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Principal Component Analysis

Study on Indian Stock Market – Nifty 50 Stocks.

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Principal Component Analysis

PCA is technique of reducing dimension, suppose we have set of n variables, A1, A2…..AN. we know the co-variance between these A variables so we construct the linear combination W=X1A1+X2A2…XNAN. The objective of this exercise is to maximize the variance of W and choose the weight of X variable so that we can determine which of them is explaining W more efficiently.

As mentioned before we are working to reduce the dimension and also trying to find out that at given point of time with less number of variable which is capable of explaining W so that we can only focus on that many parameters.

We need to understand few of mathematical terms in order to understand this process further and they are as follow:

- **Standard Deviation:** The standard deviation of data set is a measure of how spread out the data is. In mathematical term it is square distance of each point from its mean. Adding all this and dividing them by number of observation and square root of this number will give you Standard Deviation.

- **Variance:** Variance is another method of spread dataset and it's almost identical to standard deviation. Only thing is that we do not apply square root to above observation.

- **Co-Variance:** Standard Deviation and Variance only operates on one dimension let's say we have dataset X{1,2,3,…..,6} and another dataset as Y{2,3,4,5….44} we can individually measure their Standard Deviation and Variance but if we want to measure how X & Y vary with respect to each other and there we talk about their co-movement and that is Covariance.

- **Co-Variance Matrix:** We have seen that covariance in above case is between two dimensions but what about if we have more such dataset instead of just X & Y. So when we have more such dataset we create matrix of such set and it's known to be Covariance Matrix.

- **Eigen Vectors:** We can multiply two matrices together provided they are of compatible sizes. Eigen Vector is special of this cases let's look at them with few example and try to understand them further.

$$\begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 1 \\ 3 \end{pmatrix} = \begin{pmatrix} 11 \\ 5 \end{pmatrix}$$

- The above example is on **Non-Eigen Vector**, here there is one square matrix and multiplied to vector and resultant value gives a Vector but this resultant vector is not integer multiple of original vector.

$$\begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix} \times \begin{pmatrix} 3 \\ 2 \end{pmatrix} = \begin{pmatrix} 12 \\ 8 \end{pmatrix} = 4 \times \begin{pmatrix} 3 \\ 2 \end{pmatrix}$$

- In this case we can see it's clearly case of **Eigen Vector,** since the resultant vector is 4 times the input vector.

- **Properties of Eigen Vector:**
  - They are from the family of Square Matrices. If suppose they are of dimension 3 X 3 than there will be 3 Eigen Vectors.
  - If you Scale the vector by some amount before multiplying it. You will get same multiple of it as a result, this is because you are not changing the direction but you are just making it longer.
  - All Eigen Vectors of matrix are perpendicular (orthogonal). It'll help you to represent data in terms of perpendicular Eigen Vector instead of X & Y axes.

- **Eigen Values:** This is nothing but acting as scalar multiple associated with Eigen Vector, as in above example resultant multiple got scaled up by four time of original vector.

Principal Component Analysis

PCA Introduction: PCA is also a way to identify the pattern in data and expressing data in such a way as to highlight similarities and differences. Since it becomes difficult to find out pattern in large dimension of dataset we require reducing the dimension and also at the same time don't want to lose much of information so after performing PCA we are left with limited dimension. Also, the important part of this analysis is that when we take input data they might be highly correlated and we are trying to reduce them and make component of data and this component are uncorrelated (orthogonal) to each other.

- **Dataset:** We will examine Nifty Fifty component so we take all Fifty stock constitute Nifty as an Index. The dataset used is from 02nd January, 2012 to 28th February, 2012 with price interval of 30 minutes. So in total we have 50 stocks and each stock consist of 524 data points. In order to have dataset to follow standard numbers we will do analysis on return of this dataset.
- **R Code :**
  - Dataset to be formed and to make a standard Data Frame.

```
> head(data)
          axi          baj          bha          bhe          bpc          cai          can          cip          dlf          drr          gai
1  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000
2 -0.016467769 -0.012955596 -0.004752655 -0.012803197 -0.007647035 -0.003684425 -0.012371292  0.011034380 -0.013490930  0.002579348  0.010525729
3 -0.002101577 -0.024207710  0.000000000  0.002110151 -0.000207490 -0.003698051  0.005517255  0.003086422 -0.003969384 -0.006682241  0.003097576
4  0.003436648 -0.007522521  0.000865801 -0.001265556  0.000414938  0.002574004  0.006854036  0.000000000 -0.000852636  0.002400658 -0.000773495
5 -0.002544531  0.001476257 -0.000577117 -0.005714906  0.000414766 -0.000642880 -0.007955055 -0.000616523 -0.006847388  0.000126191 -0.001419630
6 -0.001848842 -0.034178537 -0.001733353 -0.002550480  0.005582564 -0.000965096 -0.002895955  0.004154172  0.002002003 -0.001104711 -0.007779114
          gra          hcl          hdf          hbk          her          hin          hul          ici          idf          inf          itc
1  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000
2 -0.004936461 -0.000768246 -0.004146834 -0.006113351 -0.008709404 -0.009034262 -0.000489716 -0.004646350 -0.012469666 -0.000561233  0.000742482
3 -0.002096652  0.001152148 -0.002311249  0.001060758 -0.007633217 -0.008680610  0.000244888 -0.001936387  0.005983156  0.002532105 -0.001237777
4  0.001768056  0.008408764  0.001310364  0.000235571 -0.026249081 -0.010517187  0.001101254  0.002151310 -0.003259101  0.004451781 -0.000991326
5  0.001047024  0.000507357 -0.007422332 -0.002594341  0.006196724 -0.006629859  0.000611284 -0.001792436  0.000543922  0.000593274 -0.000496032
6 -0.002773927 -0.002412240 -0.000388093 -0.003667124 -0.011685106  0.000000000 -0.002447383 -0.006840711 -0.002722572 -0.001978952 -0.003728102
          jin          jpa          kot          mnm          mar          ntp          ong          pnb          pow          ran          rco
1  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000
2 -0.011001211 -0.010382349 -0.017908113 -0.009689158  0.000377308 -0.002487563 -0.000793179 -0.011155703  0.002506895 -0.006281196 -0.008547061
3  0.003092558 -0.000949217  0.004862150 -0.007511978  0.002368394 -0.003742986 -0.000198393 -0.001452817 -0.002506895  0.005544276  0.005706150
4 -0.005307399  0.004737100 -0.000828451 -0.003520098  0.002148229 -0.003129893  0.006920443 -0.004769484  0.000000000  0.001350605  0.000000000
5 -0.006450918 -0.004737100  0.002601397 -0.000881964 -0.005109598 -0.001882649 -0.001380262 -0.003992021 -0.002010051  0.012195273  0.001421464
6 -0.004697470 -0.000950119 -0.012835926 -0.002945510  0.000808516  0.000941767 -0.001579779 -0.004008021 -0.001006543 -0.006322978 -0.009275842
          rel          rin          rpo          sai          sbi          ses          sie          ste          sun          tmo          tpo
1  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000
2 -0.004834362 -0.006993035 -0.004907125 -0.003085470 -0.002115152 -0.009047012 -0.001021571 -0.011459880 -0.014037090 -0.007137005  0.005724114
3  0.001708915 -0.009843611  0.004207580 -0.001236859 -0.002400512  0.002503914 -0.001494945  0.001645188  0.004363496 -0.000826788 -0.001142205
4  0.002912658 -0.003401615 -0.002803085  0.001236859  0.002120230 -0.003758226 -0.001260637  0.001095290 -0.001114432 -0.002484473  0.010233176
5 -0.001917138 -0.002076228 -0.002107482 -0.006199648 -0.000810146 -0.032852580 -0.000078800 -0.016000341  0.000304059 -0.002213615 -0.005672165
6 -0.003559990 -0.019942186 -0.007765659 -0.015669390 -0.000530066 -0.000648719 -0.000946596 -0.002227172 -0.000709615 -0.002773927 -0.003418807
          tsl          tcs          wip          acc          amb          lnt
1  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000  0.000000000
2 -0.002812941  0.003522492 -0.007003530 -0.005821149 -0.016134587 -0.006160592
3 -0.000148269  0.005132603  0.006878896  0.000442184  0.001300390 -0.002045348
4 -0.000593296  0.004681856  0.001992281  0.001104606  0.000000000  0.002742802
5 -0.011940440  0.000976169 -0.002615683  0.001941149  0.002919710 -0.001744549
6 -0.003459430 -0.002931370 -0.001747597 -0.006012131 -0.002270149 -0.001747597
```

Principal Component Analysis

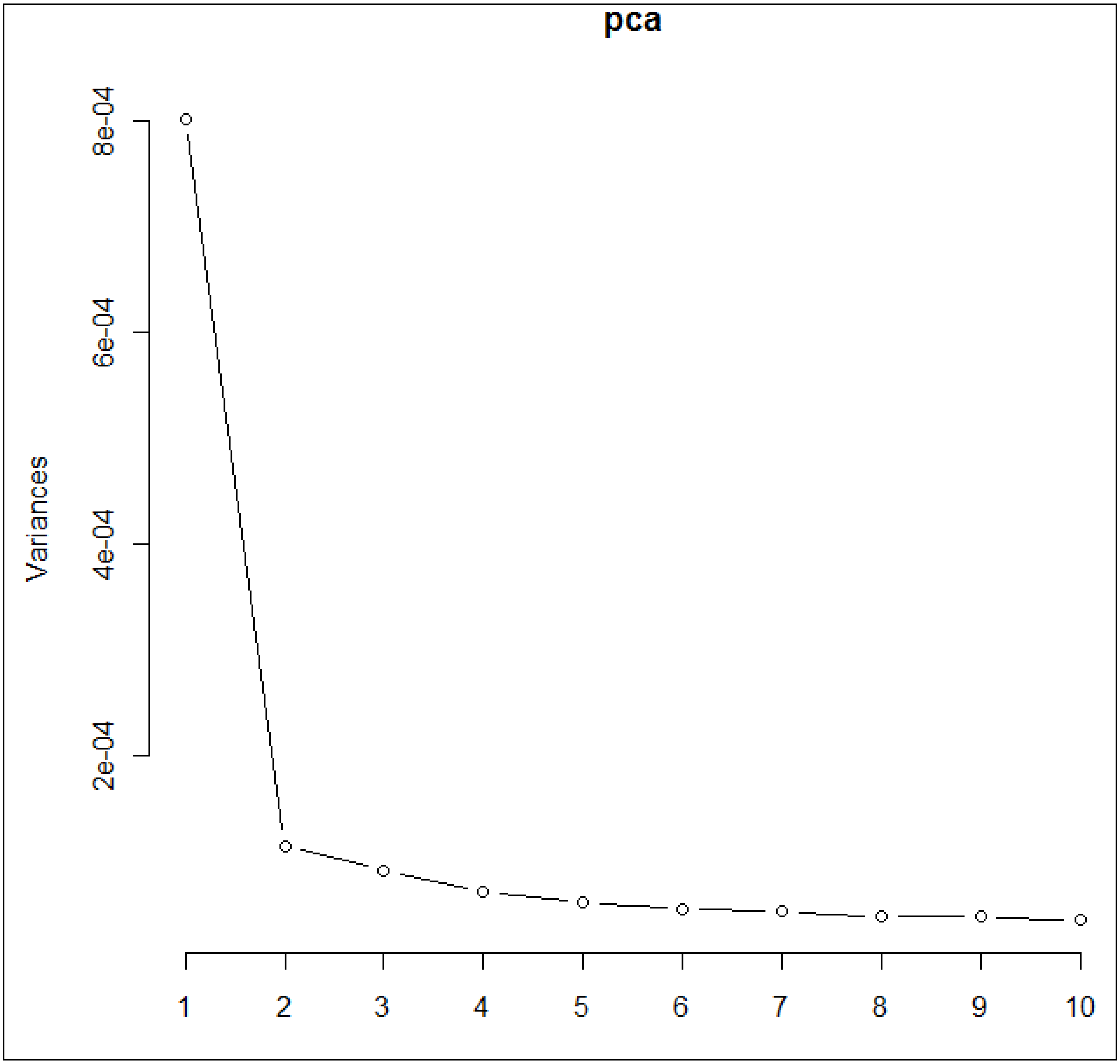
- Since everything is in order and put into one data frame it's time to run PCA on given data frame. In R there are two different commands for PCA prcomp () and princomp (). We are using prcomp () and get summary as mentioned below.

```
> pca<-prcomp(data) # do a PCA
> summary(pca)
Importance of components:
                           PC1     PC2     PC3      PC4      PC5      PC6      PC7      PC8      PC9     PC10     PC11     PC12     PC13     PC14    PC15
Standard deviation     0.02833 0.01068 0.00955 0.008443 0.007787 0.007354 0.007203 0.006914 0.006848 0.006632 0.006186 0.006163 0.006047 0.005811 0.00567
Proportion of Variance 0.37425 0.05317 0.04253 0.033240 0.028280 0.025220 0.024190 0.022290 0.021870 0.020510 0.017850 0.017710 0.017050 0.015750 0.01499
Cumulative Proportion  0.37425 0.42742 0.46995 0.503190 0.531470 0.556690 0.580880 0.603170 0.625040 0.645550 0.663390 0.681100 0.698150 0.713900 0.72889
                           PC16     PC17     PC18     PC19     PC20     PC21     PC22     PC23     PC24     PC25     PC26    PC27     PC28     PC29
Standard deviation     0.005582 0.005518 0.005348 0.005222 0.005139 0.005064 0.004938 0.004841 0.004799 0.004731 0.004577 0.00441 0.004317 0.004207
