Adult/Census Income Data Set

1 Project Topic

1.1 Task

Project task is to develop and evaluate binary classification models. The learning includes data cleaning, management, analysis, visualization, feature engineering, model development and improvement. The models of interest are Logistic Regression, Random Forest and Gaussian Naive Bayes.

1.2 Goals

Project goal is to deploy supervised machine learning models on the Adult dataset from UCI Machine Learning Repository and evaluate the performance of the predictive algorithms. Secondary goals are to clean the data, run exploratory data analysis with statistical analysis and visualization, and iterate and improve the model performance. As this is a binary classification problem, feature engineering with proper metric evaluation would be important. These activities are crucial for any machine learning task and the subsequent skills development.

2 Data

2.1 Data Source

The dataset was collected from UCI Machine Learning Repository at this link: https://archive.ics.uci.edu/ml/datasets/Census+Income.

Citation: <br>@misc{Kohavi:1994 ,
author = "Kohavi, Ronny and Becker, Barry",
year = "2017",
title = "{UCI} Machine Learning Repository",
url = "http://archive.ics.uci.edu/ml",
institution = "Silicon Graphics, Irvine, Data Mining and Visualization" }

2.2 Data Description

Data Set Characteristics: Multivariate
Number of Instances: 48842
Area: Social

Attribute Characteristics: Categorical, Integer

Number of Attributes: 14

Date Donated: 1996-05-01

Associated Tasks: Classification

Missing Values? Yes

2.3 Data Attributes

age: continuous.
workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
fnlwgt: continuous.
education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
education-num: continuous.
marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
sex: Female, Male.
capital-gain: continuous.
capital-loss: continuous.
hours-per-week: continuous.
native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.
annual-income: >50K, <=50K.

2.4 Data Summary

In [1]:
```
# Loading packages
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from scipy.stats import ttest_ind, ttest_rel
from scipy import stats
```

2.4.1 Missing Values and Loading the Data Set

Data contains (?) - a whitespace & a question mark in case of missing values. This is why na_values=' ?' argument is passed while reading the data. Also, the dataset is divided into train & test part; this was done for easier prediction. However, as we aim to develop our own models, we will split the data into training & testing later. Here, we have merged the two datasets to form a single dataframe. Furthermore, the data does not have the column names; hence, the names=colnames argument is passed.

In [2]:
```
# Defining colnames and loading the dataframe
colnames=['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status'
         'race', 'sex', 'capital-gain', 'capital-loss', 'hours-per-week', 'native-cour
df_train = pd.read_csv("adult.data", names=colnames, header=None, na_values=' ?')
df_test = pd.read_csv("adult.test", names=colnames, header=None, na_values=' ?')
df_test = df_test.tail(-1)
df = pd.concat([df_train, df_test], ignore_index = True)
```

2.4.2 Removing 'fnlwgt'

The 'fnlwgt' column reflects the weights on the files for each demographic. This weight can be used to extend the dataset to the fullest. However, for our machine learning algorithm the full dataset is not useful and this column is irrelevant. Hence, this is being removed.

In [3]:
```
df = df.drop('fnlwgt', axis=1)
```

2.4.3 Data Summary Statistics

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

Out[4]:
```
(48842, 14)
```

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

Out[5]:
```
age                object
workclass          object
education          object
education-num     float64
marital-status     object
occupation         object
relationship       object
race               object
sex                object
capital-gain      float64
capital-loss      float64
hours-per-week    float64
native-country     object
annual-income      object
dtype: object
```

-> Data Type Change

Age variable seems to be of object data type and should be of integer data type. Furthermore, there are some leading whitespaces in some columns. We need to remove them.

In [6]:
```
# Change age data type
df['age'] = df['age'].astype(str).astype(int)
```

-> Whitespace Removal

In [7]:
```
# Remove whitespaces
df = df.apply(lambda x: x.str.strip() if x.dtype == "object" else x)
```

In [8]:
```
# Data summary for numerical features
df.describe()
```

Out[8]:

	age	education-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	10.078089	1079.067626	87.502314	40.422382
std	13.710510	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	48.000000	12.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	4356.000000	99.000000

In [9]:
```
# Data summary for categorical features
df.describe(include=["O"])
```

Out[9]:

	workclass	education	marital-status	occupation	relationship	race	sex	native-country	annual-income
count	46043	48842	48842	46033	48842	48842	48842	47985	48842
unique	8	16	7	14	6	5	2	41	4
top	Private	HS-grad	Married-civ-spouse	Prof-specialty	Husband	White	Male	United-States	<=50K
freq	33906	15784	22379	6172	19716	41762	32650	43832	24720

In [10]:
```
df.head(5)
```

Out[10]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	2174.0
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	0.0
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	0.0
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0.0
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0.0

In [11]:
```
df.tail(5)
```

Out[11]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	c
48837	39	Private	Bachelors	13.0	Divorced	Prof-specialty	Not-in-family	White	Female	
48838	64	NaN	HS-grad	9.0	Widowed	NaN	Other-relative	Black	Male	
48839	38	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	
48840	44	Private	Bachelors	13.0	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	
48841	35	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	

3 Data Cleaning

3.1 Data Type Change

We have already chaged the datatype of Age variable to integer.

3.2 Whitespace Removal

Whitespaces are all removed from all the columns.

3.3 Missing Values

As already mentioned, data contains (?) - a whitespace & a question mark in case of missing values. This is why na_values=' ?' argument is passed while reading the data. Now, we will look at the number of missing values by each column.

In [12]:
```
# Count of missing values
df.isna().sum()
```

Out[12]:
```
age                  0
workclass         2799
education            0
education-num        0
marital-status       0
occupation        2809
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     857
annual-income        0
dtype: int64
```

In [13]:
```
# Percentage of missing values
df.isna().sum()/df.count()
```

Out[13]:
```
age               0.000000
workclass         0.060791
education         0.000000
education-num     0.000000
marital-status    0.000000
occupation        0.061021
relationship      0.000000
race              0.000000
sex               0.000000
capital-gain      0.000000
capital-loss      0.000000
hours-per-week    0.000000
native-country    0.017860
annual-income     0.000000
dtype: float64
```

As it turn out, only 3 columns have missing values with lower frequency (1.8% ~ 6.1% compared to all respective cases). The removal of missing values will not impact the number of observations. Furthermore, missing values arise in categorical features whose imputation will not be straightforward to handle.

In [14]:
```
# Remove NAs
df = df.dropna()
df
```

Out[14]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	ca
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	2
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	
...	...	...	...	...	...	...	...	...	...	
48836	33	Private	Bachelors	13.0	Never-married	Prof-specialty	Own-child	White	Male	
48837	39	Private	Bachelors	13.0	Divorced	Prof-specialty	Not-in-family	White	Female	
48839	38	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	
48840	44	Private	Bachelors	13.0	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5
48841	35	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	

45222 rows × 14 columns

3.4 Check of Imbalanced Data Set

In [15]:
```
# Check by target variable
df.groupby(['annual-income']).size()
```

Out[15]:
```
annual-income
<=50K     22654
<=50K.    11360
>50K       7508
>50K.      3700
dtype: int64
```

3.4.1 Cleaning target variable

It appears that the target variable has 4 outcomes. However, "<=50K." and "<=50K" can be counted as same. We will be replacing the strings here.

```
In [16]: # Clean the target variable
         df['annual-income'] = df['annual-income'].str.replace('<=50K.','<=50K')
         df['annual-income'] = df['annual-income'].str.replace('>50K.','>50K')
```

```
In [17]: df.groupby(['annual-income']).size()
```

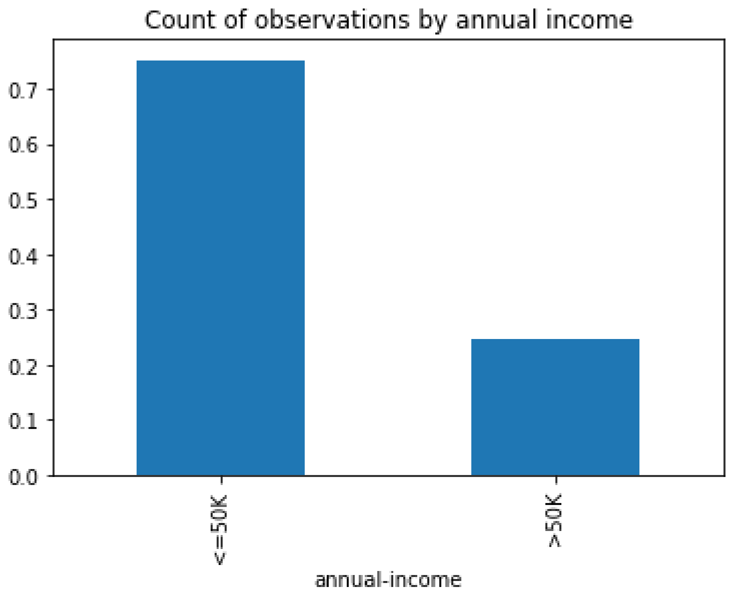
```
Out[17]: annual-income
         <=50K    34014
         >50K     11208
         dtype: int64
```

```
In [18]: df.groupby(['annual-income']).size().transform(lambda x: x/sum(x))
```

```
Out[18]: annual-income
         <=50K    0.752156
         >50K     0.247844
         dtype: float64
```

```
In [19]: df_out = df.groupby(['annual-income']).size().transform(lambda x: x/sum(x))
         df_out.plot.bar(title='Count of observations by annual income')
```

```
Out[19]: <AxesSubplot:title={'center':'Count of observations by annual income'}, xlabel='annua
         l-income'>
```



It is quite clear that the data is imbalanced in nature. We have 75% observations for <=50K annual income whereas there is only 25% for >50K.

3.5 Conclusion of Data Cleaning

The dataset had data type, whitespace, missing value notation and unexpected string errors. Missing values were not frequent; hence all the observations with missing values were removed (8% of total observations were removed) by getting a total of 44,993 observations out of 48,842.

It was also investigated that the data is imbalanced in nature with a ratio of 3:1 for annual income over 50K to annual income of equal or less than 50K.

4 Exploratory Data Analysis

We will run univariate, bivariate and multivariate analysis of all the features here. Then, scatterplots for continuous variables, box plots for continuous-categorical variables and crosstabs for categorical variables will be developed. These shall guide our understanding of the distribution as well as point us to the proper statistical tests. We will conduct independent t-tests and Chi-squared tests to find the relationship between target variables and the variable(s) in question.

Our objective is to:
1) Understand the variables & their distributions
2) Plot various graphs for easier visualization & understanding
3) Run statistical tests (t-tests and Chi-squared) to understand the impact on target variables
4) Build correlation matrix to understand the mutual impact of x variables
5) Retain only the relevant and the most significant features for model development (to reduce multicollinearity and overfitting)

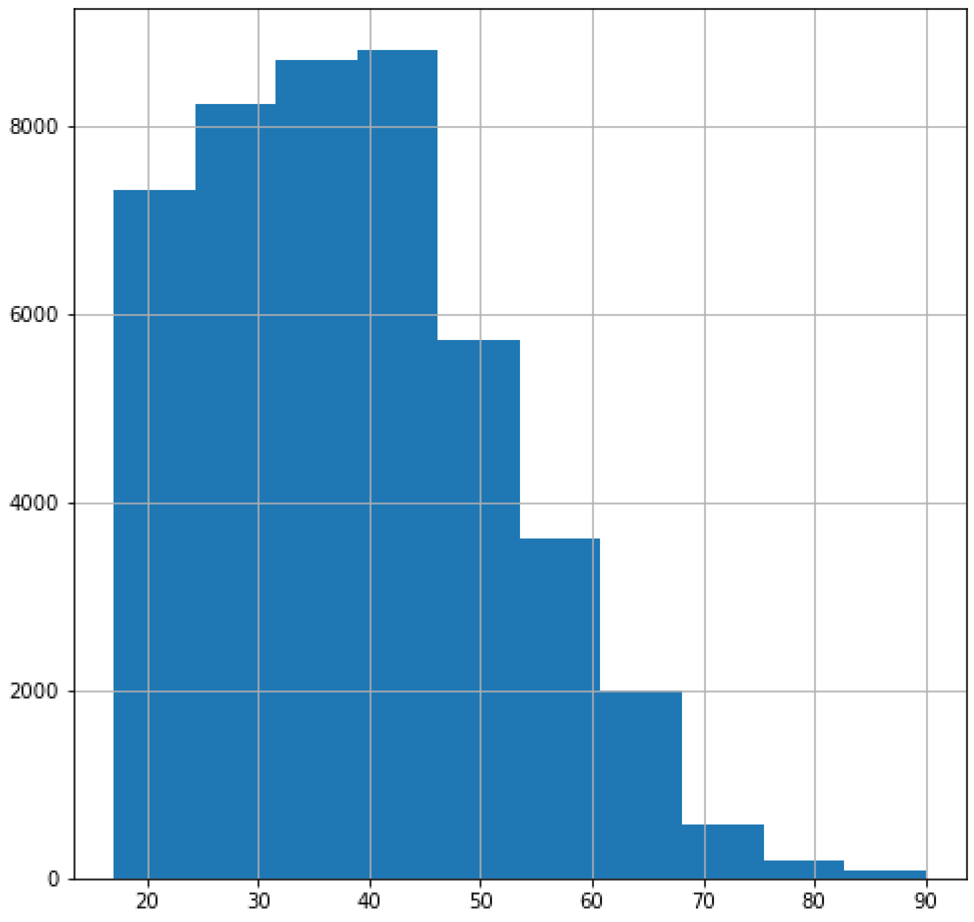
4.1 Univariate Analysis

4.1.1 Histogram of age

It appears to resemble normal distribution with a mean of 38.64 and the range of 17 to 90.

```
In [20]: df['age'].hist(figsize=(8,8))
```

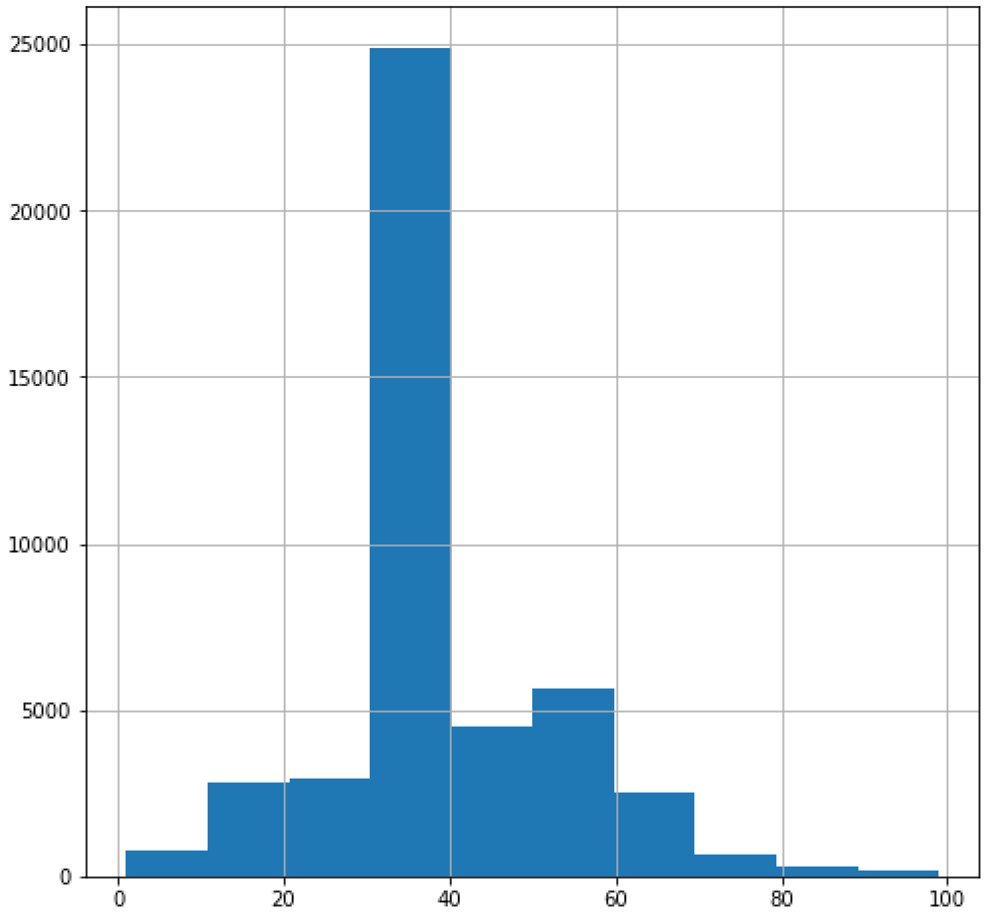
```
Out[20]: <AxesSubplot:>
```



4.1.2 Histogram of hours worked per week

It also appears to resemble normal distribution with a mean of 40.42 and the range of 1 to 99.

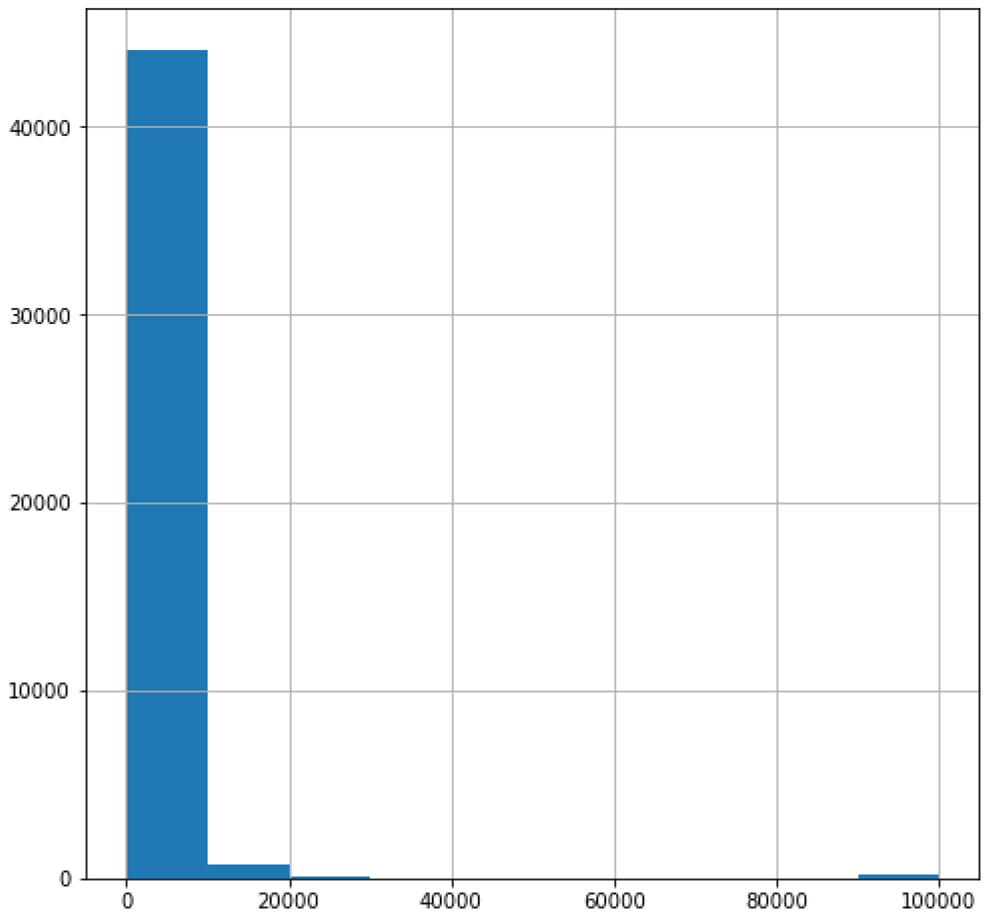
```
In [21]: df['hours-per-week'].hist(figsize=(8,8))
         plt.show()
```



4.1.3 Histogram of capital gain

Capital gain does not resemble any particular distribution.

