# !pip install nbconvert

Requirement already satisfied: nbconvert in c:\users\shobhandeb\appdata\local\programs\py thon\python310\lib\site-packages (6.5.0)

Requirement already satisfied: beautifulsoup4 in c:\users\shobhandeb\appdata\local\programs\python310\lib\site-packages (from nbconvert) (4.9.1)

Requirement already satisfied: traitlets>=5.0 in c:\users\shobhandeb\appdata\local\progra ms\python\python310\lib\site-packages (from nbconvert) (5.3.0)

Requirement already satisfied: jupyterlab-pygments in c:\users\shobhandeb\appdata\local\p rograms\python\python310\lib\site-packages (from nbconvert) (0.2.2)

Requirement already satisfied: jinja2>=3.0 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (3.0.3)

Requirement already satisfied: tinycss2 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (1.1.1)

Requirement already satisfied: packaging in c:\users\shobhandeb\appdata\local\programs\py thon\python310\lib\site-packages (from nbconvert) (21.3)

Requirement already satisfied: entrypoints>=0.2.2 in c:\users\shobhandeb\appdata\local\pr ograms\python\python310\lib\site-packages (from nbconvert) (0.4)

Requirement already satisfied: pygments>=2.4.1 in c:\users\shobhandeb\appdata\roaming\pyt hon\python310\site-packages (from nbconvert) (2.12.0)

Requirement already satisfied: MarkupSafe>=2.0 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (2.1.1)

Requirement already satisfied: nbclient>=0.5.0 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (0.6.4)

Requirement already satisfied: nbformat >= 5.1 in c:\users\shobhandeb\appdata\local\program s\python\python310\lib\site-packages (from nbconvert) (5.4.0)

Requirement already satisfied: mistune <2, >=0.8.1 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (0.8.4)

Requirement already satisfied: jupyter-core>=4.7 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (4.10.0)

Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (1.5.0)

Requirement already satisfied: bleach in c:\users\shobhandeb\appdata\local\programs\python  $310\lib\site$ -packages (from nbconvert) (5.0.0)

Requirement already satisfied: defusedxml in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbconvert) (0.7.1)

Requirement already satisfied: pywin32>=1.0 in c:\users\shobhandeb\appdata\local\programs \python\python310\lib\site-packages (from jupyter-core>=4.7->nbconvert) (304)

Requirement already satisfied: nest-asyncio in c:\users\shobhandeb\appdata\local\programs \python\python310\lib\site-packages (from nbclient>=0.5.0->nbconvert) (1.5.5)

Requirement already satisfied: jupyter-client>=6.1.5 in c:\users\shobhandeb\appdata\local \programs\python\python310\lib\site-packages (from nbclient>=0.5.0->nbconvert) (7.3.4)

Requirement already satisfied: jsonschema>=2.6 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbformat>=5.1->nbconvert) (4.6.0)

Requirement already satisfied: fastjsonschema in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from nbformat>=5.1->nbconvert) (2.15.3)

Requirement already satisfied: soupsieve>1.2 in c:\users\shobhandeb\appdata\local\program s\python\python310\lib\site-packages (from beautifulsoup4->nbconvert) (2.0.1)

Requirement already satisfied: webencodings in c:\users\shobhandeb\appdata\local\programs \python\python310\lib\site-packages (from bleach->nbconvert) (0.5.1)

Requirement already satisfied: six >= 1.9.0 in c:\users\shobhandeb\appdata\local\programs\p ython\python310\lib\site-packages (from bleach->nbconvert) (1.15.0)

Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\shobhandeb\appdata\lo cal\programs\python\python310\lib\site-packages (from packaging->nbconvert) (3.0.8)

Requirement already satisfied: attrs>=17.4.0 in c:\users\shobhandeb\appdata\local\program  $s\python\python310\lib\site-packages$  (from jsonschema>=2.6->nbformat>=5.1->nbconvert) (21 .4.0)

Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in c:\users\shobhandeb\appdata\local\programs\python\python310\lib\site-packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert) (0.18.1)

Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\shobhandeb\appdata\loca l\programs\python\python310\lib\site-packages (from jupyter-client>=6.1.5->nbclient>=0.5. 0->nbconvert) (2.8.2)

Requirement already satisfied: tornado>=6.0 in c:\users\shobhandeb\appdata\local\programs \python\python310\lib\site-packages (from jupyter-client>=6.1.5->nbclient>=0.5.0->nbconve rt) (6.1)

Requirement already satisfied:  $pyzmq \ge 23.0$  in c:\users\shobhandeb\appdata\local\programs\

python\python310\lib\site-packages (from jupyter-client>=6.1.5->nbclient>=0.5.0->nbconvert) (23.2.0)

WARNING: There was an error checking the latest version of pip.

#### Description:

In this notebook, we are going to predict whether a person's income is above 50k or below 50k using various features like age, education, and occupation.

The dataset we are going to use is the Adult census income dataset from UCI which contains about 32561 rows and 15 features that can be downloaded here: https://archive.ics.uci.edu/ml/datasets/Census+Income

The dataset contains the labels which we have to predict and the labels are discrete and binary. So the problem we have is a Supervised Classification type.

#### Data Set Information:

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0))

Prediction task is to determine whether a person makes over 50K a year.

