Adult Census Income Prediction Project

Problem Statement

• The Goal is to predict whether a person has an income of more than 50K a year or not. • This is basically a binary classification problem where a person is classified into the >50K group or <=50K group.

Import Libraries

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import seaborn as sns
import missingno as mno
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import RandomOverSampler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

In [2]:

```
df = pd.read_csv("adult.csv", na_values="?", skipinitialspace = True)
df.head(5)
```

Out[2]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

Exploratory Data Analysis (EDA)

In [3]:

```
1 df.shape
```

Out[3]:

```
(32561, 15)
```

In [4]:

```
1 df.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       30725 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      30718 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  country         31978 non-null  object
 14  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [5]:

```
1 df.columns
```

Out[5]:

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'country', 'salar
y'],
      dtype='object')
```

In [6]:

```
1 df.dtypes
```

Out[6]:

```
age               int64
workclass        object
fnlwgt            int64
education        object
education-num     int64
marital-status   object
occupation       object
relationship     object
race             object
sex              object
capital-gain      int64
capital-loss      int64
hours-per-week    int64
country          object
salary           object
dtype: object
```

In [7]:

```
1 df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	
age	32561.0	38.581647	13.640433	17.0	28.0	37.0	48.0	
fnlwgt	32561.0	189778.366512	105549.977697	12285.0	117827.0	178356.0	237051.0	14
education-num	32561.0	10.080679	2.572720	1.0	9.0	10.0	12.0	
capital-gain	32561.0	1077.648844	7385.292085	0.0	0.0	0.0	0.0	
capital-loss	32561.0	87.303830	402.960219	0.0	0.0	0.0	0.0	
hours-per-week	32561.0	40.437456	12.347429	1.0	40.0	40.0	45.0	

In [8]:

```
1 df.isnull().sum()
```

Out[8]:

```
age                0
workclass       1836
fnlwgt             0
education          0
education-num      0
marital-status     0
occupation      1843
relationship       0
race               0
sex                0
capital-gain       0
capital-loss       0
hours-per-week     0
country          583
salary             0
dtype: int64
```

In [9]:

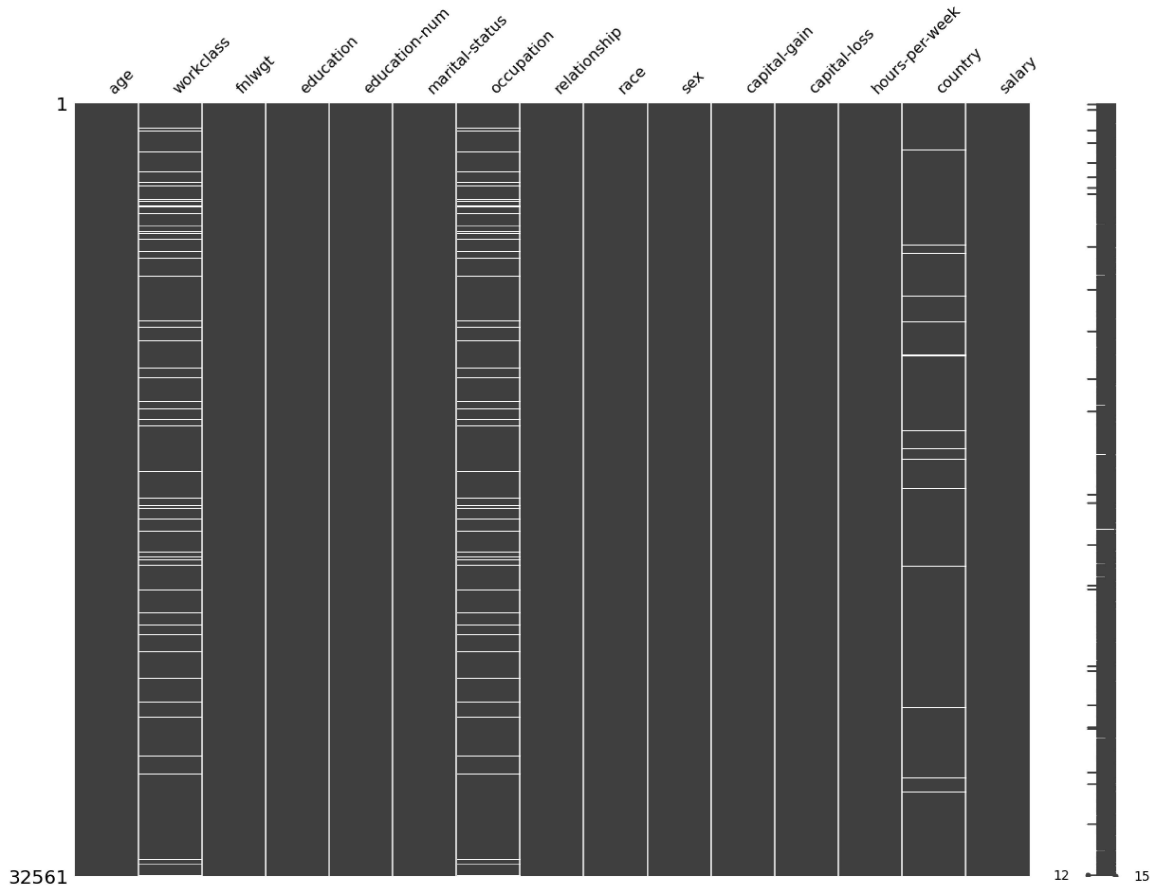
```
1 round(df.isnull().sum() / df.shape[0] * 100, 2).astype(str) + "%"
```

Out[9]:

```
age               0.0%
workclass         5.64%
fnlwgt            0.0%
education         0.0%
education-num     0.0%
marital-status    0.0%
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%
country           1.79%
salary            0.0%
dtype: object
```

In [10]:

```
mno.matrix(df, figsize = (20,15))
plt.show()
```



In [11]:

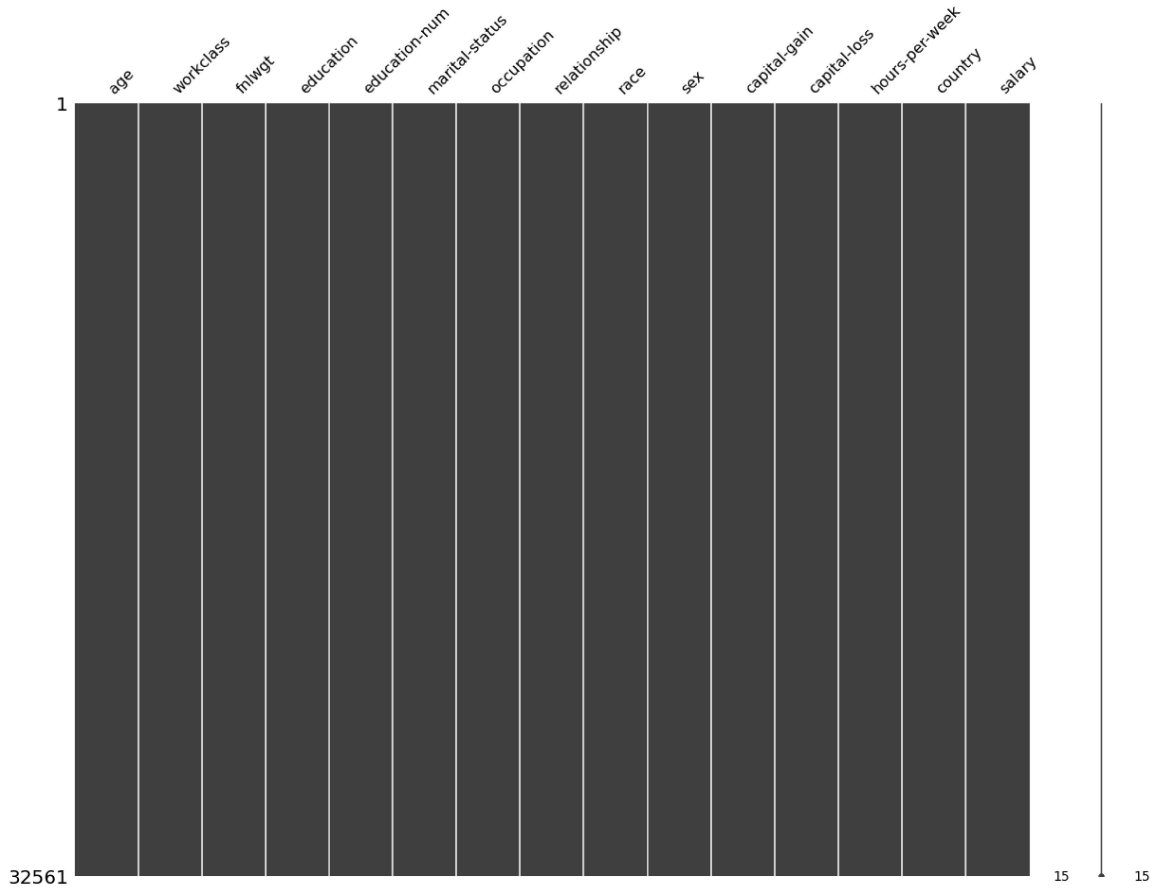
```
nan_values_columns = ['workclass', 'occupation', 'country']
```

In [12]:

```
for col in nan_values_columns:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

In [13]:

```
1 mno.matrix(df, figsize = (20,15))
2 plt.show()
```



In [14]:

```
1 df.nunique()
```

Out[14]:

```
age                73
workclass           8
fnlwgt          21648
education          16
education-num      16
marital-status      7
occupation         14
relationship        6
race                5
sex                 2
capital-gain      119
capital-loss       92
hours-per-week     94
country            41
salary              2
dtype: int64
```

In [15]:

```
round(df.nunique() / df.shape[0] * 100, 2).astype(str) + "%"
```

Out[15]:

```
age               0.22%
workclass         0.02%
fnlwgt           66.48%
education         0.05%
education-num     0.05%
marital-status    0.02%
occupation        0.04%
relationship      0.02%
race              0.02%
sex               0.01%
capital-gain      0.37%
capital-loss      0.28%
hours-per-week    0.29%
country           0.13%
salary            0.01%
dtype: object
```

In [16]:

```
df.duplicated().sum()
```

Out[16]:

```
24
```

In [17]:

```
df = df.drop_duplicates()
df.head(5)
```

Out[17]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

In [18]:

```
df.shape
```

Out[18]:

```
(32537, 15)
```

In [19]:

```
salary = df['salary'].value_counts(normalize=True)
round(salary * 100, 2).astype('str') + ' %'
```

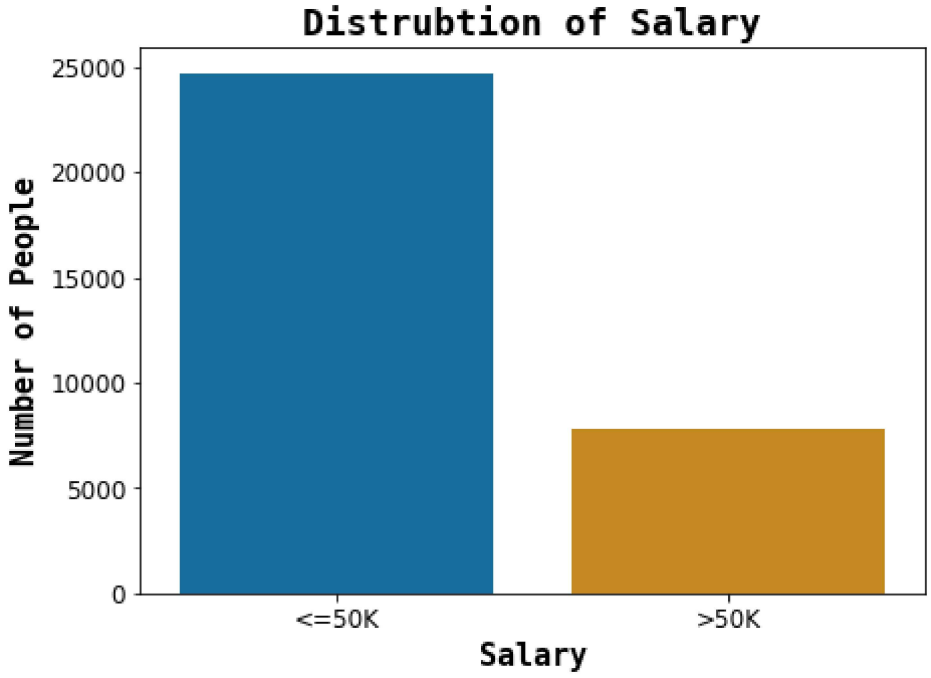
Out[19]:

```
<=50K    75.91 %
>50K     24.09 %
Name: salary, dtype: object
```

Data Visualization

In [20]:

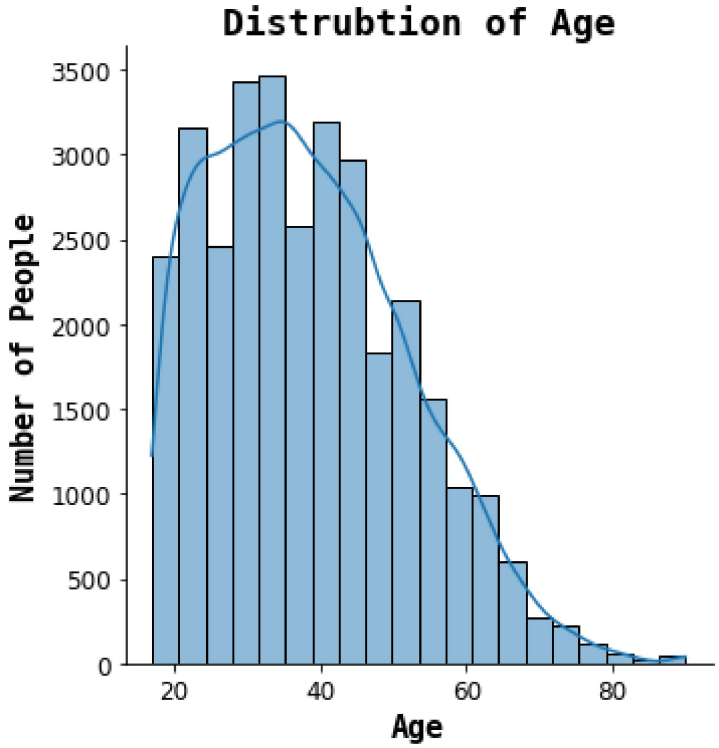
```
# barplot plot for 'Age'
salary= df['salary'].value_counts()

plt.figure(figsize=(7,5))
plt.tick_params(labelsize=12)
sns.barplot(salary.index, salary.values, palette='colorblind')
plt.title('Distrubtion of Salary', fontdict={
    'fontname':'Monospace', 'fontsize':18, 'fontweight':'bold'})
plt.xlabel('Salary', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.show()
```



In [21]:

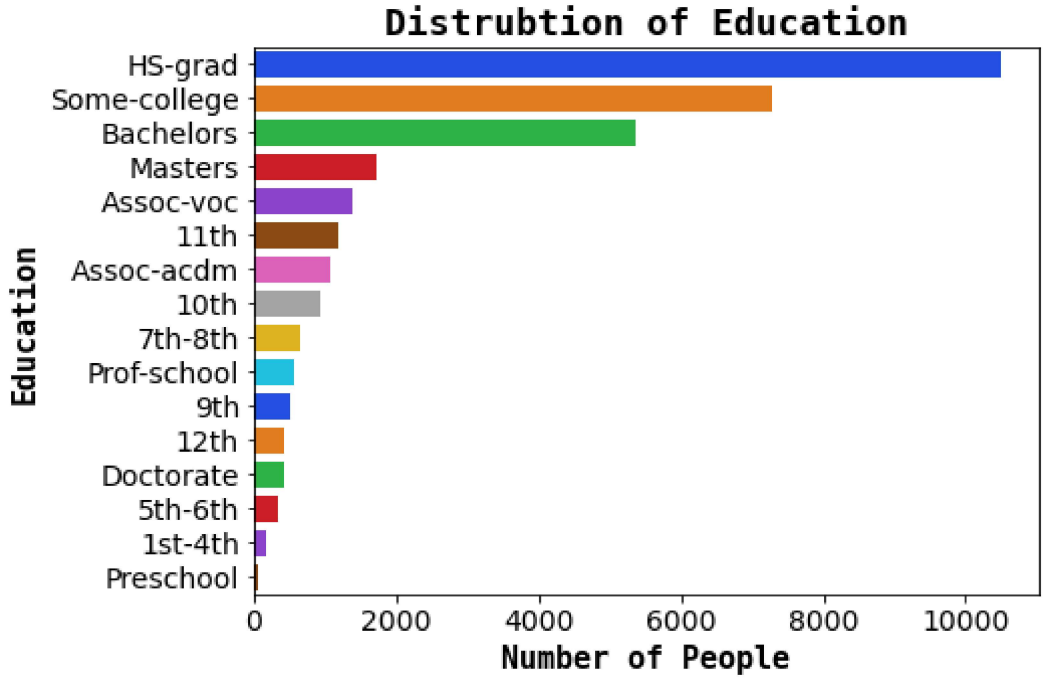
```
# distribution plot for 'Age'
age = df['age'].value_counts()

plt.figure(figsize=(20,15))
sns.displot(df['age'], bins=20, kde=True)
plt.title('Distrubtion of Age', fontdict={
    'fontname':'Monospace', 'fontsize':18, 'fontweight':'bold'})
plt.xlabel('Age', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.tick_params(labelsize=12)
plt.show()
```

```
<Figure size 1440x1080 with 0 Axes>
```



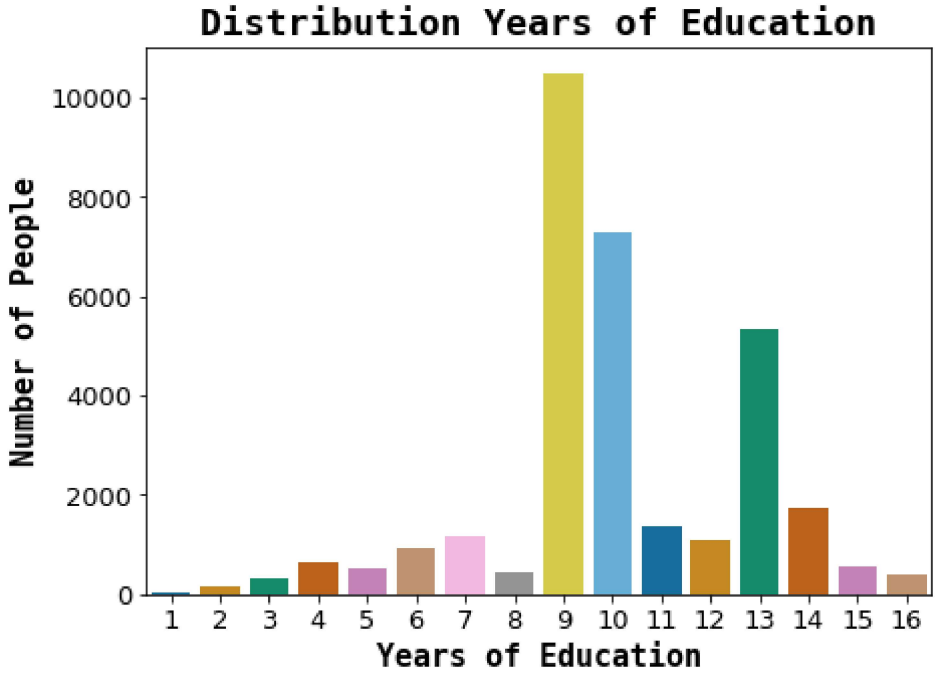
In [22]:

```
# Barplot for "Education"
education = df['education'].value_counts()

plt.figure(figsize=(7,5))
sns.barplot(education.values, education.index, palette='bright')
plt.title('Distrubtion of Education', fontdict={
    'fontname':'Monospace', 'fontsize':18, 'fontweight':'bold'})
plt.xlabel("Number of People", fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.ylabel("Education", fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.tick_params(labelsize=14)
plt.show()
```



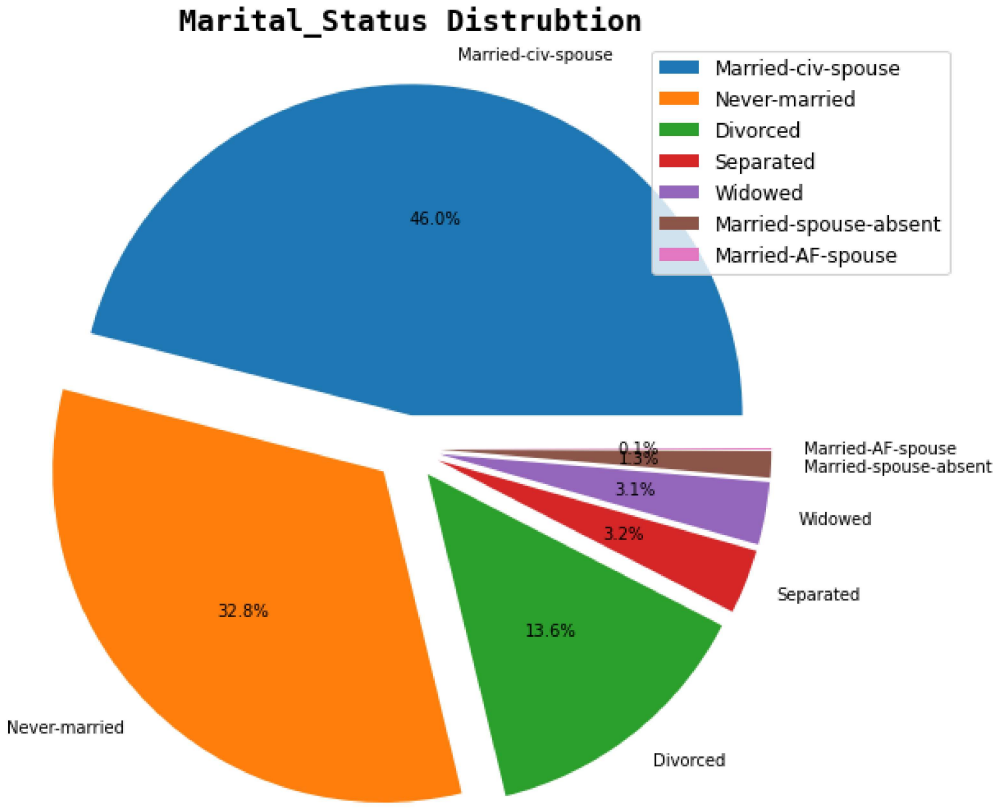
In [23]:

```
# Barplot for "Years of Education"

education_num = df['education-num'].value_counts()
plt.figure(figsize=(7,5))
sns.barplot(education_num.index, education_num.values, palette='colorblind')
plt.title('Distribution Years of Education', fontdict={
    'fontname': 'Monospace', 'fontsize': 18, 'fontweight': 'bold'})
plt.xlabel('Years of Education', fontdict={
    'fontname': 'Monospace', 'fontsize': 15, 'fontweight': 'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname': 'Monospace', 'fontsize': 15, 'fontweight': 'bold'})
plt.tick_params(labelsize=13)
plt.show()
```



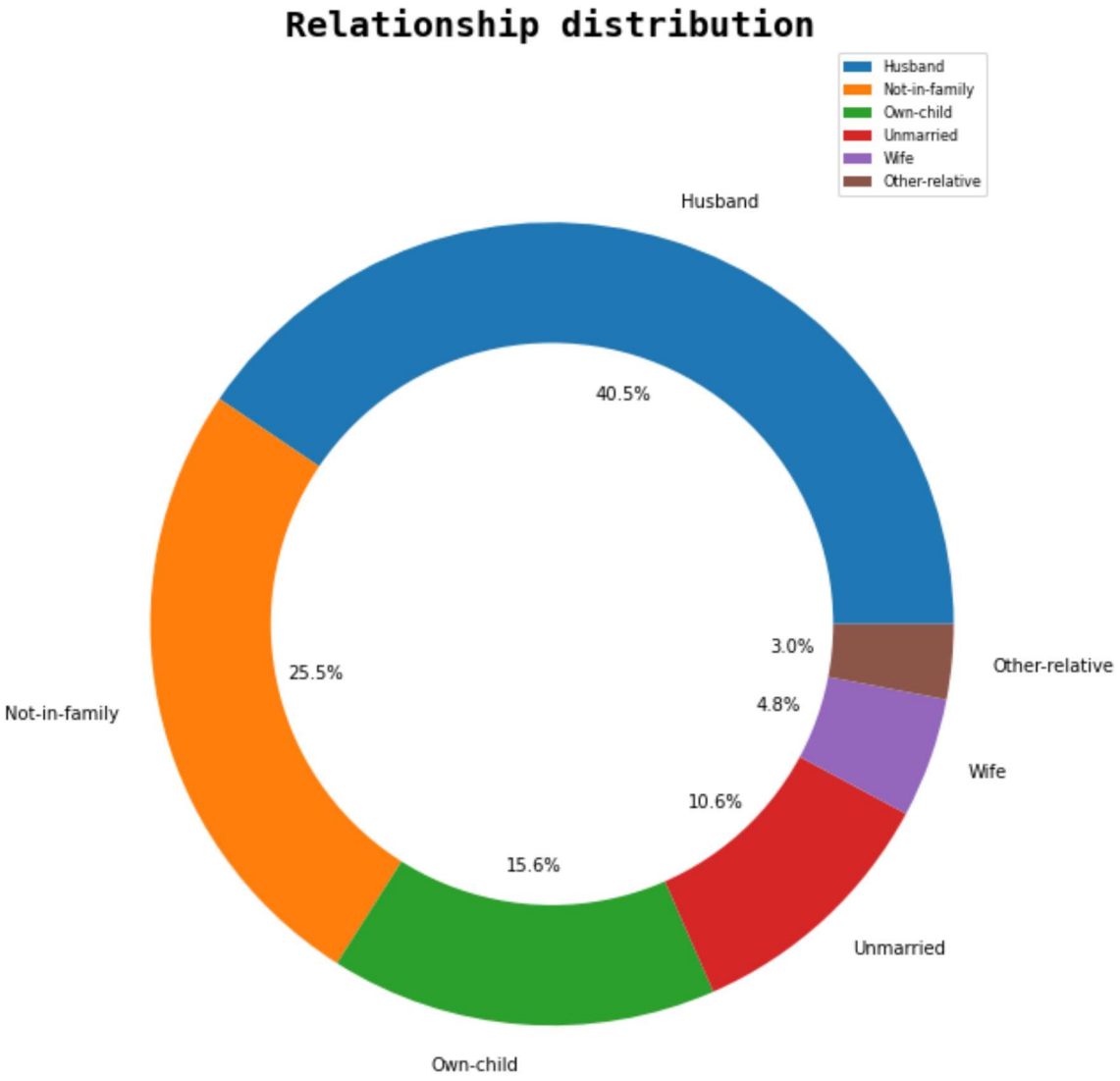
In [24]:

```
# Pie chart for "Marital Status"
marital = df['marital-status'].value_counts()

plt.figure(figsize=(12,9))
plt.pie(marital.values, labels=marital.index,
        explode=(0.10,0.10,0.10,0.10,0.10,0.10,0.10), autopct='%1.1f%%')
plt.title("Marital_Status Distrubtion",fontdict={
    'fontname': 'Monospace', 'fontsize': 18, 'fontweight': 'bold'})
plt.legend()
plt.legend(prop={'size':12})
plt.axis('equal')
plt.show()
```



