

Survival Data Analysis

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02418 Statistical Modelling: Theory and practice
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Overview

Analysis of Binary Data

The first part of the assignment deals with the study of the effect of AZT on AIDS.

Methods of analysis:

- Binomial distribution of all data
- Binomial distribution of treatment groups
- Parameter estimation of p_0 and p_1
- Profile likelihood of AZT-yes coefficient
- Logistic regression model

Analysis of the Survival Time Data

The second part of the assignment deals survival time, where we want to see whether there is a difference for the two treatment groups

Methods of analysis:

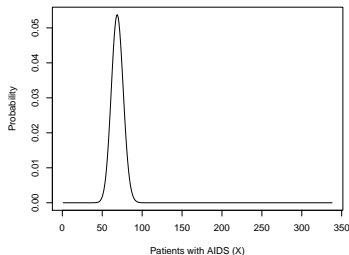
- AIDS/healthy statistics
- Survival distribution by treatment
- Cumulative incidence function
- Log-rank test
- Parametric survival model

Binomial distribution of data

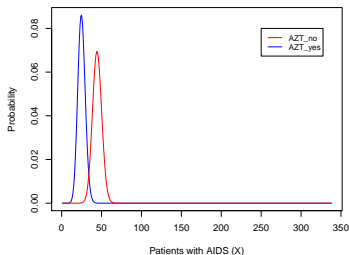
All data (AZT-yes and AZT-no)

Divided into AZT-yes and AZT-no

Binomial of all patients



Binomial of each AZT group



2-sample test for equality of proportions

X-squared	df	p-value	95% CI	prop 1	prop 2
6.171	1	0.01299	-0.21,-0.024	0.15	0.26

Conclusion

P-value (0.01299) < 0.05, therefore we reject the null hypothesis, i.e. there is a significant difference between the groups

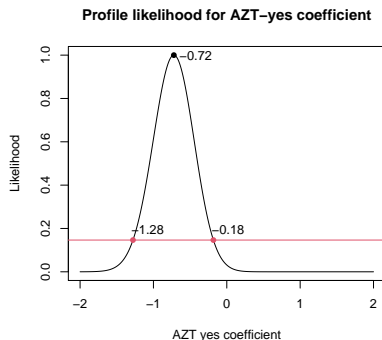
Parameter Estimation

Estimate parameters in the model (p_0 probability of AIDS in control group, p_1 probability of AIDS in treatment group)

$$p_0 = \frac{e^{\beta_0}}{1 + e^{\beta_0}} \quad (1)$$

$$p_1 = \frac{e^{\beta_0 + \beta_1}}{1 + e^{\beta_0 + \beta_1}} \quad (2)$$

- $\beta_1 = -0.7217$; Therefore there is a negative correlation when given the treatment i.e. when given AZT your log odds of having AIDS are -0.721.
- Projecting back into probability scale, $p_0 = 0.261$, $p_1 = 0.147$, therefore, when given AZT you have a lower probability of having AIDS.



Logistics Regression Model

Logistic regression model for the binary outcome AIDS="yes" versus AIDS="no" with the explanatory variable treatment with AZT (yes, no)

```
logit <- -glm(cbind(data$AIDS_yes, data$n - data$AIDS_yes) ~ data$AZT, data = data, family = "binomial") (3)
```

Odds ratio for the effect of AZT on AIDS:

- GLM outputs log odds; if coefficient is positive, the effect of this AIDS is positive and vice versa.
- The odds of having AIDS with AZT: $0.147 / (1 - 0.147) = 0.172$.
- The odd of having AIDS without AZT $0.261 / (1 - 0.261) = 0.353$.
- Computing a odd ratio we find that the odds of having AIDS is 2.05 times as high without immediate AZT treatment.

Odds ratio 95 % CI		
	2.5 %	97.5 %
(Intercept)	0.2515723	0.5004942
AZT Yes	0.2813743	0.8390689

Conclusion

GLM function supports earlier parameter estimation, in concluding that AZT has a significant effect on getting AIDS

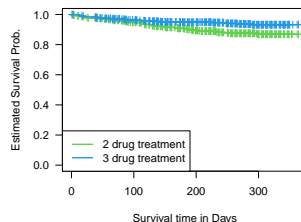
Analysis of Survival Time Data

Healthy vs AIDS/death			
	Healthy	AIDS	Probability of AIDS
Two-drug treatment	514	63	0.11
Three-drug treatment	541	33	0.06
Total	1055	99	0.08

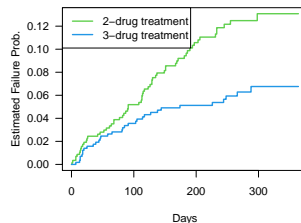
Conclusion

Log-rank Test: This tests if the survival curves of the two treatment groups are the same. Result was $p = 0.001$, therefore it is significant ($p < 0.5$). The curves are indeed NOT the same meaning that the drug makes a significant difference.

Survival Distributions by Treatment



Cumulative Incidence Functions



Parametric Survival Models

Task: Fit parametric survival models containing treatment (tx) and CD4 count (cd4) as explanatory variables.

Method: Fit exponential, Weibull and log-logistic models, concluded that log-logistic was best as it has the lowest AIC.

Log-logistic Model Summary				
	Value	95% CI	z	p
Intercept	6.82584	[6.33, 7.32]	26.82	< 2e-16
Treatment	0.84295	[0.27, 1.41]	2.91	0.0036
cd4	0.02080	[0.013, 0.028]	5.55	2.9e-08

- Time ratio for the treatment effect: The median time to survival time for new treatment is 2.32 times the median for old treatment. 95% CI:[1.32, 4.10]
- Tested Cox-snell residuals and concluded they looked normal