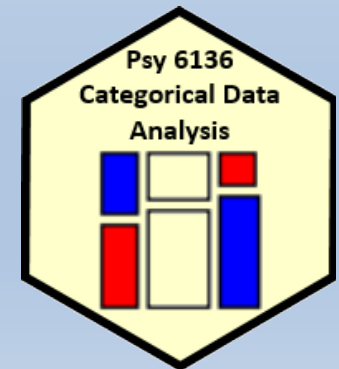


# Logistic regression



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<https://friendly.github.io/psy6136>

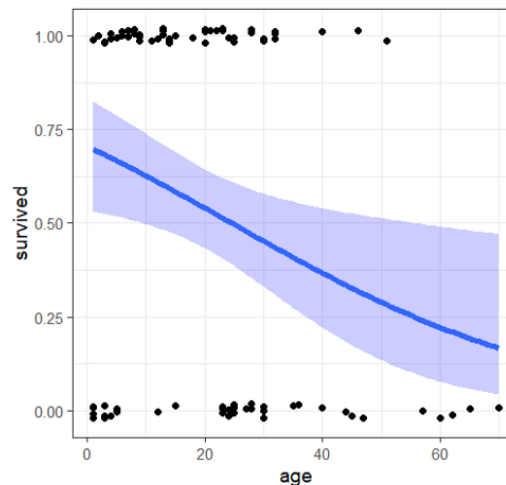


# Today's topics

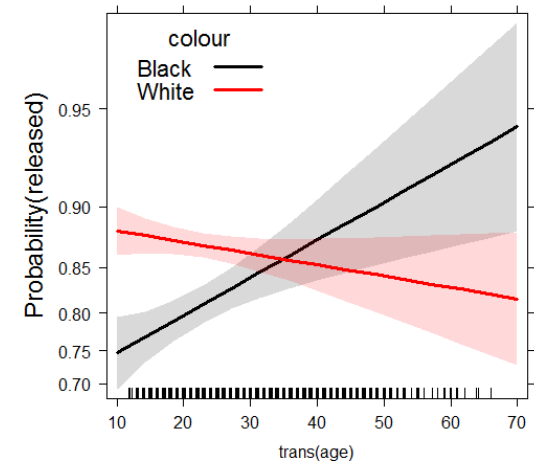
- Model-based methods: Overview
- Logistic regression: one predictor, multiple predictors, fitting
- Visualizing logistic regression
- Effect plots
- Case study: Racial profiling & marijuana arrests
- Model diagnostics

## Association models

- Loglinear models  
(contingency table form)  
[Admit][Gender Dept]  
[Admit Dept][Gender Dept]  
[AdmitDept][AdmitGender][GenderDept]
- Poisson GLMs  
(Frequency data frame)  
Freq ~ Admit + Gender \* Dept  
Freq ~ Admit\*Dept + Gender\*Dept  
Freq ~ Admit\*(Dept + Gender) +  
Gender\*Dept



Effects of skin colour and age on release





# Model-based methods: Overview

## Structure

- Explicitly assume some probability distribution for the data, e.g., binomial, Poisson, ...
- Distinguish between the **systematic** component— explained by the model— and a **random** component, which is not
- Allow a compact summary of the data in terms of a (hopefully) small number of parameters

## Advantages

- Inferences: hypothesis tests *and* confidence intervals
- Can test **individual** model terms (**anova ( )**)
- Methods for model selection: adjust balance between goodness-of-fit and parsimony
- Predicted values give **model-smoothed** summaries for plotting
- $\implies$  Interpret the fitted model graphically

# Modeling approaches: Overview

## Association models

- Loglinear models  
(contingency table form)  
[Admit][Gender Dept]  
[Admit Dept][Gender Dept]  
[AdmitDept][AdmitGender][GenderDept]
- Poisson GLMs  
(Frequency data frame)  
 $\text{Freq} \sim \text{Admit} + \text{Gender} * \text{Dept}$   
 $\text{Freq} \sim \text{Admit} * \text{Dept} + \text{Gender} * \text{Dept}$   
 $\text{Freq} \sim \text{Admit} * (\text{Dept} + \text{Gender}) + \text{Gender} * \text{Dept}$
- Ordinal variables  
 $\text{Freq} \sim \text{right} + \text{left} + \text{Diag}(\text{right}, \text{left})$   
 $\text{Freq} \sim \text{right} + \text{left} + \text{Symm}(\text{right}, \text{left})$

## Response models

- Binary response
- Categorical predictors: logit models  
 $\text{logit}(\text{Admit}) \sim 1$   
 $\text{logit}(\text{Admit}) \sim \text{Dept}$   
 $\text{logit}(\text{Admit}) \sim \text{Dept} + \text{Gender}$
- Continuous/mixed predictors
- Logistic regression models  
 $\text{Pr}(\text{Admit}) \sim \text{Dept} + \text{Gender} + \text{Age} + \text{GRE}$
- Polytomous response
- Ordinal: proportional odds model  
 $\text{Improve} \sim \text{Age} + \text{Sex} + \text{Treatment}$
- General multinomial model  
 $\text{WomenWork} \sim \text{Kids} + \text{HusbandIncome}$

# loglm() vs. glm()

With **loglm()** you can only test overall fit (**anova()**) or difference between models (**Lrstats()**)

```
> berk.mod1 <- loglm(~ Dept * (Gender + Admit), data=UCBAdmissions)
> berk.mod2 <- loglm(~(Admit + Dept + Gender)^2, data=UCBAdmissions)

> anova(berk.mod2)
Call:
loglm(formula = ~(Admit + Dept + Gender)^2, data = UCBAdmissions)

Statistics:

                X^2 df P(> X^2)
Likelihood Ratio 20.20  5 0.001144
Pearson          18.82  5 0.00207
```

What we can say:

Even the model with all pairwise associations fits poorly 😞

## Comparing models with `anova()` and `LRstats()`

```
> anova(berk.mod1, berk.mod2, test="Chisq")  
LR tests for hierarchical log-linear models
```

Model 1:

```
~Dept * (Gender + Admit)
```

Model 2:

```
~(Admit + Dept + Gender)^2
```

|           | Deviance | df | Delta(Dev) | Delta(df) | P(> Delta(Dev)) |
|-----------|----------|----|------------|-----------|-----------------|
| Model 1   | 21.74    | 6  |            |           |                 |
| Model 2   | 20.20    | 5  | 1.531      | 1         | 0.21593         |
| Saturated | 0.00     | 0  | 20.204     | 5         | 0.00114         |

```
> LRstats(berk.mod1, berk.mod2)
```

Likelihood summary table:

|           | AIC | BIC | LR | Chisq | Df | Pr(>Chisq) |
|-----------|-----|-----|----|-------|----|------------|
| berk.mod1 | 217 | 238 |    | 21.7  | 6  | 0.0014 **  |
| berk.mod2 | 217 | 240 |    | 20.2  | 5  | 0.0011 **  |

---

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

**Q: What can we say from this?**

# loglm() vs. glm()

With `glm()` you can test individual terms using `anova()` or `car::Anova()`

```
> berkeley <- as.data.frame(UCBAdmissions)
> berk.glm2 <- glm(Freq ~ (Dept+Gender+Admit)^2, data=berkeley,
                  family="poisson")
> anova(berk.glm2, test="Chisq")
Analysis of Deviance Table
```

```
Model: poisson, link: log
Response: Freq
```

```
Terms added sequentially (first to last)
```

|              | Df | Deviance | Resid. | Df | Resid. | Dev  | Pr(>Chi)   |
|--------------|----|----------|--------|----|--------|------|------------|
| NULL         |    |          |        | 23 |        | 2650 |            |
| Dept         | 5  | 160      |        | 18 |        | 2491 | <2e-16 *** |
| Gender       | 1  | 163      |        | 17 |        | 2328 | <2e-16 *** |
| Admit        | 1  | 230      |        | 16 |        | 2098 | <2e-16 *** |
| Dept:Gender  | 5  | 1221     |        | 11 |        | 877  | <2e-16 *** |
| Dept:Admit   | 5  | 855      |        | 6  |        | 22   | <2e-16 *** |
| Gender:Admit | 1  | 2        |        | 5  |        | 20   | 0.22       |

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

NB: `anova()` gives Type I, sequential tests

Not interested in these

Q: Can someone help interpret the term for Gender:Admit ?

How could I enhance the `vcdExtra` package to do this for `loglm()` models?

# Dropping & adding terms

A useful strategy for model-building is to start with some model, and consider

- The effect of dropping high-order terms, one at a time
- The effect of adding terms w/in the scope of a larger model, one at a time
- MASS:dropterm() and MASS::addterm() do this for both glm() and loglm() models

```
> MASS::dropterm(berk.glm2, test="Chisq")
```

```
Single term deletions
```

```
Model:
```

```
Freq ~ (Dept + Gender + Admit)^2
```

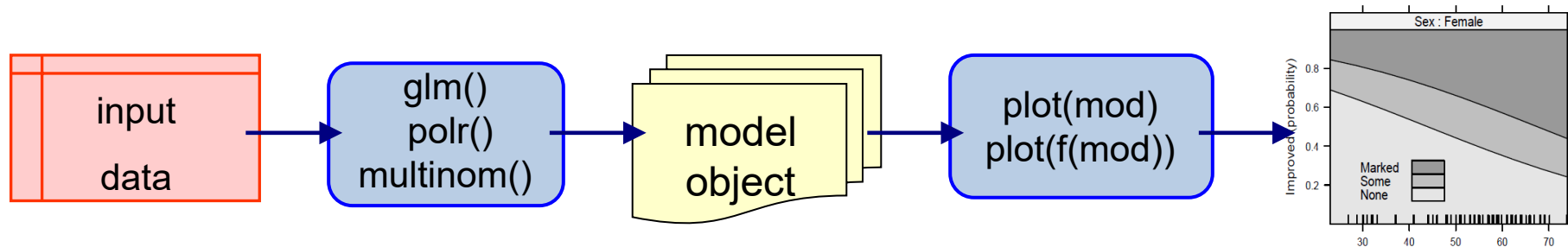
|              | Df | Deviance | AIC     | LRT     | Pr (Chi) |     |
|--------------|----|----------|---------|---------|----------|-----|
| <none>       |    | 20.20    | 217.26  |         |          |     |
| Dept:Gender  | 5  | 1148.90  | 1335.96 | 1128.70 | <2e-16   | *** |
| Dept:Admit   | 5  | 783.61   | 970.67  | 763.40  | <2e-16   | *** |
| Gender:Admit | 1  | 21.74    | 216.80  | 1.53    | 0.2159   |     |

```
---
```

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

# Fitting & graphing models: Overview

## Object-oriented approach in R:



- Fit model (`obj <- glm(...)`) → a model object
- `print(obj)` and `summary(obj)` → numerical results
- `anova(obj)` and `Anova(obj)` → tests for model terms
- `update(obj)`, `add1(obj)`, `drop1(obj)` for model selection

## Plot methods:

- `plot(obj)` often gives diagnostic plots
- Other plot methods:
  - Mosaic plots: `mosaic(obj)` for "loglm" and "glm" objects
  - Effect plots: `plot(Effect(obj))` for nearly all linear models
  - Influence plots (car): `influencePlot(obj)` for "glm" objects

# Logistic regression

## Response variable

- Binary response: success/failure, vote: yes/no
- Binomial data:  $x$  successes in  $n$  trials (grouped data)

```
glm(success ~ ..., family=binomial)
```

```
glm(cbind(Nsuccess, Nfail) ~ ..., family=binomial)
```

## Explanatory variables

- Quantitative regressors: age, dose
- Transformed regressors:  $\sqrt{\text{age}}$ ,  $\log(\text{dose})$
- Polynomial regressors:  $\text{age}^2$ ,  $\text{age}^3$ ,  $\dots$  (or better: splines)
- Categorical predictors: treatment, sex (dummy variables, contrasts)
- Interaction regressors:  $\text{treatment} \times \text{age}$ ,  $\text{sex} \times \text{age}$

This is exactly the same as in classical ANOVA, regression models



# Logistic regression: Extensions



## Response variable

- Binary response: success/failure, vote: yes/no
- Binomial data:  $x$  successes in  $n$  trials (grouped data)
- Ordinal response: none < some < severe depression
- Polytomous response: vote Liberal, Tory, NDP, Green

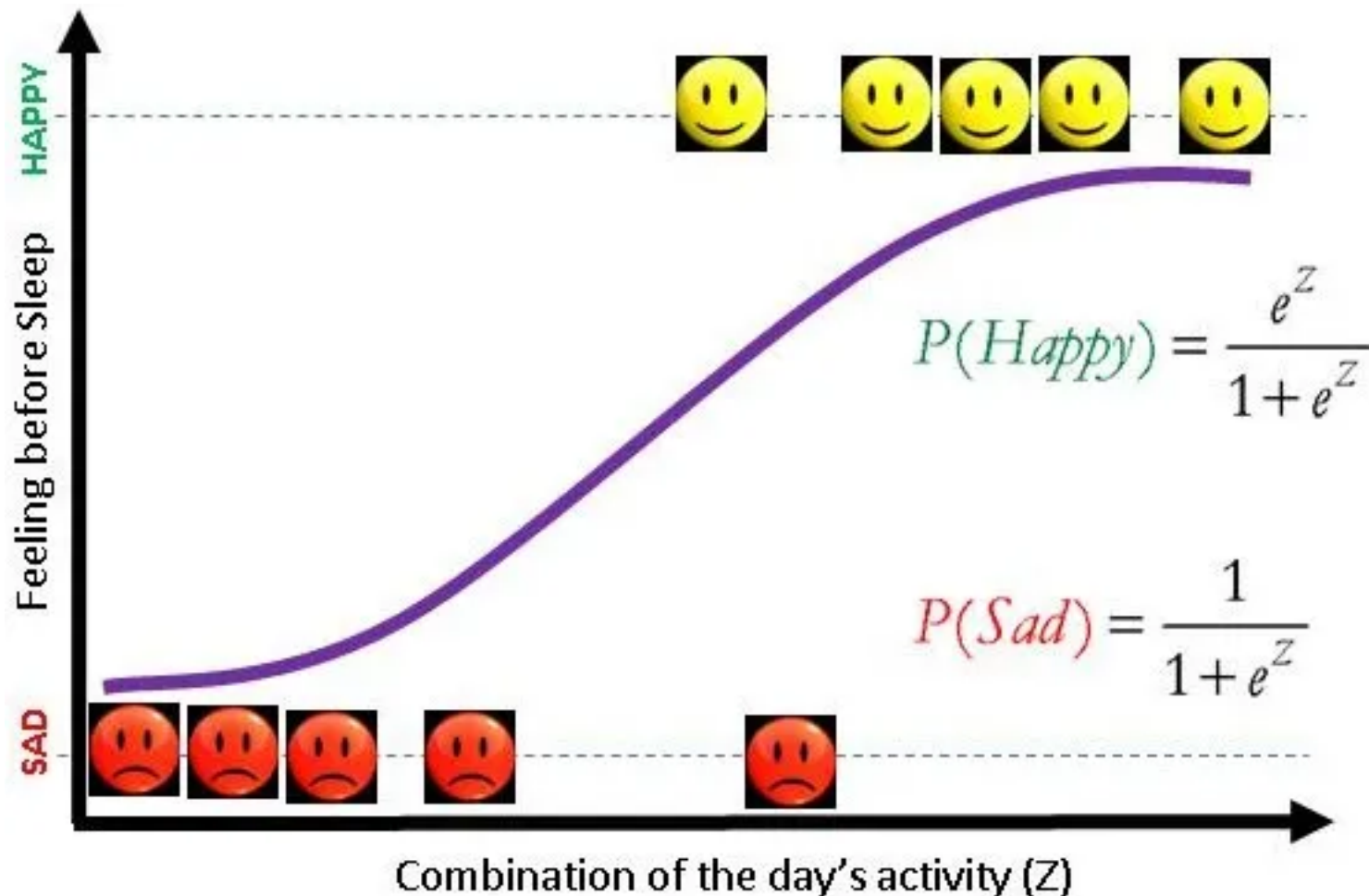
Extensions of the framework for logistic regression allow us to handle more than two discrete outcomes. Explanatory variables remain the same

## Explanatory variables

- Quantitative regressors: age, dose
- Transformed regressors:  $\sqrt{\text{age}}$ ,  $\log(\text{dose})$
- Polynomial regressors:  $\text{age}^2$ ,  $\text{age}^3$ , ... (or better: splines)
- Categorical predictors: treatment, sex (dummy variables, contrasts)
- Interaction regressors: treatment  $\times$  age, sex  $\times$  age

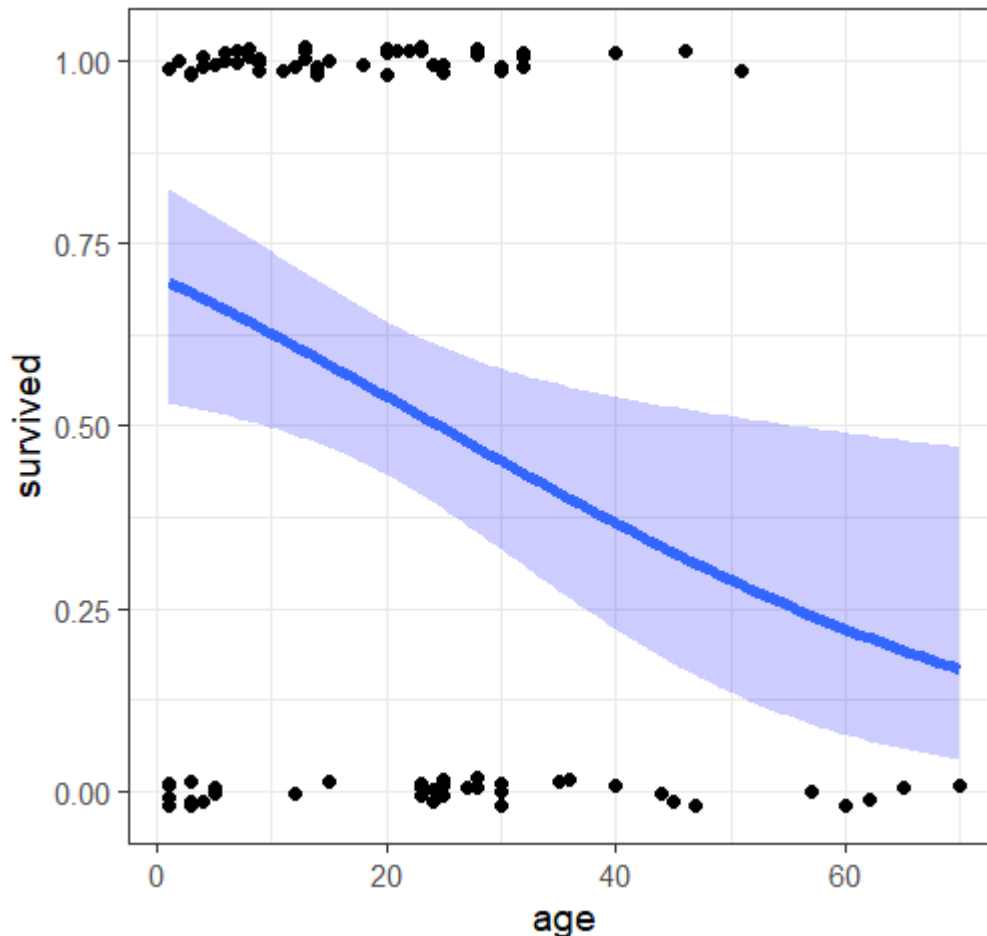
This is exactly the same as in classical ANOVA, regression models

# Logistic regression examples



# Survival in the Donner Party

Data on the Donner Party records the fate of 90 people who set out to CA in 1846. They were trapped in an early winter storm near Reno, NV. Only 48 survived.