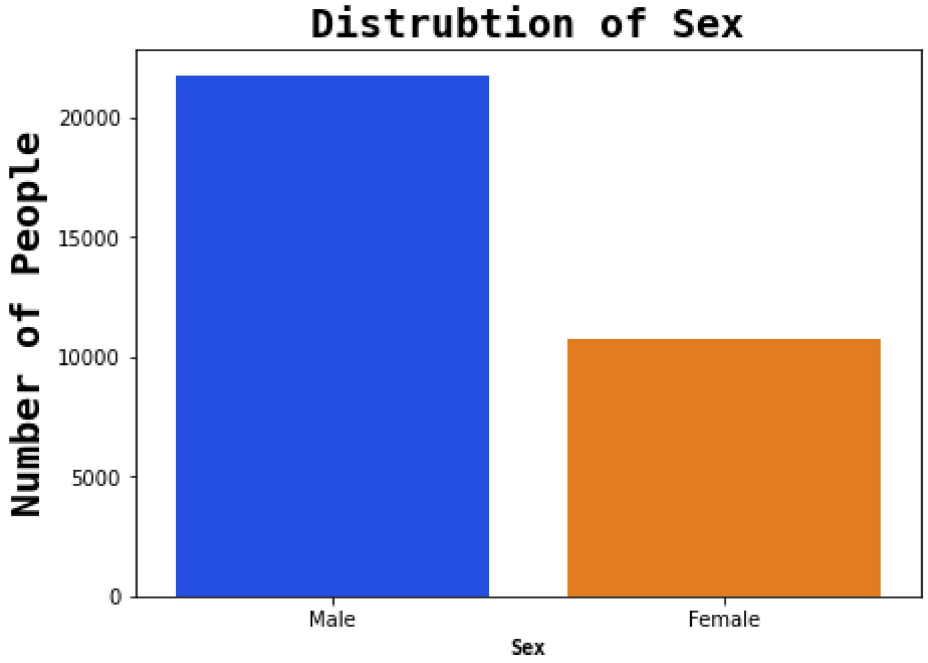
In [25]:

```
# Chart for 'Age'
relationship = df['relationship'].value_counts()

plt.figure(figsize=(9,12))
plt.pie(relationship.values,
        labels=relationship.index,
        autopct='%1.1f%%')
center_part_circle = plt.Circle((0,0), 0.7, fc='White')
plt.title('Relationship distribution', fontdict={
    'fontname': 'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
fig = plt.gcf()
fig.gca().add_artist(center_part_circle)
plt.axis('equal')
plt.legend(prop={'size':8})
plt.show()
```



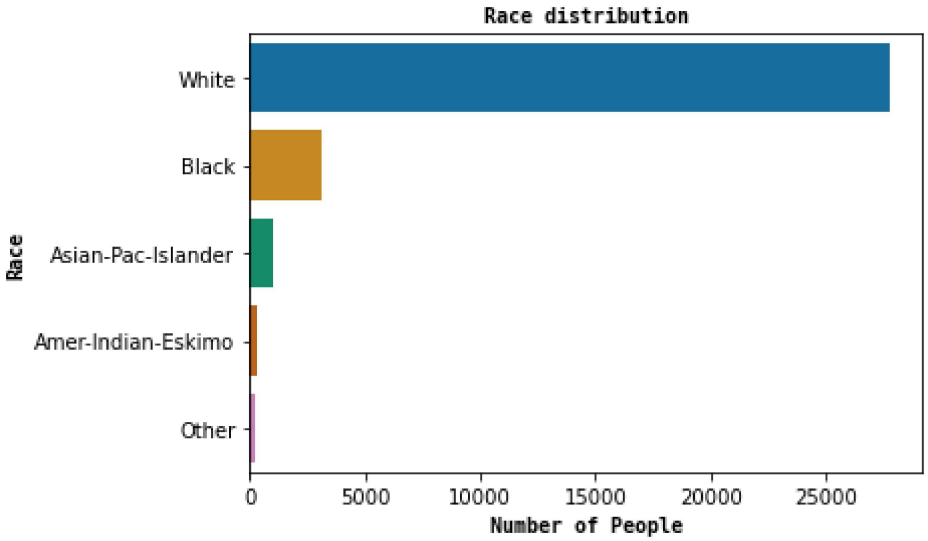
In [26]:

```
# borplot for 'Sex'

sex = df['sex'].value_counts()
plt.figure(figsize=(7,5))
sns.barplot(sex.index, sex.values, palette='bright')
plt.title('Distrubtion of Sex', fontdict={
    'fontname': 'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
plt.xlabel('Sex', fontdict={
    'fontname': 'Monospace', 'fontsize': 10, 'fontweight': 'bold'})
plt.ylabel('Number of People',  fontdict={
    'fontname': 'Monospace', 'fontsize': 20, 'fontweight': 'bold'})
plt.tick_params(labelsize=10)
plt.show()
```



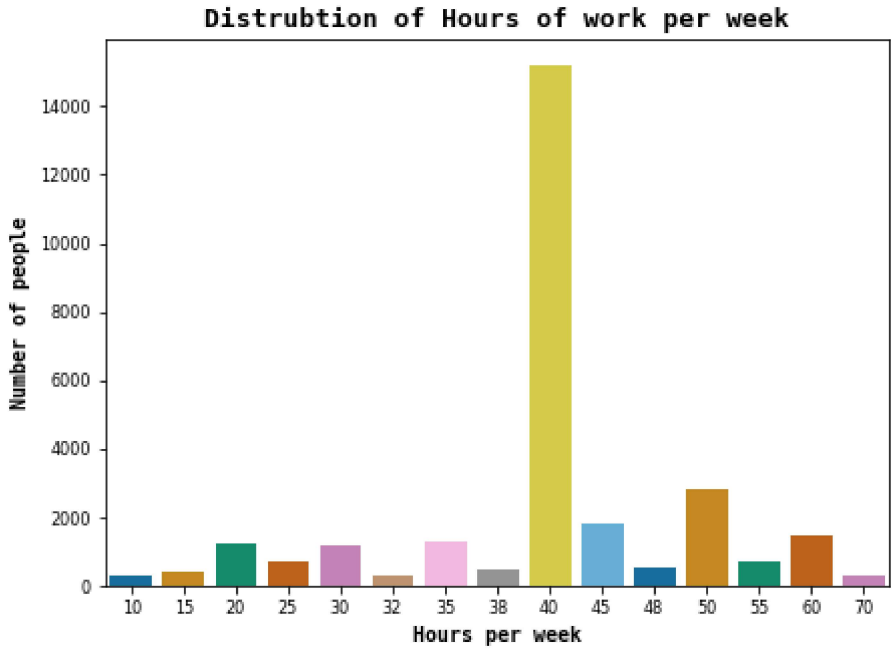
In [27]:

```
# barplot for 'Race'
race = df['race'].value_counts()

plt.figure(figsize=(6,4))
sns.barplot(race.values, race.index, palette='colorblind')
plt.title('Race distribution', fontdict={
    'fontname': 'Monospace', 'fontsize': 10, 'fontweight': 'bold'})
plt.xlabel("Number of People", fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.ylabel("Race", fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.tick_params(labelsize=10)
plt.show()
```



