Random Forest Q2 (Fraud check)

Use Random ForestRandom Forest to prepare a model on fraud data
treating those who have taxable_income <= 30000 as "Risky" and others are "Good"

1. Import Libs

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import metrics
from sklearn import externals
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
```

2. Import Data

In [2]:

```
fraud_check = pd.read_csv('Fraud_check.csv')
fraud_check
```

Out[2]:

	Undergrad	Marital.Status	Taxable.Income	City.Population	Work.Experience	Urban
0	NO	Single	68833	50047	10	YES
1	YES	Divorced	33700	134075	18	YES
2	NO	Married	36925	160205	30	YES
3	YES	Single	50190	193264	15	YES
4	NO	Married	81002	27533	28	NO
...	...	...	...	...	...	...
595	YES	Divorced	76340	39492	7	YES
596	YES	Divorced	69967	55369	2	YES
597	NO	Divorced	47334	154058	0	YES
598	YES	Married	98592	180083	17	NO
599	NO	Divorced	96519	158137	16	NO

600 rows × 6 columns

3. EDA

In [3]:

```
fraud_check.describe()
```

Out[3]:

	Taxable.Income	City.Population	Work.Experience
count	600.000000	600.000000	600.000000
mean	55208.375000	108747.368333	15.558333
std	26204.827597	49850.075134	8.842147
min	10003.000000	25779.000000	0.000000
25%	32871.500000	66966.750000	8.000000
50%	55074.500000	106493.500000	15.000000
75%	78611.750000	150114.250000	24.000000
max	99619.000000	199778.000000	30.000000

In [4]:

```
fraud_check.isna().sum()
```

Out[4]:

```
Undergrad          0
Marital.Status     0
Taxable.Income     0
City.Population    0
Work.Experience    0
Urban              0
dtype: int64
```

In [5]:

```
fraud_check.dtypes
```

Out[5]:

```
Undergrad          object
Marital.Status     object
Taxable.Income      int64
City.Population     int64
Work.Experience     int64
Urban              object
dtype: object
```

checking outliers

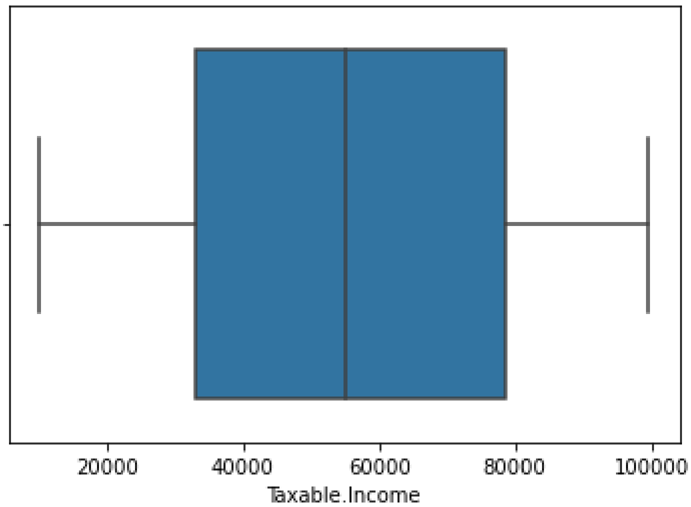
In [6]:

```
sns.boxplot(fraud_check['Taxable.Income'])
```

```
C:\Users\shubham\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futu
reWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretati
on.
  warnings.warn(
```

Out[6]:

