean)
    admit   gre    gpa   rank
mean 0.3175 587.7000 3.3899 2.4850
> apply(mydata, 2, sd)
    admit   gre    gpa   rank
sd   0.4660867 115.5165364 0.3805668 0.9444602
> table(mydata$admit, mydata$rank)
    1  2  3  4
0  28 97 93 55
1  33 54 28 12
> ggplot(data=mydata) +
  geom_boxplot(aes(x=as.factor(admit), y=gre))
```
> ggplot(data=mydata) +
+ geom_boxplot(aes(x=as.factor(admit), y=gpa))
Logistic Regression in R

```r
> mydata$rank <- factor(mydata$rank, levels=c(1, 2, 3, 4))
> myfit <- glm(admit ~ gre + gpa + rank,
+     data = mydata, family = "binomial")
> myfit

Call: glm(formula = admit ~ gre + gpa + rank, family = "binomial",
    data = mydata)

Coefficients:
(Intercept) gre gpa rank2 rank3 rank4
-3.989979 0.002264 0.804038 -0.675443 -1.340204 -1.551464

Degrees of Freedom: 399 Total (i.e. Null); 394 Residual
Null Deviance: 500
Residual Deviance: 458.5   AIC: 470.5
```
Summary of Fit

> summary(myfit)

Call:
glm(formula = admit ~ gre + gpa + rank, family = "binomial",
    data = mydata)

Deviance Residuals:
    Min      1Q  Median      3Q     Max
  -1.6268  -0.8662  -0.6388   1.1490   2.0790

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)              -3.98998   1.13995   -3.500  0.000465 ***
gre                       0.00226    0.00109    2.070  0.038465 *
gpa                       0.80404    0.33182    2.423  0.015388 *
rank2                    -0.67544    0.31649   -2.134  0.032829 *
rank3                    -1.34020    0.34531   -3.881  0.000104 ***
rank4                    -1.55146    0.41783   -3.713  0.000205 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 499.98 on 399 degrees of freedom
  Residual deviance: 458.52 on 394 degrees of freedom
  AIC: 470.52

Number of Fisher Scoring iterations: 4

Significance Tests of Fit

> anova(myfit, test="Chisq")
Analysis of Deviance Table

Model: binomial, link: logit

Response: admit

Terms added sequentially (first to last)

Df Deviance Resid. Dev Pr(>Chi)
NULL                 399   499.98
      gre         1  13.9204    486.06 0.0001907 ***
      gpa         1   5.7122    480.34 0.0168478 *
      rank        3  21.8265   458.52 7.088e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> drop1(myfit, test="Chisq")
Single term deletions
Model:

\[ \text{admit} \sim \text{gre} + \text{gpa} + \text{rank} \]

<table>
<thead>
<tr>
<th>Df</th>
<th>Deviance</th>
<th>AIC</th>
<th>LRT</th>
<th>Pr(&gt;Chi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;none&gt;</td>
<td>458.52</td>
<td>470.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>gre</td>
<td>1</td>
<td>462.88</td>
<td>472.88</td>
<td>4.3578</td>
</tr>
<tr>
<td>gpa</td>
<td>1</td>
<td>464.53</td>
<td>474.53</td>
<td>6.0143</td>
</tr>
<tr>
<td>rank</td>
<td>3</td>
<td>480.34</td>
<td>486.34</td>
<td>21.8265</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

```r
> drop1(myfit, test="LRT")
```

Single term deletions

Model:

\[ \text{admit} \sim \text{gre} + \text{gpa} + \text{rank} \]

<table>
<thead>
<tr>
<th>Df</th>
<th>Deviance</th>
<th>AIC</th>
<th>LRT</th>
<th>Pr(&gt;Chi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;none&gt;</td>
<td>458.52</td>
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</tr>
<tr>
<td>rank</td>
<td>3</td>
<td>480.34</td>
<td>486.34</td>
<td>21.8265</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Example: Contraceptive Use

```r
> cuse <-
+  read.table("http://data.princeton.edu/wws509/datasets/cuse.dat",
+            header=TRUE)
> dim(cuse)
[1] 16  5
> head(cuse)
   age education wantsMore notUsing using
1  <25   low       yes     53     6
2  <25   low       no      10     4
3  <25  high       yes    212    52
4  <25  high       no      50    10
5  25-29 low       yes     60    14
6  25-29 low       no     19    10
```


A Different Format

Note that in this data set there are multiple observations per explanatory variable configuration.

The last two columns of the data frame count the successes and failures per configuration.
Fitting the Model

When this is the case, we call the `glm()` function slightly differently.

```r
> myfit <- glm(cbind(using, notUsing) ~ age + education + wantsMore, +     data=cuse, family = "binomial")
> myfit

Call:  glm(formula = cbind(using, notUsing) ~ age + education + wantsMore, +        family = "binomial", data = cuse)

Coefficients:
  (Intercept) age25-29 age30-39 age40-49
  -0.8082  0.3894  0.9086  1.1892
educationlow wantsMoreyes
  -0.3250  -0.8330

Degrees of Freedom: 15 Total (i.e. Null); 10 Residual
Null Deviance:    165.8
Residual Deviance: 29.92    AIC: 113.4

Summary of Fit

> summary(myfit)

Call:
  glm(formula = cbind(using, notUsing) ~ age + education + wantsMore, +      family = "binomial", data = cuse)

Deviance Residuals:
     Min       1Q   Median       3Q      Max
-2.5148  -0.9376   0.2408   0.9822   1.7333

