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LAMPIRAN

Lampiran 1

Data Asuransi Kendaraan *Automobile Claim Datasets in Australia* Tahun 2004-2005

No.	W_i	X_1	X_2	X_3	X_4	X_5	Y
1	0.30	1.06	1	5	1	5	0
2	0.65	1.03	3	5	1	2	0
3	0.57	3.26	3	13	1	5	0
4	0.32	4.14	3	11	1	5	0
5	0.65	0.72	2	5	1	5	0
6	0.85	2.01	1	4	2	2	0
7	0.85	1.60	1	8	2	2	0
8	0.56	1.47	3	5	2	3	0
9	0.36	0.52	2	5	1	4	0
10	0.52	0.38	2	5	1	5	0
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
425	0.85	3.14	1	12	2	6	2
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
2045	0.61	1.80	3	10	2	3	3
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
15147	0.85	2.20	1	11	1	4	4
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
67847	0.85	2.82	3	11	1	2	1
67848	0.93	0.73	2	10	2	1	1
67849	0.32	1.33	2	11	1	4	0
67850	0.68	1.98	3	5	1	4	1
67851	0.85	3.55	3	11	2	4	0
67852	0.65	1.07	3	10	2	3	0
67853	0.91	1.23	2	10	2	4	0
67854	0.31	1.93	2	11	2	4	0
67855	0.32	0.97	1	5	1	5	1
67856	0.25	1.02	1	5	2	6	0

Lampiran 2

One-Sample Kolmogorov-Smirnov Test

		X1	X2	X3	X4	X5	X6	Y
N		67856[c]	67856[d]	67856	67856	67856	67856	67856
Poisson Parameter[a,b]	**Mean**	.46865154	1.77702	2.31	8.79	1.43	3.31	.07
Most Extreme Differences	**Absolute**			.099	.275	.239	.085	.002
	Positive			.085	.187	.174	.052	.002
	Negative			-.099	-.275	-.239	-.085	-.002
Kolmogorov-Smirnov Z				25.856	71.693	62.269	22.063	.529
Asymp. Sig. (2-tailed)				.000	.000	.000	.000	.943

a. Test distribution is Poisson.

b. Calculated from data.

c. Poisson variables are non-negative integers. The value .002738 occurs in the data. One-Sample Kolmogorov-Smirnov Test cannot be performed.

d. Poisson variables are non-negative integers. The value .180 occurs in the data. One-Sample Kolmogorov-Smirnov Test cannot be performed.

Lampiran 3

Tabel *Kolmogorov-Smirnov*

SAMPLE SIZE (N)	LEVEL OF SIGNIFICANCE FOR D = MAXIMUM [$F_0(X) - S_n(X)$]				
	.20	.15	.10	.05	.01
1	.900	.925	.950	.975	.995
2	.684	.726	.776	.842	.929
3	.565	.597	.642	.708	.828
4	.494	.525	.564	.624	.733
5	.446	.474	.510	.565	.669
6	.410	.436	.470	.521	.618
7	.381	.405	.438	.486	.577
8	.358	.381	.411	.457	.543
9	.339	.360	.388	.432	.514
10	.322	.342	.368	.410	.490
11	.307	.326	.352	.391	.468
12	.295	.313	.338	.375	.450
13	.284	.302	.325	.361	.433
14	.274	.292	.314	.349	.418
15	.266	.283	.304	.338	.404
16	.258	.274	.295	.328	.392
17	.250	.266	.286	.318	.381
18	.244	.259	.278	.309	.371
19	.237	.252	.272	.301	.363
20	.231	.246	.264	.294	.356
25	.210	.220	.240	.270	.320
30	.190	.200	.220	.240	.290
35	.180	.190	.210	.230	.270
OVER 35	$\frac{1.07}{\sqrt{N}}$	$\frac{1.14}{\sqrt{N}}$	$\frac{1.22}{\sqrt{N}}$	$\frac{1.36}{\sqrt{N}}$	$\frac{1.63}{\sqrt{N}}$

Sumber : Sidney Siegel, N. John Castellan, Jr., *Nonparametric Statistic for the Behavioral Sciences Second Edition*.

