

Unsupervised Learning - Hierarchical Clustering

Abhirup Sen

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R Markdown

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When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
# Hclust on mtcars dataset
set.seed(2835)
```

```
data(mtcars)
str(mtcars)
```

```
## 'data.frame':  32 obs. of  11 variables:
## $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
## $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
## $ disp: num  160 160 108 258 360 ...
## $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
## $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
## $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
## $ qsec: num  16.5 17 18.6 19.4 17 ...
## $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
## $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
## $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
## $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

```
dataset <- mtcars
```

```
# Step 1: Find distance matrix
?dist
```

```
## starting httpd help server ... done
```

```
d <- dist(dataset, method = 'euclidean')
d
```

```
##           Mazda RX4 Mazda RX4 Wag  Datsun 710 Hornet 4 Drive
## Mazda RX4 Wag      0.6153251
## Datsun 710         54.9086059    54.8915169
```

## Hornet 4 Drive	98.1125212	98.0958939	150.9935191	
## Hornet Sportabout	210.3374396	210.3358546	265.0831615	121.0297564
## Valiant	65.4717710	65.4392224	117.7547018	33.5508692
## Duster 360	241.4076490	241.4088680	294.4790230	169.4299647
## Merc 240D	50.1532711	50.1146059	49.6584796	121.2739722
## Merc 230	25.4683117	25.3284509	33.1803843	118.2433145
## Merc 280	15.3641921	15.2956865	66.9363534	91.4224033
## Merc 280C	15.6724727	15.5837744	67.0261397	91.4612914
## Merc 450SE	135.4307018	135.4254826	189.1954941	72.4964325
## Merc 450SL	135.4014424	135.3960351	189.1631745	72.4313532
## Merc 450SLC	135.4794674	135.4723157	189.2345426	72.5718466
## Cadillac Fleetwood	326.3395903	326.3355070	381.0926242	234.4403876
## Lincoln Continental	318.0469808	318.0429333	372.8012090	227.9726091
## Chrysler Imperial	304.7203408	304.7169175	359.3014906	218.1548299
## Fiat 128	93.2679950	93.2530993	40.9933763	184.9689734
## Honda Civic	102.8307567	102.8238713	52.7704607	191.5518700
## Toyota Corolla	100.6040368	100.5887588	47.6535017	192.6714187
## Toyota Corona	42.3075233	42.2659224	12.9654743	138.5304725
## Dodge Challenger	163.1150750	163.1134210	217.7795805	72.4403915
## AMC Javelin	149.6047203	149.6014522	204.3188913	61.3601899
## Camaro Z28	233.2228758	233.2248748	286.0049209	163.6632641
## Pontiac Firebird	248.6780270	248.6762035	303.3583889	156.2240346
## Fiat X1-9	92.5048389	92.4940020	39.8815148	184.4471198
## Porsche 914-2	44.4033659	44.4073589	13.1357109	139.1579524
## Lotus Europa	65.7328377	65.7362635	25.0948550	163.2367437
## Ford Pantera L	245.4247064	245.4293785	297.2940489	180.1140339
## Ferrari Dino	66.7661029	66.7764167	90.2415509	130.5523007
## Maserati Bora	265.6454248	265.6491465	309.7718171	229.3419352
## Volvo 142E	39.1894029	39.1626037	20.6939436	137.0363299
##	Hornet Sportabout	Valiant	Duster 360	Merc 240D
## Mazda RX4 Wag				
## Datsun 710				
## Hornet 4 Drive				
## Hornet Sportabout				
## Valiant	152.1241352			
## Duster 360	70.1767262	194.6094525		
## Merc 240D	241.5069657	89.5911056	281.2962502	
## Merc 230	233.4924012	85.0079649	265.8823313	33.6873047
## Merc 280	199.3344960	60.2909811	227.8998521	64.7754228
## Merc 280C	199.3406564	60.2655656	227.8813169	64.8898713
## Merc 450SE	84.3888482	90.6970264	106.4084264	175.1620073
## Merc 450SL	84.3683999	90.6769728	106.4320572	175.1189767
## Merc 450SLC	84.4332423	90.7092989	106.4010305	175.2118218
## Cadillac Fleetwood	116.2804201	266.6280942	119.0239068	355.6627498
## Lincoln Continental	108.0624299	259.6304391	104.5112999	348.9901277
## Chrysler Imperial	97.2049146	248.7713290	81.4297699	338.1959373
## Fiat 128	302.0377212	152.1153263	333.9792070	68.6105903
## Honda Civic	310.0324645	158.9615769	344.0518316	72.0014488
## Toyota Corolla	309.5581776	159.8302995	341.0218232	76.2806458
## Toyota Corona	252.3331988	105.2876428	282.0508820	44.0850975
## Dodge Challenger	48.9838851	103.4310693	103.9023864	192.8617917
## AMC Javelin	61.4274240	91.0444349	110.3084921	180.5479760
## Camaro Z28	70.9665308	187.8463771	10.0761203	273.8367985
## Pontiac Firebird	40.0052475	188.5272116	80.8057339	277.4606884

## Fiat X1-9	301.5669483	151.4379425	333.4843231	67.9163981	
## Porsche 914-2	254.1452553	106.0585767	285.1986201	39.4469276	
## Lotus Europa	272.3582423	130.8248192	296.4572287	72.8971106	
## Ford Pantera L	89.5934049	203.0177926	21.2655990	287.5238795	
## Ferrari Dino	215.0673853	106.5694802	226.2036333	113.3023005	
## Maserati Bora	170.7094473	242.4393015	107.7224977	313.8633093	
## Volvo 142E	248.0063378	104.1863681	275.1353516	53.6823481	
##	Merc 230	Merc 280	Merc 280C	Merc 450SE	Merc 450SL
## Mazda RX4 Wag					
## Datsun 710					
## Hornet 4 Drive					
## Hornet Sportabout					
## Valiant					
## Duster 360					
## Merc 240D					
## Merc 230					
## Merc 280	39.2994160				
## Merc 280C	39.3868519	1.5231546			
## Merc 450SE	159.8179555	122.3642489	122.3461050		
## Merc 450SL	159.7760899	122.3443771	122.3355492	0.9826495	
## Merc 450SLC	159.8495837	122.3934970	122.3586862	1.3726252	2.1383405
## Cadillac Fleetwood	349.2832611	315.3904859	315.3557081	197.8842803	197.9154476
## Lincoln Continental	341.3154316	306.6760719	306.6406187	187.5997191	187.6330806
## Chrysler Imperial	328.4335161	292.7146896	292.6989332	171.6600758	171.6743028
## Fiat 128	69.3127910	106.5053149	106.6829794	228.3247948	228.2592340
## Honda Civic	78.5387212	116.7280991	116.8711475	238.0141824	237.9588183
## Toyota Corolla	76.7731674	113.6290721	113.8118009	235.5183809	235.4481971
## Toyota Corona	21.0962017	54.3641713	54.4258314	176.6020527	176.5727477
## Dodge Challenger	185.8331870	152.8929263	152.8722437	51.8008639	51.8242520
## AMC Javelin	172.5312555	139.1457974	139.1181977	41.2080044	41.2411618
## Camaro Z28	257.7469734	219.5520854	219.5276434	98.7203049	98.7566899
## Pontiac Firebird	271.3871978	238.1726099	238.1806292	124.3368538	124.3204160
## Fiat X1-9	68.5564864	105.7412910	105.8560373	227.7627676	227.7173075
## Porsche 914-2	22.1180967	57.6458160	57.8473863	179.5034108	179.4550855
## Lotus Europa	50.1094030	74.1443580	74.3824296	193.3074449	193.2407697
## Ford Pantera L	269.9772035	231.4081306	231.4024263	112.8181834	112.8296774
## Ferrari Dino	80.6550953	56.8365103	56.8987601	131.0272205	131.0077635
## Maserati Bora	288.8755628	250.5874125	250.5774357	157.1633256	157.1768956
## Volvo 142E	24.6913548	48.8053450	48.8884618	170.4500681	170.4225164
##	Merc 450SLC	Cadillac Fleetwood	Lincoln Continental		
## Mazda RX4 Wag					
## Datsun 710					
## Hornet 4 Drive					
## Hornet Sportabout					
## Valiant					
## Duster 360					
## Merc 240D					
## Merc 230					
## Merc 280					
## Merc 280C					
## Merc 450SE					
## Merc 450SL					
## Merc 450SLC					
## Cadillac Fleetwood	197.8526242				

## Lincoln Continental	187.5671081	15.6224446		
## Chrysler Imperial	171.6557637	40.8399636	25.3714237	
## Fiat 128	228.4051825	417.7687579	410.0206984	
## Honda Civic	238.0828999	425.3271621	417.9679574	
## Toyota Corolla	235.6024098	425.3446517	417.5429986	
## Toyota Corona	176.6305359	368.3195488	360.0267515	
## Dodge Challenger	51.8012606	163.6314881	156.2805020	
## AMC Javelin	41.1929050	176.8610896	169.0925457	
## Camaro Z28	98.7035830	128.4587210	114.0932078	
## Pontiac Firebird	124.3726128	78.5385347	72.6947903	
## Fiat X1-9	227.8176554	417.2490481	409.4998363	
## Porsche 914-2	179.5720446	370.0956775	362.0145494	
## Lotus Europa	193.3969216	388.5350012	379.4716659	
## Ford Pantera L	112.8332602	134.8119464	119.7236456	
## Ferrari Dino	131.0704490	328.5441628	317.7063117	
## Maserati Bora	157.1683970	214.9366858	199.3420611	
## Volvo 142E	170.4843735	364.1000930	355.4009443	
##	Chrysler Imperial	Fiat 128	Honda Civic	Toyota Corolla
## Mazda RX4 Wag				
## Datsun 710				
## Hornet 4 Drive				
## Hornet Sportabout				
## Valiant				
## Duster 360				
## Merc 240D				
## Merc 230				
## Merc 280				
## Merc 280C				
## Merc 450SE				
## Merc 450SL				
## Merc 450SLC				
## Cadillac Fleetwood				
## Lincoln Continental				
## Chrysler Imperial				
## Fiat 128	397.2276375			
## Honda Civic	405.8152201	14.5590942		
## Toyota Corolla	404.6335386	7.8324789	14.3480626	
## Toyota Corona	346.5724649	52.8798281	63.8985563	59.8451285
## Dodge Challenger	145.9194779	254.2367888	261.8498815	261.8345312
## AMC Javelin	157.8097554	241.1203621	248.9636504	248.6917065
## Camaro Z28	91.2880886	325.6636235	335.8883188	332.6589699
## Pontiac Firebird	68.2030747	339.5857659	347.0655360	347.1667643
## Fiat X1-9	396.7597522	5.1473415	14.7807070	10.3922856
## Porsche 914-2	348.8466861	49.0644372	59.4588768	56.3243031
## Lotus Europa	364.5994326	49.9112509	64.0495153	53.8846563
## Ford Pantera L	95.3805385	337.1639236	347.8337714	343.9920962
## Ferrari Dino	300.1640703	128.3950054	141.7044478	133.4707617
## Maserati Bora	174.2936864	349.5338830	362.1620777	355.2601619
## Volvo 142E	341.2896659	61.3301247	73.3766041	67.7189421
##	Toyota Corona	Dodge Challenger	AMC Javelin	Camaro Z28
## Mazda RX4 Wag				
## Datsun 710				
## Hornet 4 Drive				
## Hornet Sportabout				

```

## Valiant
## Duster 360
## Merc 240D
## Merc 230
## Merc 280
## Merc 280C
## Merc 450SE
## Merc 450SL
## Merc 450SLC
## Cadillac Fleetwood
## Lincoln Continental
## Chrysler Imperial
## Fiat 128
## Honda Civic
## Toyota Corolla
## Toyota Corona
## Dodge Challenger      205.0347927
## AMC Javelin           191.5580526      14.0154995
## Camaro Z28            273.6316895      100.3046106 105.6062618
## Pontiac Firebird      290.6240706      85.8075196 99.2836114 86.2665759
## Fiat X1-9             51.8411748      253.6624046 240.5266823 325.1490914
## Porsche 914-2         8.6535903      206.6452569 193.3080584 276.8924414
## Lotus Europa          31.2536926      226.5004836 212.7568765 287.6179004
## Ford Pantera L        285.1287911      118.7516779 123.3832044 19.3589023
## Ferrari Dino          82.2355734      174.9280395 161.1060307 216.7489910
## Maserati Bora         299.1865216      185.9059273 185.1553411 102.5946154
## Volvo 142E            12.2505275      201.3682522 187.6978440 266.5277736
## Pontiac Firebird      Fiat X1-9 Porsche 914-2 Lotus Europa
## Mazda RX4 Wag
## Datsun 710
## Hornet 4 Drive
## Hornet Sportabout
## Valiant
## Duster 360
## Merc 240D
## Merc 230
## Merc 280
## Merc 280C
## Merc 450SE
## Merc 450SL
## Merc 450SLC
## Cadillac Fleetwood
## Lincoln Continental
## Chrysler Imperial
## Fiat 128
## Honda Civic
## Toyota Corolla
## Toyota Corona
## Dodge Challenger
## AMC Javelin
## Camaro Z28
## Pontiac Firebird
## Fiat X1-9            339.1396182
## Porsche 914-2        292.1646488 48.3775209

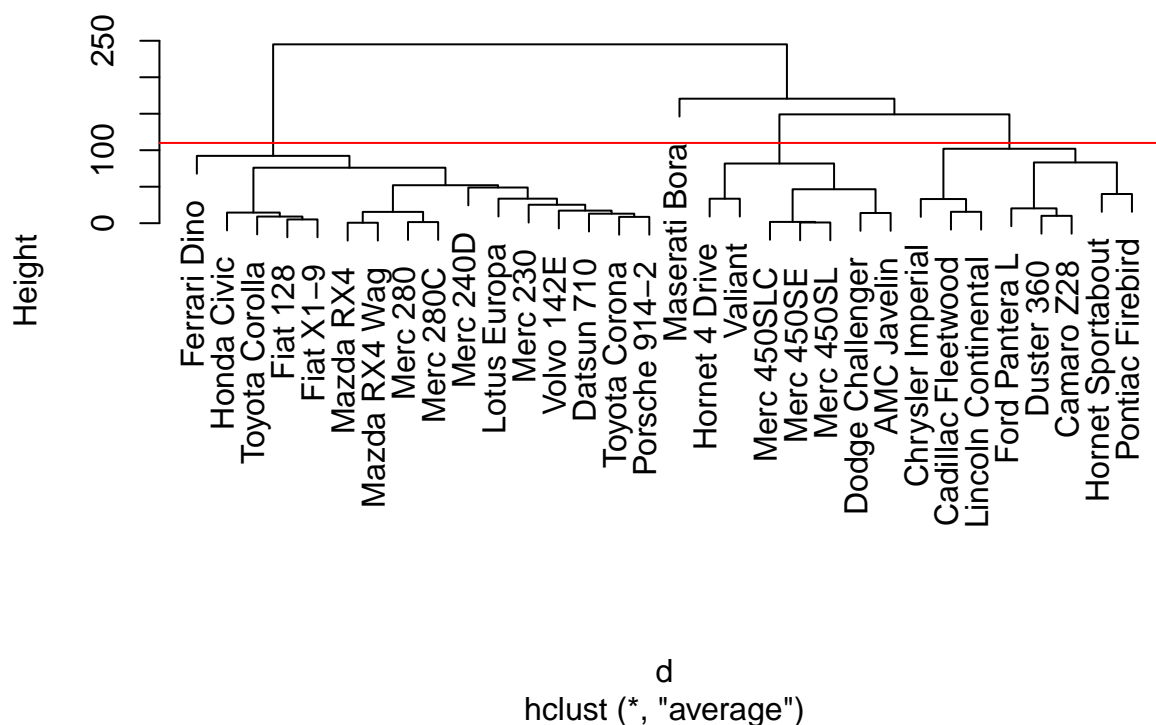
```

## Lotus Europa	311.3862342	49.8406880	33.7678653	
## Ford Pantera L	101.7389686	336.7018783	288.5852993	297.5376920
## Ferrari Dino	255.0570519	127.8210813	87.9105966	80.4553451
## Maserati Bora	188.3240020	349.1199576	303.9222549	303.2796468
## Volvo 142E	286.7497823	60.4120429	18.7555858	27.8104457
##	Ford Pantera L	Ferrari Dino	Maserati Bora	
## Mazda RX4 Wag				
## Datsun 710				
## Hornet 4 Drive				
## Hornet Sportabout				
## Valiant				
## Duster 360				
## Merc 240D				
## Merc 230				
## Merc 280				
## Merc 280C				
## Merc 450SE				
## Merc 450SL				
## Merc 450SLC				
## Cadillac Fleetwood				
## Lincoln Continental				
## Chrysler Imperial				
## Fiat 128				
## Honda Civic				
## Toyota Corolla				
## Toyota Corona				
## Dodge Challenger				
## AMC Javelin				
## Camaro Z28				
## Pontiac Firebird				
## Fiat X1-9				
## Porsche 914-2				
## Lotus Europa				
## Ford Pantera L				
## Ferrari Dino	224.4587490			
## Maserati Bora	86.9383253	223.5342175		
## Volvo 142E	277.4803312	70.4751034	289.1157363	

```
# Step 2: Apply hierarchical clustering (hclust function of stat package)
?hclust
hc = hclust(d, method = "average")
```

```
# Step 3: Plot the dendrogram
plot(hc)
# Step 4: Choosing Number of Cluster
# cut tree by height
abline (h =110, col ="red")
```

Cluster Dendrogram



```
# cut tree by number of cluster
plot(hc)
fit <- cutree(hc, k=3)
fit
```