In [28]:

```
# barplot for 'Hours per week'
hour = df['hours-per-week'].value_counts().head(15)

plt.figure(figsize=(7,5))
sns.barplot(hour.index, hour.values, palette='colorblind')
plt.title('Distrubtion of Hours of work per week', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.xlabel('Hours per week', fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.ylabel('Number of people', fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.tick_params(labelsize=8)
plt.show()
```

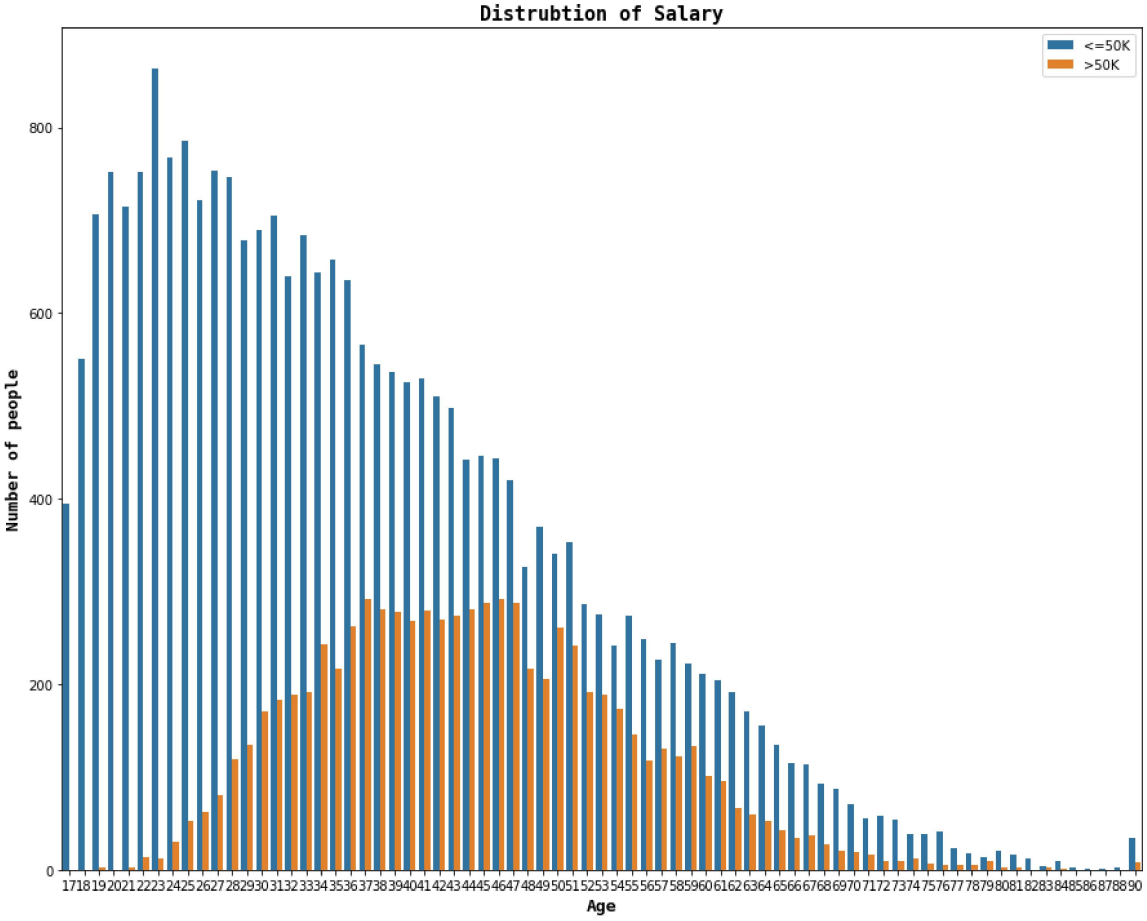


Bivariate Analysis

Bivariate analysis is a statistical technique used to analyze the relationship between two variables. In coding, bivariate analysis can be performed using a variety of programming languages and statistical software packages.

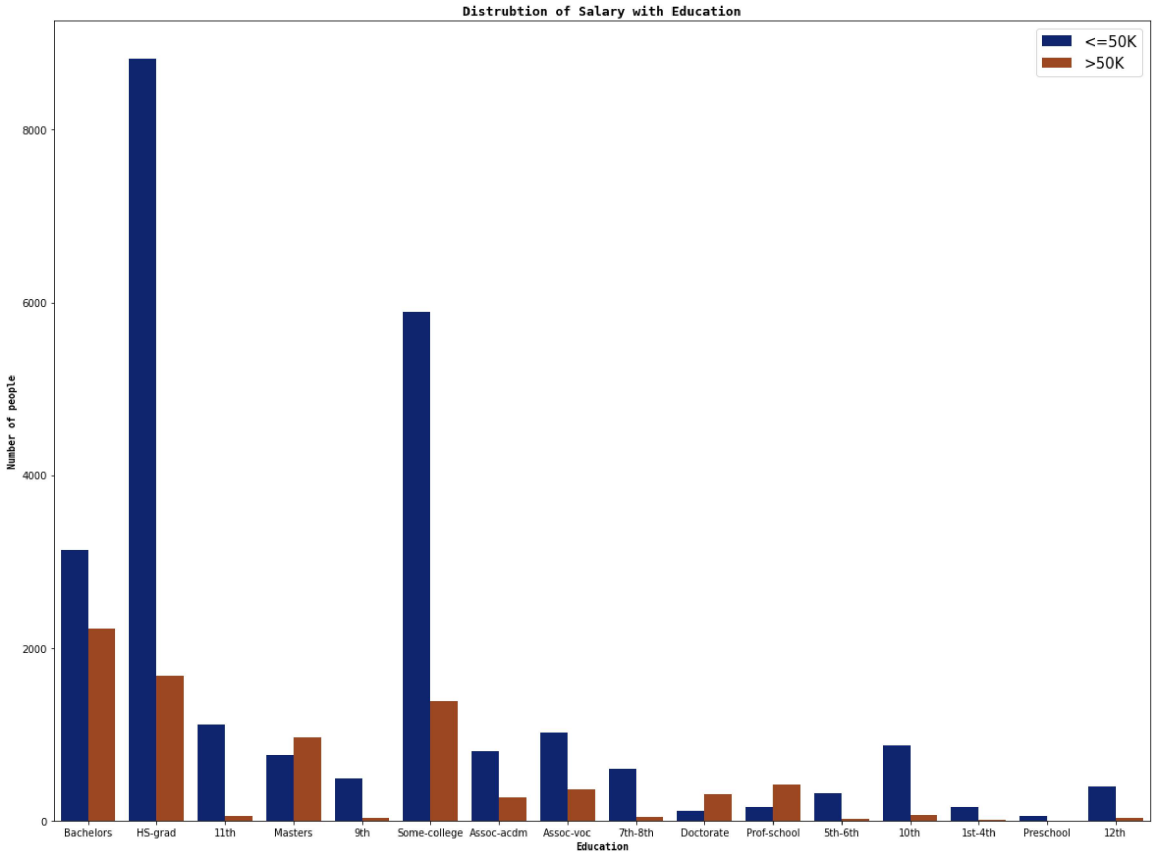
In [29]:

```
# Countplot of Salary with Age
plt.figure(figsize=(15,12))
sns.countplot(df['age'], hue=df['salary'])
plt.title('Distrubtion of Salary', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.xlabel('Age', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.ylabel('Number of people', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':10})
plt.tick_params(labelsize=10)
plt.show()
```



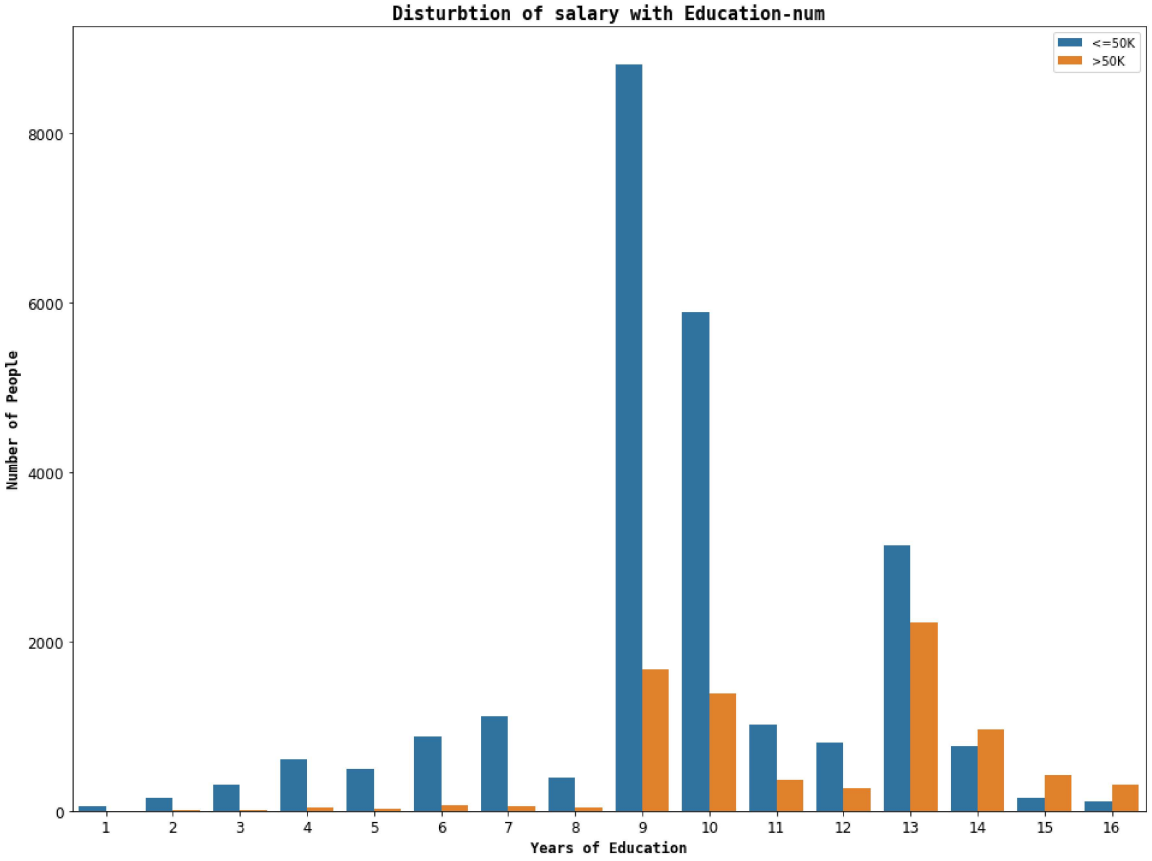
In [30]:

```
# countplot of salary by education

plt.figure(figsize=(20,15))
sns.countplot(df['education'],
              hue=df['salary'], palette='dark')
plt.title('Distrubtion of Salary with Education', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.xlabel('Education', fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.ylabel('Number of people',fontdict={
    'fontname':'Monospace', 'fontsize':10, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':15})
plt.tick_params(labelsize=10)
plt.show()
```



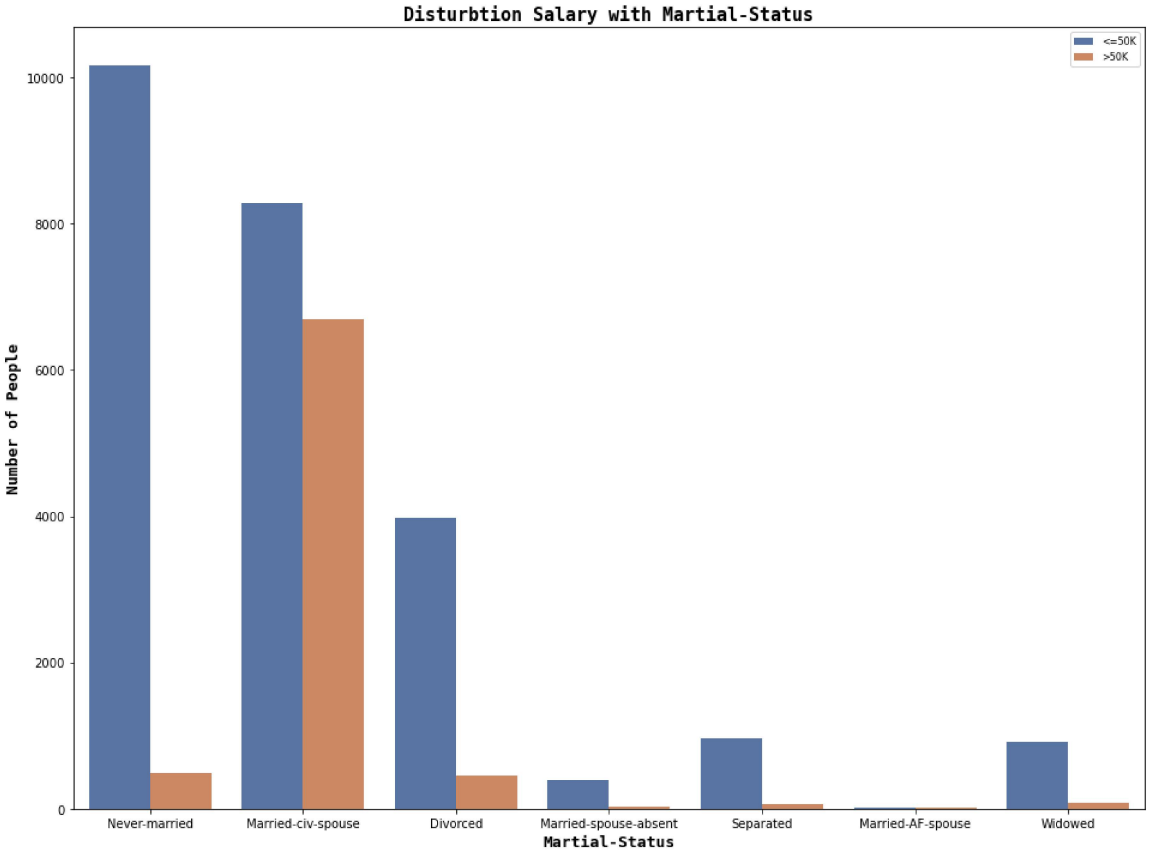
In [31]:

```
# Countplot of salary with years of Education-num

plt.figure(figsize=(16,12))
sns.countplot(df['education-num'], hue=df['salary'])
plt.title('Disturbtion of salary with Education-num', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.xlabel('Years of Education', fontdict={
    'fontname':'Monospace', 'fontsize':12, 'fontweight':'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname':'Monospace', 'fontsize':12, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':10})
plt.tick_params(labelsize=12)
plt.show()
```



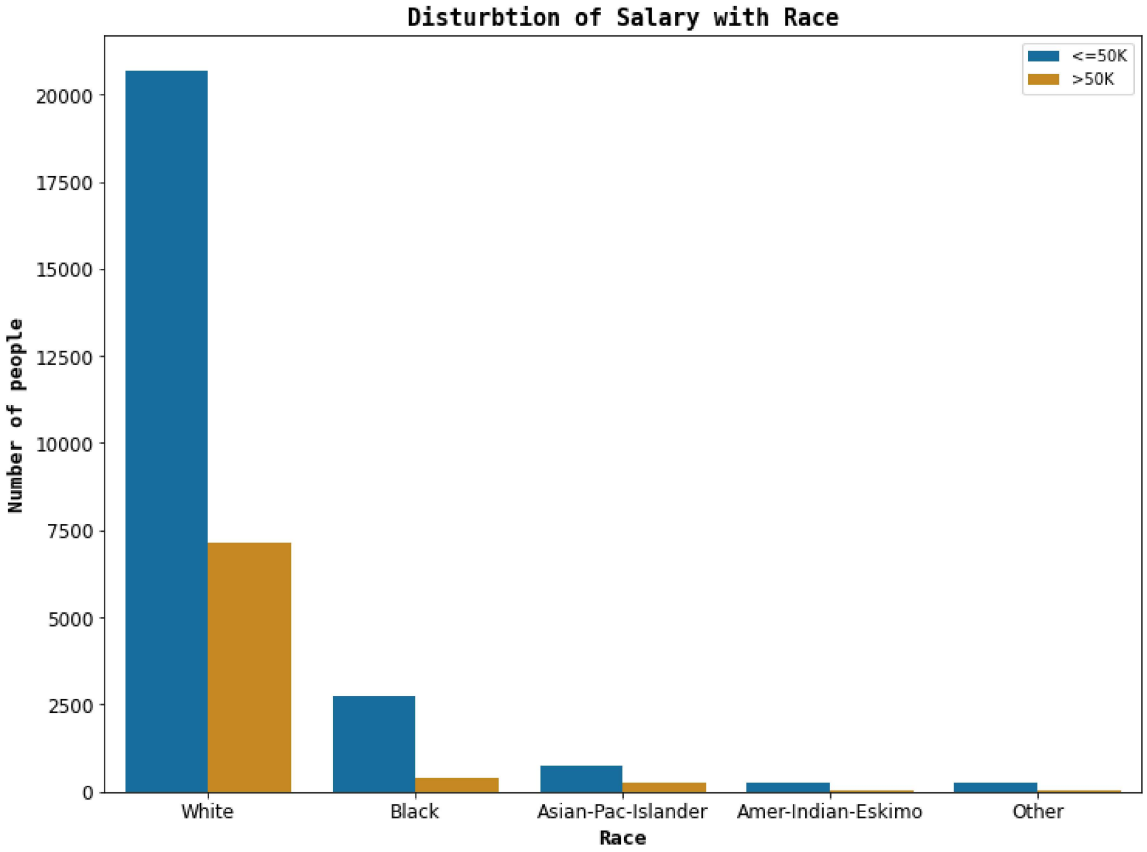
In [32]:

```
# creating of salary with Marital status

plt.figure(figsize=(16,12))
sns.countplot(df['marital-status'],
              hue=df['salary'], palette='deep')
plt.title('Disturbtion Salary with Martial-Status', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.xlabel('Martial-Status', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':8})
plt.tick_params(labelsize=10)
plt.show()
```