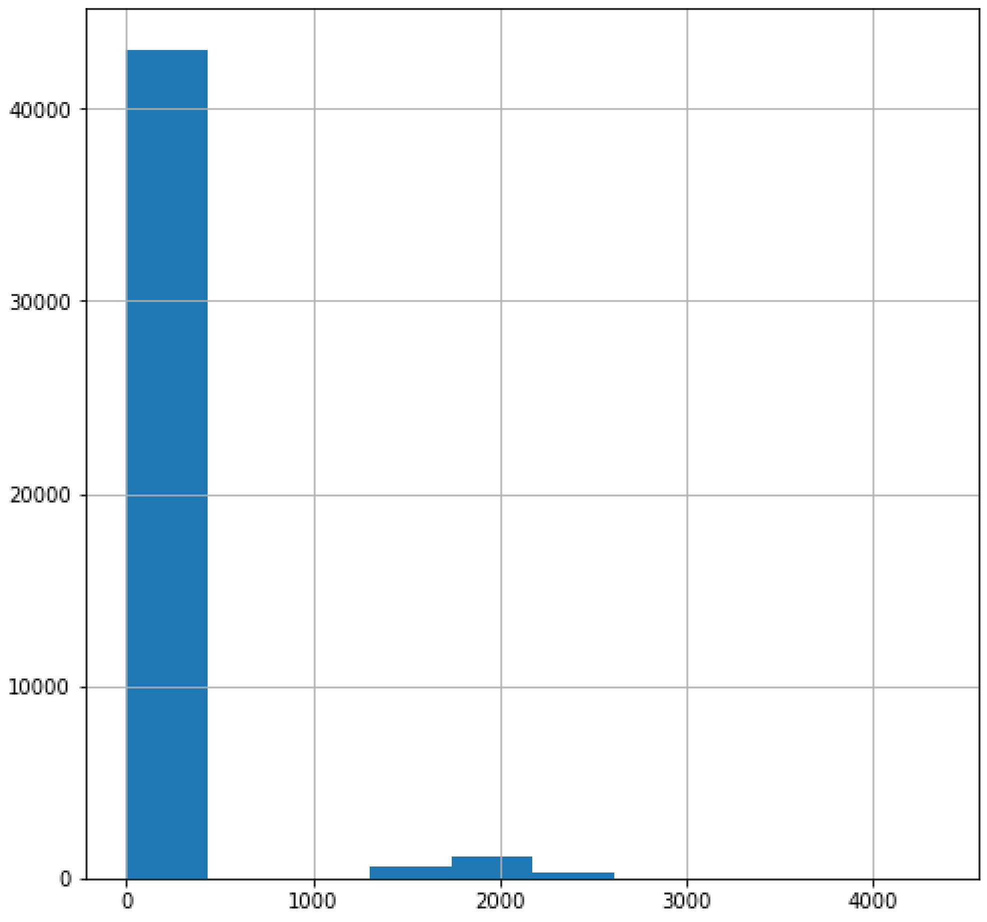
```
In [22]: df["capital-gain"].hist(figsize=(8,8))
         plt.show()
```



4.1.4 Histogram of capital loss

Capital loss does not resemble any particular distribution either.

In [23]:
```
df["capital-loss"].hist(figsize=(8,8))
plt.show()
```

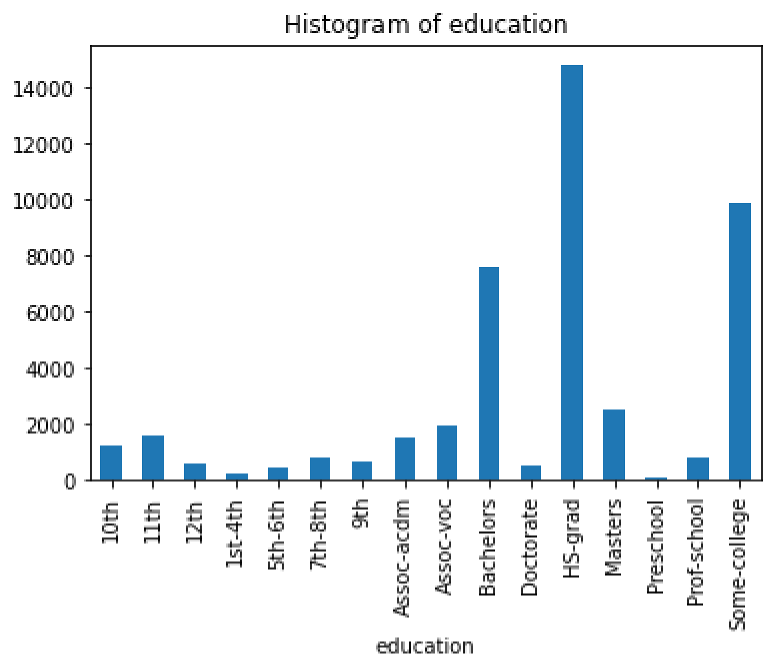


4.1.5 Histogram of education

It appears that the majority of the education is in the HS-grad bucket with the 2nd being some-college. We also find Bachelors as it stands in the 3rd ranking.

In [24]:
```
df_out = df.groupby(['education']).size()
df_out.plot.bar(title='Histogram of education')
```

Out[24]:
```
<AxesSubplot:title={'center':'Histogram of education'}, xlabel='education'>
```

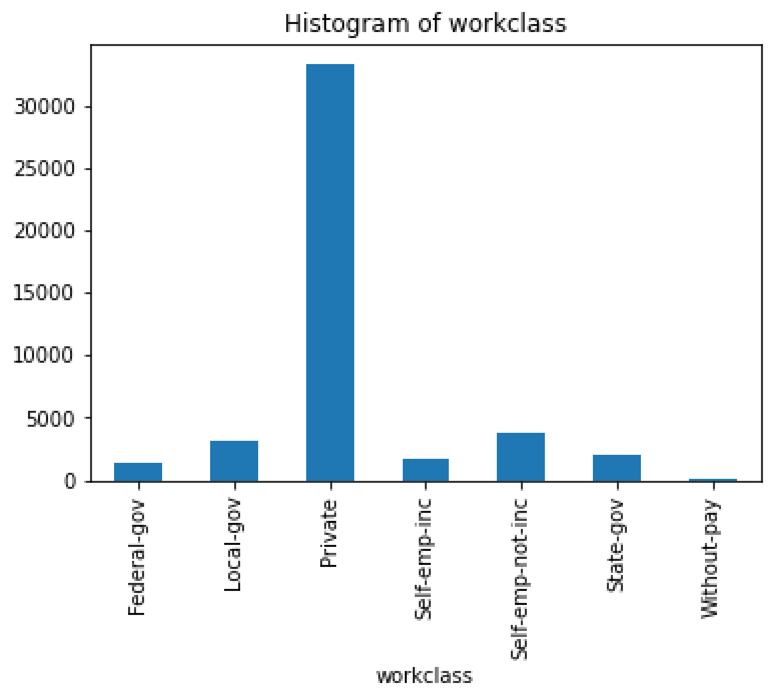


4.1.6 Histogram of workclass

Majority are in Private sector while the rest show somewhat similar frequencies.

In [25]:
```python
df_out = df.groupby(['workclass']).size()
df_out.plot.bar(title='Histogram of workclass')
```

Out[25]:
```
<AxesSubplot:title={'center':'Histogram of workclass'}, xlabel='workclass'>
```

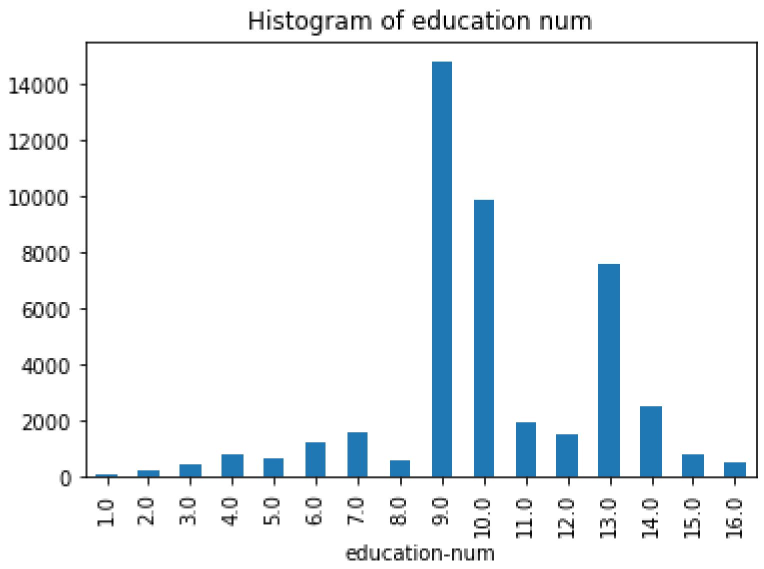


4.1.7 Histogram of education number

Majority are in categories 9.0, 10.0 and 1.03 arranged in descending order.

```
In [26]: df_out = df.groupby(['education-num']).size()
         df_out.plot.bar(title='Histogram of education num')
```

```
Out[26]: <AxesSubplot:title={'center':'Histogram of education num'}, xlabel='education-num'>
```

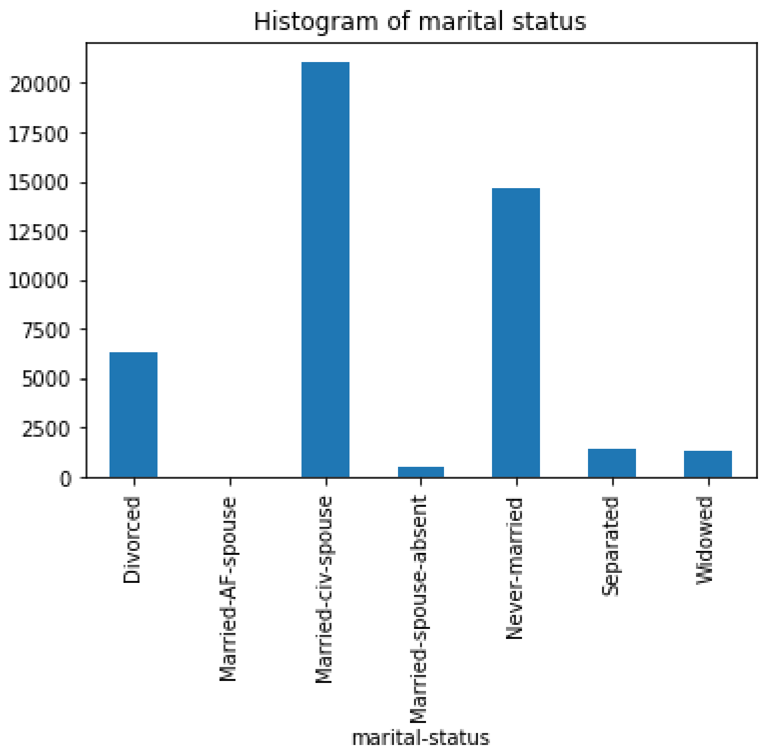


4.1.8 Histogram of marital status

Most are married with spouse and never-married comes into 2nd place. Divorced is the 3rd one.

```
In [27]: df_out = df.groupby(['marital-status']).size()
         df_out.plot.bar(title='Histogram of marital status')
```

```
Out[27]: <AxesSubplot:title={'center':'Histogram of marital status'}, xlabel='marital-status'>
```

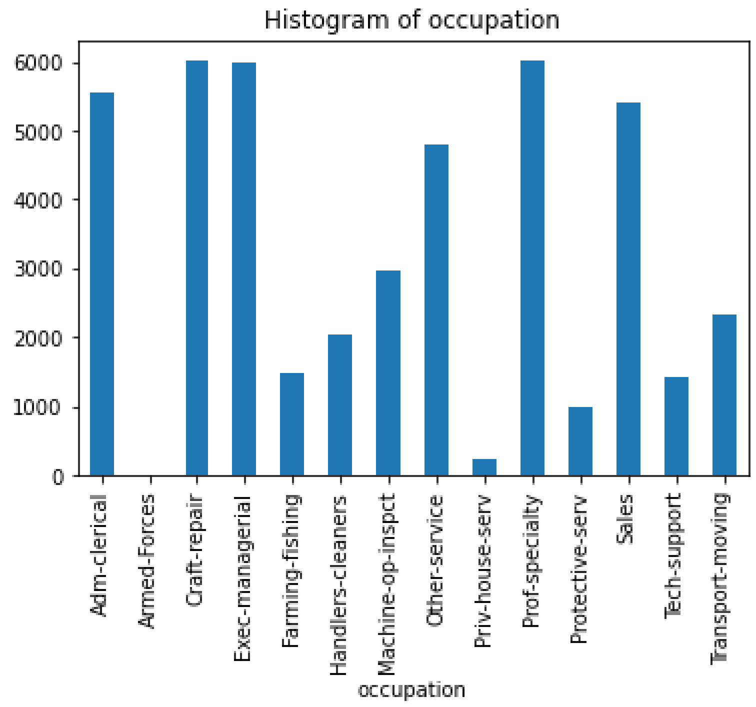


4.1.9 Histogram of occupation

This does not exhibit any particular pattern. We see high frquencies in 6 of the occupations.

```
In [28]: df_out = df.groupby(['occupation']).size()
         df_out.plot.bar(title='Histogram of occupation')
```

```
Out[28]: <AxesSubplot:title={'center':'Histogram of occupation'}, xlabel='occupation'>
```

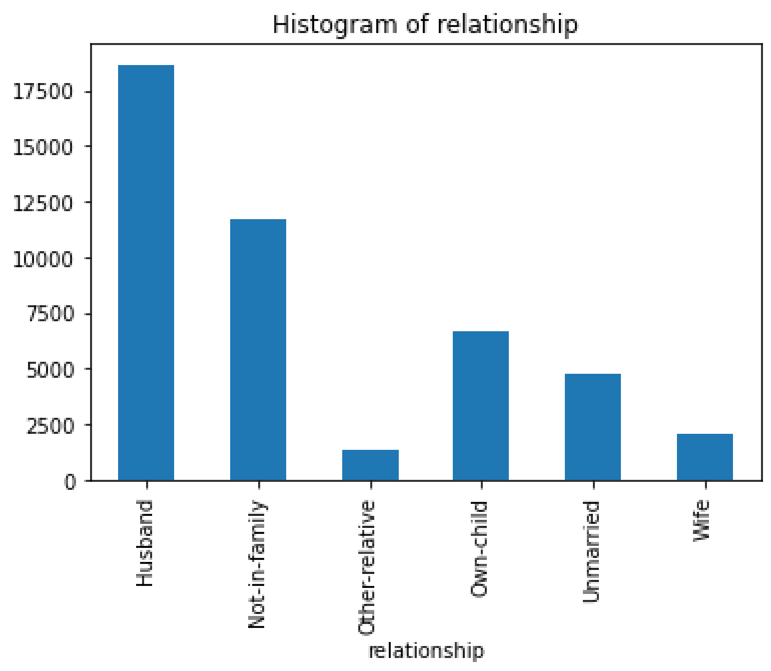


4.1.10 Histogram of relationship

Most frequent relationship reported is husband; not-in-family comes in 2nd.

```
In [29]: df_out = df.groupby(['relationship']).size()
         df_out.plot.bar(title='Histogram of relationship')
```

```
Out[29]: <AxesSubplot:title={'center':'Histogram of relationship'}, xlabel='relationship'>
```

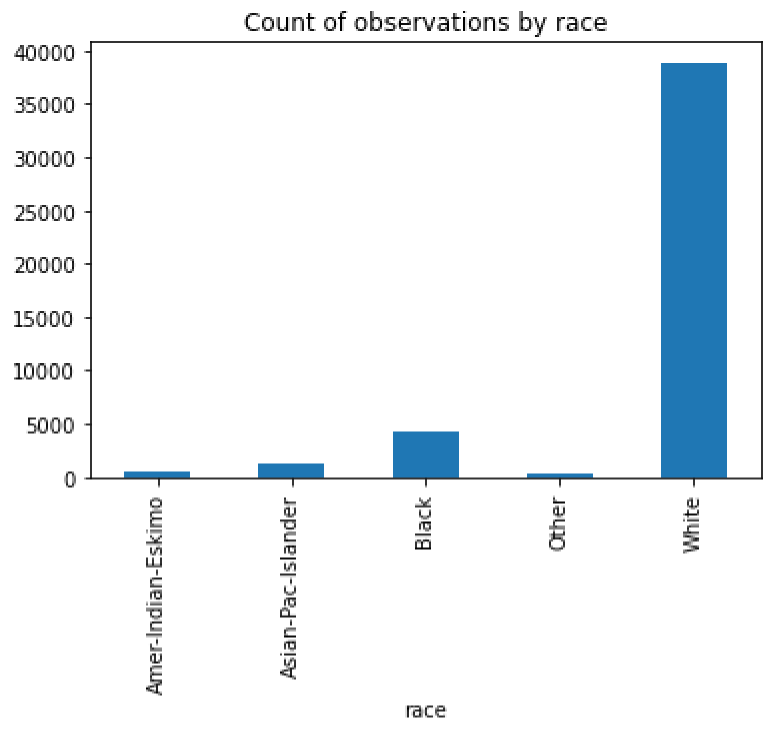


4.1.11 Histogram of race

White dominates by far in terms of observational frequency in the data for race category.

```
In [30]: df_out = df.groupby(['race']).size()
         df_out.plot.bar(title='Count of observations by race')
```

```
Out[30]: <AxesSubplot:title={'center':'Count of observations by race'}, xlabel='race'>
```

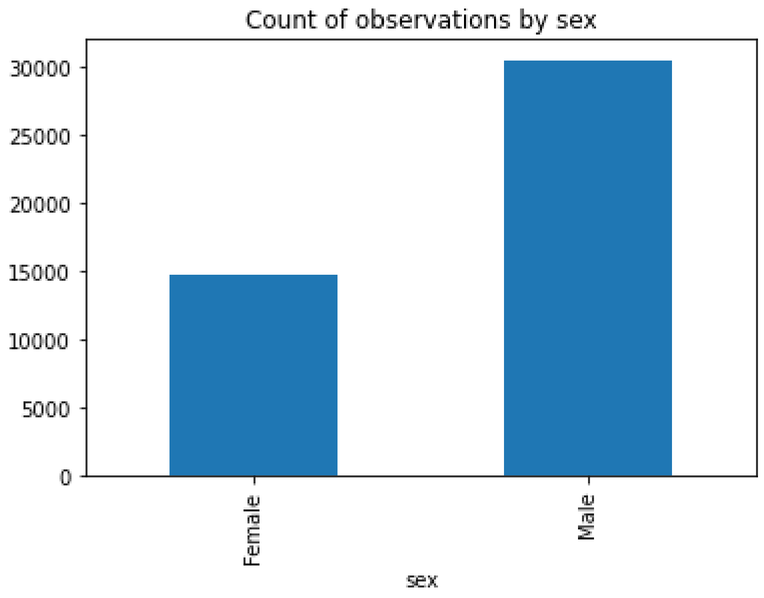


4.1.12 Histogram of sex

Male is overrepresented in the dataset with 2:1 ratio for male:female.

In [31]:
```
df_out = df.groupby(['sex']).size()
df_out.plot.bar(title='Count of observations by sex')
```

Out[31]:
```
<AxesSubplot:title={'center':'Count of observations by sex'}, xlabel='sex'>
```

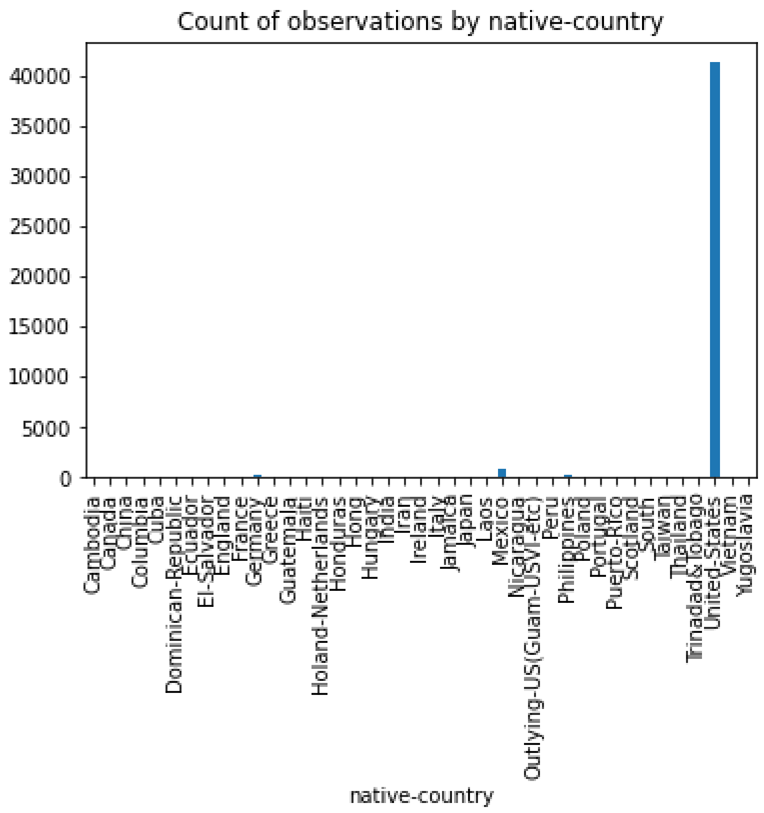


4.1.13 Histogram of native country

United States dominates the frequency for native country count.