```
<AxesSubplot:xlabel='Taxable.Income'>
```

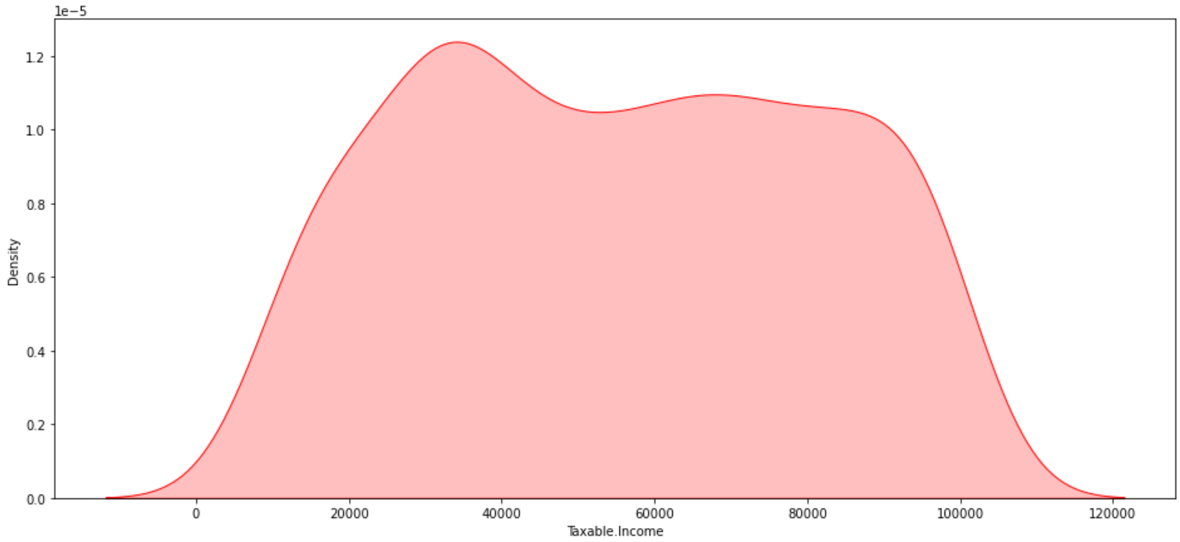


There are no outliers in the data

In [7]:

```
plt.figure(figsize=(16,7))
print("Skewness =",fraud_check['Taxable.Income'].skew())
print("Kurtosis =",fraud_check['Taxable.Income'].kurtosis())
sns.kdeplot(fraud_check['Taxable.Income'],shade=True,color='r')
plt.show()
```

```
Skewness = 0.030014788906377175
Kurtosis = -1.1997824607083138
```



Sales Data is skewed to the right and Data has negative kurtosis

In [8]:

```
obj_colum = fraud_check.select_dtypes(include='object')
obj_colum
```

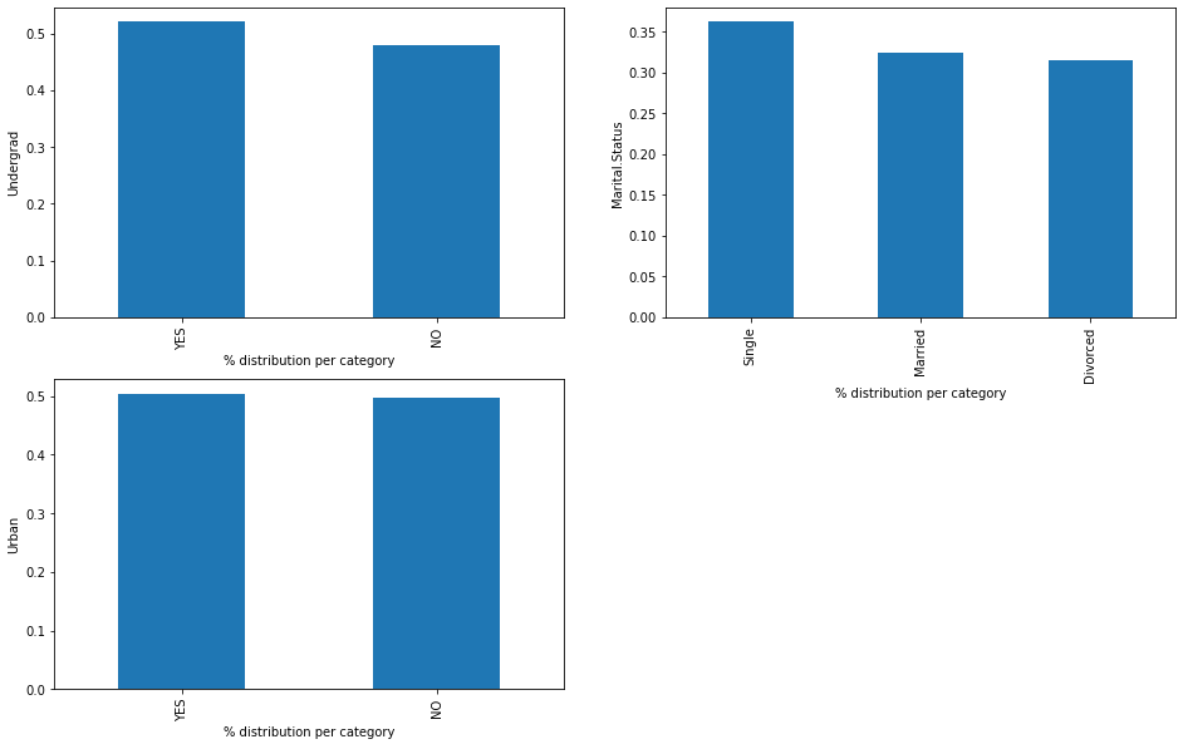
Out[8]:

	Undergrad	Marital.Status	Urban
0	NO	Single	YES
1	YES	Divorced	YES
2	NO	Married	YES
3	YES	Single	YES
4	NO	Married	NO
...	...	...	...
595	YES	Divorced	YES
596	YES	Divorced	YES
597	NO	Divorced	YES
598	YES	Married	NO
599	NO	Divorced	NO

600 rows × 3 columns

In [9]:

```
plt.figure(figsize=(16,10))
for i,col in enumerate(obj_colum,1):
    plt.subplot(2,2,i)
    fraud_check[col].value_counts(normalize=True).plot.bar()
    plt.ylabel(col)
    plt.xlabel('% distribution per category')
```



In [10]:

```
num_columns = fraud_check.select_dtypes(include=['float64','int64'])
num_columns
```

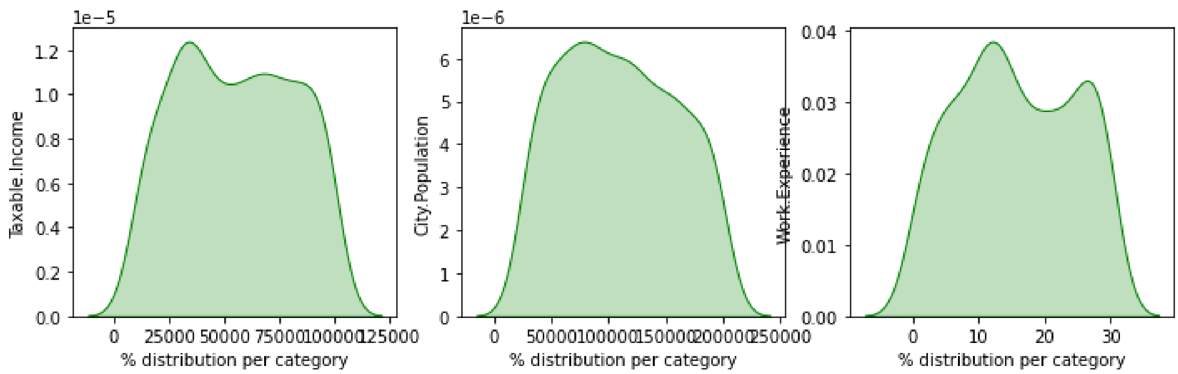
Out[10]:

	Taxable.Income	City.Population	Work.Experience
0	68833	50047	10
1	33700	134075	18
2	36925	160205	30
3	50190	193264	15
4	81002	27533	28
...	...	...	...
595	76340	39492	7
596	69967	55369	2
597	47334	154058	0
598	98592	180083	17
599	96519	158137	16

600 rows × 3 columns

In [11]:

```
plt.figure(figsize=(16,30))
for i,col in enumerate(num_columns,1):
    plt.subplot(8,4,i)
    sns.kdeplot(fraud_check[col],color='g',shade=True)
    plt.ylabel(col)
    plt.xlabel('% distribution per category')
```



In [12]:

```
pd.DataFrame(data=[num_columns.skew(),num_columns.kurtosis()],index=['skewness','kurtosis']
```

Out[12]:

	Taxable.Income	City.Population	Work.Experience
skewness	0.030015	0.125009	0.018529
kurtosis	-1.199782	-1.120154	-1.167524

In [13]:

```
df = pd.get_dummies(fraud_check, columns = ['Undergrad','Marital.Status','Urban'])
```

In [14]:

```
df
```

Out[14]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.S
0	68833	50047	10	1	0	
1	33700	134075	18	0	1	
2	36925	160205	30	1	0	
3	50190	193264	15	0	1	
4	81002	27533	28	1	0	
...	...	...	...	...	...	
595	76340	39492	7	0	1	
596	69967	55369	2	0	1	
597	47334	154058	0	1	0	
598	98592	180083	17	0	1	
599	96519	158137	16	1	0	

600 rows × 10 columns

In [15]:

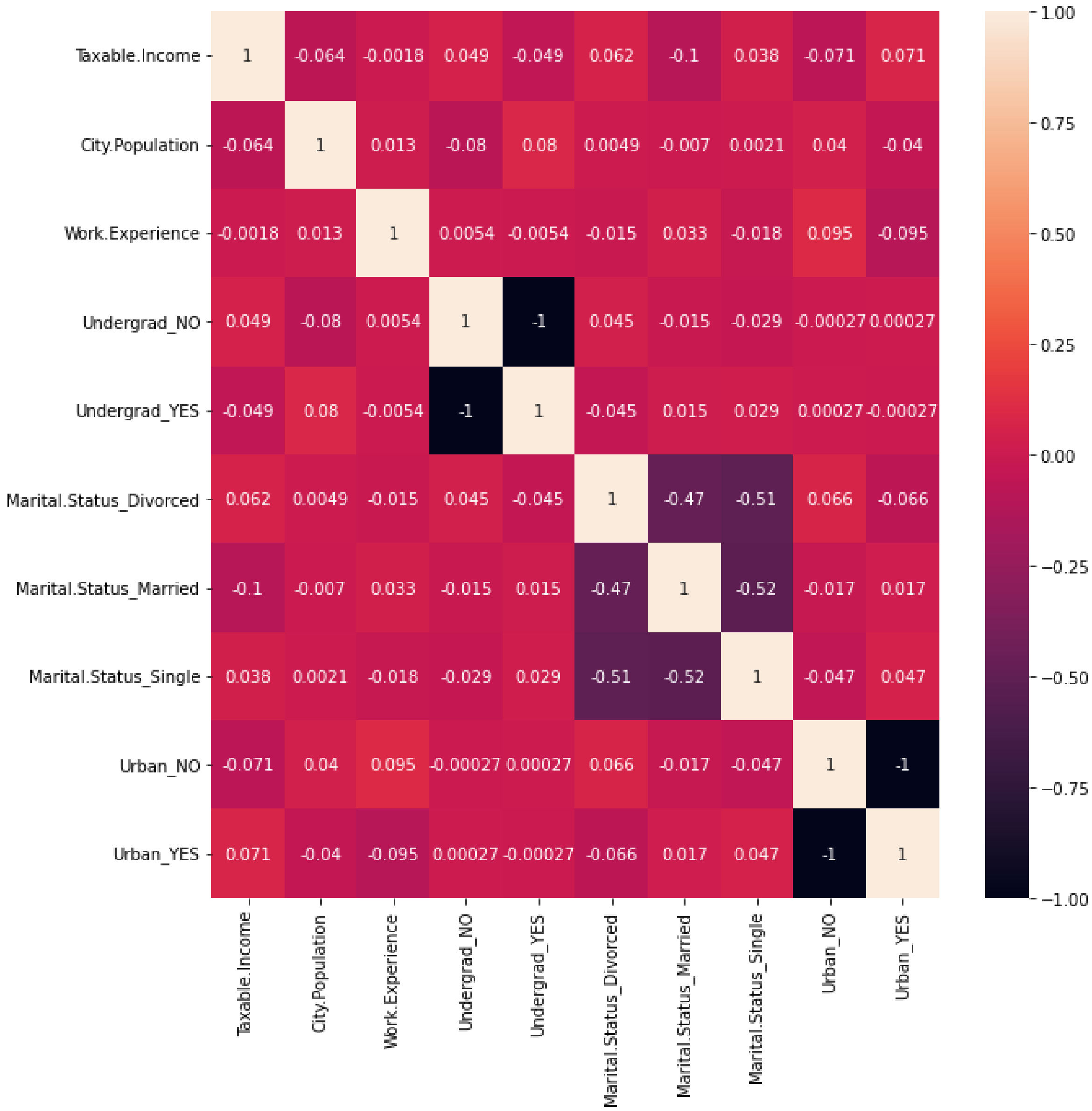
```
corr = df.corr()
```

In [16]:

```
plt.figure(figsize=(10,10))
sns.heatmap(corr,annot=True)
```

Out[16]:

<AxesSubplot:>



4. Model Building

Since the target variable is continious, we create a class of taxable_income <= 30000 as "Risky" and others are "Good"

In [17]:

```
df["Taxable.Income"]
```

Out[17]:

```
0      68833
1      33700
2      36925
3      50190
4      81002
       ...
595    76340
596    69967
597    47334
598    98592
599    96519
Name: Taxable.Income, Length: 600, dtype: int64
```

for <= 30000 = "Risky" and > 30000 = "Good"

Use cut when you need to segment and sort data values into bins. This function is also useful for going from a continuous variable to a categorical variable.

In [18]:

```
df['Taxable.Income'] = pd.cut(df["Taxable.Income"],bins=[0,30000,100000],labels=['Riskey','
```

Droping the Sales column

In [19]:

```
df.head(20)
```

Out[19]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.St
0	Good	50047	10	1	0	
1	Good	134075	18	0	1	
2	Good	160205	30	1	0	
3	Good	193264	15	0	1	
4	Good	27533	28	1	0	
5	Good	116382	0	1	0	
6	Good	80890	8	1	0	
7	Good	131253	3	0	1	
8	Good	102481	12	1	0	
9	Good	155482	4	0	1	
10	Riskey	102602	19	1	0	
11	Good	94875	6	1	0	
12	Riskey	148033	14	1	0	
13	Good	86649	16	1	0	
14	Good	57529	13	1	0	
15	Good	107764	29	1	0	
16	Riskey	34551	29	0	1	
17	Good	57194	25	0	1	
18	Good	59269	6	0	1	
19	Riskey	126953	30	1	0	

In [20]:

```
x = df.iloc[:,1:10]
x
```

Out[20]:

	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced
0	50047	10	1	0	0
1	134075	18	0	1	1
2	160205	30	1	0	0
3	193264	15	0	1	0
4	27533	28	1	0	0
...	...	...	...	...	...
595	39492	7	0	1	1
596	55369	2	0	1	1
597	154058	0	1	0	1
598	180083	17	0	1	0
599	158137	16	1	0	1

600 rows × 9 columns

In [21]:

```
y =df['Taxable.Income']

df['Taxable.Income'].value_counts()
```

Out[21]:

```
Good      476
Riskey    124
Name: Taxable.Income, dtype: int64
```

5. Model Traning

Decision Tree - Model using Entropy Criteria and Gini Criteria

Splitting data into training and testing data set

In [22]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2, stratify = y)
```

In [23]:

```
y_train.value_counts()
```

Out[23]:

```
Good      381
Riskey     99
Name: Taxable.Income, dtype: int64
```

Building Decision Tree Classifier using Entropy Criteria

In [24]:

```
model =RandomForestClassifier(n_jobs=4,n_estimators = 150, oob_score =True,criterion ='entr
model.fit(x_train,y_train)
model.oob_score_
```

Out[24]:

```
0.7354166666666667
```

In [25]:

```
pred_train = model.predict(x_train)
```

accuracy check

In [26]:

```
accuracy_score(y_train,pred_train)
```

Out[26]:

```
1.0
```

In [27]:

```
confusion_matrix(y_train,pred_train)
```

Out[27]:

```
array([[381,   0],
       [  0,  99]], dtype=int64)
```

In [28]:

```
pred_test = model.predict(x_test)
```

accuracy check

In [29]:

```
accuracy_score(y_test,pred_test)
```

Out[29]:

```
0.7416666666666667
```

In [30]:

```
confusion_matrix(y_test,pred_test)
```

Out[30]:

```
array([[89,  6],
       [25,  0]], dtype=int64)
```

In [31]:

```
df_Entropy=pd.DataFrame({'Actual':y_test, 'Predicted':pred_test})
```

In [32]:

```
df_Entropy
```

Out[32]:

	Actual	Predicted
268	Good	Good
304	Good	Good
3	Good	Good
504	Good	Riskey
482	Good	Good
...	...	...
226	Good	Good
580	Good	Good
65	Good	Good
384	Good	Good
140	Riskey	Good

120 rows × 2 columns

In [33]:

```
model.feature_importances_
```

Out[33]:

```
array([0.51998125, 0.3539363 , 0.01847467, 0.01735566, 0.01921622,
       0.02041587, 0.01673166, 0.01754803, 0.01634033])
```

In [34]:

```
feature_importance = pd.DataFrame({'feature': list(x_train.columns),
                    'importance': model.feature_importances_}).\
                     sort_values('importance', ascending = False)
```

In [35]:

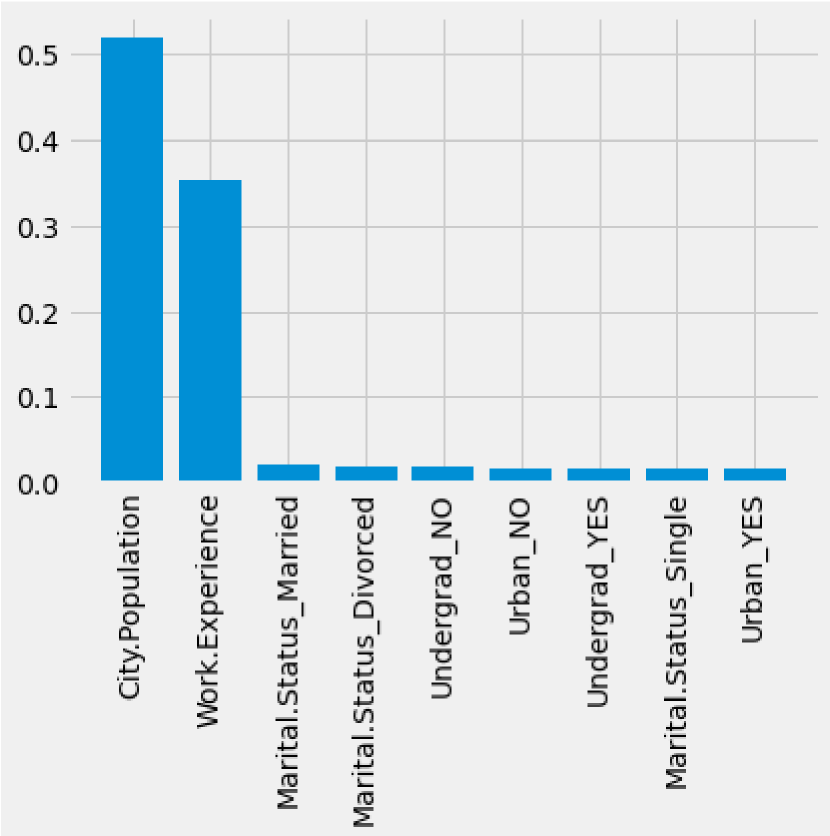
```
feature_importance
```

Out[35]:

	feature	importance
0	City.Population	0.519981
1	Work.Experience	0.353936
5	Marital.Status_Married	0.020416
4	Marital.Status_Divorced	0.019216
2	Undergrad_NO	0.018475
7	Urban_NO	0.017548
3	Undergrad_YES	0.017356
6	Marital.Status_Single	0.016732
8	Urban_YES	0.016340

In [36]:

```
plt.style.use('fivethirtyeight')
plt.bar(feature_importance['feature'],feature_importance['importance'], orientation = 'vert
plt.xticks(rotation = 90)
plt.show()
```



As seen in the above chart, City.Population is most important feature

END