PCA and t-SNE Project: cars MPG

Objective

The objective of this problem is to **explore the data, reduce the number of features by using dimensionality reduction techniques like PCA and t-SNE, and extract meaningful insights**.

Dataset

There are 8 variables in the data:

- mpg: miles per gallon
- cyl: number of cylinders
- disp: engine displacement (cu. inches) or engine size
- hp: horsepower
- wt: vehicle weight (lbs.)
- acc: time taken to accelerate from 0 to 60 mph (sec.)
- yr: model year
- car name: car model name

Importing the necessary libraries and overview of the dataset

In [65]:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

# To scale the data using z-score
from sklearn.preprocessing import StandardScaler

# Importing PCA and t-SNE
from sklearn.decomposition import PCA

from sklearn.manifold import TSNE
```

Loading the data

In [66]:

```
data = pd.read_csv("auto-mpg.csv")
```

In [67]:

```
data.head()
```

Out[67]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	ford torino

Checking the info of the data

In [68]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64
 7   car name      398 non-null    object
dtypes: float64(3), int64(3), object(2)
memory usage: 25.0+ KB
```

Observations:

- There are **398 observations and 8 columns** in the data.
- **All variables except horsepower and car name are of numeric data type.**
- The horsepower must be a numeric data type. We will explore this further.

Data Preprocessing and Exploratory Data Analysis

Checking the unique values in the 'car name' column

In [69]:

```
data["car name"].nunique()
```

Out[69]:

305

- The column 'car name' is of object data type containing a lot of unique entries and would not add values to our analysis. So I drop this column.

In [70]:

```
# Creating copy of the data so that we don't lose the original data
data1 = data.copy()

# Dropping the column 'car name'
data = data.drop(['car name'], axis = 1)
```

Checking values in the horsepower column

In [71]:

```
# Checking if there are values other than digits in the column 'horsepower'

hpIsDigit = pd.DataFrame(data.horsepower.str.isdigit())  # If the string consists of digits return True else False

data[hpIsDigit['horsepower'] == False]   # Take only those rows where horsepower is not a digit
```

Out[71]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year
32	25.0	4	98.0	?	2046	19.0	71
126	21.0	6	200.0	?	2875	17.0	74
330	40.9	4	85.0	?	1835	17.3	80
336	23.6	4	140.0	?	2905	14.3	80
354	34.5	4	100.0	?	2320	15.8	81
374	23.0	4	151.0	?	3035	20.5	82

Observations:

- There are **6 observations where horsepower is ?**. We can consider these values as **missing values**.
- We can **impute these missing values and change the data type** of horsepower column.
- First, we need to **replace the ? with np.nan**.

In [72]:

```
# Replacing ? with np.nan
data = data.replace('?', np.nan)

data[hpIsDigit['horsepower'] == False]
```

Out[72]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year
32	25.0	4	98.0	NaN	2046	19.0	71
126	21.0	6	200.0	NaN	2875	17.0	74
330	40.9	4	85.0	NaN	1835	17.3	80
336	23.6	4	140.0	NaN	2905	14.3	80
354	34.5	4	100.0	NaN	2320	15.8	81
374	23.0	4	151.0	NaN	3035	20.5	82

In [73]:

```
# Imputing the missing values with the median value of the column horsepower
data.horsepower.fillna(data.horsepower.median(), inplace = True)

data['horsepower'] = data['horsepower'].astype('float64')  # Converting the horsepower column from object data type to float
```

Summary Statistics

In [74]:

```
# Write your code here
data.describe().T
```

Out[74]:

	count	mean	std	min	25%	50%	75%	max
mpg	398.0	23.514573	7.815984	9.0	17.500	23.0	29.000	46.6
cylinders	398.0	5.454774	1.701004	3.0	4.000	4.0	8.000	8.0
displacement	398.0	193.425879	104.269838	68.0	104.250	148.5	262.000	455.0
horsepower	398.0	104.304020	38.222625	46.0	76.000	93.5	125.000	230.0
weight	398.0	2970.424623	846.841774	1613.0	2223.750	2803.5	3608.000	5140.0
acceleration	398.0	15.568090	2.757689	8.0	13.825	15.5	17.175	24.8
model year	398.0	76.010050	3.697627	70.0	73.000	76.0	79.000	82.0

**Observations:

--the car years were between 1970 and 1982

--the minimum and maximum number of car cylinders are 3 and 8 respectively.

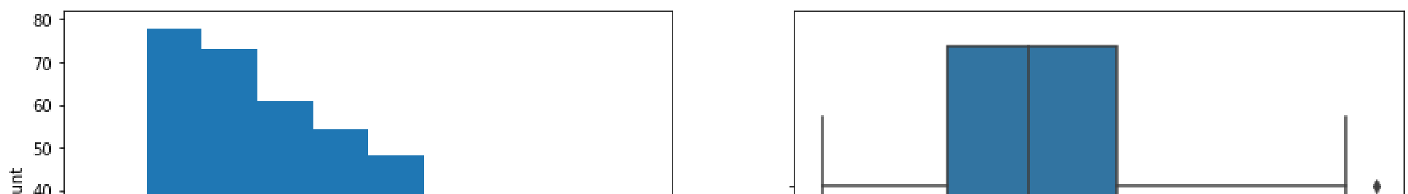
--looking at the mean and std, the std for the 7 variables in the data set are low, suggesting the variation is not much

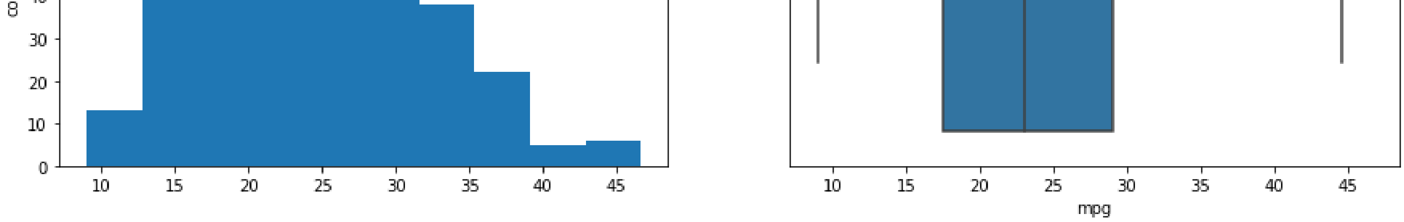
Let's check the distribution and outliers for each column in the data

In [75]:

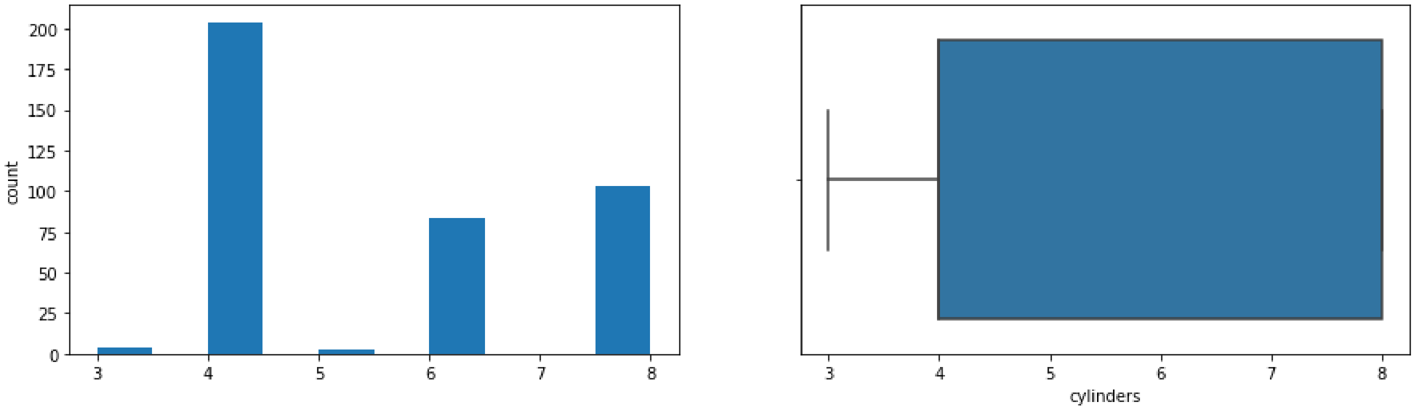
```
# Complete the below code by filling the blanks, before running this cell, to avoid any errors

for col in data.columns:
    print(col)

    print('Skew :', round(data[col].skew(), 2))

    plt.figure(figsize = (15, 4))

    plt.subplot(1, 2, 1)

    data[col].hist(bins= 10, grid= False)

    plt.ylabel('count')

    plt.subplot(1, 2, 2)

    sns.boxplot(x = data[col])

    plt.show()
```

mpg
Skew : 0.46

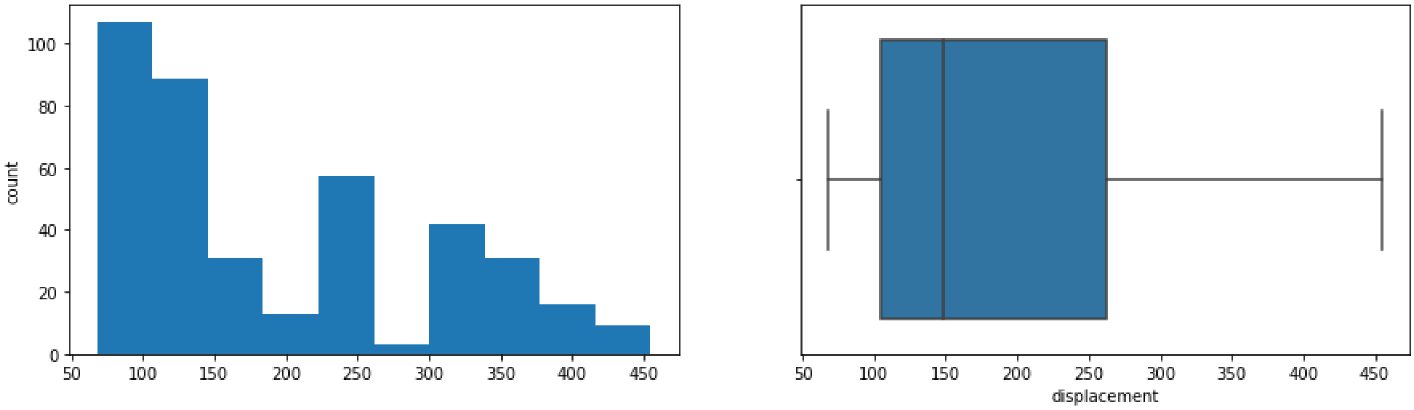




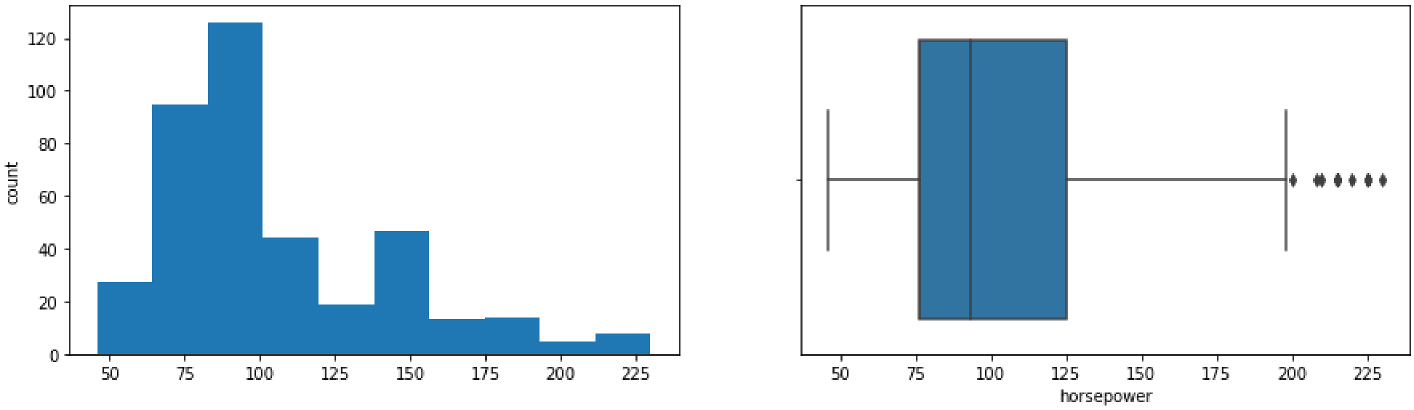
cylinders
Skew : 0.53



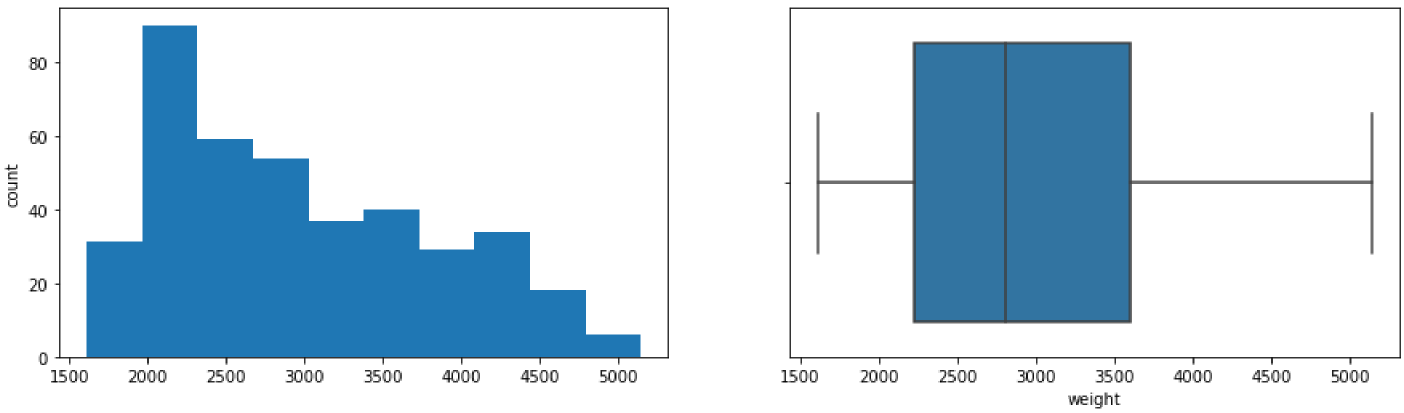
displacement
Skew : 0.72



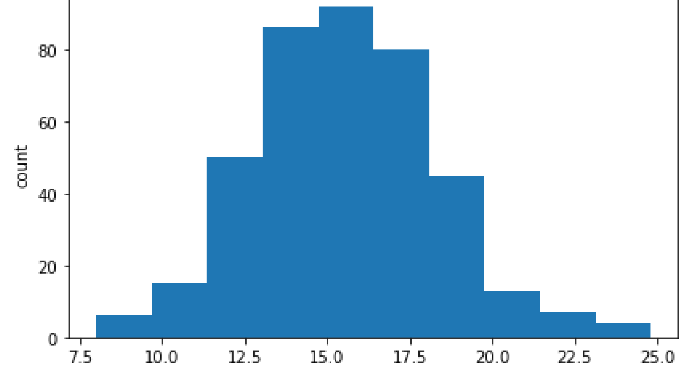
horsepower
Skew : 1.11

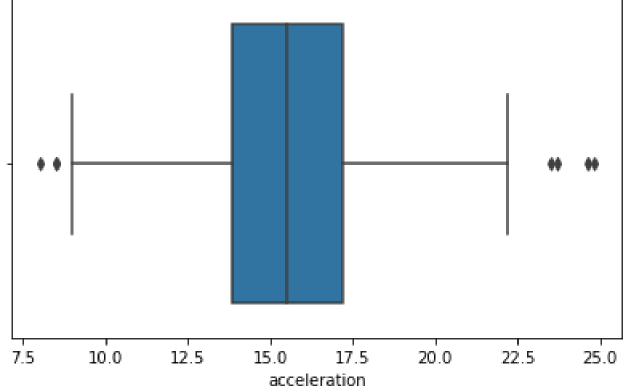


weight
Skew : 0.53

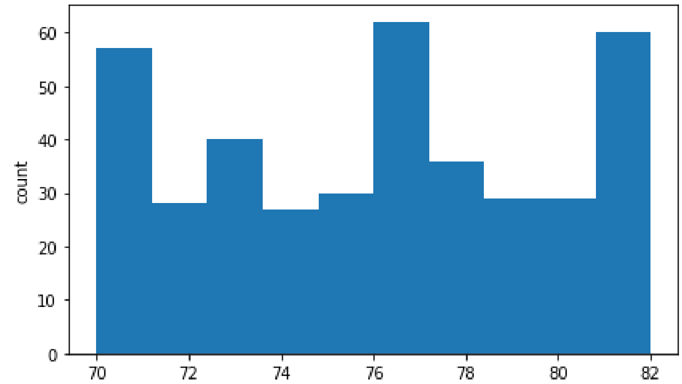


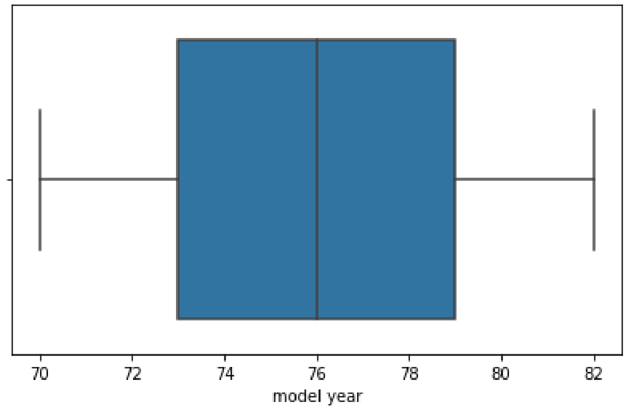
acceleration
Skew : 0.28





model year
Skew : 0.01





**Observations:

--mpg, horsepower are slightly right skewed having outliers

--number of cylinders don't have any outliers, the maximum number of cylinders is same as third quartile and also the minimum number of cylinders is same as the first quartile

--displacement, weight are right skewed with no outliers

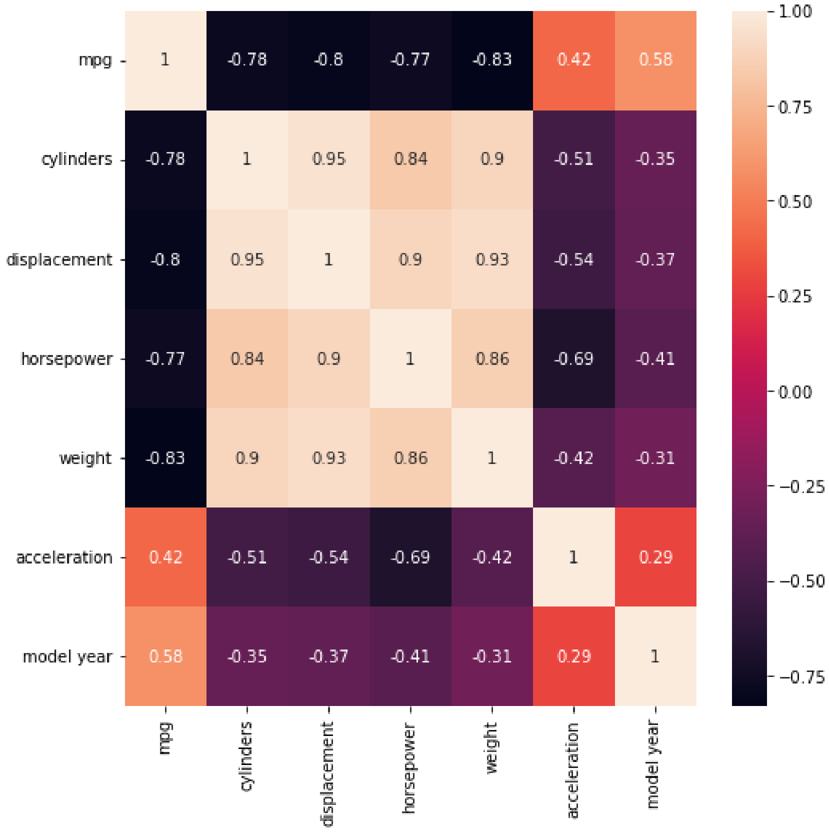
--acceleration looks nomally distributed and a bit symmetrical with outliers in the first and third quartile

--there is no skewness for model year, suggesting a symmetrical distribution

Checking the correlation

In [76]:

```
plt.figure(figsize = (8, 8))

sns.heatmap(data.corr(), annot = True)

plt.show()
```



Observations:

- The variable mpg has a strong negative correlation with cylinders, displacement, horsepower, and weight.
- horsepower and acceleration are negatively correlated.
- The variable weight has a strong positive correlation with horsepower, displacement, and cylinders.
- model year is positively correlated with mpg.

