

Principle Component Analysis on the “Various Factors of Car”

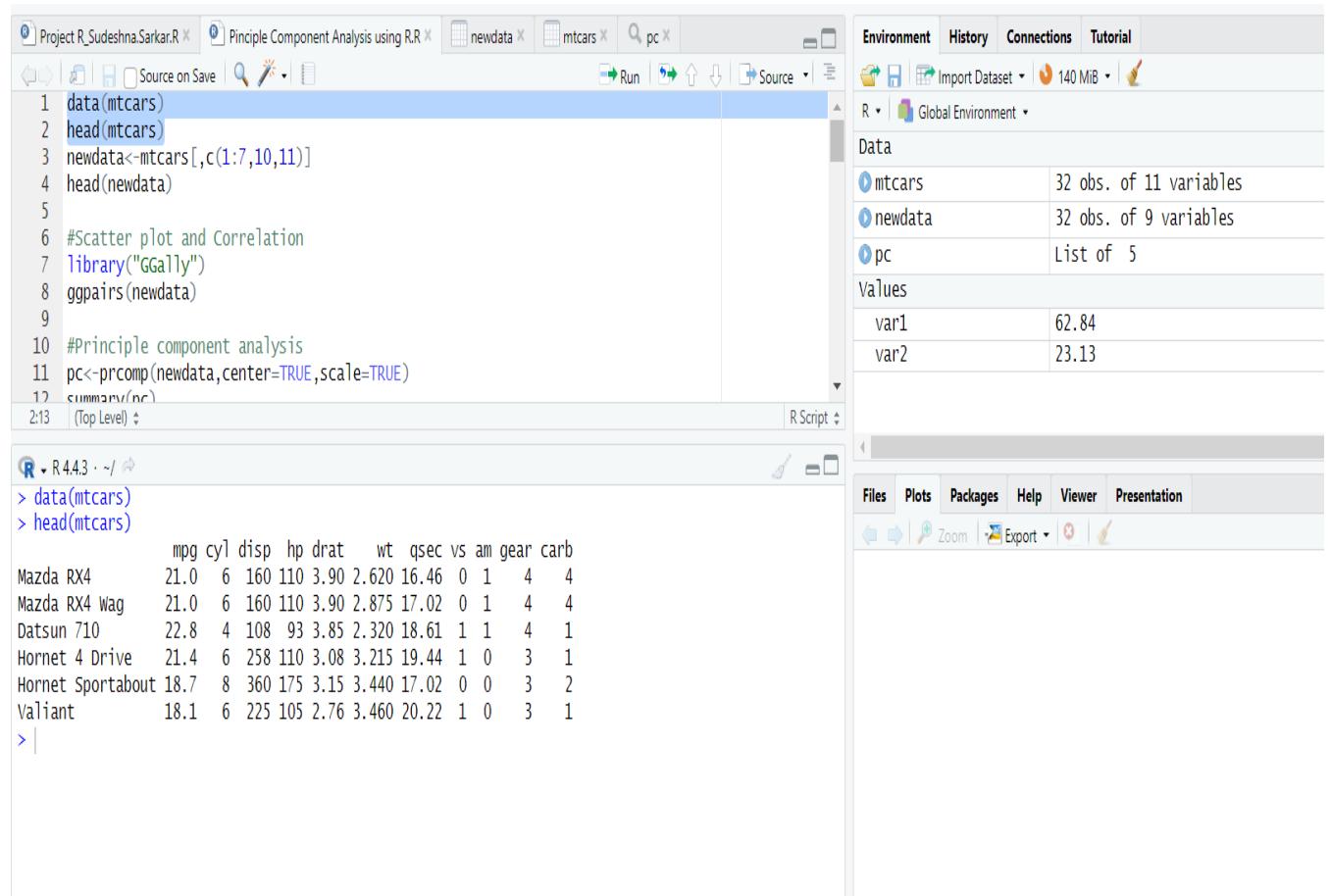
What is PCA?

⇒ **Principal Component Analysis (PCA)** is a statistical technique used to **reduce the number of variables** in a dataset while keeping the most important information.

📌 Key Points:

- PCA is a **dimensionality reduction** method.
- It helps in **data visualization, compression** and **improving machine learning models**.
- It creates new features that are **uncorrelated** and **ordered by importance**.
- It is widely used in **data science, image processing** and **pattern recognition**.

🧠 Example:



The screenshot shows the RStudio interface with the following details:

- Code Editor:** Displays R script code for performing PCA on the mtcars dataset. The code includes loading the dataset, creating a new dataset with selected columns, generating a scatter plot and correlation matrix, and performing PCA analysis.
- Environment View:** Shows the global environment with objects: mtcars (32 obs. of 11 variables), newdata (32 obs. of 9 variables), and pc (List of 5). It also displays values for var1 (62.84) and var2 (23.13).
- Console View:** Shows the R command line with the mtcars dataset loaded and its head printed.
- Data View:** Displays the first few rows of the mtcars dataset, including columns: mpg, cyl, disp, hp, drat, wt, qsec, vs, am, gear, carb.

