KNN MODEL TO DETERMINE THE INCOME LEVEL FOR US RESIDENTS

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
font={'family':'serif','color':'black','size':15,'fontweight':'bold'}
df=pd.read_csv("/content/adult.csv")
df
```

Out[1]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gen
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	M
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	M
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	M
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	M
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Fen
...	...	...	...	...	...	...	...	...	...	
19235	26	Private	240842	HS-grad	9	Never-married	Machine-op-inspct	Unmarried	Black	Fen
19236	53	Private	103931	Some-college	10	Married-civ-spouse	Prof-specialty	Husband	White	M
19237	60	Private	232618	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
19238	49	Local-gov	288548	Masters	14	Separated	Prof-specialty	Unmarried	White	Fen
19239	40	Private	220609	Some-college	10	Divorced	Exec-managerial	Not-in-family	White	Fen

19240 rows × 15 columns

In [2]:
```
# CHECK THE DATASET FOR INFORMATION ABOUT US
df['native-country'].value_counts()
```

Out[2]:
```
United-States                 17318
Mexico                          362
?                               332
Philippines                     110
Germany                          81
Puerto-Rico                      80
Canada                           77
India                            59
El-Salvador                      56
China                            56
Cuba                             53
England                          47
Dominican-Republic               41
Italy                            41
South                            40
Japan                            37
Haiti                            36
Portugal                         35
Poland                           33
Jamaica                          31
Columbia                         28
Guatemala                        27
Greece                           24
Iran                             22
Vietnam                          21
Taiwan                           20
Nicaragua                        19
Ecuador                          18
Peru                             16
Thailand                         14
Ireland                          13
Cambodia                         11
Hong                             11
Outlying-US(Guam-USVI-etc)       10
Trinadad&Tobago                  10
France                           10
Scotland                         10
Honduras                         10
Yugoslavia                        8
Hungary                           6
Laos                              6
Name: native-country, dtype: int64
```

In [3]:
```
# FILTER DATA FOR NATIVE COUNTRY: UNITED STATES
df1=df.loc[df['native-country']=='United-States']
df1
```

Out[3]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gen
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	M
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	M
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	M
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	M
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Fen
...	...	...	...	...	...	...	...	...	...	
19234	34	Private	225548	Bachelors	13	Married-civ-spouse	Protective-serv	Husband	Black	M
19235	26	Private	240842	HS-grad	9	Never-married	Machine-op-inspct	Unmarried	Black	Fen
19236	53	Private	103931	Some-college	10	Married-civ-spouse	Prof-specialty	Husband	White	M
19237	60	Private	232618	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
19238	49	Local-gov	288548	Masters	14	Separated	Prof-specialty	Unmarried	White	Fen

17318 rows × 15 columns

In [4]:
```
df1.shape
```

Out[4]: (17318, 15)

In [5]:
```
df1.size
```

Out[5]: 259770

In [6]:
```
df1.head()
```

Out[6]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	c
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	

In [7]:
```
df1.tail()
```

Out[7]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gen
19234	34	Private	225548	Bachelors	13	Married-civ-spouse	Protective-serv	Husband	Black	M
19235	26	Private	240842	HS-grad	9	Never-married	Machine-op-inspct	Unmarried	Black	Fen
19236	53	Private	103931	Some-college	10	Married-civ-spouse	Prof-specialty	Husband	White	M
19237	60	Private	232618	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
19238	49	Local-gov	288548	Masters	14	Separated	Prof-specialty	Unmarried	White	Fen

In [8]:
```
df1.columns
```

Out[8]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income'],
      dtype='object')
```

In [9]:
```
df1.dtypes
```

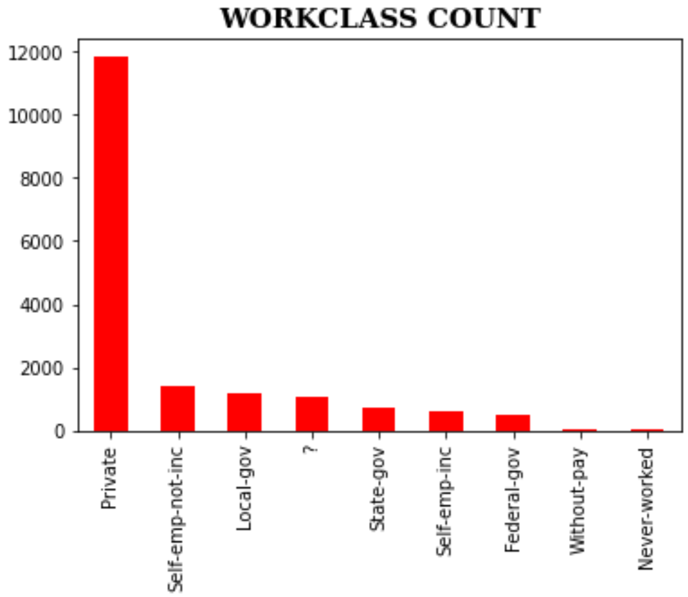
Out[9]:
```
age                  int64
workclass           object
fnlwgt               int64
education           object
educational-num      int64
marital-status      object
occupation          object
relationship        object
race                object
gender              object
capital-gain         int64
capital-loss       float64
hours-per-week     float64
native-country      object
income              object
dtype: object
```

In [ ]:
```
df1.isna().sum()
```

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

In [10]:
```python
# COUNT AND VISUALIZE
# 1.COLUMN: workclass
work=df1['workclass'].value_counts()
print(work)
work.plot(kind='bar',color='red')
plt.title("WORKCLASS COUNT",fontdict=font)
plt.show()
```

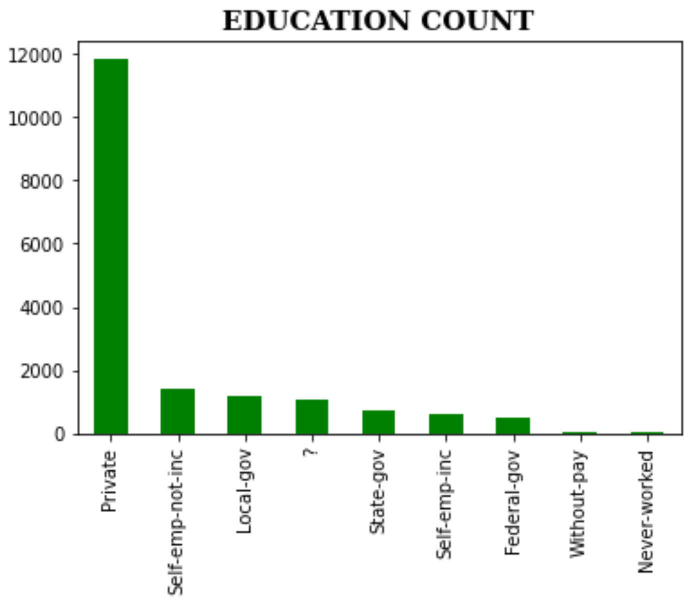
```
Private             11826
Self-emp-not-inc     1403
Local-gov            1171
?                    1044
State-gov             739
Self-emp-inc          616
Federal-gov           508
Without-pay             8
Never-worked            3
Name: workclass, dtype: int64
```



In [11]:

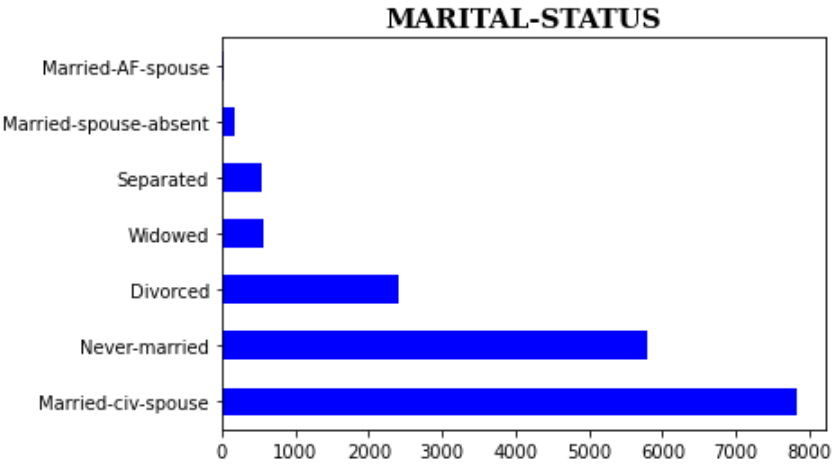
```
# 2.COLUMN: education
edu=df1['education'].value_counts()
print(edu)
work.plot(kind='bar',color='green')
plt.title("EDUCATION COUNT",fontdict=font)
plt.show()
```

```
HS-grad         5762
Some-college    3951
Bachelors       2856
Masters          970
Assoc-voc        748
11th             704
Assoc-acdm       573
10th             491
7th-8th          283
Prof-school      264
9th              225
12th             217
Doctorate        171
5th-6th           70
1st-4th           23
Preschool         10
Name: education, dtype: int64
```



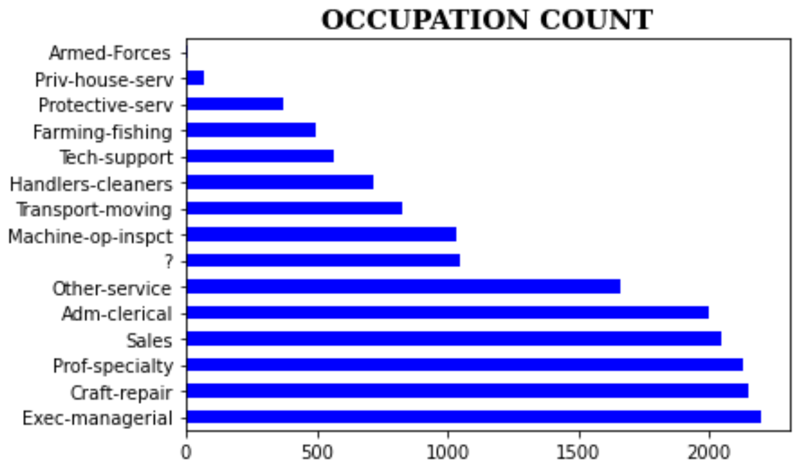
In [12]:
```
# 3.COLUMN: marital-status
mar=df1['marital-status'].value_counts()
print(mar)
mar.plot(kind='barh',color='blue')
plt.title("MARITAL-STATUS",fontdict=font)
plt.show()
```

```
Married-civ-spouse       7829
Never-married            5787
Divorced                 2419
Widowed                   570
Separated                 531
Married-spouse-absent     166
Married-AF-spouse          16
Name: marital-status, dtype: int64
```



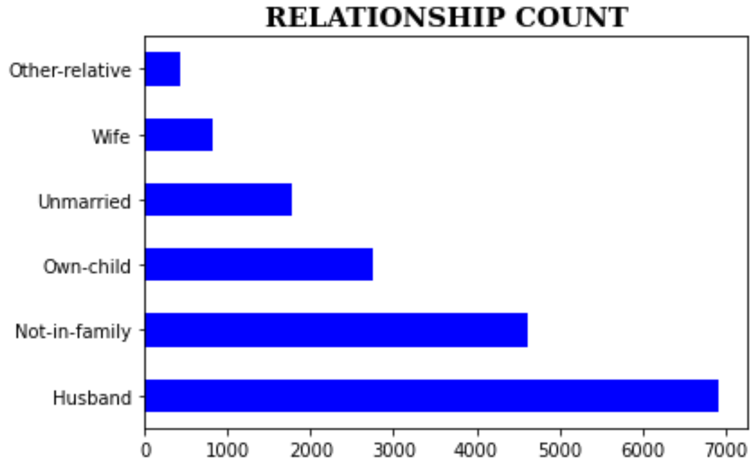
In [13]:
```
# 4.COLUMN: occupation
occ=df1['occupation'].value_counts()
print(occ)
occ.plot(kind='barh',color='blue')
plt.title("OCCUPATION COUNT",fontdict=font)
plt.show()
```

```
Exec-managerial      2197
Craft-repair         2148
Prof-specialty       2129
Sales                2044
Adm-clerical         2000
Other-service        1661
?                    1047
Machine-op-inspct    1033
Transport-moving      829
Handlers-cleaners     718
Tech-support          566
Farming-fishing       496
Protective-serv       371
Priv-house-serv        72
Armed-Forces            7
Name: occupation, dtype: int64
```



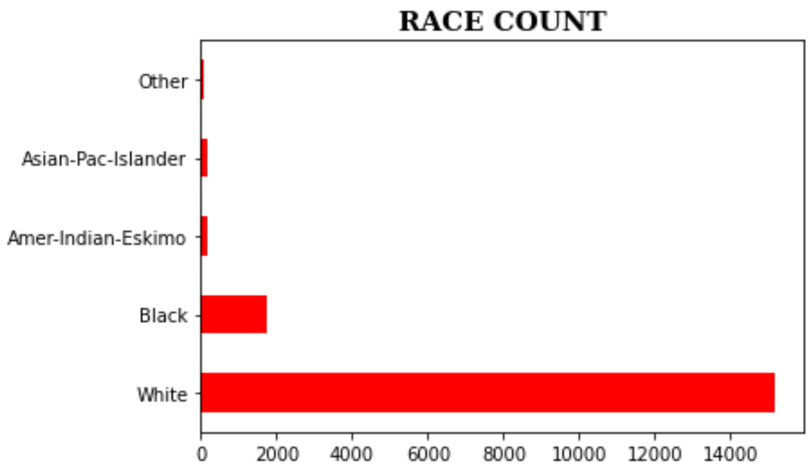
In [14]:
```
# 5.COLUMN: relationship
rel=df1['relationship'].value_counts()
print(rel)
rel.plot(kind='barh',color='blue')
plt.title("RELATIONSHIP COUNT",fontdict=font)
plt.show()
```

```
Husband           6920
Not-in-family     4619
Own-child         2747
Unmarried         1772
Wife               820
Other-relative     440
Name: relationship, dtype: int64
```



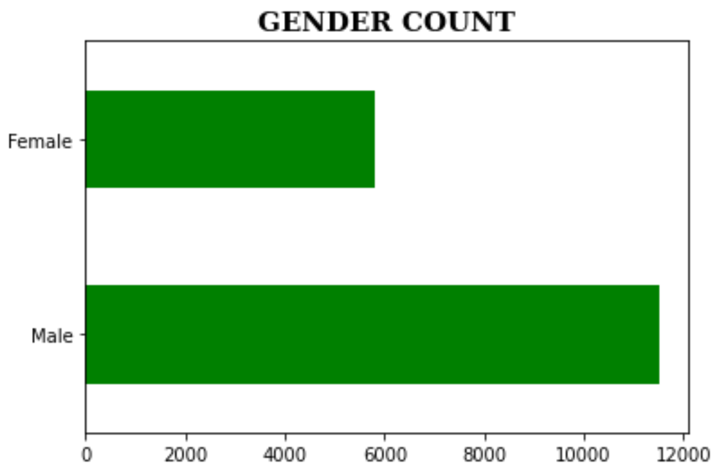
In [15]:
```
# 6.COLUMN: race
race=df1['race'].value_counts()
print(race)
race.plot(kind='barh',color='red')
plt.title("RACE COUNT",fontdict=font)
plt.show()
```

```
White                 15178
Black                  1725
Amer-Indian-Eskimo      182
Asian-Pac-Islander      164
Other                    69
Name: race, dtype: int64
```



In [16]:
```
# 7.COLUMN: gender
gen=df1['gender'].value_counts()
print(gen)
gen.plot(kind='barh',color='green')
plt.title("GENDER COUNT",fontdict=font)
plt.show()
```

```
Male      11525
Female     5793
Name: gender, dtype: int64
```



In [17]:
```
# GET DUMMY ENCODING
dummy=pd.get_dummies(df1[['workclass','education','marital-status','occupat
ion',\
                          'relationship','race','gender']],drop_first=True)
```

In [18]:
```
# CONCATENATE
df2=pd.concat([df1,dummy],axis=1)
df2
```

Out[18]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gen
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	M
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	M
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	M
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	M
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Fen
...	...	...	...	...	...	...	...	...	...	
19234	34	Private	225548	Bachelors	13	Married-civ-spouse	Protective-serv	Husband	Black	M
19235	26	Private	240842	HS-grad	9	Never-married	Machine-op-inspct	Unmarried	Black	Fen
19236	53	Private	103931	Some-college	10	Married-civ-spouse	Prof-specialty	Husband	White	M
19237	60	Private	232618	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
19238	49	Local-gov	288548	Masters	14	Separated	Prof-specialty	Unmarried	White	Fen

17318 rows × 68 columns

In [19]:
```
# DROP UNWANTED COLUMNS
df3=df2.drop(['workclass','education','marital-status','occupation',\
                         'relationship','race','gender','native-country'],a
xis=1)
```

In [20]:
```
# SEPERATING INPUT X AND OUTPUT Y
x=df3.drop(['income'],axis=1).values
y=df3['income'].values
```

In [21]:
```
# SEPERATING TRAIN-TEST DATA
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_st
ate=42)
```

In [22]:
```
# NORMALIZATION
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(x_train)
x_train=scaler.transform(x_train)
x_test=scaler.transform(x_test)
```

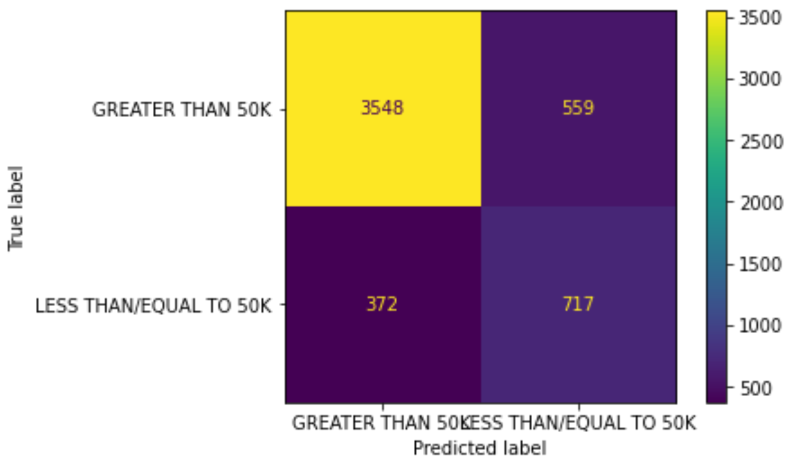
In [23]:
```
# KNN ALGORITHM
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=7)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
```

In [24]:
```
# PERFORMANCE EVALUATION
from sklearn.metrics import confusion_matrix,accuracy_score,ConfusionMatrix
Display,classification_report
mat=confusion_matrix(y_pred,y_test)
mat
```

Out[24]:
```
array([[3548,  559],
       [ 372,  717]])
```

In [25]:
```
label=['GREATER THAN 50K','LESS THAN/EQUAL TO 50K']
cmd=ConfusionMatrixDisplay(mat,display_labels=label)
cmd.plot()
```

Out[25]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fd3323
c7a60>
```



In [26]:
```
score=accuracy_score(y_pred,y_test)
score
```

Out[26]:
```
0.8208237105465743
```

In [27]:
```
report=classification_report(y_test,y_pred)
print(report)
```

```
              precision    recall  f1-score   support

       <=50K       0.86      0.91      0.88      3920
        >50K       0.66      0.56      0.61      1276

    accuracy                           0.82      5196
   macro avg       0.76      0.73      0.75      5196
weighted avg       0.81      0.82      0.82      5196
```