Who survived? Why?

Logistic regression can model the probability of the **binary (0/1)** outcome of survival

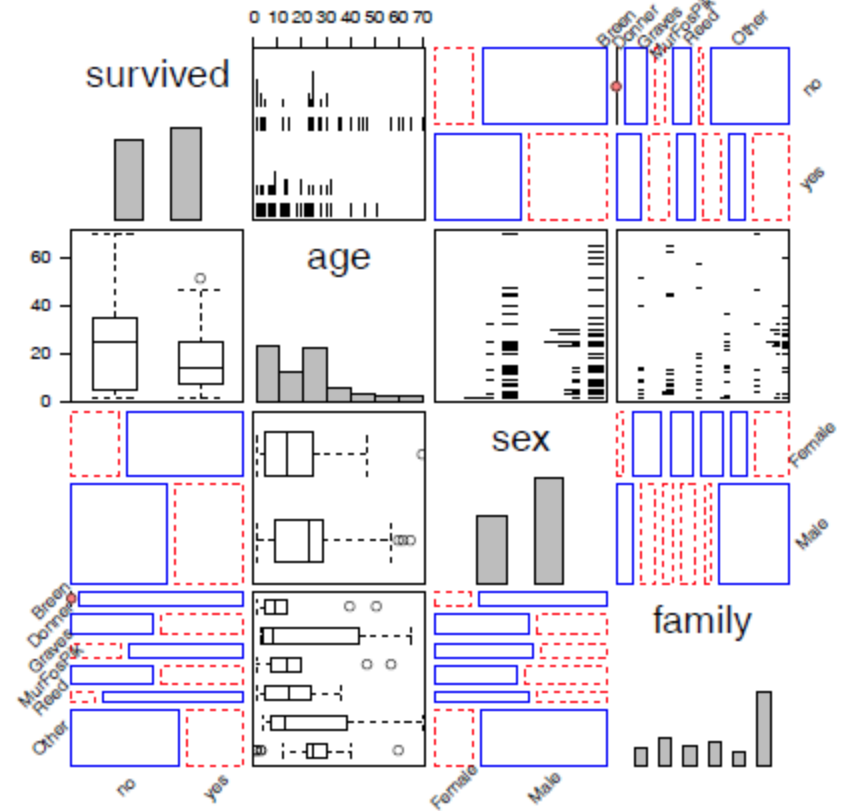
The model is **linear in log-odds**, but non-linear on the probability scale.

A quantitative predictor like age gives predicted probabilities (& CI)

Other predictors – sex, family, ... can give a more detailed understanding

# Survival in the Donner Party

- Binary response: `survived`
- Categorical predictors: `sex`, `family`
- Quantitative predictor: `age`
- Q: Is the effect of age linear?
- Q: Are there interactions among predictors?
- This is a **generalized pairs plot**, with different plots for each pair

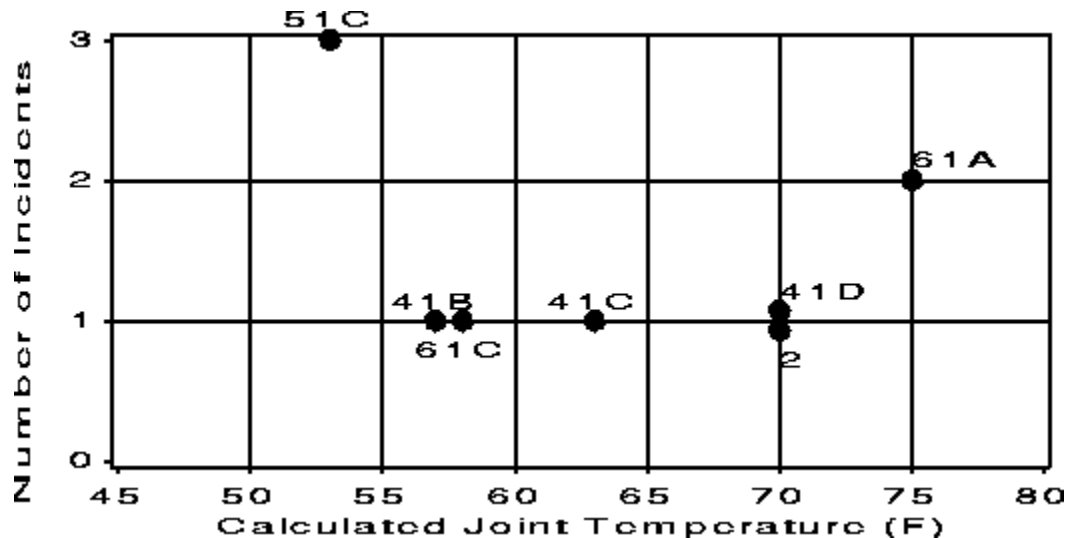


Some possible models:

```
glm(survived ~ age, data=Donner, family=binomial)
glm(survived ~ age + sex + family, data=Donner, family=binomial)
glm(survived ~ age * sex, data=Donner, family=binomial)
```

# Challenger: A dataviz disaster

- The space shuttle *Challenger* exploded 73 sec. after takeoff on January 28, 1986, killing all 7 crew
  - Subsequent investigation revealed the **proximal cause**: Low temperature → failures of the rubber O-rings joining rocket stages
  - The **anterior cause** was a failure of data analysis & visualization
- Data: 24 previous flights: temperature, # of “incidents”



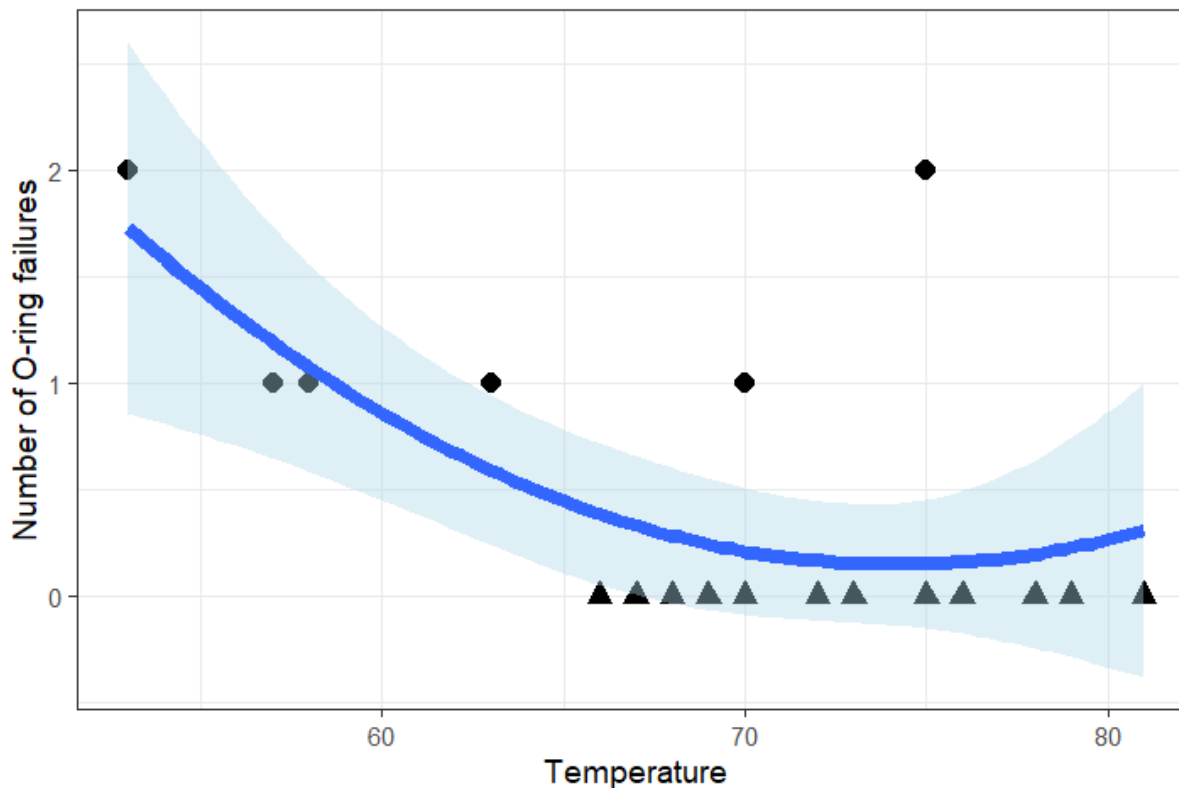
Morton-Thiokol engineers prepared this bad graph

But, they also excluded all flights where there was no damage

# Challenger: A better graph

This graph plots the number of failures out of 6 O-rings in all previous flights, including those with 0 failures

- It fits a simple quadratic regression,  $n\text{Failures} \sim \text{poly}(\text{Temperature}, 2)$
- It should have been a warning that failures increase as temperature gets lower
- But it doesn't take into account that  $n\text{Failures} \sim \text{Bin}(p, n=6)$

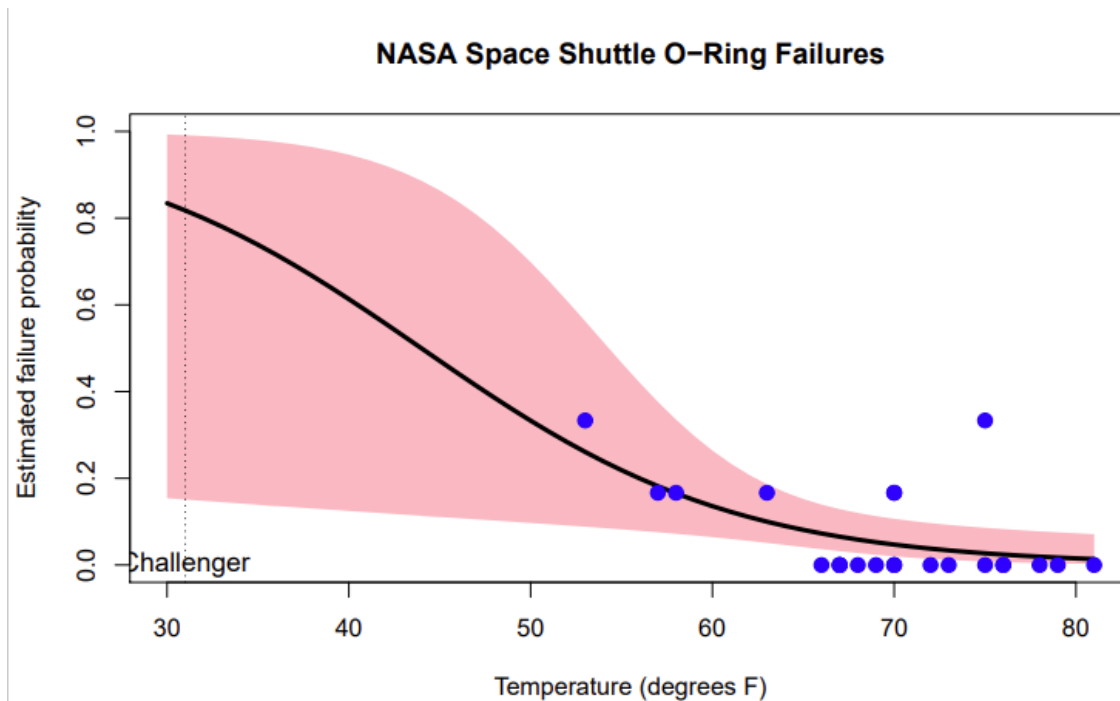


# Challenger: A better analysis

Logistic regression treats the # failures as a **binomial outcome with  $n = 6$  trials**

The model provides

- Predicted probabilities outside the range of the data
- Confidence intervals, to judge model uncertainty

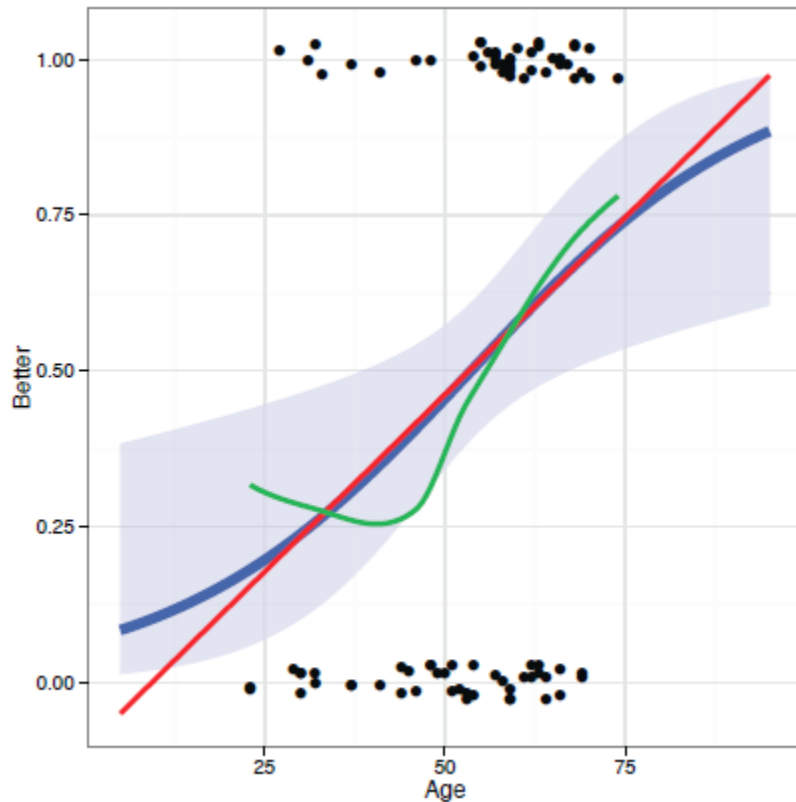


When the challenger was launched, the temp was 31° F

The CI band is very wide, but the predicted value is uncomfortably high

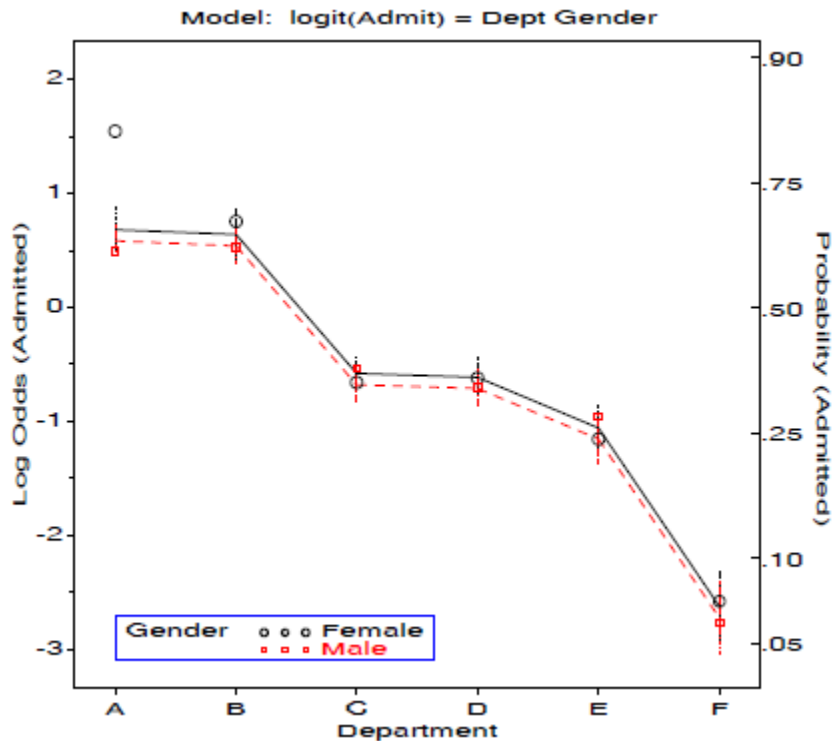
This analysis & graph might have saved lives!

# Example: Arthritis treatment



- The response variable, `Improved` is ordinal: "None" < "Some" < "Marked"
- A binary logistic model can consider just `Better = (Improved > "None")`
- Other important predictors: Sex, Treatment
- Main Q: how does treatment affect outcome?
- How does this vary with Age and Sex?
- This plot shows the binary observations, with several model-based smoothings

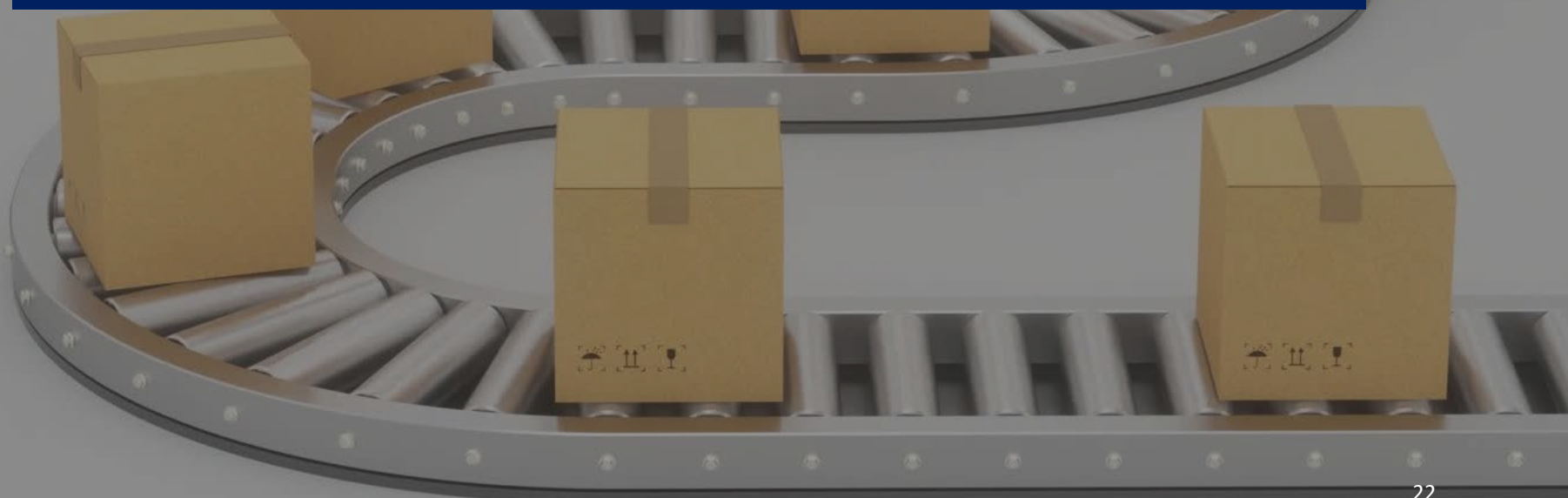
# Example: Berkeley admissions



- Admit/Reject can be considered a **binomial response** for each Dept and Gender
- Logistic regression here is analogous to an ANOVA model, but for log odds(Admit)
- (With categorical predictors, these are often called **logit** models)
- Every such model has an equivalent **loglinear** model form.
- This plot shows fitted logits for the main effects model,  $\text{Dept} + \text{Gender}$

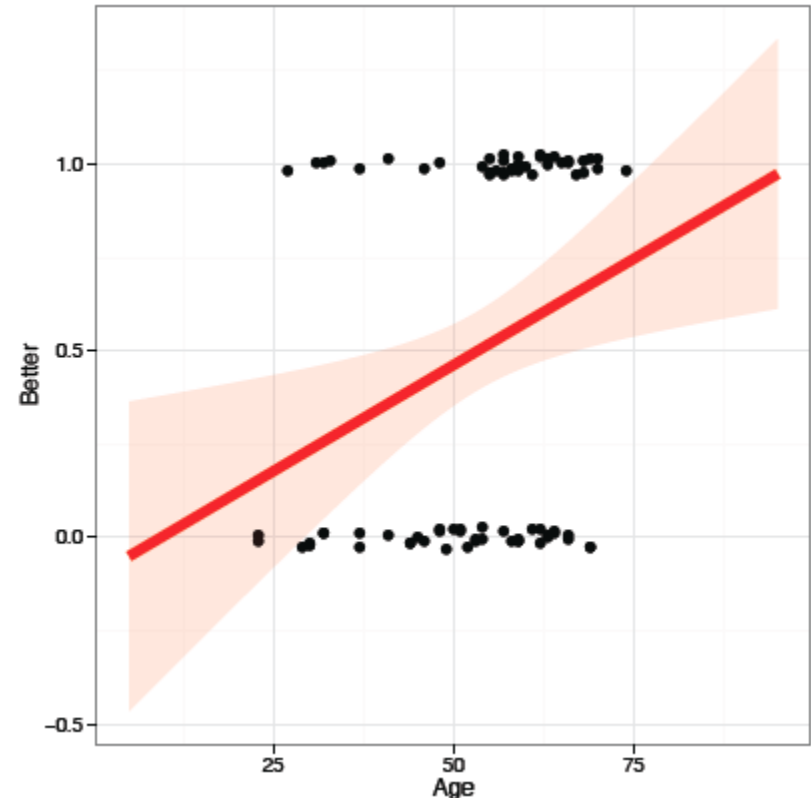
WOW! This logit model has such a simple interpretation compared to loglinear  
Can you describe it?

# The Logistic Regression Model



# Binary response: What's wrong with OLS?

- For a binary response,  $Y \in (0, 1)$ , want to predict  $\pi = \Pr(Y = 1 | x)$
- A **linear probability model** uses classical linear regression (OLS)
- Problems:
  - Gives predicted values and CIs outside  $0 \leq \pi \leq 1$
  - Homogeneity of variance is violated:  $\mathcal{V}(\hat{\pi}) = \hat{\pi}(1 - \hat{\pi}) \neq \text{constant}$
  - Inferences, hypothesis tests are wrong!



# Linear regression vs Logistic regression

OLS regression:

- Assume  $y|x \sim N(0, \sigma^2)$

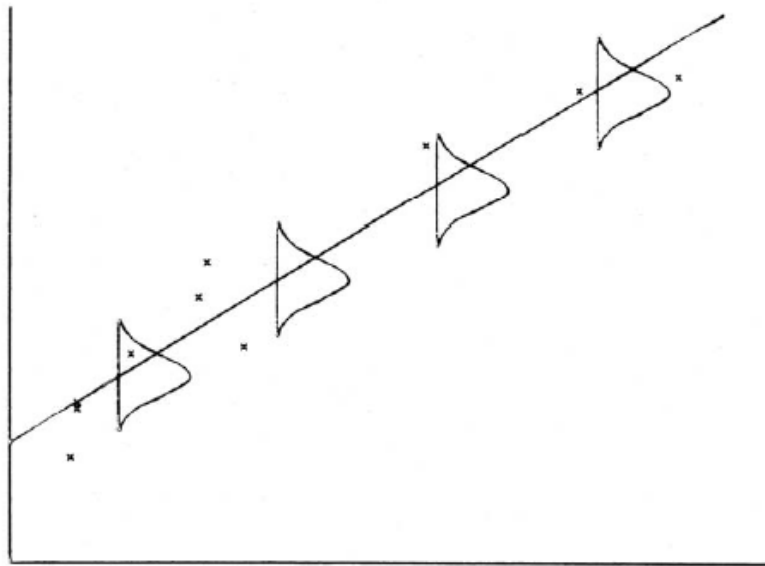


Fig. 2.1. Graphical representation of a simple linear normal regression.

Logistic regression:

- Assume  $\Pr(y=1|x) \sim \text{binomial}(p)$

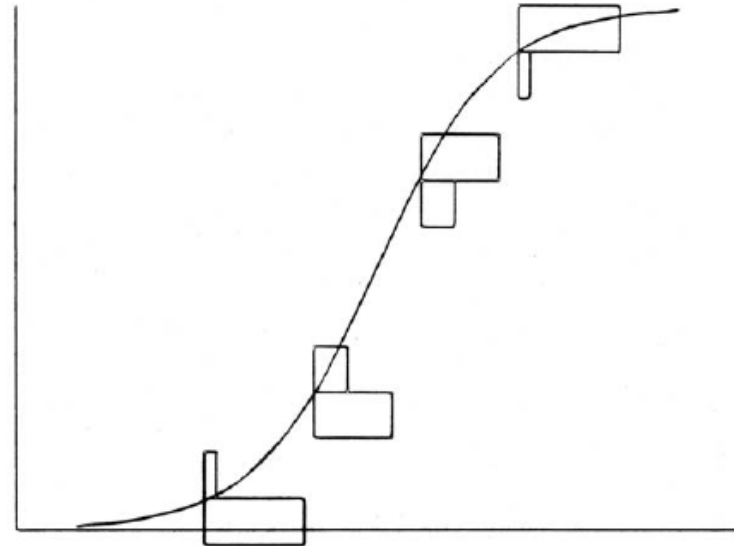


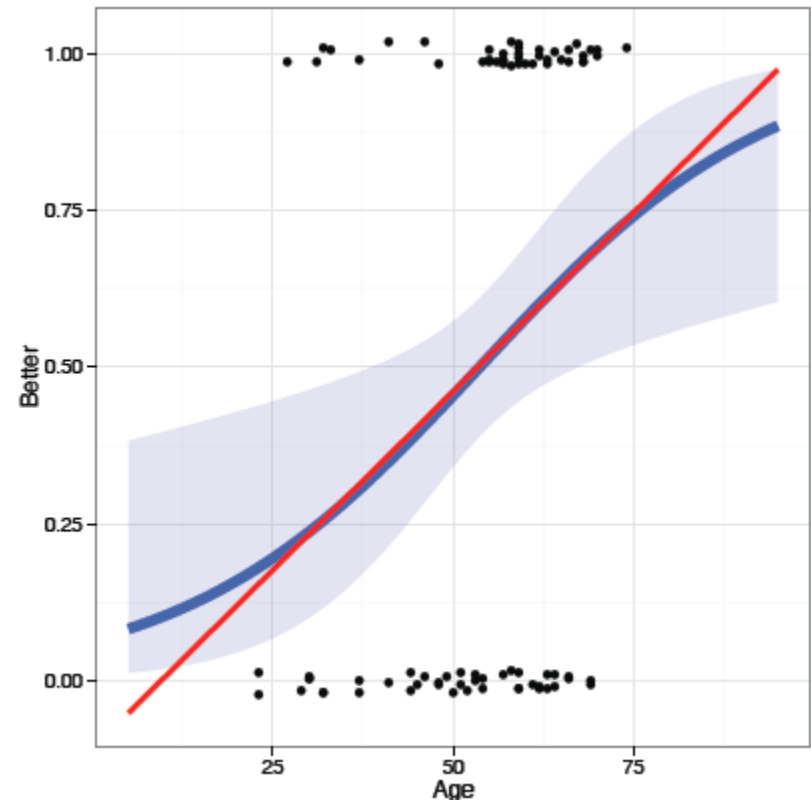
Fig. 2.2. Graphical representation of a simple linear logistic regression.

$y$  linear with  $x$   
constant residual variance

$y \sim \text{logit}(x)$   
non-constant residual variance  $\sim p(1-p)$

# Logistic regression

- Logistic regression avoids these problems
- Models  $\text{logit}(\pi_i) \equiv \log[\pi/(1 - \pi)]$
- logit is interpretable as “log odds” that  $Y = 1$
- A related **probit** model gives very similar results, but is less interpretable
- For  $0.2 \leq \pi \leq 0.8$  fitted values are close to those from linear regression.



# Logistic regression: One predictor

For a single quantitative predictor,  $x$ , the simple **linear logistic regression model** posits a linear relation between the **log odds** (or **logit**) of  $\Pr(Y = 1)$  and  $x$ ,

$$\text{logit}[\pi(x)] \equiv \log \left( \frac{\pi(x)}{1 - \pi(x)} \right) = \alpha + \beta x .$$

- When  $\beta > 0$ ,  $\pi(x)$  and the log odds increase as  $x$  increases; when  $\beta < 0$  they decrease with  $x$ .
- This model can also be expressed as a model for the probabilities  $\pi(x)$

$$\pi(x) = \text{logit}^{-1}[\pi(x)] = \frac{1}{1 + \exp[-(\alpha + \beta x)]}$$

Thinking logistically:

- Model is for the **log odds** of the marked response,  $Y = 1$
- Can always back transform with  $\text{logit}^{-1}$  to get **probability** of  $Y = 1$

# Logistic regression: One predictor

The coefficients,  $\alpha$ ,  $\beta$  of this model have simple interpretations in terms of odds & log odds

$$\text{logit}[\pi(x)] \equiv \log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta x \quad \text{odds}(Y=1) \equiv \frac{\pi(x)}{1-\pi(x)} = \exp(\alpha + \beta x) = e^\alpha (e^\beta)^x$$

$\beta$  is the change in log odds for a **unit increase** in  $x$

→ The odds of  $Y=1$  are multiplied by  $e^\beta$  for each unit increase in  $x$

$\alpha$  is the log odds **when  $x=0$**

→ The odds of  $Y=1$  when  $x=0$  is  $e^\alpha$

In R, use **`exp(coef(model))`** to get these values

Another interpretation: In terms of probability, the **slope** of the logistic regression curve is  $\beta\pi(1-\pi)$

This has the **maximum** value  $\beta/4$  when  $\pi = 1/2$

# Logistic regression: Multiple predictors

- For a binary response,  $Y \in (0, 1)$ , let  $\mathbf{x}$  be a vector of  $p$  regressors, and  $\pi_i$  be the probability,  $\Pr(Y = 1 \mid \mathbf{x})$ .
- The logistic regression model is a linear model for the *log odds*, or *logit* that  $Y = 1$ , given the values in  $\mathbf{x}$ ,

$$\begin{aligned}\text{logit}(\pi_i) \equiv \log\left(\frac{\pi_i}{1 - \pi_i}\right) &= \alpha + \mathbf{x}_i^T \boldsymbol{\beta} \\ &= \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}\end{aligned}$$

- An equivalent (non-linear) form of the model may be specified for the probability,  $\pi_i$ , itself,

$$\pi_i = \{1 + \exp(-[\alpha + \mathbf{x}_i^T \boldsymbol{\beta}])\}^{-1}$$

- The logistic model is also a *multiplicative* model for the odds of “success,”

$$\frac{\pi_i}{1 - \pi_i} = \exp(\alpha + \mathbf{x}_i^T \boldsymbol{\beta}) = \exp(\alpha) \exp(\mathbf{x}_i^T \boldsymbol{\beta})$$

Increasing  $x_{ij}$  by 1 increases  $\text{logit}(\pi_i)$  by  $\beta_j$ , and multiplies the odds by  $e^{\beta_j}$ .

# Fitting the logistic regression model

Logistic regression models are the special case of generalized linear models, fit in R using `glm(..., family=binomial)`

For this example, we define **Better** as any improvement at all

```
> data(Arthritis, package="vcd")
> Arthritis$Better <- as.numeric(Arthritis$Improved > "None")
```

Fit and print:

```
> (arth.logistic <- glm(Better ~ Age, data=Arthritis, family=binomial))

Call:  glm(formula = Better ~ Age, family = binomial, data = Arthritis)

Coefficients:
(Intercept)          Age
   -2.6421         0.0492

Degrees of Freedom: 83 Total (i.e. Null);  82 Residual
Null Deviance:      116
Residual Deviance: 109    AIC: 113
```

## The **summary()** method gives details and tests of coefficients

```
> summary(arth.logistic)

Call:
glm(formula = Better ~ Age, family = binomial, data = Arthritis)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5106  -1.1277   0.0794   1.0677   1.7611

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -2.6421     1.0732  -2.46   0.014 *
Age           0.0492     0.0194   2.54   0.011 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 116.45  on 83  degrees of freedom    G2 for H0: βAge = 0
Residual deviance: 109.16  on 82  degrees of freedom    G2 for H1: βAge ≠ 0
```

How much better is this than the null model?  $\Delta G^2_{(1)} = 116.45 - 109.16 = 7.29$

# Interpreting coefficients

```
> coef(arth.logistic)
(Intercept)    Age
-2.64207     0.04925
```

```
> exp(coef(arth.logistic))
(Intercept)    Age
0.07121     1.05048
> exp(10*coef(arth.logistic)[2])
Age
1.636
```

## Interpretations:

- log odds(Better) increase by  $\beta = 0.0492$  for each year of age
- odds(Better) multiplied by  $e^\beta = 1.05$  for each year of age— a 5% increase
- over 10 years, odds(Better) are multiplied by  $\exp(10 \times 0.0492) = 1.64$ , a 64% increase.
- $\Pr(\text{Better})$  increases by  $\beta/4 = 0.0123$  for each year (near  $\pi = \frac{1}{2}$ )

# Multiple predictors

The main interest here is the effect of Treatment. Sex and Age are **control variables**. Fit the **main effects** model (no interactions):

$$\text{logit}(\pi_i) = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3}$$

where  $x_1$  is *Age* and  $x_2$  and  $x_3$  are the factors representing *Sex* and *Treatment*, respectively. R uses dummy (0/1) variables for factors.

$$x_2 = \begin{cases} 0 & \text{if Female} \\ 1 & \text{if Male} \end{cases} \quad x_3 = \begin{cases} 0 & \text{if Placebo} \\ 1 & \text{if Treatment} \end{cases}$$

- $\alpha$  doesn't have a sensible interpretation here. Why?
- $\beta_1$ : increment in log odds(Better) for each year of age.
- $\beta_2$ : difference in log odds for male as compared to female.
- $\beta_3$ : difference in log odds for treated vs. the placebo group

# Multiple predictors: Fitting

Fit the main effects model. Use  $I(\text{Age} - 50)$  to center Age, making  $\alpha$  interpretable

```
arth.logistic2 <- glm(Better ~ I(Age - 50) + Sex + Treatment,  
                      data=Arthritis, family=binomial)
```

**lmtest::coeftest()** gives just the tests of coefficients provided by summary()

```
> lmtest::coeftest(arth.logistic2)
```

z test of coefficients:

|                  | Estimate | Std. Error | z value | Pr(> z ) |
|------------------|----------|------------|---------|----------|
| (Intercept)      | -0.5781  | 0.3674     | -1.57   | 0.116    |
| I(Age - 50)      | 0.0487   | 0.0207     | 2.36    | 0.018 *  |
| SexMale          | -1.4878  | 0.5948     | -2.50   | 0.012 *  |
| TreatmentTreated | 1.7598   | 0.5365     | 3.28    | 0.001 ** |

**broom::glance()** gives model fit statistics

```
> broom::glance(arth.logistic2)
```

```
# A tibble: 1 x 8
```

|   | null.deviance | df.null | logLik | AIC   | BIC   | deviance | df.residual | nobs  |
|---|---------------|---------|--------|-------|-------|----------|-------------|-------|
|   | <dbl>         | <int>   | <dbl>  | <dbl> | <dbl> | <dbl>    | <int>       | <int> |
| 1 | 116.          | 83      | -46.0  | 100.  | 110.  | 92.1     | 80          | 84    |

# Interpreting coefficients

```
> cbind(coef=coef(arth.logistic2),
        OddsRatio=exp(coef(arth.logistic2)),
        exp(confint(arth.logistic2)))
```

|                    | coef    | OddsRatio | 2.5 %  | 97.5 % |
|--------------------|---------|-----------|--------|--------|
| 1 (Intercept)      | -0.5781 | 0.561     | 0.2647 | 1.132  |
| 2 I(Age - 50)      | 0.0487  | 1.050     | 1.0100 | 1.096  |
| 3 SexMale          | -1.4878 | 0.226     | 0.0652 | 0.689  |
| 4 TreatmentTreated | 1.7598  | 5.811     | 2.1187 | 17.727 |

- 1 ●  $\alpha = -0.578$ : At age 50, females given placebo have odds(Better) of  $e^{-0.578} = 0.56$ .
- 2 ●  $\beta_1 = 0.0487$ : Each year of age multiplies odds(Better) by  $e^{0.0487} = 1.05$ , a 5% increase.
- 3 ●  $\beta_2 = -1.49$ : Males  $e^{-1.49} = 0.26 \times$  less likely to show improvement as females. (Or, females  $e^{1.49} = 4.437 \times$  more likely than males.)
- 4 ●  $\beta_3 = 1.76$ : Treated  $e^{1.76} = 5.81 \times$  more likely Better than Placebo

# Hypothesis testing: Questions

- **Overall test:** How does my model,  $\text{logit}(\pi) = \alpha + \mathbf{x}^T \boldsymbol{\beta}$  compare with the null model,  $\text{logit}(\pi) = \alpha$ ?

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_p = 0$$

- **One predictor:** Does  $x_k$  significantly improve my model? Can it be dropped?

$$H_0 : \beta_k = 0 \quad \text{given other predictors retained}$$

- **Lack of fit:** How does my model compare with a perfect model (saturated model)?

For ANOVA, regression, these tests are carried out using  $F$ -tests and  $t$ -tests. In logistic regression (fit by maximum likelihood) we use

- $F$ -tests  $\rightarrow$  likelihood ratio  $G^2$  tests
- $t$ -tests  $\rightarrow$  Wald  $z$  or  $\chi^2$  tests

# Maximum likelihood estimation

In classical linear models using `lm()`, we fit using ordinary least squares.  
All `glm()` models use maximum likelihood estimation— better properties

- Likelihood,  $\mathcal{L} = \Pr(\text{data} | \text{model})$ , as function of model parameters
- For case  $i$ ,

$$\mathcal{L}_i = \begin{cases} p_i & \text{if } Y = 1 \\ 1 - p_i & \text{if } Y = 0 \end{cases} = p_i^{Y_i} (1 - p_i^{1 - Y_i}) \quad \text{where} \quad p_i = 1 / (1 + \exp(\mathbf{x}_i \boldsymbol{\beta}))$$

- Under independence, joint likelihood is the product over all cases

$$\mathcal{L} = \prod_i^n p_i^{Y_i} (1 - p_i^{1 - Y_i})$$

- $\implies$  Find estimates  $\hat{\boldsymbol{\beta}}$  that maximize  $\log \mathcal{L}$ . Iterative, but this solves the “estimating equations”

$$\mathbf{X}^T \mathbf{y} = \mathbf{X}^T \hat{\boldsymbol{\rho}}$$

# Overall model tests

## Likelihood ratio test ( $G^2$ )

- Compare **nested** models, similar to F tests in OLS
- Let  $L_1$  = maximized value for **our model**

$$\text{logit}(\pi_i) = \beta_0 + \mathbf{x}_i^T \boldsymbol{\beta} \quad \text{w/ } k \text{ predictors}$$

- Let  $L_0$  = maximized likelihood for the **null model**

$$\text{logit}(\pi_i) = \beta_0 \quad \text{under } H_0: \beta_1 = \beta_2 = \dots = \beta_k$$

- Likelihood ratio test statistic:

$$G^2 = -2 \log \left( \frac{L_0}{L_1} \right) = 2(\log L_1 - \log L_0) \sim \chi_k^2$$

# Wald tests & confidence intervals

- Analogous to  $t$ -tests in OLS

- Test  $H_0: \beta_i = 0$

$$z = \frac{b_i}{s(b_i)} \sim \mathcal{N}(0,1) \quad \text{or} \quad z^2 \sim \chi_1^2$$

- Confidence interval

$$b_i \pm z_{1-\alpha/2} s(b_i)$$

```
> r1 <- lmtest::coefstest(arth.logistic2)
> r2 <- confint(arth.logistic2)
Waiting for profiling to be done...
> cbind(r1, r2)
```

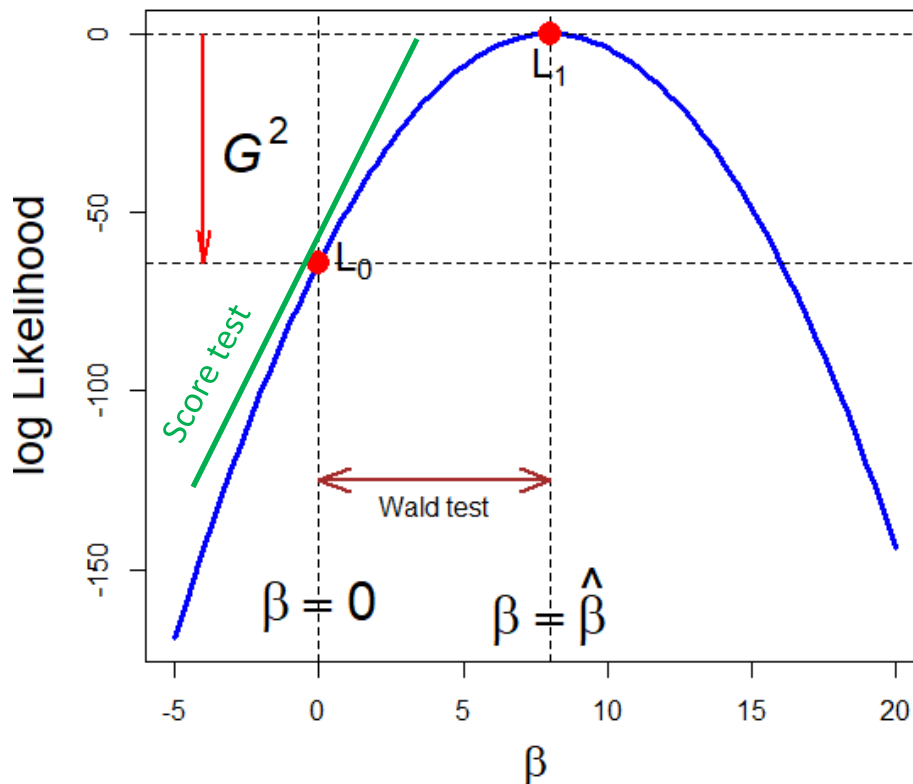
|                  | Estimate | Std. Error | z value | Pr(> z ) | 2.5 % | 97.5 % |
|------------------|----------|------------|---------|----------|-------|--------|
| (Intercept)      | -0.578   | 0.367      | -1.6    | 0.116    | -1.33 | 0.124  |
| I(Age - 50)      | 0.049    | 0.021      | 2.4     | 0.018    | 0.01  | 0.092  |
| SexMale          | -1.488   | 0.595      | -2.5    | 0.012    | -2.73 | -0.372 |
| TreatmentTreated | 1.760    | 0.536      | 3.3     | 0.001    | 0.75  | 2.875  |

# LR, Wald & Score tests

Testing Global Null Hypothesis: BETA=0

| Test             | Chi-Square | DF | Pr > ChiSq |
|------------------|------------|----|------------|
| Likelihood Ratio | 24.3859    | 3  | <.0001     |
| Score            | 22.0051    | 3  | <.0001     |
| Wald             | 17.5147    | 3  | 0.0006     |

$H_0: \beta_1 = \beta_2 = \beta_3 = 0$



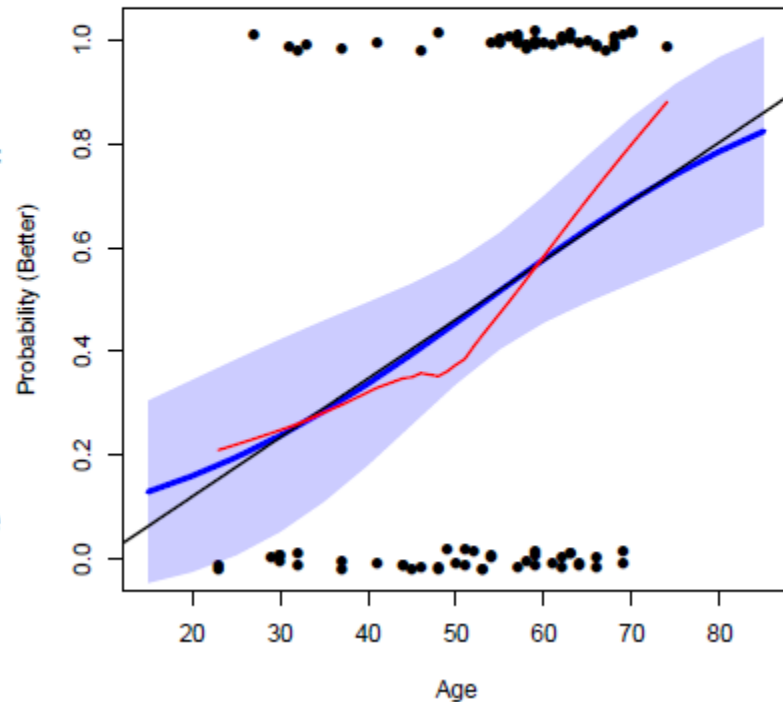
Different ways to measure departure from  $H_0: \beta = 0$

- LR test:  $\text{diff}^{\text{ce}}$  in  $\log L$
- Wald test:  $(\beta - \beta_0)^2$
- Score test: slope at  $\beta = 0$

# Plotting logistic regression data

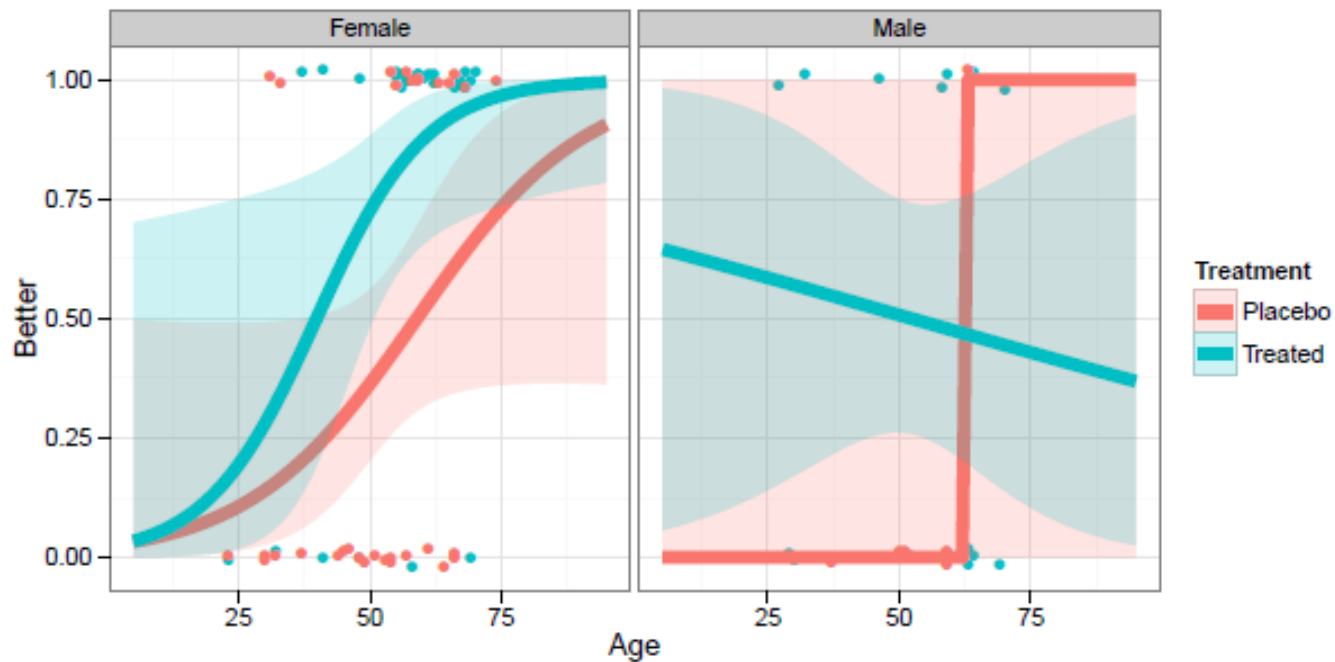
Plotting a binary response together with a fitted logistic model can be difficult because the 0/1 response leads to much overplotting.

- Need to **jitter** the points
- Useful to show the fitted logistic curve
- Confidence band gives a sense of uncertainty
- Adding a non-parametric (loess) smooth shows possible nonlinearity
- NB: Can plot either on the **response** scale (probability) or the **link** scale (logit) where effects are linear



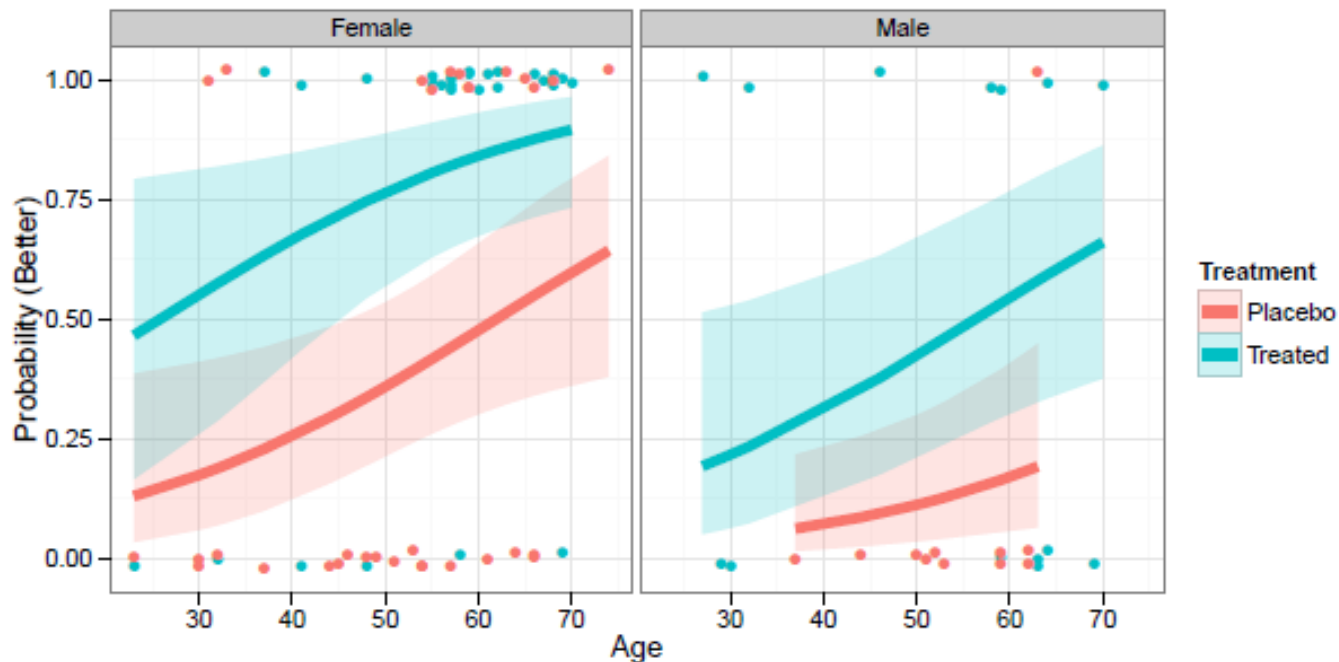
# Types of plots

- **Conditional plots:** Stratified plot of  $Y$  or  $\text{logit}(Y)$  vs. one  $X$ , conditioned by other predictors--- only that **subset** is plotted for each panel



# Types of plots

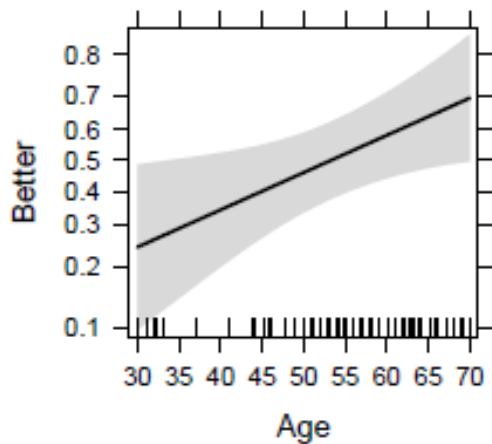
- **Full-model plots:** Plot of **fitted response surface**, showing all effects; usually shown in several panels



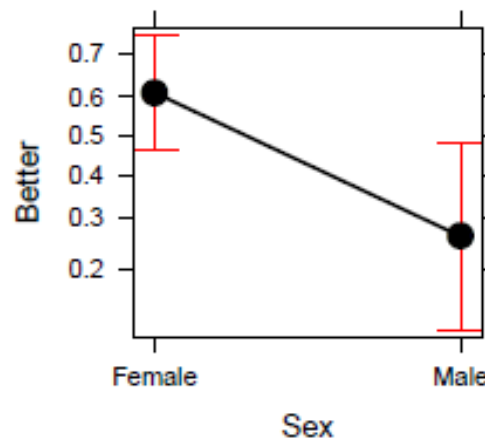
# Types of plots

- **Effect plots:** plots of predicted effects for terms in the model, **averaged over** predictors not shown in a given plot

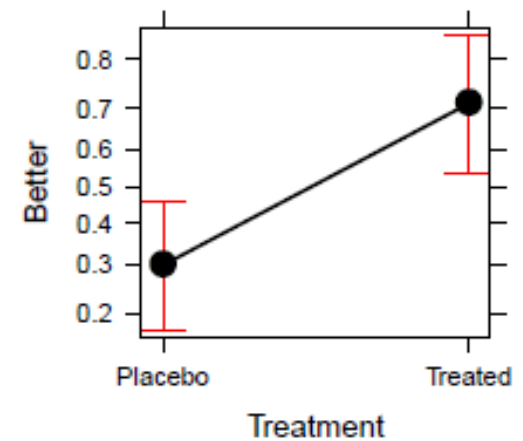
Age effect plot



Sex effect plot



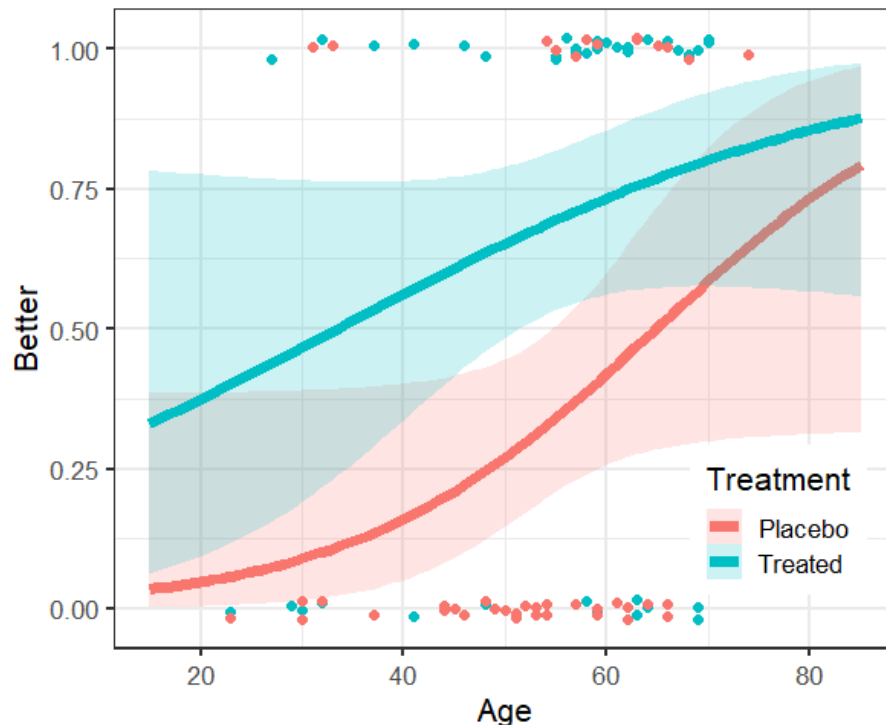
Treatment effect plot



# Conditional plots with ggplot2

Plot Arthritis data by Treatment, ignoring Sex; overlay fitted logistic reg. lines

```
gg <- ggplot(Arthritis, aes(Age, Better, color=Treatment)) +  
  xlim(15, 85) +  
  geom_jitter(height = 0.02, width = 0, size=2) +  
  stat_smooth(method = "glm", method.args=(family = "binomial"), alpha = 0.2,  
            aes(fill=Treatment), size=2.5, fullrange=TRUE) +  
  theme_bw(base_size = 16) + theme(legend.position = c(.85, .2))  
gg # show the plot
```



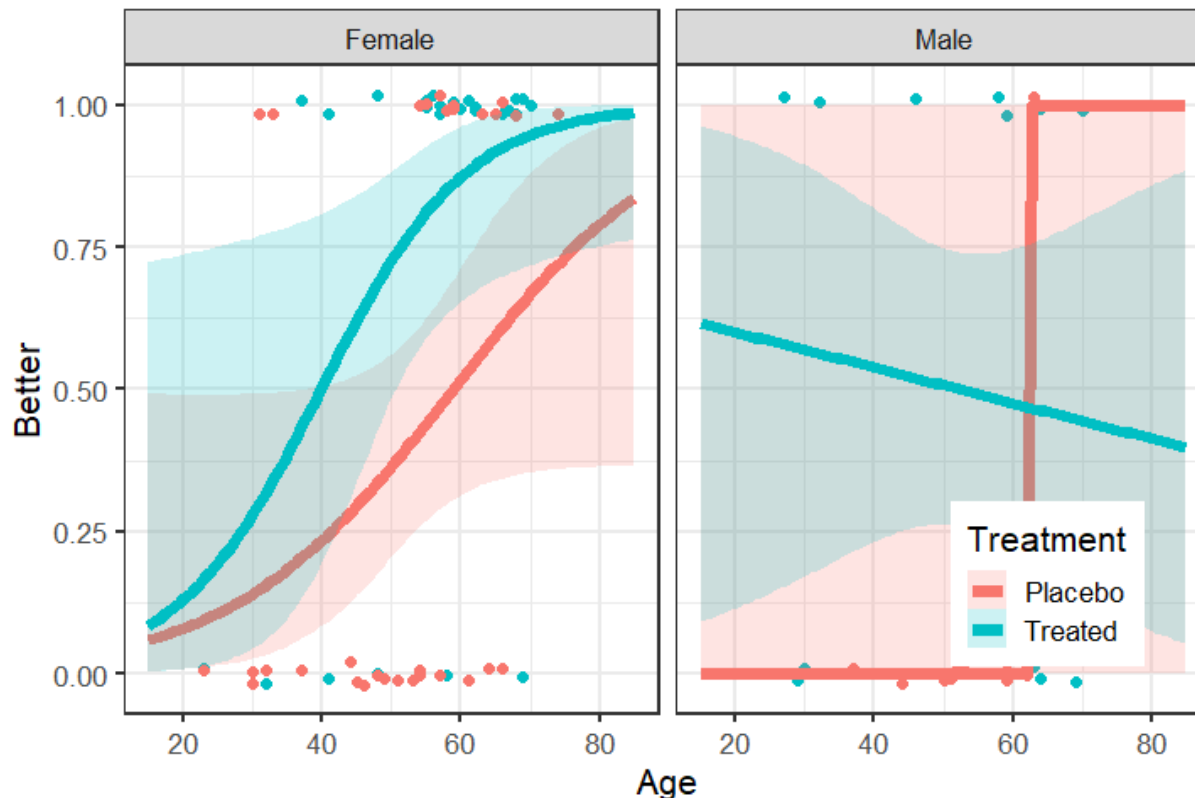
`geom_jitter()` shows the observations more distinctly

Fitted lines use `method="glm"`, `family=binomial`

# Conditional plots with ggplot2

Can show the conditional plots for M & F, simply by faceting by Sex

```
gg + facet_wrap(~ Sex)
```



Only the data for each Sex is used in each plot

Plotting the data points shows that the data for males is too thin to give good estimates of separate regression

# Full-model plots

Full-model plots show the fitted values on the logit scale or on the response scale (probability), usually with confidence bands. This often requires a bit of custom programming.

Steps:

- Obtain fitted values with `predict(model, se.fit=TRUE)` — `type="link"` (logit) is the default
- Can use `type="response"` for probability scale
- Join this to your data (`cbind()`)
- Plot as you like: `plot()`, `ggplot()`, ...

```
> arth.fit2 <- cbind(Arthritis,  
+                   predict(arth.logistic2, se.fit = TRUE))  
> head(arth.fit2[, -9], 4)  
  ID Treatment  Sex Age Improved Better  fit se.fit  
1  57   Treated Male  27     Some      1 -1.43  0.758  
2  46   Treated Male  29     None      0 -1.33  0.728  
3  77   Treated Male  30     None      0 -1.28  0.713  
4  17   Treated Male  32  Marked      1 -1.18  0.684
```

# Plotting with ggplot2

Plot the fitted log odds, confidence band and observations

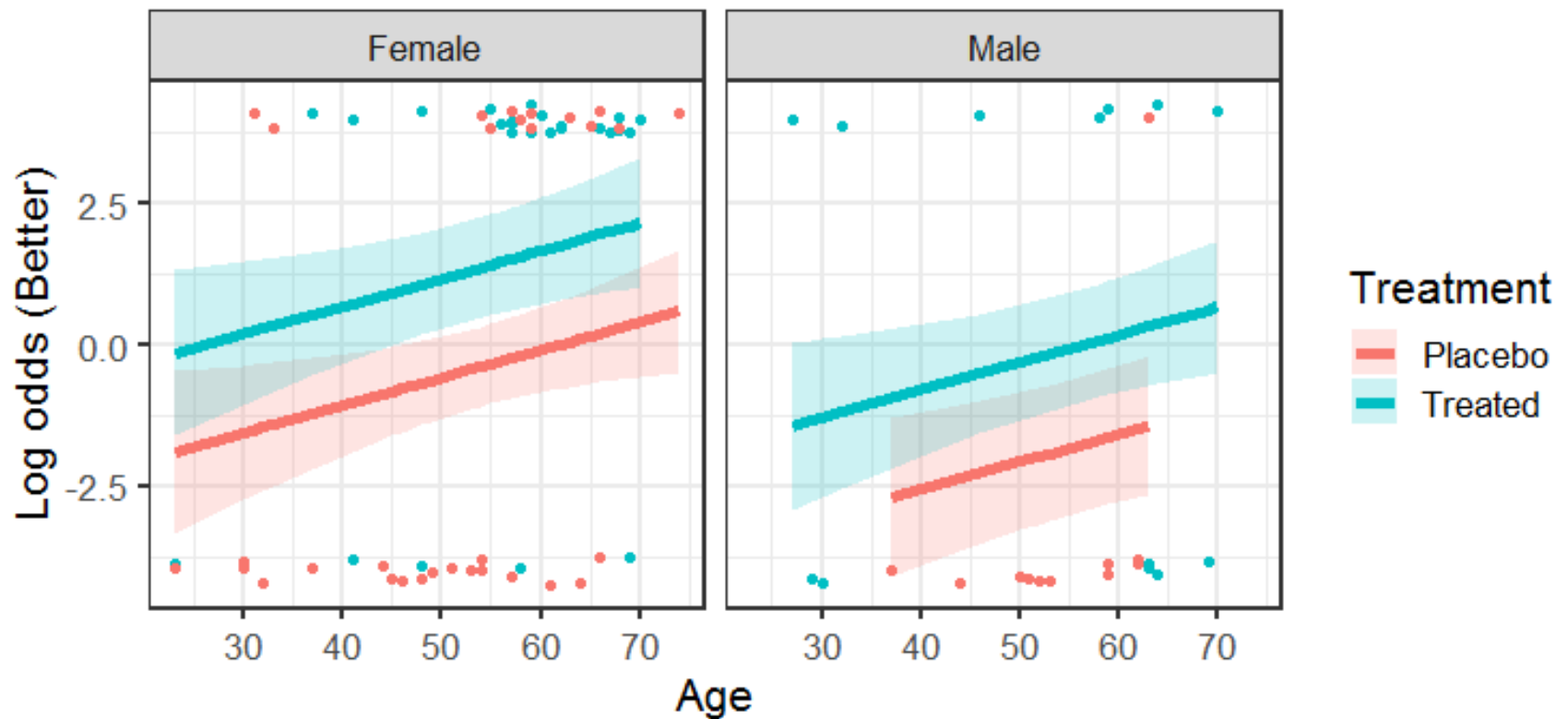
```
arth.fit2 <- arth.fit2 |>
  mutate(obs = ifelse(Better==0, -4, 4)) # show obs at -4, 4

ggplot( arth.fit2, aes(x=Age, y=fit, color=Treatment)) +
  geom_line(size = 2) +
  geom_ribbon(aes(ymin = fit - 1.96 * se.fit,
                ymax = fit + 1.96 * se.fit,
                fill = Treatment), alpha = 0.2,
            color = "transparent") +
  labs(x = "Age", y = "Log odds (Better)") +
  geom_jitter(aes(y=obs), height=0.25, width=0) +
  facet_wrap(~ Sex) +
  theme_bw(base_size = 16)
```

Using `color=Treatment` gives separate points and lines for the two groups

# Full-model plot

Plotting on the logit scale shows the **additive** effects of age, treatment and sex  
NB: easier to compare the treatment groups within the **same** panel



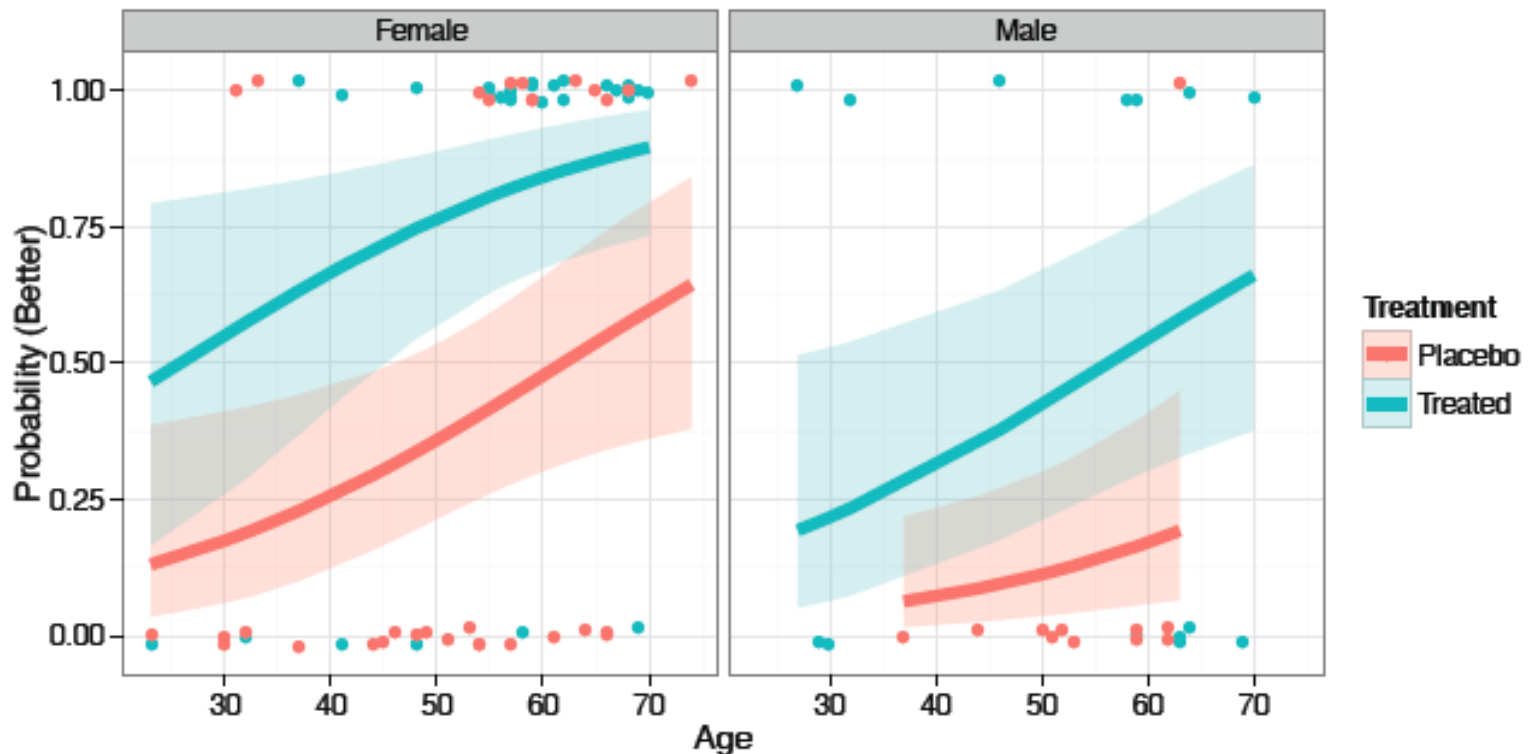
These plots show model uncertainty (confidence bands)  
Jittered points show the data

# Full-model plot

Plotting on the probability scale may be simpler to interpret

Use `predict(... type = "response")` to get fitted probabilities

```
arth.fit2r <- cbind(Arthritis,  
                    predict(arth.logistic2, se.fit = TRUE, type="response"))
```



# Models with interactions

Is the linear effect of age the same for females, males?

- We can test this by adding an **interaction** of Sex × Age
- **update()** makes it easy to add/subtract terms from a model
- **car::Anova()** gives partial tests of each term after all others

```
> arth.logistic4 <- update(arth.logistic2, . ~ . + I(Age-50):Sex)
```

```
> car::Anova(arth.logistic4)
```

```
Analysis of Deviance Table (Type II tests)
```

```
Response: Better
```

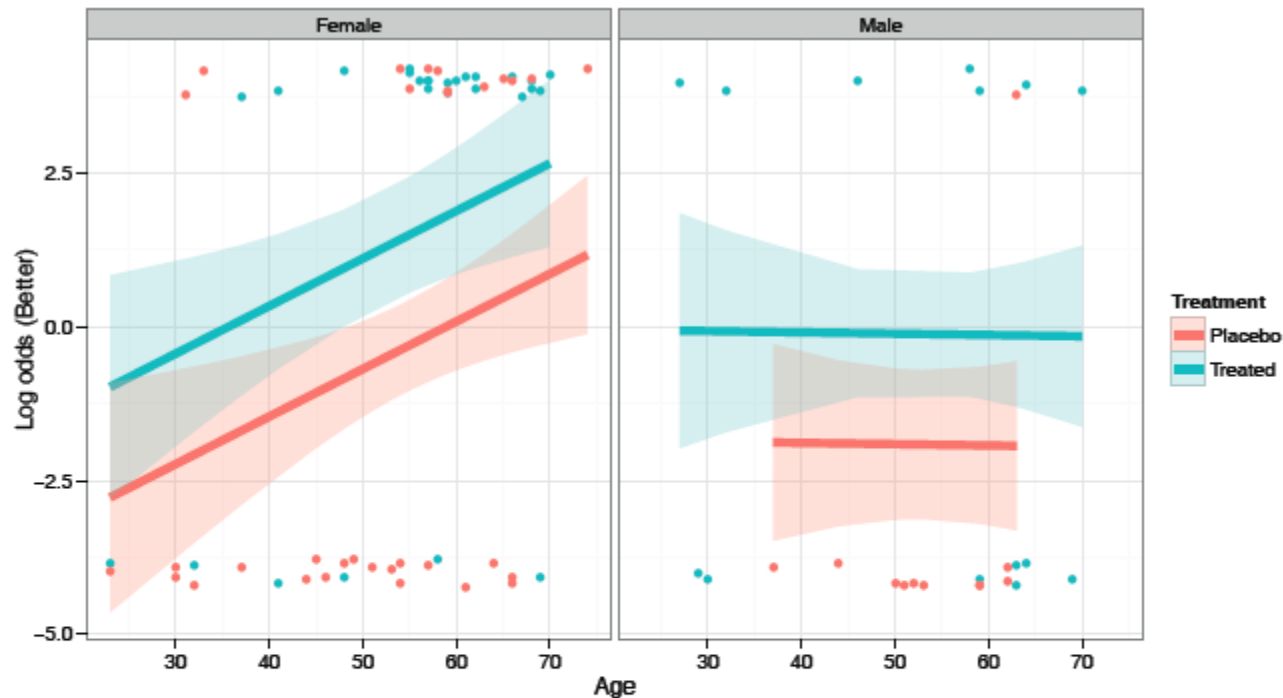
|                 | LR    | Chisq | Df      | Pr(>Chisq) |  |
|-----------------|-------|-------|---------|------------|--|
| I(Age - 50)     | 6.16  | 1     | 0.01308 | *          |  |
| Sex             | 6.98  | 1     | 0.00823 | **         |  |
| Treatment       | 11.90 | 1     | 0.00056 | ***        |  |
| I(Age - 50):Sex | 3.42  | 1     | 0.06430 | .          |  |

```
---
```

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

The interaction term Age:Sex is not quite significant, but plot the fitted model anyway

# Models with interactions



- Only the model changes
- `predict ()` automatically incorporates the revised model terms
- Plotting steps remain the same
- This interpretation is quite different!

# Effect plots: Basic ideas

Show a given **marginal** effect, **controlling** / adjusting for other model effects



## Data

|     | x1  | x2  | sex | x1x2 | y    | yhat |
|-----|-----|-----|-----|------|------|------|
| 1   | 1   | 1   | F   | 1    | 4.73 | 4.46 |
| 2   | 2   | 1   | M   | 0    | 6.10 | 5.55 |
| 3   | 3   | 1   | F   | -1   | 4.32 | 4.34 |
| 4   | 1   | 1   | F   | 1    | 4.84 | 4.46 |
| 5   | 2   | 1   | F   | 0    | 4.73 | 4.40 |
| ... | ... | ... | ... | ...  | ...  | ...  |
| 29  | 2   | 2   | M   | 0    | 6.10 | 6.15 |
| 30  | 3   | 2   | F   | 1    | 6.71 | 7.14 |

• Fit data:  $\mathbf{X}\hat{\beta} \Rightarrow \hat{y}$


• Score data  $\mathbf{X}^* \hat{\beta} \Rightarrow \hat{y}^*$


• plot vars: vary over range

• control vars: fix at means

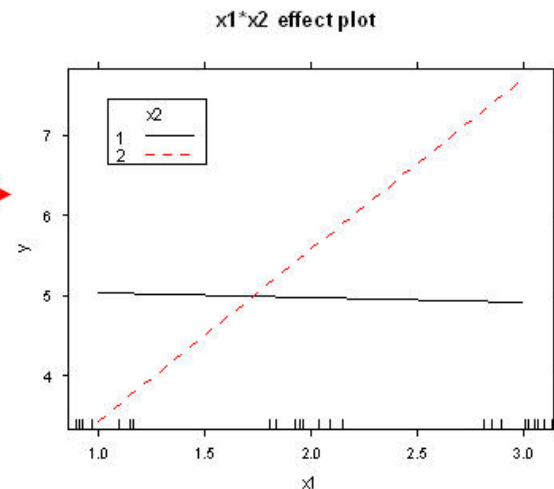
## Score data

|    | x1 | x2 | sex | x1:x2 | y  | yhat * |
|----|----|----|-----|-------|----|--------|
| 31 | 1  | 1  | 0.5 | 1     | NA | 5.030  |
| 32 | 2  | 1  | 0.5 | 2     | NA | 4.971  |
| 33 | 3  | 1  | 0.5 | 3     | NA | 4.912  |
| 34 | 1  | 2  | 0.5 | 2     | NA | 3.437  |
| 35 | 2  | 2  | 0.5 | 4     | NA | 5.574  |
| 36 | 3  | 2  | 0.5 | 6     | NA | 7.710  |


  
plot vars


  
control vars

plot



# Effect plots: Details

- For simple models, full model plots show the complete relation between response and *all predictors*.
- Fox(1987)— For complex models, often wish to plot a specific main effect or interaction (including lower-order relatives)— *controlling for other effects*
  - Fit full model to data with linear predictor (e.g., logit)  $\eta = \mathbf{X}\beta$  and link function  $g(\mu) = \eta \rightarrow$  estimate  $\mathbf{b}$  of  $\beta$  and covariance matrix  $\widehat{V}(\mathbf{b})$  of  $\mathbf{b}$ .
  - Construct “score data”
    - Vary each predictor in the term over its’ range
    - Fix other predictors at “typical” values (mean, median, proportion in the data)
    - $\rightarrow$  “effect model matrix,”  $\mathbf{X}^*$
  - Use `predict ()` on  $\mathbf{X}^*$ 
    - Calculate fitted effect values,  $\hat{\eta}^* = \mathbf{X}^* \mathbf{b}$ .
    - Standard errors are square roots of  $\text{diag } \mathbf{X}^* \widehat{V}(\mathbf{b}) \mathbf{X}^{*\top}$
  - Plot  $\hat{\eta}^*$ , or values transformed back to scale of response,  $g^{-1}(\hat{\eta}^*)$ .
- *Note:* This provides a general means to visualize interactions in *all* linear and generalized linear models.

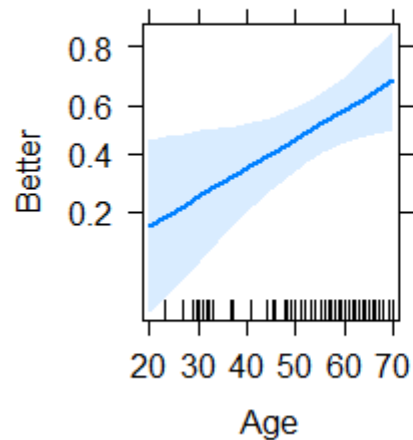
In R, there are now other packages: `marginalEffects`, `jtools::effect_plot()`, `sjplot` (mixed models), ...

# Plotting main effects

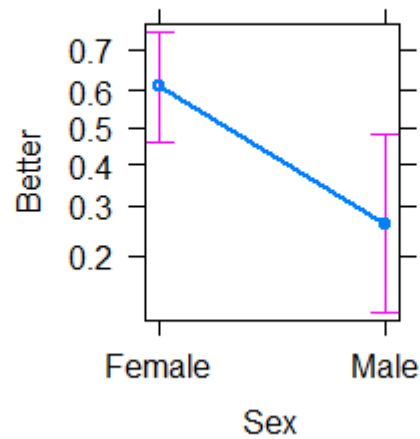
**allEffects()** calculates effects for all high-order terms in the model  
The response is plotted on the **logit** scale, but labeled with **probabilities**

```
library(effects)  
arth.eff2 <- allEffects(arth.logistic2)  
plot(arth.eff2, rows=1, cols=3, lwd=2)
```

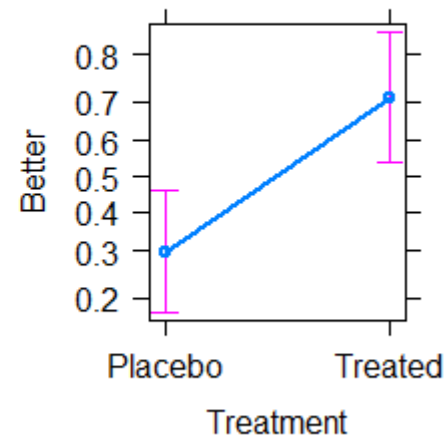
**Age effect plot**



**Sex effect plot**



**Treatment effect plot**



**Averaged  
over:**

Sex  
Treatment

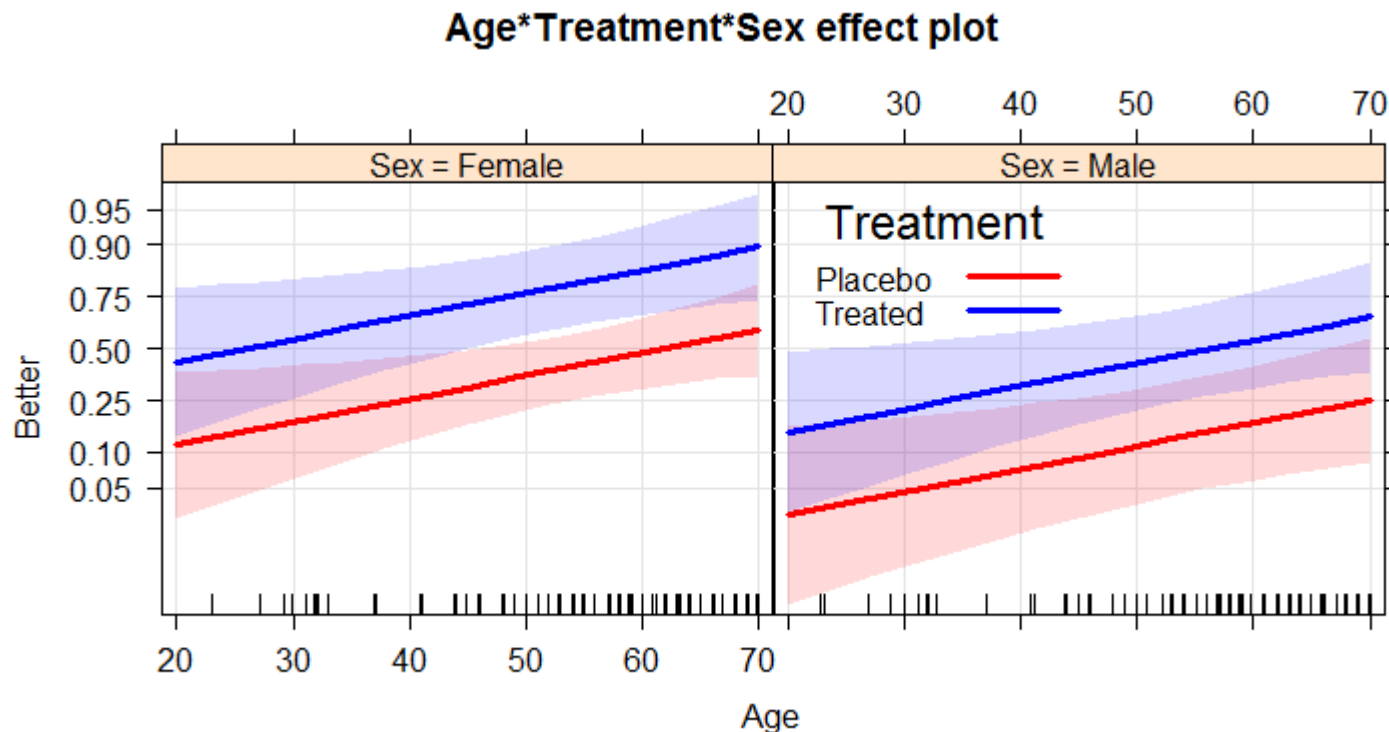
Age  
Treatment

Age  
Sex

# Full-model plot

The full-model plot is simply the `Effect()` of the **highest-order interaction** of factors

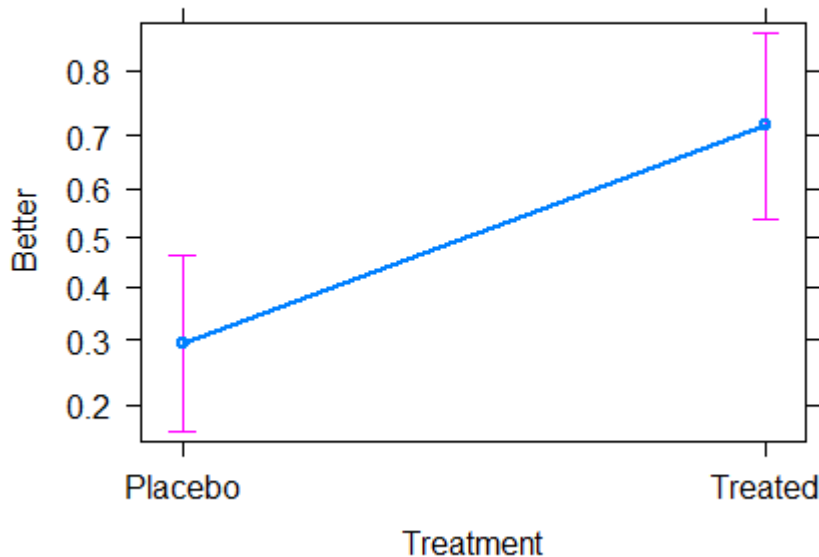
```
arth.full <- Effect(c("Age", "Treatment", "Sex"), arth.logistic2)
plot(arth.full, multiline=TRUE, ci.style="bands",
     colors = c("red", "blue"), lwd=3, . . .)
```



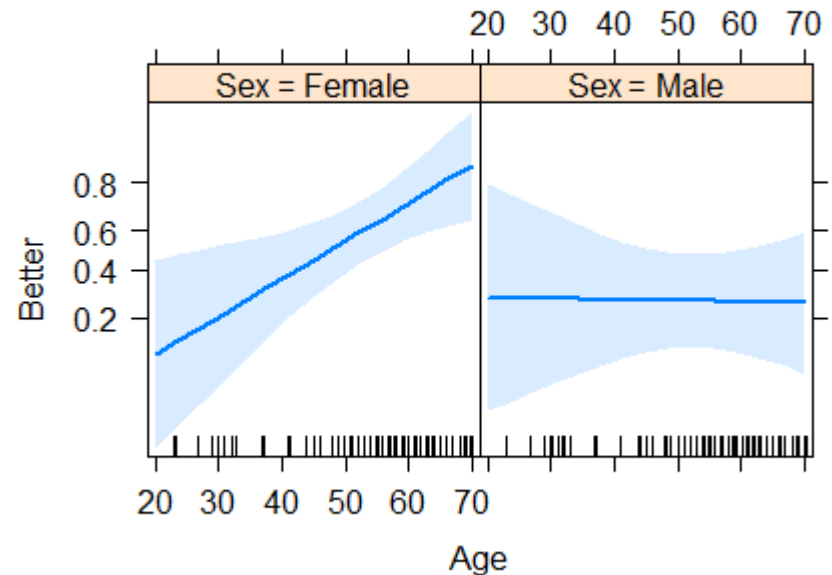
# Model with interaction of Age × Sex

```
arth.eff4 <- allEffects(arth.logistic4)  
plot(arth.eff4, lwd=2)
```

**Treatment effect plot**



**Age\*Sex effect plot**



Only the high-order terms: Treatment & Age \* Sex are shown & need to be interpreted  
Q: How would you describe this?

# Race & Crime

Toronto Star investigation of racial disparities in treatment by Toronto Police Services

FOI request → > ½ M arrests, 1997—2002

Evidence for racial profiling?

Only look at discretionary charges:

Simple marijuana possession  
Non-moving auto infractions

# THE SATURDAY STAR

The photo that never was

GARTH WOOLSEY, C3



Also inside . . .

- **Waterfront:** Dreams of what could be, B1, B4-5
- **Hydro woes:** Insulating against price spikes, E1
- **Wheels:** The Bug goes roofless, G1
- **Paul Martin:** The man who would be king, H1
- **Carol Shields:** Her last novel? Unless . . . J1

Periods of rain; windy. High 14 C

October 19, 2002

thestar.com ONTARIO EDITION

## AN INVESTIGATION INTO RACE AND CRIME



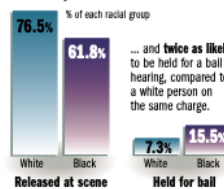
**SUING POLICE:** Jason Burke, falsely accused of dealing drugs during Caribana two years ago, says he was a victim of racial profiling.

# Singled out

Star analysis of police crime data shows justice is different for blacks and whites

### Telling numbers

Police records show that a black person in Toronto arrested on a single drug possession charge was less likely to be released at the scene.



... and twice as likely to be held for a bail hearing, compared to a white person on the same charge.

Blacks arrested by Toronto police are treated more harshly than whites, a Toronto Star analysis of crime data shows.

Black people, charged with simple drug possession, are taken to police stations more often than whites facing the same charge.

Once at the station, accused blacks are held overnight, for a bail hearing, at twice the rate of whites.

The Toronto crime data also shows a disproportionate number of black motorists are ticketed for violations that only surface following a traffic stop. This difference, say civil libertarians, community

### Managing Editor's notebook, A2

leaders and criminologists, suggests police use racial profiling in deciding whom to pull over.

The evidence is contained in a massive police database recording more than 480,000 incidents in which an individual was arrested or ticketed, for an offence dating back to 1996. It included almost 800,000 criminal and other charges. The Star obtained that data through a freedom of information request, marking the first time access to these numbers was granted to anyone outside the police

community.

Police are forbidden, by their governing board, from analyzing this data in terms of race, but The Star has no such restriction. The findings provide hard evidence of what blacks have long suspected — race matters in Canadian society especially when dealing with police.

Chief Julian Fantino disputed the findings, saying the colour of a person's skin has nothing to do with how they're treated by his officers.

"We don't treat people different-

## Chrétien expected to keep cabinet minister

Ethics report has 'wiggle room' to save MacAulay

BY TIM HARPER AND LES WHITTINGTON OTTAWA BUREAU

OTTAWA — Jean Chrétien receives a report from his ethics counsellor today that is expected to give him enough "wiggle room" to keep his solicitor-general, Lawrence MacAulay, in the federal cabinet.

Ethics counsellor Howard Wilson completed his report and delivered it to the Prime Minister's Office last night, where it was received by Chrétien's chief of staff, Percy Downie.

It was then to be relayed to Chrétien by secure fax to Beirut, where the Prime Minister is attending a summit of French-speaking nations. It was 1:30 a.m. in Beirut when the fax arrived so Chrétien would likely be reading it this morning.

Senior sources said last night that unless there is a surprise in Wilson's report, the Prince Edward Island minister will remain, Chrétien will return to Ottawa and weather the inevitable storm of opposition and media protest and forge ahead with an ethics package by mid-week.

Wilson has been investigating whether MacAulay broke ethics guidelines for cabinet ministers in the awarding of a contract and extension worth \$100,000 to Everett Roche, a Charlottetown political friend of the solicitor-general's.

Chrétien will not fire MacAulay unless he is given incontrovertible evidence of wrongdoing for two key reasons, source-

Please see MacAulay, A8

### INSIDE

Barclay L2  
Birthis B7

Ellie Tesher L2  
James Travers H2

Please see Toronto, A12

# Case study: Arrests for marijuana

- In Dec. 2002, the *Toronto Star* examined the issue of **racial profiling**, by analyzing a data base of 600,000+ arrest records from 1997-2002.
- They focused on a subset of arrests for which police action was **discretionary**, e.g., simple possession of small quantities of marijuana, where the police could:
  - Release the arrestee with a summons – like a parking ticket
  - Bring to police station, hold for bail, ... -- harsher treatment
- Response variable: released: “Yes”, “No”
  - Main predictor of interest: skin-colour of arrestee (black, white)
  - Other predictors: year, age, sex, ...

# Racial profiling: Presentation graphic

Together, we created this (nearly) **self-explaining** infographic

Title gives the main conclusion

Text description gives details

Bar width ~ charges  
Divided by % release

numbers shown in the cells

Legend gives a layman's description of shading levels

## Same charge, different treatment

Statistical analysis of single drug possession charges shows that blacks are much less likely to be released at the scene and much more likely to be held in custody for a bail hearing. Darker colours represent a stronger statistical link between skin colour and police treatment.

Degree of likelihood

- Much less* likely to occur
- Much more* likely to occur
- More* likely to occur

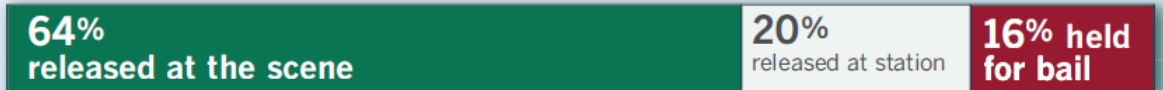
**Whites** are more likely to be released at the scene

6,662 charges laid



**Blacks** are much more likely to be held for bail hearings

2,446 charges laid



SOURCE: Toronto police arrest records 1996-2002

# Arrests for marijuana: Data

Response variable: released

Control variables:

- year, age, sex
- employed, citizen: Yes, No
- checks: # of police databases (previous arrests, convictions, parole status) where the arrestee's name was found

```
> library(car)           # for Anova()
> data(Arrests, package = "carData")
> some(Arrests)
      released colour year age  sex employed citizen checks
218         Yes  White 2000  24 Male       Yes      Yes      0
1301        No   Black 1999  17 Male       Yes      No       1
1495         Yes  White 1998  23 Male       Yes      Yes      0
1732         Yes  Black 2000  18 Male       Yes      Yes      2
1838         Yes  Black 1997  27 Male        No      Yes      5
2257         No   White 2001  19 Male        No      Yes      2
3100         No   Black 2000  19 Male        No      Yes      4
3843         Yes  White 1999  20 Male       Yes      Yes      0
4580         Yes  Black 1999  26 Male       Yes      Yes      1
4833         Yes  Black 1998  38 Male       Yes      Yes      0
```

# Arrests for marijuana: Model

year is numerical. But may be non-linear. Convert to a **factor**

Fit model with all main effects, but allow **interactions** of **colour:year** and **colour:age**

```
> Arrests$year <- as.factor(Arrests$year)
> arrests.mod <- glm(released ~ employed + citizen + checks +
                    colour*year + colour*age,
                    family=binomial, data=Arrests)
> Anova(arrests.mod)
```

Analysis of Deviance Table (Type II tests)

Response: released

|             | LR    | Chisq | Df      | Pr(>Chisq) |  |
|-------------|-------|-------|---------|------------|--|
| employed    | 72.7  | 1     | < 2e-16 | ***        |  |
| citizen     | 25.8  | 1     | 3.8e-07 | ***        |  |
| checks      | 205.2 | 1     | < 2e-16 | ***        |  |
| colour      | 19.6  | 1     | 9.7e-06 | ***        |  |
| year        | 6.1   | 5     | 0.29785 |            |  |
| age         | 0.5   | 1     | 0.49827 |            |  |
| colour:year | 21.7  | 5     | 0.00059 | ***        |  |
| colour:age  | 13.9  | 1     | 0.00019 | ***        |  |

---

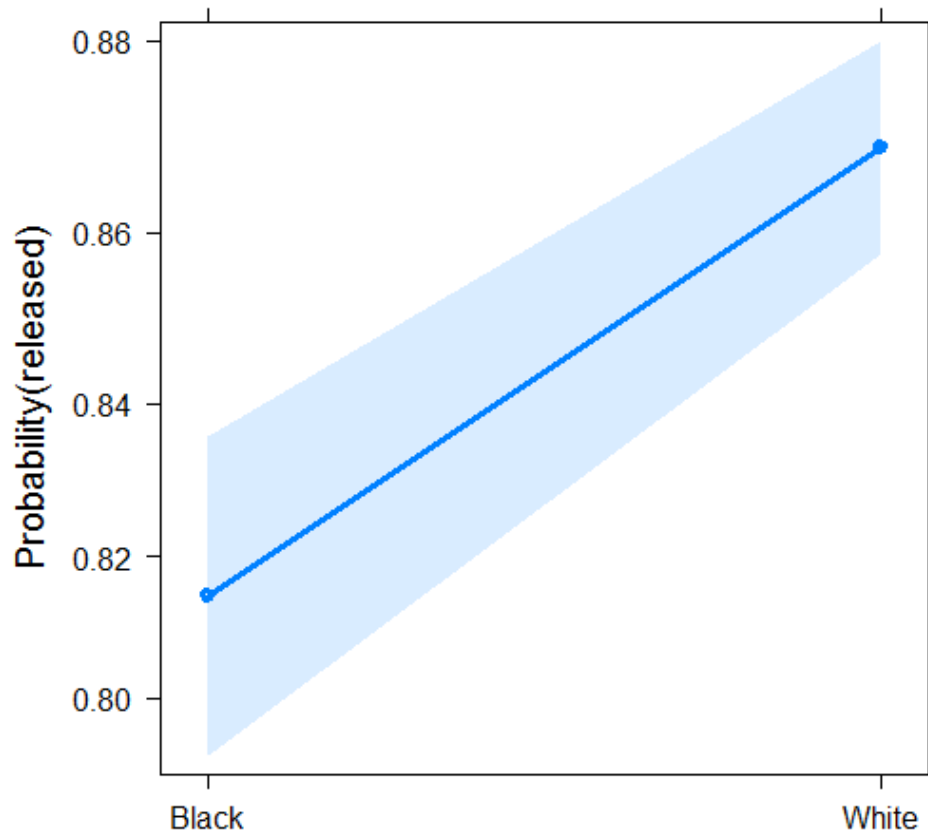
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Adjust for all other low-order effects

year, age: NS, but must be included in model for interactions to be interpretable

# Effect plot: Skin colour

```
plot(Effect("colour", arrests.mod), lwd=3, ci.style="bands", ...)
```

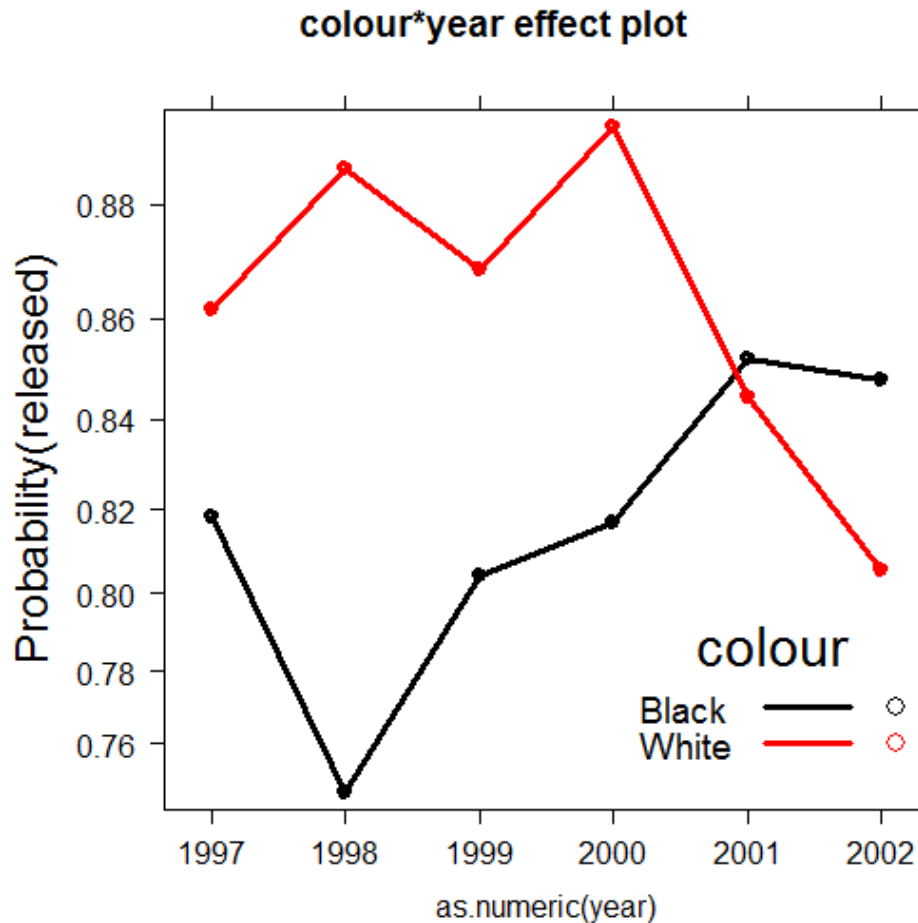


- Effect plot for colour shows average effect **controlling** (adjusting) for **all** other factors simultaneously
- (The *Star* analysis controlled for these one at a time.)
- Evidence for different treatment of blacks & whites
- Even Francis Nunziata could understand this.
- However, effect smaller than reported by the *Star*

# Effect plots: Interactions

The story turned out to be more nuanced than reported by the *Toronto Star*

```
plot(Effect(c("colour", "year"), arrests.mod), multiline=TRUE, ...)
```



Up to 2000, strong evidence for differential treatment of blacks & whites

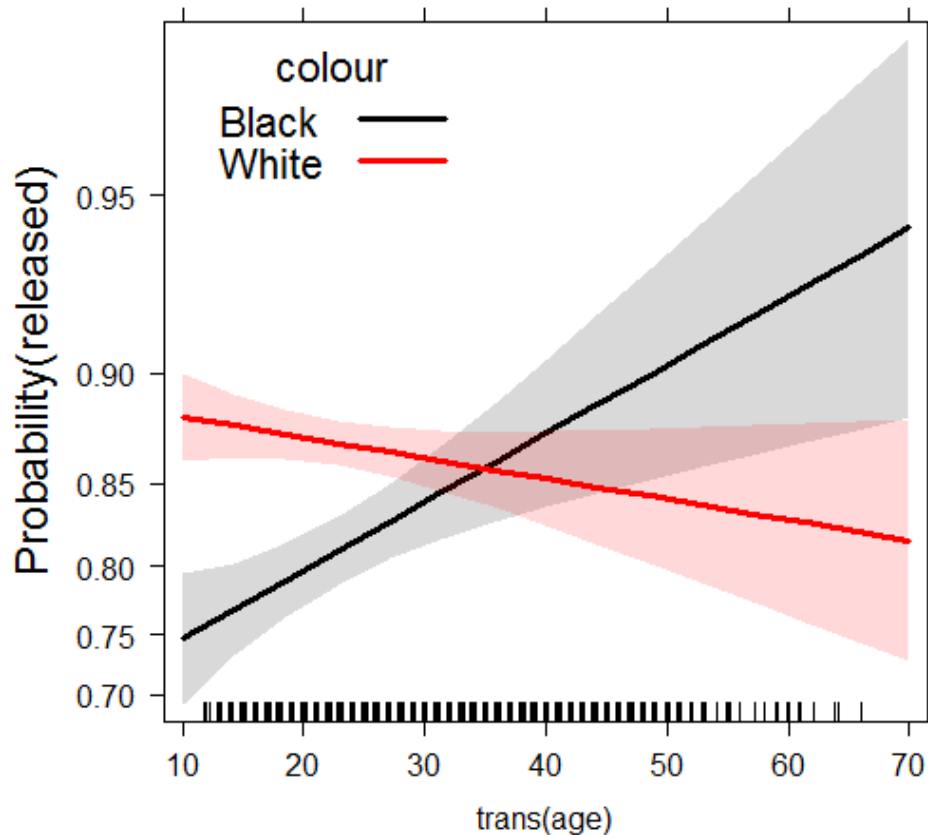
Also: evidence to support Police claim of effect of training to reduce racial effects in treatment

# Effect plots: Interactions

A more surprising finding ...

```
plot(Effect(c("colour", "year"), arrests.mod), multiline=TRUE, ...)
```

Effects of skin colour and age on release



Opposite age effects for blacks & whites:

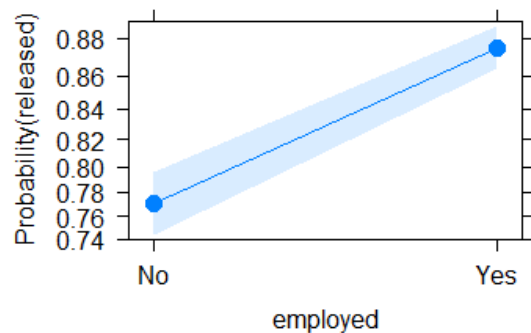
- Young blacks treated **more** harshly than young whites
- Older blacks treated **less** harshly than older whites

# Effect plots: allEffects

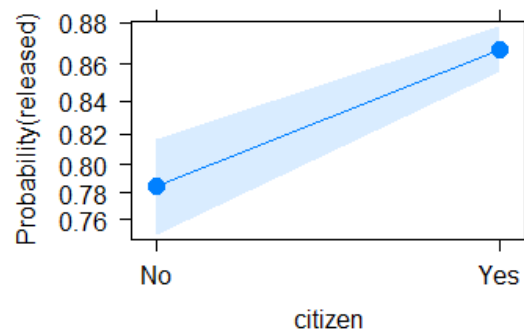
All high-order terms can be viewed together using `plot(allEffects(mod))`

```
arrests.effects <- allEffects(arrests.mod,  
xlevels=list(age=seq(15, 45, 5)))  
plot(arrests.effects, ylab="Probability(released)", ...)
```

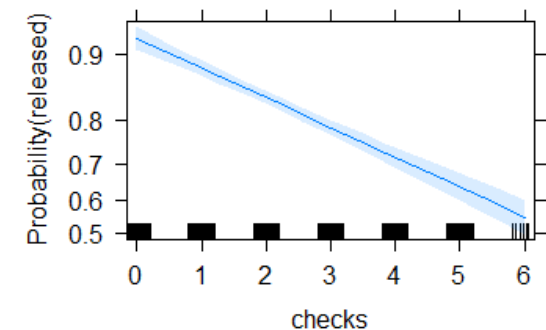
employed effect plot



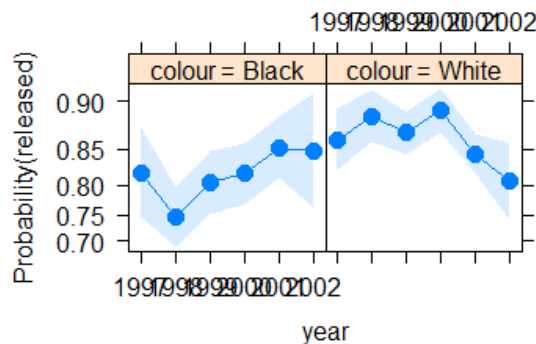
citizen effect plot



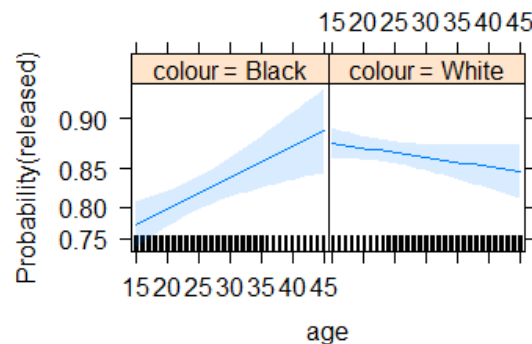
checks effect plot



colour\*year effect plot



colour\*age effect plot



# Model selection

Model selection methods: aim to identify the best subset of predictors or terms for a parsimonious, predictive model.

- GOAL: maximize fit, minimize overfitting
- Stepwise methods: forward / backward selection
- Info criteria: minimize AIC, BIC (model fit + parsimony)
- Regularization methods (LASSO / Ridge) + cross-validation

```
add1(mod1, scope= .^2, test = "Chisq")           # add best 2-way terms
drop1(mod2, test = "Chisq")                     # drop worst terms
MASS::stepAIC(mod2, direction = "backward")     # select for lowest AIC
glmnet::glmnet(x, y, family="binomial")        # LASSO / Ridge
```



Automated model selection methods are dangerous if used blindly

- F &  $\chi^2$  values may be invalid
- $R^2$  biased high, std. errors &  $p$ -values biased small
- Variable selection may be arbitrary under multicollinearity
- Allow you not to think about the problem!!!
- If you use those  $p$ -values blindly, **you go straight to HELL**

# Model selection: Arrests data

```
# all main effects
arrests.mod1 <- glm(released ~ ., family=binomial, data=Arrests)
# try adding single two-way interactions
add1(arrests.mod1, scope= ~.^2, test="Chisq")
```

Single term additions

Model:

```
released ~ colour + year + age + sex + employed + citizen + checks
```

|                 | Df | Deviance | AIC    | LRT     | Pr(>Chi)  |     |      |     |     |     |   |
|-----------------|----|----------|--------|---------|-----------|-----|------|-----|-----|-----|---|
| <none>          |    | 4292.4   | 4316.4 |         |           |     |      |     |     |     |   |
| colour:year     | 5  | 4270.9   | 4304.9 | 21.4324 | 0.0006710 | *** |      |     |     |     |   |
| colour:age      | 1  | 4278.8   | 4304.8 | 13.6001 | 0.0002262 | *** |      |     |     |     |   |
| colour:sex      | 1  | 4291.9   | 4317.9 | 0.4583  | 0.4983969 |     |      |     |     |     |   |
| colour:employed | 1  | 4292.1   | 4318.1 | 0.2761  | 0.5992589 |     |      |     |     |     |   |
| colour:citizen  | 1  | 4292.2   | 4318.2 | 0.1450  | 0.7033531 |     |      |     |     |     |   |
| colour:checks   | 1  | 4290.2   | 4316.2 | 2.1864  | 0.1392356 |     |      |     |     |     |   |
| year:age        | 5  | 4278.7   | 4312.7 | 13.6326 | 0.0181198 | *   |      |     |     |     |   |
| year:sex        | 5  | 4286.5   | 4320.5 | 5.8453  | 0.3215599 |     |      |     |     |     |   |
| year:employed   | 5  | 4287.3   | 4321.3 | 5.1167  | 0.4018001 |     |      |     |     |     |   |
| year:citizen    | 5  | 4283.0   | 4317.0 | 9.3982  | 0.0941972 | .   |      |     |     |     |   |
| ...             |    |          |        |         |           |     |      |     |     |     |   |
| employed:checks | 1  | 4290.8   | 4316.8 | 1.6254  | 0.2023424 |     |      |     |     |     |   |
| citizen:checks  | 1  | 4280.4   | 4306.4 | 11.9269 | 0.0005533 | *** |      |     |     |     |   |
| ---             |    |          |        |         |           |     |      |     |     |     |   |
| Signif. codes:  | 0  | '***'    | 0.001  | '**'    | 0.01      | '*' | 0.05 | '.' | 0.1 | ' ' | 1 |

# Model Diagnostics

A person is seen from the side, sitting at a desk with four computer monitors. The monitors display various data visualizations, including a bar chart on the left and code on the other screens. The background is a dark space filled with a glowing, interconnected network of nodes and lines, suggesting a complex data system or model. The overall scene is dimly lit, with the primary light source being the screens and the glowing network.

# Model diagnostics

As in regression and ANOVA, the validity of a logistic regression model is threatened when:

- Important predictors have been omitted from the model
- Predictors assumed to be **linear** have **non-linear** effects on  $\Pr(Y = 1)$
- Important **interactions** have been omitted
- A few “wild” observations have a large impact on the fitted model or coefficients

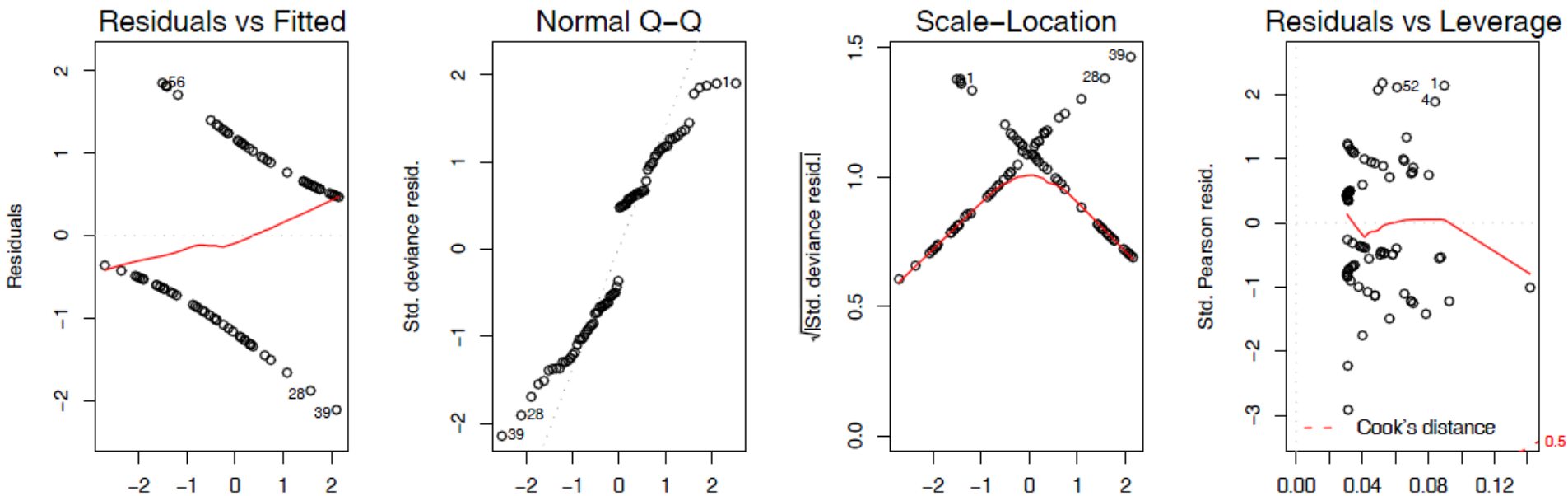
## Model specification: Tools and techniques

- Use non-parametric smoothed curves to detect non-linearity
- Consider using polynomial terms ( $X^2, X^3, \dots$ ) or **regression splines** (e.g., `ns(X, 3)`)
- Use `update(model, ...)` to test for interactions— formula: `. ~ .^2`

# Diagnostic plots in R

In R, plotting a `glm` object gives the “regression quartet” – 4 basic diagnostic plots

```
arth.mod1 <- glm(Better ~ Age + Sex + Treatment, data=Arthritis,  
                family='binomial')  
plot(arth.mod1)
```

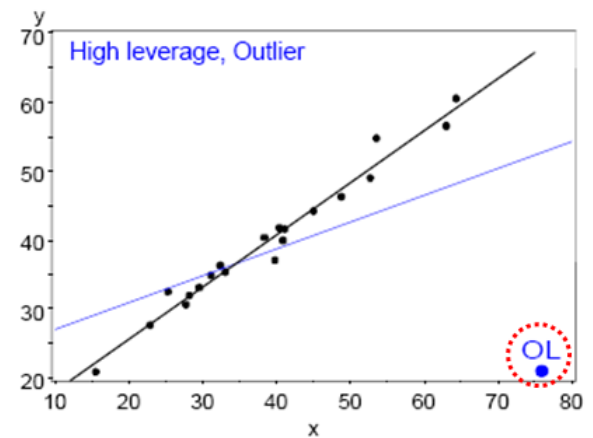
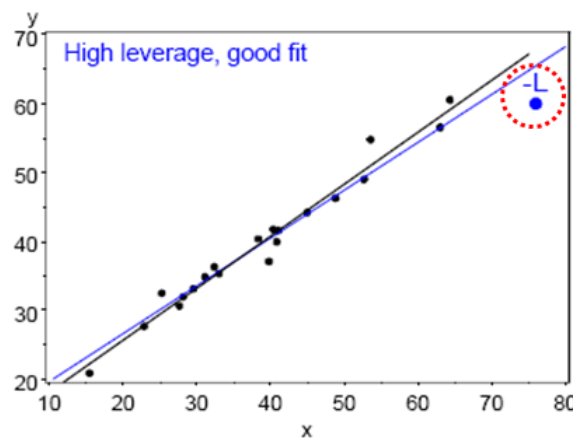
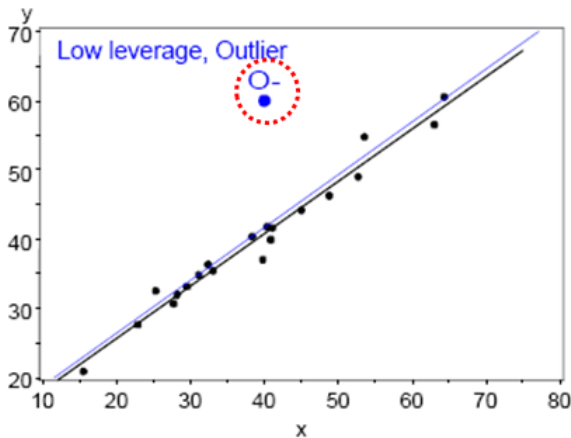


These plots often look peculiar for logistic regression models  
Better versions are available in the `car` package

# Unusual data: Leverage & Influence

- “Unusual” observations can have dramatic effects on least-squares estimates in linear models
- Three archetypal cases:
  - Typical X (low leverage), bad fit -- Not much harm
  - Unusual X (high leverage), good fit -- Not much harm
  - Unusual X (high leverage), bad fit -- **BAD, BAD, BAD**
- Influential observations: unusual in *both* X & Y
- Heuristic formula:

$$\text{Influence} = X \text{ leverage} \times Y \text{ residual}$$

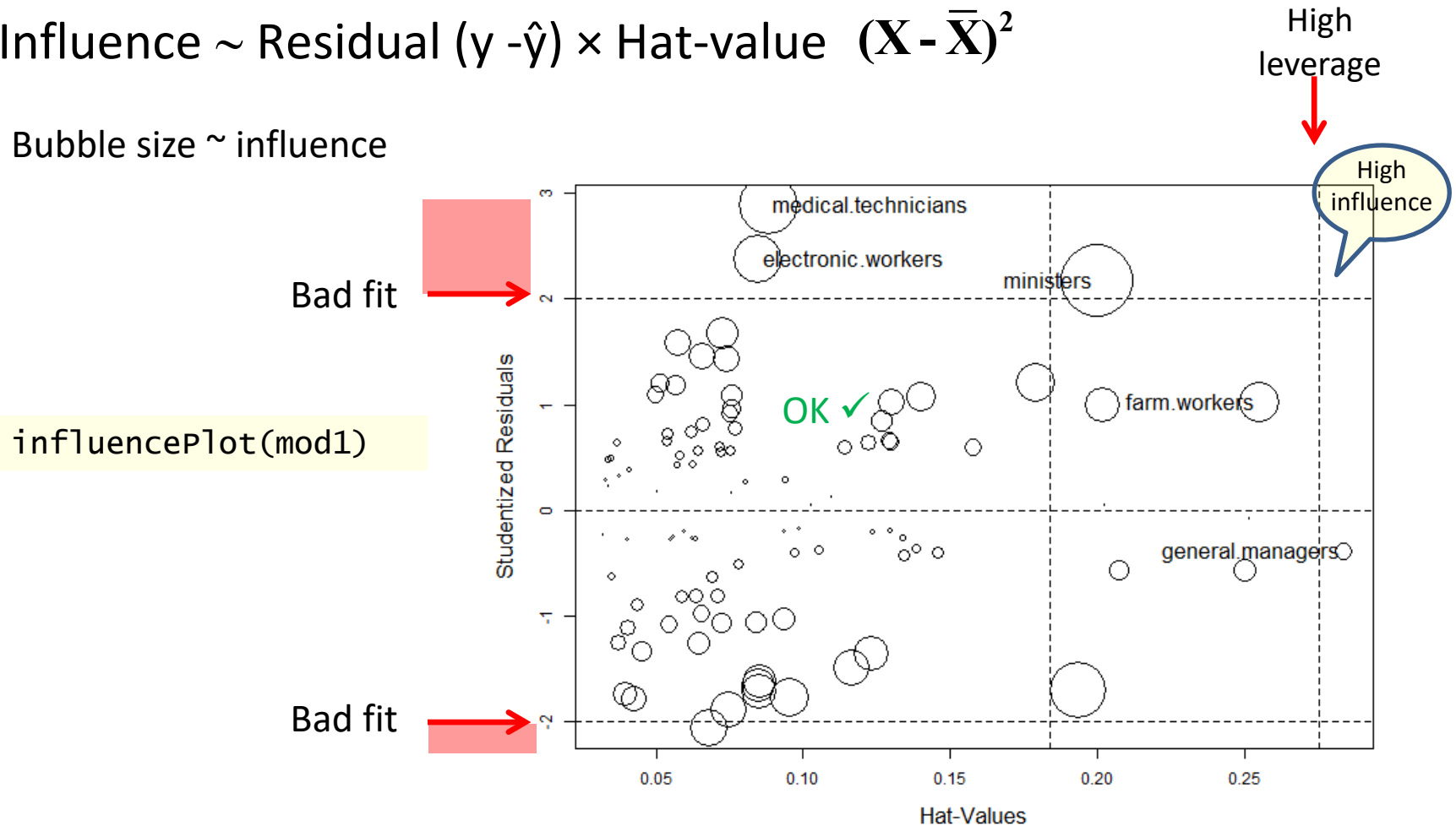


# Influence plots

Influence (Cook's D) measures impact of individual obs. on coefficients, fitted values

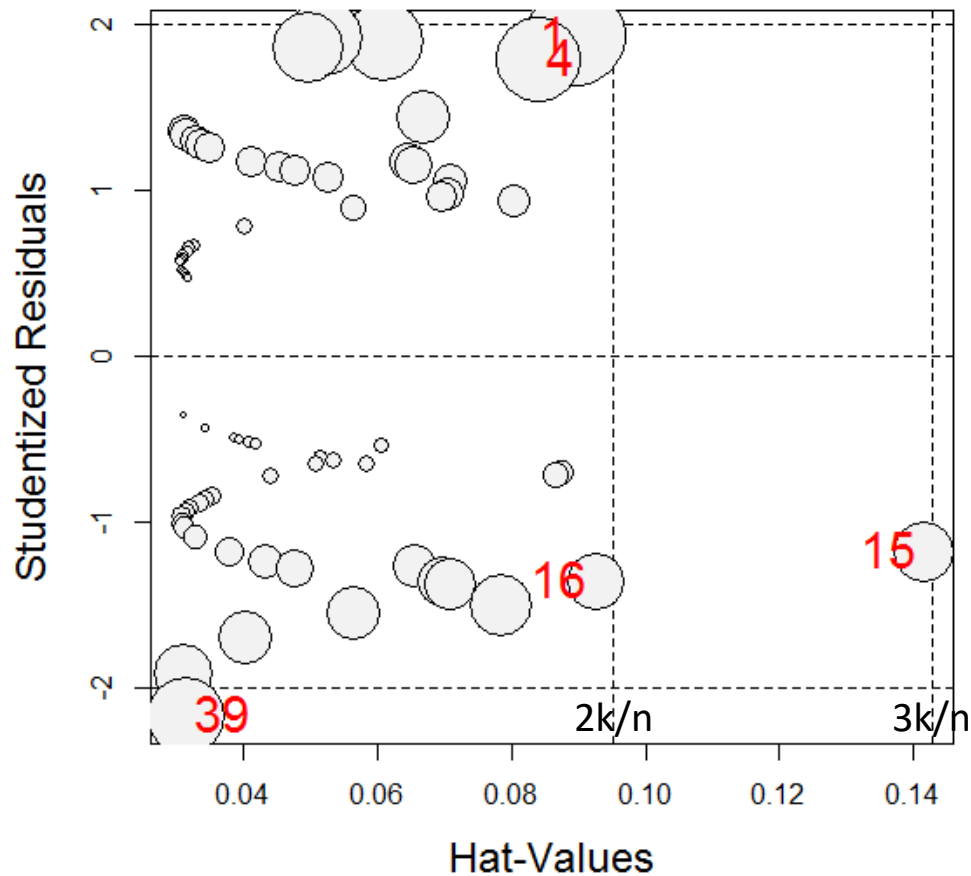
$$\text{Influence} \sim \text{Residual } (y - \hat{y}) \times \text{Hat-value } (\mathbf{X} - \bar{\mathbf{X}})^2$$

Bubble size  $\sim$  influence



# Influence plots in R

```
library(car)  
influencePlot(arth.logistic2, ...)
```



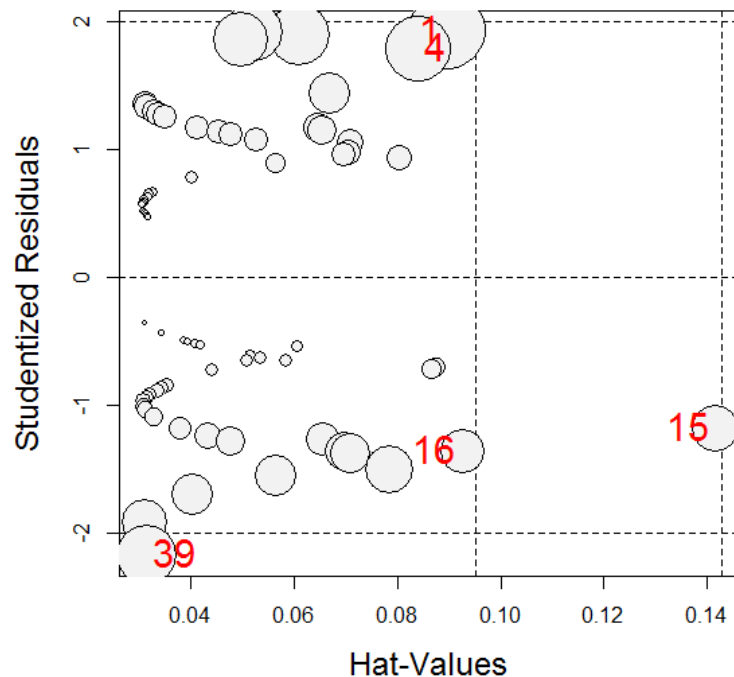
X axis: Leverage (“hat values”)  
notable values:  $> 2k/n$ ,  $3k/n$

Y axis: Studentized residuals  
Notable values: outside  $\pm 2$

Bubble size  $\sim$  Cook’s D  
(influence on coefficients)

# Which cases are influential?

|    | Treatment | Sex    | Age | Better | StudRes | Hat    | CookD  |
|----|-----------|--------|-----|--------|---------|--------|--------|
| 1  | Treated   | Male   | 27  | 1      | 1.92    | 0.0897 | 0.1128 |
| 4  | Treated   | Male   | 32  | 1      | 1.79    | 0.0840 | 0.0818 |
| 15 | Treated   | Female | 23  | 0      | -1.18   | 0.1416 | 0.0420 |
| 16 | Treated   | Female | 32  | 0      | -1.36   | 0.0926 | 0.0381 |
| 39 | Treated   | Female | 69  | 0      | -2.17   | 0.0314 | 0.0690 |



case 1: younger male: moderate Hat, better than predicted → large Cook D

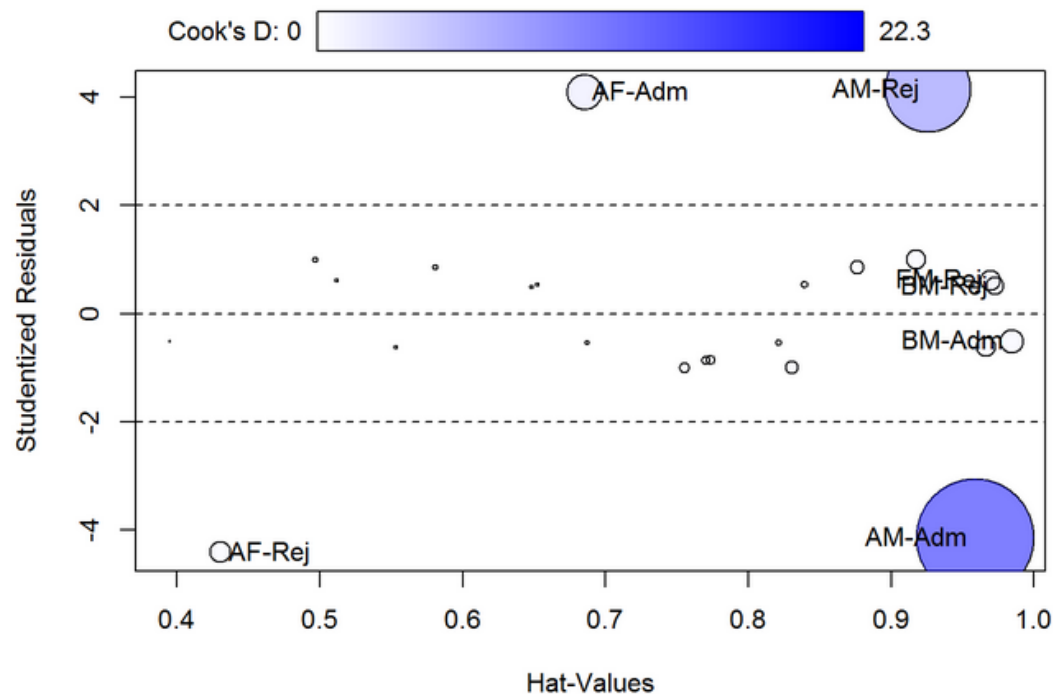
case 15: very young treated female: large Hat; did not improve

case 39: older female: small Hat, but did not improve with treatment

# UCB data: Influence plot

Recall that for the Berkeley data, the model  $\text{Freq} \sim \text{Dept} * (\text{Gender} + \text{Admit})$  fit badly:  $G^2 = 21.7$ . What caused this?

```
berk.mod <- glm(Freq ~ Dept * (Gender+Admit), data=berkeley, family="poisson")
influencePlot(berk.mod, id=list(n=3, labels=cellID))
```



It was the 4 cells for dept A

Code: <https://friendly.github.io/psy6136/R/output/berkeley-diag.R>



# Looking ahead



- Logistic regression models need not always have linear effects— models **nonlinear** in Xs sometimes useful
- **Polytomous** outcomes can be handled as well
  - e.g., Improved = {"None", "Some", "Marked"}
- If ordinal,
  - the **proportional odds** model is a simple extension
  - **nested dichotomies** provides an alternative approach
- Otherwise, **multinomial logistic regression** is the way

# Summary

- `loglm()` provides only overall tests of model fit
- Model-based methods, `glm()`, provide hypothesis tests, CIs & tests for individual terms
- Logistic regression: A `glm()` for a binary response
  - linear model for the log odds  $\Pr(Y=1)$
  - All similar to classical ANOVA, regression models
- Plotting
  - Conditional, full-model plots show data and fits
  - Effect plots show predicted effects averaged over others
- Model diagnostics
  - Influence plots are often informative