Car Model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

R 4.4.3 · ~/

```

1 data(mtcars)
2 head(mtcars)
3 newdata<-mtcars[,c(1:7,10,11)]
4 head(newdata)
5
6 #Scatter plot and Correlation
7 library("GGally")
8 ggpairs(newdata)
9
10 #Principle component analysis
11 pc<-prcomp(newdata,center=TRUE,scale=TRUE)
12 summary(pc)
13
14 (Top Level) +

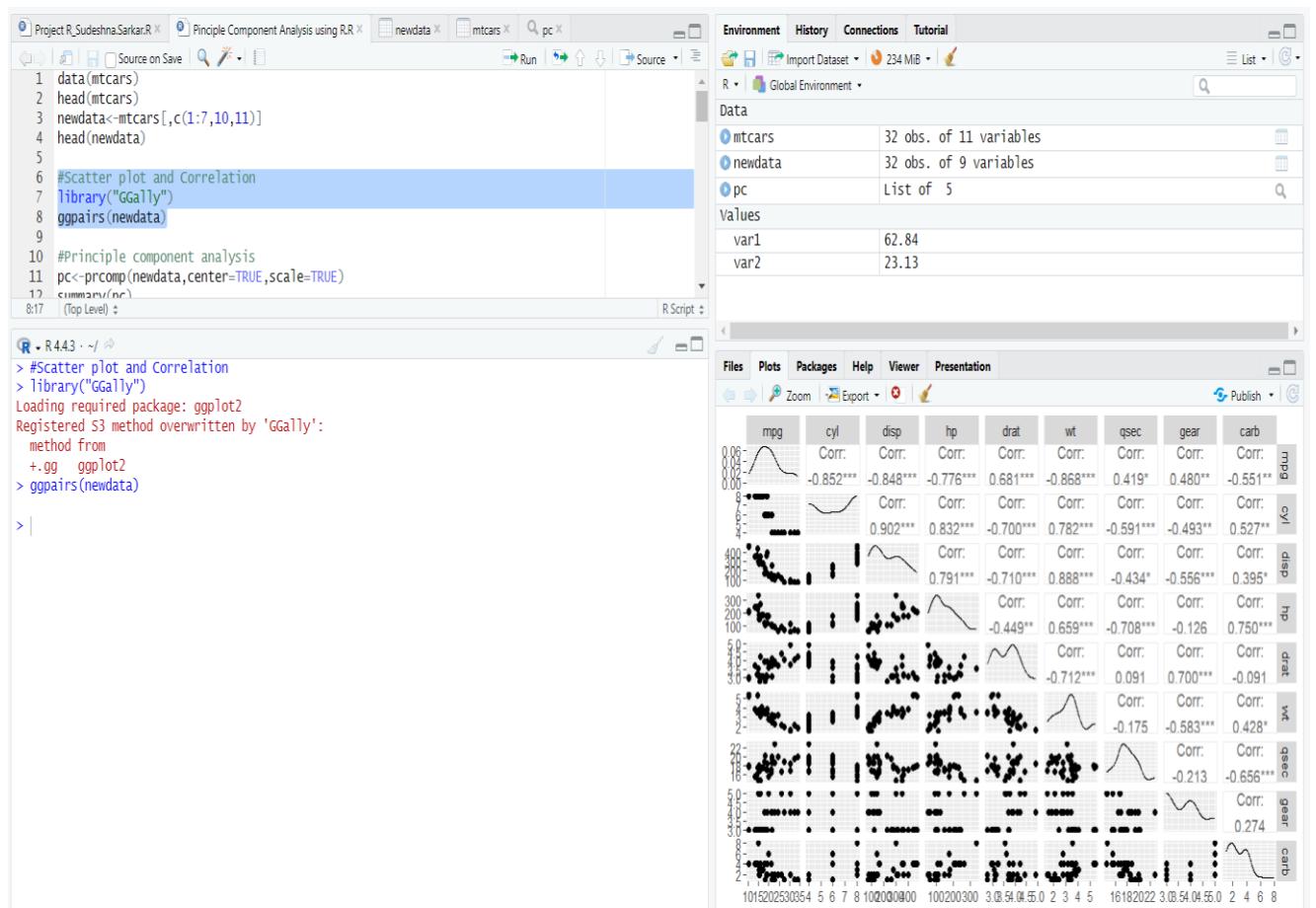
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> newdata<-mtcars[,c(1:7,10,11)]

> head(newdata)

	mpg	cyl	disp	hp	drat	wt	qsec	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	4	4
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> |



Project R_Sudeshna.Sarkar.R | Pinciple Component Analysis using R.R | newdata | mtcars | pc | Run | Source | Environment | History | Connect

```

6 #Scatter plot and Correlation
7 library("GGally")
8 ggpairs(newdata)
9
10 #Principle component analysis
11 pc<-prcomp(newdata,center=TRUE,scale=TRUE)
12 summary(pc)
13 attributes(pc)
14 print(pc)
15
16 var1<-round(pc$sdev[1]^2/sum(pc$sdev^2)*100,2)
17 var2<-round(pc$sdev[2]^2/sum(pc$sdev^2)*100,2)
18
19 #Scree plot
20 plot(pc)
21 screeplot(x=pc,type="line",main="scree plot")

```

R 4.4.3 · ~/

```

> #Principle component analysis
> pc<-prcomp(newdata,center=TRUE,scale=TRUE)
> summary(pc)
Importance of components:
PC1    PC2    PC3    PC4    PC5    PC6    PC7    PC8    PC9
Standard deviation 2.3782 1.4429 0.71008 0.51481 0.42797 0.35184 0.32413 0.2419 0.14896
Proportion of Variance 0.6284 0.2313 0.05602 0.02945 0.02035 0.01375 0.01167 0.0065 0.00247
Cumulative Proportion 0.6284 0.8598 0.91581 0.94525 0.96560 0.97936 0.99103 0.9975 1.00000
> |

```

Project R_Sudeshna.Sarkar.R | Pinciple Component Analysis using R.R | newdata | mtcars | pc | Run | Source | Environment | History | Connect

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```

R 4.4.3 · ~/

```

> print(pc)
Standard deviations (1, ..., p=9):
[1] 2.3782219 1.4429485 0.7100809 0.5148082 0.4279704 0.3518426 0.3241326 0.2418962 0.1489644

