

Pstat 150 Lab D

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```
drugt=read.table("C:/Users/kebro/Desktop/PSTAT 105/Drug Treatment.txt",header=T)
library(survival)
```

Q1a. Looking at the data in R, I see that after day 519 most of the observations became censored with only a few outliers being observed in the 600+ day range.

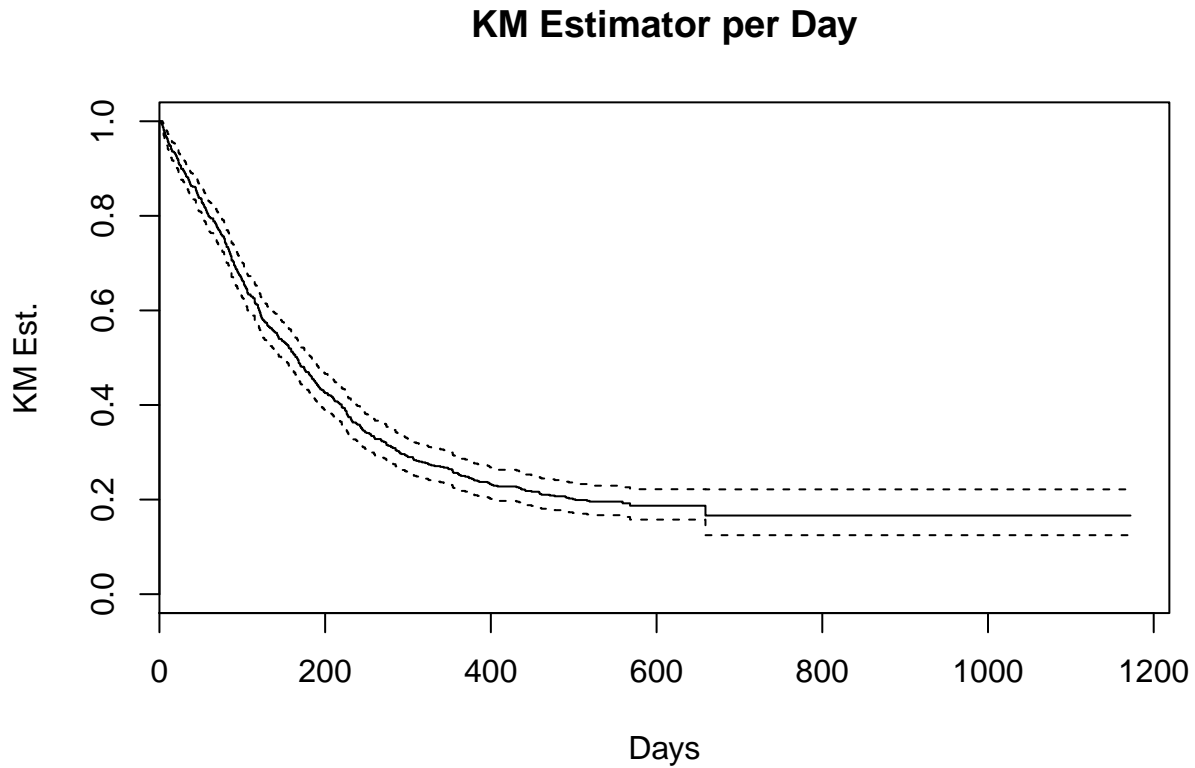
Q1b.

```
dtc=Surv(drugt$Days,drugt$Censor)
dsf=survfit(dtc~1)
dsfs=summary(dsfs)
dsfs$surv
```

```
## [1] 0.9984076 0.9936306 0.9872611 0.9808917 0.9761146 0.9697452 0.9665605
## [8] 0.9633758 0.9570064 0.9522293 0.9490446 0.9474522 0.9410828 0.9363057
## [15] 0.9347134 0.9331210 0.9299363 0.9267516 0.9219745 0.9187898 0.9108280
## [22] 0.9076433 0.9060510 0.8996815 0.8980892 0.8949045 0.8917197 0.8885350
## [29] 0.8837580 0.8821656 0.8805732 0.8757962 0.8710191 0.8662420 0.8630573
## [36] 0.8614650 0.8598726 0.8535032 0.8487261 0.8439490 0.8391720 0.8375796
## [43] 0.8359873 0.8280255 0.8264331 0.8232484 0.8184713 0.8168790 0.8121019
## [50] 0.8073248 0.8041401 0.7993631 0.7977707 0.7961783 0.7945860 0.7882166
## [57] 0.7850318 0.7818471 0.7770701 0.7738854 0.7707006 0.7691083 0.7659236
## [64] 0.7611465 0.7595541 0.7563694 0.7515924 0.7436306 0.7404459 0.7340764
## [71] 0.7292994 0.7245223 0.7197452 0.7149682 0.7054140 0.7022293 0.6958599
## [78] 0.6926752 0.6878981 0.6863057 0.6815287 0.6783439 0.6751592 0.6735669
## [85] 0.6703822 0.6656051 0.6624204 0.6608280 0.6544586 0.6512739 0.6480892
## [92] 0.6449045 0.6369427 0.6337580 0.6305732 0.6289809 0.6257962 0.6162420
## [99] 0.6130573 0.6114650 0.6050955 0.6003185 0.5955414 0.5891720 0.5843949
## [106] 0.5812102 0.5796178 0.5780255 0.5748408 0.5732484 0.5684713 0.5668790
## [113] 0.5652866 0.5636943 0.5621019 0.5589172 0.5573248 0.5557325 0.5541401
## [120] 0.5525478 0.5477707 0.5445860 0.5398089 0.5382166 0.5350318 0.5334395
## [127] 0.5318471 0.5302548 0.5286624 0.5270701 0.5254777 0.5207006 0.5191083
## [134] 0.5127389 0.5095541 0.5063694 0.5015924 0.4984076 0.4952229 0.4888535
## [141] 0.4872611 0.4824841 0.4808917 0.4792994 0.4745223 0.4713376 0.4697452
## [148] 0.4665605 0.4633758 0.4617834 0.4601911 0.4554140 0.4522293 0.4506369
## [155] 0.4474522 0.4458599 0.4426752 0.4410828 0.4378981 0.4363057 0.4331210
## [162] 0.4315287 0.4283439 0.4267516 0.4251592 0.4219745 0.4203822 0.4187898
## [169] 0.4171975 0.4156051 0.4124204 0.4092357 0.4076433 0.4060510 0.4044586
## [176] 0.4028662 0.4012739 0.3949045 0.3933121 0.3885350 0.3869427 0.3805732
## [183] 0.3773885 0.3742038 0.3694268 0.3662420 0.3630573 0.3614650 0.3598726
## [190] 0.3582803 0.3550955 0.3519108 0.3503185 0.3471338 0.3455414 0.3423567
## [197] 0.3407643 0.3391720 0.3359873 0.3343949 0.3312102 0.3280255 0.3264331
## [204] 0.3232484 0.3216561 0.3200637 0.3152866 0.3136943 0.3121019 0.3105096
## [211] 0.3089172 0.3041401 0.3025478 0.3009554 0.2977707 0.2961783 0.2945860
## [218] 0.2929936 0.2914013 0.2898089 0.2866242 0.2834395 0.2818471 0.2802548
## [225] 0.2786624 0.2770701 0.2754777 0.2738854 0.2722930 0.2707006 0.2691083
## [232] 0.2675159 0.2659236 0.2643312 0.2627389 0.2579618 0.2563694 0.2547771
## [239] 0.2531847 0.2515924 0.2500000 0.2484076 0.2468153 0.2452229 0.2436306
```

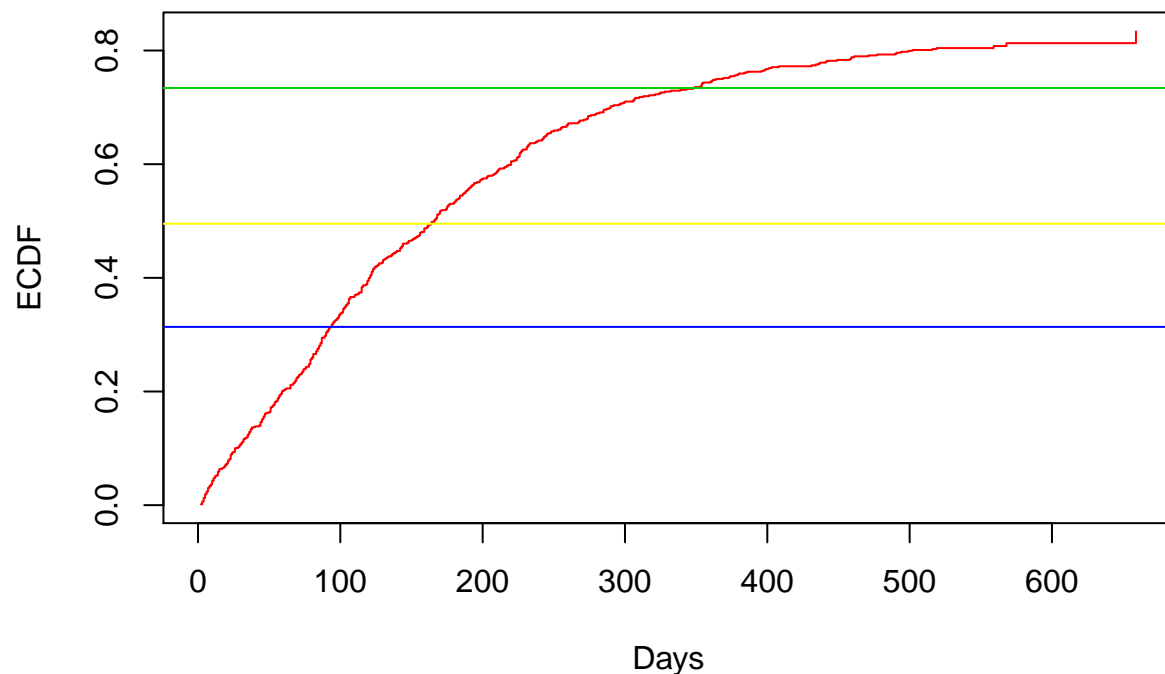
```
## [246] 0.2420382 0.2404459 0.2388535 0.2372611 0.2356688 0.2340764 0.2324841
## [253] 0.2308917 0.2292994 0.2277070 0.2261146 0.2245223 0.2229299 0.2213376
## [260] 0.2197452 0.2181529 0.2165605 0.2149682 0.2117834 0.2101911 0.2085987
## [267] 0.2070064 0.2054140 0.2038217 0.2022293 0.2006369 0.1990318 0.1973732
## [274] 0.1957146 0.1920903 0.1870353 0.1662536
```

```
plot(dsfs,main="KM Estimator per Day",xlab="Days",ylab="KM Est.")
```



Q1b.

```
dsfecdf=1-dsfs$urv
dsqt=quantile(dsfs$time,c(.25,.5,.75))
dsqe=quantile(dsfs$urv,c(.25,.5,.75))
plot(dsfs$time,dsfecdf,type="s",xlab="Days",ylab="ECDF",col="red")
abline(h=dsqe,col=c("blue","yellow","green3"))
```



```
dsqe
```

```
##      25%      50%      75%
## 0.3136943 0.4952229 0.7340764
```

```
dsqt
```

```
## 25% 50% 75%
##  81 167 276
```

We have the .25, .5, and .75 quantiles of days to be 81, 167, and 276 respectively.

Q1d.

```
drugpre=subset(drugt,IVDrug=="Previous",data=drugt)
drugrec=subset(drugt,IVDrug=="Recent",data=drugt)
drugnev=subset(drugt,IVDrug=="Never",data=drugt)
dtpc=Surv(drugpre$Days,drugpre$Censor)
dtrc=Surv(drugrec$Days,drugrec$Censor)
dtnc=Surv(drugnev$Days,drugnev$Censor)
dspf=survfit(dtpc~1)
dsrf=survfit(dtrc~1)
dsnf=survfit(dtnc~1)
dspfs=summary(dspf)
dsrfs=summary(dsrf)
dsnfs=summary(dsnf)
dspqt=quantile(dspfs$time,c(.25,.5,.75))
dsrqt=quantile(dsrfs$time,c(.25,.5,.75))
dsnqt=quantile(dsnfs$time,c(.25,.5,.75))
```

```
##.25,.5,.75 Quantiles for the previous, recent, and never observations in terms of time  
dspqt
```

```
##      25%      50%      75%  
## 60.75 124.50 231.50
```

```
dsrqt
```

```
## 25% 50% 75%  
## 70 136 246
```

```
dsnqt
```

```
##      25%      50%      75%  
## 83.75 156.50 244.25
```

Q1e.

```
dspqe=quantile(dspfs$urv,c(.25,.5,.75))  
dsrqe=quantile(dsrfs$urv,c(.25,.5,.75))  
dsnqe=quantile(dsnfs$urv,c(.25,.5,.75))  
dspqe[1]
```

```
##      25%  
## 0.3869565
```

```
dsrqe[1]
```

```
##      25%  
## 0.3091603
```

```
dsrqe[1]
```

```
##      25%  
## 0.3091603
```

```
##95% Conf int for KM estimator for previous IV users after 75% mark  
c(.295,.474)
```

```
## [1] 0.295 0.474
```

```
##95% Conf int for KM estimator for recent IV users after 75% mark  
c(.2508,.363)
```

```
## [1] 0.2508 0.3630
```

```
##95% Conf int for KM estimator for people that have never had an IV after 75% mark  
c(.255,.374)
```

```
## [1] 0.255 0.374
```

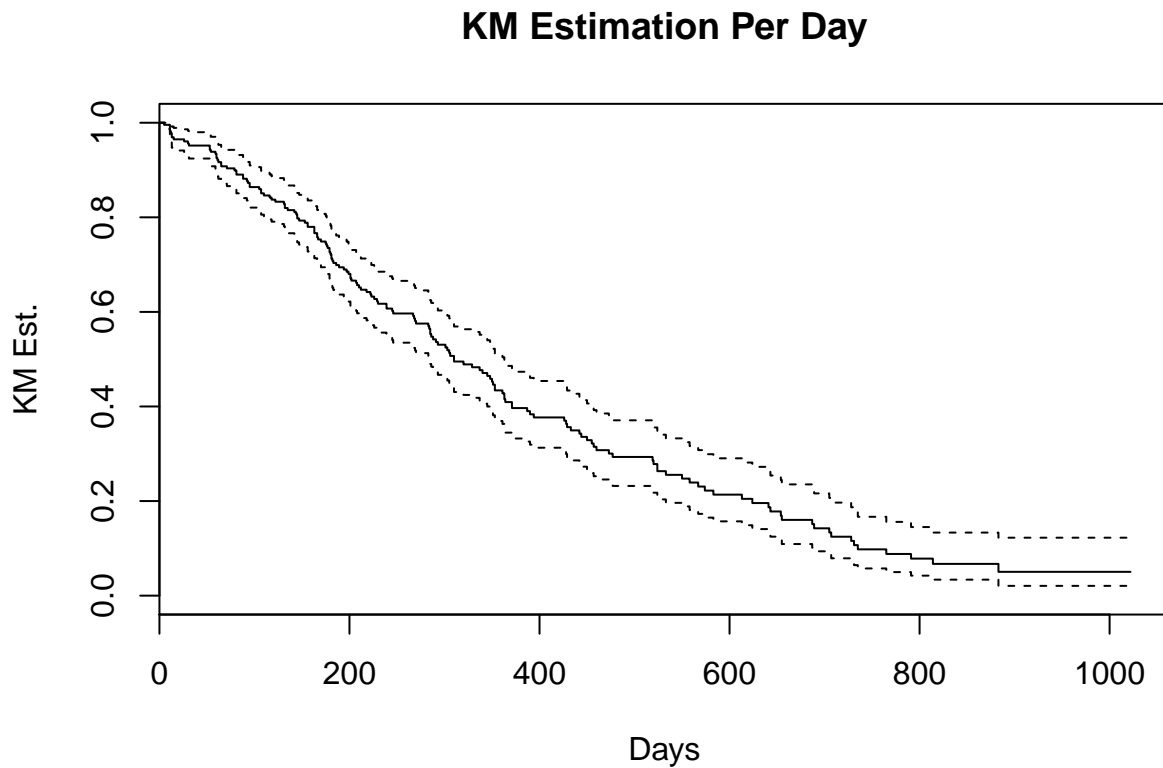
From these confidence intervals, It can be said that there does not exist a significant difference between groups. Q2.

```
lungt=read.table("C:/Users/kebro/Desktop/PSTAT 105/lung.txt",header=T)  
library(survival)
```

Q2a.

```
lungsurv=Surv(lungt$time,abs(-1*lungt$status+1))  
lsf=survfit(lungsurv~1)
```

```
lsfs=summary(lsf)
plot(lsf,main="KM Estimation Per Day",xlab = "Days",ylab="KM Est.")
```



Q2b.

```
summary(lsf)
```

```
## Call: survfit(formula = lungsurv ~ 1)
##
##   time n.risk n.event survival std.err lower 95% CI upper 95% CI
##    5    228     1   0.9956 0.00438   0.9871    1.000
##   11    227     3   0.9825 0.00869   0.9656    1.000
##   12    224     1   0.9781 0.00970   0.9592    0.997
##   13    223     2   0.9693 0.01142   0.9472    0.992
##   15    221     1   0.9649 0.01219   0.9413    0.989
##   26    220     1   0.9605 0.01290   0.9356    0.986
##   30    219     1   0.9561 0.01356   0.9299    0.983
##   31    218     1   0.9518 0.01419   0.9243    0.980
##   53    217     2   0.9430 0.01536   0.9134    0.974
##   54    215     1   0.9386 0.01590   0.9079    0.970
##   59    214     1   0.9342 0.01642   0.9026    0.967
##   60    213     2   0.9254 0.01740   0.8920    0.960
##   61    211     1   0.9211 0.01786   0.8867    0.957
##   62    210     1   0.9167 0.01830   0.8815    0.953
##   65    209     2   0.9079 0.01915   0.8711    0.946
##   71    207     1   0.9035 0.01955   0.8660    0.943
##   79    206     1   0.8991 0.01995   0.8609    0.939
```

##	81	205	2	0.8904	0.02069	0.8507	0.932
##	88	203	2	0.8816	0.02140	0.8406	0.925
##	92	201	1	0.8772	0.02174	0.8356	0.921
##	93	199	1	0.8728	0.02207	0.8306	0.917
##	95	198	2	0.8640	0.02271	0.8206	0.910
##	105	196	1	0.8596	0.02302	0.8156	0.906
##	107	194	2	0.8507	0.02362	0.8056	0.898
##	110	192	1	0.8463	0.02391	0.8007	0.894
##	116	191	1	0.8418	0.02419	0.7957	0.891
##	118	190	1	0.8374	0.02446	0.7908	0.887
##	122	189	1	0.8330	0.02473	0.7859	0.883
##	131	188	1	0.8285	0.02500	0.7810	0.879
##	132	187	2	0.8197	0.02550	0.7712	0.871
##	135	185	1	0.8153	0.02575	0.7663	0.867
##	142	184	1	0.8108	0.02598	0.7615	0.863
##	144	183	1	0.8064	0.02622	0.7566	0.859
##	145	182	2	0.7975	0.02667	0.7469	0.852
##	147	180	1	0.7931	0.02688	0.7421	0.848
##	153	179	1	0.7887	0.02710	0.7373	0.844
##	156	178	2	0.7798	0.02751	0.7277	0.836
##	163	176	3	0.7665	0.02809	0.7134	0.824
##	166	173	2	0.7577	0.02845	0.7039	0.816
##	167	171	1	0.7532	0.02863	0.6991	0.811
##	170	170	1	0.7488	0.02880	0.6944	0.807
##	175	167	1	0.7443	0.02898	0.6896	0.803
##	176	165	1	0.7398	0.02915	0.6848	0.799
##	177	164	1	0.7353	0.02932	0.6800	0.795
##	179	162	2	0.7262	0.02965	0.6704	0.787
##	180	160	1	0.7217	0.02981	0.6655	0.783
##	181	159	2	0.7126	0.03012	0.6559	0.774
##	182	157	1	0.7081	0.03027	0.6511	0.770
##	183	156	1	0.7035	0.03041	0.6464	0.766
##	186	154	1	0.6989	0.03056	0.6416	0.761
##	189	152	1	0.6943	0.03070	0.6367	0.757
##	194	149	1	0.6897	0.03085	0.6318	0.753
##	197	147	1	0.6850	0.03099	0.6269	0.749
##	199	145	1	0.6803	0.03113	0.6219	0.744
##	201	144	2	0.6708	0.03141	0.6120	0.735
##	202	142	1	0.6661	0.03154	0.6071	0.731
##	207	139	1	0.6613	0.03168	0.6020	0.726
##	208	138	1	0.6565	0.03181	0.5970	0.722
##	210	137	1	0.6517	0.03194	0.5920	0.717
##	212	135	1	0.6469	0.03206	0.5870	0.713
##	218	134	1	0.6421	0.03218	0.5820	0.708
##	222	132	1	0.6372	0.03231	0.5769	0.704
##	223	130	1	0.6323	0.03243	0.5718	0.699
##	226	126	1	0.6273	0.03256	0.5666	0.694
##	229	125	1	0.6223	0.03268	0.5614	0.690
##	230	124	1	0.6172	0.03280	0.5562	0.685
##	239	121	2	0.6070	0.03304	0.5456	0.675
##	245	117	1	0.6019	0.03316	0.5402	0.670
##	246	116	1	0.5967	0.03328	0.5349	0.666
##	267	112	1	0.5913	0.03341	0.5294	0.661
##	268	111	1	0.5860	0.03353	0.5239	0.656

##	269	110	1	0.5807	0.03364	0.5184	0.651
##	270	108	1	0.5753	0.03376	0.5128	0.645
##	283	104	1	0.5698	0.03388	0.5071	0.640
##	284	103	1	0.5642	0.03400	0.5014	0.635
##	285	101	2	0.5531	0.03424	0.4899	0.624
##	286	99	1	0.5475	0.03434	0.4841	0.619
##	288	98	1	0.5419	0.03444	0.4784	0.614
##	291	97	1	0.5363	0.03454	0.4727	0.608
##	293	94	1	0.5306	0.03464	0.4669	0.603
##	301	91	1	0.5248	0.03475	0.4609	0.597
##	303	89	1	0.5189	0.03485	0.4549	0.592
##	305	87	1	0.5129	0.03496	0.4488	0.586
##	306	86	1	0.5070	0.03506	0.4427	0.581
##	310	85	2	0.4950	0.03523	0.4306	0.569
##	320	82	1	0.4890	0.03532	0.4244	0.563
##	329	81	1	0.4830	0.03539	0.4183	0.558
##	337	79	1	0.4768	0.03547	0.4121	0.552
##	340	78	1	0.4707	0.03554	0.4060	0.546
##	345	77	1	0.4646	0.03560	0.3998	0.540
##	348	76	1	0.4585	0.03565	0.3937	0.534
##	350	75	1	0.4524	0.03569	0.3876	0.528
##	351	74	1	0.4463	0.03573	0.3815	0.522
##	353	73	2	0.4340	0.03578	0.3693	0.510
##	361	70	1	0.4278	0.03581	0.3631	0.504
##	363	69	2	0.4154	0.03583	0.3508	0.492
##	364	67	1	0.4092	0.03582	0.3447	0.486
##	371	65	2	0.3966	0.03581	0.3323	0.473
##	387	60	1	0.3900	0.03582	0.3258	0.467
##	390	59	1	0.3834	0.03582	0.3193	0.460
##	394	58	1	0.3768	0.03580	0.3128	0.454
##	426	55	1	0.3700	0.03580	0.3060	0.447
##	428	54	1	0.3631	0.03579	0.2993	0.440
##	429	53	1	0.3563	0.03576	0.2926	0.434
##	433	52	1	0.3494	0.03573	0.2860	0.427
##	442	51	1	0.3426	0.03568	0.2793	0.420
##	444	50	1	0.3357	0.03561	0.2727	0.413
##	450	48	1	0.3287	0.03555	0.2659	0.406
##	455	47	1	0.3217	0.03548	0.2592	0.399
##	457	46	1	0.3147	0.03539	0.2525	0.392
##	460	44	1	0.3076	0.03530	0.2456	0.385
##	473	43	1	0.3004	0.03520	0.2388	0.378
##	477	42	1	0.2933	0.03508	0.2320	0.371
##	519	39	1	0.2857	0.03498	0.2248	0.363
##	520	38	1	0.2782	0.03485	0.2177	0.356
##	524	37	2	0.2632	0.03455	0.2035	0.340
##	533	34	1	0.2554	0.03439	0.1962	0.333
##	550	32	1	0.2475	0.03423	0.1887	0.325
##	558	30	1	0.2392	0.03407	0.1810	0.316
##	567	28	1	0.2307	0.03391	0.1729	0.308
##	574	27	1	0.2221	0.03371	0.1650	0.299
##	583	26	1	0.2136	0.03348	0.1571	0.290
##	613	24	1	0.2047	0.03325	0.1489	0.281
##	624	23	1	0.1958	0.03297	0.1407	0.272
##	641	22	1	0.1869	0.03265	0.1327	0.263

```
##      643      21      1  0.1780 0.03229      0.1247      0.254
##      654      20      1  0.1691 0.03188      0.1169      0.245
##      655      19      1  0.1602 0.03142      0.1091      0.235
##      687      18      1  0.1513 0.03090      0.1014      0.226
##      689      17      1  0.1424 0.03034      0.0938      0.216
##      705      16      1  0.1335 0.02972      0.0863      0.207
##      707      15      1  0.1246 0.02904      0.0789      0.197
##      728      14      1  0.1157 0.02830      0.0716      0.187
##      731      13      1  0.1068 0.02749      0.0645      0.177
##      735      12      1  0.0979 0.02660      0.0575      0.167
##      765      10      1  0.0881 0.02568      0.0498      0.156
##      791      9       1  0.0783 0.02462      0.0423      0.145
##      814      7       1  0.0671 0.02351      0.0338      0.133
##      883      4       1  0.0503 0.02285      0.0207      0.123
```

```
##95% conf int of KM estimator for 150 days
c(.7421,.848)
```

```
## [1] 0.7421 0.8480
```

Q2c.

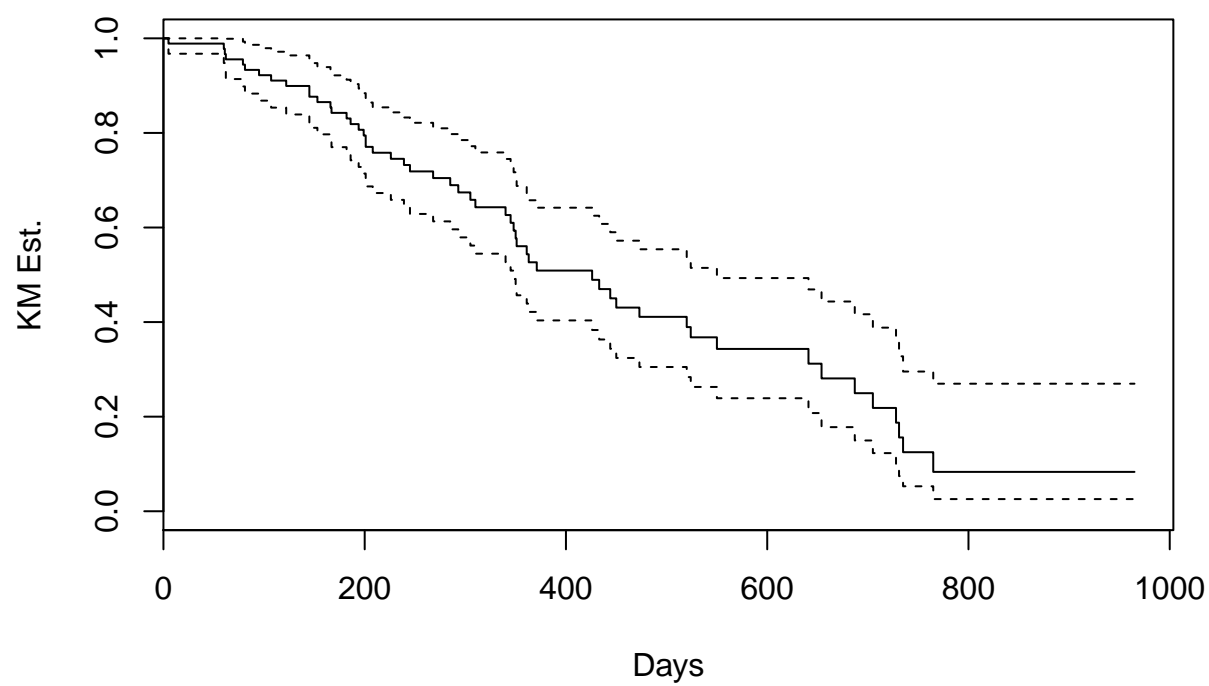
```
##95% conf int of median survival time
lsf
```

```
## Call: survfit(formula = lungsurv ~ 1)
##
##           n  events  median 0.95LCL 0.95UCL
##        228    165    310    285    363
```

we have a 95% conf int of {285,363} Q2d.

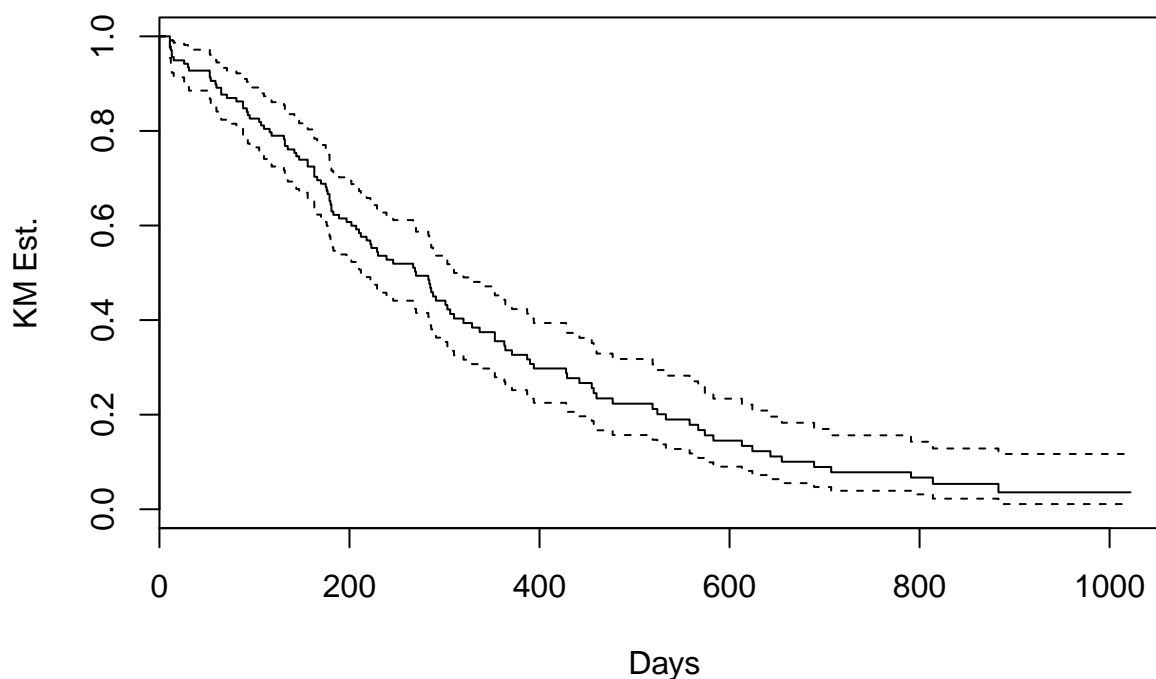
```
lungmale=subset(lungt,lungt$sex==1)
lungfemale=subset(lungt,lungt$sex==2)
lungmalesf=Surv(lungmale$time,abs(-1*lungmale$status+1))
lungfemalesf=Surv(lungfemale$time,abs(-1*lungfemale$status+1))
lungmfs=survfit(lungmalesf~1)
lungffs=survfit(lungfemalesf~1)
plot(lungffs,main="Female KM Estimation Per Day",xlab = "Days",ylab="KM Est.")
```


Female KM Estimation Per Day



```
plot(lungmfs,main="Male KM Estimation Per Day",xlab = "Days",ylab="KM Est.")
```

Male KM Estimation Per Day



From these plot it appears that women have higher survival rates seemingly along the entire

Q2e. MvF median surv times

```
lungmfs
```

```
## Call: survfit(formula = lungmalesf ~ 1)
##
##      n  events  median 0.95LCL 0.95UCL
##   138    112    270    212    310
```

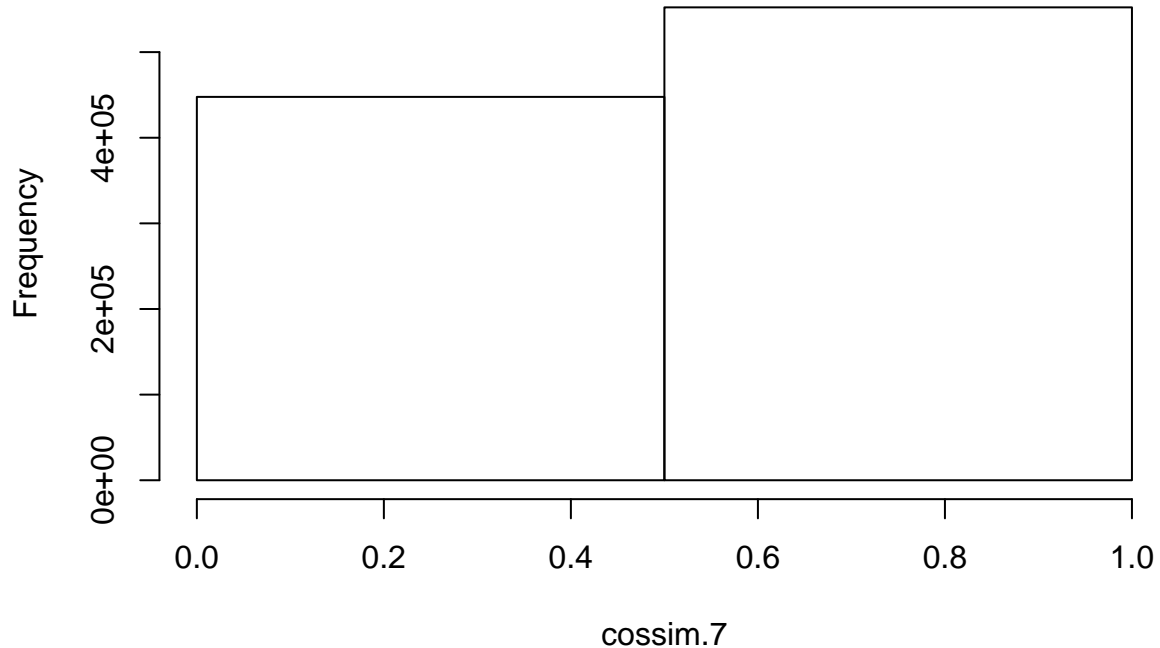
```
lungffs
```

```
## Call: survfit(formula = lungfemalesf ~ 1)
##
##      n  events  median 0.95LCL 0.95UCL
##    90     53   426    348    550
```

From these confidence intervals and medians, I believe it is rather clear that women tend to survive longer than men. However, i do not believe that this tells the whole story as other factors not measured in this data set could be rather impactful to survival time. Q3.1,000,000 sims

```
simexp=rexp(10^6)
cossim=cos(simexp)
cossim.7=(cossim>.7)/1
cossim.7h=hist(cossim.7,breaks=c(0,.5,1))
```

Histogram of cossim.7



```
cossim.7p=cossim.7h$counts[2]/(10^6)
cossim.7p ##Probability Cos(x)>.7
```

```
## [1] 0.552281
```

```
##95% conf int for P(cos(x)>.7)
```

```
c(cossim.7p-1.96*sqrt(cossim.7p*(1-cossim.7p)/(10^6)),
  cossim.7p+1.96*sqrt(cossim.7p*(1-cossim.7p)/(10^6)))
```

```
## [1] 0.5513064 0.5532556
```

Q4a.1000 runs of 50 sims

```
n=50
```

```
m=1000
```

```
ex.test=rep(999,m)
```

```
rnd.x=matrix(rep(999,50000),1000,50)
```

```
for(j in 1:m){
```

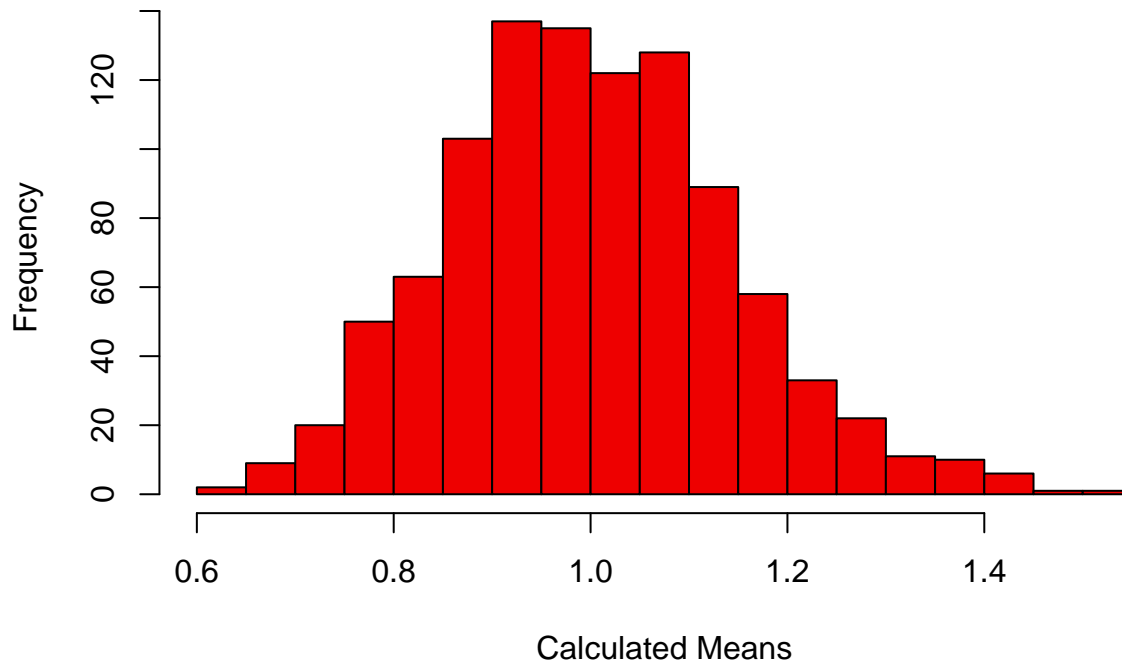
```
  rnd.x[j,]=c(rexp(n))
```

```
  ex.test[j]=mean(rnd.x[j,])
```

```
}
```

```
hist(ex.test,breaks=30,col="red2",main="Hist from Simulation",xlab="Calculated Means")
```

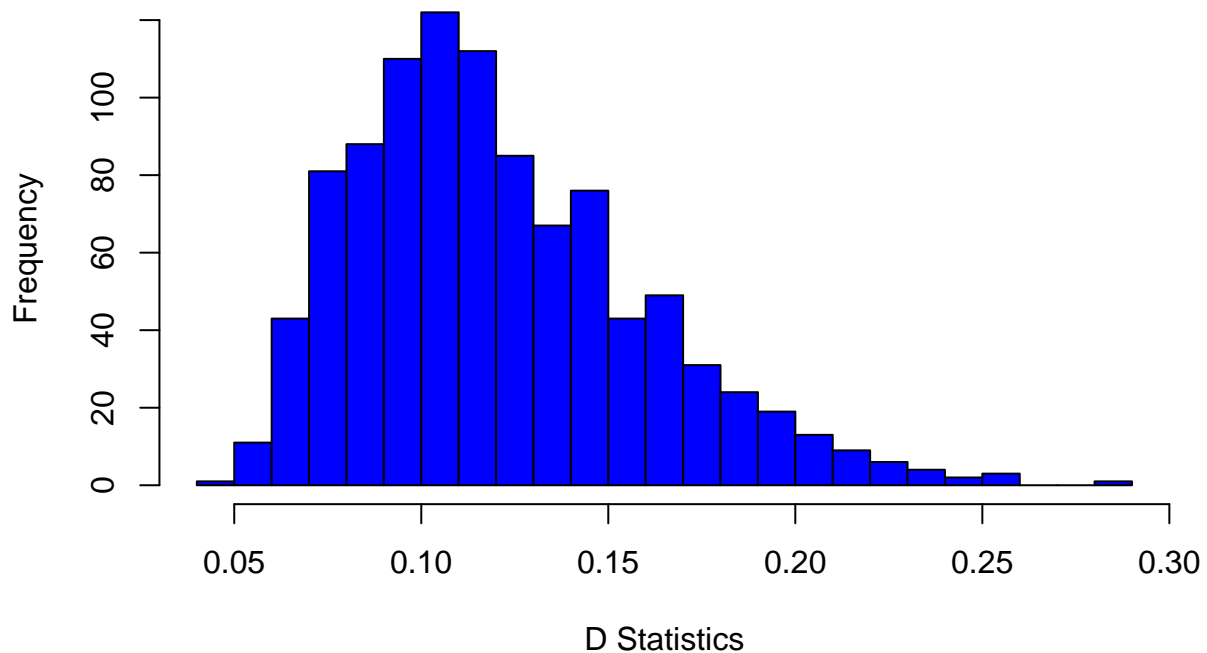
Hist from Simulation



Q4b. KS-test of samples

```
kssim=rep(999,1000)
for(j in 1:m){
  ksdj=ks.test(rnd.x[j,],pexp)
  kssim[j]=ksdj$statistic
}
histks=hist(kssim,breaks=30,main="Simulated KS-test Statistics",xlab="D Statistics",col="blue")
```

Simulated KS-test Statistics



Q4c.

```
quantile(kssim,.95)
```

```
##      95%
```

```
## 0.1936762
```

Q4d.

```
#computer ran a single batch in .16 seconds
#7200 secs in 2hrs means 45000 batches
#to avoid time issues when knitting this block will be ## out
```

```
#kssim2h=rep(999,m)
#rnd2h.x=matrix(rep(999,50000),1000,50)
#batch=matrix(rep(999,4.5e+07),45000,1000)
#for(j in 1:45000){
#for(k in 1:m){
  #rnd2h.x[k,]=c(rexp(n))
  #ex.test[k]=mean(rnd2h.x[k,])
  #ksdj2h=ks.test(rnd2h.x[k,],pexp)
  #kssim2h[k]=ksdj2h$statistic
  #batch[j,]=kssim2h
}}
```

```
#sim2h=quantile(batch,.95)
#sim2h
```

To avoid problems during knitting, I am stating the calculated simulation .95 quantile to be .1884515.

Q4e. Crit value from Stephens table 1.4

```
(.1884515-.2/50)*(sqrt(50)+.26+.5/sqrt(50))
```

```
## [1] 1.365269
```

From this calculation we get a T value that corresponds to the <1% level.

Q5a.

```
library(MASS)
ofsd=sd(geyser$waiting)
ofsd ##sample standard deviation of geyser data set
```

```
## [1] 13.89032
```

Q5b.

```
geysermat=rep(999,1000)
for(j in 1:1000){
  sampof=sample(geyser$waiting,299,replace = T)
  geysermat[j]=sd(sampof)
}
(sd(geysermat))^2
```

```
## [1] 0.1501207
```

Q5c.

```
geyseriqr=rep(999,1000)
for(j in 1:1000){
  sampofiqr=sample(geyser$waiting,299,replace = T)
  geyseriqr[j]=IQR(sampofiqr)
}
(sd(geyseriqr))^2
```

```
## [1] 2.863103
```

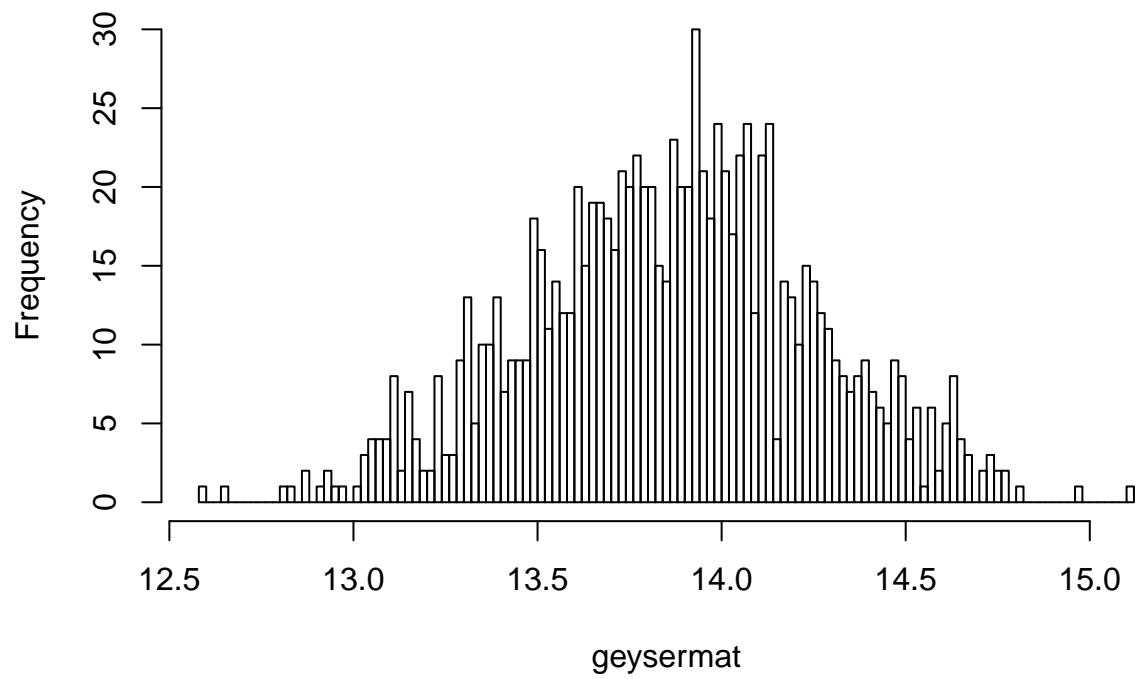
Q5d.

```
geysermad=rep(999,1000)
for(j in 1:1000){
  sampofmad=sample(geyser$waiting,299,replace = T)
  geysermad[j]=mad(sampofmad)
}
(sd(geysermad))^2
```

```
## [1] 2.965954
```

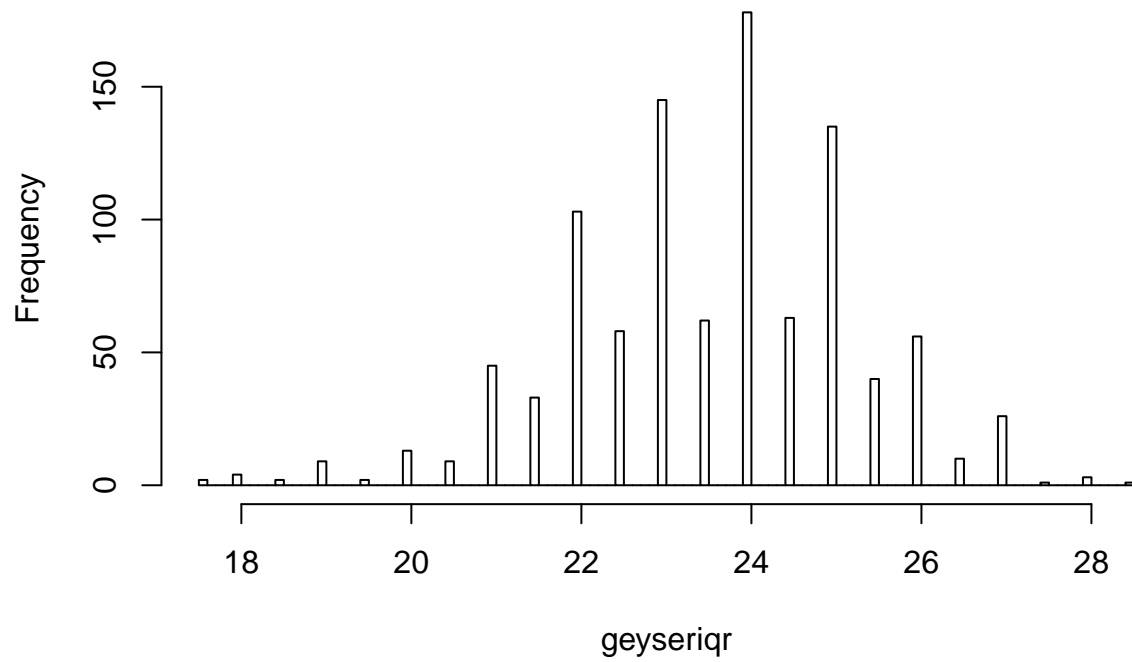
```
hist(geysermat,breaks=100)
```

Histogram of geysermat



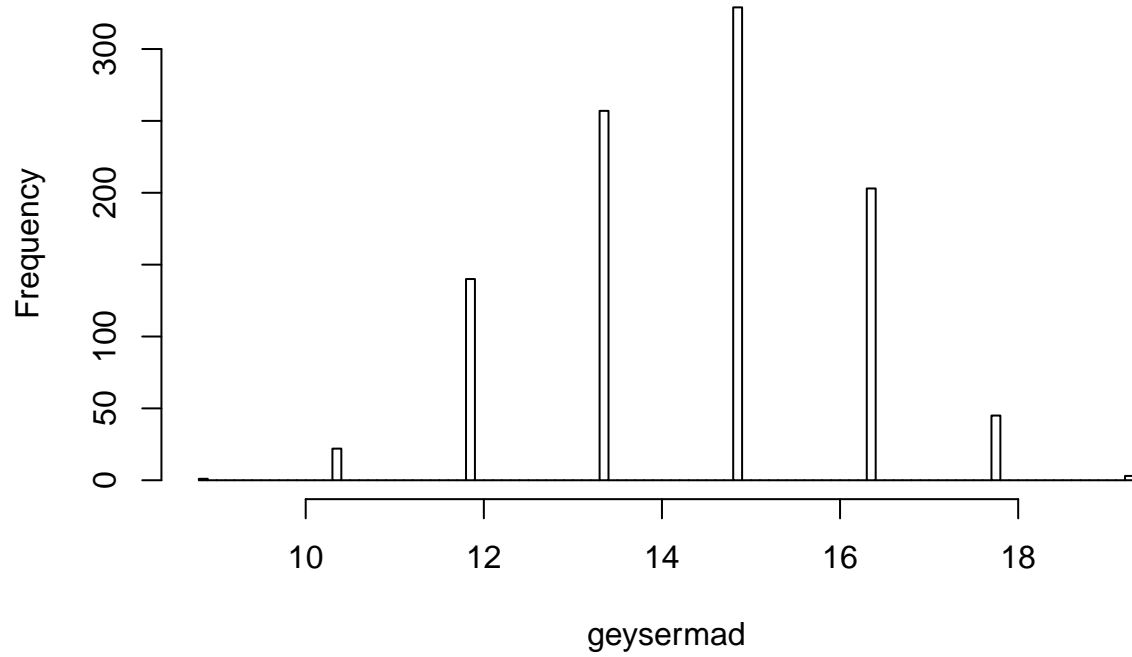
```
hist(geyseriqr,breaks=100)
```

Histogram of geyseriqr



```
hist(geysermad,breaks=100)
```


Histogram of geysermad



Based on the histograms of the standard deviation estimates, the SD function has the most normally distributed data. As such, personally, i prefer the sd function over the other two estimation functions.