Lampiran 4

Syntaks Rstudio untuk memperoleh model Regresi Poisson

#Beberapa package yang perlu diinstal

>install.packages("xts")

>library(xts)

>install.packages("sp")

>library(sp)

>install.packages("CASdatasets", repos = "http://cas.uqam.ca/pub/R/", type='source')

>library(CASdatasets)

>install.packages(“MASS”)

> library(MASS)

> summary(model.freqP <-glm(ClaimNb ~ VehValue + VehAge + VehBody + Gender + DrivAge + offset(log(Exposure)), family=poisson("log"), data=ausprivauto0405[ausprivauto0405$Exposure > 0,]))

Lampiran 5

Output Model Regresi Poisson

```
Call:
glm(formula = ClaimNb ~ VehValue + VehAge + VehBody + Gender +
    DrivAge + offset(log(Exposure)), family = poisson("log"),
    data = ausprivauto0405[ausprivauto0405$Exposure > 0, ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9082  -0.4524  -0.3462  -0.2213   4.5123

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              -1.19827    0.32076  -3.736 0.000187 **
*
VehValue                  0.02390    0.01720   1.390 0.164623
VehAgeoldest cars        -0.05933    0.04108  -1.444 0.148706
VehAgeyoung cars          0.11145    0.03967   2.810 0.004958 **
VehAgeyoungest cars       0.05550    0.04819   1.152 0.249471
VehBodyConvertible       -1.67029    0.66784  -2.501 0.012383 *
VehBodyCoupe             -0.51094    0.33695  -1.516 0.129432
VehBodyHardtop           -0.83353    0.32785  -2.542 0.011009 *
VehBodyHatchback         -0.97543    0.31821  -3.065 0.002174 **
VehBodyMinibus           -0.98426    0.35005  -2.812 0.004927 **
VehBodyMotorized caravan -0.38795    0.40942  -0.948 0.343344
VehBodyPanel van         -0.85291    0.33883  -2.517 0.011829 *
VehBodyRoadster          -0.56485    0.65987  -0.856 0.391995
VehBodySedan             -0.92396    0.31764  -2.909 0.003628 **
VehBodyStation wagon     -0.91190    0.31806  -2.867 0.004143 **
VehBodyTruck             -0.96325    0.32836  -2.933 0.003352 **
VehBodyUtility           -1.12006    0.32208  -3.478 0.000506 **
*
GenderMale               -0.02289    0.03009  -0.761 0.446929
DrivAgeolder work. people 0.21907    0.04891   4.479 7.50e-06 **
*
DrivAgeoldest people      0.01580    0.06433   0.246 0.806052
DrivAgeworking people     0.24752    0.04904   5.048 4.47e-07 **
*
DrivAgeyoung people       0.30747    0.05068   6.067 1.30e-09 **
*
DrivAgeyoungest people    0.47769    0.05904   8.091 5.93e-16 **
*
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 25507  on 67855  degrees of freedom
Residual deviance: 25343  on 67833  degrees of freedom
AIC: 34824

Number of Fisher Scoring iterations: 6
```

Lampiran 6

Syntaks dan Output Model Regresi Binomial Negatif

```
> library(MASS)

> summary(model.freqNB <-glm.nb(ClaimNb ~ VehValue + VehAge + VehBody

+ Gender + DrivAge + offset(log(Exposure)),

data=ausprivauto0405[ausprivauto0405$  Exposure > 0,]))
```

Output :

```
> library(MASS)
> summary(model.freqNB <-glm.nb(ClaimNb ~ VehValue + VehAge + VehBody + G
ender + DrivAge + offset(log(Exposure)), data=ausprivauto0405[ausprivauto
0405$Exposure > 0,]))
Call:
glm.nb(formula = ClaimNb ~ VehValue + VehAge + VehBody + Gender +
    DrivAge + offset(log(Exposure)), data = ausprivauto0405[ausprivauto04
05$Exposure >
    0, ], init.theta = 2.259193458, link = log)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8702  -0.4478  -0.3443  -0.2209   4.0965

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              -1.20475    0.33898  -3.554 0.000379 ***
VehValue                  0.02510    0.01761   1.425 0.154129
VehAgeoldest cars        -0.05695    0.04191  -1.359 0.174202
VehAgeyoung cars          0.11057    0.04056   2.726 0.006410 **
VehAgeyoungest cars       0.05229    0.04926   1.062 0.288415
VehBodyConvertible       -1.66779    0.68212  -2.445 0.014485 *
VehBodyCoupe             -0.50418    0.35526  -1.419 0.155852
VehBodyHardtop           -0.82954    0.34608  -2.397 0.016532 *
VehBodyHatchback         -0.96779    0.33647  -2.876 0.004024 **
VehBodyMinibus           -0.98261    0.36790  -2.671 0.007566 **
VehBodyMotorized caravan -0.38191    0.42929  -0.890 0.373659
VehBodyPanel van         -0.85100    0.35711  -2.383 0.017173 *
VehBodyRoadster          -0.57352    0.68854  -0.833 0.404874
VehBodySedan             -0.91782    0.33591  -2.732 0.
**
VehBodyStation wagon     -0.90735    0.33633  -2.698 0.006980 **
VehBodyTruck             -0.96101    0.34654  -2.773 0.005552 **
VehBodyUtility           -1.11621    0.34026  -3.280 0.001036 **
GenderMale               -0.02269    0.03074  -0.738 0.460470
DrivAgeolder work. people  0.21975    0.04983   4.410 1.04e-05 ***
DrivAgeoldest people       0.01496    0.06548   0.228 0.819310
DrivAgeworking people      0.24843    0.04997   4.971 6.65e-07 ***
DrivAgeyoung people        0.30730    0.05169   5.945 2.76e-09 ***
DrivAgeyoungest people     0.48138    0.06035   7.977 1.50e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for Negative Binomial(2.2592) family taken to be 1)

    Null deviance: 23577  on 67855  degrees of freedom
Residual deviance: 23420  on 67833  degrees of freedom
AIC: 34786

Number of Fisher Scoring iterations: 1
              Theta:  2.259
          Std. Err.:  0.417

 2 x log-likelihood:  -34738.308
```

Lampiran 7

Syntaks dan Output Model Regresi Poisson 2

```
> library(MASS)
> summary(model.freqP <-glm(ClaimNb ~ VehValue + VehAge + VehBody + Gender + DrivAge + offset(log(Exposure)), family=poisson("log"), data=ausprivauto0405[ausprivauto0405$Exposure > 0,]))
```

Output:

```
Call:
glm(formula = ClaimNb ~ VehAge + VehBody + DrivAge + offset(log(E
xposure)),
    family = poisson("log"), data = ausprivauto0405[ausprivauto04
05$Exposure >
        0, ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9012  -0.4525  -0.3464  -0.2215   4.5301

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)               -1.16900    0.31874  -3.668 0.000245 **
*
VehAgeoldest cars         -0.07893    0.03877  -2.036 0.041770 *
VehAgeyoung cars           0.12734    0.03798   3.353 0.000801 **
*
VehAgeyoungest cars        0.08494    0.04308   1.971 0.048673 *
VehBodyConvertible        -1.52138    0.65842  -2.311 0.020852 *
VehBodyCoupe              -0.49878    0.33686  -1.481 0.138691
VehBodyHardtop            -0.82380    0.32780  -2.513 0.011965 *
VehBodyHatchback          -0.98946    0.31773  -3.114 0.001845 **
VehBodyMinibus            -0.96918    0.34992  -2.770 0.005610 **
VehBodyMotorized caravan  -0.34923    0.40843  -0.855 0.392518
VehBodyPanel van          -0.86285    0.33876  -2.547 0.010862 *
VehBodyRoadster           -0.51845    0.65889  -0.787 0.431367
VehBodySedan              -0.92915    0.31749  -2.927 0.003427 **
VehBodyStation wagon      -0.89131    0.31777  -2.805 0.005034 **
VehBodyTruck              -0.95912    0.32827  -2.922 0.003481 **
VehBodyUtility            -1.11938    0.32206  -3.476 0.000509 **
*
DrivAgeolder work. people  0.21879    0.04889   4.475 7.65e-06 **
*
DrivAgeoldest people       0.01199    0.06427   0.187 0.852014
DrivAgeworking people      0.24848    0.04899   5.072 3.94e-07 **
*
DrivAgeyoung people        0.30816    0.05063   6.087 1.15e-09 **
*
DrivAgeyoungest people     0.47804    0.05903   8.099 5.56e-16 **
*
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 25507  on 67855  degrees of freedom
Residual deviance: 25345  on 67835  degrees of freedom
AIC: 34822

Number of Fisher Scoring iterations: 6
```

Lampiran 8

Syntaks dan Output Model Regresi Binomial Negatif 2

```
> summary(model.freqNB2 <-glm.nb(ClaimNb ~ VehAge + VehBody + Dri
vAge + offset(log(Exposure)), data=ausprivauto0405[ausprivauto040
5$Exposure > 0,]))
```

Output :

```
Call:
glm.nb(formula = ClaimNb ~ VehAge + VehBody + DrivAge + offset(lo
g(Exposure)),
    data = ausprivauto0405[ausprivauto0405$Exposure > 0, ], init.
theta = 2.26041257,
    link = log)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8637  -0.4480  -0.3444  -0.2211   4.1556

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)             -1.17389    0.33706  -3.483 0.000496 **
*
VehAgeoldest cars       -0.07741    0.03954  -1.957 0.050296 .
VehAgeyoung cars         0.12724    0.03883   3.277 0.001050 **
VehAgeyoungest cars      0.08306    0.04403   1.887 0.059207 .
VehBodyConvertible      -1.51297    0.67287  -2.249 0.024542 *
VehBodyCoupe            -0.49128    0.35525  -1.383 0.166692
VehBodyHardtop          -0.81872    0.34610  -2.366 0.018003 *
VehBodyHatchback        -0.98211    0.33607  -2.922 0.003474 **
VehBodyMinibus          -0.96621    0.36783  -2.627 0.008620 **
VehBodyMotorized caravan -0.34201   0.42845  -0.798 0.424715
VehBodyPanel van        -0.86015    0.35711  -2.409 0.016011 *
VehBodyRoadster         -0.52372    0.68765  -0.762 0.446296
VehBodySedan            -0.92280    0.33584  -2.748 0.006000 **
VehBodyStation wagon    -0.88511    0.33612  -2.633 0.008455 **
VehBodyTruck            -0.95583    0.34653  -2.758 0.005811 **
VehBodyUtility          -1.11452    0.34031  -3.275 0.001057 **
DrivAgeolder work. people  0.21937   0.04981   4.404 1.06e-05 **
*
DrivAgeoldest people       0.01097   0.06542   0.168 0.866770
DrivAgeworking people      0.24930   0.04992   4.993 5.93e-07 **
*
DrivAgeyoung people        0.30782   0.05163   5.962 2.50e-09 **
*
DrivAgeyoungest people     0.48159   0.06033   7.982 1.44e-15 **
*
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(2.2604) family taken
to be 1)

    Null deviance: 23578  on 67855  degrees of freedom
Residual deviance: 23423  on 67835  degrees of freedom
```

```
AIC: 34785

Number of Fisher Scoring iterations: 1


              Theta:  2.260
          Std. Err.:  0.417

 2 x log-likelihood:  -34740.666
```