Proportion of Variance 0.014530 0.014200 0.013340 0.012710 0.012320 0.011960 0.011370 0.010930 0.010740 0.010440 0.009770 0.00907 0.008690 0.008250
Cumulative Proportion  0.743420 0.757610 0.770950 0.783660 0.795980 0.807940 0.819310 0.830240 0.840980 0.851410 0.861180 0.87025 0.878940 0.887190
                           PC30     PC31     PC32     PC33     PC34     PC35     PC36     PC37    PC38     PC39     PC40     PC41     PC42     PC43
Standard deviation     0.004147 0.004081 0.003979 0.003924 0.003842 0.003698 0.003657 0.003629 0.00360 0.003465 0.003424 0.003309 0.003259 0.003155
Proportion of Variance 0.008020 0.007760 0.007380 0.007180 0.006880 0.006380 0.006240 0.006140 0.00604 0.005600 0.005470 0.005100 0.004950 0.004640
Cumulative Proportion  0.895210 0.902970 0.910350 0.917530 0.924420 0.930790 0.937030 0.943170 0.94922 0.954810 0.960280 0.965390 0.970340 0.974980
                           PC44     PC45     PC46     PC47     PC48     PC49     PC50
Standard deviation     0.003140 0.003005 0.002958 0.002752 0.002642 0.002438 0.002349
Proportion of Variance 0.004600 0.004210 0.004080 0.003530 0.003250 0.002770 0.002570
Cumulative Proportion  0.979580 0.983790 0.987870 0.991400 0.994650 0.997430 1.000000
```

- We can also analyze standard deviation of each component. The standard deviation of component is stored in a named element called "sdev" of the output variable made by prompt()

```
> pca$sdev
 [1] 0.028330367 0.010678094 0.009550572 0.008443477 0.007787333 0.007354357 0.007203057 0.006913715 0.006848416 0.006632094 0.006186295 0.006162892
[13] 0.006046866 0.005810900 0.005669988 0.005581548 0.005517806 0.005347973 0.005221628 0.005139436 0.005063774 0.004938394 0.004841324 0.004798857
[25] 0.004730620 0.004577128 0.004409911 0.004316621 0.004206553 0.004147006 0.004080708 0.003979123 0.003924286 0.003841931 0.003698097 0.003657357
[37] 0.003629231 0.003599819 0.003465205 0.003424375 0.003308518 0.003258514 0.003155222 0.003140318 0.003004610 0.002958247 0.002752459 0.002641542
[49] 0.002438407 0.002348864
```

- In order to decide how many component to be retained, it is common to summarize the result in term of scree plot, which we can do using R "screeplot ()" function.
- Screeplot(pca, type="lines")



The above screeplot shows very high variation for 1st and 2nd component and then after decay as component progress further. It helps us to decide upon how many components needed. As we can see above plot becomes very steep after decaying from 8th point onward.

```
> pca$rotation[,1:8]
           PC1          PC2          PC3          PC4          PC5          PC6          PC7          PC8
axi 0.20158279  0.136362181  0.213680051 -0.072466576  0.081633481 -0.084947666  0.067294105 -0.040739055
baj 0.07849545  0.062380135 -0.007897118  0.188342057 -0.196781005 -0.159197931  0.135382618 -0.063490067
bha 0.09141093  0.035054841  0.003645719  0.065591876  0.045871278 -0.287043484 -0.326637781  0.291767999
bhe 0.17597536  0.083931496  0.309179278 -0.338127795 -0.299498188  0.278254107 -0.286134729 -0.048038767
bpc 0.04972989 -0.015172923  0.019010001  0.270196773  0.284568526 -0.028030705  0.050169534 -0.290891738
cai 0.06890459 -0.014215044 -0.043399974  0.124885977 -0.303449359  0.134659510  0.081660284 -0.217484807
can 0.17634302  0.095292576  0.130608704 -0.003843119  0.177227715  0.005141722  0.038424148 -0.059208242
cip 0.04723816  0.001475693 -0.018657120  0.148250649 -0.091061775 -0.021243887 -0.029903248 -0.073745544
dlf 0.20774736  0.048333274  0.023793640 -0.004715279  0.054584279 -0.050611693  0.033948797  0.200329890
drr 0.02425967 -0.015288565 -0.023851393  0.111409149  0.013667987 -0.078851783 -0.014955582 -0.081718172
gai 0.05759542 -0.024147801 -0.067657712  0.114094802  0.029807239 -0.079474147 -0.041174893  0.061141077
gra 0.05664522  0.058624930 -0.009133670  0.173236966 -0.050250702 -0.079046924  0.017189795  0.099304436
hcl 0.04909828  0.039801312 -0.048866886  0.073864834 -0.165551859  0.234159440  0.082204298  0.007188448
hdf 0.04969713  0.033611592  0.075718587  0.068145592  0.059427530 -0.028758779  0.015797597 -0.066412408
hbk 0.09094204  0.020354113  0.028934821  0.140796630  0.062768222 -0.048659459  0.015296359 -0.062516060
her 0.08208523  0.061196339  0.031324779  0.124429673 -0.163294692 -0.183485980  0.256911939 -0.105931363
hin 0.21925698  0.175494294 -0.290503029  0.038401325  0.281938639  0.135338028  0.114193421  0.015262718
hul 0.04477554  0.054098436 -0.006599584  0.121727590 -0.009853633 -0.022620375  0.008425518  0.008403293
ici 0.14396886  0.117715346  0.146366385 -0.057895327  0.055905675 -0.033149912  0.077699309  0.042299725
idf 0.18143652  0.092839701  0.206567198 -0.183493964  0.290830732  0.095462377 -0.118533654 -0.305665086
inf 0.03305164  0.045713732 -0.107696626  0.048865138 -0.159366058  0.264718441  0.079502712  0.101145526
itc 0.01474017  0.051767048 -0.021963719  0.112277249 -0.034685887 -0.002613364  0.037838587 -0.012335359
jin 0.13855009 -0.002570891  0.015748941 -0.008730818 -0.224164427  0.054032863 -0.083789138  0.004594217
jpa 0.23987855  0.038857710  0.098352738 -0.016802282 -0.035454286  0.108972199 -0.001899589  0.235631257
kot 0.14600386  0.038963551  0.164453229  0.104493759  0.036538162 -0.129047519  0.120863228 -0.046829331
mnm 0.11581830  0.099933393 -0.029132253  0.051921919 -0.110394556 -0.069467695  0.043559492  0.115287263
mar 0.10281134  0.067590563  0.009495376  0.123997762 -0.049751953  0.026214827  0.128480340  0.019892686
ntp 0.07982801 -0.010521656  0.011938531  0.055888260 -0.022040763  0.019924570 -0.161726174 -0.010768929
ong 0.05308709  0.023613557  0.037083135  0.098934860 -0.046616894  0.067140325 -0.094584827 -0.142312598
pnb 0.16035121  0.093121083  0.234785404 -0.001525400  0.011303632 -0.103048305  0.053660049 -0.046833319
pow 0.07069259  0.020964304 -0.039279423  0.096279990 -0.042448630 -0.068206969 -0.040486107 -0.018562831
ran 0.06453054  0.025502836  0.206930717  0.091509414 -0.029075217 -0.081339216 -0.008377481  0.002391541
rco 0.26263268 -0.454309029  0.038060446 -0.052188319  0.125235758 -0.001945091  0.116729369  0.186275909
rel 0.09715646 -0.004545757 -0.046204878  0.184978016 -0.033424243 -0.054178136  0.116759113 -0.171727556
rin 0.25947039 -0.521630288  0.048608480 -0.003403994 -0.009554161  0.089078619  0.074068269  0.206497051
rpo 0.23405257 -0.504694048 -0.084620181  0.151121373  0.007333114  0.082753910 -0.076969758 -0.254757722
sai 0.19696832  0.033822047 -0.098456752 -0.118873643 -0.112911999  0.067843349  0.035101990 -0.073365309
sbi 0.17130056  0.085165018  0.177511757 -0.119176073  0.102322341 -0.056553089  0.137897745 -0.032758845
ses 0.26784344  0.023159475 -0.486234981 -0.489427011 -0.174202557 -0.477321849  0.048817743 -0.168224664
sie 0.07072898  0.085439834  0.022329496  0.124217127 -0.080757950  0.074524696  0.015763108 -0.044243999
ste 0.22951477  0.194752679 -0.395398283  0.073476701  0.318905574  0.300324052 -0.348991576  0.017991092
sun 0.03699518  0.062457812 -0.064541596  0.202354599 -0.028126097 -0.055110779  0.038867623 -0.116162157
tmo 0.14954619  0.123063475  0.034912832  0.058605277  0.015678122  0.050153735  0.149836855  0.045331127
tpo 0.12471273 -0.019725426  0.006210675  0.234759202 -0.269915628 -0.141087904 -0.549964101 -0.157829532
tsl 0.19847895  0.076250128 -0.125736078 -0.040927839 -0.034193710  0.061524065  0.083922249 -0.046595638
tcs 0.04281656  0.091638981 -0.145291314  0.077912682 -0.134941684  0.232831231  0.156937320  0.126919701
wip 0.05256595  0.091413346 -0.103537309  0.012127444 -0.178494677  0.189308081  0.152905469  0.123538560
acc 0.08258197  0.087579702  0.010566632  0.124700814  0.022402536 -0.150319736 -0.079607746  0.307048393
amb 0.09485353  0.081593583  0.009684844  0.168020293 -0.006176252 -0.134636534 -0.092311724  0.329229490
lnt 0.18669640  0.116397118  0.151409010 -0.036122031 -0.103371951  0.056478417  0.007393083 -0.018131927
```

- The next step is to see loadings for principal components, they are stored in named element "rotation" of the variable returned by "prcomp ()". This contain matrix with the loadings of each component. We'll see first eight components as it explain 60% variation as we have observed before in "summary (pca)".
- Now let's look at first component PC1 which explain in term of linear relation as follow.

  PC1= 0.20158279*axi+0.0784954*baj………………………………….………+0.18669640*lnt.

- Note that the square of loadings sum to 1, as this is a constraint used in calculating loadings. >sum((pca$rotation[,1])^2)
- [1] 1

Principal Component Analysis

Stock	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	Stock
AXI	-0.032%	-0.022%	-0.034%	0.012%	-0.013%	0.014%	-0.011%	0.007%	
BAJ	0.100%	0.079%	-0.010%	0.239%	-0.250%	-0.202%	0.172%	-0.081%	
BHA	-0.013%	-0.005%	-0.001%	-0.009%	-0.007%	0.041%	0.047%	-0.042%	
BHE	0.177%	0.084%	0.310%	-0.339%	-0.300%	0.279%	-0.287%	-0.048%	0.063%
BPC	0.023%	-0.007%	0.009%	0.127%	0.134%	-0.013%	0.024%	-0.137%	
CAI	0.052%	-0.011%	-0.033%	0.095%	-0.231%	0.102%	0.062%	-0.165%	
CAN	0.107%	0.058%	0.079%	-0.002%	0.107%	0.003%	0.023%	-0.036%	0.049%
CIP	-0.011%	0.000%	0.004%	-0.034%	0.021%	0.005%	0.007%	0.017%	
DLF	0.050%	0.012%	0.006%	-0.001%	0.013%	-0.012%	0.008%	0.048%	
DRR	0.005%	-0.003%	-0.005%	0.023%	0.003%	-0.016%	-0.003%	-0.017%	
GAI	0.003%	-0.001%	-0.004%	0.006%	0.002%	-0.004%	-0.002%	0.003%	
GRA	-0.024%	-0.025%	0.004%	-0.075%	0.022%	0.034%	-0.007%	-0.043%	
HCL	0.021%	0.017%	-0.021%	0.032%	-0.071%	0.101%	0.035%	0.003%	
HDF	0.004%	0.003%	0.006%	0.006%	0.005%	-0.002%	0.001%	-0.005%	
HBK	0.023%	0.005%	0.007%	0.035%	0.016%	-0.012%	0.004%	-0.016%	
HER	0.016%	0.012%	0.006%	0.024%	-0.032%	-0.036%	0.051%	-0.021%	
HIN	-0.007%	-0.006%	0.010%	-0.001%	-0.009%	-0.005%	-0.004%	-0.001%	
HUL	-0.003%	-0.004%	0.001%	-0.009%	0.001%	0.002%	-0.001%	-0.001%	
ICI	-0.024%	-0.020%	-0.025%	0.010%	-0.009%	0.006%	-0.013%	-0.007%	
IDF	0.160%	0.082%	0.182%	-0.162%	0.257%	0.084%	-0.105%	-0.270%	0.067%
INF	0.015%	0.021%	-0.050%	0.023%	-0.074%	0.123%	0.037%	0.047%	
ITC	-0.002%	-0.008%	0.004%	-0.018%	0.006%	0.000%	-0.006%	0.002%	
JIN	-0.018%	0.000%	-0.002%	0.001%	0.030%	-0.007%	0.011%	-0.001%	
JPA	0.110%	0.018%	0.045%	-0.008%	-0.016%	0.050%	-0.001%	0.108%	0.047%
KOT	-0.099%	-0.026%	-0.111%	-0.071%	-0.025%	0.087%	-0.082%	0.032%	
MNM	0.011%	0.010%	-0.003%	0.005%	-0.011%	-0.007%	0.004%	0.011%	
MAR	0.007%	0.005%	0.001%	0.009%	-0.003%	0.002%	0.009%	0.001%	
NTP	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	
ONG	-0.008%	-0.004%	-0.006%	-0.016%	0.007%	-0.011%	0.015%	0.023%	
PNB	-0.074%	-0.043%	-0.108%	0.001%	-0.005%	0.047%	-0.025%	0.022%	
POW	-0.019%	-0.006%	0.010%	-0.026%	0.011%	0.018%	0.011%	0.005%	
RAN	0.025%	0.010%	0.081%	0.036%	-0.011%	-0.032%	-0.003%	0.001%	
RCO	0.069%	-0.119%	0.010%	-0.014%	0.033%	-0.001%	0.031%	0.049%	
REL	0.020%	-0.001%	-0.010%	0.039%	-0.007%	-0.011%	0.025%	-0.036%	
RIN	0.958%	-1.925%	0.179%	-0.013%	-0.035%	0.329%	0.273%	0.762%	0.294%
RPO	0.342%	-0.737%	-0.124%	0.221%	0.011%	0.121%	-0.112%	-0.372%	0.083%
SAI	0.088%	0.015%	-0.044%	-0.053%	-0.050%	0.030%	0.016%	-0.033%	
SBI	-0.001%	0.000%	-0.001%	0.001%	0.000%	0.000%	-0.001%	0.000%	
SES	0.159%	0.014%	-0.289%	-0.291%	-0.104%	-0.284%	0.029%	-0.100%	0.027%
SIE	0.031%	0.037%	0.010%	0.054%	-0.035%	0.032%	0.007%	-0.019%	
STE	0.047%	0.040%	-0.081%	0.015%	0.065%	0.062%	-0.072%	0.004%	
SUN	-0.010%	-0.017%	0.018%	-0.057%	0.008%	0.015%	-0.011%	0.033%	
TMO	0.041%	0.033%	0.009%	0.016%	0.004%	0.014%	0.041%	0.012%	
TPO	-0.027%	0.004%	-0.001%	-0.052%	0.059%	0.031%	0.121%	0.035%	

TSL	0.052%	0.020%	-0.033%	-0.011%	-0.009%	0.016%	0.022%	-0.012%	
TCS	0.006%	0.013%	-0.020%	0.011%	-0.019%	0.033%	0.022%	0.018%	
WIP	0.023%	0.041%	-0.046%	0.005%	-0.079%	0.084%	0.068%	0.055%	
ACC	0.001%	0.001%	0.000%	0.002%	0.000%	-0.002%	-0.001%	0.005%	
AMB	-0.014%	-0.012%	-0.001%	-0.026%	0.001%	0.020%	0.014%	-0.050%	
LNT	-0.086%	-0.054%	-0.070%	0.017%	0.048%	-0.026%	-0.003%	0.008%	
Total	2.271%	-2.424%	-0.141%	-0.223%	-0.545%	1.103%	0.439%	-0.201%	
Variation	37.43%	5.32%	4.25%	3.32%	2.83%	2.52%	2.42%	2.23%	

Conclusion:

- The above summary represent what we have seen before the linear relationship and if we multiply them with our last return value to see how much each stock contributes in terms of return. This will give us the values for PC (Column level Multiplication).
    - PC1= 0.2015*-0.0016+0.078*0.0127……….....…………………….………+0.1866*-0.046.

- Since 37.43% of variation is explained by 1st Principal component we can pick up stock from that to see who is contributing to highest. In such case using filter of -0.1% and 0.1% we can select stocks and result is as follows:
    - BHEL
    - IDFC
    - Reliance Infra
    - Reliance Power
    - Sesa Goa
    - Canara Bank
    - J.P.Associates.

- Since we have selected stock using above mentioned filter further we can see how consistence they are across PC and which again filter them as follows :
    - BHEL
    - IDFC
    - Reliance Infra
    - Reliance Power
    - Sesa Goa