# Machine Learning I Group Work

Adriana Ricklin, Yvonne Schaerli, Christina Sudermann, Carole Mattmann 5 Maerz 2020

## **Packages**

```
library(ggplot2)
## Registered S3 methods overwritten by 'ggplot2':
    method
                   from
##
     [.quosures
                   rlang
     c.quosures
                   rlang
##
    print.quosures rlang
library(gridExtra)
## Warning: package 'gridExtra' was built under R version 3.6.2
Import and data cleaning
insurance <- read.csv(".../01_data/insurance.csv", header=TRUE)</pre>
str(insurance)
## 'data.frame':
                   1338 obs. of 7 variables:
## $ age : int 19 18 28 33 32 31 46 37 37 60 ...
## $ sex
             : Factor w/ 2 levels "female", "male": 1 2 2 2 2 1 1 1 2 1 ...
## $ bmi
             : num 27.9 33.8 33 22.7 28.9 ...
```

```
## $ bmi : num 27.9 33.8 33 22.7 28.9 ...
## $ children: int 0 1 3 0 0 0 1 3 2 0 ...
## $ smoker : Factor w/ 2 levels "no", "yes": 2 1 1 1 1 1 1 1 1 1 1 ...
## $ region : Factor w/ 4 levels "northeast", "northwest", ...: 4 3 3 2 2 3 3 2 1 2 ...
## $ charges : num 16885 1726 4449 21984 3867 ...
# smoker = 1 / nonsmoker = 0
insurance$smoker <- as.character(insurance$smoker)
insurance$smoker[insurance$smoker == "yes"] <- "1"
insurance$smoker[insurance$smoker == "no"] <- "0"
insurance$smoker <- as.factor(insurance$smoker)</pre>
```

```
bmi children smoker
                                   region
                                          charges
##
    age
         sex
## 1 19 female 27.900 0 1 southwest 16884.924
## 2 18 male 33.770
                       1
                             0 southeast 1725.552
                       3
## 3 28 male 33.000
                             0 southeast 4449.462
                       0
## 4 33
         male 22.705
                             0 northwest 21984.471
                       0
## 5 32
         male 28.880
                             0 northwest 3866.855
                             0 southeast 3756.622
## 6 31 female 25.740
                       0
```

## Linear models -> Christina

## Linear models (GAM & Polynomial) -> Yvonne

## GLM and cross validation -> Carole

## Generalised Linear Models for count data

## Original data

The number of children an insured person has is analysed. We have the following data on children per person. The number of children ranges from 0 to 5 with a median of 1.

```
summary(insurance$children)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 0.000 0.000 1.000 1.095 2.000 5.000
```

#### Poisson model

To model count data (number of children) the poisson model is used. An analysis performed beforehand showed that only the variables "charges" and "smoker" have a significant impact on the number of children.

```
##
## Call:
## glm(formula = children ~ smoker + charges, family = "poisson",
##
       data = insurance)
##
##
  Deviance Residuals:
      Min
                 1Q
                     Median
                                   3Q
                                           Max
   -1.8561 -1.4318 -0.1057
                               0.7768
                                        2.9717
##
##
## Coefficients:
##
                 Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.706e-02 4.213e-02 -0.880
                                               0.3790
               -3.239e-01 1.058e-01 -3.061
                                               0.0022 **
## smoker1
                1.419e-05 3.365e-06
                                       4.217 2.48e-05 ***
## charges
##
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
  (Dispersion parameter for poisson family taken to be 1)
##
##
       Null deviance: 2001.6 on 1337 degrees of freedom
## Residual deviance: 1984.1 on 1335
                                       degrees of freedom
## AIC: 3879.4
##
## Number of Fisher Scoring iterations: 5
```

To get the coefficients, the log transformation needs to be reversed:

## exp(coef(glm.children))

```
## (Intercept) smoker1 charges
## 0.9636169 0.7233085 1.0000142
```

Smoker (factor): The model shows that for the factor smoker (yes/no), a smoker has on average 72% of the number of children a non-smoker has. The more common-sense interpretation might be the other way around, that people who have 1 or more children smoke less, but for the moment we have no proof of that.

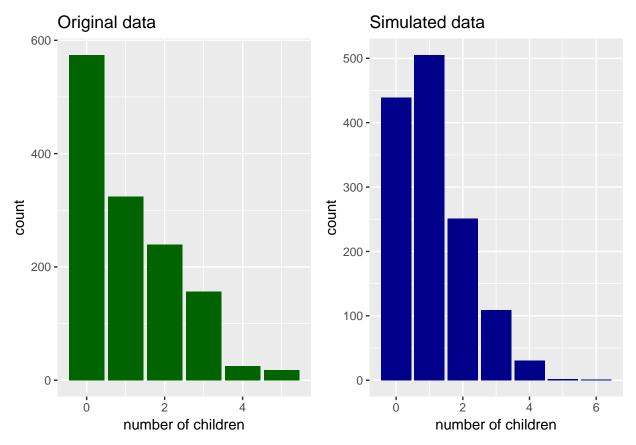
Charges: A person with higher charges will on average have more children. If charges are increased by 1000 dollars, the calculated number of children increases by 1.4%.

## Simulation of data and comparison

With the calculated model, data is simulated:

```
##
         sim_1
##
            :0.000
    Min.
##
    1st Qu.:0.000
    Median :1.000
            :1.102
##
    Mean
##
    3rd Qu.:2.000
            :6.000
##
    Max.
```

The original and the simulated data are compared visually. The number of children from the simulated data (0-6) seem to be plausible. The distribution has a strong downwards trend starting at 1 like the original data. However the model does not seem to generate enough data with 0 children.



### Generalised Linear Models for binomial data

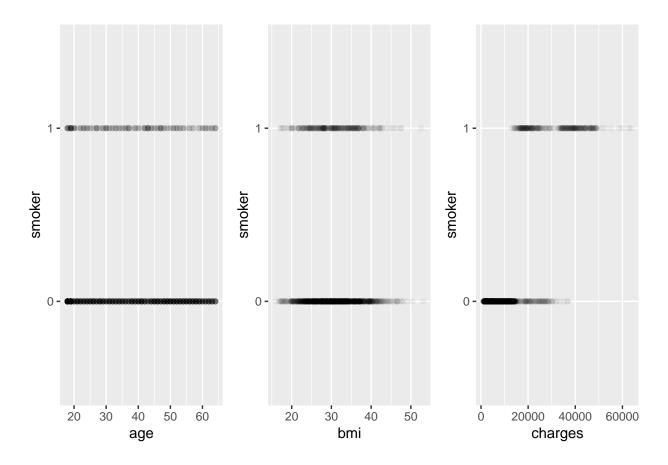
A model is fitted that predicts if a person is a smoker or not. Only the significant values age, bmi and charges are used.

```
glm.smoker.2 <- glm(smoker ~ age+bmi+charges,</pre>
                    data=insurance,
                    family = "binomial")
summary(glm.smoker.2)
##
## Call:
   glm(formula = smoker ~ age + bmi + charges, family = "binomial",
##
       data = insurance)
##
## Deviance Residuals:
##
        Min
                   1Q
                         Median
                                        3Q
                                                 Max
## -3.09442 -0.10998 -0.04475
                                 -0.00970
                                             1.53727
##
## Coefficients:
##
                 Estimate Std. Error z value Pr(>|z|)
## (Intercept) 5.311e+00 1.029e+00
                                        5.163 2.43e-07 ***
               -9.875e-02 1.300e-02 -7.597 3.02e-14 ***
## age
## bmi
               -3.481e-01
                           4.309e-02
                                      -8.078 6.60e-16 ***
                3.822e-04 2.917e-05 13.104 < 2e-16 ***
## charges
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 1356.63 on 1337
                                        degrees of freedom
## Residual deviance: 311.98 on 1334 degrees of freedom
## AIC: 319.98
##
## Number of Fisher Scoring iterations: 8
exp(coef(glm.smoker.2))
## (Intercept)
                                    bmi
                                            charges
                       age
## 202.5686249
                 0.9059677
                              0.7060520
                                          1.0003823
```

Age and BMI has a negative effect on smoker. This means the higher a persons BMI and age, the lower the probability that the person is a smoker. Charges has a positive effect. This means the higher a persons charges, the higher is the possibility that the person smokes.

## Graphical analysis

This can also be explored graphically, at least for charges it is clearly visible that smokers have higher charges.



## Estimating the model performance

##

## obs

fit

0 1028

0

1

36

The predicted values are transformed into binary (beforehand they inicated the probability) and compared with the actual data.

```
fitted.smoker.disc <- ifelse(fitted(glm.smoker.2) < 0.5,</pre>
                             yes = 0, no = 1)
head(fitted.smoker.disc)
## 1 2 3 4 5 6
## 1 0 0 1 0 0
d.obs.fit.smoker <- data.frame(obs = insurance$smoker,</pre>
                               fitted = fitted.smoker.disc)
head(d.obs.fit.smoker)
     obs fitted
##
## 1
       1
               1
               0
## 2
       0
## 3
       0
               0
##
       0
               1
               0
## 5
       0
               0
## 6
We observe the following fit:
```

## 1 23 251

 ${\bf Cross\ Validation\ \text{--} Carole}$