Rotation (n x k) = (9 x 9):
PC1      PC2      PC3      PC4      PC5      PC6      PC7
mpg   -0.3931477  0.02753861 -0.22119309 -0.006126378 -0.3207620  0.72015586  0.38138068
cyl    0.4025537  0.01570975 -0.25231615  0.040700251  0.1171397  0.22432550  0.15893251
disp   0.3973528  -0.08888469 -0.07825139  0.339493732 -0.4867849 -0.01967516  0.18233095
hp    0.3670814  0.26941371 -0.01721159  0.068300993 -0.2947317  0.35394225 -0.69620751
drat  -0.3118165  0.34165268  0.14995507  0.845658485  0.1619259 -0.01536794 -0.04767957
wt     0.3734771  -0.17194306  0.45373418  0.191260029 -0.1874822 -0.08377237  0.42777608
qsec  -0.2243508  -0.48404435  0.62812782 -0.030329127 -0.1482495  0.25752940 -0.27622581
gear  -0.2094749  0.55078264  0.20658376 -0.282381831 -0.5624860 -0.32298239  0.08555707
carb  -0.2445807  0.48431310  0.46412069 -0.214492216  0.3997820  0.35706914  0.20604210
PC8      PC9
mpg   0.12465987  0.11492862
cyl   -0.81032177  0.16266295
disp   0.06416707  -0.66190812
hp    0.16573993  0.25177306
drat  -0.13505066  0.03809096
wt     0.19839375  0.56918844
qsec  -0.35613350  -0.16873731
gear  -0.31636479  0.04719694
carb  0.10832772  -0.32045892

```

Project R_Sudeshna.Sarkar.R Pinciple Component Analysis using R.R newdata mtcars pc

```

10 #PRINCIPLE COMPONENT analysis
11 pc<-prcomp(newdata,center=TRUE,scale=TRUE)
12 summary(pc)
13 attributes(pc)
14 print(pc)
15
16 var1<-round(pc$sdev[1]^2/sum(pc$sdev^2)*100,2)
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18
19 #Scree plot
20 plot(pc)
21 screeplot(x=pc,type="line",main="Scree plot")
18:1 (Top Level) ↴ R Script ↴

