PCA on BigMart Sales DataSet

Objective

- Identify Principal Components of Bigmart Sales using Principal Component Analysis.
- PLot the Result of PCA.

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Importing Essential Librares

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import io
import requests
from sklearn.impute import SimpleImputer
from sklearn.decomposition import PCA
```

In [2]:

```
## Loading DataSet

url1 = "https://raw.githubusercontent.com/shsarv/ML-and-its-Application/main/PCA%20on%20Bigmart%20Dataset/Train.csv"
url2="https://raw.githubusercontent.com/shsarv/ML-and-its-Application/main/PCA%20on%20Bigmart%20Dataset/Test.csv"
s = requests. get(url1).content
train = pd. read_csv(io. StringIO(s. decode('utf-8')))
s2=requests. get(url2).content
test= pd. read_csv(io. StringIO(s2. decode('utf-8')))
```

Since We have to do find the Principal Component using Principal Component Analysis, we will using only training data to work upon.

In [3]:

```
train.head()
```

Out[3]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment
0	FDA15	9.30	Low Fat	0.016047	Dairy	249.8092	OUT049	

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment
1	DRC01	5.92	Regular	0.019278	Soft Drinks	48.2692	OUT018	
2	FDN15	17.50	Low Fat	0.016760	Meat	141.6180	OUT049	
3	FDX07	19.20	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	
4	NCD19	8.93	Low Fat	0.000000	Household	53.8614	OUT013	

Information about Dataset

In [4]:

```
#Information about the dataSet

train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Item_Identifier            8523 non-null   object 
 1   Item_Weight                7060 non-null   float64
 2   Item_Fat_Content           8523 non-null   object 
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object 
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object 
 7   Outlet_Establishment_Year  8523 non-null   int64  
 8   Outlet_Size                6113 non-null   object 
 9   Outlet_Location_Type       8523 non-null   object 
 10  Outlet_Type                8523 non-null   object 
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

In [5]:

```
train.shape
```

Out[5]:

```
(8523, 12)
```

In [6]:

```
train.describe()
```

Out[6]:

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	Item_Outlet_Sales
count	7060.000000	8523.000000	8523.000000	8523.000000	8523.000000
mean	12.857645	0.066132	140.992782	1997.831867	2181.288914
std	4.643456	0.051598	62.275067	8.371760	1706.499616
min	4.555000	0.000000	31.290000	1985.000000	33.290000
25%	8.773750	0.026989	93.826500	1987.000000	834.247400
50%	12.600000	0.053931	143.012800	1999.000000	1794.331000
75%	16.850000	0.094585	185.643700	2004.000000	3101.296400
max	21.350000	0.328391	266.888400	2009.000000	13086.964800

In [7]:

```
train.isnull().sum()
```

Out[7]:

```
Item_Identifier                 0
Item_Weight                  1463
Item_Fat_Content                0
Item_Visibility                 0
Item_Type                       0
Item_MRP                        0
Outlet_Identifier               0
Outlet_Establishment_Year       0
Outlet_Size                  2410
Outlet_Location_Type            0
Outlet_Type                     0
Item_Outlet_Sales               0
dtype: int64
```

Data Preprocessing

Handling Missing Values

We Will be Using *Simple Imputer* for imputing the missing values and using *Most_Frequent* Strategy for String Attributes and *Mean* otherwise.

In [8]:

```
imputer=SimpleImputer()
train[['Item_Weight']]=imputer.fit_transform(train[['Item_Weight']])
im = SimpleImputer(strategy='most_frequent')
train[['Outlet_Size']]=im.fit_transform(train[['Outlet_Size']])
train.isnull().sum()
```

Out[8]:

```
Item_Identifier              0
Item_Weight                  0
Item_Fat_Content             0
Item_Visibility              0
Item_Type                    0
Item_MRP                     0
Outlet_Identifier            0
Outlet_Establishment_Year    0
Outlet_Size                  0
Outlet_Location_Type         0
Outlet_Type                  0
Item_Outlet_Sales            0
dtype: int64
```

In [9]:

```
# Converting year to timespan

train['Outlet_Establishment_Year'] = 2020 - train['Outlet_Establishment_Year']
train['Outlet_Establishment_Year'].value_counts()
```

Out[9]:

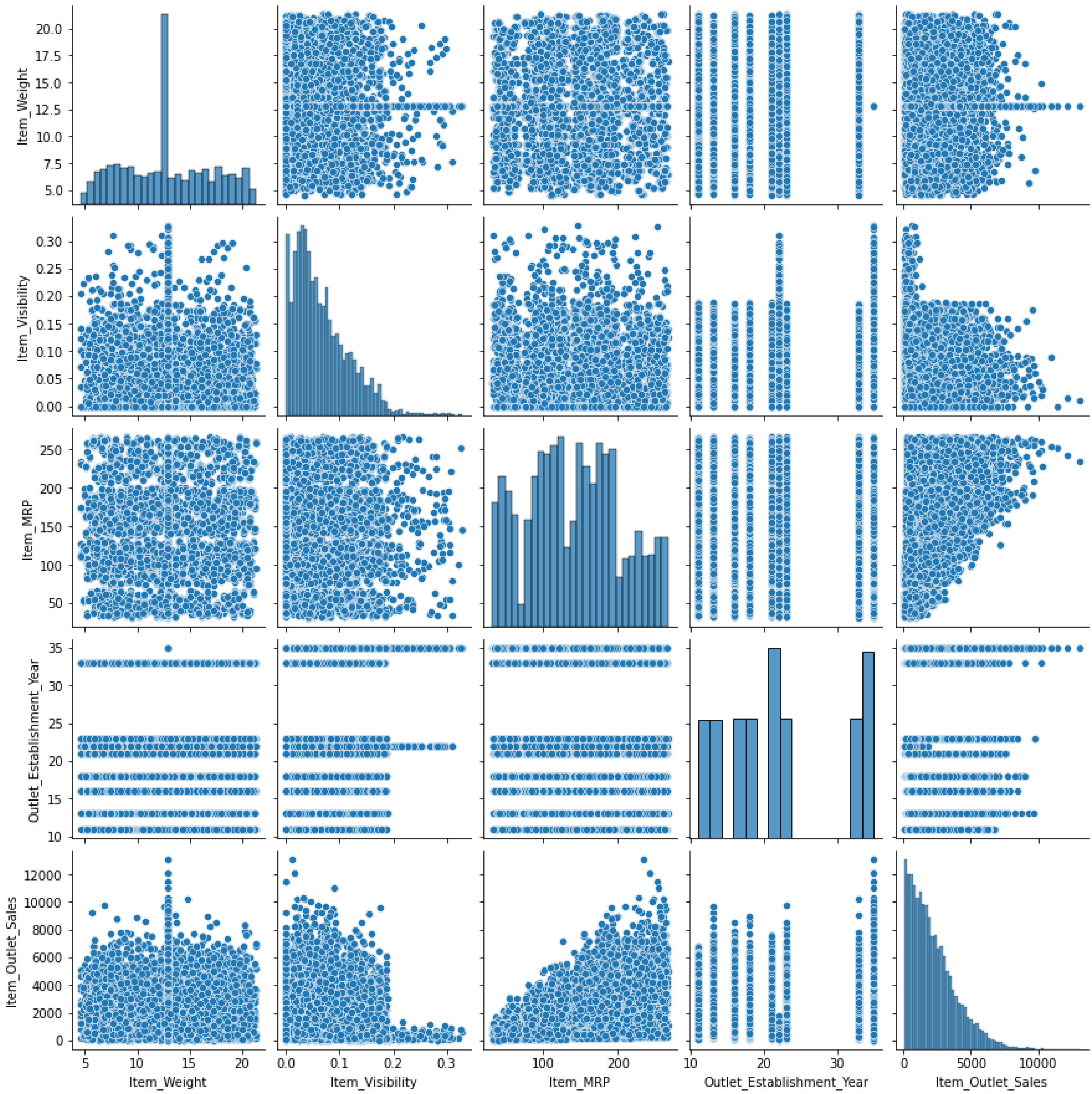
```
35    1463
33     932
23     930
21     930
16     930
18     929
11     928
13     926
22     555
Name: Outlet_Establishment_Year, dtype: int64
```

In [10]:

```
# Pairplot between only the int attributes

sns.pairplot(train)
```

