Person’s Income

Submitted by: Rida Riaz

Introduction

I take a dataset of multiple people with different race, native country, marital status, gender etc and check whose income is greater than 50K.

I also use many visualizations graphs and plots to visualize the data.

Other than this I also use multiple algorithm like AdaBoost, decision tree, random forest, naïve bayes, and KNN etc. to check which algorithm gives the best accuracy.

Dataset Information

Dataset name: Census.cvs

Data set Columns

In [3]:
```
census = pd.read_csv('census.csv')
census.head()
```

Out[3]:

ge	workclass	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week	native.country	income
90	?	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40	United-States	<=50K
82	Private	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18	United-States	<=50K
66	?	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	?	United-States	<=50K
54	Private	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40	United-States	<=50K
41	Private	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40	United-States	<=50K

In [4]:
```
census.columns
```

Out[4]:
```
Index(['age', 'workclass', 'education', 'education.num', 'marital.status',
       'occupation', 'relationship', 'race', 'sex', 'capital.gain',
       'capital.loss', 'hours.per.week', 'native.country', 'income'],
      dtype='object')
```

In [5]:
```
print("Shape of the Dataframe:", census.shape)
```

```
Shape of the Dataframe: (32561, 14)
```

Data Handling

Dataset name: Census.cvs

Converting ‘?’ with NaN

```
census.replace('?', np.nan, inplace = True)
```

```
print('Summary Of the dataframe:\n')
print(census.info(),'\n')
```

```
Summary Of the dataframe:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32556 non-null  object
 1   workclass       30725 non-null  object
 2   education       32561 non-null  object
 3   education.num   32561 non-null  int64
 4   marital.status  32561 non-null  object
 5   occupation      30718 non-null  object
 6   relationship    32561 non-null  object
 7   race            32561 non-null  object
 8   sex             32561 non-null  object
 9   capital.gain    32561 non-null  int64
 10  capital.loss    32561 non-null  int64
 11  hours.per.week  32556 non-null  object
 12  native.country  31978 non-null  object
 13  income          32561 non-null  object
dtypes: int64(3), object(11)
memory usage: 3.5+ MB
None
```

Coverting the datatype of "age", "hours.per.week"

```
census['age'] = census['age'].astype('float')
census['hours.per.week'] = census['hours.per.week'].astype("float")
```

```
print('Summary Of the dataframe:\n')
print(census.info(),'\n')
```

```
Summary Of the dataframe:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32556 non-null  float64
 1   workclass       30725 non-null  object
 2   education       32561 non-null  object
 3   education.num   32561 non-null  int64
 4   marital.status  32561 non-null  object
 5   occupation      30718 non-null  object
 6   relationship    32561 non-null  object
 7   race            32561 non-null  object
 8   sex             32561 non-null  object
 9   capital.gain    32561 non-null  int64
 10  capital.loss    32561 non-null  int64
 11  hours.per.week  32556 non-null  float64
 12  native.country  31978 non-null  object
 13  income          32561 non-null  object
dtypes: float64(2), int64(3), object(9)
memory usage: 3.5+ MB
None
```

Replace missing numerical value with median and then change the datatype from float to int

```
census['age'] = census['age'].fillna(census['age'].median())
census['hours.per.week'] = census['hours.per.week'].fillna(census['hours.per.week'].median())
```

```
census['age'] = census['age'].astype('int')
census['hours.per.week'] = census['hours.per.week'].astype("int")
```

```
print('Summary Of the dataframe:\n')
print(census.info(),'\n')
```

```
Summary Of the dataframe:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int32 
 1   workclass       30725 non-null  object
 2   education       32561 non-null  object
 3   education.num   32561 non-null  int64 
 4   marital.status  32561 non-null  object
 5   occupation      30718 non-null  object
 6   relationship    32561 non-null  object
 7   race            32561 non-null  object
 8   sex             32561 non-null  object
 9   capital.gain    32561 non-null  int64 
 10  capital.loss    32561 non-null  int64 
 11  hours.per.week  32561 non-null  int32 
 12  native.country  31978 non-null  object
 13  income          32561 non-null  object
dtypes: int32(2), int64(3), object(9)
memory usage: 3.2+ MB
None
```

Filling all the missing categorical values with the values whose frequency is greater

```
census['workclass'].replace(np.nan, census['workclass'].value_counts().idxmax() , inplace=True)
census['occupation'].replace(np.nan, census['occupation'].value_counts().idxmax() , inplace=True)
census['native.country'].replace(np.nan, census['native.country'].value_counts().idxmax() , inplace=True)
```

```
print('Checking for Null values in the dataframe:\n',census.isnull().sum(),'\n')
```

```
Checking for Null values in the dataframe:
 age               0
workclass         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
```

Exploratory Data Analysis

Dataset name: Census.cvs

Data Description

```
census.describe(include = "all").transpose()
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
age	32561.0	NaN	NaN	NaN	38.581217	13.63944	17.0	28.0	37.0	48.0	90.0
workclass	32561	8	Private	24532	NaN	NaN	NaN	NaN	NaN	NaN	NaN
education	32561	16	HS-grad	10501	NaN	NaN	NaN	NaN	NaN	NaN	NaN
education.num	32561.0	NaN	NaN	NaN	10.080679	2.57272	1.0	9.0	10.0	12.0	16.0
marital.status	32561	7	Married-civ-spouse	14976	NaN	NaN	NaN	NaN	NaN	NaN	NaN
occupation	32561	14	Prof-specialty	5983	NaN	NaN	NaN	NaN	NaN	NaN	NaN
relationship	32561	6	Husband	13193	NaN	NaN	NaN	NaN	NaN	NaN	NaN
race	32561	5	White	27816	NaN	NaN	NaN	NaN	NaN	NaN	NaN
sex	32561	2	Male	21790	NaN	NaN	NaN	NaN	NaN	NaN	NaN
capital.gain	32561.0	NaN	NaN	NaN	1077.648844	7385.292085	0.0	0.0	0.0	0.0	99999.0
capital.loss	32561.0	NaN	NaN	NaN	87.30383	402.960219	0.0	0.0	0.0	0.0	4356.0
hours.per.week	32561.0	NaN	NaN	NaN	40.437548	12.345947	1.0	40.0	40.0	45.0	99.0
native.country	32561	41	United-States	29753	NaN	NaN	NaN	NaN	NaN	NaN	NaN
income	32561	2	<=50K	24720	NaN	NaN	NaN	NaN	NaN	NaN	NaN

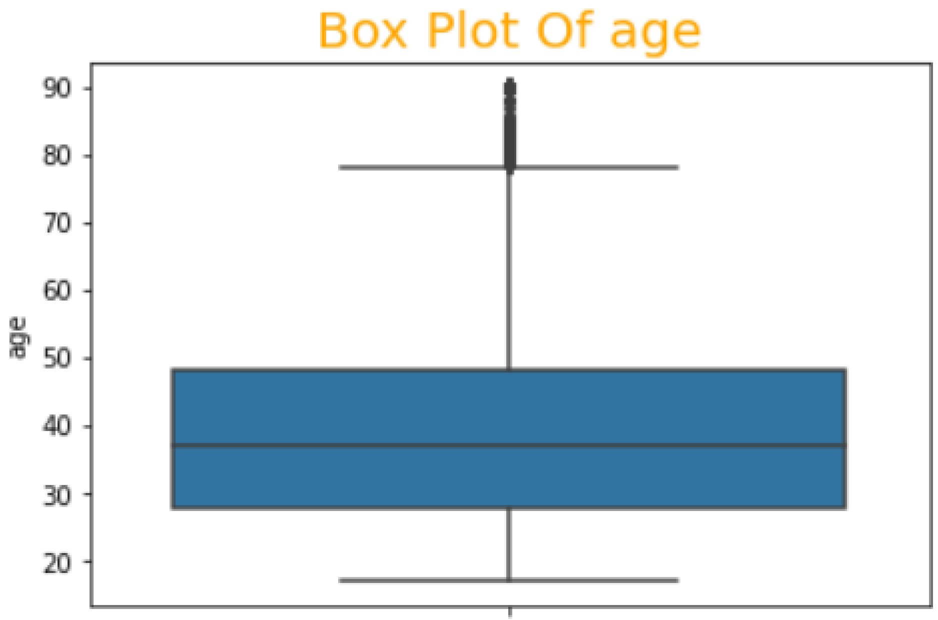
Data Description

- **age:** This represent age of the person. Minimum age of the person is 17 and maximum is 90. As mean > median, it's **rightly skewed**.
- **workclass:** This column represent the sector in which a person work. It has 8 unique values. And mostly people worked in **private sector** (24532)
- **Education:** This column represent the education of a person. It has 16 unique values. And mostly people are **HS-grad** (10501)
- **education.number:** Level of education range from 1 - 16. As Mean slightly > Median, it's **slightly rightly skewed.**
- **marital.status:** The column represent the marital status of a person. It has 7 unique values. And mostly people are **Married-civ-spouse** (14976)
- **occupation:** The column represent the occupation of a person. It has 14 unique values. And mostly people are **Prof-specialty** (5983)
- **relationship:** The column represent the relationship of a person in family. It has 6 unique values. And mostly people are **Husband** (13193)
- **race:** The column represent the race of a person. It has 5 unique values. And mostly people are of **White race**(27816)
- **sex:** The column represent the gender of a person. It has 2 unique values. And mostly people are **Male** (21790)
- **capital.gain:** Capital gain by a person from 0 - 99999. As Mean highlty > Median, it's **Highly rightly skewed.**
- **capital.loss:** Capital loss by a person from 0 - 4356. As Mean highlty > Median, it's **Highly rightly skewed.**
- **hours.per.week:** This represent the working hours of the person in a week. Minimum working hours by the person is 1 and maximum is 99. As Mean slightly > Median, it's **slightly rightly skewed.**
- **native.country:** The column represent the native country of a person. It has 41 unique values. And mostly people's native country is **United-States**(29753)
- **income:** Our taget column value is income and we wanted to check whose person like which race, education,etc people have income greater than **50K**

Univariate Analysis - by Boxplot

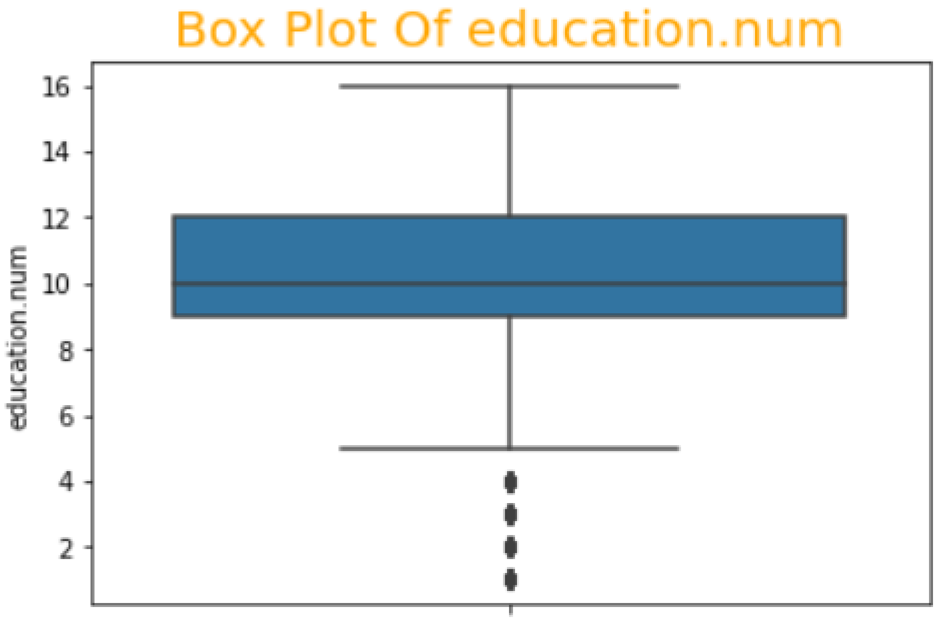
```
sns.boxplot(y="age", data=census)
plt.title(f"Box Plot Of age" , fontsize=20,
          color="orange")
```

```
Text(0.5, 1.0, 'Box Plot Of age')
```




```
sns.boxplot(y="education.num", data=census)
plt.title(f"Box Plot Of education.num", fontsize=20,
          color="orange")
```

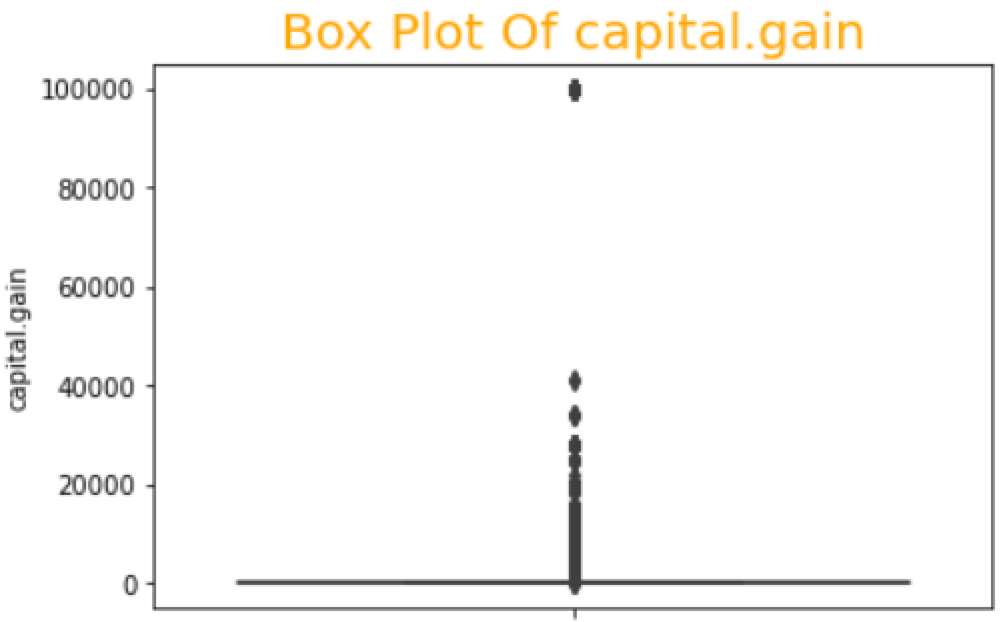
```
Text(0.5, 1.0, 'Box Plot Of education.num')
```



Univariate Analysis - by Boxplot

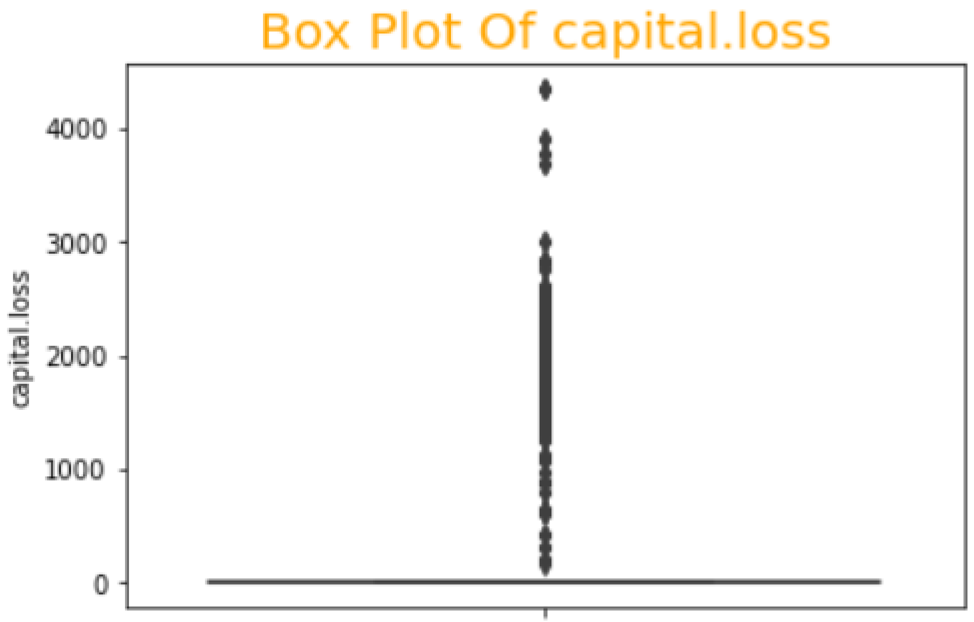
```
sns.boxplot(y="capital.gain", data=census)
plt.title(f"Box Plot Of capital.gain" , fontsize=20,
          color="orange")
```

```
Text(0.5, 1.0, 'Box Plot Of capital.gain')
```




```
sns.boxplot(y="capital.loss", data=census)
plt.title(f"Box Plot Of capital.loss" , fontsize=20,
          color="orange")
```

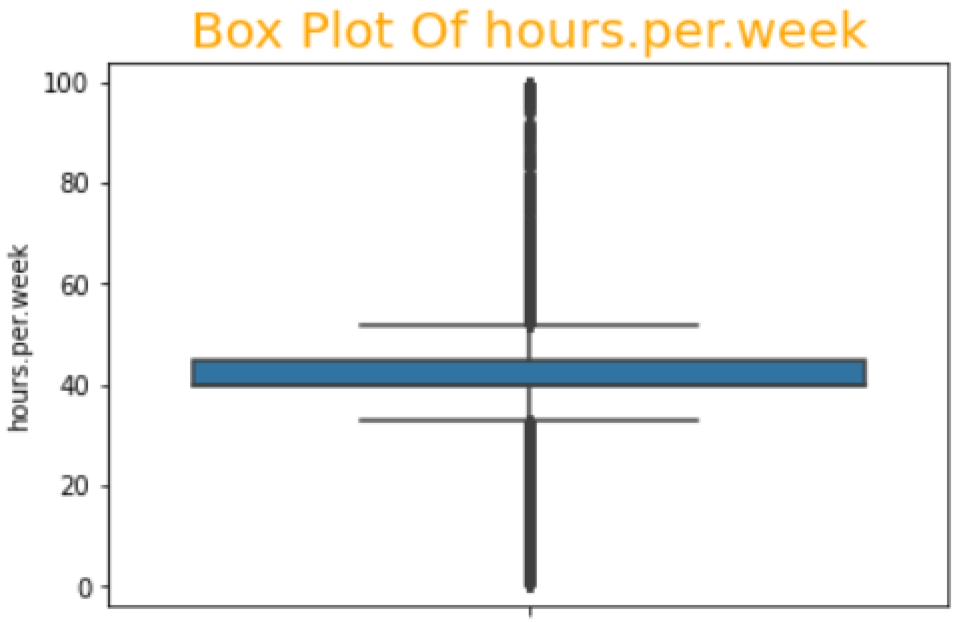
```
Text(0.5, 1.0, 'Box Plot Of capital.loss')
```



Univariate Analysis - by Boxplot

