

## Influential Points: R lab(Part II)

```
?LifeCycleSavings
```

```
names(LifeCycleSavings)
```

```
rownames(LifeCycleSavings)
```

```
nrow(LifeCycleSavings)
```

```
fit=lm(sr~., data= LifeCycleSavings)
```

```
influence.measures(fit)
```

```
> influence.measures(fit)
Influence measures of
lm(formula = sr ~ ., data = LifeCycleSavings) :
```

	dfb.1	dfb.pp15	dfb.pp75	dfb.dpi	dfb.ddpi	dffit	cov.r	cook.d	hat	inf
Australia	0.01232	-0.01044	-0.02653	0.04534	-0.000159	0.0627	1.193	8.04e-04	0.0677	
Austria	-0.01005	0.00594	0.04084	-0.03672	-0.008182	0.0632	1.268	8.18e-04	0.1204	
Belgium	-0.06416	0.05150	0.12070	-0.03472	-0.007265	0.1878	1.176	7.15e-03	0.0875	
Bolivia	0.00578	-0.01270	-0.02253	0.03185	0.040642	-0.0597	1.224	7.28e-04	0.0895	
Brazil	0.08973	-0.06163	-0.17907	0.11997	0.068457	0.2646	1.082	1.40e-02	0.0696	
Canada	0.00541	-0.00675	0.01021	-0.03531	-0.002649	-0.0390	1.328	3.11e-04	0.1584	
Chile	-0.19941	0.13265	0.21979	-0.01998	0.120007	-0.4554	0.655	3.78e-02	0.0373	*
China	0.02112	-0.00573	-0.08311	0.05180	0.110627	0.2008	1.150	8.16e-03	0.0780	
Colombia	0.03910	-0.05226	-0.02464	0.00168	0.009084	-0.0960	1.167	1.88e-03	0.0573	
Costa Rica	-0.23367	0.28428	0.14243	0.05638	-0.032824	0.4049	0.968	3.21e-02	0.0755	
Denmark	-0.04051	0.02093	0.04653	0.15220	0.048854	0.3845	0.934	2.88e-02	0.0627	
Ecuador	0.07176	-0.09524	-0.06067	0.01950	0.047786	-0.1695	1.139	5.82e-03	0.0637	
Finland	-0.11350	0.11133	0.11695	-0.04364	-0.017132	-0.1464	1.203	4.36e-03	0.0920	
France	-0.16600	0.14705	0.21900	-0.02942	0.023952	0.2765	1.226	1.55e-02	0.1362	
Germany	-0.00802	0.00822	0.00835	-0.00697	-0.000293	-0.0152	1.226	4.74e-05	0.0874	
Greece	-0.14820	0.16394	0.02861	0.15713	-0.059599	-0.2811	1.140	1.59e-02	0.0966	
Guatemala	0.01552	-0.05485	0.00614	0.00585	0.097217	-0.2305	1.085	1.07e-02	0.0605	
Honduras	-0.00226	0.00984	-0.01020	0.00812	-0.001887	0.0482	1.186	4.74e-04	0.0601	
Iceland	0.24789	-0.27355	-0.23265	-0.12555	0.184698	-0.4768	0.866	4.35e-02	0.0705	
India	0.02105	-0.01577	-0.01439	-0.01374	-0.018958	0.0381	1.202	2.97e-04	0.0715	
Ireland	-0.31001	0.29624	0.48156	-0.25733	-0.093317	0.5216	1.268	5.44e-02	0.2122	
Italy	0.06619	-0.07097	0.00307	-0.06999	-0.028648	0.1388	1.162	3.92e-03	0.0665	
Japan	0.63987	-0.65614	-0.67390	0.14610	0.388603	0.8597	1.085	1.43e-01	0.2233	
Korea	-0.16897	0.13509	0.21895	0.00511	-0.169492	-0.4303	0.870	3.56e-02	0.0608	
Luxembourg	-0.06827	0.06888	0.04380	-0.02797	0.049134	-0.1401	1.196	3.99e-03	0.0863	
Malta	0.03652	-0.04876	0.00791	-0.08659	0.153014	0.2386	1.128	1.15e-02	0.0794	
Norway	0.00222	-0.00035	-0.00611	-0.01594	-0.001462	-0.0522	1.168	5.56e-04	0.0479	
Netherlands	0.01395	-0.01674	-0.01186	-0.00433	0.022591	0.0366	1.229	2.74e-04	0.0906	
New Zealand	-0.06002	0.06510	0.09412	-0.02638	-0.064740	0.1469	1.134	4.38e-03	0.0542	
Nicaragua	-0.01209	0.01790	0.00972	-0.00474	-0.010467	0.0397	1.174	3.23e-04	0.0504	
Panama	0.02828	-0.05334	0.01446	-0.03467	-0.007889	-0.1775	1.067	6.33e-03	0.0390	
Paraguay	-0.23227	0.16416	0.15826	0.14361	0.270478	-0.4655	0.873	4.16e-02	0.0694	
Peru	-0.07182	0.14669	0.09148	-0.08585	-0.287184	0.4811	0.831	4.40e-02	0.0650	
Philippines	-0.15707	0.22681	0.15743	-0.11140	-0.170674	0.4884	0.818	4.52e-02	0.0643	
Portugal	-0.02140	0.02551	-0.00380	0.03991	-0.028011	-0.0690	1.233	9.73e-04	0.0971	
South Africa	0.02218	-0.02030	-0.00672	-0.02049	-0.016326	0.0343	1.195	2.41e-04	0.0651	
South Rhodesia	0.14390	-0.13472	-0.09245	-0.06956	-0.057920	0.1607	1.313	5.27e-03	0.1608	
Spain	-0.03035	0.03131	0.00394	0.03512	0.005340	-0.0526	1.208	5.66e-04	0.0773	
Sweden	0.10098	-0.08162	-0.06166	-0.25528	-0.013316	-0.4526	1.086	4.06e-02	0.1240	
Switzerland	0.04323	-0.04649	-0.04364	0.09093	-0.018828	0.1903	1.147	7.33e-03	0.0736	
Turkey	-0.01092	-0.01198	0.02645	0.00161	0.025138	-0.1445	1.100	4.22e-03	0.0396	
Tunisia	0.07377	-0.10500	-0.07727	0.04439	0.103058	-0.2177	1.131	9.56e-03	0.0746	
United Kingdom	0.04671	-0.03584	-0.17129	0.12554	0.100314	-0.2722	1.189	1.50e-02	0.1165	
United States	0.06910	-0.07289	0.03745	-0.23312	-0.032729	-0.2510	1.655	1.28e-02	0.3337	*
Venezuela	-0.05083	0.10080	-0.03366	0.11366	-0.124486	0.3071	1.095	1.89e-02	0.0863	
Zambia	0.16361	-0.07917	-0.33899	0.09406	0.228232	0.7482	0.512	9.66e-02	0.0643	*
Jamaica	0.10958	-0.10022	-0.05722	-0.00703	-0.295461	-0.3456	1.200	2.40e-02	0.1408	
Uruguay	-0.13403	0.12880	0.02953	0.13132	0.099591	-0.2051	1.187	8.53e-03	0.0979	
Libya	0.55074	-0.48324	-0.37974	-0.01937	-1.024477	-1.1601	2.091	2.68e-01	0.5315	*
Malaysia	0.03684	-0.06113	0.03235	-0.04956	-0.072294	-0.2126	1.113	9.11e-03	0.0652	

Here, the hat column contains the hat values i.e., diagonal entries of hat matrix  $X(XX')^{-1}X'$ .

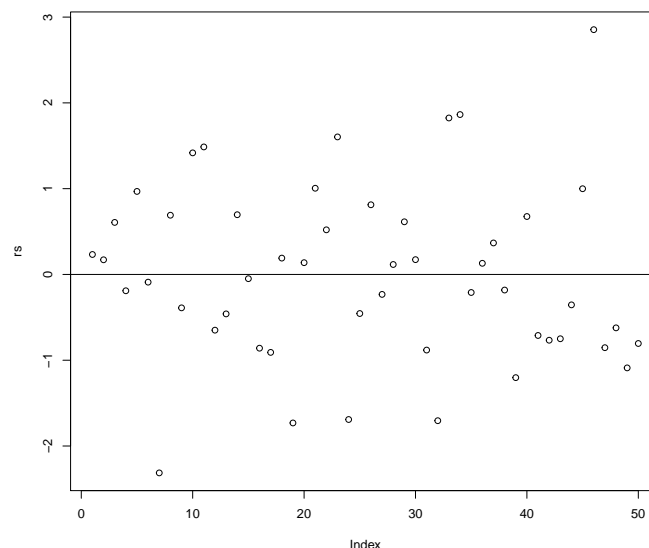
Now based on all these columns we get here, we have to conclude which are the influential cases. There are various cut off values of these parameters by which we conclude. For more information on cut off values and their justifications follow **Besley Kuh Welsch**.

Here we get a column named *inf* from which we directly get those points which are influential. Eg.- here Chile, United States, Zambia, Libya are four influential points. So they need another law, but they have to be in our data, we also have to check if there is any typo or not in recording these influential points.

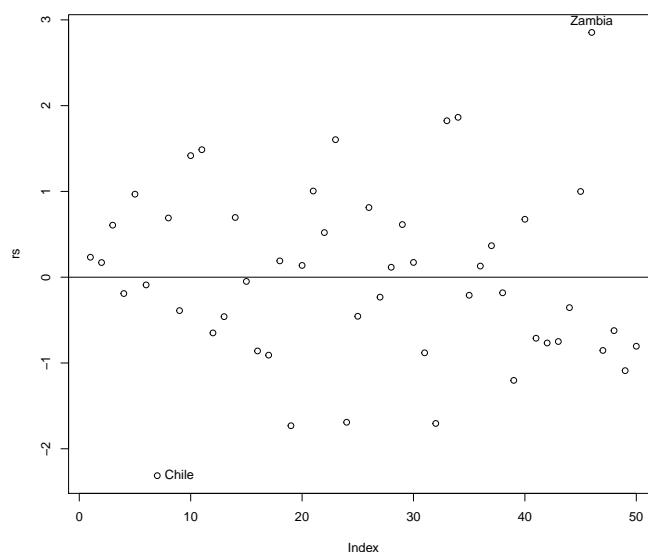
Now we may want to check the parameters to detect influential points individually. So, we can find out the r-student values by using the function `rstudent()`.

```
rs=rstudent(fit)
plot(rs);
abline(h=0)
identify(rs, lab= rownames(LifeCycleSavings))
```

Now we plot these r-student values with the line  $rs=0$ . The plot is shown below:



From r-student values we can identify the outliers only, it doesn't tell us if a point is influential or not. Now from the plot we can identify that there are two outlier points plotted on the graph, and to know which points are these we use the function `identify()`. It takes the plotted values and labels associated with those plotted points as its input. By using this function we can locate the outlier points in our plot by selecting the points using the cursor(which changes into locator) and we get the names associated, thus we can identify these points. The plot after identifying these points is shown below:

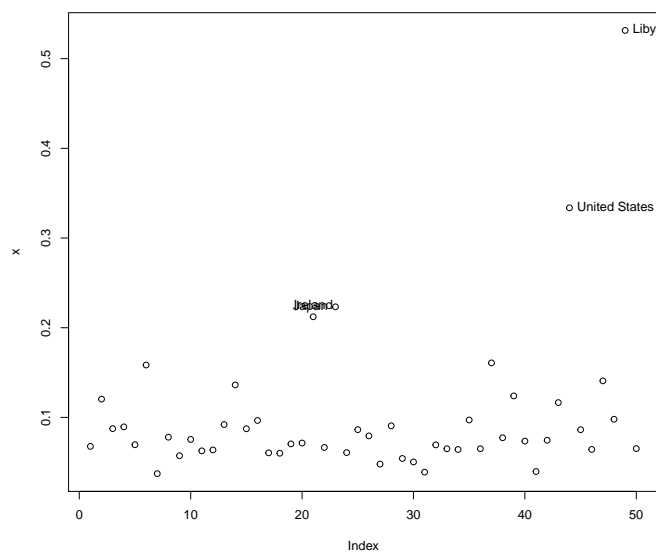


So, by identifying the outliers we get two points which are Zambia and Chile which we got as influential points using the function *influence.measure()*. So, out of four influential points two are outliers and the remaining points are not outliers.

```
checkplot= function(x,lab){
  plot(x)
  identify(x, lab=lab)
}

checkplot(hatvalues(fit),rownames(LifeCycleSavings))
```

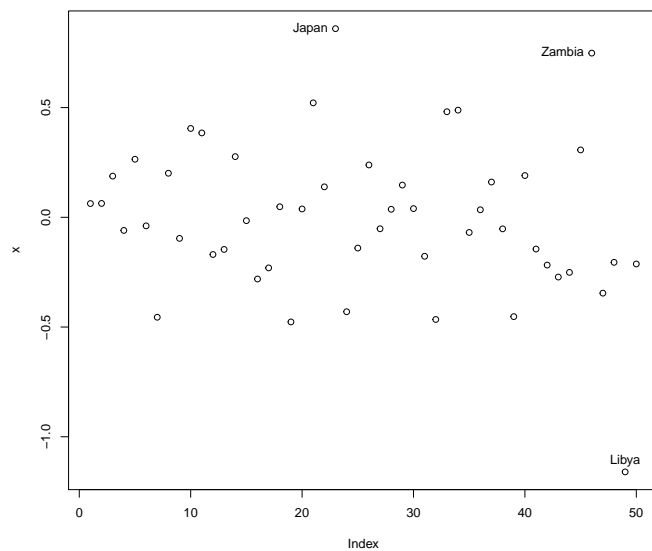
Now let's take a look at the hat-values. To do the plots easily we write a function *checkplot()* which takes the value to be plotted and the names associated with those points as inputs and gives the plot and an option to identify points on the plot as output. So using this function we plot hat-values and identify those points which don't behave like the other points behave. The plot is given below:



From the plot we report that Libya and USA are some special points i.e., they don't behave like the bulk of the data. And we also notice that Japan and Ireland also differs a little bit from the general behaviour of other data-points so we may consider these two points separately.

```
checkplot(dffits(fit),rownames(LifeCycleSavings))
```

Now let's look at dffits. By the same way we plot the values of dffits. The plot is given below:



From this plot we get Libya, Zambia and Japan as influential points, where Libya and Zambia are already reported.

So, this is how we carry out influence analysis. But above all we should remember that by doing this analysis we can identify those certain points which are potentially dangerous. Now at last we should check if there is any typo in recording the values of these points, we should check these values with the domain knowledge etc.