Coefficients:  Estimate Std. Error z value Pr(>|z|)
  (Intercept)   -0.8082   0.1590    -5.083  3.71e-07 ***
  age25-29      0.3894   0.1759     2.214  0.02681 *
  age30-39      0.9086   0.1646     5.519  3.40e-08 ***
  age40-49      1.1892   0.2144     5.546  2.92e-08 ***
  educationlow  -0.3250   0.1240    -2.620  0.00879 **
  wantsMoreyes  -0.8330   0.1175    -7.091  1.33e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 165.772  on 15  degrees of freedom
Residual deviance: 29.917  on 10  degrees of freedom
AIC: 113.43

Number of Fisher Scoring iterations: 4
Significance Tests of Fit

```r
> drop1(myfit, test="Chisq")
Single term deletions

Model:
cbind(using, notUsing) ~ age + education + wantsMore

Df Deviance  AIC  LRT Pr(>Chi)
<none>      29.917 113.42
age         3  73.865 151.37  43.948 1.548e-09 ***
education   1  36.888 118.40   6.971  0.008286 **
wantsMore   1  80.418 161.93  50.501 1.191e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

More on this Data Set

See http://data.princeton.edu/R/glms.html for more on fitting logistic regression to this data set.

A number of interesting choices are made that reveal more about the data.

**Generalized Linear Models**

**Review: Multiparameter Fisher Info Matrix**

Suppose that $X_1, X_2, \ldots, X_n \overset{iid}{\sim} F_{\theta}$ where $\theta = (\theta_1, \theta_2, \ldots, \theta_d)^T$ has MLE $\hat{\theta}_n$.

The Fisher Information Matrix $I_n(\theta)$ is the $d \times d$ matrix with $(i, j)$ entry

$$I_n(\theta)_{i,j} = -\sum_{k=1}^{n} E \left( \frac{\partial^2}{\partial \theta_i \partial \theta_j} \log f(X_k; \theta) \right).$$

**Review: Multiparameter Asymptotic MVN**

Under appropriate regularity conditions, as $n \to \infty$,

$$\left( \hat{\theta}_n - \theta \right) \overset{D}{\to} MVN_d \left( 0, I_n(\theta)^{-1} \right)$$

and

$$\left( \hat{\theta}_n - \theta \right)^T I_n(\hat{\theta}_n) \left( \hat{\theta}_n - \theta \right) \overset{D}{\to} \chi^2_d.$$

**GLM Definition**

The generalized linear model (GLM) builds from OLS and GLS to allow for the case where $Y \mid X$ is distributed according to an exponential family distribution. The estimated model is

$$g(\mathbb{E}[Y \mid X]) = X\beta$$

where $g(\cdot)$ is called the link function. This model is typically fit by numerical methods to calculate the maximum likelihood estimate of $\beta$. 
Exponential Family Distributions

Recall that if $Y$ follows an EFD then it has pdf of the form

$$f(y; \theta) = h(y) \exp \left\{ \sum_{k=1}^{d} \eta_k(\theta)T_k(y) - A(\eta) \right\}$$

where $\theta$ is a vector of parameters, $\{T_k(y)\}$ are sufficient statistics, $A(\eta)$ is the cumulant generating function.

The functions $\eta_k(\theta)$ for $k = 1, \ldots, d$ map the usual parameters $\theta$ (often moments of the rv $Y$) to the natural parameters or canonical parameters.

$\{T_k(y)\}$ are sufficient statistics for $\{\eta_k\}$ due to the factorization theorem.

$A(\eta)$ is sometimes called the log normalizer because

$$A(\eta) = \log \int h(y) \exp \left\{ \sum_{k=1}^{d} \eta_k(\theta)T_k(y) \right\}.$$

**Natural Single Parameter EFD**

A natural single parameter EFD simplifies to the scenario where $d = 1$ and $T(y) = y$

$$f(y; \eta) = h(y) \exp \{ \eta(y) - A(\eta) \}$$

where without loss of generality we can write $\text{E}[Y] = \theta$.

**Dispersion EFDs**

The family of distributions for which GLMs are most typically developed are dispersion EFDs. An example of a dispersion EFD that extends the natural single parameter EFD is

$$f(y; \eta) = h(y, \phi) \exp \left\{ \frac{\eta(\phi)y - A(\eta)}{\phi} \right\}$$

where $\phi$ is the dispersion parameter.

**Example: Normal**

Let $Y \sim \text{Normal}(\mu, \sigma^2)$. Then:

$$\theta = \mu, \eta(\mu) = \mu$$

$$\phi = \sigma^2$$

$$A(\mu) = \frac{\mu^2}{2}$$

$$h(y, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} \frac{y^2}{\sigma^2}}$$

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EFD for GLMs

There has been a very broad development of GLMs and extensions. A common setting for introducing GLMs is the dispersion EFD with a general link function \( g(\cdot) \).

See the classic text *Generalized Linear Models*, by McCullagh and Nelder, for such a development.

**Components of a GLM**

1. **Random**: The particular exponential family distribution.
   \[
   Y \sim f(y; \eta, \phi)
   \]

2. **Systematic**: The determination of each \( \eta_i \) from \( X_i \) and \( \beta \).
   \[
   \eta_i = X_i \beta
   \]

3. **Parametric Link**: The connection between \( E[Y_i|X_i] \) and \( X_i \beta \).
   \[
   g(E[Y_i|X_i]) = X_i \beta
   \]

**Link Functions**

Even though the link function \( g(\cdot) \) can be considered in a fairly general framework, the *canonical link function* \( \eta(\cdot) \) is often utilized.

The canonical link function is the function that maps the expected value into the natural parameter.