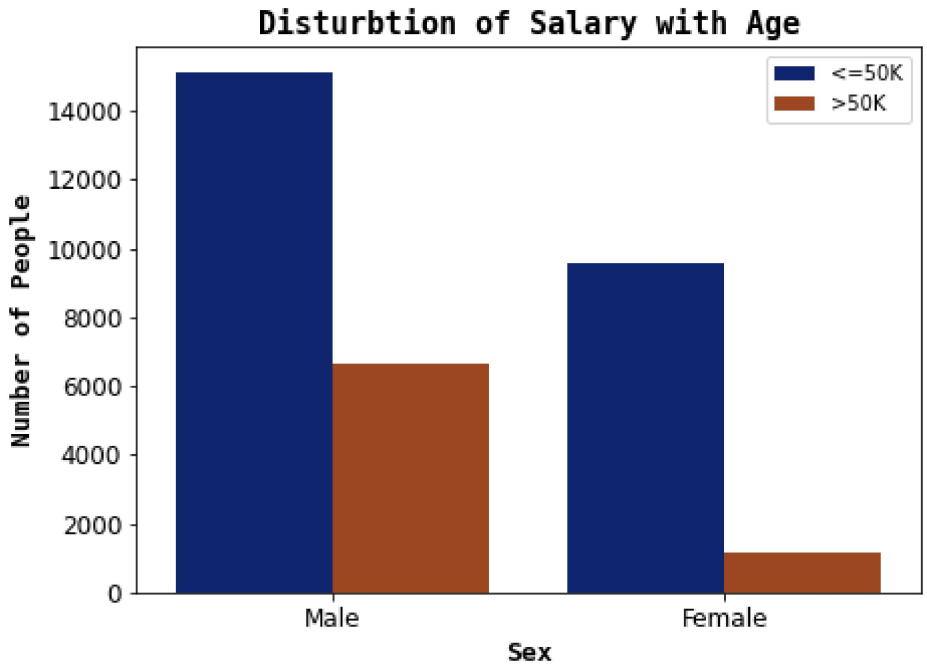
In [33]:

```
# creating countplot of salary with race

plt.figure(figsize=(12,9))
sns.countplot(df['race'],
              hue=df['salary'], palette='colorblind')
plt.title('Disturbtion of Salary with Race', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.xlabel('Race', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.ylabel('Number of people', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':10})
plt.tick_params(labelsize=12)
plt.show()
```



In [34]:

```
# creating countplot of salary with sex

plt.figure(figsize=(7,5))
sns.countplot(df['sex'],
              hue=df['salary'], palette='dark')
plt.title('Disturbtion of Salary with Age', fontdict={
    'fontname':'Monospace', 'fontsize':15, 'fontweight':'bold'})
plt.xlabel('Sex', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.ylabel('Number of People', fontdict={
    'fontname':'Monospace', 'fontsize':13, 'fontweight':'bold'})
plt.legend(loc=1, prop={'size':10})
plt.tick_params(labelsize=12)
plt.show()
```



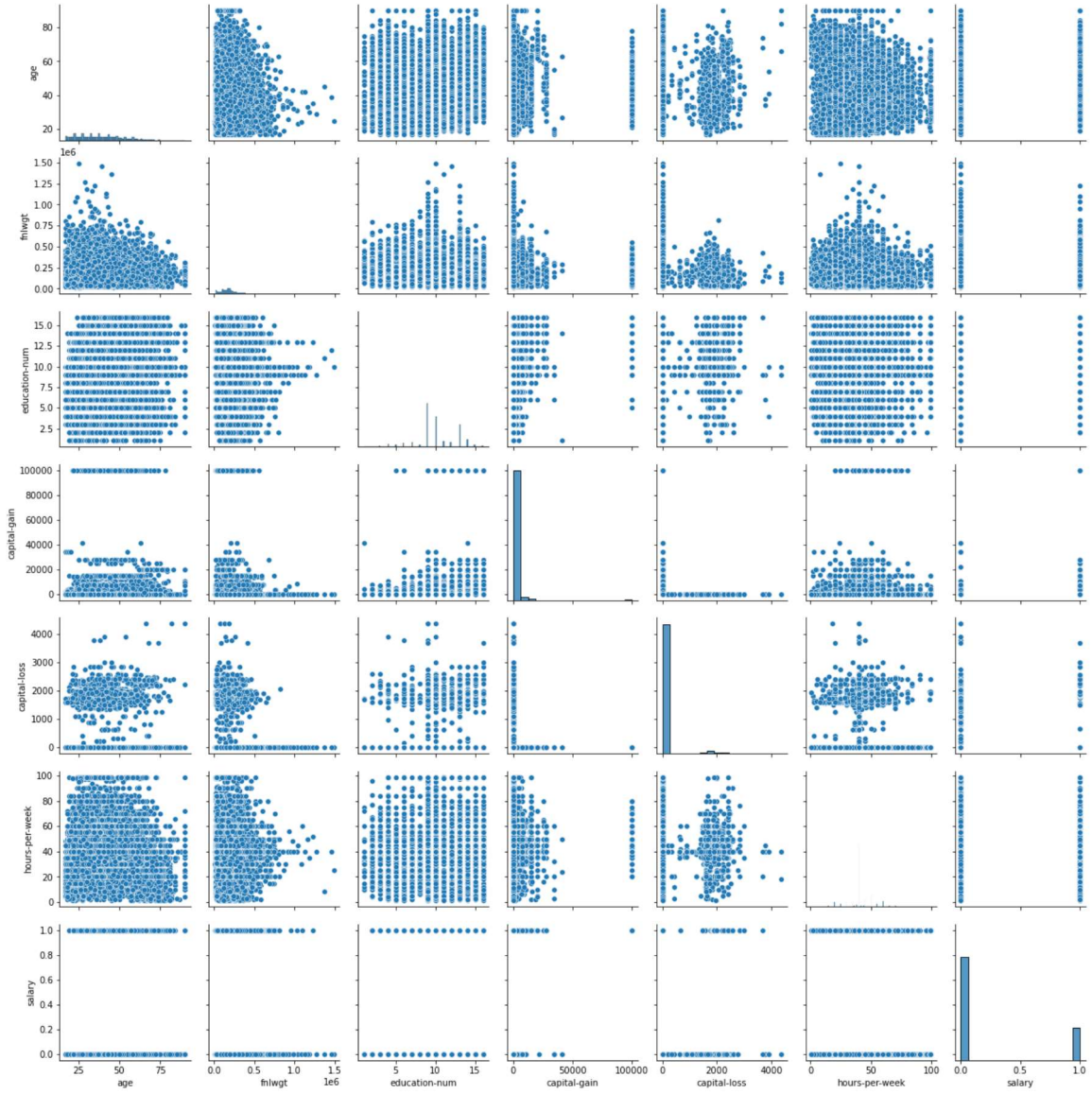
Multiple Plot with help of Pairplot

In [35]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['salary'] = le.fit_transform(df['salary'])
```

In [36]:

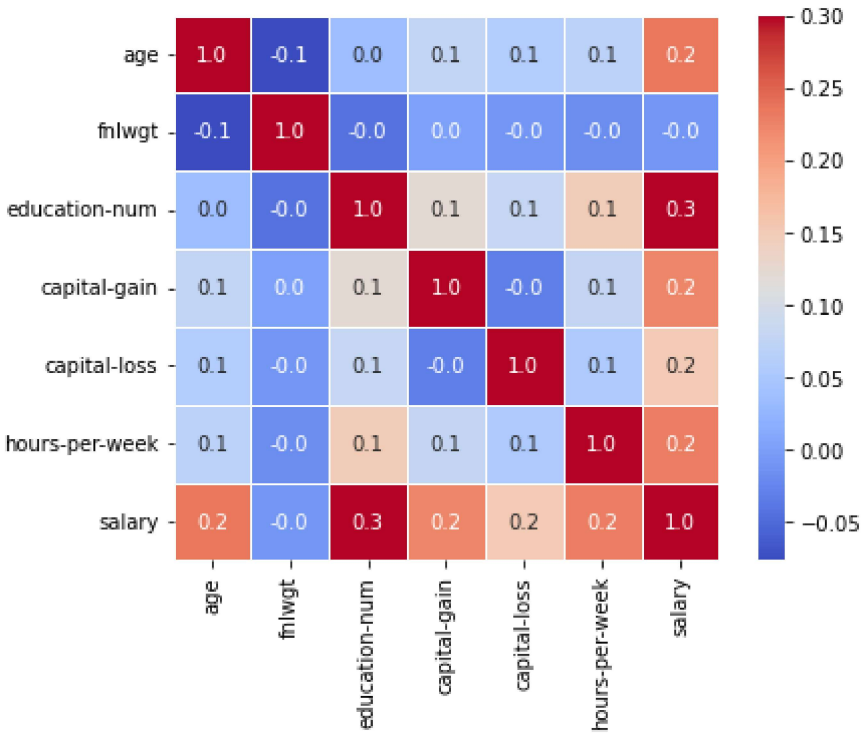
```
# pairplot of df (adult dataset)
sns.pairplot(df)
plt.show()
```



Correlation

In [37]:

```
# Correlation matrix

corr = df.corr()
f,ax = plt.subplots(figsize=(7,5))
sns.heatmap(corr, cbar = True, square = True, annot = True, fmt= '.1f',
            xticklabels= True, yticklabels= True, vmax=0.3,
            cmap="coolwarm", linewidths=.5, ax=ax)
plt.show()
```



LabelEncoder

In [38]:

```
for col in df.columns:
    if df[col].dtypes == 'object':
        encoder = LabelEncoder()
        df[col] = encoder.fit_transform(df[col])
```

In [39]:

```
X = df.drop('salary',axis=1)
Y = df['salary']
```

```
for col in X.columns:
    scaler = StandardScaler()
    X[col] = scaler.fit_transform(X[col].values.reshape(-1,1))
```

Modelling

In [40]:

```
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=42)
```

In [41]:

```
ros.fit(X, Y)
```

Out[41]:

▸ RandomOverSampler

In [42]:

```
X_resampled, Y_resampled = ros.fit_resample(X, Y)
```

In [43]:

```
round(Y_resampled.value_counts(normalize=True) * 100, 2).astype('str') + ' %'
```

Out[43]:

```
0    50.0 %
1    50.0 %
Name: salary, dtype: object
```

In [44]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(
X_resampled, Y_resampled, test_size=0.2, random_state=42)
```

In [45]:

```
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)
```

```
X_train shape: (39516, 14)
X_test shape: (9880, 14)
Y_train shape: (39516,)
Y_test shape: (9880,)
```

Logistic Regression

In [46]:

```
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(random_state=42)
```

In [47]:

```
log_reg.fit(X_train, Y_train)
```

Out[47]:

▸ LogisticRegression

In [48]:

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

In [49]:

```
print("Logistic Regression:")
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_log_reg)* 100, 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_log_reg) * 100, 2))
```

```
Logistic Regression:
Accuracy Score:  65.37
F1 Score:  63.23
```

KNN Classifier

In [50]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
```

In [51]:

```
knn.fit(X_train, Y_train)
```

Out[51]:

▸ KNeighborsClassifier

In [52]:

```
Y_pred_knn = knn.predict(X_test)
```

In [53]:

```
print('KNN Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_knn) * 100, 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_knn) * 100, 2))
```

```
KNN Classifier:
Accuracy Score:  72.75
F1 Score:  74.82
```

Support Vector Classifier (SVC)

In [54]:

```
from sklearn.svm import SVC
svc = SVC(random_state=42)
```

In [55]:

```
svc.fit(X_train, Y_train)
```

Out[55]:

▸ SVC

In [56]:

```
Y_pred_svc = svc.predict(X_test)
```

In [57]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_svc) * 100 , 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_svc) * 100 , 2))
```

```
Support Vector Classifier:
Accuracy Score:  59.23
F1 Score:  32.01
```

Naive Bayes Classifier

In [58]:

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
```

In [59]:

```
nb.fit(X_train, Y_train)
```

Out[59]:

▸ GaussianNB

In [60]:

```
Y_pred_nb = nb.predict(X_test)
```

In [61]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_nb) * 100, 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_nb) * 100 , 2))
```

```
Support Vector Classifier:
Accuracy Score:  62.59
F1 Score:  44.98
```

Decision Tree Classifier

In [62]:

```
from sklearn.tree import DecisionTreeClassifier
dec_tree = DecisionTreeClassifier(random_state=42)
```

In [63]:

```
dec_tree.fit(X_train, Y_train)
```

Out[63]:

▸ DecisionTreeClassifier

In [64]:

```
Y_pred_dec_tree = dec_tree.predict(X_test)
```

In [65]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_dec_tree)* 100, 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_dec_tree) * 100, 2))
```

```
Support Vector Classifier:
Accuracy Score:  91.13
F1 Score:  91.57
```

Random Forest Classifier

In [66]:

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(random_state=42)
```

In [67]:

```
rf.fit(X_train, Y_train)
```

Out[67]:

▸ RandomForestClassifier

In [68]:

```
Y_pred_rf = rf.predict(X_test)
```

In [69]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_rf) * 100 , 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_rf)* 100 , 2))
```

```
Support Vector Classifier:
Accuracy Score:  92.98
F1 Score:  93.23
```

XGB Classifier

In [70]:

```
from xgboost import XGBClassifier
xgb = XGBClassifier()
```

In [71]:

```
xgb.fit(X_train, Y_train)
```

Out[71]:

▸ XGBClassifier

In [72]:

```
Y_pred_xgb = xgb.predict(X_test)
```

In [73]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_xgb) * 100 , 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_xgb) * 100 , 2))
```

```
Support Vector Classifier:
Accuracy Score:  86.95
F1 Score:  87.33
```

AdaBoost Classifier

In [74]:

```
from sklearn.ensemble import AdaBoostClassifier
adaboost = AdaBoostClassifier(random_state=42)
```

In [75]:

```
adaboost.fit(X_train, Y_train)
```

Out[75]:

▸ AdaBoostClassifier

In [76]:

```
Y_pred_adaboost = adaboost.predict(X_test)
```

In [77]:

```
print('Support Vector Classifier: ')
print('Accuracy Score: ',
      round(accuracy_score(Y_test, Y_pred_adaboost) * 100, 2))
print('F1 Score: ',
      round(f1_score(Y_test, Y_pred_adaboost) * 100, 2))
```

```
Support Vector Classifier:
Accuracy Score:  82.18
F1 Score:  82.42
```

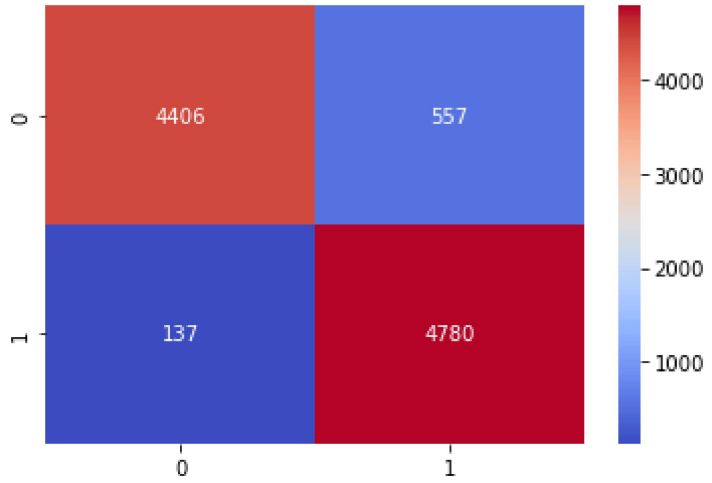
Confusion Matrix

In [78]:

```
from sklearn.metrics import confusion_matrix
con_mat = confusion_matrix(Y_test, Y_pred_rf)
```

In [79]:

```
sns.heatmap(con_mat, annot=True, cmap='coolwarm', fmt='d')
plt.show()
```



Classification Report

In [80]:

```
from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.97      0.89      0.93      4963
           1       0.90      0.97      0.93      4917

    accuracy                           0.93      9880
   macro avg       0.93      0.93      0.93      9880
weighted avg       0.93      0.93      0.93      9880
```

In [ ]:

```

```