

Oceń istotność klimatyzacji i wspomagania kierownicy

		slaba	wazna	istotna
kobieta	18-23	26	12	7
	24-40	9	21	15
	> 40	5	14	41
mezczyzna	18-23	40	17	8
	24-40	17	15	12
	> 40	8	15	18

```
> sam <- read.csv2("car pref.csv",header=T)
> str(sam)
'data.frame': 6 obs. of 5 variables:
 $ plec : Factor w/ 2 levels "kobieta","mezczyzna": 1 1 1 2 2 2
 $ wiek : Factor w/ 3 levels "> 40","18-23",...: 2 3 1 2 3 1
 $ slaba : int 26 9 5 40 17 8
 $ wazna : int 12 21 14 17 15 15
 $ istotna: int 7 15 41 8 12 18
> sam
      plec wiek slaba wazna istotna
1  kobieta 18-23   26    12        7
2  kobieta 24-40    9    21       15
3  kobieta > 40    5    14       41
4 mezczyzna 18-23   40    17        8
5 mezczyzna 24-40   17    15       12
6 mezczyzna > 40    8    15       18
```

```
> sam.cum <- vglm(cbind(slaba,wazna,istotna) ~ plec+wiek,
+                 cumulative(parallel = T), sam)
> summaryvglm(sam.cum)
```

Call:
vglm(formula = cbind(slaba, wazna, istotna) ~ plec + wiek, family =
cumulative(parallel = T),
data = sam)

Pearson Residuals:

	logit(P[Y<=1])	logit(P[Y<=2])
1	0.95793	-0.098683
2	-0.96742	0.846533
3	-0.34411	-0.619797
4	-0.42225	-0.646801
5	0.31052	-0.381841
6	0.36443	0.714200

Coefficients:

	Value	Std. Error	t value
(Intercept):1	-2.18892	0.25767	-8.4951
(Intercept):2	-0.57748	0.22152	-2.6070
plecmezczyzna	0.57622	0.22611	2.5484
wiek18-23	2.23246	0.29042	7.6871
wiek24-40	1.08536	0.28179	3.8516

Number of linear predictors: 2

Names of linear predictors: logit(P[Y<=1]), logit(P[Y<=2])

Dispersion Parameter for cumulative family: 1

Residual Deviance: 4.53207 on 7 degrees of freedom

Log-likelihood: -25.6671 on 7 degrees of freedom

Number of Iterations: 4

```
> print(sam.cum@y,digits=2)
  slaba wazna istotna
1 0.578 0.27 0.16
2 0.200 0.47 0.33
3 0.083 0.23 0.68
4 0.615 0.26 0.12
5 0.386 0.34 0.27
6 0.195 0.37 0.44

> print(fitted.values(sam.cum),digits=2)
  slaba wazna istotna
1 0.51 0.33 0.160  $\log(\pi_1/(\pi_2 + \pi_3)) = -2.19 + 2.23$  ;  $\log((\pi_1 + \pi_2)/\pi_3) = -0.58 + 2.23$ 
2 0.25 0.38 0.376
3 0.10 0.26 0.640
4 0.65 0.25 0.097
5 0.37 0.38 0.253
6 0.17 0.33 0.500
```

Call:
 vglm(formula = cbind(slaba, wazna, istotna) ~ plec + wiek, family =
 cumulative(parallel = F),
 data = sam)

Pearson Residuals:

	logit(P[Y<=1])	logit(P[Y<=2])
1	0.79366	0.23746
2	-0.66798	0.53146
3	-0.32852	-0.62802
4	-0.69114	-0.22426
5	0.57329	-0.62731
6	0.33999	0.73078

Coefficients:

	Value	Std. Error	t value
(Intercept):1	-2.19565	0.32917	-6.6704
(Intercept):2	-0.57655	0.23313	-2.4730
plecmezczyzna:1	0.59071	0.26736	2.2094
plecmezczyzna:2	0.57225	0.26851	2.1312
wiek18-23:1	2.25992	0.35864	6.3013
wiek18-23:2	2.10268	0.34508	6.0933
wiek24-40:1	1.01352	0.38046	2.6639
wiek24-40:2	1.15365	0.30934	3.7294

Number of linear predictors: 2

Names of linear predictors: logit(P[Y<=1]), logit(P[Y<=2])

Dispersion Parameter for cumulative family: 1

Residual Deviance: 3.8306 on 4 degrees of freedom

Log-likelihood: -25.31637 on 4 degrees of freedom

Number of Iterations: 5

```
> pchisq(2 * (logLik(sam.cum) - logLik(sam.cumnpar)),
+       df = 7 - 4, lower.tail = F)
[1] 1
```

```
> dev.pvalue <- function (model1, model2) {
+   pchisq(deviance(model1) - deviance(model2),
+         df = df.residual(model1)-df.residual(model2), lower.tail = F)
+ }
> dev.pvalue(sam.cum,sam.cumnpar)
[1] 0.872859
```

```
> llik.pvalue <- function (model1, model2) {
```

```
+ pchisq(2 * (logLik(model1) - logLik(model2)),
+       df = df.residual(model1)-df.residual(model2), lower.tail = F)
+ }
> lik.pvalue(sam.cum,sam.cumnpa)
[1] 1
```

```
> sam.acat <- vglm(cbind(slaba,wazna,istotna) ~ plec+wiek,acat, sam)
> summaryvglm(sam.acat)
```

```
Call:
vglm(formula = cbind(slaba, wazna, istotna) ~ plec + wiek, family = acat,
      data = sam)
```

```
Pearson Residuals:
      log(P[Y=2]/P[Y=1]) log(P[Y=3]/P[Y=2])
1          -0.66013          -0.33828
2           0.69753          -0.57779
3           0.18263           0.71000
4           0.56290           0.40425
5          -0.63342           0.64241
6          -0.12802          -0.84141
```

```
Coefficients:
              value Std. Error t value
(Intercept):1    0.99691    0.36851  2.7053
(Intercept):2    0.88077    0.25961  3.3927
plecmezczyzna:1 -0.38813    0.30051 -1.2916
plecmezczyzna:2 -0.42489    0.30057 -1.4136
wiek18-23:1     -1.58771    0.40290 -3.9407
wiek18-23:2     -1.32904    0.39251 -3.3860
wiek24-40:1     -0.45944    0.42268 -1.0870
wiek24-40:2     -0.97920    0.34242 -2.8596
```

```
Number of linear predictors: 2
```

```
Names of linear predictors: log(P[Y=2]/P[Y=1]), log(P[Y=3]/P[Y=2])
```

```
Dispersion Parameter for acat family: 1
```

```
Residual Deviance: 3.93871 on 4 degrees of freedom
```

```
Log-likelihood: -25.37042 on 4 degrees of freedom
```

```
Number of Iterations: 3
```

```
> pu.or <- function(b,sb,q=1.96) {
+   print(c(exp(b-q*sb),exp(b+q*sb)),digits=2)
+ }
```

```
#mężczyzna
> pu.or(-0.38813,0.30051)
[1] 0.38 1.22
> pu.or(-0.42489,0.30057)
[1] 0.36 1.18
```

```
> pu.or(-0.45944,0.42268)#wiek24-40:1
[1] 0.28 1.45
```

```
> sam.acatw <- vglm(cbind(slaba,wazna,istotna) ~ wiek,acat, sam)
> summaryvglm(sam.acatw)
```

```
Call:
vglm(formula = cbind(slaba, wazna, istotna) ~ wiek, family = acat,
      data = sam)
```

```
Pearson Residuals:
      log(P[Y=2]/P[Y=1]) log(P[Y=3]/P[Y=2])
```

1	0.24392	0.31726
2	1.35985	0.14700
3	0.66976	1.45820
4	-0.20296	-0.26398
5	-1.37521	-0.14866
6	-0.81023	-1.76401

Coefficients:

	Value	Std. Error	t value
(Intercept):1	0.80235	0.33378	2.4039
(Intercept):2	0.71024	0.22679	3.1318
wiek18-23:1	-1.62471	0.40130	-4.0486
wiek18-23:2	-1.36949	0.39062	-3.5060
wiek24-40:1	-0.47692	0.42148	-1.1315
wiek24-40:2	-0.99792	0.34095	-2.9269

Number of linear predictors: 2

Names of linear predictors: $\log(P[Y=2]/P[Y=1])$, $\log(P[Y=3]/P[Y=2])$

Dispersion Parameter for acat family: 1

Residual Deviance: 10.44389 on 6 degrees of freedom

Log-likelihood: -28.62301 on 6 degrees of freedom

Number of Iterations: 4

```
> dev.pvalue(sam.acatw,sam.acat)
```

```
[1] 0.03867396
```

```
> llik.pvalue(sam.acatw,sam.acat)
```

```
[1] 1
```

```
> print(fitted.values(sam.acat),digits=2)
```

	slaba	wazna	istotna
1	0.524	0.29	0.19
2	0.235	0.40	0.36
3	0.098	0.26	0.64
4	0.652	0.25	0.10
5	0.351	0.41	0.24
6	0.174	0.32	0.51

```
> sam.sratio <- vglm(cbind(slaba,wazna,istotna) ~ plec+wiek,
+                    sratio(parallel=T, reverse=T), sam)
> summaryvglm(sam.sratio)
```

Call:

```
vglm(formula = cbind(slaba, wazna, istotna) ~ plec + wiek, family =
sratio(parallel = T,
reverse = T), data = sam)
```

Pearson Residuals:

	$\text{logit}(P[Y=2 Y \leq 2])$	$\text{logit}(P[Y=3 Y \leq 3])$
1	-0.66920	-0.45810
2	0.95693	-0.68425
3	-0.68095	1.11955
4	0.78748	0.21289
5	-0.18895	0.10870
6	-0.59534	-0.52284

Coefficients:

	Value	Std. Error	t value
(Intercept):1	1.41937	0.25955	5.4687
(Intercept):2	0.45966	0.20233	2.2718
plecmezczyzna	-0.54043	0.20227	-2.6719
wiek18-23	-1.96319	0.25841	-7.5972
wiek24-40	-0.93685	0.24868	-3.7673

Number of linear predictors: 2

Names of linear predictors: $\text{logit}(P[Y=2|Y \leq 2])$, $\text{logit}(P[Y=3|Y \leq 3])$

Dispersion Parameter for sratio family: 1

Residual Deviance: 5.11479 on 7 degrees of freedom

Log-likelihood: -25.95846 on 7 degrees of freedom

Number of Iterations: 4

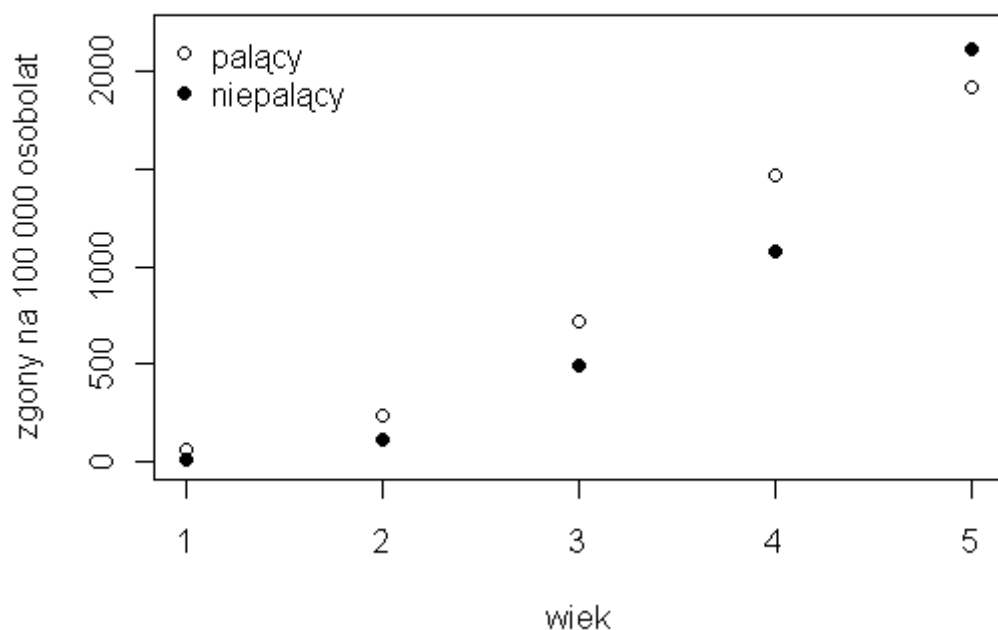
REGRESJA POISSONA

Zgony z powodu niedokrwiennej choroby serca po 10 latach obserwacji
(lekarze z Wlk Brytanii)

wiek	palenie	zgony	osobolata
35 to 44	smoker	32	52407
45 to 54	smoker	104	43248
55 to 64	smoker	206	28612
65 to 74	smoker	186	12663
75 to 84	smoker	102	5317
35 to 44	non-smoker	2	18790
45 to 54	non-smoker	12	10673
55 to 64	non-smoker	28	5710
65 to 74	non-smoker	28	2585
75 to 84	non-smoker	31	1462

```
> pal <- transform(pal, w=rep(1:5,2),w2=rep(1:5,2)^2 )
> str(pal)
'data.frame': 10 obs. of 6 variables:
 $ wiek      : Factor w/ 5 levels "35 to 44","45 to 54",...: 1 2 3 4 5 1 2 3
4 5
 $ palenie   : Factor w/ 2 levels "non-smoker","smoker": 2 2 2 2 2 1 1 1 1 1
 $ zgony     : int 32 104 206 186 102 2 12 28 28 31
 $ osobolata: int 52407 43248 28612 12663 5317 18790 10673 5710 2585 1462
 $ w        : int 1 2 3 4 5 1 2 3 4 5
 $ w2       : num 1 4 9 16 25 1 4 9 16 25

> with(pal,plot(w[1:5],zgony[1:5]*100000/osobolata[1:5],ylim=c(0,2200),
+           xlab="wiek",ylab="zgony na 100 000 osobolat"))
> with(pal,points(w[1:5],zgony[6:10]*100000/osobolata[6:10],pch=16))
> legend("topleft",c("palacy","niepalacy"),bty="n",pch=c(1,16))
```



```
> pal.m2 <- glm(zgony ~ w +w2+ palenie + w*palenie,offset=log(osobolata),
+               family=poisson, data=pal)
> summary(pal.m2)
```

Call:
 glm(formula = zgony ~ w + w2 + palenie + w * palenie, family = poisson,
 data = pal, offset = log(osobolata))

Deviance Residuals:

1	2	3	4	5	6	7	8	9	10
0.43820	-0.27329	-0.15265	0.23393	-0.05700	-0.83049	0.13404	0.64107	-0.41058	-0.01275

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-10.79176	0.45008	-23.978	< 2e-16 ***
w	2.37648	0.20795	11.428	< 2e-16 ***
w2	-0.19768	0.02737	-7.223	5.08e-13 ***
paleniesmoker	1.44097	0.37220	3.872	0.000108 ***
w:paleniesmoker	-0.30755	0.09704	-3.169	0.001528 **

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

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 935.0673 on 9 degrees of freedom
 Residual deviance: 1.6354 on 5 degrees of freedom
 AIC: 66.703

Number of Fisher Scoring iterations: 4

```
expected <- predict(pal.m2,type="response")
Pearsonres <- with(pal,(zgony-expected)/sqrt(expected))
Devianceres <-with(pal,
+                 sign(zgony-expected)*
+                 sqrt(2*(zgony*log(zgony/expected)-(zgony-expected))))

> with(pal,
```

```
+ cbind(wiek,palenie,zgony,expected,Pearsonres,Devianceres))
```

	wiek	palenie	zgony	expected	Pearsonres	Devianceres
1	1	2	32	29.6	0.444	0.438
2	2	2	104	106.8	-0.272	-0.273
3	3	2	206	208.2	-0.152	-0.153
4	4	2	186	182.8	0.235	0.234
5	5	2	102	102.6	-0.057	-0.057
6	1	1	2	3.4	-0.766	-0.830
7	2	1	12	11.5	0.135	0.134
8	3	1	28	24.7	0.655	0.641
9	4	1	28	30.2	-0.405	-0.411
10	5	1	31	31.1	-0.013	-0.013

Tempo przyrostu (Rate ratio)

$$RR = \frac{E(Y_i | present)}{E(Y_i | absent)} = e^{\beta_j}$$

```
> exp(coef(pa1.m2)[2:5])
```

w	w2	paleniesmoker	w:paleniesmoker
10.77	0.82	4.22	0.74