In this case, \( Y|X \) is distributed according to an exponential family distribution with

\[
\eta(E[Y|X]) = X \beta.
\]

**Calculating MLEs**

Given the model \( g(E[Y|X]) = X \beta \), the EFD should be fully parameterized. The Newton-Raphson method or Fisher’s scoring method can be utilized to find the MLE of \( \beta \).

**Newton-Raphson**

1. Initialize \( \beta^{(1)} \). For \( t = 1, 2, \ldots \)
2. Calculate the score \( s(\beta^{(t)}) = \nabla \ell(\beta; X, Y) \big|_{\beta=\beta^{(t)}} \) and observed Fisher information
   \[
   H(\beta^{(t)}) = -\nabla \nabla^T \ell(\beta; X, Y) \big|_{\beta=\beta^{(t)}}.
   \]
   Note that the observed Fisher information is also the negative Hessian matrix.
3. Update \( \beta^{(t+1)} = \beta^{(t)} + H(\beta^{(t)})^{-1}s(\beta^{(t)}) \).
4. Iterate until convergence, and set \( \hat{\beta} = \beta^{(\infty)} \).

**Fisher’s scoring**

1. Initialize \( \beta^{(1)} \). For \( t = 1, 2, \ldots \)
2. Calculate the score \( s(\beta^{(t)}) = \nabla \ell(\beta; X, Y) \big|_{\beta=\beta^{(t)}} \) and expected Fisher information
   \[
   I(\beta^{(t)}) = -E \left[ \nabla \nabla^T \ell(\beta; X, Y) \big|_{\beta=\beta^{(t)}} \right].
   \]
3. Update $\beta^{(t+1)} = \beta^{(t)} + I(\beta^{(t)})^{-1}s(\beta^{(t)})$.

4. Iterate until convergence, and set $\hat{\beta} = \beta^{(\infty)}$.

When the canonical link function is used, the Newton-Raphson algorithm and Fisher’s scoring algorithm are equivalent.

Exercise: Prove this.

**Iteratively Reweighted Least Squares**

For the canonical link, Fisher’s scoring method can be written as an iteratively reweighted least squares algorithm, as shown earlier for logistic regression. Note that the Fisher information is

$$I(\beta^{(t)}) = X^T W X$$

where $W$ is an $n \times n$ diagonal matrix with $(i, i)$ entry equal to $\text{Var}(Y_i | X; \beta^{(t)})$.

The score function is

$$s(\beta^{(t)}) = X^T (Y - X\beta^{(t)})$$

and the current coefficient value $\beta^{(t)}$ can be written as

$$\beta^{(t)} = (X^T W X)^{-1} X^T W X \beta^{(t)}.$$ 

Putting this together we get

$$\beta^{(t)} + I(\beta^{(t)})^{-1}s(\beta^{(t)}) = (X^T W X)^{-1} X^T W z^{(t)}$$

where

$$z^{(t)} = X\beta^{(t)} + W^{-1} (Y - X\beta^{(t)}).$$

This is a generalization of the iteratively reweighted least squares algorithm we showed earlier for logistic regression.

**Estimating Dispersion**

For the simple dispersion model above, it is typically straightforward to calculate the MLE $\hat{\phi}$ once $\hat{\beta}$ has been calculated.

**CLT Applied to the MLE**

Given that $\hat{\beta}$ is a maximum likelihood estimate, we have the following CLT result on its distribution as $n \to \infty$:

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{D} \text{MVN}_p(0, \phi(X^T W X)^{-1})$$
Approximately Pivotal Statistics

The previous CLT gives us the following two approximations for pivotal statistics. The first statistic facilitates getting overall measures of uncertainty on the estimate $\hat{\beta}$.

$$\hat{\phi}^{-1}(\hat{\beta} - \beta)^T(X^T \hat{W} X)(\hat{\beta} - \beta) \sim \chi^2_p$$

This second pivotal statistic allows for performing a Wald test or forming a confidence interval on each coefficient, $\beta_j$, for $j = 1, \ldots, p$.

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{\hat{\phi}[(X^T \hat{W} X)^{-1}][jj]}} \sim \text{Normal}(0, 1)$$

Deviance

Let $\hat{\eta}$ be the estimated natural parameters from a GLM. For example, $\hat{\eta} = X \hat{\beta}$ when the canonical link function is used.

Let $\hat{\eta}_n$ be the saturated model where $Y_i$ is directly used to estimate $\eta_i$ without model constraints. For example, in the Bernoulli logistic regression model $\eta_n = Y$, the observed outcomes.

The deviance for the model is defined to be

$$D(\hat{\eta}) = 2\ell(\hat{\eta}; X, Y) - 2\ell(\hat{\eta}; X, Y)$$

Generalized LRT

Let $X_0$ be a subset of $p_0$ columns of $X$ and let $X_1$ be a subset of $p_1$ columns, where $1 \leq p_0 < p_1 \leq p$. Also, assume that the columns of $X_0$ are a subset of $X_1$.

Without loss of generality, suppose that $\beta_0 = (\beta_1, \beta_2, \ldots, \beta_{p_0})^T$ and $\beta_1 = (\beta_1, \beta_2, \ldots, \beta_{p_1})^T$.

Suppose we wish to test $H_0 : (\beta_{p_0+1}, \beta_{p_0+2}, \ldots, \beta_{p_1}) = 0$ vs $H_1 : (\beta_{p_0+1}, \beta_{p_0+2}, \ldots, \beta_{p_1}) \neq 0$.

We can form $\hat{\eta}_0 = X \hat{\beta}_0$ from the GLM model $g(E[Y|X_0]) = X_0 \beta_0$. We can analogously form $\hat{\eta}_1 = X \hat{\beta}_1$ from the GLM model $g(E[Y|X_1]) = X_1 \beta_1$.

The $2\log$ generalized LRT can then be formed from the two deviance statistics

$$2\log \lambda(X, Y) = 2\log \frac{L(\hat{\eta}_1; X, Y)}{L(\hat{\eta}_0; X, Y)} = D(\hat{\eta}_0) - D(\hat{\eta}_1)$$

where the null distribution is $\chi^2_{p_1-p_0}$.

Example: Grad School Admissions

Let’s revisit a logistic regression example now that we know how the various statistics are calculated.

```r
> mydata <- 
+    read.csv("https://stats.idre.ucla.edu/stat/data/binary.csv")
> dim(mydata)
> head(mydata)
```

Fit the model with basic output. Note the argument family = "binomial".

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```r
> mydata$rank <- factor(mydata$rank, levels=c(1, 2, 3, 4))
> myfit <- glm(admit ~ gre + gpa + rank,
+               data = mydata, family = "binomial")
> myfit
Call: glm(formula = admit ~ gre + gpa + rank, family = "binomial",
         data = mydata)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)  
(Intercept) -3.989979   1.139951  -3.500   0.000465 ***
gre          0.002264   0.001094   2.070   0.038465 *
gpa          0.804038   0.331819   2.423   0.015388 *
rank2       -0.675443   0.316490  -2.134   0.032829 *
rank3       -1.340204   0.345306  -3.881   0.000104 ***
rank4       -1.551464   0.417832  -3.713   0.000205 ***
---
Signif. codes:  ** 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 499.98  on 399  degrees of freedom
    Residual deviance: 458.52  on 394  degrees of freedom
    AIC: 470.52

Number of Fisher Scoring iterations: 4
```

This shows the fitted coefficient values, which is on the link function scale – logit aka log odds here. Also, a Wald test is performed for each coefficient.

```r
> summary(myfit)
Call:
glm(formula = admit ~ gre + gpa + rank, family = "binomial",
    data = mydata)

Deviance Residuals:
     Min       1Q   Median       3Q      Max
-1.6268  -0.8662  -0.6388   1.1490   2.0790

Coefficients:  
            Estimate Std. Error z value Pr(>|z|)  
(Intercept) -3.989979   1.139951  -3.500   0.000465 ***
gre          0.002264   0.001094   2.070   0.038465 *
gpa          0.804038   0.331819   2.423   0.015388 *
rank2       -0.675443   0.316490  -2.134   0.032829 *
rank3       -1.340204   0.345306  -3.881   0.000104 ***
rank4       -1.551464   0.417832  -3.713   0.000205 ***
---
Signif. codes:  ** 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 499.98  on 399  degrees of freedom
    Residual deviance: 458.52  on 394  degrees of freedom
    AIC: 470.52
```

Here we perform a generalized LRT on each variable. Note the `rank` variable is now tested as a single factor variable as opposed to each dummy variable.

```r
> drop1(myfit, test="LRT")
```

Single term deletions
Model:
\[ \text{admit} \sim \text{gre} + \text{gpa} + \text{rank} \]

<table>
<thead>
<tr>
<th>Df</th>
<th>Deviance</th>
<th>AIC</th>
<th>LRT</th>
<th>Pr(&gt;Chi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;none&gt;</td>
<td>458.52</td>
<td>470.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>gre</td>
<td>1</td>
<td>462.88</td>
<td>472.88</td>
<td>4.3578</td>
</tr>
<tr>
<td>gpa</td>
<td>1</td>
<td>464.53</td>
<td>474.53</td>
<td>6.0143</td>
</tr>
<tr>
<td>rank</td>
<td>3</td>
<td>480.34</td>
<td>486.34</td>
<td>21.8265</td>
</tr>
</tbody>
</table>

---

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

```r
mydata <- data.frame(mydata, probs = myfit$fitted.values)
> ggplot(mydata) + geom_point(aes(x=gpa, y=probs, color=rank)) +
  geom_jitter(aes(x=gpa, y=admit), width=0, height=0.01, alpha=0.3)
```

```r
> ggplot(mydata) + geom_point(aes(x=gre, y=probs, color=rank)) +
  geom_jitter(aes(x=gre, y=admit), width=0, height=0.01, alpha=0.3)
```
```
> ggplot(mydata) + geom_boxplot(aes(x=rank, y=probs)) +
+  geom_jitter(aes(x=rank, y=probs), width=0.1, height=0.01, alpha=0.3)
```
### glm() Function

The `glm()` function has many different options available to the user.

```r
glm(formula, family = gaussian, data, weights, subset,
    na.action, start = NULL, etastart, mustart, offset,
    control = list(...), model = TRUE, method = "glm.fit",
    x = FALSE, y = TRUE, contrasts = NULL, ...)
```

To see the different link functions available, type:

```r
help(family)
```

### Nonparametric Regression

#### Simple Linear Regression

Recall the set up for simple linear regression. For random variables \((X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\), simple linear regression estimates the model

\[
Y_i = \beta_1 + \beta_2 X_i + E_i
\]
where \( E[E_i | X_i] = 0 \), \( \text{Var}(E_i | X_i) = \sigma^2 \), and \( \text{Cov}(E_i, E_j | X_i, X_j) = 0 \) for all \( 1 \leq i, j \leq n \) and \( i \neq j \).

Note that in this model \( E[Y | X] = \beta_1 + \beta_2 X \).

**Simple Nonparametric Regression**

In *simple nonparametric regression*, we define a similar model while eliminating the linear assumption:

\[
Y_i = s(X_i) + E_i
\]

for some function \( s(\cdot) \) with the same assumptions on the distribution of \( E | X \). In this model, we also have

\[
E[Y | X] = s(X).
\]

**Smooth Functions**

Suppose we consider fitting the model \( Y_i = s(X_i) + E_i \) with the restriction that \( s \in C^2 \), the class of functions with continuous second derivatives. We can set up an objective function that regularizes how smooth vs. wiggly \( s \) is.

Specifically, suppose for a given set of observed data \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\) we wish to identify a function \( s \in C^2 \) that minimizes for some \( \lambda \)

\[
\sum_{i=1}^{n} (y_i - s(x_i))^2 + \lambda \int |s''(x)|^2 dx
\]

**Smoothness Parameter \( \lambda \)**

When minimizing

\[
\sum_{i=1}^{n} (y_i - s(x_i))^2 + \lambda \int |s''(x)|^2 dx
\]

it follows that if \( \lambda = 0 \) then any function \( s \in C^2 \) that interpolates the data is a solution.

As \( \lambda \to \infty \), then the minimizing function is the simple linear regression solution.

**The Solution**

For an observed data set \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\) where \( n \geq 4 \) and a fixed value \( \lambda \), there is an exact solution to minimizing

\[
\sum_{i=1}^{n} (y_i - s(x_i))^2 + \lambda \int |s''(x)|^2 dx.
\]

The solution is called a **natural cubic spline**, which is constructed to have knots at \( x_1, x_2, \ldots, x_n \).

**Natural Cubic Splines**

Suppose without loss of generality that we have ordered \( x_1 < x_2 < \cdots < x_n \). We assume all \( x_i \) are unique to simplify the explanation here, but ties can be dealt with.

A **natural cubic spline** (NCS) is a function constructed from a set of piecewise cubic functions over the range \([x_1, x_n]\) joined at the knots so that the second derivative is continuous at the knots. Outside of the range \(< x_1 \text{ or } > x_n\), the spline is linear and it has continuous second derivatives at the endpoint knots.
**Basis Functions**

Depending on the value $\lambda$, a different ncs will be constructed, but the entire family of ncs solutions over $0 < \lambda < \infty$ can be constructed from a common set of basis functions.

We construct $n$ basis functions $N_1(x), N_2(x), \ldots, N_n(x)$ with coefficients $\theta_1(\lambda), \theta_2(\lambda), \ldots, \theta_n(\lambda)$. The NCS takes the form

$$s(x) = \sum_{i=1}^{n} \theta_i(\lambda) N_i(x).$$

Define $N_1(x) = 1$ and $N_2(x) = x$. For $i = 3, \ldots, n$, define $N_i(x) = d_{i-1}(x) - d_{i-2}(x)$ where

$$d_i(x) = \frac{(x - x_i)^3 - (x - x_n)^3}{x_n - x_i}.$$

Recall that we’ve labeled indices so that $x_1 < x_2 < \cdots < x_n$.

**Calculating the Solution**

Let $\theta = (\theta_1(\lambda), \theta_2(\lambda), \ldots, \theta_n(\lambda))^T$ and let $N$ be the $n \times n$ matrix with $(i,j)$ entry equal to $N_j(x_i)$. Finally, let $\Omega$ be the $n \times n$ matrix with $(i,j)$ entry equal to $\int N''_i(x) N''_j(x) dx$.

The solution to $\theta$ are the values that minimize

$$(y - N\theta)^T(y - N\theta) + \lambda \theta^T \Omega \theta.$$

which results in

$$\hat{\theta}(\lambda) = (N^T N + \lambda \Omega)^{-1} N^T y.$$

**Linear Operator**

Letting

$$S(\lambda) = N(N^T N + \lambda \Omega)^{-1} N^T$$

it follows that the fitted values are

$$\hat{y} = S(\lambda) y.$$

Thus, the fitted values from a NCS are constructed by taking linear combination of the response variable values $y_1, y_2, \ldots, y_n$.

**Degrees of Freedom**

Recall that in OLS, we formed projection matrix $P = X(X^T X)^{-1} X^T$ and noted that the number of columns $p$ of $X$ is also found in the trace of $P$ where $\text{tr}(P) = p$.

The effective degrees of freedom for a model fit by a linear operator is calculated as the trace of the operator.

Therefore, for a given $\lambda$, the effective degrees of freedom is

$$df(\lambda) = \text{tr}(S(\lambda)).$$
Bayesian Interpretation

Minimizing
\[
\sum_{i=1}^{n} (y_i - s(x_i))^2 + \lambda \int |s''(x)|^2 dx
\]
is equivalent to maximizing
\[
\exp \left\{ - \sum_{i=1}^{n} \frac{(y_i - s(x_i))^2}{2\sigma^2} \right\} \exp \left\{ - \frac{\lambda}{2\sigma^2} \int |s''(x)|^2 dx \right\}.
\]

Therefore, the NCS solution can be interpreted as calculating the MAP where \(Y|X\) is Normal and there's an Exponential prior on the smoothness of \(s\).

Bias and Variance Trade-off

Typically we will choose some \(0 < \lambda < \infty\) in an effort to balance the bias and variance. Let \(\hat{Y} = \hat{s}(X; \lambda)\) where \(\hat{s}(\cdot; \lambda)\) minimizes the above for some chosen \(\lambda\) on an independent data set. Then

\[
E \left[ (Y - \hat{Y})^2 \right] = E \left[ (s(x) - E[\hat{s}(x; \lambda)])^2 + \text{Var}(E) \right]
\]

\[
= (s(x) - E[\hat{s}(x; \lambda)])^2 + \text{Var}(s(x)) + \text{Var}(E)
\]

where all of the above calculations are conditioned on \(X = x\).

In minimizing
\[
\sum_{i=1}^{n} (y_i - s(x_i))^2 + \lambda \int |s''(x)|^2 dx
\]
the relationship is such that:

\[
\uparrow \lambda \implies \text{bias}^2 \uparrow, \text{variance} \downarrow
\]

\[
\downarrow \lambda \implies \text{bias}^2 \downarrow, \text{variance} \uparrow
\]

Choosing \(\lambda\)

There are several approaches that are commonly used to identify a value of \(\lambda\), including:

- Scientific knowledge that guides the acceptable value of \(d\lambda\)
- Cross-validation or some other prediction quality measure
- Model selection measures, such as Akaike information criterion (AIC) or Mallows \(C_p\)
Smoothers and Spline Models

We investigated one type of nonparametric regression model here, the NCS. However, in general there are many such “smoother” methods available in the simple nonparametric regression scenario.

Splines are particularly popular since splines are constructed from putting together polynomials and are therefore usually tractable to compute and analyze.

Smoothers in R

There are several functions and packages available in R for computing smoothers and tuning smoothness parameters. Examples include:

- `splines` library
- `smooth.spline()`
- `loess()`
- `lowess()`

Example

```r
> y2 <- smooth.spline(x=x, y=y, df=2)
> y5 <- smooth.spline(x=x, y=y, df=5)
```
Generalized Additive Models

Ordinary Least Squares

Recall that OLS estimates the model

\[ Y_i = \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + E_i = X_i \beta + E_i \]
where \( \mathbb{E}[E|X] = 0 \) and \( \text{Cov}(E|X) = \sigma^2 I \).

### Additive Models

The **additive model** (which could also be called “ordinary nonparametric additive regression”) is of the form

\[
Y_i = s_1(X_{i1}) + s_2(X_{i2}) + \ldots + s_p(X_{ip}) + E_i = \sum_{j=1}^{p} s_j(X_{ij}) + E_i
\]

where the \( s_j(\cdot) \) for \( j = 1, \ldots, p \) are a set of nonparametric (or flexible) functions. Again, we assume that \( \mathbb{E}[E|X] = 0 \) and \( \text{Cov}(E|X) = \sigma^2 I \).

### Backfitting

The additive model can be fit through a technique called **backfitting**.

1. Initialize \( s_j^{(0)}(x) \) for \( j = 1, \ldots, p \).
2. For \( t = 1, 2, \ldots \), fit \( s_j^{(t)}(x) \) on response variable

\[
y_i - \sum_{k \neq j} s_k^{(t-1)}(x_{ij}).
\]
3. Repeat until convergence.

Note that some extra steps have to be taken to deal with the intercept.

### GAM Definition

\( Y|X \) is distributed according to an exponential family distribution. The extension of additive models to this family of response variable is called **generalized additive models** (GAMs). The model is of the form

\[
g(\mathbb{E}[Y_i|X_i]) = \sum_{j=1}^{p} s_j(X_{ij})
\]

where \( g(\cdot) \) is the link function and the \( s_j(\cdot) \) are flexible and/or nonparametric functions.

### Overview of Fitting GAMs

Fitting GAMs involves putting together the following three tools:

1. We know how to fit a GLM via IRLS
2. We know how to fit a smoother of a single explanatory variable via a least squares solution, as seen for the NCS
3. We know how to combine additive smoothers by backfitting

### GAMs in R

Three common ways to fit GAMs in R:

1. Utilize `glm()` on explanatory variables constructed from `ns()` or `bs()`
2. The `gam` library
3. The `mgcv` library
Example

```r
> set.seed(508)
> x1 <- seq(1, 10, length.out=50)
> n <- length(x1)
> x2 <- rnorm(n)
> f <- 4*log(x1) + sin(x1) - 7 + 0.5*x2
> p <- exp(f)/(1+exp(f))
> summary(p)

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.001842 0.074171 0.310674 0.436162 0.860387 0.944761

> y <- rbinom(n, size=1, prob=p)
> mean(y)
[1] 0.42
> df <- data.frame(x1=x1, x2=x2, y=y)

Here, we use the `gam()` function from the `mgcv` library. It automates choosing the smoothness of the splines.

```r
> library(mgcv)
> mygam <- gam(y ~ s(x1) + s(x2), family = binomial(), data=df)
> library(broom)
> tidy(mygam)

# A tibble: 2 x 5
  term  edf ref.df statistic  p.value
  <chr> <dbl> <dbl>     <dbl>    <dbl>
1 s(x1) 1.87 2.37      12.7  0.00531
2 s(x2) 1.00 1.00      1.16  0.28084

> summary(mygam)

Family: binomial
Link function: logit

Formula:
y ~ s(x1) + s(x2)

Parametric coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | -1.1380    | 0.6723  | -1.693   | 0.0905  |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:

<table>
<thead>
<tr>
<th>edf</th>
<th>ref.df</th>
<th>Chi.sq</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(x1)</td>
<td>1.87</td>
<td>12.743</td>
<td>0.00531</td>
</tr>
<tr>
<td>s(x2)</td>
<td>1.00</td>
<td>1.163</td>
<td>0.28084</td>
</tr>
</tbody>
</table>

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) = 0.488 Deviance explained = 47%
UBRE = -0.12392 Scale est. = 1 n = 50

True probabilities vs. estimated probabilities.
Smother estimated for x1.

> plot(mygam, select=1)
Smoother estimated for $x_2$.

> plot(mygam, select=2)
Here, we use the `glm()` function and include as an explanatory variable a NCS built from the `ns()` function from the `splines` library. We include a `df` argument in the `ns()` call.

```r
library(splines)
myglm <- glm(y ~ ns(x1, df=2) + x2, family = binomial(), data=df)
tidy(myglm)
# A tibble: 4 x 5
term estimate std.error statistic p.value
<chr>   <dbl>    <dbl>     <dbl>    <dbl>
1 (Intercept) -10.9   5.31      -2.06      0.0396
2 ns(x1, df = 2)1 21.4   10.1       2.11      0.0348
3 ns(x1, df = 2)2  6.33   2.11      3.00      0.00272
4 x2         0.734   0.609      1.21      0.228
```

The spline basis evaluated at `x1` values.

```r
ns(x1, df=2)
1     2
[1,] 0.00000000 0.00000000
[2,] 0.03114456 -0.02075171
[3,] 0.06220870 -0.04138180
[4,] 0.09311200 -0.06176867
```
[5]  0.12377405 -0.08179071
[6]  0.15411442 -0.10132630
[7]  0.18405270 -0.12025384
[8]  0.21350847 -0.13845171
[9]  0.24240131 -0.15579831
[10] 0.27065081 -0.17217201
[11] 0.29817654 -0.18745121
[12] 0.32489808 -0.20151430
[13] 0.35073503 -0.21423967
[14] 0.37560695 -0.22550571
[15] 0.39943343 -0.23519080
[16] 0.42213406 -0.24317334
[17] 0.44362840 -0.24933170
[18] 0.46383606 -0.25354429
[19] 0.48267660 -0.25568949
[20] 0.50006961 -0.25564569
[21] 0.51593467 -0.25329128
[22] 0.53019136 -0.24850464
[23] 0.54275927 -0.24116417
[24] 0.55355797 -0.23114825
[25] 0.56250705 -0.21833528
[26] 0.56952943 -0.20260871
[27] 0.57462513 -0.18396854
[28] 0.57787120 -0.16253131
[29] 0.57934806 -0.13841863
[30] 0.57913614 -0.11175212
[31] 0.57731586 -0.08265339
[32] 0.57396762 -0.05124405
[33] 0.56917185 -0.01764570
[34] 0.56300897  0.01802003
[35] 0.55555939  0.05563154
[36] 0.54690354  0.09506722
[37] 0.53712183  0.13620546
[38] 0.52629468  0.17892464
[39] 0.51450251  0.22310315
[40] 0.50182573  0.26861939
[41] 0.48834478  0.31535174
[42] 0.47414005  0.36317859
[43] 0.45929198  0.41197833
[44] 0.44388099  0.46162934
[45] 0.42798748  0.51201003
[46] 0.41169188  0.56299877
[47] 0.39507460  0.61447395
[48] 0.37821607  0.66631397
[49] 0.36119670  0.71839720
[50] 0.34409692  0.77060206

attr("degree")
[1] 3

attr("knots")
50%
5.5

attr("Boundary.knots")
[1] 1 10
Plot of basis function values vs x1.

> summary(myglm)

Call:
glm(formula = y ~ ns(x1, df = 2) + x2, family = binomial(), data = df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0214   -0.3730   -0.0162    0.5762    1.7616

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -10.9229    5.3079  -2.058  0.03960 *
ns(x1, df = 2)1   21.3848   10.1318   2.111  0.03480 *
ns(x1, df = 2)2    6.3266    2.1103   2.998  0.00272 **
x2 0.7342 0.6089 1.206 0.2279

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 68.029 on 49 degrees of freedom
Residual deviance: 35.682 on 46 degrees of freedom
AIC: 43.682

Number of Fisher Scoring iterations: 7

> drop1(myglm, test="LRT")
Single term deletions

Model:
y ~ ns(x1, df = 2) + x2

Df Deviance AIC LRT Pr(>Chi)
<none> 35.682 43.682
ns(x1, df = 2) 2 65.205 69.205 29.523 3.884e-07 ***
x2 1 37.274 43.274 1.592 0.207

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

True probabilities vs. estimated probabilities.

> plot(p, myglm$fitted.values, pch=19); abline(0,1)
Bootstrap for Statistical Models

Homoskedastic Models

Let’s first discuss how one can utilize the bootstrap on any of the three homoskedastic models:

- Simple linear regression
- Ordinary least squares
- Additive models

Residuals

In each of these scenarios we sample data \((X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\). Let suppose we calculate fitted values \(\hat{Y}_i\) and they are unbiased:

\[
E[\hat{Y}_i | X] = E[Y_i | X].
\]

We can calculate residuals \(\hat{E}_i = Y_i - \hat{Y}_i\) for \(i = 1, 2, \ldots, n\).
Studentized Residuals

One complication is that the residuals have a covariance. For example, in OLS we showed that

$$\text{Cov}(\hat{E}) = \sigma^2 (I - P)$$

where $P = X(X^T X)^{-1} X^T$.

To correct for this induced heteroskedasticity, we studentize the residuals by calculating

$$R_i = \frac{\hat{E}_i}{\sqrt{1 - P_{ii}}}$$

which gives $\text{Cov}(R) = \sigma^2 I$.

Confidence Intervals

The following is a bootstrap procedure for calculating a confidence interval on some statistic $\hat{\theta}$ calculated from a homoskedastic model fit. An example is $\hat{\beta}_j$ in an OLS.

1. Fit the model to obtain fitted values $\hat{Y}_i$, studentized residuals $R_i$, and the statistic of interest $\hat{\theta}$.
   For $b = 1, 2, \ldots, B$.
2. Sample $n$ observations with replacement from $\{R_i\}_{i=1}^n$ to obtain bootstrap residuals $R_{i1}^*, R_{i2}^*, \ldots, R_{in}^*$.
3. Form new response variables $Y_{i*} = \hat{Y}_i + R_{i*}$.
4. Fit the model to obtain $\hat{Y}_{i*}$ and all other fitted parameters.
5. Calculate statistic of interest $\hat{\theta}_{i*}$.

The bootstrap statistics $\hat{\theta}_{(1)}, \hat{\theta}_{(2)}, \ldots, \hat{\theta}_{(B)}$ are then utilized through one of the techniques discussed earlier (percentile, pivotal, studentized pivotal) to calculate a bootstrap CI.

Hypothesis Testing

Suppose we are testing the hypothesis $H_0 : \text{E}[Y|X] = f_0(X)$ vs $H_1 : \text{E}[Y|X] = f_1(X)$. Suppose it is possible to form unbiased estimates $f_0(X)$ and $f_1(X)$ given $X$, and $f_0$ is a restricted version of $f_1$.

Suppose also we have a statistic $T(\hat{f}_0, \hat{f}_1)$ for performing this test so that the larger the statistic, the more evidence there is against the null hypothesis in favor of the alternative.

The big picture strategy is to bootstrap studentized residuals from the unconstrained (alternative hypothesis) fitted model and then add those to the constrained (null hypothesis) fitted model to generate bootstrap null data sets.

1. Fit the models to obtain fitted values $\hat{f}_0(X_i)$ and $\hat{f}_1(X_i)$, studentized residuals $R_i$ from the fit $\hat{f}_1(X_i)$, and the observed statistic $T(\hat{f}_0, \hat{f}_1)$.
   For $b = 1, 2, \ldots, B$.
2. Sample $n$ observations with replacement from $\{R_i\}_{i=1}^n$ to obtain bootstrap residuals $R_{i1}^*, R_{i2}^*, \ldots, R_{in}^*$.
3. Form new response variables $Y_{i*} = \hat{f}_0(X_i) + R_{i*}$.
4. Fit the models on the response variables $Y_{i*}$ to obtain $\hat{f}_{0*}$ and $\hat{f}_{1*}$.
5. Calculate statistic $T(\hat{f}_{0*}^{(b)}, \hat{f}_{1*}^{(b)})$.

The p-value is then calculated as

$$\frac{\sum_{b=1}^{B} 1 \left( T(\hat{f}_{0*}^{(b)}, \hat{f}_{1*}^{(b)}) \geq T(\hat{f}_0, \hat{f}_1) \right)}{B}$$
Parametric Bootstrap

For more complex scenarios, such as GLMs, GAMs, and heteroskedastic models, it is typically more straightforward to utilize a parametric bootstrap.

Extras

Source

License

Session Information

```r
> sessionInfo()
```
```
R version 3.6.0 (2019-04-26)
Platform: x86_64-apple-darwin15.6.0 (64-bit)
Running under: macOS 10.15.3

Matrix products: default
BLAS: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRlapack.dylib

locale:

attached base packages:
[1] splines stats graphics grDevices utils datasets
[7] methods base

other attached packages:
[1] mgcv_1.8-31 nlme_3.1-144 broom_0.5.2
[4] forcats_0.5.0 stringr_1.4.0 dplyr_0.8.4
[7] purrr_0.3.3 readr_1.3.1 tidyr_1.0.2
[10] tibble_2.1.3 ggplot2_3.2.1 tidyverse_1.3.0
[13] knitr_1.28

loaded via a namespace (and not attached):
[1] tidyselect_1.0.0 xfun_0.12 haven_2.2.0
[4] lattice_0.20-40 colorspace_1.4-1 vctrs_0.2.3
[7] generics_0.0.2 htmltools_0.4.0 yaml_2.2.1
[10] utf8_1.1.4 rlang_0.4.5 pillar_1.4.3
[13] withr_2.1.2 glue_1.3.1 DBI_1.1.0
[16] dbplyr_1.4.2 modelr_0.1.6 readxl_1.3.1
[19] plyr_1.8.5 lifecycle_0.1.0 munsell_0.5.0
[22] gtable_0.3.0 cellranger_1.1.0 rvest_0.3.5
[25] evaluate_0.14 labeling_0.3 fansi_0.4.1
[28] highr_0.8 Rcpp_1.0.3 scales_1.1.0
[31] backports_1.1.5 jsonlite_1.6.1 farver_2.0.3
[34] fs_1.3.1 hms_0.5.3 digest_0.6.25
[37] stringi_1.4.6 grid_3.6.0 cli_2.0.2
[40] tools_3.6.0 magrittr_1.5 lazyeval_0.2.2
[43] crayon_1.3.4 pkgconfig_2.0.3 Matrix_1.2-18
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