Scaling the data

In [77]:

```
# Scaling the data
scaler = StandardScaler()

data_scaled = pd.DataFrame(scaler.fit_transform(data), columns = data.columns)
```

In [78]:

```
data_scaled.head()
```

Out[78]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year
0	-0.706439	1.498191	1.090604	0.673118	0.630870	-1.295498	-1.627426
1	-1.090751	1.498191	1.503514	1.589958	0.854333	-1.477038	-1.627426
2	-0.706439	1.498191	1.196232	1.197027	0.550470	-1.658577	-1.627426
3	-0.962647	1.498191	1.061796	1.197027	0.546923	-1.295498	-1.627426
4	-0.834543	1.498191	1.042591	0.935072	0.565841	-1.840117	-1.627426

Principal Component Analysis

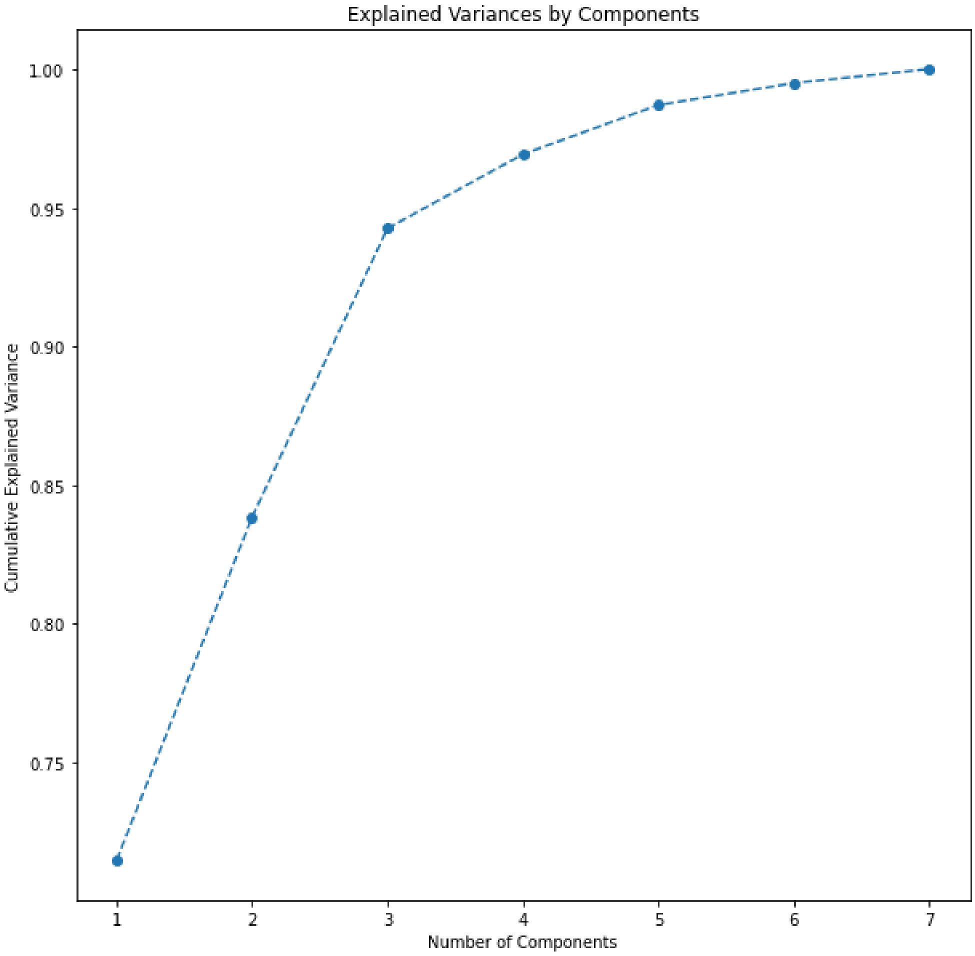
- **Apply the PCA algorithm with number of components equal to the total number of columns in the data**

In [79]:

```
# Defining the number of principal components to generate
n = data_scaled.shape[1]

# Finding principal components for the data
pca = PCA(n_components = n, random_state = 1)# Apply the PCA algorithm with random_state = 1

data_pca1 = pd.DataFrame(pca.fit_transform(data_scaled))   # Fit and transform the pca function on scaled data

# The percentage of variance explained by each principal component
exp_var = pca.explained_variance_ratio_
```

In [80]:

```python
# Visualize the explained variance by individual components
plt.figure(figsize = (10, 10))

plt.plot(range(1, 8), exp_var.cumsum(), marker = 'o', linestyle = '--')

plt.title("Explained Variances by Components")

plt.xlabel("Number of Components")

plt.ylabel("Cumulative Explained Variance")

plt.show()
```



In [81]:

```python
# Finding the least number of components that can explain more than 90% variance
sum = 0

for ix, i in enumerate(exp_var):
    sum = sum + i
    if(sum>0.90):
        print("Number of PCs that explain at least 90% variance: ", ix + 1)
        break
```

Number of PCs that explain at least 90% variance: 3

**Observations:

--The first three principal components explain approximately 90% of the original variance.

--There is 90% reduction in the dimensionality of the dataset with only a loss of 10% in variance.

In [82]:

```python
pc_comps = ['PC1', 'PC2', 'PC3']

data_pca = pd.DataFrame(np.round(pca.components_[:3,:], 2), index = pc_comps, columns = data_scaled.columns)

data_pca.T
```

Out[82]:

	PC1	PC2	PC3
mpg	-0.40	-0.21	-0.26
cylinders	0.42	-0.19	0.14
displacement	0.43	-0.18	0.10
horsepower	0.42	-0.09	-0.17
weight	0.41	-0.22	0.28
acceleration	-0.28	0.02	0.89
model year	-0.23	-0.91	-0.02

Interpreting the coefficients of the first three principal components from the below DataFrame

In [83]:

```
def color_high(val):
    if val <= -0.40:
        return 'background: pink'

    elif val >= 0.40:
        return 'background: skyblue'

data_pca.T.style.applymap(color_high)
```

Out[83]:

	PC1	PC2	PC3
mpg	-0.400000	-0.210000	-0.260000
cylinders	0.420000	-0.190000	0.140000
displacement	0.430000	-0.180000	0.100000
horsepower	0.420000	-0.090000	-0.170000
weight	0.410000	-0.220000	0.280000
acceleration	-0.280000	0.020000	0.890000
model year	-0.230000	-0.910000	-0.020000

**Observations:

--The first principal component, PC1, seems to be related to cars that have low mpg with higher number of cylinders, displacement, horsepower and weight i.e cars with low mpg will have higher cylinders, displacement, horsepower and weight

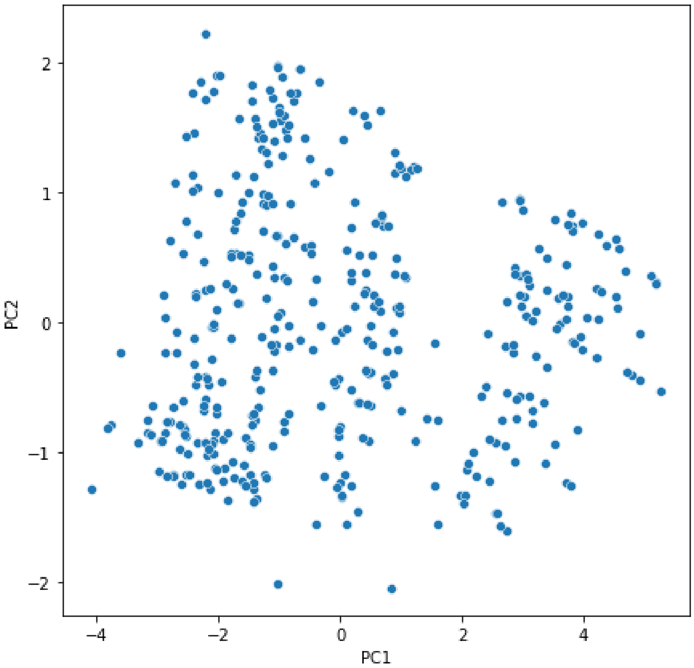
--The second principal component, PC2 have high negative value for car model year. This captures cars that were manufactured earlier in the model year range.

--The third principle componet, PC3 captures attribute of cars that have high accelaration

We can also visualize the data in 2 dimensions using the first two principal components

In [84]:

```
plt.figure(figsize = (7, 7))

sns.scatterplot(x = data_pca1[0], y = data_pca1[1])

plt.xlabel("PC1")

plt.ylabel("PC2")

plt.show()
```

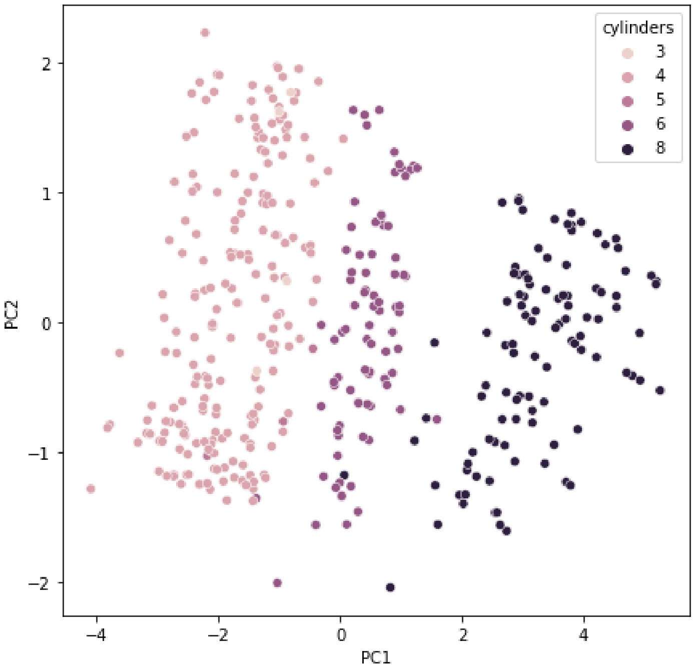


Let's try adding hue to the scatter plot

- **Create a scatter plot for the first two principal components with hue = 'cylinders'**
- **Hint:** concatenate the DataFrames 'data_pca1' and 'data' on axis = 1

In [85]:

```
df_concat = pd.concat([data_pca1, data], axis = 1)

plt.figure(figsize = (7, 7))

sns.scatterplot(data=df_concat, x = 0, y = 1, hue ='cylinders')  # Create a scatter plot with x = 0 and y = 1 using df_concat dataframe

plt.xlabel("PC1")

plt.ylabel("PC2")

plt.show()
```



**Observations:

--the scatter plot shows the plot of PC1 on x axis against PC2 on y axis colored by the number of cylinders. From the plot we can clearly see PC1 and PC2 cars with 8 cylinders, 6 cylinders and 4 cylinders except for 3 and 5 cylinders cars which are few and hidden in between other type of cylinders

t-SNE

- **Apply the t-SNE embedding with 2 components for the DataFrame 'data_scaled' (use random_state = 1)**

In [86]:

```
tsne = TSNE(n_components = 2, random_state = 1)        # Apply the t-SNE algorithm with random_state = 1
```

```
data_tsne = tsne.fit_transform(data_scaled)   # Fit and transform t-SNE function on the scaled data
```

In [87]:

```
data_tsne.shape
```

Out[87]:

(398, 2)

In [88]:

```
data_tsne = pd.DataFrame(data = data_tsne, columns = ['Component 1', 'Component 2'])
```

In [89]:

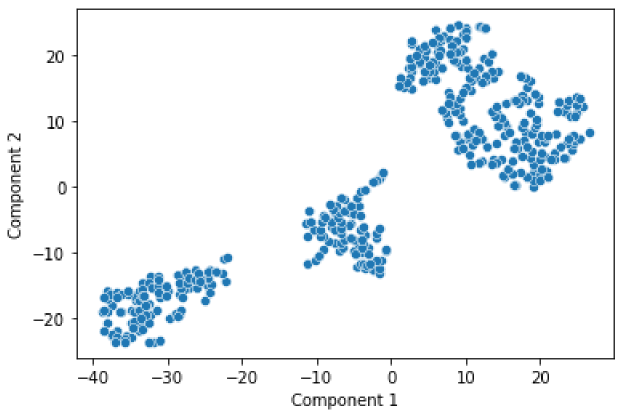
```
data_tsne.head()
```

Out[89]:

	Component 1	Component 2
0	-38.088413	-15.912958
1	-37.404369	-17.995850
2	-38.050472	-17.063194
3	-37.718334	-16.476006
4	-38.404663	-16.763493

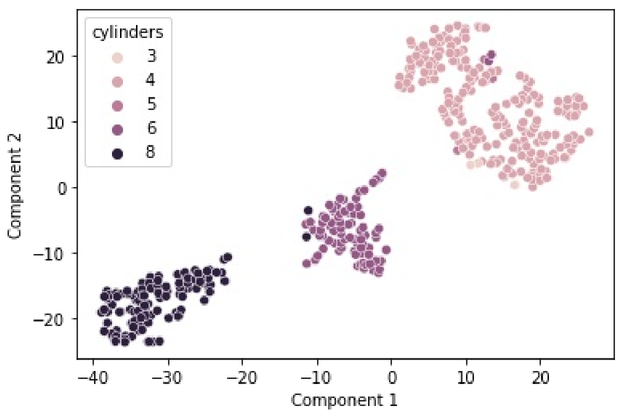
In [90]:

```
sns.scatterplot(x = data_tsne.iloc[:,0], y = data_tsne.iloc[:,1])

plt.show()
```



In [91]:

```
# Let's see the scatter plot of the data w.r.t number of cylinders
sns.scatterplot(x = data_tsne.iloc[:,0], y = data_tsne.iloc[:,1], hue = data.cylinders)

plt.show()
```



**Observations:

--t-SNE was able to cluster and reduce the dimensionality of the Car data. We can see 3 group of cars clearly seperated without having to specify perplexity

In [92]:

```
# Let's assign points to 3 different groups
def grouping(x):
    first_component = x['Component 1']
```

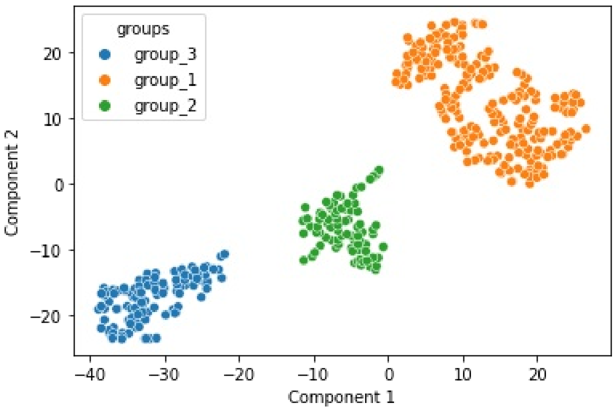
```
    second_component = x['Component 2']

    if (first_component > 0) and (second_component > -5):
        return 'group_1'

    if (first_component > -20 ) and (first_component < 5):
        return 'group_2'

    else:
        return 'group_3'
```

In [93]:

```
data_tsne['groups'] = data_tsne.apply(grouping, axis = 1)
```

In [94]:

```
sns.scatterplot(x = data_tsne.iloc[:,0], y = data_tsne.iloc[:,1], hue = data_tsne.iloc[:,2])

plt.show()
```

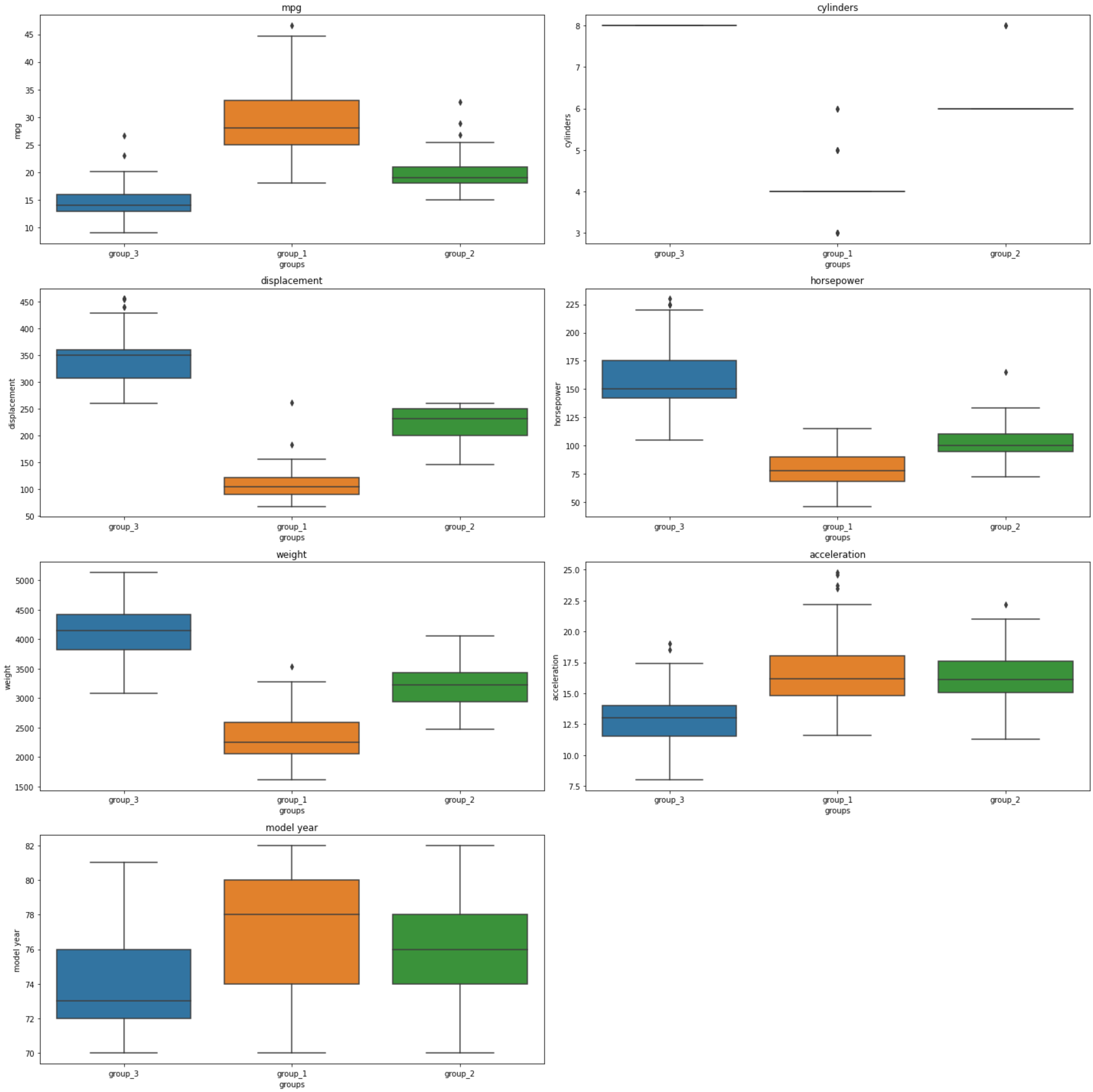


In [95]:

```
data['groups'] = data_tsne['groups']
```

In [96]:

```
all_col = data.columns.tolist()

plt.figure(figsize = (20, 20))

for i, variable in enumerate(all_col):
    if i == 7:
        break

    plt.subplot(4, 2, i + 1)

    sns.boxplot(y=data[variable], x=data['groups'])     # Create the boxplot with groups on the x-axis and variable on the y-axis (use the DataFrame 'data')

    plt.tight_layout()

    plt.title(variable)

plt.show()
```



**Observations:

**Observations:

--There are three groups in the data. Each group has a different set of characteristics.

--Group 1 represent cars with with less weight and horsepower having higher miles per gallon (mpg), 50% of these cars were manufactured between 1974 to 1980 having mostly 4 cylinders.

--Group 2 represents cars with average level attributes for mpg, displacement, horsepower, weight. 50% of these cars were manufactured 1975 to 1978 having mostly 6.

--Group 3 represents cars with more with weights and horsepower having lower miles per gallon (mpg) and slow accelaration, 50% of these cars were manufactured between 1972 to 1976 having mostly 8 cylinders.

In [ ]: