Supervised Machine Learning of Adult Dataset

February 22, 2023

[1]:
```
%%latex
\tableofcontents
```

Contents

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 to 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 analyses 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: @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

Listing of attributes:

50K, <=50K.

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.

2.4 Data Summary

[1]:
```python
# 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
import pandoc
```

2.4.1 Missing Values and Loading the Dataset

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.

[2]:
```python
# Defining colnames and loading the dataframe
colnames=['age', 'workclass', 'fnlwgt', 'education', 'education-num',␣
 ↪'marital-status', 'occupation', 'relationship',
         'race', 'sex', 'capital-gain', 'capital-loss', 'hours-per-week',␣
 ↪'native-country', 'annual-income']
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 not relevant. Hence, this is being removed.

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

2.4.3 Data Summary Statistics

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

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

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

[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 an object which should be an integer. Furthermore, there are some leading whitespaces in some columns. We need to remove them.

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

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

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

[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

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

[9]:

	workclass	education	marital-status	occupation	relationship
count	46043	48842	48842	46033	48842
unique	8	16	7	14	6
top	Private	HS-grad	Married-civ-spouse	Prof-specialty	Husband
freq	33906	15784	22379	6172	19716

	race	sex	native-country	annual-income
count	48842	48842	47985	48842
unique	5	2	41	4
top	White	Male	United-States	<=50K
freq	41762	32650	43832	24720

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

[10]:

	age	workclass	education	education-num	marital-status
0	39	State-gov	Bachelors	13.0	Never-married
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse
2	38	Private	HS-grad	9.0	Divorced
3	53	Private	11th	7.0	Married-civ-spouse
4	28	Private	Bachelors	13.0	Married-civ-spouse

	occupation	relationship	race	sex	capital-gain
0	Adm-clerical	Not-in-family	White	Male	2174.0
1	Exec-managerial	Husband	White	Male	0.0
2	Handlers-cleaners	Not-in-family	White	Male	0.0
3	Handlers-cleaners	Husband	Black	Male	0.0
4	Prof-specialty	Wife	Black	Female	0.0

	capital-loss	hours-per-week	native-country	annual-income
0	0.0	40.0	United-States	<=50K
1	0.0	13.0	United-States	<=50K
2	0.0	40.0	United-States	<=50K
3	0.0	40.0	United-States	<=50K
4	0.0	40.0	Cuba	<=50K

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

```
[11]:        age     workclass  education  education-num      marital-status  \
48837   39       Private  Bachelors           13.0            Divorced
48838   64           NaN    HS-grad            9.0             Widowed
48839   38       Private  Bachelors           13.0  Married-civ-spouse
48840   44       Private  Bachelors           13.0            Divorced
48841   35  Self-emp-inc  Bachelors           13.0  Married-civ-spouse

             occupation    relationship                race     sex  \
48837   Prof-specialty   Not-in-family               White  Female
48838              NaN  Other-relative               Black    Male
48839   Prof-specialty         Husband               White    Male
48840     Adm-clerical       Own-child  Asian-Pac-Islander    Male
48841  Exec-managerial         Husband               White    Male

       capital-gain  capital-loss  hours-per-week native-country annual-income
48837           0.0           0.0            36.0  United-States        <=50K.
48838           0.0           0.0            40.0  United-States        <=50K.
48839           0.0           0.0            50.0  United-States        <=50K.
48840        5455.0           0.0            40.0  United-States        <=50K.
48841           0.0           0.0            60.0  United-States         >50K.
```

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.

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

```
[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
```

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

[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.

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

[14]:
```
       age         workclass  education  education-num      marital-status  \
0       39         State-gov  Bachelors           13.0       Never-married
1       50  Self-emp-not-inc  Bachelors           13.0  Married-civ-spouse
2       38           Private    HS-grad            9.0            Divorced
3       53           Private       11th            7.0  Married-civ-spouse
4       28           Private  Bachelors           13.0  Married-civ-spouse
…     …                    …          …             …                   …
48836   33           Private  Bachelors           13.0       Never-married
48837   39           Private  Bachelors           13.0            Divorced
48839   38           Private  Bachelors           13.0  Married-civ-spouse
```

```
48840   44          Private  Bachelors           13.0           Divorced
48841   35     Self-emp-inc  Bachelors           13.0  Married-civ-spouse

              occupation   relationship                race     sex  \
0           Adm-clerical  Not-in-family               White    Male
1        Exec-managerial        Husband               White    Male
2      Handlers-cleaners  Not-in-family               White    Male
3      Handlers-cleaners        Husband               Black    Male
4         Prof-specialty           Wife               Black  Female
…                    …              …                   …     …
48836     Prof-specialty      Own-child               White    Male
48837     Prof-specialty  Not-in-family               White  Female
48839     Prof-specialty        Husband               White    Male
48840       Adm-clerical      Own-child  Asian-Pac-Islander    Male
48841    Exec-managerial        Husband               White    Male

       capital-gain  capital-loss  hours-per-week native-country annual-income
0            2174.0           0.0            40.0  United-States         <=50K
1               0.0           0.0            13.0  United-States         <=50K
2               0.0           0.0            40.0  United-States         <=50K
3               0.0           0.0            40.0  United-States         <=50K
4               0.0           0.0            40.0           Cuba         <=50K
…                 …             …               …              …           …
48836           0.0           0.0            40.0  United-States        <=50K.
48837           0.0           0.0            36.0  United-States        <=50K.
48839           0.0           0.0            50.0  United-States        <=50K.
48840        5455.0           0.0            40.0  United-States        <=50K.
48841           0.0           0.0            60.0  United-States         >50K.

[45222 rows x 14 columns]
```

3.4 Check of Imbalanced Dataset

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

[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.

[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')
```

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

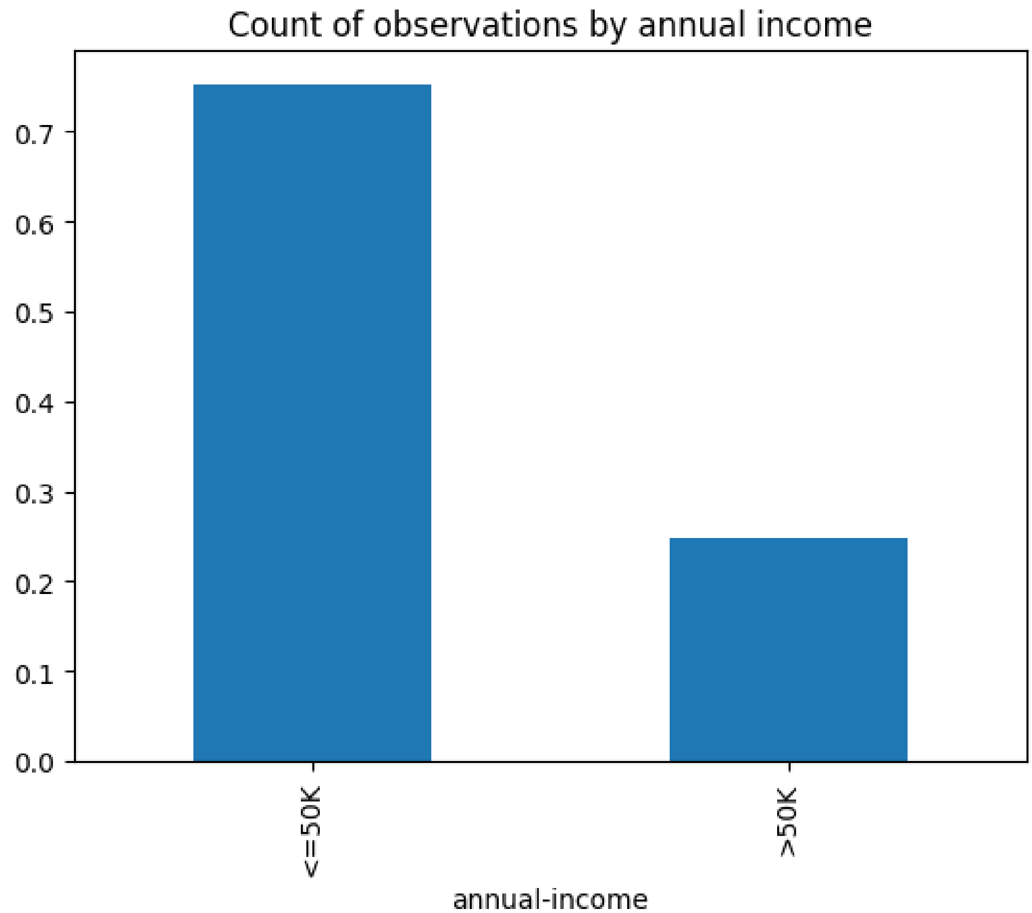
[17]:
```
annual-income
<=50K    34014
>50K     11208
dtype: int64
```

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

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

[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')
```

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



It is quite clear that the data is imbalanced in nature. We have 75% observations for <=50K annual income whereas this 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, scatterplot for continuous variables, box plot for continuous-categorical variables and crosstab 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)

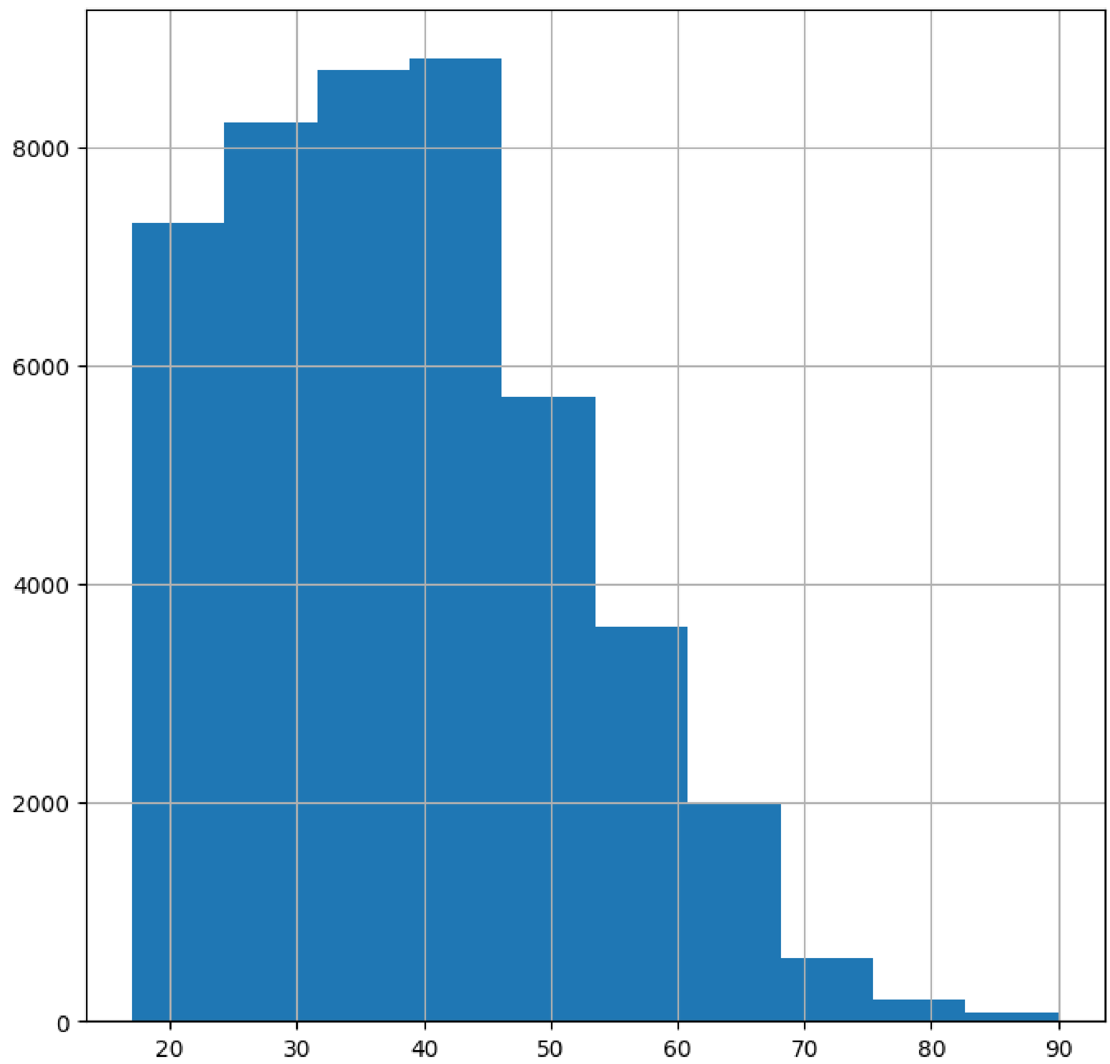
4.1 Univariate Analysis

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.

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

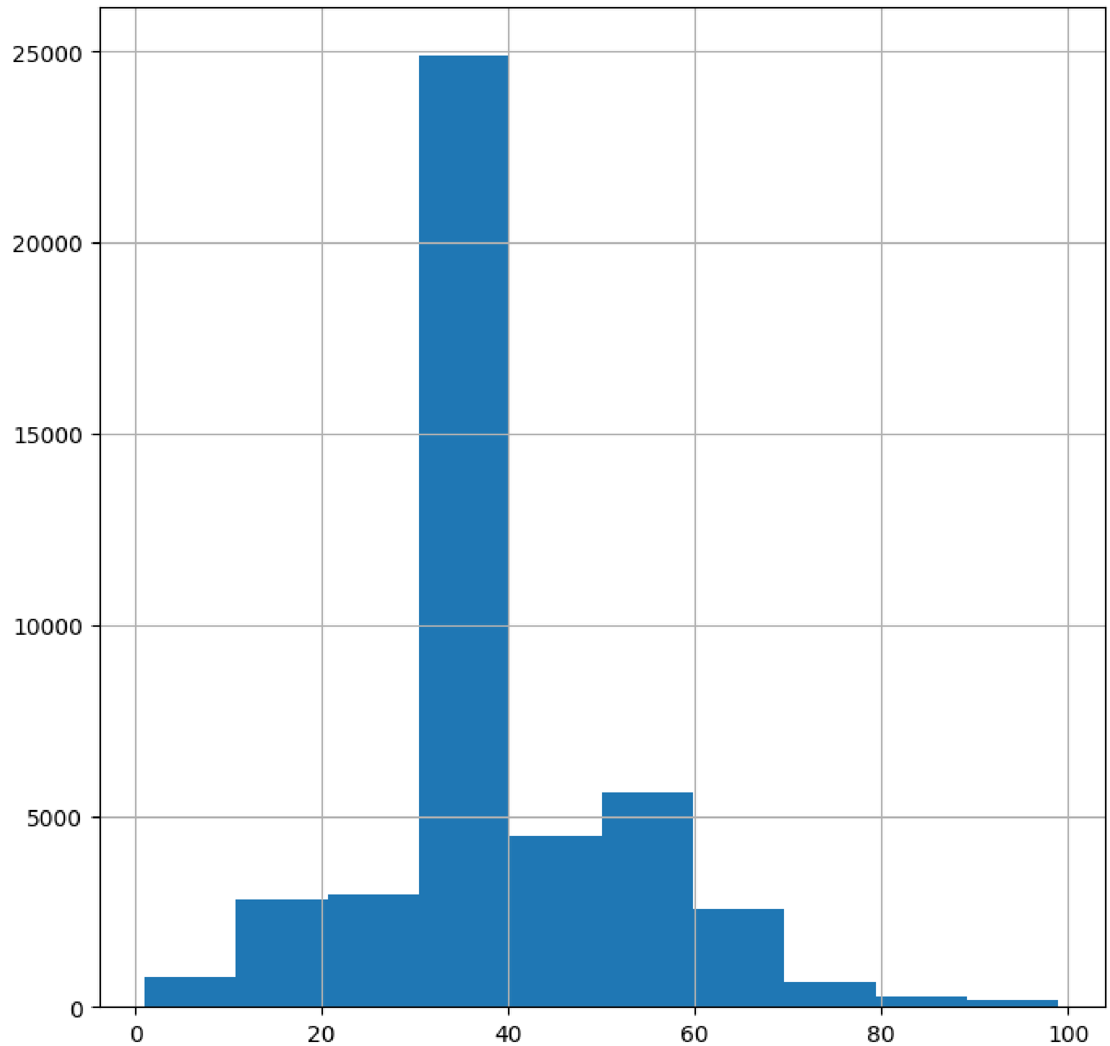
[20]: <Axes: >



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.

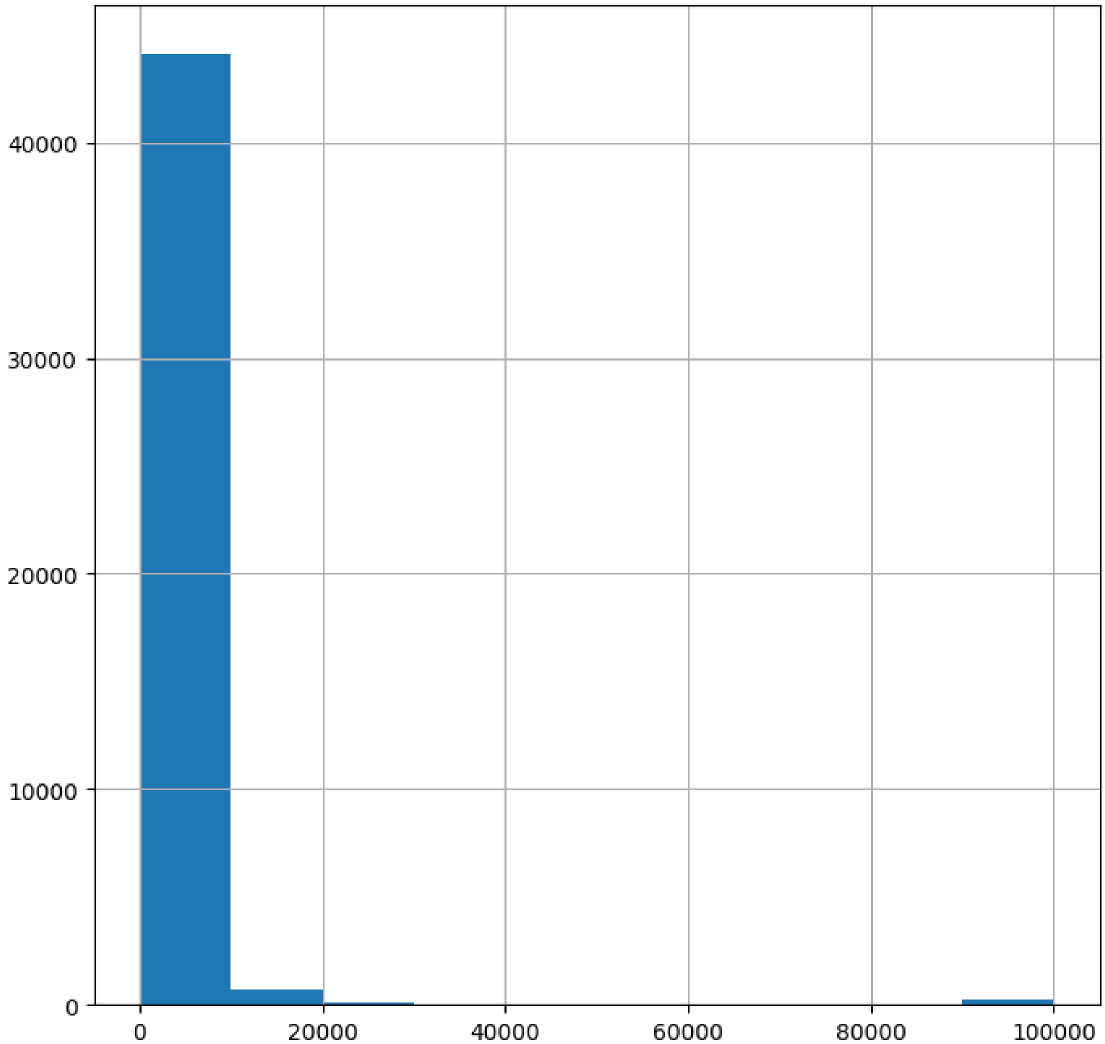
[21]:
```
df['hours-per-week'].hist(figsize=(8,8))
plt.show()
```



4.1.3 Histogram of capital gain

Capital gain does not resemble any particular distribution.

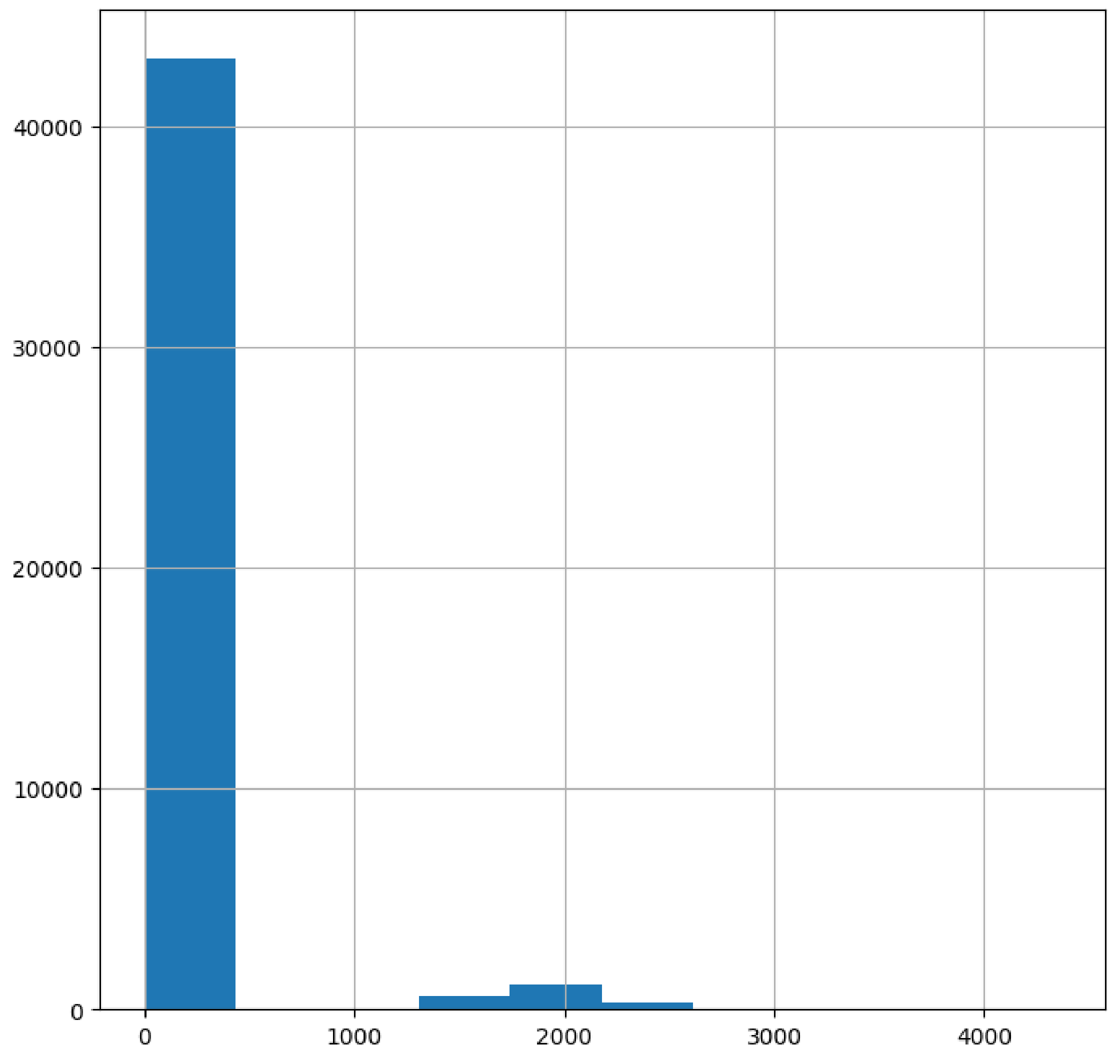
[22]:
```
df["capital-gain"].hist(figsize=(8,8))
plt.show()
```



4.1.4 Histogram of capital loss

Capital loss does not resemble any particular distribution as well.

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

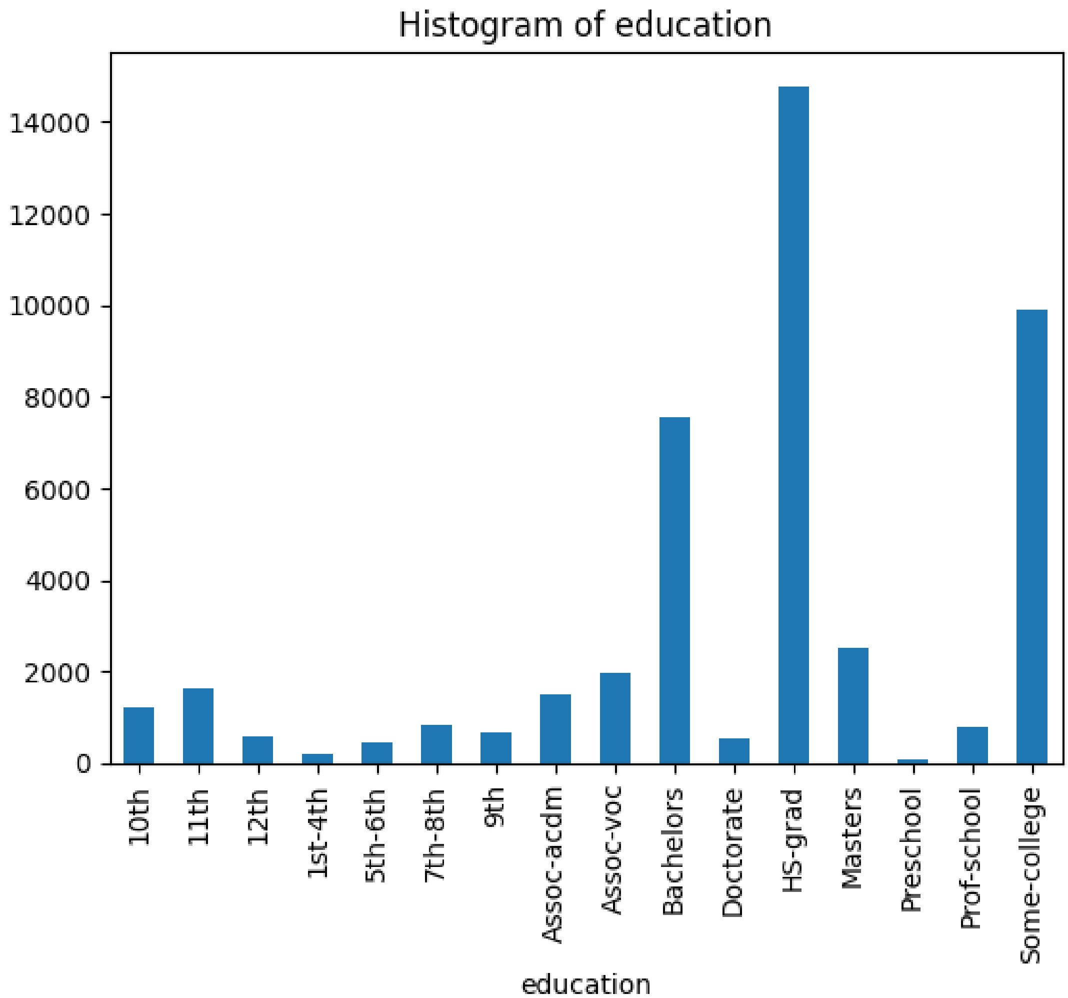


4.1.5 Histogram of education

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.

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

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

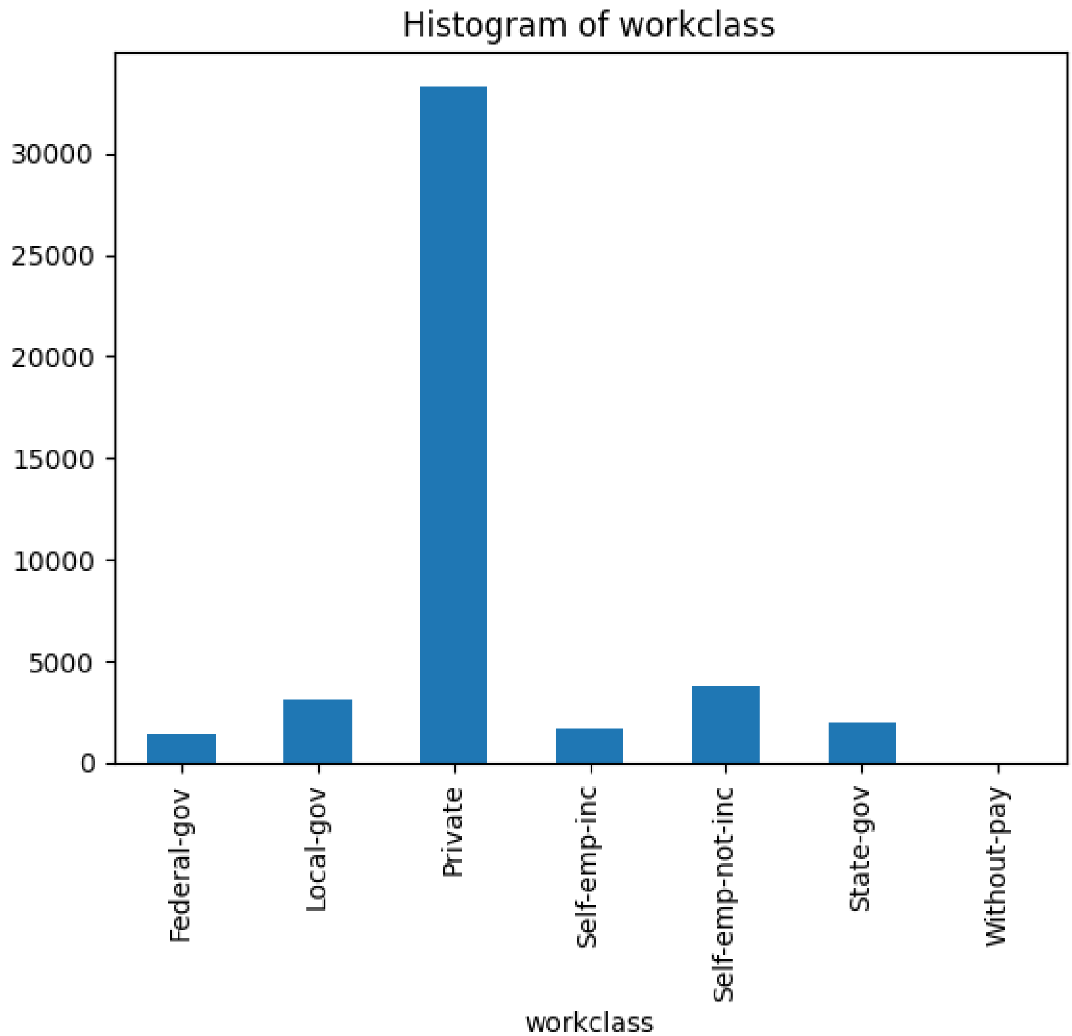


4.1.6 Histogram of workclass

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

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

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

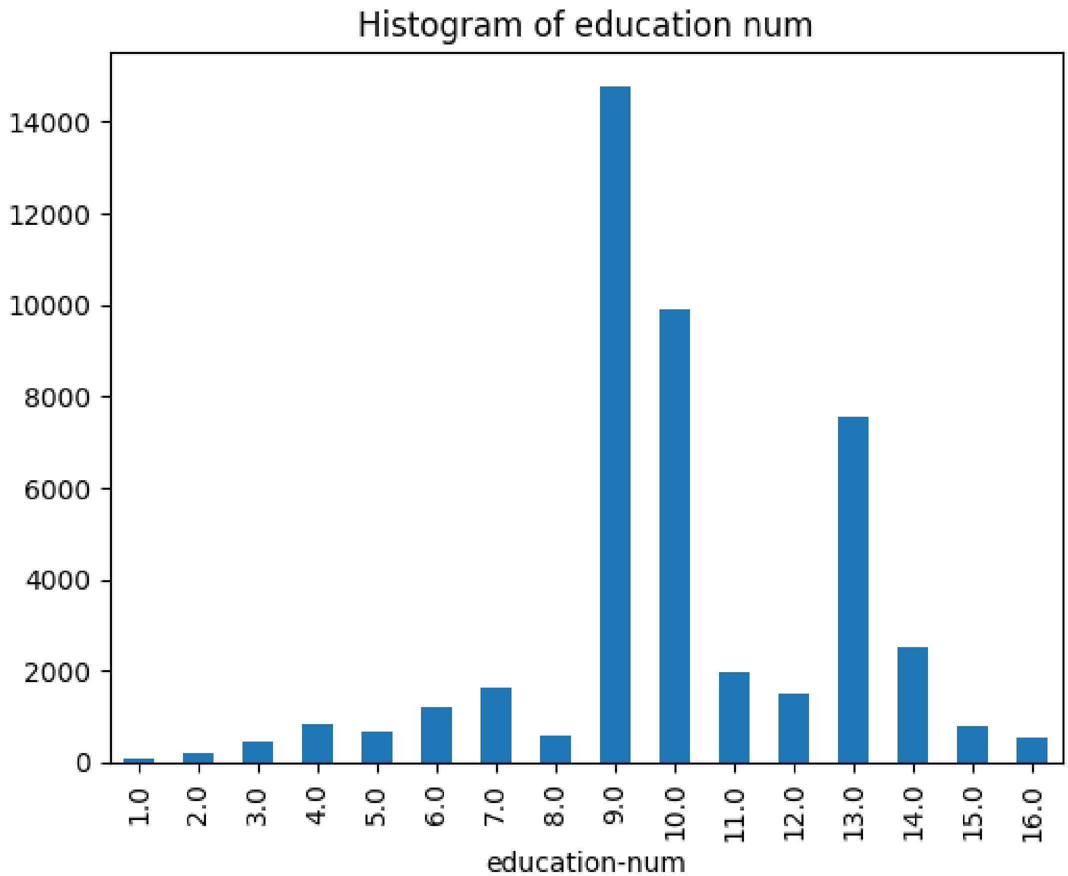


4.1.7 Histogram of education number

Majority are in 9, 10 and 13 step in descending order.

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

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

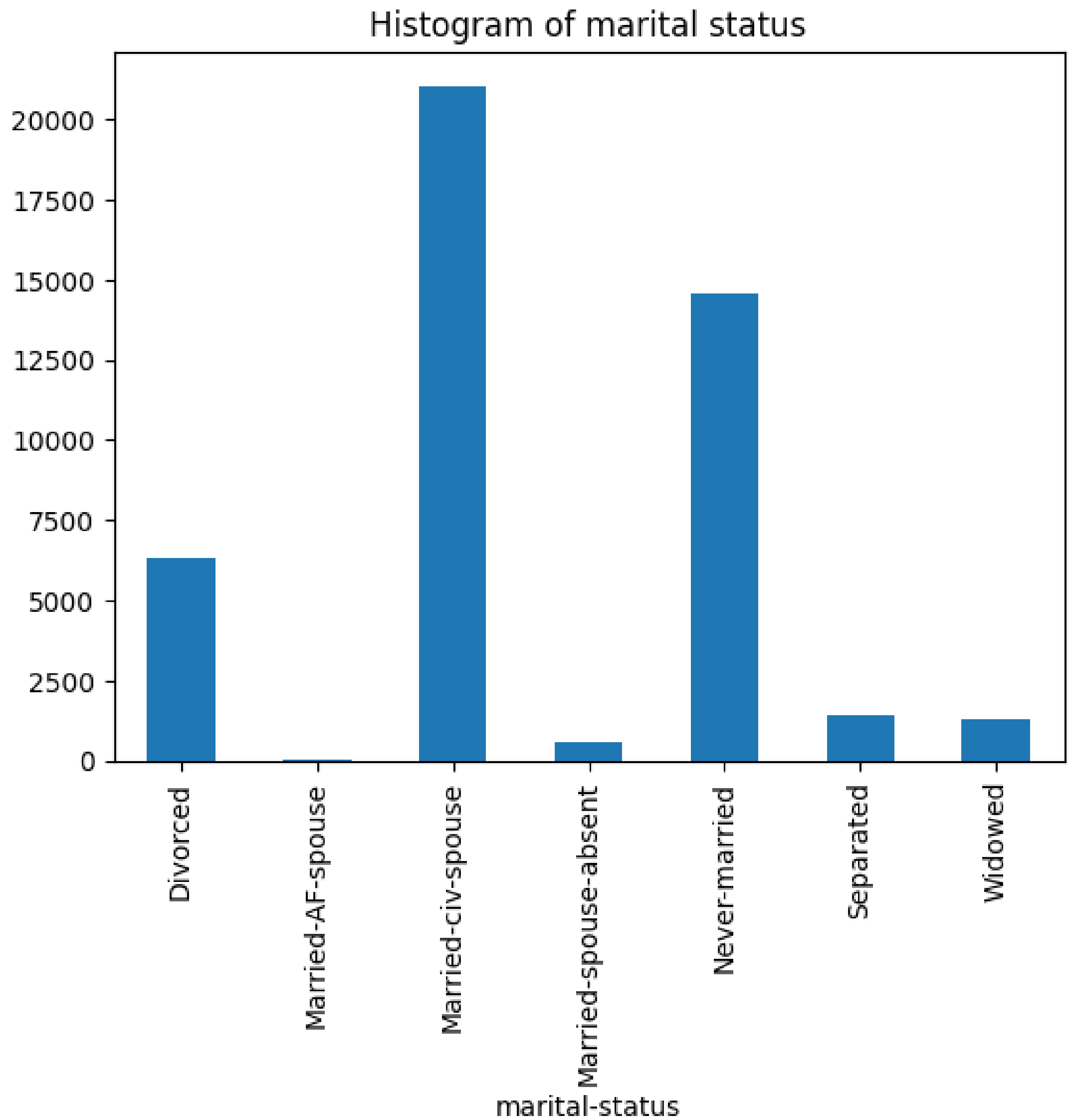


4.1.8 Histogram of marital status

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

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

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

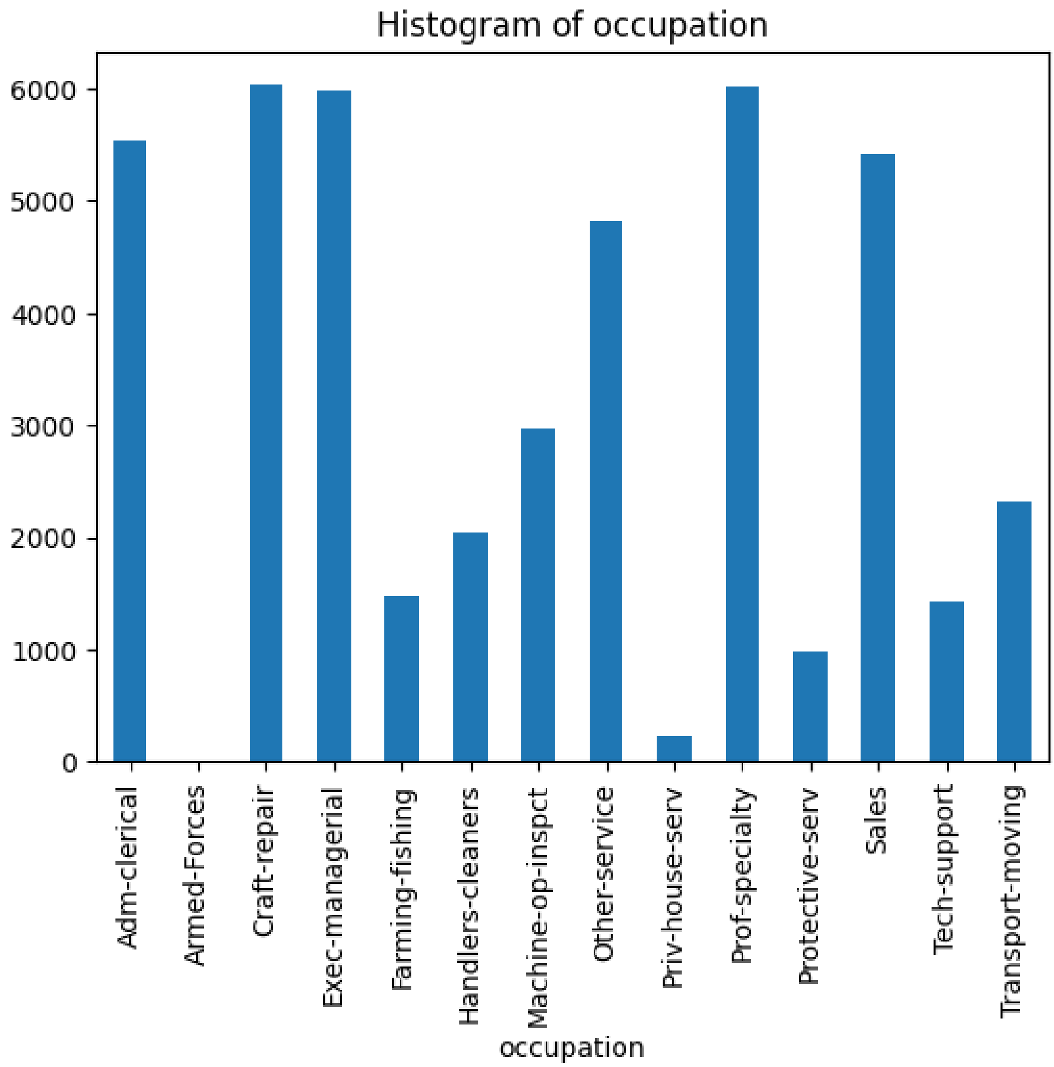


4.1.9 Histogram of occupation

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

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

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

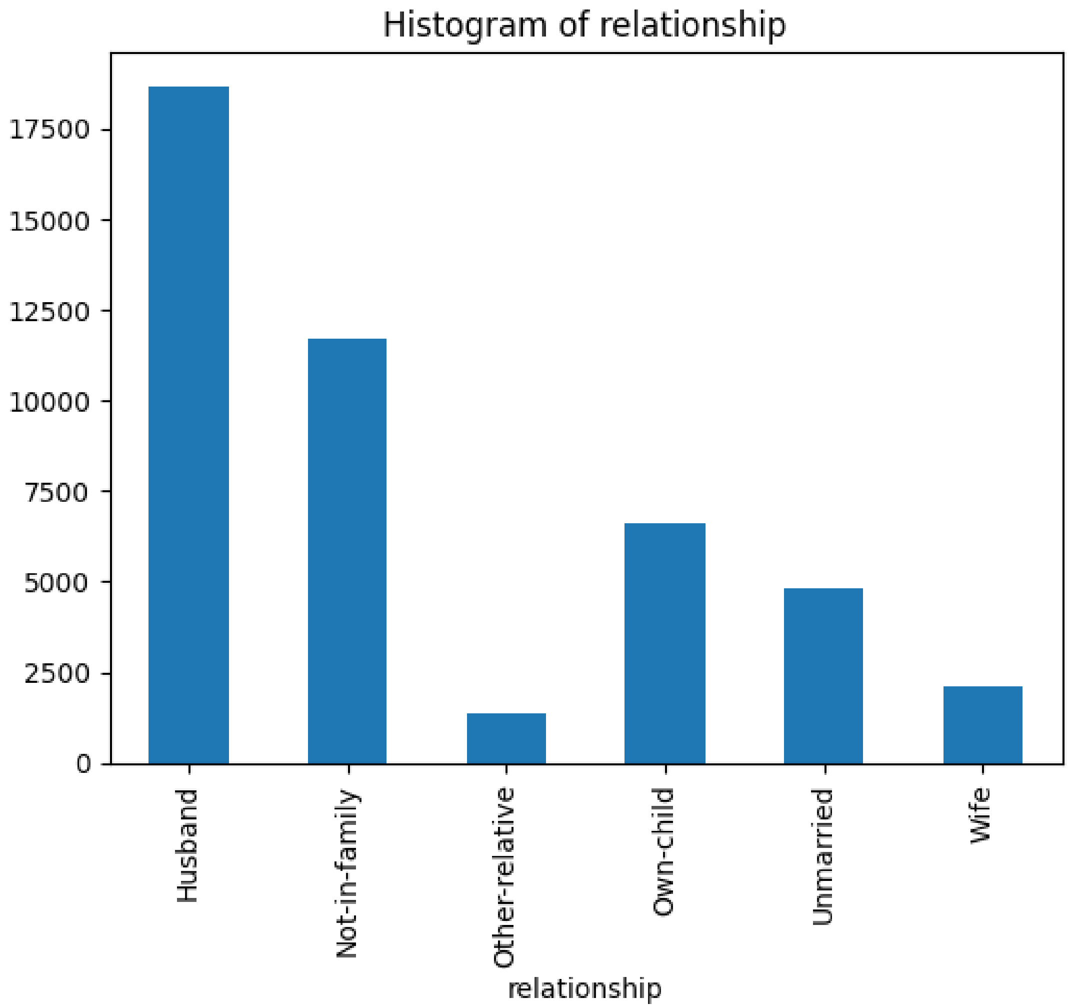


4.1.10 Histogram of relationship

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

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

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

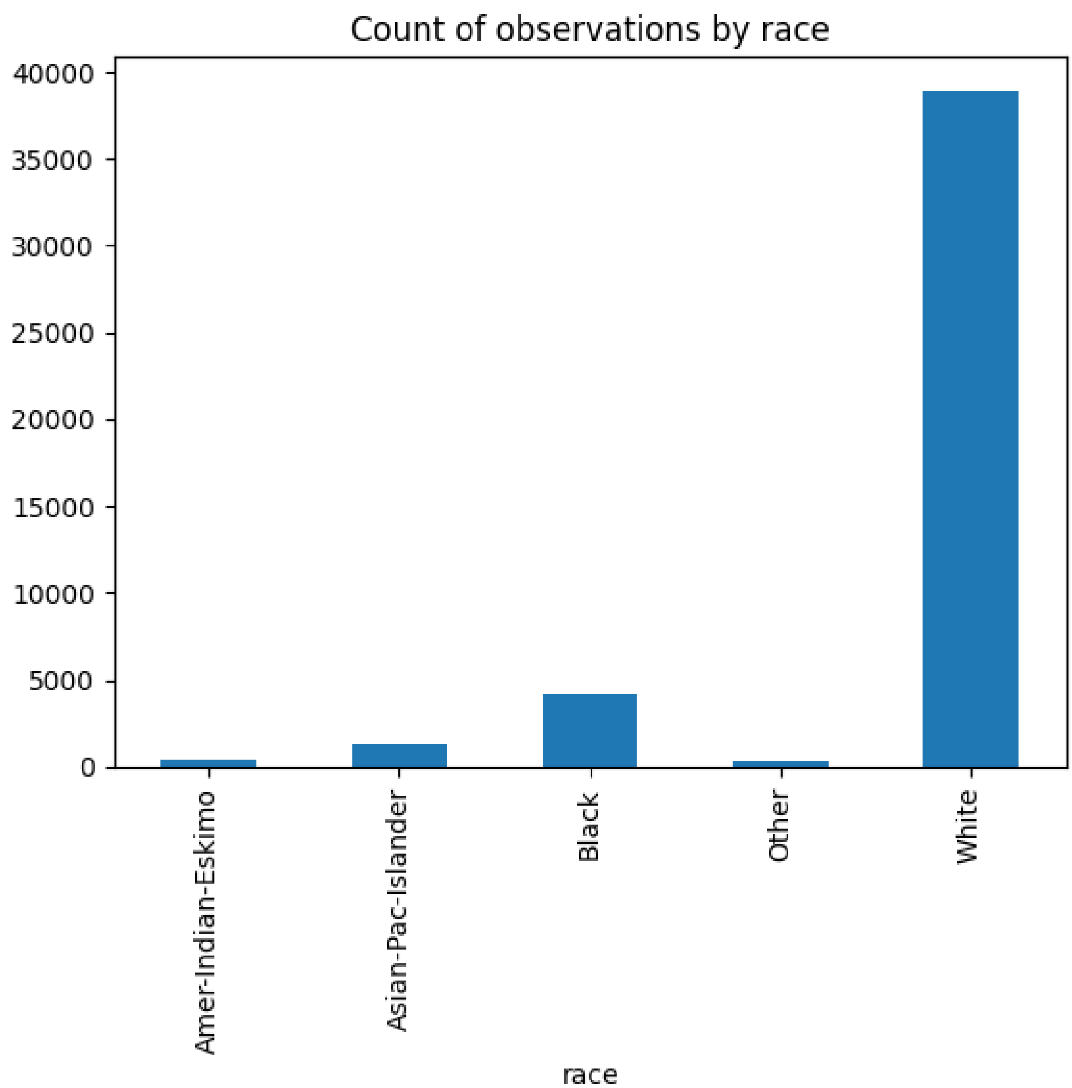


4.1.11 Histogram of race

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

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

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

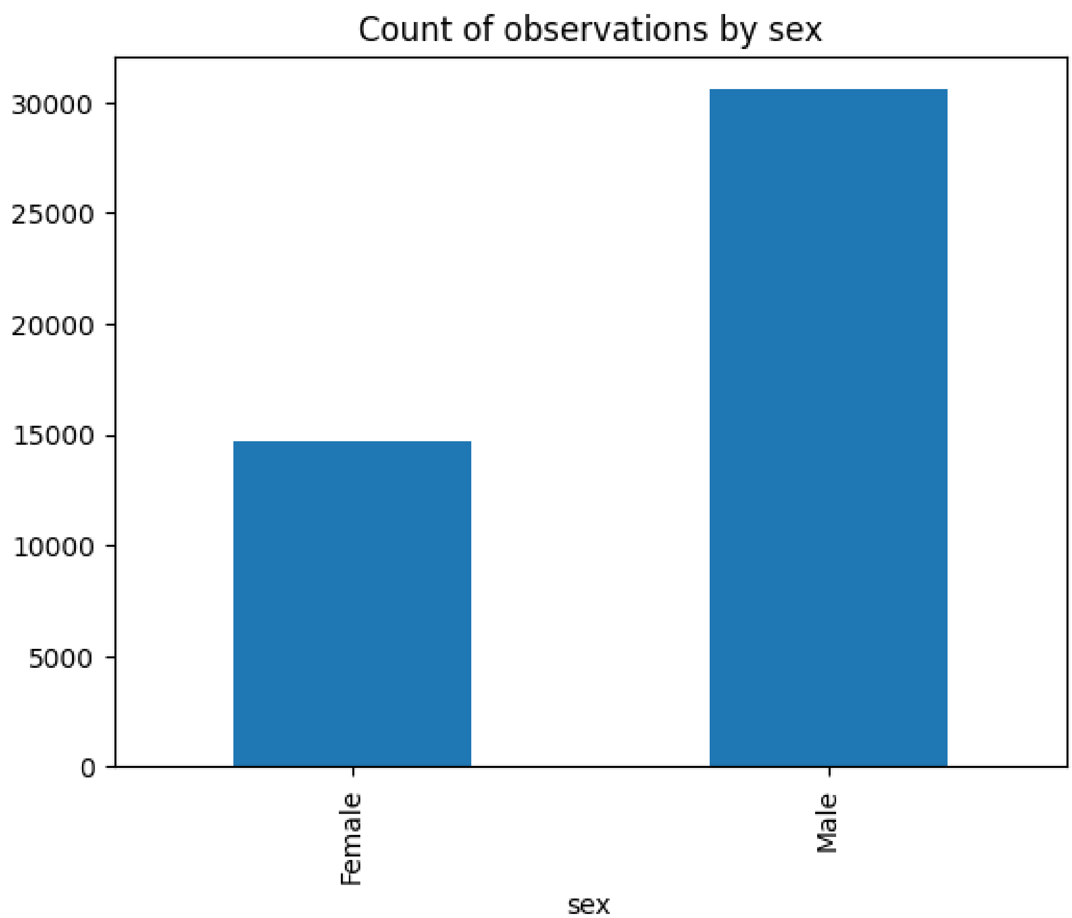


4.1.12 Histogram of sex

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

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

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

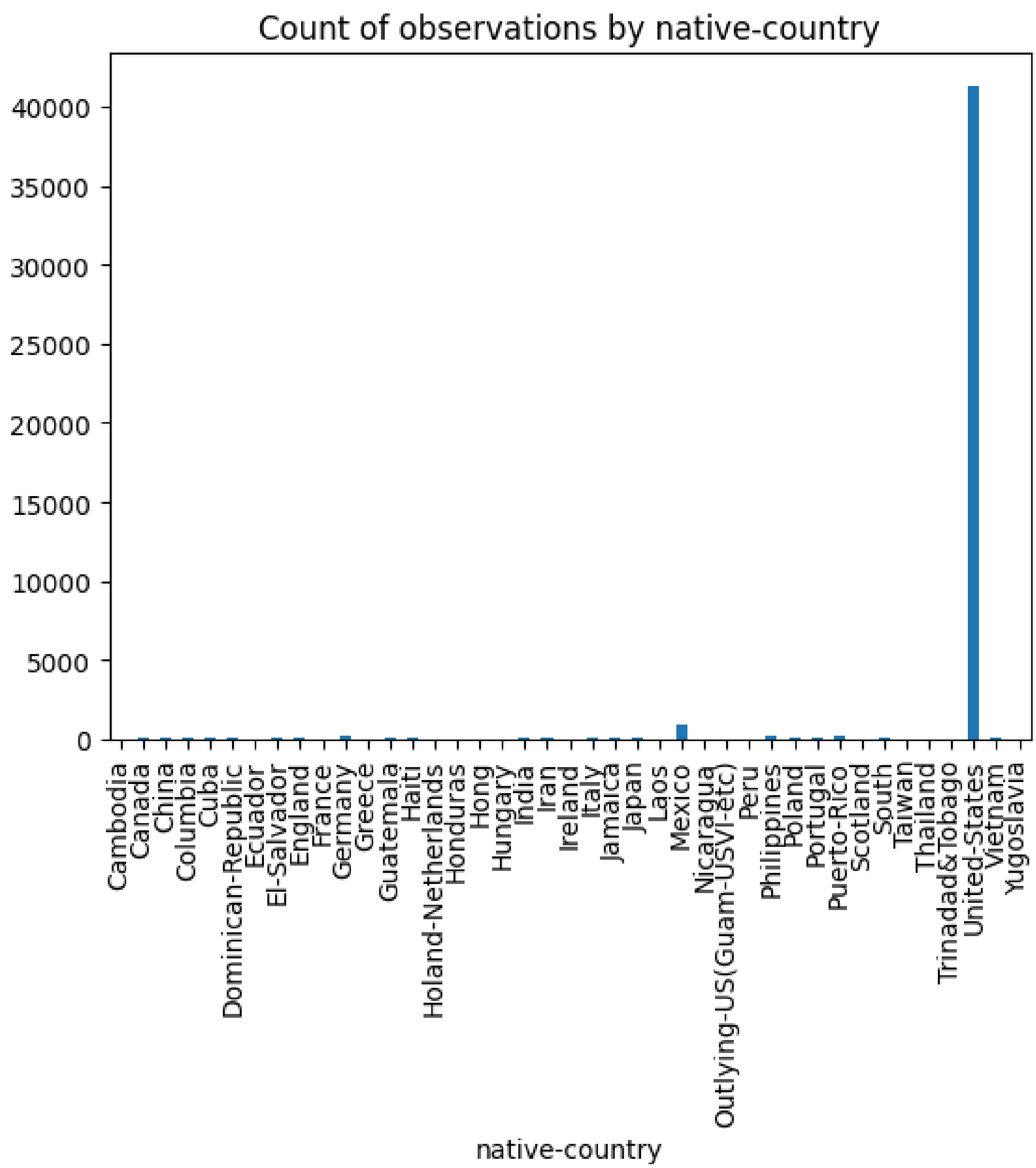


4.1.13 Histogram of native country

United States dominates the frequency for native country count.

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

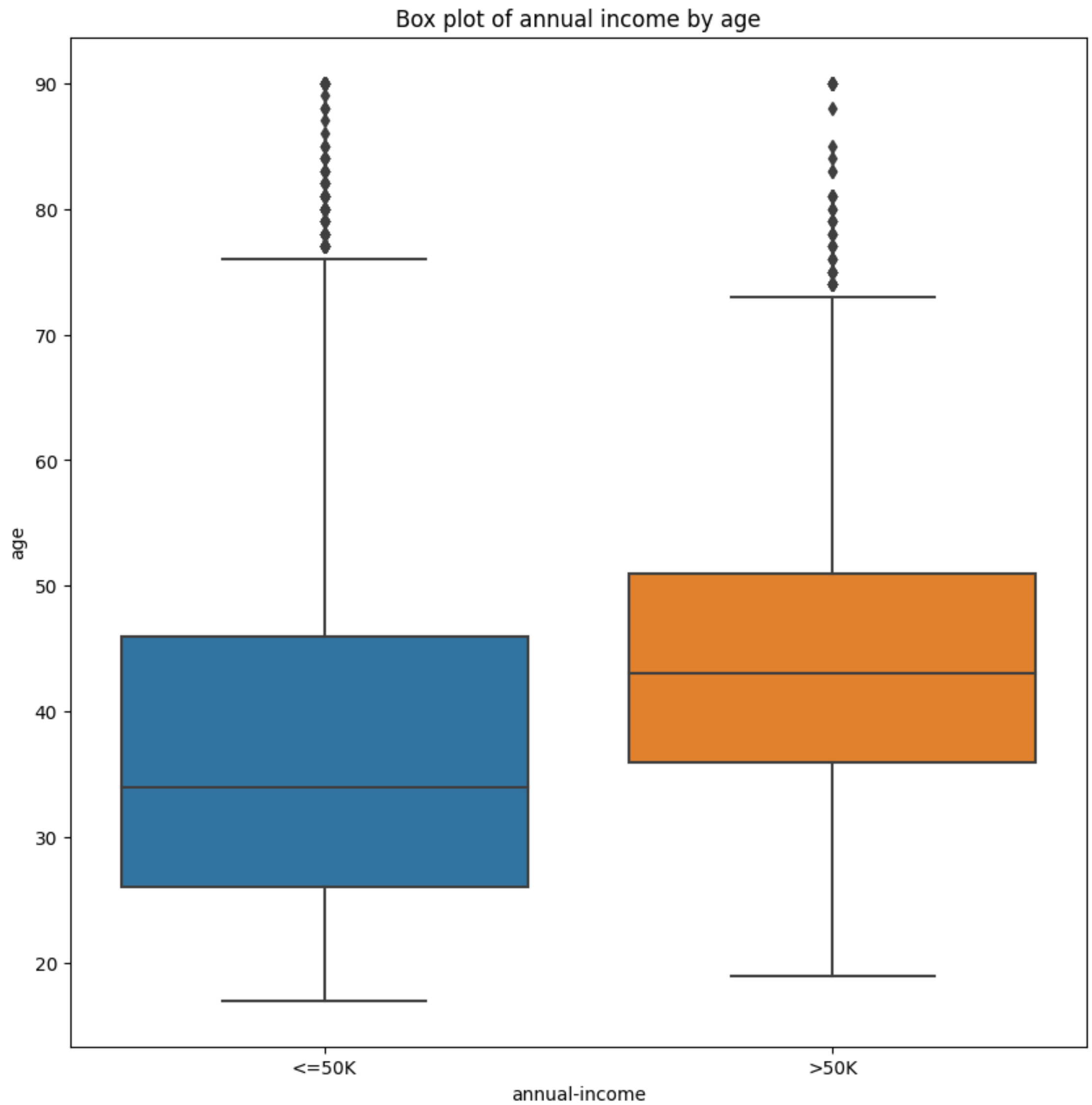
[32]:
```
<Axes: title={'center': 'Count of observations by native-country'},
xlabel='native-country'>
```



4.2 Bivariate Analysis

4.2.1 Relationship between age and annual income

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



[34]:
```python
# Mean
df[['annual-income', 'age']].groupby(['annual-income'], as_index=False).mean().
 ↪sort_values(by='age', ascending=False)
```

[34]:

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

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

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

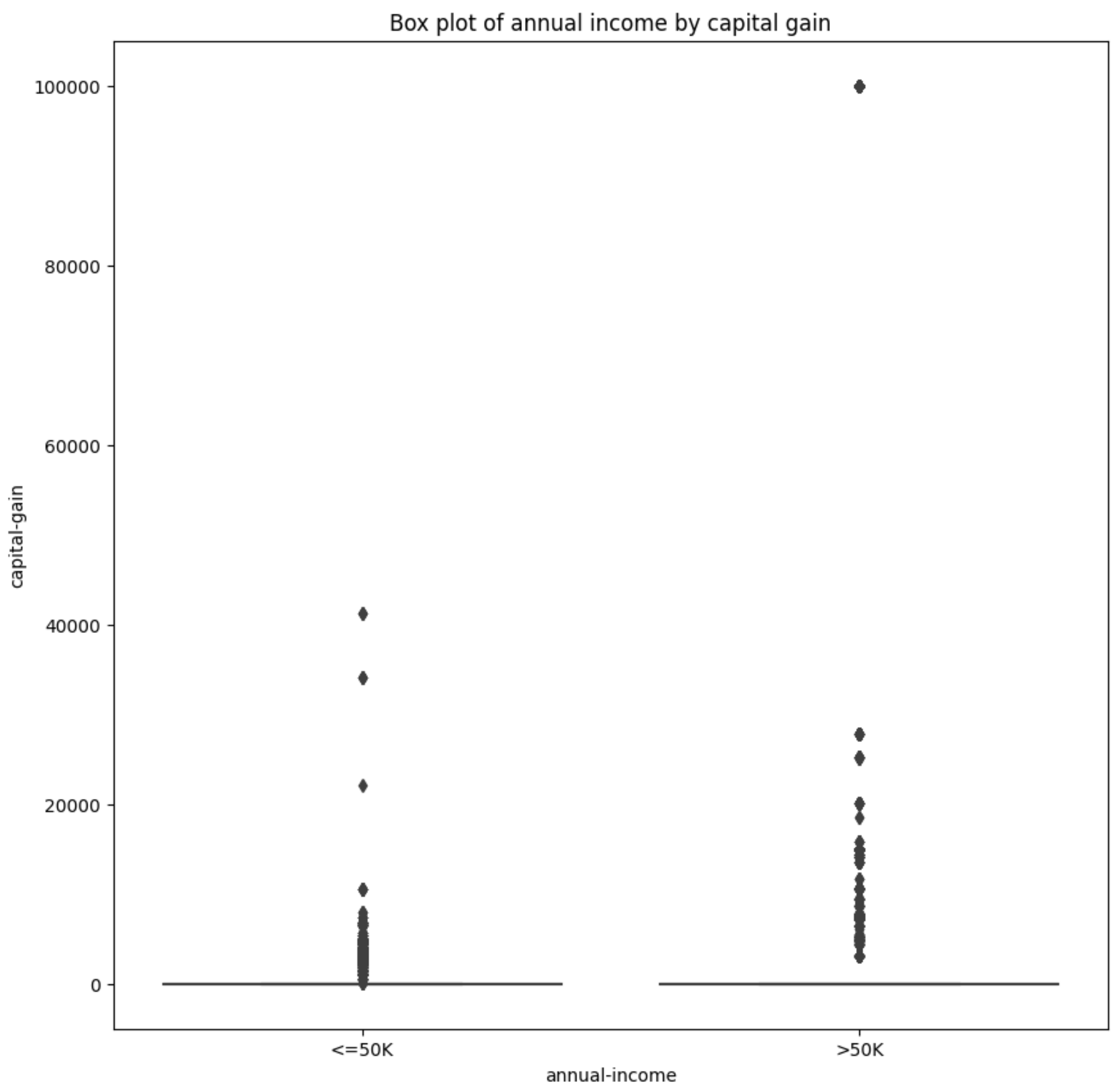
```
income_1 = data[data['annual-income']==">50K"]['age']
income_0 = data[data['annual-income']=="<=50K"]['age']

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 4.587107026879345
p value 8.491736874827582e-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 age. We can count age a discriminatory factor for our model.

4.2.2 Relationship between capital gain and annual income

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



[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)
```

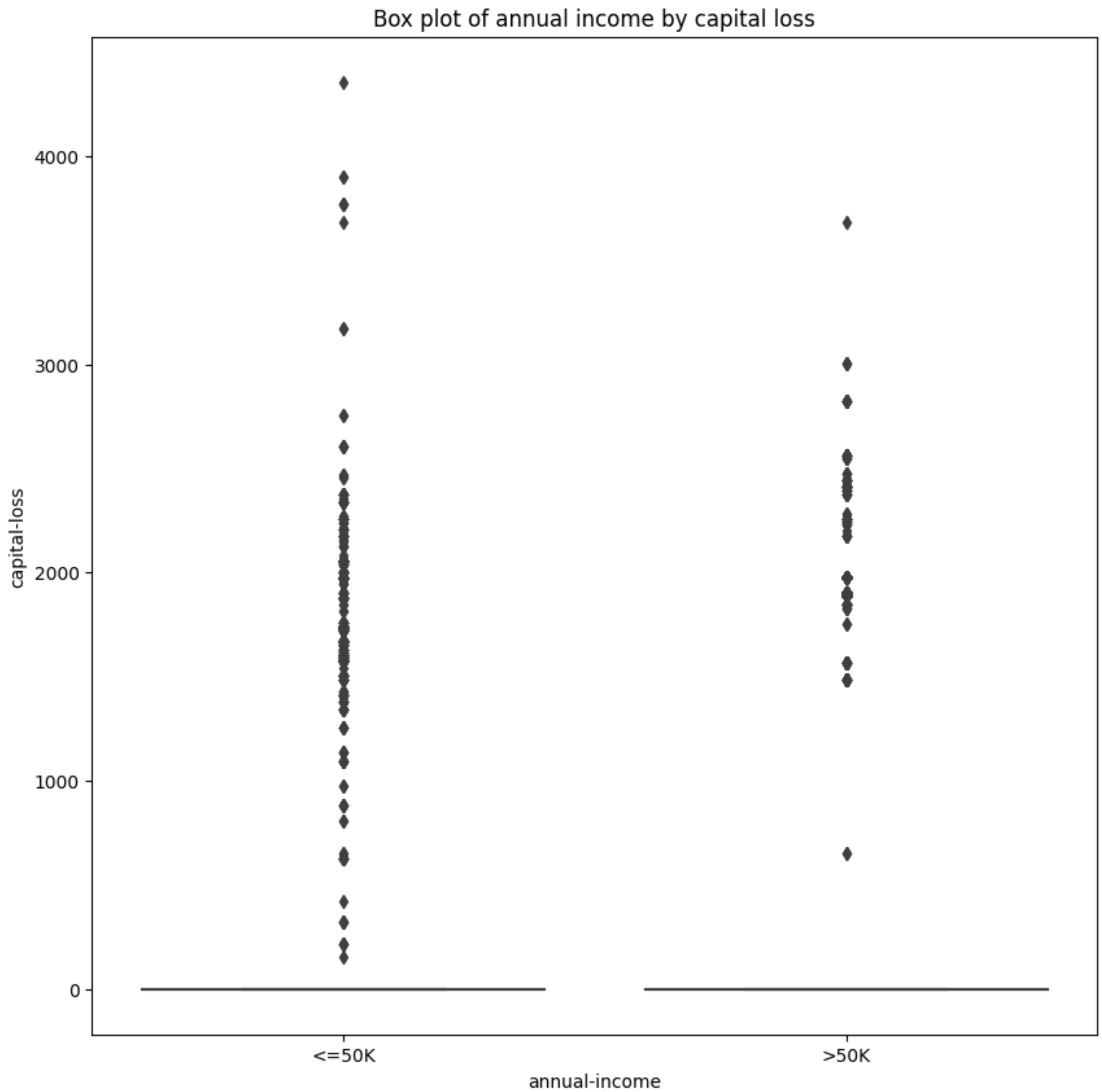
```
from scipy.stats import ttest_ind
ttest,pval = ttest_ind(income_1,income_0,equal_var = False)
print("ttest",ttest)
print('p value',pval)


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

```
ttest 3.817049484290308
p value 0.0002295071216938463
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

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



[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.

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

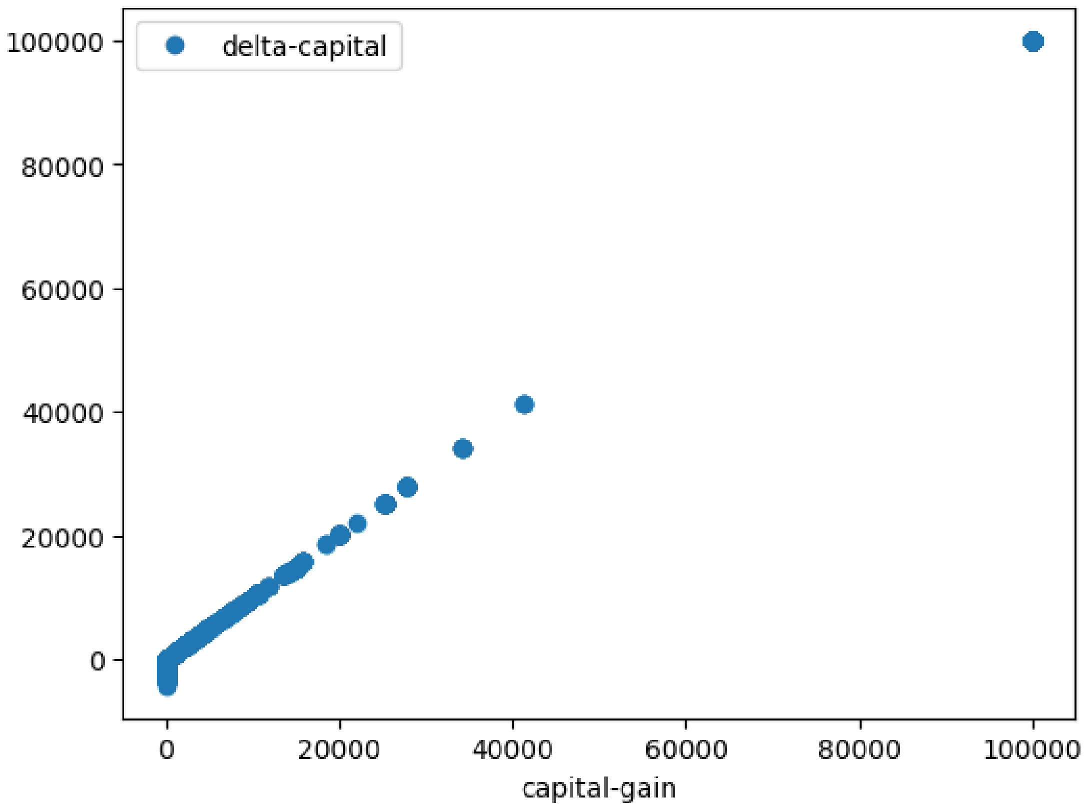
[40]:
```
count    45222.000000
mean      1012.834925
std       7530.315380
min      -4356.000000
25%          0.000000
50%          0.000000
75%          0.000000
max      99999.000000
Name: delta-capital, dtype: float64
```

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

[41]:
```
0.998554474506535
```

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

[42]:
```
<Axes: 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.

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

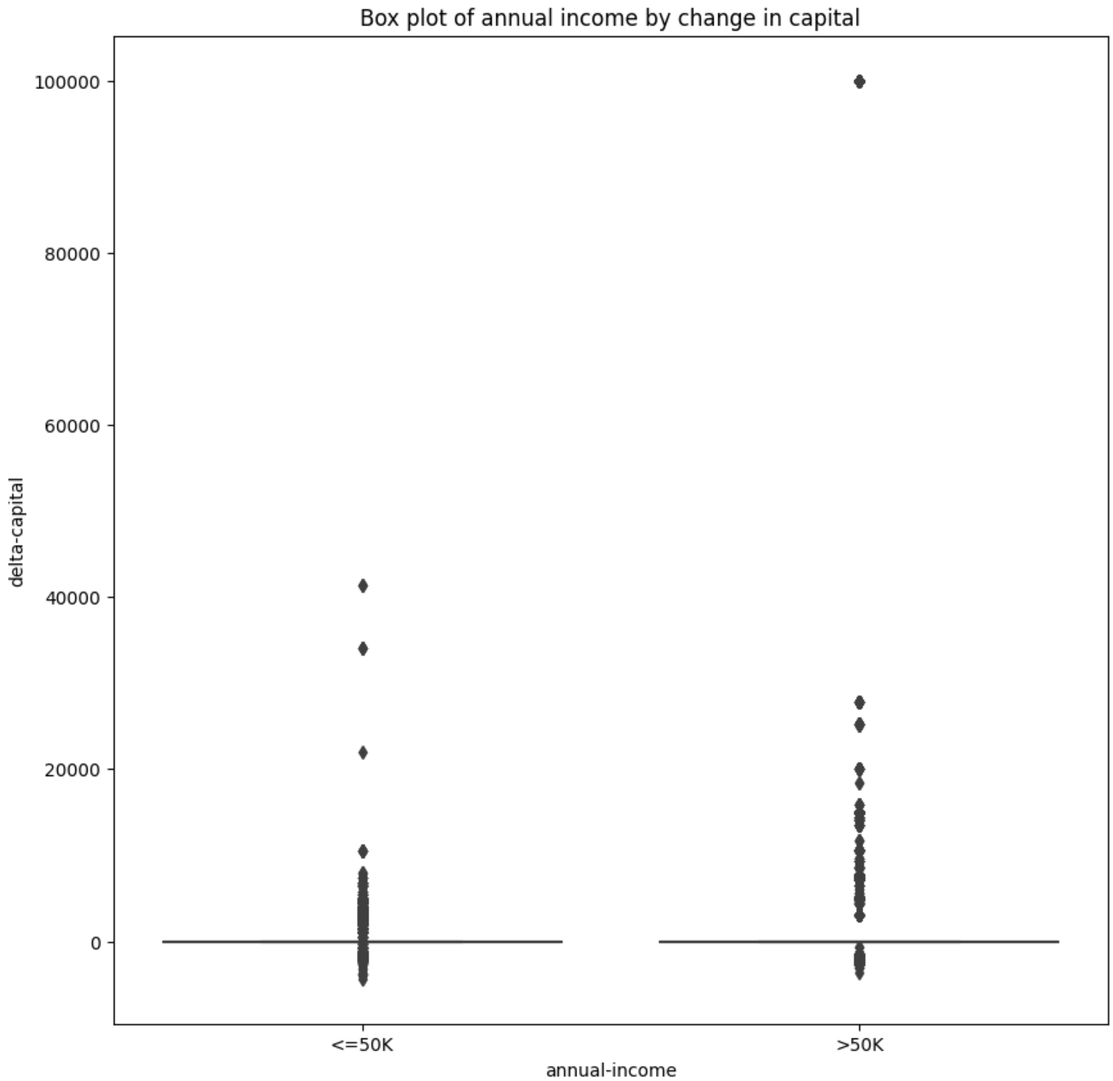
[43]:

	age	workclass	education	education-num	marital-status	\
0	39	State-gov	Bachelors	13.0	Never-married	
1	50	Self-emp-not-inc	Bachelors	13.0	Married-civ-spouse	
2	38	Private	HS-grad	9.0	Divorced	
3	53	Private	11th	7.0	Married-civ-spouse	
4	28	Private	Bachelors	13.0	Married-civ-spouse	
…	…	…	…	…	…	
48836	33	Private	Bachelors	13.0	Never-married	
48837	39	Private	Bachelors	13.0	Divorced	
48839	38	Private	Bachelors	13.0	Married-civ-spouse	
48840	44	Private	Bachelors	13.0	Divorced	
48841	35	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	

```
              occupation   relationship                 race     sex  \
0           Adm-clerical  Not-in-family                White    Male
1        Exec-managerial        Husband                White    Male
2      Handlers-cleaners  Not-in-family                White    Male
3      Handlers-cleaners        Husband                Black    Male
4         Prof-specialty           Wife                Black  Female
…                    …             …                  …      …
48836     Prof-specialty      Own-child                White    Male
48837     Prof-specialty  Not-in-family                White  Female
48839     Prof-specialty        Husband                White    Male
48840       Adm-clerical      Own-child   Asian-Pac-Islander    Male
48841    Exec-managerial        Husband                White    Male

       hours-per-week native-country annual-income  delta-capital
0                40.0  United-States         <=50K         2174.0
1                13.0  United-States         <=50K            0.0
2                40.0  United-States         <=50K            0.0
3                40.0  United-States         <=50K            0.0
4                40.0           Cuba         <=50K            0.0
…                 …            …            …            …
48836            40.0  United-States         <=50K            0.0
48837            36.0  United-States         <=50K            0.0
48839            50.0  United-States         <=50K            0.0
48840            40.0  United-States         <=50K         5455.0
48841            60.0  United-States          >50K            0.0

[45222 rows x 13 columns]
```

4.2.5 Relationship between delta capital and annual income

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



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

[45]:

	age	workclass	education	education-num	marital-status	\
1246	54	Self-emp-inc	Prof-school	15.0	Married-civ-spouse	
1368	52	Private	HS-grad	9.0	Married-civ-spouse	
1482	53	Self-emp-inc	HS-grad	9.0	Married-civ-spouse	
1528	52	Private	Bachelors	13.0	Married-civ-spouse	
1616	46	Private	Prof-school	15.0	Married-civ-spouse	
…	…	…	…	…	…	
47739	32	Self-emp-inc	Bachelors	13.0	Married-civ-spouse	
48582	61	Self-emp-not-inc	Masters	14.0	Married-civ-spouse	
48591	36	Private	Bachelors	13.0	Never-married	

```
48598   42          Private    Bachelors          13.0  Married-civ-spouse
48629   59     Self-emp-inc  Prof-school          15.0  Married-civ-spouse

             occupation   relationship                race   sex  \
1246    Prof-specialty        Husband                White  Male
1368   Exec-managerial        Husband   Asian-Pac-Islander  Male
1482             Sales        Husband                White  Male
1528   Exec-managerial        Husband                White  Male
1616    Prof-specialty        Husband                White  Male
…                  …              …                  …   …
47739  Exec-managerial        Husband                White  Male
48582   Prof-specialty        Husband                White  Male
48591   Prof-specialty  Not-in-family                White  Male
48598   Prof-specialty        Husband                White  Male
48629  Exec-managerial        Husband                White  Male

       hours-per-week native-country annual-income  delta-capital
1246             60.0  United-States          >50K        99999.0
1368             40.0          Japan          >50K        99999.0
1482             40.0  United-States          >50K        99999.0
1528             50.0  United-States          >50K        99999.0
1616             60.0  United-States          >50K        99999.0
…                 …            …            …            …
47739            60.0  United-States          >50K        99999.0
48582            30.0  United-States          >50K        99999.0
48591            45.0  United-States          >50K        99999.0
48598            42.0  United-States          >50K        99999.0
48629            84.0  United-States          >50K        99999.0

[229 rows x 13 columns]
```

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

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

[46]:
```
0.005063906947945 69
```

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

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

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

```python
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")
```

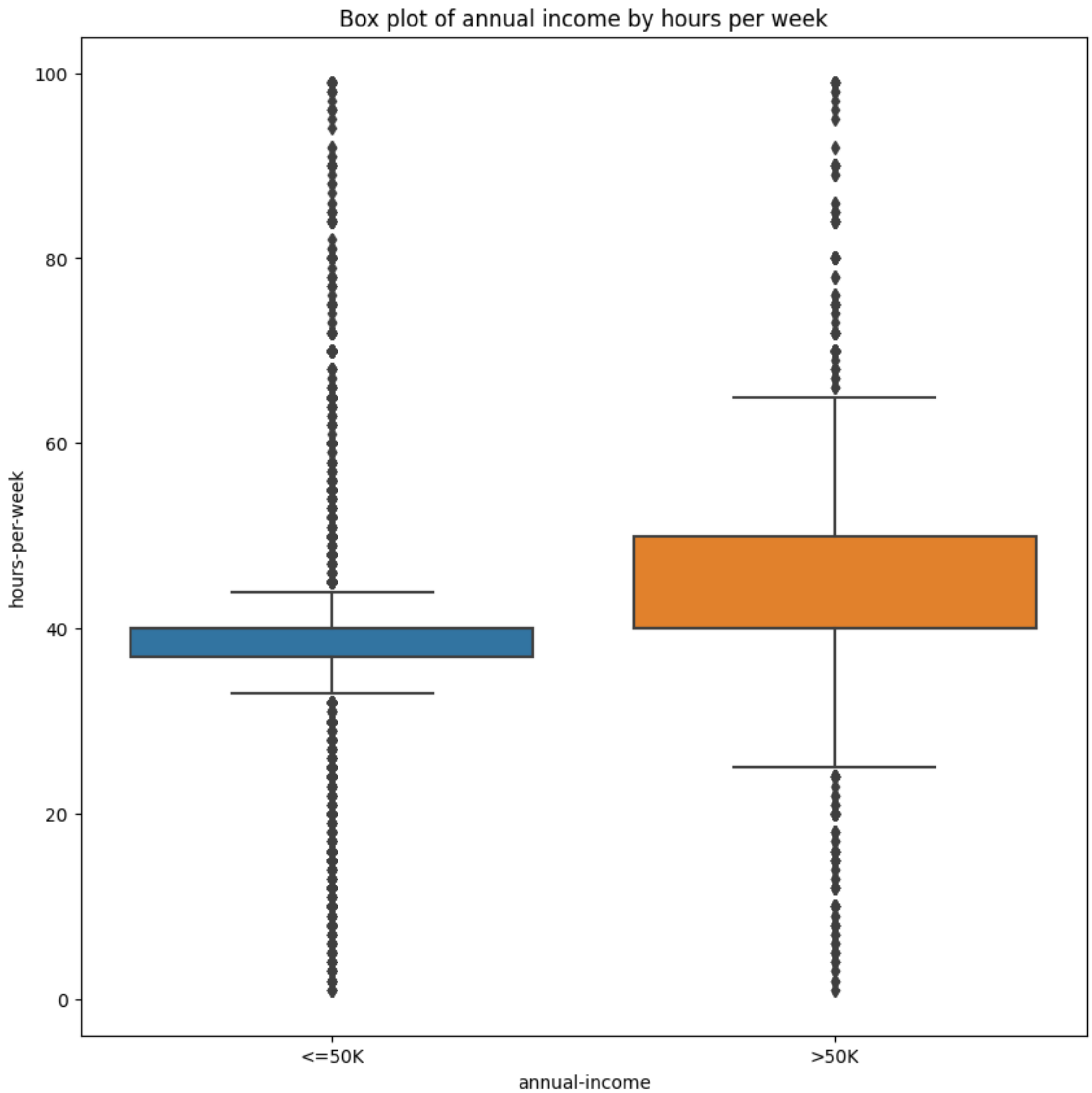
```
ttest 4.054215579898928
p value 9.664881308832429e-05
we reject null hypothesis
```

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

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

4.2.6 Relationship between hours per week and annual income

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



[50]:
```python
# mean
df[['annual-income', 'hours-per-week']].groupby(['annual-income'],
 ↪as_index=False).mean().sort_values(by='hours-per-week', ascending=False)
```

[50]:

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

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

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

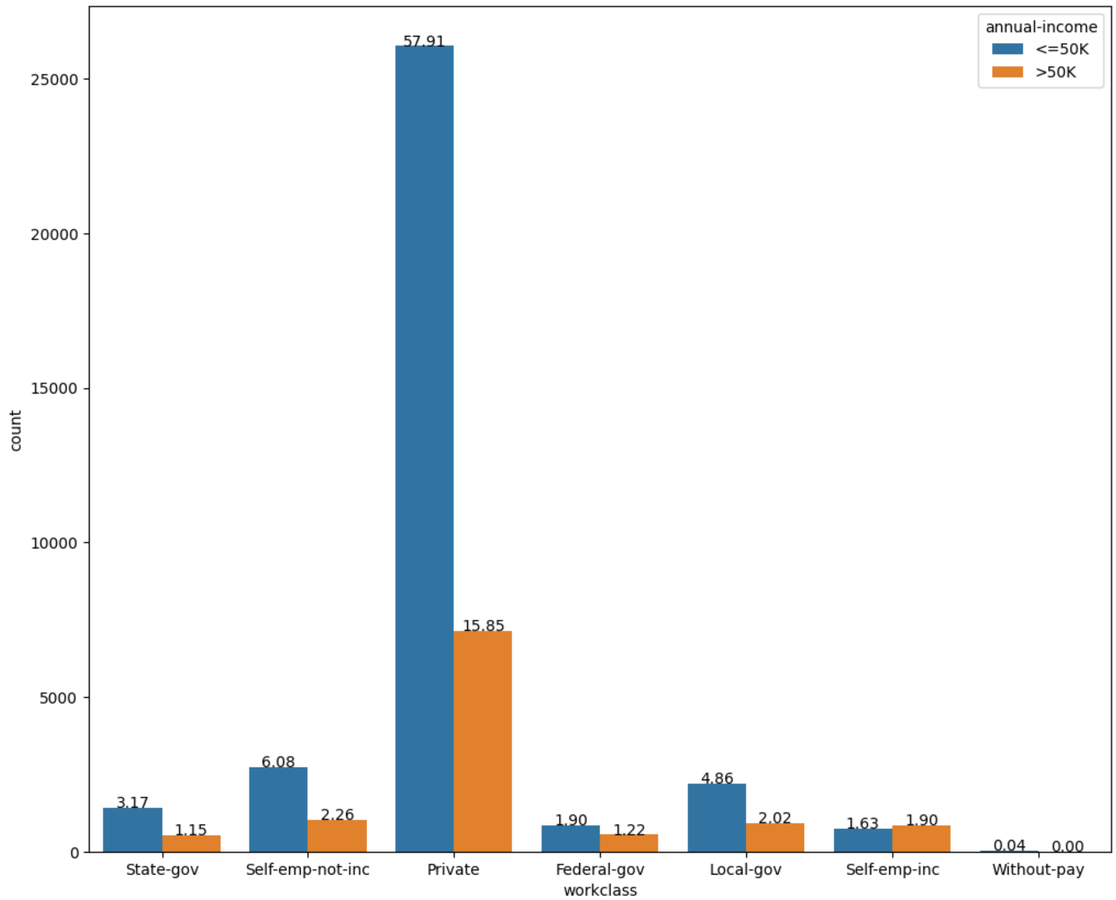
```
income_1 = data[data['annual-income']==">50K"]['hours-per-week']
income_0 = data[data['annual-income']=="<=50K"]['hours-per-week']

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 3.979275153034064
p value 9.699244228045246e-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 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

[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()
```



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

[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
```

[54]:
```
# contingency table
c_t = pd.crosstab(df['workclass'].sample(frac=0.002, replace=True,␣
↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
↪random_state=1),margins = False)
c_t
```

[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
```

[55]:
```python
# 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)')
```

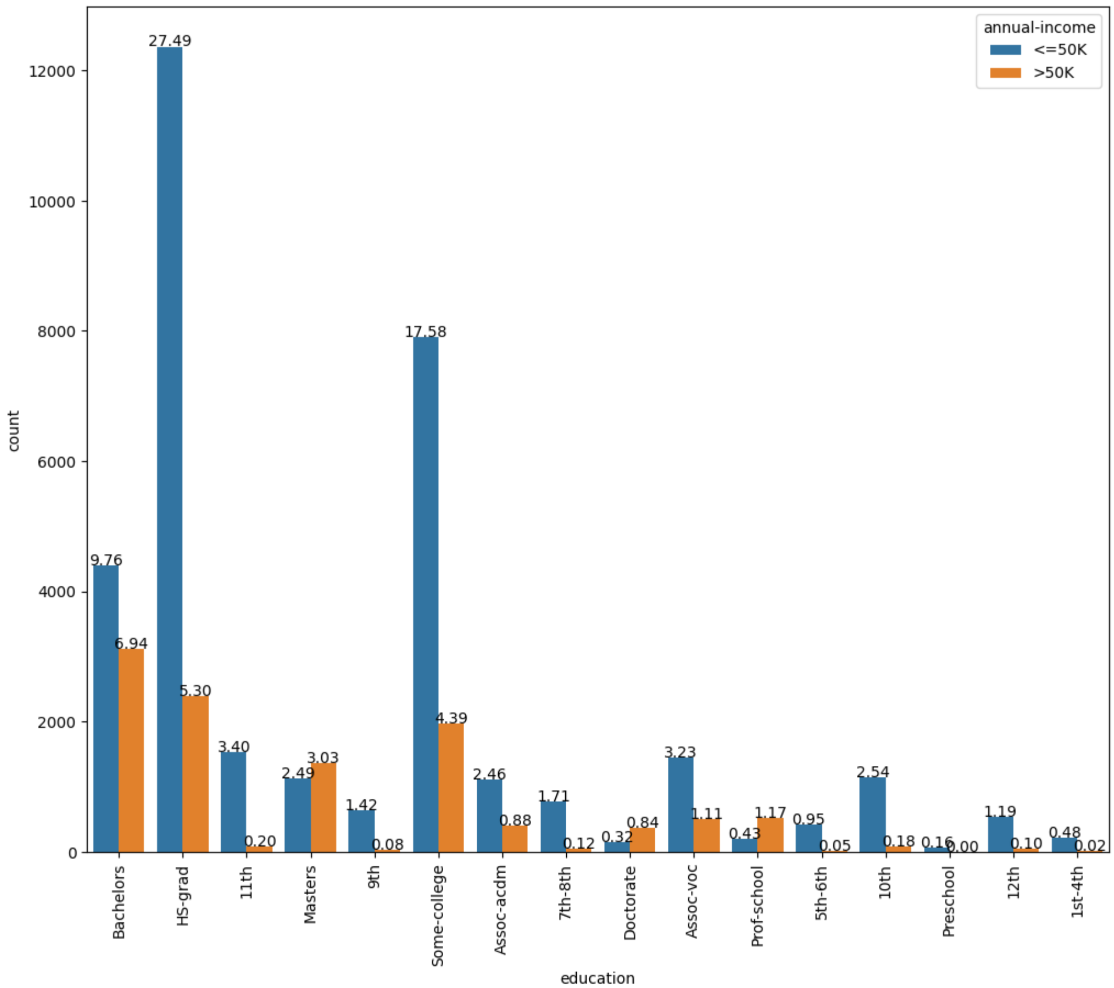
```
dof=5
p_value 0.013635700737287638
[[ 2.5         0.5       ]
 [ 1.66666667  0.33333333]
 [58.33333333 11.66666667]
 [ 4.16666667  0.83333333]
 [ 4.16666667  0.83333333]
 [ 4.16666667  0.83333333]]
probability=0.950, critical=11.070, stat=14.331
Dependent (reject H0)
```

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

[56]:
```python
# 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()
```



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

[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
```

[58]:
```
# contingency table
c_t = pd.crosstab(df['education'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[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
```

[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)
```

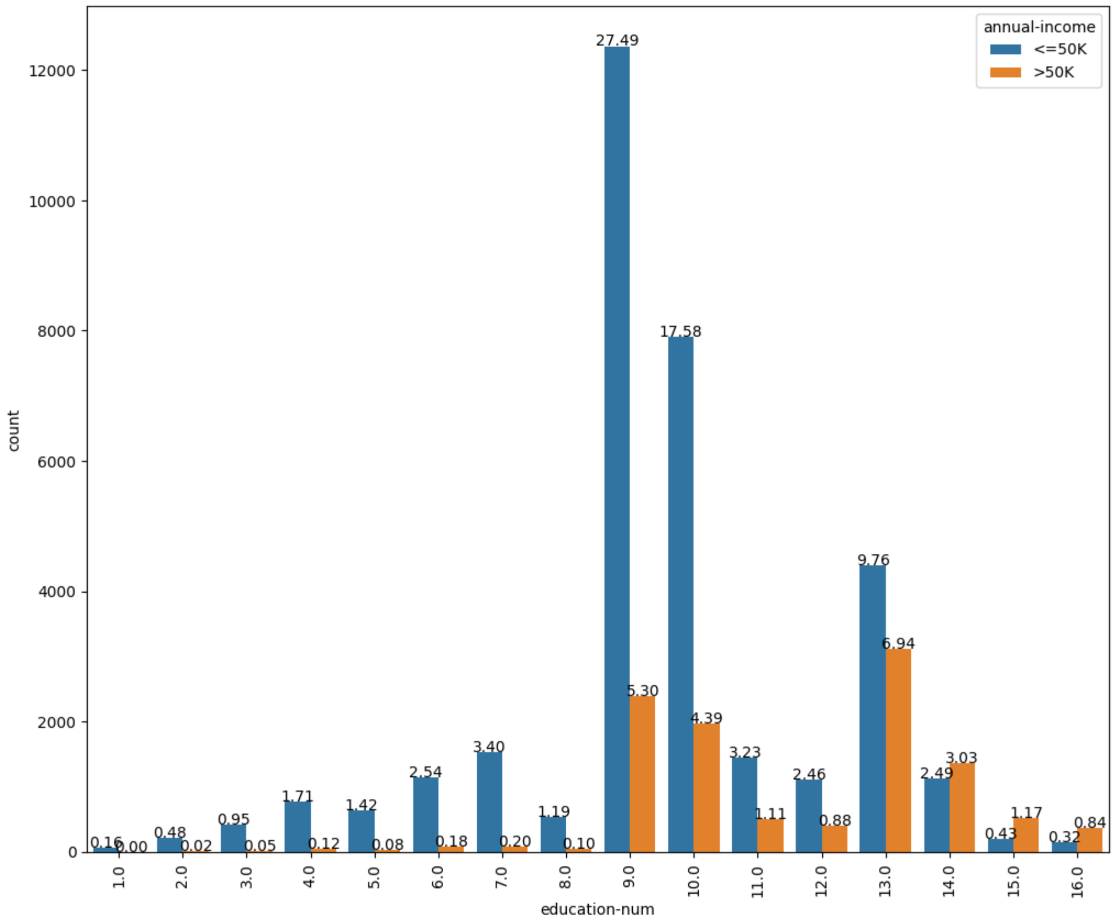
```
# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
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

[60]:
```
# 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()
```



[61]:

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

[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
```

[62]:
```
# contingency table
c_t = pd.crosstab(df['education-num'].sample(frac=0.002, replace=True,␣
↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
↪random_state=1),margins = False)
c_t
```

[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
```

[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)')
```

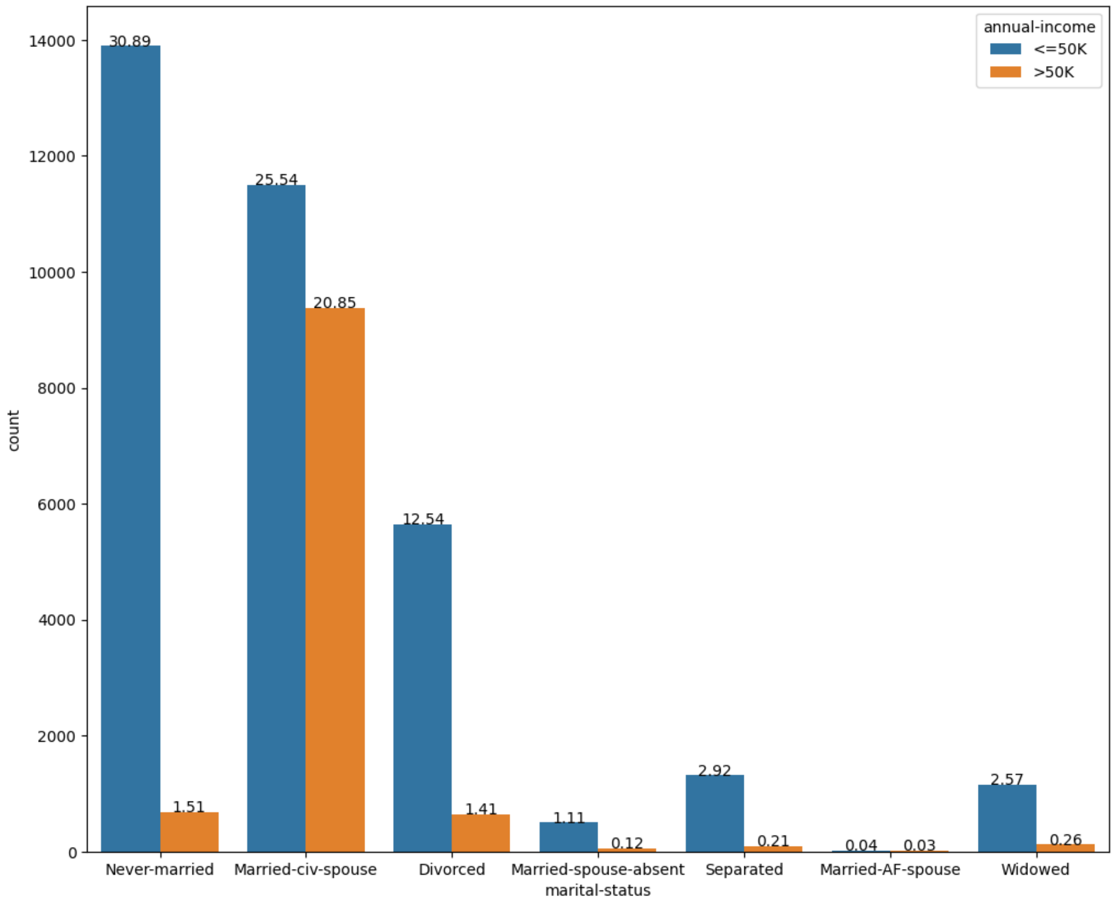
```
dof=12
p_value 0.19516031384342544
[[ 1.66666667  0.33333333]
```

```
 [ 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

[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()
```



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

[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
```

[66]:
```
# contingency table
c_t = pd.crosstab(df['marital-status'].sample(frac=0.002, replace=True,␣
↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
↪random_state=1),margins = False)
c_t
```

[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
```

[67]:
```python
# 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)')
```

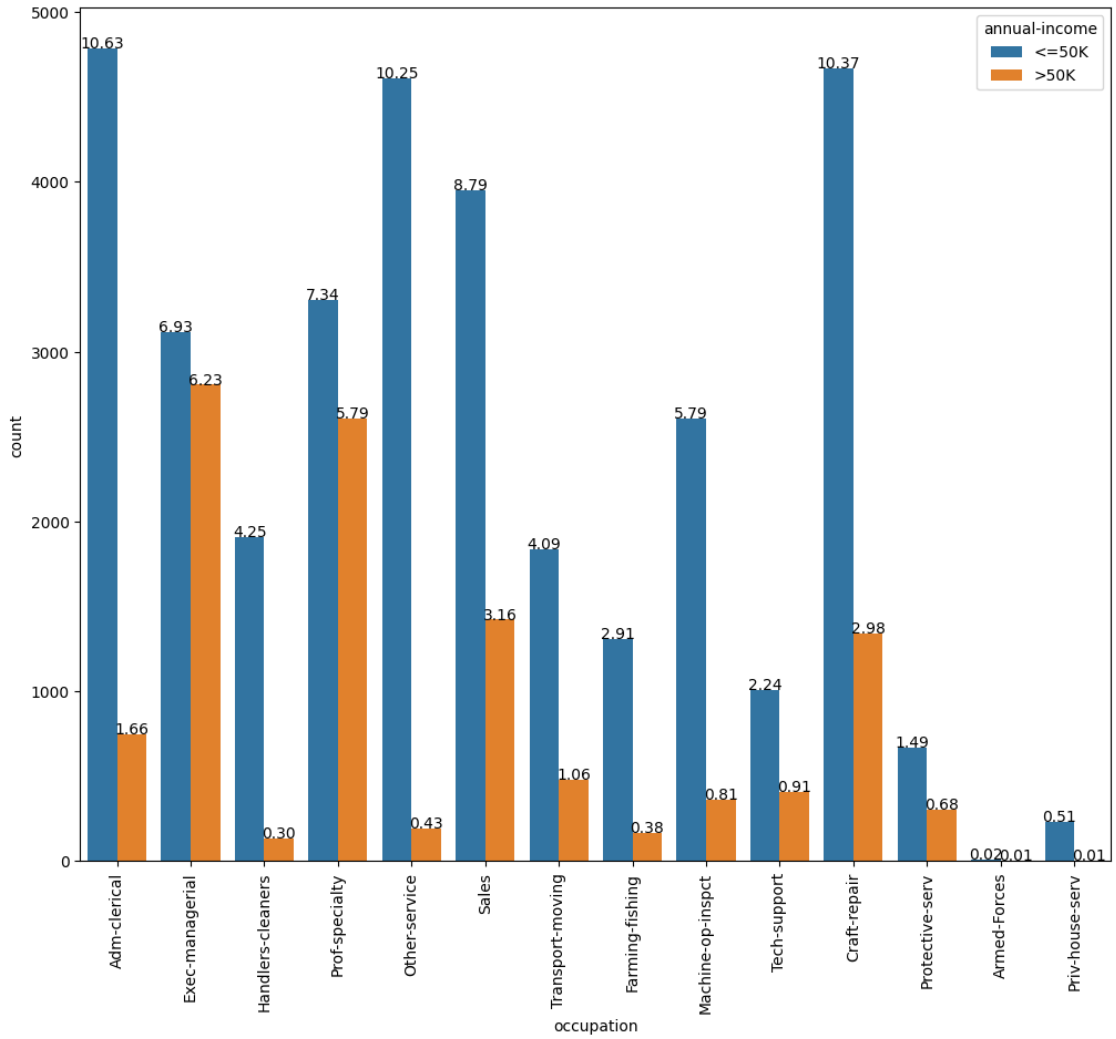
```
dof=5
p_value 0.0014920475984894538
[[14.16666667  2.83333333]
 [25.          5.        ]
 [ 2.5         0.5       ]
 [29.16666667  5.83333333]
 [ 2.5         0.5       ]
 [ 1.66666667  0.33333333]]
probability=0.950, critical=11.070, stat=19.589
Dependent (reject H0)
```

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

[68]:
```python
# 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()
```



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

[69]:
```
annual-income      <=50K  >50K
occupation
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
```

[70]:
```python
# contingency table
c_t = pd.crosstab(df['occupation'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[70]:
```
annual-income      <=50K  >50K
occupation
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
```

[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)
```

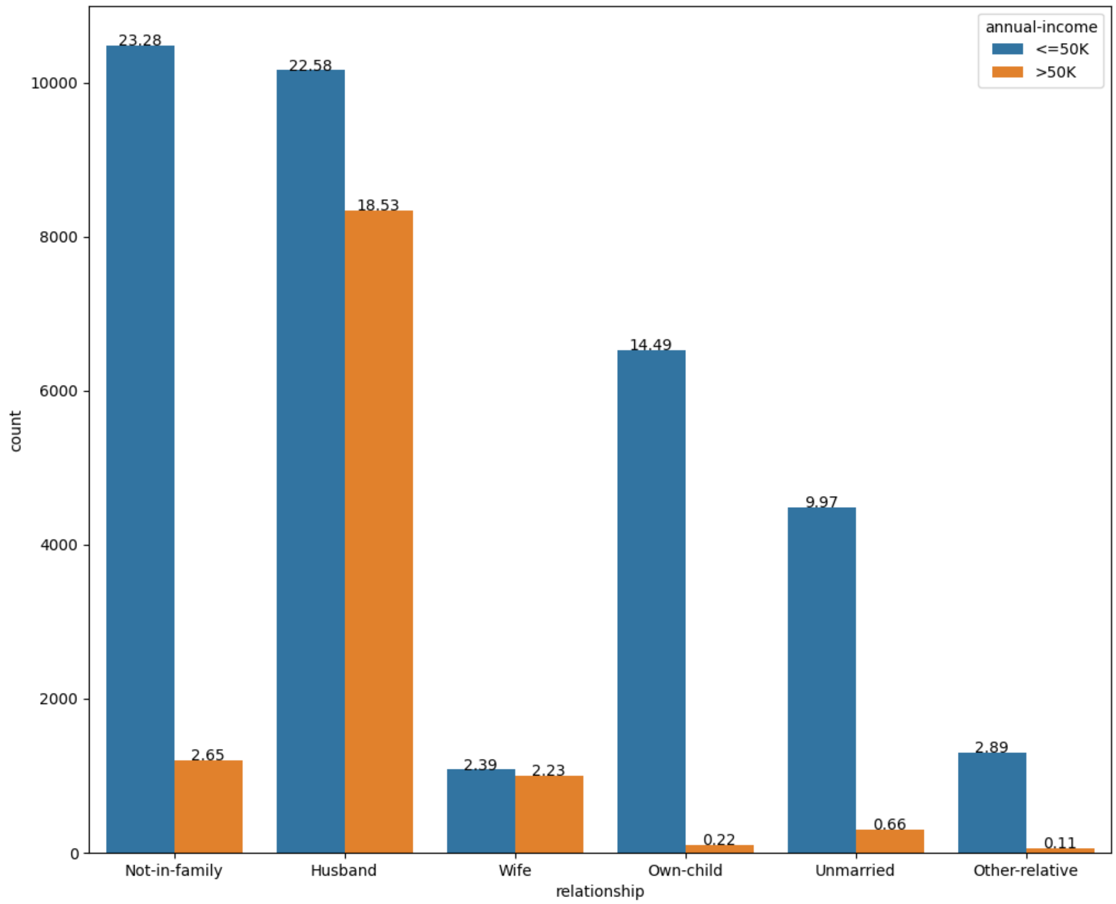
```
# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=11
p_value 0.4431988367023755
[[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

[72]:
```
# 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()
```



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

[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
```

[74]:
```
# contingency table
c_t = pd.crosstab(df['relationship'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[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
```

[75]:

```python
# 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 0.0006075262445824966
[[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)
```

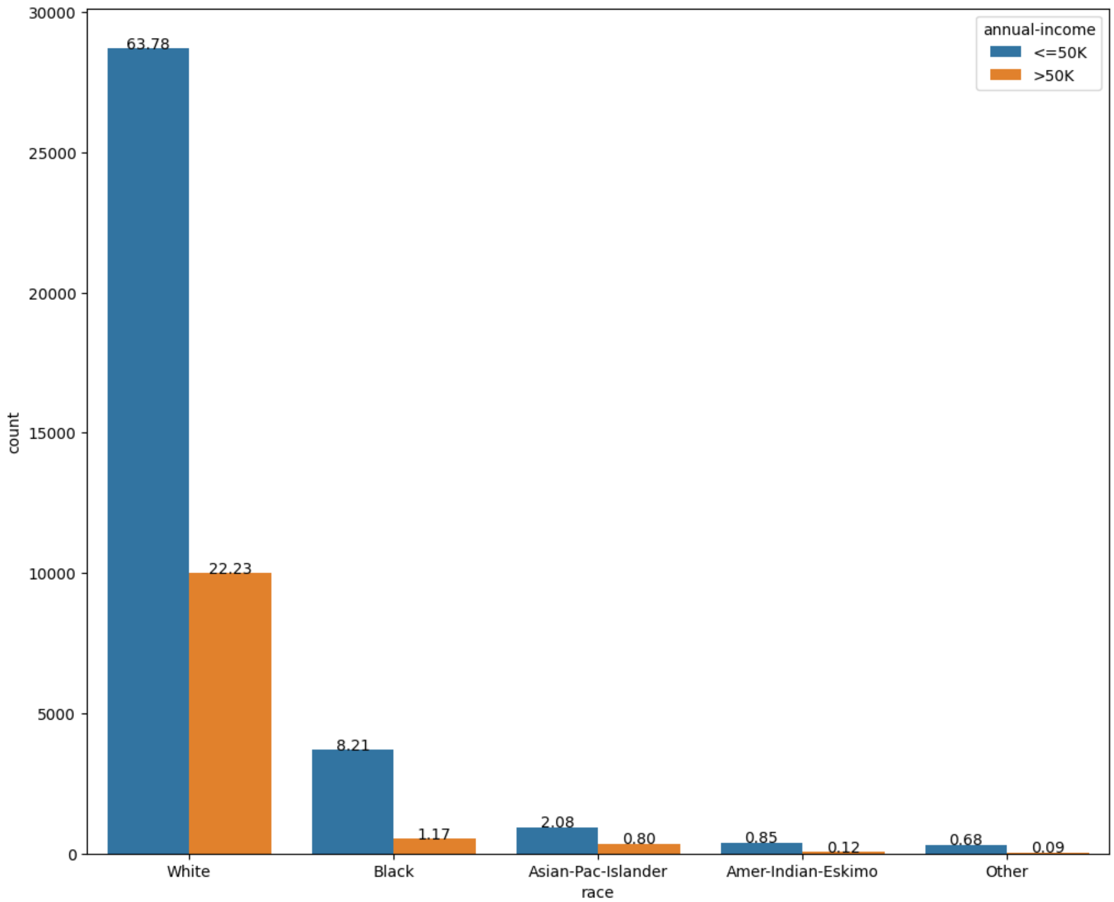
We reject the null hypothesis from the chi-squared test i.e. there is dependency between relationship and annual-income. Relationship will remain in our feature set.

4.2.13 Relationship between race and annual income

[76]:

```python
# 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()
```



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

[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
```

[78]:

```
# contingency table
c_t = pd.crosstab(df['race'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[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
```

[79]:

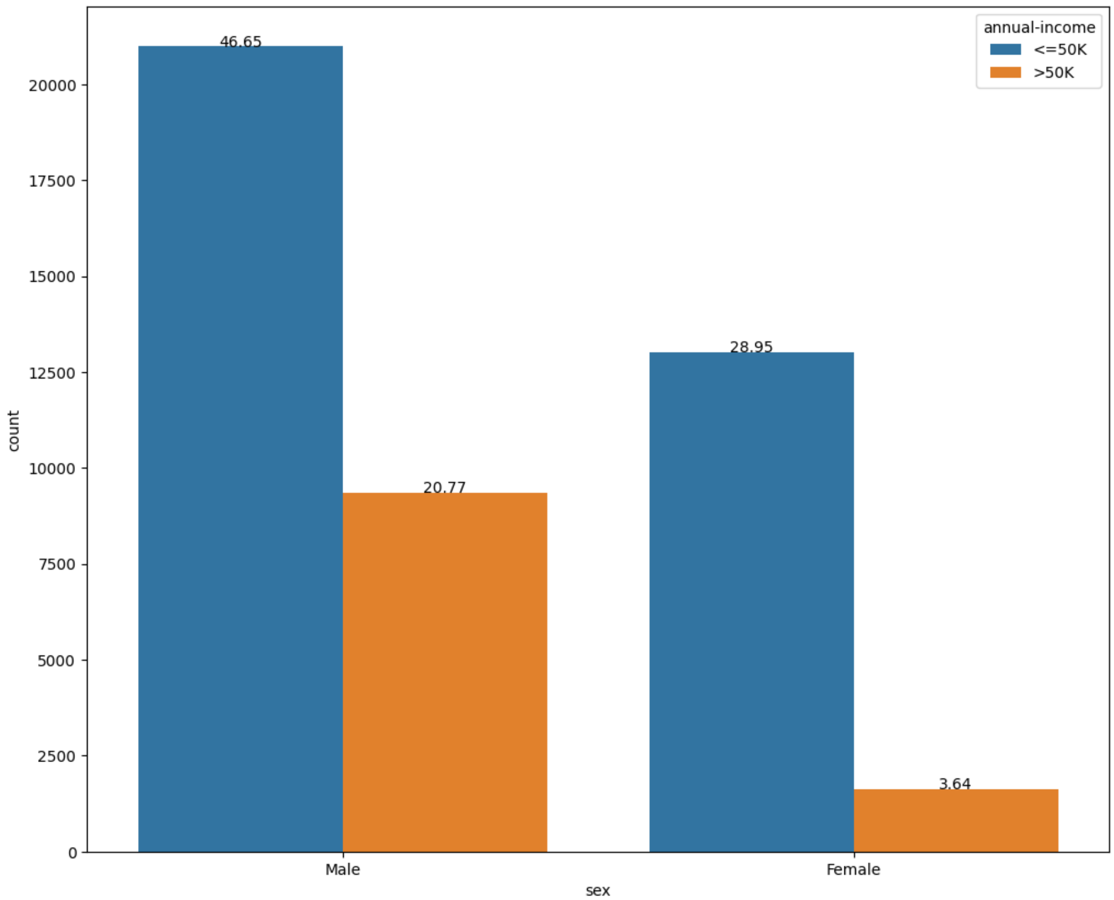
```
from scipy.stats import chi2_contingency
from scipy.stats import chi2


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

[80]:
```
# 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()
```



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

[81]:
```
annual-income  <=50K  >50K
sex
Female         13026  1636
Male           20988  9343
```

[82]:
```
# contingency table
c_t = pd.crosstab(df['sex'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[82]:
```
annual-income  <=50K  >50K
sex
Female            29     5
Male              46    10
```

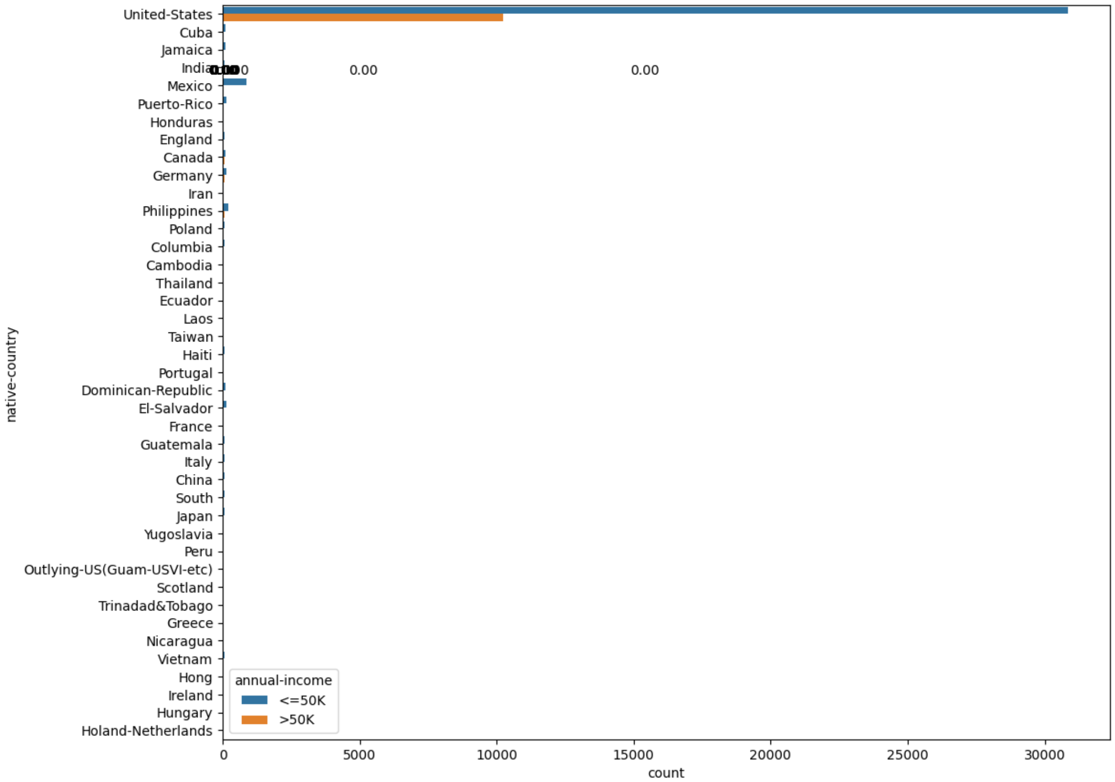
[83]:
```
# chi-squared test
from scipy.stats import chi2_contingency
from scipy.stats import chi2


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

[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()
```



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

[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
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
```

[86]:
```
# contingency table
c_t = pd.crosstab(df['native-country'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),df['annual-income'].sample(frac=0.002, replace=True,␣
 ↪random_state=1),margins = False)
c_t
```

[86]:
```
annual-income   <=50K  >50K
native-country
Germany             2     0
Haiti               0     1
Mexico              5     0
Puerto-Rico         1     0
United-States      67    14
```

[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)')
```

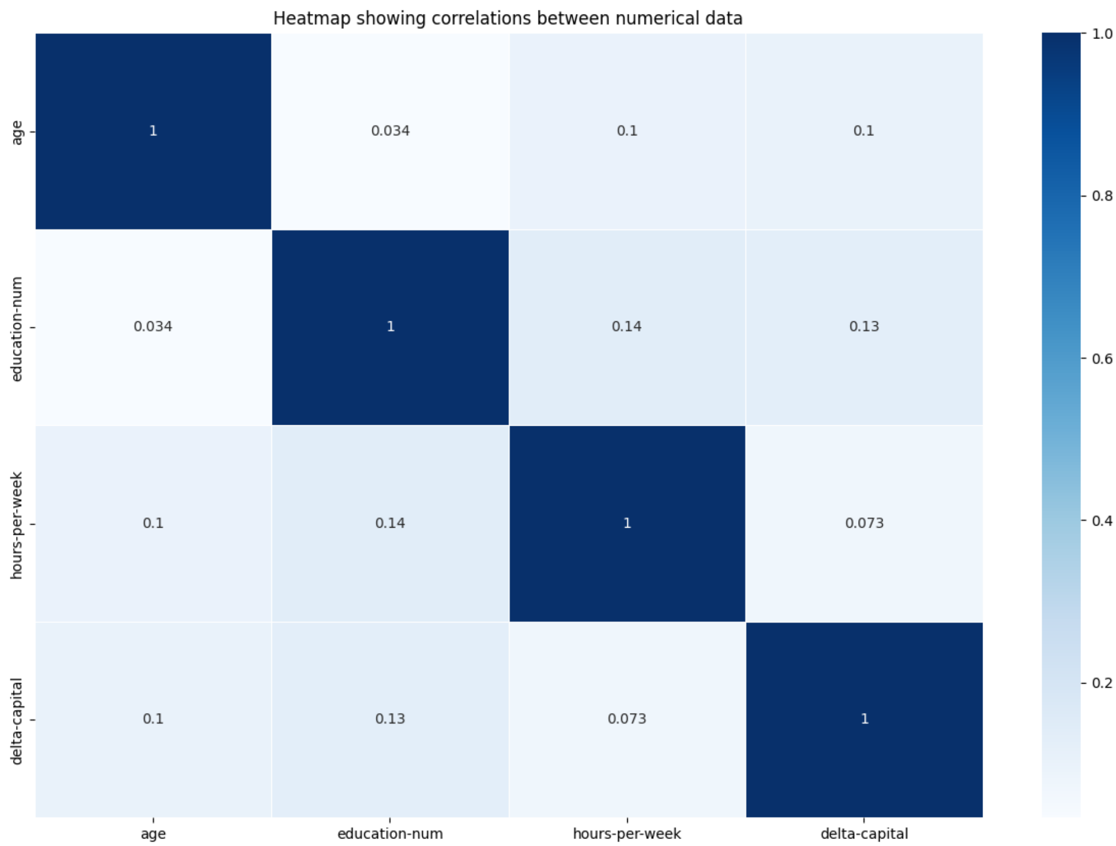
```
dof=4
p_value 0.15725046256468317
[[ 1.66666667  0.33333333]
 [ 0.83333333  0.16666667]
 [ 4.16666667  0.83333333]
 [ 0.83333333  0.16666667]
 [67.5        13.5       ]]
probability=0.950, critical=9.488, stat=6.622
Independent (fail to reject H0)
```

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

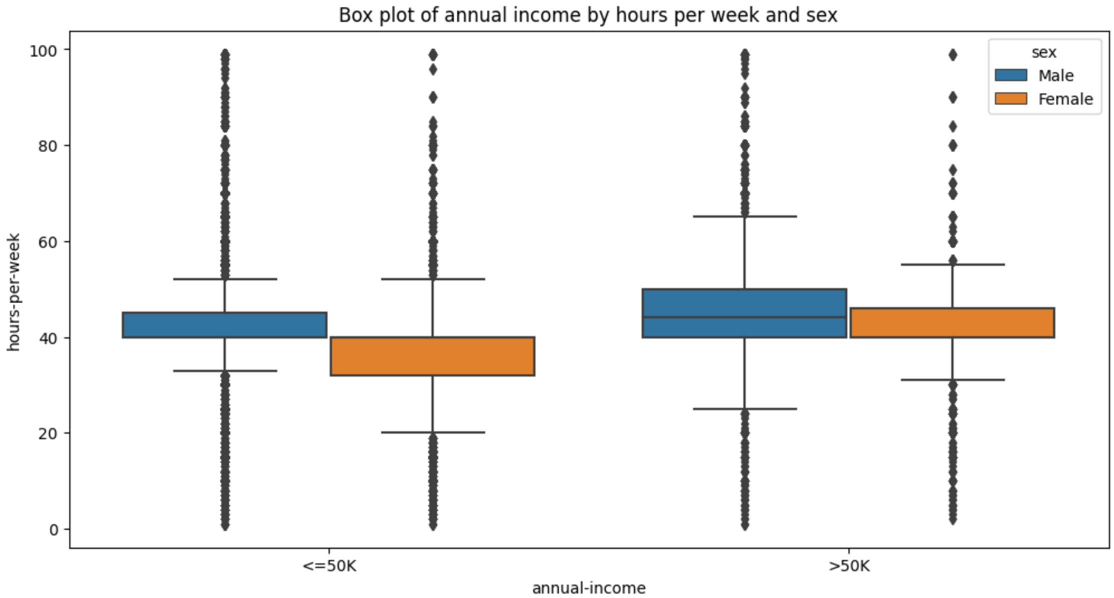
4.3.1 Correlation Matrix

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



4.3.2 Multivariate Categorical Analysis

[89]:
```
plt.figure(figsize=(12,6))
sns.boxplot(x='annual-income',y ='hours-per-week', hue='sex',data=df).
 ↪set_title("Box plot of annual income by hours per week and sex")
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?

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

[90]:
```
relationship           Husband  Not-in-family  Other-relative  Own-child  \
marital-status
Divorced                     0           3419             166        429
Married-AF-spouse           11              0               1          1
Married-civ-spouse       18487             19             184        125
Married-spouse-absent        0            281              44         57
Never-married                0           6676             820       5860
Separated                    0            584              75        130
Widowed                      0            687              59         20

relationship           Unmarried  Wife
marital-status
Divorced                    2263     0
Married-AF-spouse              0    18
Married-civ-spouse             0  2059
Married-spouse-absent        169     0
Never-married               1222     0
Separated                    618     0
Widowed                      509     0
```

[91]:
```
# contingency table
c_t = pd.crosstab(df['marital-status'].sample(frac=0.002, replace=True,␣
↪random_state=1),df['relationship'].sample(frac=0.002, replace=True,␣
↪random_state=1),margins = False)
c_t
```

[91]:
```
relationship           Husband  Not-in-family  Other-relative  Own-child  \
marital-status
Divorced                     0              7               2          0
Married-civ-spouse          24              0               0          1
Married-spouse-absent        0              3               0          0
Never-married                0             14               4         15
Separated                    0              3               0          0
Widowed                      0              0               0          0

relationship           Unmarried  Wife
marital-status
Divorced                       8     0
Married-civ-spouse             0     5
Married-spouse-absent          0     0
Never-married                  2     0
Separated                      0     0
Widowed                        2     0
```

[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.

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

[93]:
```
   age         workclass  education  education-num      marital-status  \
0   39         State-gov  Bachelors           13.0       Never-married
1   50  Self-emp-not-inc  Bachelors           13.0  Married-civ-spouse
2   38           Private    HS-grad            9.0            Divorced
```

```
3       53            Private       11th           7.0  Married-civ-spouse
4       28            Private  Bachelors          13.0  Married-civ-spouse
…     …               …        …            …               …
48836   33            Private  Bachelors          13.0       Never-married
48837   39            Private  Bachelors          13.0            Divorced
48839   38            Private  Bachelors          13.0  Married-civ-spouse
48840   44            Private  Bachelors          13.0            Divorced
48841   35       Self-emp-inc  Bachelors          13.0  Married-civ-spouse

              occupation   relationship                race     sex  \
0           Adm-clerical  Not-in-family               White    Male
1        Exec-managerial        Husband               White    Male
2      Handlers-cleaners  Not-in-family               White    Male
3      Handlers-cleaners        Husband               Black    Male
4         Prof-specialty           Wife               Black  Female
…                    …              …                 …      …
48836     Prof-specialty      Own-child               White    Male
48837     Prof-specialty  Not-in-family               White  Female
48839     Prof-specialty        Husband               White    Male
48840       Adm-clerical      Own-child  Asian-Pac-Islander    Male
48841    Exec-managerial        Husband               White    Male

       hours-per-week native-country  delta-capital  >50K
0                40.0  United-States         2174.0     0
1                13.0  United-States            0.0     0
2                40.0  United-States            0.0     0
3                40.0  United-States            0.0     0
4                40.0           Cuba            0.0     0
…                 …              …             …    …
48836            40.0  United-States            0.0     0
48837            36.0  United-States            0.0     0
48839            50.0  United-States            0.0     0
48840            40.0  United-States         5455.0     0
48841            60.0  United-States            0.0     1

[44993 rows x 13 columns]
```

[94]:

```
# 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()
```

[94]:
```
   age         workclass  education  education-num      marital-status  \
0   39         State-gov  Bachelors           13.0       Never-married
1   50  Self-emp-not-inc  Bachelors           13.0  Married-civ-spouse
2   38           Private    HS-grad            9.0            Divorced
3   53           Private       11th            7.0  Married-civ-spouse
4   28           Private  Bachelors           13.0  Married-civ-spouse

          occupation   relationship   race     sex  hours-per-week  \
0       Adm-clerical  Not-in-family  White    Male            40.0
1    Exec-managerial        Husband  White    Male            13.0
2  Handlers-cleaners  Not-in-family  White    Male            40.0
3  Handlers-cleaners        Husband  Black    Male            40.0
4     Prof-specialty           Wife  Black  Female            40.0

  native-country  delta-capital  >50K  marital-status-ratio
0  United-States         2174.0     0              0.049003
1  United-States            0.0     0              0.816552
2  United-States            0.0     0              0.112549
3  United-States            0.0     0              0.816552
4           Cuba            0.0     0              0.816552
```

[95]:
```python
# 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()
```

[95]:
```
   age         workclass  education  education-num      marital-status  \
0   39         State-gov  Bachelors           13.0       Never-married
1   50  Self-emp-not-inc  Bachelors           13.0  Married-civ-spouse
2   38           Private    HS-grad            9.0            Divorced
3   53           Private       11th            7.0  Married-civ-spouse
4   28           Private  Bachelors           13.0  Married-civ-spouse

          occupation   relationship   race     sex  hours-per-week  \
0       Adm-clerical  Not-in-family  White    Male            40.0
1    Exec-managerial        Husband  White    Male            13.0
2  Handlers-cleaners  Not-in-family  White    Male            40.0
3  Handlers-cleaners        Husband  Black    Male            40.0
4     Prof-specialty           Wife  Black  Female            40.0

  native-country  delta-capital  >50K  marital-status-ratio  \
0  United-States         2174.0     0              0.049003
1  United-States            0.0     0              0.816552
```

```
2  United-States          0.0    0             0.112549
3  United-States          0.0    0             0.816552
4           Cuba          0.0    0             0.816552

   relationship-ratio
0            0.113806
1            0.820849
2            0.113806
3            0.820849
4            0.932093
```

[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()
```

[96]:

```
   age         workclass  education  education-num      marital-status  \
0   39         State-gov  Bachelors           13.0       Never-married
1   50  Self-emp-not-inc  Bachelors           13.0  Married-civ-spouse
2   38           Private    HS-grad            9.0            Divorced
3   53           Private       11th            7.0  Married-civ-spouse
4   28           Private  Bachelors           13.0  Married-civ-spouse

          occupation   relationship   race     sex  hours-per-week  \
0       Adm-clerical  Not-in-family  White    Male            40.0
1    Exec-managerial        Husband  White    Male            13.0
2  Handlers-cleaners  Not-in-family  White    Male            40.0
3  Handlers-cleaners        Husband  Black    Male            40.0
4     Prof-specialty           Wife  Black  Female            40.0

  native-country  delta-capital  >50K  marital-status-ratio  \
0  United-States         2174.0     0              0.049003
1  United-States            0.0     0              0.816552
2  United-States            0.0     0              0.112549
3  United-States            0.0     0              0.816552
4           Cuba            0.0     0              0.816552

   relationship-ratio  workclass-ratio
0            0.113806         0.361851
1            0.820849         0.372305
2            0.113806         0.273680
3            0.820849         0.273680
4            0.932093         0.273680
```

[97]:
```
# Dropping the unnecessary and duplicate columns
df_main = df_cat.drop(['workclass', 'education', 'education-num',
 'marital-status', 'occupation', 'relationship', 'race', 'sex',
 'native-country'],
                        axis=1)
df_main
```

[97]:
```
       age  hours-per-week  delta-capital  >50K  marital-status-ratio  \
0       39            40.0         2174.0     0              0.049003
1       50            13.0            0.0     0              0.816552
2       38            40.0            0.0     0              0.112549
3       53            40.0            0.0     0              0.816552
4       28            40.0            0.0     0              0.816552
…     …              …             …     …                   …
48836   33            40.0            0.0     0              0.049003
48837   39            36.0            0.0     0              0.112549
48839   38            50.0            0.0     0              0.816552
48840   44            40.0         5455.0     0              0.112549
48841   35            60.0            0.0     1              0.816552

       relationship-ratio  workclass-ratio
0                0.113806         0.361851
1                0.820849         0.372305
2                0.113806         0.273680
3                0.820849         0.273680
4                0.932093         0.273680
…                     …                …
48836            0.015488         0.273680
48837            0.113806         0.273680
48839            0.820849         0.273680
48840            0.015488         0.273680
48841            0.820849         1.164850

[44993 rows x 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.

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

[98]:

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

       relationship-ratio  workclass-ratio
0                0.113806         0.361851
1                0.820849         0.372305
2                0.113806         0.273680
3                0.820849         0.273680
4                0.932093         0.273680
…                     …                …
48836            0.015488         0.273680
48837            0.113806         0.273680
48839            0.820849         0.273680
48840            0.015488         0.273680
48841            0.820849         1.164850

[44993 rows x 7 columns]
```

5.4 Multicollinearity Test

[99]:

```python
# correlation
df_main.corr()
```

[99]:

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

                      marital-status-ratio  relationship-ratio  \
age                               0.328106            0.328060
hours-per-week                    0.227597            0.232395
delta-capital                     0.090984            0.093188
>50K                              0.447275            0.452557
```

```
marital-status-ratio               1.000000            0.978280
relationship-ratio                 0.978280            1.000000
workclass-ratio                    0.126962            0.127243

                      workclass-ratio
age                          0.155725
hours-per-week               0.125499
delta-capital                0.071764
>50K                         0.156016
marital-status-ratio         0.126962
relationship-ratio           0.127243
workclass-ratio              1.000000
```

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

[100]:
```
df_main.drop('marital-status-ratio', axis=1).corr()
```

[100]:
```
                         age  hours-per-week  delta-capital      >50K  \
age                 1.000000        0.100464       0.104338  0.234130
hours-per-week      0.100464        1.000000       0.073258  0.222599
delta-capital       0.104338        0.073258       1.000000  0.278057
>50K                0.234130        0.222599       0.278057  1.000000
relationship-ratio  0.328060        0.232395       0.093188  0.452557
workclass-ratio     0.155725        0.125499       0.071764  0.156016

                    relationship-ratio  workclass-ratio
age                           0.328060         0.155725
hours-per-week                0.232395         0.125499
delta-capital                 0.093188         0.071764
>50K                          0.452557         0.156016
relationship-ratio            1.000000         0.127243
workclass-ratio               0.127243         1.000000
```

[101]:
```
df_main.drop('relationship-ratio', axis=1).corr()
```

[101]:
```
                           age  hours-per-week  delta-capital      >50K  \
age                   1.000000        0.100464       0.104338  0.234130
hours-per-week        0.100464        1.000000       0.073258  0.222599
delta-capital         0.104338        0.073258       1.000000  0.278057
>50K                  0.234130        0.222599       0.278057  1.000000
marital-status-ratio  0.328106        0.227597       0.090984  0.447275
workclass-ratio       0.155725        0.125499       0.071764  0.156016

                      marital-status-ratio  workclass-ratio
age                               0.328106         0.155725
hours-per-week                    0.227597         0.125499
delta-capital                     0.090984         0.071764
```

```
>50K                                0.447275         0.156016
marital-status-ratio                1.000000         0.126962
workclass-ratio                     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.

[102]:
```python
df_main = df_main.drop('relationship-ratio', axis=1)
df_main
```

[102]:
```
            age  hours-per-week  delta-capital  >50K  marital-status-ratio  \
0      0.037252       -0.074059       0.635266     0              0.049003
1      0.869469       -2.327318      -0.194218     0              0.816552
2     -0.038404       -0.074059      -0.194218     0              0.112549
3      1.096438       -0.074059      -0.194218     0              0.816552
4     -0.794965       -0.074059      -0.194218     0              0.816552
…           …             …             …    …                   …
48836 -0.416684       -0.074059      -0.194218     0              0.049003
48837  0.037252       -0.407875      -0.194218     0              0.112549
48839 -0.038404        0.760481      -0.194218     0              0.816552
48840  0.415533       -0.074059       1.887121     0              0.112549
48841 -0.265372        1.595021      -0.194218     1              0.816552

       workclass-ratio
0             0.361851
1             0.372305
2             0.273680
3             0.273680
4             0.273680
…                  …
48836         0.273680
48837         0.273680
48839         0.273680
48840         0.273680
48841         1.164850

[44993 rows x 6 columns]
```

[103]:
```python
# 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)
```

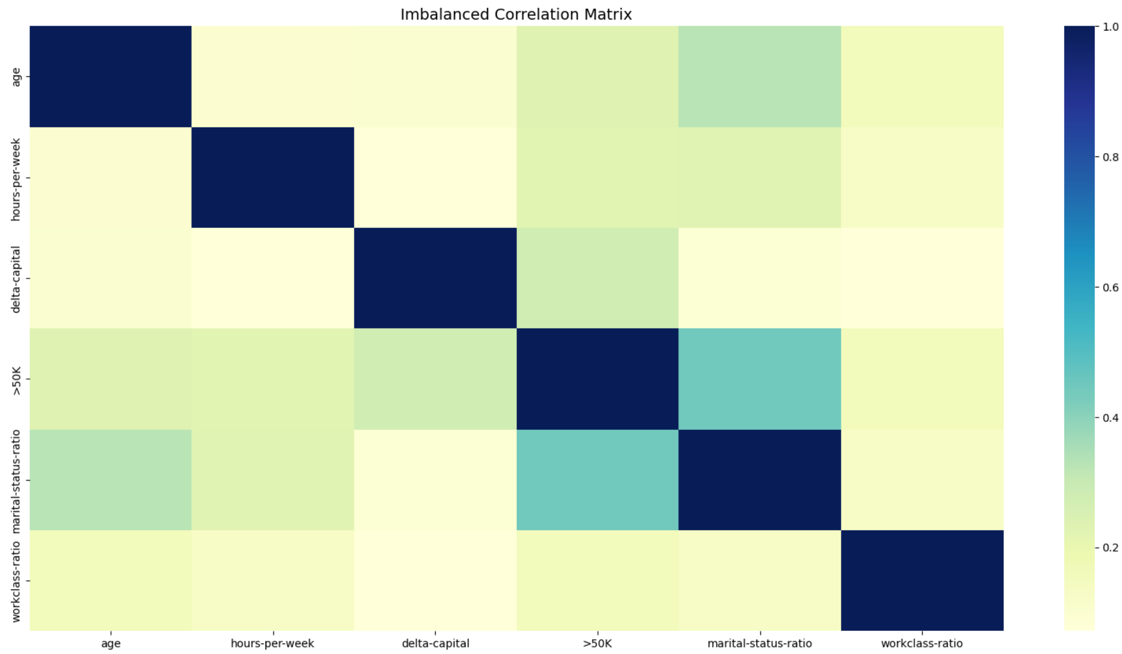
```
               feature       VIF
0                  age  1.077494
1       hours-per-week  1.035994
2        delta-capital  1.016057
3  marital-status-ratio  2.128422
4      workclass-ratio  2.005329
```

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 Over-sampling Technique

Our dataset is imbalanced in nature with minority class being 25%. Here we can use SMOTE to over-sample the minority class and feed into 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.

[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()
```

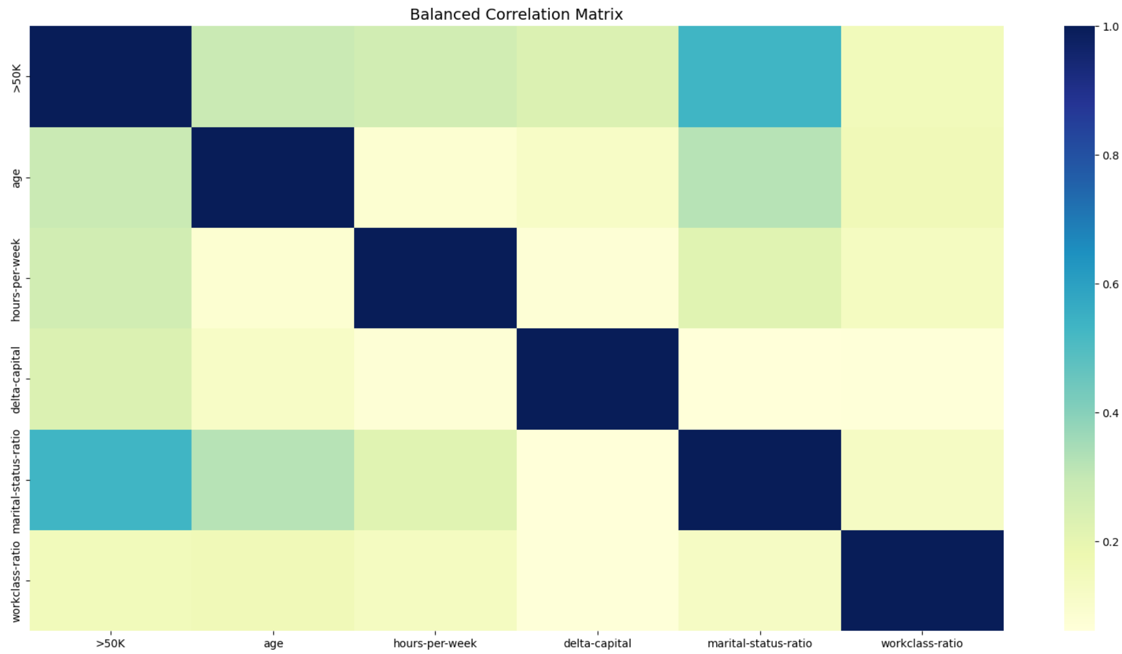



```
[105]: # over-sampling
from imblearn.over_sampling import SMOTE
sm = SMOTE(sampling_strategy='minority', random_state=7)
oversampled_trainX, oversampled_trainY = sm.fit_resample(df_main.drop('>50K',␣
  ↪axis=1), df_main['>50K'])
oversampled_train = pd.concat([pd.DataFrame(oversampled_trainY), pd.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

```
[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 this SMOTE technique each time after fitting a model to understand the improvement.

```
[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.

[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
```

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

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

[109]: 0.24368947451976505

[110]:
```
ytest.sum()/ytest.count()
```

[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 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

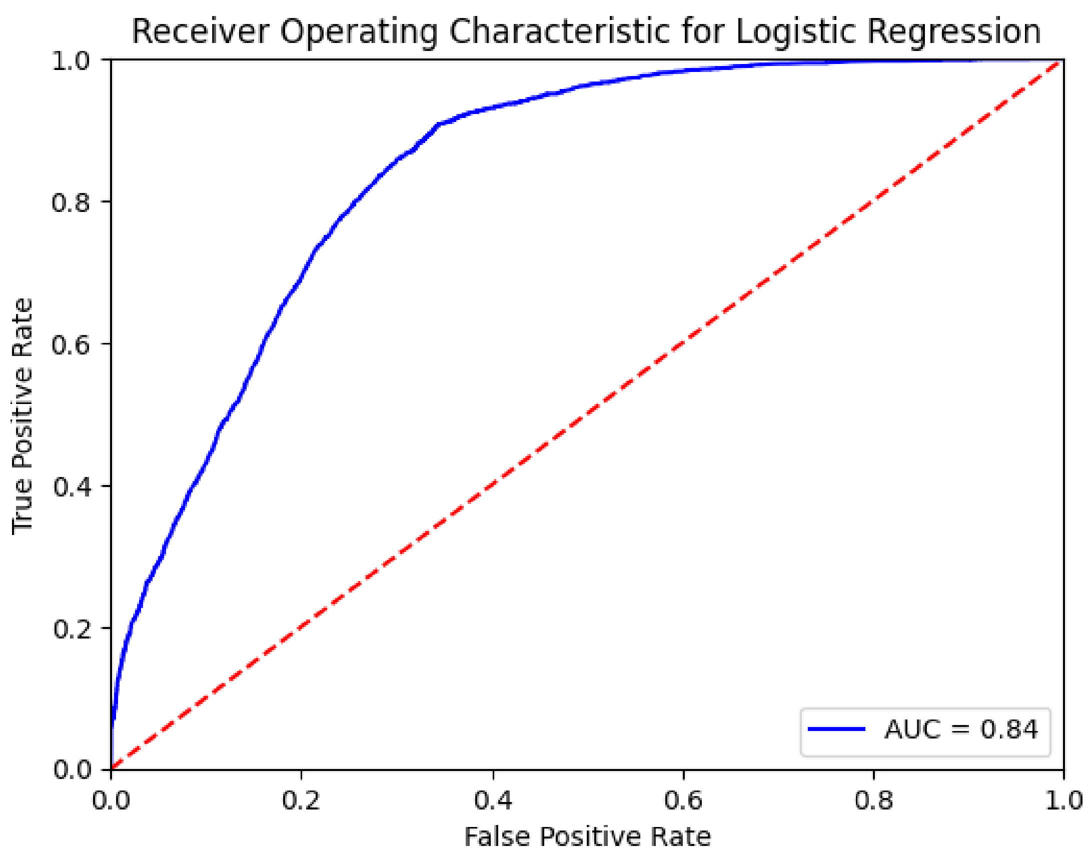
[112]:
```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

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 data
print('Logistic Regression Train accuracy %s' % logreg.score(xtrain, ytrain))␣
 ↪#Train accuracy
print('Logistic Regression Test accuracy %s' % accuracy_score(y_pred_logreg,␣
 ↪ytest)) #Test accuracy
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.

[113]:
```
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

[114]:
```
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()
```

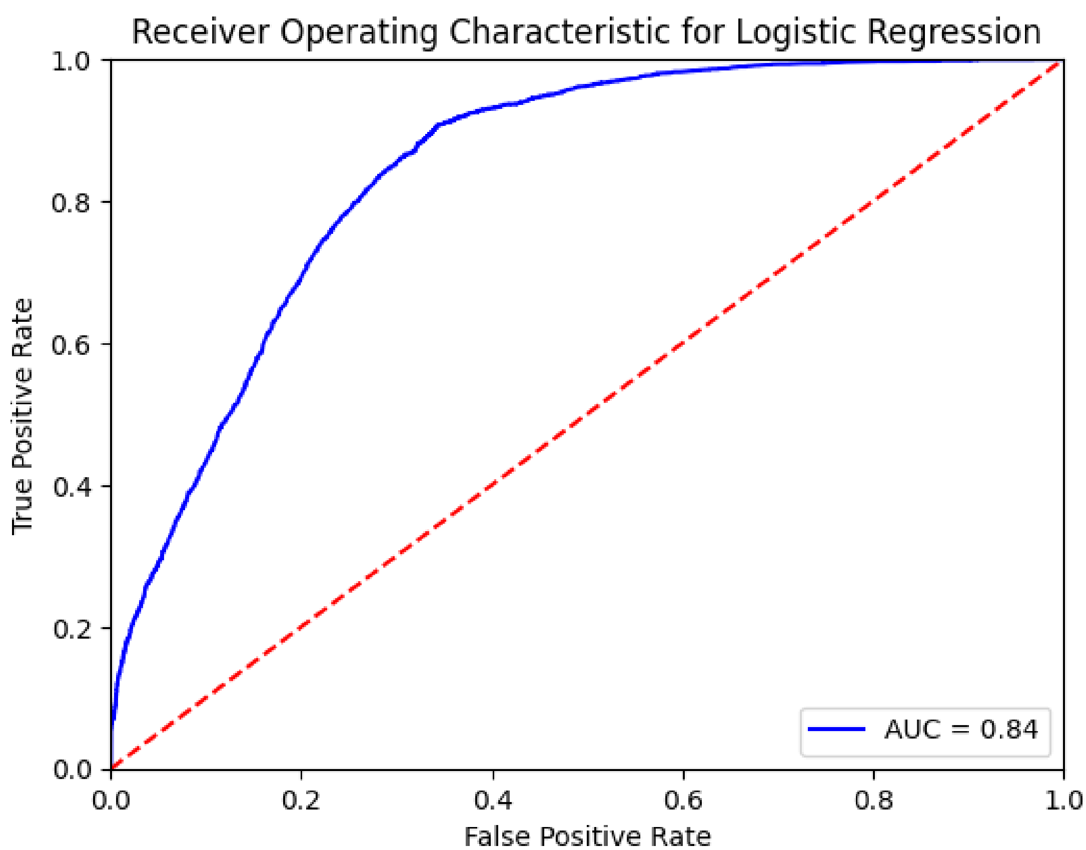
[114]:
```
0.5
```

[115]:
```
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 taking place
y_pred_logreg = logreg.predict(xtest) #Making predictions to test the model on␣
 ↪test data
print('Logistic Regression Train accuracy %s' % logreg.
 ↪score(oversampled_xtrain, oversampled_ytrain)) #Train accuracy
print('Logistic Regression Test accuracy %s' % accuracy_score(y_pred_logreg,␣
 ↪ytest)) #Test accuracy
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.

[116]:
```
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

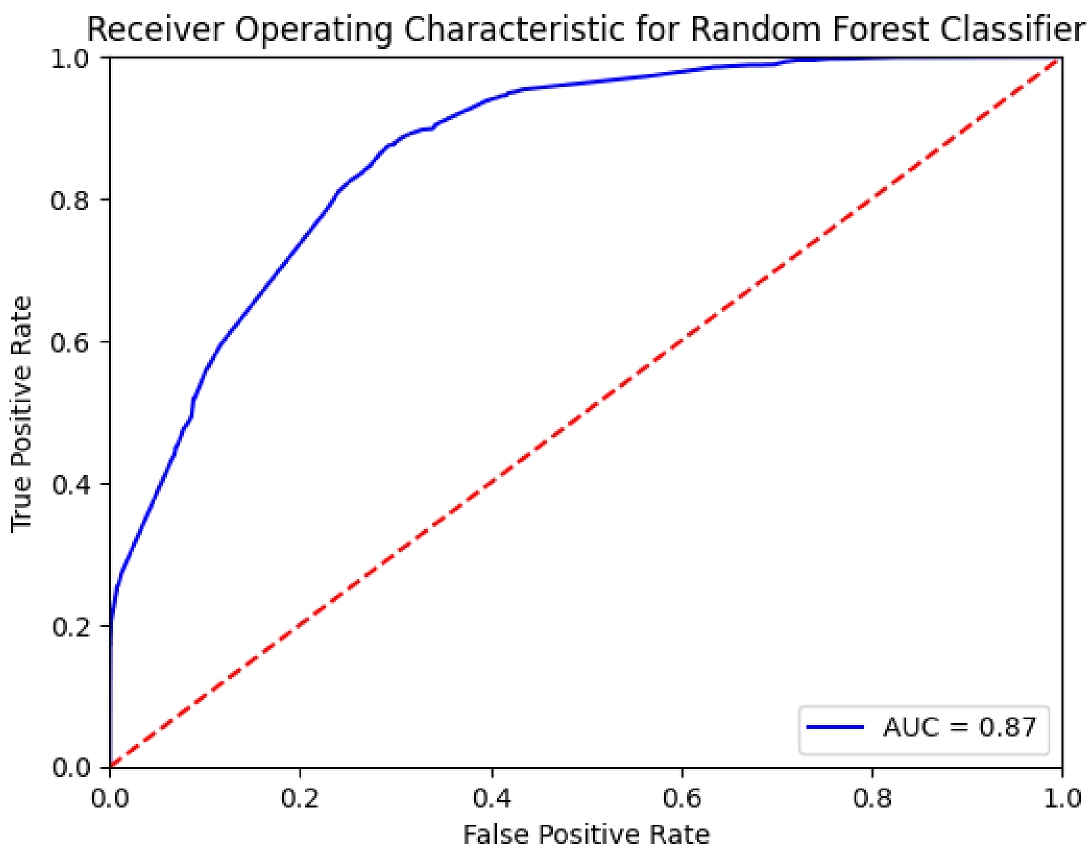
[117]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

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 accuracy
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%.

[118]:
```
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

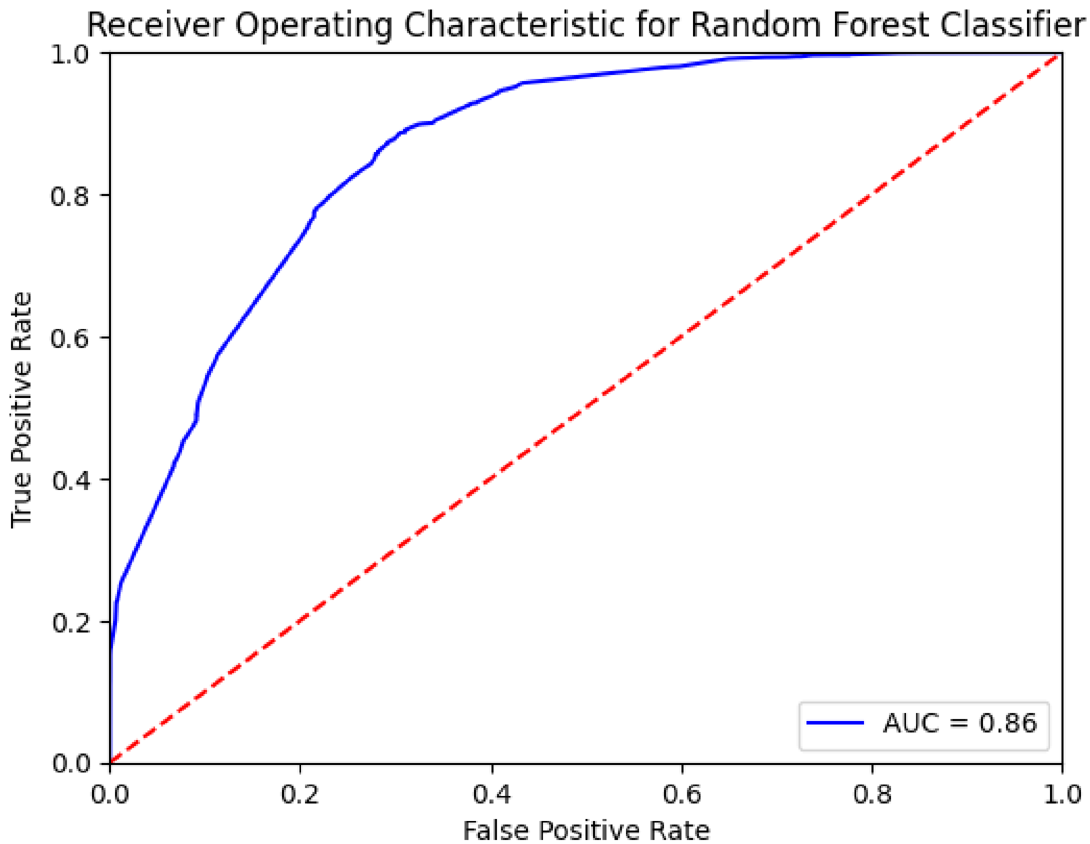
[119]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

clf = RandomForestClassifier(max_depth=2, random_state=0)
clf.fit(oversampled_xtrain, oversampled_ytrain) #This is where the training is␣
 ↪taking place
```

```
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_ytrain)) #Train accuracy
print('Random Forest Test accuracy %s' % accuracy_score(y_pred_clf, ytest))␣
↪#Test accuracy
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.

[120]:
```
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.

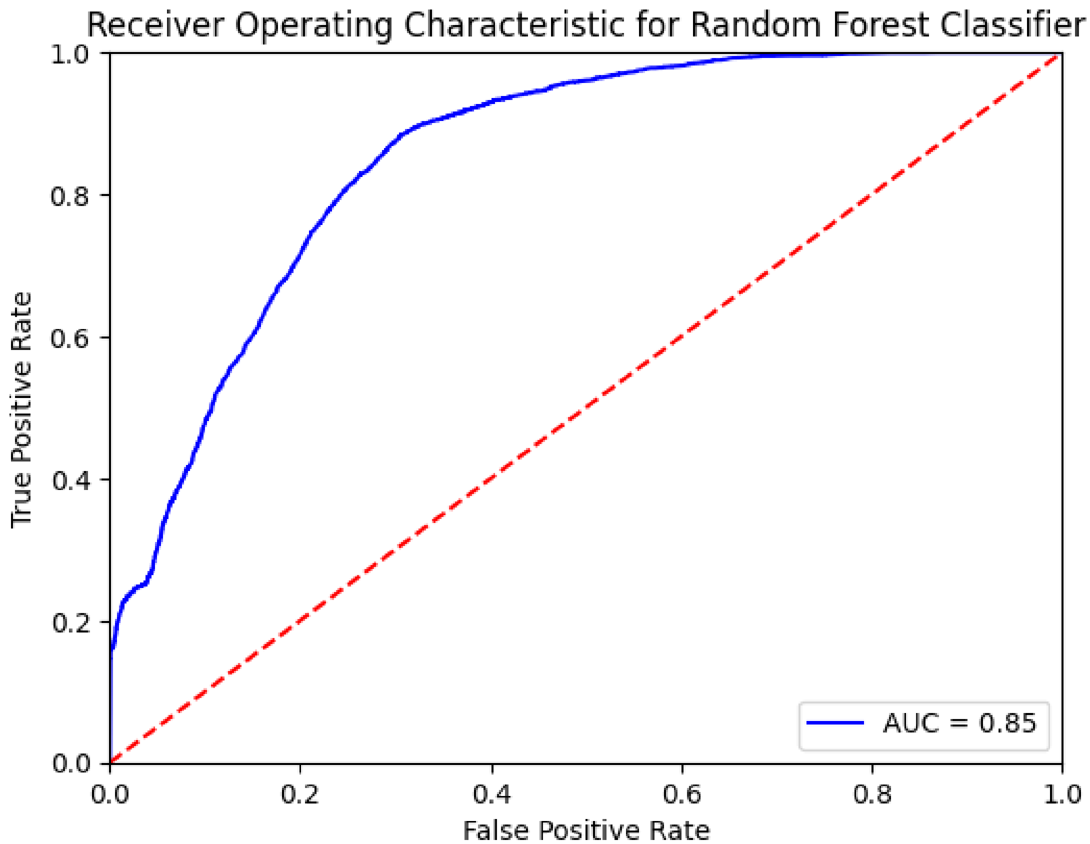
5.7.5 Gaussian Naive Bayes

[122]:
```
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 accuracy
print('Gaussian Naive Bayes Test accuracy %s' % accuracy_score(y_pred_gnb,␣
 ↪ytest)) #Test accuracy
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
Random Forest 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.

[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 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 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

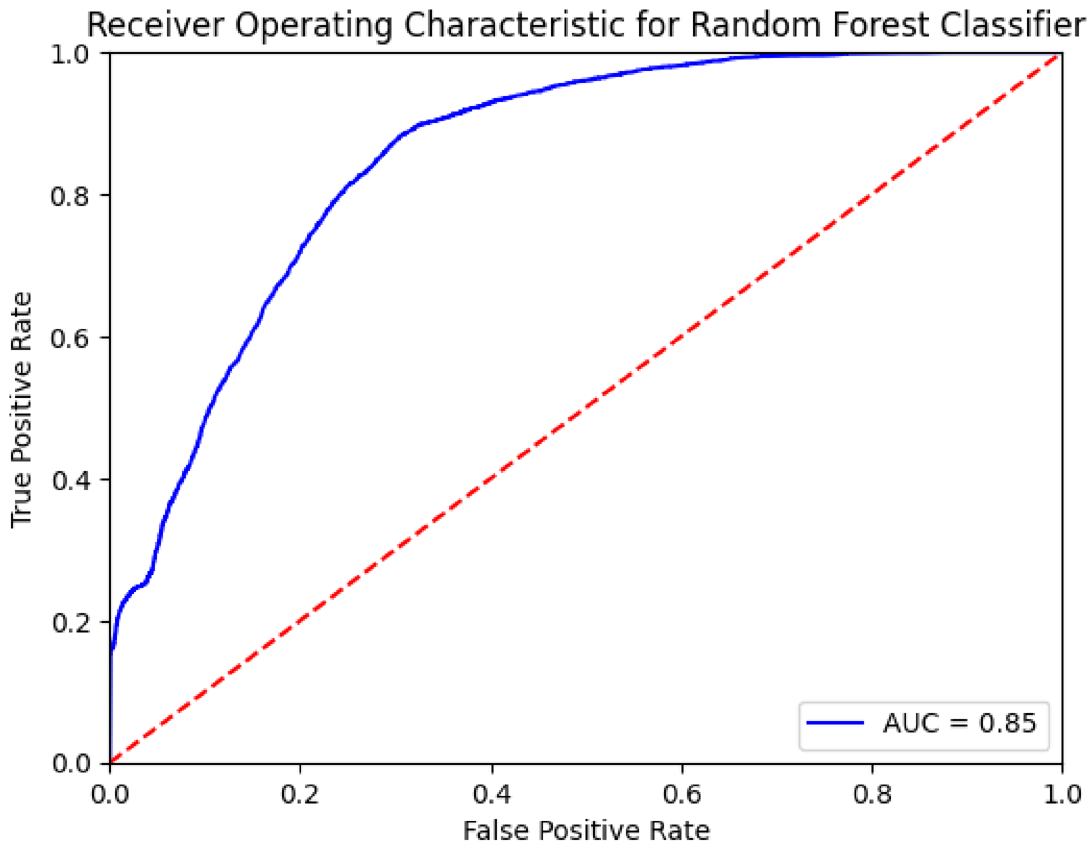
[126]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

gnb = GaussianNB()
gnb.fit(oversampled_xtrain, oversampled_ytrain) #This is where the training is␣
    ↪taking 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(oversampled_xtrain,␣
    ↪oversampled_ytrain)) #Train accuracy
print('Gaussian Naive Bayes Test accuracy %s' % accuracy_score(y_pred_gnb,␣
    ↪ytest)) #Test accuracy
print(confusion_matrix(ytest, y_pred_gnb)) #Confusion matrix
```

```python
print(classification_report(ytest, y_pred_gnb)) #Classification Report
```

```
Gaussian Naive Bayes Train accuracy 0.6751889168765743
Random Forest 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.

[125]:
```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 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()
```



SMOTE did not bring any improvement to the 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

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 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 logistic Regression 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