#### Attribute Information:

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.

```
In [2]:
```

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

```
data = pd.read_csv('adult.csv', sep=',')
```

# In [4]:

data.head()

Out[4]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	Ca
0	90	?	77053	HS-grad	9	Widowed	?	Not-in- family	White	Female	0	
1	82	Private	132870	HS-grad	9	Widowed	Exec- managerial	Not-in- family	White	Female	0	
2	66	?	186061	Some- college	10	Widowed	?	Unmarried	Black	Female	0	
3	54	Private	140359	7th-8th	4	Divorced	Machine- op-inspct	Unmarried	White	Female	0	
4	41	Private	264663	Some- college	10	Separated	Prof- specialty	Own-child	White	Female	0	
4												F

# In [5]:

data.tail()

# Out[5]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gaiı
32556	22	Private	310152	Some- college	10	Never- married	Protective- serv	Not-in- family	White	Male	
32557	27	Private	257302	Assoc- acdm	12	Married-civ- spouse	Tech- support	Wife	White	Female	(
32558	40	Private	154374	HS-grad	9	Married-civ- spouse	Machine- op-inspct	Husband	White	Male	
32559	58	Private	151910	HS-grad	9	Widowed	Adm- clerical	Unmarried	White	Female	(
32560	22	Private	201490	HS-grad	9	Never- married	Adm- clerical	Own-child	White	Male	
4											Þ

# In [6]:

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560

Data columns (total 15 columns):

#	Column	Non-Null Count	Dtype
0	age	32561 non-null	int64
1	workclass	32561 non-null	object
2	fnlwgt	32561 non-null	int64
3	education	32561 non-null	object
4	education.num	32561 non-null	int64
5	marital.status	32561 non-null	object
6	occupation	32561 non-null	object
7	relationship	32561 non-null	object
8	race	32561 non-null	object
9	sex	32561 non-null	object
10	capital.gain	32561 non-null	int64
11	capital.loss	32561 non-null	int64
12	hours.per.week	32561 non-null	int64
13	native.country	32561 non-null	object
14	income	32561 non-null	object

dtypes: int64(6), object(9)
memory usage: 3.7+ MB

# In [7]:

data.describe(include='all')

# Out[7]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	
count	32561.000000	32561	3.256100e+04	32561	32561.000000	32561	32561	32561	32561	32
unique	NaN	9	NaN	16	NaN	7	15	6	5	
top	NaN	Private	NaN	HS-grad	NaN	Married-civ- spouse	Prof- specialty	Husband	White	M
freq	NaN	22696	NaN	10501	NaN	14976	4140	13193	27816	21
mean	38.581647	NaN	1.897784e+05	NaN	10.080679	NaN	NaN	NaN	NaN	N
min	17.000000	NaN	1.228500e+04	NaN	1.000000	NaN	NaN	NaN	NaN	N
25%	28.000000	NaN	1.178270e+05	NaN	9.000000	NaN	NaN	NaN	NaN	N
50%	37.000000	NaN	1.783560e+05	NaN	10.000000	NaN	NaN	NaN	NaN	N
75%	48.000000	NaN	2.370510e+05	NaN	12.000000	NaN	NaN	NaN	NaN	N
max	90.000000	NaN	1.484705e+06	NaN	16.000000	NaN	NaN	NaN	NaN	N
4						]				Þ

# In [8]:

data.describe().T

# Out[8]:

	count	mean	std	min	25%	50%	75%	max
age	32561.0	38.581647	13.640433	17.0	28.0	37.0	48.0	90.0
fnlwgt	32561.0	189778.366512	105549.977697	12285.0	117827.0	178356.0	237051.0	1484705.0
education.num	32561.0	10.080679	2.572720	1.0	9.0	10.0	12.0	16.0
capital.gain	32561.0	1077.648844	7385.292085	0.0	0.0	0.0	0.0	99999.0
capital.loss	32561.0	87.303830	402.960219	0.0	0.0	0.0	0.0	4356.0
hours.per.week	32561.0	40.437456	12.347429	1.0	40.0	40.0	45.0	99.0

# In [9]:

data.isnull().sum()

# Out[9]:

age	0
workclass	0
fnlwgt	0
education	0
education.num	0
marital.status	0
occupation	0
relationship	0
race	0
sex	0
capital.gain	0
capital.loss	0
hours.per.week	0
native.country	0
income	0
dtype: int64	

```
In [10]:
data.isna().sum()
Out[10]:
                 0
age
workclass
                 0
                 0
fnlwgt
education
                 Ω
                 0
education.num
marital.status 0
occupation
                 0
                 0
relationship
race
sex
                 0
capital.gain
capital.loss
                 0
                 0
hours.per.week
                 0
native.country
                 0
income
dtype: int64
In [11]:
# Check for '?' in dataset
round((data.isin(['?']).sum() / data.shape[0])
     * 100, 2).astype(str) + ' %'
Out[11]:
                 0.0 %
age
                 5.64 %
workclass
fnlwgt
                  0.0 %
education
                 0.0 %
education.num
                 0.0 %
marital.status
                  0.0 %
                5.66 %
occupation
relationship
                 0.0 %
                  0.0 %
race
                 0.0 %
sex
capital.gain
                 0.0 %
capital.loss
                 0.0 %
hours.per.week
                 0.0 %
native.country 1.79 %
                 0.0 %
income
dtype: object
In [12]:
# Checking the counts of label categories
income = data['income'].value_counts(normalize=True)
round(income * 100, 2).astype('str') + '%'
Out[12]:
<=50K
       75.92 %
       24.08 %
Name: income, dtype: object
```

#### Observed:

The dataset doesn't have any null values, but it contains missing values in the form of '?' which needs to be preprocessed.

The dataset is unbalanced, as the dependent feature 'income' contains 75.92% values have income less than 50k and 24.08% values have income more than 50k.

```
In [13]:
```

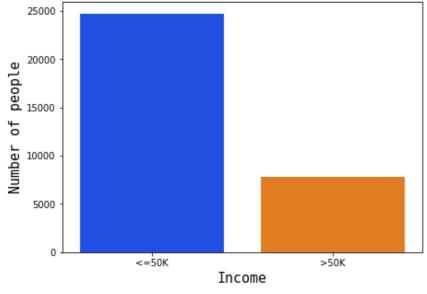
data shane

```
Out[13]:
(32561, 15)
```

```
In [14]:
```

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(

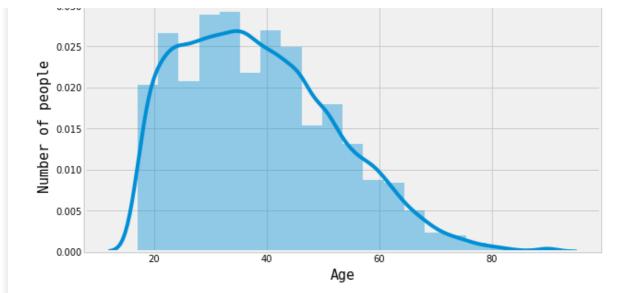




#### In [15]:

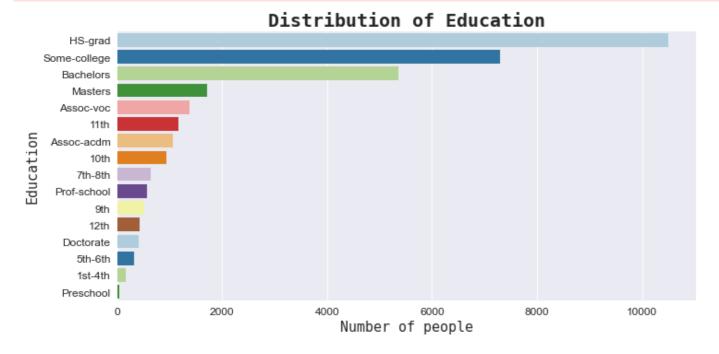
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\dis
tributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be remove
d in a future version. Please adapt your code to use either `displot` (a figure-level fun
ction with similar flexibility) or `histplot` (an axes-level function for histograms).
 warnings.warn(msg, FutureWarning)

# Distribution of Age



#### In [16]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(

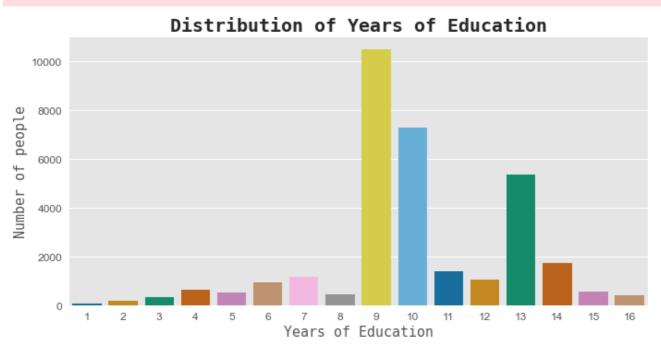


# In [17]:

```
# Creating a barplot for 'Years of Education'
education_num = data['education.num'].value_counts()

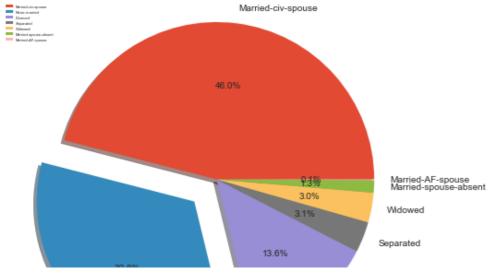
plt.style.use('ggplot')
plt.figure(figsize=(10, 5))
sns.barplot(education_num.index, education_num.values, palette='colorblind')
```

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(



# In [18]:

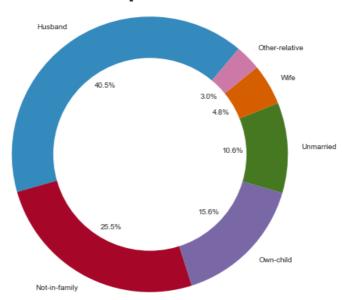






#### In [19]:

# Relationship distribution



#### In [20]:

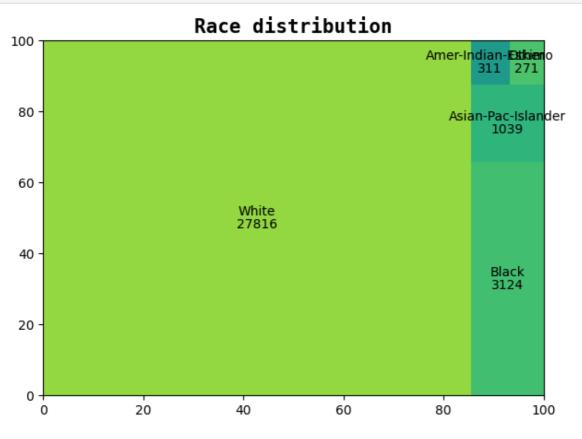
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v ersion 0.12, the only valid positional argument will be `data`, and passing other argumen ts without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
```

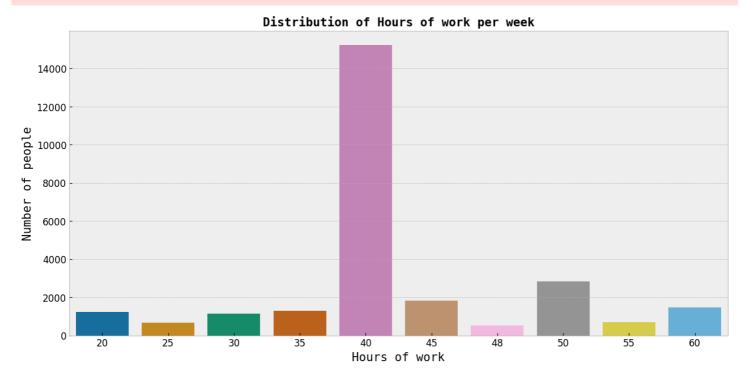
# Place of Sex

Sex

# In [21]:



C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(

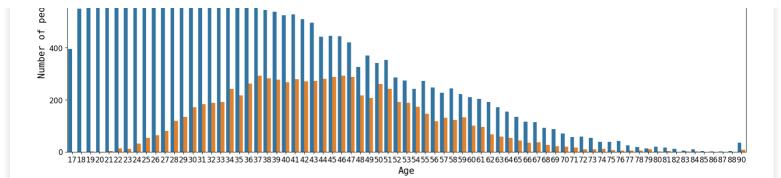


# In [23]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From vers
ion 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
warnings.warn(

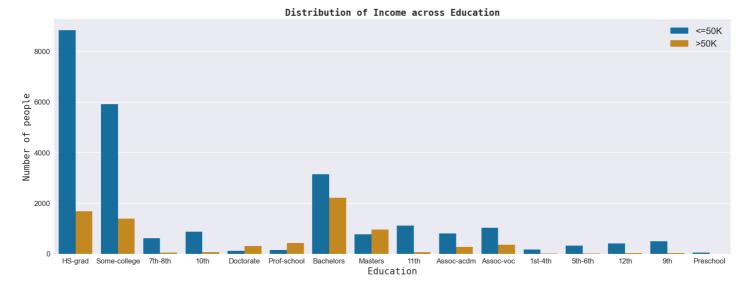
Distribution of Income across Age





#### In [24]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From vers
ion 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
warnings.warn(

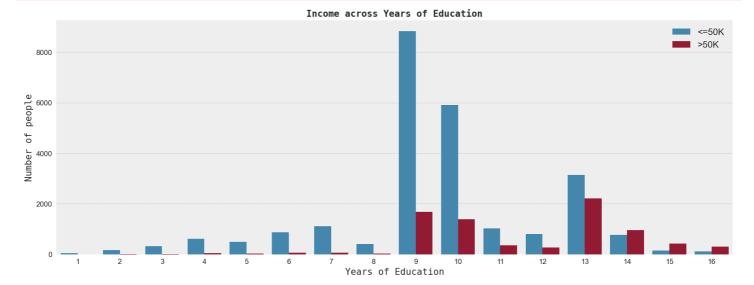


# In [25]:

```
# Creating a countplot of income across years of education
plt.style.use('bmh')
plt.figure(figsize=(20, 7))
sns.countplot(data['education.num'],
              hue=data['income'])
plt.title('Income across Years of Education', fontdict={
          'fontname': 'Monospace', 'fontsize': 15, 'fontweight': 'bold'})
plt.xlabel('Years of Education', fontdict={
           'fontname': 'Monospace', 'fontsize': 15})
plt.ylabel('Number of people', fontdict={
           'fontname': 'Monospace', 'fontsize': 15})
plt.tick params(labelsize=12)
plt.legend(loc=1, prop={'size': 15})
plt.savefig('bi2.png')
plt.show()
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\ de
annatana m. 36. ButunaManmina. Basa tha fallanina maniahla ao a lamand ana.
```

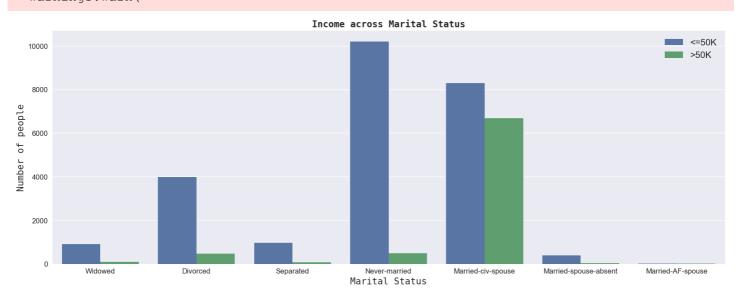
corators.py:30: ruturewarning: rass the lollowing variable as a keyword arg: x. From vers ion 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(



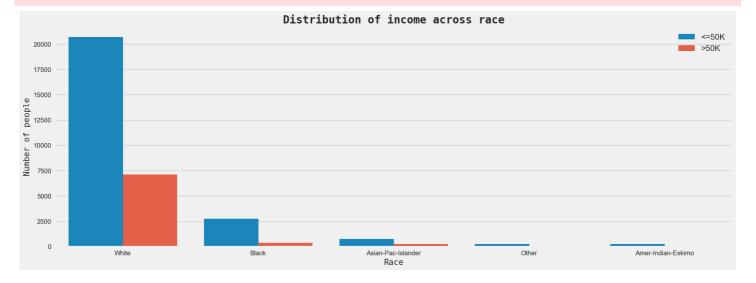
#### In [26]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From vers
ion 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(



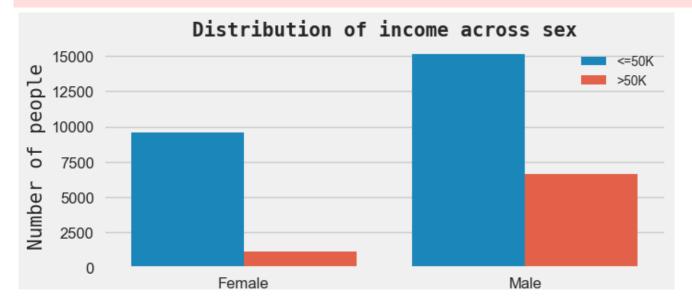
#### In [27]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From vers
ion 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
warnings.warn(



## In [28]:

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\\_de
corators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From vers
ion 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(



#### In [29]:

data.corr()

# Out[29]:

		age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week
	age	1.000000	-0.076646	0.036527	0.077674	0.057775	0.068756
	fnlwgt	-0.076646	1.000000	-0.043195	0.000432	-0.010252	-0.018768
	education.num	0.036527	-0.043195	1.000000	0.122630	0.079923	0.148123
	capital.gain	0.077674	0.000432	0.122630	1.000000	-0.031615	0.078409
	capital.loss	0.057775	-0.010252	0.079923	-0.031615	1.000000	0.054256
ı	hours.per.week	0.068756	-0.018768	0.148123	0.078409	0.054256	1.000000

#### In [30]:



# Observations:

1.Most number of people are young, white, male, high school graduates with 9 to 10 years of education and work 40 hours per week.

1. Heatmap shows that the dependent feature 'income' is highly correlated with age, numbers of years of education, capital gain and number of hours per week.

```
In [31]:
```

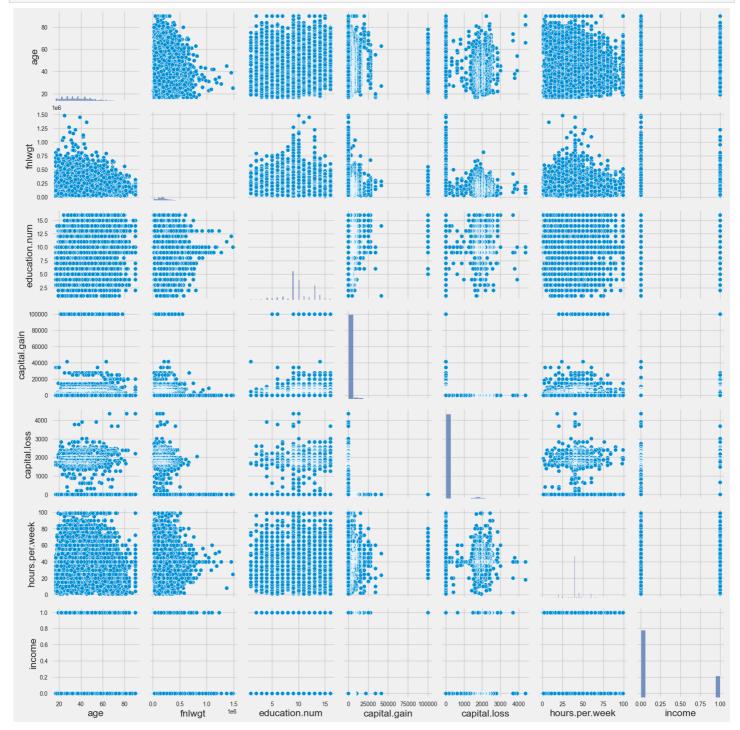
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

#### In [32]:

```
data['income'] = le.fit_transform(data['income'])
```

## In [33]:

```
# Creating a pairplot of dataset
sns.pairplot(data)
plt.savefig('multi1.png')
plt.show()
```



#### In [34]:

plt.figure(figsize=(20,15))



# In [35]:

```
data = data.replace('?', np.nan)
```

# In [36]:

```
# Checking null values
round((data.isnull().sum() / data.shape[0]) * 100, 2).astype(str) + ' %'
```

#### Out[36]:

```
0.0 %
age
workclass
                   5.64 %
                    0.0 %
fnlwgt
education
                    0.0 %
                   0.0 %
education.num
                   0.0 %
marital.status
occupation
                   5.66 %
relationship
                   0.0 %
race
                    0.0 %
sex
                    0.0 %
capital.gain
                    0.0 %
capital.loss
                    0.0 %
hours.per.week
                   0.0 %
                   1.79 %
native.country
                   0.0 %
income
dtype: object
```

# In [37]:

```
columns_with_nan = ['workclass', 'occupation', 'native.country']
In [38]:
for col in columns with nan:
    data[col].fillna(data[col].mode()[0], inplace=True)
In [39]:
from sklearn.preprocessing import LabelEncoder
for col in data.columns:
    if data[col].dtypes == 'object':
        encoder = LabelEncoder()
        data[col] = encoder.fit_transform(data[col])
In [40]:
corr data = data.corr('spearman').stack().reset index(name='corr')
corr data.loc[corr data['corr'] == 1, 'corr'] = 0 # Remove diagonal
# Use abs so that we can visualize the impact of negative correaltion
corr data['abs'] = corr data['corr'].abs()
corr data.sort values('abs', ascending=False).head(n=5)
Out[40]:
         level_0
                     level_1
                               corr
142
                 relationship -0.617570 0.617570
                       sex -0.617570 0.617570
114
      relationship
  5
                marital.status -0.374850 0.374850
            age
 75 marital.status
                       age -0.374850 0.374850
217
         income
                 relationship -0.329913 0.329913
In [41]:
import altair as alt
alt.Chart(corr_data).mark_circle().encode(
    x='level 0',
    y='level 1',
    size='abs',
    color=alt.Color('corr',
                     scale=alt.Scale(scheme='bluegreen',
                                       domain=(-1, 1))).properties(
    height=250,
    width=500)
Out[41]:
In [42]:
X = data.drop('income', axis=1)
Y = data['income']
In [43]:
\# X = data.iloc[:,:-1].values
# Y = data.iloc[:,-1].values
In [44]:
Χ
Out[44]:
                    fnlwgt education education.num marital.status occupation relationship
                                                                              race
                                                                                  sex capital.gain
      age
    0
       90
                    77053
                               11
                                                                  9
                                                                                    0
```

```
1 age workclass 1978 education education marital status occupation relationship race sex capital gain ca
                                 15
                                              10
                                                           6
       66
                  3 186061
                                                                     9
                                                                                     2
                                                                                         0
                                                                                                    0
       54
                  3 140359
                                  5
                                                           0
                                                                     6
                                                                                     4
                                                                                         0
                                                                                                    0
    3
                                               4
                                                                                4
                  3 264663
                                                                                     4
                                                                                         0
       41
                                 15
                                              10
                                                                                ...
                                                                                     ...
32556
       22
                  3 310152
                                 15
                                              10
                                                           4
                                                                     10
                                                                                1
                                                                                     4
                                                                                         1
                                                                                                    0
32557
       27
                  3 257302
                                  7
                                              12
                                                           2
                                                                     12
                                                                                5
                                                                                         0
                                                                                                    0
                  3 154374
                                                           2
                                                                                0
32558
       40
                                 11
                                               9
                                                                     6
                                                                                                    0
32559
       58
                  3 151910
                                 11
                                               9
                                                           6
                                                                     0
                                                                                4
                                                                                     4
                                                                                         0
                                                                     0
                                                                                3
                                                                                                    0
32560
       22
                  3 201490
                                 11
                                               9
                                                                                     4
                                                                                         1
In [45]:
Out[45]:
0
          0
1
          0
2
          0
3
          0
4
          0
32556
32557
          0
32558
          1
32559
          0
32560
          0
Name: income, Length: 32561, dtype: int32
In [46]:
from sklearn.ensemble import ExtraTreesClassifier
selector = ExtraTreesClassifier(random_state=42)
In [47]:
selector.fit(X, Y)
Out[47]:
          ExtraTreesClassifier
ExtraTreesClassifier(random state=42)
In [48]:
feature imp = selector.feature importances
In [49]:
for index, val in enumerate(feature imp):
    print(index, round((val * 100), 2))
0 15.59
1 4.13
2 16.71
3 3.87
4 8.66
5 8.04
6 7.27
7 8.62
8 1.47
```

9 2.84 10 8.83

```
In [50]:
X.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
                    Non-Null Count Dtype
 # Column
 0 age
                    32561 non-null int64
 1 workclass
                    32561 non-null int32
 2 fnlwgt
                     32561 non-null int64
   education
                     32561 non-null int32
 3
   education.num 32561 non-null int64
   marital.status 32561 non-null int32
 5
    occupation
                     32561 non-null
    relationship
 7
                     32561 non-null
                                     int32
 8
    race
                     32561 non-null int32
 9
    sex
                     32561 non-null int32
10 capital.gain 32561 non-null int64
11 capital.loss 32561 non-null int64
 12 hours.per.week 32561 non-null int64
13 native.country 32561 non-null int32
dtypes: int32(8), int64(6)
memory usage: 2.5 MB
In [51]:
X.columns
Out[51]:
Index(['age', 'workclass', 'fnlwgt', 'education', 'education.num',
       'marital.status', 'occupation', 'relationship', 'race', 'sex',
       'capital.gain', 'capital.loss', 'hours.per.week', 'native.country'],
      dtype='object')
In [52]:
X = X.drop(['workclass', 'education', 'race', 'sex',
            'capital.loss', 'native.country'], axis=1)
In [53]:
from sklearn.model selection import train test split
X train, X test, y train, y test = train test split(X, Y, test size = 0.3, random state
= 42)
In [54]:
X train
Out[54]:
```

11 2.81 12 9.64 13 1.53

	age	fnlwgt	education.num	marital.status	occupation	relationship	capital.gain	hours.per.week
19749	58	290661	9	2	2	0	0	40
1216	62	109463	10	5	11	4	0	33
27962	33	137088	13	2	6	0	0	40
23077	24	117767	12	4	11	3	0	20
10180	67	431426	9	2	0	5	0	2
29802	25	410240	9	4	2	3	0	40

5390	agę	1fabbanet	education.num	marital.statu <u>ş</u>	occupation	relationship	capital.gain	hours.per.weat
860	55	238192	9	2	12	0	0	40
15795	41	154076	10	2	0	0	0	50
23654	22	162667	9	4	5	3	0	50

#### In [55]:

from sklearn.linear\_model import LogisticRegression
from sklearn.metrics import accuracy\_score

#### In [56]:

```
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\lin ear\_model\\_logistic.py:444: ConvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:
 https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
 https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
 n\_iter\_i = \_check\_optimize\_result(

#### Out[56]:

▼ LogisticRegression LogisticRegression()

#### In [57]:

```
y_pred_logreg = log_reg.predict(X_test)
```

# In [58]:

accuracy\_score(y\_test, y\_pred\_logreg)

#### Out[58]:

0.7935305558399017

# In [59]:

from sklearn.metrics import classification\_report
print(classification\_report(y\_test, y\_pred\_logreg))

	precision	recall	f1-score	support
0	0.80 0.75	0.98 0.21	0.88 0.32	7429 2340
accuracy macro avg	0.77	0.59	0.79	9769 9769
weighted avg	0.79	0.79	0.75	9769

#### In [60]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
```

#### Out[60]:

```
DecisionTreeClassifier
DecisionTreeClassifier()
```

```
In [61]:
y pred dt = dt.predict(X test)
In [62]:
accuracy score(y test, y pred dt)
Out[62]:
0.8041764766096837
In [63]:
from sklearn.metrics import classification report
print(classification_report(y_test, y_pred_dt))
              precision
                           recall f1-score
                                               support
           0
                   0.87
                             0.87
                                       0.87
                                                  7429
                   0.59
                             0.60
                                       0.59
                                                  2340
                                       0.80
                                                 9769
   accuracy
                             0.73
                   0.73
                                       0.73
                                                  9769
   macro avg
                                       0.80
                                                 9769
                             0.80
weighted avg
                   0.80
In [64]:
from sklearn.svm import SVC
from sklearn.svm import LinearSVC,SVC
from sklearn.pipeline import make_pipeline
clf = SVC(C = 1.2, gamma = 0.9, kernel= 'rbf')
In [65]:
clf = clf.fit(X train, y train)
In [66]:
y pred svc = clf.predict(X test)
In [67]:
#Finding best parameters for our SVC model
# from sklearn.model selection import train test split, GridSearchCV, cross val score
# param = { 'C': [1],
     'gamma': [1],
     'kernel': ['rbf','linear','sigmoid'] }
# grid = GridSearchCV(SVC(), param, refit = True,cv=3, verbose = 3,n jobs=-1)
In [68]:
# grid.fit(X train, y train)
In [69]:
accuracy score(y test, y pred svc)
Out[69]:
0.7606715119254785
In [70]:
from sklearn.metrics import classification report
print(classification report(y test, y pred svc))
              precision
                        recall f1-score support
```

```
1
                  1.00
                           0.00
                                      0.00
                                                2340
   accuracy
                                      0.76
                                                9769
                 0.88
                          0.50
                                     0.43
  macro avq
                                               9769
                                     0.66
weighted avg
                 0.82
                           0.76
                                               9769
In [71]:
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X train scaled = scaler.fit transform(X train)
X test scaled = scaler.fit transform(X test)
In [72]:
log reg scaled = LogisticRegression()
log reg scaled.fit(X train scaled, y train)
Out[72]:
▼ LogisticRegression
LogisticRegression()
In [73]:
y pred logreg scaled = log reg scaled.predict(X test scaled)
In [74]:
accuracy score(y test, y pred logreg scaled)
Out[74]:
0.8231139318251612
In [75]:
print('=====Classification Report of Logistic Regression with Scaled Data========')
print(classification report(y test, y pred logreg scaled))
======Classification Report of Logistic Regression with Scaled Data======
             precision
                       recall f1-score support
                           0.94
                                     0.89
          \cap
                  0.84
                                                7429
          1
                  0.71
                           0.44
                                      0.54
                                                2340
                                      0.82
                                                9769
   accuracy
                 0.78 0.69
                                     0.72
                                                9769
  macro avg
                 0.81
                           0.82
                                     0.81
                                                9769
weighted avg
In [76]:
dt scaled = DecisionTreeClassifier()
dt scaled.fit(X train scaled,y train)
Out[76]:
▼ DecisionTreeClassifier
DecisionTreeClassifier()
In [77]:
y_pred_dt_scaled = dt_scaled.predict(X_test_scaled)
accuracy_score(y_test, y_pred_dt_scaled)
```

0

Out[77]:

0.76

1.00

0.86

7429

```
In [78]:
from sklearn.metrics import classification report
print('=====Classification Report of Decision Tree Classifier with Scaled Data======
print(classification report(y test, y pred dt scaled))
======Classification Report of Decision Tree Classifier with Scaled Data=======
             precision recall f1-score support
                  0.87
                           0.87
                                     0.87
                                               7429
                  0.59
                            0.60
                                     0.59
                                               2340
                                     0.80
                                               9769
   accuracy
                                    0.73
                 0.73 0.73
                                               9769
  macro avg
                 0.80
                           0.80
                                    0.80
                                               9769
weighted avg
In [90]:
from sklearn.svm import SVC
from sklearn.svm import LinearSVC,SVC
from sklearn.pipeline import make pipeline
clf_scaled = SVC(C = 1.2, gamma = 0.9, kernel= 'rbf', probability=True)
In [91]:
clf scaled = clf scaled.fit(X train scaled,y train)
In [92]:
y pred svc scaled = clf scaled.predict(X test scaled)
In [96]:
accuracy score(y test, y pred svc scaled)
Out[96]:
0.8451223257242297
In [94]:
print('=====Classification Report of Support Vector Classifier with Scaled Data=====
==== ' )
print(classification report(y test, y pred svc scaled))
======Classification Report of Support Vector Classifier with Scaled Data=======
                        recall f1-score
             precision
                                           support
          0
                  0.87
                           0.94
                                    0.90
                                               7429
          1
                  0.73
                           0.56
                                    0.63
                                               2340
                                     0.85
                                               9769
   accuracy
                       0.75
                  0.80
                                     0.77
                                               9769
  macro avg
                  0.84
                           0.85
                                     0.84
                                               9769
weighted avg
In [100]:
```

```
#ROC Curve
from sklearn.metrics import roc_curve
y_pred_prob1 = log_reg_scaled.predict_proba(X_test)[:,1]
fpr1 , tpr1, thresholds1 = roc_curve(y_test, y_pred_prob1)

y_pred_prob2 = dt_scaled.predict_proba(X_test)[:,1]
fpr2 , tpr2, thresholds2 = roc_curve(y_test, y_pred_prob2)
```

```
y_pred_prob3 = clf_scaled.predict_proba(X_test)[:,1]
fpr3 , tpr3, thresholds3 = roc_curve(y_test, y_pred_prob3)

# plt.plot([0,1],[0,1], 'k--')
plt.plot(fpr1, tpr1, label= "Logistic Regression")
plt.plot(fpr2, tpr2, label= "Decision Tree")
plt.plot(fpr3, tpr3, label= "SVC")

plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title('Receiver Operating Characteristic')
plt.show()
```

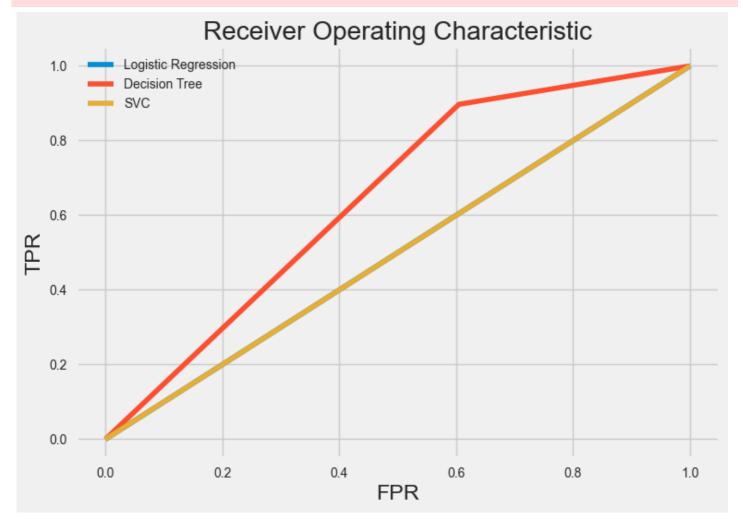
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\bas
e.py:443: UserWarning: X has feature names, but LogisticRegression was fitted without fea
ture names

warnings.warn(

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\bas
e.py:443: UserWarning: X has feature names, but DecisionTreeClassifier was fitted without
feature names

warnings.warn(

C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\bas
e.py:443: UserWarning: X has feature names, but SVC was fitted without feature names
warnings.warn(



# In [99]:

```
from sklearn.metrics import roc_auc_score

# auc scores
auc_score1 = roc_auc_score(y_test, y_pred_prob1)
auc_score2 = roc_auc_score(y_test, y_pred_prob2)
auc_score3 = roc_auc_score(y_test, y_pred_prob3)
print(auc_score1,auc_score2,auc_score3)
```

#### 0.5 0.6462428655085809 0.5

That fact that auc score of Logistic Regression and SVC are same so they got overlapped

# Summary:

Build various models like logistic regression, Decision Tree classifier, support vector classifier that gave accuracy: 79%, 80%, 76%, without hyperparameter tuning.

With scaling of the Train and Test data, the accuracy was improved for logistic regression, Decision Tree classifier, support vector classifier to 82%, 80%, 85% respectively.

In [ ]: