Treating diabetic retinopathy

1. Introduction

Diabetic retinopathy is a complication of diabetes affects the eyes, caused by damage to the blood vessels in the back of the eyes. The symptoms are varied depend on the progress, from blurriness to blindness. Diabetic retinopathy can be treated with careful management in the early stages but may require laser treatment in advanced cases. The previous research concerned two laser treatments, argon and xenon, as a treatment to delay the diabetic retinopathy. This report examines the result of the previous research, determine the efficacy of laser treatment type on visual acuity by quantifying the improvement between eyes by treatment type. The report also analyzed the potential impact of age at diagnosis and clinical risk of diabetic retinopathy have on visual activity. The response variable would be the lag-corrected time to lose vision or last follow-up in months. As a result, we showed that the treatment is significant to the lag-corrected time to loss of vision, but the treatment types showed no significant difference in the efficacy on visual acuity.

2. Methods

2.1 Statistical Methods

The response is a drop in visual acuity in each eye below 5/200 for two visits in a row. Since this event occurs over time and follow up is not complete for each observation, we used the method called survival analysis to model the time until the loss of vision. Specifically, we used two different survival analysis method, Kaplen-Meier Estimation and Cox proportional hazards model. Kaplen-Meier Estimation (K-M) considers the estimated survival from the sample by

providing the time function S(t) = *(proportion of sample that has not experienced the event until time t)*. Cox proportional hazards model assumes that each hazard function is proportional to some base hazard function and find that proportion for each individual by finding the value that minimize the log-likelihood function of the sample. The report first used the K-M to see the survival distribution of the loss of vision over time by laser, clinical risk of diabetic retinopathy, and age. Further, we used the Cox proportional hazards model to quantify the influence of different predictors for the loss of vision over time.

3. Result

3.1 Data Summary

Table 1. Brief statistic of the data

	description	Min.	Median	Mean	SD
futime	lag-corrected time to loss of vision, or last follow up in month (if participant is lost to follow-up)	0.30	74.97	35.58	21.36
risk	clinical risk of loss of acuity	6	12	9.69	1.48
age	age in years	1	58	20.78	14.81
	description	*0/argon/left/adult*		*1/xenon/right/juvenile*	
laser	treatment type (argon/xenon) 'none' for the control eye	97		100	
eye	left or right eye	216		178	
status	0 for lost to follow-up, 1 for loss of vision in eye	239		155	
type	adult or juvenile	166		228	
trt	0 for control eye, 1 for treated eye	197		197	

 Previous research collected the type of laser used for the treatment, type of eye (right/left and control/treated), age of diagnosis, treatment types of eyes, the status of the eye, clinical risk of loss of acuity, lag-corrected time to loss of vision data. The dataset consists of 9 variables with

394 objects, with no missing data. A brief statistic of the data is presented in Table 1. The point

to recall from the data is that the 'type' variable that distinguishes whether or not an adult is

 completely determined by the age variable.
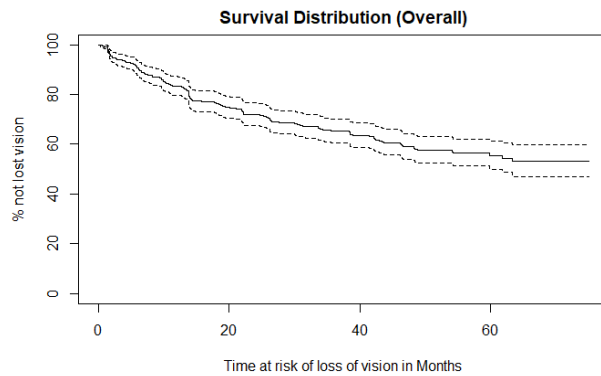
3.2 Kaplen-Meier Estimation
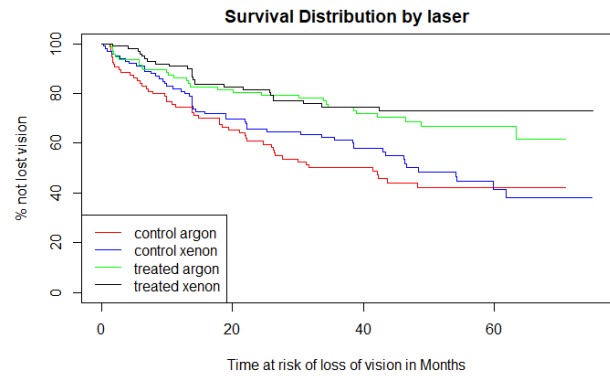

Figure 1. Survival Distribution (Overall)

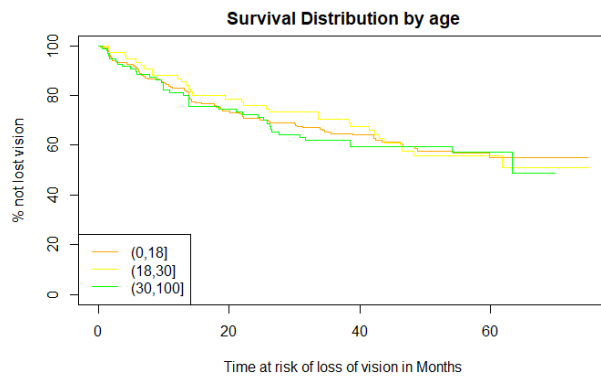*Figure 2. Survival Distribution by laser and treatment*
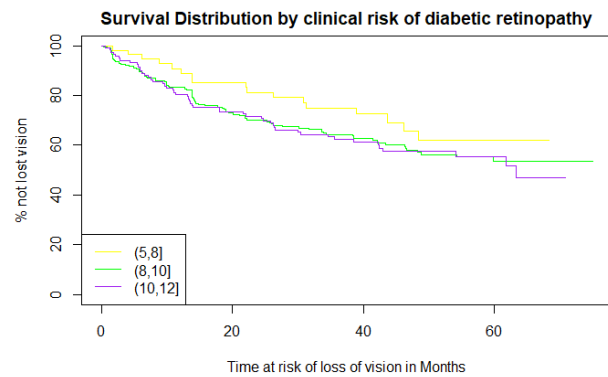

Figure 3. Survival Distribution by age

Figure 4. Survival Distribution by clinical risk

 Figure 1 ~ 4 represent the Kaplen-Meier Estimation of the time at loss of vision for different

predictors. Figure 1 displayed the loss of vision over time for all observations. In figure 1, the

time at risk of loss of vision showed a gradual slope over time, which is natural as the number of eyes that have not yet lost vision decreases over time. In figure 2, we displayed the loss of vision over time by the treatment type and treatment for the observations. Overall, the observation with treatments showed lower risk of loss of vision over time. Figure 3 and 4 displayed the loss of vision over time by the intervals of age and clinical risk.

3.3 Cox proportional hazards model

We also used the Cox proportional hazards model to quantitatively analyze the difference of the risk of loss of vision over time between different predictors. Table 2 analyzed the time to loss vision, or last follow up in month for each laser type. The model used laser, treatment, age, risk, and the interaction term between the laser and the treatment as predictors. For the laser, we can say that xenon laser treatment increases the time to loss of vision than argon laser treatment. Specifically, in the same time, the probability that the eye with xenon laser to loss vision is 84% of the probability that the eye with argon laser to loss vision. However, since the confidence interval for the predictor laser contains 1 and the p-value for the predictor is 0.397, we cannot say that the laser type of the treatment makes a significant difference in the time to loss vision.

Table 2. Time to loss vision or last follow up in months for each laser type, compare to the laser = none

	LASERXENON	TREATMENT	AGE	RISK	LASER:TRT
HAZARD RATIO	0.84	0.46	1.01	1.16	0.95
	(0.57, 1.25)	(0.29, 0.74)	(0.99, 1.02)	(1.04, 1.29)	(0.49, 1.84)
P-VALUE	0.397	0.001	0.330	0.008	0.879

For other predictors, the hazard ratio for the treatment predictor 0.46. This means that the probability of eyes with treatment to loss vision is 46% of the probability that the eye with no

treatment to loss vision. The p-value for the predictor treatment is less than 0.05. So, we can find that the treatment variable, either the eyes with the control group or the treated group, affects the time to loss vision. The hazard ratio for the risk predictor was 1.01. So, if the age of the patient increases by one year, we can say that the probability that the patient to loss vision increases to 101%. However, the p-value for the predictor age. 0.330, shows that the predictor age is not a significant predictor to predict the time to loss vision. The hazard ratio for the predictor risk was 1.16. That is, if the clinical risk of lost of acuity increased by one, the probability that the patient to loss vision would increase to 116%. Since its p-value is low enough with 0.008, the predictor risk is a significant predictor to the time to loss vision.

Finally, we have an interaction term laser: treatment with hazard ratio 0.95. So, the probability that treated eyes with xenon treatment to loss vision in a given time is 95% of the probability that treated eyes with argon treatment to loss vision in a same given time. However, its p-value points out that the interaction term is not a significant predictor for the response. In other words, the type of laser do not matter for the time to loss vision.

4. Conclusion

The purpose of this analysis was to find a significant difference between argon and xenon laser treatment for diabetic retinopathy. Moreover, we also wanted to understand the potential impact that age at diagnosis and clinical risk of diabetic retinopathy have on the time to loss of vision. The report used the Keplan-Meier Estimator and Cox proportional hazards model to quantify the impact of treatment types, ages and clinical risk to the time to loss of vision. The report concluded that the treatment, control or treated, and risk is significant to the lag-corrected time to loss of vision. The eye with treatment showed less percentage of losing vision in the future, and

the eyes with lower risk showed less percentage of losing vision in the future. However, we could not find a significant relationship between a type of laser treatments and age of diagnosis with log-corrected time to loss of vision. However, it might be possible that the numbers of data were not sufficient to find the correlation between the response and the predictor.

Assignment 2 Appendix

```r
library(survival)
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5      v purrr   0.3.4
## v tibble  3.1.4      v dplyr   1.0.7
## v tidyr   1.1.4      v stringr 1.4.0
## v readr   2.0.2      v forcats 0.5.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
knitr::opts_chunk$set(fig.width=3, fig.height=3)
dat = read.csv('C:/Users/krss9/Desktop/FS21/Stats 504/Assignment2/diabeticVision.csv')

#trt = 0 means that eye did not get a treatment. We will change those laser types to none.
#for(i in 1:nrow(dat))
#if(dat$trt[i] == 1){
#  dat$laser[i] ='none'
#}
#dat %>% filter(dat$laser == 'none') %>% head()
```

```r
dat['trt2'] = 0
dat[dat$trt == 0, 'trt2'] = 'control'
dat[dat$trt == 1, 'trt2'] = 'treated'
head(dat)
```

```
##   X id laser   eye age     type trt futime status risk    trt2
## 1 1  5 argon  left  28    adult   1  46.23      0    9 treated
## 2 2  5 argon  left  28    adult   0  46.23      0    9 control
## 3 3 14 argon right  12 juvenile   1  42.50      0    8 treated
## 4 4 14 argon right  12 juvenile   0  31.30      1    6 control
## 5 5 16 xenon right   9 juvenile   1  42.27      0   11 treated
## 6 6 16 xenon right   9 juvenile   0  42.27      0   11 control
```

```r
sd(dat$futime)
```

```
## [1] 21.3559
```

```
sum(dat$laser == 'xenon')
```

[1] 200

```
sum(dat$laser == 'argon')
```

[1] 194

```
sum(dat$eye == 'left')
```

[1] 216

```
sum(dat$eye == 'right')
```

[1] 178

```
sum(dat$status == '0')
```

[1] 239

```
sum(dat$status == '1')
```

[1] 155

```
sum(dat$type == 'adult')
```

[1] 166

```
sum(dat$type == 'juvenile')
```

[1] 228

```
sum(dat$trt == '0')
```

[1] 197

#Goals ### 1. Determine the efficacy of treatment type on visual acuity ### 2. Quantify the improvement between eyes by treatment type

3. Understand the potential impact that age at diagnosis have on visual acuity
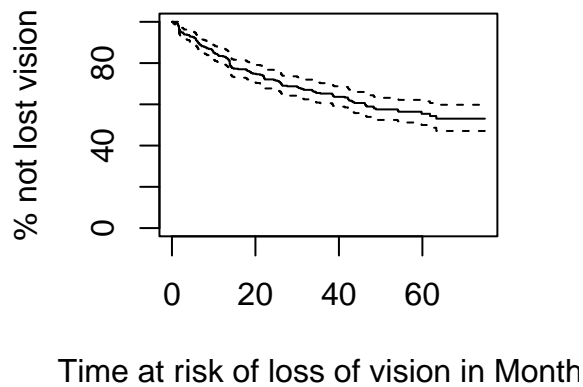
4. understand the potential impact that clinical risk of diabetic retinopathy have on visual acuity

0. Overall survival

```
survobj <- with(dat, Surv(futime, status))
fit0 <- survfit(survobj~1, data=dat)

plot(fit0, xlab="Time at risk of loss of vision in Months",
ylab="% not lost vision", yscale=100,
main ="Survival Distribution (Overall)")
```
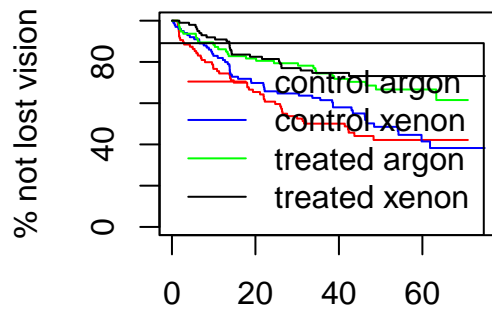
Survival Distribution (Overall

1. Survival distribution by laser

```
#dat['inter'] = dat['laser'] * dat['trt']
dat$laser_trt = paste(as.factor(dat$trt2),as.factor(dat$laser) )
fitr <- survfit(survobj~ laser_trt, data=dat)
plot(fitr, xlab="Time at risk of loss of vision in Months",
ylab="% not lost vision", yscale=100,
main="Survival Distribution by laser",
col = c('red', 'blue','green','black'))
legend('bottomleft', legend=levels(as.factor(dat$laser_trt)), col = c('red', 'blue','green', 'black'),
```

Survival Distribution by laser

% not lost vision

```
control argon
control xenon
treated argon
treated xenon
```

Time at risk of loss of vision in Month

2. Quantatitive analysis of the survival distribution by laser

```
survdiff(survobj~laser, data=dat)
```

```
## Call:
## survdiff(formula = survobj ~ laser, data = dat)
##
##                N Observed Expected (O-E)^2/E (O-E)^2/V
## laser=argon 194       79     72.8     0.534      1.01
## laser=xenon 200       76     82.2     0.473      1.01
##
##  Chisq= 1  on 1 degrees of freedom, p= 0.3
```
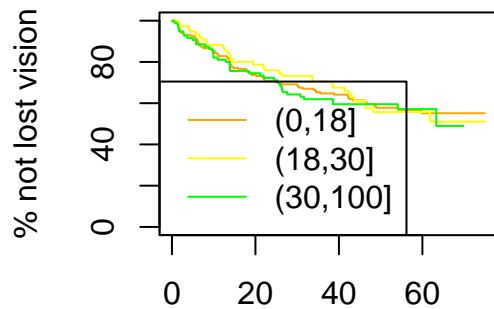
3. Survival Distrubution by age - graph

```
summary(dat$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00   10.00   16.00   20.78   30.00   58.00
```

```
dat$agedist <- cut(dat$age, breaks=c(0,18,30,100))
fitc <- survfit(survobj~agedist, data=dat)
plot(fitc,xlab="Time at risk of loss of vision in Months",
ylab="% not lost vision", yscale=100,
main="Survival Distribution by age",
col = c('orange', 'yellow', 'green'))
legend('bottomleft', legend=levels(as.factor(dat$agedist)), col = c('orange', 'yellow', 'green'), lty=1]
```

Survival Distribution by age

% not lost vision

- (0,18]
- (18,30]
- (30,100]

Time at risk of loss of vision in Month

Survival distribution by clinical risk - graph

```
summary(dat$risk)
```

```
##     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6.000   9.000  10.000   9.698  11.000  12.000
```

```
dat$riskdist <- cut(dat$risk, breaks=c(5,8,10,12))
fitr <- survfit(survobj~riskdist, data=dat)
plot(fitr,xlab="Time at risk of loss of vision in Months",
ylab="% not lost vision", yscale=100,
main="Survival Distribution by clinical risk of diabetic retinopathy",
col = c('yellow', 'green', 'purple'))
legend('bottomleft', legend=levels(as.factor(dat$riskdist)), col = c('yellow', 'green', 'purple'), lty=
```

stribution by clinical risk of diabe

% not lost vision

- (5,8]
- (8,10]
- (10,12]
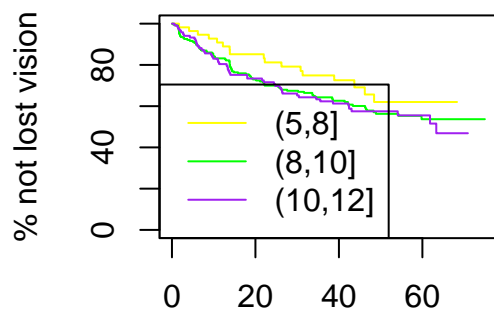
Time at risk of loss of vision in Month

More Quantatitive analysis

```
model1 = coxph(survobj~laser * trt + age + risk , data=dat)
summary(model1)
```

```
## Call:
## coxph(formula = survobj ~ laser * trt + age + risk, data = dat)
##
##   n= 394, number of events= 155
##
##                     coef exp(coef)  se(coef)      z Pr(>|z|)
## laserxenon     -0.169242  0.844304  0.199811 -0.847  0.39699
## trt            -0.766822  0.464487  0.234227 -3.274  0.00106 **
## age             0.005334  1.005349  0.005473  0.975  0.32976
## risk            0.146871  1.158204  0.055728  2.635  0.00840 **
## laserxenon:trt -0.051551  0.949755  0.338028 -0.153  0.87879
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##                exp(coef) exp(-coef) lower .95 upper .95
## laserxenon        0.8443     1.1844    0.5707    1.2490
## trt               0.4645     2.1529    0.2935    0.7351
## age               1.0053     0.9947    0.9946    1.0162
## risk              1.1582     0.8634    1.0384    1.2919
## laserxenon:trt    0.9498     1.0529    0.4896    1.8422
##
## Concordance= 0.626  (se = 0.023 )
## Likelihood ratio test= 31.48  on 5 df,    p=8e-06
## Wald test            = 29.99  on 5 df,    p=1e-05
## Score (logrank) test = 31.29  on 5 df,    p=8e-06
```

```
head(dat)
```

```
##   X id laser   eye age     type trt futime status risk    trt2    laser_trt
## 1 1  5 argon  left  28    adult   1  46.23      0    9 treated treated argon
## 2 2  5 argon  left  28    adult   0  46.23      0    9 control control argon
## 3 3 14 argon right  12 juvenile   1  42.50      0    8 treated treated argon
## 4 4 14 argon right  12 juvenile   0  31.30      1    6 control control argon
## 5 5 16 xenon right   9 juvenile   1  42.27      0   11 treated treated xenon
## 6 6 16 xenon right   9 juvenile   0  42.27      0   11 control control xenon
##   agedist riskdist
## 1 (18,30]   (8,10]
## 2 (18,30]   (8,10]
## 3  (0,18]    (5,8]
## 4  (0,18]    (5,8]
## 5  (0,18]  (10,12]
## 6  (0,18]  (10,12]
```

```
#dat$laser = relevel(as.factor(dat$laser), ref='argon')
#coxph(survobj~laser, data=dat)
```

6

```
#coxph(survobj~agedist, data=dat)
```

```
#coxph(survobj~riskdist, data=dat)
```

Check the interactino between variables

```
#test.dat1 <- cox.zph(coxph(survobj~laser*age*risk, data=dat))
#test.dat1
```

```
#test.dat2 <- cox.zph(coxph(survobj~laser*risk, data=dat))
#test.dat2
```