Not So Happy Ending for Buddy: Labrador Adoption Rates in Austin Animal Center

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Abstract

Although Labradors are widely viewed as one of the most popular breeds in the United States, they are also a popular breed found in animal shelters https://www.cleartheshelters.com. Taking a look at the outcomes of over 6,000 Labradors in the Austin Animal Center (the largest "no-kill" animal shelter in the U.S.), we build a Cox Proportional Hazards model to see how neuter status affects Labrador adoption rates.

Data Source

The data we used was from the Austin Animal Center, downloaded from kaggle at https://www.kaggle.com/aaronschlegel/austin-animal-center-shelter-outcomes-and. The raw data included cats, dogs, birds, livestock and others. Since we were only interested in labradors we created a subset of the data which included 2,128 Labrador and Labrador Mixed breeds for a total of 6,980 observations. We decided to delete one observation which had NULL values for `outcome` and `age upon outcome` since we thought our analysis without this observation would not change. We also excluded 48 data points where the gender and neuter status of the Labrador were not known. We split the column of `sex upon outcome` into two columns for analysis: `sex` with only Male/Female entries and `neuter` with Intact/Fixed entries where "Fixed" means the dog is either neutered or spayed and intact means it was not. Another covariate we changed was `color`. There were a ridiculous amount of "color" descriptions. Our favorite color that we saw was "peach." We decided to change this column to entries of either Mixed fur pattern or Solid fur patterns to denote dogs with more than one color versus dogs that are solid colored. Our final dataset included the following:

- `color`: The descriptive fur pattern of Mixed color fur pattern or Solid color fur pattern.
- `event`: The event was 1 if the Labrador had been adopted, and censored was 0 if the Labrador had been transferred, missing (off-site, in foster care or in kennel), possible theft, euthanasia or death.
- `date_diff`: The amount of time in days the Labrador spent in the shelter.
- `sex`: The gender of the dog.
- `neuter`: If the dog is fixed or intact.

Table 1: Final Dataset

color	event	date_diff	sex	neuter
Mixed	1	63 days	Female	Fixed
Mixed	1	95 days	Female	Fixed
Mixed	1	4445 days	Male	Fixed
Mixed	1	745 days	Male	Fixed
Mixed	1	1764 days	Male	Fixed
Mixed	0	1794 days	Male	Fixed

Research Question

On average how much time do Labradors spend in animal shelters before they go to a home?

We will plot a Kaplan-Meier curve and find the median time that Labradors spent in this animal shelter.

Does the color, gender or neuter status of a Labrador affect it's chance for adoption?

We'll build a Cox Proportional Hazards (Cox PH) model with the covariates neuter status, sex, and color to answer this question. We will also explore an Accelerated Failure Time (AFT) model as our extension component, to look at a comparison of survival times.

Data Exploration

Before we start our analysis we must understand our data. We found that we had a total of 6,929 observations. Out of these, 3211 are Female (46%), 3713 have mixed fur pattern (53%), and 5726 were fixed (82%). Using the quantile function on the length of time spent in the shelter, we found that 50% of the dogs spent more than 395 days in the shelter, this is over one year!

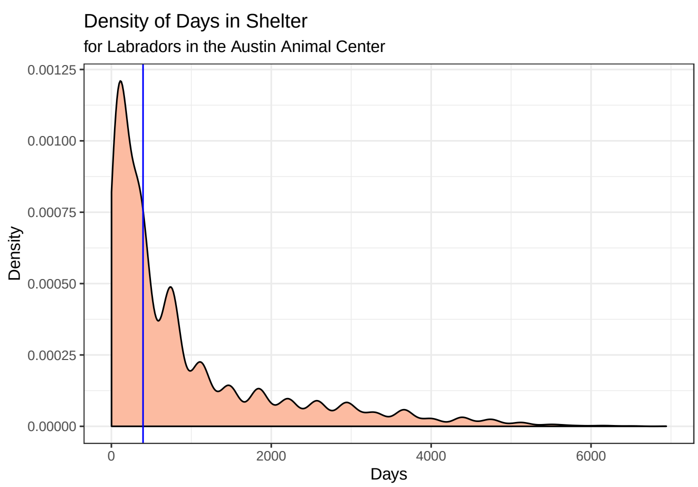


Figure 1: As a preliminary assessment of our data, and using the quantile function we find that half of the Labradors spend more than a year in the animal shelter (395 days, which is shown as the blue line). However, this form includes both censored and uncensored labradors which underestimates our value so we should take this figure lightly.