In [32]:
```
df_out = df.groupby(['native-country']).size()
df_out.plot.bar(title='Count of observations by native-country')
```

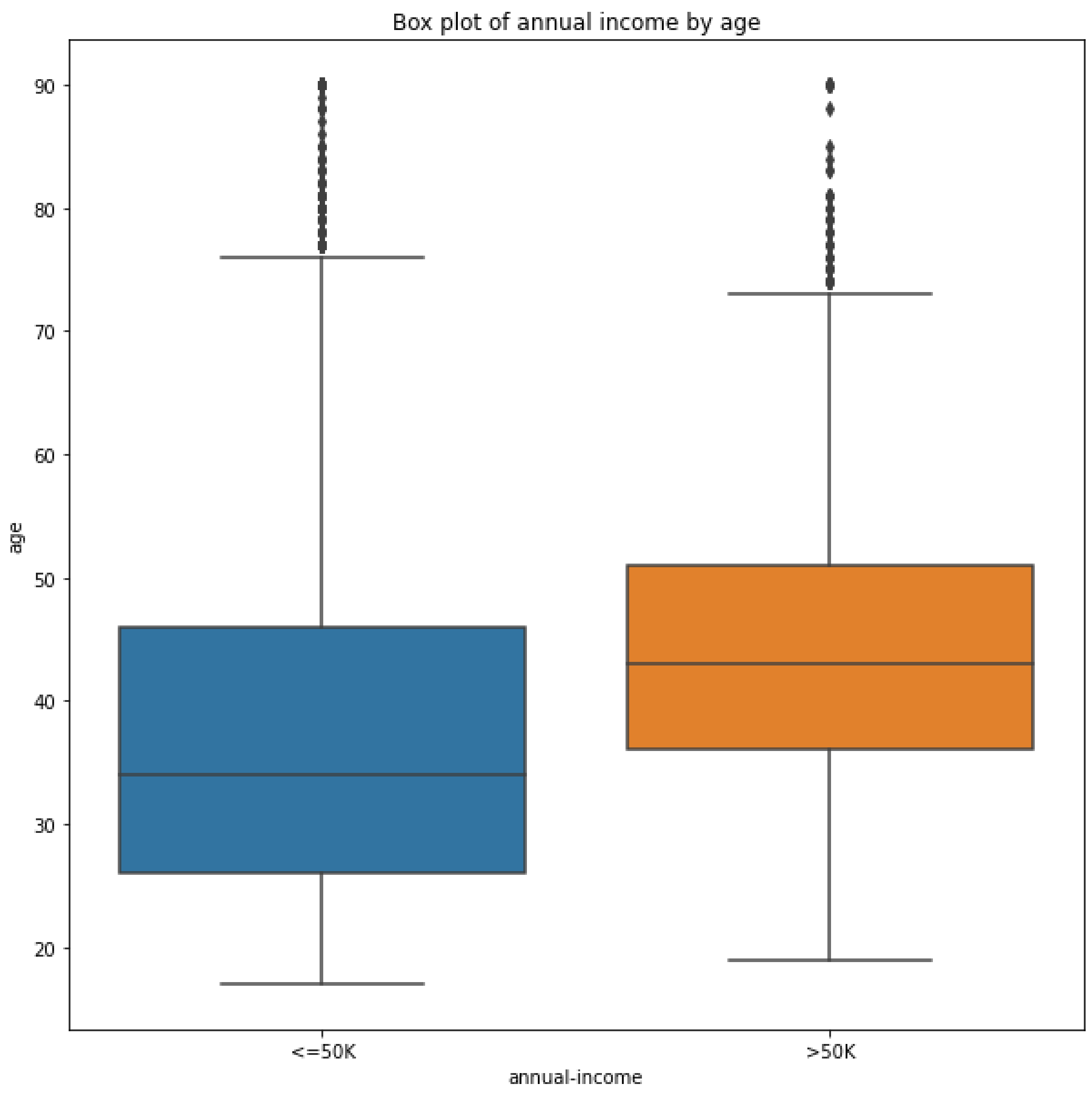
Out[32]:
```
<AxesSubplot:title={'center':'Count of observations by native-country'}, xlabel='nati
ve-country'>
```



4.2 Bivariate Analysis

4.2.1 Relationship between age and annual income

In [33]:
```
# boxplot
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="annual-income", y="age", data=df).set_title("Box plot of annual income
plt.show()
```



In [34]:
```
# Mean
df[['annual-income', 'age']].groupby(['annual-income'], as_index=False).mean().sort_va
```

Out[34]:

	annual-income	age
1	>50K	44.006067
0	<=50K	36.749427

In [35]:
```
# t-test
import random

data = df[(np.abs(stats.zscore(df["age"])) < 3)]

income_1 = data[data['annual-income']==">50K"]['age']
income_0 = data[data['annual-income']=="<=50K"]['age']

income_0 = income_0.values.tolist()
income_0 = random.sample(income_0, 100)
income_1 = income_1.values.tolist()
income_1 = random.sample(income_1, 100)
```

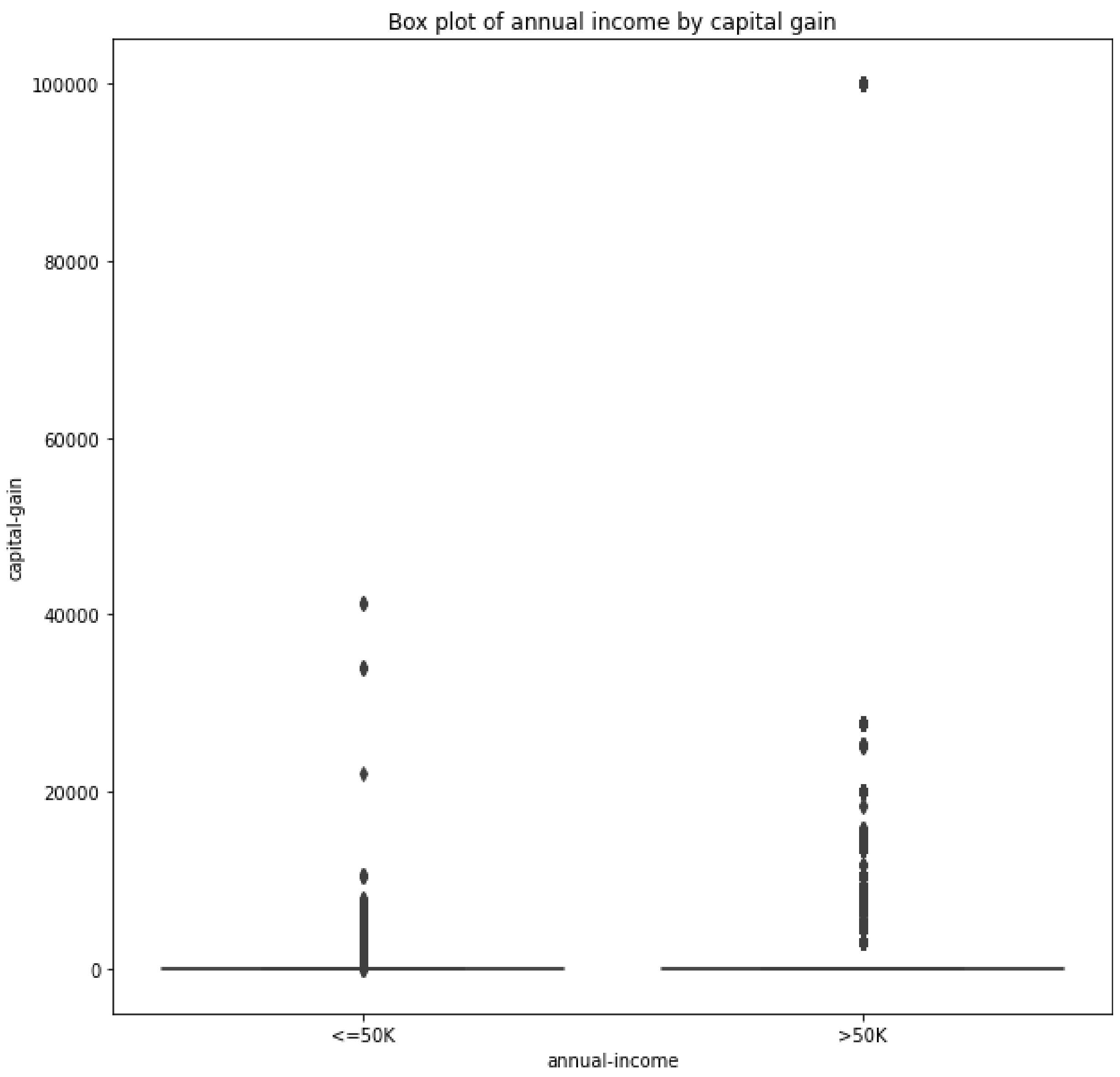
```
from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


if pval <0.05:
    print("we reject null hypothesis")
else:
    print("we accept null hypothesis")
```

```
ttest 4.308259859083891
p value 2.6523488906461604e-05
we reject null hypothesis
```

We reject the null hypothesis from the two-sample independent t-test i.e. there is significant difference in annual income by age. We can count age as a discriminatory factor for our model.

4.2.2 Relationship between capital gain and annual income

In [36]:
```
# boxplot
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="annual-income", y="capital-gain", data=df).set_title("Box plot of annua
plt.show()
```



In [37]:
```
# t-test
import random

data = df[(np.abs(stats.zscore(df["capital-gain"])) < 3)]

income_1 = data[data['annual-income']==">50K"]['capital-gain']
income_0 = data[data['annual-income']=="<=50K"]['capital-gain']

income_0 = income_0.values.tolist()
income_0 = random.sample(income_0, 100)
income_1 = income_1.values.tolist()
income_1 = random.sample(income_1, 100)

from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


if pval <0.05:
    print("we reject null hypothesis")
```

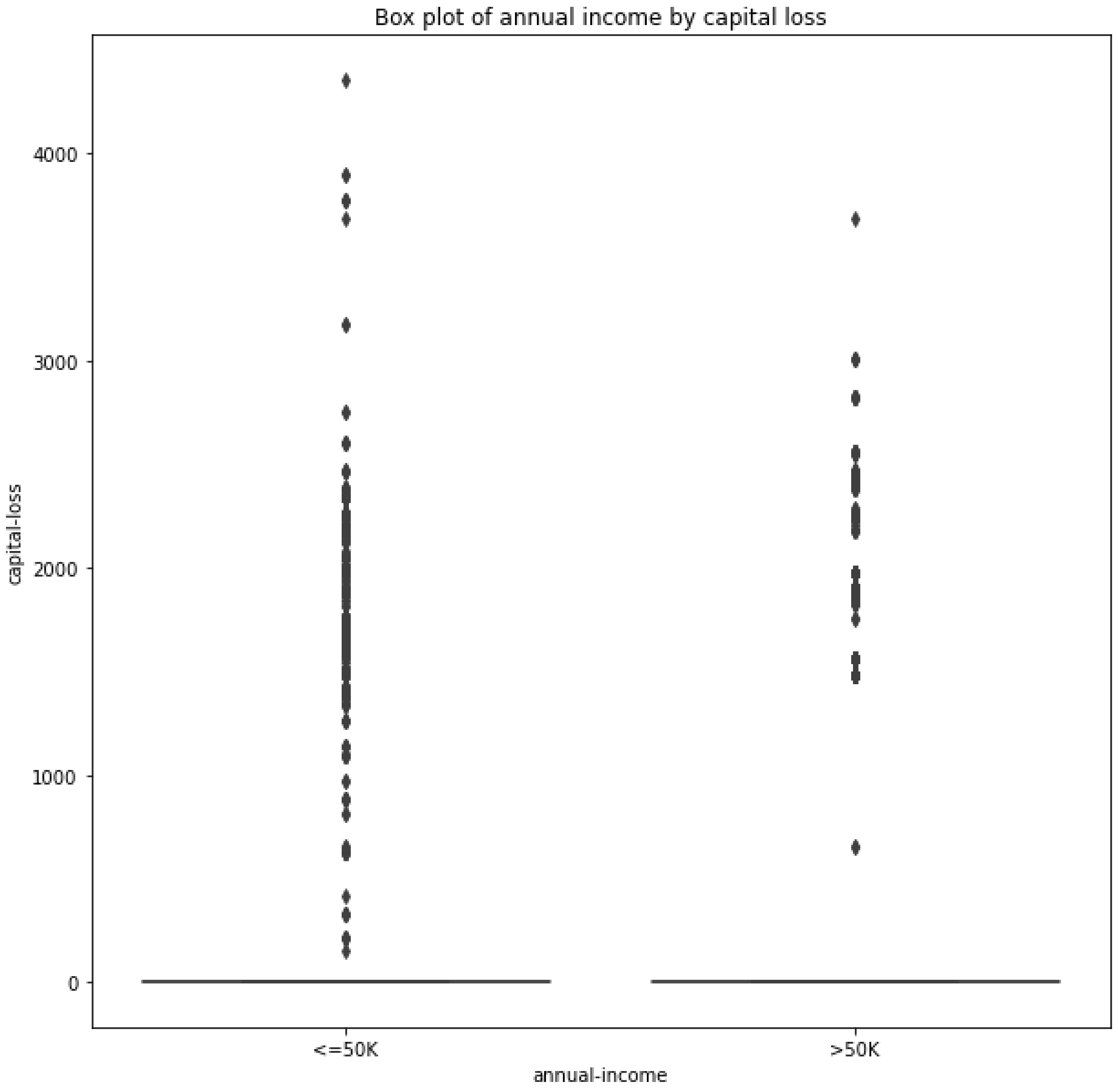
```
else:
    print("we accept null hypothesis")
```

```
ttest 3.671153279712601
p value 0.0003850957150693099
we reject null hypothesis
```

We reject the null hypothesis from the two-sample independent t-test i.e. there is significant difference in annual income by capital-gain. We can count capital-gain a discriminatory factor for our model.

4.2.3 Relationship between capital loss and annual income

In [38]:
```
# boxplot
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="annual-income", y="capital-loss", data=df).set_title("Box plot of annua
plt.show()
```



In [39]:
```
# t-test
import random
```

```
data = df[(np.abs(stats.zscore(df["capital-loss"])) < 3)]

income_1 = data[data['annual-income']==">50K"]['capital-loss']
income_0 = data[data['annual-income']=="<=50K"]['capital-loss']

income_0 = income_0.values.tolist()
income_0 = random.sample(income_0, 100)
income_1 = income_1.values.tolist()
income_1 = random.sample(income_1, 100)

from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


if pval <0.05:
    print("we reject null hypothesis")
else:
    print("we accept null hypothesis")
```

```
ttest nan
p value nan
we accept null hypothesis
```

We cannot reject the null hypothesis from the two-sample independent t-test i.e. there is no significant difference in annual income by capital-loss. Hence, We cannot count capital-loss a discriminatory factor for our model.

4.2.4 Feature Engineering

As capital-gain and capital-loss indicate the difference in capital, we can build a new feature called 'delta-capita' to signify this change in capital. If we can retain this feature only, we can exclude both capital-gain and capital-loss from the dataset.

In [40]:
```
# delta capital
df['delta-capital'] = df['capital-gain']-df['capital-loss']
df['delta-capital'].describe()
```

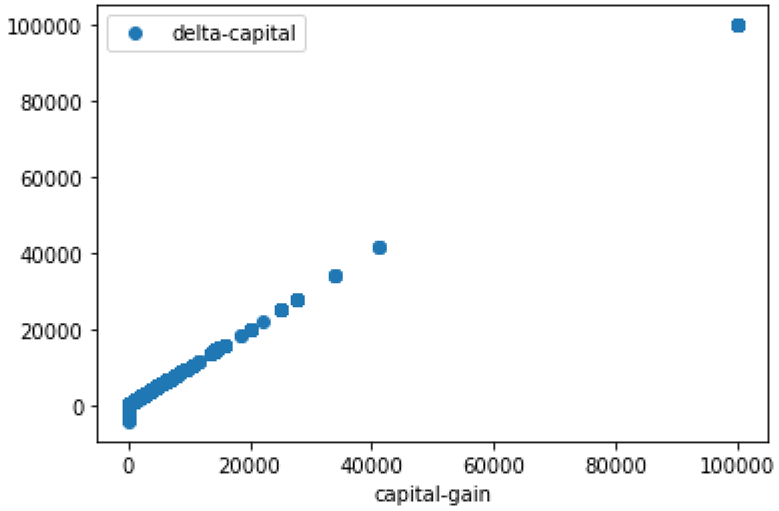
Out[40]:
```
count    45222.000000
mean      1012.834925
std       7530.315380
min      -4356.000000
25%          0.000000
50%          0.000000
75%          0.000000
max      99999.000000
Name: delta-capital, dtype: float64
```

In [41]:
```
# correlation
df['capital-gain'].corr(df['delta-capital'])
```

Out[41]:
```
0.9985544745065321
```

In [42]:
```
# scatterplot
df.plot(x='capital-gain', y='delta-capital', style='o')
```

Out[42]:
```
<AxesSubplot:xlabel='capital-gain'>
```



As the correlation between delta-capital and capital-gain is high (0.99), we can retain one of them. Also, capital-loss is found to be insignificant on annual-income (our target variable). Hence, we can remove both capital-gain & capital-loss and can only keep delta-capital in our feature set.

In [43]:
```
# removal
df = df.drop(columns = ['capital-gain', 'capital-loss'], axis=1)
df
```

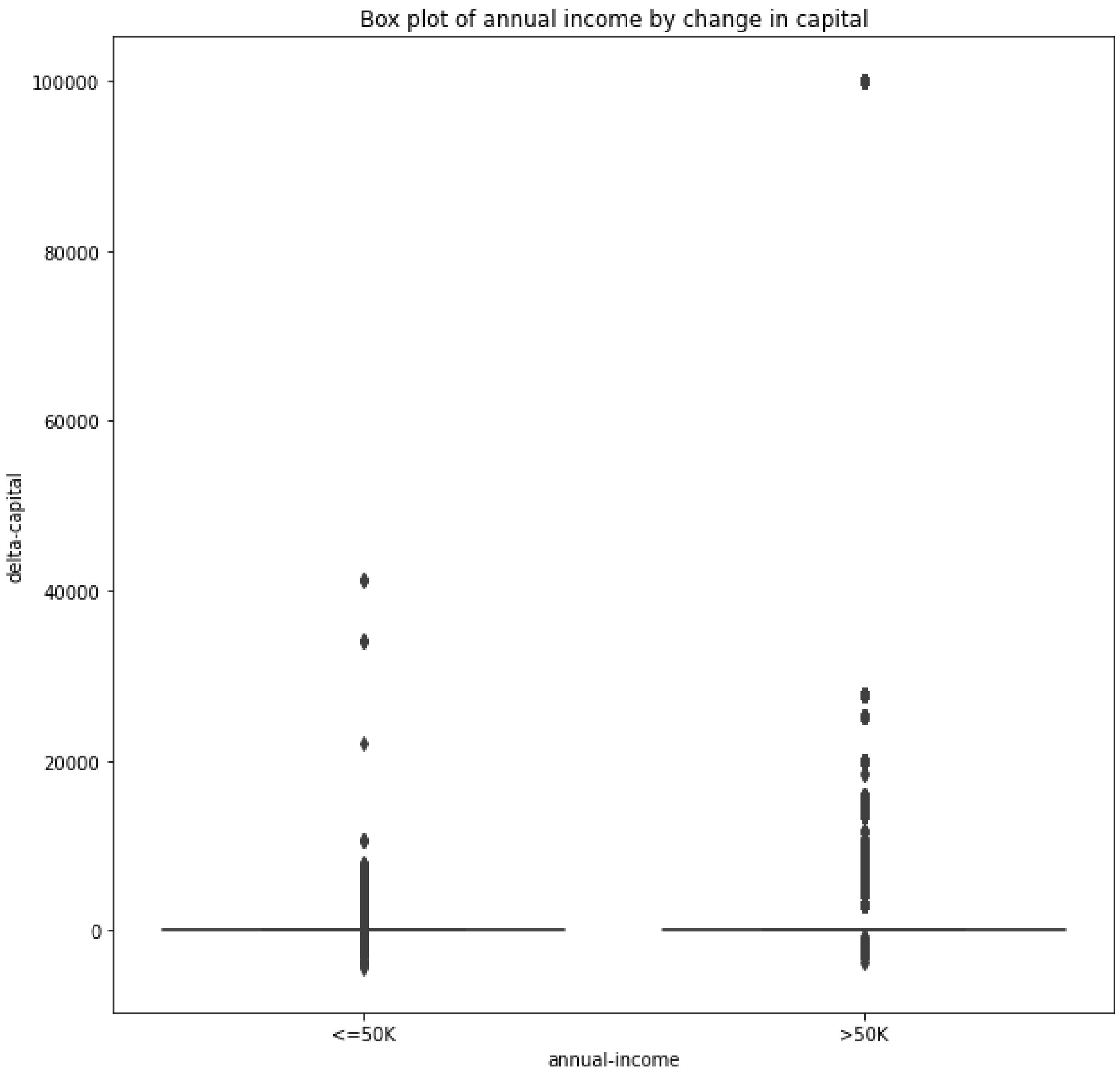
Out[43]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female
...	...	...	...	...	...	...	...	...	...
48836	33	Private	Bachelors	13.0	Never-married	Prof-specialty	Own-child	White	Male
48837	39	Private	Bachelors	13.0	Divorced	Prof-specialty	Not-in-family	White	Female
48839	38	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Husband	White	Male
48840	44	Private	Bachelors	13.0	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male
48841	35	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male

45222 rows × 13 columns

4.2.5 Relationship between delta capital and annual income

In [44]:
```
# boxplot
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="annual-income", y="delta-capital", data=df).set_title("Box plot of annu
plt.show()
```



```
In [45]: # outliers
         df.loc[(df['delta-capital'] >= 80000)]
```

Out[45]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hou p we
1246	54	Self-emp-inc	Prof-school	15.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	6
1368	52	Private	HS-grad	9.0	Married-civ-spouse	Exec-managerial	Husband	Asian-Pac-Islander	Male	4
1482	53	Self-emp-inc	HS-grad	9.0	Married-civ-spouse	Sales	Husband	White	Male	4
1528	52	Private	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	5
1616	46	Private	Prof-school	15.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	6
...	...	...	...	...	...	...	...	...	...	
47739	32	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	6
48582	61	Self-emp-not-inc	Masters	14.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	3
48591	36	Private	Bachelors	13.0	Never-married	Prof-specialty	Not-in-family	White	Male	4
48598	42	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Husband	White	Male	4
48629	59	Self-emp-inc	Prof-school	15.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	8

229 rows × 13 columns

-> Outliers

There are significant outliers in delta-capital with all of them being 99999.0. This is an unusual observation.

In [46]:
```python
# outlier count
(df['delta-capital'] >= 80000).sum()/df['delta-capital'].count()
```

Out[46]:
```
0.00506390694794569
```

Only 0.5% of the observations are outliers with abberant observations. Let's see what happens if we remove them.

In [47]:
```
# t-test without outliers
data = df.loc[~(df['delta-capital'] >= 80000)]
import random

data = data[(np.abs(stats.zscore(df["delta-capital"])) < 3)]

income_1 = data[data['annual-income']==">50K"]['delta-capital']
income_0 = data[data['annual-income']=="<=50K"]['delta-capital']

income_0 = income_0.values.tolist()
income_0 = random.sample(income_0, 100)
income_1 = income_1.values.tolist()
income_1 = random.sample(income_1, 100)

from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


if pval <0.05:
    print("we reject null hypothesis")
else:
    print("we accept null hypothesis")
```

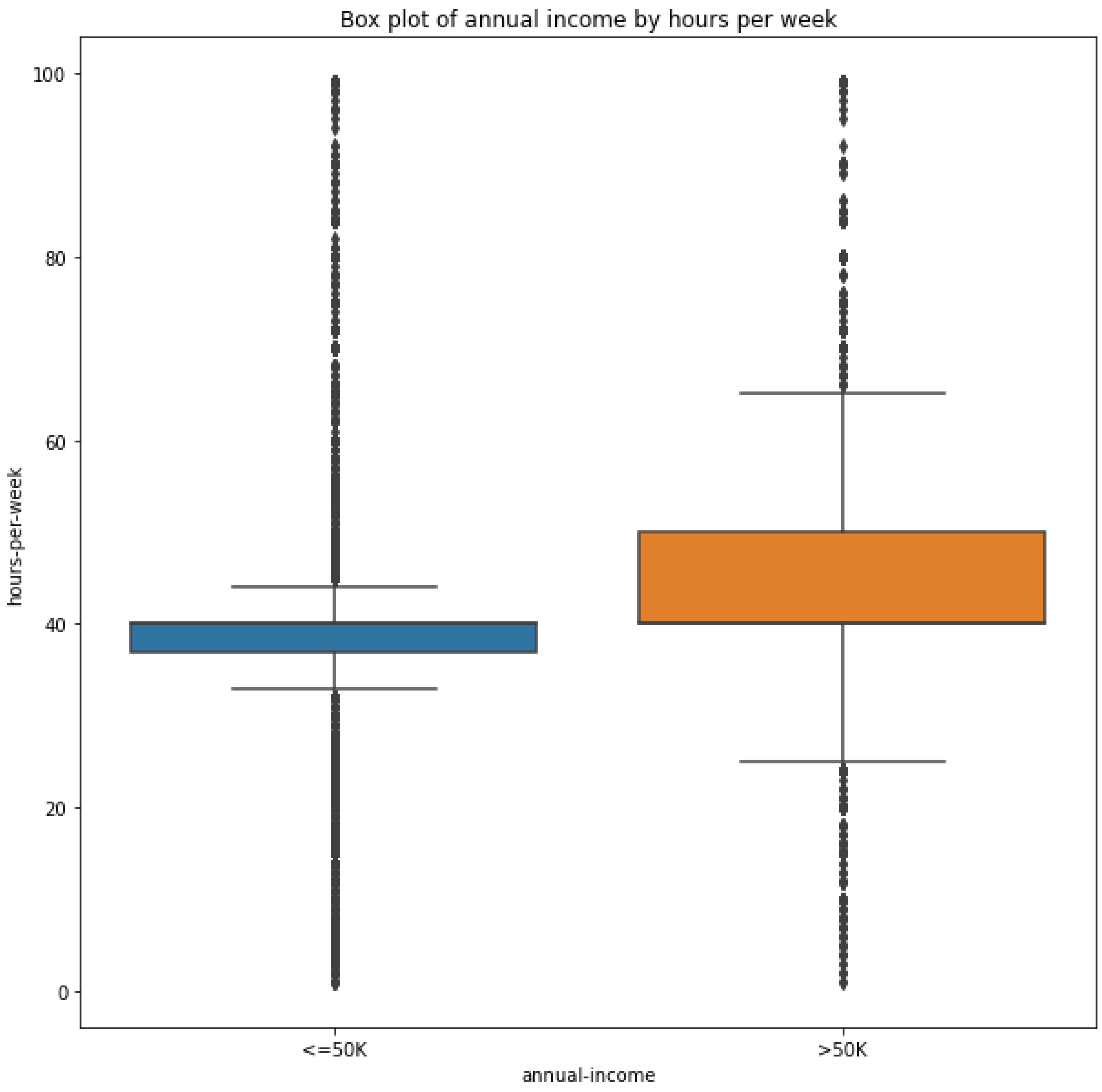
```
ttest 3.7137244474085414
p value 0.000333175832488459
we reject null hypothesis
```

The delta-capital still remains a discriminatory factor even after the removal of all outliers with 99999.0 value. We can safely remove them as they are only 0.5% of the whole data.

In [48]:
```
# removal of outliers
df = df.loc[~(df['delta-capital'] >= 80000)]
```

4.2.6 Relationship between hours per week and annual income

In [49]:
```
# boxplot
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="annual-income", y="hours-per-week", data=df).set_title("Box plot of anr
plt.show()
```



In [50]:
```
# mean
df[['annual-income', 'hours-per-week']].groupby(['annual-income'], as_index=False).mea
```

Out[50]:

	annual-income	hours-per-week
1	>50K	45.582293
0	<=50K	39.372023

In [51]:
```
# t-test
import random

data = df[(np.abs(stats.zscore(df["hours-per-week"])) < 3)]

income_1 = data[data['annual-income']==">50K"]['hours-per-week']
income_0 = data[data['annual-income']=="<=50K"]['hours-per-week']

income_0 = income_0.values.tolist()
income_0 = random.sample(income_0, 100)
income_1 = income_1.values.tolist()
income_1 = random.sample(income_1, 100)
```

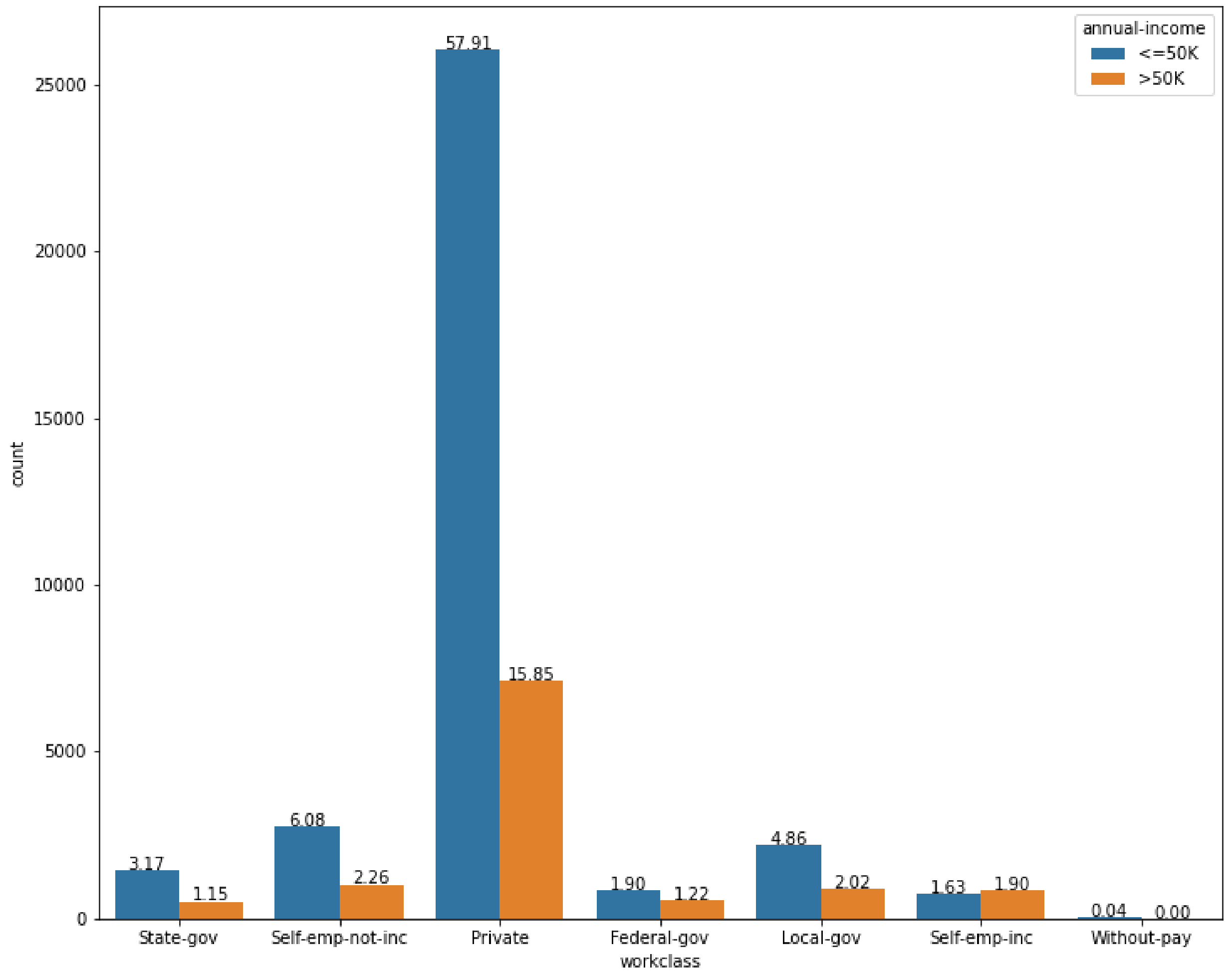
```
from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


if pval <0.05:
    print("we reject null hypothesis")
else:
    print("we accept null hypothesis")
```

```
ttest 4.971248892311286
p value 1.5513535324904089e-06
we reject null hypothesis
```

We reject the null hypothesis from the two-sample independent t-test i.e. there is significant difference in annual income by hours-per-week. Hence, We can count hours-per-week a discriminatory factor for our model.

4.2.7 Relationship between workclass and annual income

In [52]:
```
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="workclass", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.show()
```



In [53]:
```
# crosstab
pd.crosstab(df['workclass'],df['annual-income'])
```

Out[53]:

annual-income	<=50K	>50K
workclass		
Federal-gov	857	547
Local-gov	2185	909
Private	26056	7131
Self-emp-inc	734	855
Self-emp-not-inc	2737	1019
State-gov	1426	516
Without-pay	19	2

In [54]:
```
# contingency table
c_t = pd.crosstab(df['workclass'].sample(frac=0.002, replace=True, random_state=1),df
c_t
```

Out[54]:

annual-income	<=50K	>50K
workclass		
Federal-gov	2	1
Local-gov	0	2
Private	61	9
Self-emp-inc	5	0
Self-emp-not-inc	3	2
State-gov	4	1

In [55]:

```
# chi square test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

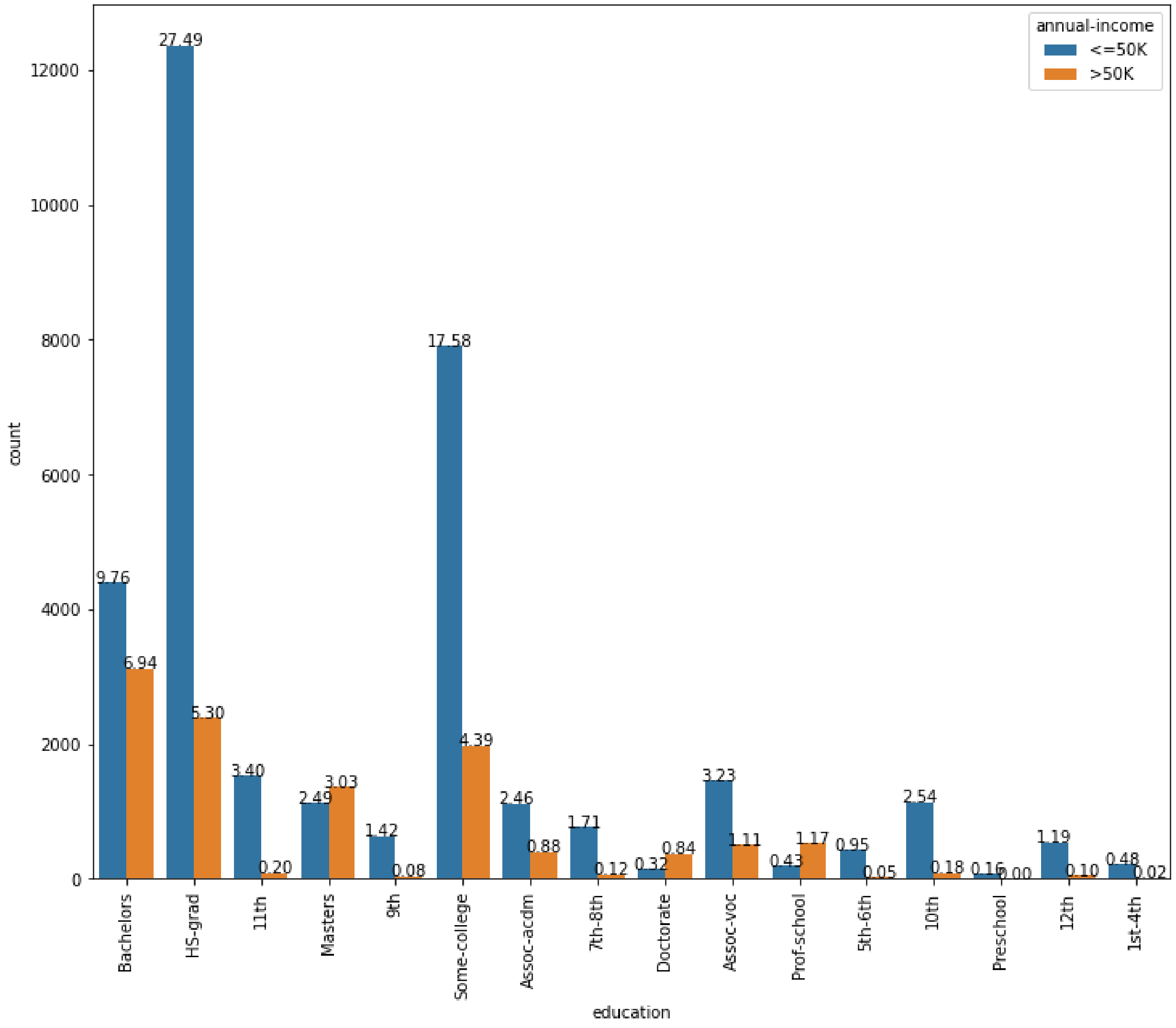
```
dof=5
p_value 0.013635700737287638
[[ 2.5         0.5       ]
 [ 1.66666667  0.33333333]
 [58.33333333 11.66666667]
 [ 4.16666667  0.83333333]
 [ 4.16666667  0.83333333]
 [ 4.16666667  0.83333333]]
probability=0.950, critical=11.070, stat=14.331
Dependent (reject H0)
```

We reject the null hypothesis from the chi-squared test i.e. there is dependency between workclass and annual-income. We can keep workclass in our feature set.

4.2.8 Relationship between education and annual income

In [56]:

```
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax  = sns.countplot(x="education", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.xticks(rotation=90)
plt.show()
```



In [57]:
```
# crosstab
pd.crosstab(df['education'],df['annual-income'])
```

Out[57]:

annual-income	<=50K	>50K
education		
10th	1141	80
11th	1530	89
12th	534	43
1st-4th	214	8
5th-6th	427	21
7th-8th	768	55
9th	638	37
Assoc-acdm	1109	398
Assoc-voc	1455	501
Bachelors	4392	3121
Doctorate	145	376
HS-grad	12367	2384
Masters	1121	1365
Preschool	71	1
Prof-school	193	525
Some-college	7909	1975

In [58]:

```
# contingency table
c_t = pd.crosstab(df['education'].sample(frac=0.002, replace=True, random_state=1),df[
c_t
```

Out[58]:

annual-income	<=50K	>50K
education		
10th	0	1
11th	2	0
12th	1	0
5th-6th	2	0
7th-8th	2	0
9th	2	0
Assoc-acdm	5	1
Assoc-voc	3	1
Bachelors	11	5
Doctorate	0	1
HS-grad	29	3
Masters	4	1
Some-college	14	2

In [59]:

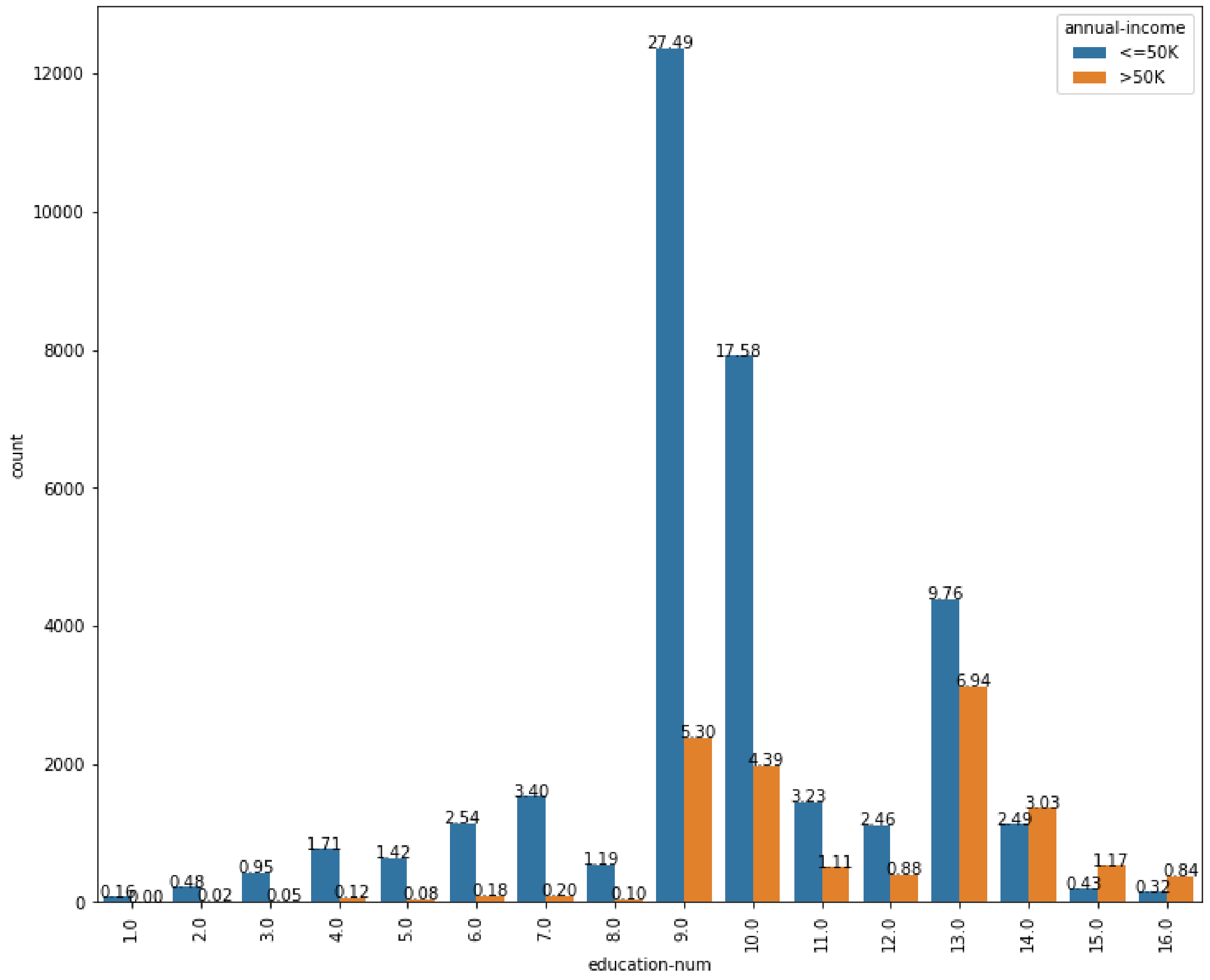
```
# chi-sqaured test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=12
p_value 0.19516031384342541
[[ 0.83333333  0.16666667]
 [ 1.66666667  0.33333333]
 [ 0.83333333  0.16666667]
 [ 1.66666667  0.33333333]
 [ 1.66666667  0.33333333]
 [ 1.66666667  0.33333333]
 [ 5.          1.        ]
 [ 3.33333333  0.66666667]
 [13.33333333  2.66666667]
 [ 0.83333333  0.16666667]
 [26.66666667  5.33333333]
 [ 4.16666667  0.83333333]
 [13.33333333  2.66666667]]
probability=0.950, critical=21.026, stat=15.915
Independent (fail to reject H0)
```

We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between education and annual-income. We will exclude education from our feature set.

4.2.9 Relationship between education num and annual income

In [60]:
```python
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="education-num", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.xticks(rotation=90)
plt.show()
```



```
In [61]: # crosstab
         pd.crosstab(df['education-num'],df['annual-income'])
```

Out[61]:

annual-income	<=50K	>50K
education-num		
1.0	71	1
2.0	214	8
3.0	427	21
4.0	768	55
5.0	638	37
6.0	1141	80
7.0	1530	89
8.0	534	43
9.0	12367	2384
10.0	7909	1975
11.0	1455	501
12.0	1109	398
13.0	4392	3121
14.0	1121	1365
15.0	193	525
16.0	145	376

In [62]:

```
# contingency table
c_t = pd.crosstab(df['education-num'].sample(frac=0.002, replace=True, random_state=1)
c_t
```

Out[62]:

annual-income	<=50K	>50K
education-num		
3.0	2	0
4.0	2	0
5.0	2	0
6.0	0	1
7.0	2	0
8.0	1	0
9.0	29	3
10.0	14	2
11.0	3	1
12.0	5	1
13.0	11	5
14.0	4	1
16.0	0	1

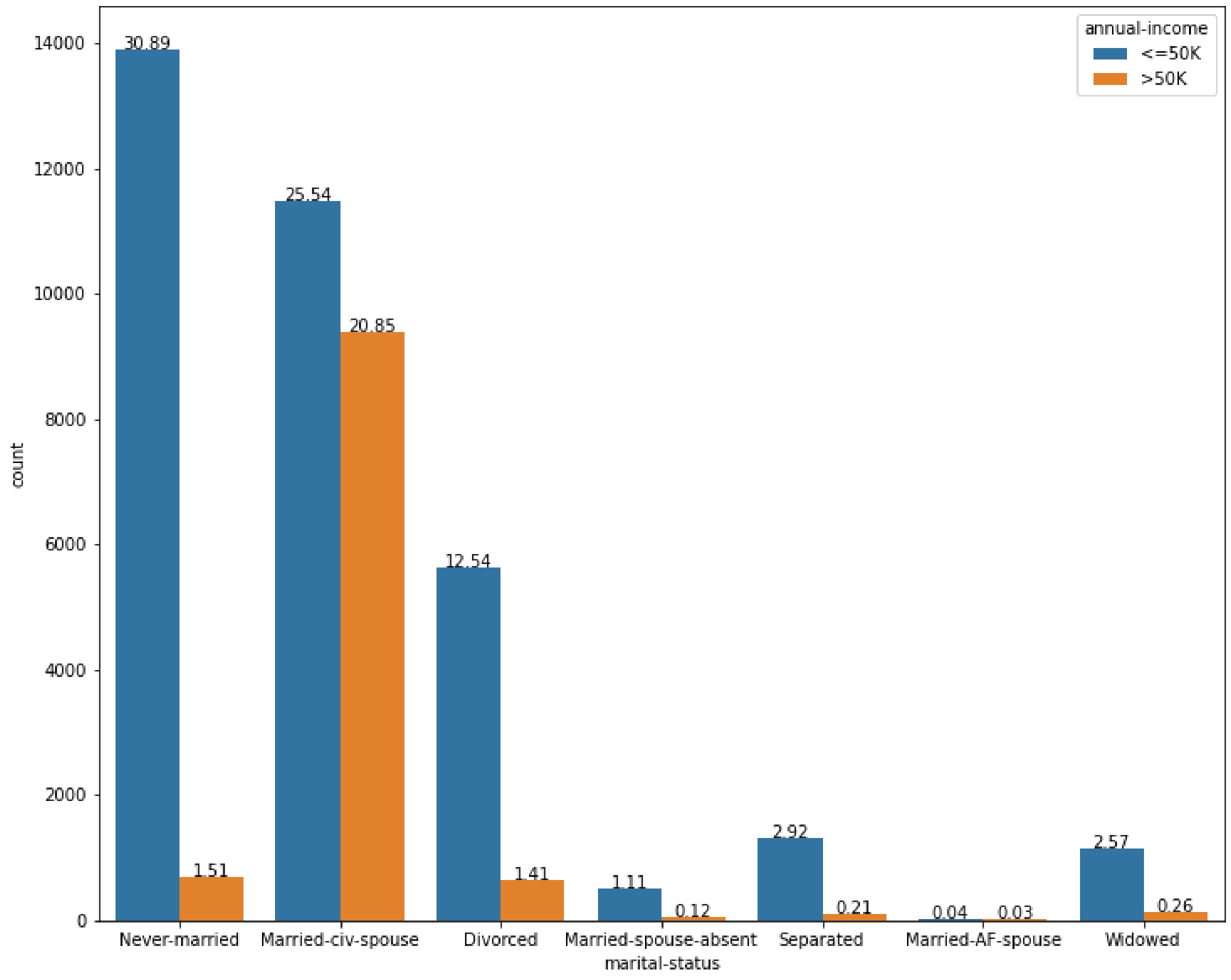
In [63]:
```
# chi-sqaured test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=12
p_value 0.19516031384342544
[[ 1.66666667  0.33333333]
 [ 1.66666667  0.33333333]
 [ 1.66666667  0.33333333]
 [ 0.83333333  0.16666667]
 [ 1.66666667  0.33333333]
 [ 0.83333333  0.16666667]
 [26.66666667  5.33333333]
 [13.33333333  2.66666667]
 [ 3.33333333  0.66666667]
 [ 5.          1.        ]
 [13.33333333  2.66666667]
 [ 4.16666667  0.83333333]
 [ 0.83333333  0.16666667]]
probability=0.950, critical=21.026, stat=15.915
Independent (fail to reject H0)
```

We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between education-num and annual-income as expected. We will exclude education from our feature set.

4.2.10 Relationship between marital status and annual income

In [64]:
```python
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="marital-status", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.show()
```



```
In [65]: # crosstab
         pd.crosstab(df['marital-status'],df['annual-income'])
```

Out[65]:

annual-income	<=50K	>50K
marital-status		
Divorced	5642	635
Married-AF-spouse	18	13
Married-civ-spouse	11491	9383
Married-spouse-absent	498	53
Never-married	13897	681
Separated	1312	95
Widowed	1156	119

```
In [66]: # contingency table
         c_t = pd.crosstab(df['marital-status'].sample(frac=0.002, replace=True, random_state=
         c_t
```

Out[66]:

annual-income	<=50K	>50K
marital-status		
Divorced	16	1
Married-civ-spouse	18	12
Married-spouse-absent	2	1
Never-married	34	1
Separated	3	0
Widowed	2	0

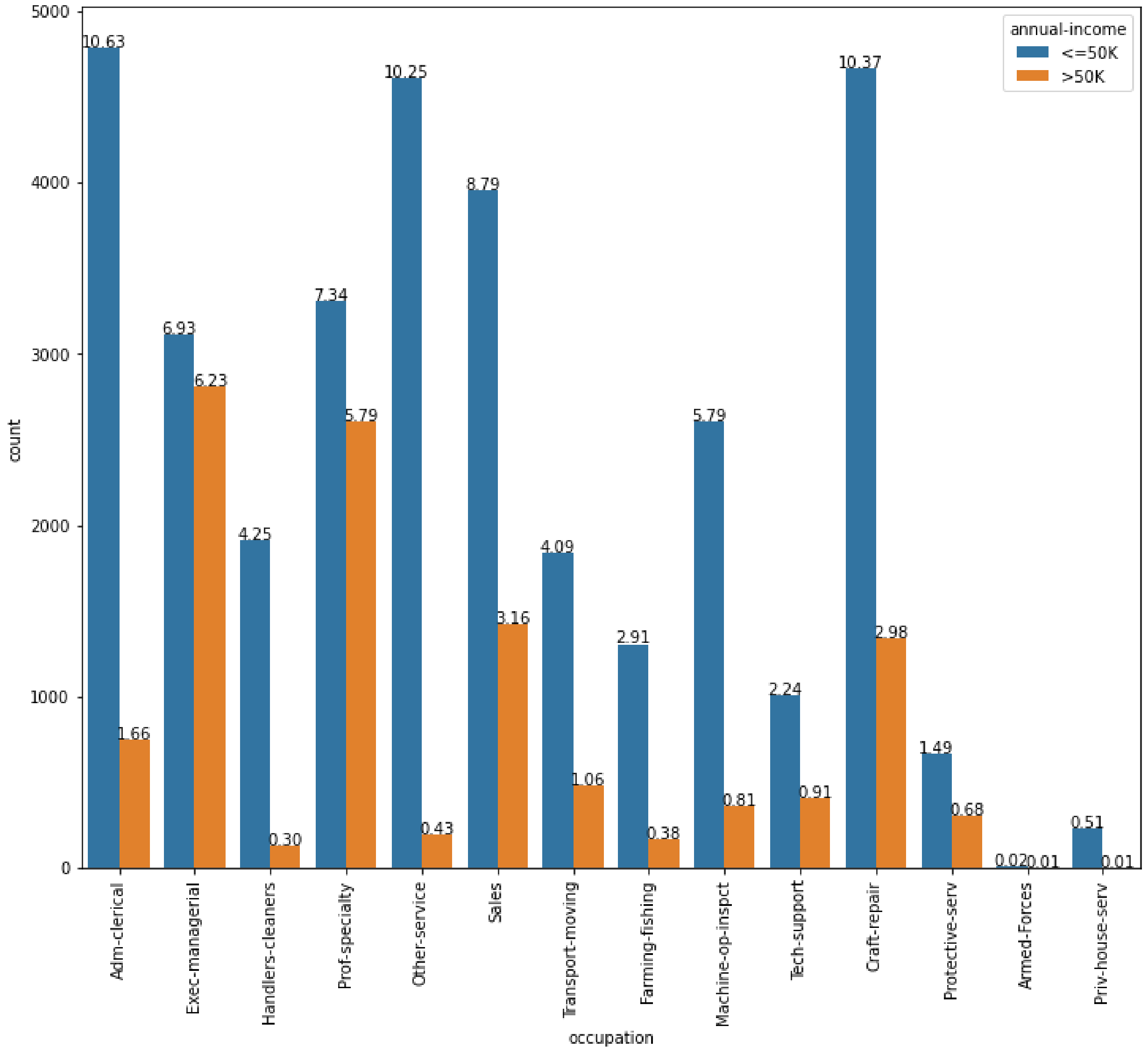
In [67]:
```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=5
p_value 0.0014920475984894538
[[14.16666667  2.83333333]
 [25.          5.        ]
 [ 2.5         0.5       ]
 [29.16666667  5.83333333]
 [ 2.5         0.5       ]
 [ 1.66666667  0.33333333]]
probability=0.950, critical=11.070, stat=19.589
Dependent (reject H0)
```

We reject the null hypothesis from the chi-squared test i.e. there is dependency between marital-status and annual-income. We will include marital-status in our feature set.

4.2.11 Relationship between occupation and annual income

In [68]:
```
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="occupation", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.xticks(rotation=90)
plt.show()
```



In [69]:
```
# crosstab
pd.crosstab(df['occupation'],df['annual-income'])
```

Out[69]:

annual-income occupation	<=50K	>50K
Adm-clerical	4784	748
Armed-Forces	10	4
Craft-repair	4665	1340
Exec-managerial	3117	2805
Farming-fishing	1308	169
Handlers-cleaners	1911	133
Machine-op-inspct	2605	364
Other-service	4612	193
Priv-house-serv	229	3
Prof-specialty	3304	2606
Protective-serv	669	305
Sales	3953	1422
Tech-support	1009	410
Transport-moving	1838	477

In [70]:
```
# contingency table
c_t = pd.crosstab(df['occupation'].sample(frac=0.002, replace=True, random_state=1),d
c_t
```

Out[70]:

annual-income occupation	<=50K	>50K
Adm-clerical	11	2
Craft-repair	11	2
Exec-managerial	9	3
Farming-fishing	3	0
Handlers-cleaners	2	0
Machine-op-inspct	5	0
Other-service	9	1
Prof-specialty	4	4
Protective-serv	2	0
Sales	13	3
Tech-support	2	0
Transport-moving	4	0

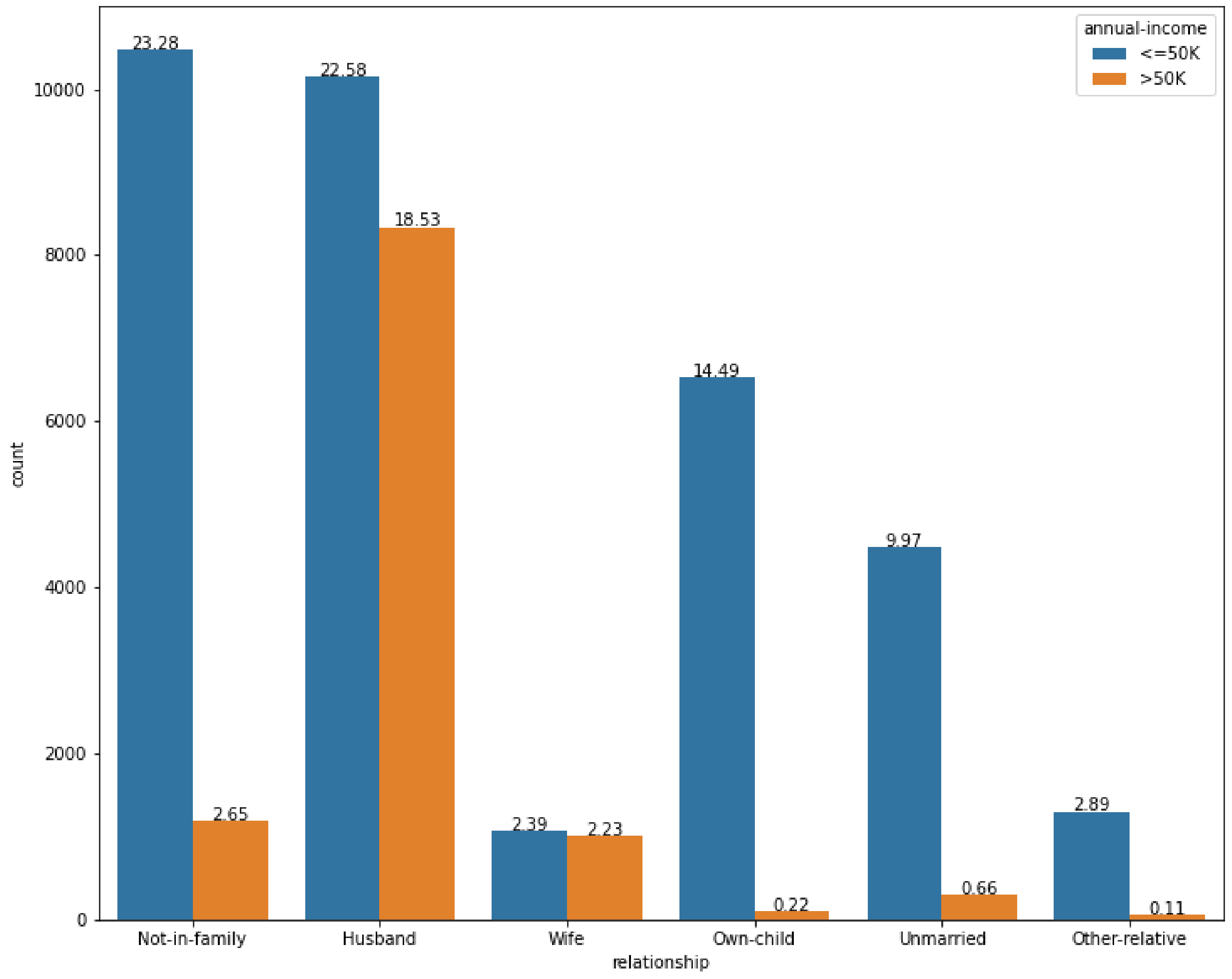
In [71]:
```python
# chi-sqaured test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=11
p_value 0.4431988367023754
[[10.83333333  2.16666667]
 [10.83333333  2.16666667]
 [10.          2.        ]
 [ 2.5         0.5       ]
 [ 1.66666667  0.33333333]
 [ 4.16666667  0.83333333]
 [ 8.33333333  1.66666667]
 [ 6.66666667  1.33333333]
 [ 1.66666667  0.33333333]
 [13.33333333  2.66666667]
 [ 1.66666667  0.33333333]
 [ 3.33333333  0.66666667]]
probability=0.950, critical=19.675, stat=11.001
Independent (fail to reject H0)
```

We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between occupation and annual-income. We will exclude occupation from our feature set.

4.2.12 Relationship between relationship and annual income

In [72]:
```python
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="relationship", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
#plt.xticks(rotation=90)
plt.show()
```



```
In [73]: # crosstab
         pd.crosstab(df['relationship'],df['annual-income'])
```

Out[73]:

annual-income	<=50K	>50K
relationship		
Husband	10159	8339
Not-in-family	10474	1192
Other-relative	1299	50
Own-child	6521	101
Unmarried	4486	295
Wife	1075	1002

```
In [74]: # contingency table
         c_t = pd.crosstab(df['relationship'].sample(frac=0.002, replace=True, random_state=1),
         c_t
```

Out[74]:

annual-income	<=50K	>50K
relationship		
Husband	15	9
Not-in-family	24	3
Other-relative	6	0
Own-child	16	0
Unmarried	12	0
Wife	2	3

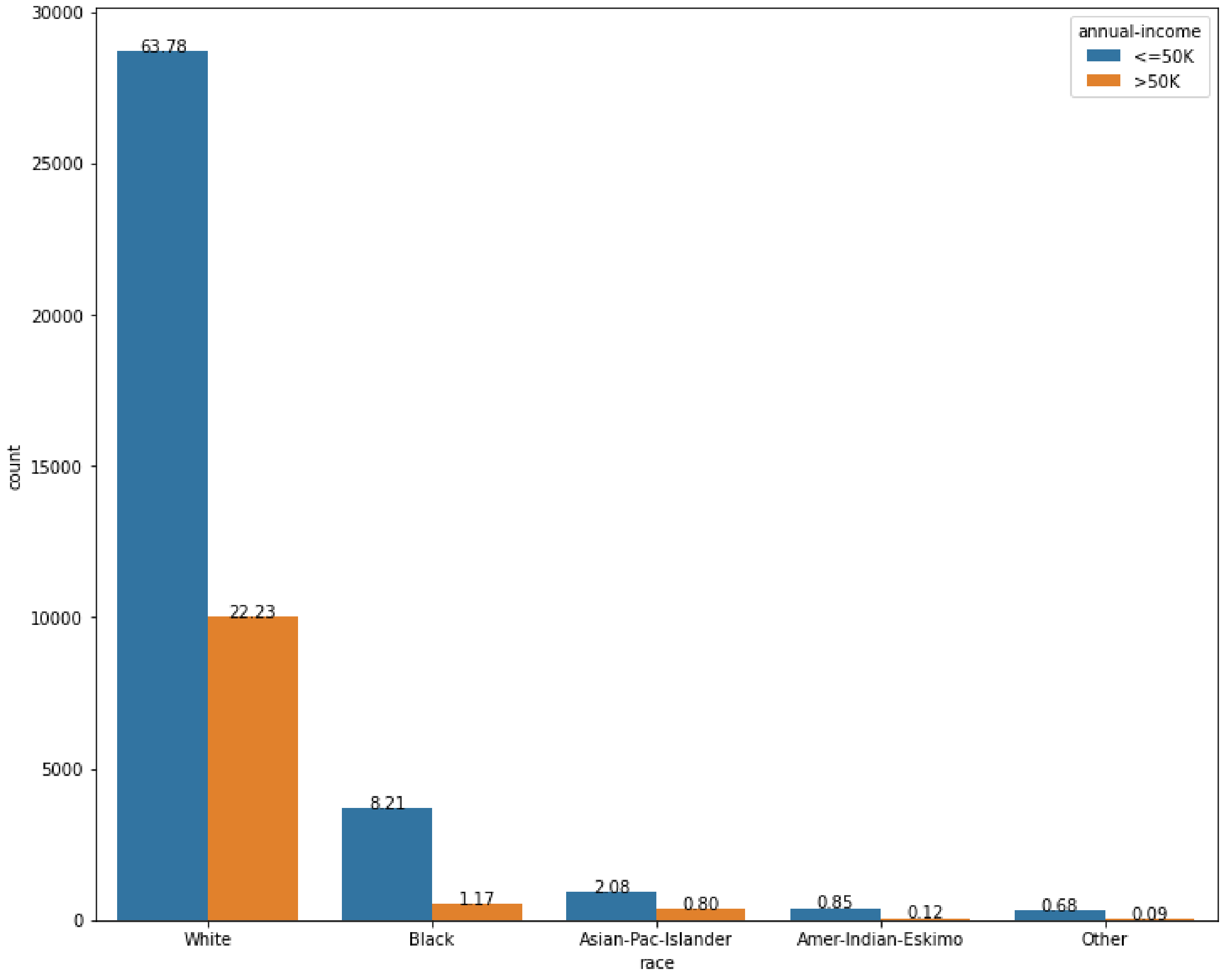
In [75]:
```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=5
p_value 0.000607526244582496
[[20.          4.        ]
 [22.5         4.5       ]
 [ 5.          1.        ]
 [13.33333333  2.66666667]
 [10.          2.        ]
 [ 4.16666667  0.83333333]]
probability=0.950, critical=11.070, stat=21.660
Dependent (reject H0)
```

We reject the null hypothesis from the chi-squared test i.e. there is dependency between relationship and annual-income. Relationship will remain in our feature set.

4.2.13 Relationship between race and annual income

In [76]:
```
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="race", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
#plt.xticks(rotation=90)
plt.show()
```



In [77]:
```
# crosstab
pd.crosstab(df['race'],df['annual-income'])
```

Out[77]:

annual-income	<=50K	>50K
race		
Amer-Indian-Eskimo	382	53
Asian-Pac-Islander	934	358
Black	3694	525
Other	308	42
White	28696	10001

In [78]:
```
# contingency table
c_t = pd.crosstab(df['race'].sample(frac=0.002, replace=True, random_state=1),df['annu
c_t
```

Out[78]:

annual-income	<=50K	>50K
race		
Amer-Indian-Eskimo	1	0
Asian-Pac-Islander	1	1
Black	14	2
Other	1	0
White	58	12

In [79]:

```python
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=4
p_value 0.6969374959913187
[[ 0.83333333  0.16666667]
 [ 1.66666667  0.33333333]
 [13.33333333  2.66666667]
 [ 0.83333333  0.16666667]
 [58.33333333 11.66666667]]
probability=0.950, critical=9.488, stat=2.211
Independent (fail to reject H0)
```

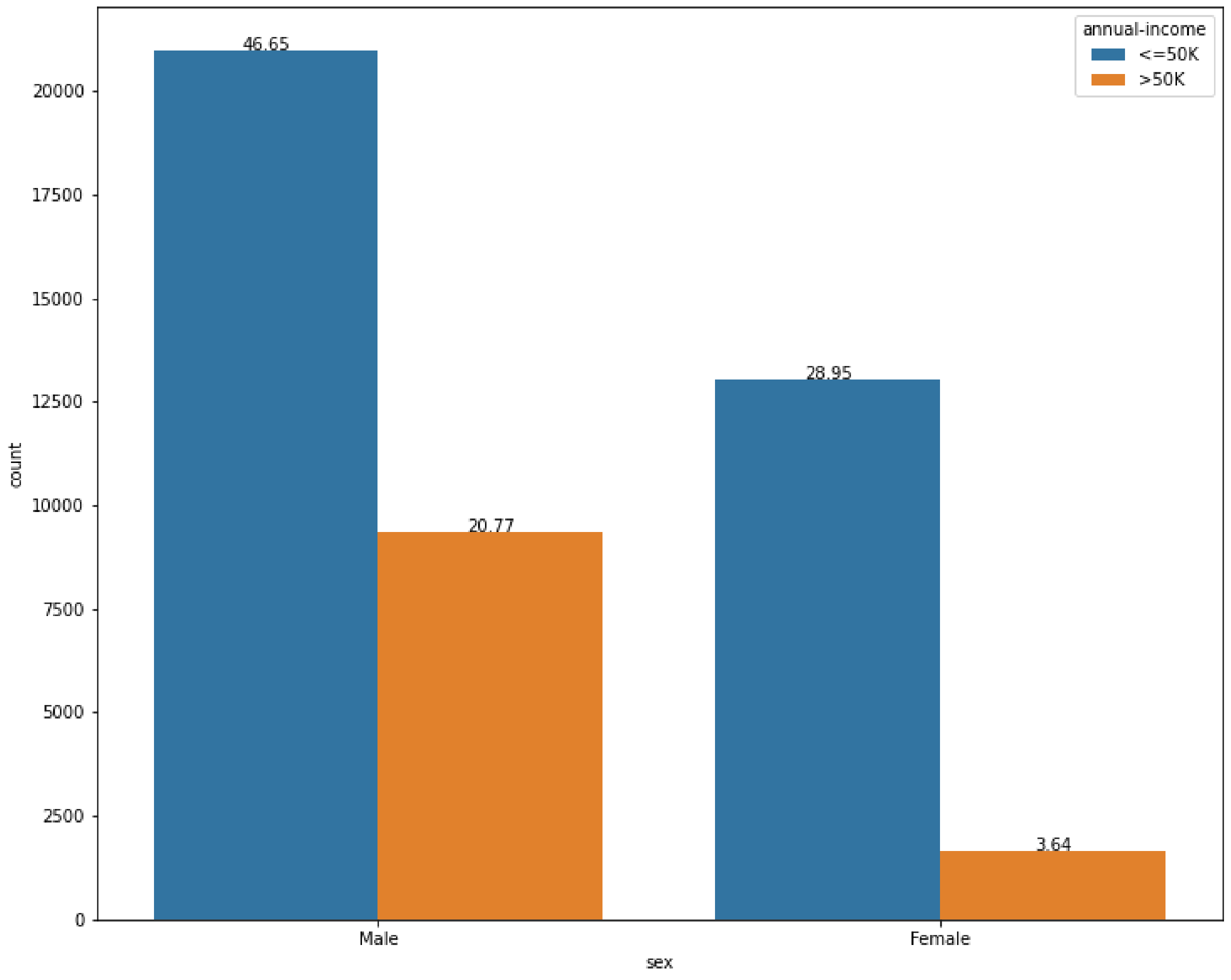
We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between race and annual-income. We will exclude race from our feature set.

4.2.14 Relationship between sex and annual income

In [80]:

```python
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(x="sex", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
```

```
#plt.xticks(rotation=90)
plt.show()
```



In [81]:
```
# crosstab
pd.crosstab(df['sex'],df['annual-income'])
```

Out[81]:

annual-income	<=50K	>50K
sex		
Female	13026	1636
Male	20988	9343

In [82]:
```
# contingency table
c_t = pd.crosstab(df['sex'].sample(frac=0.002, replace=True, random_state=1),df['annua
c_t
```

Out[82]:

annual-income	<=50K	>50K
sex		
Female	29	5
Male	46	10

In [83]:
```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

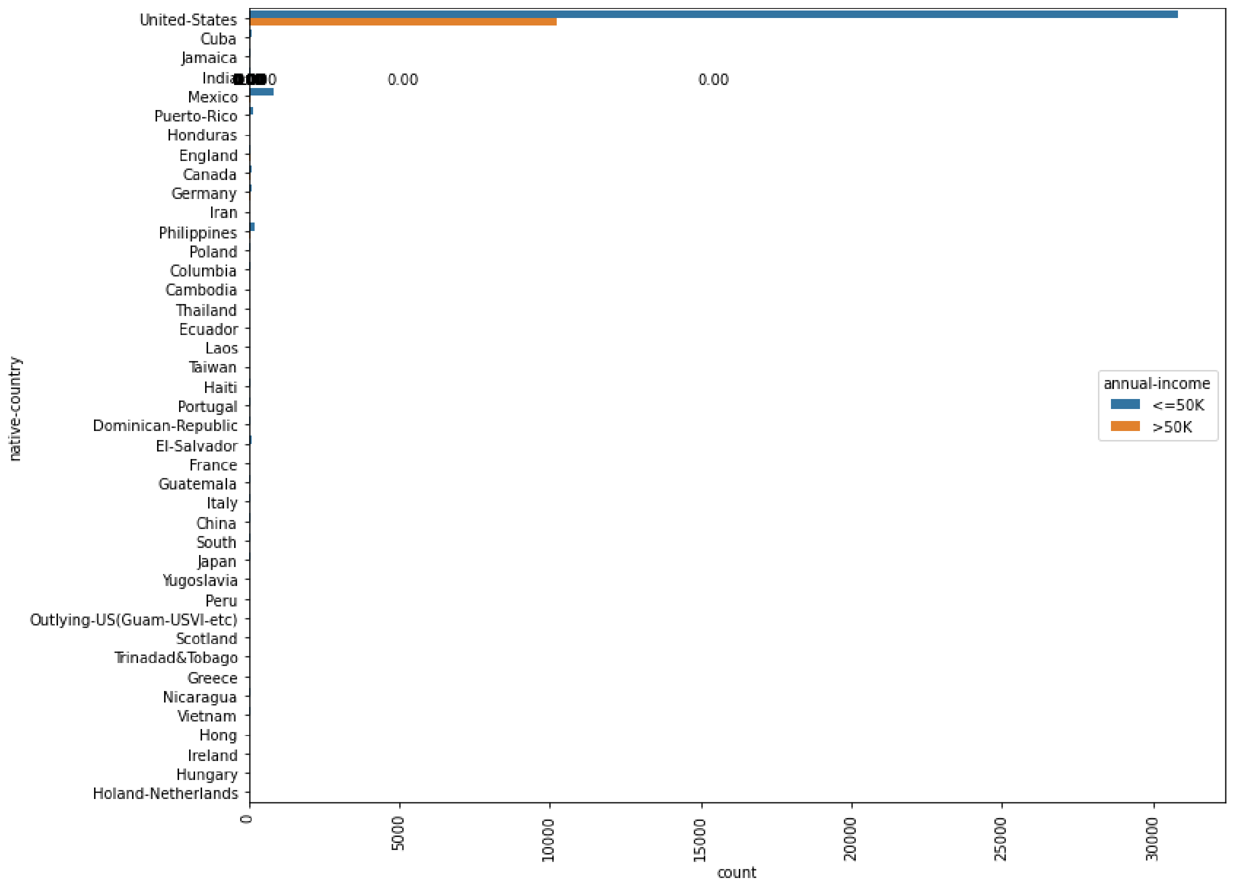
```
dof=1
p_value 0.9225433008087743
[[28.33333333  5.66666667]
 [46.66666667  9.33333333]]
probability=0.950, critical=3.841, stat=0.009
Independent (fail to reject H0)
```

We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between sex and annual-income. We will exclude sex from our feature set.

4.2.15 Relationship between native country and annual income

In [84]:
```
# histogram
plt.figure(figsize=(12,10))
total = float(len(df["annual-income"]) )

ax = sns.countplot(y="native-country", hue="annual-income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.xticks(rotation=90)
plt.show()
```

```
posx and posy should be finite values
posx and posy should be finite values
```



```
In [85]: # crosstab
         pd.crosstab(df['native-country'],df['annual-income'])
```

Out[85]:

annual-income	<=50K	>50K
native-country		
Cambodia	17	9
Canada	103	59
China	77	35
Columbia	78	4
Cuba	99	34
Dominican-Republic	92	4
Ecuador	37	6
El-Salvador	136	11
England	72	47
France	20	16
Germany	135	58
Greece	31	18
Guatemala	83	3
Haiti	60	9
Holand-Netherlands	1	0
Honduras	17	2
Hong	20	8
Hungary	12	6
India	85	58
Iran	34	22
Ireland	26	10
Italy	67	33
Jamaica	89	14
Japan	58	30
Laos	19	2
Mexico	856	45
Nicaragua	45	3
Outlying-US(Guam-USVI-etc)	21	1
Peru	41	4
Philippines	199	81
Poland	65	16
Portugal	50	12

annual-income	<=50K	>50K
native-country		
Puerto-Rico	155	20
Scotland	18	2
South	83	18
Taiwan	30	24
Thailand	24	5
Trinadad&Tobago	24	2
United-States	30844	10233
Vietnam	76	7
Yugoslavia	15	8

In [86]:

```
# contingency table
c_t = pd.crosstab(df['native-country'].sample(frac=0.002, replace=True, random_state=
c_t
```

Out[86]:

annual-income	<=50K	>50K
native-country		
Germany	2	0
Haiti	0	1
Mexico	5	0
Puerto-Rico	1	0
United-States	67	14

In [87]:

```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

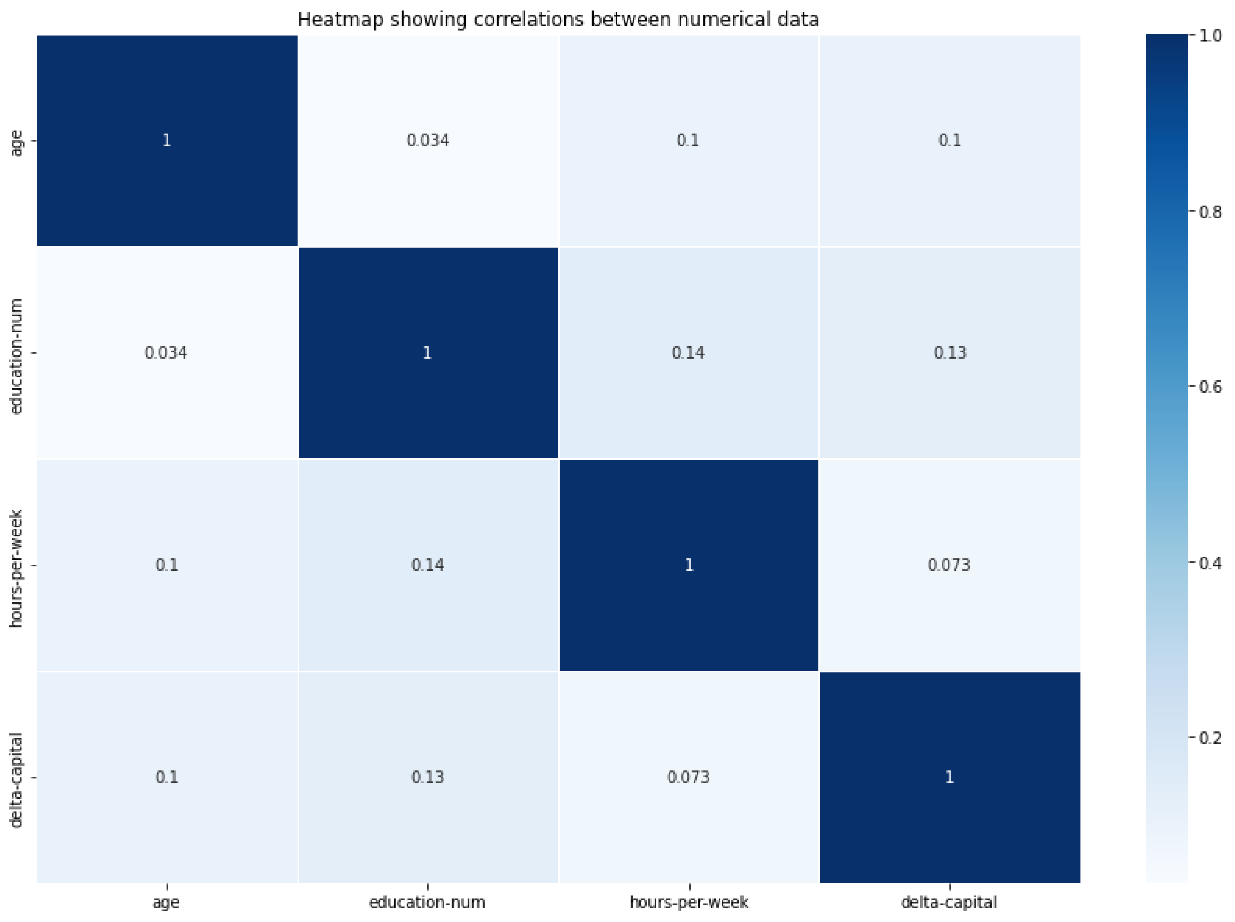
```
dof=4
p_value 0.15725046256468317
[[ 1.66666667  0.33333333]
 [ 0.83333333  0.16666667]
 [ 4.16666667  0.83333333]
 [ 0.83333333  0.16666667]
 [67.5        13.5       ]]
probability=0.950, critical=9.488, stat=6.622
Independent (fail to reject H0)
```

We cannot reject the null hypothesis from the chi-squared test i.e. there is no dependency between native country and annual-income. We will exclude native country from our feature set.

4.3 Multivariate Analysis

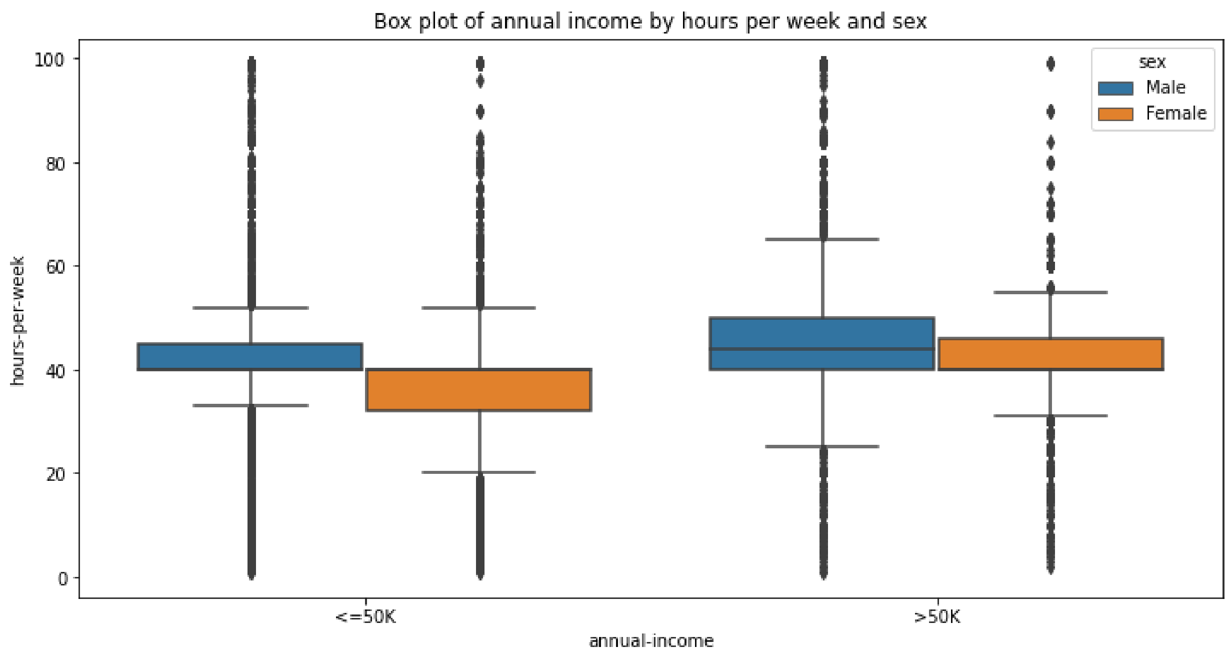
4.3.1 Correlation Matrix

In [88]:
```
plt.figure(figsize=(15,10))
sns.heatmap(df.select_dtypes(include=[np.number]).corr(),annot=True,linewidths=.5, cma
plt.title('Heatmap showing correlations between numerical data')
plt.show()
```



4.3.2 Multivariate Categorical Analysis

In [89]:
```
plt.figure(figsize=(12,6))
sns.boxplot(x='annual-income',y ='hours-per-week', hue='sex',data=df).set_title("Box p
plt.show()
```



4.4 Conclusion of Exploratory Data Analysis

We have completed our feature set from the exploratory data analysis by running thorough statistical analyses and visualizations. As per our result, these numerical features are significant for our model:
1) age
2) hours-per-week

And, these categorical features are significant:
1) relationship
2) marital-status
3) delta-capital
4) workclass

These 6 features constitute our feature set for now. By the exploratory data analysis, we have also been successful in-
A) Feature Engineering: New feature "delta-capital" was constructed which is significant and also helped us to remove 2 features (capital-gain and capital-loss).
B) Outlier detection & removal: In delta-capital, we identified outliers and removed them (~0.5%) which retained the overall data structure and improved data quality.

5 Models

As this is a binary classification problem, we will be deploying and evaluating 3 models here:

- Logistic Regression

- Random Forest
- Gaussian Naive Bayes

Even though our feature set is rigorous from EDA, we will run a Chi-squared test of dependency between "marital-status" and "relationship" variables. These two features may contain some similarity as they are derived from the same information regarding family. Furthermore, we will need to encode the categorical variables. Instead of labeling, we may need to go for target encoding or probabilistic target encoding here. We will also need to normalize/standardize the data. Then, we shall split the dataset into the train & test part to evaluate all the models on the same test set.

We will also need to look out for the problem of multicollinearity and imbalanced dataset. Finally, a proper evaluation metric must be decided to evaluate the performance.

5.1 Marital status and Relationship: Multicollinearity?

In [90]:
```
# crosstab
pd.crosstab(df['marital-status'],df['relationship'])
```

Out[90]:

relationship	Husband	Not-in-family	Other-relative	Own-child	Unmarried	Wife
marital-status						
Divorced	0	3419	166	429	2263	0
Married-AF-spouse	11	0	1	1	0	18
Married-civ-spouse	18487	19	184	125	0	2059
Married-spouse-absent	0	281	44	57	169	0
Never-married	0	6676	820	5860	1222	0
Separated	0	584	75	130	618	0
Widowed	0	687	59	20	509	0

In [91]:
```
# contingency table
c_t = pd.crosstab(df['marital-status'].sample(frac=0.002, replace=True, random_state=
c_t
```

Out[91]:

relationship marital-status	Husband	Not-in-family	Other-relative	Own-child	Unmarried	Wife
Divorced	0	7	2	0	8	0
Married-civ-spouse	24	0	0	1	0	5
Married-spouse-absent	0	3	0	0	0	0
Never-married	0	14	4	15	2	0
Separated	0	3	0	0	0	0
Widowed	0	0	0	0	2	0

In [92]:
```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


stat, p, dof, expected = chi2_contingency(c_t)
print('dof=%d' % dof)
print('p_value', p)
print(expected)

# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=25
p_value 2.9251496039601857e-17
[[ 4.53333333  5.1         1.13333333  3.02222222  2.26666667  0.94444444]
 [ 8.          9.          2.          5.33333333  4.          1.66666667]
 [ 0.8         0.9         0.2         0.53333333  0.4         0.16666667]
 [ 9.33333333 10.5         2.33333333  6.22222222  4.66666667  1.94444444]
 [ 0.8         0.9         0.2         0.53333333  0.4         0.16666667]
 [ 0.53333333  0.6         0.13333333  0.35555556  0.26666667  0.11111111]]
probability=0.950, critical=37.652, stat=136.102
Dependent (reject H0)
```

As it turned out, marital-status and relationship are dependent (as we already suspected). After encoding these two categorical variables, we will go into VIF test.

5.2 Encoding Categorical Variables

We will denote the annual income of >50K as 1 and <=50K as 0. For the X categorical variables, we will go for probabilistic target encoding.

In [93]:
```
# Encoding (1/0) for target variable
cat = pd.get_dummies(df["annual-income"], drop_first = True)
df_cat = pd.concat((df, cat), axis=1)
```

```python
df_cat = df_cat.drop(['annual-income'], axis=1)
df_cat
```

Out[93]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female
...	...	...	...	...	...	...	...	...	...
48836	33	Private	Bachelors	13.0	Never-married	Prof-specialty	Own-child	White	Male
48837	39	Private	Bachelors	13.0	Divorced	Prof-specialty	Not-in-family	White	Female
48839	38	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Husband	White	Male
48840	44	Private	Bachelors	13.0	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male
48841	35	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male

44993 rows × 13 columns

In [94]:

```python
# Target encoding for marital-status
prob=df_cat.groupby(['marital-status'])['>50K'].mean()
prob_df=pd.DataFrame(prob)
prob_df=pd.DataFrame(prob)
prob_df['<=50K']=1-prob_df['>50K']
prob_df['Probability Ratio']=prob_df['>50K']/prob_df['<=50K']
prob_encod_dictionary=prob_df['Probability Ratio'].to_dict()
df_cat['marital-status-ratio']=df_cat['marital-status'].map(prob_encod_dictionary)
df_cat.head()
```

Out[94]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hours-per-week
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	40.0
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	13.0
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	40.0
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40.0
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40.0

In [95]:
```
# Target encoding for relationship
prob=df_cat.groupby(['relationship'])['>50K'].mean()
prob_df=pd.DataFrame(prob)
prob_df['<=50K']=1-prob_df['>50K']
prob_df['Probability Ratio']=prob_df['>50K']/prob_df['<=50K']
prob_encod_dictionary=prob_df['Probability Ratio'].to_dict()
df_cat['relationship-ratio']=df_cat['relationship'].map(prob_encod_dictionary)
df_cat.head()
```

Out[95]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hours-per-week
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	40.0
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	13.0
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	40.0
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40.0
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40.0

In [96]:
```
# Target encoding for workclass
prob=df_cat.groupby(['workclass'])['>50K'].mean()
prob_df=pd.DataFrame(prob)
prob_df['<=50K']=1-prob_df['>50K']
prob_df['Probability Ratio']=prob_df['>50K']/prob_df['<=50K']
```

```
prob_encod_dictionary=prob_df['Probability Ratio'].to_dict()
df_cat['workclass-ratio']=df_cat['workclass'].map(prob_encod_dictionary)
df_cat.head()
```

Out[96]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hours-per-week
0	39	State-gov	Bachelors	13.0	Never-married	Adm-clerical	Not-in-family	White	Male	40.0
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	Exec-managerial	Husband	White	Male	13.0
2	38	Private	HS-grad	9.0	Divorced	Handlers-cleaners	Not-in-family	White	Male	40.0
3	53	Private	11th	7.0	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40.0
4	28	Private	Bachelors	13.0	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40.0

In [97]:

```
# Dropping the unnecessary and duplicate columns
df_main = df_cat.drop(['workclass', 'education', 'education-num', 'marital-status', 'c
                      axis=1)
df_main
```

Out[97]:

	age	hours-per-week	delta-capital	>50K	marital-status-ratio	relationship-ratio	workclass-ratio
0	39	40.0	2174.0	0	0.049003	0.113806	0.361851
1	50	13.0	0.0	0	0.816552	0.820849	0.372305
2	38	40.0	0.0	0	0.112549	0.113806	0.273680
3	53	40.0	0.0	0	0.816552	0.820849	0.273680
4	28	40.0	0.0	0	0.816552	0.932093	0.273680
...	...	...	...	...	...	...	...
48836	33	40.0	0.0	0	0.049003	0.015488	0.273680
48837	39	36.0	0.0	0	0.112549	0.113806	0.273680
48839	38	50.0	0.0	0	0.816552	0.820849	0.273680
48840	44	40.0	5455.0	0	0.112549	0.015488	0.273680
48841	35	60.0	0.0	1	0.816552	0.820849	1.164850

44993 rows × 7 columns

5.3 Standardizing Feature Set

We have age, hours-per-week and delta-capital whose units are years, hours and dollars respectively with varying ranges. This is why we need to standardize them. Logistic Regression assumes binomial probability distribution as well.

In [98]:
```
from sklearn.preprocessing import StandardScaler
df_main[['age', 'hours-per-week', 'delta-capital']] = StandardScaler().fit_transform(
df_main
```

Out[98]:

	age	hours-per-week	delta-capital	>50K	marital-status-ratio	relationship-ratio	workclass-ratio
0	0.037252	-0.074059	0.635266	0	0.049003	0.113806	0.361851
1	0.869469	-2.327318	-0.194218	0	0.816552	0.820849	0.372305
2	-0.038404	-0.074059	-0.194218	0	0.112549	0.113806	0.273680
3	1.096438	-0.074059	-0.194218	0	0.816552	0.820849	0.273680
4	-0.794965	-0.074059	-0.194218	0	0.816552	0.932093	0.273680
...	...	...	...	...	...	...	...
48836	-0.416684	-0.074059	-0.194218	0	0.049003	0.015488	0.273680
48837	0.037252	-0.407875	-0.194218	0	0.112549	0.113806	0.273680
48839	-0.038404	0.760481	-0.194218	0	0.816552	0.820849	0.273680
48840	0.415533	-0.074059	1.887121	0	0.112549	0.015488	0.273680
48841	-0.265372	1.595021	-0.194218	1	0.816552	0.820849	1.164850

44993 rows × 7 columns

5.4 Multicollinearity Test

In [99]:
```
# correlation
df_main.corr()
```

Out[99]:

	age	hours-per-week	delta-capital	>50K	marital-status-ratio	relationship-ratio	workclass-ratio
age	1.000000	0.100464	0.104338	0.234130	0.328106	0.328060	0.155725
hours-per-week	0.100464	1.000000	0.073258	0.222599	0.227597	0.232395	0.125499
delta-capital	0.104338	0.073258	1.000000	0.278057	0.090984	0.093188	0.071764
>50K	0.234130	0.222599	0.278057	1.000000	0.447275	0.452557	0.156016
marital-status-ratio	0.328106	0.227597	0.090984	0.447275	1.000000	0.978280	0.126962
relationship-ratio	0.328060	0.232395	0.093188	0.452557	0.978280	1.000000	0.127243
workclass-ratio	0.155725	0.125499	0.071764	0.156016	0.126962	0.127243	1.000000

The correlation value between marital-status-ratio and relationship-ratio is extremely high (0.978280).

In [100…

```
df_main.drop('marital-status-ratio', axis=1).corr()
```

Out[100]:

	age	hours-per-week	delta-capital	>50K	relationship-ratio	workclass-ratio
age	1.000000	0.100464	0.104338	0.234130	0.328060	0.155725
hours-per-week	0.100464	1.000000	0.073258	0.222599	0.232395	0.125499
delta-capital	0.104338	0.073258	1.000000	0.278057	0.093188	0.071764
>50K	0.234130	0.222599	0.278057	1.000000	0.452557	0.156016
relationship-ratio	0.328060	0.232395	0.093188	0.452557	1.000000	0.127243
workclass-ratio	0.155725	0.125499	0.071764	0.156016	0.127243	1.000000

In [101…

```
df_main.drop('relationship-ratio', axis=1).corr()
```

Out[101]:

	age	hours-per-week	delta-capital	>50K	marital-status-ratio	workclass-ratio
age	1.000000	0.100464	0.104338	0.234130	0.328106	0.155725
hours-per-week	0.100464	1.000000	0.073258	0.222599	0.227597	0.125499
delta-capital	0.104338	0.073258	1.000000	0.278057	0.090984	0.071764
>50K	0.234130	0.222599	0.278057	1.000000	0.447275	0.156016
marital-status-ratio	0.328106	0.227597	0.090984	0.447275	1.000000	0.126962
workclass-ratio	0.155725	0.125499	0.071764	0.156016	0.126962	1.000000

The correlation value does not change much for exclusion of any of those 2 features. It means we can remove any one of them. As marital-status is easier to interpret, we are removing relationship i.e. relationship-ratio from feature set.

In [102…

```
df_main = df_main.drop('relationship-ratio', axis=1)
df_main
```

Out[102]:

	age	hours-per-week	delta-capital	>50K	marital-status-ratio	workclass-ratio
0	0.037252	-0.074059	0.635266	0	0.049003	0.361851
1	0.869469	-2.327318	-0.194218	0	0.816552	0.372305
2	-0.038404	-0.074059	-0.194218	0	0.112549	0.273680
3	1.096438	-0.074059	-0.194218	0	0.816552	0.273680
4	-0.794965	-0.074059	-0.194218	0	0.816552	0.273680
...	...	...	...	...	...	...
48836	-0.416684	-0.074059	-0.194218	0	0.049003	0.273680
48837	0.037252	-0.407875	-0.194218	0	0.112549	0.273680
48839	-0.038404	0.760481	-0.194218	0	0.816552	0.273680
48840	0.415533	-0.074059	1.887121	0	0.112549	0.273680
48841	-0.265372	1.595021	-0.194218	1	0.816552	1.164850

44993 rows × 6 columns

In [103…

```
# VIF Score
from statsmodels.stats.outliers_influence import variance_inflation_factor

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["feature"] = df_main.drop('>50K', axis=1).columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(df_main.drop('>50K', axis=1).values, i)
                          for i in range(len(df_main.drop('>50K', axis=1).columns))]

print(vif_data)
```

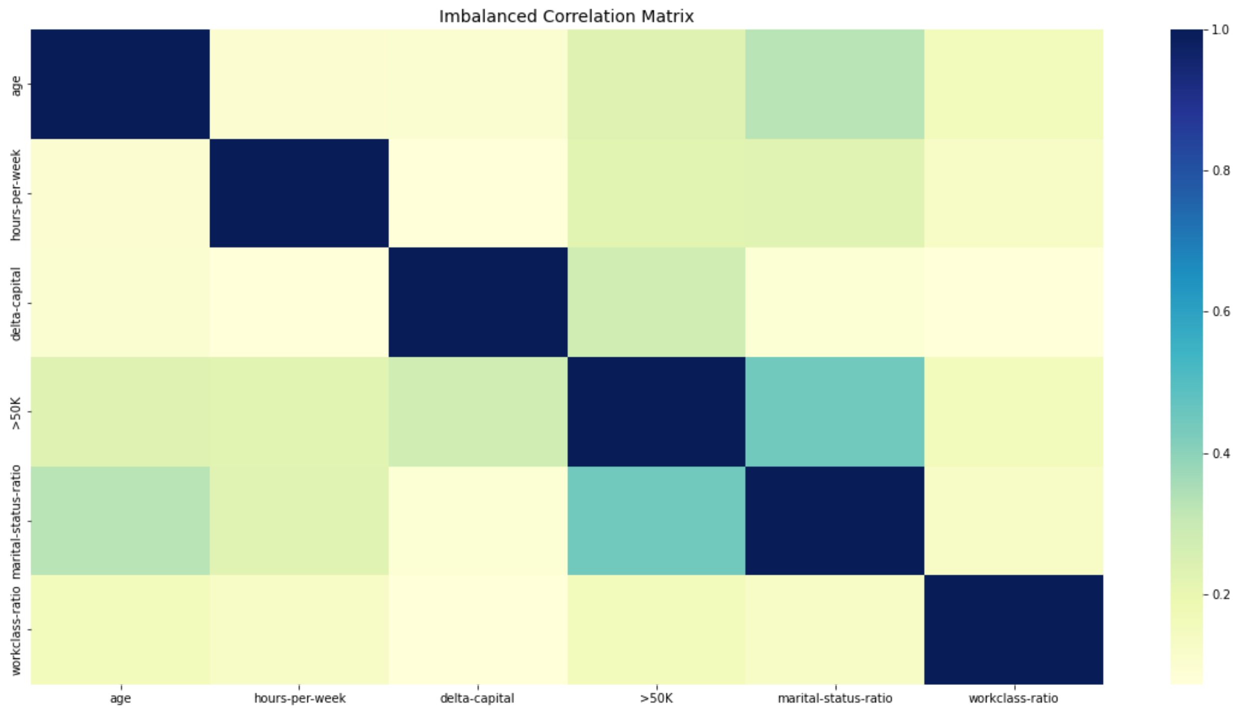
```
                feature       VIF
0                   age  1.077494
1        hours-per-week  1.035994
2         delta-capital  1.016057
3  marital-status-ratio  2.128422
4       workclass-ratio  2.005329
```

There are no VIF scores larger than 5. It means we have successfully solved the multicollinearity problem in our feature set.

5.5 SMOTE: Synthetic Minority Oversampling Technique

Our dataset is imbalanced in nature with minority class being 25%. Here we can use SMOTE to oversample the minority class and feed it into our learning model. However, this must be done after train-test split so that our models could be tested on test sets that have inherent imbalancing. Here, we have illustrated the difference in correlation matrix for our dataset after balancing.

In [104…
```
# Sample figsize in inches
fig, ax = plt.subplots(figsize=(20,10))
# Imbalanced DataFrame Correlation
corr = df_main.corr()
sns.heatmap(corr, cmap='YlGnBu', annot_kws={'size':30}, ax=ax)
ax.set_title("Imbalanced Correlation Matrix", fontsize=14)
plt.show()
```



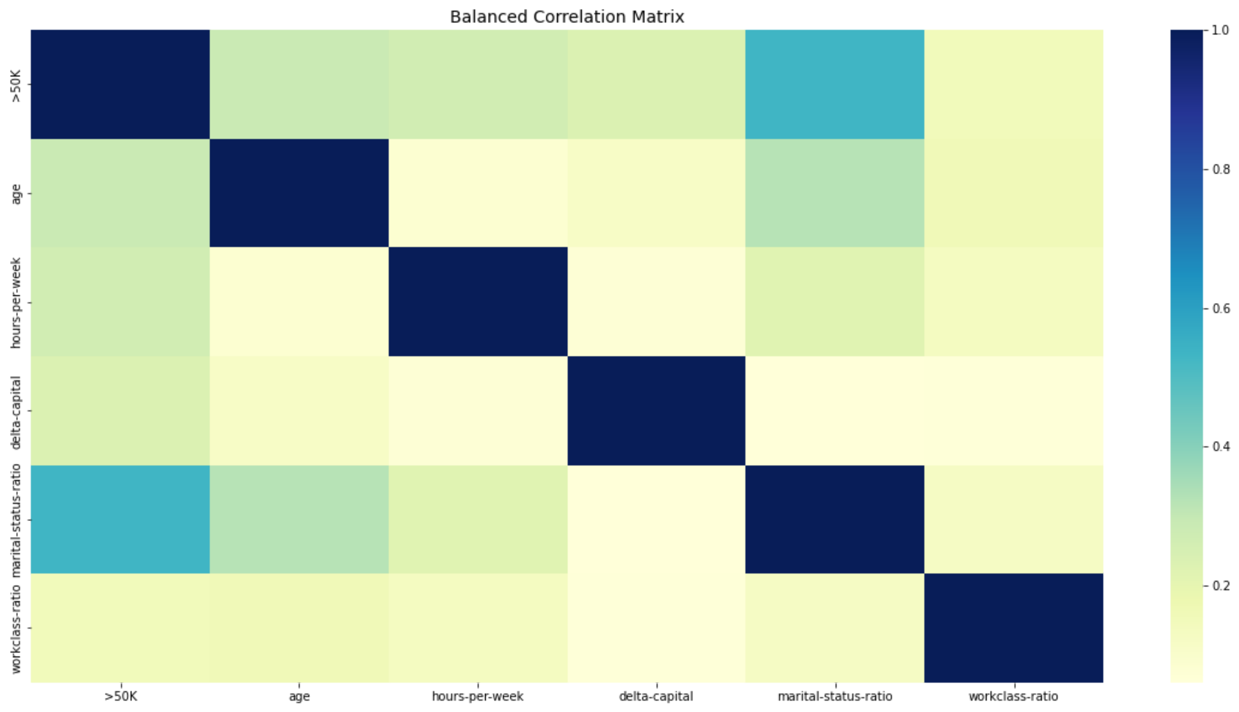
In [105…
```
# over-sampling
from imblearn.over_sampling import SMOTE
sm = SMOTE(sampling_strategy='minority', random_state=7)
oversampled_trainX, oversampled_trainY = sm.fit_resample(df_main.drop('>50K', axis=1),
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.DataFrame(oversamp
oversampled_train.groupby(['>50K']).size().transform(lambda x: x/sum(x))
```

Out[105]:
```
>50K
0    0.5
1    0.5
dtype: float64
```

As we can see, SMOTE has over-sampled the minority case and now our dataset is balanced in nature with 1:1. We will again use this technique each time after fitting a model to understand the improvement.

In [106…
```
# Sample figsize in inches
fig, ax = plt.subplots(figsize=(20,10))
# Imbalanced DataFrame Correlation
```

```
corr = oversampled_train.corr()
sns.heatmap(corr, cmap='YlGnBu', annot_kws={'size':30}, ax=ax)
ax.set_title("Balanced Correlation Matrix", fontsize=14)
plt.show()
```



The correlation values have increase after SMOTE indicating increase in discrimatory power among the feature set.

5.6 Train-Test split

We will be dividing the dataset into 70:30 ratio for training & testing. As our imbalanced dataset is 75:25 in ratio for majority to minority, we wanted to match our train & test split accordingly. We also wanted to keep this simple. This exact test set will be used for every model evaluation.

In [107…
```
from sklearn.model_selection import train_test_split

training_data, testing_data = train_test_split(df_main, test_size=0.3, random_state=25

print(f"No. of training examples: {training_data.shape[0]}")
print(f"No. of testing examples: {testing_data.shape[0]}")
```

```
No. of training examples: 31495
No. of testing examples: 13498
```

In [108…
```
xtrain = training_data.drop('>50K', axis=1)
ytrain = training_data['>50K']
xtest = testing_data.drop('>50K', axis=1)
ytest = testing_data['>50K']
```

In [109…
```
# % of >50K
ytrain.sum()/ytrain.count()
```

Out[109]:
```
0.24368947451976505
```

In [110…
```
ytest.sum()/ytest.count()
```
Out[110]:
```
0.24477700400059269
```

In our training set we have 24.37% of the minority class, and it is 24.48% in case of test set.

5.7 Evaluation Metric

Predictive accuracy can be a little misleading in the presence of class-imbalance. In such cases, more weights are placed on the majority class than on the minority class, making it more difficult for a classifier to perform well on the minority class. Whereas Area Under Curve (AUC) score represents the degree or measure of separability. A model with higher AUC is better at predicting True Positives and True Negatives. AUC score measures the total area underneath the ROC curve. AUC is scale invariant and also threshold invariant.

Hence, we are selecting AUC Score as the evaluation metric for model performance.

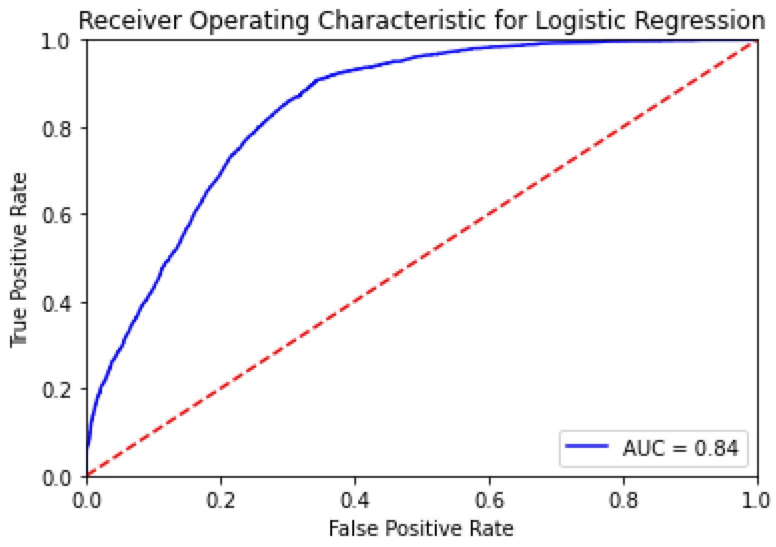
5.7.1 Logistic Regression

In [111…
```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

logreg = LogisticRegression(class_weight="balanced")
logreg.fit(xtrain, ytrain) #This is where the training is taking place
y_pred_logreg = logreg.predict(xtest) #Making predictions to test the model on test da
print('Logistic Regression Train accuracy %s' % logreg.score(xtrain, ytrain)) #Train a
print('Logistic Regression Test accuracy %s' % accuracy_score(y_pred_logreg, ytest)) #
print(confusion_matrix(ytest, y_pred_logreg)) #Confusion matrix
print(classification_report(ytest, y_pred_logreg)) #Classification Report
```
```
Logistic Regression Train accuracy 0.7225908874424511
Logistic Regression Test accuracy 0.7282560379315454
[[6946 3248]
 [ 420 2884]]
              precision    recall  f1-score   support

           0       0.94      0.68      0.79     10194
           1       0.47      0.87      0.61      3304

    accuracy                           0.73     13498
   macro avg       0.71      0.78      0.70     13498
weighted avg       0.83      0.73      0.75     13498
```

The accuracy is 77% for training and 73% for testing set in case of logistic regression.

In [112…
```
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = logreg.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
```

```
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Logistic Regression')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



The AUC score is 0.84 for logistic Regression which is quite excellent in terms of discriminatory power.

Now we will apply SMOTE to our training set to over-sample the minority class and then test the model on the same testing set. Let's see if we can find any improvement.

5.7.2 Logistic Regression using SMOTE

In [113…

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(sampling_strategy='minority', random_state=7)
oversampled_xtrain, oversampled_ytrain = sm.fit_resample(xtrain, ytrain)
oversampled_ytrain.sum()/oversampled_ytrain.count()
```

Out[113]:

```
0.5
```

In [114…

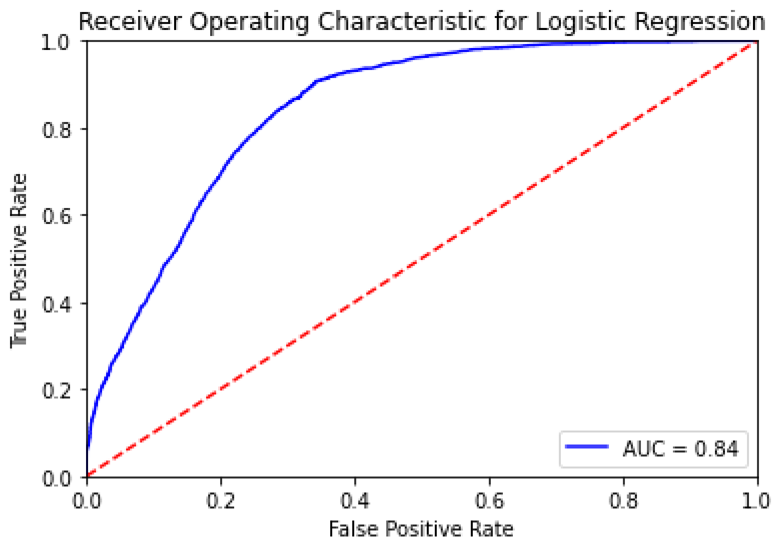
```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

logreg = LogisticRegression(class_weight="balanced")
logreg.fit(oversampled_xtrain, oversampled_ytrain) #This is where the training is taki
y_pred_logreg = logreg.predict(xtest) #Making predictions to test the model on test da
print('Logistic Regression Train accuracy %s' % logreg.score(oversampled_xtrain, overs
print('Logistic Regression Test accuracy %s' % accuracy_score(y_pred_logreg, ytest)) #
print(confusion_matrix(ytest, y_pred_logreg)) #Confusion matrix
print(classification_report(ytest, y_pred_logreg)) #Classification Report
```

```
Logistic Regression Train accuracy 0.7706968933669186
Logistic Regression Test accuracy 0.7270706771373536
[[6931 3263]
 [ 421 2883]]
              precision    recall  f1-score   support

           0       0.94      0.68      0.79     10194
           1       0.47      0.87      0.61      3304

    accuracy                           0.73     13498
   macro avg       0.71      0.78      0.70     13498
weighted avg       0.83      0.73      0.75     13498
```

The accuracy score was same before applying SMOTE.

In [115…

```
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = logreg.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Logistic Regression')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



The AUC Score is also 0.84. This means over-sampling did not improve model performance. Logistic Regression was quite capable even if there was class imbalance.

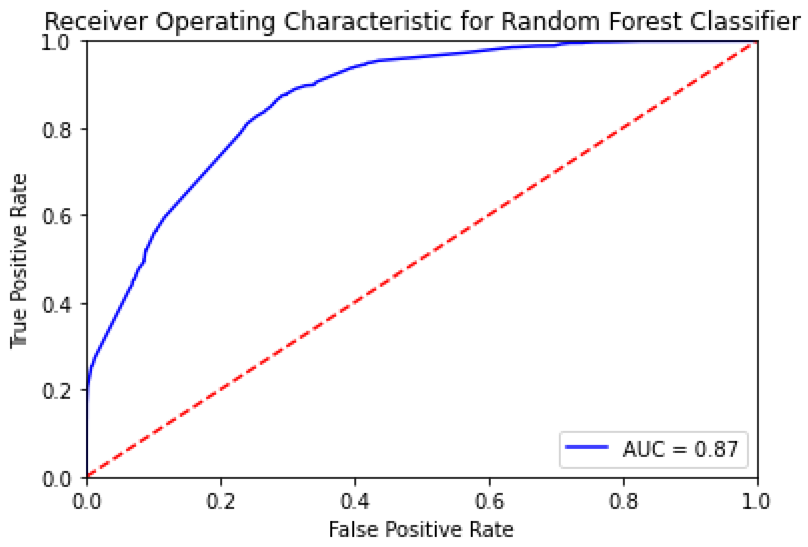
5.7.3 Random Forest

In [116…
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

clf = RandomForestClassifier(max_depth=2, random_state=0)
clf.fit(xtrain, ytrain) #This is where the training is taking place
y_pred_clf = clf.predict(xtest) #Making predictions to test the model on test data
print('Random Forest Train accuracy %s' % clf.score(xtrain, ytrain)) #Train accuracy
print('Random Forest Test accuracy %s' % accuracy_score(y_pred_clf, ytest)) #Test accu
print(confusion_matrix(ytest, y_pred_clf)) #Confusion matrix
print(classification_report(ytest, y_pred_clf)) #Classification Report
```

```
Random Forest Train accuracy 0.796856643911732
Random Forest Test accuracy 0.7972292191435768
[[10188     6]
 [ 2731   573]]
              precision    recall  f1-score   support

           0       0.79      1.00      0.88     10194
           1       0.99      0.17      0.30      3304

    accuracy                           0.80     13498
   macro avg       0.89      0.59      0.59     13498
weighted avg       0.84      0.80      0.74     13498
```

Both the training and the testing accuracy is 80%.

In [117…
```
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = clf.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Random Forest Classifier')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Random Forest's AUC score of 0.87 is better compared to Logistic Regression.

5.7.4 Random Forest using SMOTE

In [118…

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

clf = RandomForestClassifier(max_depth=2, random_state=0)
clf.fit(oversampled_xtrain, oversampled_ytrain) #This is where the training is taking
y_pred_clf = clf.predict(xtest) #Making predictions to test the model on test data
print('Random Forest Train accuracy %s' % clf.score(oversampled_xtrain, oversampled_yt
print('Random Forest Test accuracy %s' % accuracy_score(y_pred_clf, ytest)) #Test accu
print(confusion_matrix(ytest, y_pred_clf)) #Confusion matrix
print(classification_report(ytest, y_pred_clf)) #Classification Report
```

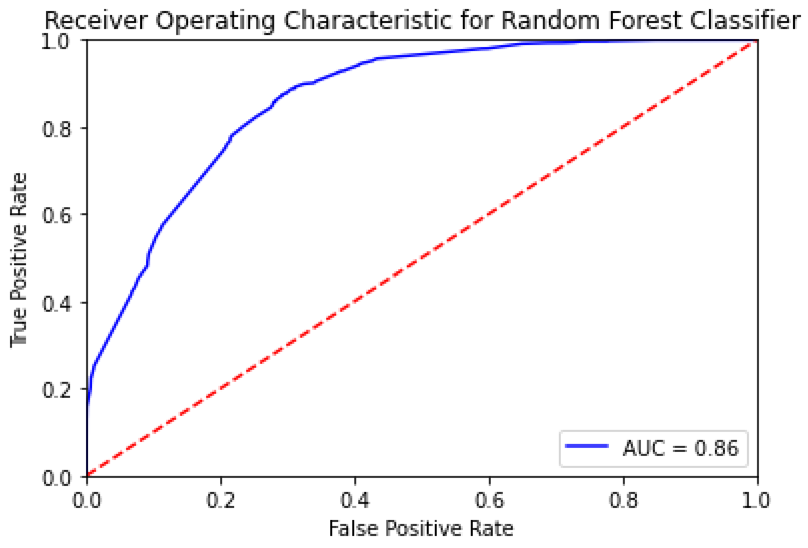
```
Random Forest Train accuracy 0.7847816960537364
Random Forest Test accuracy 0.7446288339013187
[[7152 3042]
 [ 405 2899]]
              precision    recall  f1-score   support

           0       0.95      0.70      0.81     10194
           1       0.49      0.88      0.63      3304

    accuracy                           0.74     13498
   macro avg       0.72      0.79      0.72     13498
weighted avg       0.83      0.74      0.76     13498
```

The accuracy score dropped for both train & test when using SMOTE.

In [119…

```
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = clf.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
roc_auc = metrics.auc(fpr, tpr)
```

```
# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Random Forest Classifier')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



The AUC score dropped to 0.86 when using SMOTE. This means over-sampling did not improve model performance; rather it decreased the AUC score.

5.7.5 Gaussian Naive Bayes

In [120…

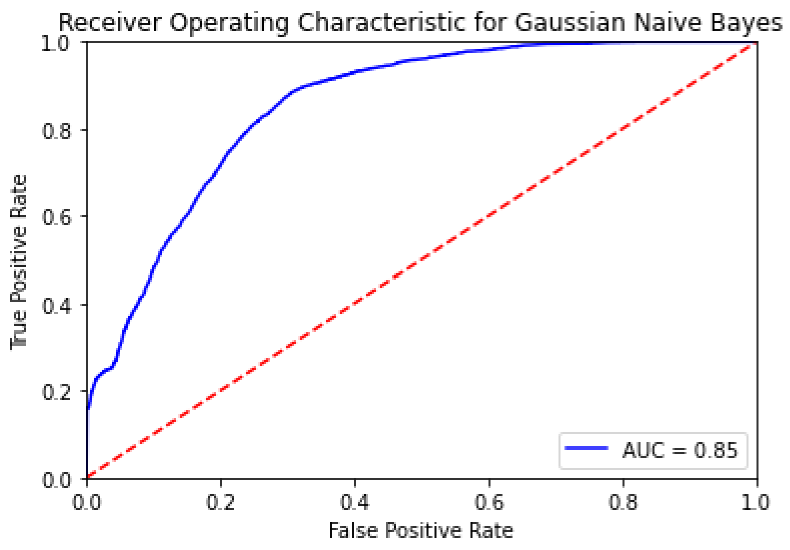
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

gnb = GaussianNB()
gnb.fit(xtrain, ytrain) #This is where the training is taking place
y_pred_gnb = gnb.predict(xtest) #Making predictions to test the model on test data
print('Gaussian Naive Bayes Train accuracy %s' % gnb.score(xtrain, ytrain)) #Train acc
print('Gaussian Naive Bayes Test accuracy %s' % accuracy_score(y_pred_gnb, ytest)) #Te
print(confusion_matrix(ytest, y_pred_gnb)) #Confusion matrix
print(classification_report(ytest, y_pred_gnb)) #Classification Report
```

```
Gaussian Naive Bayes Train accuracy 0.7951738371170027
Gaussian Naive Bayes Test accuracy 0.7952289228033783
[[9626  568]
 [2196 1108]]
              precision    recall  f1-score   support

           0       0.81      0.94      0.87     10194
           1       0.66      0.34      0.44      3304

    accuracy                           0.80     13498
   macro avg       0.74      0.64      0.66     13498
weighted avg       0.78      0.80      0.77     13498
```

Accuracy score is 80% for both training & testing set.

In [121…

```python
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = gnb.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Gaussian Naive Bayes')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



The AUC score is 0.85 for Gaussian Naive Bayes which is lowest among the 3 models without using SMOTE.

5.7.6 Gaussian Naive Bayes using SMOTE

In [122…

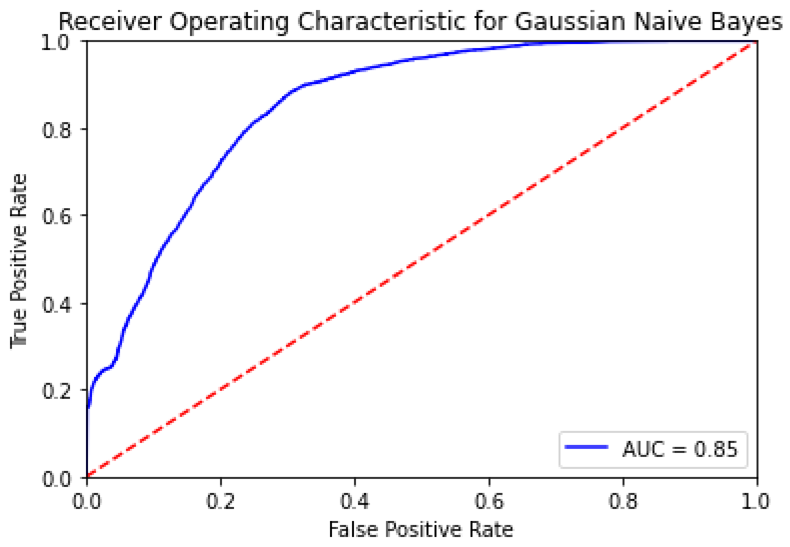
```python
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

gnb = GaussianNB()
gnb.fit(oversampled_xtrain, oversampled_ytrain) #This is where the training is taking
y_pred_gnb = gnb.predict(xtest) #Making predictions to test the model on test data
print('Gaussian Naive Bayes Train accuracy %s' % gnb.score(oversampled_xtrain, oversam
print('Gaussian Naive Bayes Test accuracy %s' % accuracy_score(y_pred_gnb, ytest)) #Te
print(confusion_matrix(ytest, y_pred_gnb)) #Confusion matrix
print(classification_report(ytest, y_pred_gnb)) #Classification Report
```

```
Gaussian Naive Bayes Train accuracy 0.6751889168765743
Gaussian Naive Bayes Test accuracy 0.7950807527041043
[[9250  944]
 [1822 1482]]
              precision    recall  f1-score   support

           0       0.84      0.91      0.87     10194
           1       0.61      0.45      0.52      3304

    accuracy                           0.80     13498
   macro avg       0.72      0.68      0.69     13498
weighted avg       0.78      0.80      0.78     13498
```

The training accuracy dropped to 68% but the testing accuracy remained at 80% when using SMOTE.

In [123…

```python
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = gnb.predict_proba(xtest)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(ytest, preds)
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic for Gaussian Naive Bayes')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



SMOTE did not bring any improvement to Gaussian Naive Bayes either.

6 Results and Analysis

The adult dataset has a total of 48842 observations with 14 attributes. It has missing data, data type errors and whitespaces. After cleaning the data, rigorous statistical analyses are completed to identify the most significant features. This brings a total of 6 features in the feature (3 numerical and 3 categorical). Correlation matrix and VIF test are used to further investigate the feature set which revealed redundancy of 1 feature. This way we get the final feature set of 5 attributes.

After this, target encoding is done to encode the categorical variables. Standardizing is done for numerical variables as they are different in units with varying ranges. Target variable is also encoded in binary fashion. The full dataset is split into a 70-30 ratio for the train & test set. The same test set is used for evaluation.

As the dataset is imbalanced in nature, SMOTE is used to over-sample the minority class. SMOTE is applied each time after a model is evaluated to understand improvement. SMOTE is only applied to the training set; the test remains the same all the time. Instead of accuracy, Area Under Curve (AUC) score is evaluated here as AUC score represents the degree or measure of separability. A model with higher AUC is better at predicting True Positives and True Negatives. AUC score measures the total area underneath the ROC curve. AUC is scale invariant and also threshold invariant.

6.1 Logistic Regression

6.1.1 Without SMOTE

Logistic Regression Train accuracy 0.72 Logistic Regression Test accuracy 0.72

```
              precision    recall  f1-score   support

           0       0.94      0.68      0.79     10194
           1       0.47      0.87      0.61      3304
```

6.1.2 With SMOTE

Logistic Regression Train accuracy 0.77 Logistic Regression Test accuracy 0.72

```
              precision    recall  f1-score   support

           0       0.94      0.68      0.79     10194
           1       0.47      0.87      0.61      3304
```

6.1.3 AUC

The AUC score for Logistic Regression is 0.84 in both cases - with or without SMOTE.

6.2 Random Forest Classifier

6.2.1 Without SMOTE

Random Forest Train accuracy 0.79 Random Forest Test accuracy 0.79

```
              precision    recall  f1-score   support

           0       0.79      1.00      0.88     10194
           1       0.99      0.17      0.30      3304
```

6.2.2 With SMOTE

Random Forest Train accuracy 0.78 Random Forest Test accuracy 0.74

```
              precision    recall  f1-score   support

           0       0.95      0.70      0.81     10194
           1       0.49      0.88      0.63      3304
```

6.2.3 AUC

The AUC score for Random Forest Classifier is 0.87 for without SMOTE and is 0.86 for with SMOTE.

6.3 Gaussian Naive Bayes

6.3.1 Without SMOTE

Gaussian Naive Bayes Train accuracy 0.79 Gaussian Naive Bayes Test accuracy 0.79

```
              precision    recall  f1-score   support

           0       0.81      0.94      0.87     10194
           1       0.66      0.34      0.44      3304
```

6.3.2 With SMOTE

Gaussian Naive Bayes Train accuracy 0.67 Gaussian Naive Bayes Test accuracy 0.79

```
              precision    recall  f1-score   support

           0       0.84      0.91      0.87     10194
           1       0.61      0.45      0.52      3304
```

6.3.3 AUC

The AUC score for Gaussian Naive Bayes is 0.85 in both cases - with or without SMOTE.

7 Discussion and Conclusion

7.1 Discussion

In terms of AUC score, Random Forest performed the nest among the 3 models with an AUC score of 0.87. Oversampling of the minority class to tackle the imbalance issue did not result in any improvement for any of the models. In summary, Random Forest without applying SMOTE performed the best. In terms of overall accuracy, both Random Forest and Gaussian Naive Bayes ranked top with a score of 80% (without applying SMOTE to any of them).

Moreover, a feature set of only 5 was an excellent discriminatory factor. It was mainly due to the rigorous statistical analyses in the EDA section along with correlation and multicollinearity tests. Furthermore, the target encoding and the standardization process improved data quality.

7.2 Conclusion

Major learning points are:

- Data cleaning is crucial for machine learning pipeline.
- Exploratory Data Analysis is critical to identify the most significant factors.

- Statistical tests can easily identify the patterns and develop a solid feature set.
- Handling of imbalanced dataset is challenging.
- Accuracy may not be the best metric all the time.
- AUC score provides a better understanding for model performance when the dataset is imbalanced.

Future improvement points are:

- Complex algorithms (e.g. stacking) can be used to improve performance
- More data can be collected to improve training function