

STK9900 – Assignment 2

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April 20, 2022

Problem 1

a)

This is a binary prediction, with a single predictor, making logarithmic regression a natural choice. The outcome of a logarithmic regression can be interpreted as a probability of either outcome, and is, unlikely e.g. linear regression bound to the interval $[0,1]$. The model takes the form

$$p(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \quad (1)$$

where $p(x)$ is the probability of one or more satellites, given a width x .

Performing the logarithmic regression in R, we get the following:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-12.3508	2.6287	-4.698	2.62e-06 ***
width	0.4972	0.1017	4.887	1.02e-06 ***

Meaning that $\beta_0 = -12.35$ and $\beta_1 = 0.497$.

b)

Let x_1 and x_0 be two width differing by 1 cm, such that $x_1 = x_0 + 1$ cm. The odds ratio between two predictor values is defined as

$$\text{OR} = \frac{p(x_1)/[1 - p(x_1)]}{p(x_0)/[1 - p(x_0)]} \quad (2)$$

which, inserting for 1, gives an odds ratio of presences of satellites of

$$\text{OR} = \frac{e^{\beta_0 + \beta_1[x_1 - x_0]}}{e^{\beta_0 + \beta_1 x_0}} = e^{\beta_1[x_1 - x_0]} = e^{\beta_1 \cdot 1 \text{ cm}} = 1.644 \quad (3)$$

This means there is a 64% increase in the *odds* of satellites with a 1 cm increase in width. The odds is the ratio between probabilities of successful and unsuccessful outcomes, and the odds ratio is simply the relative difference in this ratio between predictor values. An interesting result of logarithmic regression is the the odds ratio is independent of the actual predictor value, and only dependent on the change in predictor value. The odds increase is 64% for any 1 cm change in width.

In the limit that $p(x_0) \ll 1$ and $p(x_1) \ll 1$, the odds ratio is also the *relative ratio*, in which case the 64% can be interpreted directly as the increase in chance of satellites. However, for the mean width of 26.3 cm, we have that $p(x = 26.3 \text{ cm}) = \frac{e^{0.497 \cdot 26.3}}{1 + e^{0.497 \cdot 26.3}} = 0.674$, meaning the limit does not hold for typical values of the width.

Under the assumption that β_1 follows a normal distribution, its 95% confidence interval is $\beta_1 \pm 1.96 \cdot se(\beta_1) = [0.2989, 0.6975]$. Given that the β_1 confidence interval does not include 0, we can conclude that there is statistically significant correlation between the presence of satellites and width.

This translates into a confidence interval on the odds ratio of $e^{\beta_1 \pm 1.96 \cdot se(\beta_1)} = [1.348, 2.009]$.

c)

Weight. Weight is an obvious numerical predictor, as the values are naturally continuous, just as width. Using weight as a lone numerical predictor, we get the logarithmic regression result:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3.6947	0.8802	-4.198	2.70e-05 ***
weight	1.8151	0.3767	4.819	1.45e-06 ***

giving a 95% confidence interval of $[1.077, 2.553]$, which means that the weight also has a statistically significant correlation with the presence of satellites.

Color. As the colors are annotated in a logically ascending order, from lightest to darkest, we could leave it as a numerical predictor, to limit the number of predictors in use. However, it would be more suitable to use it as a categorical predictor, to allow for more non-linear modelling. Factoring the color with "medium light" as the reference, we get the following logarithmic regression results:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.0986	0.6667	1.648	0.0994 .
color_cat2	-0.1226	0.7053	-0.174	0.8620
color_cat3	-0.7309	0.7338	-0.996	0.3192
color_cat4	-1.8608	0.8087	-2.301	0.0214 *

We see that only the very darkest color gets a P-value below 0.05, and we can conclude that the darkest color is negatively correlated with satellite presence, although not with as much certainty as width or weight.

Spine. As with color, it makes more sense to treat the spine condition as a categorical predictor, giving the following logarithmic regression:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.8602	0.3597	2.392	0.0168 *
spine_cat2	-0.9937	0.6303	-1.577	0.1149
spine_cat3	-0.2647	0.4068	-0.651	0.5152

None of the spine conditions are correlated with satellite presence to a statistically significant degree.

d)

Using all predictors, we see that now none of them have statistically significant correlation with the satellite presence:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-8.06501	3.92855	-2.053	0.0401 *
width	0.26313	0.19530	1.347	0.1779
weight	0.82578	0.70383	1.173	0.2407
factor(color)2	-0.10290	0.78259	-0.131	0.8954
factor(color)3	-0.48886	0.85312	-0.573	0.5666
factor(color)4	-1.60867	0.93553	-1.720	0.0855 .
factor(spine)2	-0.09598	0.70337	-0.136	0.8915
factor(spine)3	0.40029	0.50270	0.796	0.4259

Especially notable are the width and weight, which were both highly significant. The explanation is pretty easy to imagine: They are almost entirely degenerate, as can be seen in figure 1. With this in mind, we chose to exclude one of them from our model. As the width is (ever so slightly) more statistically significant, we stick with the width only.

We try and add the spline and color separately, after having removed the weight, but now find that neither is statistically significant, after having included width in our model:

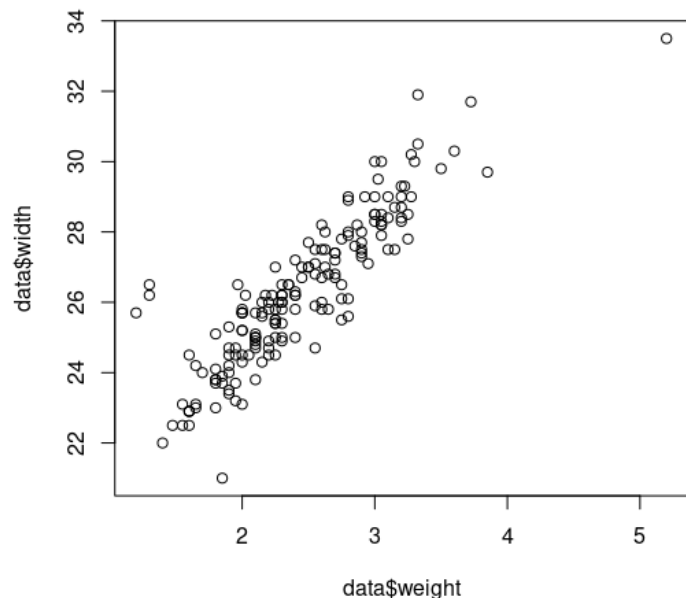


Figure 1: Scatter plot showing the relation between crab weight and width.

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-11.38519	2.87346	-3.962	7.43e-05 ***
width	0.46796	0.10554	4.434	9.26e-06 ***
factor(color)2	0.07242	0.73989	0.098	0.922
factor(color)3	-0.22380	0.77708	-0.288	0.773
factor(color)4	-1.32992	0.85252	-1.560	0.119

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-12.32899	2.78390	-4.429	9.48e-06 ***
width	0.49531	0.10480	4.726	2.28e-06 ***
factor(spine)2	-0.04290	0.70204	-0.061	0.951
factor(spine)3	0.04496	0.45222	0.099	0.921

We must therefore return to our original model of using the width as our only reliable predictor.

e)

We include width as a predictor in all our models, and test all 6 possible models with interactions between the 4 predictors.

width - weight

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.6580	12.2587	0.135	0.892
width	-0.1118	0.4827	-0.232	0.817
weight	-4.2244	5.5120	-0.766	0.443
width:weight	0.1904	0.2065	0.922	0.357

width - color

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1.75261	11.46409	-0.153	0.878
width	0.10600	0.42656	0.248	0.804
factor(color)2	-8.28735	12.00363	-0.690	0.490
factor(color)3	-19.76545	13.34251	-1.481	0.139
factor(color)4	-4.10122	13.27532	-0.309	0.757
width:factor(color)2	0.31287	0.44794	0.698	0.485
width:factor(color)3	0.75237	0.50435	1.492	0.136
width:factor(color)4	0.09443	0.50042	0.189	0.850

width - spine

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-9.8763	5.2009	-1.899	0.0576 .
width	0.4022	0.1966	2.045	0.0408 *
factor(spine)2	-4.6794	12.8215	-0.365	0.7151
factor(spine)3	-3.1353	6.1597	-0.509	0.6108
width:factor(spine)2	0.1817	0.5137	0.354	0.7236
width:factor(spine)3	0.1214	0.2345	0.518	0.6048

weight - color

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-6.85936	6.09032	-1.126	0.260
width	0.29519	0.19556	1.509	0.131

weight	0.02078	2.04378	0.010	0.992
factor(color)2	-1.02515	5.12717	-0.200	0.842
factor(color)3	-6.44370	5.58395	-1.154	0.249
factor(color)4	0.05708	5.49611	0.010	0.992
weight:factor(color)2	0.42993	1.99550	0.215	0.829
weight:factor(color)3	2.77120	2.25136	1.231	0.218
weight:factor(color)4	-0.68764	2.18951	-0.314	0.753

weight - spine

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-8.8999	4.1111	-2.165	0.0304 *
width	0.3054	0.1889	1.617	0.1059
weight	0.6414	0.9111	0.704	0.4815
factor(spine)2	-7.5008	6.5151	-1.151	0.2496
factor(spine)3	-0.2529	2.1217	-0.119	0.9051
weight:factor(spine)2	3.5066	3.0527	1.149	0.2507
weight:factor(spine)3	0.1329	0.8681	0.153	0.8784

color - spine

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-10.6940	3.0935	-3.457	0.000546 ***
width	0.4364	0.1097	3.976	7e-05 ***
factor(color)2	-0.1649	0.9609	-0.172	0.863768
factor(color)3	16.4709	2225.9261	0.007	0.994096
factor(color)4	-17.9993	3956.1804	-0.005	0.996370
factor(spine)2	17.4630	2793.2705	0.006	0.995012
factor(spine)3	-18.1302	3956.1804	-0.005	0.996343
factor(color)2:factor(spine)2	-17.7953	2793.2707	-0.006	0.994917
factor(color)3:factor(spine)2	-34.6376	3571.7094	-0.010	0.992262
factor(color)4:factor(spine)2	-15.4994	6253.4059	-0.002	0.998022
factor(color)2:factor(spine)3	18.7723	3956.1805	0.005	0.996214
factor(color)3:factor(spine)3	1.5081	4539.3953	0.000	0.999735
factor(color)4:factor(spine)3	35.0152	5594.8839	0.006	0.995007

None of the interactions are significant, and we are again left with our width-only model.

Problem 2

a)

The Poisson model is defined by the single parameter λ , which is assumed to equal both the expectation value and the variance in the data, $\lambda = E[y|x] = Var[y]$. In the Poisson model, this parameter is defined

$$\log \lambda_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \dots \quad (4)$$

When a count model has different numbers of subjects in each group, it is common to include an offset in the Poisson model. The reason for this is that the occurrences which we are counting often originate from the individual members of each group, and not the entirety of the group. In our case, we would expect the number of medals achieved to be roughly proportional to the number of athletes, and it makes more sense to model the medals achieved per athlete in a country, and not for all the athletes representing each country.

Substituting λ for $\lambda/\text{athletes}$ in the model above, we get

$$\log \frac{\lambda}{\text{athletes}} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \dots \quad (5)$$

$$\log \lambda - \log \text{athletes} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \dots \quad (6)$$

$$\log \lambda = \log \text{athletes} + \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \dots \quad (7)$$

where $\log \text{athletes}$ is called the *offset* of the model.

b)

With our chosen offset, we perform the Poisson regression, and get the following results:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2.862299	0.319076	-8.971	< 2e-16 ***
Total1996	0.011832	0.001607	7.364	1.79e-13 ***
Log.population	0.027510	0.031539	0.872	0.383
GDP.per.cap	-0.014924	0.003208	-4.652	3.29e-06 ***

The number of medals won at the previous olympic games is heavily correlated, which is rather unsurprising. Additionally,

the GDP per capita is also statistically significantly correlated with number of medals won. The log population, however, does not make the cut, at a P-value of 0.383.

However, the original claim was that "participants from larger and wealthier nations are more likely to win medals". I see no reason why we should allow our model to use the medal winnings from 1996 to predict the year 2000 model winnings, when what we aim to assess is the population and GDP impact. Using log population and GDP as the only predictors, we get the following model:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.255144	0.250782	-16.968	< 2e-16 ***
Log.population	0.179605	0.022466	7.995	1.3e-15 ***
GDP.per.cap	-0.004340	0.002726	-1.592	0.111

Now GDP is no longer statistically significant at a 95% level. However, population is highly so. This was likely because it was correlated with the 1996 medal winnings, which acted as a confounder. In reality, the log population was a great predictor of medal winnings. Removing the GDP per capita, we are left with our final model:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.34619	0.24585	-17.678	< 2e-16 ***
Log.population	0.18212	0.02256	8.073	6.84e-16 ***

In conclusion, medal winnings (per athlete) is highly positively correlated with the population size of a country, but not significantly correlated with GDP per capita.

Problem 3

a)

Figure 2 shows the Kaplan-Meier plots of deaths from liver cirrhosis with different predictors. The plots simply show, after some amount of days on the x axis, what fraction of the group (like sex) is still alive.

By eye, we see some pretty clear trends. Females seem to live longer than males, younger people seem to live longer than older, and lower levels of excess fluids in abdomen tends to outlive those with higher levels. The seemingly least decisive factor is in fact the treatment.

b)

Below is the results of the logrank test on each of the covariates. **Sex**

	N	Observed	Expected	(O-E) ² /E	(O-E) ² /V
sex=0	198	111	127	2.00	3.55
sex=1	290	181	165	1.54	3.55
Chisq=	3.5	on 1 degrees of freedom, p= 0.06			

Agegroup

	N	Observed	Expected	(O-E) ² /E	(O-E) ² /V
agegr=1	80	26	58.7	18.18	22.87
agegr=2	250	148	162.0	1.21	2.72
agegr=3	158	118	71.3	30.51	40.87
Chisq=	50.6	on 2 degrees of freedom, p= 1e-11			

Ascites

	N	Observed	Expected	(O-E) ² /E	(O-E) ² /V
asc=0	386	211	251.9	6.63	48.66
asc=1	54	39	26.2	6.30	6.94
asc=2	48	42	14.0	56.17	59.60
Chisq=	69.9	on 2 degrees of freedom, p= 7e-16			

Treatment

	N	Observed	Expected	(O-E) ² /E	(O-E) ² /V
treat=0	251	142	149	0.355	0.728
treat=1	237	150	143	0.371	0.728
Chisq=	0.7	on 1 degrees of freedom, p= 0.4			

We see that the age group and ascites have very strong effects on patient survival, at P-values of 10^{-11} and numerically zero,

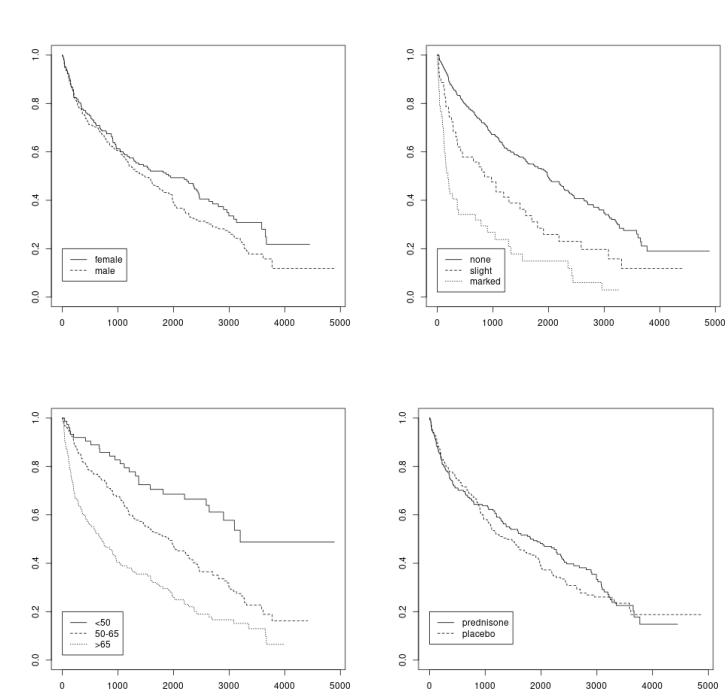


Figure 2: Kaplan-Meier plot of the fraction of surviving patients after a given amount of days, split by different variables. From the top-left: Split by sex, ascites, age, and treatment type.

respectively. The sex of the patient, while seemingly correlated by eye, is just barely not statistically significant, at a P-value of 0.06. The treatment is even less so, at a P-value of 0.4.

c)

Performing a Cox regression on the data, with age now as a numeric predictor, we get:

	coef	exp(coef)	se(coef)	z	Pr(> z)
factor(sex)1	0.461877	1.587050	0.125631	3.676	0.000236 ***
age	0.048877	1.050091	0.006844	7.141	9.26e-13 ***
factor(asc)1	0.603507	1.828520	0.175019	3.448	0.000564 ***
factor(asc)2	1.187254	3.278068	0.175224	6.776	1.24e-11 ***
factor(treat)1	0.044818	1.045837	0.117657	0.381	0.703263

Again, we see that ascites and age are very good predictors of patient survival. With our multi-predictor model, we now see that sex now is a significant predictor, at a P-value of 0.0002, far below the required 0.05 significance level. The prednisone treatment is still far from significant.

Being a multiplicative model, the hazard ratio for sex is simply $e^{\beta_{\text{sex}}}$, which, reading off the table above, gives us a ratio of $e^{0.461877} = 1.587$. This means that, with all other parameters constant, a male has a 58.7% higher hazard than a female.

The 95% confidence interval becomes $e^{\beta_{\text{sex}}} \pm 1.96se(\beta_{\text{sex}}) = [1.34, 1.83]$. As the interval does not include 1, we can conclude that the sex is a statistically significant predictor (we already new this from the P-value).

As stated before, our data can not conclude that prednisone has an effect on survival of patients.

Problem 4

a)

Figure 3 shows the distribution of reaction times after different number of sleep deprived days. There appears to be an increasing trend. At the 0th day, the mean reaction time is 256.7 ms. This increases to 350.9 ms on the 9th day.

Performing a two-way ANOVA test on the difference in the mean, with the null hypothesis that the means are identical, we get the following results:

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Reaction	1	335.2	335.2	28.94	5.52e-06 ***
Residuals	34	393.8	11.6		

This is a strongly significant increase, which also seems evident from our figure. However, an ANOVA test is not really appropriate for our data, as it contains the same subject group in both tests. Special methods are needed when analysing so-called "repeated measure" experiments.

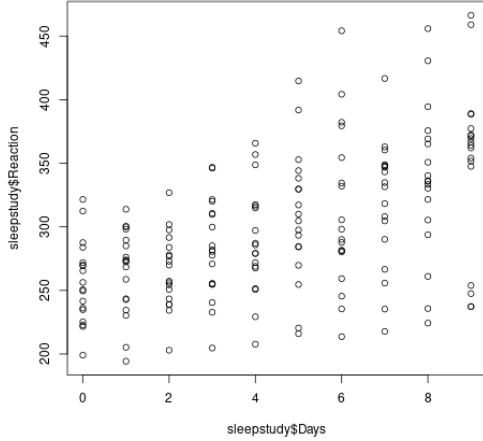


Figure 3: Scatter plot showing the recorded response time in ms of each subject after 0-9 days of sleep deprivation.

b)

Performing a linear regression on the sleep data with days only gives the following results:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	251.405	6.610	38.033	< 2e-16 ***
Days	10.467	1.238	8.454	9.89e-15 ***

There is a very clear statistical correlation between days of sleep deprivation and reaction time.

If we additionally include the subject number as a categorical predictor, we get:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	295.0310	10.4471	28.240	< 2e-16 ***
Days	10.4673	0.8042	13.015	< 2e-16 ***
factor(Subject)309	-126.9008	13.8597	-9.156	2.35e-16 ***
factor(Subject)310	-111.1326	13.8597	-8.018	2.07e-13 ***
factor(Subject)330	-38.9124	13.8597	-2.808	0.005609 **
factor(Subject)331	-32.6978	13.8597	-2.359	0.019514 *
factor(Subject)332	-34.8318	13.8597	-2.513	0.012949 *
factor(Subject)333	-25.9755	13.8597	-1.874	0.062718 .
factor(Subject)334	-46.8318	13.8597	-3.379	0.000913 ***
factor(Subject)335	-92.0638	13.8597	-6.643	4.51e-10 ***
factor(Subject)337	33.5872	13.8597	2.423	0.016486 *
factor(Subject)349	-66.2994	13.8597	-4.784	3.87e-06 ***
factor(Subject)350	-28.5311	13.8597	-2.059	0.041147 *
factor(Subject)351	-52.0361	13.8597	-3.754	0.000242 ***
factor(Subject)352	-4.7123	13.8597	-0.340	0.734300
factor(Subject)369	-36.0992	13.8597	-2.605	0.010059 *
factor(Subject)370	-50.4321	13.8597	-3.639	0.000369 ***
factor(Subject)371	-47.1498	13.8597	-3.402	0.000844 ***
factor(Subject)372	-24.2477	13.8597	-1.750	0.082108 .

Accounting for subject number, the number of days gains an even stronger level of significance. We also see that most of the subject factors have strong significance themselves, meaning that the different subject differ noticeably in their responses to sleep deprivation. A disadvantage of including the subjects as a predictor is that we increase the degrees of freedom in our model. The subjects is also an uninteresting predictor. However, the predicted slope coefficient is very similar in the two models (10.467 vs 10.4673), which is a good sign.

c)

Another drawback of the linear model is that we have no reason to suspect believe that the reaction time will respond linearly to sleep deprivation. Using a random model the days as categorical predictors solves this problem, and gives us the following results:

	Value	Std. Error	DF	t-value	p-value
(Intercept)	256.65181	11.45778	153	22.399781	0.0000
factor(Days)1	7.84395	10.47531	153	0.748804	0.4551
factor(Days)2	8.71009	10.47531	153	0.831488	0.4070
factor(Days)3	26.34021	10.47531	153	2.514504	0.0130
factor(Days)4	31.99762	10.47531	153	3.054576	0.0027
factor(Days)5	51.86665	10.47531	153	4.951325	0.0000
factor(Days)6	55.52645	10.47531	153	5.300699	0.0000
factor(Days)7	62.09878	10.47531	153	5.928111	0.0000
factor(Days)8	79.97770	10.47531	153	7.634879	0.0000
factor(Days)9	94.19942	10.47531	153	8.992521	0.0000

This models also shows us that there is a clear trend between days of sleep deprivation and reaction time. However, we get a more fine-grained result. The reaction time during the first two days of sleep deprivation is actually not significantly different from the 0th day at the 0.05 level. The 3rd day and onwards, are (with increasing significance).

The expected correlation between response time of the same subject on different days can be estimated as

$$\frac{\sigma_{\text{subj}}^2}{\sigma_{\text{subj}}^2 + \sigma_{\epsilon}^2} = \frac{37.08727}{37.08727 + 31.42592} = 0.582 \quad (8)$$

Appendix: Code

Problem 1

```
data = read.delim("/home/jonas/github/other_courses/STK9900/oblig2/data/crabs.txt", header=TRUE, sep="")

# Problem 1a
fit.width = glm(y~width, data=data, family=binomial)
summary(fit.width)

fit.weight = glm(y~weight, data=data, family=binomial)
summary(fit.weight)

# Problem 1c
fit.color = glm(y~factor(color), data=data, family=binomial)
summary(fit.color)

fit.spine = glm(y~factor(spine), data=data, family=binomial)
summary(fit.spine)

# Problem 1d
fit.all = glm(y~width+weight+factor(color)+factor(spine), data=data, family=binomial)
summary(fit.all)

fit.width.color = glm(y~width+factor(color), data=data, family=binomial)
summary(fit.width.color)

fit.width.spine = glm(y~width+factor(spine), data=data, family=binomial)
summary(fit.width.spine)

plot(data$weight, data$width)

# Problem 1e
fit.1 = glm(y~width+width*weight, data=data, family=binomial)
summary(fit.1)

fit.2 = glm(y~width+width*factor(color), data=data, family=binomial)
summary(fit.2)

fit.3 = glm(y~width+width*factor(spine), data=data, family=binomial)
summary(fit.3)

fit.4 = glm(y~width+weight*factor(color), data=data, family=binomial)
summary(fit.4)

fit.5 = glm(y~width+weight*factor(spine), data=data, family=binomial)
summary(fit.5)

fit.6 = glm(y~width+factor(color)*factor(spine), data=data, family=binomial)
summary(fit.6)
```

Problem 2

```
data = read.delim("/home/jonas/github/other_courses/STK9900/oblig2/data/olympic.txt", header=TRUE, sep="")
fit.1 = glm(Total2000~offset(Log.athletes)+Total1996+Log.population+GDP.per.cap, data=data, family=poisson)
summary(fit.1)

fit.2 = glm(Total2000~offset(Log.athletes)+Log.population+GDP.per.cap, data=data, family=poisson)
summary(fit.2)

fit.3 = glm(Total2000~offset(Log.athletes)+Log.population, data=data, family=poisson)
summary(fit.3)
```

Problem 3

```
data = read.delim("/home/jonas/github/other_courses/STK9900/oblig2/data/cirrhosis.txt", header=TRUE, sep="")
library(survival)

# Problem 3a)
surv.sex = survfit(Surv(data$time, data$status)~sex, data=data, conf.type="none")
surv.agegr = survfit(Surv(data$time, data$status)~agegr, data=data, conf.type="none")
surv.asc = survfit(Surv(data$time, data$status)~asc, data=data, conf.type="none")
surv.treat = survfit(Surv(data$time, data$status)~treat, data=data, conf.type="none")

png(file="/home/jonas/github/other_courses/STK9900/oblig2/report/figures/surv_sex.png")
plot(surv.sex, lty=1:2)
legend(1, 0.2, c("female", "male"), lty=1:2)
dev.off()

png(file="/home/jonas/github/other_courses/STK9900/oblig2/report/figures/surv_agegr.png")
plot(surv.agegr, lty=1:3)
legend(1, 0.2, c("<50", "50-65", ">65"), lty=1:3)
dev.off()

png(file="/home/jonas/github/other_courses/STK9900/oblig2/report/figures/surv_asc.png")
plot(surv.asc, lty=1:3)
legend(1, 0.2, c("none", "slight", "marked"), lty=1:3)
dev.off()

png(file="/home/jonas/github/other_courses/STK9900/oblig2/report/figures/surv_treat.png")
plot(surv.treat, lty=1:2)
legend(1, 0.2, c("prednisone", "placebo"), lty=1:2)
dev.off()

# Problem 3b)
survdiff(Surv(data$time, data$status)~sex, data=data)
survdiff(Surv(data$time, data$status)~agegr, data=data)
survdiff(Surv(data$time, data$status)~asc, data=data)
```

```

survdifff(Surv(data$time, data$status)~treat, data=data)

# Problem 3c)
fit.1 = coxph(Surv(data$time, data$status==1)~factor(sex)+age+factor(asc)+factor(treat), data=data)
summary(fit.1)

```

Problem 4

```

install.packages("lme4")
library(lme4)
data(sleepstudy)
sleepstudy

# Problem 4a)
png(file="/home/jonas/github/other_courses/STK9900/oblig2/report/figures/sleepstudy.png")
plot(sleepstudy$Days, sleepstudy$Reaction)
dev.off()

mean(sleepstudy$Reaction[sleepstudy$Days==0])
mean(sleepstudy$Reaction[sleepstudy$Days==9])

sleepstudy2 = sleepstudy[sleepstudy$Days==0 | sleepstudy$Days==9]
fit.aov = aov(Days~Reaction, data=sleepstudy)
summary(fit.aov)

# Problem 4b)
fit.lm = lm(Reaction~Days, data=sleepstudy)
summary(fit.lm)

fit.lm2 = lm(Reaction~Days+factor(Subject), data=sleepstudy)
summary(fit.lm2)

# Problem 4c)
library(nlme)
fit.random = lme(Reaction~factor(Days), random=~1|Subject, data=sleepstudy)
summary(fit.random)
37.08727^2/(37.08727^2 + 31.42592^2)

```