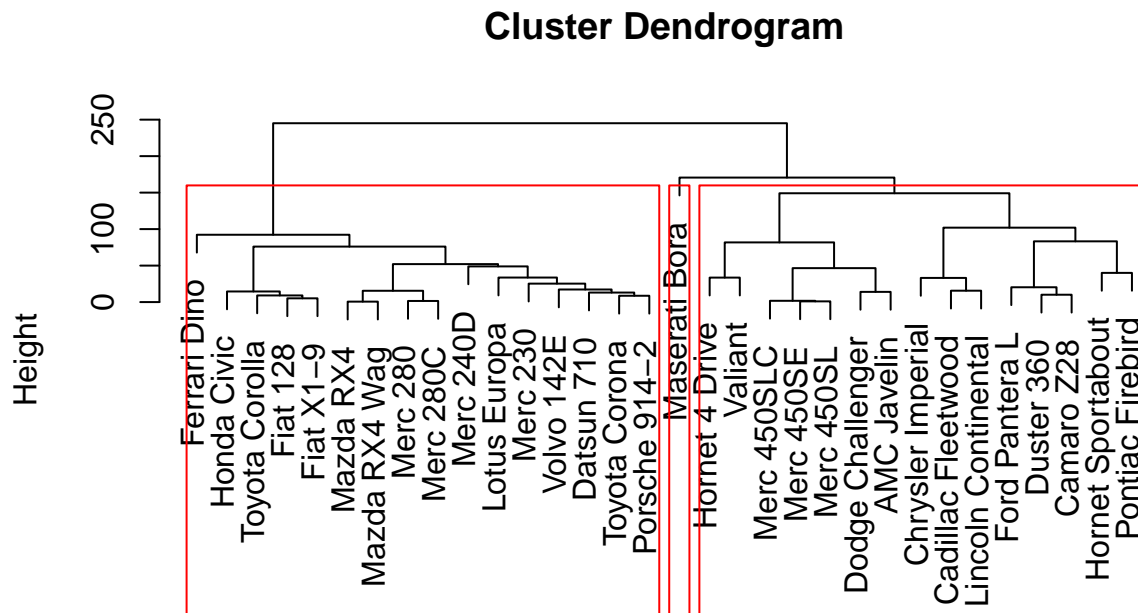
```
##          Mazda RX4      Mazda RX4 Wag      Datsun 710      Hornet 4 Drive
##                1                1                1                2
## Hornet Sportabout      Valiant      Duster 360      Merc 240D
##                2                2                2                1
##          Merc 230      Merc 280      Merc 280C      Merc 450SE
##                1                1                1                2
##          Merc 450SL      Merc 450SLC  Cadillac Fleetwood  Lincoln Continental
##                2                2                2                2
## Chrysler Imperial      Fiat 128      Honda Civic      Toyota Corolla
##                2                1                1                1
##          Toyota Corona  Dodge Challenger      AMC Javelin      Camaro Z28
##                1                2                2                2
## Pontiac Firebird      Fiat X1-9      Porsche 914-2      Lotus Europa
##                2                1                1                1
##          Ford Pantera L      Ferrari Dino      Maserati Bora      Volvo 142E
##                2                1                3                1
```

```
table(fit)
```

```
## fit
```

```
## 1 2 3
## 16 15 1
```

```
rect.hclust(hc, k=3, border="red")
```



```
d
hclust (*, "average")
```

```
# Example 2: iris dataset
```

```
# Hierarchical Clustering on iris dataset
str(iris)
```

```
## 'data.frame': 150 obs. of 5 variables:
## $ Sepal.Length: num 5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
## $ Sepal.Width : num 3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
## $ Petal.Length: num 1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
## $ Petal.Width : num 0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
## $ Species : Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1 1 1 1 1 1 1 ...
```

```
iris
```

```
## Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1 5.1 3.5 1.4 0.2 setosa
## 2 4.9 3.0 1.4 0.2 setosa
## 3 4.7 3.2 1.3 0.2 setosa
## 4 4.6 3.1 1.5 0.2 setosa
## 5 5.0 3.6 1.4 0.2 setosa
```

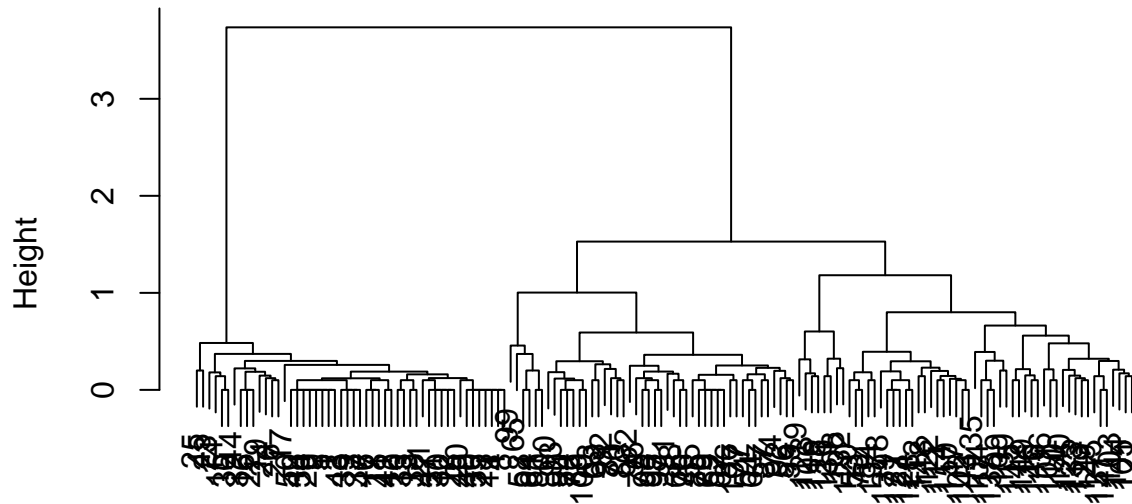

## 6	5.4	3.9	1.7	0.4	setosa
## 7	4.6	3.4	1.4	0.3	setosa
## 8	5.0	3.4	1.5	0.2	setosa
## 9	4.4	2.9	1.4	0.2	setosa
## 10	4.9	3.1	1.5	0.1	setosa
## 11	5.4	3.7	1.5	0.2	setosa
## 12	4.8	3.4	1.6	0.2	setosa
## 13	4.8	3.0	1.4	0.1	setosa
## 14	4.3	3.0	1.1	0.1	setosa
## 15	5.8	4.0	1.2	0.2	setosa
## 16	5.7	4.4	1.5	0.4	setosa
## 17	5.4	3.9	1.3	0.4	setosa
## 18	5.1	3.5	1.4	0.3	setosa
## 19	5.7	3.8	1.7	0.3	setosa
## 20	5.1	3.8	1.5	0.3	setosa
## 21	5.4	3.4	1.7	0.2	setosa
## 22	5.1	3.7	1.5	0.4	setosa
## 23	4.6	3.6	1.0	0.2	setosa
## 24	5.1	3.3	1.7	0.5	setosa
## 25	4.8	3.4	1.9	0.2	setosa
## 26	5.0	3.0	1.6	0.2	setosa
## 27	5.0	3.4	1.6	0.4	setosa
## 28	5.2	3.5	1.5	0.2	setosa
## 29	5.2	3.4	1.4	0.2	setosa
## 30	4.7	3.2	1.6	0.2	setosa
## 31	4.8	3.1	1.6	0.2	setosa
## 32	5.4	3.4	1.5	0.4	setosa
## 33	5.2	4.1	1.5	0.1	setosa
## 34	5.5	4.2	1.4	0.2	setosa
## 35	4.9	3.1	1.5	0.2	setosa
## 36	5.0	3.2	1.2	0.2	setosa
## 37	5.5	3.5	1.3	0.2	setosa
## 38	4.9	3.6	1.4	0.1	setosa
## 39	4.4	3.0	1.3	0.2	setosa
## 40	5.1	3.4	1.5	0.2	setosa
## 41	5.0	3.5	1.3	0.3	setosa
## 42	4.5	2.3	1.3	0.3	setosa
## 43	4.4	3.2	1.3	0.2	setosa
## 44	5.0	3.5	1.6	0.6	setosa
## 45	5.1	3.8	1.9	0.4	setosa
## 46	4.8	3.0	1.4	0.3	setosa
## 47	5.1	3.8	1.6	0.2	setosa
## 48	4.6	3.2	1.4	0.2	setosa
## 49	5.3	3.7	1.5	0.2	setosa
## 50	5.0	3.3	1.4	0.2	setosa
## 51	7.0	3.2	4.7	1.4	versicolor
## 52	6.4	3.2	4.5	1.5	versicolor
## 53	6.9	3.1	4.9	1.5	versicolor
## 54	5.5	2.3	4.0	1.3	versicolor
## 55	6.5	2.8	4.6	1.5	versicolor
## 56	5.7	2.8	4.5	1.3	versicolor
## 57	6.3	3.3	4.7	1.6	versicolor
## 58	4.9	2.4	3.3	1.0	versicolor
## 59	6.6	2.9	4.6	1.3	versicolor

## 60	5.2	2.7	3.9	1.4 versicolor
## 61	5.0	2.0	3.5	1.0 versicolor
## 62	5.9	3.0	4.2	1.5 versicolor
## 63	6.0	2.2	4.0	1.0 versicolor
## 64	6.1	2.9	4.7	1.4 versicolor
## 65	5.6	2.9	3.6	1.3 versicolor
## 66	6.7	3.1	4.4	1.4 versicolor
## 67	5.6	3.0	4.5	1.5 versicolor
## 68	5.8	2.7	4.1	1.0 versicolor
## 69	6.2	2.2	4.5	1.5 versicolor
## 70	5.6	2.5	3.9	1.1 versicolor
## 71	5.9	3.2	4.8	1.8 versicolor
## 72	6.1	2.8	4.0	1.3 versicolor
## 73	6.3	2.5	4.9	1.5 versicolor
## 74	6.1	2.8	4.7	1.2 versicolor
## 75	6.4	2.9	4.3	1.3 versicolor
## 76	6.6	3.0	4.4	1.4 versicolor
## 77	6.8	2.8	4.8	1.4 versicolor
## 78	6.7	3.0	5.0	1.7 versicolor
## 79	6.0	2.9	4.5	1.5 versicolor
## 80	5.7	2.6	3.5	1.0 versicolor
## 81	5.5	2.4	3.8	1.1 versicolor
## 82	5.5	2.4	3.7	1.0 versicolor
## 83	5.8	2.7	3.9	1.2 versicolor
## 84	6.0	2.7	5.1	1.6 versicolor
## 85	5.4	3.0	4.5	1.5 versicolor
## 86	6.0	3.4	4.5	1.6 versicolor
## 87	6.7	3.1	4.7	1.5 versicolor
## 88	6.3	2.3	4.4	1.3 versicolor
## 89	5.6	3.0	4.1	1.3 versicolor
## 90	5.5	2.5	4.0	1.3 versicolor
## 91	5.5	2.6	4.4	1.2 versicolor
## 92	6.1	3.0	4.6	1.4 versicolor
## 93	5.8	2.6	4.0	1.2 versicolor
## 94	5.0	2.3	3.3	1.0 versicolor
## 95	5.6	2.7	4.2	1.3 versicolor
## 96	5.7	3.0	4.2	1.2 versicolor
## 97	5.7	2.9	4.2	1.3 versicolor
## 98	6.2	2.9	4.3	1.3 versicolor
## 99	5.1	2.5	3.0	1.1 versicolor
## 100	5.7	2.8	4.1	1.3 versicolor
## 101	6.3	3.3	6.0	2.5 virginica
## 102	5.8	2.7	5.1	1.9 virginica
## 103	7.1	3.0	5.9	2.1 virginica
## 104	6.3	2.9	5.6	1.8 virginica
## 105	6.5	3.0	5.8	2.2 virginica
## 106	7.6	3.0	6.6	2.1 virginica
## 107	4.9	2.5	4.5	1.7 virginica
## 108	7.3	2.9	6.3	1.8 virginica
## 109	6.7	2.5	5.8	1.8 virginica
## 110	7.2	3.6	6.1	2.5 virginica
## 111	6.5	3.2	5.1	2.0 virginica
## 112	6.4	2.7	5.3	1.9 virginica
## 113	6.8	3.0	5.5	2.1 virginica

## 114	5.7	2.5	5.0	2.0	virginica
## 115	5.8	2.8	5.1	2.4	virginica
## 116	6.4	3.2	5.3	2.3	virginica
## 117	6.5	3.0	5.5	1.8	virginica
## 118	7.7	3.8	6.7	2.2	virginica
## 119	7.7	2.6	6.9	2.3	virginica
## 120	6.0	2.2	5.0	1.5	virginica
## 121	6.9	3.2	5.7	2.3	virginica
## 122	5.6	2.8	4.9	2.0	virginica
## 123	7.7	2.8	6.7	2.0	virginica
## 124	6.3	2.7	4.9	1.8	virginica
## 125	6.7	3.3	5.7	2.1	virginica
## 126	7.2	3.2	6.0	1.8	virginica
## 127	6.2	2.8	4.8	1.8	virginica
## 128	6.1	3.0	4.9	1.8	virginica
## 129	6.4	2.8	5.6	2.1	virginica
## 130	7.2	3.0	5.8	1.6	virginica
## 131	7.4	2.8	6.1	1.9	virginica
## 132	7.9	3.8	6.4	2.0	virginica
## 133	6.4	2.8	5.6	2.2	virginica
## 134	6.3	2.8	5.1	1.5	virginica
## 135	6.1	2.6	5.6	1.4	virginica
## 136	7.7	3.0	6.1	2.3	virginica
## 137	6.3	3.4	5.6	2.4	virginica
## 138	6.4	3.1	5.5	1.8	virginica
## 139	6.0	3.0	4.8	1.8	virginica
## 140	6.9	3.1	5.4	2.1	virginica
## 141	6.7	3.1	5.6	2.4	virginica
## 142	6.9	3.1	5.1	2.3	virginica
## 143	5.8	2.7	5.1	1.9	virginica
## 144	6.8	3.2	5.9	2.3	virginica
## 145	6.7	3.3	5.7	2.5	virginica
## 146	6.7	3.0	5.2	2.3	virginica
## 147	6.3	2.5	5.0	1.9	virginica
## 148	6.5	3.0	5.2	2.0	virginica
## 149	6.2	3.4	5.4	2.3	virginica
## 150	5.9	3.0	5.1	1.8	virginica

```
hc.average <- hclust(dist(iris[, 3:4], method = 'euclidean'), method = 'average')
plot(hc.average, main = "Hclust Linkage - Average")
```

Hclust Linkage – Average



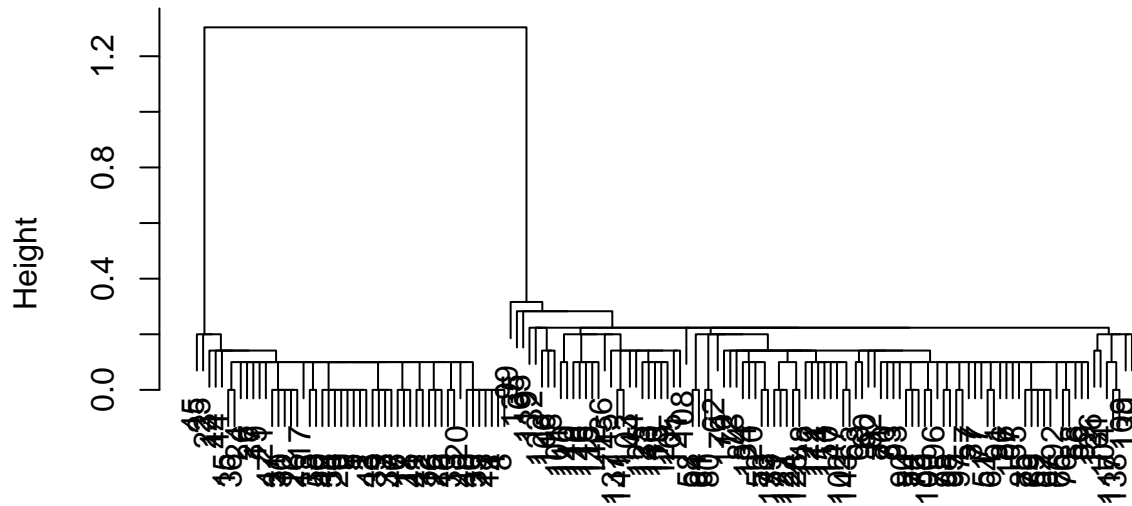
```
dist(iris[, 3:4], method = "euclidean")  
hclust (*, "average")
```

```
clusterCut <- cutree(hc.average, 3)  
table(clusterCut, iris$Species)
```

```
##  
## clusterCut setosa versicolor virginica  
##          1      50          0          0  
##          2       0         45          1  
##          3       0          5         49
```

```
hc.single <- hclust(dist(iris[, 3:4], method = 'euclidean'), method = 'single')  
plot(hc.single, main = "Hclust Linkage - Single")
```

Hclust Linkage – Single



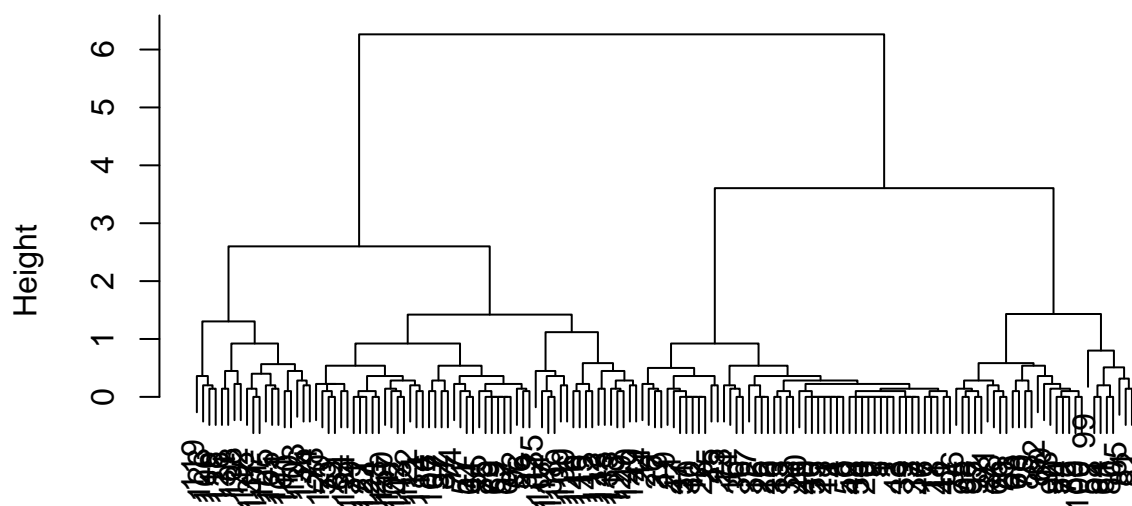
```
dist(iris[, 3:4], method = "euclidean")
hclust (*, "single")
```

```
clusterCut <- cutree(hc.single, 3)
table(clusterCut, iris$Species)
```

```
##
## clusterCut setosa versicolor virginica
##          1      50          0          0
##          2       0         49         50
##          3       0          1          0
```

```
hc.complete <- hclust(dist(iris[, 3:4], method = 'euclidean'), method = 'complete')
plot(hc.complete, main = "Hclust Linkage - Complete")
```

Hclust Linkage – Complete



```
dist(iris[, 3:4], method = "euclidean")
hclust (*, "complete")
```

```
clusterCut <- cutree(hc.complete, 3)
table(clusterCut, iris$Species)
```

```
##
## clusterCut setosa versicolor virginica
##      1      50      0      0
##      2      0      21     50
##      3      0      29      0
```

```
# Visualising the clusters
library(cluster)
clusplot(iris,
  clusterCut,
  lines = 0,
  shade = TRUE,
  color = TRUE,
  labels= 2,
  plotchar = FALSE,
  span = TRUE,
  main = paste('Clusters of Flower'),
  xlab = 'Petal.Length',
  ylab = 'Petal.Width')
```

Clusters of Flower