Out[10]:

```
<seaborn.axisgrid.PairGrid at 0x7fc93c2b15f8>
```



Encoding

In [11]:

```
# We will be using Label Encoding for Categorical Variables.

from sklearn.preprocessing import LabelEncoder
train=train.apply(LabelEncoder().fit_transform)
```

In [12]:

```
# Shape of dataSet

train.shape
```

Out[12]:

```
(8523, 12)
```

In [13]:

```
# Removing Target Attribute

y=train['Item_Outlet_Sales']
X=train.drop('Item_Outlet_Sales',axis=1)
```

In [14]:

```
#No. of Unique values in target attribute.

y.nunique()
```

Out[14]:

```
3493
```

Feature Scaling

In [15]:

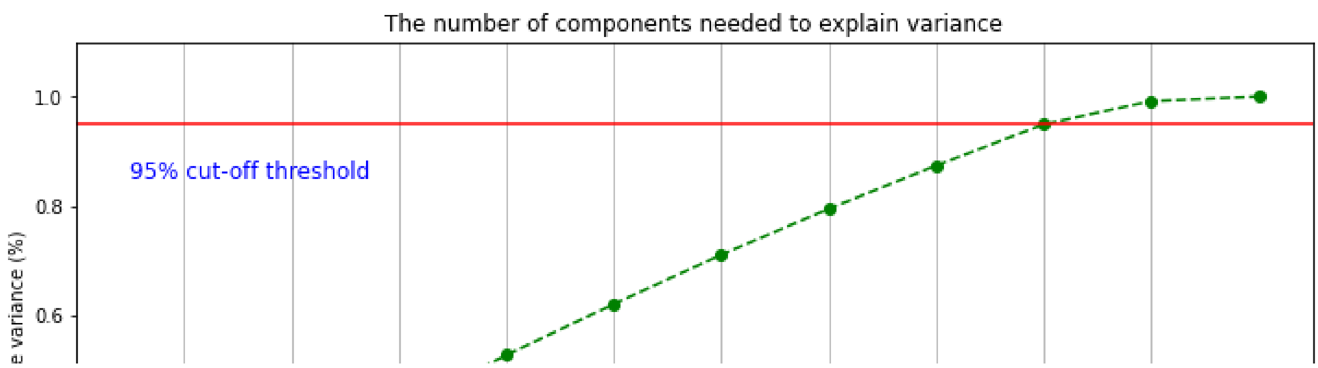
```
# Using Standard Scaling for Scaling the features.

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data= scaler.fit_transform(X)
```

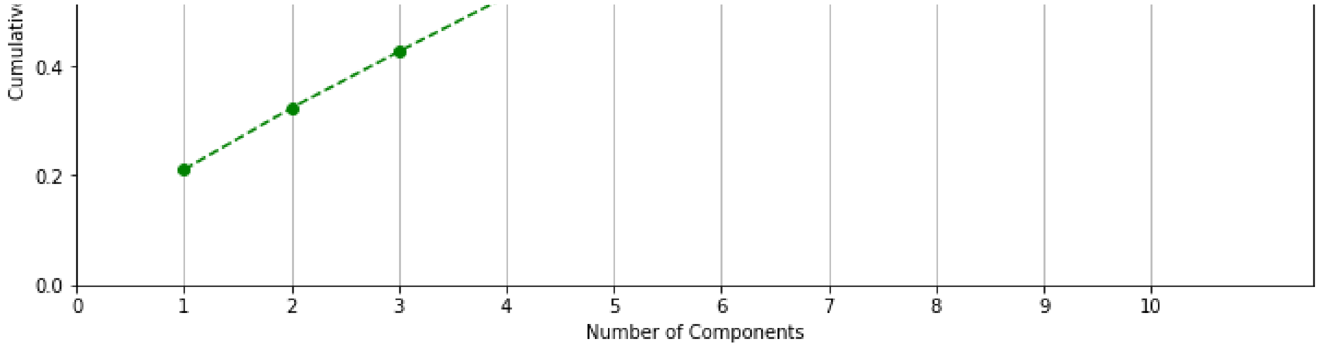
PCA

First we will try to find the best number of components of PCA neede to explain varience for this dataset.

In [16]:

```
pca = PCA().fit(data)
plt.rcParams["figure.figsize"] = (12,6)
fig, ax = plt.subplots()
xi = np.arange(1, 12, step=1)
y = np.cumsum(pca.explained_variance_ratio_)

plt.ylim(0.0,1.1)
plt.plot(xi, y, marker='o', linestyle='--', color='g')

plt.xlabel('Number of Components')
plt.xticks(np.arange(0, 11, step=1))
plt.ylabel('Cumulative variance (%)')
plt.title('The number of components needed to explain variance')

plt.axhline(y=0.95, color='r', linestyle='-')
plt.text(0.5, 0.85, '95% cut-off threshold', color = 'blue', fontsize=12)

ax.grid(axis='x')
plt.show()
```





We will be using number of components = 8.

In [17]:

```
# Reducing dimension of dataset.

pca=PCA(n_components=8)
X_reduced = pca.fit_transform(data)
```

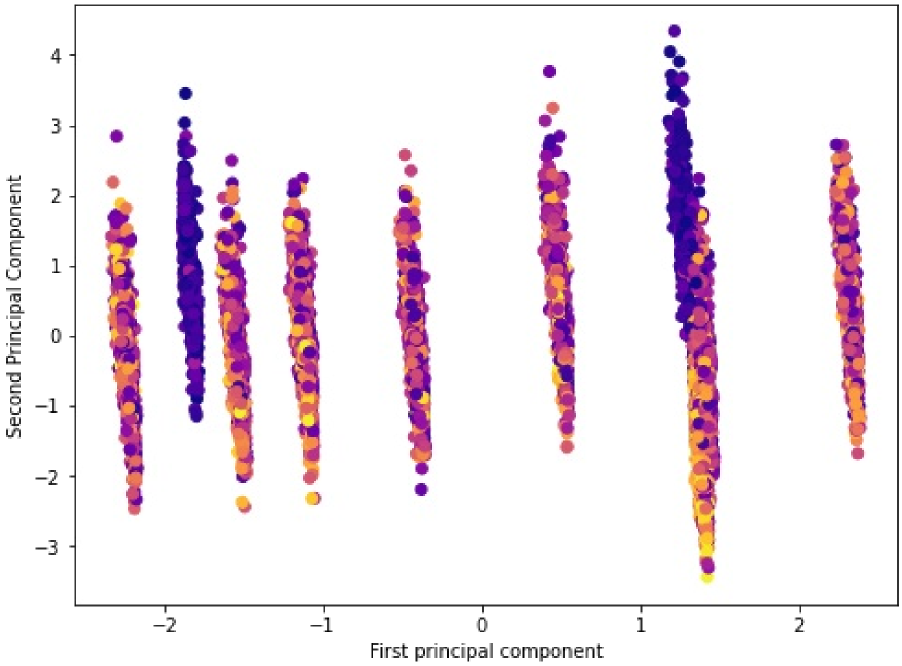
Plotting Different components of reduced Dataset.

In [18]:

```
plt.figure(figsize=(8,6))
plt.scatter(X_reduced[:,0],X_reduced[:,1],c=train['Item_Outlet_Sales'],cmap='plasma')
plt.xlabel('First principal component')
plt.ylabel('Second Principal Component')
```

