Friday, Mar 11

Using the emmeans Package for Poisson and Logistic Regression

The **emmeans** package can be used to produce *some* of the inferences that are obtained using `contrast` with respect to estimated expected rates/probabilities as well as rate/odds ratios, but largely with respect to *categorical* explanatory variables (i.e., factors).

Example: Consider the following Poisson regression model for the `ceriodaphniastrain` data.

```
fleas <- trtools::ceriodaphniastrain
fleas$strain <- factor(fleas$strain, levels = c(1,2), labels = c("a","b"))
m <- glm(count ~ concentration * strain, family = poisson, data = fleas)
summary(m)$coefficients
```

```
                      Estimate Std. Error z value   Pr(>|z|)
(Intercept)             4.4811    0.04350 103.008  0.000e+00
concentration          -1.5979    0.06244 -25.592 1.862e-144
strainb                -0.3367    0.06704  -5.022  5.114e-07
concentration:strainb   0.1253    0.09385   1.336  1.817e-01
```

We can compute the expected count for a concentration of two for each strain using `contrast`.

```
trtools::contrast(m, tf = exp,
  a = list(strain = c("a","b"), concentration = 2))
```

```
 estimate lower upper
    3.616 2.970 4.402
    3.318 2.671 4.122
```

And we can do it using `emmeans` if we specify `type = "response"` and use the `at` argument to specify an quantitative explanatory variables.

```
library(emmeans)
emmeans(m, ~ strain, type = "response", at = list(concentration = 2))
```

```
 strain rate    SE  df asymp.LCL asymp.UCL
 a      3.62 0.363 Inf      2.97      4.40
 b      3.32 0.367 Inf      2.67      4.12

Confidence level used: 0.95
Intervals are back-transformed from the log scale
```

Note that `emmeans` does produce a valid standard error on the scale of the expected count/rate which `trtools::contrast` does not (by default), and that `trtools::contrast` will show the test statistic and p-value on the log scale if we omit the `tf = exp` argument.

We can compute the rate ratio to compare the two strains at a given concentration.

```
trtools::contrast(m, tf = exp,
  a = list(strain = "a", concentration = 2),
  b = list(strain = "b", concentration = 2))
```

```
 estimate  lower upper
```

```
     1.09 0.8132  1.46
```

```r
pairs(emmeans(m, ~ strain, type = "response",
  at = list(concentration = 2)), infer = TRUE)
```

```
 contrast ratio    SE  df asymp.LCL asymp.UCL null z.ratio p.value
 a / b     1.09 0.163 Inf     0.813      1.46    1   0.576  0.5648

Confidence level used: 0.95
Intervals are back-transformed from the log scale
Tests are performed on the log scale
```

Example: Consider the following logistic regression model for the `insecticide` data.

```r
m <- glm(cbind(deaths, total-deaths) ~ insecticide * deposit,
  family = binomial, data = insecticide)
summary(m)$coefficients
```

```
                        Estimate Std. Error  z value  Pr(>|z|)
(Intercept)             -2.81091    0.35845 -7.84177 4.442e-15
insecticideboth          1.22575    0.67176  1.82468 6.805e-02
insecticideDDT          -0.03893    0.50722 -0.07676 9.388e-01
deposit                  0.62207    0.07786  7.98986 1.351e-15
insecticideboth:deposit  0.37010    0.20897  1.77109 7.655e-02
insecticideDDT:deposit  -0.14143    0.10376 -1.36301 1.729e-01
```

We can use `trtools::contrast` or `emmeans` to produce estimates of the probability of death for a given insecticide at a given deposit value.

```r
trtools::contrast(m, tf = plogis,
  a = list(insecticide = c("g-BHC","both","DDT"), deposit = 5),
  cnames = c("g-BHC","both","DDT"))
```

```
      estimate  lower  upper
g-BHC   0.5743 0.5027 0.6429
both    0.9669 0.9212 0.9865
DDT     0.3902 0.3289 0.4550
```

```r
emmeans(m, ~ insecticide, type = "response", at = list(deposit = 5))
```

```
 insecticide  prob     SE  df asymp.LCL asymp.UCL
 g-BHC       0.574 0.0360 Inf     0.503     0.643
 both        0.967 0.0149 Inf     0.921     0.987
 DDT         0.390 0.0323 Inf     0.329     0.455

Confidence level used: 0.95
Intervals are back-transformed from the logit scale
```

Again, `emmeans` produces a valid standard error on the probability scale while `trtools::contrast` does not, and `trtools::contrast` will produce test statistics and p-values on the logit scale when the `tf = plogis` argument is omitted.

We can compute odds ratios to compare the insecticides at a given deposit.

```r
pairs(emmeans(m, ~ insecticide, type = "response",
  at = list(deposit = 5)), adjust = "none", infer = TRUE)
```

```
 contrast       odds.ratio     SE  df asymp.LCL asymp.UCL null z.ratio p.value
 (g-BHC) / both       0.05  0.023 Inf     0.018      0.12    1  -6.275  <.0001
 (g-BHC) / DDT        2.11  0.423 Inf     1.424      3.12    1   3.724  0.0002
```

```
 both / DDT          45.71 22.260 Inf    17.600    118.72    1   7.849  <.0001

Confidence level used: 0.95
Intervals are back-transformed from the log odds ratio scale
Tests are performed on the log odds ratio scale
```

```r
trtools::contrast(m, tf = exp,
  a = list(insecticide = c("g-BHC","g-BHC","both"), deposit = 5),
  b = list(insecticide = c("both","DDT","DDT"), deposit = 5),
  cnames = c("g-BHC / both", "g-BHC / DDT", "both / DDT"))
```

```
             estimate    lower    upper
g-BHC / both  0.04613  0.01765   0.1206
g-BHC / DDT   2.10871  1.42385   3.1230
both / DDT   45.71097 17.59954 118.7243
```

We can flip/reverse the odds ratios if desired (which can also be done with rate ratios).

```r
pairs(emmeans(m, ~ insecticide, type = "response",
  at = list(deposit = 5)), adjust = "none", reverse = TRUE, infer = TRUE)
```

```
 contrast       odds.ratio     SE  df asymp.LCL asymp.UCL null z.ratio p.value
 both / (g-BHC)     21.677 10.628 Inf     8.293     56.67    1   6.275  <.0001
 DDT / (g-BHC)       0.474  0.095 Inf     0.320      0.70    1  -3.724  0.0002
 DDT / both          0.022  0.011 Inf     0.008      0.06    1  -7.849  <.0001

Confidence level used: 0.95
Intervals are back-transformed from the log odds ratio scale
Tests are performed on the log odds ratio scale
```

```r
trtools::contrast(m, tf = exp,
  a = list(insecticide = c("both","DDT","DDT"), deposit = 5),
  b = list(insecticide = c("g-BHC","g-BHC","both"), deposit = 5),
  cnames = c("both / g-BHC", "DDT / g-BHC", "DDT / both"))
```

```
             estimate    lower    upper
both / g-BHC 21.67723 8.292521 56.66581
DDT / g-BHC   0.47422 0.320208  0.70232
DDT / both    0.02188 0.008423  0.05682
```

Relationship Between Poisson and Logistic Regression

Suppose C_i has a binomial distribution with parameters p_i and m_i so that

$$P(C_i = c) = \binom{m_i}{c} p_i^y (1 - p_i)^{m_i - c}.$$

Define the expected count as $E(C_i) = m_i p_i = \lambda_i$. Then $p_i = \lambda_i / m_i$ so we can write

$$P(C_i = c) = \binom{m_i}{c} \left(\frac{\lambda_i}{m_i}\right)^y \left(1 - \frac{\lambda_i}{m_i}\right)^{c-y}.$$

Then it can be shown that

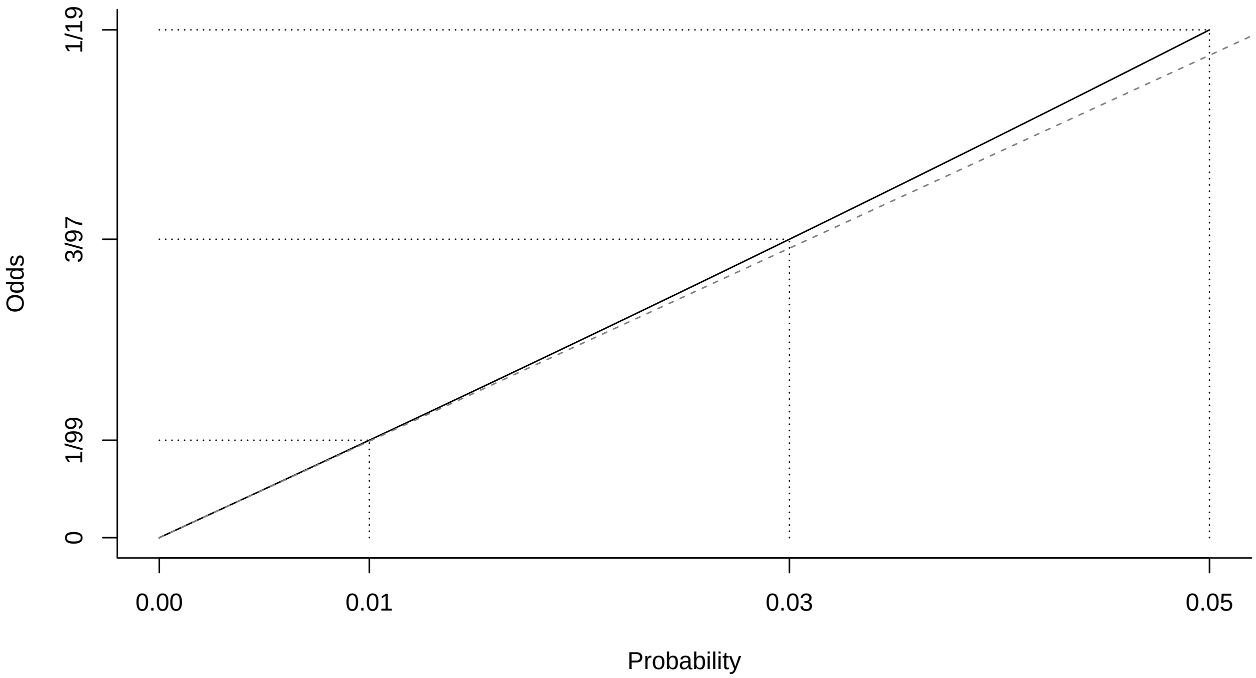
$$\lim_{m_i \to \infty} \binom{m_i}{c} \left(\frac{\lambda_i}{m_i}\right)^y \left(1 - \frac{\lambda_i}{m_i}\right)^{m_i - y} = \frac{e^{\lambda_i} \lambda_i^y}{y!},$$

which is the Poisson distribution.

Thus *in practice* if p_i is small relative to m_i we can *approximate a binomial distribution with a Poisson distribution*. Furthermore there is a close relationship between the model parameters. In logistic regression we have

$$O_i = \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}),$$

where $O_i = p_i/(1 - p_i)$ is the odds of the event. But when p_i is very small then $O_i \approx p_i$.



So then

$$p_i \approx \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}),$$

and because $E(C_i) = m_i p_i$,

$$E(C_i) \approx \exp(\log(m_i) + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}),$$

where $\log(m_i)$ is used as an offset in a Poisson regression model. That is, we can model a proportion (approximately) as a rate in a Poisson regression model for events that are rare and when m_i (i.e., the denominator of the proportion) is relatively large. This is relatively common in large-scale observational studies.

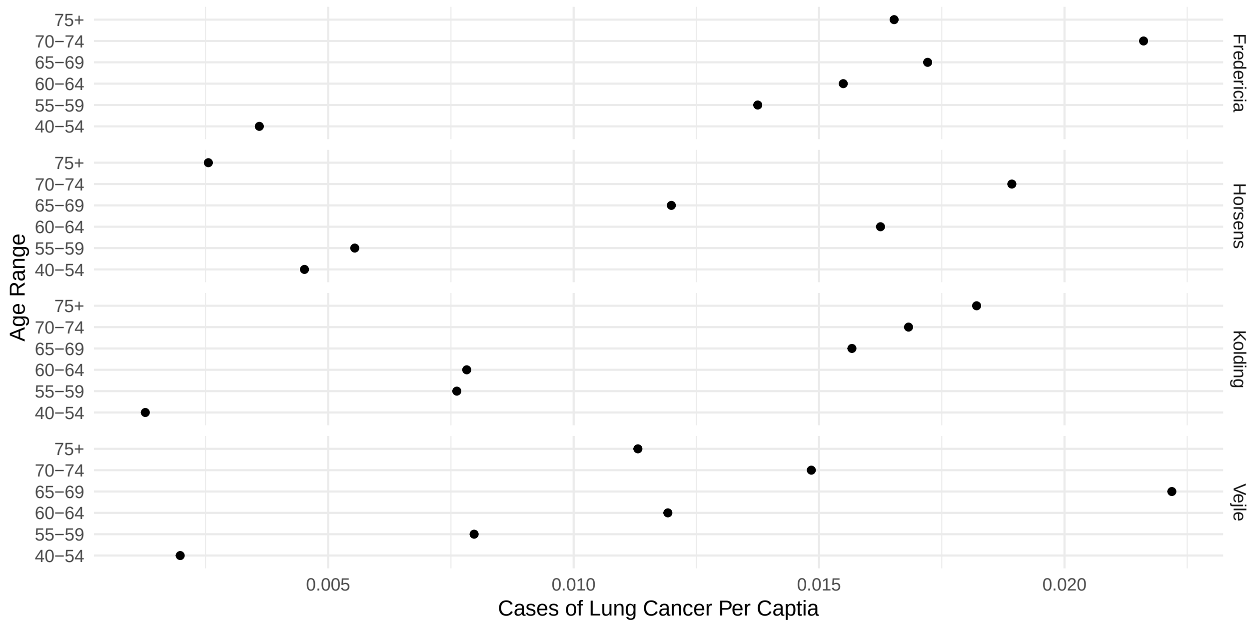
Example: Consider the following data on the incidence of lung cancer in four Danish cities.

```
library(ISwR) # for eba1977 data
head(eba1977)
```

```
        city   age  pop cases
1 Fredericia 40-54 3059    11
2    Horsens 40-54 2879    13
3    Kolding 40-54 3142     4
4      Vejle 40-54 2520     5
5 Fredericia 55-59  800    11
6    Horsens 55-59 1083     6
```

```
p <- ggplot(eba1977, aes(x = age, y = cases/pop)) +
  geom_point() + facet_grid(city ~ .) + coord_flip() +
  labs(x = "Age Range", y = "Cases of Lung Cancer Per Captia") +
```

```
  theme_minimal()
plot(p)
```



Consider both a logistic and Poisson regression models to compare the cities while controlling for age.

```
m.b <- glm(cbind(cases, pop-cases) ~ city + age, family = binomial, data = eba1977)
cbind(summary(m.b)$coefficients, confint(m.b))
```

```
             Estimate Std. Error z value   Pr(>|z|)   2.5 %    97.5 %
(Intercept)  -5.6262     0.2008 -28.021 9.132e-173 -6.0385 -5.249799
cityHorsens  -0.3345     0.1827  -1.830  6.719e-02 -0.6946  0.023561
cityKolding  -0.3764     0.1890  -1.991  4.646e-02 -0.7504 -0.007412
cityVejle    -0.2760     0.1891  -1.459  1.444e-01 -0.6503  0.093162
age55-59      1.1070     0.2490   4.445  8.771e-06  0.6159  1.596828
age60-64      1.5291     0.2325   6.577  4.812e-11  1.0760  1.991225
age65-69      1.7819     0.2305   7.732  1.061e-14  1.3335  2.240675
age70-74      1.8727     0.2365   7.918  2.415e-15  1.4105  2.341695
age75+        1.4289     0.2512   5.688  1.289e-08  0.9328  1.922467
```

```
m.p <- glm(cases ~ offset(log(pop)) + city + age, family = poisson, data = eba1977)
cbind(summary(m.p)$coefficients, confint(m.p))
```

```
             Estimate Std. Error z value   Pr(>|z|)   2.5 %    97.5 %
(Intercept)  -5.6321     0.2003 -28.125 4.911e-174 -6.0433 -5.256725
cityHorsens  -0.3301     0.1815  -1.818  6.899e-02 -0.6878  0.025582
cityKolding  -0.3715     0.1878  -1.978  4.789e-02 -0.7432 -0.004967
cityVejle    -0.2723     0.1879  -1.450  1.472e-01 -0.6441  0.094356
age55-59      1.1010     0.2483   4.434  9.230e-06  0.6114  1.589441
age60-64      1.5186     0.2316   6.556  5.528e-11  1.0672  1.979110
age65-69      1.7677     0.2294   7.704  1.314e-14  1.3213  2.224503
age70-74      1.8569     0.2353   7.891  3.005e-15  1.3970  2.323556
age75+        1.4197     0.2503   5.672  1.408e-08  0.9254  1.911381
```

The expected proportion/rate of cases in Fredericia appears to be the highest. Let's compare that city with the others while controlling for age.

```r
trtools::contrast(m.b,
  a = list(city = "Fredericia", age = "40-54"),
  b = list(city = c("Horsens","Kolding","Vejle"), age = "40-54"),
  cnames = c("vs Horsens","vs Kolding","vs Vejle"), tf = exp)
```

```
           estimate  lower upper
vs Horsens    1.397 0.9766 1.999
vs Kolding    1.457 1.0059 2.110
vs Vejle      1.318 0.9097 1.909
```

```r
trtools::contrast(m.p,
  a = list(city = "Fredericia", age = "40-54", pop = 1),
  b = list(city = c("Horsens","Kolding","Vejle"), age = "40-54", pop = 1),
  cnames = c("vs Horsens","vs Kolding","vs Vejle"), tf = exp)
```

```
           estimate  lower upper
vs Horsens    1.391 0.9746 1.985
vs Kolding    1.450 1.0035 2.095
vs Vejle      1.313 0.9086 1.897
```

Note that since there is no interaction in the model, contrasts for city will not depend on the age group. We can also compute the estimated expected proportion (i.e., probability) or expected rate for each model.

```r
trtools::contrast(m.b, a = list(city = levels(eba1977$city), age = "40-54"), tf = plogis)
```

```
 estimate    lower    upper
 0.003589 0.002424 0.005311
 0.002571 0.001701 0.003885
 0.002466 0.001625 0.003741
 0.002726 0.001787 0.004155
```

```r
trtools::contrast(m.p, a = list(city = levels(eba1977$city), age = "40-54", pop = 1), tf = exp)
```

```
 estimate    lower    upper
 0.003581 0.002419 0.005303
 0.002574 0.001704 0.003890
 0.002470 0.001628 0.003747
 0.002727 0.001789 0.004158
```

```r
d <- expand.grid(city = levels(eba1977$city), age = levels(eba1977$age))
cbind(d, glmint(m.b, newdata = d))
```

```
         city   age      fit      low      upp
1  Fredericia 40-54 0.003589 0.002424 0.005311
2     Horsens 40-54 0.002571 0.001701 0.003885
3     Kolding 40-54 0.002466 0.001625 0.003741
4       Vejle 40-54 0.002726 0.001787 0.004155
5  Fredericia 55-59 0.010780 0.007192 0.016129
6     Horsens 55-59 0.007739 0.005135 0.011648
7     Kolding 55-59 0.007424 0.004884 0.011270
8       Vejle 55-59 0.008201 0.005378 0.012487
9  Fredericia 60-64 0.016348 0.011360 0.023473
10    Horsens 60-64 0.011755 0.008104 0.017024
11    Kolding 60-64 0.011278 0.007702 0.016489
12      Vejle 60-64 0.012454 0.008520 0.018170
13 Fredericia 65-69 0.020952 0.014654 0.029876
14    Horsens 65-69 0.015086 0.010513 0.021604
```

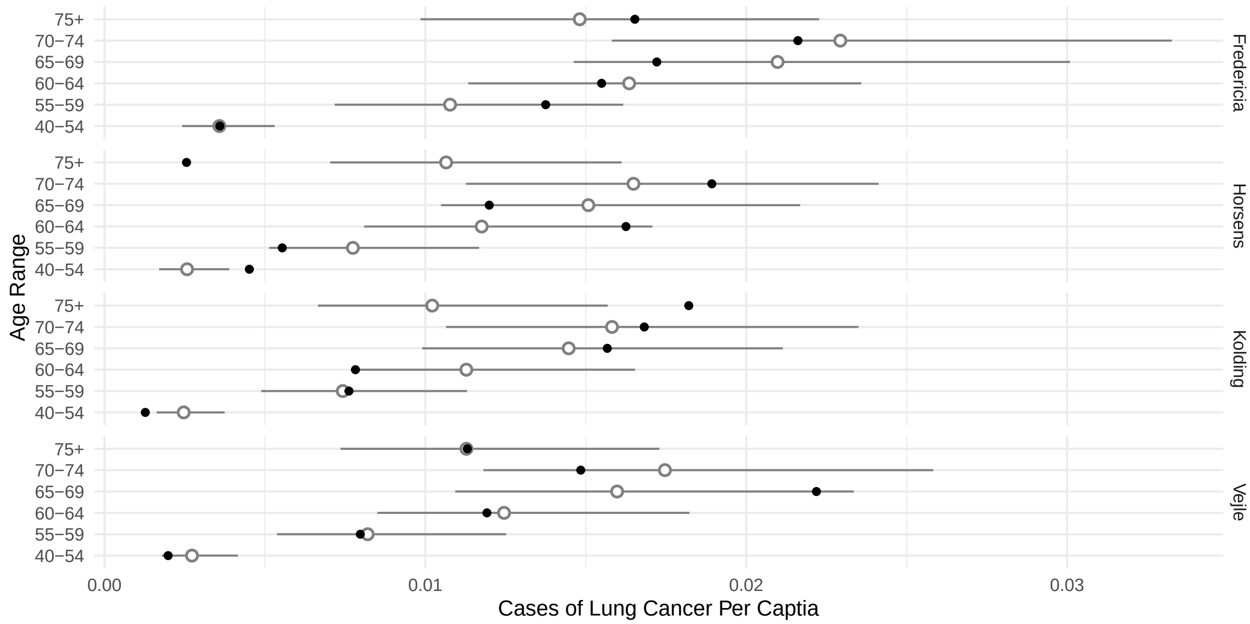
```
15    Kolding 65-69 0.014476 0.009925 0.021069
16      Vejle 65-69 0.015979 0.010956 0.023252
17 Fredericia 70-74 0.022898 0.015845 0.032986
18    Horsens 70-74 0.016496 0.011299 0.024025
19    Kolding 70-74 0.015830 0.010679 0.023407
20      Vejle 70-74 0.017471 0.011844 0.025703
21 Fredericia   75+ 0.014812 0.009872 0.022169
22    Horsens   75+ 0.010646 0.007042 0.016065
23    Kolding   75+ 0.010214 0.006661 0.015633
24      Vejle   75+ 0.011280 0.007368 0.017232
```

```r
d <- expand.grid(city = levels(eba1977$city), age = levels(eba1977$age), pop = 1)
cbind(d, glmint(m.p, newdata = d))
```

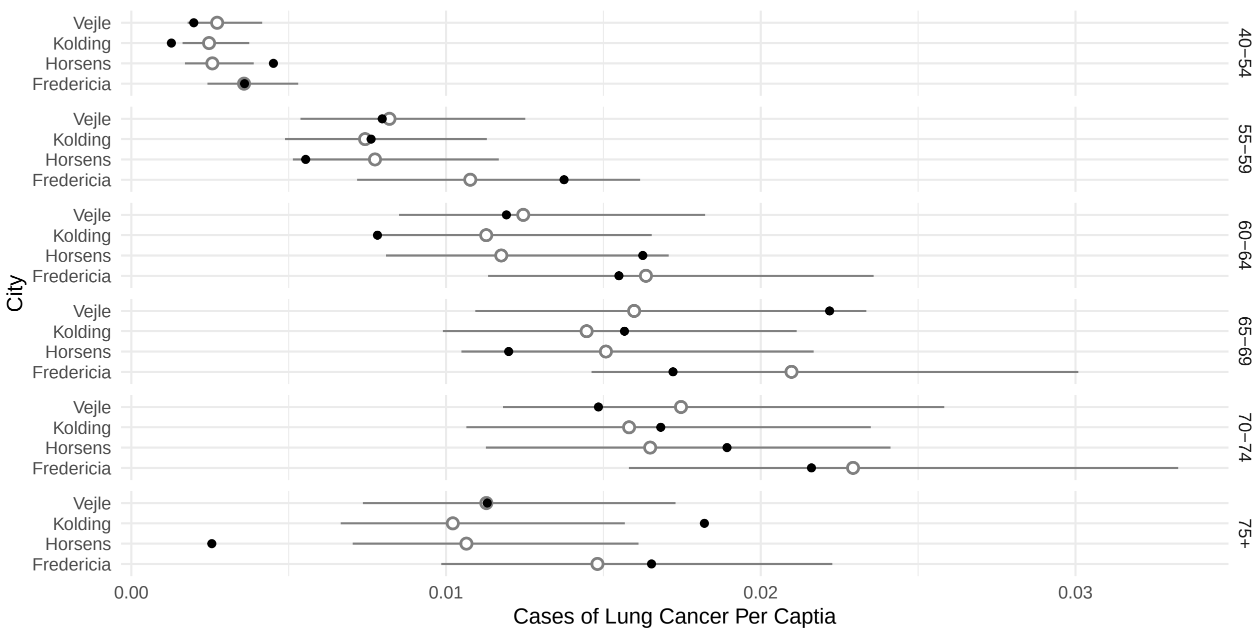
```
         city   age pop      fit      low      upp
1  Fredericia 40-54   1 0.003581 0.002419 0.005303
2     Horsens 40-54   1 0.002574 0.001704 0.003890
3     Kolding 40-54   1 0.002470 0.001628 0.003747
4       Vejle 40-54   1 0.002727 0.001789 0.004158
5  Fredericia 55-59   1 0.010769 0.007174 0.016167
6     Horsens 55-59   1 0.007742 0.005133 0.011676
7     Kolding 55-59   1 0.007427 0.004883 0.011297
8       Vejle 55-59   1 0.008202 0.005375 0.012517
9  Fredericia 60-64   1 0.016351 0.011335 0.023587
10    Horsens 60-64   1 0.011755 0.008092 0.017075
11    Kolding 60-64   1 0.011277 0.007690 0.016536
12      Vejle 60-64   1 0.012453 0.008506 0.018231
13 Fredericia 65-69   1 0.020976 0.014623 0.030090
14    Horsens 65-69   1 0.015080 0.010488 0.021681
15    Kolding 65-69   1 0.014467 0.009899 0.021141
16      Vejle 65-69   1 0.015976 0.010929 0.023354
17 Fredericia 70-74   1 0.022932 0.015810 0.033263
18    Horsens 70-74   1 0.016486 0.011266 0.024123
19    Kolding 70-74   1 0.015816 0.010646 0.023497
20      Vejle 70-74   1 0.017466 0.011810 0.025830
21 Fredericia   75+   1 0.014811 0.009848 0.022273
22    Horsens   75+   1 0.010647 0.007034 0.016116
23    Kolding   75+   1 0.010214 0.006654 0.015681
24      Vejle   75+   1 0.011280 0.007358 0.017292
```

We can use this to make some helpful plots of the estimated rates (or probabilities) of lung cancer.

```r
d <- expand.grid(age = levels(eba1977$age), city = levels(eba1977$city), pop = 1)
d <- cbind(d, glmint(m.p, newdata = d))
p <- ggplot(eba1977, aes(x = age, y = cases/pop)) +
  geom_pointrange(aes(y = fit, ymin = low, ymax = upp),
    shape = 21, fill = "white", data = d, color = grey(0.5)) +
  geom_point() + facet_grid(city ~ .) + coord_flip() +
  labs(x = "Age Range", y = "Cases of Lung Cancer Per Captia") +
  theme_minimal()
plot(p)
```

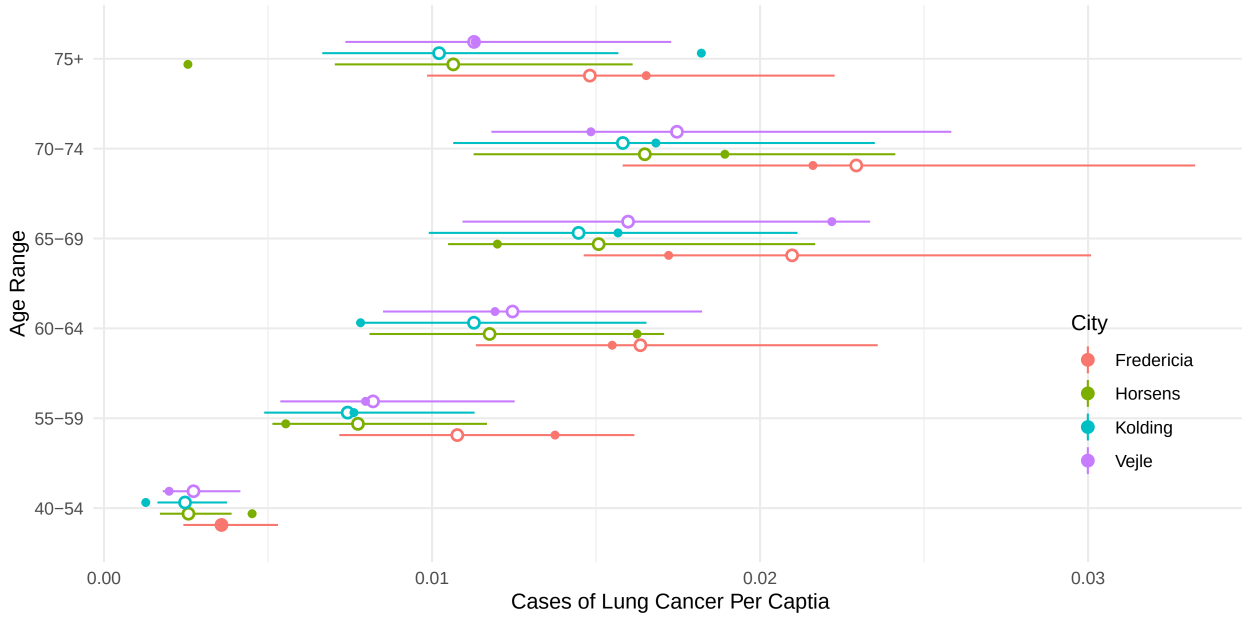



```
p <- ggplot(eba1977, aes(x = city, y = cases/pop)) +
  geom_pointrange(aes(y = fit, ymin = low, ymax = upp),
    shape = 21, fill = "white", data = d, color = grey(0.5)) +
  geom_point() + facet_grid(age ~ .) + coord_flip() +
  labs(x = "City", y = "Cases of Lung Cancer Per Captia") +
  theme_minimal()
plot(p)
```




```
p <- ggplot(eba1977, aes(x = age, y = cases/pop, color = city)) +
  geom_pointrange(aes(y = fit, ymin = low, ymax = upp),
    shape = 21, fill = "white", data = d,
      position = position_dodge(width = 0.5)) +
  geom_point(position = position_dodge(width = 0.5)) +
```

```r
  coord_flip() +
  labs(x = "Age Range", y = "Cases of Lung Cancer Per Captia",
       color = "City") +
  theme_minimal() + theme(legend.position = c(0.9,0.3))
plot(p)
```



Separation and Infinite Parameter Estimates

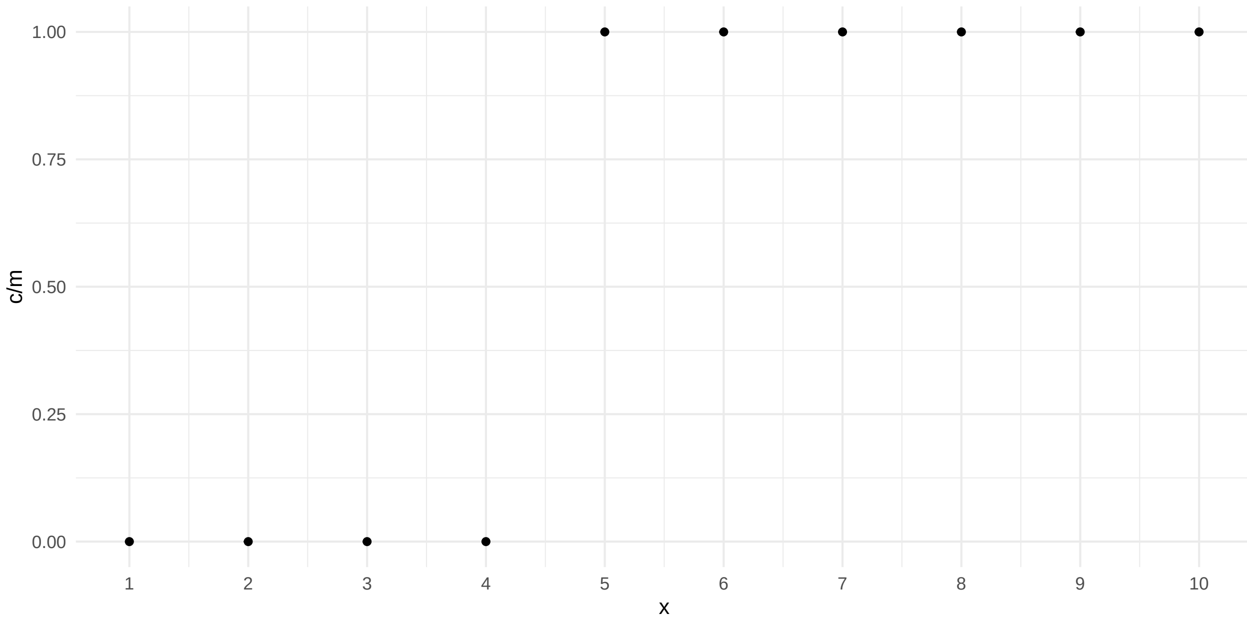
Some GLMs are prone to numerical problems due to (nearly) infinite parameter estimates.

Example: Consider the following data.

```r
mydata <- data.frame(m = rep(20, 10), c = rep(c(0,20), c(4,6)), x = 1:10)
mydata
```

```
    m  c  x
1  20  0  1
2  20  0  2
3  20  0  3
4  20  0  4
5  20 20  5
6  20 20  6
7  20 20  7
8  20 20  8
9  20 20  9
10 20 20 10
```

```r
p <- ggplot(mydata, aes(x = x, y = c/m)) + theme_minimal() +
  geom_point() + scale_x_continuous(breaks = 1:10)
plot(p)
```



If we try to estimate a logistic regression model we get errors and some extreme estimates, standard errors, and confidence intervals.

```
m <- glm(cbind(c,m-c) ~ x, family = binomial, data = mydata)
```

```
Warning: glm.fit: algorithm did not converge

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(m)$coefficients
```

```
            Estimate Std. Error   z value Pr(>|z|)
(Intercept)  -212.11     114489 -0.001853   0.9985
x              47.12      25082  0.001879   0.9985
```

```
confint(m)
```

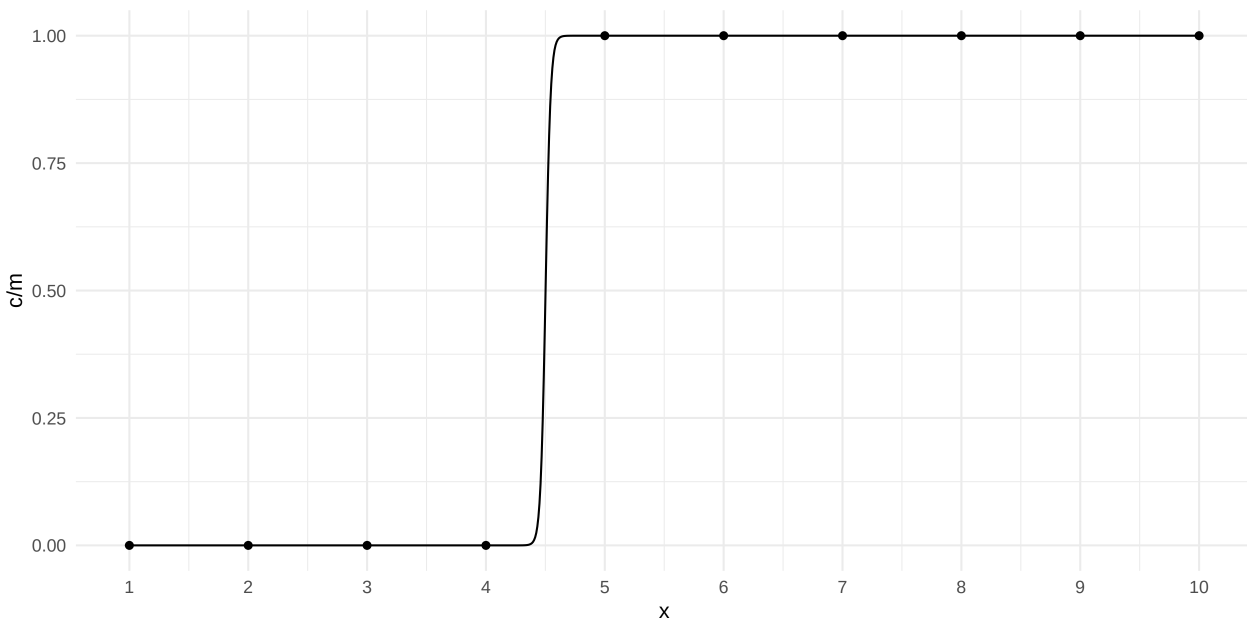
```
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: algorithm did not converge

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
             2.5 % 97.5 %
(Intercept) -29559 -28057
x             7969   1966
```

But we can still plot the model.

```
d <- data.frame(x = seq(1, 10, length = 1000))
d$yhat <- predict(m, newdata = d, type = "response")
```

```
p <- p + geom_line(aes(y = yhat), data = d)
plot(p)
```



The problem is that the estimation procedure "wants" the curve to be a step function, but that only occurs as $\beta_1 \to \infty$, and the value of x where the estimated expected response is 0.5 equals $-\beta_0/\beta_1$, and for the step function that would be 4.5, so the estimation procedure "wants" the estimate of β_0 to be $-\beta_1 5.5 = -\infty$. This is called *separation*. It is fairly obvious with a single explanatory variable, but much less so with multiple explanatory variables. The example above shows *complete separation* because we can separate the values of y based on the values of x. *Quasi-separation* occurs when this is almost true as in the following example.

```
mydata <- data.frame(m = rep(20, 50), x = seq(1, 10, length = 50),
  c = rep(c(0,20,0,20), c(24,1,1,24)))

m <- glm(cbind(c,m-c) ~ x, family = binomial, data = mydata)
```

```
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(m)$coefficients
```

```
            Estimate Std. Error z value  Pr(>|z|)
(Intercept)  -39.231      5.542  -7.079 1.448e-12
x              7.133      1.006   7.087 1.371e-12
```

```
confint(m)
```

```
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```
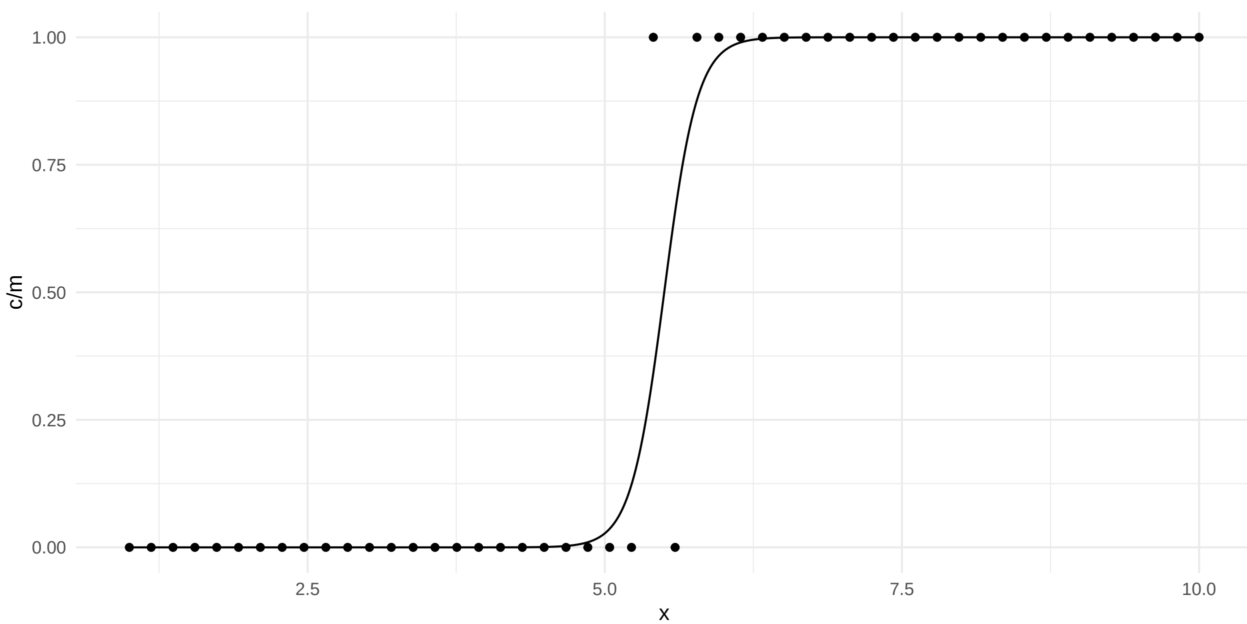

```
              2.5 %  97.5 %
(Intercept) -51.696 -29.767
x             5.414   9.397
```

```
d <- data.frame(x = seq(1, 10, length = 10000))
d$yhat <- predict(m, newdata = d, type = "response")

p <- ggplot(mydata, aes(x = x, y = c/m)) + theme_minimal()
p <- p + geom_point() + geom_line(aes(y = yhat), data = d)
plot(p)
```



Example: Consider the following data.

```
mydata <- data.frame(m = c(100,100), c = c(25,100), group = c("control","treatment"))
mydata
```

```
    m   c     group
1 100  25   control
2 100 100 treatment
```

```
m <- glm(cbind(c,m-c) ~ group, family = binomial, data = mydata)
summary(m)$coefficients
```

```
               Estimate Std. Error    z value  Pr(>|z|)
(Intercept)      -1.099  2.309e-01 -4.7571308 1.964e-06
grouptreatment   28.410  5.169e+04  0.0005496 9.996e-01
```

```r
confint(m)
```

```
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
Warning in regularize.values(x, y, ties, missing(ties), na.rm = na.rm): collapsing to
unique 'x' values
```

```
                   2.5 %     97.5 %
(Intercept)       -1.571    -0.6611
grouptreatment -1849.427 18872.0265
```

A similar problem can happen in Poisson regression where the observed count or rate in a category is zero.

Example: Consider the following data and model.

```r
mydata <- data.frame(y = c(20, 10, 50, 15, 0), x = letters[1:5])
mydata
```

```
   y x
1 20 a
2 10 b
3 50 c
4 15 d
5  0 e
```

```r
m <- glm(y ~ x, family = poisson, data = mydata)
summary(m)$coefficients
```

```
            Estimate Std. Error     z value  Pr(>|z|)
(Intercept)   2.9957  2.236e-01 13.3973220 6.268e-41
xb           -0.6931  3.873e-01 -1.7896983 7.350e-02
xc            0.9163  2.646e-01  3.4632534 5.337e-04
xd           -0.2877  3.416e-01 -0.8422469 3.996e-01
xe          -25.2983  4.225e+04 -0.0005988 9.995e-01
```

```r
confint(m)
```

```
Warning: glm.fit: fitted rates numerically 0 occurred

Warning: glm.fit: fitted rates numerically 0 occurred

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```

```
Warning: glm.fit: fitted rates numerically 0 occurred

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Warning: glm.fit: fitted rates numerically 0 occurred

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Warning: glm.fit: fitted rates numerically 0 occurred
Error: no valid set of coefficients has been found: please supply starting values
```

There are some solutions to this problem, depending on the circumstances.

1. In simple cases such as the logistic regression example with a control and treatment group, a nonparametric approach could be used for a significance test (e.g., Fisher's exact test).
2. In some cases with a categorical explanatory variable, we can omit the level(s) where the observed count is zero (in Poisson regression), or the observed proportion is 0 or 1 (in logistic regression). Clearly this precludes inferences concerning that level or its relationship with other levels.
3. For logistic regression (or similar models) a "penalized" or "bias-reduced" estimation method can be used (see the **logistf** and **brglm** packages).