We plotted a Kaplan-Meier Curve without controlling for any variables. We noticed that the confidence interval curves were tight around the actual survival curve. This proves that the data is very detailed and the information is concrete because we have enough observations to do analysis on Labradors in the Austin Animal Center.

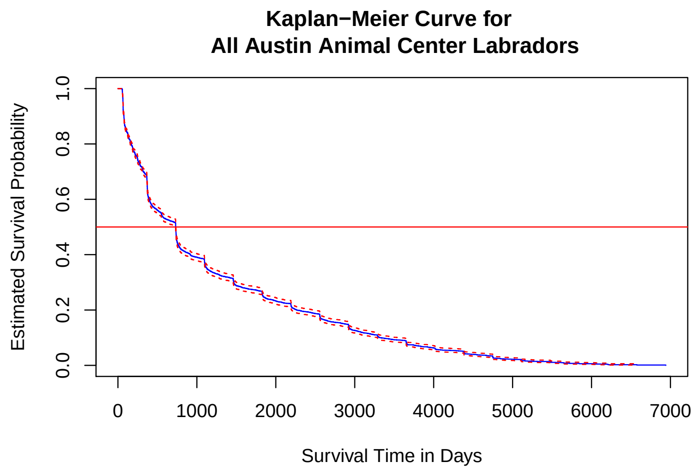


Figure 2: Kaplan-Meier curve

```
## Call: survfit(formula = labradors.surv ~ 1)
##
##        n  events  median 0.95LCL 0.95UCL
##     6929    5285     732     730     734
```

Kaplan-Meier

To visually see the survival curves we must plot Kaplan-Meier Curves for each covariate `color`, `sex` and `neuter` on time to adoption for labradors. The Kaplan-Meier curves for sex in Figure 3 shows that male Labs have higher estimated survival rates since the blue male line is above the red female line. As time increases, male and female Labs have the same or similar survival rates because the lines look like they begin to overlap after the 3,000 days mark. The Kaplan-Meier curves for neuter status in Figure 4 shows that intact Labs (labs that have not been neutered) have higher estimated survival rates than fixed labs. This means that more fixed labs are being adopted or going to homes (having the event) than labs that have not been neutered. The Kaplan-Meier curves for fur patterns in Figure 5 show labs with single colored fur patterns have higher survival rates than those with mixed fur patterns. The gaps immediately widen after the 50% survival rate mark and begin to close again nearer to the bottom.

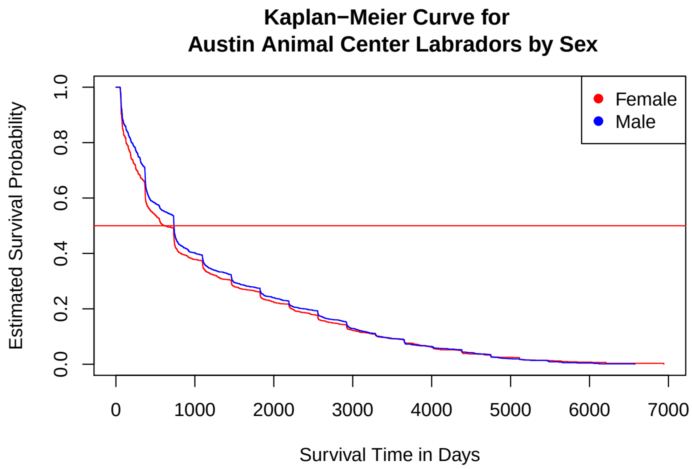


Figure 3: There is not a noticeable difference between the two curves so our pre-analysis hypothesis is that there is not going to be a significant difference.

