In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import  DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import classification_report
from sklearn import preprocessing
```

In [2]:
```
data = pd.read_csv('Fraud_check.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	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

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Undergrad        600 non-null    object
 1   Marital.Status   600 non-null    object
 2   Taxable.Income   600 non-null    int64 
 3   City.Population  600 non-null    int64 
 4   Work.Experience  600 non-null    int64 
 5   Urban            600 non-null    object
dtypes: int64(3), object(3)
memory usage: 28.2+ KB
```

In [5]:
```
data.describe()
```

Out[5]:

	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 [7]:
```
data.corr()
```

Out[7]:

	Taxable.Income	City.Population	Work.Experience
Taxable.Income	1.000000	-0.064387	-0.001818
City.Population	-0.064387	1.000000	0.013135
Work.Experience	-0.001818	0.013135	1.000000

In [8]:
```
data = data.rename({'Undergrad':'under_grad', 'Marital.Status':'mar
                    'City.Population':'city_population', 'Work.Expe
data.head()
```

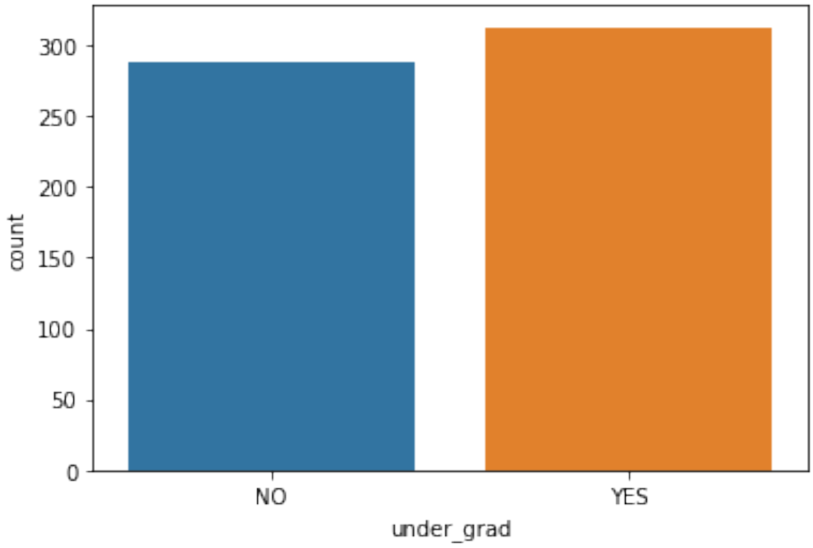
Out[8]:

	under_grad	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

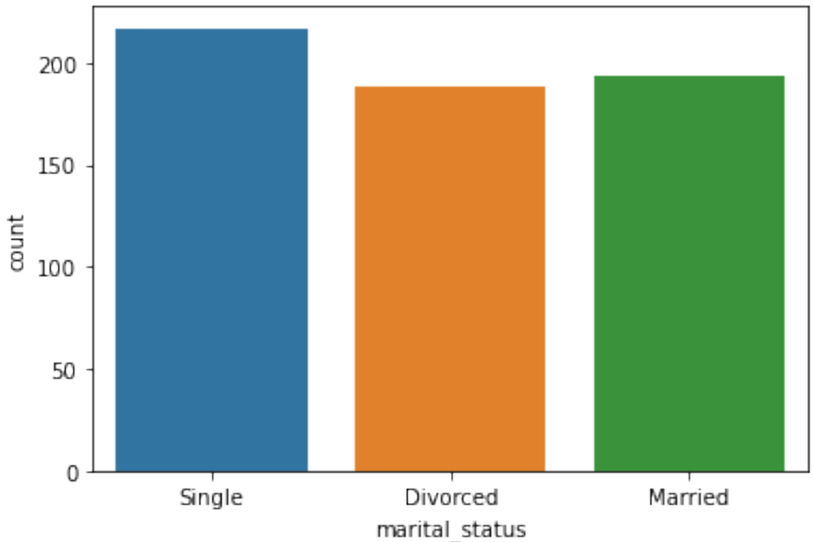
In [9]:
```
# checking count of categories for categorical columns colums
import seaborn as sns

sns.countplot(data['under_grad'])
plt.show()

sns.countplot(data['marital_status'])
plt.show()
```

```
sns.countplot(data['urban'])
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```

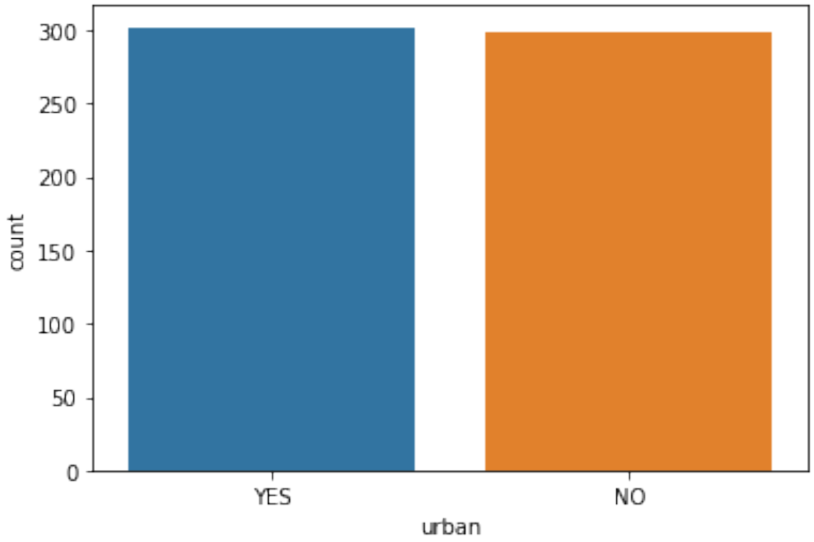



```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



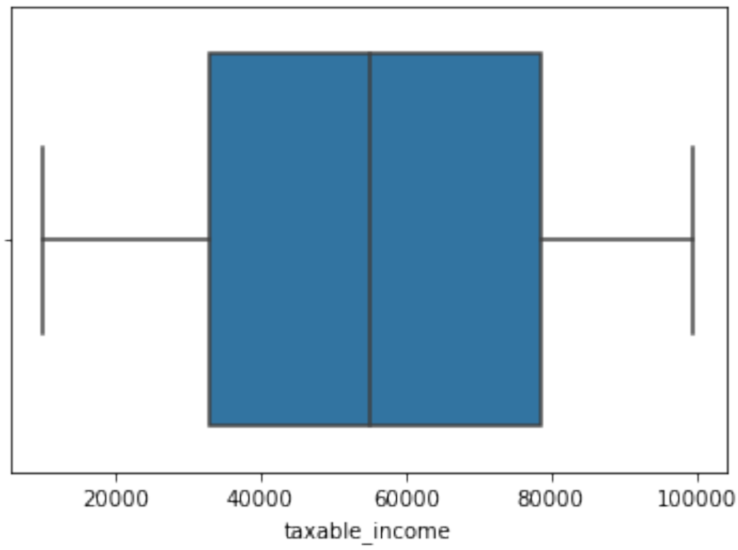

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
```

```
  warnings.warn(
```



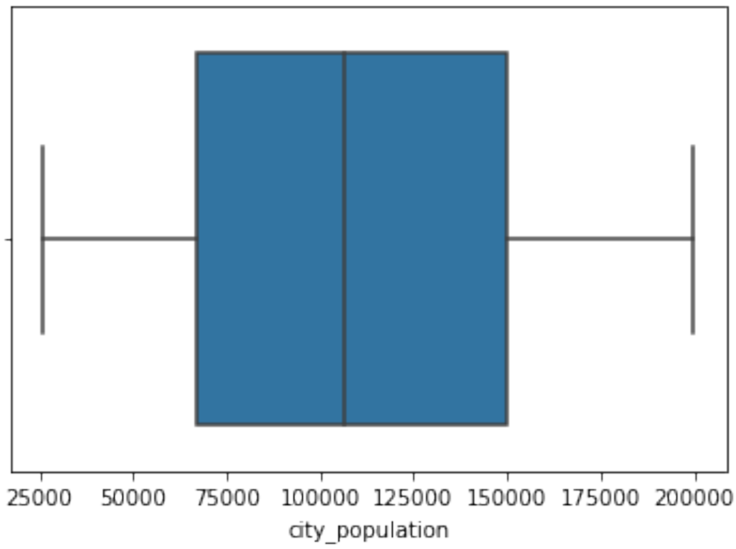
In [10]:
```
# Checking for outliers in numerical data
sns.boxplot(data['taxable_income'])
plt.show()

sns.boxplot(data['city_population'])
plt.show()

sns.boxplot(data['work_experience'])
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```

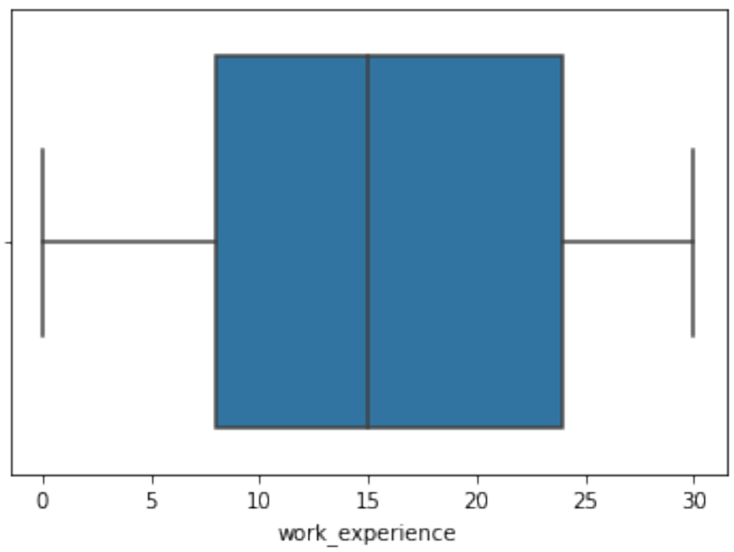