```
sns.boxplot(y="hours.per.week", data=census)
plt.title(f"Box Plot Of hours.per.week" , fontsize=20,
        color="orange")
```

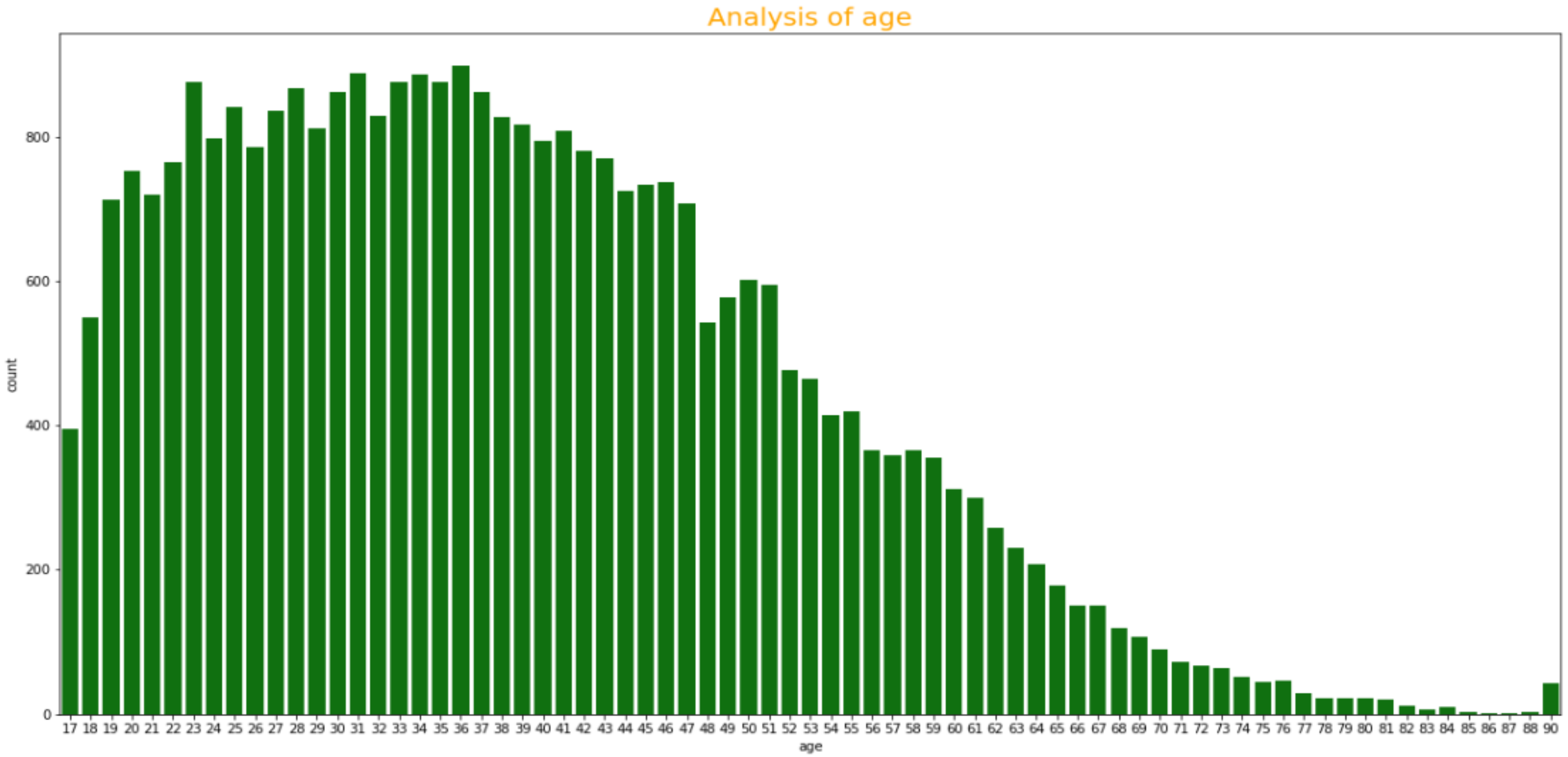
```
Text(0.5, 1.0, 'Box Plot Of hours.per.week')
```



Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census.age,color='green')
plt.title(f"Analysis of age" , fontsize=20,
          color="orange")
```

```
Text(0.5, 1.0, 'Analysis of age')
```

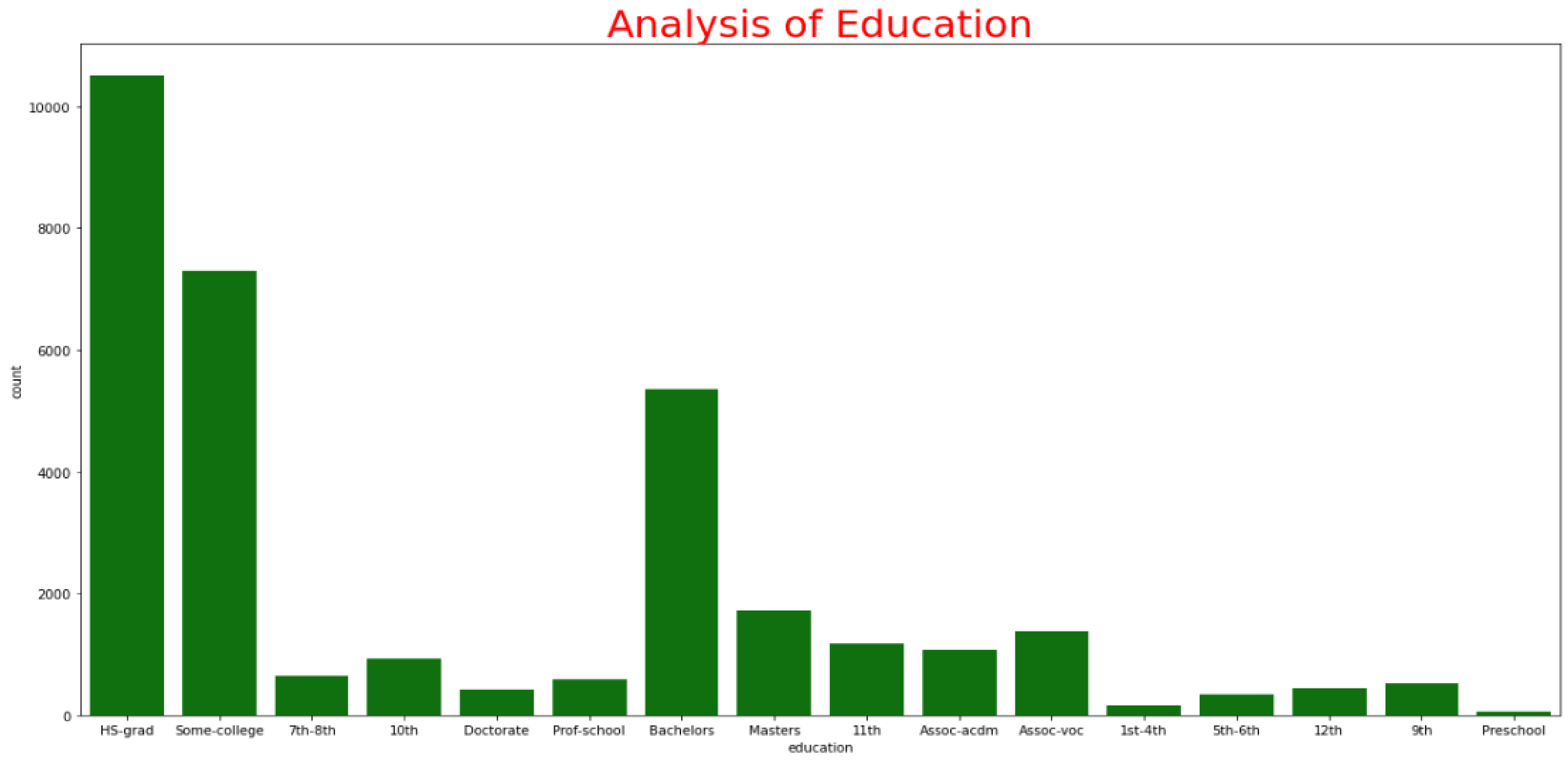


mostly people are of age 36

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census.education,color='green')
plt.title(f"Analysis of Education" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of Education')
```

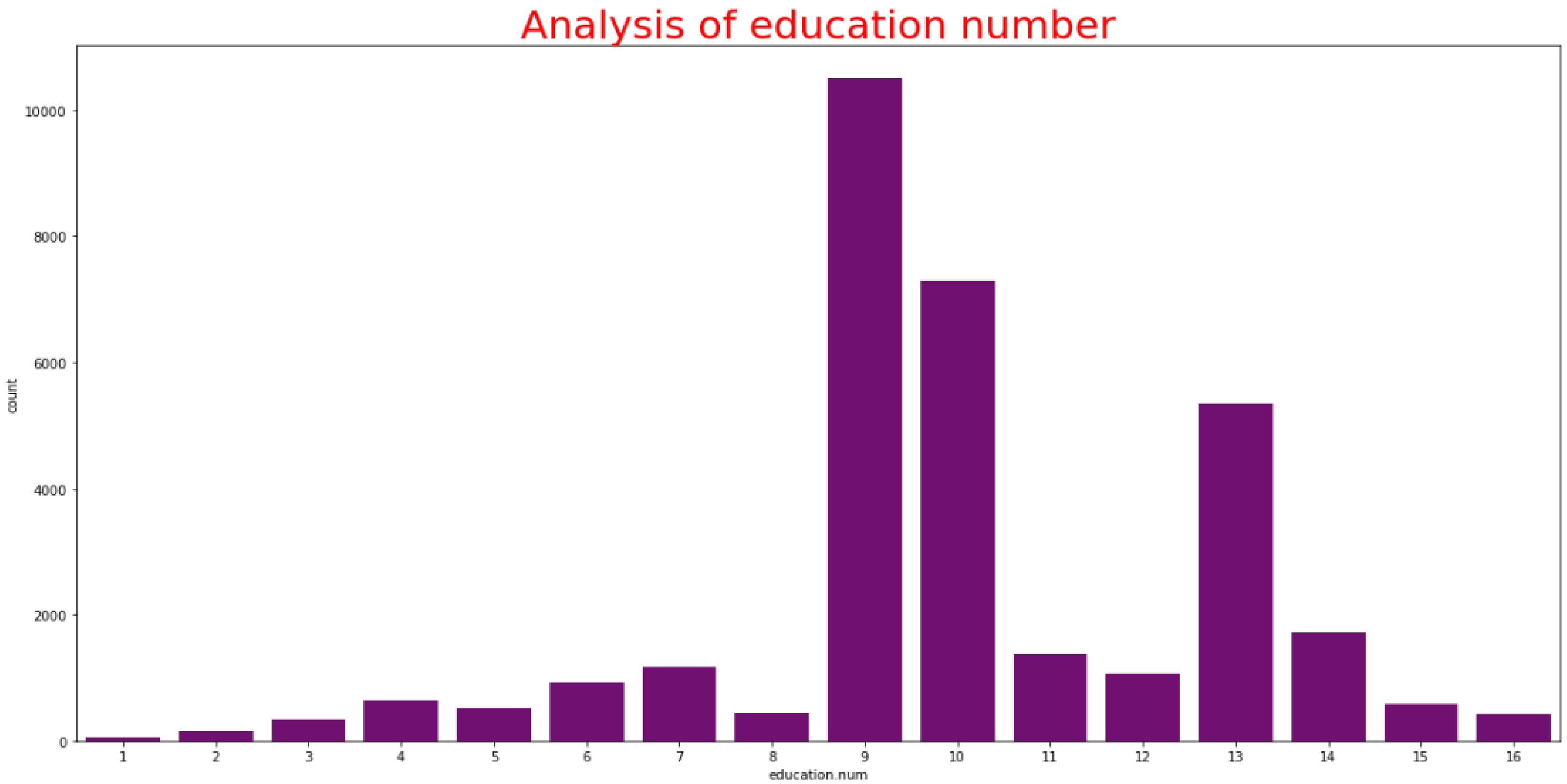


Mostly people are high school graduates

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['education.num'],color='purple')
plt.title(f"Analysis of education number" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of education number')
```

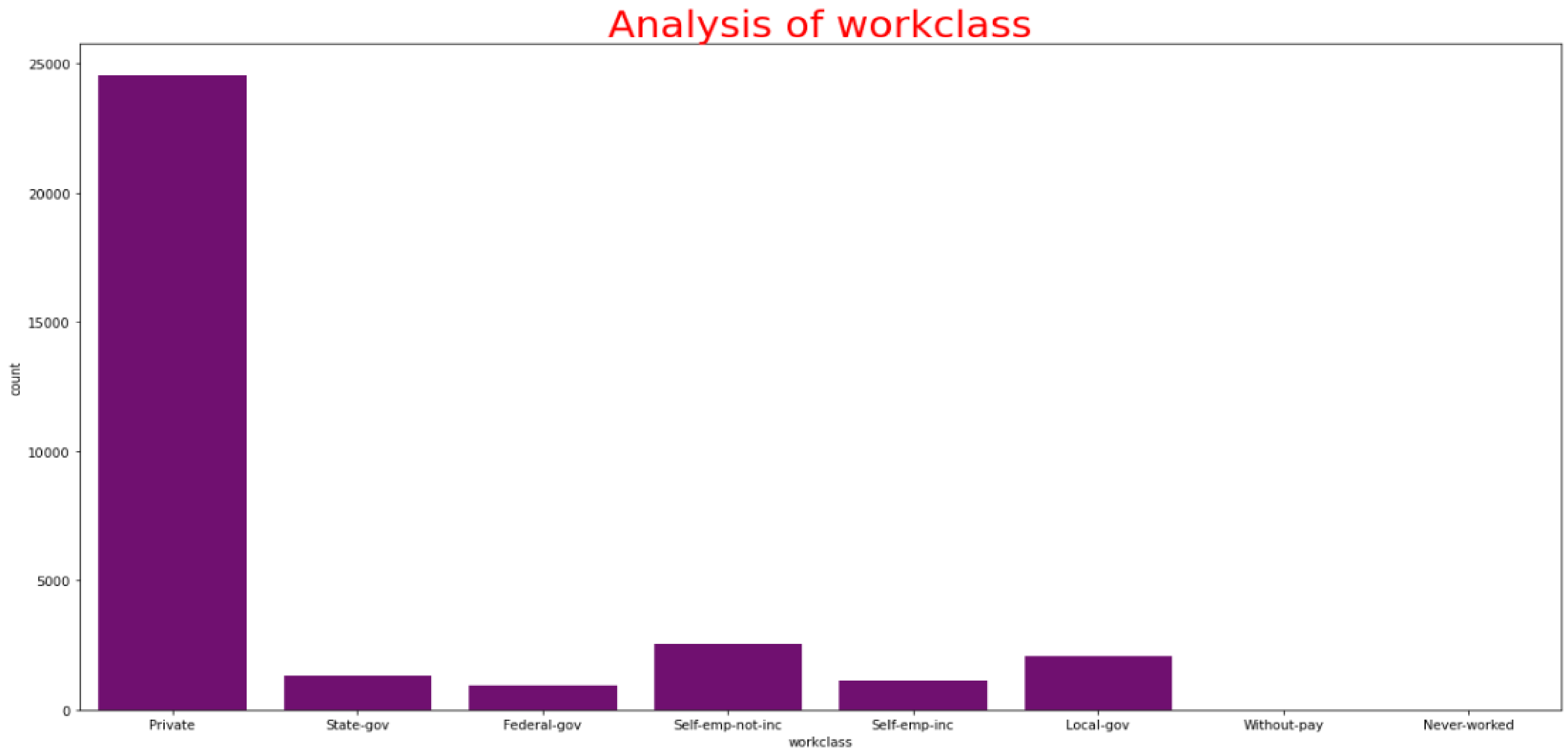


Mostly people education level is 9 which means mostly people are High-School graduates

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['workclass'],color='purple')
plt.title(f"Analysis of workclass" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of workclass')
```

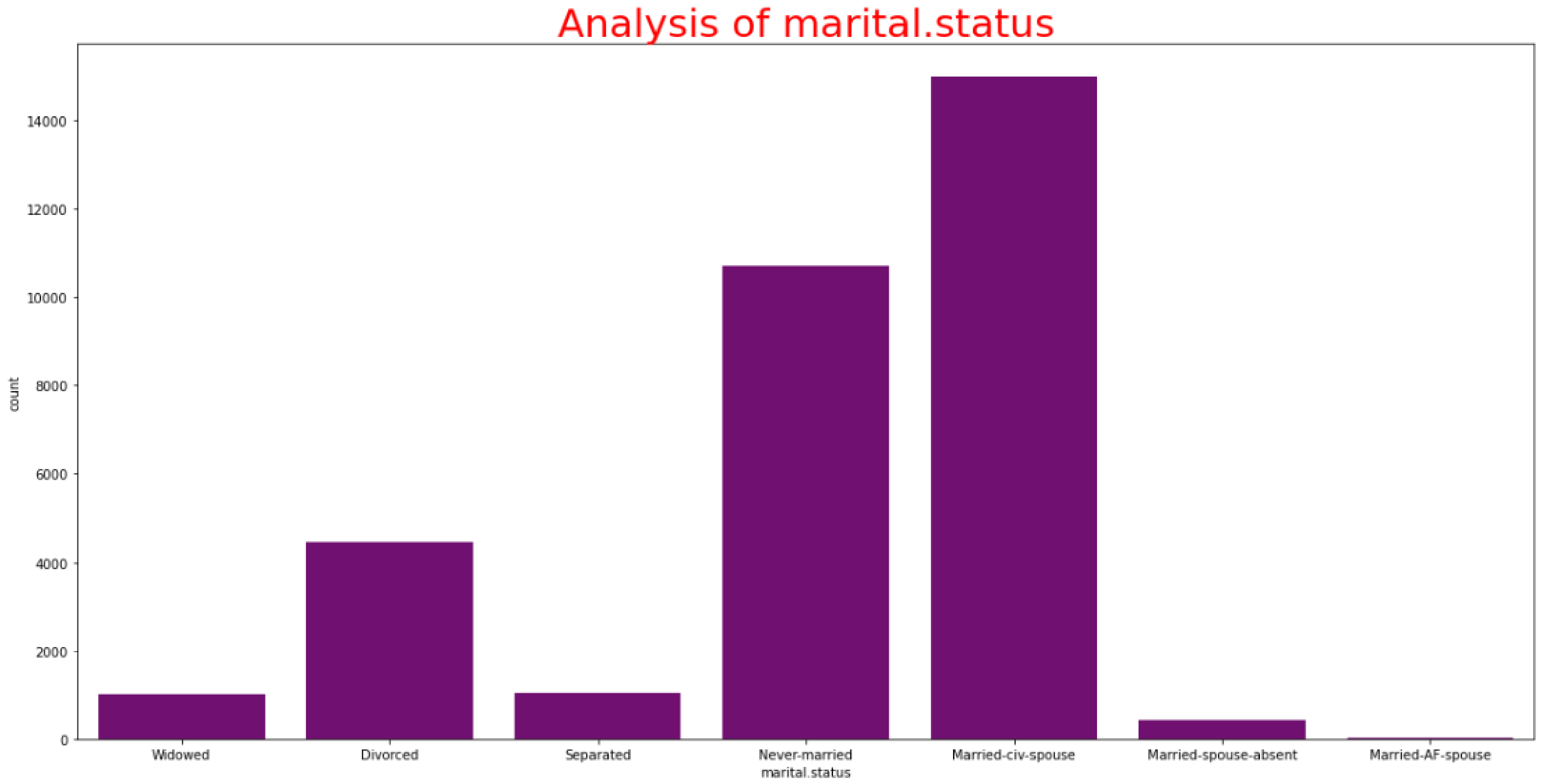


Mostly people doing jobs in private sectors

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['marital.status'],color='purple')
plt.title(f"Analysis of marital.status" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of marital.status')
```

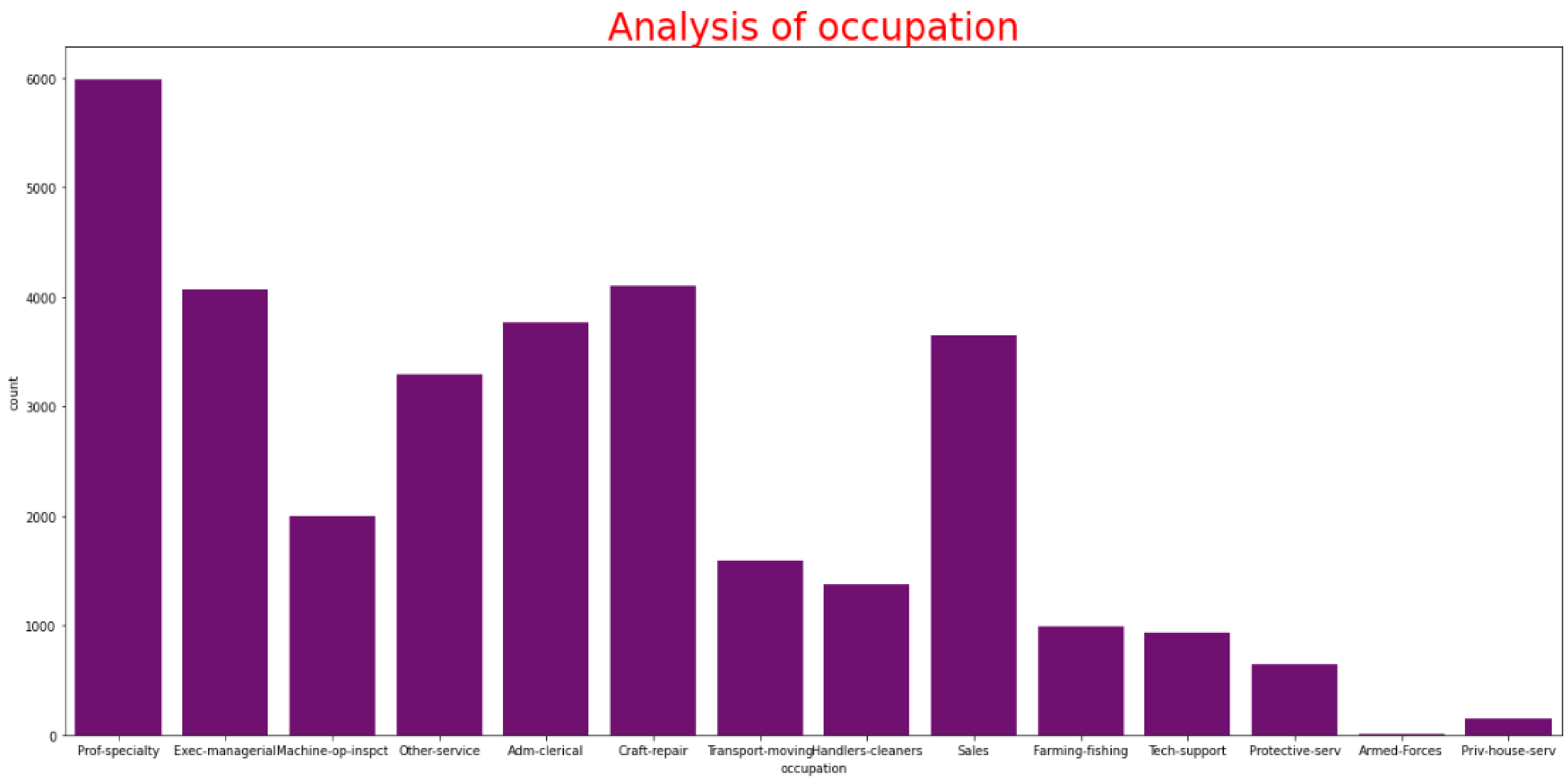


Mostly people are married-civ-spouse

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(22,10))
sns.countplot(census['occupation'],color='purple')
plt.title(f"Analysis of occupation" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of occupation')
```

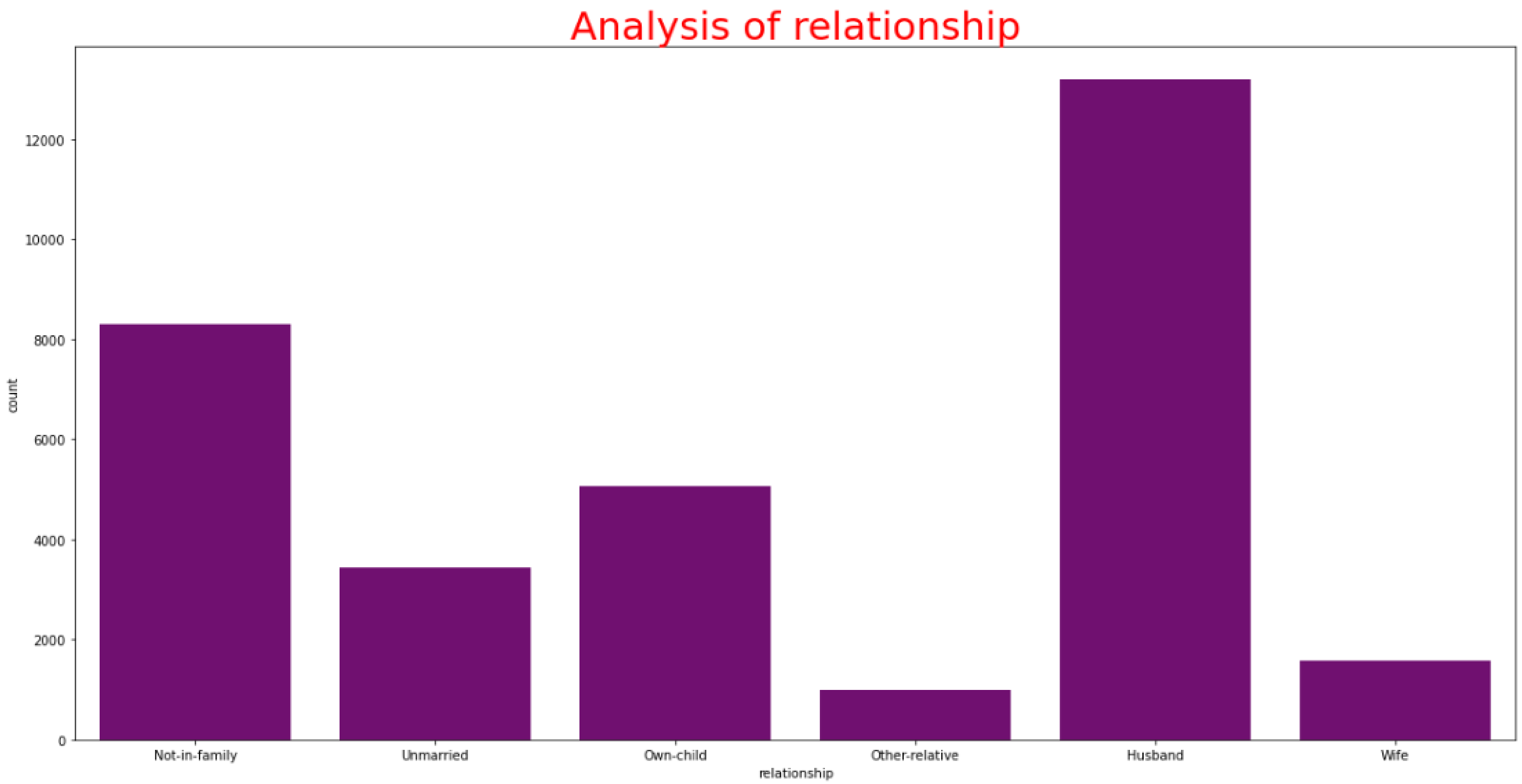


Mostly people occupation is prof-speciality

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['relationship'],color='purple')
plt.title(f"Analysis of relationship" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of relationship')
```

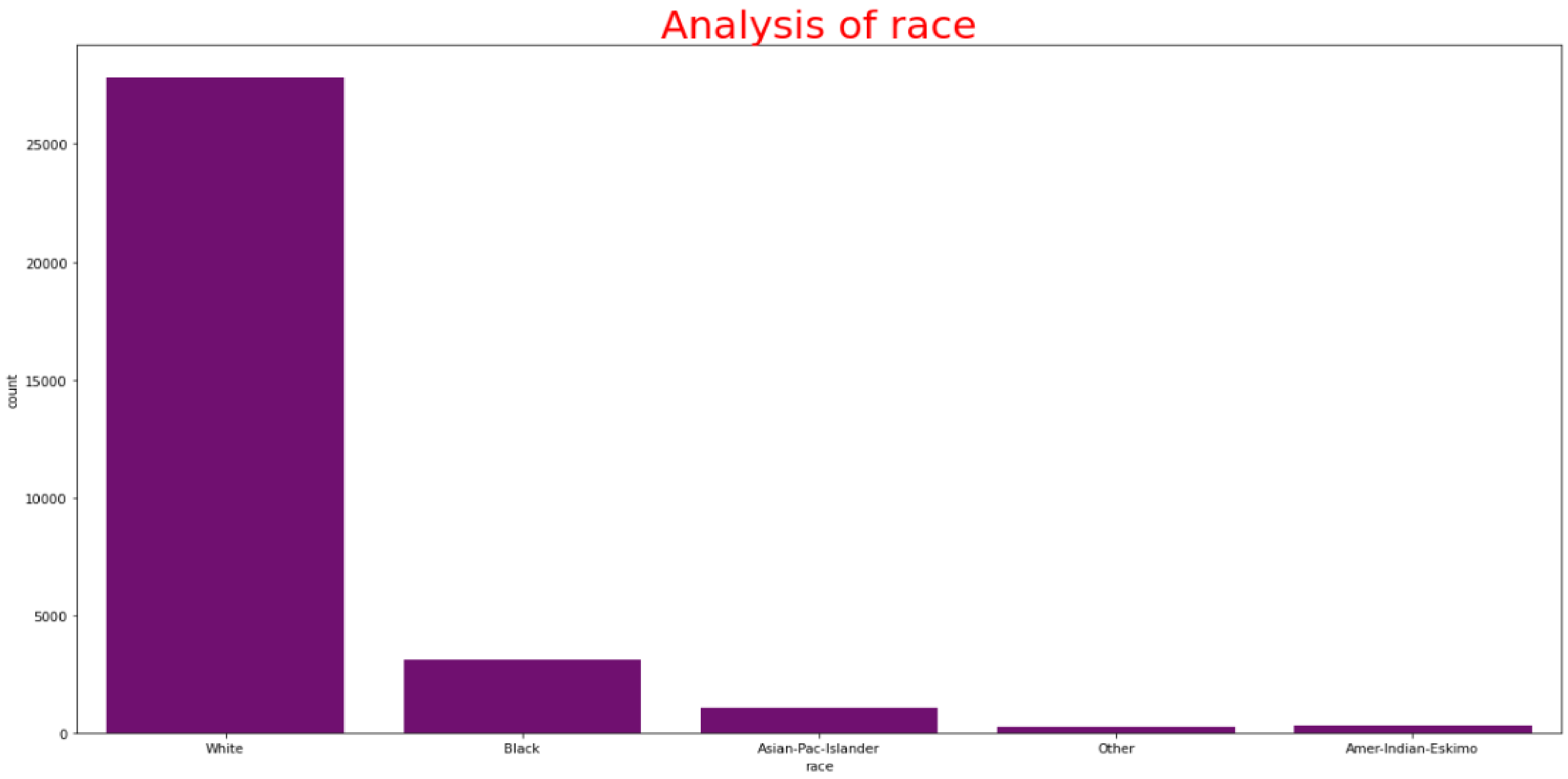


Moslty people are husbands

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['race'],color='purple')
plt.title(f"Analysis of race" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of race')
```

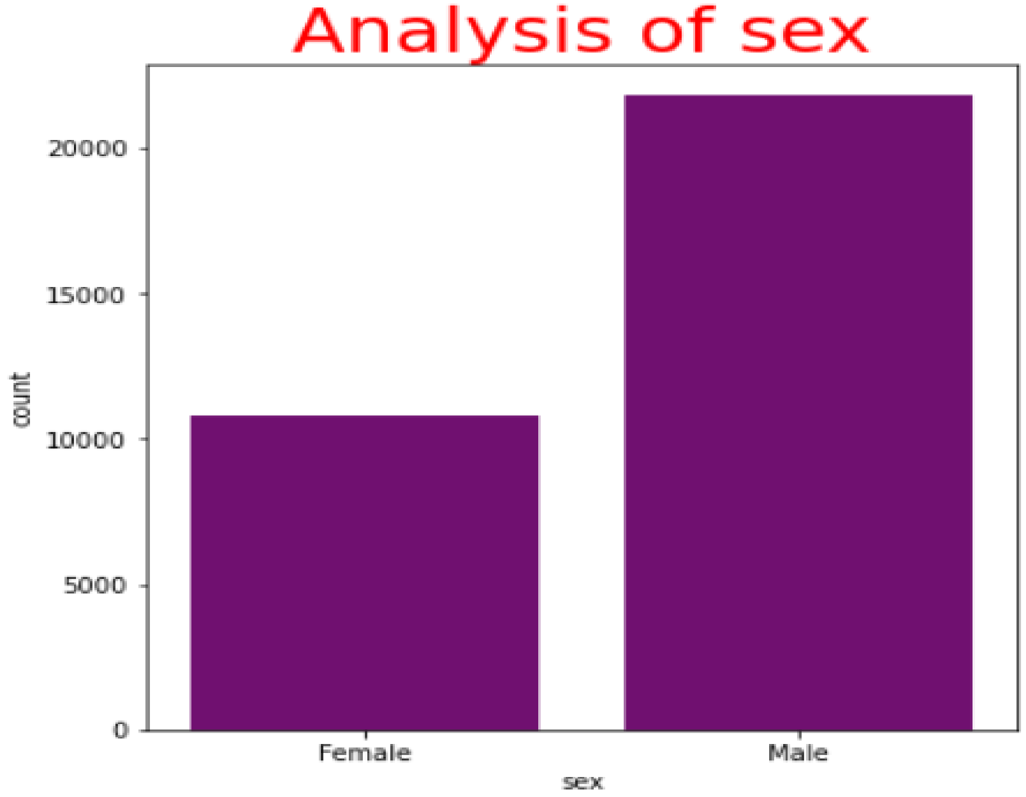


Mostly people are white

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(6,6))
sns.countplot(census['sex'],color='purple')
plt.title(f"Analysis of sex" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of sex')
```

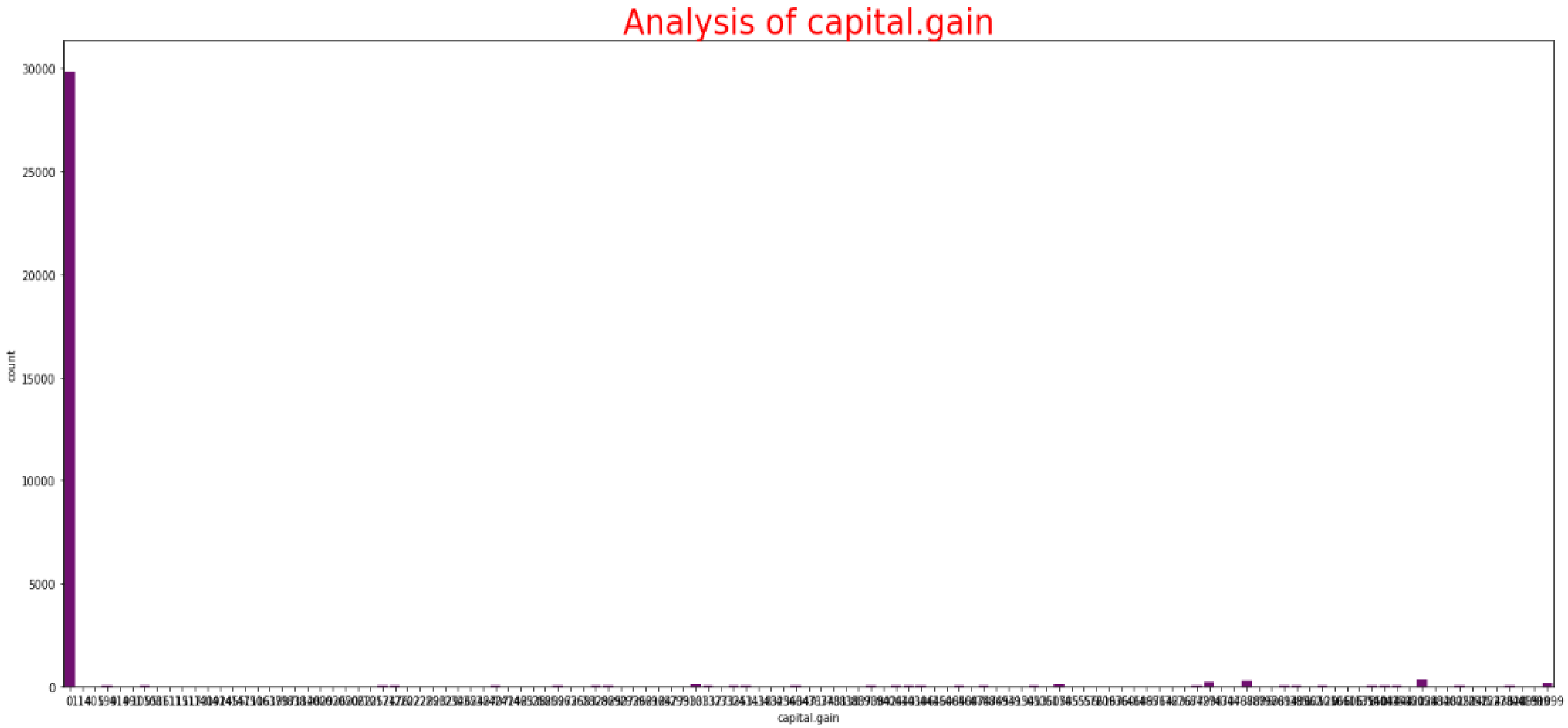


Mostly people are male

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(25,10))
sns.countplot(census['capital.gain'],color='purple')
plt.title(f"Analysis of capital.gain" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of capital.gain')
```

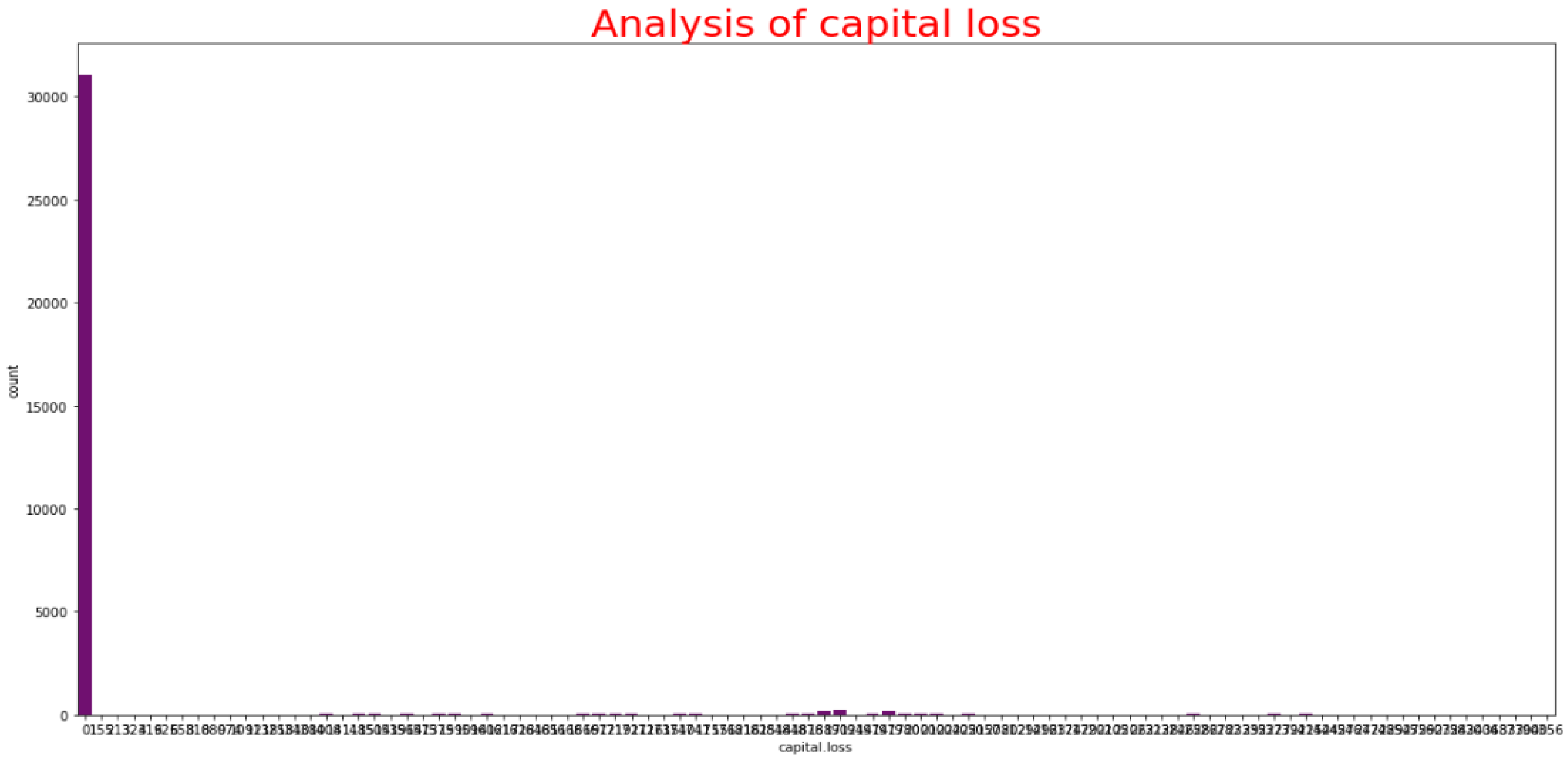


Mostly people capital gain is 0

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(20,10))
sns.countplot(census['capital.loss'],color='purple')
plt.title(f"Analysis of capital loss" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of capital loss')
```

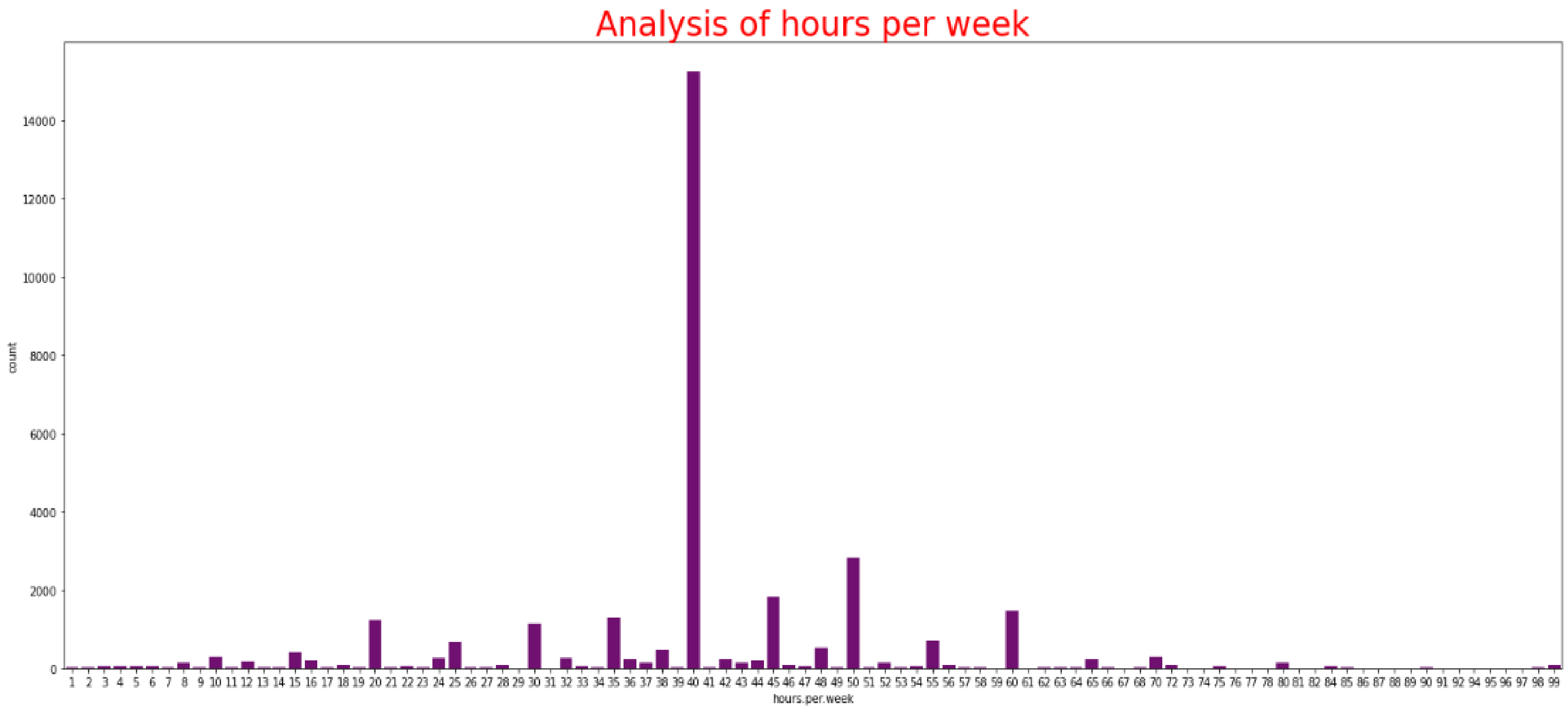


Mostly people capital loss is 0

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(25,10))
sns.countplot(census['hours.per.week'],color='purple')
plt.title(f"Analysis of hours per week" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of hours per week')
```

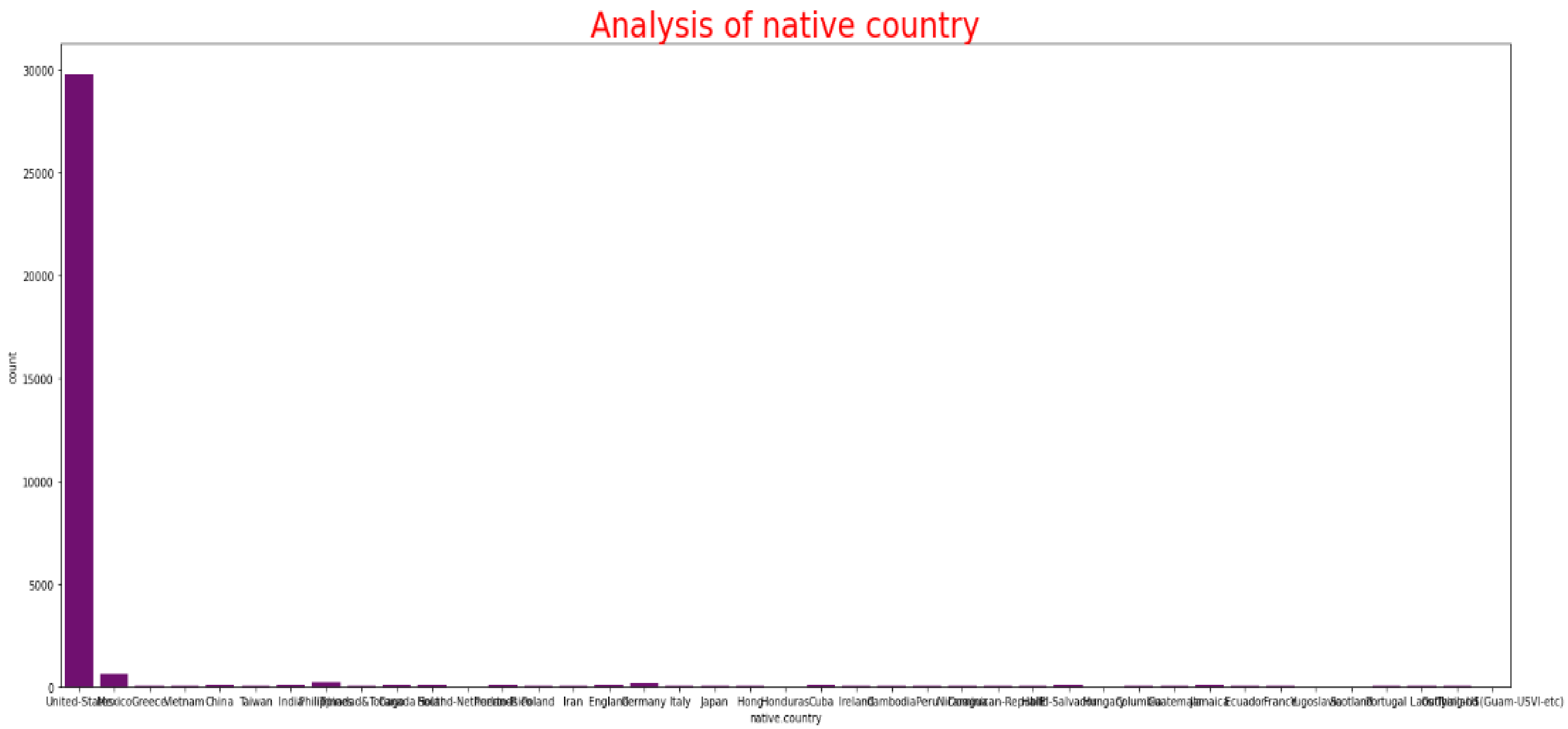


Mostly people work 40 hours per week

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(26,10))
sns.countplot(census['native.country'],color='purple')
plt.title(f"Analysis of native country" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of native country')
```

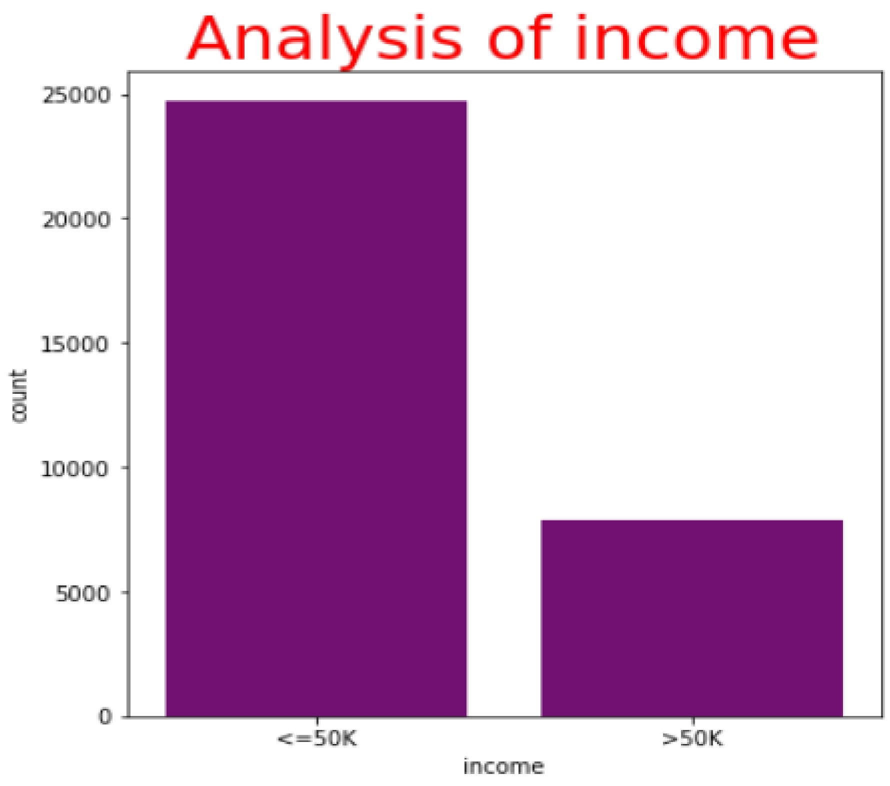


mostly people lived in United-states

Univariate Analysis - by CountPlot

```
plt.figure(figsize=(6,6))
sns.countplot(census['income'],color='purple')
plt.title(f"Analysis of income" , fontsize=30,
          color="red")
```

```
Text(0.5, 1.0, 'Analysis of income')
```

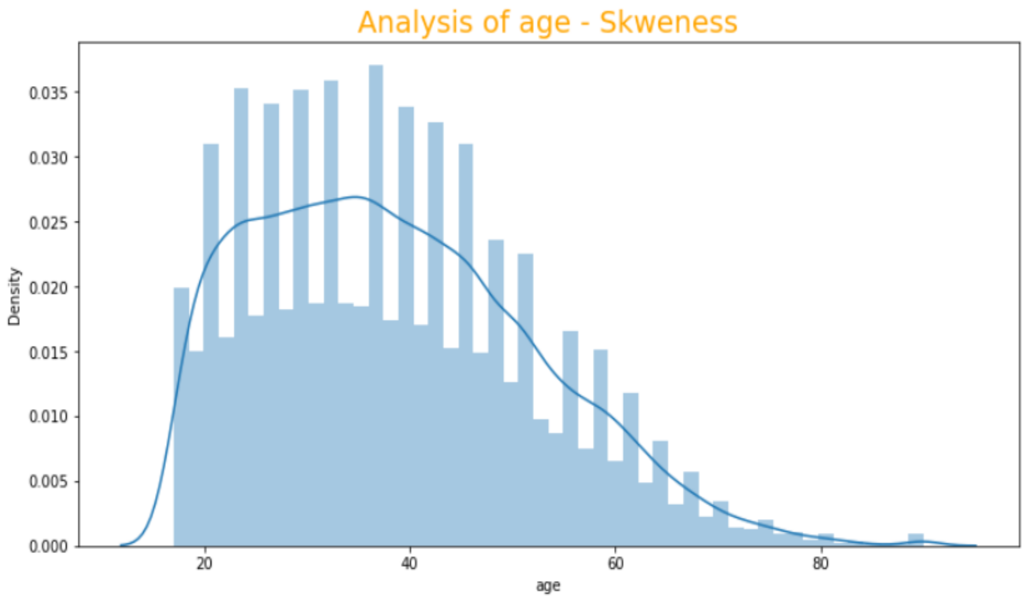


Mostly people income is <=50K

Univariate Analysis - by Distribution Plot

```
plt.figure(figsize=(12,6))
print("Skewness is :",census.age.skew())
sns.distplot(census.age)
plt.title(f"Analysis of age - Skweness" , fontsize=20,
          color="orange")
```

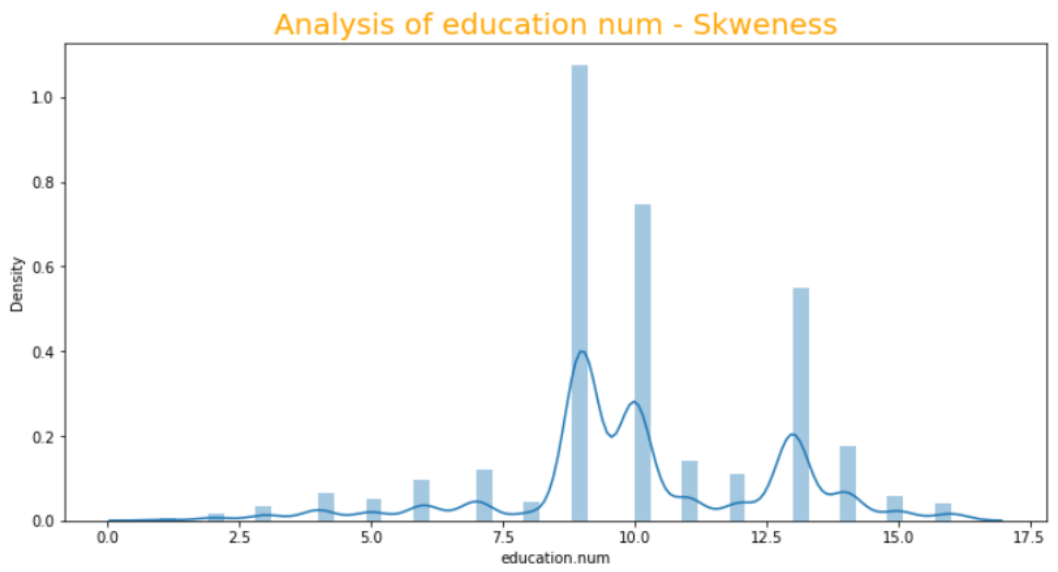
```
Skewness is : 0.5588983212766524

Text(0.5, 1.0, 'Analysis of age - Skweness')
```



Age is rightly skewed

```
plt.figure(figsize=(12,6))
print("Skewness is :",census['education.num'].skew())
sns.distplot(census['education.num'])
plt.title(f"Analysis of education num - Skweness" , fontsize=20,
          color="orange")
```

```
Skewness is : -0.31167586791022966

Text(0.5, 1.0, 'Analysis of education num - Skweness')
```



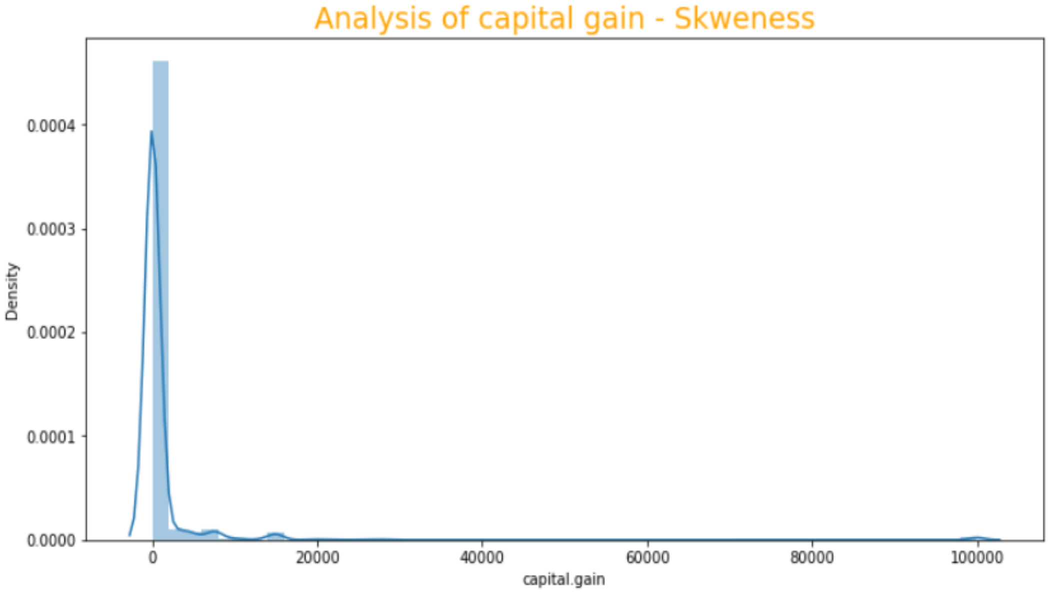
Education number is slightly rightly skewed

Univariate Analysis - by Distribution Plot

```
plt.figure(figsize=(12,6))
print("Skewness is :",census['capital.gain'].skew())
sns.distplot(census['capital.gain'])
plt.title(f"Analysis of capital gain - Skweness" , fontsize=20,
          color="orange")
```

Skewness is : 11.953847687699794

Text(0.5, 1.0, 'Analysis of capital gain - Skweness')

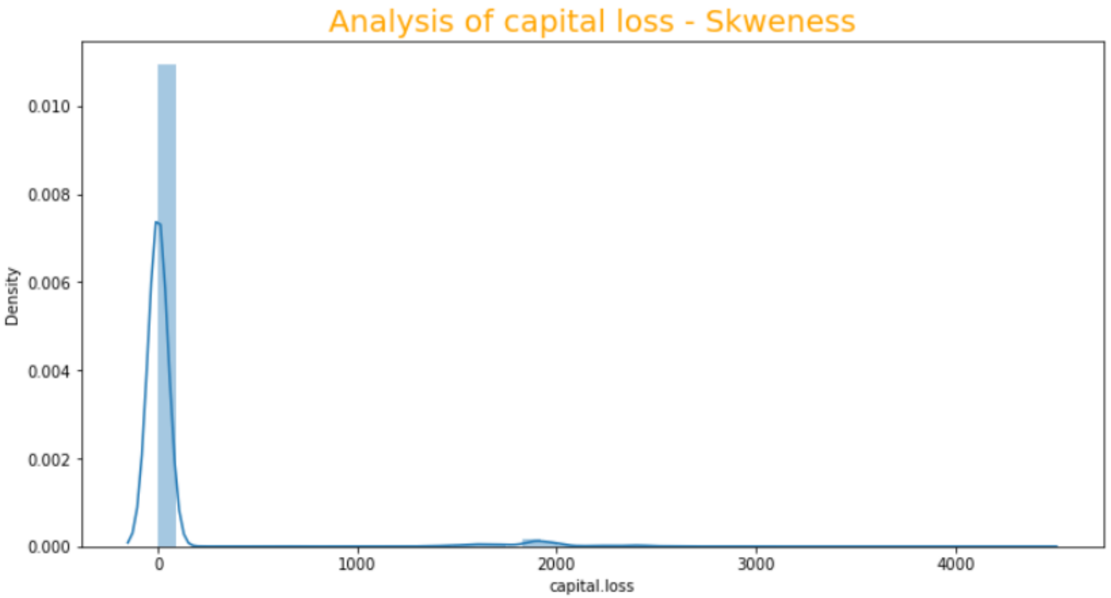


Capital gain is strongly rightly skewed

```
plt.figure(figsize=(12,6))
print("Skewness is :",census['capital.loss'].skew())
sns.distplot(census['capital.loss'])
plt.title(f"Analysis of capital loss - Skweness" , fontsize=20,
          color="orange")
```

Skewness is : 4.594629121679696

Text(0.5, 1.0, 'Analysis of capital loss - Skweness')

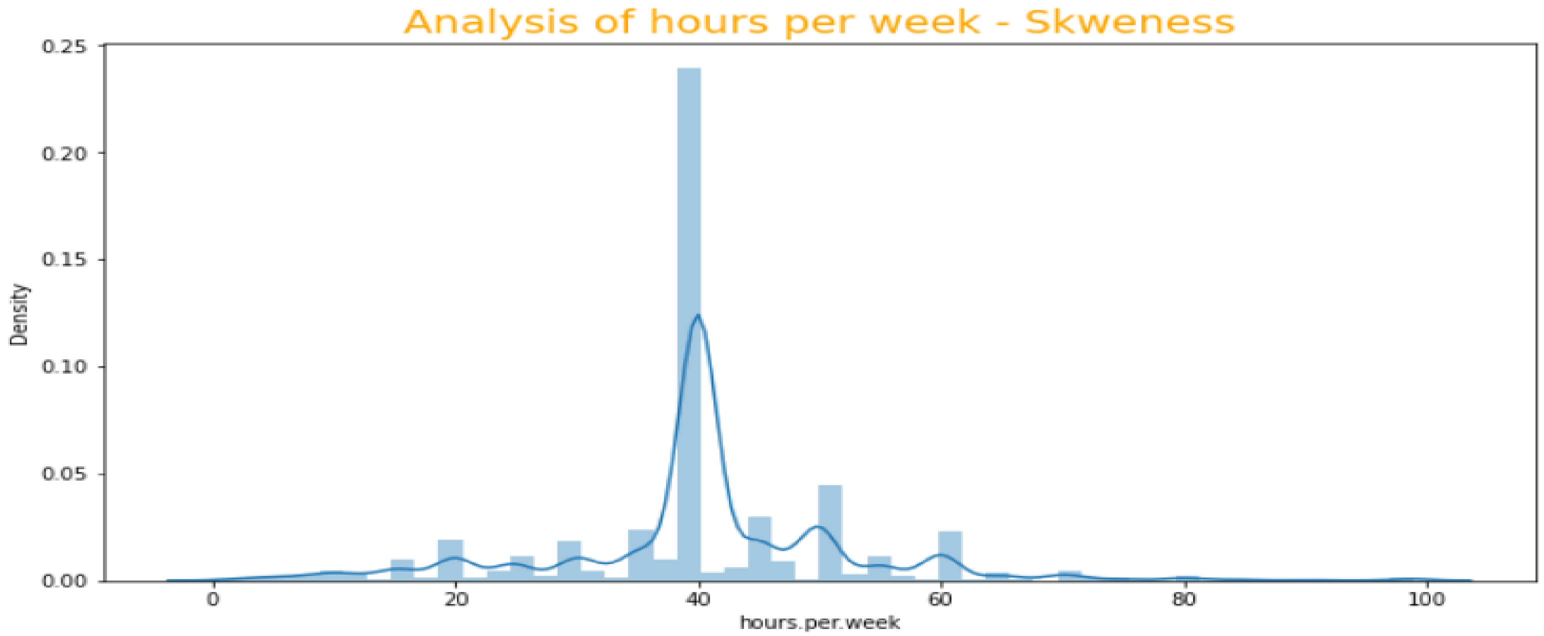


Capital loss is strongly rightly skewed

Univariate Analysis - by Distribution Plot

```
plt.figure(figsize=(12,6))
print("Skewness is :",census['hours.per.week'].skew())
sns.distplot(census['hours.per.week'])
plt.title(f"Analysis of hours per week - Skweness" , fontsize=20,
          color="orange")
```

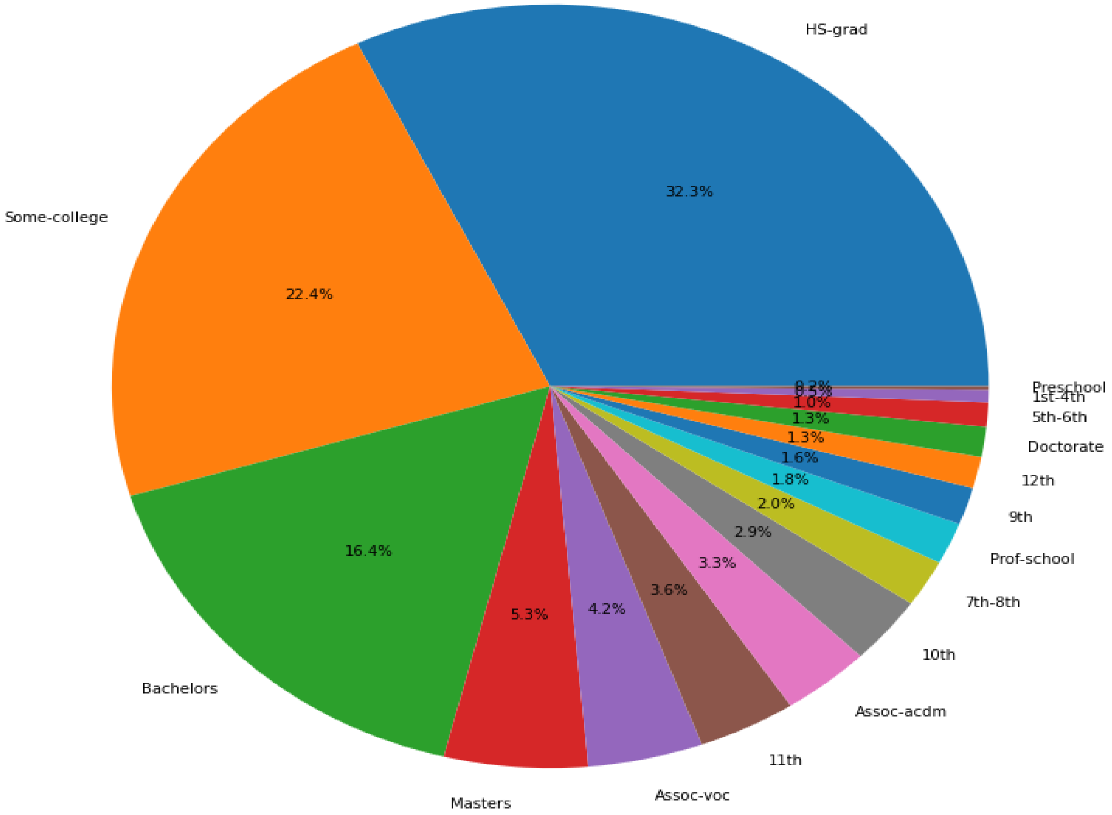
```
Skewness is : 0.2278441260001115

Text(0.5, 1.0, 'Analysis of hours per week - Skweness')
```



Hours per week is slightly rightly skewed

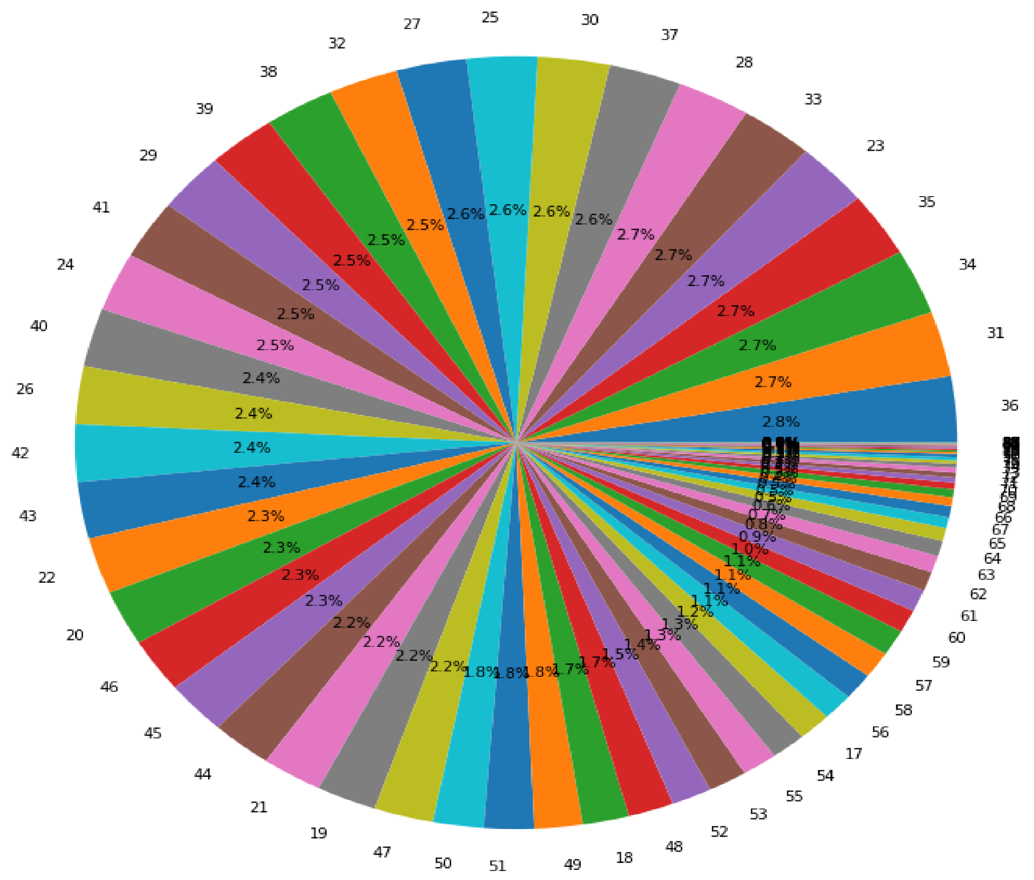
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['education'].value_counts()),labels = list(census['education'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



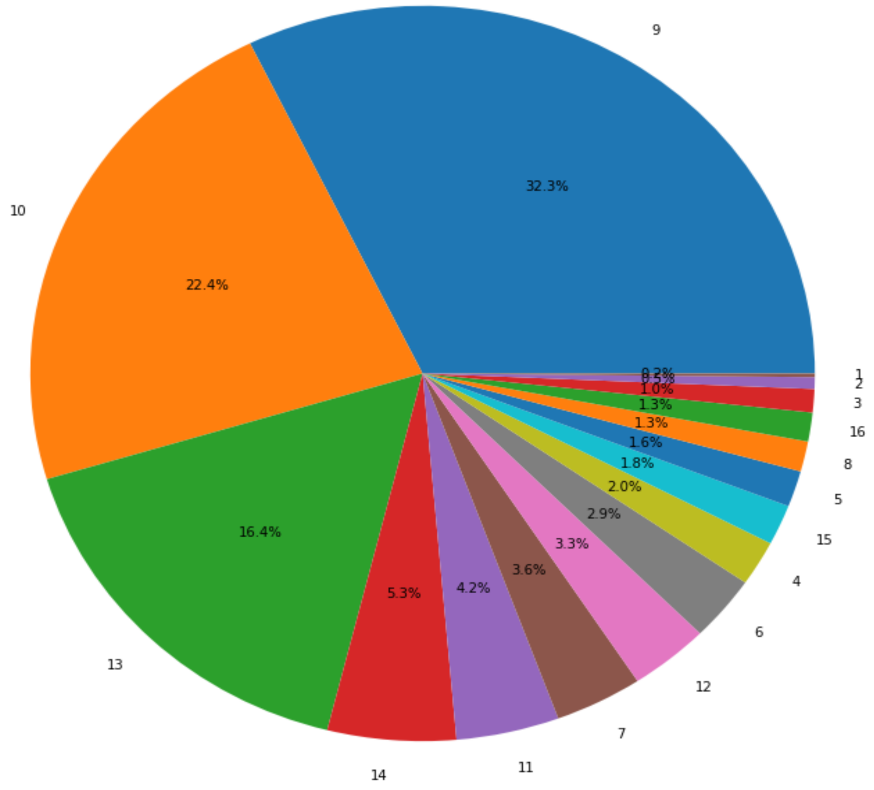
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['age'].value_counts()),labels = list(census['age'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



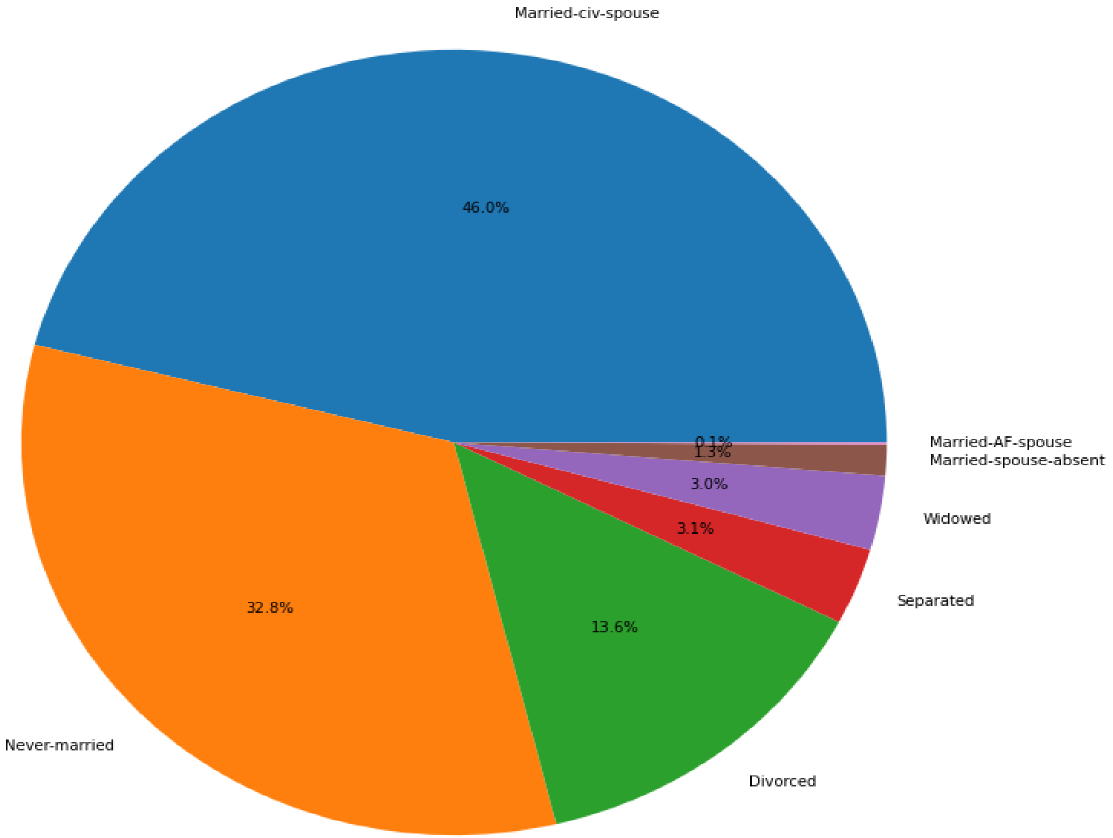
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['education.num'].value_counts()),labels = list(census['education.num'].value_counts().keys()), autopct="%0.1f
plt.show()
```



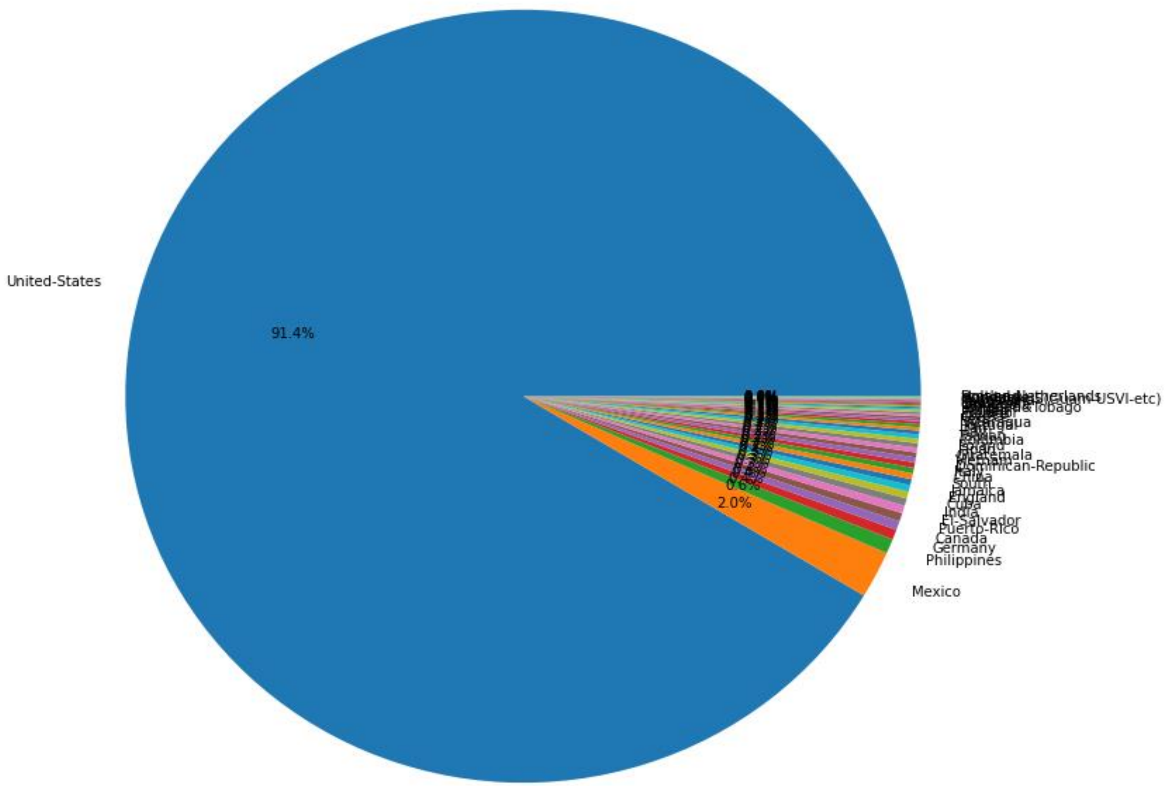
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['marital.status'].value_counts()),labels = list(census['marital.status'].value_counts().keys()),
        autopct="%0.1f%%" )
plt.show()
```



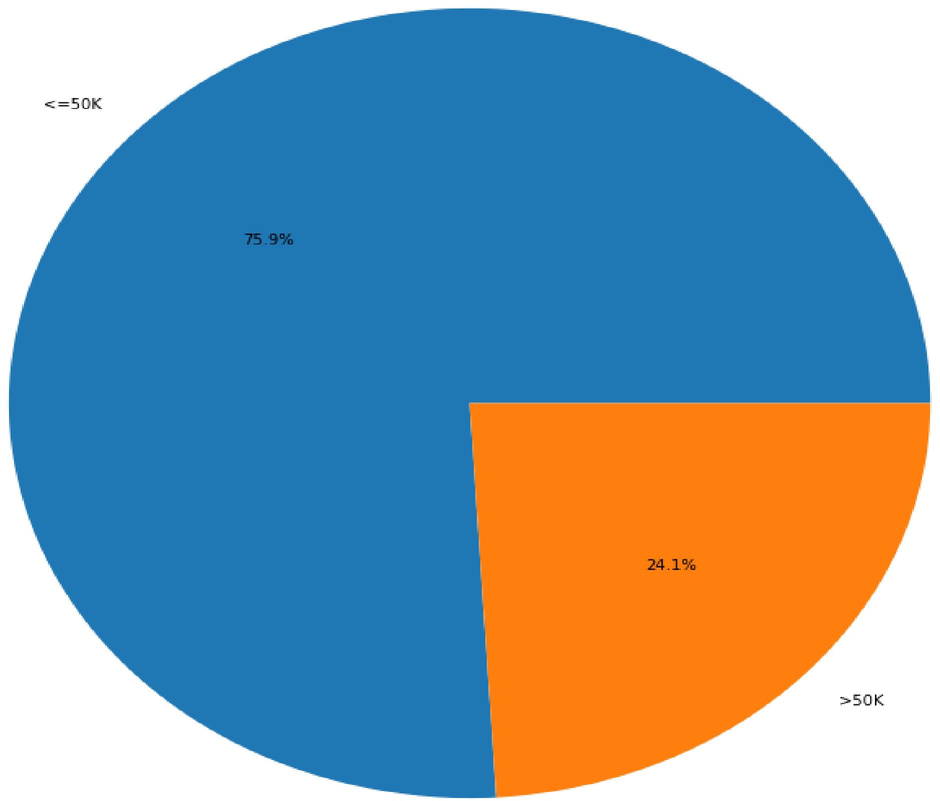
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['native.country'].value_counts()),labels = list(census['native.country'].value_counts().keys()),
        autopct="%0.1f%%" )
plt.show()
```



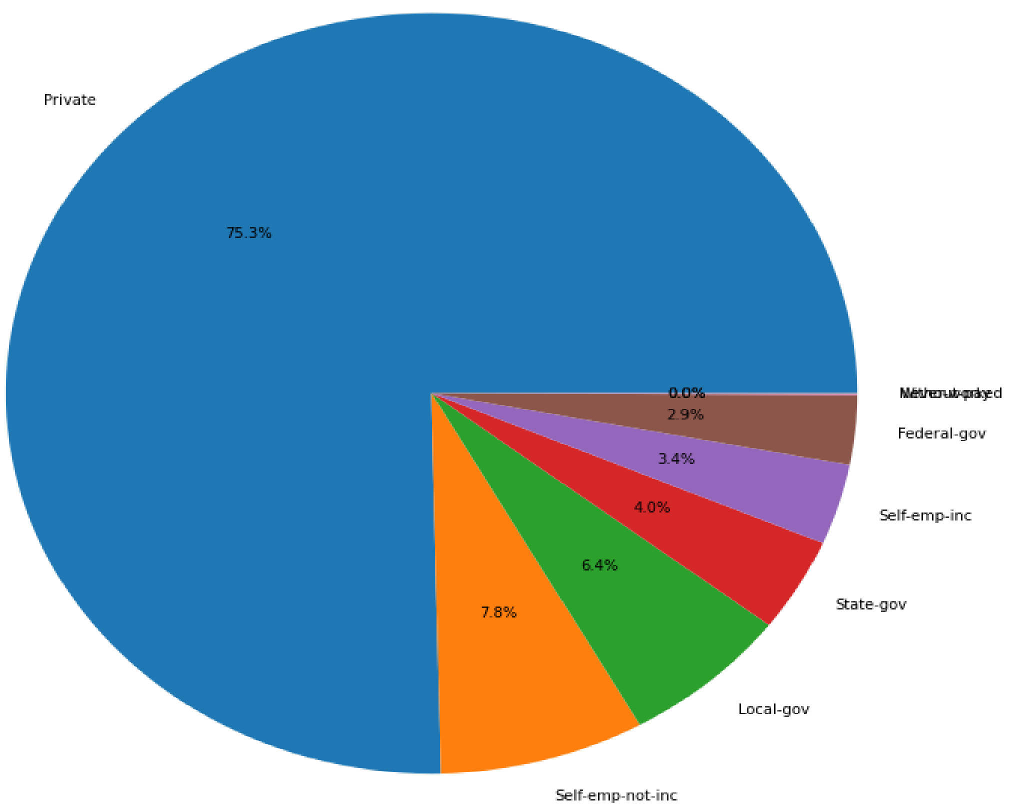
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['income'].value_counts()),labels = list(census['income'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



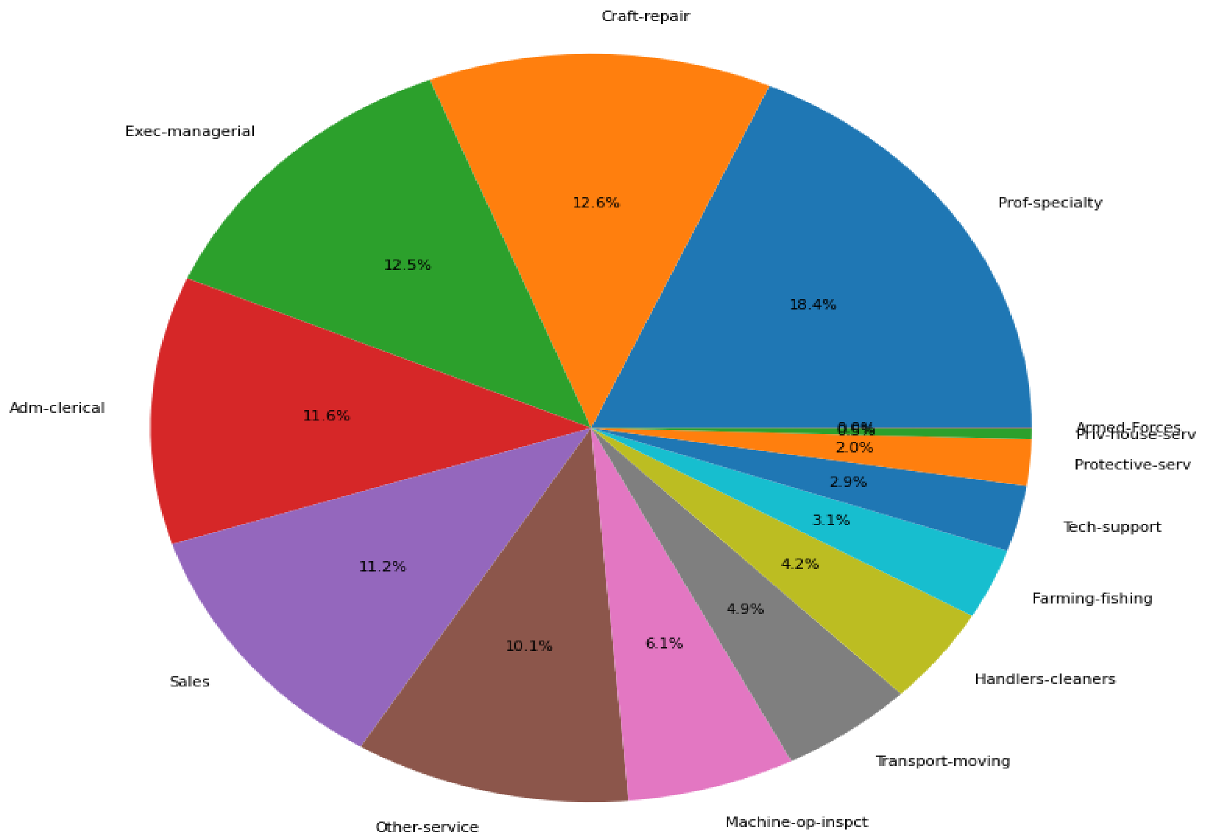
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['workclass'].value_counts()),labels = list(census['workclass'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



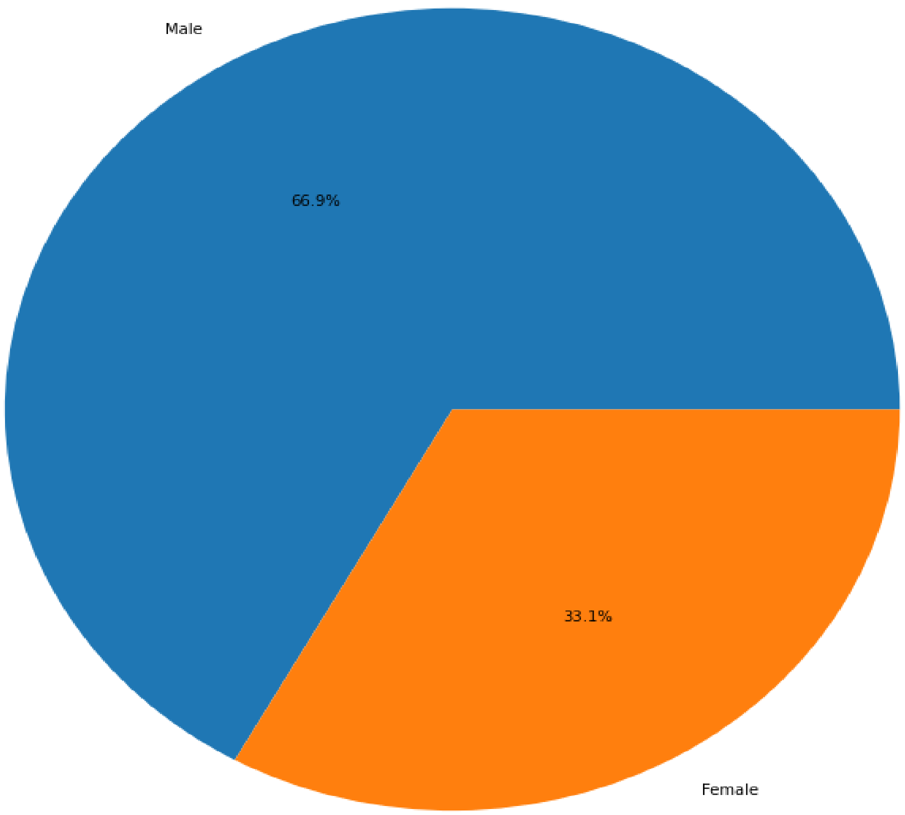
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['occupation'].value_counts()),labels = list(census['occupation'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



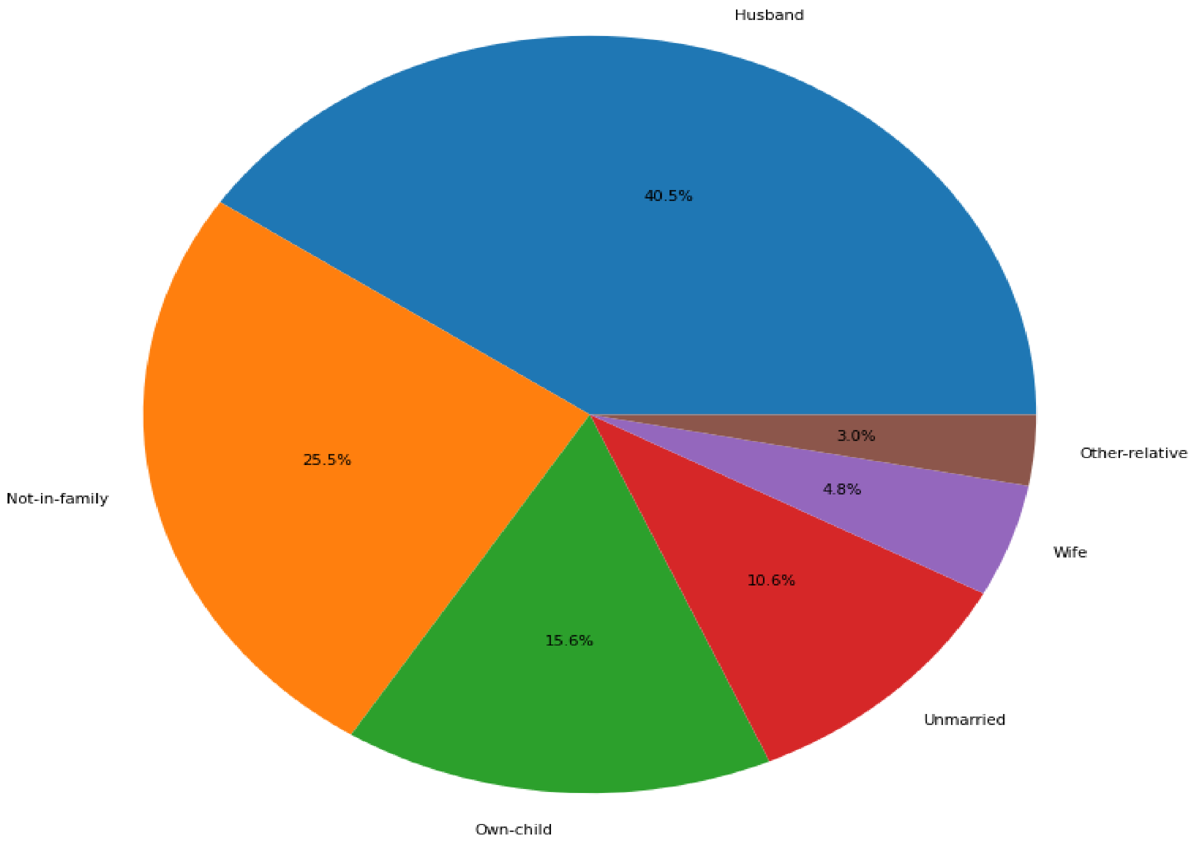
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['sex'].value_counts()),labels = list(census['sex'].value_counts().keys()), autopct="%0.1f%%" )
plt.show()
```



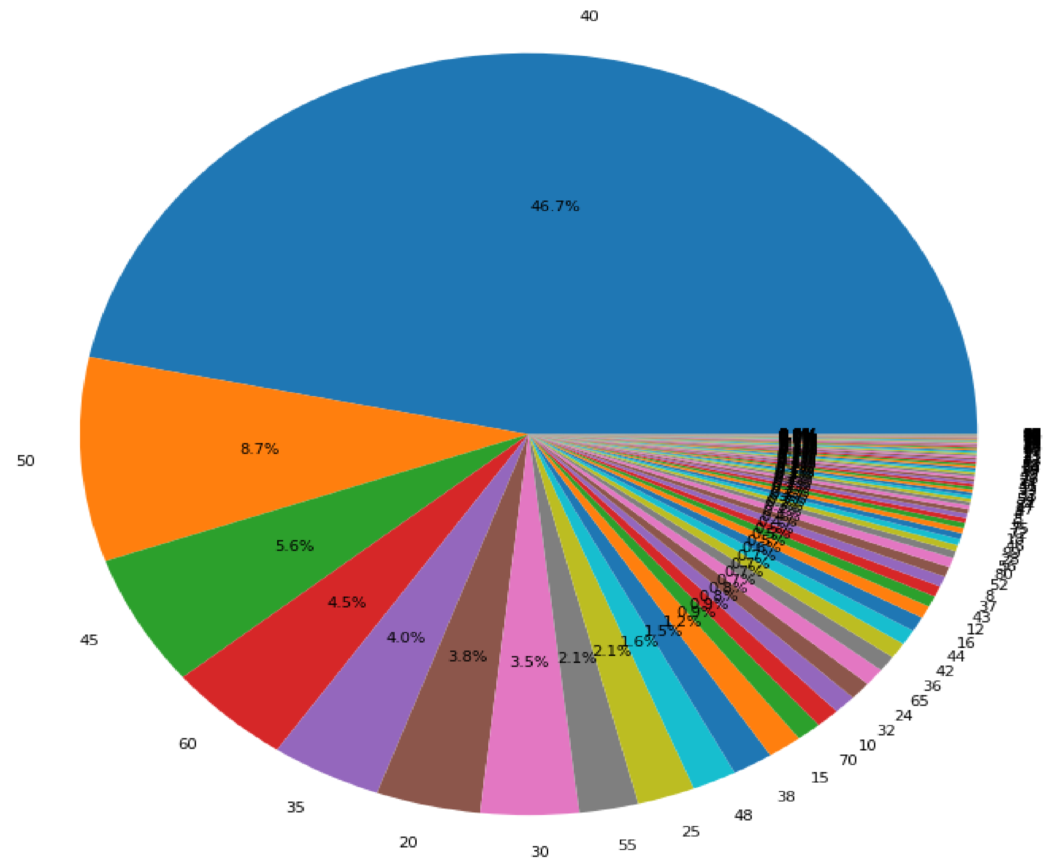
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['relationship'].value_counts()),labels = list(census['relationship'].value_counts().keys()), autopct="%0.1f%
plt.show()
```



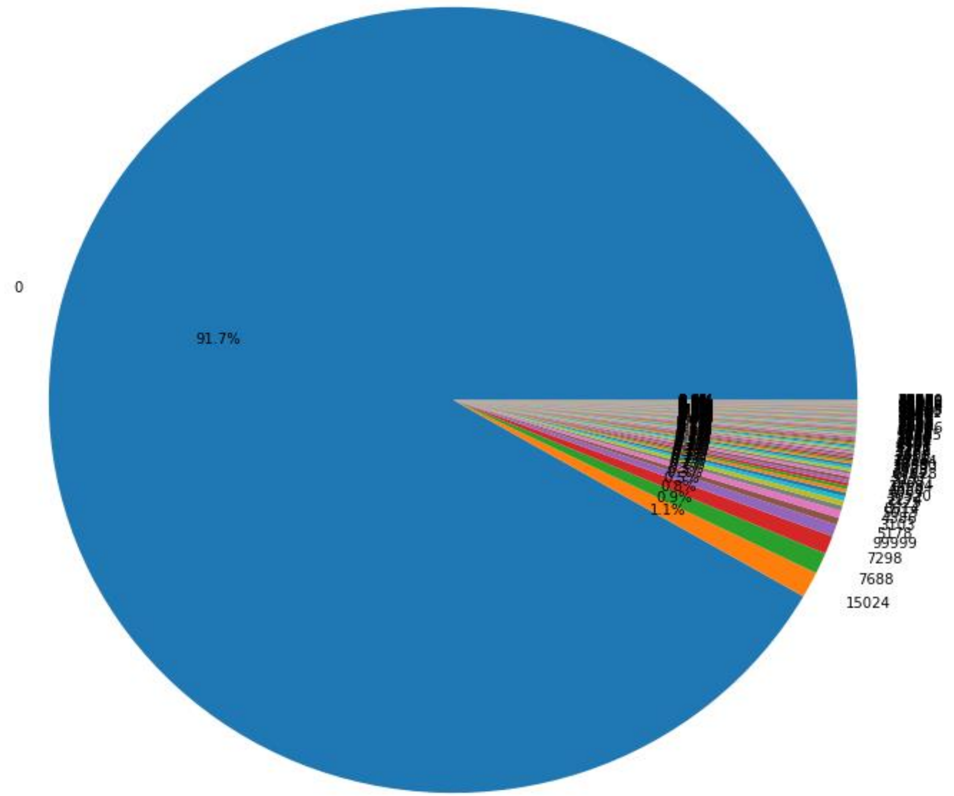
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['hours.per.week'].value_counts()),labels = list(census['hours.per.week'].value_counts().keys()), autopct="%0.
plt.show()
```



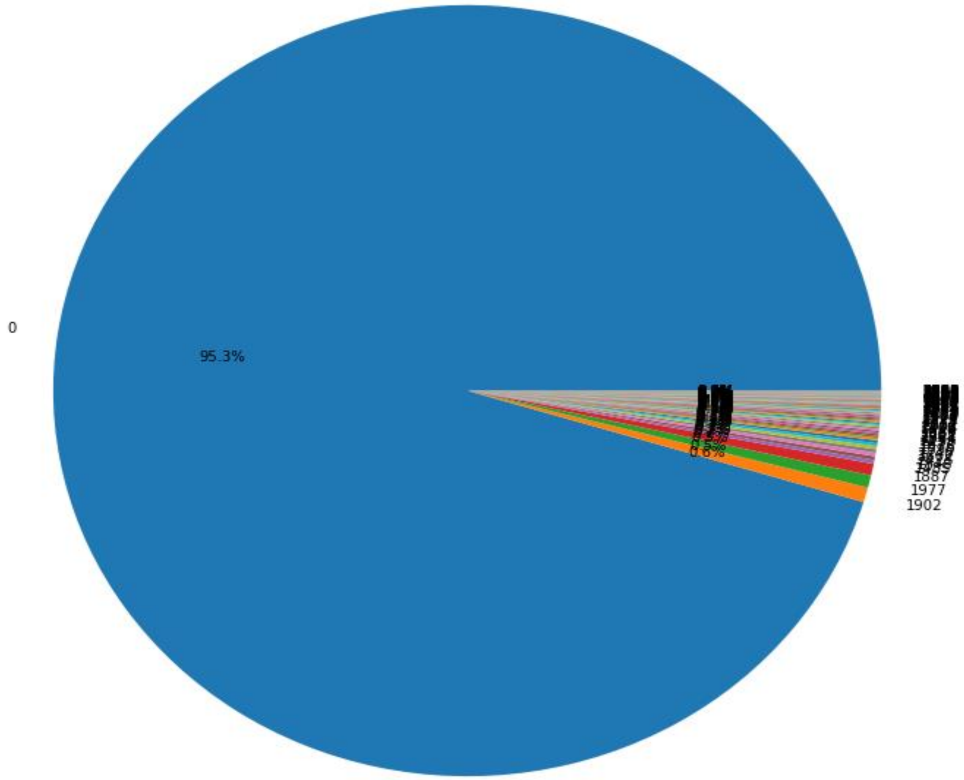
Univariate Analysis - by Pie Chart

```
plt.figure(figsize = (13,13))
plt.pie(list(census['capital.gain'].value_counts()),labels = list(census['capital.gain'].value_counts().keys()), autopct="%0.1f%
plt.show()
```



Univariate Analysis - by Pie Chart

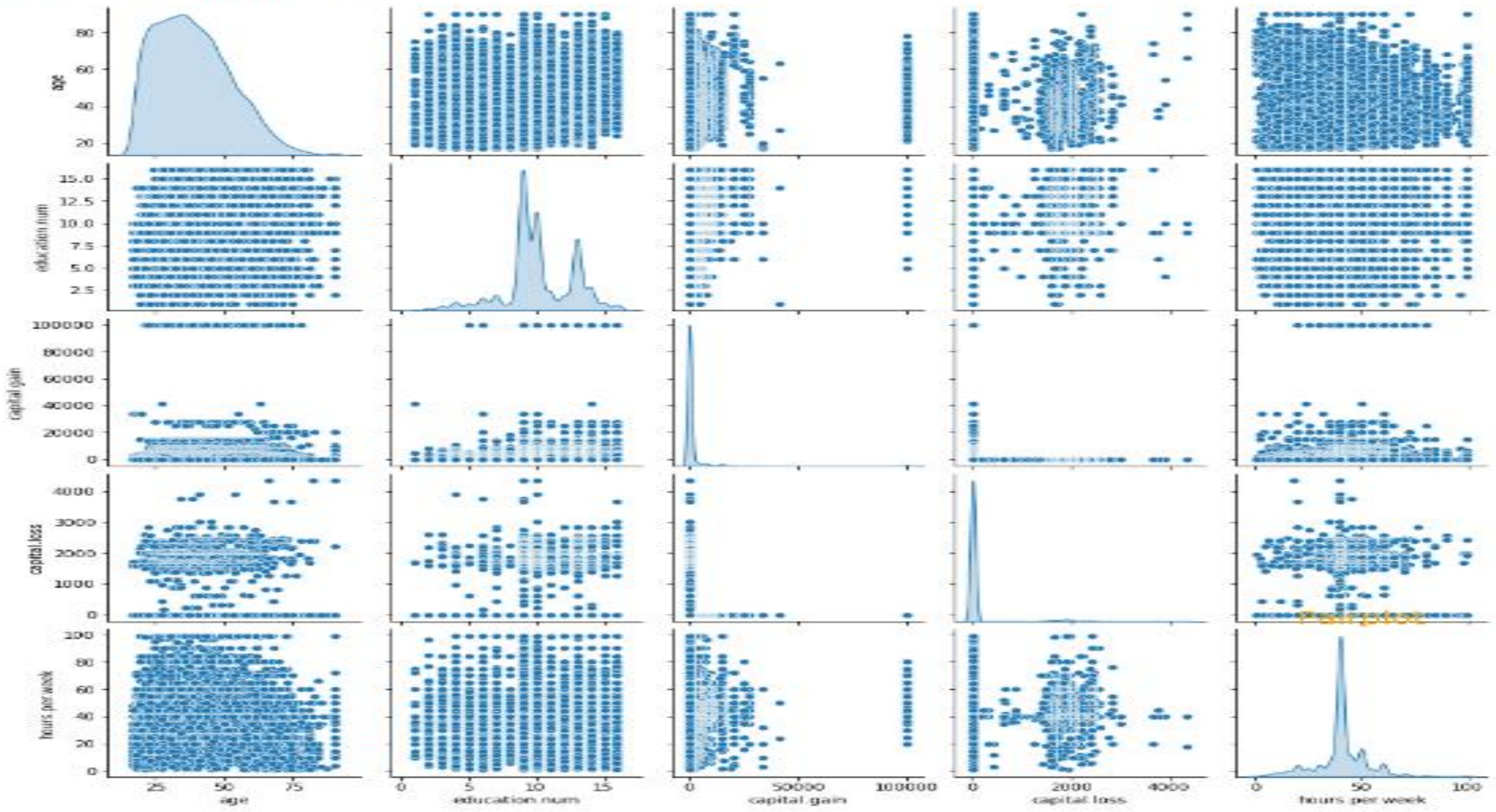
```
plt.figure(figsize = (13,13))
plt.pie(list(census['capital.loss'].value_counts()),labels = list(census['capital.loss'].value_counts().keys()), autopct="%0.1f%
plt.show()
```



Pair Plot

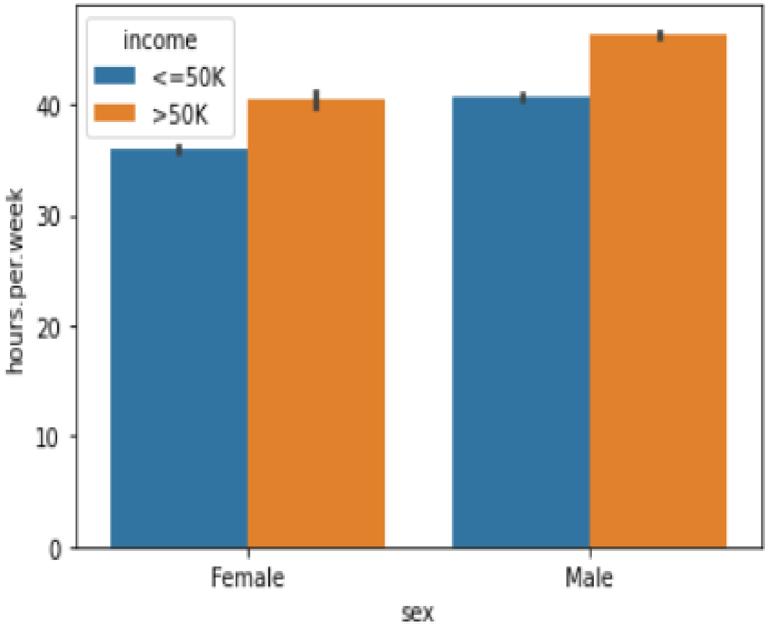
```
sns.pairplot(census, diag_kind = 'kde')
plt.title(f"Pairplot" , fontsize=20,
          color="orange")
```

```
Text(0.5, 1.0, 'Pairplot')
```

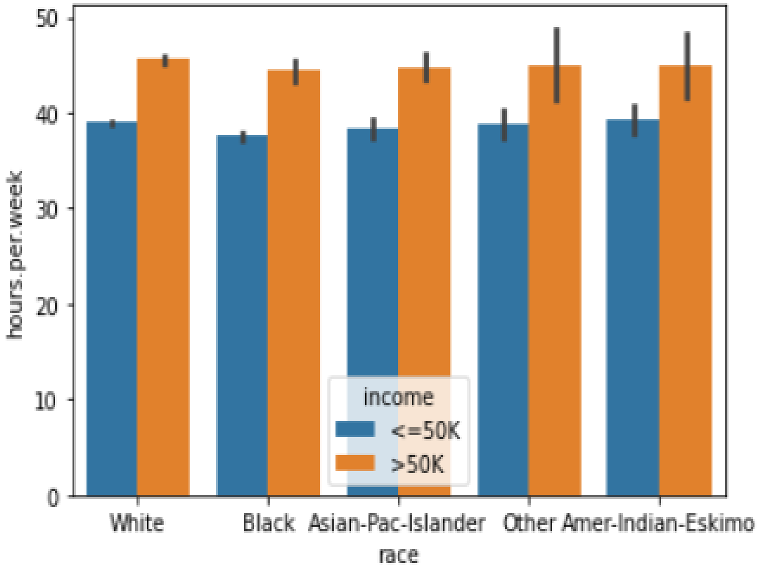


Bivariate Analysis - by Bar Plot

```
sns.barplot(x='sex',y='hours.per.week', data = census, hue='income')
plt.show()
```

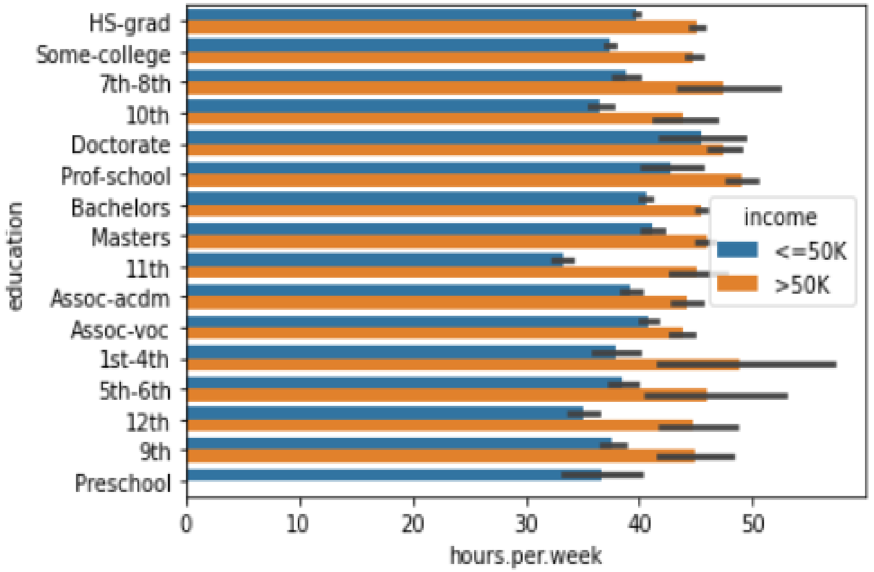



```
sns.barplot(x='race',y='hours.per.week', data = census, hue='income')
plt.show()
```

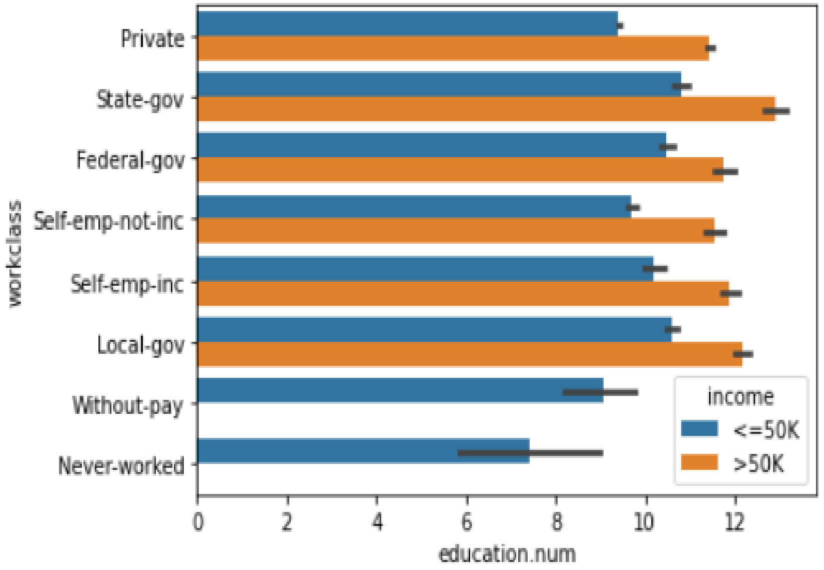


Bivariate Analysis - by Bar Plot

```
sns.barplot(x='hours.per.week',y='education', data = census, hue='income')
plt.show()
```

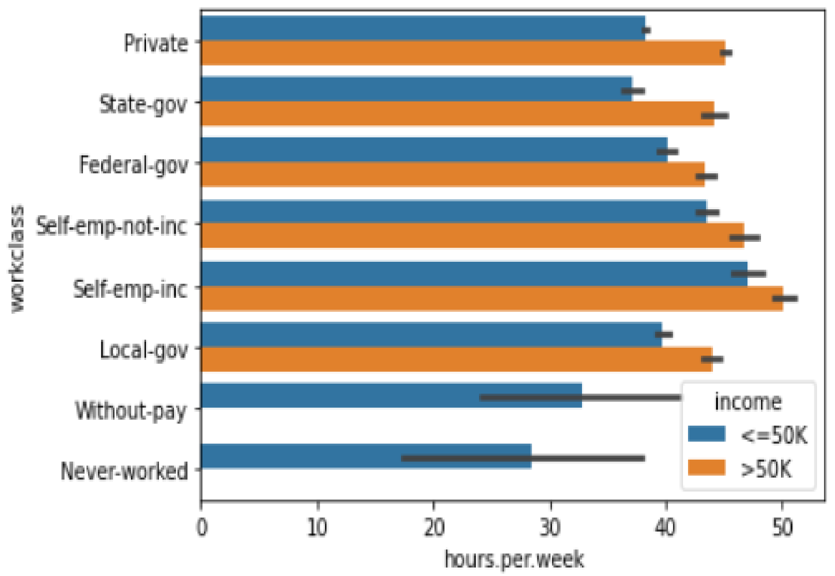



```
sns.barplot(x='education.num',y='workclass', data = census, hue='income')
plt.show()
```

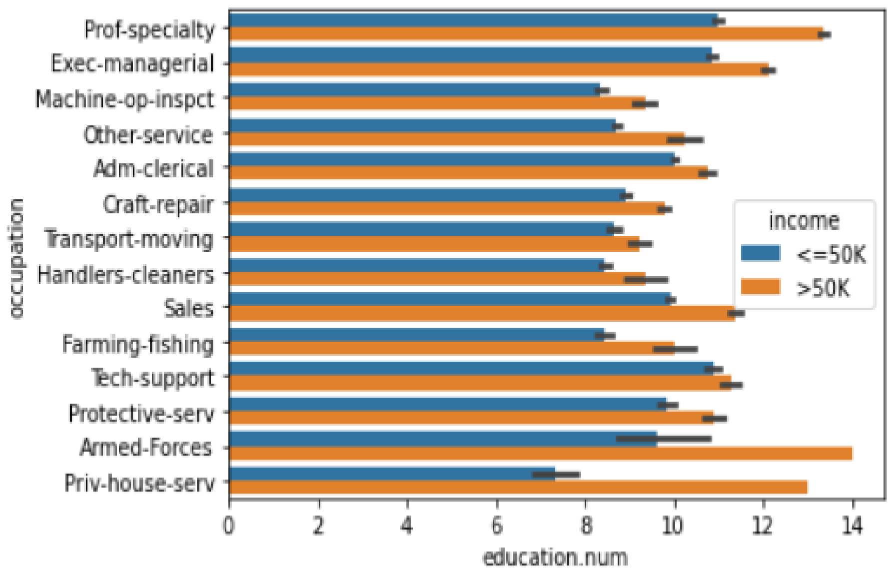


Bivariate Analysis - by Bar Plot

```
sns.barplot(x='hours.per.week',y='workclass', data = census, hue='income')
plt.show()
```

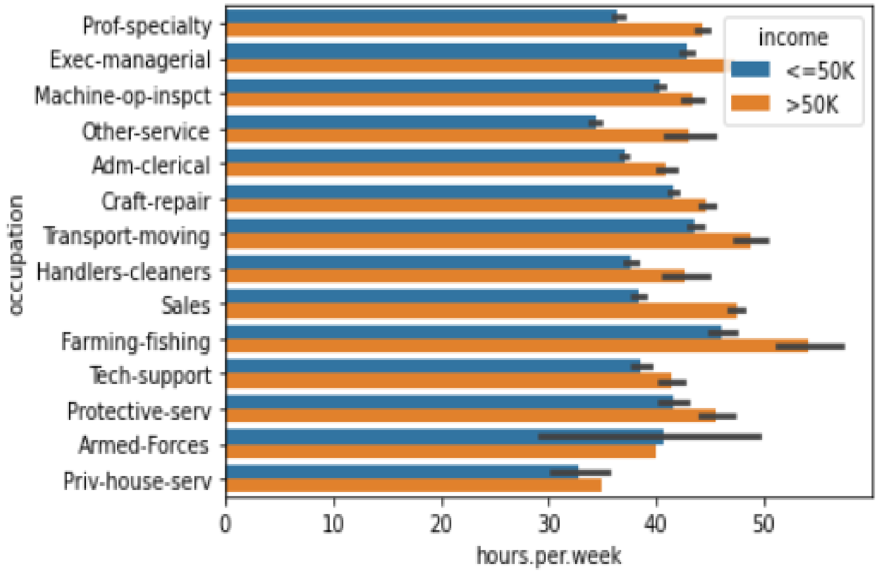



```
sns.barplot(x='education.num',y='occupation', data = census, hue='income')
plt.show()
```

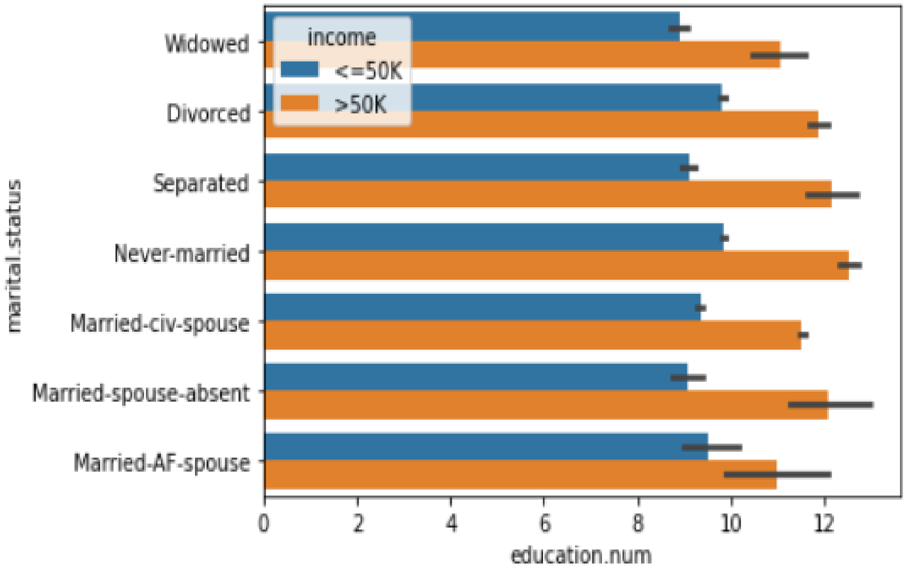


Bivariate Analysis - by Bar Plot

```
sns.barplot(x='hours.per.week',y='occupation', data = census, hue='income')
plt.show()
```

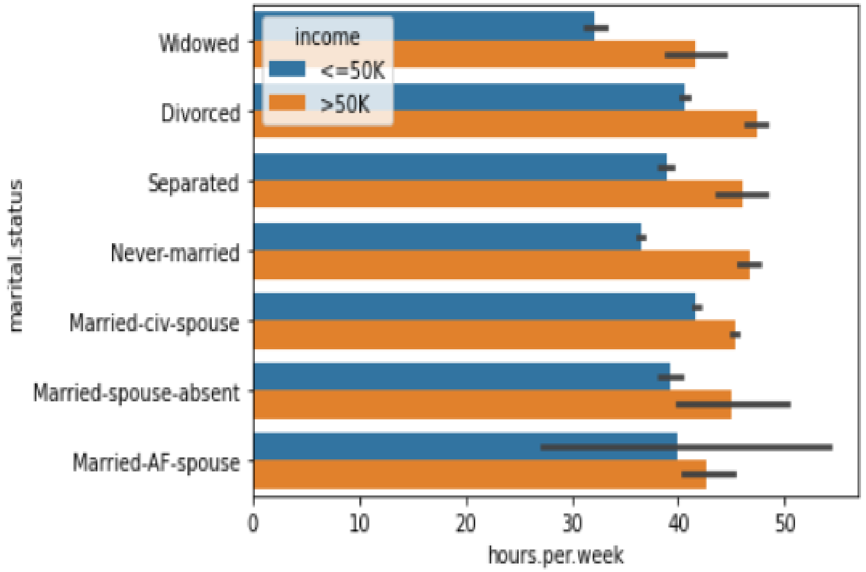



```
sns.barplot(x='education.num',y='marital.status', data = census, hue='income')
plt.show()
```

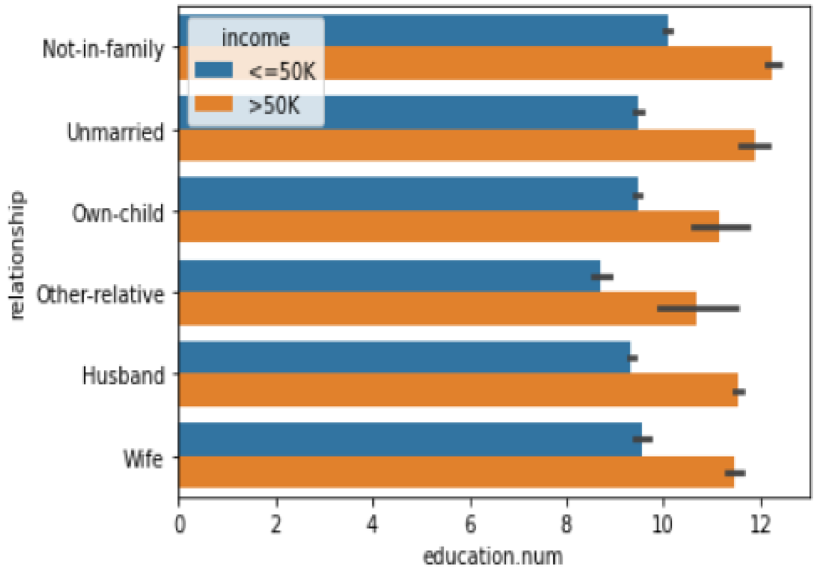


Bivariate Analysis - by Bar Plot

```
sns.barplot(x='hours.per.week',y='marital.status', data = census, hue='income')
plt.show()
```

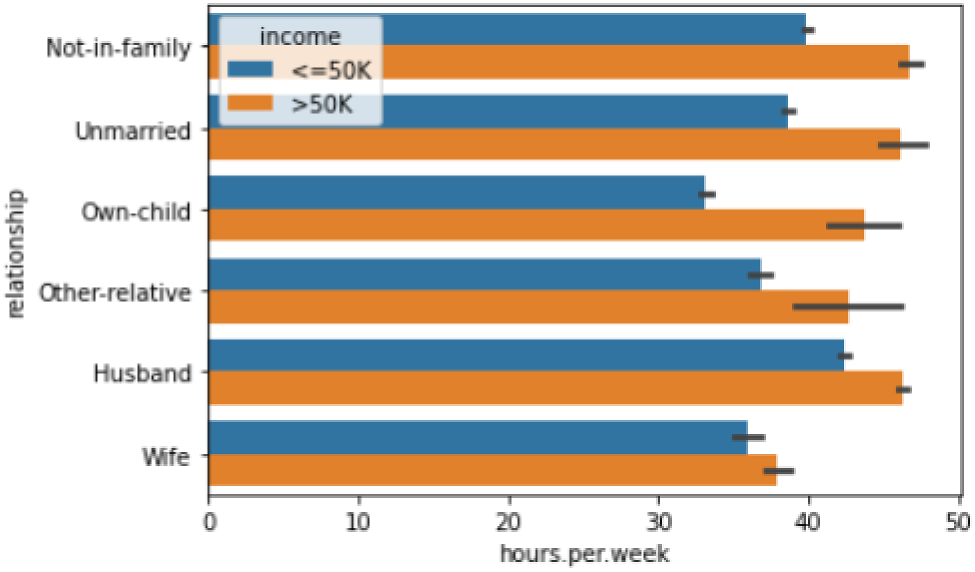



```
sns.barplot(x='education.num',y='relationship', data = census, hue='income')
plt.show()
```



Bivariate Analysis - by Bar Plot

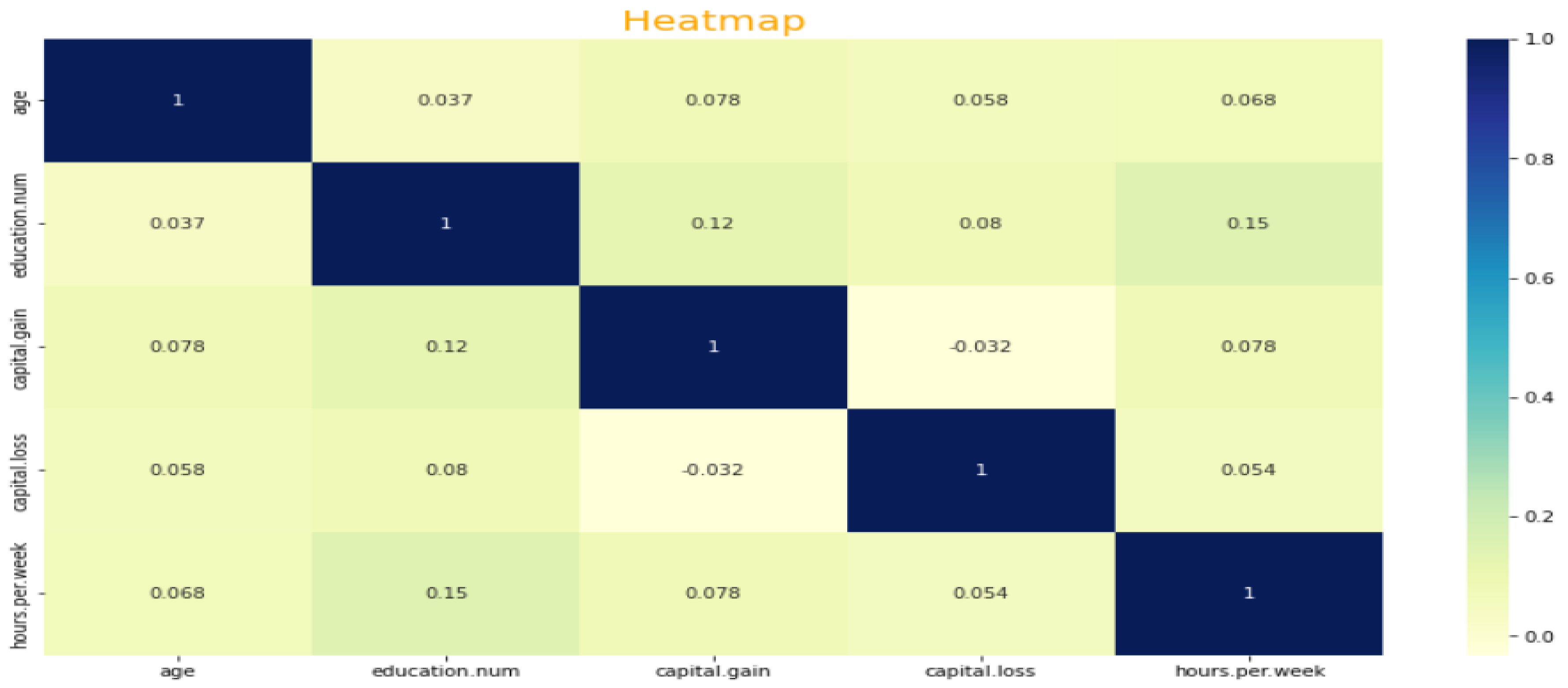
```
sns.barplot(x='hours.per.week',y='relationship', data = census, hue='income')
plt.show()
```



Bivariate Analysis - by Heat Map

```
plt.subplots(figsize =(15, 8))
sns.heatmap(corr,cmap="YlGnBu",annot=True)
plt.title(f"Heatmap" , fontsize=20,
          color="orange")
```

```
Text(0.5, 1.0, 'Heatmap')
```



Bivariate Analysis - by Correlation

```
census.corr()
```

	age	education.num	capital.gain	capital.loss	hours.per.week
age	1.000000	0.036558	0.077685	0.057786	0.068462
education.num	0.036558	1.000000	0.122630	0.079923	0.147953
capital.gain	0.077685	0.122630	1.000000	-0.031615	0.078417
capital.loss	0.057786	0.079923	-0.031615	1.000000	0.053845
hours.per.week	0.068462	0.147953	0.078417	0.053845	1.000000

AS we can see from the heat map and Correlation table the numerical columns are not really co-dependent

Modelling

Dataset name: Census.cvs

Decision Tree Classifier

```
feature_cols = ['age', 'education.num','capital.loss','capital.gain'
                , 'hours.per.week', ]
X = census[feature_cols] # Features
y = census.income # Target variable
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1) # 70% training and 30% test
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y_test, y_pred))

print ("\nAccuracy : ",
accuracy_score(y_test,y_pred)*100)

print("\nReport : ",
classification_report(y_test, y_pred))
```

```
Accuracy: 0.8156413143617566

Confusion Matrix:
  [[6853  515]
 [1286 1115]]

Accuracy :  81.56413143617566

Report :                precision    recall  f1-score   support

       <=50K       0.84      0.93      0.88      7368
        >50K       0.68      0.46      0.55      2401

    accuracy                           0.82      9769
   macro avg       0.76      0.70      0.72      9769
weighted avg       0.80      0.82      0.80      9769
```

Decision Tree Classifier

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1) # 70% training and 30% test
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(criterion = "gini",
random_state = 100,max_depth=3, min_samples_leaf=5)

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y_test, y_pred))

print ("\nAccuracy : ",
accuracy_score(y_test,y_pred)*100)

print("\nReport : ",
classification_report(y_test, y_pred))
```

```
Accuracy: 0.8023339133995291

Confusion Matrix:
  [[7363    5]
 [1926  475]]

Accuracy :  80.2333913399529

Report :               precision    recall  f1-score   support

       <=50K       0.79      1.00      0.88      7368
        >50K       0.99      0.20      0.33      2401

    accuracy                           0.80      9769
   macro avg       0.89      0.60      0.61      9769
weighted avg       0.84      0.80      0.75      9769
```

Random Forest Tree

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # 70% training and 30% test
clf=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(X_train,y_train)

y_pred=clf.predict(X_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y_test, y_pred))

print ("\nAccuracy : ",
accuracy_score(y_test,y_pred)*100)

print("\nReport : ",
classification_report(y_test, y_pred))
```

```
Accuracy: 0.8209642747466476

Confusion Matrix:
  [[6840  567]
 [1182 1180]]

Accuracy :  82.09642747466475

Report :                precision    recall  f1-score   support

       <=50K       0.85      0.92      0.89      7407
        >50K       0.68      0.50      0.57      2362

    accuracy                           0.82      9769
   macro avg       0.76      0.71      0.73      9769
weighted avg       0.81      0.82      0.81      9769
```

Random Forest Tree (finding important features)

```
#Create a Gaussian Classifier
clf=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(X_train,y_train)
```

```
RandomForestClassifier(n_jobs=1)
```

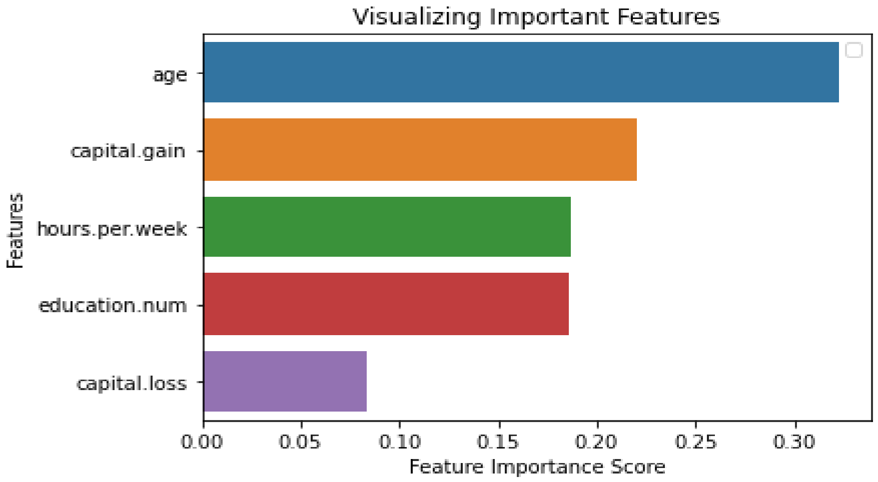
```
feature_imp = pd.Series(clf.feature_importances_,index=feature_cols).sort_values(ascending=False)
feature_imp
```

```
age               0.322942
capital.gain      0.220044
hours.per.week    0.187185
education.num     0.186264
capital.loss      0.083565
dtype: float64
```

Random Forest Tree (finding important features)

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# Creating a bar plot
sns.barplot(x=feature_imp, y=feature_imp.index)
# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend
() is called with no argument.
```



KNN Classifier

```
# Feature scaling to the training and test set of independent variables for reducing the size to smaller values
from sklearn.preprocessing import StandardScaler
X1_train, X1_test, y1_train, y1_test = train_test_split(X, y, test_size = 0.30, random_state = 0)

sc = StandardScaler()

X1_train = sc.fit_transform(X1_train)
X1_test = sc.transform(X1_test)

# Now we have to create and train the K Nearest Neighbor model with the training set
from sklearn.neighbors import KNeighborsClassifier

classifier1 = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier1.fit(X1_train, y1_train)
# Let's predict the test results
y1_pred = classifier1.predict(X1_test)

print("Accuracy:",metrics.accuracy_score(y1_test, y1_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y1_test, y1_pred))

print ("\nAccuracy : ",
accuracy_score(y1_test,y1_pred)*100)

print("\nReport : ",
classification_report(y1_test, y1_pred))
```

```
Accuracy: 0.8106254478452247

Confusion Matrix:
  [[6856  554]
 [1296 1063]]

Accuracy :  81.06254478452247

Report :                precision    recall  f1-score   support

       <=50K       0.84      0.93      0.88      7410
        >50K       0.66      0.45      0.53      2359

    accuracy                           0.81      9769
   macro avg       0.75      0.69      0.71      9769
weighted avg       0.80      0.81      0.80      9769
```

Naïve Bayes Classifier

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

X1_train = sc.fit_transform(X1_train)
X1_test = sc.transform(X1_test)
from sklearn.naive_bayes import GaussianNB

classifier1 = GaussianNB()
classifier1.fit(X1_train, y1_train)

y1_pred = classifier1.predict(X1_test)

print("Accuracy:",metrics.accuracy_score(y1_test, y1_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y1_test, y1_pred))

print ("\nAccuracy : ",
accuracy_score(y1_test,y1_pred)*100)

print("\nReport : ",
classification_report(y1_test, y1_pred))
```

```
Accuracy: 0.7954754836728427

Confusion Matrix:
  [[7043  367]
 [1631  728]]

Accuracy :  79.54754836728426

Report :               precision    recall  f1-score   support

       <=50K       0.81      0.95      0.88      7410
        >50K       0.66      0.31      0.42      2359

    accuracy                           0.80      9769
   macro avg       0.74      0.63      0.65      9769
weighted avg       0.78      0.80      0.77      9769
```

Ada Boost Classifier

```
from sklearn.ensemble import AdaBoostClassifier
abc = AdaBoostClassifier(n_estimators=50, learning_rate=1)

# Train Adaboost Classifer
model1 = abc.fit(X1_train, y1_train)
y1_pred = classifier1.predict(X1_test)

print("Accuracy:",metrics.accuracy_score(y1_test, y1_pred))
print("\nConfusion Matrix:\n ",
confusion_matrix(y1_test, y1_pred))

print ("\nAccuracy : ",
accuracy_score(y1_test,y1_pred)*100)

print("\nReport : ",
classification_report(y1_test, y1_pred))
```

```
Accuracy: 0.7954754836728427

Confusion Matrix:
  [[7043  367]
 [1631  728]]

Accuracy :  79.54754836728426

Report :               precision    recall  f1-score   support

       <=50K       0.81      0.95      0.88      7410
        >50K       0.66      0.31      0.42      2359

    accuracy                           0.80      9769
   macro avg       0.74      0.63      0.65      9769
weighted avg       0.78      0.80      0.77      9769
```

Result

- As we can see that Random forest Classifier gives the best accuracy.
- All the column are not really co-dependent on each other