Air Dataset

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Contents

1 Objective:

To analyse data and find out factors influencing air in different areas of the country.

2 Loading Libraries

```r
library(ggplot2)
library(maps)
library(ggrepel)
library(tidyverse)
library(dplyr)
library(tidyr)
library(corrplot)
library(gridExtra)
library(plotly)
library(factoextra)
library(psych)
library(GGally)
library(webshot2)
```

3 Loading data

```r
air=read.csv('indian_weather_data.csv')
#head(air)

# making numerical df
num_df=air[c("lat","lon","temperature","weather_code","co","no2","o3","so2","pm2_5","pm10","wind_speed"
num_df=data.frame(num_df)

# making categorical df
cat_df=air[c("city","sunrise","sunset","moonrise","moonset","wind_dir")]
```

4 Data Handling

4.1 Checking missing value

```
colSums(is.na(air))
```

```
##         city          lat          lon  temperature weather_code      sunrise
##            0            0            0            0            0            0
##       sunset     moonrise      moonset           co          no2           o3
##            0            0            0            0            0            0
##          so2        pm2_5         pm10   wind_speed  wind_degree     wind_dir
##            0            0            0            0            0            0
##     pressure       precip     humidity   cloudcover    feelslike     uv_index
##            0            0            0            0            0            0
##   visibility
##            0
```

There are no missing value

5 PCA: Principal Component Analysis

```
# Normalising data
scaled_df<-scale(num_df)

# Applying PCA
data.pca<-princomp(scaled_df)
summary(data.pca)
```

```
## Importance of components:
##                           Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
## Standard deviation     2.5335546 1.7258433 1.5140987 1.19297081 1.02755715
## Proportion of Variance 0.3827547 0.1776081 0.1366999 0.08486323 0.06296104
## Cumulative Proportion  0.3827547 0.5603627 0.6970626 0.78192587 0.84488691
##                            Comp.6     Comp.7     Comp.8     Comp.9    Comp.10
## Standard deviation     0.86033620 0.82063083 0.54083074 0.52940705 0.45271033
## Proportion of Variance 0.04413634 0.04015648 0.01744145 0.01671242 0.01222083
## Cumulative Proportion  0.88902325 0.92917973 0.94662118 0.96333361 0.97555444
##                            Comp.11     Comp.12     Comp.13     Comp.14
## Standard deviation     0.376134960 0.338575912 0.251403178 0.227654813
## Proportion of Variance 0.008436209 0.006835528 0.003768786 0.003090392
## Cumulative Proportion  0.983990646 0.990826174 0.994594960 0.997685352
##                           Comp.15      Comp.16      Comp.17
## Standard deviation     0.15902327 0.1152045144 1.602468e-02
## Proportion of Variance 0.00150793 0.0007914053 1.531225e-05
## Cumulative Proportion  0.99919328 0.9999846878 1.000000e+00
```

- Performing PCA requires scaling of data, princomp function was used for this purpose.
- The first five components have eigen value greater than 1. Thus, first five components retain **84% variance** of data. The first 2 components retain maximum variance 56%.
- going ahead we will check the factor loadings of first 5 components for analysis.

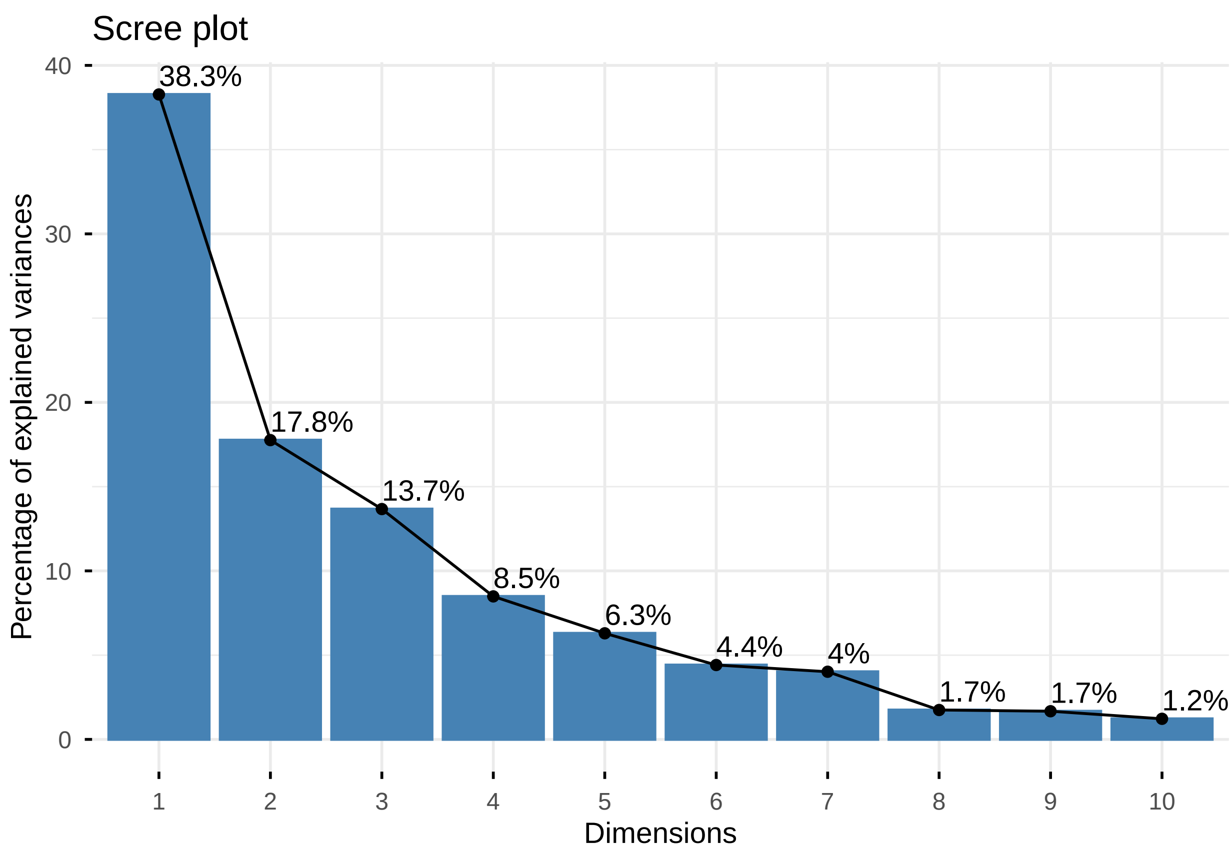
5.1 Extracting Loadings

```r
# extracting the loadings
data.pca$loadings[,1:5]
```

```
##                   Comp.1        Comp.2       Comp.3       Comp.4      Comp.5
## lat          0.298693929  0.1741996935  0.264271832  0.039111452  0.06567887
## lon          0.121570340  0.3737757341 -0.288322711  0.074254450 -0.16502060
## temperature -0.276398614 -0.3920491370 -0.016168420 -0.028792546 -0.03397166
## weather_code  0.151077988 -0.0485232318 -0.433015634 -0.267606169 -0.25553804
## co           0.348664946 -0.1977444783  0.008432181  0.029817564 -0.12049839
## no2          0.119454953 -0.1702609241 -0.073198459  0.643911842 -0.31616965
## o3           0.238100059 -0.3369639851  0.008192443 -0.078741718  0.32803458
## so2          0.311701586 -0.2264924355  0.020555419  0.207170883  0.01272117
## pm2_5        0.348722657 -0.2133589498  0.011597373 -0.006125823  0.06623659
## pm10         0.347364379 -0.2109712547  0.004900234 -0.012363201  0.06874963
## wind_speed  -0.208144702 -0.0008543208 -0.220755352  0.555330430 -0.11612031
## wind_degree  0.007514336  0.1053899469 -0.099366795  0.344485505  0.75038979
## pressure     0.262516331  0.3453643477  0.019249046  0.006053016 -0.03103226
## humidity     0.134890612  0.1227875390 -0.533724406 -0.008214219  0.08728228
## cloudcover   0.226067461 -0.0171820487  0.313975205  0.054212352 -0.28846463
## feelslike   -0.262454176 -0.4108471857 -0.053851895 -0.016649897 -0.02914395
## visibility  -0.119776506  0.1907126064  0.455927384  0.159091429 -0.03773750
```

5.2 Visualization of Principal components

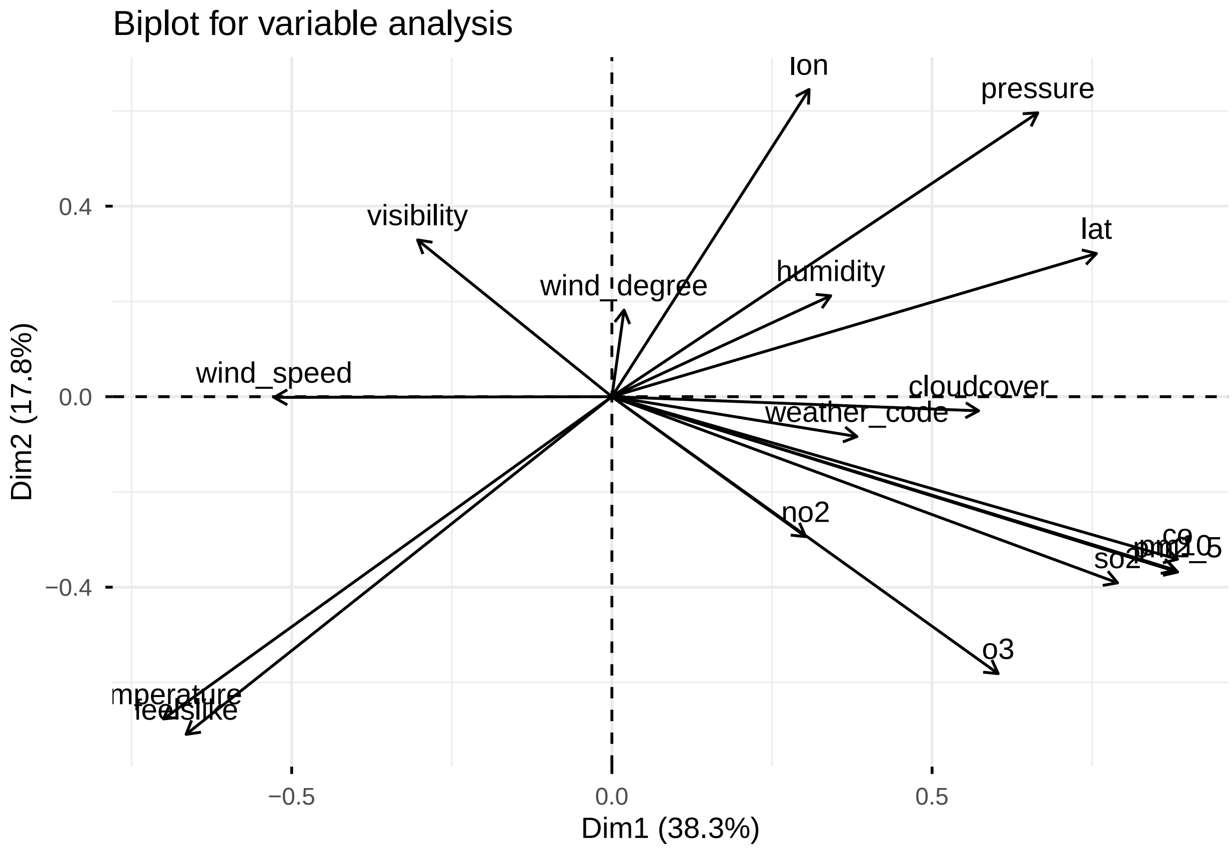
```r
fviz_eig(data.pca,addlabels = TRUE)
```



5.3 Biplot

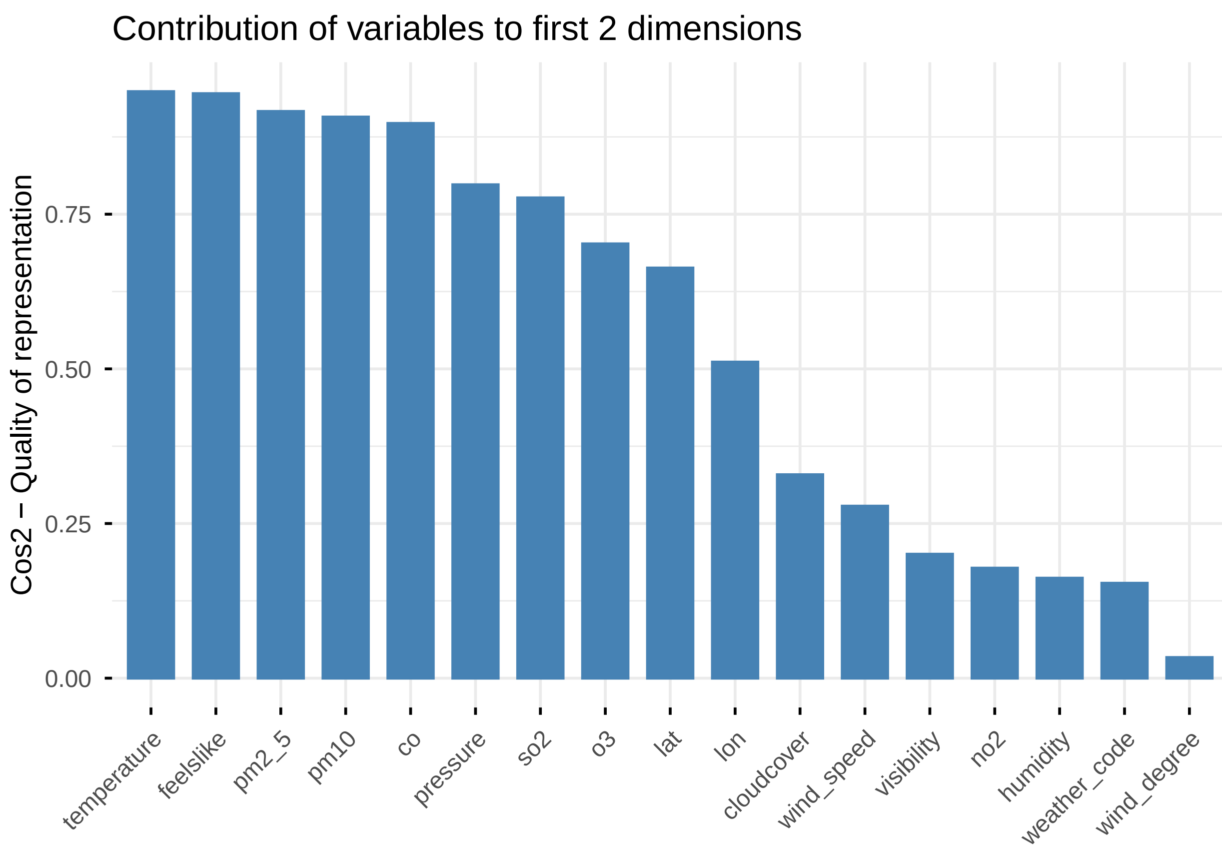
```
fviz_pca_var(data.pca,col.var="black")+
  ggtitle("Biplot for variable analysis")
```

```
## Warning: Using ‘size‘ aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use ‘linewidth‘ instead.
## i The deprecated feature was likely used in the ggpubr package.
##   Please report the issue at <https://github.com/kassambara/ggpubr/issues>.
## This warning is displayed once every 8 hours.
## Call ‘lifecycle::last_lifecycle_warnings()‘ to see where this warning was
## generated.
```



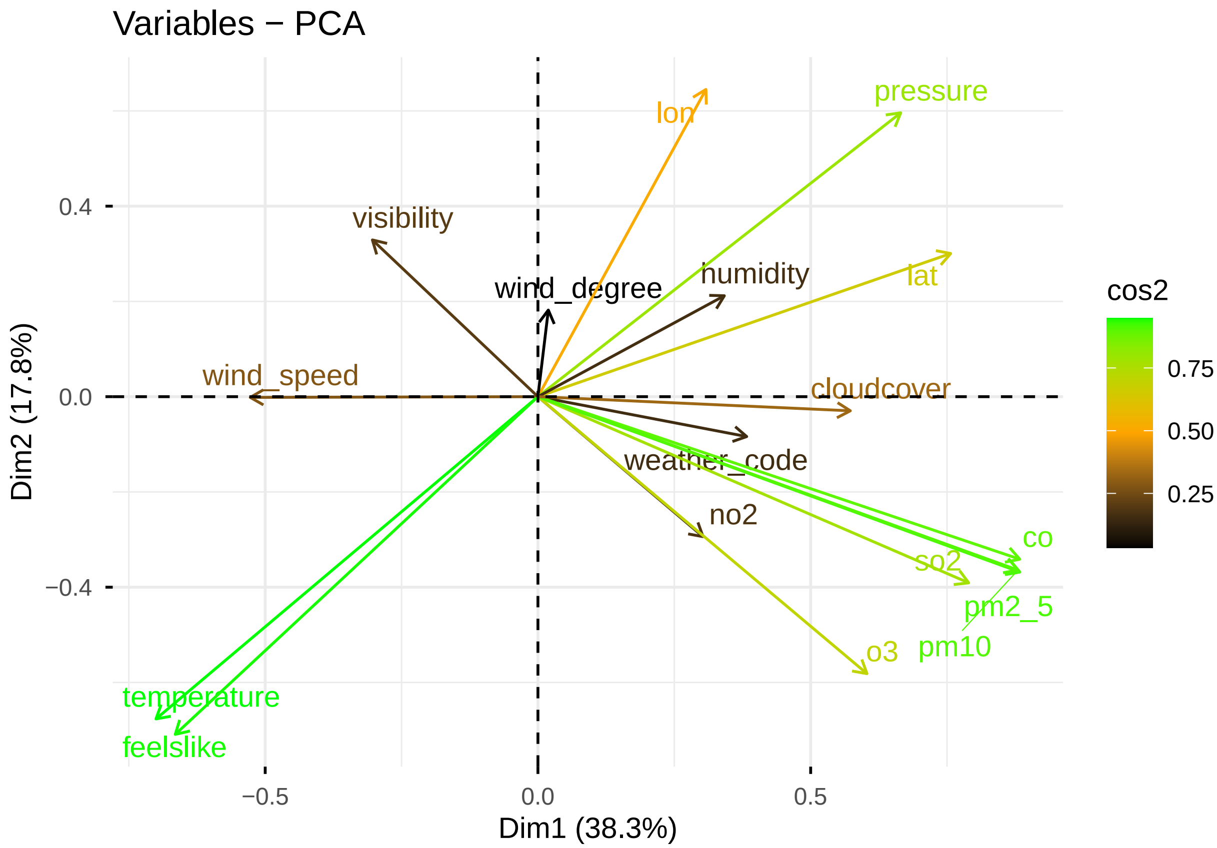
Checking contribution of each variable

```r
fviz_cos2(data.pca,choice="var",axes=1:2)+
  ggtitle("Contribution of variables to first 2 dimensions")
```



Biplot combined with cos2

```
fviz_pca_var(data.pca,col.var="cos2",
             gradient.cols=c("black","orange","green"),
             repel=TRUE)
```



5.4 Conclusion

1. **Component 1**: The variables pollutants(co2, so2, o3, pm2_5, pm10) and weather variables such as pressure humidity and cloud cover positively contribute to first dimension. The variables like wind_speed , temperature , feelslike negatively contribute to first dimension.This indicates that pollutants dominate this dimension with higher loading.**We can observe that as wind speed decreases and temperature increases small particles settle in that area leading to higher pollutants. They have inverse relationship.**

2. **Component 2:** This is weather dominant component. pollutants negatively contribute to it while weather degree, humidity, pressure a nd visibility affect it positively. **With longitude the pressure in the area increases.Visibility also contributes to this dimension significantly. As pollutants decrease visibility increases.**

3. The first 5 principal components retain **84% variance in data**. But first 2 components constitute most variance.

4. All pollutants are clustered together in biplot. Thus are positively correlated and these variables ar well reperesented. Variables feelslike , temprature , lat, long and pressure are also well represented.

6 Factor Analysis

6.1 KMO and Bartlett's Test of Sphericity

```r
# making a correlation matrix
correlation_matrix<-cor(num_df)

#KMO Test
kmo_result <- KMO(correlation_matrix)
print(kmo_result)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = correlation_matrix)
## Overall MSA =  0.7
## MSA for each item =
##          lat          lon  temperature weather_code           co          no2
##         0.80         0.68         0.72         0.60         0.83         0.33
##           o3          so2        pm2_5         pm10   wind_speed  wind_degree
##         0.82         0.77         0.75         0.75         0.57         0.33
##     pressure     humidity   cloudcover    feelslike   visibility
##         0.76         0.51         0.76         0.76         0.49
```

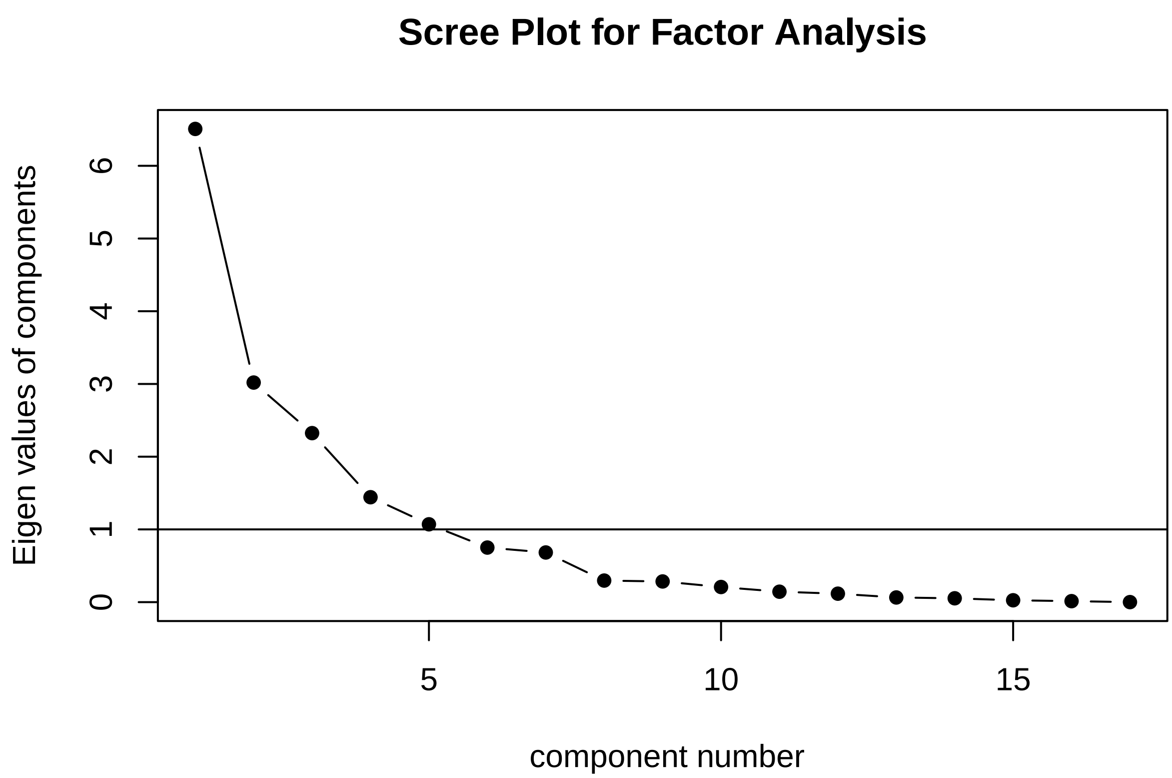
```r
# Bartlett's Test of Sphericity
cortest.bartlett(correlation_matrix, n = nrow(num_df))
```

```
## $chisq
## [1] 1760.473
##
## $p.value
## [1] 3.011205e-280
##
## $df
## [1] 136
```

1. **KMO Test :** we can observe the overall MSA value is greater than 0.69 indicating that correlation matrix is not identity matrix.
2. **Bartlett's Test of Sphericity :** We can Observe that the p-value is 1.449223e-293 <0.05 indicating that the data is suitable for factor analysis

6.2 Deciding number of factors

```r
scree(num_df, factors = FALSE, pc = TRUE,
      main = "Scree Plot for Factor Analysis")
```



Thus, 4 factors can be retained to explain the underlying structure as eigen value is greater than 1.

```r
fa<- fa(num_df, nfactors=4,rotate="varimax",scores="regression")
```

```
## In factor.stats, I could not find the RMSEA upper bound . Sorry about that
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect.  Try a
## different factor score estimation method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate = rotate, : An
## ultra-Heywood case was detected.  Examine the results carefully
```

```r
fa
```

```
## Factor Analysis using method =  minres
## Call: fa(r = num_df, nfactors = 4, rotate = "varimax", scores = "regression")
## Standardized loadings (pattern matrix) based upon correlation matrix
##                MR1   MR2   MR3   MR4    h2     u2 com
## lat           0.51  0.69 -0.24 -0.13 0.804  0.1956 2.2
## lon          -0.15  0.62  0.39  0.20 0.593  0.4067 2.1
## temperature  -0.19 -0.98 -0.09  0.01 0.997  0.0026 1.1
## weather_code  0.20  0.09  0.68 -0.07 0.519  0.4809 1.2
## co            0.91  0.21  0.19 -0.02 0.913  0.0866 1.2
## no2           0.45 -0.03 -0.03  0.67 0.661  0.3395 1.8
```

```
## o3           0.76 -0.13  0.18 -0.17 0.644  0.3555 1.3
## so2          0.88  0.13  0.09  0.16 0.819  0.1811 1.1
## pm2_5        0.93  0.18  0.21 -0.09 0.947  0.0534 1.2
## pm10         0.92  0.18  0.22 -0.10 0.933  0.0671 1.2
## wind_speed  -0.40 -0.28  0.01  0.76 0.818  0.1825 1.8
## wind_degree -0.06  0.12  0.05  0.18 0.051  0.9485 2.2
## pressure     0.21  0.84  0.08 -0.02 0.749  0.2509 1.1
## humidity     0.01  0.30  0.84  0.19 0.833  0.1666 1.4
## cloudcover   0.52  0.31 -0.27 -0.08 0.447  0.5533 2.3
## feelslike   -0.15 -0.99 -0.02  0.04 1.003 -0.0032 1.0
## visibility  -0.27  0.13 -0.68 -0.01 0.558  0.4419 1.4
##
##                        MR1  MR2  MR3  MR4
## SS loadings           5.01 3.93 2.10 1.24
## Proportion Var        0.29 0.23 0.12 0.07
## Cumulative Var        0.29 0.53 0.65 0.72
## Proportion Explained  0.41 0.32 0.17 0.10
## Cumulative Proportion 0.41 0.73 0.90 1.00
##
## Mean item complexity =  1.5
## Test of the hypothesis that 4 factors are sufficient.
##
## df null model =  136  with the objective function =  26.47 with Chi Square =  1760.47
## df of  the model are 74  and the objective function was  627.51
##
## The root mean square of the residuals (RMSR) is  0.05
## The df corrected root mean square of the residuals is  0.07
##
## The harmonic n.obs is  74 with the empirical chi square  49.28  with prob <  0.99
## The total n.obs was  74  with Likelihood Chi Square =  40055.82  with prob <  0
##
## Tucker Lewis Index of factoring reliability =  -46.288
## RMSEA index =  2.702  and the 90 % confidence intervals are  2.698 NA
## BIC =  39737.32
## Fit based upon off diagonal values = 0.98
```

6.3 Conclusion

Factors are:

1. Factor 1: positive effect: co, o3, so2, pm2_5,pm10,lat negative effect: lon, temprature
2. Factor 2: positive effect: lat,lon,pressure negative effect: temperature,feelslike
3. Factor 3: positive effect: wether_code,humidity negative effect: visibility
4. Factor 4: positive effect: no2,wind_speed

- Factor Analysis is used for identifying the **underlying structure of the data**. It helps in reducing variable and these obtained factors can be effectively used for EDA.
- The First Factor can be named as**pollutants**, Second Factor as **geographic_cond**, Third Factor is **weather_cond** , Fourth can be named as **ozone** since higher wind speed decreases no2 concentration.
- All the variables have high commonality that means they are **well represented by the factors.**

7 Data Engineering

7.1 Adding FA Score / Factors for EDA

```r
# Storing FA Scores as df
fa_scores<-as.data.frame(fa$scores)

# renaming column names
colnames(fa_scores)=c("pollutants","geographic_cond","weather_cond","ozone")

# concatenating 2 dfs air and fa_scores
df<-cbind(air,fa_scores)
#head(df)
```

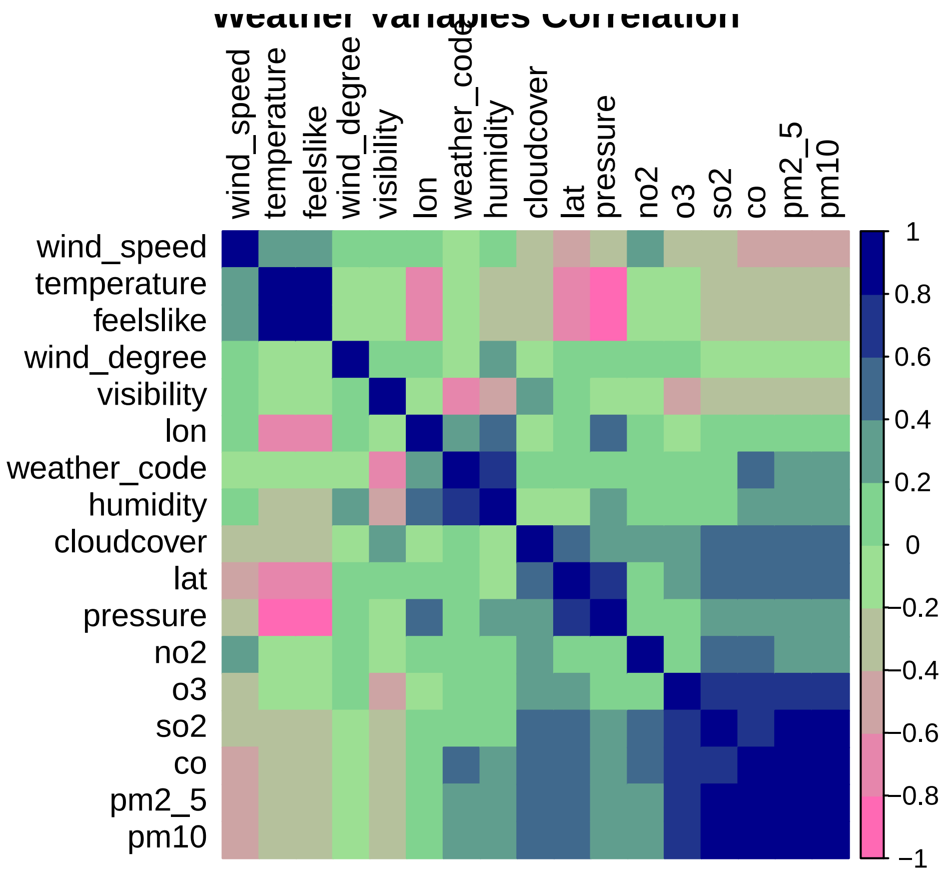
7.2 Converting Weather code and visibility to categorical variables

```r
df<-df %>%
  mutate(weather_cat=case_when(
    weather_code==113~"sunny",
    weather_code==122~"partly cloudly",
    weather_code==143~"mist",
    weather_code==116~"moderate rain",
    weather_code==119~"showers",
    weather_code==248~"fog",
    weather_code==176~"moderate rain",
  )) %>%
  mutate(visibility_cat=case_when(
    visibility<1~"very poor",
    between(visibility,1,3) ~"poor",
    between(visibility,3,5) ~"moderate",
    visibility>5 ~"good"
  )) %>%
  mutate(parts_of_India = case_when(
    between(lat, 28, 37.6) & between(lon, 68.7, 97.25) ~ "North",
    between(lat, 15, 28) & between(lon, 68, 78) ~ "West",
    between(lat, 20, 28) & between(lon, 83, 97.25) ~ "East",
    lat < 20 & between(lon, 74, 84) ~ "South",
    between(lat, 18, 26) & between(lon, 74, 85) ~ "Central",
    between(lat, 22, 28) & between(lon, 89, 97.25) ~ "Northeast",
    TRUE ~ "Other Region"
  ))
```

8 Exploratory Data Analysis

8.1 Correlation among variables

```r
# Calculate correlation with pairwise complete observations
weather_cor <- cor(num_df,
                   use = "pairwise.complete.obs")

c_color<- colorRampPalette(c("hotpink", "lightgreen","darkblue"))

corrplot(weather_cor,
         method = "color",
         title = "Weather Variables Correlation",
         order="hclust",
         col=c_color(10),
         tl.col="black"
         )
```

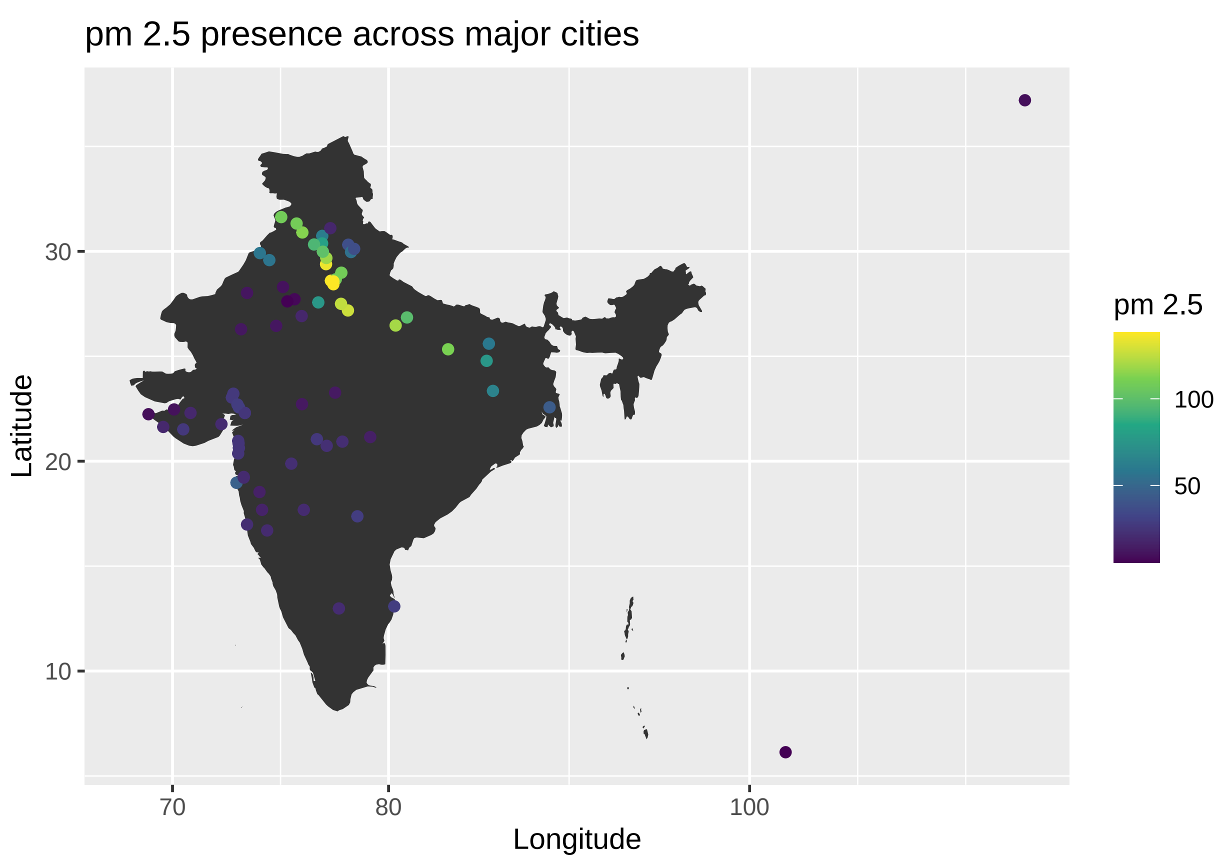


* Positive Correlation: pollutants are highly correlated such as pm2_5, pm_10, co, so2 , no2 is moderately correlated, feelslike and temperature are highly correlated.

- Moderate Correlation (positive and negative): We can see moderate correlation between co2 and weather code,longitude with temperature and feelslike,latitude with temprature and feelslike
- Negative Correlation:pressure with feelslike and temprature

8.2 pm 2.5 according to latitude and longitude values

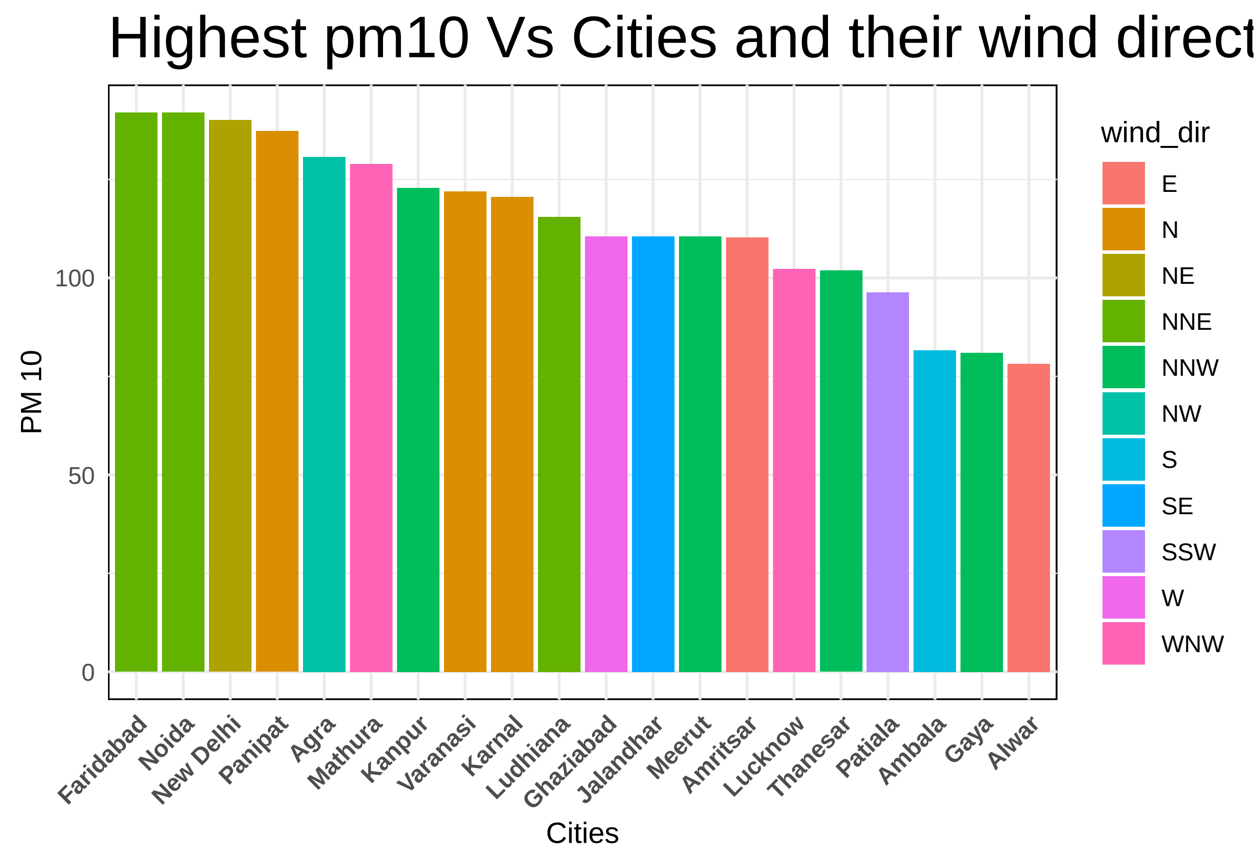
```
world<-map_data("world")

#getting the map for india
india<-subset(world,region=="India")


ggplot()+
   geom_polygon(data=india,
                aes(x=long,y=lat,group=group))+
  geom_point(data=df,
             aes(x=lon,y=lat,color=pm2_5))+
  scale_color_continuous(
    type = "viridis",
    name = "pm 2.5"
  )+
  scale_x_log10()+
  labs(
    title="pm 2.5 presence across major cities",
    x="Longitude",
    y="Latitude"
  )
```



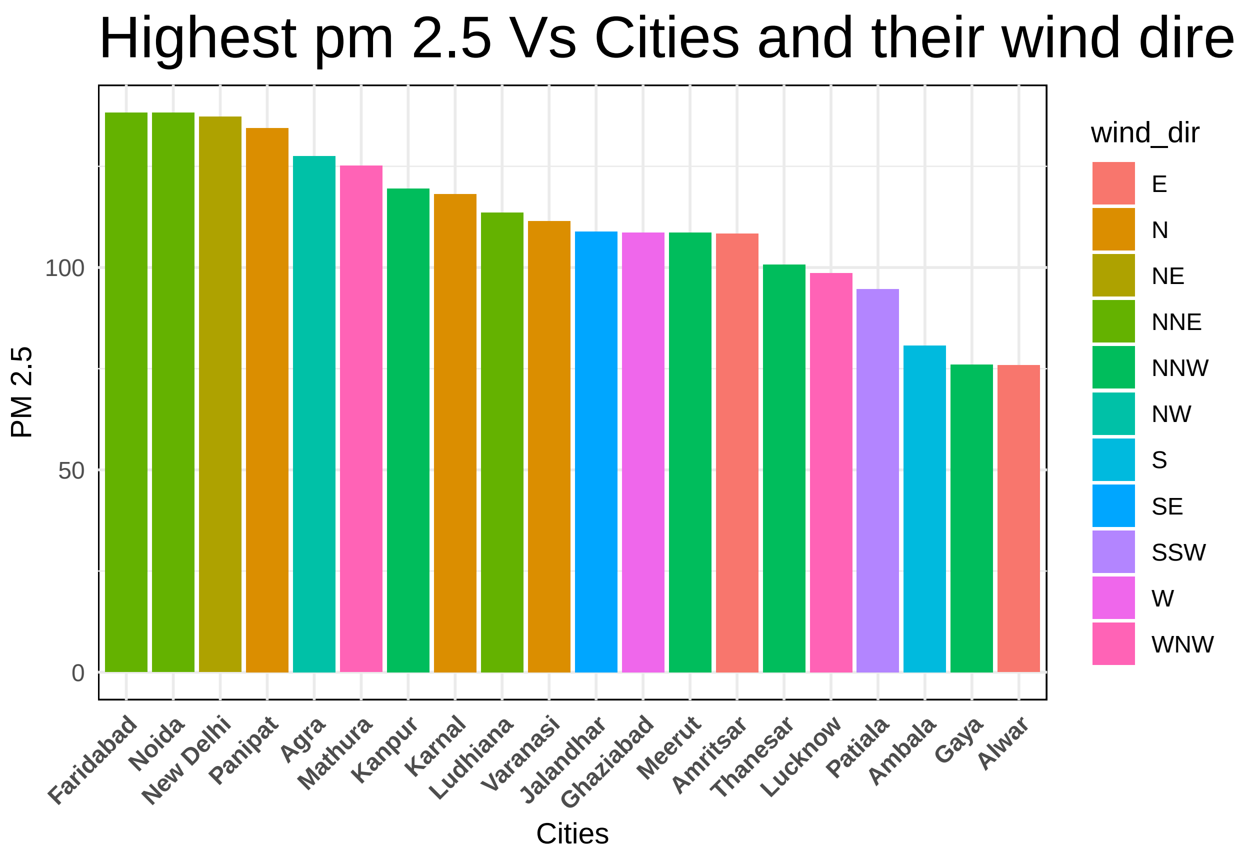
```r
# setting theme for all plots
set_theme(theme_minimal()+
            theme(
                plot.title=
                  element_text(
                    size=rel(2)),

                panel.background =
                  element_rect(color="black"),

              ))
```

8.3 Top 20 cities with worst air quality pm10 and pm2

```r
# pm10
df %>%
  arrange(desc(pm10)) %>%
  select(city,pm10,wind_dir) %>%
  slice_head(n=20) %>%
  ggplot(
    aes(x=reorder(city,-pm10),y=pm10,fill=wind_dir)
  )+
  labs(
    title="Highest pm10 Vs Cities and their wind direction",
    x="Cities",
    y="PM 10"
  ) +
  geom_bar(stat="identity")+
  theme(
      axis.text.x =
                  element_text(angle=45,
                              hjust=1,
                             face="bold")
  )
```



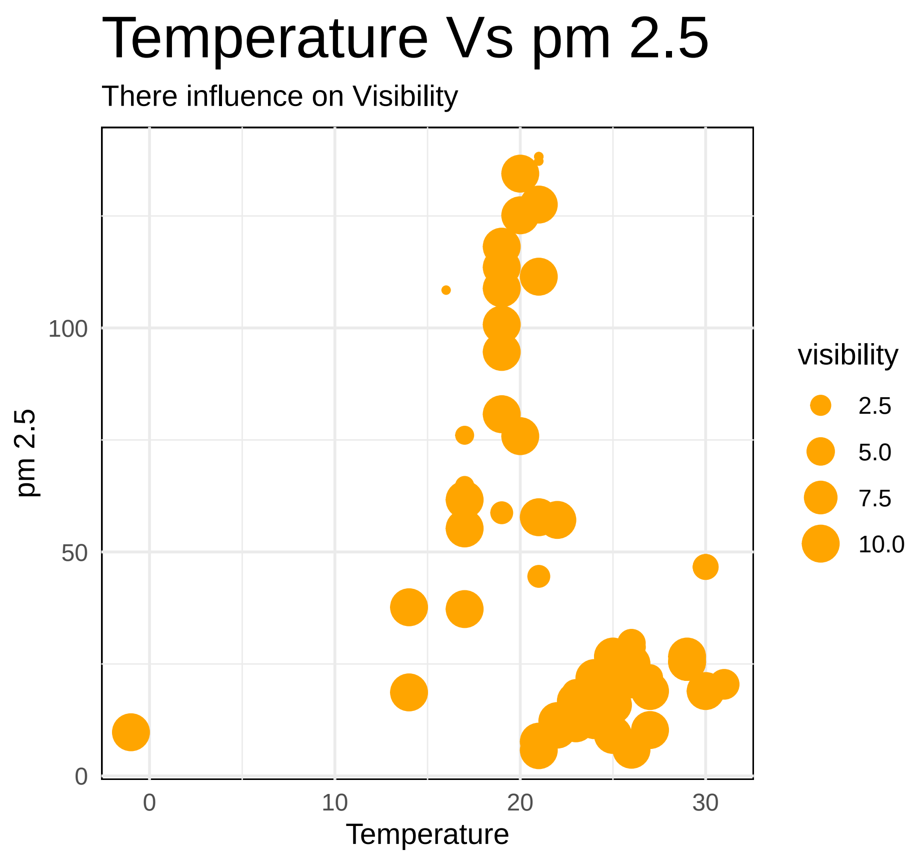

```r
df %>%
  arrange(desc(pm2_5)) %>%
  select(city,pm2_5,wind_dir) %>%
  slice_head(n=20) %>%
  ggplot(
    aes(x=reorder(city,-pm2_5),y=pm2_5,fill=wind_dir)
  )+
  geom_bar(stat="identity")+
  labs(
    title="Highest pm 2.5 Vs Cities and their wind direction",
    x="Cities",
    y="PM 2.5"
  )+
  theme(
      axis.text.x =
                  element_text(angle=45,
                               hjust=1,
                              face="bold")
  )
```



#One-on-one relationships between two continuous variables

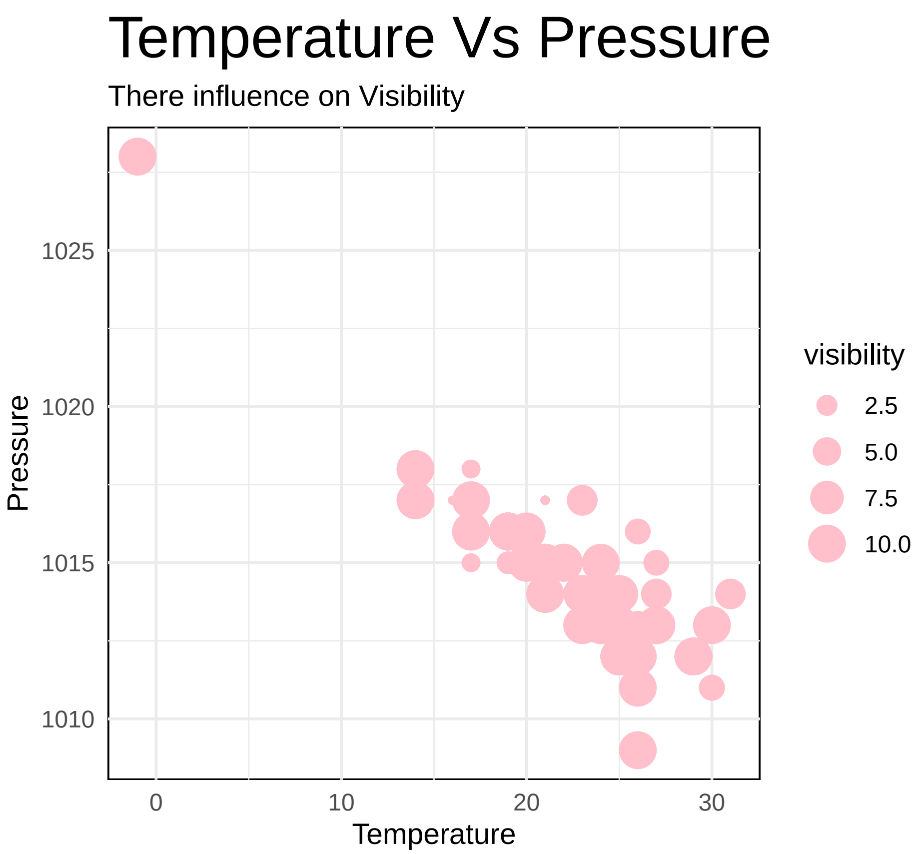
8.4 Temperature vs PM2.5 levels

```
# temperature Vs pm2.5 levels
plot1<-df %>%
  ggplot(aes(temperature,pm2_5,size=visibility))+
  geom_point(color="orange")+
  labs(
    title="Temperature Vs pm 2.5",
    subtitle="There influence on Visibility",
    x="Temperature",
    y="pm 2.5"
  )+
  theme(
    aspect.ratio = 1
  )
plot1
```



8.5 Temptrature Vs Pressure

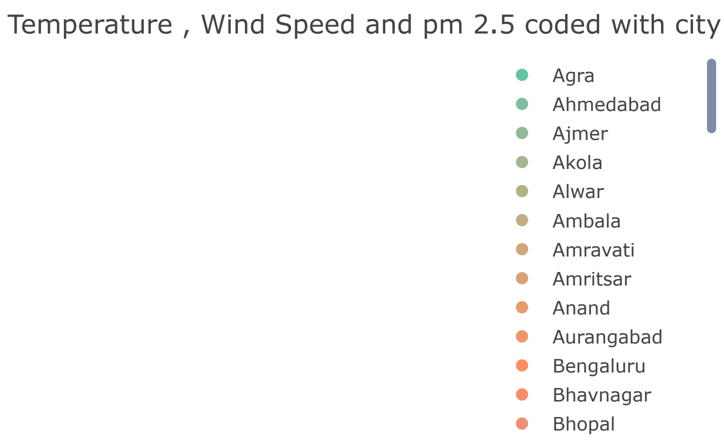
```
# temperature Vs pm2.5 levels
plot2<-df %>%
  ggplot(aes(temperature,pressure,size=visibility))+
  geom_point(color="pink")+
  labs(
    title="Temperature Vs Pressure",
    subtitle="There influence on Visibility",
    x="Temperature",
    y="Pressure"
  )+
  theme(
    aspect.ratio = 1
  )

plot2
```



8.6 Observing 3 variables Wind speed , Temprature and pm 2.5 concentration

```
fig <-plot_ly(df, x = ~wind_speed, y = ~temperature, z = ~pm2_5, color = ~city)


fig <- fig %>% add_markers()
fig <- fig %>% layout(
                    title = 'Temperature , Wind Speed and pm 2.5 coded with city',
                    scene =
                    list(xaxis = list(title = 'Wind Speed'),
                     yaxis = list(title = 'Temprature'),
                     zaxis = list(title = 'pm 2.5')))

fig
```

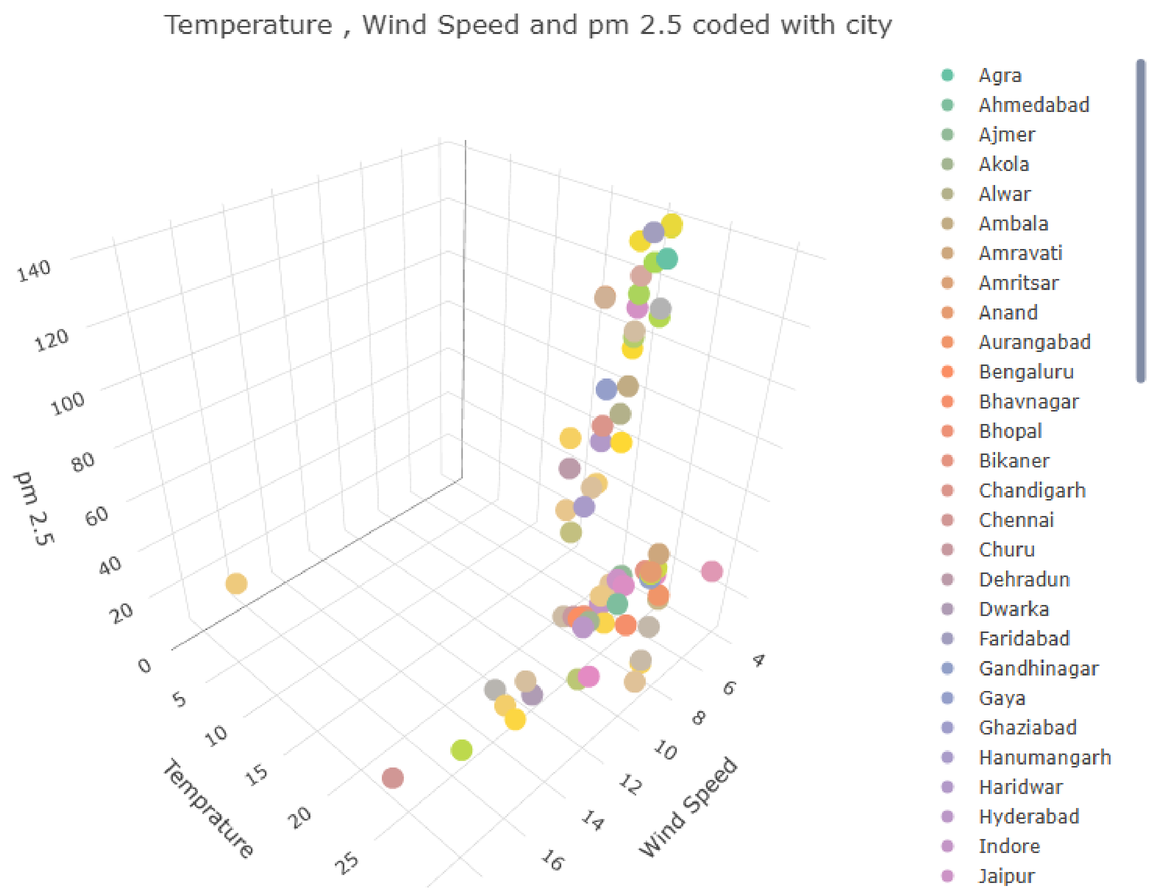
```
## Warning in RColorBrewer::brewer.pal(max(N, 3L), "Set2"): n too large, allowed maximum for palette Se
## Returning the palette you asked for with that many colors
## Warning in RColorBrewer::brewer.pal(max(N, 3L), "Set2"): n too large, allowed maximum for palette Se
## Returning the palette you asked for with that many colors
```


Temperature , Wind Speed and pm 2.5 coded with city
Agra
Ahmedabad
Ajmer
Akola
Alwar
Ambala
Amravati
Amritsar
Anand
Aurangabad
Bengaluru
Bhavnagar
Bhopal

```r
htmlwidgets::saveWidget(as_widget(fig), "temp.html")
```

```
## Warning in RColorBrewer::brewer.pal(max(N, 3L), "Set2"): n too large, allowed maximum for palette Se
## Returning the palette you asked for with that many colors
## Warning in RColorBrewer::brewer.pal(max(N, 3L), "Set2"): n too large, allowed maximum for palette Se
## Returning the palette you asked for with that many colors
```

```r
webshot2::webshot("temp.html", "plot.png", vwidth = 800, vheight = 600)
```



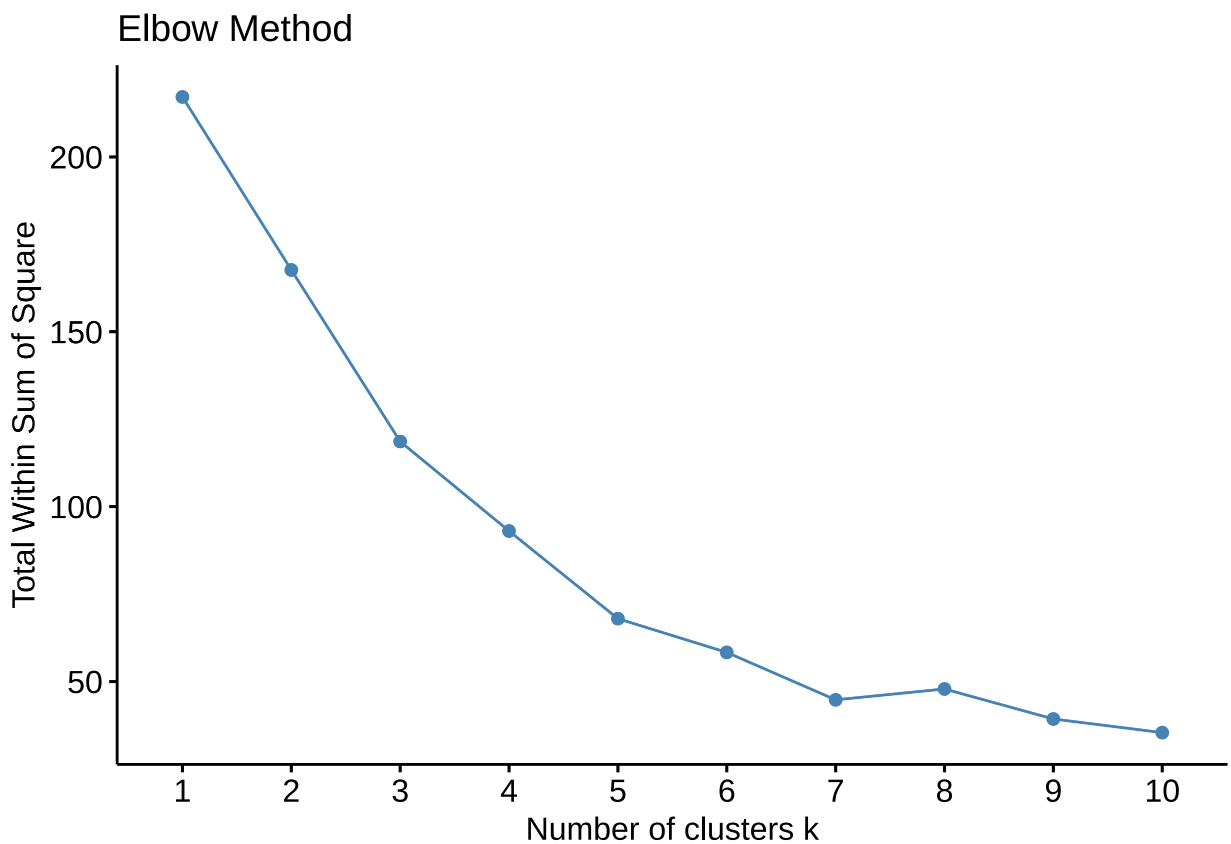
9 Clustering based on 3 Factors retained

9.1 Making dataset for clustering

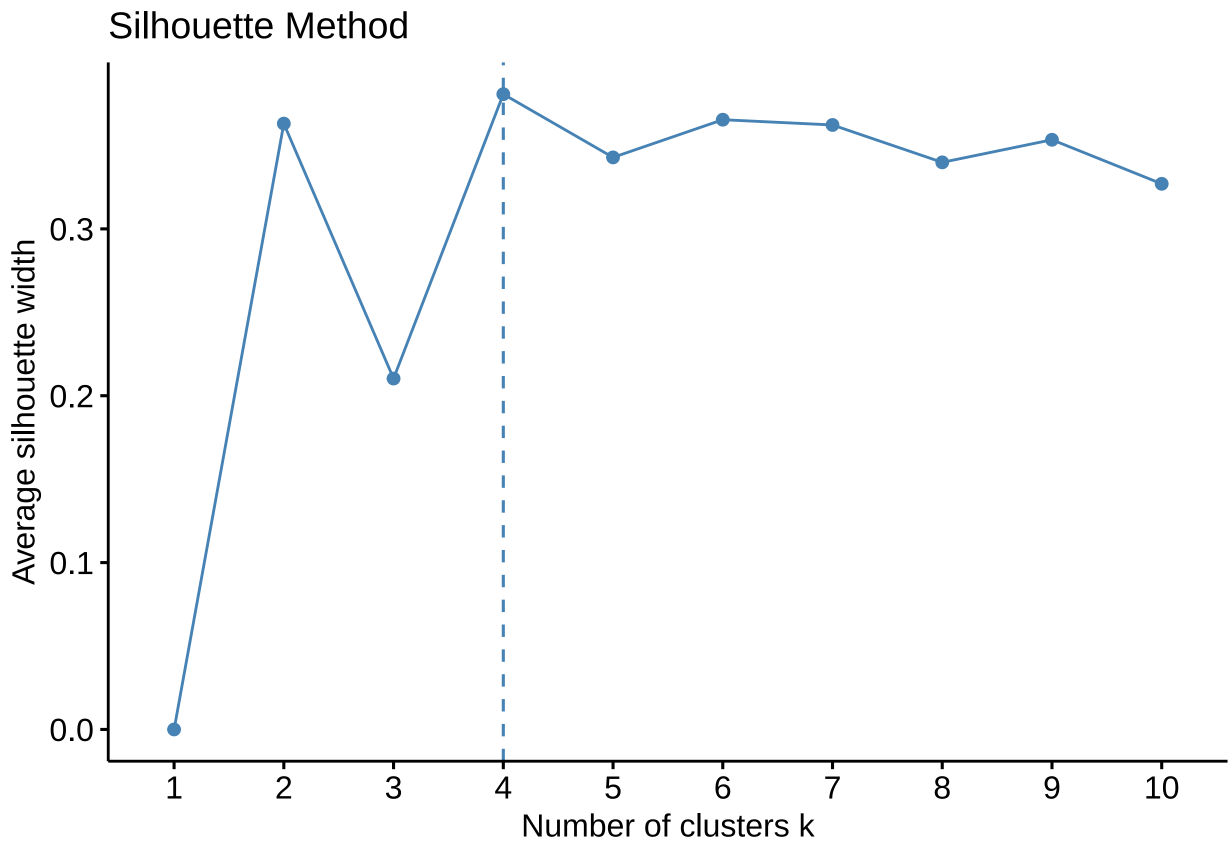
```r
# Data for clustering
k_data<-df %>%
  select("city","pollutants","weather_cond","geographic_cond")
```

9.2 Selecting number of clusters

```
fviz_nbclust(k_data[,c("pollutants","weather_cond","geographic_cond")], kmeans, method = "wss") +
  ggtitle("Elbow Method")
```




```
fviz_nbclust(k_data[,c("pollutants","weather_cond","geographic_cond")], kmeans, method = "silhouette") +
  ggtitle("Silhouette Method")
```



Performing K-means clustering

```r
# Perform k-means clustering (e.g., 4 clusters)
set.seed(123)
kmeans_result <- kmeans(k_data[,c("pollutants","weather_cond","geographic_cond")], centers = 4, nstart =
print(kmeans_result)
```

```
## K-means clustering with 4 clusters of sizes 11, 12, 13, 38
##
## Cluster means:
##   pollutants weather_cond geographic_cond
## 1  1.0521595   1.52978703       0.3104511
## 2  1.3119575  -0.79206252       0.3998618
## 3 -0.6659475  -0.62980568       1.2501290
## 4 -0.4910507   0.02275176      -0.6438153
##
## Clustering vector:
##  [1] 1 4 1 4 4 4 4 4 4 3 1 1 4 4 4 1 3 1 4 2 2 1 1 1 1 2 2 2 1 2 2 2 3 3 3 3 4 3
## [39] 3 4 2 3 3 3 2 2 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 2 4 4 4 4 4 4 4 4 4 3 3 4
##
## Within cluster sum of squares by cluster:
## [1] 16.630440  5.361423 34.609670 35.293387
##  (between_SS / total_SS =  57.7 %)
##
## Available components:
##
```

```
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

9.3 Storing Clusters as factor

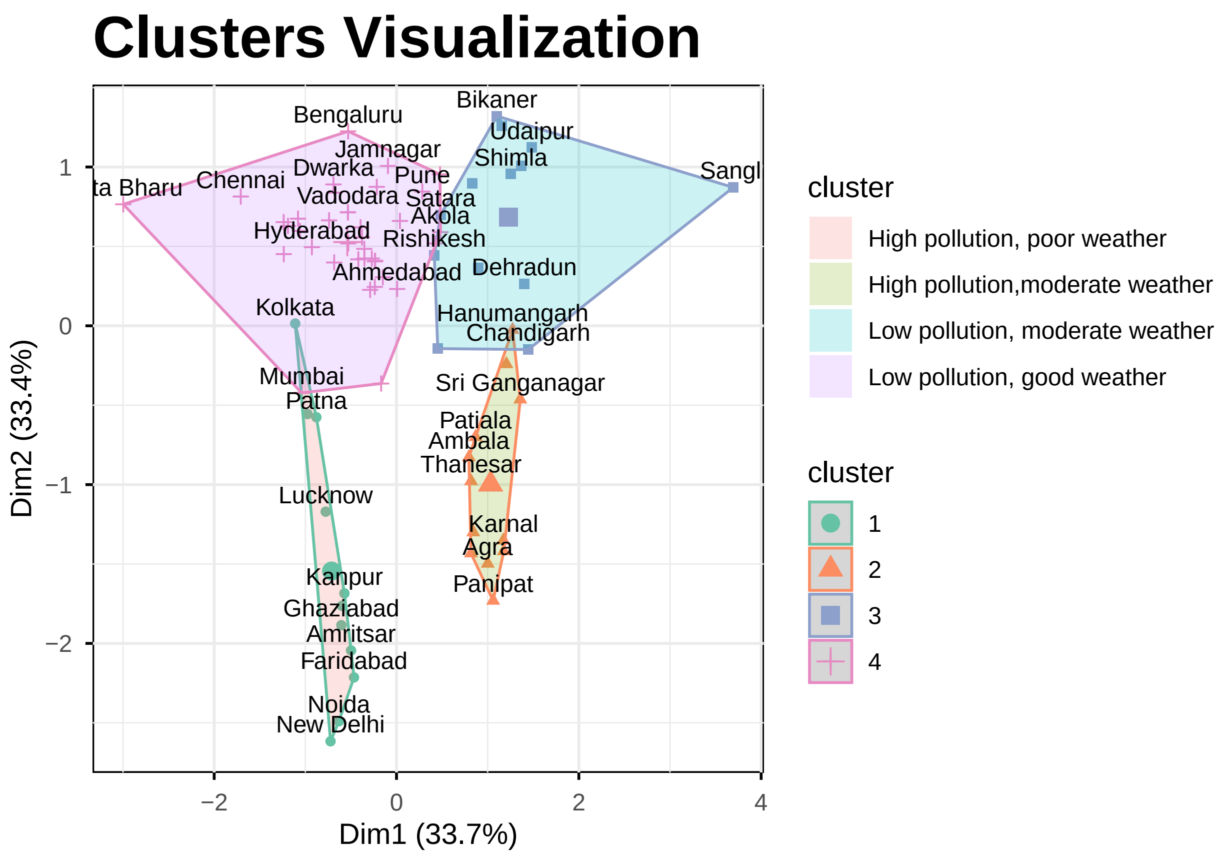
```r
k_data$cluster <- as.factor(kmeans_result$cluster)
head(k_data)
```

```
##        city pollutants weather_cond geographic_cond cluster
## 1 New Delhi  2.3898941    1.2332044     -0.27910897       1
## 2    Mumbai  0.7275207   -0.1247146     -1.75305313       4
## 3   Kolkata -0.6789153    1.6993385      0.27044612       1
## 4   Chennai -1.3535364    1.5147861     -0.62542879       4
## 5 Bengaluru -1.4458486    0.3791381     -0.07514414       4
## 6 Hyderabad -0.6457790    0.5358054     -0.64707795       4
```

9.4 Visualizing clusters

```r
city_names<-k_data$city
fviz_cluster(kmeans_result, data = k_data[,c("pollutants","weather_cond","geographic_cond")],
             palette = "Set2", ggtheme = theme_minimal(),
             geom = "point") +
  geom_text(aes(label = city_names),
            check_overlap = TRUE,
            size = 3,
            vjust = -0.5)+
 labs(
   title="Clusters Visualization"
 )+
  theme(
    plot.title =
      element_text(face = "bold",
                   size=rel(2)),
    panel.background =
                  element_rect(color="black")
  )+
  scale_fill_discrete(labels = c("High pollution, poor weather", "High pollution,moderate weather", "Lo
```

```
## Scale for fill is already present.
## Adding another scale for fill, which will replace the existing scale.
```



10 Key Insights

- The cities in the north like Noida, Delhi , Kanpur , Lucknow, Patna, Agra , Karnal lie in north of India. Pollution in these areas could be due to **stubble burning** and bad weather conditions like **low wind speed and high temperature**.
- The cities like Ahmedabad, Vadodra , Vapi , Mumbai, Chennai seem to have low pollution due to good geographical condition - **proximity costal area or water body.**
- The cities like Dehradun, Shimla, Sangli , Udaipur , Bikaner do not have major industries that contribute to bad air quality. They are mostly **destinations for vacations.**
- Other cities like Ambala, Thanesar, Karnal, Agra are **major manufacturing hub**s. In Agra the pollution can also be linked to** tourism** that leads to rise in levels of co and no.
- We can easily observe that the most polluted cities Faridabad , Noida , New Delhi , Agra etc are in **north of India**. Irregular farming practices like **stubble burning, livestock farming and excessive use of chemical fertilizers and pesticides** is responsible for pollution . In addition to that **vehicular emission, improper waste disposal and manufacturing company's non-compliance to regulations** lead to rise in pollutants.

11 Actions

- Adoption of Sustainable Agricultural Practices (PUSA Bio decomposer) and raising their awareness. This process leads to long term benefits to soil health , economic and environmental benefit.

- Implementing stringent rules and penalties on manufacturing organisation that do not treat gases before its emission in enviornment.
- Simple solutions like car pooling , household waste management , implementation and usage of public transportation is the key to reduce pollutants.
- Incentivizing diversification of crops and providing financial assistance and to farmers for it.
- Specific policies can be developed for all high polluted clustered cities with similar geographical and weather condition.