EDA + Logistic Regression + PCA

Table of Contents

The contents of this kernel is divided into various topics which are as follows:-

Import python Liberaries

In [1]:
```
import numpy as np
import pandas as pd
```

import liberaries for plotting

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Ignore warning

In [3]:
```
import warnings
warnings.filterwarnings("ignore")
```

import dataset

In [4]:
```
df = pd.read_csv(r'E:\NIT(Data Science)by (prakash senapati sir (kodi))\Da
```

Exploratory Data Analysis

check the dataset

In [5]:
```
df.shape
```

Out[5]: (32561, 15)

there are 32561 instances and 15 attribute in the dataset

preview data

In [6]:

```
df.head()
```

Out[6]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationsh
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-fam
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-fam
2	66	?	186061	Some-college	10	Widowed	?	Unmarri
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarri
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-ch

View summary of dataframe

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Summary of the dataset shows that there are no missing values. But the preview shows that the dataset contains values coded as `?`. So, I will encode `?` as NaN values.

Encode ? as NaNs

In [8]:
```
df[df == "?"] = np.nan
```

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       30725 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      30718 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  31978 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

impute missing values with code

In [10]:
```
for col in ["workclass", "occupation", "native.country"]:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

check again for missing value

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

now there is no missing value

Setting feature vector and target variable

In [12]:
```
x = df.drop(["income"], axis=1)
```

In [13]:
```
y = df["income"]
```

In [14]:
```
x.head()
```

Out[14]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationsh
0	90	Private	77053	HS-grad	9	Widowed	Prof-specialty	Not-in-fam
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-fam
2	66	Private	186061	Some-college	10	Widowed	Prof-specialty	Unmarri
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarri
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-ch

Split data into separate train and test dataset

In [15]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
```

Feature Engineering

Encode categorical variables

In [17]:
```
from sklearn import preprocessing
```

In [18]:
```
categorical = ["workclass", "education", "marital.status", "occupation", '
for feature in categorical:
    le = preprocessing.LabelEncoder()
    x_train[feature] = le.fit_transform(x_train[feature])
    x_test[feature] = le.transform(x_test[feature])
```

Feature Scaling

In [19]:
```
from sklearn.preprocessing import StandardScaler
```

In [20]:
```
scaler = StandardScaler()
```

In [21]:
```
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)
```

In [22]:
```
pd.DataFrame(scaler.transform(x_test), columns = x.columns)
```

Out[22]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation
0	1.273263	-0.090641	0.798307	-1.107252	-1.980744	2.255673	1.232533
1	-1.436476	-0.090641	0.448823	0.184396	-0.423425	0.926666	-0.278542
2	-1.143531	-0.090641	-0.608164	1.217715	-0.034095	0.926666	0.225150
3	-0.118225	-2.781760	-1.332357	-0.332263	1.133894	-0.402341	0.728841
4	0.760610	-0.090641	2.202540	0.442726	1.523223	-0.402341	1.232533
...	...	...	...	...	...	...	...
9764	-0.118225	1.703439	-1.518569	0.184396	-0.423425	-0.402341	-0.530388
9765	-0.923823	-0.090641	-0.228829	0.184396	-0.423425	-0.402341	1.232533
9766	-0.997059	-0.090641	-0.312141	1.217715	-0.034095	0.926666	0.728841
9767	-0.337933	-0.090641	-0.393536	0.184396	-0.423425	0.926666	-0.026696
9768	0.833846	-0.090641	-0.901761	-0.590592	0.355234	-0.402341	-1.034080

9769 rows × 14 columns

In [23]:
```
x_train.head()
```

Out[23]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	r
0	0.101484	2.600478	-1.494279	-0.332263	1.133894	-0.402341	-0.782234	
1	0.028248	-1.884720	0.438778	0.184396	-0.423425	-0.402341	-0.026696	
2	0.247956	-0.090641	0.045292	1.217715	-0.034095	0.926666	-0.782234	
3	-0.850587	-1.884720	0.793152	0.184396	-0.423425	0.926666	-0.530388	
4	-0.044989	-2.781760	-0.853275	0.442726	1.523223	-0.402341	-0.782234	

Logistic Regression Model with all Features

In [24]:
```
from sklearn.linear_model import LogisticRegression
```

In [25]:
```
from sklearn.metrics import accuracy_score
```

In [26]:
```
logreg = LogisticRegression()
```

In [27]:
```
logreg.fit(x_train, y_train)
```

Out[27]:
```
▾ LogisticRegression
LogisticRegression()
```

In [28]:
```
y_pred = logreg.predict(x_test)
```

In [29]:
```
print("Logistic Regression accuracy score with all the feature: {0:0.4f}".
```

```
Logistic Regression accuracy score with all the feature: 0.2415
```

Logistic Regression with PCA

lets get to the PCA implementation

In [30]:
```
from sklearn.decomposition import PCA
```

In [31]:
```
pca = PCA()
```

In [32]:
```
x_train = pca.fit_transform(x_train)
```

In [33]:
```
pca.explained_variance_ratio_
```

Out[33]:
```
array([0.14757168, 0.10182915, 0.08147199, 0.07880174, 0.07463545,
       0.07274281, 0.07009602, 0.06750902, 0.0647268 , 0.06131155,
       0.06084207, 0.04839584, 0.04265038, 0.02741548])
```

We can see that approximately 97.25% of variance is explained by the first 13 variables.

-Only 2.75% of variance is explained by the last variable. So, we can assume that it carries little information.

-So, I will drop it, train the model again and calculate the accuracy.

Logistic Regression with first 13 feature

In [34]:
```
x = df.drop(["income","native.country"], axis=1)
```

In [35]:
```
y = df["income"]
```

In [36]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
```

In [37]:
```
categorical = ['workclass', 'education', 'marital.status', 'occupation',
for feature in categorical:
    le = preprocessing.LabelEncoder()
    x_train[feature] = le.fit_transform(x_train[feature])
    x_test[feature] = le.transform(x_test[feature])
```

In [38]:
```
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)
```

In [39]:
```
x_test = pd.DataFrame(scaler.transform(x_test), columns = x.columns)
```

In [40]:
```
logreg = LogisticRegression()
```

In [41]:
```
logreg.fit(x_train, y_train)
```

Out[41]:
```
▾ LogisticRegression
LogisticRegression()
```

In [42]:
```
y_pred = logreg.predict(x_test)
```

In [43]:
```
print('Logistic Regression accuracy score with the first 13 features: {0:0
```

```
Logistic Regression accuracy score with the first 13 features: 0.8213
```

Logistic Regression WITH FIRST 12 feature

In [44]:
```
x = df.drop(["income","native.country", "hours.per.week"], axis=1)
```

In [45]:
```
y = df["income"]
```

In [46]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
```

In [47]:
```
categorical = ['workclass', 'education', 'marital.status', 'occupation',
for feature in categorical:
    le = preprocessing.LabelEncoder()
    x_train[feature] = le.fit_transform(x_train[feature])
    x_test[feature] = le.transform(x_test[feature])
```

In [48]:
```
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)
```

In [49]:
```
x_test = pd.DataFrame(scaler.transform(x_test), columns = x.columns)
```

In [50]:
```
logreg.fit(x_train, y_train)
```

Out[50]:
```
▾ LogisticRegression
LogisticRegression()
```

In [51]:
```
y_pred = logreg.predict(x_test)
```

In [52]:
```
print('Logistic Regression accuracy score with the first 13 features: {0:0
```

```
Logistic Regression accuracy score with the first 13 features: 0.8227
```

Logistic Regression WITH FIRST 11 feature

In [53]:
```
x = df.drop(["income","native.country", "hours.per.week", "capital.loss"],
```

In [54]:
```
y = df["income"]
```

In [55]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
```

In [56]:
```
categorical = ['workclass', 'education', 'marital.status', 'occupation',
for feature in categorical:
    le = preprocessing.LabelEncoder()
    x_train[feature] = le.fit_transform(x_train[feature])
    x_test[feature] = le.transform(x_test[feature])
```

In [57]:
```
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)
```

In [58]:
```
x_test = pd.DataFrame(scaler.transform(x_test), columns = x.columns)
```

In [59]:
```
logreg.fit(x_train, y_train)
```

Out[59]:
```
▾ LogisticRegression
LogisticRegression()
```

In [60]:
```
y_pred = logreg.predict(x_test)
```

In [61]:
```
print('Logistic Regression accuracy score with the first 13 features: {0:(
```

```
Logistic Regression accuracy score with the first 13 features: 0.8186
```

:-We can see that accuracy has significantly decreased to 0.8187 if I drop the last three features.

-Our aim is to maximize the accuracy. We get maximum accuracy with the first 12 features and the accuracy is 0.8227.

Select right number of dimentions

In [62]:
```
x = df.drop(["income"], axis=1)
```

In [63]:
```
y = df["income"]
```

In [64]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
```

In [65]:
```
categorical = ['workclass', 'education', 'marital.status', 'occupation',
for feature in categorical:
    le = preprocessing.LabelEncoder()
    x_train[feature] = le.fit_transform(x_train[feature])
    x_test[feature] = le.transform(x_test[feature])
```

In [66]:
```
x_train = pd.DataFrame(scaler.fit_transform(x_test), columns = x.columns)
```

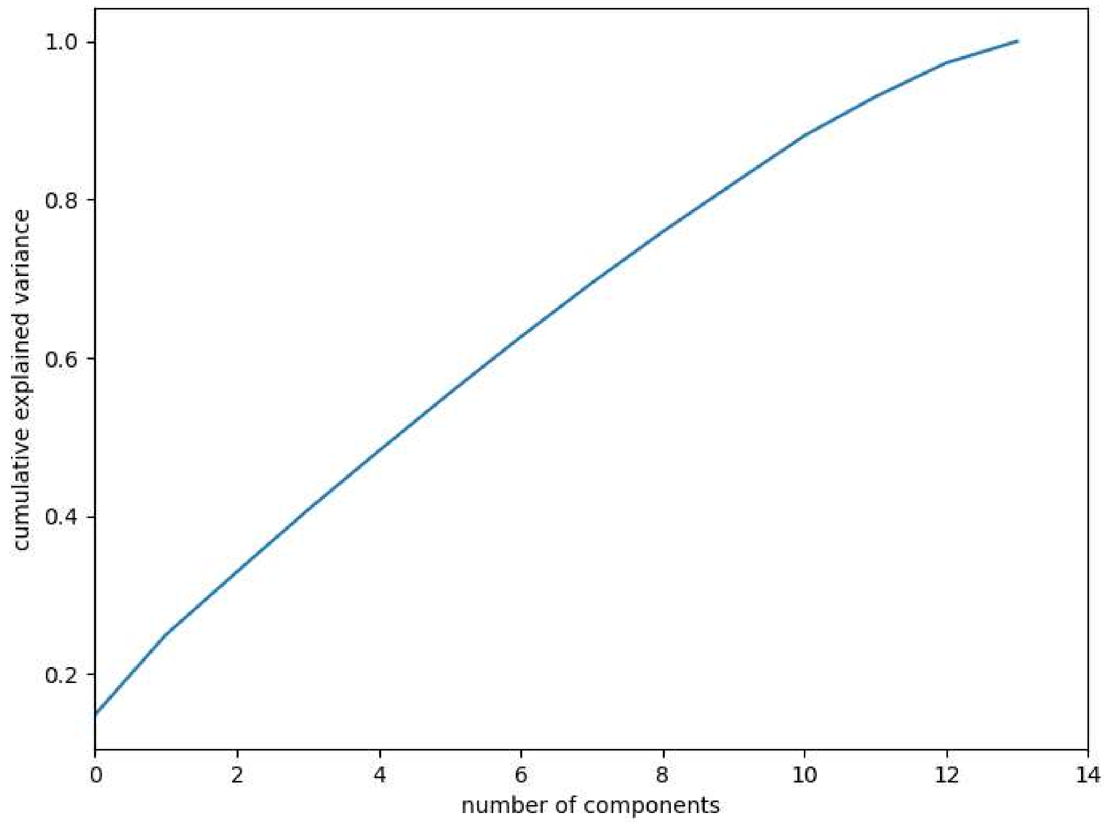
In [67]:
```
pca = PCA()
pca.fit(x_train)
cumsum = np.cumsum(pca.explained_variance_ratio_)
dim = np.argmax(cumsum >= 0.90) + 1
```

In [68]:
```
print("The numnber of dimensions required to preserve 90% of variance is",
```

```
The numnber of dimensions required to preserve 90% of variance is 12
```

plot explained variance ratio with number of dimensions

In [69]:
```
plt.figure(figsize=(8,6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlim(0,14,1)
plt.xlabel("number of components")
plt.ylabel("cumulative explained variance")
plt.show()
```



Conclusion

-In this kernel, I have discussed Principal Component Analysis – the most popular dimensionality reduction technique.

-I have demonstrated PCA implementation with Logistic Regression on the adult dataset.

-I found the maximum accuracy with the first 12 features and it is found to be 0.8227.

-As expected, the number of dimensions required to preserve 90 % of variance is found to be 12.

-Finally, I plot the explained variance ratio with number of dimensions. The graph confirms that approximately 90% of variance is explained by the first 12 components.

In [ ]: