

# Logistic Regression

# Logistic regression

- ▶ When response variable is measured/counted, regression can work well.
- ▶ But what if response is yes/no, lived/died, success/failure?
- ▶ Model *probability* of success.
- ▶ Probability must be between 0 and 1; need method that ensures this.
- ▶ *Logistic regression* does this. In R, is a *generalized linear model* with binomial “family”:

```
glm(y ~ x, family="binomial")
```

- ▶ Begin with simplest case.

# Packages

```
library(MASS)
library(tidyverse)
library(marginaleffects)
library(broom)
library(nnet)
library(conflicted)
conflict_prefer("select", "dplyr")
conflict_prefer("filter", "dplyr")
conflict_prefer("rename", "dplyr")
conflict_prefer("summarize", "dplyr")
```

# The rats, part 1

► Rats given dose of some poison; either live or die:

dose	status
------	--------

0	lived
---	-------

1	died
---	------

2	lived
---	-------

3	lived
---	-------

4	died
---	------

5	died
---	------

## Read in:

```
my_url <- "http://ritsokiguess.site/datafiles/rat.txt"
rats <- read_delim(my_url, " ")
rats
```

```
# A tibble: 6 x 2
```

```
  dose status
```

```
<dbl> <chr>
```

```
1     0 lived
```

```
2     1 died
```

```
3     2 lived
```

```
4     3 lived
```

```
5     4 died
```

```
6     5 died
```

# Basic logistic regression

- Make response into a factor first:

```
rats2 <- rats %>% mutate(status = factor(status))
```

- then fit model:

```
status.1 <- glm(status ~ dose, family = "binomial", data = rats2)
```

# Output

```
summary(status.1)
```

Call:

```
glm(formula = status ~ dose, family = "binomial", data = rats2)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	1.6841	1.7979	0.937	0.349
dose	-0.6736	0.6140	-1.097	0.273

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 8.3178 on 5 degrees of freedom  
Residual deviance: 6.7728 on 4 degrees of freedom  
AIC: 10.773

Number of Fisher Scoring iterations: 4

## Interpreting the output

- ▶ Like (multiple) regression, get tests of significance of individual  $x$ 's
- ▶ Here not significant (only 6 observations).
- ▶ “Slope” for dose is negative, meaning that as dose increases, probability of event modelled (survival) decreases.



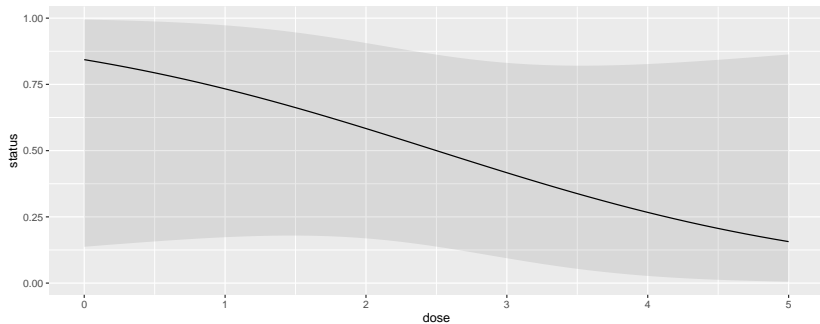
## Output part 2: predicted survival probs

```
cbind(predictions(status.1)) %>%  
  select(dose, estimate)
```

	dose	estimate
1	0	0.8434490
2	1	0.7331122
3	2	0.5834187
4	3	0.4165813
5	4	0.2668878
6	5	0.1565510

## On a graph

```
plot_cap(status.1, condition = "dose")
```



## The rats, more

- ▶ More realistic: more rats at each dose (say 10).
- ▶ Listing each rat on one line makes a big data file.
- ▶ Use format below: dose, number of survivals, number of deaths.

dose	lived	died
0	10	0
1	7	3
2	6	4
3	4	6
4	2	8
5	1	9

- ▶ 6 lines of data correspond to 60 actual rats.
- ▶ Saved in rat2.txt.

## These data

```
my_url <- "http://ritsokiguess.site/datafiles/rat2.txt"
rat2 <- read_delim(my_url, " ")
rat2
```

```
# A tibble: 6 x 3
  dose lived died
  <dbl> <dbl> <dbl>
1     0    10     0
2     1     7     3
3     2     6     4
4     3     4     6
5     4     2     8
6     5     1     9
```

## Create response matrix:

- ▶ Each row contains *multiple* observations.
- ▶ Create *two-column* response:
  - ▶ #survivals in first column,
  - ▶ #deaths in second.

```
response <- with(rat2, cbind(lived, died))  
response
```

	lived	died
[1,]	10	0
[2,]	7	3
[3,]	6	4
[4,]	4	6
[5,]	2	8
[6,]	1	9

- ▶ Response is R matrix:

```
class(response)
```

```
[1] "matrix" "array"
```

# Fit logistic regression

► using response you just made:

```
rat2.1 <- glm(response ~ dose,  
  family = "binomial",  
  data = rat2  
)
```

# Output

```
summary(rat2.1)
```

Call:

```
glm(formula = response ~ dose, family = "binomial", data = rat2)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	2.3619	0.6719	3.515	0.000439	***
dose	-0.9448	0.2351	-4.018	5.87e-05	***

---

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 27.530 on 5 degrees of freedom  
Residual deviance: 2.474 on 4 degrees of freedom  
AIC: 18.94

Number of Fisher Scoring iterations: 4

## Predicted survival probs

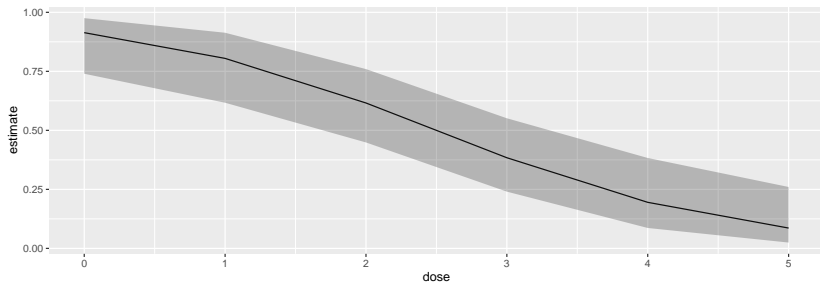
```
new <- datagrid(model = rat2.1, dose = 0:5)
cbind(predictions(rat2.1, newdata = new))
```

	rowid	estimate	p.value	s.value	conf.low	conf.hi
1	1	0.9138762	0.0004389651	11.153606	0.73983042	0.97536
2	2	0.8048905	0.0031438277	8.313262	0.61695841	0.91353
3	3	0.6159474	0.1721141940	2.538562	0.44876099	0.75959
4	4	0.3840526	0.1721142921	2.538561	0.24040837	0.55123
5	5	0.1951095	0.0031438384	8.313257	0.08646093	0.38304
6	6	0.0861238	0.0004389668	11.153600	0.02463288	0.26016



## On a picture

```
cbind(predictions(rat2.1, newdata = new)) %>%  
  select(estimate, conf.low, conf.high, dose) %>%  
  ggplot(aes(x = dose, y = estimate,  
             ymin = conf.low, ymax = conf.high)) +  
    geom_line() + geom_ribbon(alpha = 0.3)
```



## Comments

- ▶ Significant effect of dose.
- ▶ Effect of larger dose is to *decrease* survival probability (“slope” negative; also see in decreasing predictions.)
- ▶ Confidence intervals around prediction narrower (more data).

# Multiple logistic regression

- ▶ With more than one  $x$ , works much like multiple regression.
- ▶ Example: study of patients with blood poisoning severe enough to warrant surgery. Relate survival to other potential risk factors.
- ▶ Variables, 1=present, 0=absent:
  - ▶ survival (death from sepsis=1), response
  - ▶ shock
  - ▶ malnutrition
  - ▶ alcoholism
  - ▶ age (as numerical variable)
  - ▶ bowel infarction
- ▶ See what relates to death.

## Read in data

```
my_url <-  
  "http://ritsokiguess.site/datafiles/sepsis.txt"  
sepsis <- read_delim(my_url, " ")
```

Make sure categoricals really are

```
sepsis %>%  
  mutate(across(-age, \(x) factor(x))) -> sepsis
```

## The data (some)

```
sepsis
```

```
# A tibble: 106 x 6
```

	death	shock	malnut	alcohol	age	bowelinf
	<fct>	<fct>	<fct>	<fct>	<dbl>	<fct>
1	0	0	0	0	56	0
2	0	0	0	0	80	0
3	0	0	0	0	61	0
4	0	0	0	0	26	0
5	0	0	0	0	53	0
6	1	0	1	0	87	0
7	0	0	0	0	21	0
8	1	0	0	1	69	0
9	0	0	0	0	57	0
10	0	0	1	0	76	0

```
# i 96 more rows
```

## Fit model

```
sepsis.1 <- glm(death ~ shock + malnut + alcohol + age +  
  bowelinf,  
  family = "binomial",  
  data = sepsis  
)
```

## Output part 1

```
tidy(sepsis.1)
```

```
# A tibble: 6 x 5
```

	term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
1	(Intercept)	-9.75	2.54	-3.84	0.000124
2	shock1	3.67	1.16	3.15	0.00161
3	malnut1	1.22	0.728	1.67	0.0948
4	alcohol1	3.35	0.982	3.42	0.000635
5	age	0.0922	0.0303	3.04	0.00237
6	bowelinf1	2.80	1.16	2.40	0.0162

- ▶ All P-values fairly small
- ▶ but malnut not significant: remove.



## Removing malnut

```
sepsis.2 <- update(sepsis.1, . ~ . - malnut)
tidy(sepsis.2)
```

```
# A tibble: 5 x 5
```

	term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
1	(Intercept)	-8.89	2.32	-3.84	0.000124
2	shock1	3.70	1.10	3.35	0.000797
3	alcohol1	3.19	0.917	3.47	0.000514
4	age	0.0898	0.0292	3.07	0.00211
5	bowelinf1	2.39	1.07	2.23	0.0260

► Everything significant now.

## Comments

- ▶ Most of the original  $x$ 's helped predict death. Only `malnut` seemed not to add anything.
- ▶ Removed `malnut` and tried again.
- ▶ Everything remaining is significant (though `bowelinf` actually became *less* significant).
- ▶ All coefficients are *positive*, so having any of the risk factors (or being older) *increases* risk of death.

# Predictions from model without “malnut”

► A few (rows of original dataframe) chosen “at random”:

```
sepsis %>% slice(c(4, 1, 2, 11, 32)) -> new  
new
```

```
# A tibble: 5 x 6  
  death shock malnut alcohol   age bowelinf  
  <fct> <fct> <fct> <fct>   <dbl> <fct>  
1 0      0      0      0      26 0  
2 0      0      0      0      56 0  
3 0      0      0      0      80 0  
4 1      0      0      1      66 1  
5 1      0      0      1      49 0
```

```
cbind(predictions(sepsis.2, newdata = new)) %>%  
  select(estimate, conf.low, conf.high, shock:bowelinf)
```

	estimate	conf.low	conf.high	shock	malnut	alcohol	age	bowelinf
1	0.001415347	6.272642e-05	0.03103047	0	0	0	26	0
2	0.020552383	4.102504e-03	0.09656596	0	0	0	56	0
3	0.153416834	5.606838e-02	0.35603441	0	0	0	80	0
4	0.931290137	5.490986e-01	0.99341482	0	0	1	66	1
5	0.213000997	7.639063e-02	0.46967947	0	0	1	49	0

## Comments

- ▶ Survival chances pretty good if no risk factors, though decreasing with age.
- ▶ Having more than one risk factor reduces survival chances dramatically.
- ▶ Usually good job of predicting survival; sometimes death predicted to survive.

## Another way to assess effects

of age:

```
new <- datagrid(model = sepsis.2, age = seq(30, 70, 10))  
new
```

	death	shock	alcohol	bowelinf	age
1	0	0	0	0	30
2	0	0	0	0	40
3	0	0	0	0	50
4	0	0	0	0	60
5	0	0	0	0	70

## Assessing age effect

```
cbind(predictions(sepsis.2, newdata = new)) %>%  
  select(estimate, shock:age)
```

	estimate	shock	alcohol	bowelinf	age
1	0.002026053	0	0	0	30
2	0.004960283	0	0	0	40
3	0.012092515	0	0	0	50
4	0.029179226	0	0	0	60
5	0.068729752	0	0	0	70

# Assessing shock effect

```
new <- datagrid(shock = c(0, 1), model = sepsis.2)
new
```

	death	alcohol	age	bowelinf	shock
1	0	0	51.28302	0	0
2	0	0	51.28302	0	1

```
cbind(predictions(sepsis.2, newdata = new)) %>%
  select(estimate, death:shock)
```

	estimate	death	alcohol	age	bowelinf	shock
1	0.01354973	0	0	51.28302	0	0
2	0.35742607	0	0	51.28302	0	1

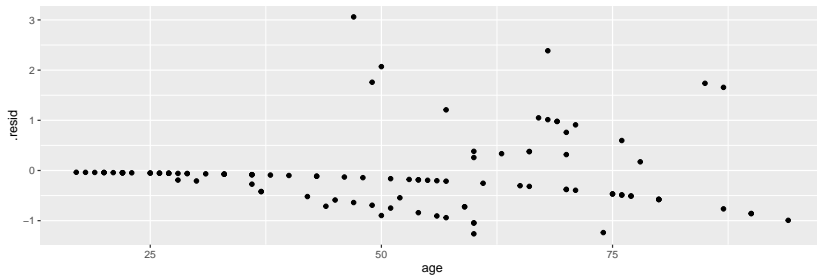
## Assessing proportionality of odds for age

- ▶ An assumption we made is that log-odds of survival depends linearly on age.
- ▶ Hard to get your head around, but basic idea is that survival chances go continuously up (or down) with age, instead of (for example) going up and then down.
- ▶ In this case, seems reasonable, but should check:



# Residuals vs. age

```
sepsis.2 %>% augment(sepsis) %>%  
  ggplot(aes(x = age, y = .resid)) +  
  geom_point()
```



## Comments

- ▶ No apparent problems overall.
- ▶ Confusing “line” across: no risk factors, survived.

# Probability and odds

- ▶ For probability  $p$ , odds is  $p/(1 - p)$ :

Prob.		Odds	log-odds	in words
0.5	$0.5/0.5 = 1/1 = 1.00$		0.00	"even money"
0.1	$0.1/0.9 = 1/9 = 0.11$		-2.20	"9 to 1"
0.4	$0.4/0.6 = 1/1.5 = 0.67$		-0.41	"1.5 to 1"
0.8	$0.8/0.2 = 4/1 = 4.00$		1.39	"4 to 1 on"

- ▶ Gamblers use odds: if you win at 9 to 1 odds, get original stake back plus 9 times the stake.
- ▶ Probability has to be between 0 and 1
- ▶ Odds between 0 and infinity
- ▶ Log-odds can be anything: any log-odds corresponds to valid probability.

## Odds ratio

- ▶ Suppose 90 of 100 men drank wine last week, but only 20 of 100 women.
- ▶ Prob of man drinking wine  $90/100 = 0.9$ , woman  $20/100 = 0.2$ .
- ▶ Odds of man drinking wine  $0.9/0.1 = 9$ , woman  $0.2/0.8 = 0.25$ .
- ▶ Ratio of odds is  $9/0.25 = 36$ .
- ▶ Way of quantifying difference between men and women: “odds of drinking wine 36 times larger for males than females”.

## Sepsis data again

- Recall prediction of probability of death from risk factors:

```
sepsis.2.tidy <- tidy(sepsis.2)
sepsis.2.tidy
```

```
# A tibble: 5 x 5
```

	term <chr>	estimate <dbl>	std.error <dbl>	statistic <dbl>	p.value <dbl>
1	(Intercept)	-8.89	2.32	-3.84	0.000124
2	shock1	3.70	1.10	3.35	0.000797
3	alcohol1	3.19	0.917	3.47	0.000514
4	age	0.0898	0.0292	3.07	0.00211
5	bowelinf1	2.39	1.07	2.23	0.0260

- Slopes in column estimate.

## Multiplying the odds

- Can interpret slopes by taking “exp” of them. We ignore intercept.

```
sepsis.2.tidy %>%  
  mutate(exp_coef=exp(estimate)) %>%  
  select(term, exp_coef)
```

```
# A tibble: 5 x 2  
  term      exp_coef  
  <chr>      <dbl>  
1 (Intercept) 0.000137  
2 shock1      40.5  
3 alcohol1    24.2  
4 age         1.09  
5 bowelinf1   10.9
```

# Interpretation

```
# A tibble: 5 x 2
  term          exp_coeff
<chr>         <dbl>
1 (Intercept)  0.000137
2 shock1       40.5
3 alcohol1     24.2
4 age          1.09
5 bowelinf1    10.9
```

- ▶ These say “how much do you *multiply* odds of death by for increase of 1 in corresponding risk factor?” Or, what is odds ratio for that factor being 1 (present) vs. 0 (absent)?
- ▶ Eg. being alcoholic vs. not increases odds of death by 24 times
- ▶ One year older multiplies odds by about 1.1 times. Over 40 years, about  $1.09^{40} = 31$  times.

# Odds ratio and relative risk

- ▶ **Relative risk** is ratio of probabilities.
- ▶ Above: 90 of 100 men (0.9) drank wine, 20 of 100 women (0.2).
- ▶ Relative risk  $0.9/0.2=4.5$ . (odds ratio was 36).
- ▶ When probabilities small, relative risk and odds ratio similar.
- ▶ Eg. prob of man having disease 0.02, woman 0.01.
- ▶ Relative risk  $0.02/0.01 = 2$ .



## Odds ratio vs. relative risk

- Odds for men and for women:

```
(od1 <- 0.02 / 0.98) # men
```

```
[1] 0.02040816
```

```
(od2 <- 0.01 / 0.99) # women
```

```
[1] 0.01010101
```

- Odds ratio

```
od1 / od2
```

```
[1] 2.020408
```

- Very close to relative risk of 2.

## More than 2 response categories

- ▶ With 2 response categories, model the probability of one, and prob of other is one minus that. So doesn't matter which category you model.
- ▶ With more than 2 categories, have to think more carefully about the categories: are they
- ▶ *ordered*: you can put them in a natural order (like low, medium, high)
- ▶ *nominal*: ordering the categories doesn't make sense (like red, green, blue).
- ▶ R handles both kinds of response; learn how.

## Ordinal response: the miners

- ▶ Model probability of being in given category *or lower*.
- ▶ Example: coal-miners often suffer disease pneumoconiosis. Likelihood of disease believed to be greater among miners who have worked longer.
- ▶ Severity of disease measured on categorical scale: none, moderate, severe.

## Miners data

► Data are frequencies:

Exposure	None	Moderate	Severe
5.8	98	0	0
15.0	51	2	1
21.5	34	6	3
27.5	35	5	8
33.5	32	10	9
39.5	23	7	8
46.0	12	6	10
51.5	4	2	5

## Reading the data

Data in aligned columns with more than one space between, so:

```
my_url <- "http://ritsokiguess.site/datafiles/miners-tab.txt"  
freqs <- read_table(my_url)
```

## The data

```
freqs
```

```
# A tibble: 8 x 4
```

	Exposure	None	Moderate	Severe
	<dbl>	<dbl>	<dbl>	<dbl>
1	5.8	98	0	0
2	15	51	2	1
3	21.5	34	6	3
4	27.5	35	5	8
5	33.5	32	10	9
6	39.5	23	7	8
7	46	12	6	10
8	51.5	4	2	5

# Tidying

```
freqs %>%  
  pivot_longer(-Exposure, names_to = "Severity", values_to = "Count")  
  mutate(Severity = fct_inorder(Severity)) -> miners
```

# Result

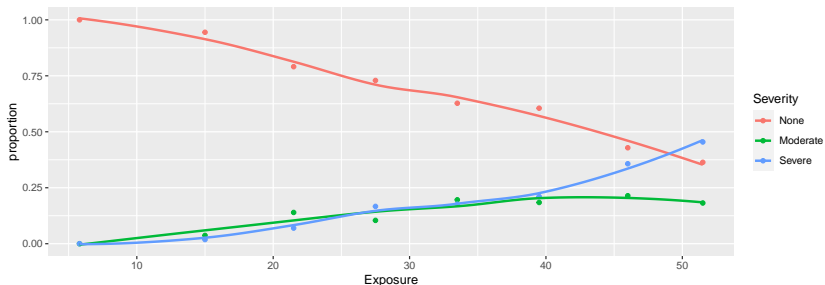
```
miners
```

```
# A tibble: 24 x 3
  Exposure Severity Freq
  <dbl> <fct>    <dbl>
1     5.8 None      98
2     5.8 Moderate    0
3     5.8 Severe     0
4     15 None      51
5     15 Moderate    2
6     15 Severe     1
7    21.5 None     34
8    21.5 Moderate    6
9    21.5 Severe     3
10   27.5 None     35
# i 14 more rows
```



# Plot proportions against exposure

```
miners %>%  
  group_by(Exposure) %>%  
  mutate(proportion = Freq / sum(Freq)) -> prop  
ggplot(prop, aes(x = Exposure, y = proportion,  
                  colour = Severity)) +  
  geom_point() + geom_smooth(se = F)
```



## Reminder of data setup

```
miners
```

```
# A tibble: 24 x 3
```

	Exposure	Severity	Freq
	<dbl>	<fct>	<dbl>
1	5.8	None	98
2	5.8	Moderate	0
3	5.8	Severe	0
4	15	None	51
5	15	Moderate	2
6	15	Severe	1
7	21.5	None	34
8	21.5	Moderate	6
9	21.5	Severe	3
10	27.5	None	35

```
# i 14 more rows
```

## Fitting ordered logistic model

Use function `polr` from package `MASS`. Like `glm`.

```
sev.1 <- polr(Severity ~ Exposure,  
  weights = Freq,  
  data = miners  
)
```

## Output: not very illuminating

```
sev.1 <- polr(Severity ~ Exposure,  
  weights = Freq,  
  data = miners,  
  Hess = TRUE  
)
```

```
summary(sev.1)
```

Call:

```
polr(formula = Severity ~ Exposure, data = miners, weights = Freq,  
     Hess = TRUE)
```

Coefficients:

	Value	Std. Error	t value
Exposure	0.0959	0.01194	8.034

Intercepts:

	Value	Std. Error	t value
None Moderate	3.9558	0.4097	9.6558
Moderate Severe	4.8690	0.4411	11.0383

Residual Deviance: 416.9188

AIC: 422.9188

# Does exposure have an effect?

Fit model without Exposure, and compare using anova. Note 1 for model with just intercept:

```
sev.0 <- polr(Severity ~ 1, weights = Freq, data = miners)
anova(sev.0, sev.1)
```

Likelihood ratio tests of ordinal regression models

Response: Severity

	Model	Resid. df	Resid. Dev	Test	Df	LR stat.
1	1	369	505.1621			
2	Exposure	368	416.9188	1 vs 2	1	88.24324
	Pr(Chi)					
1						
2	0					

Exposure definitely has effect on severity of disease.

## Another way

- ▶ What (if anything) can we drop from model with exposure?

```
drop1(sev.1, test = "Chisq")
```

Single term deletions

Model:

Severity ~ Exposure

	Df	AIC	LRT	Pr(>Chi)
<none>		422.92		
Exposure	1	509.16	88.243	< 2.2e-16 ***

---

Signif. codes:

0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

- ▶ Nothing. Exposure definitely has effect.

## Predicted probabilities 1/2

```
freqs %>% select(Exposure) -> new  
new
```

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

```
  Exposure
```

```
    <dbl>
```

```
1      5.8
```

```
2     15
```

```
3    21.5
```

```
4    27.5
```

```
5    33.5
```

```
6    39.5
```

```
7     46
```

```
8    51.5
```

## Predicted probabilities 2/2

```
cbind(predictions(sev.1, newdata = new)) %>%  
  select(group, estimate, Exposure) %>%  
  pivot_wider(names_from = group, values_from = estimate)
```

# A tibble: 8 x 4

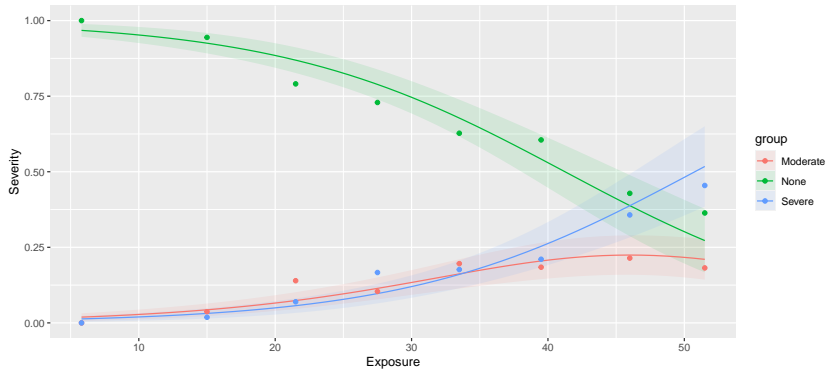
	Exposure	None	Moderate	Severe
	<dbl>	<dbl>	<dbl>	<dbl>
1	5.8	0.968	0.0191	0.0132
2	15	0.925	0.0433	0.0314
3	21.5	0.869	0.0739	0.0569
4	27.5	0.789	0.114	0.0969
5	33.5	0.678	0.162	0.160
6	39.5	0.542	0.205	0.253
7	46	0.388	0.224	0.388
8	51.5	0.272	0.210	0.517





# The graph

ggg



## Comments

- ▶ Model appears to match data well enough.
- ▶ As exposure goes up, prob of None goes down, Severe goes up (sharply for high exposure).
- ▶ So more exposure means worse disease.

## Unordered responses

- ▶ With unordered (nominal) responses, can use *generalized logit*.
- ▶ Example: 735 people, record age and sex (male 0, female 1), which of 3 brands of some product preferred.
- ▶ Data in `mlogit.csv` separated by commas (so `read_csv` will work):

```
my_url <- "http://ritsokiguess.site/datafiles/mlogit.csv"
brandpref <- read_csv(my_url)
```

## The data (some)

```
brandpref
```

```
# A tibble: 735 x 3
```

```
  brand  sex  age  
  <dbl> <dbl> <dbl>
```

1	1	0	24
2	1	0	26
3	1	0	26
4	1	1	27
5	1	1	27
6	3	1	27
7	1	0	27
8	1	0	27
9	1	1	27
10	1	0	27

```
# i 725 more rows
```

## Bashing into shape

- ▶ sex and brand not meaningful as numbers, so turn into factors:

```
brandpref %>%  
  mutate(sex = ifelse(sex == 1, "female", "male"),  
         sex = factor(sex),  
         brand = factor(brand)  
  ) -> brandpref
```

## Fitting model

- ▶ We use multinom from package nnet. Works like polr.

```
brands.1 <- multinom(brand ~ age + sex, data = brandpref)
```

```
# weights:  12 (6 variable)
initial  value 807.480032
iter   10 value 702.990572
final   value 702.970704
converged
```

## Can we drop anything?

- ▶ Unfortunately drop1 seems not to work:

```
drop1(brands.1, test = "Chisq", trace = 0)
```

```
trying - age
```

```
Error in if (trace) {: argument is not interpretable as logical
```

- ▶ So, fall back on fitting model without what you want to test, and comparing using anova.



## Do age/sex help predict brand? 1/3

Fit models without each of age and sex:

```
brands.2 <- multinom(brand ~ age, data = brandpref)
```

```
# weights:  9 (4 variable)
initial  value 807.480032
iter   10 value 706.796323
iter   10 value 706.796322
final   value 706.796322
converged
```

```
brands.3 <- multinom(brand ~ sex, data = brandpref)
```

```
# weights:  9 (4 variable)
initial  value 807.480032
final   value 791.861266
converged
```

## Do age/sex help predict brand? 2/3

```
anova(brands.2, brands.1)
```

Likelihood ratio tests of Multinomial Models

Response: brand

	Model	Resid. df	Resid. Dev	Test	Df	LR stat.
1	age	1466	1413.593			
2	age + sex	1464	1405.941	1 vs 2	2	7.651236

Pr(Chi)

1	
2	0.02180496

```
anova(brands.3, brands.1)
```

Likelihood ratio tests of Multinomial Models

Response: brand

	Model	Resid. df	Resid. Dev	Test	Df	LR stat.
1	sex	1466	1583.723			
2	age + sex	1464	1405.941	1 vs 2	2	177.7811

Pr(Chi)

1	
2	0

## Do age/sex help predict brand? 3/3

- ▶ age definitely significant (second anova)
- ▶ sex significant also (first anova), though P-value less dramatic
- ▶ Keep both.
- ▶ Expect to see a large effect of age, and a smaller one of sex.

## Another way to build model

- ▶ Start from model with everything and run step:

```
step(brands.1, trace = 0)
```

```
trying - age
```

```
trying - sex
```

Call:

```
multinom(formula = brand ~ age + sex)
```

Coefficients:

	(Intercept)	age	sexmale
2	-11.25127	0.3682202	-0.5237736
3	-22.25571	0.6859149	-0.4658215

Residual Deviance: 1405.941

AIC: 1417.941

- ▶ Final model contains both age and sex so neither could be removed.

# Making predictions

Find age 5-number summary, and the two sexes:

```
summary(brandpref)
```

brand	sex	age
1:207	female:466	Min. :24.0
2:307	male :269	1st Qu.:32.0
3:221		Median :32.0
		Mean :32.9
		3rd Qu.:34.0
		Max. :38.0

Space the ages out a bit for prediction (see over).

# Combinations

```
new <- datagrid(age = c(24, 30, 33, 35, 38),  
                sex = c("female", "male"), model = brands.1  
new
```

	brand	age	sex
1	2	24	female
2	2	24	male
3	2	30	female
4	2	30	male
5	2	33	female
6	2	33	male
7	2	35	female
8	2	35	male
9	2	38	female
10	2	38	male

## The predictions

```
cbind(predictions(brands.1, newdata = new)) %>%  
  select(group, estimate, age, sex) %>%  
  pivot_wider(names_from = group, values_from = estimate)
```

# A tibble: 10 x 5

	age	sex	`1`	`2`	`3`
	<dbl>	<fct>	<dbl>	<dbl>	<dbl>
1	24	female	0.915	0.0819	0.00279
2	24	male	0.948	0.0502	0.00181
3	30	female	0.500	0.407	0.0933
4	30	male	0.625	0.302	0.0732
5	33	female	0.203	0.500	0.297
6	33	male	0.296	0.432	0.272
7	35	female	0.0840	0.432	0.484
8	35	male	0.131	0.397	0.472
9	38	female	0.0162	0.252	0.732
10	38	male	0.0260	0.239	0.735

## Comments

- ▶ Young males prefer brand 1, but older males prefer brand 3.
- ▶ Females similar, but like brand 1 less and brand 2 more.
- ▶ A clear brand effect, but the sex effect is less clear.



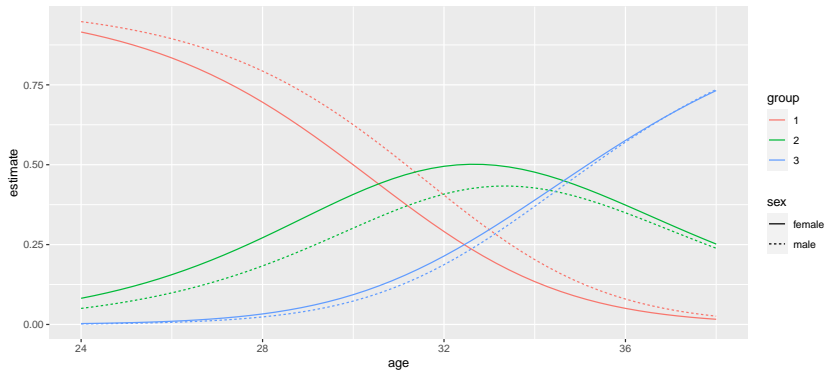
# Making a plot

- ▶ `plot_cap` doesn't quite work
- ▶ so don't draw, edit, *then* make graph:

```
plot_cap(brands.1, condition = c("age", "brand", "sex"),  
          type = "probs", draw = FALSE) %>%  
  ggplot(aes(x = age, y = estimate, colour = group,  
             linetype = sex)) +  
  geom_line() -> g
```

# The graph

σ<sub>α</sub>



## Digesting the plot

- ▶ Brand vs. age: younger people (of both genders) prefer brand 1, but older people (of both genders) prefer brand 3. (Explains significant age effect.)
- ▶ Brand vs. sex: females (solid) like brand 1 less than males (dashed), like brand 2 more (for all ages).
- ▶ Not much brand difference between genders (solid and dashed lines of same colours close), but enough to be significant.
- ▶ Model didn't include interaction, so modelled effect of gender on brand same for each age, modelled effect of age same for each gender. (See also later.)

## Alternative data format

Summarize all people of same brand preference, same sex, same age on one line of data file with frequency on end:

```
brandpref
```

```
# A tibble: 735 x 3
  brand sex    age
  <fct> <fct> <dbl>
1 1     male    24
2 1     male    26
3 1     male    26
4 1    female    27
5 1    female    27
6 3    female    27
7 1     male    27
8 1     male    27
9 1    female    27
10 1    male    27
# i 725 more rows
```

## Getting alternative data format

```
brandpref %>%  
  group_by(age, sex, brand) %>%  
  summarize(Freq = n()) %>%  
  ungroup() -> b  
b
```

# A tibble: 65 x 4

	age	sex	brand	Freq
	<dbl>	<fct>	<fct>	<int>
1	24	male	1	1
2	26	male	1	2
3	27	female	1	4
4	27	female	3	1
5	27	male	1	4
6	28	female	1	6
7	28	female	2	2
8	28	female	3	1
9	28	male	1	4
10	28	male	3	2

## Fitting models, almost the same

- ▶ Just have to remember weights to incorporate frequencies.
- ▶ Otherwise multinom assumes you have just 1 obs on each line!
- ▶ Again turn (numerical) sex and brand into factors:

```
b %>%  
  mutate(sex = factor(sex)) %>%  
  mutate(brand = factor(brand)) -> bf  
b.1 <- multinom(brand ~ age + sex, data = bf, weights = Freq)  
b.2 <- multinom(brand ~ age, data = bf, weights = Freq)
```

## P-value for sex identical

```
anova(b.2, b.1)
```

Likelihood ratio tests of Multinomial Models

Response: brand

	Model	Resid. df	Resid. Dev	Test	Df	LR stat.
1	age	126	1413.593			
2	age + sex	124	1405.941	1 vs 2	2	7.651236

Pr(Chi)

1	
2	0.02180496

Same P-value as before, so we haven't changed anything important.

## Trying interaction between age and gender

```
brands.4 <- update(brands.1, . ~ . + age:sex)
```

```
# weights: 15 (8 variable)
initial value 807.480032
iter 10 value 703.191146
iter 20 value 702.572260
iter 30 value 702.570900
iter 30 value 702.570893
iter 30 value 702.570893
final value 702.570893
converged
```

```
anova(brands.1, brands.4)
```

Likelihood ratio tests of Multinomial Models

Response: brand

	Model	Resid. df	Resid. Dev	Test	Df
1	age + sex	1464	1405.941		
2	age + sex + age:sex	1462	1405.142	1 vs 2	2
	LR stat.	Pr(Chi)			
1					
2	0.7996223	0.6704466			

- No evidence that effect of age on brand preference differs for the two genders.

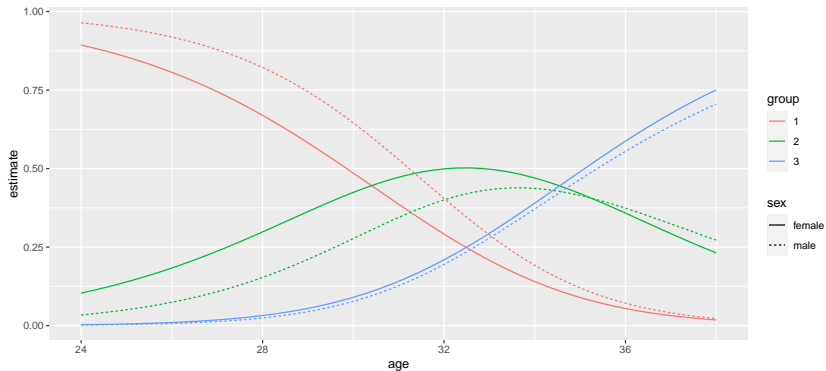


## Make graph again

```
plot_cap(brands.4, condition = c("age", "brand", "sex"),  
          type = "probs", draw = FALSE) %>%  
  ggplot(aes(x = age, y = estimate, colour = group,  
             linetype = sex)) +  
  geom_line() -> g4
```

# Not much difference in the graph

g4



# Compare model without interaction

09