Out[18]:

```
Text(0, 0.5, 'Second Principal Component')
```

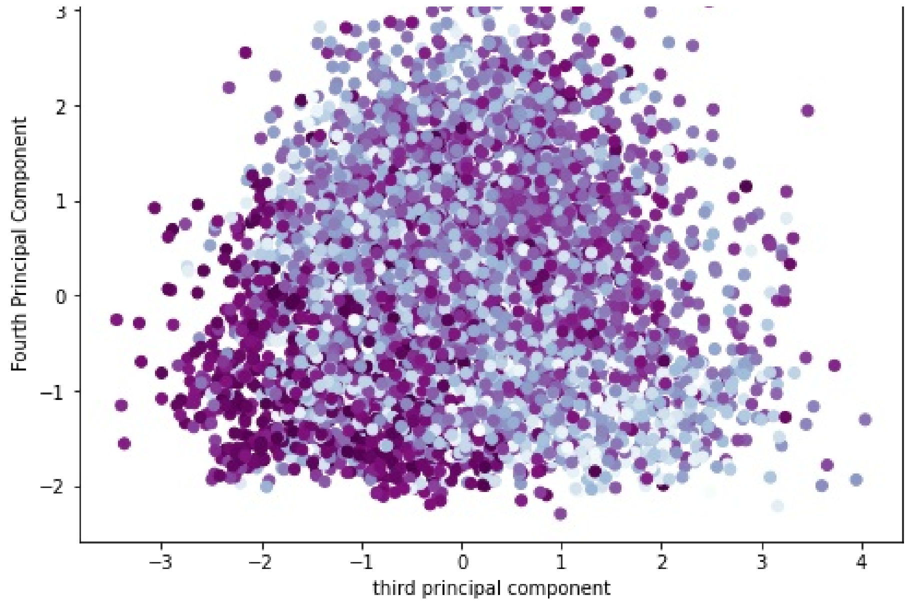


In [19]:

```
plt.figure(figsize=(8,6))
plt.scatter(X_reduced[:,2],X_reduced[:,3],c=train['Item_Outlet_Sales'],cmap='BuPu_r')
plt.xlabel('third principal component')
plt.ylabel('Fourth Principal Component')
```

Out[19]:

```
Text(0, 0.5, 'Fourth Principal Component')
```

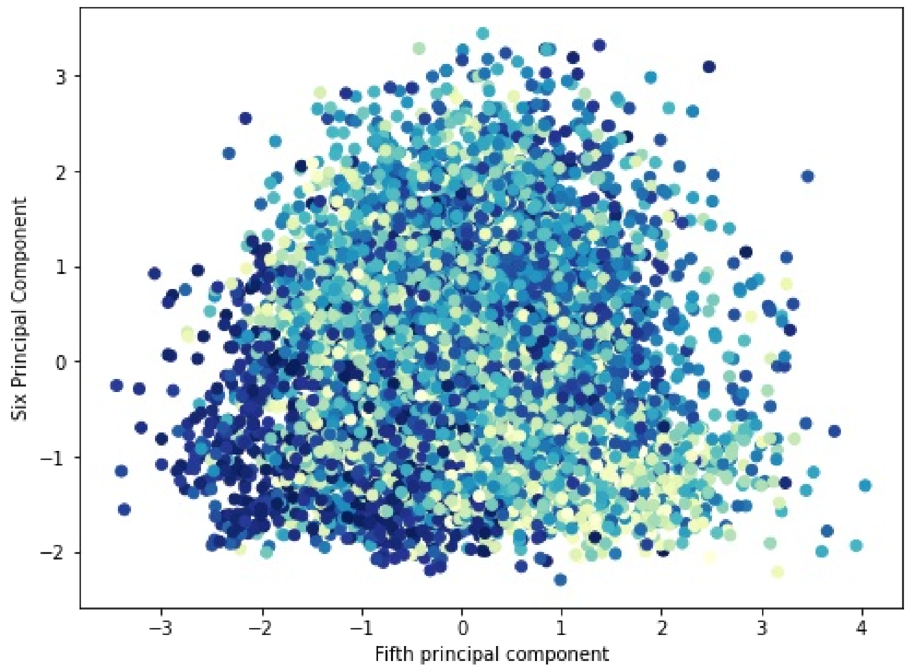


In [20]:

```
plt.figure(figsize=(8,6))
plt.scatter(X_reduced[:,2],X_reduced[:,3],c=train['Item_Outlet_Sales'],cmap='YlGnBu_r')
plt.xlabel('Fifth principal component')
plt.ylabel('Six Principal Component')
```

Out[20]:

```
Text(0, 0.5, 'Six Principal Component')
```



Eigen Values

In [21]:

```
## eigen values found

pca.explained_variance_
```

Out[21]:

```
array([2.32001808, 1.23974763, 1.13553087, 1.10430182, 1.02683609,
       0.99103803, 0.92397144, 0.87046028])
```

Eigen vectors / Pricipal Components

In [22]:

In [22]:

```python
## Eigen vectors found

pca.components_
```

Out[22]:

```
array([[ 0.00512111,  0.01843504,  0.00132496, -0.0242439 ,  0.00311068,
        -0.00352507, -0.51671924,  0.0047183 , -0.52741908,  0.61978444,
         0.26400308],
       [-0.21491984, -0.25479418,  0.35750947,  0.50872061, -0.30373805,
        -0.07523582, -0.32613097, -0.09906718, -0.03067543, -0.04000401,
        -0.53445811],
       [-0.35802384, -0.0679546 ,  0.55924353, -0.17710592, -0.43152486,
        -0.18455935,  0.28130028,  0.05169507,  0.01056746,  0.04168553,
         0.46813869],
       [-0.08559108, -0.56411535, -0.09999157, -0.35593341,  0.10630157,
        -0.08405195, -0.00891146, -0.71844944,  0.03632641,  0.03909148,
        -0.0173096 ],
       [-0.65389663,  0.1230145 ,  0.16867181,  0.05803785,  0.51428509,
         0.50761898,  0.00377117, -0.05359348,  0.00994157,  0.00958717,
         0.01498844],
       [-0.40250158, -0.01110635, -0.20525906,  0.04760589,  0.35498247,
        -0.78862416, -0.01211937,  0.20460656, -0.03442673, -0.02321587,
        -0.04237931],
       [-0.01795732, -0.74710244, -0.21967645,  0.21520165,  0.03182364,
         0.21936986,  0.14469887,  0.48153792, -0.07378835,  0.00181832,
         0.19886064],
       [ 0.03945078, -0.13180929,  0.28367636, -0.68534892,  0.08272242,
         0.04542844, -0.15229907,  0.40129518, -0.18894995, -0.13173306,
        -0.42976654]])
```

In [23]:

```python
# Creating pandas dataframe of the pca Components

df_comp = pd.DataFrame(pca.components_,columns=X.columns)
```

In [24]:

```python
df_comp
```

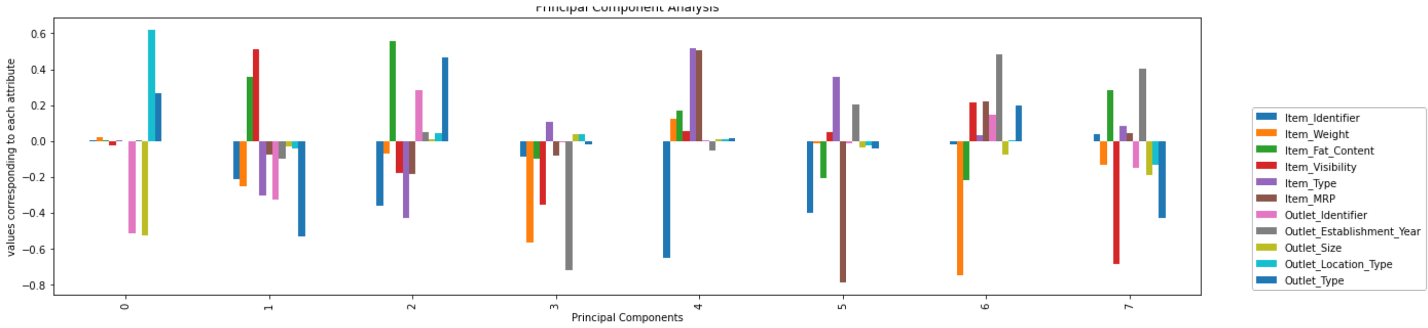
Out[24]:

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_
0	0.005121	0.018435	0.001325	-0.024244	0.003111	-0.003525	-0.516719	0.00
1	-0.214920	-0.254794	0.357509	0.508721	-0.303738	-0.075236	-0.326131	-0.09
2	-0.358024	-0.067955	0.559244	-0.177106	-0.431525	-0.184559	0.281300	0.05
3	-0.085591	-0.564115	-0.099992	-0.355933	0.106302	-0.084052	-0.008911	-0.71
4	-0.653897	0.123015	0.168672	0.058038	0.514285	0.507619	0.003771	-0.05
5	-0.402502	-0.011106	-0.205259	0.047606	0.354982	-0.788624	-0.012119	0.20
6	-0.017957	-0.747102	-0.219676	0.215202	0.031824	0.219370	0.144699	0.48
7	0.039451	-0.131809	0.283676	-0.685349	0.082722	0.045428	-0.152299	0.40

In [25]:

```python
ax=df_comp.plot(kind="bar",figsize=(20,5))
ax.set_xticks(df_comp.index)
ax.set_xticklabels(df_comp.index,rotation=90)
plt.title('Principal Component Analysis')
plt.xlabel('Principal Components')
plt.ylabel('values corresponding to each attribute')
plt.legend(loc=4 , bbox_to_anchor=(1.2, 0))
plt.show();
```

Principal Component Analysis

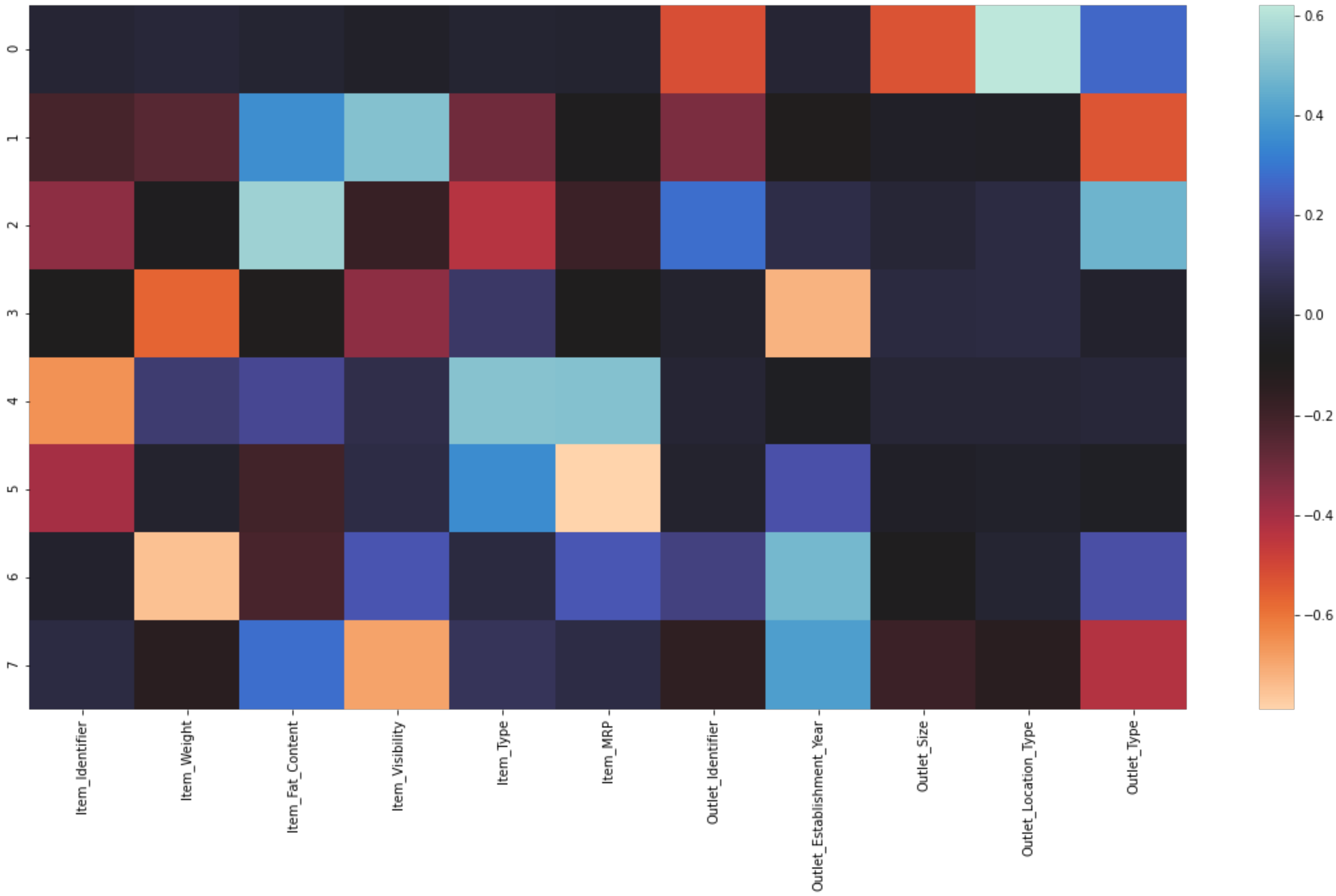


In [26]:

```
# heatmap

plt.figure(figsize=(20,10))
sns.heatmap(df_comp,cmap='icefire_r')
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc935c5f7b8>
```



Thank you.