

R Lab : lars()

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26 OCTOBER 2022

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*"THE FUTURE BELONGS TO THOSE WHO BELIEVE IN THE BEAUTY OF THEIR DREAMS."*

Eleanor Roosevelt

Hello there, readers ! Yes, you. I need your eyes and attention here in 3 ..... 2 ..... 1 .....

Today, what we are interested to discuss is about `lars()` using R.

The first thing that we shall try to learn is ridge regression for which we shall use a default installed package, we load the package `MASS` using the command :

```
library(MASS)
```

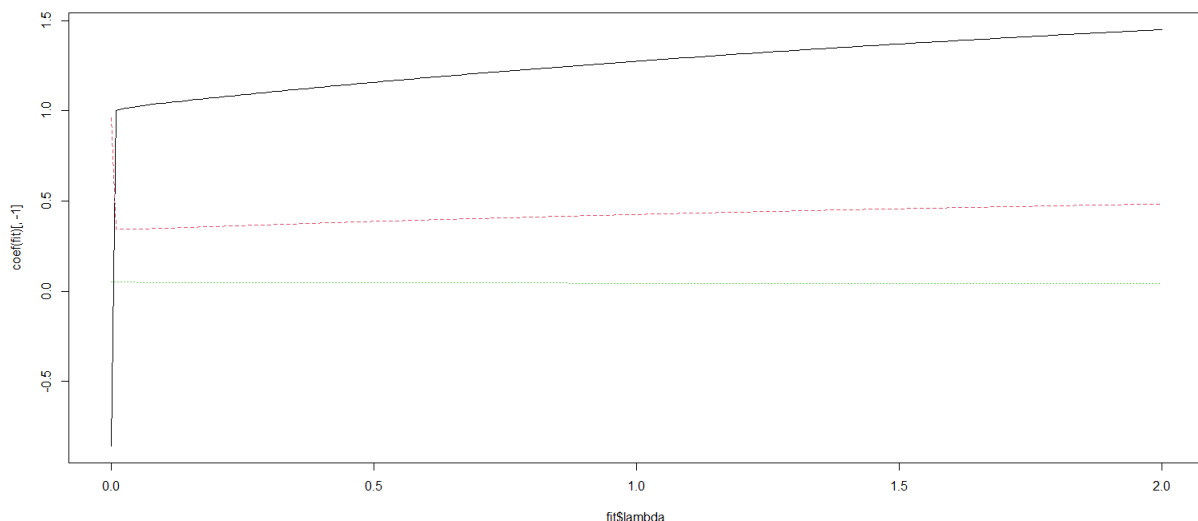
Now, we shall use the function `lm.ridge`. Here we specify the value of `lambda` which is the `lambda` of the adhoc formulation or we specify a list of `lambda` values if we donot know what value of `lambda` suits the most. So we use the following R command :

```
fit = lm.ridge(y ~ x1 + x2 + x3, lambda = seq(0, 2, len = 200))
```

Here, we used a sequence from 0 to 2 of length 200 , so we get a list of values of `lambda` starting from 0 with an increment of some delta amounts each time. Now if look at the output using the command `fit` , we see that it is a very large output data which is not a desirable output. So, we find the coefficient using the `coef` function. We plot the different fitted things against `lambda` excluding the intercept term using the following R command:

```
matplot(fit$lambda, coef(fit)[, -1], ty = 'l')
```

We get the following output :



Here, the black line is the coefficient of `x1`, the red line is the coefficient of `x2` and the green line is the coefficient of `x3`. From the plotted figure we observe the coefficient of `x3` remains more or less flat throughout but coefficient of `x1` and `x2` changes drastically. Initially black line is less than -0.5 and the red line is more than +0.5 but the second we increased `lambda` by a small delta amount the values comes down to certain values and then they become stable throughout the increment of value of `lambda`.

The coefficient which is not locked in a multiple linear relationship i.e the green line is always

flat , whcih means it is stable throughout. This indicates the presence of multicolliearity, where the first two coefficients are the first two columns of our design matrix which are involved in multicollinear relationship.

Such plots known as Ridge Trace, is also a good diagnostiic tool. For lambda greater than 0 where things get stabilized, we use those values with more confidence.

Now we use the following R command to look into the coefficients :

*coef(fit)*

The output is

		x1	x2	x3
0.00000000	0.18546193	-0.8573656	0.9615618	0.04986391
0.01005025	0.09694658	0.9996151	0.3444963	0.04980413
0.02010050	-0.01086024	1.0109242	0.3429083	0.04973831
0.03015075	-0.11815329	1.0168772	0.3430956	0.04967278
0.04020101	-0.22489369	1.0214704	0.3437257	0.04960756
0.05025126	-0.33107684	1.0255088	0.3445302	0.04954264
0.06030151	-0.43670390	1.0292616	0.3454194	0.04947803
0.07035176	-0.54177763	1.0328444	0.3463548	0.04941373
0.08040201	-0.64630137	1.0363150	0.3473173	0.04934973
0.09045226	-0.75027871	1.0397057	0.3482960	0.04928602
0.10050251	-0.85371332	1.0430361	0.3492847	0.04922262
0.11055276	-0.95660894	1.0463183	0.3502792	0.04915951
0.12060302	-1.05896929	1.0495608	0.3512768	0.04909669
0.13065327	-1.16079809	1.0527693	0.3522758	0.04903417
0.14070352	-1.26209905	1.0559480	0.3532748	0.04897194
0.15075377	-1.36287585	1.0591000	0.3542728	0.04890999
0.16080402	-1.46313214	1.0622275	0.3552691	0.04884833
0.17085427	-1.56287154	1.0653325	0.3562632	0.04878695
0.18090452	-1.66209765	1.0684163	0.3572546	0.04872586
0.19095477	-1.76081404	1.0714801	0.3582432	0.04866504
0.20100503	-1.85902423	1.0745248	0.3592285	0.04860451
0.21105528	-1.95673174	1.0775512	0.3602105	0.04854424
0.22110553	-2.05394002	1.0805599	0.3611889	0.04848426
0.23115578	-2.15065254	1.0835516	0.3621637	0.04842454
0.24120603	-2.24687268	1.0865267	0.3631347	0.04836510
0.25125628	-2.34260384	1.0894855	0.3641019	0.04830592
0.26130653	-2.43784935	1.0924285	0.3650652	0.04824701
0.27135678	-2.53261255	1.0953561	0.3660246	0.04818836
0.28140704	-2.62689672	1.0982684	0.3669801	0.04812998
0.29145729	-2.72070512	1.1011657	0.3679315	0.04807186
0.30150754	-2.81404097	1.1040484	0.3688790	0.04801399
0.31155779	-2.90690749	1.1069166	0.3698224	0.04795639
0.32160804	-2.99930784	1.1097704	0.3707618	0.04789904
0.33165829	-3.09124517	1.1126102	0.3716971	0.04784195
0.34170854	-3.18272260	1.1154361	0.3726285	0.04778510
0.35175879	-3.27374320	1.1182482	0.3735558	0.04772851
0.36180905	-3.36431005	1.1210467	0.3744790	0.04767217
0.37185930	-3.45442618	1.1238317	0.3753983	0.04761607
0.38190955	-3.54409460	1.1266034	0.3763135	0.04756023

0.39195980	-3.63331827	1.1293620	0.3772248	0.04750462
0.40201005	-3.72210017	1.1321075	0.3781321	0.04744926
0.41206030	-3.81044322	1.1348400	0.3790354	0.04739414
0.42211055	-3.89835032	1.1375598	0.3799347	0.04733925
0.43216080	-3.98582434	1.1402669	0.3808302	0.04728461
0.44221106	-4.07286814	1.1429613	0.3817217	0.04723020
0.45226131	-4.15948455	1.1456433	0.3826093	0.04717603
0.46231156	-4.24567636	1.1483129	0.3834930	0.04712208
0.47236181	-4.33144636	1.1509703	0.3843729	0.04706837
0.48241206	-4.41679730	1.1536154	0.3852489	0.04701490
0.49246231	-4.50173190	1.1562485	0.3861211	0.04696164
0.50251256	-4.58625288	1.1588696	0.3869894	0.04690862
0.51256281	-4.67036292	1.1614788	0.3878540	0.04685582
0.52261307	-4.75406468	1.1640762	0.3887148	0.04680325
0.53266332	-4.83736079	1.1666619	0.3895719	0.04675090
0.54271357	-4.92025386	1.1692360	0.3904253	0.04669877
0.55276382	-5.00274650	1.1717985	0.3912749	0.04664686
0.56281407	-5.08484127	1.1743496	0.3921209	0.04659517
0.57286432	-5.16654071	1.1768893	0.3929632	0.04654369
0.58291457	-5.24784736	1.1794177	0.3938018	0.04649243
0.59296482	-5.32876372	1.1819349	0.3946369	0.04644139
0.60301508	-5.40929227	1.1844409	0.3954683	0.04639055
0.61306533	-5.48943547	1.1869359	0.3962961	0.04633993
0.62311558	-5.56919577	1.1894199	0.3971204	0.04628952
0.63316583	-5.64857559	1.1918930	0.3979412	0.04623932
0.64321608	-5.72757732	1.1943552	0.3987584	0.04618933
0.65326633	-5.80620336	1.1968067	0.3995721	0.04613954
0.66331658	-5.88445605	1.1992476	0.4003823	0.04608996
0.67336683	-5.96233775	1.2016777	0.4011891	0.04604058
0.68341709	-6.03985077	1.2040974	0.4019925	0.04599141
0.69346734	-6.11699742	1.2065066	0.4027924	0.04594243
0.70351759	-6.19377997	1.2089053	0.4035889	0.04589366
0.71356784	-6.27020070	1.2112938	0.4043820	0.04584508
0.72361809	-6.34626184	1.2136719	0.4051718	0.04579670
0.73366834	-6.42196564	1.2160399	0.4059583	0.04574852
0.74371859	-6.49731429	1.2183977	0.4067414	0.04570053
0.75376884	-6.57230998	1.2207454	0.4075212	0.04565274
0.76381910	-6.64695489	1.2230832	0.4082978	0.04560514
0.77386935	-6.72125118	1.2254110	0.4090710	0.04555773
0.78391960	-6.79520097	1.2277289	0.4098411	0.04551051
0.79396985	-6.86880640	1.2300370	0.4106079	0.04546348
0.80402010	-6.94206956	1.2323353	0.4113715	0.04541664
0.81407035	-7.01499254	1.2346239	0.4121319	0.04536998
0.82412060	-7.08757742	1.2369029	0.4128892	0.04532351
0.83417085	-7.15982623	1.2391724	0.4136433	0.04527723
0.84422111	-7.23174102	1.2414323	0.4143942	0.04523112
0.85427136	-7.30332380	1.2436827	0.4151421	0.04518520
0.86432161	-7.37457658	1.2459238	0.4158869	0.04513947
0.87437186	-7.44550135	1.2481555	0.4166285	0.04509391
0.88442211	-7.51610008	1.2503780	0.4173672	0.04504853

0.89447236	-7.58637472	1.2525912	0.4181028	0.04500333
0.90452261	-7.65632721	1.2547952	0.4188353	0.04495830
0.91457286	-7.72595948	1.2569902	0.4195649	0.04491346
0.92462312	-7.79527343	1.2591761	0.4202915	0.04486878
0.93467337	-7.86427097	1.2613529	0.4210151	0.04482428
0.94472362	-7.93295396	1.2635209	0.4217358	0.04477996
0.95477387	-8.00132428	1.2656799	0.4224535	0.04473580
0.96482412	-8.06938377	1.2678301	0.4231683	0.04469182
0.97487437	-8.13713427	1.2699715	0.4238802	0.04464801
0.98492462	-8.20457759	1.2721042	0.4245892	0.04460436
0.99497487	-8.27171556	1.2742282	0.4252954	0.04456088
1.00502513	-8.33854995	1.2763435	0.4259986	0.04451757
1.01507538	-8.40508255	1.2784503	0.4266991	0.04447443
1.02512563	-8.47131511	1.2805486	0.4273968	0.04443145
1.03517588	-8.53724940	1.2826384	0.4280916	0.04438863
1.04522613	-8.60288715	1.2847197	0.4287836	0.04434598
1.05527638	-8.66823008	1.2867927	0.4294729	0.04430348
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1.07537688	-8.79803832	1.2909137	0.4308432	0.04421898
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1.11557789	-9.05419138	1.2990573	0.4335513	0.04405188
1.12562814	-9.11751776	1.3010730	0.4342217	0.04401050
1.13567839	-9.18056264	1.3030807	0.4348893	0.04396927
1.14572864	-9.24332763	1.3050804	0.4355544	0.04392820
1.15577889	-9.30581434	1.3070723	0.4362168	0.04388727
1.16582915	-9.36802434	1.3090562	0.4368766	0.04384650
1.17587940	-9.42995921	1.3110324	0.4375339	0.04380589
1.18592965	-9.49162050	1.3130008	0.4381885	0.04376542
1.19597990	-9.55300977	1.3149614	0.4388406	0.04372510
1.20603015	-9.61412856	1.3169144	0.4394902	0.04368493
1.21608040	-9.67497838	1.3188598	0.4401372	0.04364491
1.22613065	-9.73556076	1.3207975	0.4407817	0.04360503
1.23618090	-9.79587719	1.3227277	0.4414237	0.04356530
1.24623116	-9.85592917	1.3246504	0.4420633	0.04352572
1.25628141	-9.91571817	1.3265656	0.4427003	0.04348628
1.26633166	-9.97524568	1.3284734	0.4433349	0.04344698
1.27638191	-10.03451314	1.3303739	0.4439670	0.04340783
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1.33668342	-10.38473732	1.3416236	0.4477092	0.04317587
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1.49748744	-11.27542695	1.3703957	0.4572812	0.04258108
1.50753769	-11.32909235	1.3721372	0.4578606	0.04254500
1.51758794	-11.38252969	1.3738721	0.4584378	0.04250905
1.52763819	-11.43574018	1.3756006	0.4590129	0.04247323
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1.54773869	-11.54148547	1.3790385	0.4601567	0.04240196
1.55778894	-11.59402264	1.3807479	0.4607255	0.04236650
1.56783920	-11.64633775	1.3824510	0.4612921	0.04233117
1.57788945	-11.69843197	1.3841478	0.4618567	0.04229596
1.58793970	-11.75030647	1.3858384	0.4624192	0.04226088
1.59798995	-11.80196240	1.3875228	0.4629797	0.04222591
1.60804020	-11.85340091	1.3892010	0.4635381	0.04219106
1.61809045	-11.90462314	1.3908731	0.4640944	0.04215633
1.62814070	-11.95563023	1.3925391	0.4646488	0.04212172
1.63819095	-12.00642330	1.3941990	0.4652011	0.04208722
1.64824121	-12.05700348	1.3958529	0.4657514	0.04205285
1.65829146	-12.10737186	1.3975008	0.4662997	0.04201859
1.66834171	-12.15752955	1.3991427	0.4668460	0.04198444
1.67839196	-12.20747766	1.4007786	0.4673904	0.04195041
1.68844221	-12.25721726	1.4024086	0.4679328	0.04191650
1.69849246	-12.30674943	1.4040328	0.4684732	0.04188270
1.70854271	-12.35607525	1.4056511	0.4690117	0.04184901
1.71859296	-12.40519578	1.4072635	0.4695482	0.04181544
1.72864322	-12.45411208	1.4088702	0.4700829	0.04178198
1.73869347	-12.50282520	1.4104711	0.4706156	0.04174863
1.74874372	-12.55133618	1.4120662	0.4711464	0.04171539
1.75879397	-12.59964606	1.4136557	0.4716753	0.04168226
1.76884422	-12.64775587	1.4152395	0.4722023	0.04164924
1.77889447	-12.69566663	1.4168176	0.4727275	0.04161633
1.78894472	-12.74337936	1.4183901	0.4732507	0.04158353
1.79899497	-12.79089505	1.4199570	0.4737722	0.04155084
1.80904523	-12.83821473	1.4215184	0.4742917	0.04151826
1.81909548	-12.88533937	1.4230742	0.4748095	0.04148578
1.82914573	-12.93226998	1.4246245	0.4753254	0.04145341
1.83919598	-12.97900752	1.4261694	0.4758394	0.04142115
1.84924623	-13.02555298	1.4277088	0.4763517	0.04138899
1.85929648	-13.07190732	1.4292427	0.4768622	0.04135694
1.86934673	-13.11807150	1.4307713	0.4773709	0.04132500
1.87939698	-13.16404648	1.4322945	0.4778777	0.04129315
1.88944724	-13.20983322	1.4338124	0.4783829	0.04126141

```

1.89949749 -13.25543264 1.4353249 0.4788862 0.04122978
1.90954774 -13.30084570 1.4368322 0.4793878 0.04119824
1.91959799 -13.34607331 1.4383342 0.4798876 0.04116681
1.92964824 -13.39111640 1.4398309 0.4803857 0.04113548
1.93969849 -13.43597590 1.4413225 0.4808821 0.04110425
1.94974874 -13.48065271 1.4428089 0.4813767 0.04107312
1.95979899 -13.52514773 1.4442901 0.4818697 0.04104209
1.96984925 -13.56946188 1.4457661 0.4823609 0.04101116
1.97989950 -13.61359604 1.4472371 0.4828504 0.04098033
1.98994975 -13.65755110 1.4487030 0.4833383 0.04094960
2.00000000 -13.70132794 1.4501638 0.4838244 0.04091897

```

The first column gives lambda, the second column gives intercept values while the third, fourth and fifth columns give values of intercepts of x1, x2 and x3 respectively.

But how to choose the value of lambda?

The best way to choose is by looking at the digits as it gives a subjective understanding. But if we want an objective way of choosing it, we use the command :

```
select(fit)
```

We get the output as

```

modified HKB estimator is 0.00080552
modified L-W estimator is 0.0005637402
smallest value of GCV at 0.01005025

```

So, we notice that there are certain methods of estimating the tuning parameter such as HKB, L-W, GCV (generalised cross validation) methods. Though the values for different methods are quite different but it doesn't matter much because when lambda is slightly more than 0, things start getting stabilised. So, this is known as ridge regression.

That's all for this session, we shall continue with Lasso in R lab in our next session.

Thank You for reading with patience.

**NOTE :** The whole R code that we used for this session is given below for reference purpose:

```

x1=1:100
x2=3*x1 + rnorm(100)/10
x3=x1*x1
tmp=c()
for(i in 1:100){
y = 1+2*x1+0.05*x3+4*rnorm(100)
tmp=rbind(tmp, lm(y~x1+x2+x3)$coef)}
library(MASS)
fit = lm.ridge(y~x1+x2+x3,lambda=seq(0,2,len=200))
matplot(fit$lambda,coef(fit)[,-1],ty='l')
coef(fit)
select(fit)

```

**NOTE :** WHEN THE R CODE THAT IS BEING USED ABOVE IS RUN A NUMBER OF TIMES , YOU MAY NOTICE THAT THE PLOT CHANGES AND ALSO THE COEF RANGE IN THE PLOT CHANGES BUT THE BASIC IDEA OF ATTAINING STABILITY DOESNOT CHANGES WITH A SLIGHT INCREAMENT OF VALUE OF LAMBDA FROM 0. SO, WHEN YOU RUN THE CODE THE PLOT MAY NOT RESEMBLE THA ONE ATTACHED HERE. ALSO THE VALUES OF `coef(fit)` MAY NOT RESEMBLE THE SAME AS HERE.