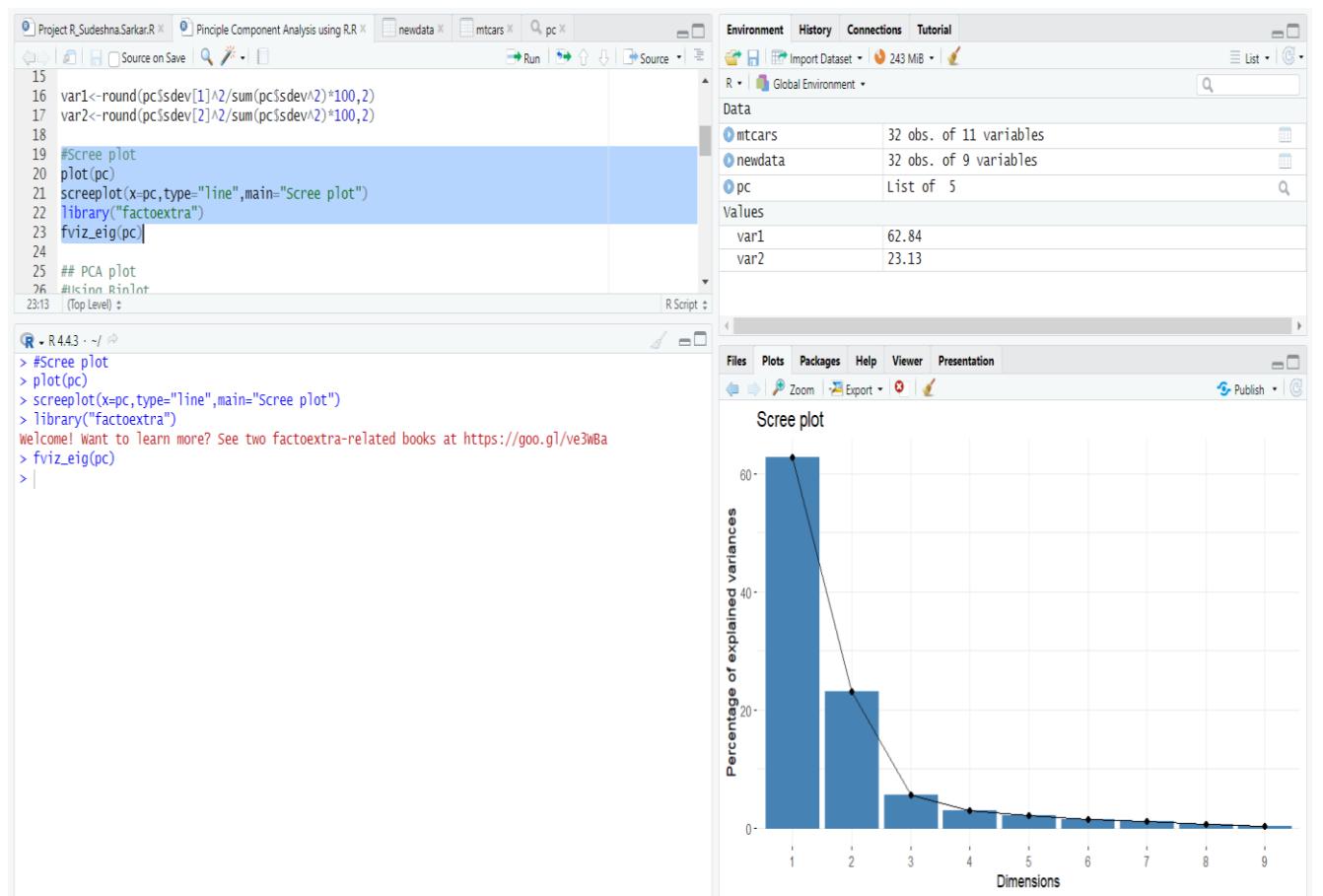
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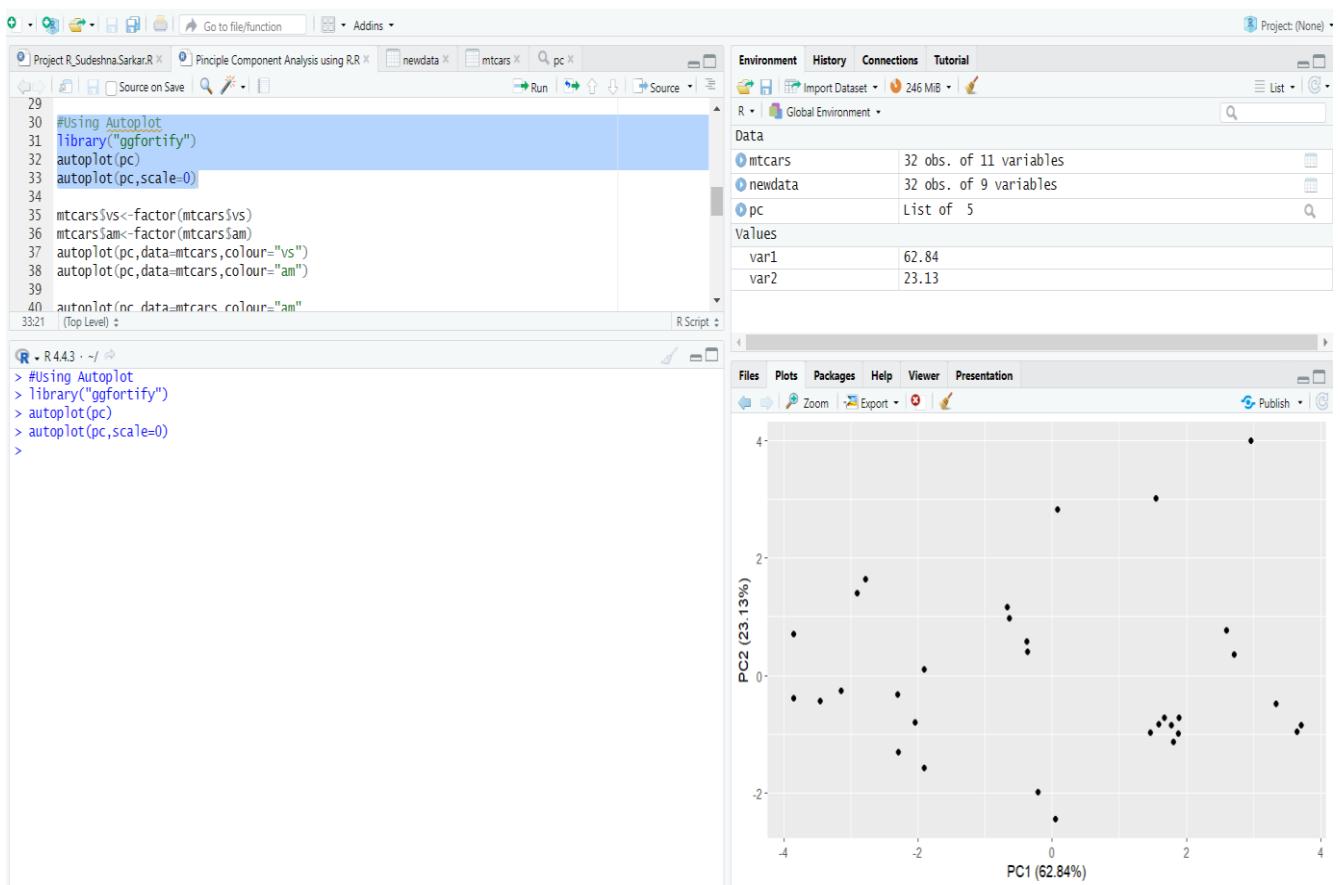
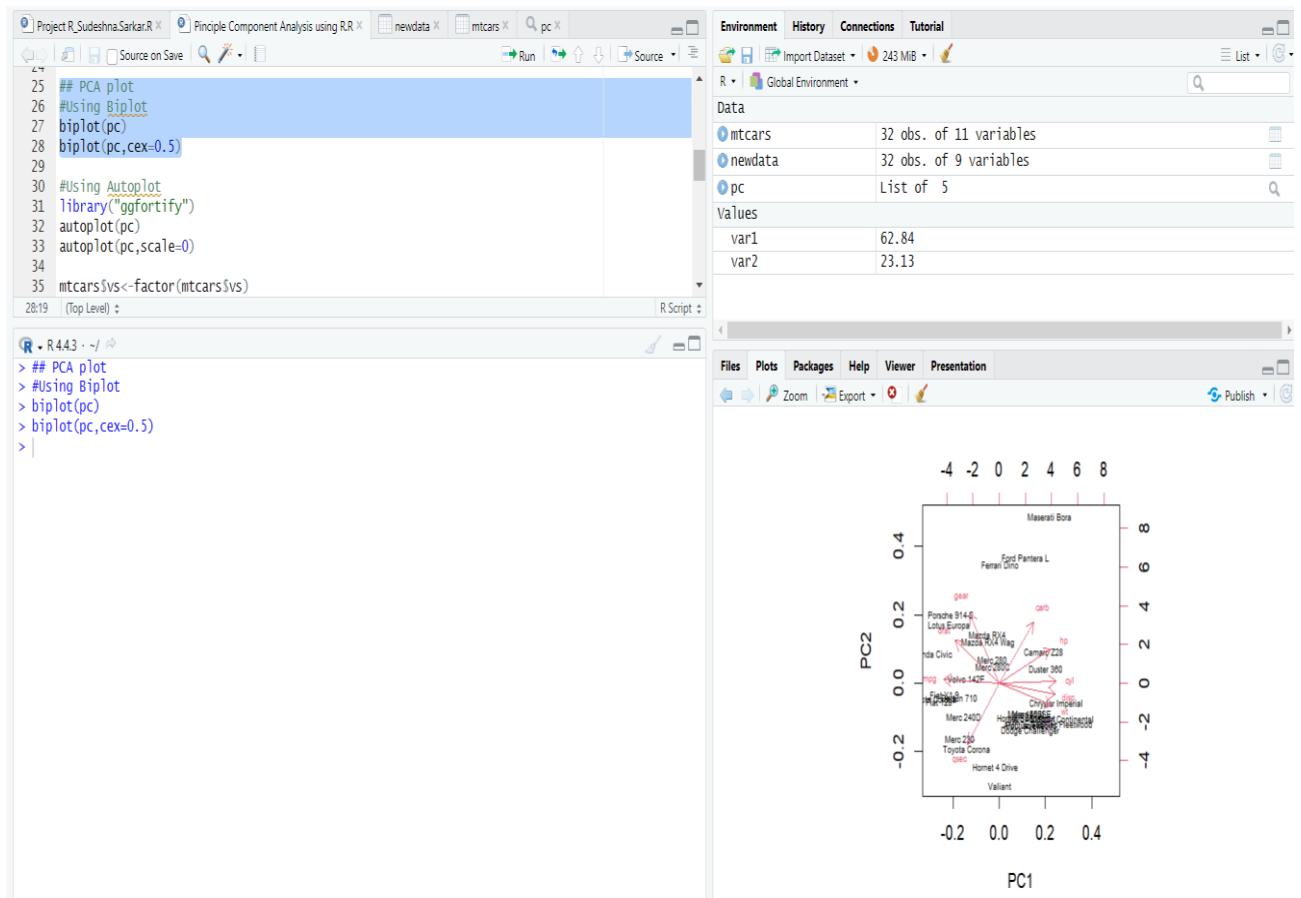
R 4.4.3 · ~/ ↴

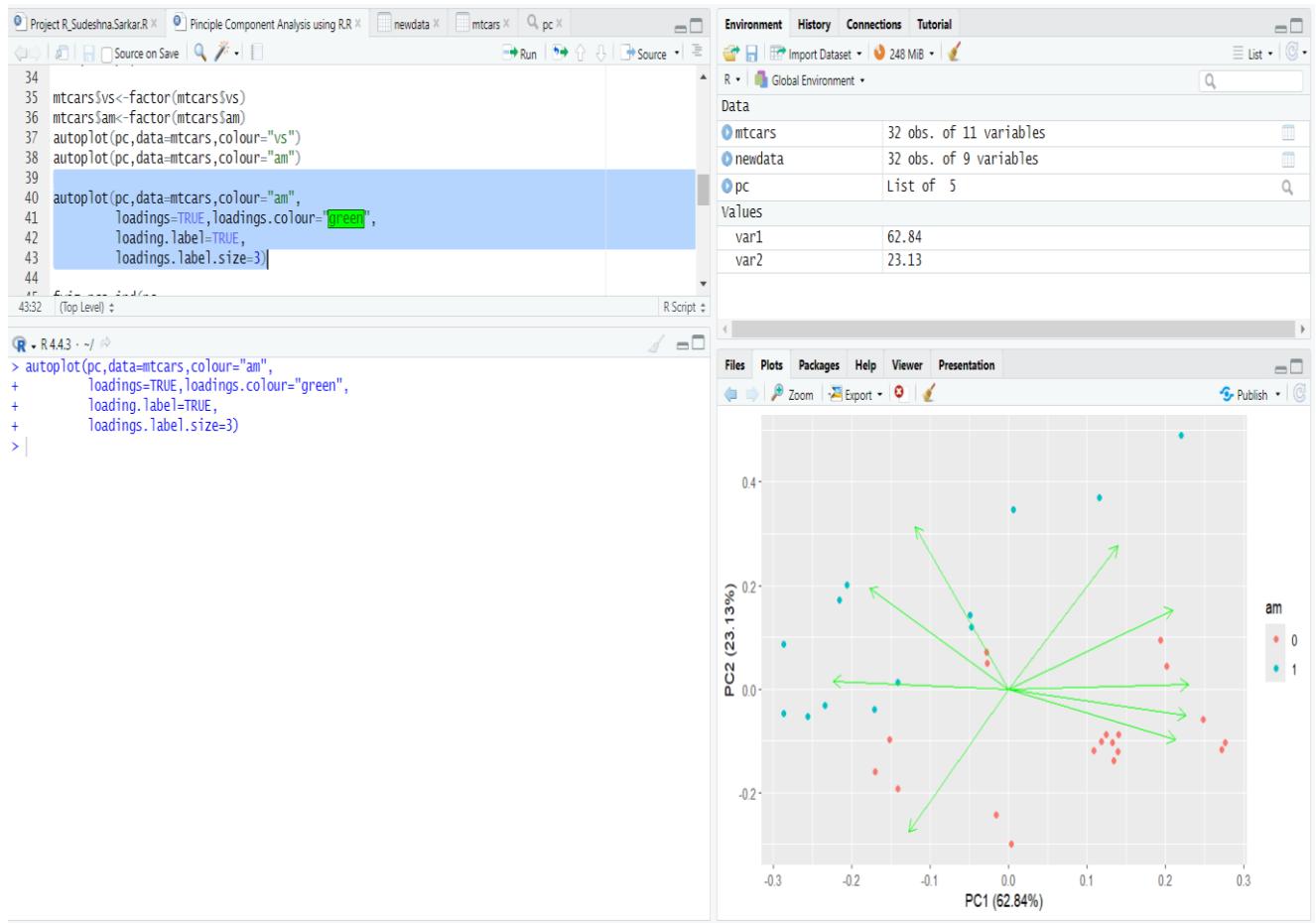
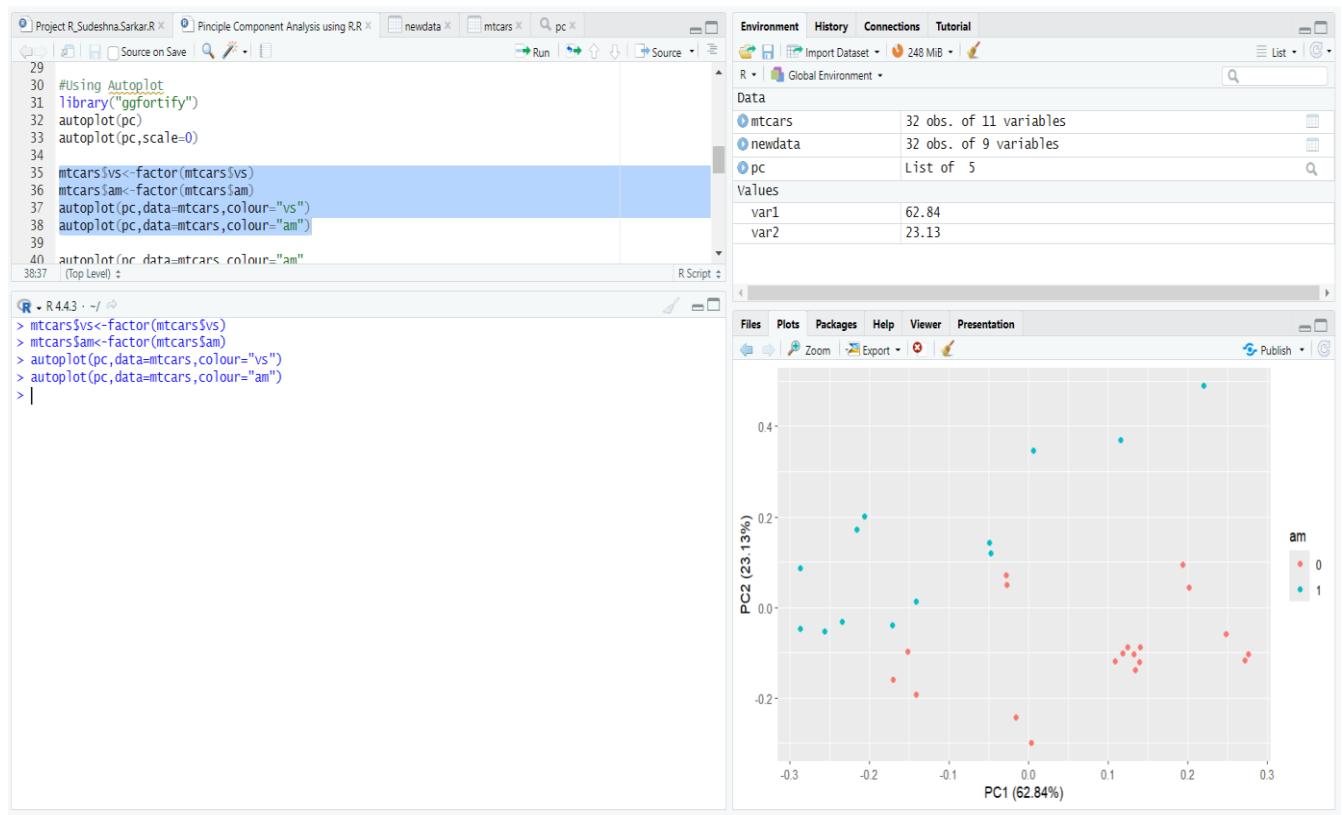
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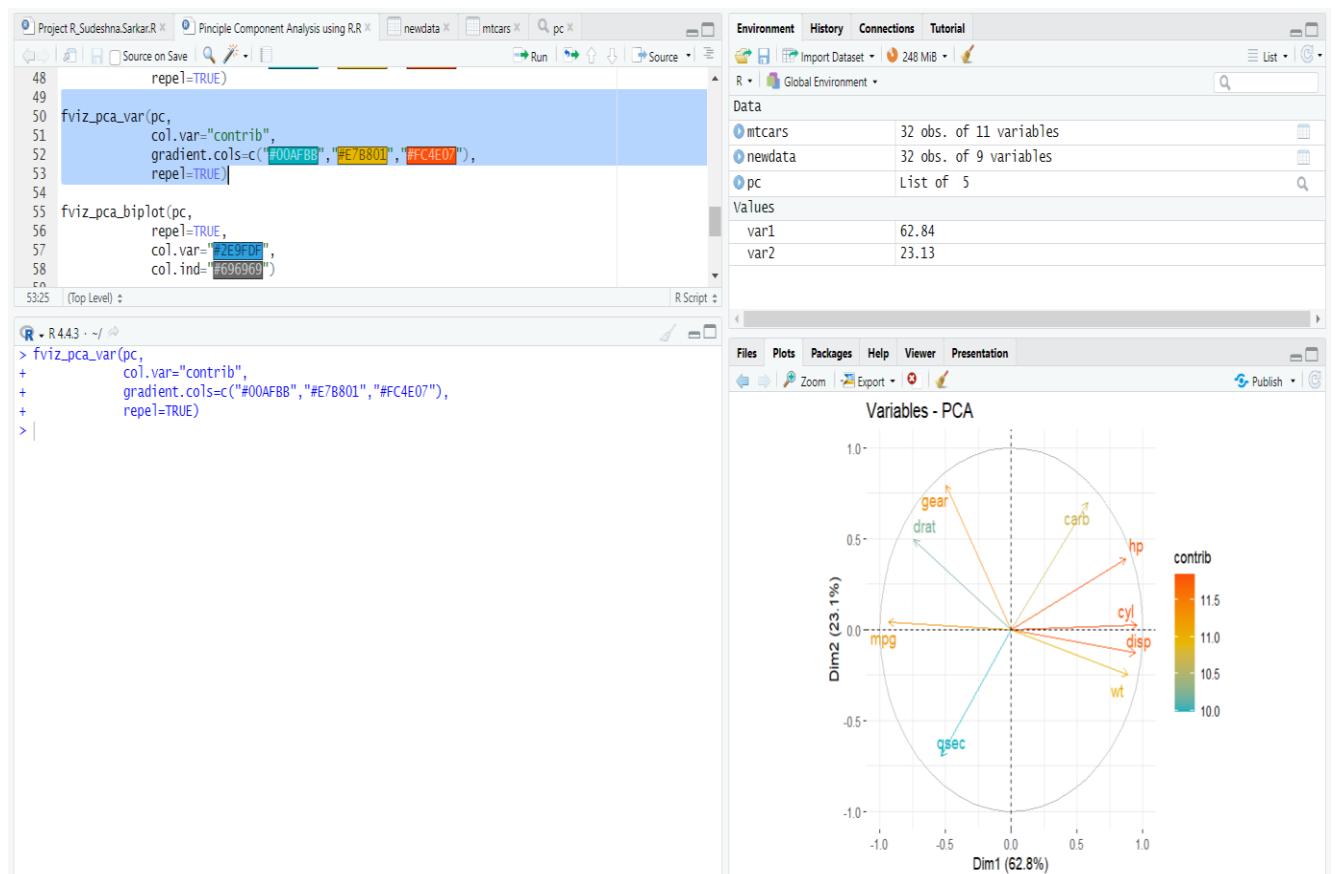
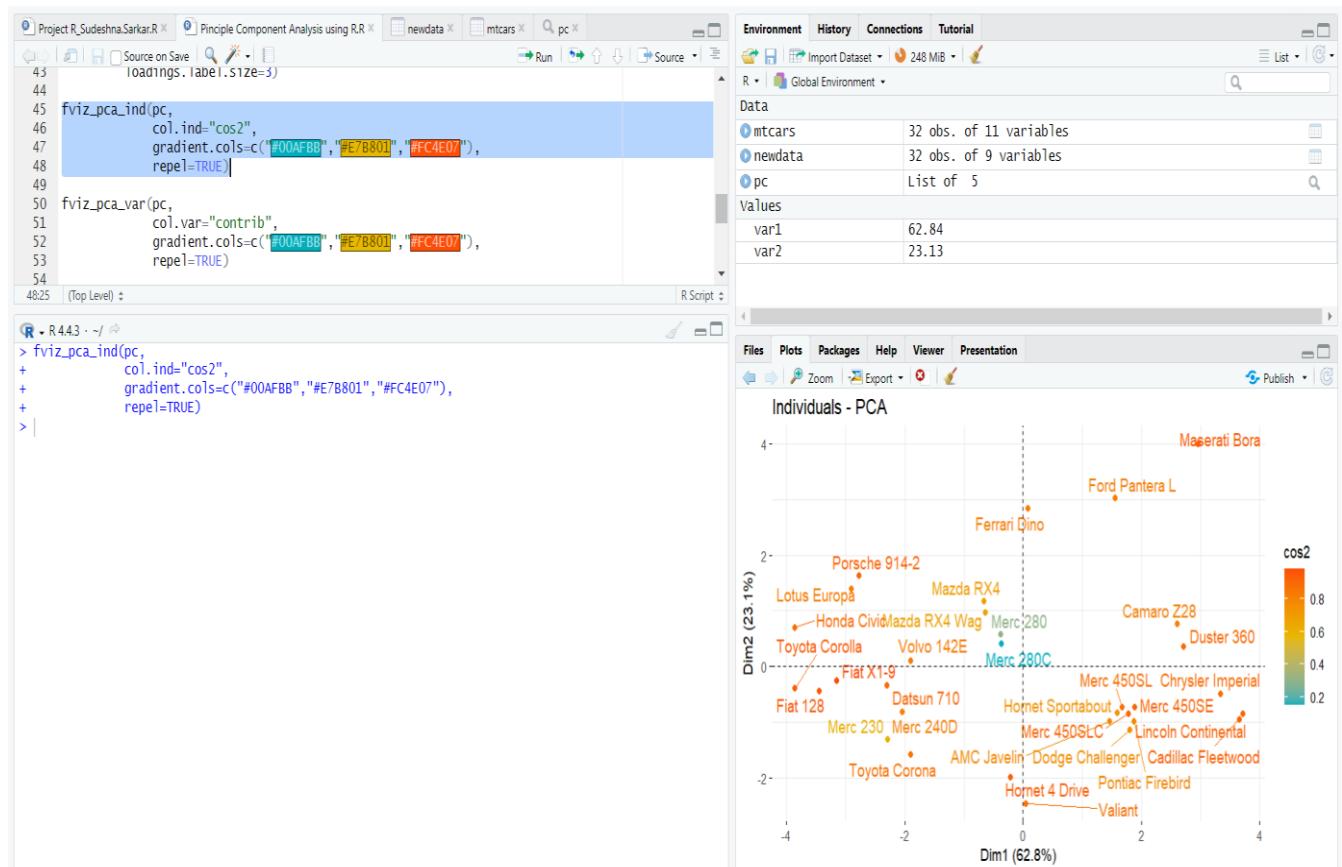
> var1<-round(pc$sdev[1]^2/sum(pc$sdev^2)*100,2)
> var2<-round(pc$sdev[2]^2/sum(pc$sdev^2)*100,2)
>

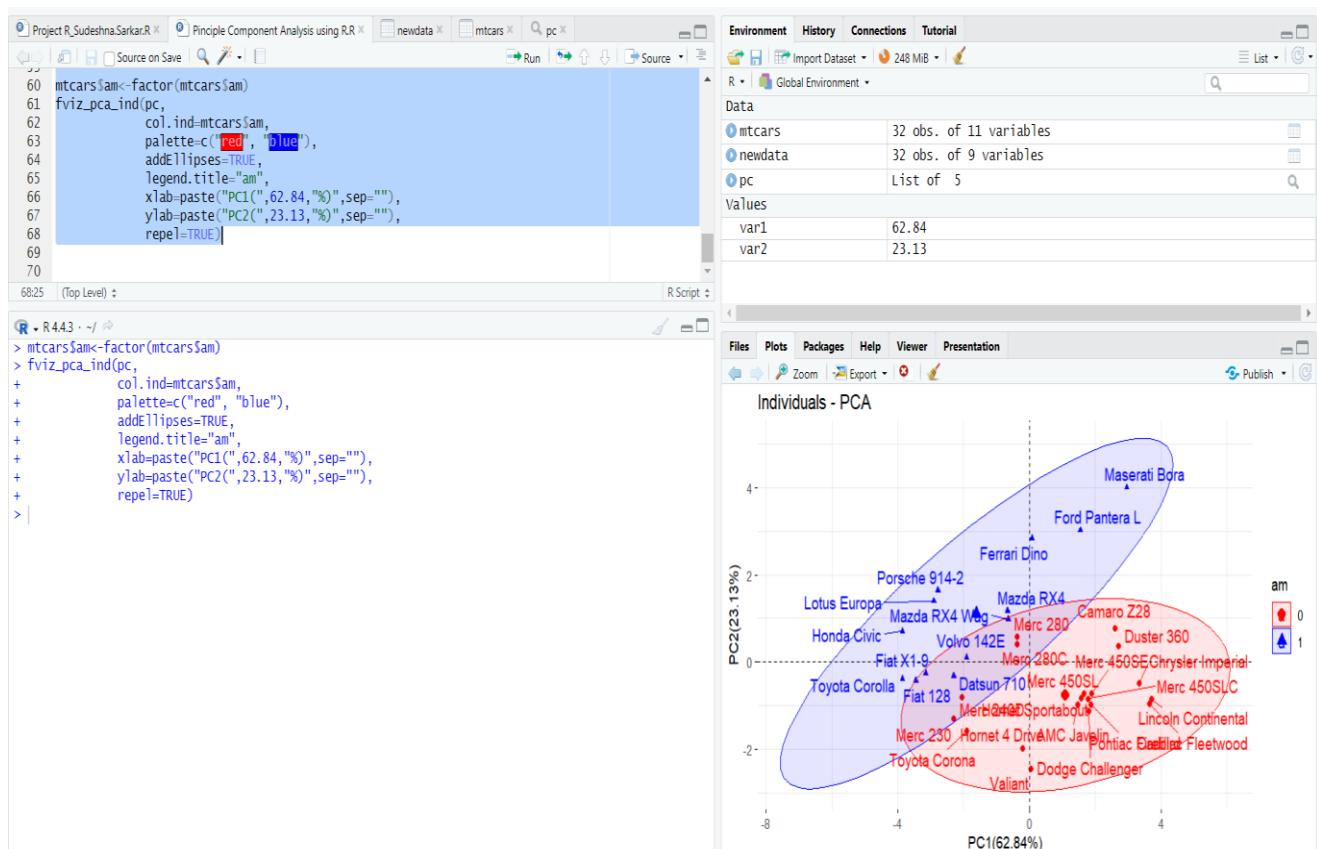
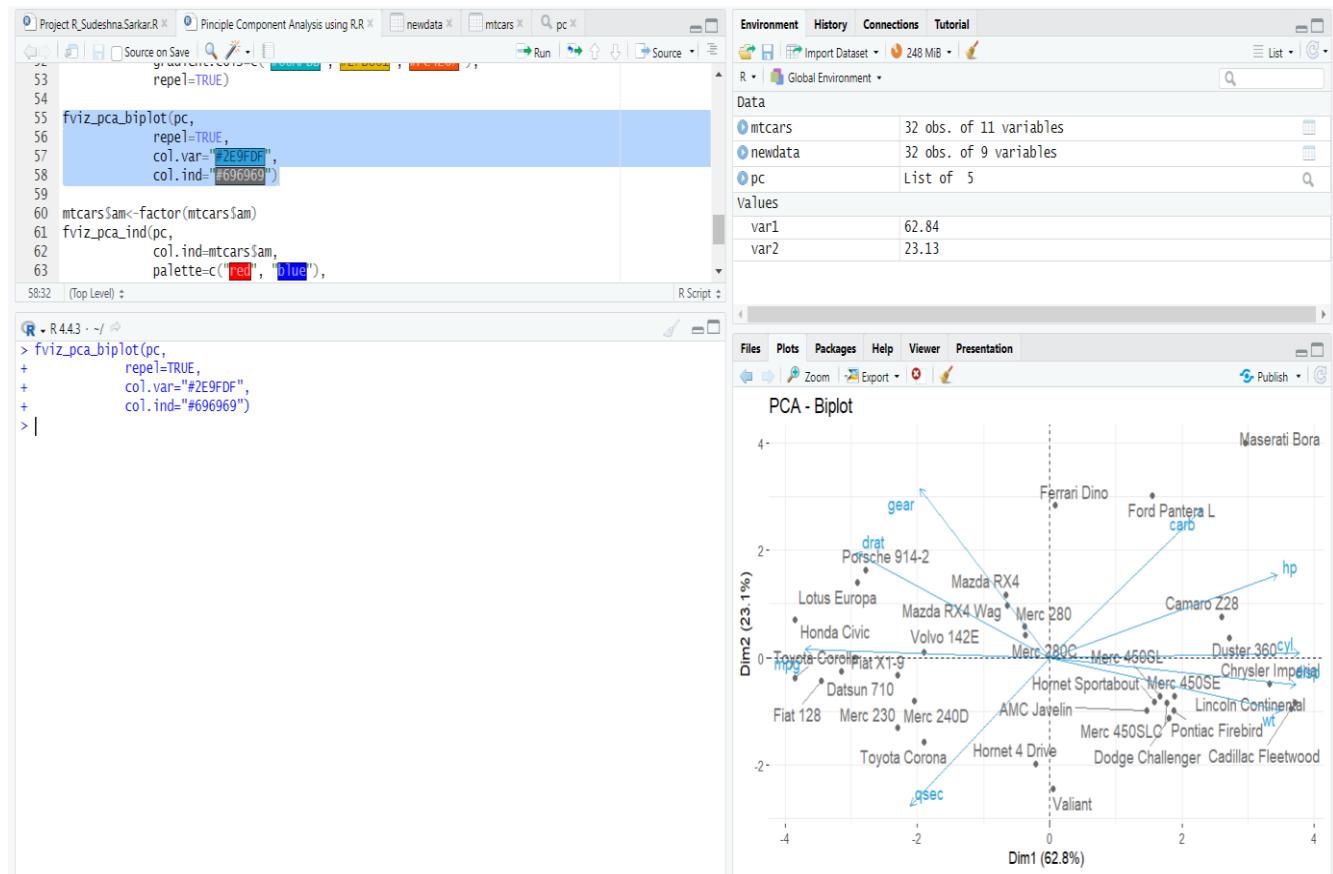
```











Key Insight:

This PCA result shows that the dimensionality of the dataset can be reduced from **9 variables** to **2 or 3 principal components** while still retaining most of the important information — helpful for visualization and analysis.

The Principal Component Analysis (PCA) on the dataset helps us understand the most important patterns in a simpler way. The first main component (PC1) explains about 62.86% of the total data variation and the second one (PC2) adds 17.61%. Together, they explain around 80.47% of the total information, which is quite a lot. This means we can focus on just these **two components instead of all 9 original variables**. The results also show how each original feature, like **mileage (mpg)** or **weight (wt)**, **affects the components**. Overall, PCA makes the data easier to understand and analyse.