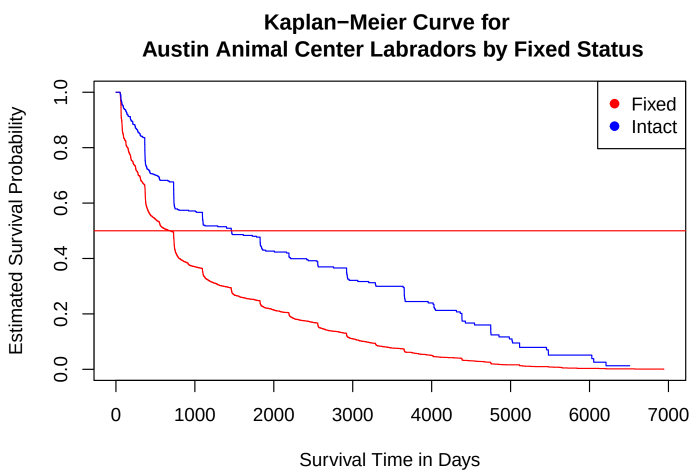


Figure 4: We see a bigger difference in the two survival curves between fixed and intact Labradors, mainly that fixed has a lower survival probability over time. However, this might be because there are many more observations on fixed labs than on intact labs, (fixed has about 4,000 more observations) so we will proceed with caution in our analysis because of this fact.

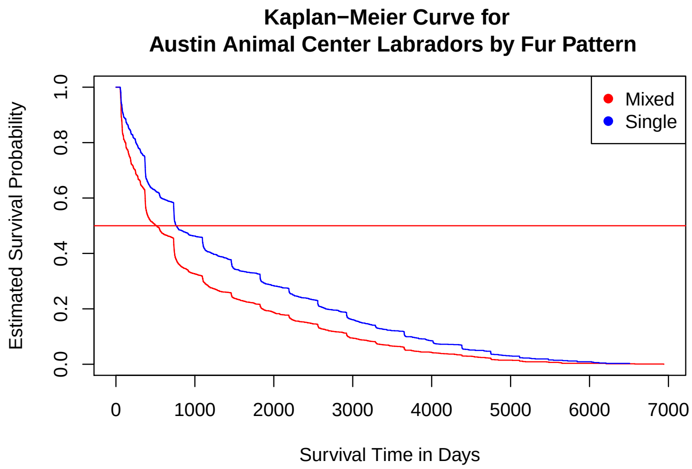


Figure 5: There appears to be an even amount of labs with mixed and solid fur patterns. There seems to be a slight difference in survival probability between the two fur patterns with mixed having a lower survival probability.

Log Rank Tests

The log lank test allows us to compare 2 or more survival curves, more specifically, that there is a significant difference between the survival curves. The null hypothesis that we are testing is that there is no difference in survival curves. The low p-value means we reject our null hypothesis.

```
## Call:
## survdiff(formula = labradors.surv ~ labradors.df$sex)
##
##                             N Observed Expected (O-E)^2/E (O-E)^2/V
## labradors.df$sex=Female 3211     2442     2347      3.87         7
## labradors.df$sex=Male   3718     2843     2938      3.09         7
##
##  Chisq= 7  on 1 degrees of freedom, p= 0.008
```

```
## Call:
## survdiff(formula = labradors.surv ~ labradors.df$neuter)
##
##                                N Observed Expected (O-E)^2/E (O-E)^2/V
## labradors.df$neuter=Fixed  5726     4884     4585      19.5       149
## labradors.df$neuter=Intact 1203      401      700     127.9       149
##
##  Chisq= 149  on 1 degrees of freedom, p= <2e-16
```

```
## Call:
## survdiff(formula = labradors.surv ~ labradors.df$color)
```

```
##
##                              N Observed Expected (O-E)^2/E (O-E)^2/V
## labradors.df$color=Mixed 3713     2853     2437      70.9       134
## labradors.df$color=Solid 3216     2432     2848      60.7       134
##
##  Chisq= 134  on 1 degrees of freedom, p= <2e-16
```

After performing log-rank tests for the 3 covariates (`sex`, fur pattern, fixed status) individually, we see that the p-value for each log-rank test is less than $\alpha = 0.05$. The null hypothesis for each test is that the survival curves for the covariate are not significantly different, but since the p-values for each test are less than $\alpha = 0.05$, we can conclude that each of the covariates' survival curves are statistically significantly different.

Model Building

To pick the right covariates for our model we use the anova function on the full model which includes all three covariates that we are examining. The anova function below indicates that each of the covariates are significant to include in our model since each one has a p-value of less than 0.05. Since the last covariate also has a significant p-value then we can conclude that each previous covariate in the model is also included and thus also significant. In anova, order of covariates matter and each new covariate is added to the previous model and evaluated.

```
## Analysis of Deviance Table
##  Cox model: response is Surv(date_diff, event)
## Terms added sequentially (first to last)
##
##         loglik    Chisq Df Pr(>|Chi|)
## NULL   -41263
## neuter -41177 171.8988  1    < 2e-16 ***
## color  -41120 113.6214  1    < 2e-16 ***
## sex    -41117   6.0749  1    0.01371 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We also use the backward elimination method in the step function which indicates that we should include all three of our covariates. The step function uses the Akaike Information Criterion (AIC) to measure each model quality and gives us the best model for the specificied stepwise search (i.e. backward, forward, or both).

```
## Start:  AIC=82239.47
## Surv(date_diff, event) ~ neuter + color + sex
##
##          Df   AIC
```

```
## <none>      82239
## - sex     1 82244
## - color   1 82351
## - neuter  1 82390
```

```
## Call:
## coxph(formula = Surv(date_diff, event) ~ neuter + color + sex,
##     data = labradors.df)
##
##                  coef exp(coef) se(coef)       z      p
## neuterIntact -0.59223   0.55309  0.05215 -11.357 <2e-16
## colorSolid   -0.29497   0.74455  0.02778 -10.617 <2e-16
## sexMale      -0.06811   0.93416  0.02761  -2.467 0.0136
##
## Likelihood ratio test=291.6  on 3 df, p=< 2.2e-16
## n= 6929, number of events= 5285
```

Model Checking

In order to build our Cox PH model we must check to see if the proportional hazard assumptions are met. We will do this by graphical evaluation of the log-log plots and by doing a residuals test using the cox.zph() function.

When evaluating the log-log plots we want to make sure that the survival curves don't cross and that the curves look proportional to one another through time. These criteria imply that the proportional hazards assumption is met. Figure 6 shows the log-log plot for the `sex` covariate. We see that the curves cross and overlap both at the beginning and end of the curves. This suggests that the PH assumption is violated. Figure 7 shows the log-log plot for the `neuter` covariate. We see that the survival curves cross in the beginning, but then seem to be proportional until the very end. Because of this, we will also assume the PH assumption is violated. In Figure 8, the log-log plot for the `color` covariate shows an increase in the gap between the curves, and then a decline in the size of the gap through time. This suggests that the hazard proportion is not constant and that the PH assumtions do not hold.

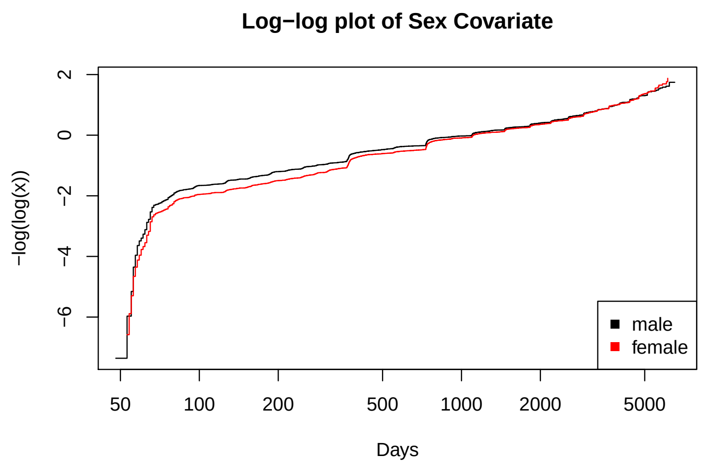


Figure 6: The log-log plot for the sex covariate violates the PH assumptions we are checking because the curves appear to be crossing in various places.

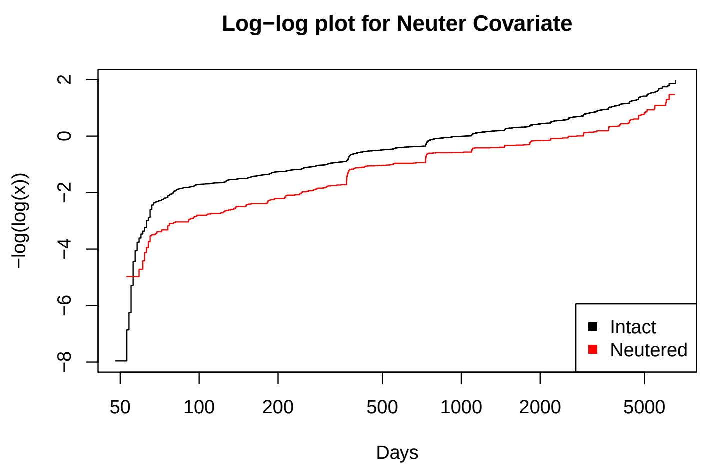


Figure 7: The log-log plot for the neuter covariate shows crossing lines in the very beginning but overall looks parallel after that. We may want to perform another test because there may be a PH violation.

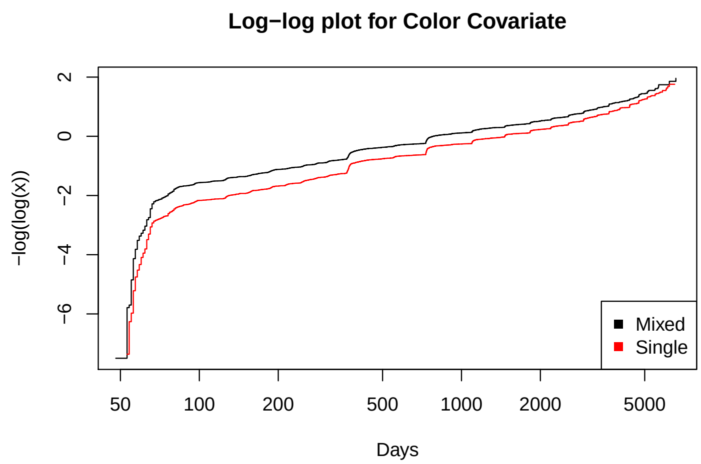


Figure 8: The survival curves appear to get closer to each other as time progresses. This means that the hazard ratio is no longer constant and it depends on time.

Using the Goodness-of-Fit test (table below) to further evaluate the PH assumptions, we test the null hypothesis that there is no correlation between the residuals and survival times. To do this we use the cox.zph() function in `R`. In the table below we see that for `color` and `sex` we reject the null hypothesis. This means that `color` and `sex` violate the PH assumptions. Notice that we do not reject the null hypothesis for the `neuter` variable which means that PH assumptions hold. We will move forward with this conclusion since our graphical evaluations were not clear. Our next step is to deal with the covariates that violate the PH assumption. We will do this by stratifying those covariates.

```
##                   rho  chisq        p
## neuterIntact 0.00847  0.379 5.38e-01
## colorSolid   0.07001 25.564 4.28e-07
## sexMale      0.06162 20.026 7.64e-06
```

Interaction Terms

We use likelihood ratio tests to consider if we need to include any interaction terms in our stratified Cox PH model. The potential interaction terms are `Neuter`* `strata(Sex)` and `Neuter` * `Strata(Color)`. The likelihood ratio tests performed on the models with and without interaction terms reveals that the only significant interaction was between `Neuter` and `strata(Sex)`. Therefore, our final stratified Cox PH model is `Surv ~ Neuter * strata(Sex) + strata(Color)`.

```
## Call:
## coxph(formula = Surv(date_diff, event) ~ neuter * strata(sex) +
```

```
##     strata(color), data = labradors.df)
##
##                                  coef exp(coef) se(coef)      z       p
## neuterIntact                  -0.7648    0.4654   0.0833 -9.181 < 2e-16
## neuterIntact:strata(sex)Male  0.2919    1.3390   0.1070  2.729 0.00635
##
## Likelihood ratio test=161.9  on 2 df, p=< 2.2e-16
## n= 6929, number of events= 5285
```

Hazard Ratio and Confidence Interval

We visualize the hazard ratio and the 95% confidence interval of the neuter covariate via figure 9. We see that intact labs are centered at 0.54 with a 95% confidence interval of (0.48, 0.59). Since 1 is not included in the 95% confidence interval, we can conclude that there is an effect with neuter status. This means that the hazard rate of the intact labs is 46% lower than fixed labs.

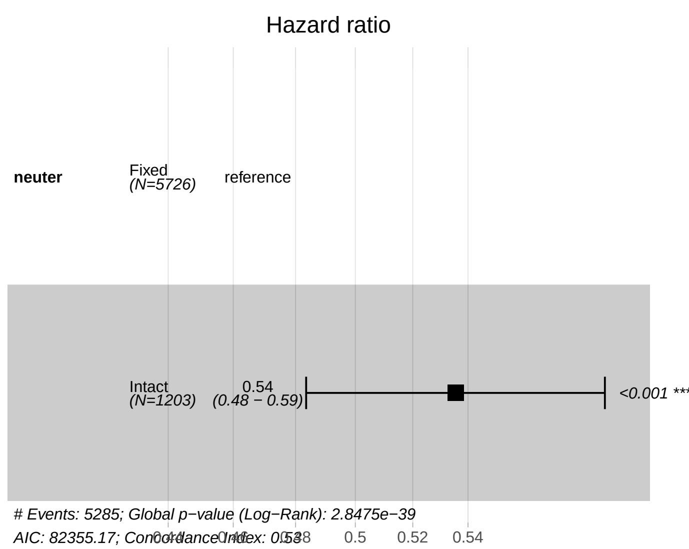
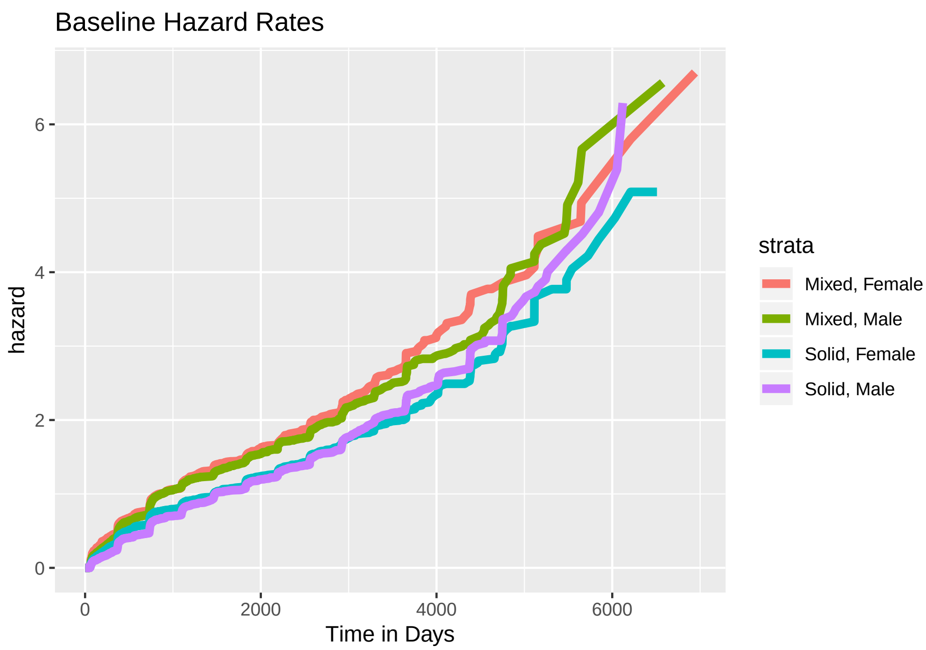


Figure 9: Hazard Ratio of Neuter Variable

We graphed the baseline hazard plot for each strata (strata(sex) including male and female and strata(color) including mixed color and solid color) of our model, so we have these four curves. We figured out that the hazard ratio is the adoption rate of corresponded group of labradors, meaning that the higher hazard ratio a group has, the larger adoption rate of the group is. As we could see, solid color female labradors have been, for most of the time, the least popular group, while between 0 and approximately 4800 days, mixed color female labradors seem to have the largest adoption rate. In addition, between approximately 4800 days and approximately 5500 days, we could see mixed color female labradors and mixed color male labradors go back and forth for having the largest adoption rate. After that, mixed color male labradors seem to consistently have the highest adoption rate while the solid color male labradors seem to have the tendency to be the most popular at the 6000 days mark and onwards.



Extension: Accelerated Failure Times

For our extension we will try to make an Accelerated Failure Time (AFT) model. The AFT model is different than the PH model in that the AFT model is used to compare survival times where the acceleration factor γ is the key measure that describes the difference in survival times. This is analogous to the hazard ratio in the PH model. In order to obtain this acceleration factor we must first explore which parametric survival model to use because if a parametric survival model doesn't make sense to our data, we won't be able to create an AFT model. We analyze the plot of $log(-log(\hat{S}(t)))$ on $log(t)$ where t is time in days, and $\hat{S}(t)$ is the Kaplan-Meier estimated survival times.

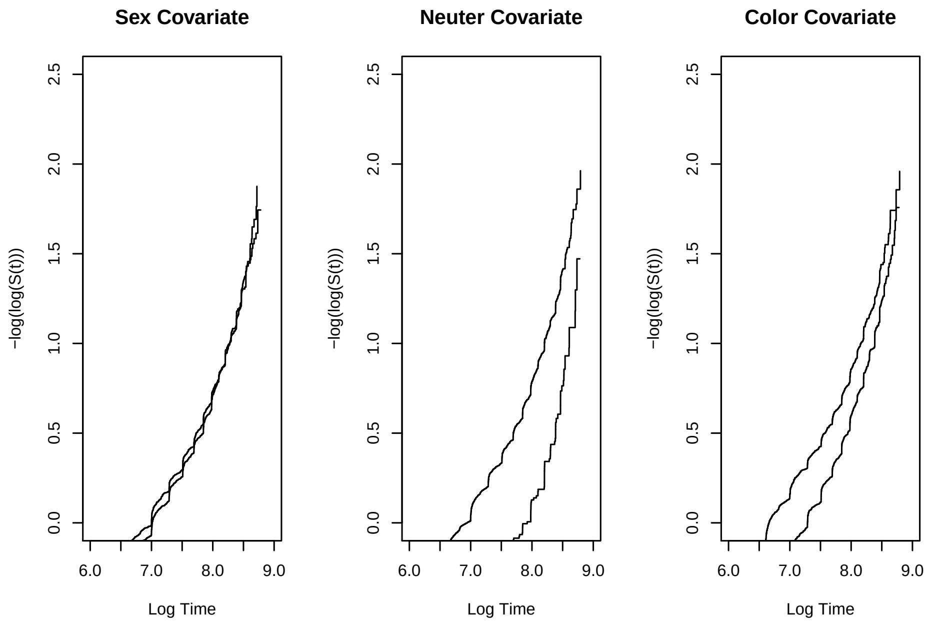


Figure 10: We plot the log(-log(survival time)) on the log(time) to check if the AFT assumptions hold for Weibull and Exponential.

Figure 10 indicates that the AFT assumptions are not met for both exponential and weibull. For Weibull, we would look for parallel straight lines, and if their slope is one this would indicate that the AFT assumption holds for exponential. Since we see that these lines are not straight and not parallel, due to the curves making a “horn” shape, then it is clear that the AFT assumption does not hold. This means we cannot use the Exponential or Weibull distributions. Next, we check log-logistic. In Figure 11 we want to look for indicators of the proportional odds assumptions and the log-logistic assumptions. If these two assumptions are met, then the AFT assumption is also met. We see that the lines are not parallel, which violates the proportional odds assumptions. Since the lines are curved, and not straight, this violates the log-logistic assumptions. We also cannot use the log-logistic model.

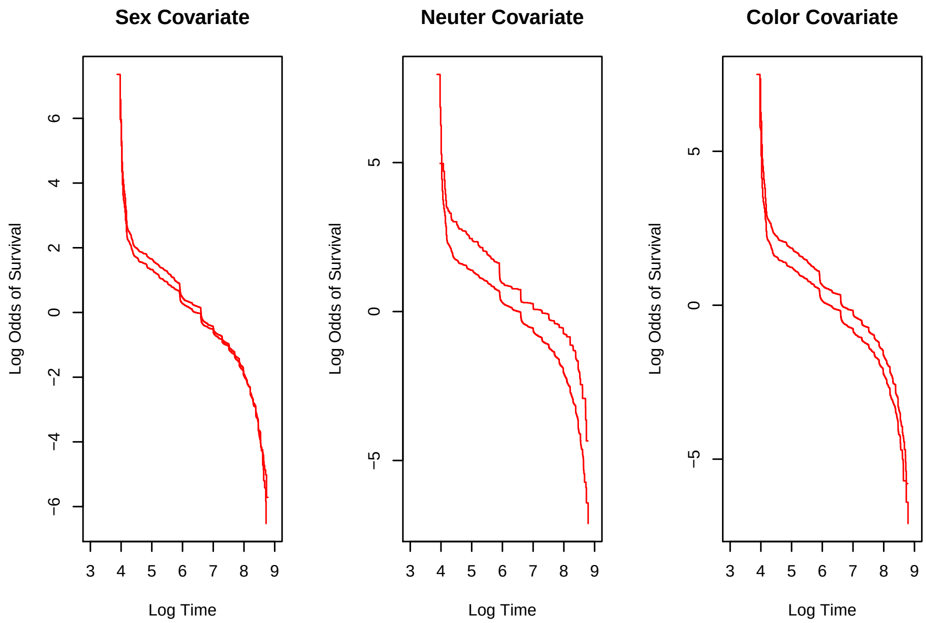


Figure 11: The log(survival odds) on the log(time) allows us to check if AFT Assumptions hold by looking for log-logistic assumptions (straight lines) and proportional odds assumption (parallel curves)

After observing these assumption failures, we have decided that it may not be possible to create an AFT model that makes sense for our data.

Conclusion/Discussion

The data from the Austin Animal Center had over 80,000 observations from 2013-2018. We reduced our observations to a subset of only labradors and labrador mixes, which produced a data set of 6,929 observations. We plotted Kaplan-Meier curves to see the estimated survival probabilities and found that on average, labradors spent 732 days at the Austin Animal Center before going to a home. The log rank tests let us see which survival curves were significantly different in each of the covariates, and allowed us to probe which covariates were potentially influential on adoption rates. All of the covariates turn out to be significant for our model, which led us to check the PH assumptions. The only covariate that did not violate the assumption was `neuter` so we stratified on `sex` and on `color`. We used the likelihood ratio test to see if we should include any significant interaction terms in our model. We concluded that there was a significant interaction between `neuter` and `sex`. This led us to finalizing the final model: `Surv` ~ `Neuter` * `Strata(Sex)` + `Strata(Color)`. Afterwards, we estimated the hazard ratio of Intact labs being 54% that of Fixed labs. Its 95%

confidence interval for `neuter` was (0.48, 0.59). Plotting the baseline hazard rates for the stratified covariates shows us that there are slight differences in the baseline hazard ratios of the different `color` and `sex` groups. From all the tests we performed, we saw that `neuter` ,`sex` and `color` were significant covariates for influencing labrador adoption rates at Austin Animal Center.

For our extension we attempted to find a suitable distribution for an AFT model. However, our analysis showed that we were not able to find a model that would make sense to use with our data and pass the AFT assumptions.