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STAT 567
PROJECT REPORT

SURVIVAL ANALYSIS OF HEROIN ADDICTS

Background and introduction:

Current illicit drug use among teens is continuing to increase in many countries around the world. Heroin is an addictive drug that is one of the most abused drugs and is processed from morphine and usually appears as a white or brown powder. According to the 2006 National Survey on Drug Use and Health (NSDUH), approximately 3.8 million Americans aged 12 or older reported trying heroin at least once during their lifetimes, representing 1.5% of the population aged 12 or older. A variety of effective treatments are available for heroin addiction. For example, methadone, a synthetic opiate that blocks the effects of heroin and eliminates withdrawal symptoms, has proven successful for the treatment of heroin addiction.

Dataset:

The addicts dataset was obtained from a 2007 Australian study by Caplehorn et al., and contains information on 238 heroin addicts. In a 2007 Australian study by Caplehorn et al., two methadone treatment clinics for heroin addicts were compared to assess patient time remaining under methadone treatment. A patient's survival time was determined as the time, in days, until the person dropped out of the clinic or was censored. The two clinics differed according to their live-in policies for patients.

The variables are defined as follows.

ID—Patient ID.
SURVT—The time (in days) until the patient dropped out of the clinic or was censored.
STATUS—indicates whether the patient dropped out of the clinic (coded 1) or was censored (coded 0).
CLINIC—indicates which methadone treatment clinic the patient attended (coded 1 or 2).
PRISON—Indicates whether the patient had a prison record (coded 1) or not (coded 0).
DOSE—A continuous variable for the patient's maximum methadone dose (mg/day).

Methods

The dataset will be analyzed to assess the patients survival time as a function of dose of methadone given to the patient, prison record and the clinic admitted. The survival functions will be estimated and compared across the clinics using a stratified approach. We run a cox proportional hazard model to obtain the regression coefficients, their standard errors, and a Wald test statistic (z) for each covariate, with corresponding p-value and 95% confidence interval. Thus we determine the effect of clinic, prison record and dose on the survival time of the addicts. If the proportional hazard assumption is not met for any of the covariates, then we can build a stratified cox model.

We also run a parametric accelerated failure time (AFT) models besides proportional hazards (PH) models. Whereas the key assumption of a PH model is that hazard ratios are constant over time, the key assumption for AFT model is that survival time accelerates (or decelerates) by a constant factor when comparing different levels of covariates.The most common distribution for parametric modeling of survival data is the Weibull distribution which will be used for the estimation of parameters.

We also estimate the CDF using both the parametric and non-parametric methods.

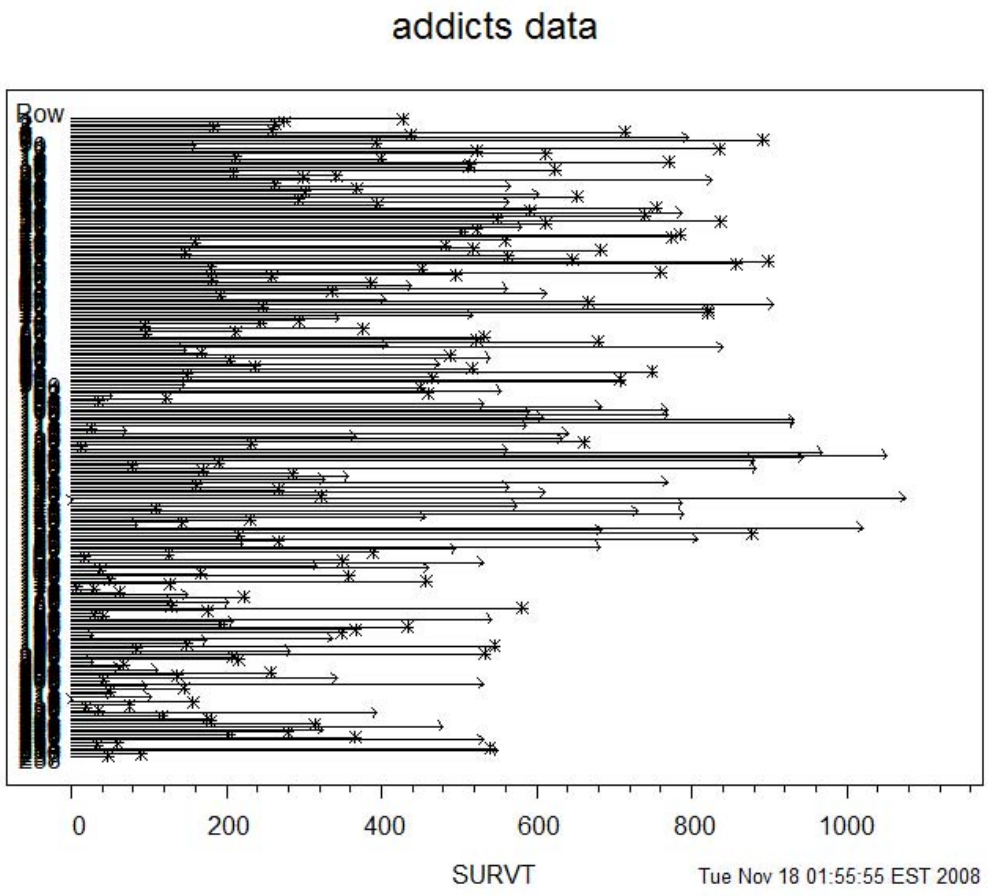
Results:

The results are divided in to two sections:

1. ADDICTS data exploration.
2. Parametric and non-parametric models.

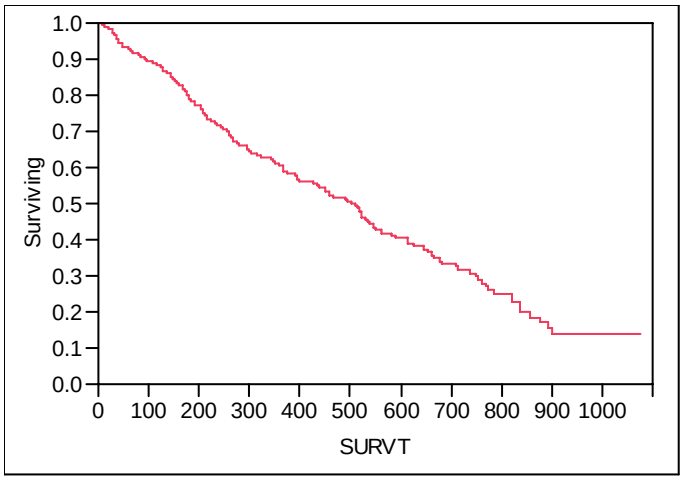
1. EXPLORATION OF ADDICTS DATA

This figure below is a life data event plot from SPLIDA that shows the survival times of all the patients in the addicts dataset.



Survival plots:

Survival Plot



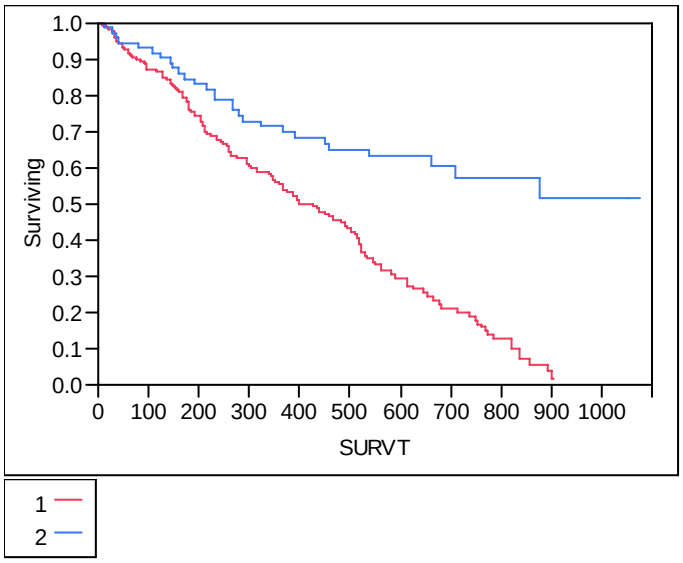
Quantiles

Group	Median Time	Lower95%	Upper95%	25% Failures	75% Failures
Combined	504	394	550	212	821

The **median** survival time is **504** days with a 95% CI **of [394, 550]**. Samples of survival times are frequently skewed, therefore, the median is a better measure of central location than mean.

Below is the survival plots drawn separately for the two clinics using JMP software.

Survival Plot



The above graph provides important results regarding the comparison of the two clinics. The curve for clinic 2 consistently lies above the curve for clinic 1, indicating that clinic 2 does better than clinic 1 in retaining its patients in methadone treatment. Further, because the two curves diverge after about a year, it appears that clinic 2 is vastly superior to clinic 1 after one year but only slightly better than clinic 1 prior to one year.

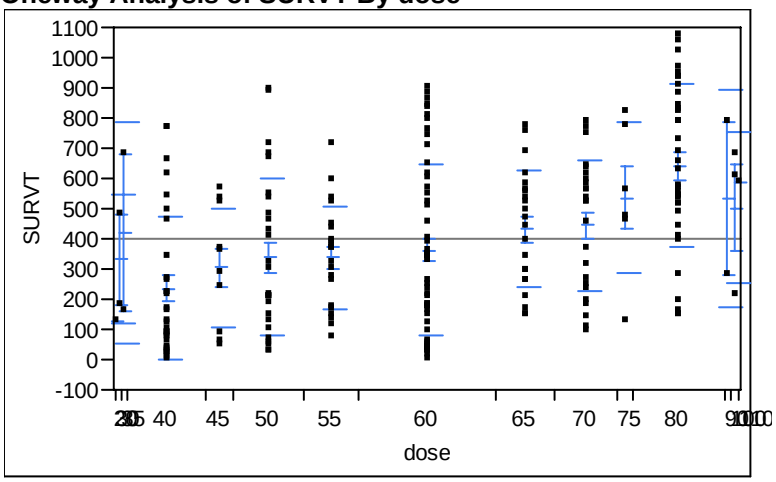
Tests Between Groups

Test	ChiSquare	DF	Prob>ChiSq
Log-Rank	27.8927	1	<.0001
Wilcoxon	11.6268	1	0.0007

Both the Log-rank and wilcoxon tests yield significant p-values. Hence it suggests that there is significant difference in survival times between the two clinics.

Then we explored the relationship between dose and survival time using bivariate fits;

Oneway Analysis of SURVT By dose



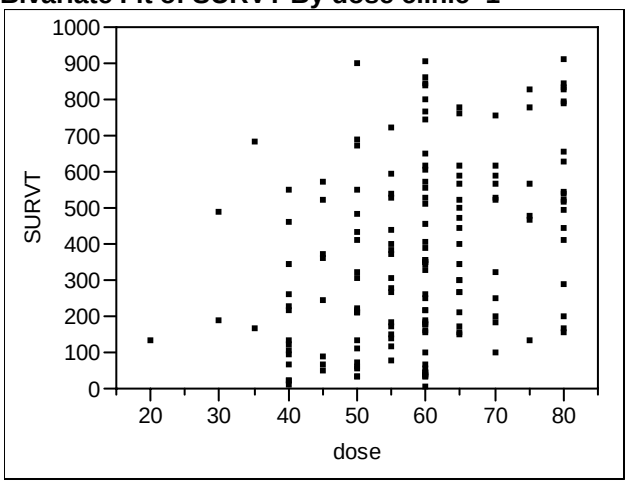
Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 95%	Upper 95%
20	1	127.000	.	.	.	.
30	2	332.500	211.425	149.50	-1567	2232.1
35	2	419.500	366.988	259.50	-2878	3716.8
40	30	234.567	236.187	43.12	146	322.8
45	10	305.200	197.681	62.51	164	446.6
50	27	338.778	261.266	50.28	235	442.1
55	21	338.381	169.413	36.97	261	415.5
60	52	362.788	280.566	38.91	285	440.9
65	22	430.455	193.170	41.18	345	516.1
70	24	444.417	218.883	44.68	352	536.8
75	6	536.167	250.848	102.41	273	799.4
80	35	641.600	269.176	45.50	549	734.1
90	2	535.000	360.624	255.00	-2705	3775.1
100	3	502.667	251.003	144.92	-121	1126.2
110	1	587.000	.	.	.	.

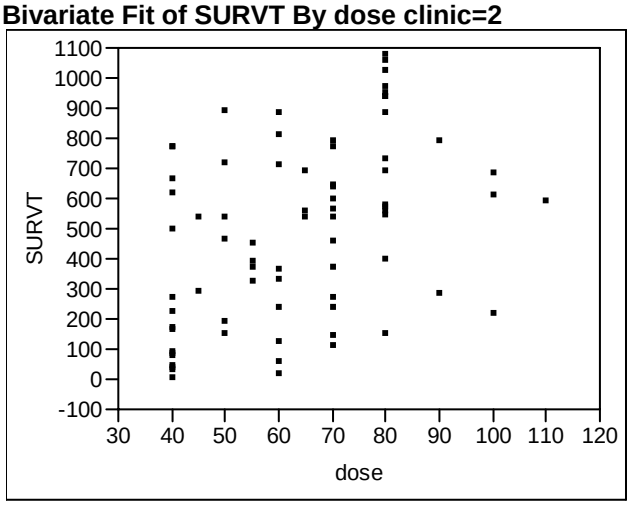
As we can see the survival times tend to be high at a dose of about 80mg.

Then to check if the effect of dose are different in the two clinics, we did the bivariate fits for the data from the two clinics independently.

Bivariate Fit of SURVT By dose clinic=1



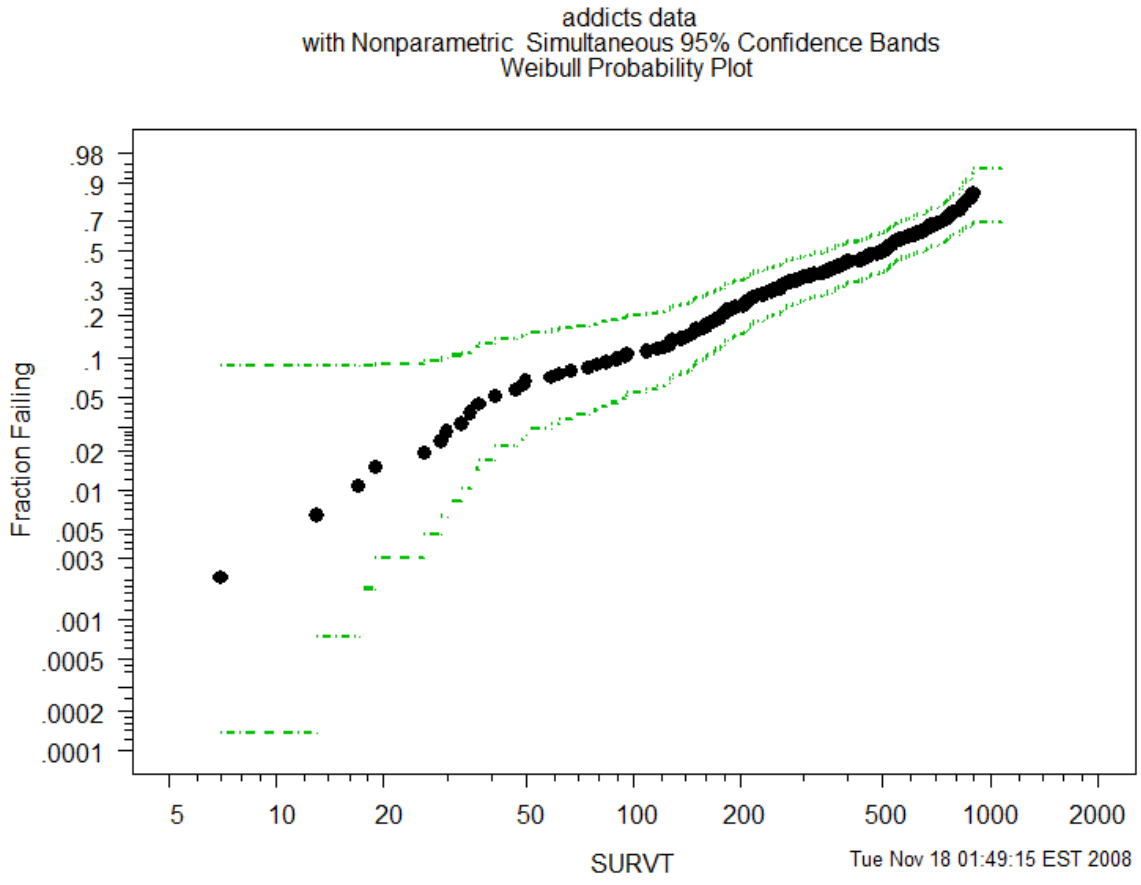
Bivariate Fit of SURVT By dose clinic=2



The trend of higher survival times at high doses of around 80 is still observed in both the clinics. Also doses above 80mg are administered only in clinic 2 which don't appear to any effective.

Estimation of F(t) using non-parametric methods

Then we also investigated the distribution of survival times using the non-parametric methods. We estimated a CDF F(t) from the data without having to assume an underlying parametric distribution.



Refer to Table-2 in the appendix for the CDF estimates at different survival times.

Estimation of F(t) using parametric methods:

Since weibull fits the best, we used it to estimate the CDF.

```
Using addicts data
Parametric ML CDF Estimates
Pointwise Approximate 95% Confidence Intervals

 Weibull Distribution

  SURVT      Fhat  Std.Err. 95% Lower 95% Upper
      5 0.0027191 0.0011030 0.0012275  0.006018
```

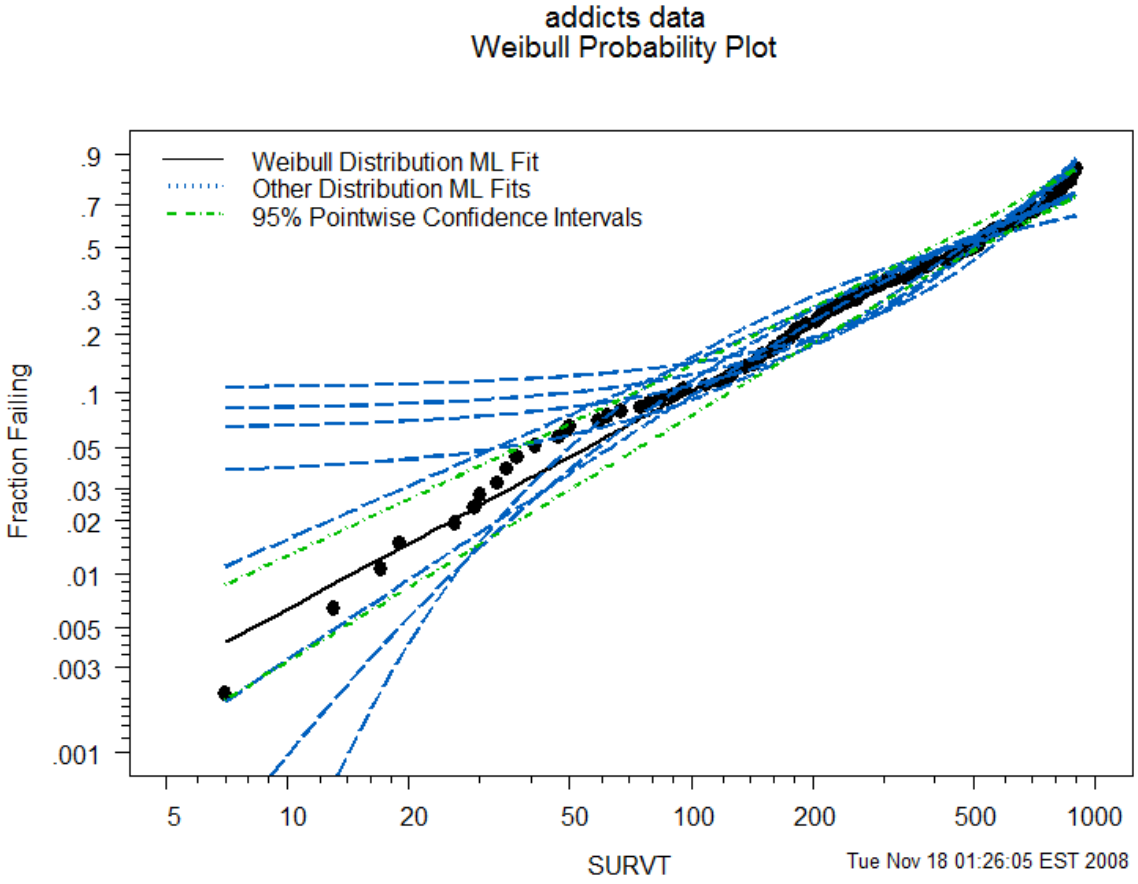
```
    10 0.0063508 0.0022084 0.0032105  0.012543
    20 0.0147968 0.0042896 0.0083746  0.026079
    50 0.0448251 0.0095761 0.0294368  0.067971
   100 0.1017507 0.0159607 0.0746360  0.137956
   200 0.2220433 0.0230683 0.1806161  0.271290
   500 0.5381122 0.0292596 0.4819786  0.596318
  1000 0.8359168 0.0285565 0.7760946  0.887275
  2000 0.9854332 0.0084280 0.9606136  0.996032


Using addicts data
Parametric ML Quantile Estimates
Pointwise Approximate 95% Confidence Intervals

 Weibull Distribution

      p   Quanhat  Std.Err. 95% Lower 95% Upper
  0.001    2.2102   0.85449    1.0360    4.7154
  0.005    8.2238   2.44737    4.5895   14.7363
  0.010   14.5017   3.76389    8.7195   24.1183
  0.050   54.7788   9.44468   39.0709   76.8020
  0.100   98.5179  13.39002   75.4787  128.5896
  0.200  181.6576  18.38385  148.9743  221.5112
  0.300  266.2792  22.13822  226.2399  313.4046
  0.400  356.8921  25.99746  309.4083  411.6631
  0.500  457.7392  30.99575  400.8474  522.7055
  0.600  574.7100  38.31020  504.3216  654.9225
  0.700  718.0249  49.65973  627.0022  822.2615
  0.800  909.7552  68.46394  784.9954 1054.3432
  0.900 1218.2888 105.40978 1028.2575 1443.4396
  0.990 2143.9007 247.49322 1709.7848 2688.2392
```

The approximate 95% likelihood confidence interval for 0.1 Quantile SURVT is: **[73.72 126.08]**
The approximate 95% likelihood confidence interval for beta is: **[1.067 1.399]**

The 0.10 quantile is 98.50 days meaning the 90% of them have survival times above 98.5 days.

Which distribution fits best?

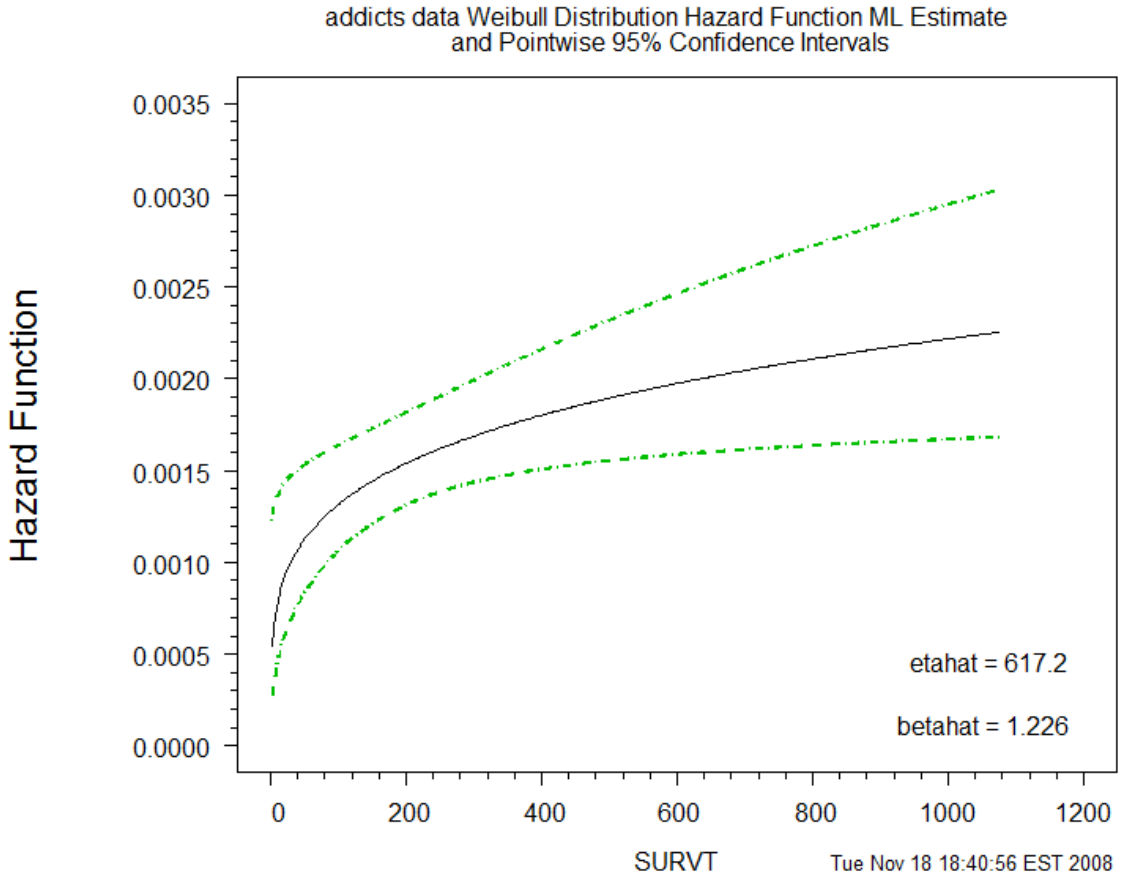
It is necessary to examine which distribution best fits the data and then make useful inference based on the distribution. Here in the plot below I have shown the fit of the weibull distribution with all other distributions such as exponential, normal, log normal etc., and the table below shows their log likelihood values. From these values we can see that Weibull distribution best fits the data.

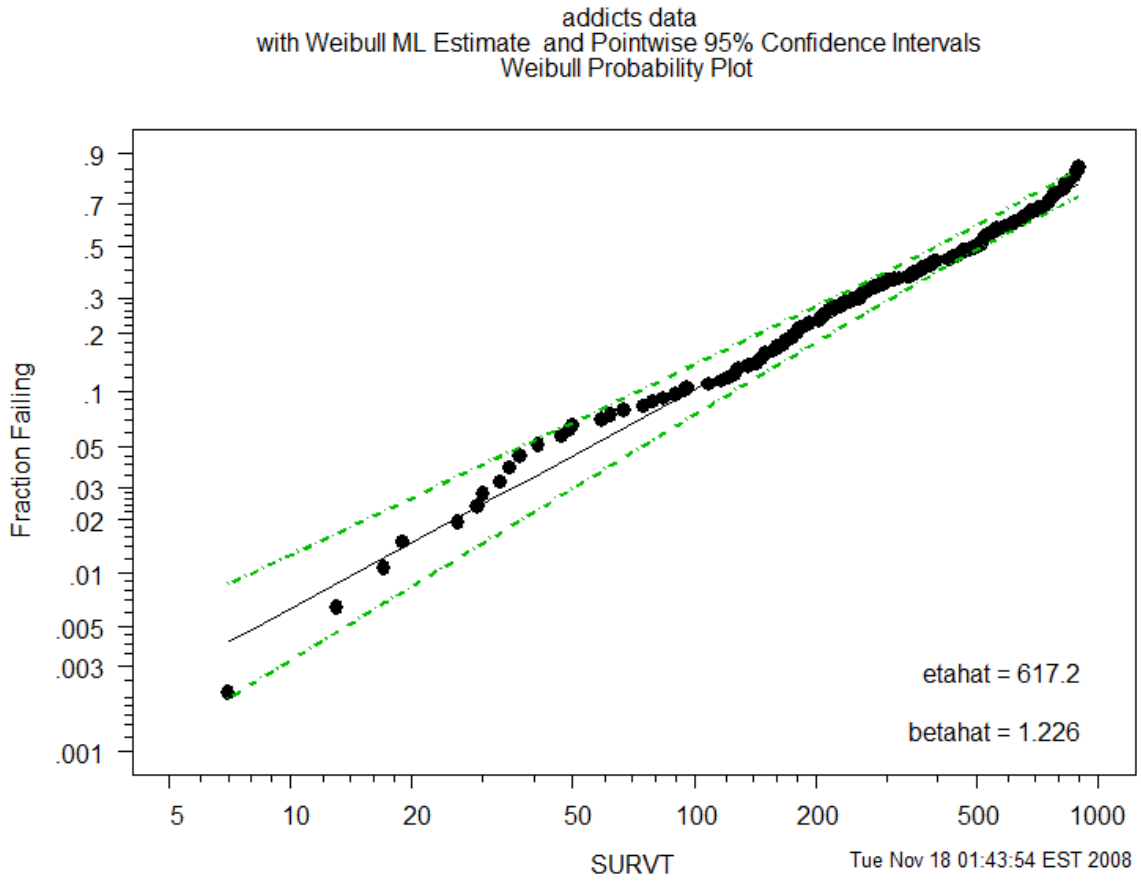



```
Maximum likelihood estimation results:

Response units: SURVT

Weibull Distribution
              Log likelihood      mu    se_mu    sigma se_sigma
1     weibull          -1115   6.425  0.06709   0.8154  0.05633
2 exponential          -1119   6.460  0.08165   1.0000  0.00000
3     frechet          -1143   5.557  0.10980   1.5022  0.08345
4         lev          -1131 361.479 21.87458 298.7874 19.31906
```

```
5    logistic          -1150 497.523 25.37421 203.3300 13.35538
6 loglogistic          -1120   6.095  0.07953   0.6638  0.04560
7   lognormal          -1124   6.060  0.08814   1.2103  0.07263
8      normal          -1145 512.592 24.30967 334.0941 20.00014
9         sev          -1166 665.516 24.65546 301.6447 18.69764
```

There are several ways to view this distribution, including probability plots, survival plots hazard plots etc.






```
Response units: SURVT

Weibull Distribution

Log likelihood at maximum point: -1115

  Parameter                    Approx Conf. Interval
                  MLE Std.Err. 95% Lower 95% Upper
         mu    6.4251  0.06709    6.2937    6.5566
      sigma    0.8154  0.05633    0.7121    0.9336
 weibull.eta 617.1719 41.40504  541.1285  703.9014
weibull.beta   1.2264  0.08473    1.0711    1.4043
```

The ML estimate of mean survival time for the addicts data is **577.4.**
An approximate 95% confidence interval is **[502.3, 663.7].**

A beta less than 1 models a hazard rate that decreases with time, as in the infant mortality period. A beta equal to 1 models a constant hazard rate, as in the normal life period. And a beta greater than 1 models an increasing hazard rate.

Because beta is > 1 and < 2 in our case, the hazard rate is rapid.

2. PARAMETRIC AND NON-PARAMETRIC MODELS

Cox proportional hazards model:

We then fit the cox proportional hazards model to the addicts data. The proportional hazard model is the most general of the regression models because it is not based on any assumptions concerning the nature or shape of the underlying survival distribution. The model assumes that the underlying hazard rate (rather than survival time) is a function of the independent variables (covariates). No assumptions are made about the nature or shape of the hazard function. Thus, in a sense, Cox's regression model may be considered to be a nonparametric method.

Fitting a proportional hazards model using JMP

Proportional Hazards Fit
Censored By: Type

Whole Model

Number of Events	150
Number of Censorings	88
Total Number	238

Model	-LogLikelihood	ChiSquare	DF	Prob>Chisq
Difference	32.2595	64.5190	3	<.0001
Full	673.4024			
Reduced	705.6619			

Parameter Estimates

Term	Estimate	Std Error	Lower CL	Upper CL
clinic[1]	0.5044348	0.1074355	0.3017243	0.7244106
prison	0.32651075	0.1672211	-0.003021	0.6542581
dose	-0.0353962	0.0063795	-0.047935	-0.022911

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
clinic	1	1	26.2986694	**<.0001**
prison	1	1	3.77186664	**0.0521**
dose	1	1	30.8238023	**<.0001**

There are three statistical objectives typically considered. One is to test for the significance of the treatment status variable, adjusted for other variables. Another is to obtain a point estimate of the effect of treatment status, adjusted for other variables. And a third is to obtain a confidence interval for this effect.

To test for the significance of the treatment effects, we look at the log likelihood ratio test results for all the different explanatory variables. The Effect Likelihood-Ratio Test tests whether or not a variable is important given the other variable is already in the model. All the variables including clinic, prison and dose have significant p-values indicating that they have a significant effect on the survival time. However the 95% CI of the regression estimate for prison contains zero. So there is little statistical evidence

that prison record affects the survival time of the addicts. Hence prison record might not be a good predictor of the survival time.

Risk Ratios
Unit Risk Ratios
Per unit change in regressor

Term	Risk Ratio	Lower CL	Upper CL	Reciprocal
prison	1.386123	0.996984	1.923715	0.7214366
dose	0.965223	0.953196	0.97735	1.0360301

Range Risk Ratios
Per change in regressor over entire range

Term	Risk Ratio	Lower CL	Upper CL	Reciprocal
prison	1.386123	0.996984	1.923715	0.7214366
dose	0.041351	0.013378	0.127205	24.183089

Risk Ratios for clinic

Level1	/Level2	Risk Ratio	Reciprocal
2	1	0.3646309	2.7424991

Above is a table showing risk ratios for the effect of each variable adjusted for the other variables in the model. Also the 95% CI of risk ratio for prison record contains 1 which again suggests that hazard for prisoners is not very different from the non-prisoners. The risk ratio clinic2/clinic1 is 0.36 suggesting that clinic 1 is associated with higher hazard compared to clinic 2. Our analysis of the output has led us to conclude that the model is appropriate and that, using this model, we get statistically significant risk ratios for clinic and dose.

Parametric survival models:

A parametric survival model is one in which survival time (the outcome) is assumed to follow a known distribution. Examples of distributions that are commonly used for survival time are: the Weibull, the exponential (a special case of the Weibull), the log-logistic, the lognormal, and the generalized gamma. Linear regression, logistic regression, and Poisson regression are examples of parametric models that are commonly used in the health sciences. With these models, the outcome is assumed to follow some distribution

The Cox proportional hazards model, by contrast, is not a fully parametric model. Rather it is a semiparametric model because even if the regression parameters (the betas) are known, the distribution of the outcome remains unknown. The baseline survival (or hazard) function is not specified in a Cox model.

Now we fit parametric models to the addicts data.

Parametric accelerated failure time (AFT) models

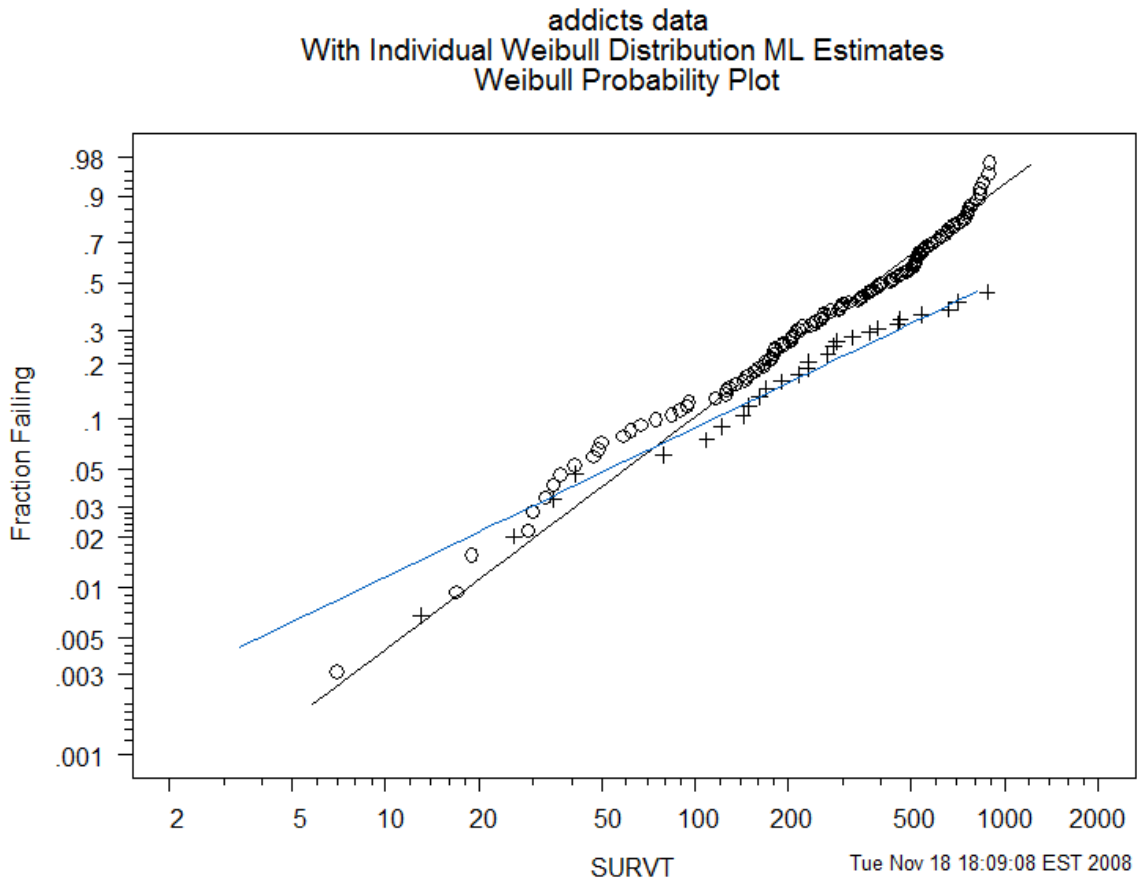
We also run a parametric accelerated failure time (AFT) models besides proportional hazards models. Whereas the key assumption of a PH model is that hazard ratios are constant over time, the key assumption for AFT model is that survival time accelerates (or decelerates) by a constant factor when comparing different levels of covariates. The most common distribution for parametric modeling of survival data is the Weibull distribution which will be used for the estimation of parameters.

ALT multiple regression using all the explanatory variables yielded the following results:

```
Maximum likelihood estimation results:

Response units: SURVT

Weibull Distribution

Variable: Relationship (g)
1 clinic: Linear
2 prison: Linear
3 dose: Linear

Model formula:
Location ~ clinic + prison + dose

Log likelihood at maximum point: -1084

  Parameter                      Approx Conf. Interval
                  MLE Std.Err. 95% Lower 95% Upper
 (Intercept)  4.10485  0.32806   3.46186  4.747828
      clinic  0.70904  0.15722   0.40089  1.017196
      prison -0.22947  0.12079  -0.46621  0.007275
        dose  0.02443  0.00459   0.01543  0.033421
       sigma  0.72982  0.04931   0.63931  0.833151
weibull.beta  1.37019  0.09257   1.20026  1.564184
```

We get similar results an in PH model. Clinic and dose are significant based on the 95% CI of the estimates which does not include 0. However the 95% CI includes 0 for the prison estimate which again suggests that there is not enough evidence to support that prison record affects the survival time.

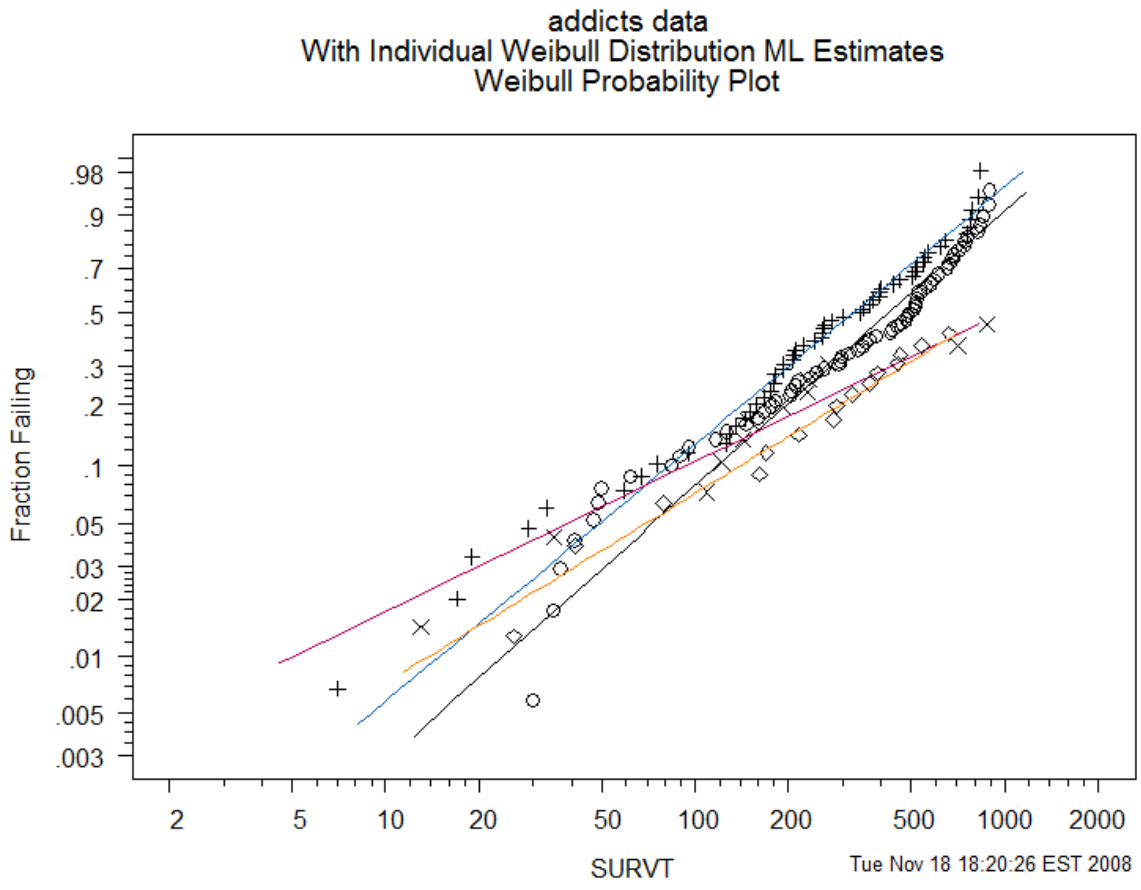
Here is a probability plot (individual conditions) that shows separate regression analyses for the two clinics.




```
Weibull Distribution
          Log likelihood    eta se_eta   beta se_beta
1 1clinic         -868.4  490.1  31.75 1.4012  0.1047
2 2clinic         -228.4 1413.8 365.51 0.8993  0.1526
```

As we can see, the weibull shape parameters are not the same between the same groups. Also there is a huge difference in the log likelihoods.

Here is a probability plot (individual conditions) that shows separate regression analyses for the all combinations of the levels of dose and prison record.




```
Weibull Distribution
                  Log likelihood eta    se_eta   beta se_beta
1 1clinic;0prison         -476.2 544.9  45.60 1.4728  0.1537
2 1clinic;1prison         -390.3  422.7  41.24 1.3753  0.1471
3 2clinic;1prison         -105.5 1544.6 655.71 0.8025  0.1976
4 2clinic;0prison         -122.7 1298.4 408.59 1.0115  0.2364
```

It looks here again the major differentiating factor is clinic and within each clinic there is no difference in the likelihood across different prison records.

Conclusions:

From the analysis we can see how the dose of methadone and prison record affects the survival time of the addicts. Both the parametric and non-parametric models suggest that there is evidence to support that dose has a significant effect on the survival times of the addicts. Bivariate plots reveal that at a dose of around 80mg, the survival times of the patients were high and this could be about the optimal dose that is needed to treat the patients. It will be also be interesting to see how the prison record affects his level of his addiction and thus the survival time. Though it is expected that most of the people with prison record would have higher levels of addiction to heroin and less survival times compared to the ones without any felony record, we do not observe a significant relationship between the prison record and survival record. Also we see how the two different clinics are contributing to the variation in the survival times. The two clinics seem to be very different in terms of administering the doses. The type of patients admitted could be different between the two clinics. Long term addicts might be admitted in one clinic and addicts exposed to low or moderate levels of heroin might be admitted to another one which could be causing the difference. We have also explored the distribution of survival times using bivariate plots, quantiles and cumulative distribution function.

APPENDIX:

Table 1: RAW DATA:

clinic	status	SURVT	prison
1	1	428	0
1	1	275	1
1	1	262	0
1	1	183	0
1	1	259	1
1	1	714	0
1	1	438	1
1	0	796	1
1	1	892	0
1	1	393	1
1	0	161	1
1	1	836	1
1	1	523	0
1	1	612	0
1	1	212	1
1	1	399	1
1	1	771	1
1	1	514	1
1	1	512	0
1	1	624	1
1	1	209	1
1	1	341	1
1	1	299	0
1	0	826	0
1	1	262	1
1	0	566	1
1	1	368	1
1	1	302	1
1	0	602	0
1	1	652	0
1	1	293	0
1	0	564	0
1	1	394	1
1	1	755	1
1	1	591	0
1	0	787	0
1	1	739	0
1	1	550	1
1	1	837	0
1	1	612	0
1	0	581	0
1	1	523	0
1	1	504	1
1	1	785	1
1	1	774	1
1	1	560	0
1	1	160	0
1	1	482	0
1	1	518	0
1	1	683	0
1	1	147	0
1	1	563	1
1	1	646	1
1	1	899	0
1	1	857	0
1	1	180	1
1	1	452	0
1	1	760	0
1	1	496	0
1	1	258	1
1	1	181	1
1	1	386	0
1	0	439	0

clinic	status	SURVT	prison
1	0	563	0
1	1	337	0
1	0	613	1
1	1	192	1
1	0	405	0
1	1	667	0
1	0	905	0
1	1	247	0
1	1	821	0
1	1	821	1
1	0	517	0
1	0	346	1
1	1	294	0
1	1	244	1
1	1	95	1
1	1	376	1
1	1	212	0
1	1	96	0
1	1	532	0
1	1	522	1
1	1	679	0
1	0	408	0
1	0	840	0
1	0	148	1
1	1	168	0
1	1	489	0
1	0	541	0
1	1	205	0
1	0	475	1
1	1	237	0
1	1	517	0
1	1	749	0
1	1	150	1
1	1	465	0
2	1	708	1
2	0	713	0
2	0	146	0
2	1	450	0
2	0	555	0
2	1	460	0
2	0	53	1
2	1	122	1
2	1	35	1
2	0	532	0
2	0	684	0
2	0	769	1
2	0	591	0
2	0	769	1
2	0	609	1
2	0	932	1
2	0	932	1
2	0	587	0
2	1	26	0
2	0	72	1
2	0	641	0
2	0	367	0
2	0	633	0
2	1	661	0
2	1	232	1
2	1	13	1
2	0	563	0
2	0	969	0
2	0	1052	0
2	0	944	1
2	0	881	0
2	1	190	1
2	1	79	0
2	0	884	1
2	1	170	0

clinic	status	SURVT	prison
2	1	286	0
2	0	358	0
2	0	326	1
2	0	769	1
2	1	161	0
2	0	564	1
2	1	268	1
2	0	611	1
2	1	322	0
2	0	1076	1
2	0	2	1
2	0	788	0
2	0	575	0
2	1	109	1
2	0	730	1
2	0	790	0
2	0	456	1
2	1	231	1
2	1	143	1
2	0	86	1
2	0	1021	0
2	0	684	1
2	1	878	1
2	1	216	0
2	0	808	0
2	1	268	1
2	0	222	0
2	0	683	0
2	0	496	0
2	1	389	0
1	1	126	1
1	1	17	1
1	1	350	0
2	0	531	1
1	0	317	1
1	0	461	1
1	1	37	0
1	1	167	1
1	1	358	0
1	1	49	0
1	1	457	1
1	1	127	0
1	1	7	1
1	1	29	1
1	1	62	0
1	0	150	1
1	1	223	1
1	0	129	1
1	0	204	1
1	1	129	1
1	1	581	0
1	1	176	0
1	1	30	0
1	1	41	0
1	0	543	0
1	0	210	1
1	1	193	1
1	1	434	0
1	1	367	0
1	1	348	1
1	0	28	0
1	0	337	0
1	0	175	1
2	1	149	1
1	1	546	1
1	1	84	0
1	0	283	1
1	1	533	0
1	1	207	1

clinic	status	SURVT	prison
1	1	216	0
1	0	28	0
1	1	67	1
1	0	62	1
1	0	111	0
1	1	257	1
1	1	136	1
1	0	342	0
2	1	41	0
2	0	531	1
1	0	98	0
1	1	145	1
1	1	50	0
1	0	53	0
1	0	103	1
1	0	2	1
1	1	157	1
1	1	75	1
1	1	19	1
1	1	35	0
2	0	394	1
1	1	117	0
1	1	175	1
1	1	180	1
1	1	314	0
1	0	480	0
1	0	325	1
2	1	280	0
1	1	204	0
2	1	366	0
2	0	531	1
1	1	59	1
1	1	33	1
2	1	540	0
2	0	551	0
1	1	90	0
1	1	47	0

Table 2:

Nonparametric estimates from addicts data
with approximate 95% simultaneous confidence intervals

numeric matrix: 141 rows, 6 columns.

	SURVT-lower	SURVT-upper	Fhat	SE_Hat	95% Lower	95% Upper
1	0	7	0.000000	0.000000	0.0000000	0.00000
2	7	13	0.004237	0.004228	0.0001345	0.08709
3	13	17	0.008475	0.005967	0.0007388	0.08709
4	17	19	0.012712	0.007292	0.0017348	0.08709
5	19	26	0.016949	0.008402	0.0030227	0.08929
6	26	29	0.021186	0.009374	0.0045368	0.09322
7	29	30	0.025461	0.010261	0.0062418	0.09802
8	30	33	0.029735	0.011071	0.0080994	0.10315
9	33	35	0.034009	0.011818	0.0100864	0.10846
10	35	37	0.042558	0.013169	0.0143810	0.11926
11	37	41	0.046832	0.013787	0.0166636	0.12469
12	41	47	0.055381	0.014929	0.0214535	0.13553
13	47	49	0.059655	0.015462	0.0239471	0.14092
14	49	50	0.063929	0.015971	0.0264989	0.14629
15	50	59	0.068204	0.016460	0.0291043	0.15163
16	59	62	0.072518	0.016940	0.0317763	0.15702
17	62	67	0.076831	0.017402	0.0344954	0.16239
18	67	75	0.081166	0.017852	0.0372675	0.16776
19	75	79	0.085520	0.018291	0.0400906	0.17314
20	79	84	0.089875	0.018715	0.0429531	0.17849
21	84	90	0.094230	0.019125	0.0458530	0.18381
22	90	95	0.098605	0.019527	0.0487982	0.18914
23	95	96	0.102981	0.019916	0.0517771	0.19444

	SURVT-lower	SURVT-upper	Fhat	SE_Hat	95% Lower	95% Upper
24	96	109	0.1074	0.02029	0.05479	0.1997
25	109	117	0.1118	0.02067	0.05785	0.2050
26	117	122	0.1162	0.02104	0.06096	0.2104
27	122	126	0.1207	0.02140	0.06409	0.2157
28	126	127	0.1251	0.02174	0.06725	0.2209
29	127	129	0.1295	0.02208	0.07044	0.2262
30	129	136	0.1340	0.02241	0.07365	0.2314
31	136	143	0.1384	0.02274	0.07690	0.2366
32	143	145	0.1429	0.02305	0.08017	0.2418
33	145	147	0.1474	0.02336	0.08347	0.2470
34	147	149	0.1519	0.02366	0.08680	0.2522
35	149	150	0.1564	0.02396	0.09017	0.2574
36	150	157	0.1609	0.02426	0.09355	0.2626
37	157	160	0.1654	0.02455	0.09698	0.2678
38	160	161	0.1700	0.02483	0.10042	0.2730
39	161	167	0.1745	0.02510	0.10388	0.2782
40	167	168	0.1791	0.02538	0.10738	0.2834
41	168	170	0.1836	0.02564	0.11089	0.2885
42	170	175	0.1882	0.02590	0.11443	0.2937
43	175	176	0.1927	0.02615	0.11798	0.2988
44	176	180	0.1973	0.02640	0.12156	0.3040
45	180	181	0.2065	0.02689	0.12878	0.3142
46	181	183	0.2111	0.02712	0.13242	0.3193

	SURVT-lower	SURVT-upper	Fhat	SE_Hat	95% Lower	95% Upper
47	183	190	0.2157	0.02735	0.1361	0.3244
48	190	192	0.2203	0.02757	0.1397	0.3294
49	192	193	0.2248	0.02779	0.1434	0.3344
50	193	204	0.2294	0.02800	0.1471	0.3395
51	204	205	0.2340	0.02821	0.1508	0.3445

52	205	207	0.2386	0.02841	0.1546	0.3495
53	207	209	0.2432	0.02861	0.1583	0.3545
54	209	212	0.2479	0.02881	0.1621	0.3595
55	212	216	0.2571	0.02919	0.1697	0.3695
56	216	223	0.2664	0.02955	0.1774	0.3795
57	223	231	0.2711	0.02973	0.1813	0.3845
58	231	232	0.2758	0.02991	0.1852	0.3895
59	232	237	0.2804	0.03008	0.1891	0.3945
60	237	244	0.2851	0.03024	0.1930	0.3994
61	244	247	0.2898	0.03040	0.1969	0.4044
62	247	257	0.2945	0.03056	0.2009	0.4093
63	257	258	0.2991	0.03071	0.2048	0.4142
64	258	259	0.3038	0.03086	0.2088	0.4191
65	259	262	0.3085	0.03101	0.2128	0.4240
66	262	268	0.3178	0.03128	0.2208	0.4338
67	268	275	0.3272	0.03154	0.2288	0.4435
68	275	280	0.3318	0.03167	0.2329	0.4483
69	280	286	0.3365	0.03179	0.2369	0.4531

	SURVT-lower	SURVT-upper	Fhat	SE_Fhat	95% Lower	95% Upper
70	286	293	0.3412	0.03191	0.2410	0.4580
71	293	294	0.3459	0.03203	0.2451	0.4628
72	294	299	0.3506	0.03214	0.2492	0.4676
73	299	302	0.3553	0.03225	0.2533	0.4724
74	302	314	0.3600	0.03236	0.2575	0.4772
75	314	322	0.3647	0.03246	0.2616	0.4820
76	322	337	0.3695	0.03256	0.2658	0.4868
77	337	341	0.3743	0.03267	0.2700	0.4917
78	341	348	0.3792	0.03277	0.2743	0.4967
79	348	350	0.3841	0.03288	0.2786	0.5017
80	350	358	0.3890	0.03298	0.2830	0.5067
81	358	366	0.3939	0.03308	0.2873	0.5117
82	366	367	0.3989	0.03318	0.2917	0.5167
83	367	368	0.4039	0.03328	0.2961	0.5218
84	368	376	0.4089	0.03338	0.3006	0.5268
85	376	386	0.4139	0.03347	0.3050	0.5319
86	386	389	0.4189	0.03355	0.3095	0.5369
87	389	393	0.4239	0.03364	0.3140	0.5419
88	393	394	0.4289	0.03371	0.3185	0.5469
89	394	399	0.4339	0.03379	0.3230	0.5519
90	399	428	0.4390	0.03386	0.3276	0.5569
91	428	434	0.4441	0.03394	0.3322	0.5620
92	434	438	0.4493	0.03401	0.3368	0.5672

	SURVT-lower	SURVT-upper	Fhat	SE_Fhat	95% Lower	95% Upper
93	438	450	0.4544	0.03408	0.3415	0.5722
94	450	452	0.4596	0.03415	0.3462	0.5774
95	452	457	0.4648	0.03422	0.3509	0.5825
96	457	460	0.4701	0.03428	0.3557	0.5877
97	460	465	0.4753	0.03434	0.3604	0.5929
98	465	482	0.4806	0.03440	0.3653	0.5981
99	482	489	0.4860	0.03447	0.3702	0.6034
100	489	496	0.4914	0.03453	0.3751	0.6087
101	496	504	0.4968	0.03458	0.3800	0.6140
102	504	512	0.5023	0.03463	0.3850	0.6193
103	512	514	0.5078	0.03468	0.3900	0.6247
104	514	517	0.5132	0.03473	0.3951	0.6300
105	517	518	0.5187	0.03476	0.4001	0.6353
106	518	522	0.5242	0.03480	0.4052	0.6406
107	522	523	0.5298	0.03483	0.4103	0.6459
108	523	532	0.5408	0.03488	0.4206	0.6565
109	532	533	0.5466	0.03491	0.4259	0.6620
110	533	540	0.5524	0.03495	0.4312	0.6676
111	540	546	0.5582	0.03497	0.4366	0.6732
112	546	550	0.5642	0.03501	0.4421	0.6789

113	550	560	0.5701	0.03503	0.4476	0.6846
114	560	563	0.5763	0.03507	0.4533	0.6905
115	563	581	0.5824	0.03509	0.4590	0.6964
	SURVT-lower	SURVT-upper	Fhat	SE_Fhat	95% Lower	95% Upper
116	581	591	0.5892	0.03517	0.4650	0.7029
117	591	612	0.5961	0.03525	0.4712	0.7097
118	612	624	0.6111	0.03550	0.4843	0.7245
119	624	646	0.6187	0.03561	0.4909	0.7319
120	646	652	0.6267	0.03574	0.4978	0.7397
121	652	661	0.6346	0.03586	0.5048	0.7474
122	661	667	0.6425	0.03595	0.5118	0.7551
123	667	679	0.6505	0.03601	0.5188	0.7626
124	679	683	0.6584	0.03606	0.5259	0.7701
125	683	708	0.6664	0.03609	0.5330	0.7775
126	708	714	0.6749	0.03616	0.5405	0.7856
127	714	739	0.6837	0.03623	0.5482	0.7939
128	739	749	0.6928	0.03631	0.5560	0.8023
129	749	755	0.7018	0.03635	0.5639	0.8107
130	755	760	0.7108	0.03635	0.5720	0.8189
131	760	771	0.7199	0.03632	0.5800	0.8270
132	771	774	0.7299	0.03638	0.5886	0.8362
133	774	785	0.7399	0.03638	0.5972	0.8451
134	785	821	0.7499	0.03633	0.6060	0.8539
135	821	836	0.7749	0.03675	0.6248	0.8768
136	836	837	0.7881	0.03690	0.6346	0.8885
137	837	857	0.8014	0.03689	0.6448	0.8997
138	857	878	0.8156	0.03688	0.6551	0.9115
	SURVT-lower	SURVT-upper	Fhat	SE_Fhat	95% Lower	95% Upper
139	878	892	0.8297	0.03667	0.6658	0.9226
140	892	899	0.8468	0.03675	0.6755	0.9362
141	899	1076	0.8638	0.03639	0.6859	0.9485