```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
```

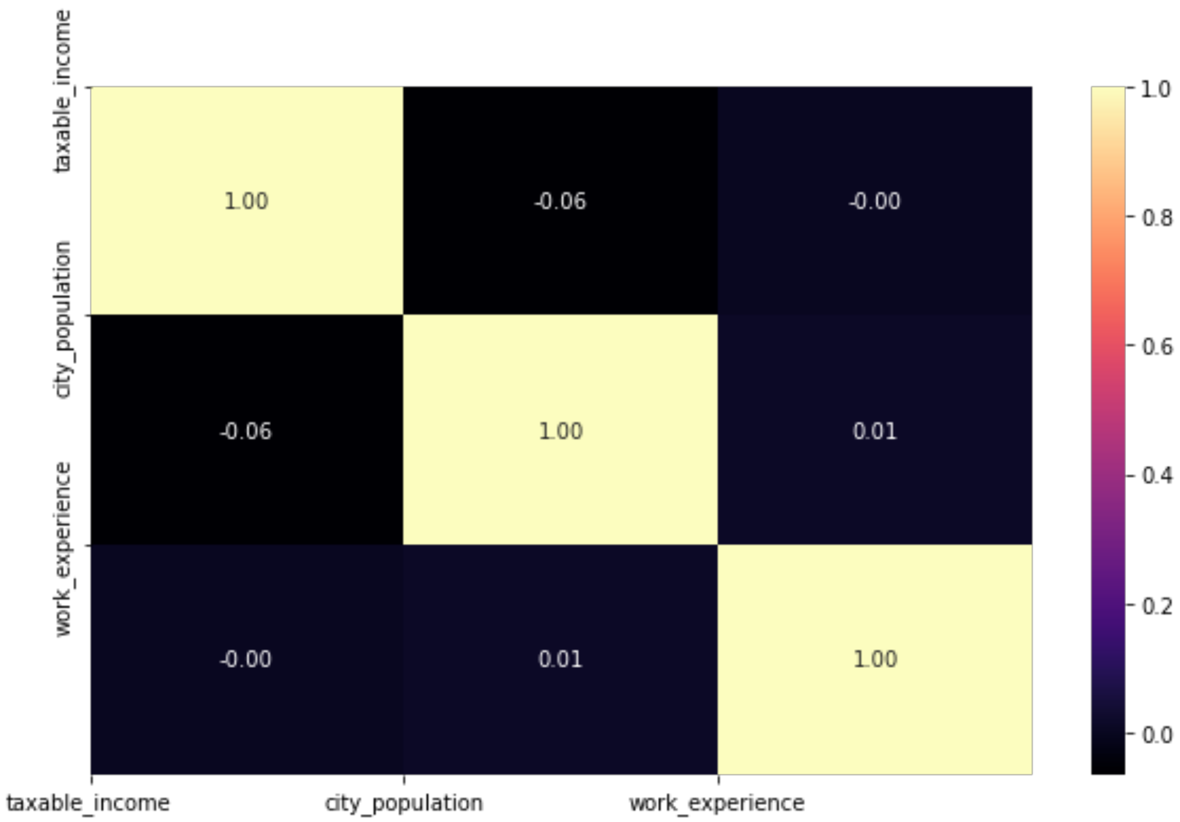
```
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```




```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



In [11]:
```
# Correlation analysis for data
corr = data.corr()
#Plot figsize
fig, ax = plt.subplots(figsize=(10, 6))
#Generate Heat Map, allow annotations and place floats in map
sns.heatmap(corr, cmap='magma', annot=True, fmt=".2f")
#Apply xticks
plt.xticks(range(len(corr.columns)), corr.columns);
#Apply yticks
plt.yticks(range(len(corr.columns)), corr.columns)
#show plot
plt.show()
```



In [12]:
```
data['taxable_category'] = pd.cut(x = data['taxable_income'], bins
data
```

Out[12]:

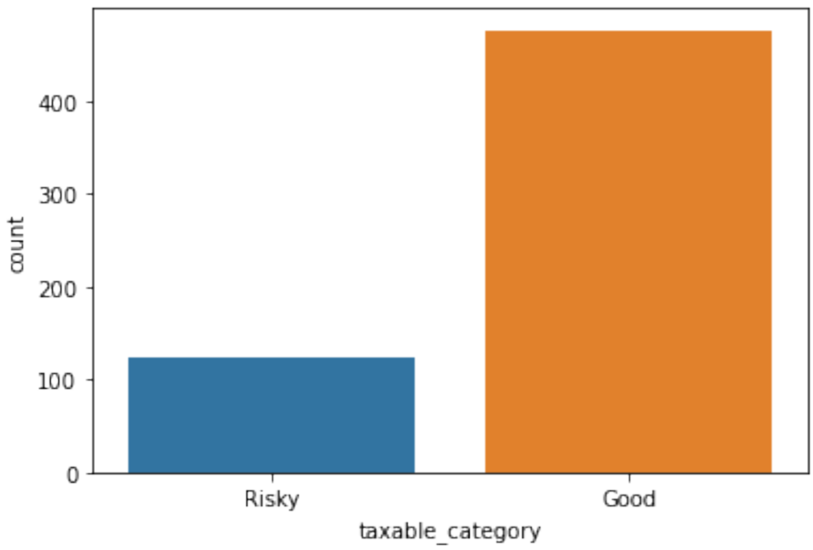
	under_grad	marital_status	taxable_income	city_population	work_experience	urban
0	NO	Single	68833	50047	10	YES
1	YES	Divorced	33700	134075	18	YES
2	NO	Married	36925	160205	30	YES
3	YES	Single	50190	193264	15	YES
4	NO	Married	81002	27533	28	NO
...	...	...	...	...	...	...
595	YES	Divorced	76340	39492	7	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 × 7 columns

In [13]:
```
sns.countplot(data['taxable_category'])
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:
36: FutureWarning: Pass the following variable as a keyword arg: x
. From version 0.12, the only valid positional argument will be `d
ata`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```

Out[13]: <AxesSubplot:xlabel='taxable_category', ylabel='count'>



In [14]:
```
data['taxable_category'].value_counts()
```

Out[14]:
```
Good     476
Risky    124
Name: taxable_category, dtype: int64
```

In [15]:
```
#encoding categorical data
label_encoder = preprocessing.LabelEncoder()

data['under_grad'] = label_encoder.fit_transform(data['under_grad']
data['marital_status'] = label_encoder.fit_transform(data['marital_
data['urban'] = label_encoder.fit_transform(data['urban'])
data['taxable_category'] = label_encoder.fit_transform(data['taxabl
data.sample(10)
```

Out[15]:

	under_grad	marital_status	taxable_income	city_population	work_experience	urban
480	0	0	85972	72252	26	1
363	1	2	21696	52584	7	1
462	0	0	16690	149327	17	0
190	0	2	73620	90459	19	0
26	1	0	55299	169128	15	0
389	1	2	64225	183187	5	1
27	1	2	87778	28542	12	1
56	0	1	34703	69832	25	1
28	1	2	10379	128766	5	1
290	1	1	48169	193003	30	1

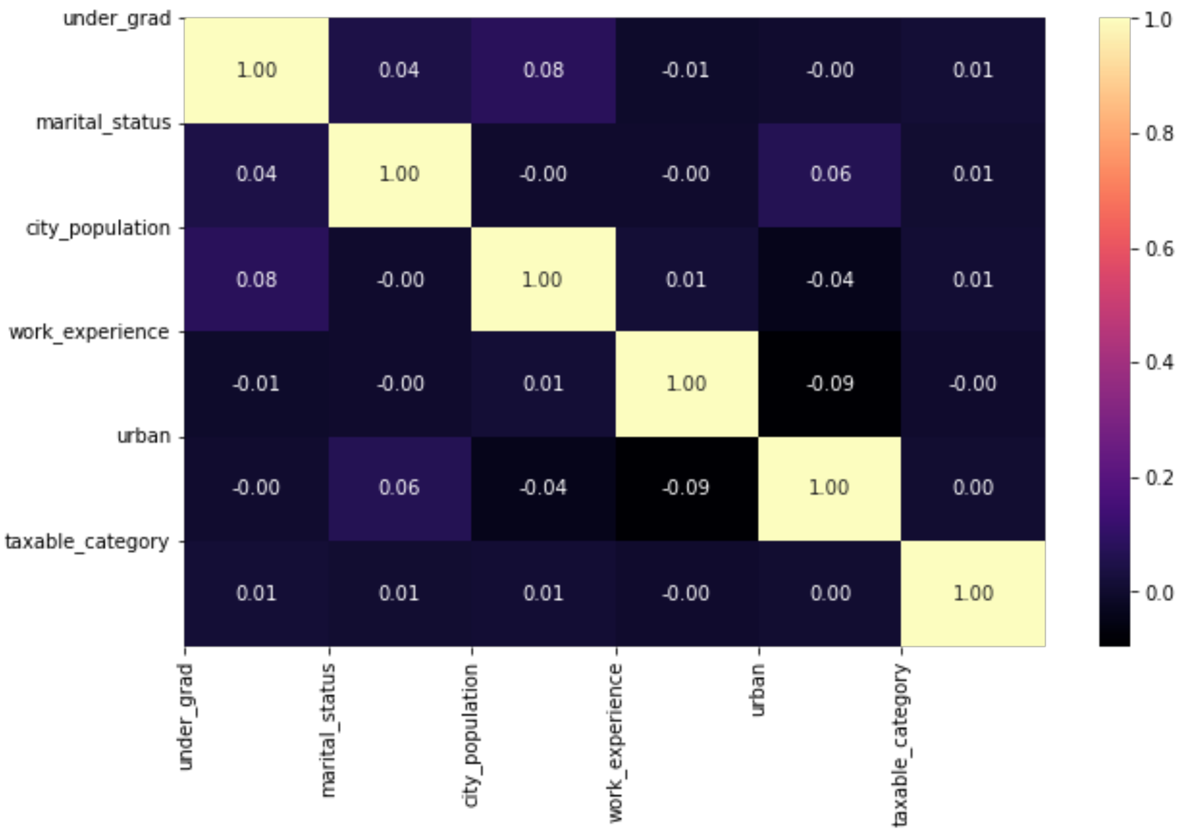
In [16]:
```
# dropping column taxable_income
data1 = data.drop('taxable_income', axis = 1)
data1
```

Out[16]:

	under_grad	marital_status	city_population	work_experience	urban	taxable_category
0	0	2	50047	10	1	0
1	1	0	134075	18	1	0
2	0	1	160205	30	1	0
3	1	2	193264	15	1	0
4	0	1	27533	28	0	0
...	...	...	...	...	...	...
595	1	0	39492	7	1	0
596	1	0	55369	2	1	0
597	0	0	154058	0	1	0
598	1	1	180083	17	0	0
599	0	0	158137	16	0	0

600 rows × 6 columns

In [17]:
```
# Correlation analysis for data11
corr = data1.corr()
#Plot figsize
fig, ax = plt.subplots(figsize=(10, 6))
#Generate Heat Map, allow annotations and place floats in map
sns.heatmap(corr, cmap='magma', annot=True, fmt=".2f")
#Apply xticks
plt.xticks(range(len(corr.columns)), corr.columns);
#Apply yticks
plt.yticks(range(len(corr.columns)), corr.columns)
#show plot
plt.show()
```



In [18]:
```
# Dividing data into independent variables and dependent variable
X = data1.drop('taxable_category', axis = 1)
y = data1['taxable_category']
```

In [19]:
```
X
```

Out[19]:

	under_grad	marital_status	city_population	work_experience	urban
0	0	2	50047	10	1
1	1	0	134075	18	1
2	0	1	160205	30	1
3	1	2	193264	15	1
4	0	1	27533	28	0
...	...	...	...	...	...
595	1	0	39492	7	1
596	1	0	55369	2	1
597	0	0	154058	0	1
598	1	1	180083	17	0
599	0	0	158137	16	0

600 rows × 5 columns

In [20]:
```
y
```

Out[20]:
```
0      0
1      0
2      0
3      0
4      0
      ..
595    0
596    0
597    0
598    0
599    0
Name: taxable_category, Length: 600, dtype: int64
```

In [21]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size
```

In [22]:
```
x_train
```

Out[22]:

	under_grad	marital_status	city_population	work_experience	urban
509	0	1	65531	27	1
149	0	2	49505	25	0
124	1	0	139324	13	0
428	1	1	128266	24	1
465	0	0	116282	21	0
...	...	...	...	...	...
71	0	2	105680	22	0
106	1	2	58535	20	1
270	0	1	130680	5	0
435	0	0	111774	4	1
102	1	0	91488	23	0

402 rows × 5 columns

In [23]:
```

x_test
```

Out[23]:

	under_grad	marital_status	city_population	work_experience	urban
110	0	2	32450	19	1
419	0	1	138074	20	0
565	0	0	31064	28	0
77	1	1	118344	26	0
181	0	0	36116	20	0
...	...	...	...	...	...
231	1	2	153147	2	0
403	0	0	130912	27	1
278	0	1	114823	11	0
472	0	1	151963	11	1
350	0	1	89949	25	0

198 rows × 5 columns

In [24]:
```
y_train
```

Out[24]:
```
509    1
149    0
124    0
428    1
465    1
      ..
71     0
106    1
270    0
435    0
102    0
Name: taxable_category, Length: 402, dtype: int64
```

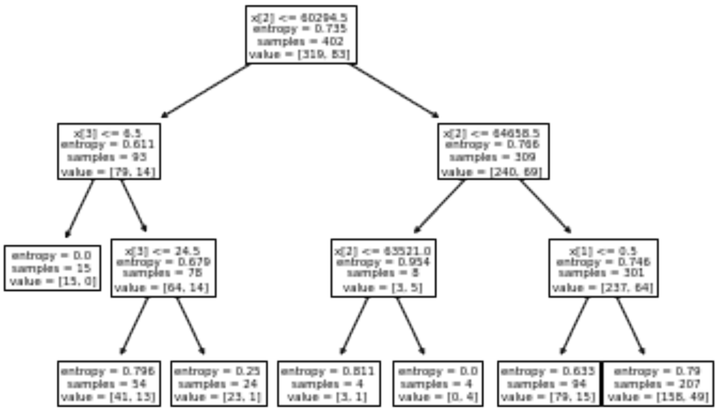
In [25]:
```
y_test
```

Out[25]:
```
110    1
419    0
565    0
77     0
181    1
      ..
231    0
403    0
278    1
472    0
350    0
Name: taxable_category, Length: 198, dtype: int64
```

In [26]:
```
model_c5 = DecisionTreeClassifier(criterion = 'entropy', max_depth=
model_c5.fit(x_train, y_train)
```

Out[26]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=3)
```

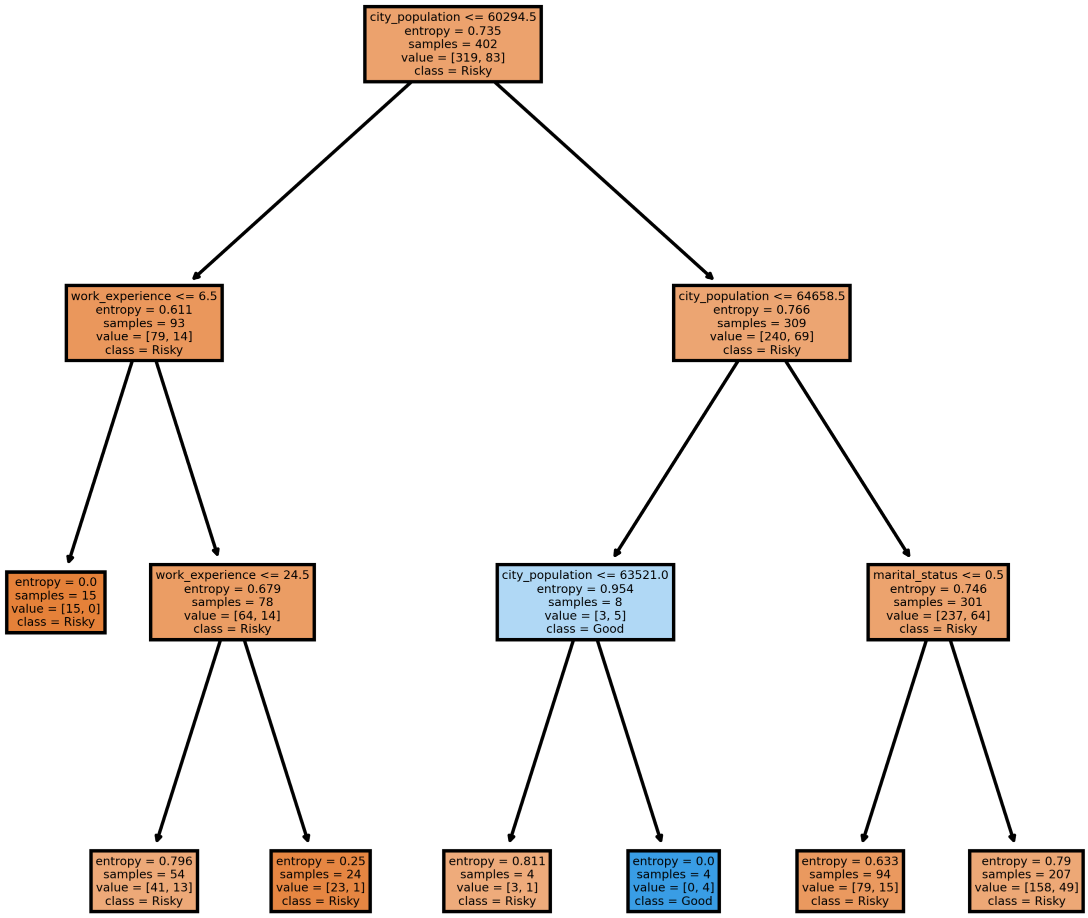
In [27]:
```
# Plotting Decision tree
tree.plot_tree(model_c5);
```



In [28]:
```
data1.columns
```

Out[28]:
```
Index(['under_grad', 'marital_status', 'city_population', 'work_ex
perience',
       'urban', 'taxable_category'],
      dtype='object')
```

In [29]:
```
fn=['under_grad', 'marital_status', 'city_population', 'work_experi
      'urban', 'taxable_category']
cn=['Risky', 'Good']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (6,6), dpi=6
tree.plot_tree(model_c5,
               feature_names = fn,
               class_names=cn,
               filled = True);
```



In [30]:
```
# Predicting Data
preds = model_c5.predict(x_test)
pd.Series(preds).value_counts()
```

Out[30]:
```
0    197
1      1
dtype: int64
```

In [31]:
```
preds
```

Out[31]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0])
```

In [32]:
```
# Creating cross tables for checking model
pd.crosstab(y_test, preds)
```

Out[32]:

col_0	0	1
taxable_category		
0	156	1
1	41	0

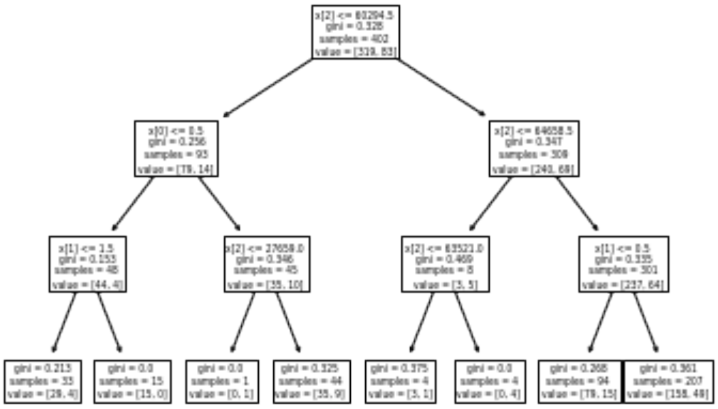
In [33]:
```
# Checking accuracy of model
model_c5.score(x_test, y_test)
```

Out[33]:
```
0.7878787878787878
```

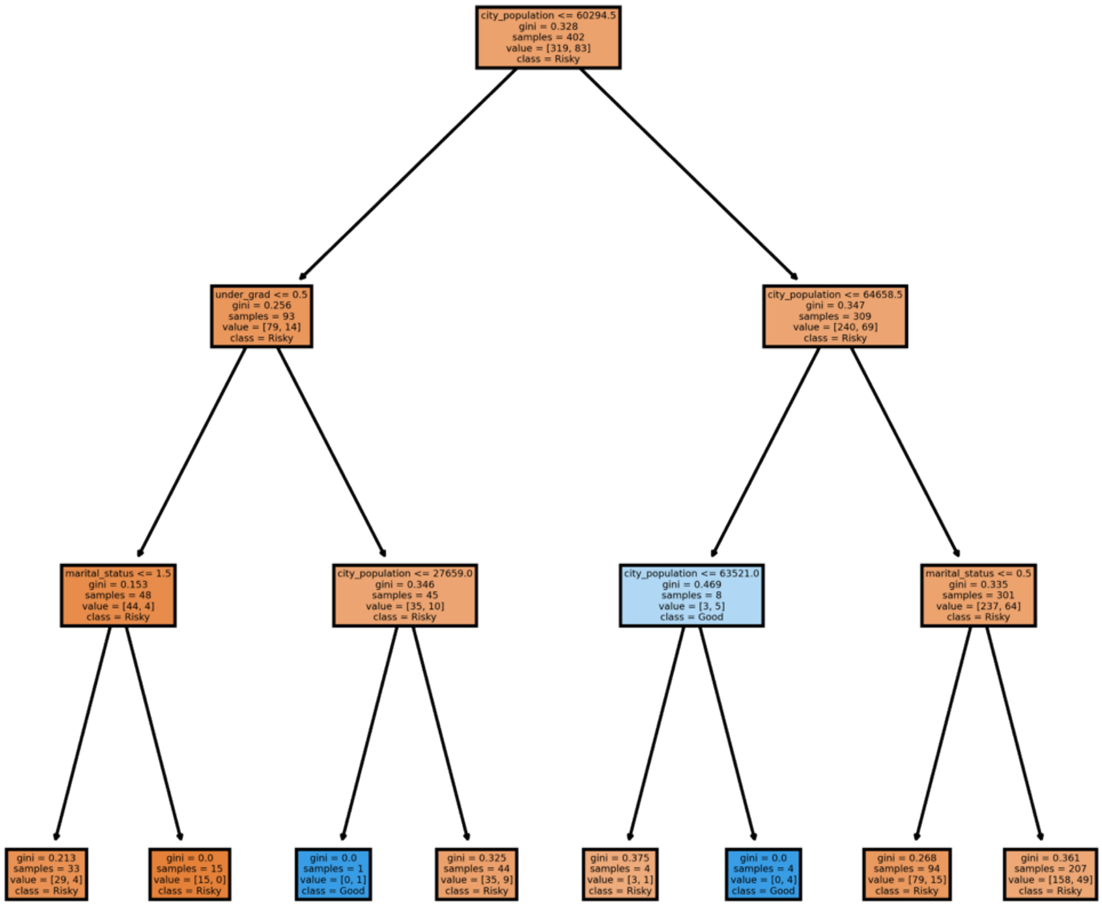
In [34]:
```
model_CART = DecisionTreeClassifier(criterion = 'gini', max_depth=
model_CART.fit(x_train, y_train)
```

Out[34]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3)
```

In [35]:
```
# Plotting Decision tree
tree.plot_tree(model_CART);
```



In [36]:
```
fn=['under_grad', 'marital_status', 'city_population', 'work_experi
      'urban', 'taxable_category']
cn=['Risky', 'Good']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (6,6), dpi=6
tree.plot_tree(model_CART,
               feature_names = fn,
               class_names=cn,
               filled = True);
```



In [37]:
```
# Predicting Data
preds = model_CART.predict(x_test)
pd.Series(preds).value_counts()
```

Out[37]:
```
0    197
1      1
dtype: int64
```

In [38]:
```
preds
```

Out[38]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0])
```

In [39]:
```
# Creating cross tables for checking model
pd.crosstab(y_test, preds)
```

Out[39]:

col_0	0	1
taxable_category		
0	156	1
1	41	0

In [40]:
```
# Checking accuracy of model
model_CART.score(x_test, y_test)
```

Out[40]:
```
0.7878787878787878
```

In [ ]: